

Have Baryonic Acoustic Oscillations in the galaxy distribution really been measured?

Anna Cabré¹, Enrique Gaztañaga²

¹*Department of Physics and Astronomy, University of Pennsylvania, 209, South 33rd Street, Philadelphia, PA 19104-6396, USA*

²*Instituto de Ciencias del Espacio (IEEC/CSIC), F. de Ciencias, Torre C5- Par-2a, Bellaterra, 08193 Barcelona, Spain.*

Accepted —. Received —; in original form —

ABSTRACT

Recent publications claim that there is no convincing evidence for measurements of the baryonic acoustic (BAO) feature in galaxy samples using either monopole or radial information. Different claims seem contradictory: data is either not consistent with the BAO model or data is consistent with both the BAO model and featureless models without BAO. We investigate this point with a set of 216 realistic mock galaxy catalogs extracted from MICE7680, one of the largest volume dark matter simulation run to date, with a volume of 1300 cubical gigaparsecs. Our mocks cover similar volume, densities and bias as the real galaxies and provide 216 realizations of the Λ or $\omega = -1$ Cold Dark Matter (ω CDM) BAO model. We find that only 20% of the mocks show a statistically significant (3 sigma) preference for the true (input) ω CDM BAO model as compared to a featureless (non-physical) model without BAO. Thus the volume of current galaxy samples is not yet large enough to claim that the BAO feature has been detected. Does this mean that we can not locate the BAO position? Using a simple (non optimal) algorithm we show that in 50% (100%) of the mocks we can find the BAO position within 5% (20%) of the true value. These two findings are not in contradiction: the former is about model selection, the later is about parameter fitting within a model. We conclude that current monopole and radial BAO measurements can be used as standard rulers if we assume ω CDM type of models.

Key words: galaxies: statistics, cosmology: theory, large-scale structure.

1 INTRODUCTION

Primordial fluctuations generated acoustic waves in the early universe photon-baryon plasma. Those waves were frozen at decoupling, $z \sim 1100$, then baryon acoustic oscillations (BAO) were imprinted in the cosmic microwave background (CMB) at the sound horizon scale, as a series of peaks in the power spectrum or a single peak in the 2-point correlation function (see eg Peebles and Yu, 1970 and Komatsu et al 2010 for the latest measurements by WMAP).

BAO can also be seen at the present in matter power spectrum, and its position, r_{BAO} can be used as a standard cosmological ruler. Measurements in the radial (redshift direction), Δz , can be used to estimate the Hubble rate as $H(z) = c\Delta z/r_{BAO}$, while angular measurements, $\Delta\theta$, can be used to estimate the angular diameter distance: $D_A(z) = r_{BAO}/\Delta\theta$. Baryon acoustic oscillations in the galaxy correlations of the Sloan Digital Sky Survey (SDSS) luminous red galaxy (LRG) sample have been used to constrain cosmological parameters (eg Eisenstein et al 2005, Hutsi et al 2006, Sanchez et al 2009, Percival et al 2010,

Reid et al 2010, Kazin et al 2010a and references therein). Different studies use different ways to extract the BAO signal and quantify the significance of the measurements (see Sanchez et al 2008). For example, Eisenstein et al 2005 and Sanchez et al 2009 used the full shape of the 2-point correlation to ω CDM class of models and found constraints to the combination distance $D_v(z) = (D_A^2/H)^{1/3}$ to the galaxy sample mean redshift based on a global χ^2 fitting, while Percival et al 2010 used a fit to the oscillatory components in the power spectrum to find constraints on $D_v(z)$.

These previous analysis used the monopole component of the correlation function, where all pairs are averaged with independence of their orientation. Okumura et al 2008 did a separate analysis of pairs as a function of orientation but avoiding the radial direction. Gaztanaga, Cabré and Hui (2009, GCH hereafter) presented constraints to $H(z)$ based on the radial correlation, which uses only those pairs aligned with the redshift direction. This reduces the number of observational data but boost the contrast on the BAO peak because of redshift space distortions. At intermediate scales, lower than BAO, the correlation function becomes negative

in the line-of-sight direction, creating a better contrast in the BAO position, easier to detect than in real space. Also, non-linearities, magnification and bias can boost the peak (see GCH and Tian et al 2010 for further details).

