Primordial Features from Linear to Nonlinear Scales

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[arXiv:1906.08758]

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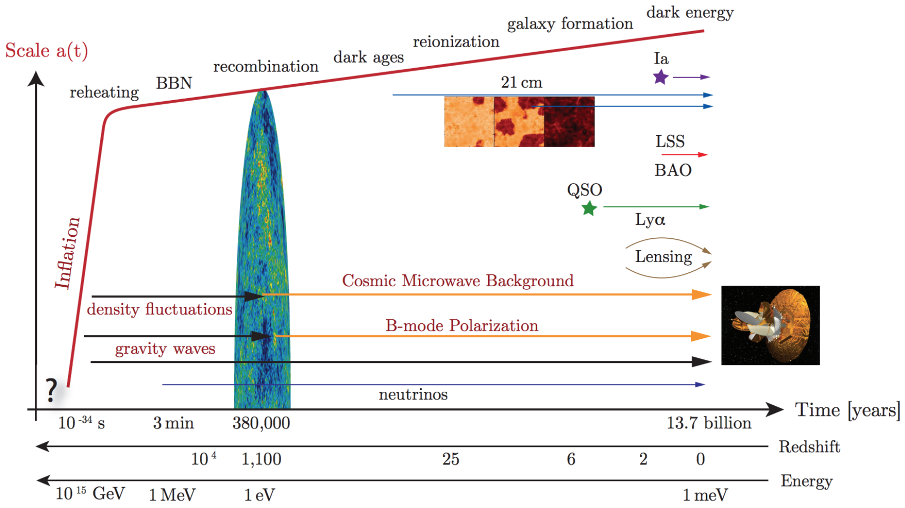
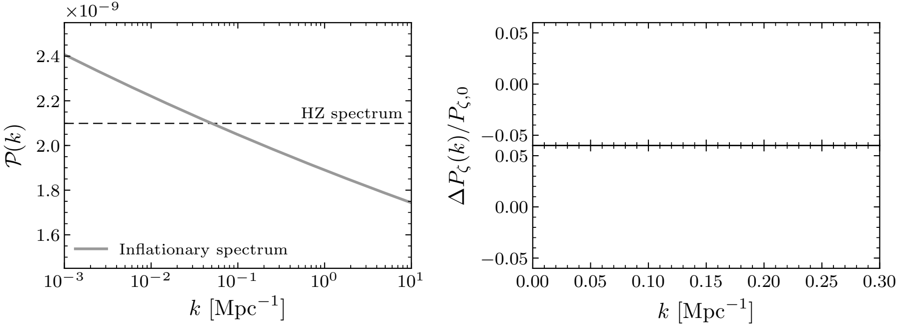
Inflation in one plot



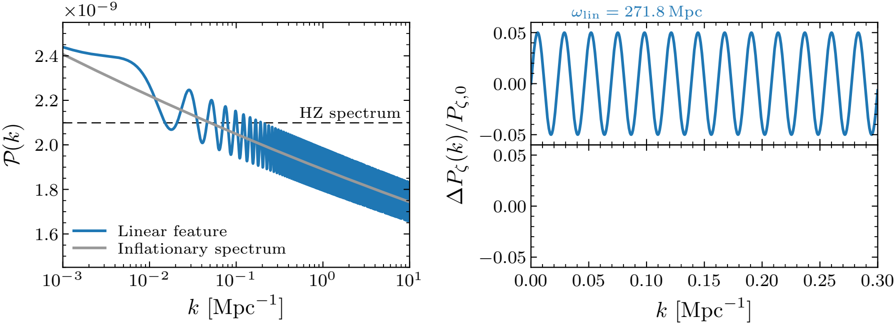
Baumann (2009)

No features



$$P_{\zeta,0}(k) = \frac{2\pi^2}{k^3}\mathcal{P}_{\zeta,0}(k) = \frac{2\pi^2 A_s}{k^3}\left(\frac{k}{k_*}\right)^{n_s-1}$$

