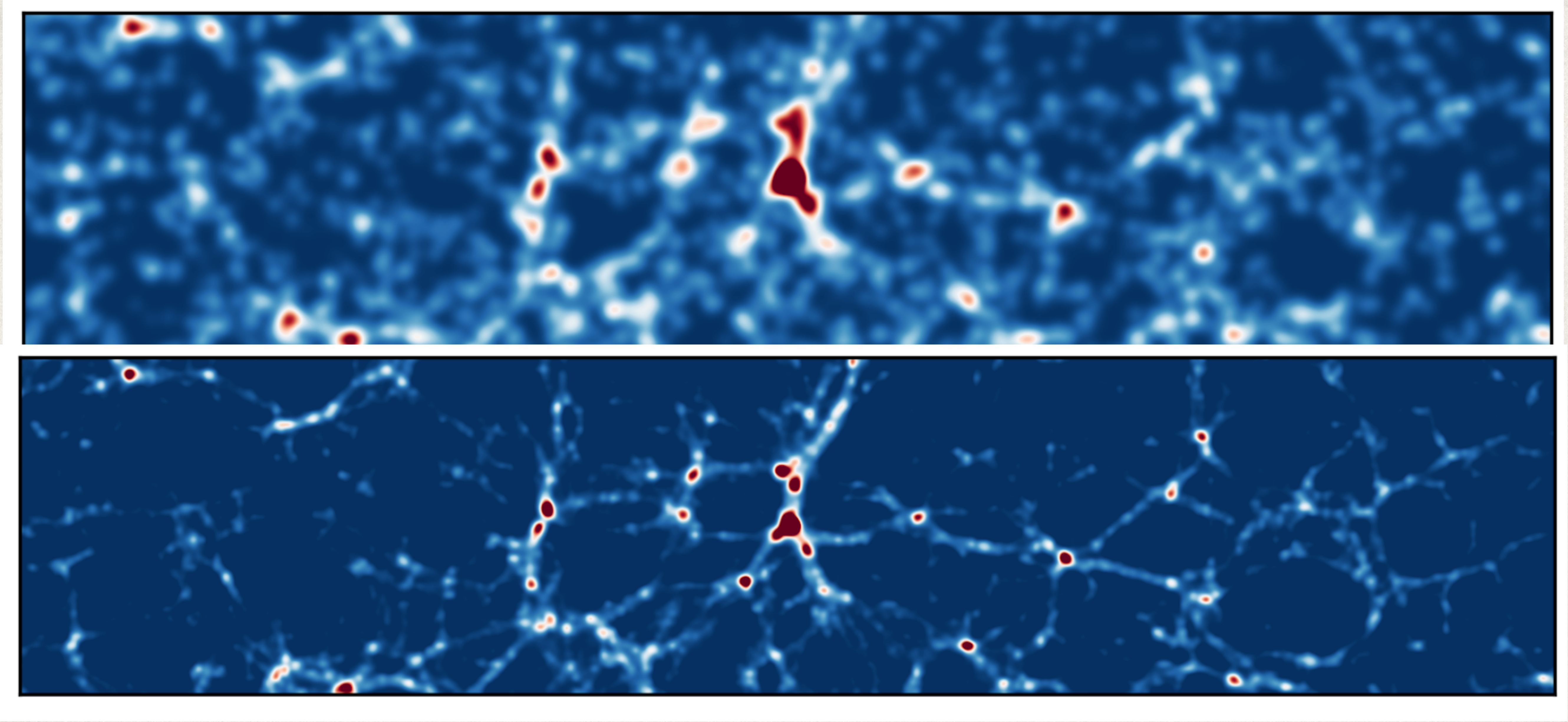


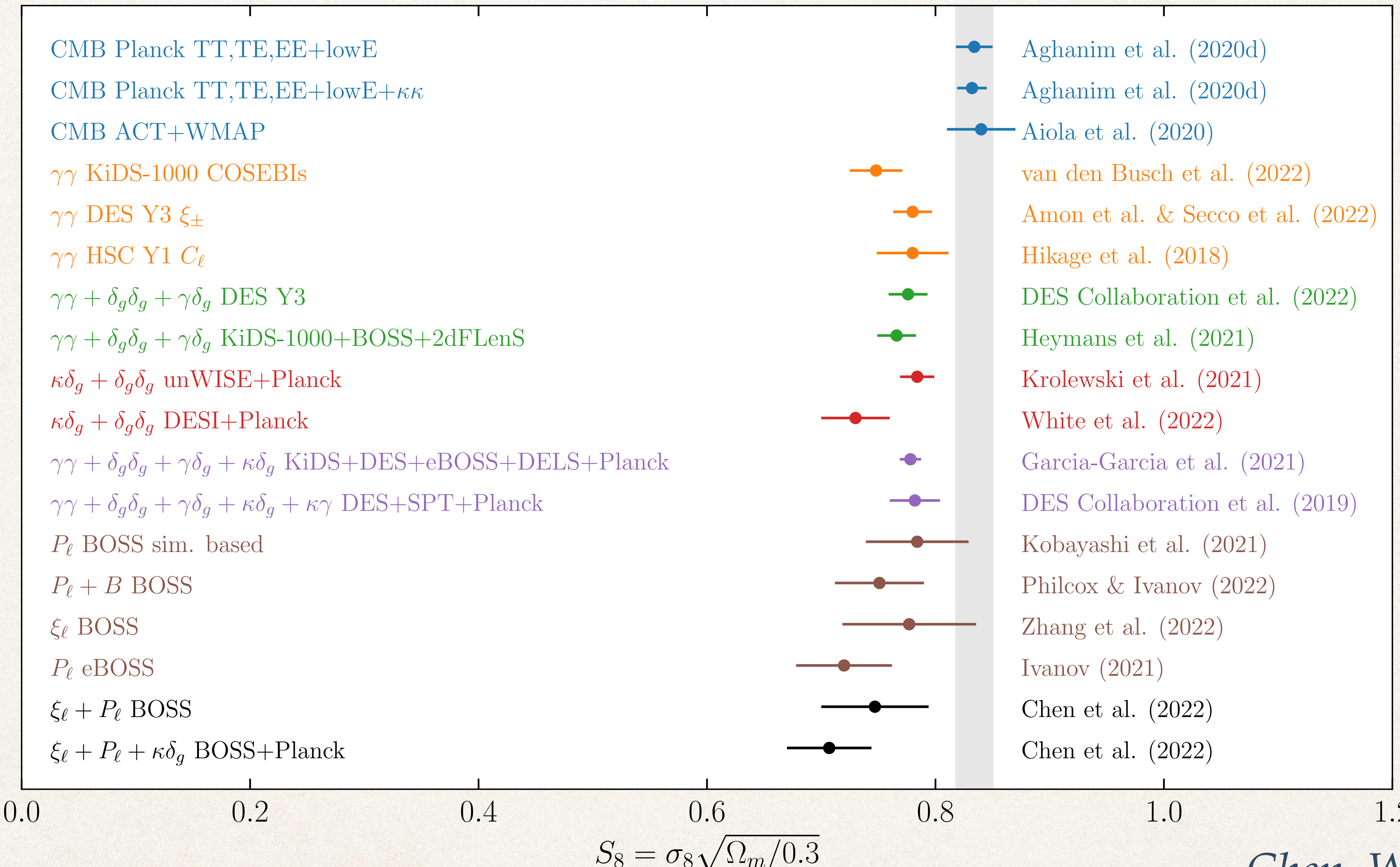
Combining Galaxy Clustering and Lensing with Hybrid EFT

Joe DeRose — Lawrence Berkeley National Laboratory

work with Nick Kokron, Stephen Chen, Martin White ++

11/10/22 — APEC Seminar — IPMU

Tension?



Chen, White, DeRose & Kokron 2022

Hints of tension between measurements of the amplitude of the matter power spectrum from the CMB and from galaxy surveys.

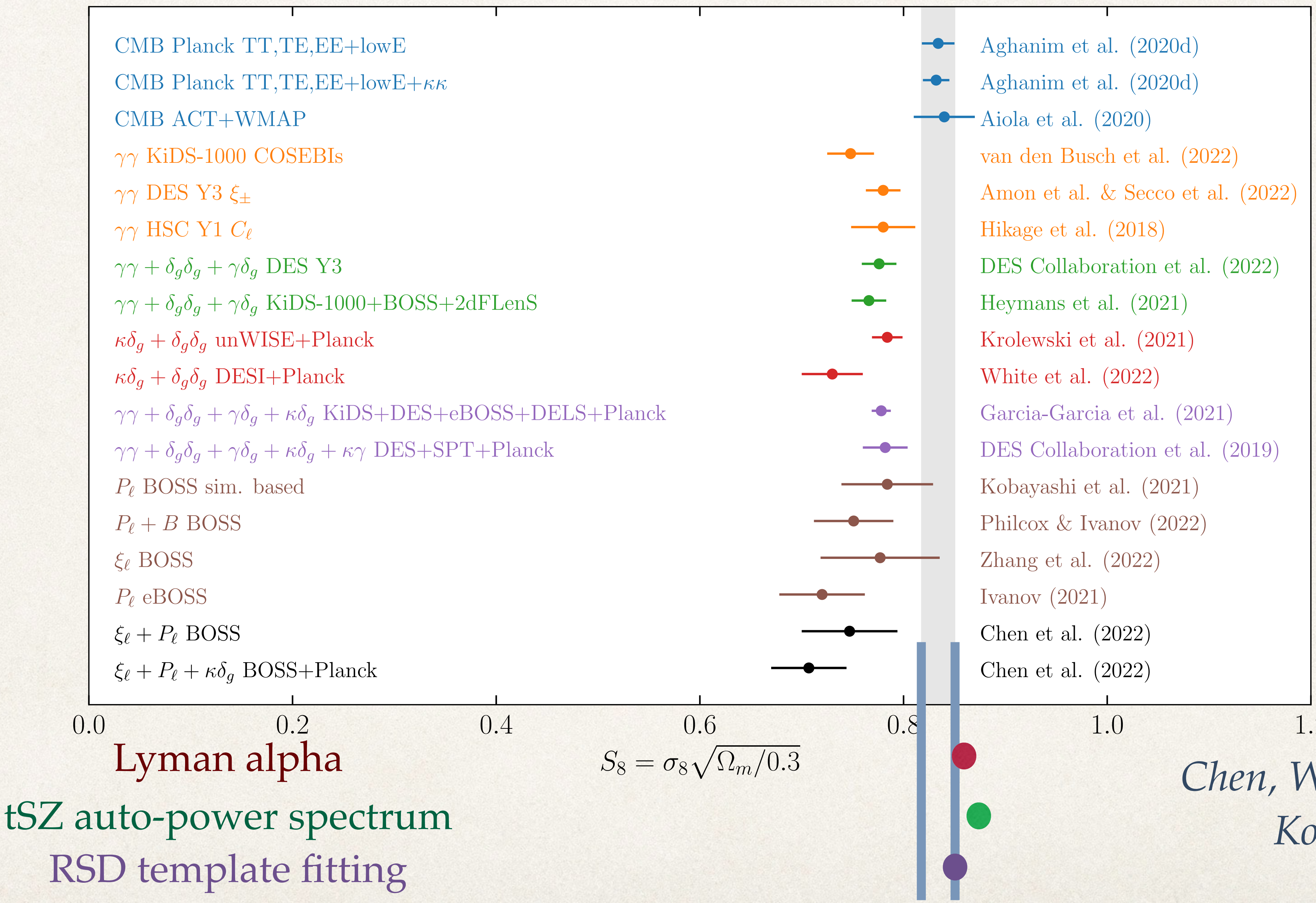
Why might this be interesting?

The growth of large scale structure is a competition between the expansion of the universe and gravitational collapse.

- Depends on law of gravity
- Expansion sensitive to metric (curvature)
- Depends on mass/energy density of particle species

- CMB fits predict growth of structure from snapshot of early universe.
- Use LSS to compare to this prediction, differences have implications for all of the above.

Tension?

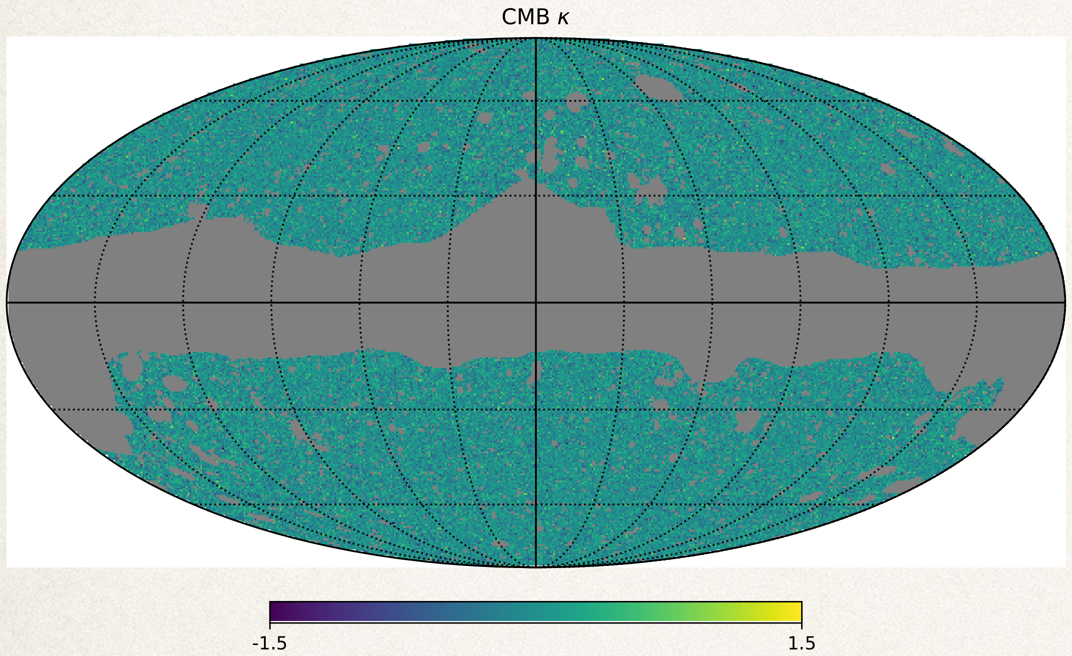


Chen, White, DeRose & Kokron 2022

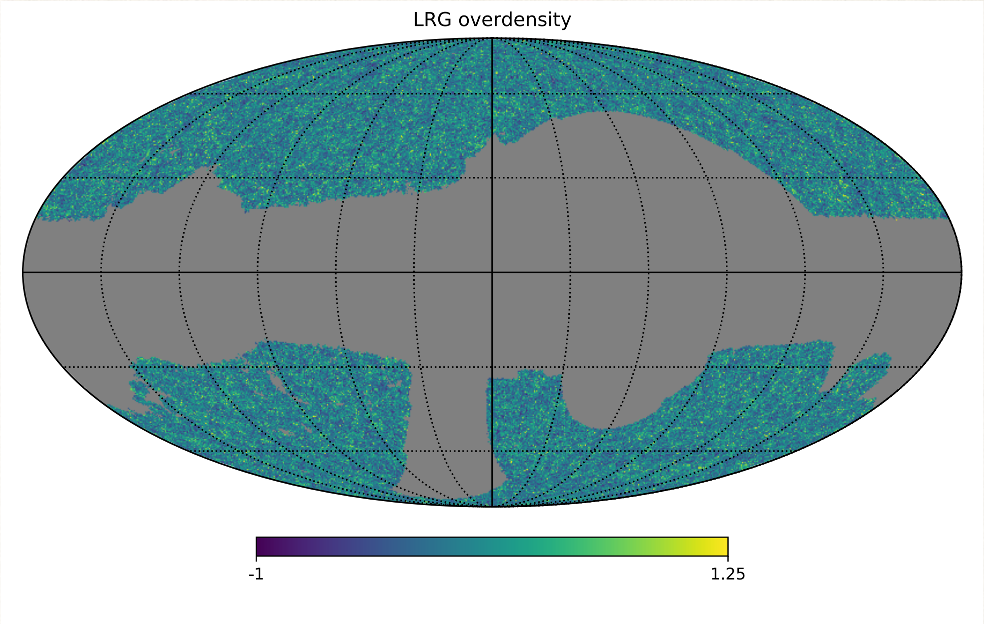
(modeling or data) systematics driving the trends?

