EFT of LSS at the Field Level

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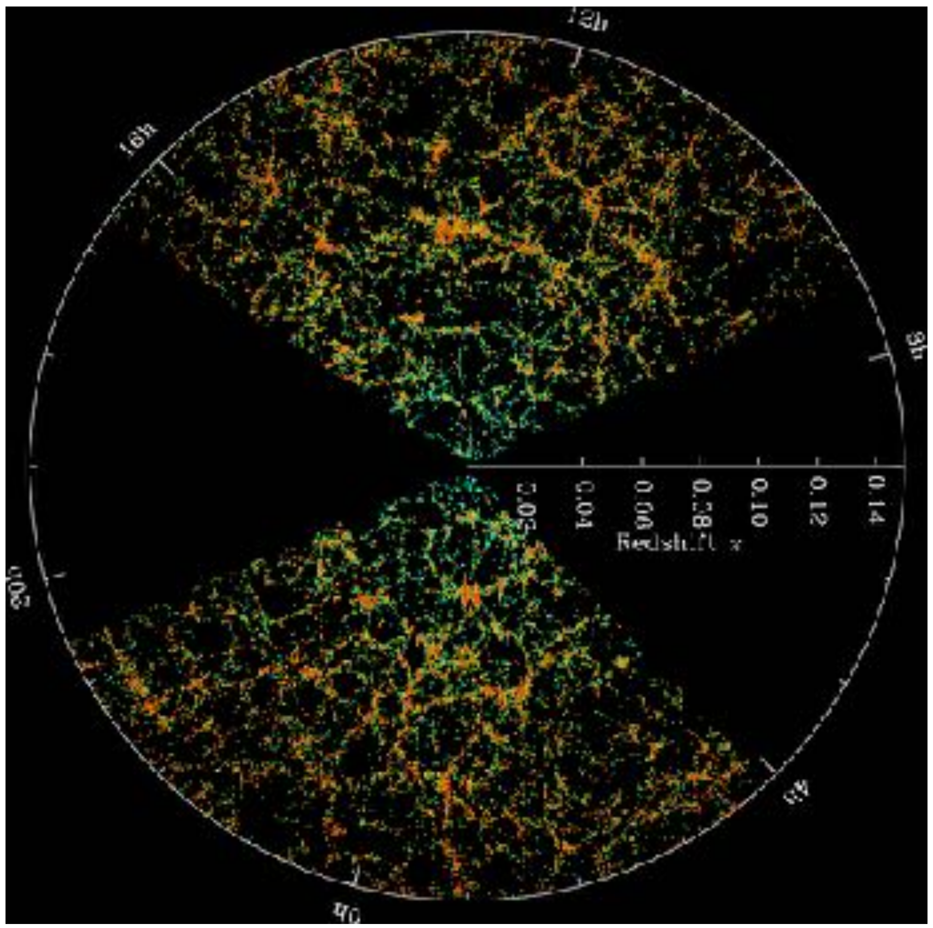
EFT of LSS in a nutshell

SDSS



Future:

Euclid, LSST, DESI, SPHEREx …

Precise maps of galaxy number density up to z~3

The main observable is galaxy density contrast $\delta^{(g)}(\boldsymbol{x})$

Why are we interested in galaxy clustering on large scales?

EFT of LSS in a nutshell

On large scales, the universe “remembers” the initial conditions

Gravitation is the dominant force

$$\partial_\tau \delta + \nabla[(1+\delta)\boldsymbol{v}] = 0$$
$$\partial_\tau \boldsymbol{v} + \mathcal{H}\boldsymbol{v} + \nabla\Phi + \boldsymbol{v}\cdot\nabla\boldsymbol{v} = \boxed{-c_s^2 \nabla\delta + \cdots}$$
$$\nabla^2\Phi = \frac{3}{2}\mathcal{H}^2\Omega_m\delta$$

…
Baumann, Nicolis, Senatore, Zaldarriaga (2010)
Carrasco, Hertzberg, Senatore (2012)
…

Bias expansion $\delta^{(g)} = \mathcal{F}[\nabla_i\nabla_j\Phi] = b_1\delta + b_2\delta^2 + b_{s^2}(\nabla_i\nabla_j\Phi)^2 + \tilde{b}\nabla^2\delta \cdots$ + noise

does not conserve
mass and momentum!

…
McDonald, Roy (2009)
Assassi, Baumann, Green, Zaldarriaga (2014)
Senatore (2015)
…

