



Cosmological Constraints from Full-scale Clustering and Galaxy–Galaxy Lensing with DESI DR1

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Abstract

We present constraints on cosmic structure growth from the analysis of galaxy clustering and galaxy–galaxy lensing with galaxies from the Dark Energy Spectroscopic Instrument (DESI) Data Release 1. Our analysis includes four samples drawn from the Bright Galaxy Survey (BGS) and the luminous red galaxy (LRG) target classes. Projected galaxy clustering measurements from DESI are supplemented with lensing data from the Dark Energy Survey (DES), the Kilo-Degree Survey (KiDS), and the Hyper Suprime-Cam (HSC) survey around the same targets. Our method relies on a simulation-based modeling framework using the AbacusSummit simulations and a complex halo occupation distribution model that incorporates assembly bias. We analyze scales down to $0.4 h^{-1}$ Mpc for clustering and $2.5 h^{-1}$ Mpc for lensing, leading to stringent constraints on $S_8 = \sigma_8 \sqrt{\Omega_m}/0.3$ and Ω_m when fixing other cosmological parameters to those preferred by the cosmic microwave background. We find $S_8 = 0.797^{+0.023}_{-0.024}$ and $\Omega_m = 0.292 \pm 0.011$ when using lensing measurements from DES and KiDS. Similarly, for HSC, we find $S_8 = 0.791^{+0.020}_{-0.021}$ and $\Omega_m = 0.300 \pm 0.009$ when assuming the best-fit photometric redshift offset suggested by the HSC collaboration. Overall, our results are in good agreement with other results in the literature while continuing to highlight the constraining power of nonlinear scales.

Unified Astronomy Thesaurus concepts: Weak gravitational lensing (1797); Cosmological parameters from large-scale structure (340); Sigma8 (1455)

1. Introduction

The advent of large galaxy surveys, such as the Sloan Digital Sky Survey (SDSS; F. Beutler et al. 2012; L. Samushia et al. 2012), Baryon Oscillation Spectroscopic Survey (BOSS; B. Reid et al. 2016; R. Ahumada et al. 2020), the Dark Energy Survey (DES; B. Flaugher et al. 2015; T. M. C. Abbott et al. 2022), the Subaru Hyper Suprime-Cam (HSC) survey (H. Aihara et al. 2018; S. More et al. 2023), the Kilo-Degree Survey (KiDS; K. Kuijken et al. 2015; M. Asgari et al. 2021), and, most recently, the Dark Energy Spectroscopic Instrument (DESI; M. Levi et al. 2013; DES Collaboration et al. 2016a, 2016b; DESI Collaboration et al. 2022; J. Guy et al. 2023; E. F. Schlafly et al. 2023; J. H. Silber et al. 2023; DESI Collaboration et al. 2024a, 2024b, 2026; T. N. Miller et al. 2024; C. Poppett et al. 2024), has ushered in a new era in precision measurements of the large-scale structure of the Universe. These new measurements of matter and galaxy distributions have delivered important insights into the properties of dark energy and gravity as well as tests of our cosmological models (see, e.g., T. M. C. Abbott et al. 2022; S. Sugiyama et al. 2023; M. Abdul Karim et al. 2025; A. G. Adame et al. 2025a; M. Ishak et al. 2025; A. H. Wright et al. 2025; DES Collaboration et al. 2026). Alongside the advance in data quality and quantity, there has been significant effort to develop new analysis methods that can extract more cosmological information from existing data.

One promising avenue to maximize information is to extend the analysis of the galaxy and matter distribution to so-called nonlinear scales, i.e., scales smaller than $\mathcal{O}(10 h^{-1})$ Mpc. Interpreting nonlinear scales is challenging due to nonlinear gravitational effects, the complex relationship between galaxies and dark matter halos (R. H. Wechsler & J. L. Tinker 2018), and the impact of baryonic physics on the matter distribution (see, e.g., M. P. van Daalen et al. 2011; V. Springel et al. 2018; M. P. van Daalen et al. 2020). However, recent studies have shown how to address these issues through advancements in cosmological simulations and machine learning (see, e.g., S. Yuan et al. 2022; C. Hahn et al. 2023a; J. U. Lange et al. 2023; H. Miyatake et al. 2023; Z. Zhai et al. 2023, for recent applications), leading to more stringent cosmological constraints. For example, whereas a conventional analytic galaxy bias model may be applicable down to $6 h^{-1}$ Mpc when using point-mass marginalization (A. Porredon et al. 2022), using a simulation-based halo occupation distribution model, J. U. Lange et al. (2023) analyzed scales down to $2.5 h^{-1}$ Mpc without point-mass marginalization. Other promising directions include the analysis of higher-order clustering (see, e.g., C. Hahn & F. Villaescusa-Navarro 2021; G. Valogiannis et al. 2024; W. Liu et al. 2025), including field-level inference (see, e.g., N.-M. Nguyen et al. 2024) and more physically motivated priors on bias parameters (see, e.g., M. M. Ivanov et al. 2025).

In this work, we focus on the combined analysis of galaxy clustering and weak gravitational lensing. The clustering of galaxies is measured with data from DESI Data Release 1. We supplement these clustering measurements with lensing measurements from the latest publicly available lensing data from DES, KiDS, and HSC. Such an analysis, sometimes called a “ 2×2 pt” analysis, places constraints on



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$S_8 = \sigma_8 \sqrt{\Omega_m/0.3}$, where σ_8 is the rms of matter fluctuations on a scale of $8 h^{-1}$ Mpc, and Ω_m is the matter density. The present analysis focuses on analyzing nonlinear scales using advanced simulation-based modeling. It is complementary to another study by A. Porredon et al. (2026) that analyzes the matter and galaxy distribution on larger scales and also includes cosmic shear data in a so-called “ 3×2 pt” analysis.

Our analysis provides new insights into the so-called S_8 -tension, a possible discrepancy between inferred values of S_8 between studies of the cosmic microwave background (CMB) and low-redshift probes such as gravitational lensing (E. Abdalla et al. 2022). While such a tension may also exist on larger scales (T. M. C. Abbott et al. 2022; R. Dalal et al. 2023; A. H. Wright et al. 2025), nonlinear scales are particularly sensitive to it. Early work by M. Cacciato et al. (2013), who studied lensing and clustering down to small scales, found values for S_8 significantly lower than that preferred by the Planck Collaboration et al. (2020) CMB analysis, $S_8 = 0.825 \pm 0.011$. Whereas the analysis by M. Cacciato et al. (2013) was based on an analytic halo model, many recent studies employ simulation-based modeling to predict galaxy clustering and lensing. One such example is the study by A. Leauthaud et al. (2017) that showed that the lensing amplitude at fixed clustering is significantly over-predicted when one assumes cosmological parameters preferred by CMB studies. However, this discrepancy may also be related to galaxy physics such as baryonic feedback and galaxy assembly bias (A. Leauthaud et al. 2017; J. U. Lange et al. 2019b; A. Amon & G. Efstathiou 2022; J. Chaves-Montero et al. 2023). Subsequent studies mitigated the impact of unknown galaxy physics through scale cuts but generally continued to find low values for S_8 . For example, H. Miyatake et al. (2023), analyzing HSC data together with clustering measurements from the Baryon Oscillation Spectroscopic Survey (BOSS; B. Reid et al. 2016; R. Ahumada et al. 2020), found $S_8 = 0.763^{+0.040}_{-0.036}$. Similarly, the analysis of BOSS clustering and DES and KiDS lensing by J. U. Lange et al. (2023) yielded $S_8 = 0.792 \pm 0.022$ (also see B. D. Wibking et al. 2020; A. Amon et al. 2023; A. Dvornik et al. 2023). In this work, we build upon these studies using new measurements from DESI, the successor to BOSS.

We begin by outlining our data and measurements in Section 2. Next, we describe our analysis method, including tests on simulated mock catalogs, in Section 3. Our main results are presented in Section 4 before discussing and summarizing our findings in Section 5.

