

Novel Techniques for the Calibration of Systematics in Next Generation Galaxy Surveys

by

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Author's Declaration

This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Statement of Contributions

Chapters 1 and 4 were entirely written by Alan Bao-Huy Nguyen. This thesis additionally consists in part of two manuscripts written for publication. Chapters 2 consists of material written primarily by Alan Bao-Huy Nguyen for [1]. Chapter 3 consists of material written primarily by Alan Bao-Huy Nguyen for [2]. Other author's writing contributions and exceptions to sole authorship of material are as follows:

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Abstract

Baryon Acoustic Oscillation (BAO) observations offer a robust method for measuring cosmological expansion. However, the BAO signal in a sample of galaxies can be diluted and shifted by interlopers – galaxies that have been assigned the wrong redshifts. Because of the slitless spectroscopic method adopted by the Roman and Euclid space telescopes, the galaxy samples resulting from single line detections will have relatively high fractions of interloper galaxies. Interlopers with a small displacement between true and false redshift have the strongest effect on the measured clustering. In order to model the BAO signal, the fraction of such interlopers and their clustering need to be accurately known.

We introduce a new method to self-calibrate these quantities by shifting the contaminated sample towards or away from us along the line of sight by the interloper offset, and measuring the cross-correlations between these shifted samples. The contributions from the different components are shifted in scale in this cross-correlation compared to the auto-correlation of the contaminated sample, enabling the decomposition and extraction of the component terms. We demonstrate the application of the method using numerical simulations and show that an unbiased BAO measurement can be extracted. Unlike previous attempts to model the effects of contaminants, self-calibration allows us to make fewer assumptions about the form of the contaminants such as their bias.

We also introduce a new statistical technique to cosmology, called the Leave One Out-Probability Integral Transform (LOO-PIT), as a complementary test to the standard best fit statistic χ^2 . This technique combines two concepts: LOO-CV (Leave One Out-Cross Validation), and the well known Probability Integral Transform (PIT). LOO-PIT primarily has the advantage of diagnosing the type of modelling failure as well as relaxing the constraint of assuming Gaussian likelihoods in one’s data analysis, paving the way for more general methods. While it is a general method, we apply LOO-PIT to the problem of diagnosing unknown interlopers in galaxy catalogues.

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Dedication

This thesis is dedicated to Optimus Prime.

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Chapter 1

Introduction to Cosmology and Clustering

“In the beginning the universe was created. This has made a lot of people very angry and has been widely regarded as a bad move.”

Douglas Adams

For as long as humans have walked this Earth, we have looked up into the night sky with wonder. We drew pictures and told tales of the stars, connecting the short lives we lived to the seemingly everlasting and static cosmos. With each new empire’s rise, new stories and superstitions were further ingrained into our collective psyche.

Yet it is only recently that hints of the true nature of the universe have begun to be revealed. It has only been 400 years since it was proposed that the Earth was not the centre of the universe, and just over 100 years since the “Great Debate” between Shapley and Curtis. Indeed, only in the late 1920s did Edwin Hubble prove that Andromeda was not a nebula within our galaxy, but an entirely separate galaxy. This was soon followed by perhaps an even more startling discovery: that there were many other galaxies, or “extragalactic nebulae,” and that nearly all of them were moving away from us! It was this fact that led astronomers to believe that the universe, as a whole, is expanding.

The 20th century would still yield more mysteries. In the same way astronomers used redshifts to measure the recession of galaxies, they measured the rotation of galaxies outside our own. These measurements resulted in a strange discrepancy: the amount of matter inferred from the brightness of a galaxy could not account for the motion of its constituent

stars and gas. Astronomers called this missing piece “*Dark Matter*” (DM). While first invoked to describe this issue with galaxy rotation curves, in the years since, DM has been found to be able to describe many other phenomena we observe in the universe, from gravitational lensing to the very structure of the Cosmic Microwave Background (CMB).

Within the last 20 years, there has been increasing evidence that the universe is not only expanding, but that its expansion is accelerating [15, 16]. This is most often explained by adding in another component of the universe: “*Dark Energy (DE)*.” This usually takes the form of a cosmological constant, Λ , and together with DM forms the so-called “*Dark Sector*” of the universe.

With the current state of observations, astronomers have been able to constrain some broad properties of DM and DE, but unfortunately their true nature remains elusive. For example, it seems that DM must be “cold,” as hot DM would not allow for the formation of structure in the universe as we see it. Thus, together with the Λ of the cosmological constant, the current best model for the universe is known as the “ Λ -Cold Dark Matter” or Λ CDM model. Along with these two major components, the universe also contains baryonic (or normal) matter, neutrinos, radiation, and curvature. Our models also assume that the universe is isotropic and homogeneous. While it is obviously true that galaxies, stars, and even people violate this principle, it appears to hold when averaged over sufficiently large scales, thus in this work, we will assume this Λ CDM picture, with *statistical* isotropy and homogeneity, unless otherwise stated.

In the following sections of this Introduction, we will cover the necessary background for the study of Large Scale Structure (LSS) Cosmology and the context for the following chapters.

1.1 The Development of the Λ CDM Model

In this section, we will briefly cover the development of the Λ CDM model and some major pieces of evidence for it.

1.1.1 Mathematical Background and Conventions

The universe is described by the Friedmann–Lemaître–Robertson–Walker (FLRW) metric:

$$ds^2 = -cdt^2 + a^2(t)d\Sigma^2 \quad , \quad (1.1)$$

where Σ sums over a three dimensional space with uniform curvature, and $a(t)$ is the scale factor, accounting for a uniform expansion of space. By convention, we normalize $a(t)$ to the current time, t_0 , such that $a(t_0) = 1$.

The scale factor is related to the redshift z (see Section 1.2.1):

$$a = \frac{1}{1+z} \quad . \quad (1.2)$$

Thus for a given redshift, we can track the expansion of the universe. This expansion is written in terms of the Hubble parameter:

$$H(t) = \frac{\dot{a}}{a} \quad . \quad (1.3)$$

This parameter is used in the first of two Friedmann equations which gives the expansion of the universe:

$$H^2(t) = \frac{8\pi G}{3}\rho_{\text{total}} - \frac{kc^2}{a^2} + \frac{\Lambda c^2}{3}, \quad (1.4)$$

where ρ_{total} is the total matter and radiation energy density, k parameterises an open, flat or closed universe with $k = -1, 0, 1$, and Λ is the aforementioned cosmological constant.

The second equation gives the acceleration of the expansion:

$$\frac{\ddot{a}}{a} = -\frac{4\pi G}{3}\left(\rho + \frac{3p}{c^2}\right) + \frac{\Lambda c^2}{3}, \quad (1.5)$$

where p is pressure. Together with the continuity equation,

$$\dot{\rho} + 3H(\rho + p) = 0, \quad (1.6)$$

we have a description of our isotropic, homogeneous universe with constant curvature. There are now several conventions used in modern cosmology that will be useful to review.

Instead of dealing directly with the density ρ , we often use density parameters,

$$\Omega_i = \frac{\rho_i}{\rho_{\text{crit}}}, \quad (1.7)$$

where the subscript i denotes a given component of the universe, and ρ_{crit} is the critical density defined as:

$$\rho_{\text{crit}} = \frac{3H^2}{8\pi G}. \quad (1.8)$$

This is the density required to make the spatial curvature of the universe, with only matter and radiation, precisely equal to zero. Thus, the total energy content of the universe is related to the global geometry.

It is also helpful to write out the Hubble parameter in terms of the density parameters of the components of the universe and the Hubble constant:

$$H(a) = H_0 \sqrt{\Omega_{\text{M}} a^{-3} + \Omega_{\gamma} a^{-4} + \Omega_{\Lambda}}, \quad (1.9)$$

where Ω_{M} , Ω_{γ} , Ω_{Λ} , are the density parameters for matter, radiation and DE, respectively.

Similar to the normalisation of the scale factor, H_0 is simply the present day value of the Hubble parameter.

We now introduce some other notation. The overdensity is defined:

$$\delta(\vec{r}) = \frac{\rho(\vec{r}) - \bar{\rho}}{\bar{\rho}}. \quad (1.10)$$

This is generally used as opposed to the physical density. As no survey can observe the entire universe, we often normalise the measured physical density to this dimensionless overdensity.

We can then use this overdensity in the calculation of the two point correlation function:

$$\xi(\vec{r}) = \langle \delta(\vec{x}_1) \delta(\vec{x}_2) \rangle, \quad (1.11)$$

where $\vec{r} = \vec{x}_2 - \vec{x}_1$. This function measures the excess probability that given a galaxy at position $\vec{x}_1$, one would find another at $\vec{x}_2$. It is illustrative to consider the following (adapted from [17]): Consider two small regions δV_1 , δV_2 in one's survey volume, with the separation vector $\vec{r}$. This volume has a mean number density $\bar{n}$. Hence the expected number of galaxy pairs between these two regions is given by:

$$\langle n_{\text{pairs}} \rangle = \bar{n}(1 + \xi(\vec{r}))\delta V_1 \delta V_2. \quad (1.12)$$

We can see that if $\xi(\vec{r}) = 0$, at that scale and in that direction, the galaxies, or objects in general, are unclustered relative to the mean. Thus $\xi > 0$ tells one that there is more dense clustering. The reverse is also true: $\xi < 0$ indicates less clustering, or “anti-clustering.”

A closely related summary statistic is the power spectrum. It is simply the Fourier transform of the two point correlation function:

$$P(k) = \int \xi(r) e^{i\vec{k} \cdot \vec{r}} d^3r. \quad (1.13)$$

This is often used as it is easier to measure clustering in Fourier space. However, both quantities contain the same information thus the choice of which to use is generally up to the practitioner.

As the overdensity field is mostly Gaussian, it is mostly characterised by the two point statistics. However, higher order statistics are useful in searching for deviations from this ideal. The study of primordial non-Gaussianity (PNG) and searches for the related parameter, f_{NL} , have employed several higher order or modified statistics, like the bispectrum and the marked power spectrum [18, 19, 20, 21], search for signatures of more exotic models of inflation. As well, the trispectrum was recently employed to search for signatures of large scale parity violation, although the supposed detection is now on much shakier ground [22, 23]. These measurements seem to hint at some additional information hidden in the galaxy field.¹

¹Perhaps confusingly, the *bispectrum* and *trispectrum* correspond to the three and four point correlation functions, respectively. It is not clear who we can blame for this. We can make ourselves feel a bit better if we consider the bispectrum to be the spectrum of two k vectors separated by an angle, and similarly for the trispectrum.

1.1.2 Notable Evidence for Λ CDM

In this section, we will discuss some broad successes of the Λ CDM model, in roughly cosmological chronological order from the Big Bang to the present.

The Cosmic Microwave Background

As noted above, nearly all observed galaxies are receding away from us, and from each other as well. This implies in the past galaxies were more concentrated. Taking this idea to its extreme results in the concept of the “Big Bang:” the universe had a beginning, exploding from an extremely dense state about 14 billion years ago. While maligned by scientists like Fred Hoyle, the discovery of the CMB in 1964 provided sufficient proof of the theory’s predictions: the universe had, at one point in the past, been dense, hot, and much closer together.

During this early period in the universe, the matter and radiation in the universe existed in the dense plasma like state, opaque to photons. Around $z = 1100$, the universe had expanded and cooled down enough for the photons to decouple from the baryons and freely stream throughout the universe. It is this surface of last scattering that we observe when we look at the CMB.

Imprinted onto the surface of last scattering is a particular pattern of CMB anisotropies, shown in Figure 1.1. From this pattern, we can infer some information about various components that makeup the universe. Let us review the mechanism that creates this pattern.

While the initial plasma was fairly uniform, there existed small anisotropies in the fluid. These irregularities were acted upon by two primary forces: the gravity from the dark matter potential wells, and the outward (relative to a central overdensity) radiation pressure. While baryons make up a much smaller fraction of mass compared to dark matter, they act to increase the effective mass of the fluid itself. This effect will be discussed in more detail with the discussion of the second acoustic peak. These forces act on the photon-baryon fluid like a mass suspended from a spring. As the fluid compresses under its own gravity, falling into the gravitational well, the radiation pressure acts to oppose this motion. Once the pressure builds up enough it pushes the fluid outwards until gravity takes over again, oscillating over time. The peaks seen in Figure 1.1 are the imprint of these oscillations. At the time of decoupling, certain harmonics were caught at extremes of the oscillations, and thus we are left with mostly the imprint of the most extreme temperature fluctuations. These appear as the most prominent anisotropies in the CMB.

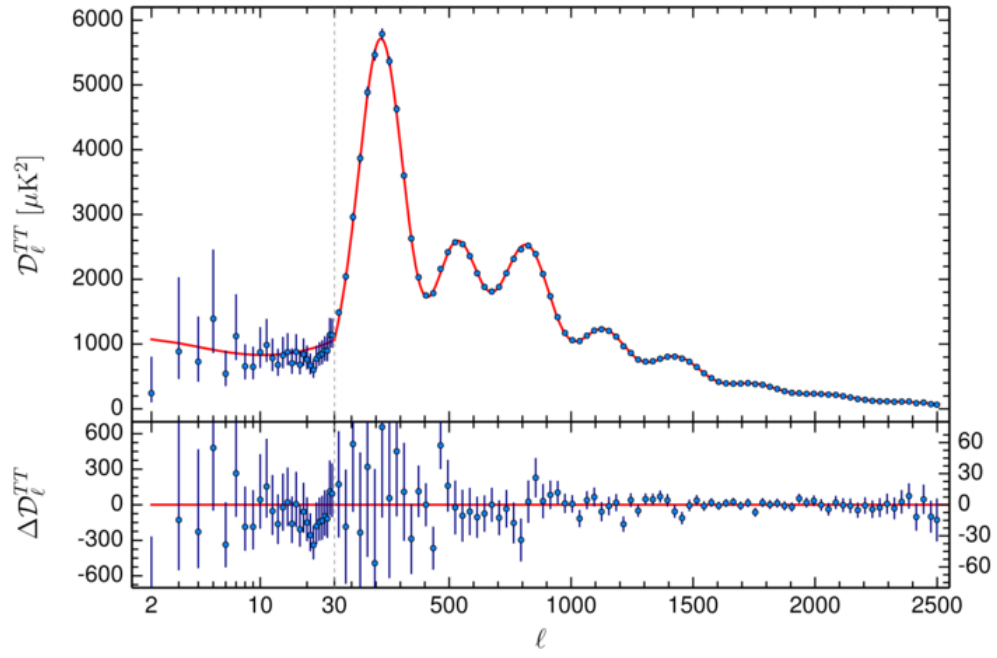


Figure 1.1: The CMB TT powerspectrum as measured by the Planck satellite. From Figure 1 of [9].

The first peak corresponds to the harmonic that had enough time from the beginning of the oscillations to compress exactly once. The second had time for one compression and one rarefaction. The third had an additional compression and so on. Odd numbered peaks therefore correspond to compressions, and even peaks are rarefactions. This separation helps probe the various constituents of the universe; by studying just the first few peaks, we find information about all the major components of the universe.

The first peak is clearly the most prominent and corresponds to the size of the sound horizon. This is the fundamental harmonic of this series of oscillations and is defined by the maximum distance an acoustic, or sound, wave could have travelled up to decoupling. Furthermore, the position of this first peak provides a sensitive measure of the overall curvature of the universe. The position of the first peak tells us that the total energy density in the universe is close to critical. That is, the amount of energy in the universe makes it flat. Now, there are numerous ways to measure the dark matter density in the universe which makes up the bulk of the matter-radiation density.² These all lead to a dark matter density that is much less than the critical density and the other “well-known” components cannot make up for it. This is even more evidence for the mysterious dark energy!

The second peak is most useful in determining the amount of baryons in the universe, relative to the amount of photons. Perhaps it is more accurate to say the *ratio* between the first and second peaks is the observable for the baryon to photon ratio. Due to the difference between the compressed peaks and the rarefied peaks, the greatest effect of adding in more baryons is the relative amplification of the odd compression peaks. This is simple to conceptualise: with more baryons coupled to the photons, all else equal, the oscillations fall deeper into the potential wells and rebound less. Since the CMB power spectrum does not care about the sign of the anisotropy, we would see greater power in the odd peaks relative to the even ones.

Baryon Acoustic Oscillations

The idea of the sound horizon also manifests in more late-time measurements. In galaxy catalogues, the baryon acoustic oscillation (BAO) feature also comes from the same sound horizon that determines the harmonic series of CMB power spectrum peaks. The angular size of the first CMB peak corresponds to a *comoving* distance scale in the three dimensional universe. The same density wave that results in the CMB temperature fluctuations also

²Implied from the CMB, measured from weak gravitational lensing, measurements of galaxy clusters, etc.

imprints a physical density fluctuation. These can be thought of as shells around a central overdensity.

Let us illustrate this with one shell. Prior to decoupling/recombination, imagine a single overdense region. Let us assume this is an adiabatic fluctuation, that is we have an overdensity in all three major components: dark matter, baryonic matter, and radiation. We will ignore neutrinos. At some initial time, all three components are concentrated at some single point. However, as time moves on, the radiation pressure pushes the coupled baryon-photon fluid outwards at the sound speed in a spherical sound wave. The dark matter remains mostly at the centre of its gravitational well, as it does not interact with the radiation. Around $z = 1100$, the photons decouple from the baryons and stream freely. This leaves a spherical shell of baryons around the central dark matter. An illustration of what this looks like for matter is shown below.

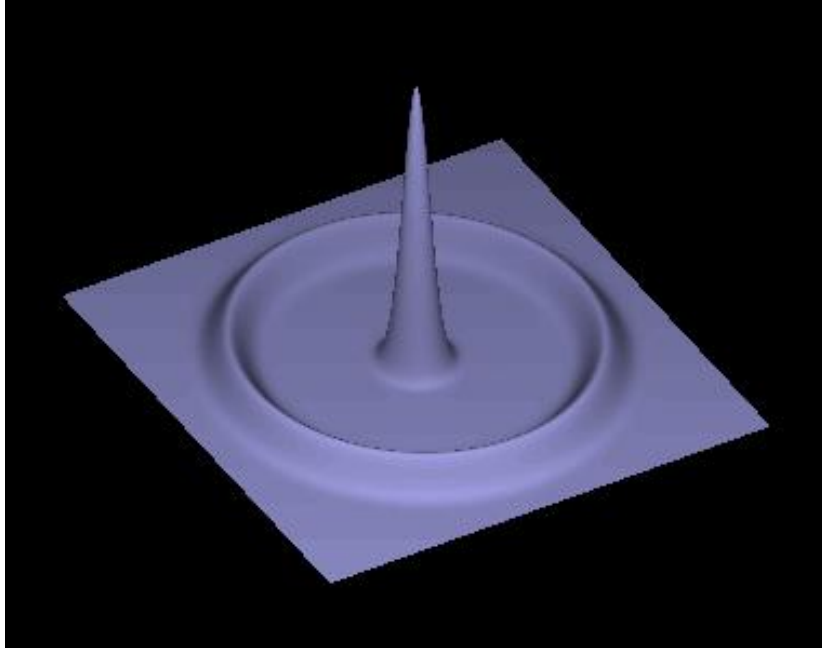


Figure 1.2: An illustration of a single BAO shell. From [10].

Of course the universe isn't a single one of these shell and core configurations, but many of them seeded by the primordial density fluctuations. Along with the initial distribution of dark and baryonic matter, this pattern gets encoded into the distribution of galaxies. As we see both the central and shell regions presenting an overdensity, gas will tend to fall into these regions and form clusters and galaxies. Since the distance from the centre to the

shell is exactly the sound horizon (in an ideal case at least), galaxies will be slightly more likely to be separated by a comoving distance about 150 Mpc. This can be detected by the statistics outlined in Section 1.1.1. This detection is somewhat complicated by late time evolution of galaxy clusters, as this process is highly non-linear. Fortunately, there exist reconstruction techniques built to partially undo this evolution, allowing us to not only obtain clean BAO detections, but also to get at the primordial density field immediately after recombination.

In general, the BAO method is straightforward. We have a standard ruler that expands with the expansion of the universe. We also can build a fiducial model of the universe. This model predicts the size of this ruler as a function of redshift. Thus, we may measure the expansion of the universe using BAO by measuring the size of the standard ruler in various redshift bins and at various times. We may then compare the measurements to the fiducial cosmology via the AP effect or by direct comparison.

In practice, distances are converted to comoving distances before analysis. Thus, we would hope to measure a BAO position that is consistent with the Λ CDM prediction of $100 h^{-1}\text{Mpc}$ in all redshift bins. This is illustrated in Figure 1.3. The correlation function of various tracers at different lookback time are compared to the Λ CDM prediction. Note that the two LRG points appear to inconsistent with the Λ CDM prediction.

Standard Candles

Instead of using the BAO standard ruler, it is possible to apply another standard. Indeed, the use of standard candles is even older than the standard ruler. This method relies on measuring an object where the intrinsic brightness is known. Hubble’s first measurement of the expansion rate used one such standard candle: Cepheid variable stars. These stars pulsate over time, and it was determined that the stars’ pulsation period is closely related to its luminosity. This was discovered by the astronomer Henrietta Swan Leavitt. If a star’s intrinsic brightness is known, its distance can be easily determined using the inverse square law. Its velocity is then easily determined by redshift. Thus, these objects provide a separate measurement of the expansion of the universe. Other standard candles include the RR Lyrae variable stars, Type Ia supernova, as well as kilonovae. Measurements of extragalactic standard candles have indeed proved that the universe is expanding as predicted by Λ CDM [16].

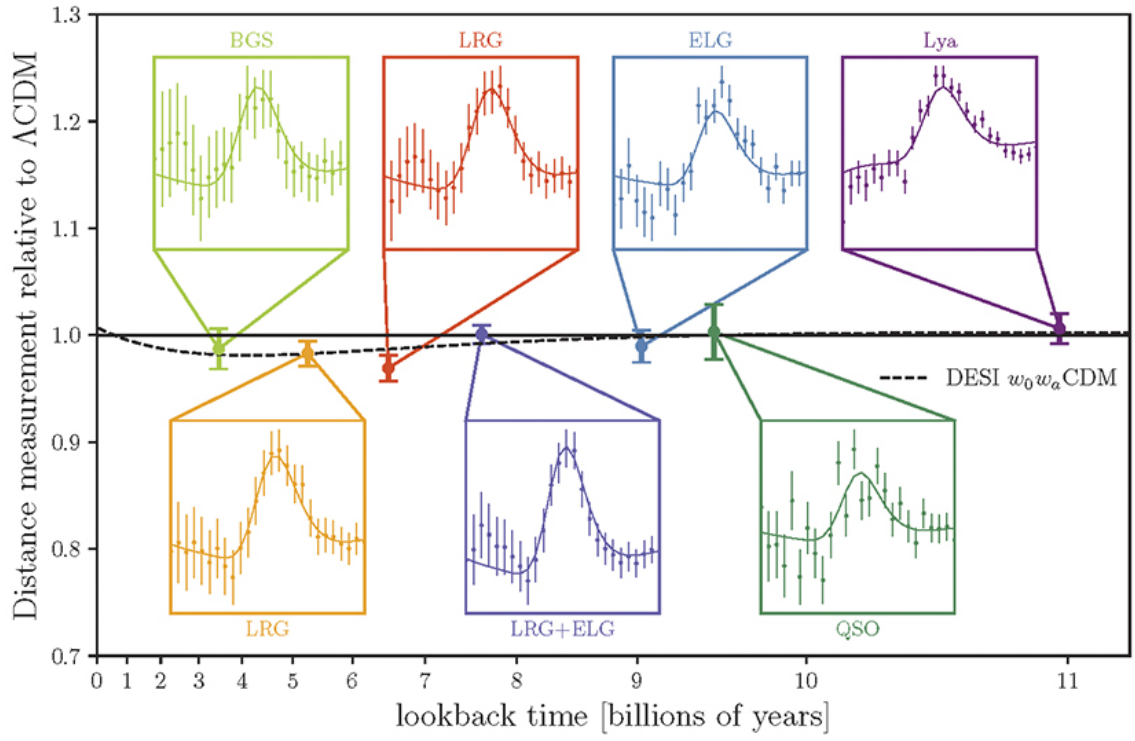


Figure 1.3: An illustration of the various BAO measurements done by DESI. Credit: Arnaud de Mattia/DESI collaboration [11].

Evidence for Dark Matter

There is also substantial evidence for the other piece of Λ CDM in the nearby universe. While dark matter was initially invoked to explain then anomalous galaxy rotation curves, it is now a necessary component of many pieces of the cosmological puzzle. Chief among these is the amount of weak lensing we observe. One may be familiar with the stunning images of strong lensing events, where the light of a background galaxy is twisted into a spectacular Einstein ring by a foreground lens.

The weak lensing regime is much less visually striking. It is nevertheless crucial to account for. The light of every galaxy is distorted by all the matter between its emission and our observation.³ This leads to a predictable distortion of galaxy shapes, correlated to the distribution of total matter in the universe. This is where an issue arises. Simply put, there is not enough mass accounted for by the luminous matter in galaxies and galaxy clusters to cause the observed weak gravitational lensing signal in the universe. There must be additional matter present in the universe! Through these measurements, we have found that not only is there another mysterious component of matter, but that it makes up 85% of the matter in the universe.

Furthermore, this dark matter must be cold, meaning that its kinetic energy is negligible relative to its mass energy [24]. In other words, it is non-relativistic. There are several pieces of evidence for this. If dark matter is cold, then structure in the universe forms “hierarchically.” This means small clumps of matter build up into the structures we see today. If dark matter is hot, or relativistic, then structure would form in the opposite way, or top down. The largest structures would form first, then fragment into smaller pieces like clusters and galaxies. Our observations of the CMB clearly show that the universe was once very smooth, supporting the CDM paradigm.

1.1.3 Potential deviations from Λ CDM

As successful as the standard Λ CDM model has been at explaining our cosmological observations, there still exist some issues within the model. We will briefly discuss the two major tensions: the H_0 and S_8 tensions.

As outlined in Section 1.1.1, the Hubble constant, H_0 , parameterises the expansion rate of the universe. The tension lies in two separate measurements of this parameter that do not agree, by around 5σ .

³Really it is all the mass/energy density.

The first measurement, or set of measurements, is often led by the value of H_0 inferred by the CMB as measured by the *Planck* satellite at (67.27 ± 0.60) km s⁻¹ Mpc⁻¹ [9]. Along with this measurement, a number of other probes like elemental abundances from Big Bang Nucleosynthesis (BBN), BAO, and deep galaxy surveys, also probe H_0 using high redshift measurements. Thus, these are generally called *early time* measurements.

The competitor is a set of measurements based on the local distance ladder. These are primarily made up of measurements of nearby supernovae (Pantheon) and Cepheid variable stars (SH0ES), and gives a value of H_0 at (73.2 ± 1.3) km s⁻¹ Mpc⁻¹ [25, 26]. As these probes are relatively low redshift, these are called *late time* measurements.

Some recent constraints on the Hubble constant are summarised in the following table:

Planck CMB + BAO	BBN+BAO	Cepheids+SN Ia	Gravitational Waves
67.66 ± 0.42 [27]	66.98 ± 1.18 [28]	73.2 ± 1.3 [25, 26]	$68^{+12}_{-7.0}$ [29]

Table 1.1: Recent H_0 constraints from major methods. Values given in km s⁻¹ Mpc⁻¹.

In a similar dichotomy, there is also tension between the early and late time measurements of S_8 :

$$S_8 = \sigma_8 \sqrt{\Omega_M/0.3},^4 \quad (1.14)$$

where σ_8 measures the amplitude of the linear matter power spectrum in a box with side lengths $8 h^{-1}$ Mpc. This tension is not quite as large as the H_0 tension, only about 2-3 σ . However, it does appear across the same probes and with the same late vs. early time split.

While it is certainly possible that there still exists some yet unknown systematic in these measurements, the existence of this tension across the variety of probes used implies that this may be a very real effect. As a result, several attempts to modify Λ CDM to explain this discrepancy have been put forth, to varying degrees of success. There is currently no agreed upon model that solves both problems. Crucially, any “successful” modification must resolve both tensions simultaneously. We will see why this is more difficult than expected. See [30] for a more complete picture of the landscape of modifications, and [31] for a more thorough review of the tensions.

One idea that has been recently popular is early dark energy (EDE). It is conceptually very simple: there is simply an additional scalar field that contributes to the expansion prior to late time evolution. It then “turns off” afterwards, allowing the normal Λ CDM

⁴This parameter is often used in weak lensing survey analyses due to degeneracy between σ_8 and Ω_M .

expansion. While EDE does provide a sufficiently good fit to both *Planck* and SH0ES, it generally fails to solve the S_8 tension, often making it worse [32].

Another recent development in this field is from the recent DESI BAO data release. While Λ CDM assumes a flat cosmology with the EoS parameter of DE: $w = -1$, there have been some alternative proposals that consider an evolving EoS parameter. This has been parameterised as:

$$w(a) = w_0 + w_a(1 - a). \quad (1.15)$$

Thus this model is referred to as w_0w_a CDM. While the DESI BAO fits to vanilla Λ CDM are consistent, fits to w_0w_a CDM seem to indicate that this idea of evolving DE is preferred [33].

1.2 Cosmological Measurements

In this section we will primarily discuss measurements of the two point correlation function, as well as fitting methods.

1.2.1 Redshift

Perhaps the most important quantity that we measure in galaxy surveys are redshifts. Generally speaking, the redshift is an increase in the wavelength of emitted light from a source, due to its motion away from the observer. Similarly, there is the less common blueshift, where the emitted wavelength is decreased due to the source's motion towards the observer. This is much like the Doppler effect that sound waves experience.⁵

As the universe is expanding, it is therefore much more common to measure objects with a net redshift. We define this redshift measurement in terms of the rest frame wavelength and the measured wavelength:

$$z = \frac{\lambda_{\text{measured}} - \lambda_{\text{rest}}}{\lambda_{\text{rest}}}. \quad (1.16)$$

An example spectrum is shown in Figure 1.4. We can see that the $\text{H}\alpha$ line does not appear at its rest frame wavelength of 6563 Angstroms, but is past 7000 Angstroms. Using the above formula and these wavelengths, the redshift of the galaxy was determined to be 0.086.

The rest frame wavelength in a redshift measurement must be assumed. This is generally not a major issue in surveys, as multiple emission lines are measured and separations are compared. However, one can imagine if the rest frame wavelength is incorrectly assumed, the measurement of the redshift will be incorrect. This can have catastrophic effects on cosmological measurements, as we will discuss in Chapters 2 and 3.

We can also relate the redshift to the recession velocity via the following:

$$z \approx \frac{v}{c}. \quad (1.17)$$

This is valid for $v \ll c$. That is, objects with small relative velocities. The full form taking into account relativistic effects is given by:

⁵It is important to note that the redshift due to the expansion of the universe is indeed a different physical mechanism than the redshift caused by moving galaxies.

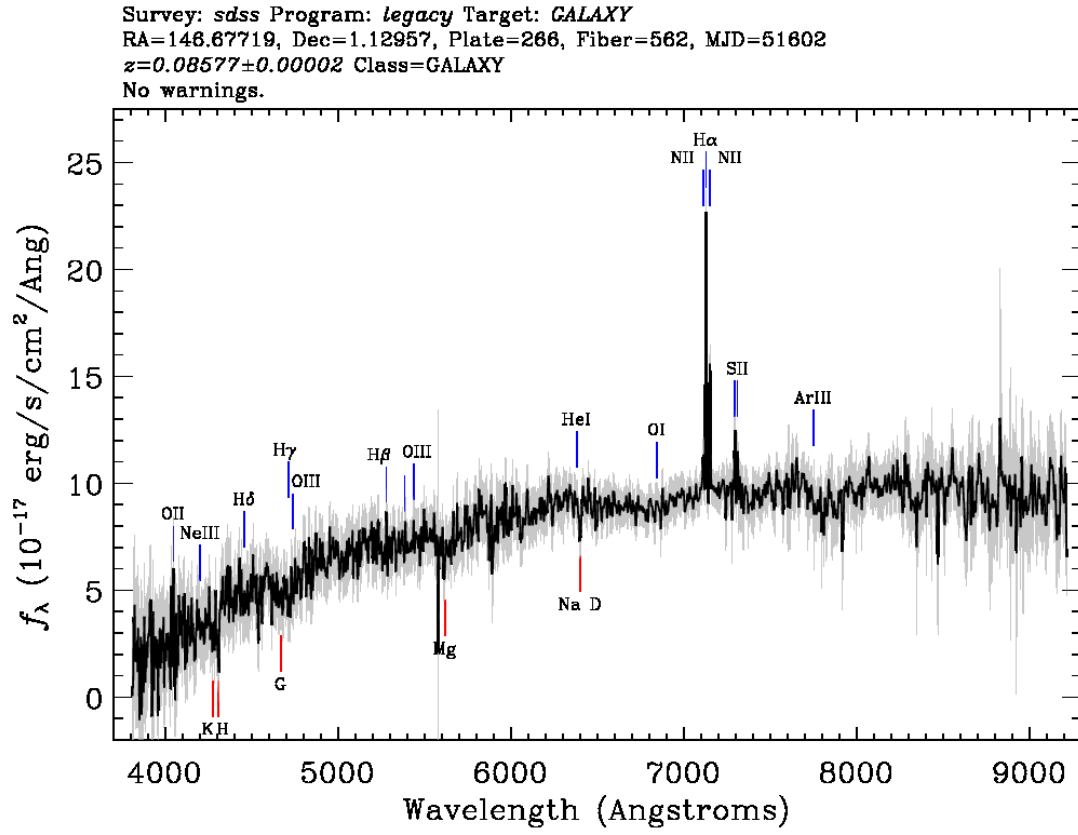


Figure 1.4: An example H α galaxy spectrum from SDSS DR8. Credit: SDSS Collaboration [12].

$$1 + z = \frac{1 + v \cos(\theta)/c}{\sqrt{1 - v^2/c^2}}, \quad (1.18)$$

where θ is the angle between the separation vector between the source and the observer, and the relative velocity vector. These are useful for measurements of cosmological distances via the Hubble–Lemaître Law.

1.2.2 Correlation Function and Power Spectra Measurements

As the two point correlation function is meant to measure excess clustering at various scales, it is straightforward to apply the following naive estimator:

$$\xi(\vec{r}) = \frac{DD(\vec{r})}{RR(\vec{r})} - 1, \quad (1.19)$$

where $DD(\vec{r})$ is the number of pairs at $\vec{r}$ separation in one’s galaxy sample, and $RR(\vec{r})$ is the number of pairs at the same separation in a uniformly distributed sample with the same number density: randoms. For simple survey geometries, these randoms are easily calculated analytically. As advertised, when $\xi > 0$, there are more pairs than expected from a uniform, unclustered sample, and with $\xi < 0$ there are fewer.

While this estimator is often used, however there are competing estimators, such as the Landy–Szalay estimator (LS) [34]:

$$\xi(\vec{r}) = \frac{DD(\vec{r}) - 2DR(\vec{r}) + RR(\vec{r})}{RR(\vec{r})}, \quad (1.20)$$

where DR are the galaxy-random pairs. These estimators are equal in the limiting cases of simple geometry and high point density. However, real surveys guarantee neither of these, thus the LS estimator is less biased when confronted with low densities and realistic geometries. In addition, the LS estimator has close to Poisson variance compared to the naive estimator which can show much greater variance [34]. One drawback to this LS estimator is that it is not as simple to analytically calculate the DR pairs, slowing the calculation. In the following chapters, we use the naive estimator for our correlation function calculations (Equation 2.7), as is the default for the PYTHON package NBODYKIT [6].

It is common to project the two dimensional correlation function or power spectrum into a basis of one dimensional multipoles using the well known Legendre polynomials (here written as Rodrigues' formula):

$$L_\ell = \frac{1}{2^\ell \ell!} \frac{d^\ell}{d\mu^\ell} (\mu^2 - 1)^\ell. \quad (1.21)$$

Given the two dimensional statistic, one may extract a multipole of order ℓ :

$$\xi_\ell(r) = \frac{2\ell + 1}{2} \int_{-1}^1 \xi(r, \mu) L_\ell(\mu) d\mu, \quad (1.22)$$

$$P_\ell(k) = \frac{2\ell + 1}{2} \int_{-1}^1 P(k, \mu) L_\ell(\mu) d\mu, \quad (1.23)$$

where μ is the cosine of the angle between the separation vector (in configuration or Fourier space) and the line of sight.

As the Legendre polynomials form a complete basis, we can also reconstruct a two dimensional statistic from its multipoles:

$$\xi(r, \mu) = \sum_{\ell=0}^{\infty} \xi_\ell(r) L_\ell(\mu), \quad (1.24)$$

$$P(r, \mu) = \sum_{\ell=0}^{\infty} P_\ell(r) L_\ell(\mu). \quad (1.25)$$

Note that while the sums written above are taken to $\ell \rightarrow \infty$, in practice, much of the information is contained within the zeroth moment or the monopole, and in general, the odd multipoles vanish due to the isotropy in μ , since they are odd functions in μ .⁶ As such, for the analyses presented in later chapters, we will assume that the first two or three even moments (monopole, quadrupole, hexadecapole) are sufficient to characterise our two point statistic.

In real space, the two point statistic is exactly isotropic, thus higher order multipoles vanish and we are left with only the monopole. This is shown in Figure 1.5. However, in redshift space, this is not longer true. We also can see other effects on the two point statistics that can stem from poor estimations of the fiducial cosmology.

⁶There are some exceptions to this rule, usually by construction, which we will explore in Chapter 2.

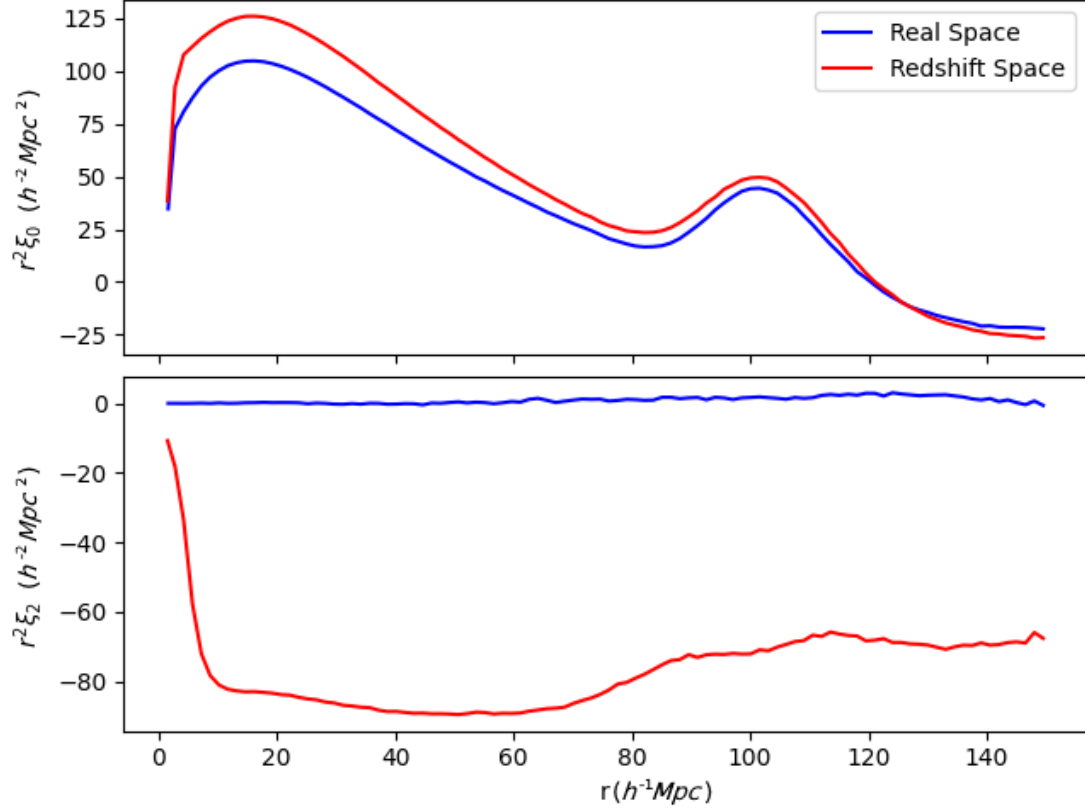


Figure 1.5: The mean of monopoles and quadrupoles measured from 1000 Quijote mocks, in real space (blue) and redshift space (red) (See Section 2.2.3). We see there is not a significant change in shape of the monopole, but the addition of RSD effects results in a drastically different quadrupole. This is due to RSD only affecting line of sight positions, not transverse positions.

