Lensing Measurements of the Mass Distribution in SDSS Voids

Joseph Clampitt, Bhuvnesh Jain

1 Department of Physics and Astronomy, Center for Particle Cosmology, University of Pennsylvania, 209 S. 33rd St., Philadelphia, PA 19104, USA

8 April 2014

ABSTRACT

We measure weak lensing mass profiles of voids from a volume-limited sample of SDSS Luminous Red Galaxies (LRGs). We find voids using an algorithm designed to maximize the lensing signal by dividing the survey volume into 2D slices, and then finding holes in this 2D distribution of LRGs. We perform a stacked shear measurement on about 20,000 voids with radii between $15 - 40$ Mpc$/h$ and redshifts between $0.16 - 0.37$. We detect the characteristic radial shear signal of voids with a statistical significance that exceeds $13\sigma$. The mass profile corresponds to a fractional underdensity of about -0.4 inside the void radius and a slow approach to the mean density indicating a partially compensated void structure. We compare our measured shape and amplitude with the predictions of Krause et al. 2013. Voids in the galaxy distribution have been extensively modeled using simulations and measured in the SDSS. We discuss how the addition of void mass profiles can enable studies of galaxy formation and cosmology.

Key words: voids, weak lensing

1 INTRODUCTION

The first measurement of lensing from stacked galaxies was observed almost twenty years ago by Brainerd et al. (1996). Since then, applications of this technique to the Sloan Digital Sky Survey (SDSS) have made stacked galaxy lensing an indispensable measure of galaxy halo masses, e.g., Mandelbaum et al. (2005) and Sheldon et al. (2009). More recently, in Clampitt et al. (2014), we measured the stacked lensing signal of filaments connecting neighboring Luminous Red Galaxies (LRGs). With our $15\sigma$ detection, we were able to study the thickness and mass density of voids. With the goal of obtaining such a measurement of voids, we construct a void catalog from holes in the LRG distribution of SDSS, measure the void tangential shear profile, and constrain their density profiles.

There are many void finders in the literature, all differing in implementation and the resulting set of voids found. Colberg et al. (2008) makes a comparison of 13 algorithms. In recent years, methods involving a Voronoi tessellation coupled with a watershed transform have become popular (Neyrinck 2008; Lavaux & Wandelt 2012). These methods have also been successfully applied to data, yielding void catalogs from surveys such as SDSS (Sutter et al. 2012). A lensing analysis of the Sutter et al. (2012) catalog was carried out by Melchior et al. (2013). However, despite careful attention to details of the shear measurement, the small number of voids in the catalog was likely a factor in the marginal detection significance.

Recent work has studied in more detail the properties of dark matter voids in simulations. Hamaus et al. (2014) found that previous fits to simulation density profiles were too simple and provide fitting formulae with parameters that can be adapted to voids with a range of sizes. Sutter et al. (2013) and Sutter et al. (2014) have worked to connect the theory of voids found in the dark matter to those found in galaxies by using Halo Occupation Distribution models to mimic realistic surveys. Excursion set work has focused on providing semi-analytical models of void abundances (Sheth & van de Weygaert 2004; Paranjape et al. 2012), as well as connecting these models to void counts from simulations (Jennings et al. 2013).

Once void catalogs are constructed, they have numerous other applications. Hoyle et al. (2012) used a different void finder (Hoyle & Vogeley 2002; Pan et al. 2012) to study the photometric properties of void galaxies. They find that void galaxies are bluer than those in higher density environments, but do not vary much within the void itself. Cosmological probes such as the Alcock-Paczynski test (Lavaux & Wandelt 2012, Sutter et al. 2012b) and void-galaxy correlations (Hamaus et al. 2014) have been proposed. Finally, voids also provide a sensitive test of some modified gravity theories (Li et al. 2012; Clampitt et al. 2013).

Section 2 describes our basic void-finding algorithm, as
well as our cuts to select a subsample useful for lensing. Section 3 explains our weak lensing measurement, null tests, and expected signal-to-noise. Section 4 presents our results on void density profiles, including both a fitted model and model-independent statements. Finally, Section 5 summarizes our results, caveats, and directions for future work.

2 VOID FINDING

For lensing purposes, the two numbers output by a void finder that matter most are the void center location and radius on the sky. The center is needed for the stacked tangential shear measurement, and the radius so that the background sources for each void in the stack can be placed in the appropriate bin relative to that void’s edge.

2.1 Algorithm

2.1.1 Redshift slices

We use the SDSS DR7-Full LRG catalog of Kazin et al. (2010), which contains $\sim 66,500$ LRGs between $0.16 < z < 0.37$, a roughly volume limited part of the sample. The sky coverage is approximately 7,500 sq. deg. The problem with using the deeper magnitude-limited sample is that too many false voids will be found, i.e., voids which are due to gaps in LRG coverage rather than real density minima. These false voids would dilute the lensing signal when stacked.

