HARVARD UNIVERSITY

The CMB x LSS Skew-Spectrum

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Based on arxiv:2202.11724 with Shu-Fan Chen and Cora Dvorkin

Outline

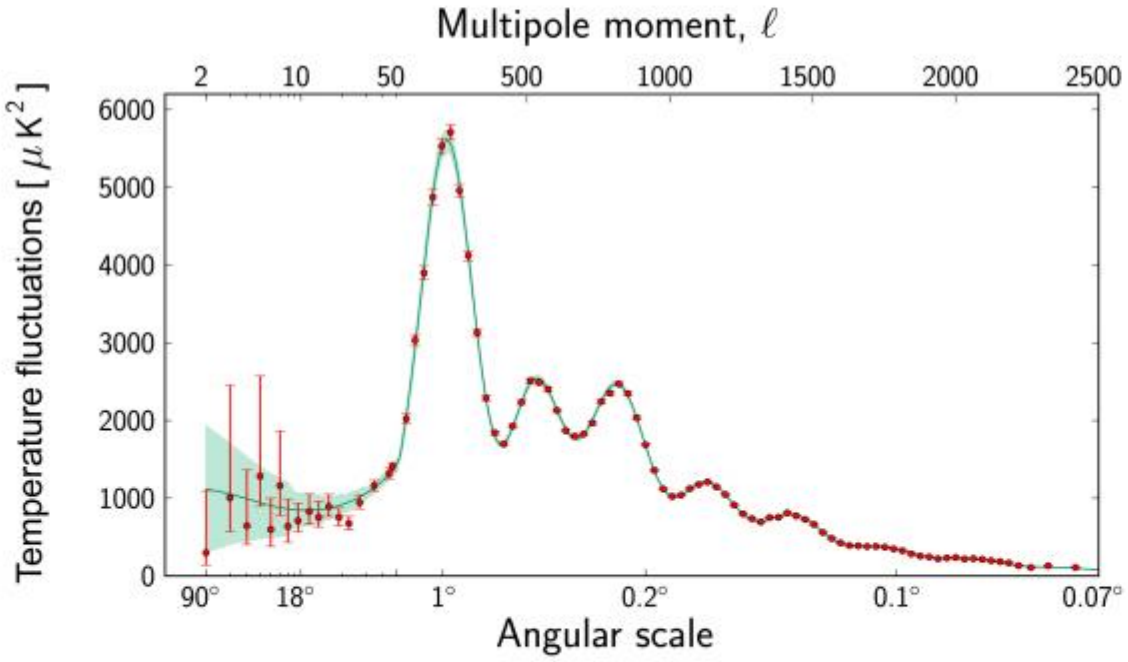
- ❑Background
- ❑Skew-Spectra
- ❑Fisher Analysis
- ❑Simulations Analysis

Today in Cosmology

- ΛCDM model well constrained by CMB T&P!

- There are still potential issues:
  - H_0 tension (now 5 sigma)
  - S_8 tension (2-3 sigma)

- And new physics to constrain:
  - Nature of Dark Matter
  - Inflation
  - …



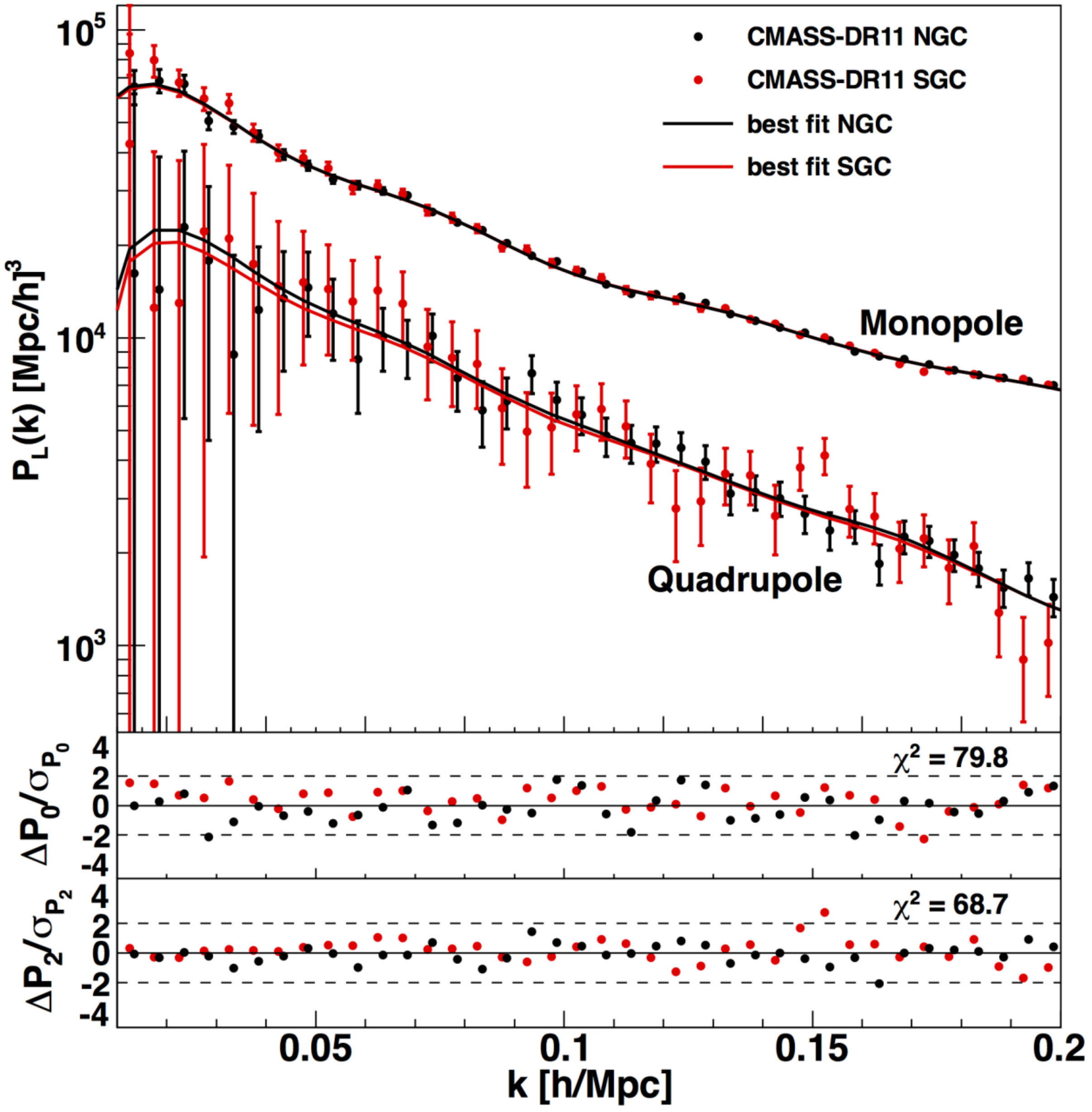
Large-Scale Structure

- In principle, access to order-of-magnitude more modes

Better constraints!

Resolve issues

+ avenue for new physics!

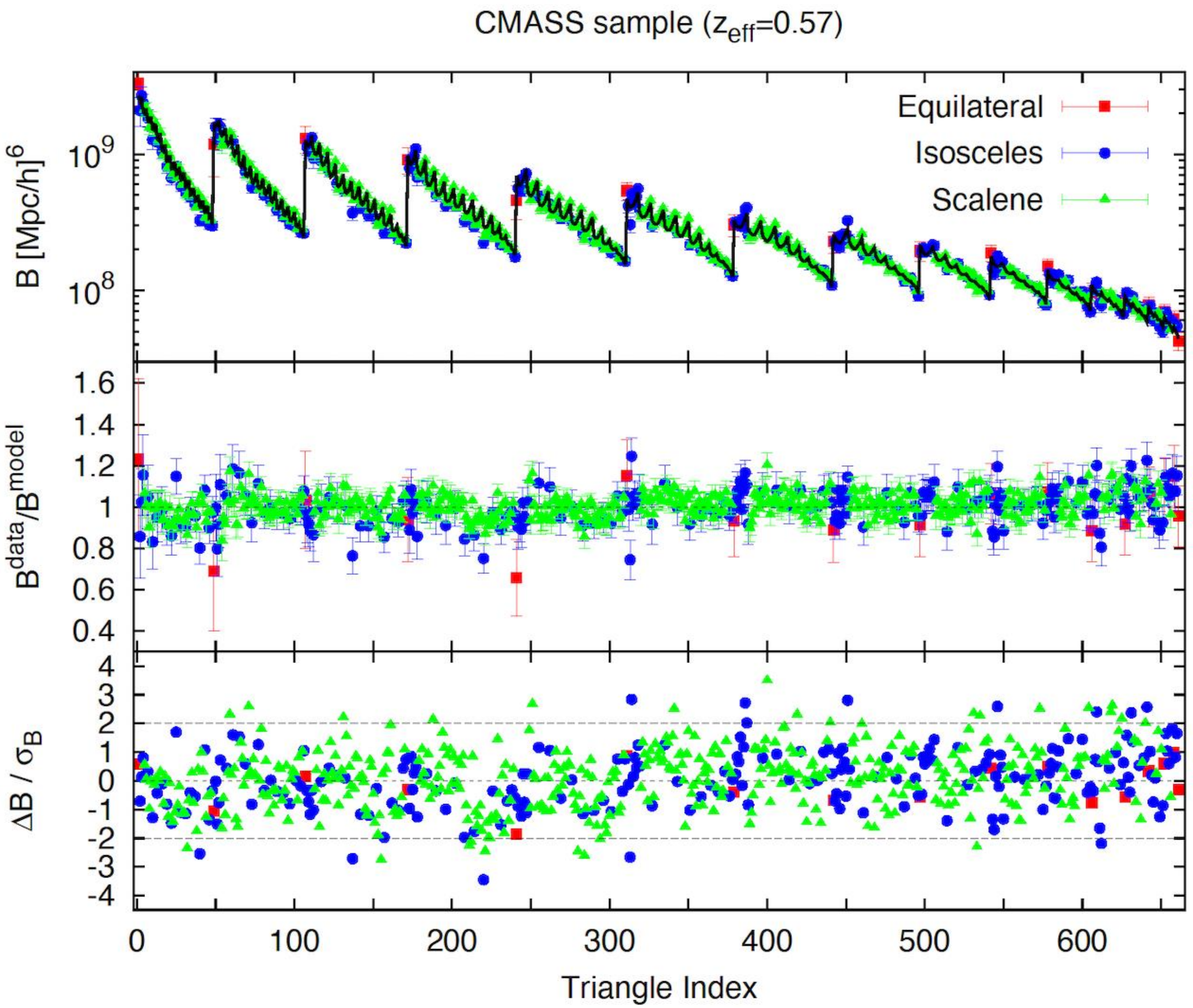


BOSS power spectra – Beutler et al (2014)

