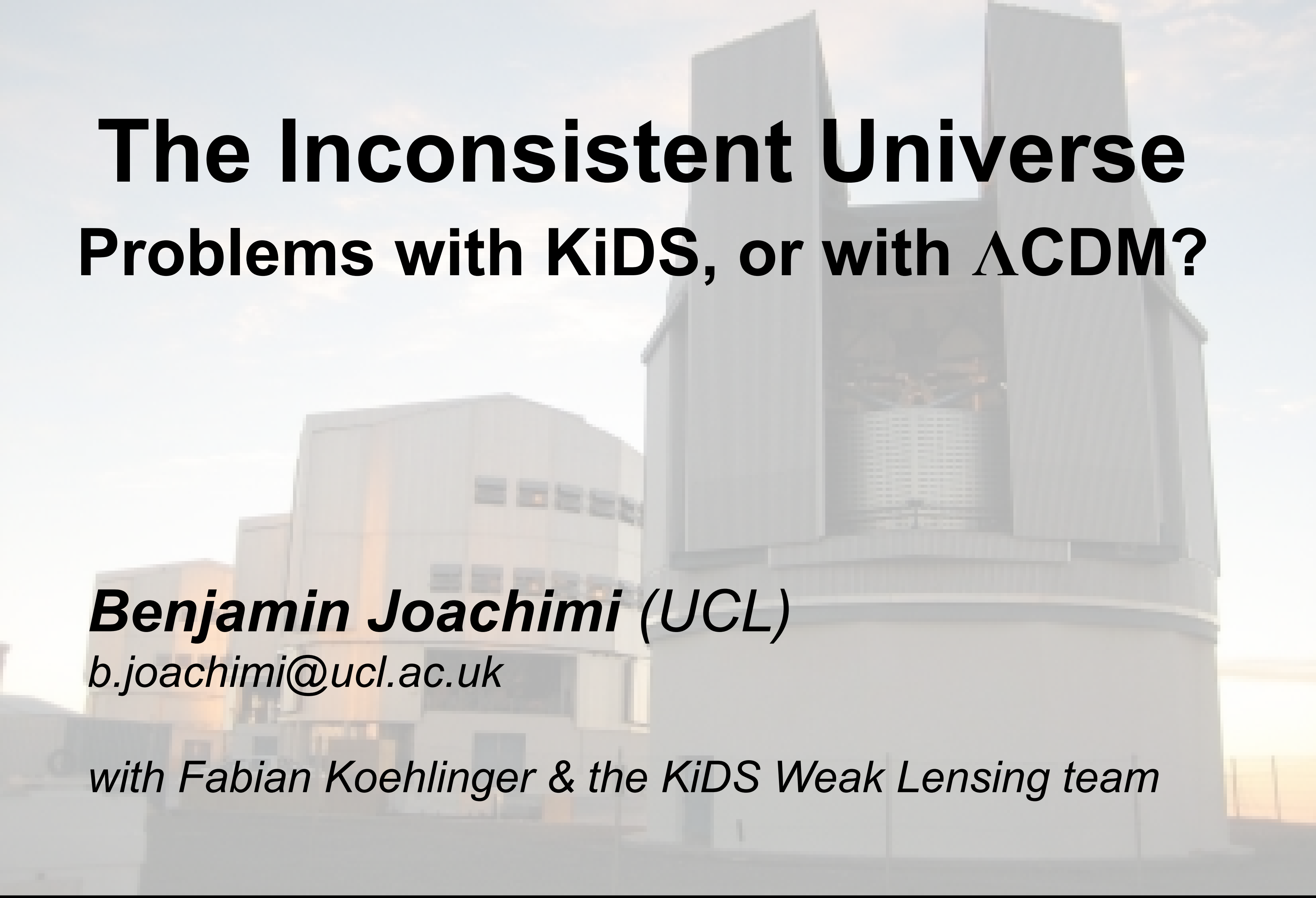


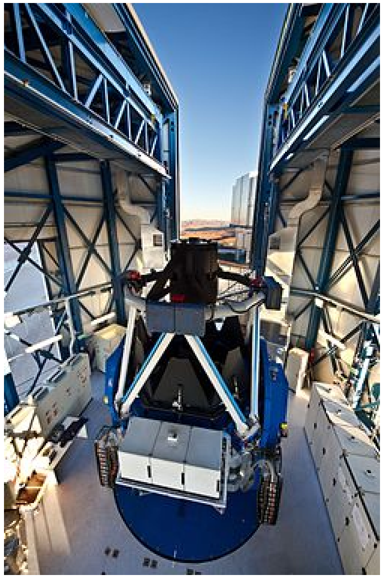
The Inconsistent Universe

Problems with KiDS, or with ΛCDM?

Benjamin Joachimi *(UCL)*
b.joachimi@ucl.ac.uk

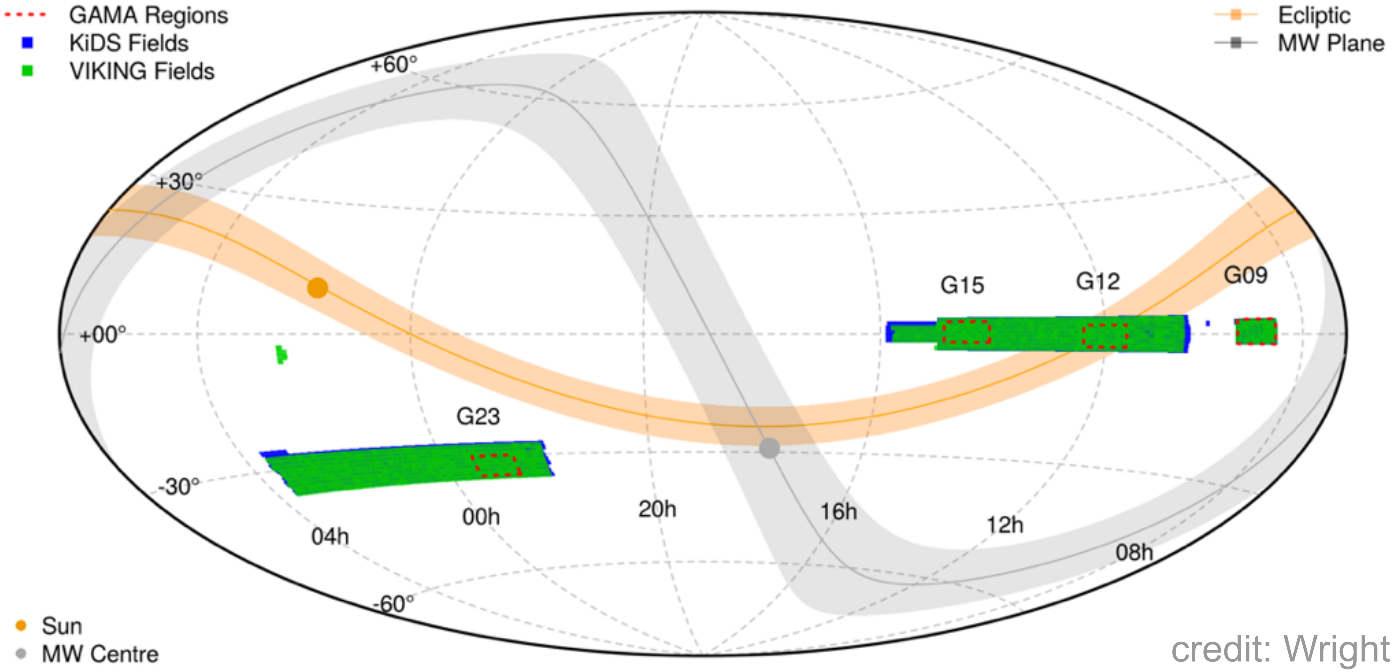
with Fabian Koehlinger & the KiDS Weak Lensing team

KiDS



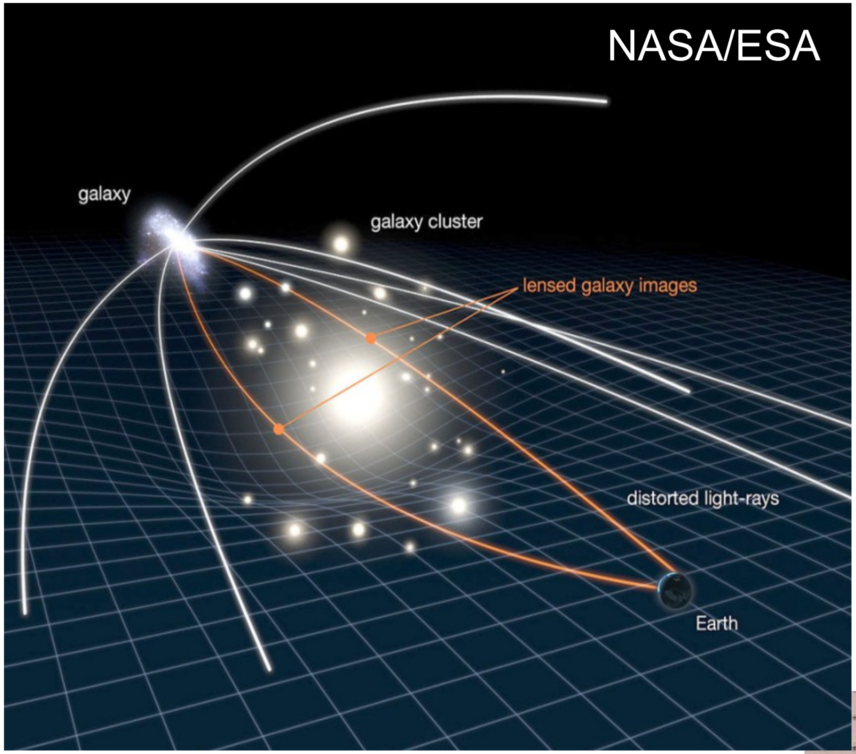
Kilo Degree Survey

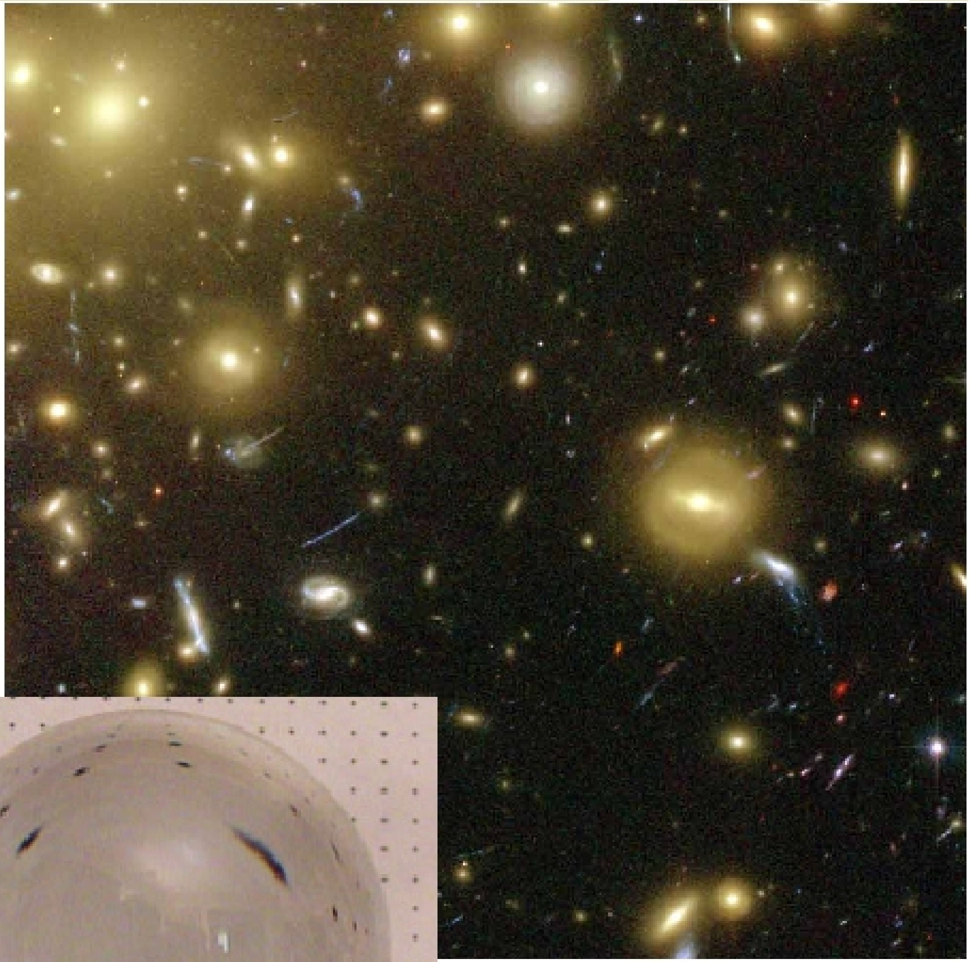
- on the 2.6m VLT Survey Telescope
- aim: ~1400 deg^2 (spring 2019)
- ugri + zYJHK (VIKING)
- prioritised overlap with GAMA Survey
- ESO Public Survey: DR4 now public
- current papers based on 450 deg^2



