Unveiling the Intrinsic Alignment of Galaxies with Self-calibration and DECaLS DR3 Data

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Abstract

Galaxy intrinsic alignment (IA) is a source of both systematic contamination of cosmic shear measurement and its cosmological applications and valuable information on the large-scale structure of the universe and galaxy formation. The self-calibration (SC) method was designed to separate IA from cosmic shear, free of IA modeling. It was first successfully applied to the KiDS450 and KV450 data. We improve the SC method in several aspects and apply it to the DECaLS DR3 shear + photo-z catalog and significantly improve the IA detection to ~14σ. We find a strong dependence of IA on galaxy color, with strong IA signal (~17σ) for red galaxies, while the IA signal for blue galaxies is consistent with zero. The detected IAs for red galaxies are in reasonable agreement with the nonlinear tidal alignment model, and the inferred IA amplitude increases with redshift. Our measurements rule out the constant IA amplitude assumption at ~3.9σ for the red sample. We address the systematics in the SC method carefully and perform several sanity checks. We discuss various caveats, such as redshift/shear calibrations and possible improvements in the measurement, theory, and parameter fitting that will be addressed in future works.

Unified Astronomy Thesaurus concepts: Weak gravitational lensing (1797); Galaxy formation (595); Galaxy physics (612); Large-scale structure of the universe (902); Astrostatistics techniques (1886); Two-point correlation function (1951)

1. Introduction

For many cosmological probes, systematic errors in observation, theory, or both are becoming the dominant source of errors. They may already be responsible for several tensions in cosmology, such as the $H_0$ tension (Bernal et al. 2016; Freedman et al. 2019; Lin et al. 2019; Riess et al. 2019; Planck Collaboration et al. 2020). Another example is the $S_8 = σ_8/(Ω_m^{0.3})^{0.5}$ tension between the Planck cosmic microwave background experiment (Planck Collaboration et al. 2020) and stage III weak lensing surveys such as the Kilo Degree Survey (KiDS; Hildebrandt et al. 2017, 2020a; Asgari et al. 2020), Hyper Suprime-Cam (HSC; Hikage et al. 2019; Hamana et al. 2020), and Dark Energy Survey (DES; Troxel et al. 2018), with the $S_8$ differences varying between ~3σ and ~1σ. A variety of tests have been carried out in investigating the $S_8$ tension (e.g., Troxel et al. 2018; Asgari et al. 2019; Chang et al. 2019; Joudaki et al. 2020).

Among systematic errors in weak lensing cosmology based on cosmic shear measurement, the galaxy intrinsic alignment (IA) is a prominent one. Cosmic shear is extracted from galaxy shapes, with the underlying assumption that the intrinsic galaxy shapes have no spatial correlation. However, this assumption is invalid, since the large-scale structure environment induces spatial correlation in the galaxy shapes. In the context of weak lensing, the spatially correlated part in the galaxy shapes (ellipticities) is called IA. It has been predicted by theory/simulations (e.g., Croft & Metzler 2000; Catelan et al. 2001; Crittenden et al. 2001; Jing 2002; Hirata & Seljak 2004; Joachimi et al. 2013; Kiessling et al. 2015; Blazek et al. 2015, 2019; Chisari et al. 2017; Xia et al. 2017) and detected in observations (e.g., Lee & Pen 2001; Heymans et al. 2004; Bridle & King 2007; Okumura et al. 2009; Dosset & Ishak 2013; Kong et al. 2015; Krause et al. 2016; Kirk et al. 2015; Troxel et al. 2018; Samuroff et al. 2019; Yao et al. 2020). It is one of the key limiting factors to fully realize the power of weak lensing cosmology (Heavens 2002; Refregier 2003; Hoekstra & Jain 2008; LSST Science Collaboration et al. 2009; Weinberg et al. 2013; Troxel & Ishak 2015; Joachimi et al. 2015; Kilbinger 2015; Mandelbaum 2018).

In cosmic shear data analysis, IA is often mitigated by fitting against an assumed fiducial IA template (Troxel et al. 2018; Hildebrandt et al. 2017, 2020a; Hikage et al. 2019; Hamana et al. 2020). In contrast, the self-calibration (SC) methods (Zhang 2010a, 2010b) were designed to remove the IA contamination without assumption on the IA model. This model independence is achieved due to an intrinsic difference between the weak lensing field and the IA field. The former is a 2D (projected) field with a profound source–lens asymmetry, while the latter is a statistically isotropic 3D field. The SC2008 method (Zhang 2010a) has been applied to stage IV survey forecasts (Yao et al. 2017, 2019), while the SC2010 method (Zhang 2010b) has been examined in simulation (Meng et al. 2018) and combined with SC2008 in the forecast (Yao et al. 2019). These studies showed that the SC method is generally accurate in IA removal/measurement.

Yao et al. (2020) first applied the SC2008 method to the KiDS450 (Hildebrandt et al. 2017) and KV450 (Hildebrandt et al. 2020a) shear catalogs. To implement the SC method and incorporate it with various observational effects, such as photo-z errors, Yao et al. (2020) built a lensing–IA separation (LIS) pipeline and succeeded in the IA detection. To further test the
applicability of the SC method and improve the IA detection and applications, we apply the same LIS pipeline to the Dark Energy Camera Legacy Survey Data Release 3 (DECaLS DR3) shear catalog (Phriksee et al. 2020). Comparing to previous work, we have significantly more galaxies and larger sky coverage. We use the photo-z obtained from k nearest neighbors (kNN; Zou et al. 2019). These improvements result in more significant IA detection and allow us to reveal more detailed information on IA, such as its redshift and color dependence.

This paper is organized as follows. In Section 2, we briefly describe the SC method and LIS pipeline. We also describe the theoretical model to compare with. Section 3 describes the DECaLS DR3 data used for the analysis. Section 4 presents the main results, and Section 5 discusses further implications and possible caveats. We include more technical details in Appendices A–D.

2. The SC Method and the LIS Pipeline

The observed galaxy shape $\gamma_{\text{obs}}$ contains three components:

$$\gamma_{\text{obs}} = \gamma^G + \gamma^N + \gamma^I. \quad (1)$$

Here the superscript $G$ denotes gravitational lensing. The galaxy shape noise has a spatially uncorrelated part that we denote with the superscript $N$ and a spatially correlated part (the IA) that we denote with the superscript $I$. When cross-correlation $\gamma^{\text{obs}}$ with galaxy number density $\delta_g$, the $\gamma^N$ term has no contribution. The measured correlation will contain two parts:

$$\langle \gamma^{\text{obs}} \delta_g \rangle = \langle \gamma^G \delta_g \rangle + \langle \gamma^I \delta_g \rangle. \quad (2)$$

The first term on the right-hand side of the equation is the (lensing part) Gg correlation, and the second term is the (IA part) Ig correlation. The first step of SC2008 is to separate and measure Ig (and Gg) without resorting to IA modeling. The second step is to convert Ig into the GI term contaminating the measurement of cosmic shear autocorrelation through a scaling relation found in Zhang (2010a). The current paper is restricted to the first step, since no results on the cosmic shear autocorrelation will be presented here. We focus on the Ig measurement and its application.

2.1. Separating Gg and Ig

For a pair of galaxies, we denote the photo-z of the galaxy used for shape measurement as $z_g^P$ and the photo-z of the galaxy used for number density measurement as $z_g^N$. Both the IA and the galaxy number density fields are statistically isotropic 3D fields. Therefore, the $\langle Ig \rangle$ correlation with $z_g^P < z_g^N$ is identical to $\langle Ig \rangle$ with $z_g^P > z_g^N$. Namely, it is insensitive to the ordering of the $(z_g^P, z_g^N)$ pair in redshift space. This holds for both real (spectroscopic) and photometric redshift. In contrast, the lensing correlation requires $z_g > z_g$ for the true redshift ($z$). Therefore, in the photo-z ($z_g^P$) space, the $\langle Gg \rangle$ correlation is smaller for the pairs with $z_g^P < z_g^P$, compared with the $z_g^P > z_g^P$ pairs.7

Therefore, we can form two sets of two-point statistics measured from the same data in the same photo-z bin (e.g., the $i$th photo-z bin). In terms of the angular power spectrum,

$$C_{gg}^{Ig} = C_{gg}^{Gg} + C_{gg}^{Ig}, \quad (3a)$$
$$C_{gg}^{IG} = C_{gg}^{Gg} + C_{gg}^{IG}. \quad (3b)$$

Here $C_{gg}^{Ig}$ is the galaxy shape number density angular power spectrum for all pairs in the $i$th redshift bin, while $C_{gg}^{IG}$ is only for pairs with $z_i^P < z_i^P$. According to the above analysis, with this “$S$” selection, the lensing signal drops from $C_{gg}^{Gg}$ to $C_{gg}^{IG}$, while the IA signal $C_{gg}^{Ig}$ remains the same.

