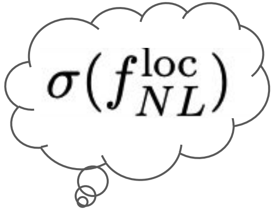
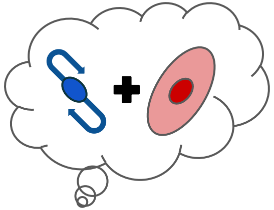
Learning to Concentrate: Multi-tracer Forecasts on Local Primordial Non-Gaussianity with Machine-Learned Bias



SPHEREx Cosmology Group



Jamie Sullivan
(work w/ Tijan Prijon & Uroš Seljak)

arXiv:2303.08901

Counting Inflationary Fields

Initial gravitational potential largely Gaussian

But primordial physics can add non-Gaussianity (PNG)

E.g. multi-field inflation produces *local* PNG:

$$\phi = \phi_G + f_{NL}^{\mathrm{loc}} \left[\phi_G^2 - \langle \phi_G^2 \rangle\right]$$

Measure this through local f_{NL}

Maldacena03, Acquaviva03, Komatsu&Spergel01

Inflation in LSS via LPNG Bias

Planck has constrained local f_{NL} to be 0.0 ± 5.1

But large-scale structure (LSS) has more modes

To get to galaxies, need a bias model:

$$\delta_g = b\,\delta + ...$$

$$\delta \propto k^2 \phi$$

Planck15, Dalal+08, Slosar+08,

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15 years ago, it was realized there is an **extra** bias signal

Planck15, Dalal+08, Slosar+08, image from Dore 18

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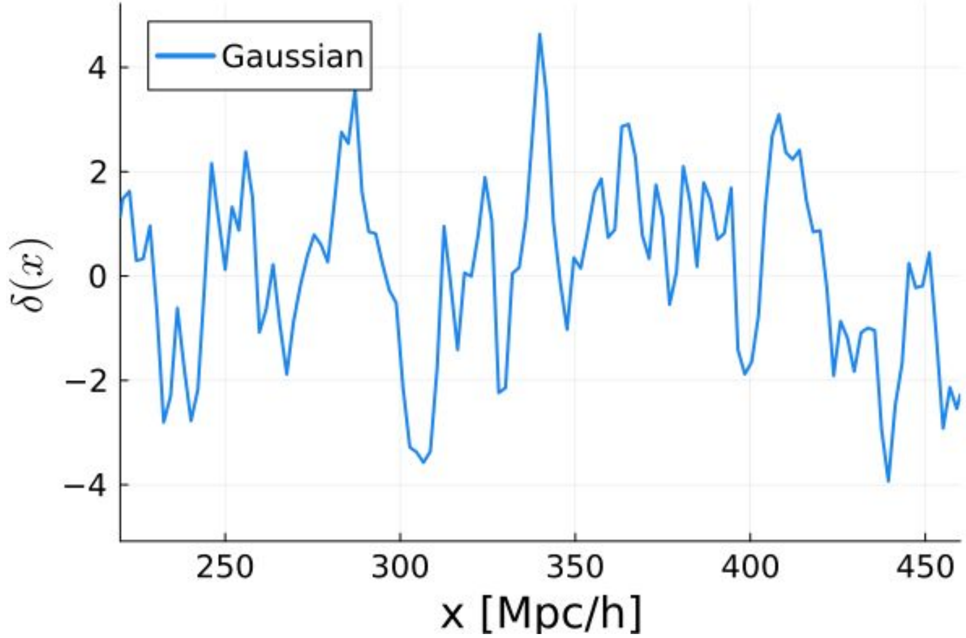
$$\delta_g = b\,\delta + \boxed{b_\phi\, f_{\rm NL}^{\rm (loc)}\, \phi} + \ldots$$

Why extra bias? - Cartoon LPNG

LPNG “adds” long-wavelength potential mode

Long-wavelength potential “acts like local σ_8”



Why extra bias? - Cartoon LPNG

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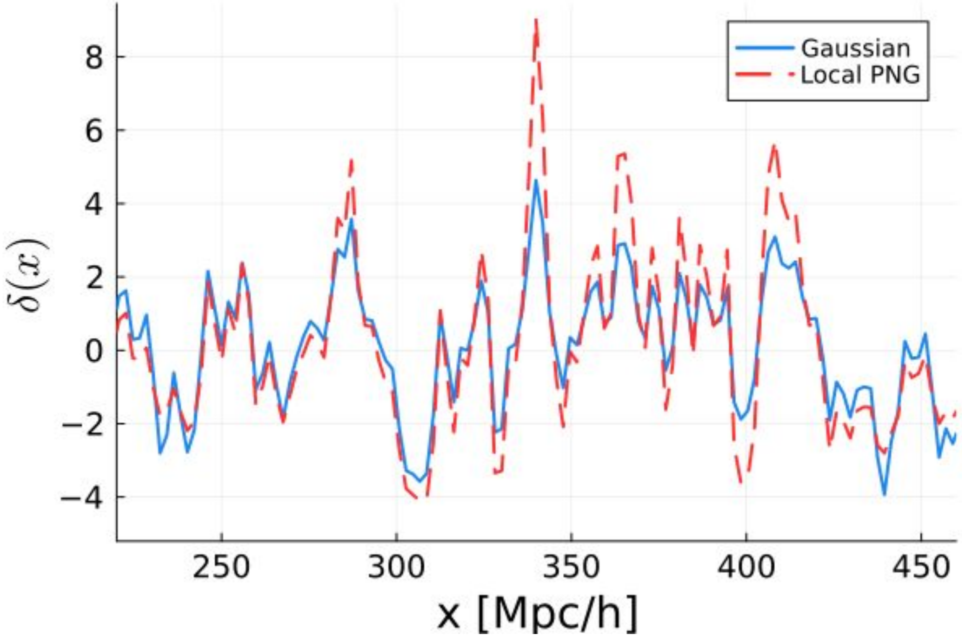
Boosts variance

Affects halo formation



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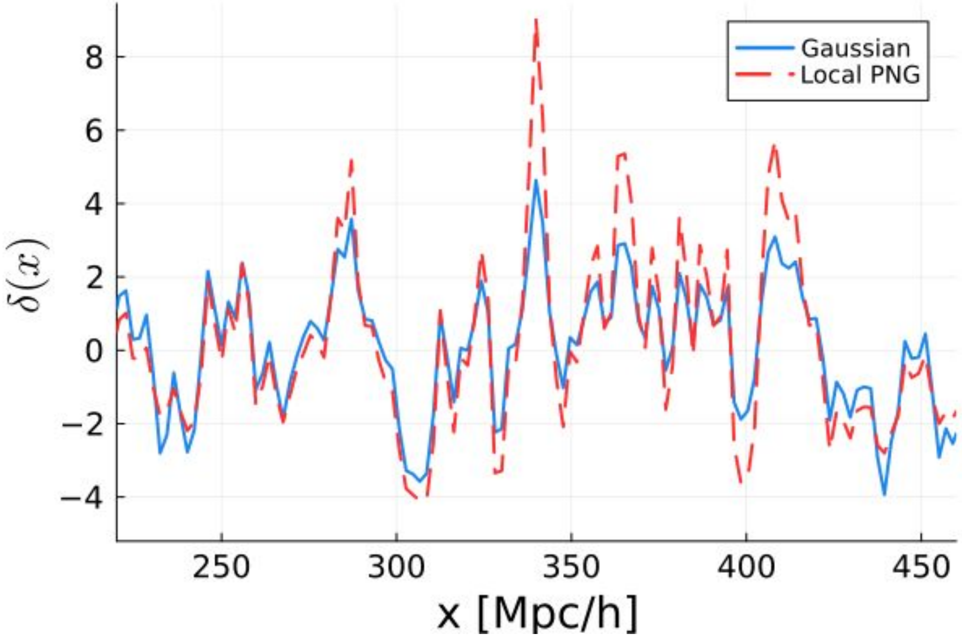
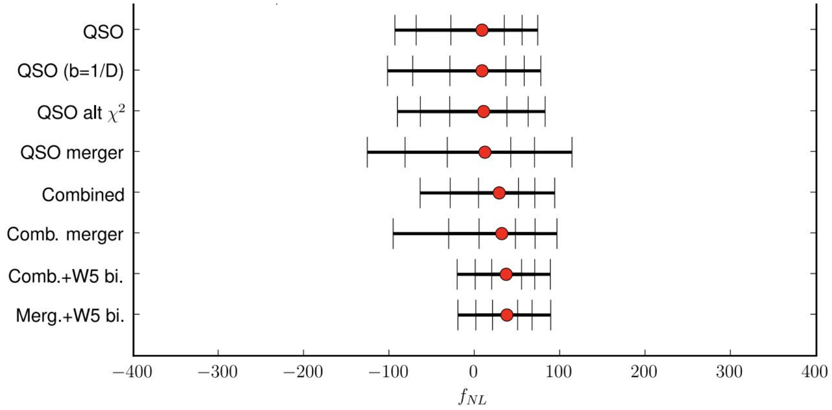
And in data…?



