Euclid: Forecasts from redshift-space distortions and the Alcock–Paczynski test with cosmic voids


(Affiliations can be found after the references)

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ABSTRACT

Euclid is poised to survey galaxies across a cosmological volume of unprecedented size, providing observations of more than a billion objects distributed over a third of the full sky. Approximately 20 million of these galaxies will have their spectroscopy available, allowing us to map the three-dimensional large-scale structure of the Universe in great detail. This paper investigates prospects for the detection of cosmic voids therein and the unique benefit they provide for cosmological studies. In particular, we study the imprints of dynamic (redshift-space) and geometric (Alcock–Paczynski) distortions of average void shapes and their constraining power on the growth of structure and cosmological distance ratios. To this end, we made use of the Flagship mock catalog, a state-of-the-art simulation of the data expected to be observed with Euclid. We arranged the data into four adjacent redshift bins, each of which contains about 11 000 voids and we estimated the stacked void-galaxy cross-correlation function in every bin. Fitting a linear-theory model to the data, we obtained constraints on $f/b$ and $D_M/H$, where $f$ is the linear growth rate of density fluctuations, $b$ the galaxy bias, $D_M$ the comoving angular diameter distance, and $H$ the Hubble rate. In addition, we marginalized over two nuisance parameters included in our model to account for unknown systematic effects in the analysis. With this approach, Euclid will be able to reach a relative precision of about 4% on measurements of $f/b$ and 0.5% on $D_M/H$ in each redshift bin. Better modeling or calibration of the nuisance parameters may further increase this precision to 1% and 0.4%, respectively. Our results show that the exploitation of cosmic voids in Euclid will provide competitive constraints on cosmology even as a stand-alone probe. For example, the equation-of-state parameter, $w$, for dark energy will be measured with a precision of about 10%, consistent with previous more approximate forecasts.

Key words. cosmology: observations – cosmological parameters – dark energy – large-scale structure of Universe – methods: data analysis – surveys

1. Introduction

The formation of cosmic voids in the large-scale structure of the Universe is a consequence of the gravitational interaction of its initially smooth distribution of matter eventually evolving into collapsed structures that make up the web cosmology (Zeldovich 1970). This process leaves behind vast regions of nearly empty space that constitute the largest known structures in the Universe. Since their first discovery in the late 1970s (Gregory & Thompson 1978; Jöeveer et al. 1978), cosmic voids have intrigued scientists given their peculiar nature (e.g., Kirshner et al. 1981; Bertschinger 1985; White et al. 1987; van de Weygaert & van Kampen 1993; Peebles 2001). However, only the recent advances in surveys, such as 6dFGS (Jones et al. 2004), BOSS (Dawson et al. 2013), DES (The Dark Energy Survey Collaboration 2005), eBOSS (Dawson et al. 2016),
KiDS (de Jong et al. 2013), SDSS (Eisenstein et al. 2011), and VIPERS (Guzzo et al. 2014), have enabled systematic studies of statistically significant sample sizes (e.g., Pan et al. 2012; Sutter et al. 2012a), placing the long-overlooked field of cosmic voids into a new focus of interest in astronomy. In conjunction with the extensive development of large simulations (e.g., Springel 2005; Schaye et al. 2015; Dolag et al. 2016; Potter et al. 2017), this has sparked a plethora of studies on voids and their connection to galaxy formation (Hoyle et al. 2005; Patrii et al. 2006; Kreckel et al. 2012; Ricciardelli et al. 2014; Hабоузит et al. 2020; Panchal et al. 2020), large-scale structure (Sheth & van de Weygaert 2004; Hahn et al. 2007; van de Weygaert & Schaap 2009; Jennings et al. 2013; Hamaus et al. 2014a; Chan et al. 2014; Voiodic et al. 2020), the nature of gravity (Clampitt et al. 2013; Zivick et al. 2015; Cai et al. 2015; Barreira et al. 2015; Achitouv 2016; Voiodic et al. 2017; Falck et al. 2018; Sahlin & Silk 2018; Baker et al. 2018; Paillas et al. 2019; Davies et al. 2019; Perico et al. 2019; Alam et al. 2021; Contarini et al. 2021; Wilson & Bean 2021), properties of dark matter (Leclercq et al. 2015; Yang et al. 2015; Reed et al. 2015; Baldi & Villaescusa-Navarro 2018), dark energy (Lee & Park 2009; Bos et al. 2012; Spolyar et al. 2013; Pisani et al. 2015a; Pollina et al. 2016; Verza et al. 2019), massive neutrinos (Massara et al. 2015; Banerjee & Dalal 2016; Sahlin 2019; Kreisch et al. 2019; Schuster et al. 2019; Zhang et al. 2020; Bayer et al. 2021), inflation (Chan et al. 2019), and cosmology in general (Lavaux & Wandelt 2012; Sutter et al. 2012b; Hamaus et al. 2014b, 2016, 2020; Correa et al. 2019, 2022; Contarini et al. 2019; Nadathur et al. 2019, 2020; Paillas et al. 2021; Kreisch et al. 2021). We refer to Pisani et al. (2019) for a more extensive recent summary.

