

# Precision measurements of the cosmological distance scale with upcoming galaxy redshift surveys

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Standard reconstruction and some problems

Iterative reconstruction

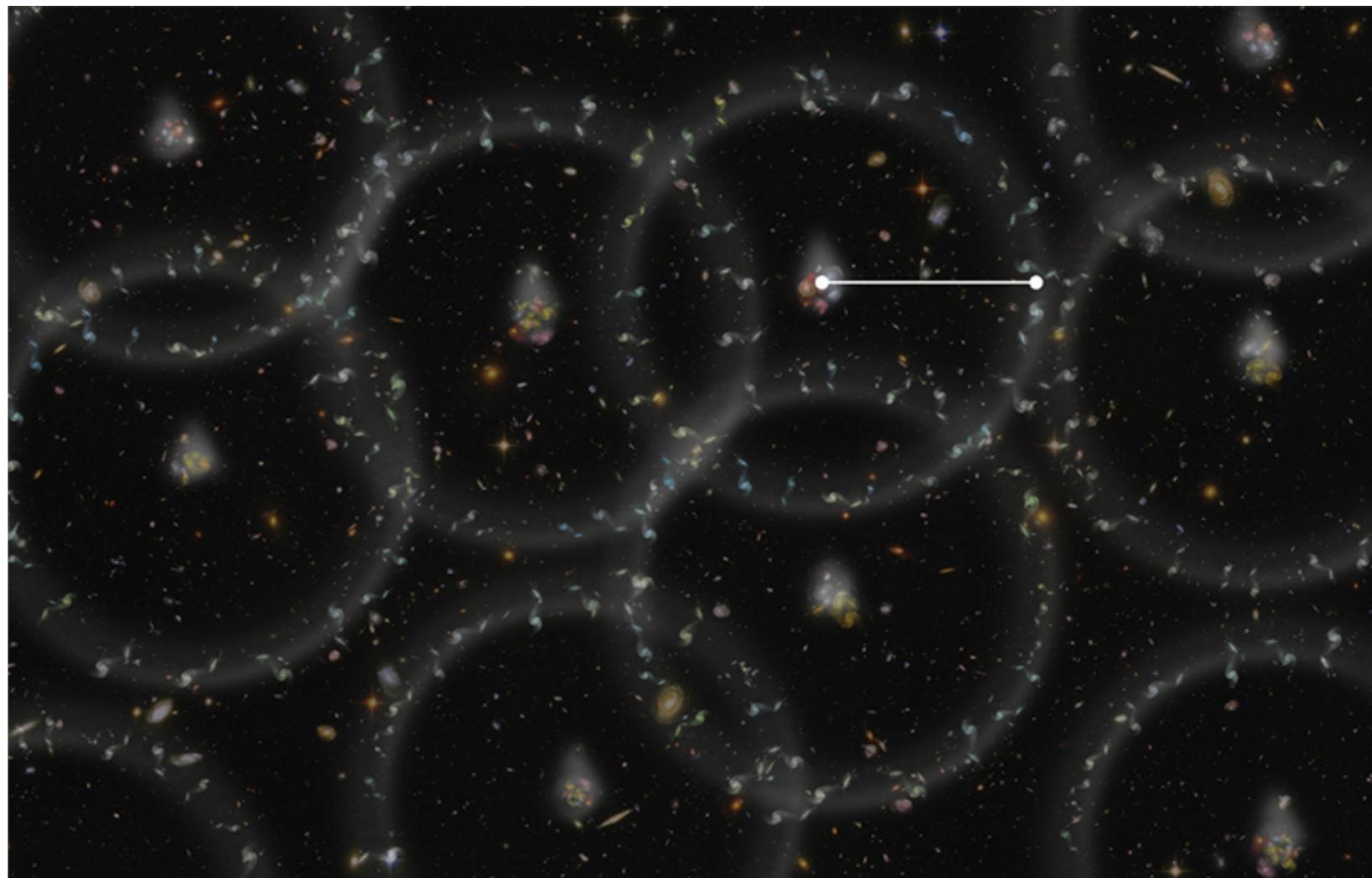
Summary

# Baryon Acoustic Oscillation (BAO)

The baryon-photon plasma propagated as a sound wave before recombination

Over-dense region of baryon (ring shape) got frozen at recombination

The characteristic pattern can be seen in the late-time galaxy distribution



(Credit: Zosia Rostomian, LBNL)

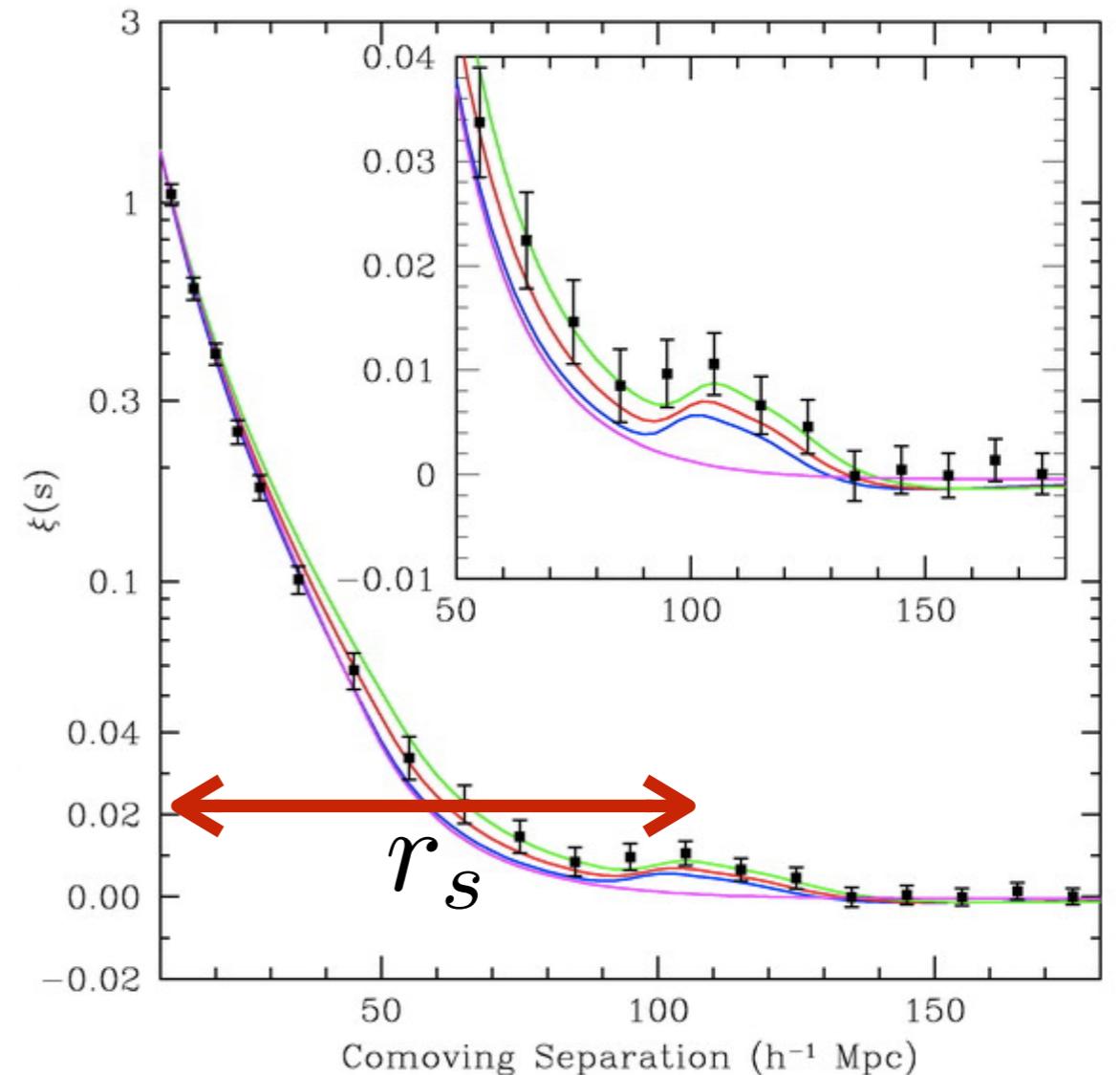
# Distance measurement with BAO

The BAO pattern emerges as a peak in the galaxy correlation function

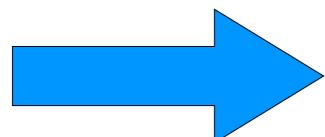
$$\langle n_g(\mathbf{x}_1) n_g(\mathbf{x}_2) \rangle \equiv \bar{n}_g^2(1 + \xi(|\mathbf{x}_1 - \mathbf{x}_2|))$$

The peak location ( $r_s$ ) is precisely determined by CMB observations

If we wrongly estimate the separation distances between galaxy pairs, the BAO peak is shifted



(Eisenstein+ 2005)



We can measure the cosmological distance scale  
by focusing the position of BAO peak (*standard ruler*)

# Dark energy and the distance scale

Distances to galaxies depend on the cosmological parameters

line-of-sight

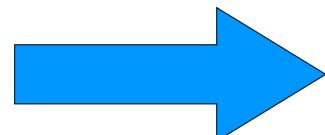
$$H(z), D_A(z) [H_0, \Omega_\Lambda, w, \dots]$$

perpendicular

Eq. of state for DE:  $p_\Lambda = w\rho_\Lambda$

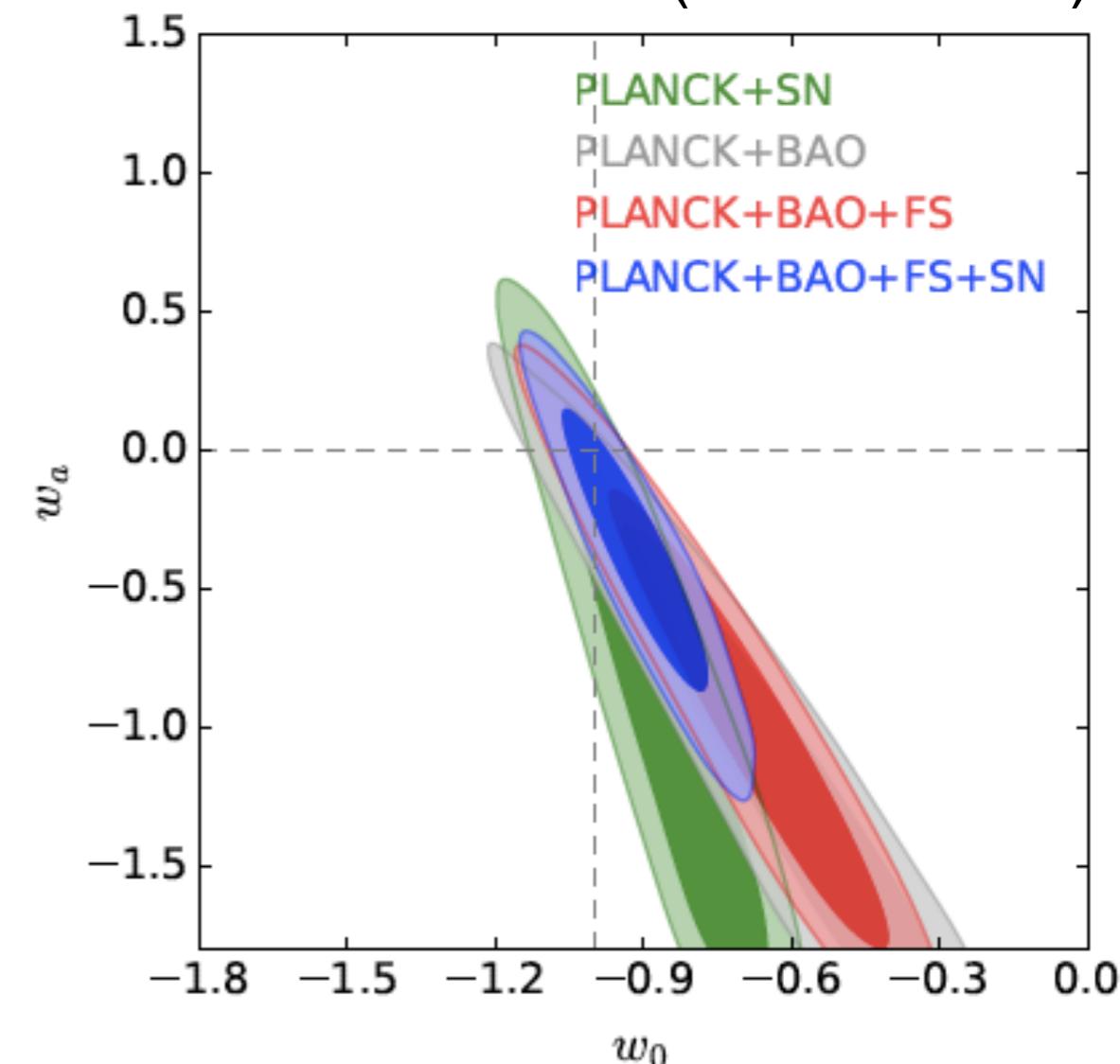
$w < -1/3$  : for accelerated expansion

$w(a) = w_0 + (1 - a)w_a$  : in general



need to measure the distance scale more precisely to understand the property of DE

(Alam+ 2016)



# Degradation of the BAO signature

## 1). Peak broadening

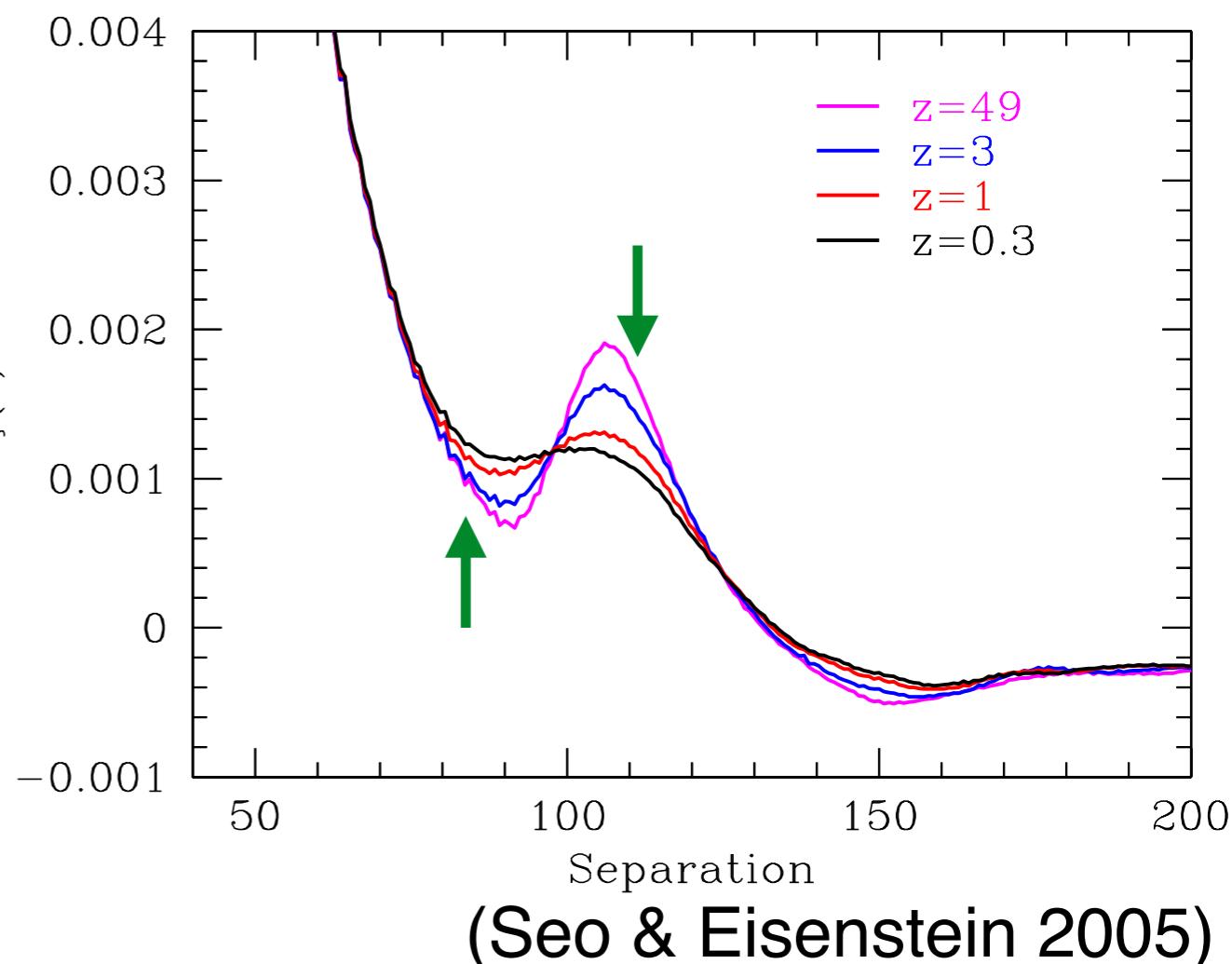
Peculiar velocities of galaxies smear out the BAO feature

## 2). Redshift space distortion (RSD)

The movements along the line of sight affect on the redshift determination (observed in “redshift space”)



**increasing the distance errors**



→ need to handle with nonlinear effects...

