DARK ENERGY SURVEY

DES-BRAZIL

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Combining Cosmological Probes: Cluster Counts and Angular Power Spectrum

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Work with Fabien Lacasa 1603.00918
Work in progress with Lacasa, Hoffmann and Gaztañaga

Madrid 2016 Cosmology with 21 cm Surveys,
Cosmic Microwave Background and Large Scale Structure

Outline

- Introduction and motivation (DES-centric)
- Modelling n-point functions in the halo model
- Impact of including cross-covariance between cluster number counts and the galaxy angular power spectrum – Fisher matrix approach
- Testing the model with simulations
- Conclusions

Cosmology has become a data-driven science.

Many probes are used to extract information about cosmology.

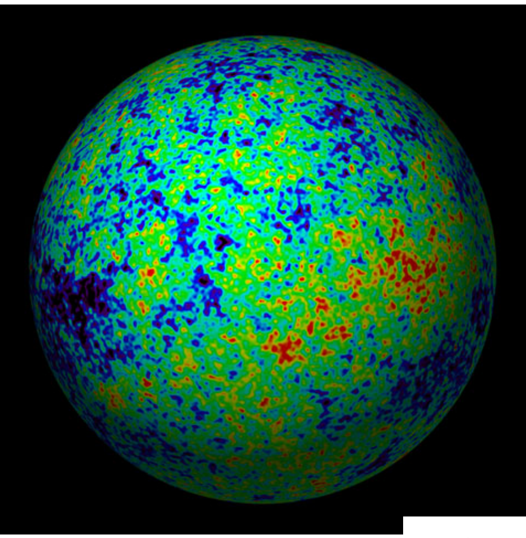
Important to combine them to break degeneracies and improve bounds.

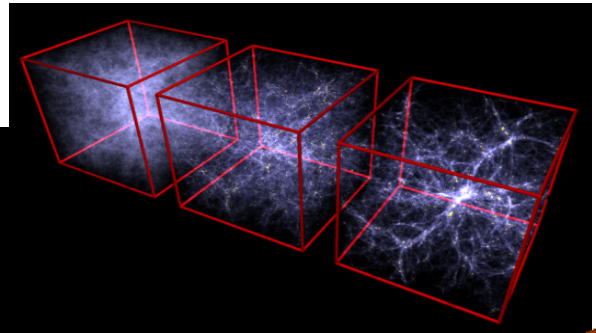
Cosmological probes

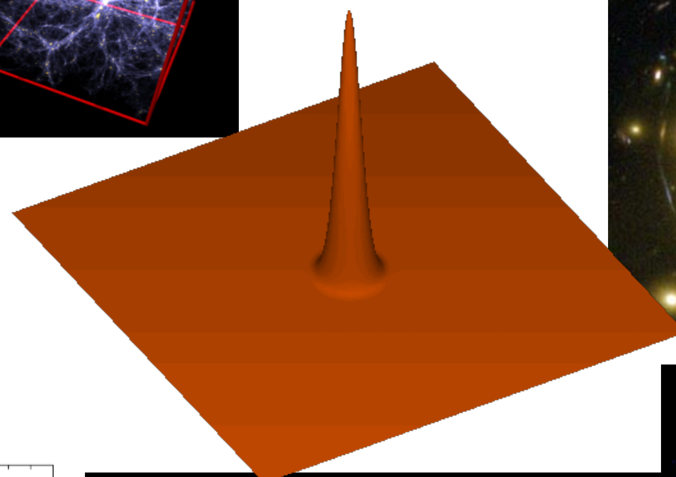
- Cosmic Microwave Background (CMB)
- Big bang nucleosynthesis (BBN)
- Supernovae Ia
- Gravitational lensing
- Distribution of galaxies (including BAO)
- Number count of clusters of galaxies

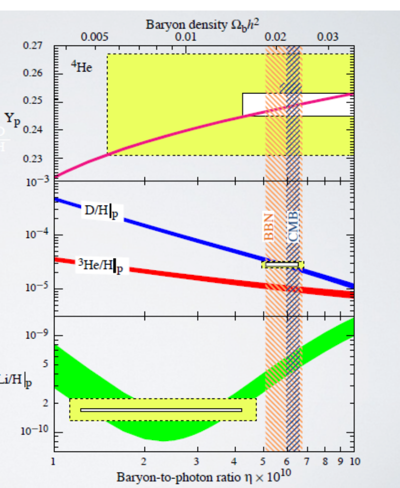
} today

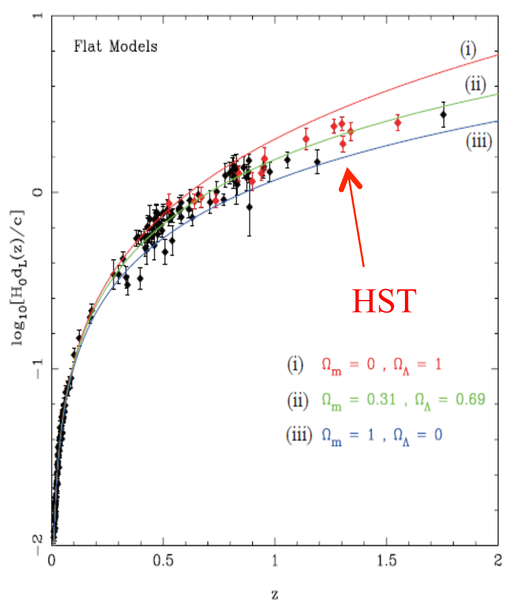
Cosmological probes

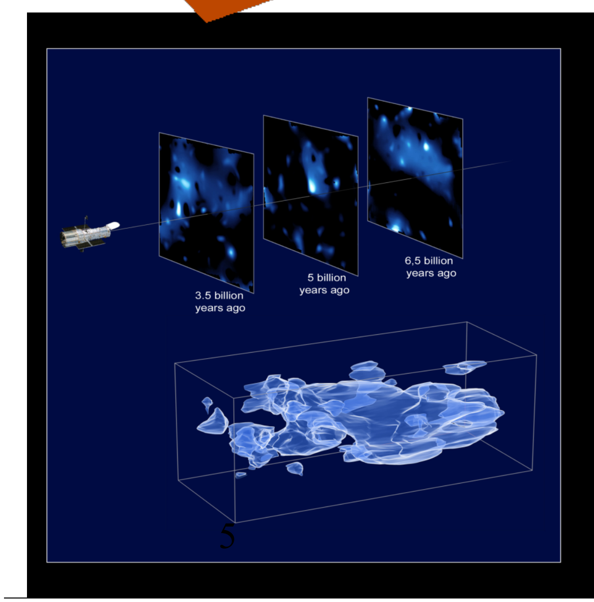


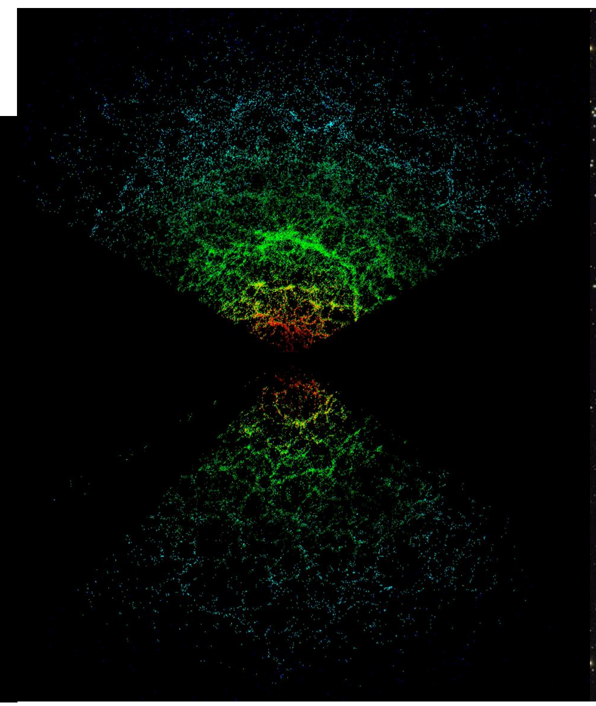












Large scale galaxy surveys are instrumental for the determination of cosmological parameters:

SDSS, BOSS, eBOSS
DES
PAU, J-PAS
DESI
LSST
...

DES Science Summary

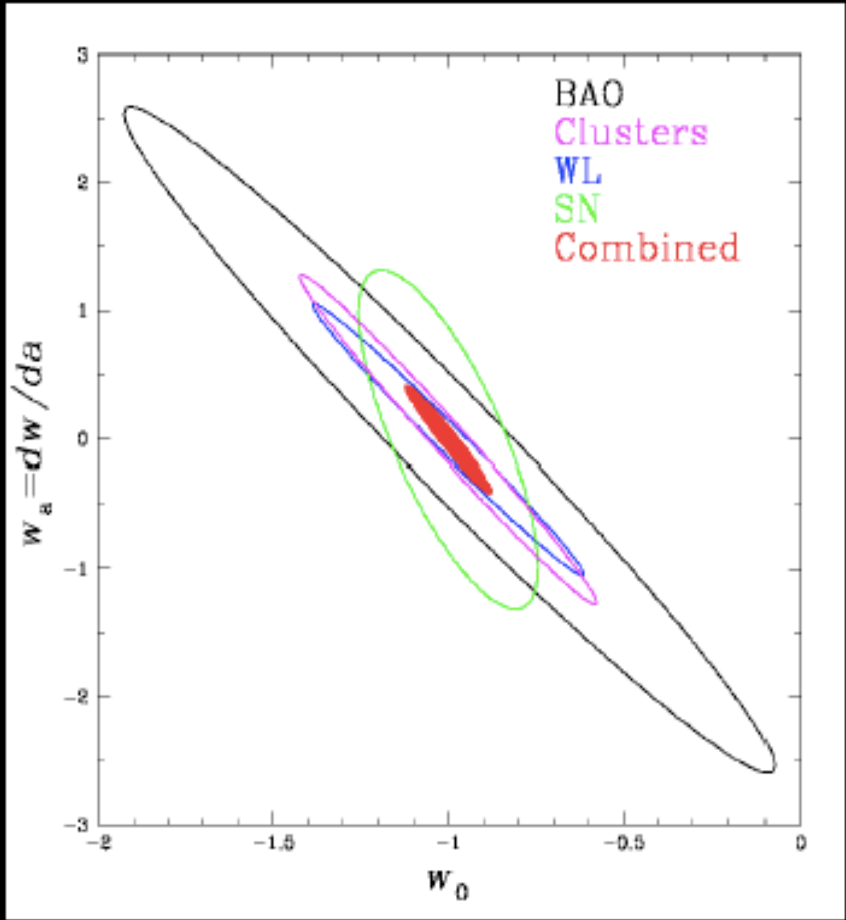
DARK ENERGY SURVEY

Four Probes of Dark Energy

- Galaxy Clusters
  - Tens of thousands of clusters to z~1
  - Synergy with SPT, VHS
- Weak Lensing
  - Shape and magnification measurements of 200 million galaxies
- Baryon Acoustic Oscillations
  - 300 million galaxies to z = 1 and beyond
- Supernovae
  - 30 sq deg time-domain survey
  - 3500 well-sampled SNe Ia to z ~1

Forecast Constraints on DE Equation of State

$$w(a) = w_0 + w_a(1 - a(t)/a_0)$$



DES forecast

Parameter estimation: likelihood function requires a covariance matrix

Some probes are not independent: need cross-correlations.

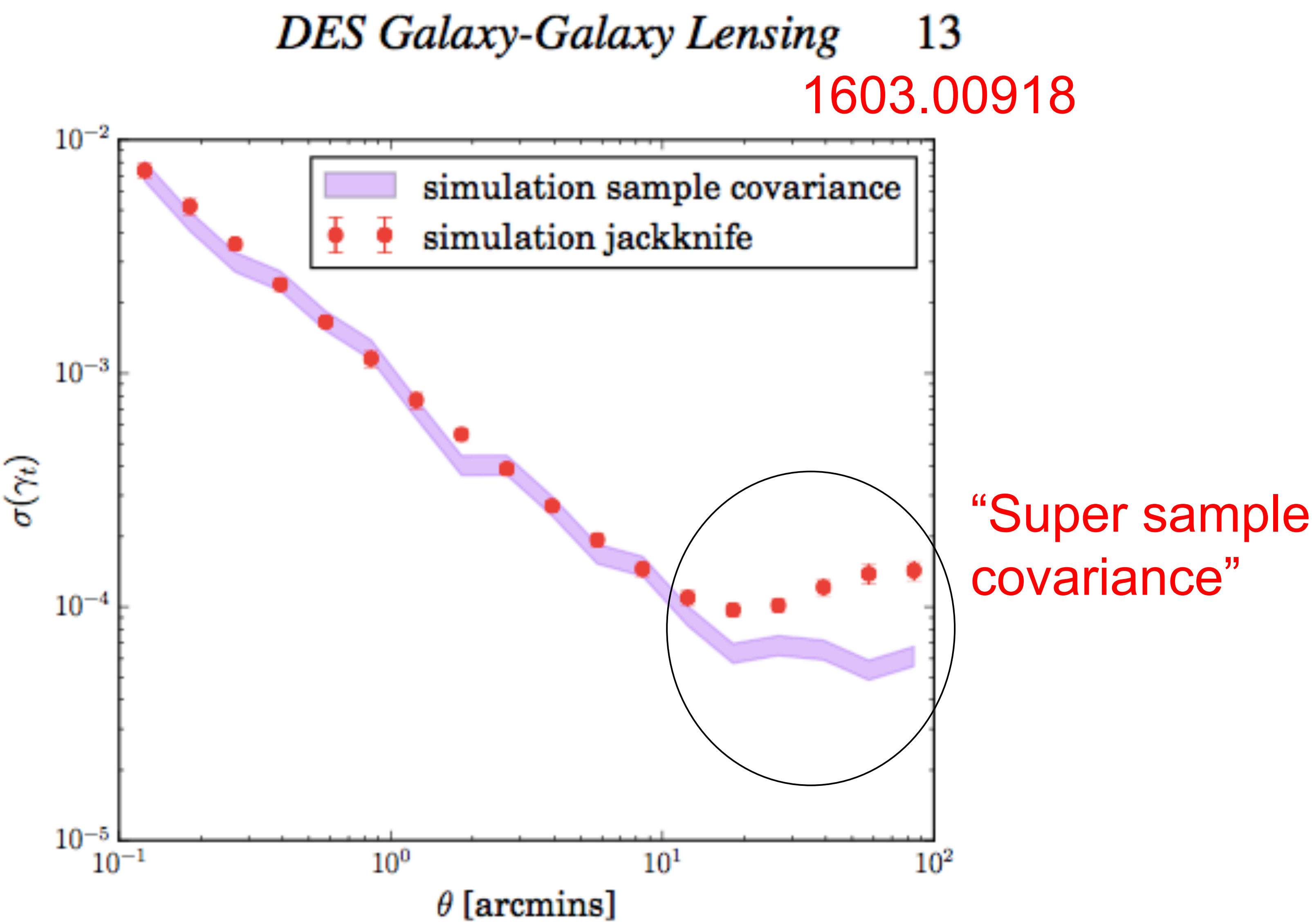
Aim: model the covariance matrix for cluster number counts and angular power spectrum

How to estimate covariances?

