aquila-consortium.org

LEFTfield

$\mathbf{x} = \mathbf{x}_{\mathrm{fl}}(\tau)$

EFT meets Field-Level Inference

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with
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$\mathbf{q} = \mathbf{x}_{\mathrm{fl}}(0)$

Perspectives on LSS, FZU Prague, June 2023

Outline

A. Theory: EFT at the field level

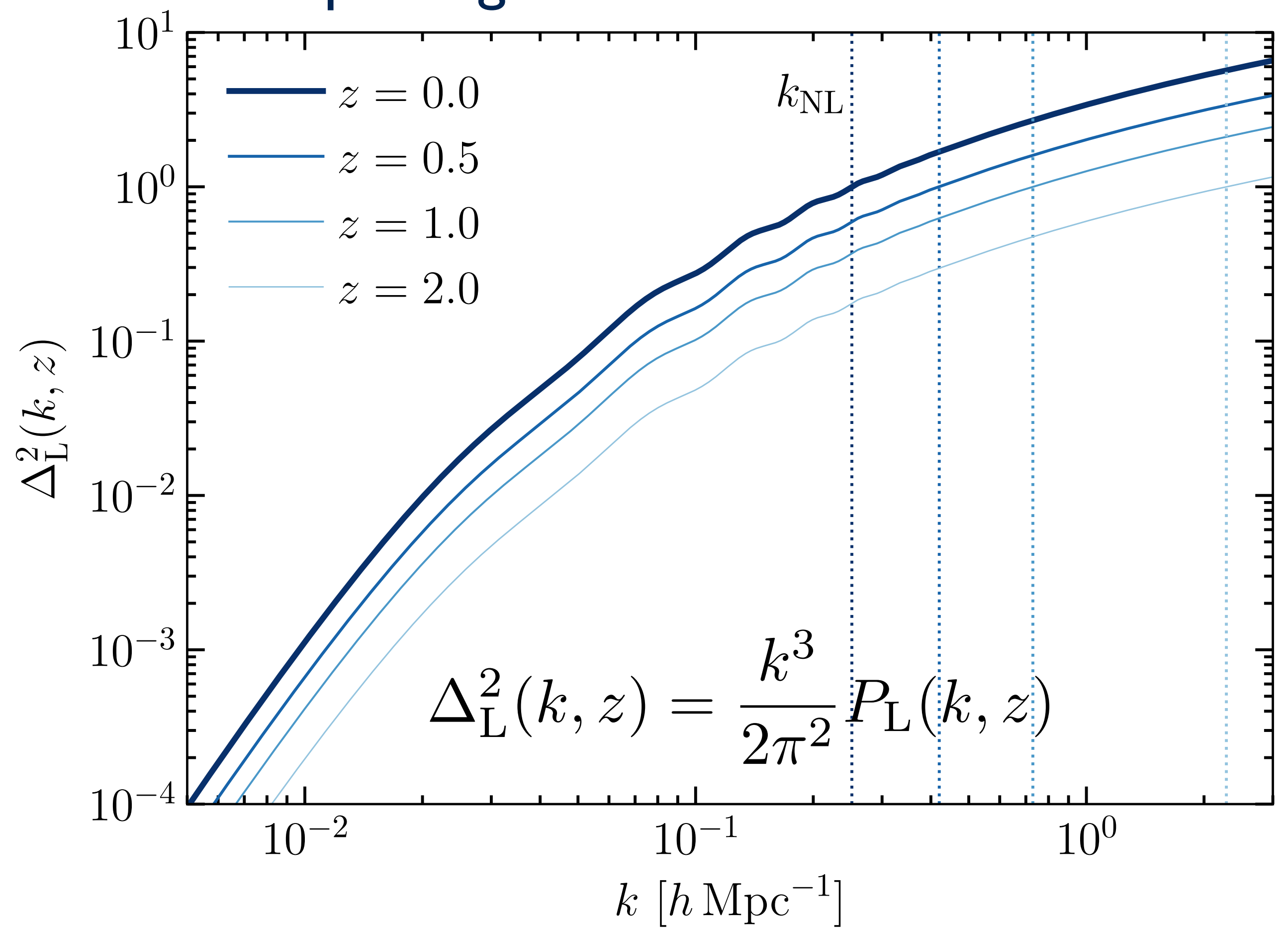
B. Inference: Field-level and LFI

A. Theory: EFT at the field level

Cold Dark Matter cosmology in a nutshell

- *Inflation+CMB* -> scale-invariant, adiabatic, approx. Gaussian initial conditions
- Large-scale fluctuations are small (still linear today)
- Structure forms *hierarchically from small to large scales*
- *Perturbative expansion* in fluctuations on large scales

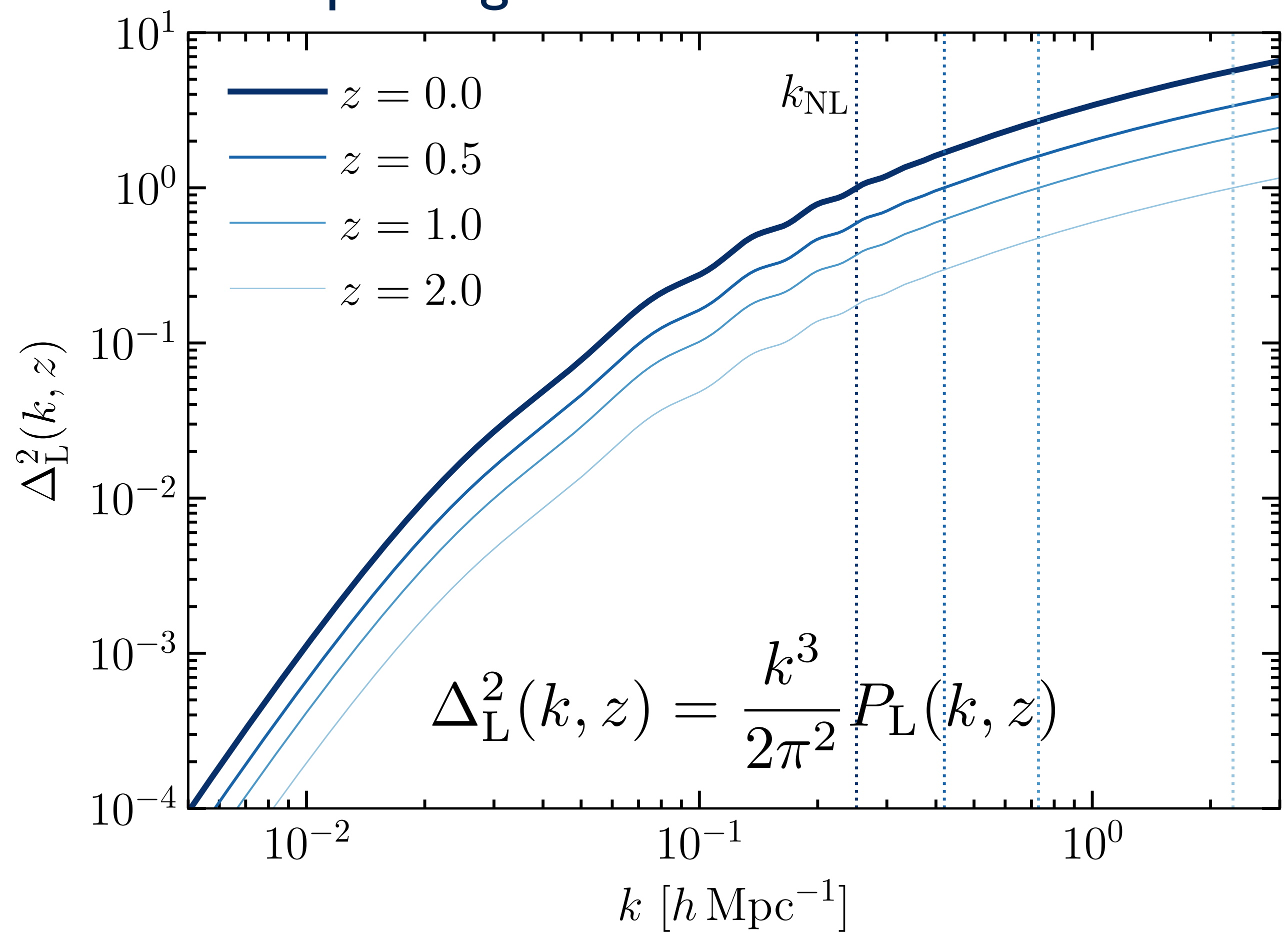
variance of matter fluctuations per logarithmic k interval



Theory of galaxy clustering

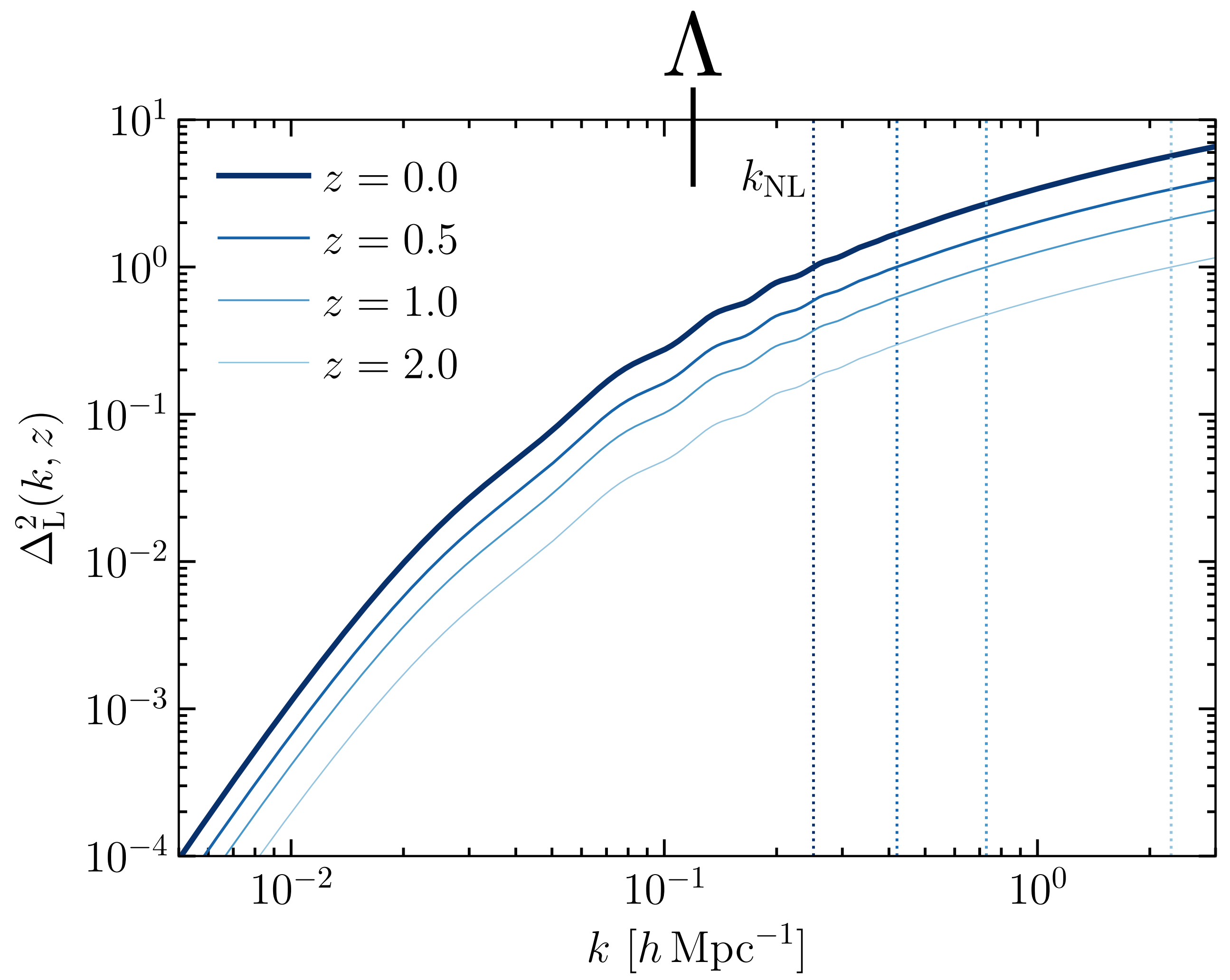
- Perturbations in our universe are small on large scales
  - Perturbation theory works on quasilinear scales $k < k_{NL}$
- Goal: describe galaxy clustering up to a given scale and accuracy using a finite number of free (A) bias parameters and (B) stochastic amplitudes

variance of matter fluctuations
per logarithmic k interval



EFT approach

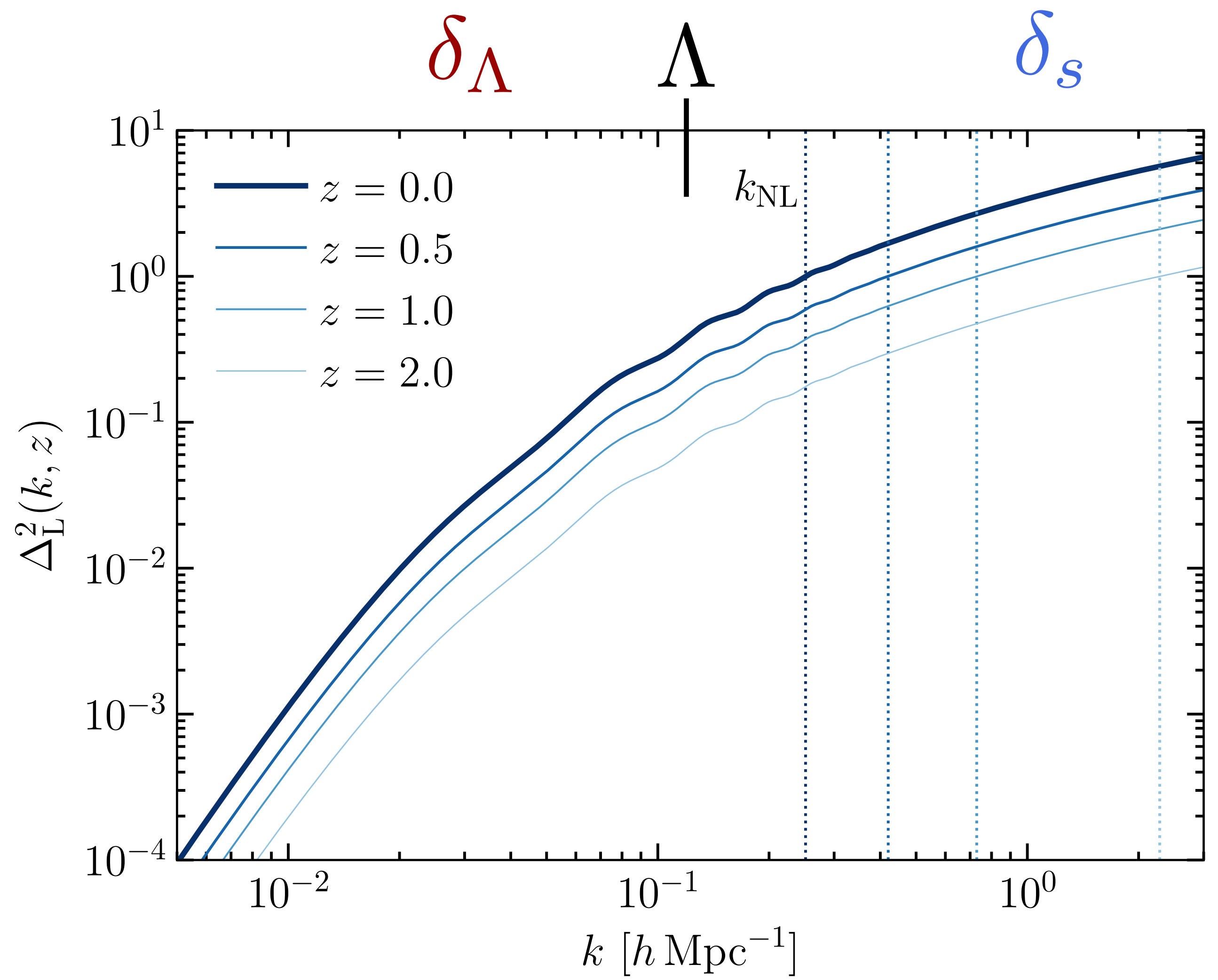
- Idea: trust our theory for $k < \Lambda$



