

# CMB lensing cross-correlations with large-scale structure surveys

# Probes of late-time structure



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$$\gamma_g(\hat{\mathbf{n}})$$

$$N_c(\lambda, z)$$

$$\delta_c(\hat{\mathbf{n}}; \lambda)$$

$$v_r(\hat{\mathbf{n}})$$

$$\kappa(\hat{\mathbf{n}})$$

$$y(\hat{\mathbf{n}})$$

$$\Delta_{\text{CMB}}(\hat{\mathbf{n}})$$

$$\Delta_{\text{kSZ}}(\hat{\mathbf{n}})$$

$$\Delta_{\text{CIB}}(\hat{\mathbf{n}})$$

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I'll talk about this

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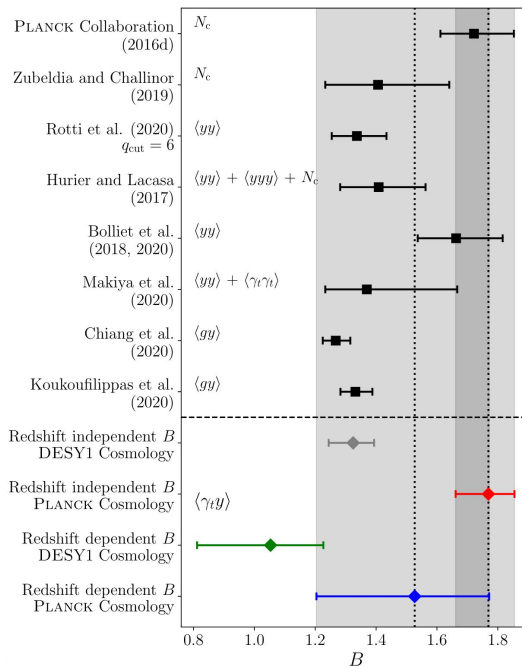
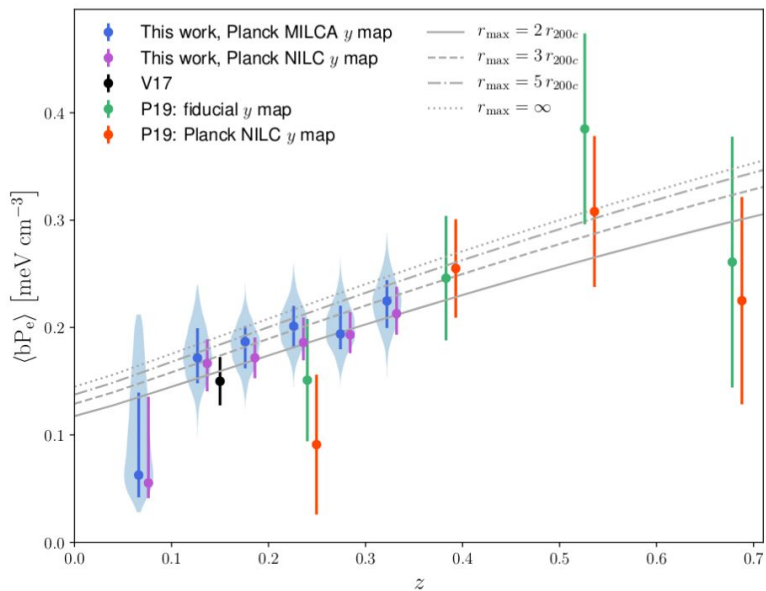
$$\Delta_{\text{CIB}}(\hat{\mathbf{n}})$$

# What I won't talk about: tSZ tomography

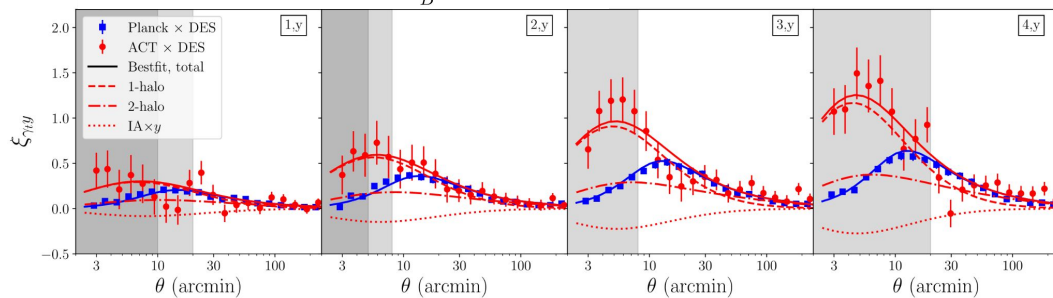
- Constrain z-evolution of gas pressure and mass bias
- Connection to gas thermodynamics.



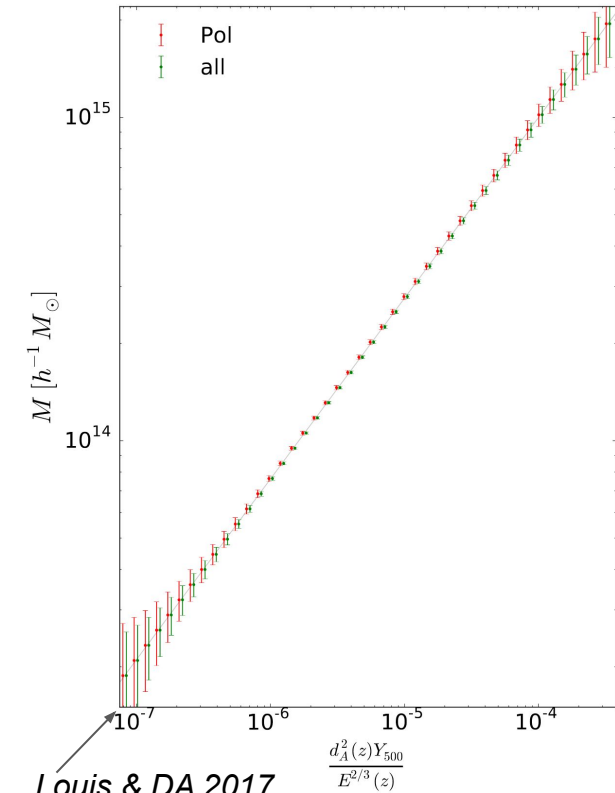
Koukoufilippas et al. 2019



Pandey et al. 2021  
Gatti et al. 2021



# What I won't talk about: mass calibration

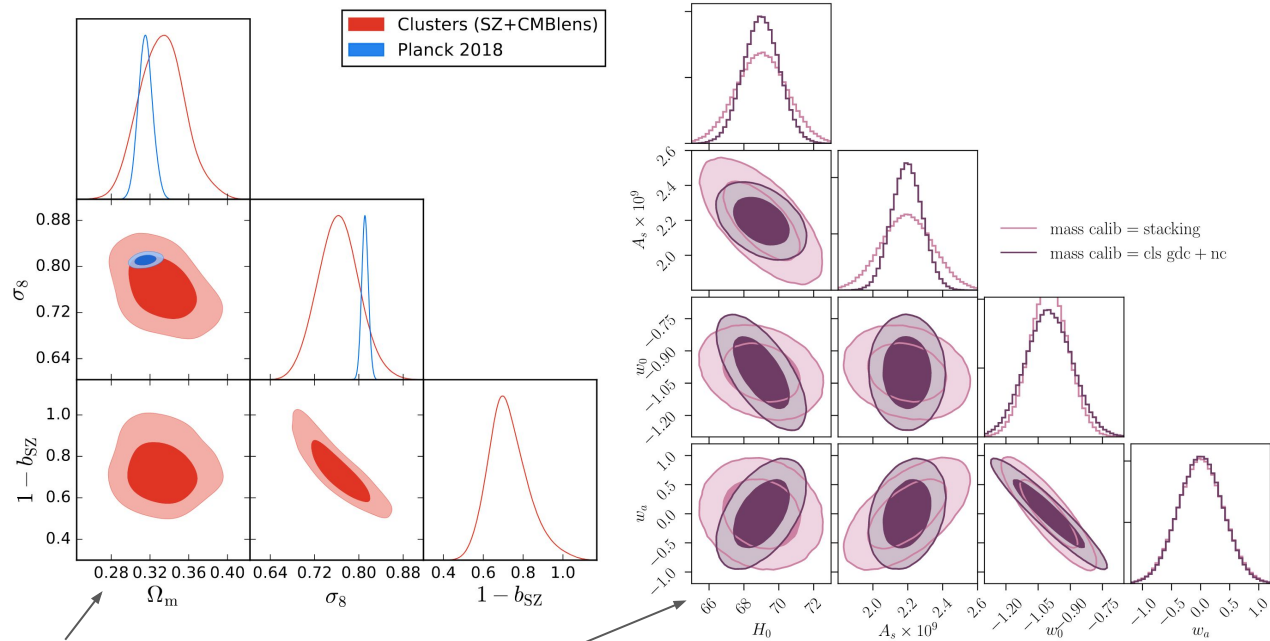


Louis & DA 2017

Bartlett & Melin 2015

Madhavacheril et al. 2018

Raghunathan et al. 2021



Zubeldia & Challinor 2019

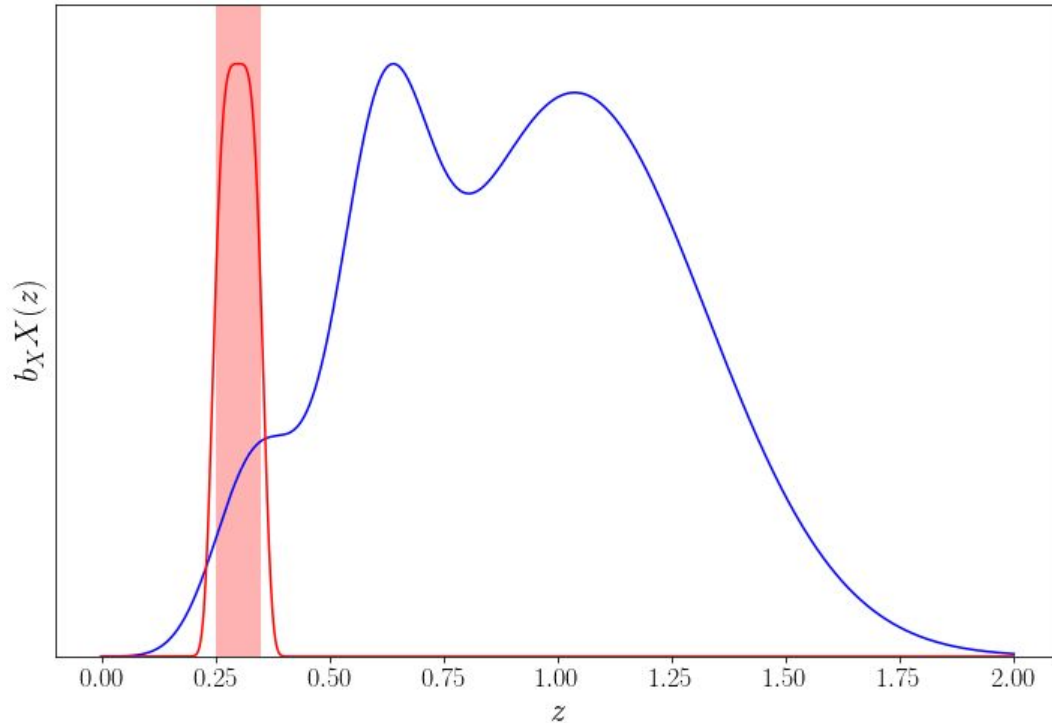
Baxter et al. 2018

Nicola et al. 2020

- CMB lensing can constrain cluster masses with very high precision.
- Particularly important at high  $z$ .