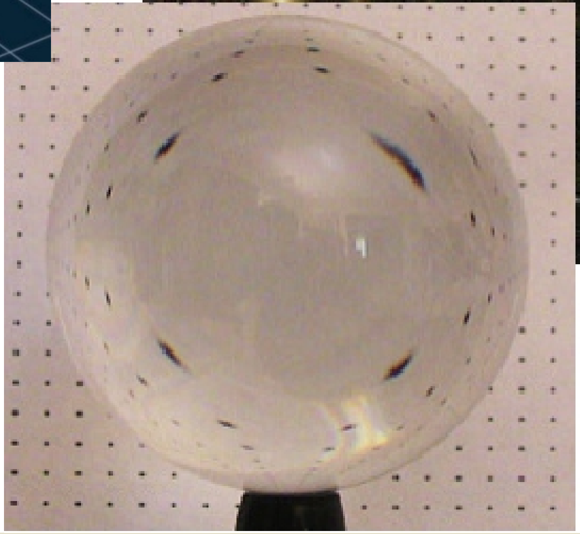
credit: Wright

Weak lensing in a nutshell





galaxy cluster
Abell 1689

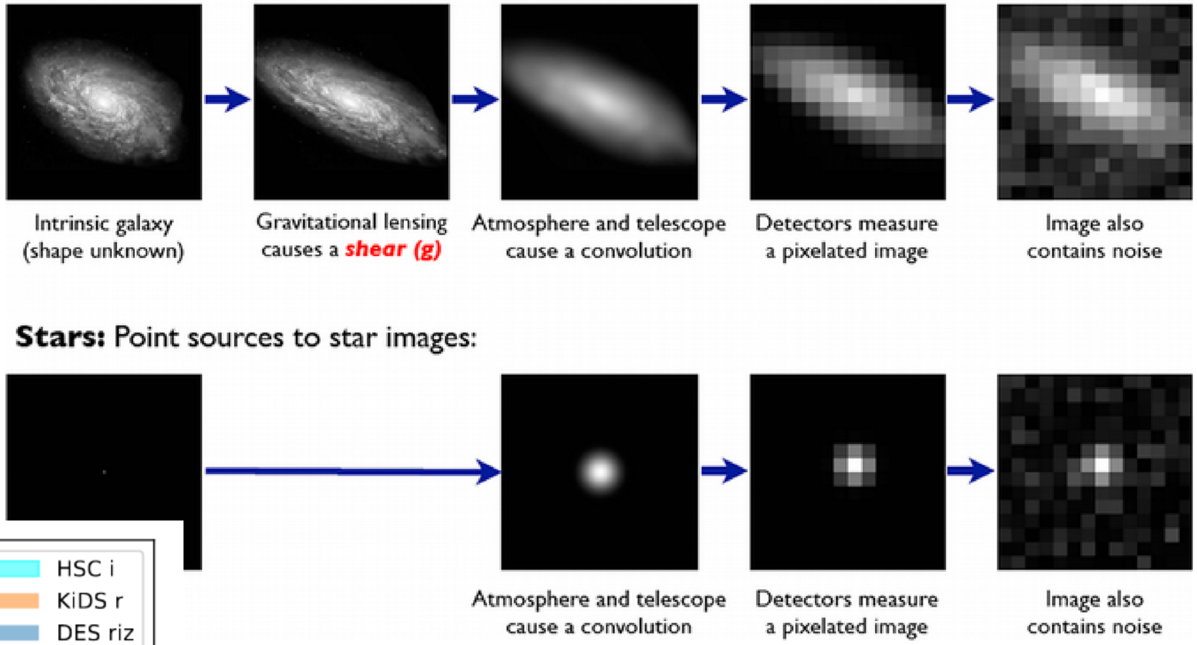


ball lens

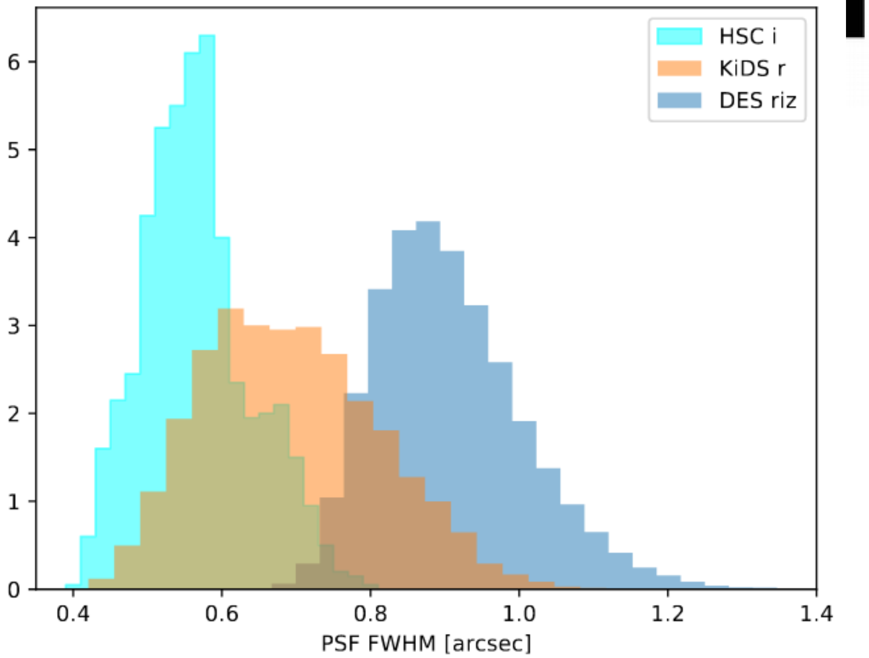
If the signal is weak, need averaging over many source images.

Shear measurement

GREAT08



Kuijken+ (2019)

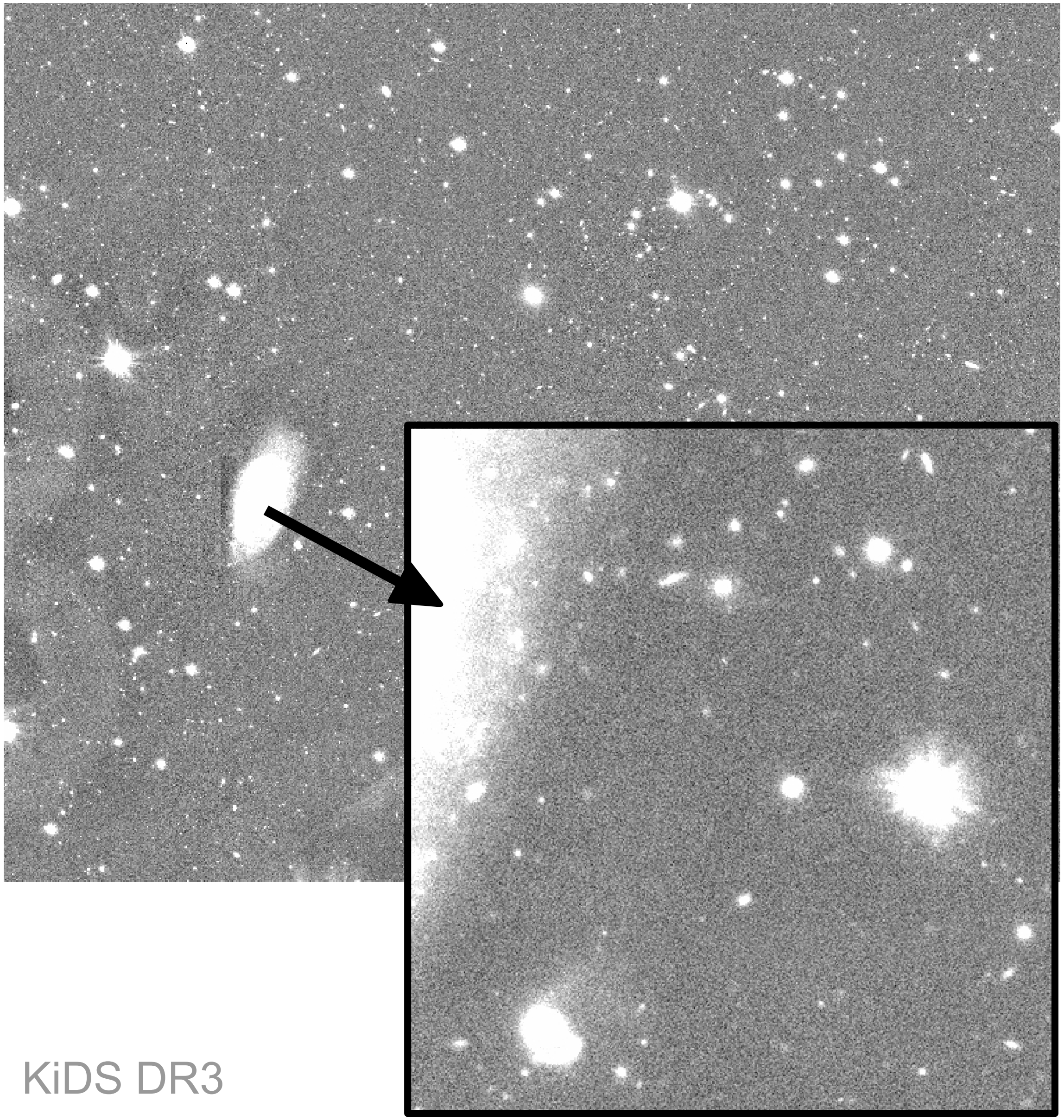


- likelihood fitting of galaxy model with *lens*fit (Miller et al. 2013)
- fit ellipticity, centroid, flux, size, bulge-to-disc ratio