EFT approach

- Idea: trust our theory for *k* < *Λ*
- Split *initial* perturbations into large scale (< Λ) and small scale (>= Λ):

$$\delta(\boldsymbol{x},\tau) \equiv \frac{\rho_m(\boldsymbol{x},\tau)}{\bar{\rho}_{,}(\tau)} - 1 = \delta_\Lambda + \delta_s$$



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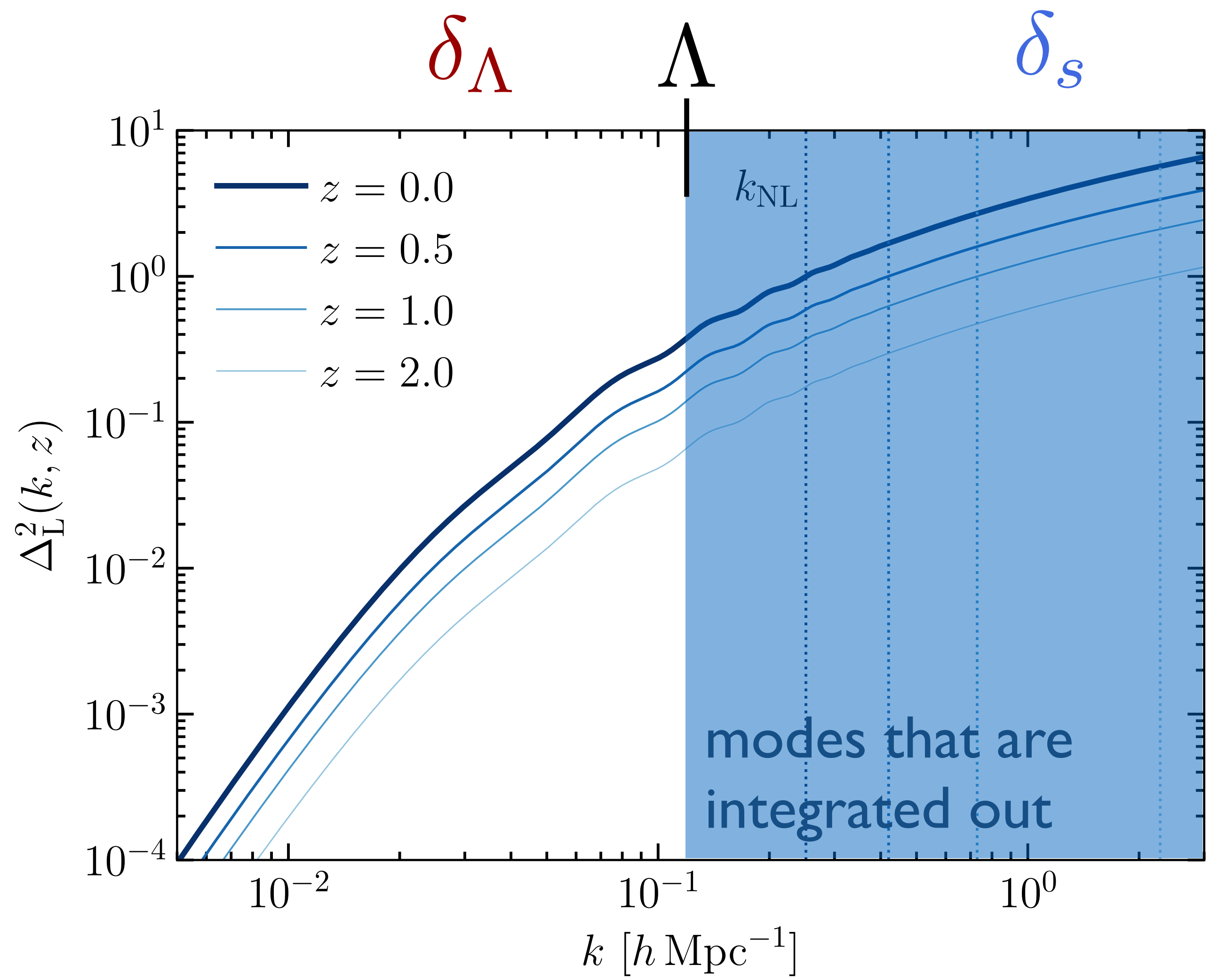


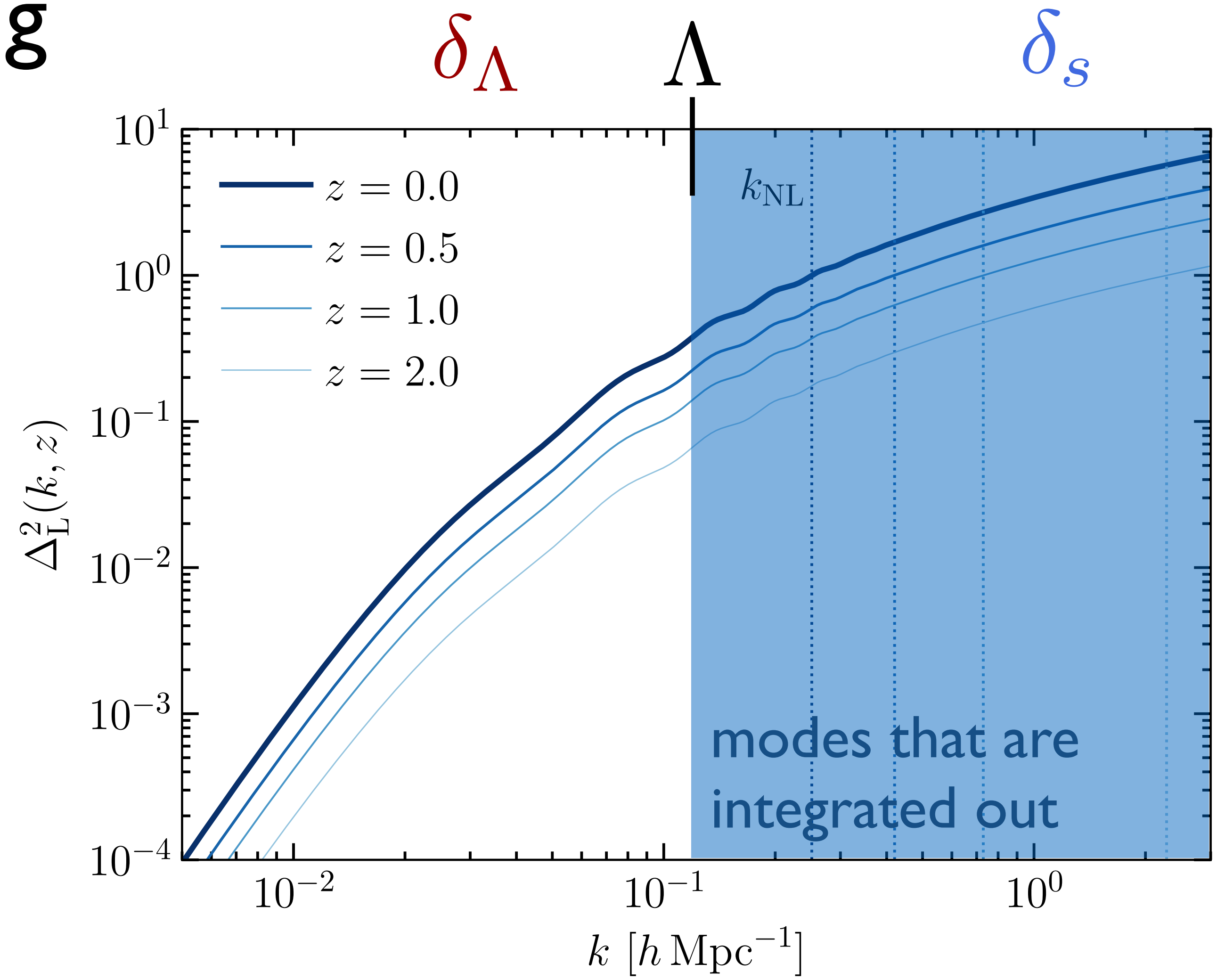
- Then, we integrate out (marginalize over) perturbations with k > Λ

(A) Bias

- Incorporate effect of large-scale perturbations explicitly using bias expansion, with free coefficients b_O

$$\delta_g(\boldsymbol{x}) = \sum_O b_O O(\boldsymbol{x})$$

  - Fields O are constructed from δ_Λ



(A) Bias

- Incorporate effect of large-scale perturbations explicitly using bias expansion, with free coefficients b_O

$$\delta_g(\boldsymbol{x}) = \sum_O b_O O(\boldsymbol{x}) + \varepsilon(\boldsymbol{x})$$

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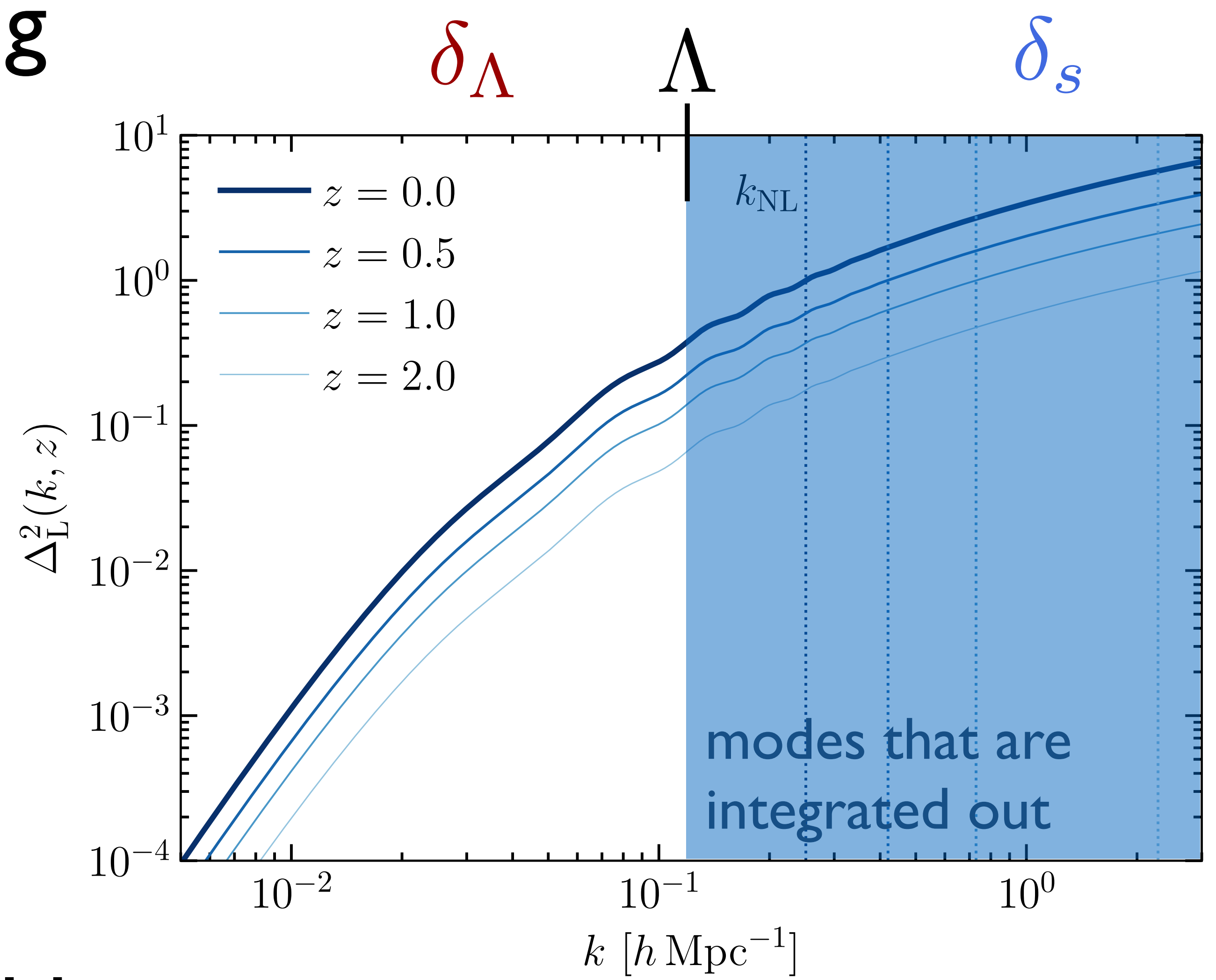
- Small-scale perturbations add noise ε