But this degradation is mainly caused by **large-scale flow**

# Reconstruction of the linear density field

1). estimate the **displacement** from the observed density filed

**Zeldovich approximation (ZA)**

$$\delta \equiv \frac{\rho - \bar{\rho}}{\bar{\rho}}$$

$$\boxed{\tilde{\mathbf{S}}^{(1)}(\mathbf{k})} = \frac{i\mathbf{k}}{k^2} \tilde{\delta}_L(\mathbf{k}) G(k) \text{(in Fourier space)}$$

$$G(k) = \exp[-0.5 k^2 \Sigma^2]$$

smoothing scale

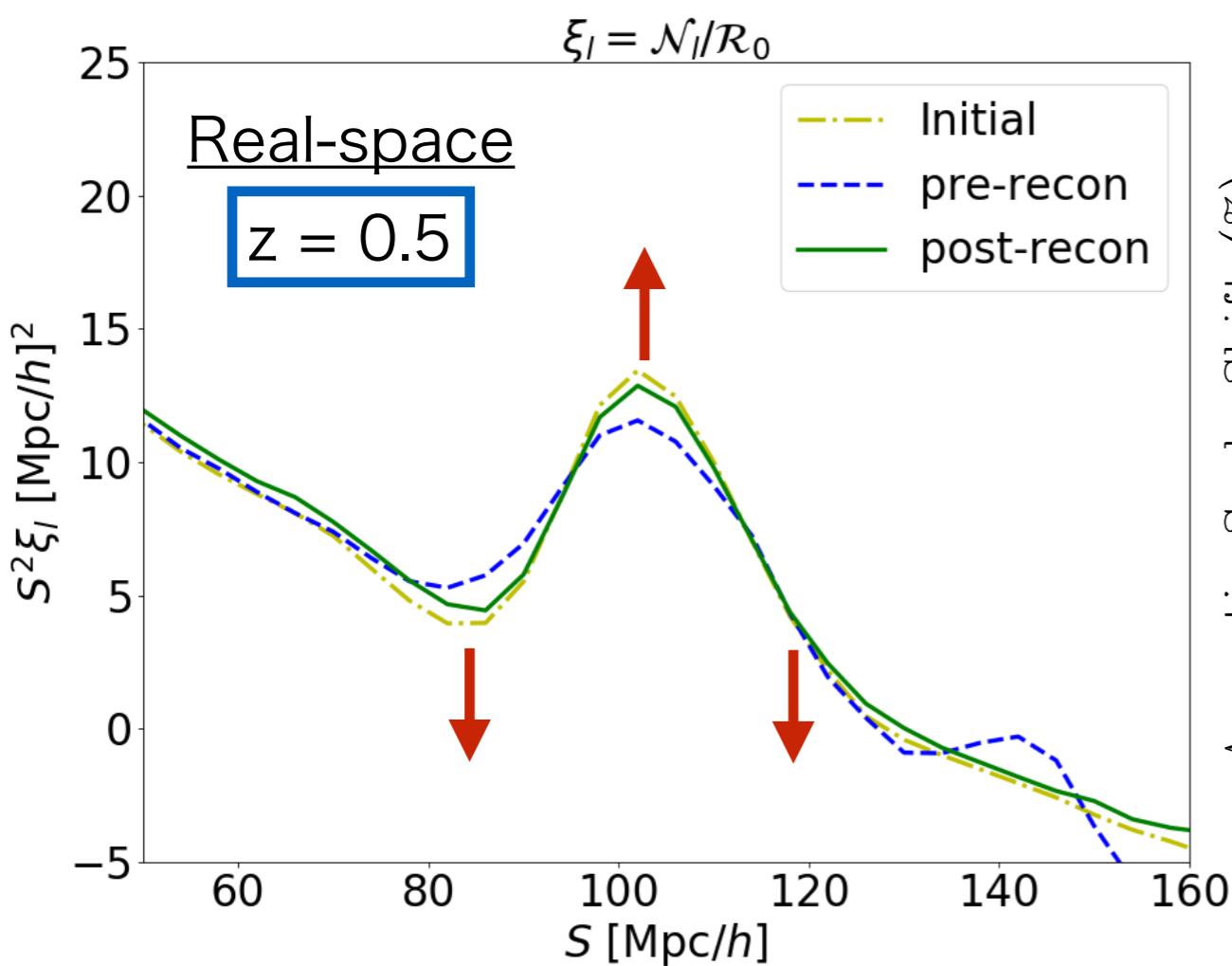
2). shift galaxy particles and uniform random particles by that

Galaxy:  $\mathbf{S}^{(s)}(\mathbf{q}, t) = \mathbf{S}^{(1)} + f(\mathbf{S}^{(1)} \cdot \hat{\mathbf{z}}) \hat{\mathbf{z}}$  Redshift-space distortion

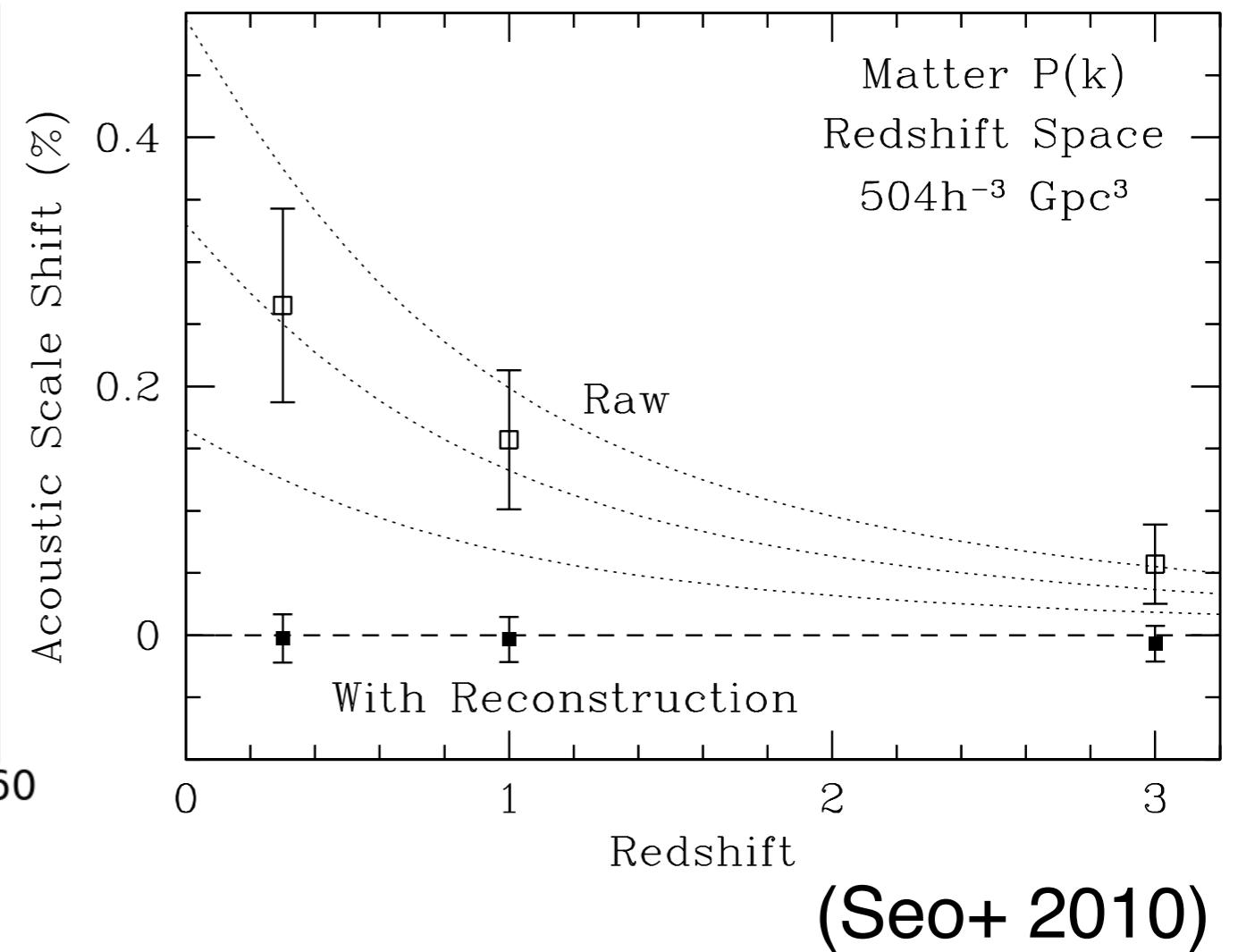
Random:  $\mathbf{S}^{(1)}$  where  $f = \frac{d \ln D}{d \ln a}$  : Linear growth rate

it's like moving "density contrasts"