- Jackknife
- Subsampling
- Bootstrap
- Mocks
- Theoretical covariance (non-gaussian, model dependence)

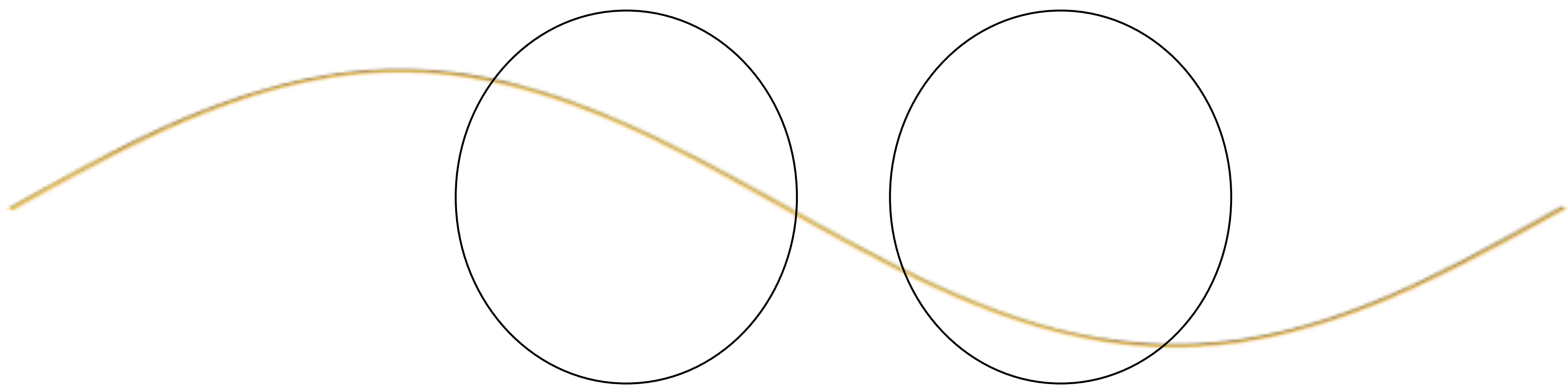
Jury is still out

Super sample covariance



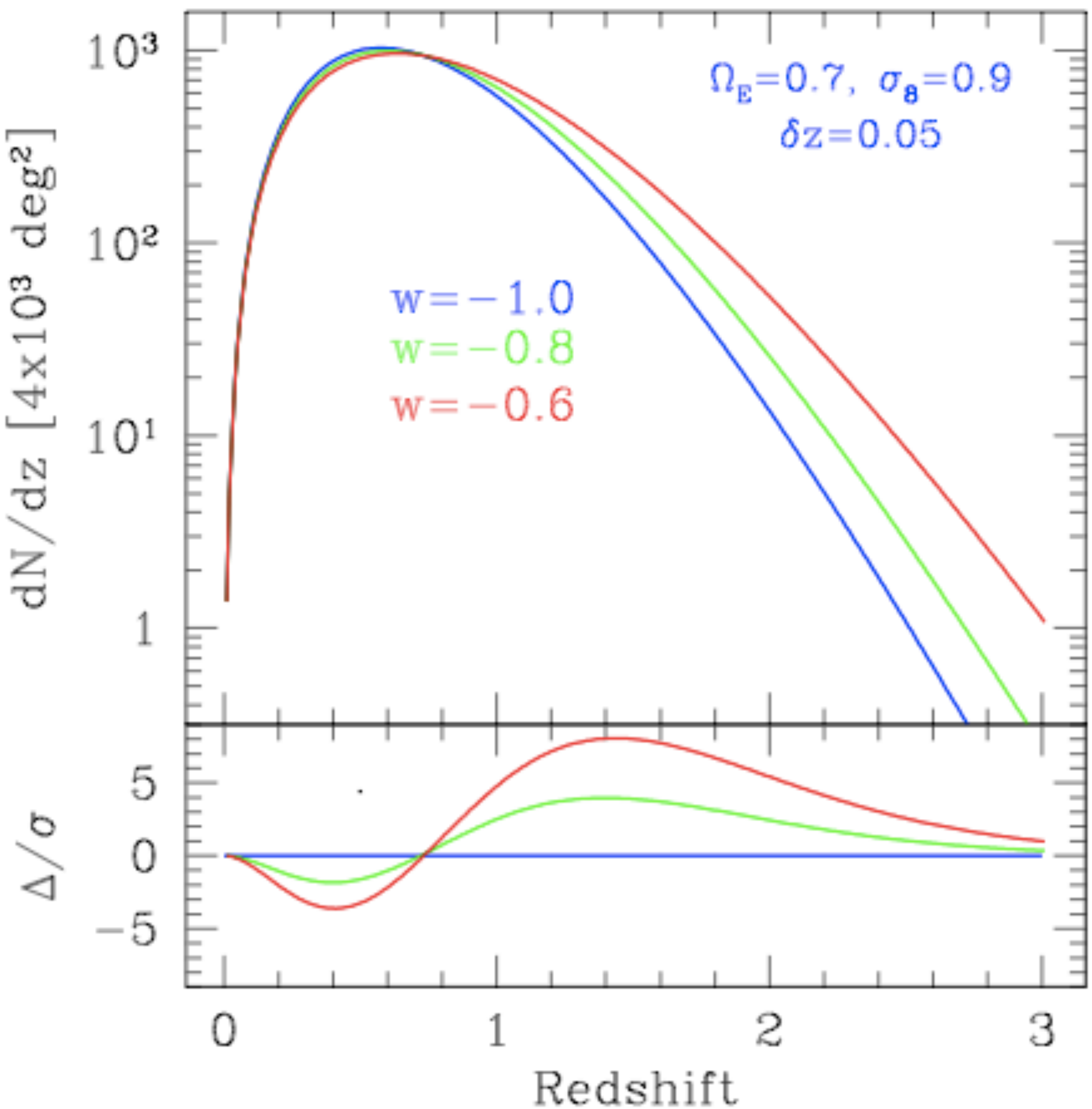
Super sample covariance

Influence of long wavelength modes (larger than the sample)



Change the background density. Can be treated as "separated universes", each one with a different background density.

Counts of galaxy clusters are excellent probes of Dark Energy (probes both geometry and growth):



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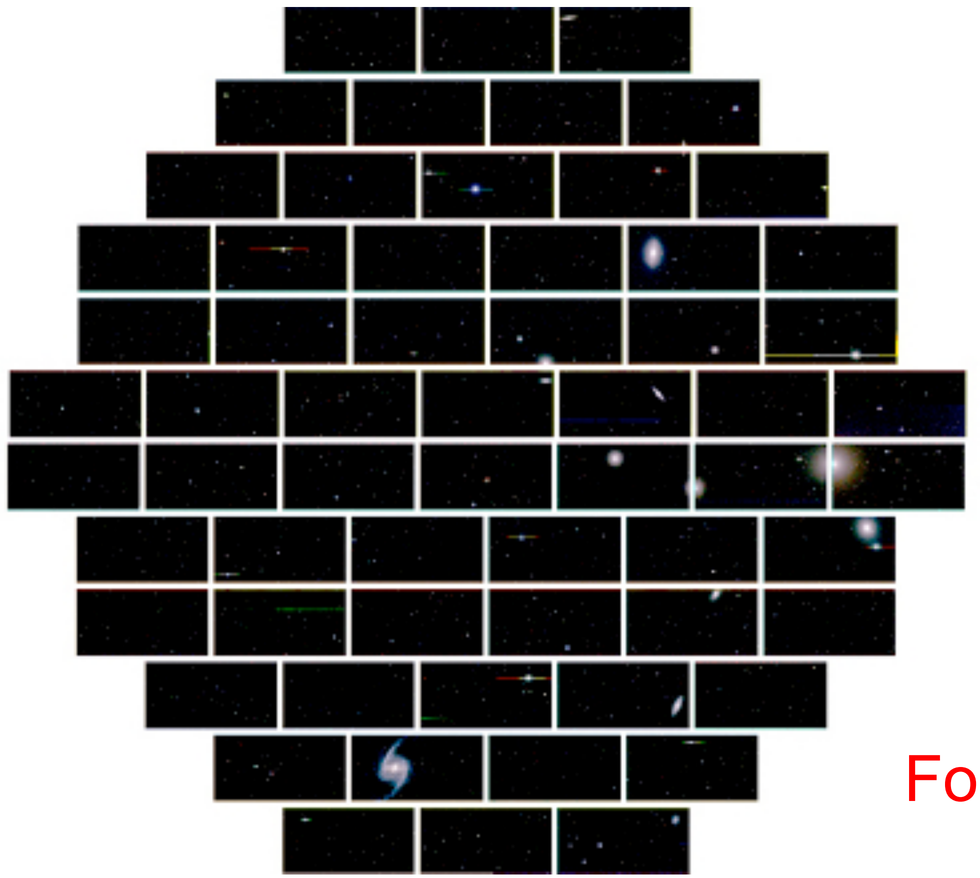
However, it is difficult to find clusters and their masses:



Fornax cluster

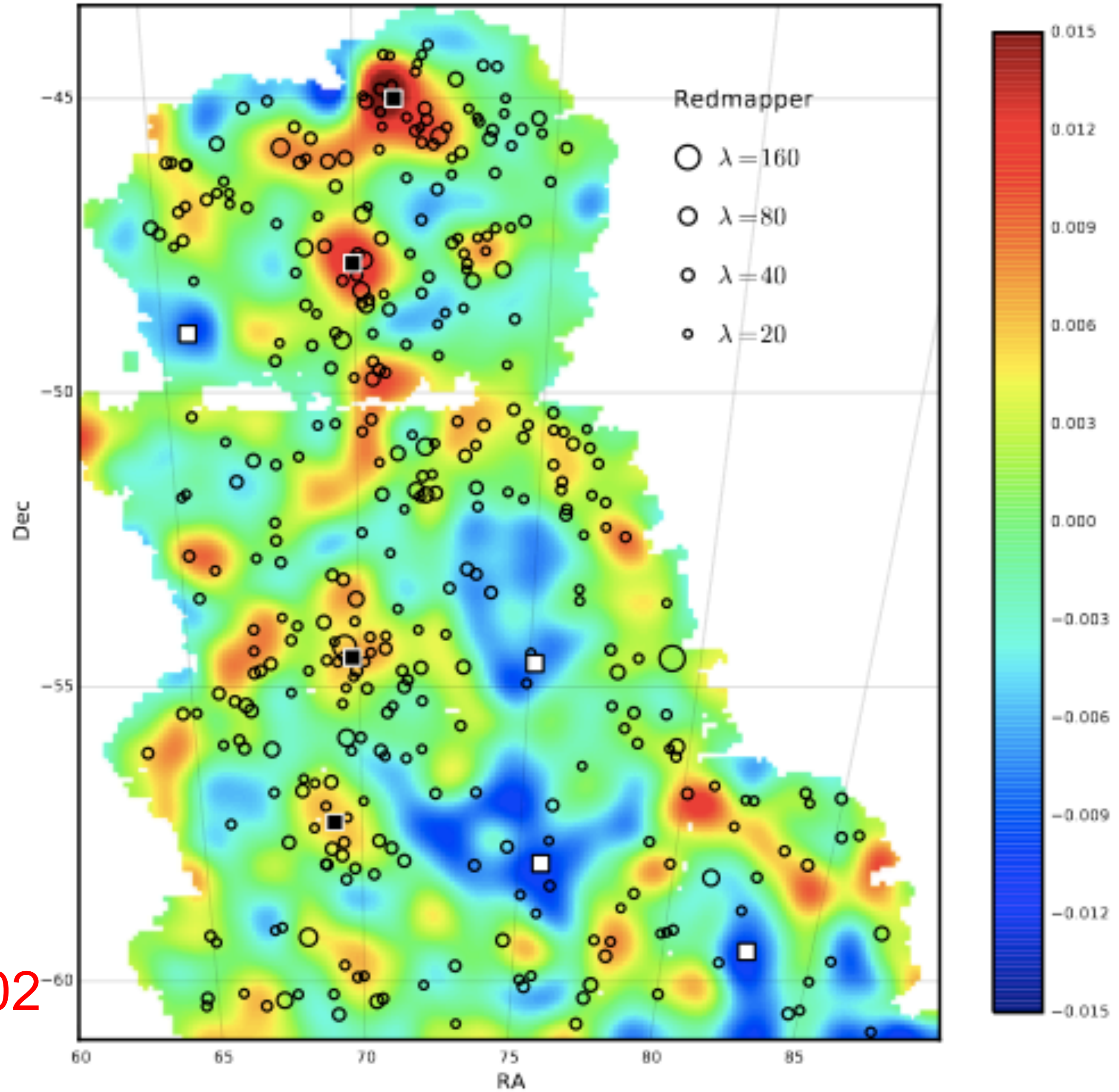
However, it is difficult to find clusters and their masses:

Cluster finding algorithms: cluster catalogue already available for SVA – work is ongoing for Y1, Y2, …
Brazilian group working on WAZP

Mass-observable relations:
cross-correlations with gravitational lensing, x-rays, SZ
DES has an agreement with STP (similar region) – see, eg 1603.03904

Constraints at the 5% level on the dark energy equation of state require that systematic biases in the mass estimators must be controlled at better than the ~ 10% level – tough job!