The typical weak lensing galaxy

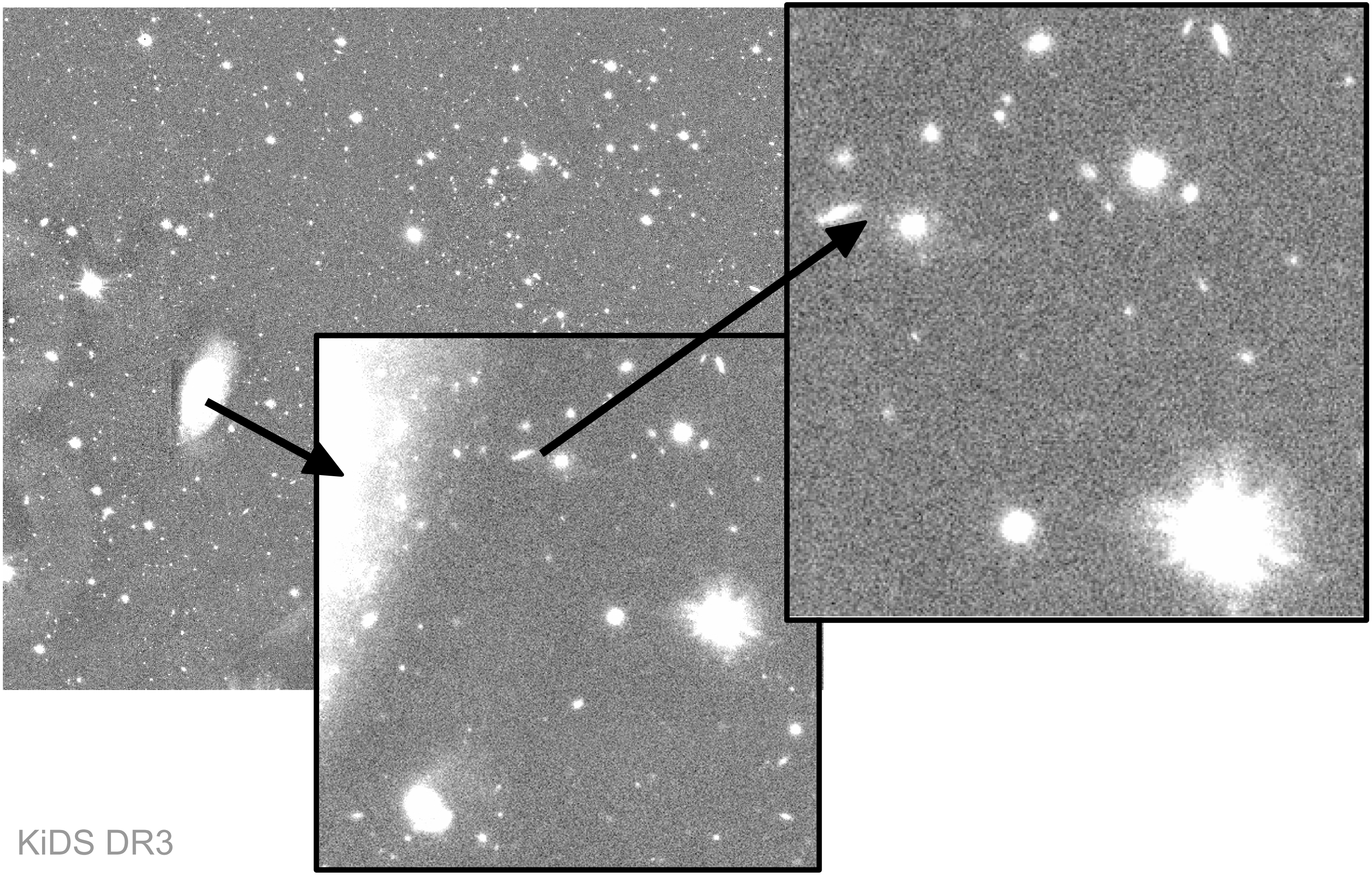
KiDS DR3

The typical weak lensing galaxy



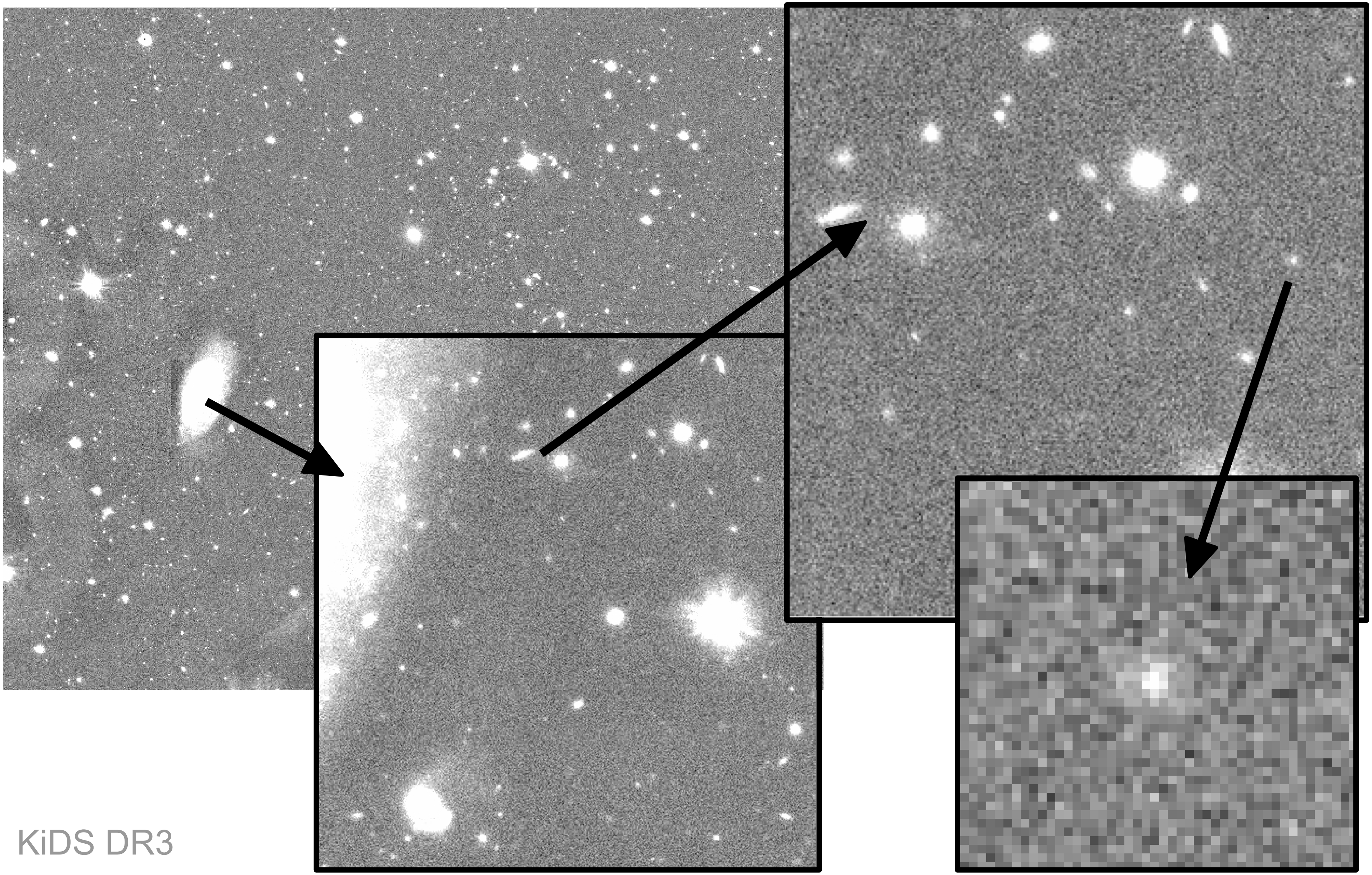
KiDS DR3

The typical weak lensing galaxy

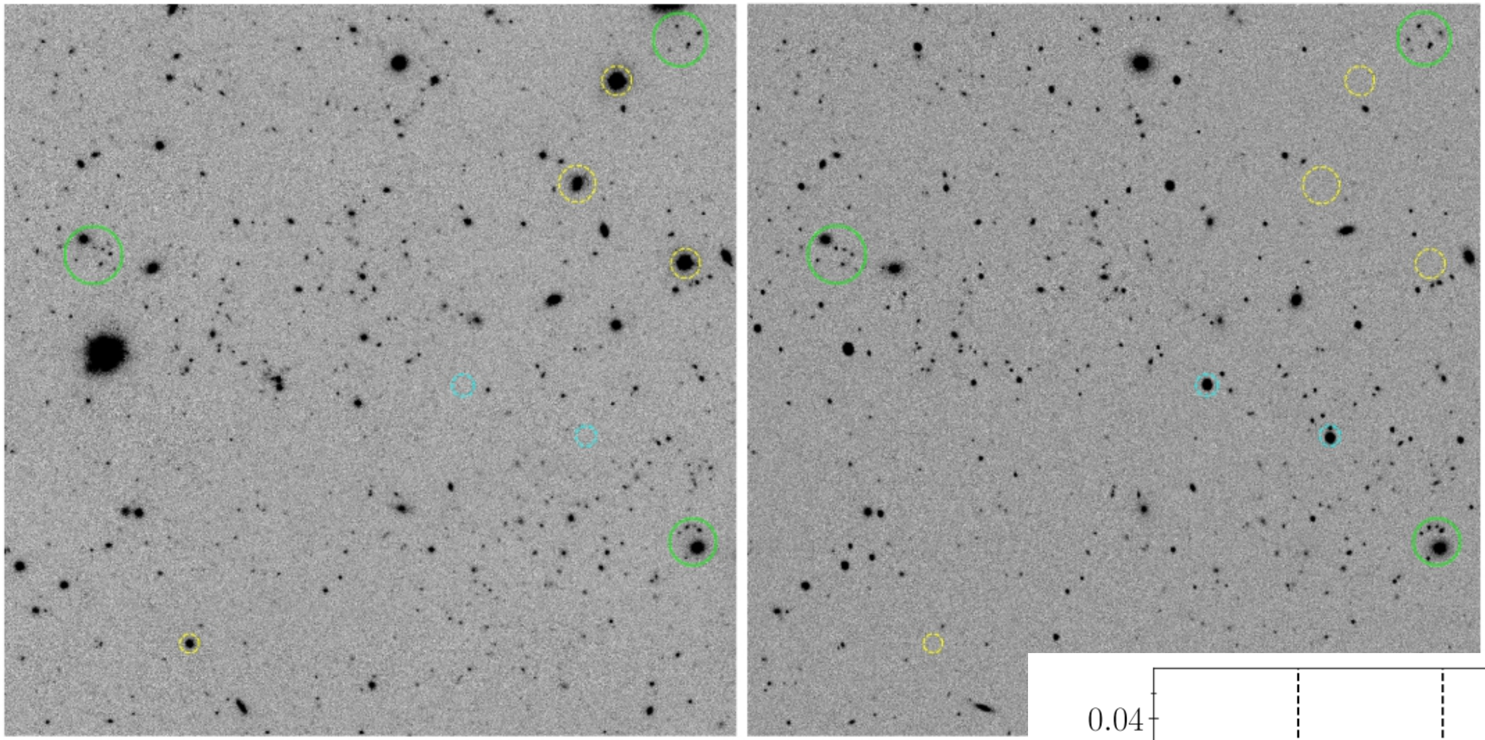


KiDS DR3

The typical weak lensing galaxy


KiDS DR3

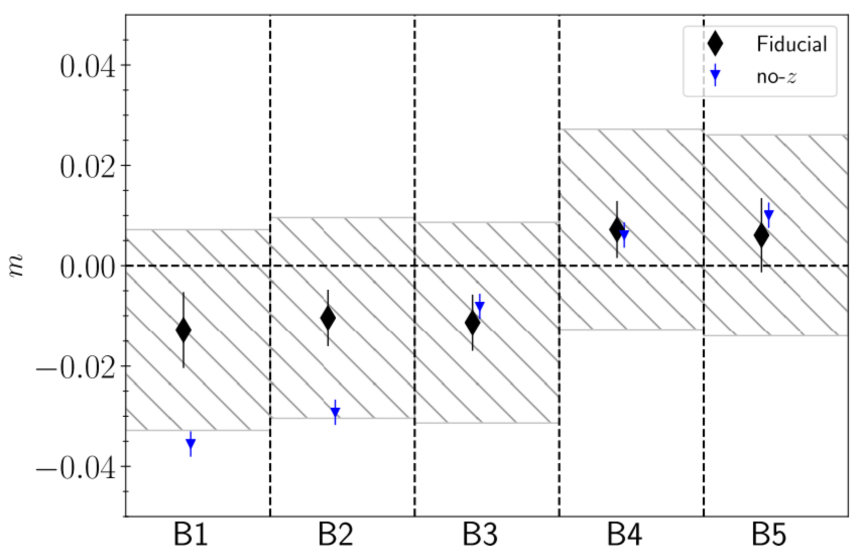
Shear calibration



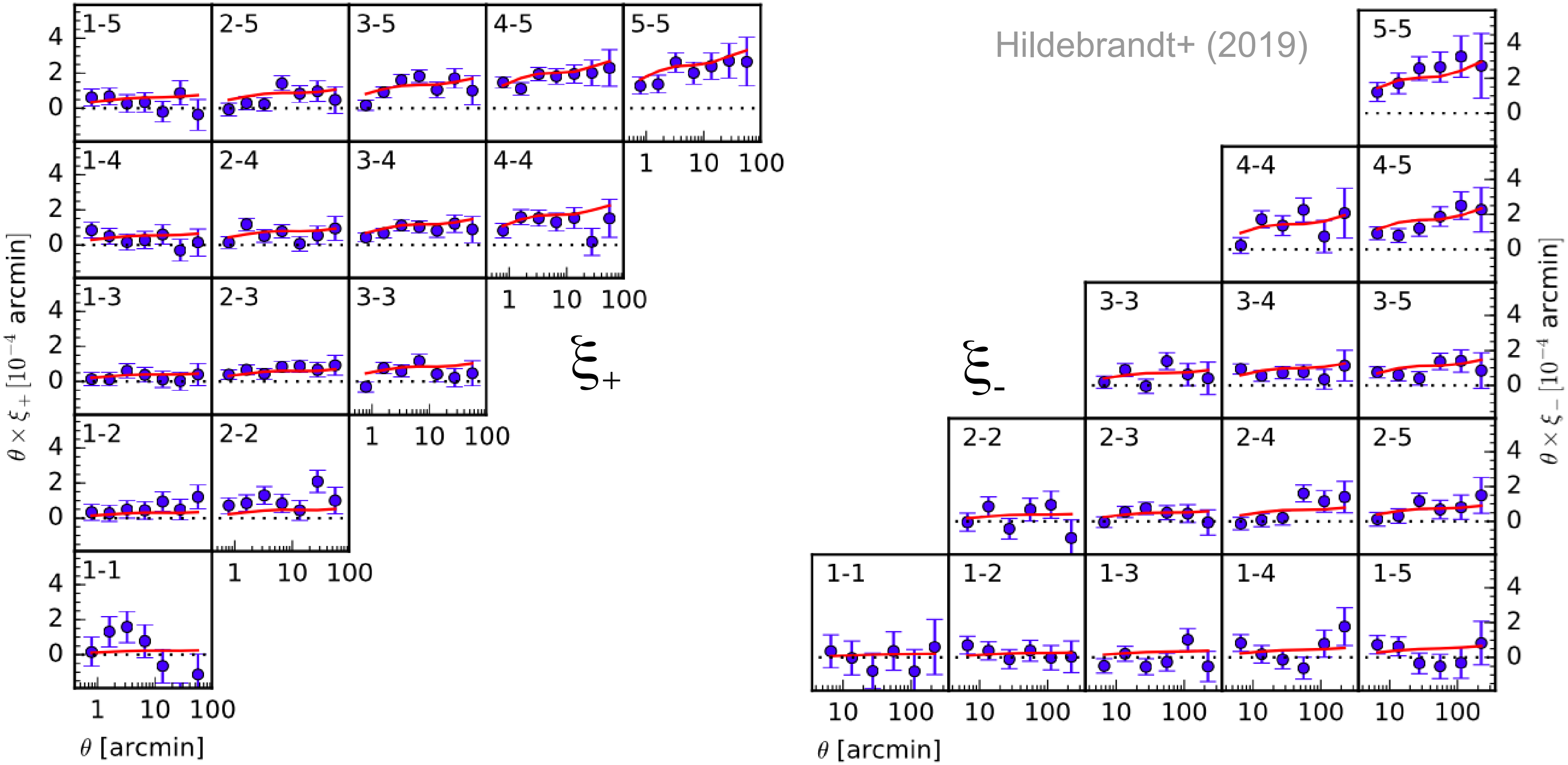
Kannawadi+ (2019)

real VST vs. COSMOS emulation

multiplicative shear bias



Measurements

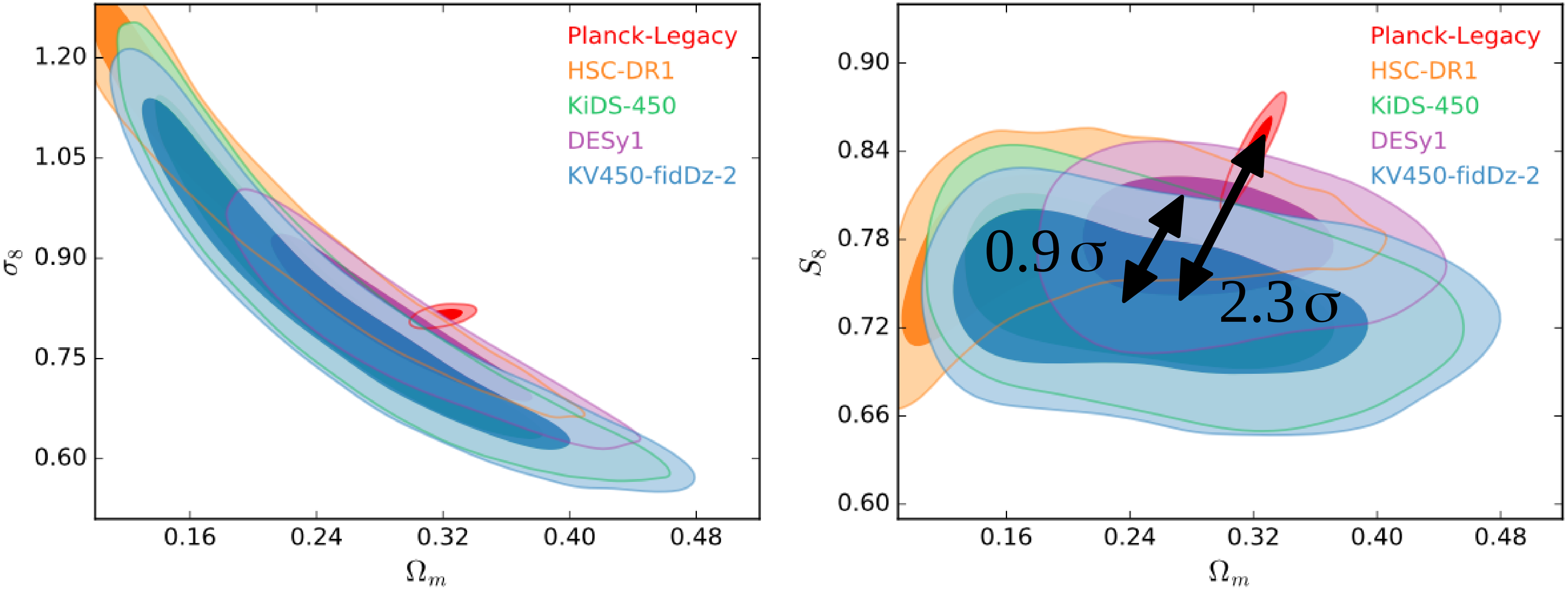


Hildebrandt+ (2019)

- best-fit cosmological model incl. intrinsic alignments and baryon feedback
- errors from fully analytic covariance