Large-Scale Structure

- Contrast to CMB, LSS contains lot of info in higher order correlators, e.g. bispectrum

- Recently measured and analysed for BOSS



Gil-Marin (2020)

CMB Weak Lensing

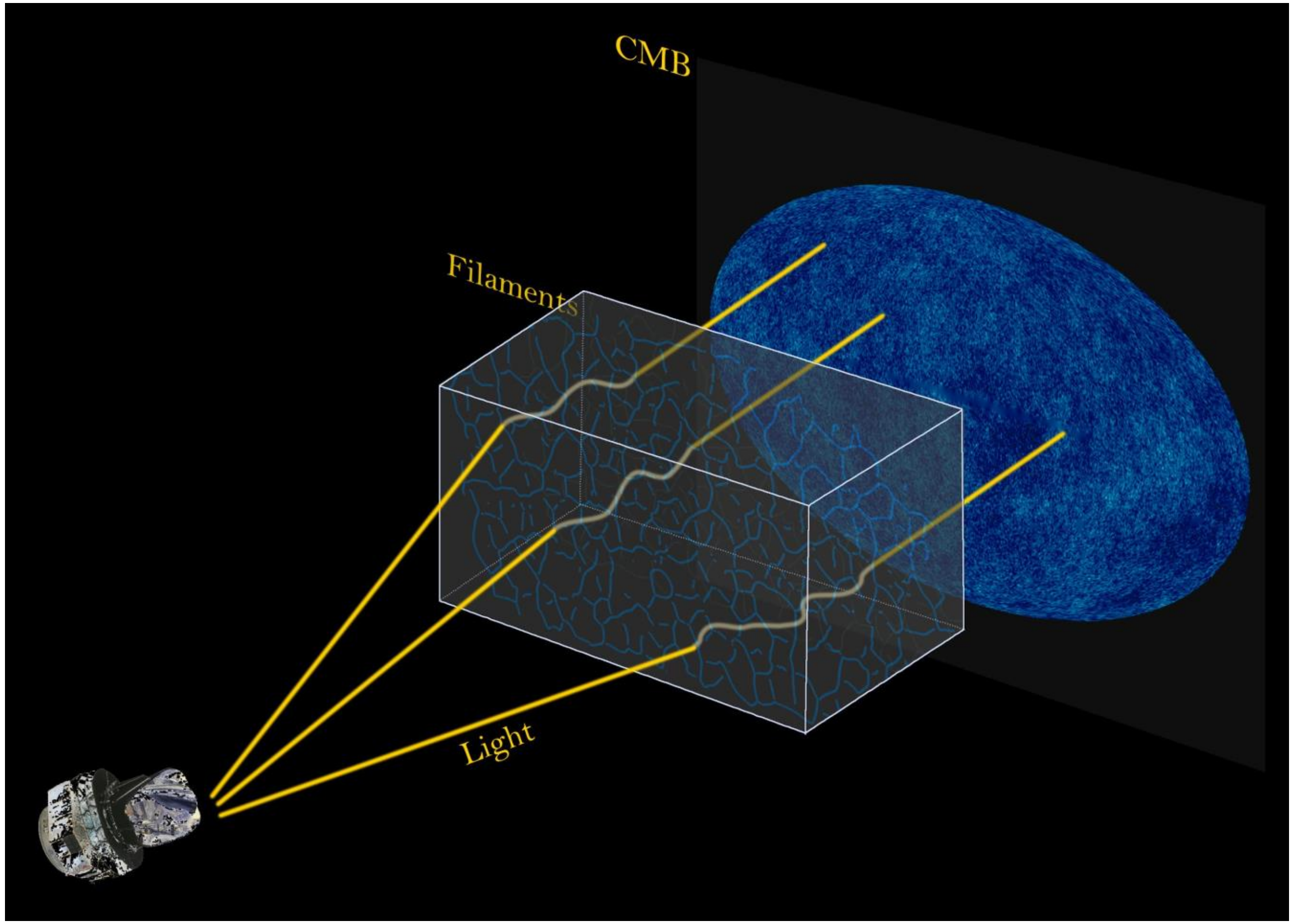
- CMB photons deflected by matter from source to present

Determined by intermediate matter

↑

➡ $\tilde{T}(\hat{x}) = T(\hat{x} + \hat{d})$

➡ $\kappa(\hat{\boldsymbol{n}}) \quad = \quad \nabla \cdot \hat{d}(\boldsymbol{n})$

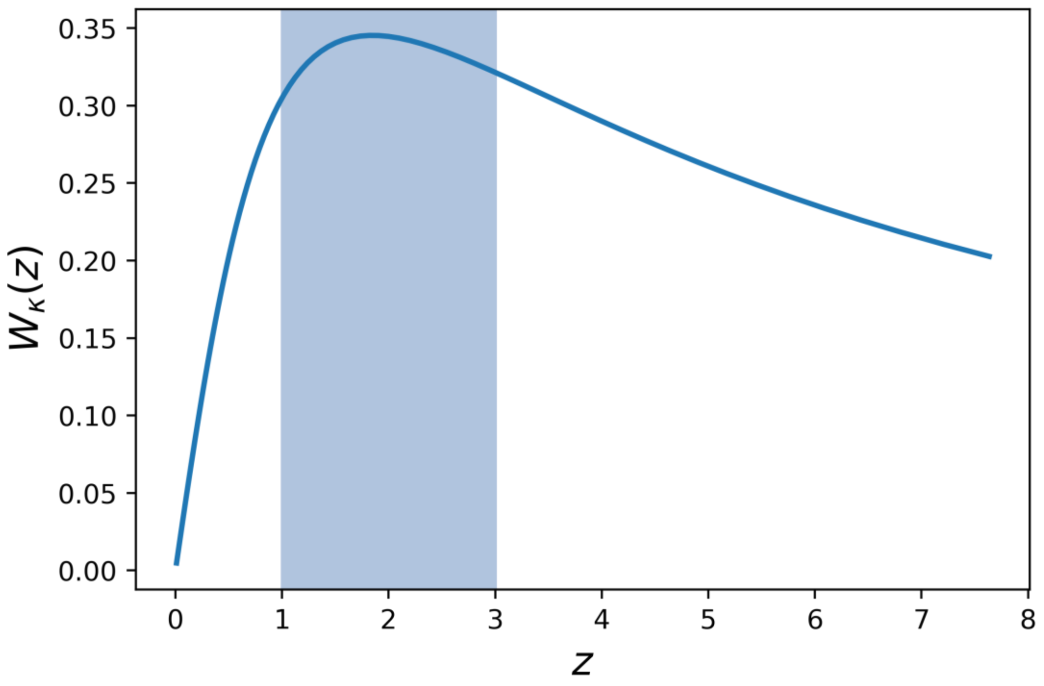


CMB Weak Lensing

- CMB photons deflected by matter from source to present

$$\kappa(\hat{n}) = \int_0^\infty \mathrm{d}\chi\, W_\kappa(\chi)\delta_m(\chi, \hat{n}),$$

$$W_\kappa(\chi) = \frac{3}{2}\Omega_{m0}H_0^2\frac{1+z(\chi)}{H(\chi)}\frac{\chi(\chi_s-\chi)}{\chi_s}\theta(\chi_s-\chi)$$



Kernel peaks z=1-3

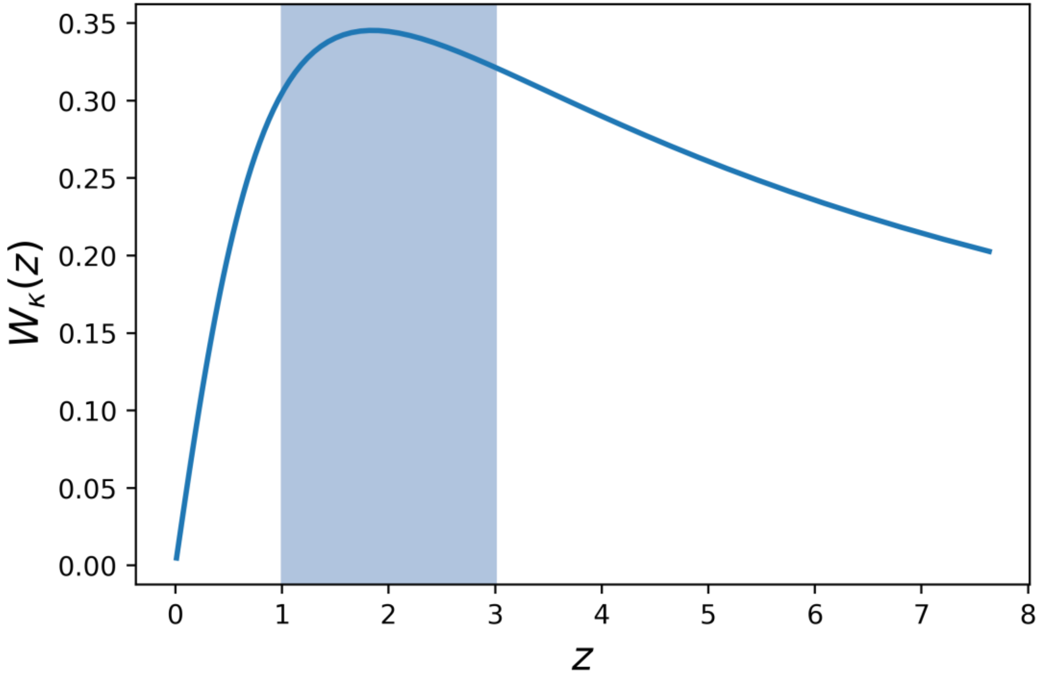
CMB Weak Lensing

- CMB photons deflected by matter from source to present

$$\kappa(\hat{n}) = \int_0^\infty \mathrm{d}\chi \, W_\kappa(\chi) \delta_m(\chi, \hat{n}),$$

$$W_\kappa(\chi) = \frac{3}{2}\Omega_{m0} H_0^2 \frac{1+z(\chi)}{H(\chi)} \frac{\chi(\chi_s - \chi)}{\chi_s} \theta(\chi_s - \chi)$$

Correlated with Galaxies!



