CMB lensing cross-correlations with large-scale structure surveys
Probes of late-time structure

- $\delta_g(\hat{n})$
- $\gamma_g(\hat{n})$
- $N_c(\lambda, z)$
- $\delta_c(\hat{n}; \lambda)$
- $\nu_r(\hat{n})$

- $\kappa(\hat{n})$
- $y(\hat{n})$
- $\Delta_{CMB}(\hat{n})$
- $\Delta_{KSZ}(\hat{n})$
- $\Delta_{CTB}(\hat{n})$
Probes of late-time structure

I'll talk about this
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

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

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
What I will talk about: tomography

\[ x(\theta, \phi) = \int dz \bar{X}(z) \left[ 1 + \delta_X(\theta, \phi, z) \right] \]

\[ \langle x \delta_g(z_*) \rangle \propto b_X(z_*) \bar{X}(z_*) \]
What I will talk about: tomography

Over time tomography has become synonymous with “$N \times 2pt$” or “extracting information from a combination of projected tracers of structure”

Hadziyska et al. 2021
Tomographic reconstruction: growth

- Consider CMB lensing + $\delta_g$:

\[
C_{\ell}^{\kappa g} \propto \sigma_8^2 b_g \\
C_{\ell}^{gg} \propto (\sigma_8 b_g)^2
\]

So you can measure $\sigma_8(z)$
Tomographic reconstruction: growth

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C.f.: Hang et al. 2021, Krolewski et al. 2021
Tomographic reconstruction: growth

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C.f.: Hang et al. 2021, Krolewski et al. 2021

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

Yu et al. 2021
Tomographic reconstruction: growth

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C.f.: Hang et al. 2021, Krolewski et al. 2021

- Due to projection you are also sensitive to $\chi(z)$, and $P(k)$.
  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 $S_8$
Tomographic reconstruction: growth

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 ($k_{\text{max}} = 0.15 \text{ Mpc}^{-1}$)

\[ P_L(k, z) = D^2(z) P_L(k, 0) \]
Tomographic reconstruction: growth

Growth reconstruction: results

\[ S_8(z) = \sigma_8(z) \sqrt{\Omega_m/0.3} \]

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\( z \) values: 0.00, 0.25, 0.50, 0.75, 1.00, 1.25, 1.50, 1.75, 2.00

Graphs showing the growth reconstruction results with various models and data sets.
Results:
- Lower growth (~2σ) at 0.2<z<0.6
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- Lower growth ($\sim 2\sigma$) at $0.2 < z < 0.6$
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- Lower growth ($\sim 2\sigma$) at $0.2 < z < 0.6$
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- Tension driven by shear data
- Clustering + CMB$\kappa$ compatible with Planck (but also with shear).

But see *Krolewski et al. 2021*!
Growth reconstruction: results

Results:
- Lower growth (~2σ) at 0.2<z<0.6
- North and South data recover compatible growth histories
- Tension driven by shear data
- Clustering + CMBκ compatible with planck (but also with shear).
- Most constraining power at z<0.8. QSOxκ 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 $S_8$
- Driven by cosmic shear data

Tomographic reconstruction: growth

Garcia-Garcia et al. 2021
Arguably the most pernicious non-theoretical systematic:
- Need to characterize all modes of uncertainty in the N(z)

_Hadzhiyska et al. 2020_
Arguably the most pernicious non-theoretical systematic:
- Need to characterize all modes of uncertainty in the N(z) 
  *Hadzhiyska et al. 2020*
- Can be self-calibrated through internal correlations (to some extent) 
  *Nicola et al. 2020, Schaan et al. 2020*
Arguably the most pernicious non-theoretical systematic:
- Need to characterize all modes of uncertainty in the $N(z)$
  \cite{Hadzhiyska2020}
- Can be self-calibrated through internal correlations
  (to some extent)
  \cite{Nicola2020, Schaan2020}
- CMB $\kappa$ x-corrs less sensitive to $N(z)$ uncertainties...
- ... so it can help calibrate:
  - $N(z)$ width
  - Hight-z tail of faint samples
  \cite{Alonso2020}
X-correlation systematics: shear calibration

Calibratable through $kx\gamma$ (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

\[ 1 + \Delta_g \approx 1 + b_1 \Delta_M + b_2 \Delta^2_M + b_s S^2 + b_\nabla \nabla^2 \Delta_m \]
- Galaxy clustering is (by far!) the highest S/N tracer.
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- At LSST/S4 sensitivities we will need to go beyond linear bias (even on conservative scales).
- 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
Tomographic reconstruction: growth

Garcia-Garcia et al. 2021

Growth reconstruction: the analysis

Data analysis:
- Independent $C_\ell$-based analysis
- Analytical covariances inc. mode-coupling.
- $N_d = 1275$
- Sanity checks:
  * B-modes
  * Impact of GC systematics via deprojection
  * Goodness-of-fit tests

![PDF](image)

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<th>Bin 1</th>
<th>Bin 2</th>
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<td>0.460</td>
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Beefing up clustering

Hybrid EFT bias expansion

- Implementation based on ABACUS simulation.
- Smooth transition between LPT and sims.
Beefing up clustering

Hybrid EFT bias expansion

\[ P_{\alpha\beta}(k; \tilde{\theta}) = P_{\alpha\beta}(k; \tilde{\theta}_*) + (\tilde{\theta} - \tilde{\theta}_*) \cdot \nabla_\theta P_{\alpha\beta}(k) \]

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- Markedly improved performance in goodness of fit on high-k
Beefing up clustering

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- Markedly improved performance in goodness of fit on high-k
- 35% better $\Omega_m$
- 10% better $S_8$

Potential gains in $H_0$