Case Study: DESI LRGs x Planck CMB lensing

DESI *imaging* LRGs x Planck lensing



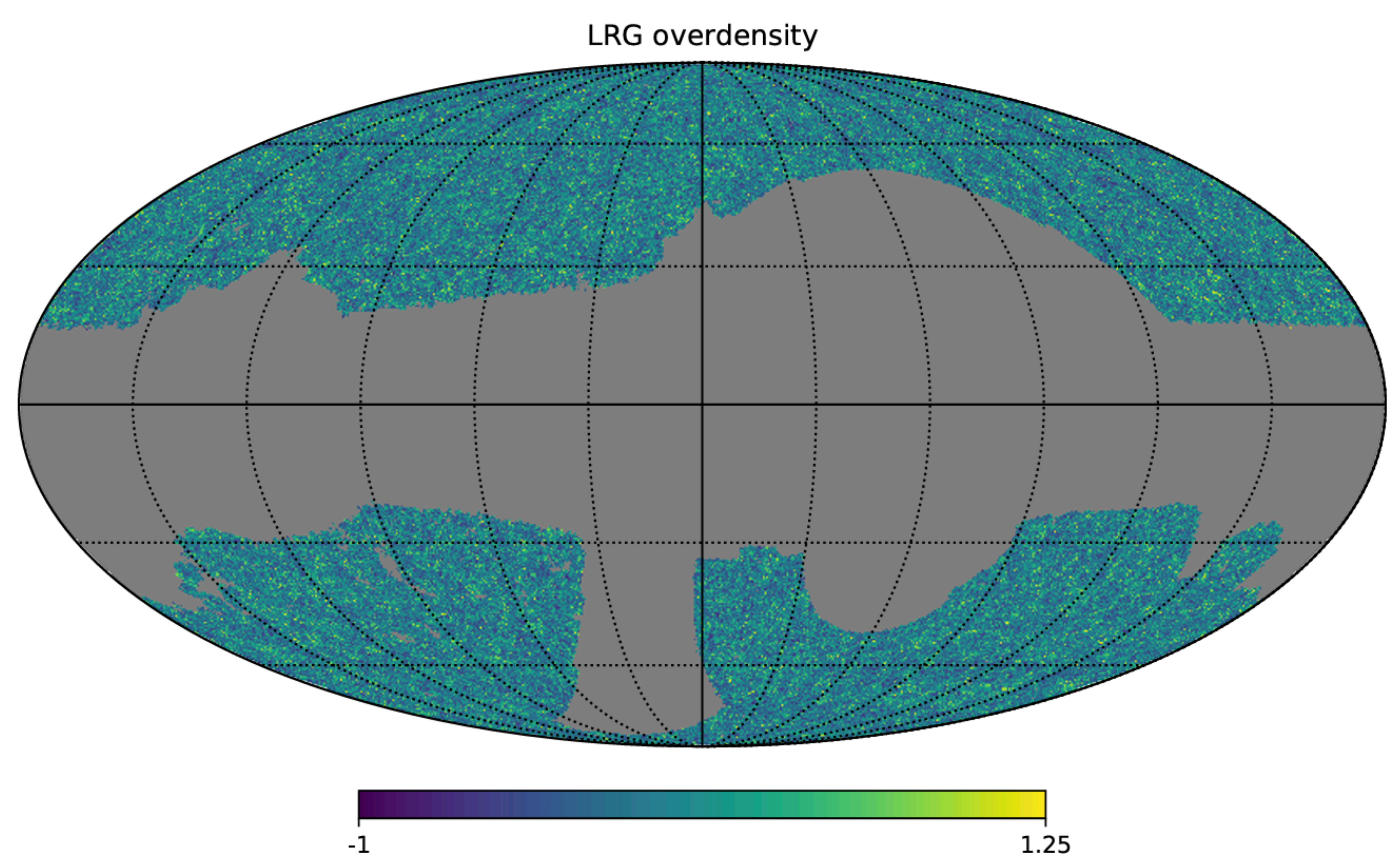
x



M. White, R. Zhou, JDR et al. 2022

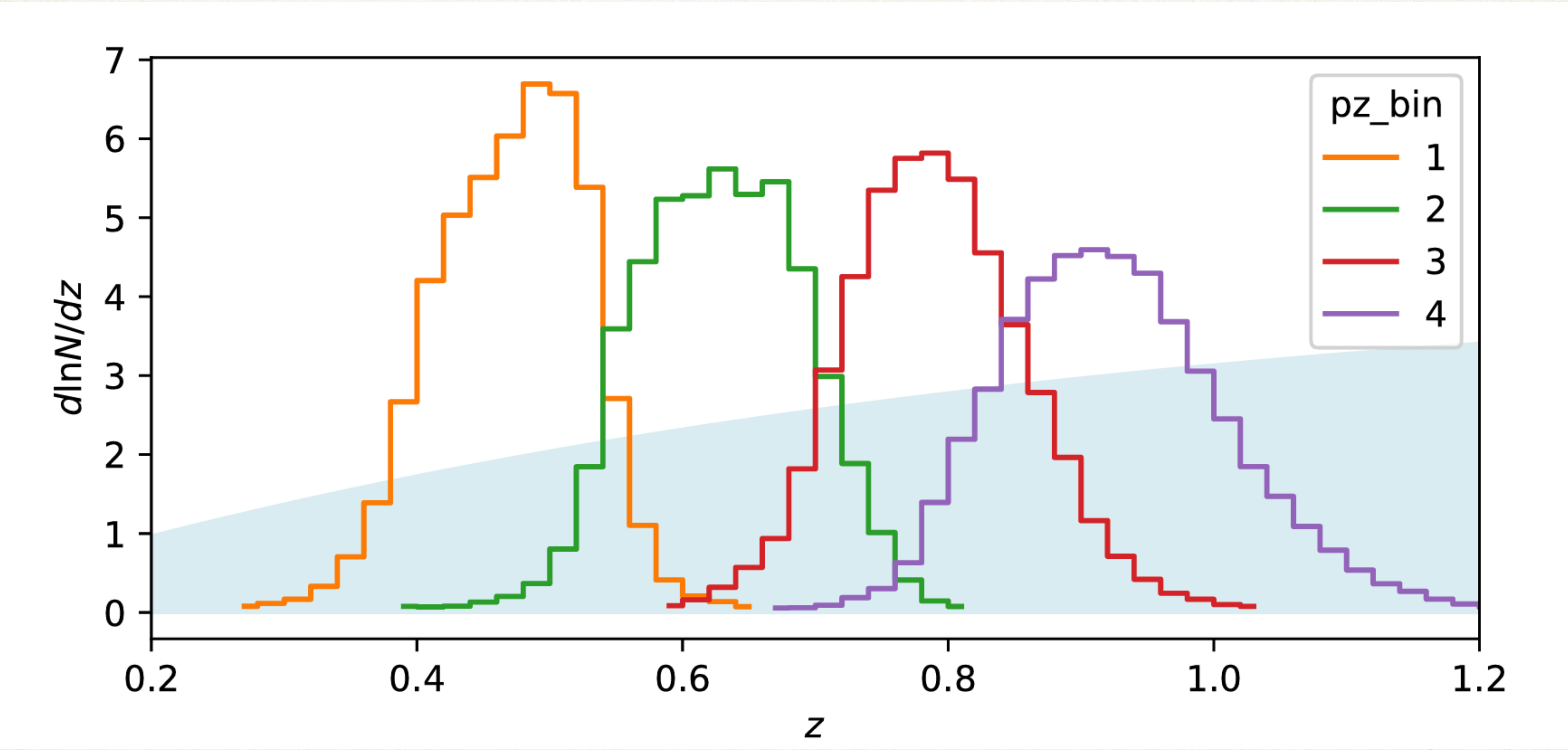
- Use “standard” SMICA lensing convergence map from Planck.
- DESI LRGs from Legacy Imaging Survey data.
- 18k square degrees of overlap, $0.3 < z < 1.1$.

DESI LRGs: Low angular systematics



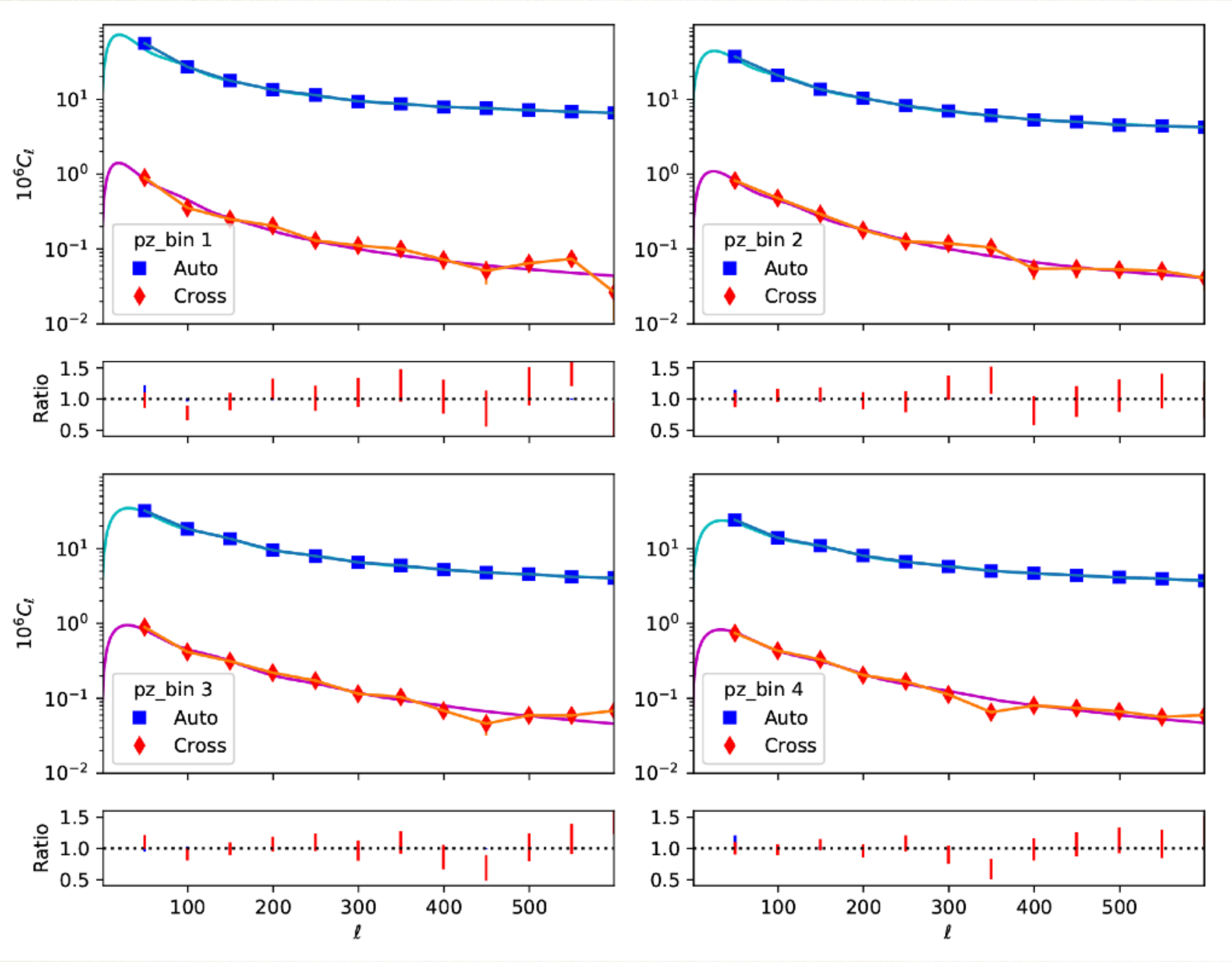
LSS visible even in raw maps!

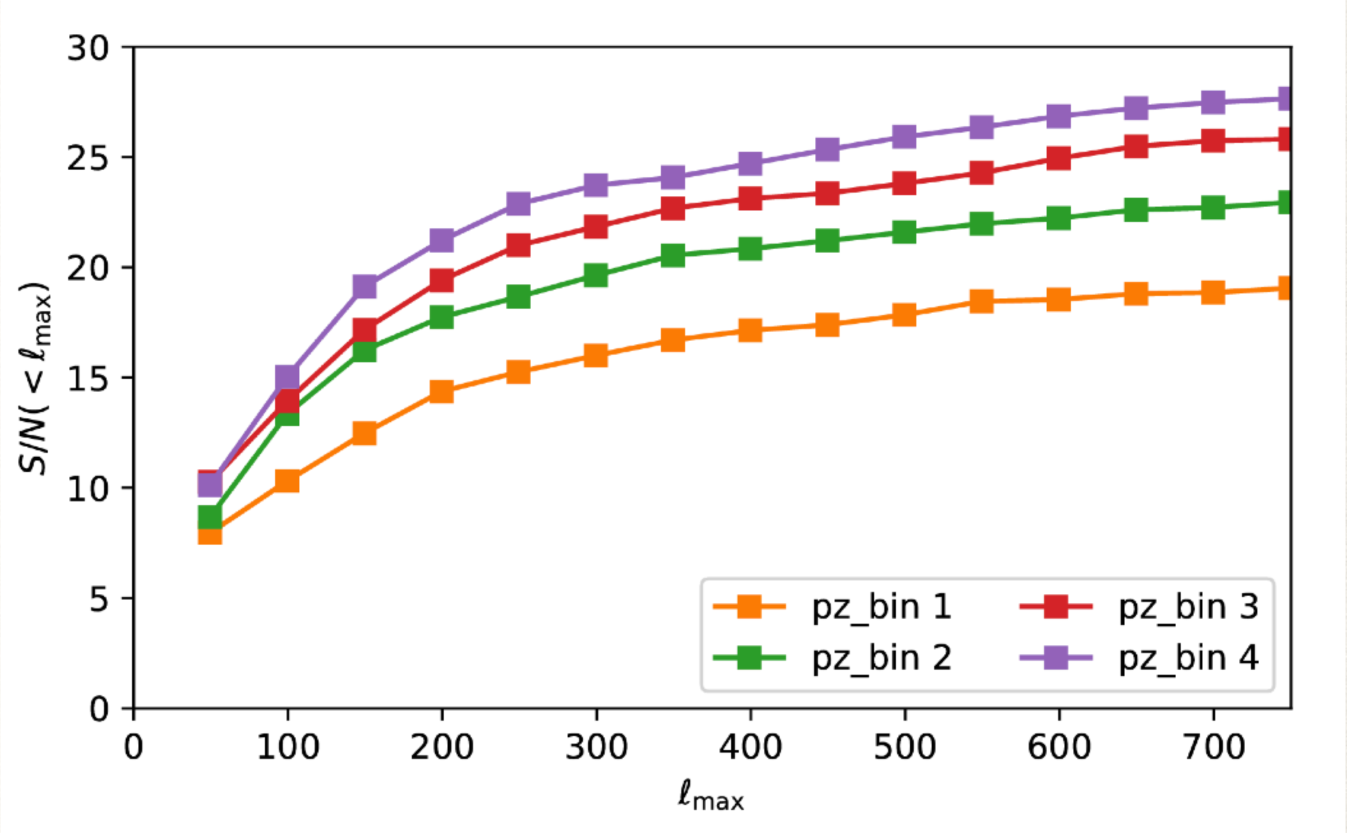
DESI LRGS: Low redshift systematics



LRG spectroscopic completeness is ~99%, so we can safely use redshift distributions measured from early DESI data to calibrate n(z)s for full 18k square degrees of the DESI imaging survey data.

Signal dominated only on large scales





We use auto and cross angular power spectra as our summary statistic. Signal saturates at about $\ell \sim 400$.