The drop in the lensing signal can be determined by the $Q$ parameter,

$$Q_i(\ell) \equiv \frac{C_{gg}^{IG}(\ell)}{C_{gg}^{Gg}(\ell)}. \quad (4)$$

Here $Q(\ell)$ has only a weak dependence on cosmology and $\ell$ (Zhang 2010a; Yao et al. 2017). This makes the SC method cosmology-independent to good accuracy. But it is sensitive to the photo-z quality. Here $Q = 0$ for perfect photo-z (the photo-z is accurate so that the lensing signal drops fully due to the selection), $Q \to 1$ for poor photo-z, and $Q \in (0, 1)$ in general.

We are then able to separate Gg and Ig (Zhang 2010a; Yao et al. 2020):

$$C_{gg}^{Gg}(\ell) = \frac{C_{gg}^{IG}(\ell) - C_{gg}^{IGS}(\ell)}{1 - Q_i(\ell)}, \quad (5)$$
$$C_{gg}^{IG}(\ell) = \frac{C_{gg}^{IGS}(\ell) - Q_i(\ell)C_{gg}^{IGS}(\ell)}{1 - Q_i(\ell)}. \quad (6)$$

In this work, we extended the formalism of SC to the correlation function, considering two additional effects and comparing to previous works (Zhang 2010a; Yao et al. 2017, 2020), (1) the scale-dependent $Q_i(\ell)$ and (2) impact from nonsymmetric redshift distribution, leading to $w_{gg}^{IG} \approx w_{gg}^{Ig}$ or $C_{gg}^{IGS} \approx C_{gg}^{Ig}$. As a result, we have

$$w_{gg}^{Gg}(\theta) = w_{gg}^{Gg}(\theta) + w_{gg}^{IG}(\theta), \quad (7a)$$
$$w_{gg}^{IGS}(\theta) = w_{gg}^{IGS}(\theta) + w_{gg}^{IGS}(\theta), \quad (7b)$$

which gives us

$$w_{gg}^{Gg}(\theta) = \frac{Q_i(\ell)w_{gg}^{Gg}(\theta) - w_{gg}^{IGS}(\theta)}{Q_i(\ell) - Q_i(\ell)}, \quad (8a)$$
$$w_{gg}^{IG}(\theta) = \frac{w_{gg}^{IGS}(\theta) - Q_i(\ell)w_{gg}^{Gg}(\theta)}{Q_i(\ell) - Q_i(\ell)}. \quad (8b)$$

Here the $Q$ values are calculated theoretically with a fiducial cosmology and the redshift distributions from data. The $Q_i^{Gg}$ is defined as

$$Q_i^{Gg}(\theta) \equiv \frac{w_{gg}^{Gg}(\theta)}{w_{gg}^{Gg}(\theta)}, \quad (9)$$

which is similar to the previous definition (Equation (4)) using angular power spectra. With this definition, we no longer need to assume a constant $Q$ value as before (Yao et al. 2020); instead, the angular scale dependency $Q_i^{Gg}(\theta)$ is taken into consideration for a more precise LIS.

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7 In the limit of negligible photo-z error, the $\langle Gg \rangle$ correlation vanishes for $z_g^P < z_g^P$ pairs. In reality, photo-z has both scatters and outliers, and the $\langle Gg \rangle$ correlation persists even for $z_g^P < z_g^P$ pairs.
Similarly, $Q_{i}^{k}$ is defined as
\[
Q_{i}^{k}(\theta) = w_{i}^{G}f_{i}(\theta)/w_{i}^{G}(\theta)
\]  
(10)
to account for the nonsymmetric redshift distribution, which could potentially make $Q_{i}^{k}$ deviate from 1 ($w_{i}^{G}f_{i} = w_{i}^{G}$).

Here $\{w_{i}^{G}, w_{i}^{G}f_{i}\}$ are direct observables, and $\{Q_{i}^{G}, Q_{i}^{k}\}$ can be robustly calculated given a photo-z probability distribution function (PDF), so we can separate and measure both $w_{i}^{G}$ and $w_{i}^{k}$ as in Equations 8(a) and (b). A key step in our method is to calculate $Q$. The calculation is straightforward but technical. We present a detailed description in Appendix B.

2.2. Interpreting the Separated Gg and Ig

The next step is to extract the physics out of the Gg and Ig separated above. We need to compare with the theoretically predicted $w_{i}^{G}$ and $w_{i}^{k}$. In this section, we briefly describe the basic theory of weak lensing and IA. The comparison between theory and observation will be presented in Section 4.

The lensing–galaxy cross power spectrum is calculated by the Limber equation,
\[
C_{ii}^{Gg}(\ell) = \int_{0}^{\infty} \frac{W(\chi)n_{i}(\chi)}{\chi^{2}} b_{\ell}P_{s}\left(k = \frac{\ell}{\chi}; \chi\right)d\chi.
\]  
(11)
Here $W_{i}$ is the lensing efficiency function. For a flat universe,
\[
W_{i}(\chi_{L}) = \frac{3}{2}\Omega_{m}\frac{H_{0}^{2}}{c^{2}}(1 + z_{L}) \int_{\chi_{L}}^{\infty} n_{i}(\chi)S_{\chi}\left(\frac{\chi - \chi_{L}}{\chi_{L}}\right)d\chi.
\]  
(12)

Here $n_{i}(\chi)$ is the galaxy distribution of the $i$th photo-z bin in the comoving distance space and linked to the galaxy distribution in the true redshift space by $n_{i}(\chi) = n_{i}(z)dz/d\chi$. Here $\chi$ is the comoving distance, $b_{\ell}$ is the galaxy bias, and $P_{s}$ is the matter power spectrum. Similarly, the IA–galaxy cross angular power spectrum $C_{ii}^{k}$ is given by
\[
C_{ii}^{k}(\ell) = \int_{0}^{\infty} \frac{n_{i}(\chi)n_{i}(\chi)}{\chi^{2}} b_{\ell}P_{s,\ell}\left(k = \frac{\ell}{\chi}; \chi\right)d\chi.
\]  
(13)
In this expression, $P_{s,\ell}$ is the 3D matter–IA power spectrum, which depends on the IA model being used (or the “true” IA model). For comparison, we adopt the nonlinear tidal alignment model (Catelan et al. 2001; Hirata & Seljak 2004) as the fiducial IA model. It is widely used in the other stage III surveys (Hildebrandt et al. 2017, 2020a; Troxel et al. 2018; Chang et al. 2019; Hikage et al. 2019; Hamana et al. 2020). In this model,
\[
P_{s,\ell} = -A_{IA}(L, z)\frac{C_{1}\rho_{m,0}}{D(z)}P_{k}(k; \chi),
\]  
(14)
where $\rho_{m,0} = \rho_{\text{crit}}\Omega_{m,0}$ is the mean matter density of the universe at $z = 0$, and $C_{1} = 5 \times 10^{-14} (h^{2}M_{0}/\text{Mpc}^{-3})$ is the empirical amplitude found in Bridle & King (2007). In this work, we adopt $C_{1}\rho_{\text{crit}} \approx 0.0134$ as in Krause et al. (2016) and Yao et al. (2020). Here $D(z)$ is the linear growth factor normalized to 1 today, and $A_{IA}(L, z)$ is the IA amplitude parameter, which is expected to be luminosity ($L$) and redshift ($z$)-dependent. In this work, we will investigate the possible redshift dependence and the galaxy type dependence of this $A_{IA}$ parameter.

