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Precision photometric redshift calibration for galaxy–galaxy weak lensing*

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ABSTRACT

Accurate photometric redshifts are among the key requirements for precision weak lensing measurements. Both the large size of the Sloan Digital Sky Survey (SDSS) and the existence of large spectroscopic redshift samples that are flux-limited beyond its depth have made it the optimal data source for developing methods to properly calibrate photometric redshifts for lensing. Here, we focus on galaxy–galaxy lensing in a survey with spectroscopic lens redshifts, as in the SDSS. We develop statistics that quantify the effect of source redshift errors on the lensing calibration and on the weighting scheme, and show how they can be used in the presence of redshift failure and sampling variance. We then demonstrate their use with 2838 source galaxies with spectroscopy from DEEP2 and zCOSMOS, evaluating several public photometric redshift algorithms, in two cases including a full $p(z)$ for each object, and find lensing calibration biases as low as <1 per cent (due to fortuitous cancellation of two types of bias) or as high as 20 per cent for methods in active use (despite the small mean photoz bias of these algorithms). Our work demonstrates that lensing-specific statistics must be used to reliably calibrate the lensing signal, due to asymmetric effects of (frequently non-Gaussian) photoz errors. We also demonstrate that large-scale structure (LSS) can strongly impact the

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photoz calibration and its error estimation, due to a correlation between the LSS and the photoz errors, and argue that at least two independent degree-scale spectroscopic samples are needed to suppress its effects. Given the size of our spectroscopic sample, we can reduce the galaxy–galaxy lensing calibration error well below current SDSS statistical errors.

Key words: gravitational lensing – galaxies: distances and redshifts.

1 INTRODUCTION

Galaxy–galaxy lensing is the deflection of light from distant source galaxies due to the matter in more nearby lens galaxies. In the weak regime, gravitational lensing induces 0.1–10 per cent level tangential shear distortions of the shapes of background galaxies around foreground galaxies, allowing direct measurement of the galaxy–matter correlation function around galaxies. Due to the very small signal, typical measurements involve stacking thousands of lens galaxies to get an averaged lensing signal.

Since the initial detections of galaxy–galaxy (g–g) lensing (Tyson et al. 1984; Brainerd, Blandford & Smail 1996; Hudson et al. 1998; Fischer et al. 2000; McKay et al. 2001; Smith et al. 2001), it has been used to address a wide variety of astrophysical questions using data from numerous sources. These applications include (but are not limited to) determining the relation between stellar mass, luminosity and halo mass to constrain models of galaxy formation (Hoekstra et al. 2005; Heymans et al. 2006a; Mandelbaum et al. 2006c); understanding the relation between halo mass from lensing and bias from galaxy clustering to constrain cosmological parameters (Sheldon et al. 2004; Seljak et al. 2005); measuring galaxy density profiles (Hoekstra, Yee & Gladders 2004; Mandelbaum et al. 2006b) and understanding the extent of tidal stripping of the matter profiles of cluster satellite galaxies (Natarajan, Kneib & Smail 2002; Limousin et al. 2007). In the future, galaxy–galaxy lensing will be used for geometrical tests that constrain the scalefactor $a(t)$ and curvature Ω_K of the Universe (Jain & Taylor 2003; Bernstein & Jain 2004; Bernstein 2006). As data continue to pour in, and future surveys are planned with even greater statistical power, the time has come to place galaxy–galaxy lensing on a firmer foundation by addressing systematics to greater precision.

The g–g lensing signal calibration depends on several systematics, including the calibration of the shear (Heymans et al. 2006b; Massey et al. 2007) and theoretical uncertainties such as galaxy intrinsic alignments (Agustsson & Brainerd 2006; Altay, Colberg & Croft 2006; Heymans et al. 2006c; Mandelbaum et al. 2006b; Faltenbacher et al. 2007), both areas in which there is significant ongoing work. Here, we focus on the proper calibration of the source redshift distribution for galaxy–galaxy lensing in the case where all lens redshifts are known. The Sloan Digital Sky Survey (SDSS) has the rather unique capability of offering spectroscopic redshifts for all lenses, which both removes any calibration bias due to error in lens redshift estimation, and also allows us to compute the signal as a function of physical transverse (instead of angular) separation from the lenses, simplifying theoretical interpretation. While several theoretical studies have estimated the effects of photoz errors for shear–shear autocorrelations (Huterer et al. 2006; Ma, Hu & Huterer 2006; Abdalla et al. 2007; Bernstein & Ma 2007), we present the first such analysis for galaxy–galaxy lensing, in which we not only offer statistics to use to evaluate the calibration bias, but also carry out an analysis with attention to practical issues such as sampling variance in the calibration sample. This work will therefore enable future g–g lensing analyses with other data sets to address other scientific questions, and reveal potential issues with spectroscopic calibration of photometric redshifts that are more general than just g–g lensing. We also address the extension of these techniques to galaxy–galaxy lensing without lens redshifts, and to cosmic shear, in Appendix A.

Currently, there are two methods used for source redshift determination in g–g lensing. The first is the use of an average redshift distribution for the sources. The primary difficulty with this method is finding a sample of galaxies with spectroscopy that has the same selection criteria as the source galaxies. Weak lensing requires well-determined shapes for each source, so a lensing source catalogue is not purely flux-limited, and literature estimates of $\mathrm{d}N/\mathrm{d}z$ for flux-limited samples may not be appropriate (we show in this paper that for SDSS, the lensing-selected sample is at a higher mean redshift than the corresponding flux-limited sample at fixed magnitude). The solution is to find a spectroscopic sample that overlaps the source sample and is at least as deep, using it to determine the redshift distribution using only lensing-selected galaxies in the spectroscopic sample. For deeper lensing surveys, no such spectroscopic sample exists. In other cases, it exists but may be quite small, with large uncertainty in $\mathrm{d}N/\mathrm{d}z$ due to Poisson error and, more significantly, large-scale structure (LSS). The second difficulty is that without individual redshift estimates for each source, there is no way to remove sources that are physically associated with lenses from the source sample, which can lead to dilution of the lensing signal by non-lensed galaxies (a systematic that is easily controlled) and, more significantly, signal suppression due to intrinsic alignments [which cannot yet be easily controlled (Agustsson & Brainerd 2006; Mandelbaum et al. 2006b), and which can cause contamination larger than the size of the statistical errors for small transverse separations].

The second method is to use broad-band photometry to measure a photometric redshift (photoz) for each source galaxy. Photoz estimation exploits the fact that even with broad passbands, we can still learn enough about the spectral energy distribution to estimate the redshift. While photoz estimation that yields accurate values over a wide range of redshifts for all galaxy types is difficult, there have been several recent successes in this field (Feldmann et al. 2006; Ilbert et al. 2006). To fully constrain the calibration of the g–g lensing signal, we must understand the full photoz error distribution as a function of many parameters, particularly those relevant to galaxy–galaxy lensing, such as brightness, colour, environment and of course redshift. Since the photoz error distributions will depend on a complex interplay between the widths and shapes of the filter functions, the set of filters used in the photoz estimates, the photometry error distributions and the spectral energy distributions of the galaxies themselves, the photoz error distributions will not be symmetric or Gaussian in general, even if the photometric errors in flux are Gaussian (the magnitude errors are not in any case, and some photoz methods use magnitudes instead of fluxes). To be accurate, this photoz error distribution must be determined with a sample

of galaxies with the same selection criteria (depth, colour, etc.) as the source sample. This is quite important because, as the photometry gets noisier, the photoz error distribution can not just broaden, but can also develop asymmetry, tails and other non-Gaussian properties.

So, as for methods that use a statistical source redshift distribution, we once again must find a large spectroscopic sample with the same selection criteria as our source catalogue. (Some photoz methods also require a training sample with the same selection criteria as the source sample.) The completeness and rate of spectroscopic redshift failure are both potentially important, particularly if the spectroscopic redshift failures all lie in a specific region of redshift or colour space. If a photoz method has a significant failure fraction, then we may be forced to eliminate a large fraction of the source sample, thus increasing statistical error significantly. Three major advantages of photoz values for lensing are that they (1) allow us to eliminate some fraction of the physically associated lens–source pairs, thus reducing the effects of intrinsic alignments, (2) allow us to optimally weight each galaxy by the expected signal and (3) allow us to reduce, if not eliminate, 'sources' that are in the foreground from the sample entirely (a special case of optimal weighting).

We present a method to obtain robust, per cent level calibration of the g–g lensing signal using a sample of several thousand spectroscopic redshifts selected from the source sample (i.e. with the same selection criteria). The sources of spectroscopy we use to demonstrate this method are the DEEP2 and zCOSMOS surveys (described in Section 2). The use of two surveys in two areas of the sky carried out with two different telescopes is important, because (a) they do not have the same patterns of redshift failure and (b) the LSS in the two surveys is not correlated with each other, so effects of sampling (cosmic) variance are reduced for the combined sample. In addition, we use space-based data for the full COSMOS sample to quantify the efficacy of our star/galaxy separation scheme.

We then use this method to analyse the redshift-related calibration bias of the lensing signal in previous g–g lensing analyses that used our SDSS source catalogue (Hirata et al. 2004; Mandelbaum et al. 2005; Seljak et al. 2005; Mandelbaum et al. 2006a,b,c; Mandelbaum & Seljak 2007). Our calibration bias analysis is quite important, as our statistical error for some applications has dropped below 5 per cent, making our systematics requirements more stringent.

More importantly, we take a broad view, testing not just the redshift determination methods that we have used in the past, but also several new ones that have been developed in the past few years, in order to determine which ones are most useful for lensing. In the process, we determine which common photoz failure modes and error distributions are most problematic for g–g lensing. The results of our analysis will be useful not only for SDSS g–g lensing, and the method we present is generally useful for future weak lensing analyses (and generalisable to scenarios without spectroscopy for lenses and to shear–shear autocorrelations), particularly as larger, deeper spectroscopic data sets are becoming available.

In Section 2, we describe the lensing source catalogue and the spectroscopic redshift samples. Section 3 includes a description of the source redshift determination algorithms that we will test in this work. In Section 4, we describe our method for determining the source redshift-related calibration bias, including handling complexities such as LSS. We present the results of our analysis in Section 5, and discuss the implications of these results in Section 6.

When computing angular diameter distances, we assume a flat cosmology with $\Omega_{\rm m} = 0.27$ and $\Omega_\Lambda = 0.73$.

2 DATA

2.1 SDSS

The data used for the lensing source catalogue are obtained from the SDSS (York et al. 2000), an ongoing survey to image roughly π sr of the sky, and follow up approximately one million of the detected objects spectroscopically (Eisenstein et al. 2001; Richards et al. 2002; Strauss et al. 2002). The imaging is carried out by drift-scanning the sky in photometric conditions (Hogg et al. 2001; Ivezić et al. 2004), in five bands (*ugriz*) (Fukugita et al. 1996; Smith et al. 2002) using a specially designed wide-field camera (Gunn et al. 1998). These imaging data are used to create the source catalogue that we use in this paper. In addition, objects are targeted for spectroscopy using these data (Blanton et al. 2003b) and are observed with a 640-fibre spectrograph on the same telescope (Gunn et al. 2006). All of these data are processed by completely automated pipelines that detect and measure photometric properties of objects, and astrometrically calibrate the data (Lupton et al. 2001; Pier et al. 2003; Tucker et al. 2006). The SDSS is well underway, and has had seven major data releases (Stoughton et al. 2002; Abazajian et al. 2003, 2004; Finkbeiner et al. 2004; Abazajian et al. 2005; Adelman-McCarthy et al. 2006, 2007a,b).

The source sample we describe was originally presented in Mandelbaum et al. (2005), hereafter M05. It includes over 30 million galaxies from the SDSS imaging data with *r*-band model magnitude brighter than 21.8. Shape measurements are obtained using the REGLENS pipeline, including point spread function (PSF) correction done via re-Gaussianization (Hirata & Seljak 2003) and with selection criteria designed to avoid various shear calibration biases. A full description of this pipeline can be found in M05.

2.2 DEEP2

The DEEP2 Galaxy Redshift Survey (Davis et al. 2003; Madgwick et al. 2003; Coil et al. 2004; Davis et al. 2005) consists of spectroscopic observation of four fields using the DEep Imaging Multi-Object Spectrograph (DEIMOS, Faber et al. 2003) on the Keck Telescope. This paper uses data from field 1, the Extended Groth Strip (EGS), centred at RA $14^{\rm h}17^{\rm m}$, Dec. $+52^\circ30'$ (J2000) and with dimensions 120×15 arcmin^2 (Davis et al. 2007). Galaxies brighter than $R_{\rm AB} = 24.1$ were observed in all four DEEP2 fields, but in the other three fields besides EGS, two colour cuts were made to exclude galaxies with redshifts below $z \sim 0.7$. The DEEP2 EGS sample, in contrast, includes objects of all colours with $R_{\rm AB} < 24.1$, although colour-selected $z < 0.75$ objects with $21.5 < R_{\rm AB} < 24.1$ receive slightly lower selection weight. This is the sample from which a bright subset, $r < 21.8$, was extracted for this paper. The selection probabilities for all objects are well known, allowing us to account for this deweighting directly, though this has little impact for this study, since only a small fraction of galaxies with useful SDSS shape measurements are fainter than $R = 21.5$, and they have little statistical weight due to their larger shape measurement errors. Due to saturation of the Canada–France–Hawaii Telescope (CFHT) detectors used for target selection, no galaxies brighter than $R_{\rm AB} \approx 17.6$ were targeted; these galaxies constitute a very small fraction of our source sample.

For this paper, we use all EGS data collected through the spring of 2005, a parent catalogue of more than 13 000 spectra (Davis et al. 2007). The 155 DEEP2 EGS objects with $r < 21.8$ (the limit of our source catalogue) that failed to yield redshifts in initial DEEP2 analyses were re-examined in detail; after this effort, the net redshift

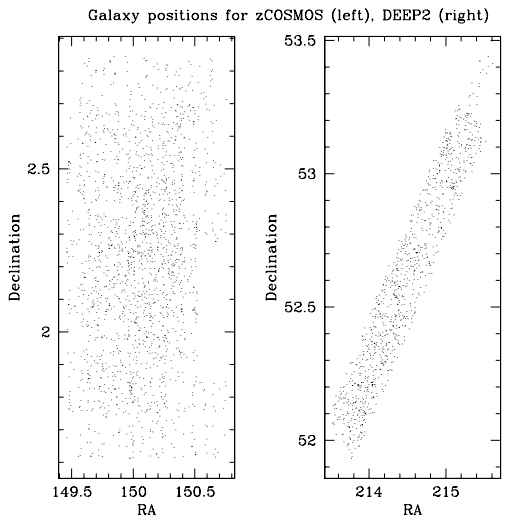

Figure 1. Positions of the zCOSMOS (left-hand panel) and DEEP2 (right-hand panel) spectroscopic galaxies used in this work.

success rate (defined as DEEP2 quality 3 or 4) was 96 per cent, significantly higher than for the full EGS sample. The positions of the DEEP2 EGS matches in our source catalogue are shown in the right-hand panel of Fig. 1. There are ∼1530 SDSS galaxies in this region with matches in DEEP2 at $r < 21.8$. Roughly 65 per cent of those pass the lensing selection, leaving us with a sample of 1013.

2.3 zCOSMOS

The other redshift survey used for this work is zCOSMOS (Lilly et al. 2007), which uses the Visible Multi-Object Spectrograph (VIMOS; LeFevre et al. 2003) on the 8-m European Southern Observatory's Very Large Telescope (ESO VLT) to obtain spectra for galaxies in the COSMOS field, which is 1.7 deg^2 centred at RA 10^h, Dec. $+2°12'21''$. We use data from the zCOSMOS-bright survey, which is purely flux-limited to $I_{AB} = 22.5$, well beyond the flux limit of our source catalogue, and currently contains $\sim 10^4$ galaxies (Lilly et al., in preparation). Observations began in 2005 and will take at least three years to complete.

One important benefit of the zCOSMOS data is that due to its location in the Cosmological Evolution Survey (COSMOS) field (Capak et al. 2007; Scoville et al. 2007a,b; Taniguchi et al. 2007), there is very deep broad-band observing data from a variety of telescopes in addition to a single passband observation from the Advanced Camera for Surveys (ACS) on the *Hubble Space Telescope* (*HST*). This photometry has been used to generate extremely high-quality photometric redshifts using the Zurich Extragalactic Bayesian Redshift Analyser (ZEBRA; Feldmann et al. 2006), which will be described further in Section 3, and several other photoz codes (Mobasher et al. 2007). Using data with $u*$, B, V, g', r', i', z' and K_s photometry, the photometric redshift accuracy for the bright, I-selected sample is remarkable, $\sigma_{\Delta z/(1+z)} < 0.03$. This accuracy is achieved using 10 per cent of the zCOSMOS sample as a training set. In cases of spectroscopic redshift failure, these nearly noiseless photoz values can be used instead. We will demonstrate explicitly that the effect on the estimated lensing redshift calibration bias of using their photoz values for redshift failures is within the statistical error. Consequently, the nominal 8 per cent spectroscopic redshift failure rate for zCOSMOS galaxies in our source catalogue is effectively zero for our purposes.

The *HST* imaging in the full COSMOS field was also used for another test because it enables star/galaxy separation to be performed more accurately than in SDSS. Consequently, we use the full COSMOS galaxy sample to match against our source catalogue and identify the stellar contamination fraction to high accuracy.

The positions of the zCOSMOS matches in our source catalogue are shown in the left-hand panel of Fig. 1. We have spectra in an area covering ∼1.5 deg^2, 88 per cent of the eventual area of the zCOSMOS survey. The sampling is denser in some regions than in others (and will eventually be filled out evenly in the full area). In this region, there are ∼3000 SDSS galaxies with $r < 21.8$; roughly 65 per cent pass our lensing selection cuts, leaving us with 1825 matches in the source catalogue.

3 REDSHIFT DETERMINATION ALGORITHMS

Here we describe the source redshift determination algorithms in more detail. We begin with those used in our current lensing source catalogue, for which we want to assess calibration biases in past works, then describe methods that have more recently become available.

3.1 Previous methods

In our catalogue, which was created in 2004, we used three approaches to source redshift determination, all described in detail in M05. For the $r < 21$ sources, we used photometric redshifts from kphotoz v3_2 (Blanton et al. 2003a) and their error distributions determined using a sample of 162 galaxies in the DEEP2 EGS. We also required $z_p > z_l + 0.1$ to avoid contamination from physically associated lens–source pairs. For the $r > 21$ sources, we used a source redshift distribution from DEEP2 EGS (from fitting to 116 redshifts), which means that we lack individual redshift estimates for each source. The sample of redshifts used for this early work with the EGS was a factor of 3.5 smaller than the EGS sample used for this work, or a factor of 10 smaller than the combined EGS + zCOSMOS sample used here. For the high-redshift luminous red galaxies (LRG) source sample (see selection criteria in M05), we used well-calibrated photometric redshifts and their error distributions determined using data from the 2dF SDSS LRG and Quasar Survey (2SLAQ), as presented in Padmanabhan et al. (2005).

