Constraining Dark Energy with Stacked Concave Lenses

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Abstract

Low-density regions are less affected by the nonlinear structure formation and baryonic physics. They are ideal places for probing the nature of dark energy, a possible explanation for the cosmic acceleration. Unlike void lensing, which requires identifications of individual voids, we study the stacked lensing signals around the low-density positions (LDPs), defined as places that are devoid of foreground bright galaxies in projection. The method allows a direct comparison with numerical results by drawing correspondence between the bright galaxies with halos. It leads to lensing signals that are significant enough for differentiating several dark energy models. In this work, we use the CFHTLenS catalog to define LDPs, as well as measuring their background lensing signals. We consider several different definitions of the foreground bright galaxies (redshift range and magnitude cut). Regarding the cosmological model, we run six simulations: the first set of simulations have the same initial conditions, with \( w_{\text{de}} = -1, -0.5, -0.8, -1.2 \); the second set of simulations include a slightly different \( \Lambda \)CDM model and a \( w(z) \) model from Zhao et al. The lensing results indicate that the models with \( w_{\text{de}} = -0.5, -0.8 \) are not favored, and the other four models all achieve comparable agreement with the data.

Key words: large-scale structure of universe – dark energy – galaxies: halos – gravitational lensing: weak

1. Introduction

The acceleration of the cosmic expansion remains a mystery today (Riess et al. 1998; Perlmutter et al. 1999; Weinberg et al. 2013; Komatsu et al. 2014; Planck Collaboration et al. 2014). It is not yet clear if it is necessary to go beyond the simplest \( \Lambda \)CDM model by introducing a nontrivial equation of state \( w(z) \) for dark energy (Huterer & Turner 1999). Recently, from the baryon acoustic oscillation measurement of the BOSS data, there has been intriguing evidence showing a deviation of \( w(z) \) from \(-1\) (Zhao et al. 2017). It is desirable to test the nature of dark energy with alternative cosmological probes. We propose to do so with the weak lensing effect around low-density regions.

Low-density regions have the advantages of being much less affected by nonlinear evolution and baryonic physics. They are likely the ideal places to test dark energy models with weak lensing. Previous efforts largely focus on the lensing effect of voids, a typical type of low-density region that is devoid of matter over a significant cosmic volume.

A major challenge of void lensing is about identifying the voids. Current void-finding algorithms are mostly based on the distribution of galaxies with spectroscopic redshifts. Sánchez et al. (2017) have summarized these algorithms into several groups: Watershed Void Finders (Platen et al. 2007; Neyrinck 2008; Lavaux & Wandelt 2012; Nadathur et al. 2015), growth of spherical underdensities (Hoyle & Vogeley 2002; Colberg et al. 2005; Padilla et al. 2005; Cecarelli et al. 2006; Li 2011), hybrid methods (Jennings et al. 2013), dynamical criteria (Elyiv et al. 2015), and Delaunay Triangulation (Zhao et al. 2016). There are however three main shortcomings in traditional ways of doing void lensing: (1) void centers cannot be unambiguously identified due to their intrinsically irregular shapes, making it difficult to precisely predict or understand the stacked void lensing signals with a physical model; (2) spectroscopic galaxy surveys are generally expensive, and suffer from complicated influences from the selection effects; (3) due to the limited number density of voids and the scatter of their sizes, the stacked lensing signals do not yet have a high significance.

More recently, there is a trend to study the lensing effect of low-density regions defined by the projected galaxy distributions (Clampitt & Jain 2015; Gruen et al. 2016, 2018; Barreira et al. 2017; Sánchez et al. 2017; Friedrich et al. 2018; Brouwer et al. 2018; Davies et al. 2018). Compared to void lensing, these new methods only need photo-z information, and the stacked lensing signals generally have much higher significance. For example, Gruen et al. (2016) use a photometrically selected luminous red galaxy sample (redMaGiC) as the foreground galaxies in their paper. By dividing the sky into cells, they assign each cell a weighted and smoothed galaxy count. They do shear measurements around cells with different galaxy counts using the DES lensing catalog. Their follow-up works can be found in Gruen et al. (2018) and Friedrich et al. (2018), in which a complete cosmological analysis is presented within the LCDM models.

Our approach has similarities to their method, but also differences. We consider these low-density positions (LDPs), which are defined by excluding the foreground bright galaxies from the sky with a critical radius in projection. This is a direct way to define the low-density regions, without defining the galaxy density map. These positions can be similarly defined in \( N \)-body simulations by drawing correspondence between the foreground bright galaxies and halos/subhalos through, e.g., subhalo abundance matching (SHAM; e.g., Vale & Ostriker 2004). These operations are straightforward to realize, and enable us to directly compare the stacked lensing signals around LDPs with the simulation predictions. The motivation of this paper is to differentiate several different dark energy models through this type of comparison.
This paper is organized as follows: in Section 2, we introduce the basic theory of weak lensing, and the method for stacking the lensing signals from low-density regions in both observations and numerical simulations; Section 3 shows our main results for several different dark energy models; Section 4 gives our conclusion and discussions about related issues.