## Reconstructed correlation function

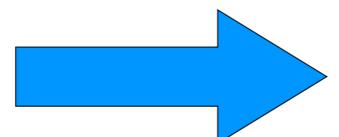


## Restored BAO peak



The BAO peak is actually recovered

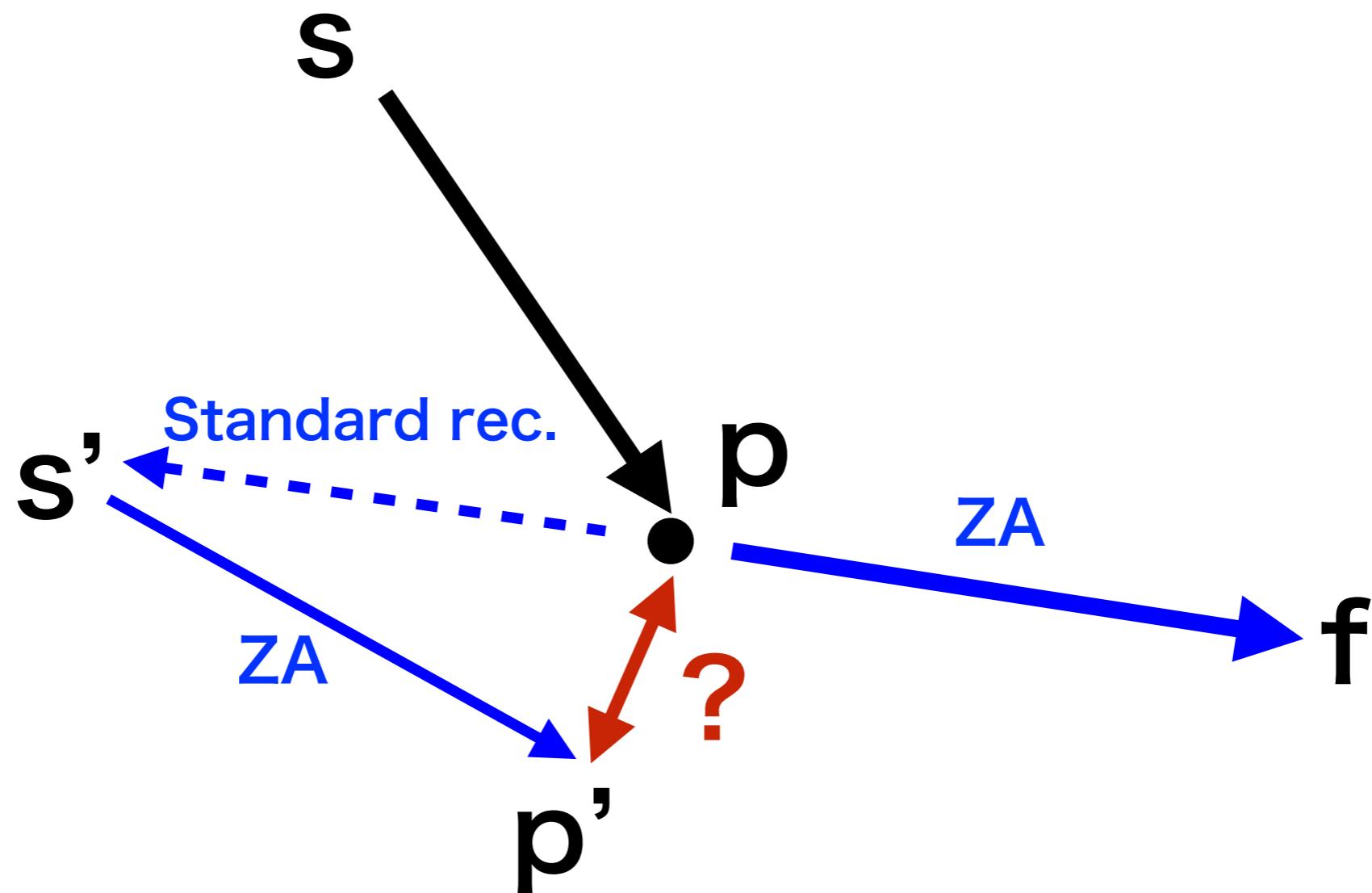
The peak shift is also suppressed



improving the statistical precision  
by a factor of 1.5 - 2

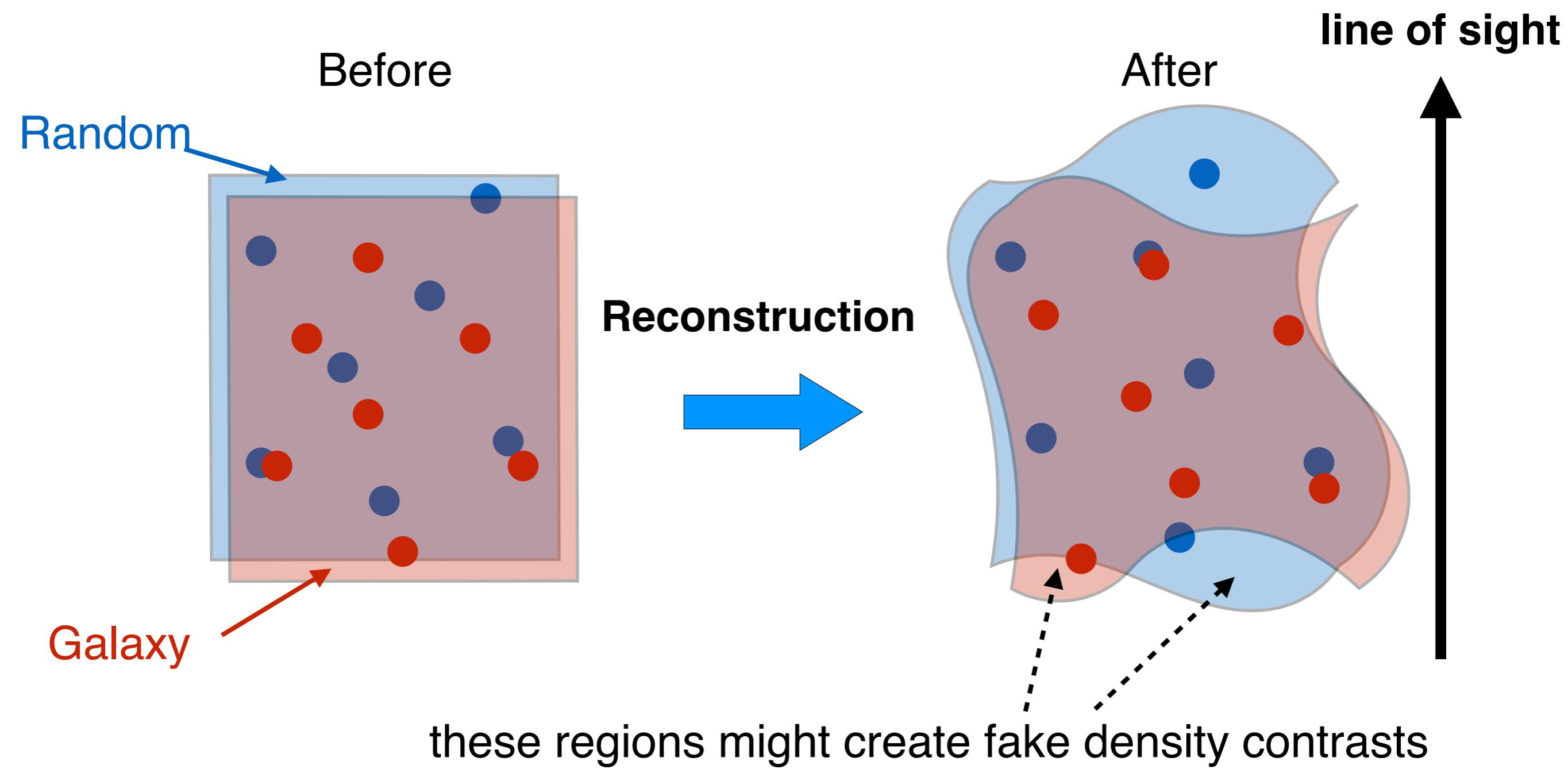
# Problems in the standard reconstruction

## 1). Inconsistency between displacements



# Problems in the standard reconstruction

## 2). Fake density contrasts



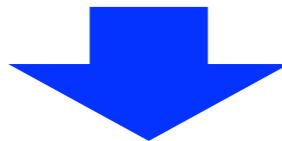
# Impact of the smoothing scale

$$\tilde{\mathbf{S}}^{(1)}(\mathbf{k}) = \frac{i\mathbf{k}}{k^2} \tilde{\delta}_L(\mathbf{k}) G(k)$$
$$G(k) = \exp[-0.5k^2 \Sigma^2]$$

smoothing scale

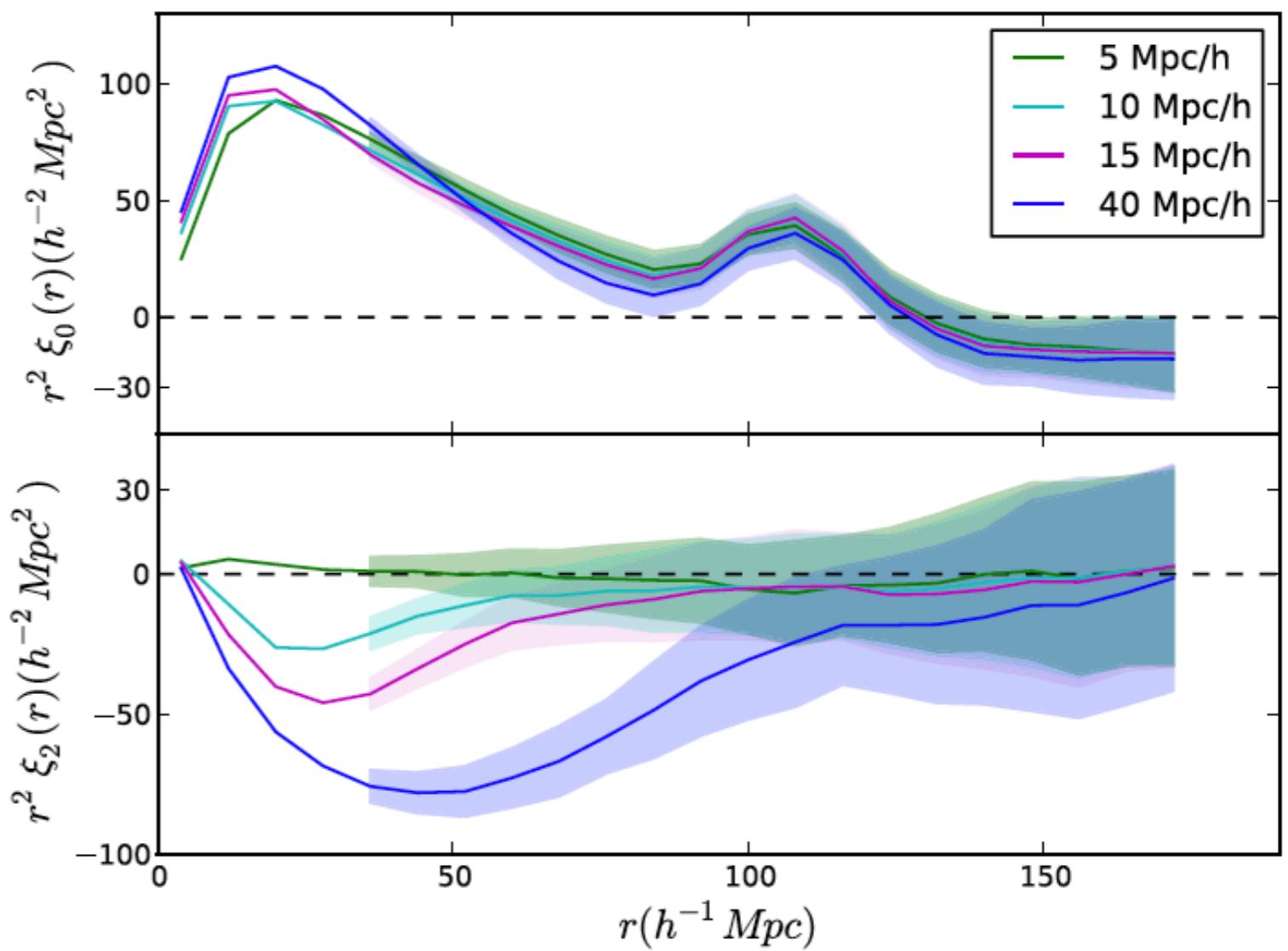
introduced with intent to avoid shot noise effects

but impacts on the results of reconstruction even on large scales (around the BAO peak)



actually affects the (anisotropic) distance measurements

(Vargas-Magaña+ 2017)



# Ongoing galaxy survey projects

## DESI

Telescope: 4m  
Area: 14000 sq. deg.  
Redshift: 0.0 - 1.6  
Target: LRG, ELG

**large volume size**

→ BAO → Dark energy

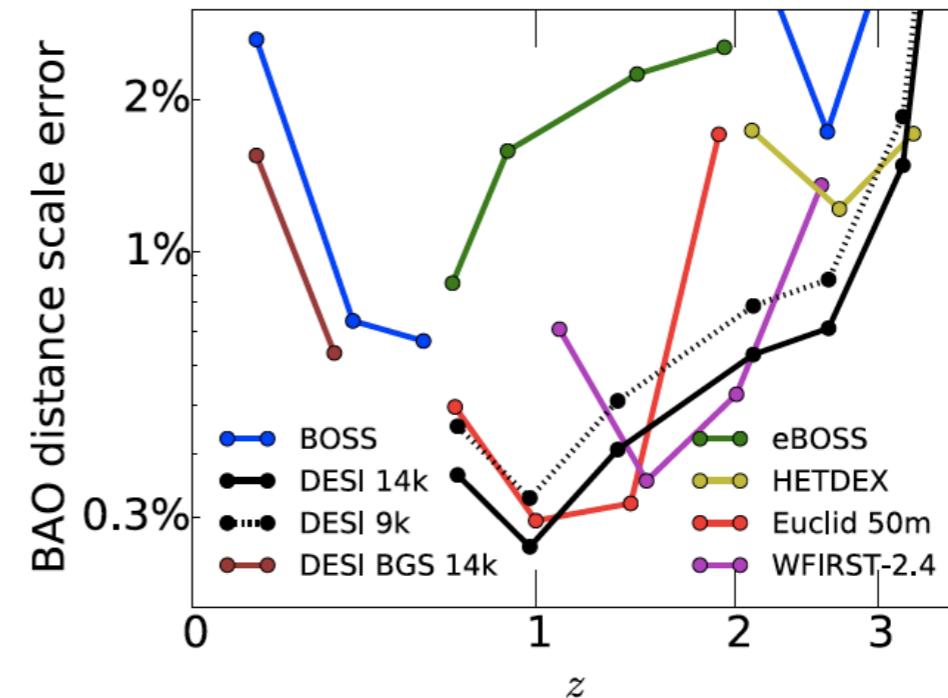
## PFS

Telescope: 8.2m  
Area: 1400 sq. deg.  
Redshift: 0.6 - 2.4  
Target: ELG

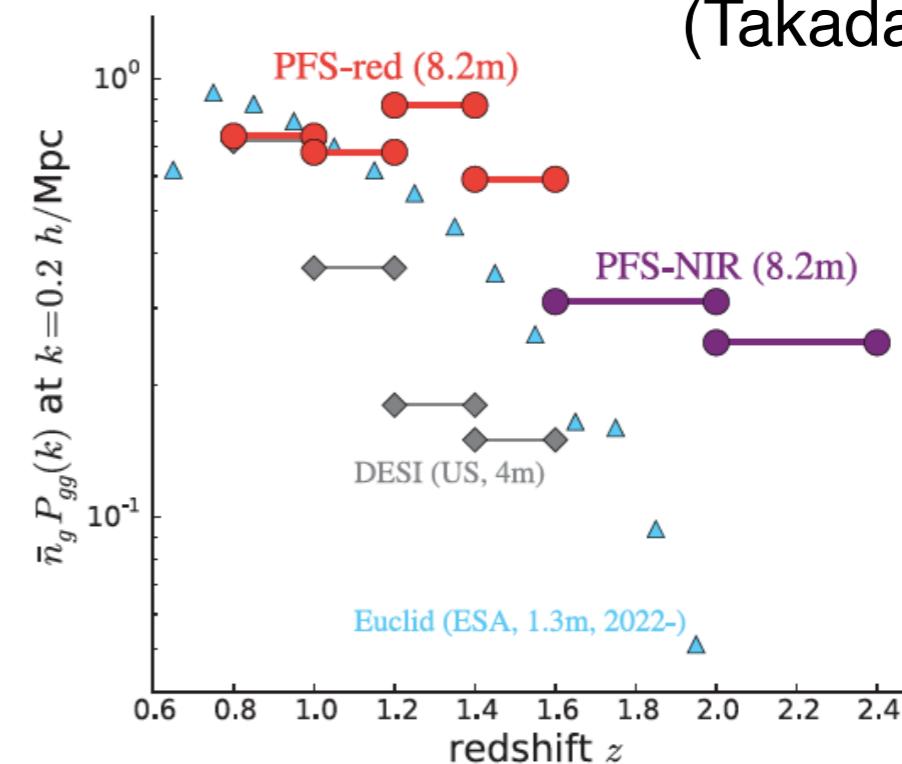
**high number density, deeper**

→ RSD → neutrino mass

(DESI Collaboration, 2016)



(Takada+ 2018)



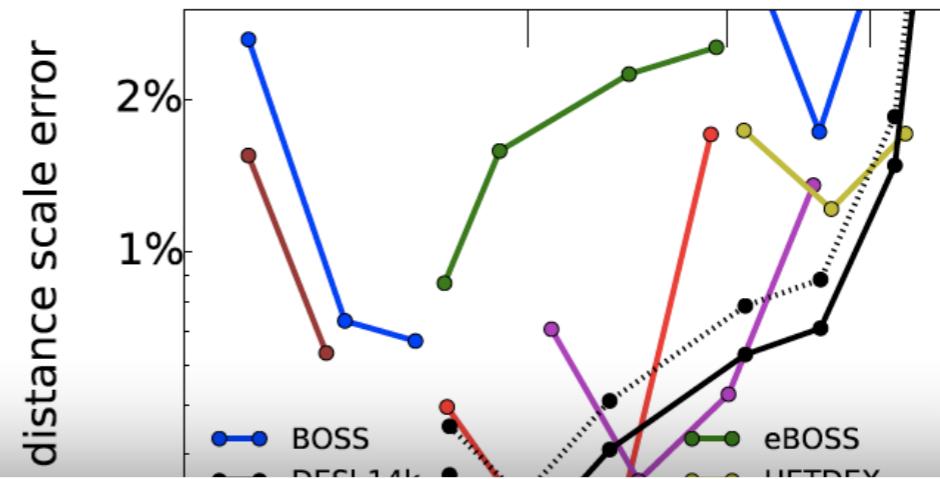
# Ongoing galaxy survey projects

## DESI

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large volume, deep

(DESI Collaboration, 2016)



Need to solve the problems in the standard rec. and improve the **reliability** of the BAO standard ruler !

