The clustering of the SDSS-IV extended Baryon Oscillation Spectroscopic Survey DR14 quasar sample: anisotropic clustering analysis in configuration space

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ABSTRACT
We explore the cosmological implications of anisotropic clustering measurements of the quasar sample from Data Release 14 (DR14) of the Sloan Digital Sky Survey IV extended Baryon Oscillation Spectroscopic Survey (eBOSS) in configuration space. The ∼147 000 quasar sample observed by eBOSS offers a direct tracer of the density field and bridges the gap of previous baryon acoustic oscillation measurements between redshift 0.8 < z < 2.2. By analysing the two-point correlation function characterized by clustering wedges $\xi_w(s)$ and multipoles $\xi_\ell(s)$, we measure the angular diameter distance, Hubble parameter, and cosmic structure growth rate. We define a systematic error budget for our measurements based on the analysis of N-body simulations and mock catalogues. Based on the DR14 large-scale structure quasar sample at the effective redshift $z_{\text{eff}} = 1.52$, we find the growth rate of cosmic structure $f_{\sigma_8}(z_{\text{eff}}) = 0.396 \pm 0.079$, and the geometric parameters $D_M(z)/r_d = 26.47 \pm 1.23$, and $F_{\text{AP}}(z) = 2.53 \pm 0.22$, where the uncertainties include both statistical and systematic errors. These values are in excellent agreement with the best-fitting standard Λ cold dark matter model to the latest cosmic microwave background data from Planck.

Key words: cosmology – data analysis – large-scale structure of Universe – quasars.

1 INTRODUCTION

In the standard cosmological picture, the baryonic material in the early universe forms a hot plasma as it is tightly coupled to the photons via Compton scattering. Primordial inhomogeneities produce spherical acoustic waves that propagate outward from overdense regions. As the Universe evolves, the photons and baryonic matter decouple at the epoch of recombination and freeze the acoustic waves (Peebles & Yu 1970; Sunyaev & Zeldovich 1970), which leave an imprint on the large-scale structure (LSS) of the Universe known as the baryon acoustic oscillations (BAOs). This feature can be detected by analysing two-point statistics of the matter distribution, such as the power spectrum or the correlation function (Eisenstein & Hu 1998; Meiksin, White & Peacock 1999; Matsubara 2004). Since the scale associated with the BAO feature is closely related to the sound horizon at the drag redshift, $r_d \simeq 150$ Mpc, it can be used as a robust standard ruler to measure cosmic distances. Measurements of the BAO scale in the directions parallel and perpendicular to the line of sight at different redshifts can be used to probe the redshift evolution of the Hubble parameter, $H(z)$, and the angular diameter distance, $D_M(z)$, through the Alcock–Paczynski (AP) test (Alcock & Paczynski 1979; Blake & Glazebrook 2003; Linder 2003).

At low and intermediate redshifts, $z \lesssim 1$, BAO measurements can be obtained using galaxies as tracers of the LSS of the Universe. The first detections of the BAO signal in LSS by Cole et al. (2005) and Eisenstein et al. (2005) used data from the two-degree Field Galaxy

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Redshift survey (Colless et al. 2001, 2003) and the luminous red galaxy (LRG) sample of the Sloan Digital Sky Survey (SDSS, York et al. 2000), respectively. Present-day distance measurements based on galaxy clustering have reached per cent level precision (Anderson et al. 2012, 2014a,b; Alam et al. 2017). At higher redshift, $z \sim 2.5$, the auto-correlation of $H$ i absorption lines (Busca et al. 2013; Delubac et al. 2015; Bautista et al. 2017) and cross-correlation with quasars (Font-Ribera et al. 2014) has also been used to detect the BAO signal.

Clustering measurements based on galaxy redshift surveys provide additional cosmological information beyond that contained in the BAO feature. A particularly important source of information is the signature of the so-called redshift-space distortions (RSD), induced by the line-of-sight component of the peculiar velocities of the galaxies. As the peculiar velocity field is sourced by the matter overdensity, the analysis of the resulting pattern of anisotropies in the clustering of the tracers can be used to constrain the growth rate of cosmic structures, usually expressed in terms of the combination $f\sigma_8(z)$ (Guzzo et al. 2008).

In this work, we employ quasars as tracers of the LSS of the Universe. Quasars, whose luminosities are powered by supermassive black holes at their centres, are intrinsically much more luminous than galaxies and can be detected at higher redshifts. Thus, they open a new redshift range for LSS clustering analyses. The Data Release 14 (DR14) quasar sample from the extended Baryon Oscillation Spectroscopic Survey (eBOSS, Dawson et al. 2016), covers the redshift range $0.8 < z < 2.2$, bridging the gap between the measurements inferred from the clustering of galaxies and those recovered from the Ly $\alpha$ forest of high-redshift quasars. We characterize the spatial distribution of the eBOSS DR14 quasar sample by means of clustering statistics in configuration space. We measure the two-point correlation function and decompose it into Legendre polynomials (Padmanabhan & White 2008; Samushia et al. 2014) and clustering wedges (Kazin et al. 2013; Sánchez et al. 2013, 2014, 2017). The analysis of the full shape of these measurements allows us to exploit the joint information from BAO and RSD, which we compress into measurements of the geometric parameter combinations $D_V(z)/D_M(z)$, where $D_V(z)\propto(D_M(z)/H(z))^{1/3}$, and $F_{\delta p}\propto D_M(z)/H(z)$, and the growth rate parameter $f\sigma_8(z)$.

This work is part of a series of papers analysing the anisotropic clustering pattern of the DR14 LSS quasar sample (Gil-Marín et al. 2018; Ruggeri et al. 2018; Zarrouk et al. 2018; Zhao et al. 2018). Of these analyses, those of Gil-Marín et al. (2018) and Zarrouk et al. (2018) are more similar to this paper. Gil-Marín et al. (2018) use the RSD model of Taruya, Nishimichi & Saito (2010) to extract cosmological information from the full shape of Legendre multipoles in Fourier space. Zarrouk et al. (2018) use configuration-space clustering measurements identical to the ones in this paper, but applying a different model based on convolution Lagrangian perturbation theory (CLPT, Carlson, Reid & White 2013) and the Gaussian streaming model of RSD (Reid & White 2011). The analyses of Ruggeri et al. (2018) and Zhao et al. (2018) are based on Fourier-space measurements, but computed after applying a set of redshift-dependent weights to the QSO eBOSS catalogues that allow for lossless compression of the information along the redshift direction. A full comparison between the conventional analyses and the redshift-weighted methods can be found in Zarrouk et al. (2018).

This paper is structured as follows: Section 2 provides detailed information on the eBOSS DR14 quasar survey, presents our anisotropic clustering measurements based on this sample, and describes our methodology to obtain cosmological constraints out of them. This section also introduces the mock catalogues that are used to estimate the covariance matrix of our clustering measurements and for model testing. Section 3 contains a short review of our model of the anisotropic correlation function and its validation using the mock catalogues and N-body simulations. In Section 4, we present the geometric constraints and measurements of the growth of structure derived from the eBOSS quasar sample. Finally, Section 5 presents a summary of our main results and our conclusions.

