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

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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 Lambda or 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 ∼ 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), ∆z, can be used to estimate the Hubble rate as \( H(z) = c\Delta z/r_{BAO} \), while angular measurements, ∆θ, 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 \( D_A(z) = (D_{A}^2/H)_{1/3} \) to the galaxy sample mean redshift based on a global χ² fitting, while Percival et al 2010 used a fit to the oscillatory components in the power spectrum to find constraints on \( D_A(z) \).

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. Gaztananaga, 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 \( \chi^2 \) 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 \( \omega \mathrm{CDM} \). They compare different classes of models: the standard BAO \( \omega \mathrm{CDM} \) 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 \( \omega \mathrm{CDM} \) 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 \( \omega \mathrm{CDM} \) but conclude that there is no convincing evidence for radial BAO because the \( \xi = 0 \) model fit the data better than \( \omega \mathrm{CDM} \). They argue that there are no parameters in the \( \xi = 0 \) model while for \( \omega \mathrm{CDM} \) several parameters where fitted in GCH. After including the penalty for adding parameters, they find that \( \omega \mathrm{CDM} \) 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 \( \omega \mathrm{CDM} \) model with free parameters. The original Eisenstein et al (2005) results can also be well fitted with a power-law model\(^1\). 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 \( \omega \mathrm{CDM} \) (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 \( \omega \mathrm{CDM} \) 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 \( \omega \mathrm{CDM} \), one can still constrain the parameters of \( \omega \mathrm{CDM} \) 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 \( \omega \mathrm{CDM} \)? In other words: is the volume of current data large enough to pass a null detection test to choose \( \omega \mathrm{CDM} \) over some other model? 2) can we constrain the parameters of the \( \omega \mathrm{CDM} \) 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 \( \omega \mathrm{CDM} \) 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 \( \omega \mathrm{CDM} \) 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 \( \omega \mathrm{CDM} \) (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 \( \beta \) 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
To compare to simulations we have scaled the LRG data as:

\[ A \left[ \xi(r) + K \right] \]

with \( A = 1.2 \) and \( K = -0.005 \). The value of \( A \) accounts for the differences between the simulation and LRG data in \( \beta \), 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 Sancheza 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 \( \omega_c \)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 1987). We use the correlation function \( \xi(r) \) measured in the \( i \)-th mock at separation \( r \) to perform a \( \chi^2 \) fit and find the best fit amplitude \( A_i \) for either BAO or no-BAO models (which are labeled generically as \( \xi_n \)):

\[
\chi_i^2 = \sum_{jk} \left[ \xi_i(r_j) - A_i \xi_n(r_j) \right] C^{-1}_{jk} \left[ \xi_i(r_k) - A_i \xi_n(r_k) \right]
\]

The indexes \( j \) and \( k \) run over the \( N_b = 20 \) bin separations, i.e \( \nu = 19 \) 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:

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

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 \( \chi_i^2 \) for the BAO model peaks around \( \chi_i^2 \approx \nu = 19 \) and is quite broad (\( \Delta \chi^2 \approx \sqrt{2\nu} \approx 6 \), as expected). The no-BAO model peaks at larger values (\( \chi_i^2 \approx 24 \)) and is slightly broader (\( \Delta \chi^2 \approx 7.7 \)). 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 \( \beta \), bias and \( z \) mentioned above.

In Fig.2 we plot the histogram of the differences between the \( \chi_i^2 \) 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 3\( \sigma \) 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
difference in \( \chi \) only \( \Delta \) more than 3 \( \sigma \) scales). This means than in 80% of the cases one does not expect to be able to distinguish between the two models (at more than 3\( \sigma \) CL). This result is not surprising. The mean difference in \( \chi^2 \) between the BAO and no-BAO model is only \( \Delta \chi^2 \approx -5 \), which in comparable to the width of the \( \chi^2 \) 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 \( \omega \)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 effects. 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 \( \chi^2 \) likelihood (including covariance) to a BAO model which consists in the mean of the mocks, \( \xi_{BAO}(r) \), shifted by two free parameters: the amplitude \( A \) and a scale shift \( \alpha \), ie \( A \xi_{BAO}(\alpha r) \). 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 \( \omega \)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 \( \omega \)CDM. The answer to this question seems negative. We have shown in Fig.2 that the distribution of \( \chi^2 \) 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, \( \Delta \chi^2 \approx -5 \), 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: \( \Delta \chi^2 \approx -1.1 \). When we compare the BAO model to a power-law fit (with 2 parameters) we find \( \chi^2_{BAO} - \chi^2_{power-law} \approx 0.4\).\)

Our mocks have slightly different values of \( \beta \) 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 \( \approx -5 \)) 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 \(\omega \text{CDM}\) also produce similar \(\Delta \chi^2\). But a value of \(\Delta \chi^2 \approx -5\) is comparable to the width of a \(\chi^2\) distribution with 19 degrees of freedom (which is \(\Delta \chi^2 \approx 6\)). This is why the result is not significant. Our conclusion is quite robust with 19 degrees of freedom (which is \(\Delta \chi^2\) of \(\Delta \chi^2\) certainties of \(\Delta \chi^2\)).

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REFERENCES

Cabrè, 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 Cabrè, 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, PhysRevD, 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