1.2.3 The Alcock–Paczynski Effect and Redshift Space Distortions

In this section, we will review the effects of Redshift Space Distortions (RSD) and the Alcock–Paczynski distortion.

Redshift space distortions are an observational effect that comes down to a single problem: we generally do not measure the distance to a galaxy, we measure the redshift, converting it to a distance via the Hubble–Lemaître Law. As redshifts are the result of a galaxy’s relative velocity to us (and the overall expansion of the universe), this causes issues. While the majority of a galaxy’s velocity is recession due to Hubble expansion, there are *peculiar* velocities associated with galaxies falling in to and moving around gravitational potentials.⁷

The line of sight position of a galaxy in redshift space can be written down as:

$$s = \frac{1}{H_0}(cz_{\text{true}} + v_{\text{pec}}) \quad (1.26)$$

Note that this equation is valid for velocities much smaller than c . It makes use of Equation 1.17 to relate the true redshift to the recession due to the expansion of the universe.

These effects can be split into two main types based on the actual physical scales: the large scale RSD, or Kaiser effect⁸, and small scale RSD, or the Fingers-of-God (FoG) effect [35, 36].

Consider a large scale cluster, shown on the left column of Figure 1.6. On the edges of this cluster, galaxies (represented by the black dots) will tend to be falling into the well. This is the peculiar velocity they have, in addition to their recession velocity. In real space, the cluster is perfectly spherical. However, in redshift space, the effect of this infalling squashes the sphere along the line of sight. Note that the positions of galaxies with peculiar velocities orthogonal to the line of sight are unaffected by these peculiar velocities, as our distance measurements are only dependent on the line of sight direction.

Now let us consider the small scale case, shown in the right column of Figure 1.6. Again, in real space this smaller cluster is spherical. If there were relatively small infall velocities, we would see a smaller version of the Kaiser effect. However, if the galaxies

⁷In this case, peculiar does not mean weird or strange! It is simply any velocity a galaxy has that is not due to Hubble expansion.

⁸Some have called this the Pancakes-of-God (PoG) effect.

have sufficiently large peculiar velocities, we could see the sphere stretched along the line of sight, in redshift space.

While the Kaiser effect is generally simple to quantify as it is a linear effect, the FoG is more difficult due to its non-linear nature. The effect of these on modelling and the two point statistics are covered in Section 2.3.3.

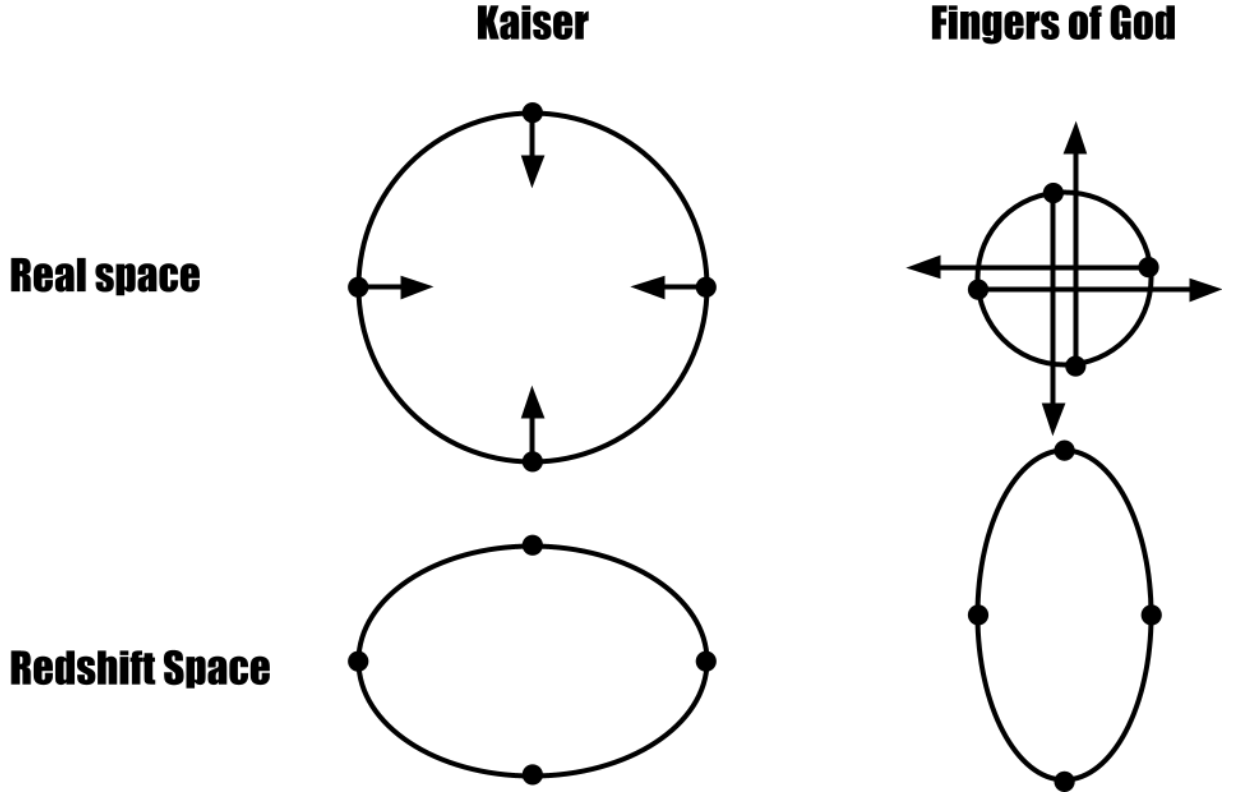


Figure 1.6: An illustration of the Kaiser and FoG effects. The velocity vectors in the FoG column are offset for visual clarity.

Another type of distortion is the Alcock–Paczynski (AP) distortion. This is also a result of the fact that we generally do not measure distances directly. Outside of RSD, we still require some fiducial cosmological model to convert redshifts to distances. The AP effect becomes important when that fiducial model is incorrect. In this work, we will

parameterise it as [37]:

$$\alpha = \left[\frac{D_{\text{A, true}}^2(z) H_{\text{fid}}(z)}{D_{\text{A, fid}}^2(z) H_{\text{true}}(z)} \right]^{1/3} \frac{r_{\text{s, fid}}}{r_{\text{s, true}}}, \quad 1 + \epsilon = \left[\frac{D_{\text{A, fid}}^2(z) H_{\text{fid}}(z)}{D_{\text{A, true}}^2(z) H_{\text{true}}(z)} \right]^{1/3}. \quad (1.27)$$

Here, α is the spherically averaged isotropic dilation parameter, and ϵ is the anisotropic warping parameter. D_A is the angular diameter distance, and H is the Hubble parameter. r_s is the comoving sound horizon at the baryon drag epoch. Using these parameters, we may relate the true parallel and perpendicular separations,

$$r_{\parallel, \text{true}} = \alpha(1 + \epsilon)^2 r_{\parallel, \text{fid}}, \quad r_{\perp, \text{true}} = \alpha(1 + \epsilon)^{-1} r_{\perp, \text{fid}}. \quad (1.28)$$

The fiducial Cartesian coordinates and true polar coordinates can be related as follows (where we have dropped the fid subscript for clarity),

$$r_{\text{true}} = \alpha \sqrt{(1 + \epsilon)^4 r_{\parallel}^2 + (1 + \epsilon)^{-2} r_{\perp}^2}, \quad \mu_{\text{true}} = \frac{(1 + \epsilon)^2 r_{\parallel}}{\sqrt{(1 + \epsilon)^4 r_{\parallel}^2 + (1 + \epsilon)^{-2} r_{\perp}^2}}. \quad (1.29)$$

In using Equation 1.27 we consider a spherical average over two directional α , with ϵ carrying the directional information. A more illustrative parameterisation uses the following:

$$\alpha_{\perp} = \frac{D_{\text{A}}(z) r_{\text{s, fid}}}{D_{\text{A, fid}}(z) r_{\text{s}}}, \quad \alpha_{\parallel} = \frac{H_{\text{fid}}(z) r_{\text{s, fid}}}{H(z) r_{\text{s}}}. \quad (1.30)$$

Here we can see clearly the effect of an incorrect fiducial cosmology. Along the line of sight ($\alpha_{\parallel}$), the distance measurement is distorted according to the inverse Hubble parameter (since $d_{\parallel} \propto 1/H(z)$). In the transverse direction, the measurement is the angular diameter distance D_A . Thus, a cosmological measurement that contains both of these measurements can detect deviations from the fiducial cosmology.

1.3 Surveys and BAO measurements

In this section, we will review the history of past spectroscopic surveys and BAO measurements. We will then discuss the future of these surveys and expected missions in the coming years.

1.3.1 Past Surveys

The very first attempt to map the large scale structure of the universe, the CfA Redshift Survey, was undertaken at the Smithsonian Astrophysical Observatory in 1977. When its observing run was completed in 1982, a followup program was started in 1985, running for about 10 years. Together these surveys revealed that galaxies were not uniformly distributed across the universe but clustered, forming filaments separated by underdense voids. This was the first time astronomers began to realise that not only was the universe clustered, but that this clustering encoded information about the cosmos [38].

After CfA, there were a slew of other cosmological surveys with the aims to create larger and larger maps of the universe. We will discuss the first two here: 2dFGRS and SDSS. The older of the two, the Two-degree-Field Galaxy Redshift Survey (2dFGRS) was conducted by the Australian Astronomical Observatory between 1997 and 2001. Until 2003, it was the largest ever redshift survey. 2dFGRS covered an area of 1500 square degrees in two regions around the galactic poles, reaching out to redshifts of about $z = 0.3$. This survey was among the first to make use of optical fibres for its spectroscopy, allowing for the measurements of 400 spectra at once. The Sloan Digital Sky Survey, or SDSS, started just after 2dFGRS, beginning operation in 2000. It uses a 2.5 metre telescope at Apache Point Observatory and its first survey SDSS-I would cover 8000 square degrees. Like 2dFGRS, (and later DESI), SDSS used fibres, observing 640 spectra at once. Both these surveys announced their detection of the BAO signal at around the same time in 2005, and the credit for the discovery has been given to both teams as a result [39, 40]. Both teams would conduct follow-up surveys, with 6dFGS, and SDSS-II through SDSS-V. Notable among the SDSS extensions is BOSS, the Baryon Oscillation Spectroscopic Survey, part of SDSS-III. It increased the number of fibres to 1000 and was designed specifically to measure the BAO feature. In 2014, BOSS announced the first sub-percent constraint on the BAO scale in history [41].

1.3.2 Current and Upcoming Missions

Following the footsteps of their predecessors, a number of large scale structure surveys have either recently begun operation or will do so in the coming decade. In this section, we will briefly overview DESI, Euclid, and the Rubin Observatory.

The Dark Energy Spectroscopic Instrument, or DESI, is an advanced spectrograph mounted on the Mayall Telescope at Kitt Peak National Observatory, funded by the United States Department of Energy and operated by Lawrence Berkeley National Laboratory. Its

focal plane is made of 5000 fibres, robotically positioned, that feed into 10 spectrographs held in a separate climate controlled room. This technology allows DESI to observe 5000 individual spectra at once, one per fibre. The robotic control of the fibres allows for unprecedented speed in positioning. DESI is primarily an optical instrument, taking spectra over a wavelength range of 360 nm to 980 nm. This corresponds to a redshift range of up to $z = 1.7$ for emission line galaxies, and a further $z = 3.5$ for Lyman- α observations of quasars. DESI started operation in 2021.

As one might expect from its name, DESI's primary science focus is to study the nature of dark energy, through galaxy clustering and BAO and RSD measurements. DESI has defined four classes of galaxies, ranging from nearby to far away. Up to $z = 0.4$, DESI will target bright galaxies (BGS). These are the easiest to measure, but they provide information about the most recent era of the universe. The next sample are luminous red galaxies (LRGs). These will push the survey out to $z = 1$. Next, are ELGs, emission line galaxies, so called due to strong emission lines due to high star formation and young stellar populations. These will be detected out to $z = 1.6$. Finally, the furthest sample that DESI will observe are the QSOs, or quasars. These objects are the brightest in the universe allowing for their detection at large redshifts. Lyman- α absorption due to neutral hydrogen along the line of sight between DESI and the quasars also produce a map of that hydrogen, adding more information to the matter clustering signal, extending it to a maximum of $z = 3.5$. In all, DESI will map over 40 million galaxies over its initial survey providing the largest ever (in terms of number) map of the universe [42].

Euclid is a space telescope that was launched from Cape Canaveral on July 1, 2023. It currently orbits the Sun at the Sun-Earth L2 point. Euclid is operated by the European Space Agency and the international Euclid Consortium. Euclid carries two instruments: the VIS, for imaging at optical wavelengths, and the NISP, an infrared instrument.

The VIS operates at a wavelength range of 550 - 900 nm, in the optical regime. It will have an average pixel scale of 0.23 arcseconds with a field of view of approximately 0.6 square degrees. The NISP, or near infrared spectrometer and photometer, covers a slightly smaller field of view at 0.53 square degrees. The NISP science is split into two channels: photometry and spectroscopy. The low precision redshift measurements from the photometry channel will be done over three broadband filters. The spectroscopy channel will make use of slitless spectroscopy via the use of grisms.

Euclid is billed as an explorer of the dark universe. Thus, Euclid has two primary science objectives: determining the nature of dark matter and that of dark energy. Euclid will use its VIS to measure galaxy shapes as part of a weak gravitational lensing survey to map the distribution and clustering of dark matter in the universe. Secondly, Euclid will

measure the BAO standard ruler across the sky. This survey will cover over 1/3 of the sky (15000 square degrees) and provide an extremely wide area map of the cosmos. While the latest SDSS release has covered a similar volume, Euclid will collect galaxy positions from an order of magnitude more sources, greatly increasing the statistical power of its catalogue [43].

Finally, the Vera C. Rubin Observatory is slated for first light in 2025. It is located in northern Chile, near the current site of Gemini South. It was formerly known as the Large Synoptic Survey Telescope, and was named for the pioneering astronomer Vera Rubin. It will house a telescope with a large 8.4 metre mirror, and features an extremely wide field of view of 9.6 square degrees. Its images will be captured by an array of 189 CCDs with 3.2 billion pixels. Its camera, the largest ever built, is equipped with 6 standard broadband filters.

Outside of cosmology, Rubin will survey other objects, like those within our Solar System and the many constituents of the Milky way. But of most relevance to this work Rubin will seek to improve our understanding of the nature of dark energy and dark matter. It will conduct a survey called the Legacy Survey of Space and Time (LSST).⁹ This survey will cover the entire Southern Sky over 10 years of observation. This is just under 20,000 square degrees. Its final survey will boast 20 billion galaxies images complete with photometric redshifts. This will be the widest and deepest photometric survey ever done, with g and r band limiting magnitudes reaching 26.9 [44].

1.4 Upcoming Chapters

The remainder of this thesis will make use of the background covered in this chapter to present tools built to mitigate the issue of emission line interlopers in grism surveys like Euclid and the Nancy Grace Roman Space Telescope. There has been some work done on this problem, from modelling of the contamination to estimating the fraction of interlopers present in the catalogue [45, 46]. Chapter 2 will present the most recent step in interloper modelling. We will introduce a self-calibration method that allows the practitioner to make fewer assumptions about the populations of galaxies and interlopers. Chapter 3 will present a general method for detecting modelling issues, and we test its sensitivity on the interloper problem.

⁹Great name.

Chapter 2

Self-calibrating BAO measurements in the presence of Small Displacement Interlopers

The following chapter is partially made up of material from [1].

The Roman Space Telescope [47] and Euclid [48] missions will soon provide astronomers with the next generation of space-based galaxy surveys. Both surveys will make use of slitless spectroscopy to obtain galaxy redshifts, where a grism in the optical path is used to disperse all incident light. While this method has the potential to quickly measure redshifts, it is not without its own sources of systematic error. The primary source of error we will study is the contamination of samples by interlopers arising due to line misidentification. It is crucial to correct for this systematic, otherwise the improved statistical error gained from the larger sample size is outweighed by the interloper contamination.

We present a new method for estimating the galaxy target-interloper cross-correlation term based on measuring the cross-correlation between two replications of the contaminated catalogue, with the replications obtained by shifting the original catalogue along the line of sight (LOS) by $\pm 1 \times$ the interloper displacement. For simplicity and to demonstrate the method, we only consider the technique under the assumption of a global plane parallel LOS, approximating samples at large distance. The extension to wide, nearby, samples is left to future work. It is likely that this extension will degrade the sensitivity of our method as many of the features we see will lose their sharpness. Shifting the sample along the LOS, we change the scales of the target, interloper, and target-interloper cross-clustering terms compared to the corresponding terms in the auto-correlation of the contaminated sample.

In this way, we may estimate the cross terms without any assumptions regarding the relative bias between targets and interlopers.

We can then use the measured cross-correlation between the two replicated catalogues in the model of the auto-correlation of the contaminated sample, based on fitting a linear model from CAMB [49] coupled with nuisance parameters allowing for deviations from this model [50]. We use this model to find an unbiased estimation of the Alcock–Paczynski isotropic and anisotropic dilation parameters α and ϵ [37] from mock catalogues, in addition to the fraction of interlopers f_i .

This chapter is structured as follows. In Section 2.1, we outline the survey of the Roman Telescope, as well as introducing the interloper problem. In Section 2.2, we discuss the effect of interlopers on the two point correlation function. In Section 2.3, we present our model for estimating the target-interloper cross term and the contaminated correlation function. In Section 2.4, we present results given by our pipeline. In Section 2.5, we discuss some limitations of the method and its application to real survey data. Finally, we conclude in Section 2.6.

2.1 The Nancy Grace Roman Space Telescope

The upcoming Nancy Grace Roman Space Telescope (formerly WFIRST) will launch by 2027. It will carry instruments capable of Hubble Space Telescope-level resolution with a field of view 100 times larger. Roman will perform large scale structure surveys using slitless spectroscopy to map the universe, along with probes like weak lensing, supernovae and baryon acoustic oscillations (BAO). In addition, Roman will carry an advanced coronagraph instrument. It should be capable of detecting reflected starlight off of planetary companions up to 1 billion times fainter than their star and a minimum angular separation of 0.15 arcseconds. This test instrument stands to pave the way for the next generation of future missions aiming to image Earth-like exoplanets.

While Roman will have a similar sized mirror (2.4 metres) compared to the Hubble Space Telescope, its Wide Field Instrument (WFI) provides a massive increase in field of view at 0.28 square degrees. This is a viewing area over 100 times greater than Hubble or the James Webb Space Telescope (JWST) at a similar angular resolution of about 0.1 arcseconds. It covers roughly the same wavelength range as Hubble from ~ 0.5 - $2.3 \mu\text{m}$.

The Roman Space Telescope will carry out three core community surveys, listed below:

- The Galactic Bulge Time Domain Survey

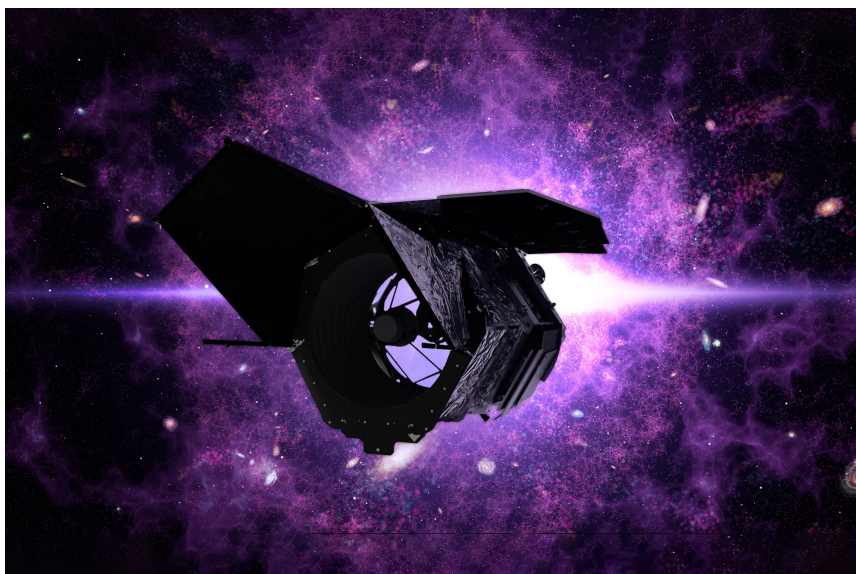


Figure 2.1: An artist's impression of the Nancy Grace Roman Space Telescope. Credit: NASA [13].

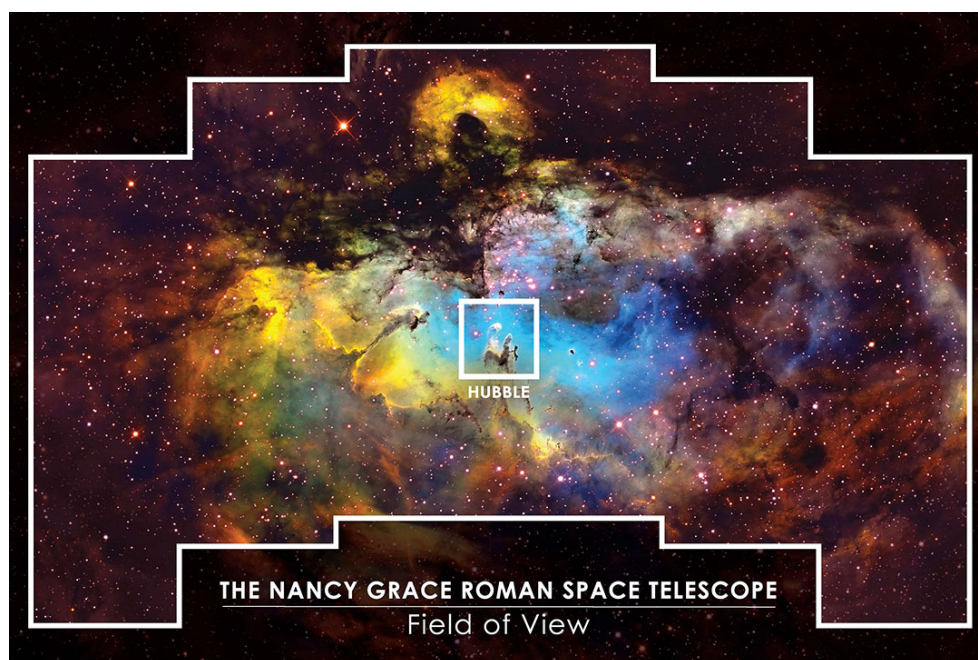


Figure 2.2: Roman's field of view compared to Hubble's. Credit: STScI [14].

- The High Latitude Time Domain Survey
- The High Latitude Wide Area Survey

The Galactic Bulge Time Domain Survey will search the Milky Way for changes in the brightness of its constituent stars. This will likely lead to the detection of the farthest exoplanet ever discovered. With Roman’s wide field of view, the observatory will monitor millions of stars for changes in brightness, telltale signs of the transit of an orbiting exoplanet. In addition to standard lightcurve measurements, Roman will also have the capability to detect microlensing events. This will allow for the detection of exoplanets farther from their host star than ever before, in addition to other objects like rogue planets, neutron stars, and stellar mass black holes. Finally, studies of stellar seismology will allow scientists to learn about the internal structure of stars.

The High Latitude Time Domain Survey then focuses Roman’s timing sensitive instruments out beyond our galaxy. Roman will observe select patches of the sky once every five days, revealing transient behaviour in the cosmos. Targeted objects will include Type Ia supernovae that can be used to track the expansion of the universe, adding to the body of data that can be used to measure the Hubble constant. Roman will reveal black holes formed of neutron star mergers, and the subsequent kilonova explosions. In addition, Roman will probe variable systems, searching for evidence of tidal disruption of stars by nearby black holes as well as extremely bright quasars.

Roman’s main cosmological functions will be through the use of large scale structure surveys. The High Latitude Wide Area Survey will consist of combined imaging and spectroscopy over about two years of observing. Imaging data will collect galaxy shape measurements from cosmic shear and weak lensing, over four near infrared bands (Y, J, H, and F184) to a depth of 26–27 AB magnitude. The spectroscopic component will measure over 10 million galaxy positions out to $z = 3$ and help construct 3-D maps of the cosmos. Roman will target $H\alpha$ (656.3 nm) as a primary emission line up to $z = 2$, and [OIII] (500.7 nm) in the range $z = 2 - -3$. Roman observations will require the minimum of two detections with a primary detection of 5σ and a secondary of 3.5σ . Together these measurements can help to pin down the expansion rate and matter distribution. Galaxy count numbers should far exceed previous surveys like BOSS, and will be comparable to DESI on the order of tens of millions of sources. Compared to DESI and Euclid’s wide surveys covering more than 10,000 square degrees, Roman’s Wide Area survey will only cover 2000 degrees. Yet, Roman’s expected number density will greatly exceed both other missions, and its imaging instruments have a limiting magnitude two orders of magnitude fainter than Euclid (AB magnitude ~ 24 for Euclid and ~ 26 for Roman), and a grism spectroscopy depth better by a factor of two [43, 51].

Roman will make use of slitless spectroscopy with a grism.¹ The combination of diffraction grating and prism (hence “grism”) allows for imaging and spectroscopy to be done on the same instrument. In practice, the grism is placed in the path of a collimated beam. The grating will then disperse the light according to wavelength as usual. Then, the prism will redirect the light such that the dispersed spectrum can be seen directly on the camera, centred on the source position in the image. This technique allows for faster measurements of spectra and more efficient usage of the imaging modules as imaging and spectroscopy are no longer entirely separate channels. However, this new slitless spectroscopy technique introduces some of its own new systematics.

One interesting systematic is confusion.² As the grism disperses the spectrum onto the image, at small angular scales there is a chance for two spectra to overlap. This can render both spectra unusable, limiting the density of measurements at small angular scales. We can imagine fixing this issue by rolling the spacecraft to change the position angle of the spectra, but this will not guarantee that we do not overlap with a different spectrum! Additionally, due to the position of the spacecraft solar panels, the allowed roll angles are tightly constrained. This problem will require further work before it can be sufficiently mitigated.

The primary systematic that this work will deal with is emission line interlopers. These can arise when the redshift is wrongly estimated, shifting the derived distance of the galaxy along the line of sight. While Roman will require the detection of at least two emission lines to measure a redshift, it would be beneficial to extend the sample out to a region where only one of the lines will meet the signal to noise requirement. This could greatly improve the statistical power of a survey, but only if the additional systematic is sufficiently dealt with. In this regime, interlopers may be common, as the observer must assume the line they are looking at, and any incorrect assumptions will result in these interlopers. Between $z = 1 - -2$, Roman will use $H\alpha$ as its primary line. This region is less prone to interlopers for two reasons. First, due to the lower redshift, the signal to noise cutoff would not remove as many observations from the catalogue. However, even if there are interlopers, they would only bias the BAO measurement if the shift due to confusion is close to the BAO scale. In the case of $H\alpha$, there are not any strong candidates that would cause the required $\sim 100h^{-1}\text{Mpc}$ shift. This is also why interlopers are considered less of a priority for Euclid.³ However, at higher redshift ($z = 2 - -3$), Roman will use the [OIII] line as the primary emission line. Unfortunately, the average shift for confusing [OIII] with the nearby $H\beta$ is about $\sim 90h^{-1}\text{Mpc}$, more than close enough to distort the BAO

¹The Euclid spacecraft also uses a grism.

²Not emission line confusion.

³Compared to something like ice buildup.

significantly. Furthermore, the contamination need only be $\sim 2\%$ to significant bias the BAO AP measurement [52]. Thus, it is critical to correct this systematic, lest any gained statistical power be outweighed.

In the remainder of this chapter, we will introduce a self-calibrating model, allowing one to extract unbiased BAO measurements using a modified template fit.

2.2 The Effects of Small Displacement Interlopers

2.2.1 The Interloper Displacement

Interloper displacements are fixed in observed redshift, dependent on the offset in wavelength between the assumed and true lines. For a galaxy survey, we typically convert from redshifts to distances using a fiducial cosmological model, and so the interloper displacement in our map depends on the fiducial rather than the true cosmology. The comoving proper distance between an object with true redshift z_{true} but displaced to z_{false} is:

$$\Delta_{\text{fid}} = \int_{z_{\text{false}}}^{z_{\text{true}}} \frac{cdz}{H_{\text{fid}}(z)} \approx \frac{c}{H_{\text{fid}}(z_{\text{false}})} (z_{\text{true}} - z_{\text{false}}), \quad (2.1)$$

where H_{fid} is the Hubble parameter in the fiducial cosmology, and c is the speed of light. If we consider the case of [OIII]-H β interlopers, this simplifies to

$$\Delta_{\text{fid}} \approx 87.41 \frac{1 + z_{\text{true}}}{(\Omega_{\Lambda, \text{fid}} + \Omega_{m, \text{fid}}(1 + z_{\text{true}})^3)^{1/2}} h^{-1} \text{Mpc}, \quad (2.2)$$

with $\Omega_{\Lambda, \text{fid}}$ and $\Omega_{m, \text{fid}}$ being the energy density of the cosmological constant and matter in the fiducial cosmology, respectively.⁴ For the range of redshifts of interest to Roman, $z = 1.0 - 2.8$, and a Planck-like cosmology, this interloper shift ranges from $80 h^{-1} \text{Mpc}$ to $97 h^{-1} \text{Mpc}$, quite close to the BAO feature.

2.2.2 The Contaminated Correlation Function

With the introduction of interlopers into the target sample, the correlation function becomes “contaminated” as some fraction, f_i , of galaxies within the observed sample is displaced along the LOS. We will refer to the contaminated correlation function as ξ_{cc} .

⁴We remind the reader of the restframe wavelengths of [OIII] and H β : 500.7 nm and 486.1 nm.

Furthermore, we will refer to the populations of interlopers and galaxy targets with the subscripts i and g respectively. The overdensity can then be written using two terms,

$$\delta_c(\vec{x}) = (1 - f_i)\delta_g(\vec{x}) + f_i\delta_i(\vec{x}).^5 \quad (2.3)$$

Now we can model the contaminated correlation function as

$$\xi_{cc}(\vec{r}, f_i) = \langle \delta_c(\vec{x}_1)\delta_c(\vec{x}_2) \rangle \quad (2.4)$$

$$= \langle [(1 - f_i)\delta_g(\vec{x}_1) + f_i\delta_i(\vec{x}_1)][(1 - f_i)\delta_g(\vec{x}_2) + f_i\delta_i(\vec{x}_2)] \rangle \quad (2.5)$$

$$= (1 - f_i)^2\xi_{gg}(\vec{r}) + f_i^2\xi_{ii}(\vec{r}) + 2f_i(1 - f_i)\xi_{gi}(\vec{r}), \quad (2.6)$$

with $\vec{r} = \vec{x}_2 - \vec{x}_1$. Note the convention adopted follows that of [45], and has the interloper catalogue already shifted along the LOS, meaning the interlopers are considered at their observed rather than true positions.

Hereafter we will write the correlation functions as ξ rather than $\xi(\vec{r})$ for simplicity. The first two terms are the auto-correlations of galaxy targets and interlopers with an amplitude dependent on the interloper fraction. These terms contain most of the cosmological information and the familiar BAO peak. The third term is the cross-correlation between the galaxy targets and interlopers. When interlopers are at their true positions, there is a strong small scale clustering signal, as with galaxy-galaxy or interloper-interloper pairs. When interlopers are displaced along the LOS due to line confusion, this small scale clustering of the galaxy-interloper cross correlation is shifted to the displacement scale. This component typically skews the BAO peak in the contaminated catalogue clustering towards the interloper displacement and hence biases the standard BAO measurement.

2.2.3 Adding Interlopers into Simulations

For the purposes of testing our model, we employ 1000 halo catalogues from the Quijote suite of N-body simulations [53]. Our aim is to demonstrate the method, so the distribution of emission line galaxies in our simulations does not need to be realistic. We therefore choose not to populate the haloes with galaxies, but instead use the halo positions themselves. The simulations have a box length of $1 h^{-1}\text{Gpc}$ and use the fiducial Quijote suite parameters [53]. In this configuration, the minimum halo mass is equal to

⁵Here δ_c refers to the contaminated overdensity.

$1.31 \times 10^{13} h^{-1} \text{M}_{\odot}$. While it is true that we expect to find [OIII]-H β interlopers in Roman-like catalogues mostly in redshift ranges greater than $z = 1.8$ [51], we use the catalogue snapshots at $z = 1$. This range includes a greater density of objects, more consistent with the expected [OIII] mean density at $z = 1.8 - 2.8$ [54]. We do use different interloper displacements corresponding to a redshift variation along the full Roman redshift range, as outlined in Section 2.2.1.

For each of the 1000 halo catalogues, we select a fraction f_i of the total haloes, label them as interlopers, and shift them towards the observer along the LOS by a given shift Δ . We generate catalogues with interloper fraction $f_i = (0.005, 0.01, 0.02, 0.05, 0.10, 0.15)$ and interloper shift $\Delta = (85, 90, 97) h^{-1} \text{Mpc}$. We then measure the correlation function using NBODYKIT [6] and the standard estimator,

$$\xi = \frac{DD}{RR} - 1, \quad (2.7)$$

where DD are the normalised catalogue-catalogue pairs and RR are the expected random-random pairs calculated from the average halo density. We then extract the monopole, quadrupole, and hexadecapole moments. The effects of interlopers on the real-space monopole and quadrupole are shown in Figure 2.3, showing the average of 1000 contaminated correlation function measurements with various interloper fractions and shifts.

We also consider injecting interlopers into samples that also include redshift-space distortions. Here we move the full sample of haloes into redshift-space by shifting the line-of-sight displacements based on the halo velocities, before selecting a fraction of the haloes as interlopers. For simplicity we assume that all lines-of-sight are parallel — along one axis of the simulation.

To illustrate the effect of differing galaxy biases between the galaxy target and interloper samples, we also generate a set of catalogues with a different selection of haloes for targets and interlopers. For these, all objects are ordered by mass and we select objects with the greatest mass as interlopers, down to the interloper fraction for the given catalogue. For example, for a catalogue with $f_i = 0.1$, the top 10 percent most massive objects are selected as interlopers.

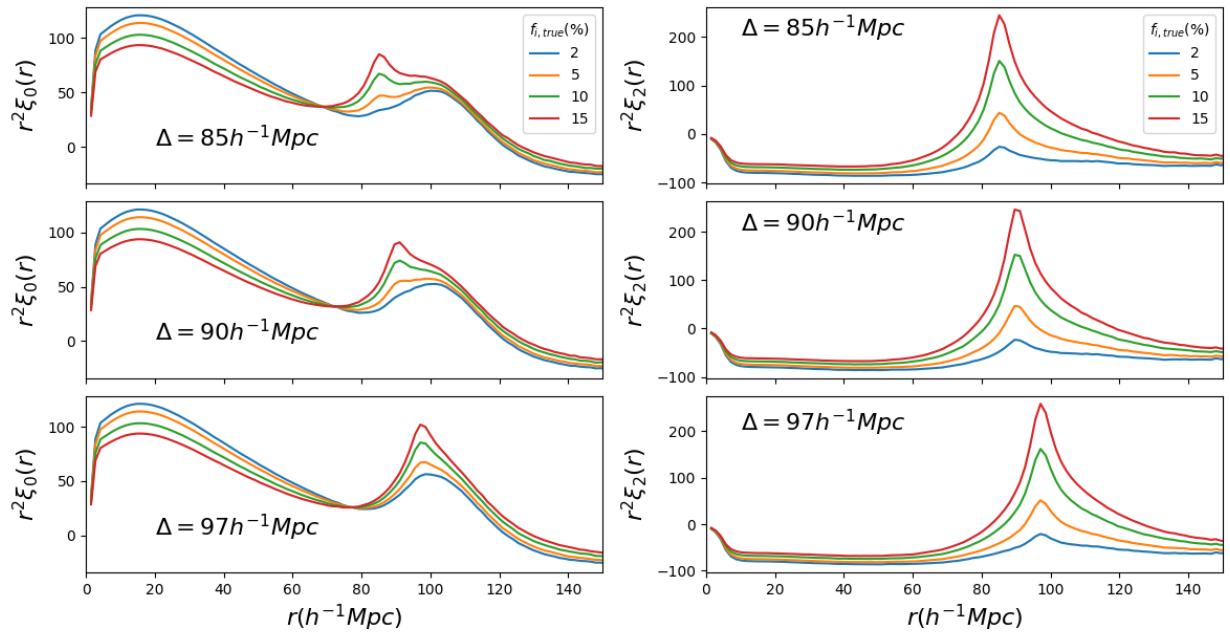


Figure 2.3: The mean monopole (left) and quadrupole (right) of the correlation function measured from 1000 Quijote mocks for different interloper fractions and displacements. The vertical axis units are $(h^{-2} \text{Mpc}^2)$.

2.3 Modeling the BAO Feature with Interlopers

2.3.1 Overview of Method

In order to model Equation 2.6, we need to estimate the galaxy target-interloper cross term accurately. Because of the interloper shift, the value of this term around the BAO scale comes from the small-scale target-interloper correlation function in true units (where interloper galaxies are at the true position), which are typically difficult to model due to nonlinearities.

We present an empirical method for measuring this term that uses the fact that we know Δ exactly and can use this to artificially apply further shifts to the contaminated catalogue, to create a new clustering measurement where the components that appear in Equation 2.6 are further separated in scale.⁶ In this revised cross-correlation, the corrections for the nuisance terms can be modelled using the large-scale clustering, such that we do not require a theoretical model of the small-scale clustering signal. This concept works in redshift-space and for situations where target and interloper galaxies have different biases.

The following subsections describe this process in detail.

2.3.2 The Near-Far Shifted Correlation Function

We introduce two additional catalogues. The *far-shifted* catalogue is the contaminated catalogue with all object positions shifted *away* from the observer by the known interloper shift. The *near-shifted* catalogue is the same contaminated catalogue with the object positions moved *towards* the observer by one interloper shift. Each catalogue is still made up of galaxy targets and interlopers. A schematic diagram for this process is shown in Figure 2.4.

We use the cross correlation between the near-shifted and far-shifted catalogues:

$$\xi_{c_n c_f} = (1 - f_i)^2 \xi_{g_n g_f} + f_i^2 \xi_{i_n i_f} + f_i(1 - f_i) \xi_{g_n i_f} + f_i(1 - f_i) \xi_{i_n g_f}, \quad (2.8)$$

with the subscript f referring to *far-shifted* components and the subscript n referring to *near-shifted* components. Note that unlike the case in Equation 2.6, the target-interloper and interloper-target cross correlations are now not equal and thus cannot be combined into a single term.

⁶The value of Δ is dependent on the assumption of an underlying fiducial cosmological model. The choice of fiducial model does not affect the method.