2. Method

2.1. Overview

The background tangential shear is related to the stacked excess surface density of the foreground (see, e.g., Peacock 1999)

$$\Delta \Sigma(R) \equiv \sum_{\epsilon} (\epsilon_1, \epsilon_2) \langle \gamma_\epsilon \rangle(R) = \Sigma(\epsilon R) - \Sigma(R),$$

where $R$ is the distance to the center, and $\Sigma(\epsilon R)$ is the critical surface density in comoving unit, which is defined as

$$\Sigma(\epsilon R) = \frac{\epsilon^2}{4\pi G} \frac{D_L(z_L)}{D_A(z_i) D_L(z_s) D_A(z_L)} (1 + \epsilon z)^2,$$

where $z_\epsilon$ and $z_i$ are the redshifts of the source and the lens, respectively, $(z_L < z_s)$. $\Sigma(\epsilon R)$ is the mean surface density within $R$, and $\Sigma(R)$ is the surface density at $R$. $D_A$ refers to the angular diameter distance. By stacking the background shear signals, Equation (2) allows us to probe the average surface density profile around the foreground objects (e.g., galaxies, cluster centers, void centers, etc.) directly, with an enhanced significance and better circular symmetry.

There are, in principle, no restrictions on how one defines the foreground positions as long as they are physically meaningful. For our purpose of studying the properties of dark energy, we consider stacking the shear signals around LDPs, which are simply defined as places that are away from foreground bright galaxies (within a certain narrow redshift range) by more than a critical distance in projection. LDPs defined in such a way generally point to low-density regions. They provide abundant foreground positions for shear-stacking, leading to highly significant lensing signals, as shown in the rest of the paper.

2.2. Observational Data

We use the shear catalog from the Canada–France–Hawaii Telescope Lensing Survey (CFHTLenS)$^5$, which comprises 171 pointings with an effective survey area of about 154 deg$^2$. The CFHTLenS data set is based on the wide part of CFHTLS carried out in four patches: W1, W2, W3, W4. It has deep photometry in five broad bands $u'g'i'rz'$ (also the $y'$ band as a supplement to i' band) and limiting magnitude in the i' band of $i'_{AB} \sim 25.5$. Heymans et al. (2012) present the CFHTLenS data analysis pipeline, which summarizes the weak lensing data processing with THESI (Erben et al. 2013), shear measurement with Lensfit (Miller et al. 2013), and photometric redshift measurement with the Bayesian photometric redshift code (Hildebrandt et al. 2012).

For each galaxy in the shear catalog, we are provided with an inverse-variance weight $w$, the shape measurement $\epsilon_{1,2}$, the shear correction terms from calibration, the apparent and absolute magnitudes (including extinctions and magnitude error) in five bands, the probability distribution function (PDF) of redshift, as well as the peak $z_p$ of the PDF. The stacked shears are calculated as (Miller et al. 2013)

$$\gamma_{1,2} = \frac{\sum_{LDP} w_i (c_{1,2} - c_{1,2})}{\sum_{i} w_i (1 + m_i)},$$

where $m_i$ and $c_i$ are the multiplicative and additive calibration terms, respectively.

In order to generate the positions of the LDPs, we use the foreground bright galaxies above a certain absolute magnitude, so that the galaxy sample is complete in the unmasked areas. This allows us to draw correspondence between the observed galaxies and the halos in simulations, and to construct the average excess surface density profile around the LDPs in both cases for comparison. For example, Figure 1 shows the source distribution in W1 from the CFHTLenS catalog with the i' band apparent magnitude less than 25.5 in the W1 area. The differences in number densities across different fields is quite obvious. The empty areas in this map are masked out for bright stars. If only the bright galaxies are kept, the sample becomes statistically homogeneous in the unmasked areas for redshifts that we are interested in. As an example, we show the distribution of galaxies with $0.35 < z < 0.535$ and $i'$-band absolute magnitude $M_{i'} < -21.5$ in Figure 2.

The positions of the LDPs are identified through the following procedures:

1. Generating the LDP candidates

First of all, we require each foreground galaxy to be brighter than a critical absolute magnitude $M_{i'}$, in the $i'$-band, with redshift between $z_m - 0.1 < z_m + 0.1$, where $z_m$ is the median redshift. We circle around each foreground galaxy with radius $R_c$. Regions within the radius are removed, and the remaining positions are the candidates for LDPs. In principle, there are infinite LDPs. In this work, for simplicity, we put the LDPs on a uniform grid, with the grid size equal to 0.37 arcmin. The thickness of the redshift slice is set to 0.2 considering the typical redshift dispersion $\sigma_z$.$^6$ Here is set to 1 or 1.5 arcmin

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$^5$ http://cfhtlens.org

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Figure 1. Source distribution in W1 from the CFHTLenS catalog with apparent magnitude $M_{i'} < 25.5$. The empty areas in this map are masked out for bright stars.