2. Measurements

Our analysis relies on galaxy clustering measurements from DESI Data Release 1, supplemented with gravitational lensing measurements from DES Year 3 (Y3; M. Gatti et al. 2021), the KiDS Data Release 4 (KiDS-1000; B. Giblin et al. 2021), and HSC Y3 (X. Li et al. 2022) data. The measurements are described in detail in S. Heydenreich et al. (2025), and we summarize the most salient points here. All measurements assume $\Omega_m = 0.3075$ (Planck Collaboration et al. 2016) to convert redshifts and angles into physical coordinates.

2.1. DESI Samples

The different galaxy samples were investigated in S. Yuan et al. (2024), and balance increased number density with the

need for negligible redshift evolution within each sample. DESI targets different classes of extragalactic objects. Those at lower redshift, $z < 1$, i.e., those for which we can get precise galaxy–galaxy lensing measurements, are the Bright Galaxy Survey (BGS) and the luminous red galaxy (LRG) sample.

The BGS Bright targets include all objects with an apparent r -band magnitude brighter than 19.5 (C. Hahn et al. 2023b) and cover an area of around 7500 deg^2 (A. G. Adame et al. 2025b). Due to being a flux-limited survey, the BGS includes many low-redshift targets with a strongly redshift-dependent number density. As a result, we need to apply additional cuts on the absolute k -corrected and evolution-corrected magnitudes M_r (J. Moustakas et al. 2023; DESI Collaboration et al. 2024b). We have three BGS samples, BGS1, BGS2, and BGS3. Their redshift ranges are defined by the boundaries [0.1, 0.2, 0.3, 0.4], and the absolute luminosity thresholds are $M_r < -19.5$, -20.5 , and -21 , respectively. However, we do not use BGS1 in our analysis since our simulations do not have sufficient mass resolution to model this low-luminosity sample. In particular, the number density of BGS1 significantly exceeds the number of resolved halos in the simulation. Since the number density of central galaxies cannot exceed that of resolved halos, this forces a very high satellite fraction in the fit and an overall unacceptable χ^2 . A set of higher-resolution simulations would be needed to effectively model this sample.

The LRG sample has a slightly more complicated selection based on the g , r , z , and $W1$ magnitudes (R. Zhou et al. 2023) and covers an area of around 5700 deg^2 . Fortunately, the LRG selection does not result in a strongly redshift-dependent number density. Thus, we define three LRG samples, LRG 1, LRG 2, and LRG 3, by the redshift boundaries [0.4, 0.6, 0.8, 1.1]. However, for our main analysis, we do not use LRG 3 since these measurements are potentially strongly contaminated by intrinsic alignments, lens magnification, and other lensing systematics (S. Heydenreich et al. 2025).

For all samples, we use the galaxy number density n_{gal} as a constraint. The number density, like the clustering measurements described below, does correct for incompleteness in the DESI fiber assignment using weights. Uncertainties are derived from jackknife resampling. The number densities are $(3.71 \pm 0.03) \times 10^{-3}$, $(1.38 \pm 0.01) \times 10^{-3}$, $(5.70 \pm 0.03) \times 10^{-4}$, and $(5.69 \pm 0.03) \times 10^{-4} h^3 \text{ Mpc}^{-3}$ for BGS2, BGS3, LRG 1, and LRG 2, respectively.

2.2. Galaxy Clustering

Galaxy clustering is measured via the projected two-point correlation function w_p ,

$$w_p(r_p) = 2 \int_0^{\pi_{\text{max}}} \xi(r_p, r_\pi) dr_\pi. \quad (1)$$

In the above equation, $\xi(r_p, r_\pi)$ denotes the redshift-space two-point correlation function as a function of the perpendicular, r_p , and line-of-sight direction, r_π . By integrating along the line-of-sight direction out to $\pi_{\text{max}} = 80 h^{-1} \text{ Mpc}$, we reduce sensitivity to redshift-space distortions. The clustering measurements are corrected for fiber incompleteness via pairwise-inverse-probability (PIP) weights and angular upweighting (D. Bianchi et al. 2018, 2025).

We measure w_p in 14 logarithmic, comoving r_p bins going from 10^{-1} to $10^{1.8} h^{-1} \text{Mpc}$ but only use data above $0.4 h^{-1} \text{Mpc}$ for our analysis. Uncertainties are estimated from jackknife resampling with 128 equal-area patches on the sky. Finally, for the inverse of the covariance matrix, we use the Hartlap correction factor (J. Hartlap et al. 2007).

2.3. Gravitational Lensing

We also measure the galaxy–galaxy lensing signal around DESI samples to probe the mass distribution around them. Galaxy shape measurements come from the publicly available DES, KiDS, and HSC catalogs. The DES weak-lensing catalogs are based on the Y3 dataset, utilize four tomographic bins based on *riz* colors, have an effective number density of 6 arcmin^{-2} , and span an area of around 4100 deg^2 . KiDS uses a more extensive nine-band photometry to define its five tomographic bins and has a similar number density over a smaller 800 deg^2 area. Given its area, it is called the KiDS-1000 dataset. Finally, the HSC Y3 data are significantly deeper with a number density of 15 arcmin^{-2} , four tomographic bins derived from five optical bands, but a much smaller 433 deg^2 area.

The galaxy–galaxy lensing amplitude is a measure of the so-called excess surface density $\Delta\Sigma$ around galaxies,

$$\Delta\Sigma(r_p) = \frac{2}{r_p^2} \int_0^{r_p} \hat{r}_p \Sigma(\hat{r}_p) d\hat{r}_p - \Sigma(r_p), \quad (2)$$

where $\Sigma(r_p)$ is the projected mass density at a certain distance r_p perpendicular to the line of sight. In practice, $\Delta\Sigma$ is inferred from the mean tangential shear γ_t ,

$$\gamma_t(r_p) = \frac{\Delta\Sigma(r_p)}{\Sigma_{\text{crit}}(z_l, z_s)} \quad (3)$$

of “source” galaxies in DES Y3, KiDS-1000, and HSC Y3 around DESI “lens” galaxies. In the above equation, Σ_{crit} is the critical surface density and depends on both the lens, z_l , and the source redshift, z_s . We refer the reader to S. Heydenreich et al. (2025) for a detailed discussion of how these measurements are performed. These measurements include corrections for fiber incompleteness using individual inverse-probability weights, which have been shown to be accurate to better than $\lesssim 1\%$ in simulations (J. U. Lange et al. 2024). Additionally, S. Heydenreich et al. (2025) found no residual correlation between measured lensing amplitudes and the number of overlapping tiles for each galaxy. This indicates that correction for fiber incompleteness is robust. We use the lensing measurements employing the conservative lens-source cuts, as outlined in Table 1 of S. Heydenreich et al. (2025). Employing such cuts reduces systematic uncertainties related to, among others, intrinsic alignments and boost factors (J. U. Lange et al. 2024). This implies that we do not use DES and KiDS lensing measurements for LRG 2. We correct for lens magnification (S. Unruh et al. 2020) assuming the best-fit Planck Collaboration et al. (2020) cosmological parameters. Since lens magnification is a small, $\lesssim 10\%$ effect, we neglect its cosmological dependence. We also do not explicitly correct for intrinsic alignment contamination since the effect is expected to be small given that it is only relevant if lenses and sources are at the same redshift. Using the data from

J. U. Lange et al. (2024), we estimate that, for our lens-source cuts and a minimum scale of $r_p = 2.5 h^{-1} \text{Mpc}$, the impact is well below $\Delta\chi^2 < 1$ with most of the significance occurring for LRG 1 lenses and sources from DES and KiDS. That said, there is substantial uncertainty on the magnitude of intrinsic alignments, and future studies using higher-precision lensing measurements should investigate potential corrections for intrinsic alignments.