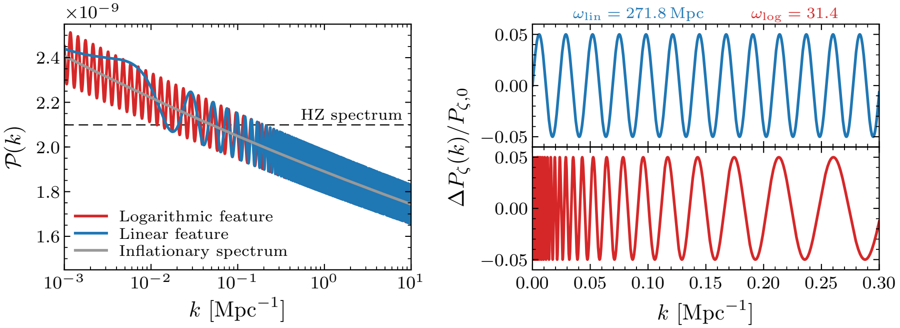
Linear features



$$\frac{\Delta P_\zeta(k)}{P_{\zeta,0}(k)} = A_{\rm lin} \sin\left(\omega_{\rm lin} k + \phi_{\rm lin}\right)$$

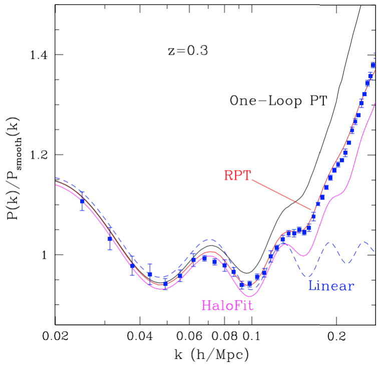
[Sharp Features]
Starobinsky (1992)
Adams, Cresswell & Easther (1997)
...

Logarithmic features



$$\frac{\Delta P_\zeta(k)}{P_{\zeta,0}(k)} = A_{\rm log} \sin\left(\omega_{\rm log} log(k/k_*) + \phi_{\rm log}\right)$$

[Resonant features]
Chen, Easther & Lim (2008)
Silverstein & Westphal (2008)
Flauger, McAllister, Pajer & Westphal (2010)
...



Crocce & Scoccimarro (2008)

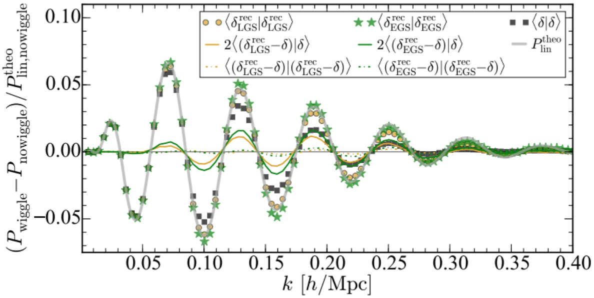
$$P_g(k) = b_1^2 \left[e^{-k^2\Sigma_{\rm nl}^2/2} P_{\rm lin}(k) + P_{\rm MC}(k) \right]$$

$$P_{\rm MC}(k) \simeq 2 \int F_2^2(\mathbf{k}-\mathbf{q},\mathbf{q}) P_{\rm lin}(|\mathbf{k}-\mathbf{q}|) P_{\rm lin}(q) d^3q$$

Heavens & Matarrese (1998), McDonald (2006),
Smith et al. (2007), Carlson et al. (2009)
Blas et al. (2016)
. . .

Density-field reconstruction

$$\nabla \cdot \Psi + \frac{f}{b} \nabla \cdot (\Psi_s \hat{s}) = -\frac{\delta_g}{b} \quad \text{with} \quad f = \frac{d \ln D}{d \ln a}$$



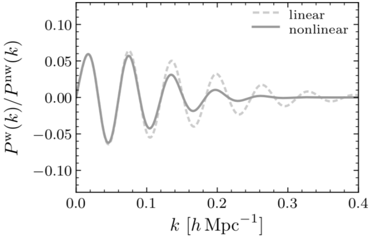
Schmittfull, FB et al. (2016)

$$\Sigma_{\rm nl}^{\rm post-recon} < \Sigma_{\rm nl}^{\rm pre-recon}$$

$$P_{\rm MC}^{\rm post-recon} \approx 0$$

Eisenstein et al. (2007), Padmanabhan et al. (2009)
Padmanabhan et al. (2012) . . .