From an observational perspective, voids are an abundant structure type that, together with halos, filaments, and walls, build up the cosmic web. It is therefore natural to utilize them in the search for those observables that have traditionally been measured via galaxies or galaxy clusters, which trace the overdense regions of large-scale structure. This strategy has proven itself to be very promising in recent years, uncovering a treasure trove of untapped signals that carry cosmologically relevant information, such as the integrated Sachs–Wolfe (ISW; Ilić et al. 2013; Cai et al. 2010, 2014; Hабоузит et al. 2020), relevant information, such as the integrated Sachs–Wolfe (ISW; Ilić et al. 2013; Cai et al. 2010, 2014; Hабоузит et al. 2020), the very accelerated expansion of the Universe (e.g., Alam et al. 2013), which necessarily results in large-scale distortions of structure in the Universe that exhibits random orientations. Nevertheless, the principle is still valid on those scales in a statistical sense, that is, for an ensemble average over patches of similar extent from different locations in the Universe. If the physical size of such patches is known (a so-called standard ruler), this enables an inertial observer to determine cosmological distances and the expansion history. The BAO feature in the galaxy distribution is a famous example for a standard ruler, it has been exploited for distance measurements with great success in the past (e.g., Alam et al. 2017, 2021) and constitutes one of the main cosmological probes of Euclid (Laureijs et al. 2011).

A related approach may be pursued with so-called standard spheres, namely, patches of a known physical shape (in particular, spherically symmetric ones). This method has originally been proposed by Alcock & Paczynski (1979, hereafter AP) as a probe of the expansion history, it was later demonstrated that voids are well suited for this type of experiment (Ryden 1995; Lavaux & Wandelt 2012). In principle, it applies to any type of structure in the Universe that exhibits random orientations (such as halos, filaments, or walls), which necessarily results in a spherically symmetric ensemble average. However, the expansion history can only be probed with structures that have not decoupled from the Hubble flow via gravitational collapse. Furthermore, spherical symmetry is broken by peculiar line-of-sight motions of the observed objects that make up this structure. These cause a Doppler shift in the received spectrum and, hence, affect the redshift–distance relation to the source (Kaiser 1987).

In order to apply the AP test, one has to account for those RSD, which requires the modeling of peculiar velocities. For the complex phase-space structure of halos, respectively galaxy clusters as their observational counterparts, this is a very challenging problem. For filaments and walls, the situation is only marginally improved, since they have experienced shell crossing in at least one dimension. On the other hand, voids have hardly undergone any shell crossing in their interiors (Shandarin 2011; Abel et al. 2012; Sutter et al. 2014b; Hahn et al. 2015), providing an environment that is characterized by a coherent flow of matter and on that is therefore very amenable to dynamical models.

According to the cosmological principle, the Universe obeys homogeneity and isotropy on very large scales, which is supported by recent observations (e.g., Scrimgeour et al. 2012; Laurent et al. 2016; Ntielis et al. 2017; Gonzalves et al. 2021). However, below the order of $10^2\,\text{Mpc}$ scales, we observe the structures that form the cosmic web, which break these symmetries locally. Nevertheless, the principle is still valid on those scales in a statistical sense, that is, for an ensemble average over patches of similar extent from different locations in the Universe. If the physical size of such patches is known (a so-called standard ruler), this enables an inertial observer to determine cosmological distances and the expansion history. The BAO feature in the galaxy distribution is a famous example for a standard ruler, it has been exploited for distance measurements with great success in the past (e.g., Alam et al. 2017, 2021) and constitutes one of the main cosmological probes of Euclid (Laureijs et al. 2011).

The Euclid satellite mission is a “Stage-IV” dark energy experiment (Albrecht et al. 2006) that will operate current surveys in the number of observed galaxies and in coverage of cosmological volume (Laureijs et al. 2011). Scheduled for launch in 2022, an assessment of its science performance is timely (Amendola et al. 2018; Euclid Collaboration 2020) and the scientific return that can be expected from voids is being investigated in a series of companion papers within the Euclid Collaboration. These papers cover different observables, such as the void size function (Contarini et al., in prep.), the void–galaxy cross-correlation function after velocity-field reconstruction (Radinović et al., in prep.), or void lensing (Bonici et al., in prep.), providing independent forecasts on their cosmologically constraining power. In this paper, we present a mock-data analysis of the stacked void–galaxy cross-correlation function in redshift space based on the Flagship simulation (Potter et al. 2017), which provides realistic galaxy catalogs as expected to be observed with Euclid. In the following, we outline the theoretical background in Sect. 2, describe the mock data in Sect. 3, and present our results in Sect. 4. The implications of our findings are then discussed in Sect. 5 and our conclusions are summarized in Sect. 6.
In fact, with the help of $N$-body simulations, it has been shown that local mass conservation provides a very accurate description, even at linear order in the density fluctuations (Hamaus et al. 2014c). In that case, the velocity field $u$ relative to the void center is given by (Peebles 1980)

$$u(r) = -\frac{f(z)H(z)}{3+rz}\Delta(r)r,$$  

(1)

where $r$ is the comoving real-space distance vector to the void center, $H(z)$ the Hubble rate at redshift $z$, $f(z)$ is the linear growth rate of density perturbations $\delta$, and $\Delta(r)$ is the average matter-density contrast enclosed in a spherical region of radius $r$:

$$\Delta(r) = \frac{3}{r} \int_0^r \delta(r') r'^2 \, dr'.$$  

(2)

The comoving distance vector $s$ in redshift space receives an additional contribution from the line-of-sight component of $u$ (indicated by $u_l$), caused by the Doppler effect,

$$s = r + \frac{1+z}{H(z)}u_l = r - \frac{f(z)}{3} \Delta(r)r_l.$$  

(3)