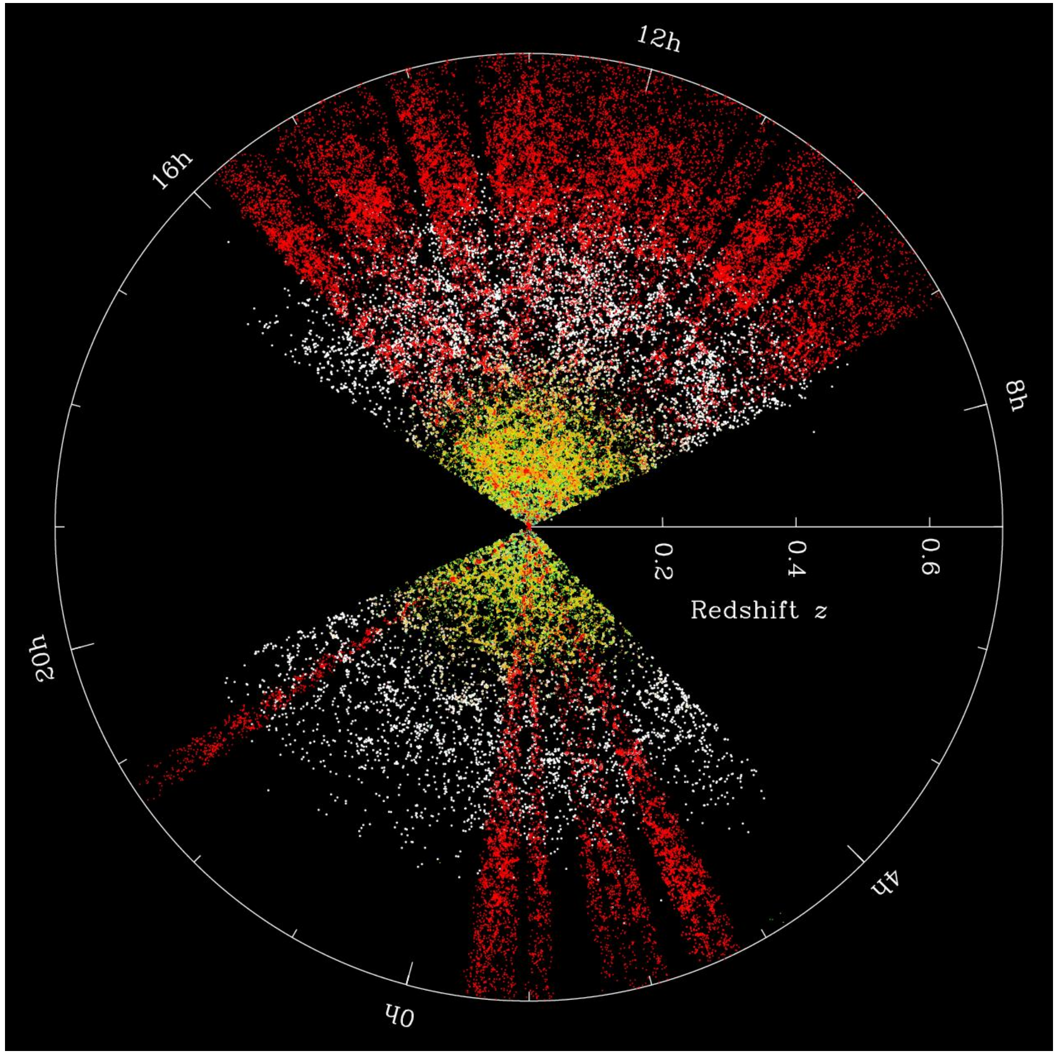
Kernel peaks z=1-3

Tomography

- Observe galaxy angular positions
  + redshifts

$$\delta_g^i(\hat{n}) = \int_0^\infty \mathrm{d}\chi \, W_g^i(\chi) \delta_g(\chi, \hat{n}) \,,$$

$$W_g^i(\chi) = \frac{1}{\bar{n}_i} \frac{\mathrm{d}n_i}{\mathrm{d}\chi} \,, \quad \bar{n}_i \equiv \int_0^\infty \mathrm{d}\chi \, \frac{\mathrm{d}n_i}{\mathrm{d}\chi}$$



SDSS III - BOSS

Projected Observables

- Power spectra:

$$\langle \delta^a_{\ell m} \delta^{b*}_{\ell' m'} \rangle = \delta^{\rm K}_{\ell\ell'} \delta^{\rm K}_{mm'} C^{ab}_\ell$$

- Bispectra:

$$\langle \delta^a_{\ell_1 m_1} \delta^b_{\ell_2 m_2} \delta^c_{\ell_3 m_3} \rangle = \mathcal{G}^{m_1 m_2 m_3}_{\ell_1 \ell_2 \ell_3} b^{abc}_{\ell_1 \ell_2 \ell_3}$$

…

- Polyspectra (in principle)

Projected Observables

- Bispectra: $$\langle \delta^a_{\ell_1 m_1} \delta^b_{\ell_2 m_2} \delta^c_{\ell_3 m_3} \rangle = \mathcal{G}^{m_1 m_2 m_3}_{\ell_1 \ell_2 \ell_3} b^{abc}_{\ell_1 \ell_2 \ell_3}$$

Projected Observables

- Bispectra:

$$\langle \delta^a_{\ell_1 m_1} \delta^b_{\ell_2 m_2} \delta^c_{\ell_3 m_3} \rangle = \mathcal{G}^{m_1 m_2 m_3}_{\ell_1 \ell_2 \ell_3} \boxed{b^{abc}_{\ell_1 \ell_2 \ell_3}}$$

- Theory angular bispectra obtained by projecting Fourier space ones

$$B(\boldsymbol{k}_1, \boldsymbol{k}_2, \boldsymbol{k}_3) \xrightarrow{\int \mathrm{d}\chi} b_{\ell_1 \ell_2 \ell_3}$$

Perturbation Theory/N-body

Projected Observables

- Bispectra: $$\langle \delta^a_{\ell_1 m_1} \delta^b_{\ell_2 m_2} \delta^c_{\ell_3 m_3} \rangle = \mathcal{G}^{m_1 m_2 m_3}_{\ell_1 \ell_2 \ell_3} b^{abc}_{\ell_1 \ell_2 \ell_3}$$
- In perturbation theory, can be written as:

$$b^{abc}_{\ell_1 \ell_2 \ell_3} = \sum_{n_1 n_2 n_3} c^{abc}_{n_1 n_2 n_3} \int_0^\infty \mathrm{d}r\, r^2 \tilde{I}^{ac}_{\ell_1}(r; n_1) \tilde{I}^{bc}_{\ell_2}(r; n_2) \tilde{I}^{c}_{\ell_3}(r; n_3)$$

$$\tilde{I}^{ab}_\ell(r; n) \equiv 4\pi \int_0^\infty \mathrm{d}\chi\, W_a(\chi) D_+(\chi) \int_0^\infty \mathrm{d}k\, k^{2+n} j_\ell(kr) j_\ell(kr) P^{ab}(k)$$

$$\tilde{I}^{a}_\ell(r; n) \equiv 4\pi \int_0^\infty \mathrm{d}\chi\, W_a(\chi) D_+^2(\chi) \int_0^\infty \mathrm{d}k\, k^{2+n} j_\ell(kr) j_\ell(kr)$$

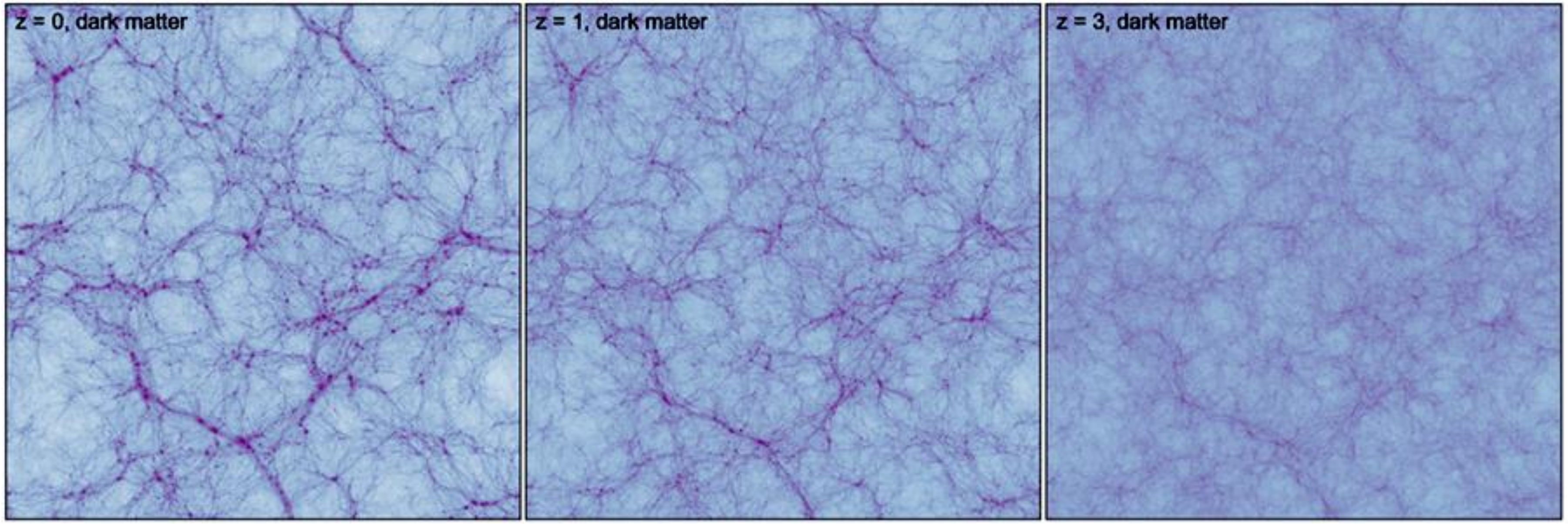
} Can be computed efficiently using Limber/FFTLog!