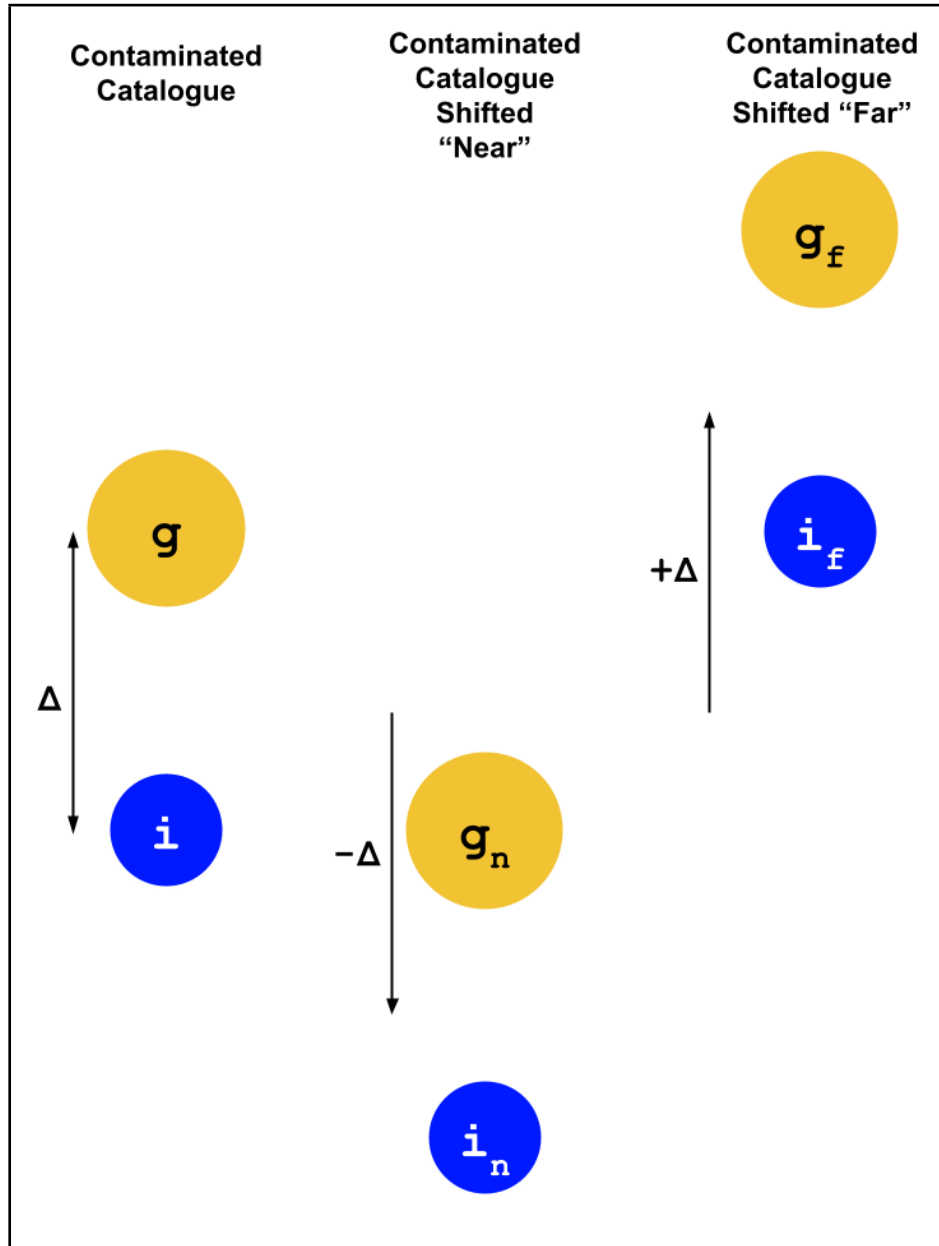


Figure 2.4: Schematic diagram of the contaminated galaxy catalogue on the left and the effect of shifting it to generate the near-shifted and far-shifted catalogues. Galaxy targets at their true positions are labelled with g while interlopers are labelled with i . The interloper shift is Δ .

The key insight that led to this approach is that the near-shifted targets are still separated by the same distance from the far-shifted interlopers as the original interloper-target pairs. Hence the cross term $\xi_{g_n i_f}$ in Equation 2.8 is equal to the cross term ξ_{gi} in Equation 2.6. Note that the direction of the displacement between galaxy targets and interlopers is reversed in $\xi_{g_n i_f}$ compared to ξ_{gi} (see Figure 2.4). This does not cause any issues, as we are only interested in fitting for even multipoles of the correlation function. Furthermore, this term dominates the near-far cross correlation. Unfortunately, the other terms in Equation 2.8 are not negligible and need to be included in the model. The contributions of each component to Equation 2.8 are shown as dashed colored lines in Figure 2.5, while the full near-far cross correlation is displayed in black.

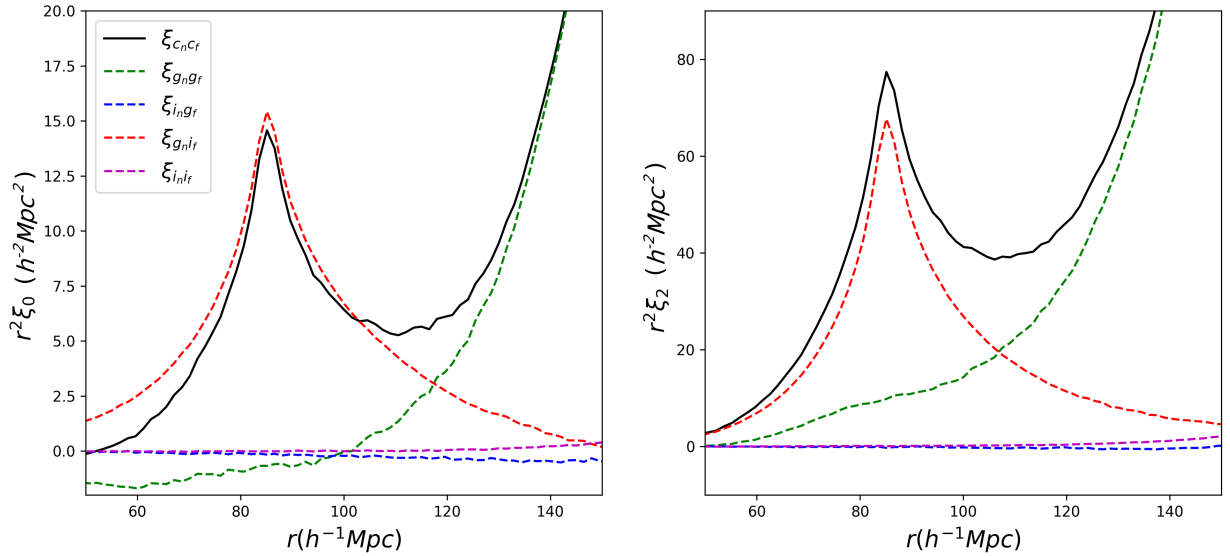


Figure 2.5: Contributions of each term of 2.8 to the total near/far-shifted cross correlation $\xi_{c_n c_f}$. The monopole is shown on the left and the quadrupole on the right.

As anticipated, $\xi_{g_n i_f}$ dominates the expression. As the scales and shape of this term match those in the contaminated auto-correlation, and we are interested in fitting BAO on scales $\sim 50\text{--}150 h^{-1}\text{Mpc}$, these are also the scales for which we need to model the other components. The next most important component is $\xi_{g_n g_f}$, followed by $\xi_{i_n i_f}$. In these terms, pairs of galaxy targets or interlopers that are at small separation $r_{\parallel}$ along the LOS in the original contaminated catalogue are mapped to a separation $r_{\parallel} + 2\Delta \sim r_{\parallel} + 200 h^{-1}\text{Mpc}$ in the near-far shifted cross-correlation. Thus most of the small-scale clustering is mapped outside the fitting range. On the other hand, galaxy targets or interlopers that are at a large separation ($\sim 2\Delta$) along the LOS in the original contaminated catalogue, become

pairs at small to intermediate separation in the near-far shifted cross-correlation. When considering near-far pairs perpendicular to the LOS, those that are at $\sim 50 - 150 h^{-1}\text{Mpc}$ correspond to objects that are at distance larger than $\sim 2\Delta$ in the original contaminated catalogue. Because of this, ξ_{gngf} and ξ_{ini_f} are sourced by large-scale clustering, they have a small amplitude at the BAO scale — ξ_{ini_f} is additionally suppressed by the factor f_i^2 — and they can be modelled using linear theory. Similarly, the final term ξ_{ingf} is also the result of large-scale pairs in the contaminated catalogue and has a very small amplitude, making it important only when we work in redshift space, due to the Kaiser effect.

Now returning to Equation 2.8, we can rearrange to isolate the target-interloper cross term,

$$f_i(1 - f_i)\xi_{gngf}(\vec{r}) = \xi(\vec{r}, f_i)_{cncf} - (1 - f_i)^2\xi_{gngf} - f_i^2\xi_{ini_f} - f_i(1 - f_i)\xi_{ingf}. \quad (2.9)$$

As $\xi_{gi} = \xi_{gngf}$, we can substitute into Equation 2.6 and form a model for the contaminated correlation function:

$$\xi_{cc} = (1 - f_i)^2\xi_{gg} + f_i^2\xi_{ii} + 2\xi_{cncf} - 2(1 - f_i)^2\xi_{gngf} - 2f_i^2\xi_{ini_f} - 2f_i(1 - f_i)\xi_{ingf}. \quad (2.10)$$

We now have a model for the contaminated correlation function using only the measured near/far-shifted cross correlation ξ_{cncf} and the usual large-scale auto-correlation template to describe ξ_{gg} , ξ_{ii} , and terms that may be modelled with the same auto-correlation.

2.3.3 Fitting a two point correlation function

If we are only interested in the BAO information contained within the two point correlation function, it is standard to perform a template fit of the following form:

$$\xi_{\text{model}, \ell}(a_1, a_2, a_3, B, \alpha, \epsilon, r) = \frac{a_1}{r^2} + \frac{a_2}{r} + a_3 + B \times \xi_{\text{galaxy}, \ell}(\alpha, \epsilon, r), \quad (2.11)$$

where α and ϵ are the aforementioned AP parameters, the multiplicative factor B is added to adjust the amplitude, and a polynomial term $A(r)$ is added to account for scale dependent bias and match the overall broadband shape [50]. ξ_{galaxy} is the correlation function template.⁷

⁷This polynomial is generally of the form shown in Equation 2.11. However, the exact form is usually unimportant.

The first step of a template fit is to generate a template based on a fiducial cosmology.⁸ This is done using a code like CAMB [49]. In this work, we use the fiducial cosmology of the Quijote simulations [53]. This results in an estimate for the linear matter power spectrum in real space. We then must manually input two effects, the non-linear BAO damping and the RSD. When the BAO was first imprinted on the matter distribution, the feature would have been relatively sharp. Over time, under the influence of gravity, this feature gets “smeared out” as galaxies move around. There is a technique known as reconstruction that attempts to undo this effect, but in this work we will simply try to account for it in our template. The model for the BAO damping is straightforward: we separate the linear matter power spectrum into the BAO wiggles and the smooth no-wiggles power spectrum,

$$P(k, \mu) = [P_{\text{lin}} - P_{\text{smooth}}]e^{-\frac{1}{2}k^2(\mu^2\Sigma_{\parallel}^2 + (1-\mu^2)\Sigma_{\perp}^2)} + P_{\text{smooth}}. \quad (2.12)$$

Here the linear matter power spectrum from CAMB is P_{lin} , and P_{smooth} is the power spectrum with the BAO wiggles removed.⁹ The BAO damping parameters $\Sigma_{\parallel}$ and $\Sigma_{\perp}$ are derived from the fiducial cosmology at a given redshift. In this work, we use $\Sigma_{\perp} = 4.8 \ h^{-1}\text{Mpc}$ and $\Sigma_{\parallel} = 7.3 \ h^{-1}\text{Mpc}$ evaluated at $z = 1$ in the fiducial cosmology [56].¹⁰

We then may add in RSD effects. In this work, we will only deal with large scale RSD and neglect small scale non-linear effects. Thus we consider only the Kaiser effect [35] and not the Fingers-of-God (FoG) [36] features. The redshift space power spectrum can then be written in terms of the real space template:

$$P_{\text{redshift}}(k, \mu) = \left(1 + \frac{f}{b}\mu^2\right)^2 P_{\text{real}}(k, \mu), \quad (2.13)$$

where b is the linear galaxy bias ($b = \delta_{\text{galaxy}}/\delta_{\text{matter}}$), and $f \approx \Omega_{\text{M}}^{0.55}$ is an estimate for the logarithmic derivative of the linear growth rate G with respect to the scale factor.¹¹ This is known as the Kaiser formula [35].

Once estimates to correct for non-linearity have been encoded into the power spectrum, it is then straightforward to perform the Fourier transform to get the two point correlation function.

Even with these corrections, it is still not enough to fully capture the shape of the true correlation function. However, this doesn’t pose a major issue if our goal is to measure

⁸Obviously.

⁹There are a number of ways to do this. See Appendix A of [55] for two common methods.

¹⁰The effect of changing these parameters on the correlation function template is shown in [57].

¹¹We have set $b = 2.8$ for the templates used in this work.

the AP parameters. The described treatment of the power spectrum accurately captures the shape of the BAO peak, thus the polynomial term serves simply to fit the broadband features of the correlation. While the exact form of the polynomial is not important, it is essential that one's broadband term not have too much freedom. Allowing for too much flexibility will allow this nuisance term to fit some of the BAO information, biasing the result. Finally, it is important to note the correlation function we measure is the correlation function of galaxies, which imperfectly traces the matter distribution. In this work, we assume a linear galaxy bias as shown above. Since the power spectrum we obtain from CAMB is a linear *matter* power spectrum, we multiply by a estimate of the galaxy bias.¹² The parameter B serves to correct this guess in a simple way. There is some degeneracy between B and the polynomial that is mitigated by the polynomial being scale dependent. However, we will see an example of a strong degeneracy between B and another amplitude parameter in Chapter 2.

2.3.4 Including interlopers in the BAO model

Before a correlation function or power spectrum may be measured, a fiducial cosmology must be assumed to translate redshifts into physical separations. The BAO technique is based on the peak being shifted if there is a difference between the true cosmology and the assumed fiducial cosmology. This distortion is characterised using the Alcock-Paczynski (AP) parameters α and ϵ (see Section 1.2.3).

In order to extract the BAO signal and marginalise over other information in the correlation function, it is standard to fit a model as described in Section 2.3.3.¹³ With this form for the auto-correlation multipoles, we may combine with Equation 2.10 to construct

¹²Actually, we multiply by b^2 , since these are *two* point statistics of the density field.

¹³For this chapter, we have also considered using analytic templates from HALOFIT [58, 59] as the real-space matter power spectrum when modeling ξ_{galaxy} in the additional terms describing the near-far shifted correlation functions in Equation 2.14 (last two rows) to see if these impact our fits. We find little difference, a consequence of only needing to model these terms on large scales

models for the multipole moments of the contaminated correlation function:

$$\begin{aligned}
\xi_{cc,\ell}(r) &= \frac{a_{1,\ell}}{r^2} + \frac{a_{2,\ell}}{r} + a_{3,\ell} + (B_1(1 - f_i)^2 + B_2 f_i^2) \times \xi_{\text{galaxy},\ell}(\alpha, \epsilon, r) \\
&+ 2\xi_{cncf,\ell}(r) \\
&- 2(B_1(1 - f_i)^2 + B_2 f_i^2) \times (\mathcal{M}_{2\Delta}[\xi_{\text{galaxy}}])_l(\alpha, \epsilon, r) \\
&- 2\sqrt{B_2 f_i} \sqrt{B_1(1 - f_i)} \times (\mathcal{M}_{3\Delta}[\xi_{\text{galaxy}}])_l(\alpha, \epsilon, r),
\end{aligned} \tag{2.14}$$

Here, we have used a mapping shift operator, $\mathcal{M}_X$, introduced in [45], acting on the full two dimensional correlation function ξ_{galaxy} . This operator acts on the argument of a correlation function by mapping a separation (r, μ) into $(r_{\text{shift}}, \mu_{\text{shift}})$ to describe the distortion due to a increase in LOS separation X between the two objects in each pair count.¹⁴ For any pair with initial separation (r, μ) , the shifted coordinates are given by a simple trigonometric mapping for a LOS shift X

$$r_{\text{shift}}(r, \mu) = \sqrt{r^2 + X^2 - 2Xr\mu}, \quad \mu_{\text{shift}}(r, \mu) = \frac{r\mu - X}{r_{\text{shift}}(r, \mu)}. \tag{2.15}$$

For example, we have written our unweighted estimate of ξ_{gngf} as $\xi_{gngf} \approx \mathcal{M}_{2\Delta}[\xi_{gg}]$. This takes the auto-correlation of galaxies, at their true positions, and generates the cross-correlation of two catalogues of galaxies separated by 2Δ . In ξ_{gngf} , the galaxy target/interloper populations are shifted 2Δ from their observed positions (as with all terms in the near/far shifted correlation), but the interlopers had been already shifted by 1Δ from their true positions. Thus, we write the unweighted estimate of ξ_{gngf} as $\xi_{gngf} \approx \mathcal{M}_{3\Delta}[\xi_{gg}]$.

For the third and fourth lines of Equation 2.14, note that the polynomial term described above is not included in the estimate of the auto-correlation. As described in Section 2.3.2, these terms are derived from the large-scale correlation, and can be modelled using linear theory. Thus, the polynomial term is not required here.

We have written these equations in a way that allows us to include differing bias schemes for interlopers and targets. We consider that a reasonable estimate is to separate the amplitude parameter B into B_1 and B_2 to account for two different biases, weighted by the interloper fraction for targets and interlopers. This also allows us to estimate ξ_{gngf} as

¹⁴Initially pairs have separation $\vec{r} = \vec{x}_2 - \vec{x}_1$. After increasing the separation by $\vec{X}$ (with direction along the LOS), the new separation vector is $\vec{r}' = \vec{x}_2' - \vec{x}_1'$, where $\vec{x}_2' = \vec{x}_2 + \vec{X}$ and $\vec{x}_1' = \vec{x}_1$. Only one of the galaxy positions are changed.

we can use the mapping for 3Δ , while adding in factors of $\sqrt{B_1}$ and $\sqrt{B_2}$ (since B_1, B_2 are the squares of the usual biases) to correctly scale the term along with the others. However, unless otherwise stated, we combine both B_1, B_2 , when fitting mocks with only a single bias.

When fitting both multipoles simultaneously, this results in a model with 11 parameters. When not working in redshift-space, we have found that we can omit the last term in the models containing $\mathcal{M}_{3\Delta}$.

2.4 Testing the method using simulations

In this section, we present the results of fitting our model to the contaminated catalogues in the simulations. We fit the mean of both the monopole and quadrupole moments of 1000 correlation functions in redshift space via a Markov-chain Monte Carlo (MCMC) analysis using the EMCEE package [4] and minimizing the following posterior distribution [60]:

$$f(\xi^{\text{model}}|\xi^{\text{data}}, C) \propto \left[1 + \frac{\chi^2}{n_s - 1}\right]^{-\frac{m}{2}}, \quad (2.16)$$

where n_s is the number of simulations, m is given by Equation 54 in [60], and $\chi^2 = (\xi^{\text{model}} - \xi^{\text{data}})^T C^{-1} (\xi^{\text{model}} - \xi^{\text{data}})$ with C^{-1} being the inverse of the covariance matrix

$$C_{ij}[\xi(r_i)\xi(r_j)] = \frac{1}{n_s(n_s - 1)} \sum_{n=1}^{n_s} [\xi_n(r_i) - \bar{\xi}(r_i)][\xi_n(r_j) - \bar{\xi}(r_j)] \quad (2.17)$$

evaluated for all points in $\xi = \xi^{\text{data}} = \xi_{cc} - 2\xi_{cncf}$. The BAO fit is performed using the monopole and quadrupole within the range $r \in [50, 120] h^{-1}\text{Mpc}$.

In order to quantify the performance of our BAO fitting model in Equation 2.14, and how this depends on the amount of interlopers in the contaminated catalogue and on the particular value for the interloper displacement (thus the redshift of the survey), we consider 12 different scenarios given by the combination of 3 different values for the interloper displacement $\Delta = (85, 90, 97 h^{-1}\text{Mpc})$ and 4 values for the interloper fraction $f_i = (0.02, 0.05, 0.10, 0.15)$.

2.4.1 Results

First, we performed the BAO fit using a model that does not account for the presence of interlopers (using the first line only in Equation 2.14) to quantify how interlopers bias the estimation for the dilation parameters α and ϵ . Our findings are consistent with those in [52, 45]: the systematic errors on both dilation parameters increase with the interloper fraction of the contaminated catalogue and they reach maximum values up to 0.048 and 0.15 for α and ϵ , respectively, when $f_i = 0.15$. Results for the 12 combinations of interloper fractions and displacements are shown in red in Figure 2.6. In general, bias in the estimates for the AP parameters increases with interloper fraction, and the bias increases faster if the interloper displacement is further from the BAO peak. For example, consider $\Delta = 85 \ h^{-1}\text{Mpc}$, the displacement we consider that is furthest from the BAO peak. The systematic error on ϵ ranges from about 0.05 to 0.15. However, with $\Delta = 97 \ h^{-1}\text{Mpc}$, much closer to the BAO peak at $\sim 100 \ h^{-1}\text{Mpc}$, the bias on ϵ is both smaller at $f_i = 0.02$ and only reaches ~ 0.07 , spanning only half the range as the case with $\Delta = 85 \ h^{-1}\text{Mpc}$. The average systematic error on all three parameters (α, ϵ, f_i) decreases with increasing interloper displacement Δ , as the interloper peak overlaps more with the BAO peak. For $\Delta > r_{BAO}$, the trend of increasing parameter bias with increasing interloper displacement does not continue, as investigated in [45]. As the interloper peak is shifted further away from the BAO peak, it moves outside the fitting range and its effects on the AP parameters are significantly reduced. The peak systematic error in both parameters is obtained when the absolute difference between the positions of the two peaks is $\sim 30 \ h^{-1}\text{Mpc}$ [45].

The fitting model requires describing the uncontaminated galaxy correlation function ξ_{galaxy} , which involves the use of a linear prediction for the matter power spectrum coupled to a model for the BAO damping to account for the nonlinear evolution around the BAO scale only, and a linear bias scheme to describe the difference between the matter and galaxy clustering. These are approximations: additional parameters, such as amplitude parameters and polynomial terms, are introduced to account for residual nonlinearities. In order to distinguish between any bias caused by these approximations and the novel way in which we model the galaxy target-interloper cross-correlation via Equation 2.9, we consider a model where ξ_{galaxy} is directly measured in simulations and inserted in all the terms in Equation 2.14. Results are shown as blue points in Figure 2.6 and in Table A.1. The model is accurate and gives unbiased estimates of all three parameters of interest. The majority of systematic errors are within the statistical errors, with the systematic error of all three parameters remaining consistent regardless of interloper fraction or displacement.

We proceed by implementing the full model where ξ_{galaxy} is computed from the CAMB

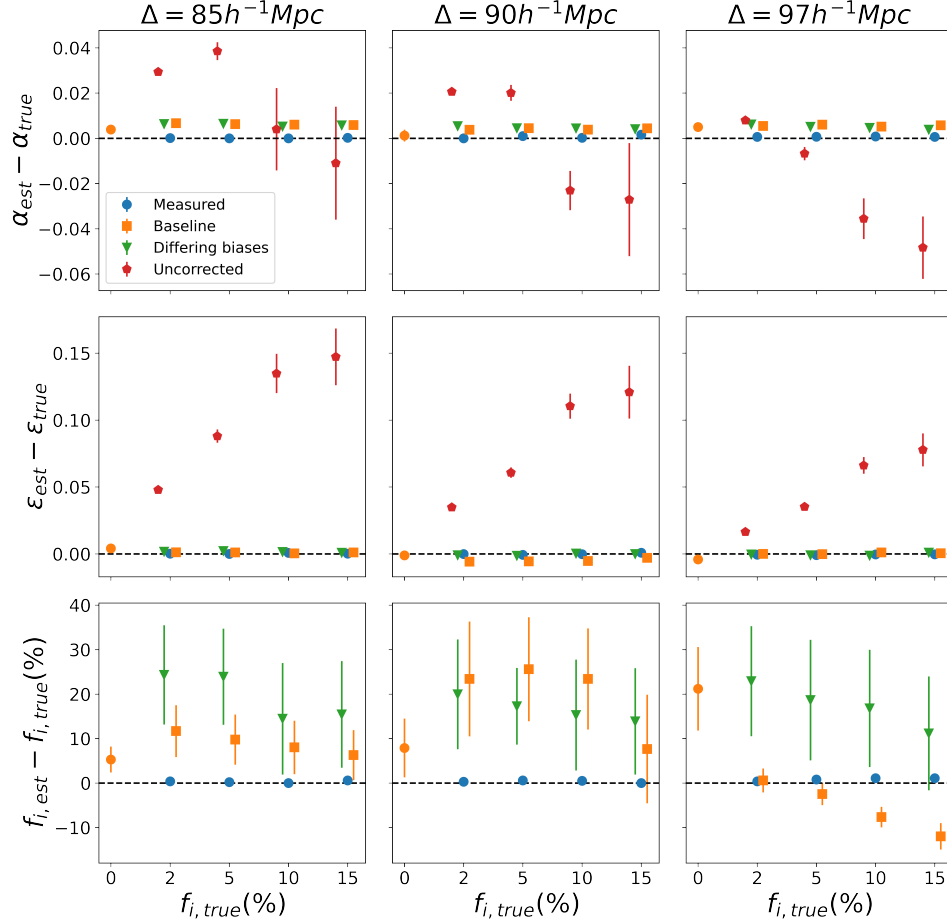


Figure 2.6: Systematic errors for α (top row), ϵ (middle row), and f_i (bottom row), plotted against the true fraction of interlopers. The case with no correction for the presence of interlopers is shown with the red pentagons (“Uncorrected”). Fits using the measured galaxy auto-correlation are shown with the blue circles (“Measured”). Fits using an estimated galaxy auto-correlation derived from CAMB are shown with the orange squares (“Baseline”). Fits using mocks where interlopers are more strongly biased are shown in the green triangles (“Differing Biases”).

power spectrum and following the procedure explained in Section 2.3.4. These fits are the main results of this chapter, and are shown as orange squares in Figure 2.6 and they are reported in Table A.2. In this case, both the statistical and systematic errors increase compared to using the measured galaxy auto-correlation. In particular, the systematic error is about $0.4 - 0.6\%$ for α , but it is consistent with the systematic error attributed to the standard pre-reconstruction BAO fit pipeline without the presence of interlopers [61]. Estimates for ϵ remain relatively unchanged and generally are still within statistical errors. As expected, we see significantly poorer results for f_i in particular. The case using $\Delta = 90 \ h^{-1}\text{Mpc}$ is notably different from the other two, with more biased estimates of f_i and ϵ , and less biased estimates of α . With this displacement case, f_i is significantly overestimated regardless of interloper fraction. The opposite is true for $\Delta = 97 \ h^{-1}\text{Mpc}$, with the interloper fraction underestimated for most interloper fractions. See Table A.2. We also consider applying the full model (all lines of Equation 2.14) to catalogues with no interlopers. Without any contaminants, there is no signal to be fitted, so the model is free to fit noise, thus f_i is poorly constrained and any degeneracies with the BAO model become more important. However, both systematic and statistical errors on the AP parameters are unaffected compared to the baseline case and are still consistent with the standard pre-reconstruction BAO fit pipeline without the presence of interlopers [61]. Thus, the application of our model to data without interlopers will not bias other parameters. These points are shown in orange at $f_{i,\text{true}} = 0$ in Figure 2.6 and Figure 2.8.

Finally, we consider the catalogues where interlopers have greater bias than galaxy targets. The results are reported in Table A.3 and are shown in Figure 2.6 as green triangles. In this case, it is necessary to use the two amplitude parameters B_1 and B_2 to scale for the relative bias between galaxy targets and interlopers. We see increased statistical error on estimates of f_i , and now this parameter is consistently overestimated by $1-2\sigma$. This is in better agreement with the true values, although only due to the inflated uncertainty. The estimates for ϵ remain robust regardless of the testing case.

2.5 Discussion

2.5.1 Galaxy bias

The primary difference between fits using the measured galaxy auto-correlation and using a CAMB template are the estimates of f_i . While the estimates using the measured correlation function give unbiased estimates for f_i , when CAMB is used, the B parameter is required to adjust the amplitude, and in the case with differing galaxy biases, we require two B_i . These

parameters are highly degenerate with f_i (see Figure 2.7), as they are all amplitude-like parameters. It is possible to improve the estimation of f_i when using CAMB by changing the prior on B from a flat to a Gaussian prior centred on $B = 1$ and with standard deviation $= 0.02$ to allow for some flexibility. We use a centre of $B = 1$, as this parameter is not an absolute bias compared to the matter power spectrum. Indeed, when producing the correlation function templates in Section 2.3.3, an estimate of the halo bias b in the Quijote simulations is used. Thus, B serves to correct this estimate, and for a reasonable estimate, we would expect $B \approx 1$. We show the results using this Gaussian prior in Figure 2.8 in orange. This prior gives estimates that are consistent, within uncertainties, with the AP parameters as compared to the flat prior case (displayed in orange in the same figure).

In the case where target and interloper galaxies exhibit differing biases, it is not as simple to set a similar prior on both B_1 and B_2 . If we consider the Gaussian prior for B_1 and B_2 , set around 1, it needs to be wide enough to capture a sufficient range of possible different biases. This makes no difference compared to a flat prior. Conversely, if we consider offsetting the priors for B_1 and B_2 , this assumes we know which population, targets or interlopers, are more biased, which is an assumption we do not make in this work. We have tested the effect of knowing the relative bias of targets and interlopers. We performed the fit using the measured galaxy autocorrelation template with the relative biases, B_1, B_2 , fixed to their values measured from the mocks. This gives values for f_i well within 1σ of the truth. While it is indeed possible to compare the biases of [OIII] and $H\beta$ objects, interlopers are a subsample of a full $H\beta$ sample - those that do not have [OIII] emission allowing misclassification. Thus, they do not necessarily share the same bias, and accurately estimating the difference in bias is as not straightforward. The use of future deep fields can help constrain the bias of the interloper subsample and will allow for reasonable priors on B_1 and B_2 .

There is also the possibility of placing a prior on the fraction of interlopers. This, like a prior on B is equivalent to knowing the halo or galaxy bias to some confidence, is equivalent of some knowledge of the expected interloper fraction. Observational estimates are indeed possible using other surveys, for example via [OIII]/ $H\beta$ equivalent width ratios measured from the MOSDEF Survey [62], giving an expected interloper fraction around 5% for Roman [52]. Upcoming deep fields may also be used to place constraints on the expected f_i . It is then trivial to place a Gaussian prior on the interloper fraction within our method.

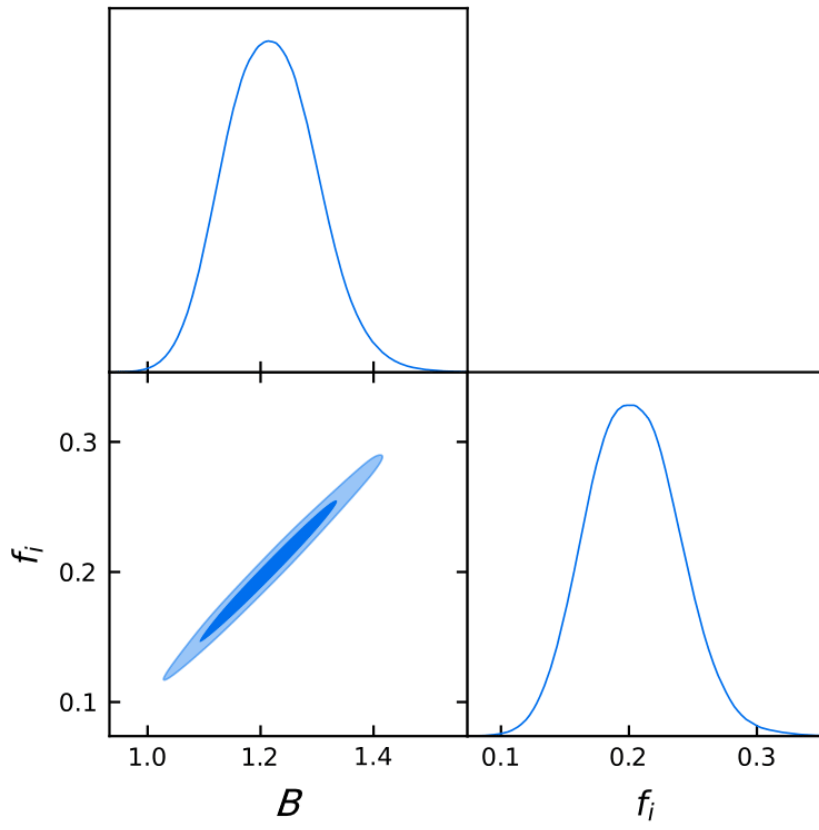


Figure 2.7: The posterior distributions of B and f_i from the case using $\Delta = 85 \ h^{-1}\text{Mpc}$ and $f_{i,true} = 0.1$.

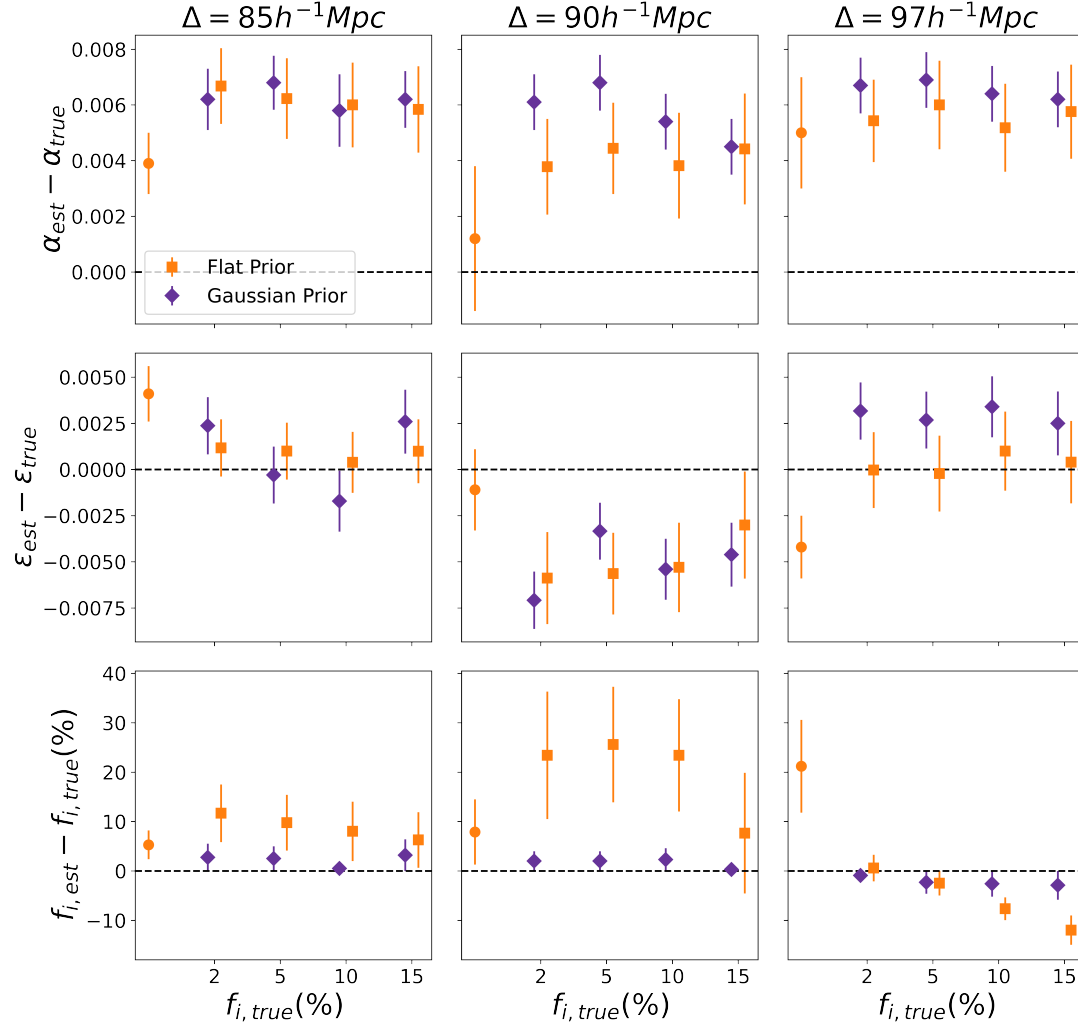


Figure 2.8: Improved parameter estimates applying a Gaussian prior, shown in purple diamonds, on B for single bias baseline case. Systematic errors for α (top row), ϵ (middle row), and f_i (bottom row), plotted against the true fraction of interlopers. Vertical scales are the same as Figure 2.6. The improvement is significant in the estimates of f_i .

2.5.2 Limitations of the Simulation Box

While we work in a simulation box with periodic boundary conditions, the total number of pairs in $\xi_{c_n c_f}$ is unchanged compared to ξ_{cc} . All pairs with the same initial separation will have the same new separation after the shift, and the information contained in both correlation functions is the same. However, in the near-far cross-correlation we have changed the relative scales at which the different components overlap, which allows us to more cleanly separate and model them to extract the cross-correlation term.

In a survey volume, we cannot apply a periodic boundary condition as in the simulation box, as galaxies at high redshift are uncorrelated with those at lower redshift. Thus, the randoms required to “normalise” the correlation function shifted near are different from those required for the correlation function shifted far. Instead, we would need to additionally shift the randoms used to determine the expected density and the correlation function. Thus, the pair counts at all scales should be compared to their expected counts in a random field, without missing the correct normalisations for the large scale correlation we introduce via the near/far shift.

There will be a number of other complications when moving to a realistic lightcone survey. First, the assumption of a constant redshift across the simulation box is not true for a survey lightcone. As the interloper displacement is redshift dependent, it varies across the survey and the measured interloper peak appears broadened. Second, our method requires shifting the catalogue by exactly the interloper displacement to obtain the near/far catalogues. Applying a single shift (e.g. given by the average survey redshift) will result in a distorted estimate for the galaxy target-interloper cross term. This effect may be somewhat mitigated by performing the analysis in fine redshift slices. Under a sufficiently fine binning, the assumption of a single redshift can hold for each bin. We note that these fine redshift slices will lose the statistical power of the large survey volume unless a careful treatment is applied to recombine them. Moreover, when shifting a lightcone catalogue, the resulting near/far catalogues are subjected to a geometric distortion due to a non-parallel LOS across the survey: The catalogues’ volume changes as well as the angular distance between objects and the angular BAO scale.¹⁵ Therefore, the underlying correlation function of the near shifted catalogue is not the same as that of the far shifted catalogue and the cross-correlation between these samples will result in a distorted correlation function. All these effects will need to be carefully quantified and taken into account when deploying our method to surveys.

¹⁵Galaxies shifted far also will become more separated in the plane of the sky due to the changing line of sight. Similarly, galaxies shifted near will become closer together on the plane of the sky.

2.5.3 Testing for additional systematics

We now compare how the statistical and systematic errors change between our baseline model including the near-far derived correction for interlopers, with results of fits using the following data inputs and covariances.

- *The Noiseless Near/Far Correlation* (ξ_{gg} , C_{gg})

We test if the inclusion of the near/far shifted measurements biases the BAO measurement. Here, as opposed to considering $\xi_{cc} - 2\xi_{cncf}$ for each simulation, we now consider subtracting the mean $\bar{\xi}_{cncf}$ from ξ_{cc} for each simulation. For this, the covariance should be that calculated from only ξ_{cc} . In practice, we consider a single fit to the mean over all simulations rather than fitting to each, and so this method only differs in the covariance matrix used. Fitting with C_{cc} results in systematic errors for the AP parameters that are nearly identical to our baseline, but with statistical errors that are on average 30% smaller for interloper fractions of 2% - 15%, with a weak dependence on fraction. Thus, including the near/far shifted measurements in the covariance does not bias the results, but it does increase the uncertainty.

- *Comparison to standard BAO template fit* (ξ_{gg} , C_{gg})

We also compare our results for the AP parameters to a fit on a dataset without interlopers. In this case, the data vector is ξ_{gg} , the auto-correlation of galaxies, with associated covariance C_{gg} , and the fitting model is given by the first line of Equation 2.14 with f_i set to zero. The systematic error for α and ϵ in this case is consistent with the ones obtained using our method applied to contaminated catalogues, while the statistical errors on the AP parameters decreased by approximately 25%-40% compared to interloper fractions of 2%-15%. Therefore, the systematic error in our method is due to the standard BAO modelling procedure.

2.5.4 Dipole of the near/far cross-correlation

In a 2D correlation function, a non-zero dipole arises when the function is not invariant under reflection symmetry along the LOS or, equivalently, under a change in the sign of μ , the cosine of the angle between the LOS and the direction connecting each pair of objects. Changing the sign of μ corresponds to considering the pair AB instead of the pair BA. When measuring a cross-correlation function, one selects two different populations, then chooses which one appears first in the pair counting, and separations and angles between

the first and second groups are determined for each pair. In an auto-correlation, this choice is not made. The near/far shifted correlation function is a cross-correlation between the same catalogue shifted in two opposite directions, so that the first object in the pairs always belongs to the near-shifted catalogue, and the second object always belong to the far-shifted catalogue. Thus we expect a dipole in the near/far contaminated correlation function.

This dipole is due to two effects. First, an artificial dipole appears into the near/far shifted correlation because that is a cross-correlation between the same catalog shifted along the LOS in two different directions. The shift creates an artificial dipole in the contaminated clustering through the terms $\xi_{g_n g_f}$ and $\xi_{i_n i_f}$. The near/far dipole also has features that are due to the presence of interlopers in the contaminated catalogue.