This equation determines the mapping between real and redshift space at linear order. Its Jacobian can be expressed analytically and yields a relation between the void-galaxy cross-correlation functions $\xi$ in both spaces (a superscript $s$ indicates redshift space),

$$\xi^s(s) \approx \xi(r) + \frac{f}{3} \Delta(r) + f\mu^2[\delta(r) - \Delta(r)],$$  

(4)

where $\mu = r_l/r$ denotes the cosine of the angle between $r$ and the line of sight (see Cai et al. 2016; Hamaus et al. 2017, 2020, for a more detailed derivation). The real-space quantities $\xi(r)$, $\delta(r)$ and its integral $\Delta(r)$ on the right-hand side of Eq. (4) are a priori unknown, but they can be related to the observables with some basic assumptions. Firstly, $\xi(r)$ can be obtained via deprojection of the projected void-galaxy cross-correlation function $\xi^s_p(s_{\perp})$ in redshift space (Pisani et al. 2014; Hawken et al. 2017),

$$\xi^s(s) = -\frac{1}{3} \int_0^\infty \frac{d\xi^s_p(s_{\perp})}{ds_{\perp}} \left(s_{\perp}^2 - r^2\right)^{-1/2} \, ds_{\perp}. $$  

(5)

By construction $\xi^s_p(s_{\perp})$ is insensitive to RSD, since the line-of-sight component $s_{\parallel}$ is integrated out in the definition and the projected separation $s_{\perp}$ on the plane of the sky is identical to its real-space counterpart $r_{\perp}$,

$$\xi^s_p(s_{\perp}) = \xi^s(s) \, ds_{\parallel} = 2 \int_{s_{\perp}}^\infty r \, \xi(r) \left(r^2 - s_{\perp}^2\right)^{-1/2} \, dr.$$  

(6)

Equations (5) and (6) are also referred to as inverse and forward Abel transform, respectively (Abel et al. 1842; Bracewell 1999).

Secondly, the matter fluctuation $\delta(r)$ around the void center can be related to $\xi(r)$ assuming a bias relation for the galaxies in that region. Based on simulation studies, it has been demonstrated that a linear relation of the form $\xi(r) = b \delta(r)$ with a proportionality constant $b$ serves that purpose with sufficiently high accuracy. Moreover, it has been shown that the value of $b$ is linearly related to the large-scale linear galaxy bias of the tracer distribution, and coincides with it for sufficiently large voids (Sutter et al. 2014c; Pollina et al. 2017, 2019; Contarini et al. 2019; Ronconi et al. 2019). With this, Eq. (4) can be expressed as

$$\xi^s(s) \approx \xi(r) + \frac{f}{3} b \xi(r) + \frac{f}{3} b^2 [\xi(r) - \xi(r)].$$  

(7)

where

$$\tilde{\xi}(r) = 3r^3 \int_0^r \xi(r') r'^2 \, dr'.$$  

(8)

Now, together with Eq. (3) to relate real and redshift-space coordinates, Eq. (7) provides a description of the observable void-galaxy cross-correlation function at linear order in perturbation theory.

In order to determine the distance vector $s$ for a given void-galaxy pair, it is necessary to convert their observed separation in angle $\delta\theta$ and redshift $\delta z$ to comoving distances via

$$s_\perp = D_{\Delta}(\delta\theta), \quad s_\parallel = \frac{c}{H(z)} \delta z,$$  

(9)

where $D_{\Delta}(\delta\theta)$ is the comoving angular diameter distance. Both $H(z)$ and $D_{\Delta}(\delta\theta)$ depend on cosmology, so any evaluation of Eq. (9) requires the assumption of a fiducial cosmological model. To maintain the full generality of the model, it is customary to introduce two AP parameters that inherit the dependence on cosmology via (e.g., Sánchez et al. 2017b)

$$q_L = \frac{s^\perp_\perp}{s^\perp_\parallel} = \frac{D^\perp_\perp}{D^\perp_\parallel} H(z), \quad q_\parallel = \frac{s^\parallel_\parallel}{s^\parallel_\parallel} = H(z) / H(z).$$  

(10)

In this notation, the starred quantities are evaluated in the true underlying cosmology, which is unknown, while the un-starred ones correspond to the assumed fiducial values of $D_{\Delta}$ and $H$. Equation (9) can be rewritten as $s^\perp_\perp = q_L D_{\Delta}(\delta\theta)$ and $s^\parallel_\parallel = q_\parallel c / H(z)$, which is valid for a wide range of cosmological models. In the special case where the fiducial cosmology coincides with the true one, we have $q_L = q_\parallel = 1$. This method is known as the AP test, providing cosmological constraints via measurements of $D_{\Delta}(\delta\theta)$ and $H(z)$. Without an absolute calibration scale the parameters $q_L$ and $q_\parallel$ remain degenerate in the AP test and it is only their ratio,

$$\varepsilon = \frac{q_L}{q_\parallel} = \frac{D^\perp_\perp / H(z)}{D^\perp_\parallel / H(z)},$$  

(11)

that can be determined, providing a measurement of $D^\perp_\parallel H(z)^\parallel$. We adopt a flat Λ cold dark matter (CDM) cosmology as our fiducial model, where

$$D_{\Delta}(\delta\theta) = \int_0^\infty \frac{c}{H(z')} \, dz', \quad H(z) = H_0 \sqrt{\Omega_m(1+z)^3 + \Omega_\Lambda},$$  

(12)

with the present-day Hubble constant, $H_0$, matter-density parameter, $\Omega_m$, and cosmological constant parameter, $\Omega_\Lambda = 1 - \Omega_m$. This model includes the true input cosmology of the Flagship simulation with parameter values stated in Sect. 3 below, which is also used for void identification. The impact of the assumed cosmology on the latter has previously been investigated and was found to be negligible (e.g., Hamaus et al. 2020). In Sect. 5, we additionally consider an extended wCDM model to include the equation-of-state parameter, $w$, for dark energy.