Chen, Lee, Dvorkin (2021)

Gravitational Sources of non-Gaussianity

δ_{NL} ← δ_L

Gravitational evolution



IllustrisTNG (2021)

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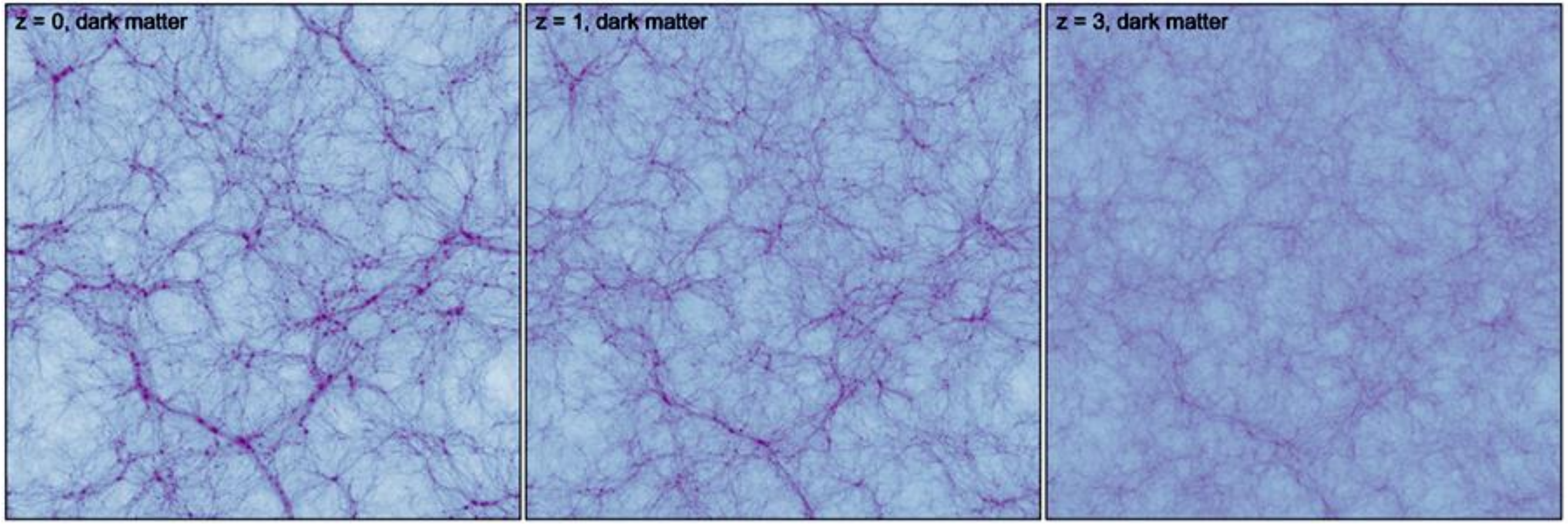


EFT of LSS

IllustrisTNG (2021)

Gravitational Sources of non-Gaussianity

δ_{NL} ← δ_L

Gravitational evolution

- Galaxy bispectrum:

$$\begin{aligned} B^{ggg}(\boldsymbol{k}_1, \boldsymbol{k}_2, \boldsymbol{k}_3) = & \, 2\left(\frac{17}{21}b_1^3 + b_1^2 b_2 - \frac{2}{3}b_1^2 b_{\mathcal{G}_2}\right)\mathbf{P}_0(\hat{\boldsymbol{k}}_1 \cdot \hat{\boldsymbol{k}}_2)P(k_1)P(k_2) \\ & + 2b_1^3 \frac{1}{2}\left(\frac{k_1}{k_2} + \frac{k_2}{k_1}\right)\mathbf{P}_1(\hat{\boldsymbol{k}}_1 \cdot \hat{\boldsymbol{k}}_2)P(k_1)P(k_2) \\ & + 2\left(\frac{4}{21}b_1^3 + \frac{2}{3}b_1^2 b_{\mathcal{G}_2}\right)\mathbf{P}_2(\hat{\boldsymbol{k}}_1 \cdot \hat{\boldsymbol{k}}_2)P(k_1)P(k_2) \\ & + 2 \text{ perms.} \end{aligned}$$

Desjacques, Jeong, Schmidt (2018)

Gravitational Sources of non-Gaussianity

δ_{NL} ← δ_L

Gravitational evolution

- Galaxy bispectrum:

$$
\begin{aligned}
B^{ggg}(\boldsymbol{k}_1, \boldsymbol{k}_2, \boldsymbol{k}_3) = 2\left(\frac{17}{21}b_1^3 + b_1^2 b_2 - \frac{2}{3}b_1^2 b_{\mathcal{G}_2}\right)&\boxed{\mathbf{P}_0(\hat{\boldsymbol{k}}_1 \cdot \hat{\boldsymbol{k}}_2)} P(k_1)P(k_2) \\
+ 2b_1^3 \frac{1}{2}\left(\frac{k_1}{k_2} + \frac{k_2}{k_1}\right)&\boxed{\mathbf{P}_1(\hat{\boldsymbol{k}}_1 \cdot \hat{\boldsymbol{k}}_2)} P(k_1)P(k_2) \\
+ 2\left(\frac{4}{21}b_1^3 + \frac{2}{3}b_1^2 b_{\mathcal{G}_2}\right)&\boxed{\mathbf{P}_2(\hat{\boldsymbol{k}}_1 \cdot \hat{\boldsymbol{k}}_2)} P(k_1)P(k_2) \\
+ 2\ \text{perms.}&
\end{aligned}
$$

Desjacques, Jeong, Schmidt (2018)

Post-Born Corrections

- Correction to Born approximation produces second order terms

Born: $$\kappa(\hat{n}) = \int_0^\infty \mathrm{d}\chi\, W_\kappa(\chi)\delta_m(\chi, \hat{n})$$

$$\kappa^{(2)}(\boldsymbol{L}) = -4\int \mathrm{d}\chi W_\kappa(\chi, \chi_s) \int \mathrm{d}\chi' W_\kappa(\chi', \chi) \int_{L'} \boldsymbol{L}' \cdot \boldsymbol{L}\boldsymbol{L}' \cdot (\boldsymbol{L} - \boldsymbol{L}')\Psi(\boldsymbol{L}', \chi)\Psi(\boldsymbol{L} - \boldsymbol{L}', \chi')$$

Generate tree-level bispectra

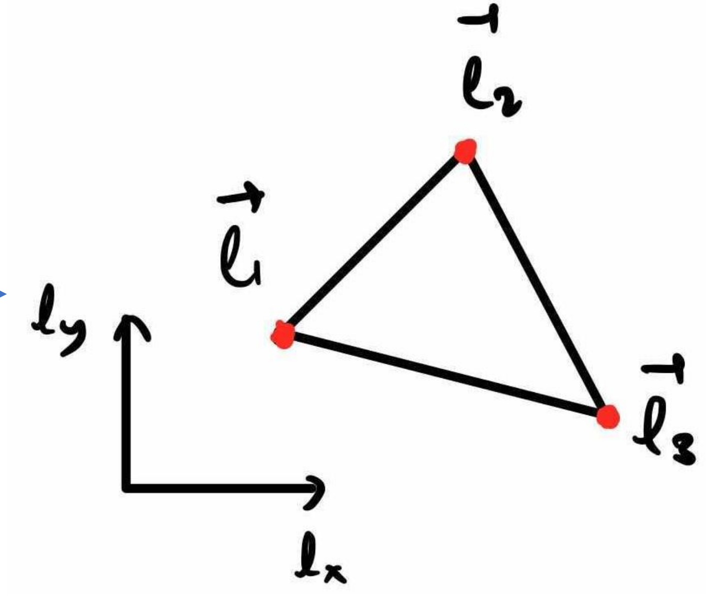
- Subdominant for power spectra but important for bispectra even at low ell

Pratten, Lewis (2016)

Bispectrum Measurement

- Need to compute average over all triangles

$$\hat{b}^{abc}_{i,j,k} = \frac{1}{N_{i,j,k}} \int_{\ell_i}^{\ell_{i+1}} \frac{\mathrm{d}^2\ell_1}{(2\pi)^2} \int_{\ell_j}^{\ell_{j+1}} \frac{\mathrm{d}^2\ell_2}{(2\pi)^2} \int_{\ell_k}^{\ell_{k+1}} \frac{\mathrm{d}^2\ell_3}{(2\pi)^2} (2\pi)^2 \delta_{\mathrm{D}}(\boldsymbol{\ell}_1 + \boldsymbol{\ell}_2 + \boldsymbol{\ell}_3) \delta^a(\boldsymbol{\ell}_1) \delta^b(\boldsymbol{\ell}_2) \delta^c(\boldsymbol{\ell}_3)$$



- Expensive! Requires O(N^3) operations

  Can we compress this efficiently?