We begin by cutting the volume probed by LRGs into slices of comoving thickness $2s_v$, in the line-of-sight direction. For a slice centered at $r_{los}$, we assign (i) $r_{los}$ as the center for all candidate voids found within that slice, and (ii) $s_v$ as the radius in the line-of-sight direction. That these values are reasonable estimates for the void location and size will be verified later (Fig. 1). We use values of $s_v$ between 10 Mpc/h and 50 Mpc/h; as described in § 2.2.4, for any void found in multiple slices we use the largest slice size to assign $s_v$. We show an example of the LRG distribution within a slice in Fig. 1 at $z \sim 0.25$ and with thickness $2s_v = 50$ Mpc/h. The black points show all LRGs in the slice.

2.1.2 2D hole-finding algorithm

The next step is to select the holes in that slice. Our algorithm is as follows:

(i) Pixelize the redshift slice using a fine HEALpix grid with nside=256.

(ii) Define the set of pixels containing LRGs as $L_1$. To define $L_i$ for $i > 1$, take the set of pixels which touch at least one of the $L_{i-1}$ pixels on a side or corner (each pixel has 8 possible neighbors) and add this set of neighbors to $L_{i-1}$ to obtain $L_i$.

(iii) Call the set of pixels in the survey area $U$. Define the set of empty pixels as the set difference $P_i = U - L_i$.

(iv) Divide $P_i$ into N sets of disconnected pixels, $P_{i,j}$ where $j \in \{1, ..., N\}$. Two sets of pixels are disconnected from each other if they share no pixels and no neighboring pixels.

(v) Define $N_{th}$ as the threshold number of pixels required for a void candidate. Any of the $P_{i,j}$ with $N_{th}$ or fewer pixels are removed from $P_i$ and a void candidate with RA, DEC given by the average RA, DEC of those pixels is recorded. Define $P_i'$ as the set of pixels which are part of any disconnected set with $N_{th} + 1$ or greater pixels. We use $N_{th} = 23$, but the results are not very sensitive to this number: if any set of pixels go from above the threshold to vanishing between iteration levels, we also count those as a void candidate.

(vi) Now define $P_2 = P_i' - L_2$. To recap, $P_2$ contains all pixels which are at least 2 pixels away from an LRG, and were not already counted as part of a void candidate in step (v).

(vii) Steps (iv) - (vi) are repeated using $P_2$, finding more void candidates and giving $P_3$. This process continues until no more pixels remain in $P_i$ for some $i$. \footnote{Our algorithm ends when $P_i = \emptyset$.}

The centers of the resulting void candidates for one slice are plotted as the colored points in Fig. 1. For each void candidate, we keep track of the iteration level at which it was identified, i.e., if found in set $P_i$ that object has an iteration level of $i$. Different colors and symbols indicate different iteration levels. For example, the green circles were all identified during the third iteration level. The two purple diamonds in Fig. 1 were identified much later, at level 11. The number of objects found at various iterations of the algorithm is shown in the top left panel of Fig. 3. The number drops quickly with iteration level.

2.1.3 Assigning radii to different iterations

Before cuts can be made on the properties of the candidate voids, we need to assign to each a comoving radius on the sky. The void-finding algorithm naturally works in angular space, so we begin by mapping each iteration level at which a void was found to a specific angle. This is done empirically by binning the 2D LRG density around the candidate void centers for each iteration level, and taking the maximum of the LRG density ridge as the typical angle for that iteration.

The LRG ridge around all voids from a given level is shown for four levels in Fig. 2. If the angle of the peak is plotted as a function of iteration level, as in the right panel of Fig. 2, the points all lie on a line, $\theta_v/\degree = 0.32 \times (\text{level}) + 0.24$. Above iteration level 8, the ridge becomes smeared out and the linear relationship has more scatter. However, since each level removes one more layer of pixels around the LRGs, the slope calibrated using the lower iterations can be extrapolated to the higher ones. Note also that the number of objects falls off quickly with iteration level (Fig. 3) so that any inaccuracies beyond level 8 are of diminishing importance. Thus, we use this linear relationship to assign $\theta_v$ for all the void candidates. This angle is then converted to comoving distance according to

$$R_v = r_{los} \theta_v,$$

where again $r_{los}$ is the comoving distance to the void center.

2.2 Cleaning the catalog

Having found a large set of candidate voids numbering $\sim 68,000$ objects, we next remove those which are not likely to be legitimate large scale structures. These include chance alignments of LRGs in the projection, fake voids due to the
Figure 1. Slice thickness of 50 Mpc/$h$, corresponding to voids with line of sight size radius $s_v = 25$ Mpc/$h$. The black points show pixels containing LRGs in this slice. This is an intermediate redshift ($z \sim 0.25$) slice with intermediate volume and 2D LRG density. The colored circles and diamonds show the output of our void finder for various iteration levels, as marked in the legend. Note that not all objects found at this stage remain in the final catalog.

survey masks and edges, double holes joined by thin “necks,” and multiple detections of the same holes.