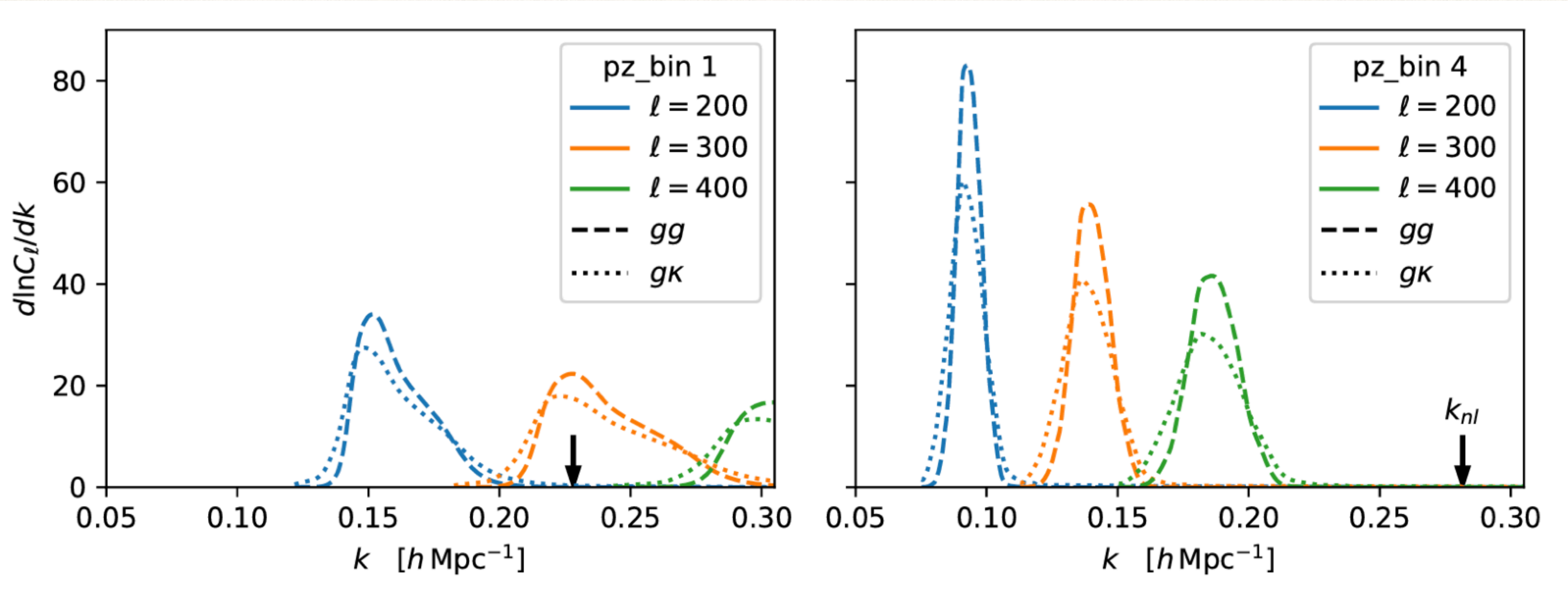
A purely perturbation theory model

We use convolutional Lagrangian effective field theory (CLEFT) for our model

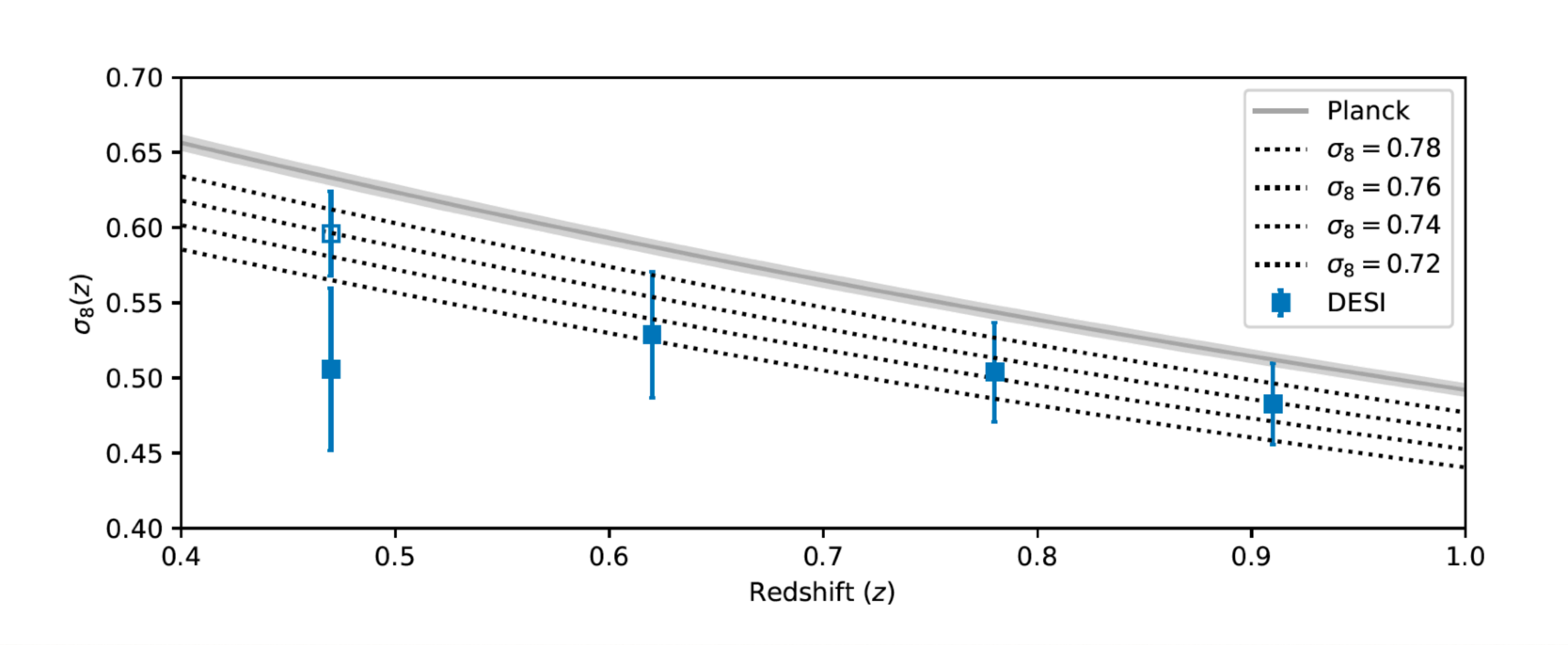
$$P_{\rm gg} = \left(1 - \frac{\alpha_a k^2}{2}\right) P_{\rm Z} + P_{\rm 1-loop} + b_1 P_{\rm b_1} + b_2 P_{\rm b_2} + b_1 b_2 P_{\rm b_1 b_2} + b_1^2 P_{\rm b_1^2} + b_2^2 P_{\rm b_2^2}$$

$$P_{\rm gm} = \left(1 - \frac{\alpha_\times k^2}{2}\right) P_{\rm Z} + P_{\rm 1-loop} + \frac{b_1}{2} P_{\rm b_1} + \frac{b_2}{2} P_{\rm b_2}$$

thus we must limit our analysis to $k < k_{nl}$



Tension?

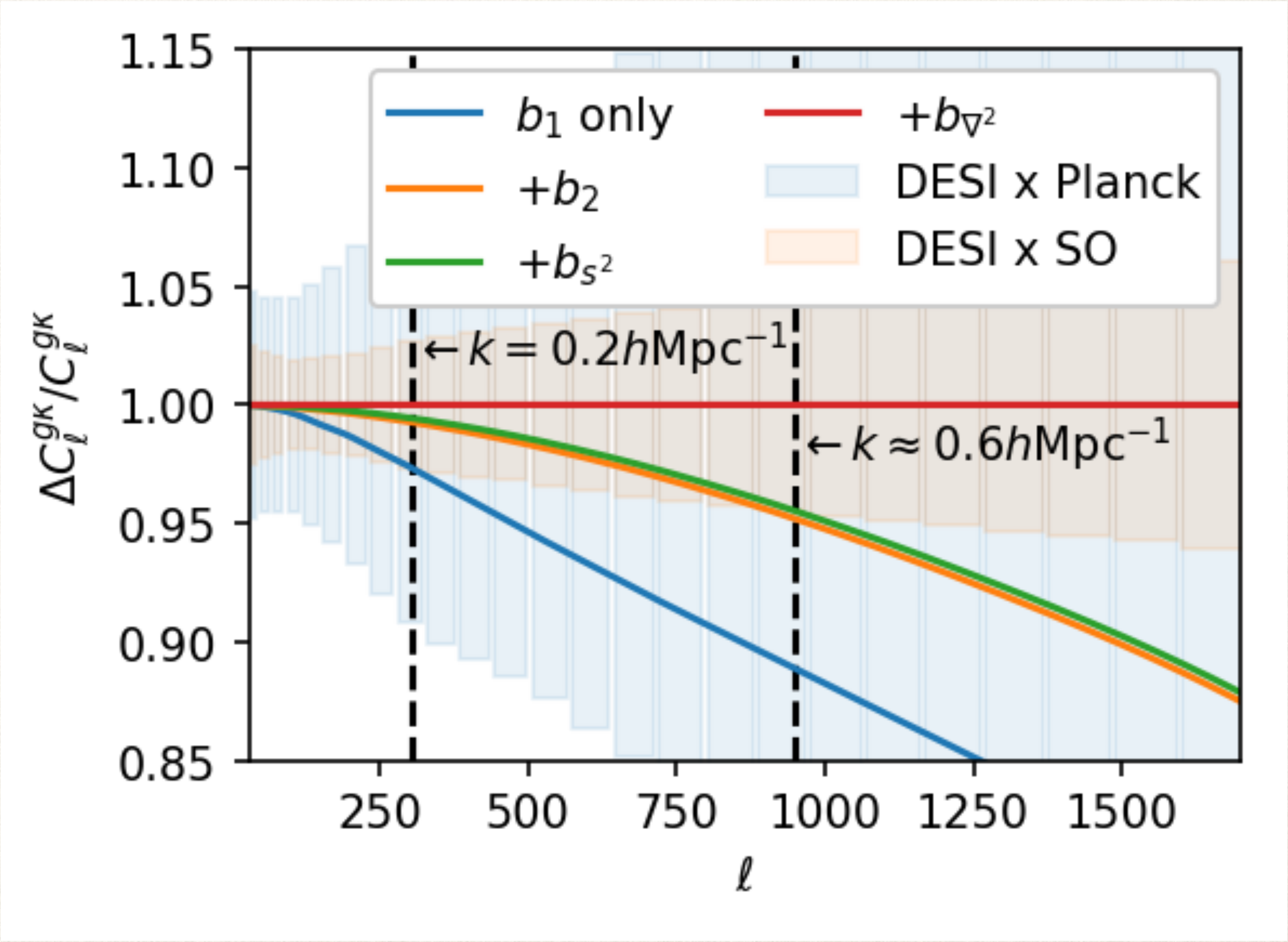


M. White, R. Zhou, JDR et al. 2022

Projection effects complicate Bayesian interpretation of tensions. What can we do to alleviate this issue?

Limitations of current analyses

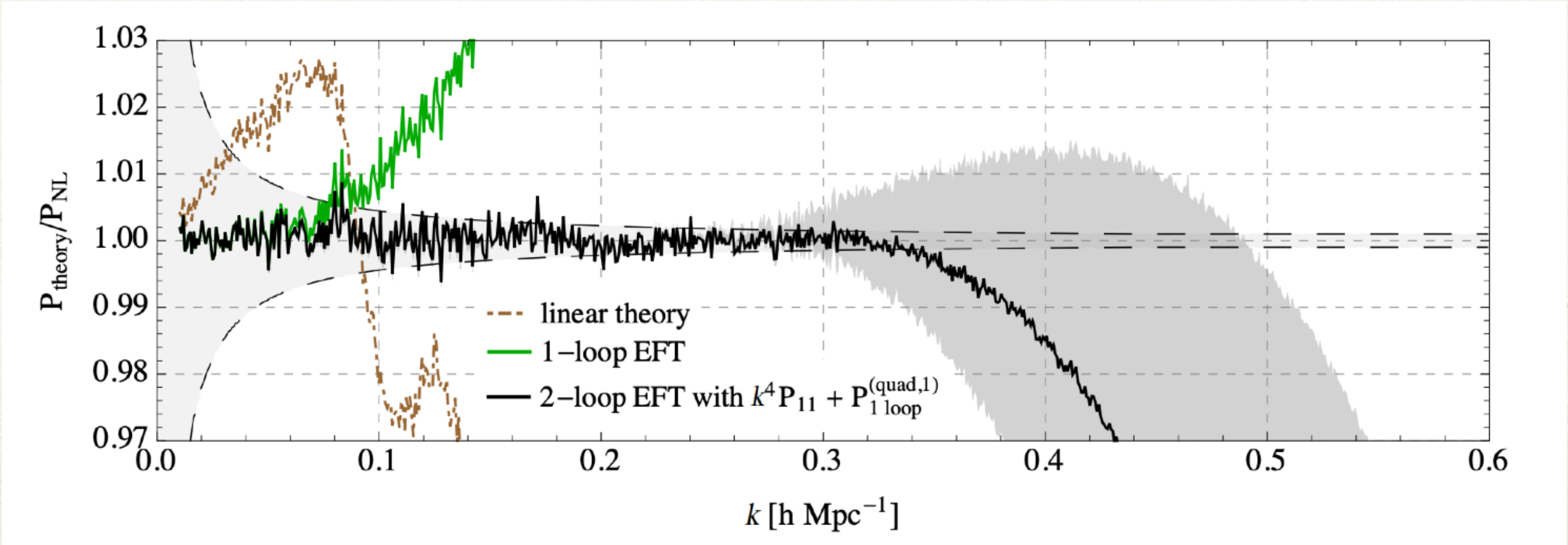
- With Planck, high ell **CMB lensing** cross correlations are noise dominated, but with upcoming CMB surveys this will no longer be the case.
- **Galaxy-galaxy lensing** already throwing away a lot of data due to non-linear modeling uncertainty.



Chen, White, JDR, Kokron 2022

Perturbation theory or Simulations?

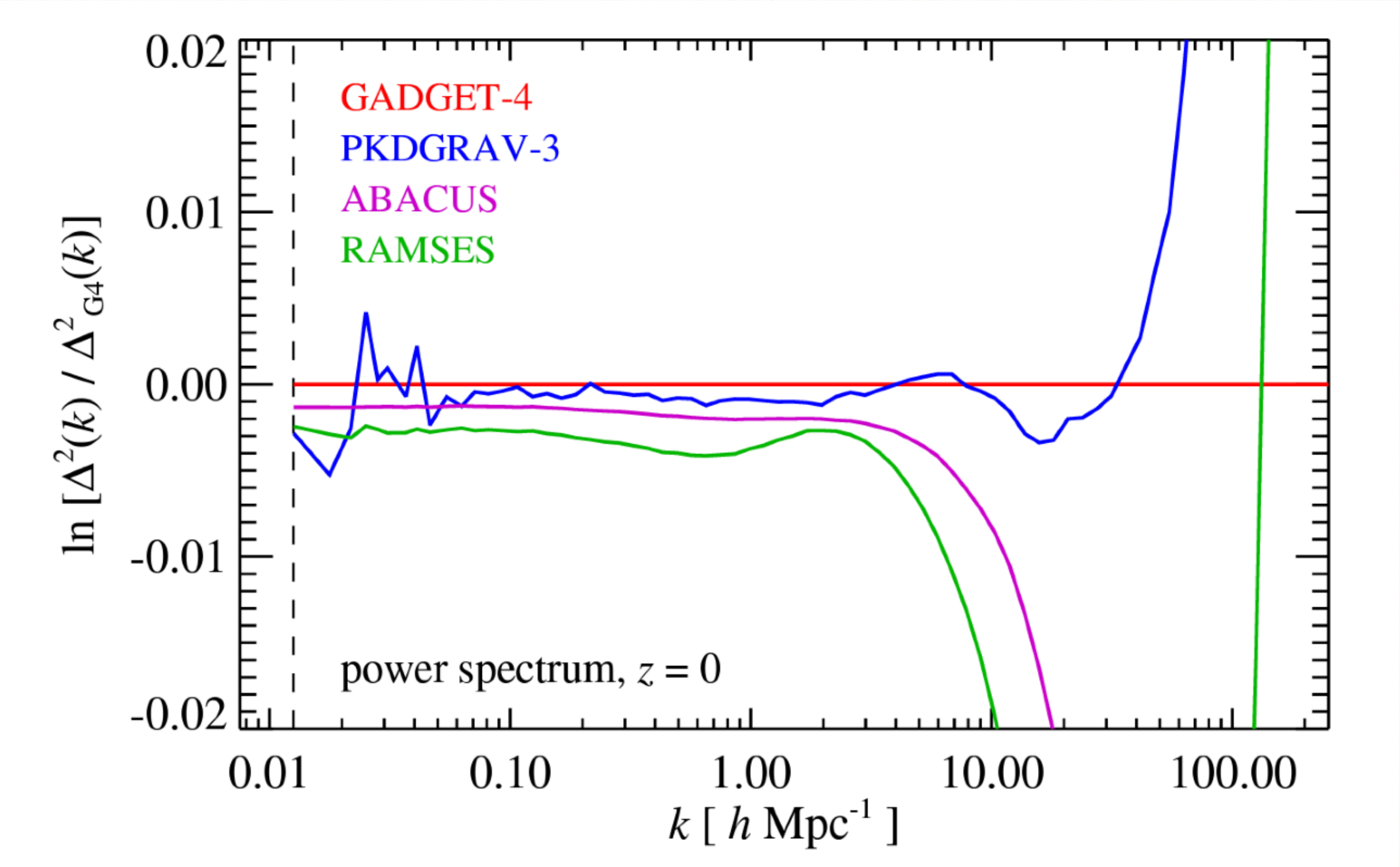
- Perturbation theory:
  - Accurate, flexible, fast, but low k reach.
  - Ansatz: $\delta_g(\mathbf{x}) \sim \sum_i b_i \delta_m(\mathbf{x})^i$; $\delta_m(\mathbf{x}) = \sum_n \delta_m^n(\mathbf{x})$
- In real space, the scale to which we can perturbatively compute the matter field is often the limiting factor.



Foreman et al 2015

Simulation or Perturbation theory?

N-body simulations are converged to $k \sim 1$



Springel et al 2021

Simulation or Perturbation theory?

Main difficulty with using simulations is connecting to galaxy distribution.