We measure $\Delta\Sigma$ in 13 logarithmic, comoving bins going from 10^{-1} to $10^{1.6} h^{-1} \text{Mpc}$. To avoid sensitivity to baryonic effects and subhalo lensing (see, e.g., Y. Zu & R. Mandelbaum 2015; J. U. Lange et al. 2019b; S. Amodeo et al. 2021), we only use scales larger than $2.5 h^{-1} \text{Mpc}$ for our analysis. While baryonic effects will also impact the distribution of satellite galaxies and thereby clustering, we marginalize over this in our analysis. This is why we employ a lower minimum scale for clustering than lensing. We estimate uncertainties using the same jackknife procedure as for clustering. We ignore possible correlations between clustering and lensing amplitudes. Those are expected to be small (P. L. Taylor & K. Marković 2022), especially given that clustering is measured over the full DESI footprint, 7500 and 5700 deg^2 for BGS and LRG, respectively, whereas the lensing amplitude measurements are limited to $\lesssim 1000 \text{ deg}^2$ overlap areas with the lensing surveys.

For our cosmological analysis, we combine lensing measurements made for the same DESI lenses but different source samples, i.e., different lensing surveys. Specifically, if we have n lensing estimates μ_i with associated covariances Σ_i , the combined covariance is

$$\Sigma_{\text{tot}} = \left(\sum_{i=1}^n \Sigma_i^{-1} \right)^{-1}, \quad (4)$$

and the combined estimate becomes

$$\mu_{\text{tot}} = \Sigma_{\text{tot}} \sum_{i=1}^n \Sigma_i^{-1} \mu_i. \quad (5)$$

We derive two sets of combined lensing measurements for each of the DESI samples. One set includes all lensing measurements from DES and KiDS, and the other one includes the HSC measurements. Within the DESI footprint, DES and KiDS do not overlap spatially, allowing us to treat these measurements as independent. On the other hand, the HSC footprint in DESI overlaps with both DES and KiDS. Thus, the combined DES and KiDS lensing measurements have a nonzero covariance with the HSC measurements. In the following, we will refer to the combined DES and KiDS lensing measurements as DES/KiDS. The DES/KiDS footprints have a roughly $\sim 1000 \text{ deg}^2$ overlap with DESI Y1 while HSC Y3 has a smaller $\sim 400 \text{ deg}^2$ overlap but higher source density.

Finally, the HSC Y3 lensing measurements are significantly affected by uncertainties in the photometric redshift calibration (M. M. Rau et al. 2023). In their 3×2 pt analysis, X. Li et al. (2023) used a self-calibration to show that applying an additional offset of $+0.115$ and $+0.192$ to the mean redshift of the third and fourth tomographic bin, respectively, significantly improves the fit. A similar result was found by S. Heydenreich et al. (2025). Thus, by default, we assume these offsets to make our HSC Y3 lensing measurements. Later, we also discuss how our results would change if no

offsets were applied to the fiducial HSC Y3 calibration in M. M. Rau et al. (2023).

3. Methods

For the most part, our analysis method closely follows previous work by J. U. Lange et al. (2022, 2023), which we summarize here briefly.

3.1. Simulations

We start with a set of cosmological N -body simulations spanning a range of cosmologies, i.e., cosmological parameters. In previous work, the Aemulus Alpha simulations (J. DeRose et al. 2019) were used whereas we employ the AbacusSummit suite (L. H. Garrison et al. 2021; N. A. Maksimova et al. 2021) in this work primarily due to its larger volume and higher resolution. From AbacusSummit, we select all cosmologies that vary Ω_m and σ_8 with respect to the base Planck Collaboration et al. (2020) CMB cosmology while keeping neutrino and dark energy properties as well as the shape of primordial power spectrum, i.e., the spectral index n_s and the running of the spectral index, fixed. More explicitly, we use the cosmologies 0, 1, 4, 100, 101, 102, 103, 112, 113, 116, 117, 118, 125, 126, 130, 131, 133, and 134. Furthermore, we add the cosmologies 137, 140, and 144. While these do vary the spectral index n_s , they add important coverage in the S_8 – Ω_m plane. The S_8 -range probed by these simulations is 0.73 to 0.93 whereas Ω_m goes from 0.255 to 0.388.

We note that all cosmological parameters besides Ω_m and S_8 are assumed fixed in our analysis. The spectral index, with the exception of simulations 137, 140, and 144, is fixed at $n_s = 0.9649$ (Planck Collaboration et al. 2020). Similarly, there is no running of the spectral index, the sum of the neutrino masses is 0.06 eV, $N_{\text{eff}} = 3.0328$, and dark energy is assumed to be constant, $w_0 = -1$ and $w_a = 0$. Note that, conversely, the Hubble parameter $h = H_0/(100 \text{ km s}^{-1} \text{ Mpc}^{-1})$ is varied in these simulations, primarily because the CMB acoustic scale θ_* is kept fixed when varying Ω_m . In principle, this implies that H_0 and Ω_m are varied together. However, since gravitational lensing is much more sensitive to Ω_m than H_0 , we interpret all changes in the goodness of fit as constraints on Ω_m and S_8 . Ultimately, the main focus of this work is testing the consistency between the CMB and low-redshift measurements of cosmic structure, i.e., S_8 and Ω_m . Thus, for this comparison, we are not interested in varying other cosmological parameters beyond those ranges permitted by the CMB. Since constraints on S_8 are not strongly degenerate with other parameters in the ranges allowed by the CMB (see, e.g., W. Gao et al. 2026), keeping them fixed, our analysis seems unlikely to significantly affect this consistency assessment but should be kept in mind as a caveat.

For each cosmology, we select the base simulation with 6192^3 particles and a volume of $(2 h^{-1} \text{ Gpc})^3$, resulting in a particle resolution of $2.11 \times 10^9 (\Omega_m/0.314) h^{-1} M_\odot$. For each simulation, we use catalogs of all halos (B. Hadzhiyska et al. 2022) with at least 300 particles and a random 0.025% of all particles to sample the lensing field. These catalogs are extracted at redshifts 0.2, 0.3, 0.4, 0.5, and 0.8.⁶⁴

⁶⁴ Cosmology 103 does not have data for redshift 0.8. Therefore, we do not use that cosmology for fits involving the high-redshift LRG 2 sample.

3.2. Galaxy Model

Halos in the AbacusSummit simulations are populated with galaxies via a halo occupation distribution (HOD; A. A. Berlind & D. H. Weinberg 2002; J. S. Bullock et al. 2002; Z. Zheng et al. 2007) model. The number of centrals, N_{cen} , per dark matter halo as a function of its halo mass M is given by

$$\langle N_{\text{cen}} | M \rangle = \frac{f_\Gamma}{2} \left(1 + \text{erf} \left[\frac{\log M - \log M_{\text{min}}}{\sigma_{\log M}} \right] \right), \quad (6)$$

whereas the number of satellites, N_{sat} , obeys

$$\langle N_{\text{sat}} | M \rangle = \left(\frac{M - M_0}{M_1} \right)^\alpha. \quad (7)$$

In the above equations, f_Γ , $\log M_{\text{min}}$, $\sigma_{\log M}$, M_0 , M_1 , and α are free parameters that we marginalize over in our analysis. The parameter f_Γ accounts for potential color incompleteness at high stellar masses for LRGs and is fixed to unity for the BGS samples.

The above parameterization describes a simple mass-only HOD and is supplemented with the decorated HOD framework (A. P. Hearin et al. 2016) to allow for galaxy assembly bias based on halo concentration. This gives two more free parameters, A_{cen} and A_{sat} , controlling the amount of assembly bias for centrals and satellites, respectively. Specifically, the number of centrals is modified based on the halo concentration c according to

$$\langle N_{\text{cen}} | M, c \rangle = \langle N_{\text{cen}} | M \rangle \pm A_{\text{cen}} \min(\langle N_{\text{cen}} | M \rangle, 1 - \langle N_{\text{cen}} | M \rangle). \quad (8)$$

In the above equation, the second term is added if the halo concentration is above the median concentration for halos of that mass and subtracted otherwise. Similarly, the satellite number becomes

$$\langle N_{\text{sat}} | M, c \rangle = \langle N_{\text{sat}} | M \rangle \pm A_{\text{sat}} \langle N_{\text{sat}} | M \rangle. \quad (9)$$

Both A_{cen} and A_{sat} are limited to the range $[-1, +1]$ to ensure the expected number of galaxies is always nonnegative.