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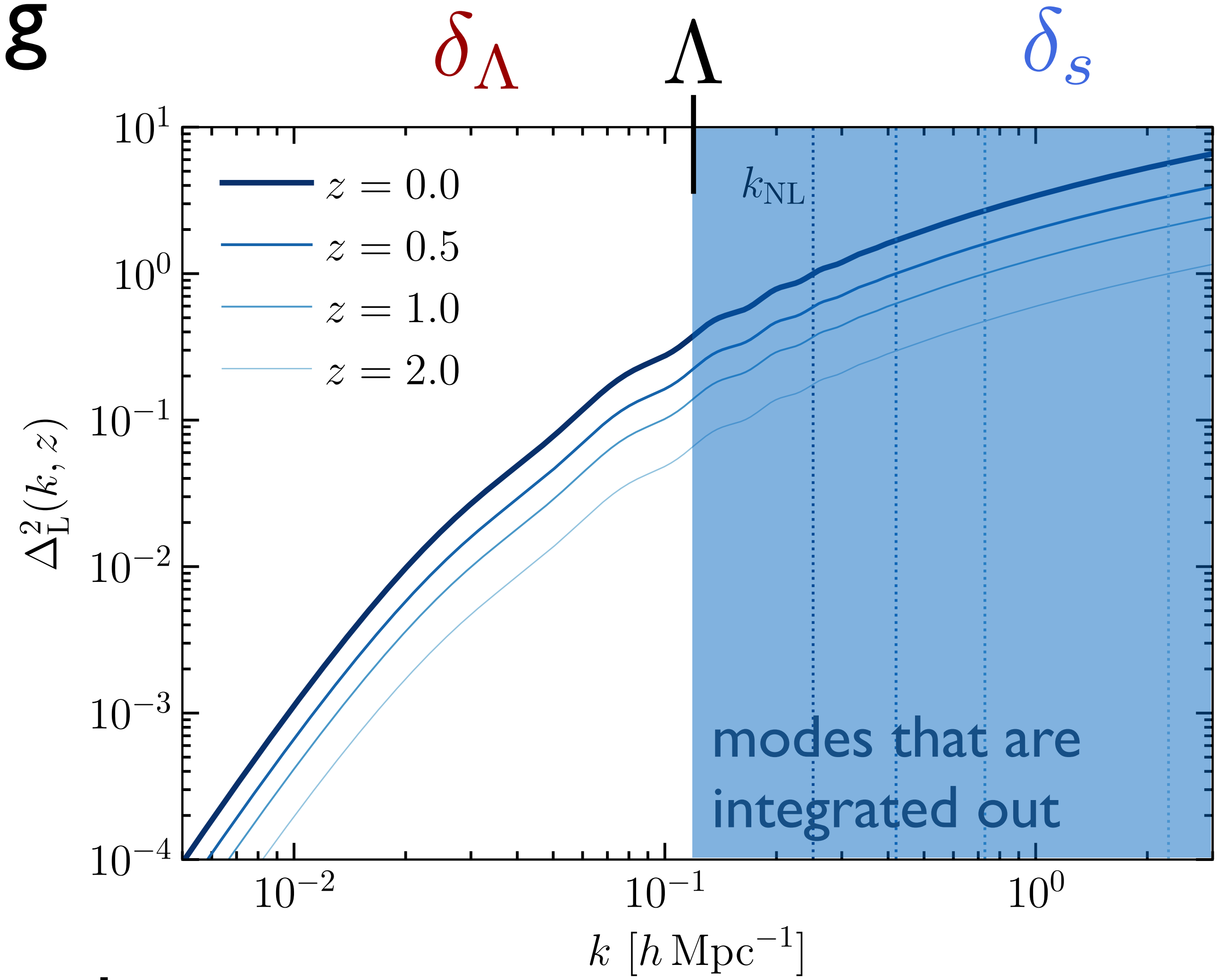
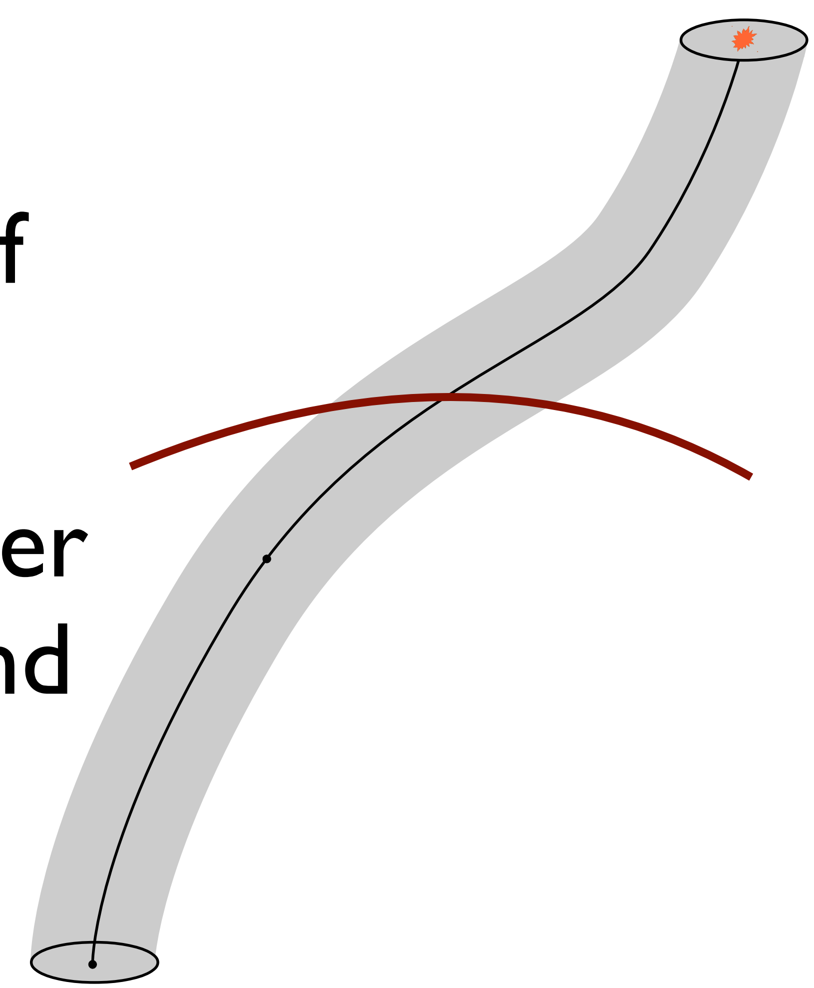


- Can understand this as expanding the source term in the continuity eqn: $\dot{n}_g(\boldsymbol{x},t) + \partial_i(n_g u^i_g(\boldsymbol{x},t)) = f_{\rm eff}[\partial_i\partial_j\Phi(\boldsymbol{x},t), \boldsymbol{x}]$

(A) Bias

- Which bias terms $O(x)$ we need to include:
  - Well understood by now
  - Include dependence on full history of structure formation
  - Includes "local bias" (powers of matter density) as well as tidal fields, time and space derivatives thereof
- Displacement terms protected by equivalence principle have *fixed* coefficients!



Desjacques, Jeong, FS; Phys. Rept. (2018)

Bias: details

- The bias expansion should contain all possible terms we can make out of time and spatial derivatives of density and tidal field
    - Spatial derivatives suppressed by $k\,R_*$, where R_* is spatial length scale associated with galaxy formation
- Convenient, complete expansion in terms of PT contributions to Lagrangian distortion tensor $\boldsymbol{M}^{(n)}$ up to a given order ($n <= N$):

$$\frac{\partial x^i}{\partial q^j} = \delta^i{}_j + \partial_{q,j} s^i(\boldsymbol{q},\tau) =: \delta^i{}_j + M^i{}_j(\boldsymbol{q},\tau)$$

$$\begin{array}{ll}
1^{\rm st} & \mathrm{tr}[M^{(1)}] \quad \Leftrightarrow \delta \\
2^{\rm nd} & \mathrm{tr}[(M^{(1)})^2]\,,\ (\mathrm{tr}[M^{(1)}])^2 \\
3^{\rm rd} & \mathrm{tr}[(M^{(1)})^3]\,,\ \mathrm{tr}[(M^{(1)})^2]\,\mathrm{tr}[M^{(1)}],\ (\mathrm{tr}[M^{(1)}])^3\,,\ \mathrm{tr}[M^{(1)}M^{(2)}] \\
4^{\rm th} & \mathrm{tr}[(M^{(1)})^4]\,,\ \mathrm{tr}[(M^{(1)})^3]\,\mathrm{tr}[M^{(1)}]\,,\ \left(\mathrm{tr}[(M^{(1)})^2]\right)^2\,,\ (\mathrm{tr}[M^{(1)}])^4\,, \\
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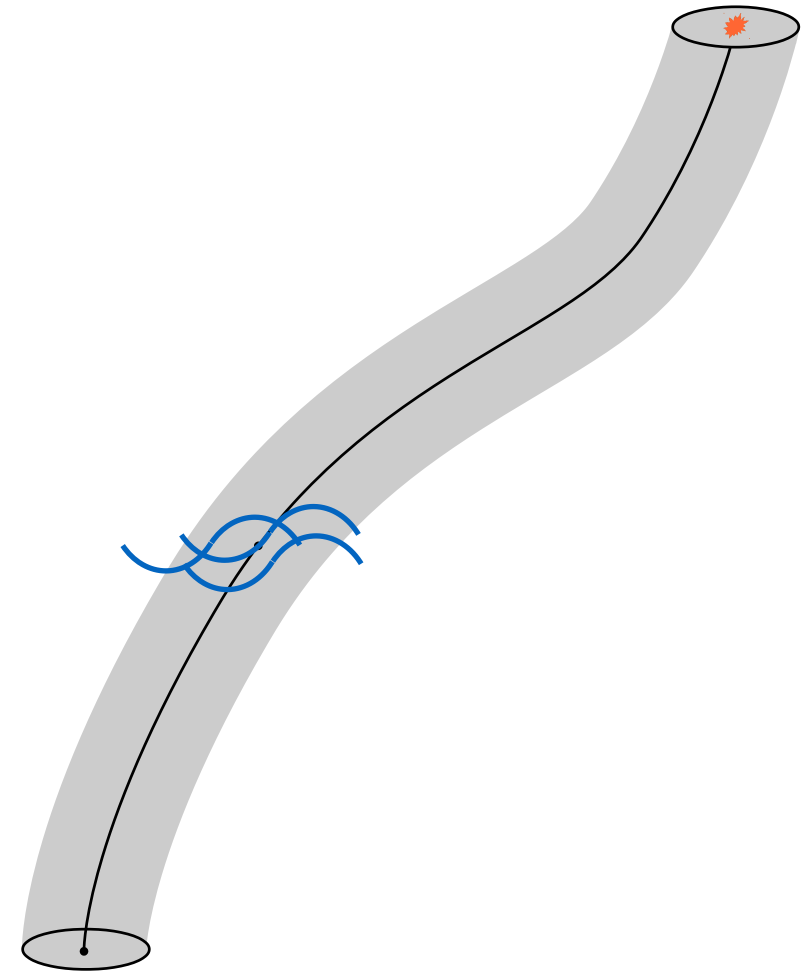
\end{array}$$

(B) Stochasticity

- ε arises from local (in real space) superposition of many small-scale perturbations
- Central limit theorem: $\varepsilon(k)$ is approximately Gaussian distributed (the lower k, the more Gaussian it is)
- Local in real space: power spectrum is white noise at low k, with corrections* ~k^2:



* Also, density dependence: coupling of ε and δ

$$\langle \varepsilon(\boldsymbol{k}) \varepsilon^*(\boldsymbol{k}') \rangle = (2\pi)^3 \delta_D(\boldsymbol{k} - \boldsymbol{k}') \left[P_\varepsilon + k^2 P_\varepsilon^{\{2\}} + \cdots \right]$$

Desjacques, Jeong, FS; Phys. Rept. (2018)

Partition function for galaxies

- Idea: couple solutions to EOM to source term
- After integrating out *initial* modes above Λ, obtain

$$
\begin{aligned}
Z_\Lambda[J_\Lambda] = \int \mathcal{D}\delta_{\mathrm{in},\Lambda} \exp\Bigg[&- \frac{1}{2}\delta^i_{\mathrm{in},\Lambda} \left(P^{-1}_{\mathrm{L},\Lambda}\right)_{ij} \delta^j_{\mathrm{in},\Lambda} \\
&+ J_{\Lambda,i} \sum_{m=1}^{\infty} \frac{1}{m!} K^i_{i_1\dots i_m}(\Lambda) \delta^{i_1}_{\mathrm{in},\Lambda} \cdots \delta^{i_m}_{\mathrm{in},\Lambda} \\
&+ \frac{1}{2} J_{\Lambda,i} J_{\Lambda,j} \sum_{m=0}^{\infty} \frac{1}{m!} K^{ij}_{i_1\dots i_m}(\Lambda) \delta^{i_1}_{\mathrm{in},\Lambda} \cdots \delta^{i_m}_{\mathrm{in},\Lambda} \\
&+ \frac{1}{6} J_{\Lambda,i} J_{\Lambda,j} J_{\Lambda,k} \sum_{m=0}^{\infty} \frac{1}{m!} K^{ijk}_{i_1\dots i_m}(\Lambda) \delta^{i_1}_{\mathrm{in},\Lambda} \cdots \delta^{i_m}_{\mathrm{in},\Lambda} + \dots \Bigg] .
\end{aligned}
$$

Carroll, Pollack, Leichenauer; 1310.2920
Cabass, FS; 1909.04022

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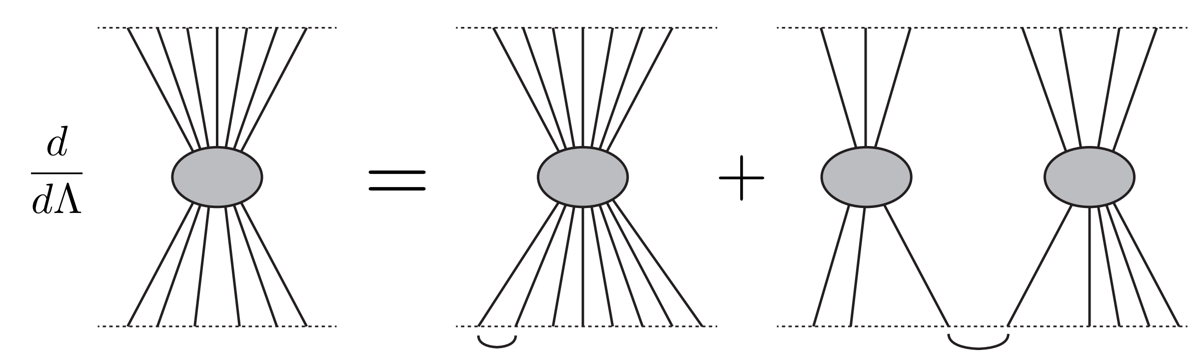
\end{aligned}
$$

- Doesn't depend on cutoff Λ -> RG equations



$P_{L,\Lambda}$ is cut linear propagator

Carroll, Pollack, Leichenauer; 1310.2920
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- *O(J)* contributions: bias

$$\delta^i_{g,\mathrm{det},\Lambda}[\delta_{\mathrm{in},\Lambda}] = \sum_{m=1}^\infty \frac{1}{m!}K^i_{i_1\dots i_m}(\Lambda)\delta^{i_1}_{\mathrm{in},\Lambda}\cdots\delta^{i_m}_{\mathrm{in},\Lambda} \quad ; \quad \frac{1}{m!}K^i_{i_1\dots i_m}(\Lambda) = \sum_{n=1}^m \sum_{O^{[n]}} b_O(\Lambda) F^O_m(\boldsymbol{k}_{i_1},\dots \boldsymbol{k}_{i_m})$$

- *O(J²), O(J³), …* contributions: stochasticity

Carroll, Pollack, Leichenauer; 1310.2920
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B. Inference: Field-level and LFI

A broad view of cosmology inference

- Given cosmological parameters θ, we can hope to predict

1. Statistics of initial conditions
2. How a given $\delta_{\mathrm{in}}(x)$ evolves into the final density field

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A broad view of cosmology inference

- Given cosmological parameters θ, we can hope to predict

1. Statistics of initial conditions

   Prior $P_{\rm prior}\left(\vec{\delta}_{\rm in}, \theta\right)$

2. How a given $\delta_{\rm in}(\boldsymbol{x})$ evolves into the final density field

   deterministic evolution

   $\vec{\delta}_{\rm fwd}[\vec{\delta}_{\rm in}, \theta]$

Bayesian cosmology inference

- The *full posterior of cosmological parameters given the data* is then given by

$$P(\theta) \propto \int \mathcal{D}\boldsymbol{\delta}_{\rm in}\, P\left(\boldsymbol{\delta}_g \middle| \boldsymbol{\delta}_{\rm fwd}[\boldsymbol{\delta}_{\rm in}, \theta]\right) P_{\rm prior}\left(\boldsymbol{\delta}_{\rm in}, \theta\right)$$

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Multivariate Gaussian, diagonal covariance in Fourier space

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$$= \int d\{b_O\}\, P\left(\boldsymbol{\delta}_g \middle| \boldsymbol{\delta}_{\rm fwd}[\boldsymbol{\delta}_{\rm in}, \theta]\right) P_{\rm prior}(\{b_O\})$$

conditional probability of galaxy density given matter density
- contains all physics of galaxy formation

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Functional integral

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- Standard approach proceeds via *data compression*: replace galaxy density field with much smaller data vector (e.g., power spectrum in bins of k)
- Then, the functional integral over initial conditions (a.k.a taking ensemble average) is done either
  - semi-analytically (loop integrals in PT / EFT approach - formally, sending Λ to infinity)
  - numerically (emulators based on ensemble of simulations)

Bayesian cosmology inference

$$P(\theta) \propto \int \mathcal{D}\boldsymbol{\delta}_{\rm in}\, P\left(\boldsymbol{\delta}_g \middle| \boldsymbol{\delta}_{\rm fwd}[\boldsymbol{\delta}_{\rm in}, \theta]\right) P_{\rm prior}\left(\boldsymbol{\delta}_{\rm in}, \theta\right)$$

- Can we make progress *without* this (lossy) data compression?