2 THE CLUSTERING OF QUASARS IN EBOSS

2.1 The extended Baryon Oscillation Spectroscopic Survey

The eBOSS is a part of SDSS-IV (Blanton et al. 2017) and mainly focuses on mapping the distribution of LSS using a variety of tracers: LRGs $0.6 < z < 0.8$, emission line galaxies $0.7 < z < 1.1$, and a low-redshift quasar sample at $0.8 < z < 2.2$ (hereafter, LSS quasars) that is the focus of this paper. The eBOSS DR14 sample consists of two sky regions: with 116 866 objects in the Northern Galactic Cap (NGC) and 77 935 in the Southern Galactic Cap (SGC). The survey footprint covers an area of ca. 21 122.92 deg$^2$ with a mean completeness of $\sim 0.97$.

The eBOSS quasar candidates are selected through the imaging data from SDSS-I/II/III (Gunn et al. 2006), the 2.5-meter Sloan Telescope, and the Wide Field Infrared Survey Explorer (WISE, Wright et al. 2010). In order to facilitate clustering measurements, the sample is selected homogeneously with a comoving number density of $n \simeq 10^{-5}$ (Mpc/h)$^3$. The ‘CORE’ selection is performed by a likelihood-based routine extreme deconvolution (XDQSOZ, Bovy et al. 2012) over five broad bands $ugriz$, with a mid-IR-optical colour cut from WISE imaging to help distinguish quasars from stars (Myers et al. 2015). Apart from the ‘CORE’ sample, another selection based on variability in multi-epoch imaging from the Palomar Transient Factory (Rau et al. 2009) was also applied.

The targets are observed by the BOSS double-arm spectrographs (Smee et al. 2013). The DR14 LSS quasar catalogue comes from three sources: Legacy survey, a previous SDSS project, with confident redshift measurements; SEQUELS, a pilot survey for eBOSS started during SDSS-III; and eBOSS, which contains over 75 per cent of the redshifts in the DR14 LSS catalogues.

The selected quasar targets and the corresponding redshift information are combined to construct the LSS quasar catalogue. The redshift estimate starts with the SDSS pipeline, which is based on principal component analysis. When the identification and redshift of a target is considered inaccurate, a further visual inspection is applied. If the Mg $\alpha$ emission line is present at a spectra, its peak is used as an estimator of the redshift. The redshift estimate based on this broad emission line is considered as the most robust estimate given the redshift range of the DR14 sample. Otherwise, the peak of C iv is used (Pâris et al. 2012), but this line is potentially affected by the quasar outflow (Hewett & Wild 2010; Shen et al. 2016). The uncertainty in redshift determination can have an impact on the clustering measurement, given that our sample sits at a relatively high redshift. This effect needs to be taken into account in our clustering modelling, and we will further stress this point in Section 3.1.

2.2 Anisotropic clustering measurements

The correlation function $\xi(s)$ characterizes the probability (in excess of random) of observing pairs of galaxies as a function of their separation, $s$. Assuming rotational symmetry along the line-of-sight direction, the correlation function is reduced to the two-dimensional...
function $\xi(s) \equiv \xi(\mu, s)$, where $\mu = \cos(\theta)$, and $\theta$ is the angle between the separation vector $s$ and the line-of-sight direction. The analysis of the full two-dimensional correlation function $\xi(\mu, s)$ poses two problems: its low signal-to-noise ratio and the large size of its covariance matrix. Fortunately, the information of the full anisotropic correlation function can be condensed into a small set of one-dimensional projections, such as the Legendre multipoles obtained by expanding $\xi(\mu, s)$ in terms of Legendre polynomials, given by

$$\xi_\ell(s) \equiv \frac{2\ell + 1}{2} \int_{-1}^{1} \xi(\mu, s) L_\ell(\mu) \, d\mu,$$

or, alternatively, by computing angular averages over wide $\mu$-bins, commonly referred to as clustering wedges (Kazin, Sánchez & Blanton 2012)

$$\xi_{\Delta \mu}(s) \equiv \frac{1}{\Delta \mu} \int_{\mu_1}^{\mu_2} \xi(\mu, s) \, d\mu,$$

where $\Delta \mu = \mu_2 - \mu_1$. These statistics are related by

$$\xi_{\Delta \mu}(s) = \sum_{\ell} \xi_{\ell}(s) \, L_\ell,$$

where $L_\ell$ is the average of the Legendre polynomial of the order of $\ell$ over the $\mu$-bin of the clustering wedge. We consider measurements of the Legendre multipole, quadrupole, and hexadecapole moments ($\ell = 0, 2, 4$), as well as of wedges defined in terms of two and three wide angular bins obtained by dividing the $\mu$ range from 0 to 1 into two and three equal-width intervals. We refer to the individual wedges obtained in this manner by $\xi_{\text{FW-generated}}(s)$, with $n = 2, 3$, for the intervals $(i-1)/n < \mu < ih$.

Note that the observed quasar density in the eBOSS catalogue is affected by the systematic effects, and observing and targeting strategies. Therefore, a series of weights need to be applied to correct for these effects, which are as follows:

(i) Systematic weight $w_{\text{sys}}$ is introduced to remove the Galactic extinction and magnitude limiting dependency.

(ii) Close pair weight $w_{\text{cp}}$ is used to upweight a quasar in case the projected spatial separation between this quasar and its close neighbour is below the fiber resolution.

(iii) Focal plane weight $w_{\text{fp}}$ corrects for the failure in obtaining redshift due to the position of the fiber with respect to the focal plane coordinate.

(iv) A radial weight $w_{\text{R}}$ (Feldman, Kaiser & Peacock 1994) is applied to minimize the variance of measurement, $w_{\text{R}} = (1 + P_n(z))^{-1}$, where we have set $P_n = 6000 h^{-3} \text{Mpc}^3$ and $n(z)$ is the expected number density as a function of redshift.

The final weight applied to the objects is defined by

$$w_{\text{fin}} = w_{\text{R}} w_{\text{sys}} w_{\text{cp}} w_{\text{fp}}.$$  

Fig. 1 shows the Legendre multipoles $\xi_{\ell = 0, 2, 4}(s)$ (left-hand panel) and clustering wedges (right-hand panel) as a function of the pair separation with binning of $ds = 8 h^{-1} \text{Mpc}$. The error bars correspond to the best fit to the data points using the theoretical model described in Section 3.1.

We first measured the full two-dimensional correlation function $\xi(\mu, s)$ of the quasar sample using the estimator of Landy & Szalay (1993) and computed the Legendre multipoles and $\mu$-wedges using equations (1) and (2). We employed a random catalogue following the same selection function as the real eBOSS data, but containing 40 times more objects.

The redshift of each quasar in the catalogue was transformed into a redshift due to the position of the fiber with respect to the focal plane coordinate. The redshift of each quasar in the catalogue was transformed into a redshift due to the position of the fiber with respect to the focal plane coordinate.
given by

\[ q_\perp = \frac{D_M(z_m)}{D_M(z_m)}, \quad \mu \]

\[ q_\parallel = \frac{H'(z_m)}{H(z_m)}, \quad (6) \]

This rescaling distorts the shape of the measured correlation function \( \xi(s, \mu) \rightarrow \xi(s, \mu') \), with (Ballinger, Peacock & Heavens 1996)

\[ s = s' \sqrt{q_\perp^2(\mu')^2 + q_\perp^2(1 - \mu'^2)} \]

and

\[ \mu = \frac{q_\parallel \mu'}{\sqrt{q_\perp^2(\mu')^2 + q_\perp^2(1 - \mu'^2)}}. \]

The geometric distortions described by equations (7) and (8) are the basis of the use of the BAO signal in the directions transverse and parallel to the line of sight to obtain measurements of the angular diameter distance \( D_M(z_m) \) and the Hubble parameter \( H(z_m) \) (Blake & Glazebrook 2003; Hu & Haiman 2003; Linder 2003). As the intrinsic BAO position depends on the sound horizon at drag epoch, \( r_d \), the information of the measurements is often expressed in terms of rescaling parameters that include the fiducial sound horizon

\[ \alpha_\perp = q_\perp \frac{r_d}{r_d} \]

\[ \alpha_\parallel = q_\parallel \frac{r_d}{r_d} \]

which are commonly referred to as AP parameters (Alcock & Paczynski 1979). It is worth noticing that when fitting the full shape of the correlation function, it is not possible to fully separate the BAO feature from the rest of the information included in the correlation function, i.e. the rescaling by the sound horizon can be due to other reason than the shift of BAO peak. Nevertheless, it is still a good approximation since the BAO is a key feature in the correlation function.