GCH presented two ways to analyze the BAO data: the peak and the shape method. In the peak method they find the location of the peak and use it as standard ruler to measure $H(z)$. In the shape method they use a χ^2 fit to the full shape of the correlation and find the best shift in the distance $H(z)/H_0$. The shape method was also used to test if the data was compatible with the shape of the correlation expected in ω CDM. They compare different classes of models: the standard BAO ω CDM model, a similar class of models without BAO (so called no-wiggle model in Eisenstein & Hu 1998) and a model with zero correlation $\xi = 0$. The no-BAO model has $\Delta\chi^2 = 10$ with respect to the best fitting ω CDM model while a model with $\xi = 0$ has $\Delta\chi^2 = 4$. Kazin et al (2010b) did an independent analysis of the SDSS catalog and found similar results for the correlation measurements and errors. In their interpretation they did not explore the parameter space of ω CDM but conclude that there is no convincing evidence for radial BAO because the $\xi = 0$ model fit the data better than ω CDM. They argue that there are no parameters in the $\xi = 0$ model while for ω CDM several parameters were fitted in GCH. After including the penalty for adding parameters, they find that ω CDM is not significantly better than $\xi = 0$.

But a similar argument could be extended to the BAO monopole measurements. For example, if one fits a constant correlation to the LRG correlation function in Fig.17 of Sanchez et al (2009) to scales larger than 70 Mpc/h one finds that this model can not be distinguished from a ω CDM model with free parameters. The original Eisenstein et al (2005) results can also be well fitted with a power-law model¹. Does this mean that the BAO feature has not been detected at all? These are important points to clarify as it is common practice to include BAO measurements when fitting cosmological models to provide evidence for dark energy models (eg Sanchez et al 2009; Komatsu et al 2010; Kazin et al 2010a; Gaztanaga, Miquel & Sanchez 2009).

Other recent studies seem to reach a similar conclusion, that the BAO feature has not been detected, but using an argument that seems to go in the opposite direction. Rather than finding that data is too noisy and compatible with featureless models, they find that the data is not consistent with ω CDM (eg see Labini et al 2009, Labatie et al 2010). Also see Martinez et al 2009 for a study of peak detection using DR7 monopole. We will investigate this here to find, as in previous analysis (eg GCH, Sanchez et al 2009, Kazin et al 2010a) that data is in good agreement with ω CDM although we should stress that this statement will depend on the specific test we use.

We will argue that there are two separate questions mixed up in the above line of argumentation: model selection and parameter fitting. We will find that while current data can not be used to select ω CDM, one can still constrain the parameters of ω CDM if this model is assumed. To show this, we will set out to address two main questions: 1) can we use current BAO data to favor ω CDM? In other words: is the volume of current data large enough to pass a null detection test to choose ω CDM over some other model? 2)

can we constrain the parameters of the ω CDM model, and in particular the BAO position with current data?

We will investigate these points with a set of 216 mock galaxy catalogs extracted from MICE7680 (see Fosalba et al 2008, Crocce et al 2009), one of the largest volume dark matter simulation run to date. The mocks are made to match the SDSS LRG DR6 sample and should therefore provide a good representation of biased ω CDM realizations. We will use these mocks to explore the peak and the shape method applied to the monopole. We use the monopole here (rather than radial BAO) for several reasons: shape measurements have larger signal-to-noise, theoretical modeling of monopole is better understood (see GCH) and the monopole BAO has been more widely used to test cosmological models. Rather than comparing the ω CDM with some add-hoc correlation (power-law, constant or some combination) we choose to focus on comparing BAO and no-BAO models. This has the advantage of being a well defined procedure (quite standard in the literature) where we have the same number of parameters in each case, which simplifies the interpretation of the statistical significance when comparing two different models with different number of parameters (eg see Liddle 2009).

Throughout we assume a standard cosmological model, with $\Omega_M = 0.25, \Omega_\Lambda = 0.75, \Omega_b = 0.044, n_s = 0.95, \sigma_8 = 0.8$ and $h \equiv H_0/(100 \text{ km s}^{-1} \text{ Mpc}^{-1}) = 0.7$.