The theoretical predictions of $w_{i}^{G}$ and $w_{i}^{k}$ are then given by the Hankel transformation,
\[
w_{i}(\theta) = \frac{w_{i}^{G}f_{i}(\theta)}{w_{i}^{G}(\theta)} = \frac{1}{2\pi} \int_{0}^{\infty} d\ell C(\ell)L_{2}(\ell\theta).
\]  
(15)
Here $J_{2}(x)$ is the Bessel function of the first kind of order 2. We adopt the CCL library$^{8}$ (Chisari et al. 2019) for the theoretical calculations. These results are cross-checked with CAMB$^{9}$ (Lewis et al. 2000) in previous work (Yao et al. 2020). The cosmological parameters being used to calculate the theoretical predictions are the best-fit cosmology of Planck2020 and KV450, as shown in Table 1. The impact from the uncertainties in the cosmological parameters on the theoretical predictions is negligible, compared with that from uncertainties in the galaxy bias $b_{g}$ and IA amplitude $A_{IA}$. Also, $\sigma_{k}$ strongly degenerates with $b_{g}$ in our case, and they both enter the estimation of $w_{i}^{G}$ and $w_{i}^{k}$ in the same way. Therefore, for the purpose of studying IA, it is valid to fix the cosmology.

3. Survey Data

We apply our method to the DECaLS DR3, which is part of the Dark Energy Spectroscopic Instrument (DESI) Legacy Imaging Surveys (Dey et al. 2019). The DECaLS DR3 contains images covering 4300 deg$^{2}$ in the $g$ band, 4600 deg$^{2}$ in the $r$ band, and 8100 deg$^{2}$ in the $z$ band. In total, 4200 deg$^{2}$ have been observed in all three optical bands. The DECaLS data are processed by Tractor (Meisner et al. 2017; Lang et al. 2014).

The sources from the Tractor catalog are divided into five morphological types, namely,

1. point source (PSF),
2. simple galaxies (SIMP; an exponential profile with a fixed 0.45 effective radius and round profile),
3. de Vaucouleurs (DEV; elliptical galaxies),
4. exponential (EXP; spiral galaxies), and
5. composite model (COMP; composite profiles that are de Vaucouleurs and exponential with the same source center).

In this catalog, the sky-subtracted images are stacked in five different ways: one stack per band, one “flat” spectral energy distribution (SED) stack each of the $g$, $r$, and $z$ bands, and one “red” ($g - r = 1$ mag and $r - z = 1$ mag) SED stack of all bands. The sources are kept above the detection limit in any stack as candidates. The PSF (delta function) and SIMP models are adjusted on individual images, which are convolved by their own PSF model.

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$^{8}$ Cosmology Library: https://github.com/LSSTDESC/CCL.

$^{9}$ Code for Anisotropies in the Microwave Background: https://camb.info/.
The galaxy ellipticities \( e_{1,2} \) are free parameters of the above SIMP, DEV, EXP, and COMP models but not the PSF model. The ellipticities are estimated by a joint fit on the optical \( g, r, \) and \( z \) bands. We model potential measurement bias with a multiplicative \((m)\) and additive bias \((c; \text{Heymans et al. 2012; Miller et al. 2013; Hildebrandt et al. 2017})\),

\[
\gamma_{\text{obs}} = (1 + m) \gamma_{\text{true}} + c.
\]  

(16)

The additive bias is expected to come from residuals in the anisotropic PSF correction. It depends on galaxy sizes. The multiplicative bias \( c \) is subtracted from each galaxy in the catalog. The multiplicative bias comes from the shear measurement. It can be generated by many effects, such as measurement method (Mandelbaum et al. 2015), blending, and crowding (Euclid Collaboration et al. 2019). In order to calibrate our shear catalog, we cross-matched the DECaLS DR3 objects with the Canada–France–Hawaii Telescope (CFHT) Stripe 82 objects and then computed the correction parameters (Phriksee et al. 2020). In addition, the data from the DECaLS DR3 catalog were tested with the Obiwan simulations (K. Burleigh et al. 2020, in preparation; Kong et al. 2020), also described in Table A1 in Phriksee et al. (2020).

We employ the photo-z from Zou et al. (2019), which is based on the algorithm of kNN and local linear regression. The photo-z is obtained from five photometric bands: three optical bands \((g, r, \) and \( z \)) and two infrared bands (Wide-field Infrared Survey Explorer W1 and W2). We use samples with \( r < 23 \) mag. The training sample includes \( \sim2.2 \) million spectroscopic galaxies.

For each galaxy we use in this work, we add two extra selections. One is to remove some galaxies with extreme shear multiplicative bias (requiring \( 1 + m > 0.5 \)). We note that many selection effects could potentially bias the shear calibration, with more details in Li et al. (2020), Huff & Mandelbaum (2017), and Sheldon & Huff (2017) and discussion of their potential impact on this work in Appendix C. The other is to require a small estimated photo-z error \((\Delta z < 0.1)\). Together with the selection of \( 0.1 < z < 0.9 \), we obtain 23 million galaxies for the SC analysis. We divide them into four photo-z bins \((0.1 < z < 0.3, 0.3 < z < 0.5, 0.5 < z < 0.7, \) and \( 0.7 < z < 0.9 \)) for each galaxy, our kNN photo-z algorithm also provides a Gaussian estimation of the photo-z error. We further apply this Gaussian scatter to obtain the redshift PDF for each galaxy. The overall photo-z distribution \( n_p(z^p) \) and true-z distribution \( n(\gamma) \) are shown in Figure 1. A more detailed discussion of the photo-z quality is included in Appendix A, where we show that the Gaussian PDF is not accurate; however, the overall scatter is accurate, which is of most importance in the SC analysis (Zhang 2010b). The possible impact of biased \( n(\gamma) \) is discussed in Appendix C.

4. Results

We present the measurement of \( w^{\gamma g} \) and \( w^{\gamma g} \) in Section 4.1, \( Q^{\gamma g} \) and \( Q^{\gamma g} \) in Section 4.2, and \( w_g^{\gamma g} \) and \( w_h^{\gamma g} \) in Section 4.3. All of the analysis in this work uses the default pipeline developed by J.Y. in Yao et al. (2020). The two-point correlation functions described in Equation (17) are performed with the TreeCorr code (Jarvis et al. 2004).

4.1. \( w^{\gamma g} \) and \( w^{\gamma g} \) Measurement

We adopt the following estimator (Mandelbaum et al. 2006; Singh et al. 2017; Yao et al. 2020) to calculate \( w^{\gamma g} \) and \( w^{\gamma g} \): 

\[
w^{\gamma g} = \frac{\sum_{i=1}^{n}\gamma_i - \sum_{i=1}^{n}w_i\gamma_i}{\sum_{i=1}^{n}w_i},
\]

(17)

Here \( \sum_{i=1}^{n}w_i \) means summing over all of the tangential ellipticity \((E)\)-galaxy number counts in the data \((D)\) pairs, and \( \sum_{i=1}^{n}w_i \) means summing over all of the tangential ellipticity \((E)\)-galaxy number counts in the random catalog \((R)\) pairs. The numerators give the stacked tangential shear weighted by the weight \( w_i \) from the shear measurement algorithm of the \( i \)th galaxy. The denominators give the normalization considering the number of pairs, the shear weight \( w_i \), and the calibration for shear multiplicative bias \((1 + m_i)\). Here we note that, after normalization with the number of galaxies, the two denominators \( \sum_{i=1}^{n}w_i\gamma_i \) and \( \sum_{i=1}^{n}(1 + m_i)w_i \) are generally considered the same at the large scale of our interest, as the boost factor (the ratio of these two) is normally considered as 1 (Mandelbaum et al. 2005; Singh et al. 2017).

For the random catalog, we use the DECaLS DR7 random catalog and fit it into the DECaLS DR3 shear catalog footprint (Phriksee et al. 2020) with Healpy. The size of our random catalog is \( \sim10 \) times the size of the whole DECaLS DR3 shear catalog. This random catalog is used in Equation (17) for the R part, while for the D part, we use the galaxies in each tomographic bin. So the random sample size is much larger than real data. After the random subtraction, the null test with \( \gamma^{\gamma g} \) (the 45° rotation of \( \gamma \)) of Equation (17) is consistent with zero.