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Figure 2. Source distribution in W1 from the CFHTLenS catalog with apparent magnitude $M_{i'} < 25.5$. The empty areas in this map are masked out for bright stars.
in order to generate enough LDPs. The $M_{\text{ag}}$ here refers to the critical magnitude in one particular LCDM model (CW1 in Section 2.3). For other cosmologies, we use almost the same foreground galaxy sample.\(^8\) To ensure a clean and complete foreground galaxy sample for generating LDPs, we make three constraints here:

(a) We only use sources with star_flag = 0 to decrease the star contaminations (but not vanished). Overall, the fraction of sources with star_flag = 1 is around 3%. The ratio becomes $\sim$20% for galaxies satisfying $0.335 < z < 0.535$ and $M_{\text{ag}} < -21$. In general, the ratio changes with magnitude and redshift.

(b) Galaxies that have two or more close height peaks in redshift PDF are removed to reduce the redshift uncertainty. Most of these sources are actually stars. It further removes $\sim$3% of the sources for galaxies under the condition star_flag = 0, $M_{\text{ag}} < -21$, $0.335 < z < 0.535$. This ratio changes with magnitude and $z_m$.

(c) We also remove galaxies with absolute magnitude $M_{\text{ag}} < -99$ in the original catalogs, which indicates problems in the measurement. This corresponds to the removal of 10% of additional sources. In Section 4, we show that these sources generally yield low galaxy–galaxy lensing signals, and therefore should not be the foreground galaxies we consider.

After the above selection of galaxies, our $i$-band luminosity function is consistent with the CFHTLS-DEEP-SURVEY luminosity function derived by Ramos et al. (2011).

2. Generating the mask maps

We use the CFHTLenS Mosaic mask files (Erben et al. 2013) in this step. In order to produce the mask maps in (R.A., decl.) units, we generate the uniform grids for W1–4 first. Then we apply VENICE\(^9\) with these official files to accurately mask these positions near the mask boundaries.

3. Finding out the LDPs from candidates

Some of the candidate LDPs generated in step 1 should be removed if they are close to the masked regions. We require the ratio of the masked area to $\pi R_s^2$ around each candidate LDP to be less than 10%. To get rid of the survey edge effects, we also remove the LDPs whose distances from the edges of the survey area are less than $R_s$.

For LDPs generated through steps 1–3, we measure their stacked excess surface density $\Delta \Sigma(R)$ using background galaxies, and compare it with predictions of different cosmological simulations introduced in the next section.

2.3. Simulation

We run two sets of simulations named as CW (standing for constant $w$) and WZ (referring to $w$ as a function of $z$), the parameters of which are given in Table 1. In all of our simulations, we set $\Omega_{de} + \Omega_c + \Omega_b = 1$. 2LPT and Gadget2 are used to create initial conditions and run the simulations (Springel & Hernquist 2002; Springel 2005). Both CW and WZ simulations are run from initial redshift 72 with particle number 1024\(^3\) and boxsize 600 Mpc $h^{-1}$. We use the FoF group finder to find the halos, and the subhalo finder HBT (Han et al. 2012) to find the subhalos.

(i) For CW1, we produce the initial condition following $\sigma_8 = 0.85$, $\Omega_c = 0.223$, $\Omega_b = 0.045$, $n_s = 1$). For CW2,3,4 the same initial conditions are used, with updated $H(z)$ for different $w_{de}$ models in Gadget2. The value of $\sigma_8$ in the four simulations reduces with increasing $w$.

(ii) For the second set, we adopt the best-fit cosmological parameters from Zhao et al. (2017) for LCDM and the dynamical dark energy $w(z)$ model, and use CAMB (Lewis et al. 2000) to generate the initial power spectrum for the simulation.

The LDPs in simulations are defined in the following way:

1. Connecting halos/subhalos with galaxies through SHAM

There are different methods in literature to populate galaxies in dark matter halos/subhalos; either through the halo occupation distribution and conditional luminosity function models (Jing et al. 1998; Berlind & Weinberg 2002; Yang et al. 2003, 2012; Zheng et al. 2005; van den Bosch et al. 2007; Leauthaud et al. 2011; Zehavi et al. 2011; Rodríguez-Puebla et al. 2015; Guo et al. 2016; Zu & Mandelbaum 2016; Rodríguez-Puebla et al. 2017; Guo et al. 2018), or via SHAM processes (e.g., Vale & Ostriker 2004; Conroy et al. 2006; Vale & Ostriker 2006; Conroy et al. 2009; Behroozi et al. 2010; Guo et al. 2010; Simha et al. 2012; Hearin et al. 2013; Guo & White 2014; Chaves-Montero et al. 2016; Wechsler & Tinker 2018; Yang et al. 2018). In this work, for simplicity, we use the SHAM method to generate mock galaxy catalogs.

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\(^8\) We always select the same amount of brightest galaxies as the foreground galaxies. For different cosmologies, the rank of the galaxy brightness may change. For example, for a given apparent magnitude at redshift $z_1$ and $z_2$, it is possible that the absolute magnitude $M_{\text{ag}}(z_1, w_{de1}) > M_{\text{ag}}(z_2, w_{de2})$ but $M_{\text{ag}}(z_1, w_{de1}) < M_{\text{ag}}(z_2, w_{de2})$, due to the change of the distance–redshift relation. However, this rarely happens for the cosmologies we use.