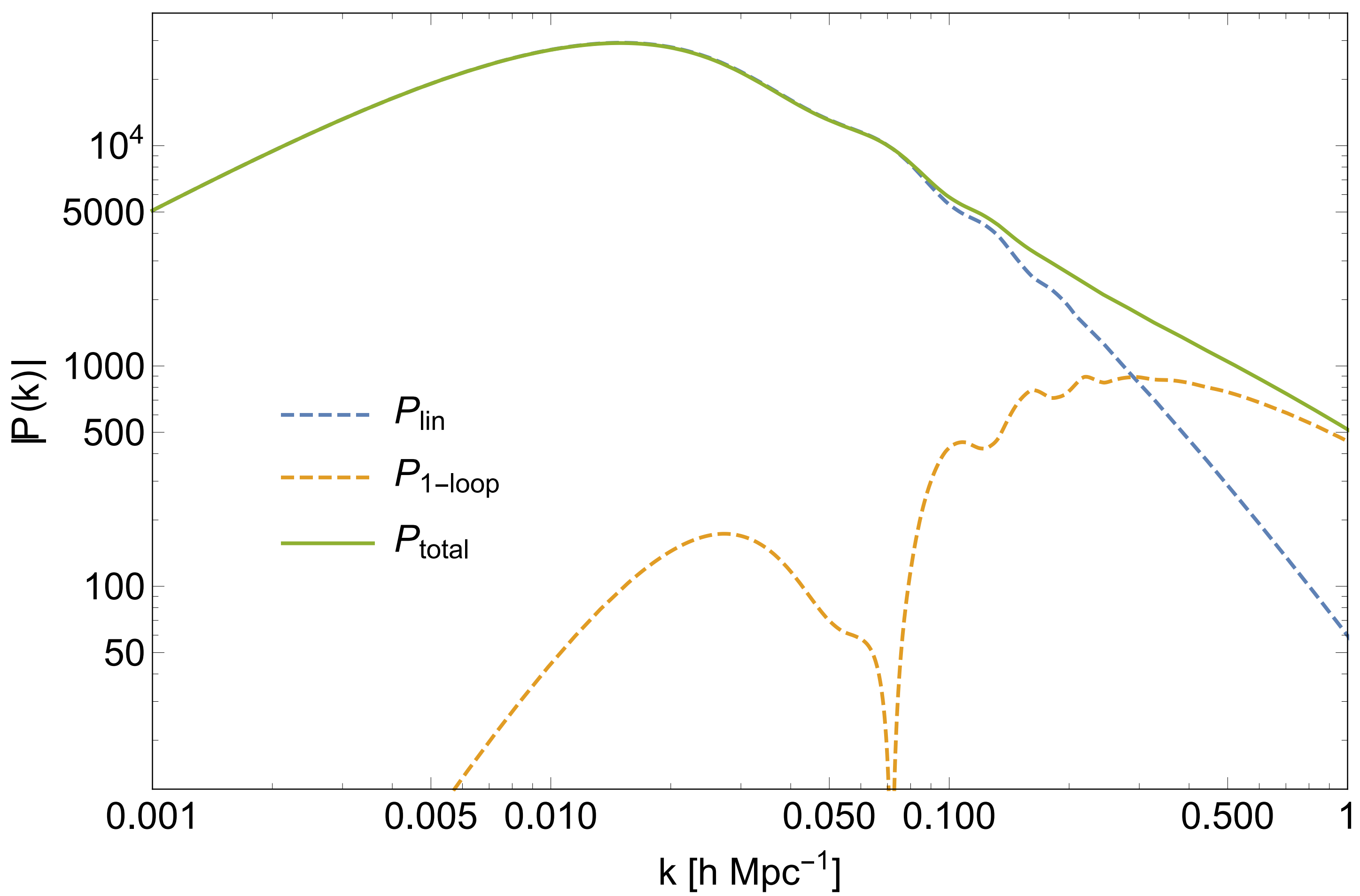
+ many subtleties and details…

EFT of LSS in a nutshell

Traditionally, the main observables are correlation functions

Power spectrum

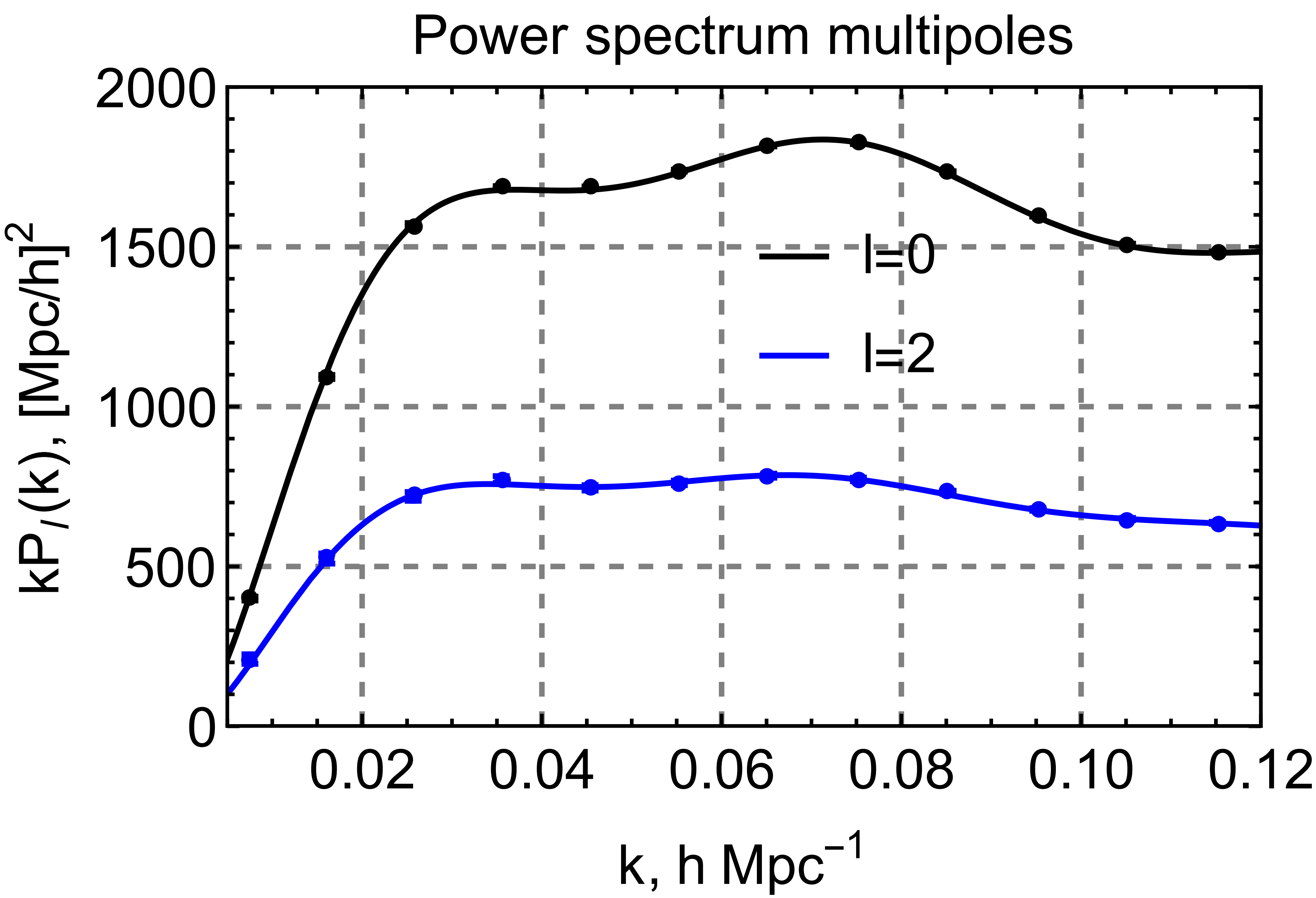
$$\langle \delta_{\boldsymbol{k}} \delta_{-\boldsymbol{k}} \rangle = \langle \delta^{(1)}_{\boldsymbol{k}} \delta^{(1)}_{-\boldsymbol{k}} \rangle + \langle \delta^{(2)}_{\boldsymbol{k}} \delta^{(2)}_{-\boldsymbol{k}} \rangle + \langle \delta^{(1)}_{\boldsymbol{k}} \delta^{(3)}_{-\boldsymbol{k}} \rangle + \langle \delta^{(3)}_{\boldsymbol{k}} \delta^{(1)}_{-\boldsymbol{k}} \rangle + \cdots$$



EFT of LSS in a nutshell

PT Challenge

D’Amico, Ivanov, Nishimichi, Senatore, MS, Takada, Zaldarriaga, Zhang (in prep.)



EFT at the filed level

Traditional analyses use n-point functions. Disadvantages:

- Cosmic variance, compromise on resolution/size of the box
- At high k hard to disentangle the effects of nonlinearities
- Overfitting (smooth curves, many parameters)
- Only a few lowest n-point functions used
- Difficult to isolate and study the noise

Can we do better?

EFT at the filed level

These problems can be solved using fields rather than summary statistics

Baldauf, Schaan, Zaldarriaga (2015)
Lazeyras, Schmit (2017)
Abidi, Baldauf (2018)
McQuinn, D'Aloisio (2018)

Advantages:

— No cosmic variance, small boxes with high resolution are enough

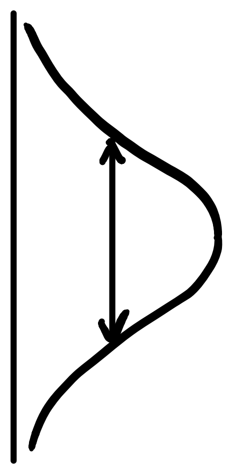
— High S/N at low *k*, no need to go to the nonlinear regime

— No overfitting, each Fourier mode (amplitude and phase) is fitted

— "All" *n*-point functions measured simultaneously

— It is easy to isolate and study the noise

EFT at the filed level



$$\xrightarrow{\text{stochastic}} \quad \delta_{lin}(\vec{k}) \quad \xrightarrow{\text{deterministic}} \quad \delta_{NL}(\vec{k})$$

$$\begin{array}{ccc} & \text{Same initial conditions} & \\ \swarrow_{\text{Sim.}} & & \searrow^{\text{PT}} \\ \delta_h^{\text{truth}} & & \delta_h \end{array}$$