Coulton, Liu et al (2018)

Skew-Spectra

- Minimum variance (bispectrum) amplitude estimator

$$\hat{f}_{\rm NL} = \frac{\sigma^2}{(4\pi f_{\rm sky})^2} \sum_{\ell_1\ell_2\ell_3} g^2_{\ell_1\ell_2\ell_3} \frac{b^{\rm th}_{\ell_1\ell_2\ell_3} \hat{b}^{\rm obs}_{\ell_1\ell_2\ell_3}}{C_{\ell_1} C_{\ell_2} C_{\ell_3}}$$

$$= \frac{\sigma^2}{(4\pi f_{\rm sky})^2} \sum_{\ell_1 m_1} \sum_{\ell_2 m_2} \sum_{\ell_3 m_3} \mathcal{G}^{m_1 m_2 m_3}_{\ell_1\ell_2\ell_3} b^{\rm th}_{\ell_1\ell_2\ell_3} \frac{\delta_{\ell_1 m_1} \delta_{\ell_2 m_2} \delta_{\ell_3 m_3}}{C_{\ell_1} C_{\ell_2} C_{\ell_3}}$$

Skew-Spectra

- Minimum variance (bispectrum) amplitude estimator

$$\hat{f}_{\rm NL} = \frac{\sigma^2}{(4\pi f_{\rm sky})^2} \sum_{\ell_1\ell_2\ell_3} g^2_{\ell_1\ell_2\ell_3} \frac{b^{\rm th}_{\ell_1\ell_2\ell_3} \hat{b}^{\rm obs}_{\ell_1\ell_2\ell_3}}{C_{\ell_1} C_{\ell_2} C_{\ell_3}}$$

$$= \frac{\sigma^2}{(4\pi f_{\rm sky})^2} \sum_{\ell_1 m_1} \sum_{\ell_2 m_2} \sum_{\ell_3 m_3} \mathcal{G}^{m_1 m_2 m_3}_{\ell_1\ell_2\ell_3} b^{\rm th}_{\ell_1\ell_2\ell_3} \frac{\delta_{\ell_1 m_1}\delta_{\ell_2 m_2}\delta_{\ell_3 m_3}}{C_{\ell_1} C_{\ell_2} C_{\ell_3}}$$

$$\Downarrow$$

$$\hat{f}_{\rm NL} \propto \sum_{\ell} \hat{\tilde{C}}_{\ell}$$

Skew-Spectra

- Minimum variance (bispectrum) amplitude estimator

$$\hat{\hat{C}}_\ell = \frac{1}{2\ell+1}\sum_m D_{\ell m}\frac{\delta^*_{\ell m}}{C_\ell}$$

$$D_{\ell m} = (-1)^m \sum_{\ell_1 m_1}\sum_{\ell_2 m_2} \mathcal{G}^{m_1 m_2 (-m)}_{\ell_1 \ell_2 \ell}\, b^{\rm th}_{\ell_1 \ell_2 \ell}\frac{\delta_{\ell_1 m_1}}{C_{\ell_1}}\frac{\delta_{\ell_2 m_2}}{C_{\ell_2}}$$

Munshi, Heavens (2009)
Fourier space: Schmittfull, Baldauf, Seljak (2015)
Moradinezhad Dizgah, Lee, Schmittfull, Dvorkin (2020)

Skew-Spectra

- With two fields 'a' and 'b':

$$\hat{\tilde{C}}_\ell^{ab} = \frac{1}{2\ell + 1} \sum_m D_{\ell m}^{ab} \tilde{\delta}_{\ell m}^{b*}$$

$$D_{\ell m}^{ab} = (-1)^m \sum_{\ell_1 m_1} \sum_{\ell_2 m_2} \mathcal{G}_{\ell_1 \ell_2 \ell}^{m_1 m_2 (-m)} \, b_{\ell_1 \ell_2 \ell}^{aab,\mathrm{th}} \tilde{\delta}_{\ell_1 m_1}^a \tilde{\delta}_{\ell_2 m_2}^a$$

$$\delta_{\ell m}^a / C_\ell^a \equiv \tilde{\delta}_{\ell m}^a$$

Decomposed Kernels

- Can we do better?

Recall: Galaxy bispectrum in redshift space:

$$B^{ggg}(\boldsymbol{k}_1, \boldsymbol{k}_2, \boldsymbol{k}_3) = 2\left(\frac{17}{21}b_1^3 + b_1^2 b_2 - \frac{2}{3}b_1^2 b_{\mathcal{G}_2}\right)\mathbf{P}_0(\hat{\boldsymbol{k}}_1 \cdot \hat{\boldsymbol{k}}_2)P(k_1)P(k_2)$$
$$+ 2b_1^3 \frac{1}{2}\left(\frac{k_1}{k_2} + \frac{k_2}{k_1}\right)\mathbf{P}_1(\hat{\boldsymbol{k}}_1 \cdot \hat{\boldsymbol{k}}_2)P(k_1)P(k_2)$$
$$+ 2\left(\frac{4}{21}b_1^3 + \frac{2}{3}b_1^2 b_{\mathcal{G}_2}\right)\mathbf{P}_2(\hat{\boldsymbol{k}}_1 \cdot \hat{\boldsymbol{k}}_2)P(k_1)P(k_2)$$
$$+ 2 \text{ perms.}$$

Schmittfull, Baldauf, Seljak (2015)

Decomposed Kernels

- Can we do better?

  Galaxy bispectrum in harmonic space:

$$b^{ggg}_{\ell_1\ell_2\ell_3} = \left(\frac{17}{21}b_1^3 + b_1^2 b_2 - \frac{2}{3}b_1^2 b_{\mathcal{G}_2}\right) h^{ggg}_{0,\ell_1\ell_2\ell_3} + b_1^3 h^{ggg}_{1,\ell_1\ell_2\ell_3} + \left(\frac{4}{21}b_1^3 + \frac{2}{3}b_1^2 b_{\mathcal{G}_2}\right) h^{ggg}_{2,\ell_1\ell_2\ell_3}$$

$$h^{aab}_{0,\ell_1\ell_2\ell_3} \to \mathbf{P}_0(\hat{\boldsymbol{k}}_1 \cdot \hat{\boldsymbol{k}}_2) P(k_1) P(k_2) + 2 \text{ perms.}$$

$$h^{aab}_{1,\ell_1\ell_2\ell_3} \to \frac{1}{2}\left(\frac{k_1}{k_2} + \frac{k_2}{k_1}\right) \mathbf{P}_1(\hat{\boldsymbol{k}}_1 \cdot \hat{\boldsymbol{k}}_2) P(k_1) P(k_2) + 2 \text{ perms.}$$

$$h^{aab}_{2,\ell_1\ell_2\ell_3} \to \mathbf{P}_2(\hat{\boldsymbol{k}}_1 \cdot \hat{\boldsymbol{k}}_2) P(k_1) P(k_2) + 2 \text{ perms.}.$$

Decomposed Kernels

- Can we do better?

  Galaxy bispectrum in harmonic space:

$$b^{ggg}_{\ell_1\ell_2\ell_3} = \left(\frac{17}{21}b_1^3 + b_1^2 b_2 - \frac{2}{3}b_1^2 b_{\mathcal{G}_2}\right) h^{ggg}_{0,\ell_1\ell_2\ell_3} + b_1^3 h^{ggg}_{1,\ell_1\ell_2\ell_3} + \left(\frac{4}{21}b_1^3 + \frac{2}{3}b_1^2 b_{\mathcal{G}_2}\right) h^{ggg}_{2,\ell_1\ell_2\ell_3}$$

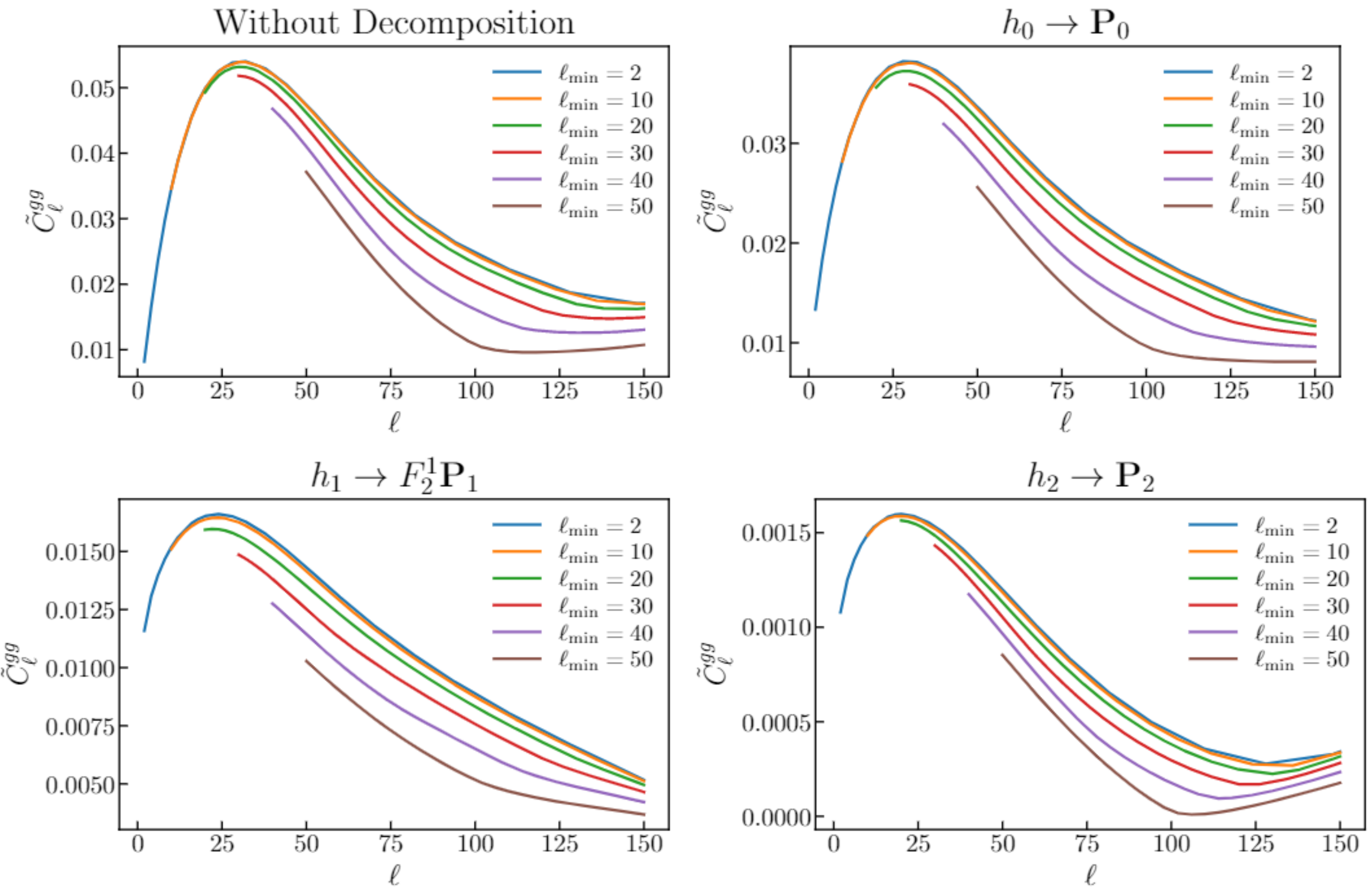
$$D^{ab,i}_{\ell m} = (-1)^m \sum_{\ell_1 m_1} \sum_{\ell_2 m_2} \mathcal{G}^{m_1 m_2 (-m)}_{\ell_1 \ell_2 \ell} \, h^{aab,i}_{\ell_1 \ell_2 \ell} \tilde{\delta}^a_{\ell_1 m_1} \tilde{\delta}^a_{\ell_2 m_2}$$