Fitting the BAO



- Model for the BAO

$$P(k) = P^{\mathrm{nw}}(k) + e^{-k^2\Sigma_{\mathrm{nl}}^2/2} P^{\mathrm{w}}_{\mathrm{BAO}}(k/\alpha)$$

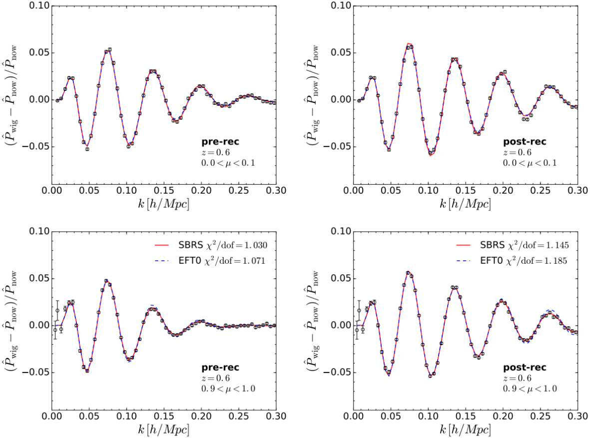
- Add broadband nuisance terms

$$A(k) = a_1 k + a_2 + \frac{a_3}{k} + \frac{a_4}{k^2} + \frac{a_5}{k^3}$$

$$P^{\mathrm{fit}}(k) = \frac{B^2}{(1 + (k\Sigma_{\mathrm{FOG}})^2/2)^2} P(k) + A(k)$$

- Marginalize to get $\mathcal{L}(\alpha)$.

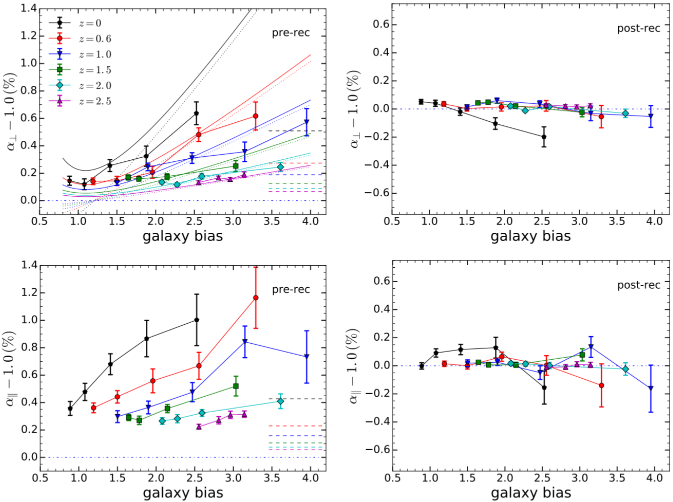
Modelling the BAO



Ding, Vlah, FB et al. (2018)

→ 2 simulations with the same phase but based on $P_{\rm lin}$ and $P_{\rm lin}^{\rm nw}$

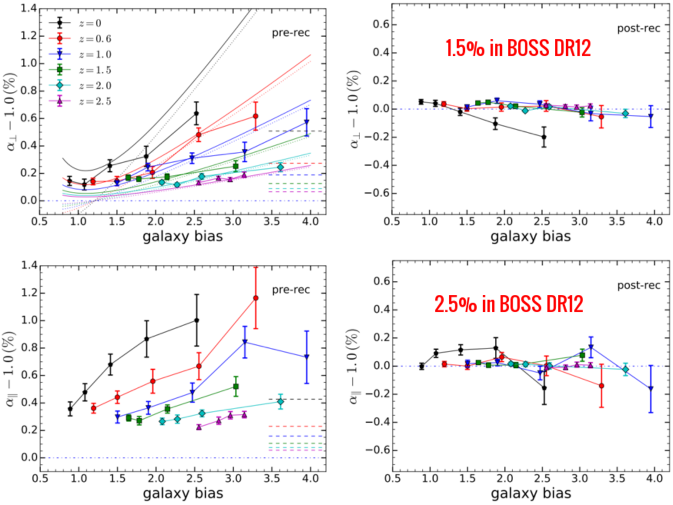
→ Allows to measure the BAO (almost) without sample variance