\(^9\) https://github.com/jcoupon/venice

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**Table 1**

| Simulation | $w_{de}$ | $\sigma_8$ | $\Omega_c$ | $\Omega_b$ | $h$ | $n_s$ |
|------------|----------|-----------|----------|----------|----|------|
| CW1        | $-1$     | 0.85      | 0.223    | 0.045    | 0.71 | 1    |
| CW2        | $-0.5$   | (0.633)   | 0.223    | 0.045    | 0.71 | 1    |
| CW3        | $-0.8$   | (0.789)   | 0.223    | 0.045    | 0.71 | 1    |
| CW4        | $-1.2$   | (0.893)   | 0.223    | 0.045    | 0.71 | 1    |

| Simulation | $w_{de}$ | $A_z$ | $\Omega_c$ | $\Omega_b$ | $h$ | $n_s$ |
|------------|----------|------|----------|----------|----|------|
| WZ1        | $-1$     | 2.2e-9 | 0.2568   | 0.0485   | 0.679 | 0.968 |
| WZ2        | $w(z)$   | 2.2e-9 | 0.24188  | 0.04525  | 0.702 | 0.966 |
To make the galaxy-SHAM, we first put the simulation box along the line of sight at redshift \( z_m \). Then, we use galaxies in the redshift range of \([z_m - 0.1, z_m + 0.1]\) to match the halos/subhalos in the simulation. We adopt the masks of observation in the simulation in order to mimic the mask distribution in observation. Assuming brighter galaxies are formed in bigger halos/subhalos, the connection between the halos/subhalos and galaxies are built up by comparing the number of halos/subhalos with mass greater than \( M \) to the number of galaxies with luminosity greater than \( L \):

\[
\int_0^\infty \phi(L) dL = \int_M^{\infty} \left[ n_h(M) + n_{ab}(M) \right] dM,
\]

where

\[
M = \begin{cases} 
M_{\text{acc}}, & \text{subhalos} \\
M_z, & \text{distinct halos},
\end{cases}
\]

where \( n_h/n_{ab} \) is the number of halos/subhalos, and \( M_{\text{acc}} \) is the mass at the last epoch when the subhalo is a distinct halo. It is commonly used in the SHAM models as it is closely related to the halo merger history. \( M_z \) is the halo mass at redshift \( z \).

We also add some scatters to the redshifts and luminosities of our mock galaxies to better mimic the real situation. First, the redshift dispersion measured in Section 2.2 is added to halos/subhalos to randomly move their positions in redshift space. We also update the absolute magnitudes of mock galaxies according to their redshift errors. Second, we introduce an additional mass uncertainty of the order \( \sigma_{bgM} = 0.3 \) to halos/subhalos to mimic the dispersion in the galaxy–halo/subhalo relation. We find that the final results are not sensitive to the value of \( \sigma_{bgM} \). We show an example of the galaxy distribution in the CW1 simulation in Figure 3, which looks quite similar to that shown in Figure 2 for real galaxies.

2. Generating the LDPs

After we generate mock galaxy catalogs, candidate LDPs are generated by excluding positions within the radius \( R_s \) around bright galaxies. We also require the ratio of the masked area to \( \pi R_s^2 \) around each LDP to be less than 10%. An example is given in Figure 4, in which the mock galaxies are marked in red color, and LDPs are marked with the blue color. The white regions are either the masked areas or the neighborhood of the mock galaxies.

The normalized surface density (\( \Sigma(R) - \Sigma_0 \))/\( \Sigma_0 \) around LDPs defined with \( \text{Mag}_{\text{c}} = -21.5, R_s = 1 \text{ arcmin}, z_m = 0.435, \) and \( dz = 0.2 \) for CW1, 2, 3, 4, where \( \Sigma_0 \) is the mean surface density around the random points.

We show the normalized surface density (\( \Sigma(R) - \Sigma_0 \))/\( \Sigma_0 \) around the LDPs of our four different CW simulations in Figure 5, where \( \Sigma_0 \) is the mean surface density around the random points. The LDPs are defined by mock galaxies with \( \text{Mag}_{\text{c}} = -21, R_s = 1 \text{ arcmin}, z_m = 0.435 \) and the slice...
thickness $d z = 0.2$. The figure shows that a higher $w$ corresponds to a shallower density profile.

3. Results

The 2D stacked shear signals around the LDPs are shown in Figure 6. The upper panel shows the original result, and the lower panel shows results after subtracting the average residual $\gamma_{1,2}$. The red line represents the shear strength of 0.001.

emerges, as shown in the lower panel of the figure. The red lines show the length for shear $\gamma = 0.001$ in the figure. In making this figure and the rest of our studies, we remove the background galaxies with $\sigma_z > 0.2$ and those with significant multiple peaks in the redshift PDF to reduce the redshift contamination. In order to increase the number of background galaxies and improve the signal-to-noise ratio $(S/N)$, here we use galaxies in all fields with shear measurement. We have also calculated the 2D shear patterns using only fields that pass the lensing residual systematics test (shown in Section 4), and found similar results. Therefore, the rest of our calculations are simply based on the full shear catalog.

