

Constraining the scatter in the mass richness relation of galaxy cluster with the correlation function

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Abstract

Cluster of galaxies are becoming a powerful tool to constrain cosmological parameters. This has motivated the design of a new wide-area cluster surveys at mm, optical/near infrared, and X-ray wavelengths. These surveys will have the potential to find hundred of thousands of clusters. The principal challenge to precision cosmology with the evolution of the abundance of clusters is the accurate calibration of the relation between the observables and halo masses. In this talk we present a method to constrain the scatter in the mass observable relation by comparing the bias measured in the cluster correlation function with the bias model. Since our goal will be to constrain the scatter in optical selected cluster in the Dark Energy Survey (DES) and in the available SDSS cluster samples our observable will be the richness. First we will study the bias in halos on a past lightcone using N-body simulations to study the errors that come from the Halo Model prediction. Finally, we assign richness to dark matter halos in the simulation to test our method.

1 Introduction

The evolution of the abundance of cluster has long been recognized as powerful tool for constraining cosmological parameters [9]. The basic idea is to compare the predicted space density of massive halos to the observed space density of clusters, which can be identified via optical, X-ray, or CMB observables that should correlate with halo mass. But this mass estimators are noisy, meaning there can be significant scatter between the observable mass tracer and cluster mass. Since the mass function is a steeply declining function of mass, a low level of scatter can change the shape and amplitude of the observed mass function significantly. Uppsampling of low mass systems into high mass bins can result in a significant boost to the number of systems with apparently high mass [5].

Scatter arises from physical variations in cluster properties at fixed halo mass, from observational noise, and from low level contamination that produces small random fluctuations in the observable. These effects are typically assumed to produce a log-normal form of $P(N|M, z)$, i.e. Gaussian scatter in $\ln M$. The calibration task is then to determine the mean relation $\langle M|N \rangle$ and the standard deviation $\sigma_{\ln M}$ called the scatter. In previous studies (see [8]), the scatter in the mass richness relation at fixed richness of maxBCG cluster sample is constrained with weak lensing, optical richness estimates and X ray data. Specifically, they use observational constraints on the mean mass richness relation and the X-ray measurement of the mean and scatter of the X-ray luminosity as a function of richness.

Here, we present a method to constrain the scatter of the mass richness relation using the spatial clustering of the cluster themselves, as characterized by the cluster correlation function [1]. Because the bias of halo clustering depends on mass, the amplitude and the scale-dependence of clustering provides information about the mass observable relation. However, in our scales of interest the underlying halo-mass bias is scale-independent. We will use dark matter simulations to test our method although our goal will be to use it in a real cluster catalog.

2 Material and method

The two simulations analyzed in this work are the DES volume v1.02 halo mock catalog light cone sky survey based on the Hubble Volume PO lightcone output [2] and the 3000(Mpc/h)³ volume snapshot at $z = 0$ [3]. The Friend of Friend (FoF) algorithm is used to determine the halo mass in the snapshot and the Spherical Overdensity (SO) with $\Delta = 200$ in the lightcone.

We create richness catalogs with three scatter values in order to measure the richness bias. We add to every lognormal mass of the dark matter halos in the lightcone $\ln M$, a variable that follows a lognormal distribution with mean zero and a standard deviation $\sigma_{\ln M}$. For simplicity $\sigma_{\ln M}$ will not vary neither with redshift nor mass. Then we assign a richness value using the mass richness relation determined for the SDSS sample using weak lensing measurements. A good summary of these is presented in the Appendix of [8] giving

$$\frac{\langle M_{obs} | N \rangle}{10^{14}} = e^{B_{M|N}} \left(\frac{N}{40} \right)^{\alpha_{M|N}} \quad (1)$$

Therefore, the probability of having the true mass M given the observed richness N follows

$$P(\ln M | N) \propto \exp - \frac{(\ln(\langle M_{obs} | N \rangle) - \ln M)^2}{2\sigma_{\ln M}^2} \quad (2)$$

2.1 The theoretical predictions of richness bias using the Halo Model

Taking into account the mass observable relation, the bias expected for the richness value N is given in terms of halos mass function $\frac{dn(M,z)}{d\ln M}$ and the underlying bias $b(\ln M, z)$ by

$$b(N, z) = \frac{\int d\ln M \frac{dn}{d\ln M} P(\ln M | N) b(\ln M, z)}{\int d\ln M \frac{dn}{d\ln M} P(\ln M | N)} \quad (3)$$

The measured bias factor for a richness cut $N > N_{th}$ can be estimated using equation 3 through

$$b(N_{th}, z) = \frac{\sum_{N=N_{th}}^{\infty} b(N, z) n_{\text{measured}}}{\sum_{N=N_{th}}^{\infty} n_{\text{measured}}(N, z)} \quad (4)$$

where n_{measured} is the number of halos per redshift and richness sample measured in the simulations created as is explained before.