In the contaminated correlation function, the 2D galaxy target-interloper cross correlation can be obtained via $\xi_{gi} \sim \mathcal{M}_\Delta[\xi_{gg}]$, where we applied the transformation $\mathcal{M}$ in Equation 2.15. In that transformation, the change $\mu \rightarrow -\mu$ is equivalent to the the change of variable $\Delta \rightarrow -\Delta$. Therefore $\xi_{ig} \sim \mathcal{M}_{-\Delta}[\xi_{gg}]$. While the two cross correlations ξ_{gi} and ξ_{ig} exhibit equal even-multipole components, they present different odd terms. The left panel in Figure 2.9 shows the dipole of the two cross correlations, as predicted via the $\mathcal{M}_{\pm\Delta}[\xi_{gg}]$ mappings as well as the mean of measurements over 10 mocks. The dipoles have the same amplitude but opposite sign as a function of separation r , thus they sum to zero. Since we cannot distinguish between interlopers and target galaxies in observed surveys, these two terms cannot be measured separately and the dipole cannot be detected.

When considering the near/far shifted correlation function, the dipoles in $\xi_{i_n g_f}$ and $\xi_{g_n i_f}$ appear at different scales, as a result of having shifted catalogues. Indeed, $\xi_{g_n i_f} \sim \mathcal{M}_\Delta[\xi_{gg}]$ and $\xi_{i_n g_f} \sim \mathcal{M}_{3\Delta}[\xi_{gg}]$, making all their multipoles (even and odd) differ as a function of separation r . The right panel of Figure 2.9 shows the dipoles in $\xi_{i_n g_f}$ and $\xi_{g_n i_f}$, which appear at different scales and do not sum to zero as in the contaminated correlation function. Additionally, they now share the same sign, another consequence of shifting the contaminated catalogue to generate the near and far shifted ones.

When measuring the near-far shifted correlation function of the full contaminated sample, one will always observe a dominant artificial dipole at exactly the shift scale, Δ_{shift} as in the monopole. Measurements over 10 mocks of the total near/far shifted correlation dipole are shown in Figure 2.10. In the presence of interlopers, additional offset dipole features will appear. As a result, the dipole can therefore be used as a initial indicator for the presence of this type of interlopers. In fact, the shift need not be equal to some integer multiple of the interloper shift to see this effect. In a situation where the interloper shift is not known, one could perform the near/far shift by any arbitrary value and the additional

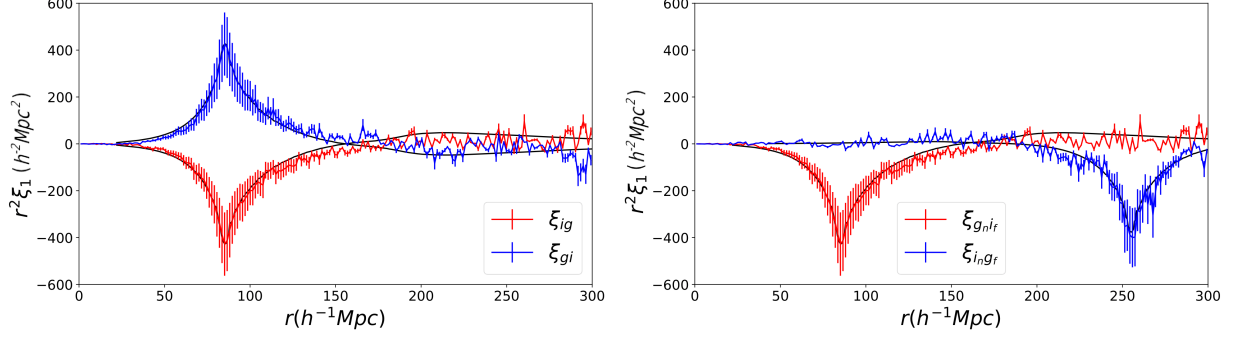


Figure 2.9: The left panel shows the measured dipole in the terms ξ_{ig} and ξ_{gi} of the contaminated correlation function (Equation 2.6). The right panel displays the measured dipole in the terms ξ_{ingf} and ξ_{gnif} in the near-far shifted correlation function (Equation 2.8). Measurements are taken as the mean of 10 mocks. Predictions are shown as the solid black lines in both panels.

interloper features would appear at $\Delta_{\text{shift}} - \Delta_{\text{interloper}}$ and $\Delta_{\text{shift}} + \Delta_{\text{interloper}}$.

2.6 Conclusions

In this chapter, we have discussed how to extract the BAO scale from a galaxy target catalogue that is contaminated with a sample of small-displacement interlopers. This is important for future spectroscopic telescope surveys, like Roman, where it is possible that the population of [OIII] galaxies is contaminated by $H\beta$ interlopers due to single-line redshift measurements. We now cover some important points of our analysis.

The contaminated correlation function has two important terms: The auto-correlation term (which may be split into a galaxy auto-correlation and interloper auto-correlation) and a galaxy target-interloper cross correlation term as a linear combination of two correlation functions. It is this auto-correlation term that we wish to isolate and measure, and thus we sought to model the cross-correlation.

We have introduced a self-calibration method to estimate this cross term. This involves taking the original contaminated catalogue and creating two new “far-shifted” and “near-shifted” catalogues, with LOS positions shifted towards or away from the observer by one interloper shift. The cross correlation of these catalogues can partially isolate the desired galaxy target-interloper cross term.

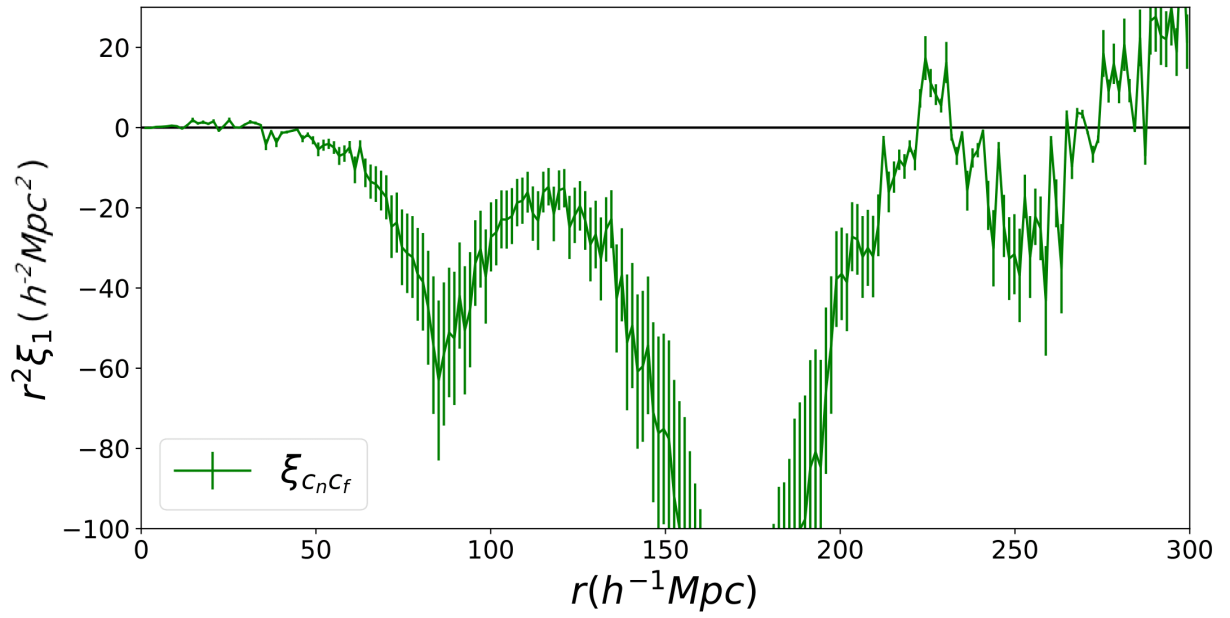


Figure 2.10: The measured dipole of the total $\xi_{c_n c_f}$ is shown in green. Measurements are taken as the mean of 10 mocks. The vertical scale has been limited to a range of $[-100, 30]$, so that the smaller features are more easily seen. The central feature peak is at ~ -1500 and is not shown on this scale.

We tested our model in various scenarios exhibiting different values for the interloper fraction and the interloper displacement Δ . In all cases, our model returns unbiased predictions for the AP dilation parameters with systematic errors less than 6.6×10^{-3} in the worst case, which is consistent with prior pre-reconstruction fitting methods that did not consider catalogues contaminated by interlopers [61]. If interlopers are present but not accounted for in the model, the systematic errors on the dilation parameters are one to two orders of magnitude greater, up to 0.048 and 0.15, for α and ϵ , respectively.

As our analysis will be useful for Roman [OIII] targets, we may predict the statistical error our method would give for a Roman survey. Using a simplistic approach, we may scale the errors we obtain from the effective volume of 1000 mocks ($1 (h^{-1}\text{Gpc})^3$ each) to the approximate volume of a survey between $z = 1.8 - 2.8$, $\sim 10 (h^{-1}\text{Gpc})^3$. We are therefore testing the method at a precision a factor of 10 times better than expected from Roman. For the range of interloper fractions and displacements we consider, the systematic errors are therefore expected to be subdominant. The effect of the self-calibration method to ameliorate the effects of interlopers, is that the statistical errors on the AP parameters increase by approximately 30%, which is only weakly dependent on the interloper fractions for a range 2% - 15%. This increase in the errors can be reduced further by providing prior information on the interlopers, for example from deep field observations.

It should also be noted that the change from a simulation box mock to survey data will require additional testing. There are effects due to varying redshift over the survey volume, and the lightcone geometry. These effects should be carefully taken into account before applying the model to real data.

Small-displacement interlopers create a strong signal in the two point correlation function that appears near the BAO peak and thus contaminates measurements of cosmological parameters. With our self-calibration model, it is possible to robustly estimate the AP dilation parameters regardless of differing bias schemes of interlopers and targets. Furthermore, our model can estimate the fraction of interlopers to within a few percent, given the parameters B , or B_1, B_2 , are well known.

In the next chapter, we will explore a method to identify “unknown unknowns,” and diagnose previously unknown effects in the data and modelling.

Chapter 3

LOO-PIT

The following chapter is made up of material from [2].

With the next generation of galaxy surveys on the horizon, including the Roman Space Telescope [47] and Euclid [48, 63], it has become more important than ever to develop more powerful tools to best extract information from these new, larger datasets.

For example, consider a small model bias on the scale of the standard deviation of the data points (see Figure 3.3 for an illustration). The standard best fit statistic χ^2 is blind to this type of modelling failure and thus is a liability for the detailed statistical analysis that is performed today. Issues like model bias and proper covariance matrix estimations are becoming more difficult to deal with in these surveys, as well as the arrival of new systematics. Thus, cross validation techniques like Leave One Out Cross Validation (LOO-CV) are becoming increasingly common in cosmological analyses for their power in posterior predictive checks [64, 65, 66].

In this chapter, we introduce a statistical technique called the Leave One Out Probability Integral Transform (LOO-PIT). While LOO-PIT has been applied in statistics prior to this, we present the first application to cosmological data. This technique combines two concepts: LOO-CV, and the well known Probability Integral Transform (PIT) [67]. LOO-PIT serves as a complementary test to the standard best fit statistic χ^2 , providing two additional metrics: a diagnostic plot showing the type of modelling failure, and an additional test statistic through the Kolmogorov–Smirnov test [68]. LOO-PIT also relaxes the constraint of assuming Gaussian likelihoods in one’s data analysis, paving the way for more general methods.

To test LOO-PIT’s power in diagnosing modelling failures, we apply the LOO-PIT technique to a recently arisen issue: emission line interlopers. Galaxy catalogues can be

contaminated by sources where the redshift has been incorrectly inferred due to emission line confusion. As the distance to a galaxy is derived from its redshift, these interlopers contaminate the clustering signal and in particular the BAO peak. We fit contaminated correlation functions with a standard BAO template and apply LOO-PIT to the posteriors obtained to determine its sensitivity to both the interloper fraction and the interloper displacement.

This chapter is structured as follows. In Section 3.1, present the LOO-PIT technique. In Section 3.3, we present results given by the LOO-PIT pipeline. In Section 3.4, we discuss some limitations of the method and its application to real survey data. Finally, we conclude in Section 3.5.

3.1 Method Outline

In this section, we provide an overview of LOO-PIT and briefly outline each of the statistical steps that power the method.

3.1.1 Outlining the LOO-PIT

This method combines two statistical ideas to form a sensitive posterior check. We apply the well known Probability Integral Transform (PIT) to Leave One Out-Cross Validation (LOO-CV).

The core of posterior predictive checks lies with the posterior predictive distribution. This is defined:

$$p(y^*|y) = \int p(y^*|\theta)p(\theta|y)d\theta. \quad (3.1)$$

Here y refers to the observed data, y^* some future data, and θ the model parameters.

The crucial idea is that if we use the correct model for the observed data, the posterior predictive and the observed data will follow the same probability density. That is, the model correctly predicts “future” observations.

In cosmology, we do not really have “future” observations to compare against, hence in performing cross validation, we must treat some subset of the observed data as the future observations and the remainder as the current observations. We have the special case in LOO-CV, where we treat each data point as a single future observation and calculate the

posterior predictive for each observation. In this work, we refer to the “left-out” data point as y_i and the remaining data as y_{-i} .

As the posterior predictive and observations should have the same probability distribution function (PDF), they should also have the same cumulative distribution function (CDF). Each observation then is a single draw from its corresponding pointwise PDF, thus if we transform it with the pointwise posterior predictive CDF, we should obtain a single draw from a uniform distribution. This process is performed for each data point, yielding a distribution of LOO-PIT values. The validation power of this method comes from comparing the LOO-PIT distribution to the standard uniform $\mathcal{U}_{[0,1]}$. If the model is incorrect for any number of reasons, the distribution produced by the PIT will not be uniform.

3.1.2 Going to the LOO: Estimating Leave One Out Posterior Predictives

It would be cost prohibitive to refit the model to obtain posteriors $p(\theta|y_{-i})$ for each LOO subset, however we can use importance sampling (IS) to obtain these probabilities from the total fit posterior $p(\theta|y)$.

By [67], if the pointwise probabilities are conditionally independent¹, the importance sampling estimate for the posterior predictive corresponding to datapoint y_i^{obs} is:

$$\hat{p}(y_i|y_{-i}) = \sum_{s=1}^S r_i^s y_i^s, \quad (3.2)$$

where r_i^s are the standard normalised importance ratios, S is the total number of parameter samples, and we have draws $y_i^s \sim p(y_i|\theta^s)$. We will also define N to be the total number of data points. These weights are given by:²

$$r_i^s = \frac{p(\theta^s|y_{-i})}{p(\theta^s|y)}. \quad (3.3)$$

In cases where the two distributions, $p(\theta|y_{-i})$ and $p(\theta|y)$, differ significantly, the distribution of the IS ratios can have a heavy right tail. The IS estimate can be dominated by these samples and give extremely noisy estimates. There are two useful “smoothing”

¹One can decompose $p(y|\theta) = \prod_i^N p(y_i|\theta)$, or, equivalently, the covariance matrix of the data is diagonal.

²In this equation, $p(\dots)$, refers to the posterior likelihood of the given draw from $p(\dots)$

algorithms to mitigate this issue with standard IS. The first is Truncated Importance Sampling (TIS) introduced by [69]. TIS involves replacing the raw IS weights with truncated weights, t^s , given by:

$$t_i^s = \min(r_i^s, \sqrt{S}\bar{r}_i), \quad (3.4)$$

where $\bar{r}_i$ is the mean of the raw IS weights over all samples. While this method is simple in application and cleanly solves the primary issue with IS by guaranteeing that TIS estimates have finite variance, TIS introduces a potentially large bias [67].

Thus, given the drawbacks of TIS, we opt for a second algorithm, Pareto Smoothed Importance Sampling (PSIS) [70]. PSIS is similar to TIS in that we replace some of the raw IS weights, however instead of a single truncation, a fit is done to the IS weights, assuming a generalized Pareto distribution given by:

$$p(x|\mu, \sigma, k) = \frac{1}{\sigma} \left(1 + k \left(\frac{x - \mu}{\sigma} \right) \right)^{-\frac{1}{k} - 1}. \quad (3.5)$$

In brief, the raw IS weights are ordered from least to greatest and indexed $s = 1, 2, \dots, S$. The top 20% are then fit to a generalised Pareto distribution using the method of [71]. Then for a given point indexed by i , the raw IS ratios are replaced as:

$$w_i^s = r_i^s, \quad s = 1, 2, \dots, S - M \quad (3.6)$$

$$w_i^{S-M+z} = \min \left(F^{-1} \left(\frac{z - 1/2}{M} \right), \max(r_i^s) \right), \quad z = 1, 2, \dots, M, \quad (3.7)$$

where F^{-1} is the inverse CDF of the generalized Pareto distribution, and M is the number of samples used for the fit. We use $M = 0.2S$.³ The final step is to truncate the smoothed weights as in TIS, but using the cutoff of $S^{3/4}\bar{w}_i$, to guarantee finite variance in the estimates.

Finally, with the smoothed weights, we have an estimate for each posterior predictive distribution using LOO-PSIS:

$$\hat{p}(y_i|y_{-i}) = \sum_{s=1}^S w_i^s y_i^s. \quad (3.8)$$

³Note that the method is robust to the misspecification of the exact form of M relative to S [70].

This is our estimate of the distribution of a single point y_i given the other data points y_{-i} , marginalised over the parameter space, thus, in this work, we refer to this as the **pointwise posterior predictive distribution**.

IS, or its refined forms, are not necessary to perform the LOO-PIT procedure. It is only to reduce the computation. If one were keen to avoid the approximations that IS and PSIS introduce, it is possible to rerun the chains for each left out data points to get the exact leave one out posteriors and avoid using IS. While this procedure is exact, it significantly increases the computation time as the number of data points increases. Using the approximations IS affords allows one to unlock the power of LOO-PIT for larger and larger datasets without being unnecessarily weighed down by long runtimes. However, there may be cases where PSIS fails due to the nature of the posteriors. In these cases, then it would be necessary to resample the posteriors, but these cases are likely rare.

3.1.3 Adding a PIT to the LOO: The Probability Integral Transform

In this section, we will briefly review the Probability Integral Transform and show how the PIT is applied to the pointwise posterior predictive distributions.

Consider a continuous random variable, X , that has the PDF, $p(X)$. Now consider the random variable Y , defined by the following transformation of X :

$$Y(X) = \int_{-\infty}^X p(X^*) dX^*, \quad (3.9)$$

simply the CDF of X . We can find the PDF of Y , $p(Y)$, in terms of $p(X)$ by the change in the PDF under a change of variables:

$$p(Y) = \left| \frac{dX}{dY} \right| p(X). \quad (3.10)$$

This is valid for any function, $Y(X)$, that is monotonic and increasing, which is always true for any CDF or empirical CDF (ECDF). Combining this with Equation 3.9, we find:

$$p(Y) = \left| \frac{1}{p(X)} \right| p(X) = 1, \quad (3.11)$$

and we have shown that the distribution of Y is uniform.

If the incorrect CDF is considered, the Jacobian will not result in $1/p(X)$, and thus the distribution of Y , $p(Y)$, will deviate from the uniform. The test is then to determine whether the distribution of these LOO-PIT values is consistent with a uniform distribution.

Before we can apply the PIT, we must estimate the pointwise posterior predictive CDF. There are numerous options that one can apply here, but for simplicity and speed, we assume the posterior predictive distributions to be Gaussian. In fact, this distribution has been shown to be close to a t-distribution [72]. The degrees of freedom of this t-distribution is related to the number of MCMC draws. Thus, we approximate to a Gaussian with a weighted mean and variance equal to that of the set of y_i^s under the PSIS weights w_i^s .

Using this CDF to transform each of the N observed datapoints y_i^{obs} will result in N LOO-PIT values. The value of the i^{th} LOOPIT draw is given by:

$$L_i = \int_{-\infty}^{y_i^{\text{obs}}} p(X^*) dX^*, \quad (3.12)$$

where $p(X^*)$ is the corresponding i^{th} pointwise posterior predictive distribution $\hat{p}(y_i|y_{-i})$.

We consider two related diagnostics to test this. First, is simply the kernel density estimate (KDE) of all the estimates together. It is straightforward to check if it is consistent with a uniform by inspection, in addition to determining the type of modelling failure based on how the LOO-PIT KDE deviates from the uniform. We can also test the uniformity of the LOO-PIT KDE using the well known Kolmogorov–Smirnov (KS) Test, yielding p -values for hypothesis testing. We have included some illustrative examples with a toy model to demonstrate some common effects in Section 3.2. We will also note here that we may compare any two LOO-PIT distributions, via a two sample KS test.

3.2 Common LOO-PIT signatures

In this section, we briefly show the three basic LOO-PIT signatures of model failure. These are underdispersed/underfitting, overdispersed/overfitting, and biased/shifted. The following figures are based on [73].

For data where the errors are underestimated, the posterior predictive distributions will be narrower than the truth. Thus, data points will tend to fall on the tails of the posterior predictives, forming the trough pattern seen in Figure 3.1. This pattern can also appear if the model is not a good fit for the data, such as fitting linear data with the wrong slope. Since the posterior predictives are based on the model, if the model and data have

significant offset, the LOO-PIT values will again be drawn from the tails of the posterior predictives.

The opposite effect occurs when the errors are over estimated. Now the posterior predictives are too wide, and data points will tend to fall close to the centroid of these distributions. Thus, the LOO-PIT draws are close to 0.5 and we will get the peak pattern shown in Figure 3.2. This pattern also appears when the model is overfitting. Suppose the 10 points of data are fit with a 10 parameter model. The model can perfectly fit each data point, thus the LOO-PIT draw for each point will be exactly 0.5.

These two signatures each have two possible causes. It is then important to correctly estimate errors and covariances, lest a true model failure be attributed to poor error estimation.

The final common signature is a shift or bias in the data. This is the effect that causes the shifts seen earlier in this work. This effect also gives LOO-PIT additional information compared to χ^2 . Depending on the direction of the bias, the LOO-PIT KDE can have either a positive or negative tilt. This is shown in Figure 3.3.

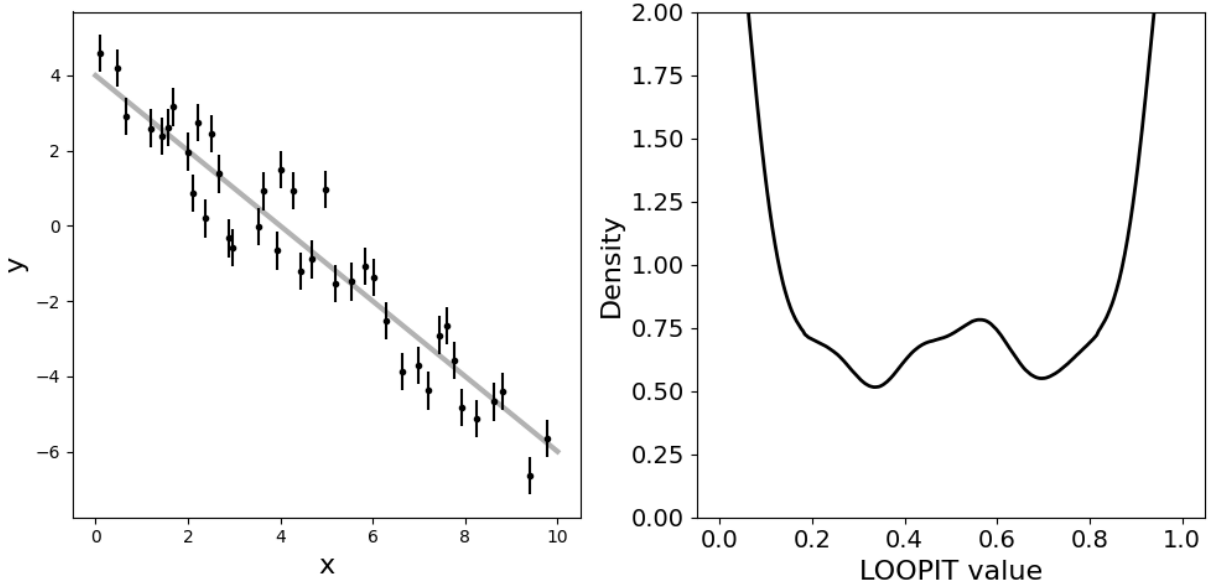


Figure 3.1: LOO-PIT values for a simple linear fit on 200 points. The data is thinned in the left plot for clarity. Here we have manually set the errorbars to 0.5 times their true values, showing the underdispersion “trough” signature.

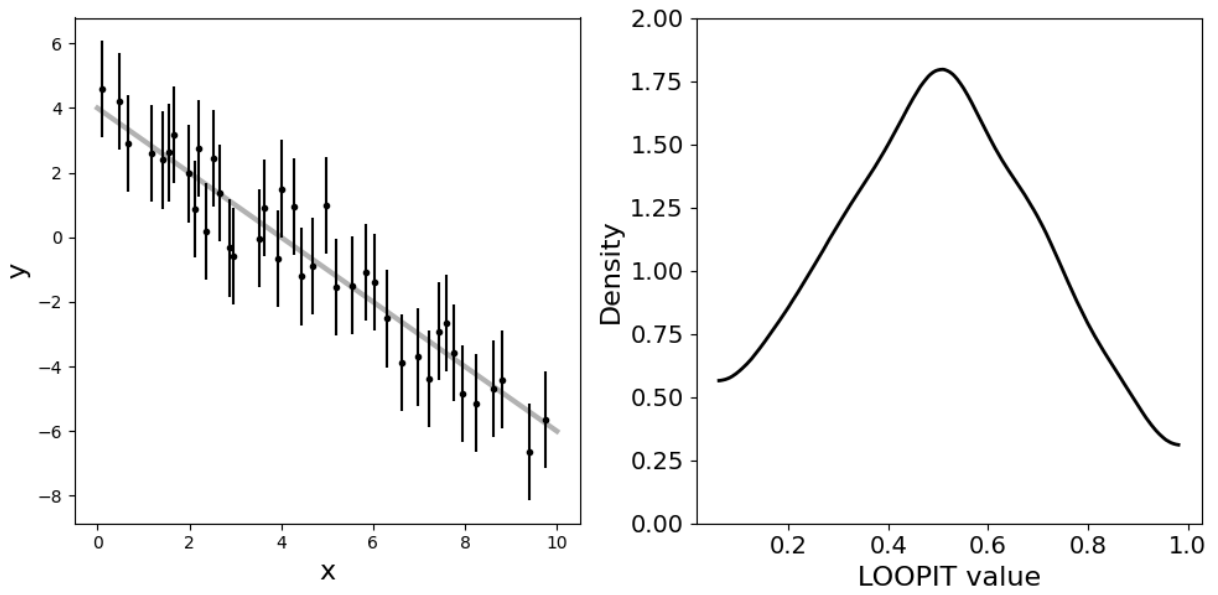


Figure 3.2: LOO-PIT values for a simple linear fit on 200 points. The data is thinned in the left plot for clarity. Here we have manually set the errorbars to 1.5 times their true values, showing the overdispersion “peak” signature.

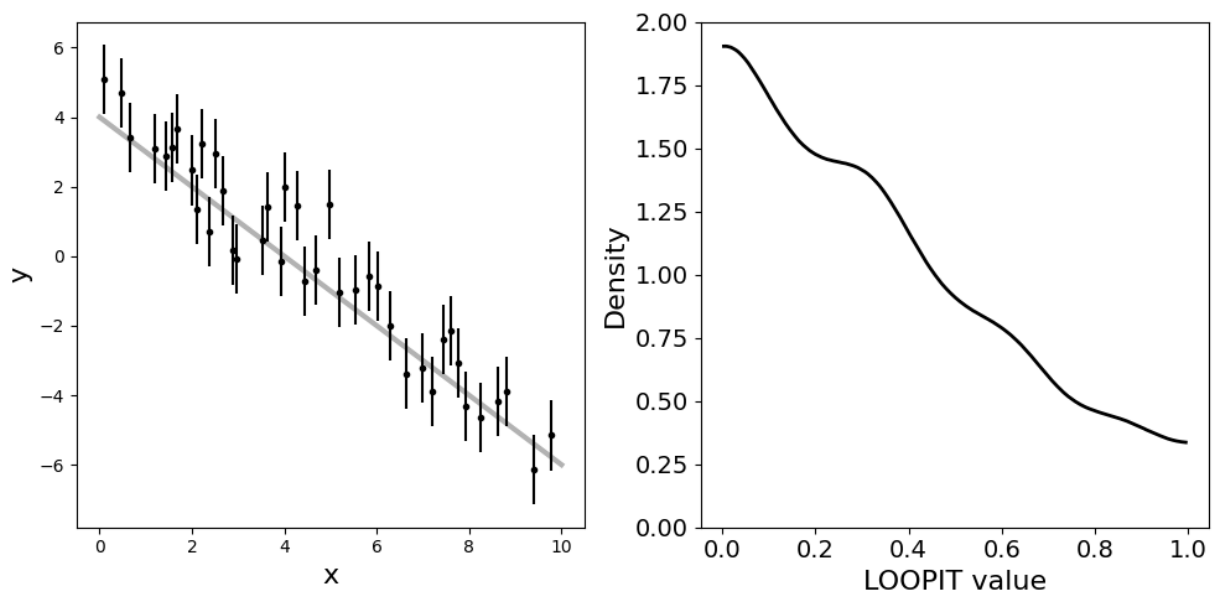


Figure 3.3: LOO-PIT values for a simple linear fit on 200 points. The data is thinned in the left plot for clarity. Here the data points are offset by $+0.5$, showing the bias “tilt” signature.

3.3 Testing the sensitivity of LOO-PIT using simulations

We use monopole and quadrupole moments of two point redshift space correlation functions as data to fit. We start with the covariance matrix and mean of the multipoles measured from 1000 Quijote mocks [53]. We then add in scatter by scaling the covariance matrix to a volume of a $10 (h^{-1}\text{Gpc})^3$ box. We fit with the standard BAO template (see Section 2.3.3). We apply a standard Markov-chain Monte Carlo (MCMC) analysis using the emcee python package [4] and the following posterior distribution [60]:

$$f(\xi^{\text{model}}|\xi^{\text{data}}, C) \propto \left[1 + \frac{\chi^2}{n_s - 1}\right]^{-\frac{m}{2}}, \quad (3.13)$$

where n_s is the number of mocks used and m is given by Equation 54 in [60]. χ^2 is the given by $(\xi^{\text{model}} - \xi^{\text{data}})^T C^{-1} (\xi^{\text{model}} - \xi^{\text{data}})$ with C^{-1} the inverse of the estimated covariance matrix:

$$C_{ij}[\xi(r_i)\xi(r_j)] = \frac{1}{n_s(n_s - 1)} \sum_{n=1}^{n_s} [\xi_n(r_i) - \bar{\xi}(r_i)][\xi_n(r_j) - \bar{\xi}(r_j)] \quad (3.14)$$

evaluated for all points in $\xi = \xi^{\text{data}} = \xi_{cc} - 2\xi_{cncf}$. The BAO fit is performed using the monopole and quadrupole within the range $r \in [50, 150] h^{-1}\text{Mpc}$.

In order to quantify the performance of LOO-PIT, and how its efficacy depends on the amount of interlopers in the contaminated catalogue and on the particular value for the interloper displacement (thus the redshift of the survey), we consider 18 different scenarios given by the combination of 3 different values for the interloper displacement $\Delta = (85, 90, 97 h^{-1}\text{Mpc})$ and 6 values for the interloper fraction $f_i = (0.005, 0.01, 0.02, 0.05, 0.10, 0.15)$.

3.3.1 Results

We first characterise the baseline LOO-PIT distribution. This is the LOO-PIT distribution derived from fits to an uncontaminated catalogue.

We perform the BAO fit on the monopole and quadrupole extracted from catalogues that contain no interlopers. For this baseline case, we generated 1000 realisations of the data using the covariance matrix scaled to a volume of $10 (h^{-1}\text{Gpc})^3$. We then perform

the BAO fit with the standard MCMC treatment, obtaining posterior distributions for all model parameters. We extract the LOO-PIT draws for each of the data points in each realisation according to the prescription outlined in Section 3.1.1, weighting the values according to leave-one-out posteriors. This results in 132000 LOO-PIT draws for each combination of interloper fraction and interloper displacement. We plot the KDE of these values in dark red in Figures 3.4, 3.5, 3.6.

We find that the baseline fit shows signs of significant overfitting with the characteristic “peak” shape (See Section 3.2). This is clearly not uniform.

After this baseline case, we then consider catalogues with varying degrees of contamination. We measure the two point correlation function monopole and quadrupoles. In this case, we generate 1000 realisations of each combination of interloper fraction and displacement, and again obtain the LOO-PIT values for each case. We plot the KDE of these sets of 132000 points in Figures 3.4, 3.5, 3.6. We also show these plots with a single realisation in Appendix B.1. While the general trend is still visible without stacking, it is clear that there is significant noise. This is unsurprising, as we are attempting to characterise a distribution, which only improves with more samples.

While the initial zero interloper baseline is non-uniform, LOO-PIT nevertheless is clearly sensitive to deviations from the baseline. In general, the LOO-PIT plots start with a “peak” shape, indicating overfitting. As the contamination increases, the height of the peak decreases. The distribution flips to the “trough” shape between interloper fractions $f_i = 0.02$ - 0.05 . In particular, we can see a transitional shape at $f_i = 0.05$. There, we see both a bump and the underfitting/underdispersion signature, forming an offset “W” shape. This is most clearly shown in the $f_i = 0.05$ case in Figure 3.6. There is a part of the model that slightly underestimates the data resulting in the bump at 0.4, but the model cannot properly capture the interloper peak, resulting in many LOO-PIT draws near 0 and 1, and the heavy left and right tails at higher contamination levels.

We can also see some separation between the $\Delta = 85 \ h^{-1}\text{Mpc}$ (Figure 3.4) case compared to the other two. While, the LOO-PIT KDE deviates in a similar way for all three cases up until $f_i = 0.02$, at $f_i = 0.05$, there is a significant negative tilt present in the $\Delta = 90, 97 \ h^{-1}\text{Mpc}$ plots (Figures 3.5, 3.6).⁴ Conversely, there is no tilt for $\Delta = 85 \ h^{-1}\text{Mpc}$. These are more clearly seen in the cases with greater levels of contamination. This is a signature of bias in the fit. A tilt in the negative direction seen in the plots indicates the model is generally underestimating the data. For the cases where the interloper peak has significant overlap with the BAO peak, the model tends to underestimate the interloper peak. In this regime, the interloper peak distorts the BAO in such a way that the standard

⁴Consider a line with negative slope.

shape is a acceptable fit, leaving the interloper contribution as outliers. However, as the interloper peak moves further from the BAO peak, these outlier points cannot be ignored by the model as their likelihoods are extremely small when compared to a standard BAO shape, and thus the model will use the polynomial to “average through” the peak in this case, resulting in more uniform central LOO-PIT draws for the $\Delta = 85 \ h^{-1}\text{Mpc}$ case for higher interloper fractions.

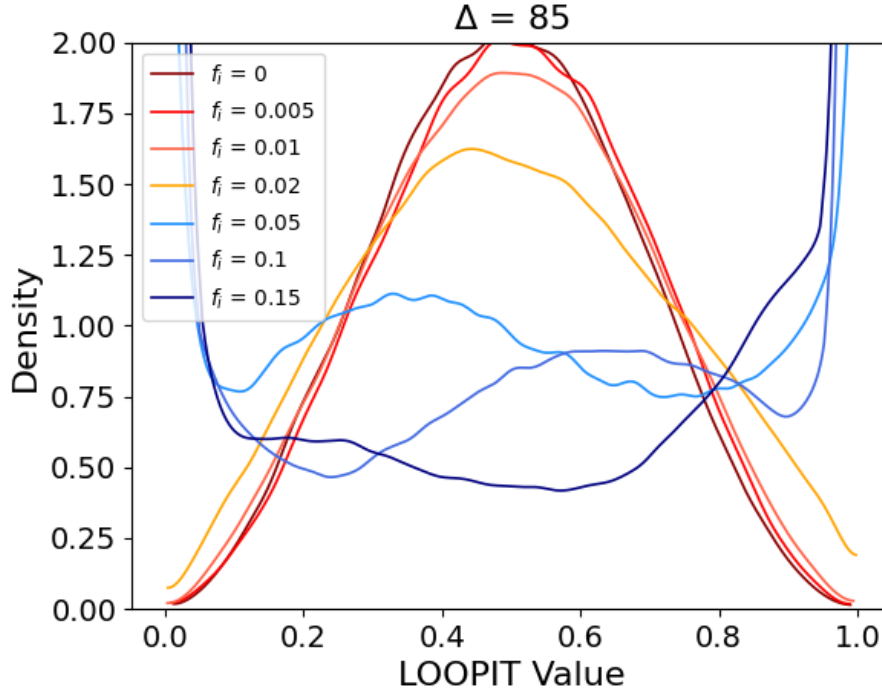


Figure 3.4: LOO-PIT values for 1000 data realisations with $\Delta = 85 \ h^{-1}\text{Mpc}$. We plot a normalised KDE for each interloper fraction f_i .

We will now quantify the performance of LOO-PIT against its main rival, χ^2 . We consider the 132000 LOO-PIT draws for the uncontaminated fit to sufficiently characterise the baseline distribution. We then compute the two sample Kolmogorov-Smirnov statistic. For a given combination of interloper fraction and interloper displacement, we compare each of the 1000 realisations to the full set of baseline LOO-PIT draws. That is, we compare the full baseline distribution from 132000 points, to the 132 points obtained from a single realisation. We obtain the KS statistic from this and derive a p -value for each realisation. Similarly, we keep the best fit χ^2 statistic from each MCMC run and calculate

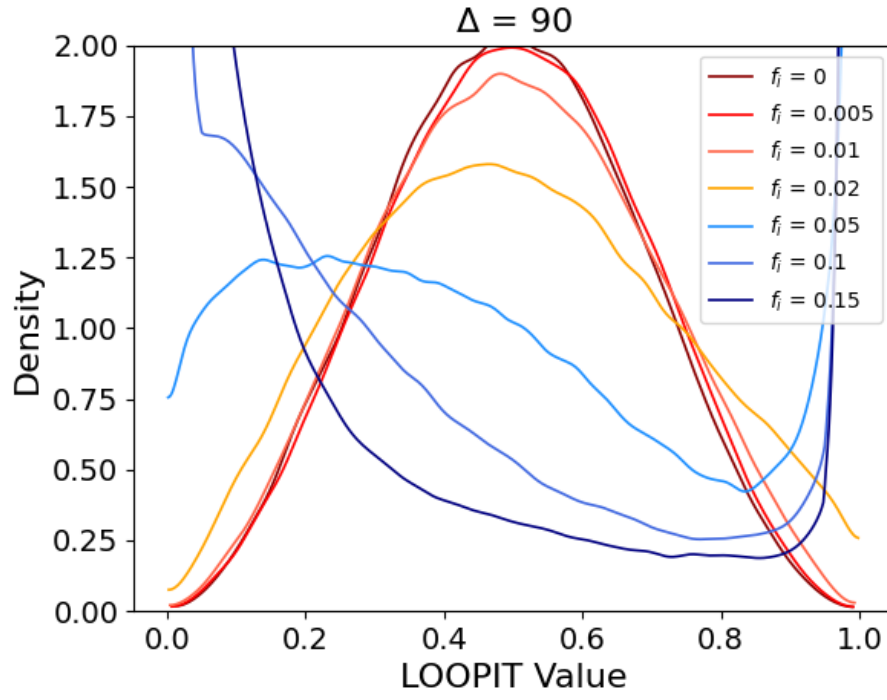


Figure 3.5: LOO-PIT values for 1000 data realisations with $\Delta = 90 \ h^{-1}\text{Mpc}$. We plot a normalised KDE for each interloper fraction f_i .