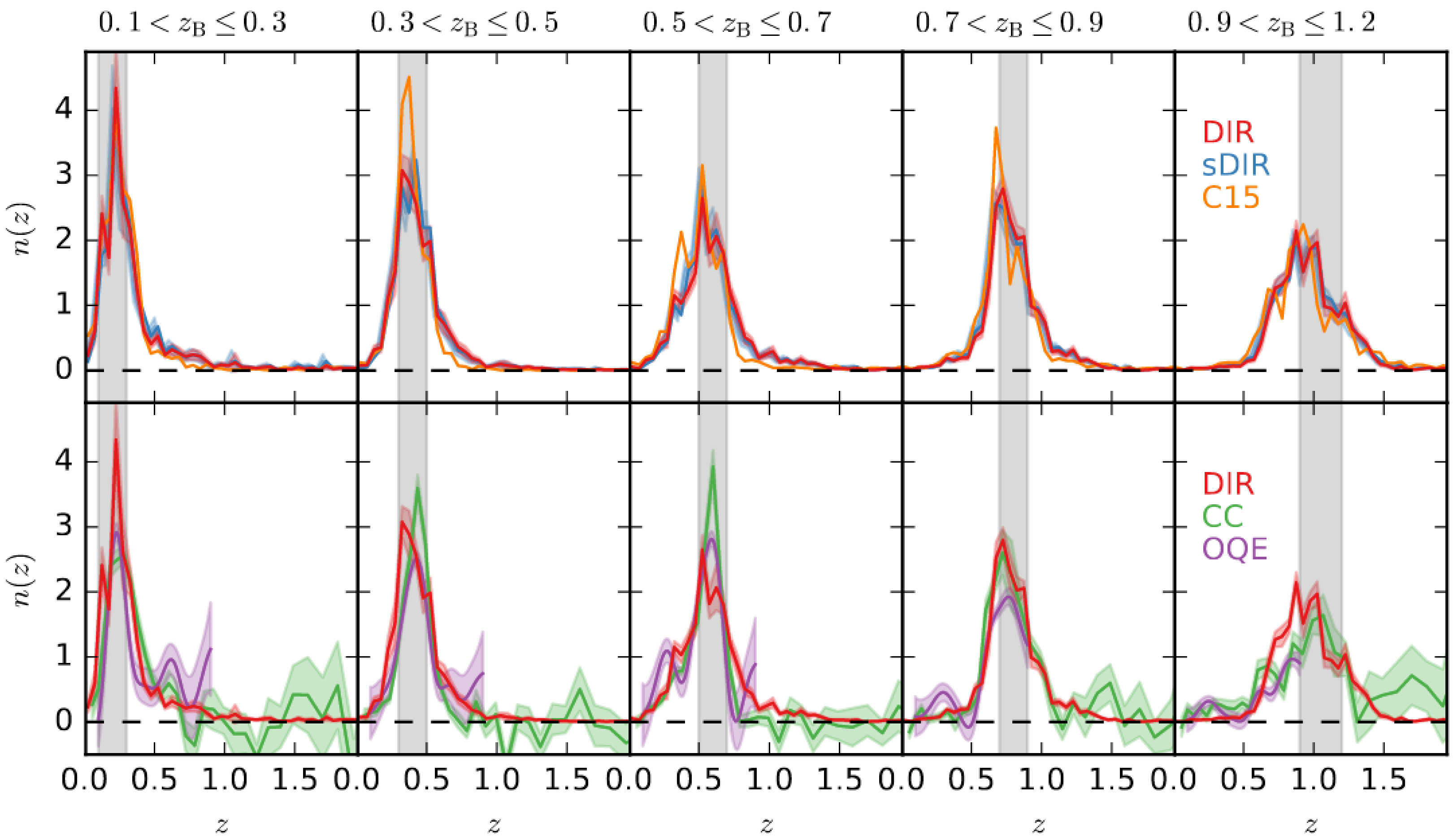
The state of the art for cosmic shear

Hildebrandt+ (2019)



$S_8 = \sigma_8 \sqrt{\Omega_m / 0.3}$ measures constraints across the banana

Redshift calibration techniques



Hildebrandt+ (2019)

reweighting spec-z

reweighting, smoothed over LSS

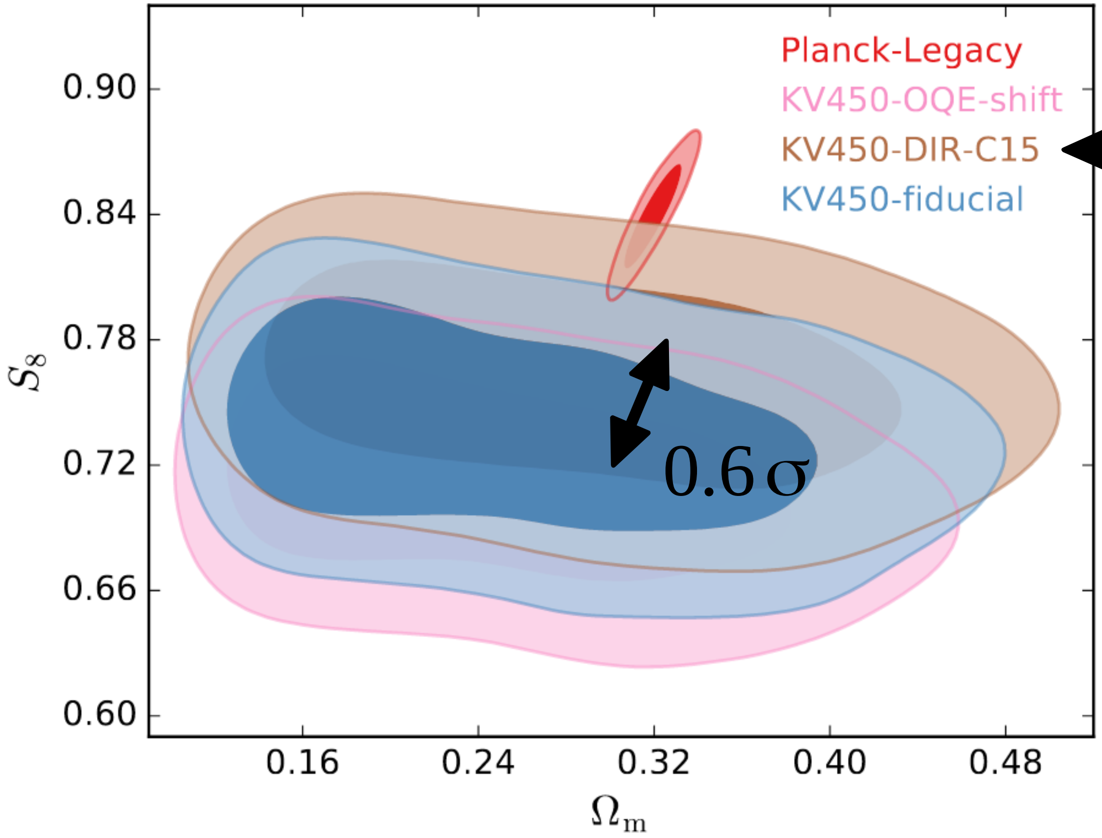
COSMOS-30 photo-z

clustering cross-correlations (small-scale)

clustering cross-correlations (large-scale)

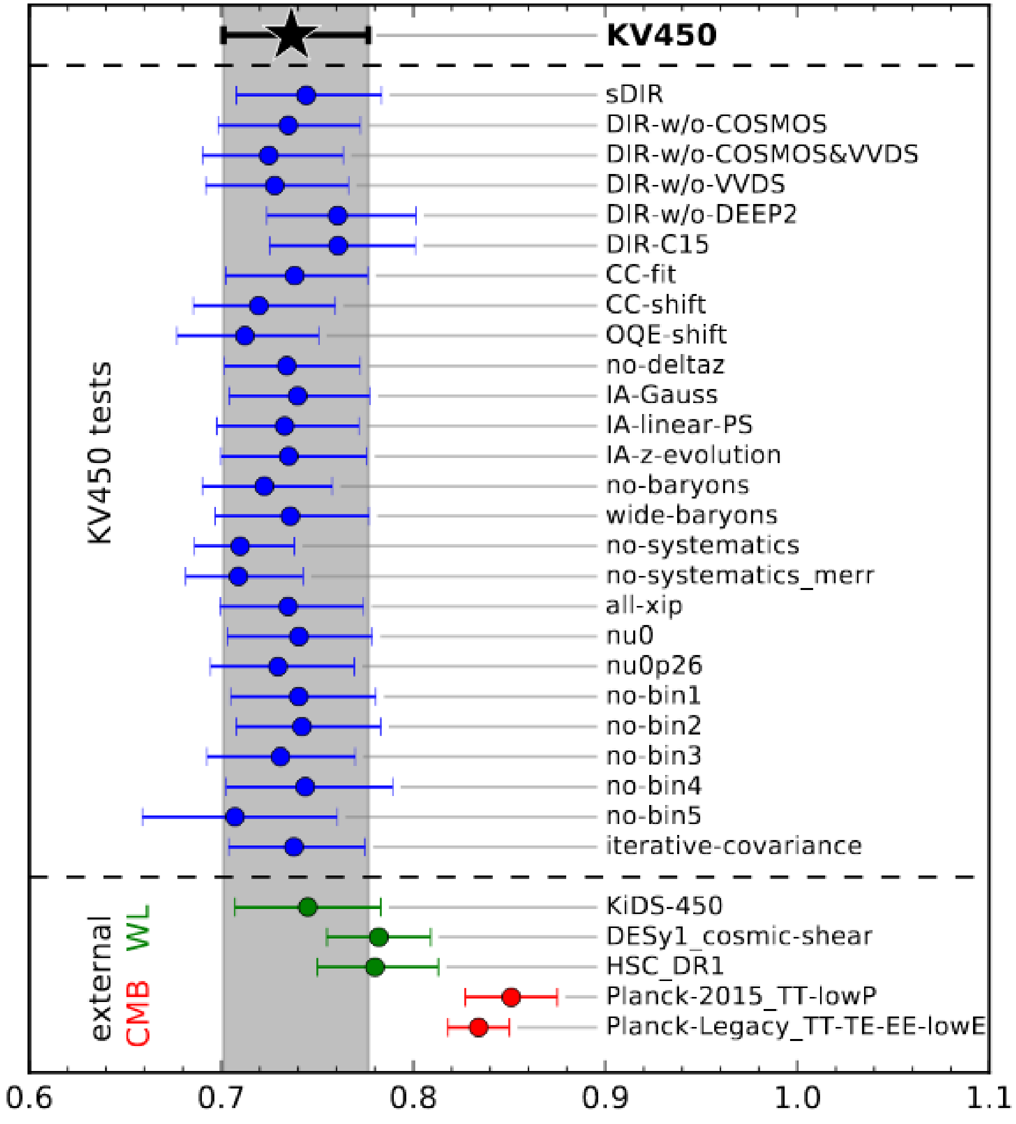
The importance of redshift calibration

Hildebrandt+ (2019)



using COSMOS-30 photo-z
[DES and HSC rely on this]

Could it be systematics?



Hildebrandt+ (2019) $S_8 \equiv \sigma_8 \sqrt{\Omega_{\rm m}/0.3}$

cosmic variance in photo-z

photo-z calibration technique

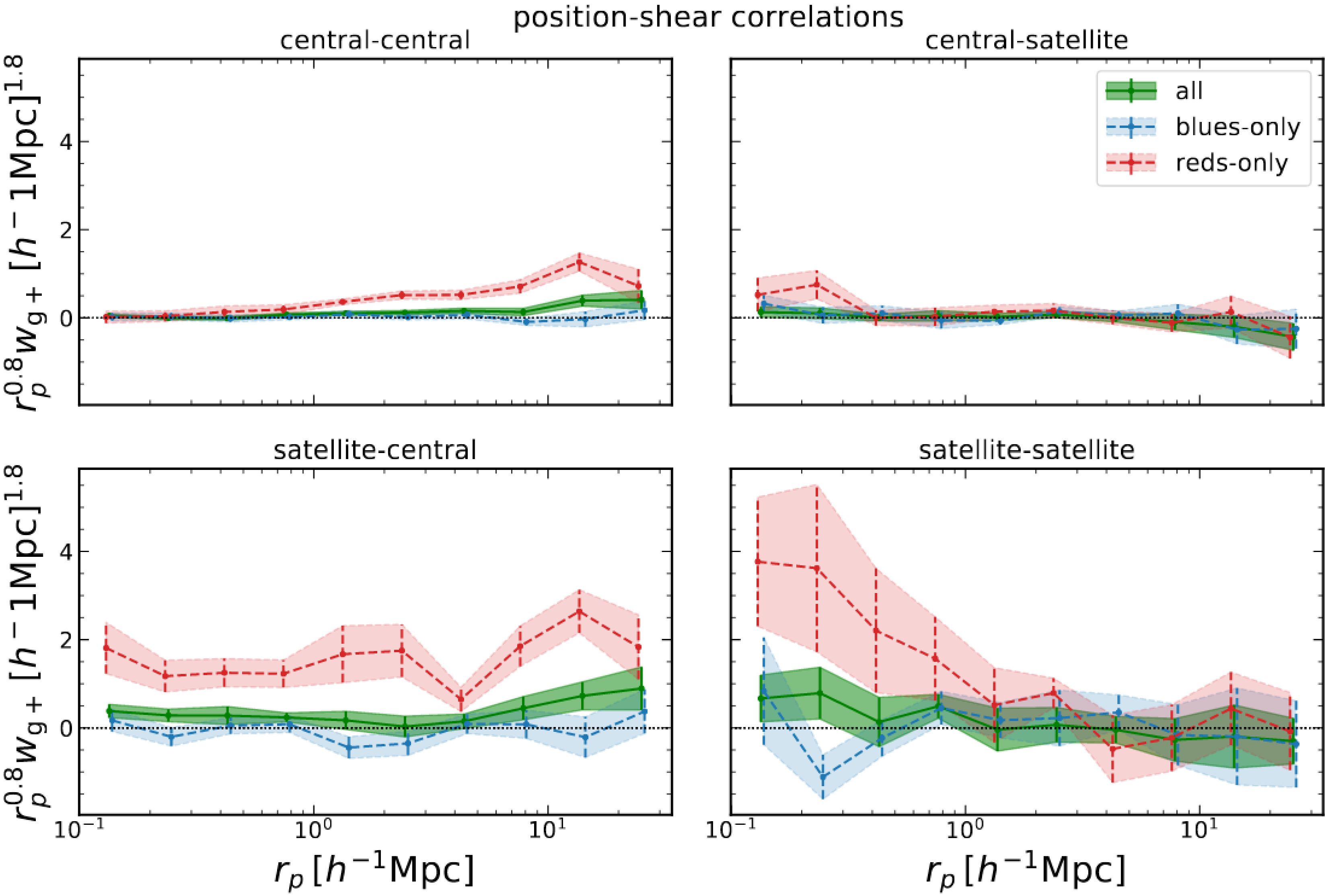
no photo-z uncertainty
intrinsic alignment modelling