LSS $f_{NL}^{(loc)}$ Constraints - SDSS quasars

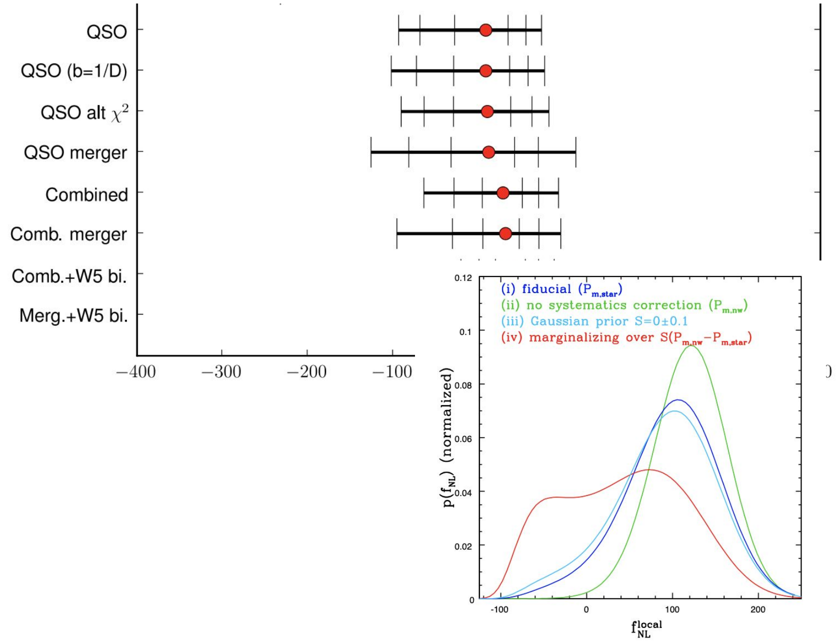
Slosar++08



LSS $f_{NL}^{(loc)}$ Constraints - SDSS quasars

Slosar++08

Ross++12



LSS $f_{NL}^{(loc)}$ Constraints - SDSS quasars

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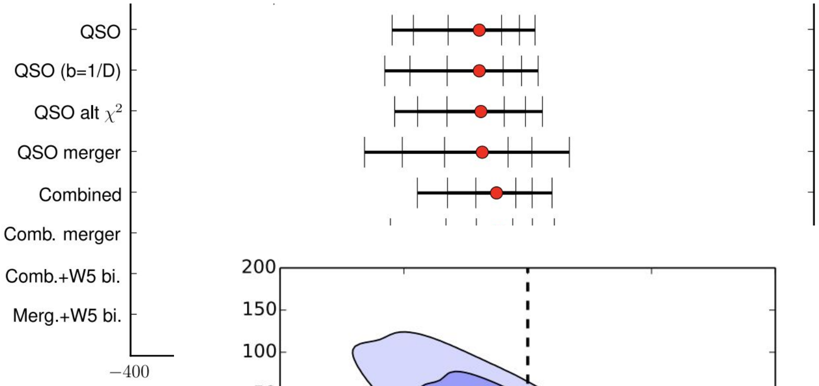
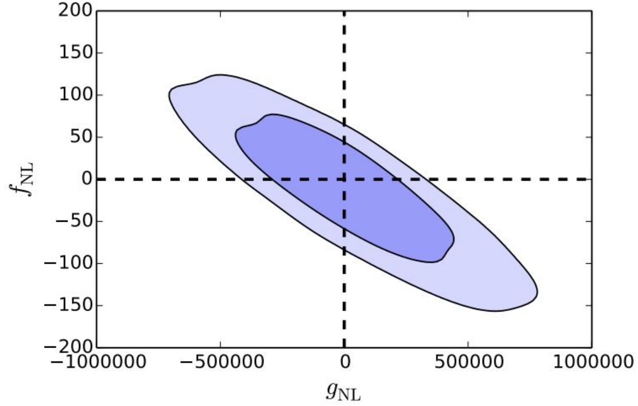
Leistedt++14





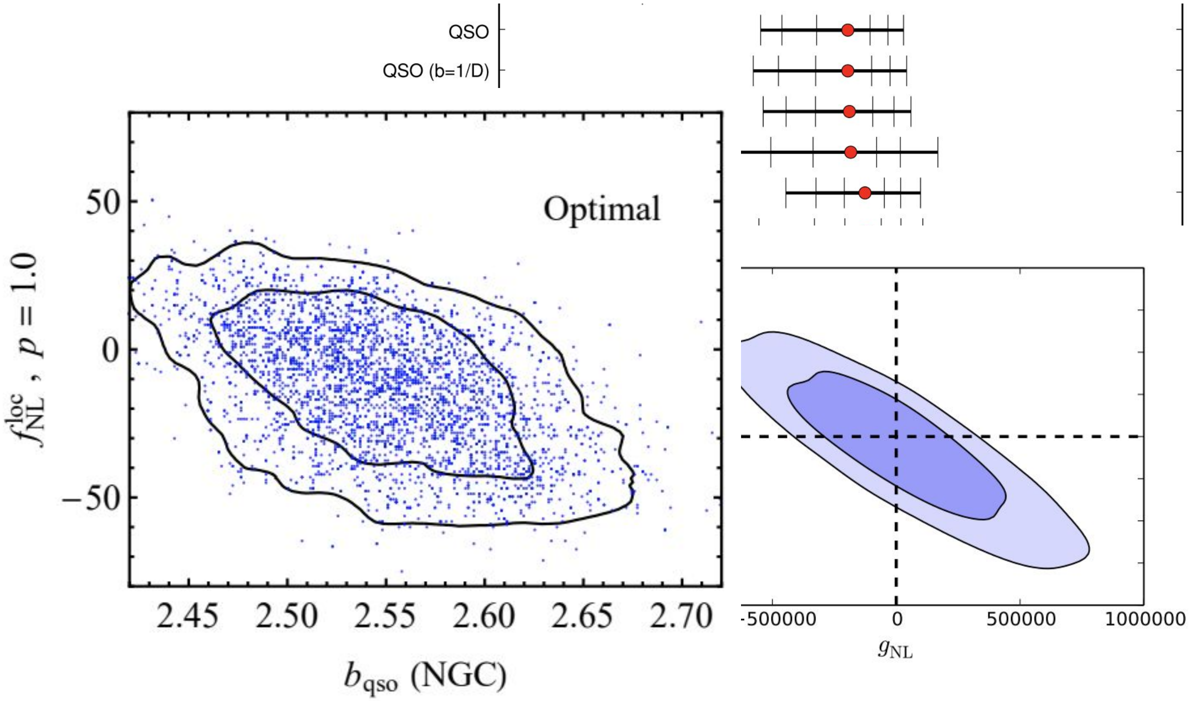
LSS $f_{NL}^{(loc)}$ Constraints - eBOSS quasars

Slosar++08

Ross++12

Leistedt++14

Castorina++19



LSS $f_{NL}^{(loc)}$ Constraints - eBOSS quasars

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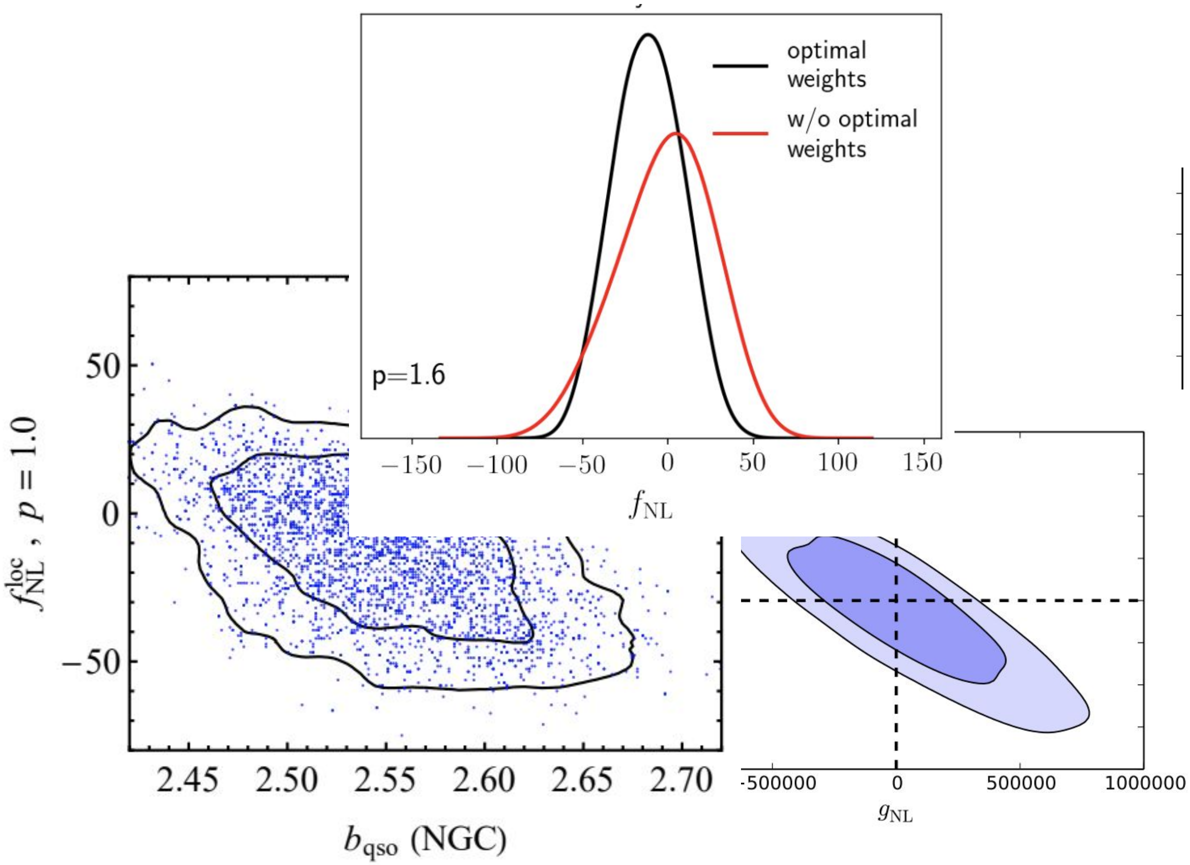
Castorina++19

Mueller++21



LSS $f_{NL}^{(loc)}$ Constraints - BOSS LRGs

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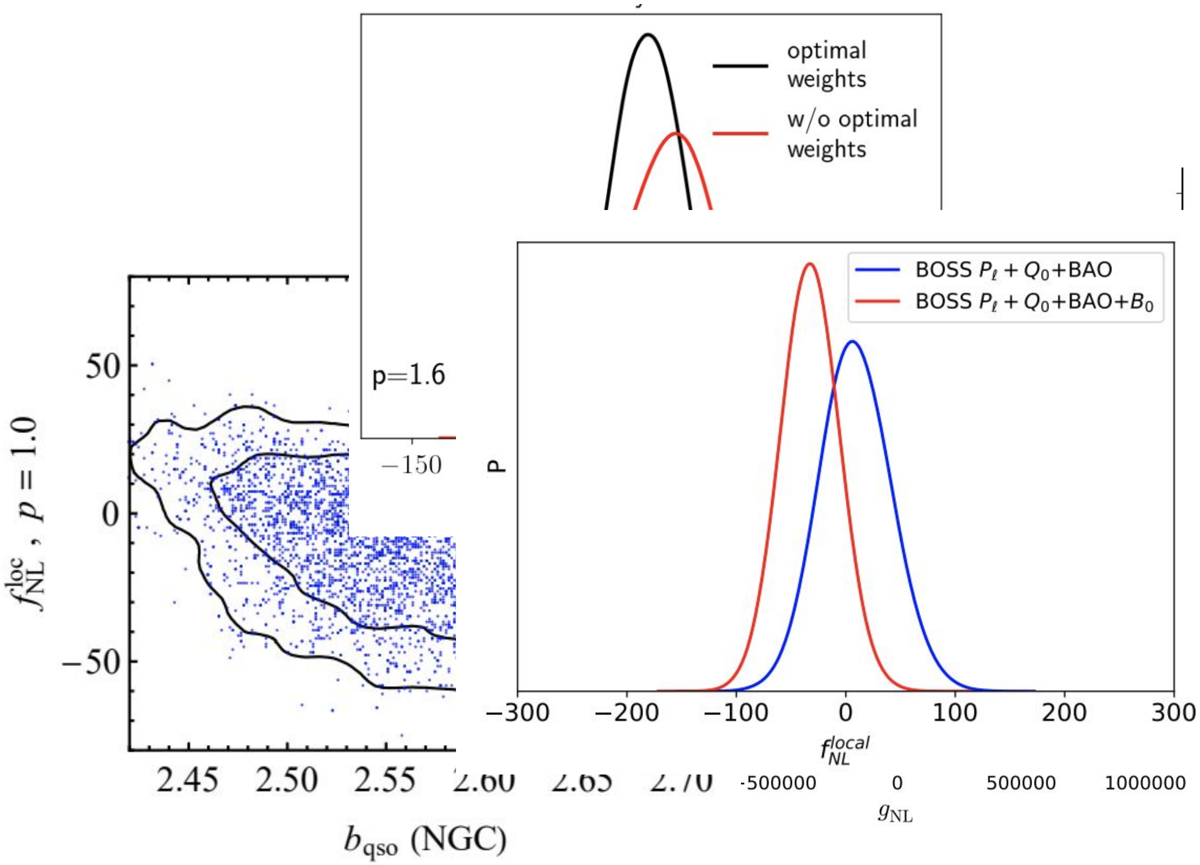
Ross++12