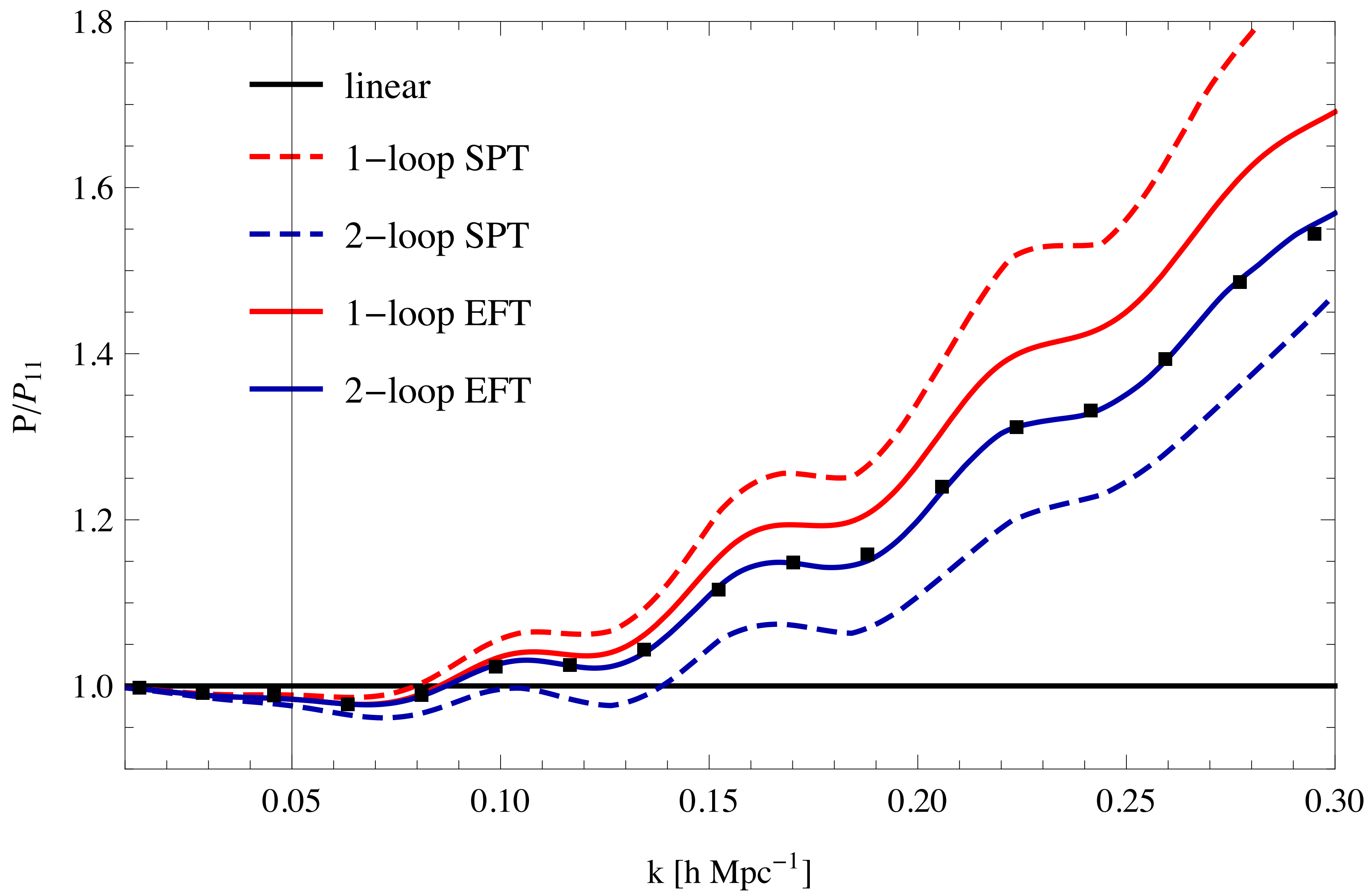
If PT was perfect, the two fields would be the same (all Fourier modes the same)

EFT at the filed level

A very clean measurement of the counterterm

$$P_{\rm count.}(k) \sim c_s^2(\tau)\big(2P_{13}^{q\to 0}(k) + 2P_{15}^{q\to 0}(k) + 2P_{24}^{q\to 0}(k) + P_{33-II}^{q\to 0}(k)\big)$$

Baldauf, Mercolli, Zaldarriaga (2015)



EFT at the filed level

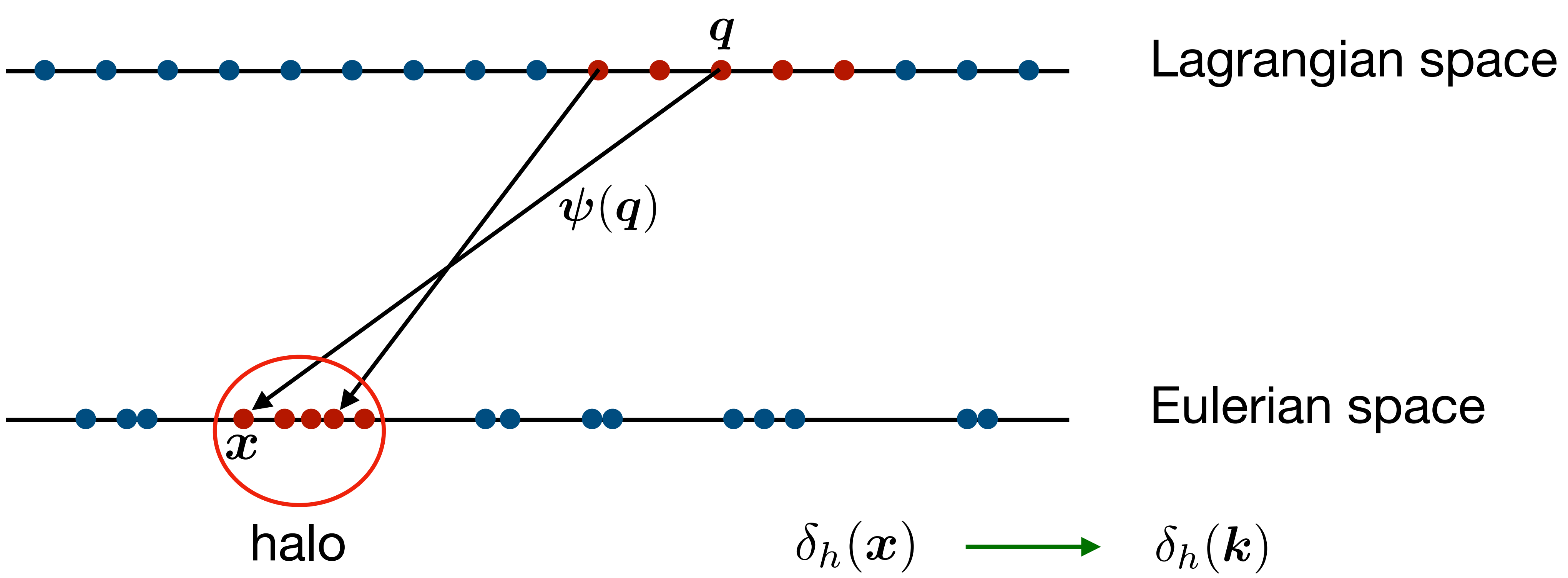
How do we find the EFT solution at the field level in practice?

Eulerian PT does not work, we need “IR resummation”

Lagrangian PT does not have this problem, but it gives only displacements

EFT at the filed level

We want a hybrid scheme



$$\boldsymbol{\psi}_1(\boldsymbol{q}) = \int_{\boldsymbol{k}} e^{i\boldsymbol{k}\cdot\boldsymbol{q}} \frac{i\boldsymbol{k}}{k^2} \delta_1(\boldsymbol{k})$$

linear displacement is large

EFT at the filed level

tidal field

$$\delta_h^{\mathrm{L}}(\boldsymbol{q}) = b_1^{\mathrm{L}}\,\delta_1(\boldsymbol{q}) \;+\; b_2^{\mathrm{L}}\,(\delta_1^2(\boldsymbol{q}) - \sigma_1^2) \;+\; b_{\mathcal{G}_2}^{\mathrm{L}}\mathcal{G}_2(\boldsymbol{q}) + \cdots$$

$$\sigma_1^2 = \langle \delta_1^2(\boldsymbol{q}) \rangle = \int_0^\infty \frac{\mathrm{d}k}{2\pi^2}\, k^2 P_{11}(k)$$

$$\delta_h(\boldsymbol{k}) \equiv \int \mathrm{d}^3\boldsymbol{x}\,(1+\delta_h(\boldsymbol{x}))\,e^{-i\boldsymbol{k}\cdot\boldsymbol{x}} = \int \mathrm{d}^3\boldsymbol{q}\,(1+\delta_h(\boldsymbol{q}))\,e^{-i\boldsymbol{k}\cdot(\boldsymbol{q}+\boldsymbol{\psi}(\boldsymbol{q}))}$$

$$\delta_h(\boldsymbol{k}) = \int \mathrm{d}^3\boldsymbol{q}\,\Big(1 + b_1^{\mathrm{L}}\,\delta_1(\boldsymbol{q}) \;+\; b_2^{\mathrm{L}}\,(\delta_1^2(\boldsymbol{q}) - \sigma_1^2) \;+\; b_{\mathcal{G}_2}^{\mathrm{L}}\mathcal{G}_2(\boldsymbol{q}) + \cdots$$
$$- i\boldsymbol{k}\cdot\boldsymbol{\psi}_2(\boldsymbol{q}) + \cdots\Big)\,e^{-i\boldsymbol{k}\cdot(\boldsymbol{q}+\boldsymbol{\psi}_1(\boldsymbol{q}))}$$