Decomposed Kernels

- Can we do better?
- Yes! Use the $h^{aab}_{i,\ell_1\ell_2\ell_3}$ as kernels instead

$$\tilde{C}^{ab,i}_{\ell} = \frac{1}{2\ell+1}\sum_{\ell_1\ell_2} g^2_{\ell_1\ell_2\ell}\frac{h^{aab}_{i,\ell_1\ell_2\ell}b^{aab,\mathrm{obs}}_{\ell_1\ell_2\ell}}{C^a_{\ell_1}C^a_{\ell_2}C^b_{\ell}}$$

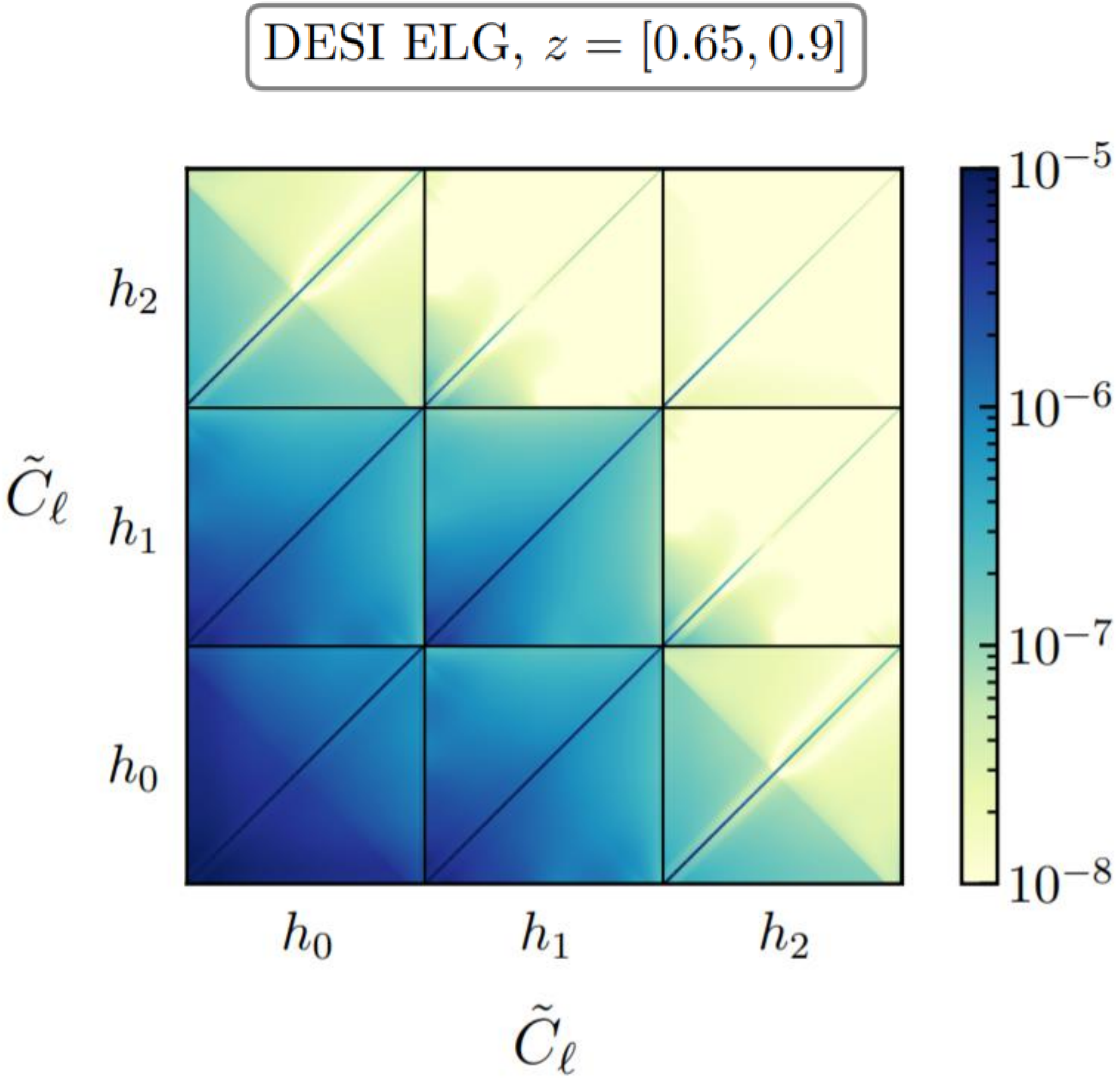
Theoretical Expression



Example skew-spectra for LSST redshift bin [0.8,1.]

Decomposed Kernels

- Covariance matrix
- Cannot ignore off-diagonals



Moradinezhad Dizgah, Lee, Schmittfull, Dvorkin (2020)

Decomposed Kernels

- Forecasted constraints for bias and A_{shot} for a single redshift bin of DESI-ELG

Decomposed Kernels

- Forecasted constraints for bias and A_{shot}[★] for a single redshift bin of DESI-ELG

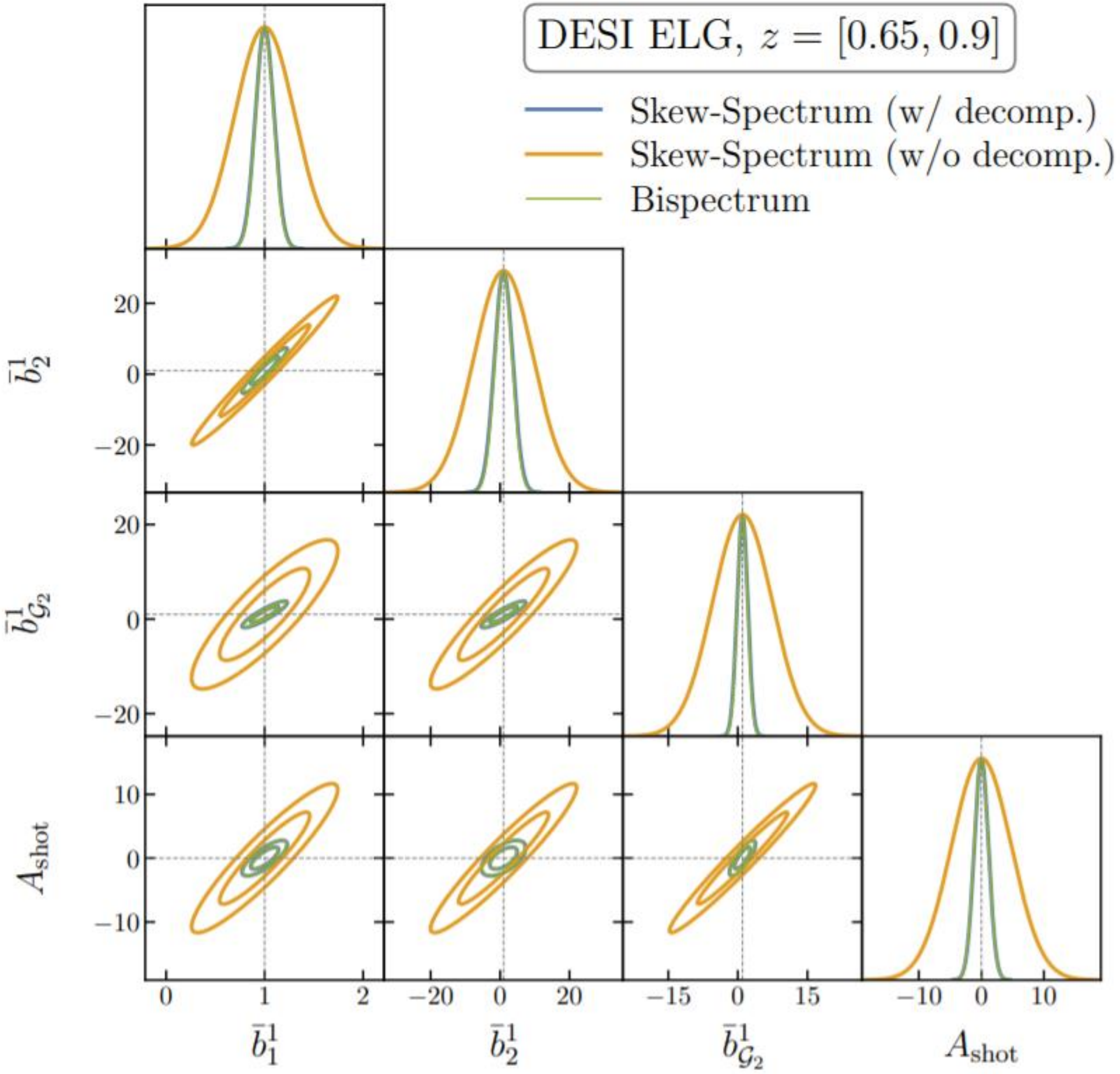
★

$$P_{\text{shot}}(k) = P_{\text{Poisson}}(1 + A_{\text{shot}})$$
$$B_{\text{shot}}(k) = B_{\text{Poisson}}(1 + A_{\text{shot}})$$