More quantitatively, we compare the 1D stacked lensing signals between observation and simulation. To estimate the stacked $\Delta \Sigma(R)$ in observation, we follow the formulae in Niikura et al. (2015)

\[
(\Delta \Sigma)(R) = \frac{1}{N} \sum_{a=1}^{N_c} \sum_{s_a} w(a, s_a) \Sigma_{\text{cr}}(\gamma; R_a),
\]

where $N_c$ is the number of LDPs, $2\Delta$ is the bin size on the logarithmic scale, $\gamma_{s_a}$ is the tangential ellipticity of the $s_a$th background galaxy for the $a$th LDP, $R$ is the average radius of the background galaxies in that radial bin, and $N$ is the normalization factor:

\[
N = \sum_{a=1}^{N_c} \sum_{s_a} w(a, s_a).
\]

We only use background galaxies with $z_b \geq z_l + 0.1$ when calculating $\Delta \Sigma(z_l, z_b)$, concerning the fact that both foreground and background galaxies have redshift dispersions.

One of our main results is shown in Figure 7 with $z_m = 0.435$, $M_{bc} = -21.5$, and $R_s = 1$ arcmin. The red solid line in the upper panel shows $\Delta \Sigma_0(R)$ calculated with
the CFHTLenS catalogs, and the blue solid line shows \( \Delta \Sigma_o(R) \) from the CW1 simulation. The \( \Delta \Sigma(R) \) with subscripts “o” and “s” represent observational and simulation signals, respectively. The lower panel is the residual \( \Delta \Sigma_o(R) - \Delta \Sigma_s(R) \), which shows agreement between the simulation and observation for CW1. Two kinds of variances are given in the figure: (a) we use the simulation of Jing et al. (2007), which has the same parameters as CW1, to estimate the cosmic variance for CFHTLenS survey areas. Each of the two CW1 simulations can be used to generate four realizations of about 150 deg\(^2\). The variance estimated from these realizations is shown as the shaded area in the figure, with the solid blue line representing the mean value. (b) For the observational signals, the variance in the red line is from bootstrap. Rather than dividing the foreground space into different subregions, we resample LDP groups that are formed by LDPs close in space. To fully capture the covariance matrix, the size of the LDP group is set to be two times larger than the largest radial bin. The corresponding normalized covariance matrix is shown in Figure 8. Correlations between the neighboring radial bins can be found in the figure.

The total S/N of the observational lensing signal can be calculated as

\[
\left( \frac{S}{N} \right)^2 = \sum_{i,j} \Delta \Sigma_o(\theta_i) C^{-1}_{i,j} \Delta \Sigma_o(\theta_j),
\]

\[
C^{-1}_{i,j} = \frac{N_s - N_D - 2}{N_s - 1} C_s^{i,j-1},
\]

\[
C_s^{i,j} = \text{cov}(\Delta \Sigma_o(\theta_i), \Delta \Sigma_o(\theta_j)),
\]

where the summation runs over all the radial bins. Since the sampled precision matrix \( C_s^{i,j} \) is biased due to the noise in \( C_s^{i,j} \), the unbiased estimator \( C_s^{-1} \) is taken (Hartlap et al. 2007; Taylor et al. 2013). Here, \( N_s \) is taken as the number of the LDP groups, and \( N_D \) is the number of the data bins. The S/N for the red line in Figure 7 is 20.473, which is significant for us to constrain cosmologies and shows the advantage of stacking signals around LDPs.

We repeat the procedures for \( R_s = 1, 1.5 \) arcmin, redshift bins \( z_m = 0.35, 0.435, 0.512 \), and magnitude cuts \( \text{Mag}_c = -21, -21.5, -22 \). It enables us to make multiple comparisons with limited information. As the apparent magnitude limit for the \( i' \)-band is higher than 24.5 on average, it allows us to make the volume-limited samples for three foreground redshifts and three magnitude \( \text{Mag}_c \) cuts.

Figures 9 and 10 show detailed scale-dependent comparisons between simulation and observational results for \( R_s = 1 \) arcmin and \( R_s = 1.5 \) arcmin, respectively. Panels in the horizontal direction of Figures 9 and 10 are for three choices of \( \text{Mag}_c \), and for three \( z_m \)’s in the vertical direction. The arrangement of each panel is similar to that of Figure 7. One can see from the figures that there is not a single best model for all cases. It also happens that the best model in one case does not perform well at all radius scales. This situation seems to be worse for \( R_s = 1.5 \) arcmin. This is likely due to the fact that the number of LDPs for \( R_s = 1.5 \) arcmin is much lower than that of \( R_s = 1 \) arcmin.