Weak lensing (mass maps) and clusters in DES:



arXiv:1504.03002

FIG. 4: The DES SV mass map along with foreground galaxy clusters detected using the Redmapper algorithm. The clusters are overlaid as black circles with the size of the circles indicating the richness of the cluster. Only clusters with richness greater than 20 and redshift between 0.1 and 0.5 are shown in the figure. The upper right corner shows the correspondence of the optical richness to the size of the circle in the plot. It can be seen that there is significant correlation between the mass map and the distribution of galaxy clusters. Several superclusters (black squares) and voids (white squares) can be identified in the joint map.

Modelling n-point functions

We want to model the cross-covariance between cluster number counts and the angular correlation function (or the angular power spectrum) of galaxies.

Cluster counts: 1-point function
Cluster count covariance: 2-point function
Correlation function: 2-point function
Cross-covariance: 3-point function
Correlation function covariance: 4-point fct

We actually want to model the full covariance matrix:

$$X = \begin{pmatrix} N_{\mathrm{cl}} \\ C_\ell^{\mathrm{gal}} \end{pmatrix}$$

$$\mathrm{Cov}(\hat{X}, \hat{X}) = \begin{pmatrix} \mathrm{Cov}(\hat{N}_{\mathrm{cl}}, \hat{N}_{\mathrm{cl}}) & \mathrm{Cov}(\hat{C}_\ell^{\mathrm{gal}}, \hat{N}_{\mathrm{cl}}) \\ \mathrm{Cov}(\hat{N}_{\mathrm{cl}}, \hat{C}_\ell^{\mathrm{gal}}) & \mathrm{Cov}(\hat{C}_\ell^{\mathrm{gal}}, \hat{C}_\ell^{\mathrm{gal}}) \end{pmatrix}$$

We will use the halo model

Halo Model ⟹ $\omega(\theta)$, C_l

⇕

Halo Model ⟹ $n(M)$

Keep basic for the moment:

- Full sky
- No redshift uncertainty
- No cluster mass uncertainty

Halo Model

See, e.g., Cooray and Sheth 2002

All mass in the Universe is contained in halos.

Matter correlation on small scales is related to the spatial distribution within the halo: halo profile

Matter correlation on large scales is related to the spatial distribution of halos: halo mass function

Halo Model

Density at a given position is given by a sum over halos i:

$$\rho(\vec{x}) = \sum_i \underbrace{\rho(\vec{x} - \vec{x}_i | M_i)}$$

Density around halo i ("halo profile")
assumed to depend only on halo mass M_i

Cluster Counts in the Halo Model

Halo mass function (comoving number density of halos per unit mass):

$$\frac{dn_h}{dM} = \langle \sum_i \delta^3(\vec{x} - \vec{x}_i)\delta(M - M_i)\rangle$$

Average cluster number counts:

$$\bar{N}_{\rm cl}(i_M, i_z) = \int_{i_M, i_z} dM\, dV\, \frac{dn_{\rm h}}{dM}$$

Cluster Counts in the Halo Model

Covariance of cluster number counts (in Fourier space):

$$\mathrm{Cov}\left(\hat{N}_{\mathrm{cl}}(i_M, i_z), \hat{N}_{\mathrm{cl}}(j_M, j_z)\right) =$$

$$\int \frac{d^3k}{(2\pi)^3}\, dM_{12}\, dV_{12}\; j_0(kr_1)\, j_0(kr_2)\, \left.\frac{dn_h}{dM}\right|_{M_1, z_1} \left.\frac{dn_h}{dM}\right|_{M_2, z_2} \underbrace{P_{\mathrm{cl}}(k|M_{12}, z_{12})}$$

Cluster power spectrum

$$j_0(x) = \frac{\sin(x)}{x}$$

Cluster Counts in the Halo Model

Covariance of cluster number counts has contributions from 1 and 2 halo terms:

$$\mathrm{Cov}_{1\mathrm{h}}\left(\hat{N}_{\mathrm{cl}}(i_M, i_z), \hat{N}_{\mathrm{cl}}(j_M, j_z)\right) = \delta_{i_M, j_M}\, \delta_{i_z, j_z}\, \frac{\bar{N}_{\mathrm{cl}}(i_M, i_z)}{4\pi}$$

1-halo term: poissonian shot noise

Cluster Counts in the Halo Model

2-halo contribution to the covariance can be conveniently written as (known as sample variance):

$$\mathrm{Cov}_{2\mathrm{h}}\left(\hat{N}_{\mathrm{cl}}(i_M, i_z), \hat{N}_{\mathrm{cl}}(j_M, j_z)\right) = \int dV_{12} \frac{\partial n_h}{\partial \delta_b}(i_M, z_1)\,\frac{\partial n_h}{\partial \delta_b}(j_M, z_2)\sigma^2_{\mathrm{proj}}(z_1, z_2)$$

$$\frac{\partial n_h}{\partial \delta_b}(i_M, z) \equiv \int_{M \in \mathrm{bin}(i_M)} dM\, \frac{dn_h}{dM}\, b_1(M, z)$$

$$\sigma^2_{\mathrm{proj}}(z_1, z_2) \equiv \int \frac{d^3k}{(2\pi)^3}\, j_0(kr_1)\, j_0(kr_2)\, P_{\mathrm{lin}}(k|z_{12})$$

$$j_0(x) = \frac{\sin(x)}{x}$$

related to the covariance of the background density

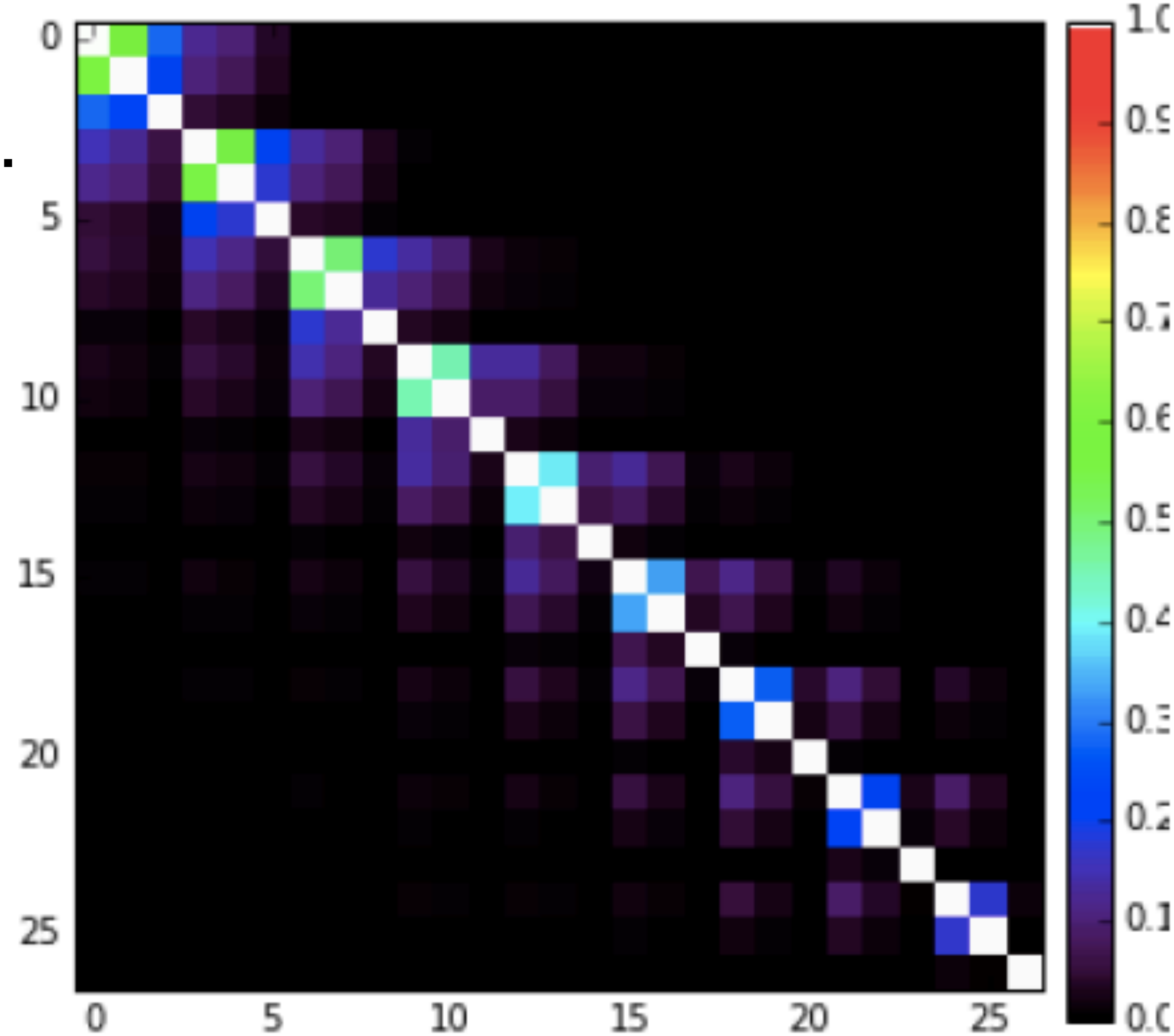
Cluster Counts in the Halo Model

For numerical results we will use the Tinker halo mass function and the NFW halo density profile. We use as a fiducial model a LCDM with Planck cosmological parameters and a linear power spectrum generated by the Eisenstein-Hu parametrization.

Cluster Counts in the Halo Model

Cluster counts covariance (3 bins of mass and 9 redshift bins)
off-diagonal entries from 2-halo contribution

Super sample cov. is more important at low z



10^{14}-$10^{14.5}$
$10^{14.5}$-10^{15}
10^{15}-$10^{15.5}$
01.<z<1.0
Δz = 0.1

Angular Power Spectrum in the Halo Model

Work with projected galaxy density contrast in a given redshift bin (to mimic photo-z surveys such as DES) and performs a spherical harmonic decomposition:

$$a_{\ell m}^{\mathrm{gal}}(i_z) = \int d^2\hat{n}\ \delta_{\mathrm{gal}}(\hat{n}, i_z)\ Y_{\ell m}^*(\hat{n})$$

and write the angular power spectrum estimator as usual:

$$\hat{C}_\ell^{\mathrm{gal}}(i_z, j_z) = \frac{1}{2\ell+1} \sum_m\ a_{\ell m}^{\mathrm{gal}}(i_z)\ \left(a_{\ell m}^{\mathrm{gal}}(j_z)\right)^*$$

Angular Power Spectrum in the Halo Model

The averaged angular power spectrum can be estimated as:

$$\bar{C}_\ell^{\rm gal}(i_z, j_z) \simeq \frac{\delta_{i_z, j_z}}{\Delta N_{\rm gal}(i_z)^2} \int dV \; \overline{n}_{\rm gal}(z)^2 \, P_{\rm gal}(k_\ell | z)$$

where we used the Limber approximation, $\Delta N_{\rm gal}(i_z)$ is the number of galaxies per steradian at redshift bin i_z and $\bar{n}_{\rm gal}(z)$ is the 3D averaged galaxy density at redshift z.

Putting galaxies in halos: the halo occupation distribution model (HOD)

Key assumption: number of galaxies N in a halo is a random variable with a pdf that depends only on the halo mass M.

Galaxies are divided into central and satellites, with different pdf's (binomial for centrals and Poisson for satellites).

$$\langle N_g | M \rangle = \langle N_{\rm cen} | M \rangle + \langle N_{\rm sat} | M \rangle$$

Putting galaxies in halos: the halo occupation distribution model (HOD)

We adopt a parametrization with 4 parameters: a mass threshold above which a halo has a large probability of containing a central galaxy, the width of the transition of the central probability, the typical mass above which a halo contains satellite galaxies and the index of the power law for the number of satellites at large halo masses.

These parameters will be either marginalized or estimated in the analysis.