Inference beyond the power spectrum

$$P(\theta) \propto \int \mathcal{D}\boldsymbol{\delta}_{\mathrm{in}} \, P\left(\boldsymbol{\delta}_g \middle| \boldsymbol{\delta}_{\mathrm{fwd}}[\boldsymbol{\delta}_{\mathrm{in}}, \theta]\right) P_{\mathrm{prior}}\left(\boldsymbol{\delta}_{\mathrm{in}}, \theta\right)$$

- Yes - basically by doing a Markov Chain Monte Carlo:

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  - Discretize field on grid/lattice (Nyquist frequency = cutoff Λ)
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  - Compare with data and repeat

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  - Forward-evolve using gravity
  - Compare with data and repeat
- Lots of interest in this approach recently

Kitaura & Ensslin, Jasche & Wandelt, Wang, Mo et al, Seljak et al, Jasche & Lavaux (2017), …

The galaxy likelihood

- Putting numerical challenges aside, we need an expression for the *field-level galaxy likelihood:*
  - conditional probability of galaxy density given matter density

$$P(\theta) \propto \int \mathcal{D}\boldsymbol{\delta}_{\rm in}\, P\left(\boldsymbol{\delta}_g \middle| \boldsymbol{\delta}_{\rm fwd}[\boldsymbol{\delta}_{\rm in}, \theta]\right) P_{\rm prior}\left(\boldsymbol{\delta}_{\rm in}, \theta\right)$$

$$= \int d\{b_O\}\, P\left(\boldsymbol{\delta}_g \middle| \boldsymbol{\delta}_{\rm fwd}[\boldsymbol{\delta}_{\rm in}, \theta]\right) P_{\rm prior}(\{b_O\})$$

EFT likelihood

- Combining knowledge about bias and stochasticity, we can write:

$$\delta_g(\boldsymbol{k}) = \delta_{g,\mathrm{det}}(\boldsymbol{k}) + \varepsilon(\boldsymbol{k})$$

$$\delta_{g,\mathrm{det}}(\boldsymbol{k}) = \sum_O b_O O(\boldsymbol{k})$$

- and insert $\varepsilon = \delta_g - \delta_{g,\mathrm{det}}$ into the Gaussian PDF for ε:

$$P[\varepsilon] \propto \exp\left[-\frac{1}{2}\int \frac{d^3\boldsymbol{k}}{(2\pi)^3} \frac{|\varepsilon(\boldsymbol{k})|^2}{P_\varepsilon(k)}\right]$$

FS, Elsner, et al; 1808:02002
Cabass, FS; 1909.04022

EFT likelihood from the partition function

- Goal: obtain joint likelihood for galaxy density modes below cutoff, $\{\delta_g(\boldsymbol{k})\}_{|\boldsymbol{k}|<\Lambda}$.
- Given by functional Fourier transform of partition function:

$$
\begin{aligned}
\mathcal{P}_\Lambda[\hat{\delta}_{g,\Lambda}] &= \left\langle \delta_{\mathrm{D}}^{[\infty]}(\delta_{g,\Lambda} - \hat{\delta}_{g,\Lambda}) \right\rangle \\
&= \int \mathcal{D}X_\Lambda \left\langle \exp\left[\mathrm{i}X_\Lambda^i(\delta_{g,\Lambda} - \hat{\delta}_{g,\Lambda})_i\right] \right\rangle \\
&= \int \mathcal{D}X_\Lambda \exp\left[-\mathrm{i}X_\Lambda^i(\hat{\delta}_{g,\Lambda})_i\right] \left\langle \exp\left[\mathrm{i}X_\Lambda^i(\delta_{g,\Lambda})_i\right] \right\rangle \\
&= (Z_\Lambda[0])^{-1} \int \mathcal{D}X_\Lambda \exp\left[-\mathrm{i}X_\Lambda^i(\hat{\delta}_{g,\Lambda})_i\right] Z_\Lambda[\mathrm{i}X_\Lambda] \,.
\end{aligned}
$$

Cabass, FS; 1909.04022

EFT likelihood

- We obtain the desired conditional probability for δ_g in *Fourier space*:

$$P\left(\vec{\delta}_g \middle| \vec{\delta}\right) \propto \left(\prod_{\boldsymbol{k}\neq 0}^{\Lambda} \sigma^2(k)\right)^{-1/2} \exp\left[-\frac{1}{2}\sum_{\boldsymbol{k}\neq 0}^{\Lambda} \frac{1}{\sigma^2(k)} \left|\delta_g(\boldsymbol{k}) - \delta_{g,\mathrm{det}}(\boldsymbol{k})\right|^2\right]$$

Finite volume in actual data
-> discrete Fourier representation

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with

$$\delta_{g,\mathrm{det}}(\boldsymbol{k}) = \sum_O b_O O(\boldsymbol{k})$$

$$\sigma^2(k) = \sigma_0^2 + \sigma_2^2 k^2$$

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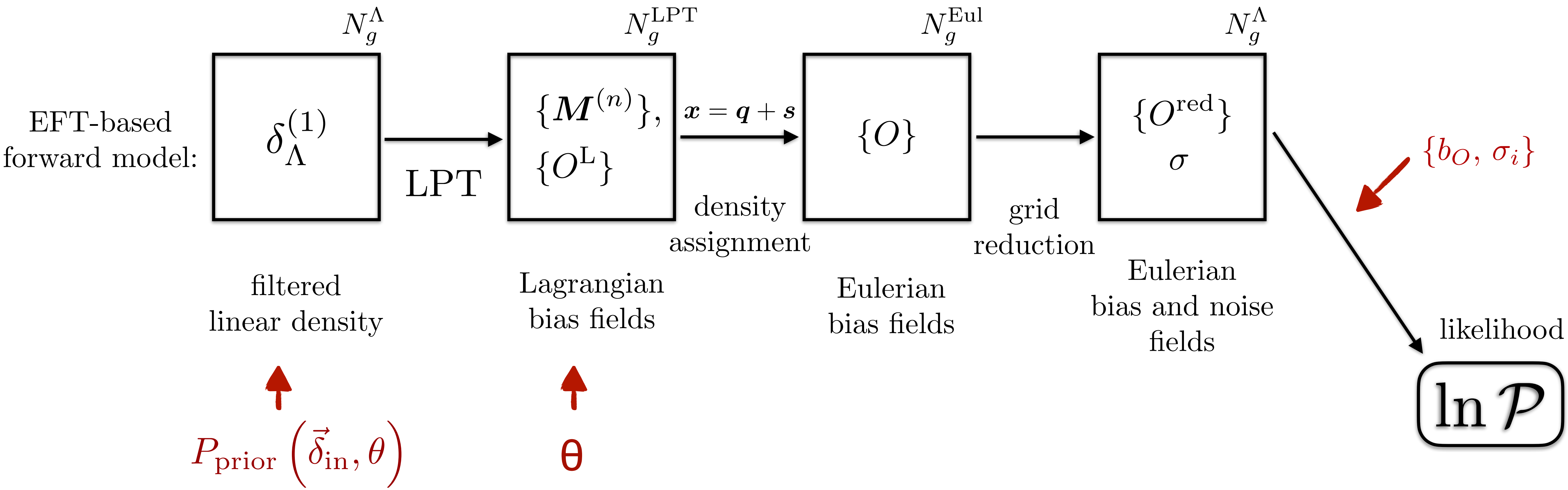
Flowchart of the inference pipeline



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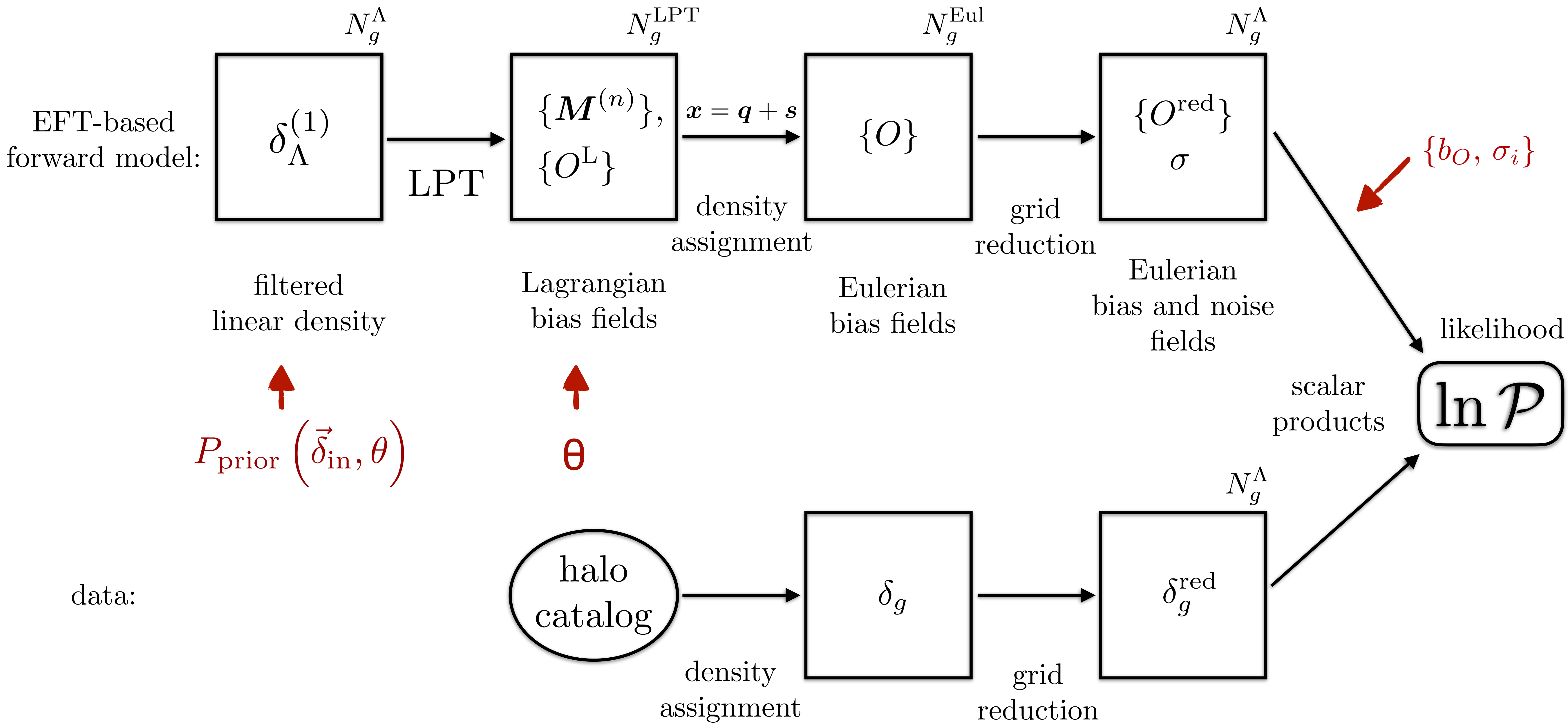
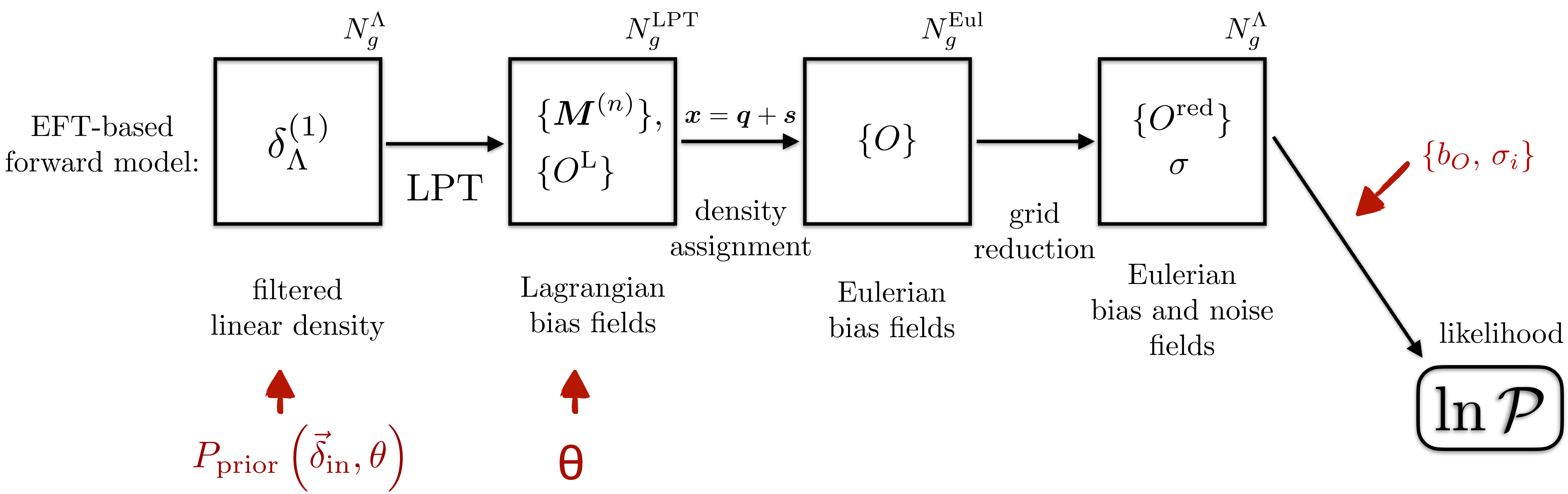