Ding, Vlah, FB et al. (2018)

$$\alpha = \alpha_\parallel^{1/3} \alpha_\perp^{2/3}$$

Modelling the BAO



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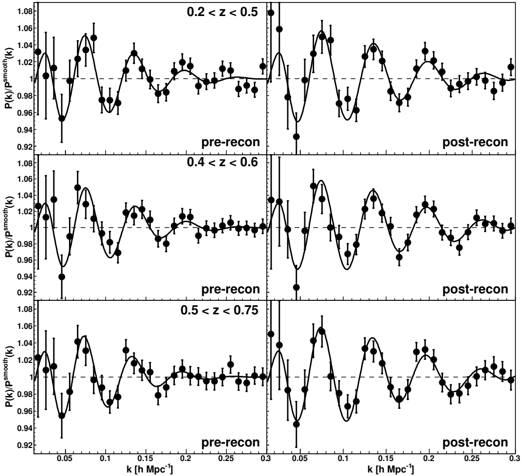
Baryon Acoustic Oscillations in BOSS DR12



FB et al. (2017)

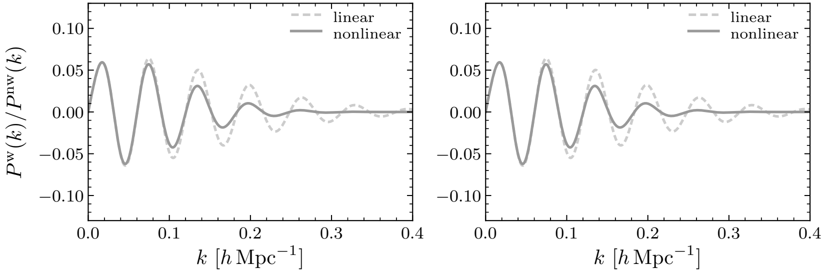
→ 2 independent 8σ detections

→ 1% distance constrains (1.5% in $D_A(z)$ and $\sim$ 2.5% in $H(z)$)

Feature damping

Linear Feature	Logarithmic Feature
Damping factor of linear features equal to BAO damping for $\omega_{\rm lin} \gtrsim 75\,\text{Mpc}$	Damping factor of log features approx. equal to BAO damping for $\omega_{\rm log} \gtrsim 10$

$$P(k) = P^{\rm nw}(k) + e^{-k^2\Sigma_{\rm nl}^2/2}\left[P^{w}_{\rm BAO}(k/\alpha)\right]$$



Feature damping

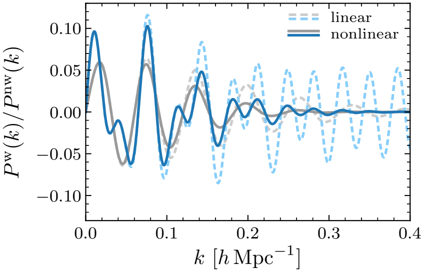
Linear Feature

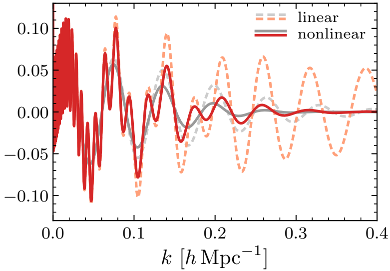
- Damping factor of linear features equal to BAO damping for $\omega_{\rm lin} \gtrsim 75\,$Mpc