We note that we are not including the sky varying survey depth in the random sample for three reasons. (1) Since our photo-z sample has a cut with \( r < 23 \) (Zou et al. 2019) to maintain high galaxy completeness, the “fake overdensity” due to this effect is expected to be low (Raichoor et al. 2017). (2) The small (due to the previous point) fake overdensity from varying the observational depth is expected to not correlate with the galaxy shapes, as both the lensing part and the IA part are parts of the large-scale structure. Therefore, the fractional contribution in the correlations as selection bias is expected to be even less than in the density field. (3) Even if a selection bias still exists in the two-point statistics, it should be captured by our jackknife resampling and is therefore appropriately included in the covariance matrix. In next-generation surveys, more detailed consideration for the random catalog should also be addressed.

We use jackknife resampling to obtain the covariance matrices of \( w^{\gamma g} \), \( w^{\gamma g} \), \( Q^{\gamma g} \), \( Q^{\gamma g} \), and the derived \( w^{\gamma g} \) and \( w^{\gamma g} \). We use a K-means clustering code, kmeans_radec, and generate 500 jackknife regions. The choice of 500 jackknife regions is to prevent biased estimation of the covariance for the length 34 data vector we are going to use (discussed in Section 4.3), based on the analysis of Mandelbaum et al. (2006) and Hartlap et al. (2007).

Figure 2 shows the measured \( w^{\gamma g} \) and \( w^{\gamma g} \). The observed \( w^{\gamma g} \) and \( w^{\gamma g} \) at all four redshift bins are statistically different, with \( 5.7 \sigma - 16.1 \sigma \) significance. This suggests that the photo-

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10 See https://obiwan.readthedocs.io for more details.
11 https://github.com/rmjarvis/TreeCorr
12 http://legacysurvey.org/dr7/files/
13 https://github.com/healy/healpy
14 https://github.com/esheldon/kmeans_radec
quality is sufficient for our needs, and the selection $z_{\ell}^\ell < z_{\ell}^\ell$ is sufficient to reduce the lensing contribution. This clear separation is a necessary condition for our SC method.

The $w^{\gamma \ell} - w^{\gamma \ell}_S$ separation is clearly more significant in this work than in Yao et al. (2020), which used KiDS450 and KV450 data. We think that this is mainly due to the larger galaxy number in our DECalS sample, especially in the second and third redshift bins. Differences in the photo-z algorithm adopted and the resulting photo-z quality may also matter. However, since we lack robust information on photo-z outliers to quantify its impact on SC, we leave this issue for further study.

We also show the theoretical curves in Figure 2 and calculate how good those fitting the $\chi^2$ are comparing to the data. This demonstrates that the nonlinear tidal alignment model can provide a reasonably good description of the measurement.

Nevertheless, we caution that they are not the best fit for $w^{\gamma \ell}$ and $w^{\gamma \ell}_S$ but rather the prediction from the best fit for $w^{\ell Gg}$ and $w^{\ell Gg}$, which we will discuss in the next subsection. The two data sets ($w^{\gamma \ell}$, $w^{\gamma \ell}_S$) versus ($w^{\ell Gg}$, $w^{\ell Gg}$) are identical if we have perfect knowledge of $Q^{Gg}$ and $Q^{Gg}$. In this work, we choose to fit against $w^{\ell Gg}$ and $w^{\ell Gg}$, since their physical meanings (the lensing–galaxy and IA–galaxy correlations) are more straightforward compared with $w^{\gamma \ell}$ and $w^{\gamma \ell}_S$. The reasonably good agreement (Figure 2) show that our best fit with scale cuts for ($w^{\ell Gg}$, $w^{\ell Gg}$) also agrees very well with the ($w^{\gamma \ell}$, $w^{\gamma \ell}_S$) measurements. In a future analysis, we can alternatively use $w^{\gamma \ell}$ and $w^{\gamma \ell}_S$ directly for the fitting. For such an exercise, we also need the covariance matrix of the two sets of observables. We discuss them in Appendix D and Figure 19. As expected, the two have a strong positive correlation, since $w^{\gamma \ell}_S$ is totally and positively included in $w^{\gamma \ell}$. Such a strong correlation must be taken into account in the related data analysis. Also due to this strong correlation, the fitted curves are visually different from the data at some level, while the fitting $\chi^2$ values are reasonable, as shown in Figure 2.

4.2. The Lensing Drop $Q^{Gg}_\ell$ and IA Drop $Q^{\ell Gg}_\ell$

Figure 3 shows the measured lensing drop $Q^{Gg}_\ell$ from the power spectra definition as in Equation (4) and $Q^{Gg}_\ell$ from the correlation function definition as in Equation (9). We leave the calculation details to Appendix B. As we explain in Section 2.1, $Q^{Gg}$ is mainly determined by the photo-z quality, with $Q^{Gg} = 0$ for perfect photo-z and $Q^{Gg} = 1$ for totally wrong photo-z. For the SC method to be applicable, $Q^{Gg}$ must be significantly smaller than unity (Zhang 2010a; Yao et al. 2020). Figure 3 shows that $Q(\ell) \sim 0.5$ for a wide range of $\ell$ and photo-z bins. Therefore, the photo-z quality is already sufficiently good to enable the SC method. Here $Q$ varies between photo-z bins. We tested that for a photo-z outlier rate of $<20\%$, the bias in $Q$ for the current stage surveys is negligible. Besides the difference in photo-z quality, the
effective width of the lensing kernel \((W_L(z_S, z_L))\) also plays a role.

According to Figure 3, as well as our previous work (Yao et al. 2020), the \(Q_{IG}^{\ell k}\) value is roughly constant in the range of \(50 < \ell < 3000\). This is the main regime of interest in weak lensing cosmology. Previously, we adopted the approximation \(\hat{Q}_i = \langle Q_i(\ell) \rangle\), which could potentially underestimate the IA signal at small scales and overestimate it at large scales. In this work, by using scale-dependent \(Q(\theta)\), as shown in the right panel of Figure 3, we get rid of this effect. However, we note that as photo-z quality improves and/or redshift increases, the \(Q\) value will become more scale-independent, so the above approximation should still hold. Thus, this is not a major problem, but it is still worth bringing out.

In Figure 3, we also include the statistical errors. They are shown by the shaded regions, while the error bars are exaggerated (20 times). The fact that the \(Q\) values have very low statistical error proves our previous statements in Yao et al. (2017, 2020).

Similarly, we show the \(Q_{IG}^{\ell k}\) measurements in Figure 4. Generally, \(Q_{IG}^{\ell k} \sim 1\) is a good assumption. However, due to the nonsymmetric photo-z distribution \(n_E(z_E)\) and true-z distribution \(n_i(z)\) shown in Figure 1, the \(Q_{IG}^{\ell k}\) for real data will deviate from 1. We tested that for the \(\sim 10\%\) overestimation for \(Q_{IG}^{\ell k}\) (if assumed to be 1) shown in Figure 4, the resulting \(w_{IG}^{\ell k}\) will be underestimated by \(\sim 20\%\). Interestingly, the final estimation of the IA amplitude \(A_{IA}\) is almost unbiased (see later in Figure 8), which is due to the corresponding changes in the covariance matrix, as well as the \(w_{IG}^{\ell k}\) signal.

Furthermore, we tested how the \(Q\) parameters depend on the assumed fiducial cosmology. We compared the calculation of \(Q_{IG}^{\ell k}\) and \(Q_{IG}^{\ell k}\) with Planck2020 and KV450 cosmology (where the main \(S_8\) tension resides), as shown in Table 1. The differences are at an \(\sim 10^{-3}\) to \(10^{-5}\) level, and the resulting bias in \(w_{IG}^{\ell k}\) is at an \(\sim 10^{-3}\) level. This proved our previous statement in Yao et al. (2017, 2020) that, by construct, the \(Q_{IG}^{\ell k}\) and \(Q_{IG}^{\ell k}\) measurements are insensitive to the fiducial cosmology. For the same reason, \(Q_{IG}^{\ell k}\) is also insensitive to the assumed IA model.