Peebles (1980)
Schmittfull, Baldauf, Seljak (2015)

Decomposed Kernels

- Forecasted constraints for bias and A_{shot} for a single redshift bin of DESI-ELG

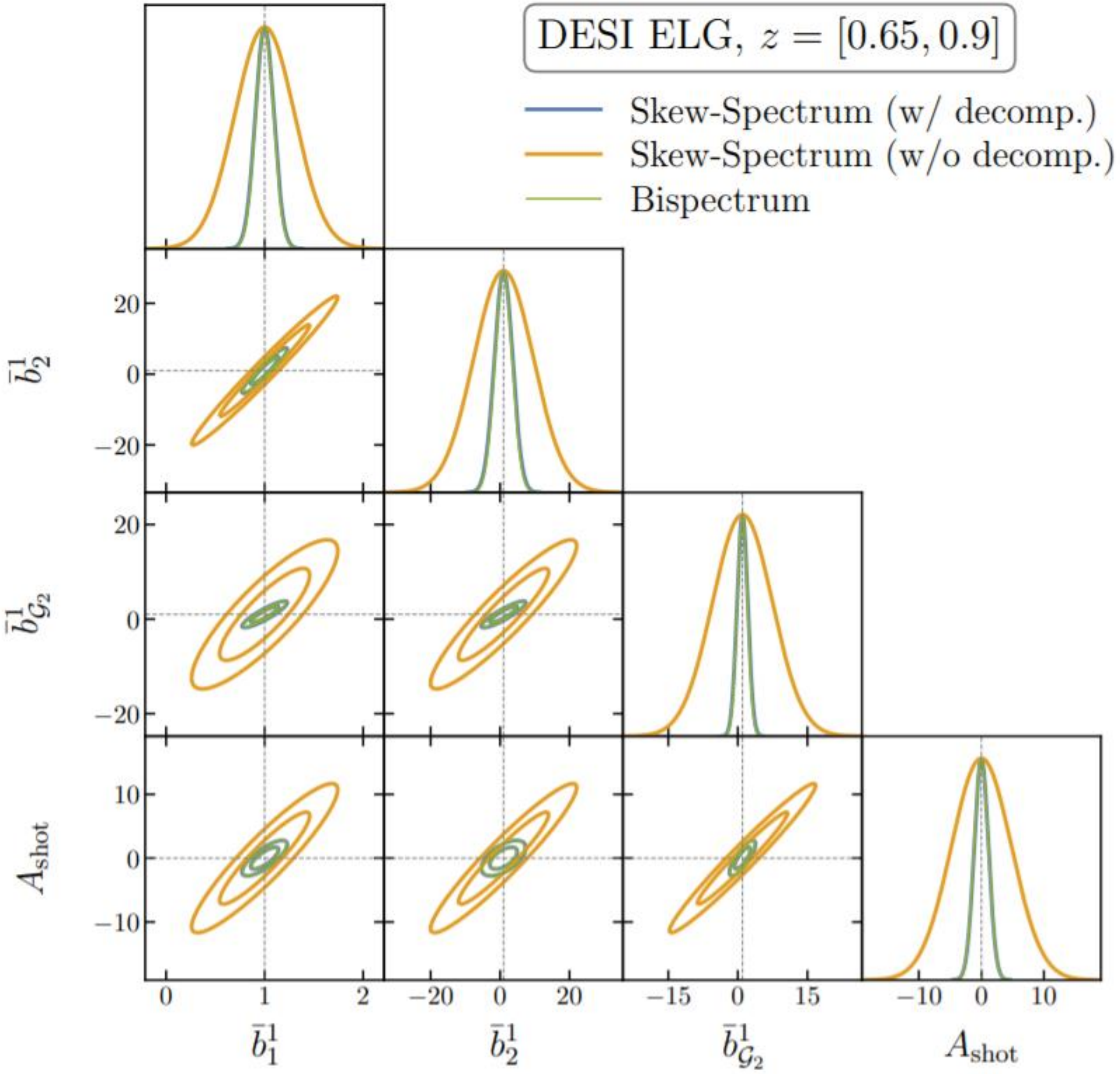


Decomposed Kernels

- Forecasted constraints for bias and A_{shot} for a single redshift bin of DESI-ELG

$$\tilde{C}_\ell = \sum_i \alpha_i \tilde{C}^i_\ell$$

Not invertible!



Algorithm to improve speed

- Bispectrum kernels can be factorized:

$$D_{\ell m}^{ab,i} = (-1)^m \sum_{\ell_1 m_1} \sum_{\ell_2 m_2} \mathcal{G}_{\ell_1 \ell_2 \ell}^{m_1 m_2 (-m)} \boxed{h_{\ell_1 \ell_2 \ell}^{aab,i}} \tilde{\delta}_{\ell_1 m_1}^{a} \tilde{\delta}_{\ell_2 m_2}^{a}$$

$$h_{\ell_1 \ell_2 \ell_3}^{abc} = \sum_{n_1 n_2 n_3} c_{n_1 n_2 n_3}^{abc} \int_0^\infty \mathrm{d}r \, r^2 \tilde{I}_{\ell_1}^{ac}(r; n_1) \tilde{I}_{\ell_2}^{bc}(r; n_2) \tilde{I}_{\ell_3}^{c}(r; n_3)$$

Algorithm to improve speed

- Bispectrum kernels can be factorized:

$$D_{\ell m}^{ab} = (-1)^m \sum_{n_1 n_2 n_3} c_{n_1 n_2 n_3}^{aab} \times \int_0^\infty \mathrm{d}r\, r^2 \sum_{\ell_1 m_1} \sum_{\ell_2 m_2} \mathcal{G}_{\ell_1 \ell_2 \ell}^{m_1 m_2 (-m)} (\tilde{I}_{\ell_1}^{ab}(r, n_1) \tilde{\delta}_{\ell_1 m_1}^{a})(\tilde{I}_{\ell_2}^{ab}(r, n_2) \tilde{\delta}_{\ell_2 m_2}^{a}) \tilde{I}_{\ell}^{b}(r, n_3)$$

$$\Delta_{\ell m}^{ab}(r, n)$$

Algorithm to improve speed

- Bispectrum kernels can be factorized:

$$D_{\ell m}^{ab} = (-1)^m \sum_{n_1 n_2 n_3} c_{n_1 n_2 n_3}^{aab} \int_0^\infty \mathrm{d}r\, r^2 D_{\ell m}^{ab}(r; n_1, n_2) \tilde{I}_\ell^b(r, n_3)$$

- Reduce to trivial convolution (modulo an integral)

$$D_{\ell m}^{ab}(r; n_1, n_2) = \int \mathrm{d}^2\hat{n}\, Y_{\ell m}^*(\hat{n}) \Delta^{ab}(\hat{n}; r, n_1) \Delta^{ab}(\hat{n}; r, n_2)$$

Algorithm to improve speed

Skew-Spectrum Estimation Algorithm

1. Obtain fields $\delta^a(\hat{n})$ and $\delta^b(\hat{n})$.
2. Compute the filtered harmonic coefficients, $\tilde{\delta}^a_{\ell m}$ and $\tilde{\delta}^b_{\ell m}$.
3. Pointwise product between $\tilde{\delta}^a_{\ell m}$ and $\tilde{I}^{ab}_\ell(r, n_i)$ to obtain $\Delta^{ab}_{\ell m}(r, n_i)$.
4. Return to position space to obtain $\Delta^{ab}(\hat{n}; r, n_i)$.
5. Compute harmonic transform of $\Delta^{ab}(\hat{n}; r, n_1)\Delta^{ab}(\hat{n}; r, n_2)$.
6. Product with $\tilde{I}^b_\ell(r, n_3)$ and integrate over r to obtain the quadratic field.
7. Cross-correlate with $\tilde{\delta}^b_{\ell m}$ to obtain $\hat{\tilde{C}}^{ab}_\ell$.

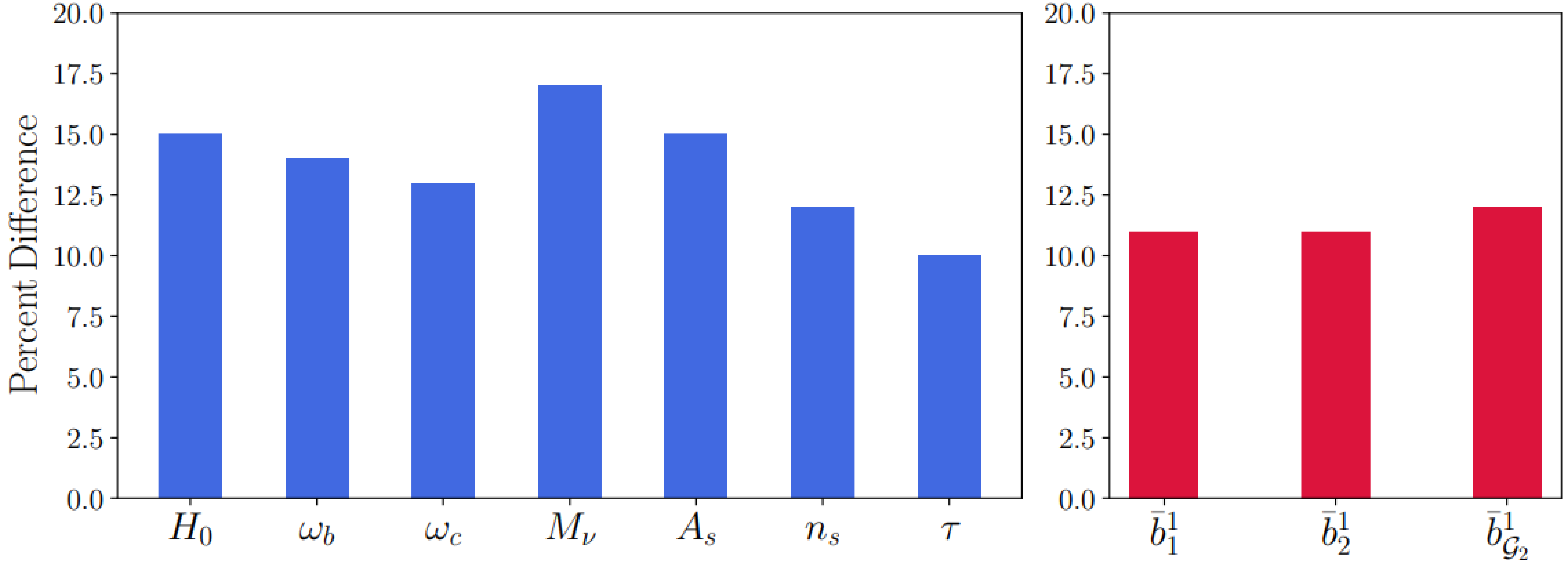
Requires O(N log N) time!