2 BAO IN GALAXY MOCKS

Appendix A in Cabré & Gaztanaga 2009 (CG09 from now on) describes how our mocks were built and also how the correlation function is estimated.¹ We include both bias and redshift distortions in the mocks. We will focus here on the monopole correlation for halo $z=0$ mocks with a bias $b \simeq 2$, similar to LRG galaxies. The correlation function for our 216 mocks, its mean and errors are displayed in Fig.1. These mocks are realistic as they cover similar volume, densities and bias as the real LRG galaxies, but they have some limitations. In general, one needs first to explore the parameters in ω CDM (and bias model) to get a good match to data. Our simulations have $\beta \equiv f(\Omega_m)/b \simeq 0.25$ and $z = 0$, which are different from the values in real data $\beta \simeq 0.34 \pm 0.03$ and $z = 0.35$ (the difference in β comes from the difference in redshift, as bias is similar, see CG09). Depending on the test used, this could result in a poor fit of models to data. Despite these limitations, we will find below a good fit of data to the mocks when we allow the amplitude to vary in the fit. This indicates that our mocks provide a good representation of the data, given the errors, at least for the questions we want to address here.

In our analysis we will pretend that each mock is a realization of the real LRG data. Our mocks are close enough to the real data to provide a realistic representation of how much variation there is from one realization of real data to the other. Indeed the jack-knife (JK) errors (and covariance matrix) in the real data are similar to the JK errors in our mocks and to the ensemble variation from mock to mock. This was shown in CG09 and can also be seen in Fig.1 where we compare the ensemble variation in mocks (short dashed lines) to the JK errors in the DR6 SDSS LRG measurements from CG09 (note that we show DR6 to be consistent with

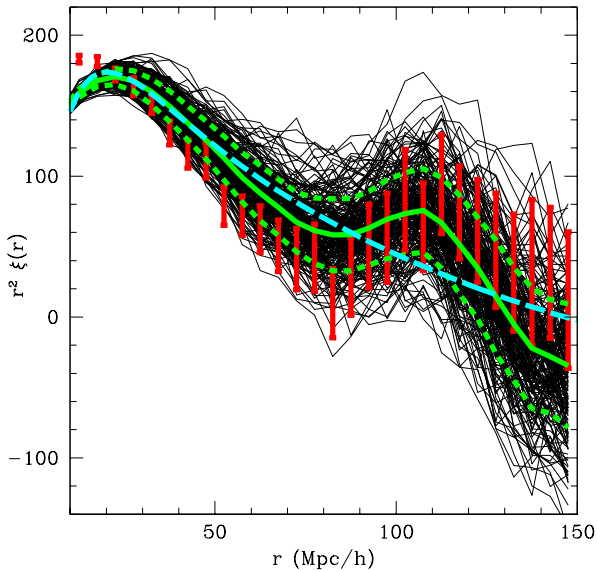


Figure 1. Thin (black) lines show the correlation function $\xi(r)$ (scaled by r^2) in each of our 216 mocks. Solid (green) line shows the BAO model (the mean of the mocks). Short dashed (green) lines encompass 1-sigma errorbars from the mean (these are mock to mock errors, the error of the mean would be $1/\sqrt{216}$ better). Long dashed (blue) line shows the no-BAO model. The (red) errorbars correspond to the real LRG data shifted as shown in Eq.1.

the mocks, but similar results are found for DR7, see GCH). To compare to simulations we have scaled the LRG data as:

$$\xi(r) \rightarrow A [\xi(r) + K] \quad (1)$$

with $A = 1.2$ and $K = -0.005$. The value of A accounts for the differences between the simulation and LRG data in β , growth and bias. The value of K represents a possible, but quite minor (0.25%), error (contamination or sampling fluctuation) in the overall mean density of the sample. This has little impact in the fit of models to data (covariance allows for a constant shift in the data) but improves the visual comparison in the figure (see Fig.17 in Sanchez et al 2009). As indicated by Fig.1 the mocks represent quite well the variation seen in the observational data.