Finally, satellite positions and velocities are drawn from an analytic Navarro–Frenk–White (NFW; J. F. Navarro et al. 1997) profile with the second moment of the velocity distribution calculated from the time-independent Jeans equation. We allow satellites to have a biased spatial and velocity distribution with respect to the dark matter within each halo (see J. U. Lange et al. 2023, for details). The spatial bias is defined by $\eta = c_{\text{sat}}/c$, where c_{sat} is the concentration parameter of the satellite distribution within a halo. Similarly, α_s controls the velocity bias and represents an additional factor to multiply satellite velocities with.

We list all galaxy parameters together with a short description and the range of values we explore in our analysis in Table 1. The ranges explored are very broad and, in many cases, cover all values that meaningfully affect the predictions while being consistent with observations. Similarly, the limits for the assembly bias parameters are the maximum ranges allowed by the model (A. P. Hearin et al. 2016). While the ranges for $\log \eta$ and α_s could, in principle, be expanded, these parameters are virtually unconstrained by the data.

The above model allows us to place simulated galaxies into dark matter-only simulations. We then use the distant-observer

Table 1

Description and Ranges of Galaxy Parameters Varied in Our Analysis

Parameter	Description	Range
$\log M_{\min}$	Mass at which $\langle N_{\text{cen}} \rangle = 0.5$	[11, 15]
$\sigma_{\log M}$	Low-mass transition of $\langle N_{\text{cen}} \rangle$	[0.1, 1.0]
f_{I}	LRG incompleteness of $\langle N_{\text{cen}} \rangle$	[0.5, 1.0]
$\log M_0$	Mass below which $\langle N_{\text{sat}} \rangle = 0$	[11, 15]
$\log M_1$	Mass at which $\langle N_{\text{sat}} \rangle \approx 1$	[11, 15]
α	Power-law index of $\langle N_{\text{sat}} \rangle$	[0.5, 2.0]
A_{cen}	Central assembly bias	[−1.0, 1.0]
A_{sat}	Satellite assembly bias	[−1.0, 1.0]
$\log \eta$	Satellite spatial bias	[−0.5, 0.5]
α_s	Satellite velocity bias	[0.8, 1.2]

approximation to measure galaxy clustering and lensing. For clustering, we take redshift-space distortions into account. For lensing, we additionally make use of down-sampled particle catalogs to estimate the excess surface density $\Delta\Sigma$, using the algorithm outlined in J. U. Lange et al. (2019b). All mock predictions use the same binning as the real data, and the clustering measurements include the Alcock–Paczynski effect (C. Alcock & B. Paczynski 1979), i.e., the assumed cosmology when converting redshifts and angles to physical coordinates. For lensing, the effect is expected to be small (S. More 2013) and is ignored.

We accelerate the prediction of galaxy clustering and lensing via TABCORR version 1.1.2. This software utilizes the tabulation method described in Z. Zheng & H. Guo (2016) and J. U. Lange et al. (2019a). In essence, we first calculate the clustering and lensing of central and satellite galaxies within halo mass and concentration bins. Afterward, the correlation functions are convolved with the HOD to make predictions for the galaxy correlation functions. Finally, we use cubic spline interpolation to make predictions for arbitrary phase-space parameters, i.e., $\log \eta$ and α_s , and redshifts. We checked that interpolation errors are small compared to observational uncertainties. Finally, we use the “efficient” configuration in TABCORR to precompute the halo correlation functions.

Finally, we note two shortcomings in our galaxy model. Most importantly, we have implicitly neglected the impact of baryonic physics on the galaxy–galaxy lensing amplitude (see, e.g., A. Leauthaud et al. 2017; J. U. Lange et al. 2019b; S. Amodeo et al. 2021; G. D. Beltz-Mohrmann & A. A. Berlind 2021; A. Amon et al. 2023; L. Bigwood et al. 2024; J. Sunseri et al. 2026). Typically, neglecting baryonic processes will lead to an overprediction of the lensing amplitude on small scales. The scale cuts we impose are intended to mitigate this issue. We tested this by implementing the baryonic suppression of the lensing amplitude found by J. U. Lange et al. (2019b) for galaxies above a mass of $10^{11} M_{\odot}$ in the original Illustris simulation (M. Vogelsberger et al. 2014). Notably, the Illustris simulation already predicts a strong suppression due to baryonic feedback compared to other simulations (A. Amon & G. Efstathiou 2022). Nonetheless, we find that the baryonic suppression changes the final DES/KIDS constraints on S_8 and Ω_m by less than 0.3σ .

In addition to baryonic feedback, by drawing satellite positions from a smooth analytic density profile, we implicitly neglect the impact of subhalos (see, e.g., Y. Zu & R. Mandelbaum 2015; J. Chaves-Montero et al. 2023) on the lensing amplitude. Unlike baryonic feedback, this

simplification will lead to an underprediction of the lensing signal on small scales. However, as for baryonic feedback, the scale cut should substantially mitigate this issue. Finally, we implement assembly bias based on halo concentration as the secondary halo property. However, recent works advocate for using other secondary halo properties such as an overdensity to model galaxy assembly bias (B. Hadzhiyska et al. 2021; X. Xu et al. 2021). Further tests are needed to determine whether using a different secondary halo property has a strong impact on our results.

3.3. Cosmological Inference

Starting with a set of observational data, $D_{\text{obs}} = \{n_{\text{gal}}, w_{\text{p}}, \Delta\Sigma\}$, our goal is to infer constraints on Ω_m and S_8 . The first step is to determine the best-fit, i.e., maximum-likelihood, galaxy model D_{mod} for each Abacus-Summit simulation with respect to the observed data. The likelihood is defined as

$$\log \mathcal{L} = -\frac{1}{2} \chi^2 = -\frac{1}{2} (D_{\text{obs}} - D_{\text{mod}})^T \times \Sigma^{-1} (D_{\text{obs}} - D_{\text{mod}}), \quad (10)$$

where Σ is the covariance matrix of the observational data. We determine the maximum-likelihood galaxy model and posterior for each simulation using NAUTILUS (J. U. Lange 2023) with 3000 live points and a stopping criterion of $f_{\text{live}} < 10^{-10}$. To determine cosmology constraints, in previous works (see, e.g., J. U. Lange et al. 2023), we “emulated” the maximum likelihood $\log \mathcal{L}_{\text{max}}$ as a function of cosmology via skew-normal distributions. In this work, we opt for a different approach where we instead emulate the maximum-likelihood model predictions as a function of cosmology. We choose this method for its computational efficiency and to have a different method to test against. Additionally, we find this method to be more precise, resulting in less uncertainty from the limited number of simulations. The observational S_8 constraints in this work do not shift significantly with the skew-normal approach but have around 30% larger uncertainties.

For each simulation representing different values for Ω_m and S_8 , we have the best-fit prediction D_{mod} .⁶⁵ First, we normalize these data vectors via $\tilde{D}_{\text{mod}} = D_{\text{mod}} / \sqrt{\text{diag}(\Sigma)}$ and reduce the dimensionality via a principal component analysis (PCA). We only keep those N_{PCA} eigenvectors u_i that explain 99.9% of the variance across cosmology, typically the first three–six eigenvectors. Finally, we fit the cosmology dependence of each PCA component x_i via a simple linear model,

$$\hat{x}_i = a_i + b_i S_8 + c_i \Omega_m + d_i S_8^2. \quad (11)$$

We chose this specific linear model because it closely corresponds to a skew-normal likelihood, with a skew in the S_8 -dimension. This allows us to estimate the best-fit model D_{mod} , and thereby best-fit likelihood, for arbitrary values of Ω_m and S_8 . To account for uncertainties in this interpolation, we

⁶⁵ Cosmologies 137, 140, and 144 vary n_s compared to all other cosmologies. We correct for this by calculating $\partial D_{\text{mod}} / \partial n_s$ using cosmologies 104 and 105 and subtracting the expected contribution of the n_s variations assuming linearity. This correction was added postunmasking when we found that the best-fit models of 137, 140, and 144 were not well predicted from the other cosmologies. Our results change by at most 0.2σ if we do not apply these corrections or do not use 137, 140, and 144 at all.