2.2.1 Cutting out chance projections

Objects with line-of-sight and transverse sizes which are very different in magnitude are likely to be chance alignments of holes in the sparse LRG sample. Thus we remove these with the requirement

$$s_v/3 < R_v < 3s_v.$$  \hspace{1cm} (2)

The vertical lines on the top center panel of Fig. 3 display this cut.

2.2.2 Random point density

An unusually high number of candidate voids will be found at the survey edges and in regions where the LRG coverage is incomplete due to masking. In order to remove such spurious voids, we use the LRG random catalog from Kazin et al. (2010), which has $\sim 16$ times as many objects as real LRGs. For each void candidate, we find the density of random points inside its angular radius $\theta_v$. The histogram of densities is shown in the lower left panel of Fig. 3. The distribution is tightly peaked at 150 points/deg$^2$, with the densest voids having up to 200 points/deg$^2$. On the low-density end, there is a long tail stretching all the way to zero due to fake voids formed from unobserved regions. We remove the few hundred objects with density less than 100 points/deg$^2$ in this tail.

2.2.3 Distance between pixels within a void

Recall that each candidate void was selected when a group of disconnected pixels fell below a pixel count threshold (§ 2.1.2). The arrangement of these remaining pixels tells us something about the nearby LRGs: if they are roughly circular around the void candidate center, then all pixels will be relatively close to that center. At the other extreme, the pixels may lie along a line, so that some pixels will be much farther from the center than others. In the first case, the distance to the nearest LRGs will be nearly the same in all directions; in the second, the LRG ridge will be indistinct after azimuthally averaging. We expect a better lensing signal for the first case, prompting another set of quality cuts.

For each set of disconnected pixels that make up a void, we calculate the maximum and average of the center to pixel
distance (in arcminutes), and divide by the total number of pixels in that set, \(N_{\text{pix}}\). These distributions are shown in the lower center and right panels of Fig. 3. respectively. The distances peak at \(3' \times N_{\text{pix}}\) but have a long tail stretching towards larger distances. We require a maximum distance below \(6' \times N_{\text{pix}}\) and an average distance below \(4' \times N_{\text{pix}}\) for each void, removing \(\sim 3,000\) objects.

2.2.4 Volume overlap between voids

Many 3D void finders assign each volume element uniquely to one void. (Even if an algorithm allows for sub-voids, these may be underdensities delineated from their parent voids by a small density wall or ridge.) In contrast, our method of finding voids in projected 2D slices requires oversampling the same volume using many different slice thicknesses. This is not a failure of the algorithm, but it does require an extra step to remove objects which are duplicates of the same underdensity. While we do not expect cosmological voids to be cylindrical, our algorithm finds cylindrically shaped regions free of galaxies. Thus for the purpose of removing duplicates we assign a volume \(V = 2s_v \times \pi R_v^2\) to each object and the fractional volume overlap \(f_{\text{vol}}\) based on the neighbor with maximum overlap. Note that this is a significant overestimate of the actual overlap fraction for elliptical or irregularly shaped voids. Based on this metric, we discard voids that overlap completely with a larger voids.

Voids are not perfectly spherical and there are random variations in the LRG distribution. Many void finders aggressively join underdensities into a new void, and calculate a new center and effective radius. Our approach is quite different, but we can get some approximation to such algorithms by lowering \(f_{\text{vol}}\). However, since our main purpose is to make a lensing measurement of void density profiles, we do not want to give up the substantial reduction in shape noise relative to using just one center for each void, as discussed in §3.4. Note that this is analogous to galaxy-galaxy lensing, where a given source galaxy contributes to the den-
Figure 3. Histograms of various void candidate properties which we use to make cuts (solid vertical lines). The first panel shows the number of objects found at each iteration level of our algorithm. The second panel requires that the ratio of the void transverse to line-of-sight size $R_v/s_v$ be near unity, specifically $1/3 < R_v/s_v < 3$. In the third panel we remove the smallest voids, requiring $15 \text{Mpc}/h < R_v$. The fourth panel cuts out false voids which appear near survey masks and edges, by looking at the density of random points within (see text for details) trim the void candidates down to a catalog of $\sim 19,000$ objects.

2.3 LRG surface density

We have sought to assign the line-of-sight and projected void sizes, $s_v$ and $R_{v\text{los}}$, based purely on the LRG distribution. However, since we have only considered the LRGs within the void’s own slice, it is not clear that the assigned $s_v$ is a good choice. We expect that if the $s_v$ values assigned by the preceding algorithm are accurate, then the 2d LRG density at the void radius, just outside the void slice should not have a significant decrement relative to the value far from the void center.

In Fig. 4 we show the LRG density within the slice of interest, i.e., LRGs within $r_{\text{los}} - s_v < r_{\text{los}} < r_{\text{los}} + s_v$, where $r_{\text{los}}$ is the line-of-sight comoving distance of the LRG and $r_{\text{los}}$ is the same for the void center. This results in a smoothed out version of the high peaks in Fig. 2, since it includes voids found at all iterations of the void-finder. The peak is lined up for all voids by binning in units of the void radius $R_v$. By $3R_v$ the LRG density has leveled off near the cosmic mean.