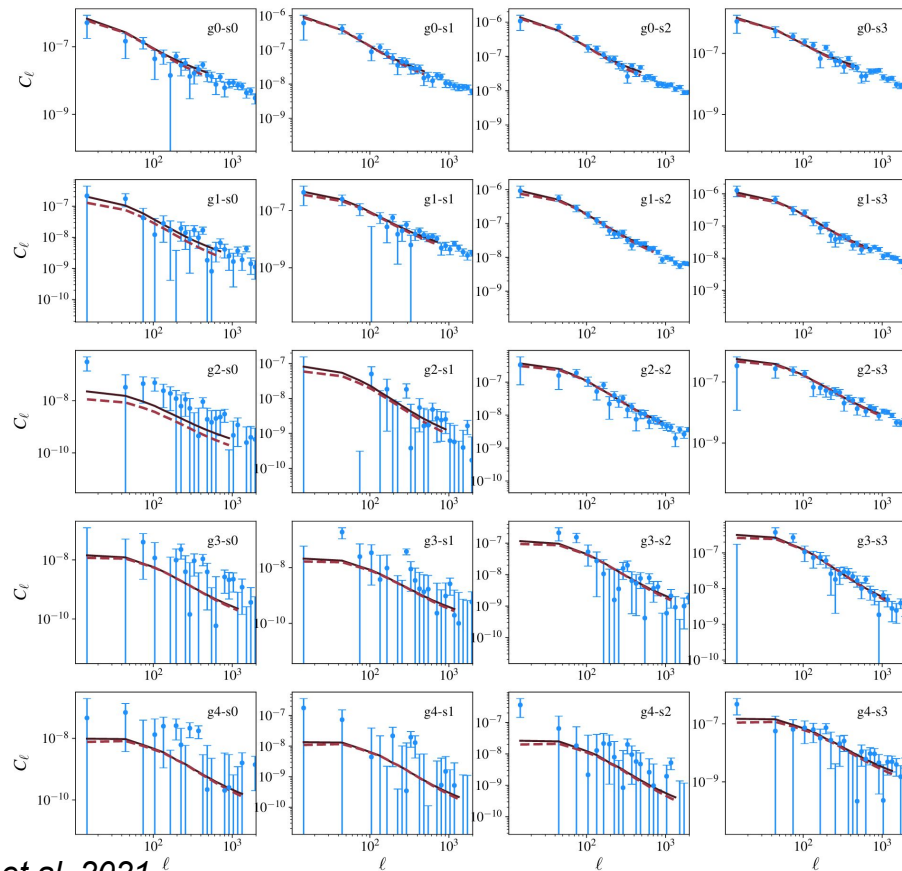
# What I will talk about: tomography

$$x(\theta, \phi) = \int dz \bar{X}(z) [1 + \delta_X(\theta, \phi, z)]$$
$$\langle x \delta_g(z_*) \rangle \propto b_X(z_*) \bar{X}(z_*)$$



# What I will talk about: tomography

Over time tomography has become synonymous with “*Nx2pt*” or “*extracting information from a combination of projected tracers of structure*”

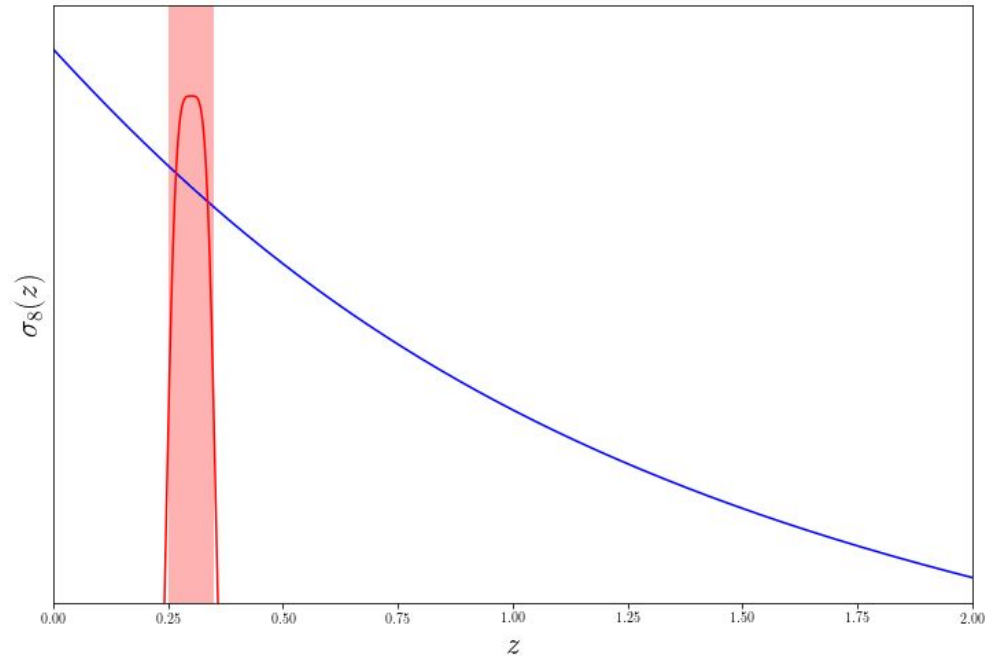


# Tomographic reconstruction: growth

- Consider CMB lensing +  $\delta_g$ :

$$C_{\ell}^{g\kappa} \propto \sigma_8^2 b_g \quad C_{\ell}^{gg} \propto (\sigma_8 b_g)^2$$

So you can measure  $\sigma_8(z)$





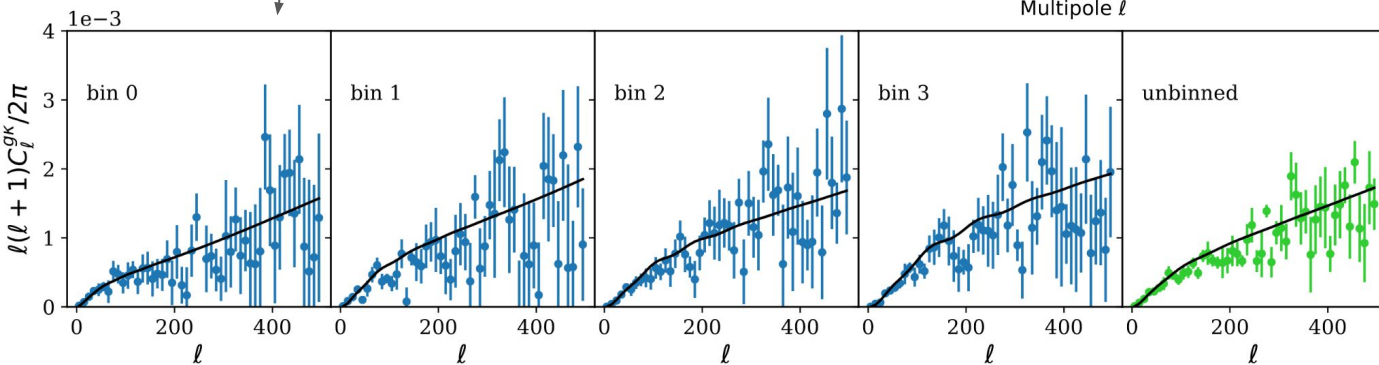
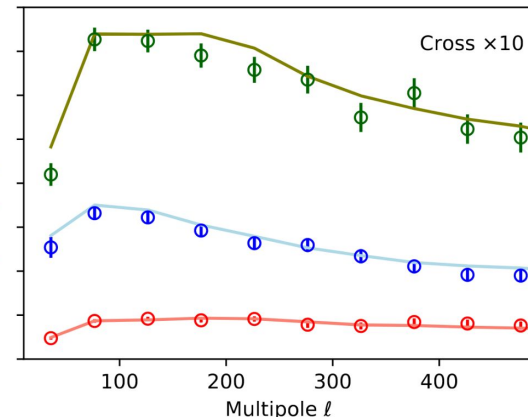
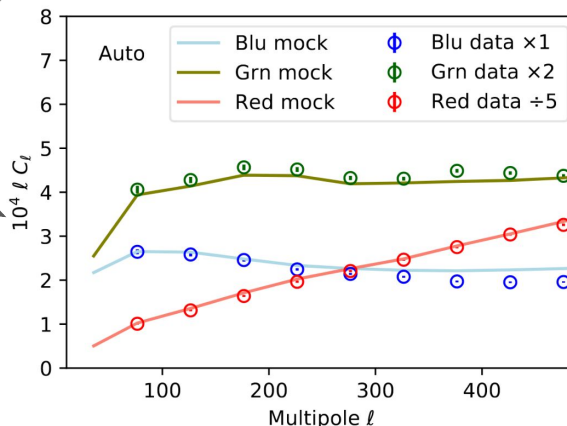
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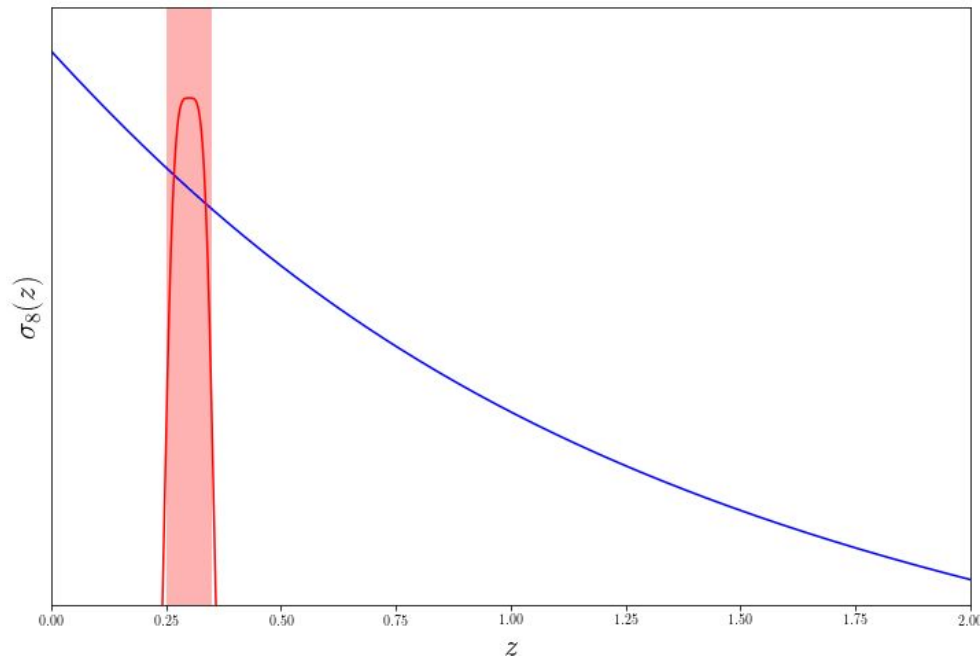
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- Due to projection you are also sensitive to  $\chi(z)$ , and  $P(k)$ .