2.1 The shape method: null test

We use two models to fit the correlation $\xi(r)$: 1) *the BAO model*: it uses the mean of all the mocks in order to have a perfect BAO model (with bias, redshift space and non-linearities effects included). 2) *the no-BAO model*: a non-physical model that imitates well the broad band correlation but does not include a BAO peak. We use the no-wiggle power spectrum of Eisenstein & Hu (2001) with same ω CDM parameters as the simulation. Fig.1 compares the BAO (solid line) with the no-BAO model (long-dashed line). Our null test is: does the data prefer the BAO to the no-BAO model at 3-sigma confidence level (CL)?

To simplify the analysis and interpretation, the only free parameter that we fit is the global amplitude A of the correlation, which includes a possible bias (as we are using halos) and a constant redshift distortion boost (Kaiser

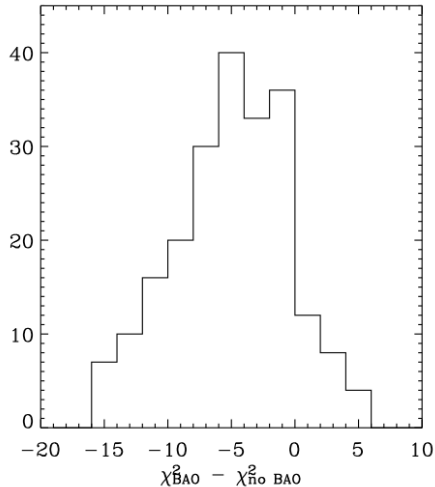


Figure 2. Histograms showing the distribution of differences in χ^2 values for different LRG mocks. The correlation function in each mock is fitted with both the standard ω CDM BAO correlation and with the no-BAO class of models. The difference between the two χ^2 values in each mock is accumulated in the histogram. There are $N_b = 20$ data bins in each fit, but only one parameter is fitted (the overall amplitude). The figure shows that only 20% of the cases show a significant preference at 3σ (ie $\Delta\chi^2 < -9$) for the BAO model over the no-BAO model. The mean for mocks is $\Delta\chi^2 = -5$. A fit to the real LRG data gives also $\Delta\chi^2 = -5$, close to the maximum.

1987). We use the correlation function $\xi_i(r_j)$ measured in the i -th mock at separation r_j to perform a χ^2 fit and find the best fit amplitude A_i for either BAO or no-BAO models (which are labeled generically as ξ_m):

$$\chi_i^2 = \sum_{jk} [\xi_i(r_j) - A_i \xi_m(r_j)] C_{jk}^{-1} [\xi_i(r_k) - A_i \xi_m(r_k)] \quad (2)$$

The indexes j and k run over the $N_b = 20$ bin separations, ie $\nu = 19$ degrees of freedom. Bins are linearly spaced with $\Delta r = 5$ Mpc/h between 30 and 130 Mpc/h (we find similar results in the range 20-150 Mpc/h). The covariance matrix C_{jk} is estimated from the mocks:

$$C_{jk} = \frac{1}{215} \sum_{i=1}^{216} [\xi_i(r_j) - \bar{\xi}(r_j)] [\xi_i(r_k) - \bar{\xi}(r_k)] \quad (3)$$

where $\bar{\xi}(r_j) \equiv \frac{1}{216} \sum_i \xi_i(r_j)$ is the mean value in bin j .

The resulting distribution of values of χ_i^2 for the BAO model peaks around $\chi_i^2 \simeq \nu = 19$ and is quite broad ($\Delta\chi^2 \simeq \sqrt{2\nu} \simeq 6$, as expected). The no-BAO model peaks at larger values ($\chi_i^2 \simeq 24$) and is slightly broader ($\Delta\chi^2 \simeq 7.7$). The real LRG data produces $\chi^2 = 20$ for the BAO model and $\chi^2 = 25$ for the no-BAO model, well within the values found for most of the mocks. Thus, given the large errorbars, the real data seems to match quite well our mocks, despite the differences in the modeled values of β , bias and z mentioned above.