Leistedt++14

Castorina++19

Mueller++21

D'Amico++22



LSS $f_{NL}^{(loc)}$ Constraints - BOSS LRGs

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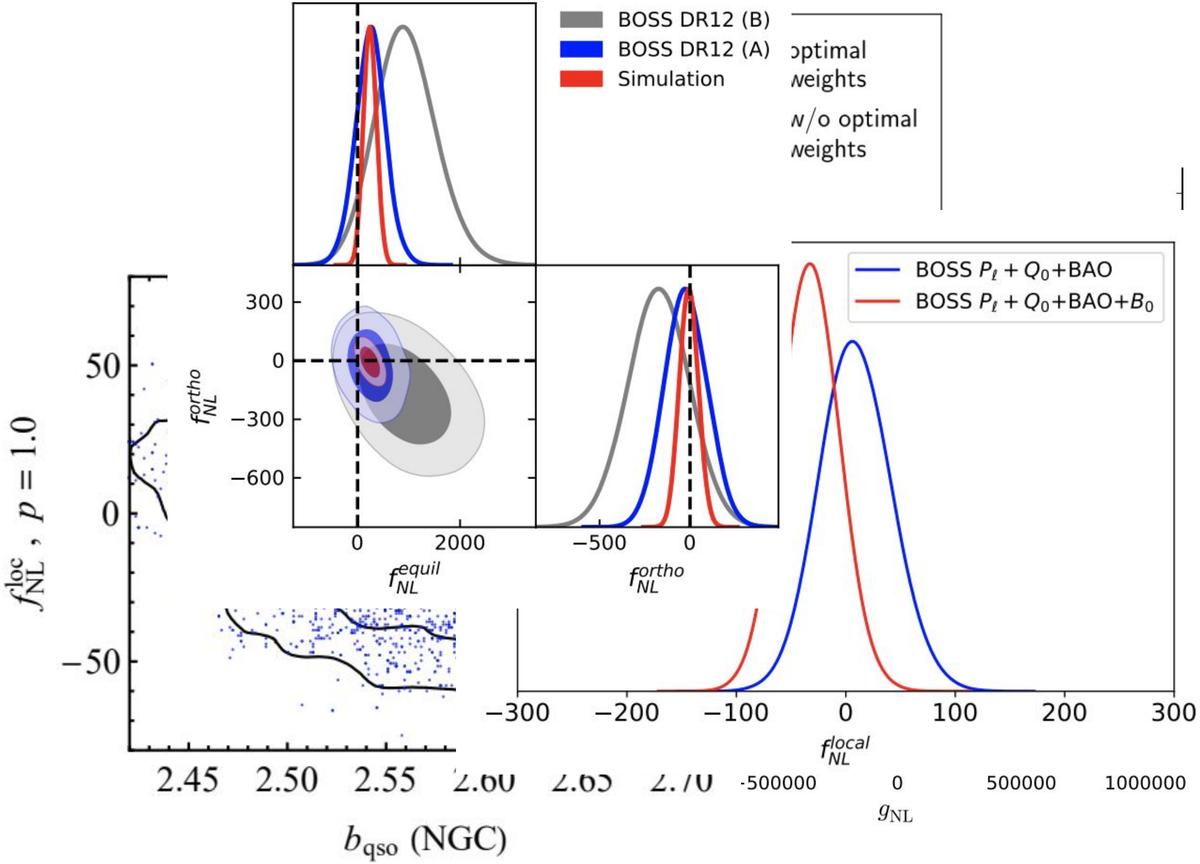
Mueller++21

D'Amico++22

Cabass++22a



LSS $f_{NL}^{(loc)}$ Constraints - BOSS LRGs

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Mueller++21

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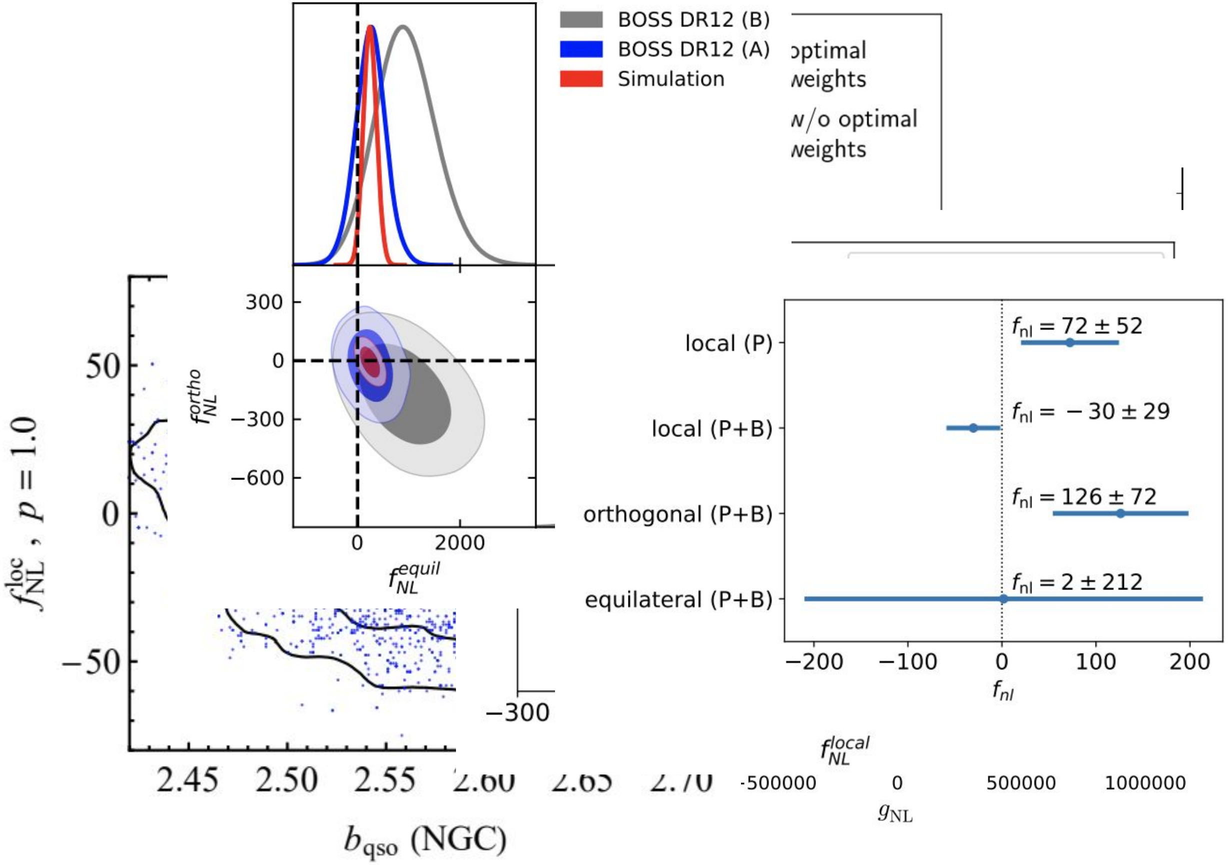
Cabass++22a