[Yu et al. 2021](#)



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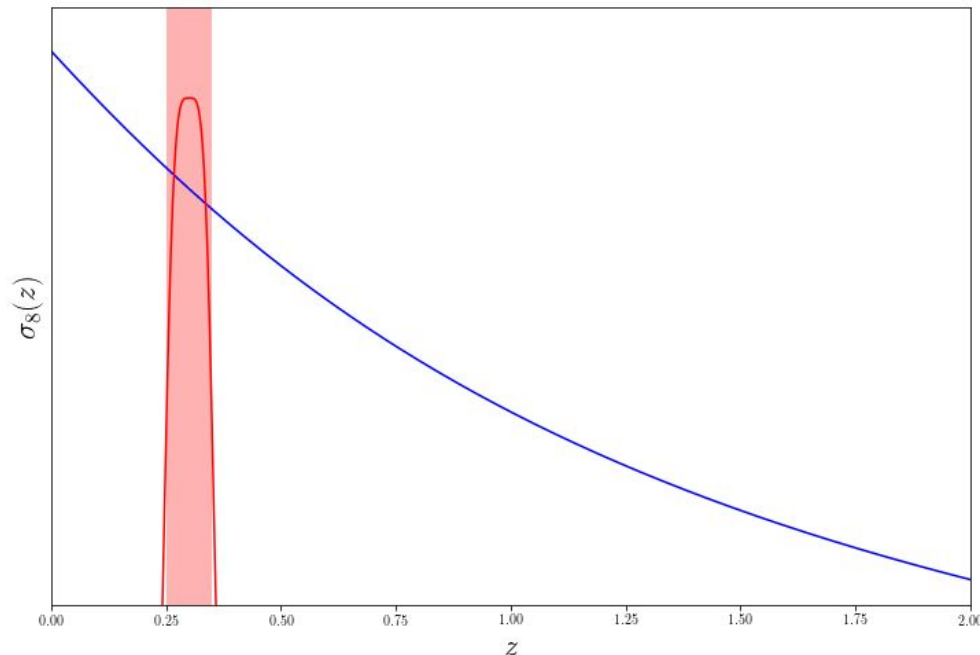
[Yu et al. 2021](#)

- LSST can do this on its own via cosmic shear, but:

1. CMB leads to significant improvements in FoM.

[Fang et al. 2021](#)

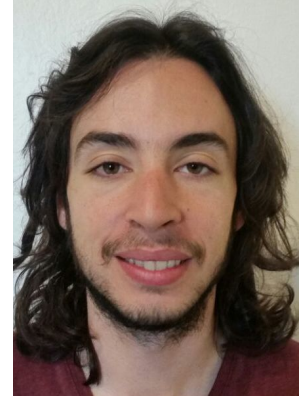
2. High redshifts?



## Growth reconstruction

**Idea:** reconstruct the linear amplitude of fluctuations from all relevant projected large-scale structure data.

- Is the growth history compatible with  $\Lambda$ CDM?
- Do different probes agree on this growth history?
- Is the current tension coming from a specific redshift range?
- + Independent analysis of existing datasets (DES, KiDS)
- + Combined constraints on  $S_8$



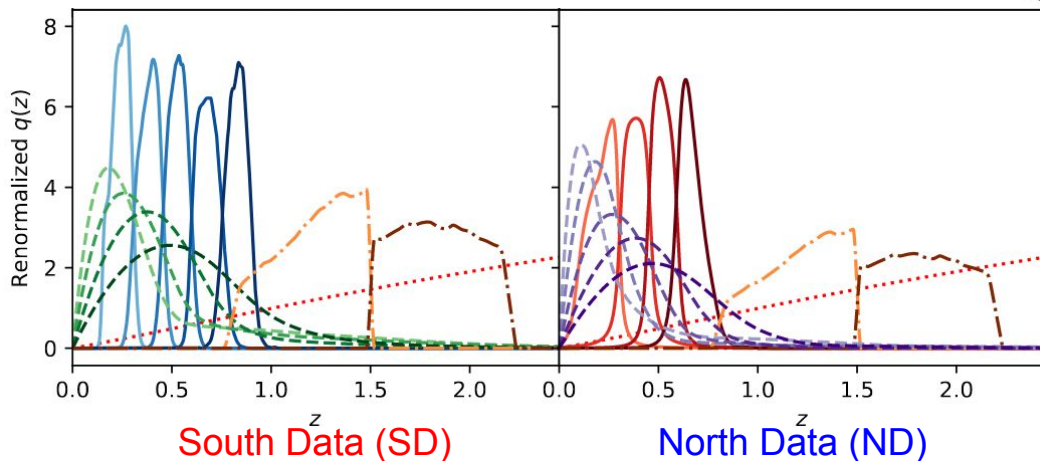
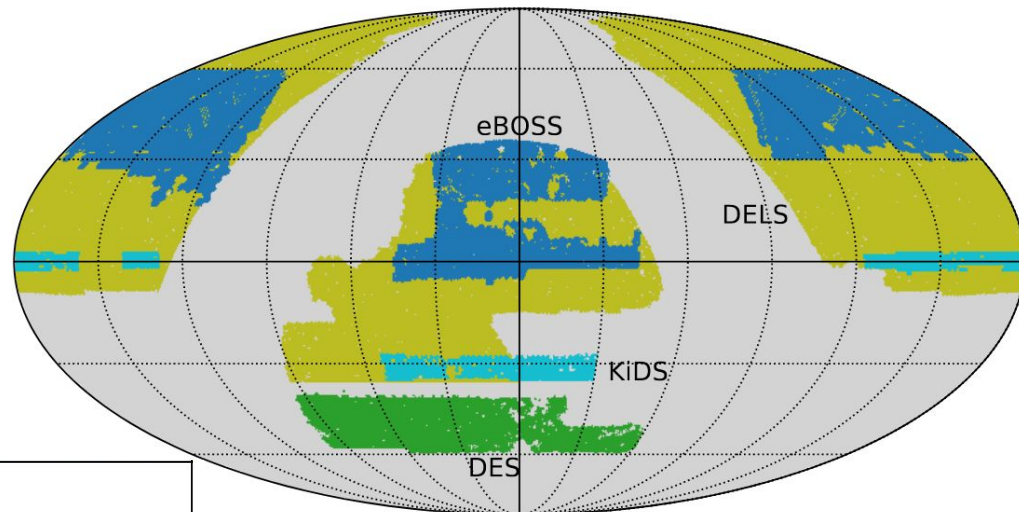
## Data:

### Shear:

- DES Y1
- KiDS-1000

### Clustering:

- DES Y1 (redMaGiC)
- DESI Legacy Survey (DELS)
- eBOSS QSO



## CMB lensing:

- Planck 2018 convergence map

[Troxel et al. 2017](#)

[Elvin-Poole et al. 2017](#)

[Asgari et al. 2017](#)

[Hang et al. 2020](#)

[Neveux et al. 2020](#)

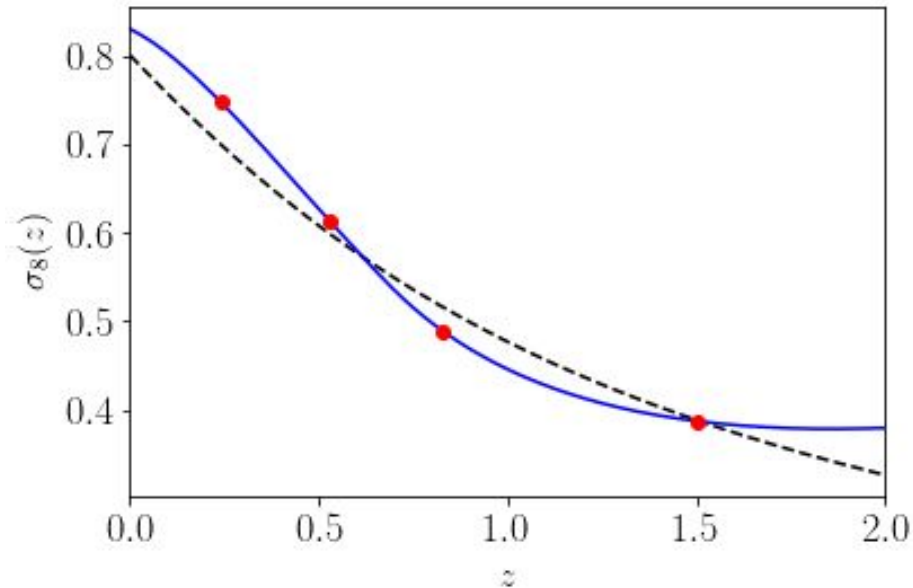
[Planck Coll. et al. 2018](#)

## Growth reconstruction: the analysis

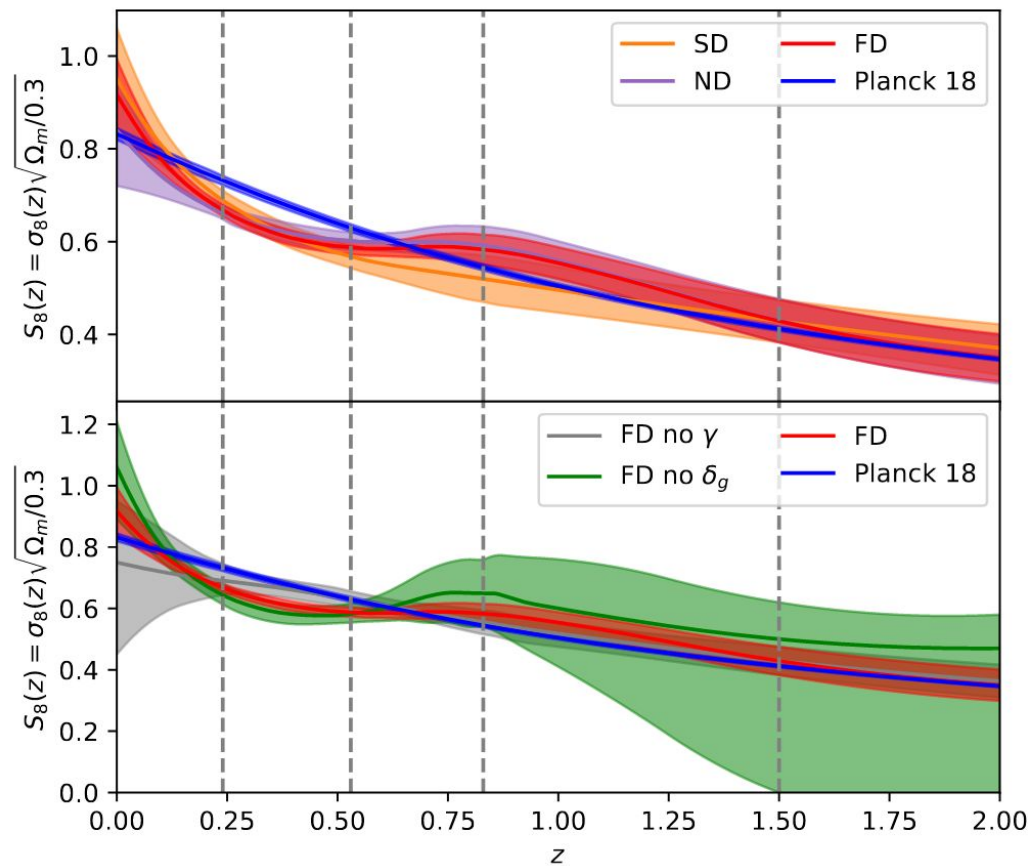
### Model:

- Background:  $\Lambda$ CDM
- Power spectrum at  $z=0$ :  $\Lambda$ CDM
- Growth history: quadratic spline with free nodes
- Non-linear matter  $P_k$ : HALOFIT
- Galaxy bias: linear ( $k_{\text{max}} = 0.15 \text{ Mpc}^{-1}$ )

$$P_L(k, z) = D^2(z) P_L(k, 0)$$



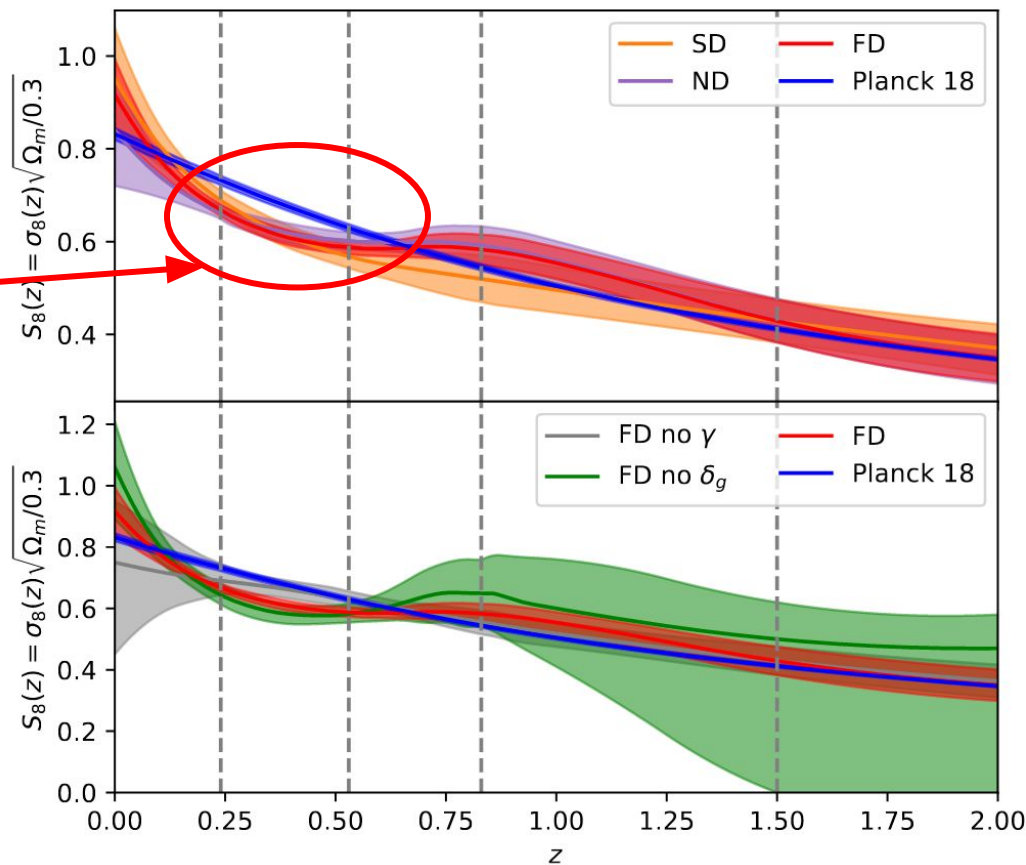
## Growth reconstruction: results



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### Results:

- Lower growth ( $\sim 2\sigma$ ) at  $0.2 < z < 0.6$

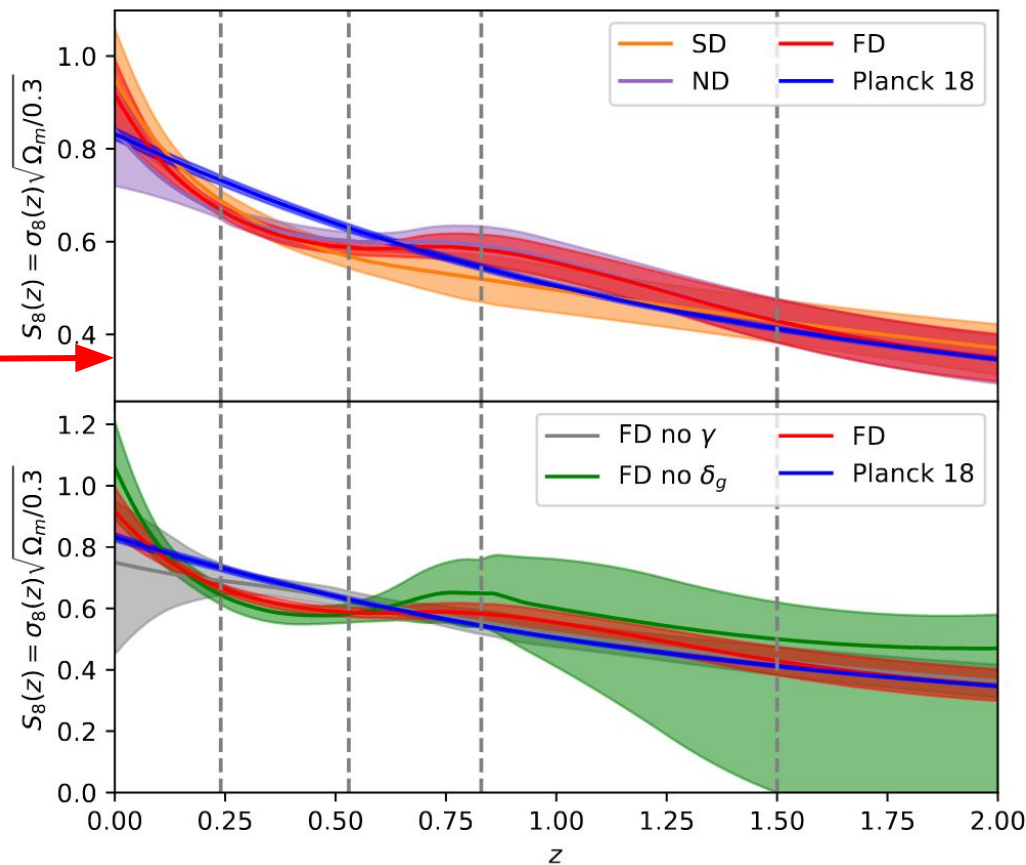




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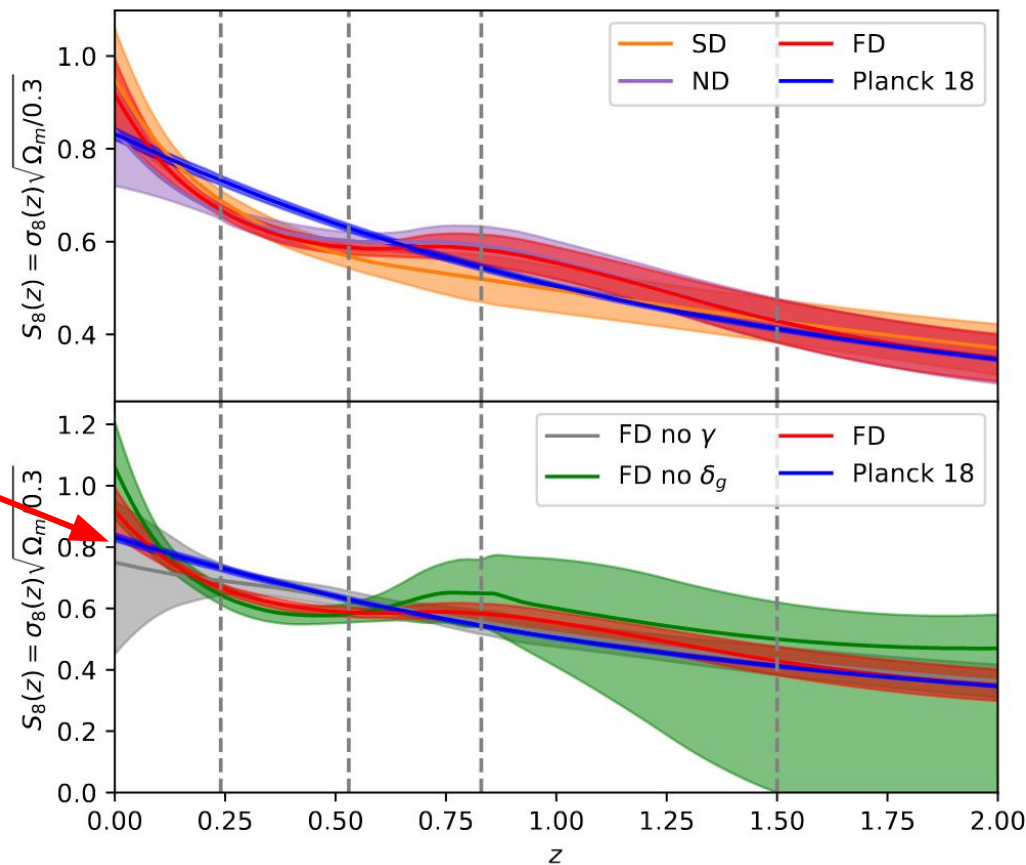
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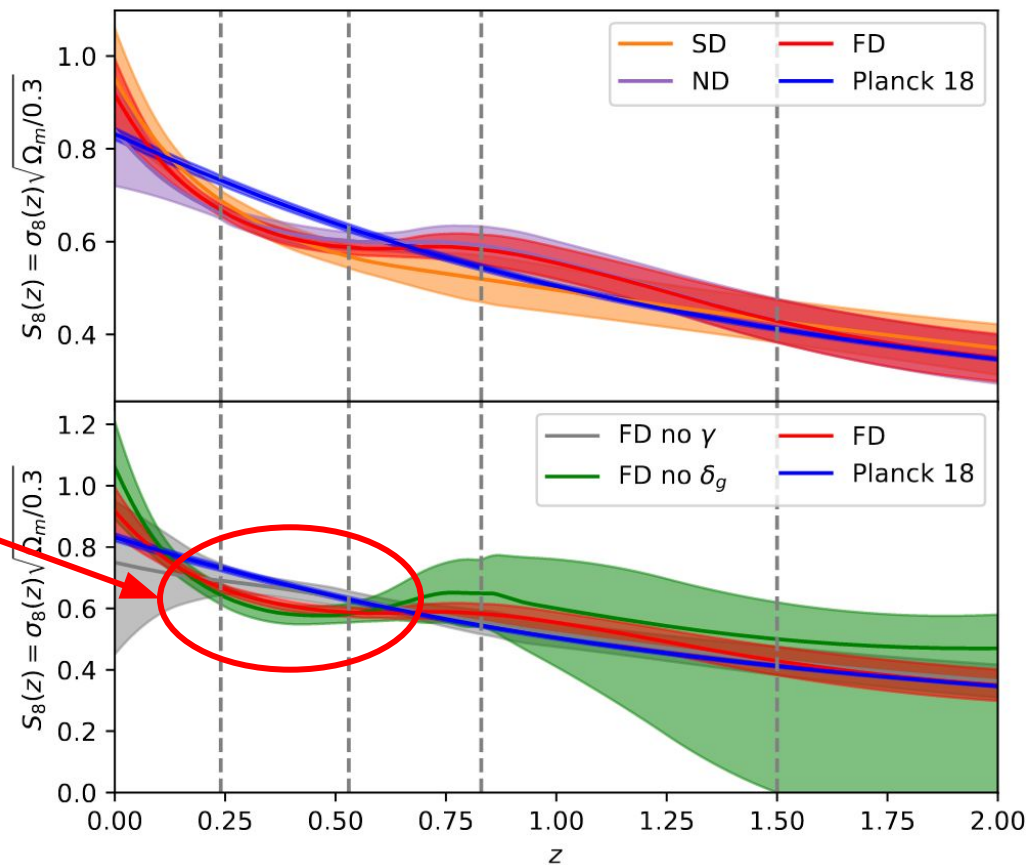
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- Clustering +  $\text{CMB}\kappa$  compatible with planck (but also with shear).