2.3 Covariance matrices and mock catalogues

We estimate the covariance matrices of the measurements described in Section 2.2 using 1000 mock catalogues constructed using EZmocks (Chuang et al. 2015a). These simulations are based on initial conditions generated using the Zel’’dovich approximation (Zel’dovich 1970), with parameters to effectively account for non-linearities and bias. The probability density function (PDF) of haloes is calibrated by mapping the density field to the BigMulti-Dark (BigMD) N-body simulations (Klypin et al. 2016). Additional scattering is added to the PDF to account for the stochastic bias, and a further fitting of the power spectrum and bispectrum is applied to account for non-linear effects and deterministic bias. The bias and Finger of God (FoG) parameters (Kaiser 1987) are calibrated against the DR14 LSS quasar catalogue, with independent treatment for the NGC and SGC. The quasars are assigned directly to the simulated dark matter particles. The light-cone mock catalogues are built using seven redshift shells, each of which is taken from a box with size of \((5\, h^{-1}\, \text{Gpc})^3\). All redshift shells for the ith mock have the same initial Gaussian density field but with different EZ-parameters. The redshift evolution of the EZ parameters is determined by solving a system of equation and equating them with the parameters measured from the data within three overlapped redshift bins. The details can be found in Ata et al. (2017). The redshift error is encoded in the EZmocks intrinsically due to the bias calibration with respect to the real data.

Each EZmock corresponds to an independent realization of a flat \(\Lambda\)CDM cosmology defined by a matter density parameter \( \Omega_m = 0.307 \), a baryon density of \( \Omega_b h^2 = 0.022 \), a dimensionless Hubble parameter \( h = 0.678 \), and no contribution from massive neutrinos. The power spectrum of these mocks is characterized by a scalar spectral index \( n_s = 0.96 \), normalized to a value of \( \sigma_8(z = 0) = 0.8225 \). These parameters correspond to a value of \( f_{\text{ns}8}(z = 1.52) = 0.378 \) at the mean redshift of the LSS quasar sample.

We computed the Legendre multi-poles and wedges of each mock catalogue using the same bin size and weights as for the real eBOSS LSS quasar sample, but assuming the true cosmology of the EZmock runs as our fiducial cosmology. These measurements were used to obtain an estimate of the full covariance matrix, \( \mathbf{C} \), associated with our clustering measurements, which were rescaled by a factor 1.03 to account for a mismatch in the number of objects in the mocks and the real eBOSS data. Fig. 2 shows the correlation matrices estimated from the EZmocks. The upper triangle shows the correlation matrix for the Legendre multi-poles, and the lower triangle presents the one for three clustering wedges. As expected, for covariance matrices with a large shot-noise contribution, the corresponding correlation matrices are dominated by the diagonal elements.

In addition to the EZmocks, we have also used a small set of high-fidelity mocks constructed from the OuterRim (Habib et al. 2016), a high-resolution \( N \)-body simulation characterized by a cubic box of size \( L = 3 \, h^{-1}\, \text{Gpc}\) evolving 10\,240\,3 dark matter particles with a force resolution of \( 6 \, h^{-1}\, \text{kpc} \) and a mass resolution per particle \( m_p = 1.82 \times 10^6 \, h^{-1}\, \text{M}_\odot \). The mocks are built from a single snapshot at \( z = 1.433 \) and based on a \((5+1)\)-parameter halo occupancy distribution model (HOD, Tinker et al. 2012), where the additional parameter is necessary for modelling the quasar duty cycle. The concentration of each halo is a function of its mass following the prescription detailed in (Ludlow et al. 2014)). The position and velocity of the satellites follow a Navarro–Frenk–White (NFW) profile (Navarro, Frenk & White 1996). Three configurations of satellite fraction were constructed for the HOD OuterRim: \( f_{\text{sat}} = 0 \) per cent, \( f_{\text{sat}} = 13 \) per cent, and \( f_{\text{sat}} = 25 \) per cent, respectively. A Gaussian smearing was applied to each configuration, to mimic the redshift error. The fiducial cosmology for OuterRim is consistent with WMAP7 (Komatsu et al. 2011), i.e. \( \Omega_m = 0.265 \), \( \Omega_b h^2 = 0.0235 \), \( h = 0.678 \), \( \sigma_8 = 0.8 \), \( n_s = 0.963 \), and zero neutrino.
mass. Further details for OuterRim simulation could be found in Zarrouk et al. (2018) and Gil-Marín et al. (2018).

2.4 The likelihood function

We use Bayesian statistics to infer our cosmological constraints. Assuming the evidence of the data is normalized to one, the posterior is given by $P(\xi|\lambda) \propto L(\xi|\lambda)P(\lambda)$, with $\lambda$ being the cosmological parameters of interest and a set of nuisance parameters that enter our model (see Section 3.1), and $\xi$ representing an array containing our clustering measurements. Assuming Gaussian-distributed data, the likelihood function is

$$L(\xi|\lambda) \propto \exp \left[ -\frac{1}{2} (\xi - \xi_{\text{model}}(\lambda))^T \Psi (\xi - \xi_{\text{model}}(\lambda)) \right],$$

(10)

where $\Psi = C^{-1}$ and $\xi_{\text{model}}(\lambda)$ represents the theoretical model used to describe our measurements for the parameters included in $\lambda$. As described in Section 2.3, we estimate the covariance matrices of our measurements from the sample variance of a set of 1000 mock catalogues. The noise in this estimate of $C$ makes its inverse a biased estimate of $\Psi$. This can be corrected by including a pre-factor in the estimate of the precision matrix as (Kaufman 1967; Hartlap, Simon & Schneider 2007)

$$\hat{\Psi} = \left(1 - \frac{N_b + 1}{N_m - 1}\right) \tilde{C}^{-1},$$

(11)

where $N_b$ represents the number of bins in the data vector and $N_m$ corresponds to the number of mocks used to estimate $C$. Although unbiased, the estimate of equation (11) remains affected by noise due to the finite number of mock catalogues, which should be propagated into the obtained constraints, increasing the parameter uncertainties (Dodelson & Schneider 2013; Taylor, Joachimi & Kitching 2013; Taylor & Joachimi 2014). As described in Percival et al. (2014), the results obtained when the estimate $\hat{\Psi}$ is used to compute the Gaussian likelihood function of equation (10) can be corrected to account for this additional uncertainty by rescaling the obtained parameter covariances by a factor that depends on $N_b$, $N_m$, and the dimension of the parameter space explored in the analysis, $N_p$. However, this simple rescaling does not provide a corrected version of the full parameter posterior distribution $P(\lambda|\xi)$.