$\rightarrow \sigma(f_{NL}^{(loc)}) \gtrsim 20$



LSS $f_{NL}^{(loc)}$ Constraints - BOSS LRGs

- Slosar++08
- Ross++12
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- Cabass++22a
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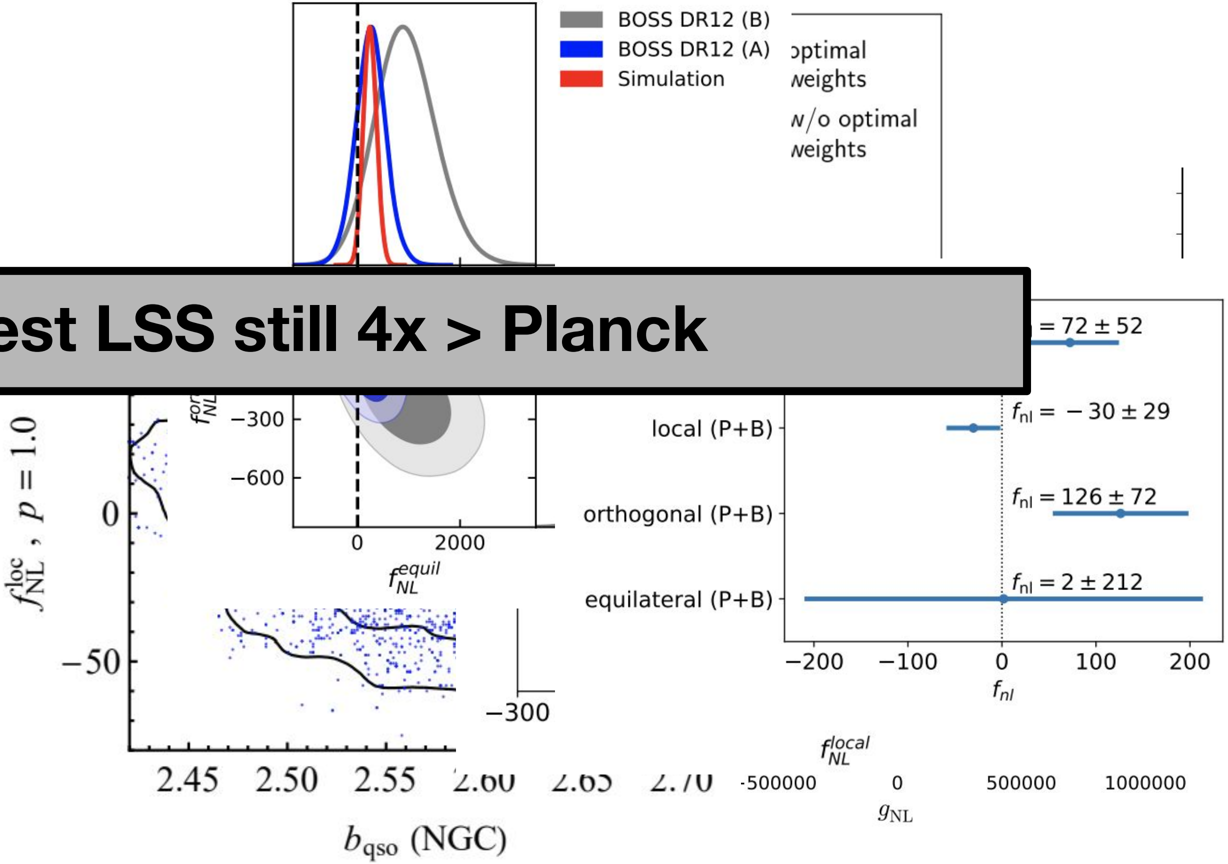
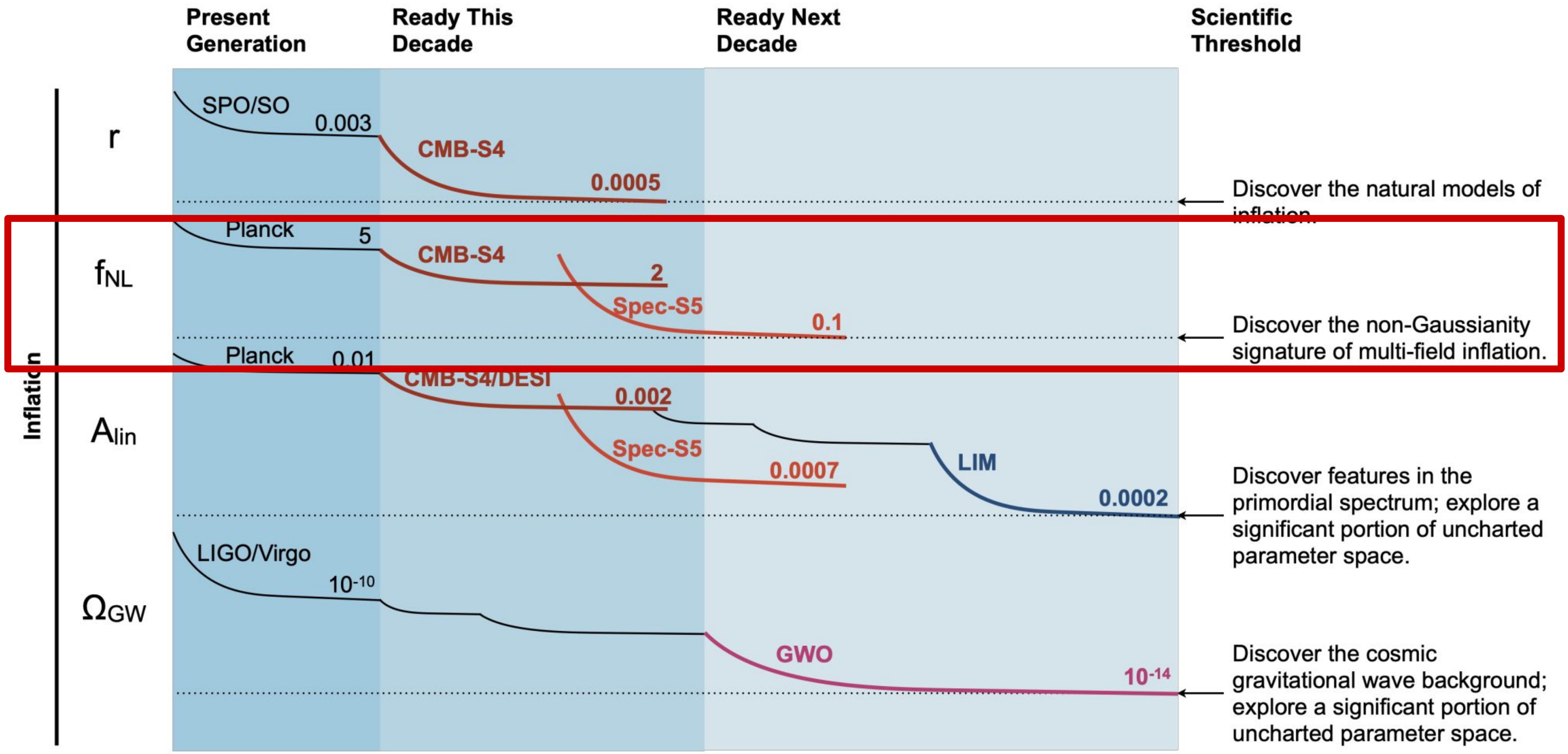


Best LSS still 4x > Planck

f_{NL} - A Primary Target for Stage 5 Spectroscopy



P5 Report, Rezaie+23

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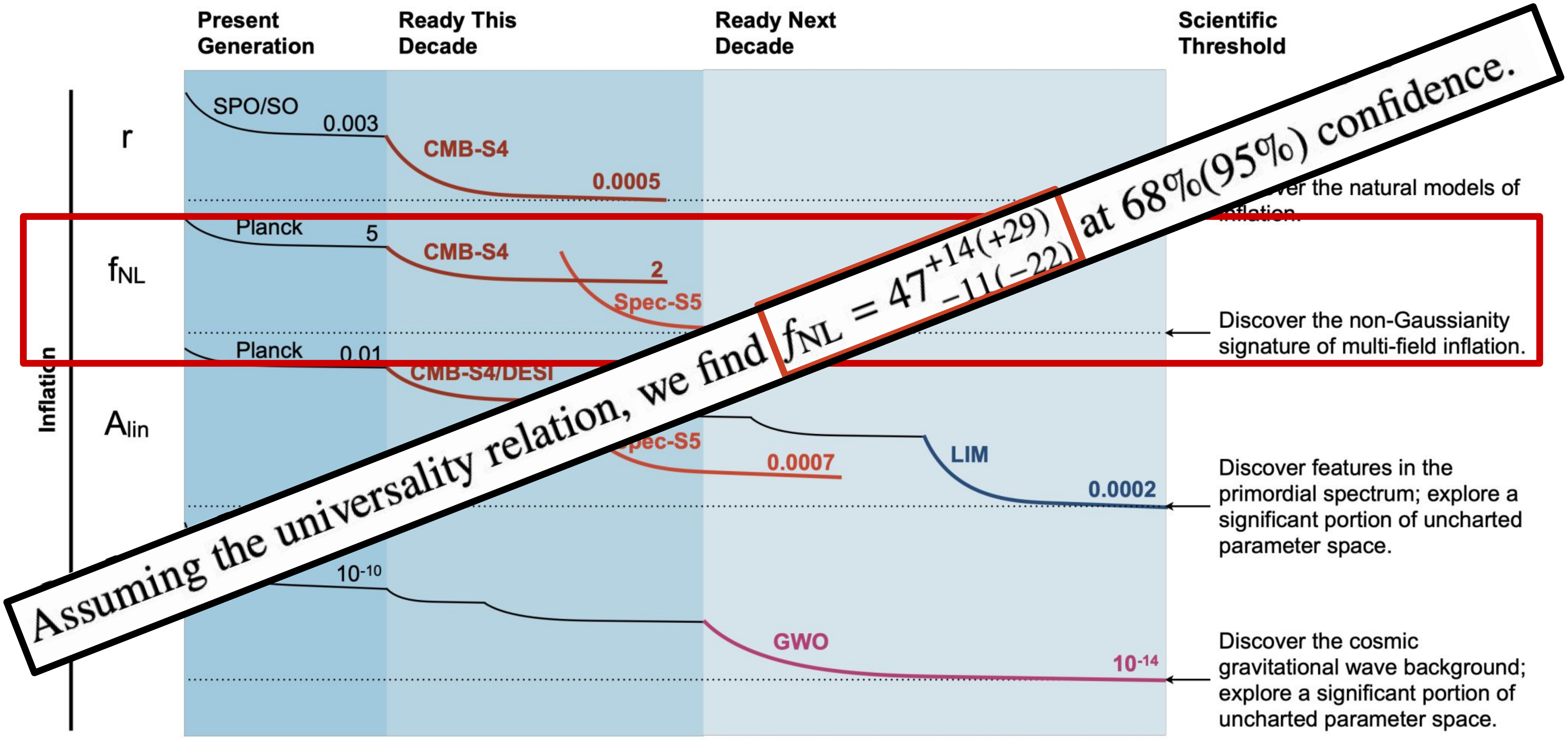