PFS

Telescope: 0.2m  
Area: 1400 sq. deg.  
Redshift: 0.6 - 2.4  
Target: ELG

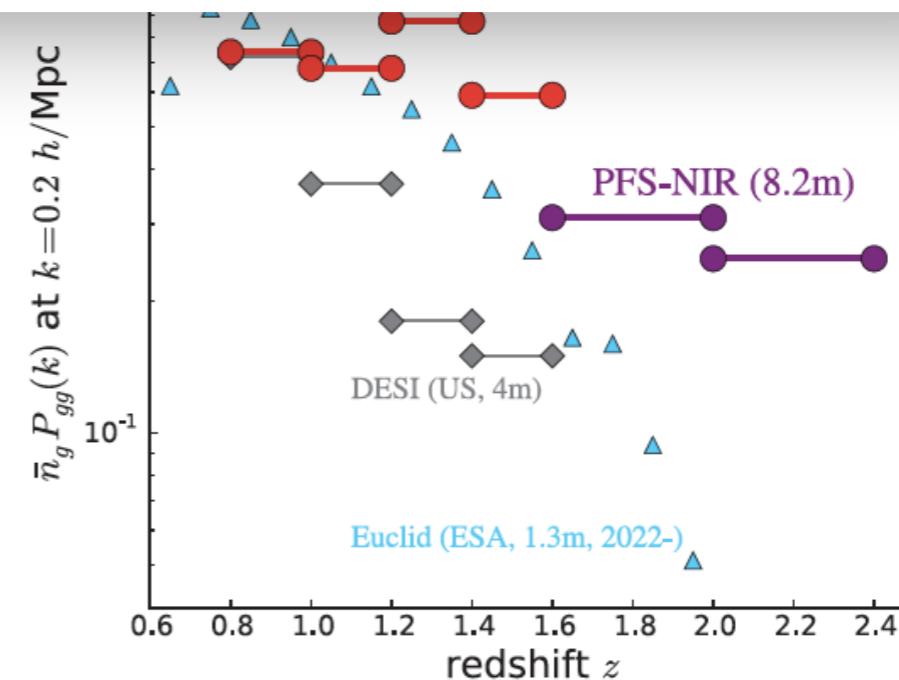
**high number density, deeper**



RSD



neutrino mass



8)

# Other methods beyond the standard

Reconstruction algorithm	Stage I: Estimate displacement	Stage II: Estimate linear density
Standard reconstruction [17]	Zeldovich $\hat{\chi}_{ZA} = \frac{ik}{k^2} W \delta_{NL}$	$\hat{\delta}_0 = \delta_d[\hat{\chi}_{ZA}] - \delta_s[\hat{\chi}_{ZA}]$
Iterative standard rec [53]	Iterative Zeldovich with fixed $W$	$\hat{\delta}_0 = \delta_d[\hat{\chi}_{ZA}] - \delta_s[\hat{\chi}_{ZA}]$
Improved standard rec [37]	Zeldovich and iterative Newton-Raphson	$\hat{\delta}_0 = \hat{\delta}_\chi = \nabla \cdot \hat{\chi}$
Standard rec with pixels [54, 55]	Zeldovich $\hat{\chi}_{ZA} = \frac{ik}{k^2} W \delta_{NL}$	Move pixels instead of galaxies
Eulerian growth-shift rec [56]	Zeldovich $\hat{\chi}_{ZA} = \frac{ik}{k^2} W \delta_{NL}$	$\hat{\delta}_0 = \delta_{NL} - \hat{\chi}_{ZA} \cdot \nabla \delta - \delta^2$
Nonlinear isobaric rec [57, 58]	Solve diff. eqn. with multigrid algorithm	$\hat{\delta}_0 = \hat{\delta}_\chi = \nabla \cdot \hat{\chi}$
New $\mathcal{O}(1)$ rec	Iteratively solve $T(k)F_Z[\nabla \cdot \chi] = W \delta_{NL}$ for $\chi$	$\hat{\delta}_0 = \hat{\delta}_\chi = \nabla \cdot \hat{\chi}$
New $\mathcal{O}(2)$ rec	Iteratively solve $T(k)F_Z[\nabla \cdot \chi] = W \delta_{NL}$ for $\chi$	$\hat{\delta}_0 = t_1(k)\hat{\delta}_\chi + t_2(k) \int_p \kappa_2 \hat{\delta}_\chi(p) \hat{\delta}_\chi(k-p)$
Extended std rec [appdx. B]	Iteratively solve $T(k)F_Z[\nabla \cdot \chi] = W \delta_{NL}$ for $\chi$	$\hat{\delta}_0 = \delta_d[\hat{\chi}] - \delta_s[\hat{\chi}]$

(Schmittfull+ 2017)

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(Schmittfull+ 2017)

Perform the standard reconstruction many times (“Iterative” method)

→ Not guaranteed to converge

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(Schmittfull+ 2017)

Perform the standard reconstruction many times (“Iterative” method)

→ Not guaranteed to converge

Estimate the non-linear displacement by solving  
the nonlinear partial differential eq. numerically

→ Is the higher-order contribution reliable?

# Iterative reconstruction method

(RH & Eisenstein, 2018; 2019)

Monaco and Efstathiou (1999)

Continuity eq.

$$\det \left[ \delta_{ab}^K + S_{l|a,b}^{(s)} \right] = \frac{\rho(\mathbf{q})}{\rho(\mathbf{s})} = \frac{1 + \delta_{\text{res}}(\mathbf{q})}{1 + \delta_s(\mathbf{s})}$$

$$\delta_{\text{res}}(\mathbf{q}) = \delta_L(\mathbf{q}) - \delta_l(\mathbf{q}) = \delta_L(\mathbf{q}) + \nabla \cdot \mathbf{S}_l^{(1)}(\mathbf{q})$$

$$\rightarrow \boxed{\delta_L(\mathbf{q}, t) = -\mu_1(\mathbf{S}_l^{(1)}) - 1 + (1 + \delta_s(\mathbf{s})) \left[ 1 + \mu_1(\mathbf{S}_l^{(s)}) + \mu_2(\mathbf{S}_l^{(s)}) + \mu_3(\mathbf{S}_l^{(s)}) \right]}$$

$$\tilde{\mathbf{S}}_l^{(1)}(\mathbf{k}) = \frac{i\mathbf{k}}{k^2} \tilde{\delta}_L(\mathbf{k}) G(k)$$

Displacements

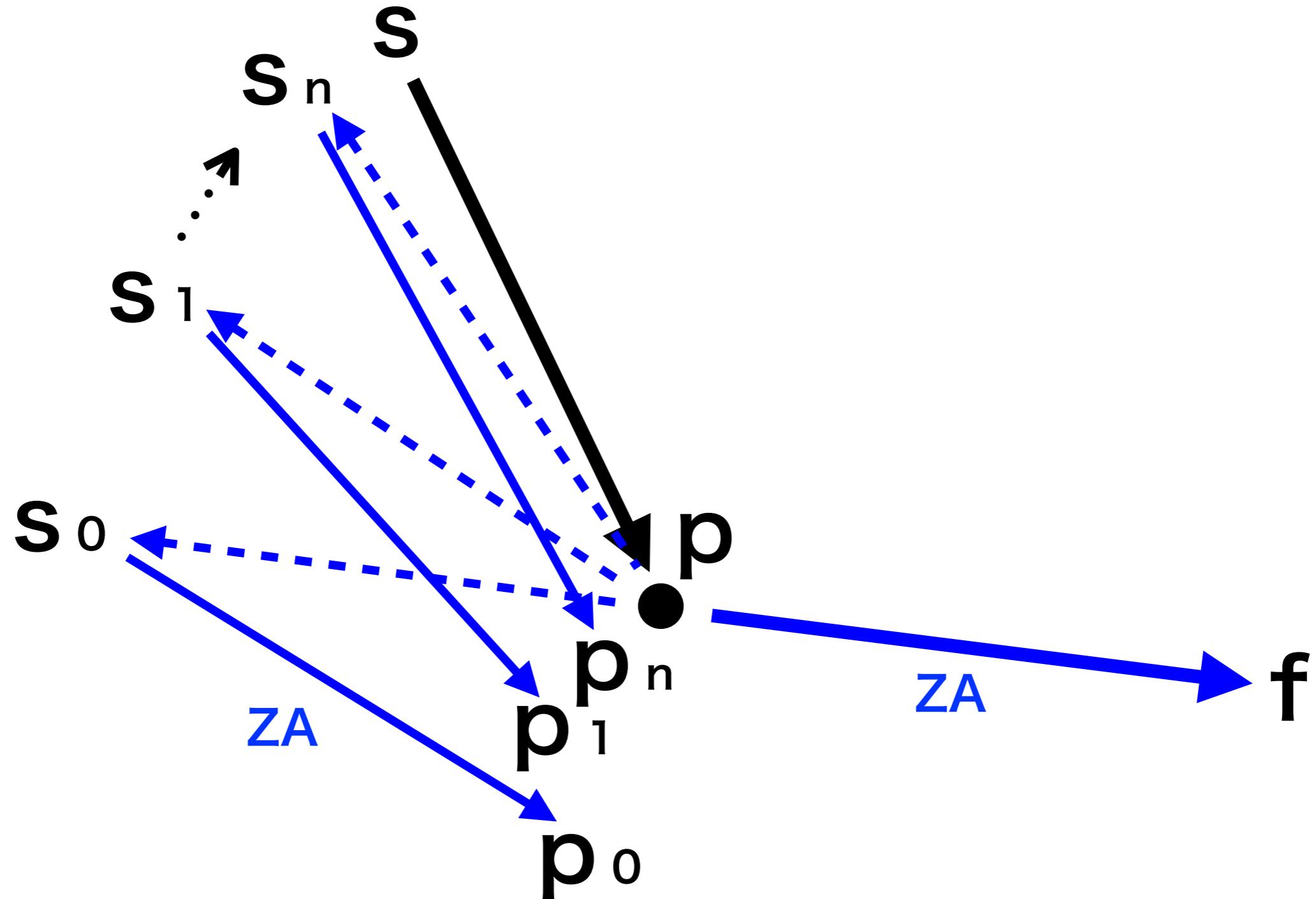
$$\begin{aligned} \mathbf{S}_l^{(s)}(\mathbf{q}, t) &= \mathbf{S}_l^{(1)} + f(\mathbf{S}_l^{(1)} \cdot \hat{\mathbf{z}}) \hat{\mathbf{z}} \\ \mathbf{s}(\mathbf{q}, t) &= \mathbf{q} + \mathbf{S}_l^{(s)}(\mathbf{q}, t) \end{aligned}$$

Redshift-space

Repeat these steps until the linear density field converges

Density fields are defined on a grid cell (no need to move particles)

# Iterative reconstruction method



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Redshift-space

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# Performance comparison

## N-body simulation

**Abacus** (Garrison+ 2017), 20 boxes

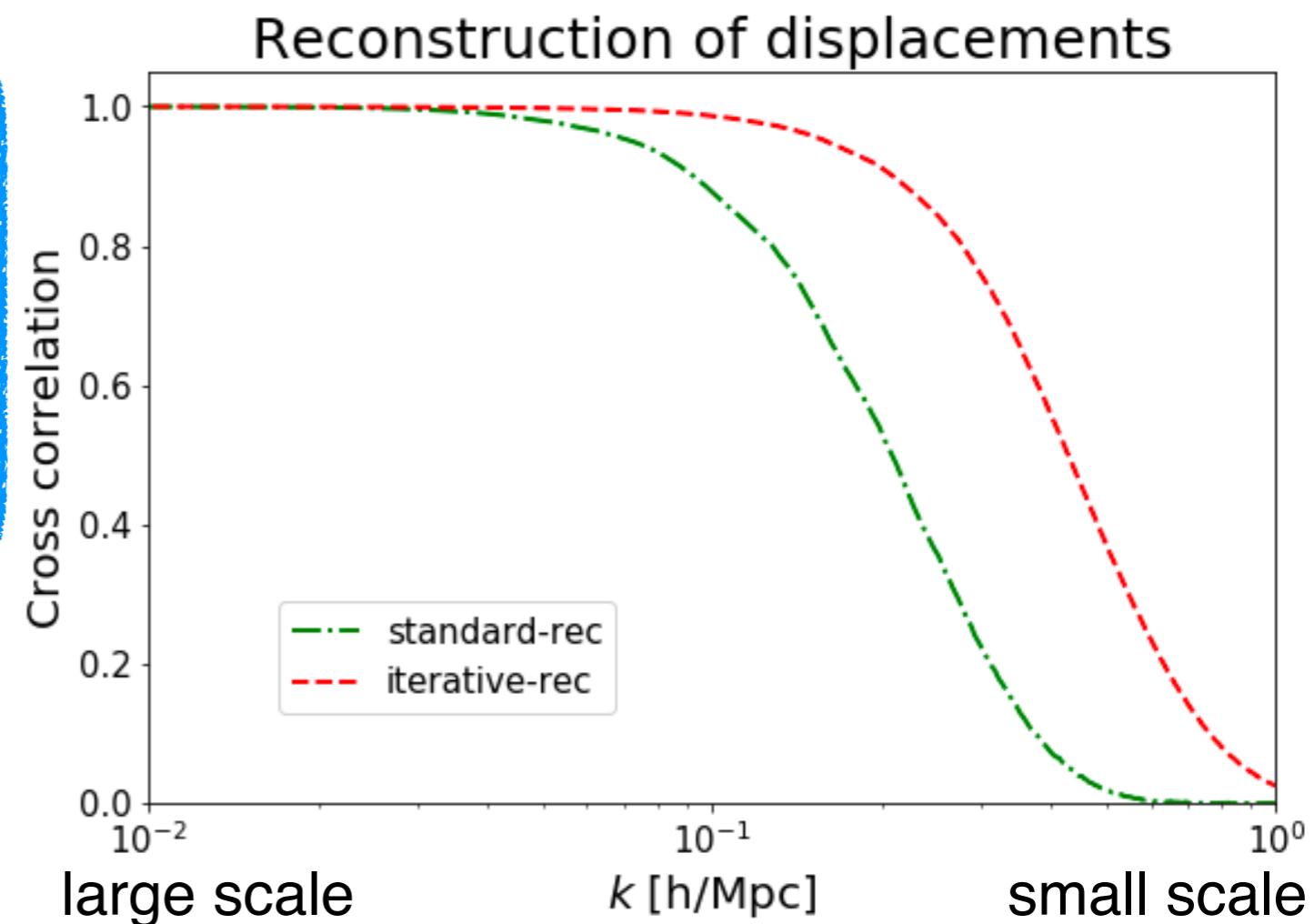
Box size: 1100 [Mpc/h]