Sellentin & Heavens (2016) followed a different approach, by marginalizing equation (10) over the true covariance matrix, conditioned on its estimated value. This procedure leads to a likelihood function that deviates from the simple Gaussian recipe, and follows a modified version of the multivariate t-distribution given by

$$L(\xi|\lambda) \propto \left[ 1 + \frac{(\xi - \xi_{\text{model}}(\lambda))^T \tilde{C}^{-1} (\xi - \xi_{\text{model}}(\lambda))}{N_m - 1} \right]^{-\frac{N_p}{2}},$$

(12)

which depends explicitly on the number of mocks on which the estimate $\tilde{C}$ is based. The results obtained by sampling this modified likelihood function correctly account for the additional uncertainty due to the noise in $\tilde{C}$, without the need to include any additional rescaling factor. We use the non-Gaussian likelihood function of equation (12) in our analysis. As discussed in Appendix A, for the number of mock catalogues used in our analysis, the results obtained by means of this likelihood function and those inferred using the standard Gaussian recipe are essentially identical.

3 THE MODEL

3.1 Modelling anisotropic clustering measurements

We base the theoretical description of our clustering measurements on a model of the power spectrum $P(\mu, k)$, which we Fourier transform to obtain the anisotropic two-point correlation function as

$$\xi(\mu, s) = \frac{1}{(2\pi)^3} \int P(\mu, k)e^{iks} \, dk.$$

(13)

We adopt the same model of non-linearities, bias, and RSDs as in the analyses of the final BOSS galaxy samples of Sánchez et al. (2017), Grebel et al. (2017), and Salazar-Albornoz et al. (2017), which extend to include the effect of non-negligible redshift errors. As this model has been discussed and tested in detail in these analyses, we will only briefly summarize it here.

The starting point of our model is the treatment of the non-linear evolution of the density field. On large scales, the evolution of density perturbations is determined by CDM; for this, we use renormalized perturbation (RPT) first proposed in Crocce & Scoccimarro (2006) supplemented by imposing Galilean invariance (gRPT, Crocce, Blas and Scoccimarro, in preparation). To describe the clustering of the quasar sample, we follow Chan, Scoccimarro & Sheth (2012) and parametrize the bias relation between the matter density fluctuations $\delta$ and the quasar density fluctuations, $\delta_q$, as

$$\delta_q = b_1 \delta + b_2 \delta^2 + \gamma_2 G_2 + \gamma_5 \Delta_3 G + \ldots,$$

(14)

where $b_1$ and $b_2$ are the standard linear and quadratic bias (Fry & Gaztanaga 1993) and the only cubic term that enters into the one-loop propagator in the RPT description of bias (same as for non-linear evolution, Crocce & Scoccimarro 2006; Bernard et al., Crocce & Scoccimarro 2008, 2012) has been written down. The non-local bias terms $\gamma_2$ and $\gamma_5$ represent the amplitude of the Galileon operators of normalized density and velocity potentials, $\Phi$ and $\Psi$,

$$G_2(\Phi_\nu) = (\nabla_\nu \Phi_\nu)^2 - (\nabla^2 \Phi_\nu)^2,$$

(15)

$$\Delta_3 G = G_2(\Phi) - G_2(\Phi_\nu).$$

(16)

Under the assumption of local-Lagrangian bias, the non-local bias parameters are determined by the linear bias $b_1$ as

$$\gamma_2 = \frac{2}{7}(b_1 - 1),$$

(17)

$$\gamma_5 = \frac{11}{42}(b_1 - 1).$$

(18)

Using these ingredients, we describe the redshift-space power spectrum as

$$P(k, \mu) = F_{\text{FOG}}(k, \mu) P_{\text{nov}}(k, \mu) \exp \left[-(k\mu\sigma_{\text{zer}})^2\right].$$

(19)

$P_{\text{nov}}(k, \mu)$ represents the ‘no-virial’ power spectrum, given by the sum of three contributions

$$P_{\text{nov}}(k, \mu) = P_{\text{nov}}^{(1)}(k, \mu) + (k\mu f)^2 P_{\text{nov}}^{(2)}(k, \mu) + (k\mu f)^4 P_{\text{nov}}^{(3)}(k, \mu),$$

(20)

where

$$P_{\text{nov}}^{(1)}(k, \mu) = P_0 + 2f^2 \mu^2 P_{\theta\theta} + f^2 \mu^4 P_{00},$$

(21)

$$P_{\text{nov}}^{(2)}(k, \mu) = \int \frac{dk}{(2\pi)^2} \frac{p^2}{p^2} \left[ B_\mu(p, k - p, -k) - B_\mu(p, k, -k - p) \right],$$

(22)

$$P_{\text{nov}}^{(3)}(k, \mu) = \int \frac{dk}{(2\pi)^2} F(p) F(k - p).$$

(23)
mary, our full model of formula (Kaiser 1987), and the true evolution of the redshift uncertainty of the eBOSS quasar. This simplified treatment of the redshift error does not reproduce the redshift error parameter, labelled as ‘smeared’. The dash–dotted lines correspond to the same model but without the redshift error parameter, labelled as ‘nosmear’. The error bars are inferred from 10^5 sets of mock catalogues (EZmocks).

Here, P^{(1)}_{novir}(k, \mu) corresponds to a non-linear version of the Kaiser formula (Kaiser 1987), and P^{(2)}_{novir}(k, \mu) and P^{(3)}_{novir}(k, \mu) are given by tree-level bispectrum and quadratic linear theory power spectrum. The modelling of the RSD is based on (Scoccimarro (2004)). Equation (21) includes the distortion of BAO on large scales, while on small scales the random motion of LSS smears the distribution along the line-of-sight direction and give rise to the FoG effect

\[ F_{\text{FOG}}(\mu, k) = \frac{1}{\sqrt{1 + f_\mu^2 k^2 a_{\text{vir}}^2}} \exp\left(\frac{-f_\mu^2 k^2 a_{\text{vir}}^2}{1 + f_\mu^2 k^2 a_{\text{vir}}^2}\right), \tag{25} \]

with a_{\text{vir}} being a free parameter that represents the kurtosis of the small-scale velocity distribution. For the analysis in this paper, the velocity dispersion \(\sigma_v\) is calculated from a linear theory prediction and is treated as scale invariant.

Given the high redshift quasar sample, the uncertainties in redshift estimates are larger compared to the galaxies and they can as well be redshift dependent (Dawson et al. 2016). The uncertainty in the redshift estimates can have impact on the small-scale clustering. We use a simple model by approximating it as a Gaussian damping to the power spectrum (Blake & Bridle 2005). A global \(\sigma_{\text{zerr}}\) being a free parameter that represents the kurtosis of the small-scale velocity distribution. For the analysis in this paper, the velocity dispersion \(\sigma_v\) is calculated from a linear theory prediction and is treated as scale invariant.

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### 3.2 Model validation

The model described in Section 3.1 was tested in detail for the analyses of the final BOSS galaxy samples (see Grieb et al. 2017; Salazar-Albornoz et al. 2017; Sánchez et al. 2017). We focus here on testing the modelling of the impact of non-negligible redshift errors. We employ our tests on the same set of EZmocks synthetic catalogues described in Section 2.3, on which we base our estimates of the covariance matrices of our measurements.

The points in Fig. 3 correspond to the mean Legendre multipoles (left-hand panel) and clustering wedges (right-hand panel) of the EZmocks. The error bars are obtained from the square root of the diagonal terms of the covariance matrix estimated from the same set of mocks. We tested our model by performing fits to these measurements using our model for various configurations in order to assess its ability to recover unbiased constraints.