Logarithmic Feature

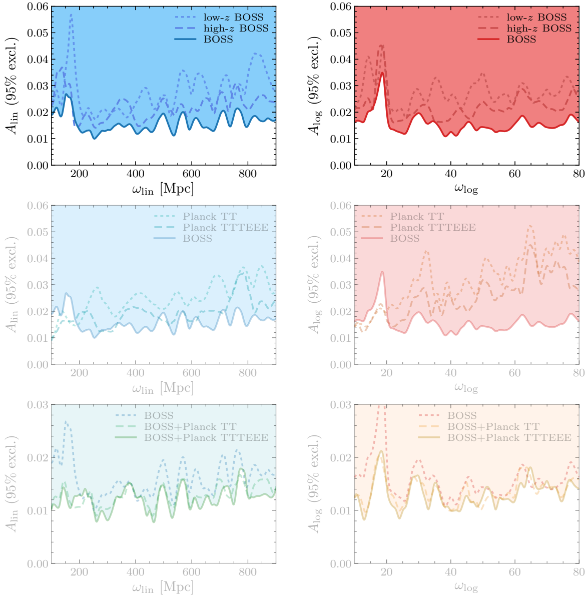
- Damping factor of log features approx. equal to BAO damping for $\omega_{\rm log} \gtrsim 10$

$$P(k) = P^{\rm nw}(k) + e^{-k^2\Sigma_{\rm nl}^2/2}\left[P^{w}_{\rm BAO}(k/\alpha) + P^{w}_{\rm lin,log}(k) + P^{w}_{\rm BAO}(k/\alpha)\delta P^{\rm lin,log}_{\zeta}(k)\right]$$





Feature constraints from BOSS DR12 and Planck

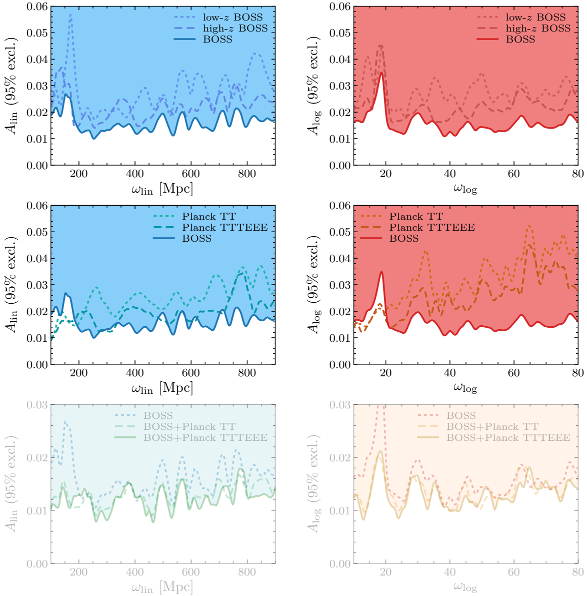


BOSS

BOSS vs. Planck

BOSS + Planck

Feature constraints from BOSS DR12 and Planck



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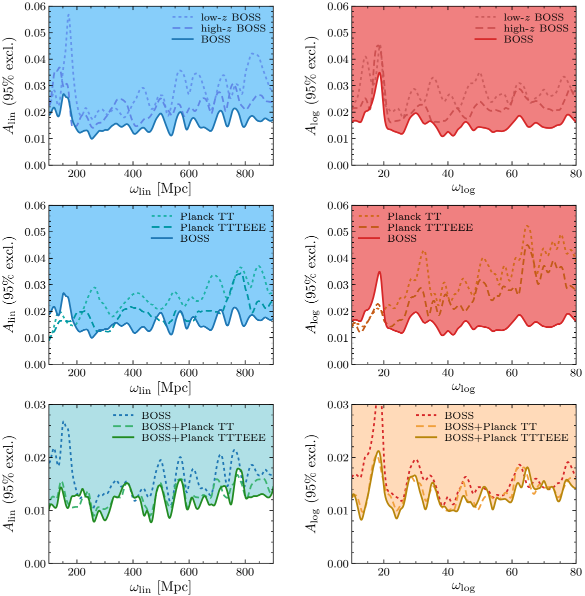
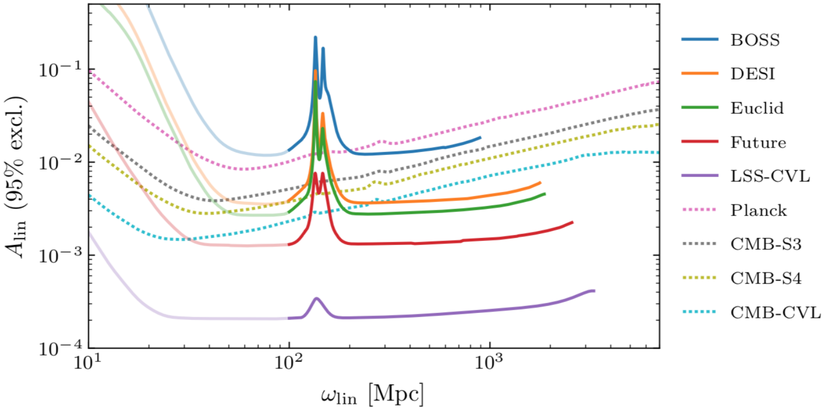