4.3. Lensing–IA Separation

With the measured \(\{w_{IG}^{\ell k}, w_{IG}^{\ell k}\}_{\ell}\) (Figure 2), \(Q_{IG}^{\ell k}\) (Figure 3), and \(Q_{IG}^{\ell k}\) (Figure 4), we are able to separate \(w_{IG}^{\ell k}\) and \(w_{IG}^{\ell k}\) by Equations 8(a) and (b). The results are shown in Figure 5, along with the normalized covariance matrix (Figure 6). We cut off small scales to prevent further contamination from nonlinear galaxy bias, massive neutrinos, baryonic effects, boost factor, etc. We cut off large scales to prevent impacts from an insufficient random catalog. The cuts are shown by the gray shaded regions. The detection of IA \(w_{IG}^{\ell k}\) is significant at all four redshift bins, and the corresponding signal-to-noise ratio \((S/N) = 3.5, 11.9, 5.5,\) and 4.1\(^{15}\).

Now we compare with the theoretical prediction of the nonlinear tidal alignment model. Since the predicted \(w_{IG}^{\ell k} \propto b_2 A_{IA} P_{\ell}\), we need to include the measurement \(w_{IG}^{\ell k} \propto b_2 P_{\ell}\) in order to break the \(b_2 A_{IA}\) degeneracy. Since both \(w_{IG}^{\ell k}\) and \(w_{IG}^{\ell k}\) are derived from the same set of data, they are expected to have a strong negative correlation. Figure 6 confirms this expectation of a strong anticorrelation. This figure shows the cross-correlation coefficient (normalized covariance matrix). \(r_{ab} \equiv \text{Cov}(a, b) / \sqrt{\text{Cov}(a, a) \text{Cov}(b, b)}\). Here \(a, b \in \{w_{IG}^{\ell k}(\theta_1), w_{IG}^{\ell k}(\theta_2), \ldots, w_{IG}^{\ell k}(\theta_1), \ldots\}\). Therefore, we should fit for \(w_{IG}^{\ell k}\) and \(w_{IG}^{\ell k}\) simultaneously and take this anticorrelation into account. We test that, if we ignore this strong anticorrelation and fit \(w_{IG}^{\ell k}\) and \(w_{IG}^{\ell k}\) separately, the best fits do not well reproduce \(w_{IG}^{\ell k}\) and \(w_{IG}^{\ell k}\) in Figure 2. When doing the fitting, we only use the \(34 \times 34\) matrix that correspond to the cuts in Figure 5.

\(^{15}\) We caution that the detection significance is likely overestimated, since we do not include uncertainties in the \(Q\) value. The induced fluctuation is \(\delta w_{IG}^{\ell k} = -w_{IG}^{\ell k} / (1 - Q_i = -w_{IG}^{\ell k} \times 2Q_i)\). Since \(w_{IG}^{\ell k}\) is \(w_{IG}^{\ell k}\) for the full sample, the induced fractional error is \(\delta w_{IG}^{\ell k} / w_{IG}^{\ell k} \sim -2Q_i\). The statistical \(Q_i\) fluctuation estimated by the jackknife method is \(\sim 10^{-3}\) and therefore negligible in the \(w_{IG}^{\ell k}\) error budget. However, the systematic error of \(Q_i\) arising from photo-z outliers may be larger. Unless \(|Q_i| > 0.5\), the detection significance of \(w_{IG}^{\ell k}\) will not be significantly affected. After we have a reliable estimation of photo-z outliers, we will quantify its impact.
We also notice that the main correlation is between $w^{gi}_G$ and $w^{gi}_I$ in the same bin $i$. There is no significant correlation between different redshift bins. This is more proof that the impact of photo-$z$ outliers on our LIS is not significant.

The theoretical fitting is carried out with a fixed cosmology (Planck cosmology in Table 1) and a fixed IA model (the nonlinear tidal alignment model). So there are only two free parameters in the fitting, namely, the galaxy bias $b_g$ and the IA amplitude $A_{IA}$. The two contain the leading-order information on the measurements, since $w^{gi}_G \propto b_g$ and $w^{gi}_I \propto b_g A_{IA}$. Furthermore, a large fraction of cosmological dependence (in particular $\sigma_8$) can be absorbed into $b_g$, since both $w^{gi}_G \propto b_g P_g$ and $w^{gi}_I \propto (b_g P_g) \times A_{IA}$. Also for this reason, the constraint on $A_{IA}$ is less cosmology-dependent than that on $b_g$. Since the major purpose of this work is to study IA, the above simplification in model fitting meets our needs. With future data of significantly improved S/N, we will perform a global fitting with relaxed constraints of cosmology and IA models.

The Markov Chain Monte Carlo (MCMC) fitting results on $b_g$ and $A_{IA}$ are shown in Figure 7, plotted with the code “corner” (Foreman-Mackey 2016). The best-fit values in this figure are used to plot the best-fit curves in Figures 2 and 5. The best-fit curves agree with both the lensing signal and the IA signal reasonably well. This suggests that the LIS method works well and supports the nonlinear tidal alignment IA model within the angular range of this work. In the future, with better data and sufficient modeling of small scales, we can further investigate IA physics in the nonlinear regime.

Figure 7 shows a clear redshift dependence on the IA amplitude $A_{IA}$. Comparing with a redshift-independent fitting with the best-fit $A_{IA} = 1.05$, our measurements rule out the constant IA amplitude assumption at $\sim 3\sigma$ (also see Figure 15 with the $A_{IA}(z)$ plot). When the redshift increases, $A_{IA}$ becomes larger. The only exception is redshift bin 2. This is likely due to larger photo-$z$ scatters and a higher red galaxy fraction of redshift bin 2. We will further discuss it in Section 4.4. We also investigated the impact of assuming $Q^{gi} = 1$ in Figure 8. We only show bins 1 and 4 for readability, but we note that the $A_{IA}$ from this assumption is consistent with the ones with varying $Q^{gi}(\theta)$.

We caution that photo-$z$ outliers can also lead to biased estimation in $A_{IA}$. Even though this is beyond the scope of this paper, we try to quantify the quality of the photo-$z$ being used in Appendix A. More sanity checks will be discussed in the next section.

The high S/N in Figure 5 motivates us to further investigate the following questions.

1. How do the IA signals depend on the galaxy color (red/blue galaxies) or other galaxy properties?
2. How does the IA amplitude evolve with redshift for red and blue galaxies?
3. How good is the current nonlinear tidal alignment model?

4.4. Separate IA Measurements for Red and Blue Galaxies

The galaxy IA is expected to rely on galaxy type, and a major dependence is the galaxy color (red/blue galaxies). Therefore, we apply the SC method separately for red and blue galaxies. The classification is done through the estimated clustering effect in color-redshift space, obtained with the kNN algorithm (Zou et al. 2019). The classification criteria are shown in Figure 9, with the total number of red/blue galaxies shown in Table 2. The overall red fraction is 32%.

4.4.1. Red Galaxies

Figure 10 shows the separated lensing and IA signals for red galaxies, along with the best-fit theoretical curves. The detection of IA ($w^{gi}_I$) for red galaxies is significant at all four redshift bins, and the corresponding S/Ns are comparable at low-$z$ and significantly higher than the full sample at high-$z$, even with a much smaller sample (Table 2). This means that blue galaxies included in the full sample contribute little to the IA signal but induce significant noise and dilute the IA measurement S/N. Generally, we achieved good fits for both the lensing part and the IA part. Overall, the nonlinear tidal alignment model is a good description of the IA of red galaxies.

We further present the effective galaxy bias obtained from the red galaxies for a sanity check in Figure 11. Since we have a better S/N with red galaxies, it will be more important to show the consistent results from different methods. We get the effective galaxy bias from the SC-separated lensing signal by calculating the ratio between the measurements from data and the theoretical predictions assuming $b_g = 1$, namely, $b_g = w^{gi}_{SC} / w^{gi}_{th}, b_g = 1$. Alternatively, it can be obtained from the angular galaxy clustering of the same sample, following $b_g = w^{gi}_{data} / w^{gi}_{theory}, b_g = 1$. In Figure 11, we show that these two methods give consistent results. This works as a further sanity check in showing that the results are robust against different systematics. The following are some examples.