3.2 New options

There are several relatively new photoz options for SDSS data, all of which have relatively low failure rates of ∼5 per cent. The first is available in the SDSS Data Release 5 (DR5) skyserver 'Photoz' table (Budavári et al. 2000; Csabai et al. 2003). The photoz values for this template method are determined by fitting observed galaxy colours to empirical templates from Coleman, Wu & Weedman (1980) extended using spectral synthesis models. There is an additional step (not used for all template methods) in which the templates are iteratively adjusted using a training sample. We have performed our tests on both the DR5 and DR6 template photoz values, and found no significant differences in performance between the two.

The second new option is available in the SDSS DR6 skyserver in the 'Photoz2' table. These photoz values were computed using a neural net (NN) algorithm similar to that of Collister & Lahav (2004) trained using a training set from many data sources combined: SDSS spectroscopic samples, 2SLAQ, CFRS, CNOC2, DEEP, DEEP2 and GOODS-N. A more complete description of both NN photoz values in the DR6 data base can be found in Oyaizu et al. (2007): the

'CC2' photoz values use colours and concentrations, while the 'D1' photoz values use magnitudes and concentrations. In the text, we will describe any difference between the DR5 and DR6 results; Oyaizu et al. (2007) recommends against using the DR5 photoz values for science applications now that the improved DR6 versions exist.

The third new option we test is the ZEBRA (Feldmann et al. 2006) algorithm, which has already been successfully used with much deeper imaging data in the COSMOS field. This method involves template fitting, but also takes a flux-limited sample of galaxies (without spectroscopic redshifts) from the data source for which we want photoz values. These data are used to create a Bayesian modification of the likelihoods based on the $N(z)$ for the full sample (Brodwin et al. 2006) and on its template distribution. In practice, this prior helps avoid scatter to low redshifts. A key question we will address is how this algorithm behaves with the significantly noisier SDSS photometry. To avoid confusion, we will refer to the high-quality ZEBRA photoz values derived using the deep photometry in the COSMOS field as 'ZEBRA' photoz values, and the ZEBRA photoz values using the much shallower SDSS photometry as 'ZEBRA/SDSS' photoz values.

To be specific about the training method, to get the ZEBRA/SDSS photoz values, half of a flux-limited sample of SDSS galaxies with zCOSMOS redshifts are used for template optimization. This part of the analysis includes fixing the redshifts of those galaxies to the spectroscopic redshift, finding the best-fitting template, and optimizing it as described in Feldmann et al. (2006). Then, a sample of 10^5 SDSS galaxies (flux-limited to $r = 22$) without spectra were used to iteratively compute the template–redshift prior.

3.3 Effects of photoz error for lensing

Finally, we clarify the effects of photoz error on the lensing calibration.

(i) A positive photoz bias, defined as a non-zero $\langle z_{\rm p} - z\rangle$, will lower the signal (because the critical surface density, defined below in equation 2, will be underestimated).

(ii) A negative photoz bias will raise the signal.

(iii) Photoz scatter will usually lower the signal due to the shape of the critical surface density near $z_{\rm l}$. This effect can be very significant for sources at redshifts below $\sim z_{\rm l} + 1.5\sigma$, where σ is the size of the scatter.

The last point is very important for a shallow survey like SDSS when the lens redshift is above $z_{\rm l} \sim 0.1$, because of the large number of sources within a few σ of the lens redshift. For a deeper survey such as the CFHT Legacy Survey (CFHTLS), with lenses and sources separated by $\Delta z \sim 0.5$ on average, this effect may in fact be negligible. The effects of photoz bias are important not just in the mean, but as a function of redshift. If low-redshift sources have non-zero photoz bias, and high-redshift sources have non-zero photoz bias in the opposite direction, so that the mean photoz bias for the full sample is zero, the effect of the opposing photoz biases on lensing calibration will not, in general, cancel out since the effect on lensing calibration tends to be more significant for the sources that are closer to the lenses.

Catastrophic photoz errors are those that are well beyond the typical scatter, typically occurring due to some systematic error, colour–redshift degeneracy, or other problem (and by definition, these photoz values are not flagged as problematic by the algorithm, so they can only be identified using a spectroscopic sample with similar selection to the target sample). The catastrophic error rate may be important, depending on the type of catastrophic error. For example, sending a few per cent of the sources to $z_{\rm p} = 0$ will not lead to calibration bias, it will simply lead to that fraction of the sources not being included because they have $z_{\rm p} < z_{\rm l}$, causing a per cent level increase in the final error. In short, it is clear that the three metrics often used to quantify the accuracy of photoz methods – the mean bias, scatter and catastrophic failure rate – are not sufficient to quantify the efficacy of a photoz method for lensing. In this paper, we will introduce a metric that is optimized towards understanding the effects of photoz values on galaxy–galaxy lensing calibration, and present results for the photoz mean bias, scatter and catastrophic failure rate only as a means of understanding the results for our lensing-optimized metric. For other science applications, the optimal metric may be quite different from what we present here.

4 METHODOLOGY

4.1 Theory

Galaxy–galaxy lensing measures the tangential shear distortions in the shapes of background galaxies induced by the mass distribution around foreground galaxies (for a review, see Bartelmann & Schneider 2001). The result is a measurement of the shear-galaxy cross-correlation as a function of relative foreground–background separation on the sky. We will assume that the redshift of the foreground galaxy is known, so we express the relative separation in terms of transverse comoving scale R. One can relate the shear distortion $\gamma_{\rm t}$ to $\Delta\Sigma(R) = \bar{\Sigma}(<R) - \Sigma(R)$, where $\Sigma(R)$ is the surface mass density at the transverse separation R and $\bar{\Sigma}(<R)$ its mean within R, via

$$\gamma_{\rm t} = \frac{\Delta\Sigma(R)}{\Sigma_{\rm c}}. \tag{1}$$

Here we use the critical mass surface density,

$$\Sigma_{\rm c} = \frac{c^2}{4\pi G}\frac{D_{\rm S}}{(1+z_{\rm L})^2 D_{\rm L} D_{\rm LS}}, \tag{2}$$

where $D_{\rm L}$ and $D_{\rm S}$ are angular diameter distances to the lens and source, $D_{\rm LS}$ is the angular diameter distance between the lens and source, and the factor of $(1+z_{\rm L})^{-2}$ arises due to our use of comoving coordinates. For a given lens redshift, $\Sigma_{\rm c}^{-1}$ rises from zero at $z_{\rm s} = z_{\rm L}$ to an asymptotic value at $z_{\rm s} \gg z_{\rm L}$; that asymptotic value is an increasing function of lens redshift.

In this work, we focus on calibration bias in $\Delta\Sigma$ due to bias in $\Sigma_{\rm c}$ arising from source redshift uncertainty.

4.2 Redshift calibration bias determination

Here, we present a method for testing the accuracy of source redshift determination that is optimized towards g–g lensing. Formally, we wish to calculate the differential surface density $\Delta\Sigma$ using our estimator $\widetilde{\Delta\Sigma}$, which is defined as a weighted sum over lens–source pairs j,

$$\widetilde{\Delta\Sigma} = \frac{\sum_j \tilde{w}_j \tilde{\gamma}_{\rm t}^{(j)} \tilde{\Sigma}_{{\rm c},j}}{\sum_j \tilde{w}_j}. \tag{3}$$

To isolate the dependence of calibration on redshift-related quantities, we will assume that the estimated tangential shear, $\tilde{\gamma}_{\rm t}$, is unbiased. $\tilde{\Sigma}_{{\rm c},j}$ (derived from our source redshift estimator) is the critical surface density estimated for a given lens–source pair j. The weights for each lens–source pair are determined using redshift information as well:

$$\tilde{w}_j = \frac{1}{\tilde{\Sigma}_{{\rm c},j}^2\left(e_{\rm rms}^2 + \sigma_{\rm e}^2\right)}, \tag{4}$$

where $e_{\rm rms}$ is the rms ellipticity per component for the source sample (shape noise), and $\sigma_{\rm e}$ is the ellipticity measurement error per component.

We want to relate our estimated $\widetilde{\Delta\Sigma}$ to the true $\Delta\Sigma$. To do so, we use the relation between the measured shear and $\Delta\Sigma$, equation (1). Putting equation (1) into equation (3) (assuming $\langle\tilde{\gamma}_{\rm t}\rangle = \gamma_{\rm t}$), we define the redshift calibration bias b_z via

$$b_z + 1 = \frac{\widetilde{\Delta\Sigma}}{\Delta\Sigma} = \frac{\sum_j \tilde{w}_j \left(\Sigma_{{\rm c},j}^{-1}\tilde{\Sigma}_{{\rm c},j}\right)}{\sum_j \tilde{w}_j}, \tag{5}$$

a weighted sum of the ratio of the estimated to the true critical surface density.

This expression must be computed as a function of lens redshift. In the limit that the sources are at much higher redshift than the lenses, $\Sigma_{\rm c}$ does not depend as strongly on the source redshift, so (for a given photometric redshift bias) $|b_z|$ will be smaller than if the lens redshift is just below the source redshift. For a lens sample with redshift distribution $p(z_{\rm l})$, the average calibration bias $\langle b_z\rangle$ can be computed as a weighted average over the redshift distribution,

$$\langle b_z\rangle = \frac{\int {\rm d}z_{\rm l}\, p(z_{\rm l})\, \tilde{w}_{\rm l}(z_{\rm l})\, b_z(z_{\rm l})}{\int {\rm d}z_{\rm l}\, p(z_{\rm l})\, \tilde{w}_{\rm l}(z_{\rm l})}, \tag{6}$$

where the redshift-dependent lens weight $\tilde{w}_{\rm l}(z_{\rm l})$ is defined as the total weight derived from all sources that contribute to the lensing signal for a given lens redshift, $\sum_j \tilde{w}_j$.

In the ideal case, we would do this calculation with a large, complete spectroscopic sample drawn at random from our source sample, sparsely sampled on the sky and therefore lacking features in the redshift distribution due to LSS. We can then find $b_z(z_{\rm l})$ on a grid of lens redshifts by forming the sums in equation (5) using all sources with spectra. Finally, we can use the total weight as a function of lens redshift and the lens redshift distribution to estimate the average redshift bias of the lensing signal.

To get the errors on the bias in this simple scenario, we can simply bootstrap resample our sample of source galaxies with spectroscopy. For a sample of $N_{\rm gal}$ galaxies, bootstrap resampling requires us to make many 'new' galaxy samples consisting of $N_{\rm gal}$ galaxies drawn from the original sample *with replacement*. Assuming that the observed galaxy redshifts accurately reflect the underlying redshift distribution, and the redshifts are uncorrelated, the mean best-fitting redshift distribution will reflect the true one, and the errors in the redshift calibration bias can be determined from the variance of the calibration biases for each bootstrap resampled data set. Since the bootstrap depends on the assumption that the objects we are bootstrapping are independent, this method only gives proper errors in the case where LSS is unimportant.

In general, there are several problems that mean we are no longer dealing with the ideal case. The first problem is sampling variance, since most redshift surveys are completed in a well-defined, small region of the sky. The second is the fact that most redshift surveys suffer from some incompleteness, and that incompleteness may be a function of apparent magnitude or colour, which means that the loss of those redshifts can make the spectroscopic sample no longer comparable to the full source sample. We attempt to ameliorate these problems by using two sources of spectroscopy on different areas of the sky and with different spectrographs and analysis pipelines, so that the LSS and incompleteness tendencies in each sample are different. Below, we address these deviations from the ideal case in more detail.

4.3 Effects of sampling variance

LSS can be problematic when using surveys on small regions of the sky to determine bias in the lensing signal due to photometric redshift error. The LSS may emphasize particular regions of the source redshift distribution that have unusual features in the photometric redshift errors. To avoid this problem, we would like to fit for a redshift distribution in a way that accounts properly for uncertainties due to sampling variance. There are many approaches to this problem in the literature, such as that demonstrated in Brodwin et al. (2006).

The simplest way around our aforementioned problem, that LSS causes the redshifts to be correlated so that the assumption behind the bootstrap is violated, is to bootstrap the bins in the redshift histogram instead. In the limit that the bins are significantly wider than the typical sample correlation length, the correlations within the bins will be far more important than the correlations between adjacent bins. Thus, the requirement that the bootstrapped data points be independent is much closer to being fulfilled. Here, we will use redshift bins with size $\Delta z = 0.05$, where each bin is considered as a pair of points $(z_i, N(z_i))$. In a given bootstrapped histogram, some redshift bins $(z_i, N(z_i))$ will be included multiple times, others not at all, but each time a given bin is used, it has the same number of galaxies as in the real data. While this method is simplistic, it has the advantage of not requiring us to understand the details of the sample selection, since the lensing selection is a very non-trivial cut to understand and simulate. The resulting errors on the best-fitting $N(z)$ from this bootstrap will include the effects of both Poisson error (which is non-negligible given the size of the samples used) and LSS. The errors are valid assuming that there are no correlations between the $150\,h^{-1}$ Mpc wide bins. We discuss this assumption, which depends not just on straightforward integration of the matter power spectrum but also redshift-space distortions, galaxy bias and magnification bias, further in Section 5.7.

For each bootstrapped histogram with bins centred at z_i containing N_i galaxies each, we minimize the function

$$\Delta^2 = \sum_i w_i^{(\Delta)} \left[N_i - N_i^{\rm (model)}\right]^2 \tag{7}$$

via summation over redshift bins i. $N_i^{\rm (model)}$ is the number of galaxies predicted to lie in bin i given the model for ${\rm d}N/{\rm d}z$, i.e.

$$N_i^{\rm (model)} = \int_{z_i-\Delta z/2}^{z_i+\Delta z/2} \frac{{\rm d}N}{{\rm d}z}\,{\rm d}z. \tag{8}$$

For each bootstrapped histogram, we also imposed a normalization condition on the fit that $\int_0^\infty {\rm d}z({\rm d}N^{\rm (model)}/{\rm d}z) = N_{\rm gal}$ (the total number of galaxies in the spectroscopic sample). In the case of Poisson error, the natural choice for $w_i^{(\Delta)}$ is $1/N_i^{\rm (model)}$. However, in the presence of LSS, which contributes significantly to the variance in each bin, the distribution of values in each bin is, in fact, unknown, so the optimal weighting scheme is unclear. Consequently, we use the simplest possible weighting scheme, $w_i^{(\Delta)} = 1$ for all i. We have, however, confirmed that if we do use $w_i^{(\Delta)} = 1/N_i^{\rm (model)}$, then the changes in the best-fitting redshift distribution parameters, and the implied changes in redshift calibration bias, are well below the 1σ level.

Our two-parameter model for the redshift distribution is

$$\frac{{\rm d}N}{{\rm d}z} \propto \left(\frac{z}{z_*}\right)^{\alpha-1} \exp\left[-0.5(z/z_*)^2\right] \tag{9}$$

which has mean redshift

$$\langle z \rangle = \frac{\sqrt{2}\, z_* \Gamma\left[(\alpha+1)/2\right]}{\Gamma\left(\alpha/2\right)}. \tag{10}$$

This choice is based purely on the empirical observation that it describes the shape of the redshift distribution better than the many other functional forms that we tried, and addition of extra parameters did not significantly improve the best-fitting Δ^2. In particular, allowing the power law inside the exponent to vary from 2 (a common choice) did not lead to any significant change to the best-fitting redshift distribution below $z = 0.8$, where the vast majority of the galaxies are located. The changes above that redshift are marginally statistically significant, but there are so few sources above that redshift that our final results for the redshift bias that we eventually want to calculate do not change within the statistical error.

We will present best-fitting redshift distributions for zCOSMOS and DEEP2 EGS separately to demonstrate that the results are consistent within the errors. We then use both samples combined to create an overall redshift distribution.

This distribution is crucial to our scheme to avoid sampling variance effects in the determination of the redshift calibration bias. To counterbalance regions of source redshift space that are overrepresented or underrepresented in our spectroscopic sample due to LSS fluctuations, we incorporate an additional weight into the calculation of the redshift bias in equation (5). For a galaxy in redshift bin i in our histogram, the LSS weight ($w_{\rm LSS}$) is the ratio of the number of galaxies predicted to lie in bin i from our best-fitting redshift distribution, to the number actually found in that bin $[N_i^{\rm (model)}/N_i]$. Thus, those regions in redshift space with too many/few galaxies due to LSS or Poisson fluctuations will be down-/up-weighted appropriately. We can then get errors on the average redshift bias $\langle b_z \rangle$ using the best-fitting redshift histograms for each bootstrap resampled histogram to derive the LSS weights. This procedure incorporates uncertainty in the source redshift distribution appropriately, since we never need to bootstrap the galaxies themselves.

In an analysis containing many patches of sky, the size of the errors can be verified by comparing the redshift bias computed in each patch of sky. Unfortunately, with only two patches of sky, this method is not an option for this work.

4.4 Redshift incompleteness and failures

For precision results, we require that the redshift completeness and quality be high. There are several tests that we can carry out to ensure that the sample is of high quality. We consider the redshift failures separately for the DEEP2 and zCOSMOS samples. In both cases, we will determine the magnitude and colour distribution of the failures relative to the full sample, to see if a particular region of redshift space is causing the problems.

For zCOSMOS, there are high-quality photoz values derived from very deep photometry which we can use in the case of spectroscopic redshift failure. To control for any effect on the computed redshift calibration bias, we also check the results using the zCOSMOS photoz values for a larger portion of the full sample, to ensure that noise in these photoz values has a negligible effect on the results.

For DEEP2 EGS, we lack redshift estimates for the failures. To place a very conservative bound on the effect of failures on the estimated calibration bias, we estimate the redshift bias with all the failures forced to $z = 0$, and then to $z = 1.5$. For both surveys, we will compare the ranges of colours and redshifts spanned by the successes and failures, to ensure that our procedures for handling redshift failure are justified.

The next issue is the quality of the non-failed redshifts, which in DEEP2 are assessed by visual inspection and repeat observations, and in zCOSMOS using the photoz values as well. For DEEP2, we have used only $Q = 3$ and 4 redshifts, which are 96 per cent of our sample, and are estimated to be 95 and 99.5 per cent reliable. For zCOSMOS, the reliabilities for $Q = 3$ and 4 objects (92 per cent of our sample) are >99 per cent. For this survey we also use $Q = 2.5$, those with slightly lower quality in principle but with extremely good matches between the spectroscopic and photometric redshift, and $Q = 9.5$ (single-line redshifts with good matches between the spectroscopic and photometric redshifts, which in this apparent magnitude and redshift range are usually from Hα), both of which also are >99 per cent reliable as determined from repeat observations.

In the DEEP2 EGS, there are also minor selection effects to control for. The first effect is the fact that no galaxies brighter than $r \sim 18.5$ were targeted. Galaxies brighter than that limit constitute only 4 per cent of the source sample, but we nonetheless include tests of the effect this has on the result.