As a first test, we fixed the values of all cosmological parameters to the correct values for the cosmology of the mocks and varied only the nuisance parameters \(b_1, b_2, \sigma_{\text{zerr}}\), and \(\sigma_{\text{zerr}}\). Given the volume and number density of the quasar LSS sample, and hence of the EZmocks, the values of the non-local bias parameters cannot be constrained by the data. We performed tests with or without varying the non-local bias parameters, and found that it has no impact on the obtained constraints or the quality of the fits. We therefore opted for setting their values in terms of \(b_1\) according to the local-Lagrangian predictions of equations (17) and (18). The dashed lines in Fig. 3 correspond to the best-fitting models obtained when the redshift error \(\sigma_{\text{zerr}}\) is treated as a free parameter and included in the fits, while the dot–dashed lines represent the results obtained when setting \(\sigma_{\text{zerr}} = 0\). Although both models provide a good description of the mock measurements, the results obtained when \(\sigma_{\text{zerr}}\) is allowed to vary provide a slightly better fit on scales 20 h^{-1}Mpc ≤ s ≤ 40 h^{-1}Mpc, as well as at the BAO feature.

As a further test of our model, the parameters \(q_1, q_4\), and \(\sigma_{\text{zerr}}\) were allowed to vary alongside the nuisance parameters of the model. Table 1 presents a summary of the full set of parameters

\[ \Delta n = \frac{\delta z}{1 + z} = \frac{\sigma_{\text{zerr}}H(z_{\text{eff}})}{1 + z}. \tag{26} \]
three clustering wedges on parameter values for the cosmology of the mocks. The constraints \( \xi_\ell \) on the monopole measured from EZmocks varies from 1 per cent to 5 per cent down to 10 per cent for scales \( \ell = 0, 2, 4 (\text{blue}) \) and three clustering wedges \( \xi_{3w}(s) \) (orange) measured from EZmocks. The different panels indicate the marginalized uncertainties on these parameters recovered from the MCMC fits for clustering wedges (brown points) and Legendre multipoles (grey points). This comparison also demonstrates that the Legendre multipoles \( \xi_\ell = 0, 2, 4 \) provide, on average, slightly tighter constraints than the measurements of \( \xi_{3w}(s) \). As we will see in Section 4, this behaviour is also the case for our fits to the real eBOSS quasar clustering measurements.

As an illustration of the impact of introducing a non-zero redshift error in our model, we performed additional fits to each mock catalogue setting \( \sigma_{\text{zerr}} = 0 \). Table 2 presents the average difference between the values recovered from the fits of Legendre multipoles and wedges of each EZmocks and their corresponding true values. The first set of values corresponds to those recovered when \( \sigma_{\text{zerr}} \) is varied with the flat prior given in Table 1, while in the second column shows the results assuming \( \sigma_{\text{zerr}} = 0 \). We have also tested using larger prior \([0, 20]\) on \( \sigma_{\text{zerr}} \) and the resulting changes in the inferred parameters are less than few per cent of \( \sigma \). The listed error is inferred from the scatter of the fitted mean value for each individual mock, and hence indicates the statistical error that can be expected for the measurements of these parameters based on one realization of the eBOSS DR14 quasar LSS sample. The comparison of these values shows that ignoring the non-negligible redshift errors affecting the measurements can potentially bias the obtained constraints, leading to an overestimation of \( f r s \) and an underestimation of \( \alpha \), for both multipoles and wedges. The inferred \( \sigma_{\text{zerr}}(z = 1.52) \) corresponds to a dispersion \( \sim 180 \zeta^{-1} \text{km} \) using equation (26). Although the impact of a non-zero redshift error in our model seems marginal from Fig. 3, the deviations between the true and inferred parameter values are significantly reduced in the case in which \( \sigma_{\text{zerr}} = 0 \) is treated as a free parameter, leading to systematic differences that are much smaller than the expected statistical uncertainties of the eBOSS sample.

Given the wide redshift range of the DR14 quasar sample, representing our results in terms of cosmological constraints at an effective redshift needs to be validated. The possible impact of light-cone effects can be assessed by means of the EZmocks mock catalogues, which cover the same redshift range as the eBOSS QSO catalogue and take into account the redshift evolution of cosmic structure. The good match between the inferred AP parameters and \( fr s \) with the fiducial values of the EZmocks justifies this approximation.

As a further tests of our model, we applied it to the analysis of the Outer Rim HOD mocks described in Section 2.2. We focus on the analysis of the samples including redshift errors (the smeared samples), as these are the ones that should more closely resemble the characteristics of the real eBOSS quasar catalogue. We restrict the analysis to the range \( 0.8 < z < 2 \), leading to a mean redshift of 1.52.
As 100 realizations are not enough to compute robust covariance matrices, we based our fits on theoretical covariance matrices computed following the Gaussian recipe of Grieb et al. (2016), for the volume and mean number density of each HOD sample. Although these simple predictions do not take into account the redshift evolution of the number density of the samples, we have found that a simple rescaling of the theoretical covariances by a factor of 1.4 gives a good match to the variance inferred from the 100 realizations. Table 3 summarizes the results obtained when fitting the mean of the Legendre multipoles and clustering wedges of the OuterRim HOD mock catalogues. We list the difference between the mean parameter values inferred from our fits and their true values. In all cases, the error quoted corresponds to the statistical uncertainty expected for one realization, which are similar to the

![Figure 5](https://example.com/figure5.png)

**Figure 5.** Upper panels: constraints on $\alpha_\perp$, $\alpha_\parallel$, and $f_{\sigma_8}$ obtained when fitting the Legendre multipoles $\xi_{l = 0, 2, 4}(s)$ (cyan) and three clustering wedges $\xi_{3w}(s)$ (purple) of each mock catalogue. The orange cross in the centre of each panel represents the values corresponding to the true cosmology of the EZmocks. Lower panel: 68 per cent confidence levels on $\alpha_\perp$, $\alpha_\parallel$, and $f_{\sigma_8}$ inferred from the fits to the Legendre multipoles (grey) and clustering wedges (brown).

![Figure 6](https://example.com/figure6.png)

**Figure 6.** Comparison of the constraints on $\alpha_\perp$, $\alpha_\parallel$, $f_{\sigma_8}$, and $b_\sigma_{\sigma_8}$ obtained from the analysis of Legendre multipoles (x-axis) and three clustering wedges (y-axis) of each of our mock catalogues. The dashed line corresponds to a one-to-one relation.