3. Mock catalogs

3.1. Flagship simulation

We employed the Euclid Flagship mock galaxy catalog (version 1.8.4), which is based on an $N$-body simulation of 12,600$^3$ (two trillion) dark matter particles in a periodic box of 3780 h$^{-1}$ Mpc on a side (Potter et al. 2017). It adopts a flat ΛCDM cosmology with parameter values $\Omega_m = 0.319$, $\Omega_b = 0.049$, $\Omega_\Lambda = 0.681$, 

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We denote the redshift of void centers with a capital Z, to distinguish it from the redshift z of galaxies, while Nv determines the minimum included void size in units of the average tracer separation. The smaller the value of Nv, the larger the contamination by spurious voids that may arise via Poisson fluctuations (Neyrinck 2008; Cousinou et al. 2019) and have been misidentified due to RSD (Pisani et al. 2015b; Correia et al. 2021, 2022). We adopt a value of Nv = 3, which leaves us with a final number of Nv = 44 356 voids with minimum effective radius of R ≈ 18.6 h−1 Mpc. This sample is further split into 4 consecutive redshift bins with an equal number of voids per bin, Nv = 11 089, as obtained by Fig. 1. The selected number of redshift bins is a trade-off between the necessary statistical power to estimate our data vectors and their covariance with sufficient accuracy in each bin, and an adequate sampling of the redshift evolution of fσ8 and D_MH (see Sect. 4). The removal of voids close to the redshift boundaries of the Flagship light cone causes their abundance to decline, which lowers the statistical constraining power in that regime.

4. Data analysis

Our data vector is represented by the void-galaxy cross-correlation function in redshift space. As this function is anisotropic, we can either consider its 2D version with coordinates perpendicular to and along the line of sight, ξ_v(s_z, s_τ), or its decomposition into multipoles by use of Legendre polynomials Pℓ of order ℓ,

\[ ξ_v^ℓ(s) = \frac{2ℓ+1}{2} \int_1^{-1} ξ_v(s, μ) P_ℓ(μ) dμ, \]

where μ = s_τ/s. We highlight that the notations ξ_v^ℓ(s), ξ_v(s_z, s_τ), and ξ_v(s, μ) all refer to the same physical quantity, albeit via their different mathematical formulations. Here, we make use of the full 2D correlation function for our model fits, since it contains all the available information on RSD and AP distortions. For the sake of completeness, we additionally provide the three multipoles of the lowest even order, ℓ = 0, 2, 4 (i.e., monopole, quadrupole, and hexadecapole). Their theoretical linear predictions directly follow from Eq. (7):

\[ ξ_v^0(s) = \left(1 + \frac{f/h}{3}\right)ξ(r), \quad ξ_v^2(s) = \frac{2f/h}{3}[ξ(r) - z(r)], \quad ξ_v^4(s) = 0. \]  

4.1. Estimator

For our mock measurements of ξ_v(s_z, s_τ), we utilize the Landy & Szalay (1993) estimator for cross correlations,

\[ ξ_v(s_z, s_τ) = \frac{⟨D_v D_v⟩ - ⟨D_v R_v⟩ - ⟨R_v D_v⟩ + ⟨R_v R_v⟩}{⟨R_v R_v⟩}, \]

where the angled brackets signify normalized pair counts of void-center and galaxy positions in the data (D_v, D_g) and corresponding random positions (R_v, R_g) in bins of s_z and s_τ. We chose a fixed binning in units of the effective void radius for each individual void and express all distances in units of R as well. This allows one to coherently capture the characteristic topology of voids from a range of sizes including their boundaries in an ensemble-average sense. The resulting statistic is also referred to as a void stack or stacked void-galaxy cross-correlation function. We have generated the randoms via sampling from the redshift distributions of galaxies and voids as depicted in Fig. 1, but with ten times

\[ R > N_v \left(\frac{4π}{3} n_v(Z)\right)^{-1/3}. \]
the number of objects and without spatial clustering. We applied the same angular footprint as for the mock data and additionally assign an effective radius to every void random, drawn from the radius distribution of galaxy voids. The latter is used to express distances from void randoms in units of the effective radius $R$ (void size function) from the entire redshift range, encompassing a total of $N_v = 44,356$ voids with $18.6 \ h^{-1} \ Mpc < R < 84.8 \ h^{-1} \ Mpc$. Poisson statistics are assumed for the error bars. We refer to our companion paper for a detailed cosmological forecast based on the void size function (Contarini et al., in prep.).

This yields the following transformation between coordinates in real and redshift space,

$$
C_{ij} = \left\langle \left( \hat{\xi}_c(s_i) - \langle \hat{\xi}_c(s_i) \rangle \right) \left( \hat{\xi}_c(s_j) - \langle \hat{\xi}_c(s_j) \rangle \right) \right\rangle,
$$

where angled brackets imply averaging over an ensemble of observations. The square root of the diagonal elements, $C_{ii}$, are used as error bars on our measurements of $\hat{\xi}_c$. Although we can only observe one universe (respectively a single Flagship mock catalog), ergodicity allows us to estimate $C_{ij}$ via spatial averaging over distinct patches. This naturally motivates the jackknife technique to be applied on the available sample of voids, which are non-overlapping. Therefore, we simply remove one void at a time in the estimator of $\hat{\xi}_c$ from Eq. (17), which provides $N_v$ jackknife samples. This approach has been tested on simulations and validated on mocks in previous analyses (Paz et al. 2013; Cai et al. 2016; Correa et al. 2019; Hamaus et al. 2020). It has further been shown that, in the limit of large sample sizes, the jackknife technique provides consistent covariance estimates compared to the ones obtained from many independent mock catalogs (Favole et al. 2021). Residual differences between the two methods indicate the jackknife approach to yield somewhat higher covariances, which renders our error forecast conservative.