The usual approximation in (C)LPT   for example: Vlah, Castorina, White (2016)

EFT at the filed level

This motivates the bias expansion with “shifted” operators

$$\tilde{\mathcal{O}}(\boldsymbol{k}) \equiv \int \mathrm{d}^3\boldsymbol{q}\; \mathcal{O}(\boldsymbol{q})\, e^{-i\boldsymbol{k}\cdot(\boldsymbol{q}+\boldsymbol{\psi}_1(\boldsymbol{q}))}$$

Schmittfull, MS, Assassi, Zaldarriaga (2018)

EFT prediction

$$\delta_h(\boldsymbol{k}) = \beta_1(k)\; \tilde{\delta}_1(\boldsymbol{k}) + \beta_2(k)\; \tilde{\delta}_2^{\perp}(\boldsymbol{k}) + \beta_{\mathcal{G}_2}(k)\; \tilde{\mathcal{G}}_2^{\perp}(\boldsymbol{k}) + \cdots \text{ + noise}$$

transfer functions

IR resummation included, correct positions of halos, spread of the BAO peak…

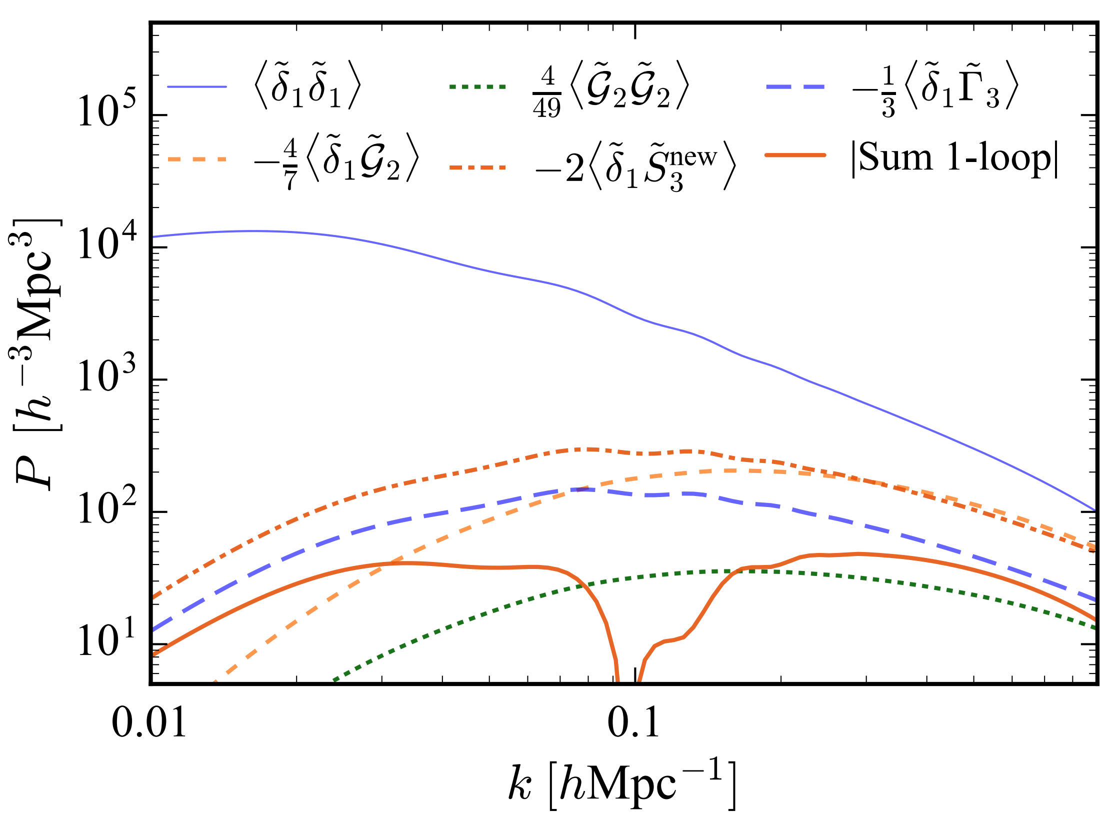
Only linear fields used in the construction

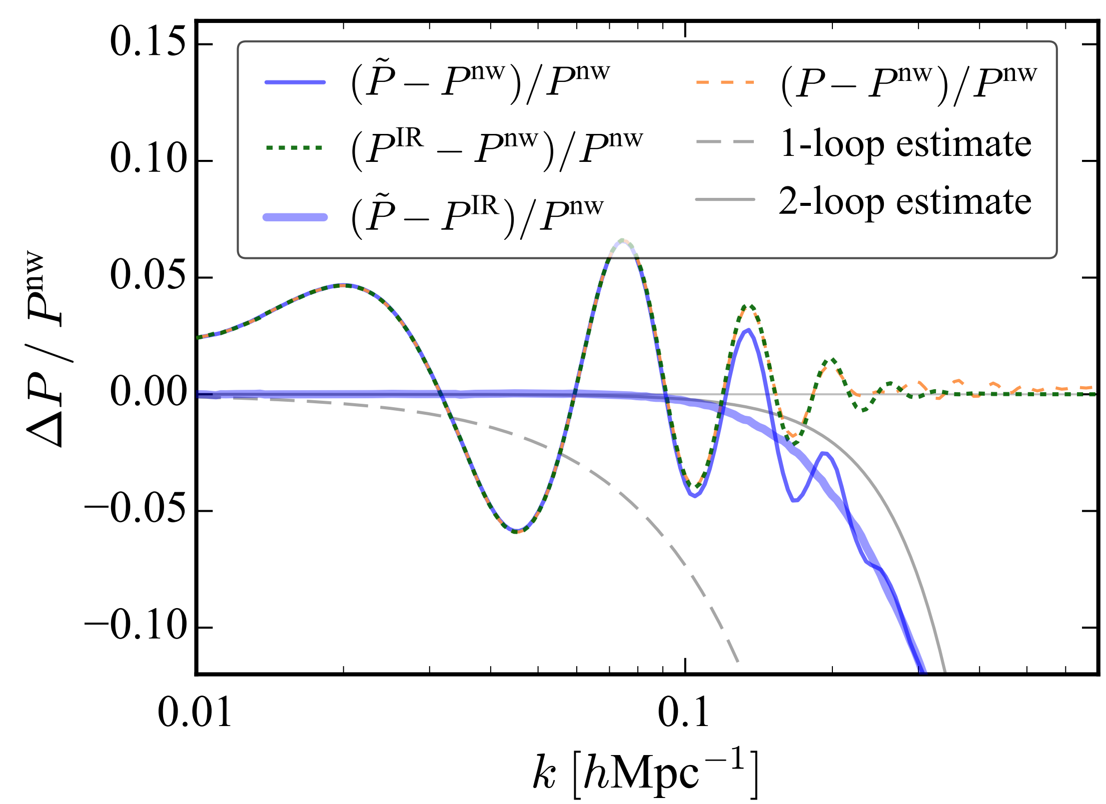
EFT at the filed level

Schmittfull, MS, Assassi, Zaldarriaga (2018)