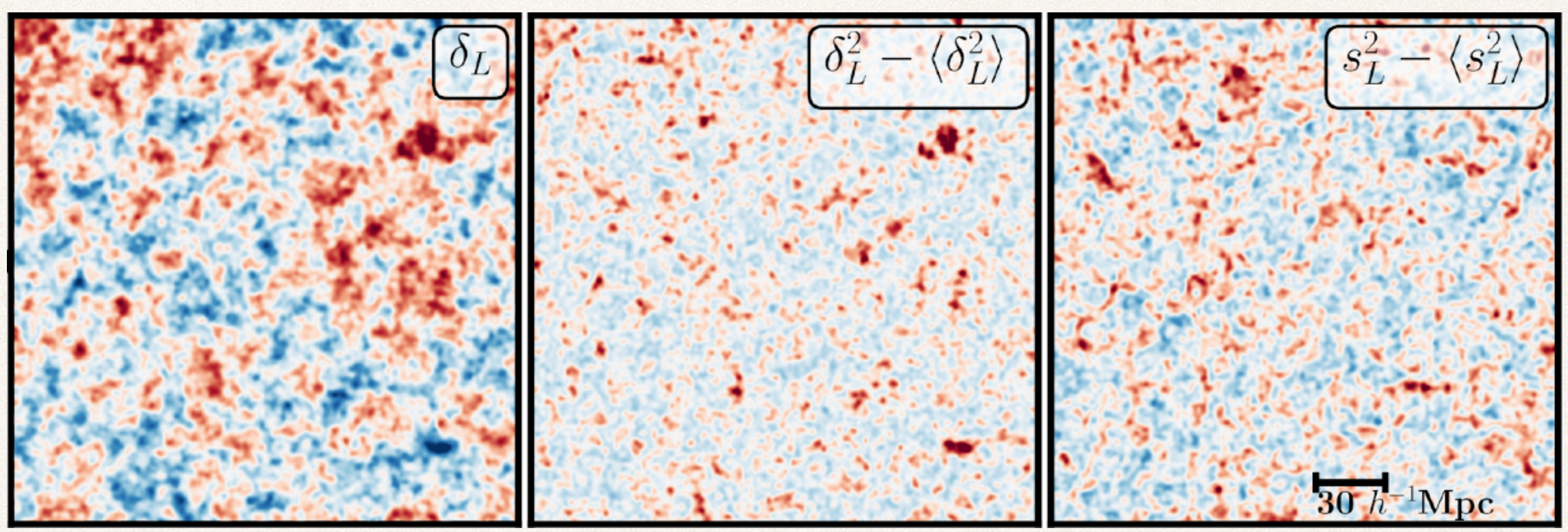
Yuan et al 2022

HOD	$\log_{10} M_{\rm cut}$	The typical mass scale to host a central	[12.5, 13.7]
	$\log_{10} M_1$	The typical mass scale for halos to host one satellite	[13.6, 15.1]
	$\log_{10} \sigma$	The turn on slope for central occupation	[-2.99, 0.96]
	α	The power-law index for the mass dependence of the number of satellites	[0.30, 1.48]
	κ	Parameter that defines the minimum mass to host a satellite	[0.00, 0.99]
	$\alpha_{\rm vel,c}$	Central velocity bias	[0.00, 0.61]
	$\alpha_{\rm vel,s}$	Satellite velocity bias	[0.58, 1.49]
	$B_{\rm cent}$	Central environment-based secondary bias	[-0.67, 0.20]
	$B_{\rm sat}$	Satellite environment-based secondary bias	[-0.97, 0.99]
Optional parameters	$A_{\rm cent}$	Central concentration-based secondary bias	[-0.99, 0.93]
	$A_{\rm sat}$	Satellite concentration-based secondary bias	[-1.00, 1.00]
	s	satellite profile bias parameter	[-0.98, 1.00]

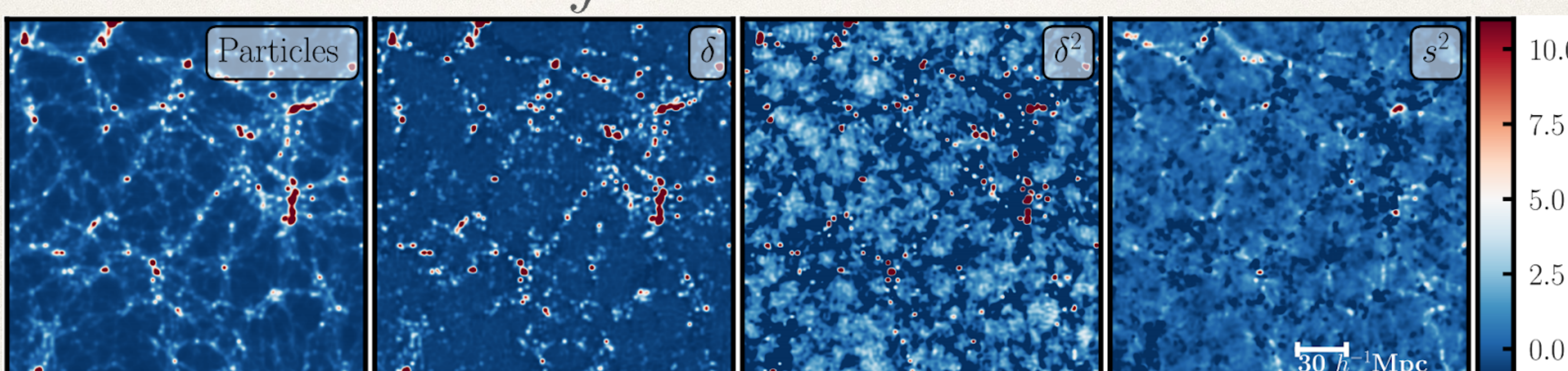
How to know when to stop?

Combining Simulations and LPT

$$F[\delta(\mathbf{q})] = 1 + b_1\delta_L(\mathbf{q}) + b_2\delta_L^2(\mathbf{q}) + b_s s^2(\mathbf{q}) + b_\nabla \nabla^2\delta_L(\mathbf{q}) + \ldots$$



$$1 + \delta^a(\mathbf{x}) = \int d^3q\, \delta^D(\mathbf{x} - \mathbf{q} - \mathbf{\Psi})F(\mathbf{q})$$

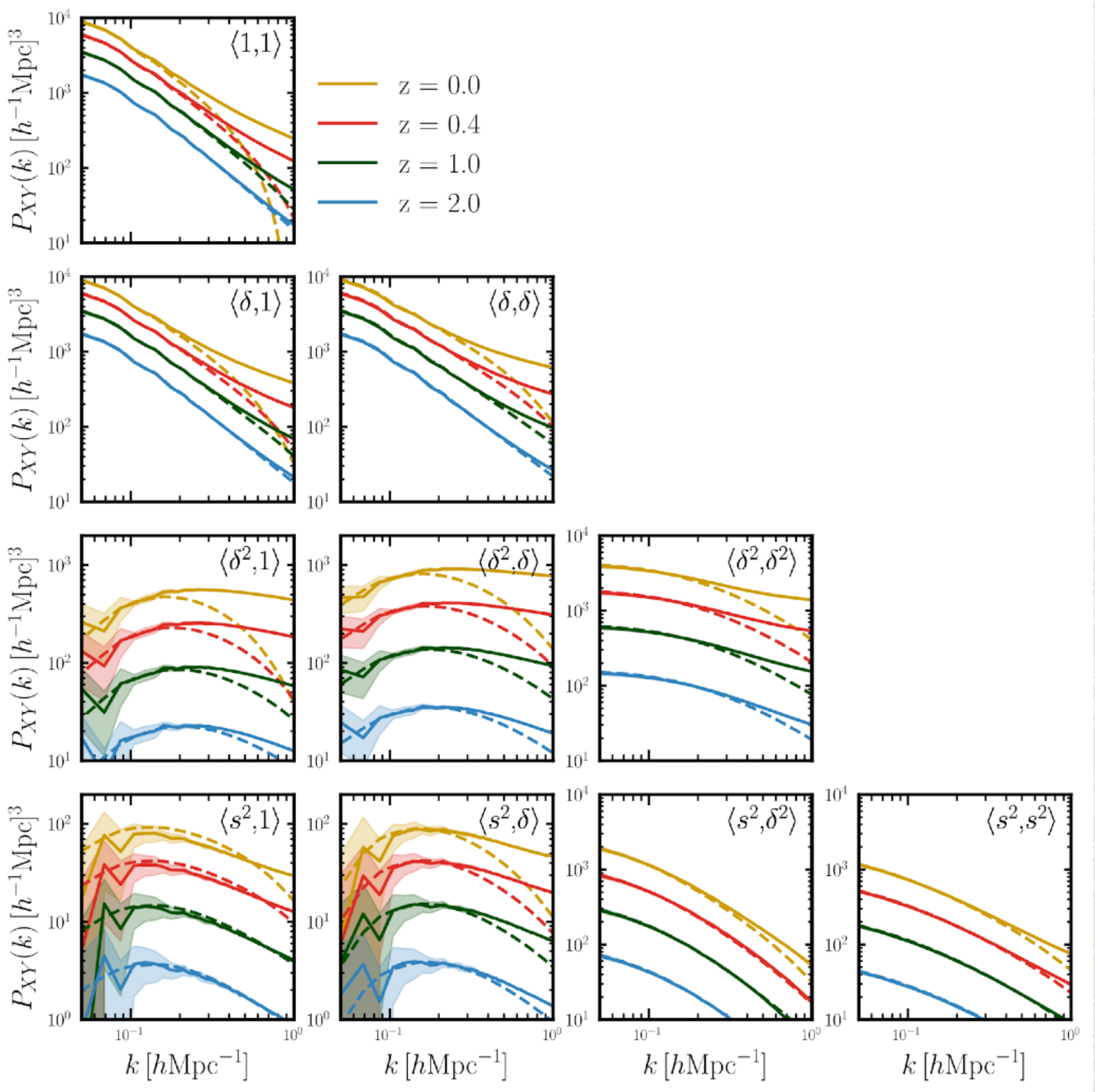


Combining Simulations and LPT

Sum up all combinations of fields to get predictions.

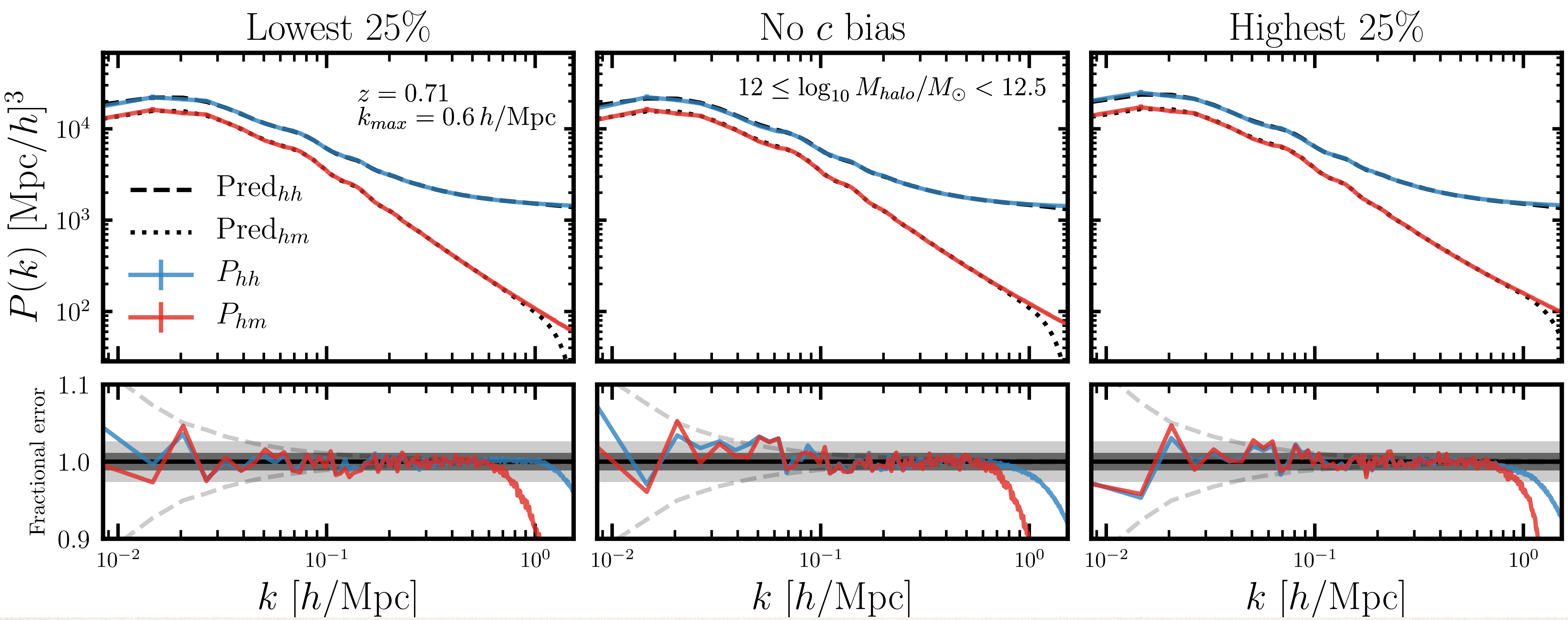
$$P_{gg}(k) = \sum_{X,Y} b_X b_Y P_{XY}(k)$$

- Asymptotes to LPT on large scales
- Much less stringent simulation requirements than HOD
- Can check convergence by including progressively higher order bias operators



Kokron, JDR, Chen, White, Wechsler 2021

Ability to fit complex samples

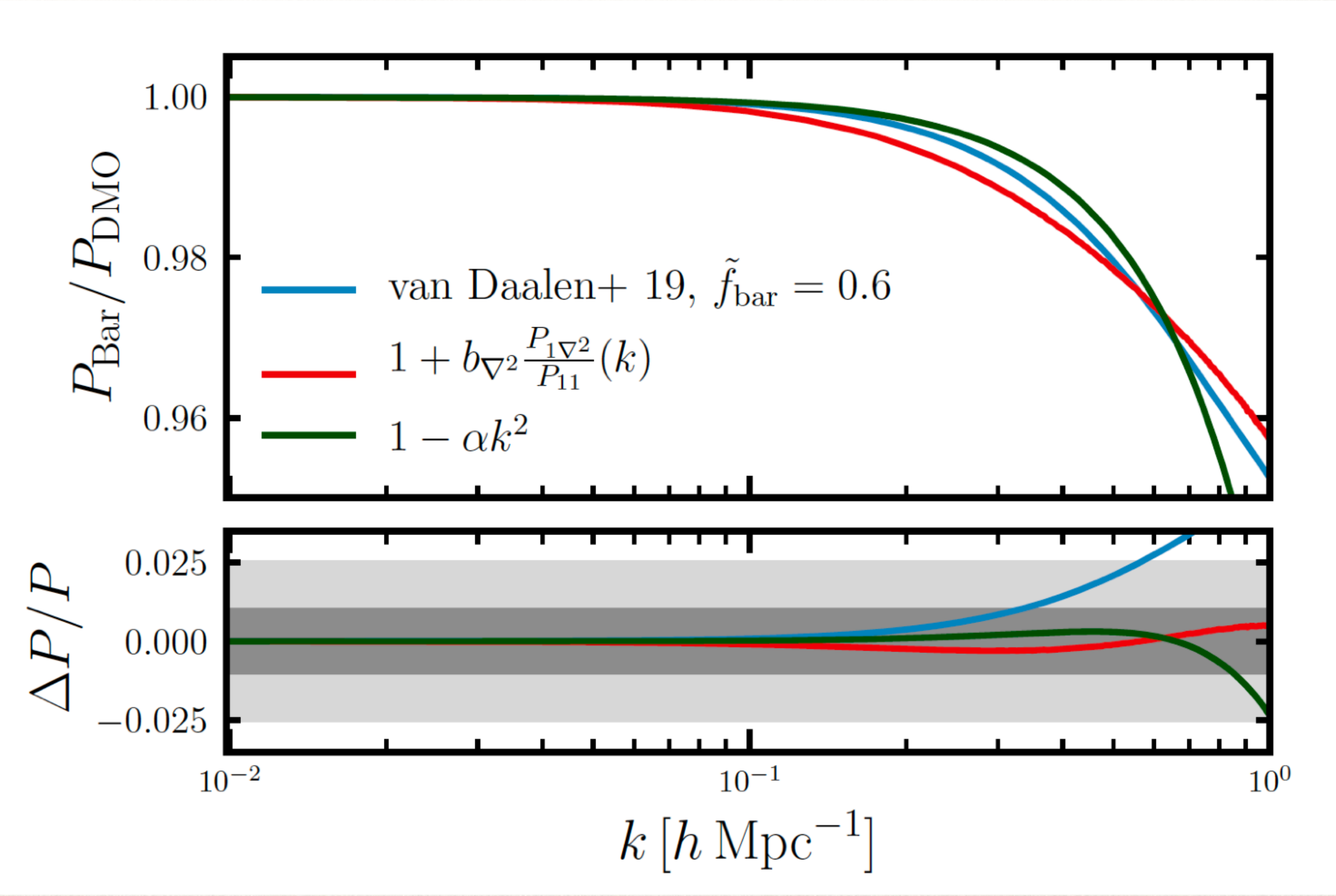


This model can handle modest amounts of assembly bias.

Fits to $k_{\mathrm{max}} \sim 0.6h\,\mathrm{Mpc}^{-1}$ lead to agreement better than 1% out to k~1

Baryons?

The $\nabla^2\delta$ bias operators (counterterm) can fit baryonic effects on the scales where the model is valid



Kokron, JDR, Chen, White, Wechsler 2021

What about higher order stats?

We can use HEFT to fit at the field level by minimizing the following loss function:

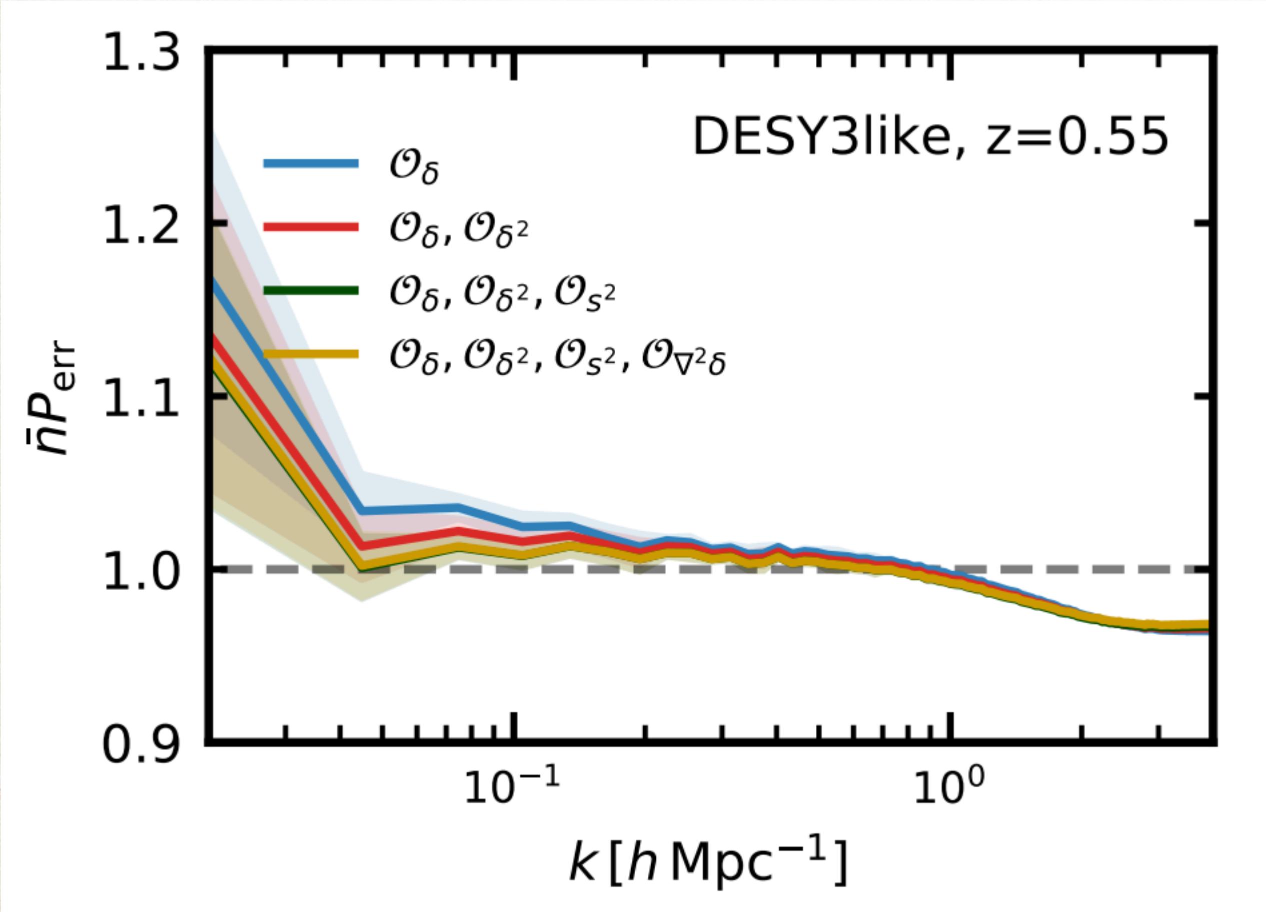
$$S \approx \int_{|\mathbf{k}|<k_{\max}} \frac{d^3k}{(2\pi)^3} \left\| \delta_h(\mathbf{k}) - \delta_m(\mathbf{k}) - \sum_i b_i \mathcal{O}_i(\mathbf{k}) \right\|^2 .$$