measure the leave-one-out scatter $\sigma_i^2 = \text{Var}(x_i - \hat{x}_i)$ between the linear model and the actual values of the PCA components and add this to the covariance matrix,

$$\Sigma \rightarrow \Sigma + \sum_{i=1}^{N_{\text{PCA}}} \sigma_i^2 (u_i \sqrt{\text{diag}(\Sigma)})^T (u_i \sqrt{\text{diag}(\Sigma)}). \quad (12)$$

For the DESI observational data, the emulation error is significantly smaller than the observational error for all samples and measurements, giving confidence that our results are not strongly affected by emulation uncertainties. For example, for the DESI observational data, $\sigma_{\text{emu}} \lesssim 0.4\sigma_{\text{obs}}$ for all samples and measurements. As an additional test, we sample the best-fit coefficients of the linear fit according to its covariance estimated from the linear regression. This exercise indicates that the uncertainty of the maximum-likelihood estimate (MLE) due to the interpolation is a factor of ~ 5 – 10 smaller than observational uncertainties. As a final test, we find that our results do not sensitively depend on the linear model or amount of variance considered. We tested a more flexible model in Equation (11) by adding an $S_8 \times \Omega_m$ and an S_8^3 term but do not find significant differences for our observational constraints. All this suggests that our results are not strongly affected by uncertainties in the interpolation over cosmology.

3.4. Verification

Before applying our analysis method to (masked) DESI data, we perform tests on simulated mock data to check for potential biases in our analysis method. The mock measurements are based on the DESI emulator mock challenge (G. Beltz-Mohrmann et al. 2026, in preparation). Mock galaxy catalogs are generated via the GalSampler method (A. Hearin et al. 2020) by transferring the galaxy–halo connection model from the diffky model (A. Alarcon et al. 2023; A. P. Hearin et al. 2023) run on the SMDPL simulation (F. Prada et al. 2012) to the UNIT simulations (C.-H. Chuang et al. 2019).

As part of the DESI emulator mock challenge, LRG-like mocks were created at redshifts 0.5 and 0.8. Thus, to most closely mimic our analysis, we choose the 0.5 mock. However, that means that, unlike for the analysis of DESI data, we only use a single galaxy sample. From the available galaxy models, we choose the one where the GalSampler method uses both halo mass and concentration. Furthermore, the intrahalo phase-space coordinates for galaxies use the hostcentric model. We refer the reader to G. Beltz-Mohrmann et al. (2026, in preparation) for more details about these simulations.

The mock catalogs are tuned to reproduce the properties of the BGS and LRG samples in the DESI Early Data Release (DESI Collaboration et al. 2024b). However, they do not include projections onto the sky or the actual DESI footprint. Instead, we use the distant-observer approximation, averaging the results from the three simulation axes chosen as the line of sight. The covariance matrix used for inference is estimated using the jackknife method with 125 equal-volume parts for each of the two UNIT simulation mocks. We note that uncertainties in these mock measurements, especially $\Delta\Sigma$, are much smaller than observational ones.

In Figure 1, we show the best-fit galaxy model on the best-fit AbacusSummit simulation. We see that our galaxy model can fit the mock data vector well with $\chi^2 = 10.6$

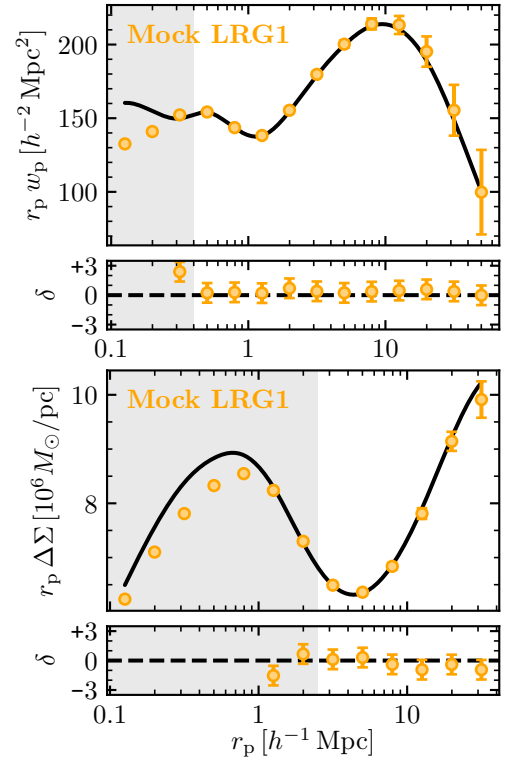


Figure 1. Best-fitting clustering and lensing predictions for the mock LRG 1 measurements. The lower smaller panels indicate the difference between observations and the model in units of the observational uncertainty. Gray regions indicate measurements not used in the fit.

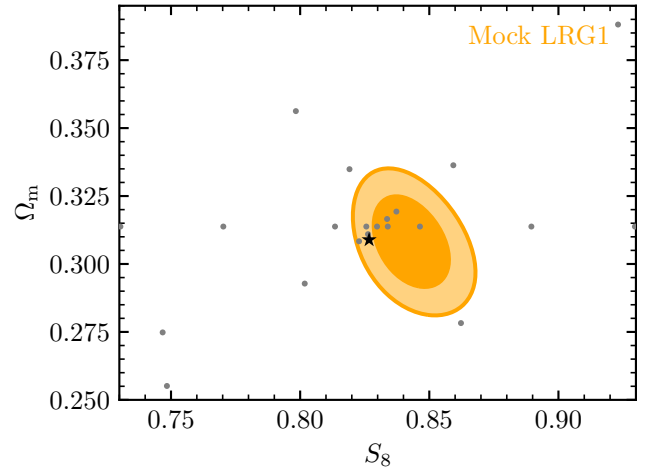


Figure 2. Mock constraints on S_8 and Ω_m . The different shaded regions indicate parameter spaces where $0 \leq \Delta\chi^2 < 2.28$ and $2.28 \leq \Delta\chi^2 < 5.99$ with respect to the best-fit cosmology, corresponding to the 68% and 95% confidence regions of a two-dimensional Gaussian distribution. The star indicates the values of S_8 and Ω_m in the UNIT simulations. Finally, small gray dots indicate the cosmological parameters of AbacusSummit simulations used in this analysis.

($\chi_\nu^2 = 10.6/(18 - 6.8 - 2)$, $p = 0.32$). In Figure 2, we show the cosmological constraints in addition to the input cosmology of the UNIT simulations. We find that the UNIT cosmology is at $\Delta\chi^2 = 3.4$ from the best-fit cosmology. For reference, for a two-dimensional Gaussian, 19% of random draws will result in a higher $\Delta\chi^2$, indicating that our cosmological constraints are consistent with being unbiased. Nonetheless, we stress the need for additional mock tests in the