### 4.2. Model and likelihood

As previously demonstrated in Hamaus et al. (2020), we include two additional nuisance parameters, $M$ and $Q$, in the theory model of Eq. (7), enabling us to account for systematic effects. Here, $M$ (monopole-like) is used as a free amplitude of the deprojected correlation function $\xi_c(r)$ in real space and $Q$ (quadrupole-like) is a free amplitude for the quadrupole term proportional to $r^2$. Here, we adopt a slightly modified, empirically motivated parametrization of this model, with enhanced coefficients for the Jacobian (second and third) terms in Eq. (7),

$$
\xi_c(s_i, s_j) = M \left\{ \xi_c(r) + \frac{x_q}{b} \xi_c(r) + 2Q \frac{f^2}{b} \mu^2 [\xi_c(r) - \bar{\xi}_c(r)] \right\}.
$$

The parameter $M$ adjusts for potential inaccuracies arising in the deprojection technique and a contamination of the void sample by spurious Poisson fluctuations, which can attenuate the amplitude of the monopole and quadrupole (Cousinou et al. 2019). The parameter $Q$ accounts for possible selection effects when voids are identified in anisotropic redshift space (Pisani et al. 2015b; Correa et al. 2021, 2022). For example, the occurrence of shell crossing and virialization affects the topology of void boundaries in redshift space (Hahn et al. 2015), resulting in the well-known finger-of-God (FoG) effect (Jackson 1972). In turn, this can enhance the Jacobian terms in Eq. (7), which motivates the empirically determined modification of their coefficients in Eq. (19). A similar result can be achieved by enhancing the values of $M$ and $Q$, but keeping the original form of Eq. (7), which can be approximately understood as a redefinition of the nuisance parameters. However, the form of Eq. (19) is found to better describe the void-galaxy cross-correlation function in terms of goodness of fit, while at the same time yields nuisance parameters that are distributed more closely around values of one. This approach is akin to other empirical model extensions that have been proposed in the literature (e.g., Achitouv 2017; Paillas et al. 2021).

For the mapping from the observed separations $s_i$ and $s_j$ to $r$ and $\mu$, we use Eq. (3) together with Eq. (10) for the AP effect. This yields the following transformation between coordinates in real and redshift space,

$$
r_{\perp} = q_{\perp}s_{\perp}, \quad r_{\parallel} = q_{\parallel}s_{\parallel} \left[ 1 - \frac{1}{3} \frac{f}{b} M \bar{\xi}_c(r) \right]^{-1},
$$

which can be solved via iteration to determine $r = (r_{\perp}^2 + r_{\parallel}^2)^{1/2}$ and $\mu = r_{\parallel}/r$, starting from an initial value of $r = s$ (Hamaus et al. 2020). In practice, we express all separations in units of the observable effective radius $R$ of each void in redshift space, but noting that the AP effect yields $R^* = q_{\perp}^{2/3} q_{\parallel}^{1/3} R$ in the true cosmology (Hamaus et al. 2020; Correa et al. 2021). When expressing Eq. (20) in units of $R^*$, only ratios of $q_{\perp}$ and $q_{\parallel}$ appear, which...
defines the AP parameter \( \varepsilon = q_x/q_y \). The latter is particularly well constrained via the AP test from standard spheres (Lavaux & Wandelt 2012; Hamaus et al. 2015).

Finally, given the estimated data vector from Eq. (17), its covariance from Eq. (18), and the model from Eqs. (19) and (20), we can construct a Gaussian likelihood \( L(\hat{\xi}(\Theta)) \) of the data \( \hat{\xi} \) given the model parameter vector \( \Theta = (f/b, \varepsilon, M, Q) \) as:

\[
\ln L(\hat{\xi}(\Theta)) = -\frac{1}{2} \sum_{ij} (\hat{\xi}(s_i) - \xi(s_j) (\Theta)) C_{ij}^{-1}(\hat{\xi}(s_i) - \xi(s_j) (\Theta)).
\]

We apply the factor of Hartlap et al. (2007) to estimate the covariance from Eq. (18), and the model from Eqs. (19) and (20), which yields consistent results. From the full Euclid footprint of about three times the size of an octant, the residual statistical noise of this procedure will be reduced further, so our mock analysis can be considered conservative in this regard.

We also plot the monopole of the redshift-space correlation function, which nicely follows the shape of the deprojected \( \xi(r) \), as expected from Eq. (16). Moreover, our model from Eqs. (19) and (20) provides a very accurate fit to this monopole everywhere apart from its innermost bins, implying that any residual errors in the model remain negligibly small in that regime. We notice an increasing amplitude of all correlation functions towards lower redshift, partly reflecting the growth of overdensities along the void walls, while their interior is gradually evacuated. The increase in mean effective radius with redshift is not of dynamical origin, it is a consequence of the declining galaxy density \( n_g(z) \), see Fig. 1. A higher space density of tracers enables the identification of smaller voids.