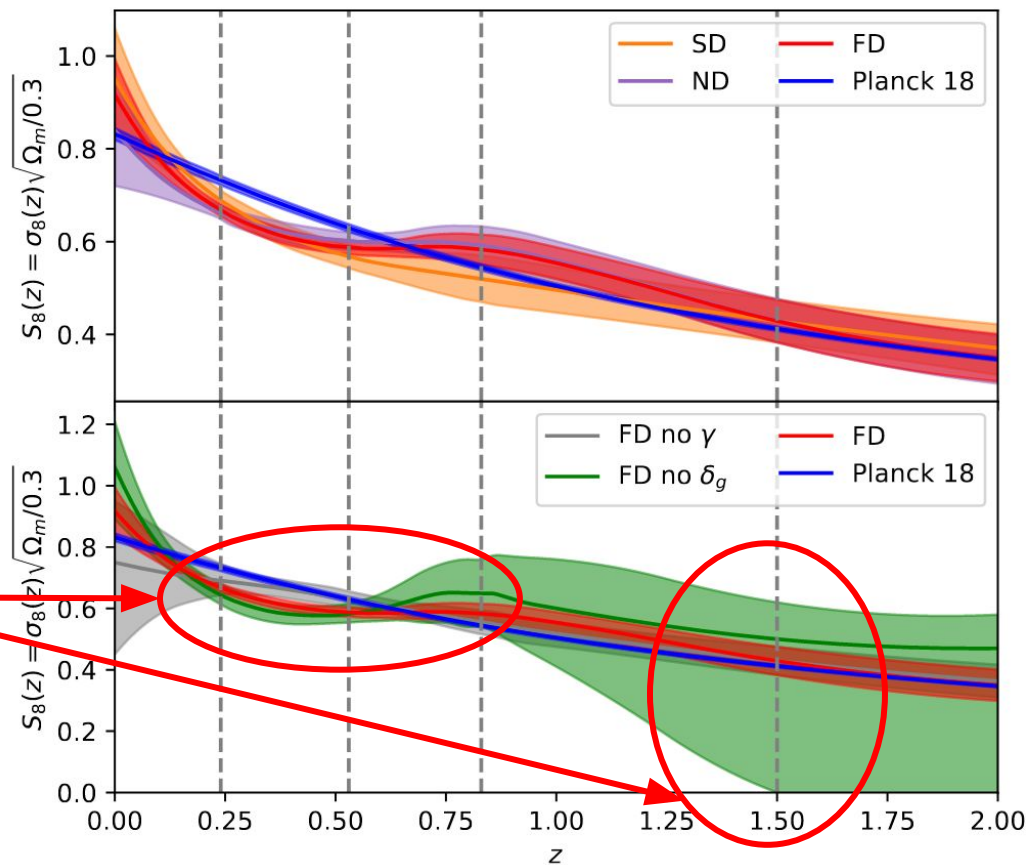


But see [Krolewski et al. 2021!](#)

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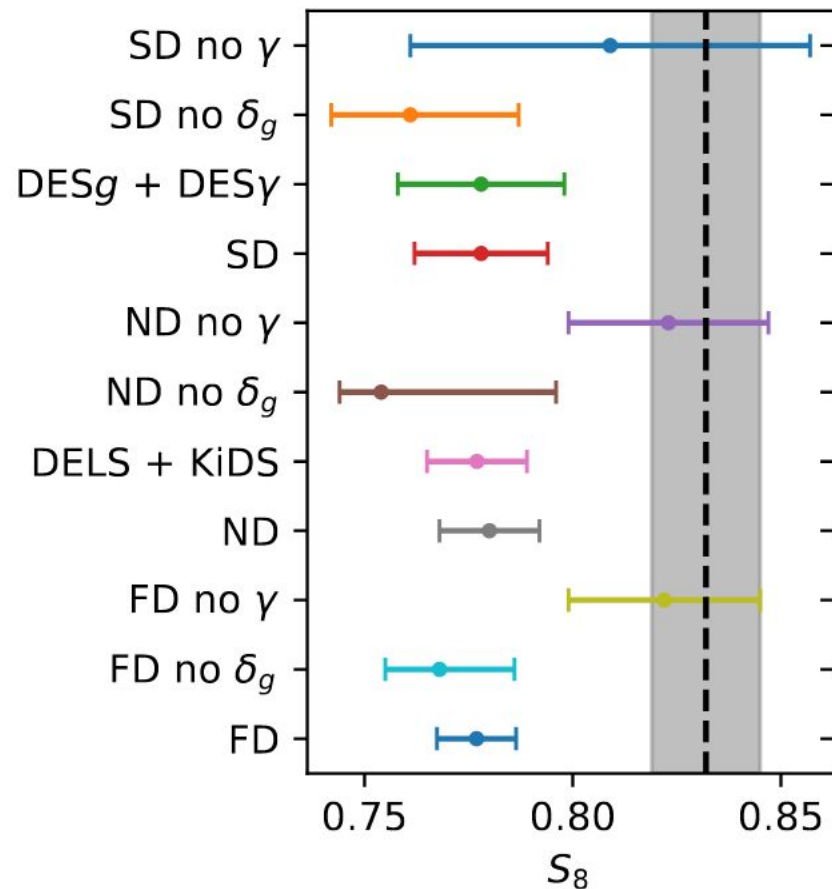
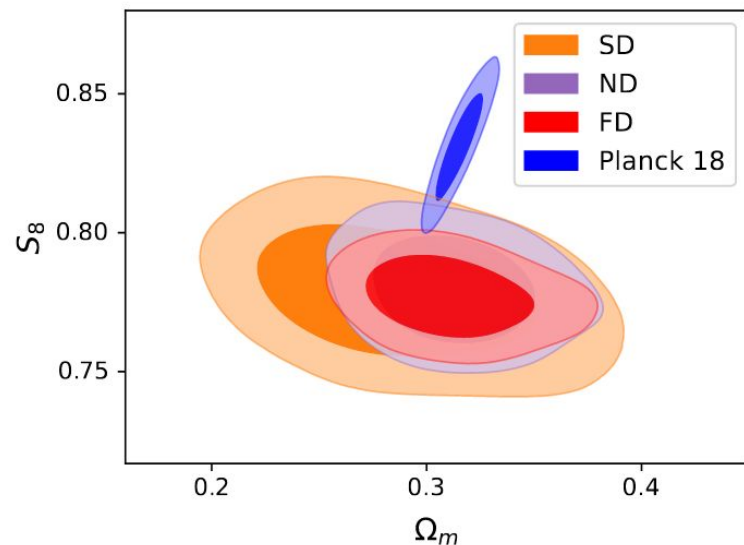
- Lower growth ( $\sim 2\sigma$ ) at  $0.2 < z < 0.6$
- North and South data recover compatible growth histories
- Tension driven by shear data
- Clustering + CMB $\kappa$  compatible with planck (but also with shear).
- Most constraining power at  $z < 0.8$ . QSO $\kappa$  vital for high- $z$  growth.



## Growth reconstruction: $\Lambda$ CDM constraints

### Results:

- $\Lambda$ CDM is an excellent fit to the low- $z$  data
- North and South data compatible
- $3.5\sigma$  tension with Planck on  $S_8$
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# X-correlation systematics: photo-z