Number of particles:  $1440^3$

Redshift:  $z = 0.5$

apply reconstruction methods to the  
**matter** density field in redshift space

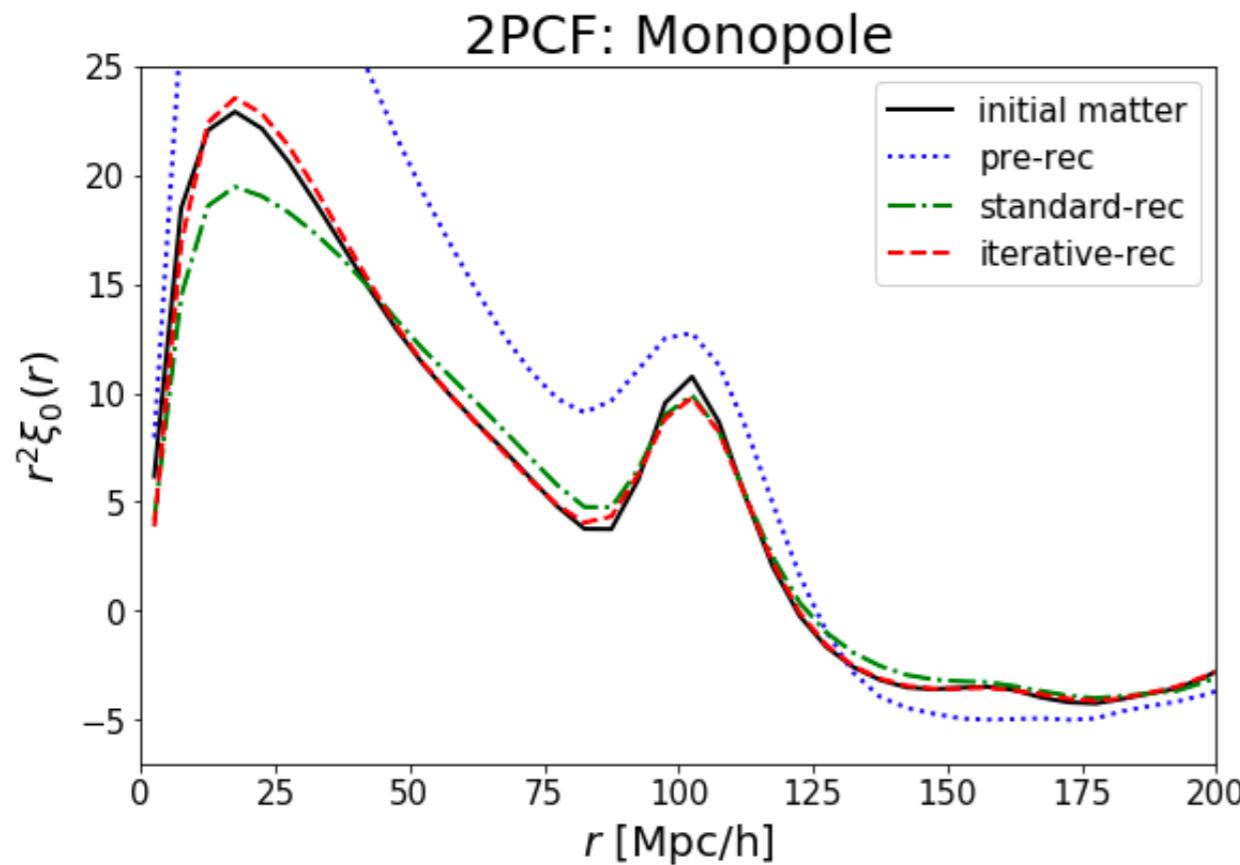
iterative method can reconstruct  
the displacements precisely up to  
smaller scale



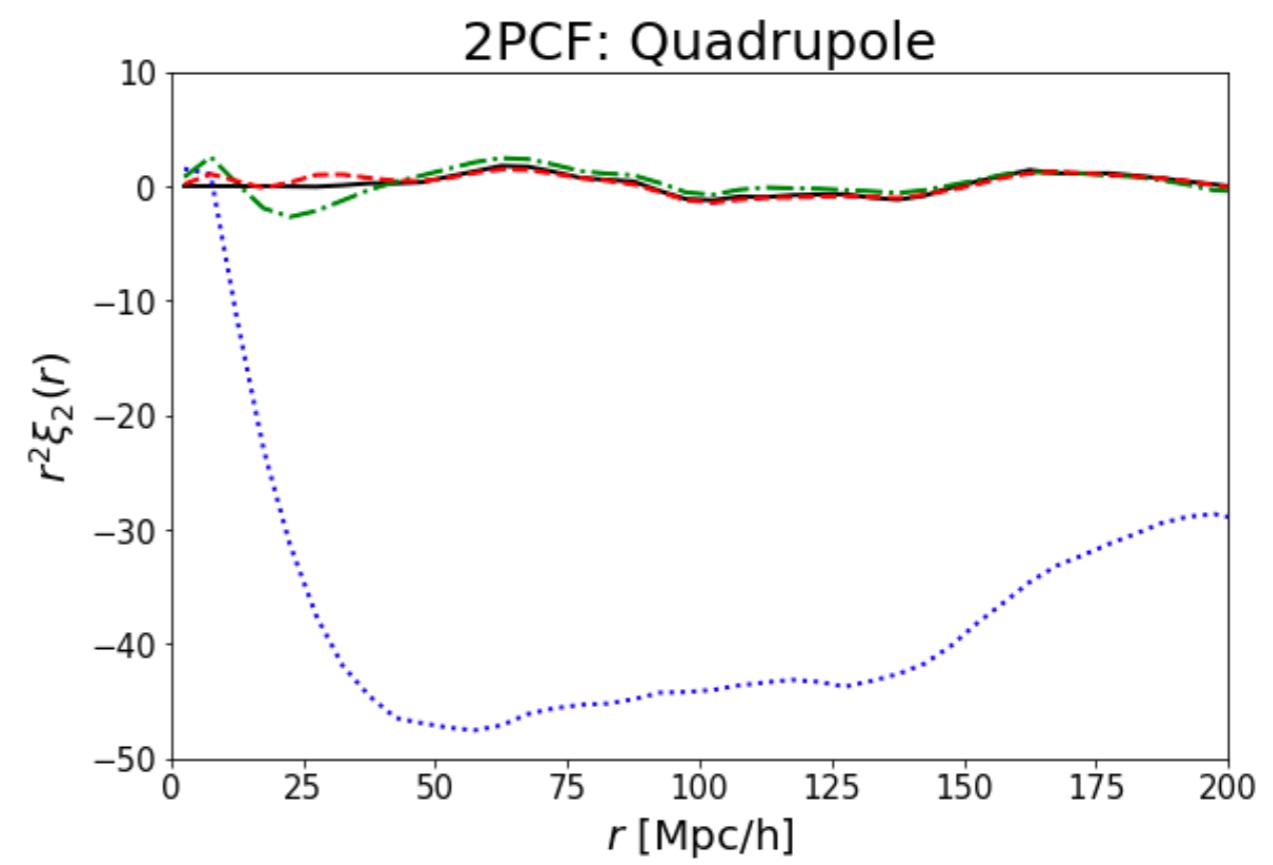
$$r(k) \equiv \frac{\langle \tilde{\mathbf{S}}_{\text{rec}} \cdot \tilde{\mathbf{S}}_{\text{true}}^* \rangle}{\sqrt{\langle |\tilde{\mathbf{S}}_{\text{rec}}|^2 \rangle \langle |\tilde{\mathbf{S}}_{\text{true}}|^2 \rangle}}$$

# Restoration of the 2-point correlation

Isotropic component



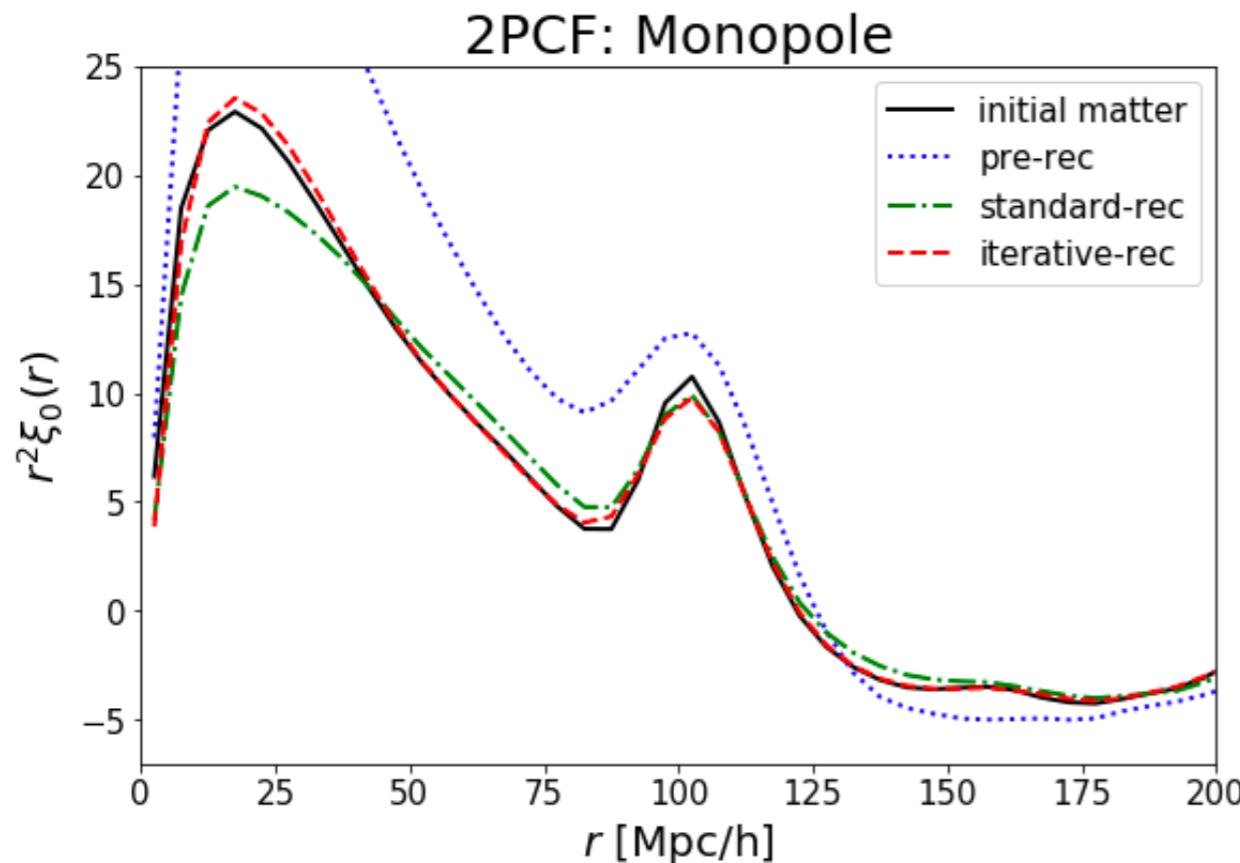
Anisotropic component



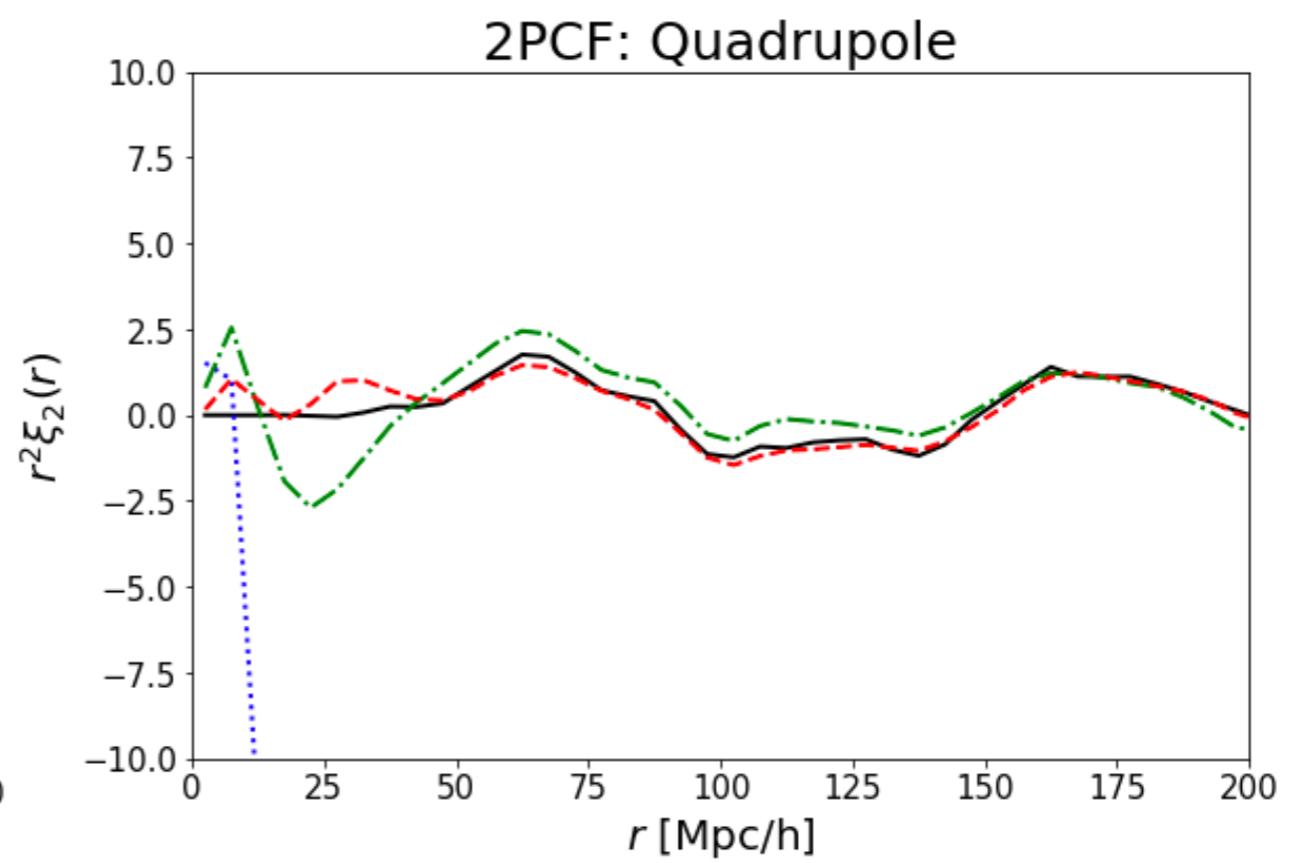
both reconstruction methods restore the 2PCFs roughly in a wide range of  $r$