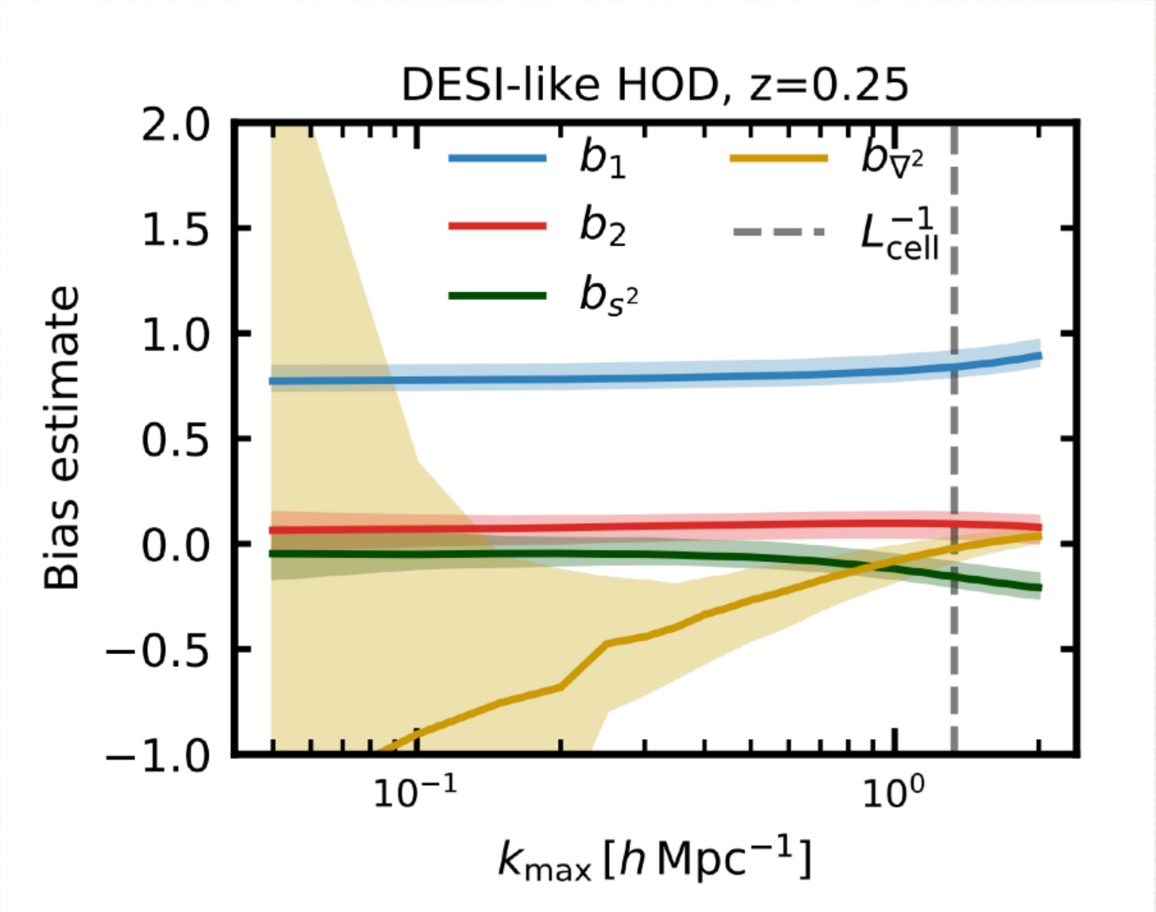
Measure residuals:

$$\hat{\epsilon}(\mathbf{k}) = \delta_h(\mathbf{k}) - \delta_m(\mathbf{k}) - \sum_i \hat{b}_i \mathcal{O}_i(\mathbf{k}).$$

Power spectrum of this should be ~poisson if model fits well. Very stringent test of the model, since it incorporates all N-point statistics.

Field level fitting



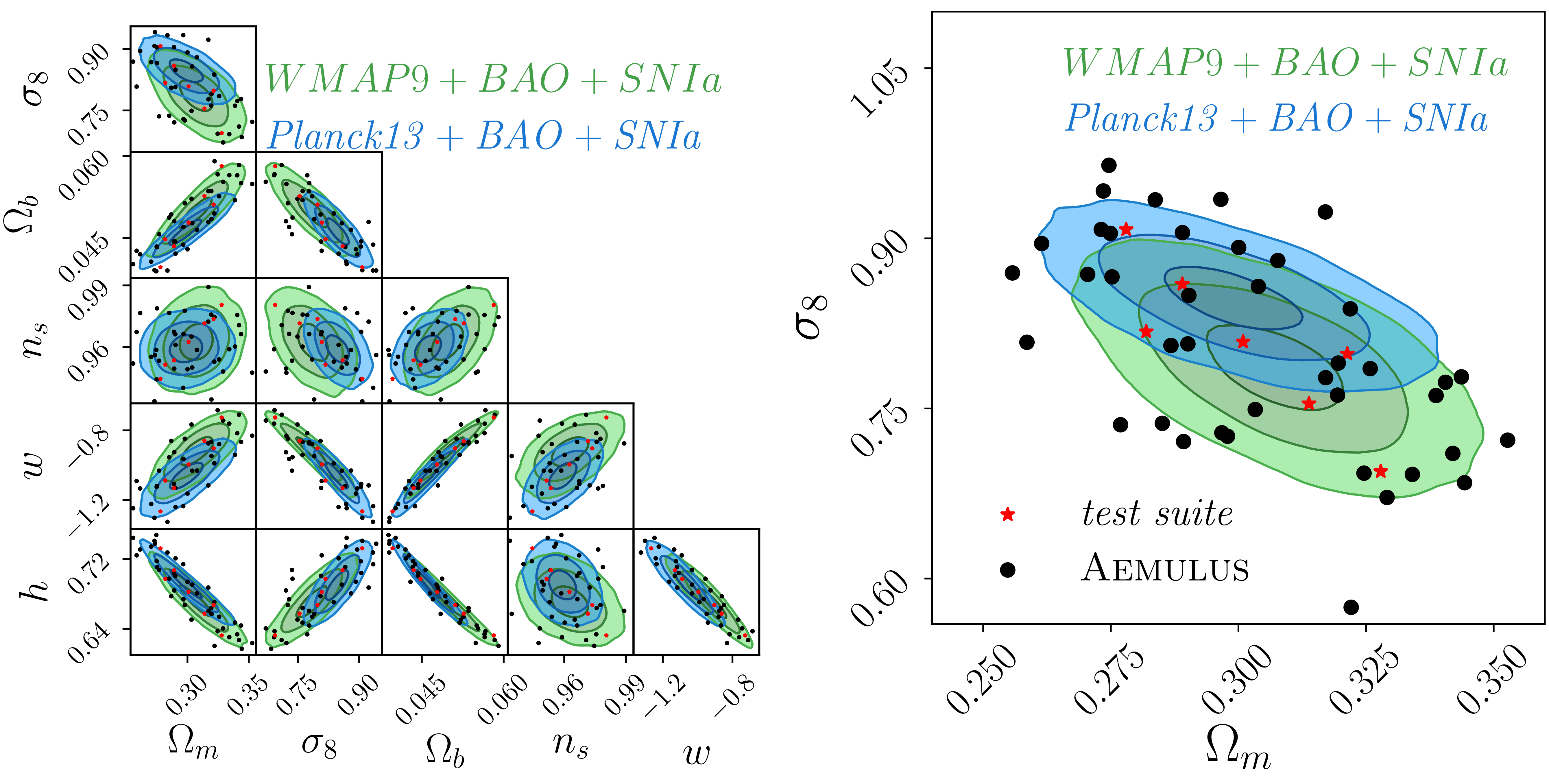


Kokron, JDR, Chen, White, Wechsler 2021

Field level fits of HEFT to HOD mocks are a very stringent test of the model

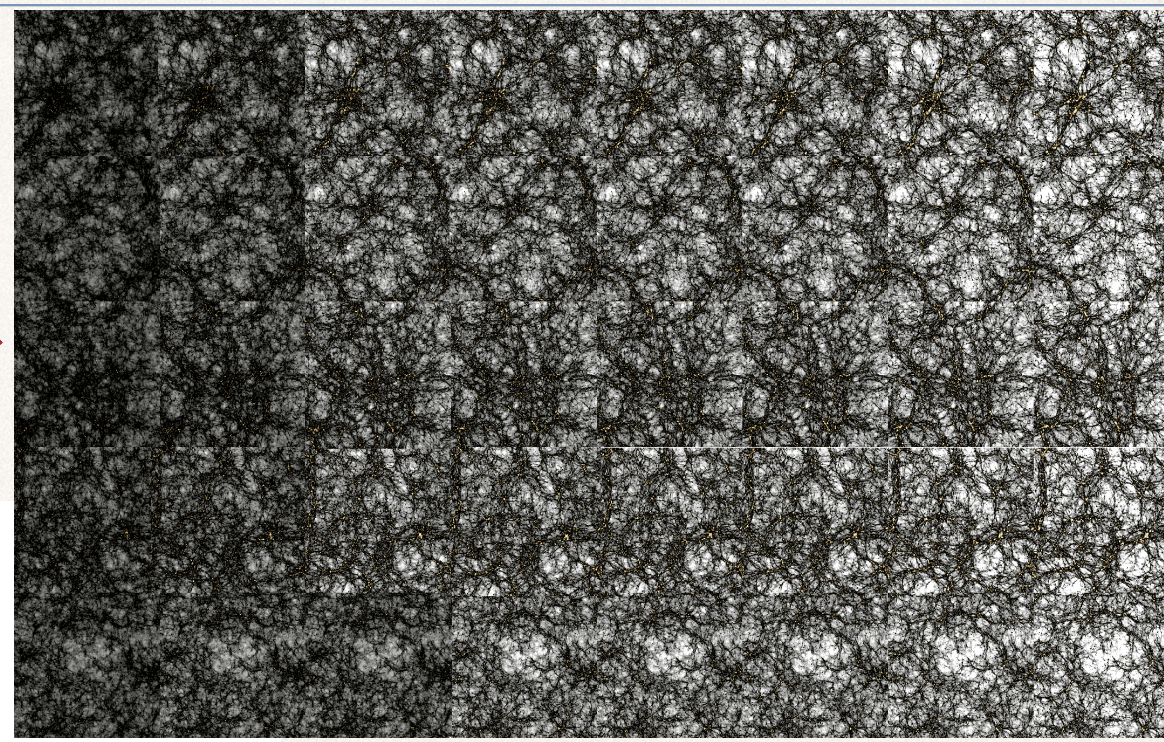
- Error power spectrum converges as we include higher order bias operators
- Inferred bias parameters do not depend on $k_{\rm max}$ for sufficiently low mass samples.