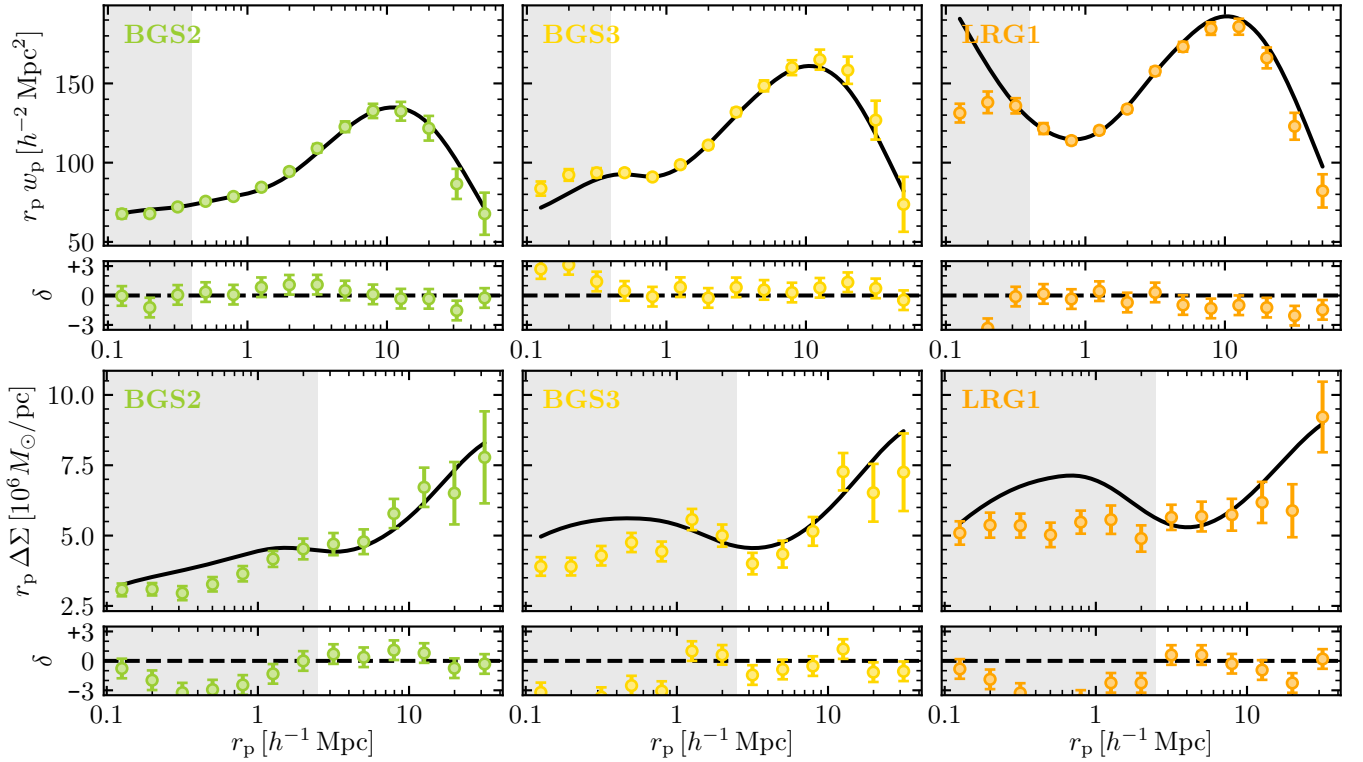


Figure 3. Similar to Figure 1 but for the DESI measurements with DES and KiDS lensing. The best-fit simulation, `AbacusSummit_base_c103_ph000`, is the one that minimizes the total χ^2 of all three samples whereas the galaxy model is optimized individually for each sample.

future, especially for the BGS sample, which may additionally be affected by the limited resolution of the AbacusSummit base simulations.

3.5. Masking

We aim to protect analysis choices in this work from confirmation bias and other subconscious effects that could bias the outcome of our analysis. To this end, we first perform a “masked” analysis on the DESI data that allows us to implement quality controls, such as checking the goodness of fit, while being insensitive to the constraints on Ω_m and S_8 . We implement a data vector masking, similar to J. Muir et al. (2020) and J. U. Lange et al. (2023). We find that simply multiplying the lensing amplitude $\Delta\Sigma$ by an unknown factor A_{lens} , while keeping w_p unchanged, moves constraints mainly along the S_8 line while having only a small impact on the goodness of fit. Thus, to create the masked observational data, we draw A_{lens} from a uniform distribution in the range [0.85, 1.15] and multiply the lensing amplitudes for all DESI samples and lensing measurements by the same A_{lens} .

When working with the masked data, based on the goodness of fit, we determined that the mass resolution of the AbacusSummit simulations was insufficient for BGS1. No other significant changes were made in response to analyzing the masked data.

4. Results

Here, we present the unmasked cosmology results. The results of this analysis were only unmasked after it was determined that the galaxy model can obtain an acceptable fit to the data and that the different DESI samples, BGS2, BGS3, LRG 1, and LRG 2, give consistent cosmological constraints.

The only significant postunmasking change was fixing an error where correlations between lensing measurements of the same lenses but different source tomographic bins were neglected. That caused uncertainties for the lensing measurements and thereby S_8 uncertainties to be underestimated by $\sim 10\%$ to 20% .

4.1. Goodness of Fit

In Figure 3, we show the best-fit model predictions for the different DESI samples studied in this work with lensing amplitudes from DES/KiDS. Figure 4 shows a similar result but for lensing amplitudes from HSC. We find that we can obtain good fits to the data of all DESI lens samples with a single simulation, i.e., cosmology. The total goodness of fit is $\chi^2 = 48.5$ with 54 data points for DES/KiDS and $\chi^2 = 55.1$ with 72 data points for HSC. We have 2 degrees of freedom (dof) for the cosmology fit, but the effective degrees of freedom of the galaxy fit are significantly less than the number of galaxy model parameters since many are effectively unconstrained, as shown in Figure 5. We estimate the effective degrees of freedom numerically. We start with the best-fit galaxy model θ_0 for each sample at the AbacusSummit cosmology 0. We then repeatedly draw mock observations from a multivariate normal distribution with the predictions from θ_0 as the mean and the observational uncertainties as the covariance. Finally, we minimize the χ^2 over the galaxy parameters and calculate the difference between the minimum χ^2 and $\chi^2(\theta_0)$. Based on the reduction in the χ^2 , we estimate the effective degrees of freedom in the galaxy parameters over all DESI samples to be around 14.0 for the DES/KiDS fits and 20.3 for the HSC fits. This gives $\chi^2_p = 48.5/(54 - 2 - 14.0)$ ($p = 0.12$) for DES/KiDS and $\chi^2_p = 55.1/(72 - 2 - 20.3)$