baryon feedback modelling
no systematics

neutrino modelling
excluding redshift bins

covariance modelling

Intrinsic alignments of GAMA galaxies

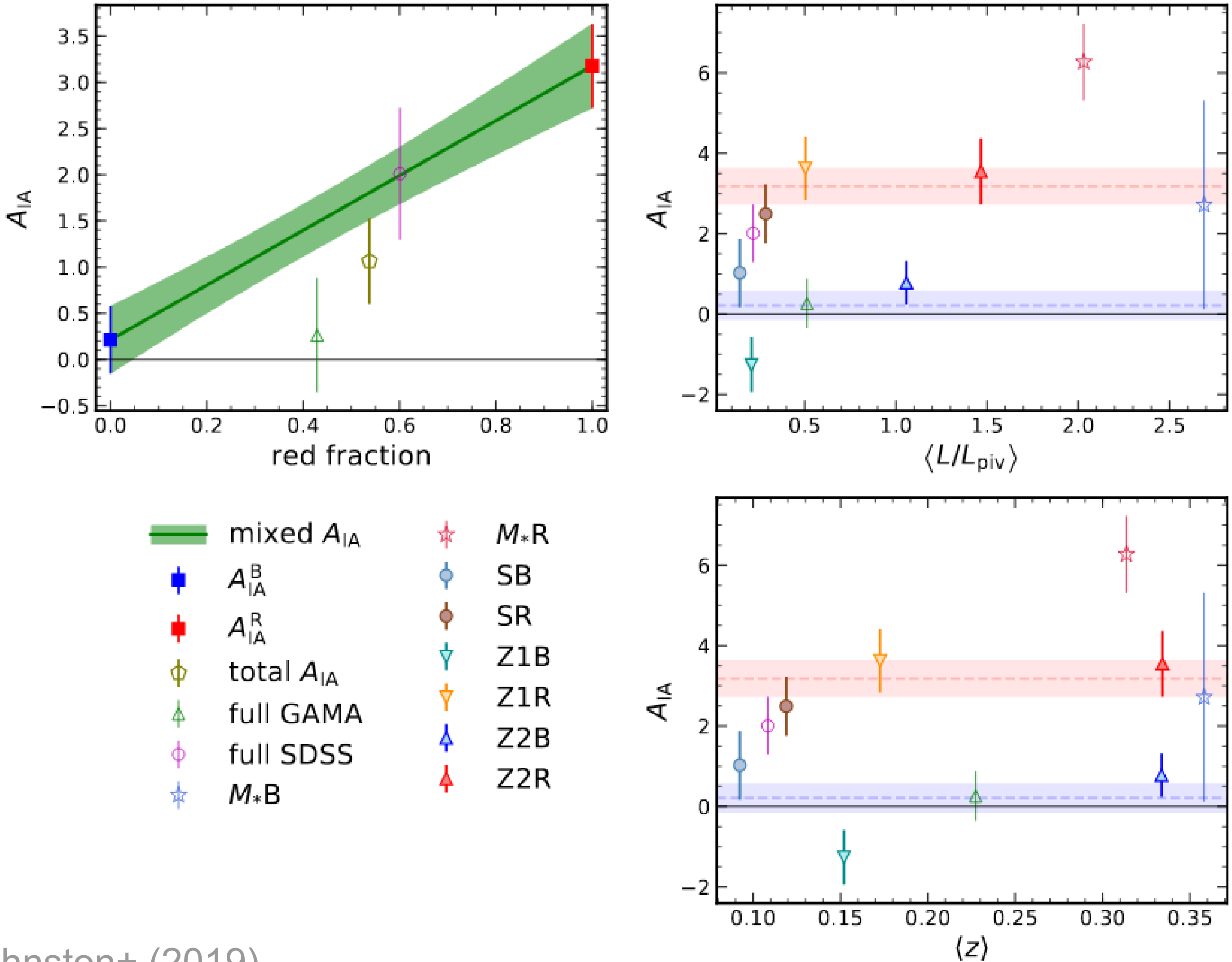


Johnston+ (2019)

Intrinsic alignments: colour dichotomy

dependence on colour/type

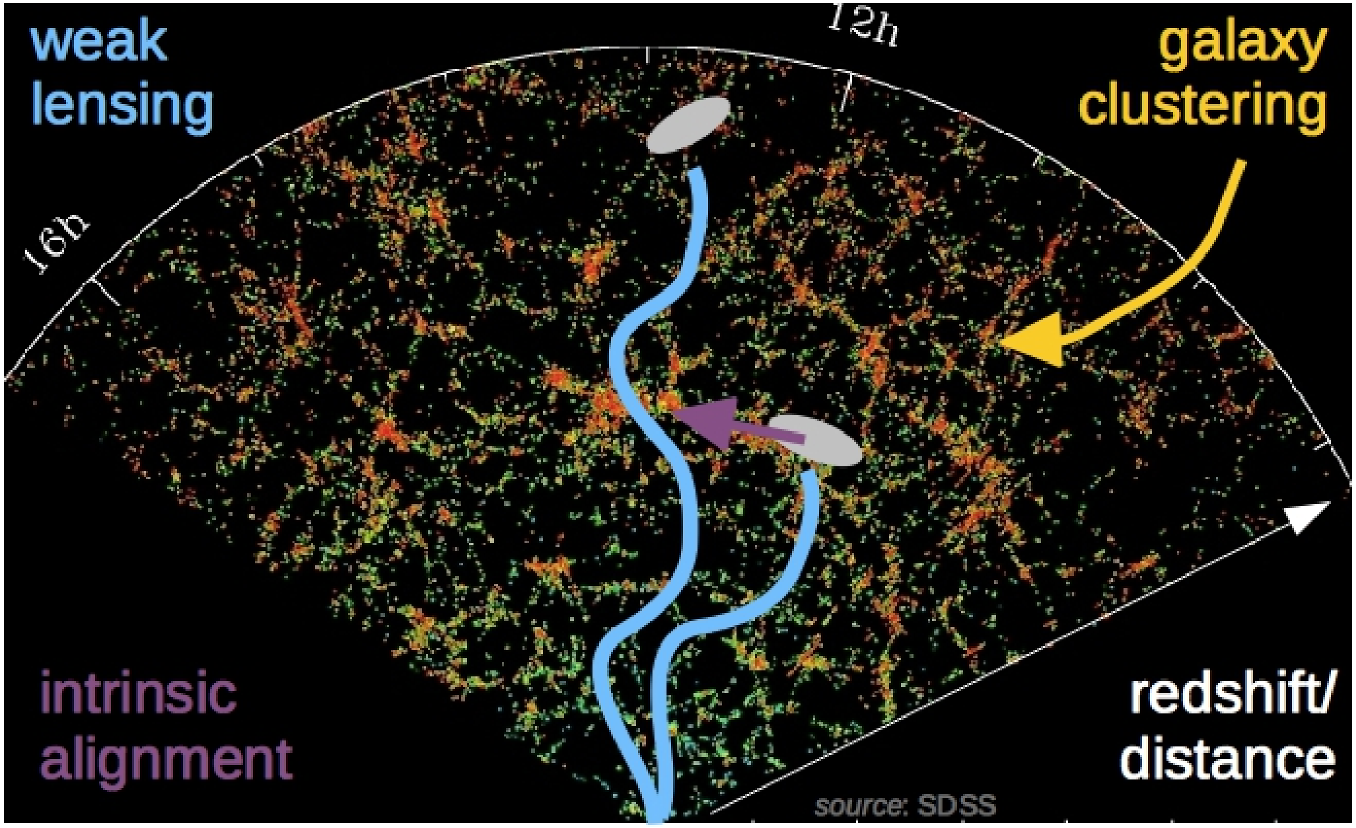
dependence on luminosity/mass



dependence on redshift

Johnston+ (2019)

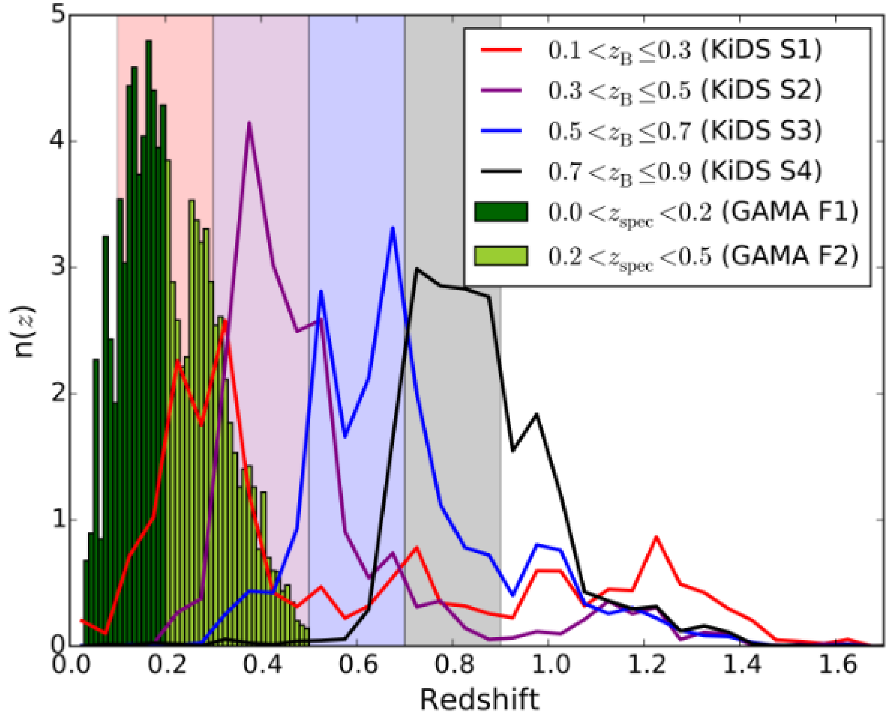
The case for joint probes analysis

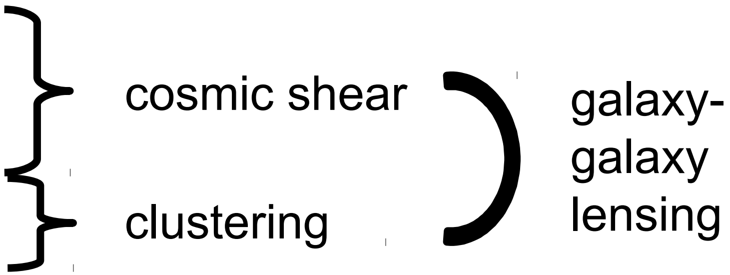


Joint clustering/weak lensing analysis enables self-calibration of intrinsic alignments, galaxy bias, n(z) uncertainties, etc.

Bernstein (2009); BJ & Bridle (2010)

Joint probes analysis setup





cosmic shear

clustering

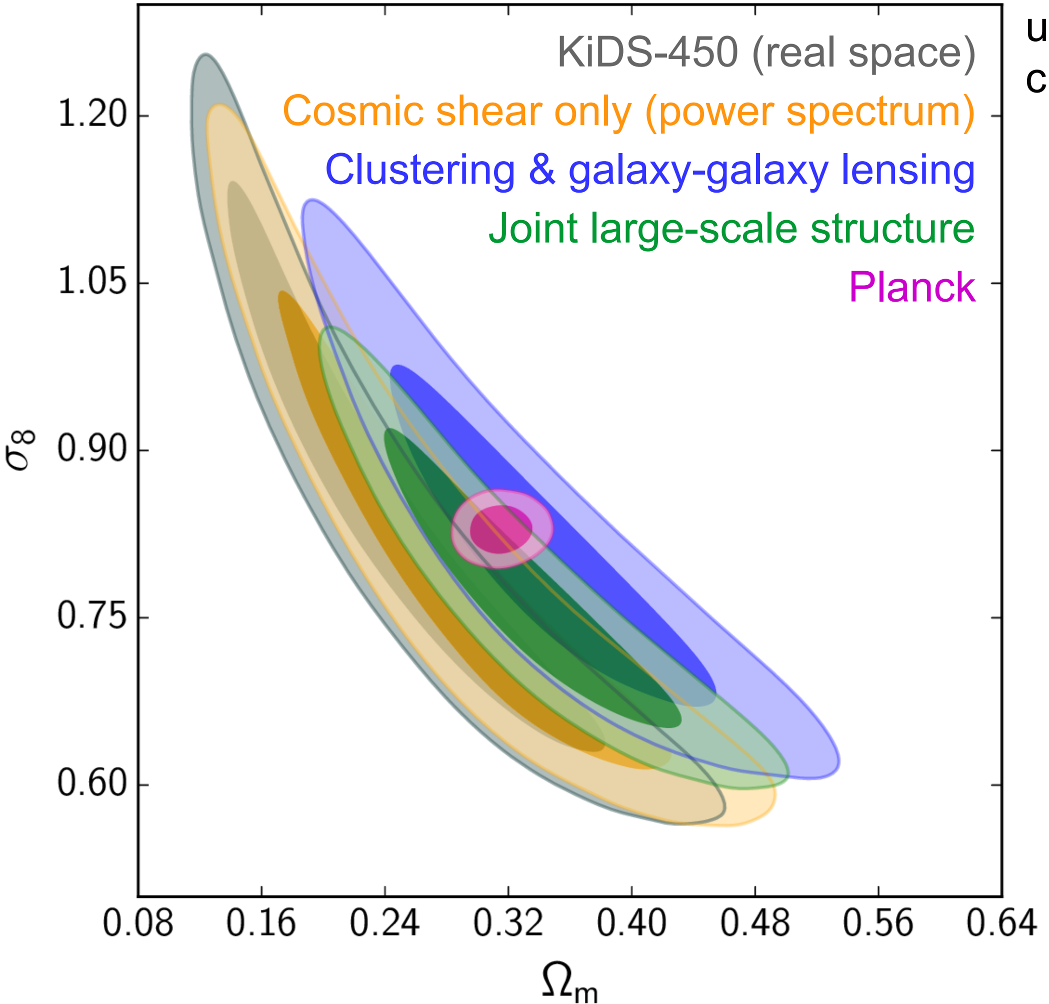
galaxy-galaxy lensing

van Uitert, BJ, et al. (2018)

- derive band power spectra as integrals over correlation functions
- joint analytic covariance, verified on N-body simulations
- same model as KiDS-450 + linear effective galaxy bias