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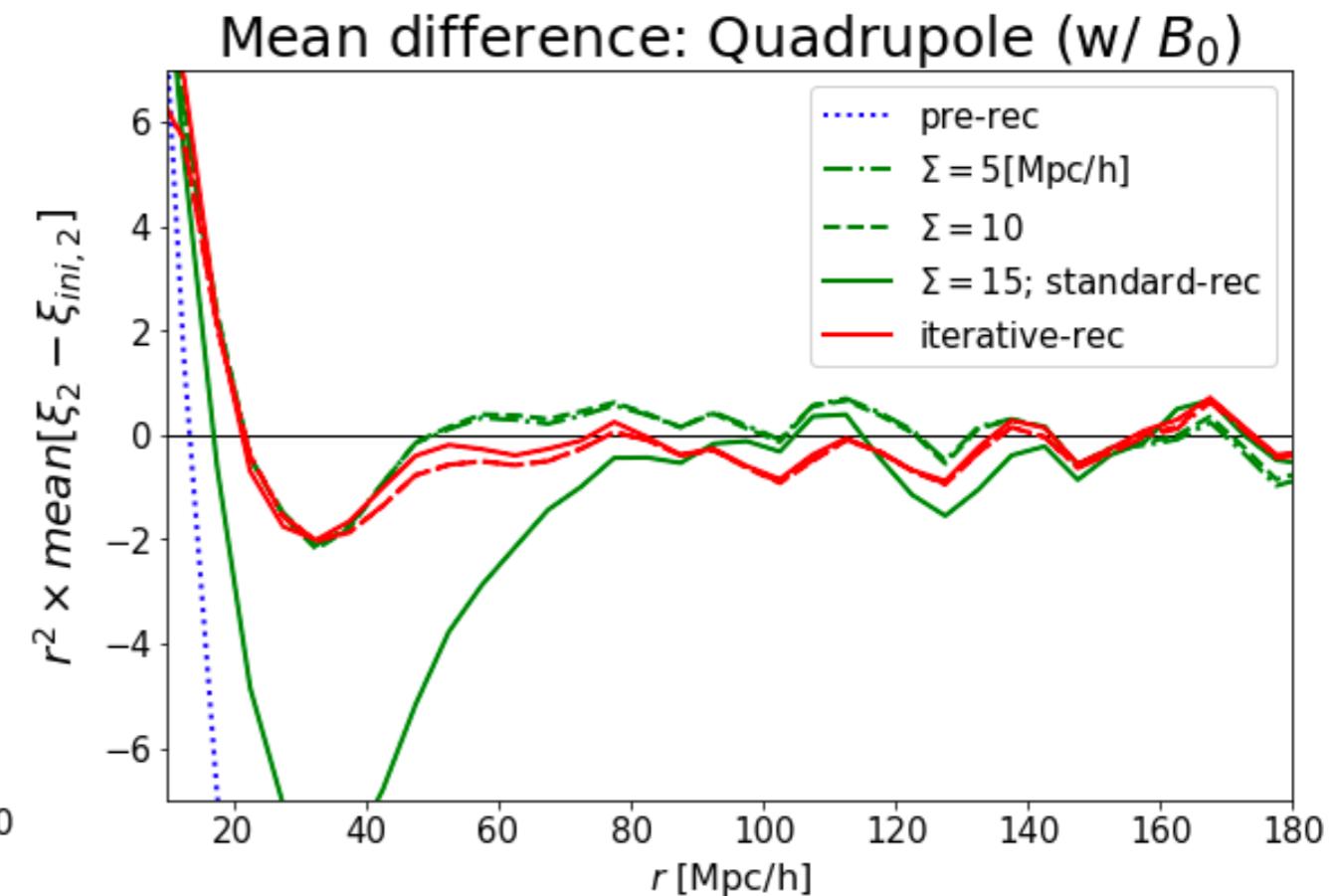
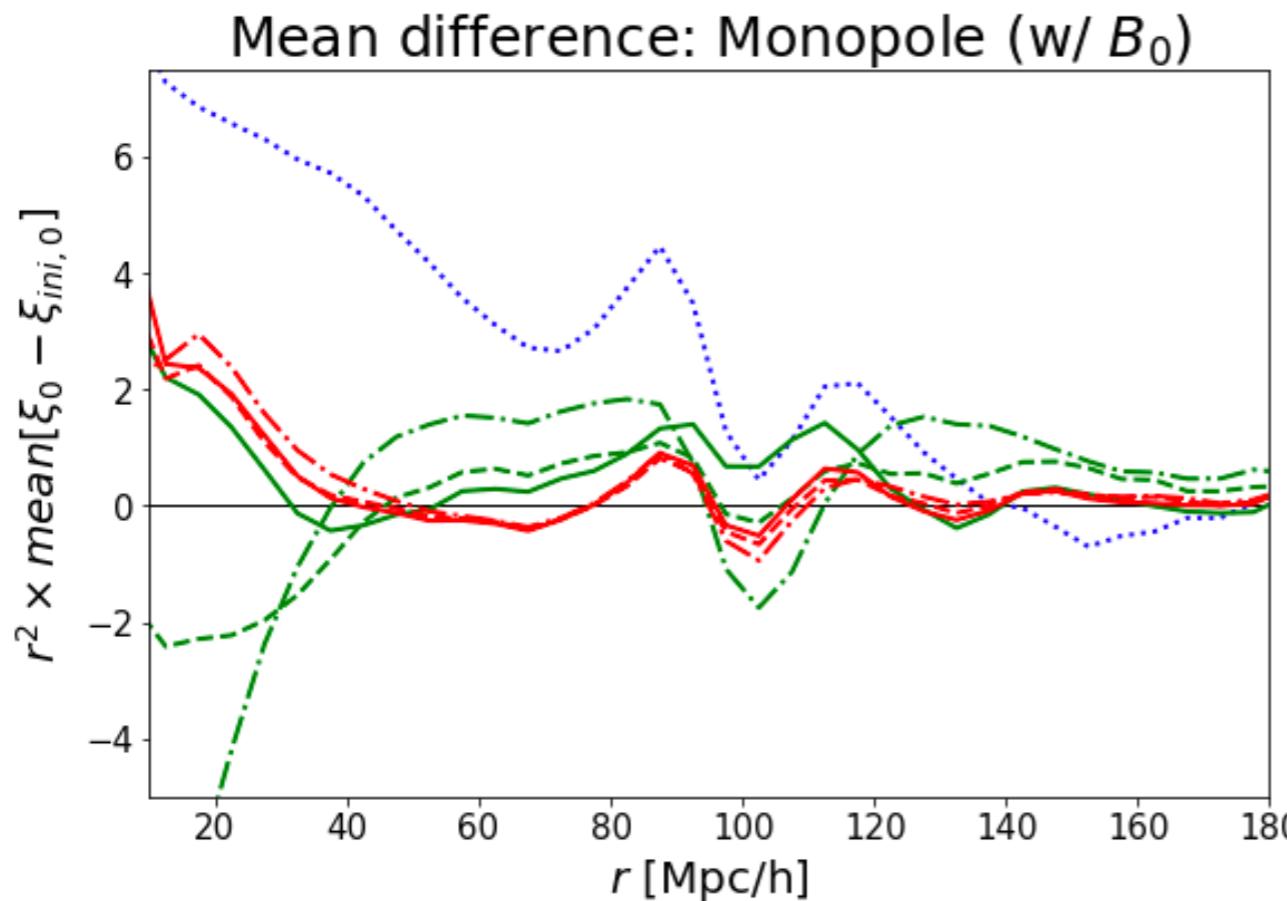


both reconstruction methods restore the 2PCFs roughly in a wide range of  $r$

the iterative method is more consistent with the initial matter especially in the range of  $50 < r < 150$  Mpc/h

# Dependence on the smoothing scale

(RH & Eisenstein, in prep.)

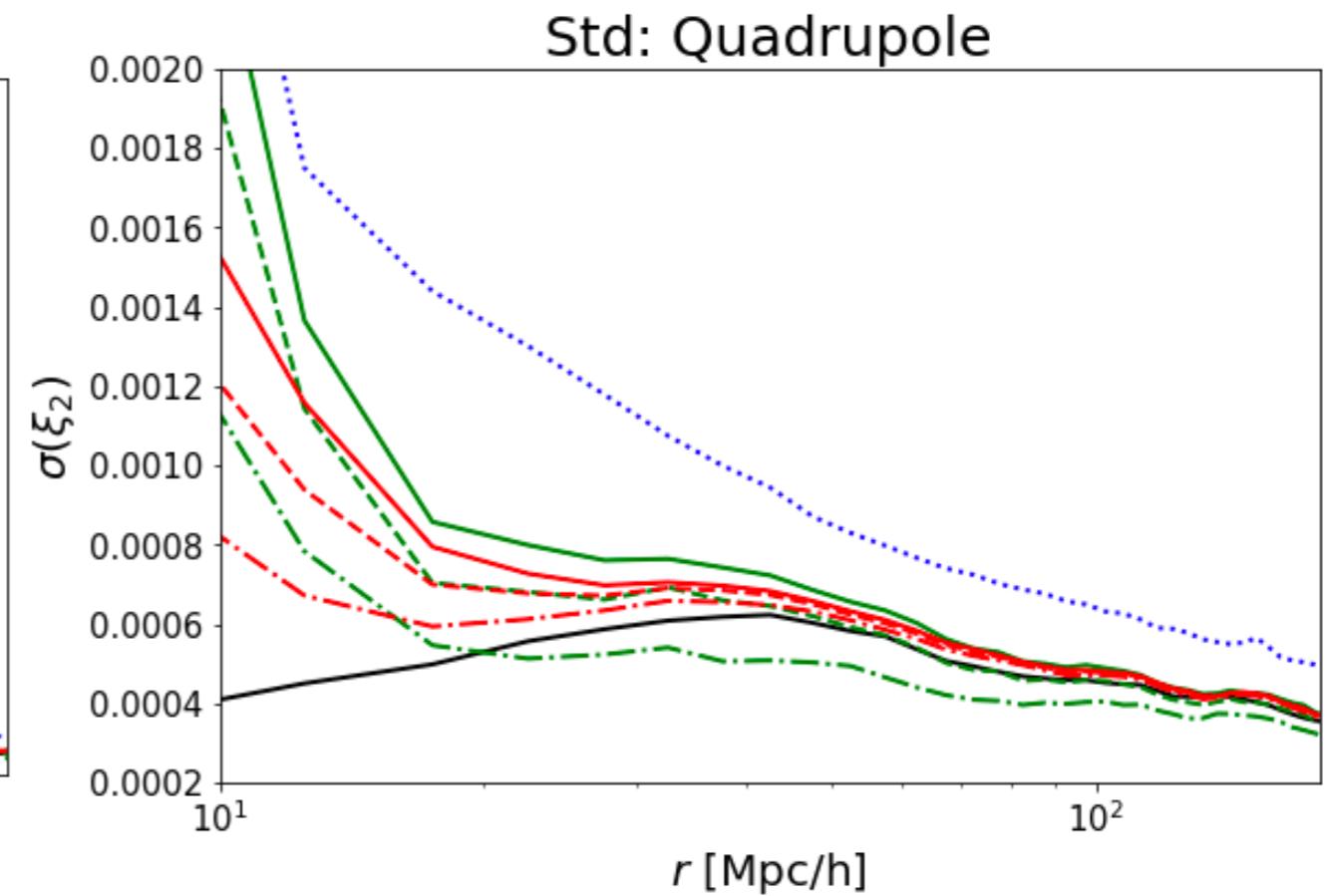
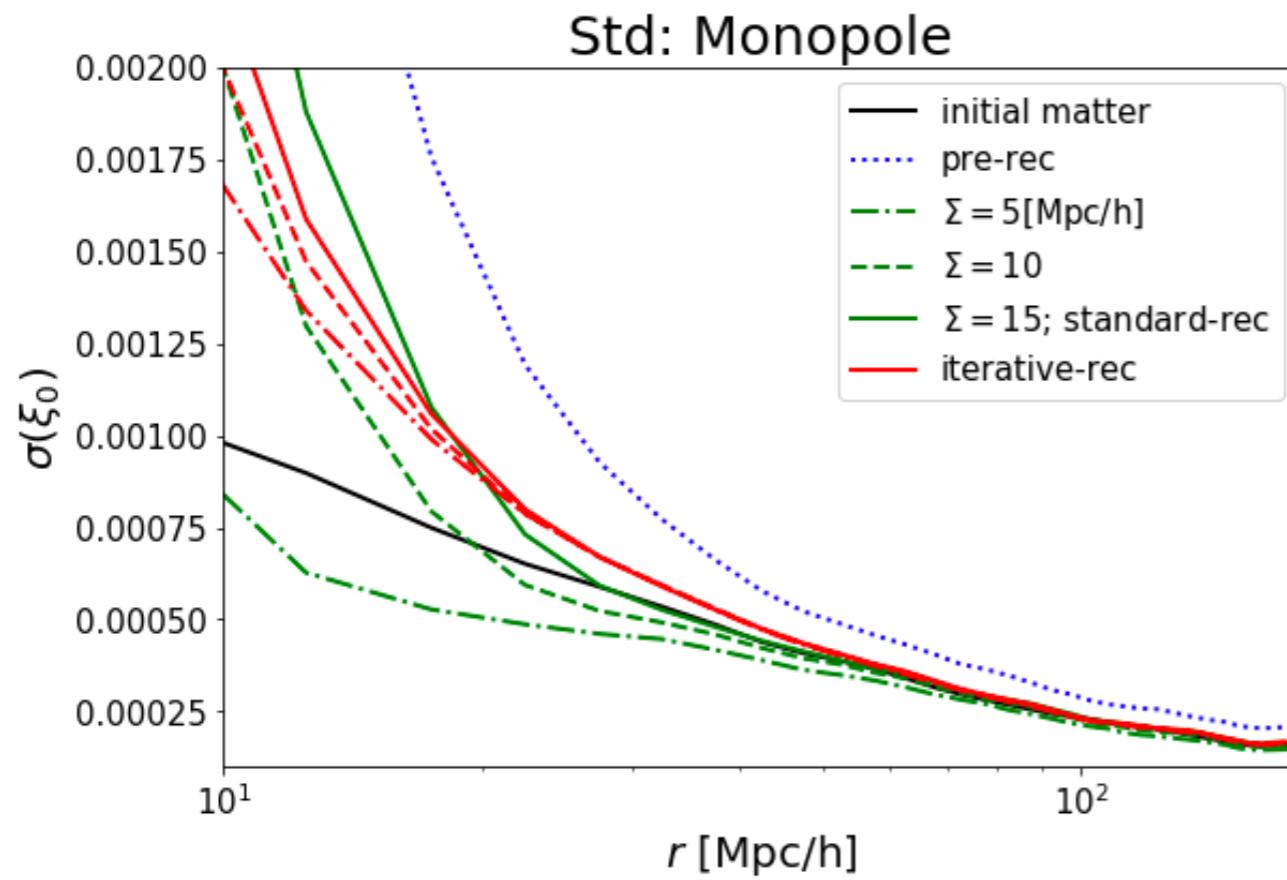


apply reconstruction methods to the  
galaxy mocks in redshift space

the iterative method is not affected  
by the smoothing scale

# Dependence on the smoothing scale

(RH & Eisenstein, in prep.)



covariance matrices (diagonal part)  
of the 2PCFs leads to errors of the  
distance measurement

dependence on the smoothing scale  
is weaker in the iterative method

# Impact on the distance measurements

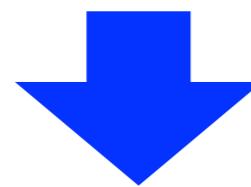
w/ nuis

Model template (Ashley *et al.*, 2017)

$$P(k, \mu) = C^2(k, \mu, \Sigma_s)((P_{\text{lin}} - P_{\text{nw}})e^{-k^2\sigma_v^2} + P_{\text{nw}})$$

$$\sigma_v^2 = (1 - \mu^2)\Sigma_{\perp}^2/2 + \mu^2\Sigma_{\parallel}^2/2,$$

$$C(k, \mu, \Sigma_s) = \frac{1 + \mu^2\beta(1 - S(k))}{(1 + k^2\mu^2\Sigma_s^2/2)} \quad S(k) = e^{-k^2\Sigma_r^2/2}$$