We also show the LRG surface density just outside the void slice, $r_{\text{los}} - 2s_v < r_{\text{los}} < r_{\text{los}} + 2s_v$ or $r_{\text{los}} + s_v < r_{\text{los}} < r_{\text{los}} + 2s_v$. This range is chosen so that the integrated line-of-sight distance, $2s_v$, is the same both inside and outside the void slice. Even at the innermost bin, the LRG density outside has risen back to a comparable value to that at $3R_v$. This is good evidence that the slice thickness of $2s_v$ is a reasonable value for the void size in the line-of-sight direction.

3 LENSING MEASUREMENT

The shear catalog is composed of 34.5 million sources, and is nearly identical to that used in [Sheldon et al. 2009], see that work for further details of the catalog. The source
redshift distribution is obtained by stacking the posterior probability distribution of the photometric redshift for each source, \( P(z_s) \). Its peak is at \( z \approx 0.35 \), and it has a substantial tail extending out to higher redshifts. The full distribution is shown in Fig. 4 of Clampitt et al. (2014), which uses precisely the same source catalog.

In what follows, we describe our lensing measurement procedure. Following the method in Mandelbaum et al. (2013), we use, as the lensing observable, the stacked surface mass density field at the radial distance \( R \) in the region around each void, estimated from the measured shapes of background galaxies as

\[
\Delta \Sigma_k(R; z_L) = \frac{\sum_j w_j \left( \frac{(\Sigma_{\text{crit}}^{-1})(z_L)}{\gamma_k(R)} \right)^{-1} \gamma_k(R)}{\sigma_{\text{shape}} + \sigma_{\text{meas},j}}.
\]

where the summation \( \sum_j \) runs over all the background galaxies in the radial bin \( R \), around all the void centers, the \( k \) indices denote the two components of shear (tangential or cross), and the weight for the \( j \)-th galaxy is given by

\[
w_j = \frac{\left( \frac{(\Sigma_{\text{crit}}^{-1})(z_L)}{\gamma_k(R)} \right)^2}{\sigma_{\text{shape}} + \sigma_{\text{meas},j}}.
\]

We use \( \sigma_{\text{shape}} = 0.32 \) for the typical intrinsic ellipticities.
and $\sigma_{\text{meas},j}$ denotes measurement noise on each background galaxy. $(\Sigma_{\text{crit}}^{-1})_{ij}$ is the lensing critical density for the $j$-th source galaxy, computed by taking into account the photometric redshift uncertainty:

$$
(\Sigma_{\text{crit}}^{-1})_{ij}(z_i) = \int_0^\infty dz_z \Sigma_{\text{crit}}^{-1}(z_i, z_z) P_j(z_z),
$$

where $z_i$ is the redshift of the void and $P_j(z_z)$ is the probability distribution of photometric redshift for the $j$-th galaxy. Note that $\Sigma_{\text{crit}}^{-1}(z_i, z_z)$ is computed as a function of lens and source redshifts for the assumed cosmology as

$$
\Sigma_{\text{crit}}^{-1}(z_i, z_z) = \frac{c^2}{4\pi G} D_A(z_i) (1 + z_i)^{-2} D_A(z_z) D_A(z_i, z_z),
$$

where the $(1 + z_i)^{-2}$ factor is due to our use of comoving coordinates, and we set $\Sigma_{\text{crit}}^{-1}(z_i, z_z) = 0$ for $z_z < z_i$ in the computation.

### 3.1 Jackknife Realizations

We divide the voids into 30 spatial jackknife regions, shown in Fig. 3 of Clampitt et al. (2014). Note that we exclude the low-DEC stripes from our analysis: they are sub-optimal for void finding due to a high ratio of perimeter to area. The remaining area is approximately 7,500 square degrees. We perform the measurement multiple times with each region omitted in turn to make $N = 30$ jackknife realizations. The covariance of the measurement (Norberg et al. 2009) is given by

$$
C[\Delta \Sigma_i, \Delta \Sigma_j] = \frac{(N - 1)}{N} \times \sum_{k=1}^N \left[ (\Delta \Sigma_i) - \bar{\Delta \Sigma_i} \right] \left[ (\Delta \Sigma_j) - \bar{\Delta \Sigma_j} \right],
$$

where the mean value is

$$
\bar{\Delta \Sigma_i} = \frac{1}{N} \sum_{k=1}^N (\Delta \Sigma_i),
$$

and $(\Delta \Sigma_i)^k$ denotes the measurement from the $k$-th realization and the $i$-th spatial bin. The covariance is measured for both components of shear; for clarity we do not denote the separate components in Eqs. 7 and 8.