In order to compare the results more directly we introduce the reduced \( \chi^2 \) to describe the discrepancy between observational and simulation signals

\[
\chi^2 = \frac{1}{N_{\text{bin}}} \sum_{i,j} \delta \Delta \Sigma(\theta_i) C^{-1}_{i,j} \delta \Delta \Sigma(\theta_j),
\]

\[
\delta \Delta \Sigma(\theta_i) = \Delta \Sigma_o(\theta_i) - \Delta \Sigma_s(\theta_i).
\]

When calculating S/N or \( \chi^2 \), we do not consider the cosmic variance. The \( \chi^2 \) results for all cases are shown in Figure 11. The upper three panels are for \( R_s = 1 \) arcmin, and the lower panels are for \( R_s = 1.5 \) arcmin. The left, middle, and right panels are for \( z_m = 0.35, 0.435, \) and 0.512, respectively. The horizontal axis is \( \text{Mag}_c \). The four solid lines in each panel show results for CW1–4 cosmologies, and the dashed lines are for WZ1–2. Among six simulations, CW1 and WZ1 are two different ΛCDM models. From these panels we find:

1. in all the panels, CW2 (\( w = -0.5 \)) always has the largest \( \chi^2 \) compared with other cosmologies;
2. CW3 (\( w = -0.8 \)) has the second largest \( \chi^2 \) in most cases;
3. the other four models, including the two ΛCDM models (CW1, WZ1), the CW4 (\( w = -1.2 \)) model, and WZ2 (dynamical \( w(z) \)), all have comparably low \( \chi^2 \) in most cases. The most pronounced exception is in the case of \( z_m = 0.435, R_s = 1.5 \) arcmin, and \( \text{Mag}_c = -22 \), in which the CW3 model yields the lowest \( \chi^2 \) in contrast.

10 Given the total area for W1–4 and the largest radius \( R_{\text{max}} \) in Figure 7, the number of groups is estimated by dividing the total area by \( 4 R_{\text{max}}^2 \). The mean number of LDPs within a group is derived by dividing the total number of LDPs with the number of groups. Then we divide all the LDPs into regularly placed small cells, with each cell containing a few LDPs. The cells are added to the groups one by one. Whenever the size of a group in a row reaches 2 \( R_{\text{max}} \), we move to another row. If the number of LDPs in a group equals the mean number, the assignment for this group is terminated. This procedure is repeated until the last cell is assigned to a group. In this way, the LDPs are divided into groups with similar numbers, avoiding the fluctuations due to the masking effects.
Figure 9. Average excess surface density profile around LDPs that are defined with $R_s = 1$ arcmin and different choices for the magnitude cut and redshift range. The left, middle, and right columns are for $Mag_c = -21, -21.5, -22$, respectively, and the top, middle, and bottom rows for $z_m = 0.35, 0.435, 0.512$. The upper part of each panel shows $\Delta \Sigma_s(R)$ from simulations. The lower part shows the residuals after subtracting $\Delta \Sigma_s(R)$ from $\Delta \Sigma_o(R)$.
Figure 10. Similar to Figure 9, but with $R_s = 1.5$ arcmin.
In this paper we study the stacked lensing signals around the LDPs, which are defined as places that are devoid of foreground bright galaxies in projection. We show how to define the foreground galaxy population and locate the LDPs in the presence of masks using the CFHTLenS data. Different redshift ranges and magnitude cuts are considered for the foreground population. The measured excess surface density profiles can be compared with the predictions from simulations. The comparison is made available by drawing correspondence between galaxies and halos/subhalos via SHAM.

With the CFHTLenS shear catalog, we have successfully measured the lensing signals around the LDPs with a high significance. These measurements are used to constrain dark energy models using simulated galaxies that have similar survey selection effects. We run six cosmological simulations [CW(1, 2, 3, 4) and WZ(1, 2)] with different dark energy equations of state, for the purpose of reproducing the mean surface density profile around the LDPs in observation. The cosmological parameters of the six simulations are given in Table 1.

Our results of the surface density measurement indicate that the CW2 ($w = -0.5$) and CW3 ($w = -0.8$) models are not favored. The two $\Lambda$CDM models (CW1 and WZ1), as well as the CW4 ($w = -1.2$) and WZ2 ($w(z)$ of Zhao et al. 2017) models, all achieve reasonably good and similar agreement with the observation. The comparisons are made for three

Figure 11. Reduced $\chi^2$ for six cosmologies with different choices of $Mag_c$, $R_s$, and $z_m$. The upper three panels are for $R_s = 1 \text{ arcmin}$, and the lower panels are for $R_s = 1.5 \text{ arcmin}$. The left, middle, and right columns are for $z_m = 0.35, 0.435, 0.512$, respectively. The horizontal axis in each plot is the magnitude cut $Mag_c$.

Figure 12. Galaxy–galaxy lensing signals for foreground galaxies in the magnitude bins of $[-21, -21.5], [-21.5, -22], [-22, -22.5]$, and $[-22, -22.5]$, and redshift range of $[0.335, 0.435]$. $N_g$ is the number of foreground galaxies.
foreground redshift bins, three magnitude cuts, and two critical radii for the definition of the LDPs.

There are a number of problems that may impact our results. Here we outline some of them.

4.1. The Impact of Throwing Away Sources with Absolute Magnitude $M_g < -99$ in the Shear Catalog

We show the galaxy–galaxy lensing signals in Figure 12 for foreground galaxies in the redshift range of $[0.335, 0.435]$. The blue, green, red, and yellow lines are for galaxies with magnitudes in the range of $[-21, -21.5], [-21.5, -22], [-22, -22.5]$, and $[-22.5, -22.5]$, respectively. For galaxies of $M_g < -99$, their lensing signals are quite low, indicating that they likely correspond to less massive sources on average (or even not galaxies). So we think it is safe for us to remove them from the foreground galaxies when generating the LDPs.