Putting galaxies in halos: the halo occupation distribution model (HOD)

3D averaged galaxy density at redshift z:

$$\overline{n}_{\rm gal}(z) = \int_{i_z} dV\, dM\, \frac{dn_h}{dM} \langle N_g | M \rangle$$

Angular Power Spectrum in the Halo Model

3D galaxy power spectrum written as a sum of 3 terms:

$$P_{\rm gal}(k|z_{12}) = P^{\rm 2h}_{\rm gal}(k|z_{12}) + P^{\rm 1h}_{\rm gal}(k|z_{12}) + P^{\rm shot}_{\rm gal}(k|z_{12})$$

Depends on galaxy bias, mass function, HOD, profiles and DM power spectrum

Depends on mass function, HOD and profiles

$$\frac{\delta_{z_1,z_2}}{\overline{n}_{\rm gal}(z_1)}$$

Cross-covariance between APS and cluster counts in the Halo Model + HOD

This cross-covariance will depend on the halo-galaxy-galaxy bispectrum:

$$\langle \delta_h(\vec{k}_1 | M_1, z_1)\, \delta_g(\vec{k}_2, z_2)\, \delta_g(\vec{k}_3, z_3) \rangle_c = (2\pi)^3\, \delta^3(\vec{k}_1 + \vec{k}_2 + \vec{k}_3)\, B_{\rm hgg}(k_{123} | M_1, z_{123})$$

Cross-covariance between APS and cluster counts in the Halo Model + HOD

Lacasa et al. (2014) proposed a diagrammatic method to compute n-point correlation functions with a set of “Feynman rules”. There are six contributions in this case:

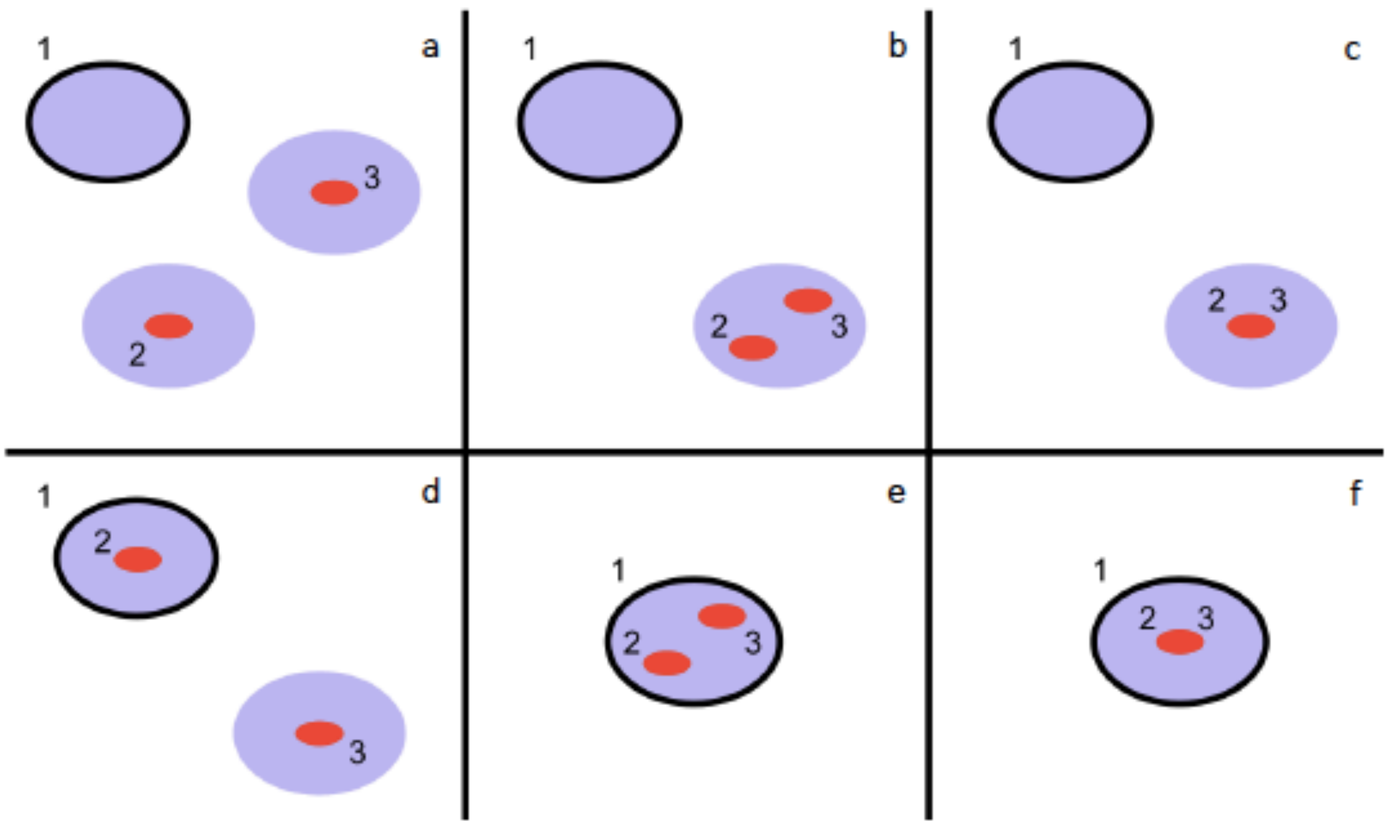
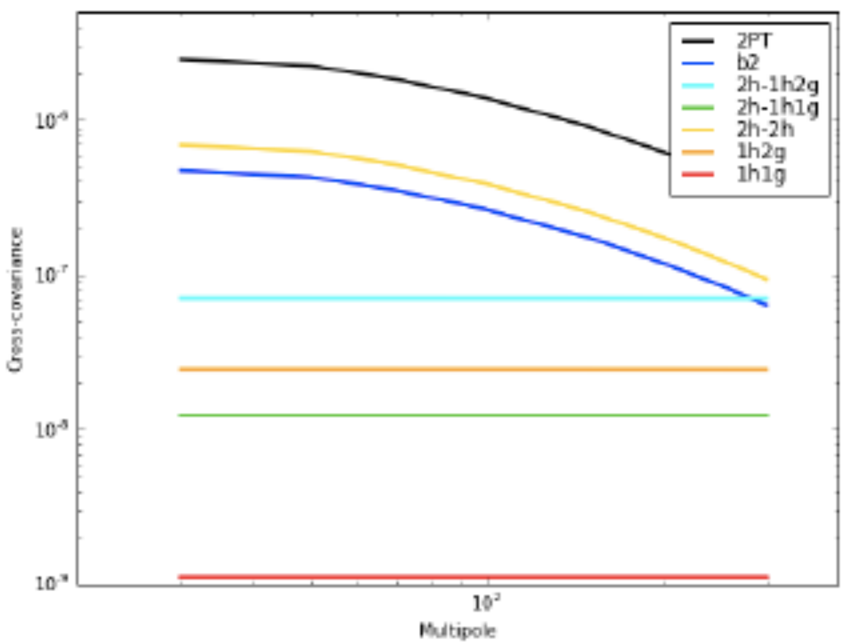


Figure 4. Diagrams for the halo-galaxy-galaxy bispectrum. From left to right and top to bottom : 3h, 2h-1h2g, 2h-1h1g, 2h-2h, 1h2g, 1h1g.

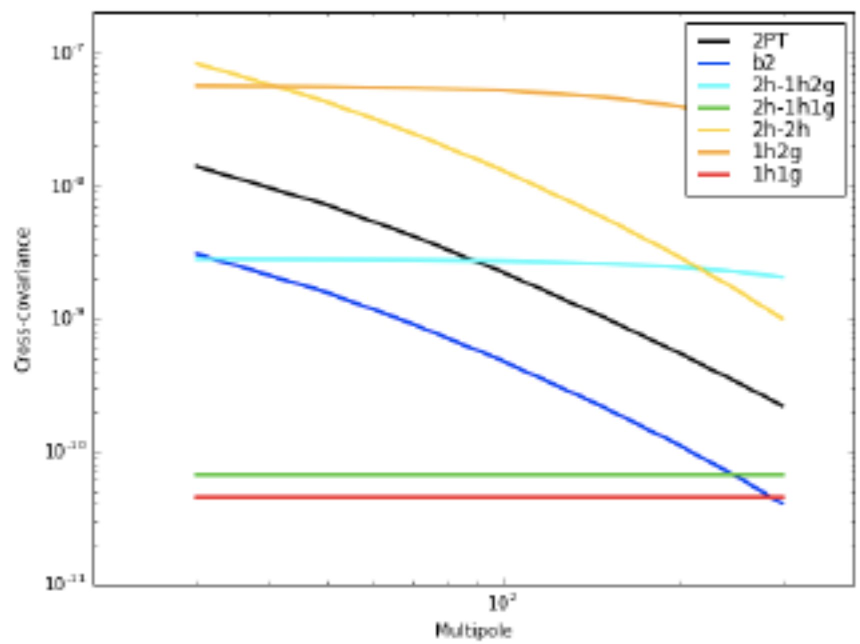
Cross-covariance between APS and cluster counts in the Halo Model + HOD

The perturbation theory term only dominates in certain regimes (high redshift, large scales, small masses). Nonlinear contributions are important!

high redshift, low mass case
0.8<z<0.9 14<logM<14.5



low redshift, high mass case
0.1<z<0.2 15<logM<15.5



Cross-covariance between APS and cluster counts: super-sample covariance

We were able to identify the contribution from super-sample covariance in our approach coming from different terms:

$$\mathrm{Cov}_{\mathrm{SSC}}\left(\hat{N}_{\mathrm{cl}}(i_M, i_z), \hat{C}_\ell^{\mathrm{gal}}(j_z)\right) =$$

$$\int dV_{12} \frac{\bar{n}_{\mathrm{gal}}(z_2)^2}{\Delta N_{\mathrm{gal}}(j_z)^2} \frac{\partial n_h}{\partial \delta_b}(i_M, z_1) \frac{\partial P_{\mathrm{gal}}(k_\ell | z_2)}{\partial \delta_b} \sigma^2_{\mathrm{proj}}(z_1, z_2)$$

Our results generalize (for second order bias and galaxy shot noise) the results of Takada and Hu (2013)

Cross-covariance between APS and cluster counts: super-sample covariance

Interpretation

$$\frac{\partial P_{\rm gal}}{\partial \delta_b}$$: reaction of galaxy power spectrum to a change in the background density

$$\frac{\partial n_h}{\partial \delta_b}$$: reaction of cluster counts to a change in the background density

"Unification" of super-sample covariance

We propose that SSC between 2 observables can always be written as

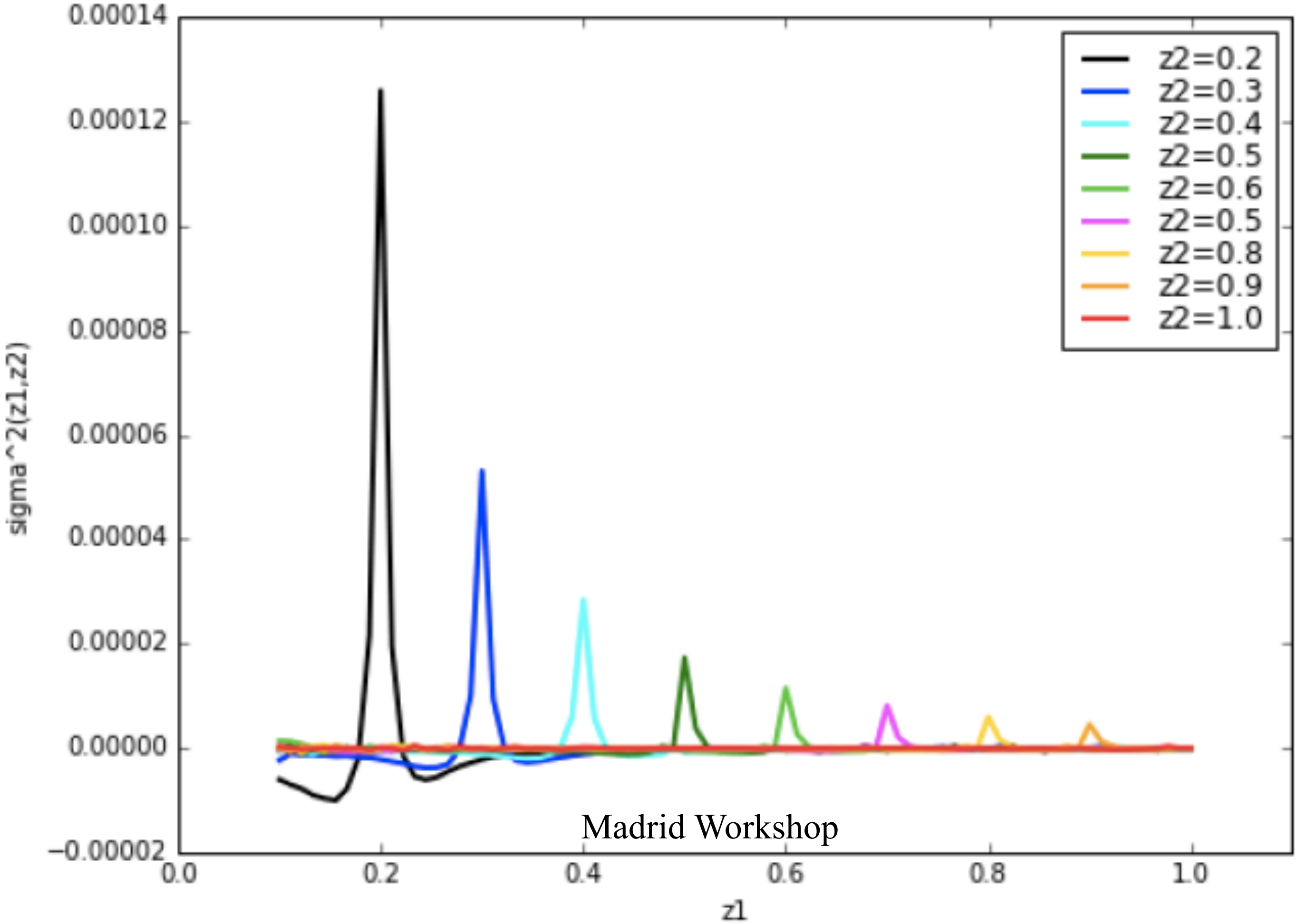
$$\mathrm{Cov}_{\mathrm{SSC}}\left(\mathcal{O}_1, \mathcal{O}_2\right) = \int dV_{12}\, \frac{\partial \mathcal{O}_1}{\partial \delta_b}(z_1)\, \frac{\partial \mathcal{O}_2}{\partial \delta_b}(z_2)\, \sigma^2_{\mathrm{proj}}(z_1, z_2)$$

$\sigma^2_{\mathrm{proj}}(z_1, z_2)$ is related to the covariance of the background density and peaks at $z_1 = z_2$

Covariance of background

$$\sigma^2_{\rm proj}(z_1,z_2) = \int \frac{{\rm d}^3\mathbf{k}}{(2\pi)^3}\, j_0(kr_1)\, j_0(kr_2)\, P_{\rm DM}(k|z_{12})$$

$$= \langle \delta_{\rm avg}(z_1)\, \delta_{\rm avg}(z_2)\rangle_c \quad \text{with} \quad \delta_{\rm avg}(z) = \int \frac{{\rm d}^2\hat{n}}{4\pi}\, \delta(r\hat{n}, z).$$



Covariance of the galaxy APS

It involves a 4-point function. The usual gaussian term comes from the unconnected part:

$$\mathrm{Cov}\left(\hat{C}_\ell^{\rm gal}(i_z), \hat{C}_{\ell'}^{\rm gal}(j_z)\right) = \frac{2\ C_\ell^{\rm gal}(i_z)^2}{2\ell+1}\ \delta_{\ell,\ell'}\ \delta_{i_z,j_z}$$

Covariance of the galaxy APS

Non-gaussian contribution contained in the 2D projected galaxy trispectrum. The 3D galaxy trispectrum has contributions from 14 diagrams and there is no analytical solution for the 2D projection.