2.2 Bias measurement. Clustering estimator with the two point correlation function.

The richness bias can be obtained from the catalogs created by measuring the two point correlation function for a richness threshold given by

$$\xi_{cl}(r) = \bar{b}^2 \xi_{mm}(r) \quad (5)$$

where the matter correlation function is obtained in the usual way via the Fourier transform of the non linear matter power spectrum ξ_{mm} . For an isotropic universe and in three dimensions is given by

$$\xi_{mm}(r) = \frac{1}{2\pi} \int P_{NL}(k) \frac{\sin(kr)}{kr} k^2 dk \quad (6)$$

where the P_{NL} is given by the non linear halofit power spectrum [11] for the Λ CDM. We measure the correlation function for each sample with the Landy-Szalay estimator [4] because it has the best noise properties, which is given by

$$\xi_{LS}(r) = 1 + \frac{N_{RR}^2}{N_{DD}^2} \frac{DD(r)}{RR(r)} - 2 \frac{N_{RR}}{N_{DD}} \frac{DR(r)}{RR(r)}. \quad (7)$$

In the lightcone simulation we place each data point in its comoving coordinate location based on its redshift and compute the comoving separation $r \pm \Delta r/2$ between two points using the vector differences. Random catalogs were constructed according to the radial and angular distributions.

3 Results

3.1 Testing the Halo Model. Halo bias and average bias description

First we want to study the errors that come from the HM predictions with the Sheth & Thormen 99 [10] prescription to describe the bias for halos. Since the simulation samples are for halos above a mass threshold, the expected value of bias for a mass sample is

$$b(M \geq M_{th}, z) = \frac{\int_{M_{th}}^{\infty} dM \frac{dn(M,z)}{dM} b(M, z)}{\int_{M_{th}}^{\infty} dM \frac{dn(M,z)}{dM}}. \quad (8)$$

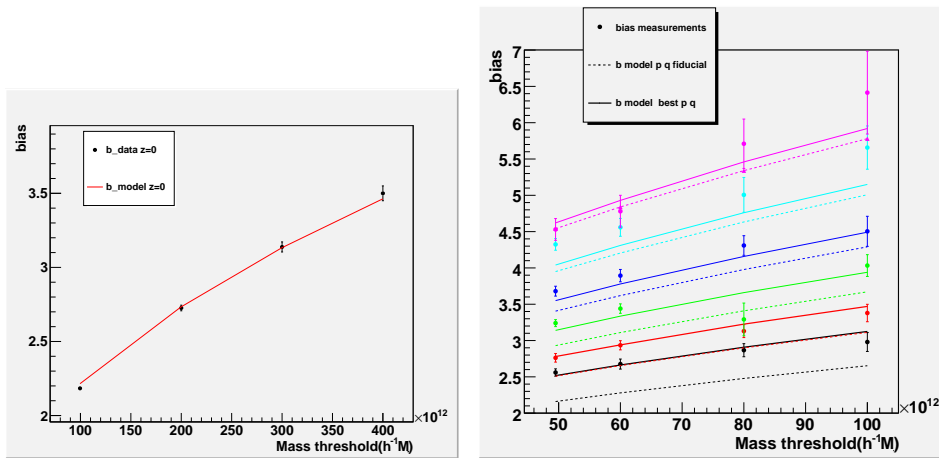


Figure 1: *Left panel:* Halo Bias model (red line) and bias measurements from LS correlation function at $z=0$ (black dots) comparison. *Right panel:* Bias measurements for halos in DESv1.02 simulation at redshifts bins 0.2-0.4 (black), 0.4-0.6 (red), 0.6-0.8 (green), 0.8-1 (blue), 1-1.2 (sky-blue), 1.2-1.4 (pink). Solid lines are the the bias model with the best p and q at the mean value of the redshift bin. Dashed lines are the bias model with the p and q fiducial values

Figure 1 shows the comparison between the bias predictions using Eq. 8 and the values measured with the correlation function with Poisson errors in the snapshot and the lightcone. The results in the snapshot show very good agreement with differences of a few percent. However, in the lightcone we predict the evolution of the bias with a good accuracy for the first two bins but for higher redshift the deviations are more significant. Note that here, we need to obtain the best p and q parameters using a chi square that compare the mass function model and measurements. See also results of [7].

3.2 Constraining the scatter

We divide the catalogs in redshift bins Δz and make cuts in richness N to measure the bias with the two point correlation function. Therefore, we have a set of n bias measurements $b_i^{\text{measured}}(N_{th}, \Delta z)$, where N_{th} is the richness threshold. We assume a model for the bias with parameters $\theta = (\Lambda, \alpha, B, \sigma_{lnM})$ given by 3 and 4, where Λ represents the dependence on the cosmological variables, α and B are the mass-richness parameters and the scatter σ_{lnM} . Since our goal is to constrain the scatter σ_{lnM} , we will consider a one dimensional likelihood given by the conditional probability distribution of the data, $\mathcal{L} = p(b^{\text{measured}} | \theta = \sigma_{lnM})$.