We minimize the log-likelihood of Eq. (21) by varying the model parameters to find the best-fit model to the mock data. As a data vector, we used the 2D void-galaxy cross-correlation \( \hat{\xi}(s_i, s_j) \), which contains the complete information on dynamic and geometric distortions from all multipole orders. However, we checked that our pipeline yields consistent constraints when only considering the three lowest even multipoles, \( \hat{\xi}(s_i) \), of order \( \ell = 0, 2, 4 \) as our data vector. The results are shown in Fig. 3 for our four consecutive redshift bins. In each case, we find extraordinary agreement between the model and the data, which is further quantified by the reduced \( \chi^2 \) being so close to unity in all bins. Again, it is possible to perceive the slight deepening of voids over time and the agglomeration of matter in their surroundings. The multipoles shown in the right column of Fig. 3 complement this view, with both monopole and quadrupole enhancing their amplitudes during void evolution, and they exhibit an excellent agreement with the model. The quadrupole vanishes towards the central void region and the model mismatch in the first few bins of the monopole has negligible impact here, as most of the anisotropic information originates from larger scales. In addition, the hexadecapole remains consistent with zero at all times, in accordance with Eq. (16).

### 4.4. Parameter constraints

Performing a full MCMC run for each redshift bin, we obtain the posteriors for our model parameters as shown in Fig. 4. We observe a similar correlation structure as in the previous BOSS analysis of Hamaus et al. (2020). Namely, a weak correlation between \( f/b \) and \( \varepsilon \), and a strong anti-correlation between \( f/b \) and \( M \). Overall, the 68% confidence regions for \( f/b \) and \( \varepsilon \) agree well with the expected input values, shown as dashed lines. In a \( \Lambda \)CDM cosmology, the linear growth rate is given by

\[
f(z) \approx \left( \frac{\Omega_m(1+z)^3}{H^2(z)/H^2_0} \right)^{1/2},
\]

with a growth index of \( \gamma = 0.55 \) (Lahav et al. 1991; Linder 2005). We take the Flagship measurements of the large-scale linear bias \( b \) from our companion paper (Contarini et al., in prep.), which uses CAMB (Lewis et al. 2000) to calculate the dark-matter correlation function to compare with the estimated galaxy auto-correlation function (see Marulli et al. 2013, 2018, for details). As we are using the correct input cosmology of Flagship to convert angles and redshifts to comoving distances following Eq. (9), we have \( \varepsilon = 1 \) as fiducial value.

For the values of the nuisance parameters, \( M \) and \( Q \), we do not have any specific expectation, but we set their defaults

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to unity as well. We also find their posteriors to be distributed around values of one, although their mean can deviate more than one standard deviation from that default value. However, the distributions of the nuisance parameters are not relevant for the cosmological interpretation of the posterior, as they can be marginalized over. The relative precision on \( f/b \) ranges between 7.3% and 8.0%, while the one on \( \varepsilon \) is between 0.87% and 0.91%. This precision corresponds to a survey area of one octant of the sky, but the footprint covered by Euclid will be roughly three times as large. Therefore, one can expect these numbers to decrease by a factor of \( \sqrt{3} \) to yield about 4% accuracy on \( f/b \) and 0.5% on \( \varepsilon \) per redshift bin.

The attainable precision can even further be increased via a calibration strategy. Hamaus et al. (2020) have shown that this is possible when the model ingredients \( \xi(r) \), \( M \), and \( Q \) are taken from external sources, instead of being constrained by the data itself, for example, from a large number of high-fidelity survey mocks. However, we emphasize that this practice introduces a prior dependence on the assumed model parameters in the mocks, so it underestimates the final uncertainty on cosmology and may yield biased results. We also note that survey mocks are typically designed to reproduce the two-point statistics of galaxies on large scales, but are not guaranteed to provide void statistics at a similar level of accuracy.

Nevertheless, for the sake of completeness we investigate the achievable precision when fixing the nuisance parameters to their best-fit values in the full analysis, while still inferring \( \xi(r) \) via deprojection of the data as before. We note that this is an arbitrary choice of calibration, in practice, the values of \( M \) and \( Q \) will depend on the type of mocks considered. The resulting posteriors on \( f/b \) and \( \varepsilon \) are shown in Fig. 5. The calibrated analysis yields a relative precision of 1.3% to 1.8% on \( f/b \) and 0.72% to 0.75% on \( \varepsilon \). Compared to the calibration-independent analysis, this amounts to an improvement by up to a factor of about 5 for constraints on \( f/b \) and 1.2 for \( \varepsilon \). Extrapolated to the full survey area accessible to Euclid, this corresponds to a precision of roughly 1% on \( f/b \) and 0.4% on \( \varepsilon \) per redshift bin. As expected, these calibrated constraints are more prone to be biased with respect to the underlying cosmology, as evident from Fig. 5 given our choice of calibration. It is also interesting to note that \( f/b \) and \( \varepsilon \) are less correlated in the calibrated analysis, since their partial degeneracy with the nuisance parameter \( M \) is removed.