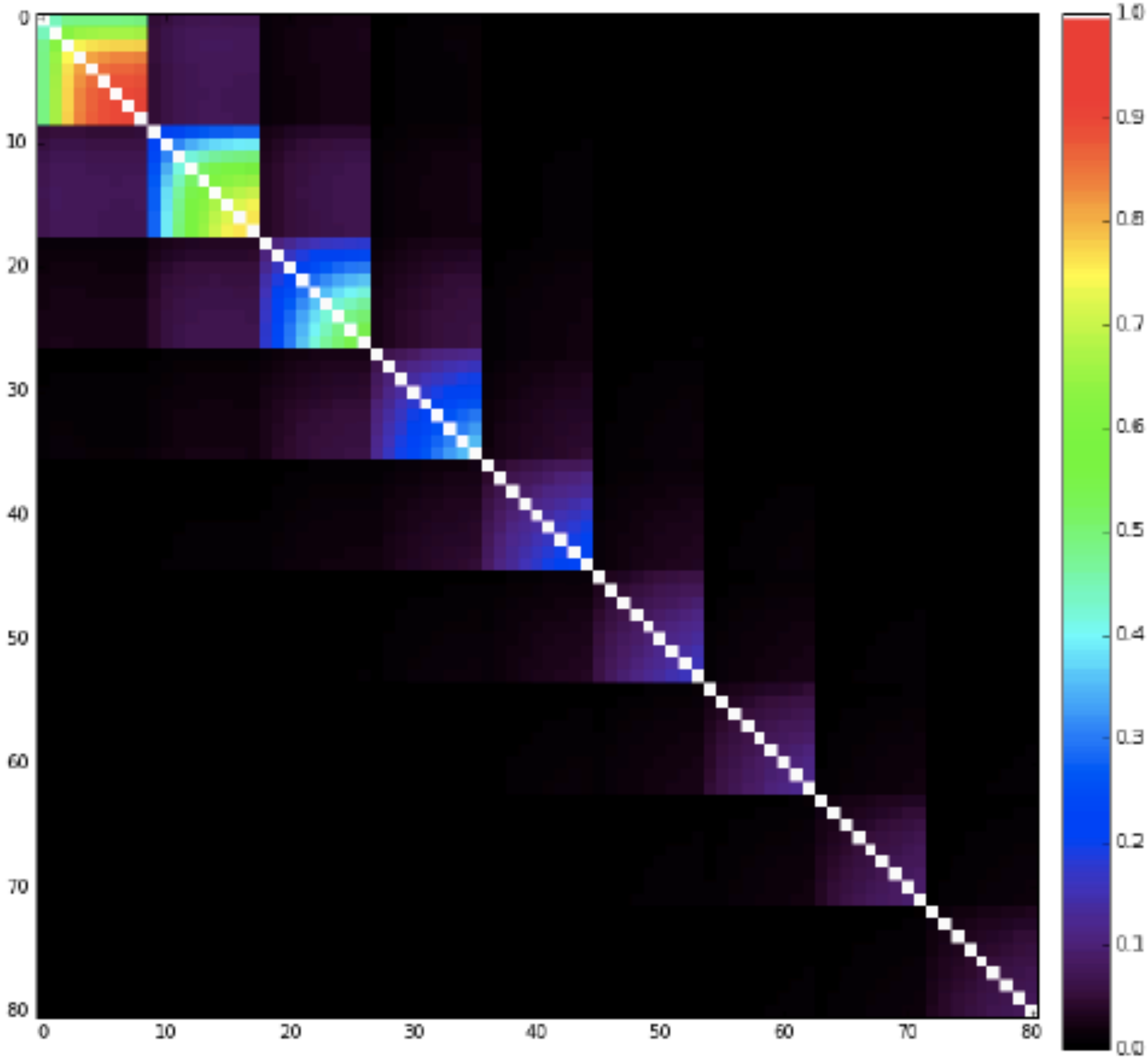
Hence we will keep the gaussian, the 1-halo term and a generalization of the SSC:

$$\mathrm{Cov}_{\mathrm{SSC}}\left(\hat{C}_\ell^{\mathrm{gal}}(i_z), \hat{C}_{\ell'}^{\mathrm{gal}}(j_z)\right) \approx \int dV_{12}\, \frac{\partial P_{\mathrm{gal}}(k_\ell, z_1)}{\partial \delta_{\mathrm{b}}} \frac{\partial P_{\mathrm{gal}}(k_{\ell'}, z_2)}{\partial \delta_{\mathrm{b}}}\, \sigma^2_{\mathrm{proj}}(z_1, z_2)$$

Covariance of the galaxy APS

l=30-300
in 9 bins of
Δl=30

9 redshift bins
of Δz=0.1
from z=0.1



Impact of including cross-correlation in the determination of parameters

Impact of joint covariance

We adopt:
9 redshift bins ($0.1<z<0.9$, $\Delta z=0.1$)
3 logarithmic mass bins ($14<\text{Log } M < 15.5$, $\Delta \text{LogM}=0.5$)

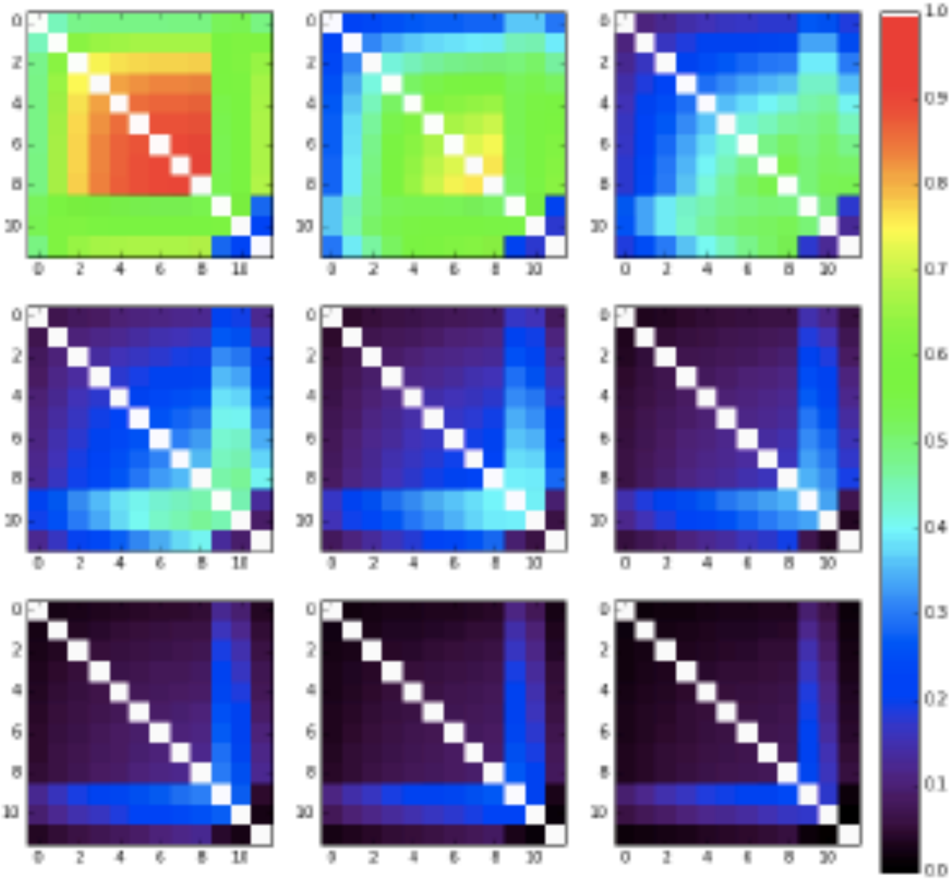
For the multipoles we considered 2 cases:

• Cosmological case (large angular scales)
9 bins, $30<l<300$, $\Delta l=30$

• HOD case (small angular scales)
7 bins, $300<l<1000$, $\Delta l=70$

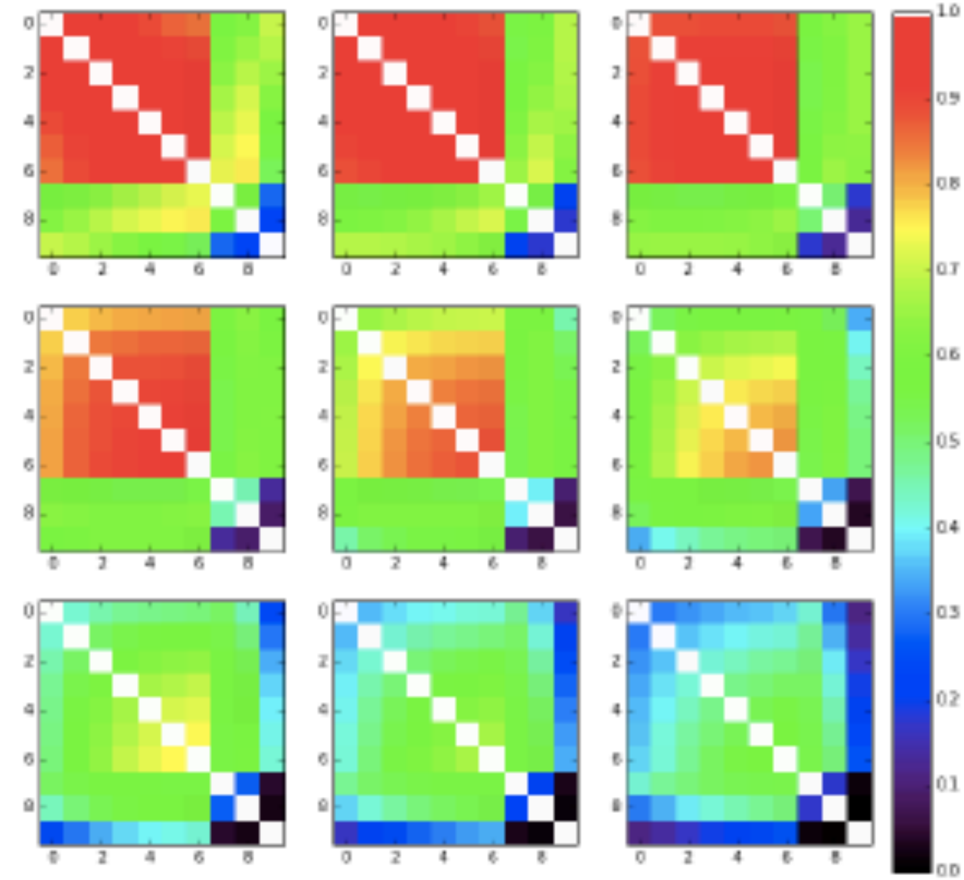
Joint covariance

Cosmological case
9 bins, $30<l<300$, $\Delta l=30$



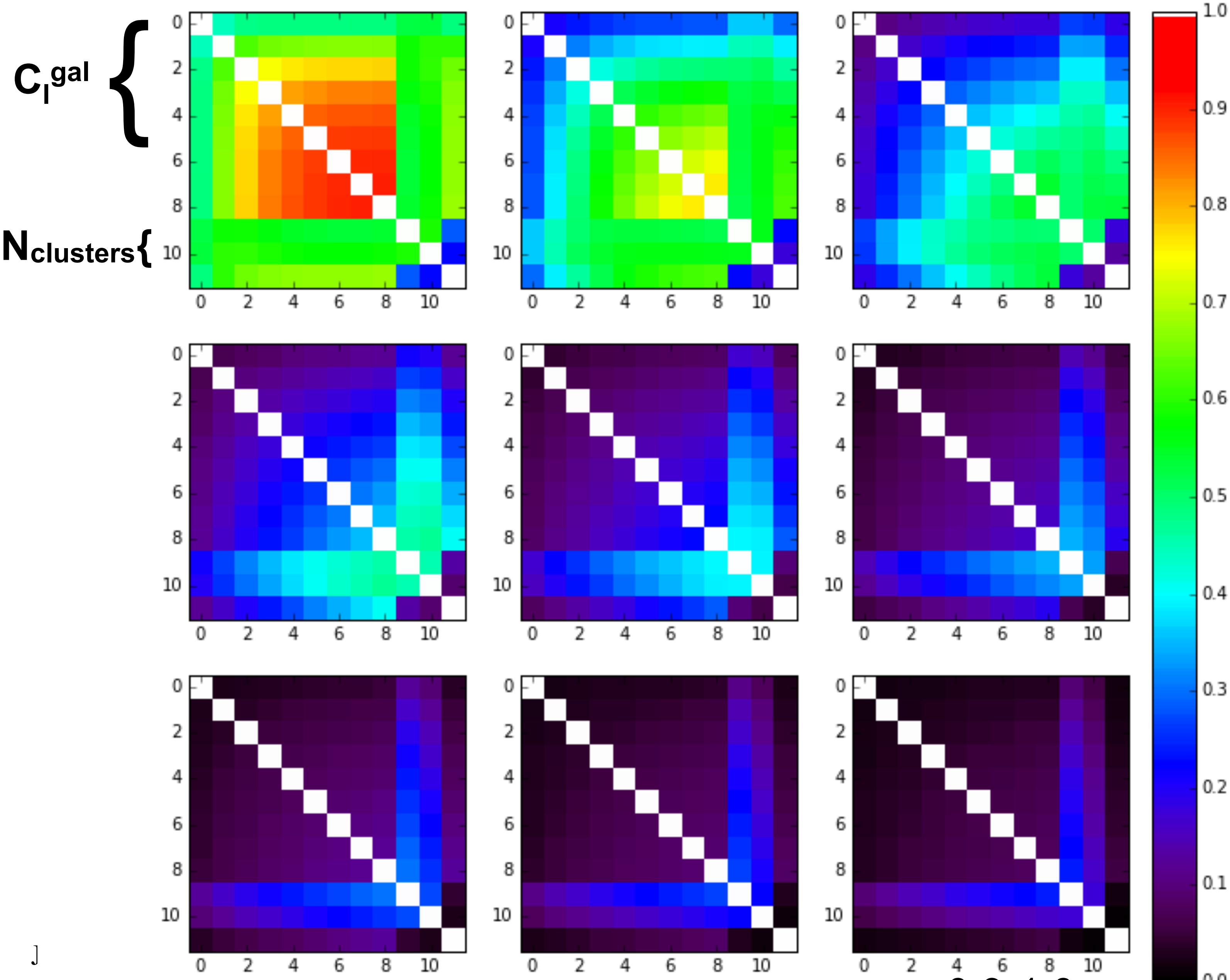
HOD case
7 bins, $300<l<1000$, $\Delta l=70$