Example of DM

$$\tilde{\delta} \;=\; \tilde{\delta}_1 \;+\; \frac{2}{7}\,\tilde{\mathcal{G}}_2 \;-\; \frac{3}{14}\,[\widetilde{\mathcal{G}_2\delta}] \;-\; \frac{2}{9}\,\tilde{\mathcal{G}}_3 \;+\; \frac{1}{6}\,\tilde{\Gamma}_3 \;-\; \tilde{\mathcal{S}}_3$$





Comparison to simulations

5 boxes, L = 500 Mpc/*h*, N = 1536^3, m = $3*10^9$ M_{sun}/*h*, z = 0.6

Halos identified using the standard FOF algorithm

4 mass bins

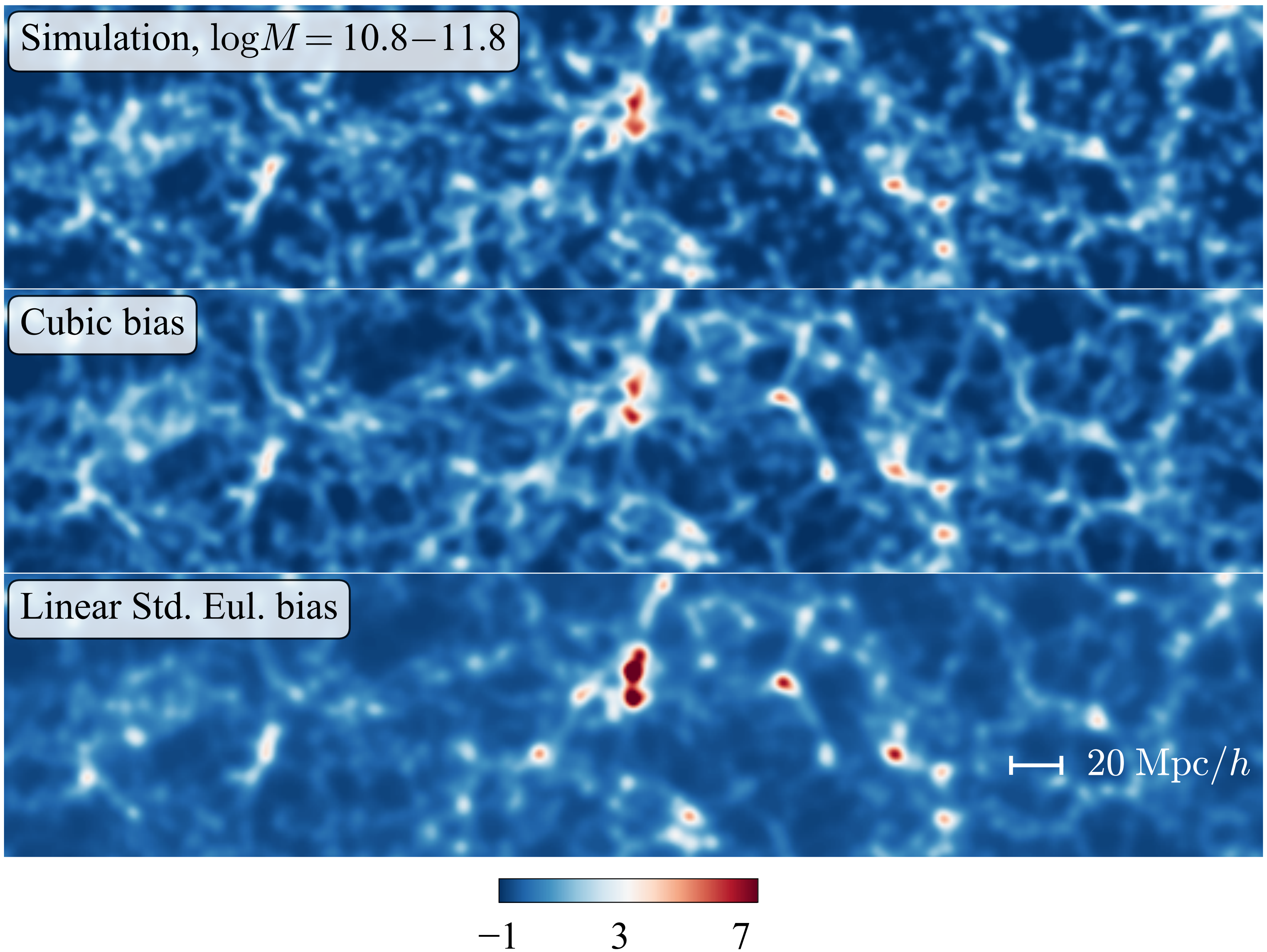
$\log M[h^{-1}\mathrm{M}_\odot]$	$\bar{n}\,[(h^{-1}\mathrm{Mpc})^{-3}]$	$\bar{n}$ is comparable to
$10.8 - 11.8$	4.3×10^{-2}	LSST [80, 81], Billion Object Apparatus [82]
$11.8 - 12.8$	5.7×10^{-3}	SPHEREx [83, 84]
$12.8 - 13.8$	5.6×10^{-4}	BOSS CMASS [85], DESI [86, 87], Euclid [88–90]
$13.8 - 15.2$	2.6×10^{-5}	Cluster catalogs

Table I. Simulated halo populations at $z = 0.6$.

Comparison to simulations

Schmittfull, MS, Assassi, Zaldarriaga (2018)

Real space slices



$\delta_h(\boldsymbol{x})$

Comparison to simulations

Bias parameters fitted minimizing the difference

$$\sum_{\boldsymbol{k}, |\boldsymbol{k}| \approx k} |\delta_h^{\rm truth}(\boldsymbol{k}) - \delta_h^{\rm model}(\boldsymbol{k})|^2$$

Fitting the bias model using the entire field, instead of *n*-point functions

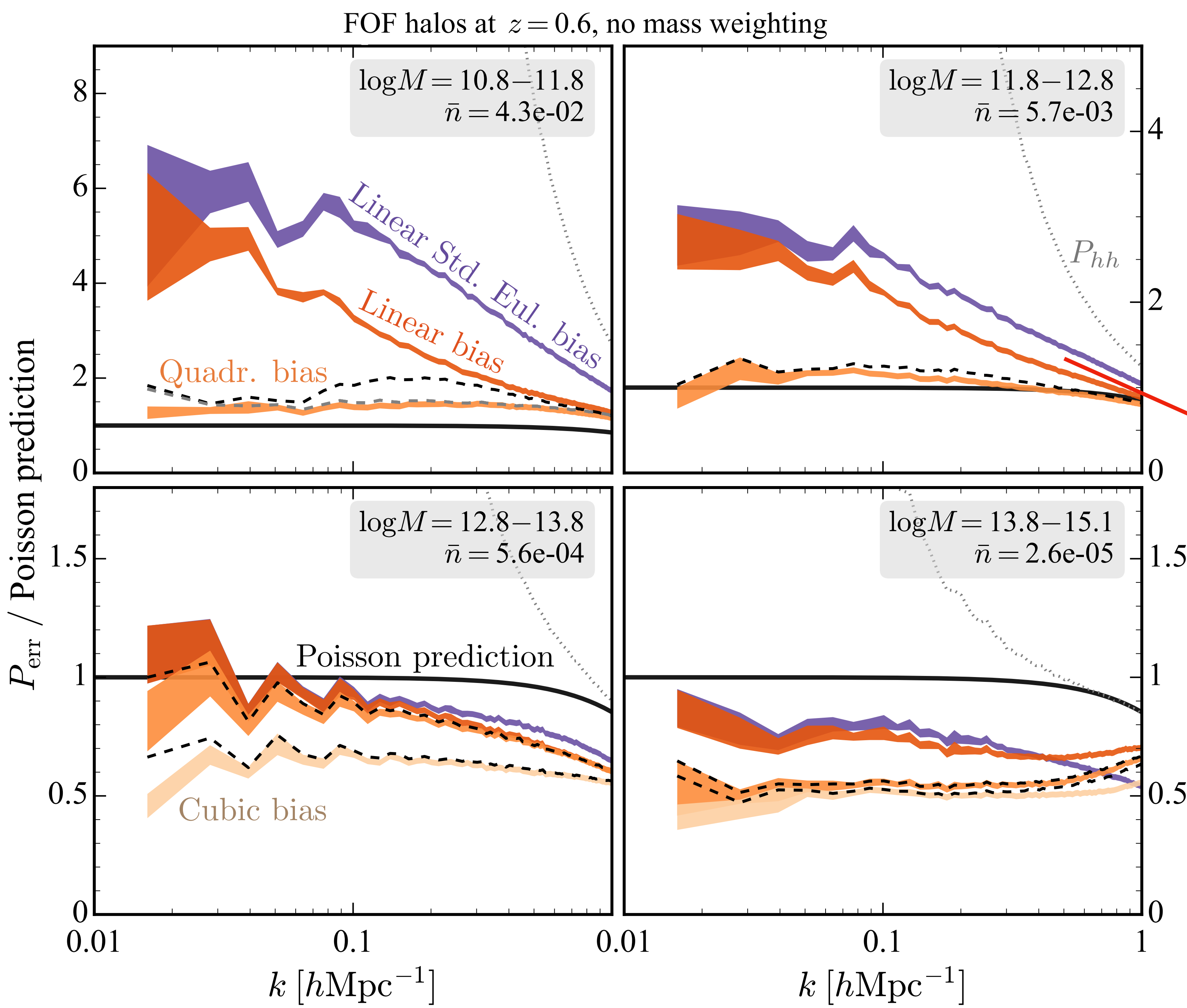
An example:

$$\delta_h^{\rm truth} = b_1 \delta + \epsilon \longrightarrow b_1(k) = \frac{\langle \delta_h^{\rm truth}(\boldsymbol{k}) \delta^*(\boldsymbol{k}) \rangle}{\langle |\delta(\boldsymbol{k})|^2 \rangle}$$

More generally, for orthogonal fields: $\beta_i(k) = \dfrac{\langle \delta_h^{\rm truth} \tilde{\mathcal{O}}_i^\perp \rangle}{\langle \tilde{\mathcal{O}}_i^\perp \tilde{\mathcal{O}}_i^\perp \rangle}$

Comparison to simulations

Schmittfull, MS, Assassi, Zaldarriaga (2018)



$$\hat{\epsilon} \equiv \delta_h^{\rm truth} - \delta_h^{\rm model}$$

$$P_{\rm err}(k) \equiv \langle |\hat{\epsilon}(\boldsymbol{k})|^2 \rangle$$

contrary to the naive expectation

Comparison to simulations

Difference on large scales comes form short modes interactions

$\delta(\vec{k}) \sim R^2 k^2$

Deterministic part of the “noise”

$\delta(\vec{k}) \sim \text{const.}$

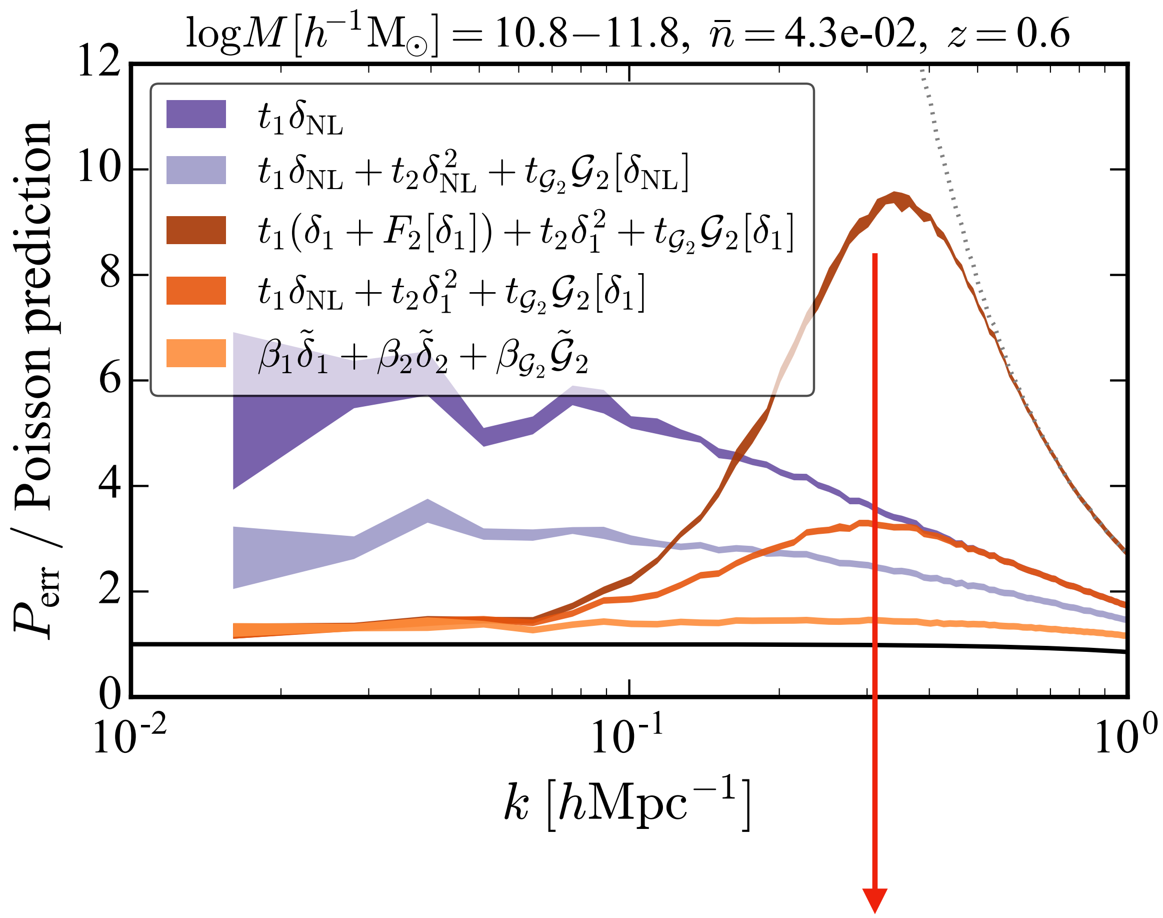
Two different kinds of long modes on large scales