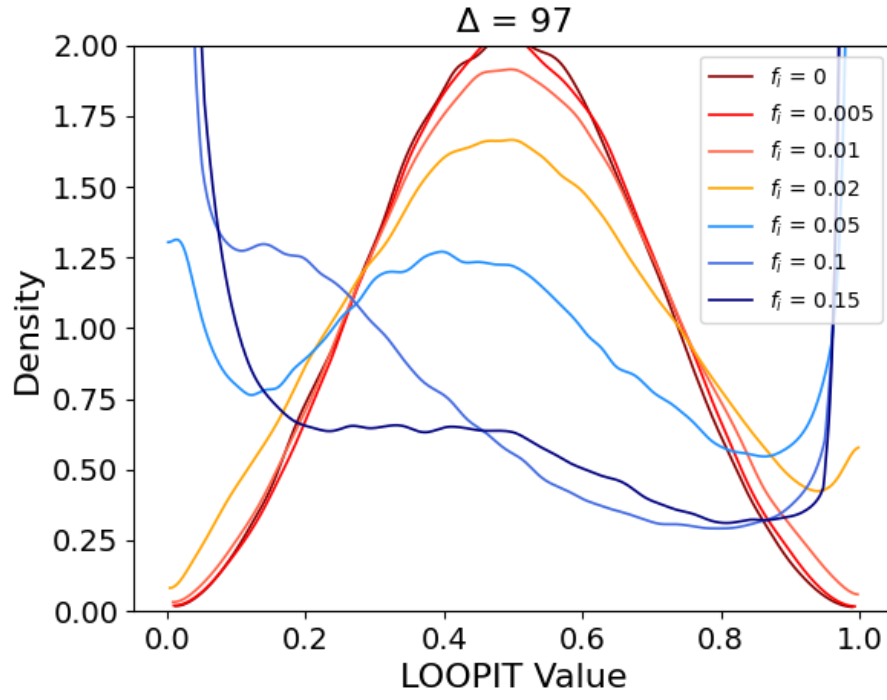


Figure 3.6: LOO-PIT values for 1000 data realisations with $\Delta = 97 \ h^{-1}\text{Mpc}$. We plot a normalised KDE for each interloper fraction f_i .

a p -value assuming 123 degrees of freedom.⁵ We set the acceptance threshold at $p = 0.05$, and consider the fraction of realisations that result in a significant detection for LOO-PIT and then χ^2 . We plot these in Figures 3.7, 3.8, 3.9.

We see that LOO-PIT appears to outperform χ^2 in nearly all test cases. In particular, LOO-PIT detects the presence of interlopers at low contamination ($f_i = 0.5 - 1\%$) at a significantly higher rate than χ^2 . That is, LOO-PIT rejects the null hypothesis (no interlopers) This improvement is greatest at $f_i = 0.5\%$ at all interloper displacements, where LOO-PIT can detect the presence of interloper contamination in more than 50% of the realisations compared to the χ^2 detection rate of approximately 5%. Across interloper displacements, this is an improvement of $\sim 45\%$. Closer to the Roman interloper limit, the improvement between χ^2 and LOO-PIT is not as great, at only a 10% improvement in the $\Delta = 90,97 h^{-1}\text{Mpc}$ cases. Note that χ^2 gives a better detection rate than LOO-PIT in the $\Delta = 85 h^{-1}\text{Mpc}$ case at $f_i = 2\%$. At contamination levels greater than $f_i = 5\%$, both tests are fully saturated, detecting the contamination in nearly 100% of realisations.

3.4 Discussion

3.4.1 LOO-PIT without stacking

We have shown results for LOO-PIT so far by stacking realisations to show smoother plots. As with all distribution based tests, the statistical power increases with the number of samples one has to compare to. While we argue that it is valid to calibrate the baseline case with 1000 realisations, when comparing this to realistic catalogues, we will only have a single realisation of the contaminated sample. An example of this is shown in Figure 3.10. For the baseline case, we plot the LOO-PIT KDE derived from 1000 realisations. For all contaminated cases, we randomly select a single Roman volume realisation. Clearly, there is some significant noise compared to the stacked plots. However, we note that the general trends described in Section 3.3 are still visible. In particular, the flip in shape between $f_i = 0.02-0.05$ is still clear, as is the negative tilt at the higher interloper fractions.

With a single realisation, LOO-PIT is more difficult to use to diagnose issues simply by inspection of the KDE plots. However, we will note that using χ^2 yields no such visible inspection method. In addition, the probability that LOO-PIT detects the interloper contamination is better or equal to χ^2 in nearly all test cases, as shown in Section 3.3.

⁵We fit 132 data points with a 9 parameter model.

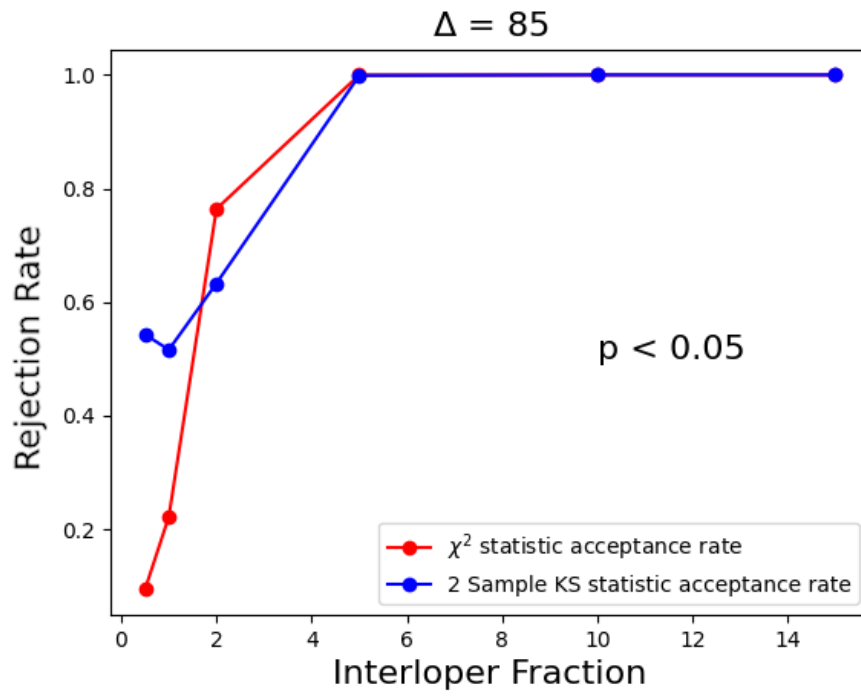


Figure 3.7: Hypothesis test rejection rates as a function of interloper fraction for a fixed interloper displacement. Here, we consider $\Delta = 85 \ h^{-1}\text{Mpc}$. LOO-PIT is plotted in blue. χ^2 is plotted in red.

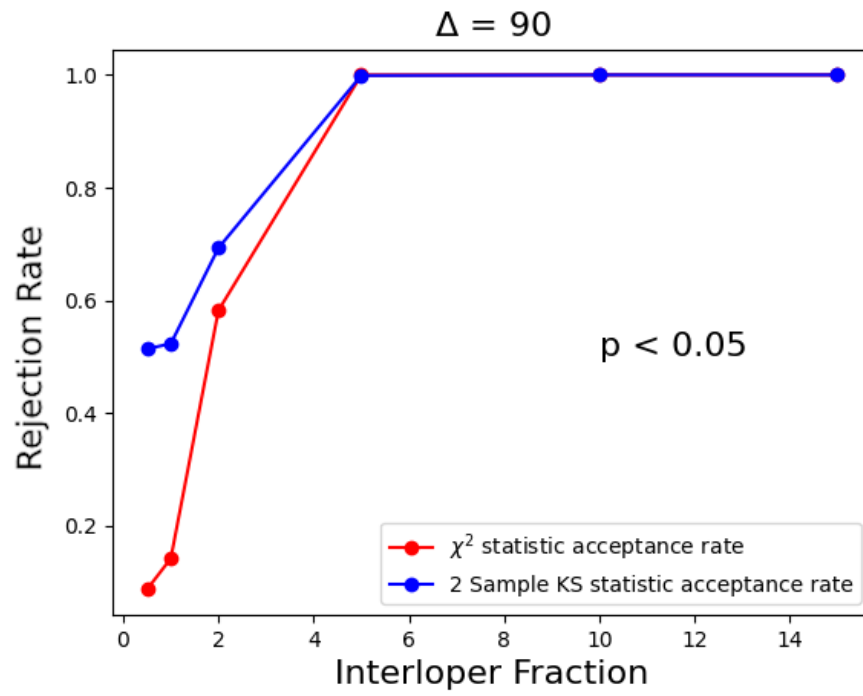


Figure 3.8: Hypothesis test rejection rates as a function of interloper fraction for a fixed interloper displacement. Here, we consider $\Delta = 90 \ h^{-1}\text{Mpc}$. LOO-PIT is plotted in blue. χ^2 is plotted in red.

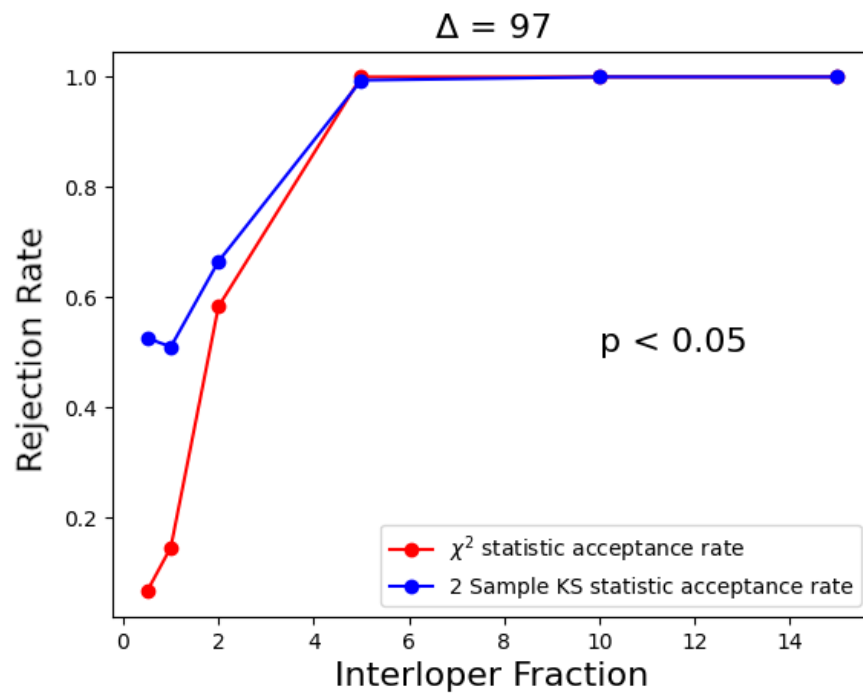


Figure 3.9: Hypothesis test rejection rates as a function of interloper fraction for a fixed interloper displacement. Here, we consider $\Delta = 97 \ h^{-1}\text{Mpc}$. LOO-PIT is plotted in blue. χ^2 is plotted in red.

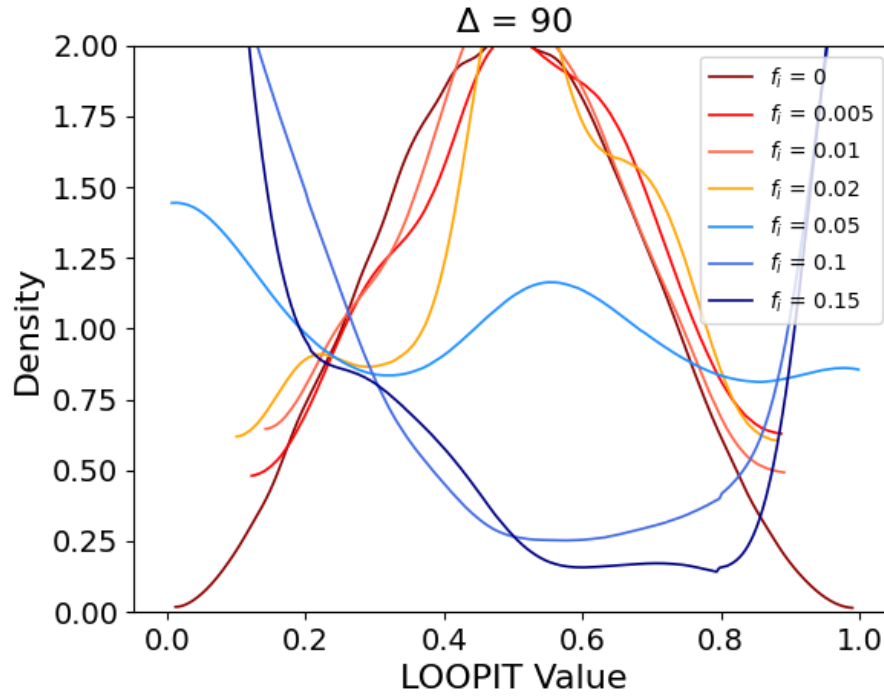


Figure 3.10: LOOPIT values for $\Delta = 90 \ h^{-1}\text{Mpc}$. We plot a normalised KDE for each interloper fraction. For all interloper fractions other than zero baseline, we have plotted the KDE of LOOPIT values derived from a single realisation. For the baseline, we plot the KDE from 1000 realisations.

3.4.2 LOO-PIT vs. χ^2

While LOO-PIT seems to outperform χ^2 in nearly all test cases, we will discuss the reasons for why.

As mentioned earlier there is a peculiar behaviour in the LOO-PIT part of the Figures 3.7, 3.8, 3.9. The LOO-PIT rejection rate appears to flatten out at 0.5 as the interloper fraction decreases to 0. This is a known issue with the KS test and may indicate issues with LOO-PIT. At large sample sizes, it is prone to a high Type I error, or false positive, rate. This problem is at odds with our desire to characterise the baseline distribution, as we require a large number of samples. This could be solved by taking a random sample from the baseline distribution at the same size as the individual LOO-PIT samples. This helps to relax the minimal bound of the test. The null hypothesis is rejected at a level α if the KS statistic satisfies:

$$D_{n,m} = \sqrt{-\ln(\alpha/2) \frac{1 + \frac{m}{n}}{2m}}, \quad (3.15)$$

where n, m are the respective sample sizes of the two samples we compare in the two sample KS test. As the sample size increases, the test becomes more sensitive at a given significance level. At large sample size, this can lead to the spurious detections we have seen in the prior sections.

3.4.3 Calibration of the baseline

The general idea of LOO-PIT is that a correctedly calibrated model will yield a uniform LOO-PIT KDE. Indeed, that was the standard approach outlined in Section 3.1. However, as the BAO template model is designed to extract the AP parameters from the correlation function, it intentionally overfits the broadband power with the polynomial terms. Thus, this standard LOO-PIT approach would not be sufficient to detect the difference between an uncontaminated and a contaminated correlation function. Therefore, our use of LOOPIT for detecting interlopers has been dependent on the calibrated baseline LOO-PIT KDE.

As we saw in Section 3.3, LOO-PIT is not limited to diagnosing modelling failures, but can differentiate between different models. For example, while we see the peak signature for interloper fraction $f_i = 0.0 - 0.02$, the peak amplitude and shape changes as the contamination increases. We would see a similar effect if we considered first a model with significantly overestimated variances on the data points, then a series of models where this

overestimation becomes less severe. Indeed, the application of LOO-PIT is more general than simply determining a simple goodness-of-fit, it provides a tool for model comparison.

This power of LOO-PIT requires an additional step in the analysis, which we have done. The calibration of a baseline LOO-PIT KDE must be done before any comparisons can be made, especially in the case where one wishes to detect deviations from this baseline. This approach will be useful for the detection of anomalies in cosmological data, as it is now commonplace to validate data pipelines on sophisticated simulations even prior to the beginning of survey missions. In these cases, it is a non-issue to calibrate a baseline LOO-PIT KDE on a set of simulations under a fiducial cosmology, like we have done in this work. For example, it would be beneficial to run LOO-PIT on a set of Roman-like mocks in the standard Λ CDM cosmology in the absence of observational systematics. Regardless of the model used for BAO or any other observation in these simulations, we could characterise the LOO-PIT KDE for a “clean” detection, allowing for us to detect deviations, like observational systematics and their severity or new physics, from this assumption as real data becomes available.

We should note that this caveat is only relevant in the case where a researcher may wish to detect an anomaly at some significance, or to compare a series of possible models. Of course, no baseline is required to perform the LOO-PIT procedure, only to perform the two sample KS test to determine detection significance. Thus, LOO-PIT may also be useful in the model building stage of the pipeline. The standard peak and trough signatures are useful for calibrating error analyses like covariances, and building a model that returns the uniform can validate a model.

3.5 Conclusions

In this chapter, we have introduced a new statistical method called the Leave One Out Probability Integral Transform or LOO-PIT for short. This is a general technique with a wide variety of applications. We apply LOO-PIT to the problem of detecting small displacement interlopers in galaxy clustering analyses. We will now review the method, its strengths, and weaknesses.

LOO-PIT combines two statistical ideas together: Leave One Out Cross Validation (LOO), and the well known Probability Integral Transform (PIT). We estimate a LOO posterior predictive distribution for each datapoint, then test this estimate via the PIT. Our test diagnostic is the KDE of LOO-PIT values, one for each data point. It is also possible to quantify the performance of LOO-PIT via hypothesis testing.

We tested the effectiveness of LOO-PIT by applying it to the analysis of contaminated correlation functions. We measured the mean of 1000 monopole and quadrupole moments from simulations, as well as the covariance matrix. We then scale the covariance matrix to a Roman like volume of $10 (h^{-1}\text{Gpc})^3$ box. We generate 1000 realisations of multipoles at this volume using the scaled covariance matrix. We fit contaminated correlation functions with various values of the interloper fraction and displacement. We find that the shape of the LOO-PIT KDEs change significantly between $f_i = 0.02$ - 0.05 for all interloper displacements. At this threshold, it is clear by eye to see deviation from the baseline. When we calibrate the baseline and perform two sample KS tests, we find that LOO-PIT outperforms or equals χ^2 in all but one test case. This improvement in detection rate is greatest at small interloper fraction. This improvement is in part due to a high rate of Type I error associated with the KS test. Thus, it is difficult to quantify LOO-PIT's performance against χ^2 at this point, and we leave the determination of an optimal test for future work.

LOO-PIT has two primary advantages over the simple χ^2 test. First, we may use any form of the data likelihoods, while χ^2 comes with the underlying assumption of Gaussian likelihoods. However, the strongest advantage of using LOO-PIT is that it includes information about the type of model failure. While LOO-PIT detects the same overdispersion and underdispersion as χ^2 , LOO-PIT can detect shifts or biases in the data relative to the model that χ^2 is blind to. This is visible in both the LOO-PIT KDE diagnostic plots and in the KS testing statistics. This additional information that LOO-PIT provides makes it a powerful tool for model comparison, and detection of systematics.

Chapter 4

Future Work and Conclusions

In this chapter, we will outline some future work that can build upon the projects discussed in the previous chapters. We will then briefly review the topics discussed in this work before concluding.

4.1 Including the dipole

In the following two sections, we will explore two methods of constraining the interloper fractions that build on the dipole of the contaminated correlation function. While it is true that the accurate recovery of cosmological parameters does not strongly depend on the accurate recovery of the interloper fraction, there may still be benefits to having a better idea of what it is given a galaxy catalogue. For example, the redshift dependent interloper fraction could track the number of $H\beta$ to [OIII] galaxies through time and help models of galaxy evolution.

As discussed in Chapter 2, the recovery of the correct interloper fraction is limited by the degeneracy between f_i and B (or B_1 and B_2). We explored breaking this degeneracy by setting a tight Gaussian prior on B . While this approach does allow for more accurate recovery of the fraction of interlopers, it is unrealistic in practice due to uncertainty in the true galaxy bias. We also discussed constraining the interloper fraction outside of the fit.

It should be possible to break the degeneracy between f_i and B , by performing the standard simultaneous fit to the monopole and quadrupole (which contain the relevant cosmological information), and include information from the dipole.

Recall Equation 2.6. As with the other multipoles, the dipole is split into components with amplitudes dependent on the fraction of interlopers. This is generally a problem as the B parameter is also an amplitude. However, B is a linear amplitude. Thus, if we compare ratios of peak heights, this ratio is no longer dependent on B . Furthermore, we know the dipole peaks will always appear at a known displacement. Therefore, for a given artificial shift and interloper shift, we can construct a quantity that is dependent only on the interloper fraction:

$$\frac{\xi_1(\Delta_{\text{shift}} - \Delta_{\text{interloper}}) + \xi_1(\Delta_{\text{shift}} + \Delta_{\text{interloper}})}{\xi_1(\Delta_{\text{shift}})} = \frac{2f_i(1 - f_i)}{f_i^2 + (1 - f_i)^2}. \quad (4.1)$$

This is simply the ratio of the amplitude of the two side dipole peaks and the central peak. Including this value into the fit only increases the degrees of freedom by 1 and should help to constrain the interloper fraction without needing another measurement other than the self-calibrating fit. It should also be noted, that this measurement can also function as a crude, but cheap, initial estimate of the interloper fraction, as it only requires measurements of the dipole at three displacements.

4.2 Direct measurement of the fraction of interlopers

We can continue to exploit the existence of the dipole to potentially measure the fraction of interlopers directly. Recall Figure 2.4 and imagine we sit on an interloper. There should be more galaxies in the far direction, than there are in the near direction at the interloper displacement. The reverse is true if we imagine sitting on a galaxy target, there will be more galaxies in the near direction than in the far direction.

Now we could exploit this to assign each object in our catalogue a probability of being an interloper based on some comparison between the number of near/far galaxies at the interloper separation. We have explored using either the difference between these counts, or the ratio. Of these two, the difference seems more attractive due to the symmetry of its range between $(-\infty, \infty)$. The ratio presents a slightly more complicated case, as its range has the lower bound of 0, but no upper bound, making it less straightforward to construct a function to map this ratio to a probability, thus we move forward using the difference as our measure.¹

We have considered several simple functions for this mapping. It must satisfy the following two conditions:

¹Note that in testing with toy catalogues with large separations, there was essentially no difference.

1. The function has domain $(-\infty, \infty)$.
2. The function has range $(0,1)$.

For example, let D be the difference between the number of far and near galaxies at the known interloper separation:

$$P_{\text{interloper}}(D) = \frac{1}{\pi} \arctan(D) + \frac{1}{2}. \quad (4.2)$$

Here if D is very positive, P tends to 1, and if D is very negative, P tends to 0. Thus, for a given form of P , the estimate for the fraction of interlopers is simply the mean over the individual probabilities:

$$f_{\text{interloper}} = \frac{1}{N} \sum_{i=1}^N P_{\text{interloper}}. \quad (4.3)$$

This idea works very well for catalogues that have a large separation between interloper and target. However, as we test more realistic catalogues, the estimate for the interloper fraction goes to 0.5, as the numbers of near/far galaxies are nearly equal. Thus, the function we are currently using is perhaps too sensitive, and requires some fine tuning before it can be applied to realistic, or even simulated, catalogues.

4.3 Alternative Tests for LOO-PIT

As we have found the KS test to be unreliable for the evaluation of the LOO-PIT distributions, we require a more useful test. There are number of possibilities that we will leave to future work to test. We have considered adding the Anderson-Darling (AD) test to the testing. While KS is most sensitive to deviations close to the centroid of the distribution, the AD test is more sensitive to the tails. By applying these tests simultaneously, we could control the rate of Type I error by requiring deviation from the baseline distribution in all parts of the CDF. There are also the set of tests based on rank statistics that may be explored, such as the Cucconi test. We leave to future work to determine which test will be optimal for use with LOO-PIT.

4.4 Conclusions

In this thesis, we presented work on the problem of small displacement interlopers in BAO analyses. We first outlined the interloper problem and emission line confusion in Chapter 2.2.

In Chapter 2, we then introduced a technique to self-calibrate a contaminated catalogue and remove the effect of interlopers on BAO analysis of the two point correlation function. This model adds several terms to the standard BAO template fit. The most important is the near/far shifted cross correlation, which serves as a preliminary estimate for the interloper-galaxy target cross correlation. We add in two correcting terms to improve this estimate and we found that our model could recover the AP parameters to a level consistent with prior pre-reconstruction methods. We discussed some issues with the method, primarily the degeneracy between the bias amplitude parameters and the fraction of interlopers. This problem prevents our model from accurately recovering an accurate estimate of the fraction of interlopers. Furthermore, additional testing was required before the method may be applied to real data. These tests include testing the model on lightcone or cutsky mocks, as well as quantifying the effect of changing redshift across the survey bins.

In Chapter 3, we presented a general statistical technique for use in model validation. we introduced the Leave-One-Out Probability Integral Transform or LOO-PIT and applied it to the problem of detecting small displacement interlopers in the two point correlation function. LOO-PIT combines Leave-One-Out Cross Validation with the well known Probability Integral Transform to provide a visual diagnostic of modelling failures that is complementary to the standard χ^2 . LOO-CV is part of a class of methods called posterior predictive checks, where one attempts to test if the model can predict the data it was fitted to. We extend the idea of LOO-CV by applying a pointwise PIT and consider the resulting LOO-PIT KDE as the primary diagnostic. While LOO-PIT may diagnose problems like under/overfitting and under/overdispersion, its usefulness comes into its power in detecting biases or shifts in the data relative to model. This is particularly useful for the interloper problem, especially at low contamination levels and at displacements close to the BAO peak, where the interloper effect could be interpreted as a scale dependent bias. We also attempted to quantify the performance of LOO-PIT against χ^2 by testing each statistic's power to reject the null hypothesis: that there are no interlopers. We apply a Kolmogorov-Smirnov test to the LOO-PIT KDEs and derive the KS statistic. We find that this statistic is not suitable for LOO-PIT as we find a significant rate of Type I error in the null case. We leave it future work to determine a more suitable test for LOO-PIT.

Finally, we introduced some interesting extensions and future projects that may be derived from the work presented in this thesis.

References

- [1] Alan B. H. Nguyen, Elena Massara, and Will J. Percival. Self-calibrating BAO measurements in the presence of small displacement interlopers. *JCAP*, 2024(4):008, April 2024.
- [2] Alan B. H. Nguyen, Marco Bonici, and Will J. Percival. The leave one out - probability integral transform: Loo-pit. In preparation.
- [3] Ravin Kumar, Colin Carroll, Ari Hartikainen, and Osvaldo Martin. Arviz a unified library for exploratory analysis of bayesian models in python. *Journal of Open Source Software*, 4(33):1143, 2019.
- [4] Daniel Foreman-Mackey, David W. Hogg, Dustin Lang, and Jonathan Goodman. emcee: The MCMC Hammer. *PASP*, 125(925):306, March 2013.
- [5] J. D. Hunter. Matplotlib: A 2d graphics environment. *Computing in Science & Engineering*, 9(3):90–95, 2007.
- [6] Nick Hand, Yu Feng, Florian Beutler, Yin Li, Chirag Modi, Uroš Seljak, and Zachary Slepian. nbodykit: An Open-source, Massively Parallel Toolkit for Large-scale Structure. *The Astronomical Journal*, 156(4):160, October 2018.
- [7] Charles R. Harris, K. Jarrod Millman, Stéfan J. van der Walt, Ralf Gommers, Pauli Virtanen, David Cournapeau, Eric Wieser, Julian Taylor, Sebastian Berg, Nathaniel J. Smith, Robert Kern, Matti Picus, Stephan Hoyer, Marten H. van Kerkwijk, Matthew Brett, Allan Haldane, Jaime Fernández del Río, Mark Wiebe, Pearu Peterson, Pierre Gérard-Marchant, Kevin Sheppard, Tyler Reddy, Warren Weckesser, Hameer Abbasi, Christoph Gohlke, and Travis E. Oliphant. Array programming with NumPy. *Nature*, 585(7825):357–362, September 2020.

- [8] Pauli Virtanen, Ralf Gommers, Travis E. Oliphant, Matt Haberland, Tyler Reddy, David Cournapeau, Evgeni Burovski, Pearu Peterson, Warren Weckesser, Jonathan Bright, Stéfan J. van der Walt, Matthew Brett, Joshua Wilson, K. Jarrod Millman, Nikolay Mayorov, Andrew R. J. Nelson, Eric Jones, Robert Kern, Eric Larson, C J Carey, İlhan Polat, Yu Feng, Eric W. Moore, Jake VanderPlas, Denis Laxalde, Josef Perktold, Robert Cimrman, Ian Henriksen, E. A. Quintero, Charles R. Harris, Anne M. Archibald, Antônio H. Ribeiro, Fabian Pedregosa, Paul van Mulbregt, and SciPy 1.0 Contributors. SciPy 1.0: Fundamental Algorithms for Scientific Computing in Python. *Nature Methods*, 17:261–272, 2020.
- [9] Planck Collaboration, P. A. R. Ade, N. Aghanim, M. Arnaud, M. Ashdown, J. Aumont, C. Baccigalupi, A. J. Banday, R. B. Barreiro, J. G. Bartlett, N. Bartolo, E. Battaner, R. Battye, K. Benabed, A. Benoît, A. Benoit-Lévy, J. P. Bernard, M. Bersanelli, P. Bielewicz, J. J. Bock, A. Bonaldi, L. Bonavera, J. R. Bond, J. Borrill, F. R. Bouchet, F. Boulanger, M. Bucher, C. Burigana, R. C. Butler, E. Calabrese, J. F. Cardoso, A. Catalano, A. Challinor, A. Chamballu, R. R. Chary, H. C. Chiang, J. Chluba, P. R. Christensen, S. Church, D. L. Clements, S. Colombi, L. P. L. Colombo, C. Combet, A. Coulais, B. P. Crill, A. Curto, F. Cuttaia, L. Danese, R. D. Davies, R. J. Davis, P. de Bernardis, A. de Rosa, G. de Zotti, J. Delabrouille, F. X. Désert, E. Di Valentino, C. Dickinson, J. M. Diego, K. Dolag, H. Dole, S. Donzelli, O. Doré, M. Douspis, A. Ducout, J. Dunkley, X. Dupac, G. Efstathiou, F. Elsner, T. A. Enßlin, H. K. Eriksen, M. Farhang, J. Fergusson, F. Finelli, O. Forni, M. Frailis, A. A. Fraisse, E. Franceschi, A. Frejsel, S. Galeotta, S. Galli, K. Ganga, C. Gauthier, M. Gerbino, T. Ghosh, M. Giard, Y. Giraud-Héraud, E. Giusarma, E. Gjerløw, J. González-Nuevo, K. M. Górski, S. Gratton, A. Gregorio, A. Gruppuso, J. E. Gudmundsson, J. Hamann, F. K. Hansen, D. Hanson, D. L. Harrison, G. Helou, S. Henrot-Versillé, C. Hernández-Monteagudo, D. Herranz, S. R. Hildebrandt, E. Hivon, M. Hobson, W. A. Holmes, A. Hornstrup, W. Hovest, Z. Huang, K. M. Huffenberger, G. Hurier, A. H. Jaffe, T. R. Jaffe, W. C. Jones, M. Juvela, E. Keihänen, R. Keskitalo, T. S. Kisner, R. Kneissl, J. Knoche, L. Knox, M. Kunz, H. Kurki-Suonio, G. Lagache, A. Lähteenmäki, J. M. Lamarre, A. Lasenby, M. Lattanzi, C. R. Lawrence, J. P. Leahy, R. Leonardi, J. Lesgourgues, F. Levrier, A. Lewis, M. Liguori, P. B. Lilje, M. Linden-Vørnle, M. López-Caniego, P. M. Lubin, J. F. Macías-Pérez, G. Maggio, D. Maino, N. Mandolesi, A. Mangilli, A. Marchini, M. Maris, P. G. Martin, M. Martinelli, E. Martínez-González, S. Masi, S. Matarrese, P. McGehee, P. R. Meinhold, A. Melchiorri, J. B. Melin, L. Mendes, A. Mennella, M. Migliaccio, M. Millea, S. Mitra, M. A. Miville-Deschênes, A. Moneti, L. Montier, G. Morgante, D. Mortlock, A. Moss, D. Munshi, J. A. Murphy, P. Naselsky, F. Nati, P. Natoli, C. B. Netterfield,

H. U. Nørgaard-Nielsen, F. Noviello, D. Novikov, I. Novikov, C. A. Oxborrow, F. Paci, L. Pagano, F. Pajot, R. Paladini, D. Paoletti, B. Partridge, F. Pasian, G. Patanchon, T. J. Pearson, O. Perdereau, L. Perotto, F. Perrotta, V. Pettorino, F. Piacentini, M. Piat, E. Pierpaoli, D. Pietrobon, S. Plaszczynski, E. Pointecouteau, G. Polenta, L. Popa, G. W. Pratt, G. Prézeau, S. Prunet, J. L. Puget, J. P. Rachen, W. T. Reach, R. Rebolo, M. Reinecke, M. Remazeilles, C. Renault, A. Renzi, I. Ristorcelli, G. Rocha, C. Rosset, M. Rossetti, G. Roudier, B. Rouillé d'Orfeuil, M. Rowan-Robinson, J. A. Rubiño-Martín, B. Rusholme, N. Said, V. Salvatelli, L. Salvati, M. Sandri, D. Santos, M. Savelainen, G. Savini, D. Scott, M. D. Seiffert, P. Serra, E. P. S. Shellard, L. D. Spencer, M. Spinelli, V. Stolyarov, R. Stompor, R. Sudiwala, R. Sunyaev, D. Sutton, A. S. Suur-Uski, J. F. Sygnet, J. A. Tauber, L. Terenzi, L. Toffolatti, M. Tomasi, M. Tristram, T. Trombetti, M. Tucci, J. Tuovinen, M. Türlér, G. Umana, L. Valenziano, J. Valiviita, F. Van Tent, P. Vielva, F. Villa, L. A. Wade, B. D. Wandelt, I. K. Wehus, M. White, S. D. M. White, A. Wilkinson, D. Yvon, A. Zacchei, and A. Zonca. Planck 2015 results. XIII. Cosmological parameters. *A&A*, 594:A13, September 2016.

- [10] D. Eisenstein. <https://lweb.cfa.harvard.edu/deisenst/acousticpeak/>.
- [11] Lauren Biron. First results from desi make the most precise measurement of our expanding universe, Apr 2024.
- [12] Hiroaki Aihara, Carlos Allende Prieto, Deokkeun An, Scott F. Anderson, Éric Aubourg, Eduardo Balbinot, Timothy C. Beers, Andreas A. Berlind, Steven J. Bickerton, Dmitry Bizyaev, Michael R. Blanton, John J. Bochanski, Adam S. Bolton, Jo Bovy, W. N. Brandt, J. Brinkmann, Peter J. Brown, Joel R. Brownstein, Nicolas G. Busca, Heather Campbell, Michael A. Carr, Yanmei Chen, Cristina Chiappini, Johan Comparat, Natalia Connolly, Marina Cortes, Rupert A. C. Croft, Antonio J. Cuesta, Luiz N. da Costa, James R. A. Davenport, Kyle Dawson, Saurav Dhital, Anne Ealet, Garrett L. Ebelke, Edward M. Edmondson, Daniel J. Eisenstein, Stephanie Escoffier, Massimiliano Esposito, Michael L. Evans, Xiaohui Fan, Bruno Femenía Castellá, Andreu Font-Ribera, Peter M. Frinchaboy, Jian Ge, Bruce A. Gillespie, G. Gilmore, Jonay I. González Hernández, J. Richard Gott, Andrew Gould, Eva K. Grebel, James E. Gunn, Jean-Christophe Hamilton, Paul Harding, David W. Harris, Suzanne L. Hawley, Frederick R. Hearty, Shirley Ho, David W. Hogg, Jon A. Holtzman, Klaus Honscheid, Naohisa Inada, Inese I. Ivans, Linhua Jiang, Jennifer A. Johnson, Cathy Jordan, Wendell P. Jordan, Eyal A. Kazin, David Kirkby, Mark A. Klaene, G. R. Knapp, Jean-Paul Kneib, C. S. Kochanek, Lars Koesterke, Juna A. Kollmeier, Richard G. Kron, Hubert Lampeitl, Dustin Lang, Jean-Marc Le Goff, Young Sun

Lee, Yen-Ting Lin, Daniel C. Long, Craig P. Loomis, Sara Lucatello, Britt Lundgren, Robert H. Lupton, Zhibo Ma, Nicholas MacDonald, Suvrath Mahadevan, Marcio A. G. Maia, Martin Makler, Elena Malanushenko, Viktor Malanushenko, Rachel Mandelbaum, Claudia Maraston, Daniel Margala, Karen L. Masters, Cameron K. McBride, Peregrine M. McGehee, Ian D. McGreer, Brice Ménard, Jordi Miralda-Escudé, Heather L. Morrison, F. Mullally, Demitri Muna, Jeffrey A. Munn, Hitoshi Murayama, Adam D. Myers, Tracy Naugle, Angelo Fausti Neto, Duy Cuong Nguyen, Robert C. Nichol, Robert W. O’Connell, Ricardo L. C. Ogando, Matthew D. Olmstead, Daniel J. Oravetz, Nikhil Padmanabhan, Nathalie Palanque-Delabrouille, Kaike Pan, Parul Pandey, Isabelle Pâris, Will J. Percival, Patrick Petitjean, Robert Pfaffenberger, Janine Pforr, Stefanie Phleps, Christophe Pichon, Matthew M. Pieri, Francisco Prada, Adrian M. Price-Whelan, M. Jordan Raddick, Beatriz H. F. Ramos, Céline Reylé, James Rich, Gordon T. Richards, Hans-Walter Rix, Annie C. Robin, Helio J. Rocha-Pinto, Constance M. Rockosi, Natalie A. Roe, Emmanuel Rollinde, Ashley J. Ross, Nicholas P. Ross, Bruno M. Rossetto, Ariel G. Sánchez, Conor Sayres, David J. Schlegel, Katharine J. Schlesinger, Sarah J. Schmidt, Donald P. Schneider, Erin Sheldon, Yiping Shu, Jennifer Simmerer, Audrey E. Simmons, Thirupathi Sivarani, Stephanie A. Snedden, Jennifer S. Sobeck, Matthias Steinmetz, Michael A. Strauss, Alexander S. Szalay, Masayuki Tanaka, Aniruddha R. Thakar, Daniel Thomas, Jeremy L. Tinker, Benjamin M. Tofflemire, Rita Tojeiro, Christy A. Tremonti, Jan Vandenberg, M. Vargas Magaña, Licia Verde, Nicole P. Vogt, David A. Wake, Ji Wang, Benjamin A. Weaver, David H. Weinberg, Martin White, Simon D. M. White, Brian Yanny, Naoki Yasuda, Christophe Yèche, and Idit Zehavi. The Eighth Data Release of the Sloan Digital Sky Survey: First Data from SDSS-III. *ApJS*, 193(2):29, April 2011.