We summarize all of our results in Table 1. The constraints on \( f \sigma_s \) and \( D_M H \) are derived from the posteriors on \( f/b \) and \( \varepsilon \). In the former case, we assume \( \xi(r) \propto b \sigma_s \) and, hence, we multiply \( f/b \) by the underlying value of \( b \sigma_s \) in the Flagship mock, which also assumes the relative precision on \( f/b \) and \( f \sigma_s \) to be the same. Moreover, we neglect the dependence on \( h \) that enters in the definition of \( \sigma_s \) and should be marginalized over (Sánchez 2020). For the latter case, we multiply \( \varepsilon \) by the fiducial \( D_M H \), following Eq. (11). The results on \( f \sigma_s \) and \( D_M H \) from
Fig. 3. Stacked void-galaxy cross-correlation function in redshift space. Left: $\xi(s_1, s_0)$ in 2D (color scale with black contours) and its best-fit model from Eqs. (19) and (20) (white contours). Right: monopole (blue dots), quadrupole (red triangles) and hexadecapole (green wedges) of $\xi(s_1, s_0)$ and best-fit model (solid, dashed, dotted lines). The mean void redshift, $\bar{Z}$, and effective radius, $\bar{R}$, of each redshift bin are indicated.

$\chi^2$ red = 1.00

$\bar{R} = 30.6h^{-1}\text{Mpc}$

$\bar{Z} = 0.99$

$\bar{R} = 34.5h^{-1}\text{Mpc}$

$\bar{Z} = 1.14$

$\bar{R} = 38.3h^{-1}\text{Mpc}$

$\bar{Z} = 1.33$

$\bar{R} = 43.5h^{-1}\text{Mpc}$

$\bar{Z} = 1.58$
Fig. 4. Posterior probability distribution of the model parameters that enter in Eqs. (19) and (20), obtained via MCMC from the data shown in the left of Fig. 3. Dark and light shaded areas represent 68% and 95% confidence regions with a cross marking the best fit, dashed lines indicate fiducial values of the RSD and AP parameters. The top of each column states the mean and standard deviation of the 1D marginal distributions. Adjacent bins in void redshift with mean value $\bar{Z}$ increase from the upper left to the lower right, as indicated.

Fig. 5. Posterior probability distribution of the model parameters that enter in Eqs. (19) and (20). Details are the same as in Fig. 4, but with a fixing (calibration) of the nuisance parameters $M$ and $Q$ to their best-fit values. Redshift increases from left to right, as indicated.
Table 1. RSD and AP parameter constraints.

<table>
<thead>
<tr>
<th>Data</th>
<th>$Z_{\text{min}}$</th>
<th>$Z_{\text{max}}$</th>
<th>$Z$</th>
<th>$b$</th>
<th>$f/b$</th>
<th>$f\sigma_8$</th>
<th>$e$</th>
<th>$D_M H/c$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Euclid voids (independent)</td>
<td>0.91</td>
<td>1.06</td>
<td>0.99</td>
<td>1.54</td>
<td>0.5827 ± 0.0427</td>
<td>0.4544 ± 0.0333</td>
<td>1.0127 ± 0.0088</td>
<td>1.3627 ± 0.0119</td>
</tr>
<tr>
<td>Euclid voids (calibrated)</td>
<td>1.06</td>
<td>1.23</td>
<td>1.14</td>
<td>1.81</td>
<td>0.4416 ± 0.0346</td>
<td>0.3784 ± 0.0296</td>
<td>0.9989 ± 0.0088</td>
<td>1.6391 ± 0.0144</td>
</tr>
<tr>
<td></td>
<td>1.23</td>
<td>1.44</td>
<td>1.33</td>
<td>1.92</td>
<td>0.5132 ± 0.0394</td>
<td>0.4320 ± 0.0331</td>
<td>1.0127 ± 0.0092</td>
<td>2.0517 ± 0.0186</td>
</tr>
<tr>
<td></td>
<td>1.44</td>
<td>1.76</td>
<td>1.58</td>
<td>2.20</td>
<td>0.4205 ± 0.0337</td>
<td>0.3689 ± 0.0296</td>
<td>0.9907 ± 0.0089</td>
<td>2.5543 ± 0.0230</td>
</tr>
</tbody>
</table>

Notes. Forecasted constraints on RSD and AP parameters (mean values with 68% confidence intervals) from VIDE voids in the Euclid Flagship mock catalog (top rows). Results are given in four redshift bins with minimum, maximum, and mean void redshift $Z_{\text{min}}$, $Z_{\text{max}}$, $Z$, and large-scale galaxy bias $b$. All uncertainties correspond to one octant of the sky, but the expected precision from the full Euclid footprint is a factor of about $\sqrt{3}$ higher. The bottom rows show more optimistic constraints after performing a calibration of the nuisance parameters in the model.

Fig. 6. Measurement of $f\sigma_8$ and $D_M H$ from VIDE voids in the Euclid Flagship catalog as a function of redshift $z$. The marker style distinguishes between a fully model-independent approach (green circles) and an analysis with calibrated nuisance parameters $M$ and $Q$ (red triangles) using external sources, such as simulations or mocks. Dotted lines indicate the Flagship input cosmology, the markers are slightly shifted horizontally for visibility. These results are based on one octant of the sky, the expected precision from the full Euclid footprint is a factor of about $\sqrt{3}$ higher.

Fig. 7. Comparisons of the constraining power on $\Omega_d$ from the mentioned experiments, including the one previously obtained from BOSS voids in Hamaus et al. (2020).