**Arguably the most pernicious non-theoretical systematic:**

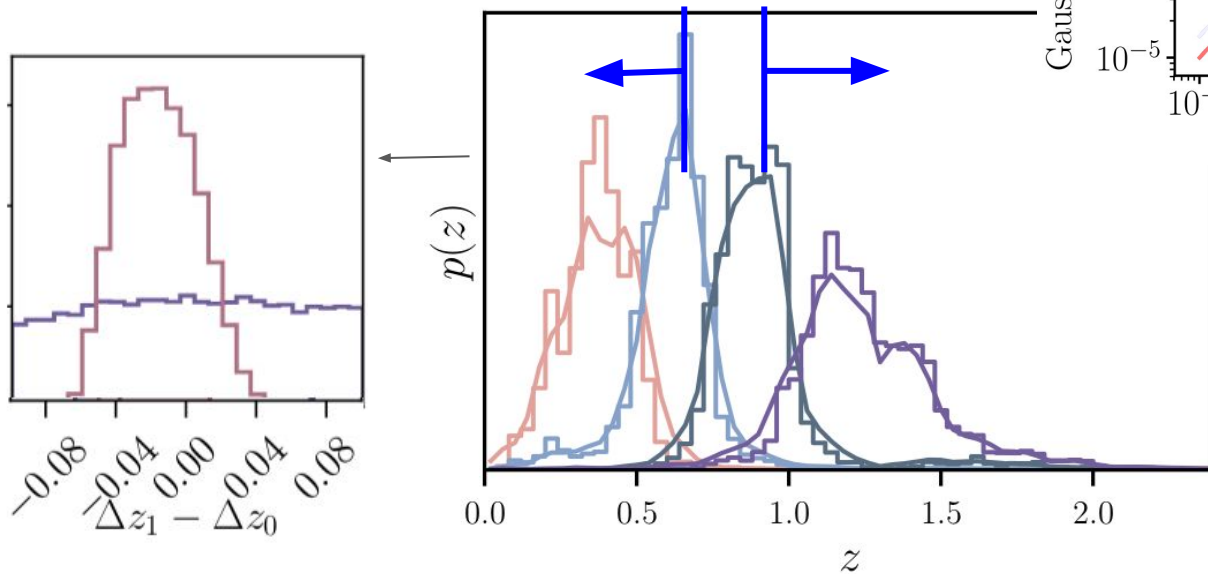
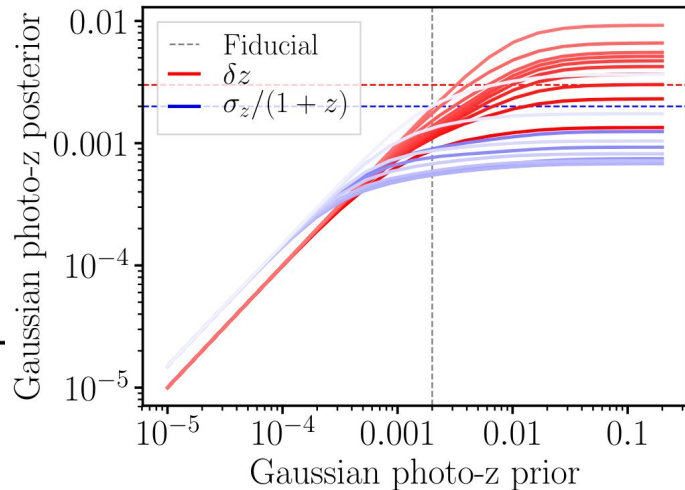
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*Hadzhiyska et al. 2020*

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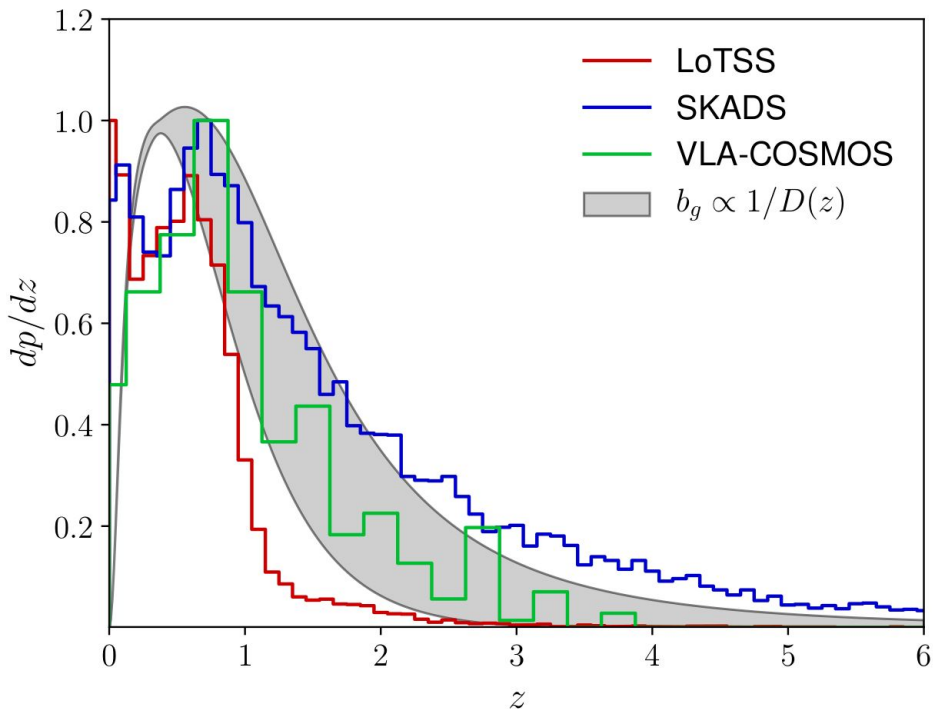
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*Nicola et al. 2020, Schaan et al. 2020*
- CMB $\kappa$  x-corrs less sensitive to  $N(z)$  uncertainties...
- ... so it can help calibrate:
  - $N(z)$  width
  - Hight- $z$  tail of faint samples*Alonso et al. 2020*

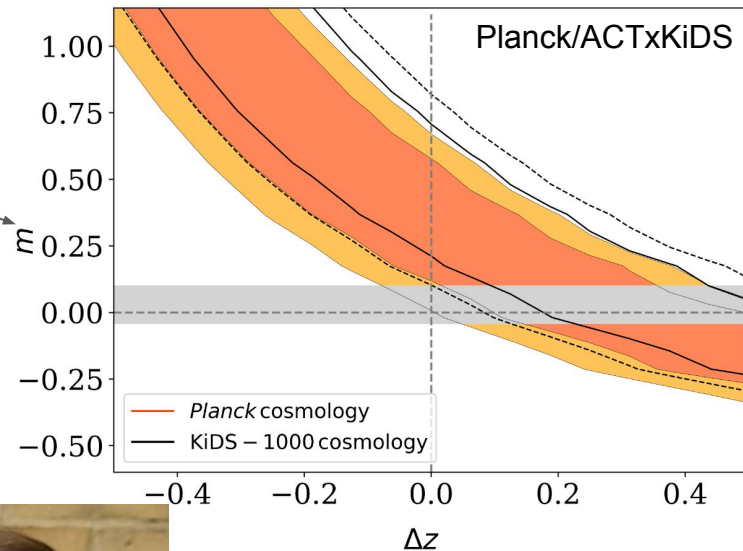
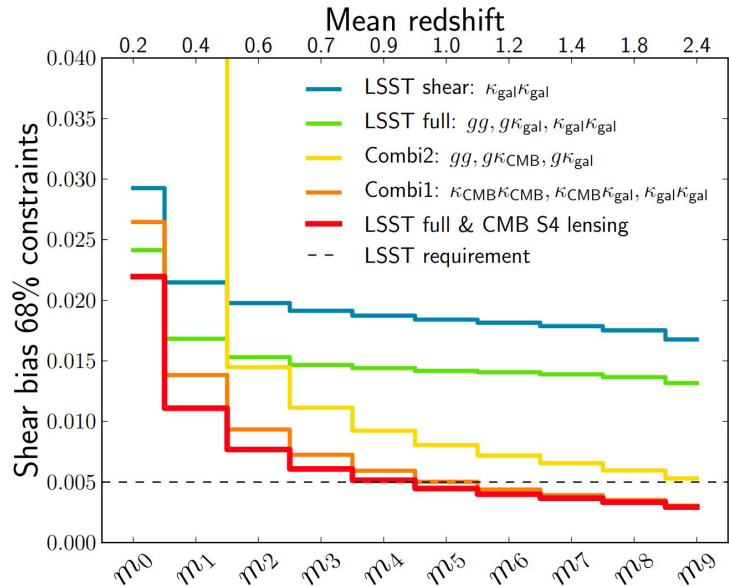




# X-correlation systematics: shear calibration

Calibratable through  $\kappa X\gamma$  (especially at high- $z$ )

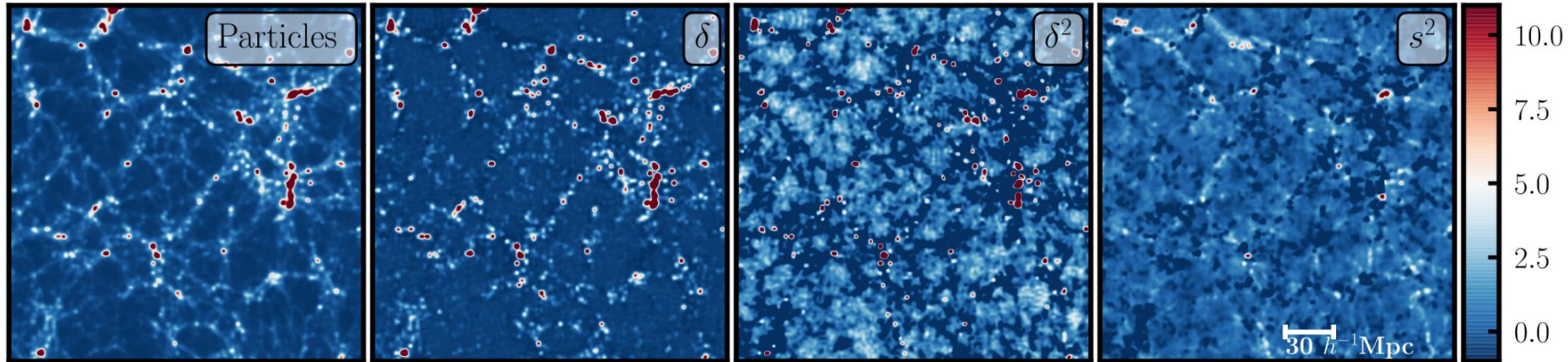
Schaan et al. 2016, Robertson et al. 2021



# X-correlation systematics: galaxy bias

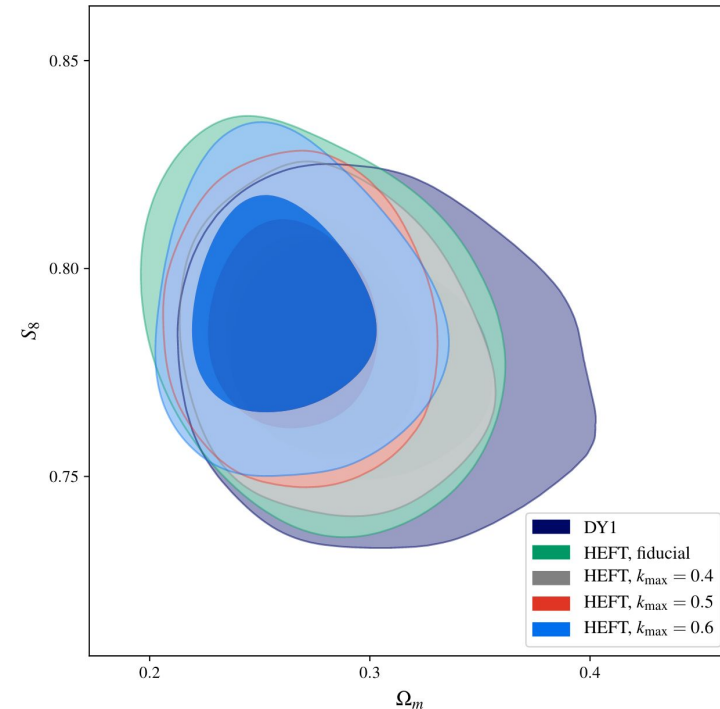
- Galaxy clustering is (by far!) the highest S/N tracer.
- Lots of data are thrown away:
  - Large-scale observational systematics (easier in x-corr)
  - **Small-scale galaxy bias**
- At LSST/S4 sensitivities we will need to go beyond linear bias (even on conservative scales).
- Promising avenue: hybrid EFT + simulations method

$$1 + \Delta_g \simeq 1 + b_1 \Delta_M + b_2 \Delta_M^2 + b_s S^2 + b_\nabla \nabla^2 \Delta_m$$