### 3.2 Null tests

We measure the tangential shear around random points and cross-component around voids, both of which should be consistent with the null hypothesis. For $N = 12$ bins and no model parameters ($n = 0$), the null has expected $\chi^2$:

$$
(\chi^2)_{\text{null}} = N - n \pm \sqrt{2N + 2n} = 12 \pm 4.9.
$$

We perform the random points test by giving each void with radius $R_v$ and redshift $z$ a random location in the survey area, avoiding masked regions in the same way as the LRG catalog. Often tests involving random points use many more random points than lens galaxies, but since void lenses are so large and many source galaxies fall in each radial bin, we need only use as many random points as we have void positions. The result for the tangential shear around random points is a $\chi^2 = 16.7$, within $1\sigma$ of the null hypothesis.

The cross-component is shown in Fig. 5 (pink triangles), and with a $\chi^2 = 8.2$ it is also within $1\sigma$ of the null hypothesis.

### 3.3 Tangential shear profile

We show the stacked lensing profile of the voids in the left panel of Fig. 5. The most significant and largest amplitude $\Delta \Sigma$ values of $\sim -0.6M_\odot/\text{pc}^2$ occur at the void radius $R_v$. The signal remains significant out to $\sim 2.5 - 3R_v$. The covariance, shown in Fig. 4, is used to calculate the detection significance. Comparing the signal to the null hypothesis, we have $\chi^2 = 94.2 (78.7)$, a $16.7\sigma (13\sigma)$ inconsistency for the pictured fiducial case (overlaps well below 50% case).

This high significance detection is further supported by the null tests described above. We check our measured statistical significance with a rough analytical estimate of the signal-to-noise below. We then discuss the implications for void density profiles.

The covariance matrix is largely diagonal up to 1.5 $R_v$. At large $R$ the off diagonal elements are mostly positive, presumably since multiple projections of source galaxies provide less independent information about the voids. In Fig. 7 we show three size bins. No systematic trend in magnitude or shape of the signal is visible from these plots. The consistency of the signal across size bins that span nearly a factor of three in void radius validates the lensing interpretation.

### 3.4 Analytical signal-to-noise estimate

The tangential shear around a void is given by

$$
\gamma_t = \frac{\Delta \Sigma}{\Sigma_{\text{crit}}} = \frac{\Sigma(< R) - \Sigma(R)}{\Sigma_{\text{crit}}}
$$

where $\Sigma_{\text{crit}}$ is defined above and is $\Sigma_{\text{crit}} \approx 6000M_\odot/\text{pc}^2$ for our typical lens and source redshifts. Inside the void radius the signal can be anticipated using the results of Krause et al. (2013): $\Delta \Sigma \approx -0.6M_\odot/\text{pc}^2$ (adjusted for the fact that our mean void radius is larger than the range considered in Krause et al). Hence the typical tangential shear is $\gamma_t \approx 10^{-4}$.

The noise is dominated by shape noise. With $\sigma_{\text{shape}} = 0.32$, and a source number density $n \approx 0.5/\text{arcmin}^2$, we can estimate the noise contribution on a stacked void lensing measurement. For $N_v$ voids of radius $\theta_v$, we get a sky coverage that exceeds $N_v\pi(2\theta_v)^2$ since the signal is measured out to at least twice the void radius. This gives a total effective number of sources $N_{\text{source}} = N_v\pi(2\theta_v)^2 \approx 1 - 2 \times 10^9$. This is at least thirty times larger than the actual number of source galaxies since each galaxy shape is used multiple times: it is projected along different directions for different void centers. As discussed above in Section is a valid procedure in cross-correlations such as ours and galaxy-galaxy lensing. The estimated shape noise is then $\sigma_{\text{shape}}/\sqrt{N_{\text{source}}} \approx 0.7 - 1 \times 10^{-5}$. The uncertainty is mainly due to the choice of a single void size to represent the distribution. The estimated signal to noise is in the range:

$$
\text{S/N} \approx 12.
$$
While the estimate above involves several approximations, it gives us a reality check on our measurement. One might still worry that shears at the $10^{-4}$ level are dominated by systematic errors. Indeed for shear-shear correlations from SDSS, that appears to be the case due to additive systematics that are spatially correlated. Such terms however cancel out cross-correlations. Published measurements of galaxy-galaxy lensing demonstrate this: at distances greater than 10 Mpc the signal falls below $10^{-4}$, see e.g. Figure 6 in Mandelbaum et al (2013). We have checked that the signal-to-noise of that measurement is consistent with ours, adjusting for the smaller number of source galaxies in their angular bin. Of course closer to the center the galaxy halo overdensity far exceeds the amplitude of the void underdensity, so integrated over all scales the significance of the galaxy-galaxy lensing measurement is higher.