The other selection effect in DEEP2 EGS occurs at magnitudes fainter than $R = 21.5$, where $z < 0.75$ objects are given slightly lower selection weights than higher z galaxies. While the fraction of source galaxies fainter than this magnitude is only ~12 per cent, we use their selection probabilities $p_{\rm sel}$ to properly compensate for this effect. To be explicit, the total weight for each source is thus a product of lensing weight $\tilde{w}_j$, the LSS weight $w_{\rm LSS}$, and $\max(p_{\rm sel})/p_{{\rm sel},j}$ (or 1 for the zCOSMOS galaxies).

Finally, we clarify our statement that our method requires the spectroscopic sample used to evaluate photoz values to be comparable to the source sample. As demonstrated above, it is possible to use weights to account for well-defined targeting priorities that might make the spectroscopic sample slightly non-representative of the source catalogue. Thus, our statement that we require the spectroscopic sample to be comparable to the source sample is really a statement that it must contain all galaxy types (spectral types, magnitudes, etc.) in the source sample with representation levels that are sufficient to overcome the noise. If some reweighting is necessary to account for under- or over-representation of a given population, then for our purposes, this is sufficient to fulfil our requirements. Thus, one could *not* use a spectroscopic sample with a strict cut-off 2 mag brighter than the flux limit of the source catalogue. One could use a spectroscopic sample that has a lower redshift success rate for fainter galaxies, as long as that lower success rate is due to statistical error, so that the failures have the same redshift distribution as the successes, rather than some systematic error (e.g. inability to determine redshifts for any object of a particular spectral type above some cut-off redshift). Reweighting schemes to account for different fractions of various galaxy populations in the training and photometric samples are being successfully used by the SDSS neural net photoz group to predict redshift distributions and photoz error distributions in the photometric samples.[1]

4.5 Direct use of photoz values

Here, we explain our use of photoz values directly for $\Sigma_{\rm c}$ estimation. One might argue that since we have a spectroscopic sample, we should estimate $\Sigma_{\rm c}$ using a deconvolved photoz error distribution. However, in this paper we test the use of photoz values directly, for several reasons.

[1] Lima et al., 2008.

First, as we have argued previously, a key advantage of using photoz values is that we can eliminate intrinsically aligned sources. Once we start eliminating sources from the sample on the basis of detailed cuts on photoz, colour or apparent magnitude, we would have to re-estimate the photoz error distribution for the sample that passes these cuts and redo the deconvolution procedure. This is computationally expensive and potentially difficult to do robustly, if the cuts result in our photoz error distribution being poorly determined due to insufficient spectroscopic galaxies that pass the cuts to properly sample the distribution. We would therefore like to find a photoz method that can lead to accurate lensing calibration on its own.

There is, in principle, one simple option that might improve the lensing calibration and that can be done without full deconvolution: we can correct each photoz for the mean photoz bias. To be accurate, this should be done as a function of galaxy colour and magnitude. We will test the results of doing so for one of the photoz methods when we present the results of our analysis.

The final reason to use photoz values directly is because that is the approach taken in many lensing papers to date, and we would like to test the accuracy of what is currently done in the field to see what improvements need to be made. In Section 5.9, we will consider using a full $p(z)$ as a new alternative approach to using the photoz alone.

5 RESULTS: APPLICATION TO SDSS LENSING

5.1 Matching results

There are 1013 and 1825 galaxies in our source catalogue with spectra from DEEP2 EGS and zCOSMOS, respectively (including redshift failures). We now characterize these matches relative to the entire source catalogue and compared to each other.

Fig. 2 shows the redshift histograms for matches between the source catalogue and the zCOSMOS and DEEP2 samples. The zCOSMOS histogram is shown both with and without precision photometric redshifts for the redshift failures, whereas for DEEP2, the failures (4 per cent) were excluded entirely. As shown, there is significant LSS in the redshift histograms, but not correlated between the two samples. Visually, the redshift histogram for DEEP2 appears to be at slightly higher redshift on average. We assess the statistical significance of any differences below.

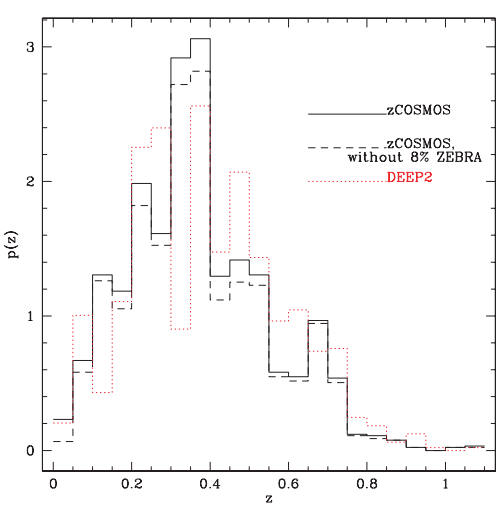

Figure 2. Redshift histogram for the matches between the source catalogue and the spectroscopic samples.

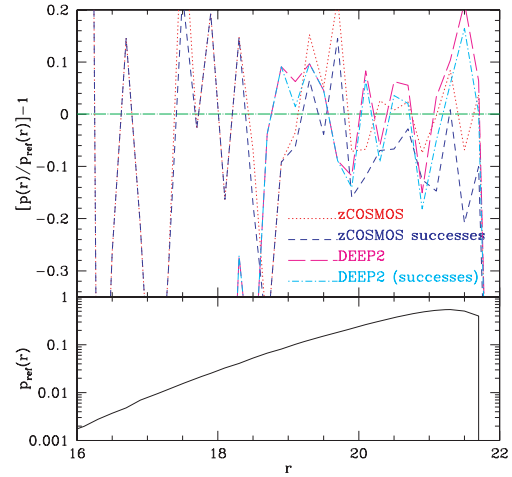

Figure 3. Bottom: r-band apparent magnitude histogram for the full source catalogue. Top: Difference between the apparent magnitude histogram for the zCOSMOS and DEEP2 samples relative to that for the full source catalogue.

Fig. 3 shows the distribution of apparent r-band magnitude $p(r)$ for the zCOSMOS and DEEP2 matches relative to that of the entire source catalogue, $p_{\rm ref}(r)$. The apparent magnitude histogram for zCOSMOS is quite similar to that for the full source catalogue (within the noise), and the failures are predominantly at the faint end. The apparent magnitude histogram for DEEP2 shows the deficit at $r < 18.5$ (4 per cent of the sample) due to targeting constraints.

Of the matches, 151 of those in zCOSMOS (8 per cent) and 38 of those in DEEP2 (4 per cent) are redshift failures (where failures are defined as having redshift success rates below 99 per cent). In Fig. 4, we show the distributions of various quantities for the zCOSMOS and DEEP2 failures as compared with the full sample. Fig. 3 shows the relation of the failures to the general sample as a function of apparent magnitude; the top part of Fig. 4 shows that the colour distribution for the failures is similar to the colour distribution for the successes. We thus have no reason to believe the failures lie in a particular region of redshift space. The DEEP2 failures

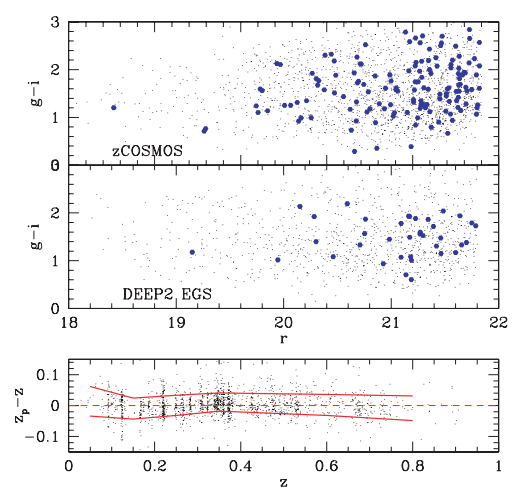

Figure 4. Colour–magnitude scatter plots for redshift successes and failures in zCOSMOS (top) and DEEP2 (middle). Successes are shown as black points and failures as blue hexagons. The bottom panel shows the zCOSMOS photoz error as a function of redshift for the redshift successes, including the 68 per cent CL errors as a function of redshift (red lines).

lie in the $0 < z < 0.75$ colour locus, just like the majority of the successes in this bright subsample of the EGS data. (This is not true for deeper redshift samples, such as the other DEEP2 fields, where failures typically occur for blue, $z > 1.5$ galaxies. The flux and apparent size cuts imposed on our sample essentially remove any such galaxies.) Inspection of the 38 DEEP2 spectra suggests that the redshift distribution is similar to that for the successes, with failures due to bad astrometry, a bad column running through the spectrum, or similar failures that do not correlate with redshift. We also show the zCOSMOS photoz error distribution as a function of redshift in the bottom of Fig. 4 for spectroscopic redshift successes. The photoz errors for this sample are indeed as small as, or even smaller than, those presented elsewhere for these photoz values (Feldmann et al. 2006). We may view this error as a 'systematic floor' to the error, with the increase in error for the ZEBRA/SDSS photoz values being ascribed to the much noisier photometry. We will see that this statistical error dominates the error budget.

Next, we present redshift distributions for each survey separately, with two purposes: (1) to demonstrate that they are consistent with being drawn from the same underlying redshift distribution and (2) to determine the weights to compensate for sampling variance as described in Section 4.3.

Fig. 5 shows the observed and best-fitting redshift histograms for zCOSMOS, DEEP2, and both surveys combined. Table 1 shows the corresponding best-fitting parameters from equation (9). The weighting to account for the DEEP2 selection at $R > 21.5$ causes a negligible change in the results. By bootstrapping the redshift histogram as described in Section 4.3, we have determined the median predicted number of galaxies in each bins, and the 68 per cent confidence limits (CLs) on that number, as shown on the plot. Because we have imposed a normalization condition on the fit, the error bars are correlated between various parts of the histogram. We can see from the plot and Table 1 that while the DEEP2 sample is at slightly higher redshift on average, the redshift distributions from zCOSMOS and DEEP2 are consistent with each other within the (Poisson plus LSS) errors. While it is difficult to compare the curves for $z > 0.7$, where the number of galaxies has declined sharply, we can compare the total fraction of the sample with $z > 0.7$ to show that they are consistent: for DEEP2 EGS, this fraction lies between [0.05, 0.12] at the 68 per cent CL; for zCOSMOS, between [0.02, 0.08]. These limits were determined using the fraction above $z > 0.7$ for the best-fitting $N(z)$ for 200 bootstrap-resampled redshift histograms, and therefore include both Poisson error and sampling variance. It is clear that any discrepancy between the best-fitting zCOSMOS and DEEP2 redshift histograms with respect to the fraction of the sample above $z > 0.7$ are not significant at the 68 per cent CL.

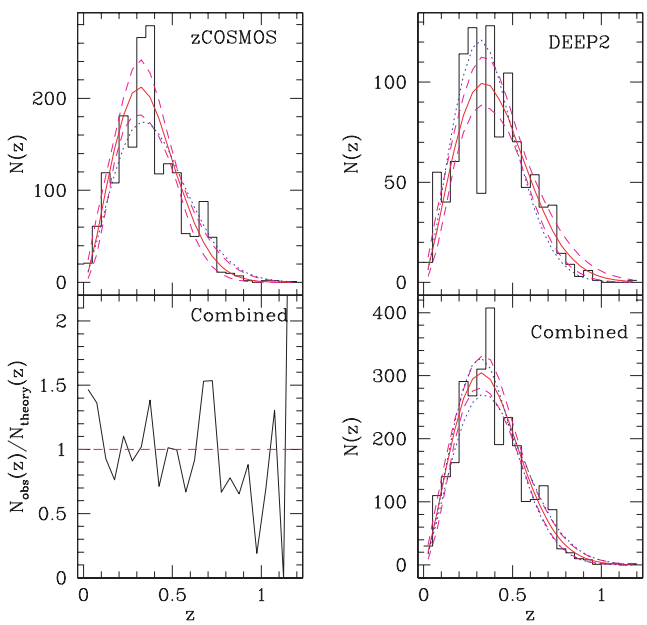

Figure 5. Top: Rescaled redshift histograms for the matches between the source catalogue and the zCOSMOS (left-hand panel) and DEEP2 (right-hand panel) sample with best-fitting histograms. The black histogram is the observed data, the smooth red curve is the best-fitting histogram, the dashed magenta lines are the $\pm 1\sigma$ errors, and the dotted blue line is the best-fitting redshift histogram for the other survey. Bottom right-hand panel: Same as above, for combined sample, with the dotted blue lines showing the results for each survey separately. Bottom left-hand panel: Ratio of observed to best-fitting $N(z)$ for the combined sample.

Table 1. Parameters of fits to redshift distribution from equation (9).

Sample	z_*	α	$\langle z \rangle$
zCOSMOS	0.259 ± 0.040	2.58 ± 0.58	0.369 ± 0.018
DEEP2 EGS	0.300 ± 0.041	2.35 ± 0.41	0.408 ± 0.025
Both	0.275 ± 0.025	2.42 ± 0.36	0.382 ± 0.012

As shown in the lower left-hand panel of Fig. 5, there is no systematic tendency for the observed and best-fitting $N_i(z)$ for the full sample to deviate from each other, only Poisson and LSS fluctuations, so the form we have chosen for $\mathrm{d}N/\mathrm{d}z$ is acceptable. (The fluctuations are quite large for $z > 1$ because the best-fitting $N_i^{(\mathrm{model})}$ drops below 1, so discreteness will cause the ratio of $N_i/N_i^{(\mathrm{model})}$ to be either zero or some large number.) It is important to note that this plot is the *unweighted* redshift distribution; inclusion of the lensing weights in equation (4) will change the effective source redshift distribution.

5.2 Photoz error distributions

As a way of understanding the trends in our lensing-optimized photoz error statistic b_z, we first examine the photoz error distribution as a function of redshift. Fig. 6 shows the photoz error as a function of the (true) redshift for the lensing-selected galaxies from zCOSMOS and DEEP2 for the photoz algorithms tested in this work. The galaxies are divided by apparent magnitude into three samples with $r < 20$, $20 \leqslant r < 21$ and $r \geqslant 21$, and we show the 68 per cent CL errors determined in bins of size $\Delta z = 0.05$ for each apparent magnitude bin. For all methods, the error distributions tend to be highly non-Gaussian, often skewed and with significant tails. While the requirement that $z_\mathrm{p} > 0$ makes skewness inevitable at low z even for a well-behaved photoz estimator, the effect persists to such high redshift for all methods that this constraint is clearly not the cause. Thus, the 68 per cent CLs as a function of redshift are more useful than a calculation of the average photoz bias and scatter. None the less, we do tabulate the mean bias $\langle z_\mathrm{p} - z \rangle$ and the overall scatter $\sigma(z_\mathrm{p})$ in Table 2 for each method, for the full sample and the $r < 21$ subset (to facilitate comparison between kphotoz, used only for $r < 21$, and the other methods).

For the kphotoz method, there is a clear tendency to fail towards very low redshift, as demonstrated by the peak in $p(z_\mathrm{p})$ for $z_\mathrm{p} < 0.05$. For lensing, such failures will be flagged as being below the lens redshift for nearly all relevant lens redshifts, thus excluding them from the source sample. Consequently, the only effect of this failure mode is to reduce the number of available sources, not to bias the weak lensing results. However, it is apparent that this method is as noisy for $r < 21$ as the other photoz algorithms are for $r < 21.8$, and

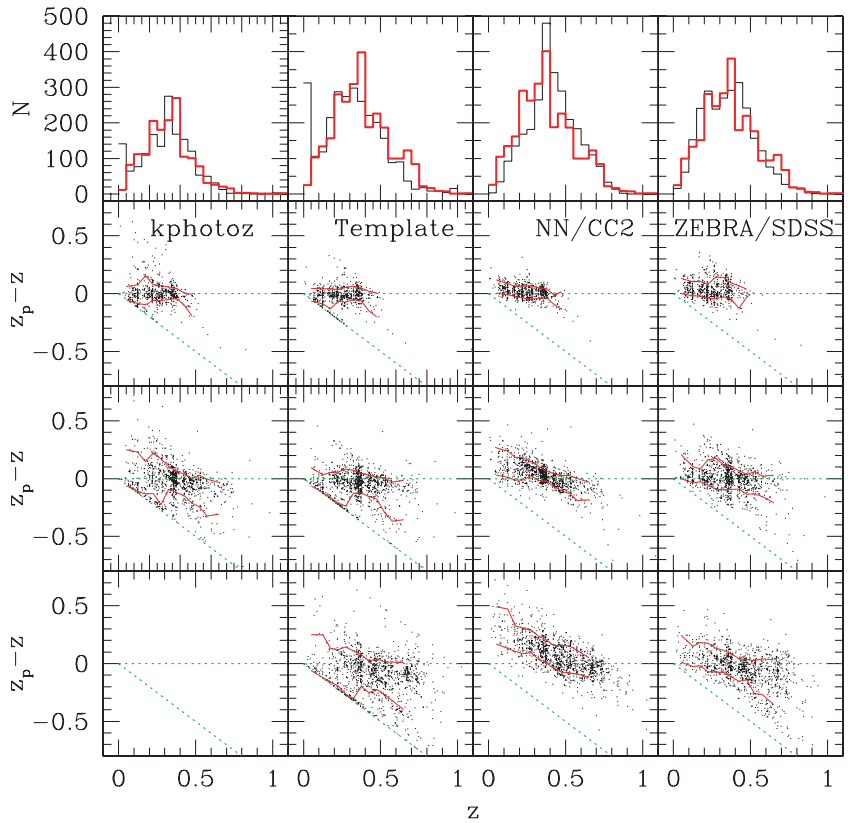

Figure 6. For each photoz method described in the text (in columns labelled according to the method), the top row shows the redshift histogram determined using the photoz (thin black line) and using the spectroscopic redshift (thick red line). The spectroscopic redshift histograms are not quite identical for all methods because we exclude photoz failures for each method and because kphotoz was only used for those galaxies with $r < 21$. The lower three panels show photometric redshift errors, for galaxies divided by apparent magnitude: $r < 20$ in the second row, $20 \leqslant r < 21$ in the third row and $r \geqslant 21$ in the fourth row. The points correspond to individual galaxies in the source catalogue with spectra; the 68 per cent CLs on the photoz error are shown as red solid lines. There are also green dashed lines indicating zero error and the lower limit on the error given that the photoz must exceed zero.

Table 2. Mean properties of the photoz algorithms, for the full sample and for $r < 21$ only in parenthesis.

Method	Mean bias	Scatter
kphotoz	(−0.015)	(0.14)
Template	−0.064 (−0.043)	0.16 (0.12)
NN/CC2	0.034 (0.013)	0.14 (0.11)
NN/D1	0.038 (0.020)	0.13 (0.10)
ZEBRA/SDSS	−0.014 (0.012)	0.15 (0.12)

that the photoz error tends to be positive for $z \lesssim 0.4$ and negative above that.