The probability of all n measurements, the likelihood, is the product of the probabilities of the individual measurements

$$\mathcal{L} = \prod_{i=1}^n p(b_i^{\text{measured}}(N_{th}, z); \theta). \quad (9)$$

We can transform from the likelihood to the probability for the parameters given the

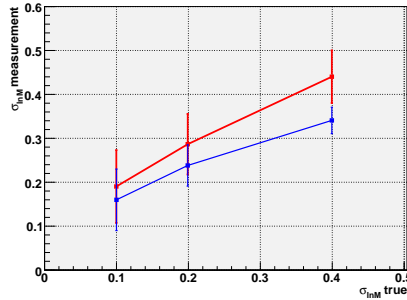


Figure 2: Most likely scatter measurement (mean and standard deviation of the Gaussian distribution) vs true value. Blue dots are the results integrating the richness bias model in all mass range and red ones are when we integrate in the mass range of our simulation.

data $p(\theta|b_i^{measured})$ using Baye’s Theorem. This requires multiplying by a prior p.d.f. For simplicity, we dont treat with priors and assume we know the cosmological parameters of the simulation and the α and B parameters. Therefore,

$$p(\sigma_{lnM}|b_i^{measured}) \propto \mathcal{L} \tag{10}$$

where we include the normalization factor in the p.d.f that involve σ_{lnM} . We perform a likelihood calculation comparing the bias model predictions with the measurements for the three catalogs created. We take only the first two redshifts bins where we have good accuracy. The results in Fig. 2 show how the errors in the scatter that we recover increase when we take into account the lower limit of mass in the lightcone simulation. Furthermore, as the predictions of the richness bias tell us, we obtain more accuracy at higher values of the scatter due to the slope of the mass function. For the true values of $\sigma_{lnM} = 0.1, 0.2$ and 0.4 we obtain a relative error of 40, 25 and 13% respectively. In Figure 3 we compare the predictions from the halo model with the most likely scatter values from the likelihood with the richness bias measurements from the catalogs created with σ_{lnM} true 0.1 and 0.4. We also include the model with the scatter 1 sigma way from the most likely. We find that the richness bias measurements with their errors are in agreement with the likelihood results.

4 Conclusion

The results show that we can constrain the scatter using the correlation function of galaxy clusters. Comparing these results with [8] we obtain similar accuracy for σ_{lnM} . Hence this is a complementary method for constrain the scatter using just one kind of observation. We still have to study the effects of the photometric errors and the error covariance for the correlation function. Moreover, since the dominant systematic found is the uncertainty in halo mass and bias function we want also to test our results with the more recent studies in N-body simulations such as [12]. The next steps are combine the likelihood for the bias with the likelihood for the number of clusters as a function of richness and redshift. Therefore we could constrain the cosmological parameters and at the same time we calibrate the mass

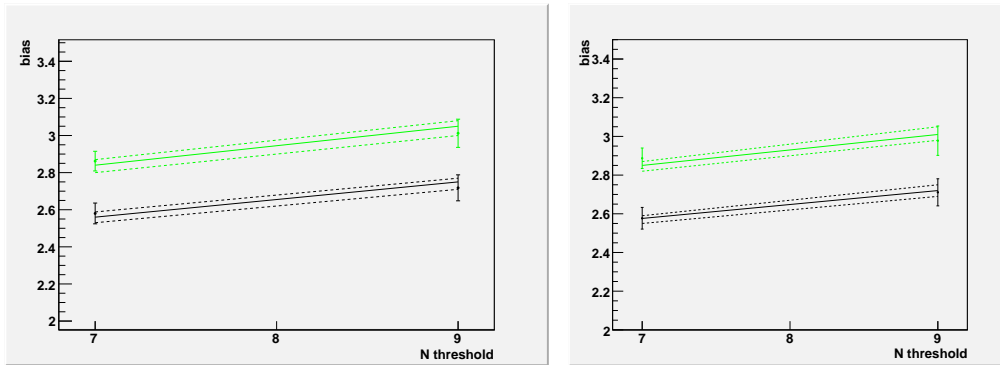


Figure 3: Richness bias model with most likely scatter value (solid line) and one sigma away (dashed lines) at mean redshift $z=0.3$ (black) and $z=0.5$ (green) for the true scatter $\sigma_{\ln M} = 0.2$ (left) 0.4 (right). Points are the richness bias measurements.

observable relation with the combined likelihood. These types of analysis are often called “self calibration” (see [6]).

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