3.5 Comparison with other work

The strength of our detection may be surprising given other work on void lensing. In particular, Melchior et al. (2013) used a conservative sample of a relatively conservative void finder (Sutter et al. 2012) which was not optimized for lensing purposes. All these factors make a difference in the potential S/N:

- Melchior et al. (2013) used the “central” sample of Sutter et al. (2012) for trygdim (the sample most comparable to ours) the usable volume is only 75% of the total. Furthermore, the void fraction volume is less in the central sample than in the total, with respect to their own usable volumes. We make a related quality cut, but which only removes $\sim 1\%$ of our sample (Fig. 5 lower left panel).
- Over most of the volume where Sutter et al. (2012) can compare with Pan et al. (2012), the former finds only half as many voids. This is for the main SDSS galaxy sample, but it is indicative of a difference in void finder aggressiveness between the two methods.
- Another point worth noting is that our assignment of void radii on the sky is optimized for lensing by setting $R_v$ to the distance to the LRG ridge in the plane of the sky. Sutter et al. (2012) starts with the void volume and then assign the void radius as $R_{\text{eff}} = (3V/4\pi)^{1/3}$, which is used by Melchior et al. (2013) to bin the background shears. Converting in this way from volume to an effective void radius assumes all three dimensions are the same, but for lensing purposes the line-of-sight size of the void is much less important than its size on the sky. We have tested the effect of assigning an $R_{\text{eff}}$ as described above to each of the voids in our fiducial sample and then remeasuring $\Delta \Sigma$ binned in $R/R_{\text{eff}}$. The result is an increase in our errors such that the detection significance drops from $16.7\sigma$ to $12.5\sigma$.

4 VOID DENSITY PROFILE

4.1 Model constraints

The 3-dimensional density profiles of voids have been studied using simulations and other theoretical approaches. One of the subtle issues is how to transition from the underdensity of the void to the cosmic mean density $\bar{\rho}$ at a sufficiently large distance from the void center. Typically a small transition zone outside the void radius allows for some degree of compensation of the profile, i.e., a region of density higher than $\bar{\rho}$. In perfectly compensated voids models, the enclosed mass at about two times the void radius is exactly the same as the mass enclosed in a region of the same size with constant density $\bar{\rho}$.

Lavaux & Wandelt (2012) fit a cubic profile inside the void radius using simulations, and Krause et al. (2013) gives the lensing prediction for this model. We use the cubic profile up to the void radius, but outside the void we use a constant density profile. Thus we require continuity at the void radius but not exact compensation. The resulting profile is given by

$$\rho(r, R_v) = \begin{cases} 
\bar{\rho}[A_0 + A_3(r/R_v^{(m)})^3] & \text{for } 0 < r < R_v^{(m)} \\
\bar{\rho}[A_0 + A_3] & \text{for } R_v^{(m)} < r 
\end{cases}, \quad (12)$$

where $A_0$, $A_3$, and $R_v^{(m)}/R_v$ are model parameters. However, we are not sensitive to $A_0$, and so have assumed its value is set by requiring that the 3d density returns to the cosmic mean density outside the void, thus $A_0 = 1 - A_3$. Then our fit just involves two parameters, $A_3$ and $R_v^{(m)}/R_v$, which are constrained as in Fig. 6. For our two parameter model the expected chi-square is $\chi^2 = 10 \pm 5.3$ so that the $\chi^2 = 13.8$.
of the best-fit model is acceptable. The right panel of Fig. 8 shows the corresponding 3d density profile for our best-fit parameters.

If we were to require compensation, as in some models explored by Krause et al. (2013), we would put some constraints on $A_0$. However, assuming that $\Sigma = \Sigma$ by $2R_v$ (see below), the data clearly prefers an uncompensated void inside $2R_v$. This is shown by the negative values of the measured $\Delta \Sigma$ up to and beyond $2R_v$ (it should be zero for a compensated void if $\Sigma(2R_v) \to \Sigma$). We see no evidence for a ridge of density well above $\bar{\rho}$ just beyond $R_v$, as suggested by the LRG profiles for the small voids. The data in fact support a projected density below the mean at $R_v$. More work is needed to understand the relationship of the LRGs to the mass profile as we expect that our void finder played some role in the details of the LRG profile.

While the minimum density at the center of the void is formally not constrained by the data, we find that the requirement that the density approach the mean at large radii, coupled with measurements between $R_v$ and $2R_v$, leave little freedom. We explored modifications to the density profile beyond $R_v$ and find that $A_0$ can be lowered by at most 0.1. The arrow in Fig. 8 (right panel) pointing to lower central densities indicates this possibility.

The solid gray bands on the x- and y-axes of Fig. 8 show 1d marginalized constraints for both parameters. The hatched bands of Fig. 8 compare the effect of stricter criteria for void overlap, for the case with overlaps well below 50%. The constraints are degraded due to throwing away a large fraction of overlapping voids, but the shift in the contours is negligible for $R_v^{(m)}$ and just over $1\sigma$ for $A_3$.

### 4.2 Estimated mass deficit inside the voids

Since the measured $\Delta \Sigma = \Sigma(< R) - \Sigma(R)$, we can estimate $\Sigma(< R_v)$ once we require $\Sigma$ to approach $\Sigma$ at some large radius. At radii above $2R_v$ both the galaxy distribution and the mass in simulations are close to the mean density. These are large scales, typically above $40 \, \text{Mpc}/h$, so it is reasonable to expect that there aren’t departures at more than a few percent level from mean density in the data as well. We therefore use our measurements at about $2R_v$ to estimate $\Sigma(< R_v)$ with this assumption. We test it by checking the range $1.5 - 2.5R_v$, at which our signal to noise is still reasonable.