Large nongaussianities at small scales and small redshifts



Joint covariance

z=0.1-0.2 z=0.2-0.3 Predictions with halo model and HOD



z=0.9-1.0

9 redshift bins : Dz=0.1
z=0.1-1

3 mass bins :
DlogM=0.5
logM=14-15.5

9 multipole bins :
Dl=30
l=30-300
(theta~0.6-6 deg)

Cross-covariance is important at all redshifts

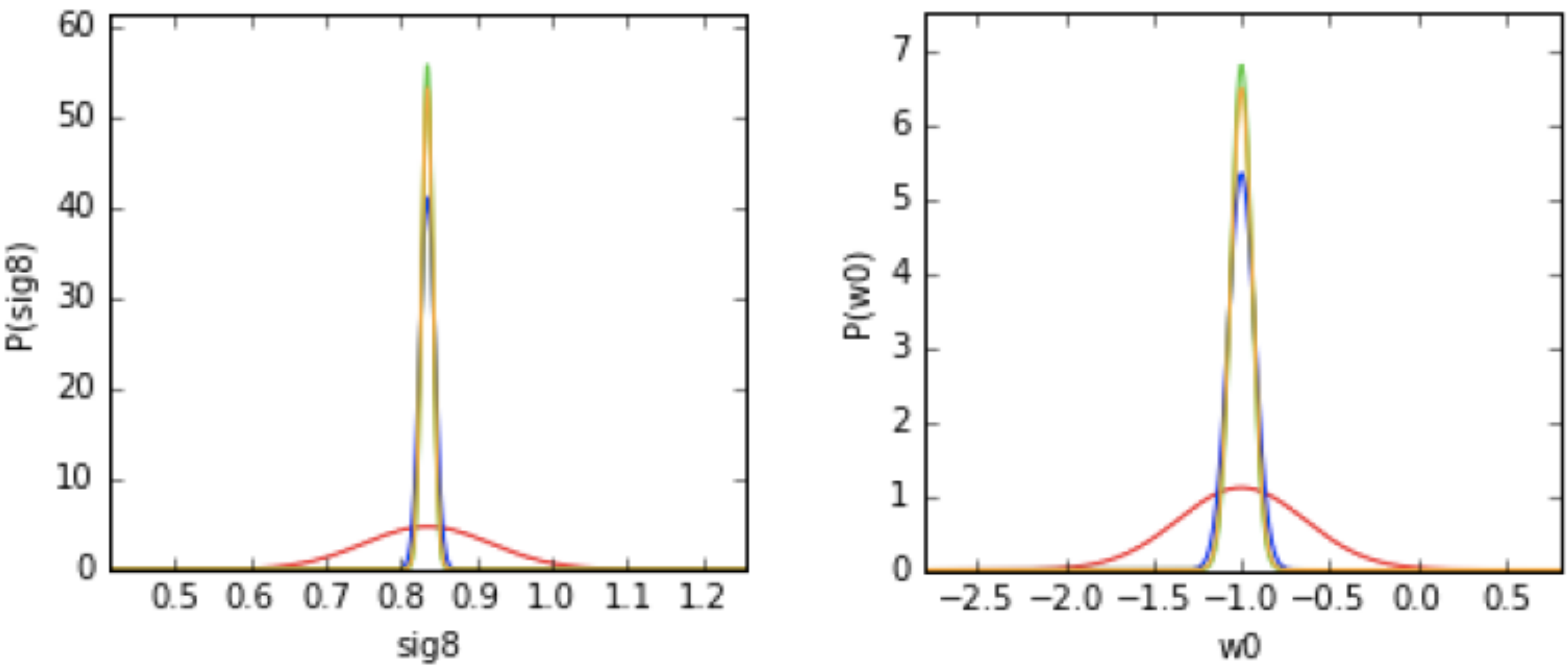
Particularly for the smaller angular scales

Impact of joint covariance

Perform a Fisher matrix analysis – cosmological case

Red line: APS only
Blue line: cluster counts only
Green line: independent APS and cluster counts
Orange line: full joint APS and cluster counts

Small difference

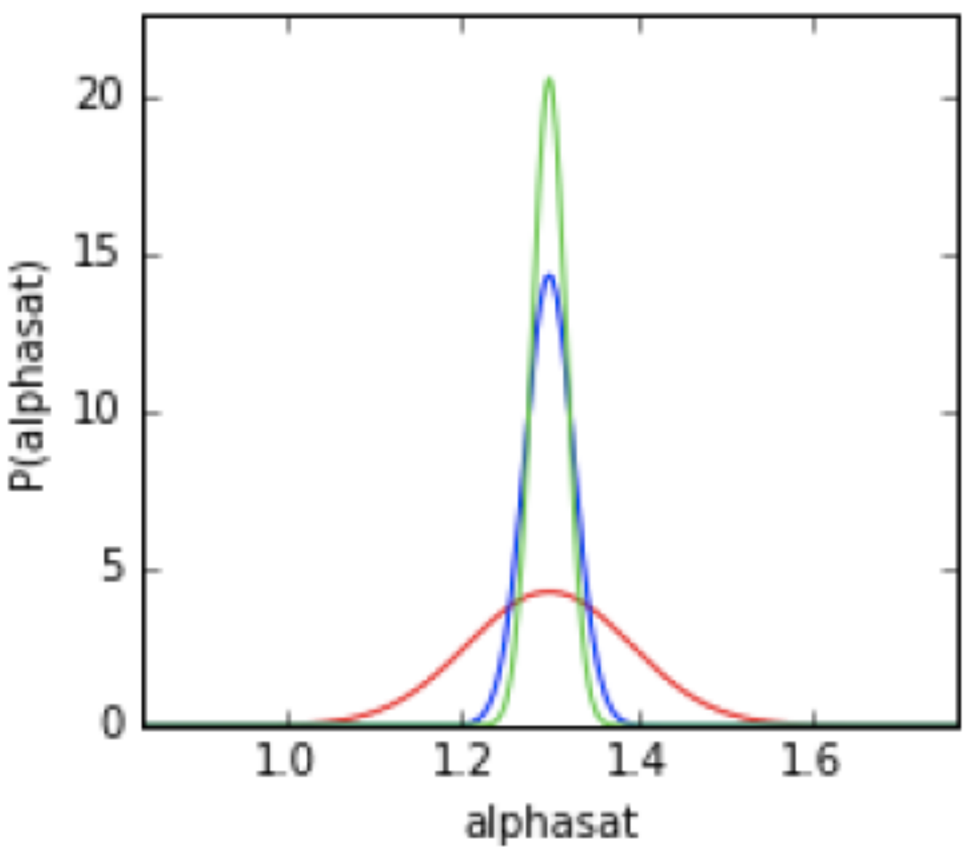


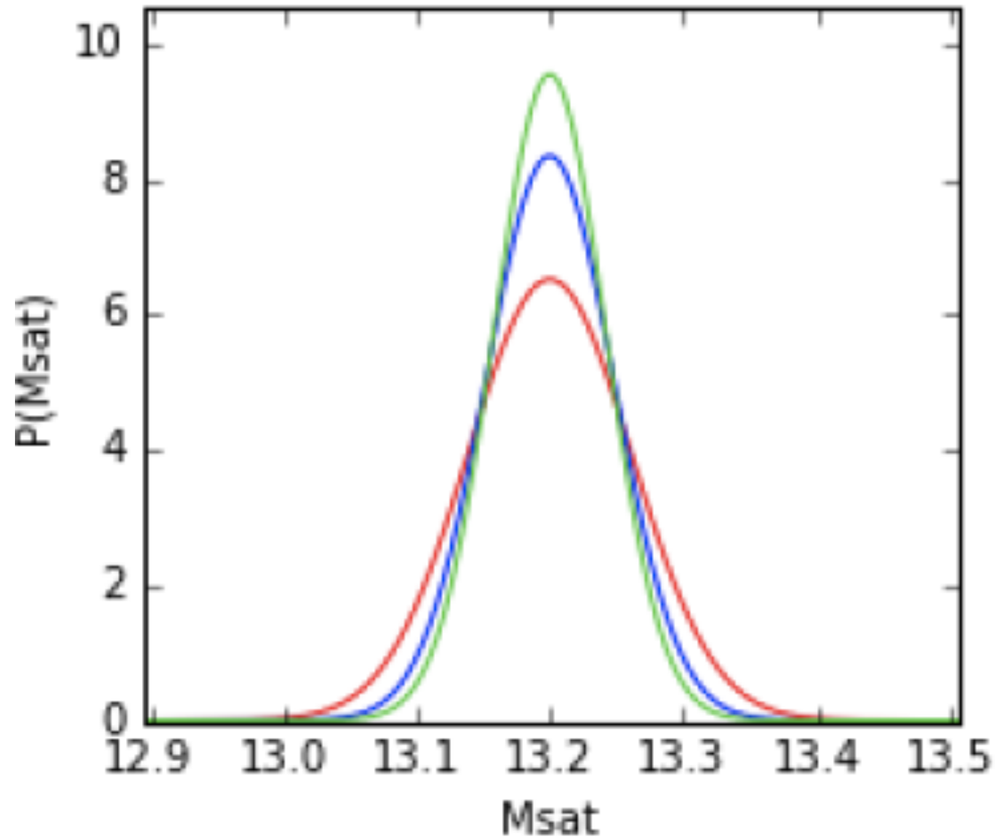
Impact of joint covariance

Perform a Fisher matrix analysis – HOD case
Cluster counts are independent of HOD!

Red line: APS only
Blue line: independent APS and cluster counts
Green line: full joint APS and cluster counts

significant difference





Impact of joint covariance

observable/parameter	σ_8	$\Omega_m h^2$	$w_{\rm DE}$
$C_\ell^{\rm gal}$	10.1 %	8.67 %	36.1 %
$N_{\rm cl}$	1.17 %	4.10 %	7.48 %
joint	0.90 %	3.08 %	6.16 %
independent	0.86 %	2.96 %	5.87 %

Table 2. 1σ marginalised error bars on cosmological parameters in the cosmological case study.

observable / parameter	$\alpha_{\rm sat}$	$\log M_{\rm min}$	$\log M_{\rm sat}$
$C_\ell^{\rm gal}$	7.20 %	0.52 %	0.46 %
joint	1.49 %	0.20 %	0.32 %
independent	2.14 %	0.23 %	0.36 %

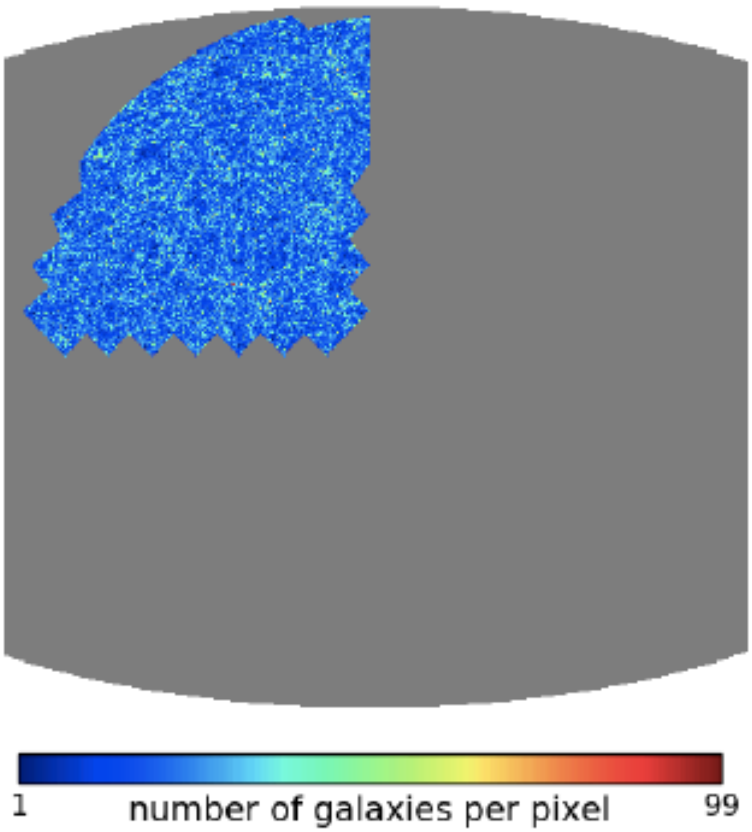
Table 3. 1σ marginalised error bars on HOD parameters in the HOD case study.

Comparison with simulations (prelim.)