- [13] Roman: Nancy grace roman space telescope, April 2024.
- [14] Leah Hustak. Nasa scientific visualization studio, May 2023.
- [15] Adam G. Riess, Alexei V. Filippenko, Peter Challis, Alejandro Clocchiatti, Alan Diercks, Peter M. Garnavich, Ron L. Gilliland, Craig J. Hogan, Saurabh Jha, Robert P. Kirshner, B. Leibundgut, M. M. Phillips, David Reiss, Brian P. Schmidt, Robert A. Schommer, R. Chris Smith, J. Spyromilio, Christopher Stubbs, Nicholas B. Suntzeff, and John Tonry. Observational Evidence from Supernovae for an Accelerating Universe and a Cosmological Constant. *AJ*, 116(3):1009–1038, September 1998.
- [16] S. Perlmutter, G. Aldering, G. Goldhaber, R. A. Knop, P. Nugent, P. G. Castro, S. Deustua, S. Fabbro, A. Goobar, D. E. Groom, I. M. Hook, A. G. Kim, M. Y. Kim,

- J. C. Lee, N. J. Nunes, R. Pain, C. R. Pennypacker, R. Quimby, C. Lidman, R. S. Ellis, M. Irwin, R. G. McMahon, P. Ruiz-Lapuente, N. Walton, B. Schaefer, B. J. Boyle, A. V. Filippenko, T. Matheson, A. S. Fruchter, N. Panagia, H. J. M. Newberg, W. J. Couch, and The Supernova Cosmology Project. Measurements of Ω and Λ from 42 High-Redshift Supernovae. *ApJ*, 517(2):565–586, June 1999.
- [17] Will J. Percival. Large Scale Structure Observations. *arXiv e-prints*, page arXiv:1312.5490, December 2013.
- [18] Planck Collaboration, P. A. R. Ade, N. Aghanim, M. Arnaud, F. Arroja, M. Ashdown, J. Aumont, C. Baccigalupi, M. Ballardini, A. J. Banday, R. B. Barreiro, N. Bartolo, S. Basak, E. Battaner, K. Benabed, A. Benoît, A. Benoit-Lévy, J. P. Bernard, M. Bersanelli, P. Bielewicz, J. J. Bock, A. Bonaldi, L. Bonavera, J. R. Bond, J. Borrill, F. R. Bouchet, F. Boulanger, M. Bucher, C. Burigana, R. C. Butler, E. Calabrese, J. F. Cardoso, A. Catalano, A. Challinor, A. Chamballu, H. C. Chiang, P. R. Christensen, S. Church, D. L. Clements, S. Colombi, L. P. L. Colombo, C. Combet, F. Couchot, A. Coulais, B. P. Crill, A. Curto, F. Cuttaia, L. Danese, R. D. Davies, R. J. Davis, P. de Bernardis, A. de Rosa, G. de Zotti, J. Delabrouille, F. X. Désert, J. M. Diego, H. Dole, S. Donzelli, O. Doré, M. Douspis, A. Ducout, X. Dupac, G. Efstathiou, F. Elsner, T. A. Enßlin, H. K. Eriksen, J. Fergusson, F. Finelli, O. Forni, M. Frailis, A. A. Fraisse, E. Franceschi, A. Frejsel, S. Galeotta, S. Galli, K. Ganga, C. Gauthier, T. Ghosh, M. Giard, Y. Giraud-Héraud, E. Gjerløw, J. González-Nuevo, K. M. Górski, S. Gratton, A. Gregorio, A. Gruppuso, J. E. Gudmundsson, J. Hamann, F. K. Hansen, D. Hanson, D. L. Harrison, A. Heavens, G. Helou, S. Henrot-Versillé, C. Hernández-Monteagudo, D. Herranz, S. R. Hildebrandt, E. Hivon, M. Hobson, W. A. Holmes, A. Hornstrup, W. Hovest, Z. Huang, K. M. Huffenberger, G. Hurier, A. H. Jaffe, T. R. Jaffe, W. C. Jones, M. Juvela, E. Keihänen, R. Keskitalo, J. Kim, T. S. Kisner, J. Knoche, M. Kunz, H. Kurki-Suonio, F. Lacasa, G. Lagache, A. Lähteenmäki, J. M. Lamarre, A. Lasenby, M. Lattanzi, C. R. Lawrence, R. Leonardi, J. Lesgourgues, F. Levrier, A. Lewis, M. Liguori, P. B. Lilje, M. Linden-Vørnle, M. López-Caniego, P. M. Lubin, J. F. Macías-Pérez, G. Maggio, D. Maino, N. Mandolesi, A. Mangilli, D. Marinucci, M. Maris, P. G. Martin, E. Martínez-González, S. Masi, S. Matarrese, P. McGehee, P. R. Meinhold, A. Melchiorri, L. Mendes, A. Mennella, M. Migliaccio, S. Mitra, M. A. Miville-Deschênes, A. Moneti, L. Montier, G. Morgante, D. Mortlock, A. Moss, M. Münchmeyer, D. Munshi, J. A. Murphy, P. Naselsky, F. Nati, P. Natoli, C. B. Netterfield, H. U. Nørgaard-Nielsen, F. Noviello, D. Novikov, I. Novikov, C. A. Oxborrow, F. Paci, L. Pagano, F. Pajot, D. Paoletti, F. Pasian, G. Patanchon, H. V. Peiris, O. Perdereau, L. Perotto, F. Perrotta, V. Pettorino, F. Piacentini, M. Piat,

- E. Pierpaoli, D. Pietrobon, S. Plaszczynski, E. Pointecouteau, G. Polenta, L. Popa, G. W. Pratt, G. Prézeau, S. Prunet, J. L. Puget, J. P. Rachen, B. Racine, R. Rebolo, M. Reinecke, M. Remazeilles, C. Renault, A. Renzi, I. Ristorcelli, G. Rocha, C. Rosset, M. Rossetti, G. Roudier, J. A. Rubiño-Martín, B. Rusholme, M. Sandri, D. Santos, M. Savelainen, G. Savini, D. Scott, M. D. Seiffert, E. P. S. Shellard, M. Shiraishi, K. Smith, L. D. Spencer, V. Stolyarov, R. Stompor, R. Sudiwala, R. Sunyaev, P. Sutter, D. Sutton, A. S. Suur-Uski, J. F. Sygnet, J. A. Tauber, L. Terenzi, L. Toffolatti, M. Tomasi, M. Tristram, A. Troja, M. Tucci, J. Tuovinen, L. Valenziano, J. Valiviita, B. Van Tent, P. Vielva, F. Villa, L. A. Wade, B. D. Wandelt, I. K. Wehus, D. Yvon, A. Zacchei, and A. Zonca. Planck 2015 results. XVII. Constraints on primordial non-Gaussianity. *A&A*, 594:A17, September 2016.
- [19] Oliver H. E. Philcox, Elena Massara, and David N. Spergel. What does the marked power spectrum measure? Insights from perturbation theory. *Phys. Rev. D*, 102(4):043516, August 2020.
- [20] Elena Massara, Francisco Villaescusa-Navarro, ChangHoon Hahn, Muntazir M. Abidi, Michael Eickenberg, Shirley Ho, Pablo Lemos, Azadeh Moradinezhad Dizgah, and Bruno Régalo-Saint Blancard. Cosmological Information in the Marked Power Spectrum of the Galaxy Field. *ApJ*, 951(1):70, July 2023.
- [21] Elena Massara, Francisco Villaescusa-Navarro, Shirley Ho, Neal Dalal, and David N. Spergel. Using the marked power spectrum to detect the signature of neutrinos in large-scale structure. *Phys. Rev. Lett.*, 126:011301, Jan 2021.
- [22] Jiamin Hou, Zachary Slepian, and Robert N. Cahn. Measurement of parity-odd modes in the large-scale 4-point correlation function of Sloan Digital Sky Survey Baryon Oscillation Spectroscopic Survey twelfth data release CMASS and LOWZ galaxies. *MNRAS*, 522(4):5701–5739, May 2023.
- [23] Oliver H. E. Philcox and Julia Ereza. Could Sample Variance be Responsible for the Parity-Violating Signal Seen in the BOSS Galaxy Survey? *arXiv e-prints*, page arXiv:2401.09523, January 2024.
- [24] G. R. Blumenthal, S. M. Faber, J. R. Primack, and M. J. Rees. Formation of galaxies and large-scale structure with cold dark matter. *Nature*, 311:517–525, October 1984.
- [25] Adam G. Riess, Stefano Casertano, Wenlong Yuan, J. Bradley Bowers, Lucas Macri, Joel C. Zinn, and Dan Scolnic. Cosmic Distances Calibrated to 1% Precision with

Gaia EDR3 Parallaxes and Hubble Space Telescope Photometry of 75 Milky Way Cepheids Confirm Tension with Λ CDM. *ApJ*, 908(1):L6, February 2021.

- [26] D. M. Scolnic, D. O. Jones, A. Rest, Y. C. Pan, R. Chornock, R. J. Foley, M. E. Huber, R. Kessler, G. Narayan, A. G. Riess, S. Rodney, E. Berger, D. J. Brout, P. J. Challis, M. Drout, D. Finkbeiner, R. Lunnan, R. P. Kirshner, N. E. Sanders, E. Schlafly, S. Smartt, C. W. Stubbs, J. Tonry, W. M. Wood-Vasey, M. Foley, J. Hand, E. Johnson, W. S. Burgett, K. C. Chambers, P. W. Draper, K. W. Hodapp, N. Kaiser, R. P. Kudritzki, E. A. Magnier, N. Metcalfe, F. Bresolin, E. Gall, R. Kotak, M. McCrum, and K. W. Smith. The Complete Light-curve Sample of Spectroscopically Confirmed SNe Ia from Pan-STARRS1 and Cosmological Constraints from the Combined Pantheon Sample. *ApJ*, 859(2):101, June 2018.
- [27] Planck Collaboration, N. Aghanim, Y. Akrami, M. Ashdown, J. Aumont, C. Baccigalupi, M. Ballardini, A. J. Banday, R. B. Barreiro, N. Bartolo, S. Basak, R. Battye, K. Benabed, J. P. Bernard, M. Bersanelli, P. Bielewicz, J. J. Bock, J. R. Bond, J. Borrill, F. R. Bouchet, F. Boulanger, M. Bucher, C. Burigana, R. C. Butler, E. Calabrese, J. F. Cardoso, J. Carron, A. Challinor, H. C. Chiang, J. Chluba, L. P. L. Colombo, C. Combet, D. Contreras, B. P. Crill, F. Cuttaia, P. de Bernardis, G. de Zotti, J. Delabrouille, J. M. Delouis, E. Di Valentino, J. M. Diego, O. Doré, M. Douspis, A. Ducout, X. Dupac, S. Dusini, G. Efstathiou, F. Elsner, T. A. Enßlin, H. K. Eriksen, Y. Fantaye, M. Farhang, J. Fergusson, R. Fernandez-Cobos, F. Finelli, F. Forastieri, M. Frailis, A. A. Fraisse, E. Franceschi, A. Frolov, S. Galeotta, S. Galli, K. Ganga, R. T. Génova-Santos, M. Gerbino, T. Ghosh, J. González-Nuevo, K. M. Górski, S. Gratton, A. Gruppuso, J. E. Gudmundsson, J. Hamann, W. Handley, F. K. Hansen, D. Herranz, S. R. Hildebrandt, E. Hivon, Z. Huang, A. H. Jaffe, W. C. Jones, A. Karakci, E. Keihänen, R. Keskitalo, K. Kiiveri, J. Kim, T. S. Kisner, L. Knox, N. Krachmalnicoff, M. Kunz, H. Kurki-Suonio, G. Lagache, J. M. Lamarre, A. Lasenby, M. Lattanzi, C. R. Lawrence, M. Le Jeune, P. Lemos, J. Lesgourgues, F. Levrier, A. Lewis, M. Liguori, P. B. Lilje, M. Lilley, V. Lindholm, M. López-Caniego, P. M. Lubin, Y. Z. Ma, J. F. Macías-Pérez, G. Maggio, D. Maino, N. Mandolesi, A. Mangilli, A. Marcos-Caballero, M. Maris, P. G. Martin, M. Martinelli, E. Martínez-González, S. Matarrese, N. Mauri, J. D. McEwen, P. R. Meinhold, A. Melchiorri, A. Mennella, M. Migliaccio, M. Millea, S. Mitra, M. A. Miville-Deschênes, D. Molinari, L. Montier, G. Morgante, A. Moss, P. Natoli, H. U. Nørgaard-Nielsen, L. Pagano, D. Paoletti, B. Partridge, G. Patanchon, H. V. Peiris, F. Perrotta, V. Pettorino, F. Piacentini, L. Polastri, G. Polenta, J. L. Puget, J. P. Rachen, M. Reinecke, M. Remazeilles, A. Renzi, G. Rocha, C. Rosset, G. Roudier, J. A. Rubiño-Martín,

- B. Ruiz-Granados, L. Salvati, M. Sandri, M. Savelainen, D. Scott, E. P. S. Shellard, C. Sirignano, G. Sirri, L. D. Spencer, R. Sunyaev, A. S. Suur-Uski, J. A. Tauber, D. Tavagnacco, M. Tenti, L. Toffolatti, M. Tomasi, T. Trombetti, L. Valenziano, J. Valiviita, B. Van Tent, L. Vibert, P. Vielva, F. Villa, N. Vittorio, B. D. Wandelt, I. K. Wehus, M. White, S. D. M. White, A. Zacchei, and A. Zonca. Planck 2018 results. VI. Cosmological parameters. *A&A*, 641:A6, September 2020.
- [28] G. E. Addison, D. J. Watts, C. L. Bennett, M. Halpern, G. Hinshaw, and J. L. Weiland. Elucidating Λ CDM: Impact of Baryon Acoustic Oscillation Measurements on the Hubble Constant Discrepancy. *ApJ*, 853(2):119, February 2018.
- [29] R. Abbott, H. Abe, F. Acernese, K. Ackley, N. Adhikari, R. X. Adhikari, V. K. Adkins, V. B. Adya, C. Affeldt, D. Agarwal, M. Agathos, K. Agatsuma, N. Aggarwal, O. D. Aguiar, L. Aiello, A. Ain, P. Ajith, T. Akutsu, S. Albanesi, R. A. Alfaidi, A. Allocca, P. A. Altin, A. Amato, C. Anand, S. Anand, A. Ananyeva, S. B. Anderson, W. G. Anderson, M. Ando, T. Andrade, N. Andres, M. Andrés-Carcasona, T. Andrić, S. V. Angelova, S. Ansoldi, J. M. Antelis, S. Antier, T. Apostolatos, E. Z. Appavuravther, S. Appert, S. K. Apple, K. Arai, A. Araya, M. C. Araya, J. S. Areeda, M. Arène, N. Armitomi, N. Arnaud, M. Arogeti, S. M. Aronson, K. G. Arun, H. Asada, Y. Asali, G. Ashton, Y. Aso, M. Assiduo, S. Assis de Souza Melo, S. M. Aston, P. Astone, F. Aubin, K. Aultoneal, C. Austin, S. Babak, F. Badaracco, M. K. M. Bader, C. Badger, S. Bae, Y. Bae, A. M. Baer, S. Bagnasco, Y. Bai, J. Baird, R. Bajpai, T. Baka, M. Ball, G. Ballardin, S. W. Ballmer, A. Balsamo, G. Baltus, S. Banagiri, B. Banerjee, D. Bankar, J. C. Barayoga, C. Barbieri, R. Barbieri, B. C. Barish, D. Barker, P. Barneo, F. Barone, B. Barr, L. Barsotti, M. Barsuglia, D. Barta, J. Bartlett, M. A. Barton, I. Bartos, S. Basak, R. Bassiri, A. Basti, M. Bawaj, J. C. Bayley, M. Bazzan, B. R. Becher, B. Bécsy, V. M. Bedakihale, F. Beirnaert, M. Bejger, I. Belahcene, V. Benedetto, D. Beniwal, M. G. Benjamin, T. F. Bennett, J. D. Bentley, M. Benyaala, S. Bera, M. Berbel, F. Bergamin, B. K. Berger, S. Bernuzzi, C. P. L. Berry, D. Bersanetti, A. Bertolini, J. Betzwieser, D. Beveridge, R. Bhandare, A. V. Bhandari, U. Bhardwaj, R. Bhatt, D. Bhattacharjee, S. Bhaumik, A. Bianchi, I. A. Bilenko, G. Billingsley, M. Bilicki, S. Bini, I. A. Birney, O. Birnholtz, S. Biscans, M. Bisch, S. Biscoveanu, A. Bisht, B. Biswas, M. Bitossi, M. A. Bizouard, J. K. Blackburn, C. D. Blair, D. G. Blair, R. M. Blair, F. Bobba, N. Bode, M. Boër, G. Bogaert, M. Boldrini, G. N. Bolingbroke, L. D. Bonavena, F. Bondu, E. Bonilla, R. Bonnand, P. Booker, B. A. Boom, R. Bork, V. Boschi, N. Bose, S. Bose, V. Bossilkov, V. Boudart, Y. Bouffanaïs, A. Bozzi, C. Bradaschia, P. R. Brady, A. Bramley, A. Branch, M. Branchesi, J. E. Brau, M. Breschi, T. Briant, J. H. Briggs, A. Brillet, M. Brinkmann, P. Brockill, A. F.

Brooks, J. Brooks, D. D. Brown, S. Brunett, G. Bruno, R. Bruntz, J. Bryant, F. Bucci, T. Bulik, H. J. Bulten, A. Buonanno, K. Burtnyk, R. Buscicchio, D. Buskulic, C. Buy, R. L. Byer, G. S. Cabourn Davies, G. Cabras, R. Cabrita, L. Cadonati, M. Caesar, G. Cagnoli, C. Cahillane, J. Calderón Bustillo, J. D. Callaghan, T. A. Callister, E. Calloni, J. Cameron, J. B. Camp, M. Canepa, S. Canevarolo, M. Cannavacciuolo, K. C. Cannon, H. Cao, Z. Cao, E. Capocasa, E. Capote, G. Carapella, F. Carbognani, M. Carlassara, J. B. Carlin, M. F. Carney, M. Carpinelli, G. Carrillo, G. Carullo, T. L. Carver, J. Casanueva Diaz, C. Casentini, G. Castaldi, S. Caudill, M. Cavaglià, F. Cavalier, R. Cavalieri, G. Cella, P. Cerdá-Durán, E. Cesarini, W. Chaibi, S. Chalathadka Subrahmanya, E. Champion, C. H. Chan, C. Chan, C. L. Chan, K. Chan, M. Chan, K. Chandra, I. P. Chang, P. Chanial, S. Chao, C. Chapman-Bird, P. Charlton, E. A. Chase, E. Chassande-Mottin, C. Chatterjee, Debarati Chatterjee, Deep Chatterjee, M. Chaturvedi, S. Chaty, K. Chatziioannou, C. Chen, D. Chen, H. Y. Chen, J. Chen, K. Chen, X. Chen, Y. B. Chen, Y. R. Chen, Z. Chen, H. Cheng, C. K. Cheong, H. Y. Cheung, H. Y. Chia, F. Chiadini, C. Y. Chiang, G. Chiarini, R. Chierici, A. Chincardini, M. L. Chiofalo, A. Chiummo, R. K. Choudhary, S. Choudhary, N. Christensen, Q. Chu, Y. K. Chu, S. S. Y. Chua, K. W. Chung, G. Ciani, P. Ciecielag, M. Cieřlar, M. Cifaldi, A. A. Ciobanu, R. Ciolfi, F. Cipriano, F. Clara, J. A. Clark, P. Clearwater, S. Clesse, F. Cleva, E. Coccia, E. Codazzo, P. F. Cohadon, D. E. Cohen, M. Colleoni, C. G. Collette, A. Colombo, M. Colpi, C. M. Compton, M. Constancio, L. Conti, S. J. Cooper, P. Corban, T. R. Corbitt, I. Cordero-Carrión, S. Corezzi, K. R. Corley, N. J. Cornish, D. Corre, A. Corsi, S. Cortese, C. A. Costa, R. Cotesta, R. Cottingham, M. W. Coughlin, J. P. Coulon, S. T. Countryman, B. Cousins, P. Couvares, D. M. Coward, M. J. Cowart, D. C. Coyne, R. Coyne, J. D. E. Creighton, T. D. Creighton, A. W. Criswell, M. Croquette, S. G. Crowder, J. R. Cudell, T. J. Cullen, A. Cumming, R. Cummings, L. Cunningham, E. Cuoco, M. Curyło, P. Dabadie, T. Dal Canton, S. Dall’Osso, G. Dálya, A. Dana, B. D’Angelo, S. Danilishin, S. D’Antonio, K. Danzmann, C. Darsow-Fromm, A. Dasgupta, L. E. H. Datrier, Sayak Datta, Sayantani Datta, V. Dattilo, I. Dave, M. Davier, D. Davis, M. C. Davis, E. J. Daw, P. F. de Alarc’ón, R. Dean, D. Debra, M. Deenadayalan, J. Degallaix, M. de Laurentis, S. Deléglise, V. Del Favero, F. de Lillo, N. de Lillo, D. Dell’Aquila, W. Del Pozzo, L. M. Demarchi, F. de Matteis, V. D’Emilio, N. Demos, T. Dent, A. Depasse, R. de Pietri, R. De Rosa, C. de Rossi, R. Desalvo, R. de Simone, S. Dhurandhar, M. C. Díaz, N. A. Didio, T. Dietrich, L. di Fiore, C. di Fronzo, C. di Giorgio, F. di Giovanni, M. di Giovanni, T. di Girolamo, A. di Lieto, A. di Michele, B. Ding, S. di Pace, I. di Palma, F. di Renzo, A. K. Divakarla, A. Dmitriev, Z. Doctor, L. Donahue, L. D’Onofrio, F. Donovan, K. L. Dooley, S. Doravari, M. Drago, J. C. Driggers, Y. Drori, J. G. Ducoin, P. Dupej, U. Dupletsa, O. Durante, D. D’Urso, P. A. Duverne, S. E. Dwyer,

C. Eassa, P. J. Easter, M. Ebersold, T. Eckhardt, G. Eddolls, B. Edelman, T. B. Edo, O. Eddy, A. Effler, S. Eguchi, J. Eichholz, S. S. Eikenberry, M. Eisenmann, R. A. Eisenstein, A. Ejlli, E. Engelby, Y. Enomoto, L. Errico, R. C. Essick, H. Estellés, D. Estevez, Z. Etienne, T. Etzel, M. Evans, T. M. Evans, T. Evstafyeva, B. E. Ewing, F. Fabrizi, F. Faedi, V. Fafone, H. Fair, S. Fairhurst, P. C. Fan, A. M. Farah, S. Farinon, B. Farr, W. M. Farr, E. J. Fauchon-Jones, G. Favaro, M. Favata, M. Fays, M. Fazio, J. Feicht, M. M. Fejer, E. Fenyvesi, D. L. Ferguson, A. Fernandez-Galiana, I. Ferrante, T. A. Ferreira, F. Fidecaro, P. Figura, A. Fiori, I. Fiori, M. Fishbach, R. P. Fisher, R. Fittipaldi, V. Fiumara, R. Flaminio, E. Floden, H. K. Fong, J. A. Font, B. Fornal, P. W. F. Forsyth, A. Franke, S. Frasca, F. Frasconi, J. P. Freed, Z. Frei, A. Freise, O. Freitas, R. Frey, P. Fritschel, V. V. Frolov, G. G. Fronzé, Y. Fujii, Y. Fujikawa, Y. Fujimoto, P. Fulda, M. Fyffe, H. A. Gabbard, B. U. Gadre, J. R. Gair, J. Gais, S. Galaudage, R. Gamba, D. Ganapathy, A. Ganguly, D. Gao, S. G. Gaonkar, B. Garaventa, C. García Núñez, C. García-Quirós, F. Garufi, B. Gateley, V. Gayathri, G. G. Ge, G. Gemme, A. Gennai, J. George, O. Gerberding, L. Gergely, P. Gewecke, S. Ghonge, Abhirup Ghosh, Archisman Ghosh, Shaon Ghosh, Shrobana Ghosh, Tathagata Ghosh, B. Giacomazzo, L. Giacoppo, J. A. Giaime, K. D. Giardino, D. R. Gibson, C. Gier, M. Giesler, P. Giri, F. Gissi, S. Gkaitatzis, J. Glanzer, A. E. Gleckl, P. Godwin, E. Goetz, R. Goetz, N. Gohlke, J. Golomb, B. Goncharov, G. González, M. Gosselin, R. Gouaty, D. W. Gould, S. Goyal, B. Grace, A. Grado, V. Graham, M. Granata, V. Granata, A. Grant, S. Gras, P. Grassia, C. Gray, R. Gray, G. Greco, A. C. Green, R. Green, A. M. Gretarsson, E. M. Gretarsson, D. Griffith, W. L. Griffiths, H. L. Griggs, G. Grignani, A. Grimaldi, E. Grimes, S. J. Grimm, H. Grote, S. Grunewald, P. Gruning, A. S. Gruson, D. Guerra, G. M. Guidi, A. R. Guimaraes, G. Guixé, H. K. Gulati, A. M. Gunny, H. K. Guo, Y. Guo, Anchal Gupta, Anuradha Gupta, I. M. Gupta, P. Gupta, S. K. Gupta, R. Gustafson, F. Guzman, S. Ha, I. P. W. Hadiputrawan, L. Haegel, S. Haino, O. Halim, E. D. Hall, E. Z. Hamilton, G. Hammond, W. B. Han, M. Haney, J. Hanks, C. Hanna, M. D. Hannam, O. Hannuksela, H. Hansen, T. J. Hansen, J. Hanson, T. Harder, K. Haris, J. Harms, G. M. Harry, I. W. Harry, D. Hartwig, K. Hasegawa, B. Haskell, C. J. Haster, J. S. Hathaway, K. Hattori, K. Haughian, H. Hayakawa, K. Hayama, F. J. Hayes, J. Healy, A. Heidmann, A. Heidt, M. C. Heintze, J. Heinze, J. Heinzl, H. Heitmann, F. Hellman, P. Hello, A. F. Helmling-Cornell, G. Hemming, M. Hendry, I. S. Heng, E. Hennes, J. Hennig, M. H. Hennig, C. Henshaw, A. G. Hernandez, F. Hernandez Vivanco, M. Heurs, A. L. Hewitt, S. Higginbotham, S. Hild, P. Hill, Y. Himemoto, A. S. Hines, N. Hirata, C. Hirose, T. C. Ho, S. Hochheim, D. Hofman, J. N. Hohmann, D. G. Holcomb, N. A. Holland, I. J. Hollows, Z. J. Holmes, K. Holt, D. E. Holz, Q. Hong, J. Hough, S. Hourihane, E. J. Howell, C. G. Hoy, D. Hoyland, A. Hreibi,

B. H. Hsieh, H. F. Hsieh, C. Hsiung, Y. Hsu, H. Y. Huang, P. Huang, Y. C. Huang, Y. J. Huang, Yiting Huang, Yiwen Huang, M. T. Hübner, A. D. Huddart, B. Hughey, D. C. Y. Hui, V. Hui, S. Husa, S. H. Huttner, R. Huxford, T. Huynh-Dinh, S. Ide, B. Idzkowski, A. Iess, K. Inayoshi, Y. Inoue, P. Iosif, M. Isi, K. Isleif, K. Ito, Y. Itoh, B. R. Iyer, V. Jaberianhamedan, T. Jacqmin, P. E. Jacquet, S. J. Jadhav, S. P. Jadhav, T. Jain, A. L. James, A. Z. Jan, K. Jani, J. Janquart, K. Janssens, N. N. Janthapur, P. Jaranowski, D. Jariwala, R. Jaume, A. C. Jenkins, K. Jenner, C. Jeon, W. Jia, J. Jiang, H. B. Jin, G. R. Johns, R. Johnston, A. W. Jones, D. I. Jones, P. Jones, R. Jones, P. Joshi, L. Ju, A. Jue, P. Jung, K. Jung, J. Junker, V. Juste, K. Kaihotsu, T. Kajita, M. Kakizaki, C. V. Kalaghatgi, V. Kalogera, B. Kamai, M. Kamiizumi, N. Kanda, S. Kandhasamy, G. Kang, J. B. Kanner, Y. Kao, S. J. Kapadia, D. P. Kapasi, C. Karathanasis, S. Karki, R. Kashyap, M. Kasprzack, W. Kastaun, T. Kato, S. Katsanevas, E. Katsavounidis, W. Katzman, T. Kaur, K. Kawabe, K. Kawaguchi, F. Kéfélian, D. Keitel, J. S. Key, S. Khadka, F. Y. Khalili, S. Khan, T. Khanam, E. A. Khazanov, N. Khetan, M. Khursheed, N. Kijbunchoo, A. Kim, C. Kim, J. C. Kim, J. Kim, K. Kim, W. S. Kim, Y. M. Kim, C. Kimball, N. Kimura, M. Kinley-Hanlon, R. Kirchhoff, J. S. Kissel, S. Klimenko, T. Klinger, A. M. Knee, T. D. Knowles, N. Knust, E. Knyazev, Y. Kobayashi, P. Koch, G. Koekoek, K. Kohri, K. Kokeyama, S. Koley, P. Kolitsidou, M. Kolstein, K. Komori, V. Kondrashov, A. K. H. Kong, A. Kontos, N. Koper, M. Korobko, M. Kovalam, N. Koyama, D. B. Kozak, C. Kozakai, V. Kringel, A. Królak, G. Kuehn, F. Kuei, P. Kuijter, S. Kulkarni, A. Kumar, Prayush Kumar, Rahul Kumar, Rakesh Kumar, J. Kume, K. Kuns, Y. Kuromiya, S. Kuroyanagi, K. Kwak, G. Lacaille, P. Lagabbe, D. Laghi, E. Lalande, M. Lalleman, T. L. Lam, A. Lamberts, M. Landry, B. B. Lane, R. N. Lang, J. Lange, B. Lantz, I. La Rosa, A. Lartaux-Vollard, P. D. Lasky, M. Laxen, A. Lazzarini, C. Lazzaro, P. Leaci, S. Leavey, S. Lebohec, Y. K. Lecoecueche, E. Lee, H. M. Lee, H. W. Lee, K. Lee, R. Lee, I. N. Legred, J. Lehmann, A. Lemaître, M. Lenti, M. Leonardi, E. Leonova, N. Leroy, N. Letendre, C. Levesque, Y. Levin, J. N. Leviton, K. Leyde, A. K. Y. Li, B. Li, J. Li, K. L. Li, P. Li, T. G. F. Li, X. Li, C. Y. Lin, E. T. Lin, F. K. Lin, F. L. Lin, H. L. Lin, L. C. C. Lin, F. Linde, S. D. Linker, J. N. Linley, T. B. Littenberg, G. C. Liu, J. Liu, K. Liu, X. Liu, F. Llamas, R. K. L. Lo, T. Lo, L. T. London, A. Longo, D. Lopez, M. Lopez Portilla, M. Lorenzini, V. Lorient, M. Lormand, G. Losurdo, T. P. Lott, J. D. Lough, C. O. Lousto, G. Lovelace, J. F. Lucaccioni, H. Lück, D. Lumaca, A. P. Lundgren, L. W. Luo, J. E. Lynam, M. Ma'Arif, R. Macas, J. B. Machtiger, M. Macinnis, D. M. MacLeod, I. A. O. MacMillan, A. Macquet, I. Magaña Hernandez, C. Magazzù, R. M. Magee, R. Maggiore, M. Magnozzi, S. Mahesh, E. Majorana, I. Maksimovic, S. Maliakal, A. Malik, N. Man, V. Mandic, V. Mangano, G. L. Mansell, M. Manske, M. Mantovani, M. Mapelli, F. Marchesoni, D. Marín Pina,

F. Marion, Z. Mark, S. Márka, Z. Márka, C. Markakis, A. S. Markosyan, A. Markowitz, E. Maros, A. Marquina, S. Marsat, F. Martelli, I. W. Martin, R. M. Martin, M. Martinez, V. A. Martinez, V. Martinez, K. Martinovic, D. V. Martynov, E. J. Marx, H. Masalehdan, K. Mason, E. Massera, A. Masserot, M. Masso-Reid, S. Mastrogiovanni, A. Matas, M. Mateu-Lucena, F. Matichard, M. Matushechkina, N. Mavalvala, J. J. McCann, R. McCarthy, D. E. McClelland, P. K. McClincy, S. McCormick, L. McCuller, G. I. McGhee, S. C. McGuire, C. McIsaac, J. McIver, T. McRae, S. T. McWilliams, D. Meacher, M. Mehmet, A. K. Mehta, Q. Meijer, A. Melatos, D. A. Melchor, G. Mendell, A. Menendez-Vazquez, C. S. Menoni, R. A. Mercer, L. Mereni, K. Merfeld, E. L. Merilh, J. D. Merritt, M. Merzougui, S. Meshkov, C. Messenger, C. Messick, P. M. Meyers, F. Meylahn, A. Mhaske, A. Miani, H. Miao, I. Michaloliakos, C. Michel, Y. Michimura, H. Middleton, D. P. Mihaylov, L. Milano, A. L. Miller, A. Miller, B. Miller, M. Millhouse, J. C. Mills, E. Milotti, Y. Minenkov, N. Mio, Ll. M. Mir, M. Miravet-Tenés, A. Mishkin, C. Mishra, T. Mishra, T. Mistry, S. Mitra, V. P. Mitrofanov, G. Mitselmakher, R. Mittleman, O. Miyakawa, K. Miyo, S. Miyoki, Geoffrey Mo, L. M. Modafferi, E. Moguel, K. Mogushi, S. R. P. Mohapatra, S. R. Mohite, I. Molina, M. Molina-Ruiz, M. Mondin, M. Montani, C. J. Moore, J. Moragues, D. Moraru, F. Morawski, A. More, S. More, C. Moreno, G. Moreno, Y. Mori, S. Morisaki, N. Morisue, Y. Moriwaki, B. Mours, C. M. Mow-Lowry, S. Mozzon, F. Muciaccia, Arunava Mukherjee, D. Mukherjee, Soma Mukherjee, Subroto Mukherjee, Suvodip Mukherjee, N. Mukund, A. Mullavey, J. Munch, E. A. Muñiz, P. G. Murray, R. Musenich, S. Muusse, S. L. Nadj, K. Nagano, A. Nagar, K. Nakamura, H. Nakano, M. Nakano, Y. Nakayama, V. Napolano, I. Nardecchia, T. Narikawa, H. Narola, L. Naticchioni, B. Nayak, R. K. Nayak, B. F. Neil, J. Neilson, A. Nelson, T. J. N. Nelson, M. Nery, P. Neubauer, A. Neunzert, K. Y. Ng, S. W. S. Ng, C. Nguyen, P. Nguyen, T. Nguyen, L. Nguyen Quynh, J. Ni, W. T. Ni, S. A. Nichols, T. Nishimoto, A. Nishizawa, S. Nissanke, E. Nitoglia, F. Nocera, M. Norman, C. North, S. Nozaki, G. Nurbek, L. K. Nuttall, Y. Obayashi, J. Oberling, B. D. O'Brien, J. O'Dell, E. Oelker, W. Ogaki, G. Oganessian, J. J. Oh, K. Oh, S. H. Oh, M. Ohashi, T. Ohashi, M. Ohkawa, F. Ohme, H. Ohta, M. A. Okada, Y. Okutani, C. Olivetto, K. Oohara, R. Oram, B. O'Reilly, R. G. Ormiston, N. D. Ormsby, R. O'Shaughnessy, E. O'Shea, S. Oshino, S. Ossokine, C. Osthelder, S. Otabe, D. J. Ottaway, H. Overmire, A. E. Pace, G. Pagano, R. Pagano, M. A. Page, G. Pagliaroli, A. Pai, S. A. Pai, S. Pal, J. R. Palamos, O. Palashov, C. Palomba, H. Pan, K. C. Pan, P. K. Panda, P. T. H. Pang, C. Pankow, F. Pannarale, B. C. Pant, F. H. Panther, F. Paoletti, A. Paoli, A. Paolone, G. Pappas, A. Parisi, H. Park, J. Park, W. Parker, D. Pascucci, A. Pasqualetti, R. Passaquietti, D. Passuello, M. Patel, M. Pathak, B. Patricelli, A. S. Patron, S. Paul, E. Payne, M. Pedraza, R. Pedurand, M. Pe-

goraro, A. Pele, F. E. Peña Arellano, S. Penano, S. Penn, A. Perego, A. Pereira, T. Pereira, C. J. Perez, C. Périgois, C. C. Perkins, A. Perreca, S. Perriès, D. Pesios, J. Petermann, D. Petterson, H. P. Pfeiffer, H. Pham, K. A. Pham, K. S. Phukon, H. Phurailatpam, O. J. Piccinni, M. Pichot, M. Piendibene, F. Piergiovanni, L. Pierini, V. Pierro, G. Pillant, M. Pillas, F. Pilo, L. Pinard, C. Pineda-Bosque, I. M. Pinto, M. Pinto, B. J. Piotrkowski, K. Piotrkowski, M. Pirello, M. D. Pitkin, A. Placidi, E. Placidi, M. L. Planas, W. Plastino, C. Pluchar, R. Poggiani, E. Polini, D. Y. T. Pong, S. Ponrathnam, E. K. Porter, R. Poulton, A. Poverman, J. Powell, M. Prachia, T. Pradier, A. K. Prajapati, K. Prasai, R. Prasanna, G. Pratten, M. Principe, G. A. Prodi, L. Prokhorov, P. Proposito, L. Prudenzi, A. Puecher, M. Punturo, F. Puosi, P. Puppo, M. Pürner, H. Qi, N. Quartey, V. Quetschke, P. J. Quinonez, R. Quitzow-James, F. J. Raab, G. Raaijmakers, H. Radkins, N. Radulesco, P. Raffai, S. X. Rail, S. Raja, C. Rajan, K. E. Ramirez, T. D. Ramirez, A. Ramos-Buades, J. Rana, P. Rapagnani, A. Ray, V. Raymond, N. Raza, M. Razzano, J. Read, L. A. Rees, T. Regimbau, L. Rei, S. Reid, S. W. Reid, D. H. Reitze, P. Relton, A. Renzini, P. Rettengo, B. Revenu, A. Reza, M. Rezac, F. Ricci, D. Richards, J. W. Richardson, L. Richardson, G. Riemschneider, K. Riles, S. Rinaldi, K. Rink, N. A. Robertson, R. Robie, F. Robinet, A. Rocchi, S. Rodriguez, L. Rolland, J. G. Rollins, M. Romanelli, R. Romano, C. L. Romel, A. Romero, I. M. Romero-Shaw, J. H. Romie, S. Ronchini, L. Rosa, C. A. Rose, D. Rosińska, M. P. Ross, S. Rowan, S. J. Rowlinson, S. Roy, Santosh Roy, Soumen Roy, D. Rozza, P. Ruggi, K. Ruiz-Rocha, K. Ryan, S. Sachdev, T. Sadecki, J. Sadiq, S. Saha, Y. Saito, K. Sakai, M. Sakellariadou, S. Sakon, O. S. Salafia, F. Salces-Carcoba, L. Salconi, M. Saleem, F. Salemi, A. Samajdar, E. J. Sanchez, J. H. Sanchez, L. E. Sanchez, N. Sanchis-Gual, J. R. Sanders, A. Sanuy, T. R. Saravanan, N. Sarin, B. Sassolas, H. Satari, B. S. Sathyaprakash, O. Sauter, R. L. Savage, V. Savant, T. Sawada, H. L. Sawant, S. Sayah, D. Schaetzl, M. Scheel, J. Scheuer, M. G. Schiowski, P. Schmidt, S. Schmidt, R. Schnabel, M. Schneewind, R. M. S. Schofield, A. Schönbeck, B. W. Schulte, B. F. Schutz, E. Schwartz, J. Scott, S. M. Scott, M. Seglar-Arroyo, Y. Sekiguchi, D. Sellers, A. S. Sengupta, D. Sentenac, E. G. Seo, V. Sequino, A. Sergeev, Y. Setyawati, T. Shaffer, M. S. Shahriar, M. A. Shaikh, B. Shams, L. Shao, A. Sharma, P. Sharma, P. Shawhan, N. S. Shcheblanov, A. Sheela, Y. Shikano, M. Shikauchi, H. Shimizu, K. Shimode, H. Shinkai, T. Shishido, A. Shoda, D. H. Shoemaker, D. M. Shoemaker, S. Shyamsundar, M. Sieniawska, D. Sigg, L. Silenzi, L. P. Singer, D. Singh, M. K. Singh, N. Singh, A. Singha, A. M. Sintes, V. Sipala, V. Skliris, B. J. J. Slagmolen, T. J. Slaven-Blair, J. Smetana, J. R. Smith, L. Smith, R. J. E. Smith, J. Soldateschi, S. N. Somala, K. Somiya, I. Song, K. Soni, V. Sordini, F. Sorrentino, N. Sorrentino, R. Soulard, T. Souradeep, E. Sowell, V. Spagnuolo, A. P. Spencer, M. Spera, P. Spinicelli, A. K. Srivastava, V. Srivastava,