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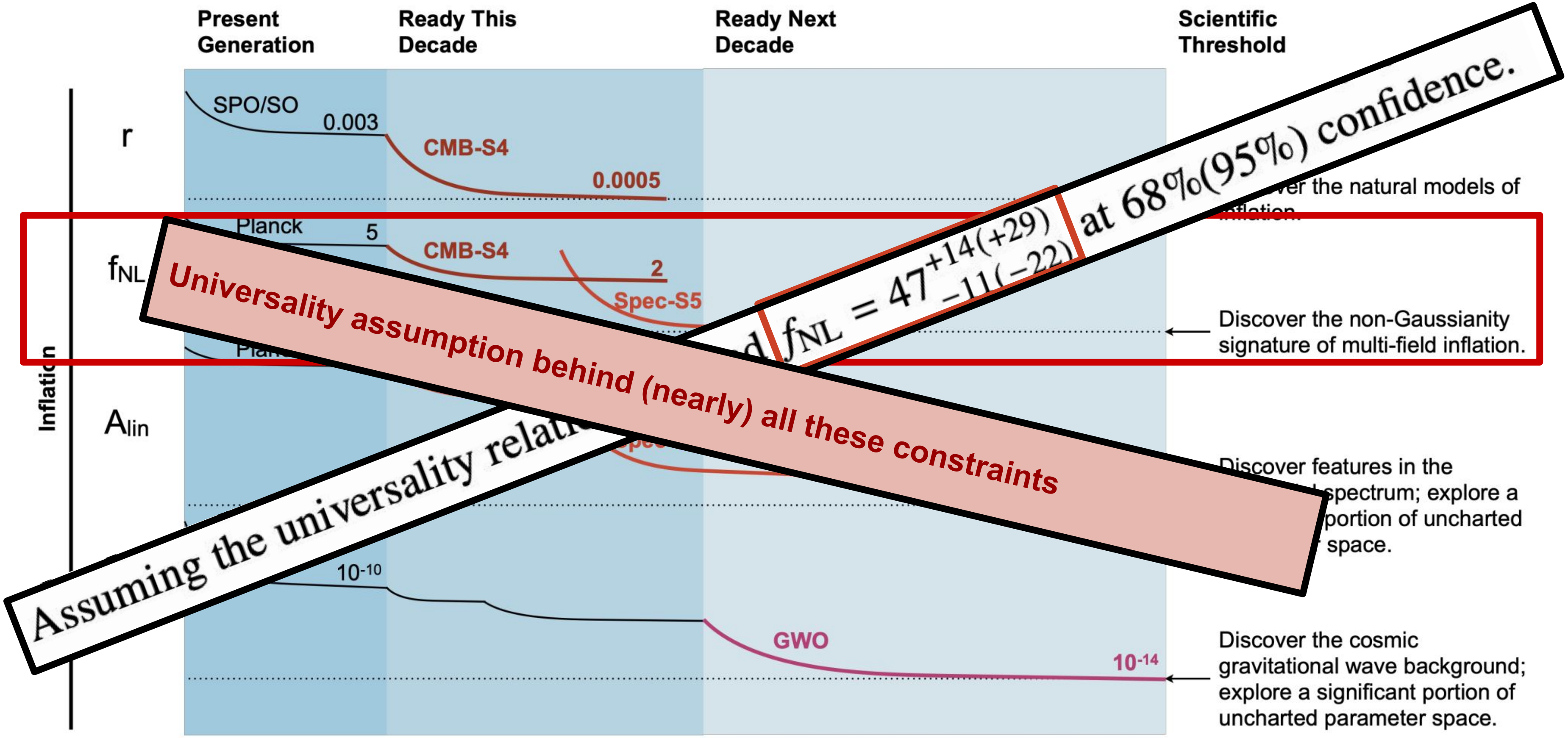


P5 Report, Rezaie+23

LPNG & Assembly Bias

Universality amounts to 1-1 map between b, b_ϕ

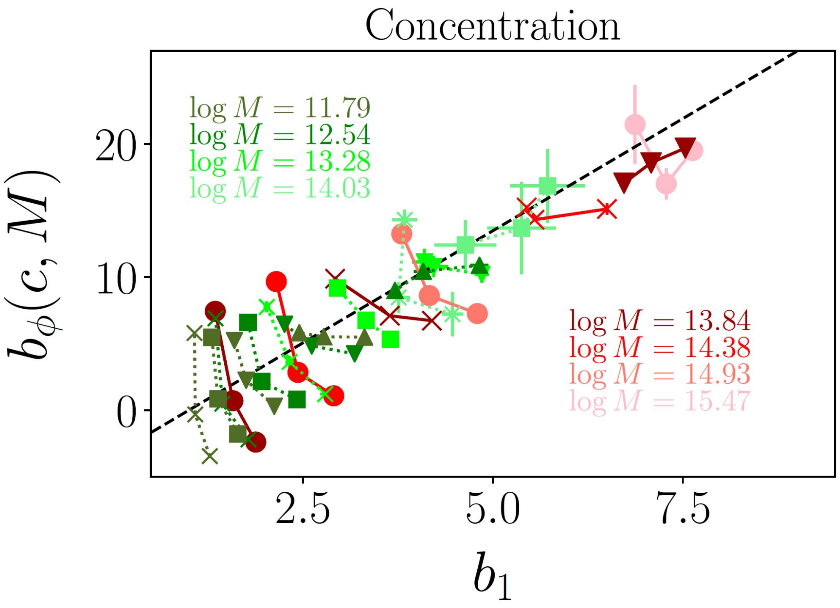
But b_ϕ is **not** just a function of mass (or ~ b)!

Splits by other quantities change b_ϕ dramatically:

Halo concentration c has a large effect

Can account for this via p:

$$b_\phi(b, p) \propto b - p$$



Slosar+08, Reid+10, Barreira+20, Lazeyras+22 (Figure), Barreira&Krause23, Marinucci++23, Lucie-Smith++23

Sub-sample Multi-tracer

Idea: Identify multi-tracer samples with sub-samples split by concentration (see also Barreira&Krause23)

Multi-tracer technique cancels sample variance

Error on f_{NL} scales like:

$$\sigma(f_{\rm NL}^{\rm (loc)}) \propto \left(\frac{b_{\phi,1}}{b_1} - \frac{b_{\phi,2}}{b_2}\right)^{-1}$$

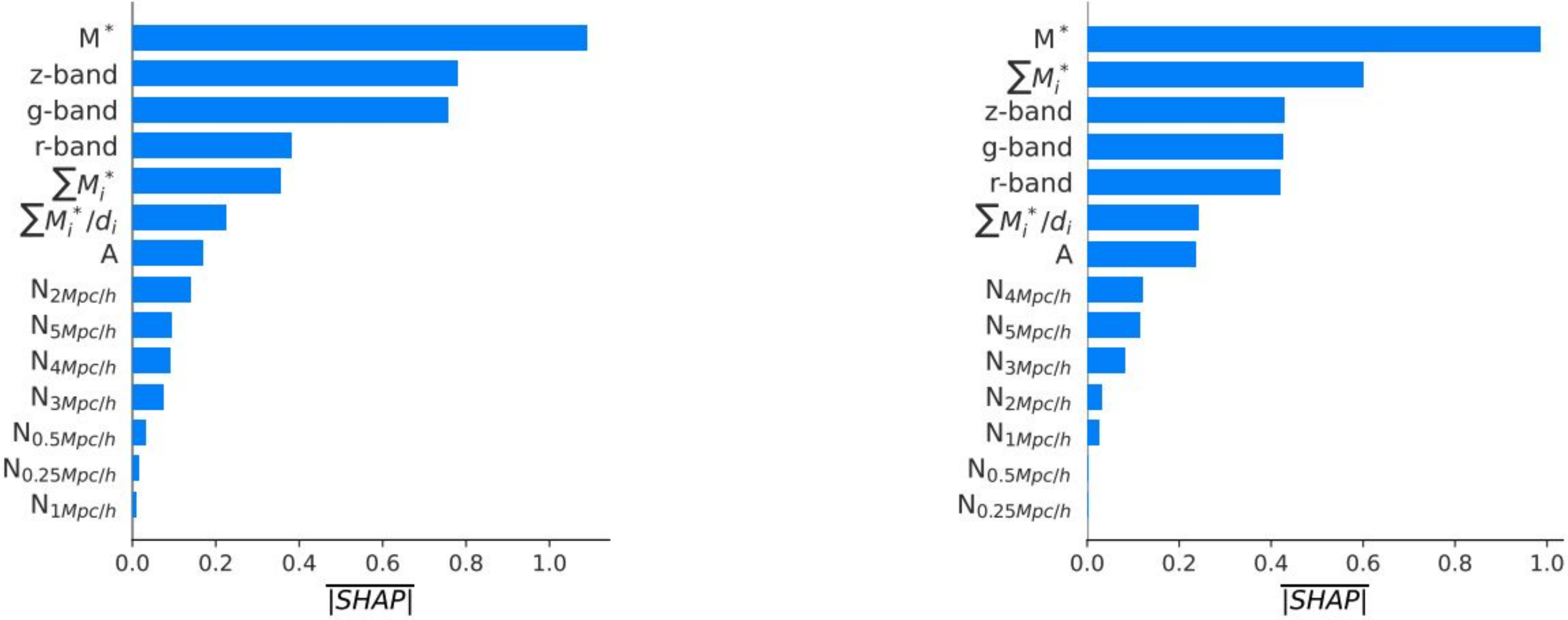
Seljak09

Multi-tracer forecast procedure

1. Apply LRG/ELG selection cuts to (redshift-space) IllustrisTNG galaxies
2. Train NN to obtain map between galaxy (M*, g,r,z, **s**,...) -> interpolated host halo b_{ϕ}
3. Predict b_{ϕ} for host halo of each galaxy
4. Divide galaxies into 3 bins by predicted b_{ϕ}

The so-divided bins are the multi-tracer (MT) samples used in the (linear) Fisher forecast - usual caveats