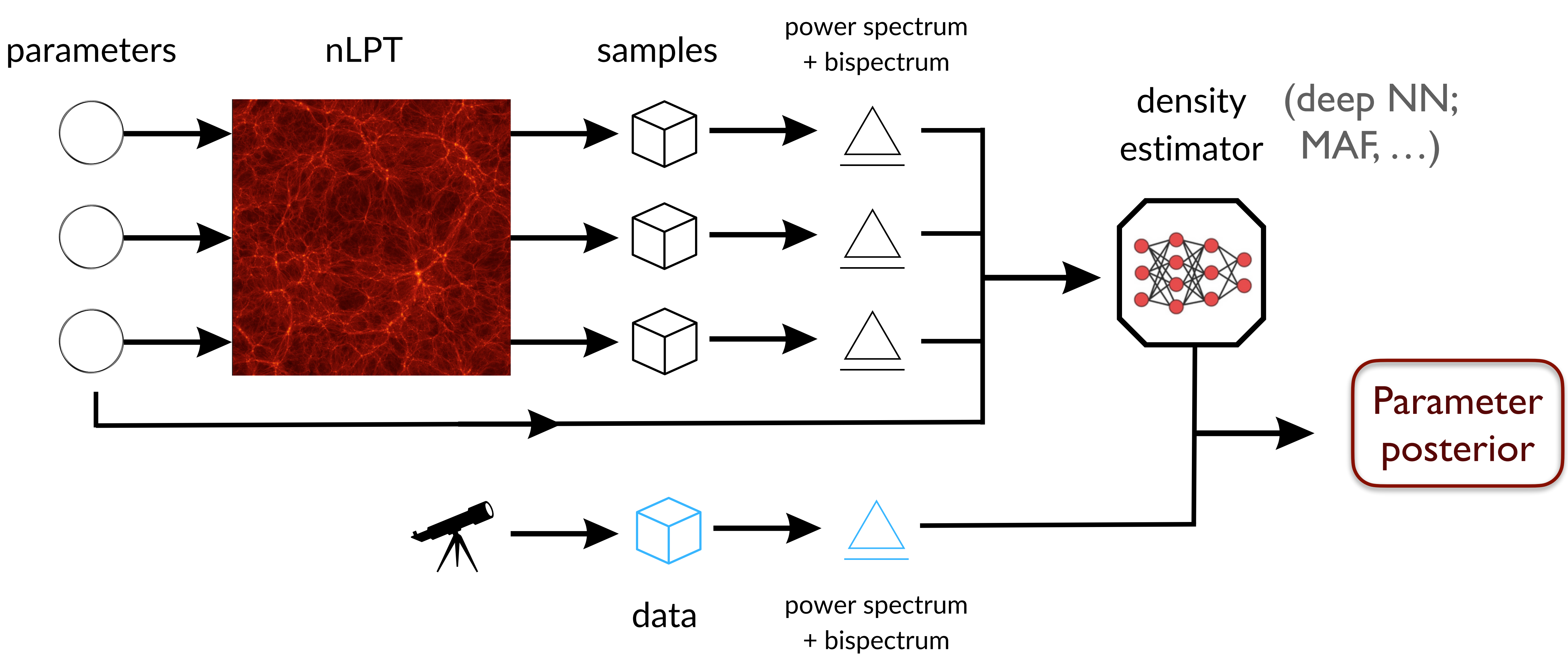
Interlude: implicit-likelihood inference (IFI/LFI)

- Use forward model as ***generator*** of simulated ("mock") data:



Interlude: implicit-likelihood inference (IFI/LFI)

Beatriz Tucci | PhD Student



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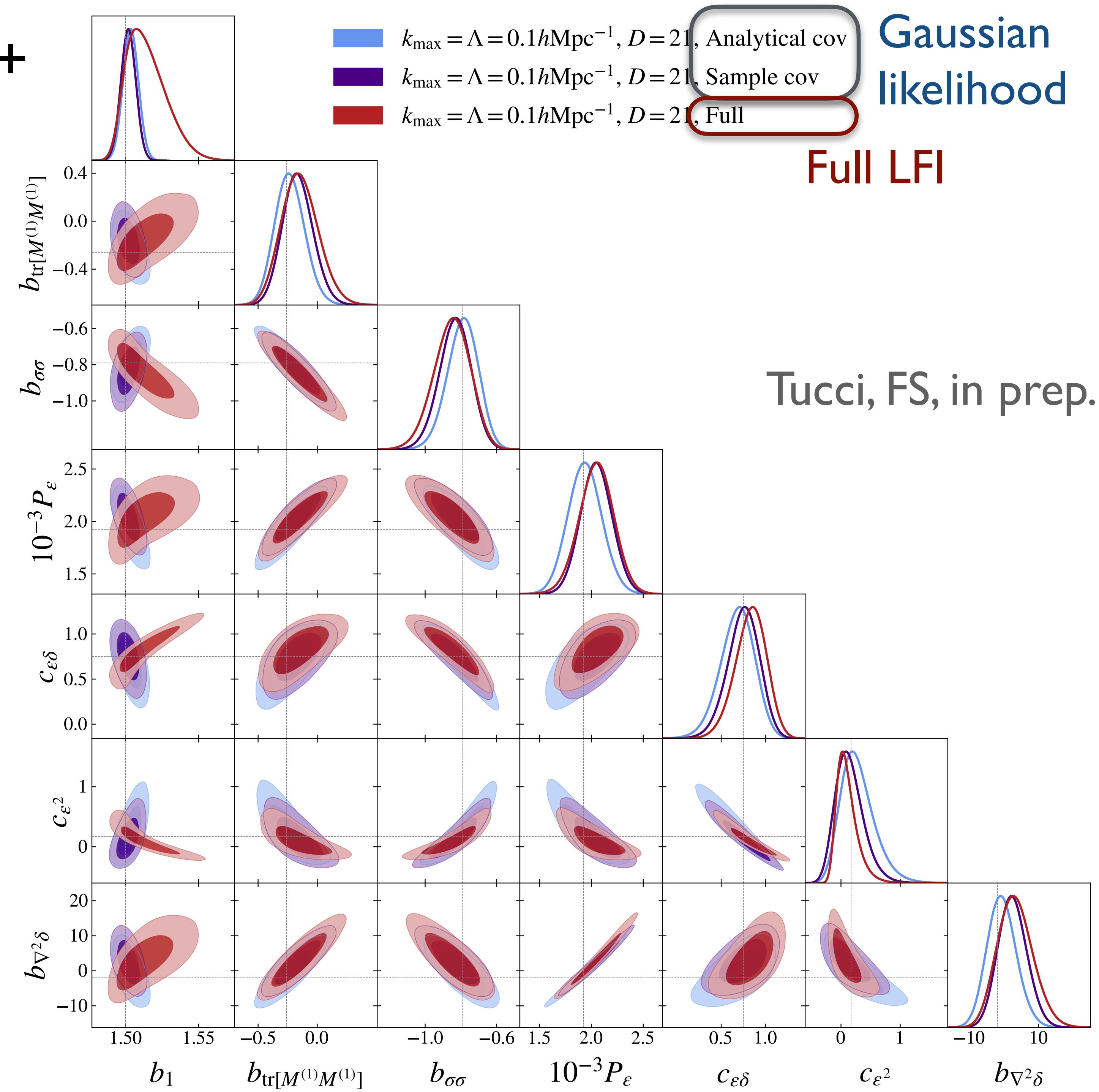
- Data vector: power spectrum + bispectrum (all configurations)
- Test on mock data set generated from same EFT model
- Fixed cosmology
- Compare ***full LFI*** with ***Gaussian likelihood*** of data



Tucci, FS, in prep.

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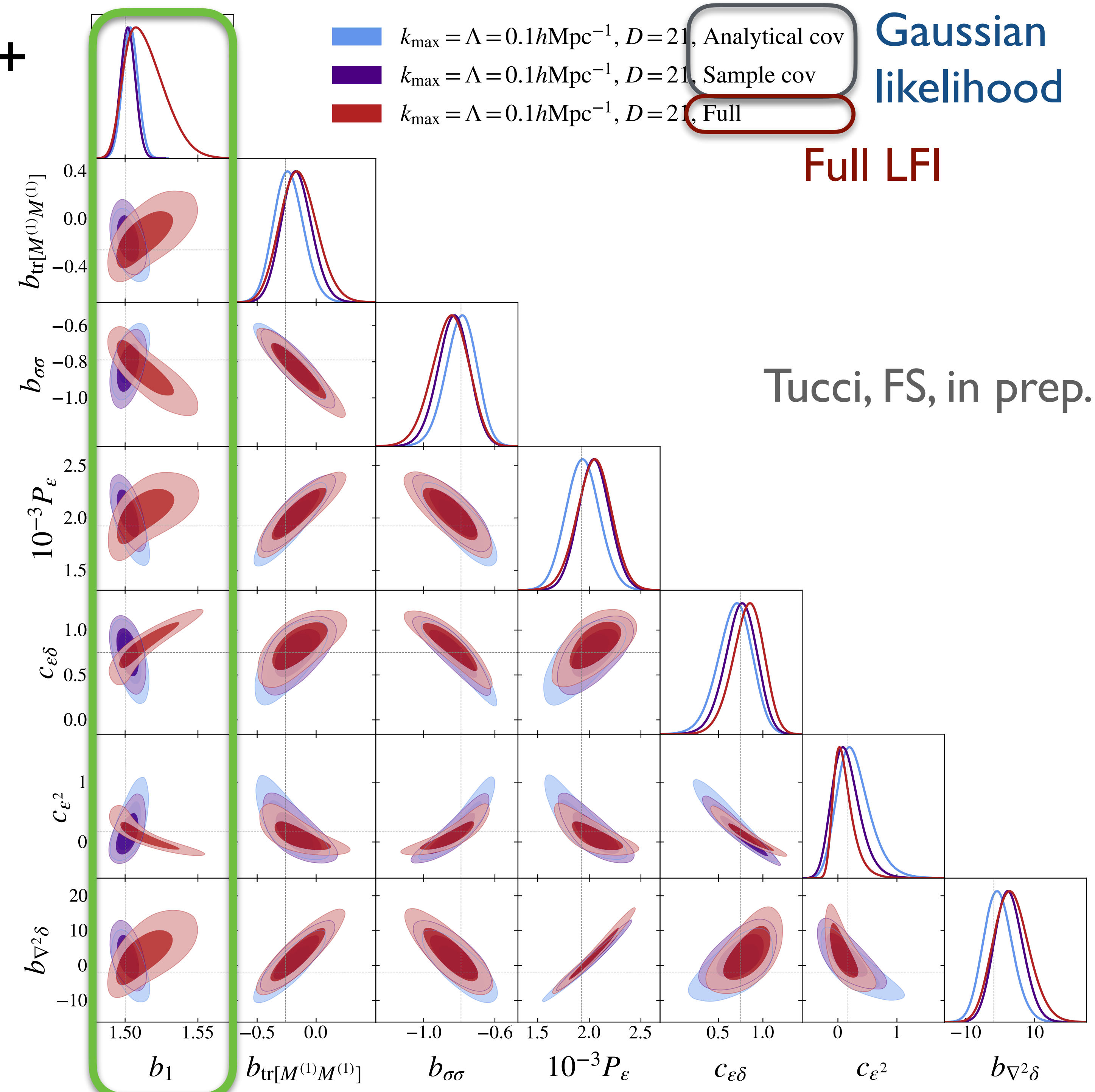
- Data vector: power spectrum + bispectrum (all configurations)
- Test on mock data set generated from same EFT model
- Fixed cosmology
- Compare ***full LFI*** with ***Gaussian likelihood*** of data vector
- Gaussian likelihood underestimates error on b_1 by 30-40% in this particular case



Tucci, FS, in prep.

Tests at *fixed* initial conditions

- Let's begin with a thought experiment:
  - We are given a halo catalog and the *normalized amplitudes of the initial conditions* for the matter density in the same volume $\delta_{\Lambda}^{(1)}$
  - Can we infer the cosmological parameters from this halo catalog?

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  - Can we infer the cosmological parameters from this halo catalog?
- Near optimal case: no cosmic variance
- Of course, not a real-world example, but applicable to halos (or galaxies) in simulations

Tests at *fixed* initial conditions

- Specifically, can we recover unbiased $\mathcal{A}_s$ (σ_8) from a halo catalog (treating bias parameters as unknown) ?
- Perfect degeneracy between b_1 and σ_8 at linear order; nonlinear information essential

FS, Cabass, Jasche, Lavaux; arXiv:2004.06707; FS, arXiv:2009.14176

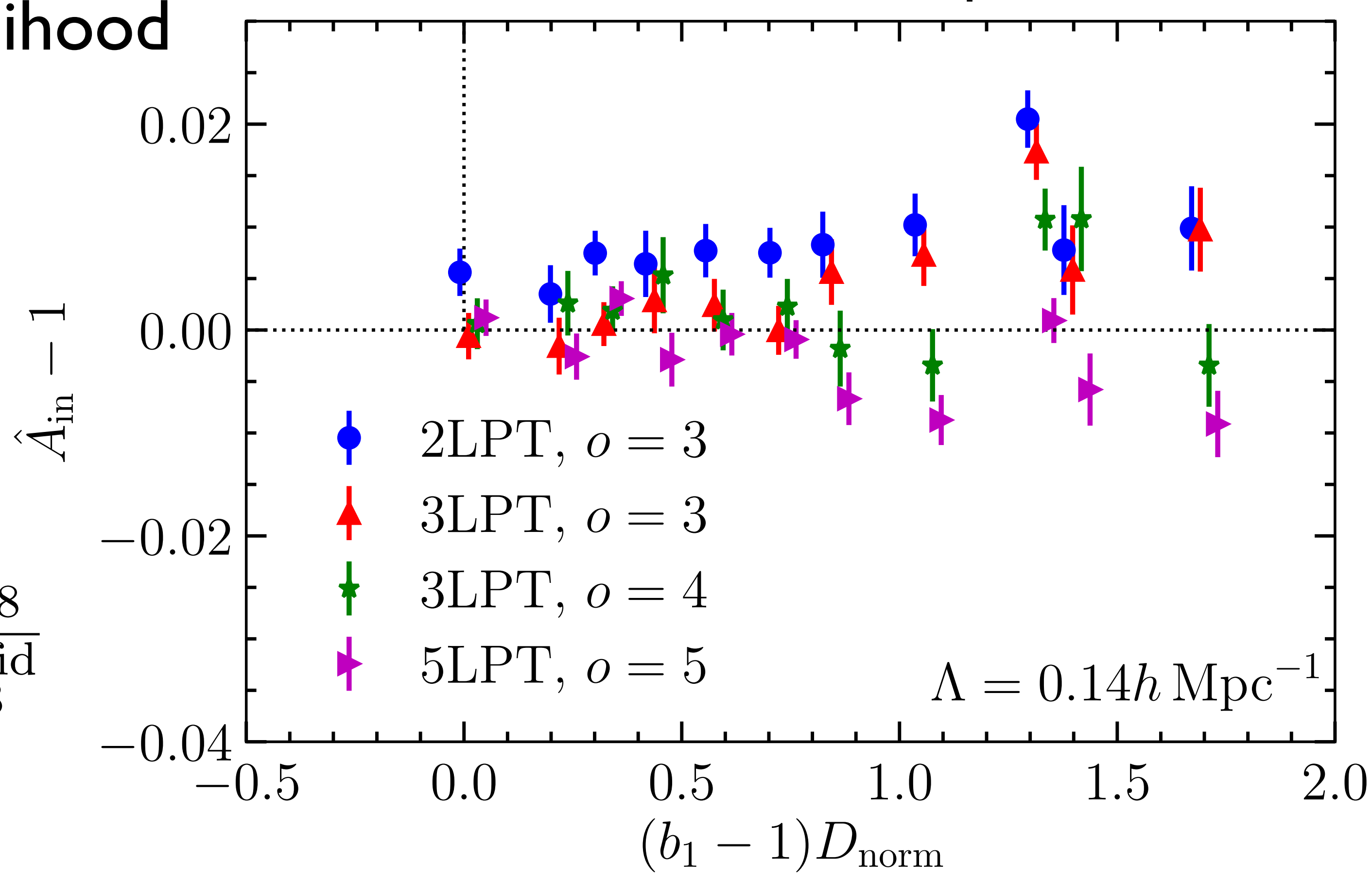
$\mathcal{A}_s$ inference from dark matter halos in simulations