BOSS

BOSS vs. Planck

BOSS + Planck

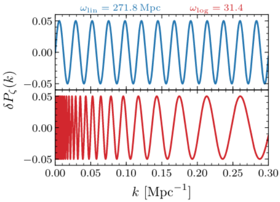
Forecasts for primordial feature constraints



→ LSS dominates on small frequencies, while the CMB can access higher frequencies

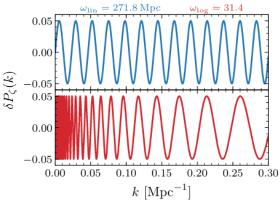
→ DESI/Euclid are going to beat even CVL-CMB experiments

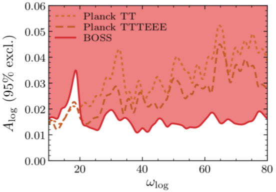
Summary



1. Many well motivated inflationary models introduce features in the primordial power spectrum
   And we know how to detect features → BAO
2. Constraints on primordial features from LSS are **already better than Planck** for a large frequency range
3. Future LSS constraints from DESI and Euclid will push into a parameter space, which is **even beyond a CVL-CMB experiment**

Summary





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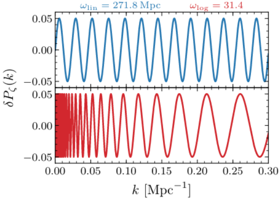

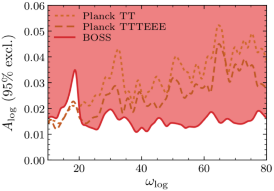

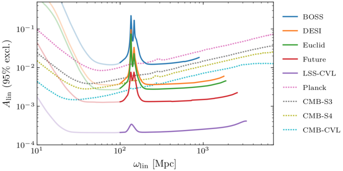

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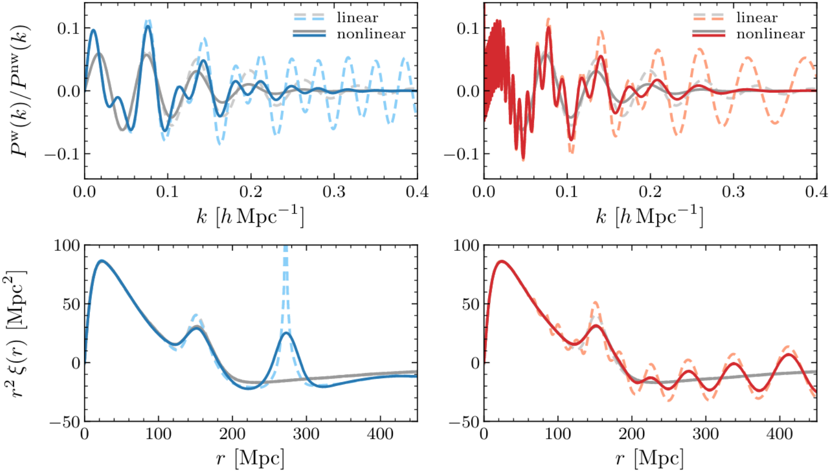
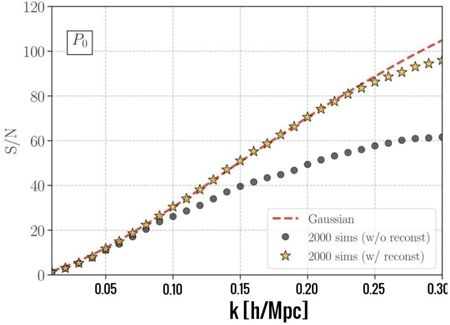
Fourier-space vs. configuration space