Feature Importance

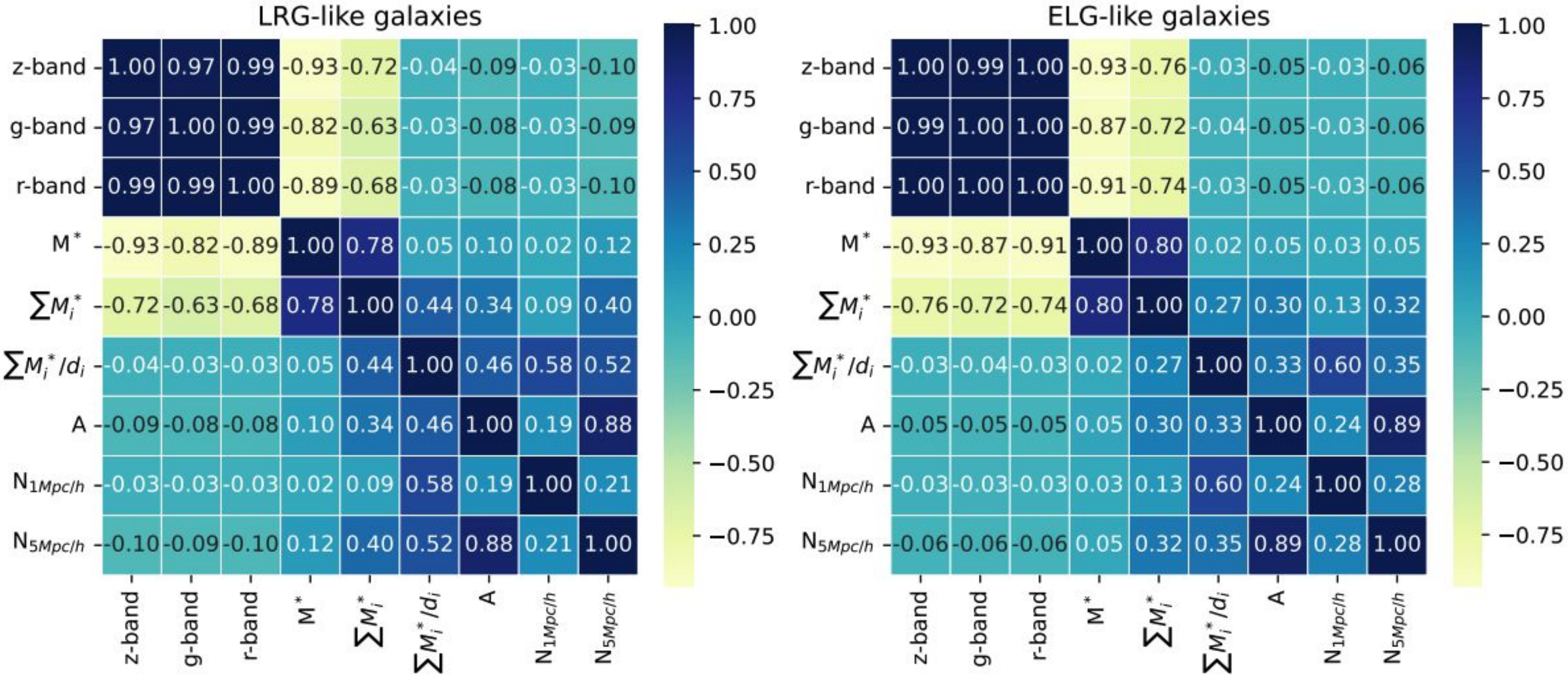


(a) ELG-like galaxies

(b) LRG-like galaxies

SHAP -> Lundberg&Lee17 NeurIPS

Pearson Correlation



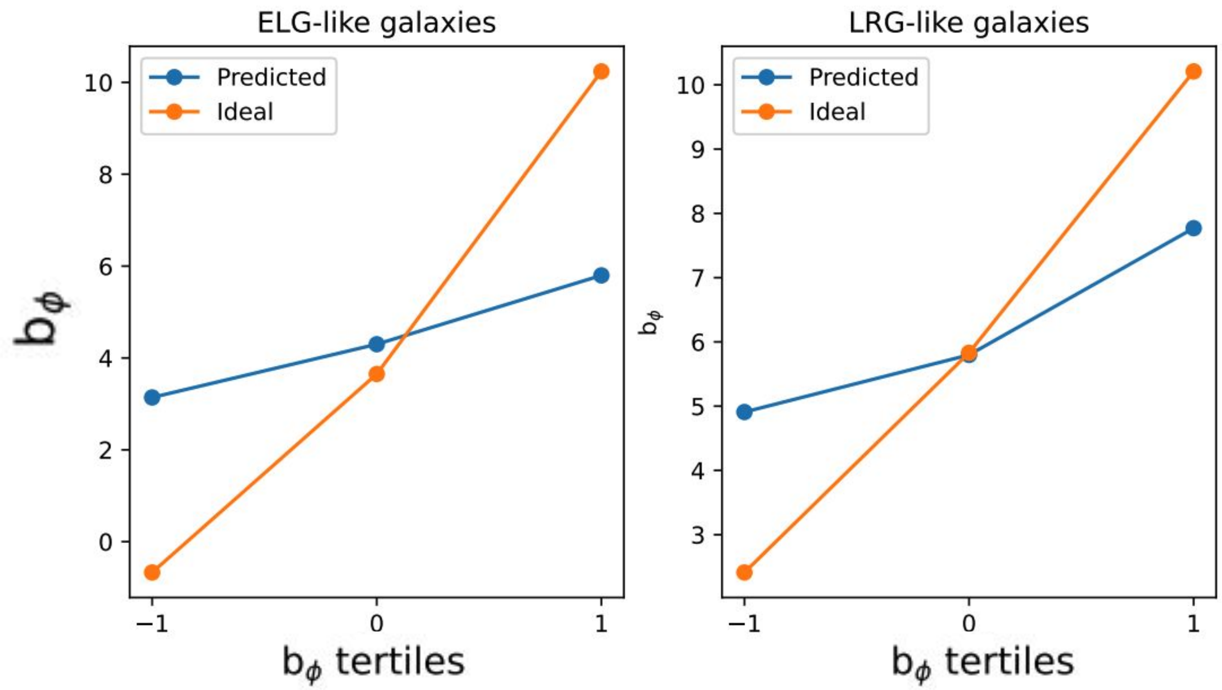
Results in split bins

Predicted - ML result

Ideal - perfect recovery

ML model bleeds significant info

Still tells us something!



DESI Galaxies

Split each sample into tertiles

Tried several combinations

Large improvement over "naive" multitracer!

ELG + LRG	$\sigma(f_{NL}^{\mathrm{loc}})$
$p = 1$	4.0
(2) ($\overline{\mathrm{LRG}}$, $\overline{\mathrm{ELG}}$), ideal	2.3
(2) ($\overline{\mathrm{LRG}}$, $\overline{\mathrm{ELG}}$), pred	2.3
(2) (LRG+, ELG+), ideal	1.4
(2) (LRG+, ELG+), pred	2.4
(3) (LRG-, LRG+, ELG-), ideal	0.8
(3) (LRG-, LRG+, ELG-), pred	2.0
(3) (LRG-, ELG+, ELG-), ideal	0.8
(3) (LRG-, ELG+, ELG-), pred	2.0
(3) (LRG-, ELG+, else), ideal	0.6
(3) (LRG-, ELG+, else), pred	1.5

Future LPNG Surveys - MT vs ST

Recall:

$$\sigma(f_{\mathrm{NL}}^{(\mathrm{loc})}) \propto \left(\frac{b_{\phi,1}}{b_1} - \frac{b_{\phi,2}}{b_2}\right)^{-1}$$

$$b_\phi(b,p) \propto b - p$$

Simplify and
assume fixed *b*:

$$\sigma(f_{\mathrm{NL}}^{(\mathrm{loc})}) \overset{\text{same b}}{\rightarrow} (\Delta p)^{-1}$$

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<u>What shape of MT vs ST should we expect?</u>

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What shape of MT vs ST should we expect?

SPHEREx - Forecast assumptions

Linear redshift space power spectrum

Redshift range: $0.1 < z < 3.0$

$f_{\rm sky} = 0.65$

$k_{\rm min} = 0.001\ h/{\rm Mpc}$

Agree with Sailer++21 on single-tracer

Redshift errors:

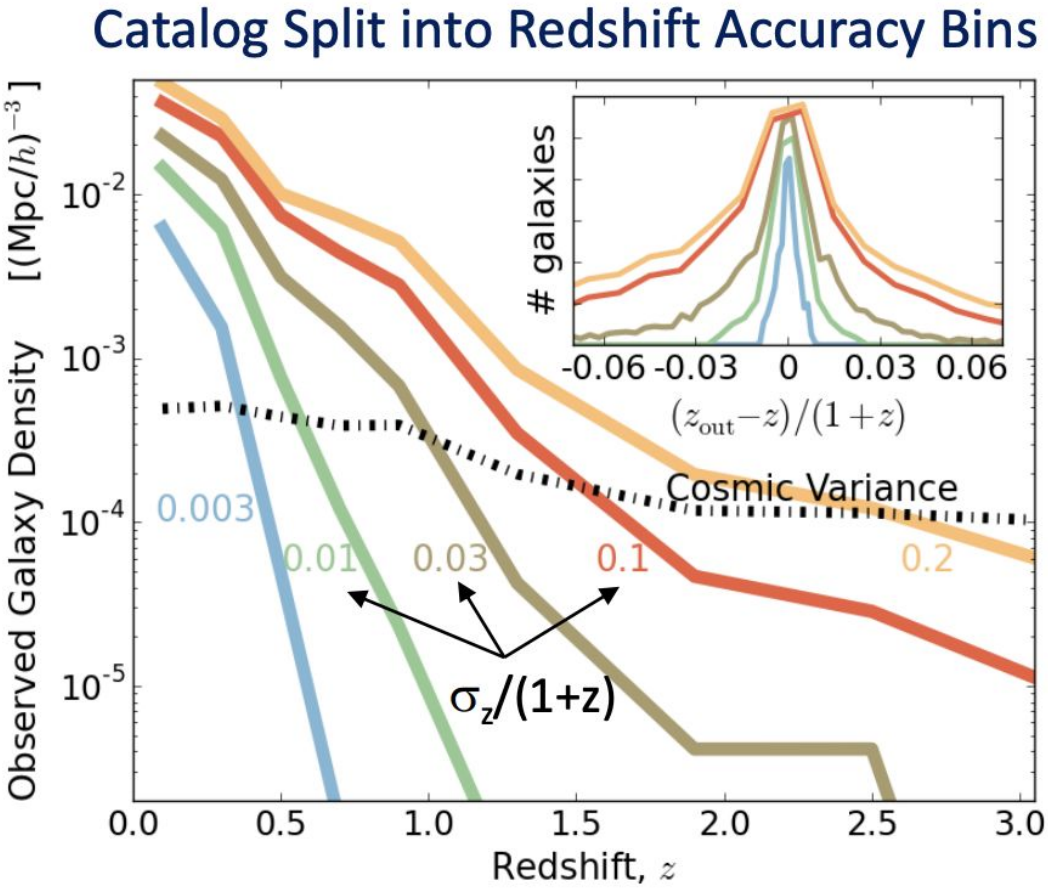
$$\exp\left(-\left[k\mu\sigma_z\frac{d\chi}{dz}\right]^2\right)$$