4.2. The Impact of the Fields Which Do Not Pass the Lensing Residual Systematics Tests

As described in Heymans et al. (2012), some CFHTLenS fields do not pass the lensing residual systematics tests, which should not be used in the shear two-point correlation tests. In Figure 13, we show the 2D stacked shear patterns around the LDPs using only fields that pass the lensing residual systematics tests. The left panel shows the original result, and the right panel shows results after subtracting the random $\sigma_{\text{rand,1,2}}$. The red line represents the shear strength of 0.001.

4.3. The Impact of the $\sigma_8$ When Comparing the Lensing Signals

The initial conditions for the CW1−4 simulation are fixed as mentioned in Section 2.3, supposing the early-time amplitude $A_s$ is well constrained by the CMB. However, it may be interesting to ask: what if we keep the late-time amplitudes the same for these simulations, although with very different $A_s$? So, we run four new simulations here as a comparison. Three new simulations are run for the CW set, named as CW5, 6, 7. Also, one new simulation is run for the WZ set, named as WZ3. For CW5, 6, 7, the parameters ($\Omega_c, \Omega_m, w_{\text{de}}, h$) are set the same as in CW1, with the $\sigma_8$ being the same as that of CW1. For WZ3, its parameters ($\Omega_c, \Omega_m, w_{\text{de}}, h$) are identical with WZ2, with the $\sigma_8$ taken from WZ1. The parameters of the simulations are given in Table 2.

All the procedures in Section 2.3 are repeated for the four simulations. The simulated lensing signals around the LDPs are compared with the observed signals in Figures 14 and 15, which are similar to Figures 9 and 10. The lensing profiles $\Delta \Sigma(R)$ for CW5, 6, 7 are found to be close to each other. Although smaller compared to Figures 9 and 10, discrepancies are still found for some cosmologies between the simulated and observed signals in the lower panels. Their corresponding $\chi^2$ results are shown in Figure 16. The $\chi^2$ is found to have larger $\chi^2$ than the others in most cases. The $\chi^2$ of CW6 ($w = -0.8$) seems to be slightly higher than the rest. These results are redshift-dependent, and the least distinguishable
Figure 14. Similar to Figure 9, but with a new set of simulations, described in Section 4.3. CW5, 6, 7 all share the same $\sigma_8$ as that of CW1, and WZ3 has the same $\sigma_8$ as that of WZ1.
Figure 15. Similar to Figure 14, but with $R_s = 1.5$ arcmin.
When \( z_m = 0.435 \) and \( R_s = 1.5 \) arcmin, different models result in comparable \( \chi^2 \).

We note that our constraints on the dark energy equation of state is still preliminary, in the sense that we have fixed the values of the other cosmological parameters for simplicity. As a next step, we plan to vary the cosmological model with more parameters, and fix those that are best constrained by cosmic microwave background (CMB). We also plan to measure again the LDP lensing signals using the Fourier_Quad method (Zhang et al. 2017, 2018), which is significantly different from the Lensfit method used by the CFHTLenS team. Also, we are looking forward to giving detailed discussions on the redshift evolution of the LDP lensing signals with larger and deeper surveys.\(^{11}\)

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\(^{11}\) https://www.darkenergysurvey.org, https://www.desi.lbl.gov, https://www.lsst.org, http://www.sdss3.org/surveys/boss.php

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**Figure 16.** Similar to Figure 11, but with a new set of simulations described in Section 4.3. CW5, 6, 7 all share the same \( \sigma_8 \) as that of CW1, and WZ3 has the same \( \sigma_8 \) as that of WZ1.
References