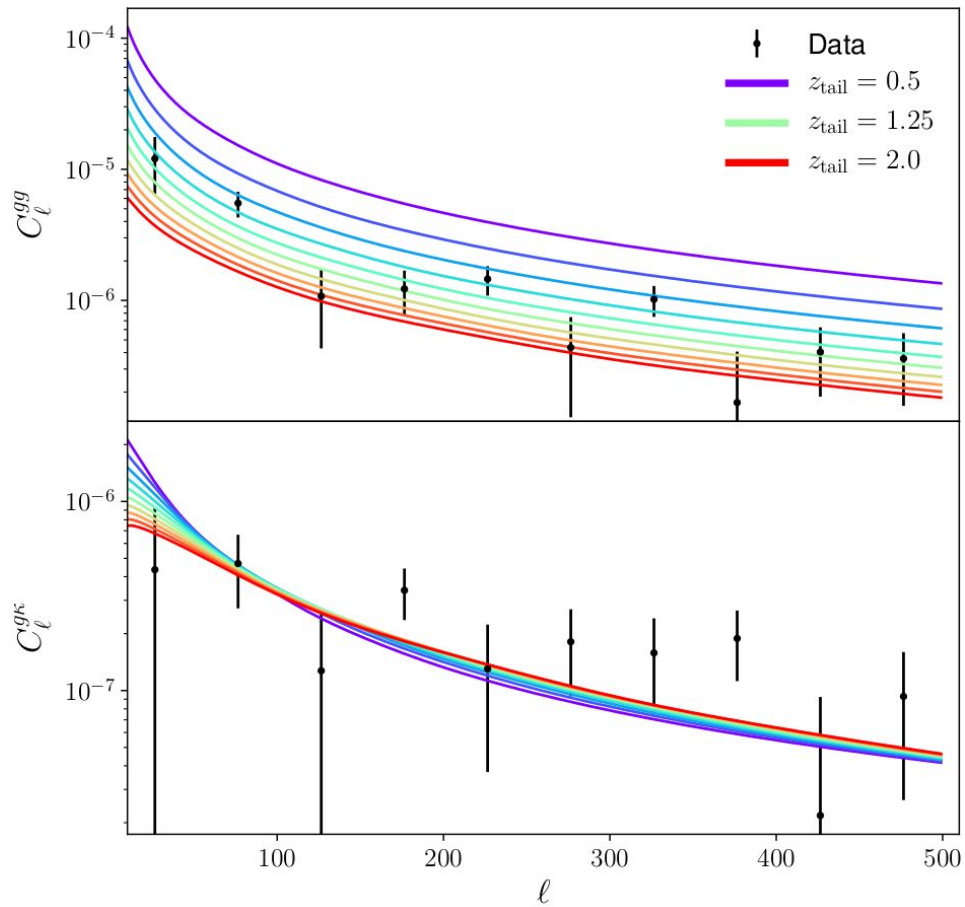


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- Promising avenue: hybrid EFT + simulations method
- Demonstration on DESY1 data ([Hadzhiyska et al. 2021](#))
  - Good fit up to  $\sim k=0.6 \text{ Mpc}^{-1}$
  - 35% better  $\Omega_m$ , 10% better  $S_8$



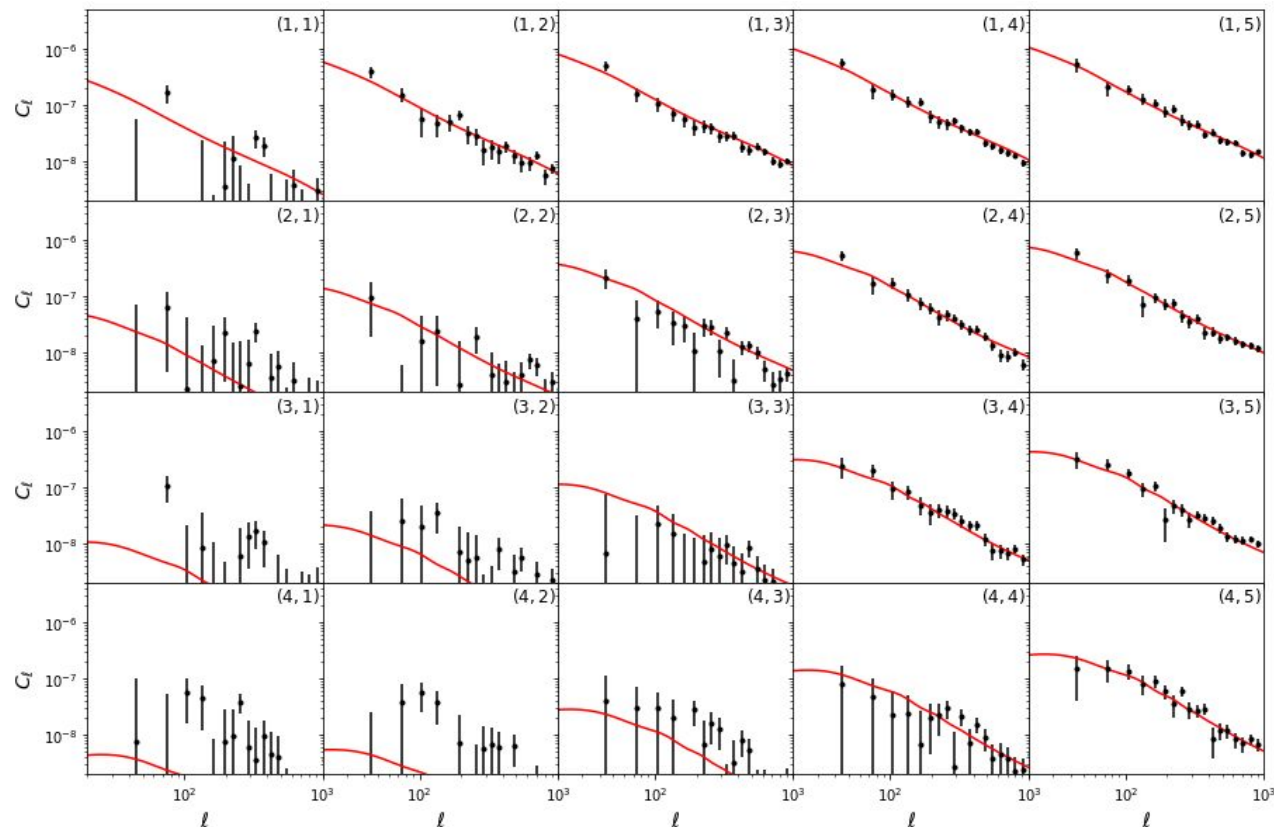
# X-correlation systematics: photo-z



## Growth reconstruction: the analysis

### Data analysis:

- Independent  $C_\ell$ -based analysis
- Analytical covariances inc. mode-coupling.
- $N_d = 1275$



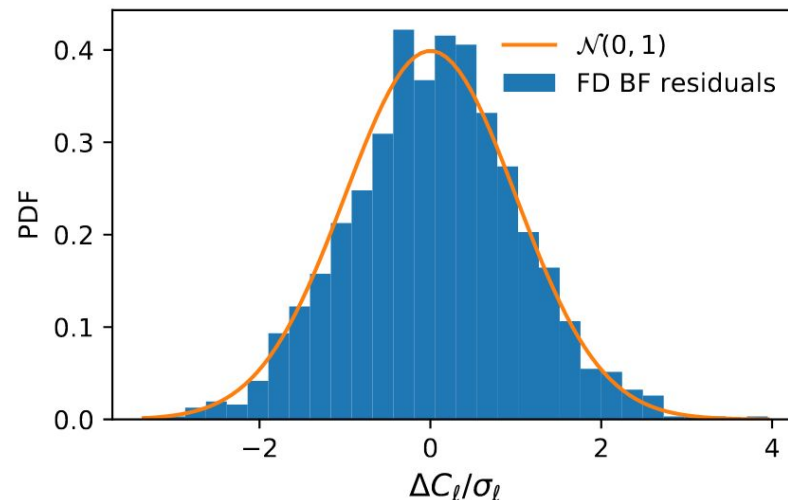
Example: Legacy survey x KiDS



## Growth reconstruction: the analysis

### Data analysis:

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- Sanity checks:
  - \* B-modes
  - \* Impact of GC systematics via deprojection
  - \* Goodness-of-fit tests

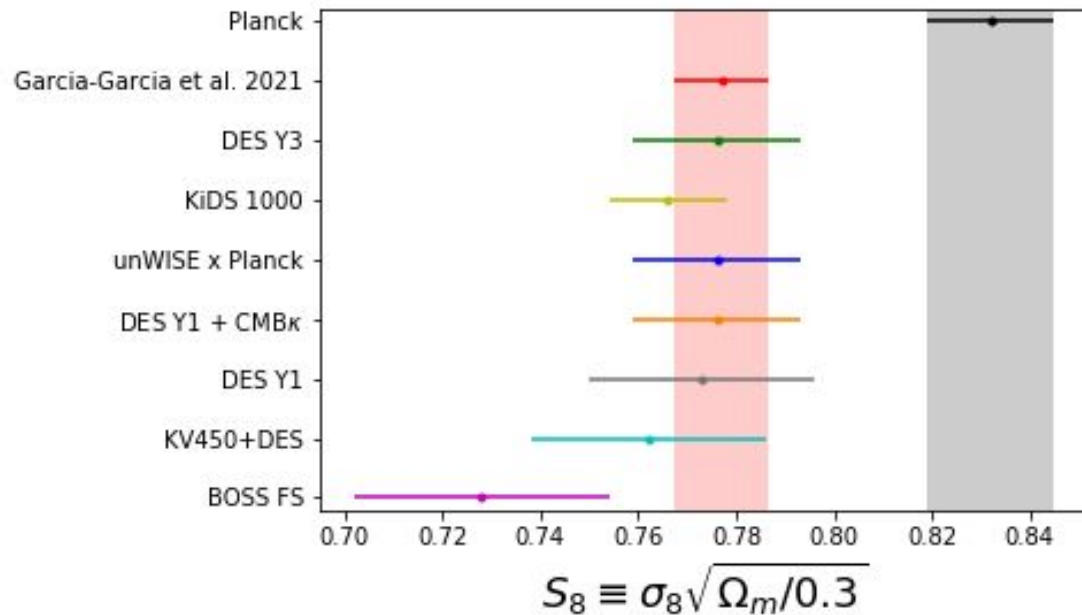


Tracer name	KiDS					Tracer name	DES $\gamma$			
	Bin 0	Bin 1	Bin 2	Bin 3	Bin 4		Bin 0	Bin 1	Bin 2	Bin 3
DELS-0	0.460	0.135	0.234	0.978	0.650	DES $g$ -0	0.396	0.733	0.704	0.294
DELS-1	0.011	0.781	0.661	0.105	0.438	DES $g$ -1	0.737	0.983	0.889	0.071
DELS-2	0.226	0.425	0.752	0.163	0.861	DES $g$ -2	0.378	0.809	0.264	0.288
DELS-3	0.483	0.324	0.567	0.569	0.269	DES $g$ -3	0.923	0.073	0.905	0.354
CMB $\kappa$	0.280	0.050	0.078	0.167	0.450	DES $g$ -4	0.517	0.048	0.889	0.459
KiDS-0	0.949	0.604	0.463	0.586	0.761	CMB $\kappa$	0.168	0.170	0.432	0.943
KiDS-1	-	0.795	0.292	0.877	0.336	DES $\gamma$ -0	0.436	0.232	0.630	0.774
KiDS-2	-	-	0.603	0.044	0.006	DES $\gamma$ -1	-	0.545	0.991	0.645
KiDS-3	-	-	-	0.977	0.406	DES $\gamma$ -2	-	-	0.813	0.245
KiDS-4	-	-	-	-	0.612	DES $\gamma$ -3	-	-	-	0.977