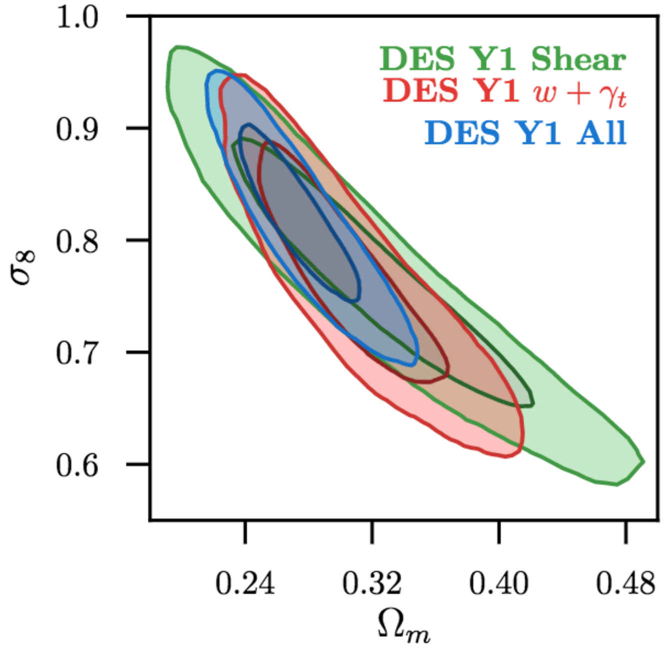
Current joint probes results

van Uitert, BJ+ (2018)



uses spectroscopic sample for clustering (from GAMA survey)

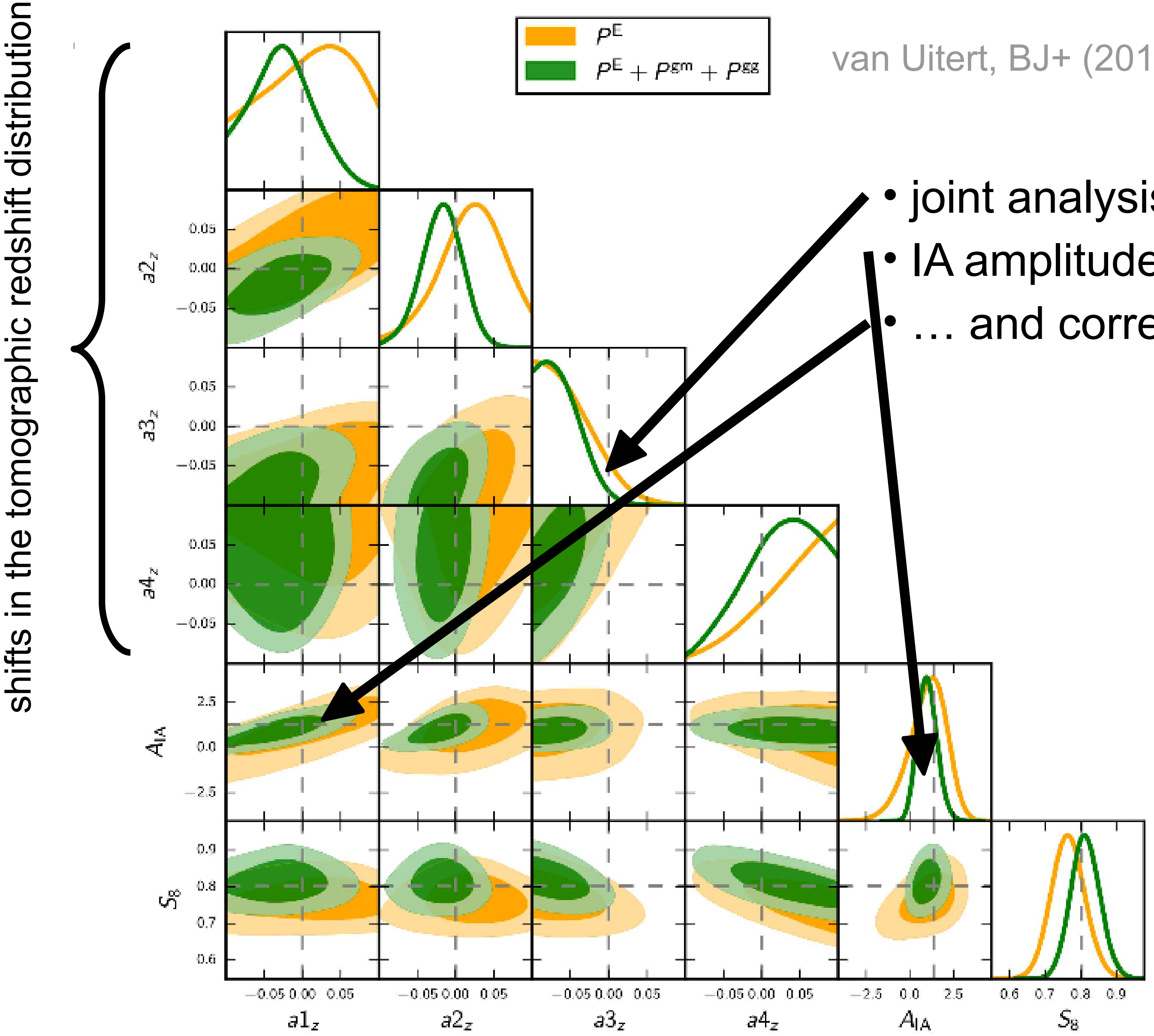
uses photometric LRG sample for clustering (internal red sequence finder)



DES Y1 (2018)

🟠 and 🔵 differ by 1.4σ but are quasi-independent

Fidelity of redshift distributions



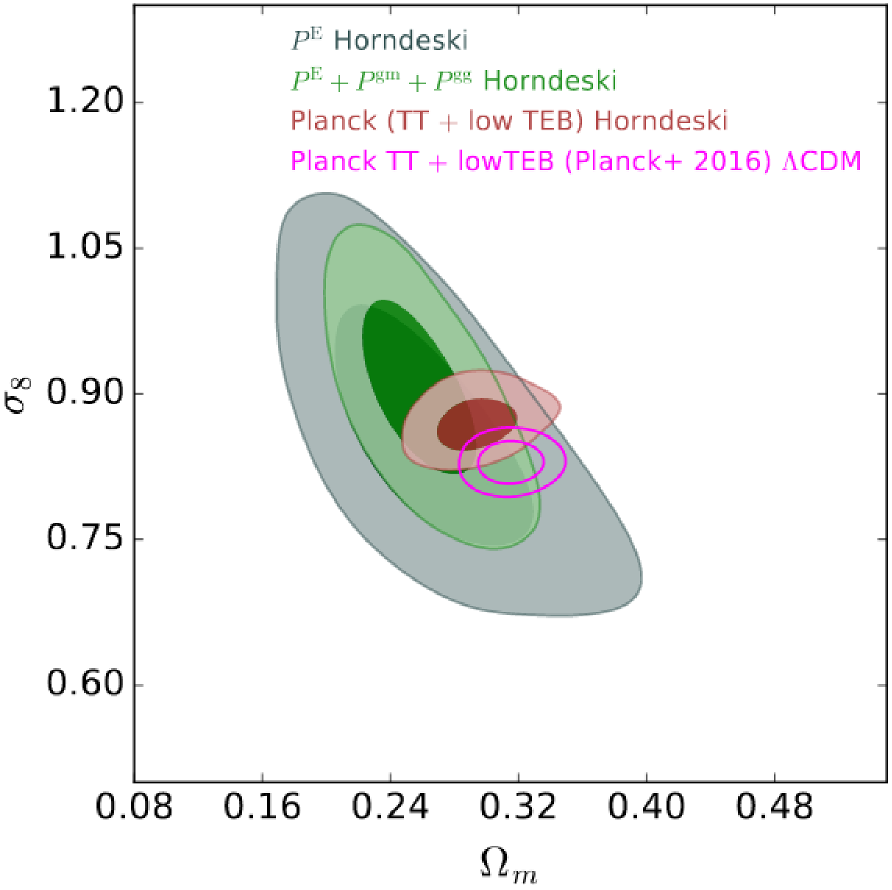
shifts in the tomographic redshift distribution

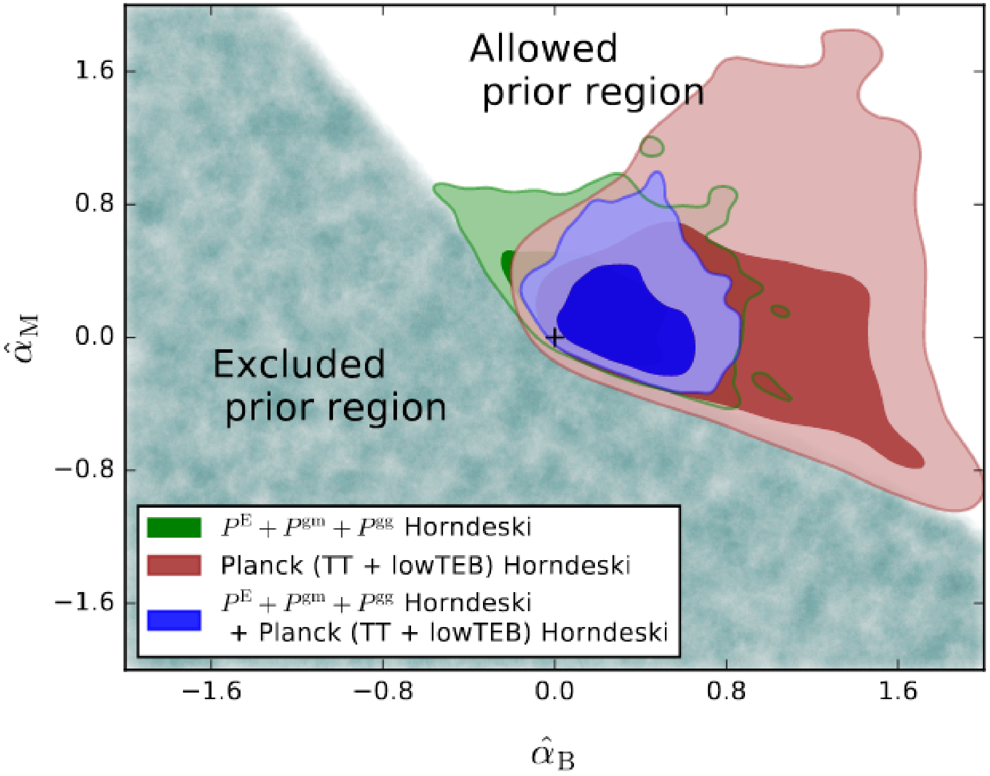
van Uitert, BJ+ (2018)

- joint analysis prefers shift of bin 3
- IA amplitude surprisingly high
- … and correlated with n(z)

Extended model – Horndeski gravity

Spurio Mancini, Koehlinger, BJ+ (2019)





α_M : Planck mass run rate

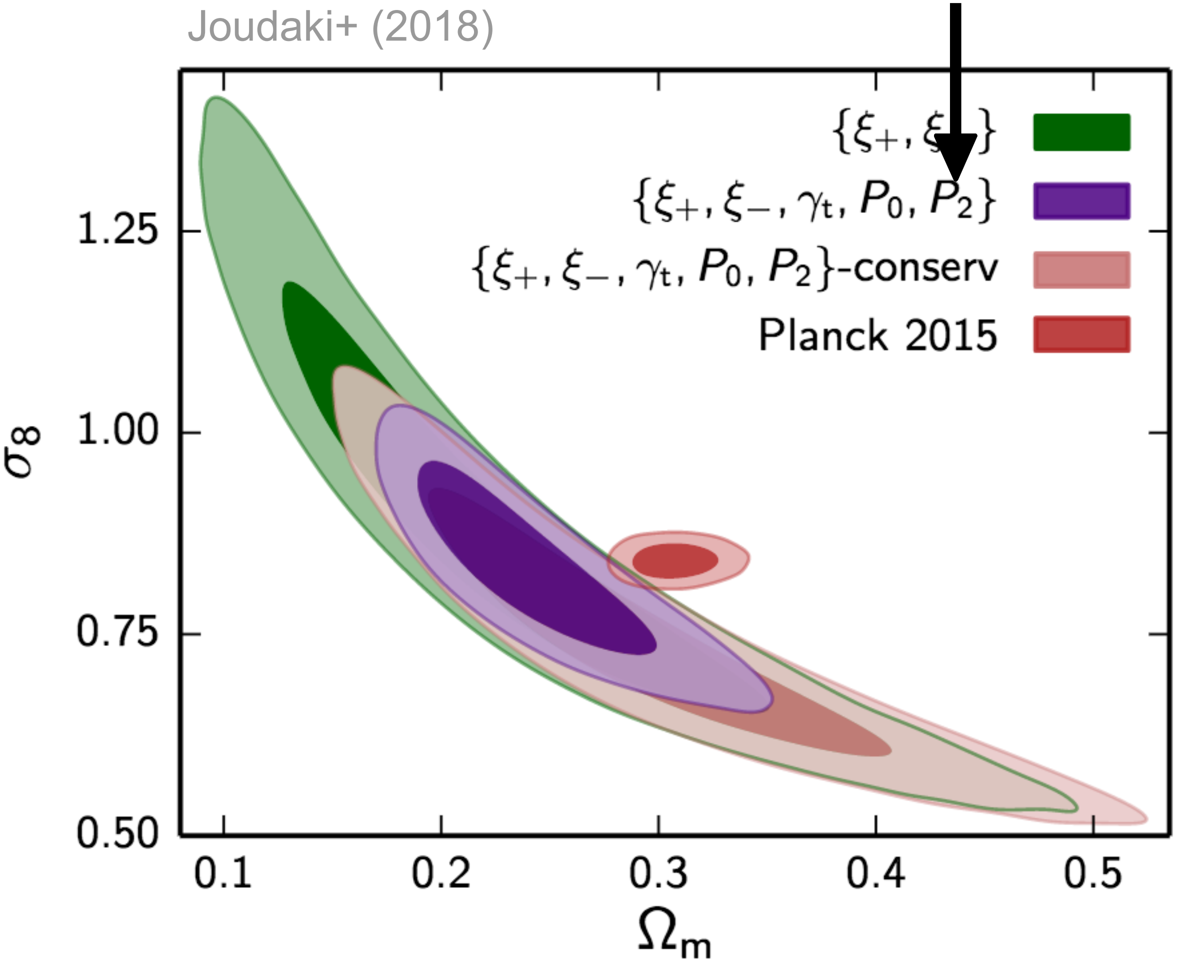
α_B : braiding ↔ fifth force

scaling with $\Omega_\Lambda(a)$

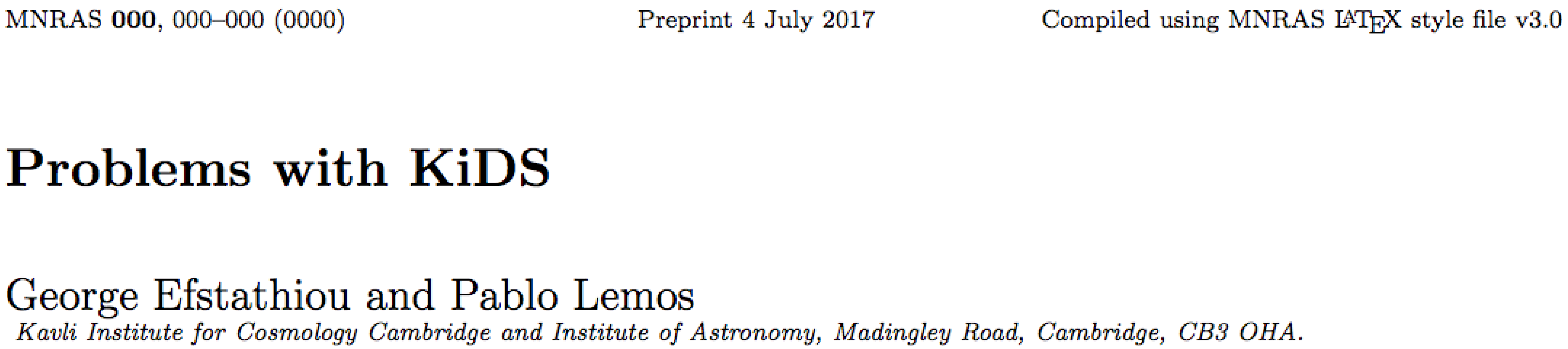
KiDS x spectroscopic clustering

quadrupole power spectrum:
includes redshift-space distortions

Joudaki+ (2018)



Is there a problem?