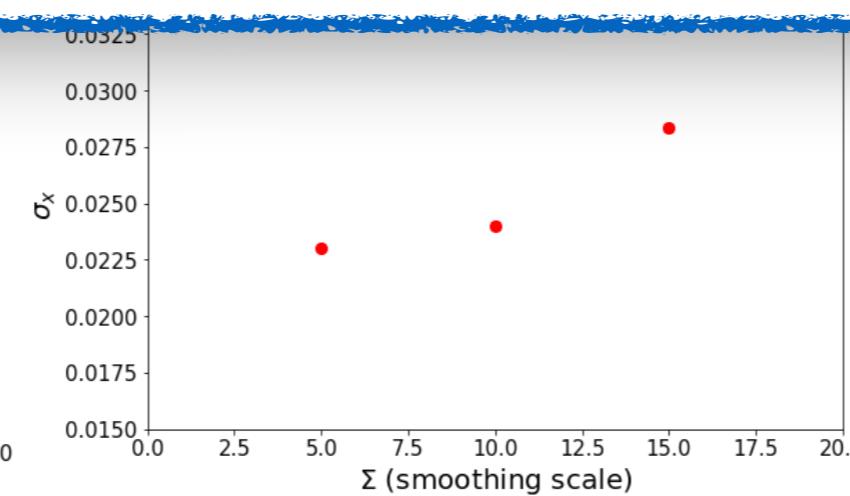
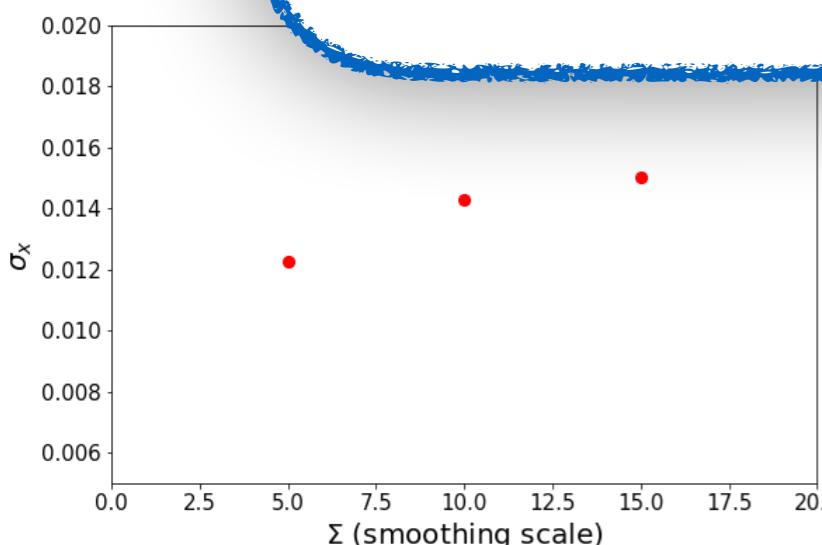
$$\xi_{0,\text{mod}}(s) = B_0\xi_0(s, \alpha_{\perp}, \alpha_{\parallel}) + A_0(s)$$

$$\xi_{2,\text{mod}}(s) = \frac{5}{2}(B_2\xi_{\mu 2}(s, \alpha_{\perp}, \alpha_{\parallel}) - B_0\xi_0(s, \alpha_{\perp}, \alpha_{\parallel})) + A_2(s)$$

$$\text{where } A_x(s) = a_{x,1}/s^2 + a_{x,2}/s + a_{x,3}$$

$$\begin{aligned}\beta &= 0 \\ \Sigma_{\perp} &= \Sigma_{\parallel} = 5 \text{ [Mpc/h]} \\ \Sigma_s &= \Sigma_r = 0 \\ B_2 &= B_0\end{aligned}$$

nuisance parameters



# Impact on the distance measurements

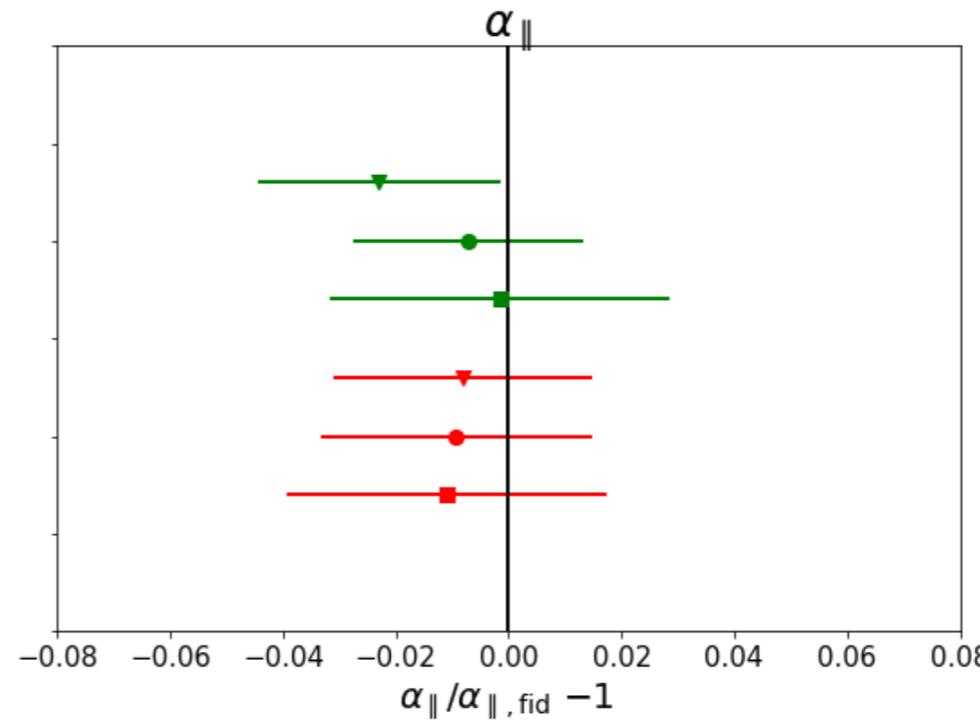
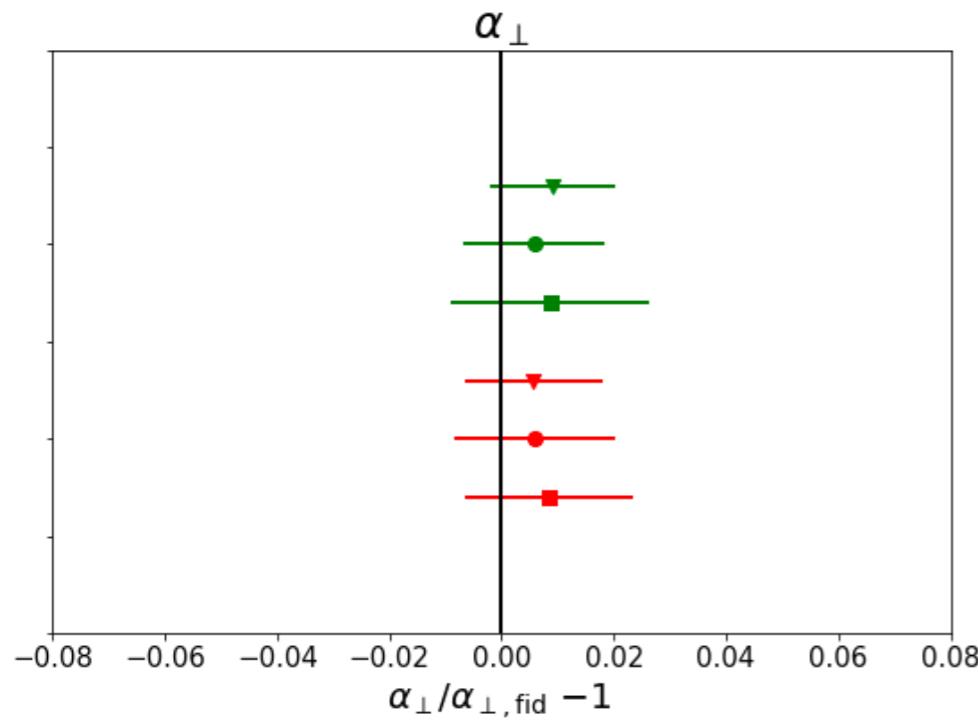
w/ nuisance parameters

**perpendicular**

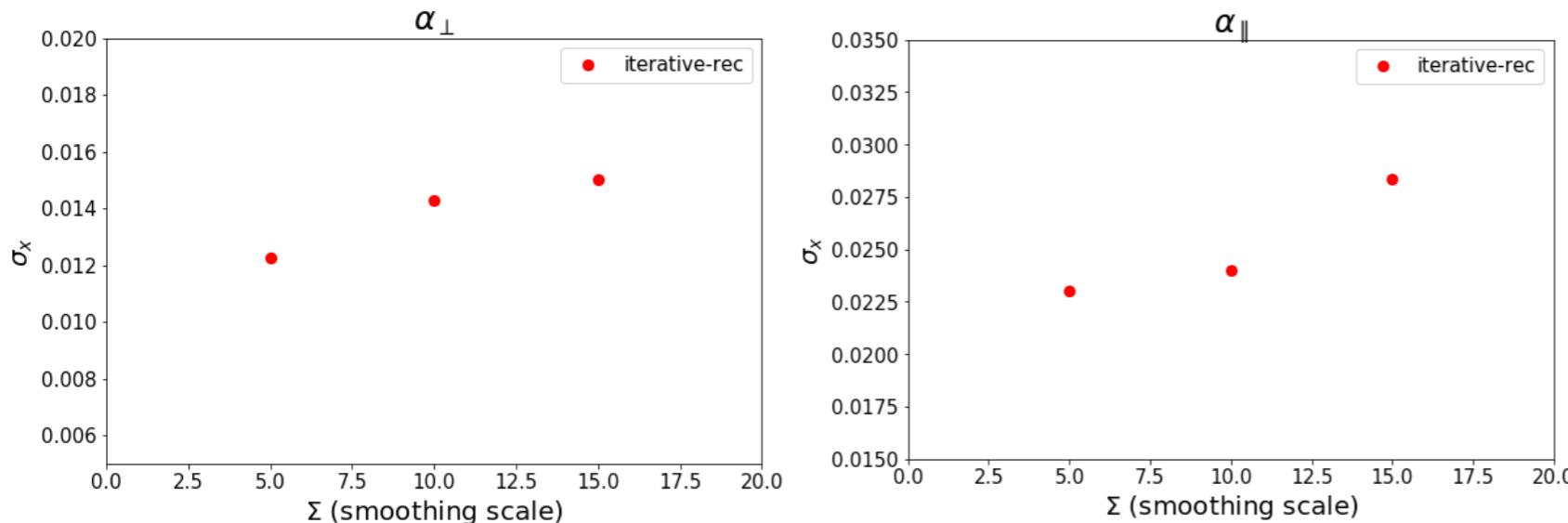
$$\alpha_{\perp} = \frac{D_M(z)r_{d,\text{fid}}}{D_M^{\text{fid}}(z)r_d},$$

**line-of-sight**

$$\alpha_{\parallel} = \frac{H^{\text{fid}}(z)r_{d,\text{fid}}}{H(z)r_d}$$



- ▼  $\Sigma = 5[\text{Mpc}/h]$
- $\Sigma = 10$
- $\Sigma = 15$ ; standard-rec
- ▼  $\Sigma = 5[\text{Mpc}/h]$
- $\Sigma = 10$
- $\Sigma = 15$ ; iterative-rec

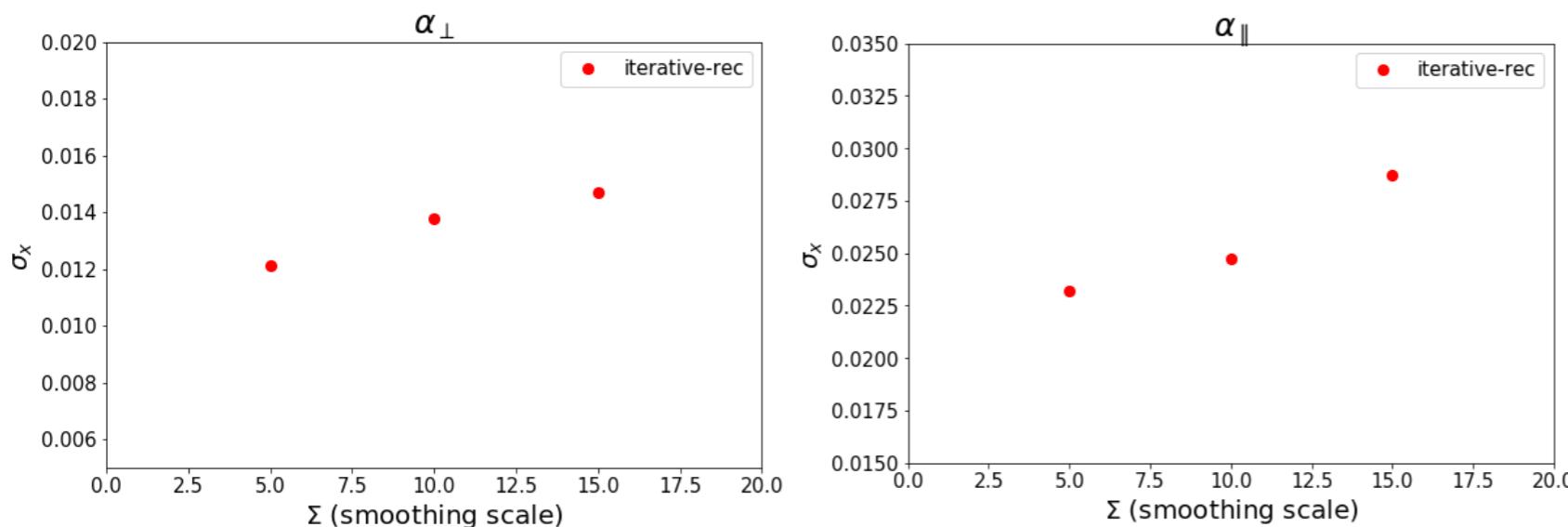
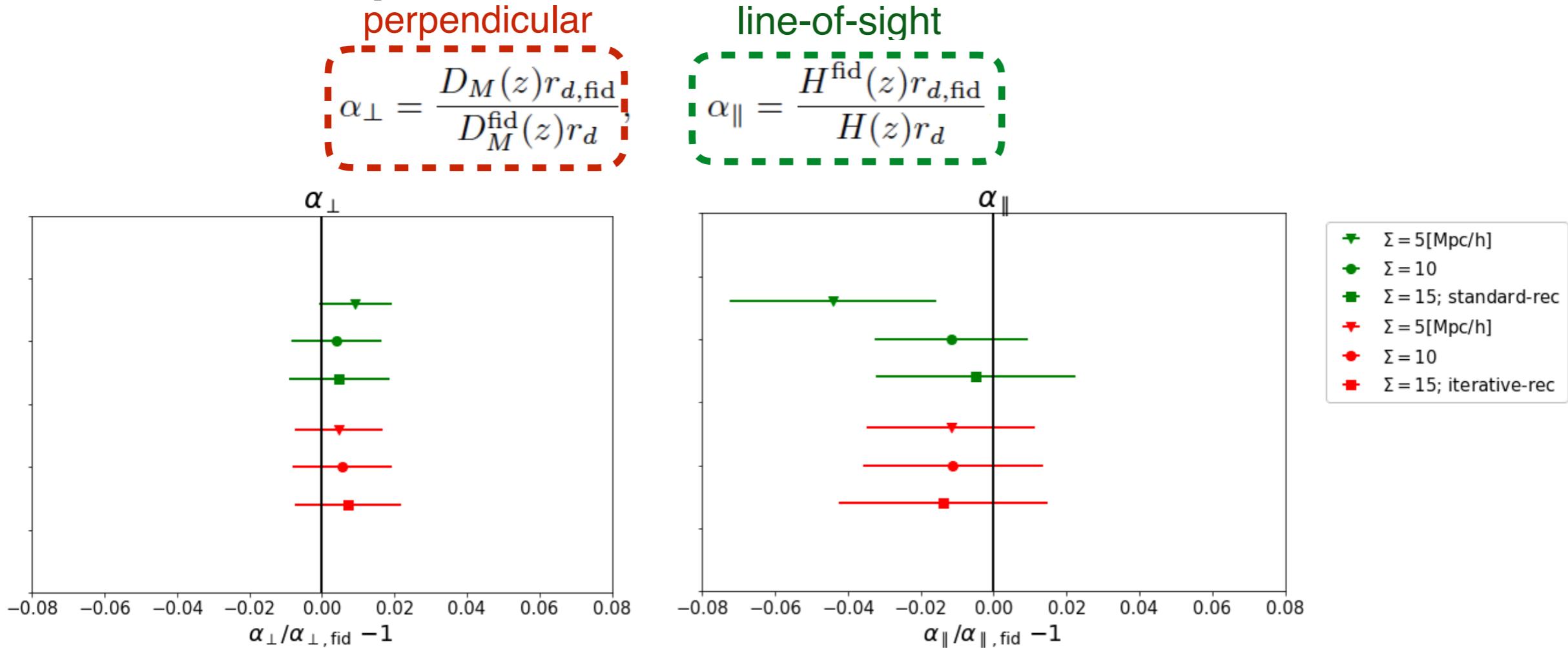