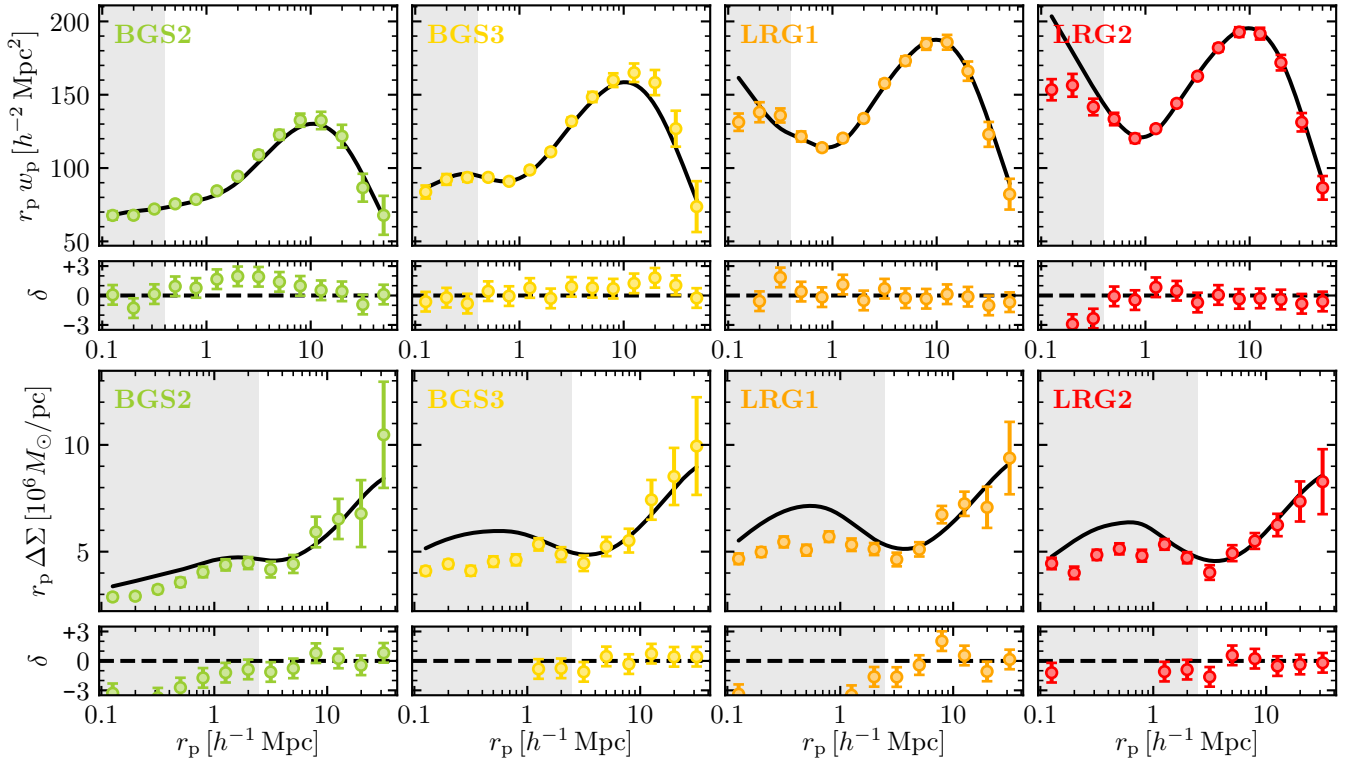


Figure 4. Similar to Figure 3 but for the DESI measurements with HSC lensing amplitudes. The best-fitting simulation is AbacusSummit_base_c118_ph000.

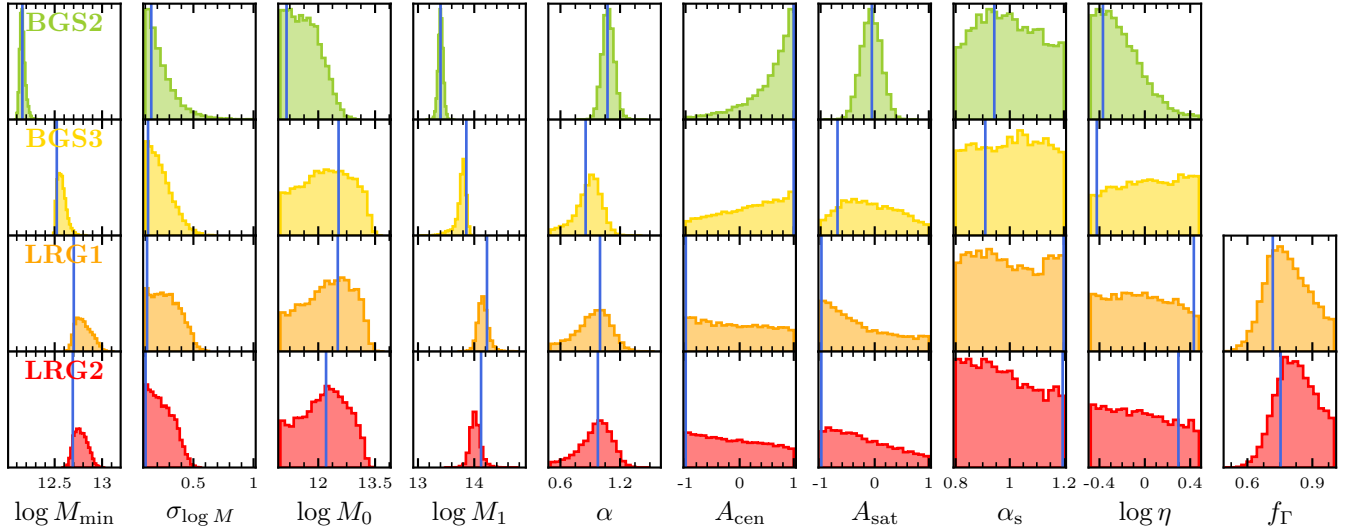


Figure 5. One-dimensional Bayesian posteriors on the galaxy model parameters for the four DESI samples with HSC lensing amplitudes under the best-fit cosmology. We also show the best-fit parameters as blue vertical lines. The different parameters are described in Section 1.

($p = 0.28$) for HSC. Overall, this indicates an acceptable fit of our Λ CDM and HOD-based model to the observational data.

4.2. Cosmology

The main result of our analysis, observational constraints on S_8 and Ω_m , is shown in Figure 6. We show the individual constraints from the different samples as well as their combination. The best-fit χ^2 when fitting all samples with a single combination of S_8 and Ω_m increases by $\Delta\chi^2 = 7.0$ for DES/KiDS and 3.7 for HSC compared to optimizing those

two parameters for each individual sample. This increase in χ^2 is consistent with reducing the dof by 4 for DES/KiDS ($\Delta\chi^2_\nu = 7.0/4$, $p = 0.14$) and 6 for HSC ($\Delta\chi^2_\nu = 3.7/6$, $p = 0.72$), indicating that the different DESI samples produce consistent results on S_8 and Ω_m . Our final marginalized (Frequentist) constraints are $S_8 = 0.797^{+0.023}_{-0.024}$ and $\Omega_m = 0.292 \pm 0.011$ for DES/KiDS and $S_8 = 0.791^{+0.020}_{-0.021}$ and $\Omega_m = 0.300 \pm 0.009$ for HSC. Estimates correspond to the MLE whereas uncertainties correspond to $\Delta\chi^2 = 1$ from the MLE, i.e., 68% confidence intervals assuming a one-dimensional normal distribution. As expected given the consistency

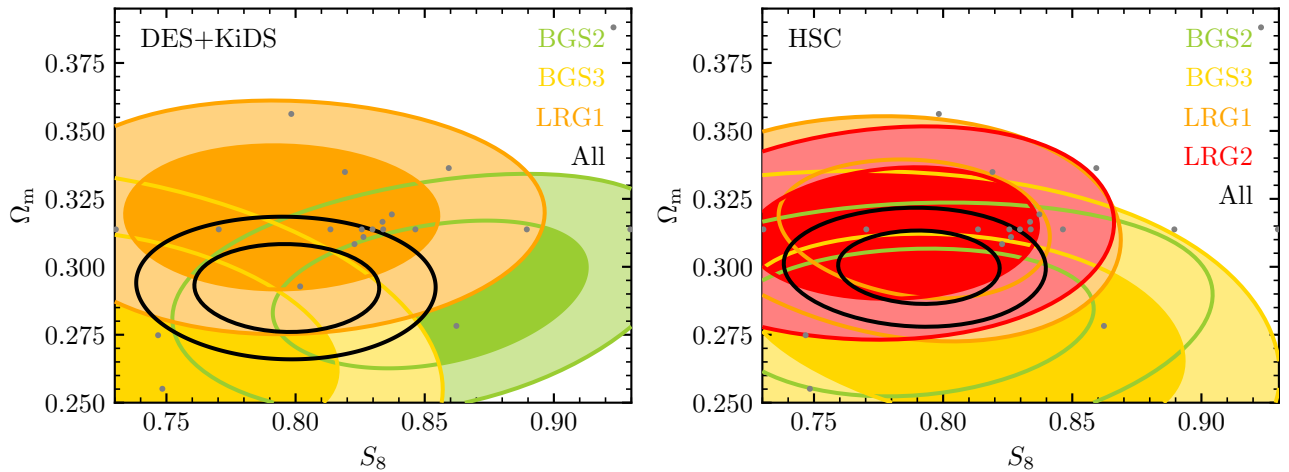


Figure 6. Observational constraints on S_8 and Ω_m for DESI clustering measurements combined with DES Y3 and KiDS-1000 lensing measurements (left) and HSC Y3 lensing amplitudes (right). The different shaded regions demarcate the $\Delta\chi^2 = 2.28$ and $\Delta\chi^2 = 5.99$ boundaries. The black contour indicates the combined results by adding the χ^2 contributions from the individual samples. As in Figure 2, small gray dots indicate the AbacusSummit simulations.

in the measured $\Delta\Sigma$ amplitudes (S. Heydenreich et al. 2025), we see consistency between the DES+KiDS and HSC constraints on S_8 and Ω_m .