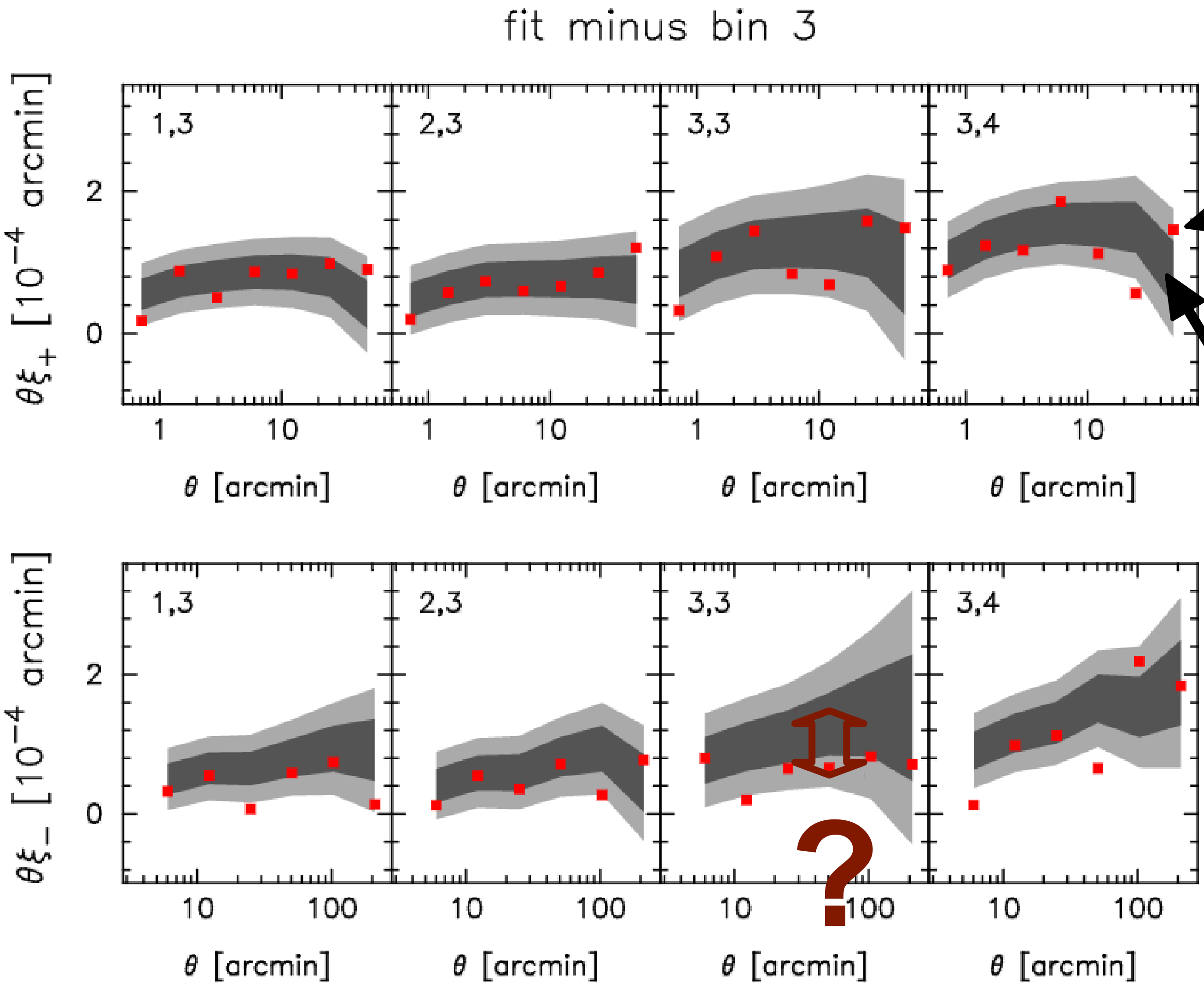
MNRAS **000**, 000–000 (0000) Preprint 4 July 2017 Compiled using MNRAS LATEX style file v3.0

Problems with KiDS

George Efstathiou and Pablo Lemos

Kavli Institute for Cosmology Cambridge and Institute of Astronomy, Madingley Road, Cambridge, CB3 OHA.

Are these measurements inconsistent?



data points

1+2σ contours around best fit to remaining data

Efstathiou & Lemos (2018)

3 tiers of consistency checks

1. Global summary statistic

→ Bayes factor

2. Posterior-level check

→ pdfs of difference in duplicated parameters

3. Data domain check

→ proxy for posterior predictive distributions

- use a Bayesian formalism
- designed for correlated datasets
- analytic solutions for Gaussian data
- intuitive tension definitions

Tier 1: Bayes factor

$$\Pr(\boldsymbol{d}\,|\,\mathrm{H}) = \int \mathrm{d}^M \boldsymbol{p}\, \Pr(\boldsymbol{d}\,|\boldsymbol{p}, \mathrm{H})\, \Pr(\boldsymbol{p}\,|\,\mathrm{H})$$

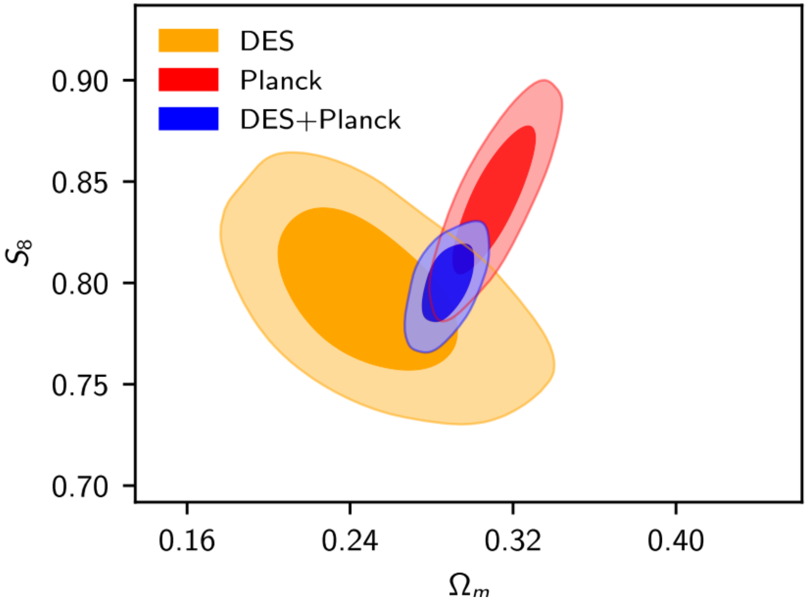
evidence

Handley & Lemos (2019)

$$\mathrm{R}_{01} = \frac{\Pr(\boldsymbol{d}\,|\,\mathrm{H}_0)}{\Pr(\{\boldsymbol{d}^{\tau}_{\mathrm{a}}, \boldsymbol{d}^{\tau}_{\mathrm{b}}\}\,|\,\mathrm{H}_1)}$$

- split the dataset
- assign one parameter set to each split

→ prior dependence



Dataset	Prior	$\log R$	$\log I$	$\log S$	d	$p(\%)$
BOSS-*Planck*	default	6.24 ± 0.30	6.15 ± 0.29	0.09 ± 0.29	2.69 ± 0.23	41.58 ± 4.38
	medium	4.49 ± 0.30	4.03 ± 0.29	0.46 ± 0.29	3.48 ± 0.24	54.80 ± 4.16
	narrow	1.30 ± 0.23	0.69 ± 0.23	0.61 ± 0.23	2.11 ± 0.23	66.31 ± 5.19
DES-*Planck*	default	2.91 ± 0.35	6.18 ± 0.35	-3.27 ± 0.35	2.50 ± 0.32	1.91 ± 0.58
	medium	0.51 ± 0.36	3.98 ± 0.36	-3.47 ± 0.36	2.03 ± 0.33	1.22 ± 0.43
	narrow	-1.88 ± 0.31	0.92 ± 0.30	-2.80 ± 0.30	1.18 ± 0.31	1.31 ± 0.60

3 tiers of consistency checks

1. Global summary statistic

→ Bayes factor

2. Posterior-level check

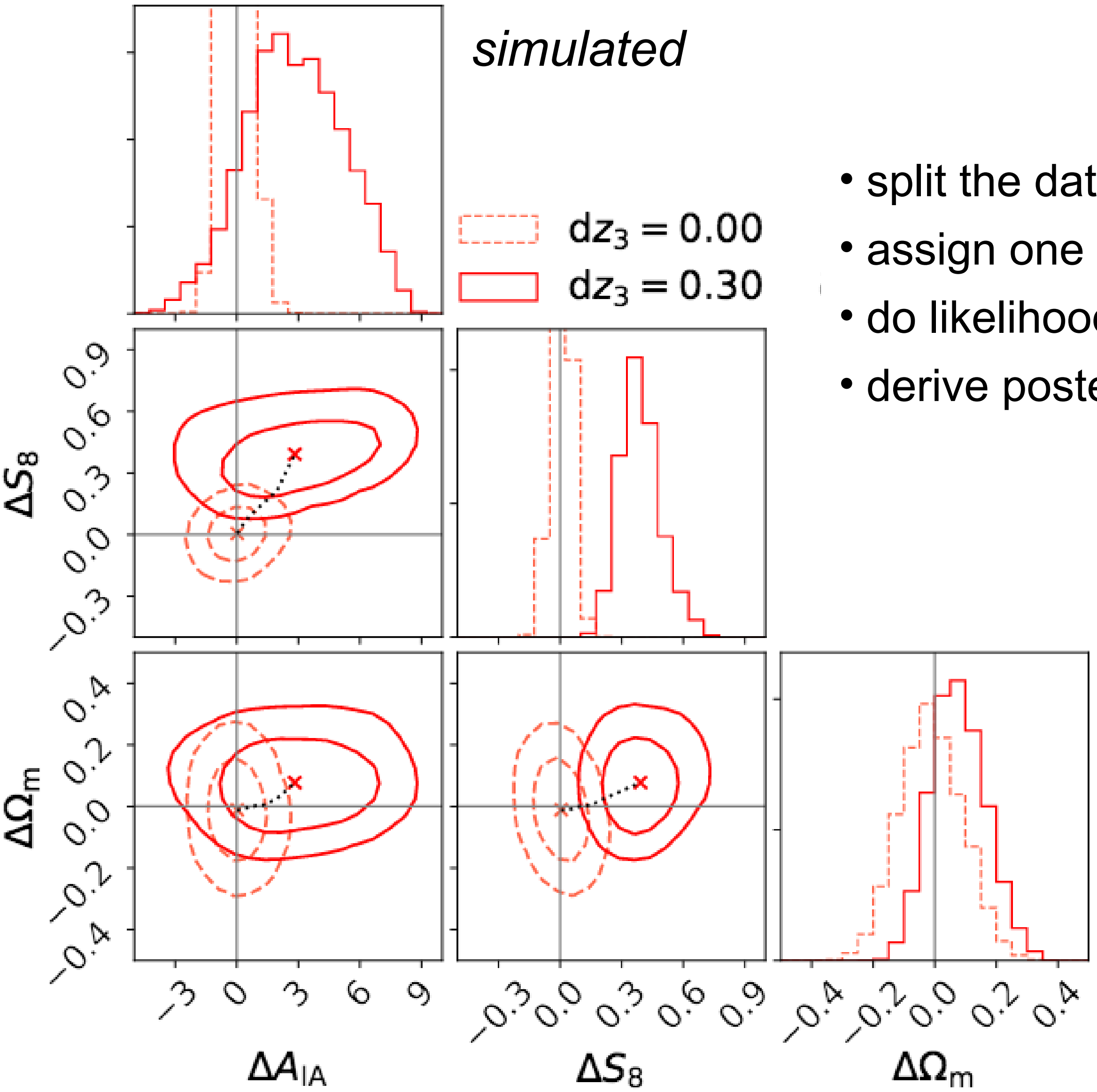
→ pdfs of difference in duplicated parameters

3. Data domain check

→ proxy for posterior predictive distributions

- use a Bayesian formalism
- designed for correlated datasets
- analytic solutions for Gaussian data
- intuitive tension definitions

Tier 2: posterior-level check



- split the dataset
- assign one parameter set to each split
- do likelihood analysis
- derive posterior of parameter differences

Koehliner, BJ+ (2019)

3 tiers of consistency checks

1. Global summary statistic

→ Bayes factor

2. Posterior-level check

→ pdfs of difference in duplicated parameters

3. Data domain check

→ proxy for posterior predictive distributions

- use a Bayesian formalism
- designed for correlated datasets
- analytic solutions for Gaussian data
- intuitive tension definitions