Fisher Analysis (DESI ELG x Planck Lensing)

- Assume Gaussian likelihood
- Vary all parameters $\boldsymbol{\lambda} = \{H_0,\, \omega_b,\, \omega_c,\, A_s,\, n_s,\, \tau,\, M_\nu\} \cup \bigcup_{i=1}^{N_{\rm bin}} \{\bar{b}_1^i,\, \bar{b}_2^i,\, \bar{b}_{\mathcal{G}_2}^i\} \cup \{A_{\rm shot}\}$
- Fix $k_{\rm max} \sim 0.1\; h{\rm Mpc}^{-1}$ to remain in tree-level regime
- Regardless, incorporate non-linearities using fitted PT kernel $F_2^{\rm fit}(\boldsymbol{k}_1, \boldsymbol{k}_2)$ ★

★ Gil-Marin, Wagner, et al (2012)
Munshi, Namikawa, et al (2020)

Results



Relative difference between marginalized errors using bispectrum vs skew-spectrum

Simulations

We apply the skew-spectra to estimate biases and A_{shot} from MassiveNuS halo catalogue + lensing (ray-traced using Lenstools)

- Angular maps of 3.5 x 3.5 deg^2
- Gridded data from simulations

Flat-sky approximation

- Sharp cutoff at $\ell = 1350$ (k~0.5 h/Mpc)
- Halos with minimum mass = $1.36\times10^{12}\, h^{-1}M_{\odot}$ at z=1.04

Petri (2016)
Liu et al (2018)

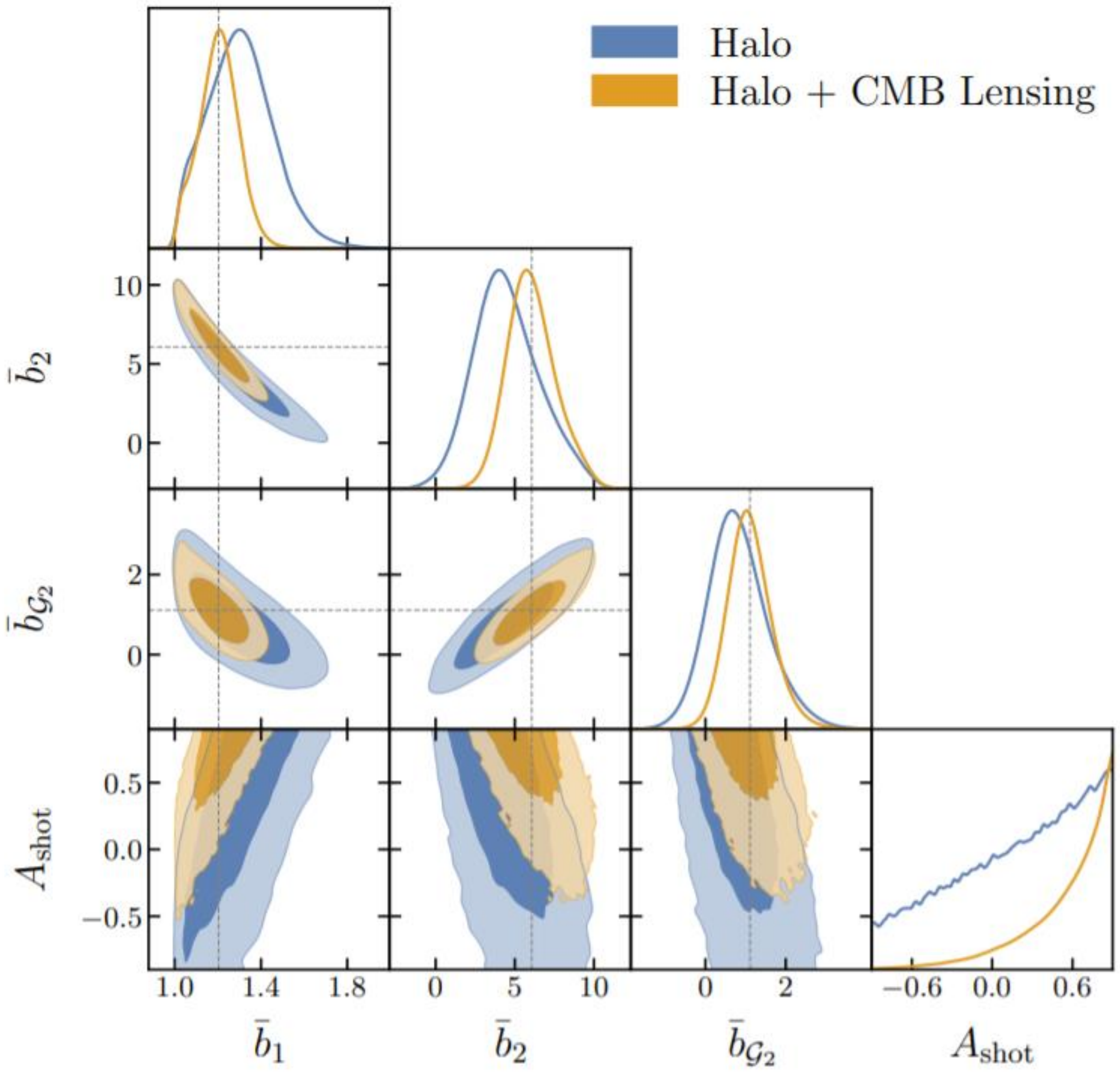
MCMC Analysis

- 68% errors for biases and 68% lower bound for A_{shot}:

Parameter	$\bar{b}_1$	$\bar{b}_2$	$\bar{b}_{\mathcal{G}_2}$	A_{shot}
Uniform Prior	$[1, 3]$	$[-2, 12]$	$[-5, 5]$	$[-1, 1]$
Halo + CMB Lensing	1.203 ± 0.091	6.068 ± 1.546	1.111 ± 0.562	≥ 0.581
Halo	1.304 ± 0.153	4.502 ± 2.104	0.822 ± 0.758	≥ 0.006

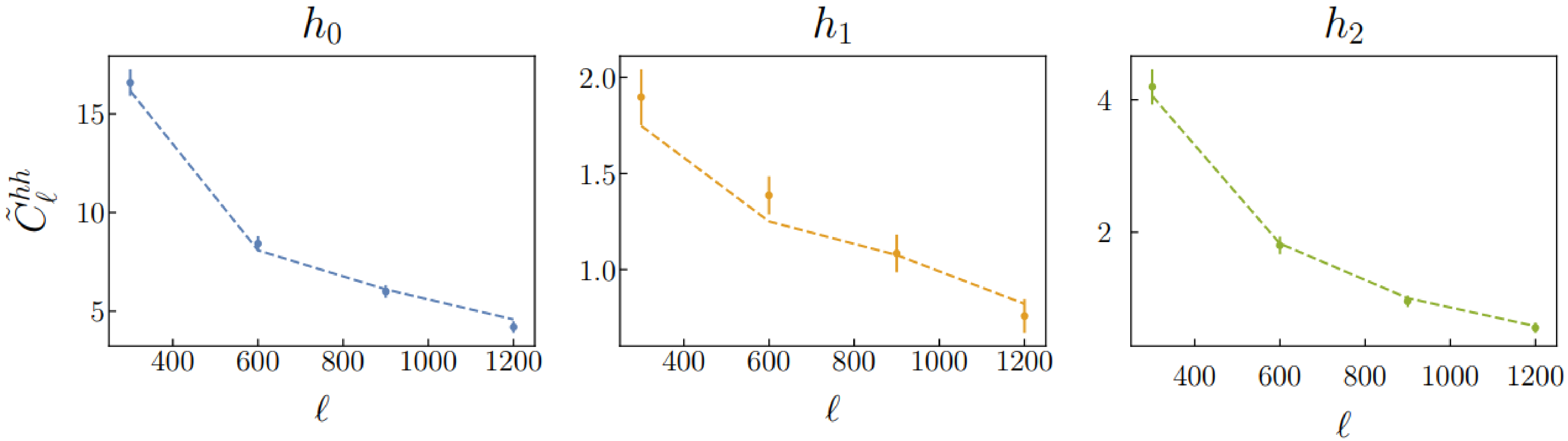
MCMC Analysis

- Posterior for halo skew-spectra and halo x lensing



MCMC Analysis

- Estimated halo-halo skew-spectra



Summary

- We compress the bispectrum to optimally capture amplitude information for CMBxLSS, finding that it also captures non-amplitude parameters as well to <17%
- We describe an algorithm to efficiently compute it from the data, requiring only O(N log N) steps
- We test our model on MassiveNuS simulations and constrain b_1 to percent level
- Future work: Analysis of BOSS data using Skew-Spectra