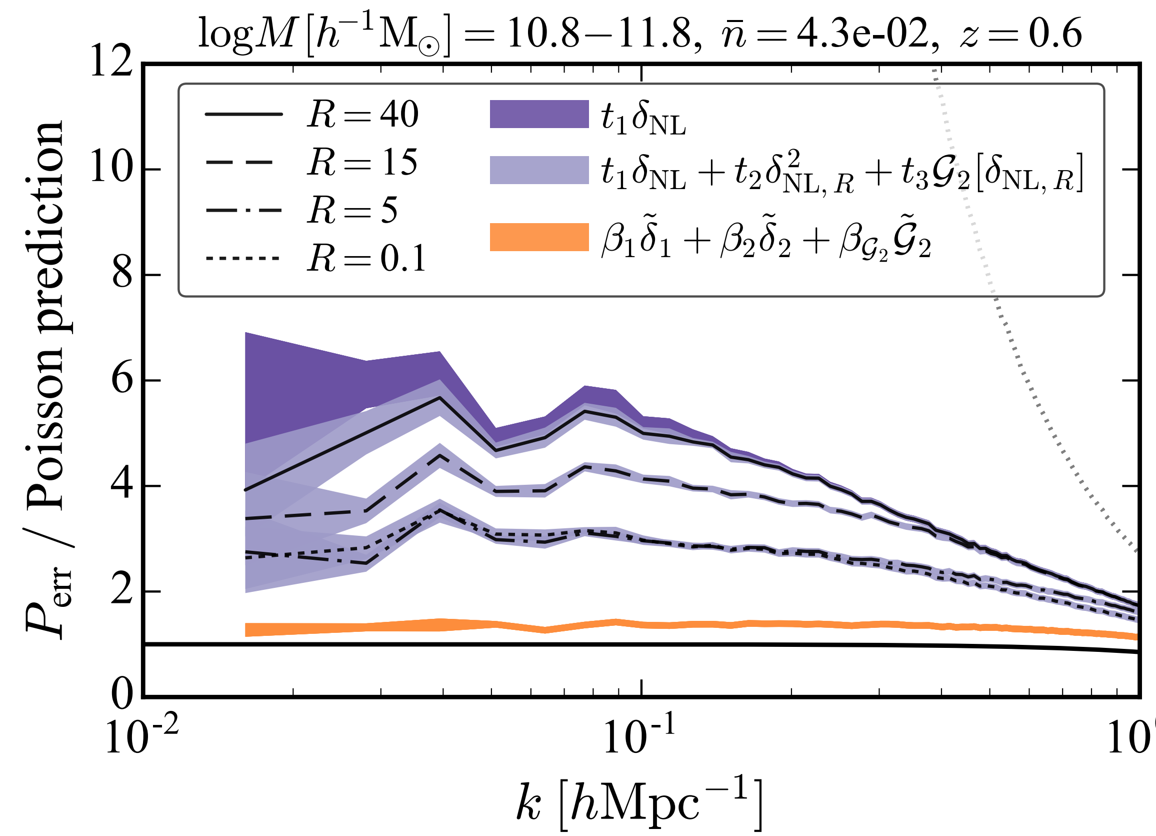
Comparison to simulations

Schmittfull, MS, Assassi, Zaldarriaga (2018)

No version of Eulerian bias scheme works

Keeping the small scales is crucial to minimize the model error





Invisible in the power spectrum: Equivalence Principle, soft theorems…

Comparison to simulations

Two different "definitions" of bias parameters. How to make sense of it?

Renormalized biases defined using low-*k* limits of tree-level diagrams

Low-*k* limits of the transfer functions are not renormalized bias parameters

$$\beta_i(k) = \frac{\langle \delta_h^{\mathrm{truth}} \tilde{\mathcal{O}}_i^{\perp} \rangle}{\langle \tilde{\mathcal{O}}_i^{\perp} \tilde{\mathcal{O}}_i^{\perp} \rangle}$$

sensitive to high k and definition of operators

Related to similar methods to measure physical biases

Lazeyras, Schmit (2017)
Abidi, Baldauf (2018)

What is the true noise?

Future directions

How to use this information about mode coupling?

Try to “reconstruct” the initial density field (very successful for the BAO peak)

Likelihood on the field level

Both these are alternatives to measuring n-point functions

Conclusions

PT at the field level is an alternative to *n*-point functions

Very useful for comparisons to simulations and measuring biases/counterterms

A simple bias model works rather well for realistic halos/galaxies

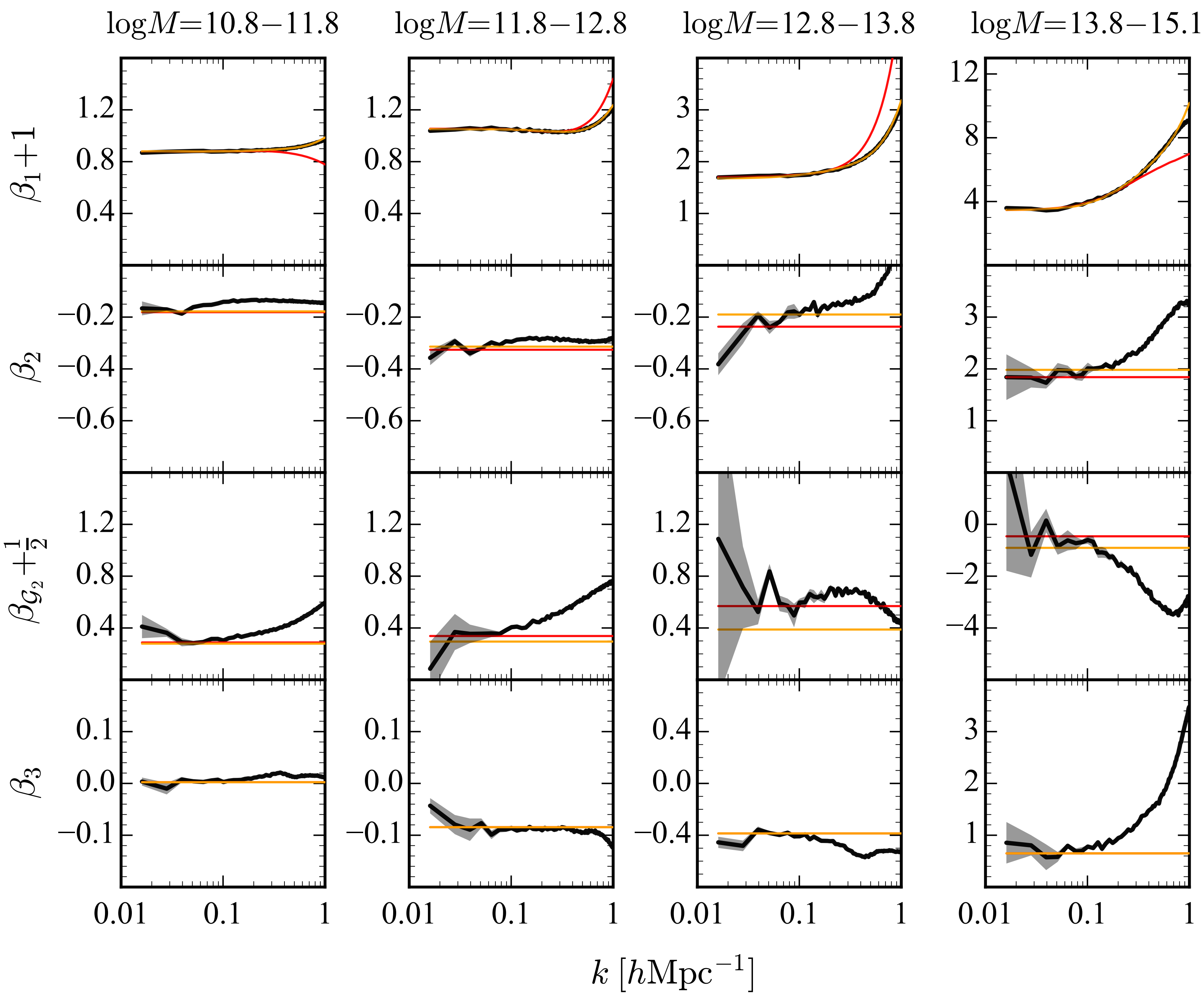
Interesting question about what is the true noise

Motivates a new approach to data analysis

Backup slides

Comparison to simulations

Transfer functions



Comparison to simulations

What is the measure of success?