Relative deviation of maximum-likelihood value of σ_8 from ground truth, for different perturbative orders

L_{box} = 2000 Mpc/h

$$A_{in} \equiv \frac{\sigma_8}{\sigma_8^{fid}}$$

Results for all mass bins and redshifts for Λ = 0.14h Mpc^{-1}



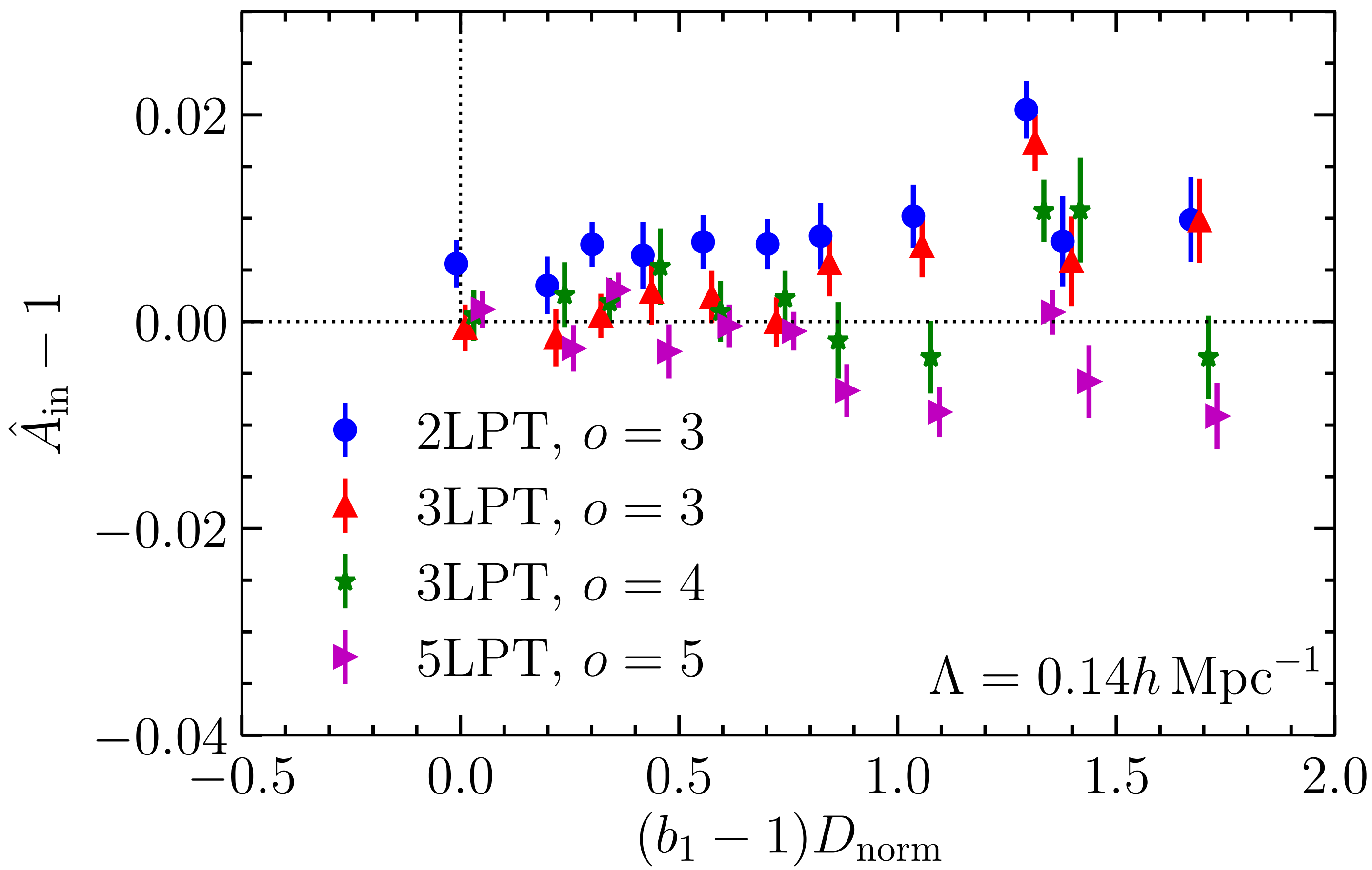
Proxy for higher-order bias terms

FS, Cabass, Jasche, Lavaux; arXiv:2004.06707; FS, arXiv:2009.14176

$\mathcal{A}_s$ inference from dark matter halos in simulations

- Residual error in σ8 at k < 0.14h/Mpc is <~ 1-2% depending on halos mass and redshift
- Most likely due to higher-order bias, and numerical errors of simulations (transients)

Results for all mass bins and redshifts for Λ = 0.14h Mpc-1



Proxy for higher-order bias terms

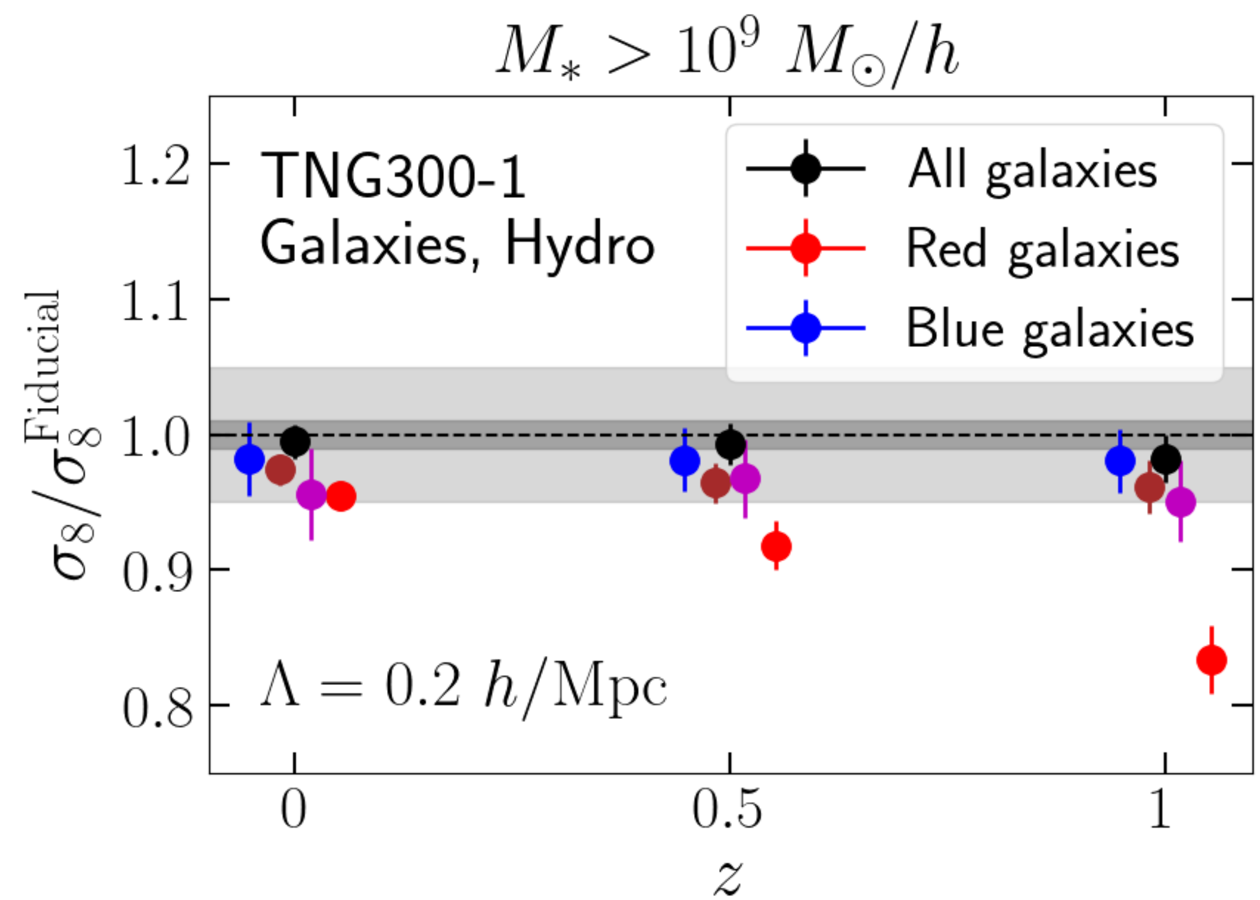
FS, Cabass, Jasche, Lavaux; arXiv:2004.06707; FS, arXiv:2009.14176

Also works for (simulated) galaxies

- Apply the same analysis to stellar-mass-selected galaxies in IllustrisTNG:

L_{box} = 300 Mpc/h

No chance to do this using power spectrum+bispectrum due to cosmic variance…



Barreira, Lazeyras, FS; arXiv:2105.02876

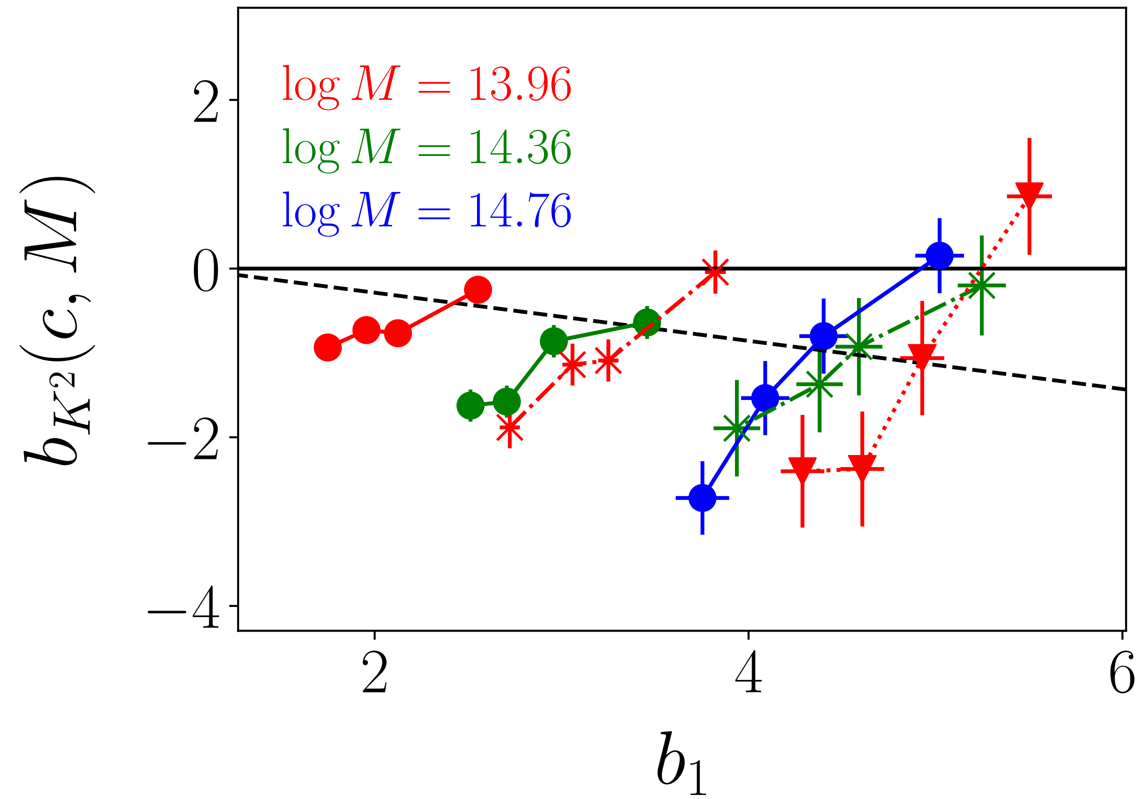
Ideal for studies of assembly bias

- Fixed-initial-condition analysis allows for precise measurements of bias parameters
- For example: detecting strong *assembly bias in tidal bias* coefficient

Colors: mass bins

Points: bias measured for 4 concentration quantiles

Dashed line: "coevolution" relation



Lazeyras, Barreira, FS, arXiv:2106.14713

BAO inference

- Lagrangian perturbation theory based forward model incorporates precise local evolution of BAO scale
  - Fixed phases (IC) -> *best possible BAO reconstruction*
- Trick: shift BAO scale in IC by rescaling:

$$f^2(k,\beta) = \frac{P_{\mathrm{L}}(k,\beta)}{P_{\mathrm{fid}}(k)} = \frac{1 + A\sin(k\beta r_{\mathrm{fid}})\exp(-k/k_{\mathrm{D}})}{1 + A\sin(k r_{\mathrm{fid}})\exp(-k/k_{\mathrm{D}})}$$