1. The sharp nonlinear galaxy bias is cut off at small scales.
2. At large scales, when the effective $b_g$ is obviously nonlinear, it could be the impact of the insufficient random catalog. Thus, it is cut off.
The photo-z outlier should impact $w_{GG}$ and $w_{GG}^*$ differently. While they are consistent, we know that the impact from the photo-z outlier is within a reasonable range. Figure 12 shows the constraints of $b_g$ for the red galaxies. We see a clear redshift evolution of $A_{IA}$; namely, $A_{IA}$ increases with increasing $z$. Even for the second and third bins, where the confidence contours are quite close, their $A_{IA}$ differs at the $\sim 2\sigma$ level, thanks to the small uncertainties from a large number of galaxies. Comparing a redshift-independent fitting with the best-fit $A_{IA} = 1.87$, our measurements rule out the

| $0.1 < z < 0.9$ | $z1$ | $z2$ | $z3$ | $z4$ |
|-----------------|------|------|------|------|
| Red+blue        | 23.4M| 2.9M | 6.1M | 9.7M | 4.7M |
| Red             | 7.4M | 0.8M | 2.3M | 3.2M | 1.1M |
| Blue            | 16.0M| 2.0M | 3.8M | 6.5M | 3.6M |
| Red fraction    | 32%  | 28%  | 38%  | 33%  | 23%  |

Figure 7. The MCMC fitting results (with 68% and 95% confidence contours) for the galaxy bias $b_g$ and IA amplitude $A_{IA}$ of each photo-z bin. We find a clear redshift-dependent evolution on the IA amplitude $A_{IA}$. The strong constraining power in bins 2 and 3 is due to their large numbers of galaxies, as shown in Figure 1. The abnormal behavior of bin 2 is due to the large fraction of red galaxies and possible bias from photo-z, which will be discussed later in this work.

Figure 8. We show the comparison between using $Q^{M}(\theta)$ as in Equation (10) and assuming $Q^{M} = 1$ as in previous work (Yao et al. 2020). The systematic error of assuming $Q^{M} = 1$ is not significant for the current stage weak lensing surveys; however, it could potentially matter for the stage IV surveys.

Figure 9. Red/blue galaxy classification through the color-redshift cut (black dashed curve) in $m_g - m_z$ vs. $z'$ space. Table 2 shows the total number of red/blue galaxies.

Table 2

The Number of Red/Blue Galaxies in Units of Millions (M)

Figure 10. Similar to Figure 5 but for red galaxies. The joint fits on the galaxy bias $b_g$ and IA amplitude $A_{IA}$ are shown in Figures 12 and 15 and Table 3.

Figure 11. Comparison between effective galaxy bias $b_g$ from the SC lensing signal ($b_g = w_{GG} / w_{GG}^*$; blue) and galaxy clustering ($b_g = w_{Gg} / w_{Gg}^*$; orange) for the red galaxies. The consistency between these two shows the accuracy of the LIS.

(3) The photo-z outlier should impact $w_{GG}$ and $w_{GG}^*$ differently. While they are consistent, we know that the impact from the photo-z outlier is within a reasonable range. Figure 12 shows the constraints of $b_g - A_{IA}$ for the red galaxies. We see a clear redshift evolution of $A_{IA}$; namely, $A_{IA}$ increases with increasing $z$. Even for the second and third bins, where the confidence contours are quite close, their $A_{IA}$ differs at the $\sim 2\sigma$ level, thanks to the small uncertainties from a large number of galaxies. Comparing a redshift-independent fitting with the best-fit $A_{IA} = 1.87$, our measurements rule out the
constant IA amplitude assumption at $\sim 3.9 \sigma$ (also see Figure 15 with the $A_{IA}(z)$ plot). For future cosmic shear or shear cross-correlation studies, it is then important to take this redshift dependence into account. This is also important in studies of galaxy formation, and it could be potentially related to Kurita et al. (2020), where the halo IA (not the galaxy IA in our work) amplitude is also found to be $z$-dependent. The connection between halo IA and galaxy IA was also discussed in Okumura et al. (2009). More details about our IA results can be seen in Figure 15 and Table 3.

Furthermore, recall that for the full (red+blue) sample, the second redshift bin has an unusually large $A_{IA}$ (Figure 7). The fact that the second and third bins have similar $A_{IA}$ for the red galaxies may also be responsible in this situation.

### 4.4.2. Blue Galaxies

Figure 13 presents the separated lensing and IA signals along with their best-fit theoretical curves for blue galaxies. The $b_S$ and $A_{IA}$ constraints are shown in Figure 14, as well as Figure 15 and Table 3. In contrast to the red galaxies, we do not detect the IA signal in bins 2–4. This generally agrees with our current understanding that the IA signals mainly exist in the red galaxies. However, we do detect the IA signal for blue galaxies in the lowest redshift bin, although the signal is weak. When fitted with the nonlinear tidal alignment IA model, the detection significance is $\sim 1 \sigma$. The current LIS method cannot fully quantify the impact of photo-$z$ outliers, plus blue galaxies normally have worse photo-$z$ measurements compared with red galaxies; therefore, whether this signal is real or not requires future exploration with better data.

### 5. Summary and Conclusions

In this work, we apply the LIS pipeline of the SC method to the DECaLS DR3 shear + photo-$z$ catalog. This allows us to measure the galaxy IA signal free of assumptions on the IA model. Therefore, the measurement not only reduces IA contamination in weak lensing cosmology but also provides valuable information on the physics of IA and galaxy formation. Comparing to our previous work with the KiDS data (Yao et al. 2020), we have improved the technique and analysis in the following ways.

1. We improved the SC formalism with a scale-dependent $Q^G(\theta)$ rather than a constant, as in Equation (9) and Figure 3. This prevents a biased estimation of $w^G$ and

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Table 3
The Best-fit $A_{IA}$ and the 1$\sigma$ Error

| $A_{IA}$ | $z_1$ | $z_2$ | $z_3$ | $z_4$ |
|---------|-------|-------|-------|-------|
| Red+blue | 0.70$^{+0.15}_{-0.20}$ | 1.19$^{+0.19}_{-0.19}$ | 1.05$^{+0.15}_{-0.19}$ | 1.47$^{+0.25}_{-0.18}$ |
| Red     | 0.82$^{+0.41}_{-0.26}$ | 1.69$^{+0.19}_{-0.17}$ | 2.00$^{+0.19}_{-0.16}$ | 3.06$^{+1.00}_{-0.46}$ |
| Blue    | 0.69$^{+0.28}_{-0.59}$ | 0.18$^{+0.37}_{-0.52}$ | $-0.49^{+0.64}_{-1.03}$ | $-0.75^{+1.12}_{-0.50}$ |
Figure 15. Color and redshift dependence of the best-fit $A_{1A}$. Dashed lines are the best fit with the constant $A_{1A}$ assumption.

$w^{\text{BG}}$ at low-$z$ that shifts power between large and small scales.

2. We improved the SC formalism by introducing the IA drop $Q^{\text{IA}} \approx 1$ due to nonsymmetric redshift distribution; see Equation (10) and Figure 4. We show in Figure 8 that for the current stage, the resulting $A_{1A}$ is not biased, even with the assumption $Q^{\text{IA}} = 1$. But it could matter for future surveys.

3. We tested for different cosmology; as in Table 1, the $Q$ parameter will be biased by $\sim 10^{-5}$ to $\sim 10^{-3}$, and the resulting $w^{\text{BG}}$ will be biased by the $\sim 10^{-3}$ level. This demonstrated that the bias from the fiducial cosmology that the SC method needs to assume is negligible. For the same reason, $Q^{\text{IA}}$, by construct, is also insensitive to the assumed IA model. The bias from the assumed IA model should be much smaller compared to Figure 8.

4. We use jackknife resampling in each step of the calculation so that all statistical uncertainties are included. We show that the statistical error on $Q$ is $\sim 10^{-3}$ in Figures 3 and 4. This demonstrates our previous statement in Yao et al. (2017) that $Q$ will not introduce much statistical error. Addressing the systematic error from the photo-$z$ outlier, on the other hand, is beyond the scope of this paper, as perfect knowledge of redshift is required.

5. We introduce the covariance between $w^{\text{BG}}$ and $w^{\text{IA}}$ in Figure 6, where the strong anticorrelation was not taken into consideration in previous work. This leads to more reliable fitting.