best fit values don't depend  
on the smoothing scale in the  
iterative method

with a smaller smoothing  
scale, the error gets smaller

# Impact on the distance measurements

w/o nuisance parameters



in the standard method,  
nuisance parameters  
compensate the difference in  
the smoothing scales

# Summary

BAO is a powerful tool to measure the cosmological distance scale and understand the property of DE

- reach more than 1% accuracy distance measurements in upcoming galaxy redshift surveys

developed an iterative reconstruction method to settle the problems in the standard reconstruction and applied it to galaxy mocks

- correlation function can be reconstructed more precisely even on large scales ( $> 50 \text{ Mpc/h}$ )

measured the distance scale using the reconstructed correlation function

- the new iterative method is not impacted by the smoothing scale unlike the standard method

considering the effect of survey geometry or number density...

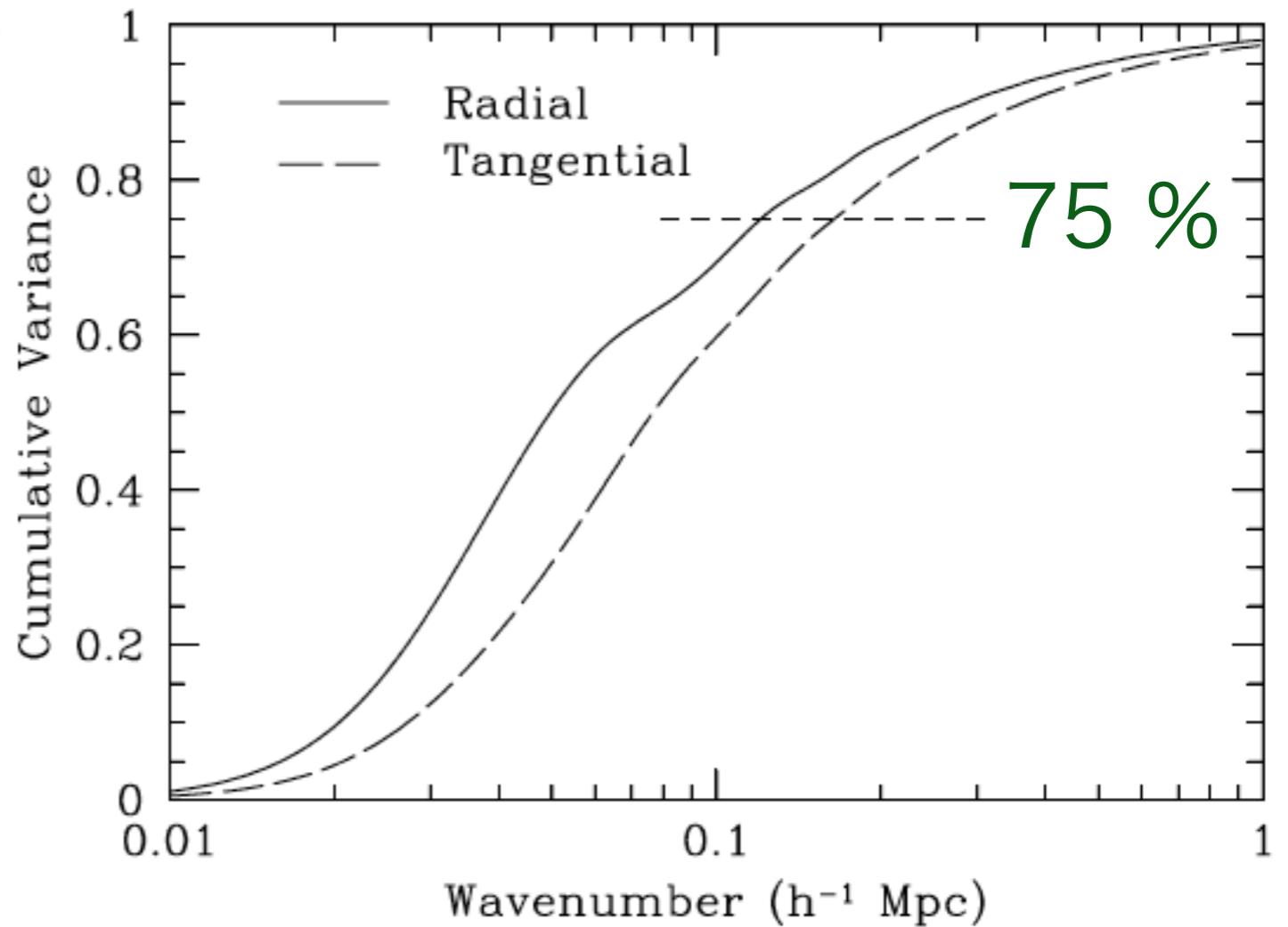


# Backup slides

# BAO peak degradation

Which scale is responsible  
for the differential motion ?

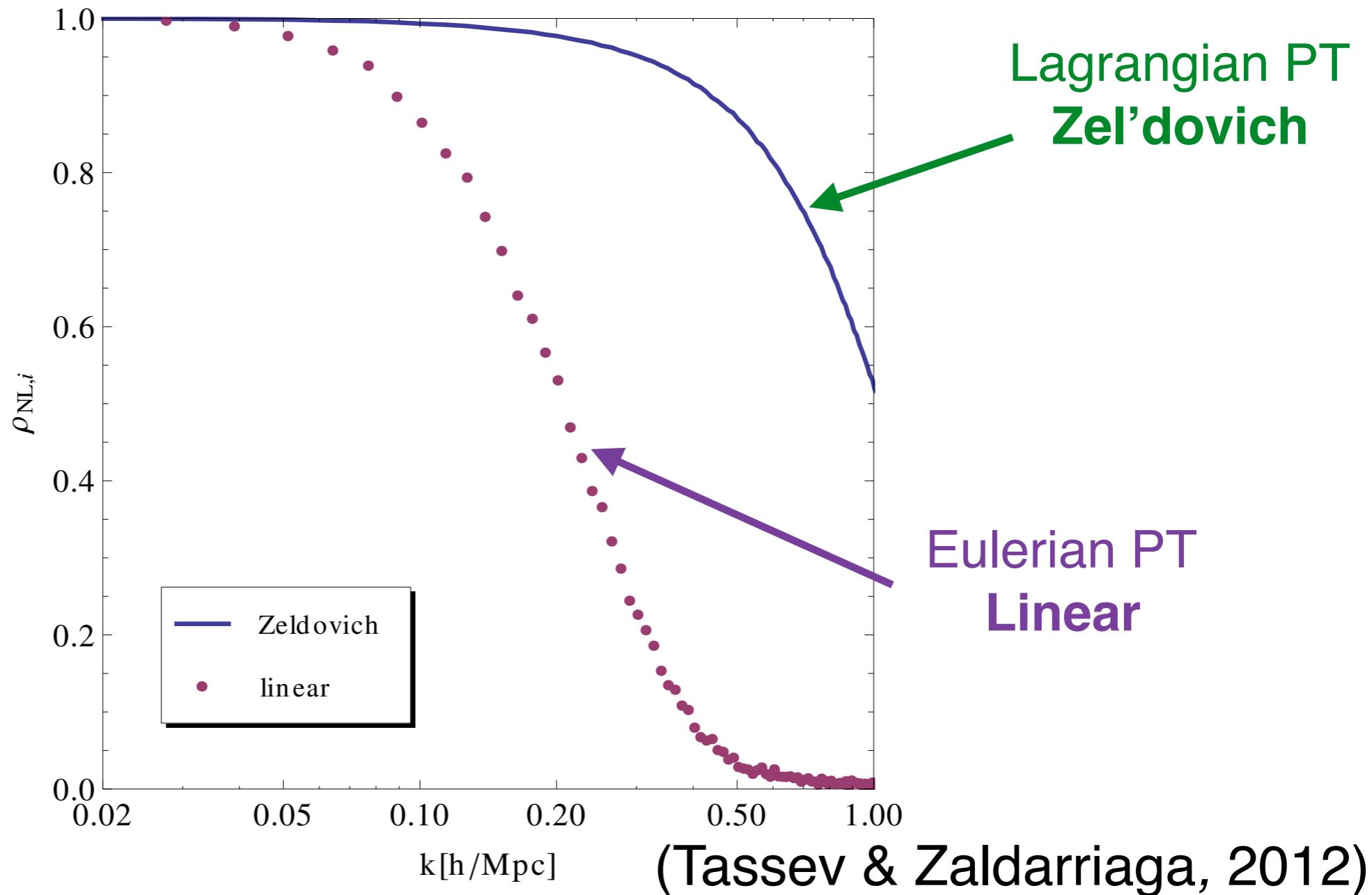
(Eisenstein+ 2007)



Cumulative variance in the differential motion of pairs initially separated by 150 Mpc as a function of cutoff wavenumber

# LPT vs EPT (1st order)

Cross correlation with the non-linear density field



Up to the **1st order**, Lagrangian PT is better

# Application to N-body simulations

(RH & Eisenstein, 2018; 2019)

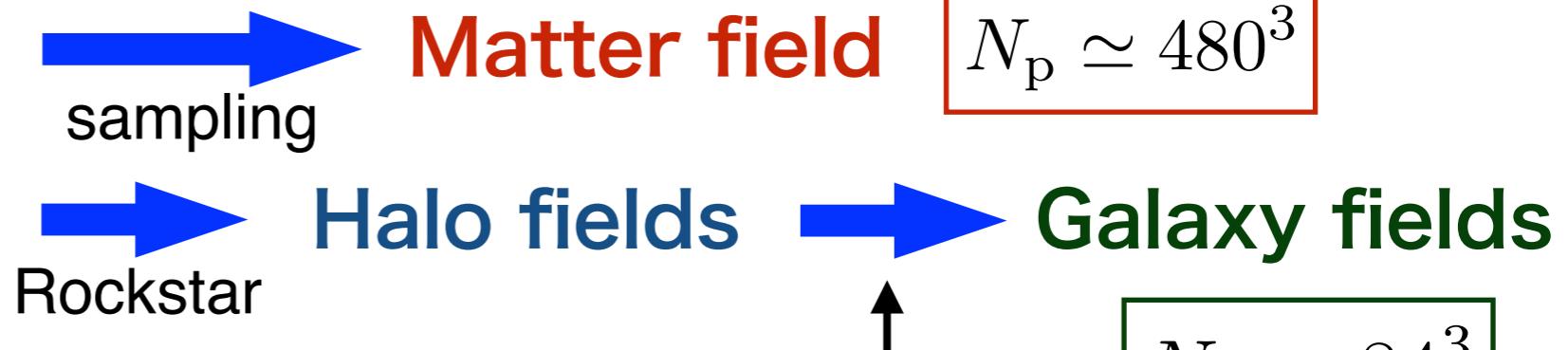
## N-body simulation

**Abacus** (Garrison+ 2017), 20 boxes

Box size: 1100 [Mpc/h]

Number of particles:  $1440^3$

Redshift:  $z = 0.5$



## Reduction of smoothing scale

Initial scale: 20 [Mpc/h]

**Final scale: 5, 10, 15 [Mpc/h]**

$$\Sigma = \frac{\Sigma_{\text{ini}}}{1.2^n}$$

**GRAND-HOD**  
(Yuan+ 2018)

## Convergence

n: the number of iteration

$$\frac{\sum [\delta_{L(n)} - \delta_{L(n-1)}]^2}{\sum \delta_s^2} < 0.01$$

over all grid points

# Galaxy as a biased tracer

(RH & Eisenstein, 2019)

Matter

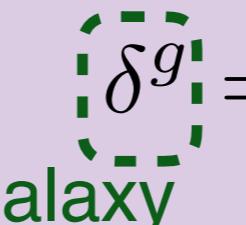
Galaxy

Density:  $\delta_s(\mathbf{s}) \rightarrow \delta_s(\mathbf{s})/b$

Linear growth rate:  $f \rightarrow \beta = f/b$

Kaiser relation:

$$\tilde{\delta}_s^g(\mathbf{k}) = (1 + \beta\mu^2)\tilde{\delta}^g(\mathbf{k})$$

where  $\mu = k_z/k$      $\beta = f/b$   
  $\tilde{\delta}^g = b \tilde{\delta}$ : Linear galaxy bias  
matter

Bias:  $b = r_{i,\text{gal}}(k_{\text{cr}})/r_{i,\text{mat}}(k_{\text{cr}})$

where  $r_i(k) = \frac{\langle \tilde{\delta} \tilde{\delta}_{\text{ini}}^* \rangle}{\langle |\tilde{\delta}_{\text{ini}}|^2 \rangle}$      $k_{\text{cr}} = 0.1 [h/\text{Mpc}]$