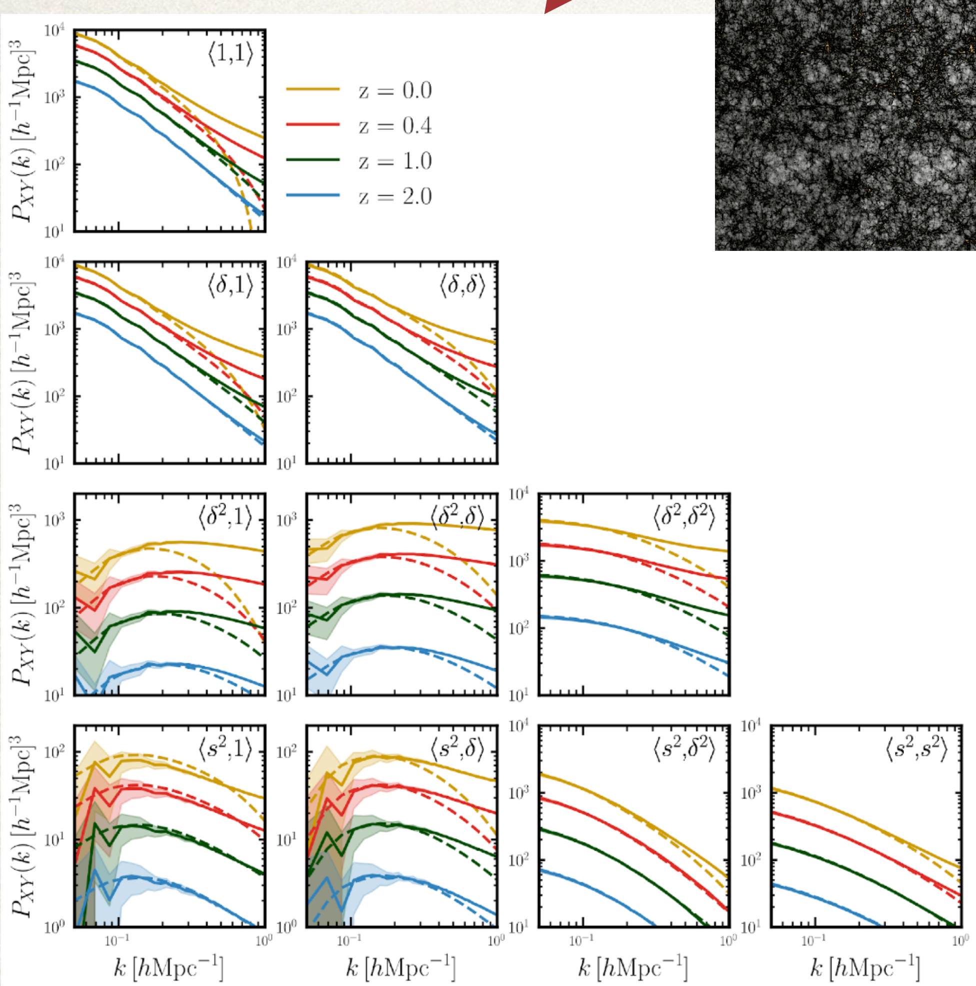
Sampling Cosmological Parameter Space



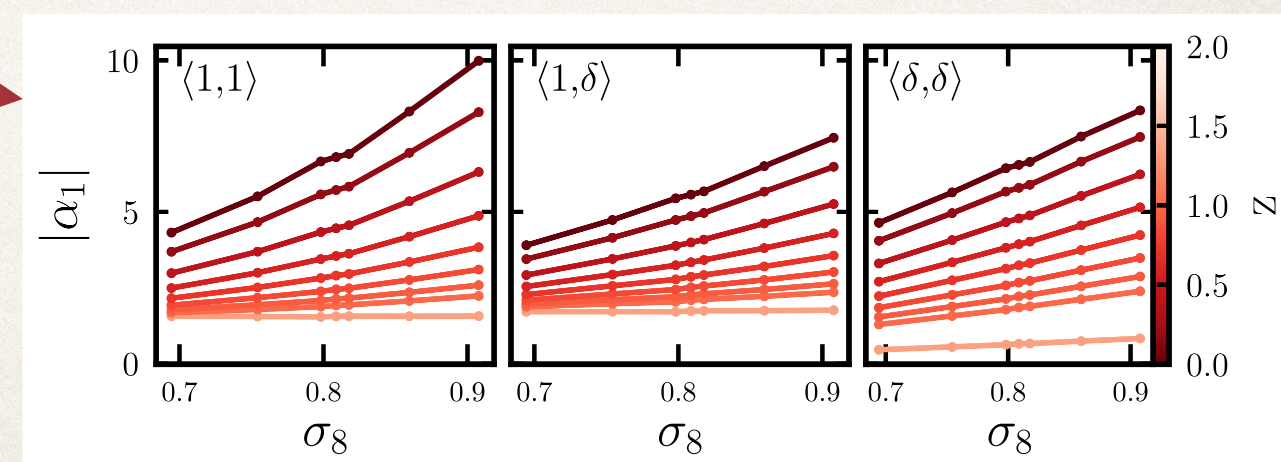
JDR et al. 2018

Emulating HEFT Spectra





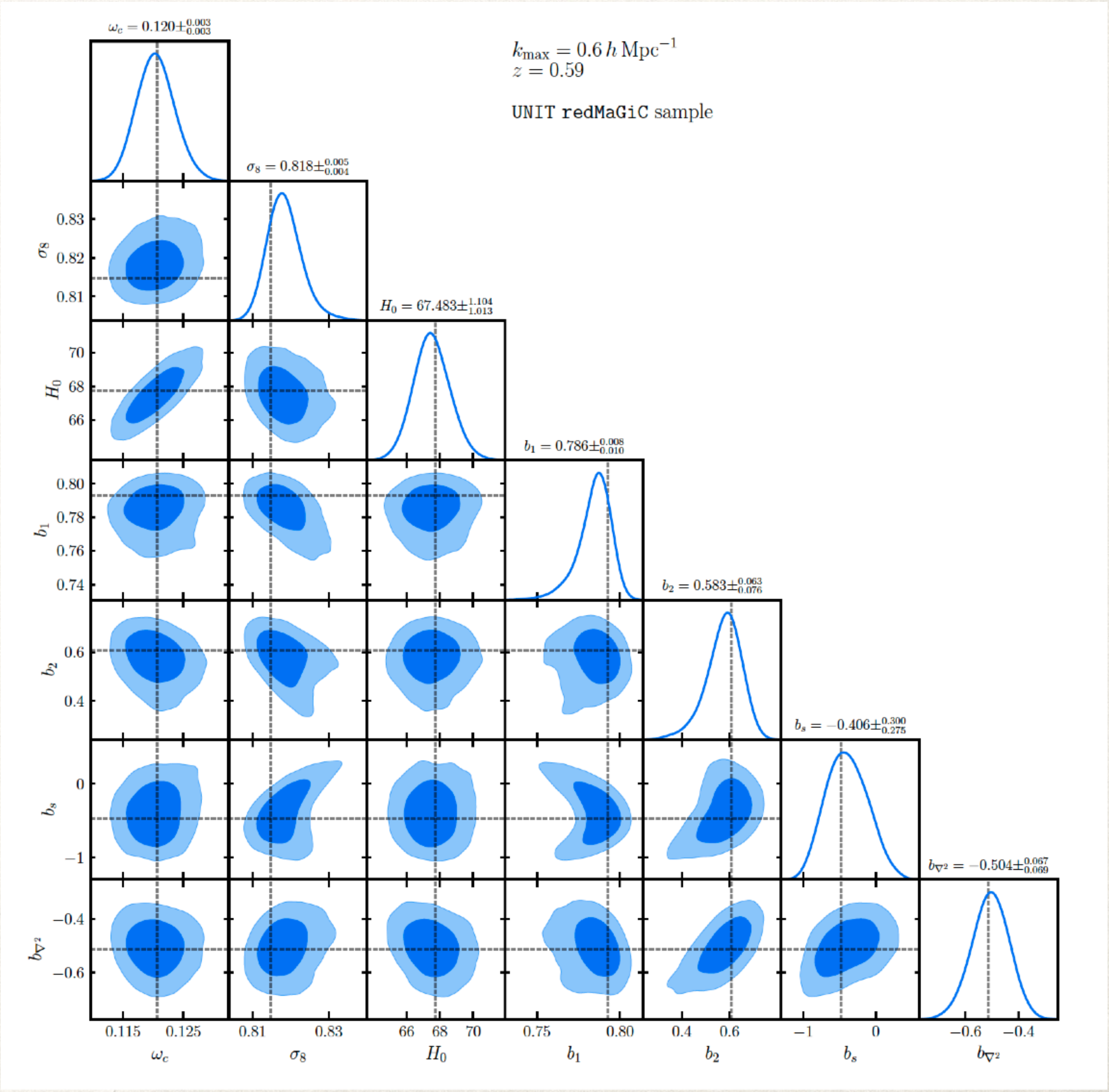
Kokron, JDR, Chen, White & Wechsler 2021



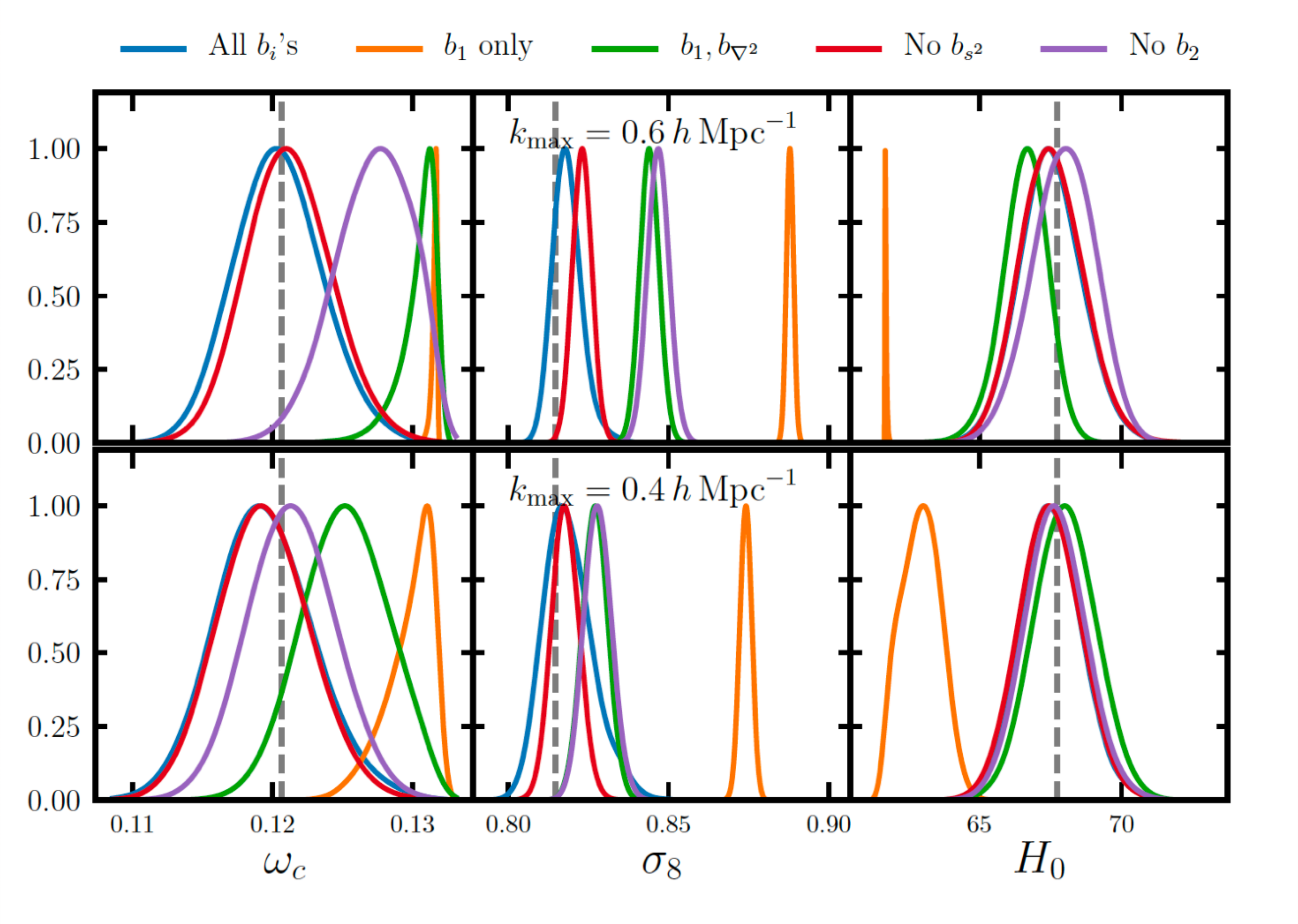
A realistic test

Construct mock data from a set of independent simulations (UNITsims), populated with an HOD that has been fit to DES data.

- UNITsims are higher resolution at a cosmology not in the training data.
- Simultaneously fit $P_{gg}(k)$ and $P_{gm}(k)$ to $k = 0.6\,h\,\mathrm{Mpc}^{-1}$



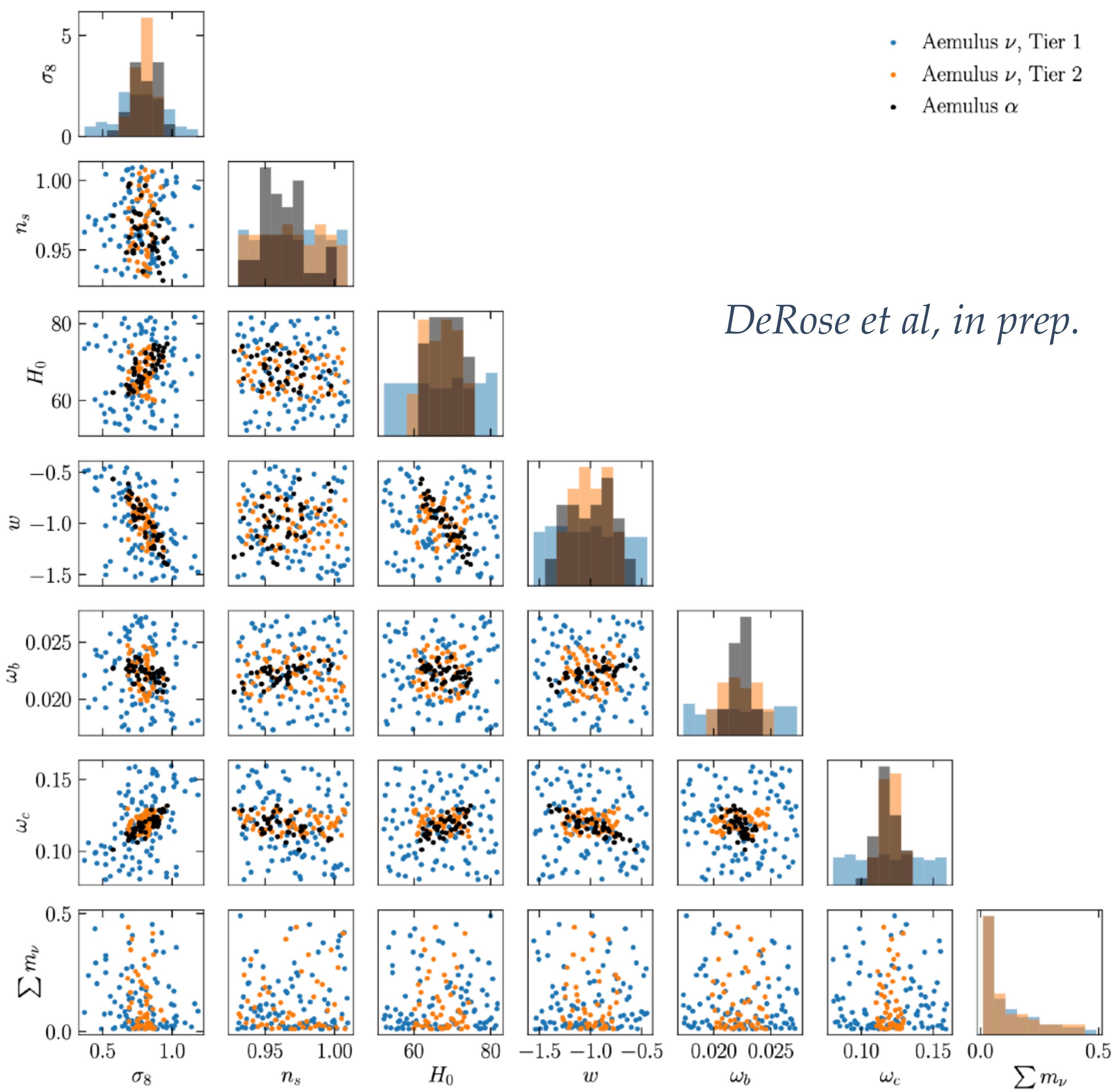
What bias parameters are necessary?



Kokron, JDR, Chen, White, Wechsler 2021

Aemulus ν

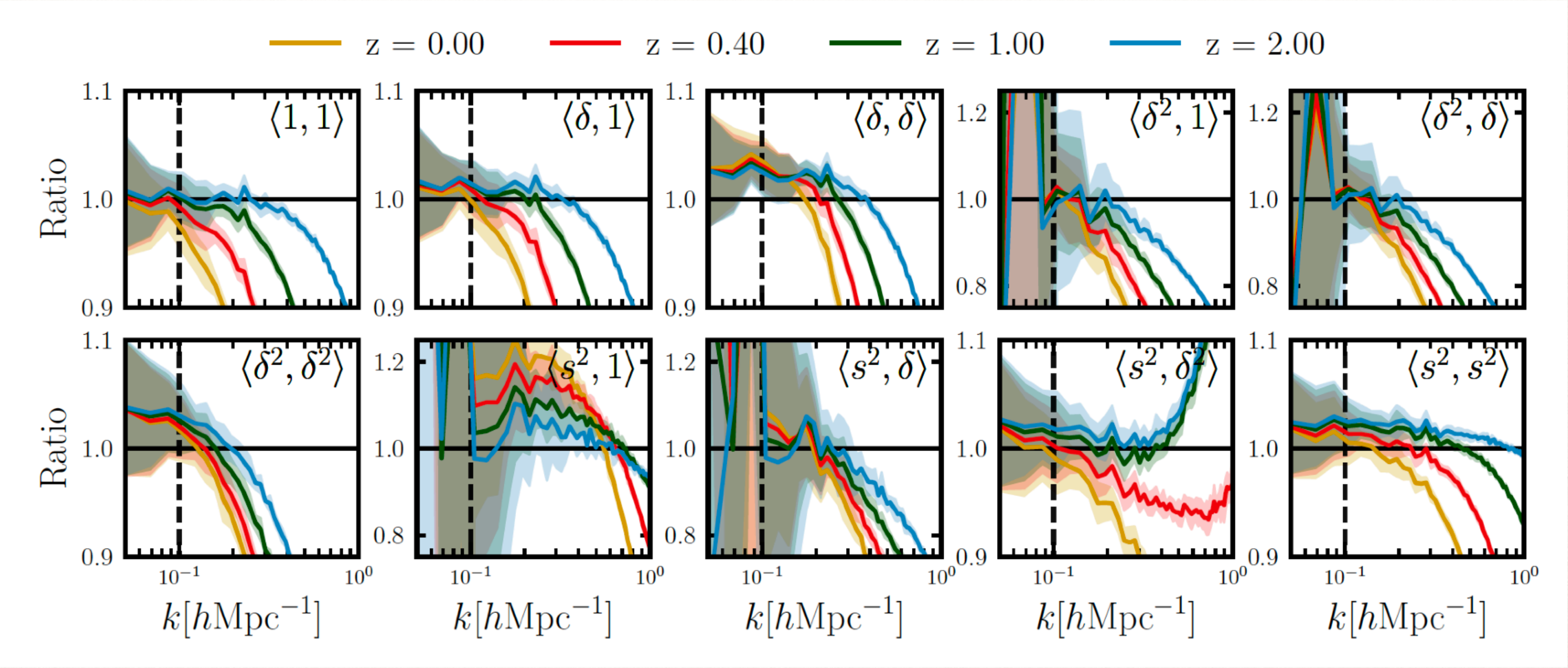
- 150 simulations in a *wνCDM* parameter space.
    - Flat, broad priors on cosmological parameters, especially important for modern analyses that prefer low S8.
- 3LPT initial conditions in order to mitigate transients in force computation —> better convergence properties.



DeRose et al, in prep.

Combining simulations and analytics

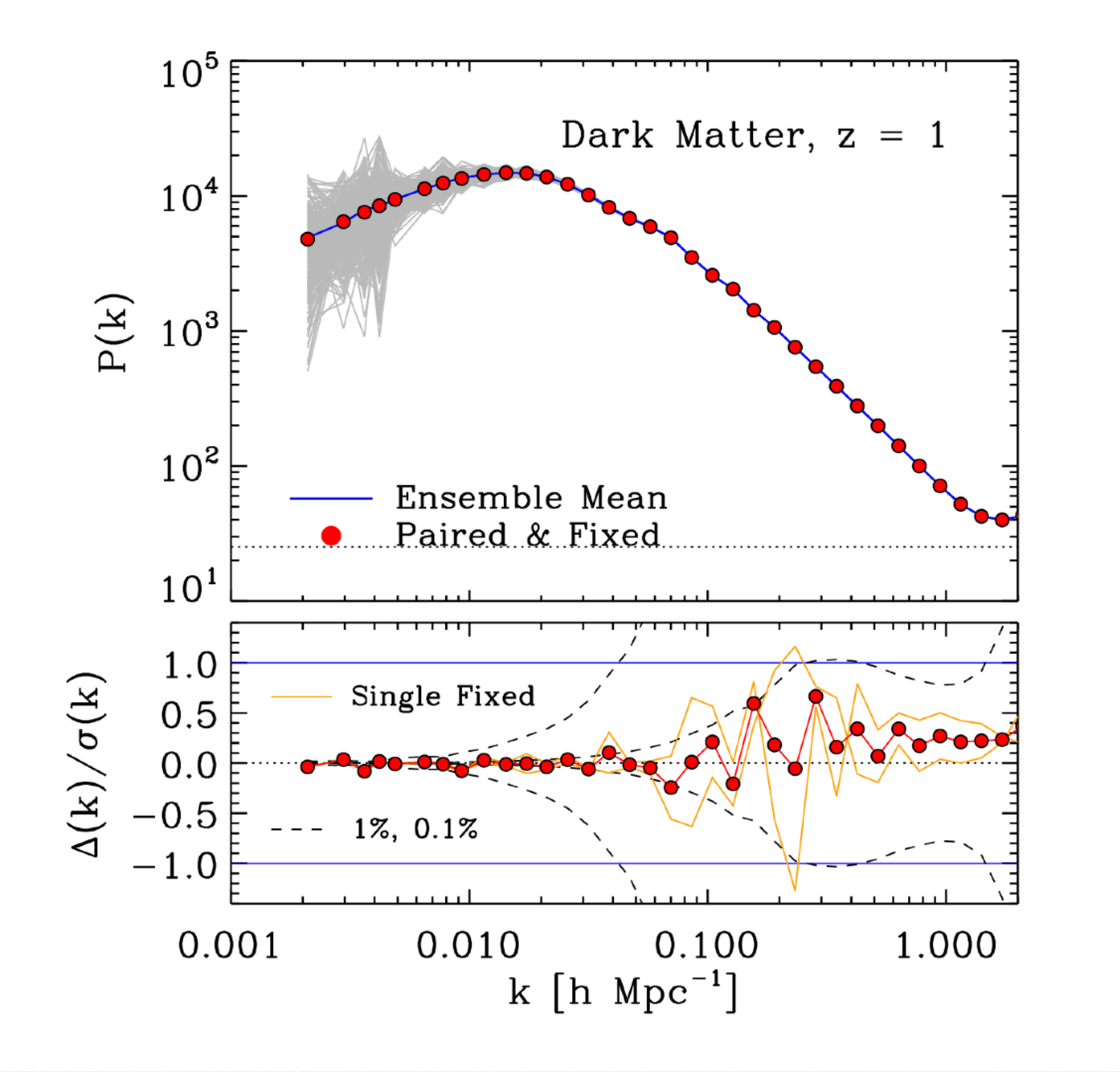
Sample variance in our simulations makes it difficult to switch to analytic theory on large scales. Also makes problem of emulation more difficult.