6. We include the impact of galaxy bias $b_g$ in this work. It was discussed as one of the most important systematics in the SC method in Yao et al. (2017). We performed a simultaneous fitting for the linear galaxy bias $b_g$ and IA amplitude $A_{1A}$ to account for its effect; see Figures 7, 12, and 14.

7. We apply additional scale cuts to prevent bias from different systematics, including nonlinear galaxy bias, insufficient modeling of the matter power spectrum at small scales, fake signal due to an insufficient random catalog at large scales, etc.

8. We include multiple sanity checks in this work to validate our results, including checking that the cross-shear ($45^\circ$ rotation) measurements are consistent with zero, comparing the resulting effective galaxy bias between the separated $w^{\text{BG}}$ and galaxy clustering $w^{\text{IA}}$, finding no significant correlation between different $z$ bins in the covariance matrix, comparing $A_{1A}$ with other analyses, etc.

With the above improvements, we obtain reliable measurements of the separated lensing signal $w^{\text{BG}}$ and IA signal $w^{\text{IA}}$. Our findings are summarized in Tables 3 and 4 and visualized in Figure 15 with the following aspects.

1. The separation and measurement of lensing and IA are more robust and statistically significant. A crucial diagnostic is the differences in the two direct observables $w^{\text{BG}}$ and $w^{\text{IA}}$. The measured difference is improved to $\sim 16\sigma$ for a single redshift bin (bin 2) and $\sim 21\sigma$ (comparing with $\sim 16\sigma$ in our previous work; Yao et al. 2020) for the full galaxy sample. For this reason, the total detection significance of the IA signal reaches $\sim 14\sigma$. The overall IA amplitude of our DECaLS DR3 sample is consistent with the KV450 (Hildebrandt et al. 2020a) results but with a stronger constraint; see Figure 15. It is also consistent with the common understanding that $A_{1A} \sim 1$.

2. We detect the IA dependence on galaxy color. For red galaxies, we detect IA in all photo-$z$ bins at $0.1 < z^p < 0.9$. The detected IA signal shows reasonable agreement with the nonlinear tidal alignment model. The red–blue separation increases the S/N of IA detection in red galaxies to $\sim 17.6\sigma$.

3. We find for blue galaxies that the IA signal is generally consistent with zero, except for the weak and tentative ($\sim 1\sigma$) detection in the lowest redshift bin at $z^p < 0.3$.

4. Our results rule out the assumption of constant IA amplitude at $\sim 3.9\sigma$ for the red sample and $\sim 3\sigma$ for the full sample. Especially for red galaxies, the IA amplitude $A_{1A}$ increases with redshift. From Figure 15, we can also see a (not clear) evolution pattern for the blue galaxies; nonetheless, the full sample also seems to have an $A_{1A}(z)$ evolution pattern, which agrees with our previous finding for KV450 (Yao et al. 2020) that IA is stronger at high-$z$.

Tests of how the calibrations of multiplicative bias and redshift distribution can affect the $A_{1A}(z)$ relation are shown in Appendix C. More tests of the $z$-dependencies for the full and blue samples can be done with a larger galaxy number and better photo-$z$ in the future. We note that similar $z$-evolution results have been found in a recent study with hydrodynamic simulations (Samuroff et al. 2020).

5. Our separated IA signals do not rely on strong assumptions about IA physics. The MCMC fitting for $b_g$ and $A_{1A}$ assumed the nonlinear tidal alignment model,
also known as the nonlinear linear alignment (NLA) model; see Equation (14). But it can also be used to investigate other alternatives, for example, Blazek et al. (2019) and Fortuna et al. (2020). Here we present the fitting \( \chi^2 \) in Table 4. We notice that for the red galaxies, in bins 2 and 3, where the IA detection is most significant, the \( \chi^2/dof \) is not ideal. This suggests possible systematics and/or potential deviation from the assumed NLA model. However, the relatively large \( \chi^2 \) could also come from a photo-z outlier (see Appendix A) that we are unable to fully address in this work. We leave this point for future studies.

With better data such as the DECaLS DR8, future data releases from KiDS/HSC/DES/LSST/etc., and possible improved photo-z estimation and shear measurements (which are beyond the scope of this paper; see discussion in Appendix C), we plan to robustly measure the IA amplitude and its dependence on the physical scale, redshift, and galaxy properties such as color and flux. We may also be able to reveal more detailed information, such as the observed negative \( b_{r-A_{IA}} \) correlation in red galaxies and the possibly positive correlation in blue galaxies (Figures 12 and 14). This information will be useful to understand galaxy formation. Furthermore, the same analysis also provides the measurement of \( w^{Gg} \), namely, the lensing–galaxy cross-correlation free of IA contaminations. These data contain useful information to constrain cosmology, as discussed in previous work (Yao et al. 2020). This method could also potentially be affected by modified gravity, as the separated lensing signal relies on the gravitational potential \( \nabla^2(\phi - \psi) \), while the IA signal relies on \( \nabla^2\phi \) (Zhang et al. 2007). We will present more cosmological studies in separate future works.

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### Appendix A

#### Validating the Photo-z Quality

We emphasize that the photo-z techniques are beyond the scope of this paper. Nonetheless, here we present the validation of the photo-z samples being used in this work, in addition to the correlation functions. We combine galaxies from UDS HSC + SPLASH (Mehta et al. 2018), ECDFS (Cardamone et al. 2010), CFHTLS Deep + WIRDS (Bielby et al. 2010), and COSMOS (Laigle et al. 2016) to get a large reliable photo-z catalog. The overall redshift distribution is quite similar to the \( n(z) \) determined from COSMOS only and was already presented in Phriksee et al. (2020). By matching the above “good photo-z catalog” with our catalog of DR3 shear and kNN photo-z, we have a resulting sample with 46,961 galaxies.

We refer to the good photo-z catalog as “true-z” in the following tests. In Figure 16, we present the direct comparison between the kNN photo-z \( z_{knn} \) shown on the x-axis) samples being used in this work and the selected good redshift \( z_{tr} \) shown on the y-axis) samples. There are clearly two outlier regions, at \( z_{knn} \sim 0.5 \) (corresponding mainly to bins 2 and 3 of this work) and 1 (which is cut off in this work). We calculated the photo-z outlier rate \( f_{\Delta z>0.15} \), defined as the fraction with \( |z_{knn} - z_{tr}| > 0.15 \), which is [0.09, 0.19, 0.26, 0.15] for the four \( z \) bins being used. The corresponding systematic shift \( (z_{knn} - z_{tr}) \) is [0.02, 0.06, 0.08, 0.01].
this redshift range, leading to some misclassification of the photo-z.

Generally, the photo-z quality in this work is suitable for the study of SC. The kNN photo-z (Zou et al. 2019) gives reliable best-fit photo-z and Gaussian scatter to present the underlying $n_z(z)$. However, we found that, due to the redshift–color degeneracy discussed in Zou et al. (2019), there are some significant redshift outliers in our bins 2 and 3, which can lead to some bias in our $w_{Gg}$ and $w_{Ig}$. This bias is smaller for red galaxies, as their photo-z is generally better. There could also be biases due to training sample selection, for example, Hartley et al. (2020), but they are beyond the scope of this paper.

Appendix B
Calculating the Lensing and IA Drop $Q$

The lensing drop $Q^{Gg}$ and IA drop $Q^{Ig}$ play crucial roles in LIS (Equations 8(a) and (b)), where $\{w_{Gg}, w_{Ig}\}$ comes from Hankel transformation as in Equation (15). Therefore, to get $Q$, we need to calculate the power spectra for $\{C_{Gg}^{Gg}, C_{Gg}^{Ig}, C_{Ig}^{Gg}, C_{Ig}^{Ig}\}$ with the given photo-z information of the survey.