Tier 3: data domain check

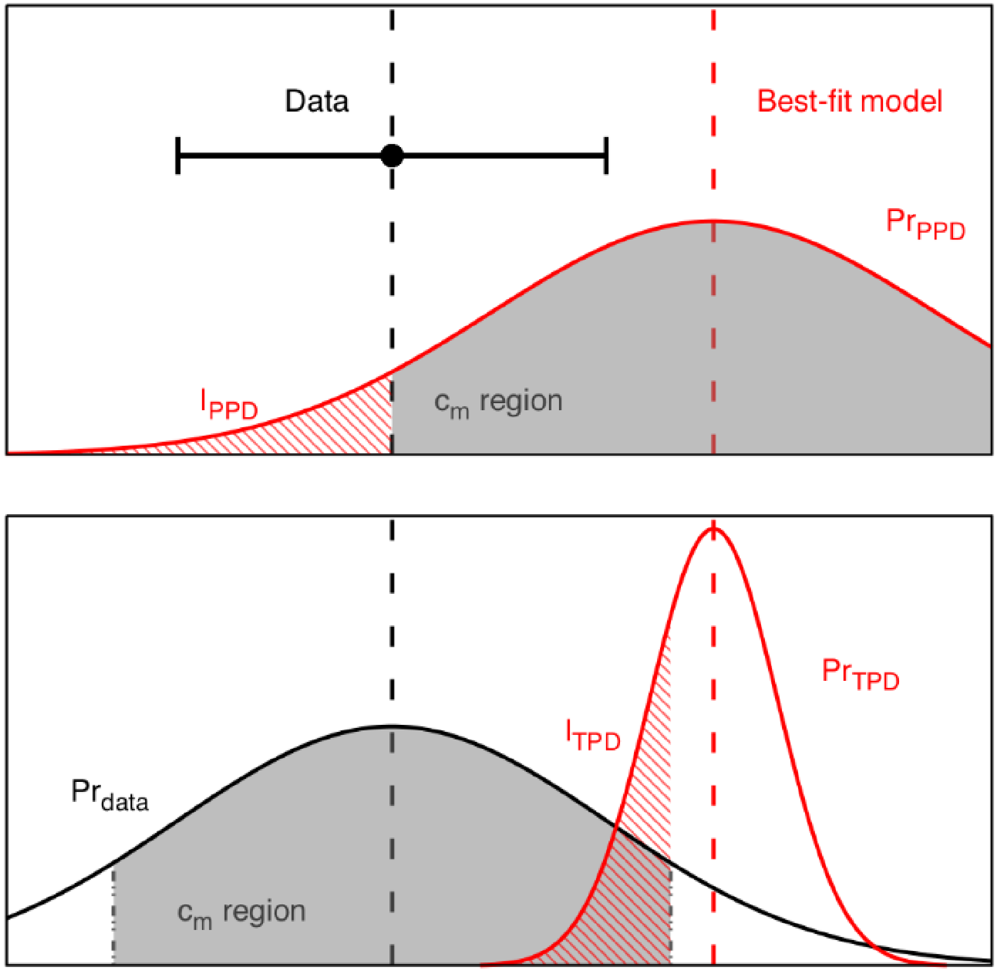
$$\mathrm{Pr}(\hat{\boldsymbol{d}} \,|\, \boldsymbol{d},\, \mathrm{H}_\alpha) = \int \mathrm{d}^M \boldsymbol{p}_\alpha \, \mathrm{Pr}(\hat{\boldsymbol{d}} \,|\, \boldsymbol{p}_\alpha, \mathrm{H}_\alpha) \, \mathrm{Pr}(\boldsymbol{p}_\alpha \,|\, \boldsymbol{d}, \mathrm{H}_\alpha)$$

synthetic data

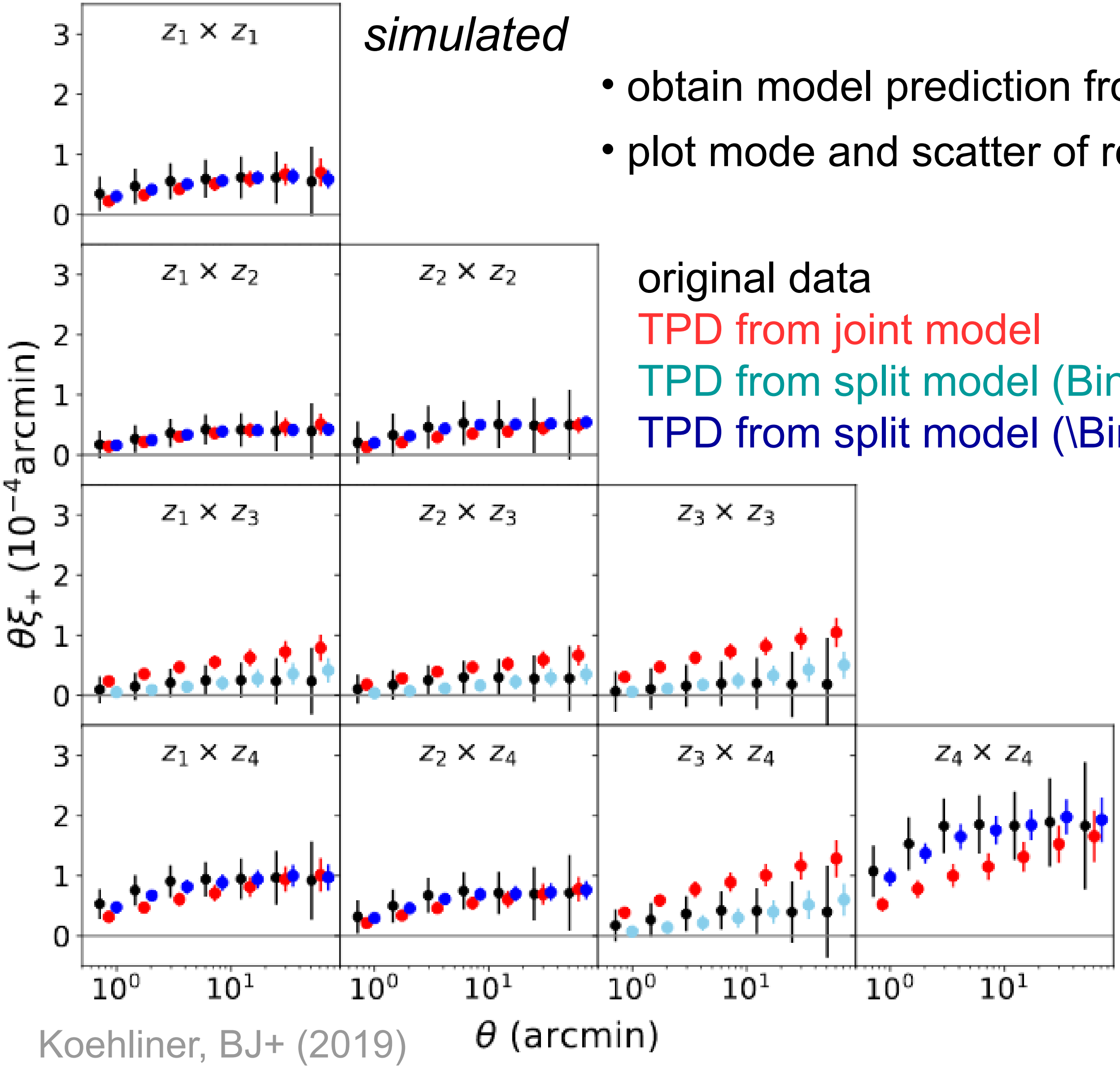
real data

Posterior **P**redictive **D**istribution

Translated **P**osterior **D**istribution



Tier 3: data domain check



simulated

- obtain model prediction from each posterior sample
- plot mode and scatter of resulting distribution (TPD)

original data
TPD from joint model
TPD from split model (Bin 3)
TPD from split model (\Bin 3)

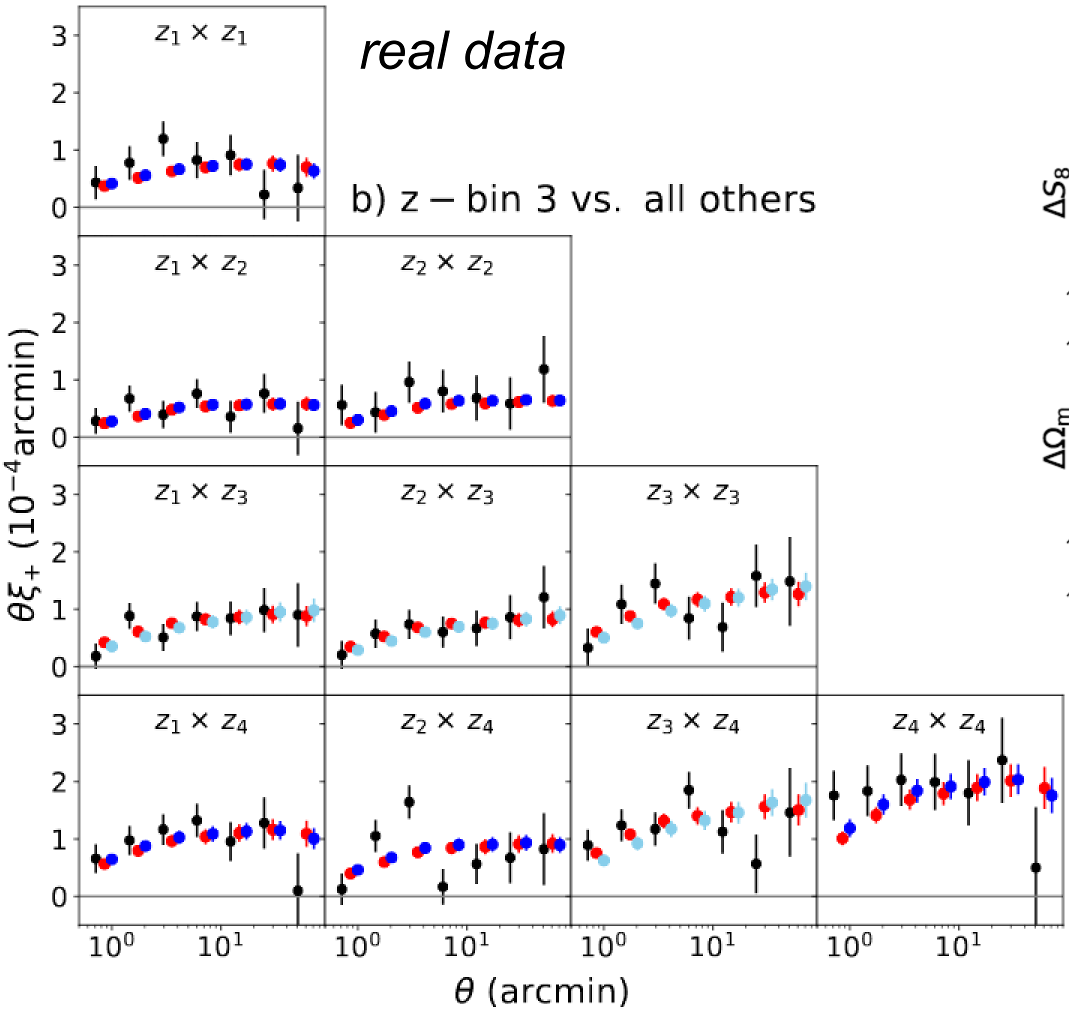
black vs blue:
→ goodness of fit

blue vs red:
→ consistency

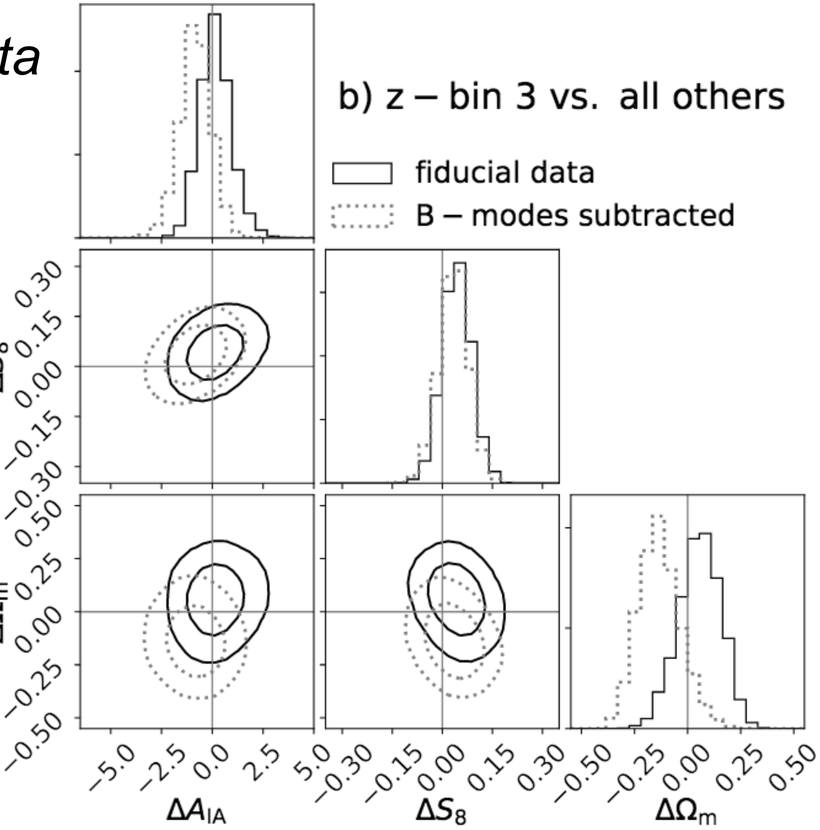
Koehliner, BJ+ (2019)

Problems with KiDS?

real data



real data



No.

Conclusions

- Current weak lensing surveys yield a consistent picture of low-z large-scale structure.

- At face value there is still a 1% chance the KiDS-Planck discrepancy is a random fluctuation.

- No known weak lensing systematics can drive the discrepancy, with the possible exception of the photometric redshift calibration.

- Despite claims to the contrary, KiDS data are internally consistent.
- Despite claims to the contrary, DES might not be consistent with Planck.

→ The next rounds of analyses by KiDS, DES, and HSC will ramp up precision and accuracy – then we will know if this is fluke or feature.

KiDS measurements: *http://kids.strw.leidenuniv.nl/sciencedata.php*