The results for the mass deficit and fractional mass deficit are shown in Table 1. Three methods are used: directly from the data as described above, using our best fit for $\rho(r)$, and using the best fit $\rho(r)$ from voids in N-body simulations with a similar tracer to our LRG halos (such tracers enclose voids with more mass in small scale structure than in voids identified using dark matter particles – Sutter et al. (2014) and Sutter, private communication). Each estimate involves some assumptions or caveats which are briefly described in the table. The mass deficit

$$\delta M = \frac{4\pi}{3} R_v^3 [\rho(< R_v) - \bar{\rho}]$$

is estimated for the 3d model fit and the fit to simulations.

While we have not attempted to place rigorous bounds on our estimated $\delta M$ values, we can see the trends between data and simulations: the two methods of estimation from the data are in reasonable agreement, and involve more mass inside voids than in simulations (the deficit is about 40% higher in the simulation fits). Projection effects and flaws in the void finder would lead us to overestimate the mass enclosed. We also note that we extended the profile from $R_v$ to $2R_v$ using different models, including a possible ridge of density above the mean, but find that the measurements leave little wiggle room.

Our measurements indicate significant levels of under-density inside the void radius: the inferred 3d fractional under-density is $\approx -0.3$ to $-0.4$ inside $R_v$. This corresponds to mass deficits comparable to the masses of the most massive clusters in the universe. The bigger voids in our sample will have up to ten times the mass deficit. Given that our LRG sample has a bias factor of about 2, we expect that voids using a less biased tracer would have lower central densities. Simulations with mock catalogs also support this trend (Sutter et al. 2014). We leave for future work the details of the mass profile and its relationship to the galaxy sample and void finder.

### 5 DISCUSSION

Void Lensing Detection. We have made the first statistically significant measurement of gravitational lensing by large voids (Fig. 5), ruling out the null hypothesis with a significance of about $13 - 16\sigma$ depending on the cuts made on the void finder. This detection may be surprising given that theoretical work (Krause et al. 2013) predicted that ambitious future surveys (in particular, Euclid) would be needed for measurements with comparable signal-to-noise. We differ from previous work in that our void finder and
Table 1. Estimated mass deficit $\delta M$ and the fractional deficit in the 3d density $\rho$ and projected density $\Sigma$ at the void radius $R_v$. The measurements, interpreted without a model in the first row, give us only projected quantities. For the model fits we give both 2d and 3d versions of the fractional density contrast. We set $R_v = 20 \, \text{Mpc}/h$ to estimate $\delta M$; for voids with other values of $R_v$, $\delta M$ scales approximately as $R_v^2$. See text for discussion of the dependence on the LRG sample and the simulation fits.

| Method                  | $\delta M(< R_v)$ | $\rho(< R_v)/\bar{\rho} - 1$ | $\Sigma(< R_v)/\bar{\Sigma} - 1$ | Assumptions                        |
|-------------------------|-------------------|-------------------------------|-----------------------------------|-----------------------------------|
| Measured $\Delta \Sigma(R_v - 2R_v)$ | $-$               | $-$                           | $-0.2$ ($-0.3$)                   | $\Sigma(R) \rightarrow \Sigma$ at $R \approx R_v(2R_v)$ |
| Best fit model          | $\approx -1 \times 10^{15} M_{\odot}$ | $-0.3$ ($-0.4$)             | $-0.22$ ($-0.32$)                 | Fix $A_0$ to recover mean density at $R \approx R_v(2R_v)$         |
| Fit from simulations    | $\approx -1.4 \times 10^{15} M_{\odot}$ | $-0.5$                       | $-0.44$                          | Different void finder. No projection effects.                  |

Caveats. The standard disclaimer with void-related work is that the results can be quite sensitive to the specific void-finder used. As highlighted above, this holds true also for our work which is designed to find voids for gravitational lensing. Our use of multiple potential void centers is helpful for lensing $S/N$ reasons, but also makes interpretation of the resulting density profile less straightforward. We expect some miscentering between the lowest dark matter density and the emptiest places in the sparse galaxy density, and our multiple centers may also add to this miscentering in some instances. However since the density profiles are very flat between the center and half the void radius, these effects are far less problematic than for galaxy or cluster lensing.

We expect our error bars accurately account for shape noise and sample variance. However, we have not accounted for possible shear calibration errors, which could bias the signal by up to 5%. In addition, two effects could result in a dilution of the signal and thus underestimation of $A_3$: inaccurate source redshifts or fake voids from chance LRG projections. We have not estimated the contribution of these effects.

Future Work. We can attempt a void lensing measurement with several different variants of the void sample. Going beyond our sparse sample of LRGs, we can apply this void finder to the SDSS Main sample. Although the volume probed will be significantly smaller, this disadvantage is offset in part by the larger number of background sources available behind lower redshift voids. Furthermore, Sutter et al. (2014) find that the voids identified using a lower galaxy luminosity threshold have a lower central dark matter density (as expected based on their lower galaxy bias as well), which should increase the lensing effect.