Kokron, JDR, Chen, White, Wechsler 2021

Sample Variance Reduction

- A few methods of improving sample variance in simulations beyond 1/N scaling exist.
- Best known: "pairing and fixing" has a few downsides
    - Abandons gaussianity of ICs
    - Still requires running 2 simulations



Angulo & Pontzen 2016

Alternative: Control Variates

Given a noisy quantity (i.e. a measurement from simulations),
but have access to a cheap correlated "control variate", we can construct:

$$\hat{y} \equiv \boxed{\hat{x}} - \beta(\boxed{\hat{c}} - \mu_c)$$

we can then optimize β to minimize the variance of $\hat{y}$, giving

$$\hat{\beta} = \frac{\mathrm{cov}[\hat{\mathrm{x}}, \hat{\mathrm{c}}]}{\mathrm{var}[\hat{\mathrm{c}}]}$$

leading to a reduction in variance of

$$\frac{\mathrm{var}[\hat{\mathrm{y}}]}{\mathrm{var}[\hat{\mathrm{x}}]} = 1 - \frac{\mathrm{Cov}^2[\hat{\mathrm{x}}, \hat{\mathrm{c}}]}{\mathrm{Var}[\hat{\mathrm{c}}]\mathrm{Var}[\hat{\mathrm{x}}]} + \frac{\hat{\beta}^2 \mathrm{Var}[\hat{\mathrm{c}}]}{M\,\mathrm{Var}[\hat{\mathrm{x}}]}$$

Alternative: Control Variates

$$\frac{\mathrm{var}[\hat{\mathrm{y}}]}{\mathrm{var}[\hat{\mathrm{x}}]} = 1 - \frac{\mathrm{Cov}^2[\hat{\mathrm{x}}, \hat{\mathrm{c}}]}{\mathrm{Var}[\hat{\mathrm{c}}]\mathrm{Var}[\hat{\mathrm{x}}]} + \frac{\hat{\beta}^2 \mathrm{Var}[\hat{\mathrm{c}}]}{M\,\mathrm{Var}[\hat{\mathrm{x}}]}$$

$$= 1 - \rho_{xc}^2 + \frac{\hat{\beta}^2 \mathrm{Var}[\hat{\mathrm{c}}]}{M\,\mathrm{Var}[\hat{\mathrm{x}}]}$$

- Application to cosmology introduced as CARPool in Chartier et al 20, Chartier & Wandelt 21, Chartier & Wandelt 22.
    - Usually use approximate N-body simulations like COLA/FastPM for $\hat{c}$
    - e.g. DESI FastPM effort (Ding et al 2022) used 500 FastPM mocks, each requiring 810 Gb of storage, and required **21M CPU hours in total**

Alternative: Control Variates

$$\frac{\mathrm{var}[\hat{\mathrm{y}}]}{\mathrm{var}[\hat{\mathrm{x}}]} = 1 - \rho_{xc}^2 + \frac{\hat{\beta}^2 \mathrm{Var}[\hat{\mathrm{c}}]}{M\,\mathrm{Var}[\hat{\mathrm{x}}]}$$

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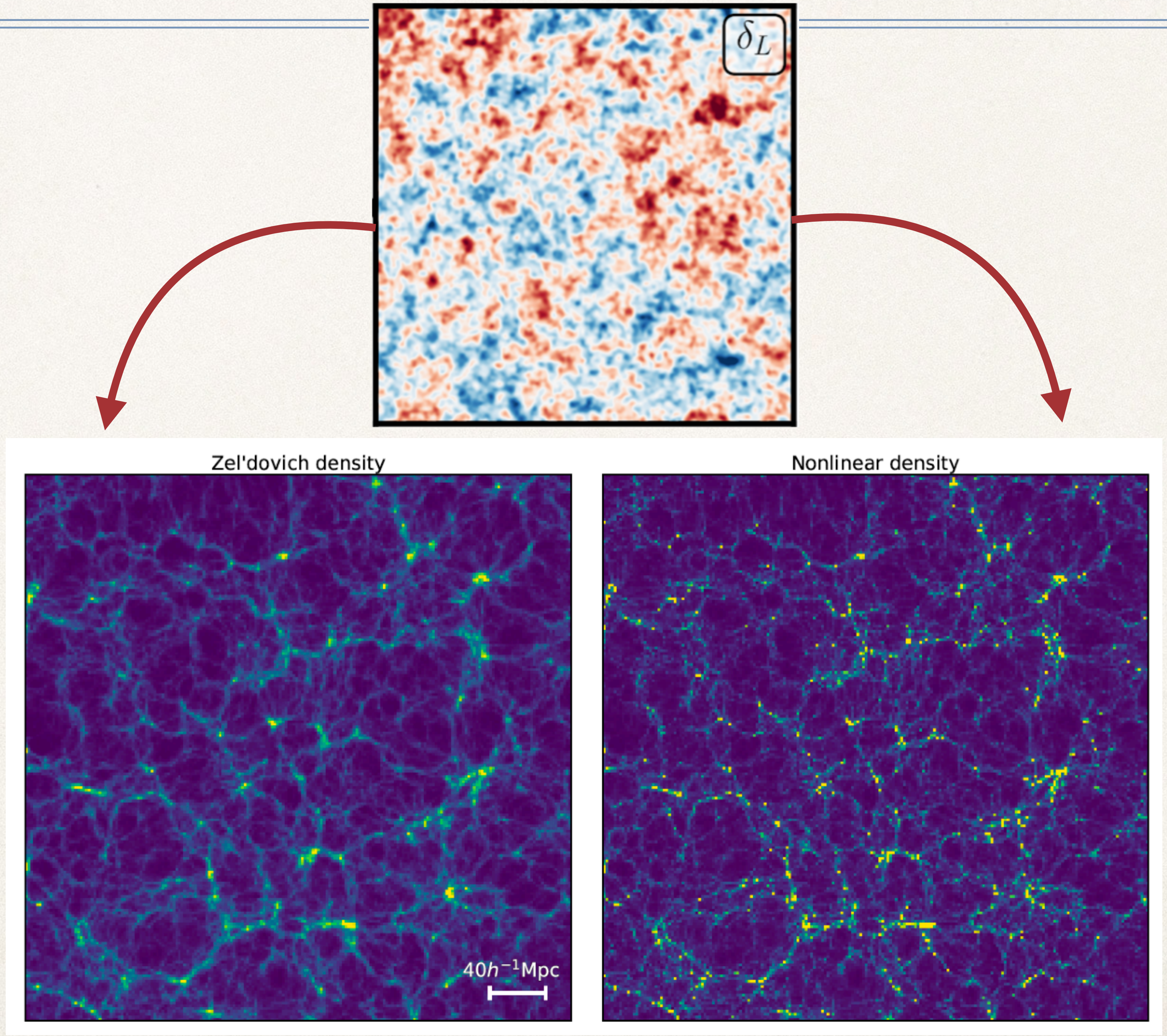
Need a control variate that is:

- **Inexpensive**
- **Highly correlated with $\hat{x}$**
- **Analytically known μ_c**

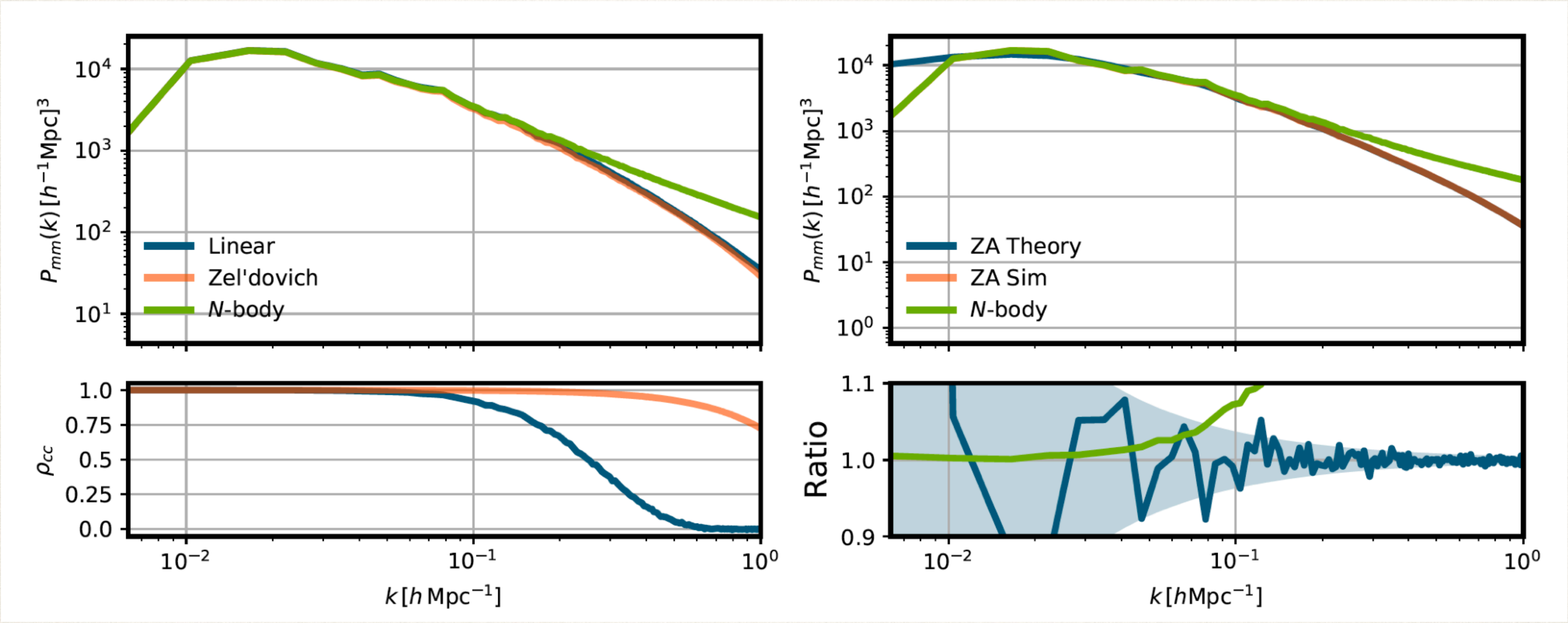
Zel'dovich approximation to the rescue



Kokron et al 2022 (incl. JDR)

Zel'dovich approximation to the rescue

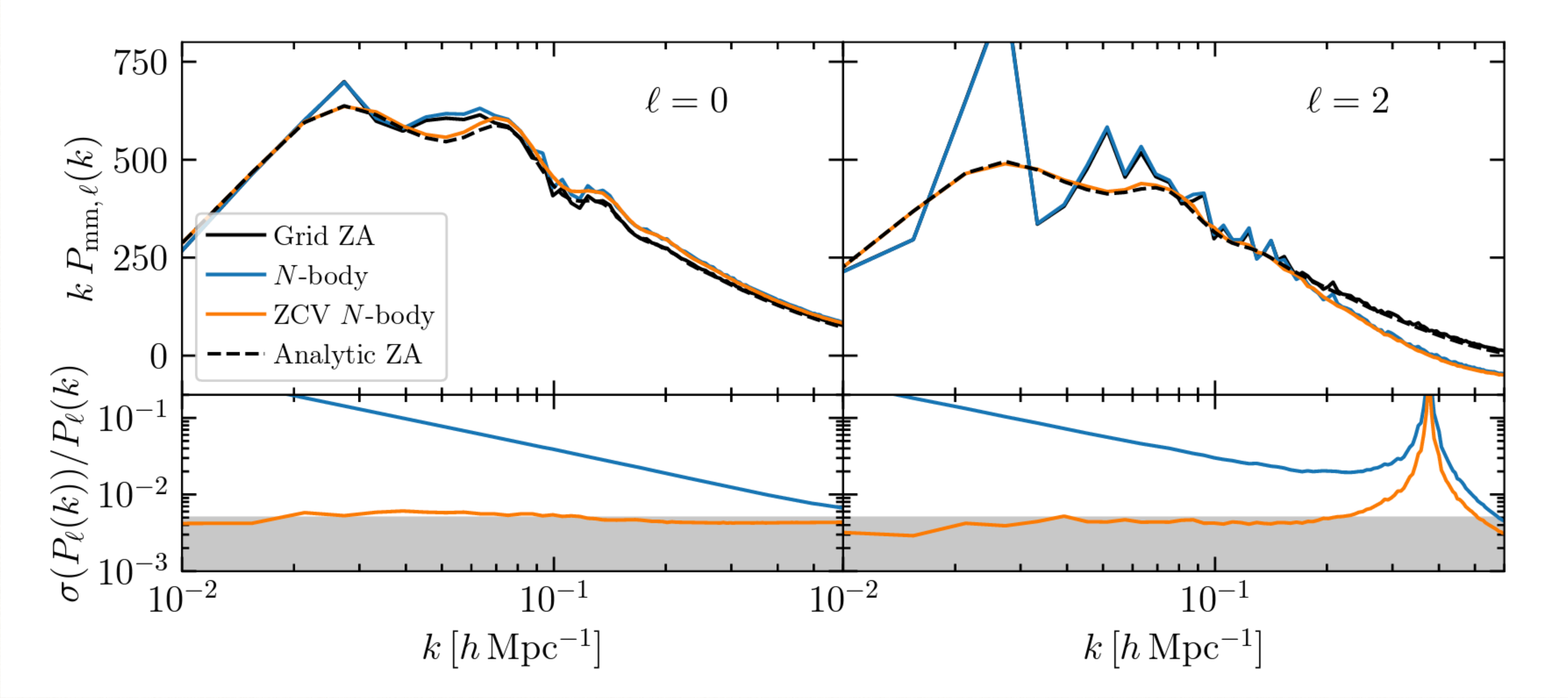
Kokron et al 2022 (incl. JDR)



ZA is **inexpensive, highly correlated** with the non-linear matter field, and **we can predict its mean** exactly.

Zel'dovich approximation to the rescue: An illustrative example

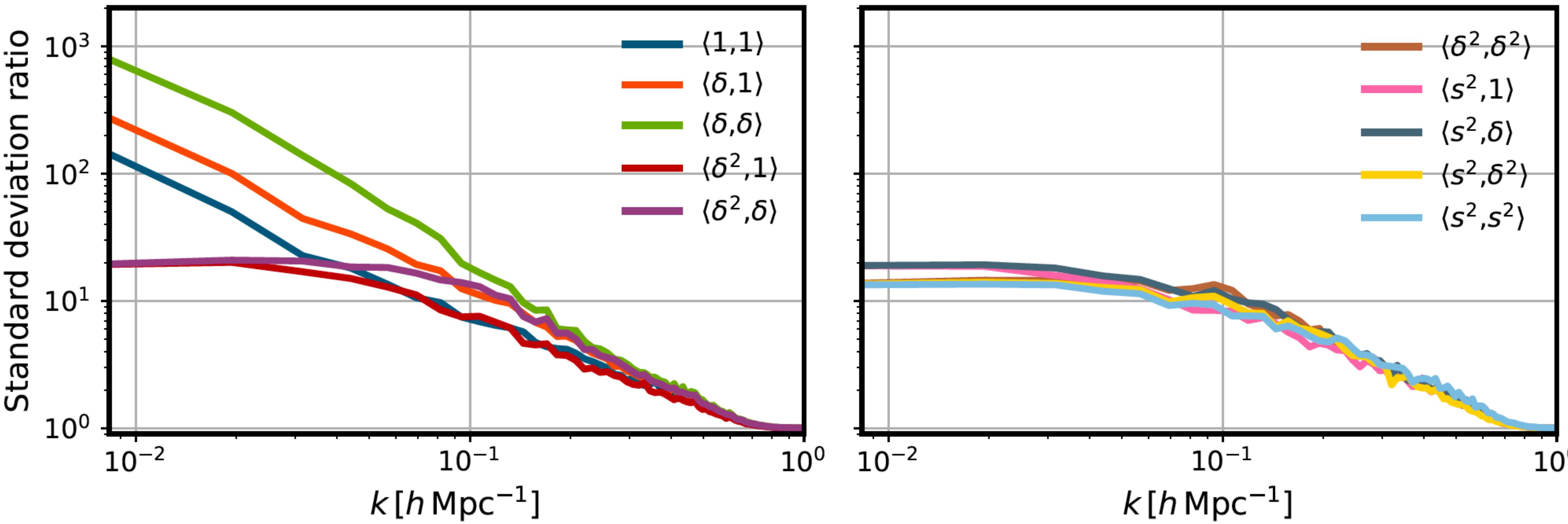
JDR et al. 2022



Because the Zel'dovich realization is highly correlated with the N-body, we can simply subtract the difference between grid ZA and analytic ZA from the N-body measurement to remove noise.