Theoretically, $C_{Gg}^{Gg}$ is given by Equation (11), and $C_{Gg}^{Ig}$ is given by

$$C_{Gg}^{Gg}(\ell) = \int_0^\infty W_i(\chi) n_i(\chi) b_i P_k \chi^2 d\chi \times \left( k = \frac{\ell}{\chi}; \chi \right) \eta^{Gg}(z) d\chi.$$

(B1)

The extra factor $\eta^{Gg}(z)$ arises from the fact that $C_{Gg}^{Gg}$ only contains pairs with $z_i^g < z_g^p$ (Zhang 2010a):

$$\eta^{Gg}(z) = \eta^{Gg}(z_L = z_g = z),$$

$$\eta^{Gg}(z_L, z_g) = \frac{2 \int dz_L \int dz_g \int_0^\infty dz_g W_L(z_L, z_g) p(z_L) p(z_g) S(z_L, z_g) n^p_i(z_g) n^p_i(z_g)}{\int dz_L \int dz_g \int_0^\infty dz_g W_L(z_L, z_g) p(z_L) p(z_g) S(z_L, z_g) n^p_i(z_g) n^p_i(z_g)}.$$

(B2)

Here $z_L$, $z_g$, and $z_g^p$ denote the lens, galaxy, and lensing source redshifts, respectively. The quantities with superscript “P” denote photometric redshifts $z_i^p$, and the ones without it are the true redshifts $z_i$. The integrals $\int dz_L^p$ and $\int dz_g^p$ are both over $[z_{i,\min}^p, z_{i,\max}^p]$, namely, the photo-z range of the $i$th tomographic bin. The lensing kernel $W_L$ for a flat universe is given by

$$W_L(z_L, z_g) = \frac{\Omega_m H_0^2}{c^2} (1 + z_L) \chi_L \left( 1 - \frac{\chi_L}{\chi_g} \right)$$

for $z_L < z_g$,

$$0$$

otherwise.

(B3)

$p(z|z^P)$ is the redshift PDF. In reality, each galaxy has its own PDF. To speed up the computation, we approximate it as a Gaussian function identical for all galaxies with the same $z_i^P$, as we adopted in previous work (Yao et al. 2017). Here $S(z_g^p, z_g^p)$ is the selection function for the “$i$” symbol,

$$S(z_g^p, z_g^p) = \begin{cases} 1 & \text{for } z_g^p < z_g^p \; \text{; } \; (B4) \\ 0 & \text{otherwise.} \end{cases}$$

In the above equation, $\sigma_z$ is the average photo-z scatter of all galaxies in the given photo-z bin. This assumption is valid because the redshift Gaussian scatter is tested in the machine-learning method (Zou et al. 2019) and also checked in Figure 17, as they have similar height and scatter compared to the true-z, despite the outlier problem.

The factor 2 in Equation (B2) arises from an integral equality theoretically predicted in Zhang (2010a):

$$\int_{z_{i,\min}^p}^{z_{i,\max}^p} dz_L \int_{z_{i,\min}^p}^{z_{i,\max}^p} dz_g W_L(z_L, z_g) p(z_L) p(z_g) S(z_L, z_g) n^p_i(z_g) n^p_i(z_g) = 2.$$ (B6)

This has also been tested numerically.

The $Q^{Ig}$ introduced in this paper share similar definitions as above. The $C_{Gg}^{Ig}$ is defined in Equation (13), while $C_{Ig}^{Ig}$ is defined as

$$C_{Ig}^{Gg}(\ell) = \int_0^\infty n_i(\chi) n_i(\chi) b_i P_k \chi^2 d\chi \times \left( k = \frac{\ell}{\chi}; \chi \right) \eta^{Ig}(z) d\chi.$$ (B7)
in which $\eta^{Ig}$ is given by

$$
\eta^{Ig}(z_L, z_S) = 2 \int dz_G \int dz_p \int dz_p' dz_G p(z_G|z_G') p(z_G|z_G') p(z_G|z_G') p(z_G|z_G') n_G(z_G') n_G(z_G') n_G(z_G')
$$
simply without the lensing kernel $W_L(z_L, z_S)$ comparing to $\eta^{Gg}$, as the $Ig$ correlation differs from the $Gg$ correlation.

The calculation of $\{Q^{Gg}(\theta), Q^{Gg}(\theta)\}$ requires the photo-z distribution $n_G(z_G')$, the true redshift distribution $n(z)$, and cosmology (e.g., through $P_G$ and $W_L(z_L, z_S)$). However, its cosmological dependence is weak, since the cosmology-dependent terms enter the same way in both $C^{Gg}$ and $C^{Gg,sl}$ and therefore largely cancel each other out in the ratio ($Q$). We tested for different cosmology in Table 1; the difference is at an $\sim 10^{-3}$ to $\sim 10^{-5}$ level for $Q$. With the development in this paper, we also show the relation of power spectra-based $Q(\ell)$ and correlation function-based $Q(\theta)$ in Figures 3 and 4.

Appendix C
Potential Biases from Shear Measurements and Redshift Distribution

To further validate our results, we investigate the impact of bias from (1) shear calibration and (2) redshift distribution $n(z)$ calibration. We choose to use the red galaxies as an example, since their IA redshift dependency $A_{IA}(z)$ in Figure 15 is the most delicate result of this work. We note that accurate calibration in either shear (Huff & Mandelbaum 2017; Sheldon & Huff 2017; Pujol et al. 2020) or redshift (Hildebrandt et al. 2017, 2020b) is beyond the scope of this paper.

To have a better assessment of the impact of biased multiplicative bias $m$, we choose to cut off the SIMP-type galaxies as in Phirke et al. (2020). The shape measurements of the SIMP subsample are quite noisy, so they contribute less in our results. Meanwhile, by removing this type of galaxy, the remaining sample is dominated by the EXP type ($>80\%$), whose multiplicative bias is accurately estimated as shown in Table A1 of Phirke et al. (2020). We no longer use the default cut of $1 + m > 0.5$, as it could also introduce some selection bias. The associated results are shown in Figure 18 with the label “slt.” Although the values of the IA amplitude $A_{IA}$ changed slightly in each $z$ bin, we note by selecting different types of galaxies that the selected galaxies should have different IA amplitudes. We emphasize that the IA redshift evolution result of the red galaxies remains the same; it rules out the constant IA amplitude assumption at $\sim 4\sigma$ (with slightly larger error bars but reduced amplitude in the low-$z$ bins, compared with the default red sample).

We further address the impact of a biased $n(z)$ estimation in the theoretical part. We match the good photo-z catalog described above (0.69M galaxies) with the “slt” red galaxy sample, resulting in 6500 matches. Instead of using the $n(z)$ given by the kNN photo-z, we choose to use the distribution from the matched good photo-z catalog in the theoretical calculation of Equations (11) and (13). In this way, the IA signal gives the orange “slt som n(z)”-labeled results in Figure 18. Still, it shows that the impact from the biased $n(z)$ is not significant, and the redshift evolution result of the red galaxies remains the same. We note that getting $n(z)$ with another catalog will also add an extra selection bias on the IA amplitude.

Even though the above two tests of shear calibration and redshift distribution calibration are not required to produce the same results as our default red galaxy sample, they still agree at some level. Therefore, we conclude that the $A_{IA}(z)$ relation found for the red galaxies is robust against the described calibration biases.

Appendix D
Covariance Matrix for the Observables

We show the normalized covariance matrix of $\{w^{\gamma g}(\theta), w^{\gamma g}(\theta)\}$ in Figure 19. It is obvious that the two observables have a strong positive correlation, simply due to the fact that the data producing $w^{\gamma g}(\theta)$ are completely included in $w^{\gamma g}(\theta)$. This positive correlation is converted into a negative correlation in the separated $w^{Gg}$ and $w^{Ig}$ (Figure 6) through our LIS

![Figure 19. Normalized covariance matrix (the correlation coefficient $r_{ab} = \text{Cov}(a, b)/\sqrt{\text{Cov}(a, a)\text{Cov}(b, b)}$ for the LIS observable data vector $\{w^{\gamma g}(\theta), w^{\gamma g}(\theta)\}$). There are nine $\theta$ bins for $w^{\gamma g}$ and nine for $w^{\gamma g}$ with the overall size for the data vector is 18 for each $z$ bin, leading to the $72 \times 72$ matrix for the full sample above. There are strong positive correlations between $w^{\gamma g}$ and $w^{\gamma g}$, important for the data analysis.](image-url)
method in Equations 8(a) and (b). The only difference is that the covariance of \( w^{\text{GR}}_b, w^{\text{GR}}_a \) is modeled statistically uncertainties from \( Q^{\text{GR}}_b, Q^{\text{GR}}_a \), which we tested to be at the \( \sim 10^{-3} \) level.

So generally, Figures 6 and 19 carry equivalent information.

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