K. Staats, C. Stachie, F. Stachurski, D. A. Steer, J. Steinlechner, S. Steinlechner, N. Stergioulas, D. J. Stops, M. Stover, K. A. Strain, L. C. Strang, G. Stratta, M. D. Strong, A. Strunk, R. Sturani, A. L. Stuver, M. Suchenek, S. Sudhagar, V. Sudhir, R. Sugimoto, H. G. Suh, A. G. Sullivan, T. Z. Summerscales, L. Sun, S. Sunil, A. Sur, J. Suresh, P. J. Sutton, Takamasa Suzuki, Takanori Suzuki, Toshikazu Suzuki, B. L. Swinkels, M. J. Szczepańczyk, P. Szewczyk, M. Tacca, H. Tagoshi, S. C. Tait, H. Takahashi, R. Takahashi, S. Takano, H. Takeda, M. Takeda, C. J. Talbot, C. Talbot, N. Tamanini, K. Tanaka, Taiki Tanaka, Takahiro Tanaka, A. J. Tanasijczuk, S. Tanioka, D. B. Tanner, D. Tao, L. Tao, R. D. Tapia, E. N. Tapia San Martín, C. Taranto, A. Taruya, J. D. Tasson, R. Tenorio, J. E. S. Terhune, L. Terkowski, M. P. Thiruganasambandam, M. Thomas, P. Thomas, E. E. Thompson, J. E. Thompson, S. R. Thondapu, K. A. Thorne, E. Thrane, Shubhanshu Tiwari, Srishti Tiwari, V. Tiwari, A. M. Toivonen, A. E. Tolley, T. Tomaru, T. Tomura, M. Tonelli, Z. Tornasi, A. Torres-Forné, C. I. Torrie, I. Tosta E Melo, D. Töyrä, A. Trapananti, F. Travasso, G. Traylor, M. Trevor, M. C. Tringali, A. Tripathee, L. Troiano, A. Trovato, L. Trozzo, R. J. Trudeau, D. Tsai, K. W. Tsang, T. Tsang, J. S. Tsao, M. Tse, R. Tso, S. Tsuchida, L. Tsukada, D. Tsuna, T. Tsutsui, K. Turbang, M. Turconi, C. Turski, D. Tuyenbayev, A. S. Ubhi, N. Uchikata, T. Uchiyama, R. P. Udall, A. Ueda, T. Uehara, K. Ueno, G. Ueshima, C. S. Unnikrishnan, A. L. Urban, T. Ushiba, A. Utina, G. Vajente, A. Vajpeyi, G. Valdes, M. Valentini, V. Valsan, N. van Bakel, M. van Beuzekom, M. van Dael, J. F. J. van den Brand, C. van den Broeck, D. C. Vander-Hyde, H. van Haevermaet, J. V. van Heijningen, M. H. P. M. van Putten, N. van Remortel, M. Vardaro, A. F. Vargas, V. Varma, M. Vasúth, A. Vecchio, G. Vedovato, J. Veitch, P. J. Veitch, J. Venneberg, G. Venugopalan, D. Verkindt, P. Verma, Y. Verma, S. M. Vermeulen, D. Veske, F. Vetrano, A. Viceré, S. Vidyant, A. D. Viets, A. Vijaykumar, V. Villa-Ortega, J. Y. Vinet, A. Virtuoso, S. Vitale, H. Vocca, E. R. G. Von Reis, J. S. A. Von Wrangel, C. Vorvick, S. P. Vyatchanin, L. E. Wade, M. Wade, K. J. Wagner, R. C. Walet, M. Walker, G. S. Wallace, L. Wallace, J. Wang, J. Z. Wang, W. H. Wang, R. L. Ward, J. Warner, M. Was, T. Washimi, N. Y. Washington, J. Watchi, B. Weaver, C. R. Weaving, S. A. Webster, M. Weinert, A. J. Weinstein, R. Weiss, C. M. Weller, R. A. Weller, F. Wellmann, L. Wen, P. Weßels, K. Wette, J. T. Whelan, D. D. White, B. F. Whiting, C. Whittle, D. Wilken, D. Williams, M. J. Williams, A. R. Williamson, J. L. Willis, B. Willke, D. J. Wilson, C. C. Wipf, T. Wlodarczyk, G. Woan, J. Woehler, J. K. Wofford, D. Wong, I. C. F. Wong, M. Wright, C. Wu, D. S. Wu, H. Wu, D. M. Wysocki, L. Xiao, T. Yamada, H. Yamamoto, K. Yamamoto, T. Yamamoto, K. Yamashita, R. Yamazaki, F. W. Yang, K. Z. Yang, L. Yang, Y. C. Yang, Y. Yang, Yang Yang, M. J. Yap, D. W. Yeeles, S. W. Yeh, A. B. Yelikar, M. Ying, J. Yokoyama, T. Yokozawa, J. Yoo, T. Yoshioka, Hang Yu, Haocun Yu, H. Yuzurihara,

- A. Zadrożny, M. Zanolin, S. Zeidler, T. Zelenova, J. P. Zendri, M. Zevin, M. Zhan, H. Zhang, J. Zhang, L. Zhang, R. Zhang, T. Zhang, Y. Zhang, C. Zhao, G. Zhao, Y. Zhao, Yue Zhao, R. Zhou, Z. Zhou, X. J. Zhu, Z. H. Zhu, A. B. Zimmerman, M. E. Zucker, J. Zweizig, The Ligo Scientific Collaboration, The VIRGO Collaboration, and The Kagra Collaboration. Constraints on the Cosmic Expansion History from GWTC-3. *ApJ*, 949(2):76, June 2023.
- [30] Nils Schöneberg, Guillermo Franco Abellán, Andrea Pérez Sánchez, Samuel J. Witte, Vivian Poulin, and Julien Lesgourgues. The H_0 Olympics: A fair ranking of proposed models. *Phys. Rep.*, 984:1–55, October 2022.
- [31] Elcio Abdalla, Guillermo Franco Abellán, Amin Aboubrahim, Adriano Agnello, Özgür Akarsu, Yashar Akrami, George Alestas, Daniel Aloni, Luca Amendola, Luis A. Anchordoqui, Richard I. Anderson, Nikki Arendse, Marika Asgari, Mario Ballardini, Vernon Barger, Spyros Basilakos, Ronaldo C. Batista, Elia S. Battistelli, Richard Battye, Micol Benetti, David Benisty, Asher Berlin, Paolo de Bernardis, Emanuele Berti, Bohdan Bidenko, Simon Birrer, John P. Blakeslee, Kimberly K. Boddy, Clecio R. Bom, Alexander Bonilla, Nicola Borghi, François R. Bouchet, Matteo Braglia, Thomas Buchert, Elizabeth Buckley-Geer, Erminia Calabrese, Robert R. Caldwell, David Camarena, Salvatore Capozziello, Stefano Casertano, Geoff C. F. Chen, Jens Chluba, Angela Chen, Hsin-Yu Chen, Anton Chudaykin, Michele Cicoli, Craig J. Copi, Fred Courbin, Francis-Yan Cyr-Racine, Bożena Czerny, Maria Dainotti, Guido D’Amico, Anne-Christine Davis, Javier de Cruz Pérez, Jaume de Haro, Jacques Delabrouille, Peter B. Denton, Suhail Dhawan, Keith R. Dienes, Eleonora Di Valentino, Pu Du, Dominique Eckert, Celia Escamilla-Rivera, Agnès Ferté, Fabio Finelli, Pablo Fosalba, Wendy L. Freedman, Noemi Frusciante, Enrique Gaztañaga, William Giarè, Elena Giusarma, Adrià Gómez-Valent, Will Handley, Ian Harrison, Luke Hart, Dhiraaj Kumar Hazra, Alan Heavens, Asta Heinesen, Hendrik Hildebrandt, J. Colin Hill, Natalie B. Hogg, Daniel E. Holz, Deanna C. Hooper, Nikoo Hosseininejad, Dragan Huterer, Mustapha Ishak, Mikhail M. Ivanov, Andrew H. Jaffe, In Sung Jang, Karsten Jedamzik, Raul Jimenez, Melissa Joseph, Shahab Joudaki, Marc Kamionkowski, Tanvi Karwal, Lavrentios Kazantzidis, Ryan E. Keeley, Michael Klasen, Eiichiro Komatsu, Léon V. E. Koopmans, Suresh Kumar, Luca Lamagna, Ruth Lazkoz, Chung-Chi Lee, Julien Lesgourgues, Jackson Levi Said, Tiffany R. Lewis, Benjamin L’Huillier, Matteo Lucca, Roy Maartens, Lucas M. Macri, Danny Marfatia, Valerio Marra, Carlos J. A. P. Martins, Silvia Masi, Sabino Matarrese, Arindam Mazumdar, Alessandro Melchiorri, Olga Mena, Laura Mersini-Houghton, James Mertens, Dinko Milaković, Yuto Minami, Vivian Miranda, Cristian Moreno-Pulido, Michele Moresco, David F. Mota,

Emil Mottola, Simone Mozzon, Jessica Muir, Ankan Mukherjee, Suvodip Mukherjee, Pavel Naselsky, Pran Nath, Savvas Nesseris, Florian Niedermann, Alessio Notari, Rafael C. Nunes, Eoin Ó Colgáin, Kayla A. Owens, Emre Özüiker, Francesco Pace, Andronikos Paliathanasis, Antonella Palmese, Supriya Pan, Daniela Paoletti, Santiago E. Perez Bergliaffa, Leandros Perivolaropoulos, Dominic W. Pesce, Valeria Pettorino, Oliver H. E. Philcox, Levon Pogosian, Vivian Poulin, Gaspard Poulot, Marco Raveri, Mark J. Reid, Fabrizio Renzi, Adam G. Riess, Vivian I. Sabla, Paolo Salucci, Vincenzo Salzano, Emmanuel N. Saridakis, Bangalore S. Sathyaprakash, Martin Schmaltz, Nils Schöneberg, Dan Scolnic, Anjan A. Sen, Neelima Sehgal, Arman Shafieloo, M. M. Sheikh-Jabbari, Joseph Silk, Alessandra Silvestri, Foteini Skara, Martin S. Sloth, Marcelle Soares-Santos, Joan Solà Peracaula, Yu-Yang Songsheng, Jorge F. Soriano, Denitsa Staicova, Glenn D. Starkman, István Szapudi, Elsa M. Teixeira, Brooks Thomas, Tommaso Treu, Emery Trott, Carsten van de Bruck, J. Alberto Vazquez, Licia Verde, Luca Visinelli, Deng Wang, Jian-Min Wang, Shao-Jiang Wang, Richard Watkins, Scott Watson, John K. Webb, Neal Weiner, Amanda Weltman, Samuel J. Witte, Radosław Wojtak, Anil Kumar Yadav, Weiqiang Yang, Gong-Bo Zhao, and Miguel Zumalacárregui. Cosmology intertwined: A review of the particle physics, astrophysics, and cosmology associated with the cosmological tensions and anomalies. *Journal of High Energy Astrophysics*, 34:49–211, June 2022.

- [32] Vivian Poulin, Tristan L. Smith, and Tanvi Karwal. The Ups and Downs of Early Dark Energy solutions to the Hubble tension: A review of models, hints and constraints circa 2023. *Physics of the Dark Universe*, 42:101348, December 2023.
- [33] DESI Collaboration, A. G. Adame, J. Aguilar, S. Ahlen, S. Alam, D. M. Alexander, M. Alvarez, O. Alves, A. Anand, U. Andrade, E. Armengaud, S. Avila, A. Aviles, H. Awan, B. Bahr-Kalus, S. Bailey, C. Baltay, A. Bault, J. Behera, S. BenZvi, A. Bera, F. Beutler, D. Bianchi, C. Blake, R. Blum, S. Brieden, A. Brodzeller, D. Brooks, E. Buckley-Geer, E. Burtin, R. Calderon, R. Canning, A. Carnero Rosell, R. Cereskaite, J. L. Cervantes-Cota, S. Chabanier, E. Chaussidon, J. Chaves-Montero, S. Chen, X. Chen, T. Claybaugh, S. Cole, A. Cuceu, T. M. Davis, K. Dawson, A. de la Macorra, A. de Mattia, N. Deiosso, A. Dey, B. Dey, Z. Ding, P. Doel, J. Edelstein, S. Eftekharzadeh, D. J. Eisenstein, A. Elliott, P. Fagrelus, K. Fanning, S. Ferraro, J. Ereza, N. Findlay, B. Flaugher, A. Font-Ribera, D. Forero-Sánchez, J. E. Forero-Romero, C. S. Frenk, C. Garcia-Quintero, E. Gaztañaga, H. Gil-Marín, S. Gontcho A Gontcho, A. X. Gonzalez-Morales, V. Gonzalez-Perez, C. Gordon, D. Green, D. Gruen, R. Gspaner, G. Gutierrez, J. Guy, B. Hadzhiyska, C. Hahn, M. M. S Hanif, H. K. Herrera-Alcantar, K. Honscheid, C. Howlett, D. Huterer, V. Iršič, M. Ishak, S. Juneau,

N. G. Karaçaylı, R. Kehoe, S. Kent, D. Kirkby, A. Kremin, A. Krolewski, Y. Lai, T. W. Lan, M. Landriau, D. Lang, J. Lasker, J. M. Le Goff, L. Le Guillou, A. Leauthaud, M. E. Levi, T. S. Li, E. Linder, K. Lodha, C. Magneville, M. Manera, D. Margala, P. Martini, M. Maus, P. McDonald, L. Medina-Varela, A. Meisner, J. Mena-Fernández, R. Miquel, J. Moon, S. Moore, J. Moustakas, N. Mudur, E. Mueller, A. Muñoz-Gutiérrez, A. D. Myers, S. Nadathur, L. Napolitano, R. Neveux, J. A. Newman, N. M. Nguyen, J. Nie, G. Niz, H. E. Noriega, N. Padmanabhan, E. Paillas, N. Palanque-Delabrouille, J. Pan, S. Penmetsa, W. J. Percival, M. M. Pieri, M. Pinon, C. Poppett, A. Porredon, F. Prada, A. Pérez-Fernández, I. Pérez-Ràfols, D. Rabinowitz, A. Raichoor, C. Ramírez-Pérez, S. Ramirez-Solano, C. Ravoux, M. Rashkovetskyi, M. Rezaie, J. Rich, A. Rocher, C. Rockosi, N. A. Roe, A. Rosado-Marin, A. J. Ross, G. Rossi, R. Ruggeri, V. Ruhlmann-Kleider, L. Samushia, E. Sanchez, C. Saulder, E. F. Schlafly, D. Schlegel, M. Schubnell, H. Seo, A. Shafieloo, R. Sharples, J. Silber, A. Slosar, A. Smith, D. Sprayberry, T. Tan, G. Tarlé, P. Taylor, S. Trusov, L. A. Ureña-López, R. Vaisakh, D. Valcin, F. Valdes, M. Vargas-Magaña, L. Verde, M. Walther, B. Wang, M. S. Wang, B. A. Weaver, N. Weaverdyck, R. H. Wechsler, D. H. Weinberg, M. White, J. Yu, Y. Yu, S. Yuan, C. Yèche, E. A. Zaborowski, P. Zarrouk, H. Zhang, C. Zhao, R. Zhao, R. Zhou, T. Zhuang, and H. Zou. DESI 2024 VI: Cosmological Constraints from the Measurements of Baryon Acoustic Oscillations. *arXiv e-prints*, page arXiv:2404.03002, April 2024.

- [34] Stephen D. Landy and Alexander S. Szalay. Bias and Variance of Angular Correlation Functions. *ApJ*, 412:64, July 1993.
- [35] Nick Kaiser. Clustering in real space and in redshift space. *Mon. Not. Roy. Astron. Soc.*, 227:1–21, July 1987.
- [36] J. C. Jackson. A critique of Rees’s theory of primordial gravitational radiation. *Mon. Not. Roy. Astron. Soc.*, 156:1P, January 1972.
- [37] C. Alcock and B. Paczynski. An evolution free test for non-zero cosmological constant. *Nature*, 281:358, October 1979.
- [38] Margaret J. Geller and John P. Huchra. Mapping the universe. *Science*, 246(4932):897–903, 1989.
- [39] Daniel J. Eisenstein, Idit Zehavi, David W. Hogg, Roman Scoccimarro, Michael R. Blanton, Robert C. Nichol, Ryan Scranton, Hee-Jong Seo, Max Tegmark, Zheng Zheng, Scott F. Anderson, Jim Annis, Neta Bahcall, Jon Brinkmann, Scott Burles, Francisco J. Castander, Andrew Connolly, Istvan Csabai, Mamoru Doi, Masataka

- Fukugita, Joshua A. Frieman, Karl Glazebrook, James E. Gunn, John S. Hendry, Gregory Hennessy, Zeljko Ivezić, Stephen Kent, Gillian R. Knapp, Huan Lin, Yeong-Shang Loh, Robert H. Lupton, Bruce Margon, Timothy A. McKay, Avery Meiksin, Jeffery A. Munn, Adrian Pope, Michael W. Richmond, David Schlegel, Donald P. Schneider, Kazuhiro Shimasaku, Christopher Stoughton, Michael A. Strauss, Mark SubbaRao, Alexander S. Szalay, István Szapudi, Douglas L. Tucker, Brian Yanny, and Donald G. York. Detection of the Baryon Acoustic Peak in the Large-Scale Correlation Function of SDSS Luminous Red Galaxies. *ApJ*, 633(2):560–574, November 2005.
- [40] Shaun Cole, Will J. Percival, John A. Peacock, Peder Norberg, Carlton M. Baugh, Carlos S. Frenk, Ivan Baldry, Joss Bland-Hawthorn, Terry Bridges, Russell Cannon, Matthew Colless, Chris Collins, Warrick Couch, Nicholas J. G. Cross, Gavin Dalton, Vincent R. Eke, Roberto De Propris, Simon P. Driver, George Efsthathiou, Richard S. Ellis, Karl Glazebrook, Carole Jackson, Adrian Jenkins, Ofer Lahav, Ian Lewis, Stuart Lumsden, Steve Maddox, Darren Madgwick, Bruce A. Peterson, Will Sutherland, and Keith Taylor. The 2dF Galaxy Redshift Survey: power-spectrum analysis of the final data set and cosmological implications. *MNRAS*, 362(2):505–534, September 2005.
- [41] Lauren Anderson, Eric Aubourg, Stephen Bailey, Dmitry Bizyaev, Michael Blanton, Adam S. Bolton, J. Brinkmann, Joel R. Brownstein, Angela Burden, Antonio J. Cuesta, Luiz A. N. da Costa, Kyle S. Dawson, Roland de Putter, Daniel J. Eisenstein, James E. Gunn, Hong Guo, Jean-Christophe Hamilton, Paul Harding, Shirley Ho, Klaus Honscheid, Eyal Kazin, David Kirkby, Jean-Paul Kneib, Antoine Labatie, Craig Loomis, Robert H. Lupton, Elena Malanushenko, Viktor Malanushenko, Rachel Mandelbaum, Marc Manera, Claudia Maraston, Cameron K. McBride, Kushal T. Mehta, Olga Mena, Francesco Montesano, Demetri Muna, Robert C. Nichol, Sebastián E. Nuza, Matthew D. Olmstead, Daniel Oravetz, Nikhil Padmanabhan, Nathalie Palanque-Delabrouille, Kaike Pan, John Parejko, Isabelle Pâris, Will J. Percival, Patrick Petitjean, Francisco Prada, Beth Reid, Natalie A. Roe, Ashley J. Ross, Nicholas P. Ross, Lado Samushia, Ariel G. Sánchez, David J. Schlegel, Donald P. Schneider, Claudia G. Scóccola, Hee-Jong Seo, Erin S. Sheldon, Audrey Simmons, Ramin A. Skibba, Michael A. Strauss, Molly E. C. Swanson, Daniel Thomas, Jeremy L. Tinker, Rita Tojeiro, Mariana Vargas Magaña, Licia Verde, Christian Wagner, David A. Wake, Benjamin A. Weaver, David H. Weinberg, Martin White, Xiaoying Xu, Christophe Yèche, Idit Zehavi, and Gong-Bo Zhao. The clustering of galaxies in the SDSS-III Baryon Oscillation Spectroscopic Survey: baryon acoustic oscillations.

tions in the Data Release 9 spectroscopic galaxy sample. *MNRAS*, 427(4):3435–3467, December 2012.

- [42] DESI Collaboration, Amir Aghamousa, Jessica Aguilar, Steve Ahlen, Shadab Alam, Lori E. Allen, Carlos Allende Prieto, James Annis, Stephen Bailey, Christophe Balleland, Otger Ballester, Charles Baltay, Lucas Beaufore, Chris Bebek, Timothy C. Beers, Eric F. Bell, José Luis Bernal, Robert Besuner, Florian Beutler, Chris Blake, Hannes Bleuler, Michael Blomqvist, Robert Blum, Adam S. Bolton, Cesar Briceno, David Brooks, Joel R. Brownstein, Elizabeth Buckley-Geer, Angela Burden, Etienne Burtin, Nicolas G. Busca, Robert N. Cahn, Yan-Chuan Cai, Laia Cardiel-Sas, Raymond G. Carlberg, Pierre-Henri Carton, Ricard Casas, Francisco J. Castander, Jorge L. Cervantes-Cota, Todd M. Claybaugh, Madeline Close, Carl T. Coker, Shaun Cole, Johan Comparat, Andrew P. Cooper, M. C. Cousinou, Martin Crocce, Jean-Gabriel Cuby, Daniel P. Cunningham, Tamara M. Davis, Kyle S. Dawson, Axel de la Macorra, Juan De Vicente, Timothée Delubac, Mark Derwent, Arjun Dey, Govinda Dhungana, Zhejie Ding, Peter Doel, Yutong T. Duan, Anne Ealet, Jerry Edelstein, Sarah Eftekharzadeh, Daniel J. Eisenstein, Ann Elliott, Stéphanie Escoffier, Matthew Evatt, Parker Fagrelus, Xiaohui Fan, Kevin Fanning, Arya Farahi, Jay Farihi, Ginevra Favole, Yu Feng, Enrique Fernandez, Joseph R. Findlay, Douglas P. Finkbeiner, Michael J. Fitzpatrick, Brenna Flaugher, Samuel Flender, Andreu Font-Ribera, Jaime E. Forero-Romero, Pablo Fosalba, Carlos S. Frenk, Michele Fumagalli, Boris T. Gaensicke, Giuseppe Gallo, Juan Garcia-Bellido, Enrique Gaztanaga, Nicola Pietro Gentile Fusillo, Terry Gerard, Irena Gershkovich, Tommaso Giannantonio, Denis Gillet, Guillermo Gonzalez-de-Rivera, Violeta Gonzalez-Perez, Shelby Gott, Or Graur, Gaston Gutierrez, Julien Guy, Salman Habib, Henry Heetderks, Ian Heetderks, Katrin Heitmann, Wojciech A. Hellwing, David A. Herrera, Shirley Ho, Stephen Holland, Klaus Honscheid, Eric Huff, Timothy A. Hutchinson, Dragan Huterer, Ho Seong Hwang, Joseph Maria Illa Laguna, Yuzo Ishikawa, Dianna Jacobs, Niall Jeffrey, Patrick Jelinsky, Elise Jennings, Linhua Jiang, Jorge Jimenez, Jennifer Johnson, Richard Joyce, Eric Jullo, Stéphanie Juneau, Sami Kama, Armin Karcher, Sonia Karkar, Robert Kehoe, Noble Kennamer, Stephen Kent, Martin Kilbinger, Alex G. Kim, David Kirkby, Theodore Kisner, Ellie Kitanidis, Jean-Paul Kneib, Sergey Koposov, Eve Kovacs, Kazuya Koyama, Anthony Kremin, Richard Kron, Luzius Kronig, Andrea Kueter-Young, Cedric G. Lacey, Robin Lafever, Ofer Lahav, Andrew Lambert, Michael Lampton, Martin Landriau, Dustin Lang, Tod R. Lauer, Jean-Marc Le Goff, Laurent Le Guillou, Auguste Le Van Suu, Jae Hyeon Lee, Su-Jeong Lee, Daniela Leitner, Michael Lesser, Michael E. Levi, Benjamin L’Huillier, Baojiu Li, Ming Liang, Huan Lin, Eric Linder, Sarah R. Loebman, Zarija Lukić, Jun Ma, Niall

MacCrann, Christophe Magneville, Laleh Makarem, Marc Manera, Christopher J. Manser, Robert Marshall, Paul Martini, Richard Massey, Thomas Matheson, Jeremy McCauley, Patrick McDonald, Ian D. McGreer, Aaron Meisner, Nigel Metcalfe, Timothy N. Miller, Ramon Miquel, John Moustakas, Adam Myers, Milind Naik, Jeffrey A. Newman, Robert C. Nichol, Andrina Nicola, Luiz Nicolati da Costa, Jundan Nie, Gustavo Niz, Peder Norberg, Brian Nord, Dara Norman, Peter Nugent, Thomas O'Brien, Minji Oh, Knut A. G. Olsen, Cristobal Padilla, Hamsa Padmanabhan, Nikhil Padmanabhan, Nathalie Palanque-Delabrouille, Antonella Palmese, Daniel Pappalardo, Isabelle Pâris, Changbom Park, Anna Patej, John A. Peacock, Hiranya V. Peiris, Xiyan Peng, Will J. Percival, Sandrine Perruchot, Matthew M. Pieri, Richard Pogge, Jennifer E. Pollack, Claire Poppett, Francisco Prada, Abhishek Prakash, Ronald G. Probst, David Rabinowitz, Anand Raichoor, Chang Hee Ree, Alexandre Refregier, Xavier Regal, Beth Reid, Kevin Reil, Mehdi Rezaie, Constance M. Rockosi, Natalie Roe, Samuel Ronayette, Aaron Roodman, Ashley J. Ross, Nicholas P. Ross, Graziano Rossi, Eduardo Roza, Vanina Ruhlmann-Kleider, Eli S. Rykoff, Cristiano Sabiu, Lado Samushia, Eusebio Sanchez, Javier Sanchez, David J. Schlegel, Michael Schneider, Michael Schubnell, Aurélia Secroun, Uros Seljak, Hee-Jong Seo, Santiago Serrano, Arman Shafieloo, Huanyuan Shan, Ray Sharples, Michael J. Sholl, William V. Shourt, Joseph H. Silber, David R. Silva, Martin M. Sirk, Anze Slosar, Alex Smith, George F. Smoot, Debopam Som, Yong-Seon Song, David Sprayberry, Ryan Staten, Andy Stefanik, Gregory Tarle, Suk Sien Tie, Jeremy L. Tinker, Rita Tojeiro, Francisco Valdes, Octavio Valenzuela, Monica Valluri, Mariana Vargas-Magana, Licia Verde, Alistair R. Walker, Jiali Wang, Yuting Wang, Benjamin A. Weaver, Curtis Weaverdyck, Risa H. Wechsler, David H. Weinberg, Martin White, Qian Yang, Christophe Yèche, Tianmeng Zhang, Gong-Bo Zhao, Yi Zheng, Xu Zhou, Zhimin Zhou, Yaling Zhu, Hu Zou, and Ying Zu. The DESI Experiment Part I: Science, Targeting, and Survey Design. *arXiv e-prints*, page arXiv:1611.00036, October 2016.

- [43] Euclid Collaboration, R. Scaramella, J. Amiaux, Y. Mellier, C. Burigana, C. S. Carvalho, J. C. Cuillandre, A. Da Silva, A. Derosa, J. Dinis, E. Maiorano, M. Maris, I. Tereno, R. Laureijs, T. Boenke, G. Buenadicha, X. Dupac, L. M. Gaspar Venancio, P. Gómez-Álvarez, J. Hoar, J. Lorenzo Alvarez, G. D. Racca, G. Saavedra-Criado, J. Schwartz, R. Vavrek, M. Schirmer, H. Aussel, R. Azzollini, V. F. Cardone, M. Cropper, A. Ealet, B. Garilli, W. Gillard, B. R. Granett, L. Guzzo, H. Hoekstra, K. Jahnke, T. Kitching, T. Maciaszek, M. Meneghetti, L. Miller, R. Nakajima, S. M. Niemi, F. Pasian, W. J. Percival, S. Pottinger, M. Sauvage, M. Scodeggio, S. Wachter, A. Zacchei, N. Aghanim, A. Amara, T. Auphan, N. Auricchio, S. Awan, A. Balestra, R. Bender, C. Bodendorf, D. Bonino, E. Branchini, S. Brau-Nogue, M. Brescia, G. P.

Candini, V. Capobianco, C. Carbone, R. G. Carlberg, J. Carretero, R. Casas, F. J. Castander, M. Castellano, S. Cavuoti, A. Cimatti, R. Cledassou, G. Congedo, C. J. Conselice, L. Conversi, Y. Copin, L. Corcione, A. Costille, F. Courbin, H. Degaudenzi, M. Douspis, F. Dubath, C. A. J. Duncan, S. Dusini, S. Farrens, S. Ferriol, P. Fos-
 alba, N. Fourmanoit, M. Frailis, E. Franceschi, P. Franzetti, M. Fumana, B. Gillis, C. Giocoli, A. Grazian, F. Grupp, S. V. H. Haugan, W. Holmes, F. Hormuth, P. Hudelot, S. Kermiche, A. Kiessling, M. Kilbinger, R. Kohley, B. Kubik, M. Kümmel, M. Kunz, H. Kurki-Suonio, O. Lahav, S. Ligorì, P. B. Lilje, I. Lloro, O. Mansutti, O. Marggraf, K. Markovic, F. Marulli, R. Massey, S. Maurogordato, M. Melchior, E. Merlin, G. Meylan, J. J. Mohr, M. Moresco, B. Morin, L. Moscardini, E. Munari, R. C. Nichol, C. Padilla, S. Paltani, J. Peacock, K. Pedersen, V. Pettorino, S. Pires, M. Poncet, L. Popa, L. Pozzetti, F. Raison, R. Rebolo, J. Rhodes, H. W. Rix, M. Roncarelli, E. Rossetti, R. Saglia, P. Schneider, T. Schrabback, A. Secroun, G. Seidel, S. Serrano, C. Sirignano, G. Sirri, J. Skottfelt, L. Stanco, J. L. Starck, P. Tallada-Crespí, D. Tavagnacco, A. N. Taylor, H. I. Teplitz, R. Toledo-Moreo, F. Torradeflot, M. Trifoglio, E. A. Valentijn, L. Valenziano, G. A. Verdoes Kleijn, Y. Wang, N. Welikala, J. Weller, M. Wetzstein, G. Zamorani, J. Zoubian, S. Andreon, M. Baldi, S. Bardelli, A. Boucaud, S. Camera, D. Di Ferdinando, G. Fabbian, R. Farinelli, S. Galeotta, J. Graciá-Carpio, D. Maino, E. Medinaceli, S. Mei, C. Neissner, G. Polenta, A. Renzi, E. Romelli, C. Rosset, F. Sureau, M. Tenti, T. Vassallo, E. Zucca, C. Baccigalupi, A. Balaguera-Antolínez, P. Battaglia, A. Biviano, S. Borgani, E. Bozzo, R. Cabanac, A. Cappi, S. Casas, G. Castignani, C. Colodro-Conde, J. Coupon, H. M. Courtois, J. Cuby, S. de la Torre, S. Desai, H. Dole, M. Fabricius, M. Farina, P. G. Ferreira, F. Finelli, P. Flose-Reimberg, S. Fotopoulou, K. Ganga, G. Gozaliasl, I. M. Hook, E. Keihänen, C. C. Kirkpatrick, P. Liebing, V. Lindholm, G. Mainetti, M. Martinelli, N. Martinet, M. Maturi, H. J. McCracken, R. B. Metcalf, G. Morgante, J. Nightingale, A. Nucita, L. Patrizii, D. Potter, G. Riccio, A. G. Sánchez, D. Sapone, J. A. Schewtschenko, M. Schultheis, V. Scottez, R. Teyssier, I. Tutusaus, J. Valiviita, M. Viel, W. Vriend, and L. Whittaker. Euclid preparation. I. The Euclid Wide Survey. *A&A*, 662:A112, June 2022.

- [44] LSST Dark Energy Science Collaboration. Large Synoptic Survey Telescope: Dark Energy Science Collaboration. *arXiv e-prints*, page arXiv:1211.0310, November 2012.
- [45] Setareh Foroozan, Elena Massara, and Will J. Percival. Correcting for small-displacement interlopers in BAO analyses. *JCAP*, 2022(10):072, October 2022.
- [46] Elena Massara, Francisco Villaescusa-Navarro, and Will J. Percival. Predicting Interloper Fraction with Graph Neural Networks. *arXiv e-prints*, page arXiv:2309.05850,

September 2023.

- [47] D. Spergel, N. Gehrels, J. Breckinridge, M. Donahue, A. Dressler, B. S. Gaudi, T. Greene, O. Guyon, C. Hirata, J. Kalirai, N. J. Kasdin, W. Moos, S. Perlmutter, M. Postman, B. Rauscher, J. Rhodes, Y. Wang, D. Weinberg, J. Centrella, W. Traub, C. Baltay, J. Colbert, D. Bennett, A. Kiessling, B. Macintosh, J. Merten, M. Mortonson, M. Penny, E. Rozo, D. Savransky, K. Stapelfeldt, Y. Zu, C. Baker, E. Cheng, D. Content, J. Dooley, M. Foote, R. Goullioud, K. Grady, C. Jackson, J. Kruk, M. Levine, M. Melton, C. Peddie, J. Ruffa, and S. Shaklan. Wide-field infrared survey telescope-astronomy focused telescope assets wfirst-afta final report, 2013.
- [48] R. Laureijs, J. Amiaux, S. Arduini, J. L. Auguères, J. Brinchmann, R. Cole, M. Cropper, C. Dabin, L. Duvet, A. Ealet, B. Garilli, P. Gondoin, L. Guzzo, J. Hoar, H. Hoekstra, R. Holmes, T. Kitching, T. Maciaszek, Y. Mellier, F. Pasian, W. Percival, J. Rhodes, G. Saavedra Criado, M. Sauvage, R. Scaramella, L. Valenziano, S. Warren, R. Bender, F. Castander, A. Cimatti, O. Le Fèvre, H. Kurki-Suonio, M. Levi, P. Lilje, G. Meylan, R. Nichol, K. Pedersen, V. Popa, R. Rebolo Lopez, H. W. Rix, H. Rottgering, W. Zeilinger, F. Grupp, P. Hudelot, R. Massey, M. Meneghetti, L. Miller, S. Paltani, S. Paulin-Henriksson, S. Pires, C. Saxton, T. Schrabback, G. Seidel, J. Walsh, N. Aghanim, L. Amendola, J. Bartlett, C. Baccigalupi, J. P. Beaulieu, K. Benabed, J. G. Cuby, D. Elbaz, P. Fosalba, G. Gavazzi, A. Helmi, I. Hook, M. Irwin, J. P. Kneib, M. Kunz, F. Mannucci, L. Moscardini, C. Tao, R. Teyssier, J. Weller, G. Zamorani, M. R. Zapatero Osorio, O. Boulade, J. J. Fomond, A. Di Giorgio, P. Guttridge, A. James, M. Kemp, J. Martignac, A. Spencer, D. Walton, T. Blümchen, C. Bonoli, F. Bortoletto, C. Cerna, L. Corcione, C. Fabron, K. Jahnke, S. Ligi, F. Madrid, L. Martin, G. Morgante, T. Pamplona, E. Prieto, M. Riva, R. Toledo, M. Trifoglio, F. Zerbi, F. Abdalla, M. Douspis, C. Grenet, S. Borgani, R. Bouwens, F. Courbin, J. M. Delouis, P. Dubath, A. Fontana, M. Frailis, A. Grazian, J. Koppenhöfer, O. Mansutti, M. Melchior, M. Mignoli, J. Mohr, C. Neissner, K. Noddle, M. Poncet, M. Scodeggio, S. Serrano, N. Shane, J. L. Starck, C. Surace, A. Taylor, G. Verdoes-Kleijn, C. Vuerli, O. R. Williams, A. Zacchei, B. Altieri, I. Escudero Sanz, R. Kohley, T. Oosterbroek, P. Astier, D. Bacon, S. Bardelli, C. Baugh, F. Bellagamba, C. Benoist, D. Bianchi, A. Biviano, E. Branchini, C. Carbone, V. Cardone, D. Clements, S. Colombi, C. Conselice, G. Cresci, N. Deacon, J. Dunlop, C. Fedeli, F. Fontanot, P. Franzetti, C. Giocoli, J. Garcia-Bellido, J. Gow, A. Heavens, P. Hewett, C. Heymans, A. Holland, Z. Huang, O. Ilbert, B. Joachimi, E. Jennins, E. Kerins, A. Kiessling, D. Kirk, R. Kotak, O. Krause, O. Lahav, F. van Leeuwen,

- J. Lesgourgues, M. Lombardi, M. Magliocchetti, K. Maguire, E. Majerotto, R. Maoli, F. Marulli, S. Maurogordato, H. McCracken, R. McLure, A. Melchiorri, A. Merson, M. Moresco, M. Nonino, P. Norberg, J. Peacock, R. Pello, M. Penny, V. Pettorino, C. Di Porto, L. Pozzetti, C. Quercellini, M. Radovich, A. Rassat, N. Roche, S. Ronayette, E. Rossetti, B. Sartoris, P. Schneider, E. Semboloni, S. Serjeant, F. Simpson, C. Skordis, G. Smadja, S. Smartt, P. Spano, S. Spiro, M. Sullivan, A. Tilquin, R. Trotta, L. Verde, Y. Wang, G. Williger, G. Zhao, J. Zoubian, and E. Zucca. Euclid definition study report, 2011.
- [49] Antony Lewis, Anthony Challinor, and Anthony Lasenby. Efficient Computation of Cosmic Microwave Background Anisotropies in Closed Friedmann-Robertson-Walker Models. *Astrophys. J.*, 538(2):473–476, August 2000.
- [50] Ashley J. Ross, Florian Beutler, Chia-Hsun Chuang, Marcos Pellejero-Ibanez, Hee-Jong Seo, Mariana Vargas-Magaña, Antonio J. Cuesta, Will J. Percival, Angela Burden, Ariel G. Sánchez, Jan Niklas Grieb, Beth Reid, Joel R. Brownstein, Kyle S. Dawson, Daniel J. Eisenstein, Shirley Ho, Francisco-Shu Kitaura, Robert C. Nichol, Matthew D. Olmstead, Francisco Prada, Sergio A. Rodríguez-Torres, Shun Saito, Salvador Salazar-Albornoz, Donald P. Schneider, Daniel Thomas, Jeremy Tinker, Rita Tojeiro, Yuting Wang, Martin White, and Gong-bo Zhao. The clustering of galaxies in the completed SDSS-III Baryon Oscillation Spectroscopic Survey: observational systematics and baryon acoustic oscillations in the correlation function. *Mon. Not. Roy. Astron. Soc.*, 464(1):1168–1191, January 2017.
- [51] Yun Wang, Zhongxu Zhai, Anahita Alavi, Elena Massara, Alice Pisani, Andrew Benson, Christopher M. Hirata, Lado Samushia, David H. Weinberg, James Colbert, Olivier Doré, Tim Eifler, Chen Heinrich, Shirley Ho, Elisabeth Krause, Nikhil Padmanabhan, David Spergel, and Harry I. Teplitz. The High Latitude Spectroscopic Survey on the Nancy Grace Roman Space Telescope. *Astrophys. J.*, 928(1):1, March 2022.
- [52] Elena Massara, Shirley Ho, Christopher M. Hirata, Joseph DeRose, Risa H. Wechsler, and Xiao Fang. Line confusion in spectroscopic surveys and its possible effects: shifts in Baryon Acoustic Oscillations position. *Mon. Not. Roy. Astron. Soc.*, 508(3):4193–4201, December 2021.
- [53] Francisco Villaescusa-Navarro, ChangHoon Hahn, Elena Massara, Arka Banerjee, Ana Maria Delgado, Doogesh Kodi Ramanah, Tom Charnock, Elena Giusarma, Yin Li, Erwan Allys, Antoine Brochard, Cora Uhlemann, Chi-Ting Chiang, Siyu He,

- Alice Pisani, Andrej Obuljen, Yu Feng, Emanuele Castorina, Gabriella Contardo, Christina D. Kreisch, Andrina Nicola, Justin Alsing, Roman Scoccimarro, Licia Verde, Matteo Viel, Shirley Ho, Stephane Mallat, Benjamin Wandelt, and David N. Spergel. The Quijote Simulations. *Astrophys. J. Supp.*, 250(1):2, September 2020.
- [54] Zhongxu Zhai, Andrew Benson, Yun Wang, Gustavo Yepes, and Chia-Hsun Chuang. Prediction of $H\alpha$ and $[O\ III]$ emission line galaxy number counts for future galaxy redshift surveys. *Mon. Not. Roy. Astron. Soc.*, 490(3):3667–3678, December 2019.
 - [55] Zvonimir Vlah, Uroš Seljak, Man Yat Chu, and Yu Feng. Perturbation theory, effective field theory, and oscillations in the power spectrum. *JCAP*, 2016(3):057, March 2016.
 - [56] J. D. Cohn, Martin White, Tzu-Ching Chang, Gil Holder, Nikhil Padmanabhan, and Olivier Doré. Combining galaxy and 21-cm surveys. *Mon. Not. Roy. Astron. Soc.*, 457(2):2068–2077, April 2016.
 - [57] Xiaoying Xu, Antonio J. Cuesta, Nikhil Padmanabhan, Daniel J. Eisenstein, and Cameron K. McBride. Measuring D_A and H at $z=0.35$ from the SDSS DR7 LRGs using baryon acoustic oscillations. *Mon. Not. Roy. Astron. Soc.*, 431(3):2834–2860, May 2013.
 - [58] R. E. Smith, J. A. Peacock, A. Jenkins, S. D. M. White, C. S. Frenk, F. R. Pearce, P. A. Thomas, G. Efstathiou, and H. M. P. Couchman. Stable clustering, the halo model and non-linear cosmological power spectra. *Mon. Not. Roy. Astron. Soc.*, 341(4):1311–1332, June 2003.
 - [59] Ryuichi Takahashi, Masanori Sato, Takahiro Nishimichi, Atsushi Taruya, and Masamune Oguri. Revising the Halofit Model for the Nonlinear Matter Power Spectrum. *Astrophys. J.*, 761(2):152, December 2012.
 - [60] Will J. Percival, Oliver Friedrich, Elena Sellentin, and Alan Heavens. Matching Bayesian and frequentist coverage probabilities when using an approximate data covariance matrix. *Mon. Not. Roy. Astron. Soc.*, 510(3):3207–3221, March 2022.
 - [61] Shadab Alam, Metin Ata, Stephen Bailey, Florian Beutler, Dmitry Bizyaev, Jonathan A. Blazek, Adam S. Bolton, Joel R. Brownstein, Angela Burden, Chia-Hsun Chuang, Johan Comparat, Antonio J. Cuesta, Kyle S. Dawson, Daniel J. Eisenstein, Stephanie Escoffier, Héctor Gil-Marín, Jan Niklas Grieb, Nick Hand, Shirley Ho, Karen Kinemuchi, David Kirkby, Francisco Kitaura, Elena Malanushenko, Viktor Malanushenko, Claudia Maraston, Cameron K. McBride, Robert C. Nichol,