SPHEREx - Redshift error samples

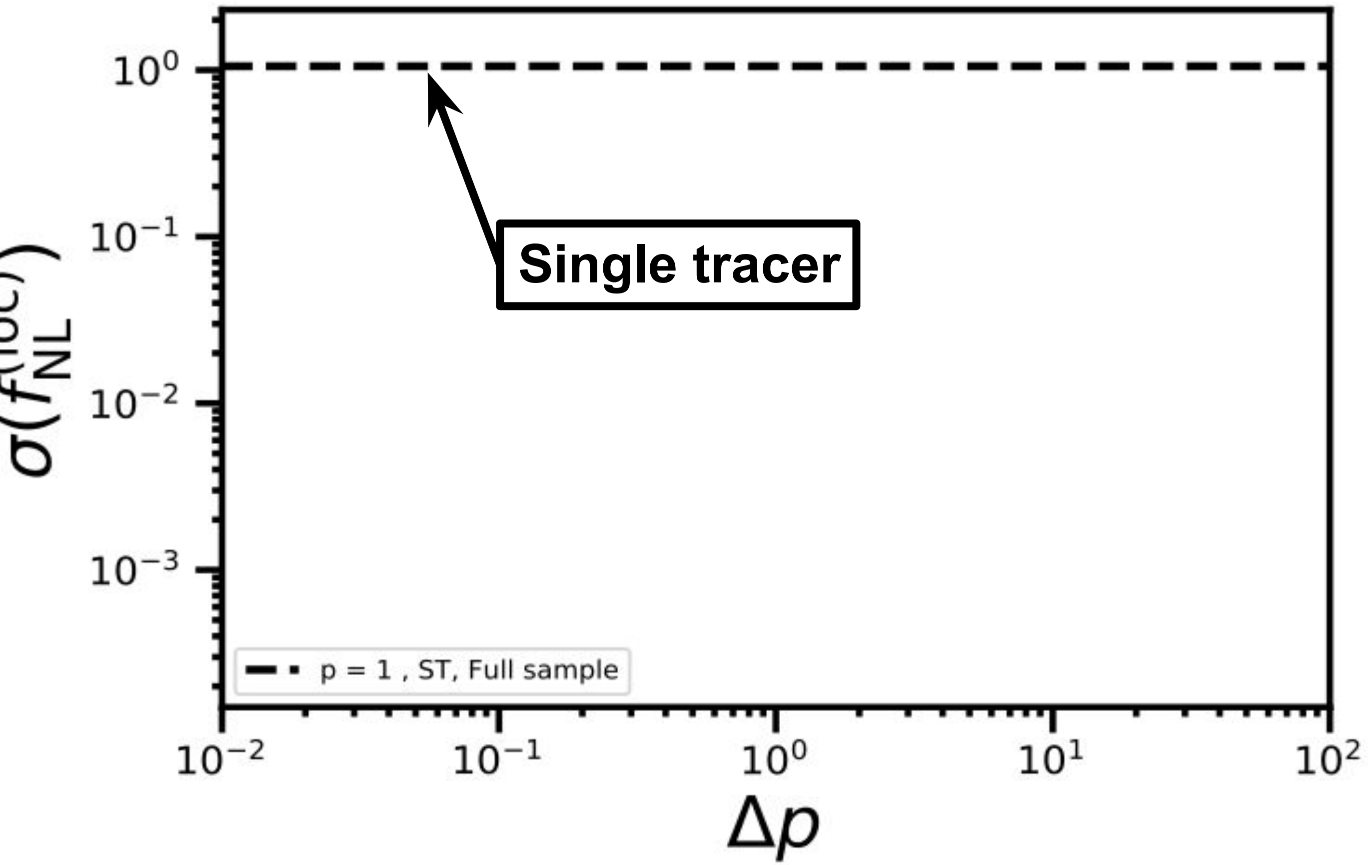
Use various combos of all 5 samples

Combos weighted by bias (following Doré+14)

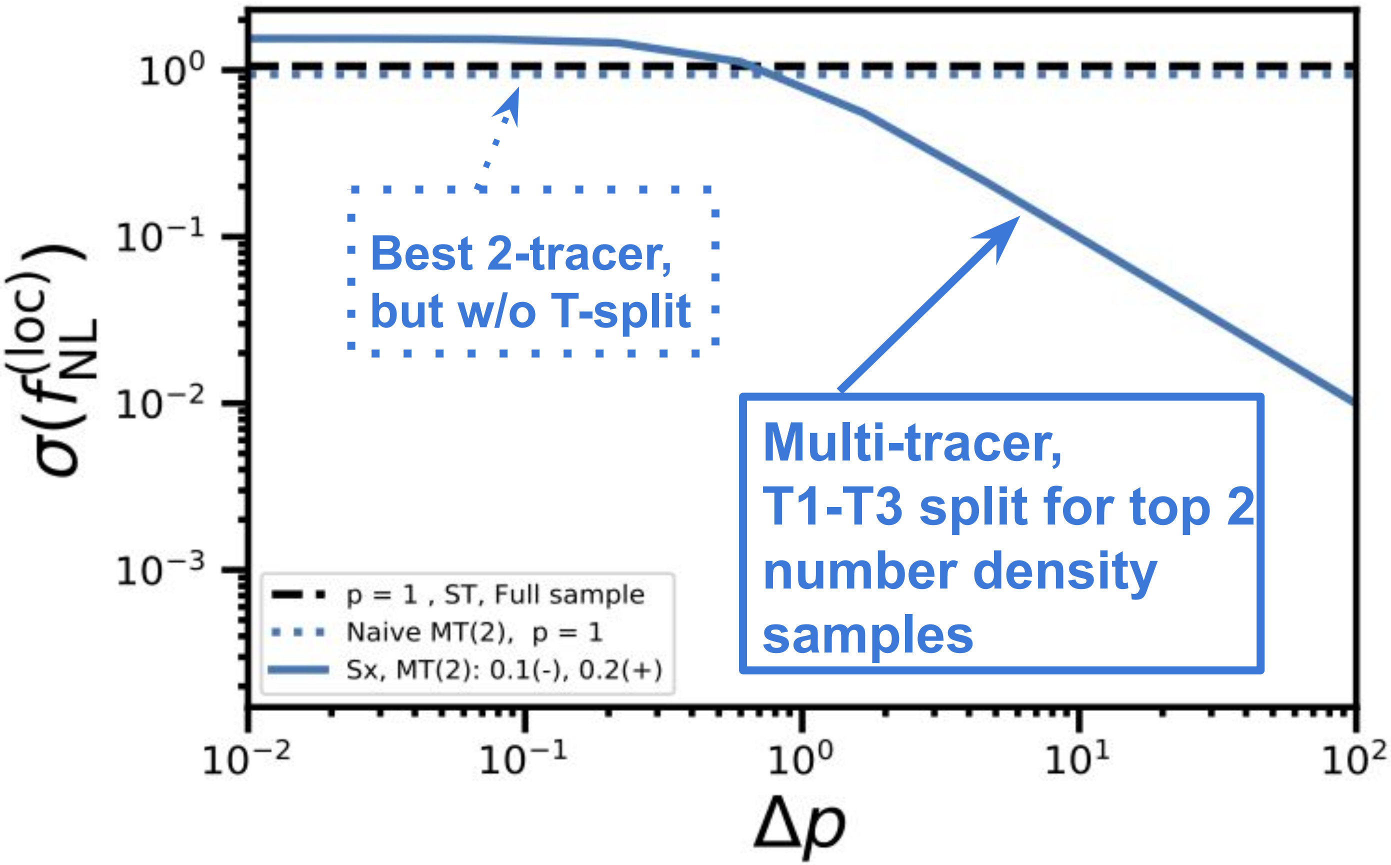
Always assume most conservative redshift error for combos