In Fig.2 we plot the histogram of the differences between the χ_i^2 values in the fits to the BAO and no-BAO models for each mock. Negative values mean that the mock prefers the BAO model over no-BAO model. A difference at 3σ CL between both models, ie $\Delta\chi^2 < -9$, only happens in the 20% of cases (up to 30% when we explore other range of

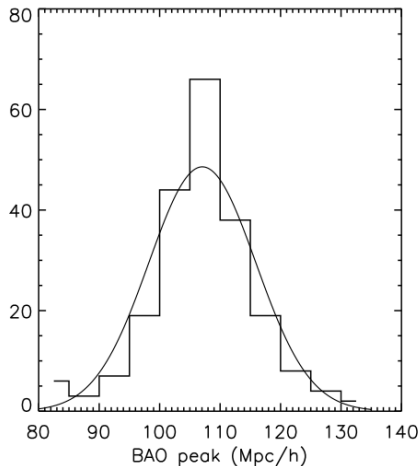


Figure 3. Histogram showing the distribution of peak BAO position measured in LRG mocks. This distribution has $r_{BAO} = 107.2 \pm 8.8$ Mpc/h as compared to $r_{BAO} = 107.5$ Mpc/h in the mean model. The distribution is quite gaussian, as shown by the line crossing the histograms. The same measurement in real LRG DR6 data yields $r_{BAO} = 112$ Mpc/h.

scales). This means that in 80% of the cases one does not expect to be able to distinguish between the two models (at more than 3σ CL). This result is not surprising. The mean difference in χ^2 between the BAO and no-BAO model is only $\Delta\chi^2 \simeq -5$, which is comparable to the width of the χ^2 distribution with 19 degrees of freedom. In other words, current errors are still too large to claim a BAO detection.

2.2 The peak method: BAO position

In the peak method, we assume that we live in a ω CDM universe and try to locate the BAO position. To keep things simple, here we locate the position of the peak by searching the maximum in the correlation function in the BAO scale, between 80-135Mpc/h (results are similar when we move around 70-150Mpc/h). The BAO feature is modified by the presence of the broad band (CDM) correlation function, which can be modeled approximately by a power law. We fit a power law to each correlation function at small scales (10 - 70Mpc/h) and subtract the correlation function from the best power law before locating the peak. GCH use a very similar peak method but do not need to subtract the power-law because the correlation is quite flat (and close to zero) in the radial direction. Sanchez et al (2010) use a similar but more elaborated version, where they fit simultaneously a power-law, a constant shift and a gaussian (BAO) peak. This would provide more accurate errors for the peak.

Fig. 3 shows the distribution of recovered BAO positions for individual mocks. This distribution is well approximated by a Gaussian (also shown in the figure). The mean BAO position is 107.2Mpc/h with a dispersion of 8.8Mpc/h, compared to mocks mean value position at 107.5Mpc/h (note that the resolution in the position of the peak is of 5Mpc/h). The position of the peak can differ slightly (less than 2%) from the sound horizon scale at decoupling (see Sánchez, Baugh and Angulo 2008 and Sánchez et al 2010) depending on the cosmology, non-linearities, and other ef-

fects. For WMAP parameters, very similar to MICE simulation, the sound horizon scale is at 107.3Mpc/h.

We find similar results when we use a fixed power-law for all mocks, the one fitted for the mean correlation function, or when using the best power-law for each mock, as one would do in real data. When we apply the same method to the real DR6 data we find $r_{BAO} = 112$ Mpc/h, well within the bulk of our mocks.

We have also tried the method to locate the BAO position proposed by Kazin et al (2010a). The mocks (or data) are fitted using a χ^2 likelihood (including covariance) to a BAO model which consists in the mean of the mocks, $\xi_m(r)$, shifted by two free parameters: the amplitude A and a scale shift α , ie $A\xi_m(\alpha r)$. We find a very similar histogram to that in Fig.3 but with smaller errorbar: 6% instead of 8%. Kazin et al (2010a) further reduced this error to 3 - 4% by using only the mocks which have a clear BAO as in the DR6 data. We will obviously get smaller errors by removing such outliers in our mocks but this later step involves more assumptions than just the existence of a peak. It not only assumes that we live in ω CDM, but selects in a subjective way (a posteriori) within a subset of realizations. Also note that in this method we are using a priori knowledge of the shape of the input model to locate the peak. In the peak method, used in Fig.3, we do not need to make such assumption and so we think this makes a stronger case for the point we want to demonstrate, even when the error is larger.