Nearly all detailed applications will require a careful study of our void selection via mock catalogs that create galaxies from HOD prescriptions or dark matter halos. Our measurements are now confined to $R_v > 15 \, \text{Mpc}/h$, in part because the contamination from fake voids due to projection effects gets worse as the void size gets smaller than the 2d tracer density. Mock catalogs will allow us to go down to smaller radii and estimate the number of fake and real small voids. With those numbers we can take into account the expected dilution of the signal.

The comparison of the galaxy distribution with the mass distribution is of great interest. The question of galaxy biasing can be understood better by having measurements in under dense regions to complement those in over dense regions. Many other questions can be posed by stacking voids in different ways: along the major axis of the galaxy distribution, varying the environment and the properties of the galaxy population, and so on. The measurement of a magnification signal behind voids would be of interest, in particular to provide a direct measurement of $\Sigma(R)$. 

Void mass functions, mass profiles, and the cross-correlation with galaxy profiles are the key ingredients in cosmological applications of voids. The velocity profiles measured in SDSS have an anisotropy and relationship to the mass profile that carry cosmological information (Lavaux & Wandelt 2012). Modified gravity theories in particular predict differences in these observables. In many respects
modeling voids is less problematic than massive nonlinear objects like galaxy clusters, and the measurements are not affected by foreground galaxies, but the use of mock catalogs to understand the selection effects in the data is likely to be essential to interpreting survey measurements.

ACKNOWLEDGMENTS

We would like to thank Gary Bernstein, Sarah Bridle, Doug Clowe, Nico Hamaus, Adam Lidz, Ravi Sheth, Paul Sutter, and Vinu Vikram for helpful discussions. Mike Jarvis and Elisabeth Krause gave us many insightful suggestions as well as valuable feedback on the paper. We are very grateful to Erin Sheldon for the use of his SDSS shear catalogs. BJ and JC are partially supported by Department of Energy grant de-sc0007901.

REFERENCES

Brainerd, T. G., Blandford, R. D., & Smail, I. 1996, ApJ, 466, 623
Clampitt, J., Cai, Y.-C., & Li, B. 2013, MNRAS, 431, 749
Clampitt, J., Jain, B., & Takada, M. 2014, [arXiv:1402.3302]
Colberg, J. M., Pearce, F., Foster, C., et al. 2008, MNRAS, 387, 933
Hamaus, N., Wandelt, B. D., Sutter, P. M., Lavaux, G., & Warren, M. S. 2014, Physical Review Letters, 112, 041304
Hamaus, N., Sutter, P. M., & Wandelt, B. D. 2014, [arXiv:1403.5499
Hoyle, F., & Vogeley, M. S. 2002, ApJ, 566, 641
Hoyle, F., Vogeley, M. S., & Pan, D. 2012, MNRAS, 426, 3041
Jennings, E., Li, Y., & Hu, W. 2013, MNRAS, 434, 2167
Kazin, E. A., Blanton, M. R., Scoccimarro, R., et al. 2010, ApJ, 710, 1444
Krause, E., Chang, T.-C., Doré, O., & Umetsu, K. 2013, ApJL, 762, L20
Lavaux, G., & Wandelt, B. D. 2012, ApJ, 754, 109
Li, B., Zhao, G.-B., & Koyama, K. 2012, MNRAS, 421, 3481
Mandelbaum, R., Hirata, C. M., Seljak, U., et al. 2005, MNRAS, 361, 1287
Mandelbaum, R., Slosar, A., Baldauf, T., et al. 2013, MNRAS, 432, 1544
Melchior, P., Sutter, P. M., Sheldon, E. S., Krause, E., & Wandelt, B. D. 2013, [arXiv:1309.2045]
Neyrinck, M. C. 2008, MNRAS, 386, 2101
Norberg, P., Baugh, C. M., Gaztañaga, E., & Croton, D. J. 2009, MNRAS, 396, 19
Pan, D. C., Vogeley, M. S., Hoyle, F., Choi, Y.-Y., & Park, C. 2012, MNRAS, 421, 926
Paranjape, A., Lam, T. Y., & Sheth, R. K. 2012, MNRAS, 420, 1648
Sheldon, E. S., Johnston, D. E., Scranton, R., et al. 2009, ApJ, 703, 2217
Sheth R. K., van de Weygaert R., 2004, MNRAS, 350, 517
Sutter, P. M., Lavaux, G., Wandelt, B. D., & Weinberg, D. H. 2012, ApJ, 761, 44
Sutter, P. M., Lavaux, G., Wandelt, B. D., & Weinberg, D. H. 2013, [arXiv:1309.5087]
Sutter, P. M., Lavaux, G., Wandelt, B. D., Weinberg, D. H., & Warren, M. S. 2014, MNRAS, 438, 3177

© 0000 RAS, MNRAS 000, 000–000