Barreira, A., Bose, S., Li, B., & Linares, C. 2017, JCAP, 02, 031
Behroozi, P. S., Conroy, C., & Wechsler, R. H. 2010, ApJ, 717, 379
Berlind, A. A., & Weinberg, D. H. 2002, ApJ, 575, 587
Brouwer, M. M., Demchenko, V., Harnois-Déraps, J., et al. 2018, MNRAS, 481, 5189
Ceccarelli, L., Padilla, N. D., Valotto, C., & Lambas, D. G. 2006, MNRAS, 373, 1440
Chaves-Montero, J., Angulo, R. E., Schaye, J., et al. 2016, MNRAS, 460, 3100
Clampitt, J., & Jain, B. 2015, MNRAS, 454, 3357
Colberg, J. M., Sheth, R. K., Diaferio, A., Gao, L., & Yoshida, N. 2005, MNRAS, 360, 216
Conroy, C., Gunn, J. E., & White, M. 2009, ApJ, 699, 486
Conroy, C., Wechsler, R. H., & Kravtsov, A. V. 2006, ApJ, 647, 201
Davies, C. T., Cautun, M., & Li, B. 2018, MNRAS, 480, L101
Elyiv, A., Marulli, F., Pollina, G., et al. 2015, MNRAS, 448, 642
Erben, T., Hildebrandt, H., Miller, L., et al. 2013, MNRAS, 433, 2545
Friedrich, O., Gruen, D., DeRose, J., et al. 2018, PhRvD, 98, 023508
Gruen, D., Friedrich, O., Krause, E., et al. 2018, PhRvD, 98, 023507
Guo, H., Zheng, Z., Behroozi, P. S., et al. 2016, MNRAS, 459, 3040
Guo, Q., & White, S. 2014, MNRAS, 437, 3228
Guo, Q., White, S., Li, C., & Boylan-Kolchin, M. 2010, MNRAS, 404, 1111
Han, J., Frenk, C. S., Eke, V. R., et al. 2012, MNRAS, 427, 1651
Hartlap, J., Simon, P., & Schneider, P. 2007, A&A, 464, 399
Hearin, A. P., Zentner, A. R., Berlind, A. A., & Newman, J. A. 2013, MNRAS, 433, 659
Heymans, C., Van Waerbeke, L., Miller, L., et al. 2012, MNRAS, 427, 146
Hildebrandt, H., Erben, T., Kuijken, K., et al. 2012, MNRAS, 421, 2355
Hoyle, F., & Vogeley, M. S. 2002, ApJ, 566, 641
Huterer, D., & Turner, M. S. 1999, PhRvD, 60, 081301
Jing, Y. P., Mo, H. J., & Börner, G. 1998, ApJ, 494, 1
Jing, Y. P., Suto, Y., & Mo, H. J. 2007, ApJ, 657, 664
Komatsu, E., Bennett, C. L., Barnes, C., et al. 2014, PTEP, 2014, 06B102
Lavaux, G., & Wandelt, B. D. 2012, ApJ, 754, 109
Leauthaud, A., Tinker, J., Behroozi, P. S., Busha, M. T., & Wechsler, R. H. 2011, ApJ, 738, 45
Lewis, A., Challinor, A., & Lasenby, A. 2000, ApJ, 538, 473
Li, B. 2011, MNRAS, 411, 2615
Miller, L., Heymans, C., Kitching, T. D., et al. 2013, MNRAS, 429, 2858
Nadathur, S., Hotchkiss, S., Diego, J. M., et al. 2015, MNRAS, 449, 3997
Neyrinck, M. C. 2008, MNRAS, 386, 2101
Niikura, H., Takada, M., Okabe, N., Martino, R., & Takahashi, R. 2015, PASJ, 67, 103
Padilla, N. D., Ceccarelli, L., & Lambas, D. G. 2005, MNRAS, 363, 977
Peacock, J. A. 1999, Cosmological Physics (Cambridge: Cambridge Univ. Press)
Perlmutter, S., Aldering, G., Goldhaber, G., et al. 1999, ApJ, 517, 565
Planck Collaboration, Ade, P. A. R., Aghanim, N., et al. 2014, A&A, 571, A1
Platen, E., van de Weygaert, R., & Jones, B. J. T. 2007, MNRAS, 380, 551
Ramos, B. H. F., Pellegrini, P. S., Benoist, C., et al. 2011, AJ, 142, 41
Riess, A. G., Filippenko, A. V., Challis, P., et al. 1998, AJ, 116, 1009
Rodríguez-Puebla, A., Avila-Reese, V., Yang, X., et al. 2015, ApJ, 799, 130
Rodríguez-Puebla, A., Primack, J. R., Avila-Reese, V., & Faber, S. M. 2017, MNRAS, 470, 651
Sánchez, C., Clampitt, J., Kovacs, A., et al. 2017, MNRAS, 465, 746
Simha, V., Weinberg, D. H., Davé, R., et al. 2012, MNRAS, 423, 3458
Springel, V. 2005, MNRAS, 364, 1105
Taylor, A., & Hernquist, L. 2002, MNRAS, 333, 649
Taylor, A., Joachimi, B., & Kitching, T. 2013, MNRAS, 432, 1928
Vale, A., & Ostriker, J. P. 2004, MNRAS, 353, 189
Vale, A., & Ostriker, J. P. 2006, MNRAS, 371, 1173
van den Bosch, F. C., Yang, X., Mo, H. J., et al. 2007, MNRAS, 376, 841
Wechsler, R. H., & Tinker, J. L. 2018, ARA&A, 56, 435
Weinberg, D. H., Mortonson, M. J., Eisenstein, D. J., et al. 2013, PhR, 530, 87
Yang, X., Mo, H. J., & van den Bosch, F. C. 2003, MNRAS, 339, 1057
Yang, X., Mo, H. J., & van den Bosch, F. C., Zhang, Y., & Han, J. 2012, ApJ, 752, 41
Yang, X., Zhang, Y., Wang, H., et al. 2018, ApJ, 860, 30
Zehavi, I., Zheng, Z., Weinberg, D. H., et al. 2011, ApJ, 736, 59
Zhang, J., Dong, F., Li, H., et al. 2018, arXiv:1808.02593
Zheng, Z., Berlind, A. A., Weinberg, D. H., et al. 2005, ApJ, 633, 791
Zu, Y., & Mandelbaum, R. 2016, MNRAS, 457, 4360