$z = 1.433$. As 100 realizations are not enough to compute robust covariance matrices, we based our fits on theoretical covariance matrices computed following the Gaussian recipe of Grieb et al. (2016), for the volume and mean number density of each HOD sample. Although these simple predictions do not take into account the redshift evolution of the number density of the samples, we have found that a simple rescaling of the theoretical covariances by a factor of 1.4 gives a good match to the variance inferred from the 100 realizations. Table 3 summarizes the results obtained when

| Statistic | Parameter | $\sigma_{\ell} \neq 0$ | $\sigma_{\ell} = 0$ |
|-----------|-----------|----------------|------------------|
| $\xi_{l}(s)$ | $\Delta \alpha_\perp$ | $0.010 \pm 0.064$ | $0.042 \pm 0.069$ |
| & $\Delta \alpha_\parallel$ | $-0.026 \pm 0.060$ | $-0.068 \pm 0.059$ |
| & $\Delta f_{\sigma_8}$ | $-0.083 \pm 0.070$ | $0.012 \pm 0.076$ |
| & $\sigma_{\ell}$ | $2.882 \pm 0.067$ | - |
| $\xi_{3w}(s)$ | $\Delta \alpha_\perp$ | $0.012 \pm 0.075$ | $0.065 \pm 0.083$ |
| & $\Delta \alpha_\parallel$ | $-0.024 \pm 0.066$ | $-0.084 \pm 0.065$ |
| & $\Delta f_{\sigma_8}$ | $0.003 \pm 0.093$ | $0.057 \pm 0.113$ |
| & $\sigma_{\ell}$ | $2.873 \pm 0.067$ | - |

Table 2. Parameter constraints for $\alpha_\perp$, $\alpha_\parallel$, and $f_{\sigma_8}$ derived from the fit to individual 10$^3$ of EZmocks using clustering wedges and Legendre multipoles. The errors are derived from the scattering of the mean value for fitting each of the chains, with fiducial value $f_{\sigma_8}(z = 1.52) = 0.378$. The fitting range is $d = 30 h^{-1}$ Mpc–156 h$^{-1}$ Mpc. The effect of fixing the redshift error $\sigma_{\ell} = 0$ can be seen on the second column.

| Stat. | Param. | $f_{\ell} = 0\%$ | $f_{\ell} = 13\%$ | $f_{\ell} = 25\%$ |
|-------|--------|----------------|----------------|----------------|
| $\xi_{l}(s)$ | $\Delta \alpha_\perp$ | $0.018 \pm 0.049$ | $-0.002 \pm 0.046$ | $-0.004 \pm 0.040$ |
| & $\Delta \alpha_\parallel$ | $0.036 \pm 0.066$ | $0.025 \pm 0.063$ | $0.018 \pm 0.054$ |
| & $\Delta f_{\sigma_8}$ | $-0.043 \pm 0.072$ | $-0.044 \pm 0.066$ | $-0.030 \pm 0.062$ |
| $\xi_{3w}(s)$ | $\Delta \alpha_\perp$ | $0.015 \pm 0.055$ | $-0.001 \pm 0.048$ | $-0.007 \pm 0.043$ |
| & $\Delta \alpha_\parallel$ | $0.034 \pm 0.076$ | $0.024 \pm 0.068$ | $0.021 \pm 0.057$ |
| & $\Delta f_{\sigma_8}$ | $-0.046 \pm 0.080$ | $-0.043 \pm 0.073$ | $-0.033 \pm 0.067$ |

Table 3. Parameter constraints for $\alpha_\perp$, $\alpha_\parallel$, and $f_{\sigma_8}$ derived from the mean of OuterRim using clustering wedges and Legendre multipoles for different satellite fractions $f_{\ell}$. The errors are derived from the symmetrised 68% percentile with fiducial value $f_{\sigma_8}(z = 1.433) = 0.382$. The fitting range is $d = 20 h^{-1}$ Mpc – 135 h$^{-1}$ Mpc.
We chose this basis to represent our results, which, taking into account the redshift-error parameter $\sigma_{zerr}$, is varied and marginalized over, as our main parameter constraints.

4 COSMOLOGICAL IMPLICATIONS

In this section, we explore the cosmological implications of our clustering measurements. In Section 4.1, we present the results obtained from fitting the model of non-linear clustering in redshift space described in Section 3.1 to the measurements of the Legendre multipoles and $\mu$-wedges of the eBOSS quasar sample. Section 4.2 compares our results with those of the eBOSS companion papers.

4.1 BAO and RSD constraints

We used the model of two-point clustering described in Section 3.1 to extract the cosmological information contained in the Legendre Multipoles and clustering wedges of the eBOSS DR14 LSS quasar sample. We followed the same methodology as in the tests of Section 3.2, i.e. we included scales in the range $20 \text{h}^{-1} \text{Mpc} \leq s \leq 156 \text{h}^{-1} \text{Mpc}$ and fitted for the parameters $\alpha_1$, $\alpha_2$, and $f_{\sigma_8}(z)$. The nuisance parameters of our model, $b_1$, $b_2$, $a_{\text{sh}}$, $\sigma_{\text{corr}}$, are included in our MCMC and marginalized over in our results, while the values of the non-local bias parameters $\gamma_2$ and $\gamma_3$ are set using equations (17) and (18). We performed analyses of the multipoles $\xi_{0,2,4}(s)$ and three clustering wedges $\xi_{2n}(s)$. For completeness, we also applied our model to the monopole-quadrupole pair, and to two wide $\mu$-wedges $\xi_{2n}(s)$. The lines in Fig. 1 correspond to the best-fitting models.

The constraints on $\alpha_1$ and $\alpha_2$ obtained from these fits can be transformed into measurements of the combinations $D_M(z)/r_d$ and $H(z)r_d$. Alternatively, these results can be expressed in terms of $D_V(z)/r_d$, where

$$D_V(z) = \left( D_M(z)^2 \frac{cz}{H(z)} \right)^{1/3}, \quad (27)$$

and the AP parameter

$$F_{\text{AP}}(z) = D_M(z)H(z)/c. \quad (28)$$

We chose this basis to represent our results, which, taking into account also the growth rate, correspond to measurements of the array

$$D = \begin{pmatrix} D_V(z_{\text{eff}})/r_d \\ F_{\text{AP}}(z_{\text{eff}}) \\ f\sigma_{8}(z_{\text{eff}}) \end{pmatrix}$$

at the effective redshift of the quasar LSS sample, $z_{\text{eff}} = 1.52$.

Fig. 7 shows the two-dimensional posterior distributions on different combinations of $D_M(z_{\text{eff}}) \Delta x_A$, $F_{\text{AP}}(z_{\text{eff}})$, and $f\sigma_{8}(z_{\text{eff}})$ obtained from the eBOSS DR14 quasar sample. The blue contours indicate the results inferred from clustering wedges, and the orange contours are those obtained from Legendre multipoles. The upper panels present the constraints obtained from the fits to $\xi_{0,2,4}(s)$ and $\xi_{2n}(s)$ cases, while the lower panels show the posterior distributions recovered from the monopole-quadrupole pair alone (i.e. excluding information from the hexadecapole) and from two clustering wedges $\xi_{2n}(s)$. Table 4 lists the one-dimensional marginalized constraints on $D_M/r_d$, $F_{\text{AP}}$, and $f\sigma_{8}$ obtained in all cases.

A comparison of the upper and lower panels of Fig. 7 illustrates the impact that adding the hexadecapole, or using three clustering wedges, has on the obtained constraints. The additional information on the full shape of $\xi(s, \mu)$ reduces the degeneracy between $F_{\text{AP}}$ and $f\sigma_{8}(z_{\text{eff}})$, leading to significantly tighter results. Fig. 7 and Table 4 also show that the fits to three multipoles $\xi_{0,2,4}(s)$ provide tighter constraints than those obtained using three wedges $\xi_{2n}(s)$. This result is in agreement with our tests on the EZmocks presented in Section 3.2, which also revealed a difference of the same level in the allowed parameter ranges recovered from multipoles and wedges.