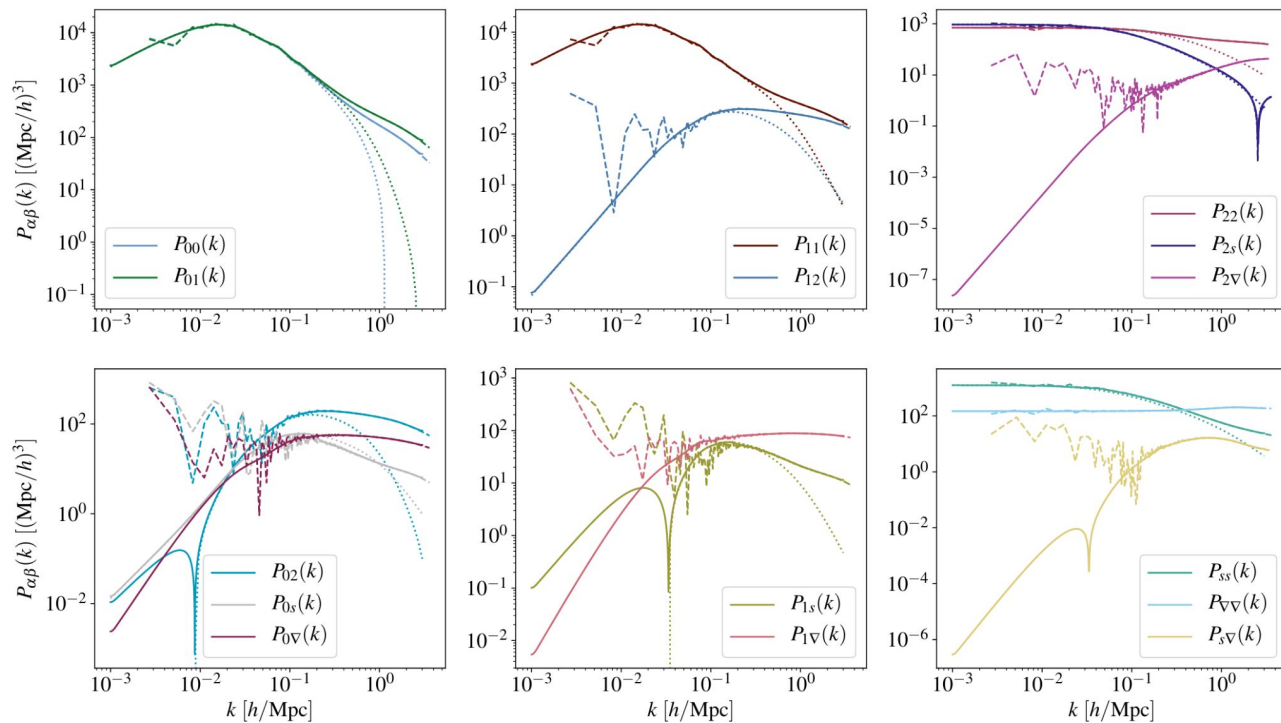
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## Hybrid EFT bias expansion



- Implementation based on [ABACUS simulation](#).
- Smooth transition between LPT and sims.



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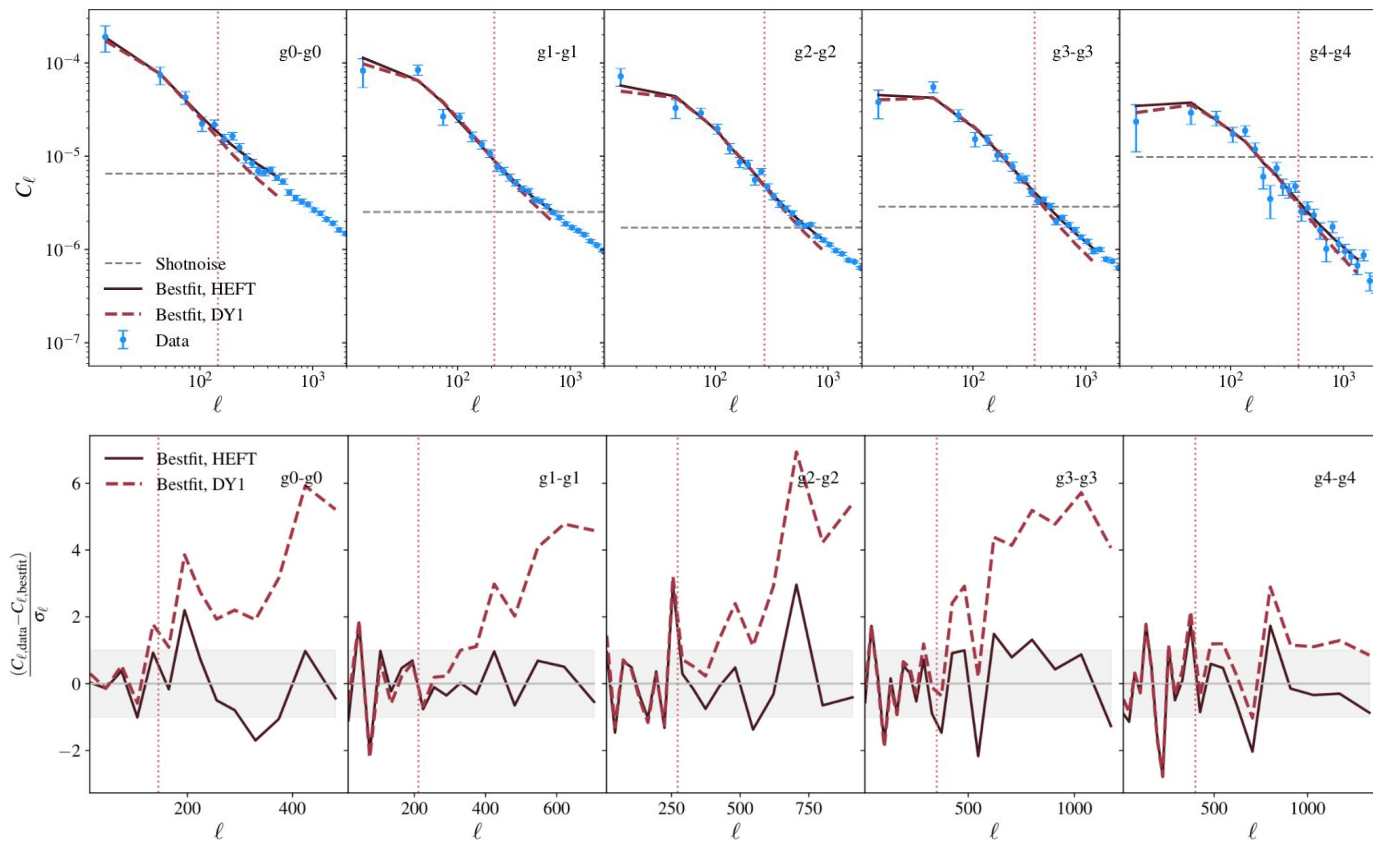
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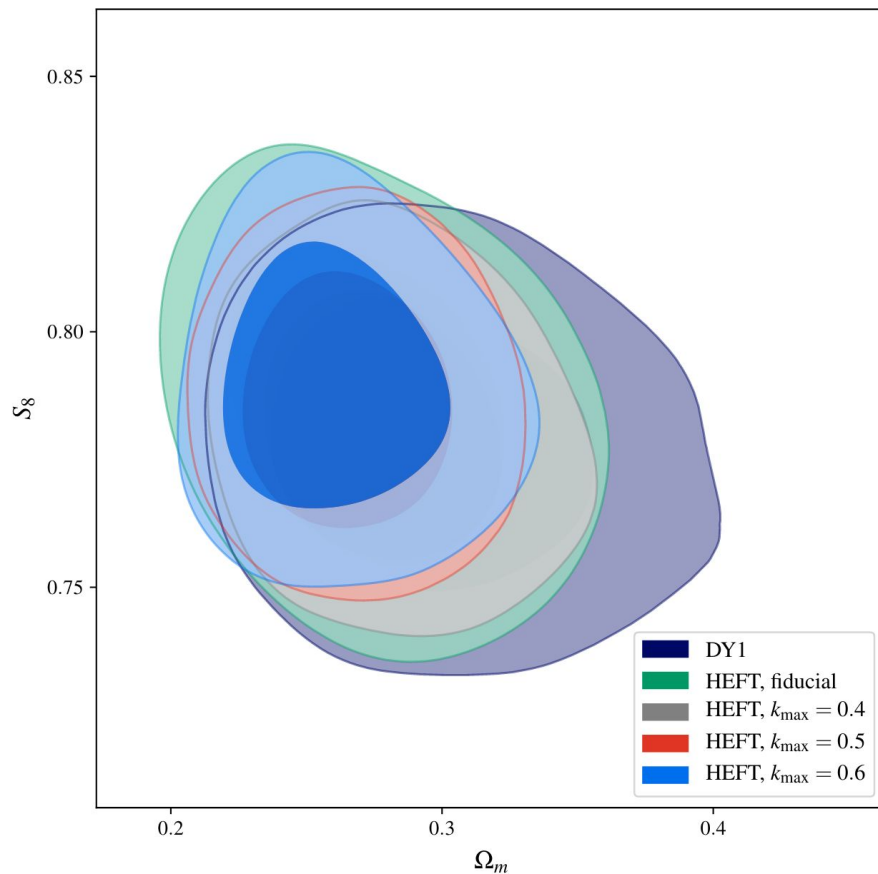
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