For HSC, the constraints listed above assume the best-fit photometric redshift offsets found by X. Li et al. (2023). If we assume no offsets, we find $S_8 = 0.841 \pm 0.020$, a $\sim 2.5\sigma$ shift, and $\Omega_m = 0.305 \pm 0.009$, instead. However, the total χ^2 increases by 7.1, indicating that this scenario is disfavored by the data analyzed in this work. Given the shift of $\Delta S_8 = 0.050$ with $\Delta\chi^2 = 7.1$, we estimate that a full marginalization over photometric redshift calibration uncertainties would roughly add $\sim \Delta S_8 / \sqrt{\Delta\chi^2} = 0.019$ to the overall uncertainty in S_8 . In other words, the results for HSC are likely limited by systematic uncertainties in the photometric redshift calibration. Since unmasking of the cosmology constraints of this work, more recent studies (J. Choppin de Janvry et al. 2026; A. Fisher et al. 2026, in preparation) suggest that photometric redshift offsets are likely significantly smaller than the best-fit values by X. Li et al. (2023), which would lead to higher inferred S_8 values. Future studies analyzing DESI and HSC data jointly will employ these updated calibrations and significantly reduce systematic uncertainties related to photometric redshifts.

We compare our results derived here against the Planck Collaboration et al. (2020) CMB results as well as recent weak-lensing results from DES, HSC, and KiDS in Figure 7. Overall, our results are consistent with the Planck Collaboration et al. (2020) constraints albeit preferring a lower value for S_8 at 1.3σ (DES+KiDS) to 1.7σ (HSC). Consequently, our results are also consistent with recent weak-lensing results, which tend to have a preference for lower S_8 than CMB constraints.

Finally, it is worth comparing our results from the combination of clustering and galaxy–galaxy lensing to those derived in A. Porredon et al. (2026). The main difference compared to our work is a different choice of scale cuts: $8 h^{-1}$ Mpc for clustering and $6 h^{-1}$ Mpc. Additionally, A. Porredon et al. (2026) use point-mass marginalization, which further reduces the sensitivity to the lensing measurements near the scale cut (J. Prat et al. 2022). Ultimately, A. Porredon et al. (2026) find $S_8 = 0.707^{+0.090}_{-0.086}$, $0.707^{+0.094}_{-0.098}$, and $0.649^{+0.091}_{-0.067}$ for DES, KiDS, and HSC, respectively. These

constraints are substantially weaker than those derived in this work, highlighting the constraining power of nonlinear scales.

5. Conclusion

In this work, we present new constraints of cosmic structure growth from the analysis of nonlinear clustering and galaxy–galaxy lensing with DESI DR1. We implement a complex, simulation-based modeling framework that accounts for important details in the galaxy–halo connection such as galaxy assembly bias. Overall, our results align well with previous literature results. In particular, comparing with A. Porredon et al. (2026), we find that the analysis of nonlinear scales substantially improves the cosmological constraining power of the data (see, e.g., B. A. Reid et al. 2014; B. D. Wibking et al. 2019; J. U. Lange et al. 2022).

Our analysis places stringent constraints on cosmic structure growth, particularly the S_8 parameter. While our maximum-likelihood value for S_8 falls below that of the Planck Collaboration et al. (2020) CMB analysis, similar to many other low-redshift studies (see, e.g., E. Abdalla et al. 2022; X. Li et al. 2023; A. H. Wright et al. 2025; DES Collaboration et al. 2026), our results are also not in significant tension with CMB results. This finding is similar to other recent studies of nonlinear clustering and lensing (B. D. Wibking et al. 2020; A. Amon et al. 2023; A. Dvornik et al. 2023; J. U. Lange et al. 2023). Our results also align with earlier studies reporting the so-called lensing-is-low problem (A. Leauthaud et al. 2017; J. U. Lange et al. 2019b). This problem arises when comparing the lensing amplitude on very small scales, down to $0.1 h^{-1}$ Mpc, to predictions of simple mass-only HOD models and without the expected impact of baryons. In this work, we take into account assembly bias and do not model the scales expected to be most strongly affected by baryonic physics. Indeed, looking at Figures 3 and 4, we see that our best-fit models consistently overpredict lensing amplitude below $1 h^{-1}$ Mpc.

The present work serves as a precursor for future studies with DESI data that promise further increases in statistical constraining power. To fully realize this potential, further steps need to be taken to reduce systematic and modeling uncertainties. In the current analysis, we exclude the lensing signal on scales below $2.5 h^{-1}$ Mpc from the analysis due to

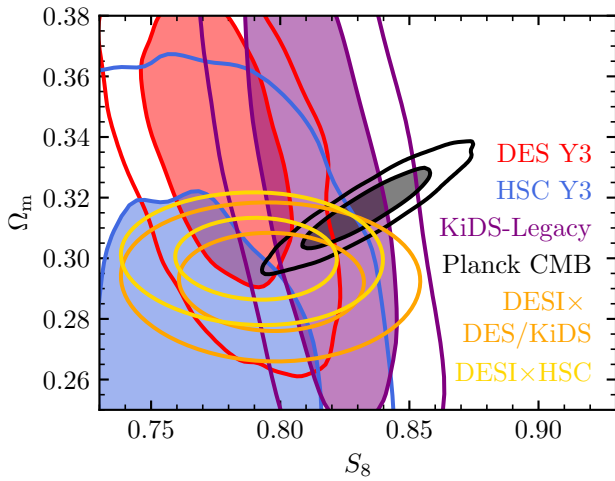


Figure 7. A comparison of the constraints derived in this work against the Planck Collaboration et al. (2020) TT,TE,EE+lowE CMB results and the latest publicly available cosmology results from DES Y3 (T. M. C. Abbott et al. 2022), HSC Y3 (X. Li et al. 2023), and KiDS-Legacy (A. H. Wright et al. 2025). Filled contours and nonfilled contours show the 68% and 95% containment ranges, respectively. For visual clarity, each of the publicly available results have been smoothed with a Gaussian kernel that has a covariance that is 4% that of the posterior.

the potential impact of baryonic physics. If we were to constrain baryonic feedback, we could potentially make use of the high-precision lensing measurements on these very small scales. Similarly, despite advances in recent years, further mock tests should be conducted to investigate the robustness of cosmological constraints from nonlinear scales (A. Doytcheva et al. 2024; The Beyond-2pt Collaboration et al. 2025; Z. Zhai et al. 2025). Finally, specifically for gravitational lensing with HSC, reducing uncertainties in the photometric redshift calibration is critical.

In the future, joint studies of clustering, lensing, and the Sunyaev–Zel’dovich effect could significantly reduce the uncertainty on baryonic physics and allow us to model smaller scales (S. Amodeo et al. 2021; L. Bigwood et al. 2024; J. Sunseri et al. 2026). In particular, the overlap of DESI with the footprint of the Atacama Cosmology Telescope (ACT) enables high-precision measurements of the kinetic Sunyaev–Zel’dovich effect (B. Hadzhiyska et al. 2025). Similarly, DESI is an excellent source for high-quality spectroscopic redshifts that will allow us to reduce uncertainties in the HSC photometric redshift calibration. This can be done both via clustering redshifts using DESI large-scale structure catalogs (R. Ruggeri et al. 2025; J. Choppin de Janvry et al. 2026) and direct calibration using DESI redshifts in deep drilling fields (J. U. Lange et al. 2026; J. Ratajczak et al. 2026).

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Data Availability

All data points shown in the published graphs are available on Zenodo: doi:10.5281/zenodo.17831718. We have released all TABCORR data products used in this work to the community on Zenodo at doi:10.5281/zenodo.15588541 as part of the TABCORR library.

Facilities: Mayall, Blanco, Subaru, ESO:VISTA, VST.

Software: ASTROPY (Astropy Collaboration et al. 2013, 2018, 2022), CORRFUNC (M. Sinha & L. H. Garrison 2020), DSIGMA (J. Lange & S. Huang 2022), HALOTOOLS (A. P. Hearin et al. 2017), MATPLOTLIB (J. D. Hunter 2007), NUMPY (S. Van Der Walt et al. 2011), SCIPY (P. Virtanen et al. 2020), TABCORR (J. U. Lange et al. 2019a), SPYDER, CLAUDE SONNET 5.

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