- Use MICE simulations
- Introduce cuts in theoretical model – octant, not full sky
- Measurements of Cl's and N_{cl}
- Measurement of Cov(Cl,Cl), Cov(Cl, N_{cl}) and Cov(N_{cl},N_{cl}) using subsamples
- Need a fit to HOD

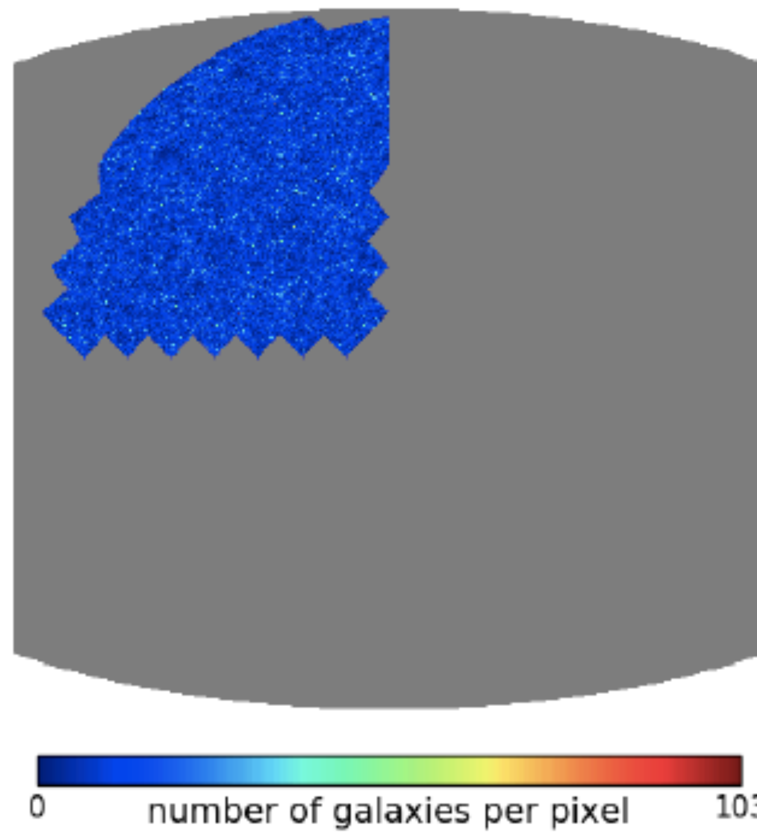
- MICE light cone between $0.5 < z < 0.6$

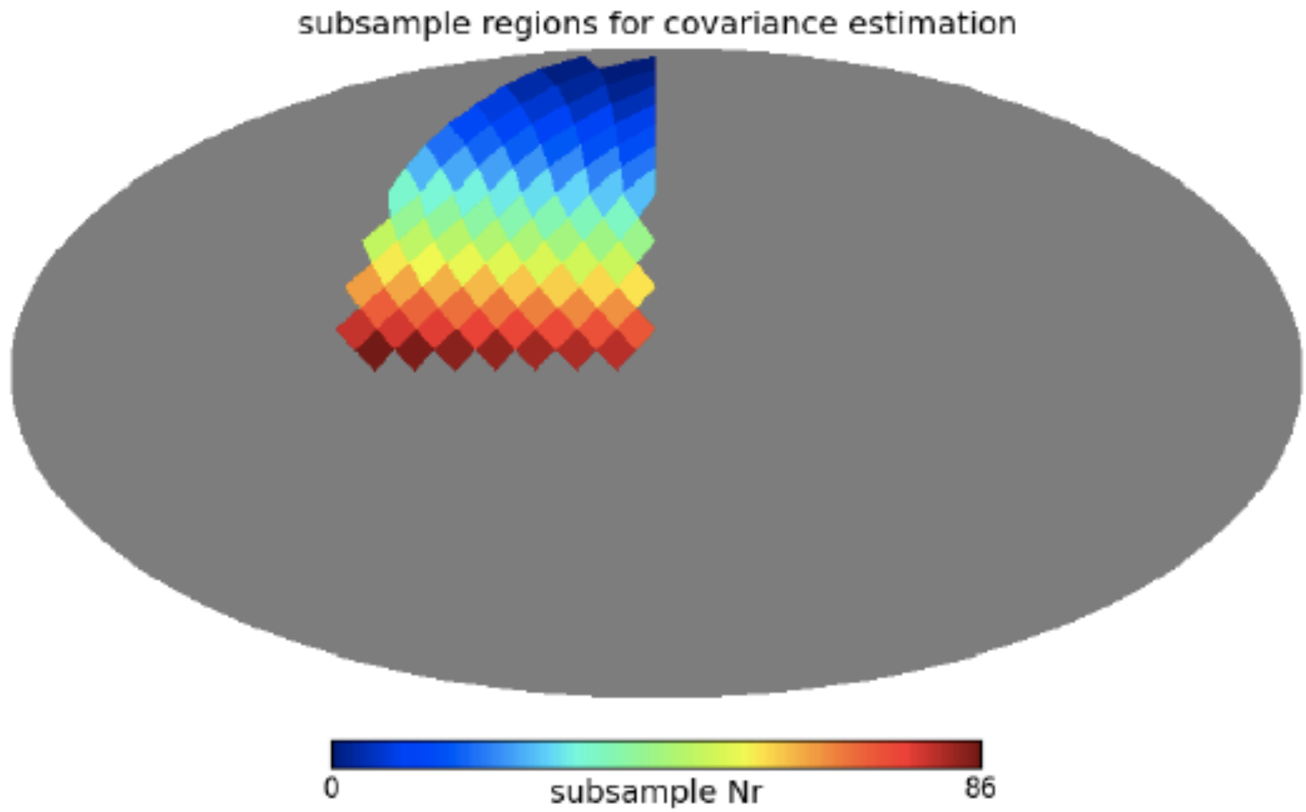
- clusters = FOF haloes
  (selected as centrals, Np>10)



healpix
maps

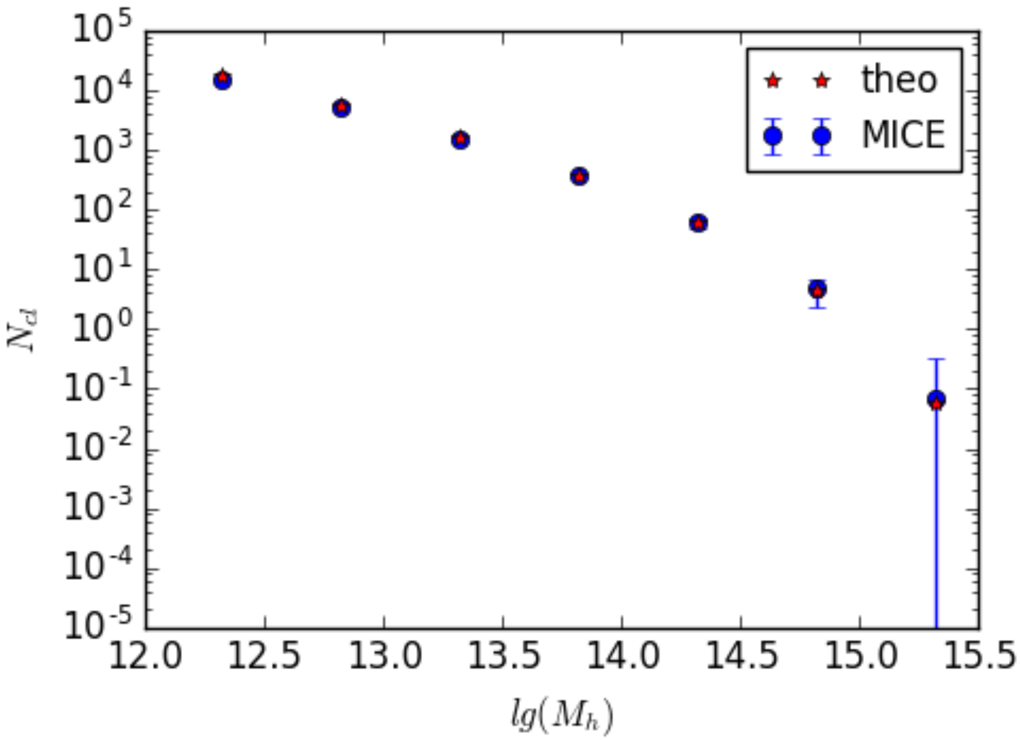
- centrals+satellites (r<22)

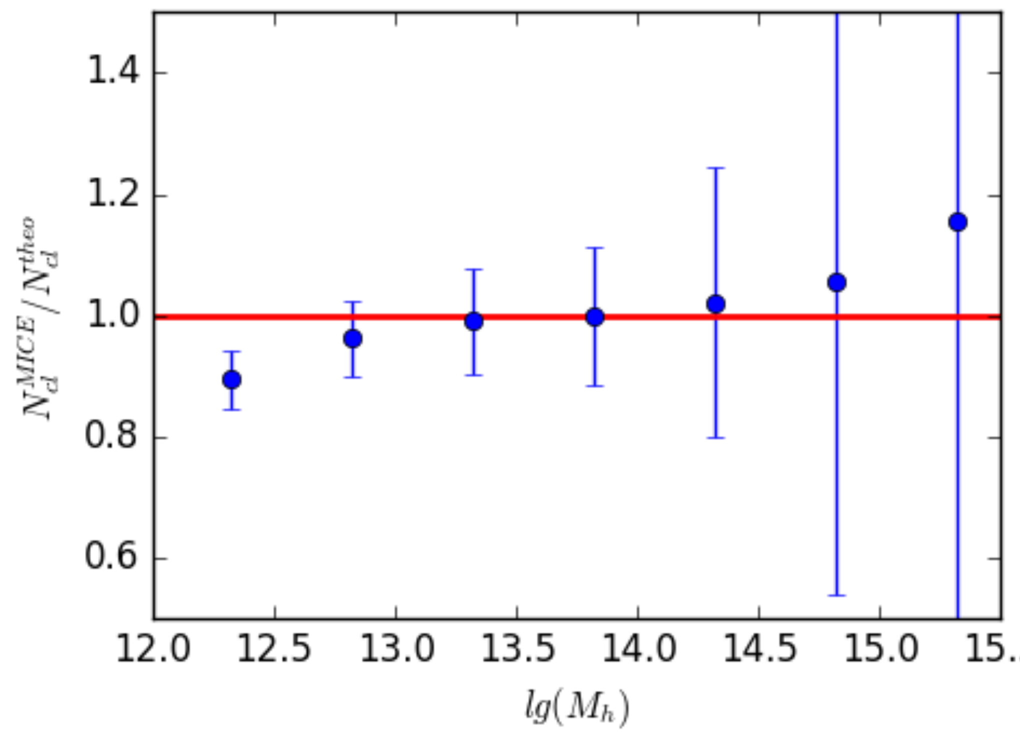




- 87 subsample regions (large healpix pixels)
- regions which exceed area of the octant are excluded

Cluster counts

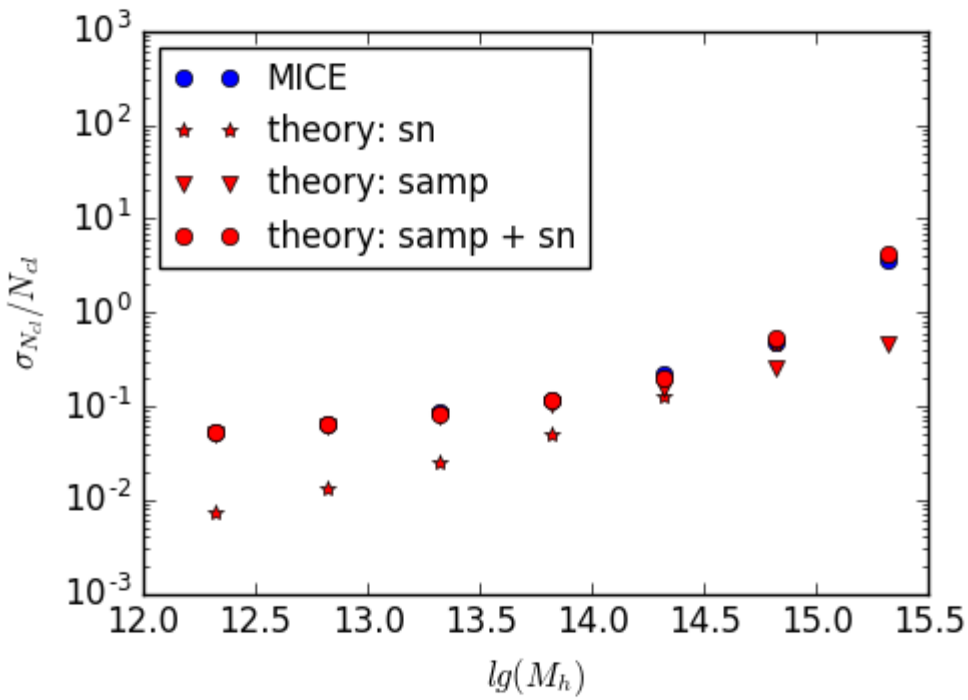




Counts comparison

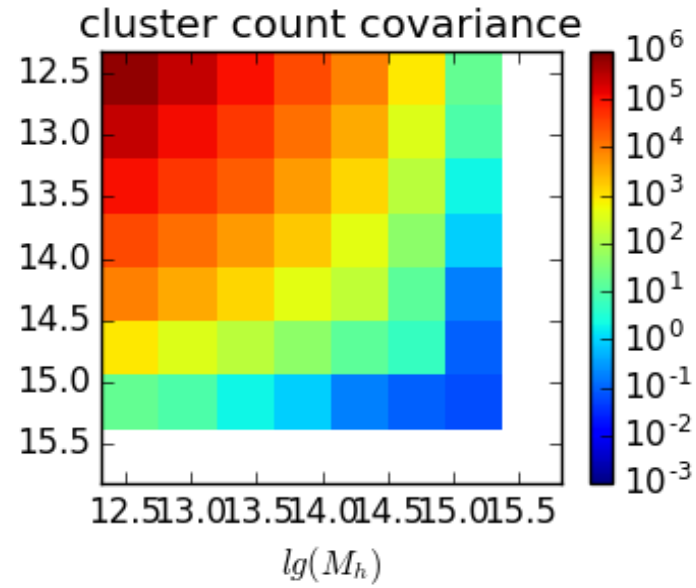
Ratio

Cluster counts covariance

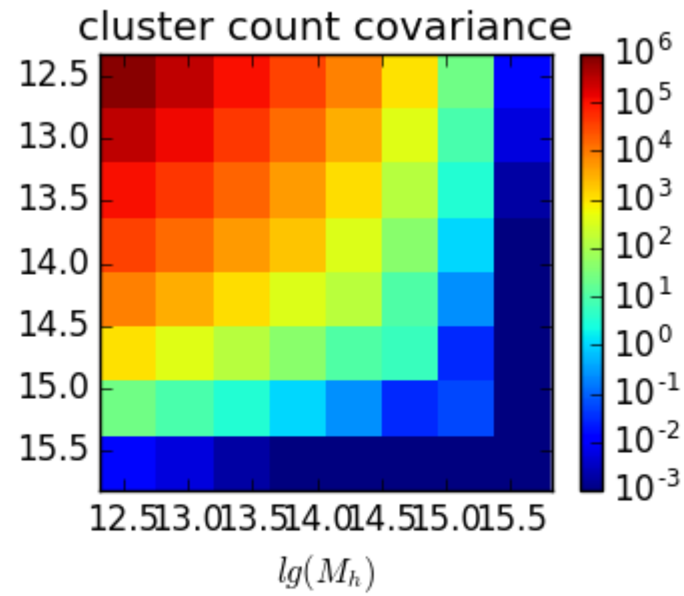


Sample variance dominates at small masses and shot noise dominates for larger masses