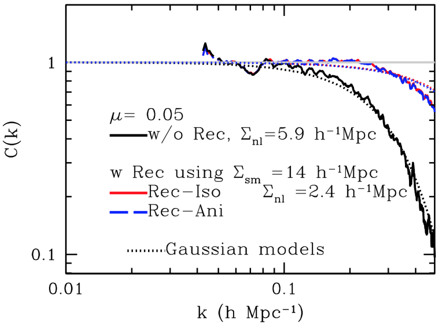
Linear Feature | Logarithmic Feature



S/N after Density-field reconstruction



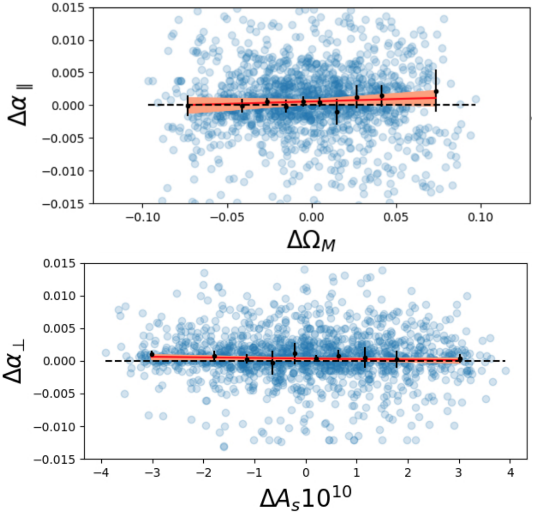
Sugiyama, FB et al. (in prep.)



Seo, FB et al. (2016)

$$(S/N)^2 = \sum_{k_1,k_2 \leq k_{\rm max}} C^{-1}(k_1,k_2)P_m(k_1)P_m(k_2)$$

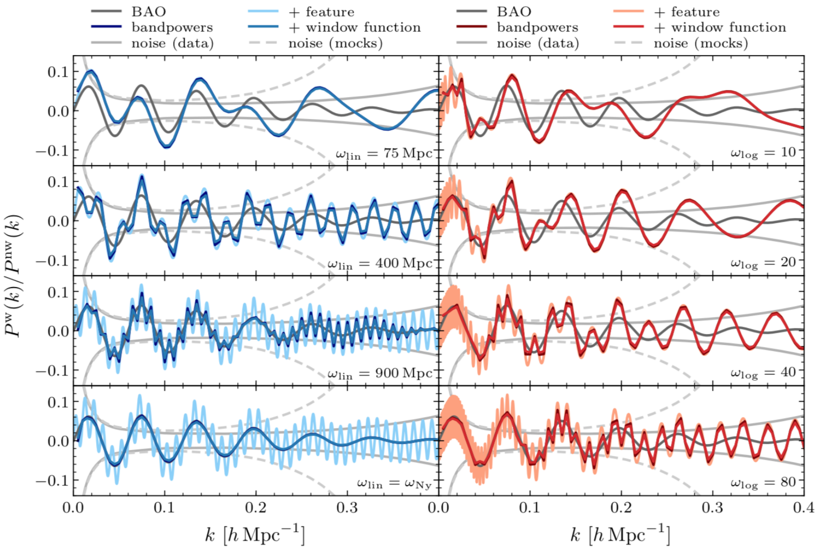
Dependence on fiducial cosmology



Carter, FB et al. (2019)

$$\alpha = \alpha_{\parallel}^{1/3}\alpha_{\perp}^{2/3}$$

Impact of the window function for features search



Transfer of power