The dotted ellipses in Fig. 7 represent the Gaussian approximation of the full parameter posterior distributions, based on their corresponding mean values, $\bar{D}$, and covariance matrices, $\Sigma$, as inferred from our MCMC. Although the results obtained from the measurements of two Legendre multipoles or wedges are clearly non-Gaussian, the constraints obtained when fitting $\xi_{0,2,4}(s)$ or $\xi_{2n}(s)$ are well described by Gaussian profiles. This behaviour means that these distributions can be well approximated by

$$\mathcal{P}(\lambda) \propto \exp \left[ -\left( \bar{D} - D_{\text{theo}}(\lambda) \right)^\top \Sigma^{-1} \left( \bar{D} - D_{\text{theo}}(\lambda) \right) \right], \quad (29)$$

where $D_{\text{theo}}(\lambda)$ represents the theoretical prediction of the distance and growth measurements $D$ obtained for the cosmological parameters $\lambda$. As discussed in Section 3.2, we treat the constraints derived from the fits to the Legendre multipoles $\xi_{0,2,4}(s)$ as our main parameter constraints. This information can be compressed in the mean parameter values obtained in this case and their corresponding covariance matrix. However, the resulting distribution would only represent the statistical uncertainties associated with our measurements, without taking into account any potential systematic errors.

We use the results from our fits to the OuterRim HOD mocks to define a systematic error budget associated with our measurements. We follow a conservative approach and take the largest deviation between our results from the fits to three Legendre Multipoles and their fiducial values as listed in Table 3 and obtain $\Delta \alpha_1 = 0.018$, $\Delta \alpha_2 = 0.036$, and $\Delta f\sigma_{8} = 0.046$. As in our companion papers, we assume that these systematic errors are independent. These values are transformed into the $D_V$-$F_{\text{AP}}$ basis in which we express our results using the Jacobian transformation.

The final covariance matrix representing our constraints from three Legendre multipoles $\xi_{0,2,4}(s)$, taking into account both statistical and systematic errors (the numbers in the brackets), is listed in Table 5. Our measurements can then be combined with the information from additional data sets by means of a Gaussian likelihood function of the form of equation (29), with the mean parameter values given by the second column of Table 4, and the covariance matrix given in Table 5, which represent the main result of this paper.
4.2 Comparison with our companion analyses

This work is part of a set of complementary RSD analyses (Gil-Marín et al. 2018; Ruggeri et al. 2018; Zarrouk et al. 2018; Zhao et al. 2018). Of these studies, the analyses of Zarrouk et al. (2018) and Gil-Marín et al. (2018) are more closely related to ours. Zarrouk et al. (2018) performed an analysis of the full shape of the configuration-space Legendre multipoles and clustering wedges for scales between 16 and 138 h\(^{-1}\) Mpc using a model based on CLPT (Carlson et al. 2013; Wang, Reid & White 2014) and the Gaussian streaming model (Peebles 1980; Fisher 1995; Scoccimarro 2004; Reid & White 2011). Gil-Marín et al. (2018) applied a model based on Taruya et al. (2010) to the Legendre multipoles in Fourier-space, \(P_\ell(k)\), for \(\ell = 0, 2, 4\) up to scales of \(k = 0.3\) h Mpc\(^{-1}\). These methods represent the results at one effective redshift bin and hereafter we refer as the conventional analyses. We focus here on a comparison among the conventional analyses.

Fig. 8 presents a comparison of the two-dimensional posterior distributions of \(D_M(z_{\text{eff}})\), \(\xi_\ell(z_{\text{eff}})\), and \(f_{sr}(z_{\text{eff}})\) at \(z_{\text{eff}} = 1.52\) from Zarrouk et al. (2018) and Gil-Marín et al. (2018) and our results based on the Legendre multipoles \(\xi_\ell(s)\), with \(\ell = 0, 2, 4\) for \(16\) h\(^{-1}\) Mpc < \(s < 160\) h\(^{-1}\) Mpc. Despite the differences in the range of scales and data used, as well as on the modelling of non-linear evolution, bias, and RSD implemented in these analyses, the derived constraints are in excellent agreement with each other, demonstrating the robustness of the results. The red contours in the same figure represent the constraints inferred from the Planck CMB measurements under the assumption of a flat \(\Lambda\)CDM cosmology. The CMB constraints, which are strongly model-dependent, are in good agreement with the results inferred from the clustering analyses of the eBOSS LSS quasar sample, demonstrating the consistency between these data sets within the context of the \(\Lambda\)CDM model.

In addition, Gil-Marín et al. (2018) have performed test by splitting the sample into three redshift bins. They found the result is not significantly affected either using a single bin or three bins, which indicates that representing the given sample one effective redshift is valid.

Complementing these conventional RSD analyses, Ruggeri et al. (2018) and Zhao et al. (2018) applied a redshift-dependent weighting scheme to the Legendre multipoles of the power spectrum to compress the information along the redshift direction. A more detailed comparison between the results of all companion papers, including those implementing redshift weighting schemes, can be found in Zhao et al. (2018) and Zarrouk et al. (2018). The consistency between the conventional analysis and the redshift-weighted method also shows that representing the sample at
For this reason, we define the constraints zero Legendre multipoles provides tighter constraints than the other help to decrease this error.

The tests of our analysis methodology on these mocks which were derived from a set of 1000 synthetic eBOSS quasar counts for the noise in our estimates of the covariance matrices, and their corresponding covariance matrix, which we provide here. Our analysis is part of a set of papers focused on extracting geometric and growth of structure constraints from the eBOSS quasar sample (Gil-Marín et al. 2018; Ruggeri et al. 2018; Zarrouk et al. 2018). In particular, the analyses of Gil-Marín et al. (2018) and Zarrouk et al. (2018), who considered the information of two-point clustering measurements in Fourier and configuration space obtained from the full redshift range 0.8 < z < 2.2, are the ones most similar to our study. A comparison of our results with those of the companion papers shows remarkable consistency, demonstrating the robustness of the obtained results with respect to choice of data and the details of modelling implemented.

The results from our analysis and those of our companion papers demonstrate that quasars can be used as robust tracers of the large-scale clustering pattern. The methodologies previously used to extract cosmological information from anisotropic clustering measurements based on galaxy samples are applicable to quasars as well, providing a powerful cosmological probe at high redshift. The application of these techniques to future quasar samples from eBOSS and other surveys, which will cover larger volumes, will provide a more complete view of the expansion and growth of structure histories of our Universe.

5 CONCLUSIONS

We have presented an analysis of the anisotropic clustering of DR14 eBOSS quasar sample in configuration space. Using quasars as tracers of the LSS has the advantage that it allows one to extend clustering analyses to higher redshift than using galaxies. We projected the information of the full two-dimensional correlation function ξ(s, μ) of the eBOSS quasar sample into Legendre multipoles ξℓ(s) with ℓ = 0, 2, 4 and clustering wedges measured using two and three μ-bins, ξ2w(s) and ξ3w(s).

Our study makes use of a state-of-the-art model of non-linear evolution, bias, and RSD that was previously applied to the analysis of the final BOSS galaxy samples (Grieb et al. 2017; Salazar-Albornoz et al. 2017; Sánchez et al. 2017), modified to account for non-negligible redshift errors. When comparing these theoretical predictions against the measurements of the Legendre multipoles and clustering wedges of the eBOSS sample, we use the likelihood function of Sellentin & Heavens (2016). This recipe correctly accounts for the noise in our estimates of the covariance matrices, which were derived from a set of 1000 synthetic eBOSS quasar catalogues. The tests of our analysis methodology on these mocks catalogues show that it can extract robust distance and growth of structure measurements from our eBOSS quasar clustering measurements for scales s ≥ 20 h−1 Mpc.

We also test our model using a full N-body simulation and define the systematic error based on the test result. Adding the systematic error inflates the error budget on f rs by about 25 per cent. Future investigation from both sides of the simulation and modelling will help to decrease this error.