Babić, FS, Tucci, arXiv:2203.06177

BAO inference

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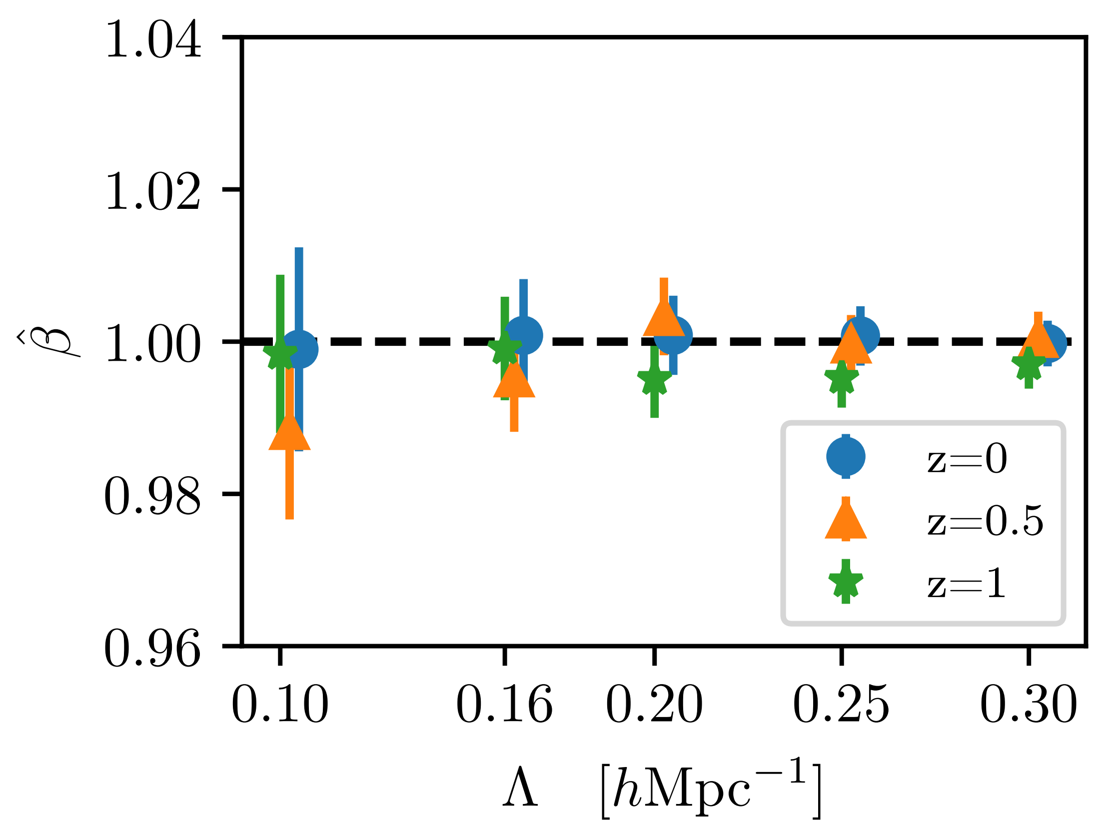
β: ratio of inferred to fiducial isotropic BAO scale



(a) $\log_{10}(M/h^{-1}M_{\odot}) = 12.5 - 13.0$

Babić, FS, Tucci, arXiv:2203.06177

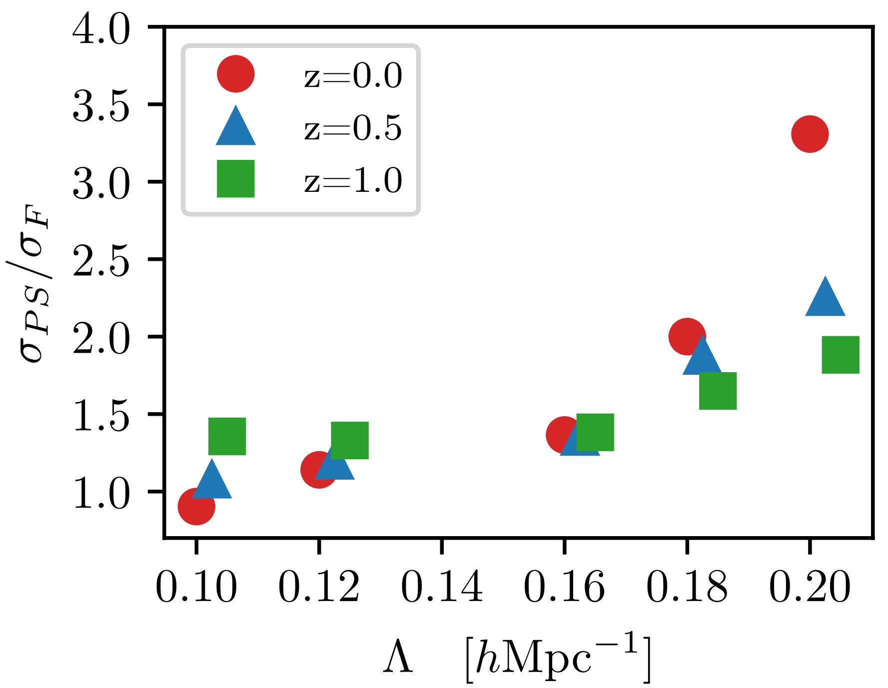
BAO inference

- Lagrangian perturbation theory based forward model incorporates precise local evolution of BAO scale
  - Fixed phases (IC) -> *best possible BAO reconstruction*
- Comparison with (pre-reconstruction) P(k)

Ratio of error bars on inferred BAO scale: P(k) over field-level EFT

Both for fixed phases.

Factor 1.5-3 improvement over no-reconstruction P(k) analysis.

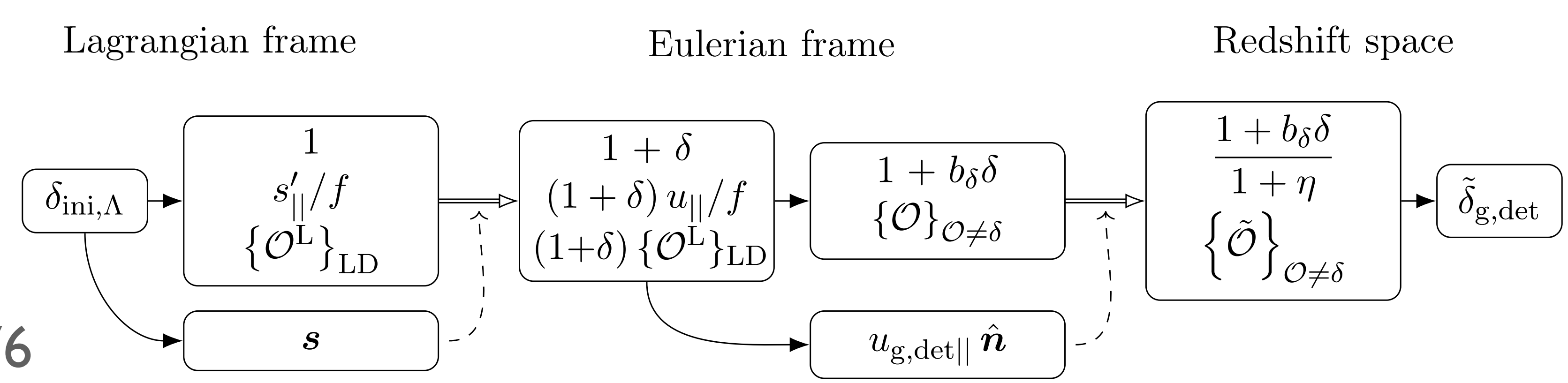


(a) $\log_{10}(M/h^{-1}M_\odot) = 12.5 - 13.0$

Babić, FS, Tucci, arXiv:2203.06177

Redshift-space distortions

- Notoriously difficult/cumbersome
- In forward model, can perform transformation to redshift space *non-perturbatively*



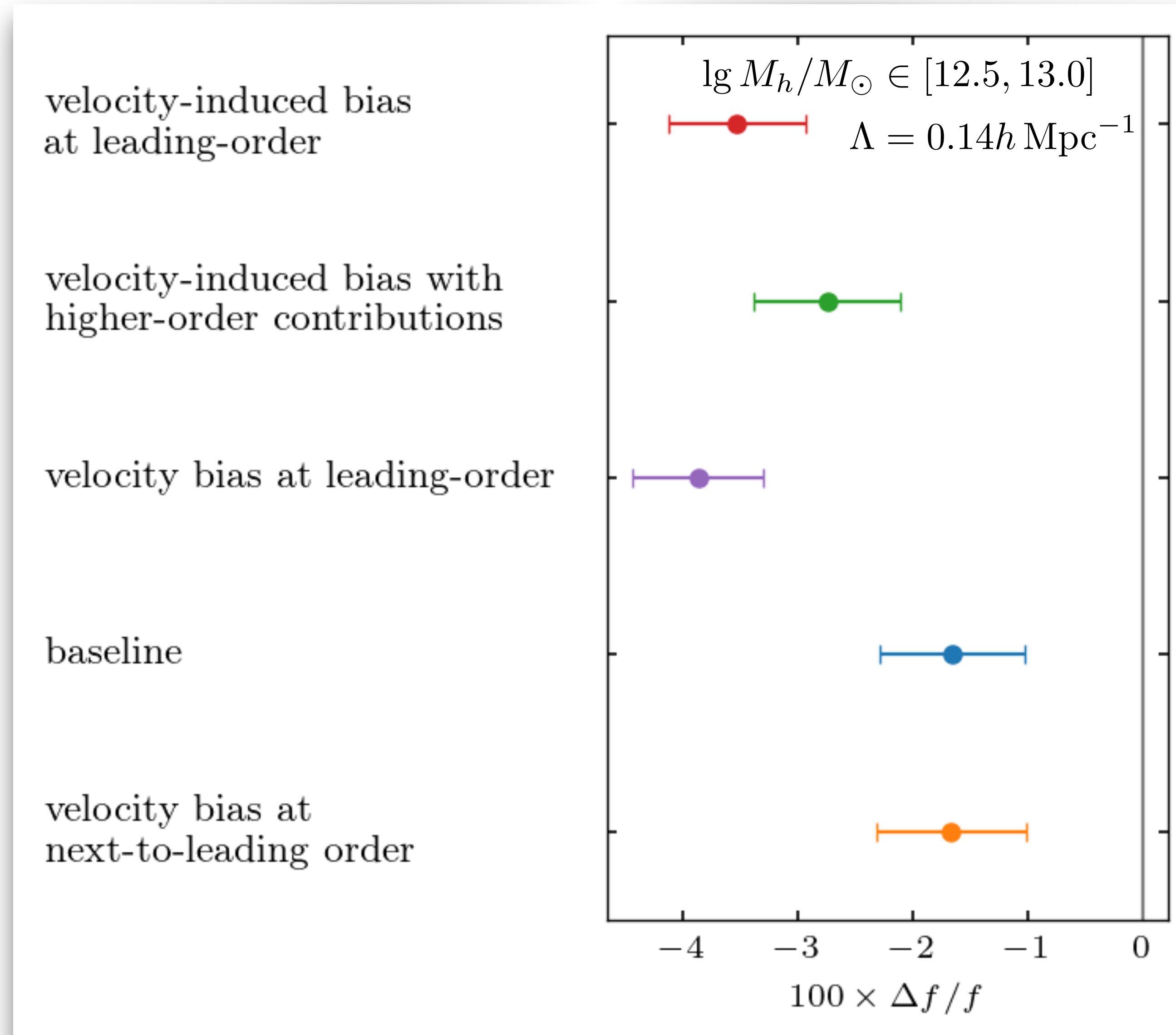
Stadler, FS, Reinecke, arXiv:2303.09876

Redshift-space distortions

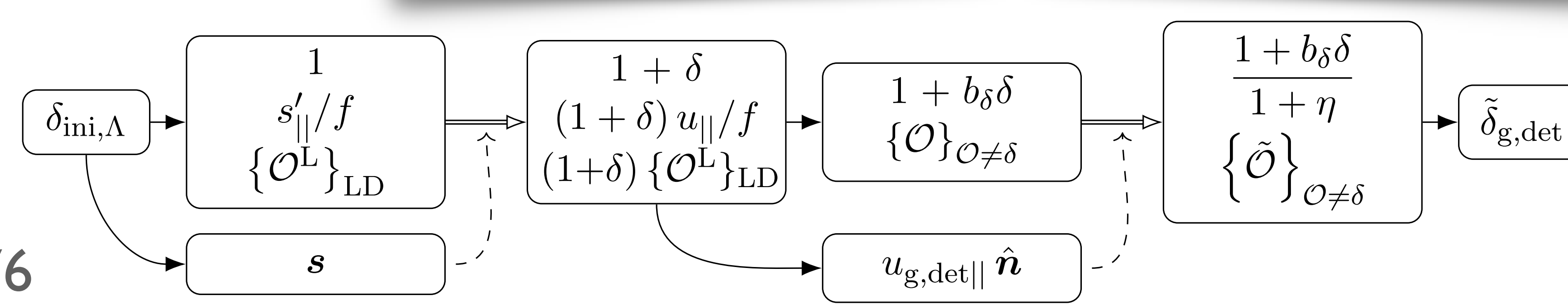
- Notoriously difficult/cumbersome
- In forward model, can perform transformation to redshift space *non-perturbatively*
- Velocity bias important:

$$u_{\mathrm{g,det}||}(\boldsymbol{x},\tau) = u_{||}(\boldsymbol{x},\tau) + \sum_{\mathcal{U}} \beta_{\mathcal{U}}(\tau)\,\mathcal{U}(\boldsymbol{x},\tau)$$

  - In standard approach, absorbed in higher-derivative contributions, but not sufficiently accurate



Lagrangian frame



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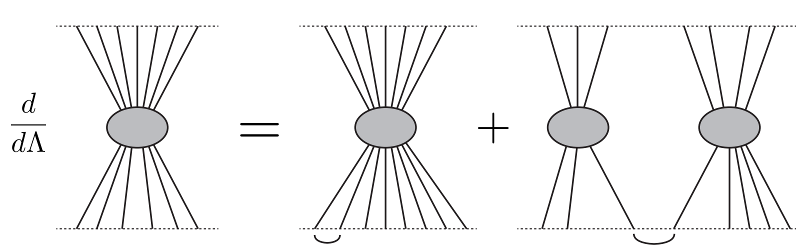