Cross-correlation coefficient: $$r_{cc}(k) \equiv \frac{\langle \delta_h^{\rm model}(\boldsymbol{k})[\delta_h^{\rm truth}(\boldsymbol{k})]^* \rangle}{\left(\langle|\delta_h^{\rm model}(\boldsymbol{k})|^2\rangle\langle|\delta_h^{\rm truth}(\boldsymbol{k})|^2\rangle\right)^{1/2}}$$

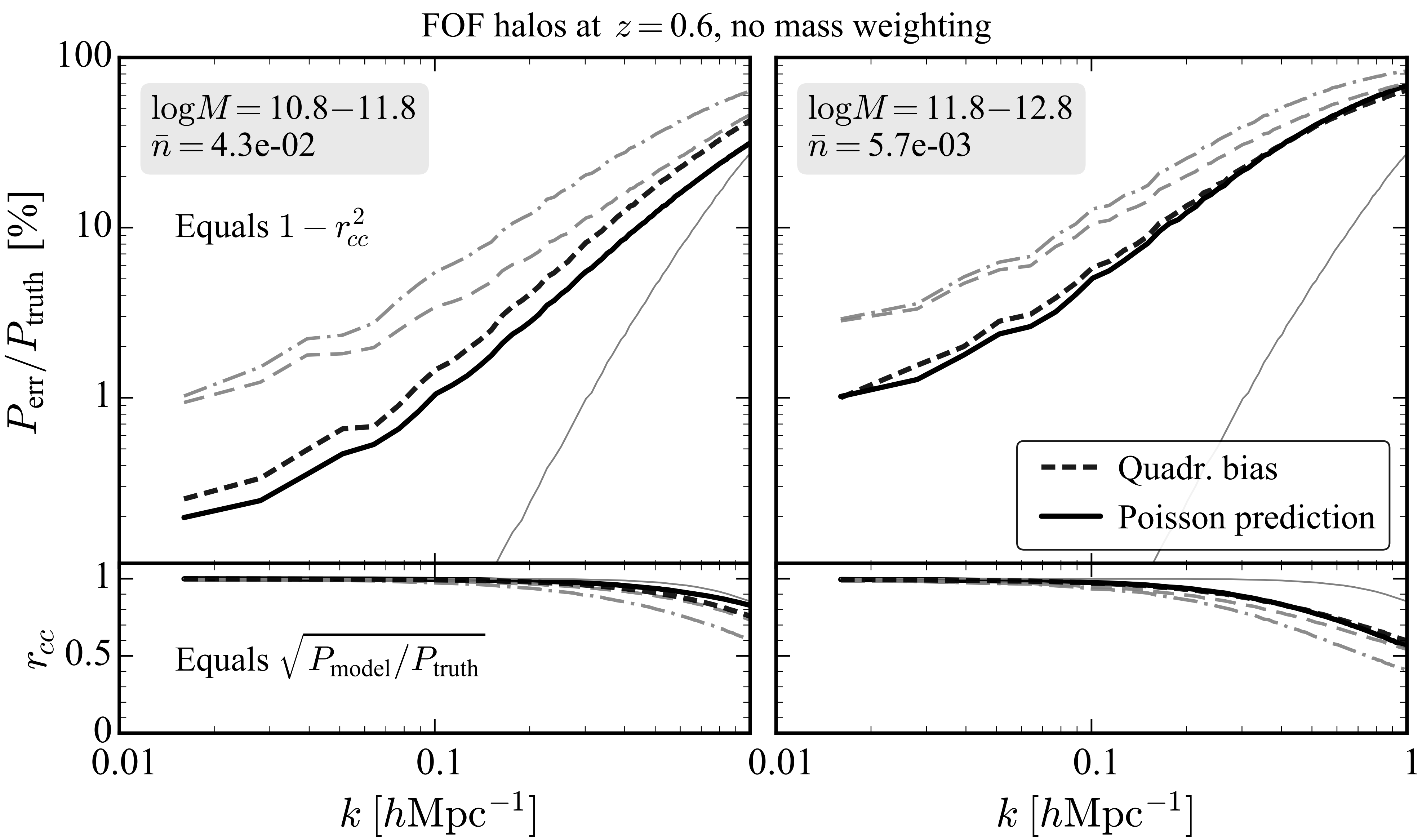
The power spectrum of the model error $$\hat{\epsilon} \equiv \delta_h^{\rm truth} - \delta_h^{\rm model}$$

$$P_{\rm err}(k) \equiv \langle|\hat{\epsilon}(\boldsymbol{k})|^2\rangle$$

For the best-fit model $$P_{\rm err}(k) = P_{\rm truth}(1 - r_{cc}^2)$$

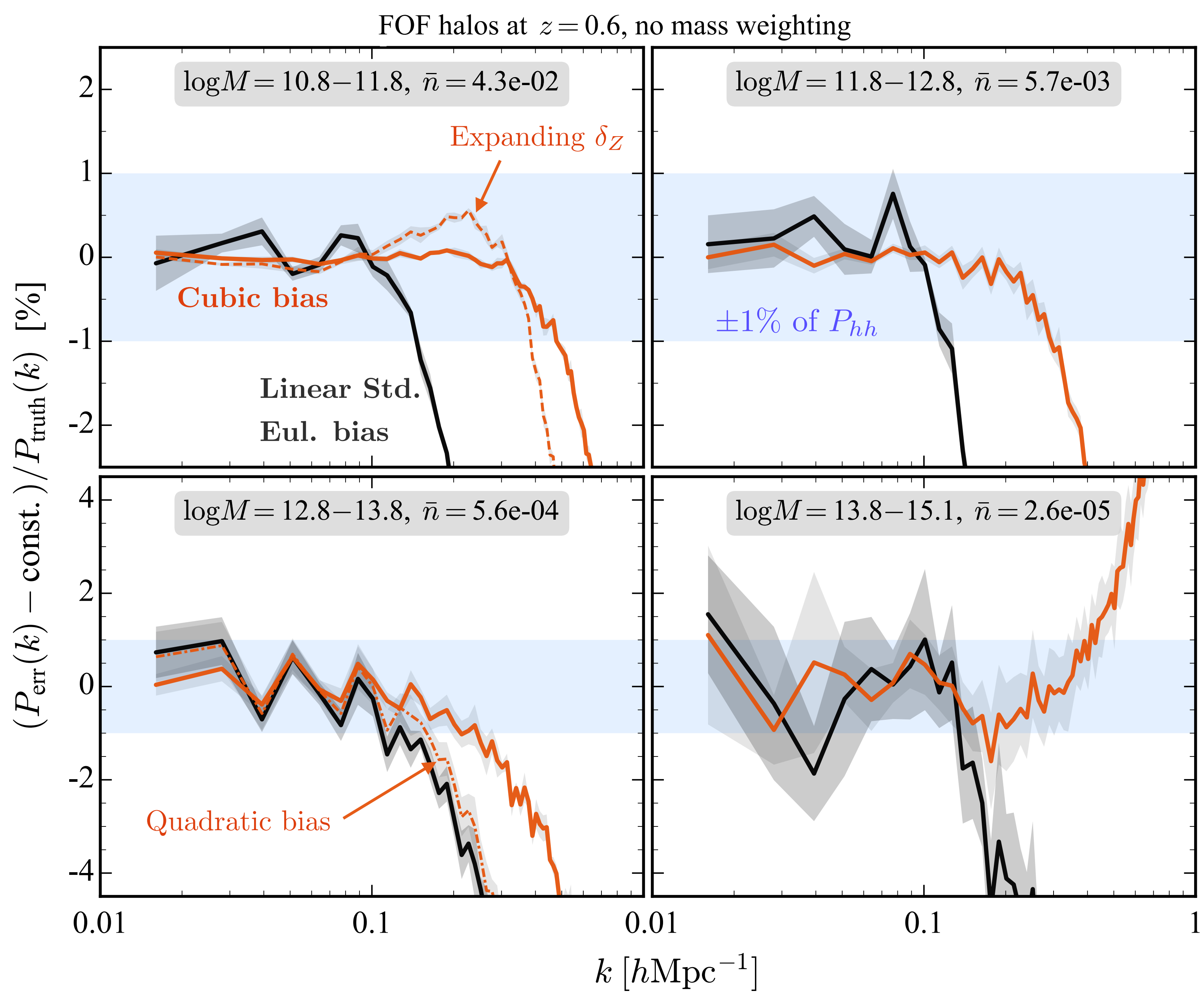
$$(P_{\rm model}/P_{\rm truth})^{1/2} = r_{cc}$$

Comparison to simulations



Comparison to simulations

The scale-dependence of the noise is relevant for data analysis



Comparison to simulations

Mass-weighting reduces the noise