For the template-based data base photoz values, there is an even stronger failure mode towards $z_p = 0$ than for kphotoz (because the template method goes fainter than the kphotoz sample). This failure mode contributes to the significantly negative 68 per cent CL limits on the photoz error, since the points suggest that ignoring these failures leads to a more symmetric error distribution. We must quantify the effect this has in reducing the total weight; even if the bias in the lensing signal due to the strong failure mode is small, the increased statistical error due to loss of sources may be problematic. This failure mode is the cause of the large mean photoz bias in Table 2.

For the neural network algorithm, the plot shows the CC2 (colour- and concentration-based) photoz values, but the trends are qualitatively similar for the D1 (magnitude- and concentration-based) photoz values. There are entries for both versions in Table 2. As shown, the method has a reasonably small overall scatter and no major failure modes. We caution the reader that the same is not true for the NN photoz values in the DR5 data base, for which there is a significant scatter to redshifts $0.75 < z_p < 1$ that more than doubles the number of sources estimated to be in this redshift range. The scatter is also larger for the DR5 NN photoz values. In both the DR5 and the DR6 versions, there is a tendency towards positive photoz bias at low to intermediate redshifts ($0 < z < 0.4$) that may bias the lensing signal low.

Finally, the ZEBRA/SDSS method also lacks a major catastrophic failure mode and has reasonably small overall photoz bias. The redshift histograms derived from the spectroscopic and photometric redshifts agree remarkably well. As for the NN/CC2 photoz values, there is a trend towards positive photoz error at low redshift and negative error at high redshift. Because of the overall lower number of sources above $z \gtrsim 0.4$, and the decreased dependence of Σ_c on source redshift at higher redshift, we have no reason to believe that the effects of the different direction of the calibration biases in the lensing signal will cancel out. We can also conclude, in comparison with the ZEBRA photoz errors in the lower panel of Fig. 4 (using the far deeper COSMOS photometry) for the same exact set of sources, that for the redshifts and magnitudes dominated by this source sample, statistical error due to noisy SDSS photometry dominates over systematic error in this photoz method.

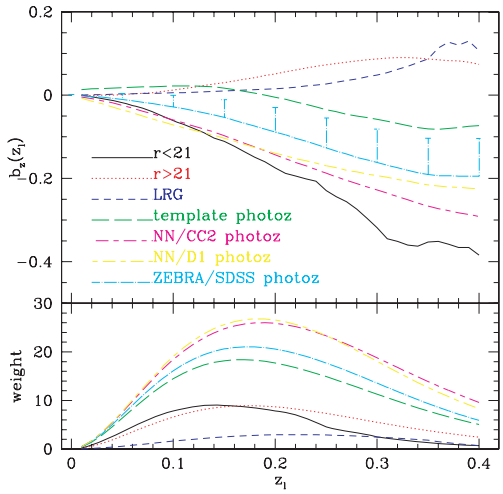

Figure 7. Redshift bias $b_z(z_l)$ (top) and weight (bottom, arbitrary units) for many methods of source redshift determination as described in the text. To make the plot simpler to read, we have left off error bars except for in one case, the ZEBRA/SDSS method, which is shown with an error bar in one direction to indicate the typical size of the uncertainty in $b_z(z_l)$ for all the methods.

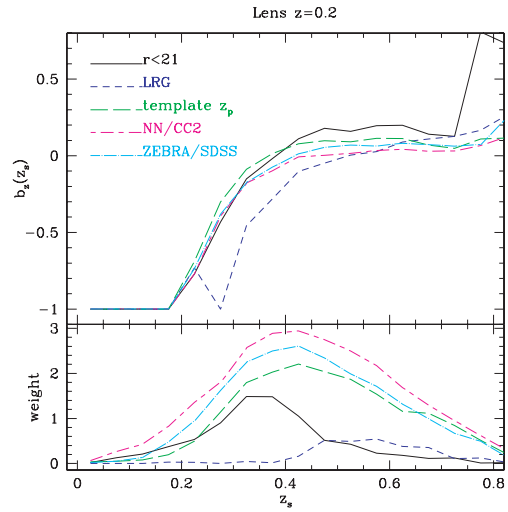

Figure 8. Redshift bias $b_z(z_s)$ (top) and weight (bottom, arbitrary units) for fixed $z_l = 0.2$ with many methods of source redshift determination as described in the text. Error bars are not shown here to make the plot simpler to read.

5.3 Redshift bias

In Fig. 7, we show the lensing calibration bias $b_z(z_l)$ for different source redshift determination methods, using the full lensing-selected spectroscopic redshift sample. The bottom panel shows the total lensing weight ascribed to the source sample for that lens redshift, determined via summation over the lensing weights described in Section 4.4. Note that the $r < 21$ and LRG samples use photoz values with the requirement that $z_p > z_l + 0.1$, to reduce contamination by physically associated sources (for consistency with our previous analyses). However, for the new photoz methods, we have not imposed any such condition (we will revisit this choice later).

As shown, the $r < 21$ sample with photoz values from kphotoz has a significant negative calibration bias that increases with lens redshift to -35 per cent at $z_l = 0.35$. As for all methods, the bias worsens with lens redshift because, for a given source with some photoz error, a higher lens redshift leads to a higher relative error in $\tilde{\Sigma}_c^{-1}$. The $r > 21$ sample (using dN/dz from DEEP2 EGS) has a small positive bias that increases to 10 per cent at $z_l = 0.35$. We assess the significance of these biases for our previous work in Section 5.4. The results for the LRG source sample confirm our assertion in previous works that for $z_l < 0.3$, this sample is essentially free of redshift bias.

The lack of significant redshift calibration bias for the template photoz code for $z_l < 0.25$ can be explained by the trends in Fig. 6: the calibration bias due to the slight negative photoz bias balances out the calibration bias due to photoz scatter. Even at higher redshift, the redshift calibation bias, while non-zero, is less significant than for the other photoz methods. The neural net and ZEBRA/SDSS photoz values, however, have significant negative bias (-30 per cent and -20 per cent, at $z_l = 0.4$), presumably because of the aforementioned tendency to positive photoz bias for $z_s < 0.4$. This difference between the three methods is also the reason why the latter two methods have high total weight for the range of lens redshift considered here, whereas the template photoz code has lower weight (i) because of its scatter to low photoz (which eliminates possible sources from the sample) and (ii) because it does not tend to scatter sources to higher photoz, which increases the weight artificially at the expense of biasing the signal. We emphasize that this higher weight for the two photoz methods does *not* mean that the error on $\Delta\Sigma$ is lower with these methods, because it may be due purely to the overestimate of $\tilde{\Sigma}_c^{-1}$. In Section 5.8, we will address the effect of using photoz values on the statistical error in $\Delta\Sigma$.

Given that kphotoz has a similarly sized photoz error ($r < 21$ only) as the other photoz methods for the full source sample (all magnitudes), it is important to understand why the lensing calibration bias is so much worse for this method. The reason this occurs is that the $r < 21$ sample is at lower mean redshift. Since those sources are closer on average to the lens redshift, the same size photoz error translates to a larger error in Σ_c.

To understand the results, we consider fixed lens redshift of $z_l = 0.2$, and show the redshift bias as a function of true source redshift for each method in Fig. 8 (again, with lensing weight as a function of source redshift as in Section 4.4). Clearly, all source redshift bins with $z_s < 0.2$ must give $b_z = -1$, because the sources are not lensed. Above $z_s = z_l = 0.2$, the calibration bias is no longer identically zero, but may be significantly negative due to scatter in the estimates of source redshift (near $z_s = z_l$, the derivative $d\Sigma_c/dz_s$ is large so photoz errors are very important). As the source redshift increases, the same photoz error becomes less important because that derivative decreases, so the calibration bias approaches zero. The other important quantity to consider is the weight in each source redshift bin; if those source redshift bins with significant bias are given little weight, then the bias does not matter. If there is no weight for $z_s < 0.2$ that means that none of the galaxies with true $z_s < 0.2$ have had photoz misestimated to be above that. This plot makes it clear that part of the reason for the significant bias for the NN, kphotoz and ZEBRA/SDSS photoz values is that they give too much weight to $z_s \lesssim 0.3$. This is less of a problem for the template photoz values, so the calibration bias for this method is much less.

Finally, we show the resulting mean calibration bias when these results are averaged over a lens redshift distribution using equation (6). Errors are determined using the prescription in Section 4.3. The lens redshift distributions that we consider are as follows: 'sm1'–'sm7' are the redshift distributions for the seven stellar mass

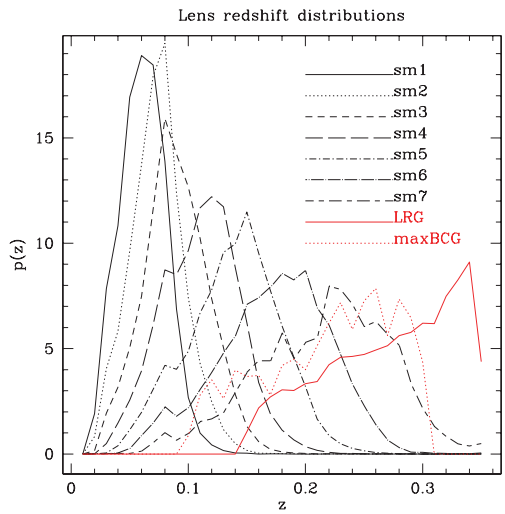

Figure 9. Lens redshift distributions for the lens samples described in the text.

bins from Mandelbaum et al. (2006c); 'LRG' is the redshift distribution for the spectroscopic LRGs, a volume-limited sample, used for lensing in Mandelbaum et al. (2006b); and 'maxBCG' is the redshift distribution of the SDSS maxBCG clusters (Koester et al. 2007a,b). These nine lens redshift distributions are plotted in Fig. 9. The stellar mass subsamples correspond roughly to luminosity samples with r-band luminosities of 0.33, 0.53, 0.72, 1.1, 1.8, 3.0 and $4.7L_*$. The LRGs are red galaxies with typical luminosities of a few L_*, and the maxBCG clusters are clusters selected from imaging data with masses $\gtrsim 5 \times 10^{13}\ h^{-1}\,\mathrm{M}_\odot$.

The average redshift calibration biases $\langle b_z \rangle$ (defined in equation 6) for the redshift determination methods given in Fig. 7 for these nine lens redshift distributions are shown in Table 3. As shown, for the stellar mass subsamples, the bias gets more significant at higher stellar mass because of the higher mean redshift. The maxBCG sample gives similar bias to sm7 because of the similar redshift range, and the LRG sample gives the worst bias because it has the highest mean redshift. The only method for which the trend is different is the template photoz code, for which the trend of $b_z(z_l)$ changes sign with redshift due to the different trends of photoz error with redshift.

As shown, the NN/D1 photoz values give nominally worse calibration bias than the NN/CC2 photoz values for lower redshift lens samples, and the reverse is true at higher redshift. This trend is consistent with the difference between the two methods in Fig. 7. We also performed the analysis with the DR5 NN photoz values, and found the lensing calibration bias for these lens redshift distributions to be similar to the NN/CC2 calibration biases, well within the 1σ errors. This result suggests that the failure mode to $0.75 < z_\mathrm{p} < 1$ in the DR5 version was not a significant source of lensing calibration bias, and the overall positive photoz bias (present in all NN photoz values tested in this paper) is the main cause.

Finally, we consider what happens if we correct for the mean photoz bias when estimating Σ_c for each source. For the template photoz values, this correction causes the mean calibration bias for sm7 to go from -0.014 to -0.14. This result may be puzzling until we consider the effects of photoz bias and scatter separately (Section 3.3). We know that photoz scatter causes a negative calibration bias, and a negative photoz error like this method has causes a positive calibration bias. When we did not correct for the mean photoz bias, these two effects apparently cancelled out. This cancellation is a non-trivial result that depends on our sample selection. With a different cut on apparent magnitude, for example, it is not clear that the effects would balance as precisely. Now that we have corrected for the effects of mean photoz bias, we are left with the suppression of the lensing signal due to the photoz scatter. For the NN/CC2 and NN/D1 photoz values, the correction for the mean photoz bias decreases calibration bias from -0.16 and -0.15 to -0.10 and -0.07, respectively, for sm7 (since the positive photoz bias and the scatter change the lensing calibration in the same direction). For ZEBRA/SDSS, the photoz bias was slightly negative, so correcting for it worsens the lensing calibration bias as for the template photoz values, but only slightly: from -0.099 to -0.125 for sm7.

From these results, we can conclude that once the effects of the mean photoz bias are removed, the effects on the lensing calibration due to scatter in the photoz values are the smallest for the SDSS NN/D1 photoz values, followed by SDSS NN/CC2, ZEBRA/SDSS, and finally are the largest for the template photoz values. This trend is consistent with the trends in Table 2 for the photoz scatter. We therefore have two possible procedures for handling calibration bias in the lensing signal: (1) to correct for the mean photoz bias before computing the lensing signal, and apply a correction to the lensing signal afterwards to account for residual calibration bias due to photoz scatter or (2) to apply a correction to the lensing signal due to the combined effects of photoz bias and scatter at once. In either case, we must depend on the fact that our calibration subsample has the same sample properties as the full source catalogue, so that corrections derived using this subsample will apply to the full catalogue.

5.4 Implications for previous work

Here we determine the implications of Table 3 for previous work with this lensing source catalogue.

First, we consider the results for Mandelbaum et al. (2006c), in which we divided the sample into stellar mass and luminosity

Table 3. Average redshift bias $\langle b_z \rangle$ for nine lens redshift distributions described in the text.

	$r < 21$	$r > 21$	LRG	Template	NN/CC2	NN/D1	ZEBRA/SDSS
sm1	-0.033 ± 0.008	0.005 ± 0.009	0.004 ± 0.003	0.020 ± 0.003	-0.039 ± 0.007	-0.051 ± 0.007	-0.018 ± 0.006
sm2	-0.043 ± 0.009	0.008 ± 0.011	0.005 ± 0.004	0.020 ± 0.004	-0.048 ± 0.008	-0.059 ± 0.008	-0.022 ± 0.007
sm3	-0.057 ± 0.011	0.013 ± 0.013	0.006 ± 0.005	0.021 ± 0.004	-0.059 ± 0.008	-0.070 ± 0.008	-0.029 ± 0.007
sm4	-0.077 ± 0.012	0.020 ± 0.015	0.007 ± 0.006	0.020 ± 0.005	-0.075 ± 0.009	-0.084 ± 0.009	-0.038 ± 0.008
sm5	-0.104 ± 0.014	0.029 ± 0.019	0.010 ± 0.008	0.015 ± 0.005	-0.096 ± 0.009	-0.102 ± 0.009	-0.053 ± 0.008
sm6	-0.136 ± 0.016	0.041 ± 0.025	0.014 ± 0.011	0.003 ± 0.007	-0.124 ± 0.011	-0.123 ± 0.011	-0.074 ± 0.010
sm7	-0.169 ± 0.018	0.055 ± 0.033	0.022 ± 0.016	-0.014 ± 0.009	-0.155 ± 0.015	-0.146 ± 0.015	-0.099 ± 0.012
LRG	-0.221 ± 0.022	0.069 ± 0.045	0.038 ± 0.022	-0.037 ± 0.014	-0.195 ± 0.021	-0.171 ± 0.021	-0.131 ± 0.018
maxBCG	-0.171 ± 0.018	0.056 ± 0.034	0.023 ± 0.016	-0.015 ± 0.009	-0.158 ± 0.015	-0.147 ± 0.015	-0.101 ± 0.013

Table 4. Average redshift bias $\langle b_z \rangle$ in previous works using this source catalogue when combining source samples.

Lens sample	$\langle b_z \rangle$
sm1	-0.016 ± 0.008
sm2	-0.020 ± 0.009
sm3	-0.025 ± 0.011
sm4	-0.032 ± 0.013
sm5	-0.039 ± 0.016
sm6	-0.045 ± 0.020
sm7	-0.046 ± 0.026
LRG	$+0.021 \pm 0.038$

subsamples with the seven redshift distributions sm1–sm7 shown in Fig. 9. For that work, the signal presented was an average over the signal using the $r < 21$ and $r > 21$ source sample with $1/\sigma^2$ weighting. To determine the average bias on this signal, we use our bootstrap-resampled $b_z(z_l)$ and $w(z_l)$, averaging the bias as a function of redshift for each resampling using the weights for these two samples, then find the average over all the resampled data sets. The average biases for sm1–sm7 are shown in Table 4.

We also consider the spectroscopic LRG lens redshift distribution, which was used for lensing in Mandelbaum et al. (2006b) and Mandelbaum & Seljak (2007). In that case, we detected a ~15 per cent suppression of the lensing signal for the $r < 21$ source sample relative to the $r > 21$ and LRG source samples. Table 3 makes it clear that this suppression was, in fact, real. To account for this suppression, we had multiplied the signal and its error by a factor of 1.18. This is equivalent to multiplying $\tilde{\Sigma}_c$ by 1.18 when computing both the weights ($\propto \tilde{\Sigma}_c^{-2}$) and the lensing signal. We thus incorporate this factor into the computation of the bias in equation (5) before taking the weighted average with the $r > 21$ sample. The average bias once the correction factor is incorporated is shown in Table 4. Because of this suppression of the weight in the $r < 21$ sample due to the calibration factor, and because of its already low weight relative to $r > 21$ for $z_l > 0.22$ (see Fig. 7), the uncertainty on the calibration bias is actually dominated by the larger $r > 21$ sample uncertainty, which is why it is larger than one might naively expect from combining the results in Table 3 for $r < 21$ and $r > 21$. It is clear that this way of combining the signal for $r < 21$ and $r > 21$ is non-optimal from the perspective of constraining calibration bias.

No results are shown for the maxBCG lensing sample because none of the previous works using this source catalogue have used it.

It is clear from this table that there was statistically significant redshift calibration bias in previous works using this source catalogue. However, the absolute value of the error is below the statistical error on the lensing signal in those works, and is smaller than the generous 8 per cent (1σ) systematic error that was used for those science results. We conclude that there is no cause for concern in using results in our previous work with this catalogue without applying a correction.

5.5 Systematics: targeting and redshift failure

In the previous sections, all quoted calibration errors were statistical. Here, we consider the size of systematic errors.

First, we include the DEEP2 redshift failures in the sample, once putting them all at $z = 0$ and then all at $z = 1.5$ (with an LSS weight of 1). We have already shown in Section 5.1 that the failures have a similar SDSS magnitude and colour distribution to the remainder of the sample. This statement is also true in the DEEP2 *BRI* photometry, placing these galaxies without spectroscopic redshifts in the $0 < z < 0.7$ colour locus (like those with successful redshift determination). Consequently, placing them all at $z = 0$ and 1.5 gives extremely conservative bounds on the systematic error due to these redshift failures. Table 5 shows the new $\langle b_z \rangle$ and the change in $\langle b_z \rangle$ compared to Table 3 for all methods of source redshift determination, including the combined $r < 21$ and $r > 21$ method used in our previous work (Section 5.4), for four lens redshift distributions: sm1, sm4, sm7 and LRG, which are at progressively higher redshifts. As shown in Table 5, these extreme assumptions change our estimated calibration bias at the $<3\sigma$ level, in most cases $<1\sigma$. If we consider that the real effect is likely many factors smaller than this (since the failures roughly follow the magnitude and colour distribution of the successes, and therefore likely the redshift distribution), this systematic is far below our 1σ uncertainty on the calibration bias, from which we can conclude that systematic effects due to the excluded DEEP2 redshift failures are negligible.