ZCV + HEFT

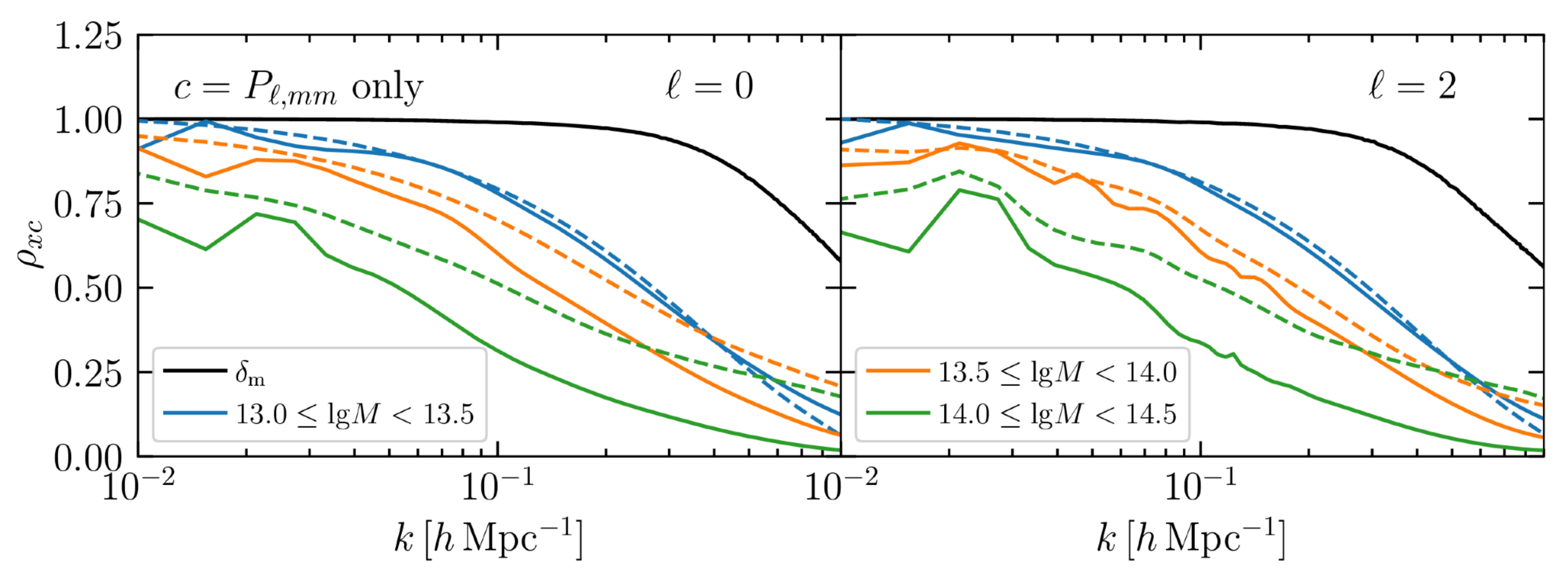
Applying Zel'dovich Control Variates to HEFT spectra leads to sub-percent errors on component spectra at all relevant scales



Kokron et al. 2022 (incl. JDR)

What about galaxy statistics?

JDR et al. 2022



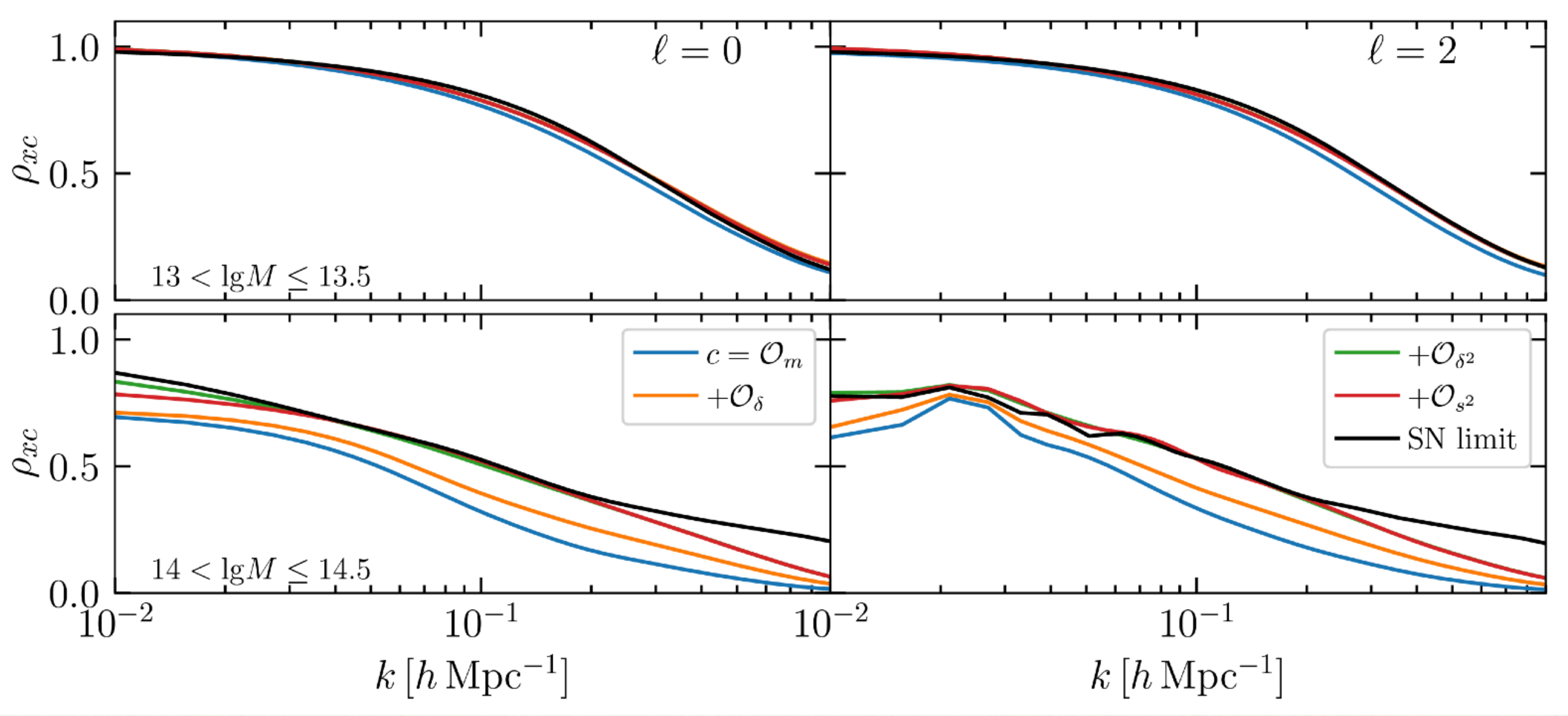
Galaxy/halo bias and shot noise lead to significant decorrelation between biased tracer power spectra and unbiased ZA.

Including non-linear bias

By including bias operators in our control variate, i.e.:

$$P_s^{tt}(\mathbf{k}) = \sum_{\mathcal{O}_i,\mathcal{O}_j} b_{\mathcal{O}_i} b_{\mathcal{O}_j} P_{ij,s}(\mathbf{k})$$

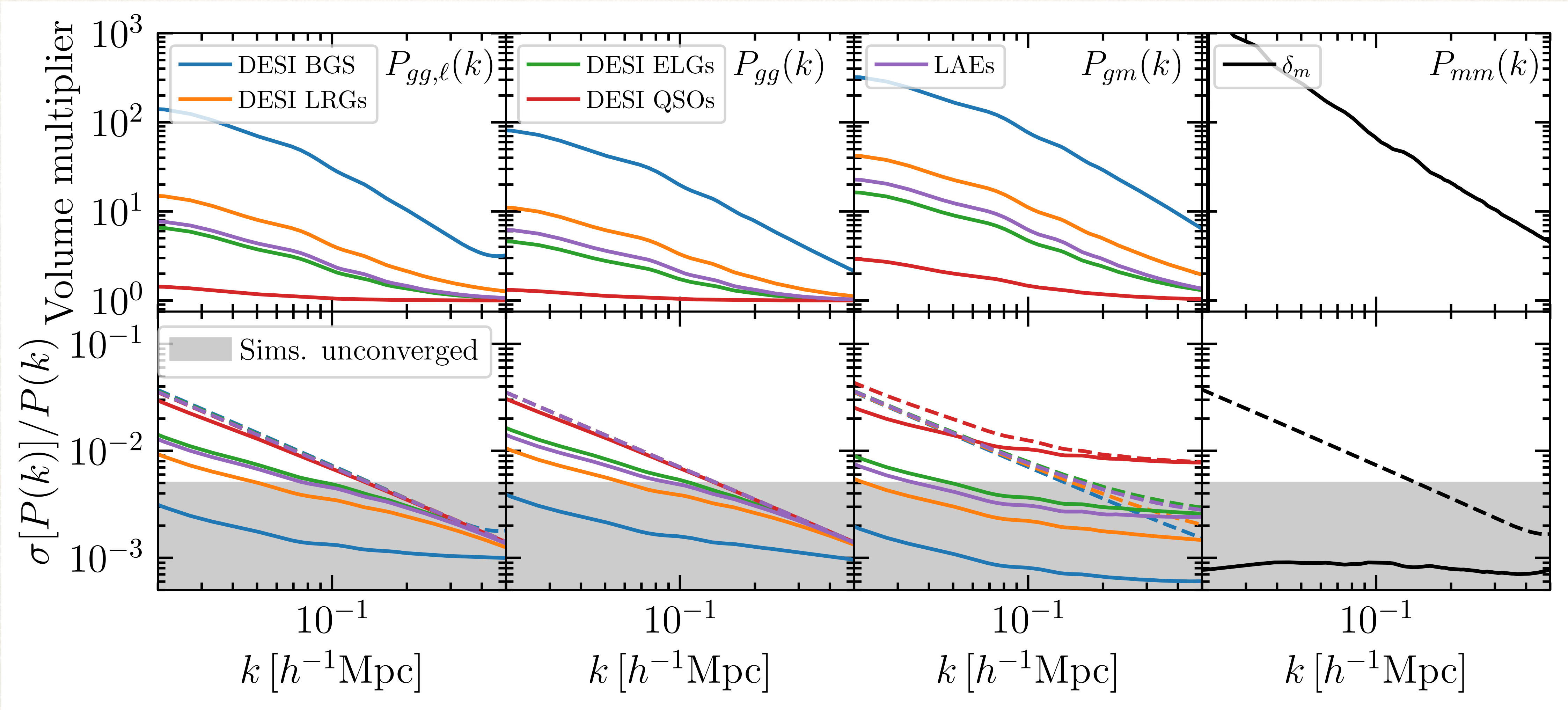
cross correlation with halo spectra reaches the limit imposed by shot noise



JDR et al. 2022

The upshot

When applying ZCV, one never needs more than (2 Gpc/h)^3 of simulated volume to remove sample variance as an important source of error for 2-point statistics in simulations.



JDR et al. 2022

Clustering & Lensing w/ DESI

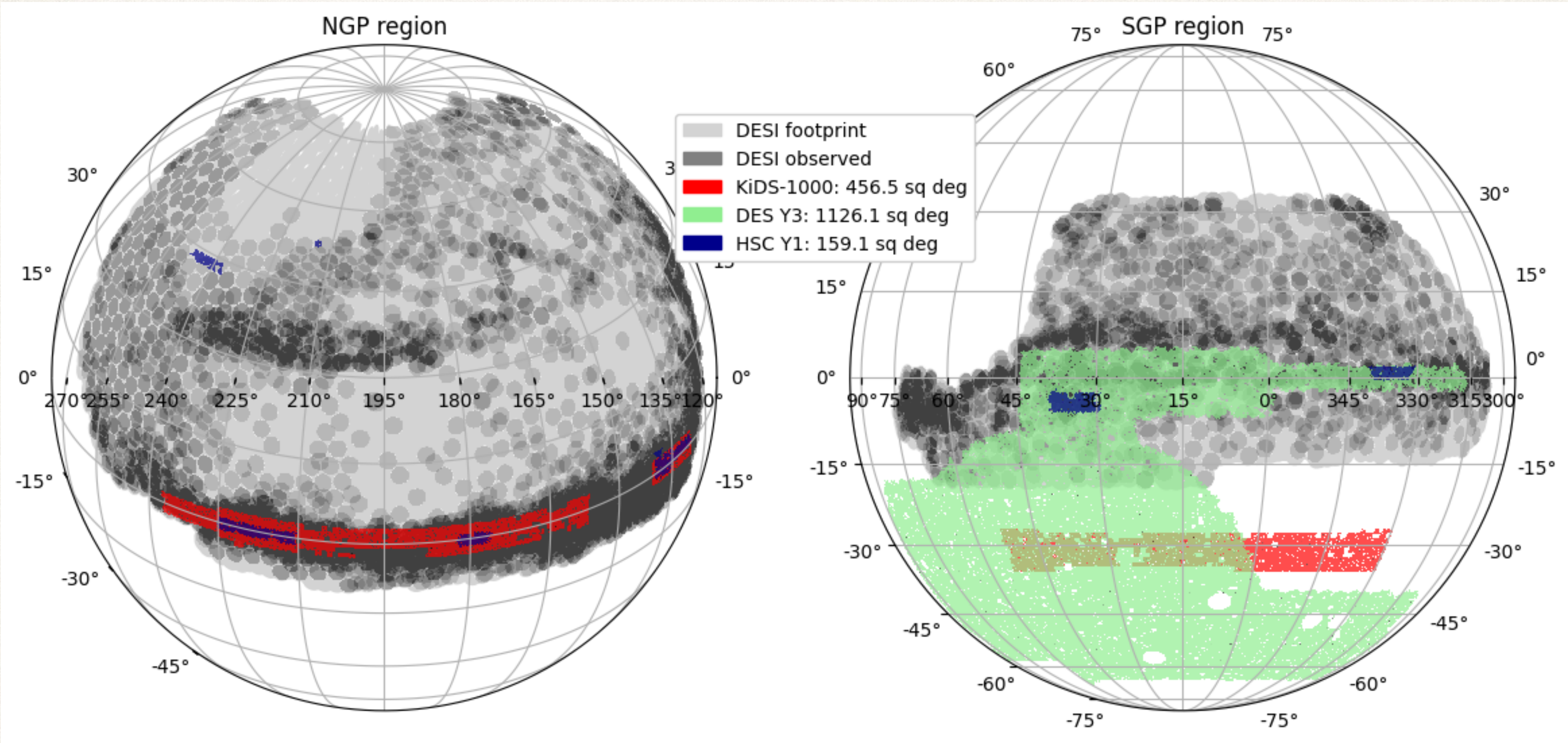


Figure: Chris Blake

Analyses applying these techniques to DESI cross correlations with galaxy and CMB lensing ongoing. Keep your eye out for them in the next ~year!

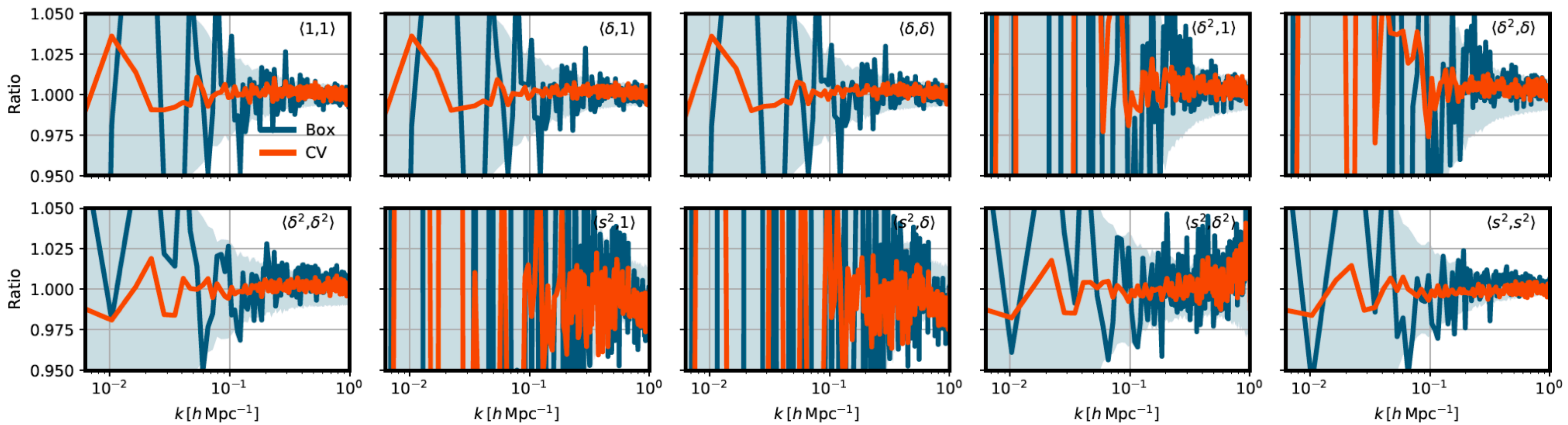
Summary

- We need new models to take full advantage of the amazing upcoming data that we are gathering.
- Combining N-body simulations and LPT into HEFT can extend the k reach of perturbation theory, with minimal additional assumptions.
- This model can be consistently combined with RSD fits.
- We can construct emulators for this model that are accurate and cover a broad cosmological parameter space.
    - Zel'dovich control variates drastically reduce variance on simulations for free, enabling denser cosmological sampling.

Thanks!

ZCV + HEFT

Applying Zeldovich Control Variates to HEFT spectra leads to sub-percent errors on component spectra at all relevant scales



Kokron et al 2022 (incl. JDR)