5. Discussion

The measurements of $f\sigma_8$ and $D_M H$ as a function of redshift can be used to constrain cosmological models. For example, an inversion of Eq. (12) provides $\Omega_d = 1 - \Omega_m$, the only free parameter of the product $D_M H$ in a flat $\Lambda$CDM cosmology. Using our Flagship mock measurements of $D_M H$ we sample the joint posterior on $\Omega_d$ from all of our redshift bins combined. Considering the full Euclid footprint to be approximately three times the size of our Flagship mock catalog, we scale the errors on $D_M H$ by a factor of $1/\sqrt{3}$ and center its mean values to the input cosmology of Flagship. The resulting posterior yields $\Omega_d = 0.6809 \pm 0.0048$, in the model-independent, and $\Omega_d = 0.6810 \pm 0.0039$, in the calibrated case from the analysis of Euclid voids alone. The corresponding result obtained by Planck in 2018 (Planck Collaboration VI 2020) is $\Omega_d = 0.6847 \pm 0.0073$, including cosmic microwave background (CMB) lensing and $\Lambda = 0.6889 \pm 0.0056$, when combined with BOSS BAO data (Alam et al. 2017). The main cosmological probes of Euclid, when altogether combined, are forecasted to achieve a 1σ uncertainty of 0.0071 on $\Omega_d$ in a pessimistic scenario and 0.0025 in an optimistic case (Euclid Collaboration 2020). The expected precision on $\Omega_d$ from the analysis of Euclid voids alone will hence likely match the level of precision from Planck and the combined main Euclid probes. The left panel of Fig. 7 provides a visual comparison of the constraining power on $\Omega_d$ from the mentioned experiments, including the one previously obtained from BOSS voids in Hamaus et al. (2020).

Furthermore, in Euclid we aim to explore cosmological models beyond $\Lambda$CDM. One minimal extension is to replace the cosmological constant, $\Lambda$, by a more general form of dark energy with density $\Omega_{de}$, and a constant equation-of-state parameter, $w$. This modifies the Hubble function in Eq. (12) to

$$H(z) = H_0 \sqrt{(1-\Omega_{de}(1+z)^3 + \Omega_{de}(1+z)^{3(1+w)})},$$

which reduces to the case of flat $\Lambda$CDM for $w = -1$. Using our rescaled and recentered mock measurements of $D_M H$, we can thus infer the posterior distribution of the parameter pair $(\Omega_{de}, w)$. The result is shown in the right panel of Fig. 7 for both the model-independent and the calibrated analysis, assuming flat priors with $\Omega_{de} \in [0, 1]$ and $w \in [-10, 10]$. We observe a mild degeneracy between $\Omega_{de}$ and $w$, which can be mitigated in the calibrated case. However, this may come at the price of an increased bias from the true cosmology. Nevertheless, these parameter constraints are extremely competitive, yielding $w = -1.01^{+0.12}_{-0.10}$ and, hence, a relative precision of about 9% in the calibrated scenario. In the model-independent analysis, we still obtain $w = -1.01^{+0.12}_{-0.10}$ with a relative precision of 11%. The constraints on $\Omega_{de}$ are similar to the ones on $\Omega_d$ from above. We note that this result is in remarkable agreement with the early Fisher forecast of Lavaux & Wandelt (2012), corroborating the robustness of the AP test with voids. The Planck Collaboration VI (2020) obtain $w = -1.57^{+0.50}_{-0.41}$ including CMB lensing in the same $\Lambda$CDM model and a combination with BAO yields a similar precision of about 10%, with $w = -1.04^{+0.10}_{-0.10}$.

The right panel of Fig. 7 provides a demonstration of how cosmic voids by themselves constrain the properties of dark energy, without the inclusion of external priors, observables, or mock data. A combination with other probes, such as void abundance (Contarin et al., in prep.), cluster abundance (Sahlén 2019), BAO (Nadathur et al. 2019), CMB, or weak lensing...
In this work, we investigate the prospects for performing a cosmological analysis using voids extracted from the spectroscopic galaxy sample of the Euclid Survey. The method we applied is based on the observable distortions of average void shapes via RSD and the AP effect. Our forecast relies on one light cone octant (5157 deg$^2$) of the Flagship simulation covering a redshift range of $0.9 < z < 1.8$, which provides the most realistic mock galaxy catalog available for this purpose to date. Exploiting a deprojection technique and assuming linear mass conservation allows us to accurately model the anisotropic void-galaxy cross-correlation function in redshift space. We explore the likelihood of the mock data given this model via MCMCs and obtain the posterior distributions for our model parameters: the ratio of growth rate and bias $f/b$, and the geometric AP distortion $e$. Two additional nuisance parameters, $M$ and $Q$, are used to account for systematic effects in the data; they can either be marginalized over (model-independent approach) or calibrated via external sources, such as survey mocks (calibrated approach). After the conversion of our model parameters to the combinations $f \sigma_8$ and $D_N H$, we forecast the attainable precision of their measurement with voids in Euclid.

We expect a relative precision of about 4% (1%) on $f \sigma_8$ and 0.5% (0.4%) on $D_N H$ without (with) model calibration for each of our four redshift bins. This level of precision will enable very competitive constraints on cosmological parameters. For example, it yields a 0.7% (0.6%) constraint on $\Omega_k$ in a flat $\Lambda$CDM cosmology and a 11% (9%) constraint on the equation-of-state parameter $w$ for dark energy in $w$CDM from the AP test with voids alone. A combination with other void statistics, or the main cosmological probes of Euclid, such as galaxy clustering and weak lensing, will enable considerable improvements in accuracy and allow for the exploration of a broader range of extended cosmological models with a larger scope of parameters.

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**References**

Abel, N. H. 1842, in Oeuvres Completes, eds. L. Sylow, & S. Lie (New York: Johnson Reprint Corp.), 27


Achitouv, I. 2017, Phys. Rev. D, 90, 103524

Achitouv, I. 2019, Phys. Rev. D, 100, 123513


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