We next consider the effects of using the zCOSMOS photoz for their redshift failures. As shown in Fig. 4, the failures have similar colours and magnitudes as the successes, so we do not anticipate that they will have a significantly different photoz error distribution from the successes shown at the bottom of that figure. To test the effect of using ZEBRA photoz values for this 8 per cent of the sample, we randomly replace the photoz values for the spectroscopic redshifts in another 8 per cent of the sample that are redshift successes.

Table 5. Change in redshift bias $\langle b_z \rangle$ for all methods of source redshift determination (including combined methods for $r < 21$ and $r > 21$ as in previous work, Section 5.4) when putting all DEEP2 failures at $z = 0$ and 1.5 as shown. The number given is the resulting redshift bias, and the number in parenthesis is the fractional change in the bias from Table 3 relative to the statistical error.

	$r < 21$	$r > 21$	LRG	Template	NN/CC2	ZEBRA/SDSS	Previous work
				Fail to $z = 0$			
sm1	−0.036 (−0.38)	−0.017 (−2.4)	−0.002 (−2.0)	0.008 (−4.0)	−0.062 (−1.9)	−0.029 (−1.8)	−0.028 (−1.5)
sm4	−0.081 (−0.33)	−0.003 (−1.5)	0.002 (−0.8)	0.007 (−2.6)	−0.094 (−1.6)	−0.050 (−1.5)	−0.044 (−0.9)
sm7	−0.173 (−0.22)	0.032 (−0.7)	0.017 (−0.3)	−0.027 (−1.4)	−0.166 (−1.0)	−0.111 (−1.0)	−0.060 (−0.5)
LRG	−0.224 (−0.14)	0.045 (−0.5)	0.033 (−0.2)	−0.050 (−0.9)	−0.218 (−0.8)	−0.143 (−0.67)	0.005 (−0.4)
				Fail to $z = 1.5$			
sm1	−0.032 (0.13)	0.009 (0.4)	0.004 (0.00)	0.022 (0.7)	−0.046 (0.43)	−0.015 (0.50)	−0.013 (0.38)
sm4	−0.075 (0.17)	0.027 (0.5)	0.008 (0.17)	0.024 (0.8)	−0.075 (0.56)	−0.034 (0.50)	−0.026 (0.46)
sm7	−0.166 (0.17)	0.074 (0.6)	0.024 (0.13)	−0.005 (1.0)	−0.140 (0.73)	−0.089 (0.83)	−0.033 (0.50)
LRG	−0.217 (0.18)	0.097 (0.6)	0.042 (0.18)	−0.025 (0.9)	−0.186 (0.71)	−0.118 (0.72)	0.043 (0.58)

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Table 6. Change in redshift bias $\langle b_z \rangle$ for all methods of source redshift determination when replacing 8 per cent of the redshifts for zCOSMOS successes with their photoz values. The number given is the resulting redshift bias, and the number in parenthesis is the fractional change in the bias from Table 3 relative to the statistical error.

	$r < 21$	$r > 21$	LRG	Template	NN/CC2	ZEBRA/SDSS	Previous work
sm1	−0.033 (0.00)	0.005 (0.00)	0.004 (0.00)	0.019 (−0.33)	−0.049 (0.00)	−0.018 (0.00)	−0.016 (0.00)
sm4	−0.078 (−0.08)	0.019 (−0.07)	0.008 (0.17)	0.020 (0.00)	−0.080 (0.00)	−0.039 (−0.13)	−0.032 (0.00)
sm7	−0.170 (−0.06)	0.055 (0.00)	0.024 (0.13)	−0.013 (0.11)	−0.151 (0.00)	−0.098 (0.08)	−0.046 (0.00)
LRG	−0.221 (0.00)	0.070 (0.02)	0.041 (0.14)	−0.035 (0.14)	−0.201 (0.00)	−0.130 (0.06)	0.022 (0.03)

We then compare the resulting calibration biases $\langle b_z \rangle$ to the original ones. These results (shown in Table 6) indicate that for all methods of source redshift distribution determination and lens redshift distributions, the use of zCOSMOS photoz values for the 8 per cent of the zCOSMOS sample that lacks redshifts changes the results well below the 1σ statistical error. We conclude that systematic error in our results due to redshift failures in either survey are unimportant, with the caveat that if the redshift failures are a systematically different population than the successes, this test would not uncover any resulting systematic error (however, we have no evidence that this is the case).

One final systematic is that in DEEP2 EGS, roughly 4 per cent of our source catalogue at bright magnitudes ($r < 18.5$) was not targeted. We must assess whether properly including these galaxies would significantly change the results. However, the small photoz error for bright objects, and the low mean redshift, makes this unlikely. In the SDSS, only a subset of these galaxies have spectroscopy, those with $r \lesssim 17.7$ (flux-limited) and fainter ones that are very red. Since including these SDSS spectroscopic redshifts will create a sample with strange selection (lacking blue galaxies at $17.7 \lesssim r < 18.5$), we instead take the spectroscopic galaxies from zCOSMOS at $r < 18.5$, choose a random subset to account for the smaller size of the DEEP2 sample, and add the resulting 42 galaxies to the DEEP2 sample. We then refit the redshift histogram for DEEP2, getting new redshift distribution parameters $z_* = 0.312 \pm 0.048$, $\alpha = 2.14 \pm 0.39$ and $\langle z \rangle = 0.400 \pm 0.025$. We see that the change in mean source redshift is well within the errors in Table 1. When computing the mean redshift bias using this augmented sample, we find that the changes are even smaller than those shown in Table 5. This is not surprising, because in that table we have taken redshift failures and put them at very extreme redshifts, whereas here we have added a comparable number of redshifts but with very good photoz values.

5.6 Agreement between the two surveys

As an additional systematics test, we compare the results when doing the full analysis separately for each survey. In this case, we use LSS weights derived using the redshift histograms for each survey separately instead of using the combined histogram. In Table 7, we show the results for each survey separately, with the bottom section showing the statistical significance of the difference. The results in this table show apparently significant discrepancies between the results with zCOSMOS and with DEEP2 separately. The fact that the statistical significance of the difference is $\lesssim 2\sigma$ for the last four columns, which use the full catalogue, but $>2\sigma$ for the first column (which uses $r < 21$ only) and $\lesssim 1\sigma$ for the second column (which uses $r > 21$ only) suggests that we should focus on the $r < 21$ sample to find the source of the discrepancy. We must understand this discrepancy in order to assess whether our results are biased or our error bars are significantly underestimated on the final, combined analysis.

In Fig. 10 we show plots for $r < 21$ that will shed light on this discrepancy. The upper left-hand plot shows $p(z)$ for $r < 21$ for both surveys. As shown, the best-fitting histograms are very similar, but the LSS fluctuations are more pronounced than for the full sample. The lower left-hand panel shows the ratio of the best-fitting number predicted in zCOSMOS to the number in DEEP2 (normalized to the

Table 7. Redshift bias $\langle b_z \rangle$ for each survey separately. The number given is the resulting redshift bias with statistical error. The bottom section gives the statistical significance on the difference in units of standard deviations.

	$r < 21$	$r > 21$	LRG	Template	NN/CC2	ZEBRA/SDSS	Previous work
				zCOSMOS			
sm1	−0.045 ± 0.013	−0.001 ± 0.012	−0.005 ± 0.007	0.020 ± 0.005	−0.051 ± 0.009	−0.021 ± 0.009	−0.026 ± 0.011
sm4	−0.101 ± 0.020	0.005 ± 0.024	−0.009 ± 0.014	0.019 ± 0.007	−0.089 ± 0.011	−0.044 ± 0.011	−0.053 ± 0.018
sm7	−0.222 ± 0.029	0.013 ± 0.063	−0.016 ± 0.033	−0.026 ± 0.019	−0.179 ± 0.027	−0.109 ± 0.025	−0.097 ± 0.044
LRG	−0.295 ± 0.034	0.011 ± 0.090	−0.012 ± 0.045	−0.059 ± 0.030	−0.242 ± 0.040	−0.146 ± 0.038	−0.048 ± 0.069
				DEEP2 EGS			
sm1	−0.013 ± 0.006	0.007 ± 0.016	0.013 ± 0.004	0.018 ± 0.004	−0.048 ± 0.010	−0.012 ± 0.007	−0.003 ± 0.010
sm4	−0.036 ± 0.009	0.028 ± 0.026	0.025 ± 0.009	0.022 ± 0.006	−0.070 ± 0.012	−0.031 ± 0.009	−0.003 ± 0.018
sm7	−0.071 ± 0.017	0.091 ± 0.053	0.062 ± 0.021	0.003 ± 0.013	−0.112 ± 0.022	−0.085 ± 0.018	0.023 ± 0.040
LRG	−0.075 ± 0.025	0.122 ± 0.072	0.089 ± 0.030	−0.007 ± 0.019	−0.145 ± 0.032	−0.111 ± 0.025	0.113 ± 0.060
				Statistical significance of difference (in units of σ)			
sm1	2.23	0.40	2.23	0.31	0.22	0.79	1.55
sm4	2.96	0.65	2.04	0.33	1.17	0.91	1.96
sm7	4.49	0.95	1.99	1.26	1.92	0.78	2.02
LRG	5.21	0.96	1.87	1.46	1.89	0.77	1.76

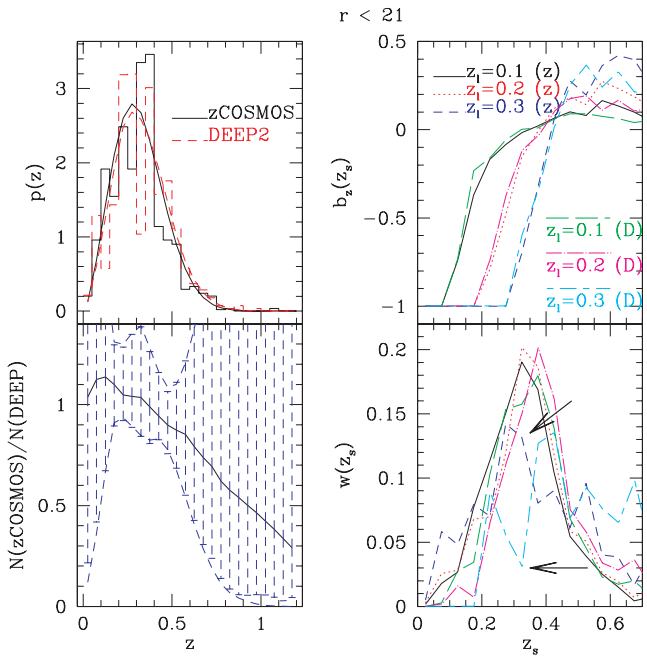

Figure 10. Results for $r < 21$ only for each survey separately, as described in more detail in the text of Section 5.6. We show the best-fitting and observed redshift histograms (upper left-hand panel); the ratio of the best-fitting redshift distributions, with shaded 68 per cent CL region (lower left-hand panel); and the lensing calibration bias b_z (upper right-hand panel) and the lensing weight as a function of source redshift (lower right-hand panel) for three lens redshifts.

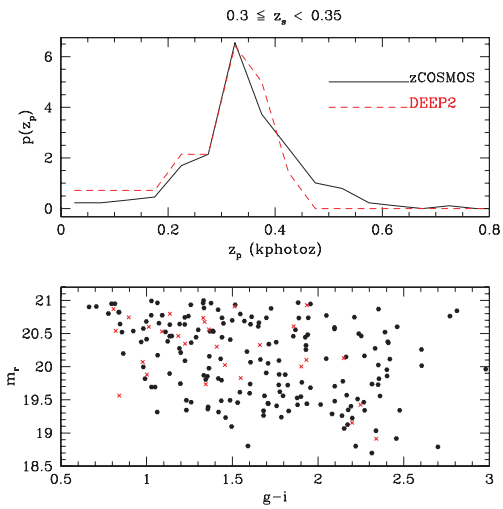

Figure 11. Photoz distribution (top) and colour–magnitude information for DEEP2 and zCOSMOS sources with $0.3 \leqslant z_s < 0.35$ (kphotoz). In the bottom panel, we show the $g - i$ colour and r-band magnitude, where the red crosses are DEEP2 and the black hexagons are zCOSMOS.

same total numbers of galaxies), with the 68 per cent confidence region shown with dashed lines. This confidence region, including both Poisson and sampling variance error, was determined as follows: for each survey, 200 bootstrap-resampled redshift histograms were created, and used to fit for the dN/dz. We then pair up the 200 best-fitting $N_i^{(\mathrm{model})}$ from zCOSMOS and from DEEP2 EGS, and determine the ratio of these values for each survey. The 200 ratios are ranked, and the middle 68 per cent are chosen to determine the 68 per cent confidence region. It is reassuring that for all redshifts, this shaded region includes a ratio of 1. It is apparent that the scarcity of redshifts at $z > 0.6$ causes the error bars on the ratio to become extremely large (well off the limits of the plot).

The top right-hand panel in Fig. 10 shows $b_z(z_s)$ for several lens redshifts. As shown, these results are very similar for the two surveys. The bottom right-hand plot shows the fractional weight $w(z_s)$ for each lens redshift and survey. In principle, the LSS weighting was designed to ensure that these curves would not have structure due to LSS fluctuations in number density as a function of redshift. We can see (particularly for $z_l = 0.3$) that the curves for each survey are quite different and have significant LSS fluctuations, so we must understand why this is the case. We have ascertained that if we use $b_z(z_s)$ from DEEP2 with the weight $w(z_s)$ from zCOSMOS, we recover the same $\langle b_z \rangle$ as when we use $b_z(z_s)$ and $w(z_s)$ from zCOSMOS, implying that the weight differences cause the discrepancy in $\langle b_z \rangle$.

To solve this problem, we consider only sources with $0.3 \leqslant z_s < 0.35$. As shown with arrows, for $z_l = 0.3$, the weight in this bin is a factor of ∼4 higher in zCOSMOS as in DEEP2. We have confirmed that this bin alone is a significant reason why the average calibration bias is on average more negative for zCOSMOS as for DEEP2. There are 179 and 21 galaxies at $r < 21$ in this bin in zCOSMOS and DEEP2, respectively. Using the LSS weights derived for each survey separately, we weight zCOSMOS and DEEP2 by factors of 0.8 and 2.25, giving weighted numbers of galaxies of 143 and 63. Thus, the weighted ratio $N(\mathrm{zCOSMOS})/N(\mathrm{DEEP2}) \sim 2.3$, where the expected value is 1.85 given the total number of galaxies in each survey. This ratio of 2.3 therefore represents a 23 per cent enhancement of zCOSMOS relative to DEEP2, due to the fact that the LSS weights were derived using all galaxies in each survey, not just those at $r < 21$ that we use here. While we can therefore conclude that LSS weighting may need to be done as a function of apparent magnitude, this 23 per cent enhancement in source number does not account for a factor of 4 enhancement in the weights.

Fig. 11 shows the photoz distribution $p(z_p)$ for kphotoz for the $r < 21$ sources in this narrow redshift slice in each survey. It is important to note that our past analyses have required $z_p > z_l + 0.1$. The photoz distributions for the zCOSMOS and DEEP2 galaxies in this redshift slice are quite different, with the DEEP2 distribution being skewed to lower photoz, and the zCOSMOS one to higher photoz. Consequently, 40 of the 179 zCOSMOS galaxies pass this photoz cut (23 per cent), as compared with two of the 29 DEEP2 galaxies (7 per cent). In terms of raw numbers, this gives an additional factor of $23/7 \sim 3.2$ enhancement of the weight in zCOSMOS on top of the previous factor of 1.2. Thus, the two factors together give nearly the factor of 4 enhancement in weight that we noted on Fig. 10 as the source of the discrepancy.

Having accounted for the source of the problem, we must understand why the photoz distributions look so different for the two surveys. The bottom panel of Fig. 11 gives colour–magnitude information for these $r < 21$, $0.3 \leqslant z_s < 0.35$ galaxies in the two surveys. As shown, the DEEP2 galaxies are both fainter and bluer on average than those in zCOSMOS at this redshift. This is consistent with the fact that the redshift histograms show a local underdensity in DEEP2 and a significant overdensity in zCOSMOS at this redshift. We have found that for this photoz method, the photoz values are biased low for *blue* galaxies, but not red galaxies. Hence, the different photoz distributions in the top panel of Fig. 11 reflect the different mixes of spectral types and different signal-to-noise ratio (S/N) detections of the galaxies in the two surveys at this source

redshift, rather than some more ominous effect such as differences in photometric calibration across the SDSS survey area.

We have confirmed that similar effects are at play in other parts of the source redshift distribution (e.g. $0.6 \leqslant z_s < 0.65$) that show significant differences in weight between the two surveys in Fig. 10. In short, the cause of the different redshift biases in the two surveys is the interplay between LSS and photoz errors, where LSS emphasizes certain spectral types that have different photoz error properties. (Explicit demonstration of how this effect can come about will be shown in Section 5.11, where we show photoz error distributions for ZEBRA/SDSS as a function of colour and magnitude.) Even in the absence of our $z_p > z_l + 0.1$ cut, the mean estimated Σ_c^{-1} would have been much higher in zCOSMOS than in DEEP2, giving the same sign of the discrepancy between the surveys as we have now [except in that case, both $b_z(z_s)$ and $w(z_s)$ would be different, not just $w(z_s)$]. This interplay between photoz values and LSS is a problem when trying to estimate the bias due to redshift calibration with a reasonably small subsample of redshifts (∼1000) on a small area of the sky. It is also avoidable in principle, if we use our sample with spectroscopic redshifts to derive photoz error distributions as a function of colour and magnitude, which may be used to obtain accurate $\mathrm{d}p/\mathrm{d}z$ for each object.

To confirm these findings, we have boxcar-smoothed the weights $\tilde{w}_s(z_s)$ shown in Fig. 10 with smoothing lengths of $\Delta z_s = 0.1,\ 0.15$ and 0.2 for $z_l = 0.1,\ 0.2$ and 0.3 [larger smoothing lengths chosen for higher z_l because the LSS fluctuations in $w(z_s)$ are more significant there]. The resulting weight functions are reasonably smooth, as shown in Fig. 12, but include some apparent mean offset in the redshift distributions for the two surveys. We find that the discrepancy between $\langle b_z \rangle$ for the two surveys is 5, 15 and 50 per cent smaller for $z_l = 0.1,\ 0.2$ and 0.3, respectively, than when using the unsmoothed $w(z_s)$. Most of the change arises from the DEEP2 mean calibration bias going to lower (more negative) values, with the zCOSMOS mean calibration bias changing only slightly. The apparent 5σ discrepancy in Table 7 for LRG lenses is thus reduced due to this smoothing to a 2.5σ discrepancy, with the remaining discrepancy presumably due to the offset in the weight histograms shown in Fig. 12.