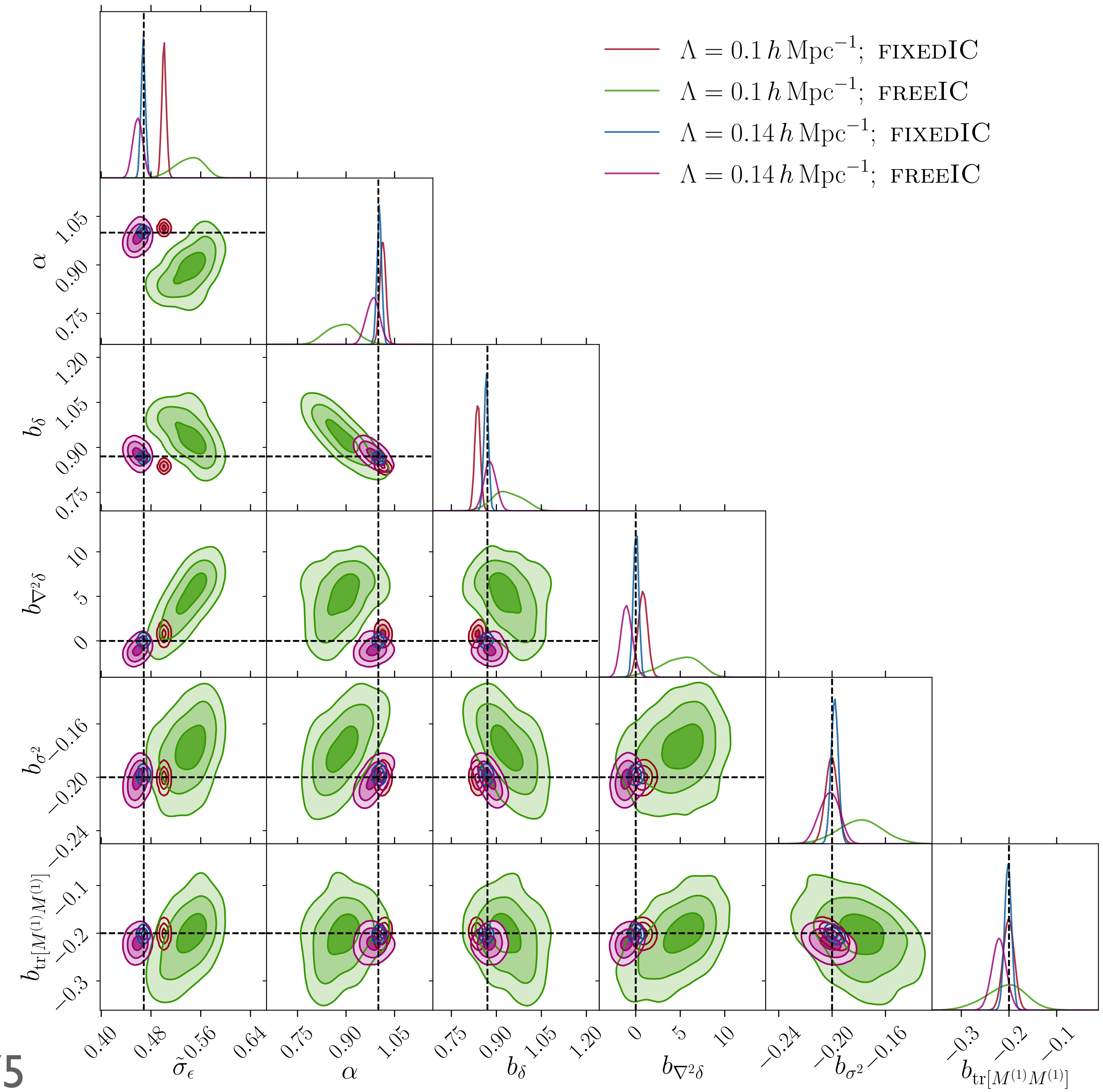

Kostić, Nguyen, FS, Reinecke, arXiv:2212.07875

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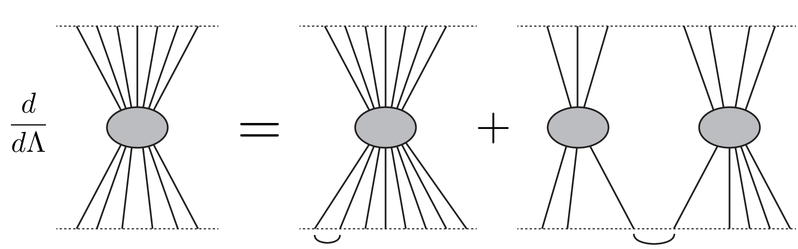

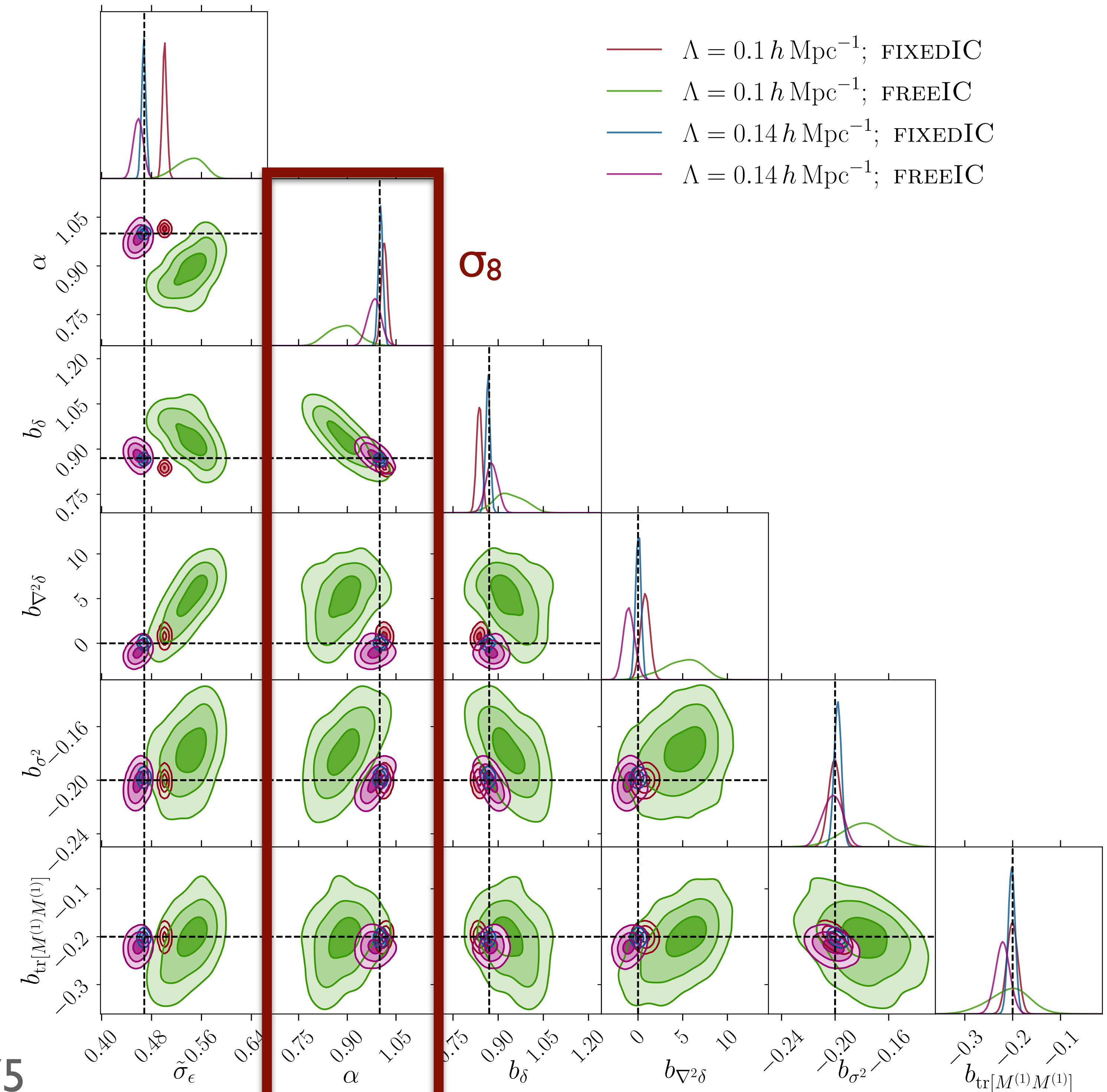

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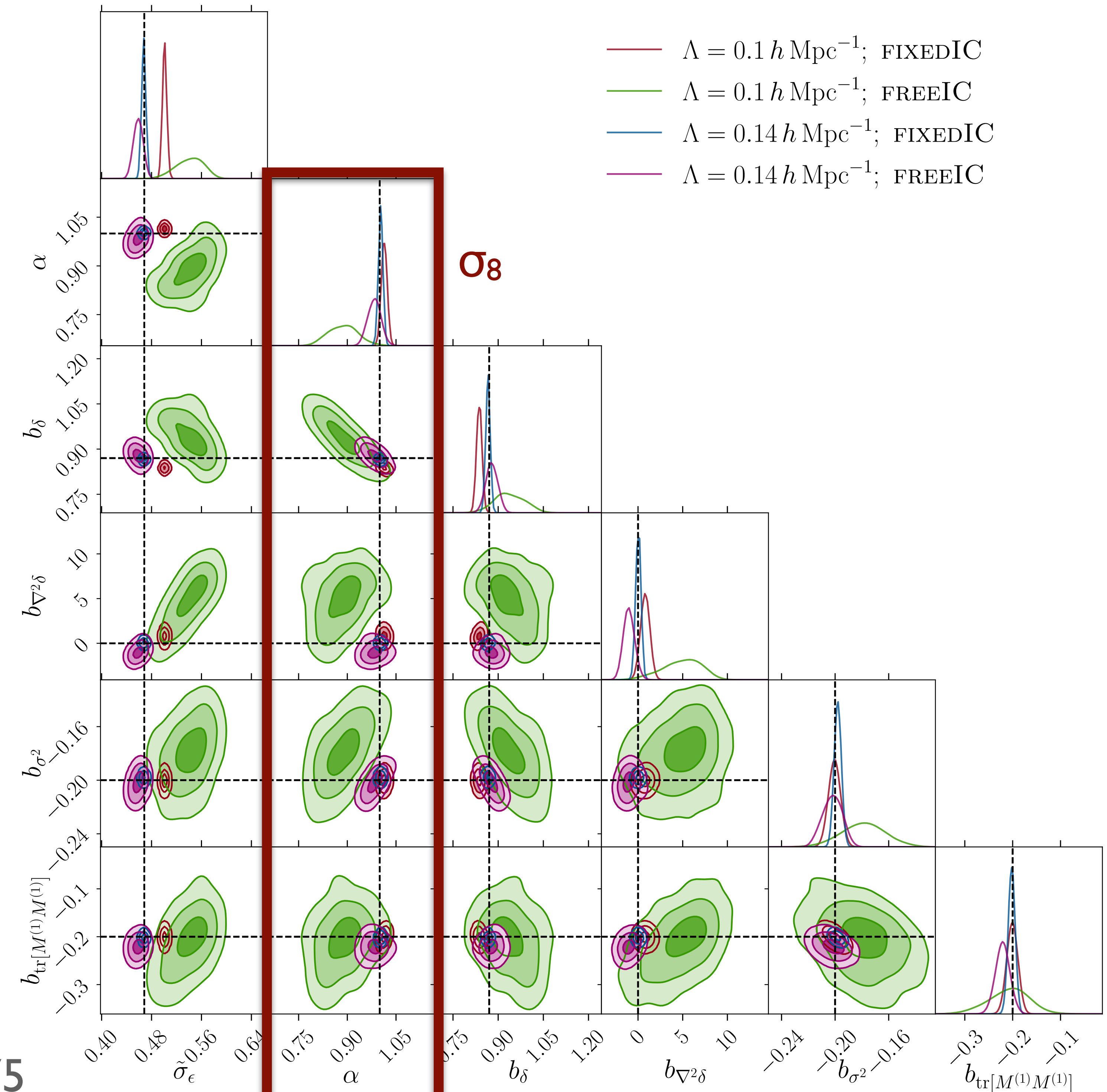
- Full HMC sampling results for mocks generated with the same model, but *different cutoffs* $\Lambda_{\mathrm{mock}} > \Lambda_{\mathrm{inference}}$
- Fisher forecast indicates that σ_8 (<=> α) constraint *improves by factor ~5 over power spectrum+bispectrum* (Λ=0.14)



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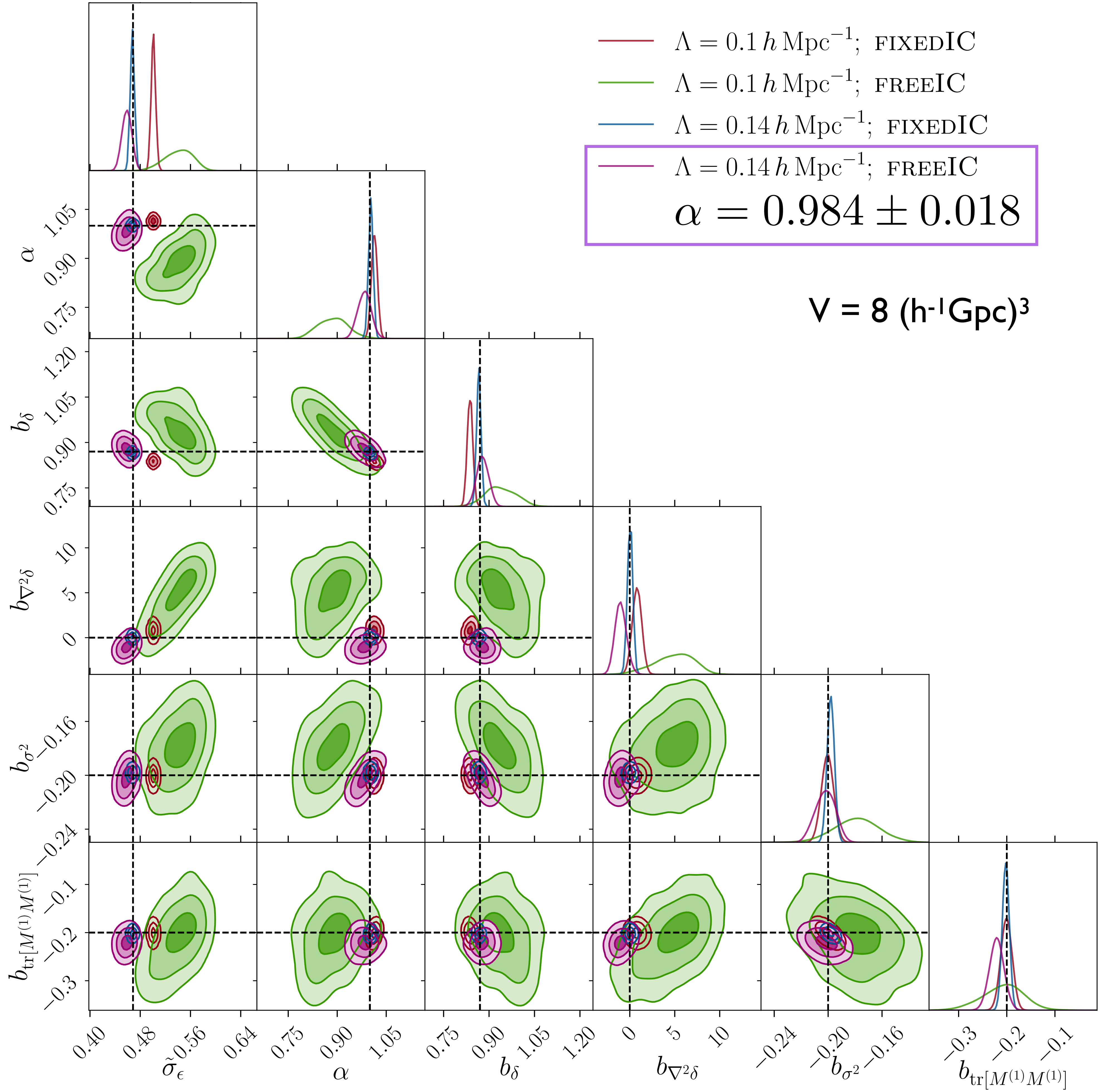

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Conclusions

- Two main messages:
  - *We can deal with complexities of galaxies rigorously on large scales -> EFT*
  - *There is much more (trustable) information in galaxy clustering than what we are using so far -> full inference* and/or new data summaries*

* For full disclosure: we still see issues when applying to fully nonlinear tracers (halos and high-Λ mocks).