It is more robust and self-consistent to locate the BAO and error using the full shape of $\xi(r)$ and a larger family of cosmological models, eg as shown in Sanchez et al (2009), avoiding any dependence on a particular cosmology in the algorithm to locate the peak. The point demonstrated here is that the BAO position is imprinted in the mocks despite the fact that they do not pass a null detection test. A comparison between methods is left for future analysis.

3 CONCLUSION

The first question we set out to address was if the volume of current BAO data is large enough to pass a null detection test for ω CDM. The answer to this question seems negative. We have shown in Fig.2 that the distribution of χ^2 differences is quite broad and one could find mocks for which the null test is passed or failed. In fact 80% of the mocks have $\Delta\chi^2 > -9$, which indicates no statistically significant (at 3-sigma CL) preference for the true BAO input model as compared to the featureless no-BAO family. Current SDSS (DR6-DR7) data seems to lie close to the peak of this distribution, $\Delta\chi^2 \simeq -5$, but according to Fig.2 this does not provide convincing evidence for the BAO model. As expected, the DR3 results in Eisenstein et al 2005 (about half of the DR6 volume) is even less significant: $\Delta\chi^2 \simeq -1.1$. When we compare the BAO model to a power-law fit (with 2 parameters) we find $\chi^2_{BAO} - \chi^2_{power-law} \simeq 0.4$.¹

Our mocks have slightly different values of β and z than the DR6 data (see Fig.1) and we wonder if this could affect the above conclusion. The important point to notice is that the BAO and no-BAO model also have a similar difference of $\Delta\chi^2$ (ie $\simeq -5$) when we compare to the DR6 data (using the same bins and covariance as in the mocks). Models with other cosmological parameters within the un-

certainties of ω CDM also produce similar $\Delta\chi^2$. But a value of $\Delta\chi^2 \simeq -5$ is comparable to the width of a χ^2 distribution with 19 degrees of freedom (which is $\Delta\chi^2 \simeq 6$). This is why the result is not significant. Our conclusion is quite robust and mostly relies in the size of the errors and covariance between bins. The covariance estimate is consistent in the data (ie from Jack-knife subsamples), in our mocks and in other mocks produced by several groups (eg Eisenstein et al 2005, CG2009, Kazin et al 2010a). We would need $\sqrt{1.8}$ times smaller errors, ie 1.8 times more data or some optimal weighting (Hamaus et al. 2010, Cai et al 2010), than DR6 (so that $\Delta\chi^2$ increases from 5 to 9) to be able to claim a 3 sigma BAO detection in the monopole.

For the radial BAO analysis, GCH reach similar conclusions. They find that the difference $\Delta\chi^2 \simeq -10$ in DR6 for 20 degrees of freedom (5Mpc/h radial bins within 40-140 Mpc/h) when comparing BAO (plus magnification) and no-BAO models (without magnification the difference is $\Delta\chi^2 \simeq -6$). This seems more significant than the monopole, probably because the radial BAO peak is boosted by redshift space distortions and magnification.

Does this mean that the BAO position can't be measured? If we assume the ω CDM model, we can locate the BAO position to better than 8% of the true value, as illustrated in Fig.3. We show that in 50% (100%) of the mocks we can find the BAO position within 5% (20%) of the true value. This error is an upper bound as we have not tried to optimize the method to locate the peak. We have compared the mocks with the real data and found no evidence for deviations away from the ω CDM. None of the 216 ω CDM realizations is identical to the measurements (or in fact to each other), but observations produce values that lie well within the histograms in Fig.2 and Fig.3 for the two simple but generic tests that we have explored here.