We now ask if the LSS fluctuations are the cause of the 2σ discrepancy with the other photoz methods. As we will show later for ZEBRA/SDSS and have confirmed for the template and neural net photoz algorithms (but do not show here), it is a general tendency of these photoz algorithms to underestimate the photoz values for blue galaxies, and slightly overestimate them for red galaxies. Consequently the same effect occurs when the mixes of spectral types are different in the two surveys, even when we are using another photoz algorithm, and this is evident in $w(z_s)$ for each survey. We therefore estimate using the same method of boxcar-smoothing the weight as a function of redshift for each survey that the 2σ discrepancies for these methods are really 1σ.

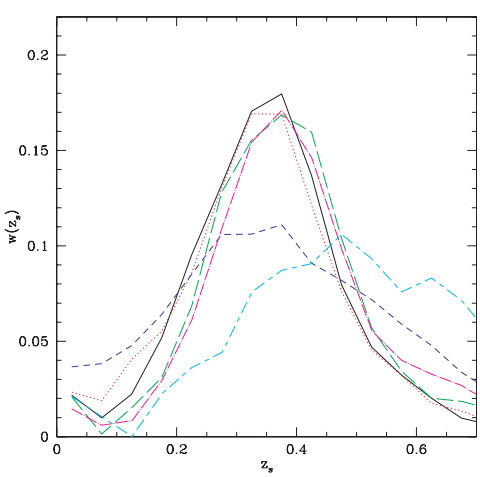

Figure 12. Smoothed weight as a function of source redshift for several lens redshifts in DEEP2 and zCOSMOS to minimize the effects of LSS. This plot is a smoothed version of the lower right-hand panel of Fig. 10, with the same line types and colours as in that plot. The smoothing algorithm is described in the text.

We now address another unusual feature of the calibration uncertainties in Table 7: the uncertainties are actually *smaller* for DEEP2 than for zCOSMOS (only slightly larger than for the combined sample), despite the fact that sampling variance is ∼20 per cent larger for DEEP2 EGS as for zCOSMOS! This result is also due to the LSS fluctuations in the weights for both surveys. The DEEP2 mean calibration bias was, as we saw previously, significantly affected by this problem, and it is also responsible for making the error bars artificially small [since our method of getting the errors does not allow $w(z_s)$ to vary as much as it should in reality]. So, our worst case 2.5 and 1σ calibration differences for LRG lenses (with kphotoz and with the other photoz methods, respectively) is actually much less significant than these numbers suggest, and therefore not a problem.

We must ask whether this effect means that our mean results are biased or our error bars are too optimistic when using the combined sample of galaxies for the two surveys. However, we are fortunate to be able to combine large samples at completely different points on the sky. The total (sample variance + Poisson) errors when using two uncorrelated fields with N_1 and N_2 galaxies are smaller than if we simply had a single field on the sky with $N_1 + N_2$ galaxies (which would be correlated with each other).

A comparison of Fig. 10 with Fig. 8 can help us answer this question. In Fig. 10, it is clear that the weight as a function of source redshift $w(z_s)$ for $z_l = 0.2$ is not smooth at all due to LSS–photoz error correlation in each survey. The fluctuations are at times ∼30 per cent off from the value one might expect if the curve is smooth. However, in Fig. 8, these curves for the combined sample are significantly smoother, with fluctuations that are at most 20 per cent for the LRG sources (the smallest and most highly clustered sample) and even less for the other samples, ∼10 per cent. We thus conclude that the effect is reduced by a factor of ∼3, and is therefore negligible for the combined sample. To verify this conclusion, we have performed the same boxcar-smoothing of the weight functions in Fig. 8 with the same smoothing lengths as for the two survey subsamples, and found that the resulting redshift calibration biases $\langle b_z \rangle$ for the combined sample changed by <0.5 per cent for sm1–sm5, <1 per cent for sm6, sm7, LRGs and maxBCG lenses. These changes are well within the 1σ errors on the calibration bias for these lens samples.

Finally, we note in the top panel of Fig. 11 that our naive requirement that $z_p > z_l + 0.1$ has required us to ignore a significant majority of the galaxies in this redshift slice, all of which are actually lensed. Since $z_l = 0.3$ and the sources are all at true redshifts $z_s > 0.3$, we could conceivably use them all for lensing; using the subset at $z_p > 0.4$ eliminates a large fraction of these sources. We return to this point in Sections 5.8 and 5.1.0.

5.7 Size of error bars on calibration bias

While we have previously asserted (Section 4.3) that correlations between the bins in the redshift histograms should be negligible, we

now present tests of this assertion, which (if violated) could cause the error bars to be underestimated. One reason why they might be violated is the existence of a supercluster that happens to lie partially within two histogram bins instead of entirely within one. While such a large LSS fluctuation is unlikely in an area of such small comoving volume, we nonetheless present tests of this possibility.

As an example of a candidate supercluster, we find a large overdensity with $0.34 < z < 0.38$ in zCOSMOS. By plotting the detailed redshift distribution in this region, we see that there are, in fact, $\sim$3 large overdensities with line of sight separations of $\sim 80\,h^{-1}$ Mpc between them. Clusters that are separated by such a large separation are unlikely to be correlated: the correlation function for dark matter at this separation is 10^{-3}, so the clusters would need to have bias of $\sim$30 to have the correlation probability to become appreciable relative to a random distribution. There should be fewer than one cluster with such a high bias in an observable universe. While magnification bias may increase the probability by a factor of a few (Hui, Gaztañaga & Loverde 2007), it does so by invoking the cross-correlation between mass and galaxies, so one loses one power of the bias, which therefore cannot bring the correlations to a level comparable to unity. These galaxy bias and magnification bias effects are difficult to simulate realistically, so we cannot turn to simulations to solve this problem.

To test the effects on the error bars of the best-fitting redshift distribution and on the final calibration bias, we redo the analysis using bins of size $\Delta z = 0.1$, which will then include these structures all in one bin. We find that for zCOSMOS, this procedure increases the errors on the final results by 30 per cent, whereas the size of the errors for DEEP2 and the combined sample (DEEP2 + zCOSMOS) are essentially unaffected.

As an additional test, we shift the original histogram bins by -0.02 in redshift, so that all three structures fall into the bin from $0.33 \leqslant z < 0.38$. We find that while the best-fitting redshift histogram is unaffected, the errors on it are significantly increased (by nearly a factor of 2 in the bins near this LSS fluctuation, and a smaller factor further away from it). To understand why it has such a large effect, we consider that it adds an additional number of galaxies ΔN to the histogram in that one bin. The penalty on the fit Δ^2 (equation 7) is therefore $(\Delta N)^2$. When we consider splitting the fluctuation equally into two bins (as we had effectively been doing before), the excess number of galaxies in each bin is $0.5\Delta N$, leading to a Δ^2 penalty of $2(0.5\Delta N)^2 = 0.5(\Delta N)^2$, half as much as if the entire overdensity is in one bin. The effect when fitting to the shifted histogram using both surveys together is nearly the same as when fitting zCOSMOS alone, whereas the errors for DEEP2 alone are unaffected (because our contrived bin-shifting did not correlate with any LSS fluctuations in DEEP2).

Given that these structures are likely to be uncorrelated, our bin-shifting that treated them as correlated leads to overestimated errors. On the other hand, our default binning puts one of them into one histogram bin, and left the other two together; we may therefore suppose that our errors for zCOSMOS and the combined sample are, in fact, slightly overestimated (since we effectively treated two of the structures as correlated). It is clear that the limited number of independent patches makes the error estimate from the bootstrap noisy, and while our final results may be treated as having conservative error bars, we cannot exclude the possibility that they may be a factor of 2 larger. However, this finding that the zCOSMOS error bars may be overestimated may also explain the fact that in the previous section, we found the calibration of the lensing signal in DEEP2 to be constrained more tightly than in zCOSMOS despite the fact that DEEP2 is smaller.

Finally, we note that bootstrapping M data points $\gg M$ times will in general lead to statistical uncertainty in the determined errors at the $1/\sqrt{M}$ level. For the case where we bootstrap a redshift histogram with 24 bins to get the best-fitting redshift distribution, and use those results to get errors on the lensing signal calibration uncertainty, the errors are therefore reliable at the $\sim$20 per cent level. This uncertainty is due to noise, rather than violation of the bootstrap assumptions as in the rest of this section.

5.8 Purity and completeness

Here we address questions of purity and completeness of the source sample for each photoz method. We define purity as the fraction of the total estimated lensing weight that is attributed to sources with spectroscopic redshift above the lens redshift (i.e. that are truly lensed). Low purity would be associated with a strong negative calibration bias. Completeness can be defined by constructing the analogues of the lensing weights in equation (4), but using the true Σ_c rather than the estimated one. We then define a 'true' w_j for each object, and find the fraction of the total summed 'true' weights that is actually used by lensed sources defined using any given photoz method. Low completeness can occur because photoz values are scattered low, so that we assume they are below the lens redshift.

These two issues, purity and completeness, are two of the three factors that determine the statistical error on the lensing signal $\Delta\Sigma$ for a given photoz method as compared with the statistical error in the optimal case where all lens and source redshifts are known. The final factor is how much a photoz method causes the weighting scheme to deviate from optimal weighting. We would like to estimate the total increase in the error on the lensing signal due to all three factors combined.

To do so, we consider the lensing signal estimator in the optimal case where all lens and source redshifts are known. In that case, we have a shear γ, a critical surface density Σ_c, and weights $w = 1/(\Sigma_c\,\sigma_\gamma)^2$. (These weights are analogous to those defined in equation 4, where σ_γ comes from shape noise and measurement error added in quadrature.) In this ideal case, the lensing signal is

$$\Delta\Sigma = \frac{\sum w(\Sigma_c\gamma)}{\sum w} \tag{11}$$

and its variance is

$$\text{Ideal var}(\Delta\Sigma) = \frac{\sum w^2\Sigma_c^2\sigma_\gamma^2}{\left(\sum w\right)^2} = \frac{\sum w}{\left(\sum w\right)^2} = \frac{1}{\sum w}. \tag{12}$$

In reality, we have an estimated critical surface density $\tilde{\Sigma}_c$, an estimated weight $\tilde{w} = 1/(\tilde{\Sigma}_c\sigma_\gamma)^2$, and a calibration bias defined via equation (5). We can relate it to the true lensing signal

$$\Delta\Sigma = \frac{\sum \tilde{w}(\tilde{\Sigma}_c\gamma)}{(1+b_z)\sum \tilde{w}}, \tag{13}$$

so its variance is

$$\text{Real var}(\Delta\Sigma) = \frac{\sum \tilde{w}^2\tilde{\Sigma}_c^2\sigma_\gamma^2}{(1+b_z)^2\left(\sum \tilde{w}\right)^2} = \frac{1}{(1+b_z)^2\left(\sum \tilde{w}\right)}. \tag{14}$$

We then rearrange the definition of b_z as follows:

$$1 + b_z = \frac{\sum \tilde{w}\left(\tilde{\Sigma}_c\Sigma_c^{-1}\right)}{\sum \tilde{w}} = \frac{\sum \sqrt{\tilde{w}w}}{\sum \tilde{w}}. \tag{15}$$

Inserting this form for $1 + b_z$ into equation (14), we find that

$$\text{Real var}(\Delta\Sigma) = \frac{\sum \tilde{w}}{(\sum \sqrt{\tilde{w}w})^2}. \tag{16}$$

Comparing equations (12) and (16), we find that

$$\frac{\text{Ideal var}(\Delta\Sigma)}{\text{Real var}(\Delta\Sigma)} = \frac{\left(\sum\sqrt{\tilde{w}w}\right)^2}{\left(\sum w\right)\left(\sum\tilde{w}\right)}. \tag{17}$$

This ratio has the form of a correlation coefficient between the square roots of the real and ideal weights for each lens–source pair, and therefore is constrained to lie between 0 and 1 (not between −1 and 1 as for correlation coefficients in general, since the weights are strictly ⩾0). It is only equal to one in the case where the estimated weight $\tilde{w}$ is strictly proportional to the ideal weight w. This is as it should be: the measured ('real') variance of the lensing signal using a given photoz method is always greater than or equal to the ideal variance. This expression encodes all three possible ways the real measurement can be degraded relative to the ideal one via loss of lensed sources, inclusion of sources that are not lensed and non-optimal weighting. This statistic is therefore another lensing-optimized metric than can be used to classify photoz algorithms for g–g lensing purposes.

Fig. 13 shows the purities (bottom left-hand panel), completeness (top left-hand panel), the variance ratio (top right-hand panel) and the implied change in variance due to non-optimal weighting (bottom right-hand panel) as a function of lens redshift for each method. We first consider the completeness as a function of lens redshift in the top left-hand panel of Fig. 13. The results for kphotoz verify our previous findings that the combination of a broad photoz error distribution with our requirement that $z_p > z_l + 0.1$ causes us to lose a significant fraction of the available lensing weight. The results for the LRG source sample verify our previous assertions that the photoz values for these sources are able to correctly put them all at high redshift, so that we do not lose essentially any of them. The template photoz completeness is ∼80 per cent on average, which is not surprising given the significant failure mode to $z_p = 0$ that causes us to lose some sources. The neural net photoz values (CC2 and D1) give the highest completeness of all the photoz methods considered here (except the highly specialized LRG source sample), in part due to the positive mean photoz error.

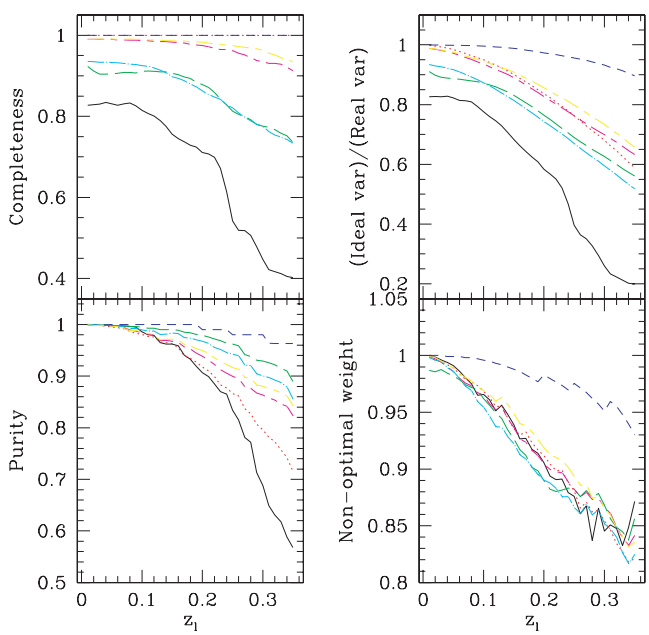

Figure 13. Left-hand panels: Completeness (top) and purity (bottom) as defined in the text as a function of lens redshift. Top right-hand panel: The resulting ratio of ideal to real variance for each method of source redshift determination. Bottom right-hand panel: The derived change in variance due to the non-optimal weighting. Redshift determination methods are as follows. Solid black: kphotoz ($r < 21$); dotted red: $r > 21$ redshift distribution; dashed blue: high-redshift LRGs; long-dashed green: template photoz values; long–short-dashed magenta: NN/CC2 photoz values; long–short-dashed yellow: NN/D1 photoz values and dot–dashed cyan: ZEBRA/SDSS.

In the lower left-hand panel of Fig. 13, we see the purity as a function of lens redshift. The swiftly declining purity above $z_l = 0.2$ for kphotoz is the main cause of the large negative calibration bias for this method for higher redshift lens samples, and is a result of large photoz error coupled with a lower mean redshift for $r < 21$ than the full samples used for the other photoz methods. The LRG source sample purity is uniformly high, dropping from 1 at $z_l = 0$ to a minimum of 0.96 at $z_l = 0.35$. This result attests to the efficiency of the colour cuts in selecting only high-redshift sources, and the small size of the photoz error distribution. Of the other photoz methods, the template photoz has the highest purity; the tendency towards a positive photoz error seen previously for the NN and ZEBRA/SDSS photoz values cause a decline in purity with redshift (though it is also the cause of their relatively high completeness) just as it causes a negative calibration bias in the lensing signal.

The upper right-hand panel of Fig. 13 shows the variance in the ideal case relative to the true variance that results from using a given photoz method. For kphotoz, this number drops as low as 0.2 for $z_l > 0.3$, implying that the errors are a factor of $\sqrt{1/0.2} \sim 2.2$ larger when using this photoz method than in the ideal case. ZEBRA/SDSS and the template photoz values give similar results for this parameter, from 0.85 at $z_l = 0$ to 0.5 at $z_l = 0.35$, implying errors ranging from 1.1 to 1.4 times the ideal. The NN photoz values give slightly better results than that, as does using a redshift distribution for $r > 21$ galaxies. The high-redshift LRGs naturally give nearly identical errors in reality than in the ideal case, because the sources are at redshifts significantly higher than the lenses, so any photoz errors cannot cause a significant deviation from optimal weighting.

Finally, the lower right-hand panel shows the estimated change in variance due to non-optimal weighting, obtained by taking the variance ratio and dividing out the effects of impurity and incompleteness. The results suggest that for all source samples except the high-redshift LRGs, the non-optimal weighting has a similar effect on the errors independent of photoz method, increasing them by ∼7 per cent at worst for this range of lens redshifts.

5.9 Using $p(z)$ distributions

Here we consider the possibility of using a full redshift probability distribution, $p(z)$, for each object, with two different sources of this distribution. The first is the posterior $p(z)$ from the ZEBRA/SDSS method. For this method, $p(z)$ is determined by marginalizing over templates T using the joint redshift–template prior $P(z, T)$ and the likelihood $L(z, T)$ from the fit χ^2:

$$p(z) \propto \sum_T L(z, T)P(z, T). \tag{18}$$

The second is a $p(z)$ distribution determined using some of the machinery described in Oyaizu et al. (2008) but independently of the photoz determination in that paper. The photoz-independent estimate of $p(z)$ (Cunha et al., in preparation) is calculated as follows: the training set comprising 639 915 spectroscopic objects from a variety of surveys is reweighted using the procedures in Oyaizu et al. (2008) and Lima et al. (2008) to match the joint, five-dimensional probability distribution of the source catalogue for which we would like to obtain photoz values. The five parameters used to create this

distribution are $u-g$, $g-r$, $r-i$, $i-z$ colours and the r-band apparent magnitude. The redshift distribution of the weighted training set provides an estimate of the true underlying distribution of the photometric sample. The estimate of $p(z)$ for each galaxy in the photometric sample is given by the weighted $z_{\rm spec}$ distribution of the 100 nearest training set neighbours in colour/magnitude space (the same four colours and r-band magnitude mentioned above). Finally, to reduce the effects of Poisson noise, LSS, and magnitude errors in the training sample, we adopt a 'moving window' smoothing technique. We calculate $p(z)$ in 140 bins in the redshift range $0 < z < 2$ with a constant bin width of 0.067. The $p(z)$ derived in this way will be referred to as the NN $p(z)$, where NN in this context refers to 'nearest neighbour' rather than 'neural net'.