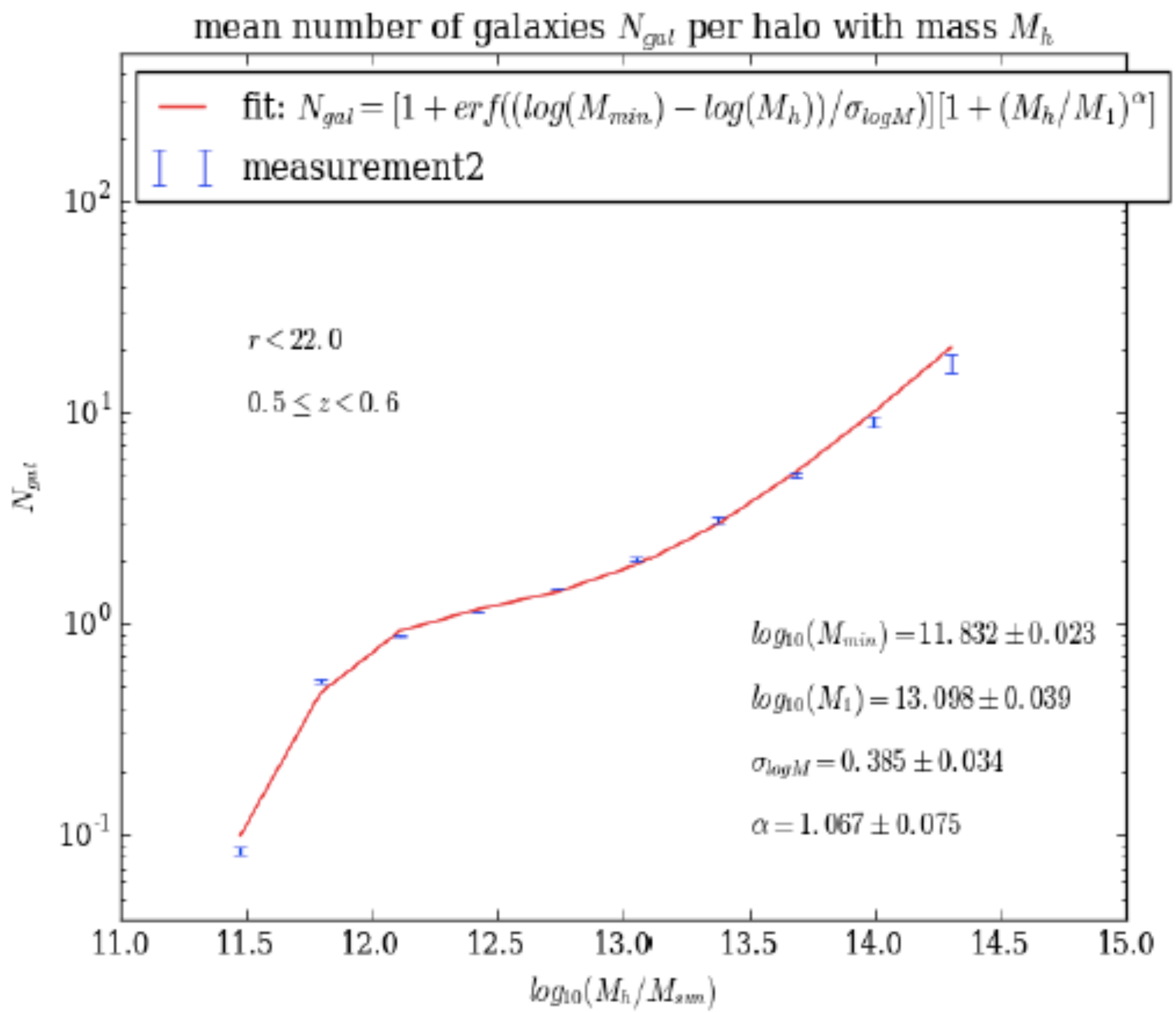
Measured covariance matrix



Theoretical covariance matrix

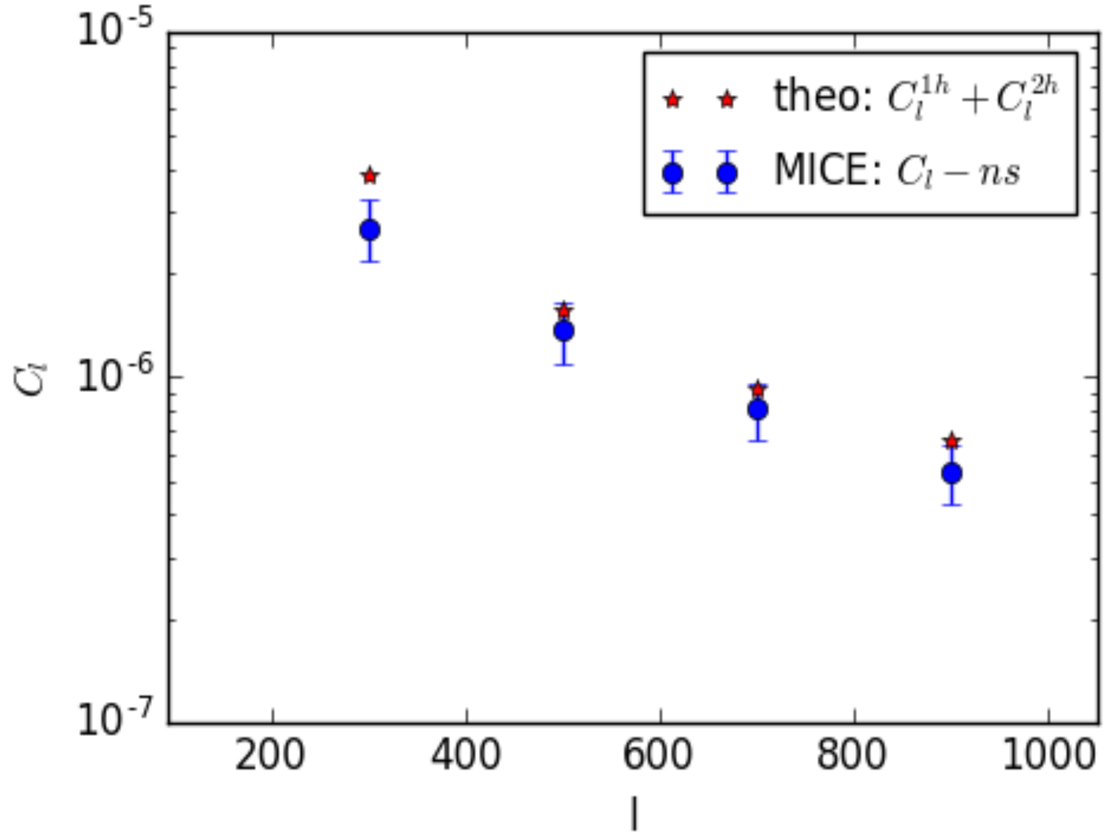


HOD fitting for Cl's



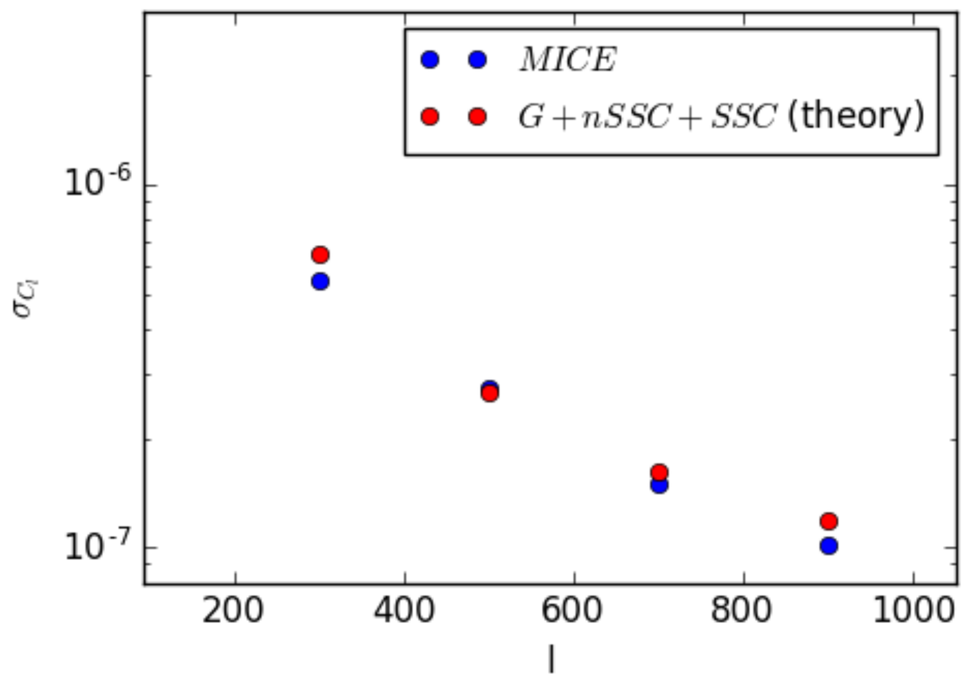
sample:
galtype = 'cent+sat'
no colour selection
r < 22
0.5<z<0.6

Cl’s



C(l) comparison

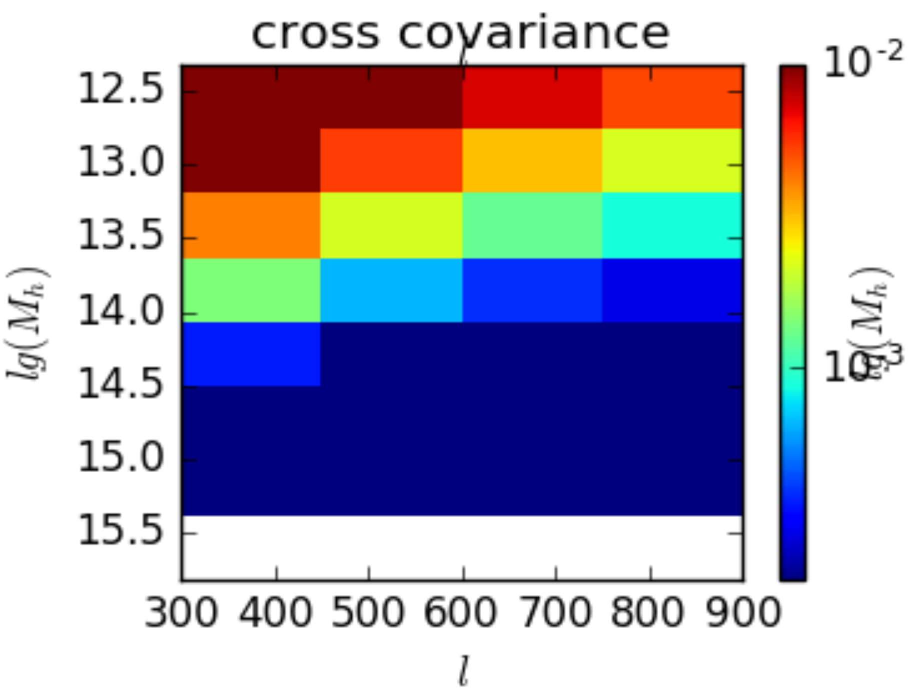
Covariance of Cl's



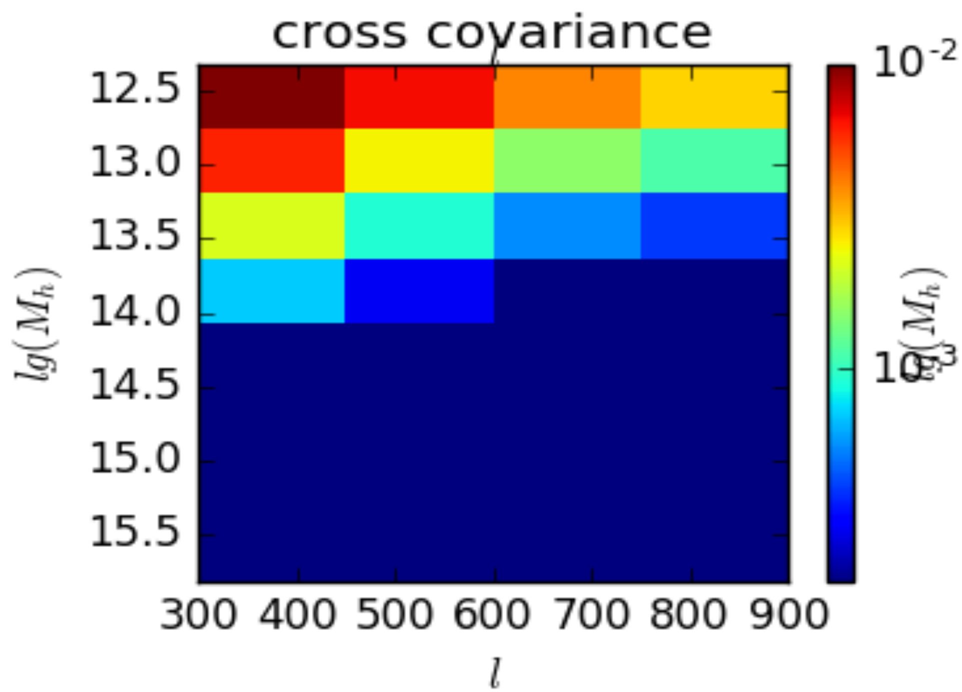
Still some disagreement

Cross covariance

Measured covariance matrix



Theoretical covariance matrix



Conclusions

• Nonlinear modelling (in the halo model + HOD approach) of the full covariance matrix involving two main observational probes: the galaxy angular power spectrum and cluster counts;

• Nongaussian contributions are important at low redshift and small scales;

• Taking into account the cross-correlation does not change significantly the determination of cosmological parameters but can affect the HOD parameters;

• Must take into account more experimental effects: photo-z errors, purity and completeness of a cluster catalog, scatter in cluster mass, etc…

• Method is being tested now in realistic simulations (MICE, with Hoffmann, Lacasa and Gaztañaga) – then apply it to real data!