Lessons learned in this study can be applied to the monopole BAO analysis (eg Eisenstein et al 2005, Sanchez et al 2009, Percival et al 2010, Kazin et al 2010a) and the radial BAO in GCH (or the BAO in the 3-point function by Gaztanaga et al 2009). Kazin et al (2010b) have argued that because ω CDM does not fit the radial BAO data significantly better than a model with $\xi = 0$ (null test), the $H(z)$ measurements presented by CGH based on the location of the radial BAO peak can not be regarded as a detection. We have shown here that his argument is not necessarily correct. If we apply such argument to the monopole BAO measurements previously cited we would conclude that we can not locate the peak position in current data because according to Fig.2 there is no significant BAO detection. But we have shown here that we can locate the BAO position with reasonable accuracy even with data that fails the null BAO detection test. A similar analysis was done with Monte Carlo mocks in GCH for the radial BAO position. Even if the shape method gives low significance, the peak method can still be used to detect the position of the peak.

Tian et al 2010 reaches similar conclusions for the radial BAO peak using different simulations. They use a wavelet technique to detect the peak and asses the significance of the detection, splitting SDSS into slices in various rotations.

Current BAO measurements can not yet be used to select ω CDM, but they can be used to locate the BAO position (or other cosmological parameters) if one assumes ω CDM or

models which produce similar clustering (and errors) to the ones in ω CDM. ¹

ACKNOWLEDGEMENTS

We would like to thank Carlton Baugh, Pablo Fosalba, Ramon Miquel and Ariel Sanchez for their comments on earlier versions of this manuscript. The MICE simulations have been developed at the MareNostrum supercomputer (BSC-CNS) thanks to grants AECT-2006-2-0011 through AECT-2010-1-0007. Data products have been stored at the Port d'Informació Científica (PIC). This work was partially supported by the Spanish Ministerio de Ciencia e Innovación (MICINN), projects AYA2009-13936, Consolider-Ingenio CSD2007- 00060 and research project 2009-SGR-1398 from Generalitat de Catalunya.

REFERENCES

- Cabré, A. and Gaztañaga, E., 2009, MNRAS, 393, 1183
 Cai Y.-C., Bernstein G., Sheth R. K., 2010, arXiv:1007.3500
 Crocce, M., et al.2009, MNRAS, 403, 1353
 Eisenstein, D. J., & Hu, W. 1998, ApJ, 496, 605
 Eisenstein D.J., et al., 2005, ApJ, 633, 560
 Fosalba, P., et al.2008, MNRAS, 391, 435
 Gaztañaga, E. and Cabré, A. and Hui, L., 2009, MNRAS, 399, 1663
 Gaztañaga, E. and Miquel, R. and Sánchez, E., 2009, PhyRevLet, 103, 9
 Gaztañaga E., Cabré A., Castander F., Crocce M., Fosalba P., 2009, MNRAS, 399, 801
 Hamaus N., Seljak U., Desjacques V., Smith R. E., Baldauf T., 2010, PhRvD, 82, 043515
 Kaiser N., 1987, MNRAS, 227, 1
 Kazin, E. et al., 2010a, ApJ, 710, 1444
 Kazin, E. et al., 2010b, ApJ, 719, 1032
 Komatsu, E., et al., 2010, astro-ph/1001.4538
 Labatie A., et al., 2010, astro-ph/1009.1232
 Labini, S. et al 2009 A&A, 505, 981-990
 Liddle A., 2009, Ann.Rev.Nucl.Part.Sci.59, 95
 Martinez, V. et al., 2009, ApJ, 696, L93
 Okumura, T., et al., 2008, ApJ, 676, 889
 Peebles, P. J. E. and Yu, J. T., 1970, ApJ, 162, 815
 Percival W., et al., 2010, MNRAS 401, 2148
 Reid, B.A., et al., 2010, MNRAS, 404, 60
 Sánchez A. G., Crocce M., Cabré A., Baugh C. M., Gaztañaga E., 2009, MNRAS, 400, 1643
 Sánchez A. G., Baugh C. M., Angulo R., 2008, MNRAS, 390, 1470
 Sanchez E., et al, 2010, arXiv, arXiv:1006.3226
 Tian, H. J. and Neyrinck, M. C. and Budavári, T. and Szalay, A. S., 2010, arXiv, 1011.2481

¹ Data and mocks used in this paper, together with covariance matrix and additional figures can be found in <http://www.ice.csic.es/mice/baodetection>.