In this section, we recompute $b_z(z_{\rm l})$ and $\langle b_z\rangle$ for various lens redshift distributions, but instead of using the photoz $z_{\rm p}$ to get $\tilde{\Sigma}_{\rm c}(z_{\rm l},\ z_{\rm s}=z_{\rm p})$, we integrate over the full $p(z)$ (normalized to integrate to unity):

$$\tilde{\Sigma}_{\rm c}^{-1}(z_{\rm l}|p(z)) = \int_0^{\infty} p(z)\Sigma_{\rm c}^{-1}(z_{\rm l}, z)\,{\rm d}z. \qquad (19)$$

We then compare the results using the two estimates of $p(z)$ to the results using the photoz alone. Fig. 14 shows the calibration bias b_z as a function of $z_{\rm l}$ using the photozs directly (as in Fig. 7) and the full estimates of $p(z)$. In Table 8, we show the calibration bias averaged over various lens redshift distributions (as in Table 3) using the full $p(z)$. As shown in both the figure and the table, most of the calibration bias is eliminated when using the full $p(z)$ from either method.

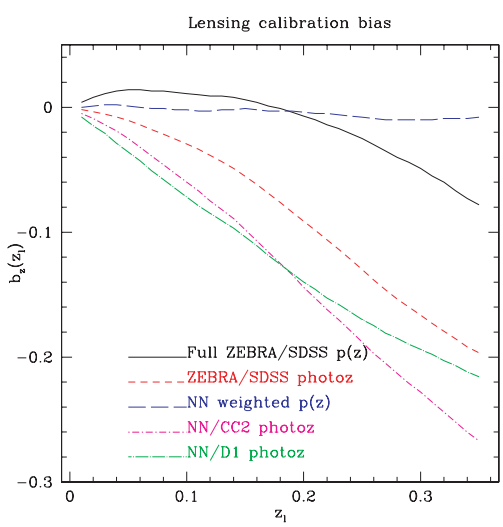

Figure 14. Lensing calibration bias $b_z(z_{\rm l})$ using photoz values alone versus using the full $p(z)$ to compute $\Sigma_{\rm c}$ as described in the text.

Table 8. Average calibration bias $\langle b_z\rangle$ for several lens redshift distributions using the full posterior $p(z)$ to get $\Sigma_{\rm c}$. The errors are approximately the same on the two columns.

Lenses	ZEBRA/SDSS $p(z)$	NN $p(z)$
sm1	0.013 ± 0.006	-0.001
sm2	0.012 ± 0.007	-0.001
sm3	0.011 ± 0.007	-0.002
sm4	0.009 ± 0.008	-0.002
sm5	0.005 ± 0.008	-0.002
sm6	-0.002 ± 0.010	-0.003
sm7	-0.013 ± 0.014	-0.005
LRG	-0.032 ± 0.018	-0.007
maxBCG	-0.014 ± 0.013	-0.006

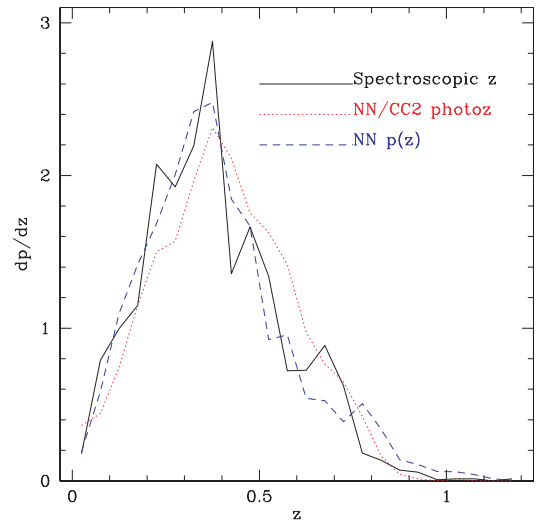

Figure 15. Redshift distribution ${\rm d}p/{\rm d}z$ for the full calibration sample using spectroscopic redshifts, NN/CC2 photoz values and the NN $p(z)$ for each object.

The fact that the bias is nearly eliminated by using the full posterior $p(z)$ is not a trivial result; when integrating over a $p(z)$, there are many effects that will change the $\Sigma_{\rm c}$ estimation in opposing directions. We have determined that the reason the negative calibration bias was nearly eliminated is the change in $\tilde{\Sigma}_{\rm c}$ for sources with photoz near the lens redshift but slightly above it. When using the photoz alone, $\Sigma_{\rm c}$ was on average underestimated due to the way it varies with source redshift near the lens. Integrating over the full $p(z)$ raises it to a more reasonable value, which both increases the signal calibration and lowers the weight given to these sources.

To understand this result in more detail, we consider Fig. 15, which shows the full spectroscopic sample redshift distributions from spectroscopy, from the NN/CC2 photoz, and from the summation of the $p(z)$ for each object. As shown, the use of $p(z)$ gives a mean redshift that is quite close to the mean redshift of the full sample, unlike for the photoz values which gives a higher mean redshift. There is a slight suggestion that the $p(z)$ for objects at $z \sim 0.6$ is getting spread to higher redshift, but these objects are such a small fraction of the sample and the critical surface density is not varying strongly with source redshift at these high redshifts, so this effect is not very important for lensing calibration with $z_{\rm l} \lesssim 0.35$. It is this correction to the mean redshift, in combination with an inclusion of a realistic estimate of the scatter for each object when estimating $\Sigma_{\rm c}$, that eliminates the non-negligible calibration bias when using NN/CC2 photoz values alone.

5.10 Avoiding physically associated pairs

One benefit of using photoz values instead of a source redshift distribution is that it is possible to eliminate some fraction of the 'source' galaxies that are physically associated with the lenses. This is important because of intrinsic alignments which can suppress the lensing signal (Agustsson & Brainerd 2006; Mandelbaum et al. 2006b).

In the absence of detailed calibration of the photoz error distribution, we can simply require $z_{\rm s} > z_{\rm l} + \epsilon$ for some ϵ, with the best chance of success if the photoz method does not have a mean positive bias $\langle z_{\rm p} - z\rangle > 0$ for all redshifts for which there are lenses.

Our current method (kphotoz), the neural network photoz values, and the ZEBRA/SDSS photoz values clearly fail this criterion. Of the methods under consideration here, only the SDSS template photoz values are optimal for avoiding the inclusion of physically associated sources with this simple scheme. This is due to their negative photoz bias, which may be a liability in some other applications and which may cause us to exclude so many sources that the statistical error on the signal is strongly degraded.

In the context of our previous work, the plots in Section 5.6 make it quite apparent that our naive $z_s > z_l + 0.1$ cut, while the best we could do with only 162 spectroscopic redshifts with which to determine the photoz error distribution, was causing us to eliminate a significant fraction of true, lensed sources from the analysis, without even fulfilling our purpose of excluding nearly all the physically associated sources.

However, the existence of this analysis will help us fix this problem for the future. With detailed understanding of the photoz error distribution from several thousand sources, we can simply construct a redshift distribution (see Section 5.11) as a function of photoz, source colour and magnitude. This distribution will tell us $p(z|z_p, r, \text{colour})$. We can then choose to only use sources with

$$\int_{z_l}^{\infty} p(z|z_p, r, \text{colour})\, dz > p_{\text{thres}} \tag{20}$$

for some threshold probability p_{thres}. The choice of p_{thres} will depend on the situation: it should be large for lens samples such as LRGs and clusters in which intrinsic alignments of satellite ellipticities have been detected (Agustsson & Brainerd 2006; Mandelbaum et al. 2006b; Faltenbacher et al. 2007), and at small transverse separations ($\lesssim$200 kpc) where the effect is similar to or larger than the statistical error. In other scenarios, such as at larger transverse separations, we may find that we can afford a lower p_{thres}, even zero (because we are only using it to remove physically associated sources to avoid intrinsic alignment contamination, not those with zero shear). A simpler alternative to this procedure for ZEBRA/SDSS and other similar methods that return a full posterior $p(z)$ is to perform the integral in equation (20) using that $p(z)$, provided that it is found to accurately describe the redshift distribution for galaxies of a given magnitude and colour.

Note that once we have applied such a cut on the source sample, the true redshift distribution of those sources is changed, so we must re-estimate the lensing calibration bias, and if we had chosen to deconvolve the photoz error distribution for more accurate estimation of the critical surface density, we would have to redo this procedure. This is one major reason we have chosen to estimate the calibration bias using photoz values directly.

Fig. 6 suggests that the optimal methods for the purpose of excluding physically associated sources with this more sophisticated method are the NN and ZEBRA/SDSS methods, because of the lack of failure modes that will complicate this procedure [i.e. because their error distributions are more compact, and therefore easier to sample fully using a spectroscopic sample of limited size, and because the $p(z)$ will not be multimodal as for the other methods]. This statement applies to samples of galaxies reasonably similar to those presented here, but would need to be re-evaluated for samples that are much deeper, bluer and/or at significantly higher redshift.

5.11 Without lensing selection

Here we show some results for a full flux-limited sample of redshifts from zCOSMOS and DEEP2. The difference between these and the previous results is that here, we do not imposed the lensing selection cuts. Instead, we have simply required that there be a match in the SDSS reductions (rerun 137) within 1 arcsec of the spectrum from zCOSMOS or DEEP2.

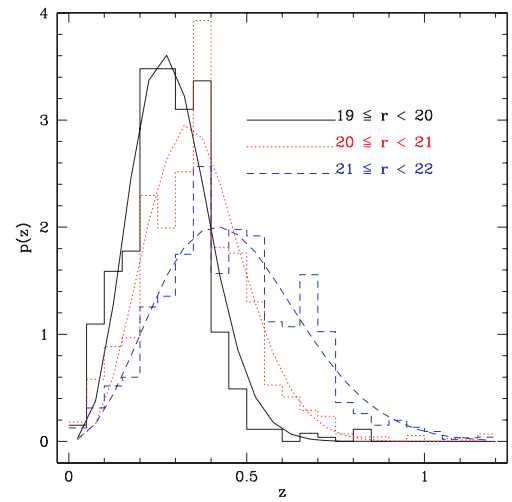

Figure 16. Redshift distributions for all photometric galaxies without lensing selection.

For this test, we use 3415 photometric galaxies from SDSS with $r < 22$ that have spectra from zCOSMOS (or zCOSMOS photoz values for the 8 per cent with redshifts with reliability <99 per cent), and 1761 from DEEP2. Fig. 16 shows the redshift histograms $p(z)$ in magnitude bins 1 mag wide, with best-fitting redshift distributions using the functional form in equation (9). The best-fitting parameters are tabulated in Table 9. For these results, we have again included the DEEP2 selection probabilities; however the selection is so flat for the magnitude range shown here that the effect on the final results is negligible.

We also use these results to test the effects of lensing selection. As an example, we use the ZEBRA/SDSS photoz values for this comparison. Fig. 17 shows the effects of lensing selection on apparent magnitude, redshift and photoz histograms. Here we require $r < 21.8$ rather than $r < 22$ in order to compare more readily against our source catalogue; this cut reduces the number of matches in the flux-limited sample by 13 per cent. The magnitude distribution in the flux-limited sample does not rise as sharply as expected at the very faint end because of difficulties with star/galaxy separation in SDSS. A previous comparison with *HST* data (Lupton et al. 2001) found that the default SDSS star/galaxy separation tends to err on the side of putting more galaxies as stars rather than vice versa, causing the galaxy counts to flatten for $r \gtrsim 21.5$ in a way that depends on the seeing (more flattening in worse seeing).

As shown, the lensing selection rate is a strong function of r-band magnitude, ranging from nearly one around $r \sim 19$ to $\sim$0.3 around the flux limit of 21.8. None the less, the redshift distribution is nearly the same for the full and the lensing-selected sample. This non-trivial

Table 9. Parameters of fits to redshift distribution from equation (9) for all photometric galaxies.

Sample	N_{gal}	z_*	α	$\langle z \rangle$
$19 \leqslant r < 20$	529	0.157 ± 0.021	4.04 ± 1.03	0.290 ± 0.015
$20 \leqslant r < 21$	1446	0.196 ± 0.031	4.15 ± 1.20	0.363 ± 0.013
$21 \leqslant r < 22$	2996	0.290 ± 0.022	3.08 ± 0.33	0.467 ± 0.017

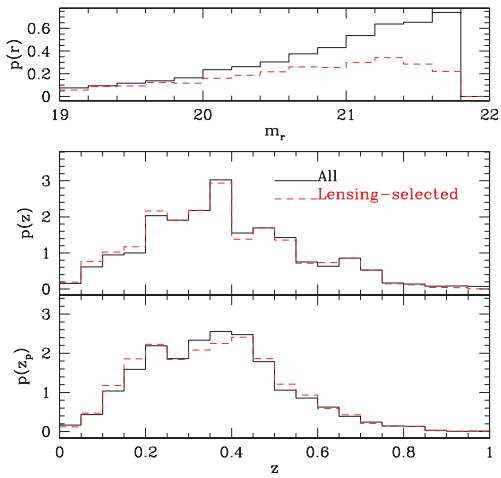

Figure 17. Magnitude (top), redshift (middle) and ZEBRA/SDSS photoz (bottom) histograms for the full flux-limited sample and for the lensing sources. For the magnitude histogram, we have normalized both to the same number of galaxies so the fraction that passes our cuts as a function of magnitude will be apparent. For the redshift and photoz histograms, the histograms for both the full and the lensing-selected sample are normalized to integrate to unity.

result requires some explanation, since we have already established (i) in the top panel of Fig. 17 that the flux-limited sample is fainter on average than the lensing-selected sample and (ii) in Fig. 16 that fainter samples are on average at higher redshift. A reconciliation of these facts would require that at a given apparent magnitude, the lensing-selected sample is at higher redshift than the flux-limited sample.

To explain this result, we consider two early-type galaxies at the same apparent magnitude but different redshifts z_1 and $z_2 > z_1$, in the limit that the differences in their redshifts is small enough that the k-correction connecting the bandpasses at the two redshifts is negligible. In that case, the more distant galaxy is more luminous by a factor of $[D_{\rm L}(z_2)/D_{\rm L}(z_1)]^2$ (where $D_{\rm L}$ here is the luminosity distance). For early-type galaxies, the physical size of the galaxy is related to luminosity via $R \propto L^{1.4}$ (e.g. Bernardi et al. 2007), so the more distant galaxy is intrinsically larger than the more nearby one by a factor of $[D_{\rm L}(z_2)/D_{\rm L}(z_1)]^{2.8}$. The angular size of the more distant galaxy relative to the more nearby one is smaller by a factor of $D_{\rm A}(z_1)/D_{\rm A}(z_2)$ ($D_{\rm A}$ is the angular diameter distance). We therefore conclude that before convolution with the PSF, the factor due to the intrinsic luminosity and size difference wins out over the factor due to the decreased angular size, so the more distant galaxy is actually larger. This argument suggests that if one of the galaxies will be eliminated due to our apparent size cut, it is the one at *lower* redshift. This counterintuitive argument (which may explain our finding above, that the lensing-selected redshift distribution is the same as the flux-limited one despite being brighter on average) is not nearly the full story, because (i) in many situations, the k-corrections or luminosity evolution will change the outcome of this result and (ii) not all galaxies are early-types following this scaling relation between luminosity and size, but it appears to be a strong enough effect that it balances out the difference in mean depth between the samples. One must also consider the effects of the luminosity function, which means that the galaxies at the same magnitude but higher redshift will be fewer in number, so while they are less likely to be eliminated by an apparent size cut, they will also be rarer to begin with.

As a test of this unexpected finding, we fit redshift distributions to the lensing-selected galaxies as a function of apparent magnitude, and compared to the mean redshifts in Table 9. For flux-limited samples, when using $19 \leqslant r < 20$, $20 \leqslant r < 21$ and $21 \leqslant r < 22$, we find mean redshifts of 0.290 ± 0.015, 0.363 ± 0.013 and 0.467 ± 0.017. For the lensing-selected samples with the same cuts on apparent magnitude, we find mean redshifts of 0.287 ± 0.015 (well within 1σ of the flux-limited sample), 0.372 ± 0.015 (0.5σ higher than the flux-limited sample) and 0.484 ± 0.015 (0.7σ higher than the flux-limited sample). The results for the faintest sample are most remarkable, because the flux-limited sample used for the fits is cut at $r = 22$, whereas the lensing-selected sample is cut at $r = 21.8$, so its mean magnitude is 0.2 mag brighter yet it is at slightly higher redshift. The effect is fortuitously of just the right size that, despite the full lensing-selected sample being brighter, the redshift distribution is nearly the same as for the flux-limited sample.

Next, we present photoz error distributions as a function of colour and magnitude for the full and the lensing-selected sample. We split the sample by colour because of the fact that photoz values are easier to compute for red galaxies than for blue ones due to their clearer colour–redshift relation. Our colour separator is redshift-dependent and purely empirical based on the sample properties, $g - i = 0.7 + 2.67z$. The slope was chosen to roughly trace the observed colour of the red ridge, with 40 per cent of the galaxies classified as red. Within each colour, we then split into roughly equal numbers of galaxies based on magnitude, so the magnitude bins are different for each colour. While we tabulate the mean photoz bias, $\langle z_{\rm p} - z\rangle$ in analogy to earlier in this paper, the plots show $p(z - z_{\rm p})$ since that can be used in combination with $p(z_{\rm p})$ to reconstruct $p(z \,|\, r, g - i)$.

Because it would take a significant amount of space to present the distributions as a function of photoz, we average them over all values of photoz. Table 10 shows the mean bias and scatter as a function of colour and magnitude. Fig. 18 shows the error distributions as a function of colour and magnitude, and a Gaussian with the sample mean bias and scatter, to make any non-Gaussianity apparent.

As shown in Table 10, the imposition of lensing selection seems to slightly decrease the scatter for blue galaxies, but has little effect for red galaxies. Fig. 18 shows that for red galaxies, the photoz error distributions are slightly non-Gaussian, whereas for blue galaxies they are significantly non-Gaussian. We also see the same pattern as for kphotoz, a positive photoz bias for red galaxies and negative for blue ones, and different sizes for the scatter. These trends will emphasize the correlation we have previously noted between LSS and photoz error. We have not attempted any more complex functional modelling, e.g. double Gaussians, but future work will use the true distributions (smoothed) rather than the Gaussians.

Table 10. Mean photoz bias and scatter for the ZEBRA/SDSS algorithm as a function of colour and magnitude for all photometric and lensing-selected galaxies.