- Matthew D. Olmstead, Daniel Oravetz, Nikhil Padmanabhan, Nathalie Palanque-Delabrouille, Kaike Pan, Marcos Pellejero-Ibanez, Will J. Percival, Patrick Petitjean, Francisco Prada, Adrian M. Price-Whelan, Beth A. Reid, Sergio A. Rodríguez-Torres, Natalie A. Roe, Ashley J. Ross, Nicholas P. Ross, Graziano Rossi, Jose Alberto Rubiño-Martín, Shun Saito, Salvador Salazar-Albornoz, Lado Samushia, Ariel G. Sánchez, Siddharth Satpathy, David J. Schlegel, Donald P. Schneider, Claudia G. Scóccola, Hee-Jong Seo, Erin S. Sheldon, Audrey Simmons, Anže Slosar, Michael A. Strauss, Molly E. C. Swanson, Daniel Thomas, Jeremy L. Tinker, Rita Tojeiro, Mariana Vargas Magaña, Jose Alberto Vazquez, Licia Verde, David A. Wake, Yuting Wang, David H. Weinberg, Martin White, W. Michael Wood-Vasey, Christophe Yèche, Idit Zehavi, Zhongxu Zhai, and Gong-Bo Zhao. The clustering of galaxies in the completed SDSS-III Baryon Oscillation Spectroscopic Survey: cosmological analysis of the DR12 galaxy sample. *Mon. Not. Roy. Astron. Soc.*, 470(3):2617–2652, September 2017.
- [62] Naveen A. Reddy, Alice E. Shapley, Ryan L. Sanders, Mariska Kriek, Alison L. Coil, Irene Shivaiei, William R. Freeman, Bahram Mobasher, Brian Siana, Mojegan Azadi, Tara Fetherolf, Francesca M. Fornasini, Gene Leung, Sedona H. Price, Tom Zick, and Guillermo Barro. The MOSDEF Survey: Significant Evolution in the Rest-frame Optical Emission Line Equivalent Widths of Star-forming Galaxies at $z = 1.4$ -3.8. *Astrophys. J.*, 869(2):92, December 2018.
- [63] Euclid Collaboration, Y. Mellier, Abdurro’uf, J. A. Acevedo Barroso, A. Achúcarro, J. Adamek, R. Adam, G. E. Addison, N. Aghanim, M. Agüena, V. Ajani, Y. Akrami, A. Al-Bahllawan, A. Alavi, I. S. Albuquerque, G. Alestas, G. Alguero, A. Allaoui, S. W. Allen, V. Allevato, A. V. Alonso-Tetilla, B. Altieri, A. Alvarez-Candal, A. Amara, L. Amendola, J. Amiaux, I. T. Andika, S. Andreon, A. Andrews, G. Angora, R. E. Angulo, F. Annibali, A. Anselmi, S. Anselmi, S. Arcari, M. Archidiacono, G. Aricò, M. Arnaud, S. Arnouts, M. Asgari, J. Asorey, L. Atayde, H. Atek, F. Atrio-Barandela, M. Aubert, E. Aubourg, T. Auphan, N. Auricchio, B. Aussel, H. Aussel, P. P. Avelino, A. Avgoustidis, S. Avila, S. Awan, R. Azzollini, C. Baccigalupi, E. Bachelet, D. Bacon, M. Baes, M. B. Bagley, B. Bahr-Kalus, A. Balaguera-Antolinez, E. Balbinot, M. Balcells, M. Baldi, I. Baldry, A. Balestra, M. Ballardini, O. Ballester, M. Balogh, E. Bañados, R. Barbier, S. Bardelli, T. Barreiro, J. C. Barriere, B. J. Barros, A. Barthelemy, N. Bartolo, A. Basset, P. Battaglia, A. J. Battisti, C. M. Baugh, L. Baumont, L. Bazzanini, J. P. Beaulieu, V. Beckmann, A. N. Belikov, J. Bel, F. Bellagamba, M. Bella, E. Bellini, K. Benabed, R. Bender, G. Benevento, C. L. Bennett, K. Benson, P. Bergamini, J. R. Bermejo-Clement, F. Bernardeau, D. Bertacca, M. Berthe, J. Berthier, M. Bethermin, F. Beutler, C. Bevilion, S. Bhar-

gava, R. Bhatawdekar, L. Bisigello, A. Biviano, R. P. Blake, A. Blanchard, J. Blazek, L. Blot, A. Bosco, C. Bodendorf, T. Boenke, H. Böhringer, M. Bolzonella, A. Bonchi, M. Bonici, D. Bonino, L. Bonino, C. Bonvin, W. Bon, J. T. Booth, S. Borgani, A. S. Borlaff, E. Borsato, A. Bosco, B. Bose, M. T. Botticella, A. Boucaud, F. Bouche, J. S. Boucher, D. Boutigny, T. Bouvard, H. Bouy, R. A. A. Bowler, V. Bozza, E. Bozzo, E. Branchini, S. Brau-Nogue, P. Brekke, M. N. Bremer, M. Brescia, M. A. Breton, J. Brinchmann, T. Brinckmann, C. Brockley-Blatt, M. Brodwin, L. Brouard, M. L. Brown, S. Bruton, J. Bucko, H. Buddelmeijer, G. Buenadicha, F. Buitrago, P. Burger, C. Burigana, V. Busillo, D. Busonero, R. Cabanac, L. Cabayol-Garcia, M. S. Cagliari, A. Caillat, L. Caillat, M. Calabrese, A. Calabro, G. Calderone, F. Calura, B. Camacho Quevedo, S. Camera, L. Campos, G. Canas-Herrera, G. P. Candini, M. Cantiello, V. Capobianco, E. Cappellaro, N. Cappelluti, A. Cappi, K. I. Caputi, C. Cara, C. Carbone, V. F. Cardone, E. Carella, R. G. Carlberg, M. Carle, L. Carminati, F. Caro, J. M. Carrasco, J. Carretero, P. Carrilho, J. Carron Duque, B. Carry, A. Carvalho, C. S. Carvalho, R. Casas, S. Casas, P. Casenove, C. M. Casey, P. Cassata, F. J. Castander, D. Castelao, M. Castellano, L. Castiblanco, G. Castignani, T. Castro, C. Cavet, S. Caviuoti, P. Y. Chabaud, K. C. Chambers, Y. Charles, S. Charlot, N. Chartab, R. Chary, F. Chaumeil, H. Cho, G. Chon, E. Ciancetta, P. Ciliegi, A. Cimatti, M. Cimino, M. R. L. Cioni, R. Claydon, C. Cleland, B. Clément, D. L. Clements, N. Clerc, S. Clesse, S. Codis, F. Cogato, J. Colbert, R. E. Cole, P. Coles, T. E. Collett, R. S. Collins, C. Colodro-Conde, C. Colombo, F. Combes, V. Conforti, G. Congedo, S. Conseil, C. J. Conselice, S. Contarini, T. Contini, L. Conversi, A. R. Cooray, Y. Copin, P. S. Corasaniti, P. Corcho-Caballero, L. Corcione, O. Cordes, O. Corpace, M. Correnti, M. Costanzi, A. Costille, F. Courbin, L. Courcoult Mifsud, H. M. Courtois, M. C. Cousinou, G. Covone, T. Cowell, C. Cragg, G. Cresci, S. Cristiani, M. Crocce, M. Cropper, P. E. Crouzet, B. Csizi, J. G. Cuby, E. Cucchetti, O. Cucciati, J. C. Cuillandre, P. A. C. Cunha, V. Cuozzo, E. Daddi, M. D'Addona, C. Dafonte, N. Dagoneau, E. Dalessandro, G. B. Dalton, G. D'Amico, H. Dannerbauer, P. Danto, I. Das, A. Da Silva, R. da Silva, G. Daste, J. E. Davies, S. Davini, T. de Boer, R. Decarli, B. De Caro, H. Degaudenzi, G. Degni, J. T. A. de Jong, L. F. de la Bella, S. de la Torre, F. Delhaise, D. Delley, G. Delucchi, G. De Lucia, J. Denniston, F. De Paolis, M. De Petris, A. Derosa, S. Desai, V. Desjacques, G. Despali, G. Desprez, J. De Vicente-Albendea, Y. Deville, J. D. F. Dias, A. Díaz-Sánchez, J. J. Diaz, S. Di Domizio, J. M. Diego, D. Di Ferdinando, A. M. Di Giorgio, P. Dimauro, J. Dinis, K. Dolag, C. Dolding, H. Dole, H. Domínguez Sánchez, O. Doré, F. Dournac, M. Douspis, H. Dreihahn, B. Droge, B. Dryer, F. Dubath, P. A. Duc, F. Ducret, C. Duffy, F. Dufresne, C. A. J. Duncan, X. Dupac, V. Duret, R. Durrer, F. Durret, S. Dusini, A. Ealet, A. Eggemeier, P. R. M. Eisenhardt, D. Elbaz, M. Y.

Elkhashab, A. Ellien, J. Endicott, A. Enia, T. Erben, J. A. Escartin Vigo, S. Escoffier, I. Escudero Sanz, J. Essert, S. Etti, M. Ezziati, G. Fabbian, M. Fabricius, Y. Fang, A. Farina, M. Farina, R. Farinelli, S. Farrens, F. Faustini, A. Feltre, A. M. N. Ferguson, P. Ferrando, A. G. Ferrari, A. Ferré-Mateu, P. G. Ferreira, I. Ferreras, I. Ferrero, S. Ferriol, P. Ferruit, D. Filleul, F. Finelli, S. L. Finkelstein, A. Finoguenov, B. Fiorini, F. Flentge, P. Focardi, J. Fonseca, A. Fontana, F. Fontanot, F. Fornari, P. Fosalba, M. Fossati, S. Fotopoulou, D. Fouchez, N. Fourmanoit, M. Frailis, D. Fraix-Burnet, E. Franceschi, A. Franco, P. Franzetti, J. Freihofer, G. Frittoli, P. A. Frugier, N. Frusciante, A. Fumagalli, M. Fumagalli, M. Fumana, Y. Fu, L. Gabarra, S. Galeotta, L. Galluccio, K. Ganga, H. Gao, J. García-Bellido, K. Garcia, J. P. Gardner, B. Garilli, L. M. Gaspar-Venancio, T. Gasparetto, V. Gautard, R. Gavazzi, E. Gaztanaga, L. Genolet, R. Genova Santos, F. Gentile, K. George, Z. Ghaffari, F. Giacomini, F. Gianotti, G. P. S. Gibb, W. Gillard, B. Gillis, M. Ginolfi, C. Giocoli, M. Girardi, S. K. Giri, L. W. K. Goh, P. Gómez-Alvarez, A. H. Gonzalez, E. J. Gonzalez, J. C. Gonzalez, S. Gouyou Beauchamps, G. Gozaliasl, J. Gracia-Carpio, S. Grandis, B. R. Granett, M. Granvik, A. Grazian, A. Gregorio, C. Grenet, C. Grillo, F. Grupp, C. Gruppioni, A. Gruppuso, C. Guerbuez, S. Guerrini, M. Guidi, P. Guillard, C. M. Gutierrez, P. Guttridge, L. Guzzo, S. Gwyn, J. Haapala, J. Haase, C. R. Haddow, M. Hailey, A. Hall, D. Hall, N. Hamaus, B. S. Haridasu, J. Harnois-Déraps, C. Harper, W. G. Hartley, G. Hasinger, F. Hassani, N. A. Hatch, S. V. H. Haugan, B. Häußler, A. Heavens, L. Heisenberg, A. Helmi, G. Helou, S. Hemmati, K. Henares, O. Herent, C. Hernández-Monteagudo, T. Heuberger, P. C. Hewett, S. Heydenreich, H. Hildebrandt, M. Hirschmann, J. Hjorth, J. Hoar, H. Hoekstra, A. D. Holland, M. S. Holliman, W. Holmes, I. Hook, B. Horeau, F. Hormuth, A. Hornstrup, S. Hosseini, D. Hu, P. Hudelot, M. J. Hudson, M. Huertas-Company, E. M. Huff, A. C. N. Hughes, A. Humphrey, L. K. Hunt, D. D. Huynh, R. Ibata, K. Ichikawa, S. Iglesias-Groth, O. Ilbert, S. Ilić, L. Ingolia, E. Iodice, H. Israel, U. E. Israelsson, L. Izzo, P. Jablonka, N. Jackson, J. Jacobson, M. Jafariyazani, K. Jahnke, H. Jansen, M. J. Jarvis, J. Jasche, M. Jauzac, N. Jeffrey, M. Jhabvala, Y. Jimenez-Teja, A. Jimenez Muñoz, B. Joachimi, P. H. Johansson, S. Joudaki, E. Jullo, J. J. E. Kajava, Y. Kang, A. Kannawadi, V. Kansal, D. Karagiannis, M. Kärcher, A. Kashlinsky, M. V. Kazandjian, F. Keck, E. Keihänen, E. Kerins, S. Kermiche, A. Khalil, A. Kiessling, K. Kiveri, M. Kilbinger, J. Kim, R. King, C. C. Kirkpatrick, T. Kitching, M. Kluge, M. Knabenhans, J. H. Knapen, A. Knebe, J. P. Kneib, R. Kohley, L. V. E. Koopmans, H. Koskinen, E. Koulouridis, R. Kou, A. Kovács, I. Kovačević, A. Kowalczyk, K. Koyama, K. Kraljic, O. Krause, S. Kruk, B. Kubik, U. Kuchner, K. Kuijken, M. Kümmel, M. Kunz, H. Kurki-Suonio, F. Lacasa, C. G. Lacey, F. La Franca, N. Lagarde, O. Lahav, C. Laigle, A. La Marca, O. La Marle, B. Lamine, M. C. Lam,

A. Lançon, H. Landt, M. Langer, A. Lapi, C. Larcheveque, S. S. Larsen, M. Lattanzi, F. Laudisio, D. Laugier, R. Laureijs, G. Lavaux, A. Lawrenson, A. Lazanu, T. Lazeyras, Q. Le Boulc'h, A. M. C. Le Brun, V. Le Brun, F. Leclercq, S. Lee, J. Le Graet, L. Legrand, K. N. Leirvik, M. Le Jeune, M. Lembo, D. Le Mignant, M. D. Lepinzan, F. Lepori, G. F. Lesci, J. Lesgourgues, L. Leuzzi, M. E. Levi, T. I. Liaudat, G. Libet, P. Liebing, S. Ligorì, P. B. Lilje, C. C. Lin, D. Linde, E. Linder, V. Lindholm, L. Linke, S. S. Li, S. J. Liu, I. Lloro, F. S. N. Lobo, N. Lodieu, M. Lombardi, L. Lombriser, P. Lonare, G. Longo, M. López-Caniego, X. Lopez Lopez, J. Lorenzo Alvarez, A. Loureiro, J. Loveday, E. Lusso, J. Macias-Perez, T. Maciaszek, M. Magliocchetti, F. Magnard, E. A. Magnier, A. Magro, G. Mahler, G. Mainetti, D. Maino, E. Maiorano, E. Maiorano, N. Malavasi, G. A. Mamon, C. Mancini, R. Mandelbaum, M. Manera, A. Manjón-García, F. Mannucci, O. Mansutti, M. Manteiga Outeiro, R. Maoli, C. Maraston, S. Marcin, P. Marcos-Arenal, B. Margalef-Bentabol, O. Marggraf, D. Marinucci, M. Marinucci, K. Markovic, F. R. Marleau, J. Marpaud, J. Martignac, J. Martín-Fleitas, P. Martin-Moruno, E. L. Martin, M. Martinelli, N. Martinet, H. Martin, C. J. A. P. Martins, F. Marulli, D. Massari, R. Massey, D. C. Masters, S. Matarrese, Y. Matsuoka, S. Matthew, B. J. Maughan, N. Mauri, L. Maurin, S. Maurogordato, K. McCarthy, A. W. McConnachie, H. J. McCracken, I. McDonald, J. D. McEwen, C. J. R. McPartland, E. Medinaceli, V. Mehta, S. Mei, M. Melchior, J. B. Melin, B. Ménard, J. Mendes, J. Mendez-Abreu, M. Meneghetti, A. Mercurio, E. Merlin, R. B. Metcalf, G. Meylan, M. Migliaccio, M. Mignoli, L. Miller, M. Miluzio, B. Milvang-Jensen, J. P. Mimoso, R. Miquel, H. Miyatake, B. Mobasher, J. J. Mohr, P. Monaco, M. Monguió, A. Montoro, A. Mora, A. Moradinezhad Dizgah, M. Moresco, C. Moretti, G. Morgante, N. Morisset, T. J. Moriya, P. W. Morris, D. J. Mortlock, L. Moscardini, D. F. Mota, L. A. Moustakas, T. Moutard, T. Müller, E. Munari, G. Murphree, C. Murray, N. Murray, P. Musi, S. Nadathur, B. C. Nagam, T. Nagao, K. Naidoo, R. Nakajima, C. Nally, P. Natoli, A. Navarro-Alsina, D. Navarro Girones, C. Neissner, A. Nersesian, S. Nesseris, H. N. Nguyen-Kim, L. Nicastro, R. C. Nichol, M. Nielbock, S. M. Niemi, S. Nieto, K. Nilsson, J. Noller, P. Norberg, A. Nourizonoz, P. Ntelis, A. A. Nucita, P. Nugent, N. J. Nunes, T. Nutma, I. Ocampo, J. Odier, P. A. Oesch, M. Oguri, D. Magalhaes Oliveira, M. Onoue, T. Oosterbroek, F. Oppizzi, C. Ordenovic, K. Osato, F. Pacaud, F. Pace, C. Padilla, K. Paech, L. Pagano, M. J. Page, E. Palazzi, S. Paltani, S. Pamuk, S. Pandolfi, D. Paoletti, M. Paolillo, P. Papaderos, K. Pardede, G. Parimbelli, A. Parmar, C. Partmann, F. Pasian, F. Passalacqua, K. Paterson, L. Patrizii, C. Pattison, A. Paulino-Afonso, R. Paviot, J. A. Peacock, F. R. Pearce, K. Pedersen, A. Peel, R. F. Peletier, M. Pellejero Ibanez, R. Pello, M. T. Penny, W. J. Percival, A. Perez-Garrido, L. Perotto, V. Pettorino, A. Pezzotta, S. Pezzuto, A. Philippon, O. Piersanti, M. Pietroni, L. Piga, L. Pilo, S. Pires,

A. Pisani, A. Pizzella, L. Pizzuti, C. Plana, G. Polenta, J. E. Pollack, M. Poncet, M. Pöntinen, P. Pool, L. A. Popa, V. Popa, J. Popp, C. Porciani, L. Porth, D. Potter, M. Poulain, A. Pourtsidou, L. Pozzetti, I. Prandoni, G. W. Pratt, S. Prezelus, E. Prieto, A. Pugno, S. Quai, L. Quilley, G. D. Racca, A. Raccanelli, G. Rácz, S. Radinović, M. Radovich, A. Ragagnin, U. Ragnit, F. Raison, N. Ramos-Chernenko, C. Ranc, N. Raylet, R. Rebolo, A. Refregier, P. Reimberg, T. H. Reiprich, F. Renk, A. Renzi, J. Retre, Y. Revaz, C. Reylé, L. Reynolds, J. Rhodes, F. Ricci, M. Ricci, G. Riccio, S. O. Ricken, S. Rissanen, I. Risso, H. W. Rix, A. C. Robin, B. Rocca-Volmerange, P. F. Rocci, M. Rodenhuis, G. Rodighiero, M. Rodriguez Monroy, R. P. Rollins, M. Romanello, J. Roman, E. Romelli, M. Romero-Gomez, M. Roncarelli, P. Rosati, C. Rosset, E. Rossetti, W. Roster, H. J. A. Rottgering, A. Rozas-Fernández, K. Ruane, J. A. Rubino-Martin, A. Rudolph, F. Ruppini, B. Rusholme, S. Sacquegna, I. Sáez-Casares, S. Saga, R. Saglia, M. Sahlén, T. Saifollahi, Z. Sakr, J. Salvalaggio, R. Salvaterra, L. Salvati, M. Salvato, J. C. Salvignol, A. G. Sánchez, E. Sanchez, D. B. Sanders, D. Sapone, M. Saponara, E. Sarpa, F. Sarron, S. Sartori, B. Sassolas, L. Saunier, M. Sauvage, M. Sawicki, R. Scaramella, C. Scarlata, L. Scharré, J. Schaye, J. A. Schewtschenko, J. T. Schindler, E. Schinnerer, M. Schirmer, F. Schmidt, F. Schmidt, M. Schmidt, A. Schneider, M. Schneider, P. Schneider, N. Schöneberg, T. Schrabback, M. Schultheis, S. Schulz, J. Schwartz, D. Sciotti, M. Scodeggio, D. Scognamiglio, D. Scott, V. Scottez, A. Secroun, E. Sefusatti, G. Seidel, M. Seiffert, E. Sellentin, M. Selwood, E. Semboloni, M. Sereno, S. Serjeant, S. Serrano, F. Shankar, R. M. Sharples, A. Short, A. Shulevski, M. Shuntov, M. Sias, G. Sikkema, A. Silvestri, P. Simon, C. Sirignano, G. Sirri, J. Skottfelt, E. Slezak, D. Sluse, G. P. Smith, L. C. Smith, R. E. Smith, S. J. A. Smit, F. Soldano, B. G. B. Solheim, J. G. Sorce, F. Sorrenti, E. Soubrie, L. Spinoglio, A. Spurio Mancini, J. Stadel, L. Stagnaro, L. Stanco, S. A. Stanford, J. L. Starck, P. Stassi, J. Steinwagner, D. Stern, C. Stone, P. Strada, F. Strafella, D. Stramaccioni, C. Surace, F. Sureau, S. H. Suyu, I. Swindells, M. Szafraniec, I. Szapudi, S. Taamoli, M. Talia, P. Tallada-Crespí, K. Tanidis, C. Tao, P. Tarrío, D. Tavagnacco, A. N. Taylor, J. E. Taylor, P. L. Taylor, E. M. Teixeira, M. Tenti, P. Teodoro Idiago, H. I. Teplitz, I. Tereno, N. Tessore, V. Testa, G. Testera, M. Tewes, R. Teyssier, N. Theret, C. Thizy, P. D. Thomas, Y. Toba, S. Toft, R. Toledo-Moreo, E. Tolstoy, E. Tommasi, O. Torbaniuk, F. Torradeflot, C. Tortora, S. Tosi, S. Tosti, M. Trifoglio, A. Troja, T. Trombetti, A. Tronconi, M. Tsedrik, A. Tsyganov, M. Tucci, I. Tutusaus, C. Uhlemann, L. Ulivi, M. Urbano, L. Vacher, L. Vaillon, I. Valdes, E. A. Valentijn, L. Valenziano, C. Valieri, J. Valiviita, M. Van den Broeck, T. Vassallo, R. Vavrek, B. Venemans, A. Venhola, S. Ventura, G. Verdoes Kleijn, D. Vergani, A. Verma, F. Vernizzi, A. Veropalumbo, G. Verza, C. Vescovi, D. Vibert, M. Viel, P. Vielzeuf, C. Viglione, A. Viitanen, F. Villaescusa-Navarro, S. Vinciguerra,

- F. Visticot, K. Voggel, M. von Wietersheim-Kramsta, W. J. Vriend, S. Wachter, M. Walmsley, G. Walth, D. M. Walton, N. A. Walton, M. Wander, L. Wang, Y. Wang, J. R. Weaver, J. Weller, D. J. Whalen, M. Wiesmann, J. Wilde, O. R. Williams, H. A. Winther, A. Wittje, J. H. W. Wong, A. H. Wright, V. Yankelevich, H. W. Yeung, S. Youles, L. Y. A. Yung, A. Zacchei, L. Zalesky, G. Zamorani, A. Zamorano Vitorelli, M. Zanon Marc, M. Zennaro, F. M. Zerbi, I. A. Zinchenko, J. Zoubian, E. Zucca, and M. Zumalacarregui. Euclid. I. Overview of the Euclid mission. *arXiv e-prints*, page arXiv:2405.13491, May 2024.
- [64] Stephen M. Feeney, Hiranya V. Peiris, Andrew R. Williamson, Samaya M. Nissanke, Daniel J. Mortlock, Justin Alsing, and Dan Scolnic. Prospects for resolving the hubble constant tension with standard sirens. *Phys. Rev. Lett.*, 122:061105, Feb 2019.
- [65] T. M. C. Abbott, F. B. Abdalla, A. Alarcon, S. Allam, J. Annis, S. Avila, K. Aylor, M. Banerji, N. Banik, E. J. Baxter, K. Bechtol, M. R. Becker, B. A. Benson, G. M. Bernstein, E. Bertin, F. Bianchini, J. Blazek, L. E. Bleem, S. L. Bridle, D. Brooks, E. Buckley-Geer, D. L. Burke, J. E. Carlstrom, A. Carnero Rosell, M. Carrasco Kind, J. Carretero, F. J. Castander, R. Cawthon, C. Chang, C. L. Chang, H-M. Cho, A. Choi, R. Chown, T. M. Crawford, A. T. Crites, M. Crocce, C. E. Cunha, C. B. D’Andrea, L. N. da Costa, C. Davis, T. de Haan, J. DeRose, S. Desai, J. De Vicente, H. T. Diehl, J. P. Dietrich, M. A. Dobbs, S. Dodelson, P. Doel, A. Drlica-Wagner, T. F. Eifler, J. Elvin-Poole, W. B. Everett, B. Flaugher, P. Fosalba, O. Friedrich, J. Frieman, J. García-Bellido, M. Gatti, E. Gaztanaga, E. M. George, D. W. Gerdes, T. Giannantonio, D. Gruen, R. A. Gruendl, J. Gschwend, G. Gutierrez, N. W. Halverson, N. L. Harrington, W. G. Hartley, G. P. Holder, D. L. Hollowood, W. L. Holzappel, K. Honscheid, Z. Hou, B. Hoyle, J. D. Hrubes, D. Huterer, B. Jain, D. J. James, M. Jarvis, T. Jeltema, M. W. G. Johnson, M. D. Johnson, S. Kent, D. Kirk, L. Knox, N. Kokron, E. Krause, K. Kuehn, O. Lahav, A. T. Lee, E. M. Leitch, T. S. Li, M. Lima, H. Lin, D. Luong-Van, N. MacCrann, M. A. G. Maia, A. Manzotti, D. P. Marrone, J. L. Marshall, P. Martini, J. J. McMahon, F. Menanteau, S. S. Meyer, R. Miquel, L. M. Mocanu, J. J. Mohr, J. Muir, T. Natoli, A. Nicola, B. Nord, Y. Omori, S. Padin, S. Pandey, A. A. Plazas, A. Porredon, J. Prat, C. Pryke, M. M. Rau, C. L. Reichardt, R. P. Rollins, A. K. Romer, A. Roodman, A. J. Ross, E. Roza, J. E. Ruhl, E. S. Rykoff, S. Samuroff, C. Sánchez, E. Sanchez, J. T. Sayre, V. Scarpine, K. K. Schaffer, L. F. Secco, S. Serrano, I. Sevilla-Noarbe, E. Sheldon, E. Shirokoff, G. Simard, M. Smith, M. Soares-Santos, F. Sobreira, Z. Staniszewski, A. A. Stark, K. T. Story, E. Suchyta, M. E. C. Swanson, G. Tarle, D. Thomas, M. A. Troxel, D. L. Tucker, K. Vanderlinde, J. D. Vieira, P. Vielzeuf, V. Vikram, A. R. Walker, R. H. Wechsler,

- J. Weller, R. Williamson, W. L. K. Wu, B. Yanny, O. Zahn, Y. Zhang, and J. Zuntz. Dark energy survey year 1 results: Joint analysis of galaxy clustering, galaxy lensing, and cmb lensing two-point functions. *Phys. Rev. D*, 100:023541, Jul 2019.
- [66] Keir K. Rogers and Hiranya V. Peiris. General framework for cosmological dark matter bounds using n -body simulations. *Phys. Rev. D*, 103:043526, Feb 2021.
 - [67] Aki Vehtari, Andrew Gelman, and Jonah Gabry. Practical bayesian model evaluation using leave-one-out cross-validation and waic. *Statistics and Computing*, 27(5):1413–1432, Aug 2016.
 - [68] Frank J. Massey. The kolmogorov-smirnov test for goodness of fit. *Journal of the American Statistical Association*, 46(253):68–78, 1951.
 - [69] Edward L Ionides. Truncated importance sampling. *Journal of Computational and Graphical Statistics*, 17(2):295–311, Jun 2008.
 - [70] Aki Vehtari, Daniel Simpson, Andrew Gelman, Yuling Yao, and Jonah Gabry. Pareto Smoothed Importance Sampling. *arXiv e-prints*, page arXiv:1507.02646, July 2015.
 - [71] Jin Zhang and Michael A. Stephens. A new and efficient estimation method for the generalized pareto distribution. *Technometrics*, 51(3):316–325, 2009.
 - [72] Wesley Johnson and Seymour Geisser. A predictive view of the detection and characterization of influential observations in regression analysis. *Journal of the American Statistical Association*, 78(381):137–144, 1983.
 - [73] Oriol Abril Pla. Loo-pit tutorial.

APPENDICES

Appendix A

Tables of Values

A.1 Tables For Chapter 2

The following tables of values were used to generate Figure 2.6. Table A.1 contains values for the fit using a measured galaxy auto-correlation function and mocks where galaxy targets and interlopers are equally biased. Table A.2 contains values for the fit using a galaxy correlation function calculated from CAMB as outlined in Section 2.3.3, and unbiased mocks. Table A.3 contains values for the fit using mocks where interlopers are more strongly biased.

$f_i^{\text{true}}(\times 10^2)$	Error on $\alpha(\times 10^3)$		Error on $\epsilon(\times 10^3)$		Error on $f_i(\times 10^2)$	
$\Delta=85$	Systematic	Statistical	Systematic	Statistical	Systematic	Statistical
2	0.1	0.7	0.2	0.6	0.4	0.3
5	0.0	1.0	0.0	0.6	0.2	0.3
10	0.0	1.0	0.7	0.8	0.0	0.3
15	0.2	0.7	0.2	0.6	0.6	0.3
$\Delta=90$	Systematic	Statistical	Systematic	Statistical	Systematic	Statistical
2	0.0	0.5	-0.1	0.5	0.3	0.5
5	1.0	1.0	-0.7	0.6	0.6	0.5
10	0.2	0.7	-0.2	0.7	0.5	0.5
15	1.6	0.8	0.8	0.6	0.0	0.6
$\Delta=97$	Systematic	Statistical	Systematic	Statistical	Systematic	Statistical
2	0.6	0.8	-0.6	0.9	0.4	0.5
5	0.7	0.7	-0.9	1.0	0.8	0.5
10	0.8	0.9	-0.4	1.0	1.1	0.6
15	0.6	0.9	-0.3	1.0	1.1	0.6

Table A.1: Systematic and statistical errors on α , ϵ , f_i from multipole fits on the mean of 1000 redshift space mocks and using measured autocorrelation. Δ given in h^{-1} Mpc. These are the blue circles labelled “Measured” in Figure 2.6.

$f_i^{\text{true}}(\times 10^2)$	Error on $\alpha(\times 10^3)$		Error on $\epsilon(\times 10^3)$		Error on $f_i(\times 10^2)$	
$\Delta=85$	Systematic	Statistical	Systematic	Statistical	Systematic	Statistical
0	3.9	1.1	4.1	1.5	5.3	2.9
2	6.7	1.4	1.2	1.6	11.7	5.8
5	6.2	1.4	1.0	1.5	9.8	5.6
10	6.0	1.5	0.4	1.6	8.0	6.0
15	5.8	1.6	1.0	1.7	6.3	5.6
$\Delta=90$	Systematic	Statistical	Systematic	Statistical	Systematic	Statistical
0	1.2	2.6	-1.1	2.2	7.9	6.6
2	3.8	1.7	-5.9	2.5	23.4	12.9
5	4.4	1.6	-5.6	2.2	25.6	11.7
10	3.8	1.9	-5.3	2.4	23.4	11.4
15	4.4	2.0	-3.0	2.9	7.7	12.2
$\Delta=97$	Systematic	Statistical	Systematic	Statistical	Systematic	Statistical
0	5.0	2.0	-4.4	1.7	21.2	9.4
2	5.4	1.5	-0.0	2.1	0.6	2.7
5	6.0	1.6	-0.2	2.1	-2.5	2.5
10	5.2	1.6	1.0	2.1	-7.6	2.3
15	5.8	1.7	0.4	2.2	-12.0	3.0

Table A.2: Systematic and statistical errors on α , ϵ , f_i from multipole fits on the mean of 1000 redshift space mocks and using CAMB autocorrelation. Δ given in h^{-1} Mpc. These are the orange squares labelled “Baseline” in Figure 2.6 and “Flat Prior” in Figure 2.8.

$f_i^{\text{true}}(\times 10^2)$	Error on $\alpha(\times 10^3)$		Error on $\epsilon(\times 10^3)$		Error on $f_i(\times 10^2)$	
$\Delta=85$	Systematic	Statistical	Systematic	Statistical	Systematic	Statistical
2	6.3	1.5	1.7	1.7	24.3	11.2
5	6.4	1.6	2.1	1.7	23.9	10.8
10	5.2	1.6	1.5	1.8	14.5	12.5
15	5.8	1.7	0.9	1.8	15.5	12.0
$\Delta=90$	Systematic	Statistical	Systematic	Statistical	Systematic	Statistical
2	5.4	1.6	-1.0	1.8	20.0	12.3
5	4.5	1.8	-1.4	1.9	17.3	8.6
10	4.4	1.6	0.3	2.0	15.3	12.4
15	4.0	1.8	-0.2	1.8	13.9	11.9
$\Delta=97$	Systematic	Statistical	Systematic	Statistical	Systematic	Statistical
2	6.2	1.7	-0.4	2.1	22.9	12.4
5	5.1	1.7	-1.0	2.4	18.7	13.6
10	4.7	1.8	-1.4	2.5	16.8	13.2
15	3.8	1.8	0.9	2.2	11.2	12.8

Table A.3: Systematic and statistical errors on α , ϵ , f_i from multipole fits on the mean of 1000 redshift space mocks interlopers more strongly biased. and using CAMB autocorrelation. Δ given in h^{-1} Mpc. These are the green triangles labelled “Differing Biases” in Figure 2.6.

Appendix B

Additional LOO-PIT Examples

B.1 Single Realisation Examples

In this appendix, we show two additional examples of LOO-PIT from a single realisation.

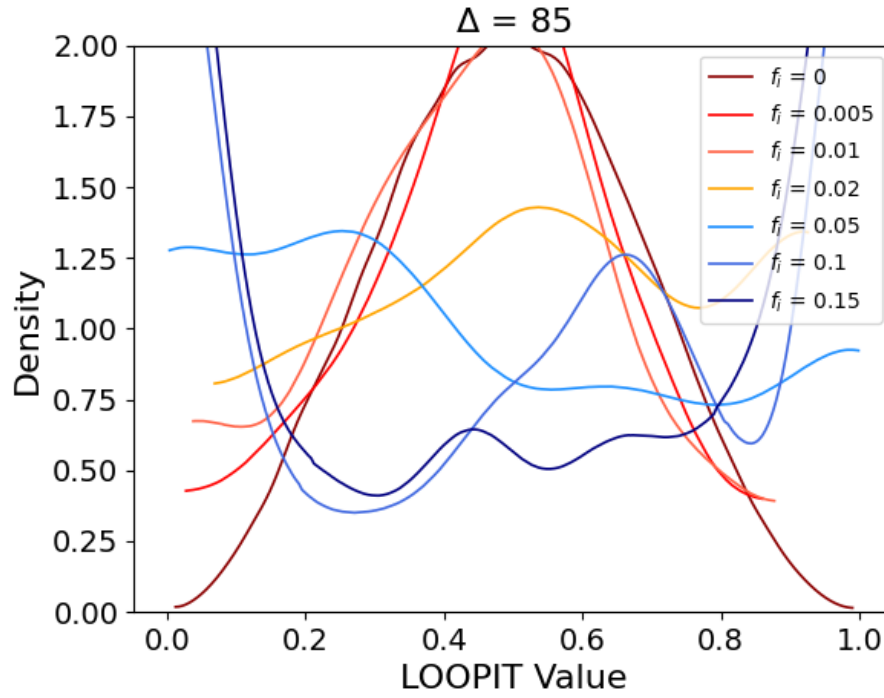


Figure B.1: LOOPIT values for $\Delta = 85 \ h^{-1}\text{Mpc}$. We plot a normalised KDE for each interloper fraction. For all interloper fractions other than zero baseline, we have plotted the KDE of LOOPIT values derived from a single realisation. For the baseline, we plot the KDE from 1000 realisations.

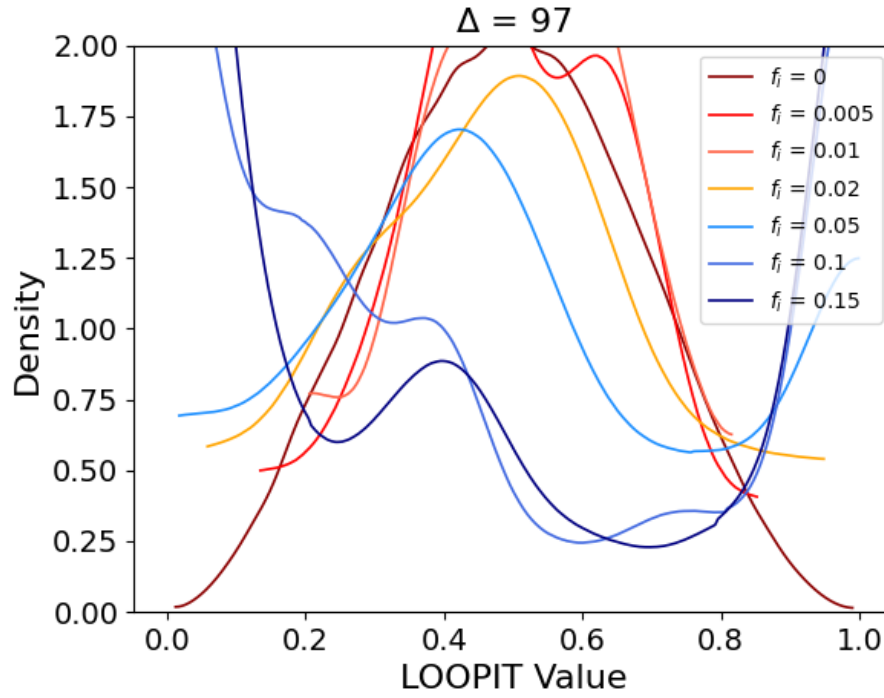


Figure B.2: LOO-PIT values for $\Delta = 97 \ h^{-1}\text{Mpc}$. We plot a normalised KDE for each interloper fraction. For all interloper fractions other than zero baseline, we have plotted the KDE of LOO-PIT values derived from a single realisation. For the baseline, we plot the KDE from 1000 realisations.