Our tests demonstrate that the analysis of the first three non-zero Legendre multipoles provides tighter constraints than the other statistics we considered. For this reason, we define the constraints derived from ξ0, 2, 4(s) as the main result of our analysis. These constraints can be expressed as measurements of the parameter combinations Dv(z eff), FAP(z eff), and f rs(z eff) at the effective redshift of the eBOSS LSS quasar sample, z eff = 1.52. The posterior distribution of these parameters is well described by a Gaussian and can be correctly represented by the mean values of these parameters and their corresponding covariance matrix, which we provide here.

Anisotropic clustering in the eBOSS DR14 quasar sample (Gil-Marín et al. 2018; Ruggeri et al. 2018; Zarrouk et al. 2018; Zhao et al. 2018). In particular, the analyses of Gil-Marín et al. (2018) and Zarrouk et al. (2018), who considered the information of two-point clustering measurements in Fourier and configuration space, are from (Gil-Marín et al. 2018), analysed in Fourier space. The red contour is from Zarrouk et al. (2018), where both are analysed in configuration. The pink contour is from (Gil-Marín et al. 2018), analysed in Fourier space.

Figure 8. Constraints on parameters f rs(z eff), Dv(z eff), and FAP(z eff) at effective redshift z eff = 1.52 from different companion papers using the same DR14 LSS quasar data set. The figure present comparison in terms of three Legendre multipoles in both configuration and Fourier space. The blue contour is the result based on the analysis in this paper, and the yellow contour is from Zarrouk et al. (2018), where both are analysed in configuration.

Table 5. Parameter covariance matrix for Dv/f rd, FAP, and f rs on the BAO and RSD analysis with different statistics configuration. The numbers in the brackets are the systematic error derived based on the test of OuterRim simulation in terms of AP parameters and transformed into Dv–FAP basis.

| Parameter | Dv/f rd | FAP | f rs |
|-----------|---------|-----|------|
| Dv/f rd   | 1.32508(+1.80486 × 10^{-1}) | 2.03452 × 10^{-2}(−1.17239 × 10^{-2}) | 2.35976 × 10^{-2} |
| FAP       | –       | 4.05164 × 10^{-3}(+7.61549 × 10^{-3}) | 8.40644 × 10^{-3} |
| f rs      | –       | –   | 4.12582 × 10^{-3}(+2.11600 × 10^{-3}) |

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The effective redshift does not introduce significant systematic errors.
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REFERENCES

Alam S. et al., 2017, MNRAS, 470, 2617
Alcock C., Paczynski B., 1979, Nature, 281, 358
Anderson L. et al., 2012, MNRAS, 427, 3435
Anderson L. et al., 2014a, MNRAS, 439, 83
Bovy J. et al., 2012, ApJ, 749, 41
Bernardeau F., Crocce M., Scoccimarro R., 2008, Phys. Rev. D, 78, 103521
Bernardeau F., Croce M., Scoccimarro R., 2012, Phys. Rev. D, 85, 123519
Blake C., Bridle S., 2005, MNRAS, 363, 1329
Blake C., Glazebrook K., 2003, ApJ, 594, 665
Blanton M. R. et al., 2017, AJ, 154, 28
Bovy J. et al., 2012, ApJ, 749, 41
Busca N. G. et al., 2013, A&A, 552, A96
Carlson J., Reid B., White M., 2013, MNRAS, 429, 1674
Chan K. C., Scoccimarro R., Sheth R. K., 2012, Phys. Rev. D, 85, 083509
Chuang C.-H., Kitaura F.-S., Prada F., Zhao C., Yepes G., 2015a, MNRAS, 446, 2621
Chuang C.-H. et al., 2015b, MNRAS, 452, 686
Cole S. et al., 2005, MNRAS, 362, 505
Colless M. et al., 2001, MNRAS, 328, 1039
Colless M. et al., 2003, preprint (arXiv: astro-ph/0306581)
Crocce M., Scoccimarro R., 2006, Phys. Rev. D, 73, 063519

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APPENDIX A: LIKELIHOOD PROFILES AND UNCERTAINTY CORRECTION

As discussed in Section 2.4, the matrix inverse operation of the covariance matrix can lead to a non-Gaussian likelihood profile if the covariance matrix is estimated from a limited number of mocks. The modified likelihood profile asymptotically approaches the simple Gaussian recipe as the number of mocks increases. If a Gaussian likelihood profile is assumed, the noise due to the limited number of mocks must be propagated into the final parameter constraints. In this case, the obtained parameter covariance matrix needs to be rescaled by a factor (Percival et al. 2014) of

\[ M = \frac{1 + B(N_b - N_p)}{1 + A + B(N_p + 1)}, \]  

(A1)

where

\[ A = \frac{2}{(N_m - N_h - 1)(N_m - N_h - 4)}, \]  

(A2)

\[ B = \frac{(N_m - N_h - 2)}{(N_m - N_h - 1)(N_m - N_h - 4)}, \]  

(A3)

with \( N_h \) being the number of bins in the data vector, \( N_p \) being the number of free parameters, and \( N_m \) being the number of simulations used to estimate the covariance matrix. Table A1 lists the correction factors \( M \) corresponding to the Legendre multipoles and clustering wedges for different rage of scales ranges.

Table A1. Factors to correct the parameter covariance matrix when different scales are included in the analysis. The values of the minimum scales are expressed in \( h^{-1}\text{Mpc} \). In all cases, the maximum scale considered was \( s_{\text{max}} = 160 h^{-1}\text{Mpc} \), the covariance matrix was estimated using \( N_m = 1000 \) mock catalogues, and the fits included \( N_p = 7 \) free parameters.

| \( s_{\text{min}} \) | \( N_h \) | \( M \) |
|-------------------|-------|-------|
| 8                 | 57    | 1.0219|
| 16                | 54    | 1.0203|
| 24                | 51    | 1.0187|
| 32                | 48    | 1.0171|

Sellentin & Heavens (2016) suggested a modified t-distributed likelihood to account for this effect. Here, we perform the test on comparing the results obtained from the real eBOSS data using the two likelihood profiles, where the covariance matrix is rescaled by the factor of equation (11) and the resulting parameter covariance is rescaled by the factor \( M \) of equation (A1). Fig. A1 shows the difference in the AP-parameters and growth rate parameter for Legendre multipoles (upper panel, lighter blue) and clustering wedges (lower panel, darker blue). The error bars are the statistical error calculated from marginalized 1D distribution by a square-wise sum of both Gaussian and modified t-distribution. Fig. A2 is a direct comparison for the parameter covariance on \( f \sigma_8, D_V, \) and \( F_{\text{AP}} \). There is only a marginal shift in the centre of the mean value with \( \Delta x \) less than 3 per cent of \( \sigma \), and the uncertainties on the inferred parameters are comparable with each other. The agreement between the parameters estimated from the two likelihood profiles confirms that the number of mocks used to estimate the covariance matrix is sufficient for the LSS quasar analysis.

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Figure A2. Parameter covariance of \( f \sigma_8, D_V, \) and \( F_{\text{AP}} \) using Gaussian likelihood profile with Hartlap correction (black) and modified t-distribution (orange).

Figure A1. Difference in the inferred parameters \( \alpha_\perp, \alpha_8, \) and \( f \sigma_8 \) by assuming the likelihood profile for Gaussian+Hartlap and modified t-distribution. The error bar is the statistical error from the marginalized 1D distribution using square-wise sum of both Gaussian and modified t-distribution.
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