		Flux-limited		Lensing-selected	
Colour	Magnitude	bias	scatter	bias	scatter
Red	$r < 19.6$	0.038	0.082	0.039	0.085
Red	$19.6 \leqslant r < 20.4$	0.029	0.098	0.035	0.101
Red	$20.4 \leqslant r < 21.1$	0.029	0.118	0.039	0.119
Red	$r \geqslant 21.1$	0.017	0.126	0.013	0.126
Blue	$r < 20.4$	0.004	0.123	0.008	0.110
Blue	$20.4 \leqslant r < 21.0$	−0.034	0.173	−0.025	0.143
Blue	$21.0 \leqslant r < 21.35$	−0.060	0.181	−0.043	0.154
Blue	$r \geqslant 21.35$	−0.104	0.201	−0.114	0.187

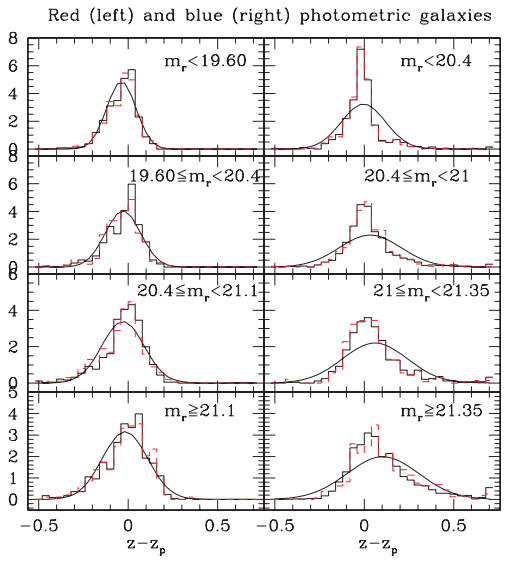

Figure 18. Photoz error distributions for the SDSS/ZEBRA method as a function of colour and magnitude for the full flux-limited sample (black, solid) and for the lensing sources (red, dashed). We have also shown the Gaussians with the mean and scatter from Table 10.

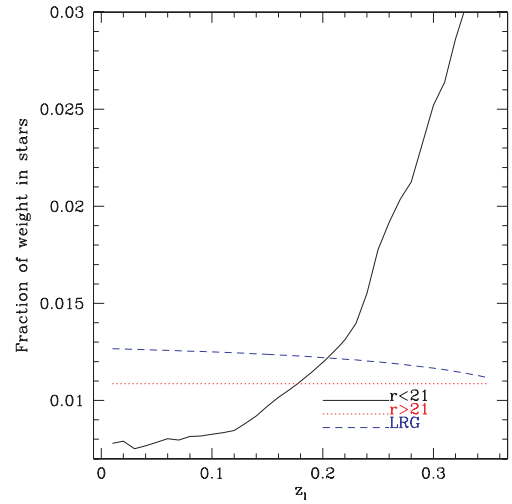

Figure 19. Fraction of the weight for our three source samples that is attributed to stellar contamination as a function of lens redshift.

5.12 Star/galaxy separation results

We also matched our source catalogue against a catalogue of objects from COSMOS with stellarity information. Their space-based photometry allows a more reliable star/galaxy classification than in SDSS. Here we use their stellarity information that is determined using both the SEXTRACTOR CLASS_STAR parameter and visual inspection, as follows.

(i) Those with CLASS_STAR $\geqslant 0.8$ are automatically counted as stars, without visual inspection.

(ii) Those with CLASS_STAR < 0.8 are visually inspected, with the decision about star/galaxy classification made based on the inspection.

Of the 7028 matches between the COSMOS catalogue and our source catalogue, 67 are identified in COSMOS as stars, or 0.95 per cent. This number is constrained to be within [0.74, 1.21] per cent at the 95 per cent CL assuming Poisson errors. To check whether this number is typical compared to the rest of the survey, we compute the mean r-band seeing in the COSMOS area compared to the entire SDSS survey area, and find that the mean seeing in the area that overlaps with COSMOS is 1.20 arcsec (PSF FWHM), compared to 1.18 arcsec in the rest of the survey. We therefore conclude that this number is fairly typical and may be applied as a correction to the entire source catalogue, provided that the stellar contamination fraction is not an extremely strong function of the PSF FWHM.

To test for this possibility, we have used three SDSS runs that overlap the COSMOS region and have r-band PSF FWHM ranging from 0.9 to 1.4, a range that includes ∼85 per cent of the source sample across the SDSS survey area. We then determined the stellar contamination fraction in bins of PSF FWHM after application of all lensing selection criteria. For the four bins with median PSF FWHM of 1.02, 1.14, 1.21 and 1.3 arcsec, the stellar contamination fractions are 1.04, 0.92, 0.79 and 0.56 per cent. The trend of decreasing stellar contamination in poorer seeing is not well understood; however, the mean source number density also decreases in poor seeing, so it seems that our cuts may be overly conservative in regions of poor seeing. This trend, when including Poisson error bars, is not quite significant at the 2σ level. However, it is apparent that the stellar contamination fraction does not shoot up rapidly in any part of this range of PSF FWHM including nearly all the source sample, so we conclude that our value of 0.95 per cent should apply to the rest of the source catalogue.

To properly apply this number to the rest of the source sample, we must take into account that the number density of stars depends on galactic latitude in some complex way. The average $\langle 1/\sin b\rangle$ for the whole source catalogue is 1.40, and for the COSMOS region it is 1.43, so we conclude that no correction for the variation of stellar density with galactic latitude is necessary. While this calculation would not work if we included regions where $\sin\ b \sim 0$ due to the strong increase in stellar number density there, our requirement that r-band extinction be less than 0.2 mag effectively eliminates these regions from the source catalogue.

However, we cannot conclude that the fractional contamination in the lensing signal is -0.0095, because it depends on the weight given to these sources. The total fraction of the weight attributed to the stellar contamination as a function of lens redshift is shown in Fig. 19 for the three source redshift determination methods used in our current catalogue. As shown, the fraction of the weight attributed to stars is in general larger than the actual stellar contamination fraction. This fraction rises significantly with redshift for the $r < 21$ sample because the stellar contamination tends to be given relatively high photoz. This is because the stellar contamination is predominantly M stars that masquerade as red galaxies at the high end of the redshift range for this sample. However, as shown in Fig. 7, the $r > 21$ sample has four times as much weight at these lens redshifts, so the contamination to the signal is not strongly affected by this increase in the contamination fraction for the $r < 21$ sample.

6 DISCUSSION

In this paper, we have proposed a method for precision calibration of the source redshift distribution for g–g lensing with lens spectroscopy using representative subsamples of the source catalogue with spectroscopy. The key components of this method are an estimator for the g–g lensing calibration bias (equation 5) and for the degradation of the statistical error due to non-optimal

weighting (equation 17). This method includes techniques for handling complications such as LSS in the spectroscopic redshift sample, and redshift failure. We then demonstrated its implementation by matching an SDSS lensing catalogue used for many previous science works against a sample of spectroscopic redshifts from DEEP2 and zCOSMOS. We have also used this method to assess the utility of three more recent photoz algorithms that have been proposed for use with SDSS data. In Appendix A, we discuss the extension of these techniques to g–g lensing with lens photoz values; with redshift distributions for the lenses and to cosmic shear.

Our results in Section 5.4 show that the galaxy–galaxy lensing calibration bias can be as high as 20–30 per cent for some of the photoz methods, especially for higher lens redshifts. This is despite the fact that for all of the photoz methods, the average redshift bias is well below the scatter. The reason for this finding is the nonlinear dependence of the critical surface density on the source redshift, which amplifies the photoz errors in a highly asymmetric way: while an underestimate of photoz to a value below the lens redshift leads to a rejection of the source galaxy and does not produce lensing bias, an overestimate leads to an enhancement of lensing weight and can produce a significant bias. One of the main lessons of present work is that lensing applications require a dedicated photoz calibration, which can give very different results from the general photoz calibration tests.

Our analysis demonstrates that the calibration bias in the lensing signal due to redshift distribution uncertainty in previous works using the SDSS source catalogue used for several previous science projects was well within the quoted systematic error of 8 per cent. Future lensing work using this source catalogue will use the results in this paper to obtain a highly accurate lensing calibration with a smaller uncertainty than in our previous work. The decreased systematic error budget due to redshift calibration uncertainty, which is now known to ∼2 per cent due to this work, is a timely improvement to SDSS g–g lensing measurements: results coming out in the next year will have total statistical error of ∼5 per cent, so the reduction in the systematic error is necessary to ensure that it does not exceed the statistical error.

For the three new photoz methods tested here, we have measured the lensing calibration bias using a statistic b_z (equation 5) which is optimized for characterization of photoz values for galaxy–galaxy lensing purposes. Another statistic, in equation (17), can be used to determine how much a photoz method causes a deviation from optimal weighting, affecting the statistical error of the measurement. We have also carefully identified important aspects of the photoz error distribution. We found that for our source sample, using the SDSS template photoz values (without any corrections for mean photoz bias) led to the smallest lensing calibration bias. This result is due to a fortuitous cancellation of lensing calibration biases due to photoz bias and scatter, and would not necessarily happen with a sample with different selection criteria. While for some applications, the presence of a failure mode that sends sources to zero redshift would be quite problematic, it does not cause any bias for lensing (though as we have already shown, it leads to increased statistical error on the lensing signal). The SDSS neural net photoz values and the ZEBRA/SDSS photoz values both cause significant lensing calibration bias, despite having a reasonable scatter, because of a significant positive photoz bias for $0 < z < 0.4$. This calibration bias can be corrected for after computation of the lensing signal using a calibration factor, since our spectroscopic sample has the same selection as the full catalogue. If the mean photoz bias is corrected for before computing the lensing signal, the SDSS neural net photoz values lead to smaller lensing calibration bias than the other two new methods, implying that the effects of photoz scatter are smaller for this method. On some level, once a reliable calibration of the photoz values for lensing is known for a given source sample, the fact that a photoz method causes calibration bias is unimportant: the deterioration of the statistical error due to the non-optimal weighting, and the inability to properly remove physically associated sources, are both more important. In that sense, the negative photoz bias of the template photoz code, which is the cause of its low lensing calibration bias, may in fact be a liability for its practical use.

We have isolated ways that sampling variance can complicate the estimation of redshift calibration bias using a small subsample of galaxies. Because LSS tends to change the fractions of blue and red galaxies, which generally have different photoz error distributions, it can bias the estimated lensing calibration bias $\langle b_z \rangle$, and can also artificially reduce the error. We have verified that our use of two degree-scale uncorrelated redshift samples drastically reduces this effect, making it negligible for our analysis.

We have also assessed the level of stellar contamination in our source catalogue using COSMOS data, and have placed stringent limits on the systematic error due to this contamination.

We have tested the use of a full $p(z)$ for estimation of the critical surface density, and find that it tends to give superior results to the use of the photoz alone, with calibration biases consistent with zero for all lens redshift distributions considered in this paper. Because of this success, we advocate further work exploring the use of a full $p(z)$ for lensing rather than a single photoz for each object.

We have learned that the details of the photoz bias and scatter as a function of redshift are important. For example, the mean bias for sources with redshift within $\Delta z \sim 0.2$ of the lenses is more important than the overall mean photoz bias. In the extension of this formalism to higher redshift, it is important to consider that both the size of the photoz error and the derivative $\mathrm{d}\Sigma_c/\mathrm{d}z_s$ determine the redshift calibration bias, so deeper surveys that can ensure a larger separation between the lenses and sources may find smaller redshift calibration bias even with comparable or larger photoz errors than for the methods demonstrated here. However, these deeper surveys may have a larger systematic uncertainty due to spectroscopic redshift failure: our high-redshift success rate meant that we were not very sensitive to this problem, but that high success rate was also a product of the relatively bright magnitude of the source sample.

For deeper surveys with a higher redshift failure rate, one can imagine two possible scenarios. The first is that the higher failure rate is due to the lower S/N of the spectra. In that case, the failure rate as a function of apparent magnitude and colour can be quantified, and included as a weight in the lensing calibration bias calculation. We would assume that for a given magnitude and colour the redshift distribution is properly being sampled despite redshift failure, so we up-weight those in regions of parameter space where failure is more likely. The second case is more pernicious: if there is a region of colour and magnitude space for which essentially all the redshifts are failures, then no amount of reweighting will be able to account for this. Consequently, for proper redshift calibration, one would need to either remove those sources entirely due to the impossibility of calibration, or get external information from some other spectrograph that is capable of obtaining redshifts for that region of colour space.

In summary, the results in this work resoundingly verify our claim that the spectroscopic sample used to assess photoz error for lensing purposes must have the same selection as the source catalogue, or selection close enough that it can be made comparable by a reweighting scheme (see Section 4.4). The photoz error is a strong function of galaxy type and apparent magnitude, and the lensing calibration is

very sensitive to details of the photoz error distribution. We have also shown that at least two independent degree-scale patches of the sky must be surveyed in order to suppress the sampling variance effects on photoz calibration (this choice would have to be re-evaluated for deeper surveys, as would our choice of redshift histogram bins $\Delta z = 0.05$). Having two independent spectroscopic surveys, DEEP2 and zCOSMOS, with nearly 3000 galaxies in total, allowed us to provide photoz calibration of the galaxy–galaxy lensing signal at a per cent level, depending on the lens sample. As more spectroscopic redshift surveys become available, it will become easier for weak lensing measurements to be carried out with tight constraints on the redshift calibration bias using this method. This is one more important step on the way towards galaxy–galaxy lensing becoming a high-precision tool for addressing questions of astrophysical and cosmological importance. Similar calibration methods must be developed and applied also to other weak lensing applications, most notably galaxy–galaxy lensing in the case where lens redshifts are not known, and shear–shear autocorrelations; we discuss the steps that would be needed for such a process in Appendix A.

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APPENDIX A: EXTENSION TO OTHER LENSING MEASUREMENTS

In this paper we have demonstrated the lensing calibration using SDSS g–g lensing data with lens redshifts. Here we discuss the extension of this analysis to other lensing scenarios, particularly

(1) galaxy–galaxy lensing with lens photoz values instead of spectroscopic redshifts;

(2) galaxy–galaxy lensing with redshift distributions for both lenses and sources and

(3) cosmic shear (shear–shear autocorrelations) with photoz values or redshift distributions for the source sample.

We discuss the first case on its own, and the second and third together.

A1 g–g lensing with lens photoz values

The first case, g–g lensing with photoz values for the lenses, involves the same lensing formalism as for g–g lensing with spectroscopic redshifts. We simply require an additional spectroscopic calibration sample for the lenses to trace their photoz error distribution. However, in addition to the multiplicative calibration bias b_z (equations 5 and 6) which will now include contributions from the lens photoz error distribution, the increased variance due to non-optimal weighting (equation 17), and the systematic calibration uncertainty to the sampling variance in the calibration sample, there is one additional effect to consider.

The conversion to transverse separation R, used to bin the stacked sources for comparison against theoretical predictions, depends on the lens redshift. In our formalism, which uses comoving coordinates, $R = \theta_{\rm ls} D_{\rm A}(z_{\rm l})(1 + z_{\rm l})$, where $\theta_{\rm ls}$ is the angular separation between the lens and source in radians. When using photoz values for lenses, we can define an estimated separation $\tilde{R}$ determined using the lens photoz. Consequently, the measured lensing signal $\widetilde{\Delta\Sigma}(\tilde{R})$ can be expressed as an integral over the photoz error distribution:

$$\widetilde{\Delta\Sigma}(\tilde{R}) = \int_0^\infty \widetilde{\Delta\Sigma}(R) p_{\rm L}(\tilde{R}|R)\,{\rm d}R, \tag{A1}$$

where $p_{\rm L}(\tilde{R}|R)$ represents the probability, given the lens photoz error distribution, that a source at separation R will be put at estimated separation $\tilde{R}$. This probability can be obtained trivially from the lens photoz error distribution expressed as $p_{\rm L}(z_{\rm p}\,|z)$ using the transformation from redshift to transverse separation and the derivative ${\rm d}R/{\rm d}z$. Even for relatively simple models for $\Delta\Sigma$ and $p_{\rm L}(z_{\rm p}\,|z)$ (e.g. power law and Gaussian, respectively) this integral does not reduce to a simple analytic expression.

Note that this effect is more pernicious in some ways than a pure calibration error, since the effect depends on the scale-dependence of the true lensing signal $\Delta\Sigma$. This error must be treated differently than a pure calibration error: rather than changing the computation of the signal by incorporating a calibration factor, this error must be incorporated at the interpretation step of the analysis, when some model is used to predict $\Delta\Sigma$. At that stage, the additional step of numerically convolving the prediction with $p_{\rm L}(\tilde{R}|R)$ can be included before comparing against the data. The convolution will change the prediction, and also induce some theoretical uncertainty depending on the statistical + sampling variance uncertainty on $p_{\rm L}(\tilde{R}|R)$. That theoretical uncertainty in the model prediction can be determined by using $p_{\rm L}(\tilde{R}|R)$ from many realizations of the data to get $\widetilde{\Delta\Sigma}(\tilde{R})$ and fit for the model parameters on each realization.

A2 Redshift distributions for g–g lensing and cosmic shear

The case of galaxy–galaxy lensing with a redshift distribution used for both lenses and sources, and the case of cosmic shear, are similar in several important aspects. In both cases, the observed signal is typically expressed as a function of shears as a function of angular separation (angle θ or multipole ℓ). Most work either does not incorporate redshift information, or uses tomographic cosmic shear in which the photoz values are used to separate the source sample into several bins, with shear–shear autocorrelation functions measured in each bin (and cross-correlation functions measured between bins). The full redshift information (${\rm d}N/{\rm d}z$, or ${\rm d}N/{\rm d}z$ for each bin) is then

incorporated at the interpretation stage of the analysis, when a model for the signal [i.e. $\Delta\Sigma(R)$ in case 2 or the convergence power spectrum in case 3] is transformed to the form of the observable to fit for the model parameters. In general, errors in the redshift distributions can lead to nontrivial changes in this prediction – not pure calibration bias, but some change with scale dependence. The choice of the wrong redshift distribution therefore leads to the selection of the wrong model parameters because the theoretical predictions have been computed in the wrong way. Here we assume that a spectroscopic training sample is being used to obtain the proper source redshift distribution in the mean, but we would like to determine the uncertainty in the model parameters due to Poisson + sampling variance uncertainty in the source redshift distribution.

In practice, this uncertainty can be trivially included in the analysis using modifications of the procedures described for galaxy–galaxy lensing with lens redshifts. For example, for g–g lensing without lens or source redshift, one can use spectroscopic training samples with the same selection as the lens and source samples to create redshift histograms and fit them to some functional form for many bootstrap resamplings of the redshift histogram pairs (z_i, N_i). One can then generate the theoretical prediction for each of the many realizations of the best-fitting redshift histogram, and fit for the model parameters on each one to see how much they vary due to the changes in the redshift histogram from realization to realization. For cosmic shear, this procedure can be adopted using a single spectroscopic calibration sample that is comparable to the source sample. The Poisson and LSS uncertainty in the redshift histograms will therefore be propagated to uncertainties on the model parameters.

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