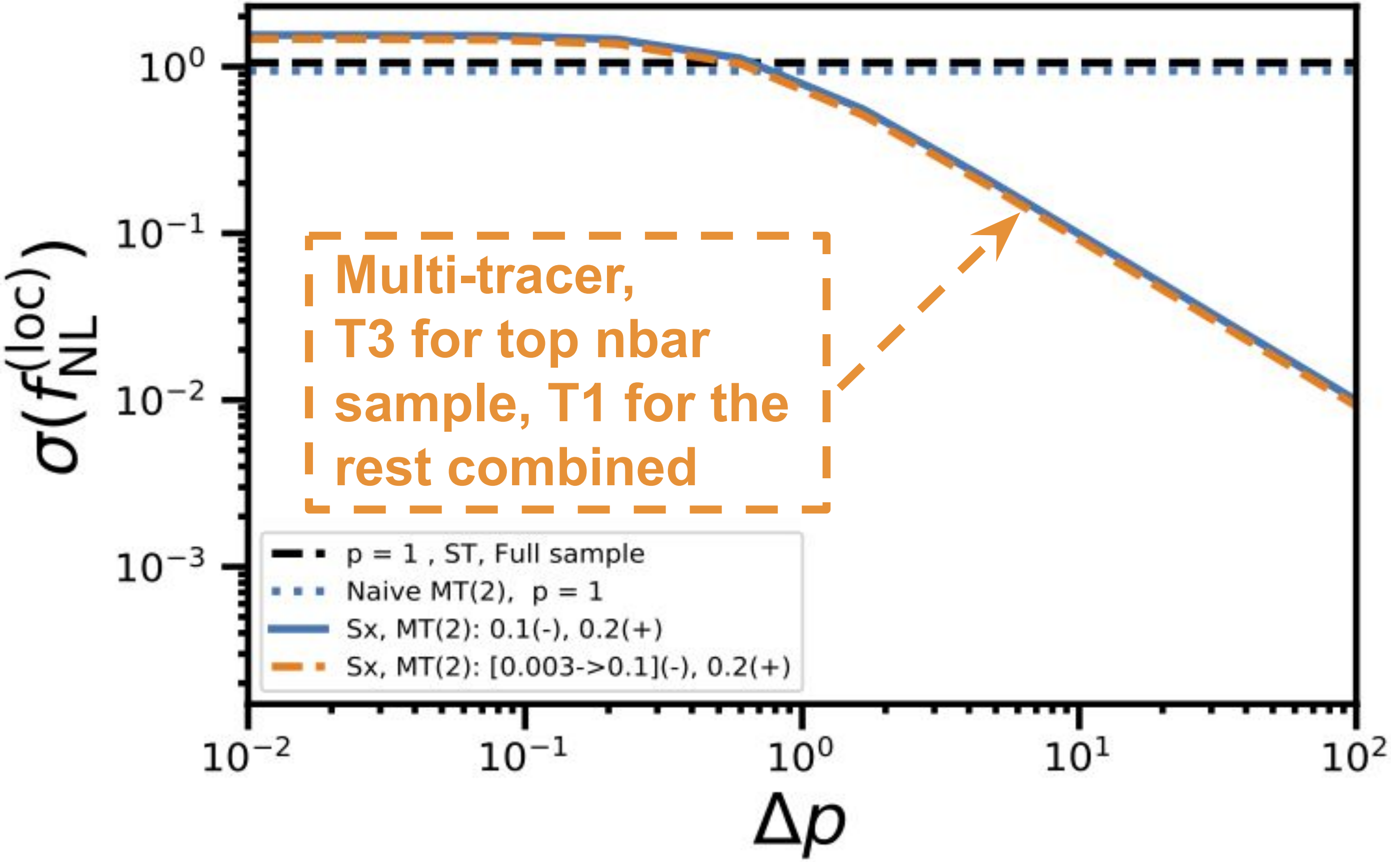
Single-tracer - combined sample



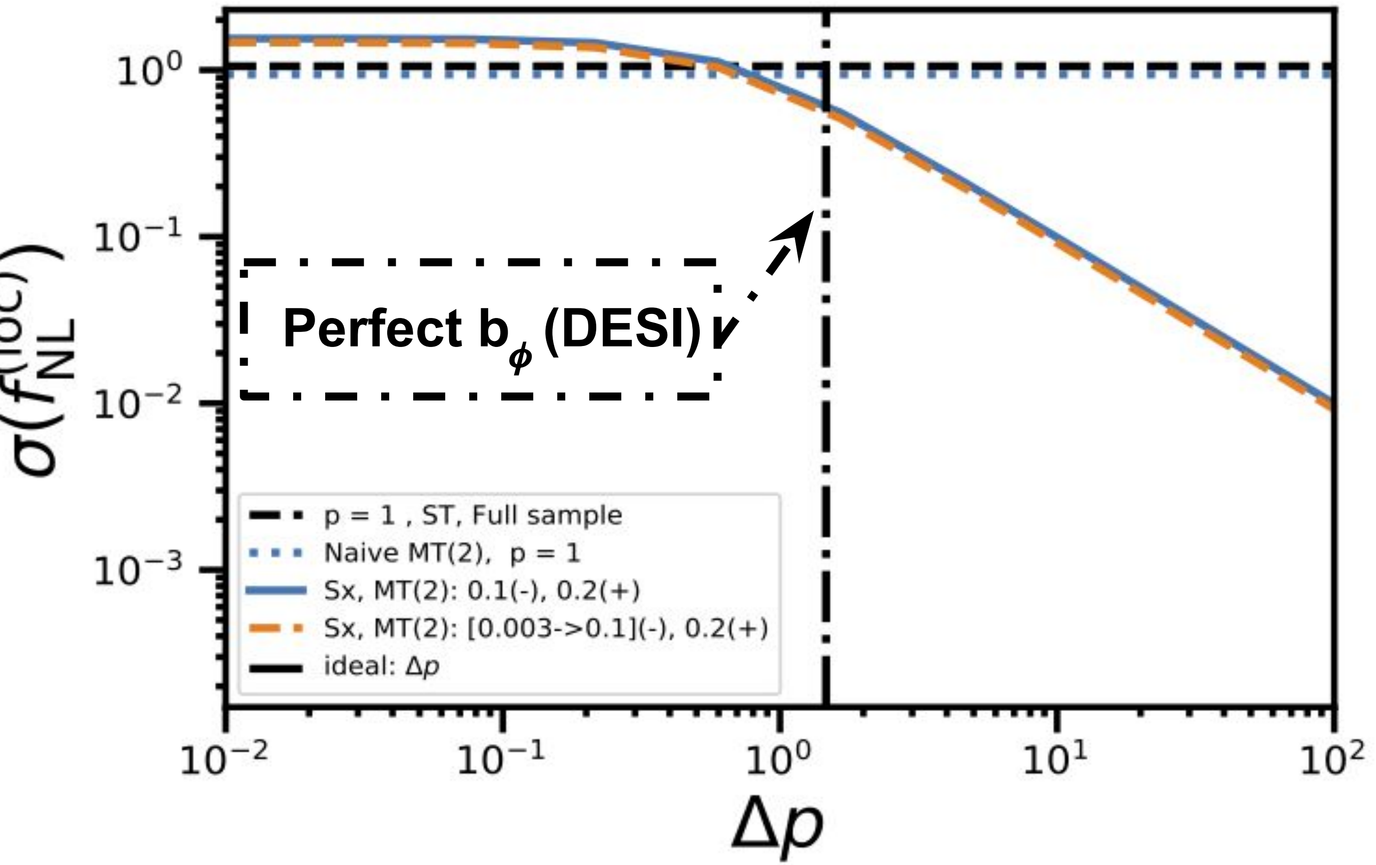
2 individual tracers



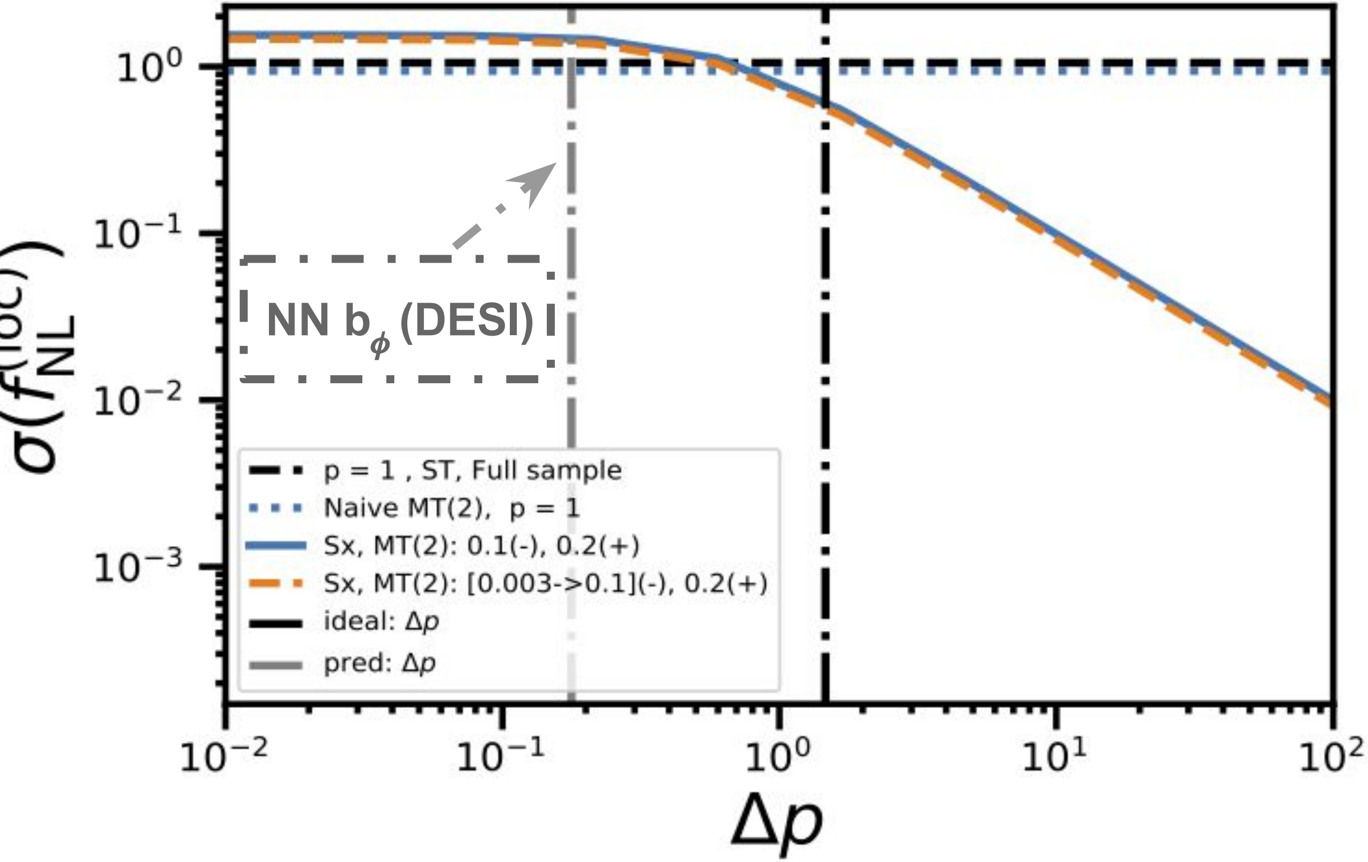
2-tracer combination



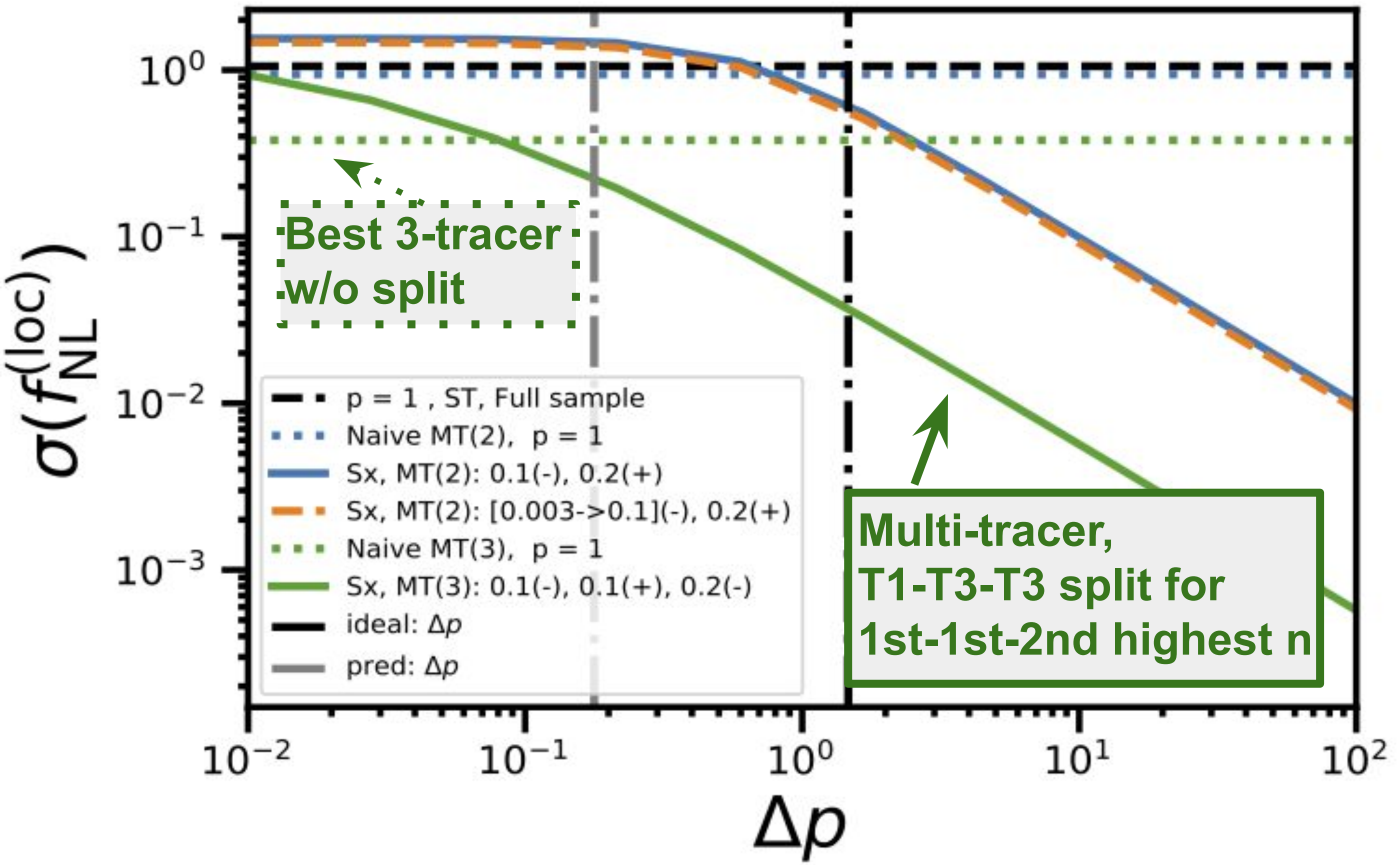
What we aspire to



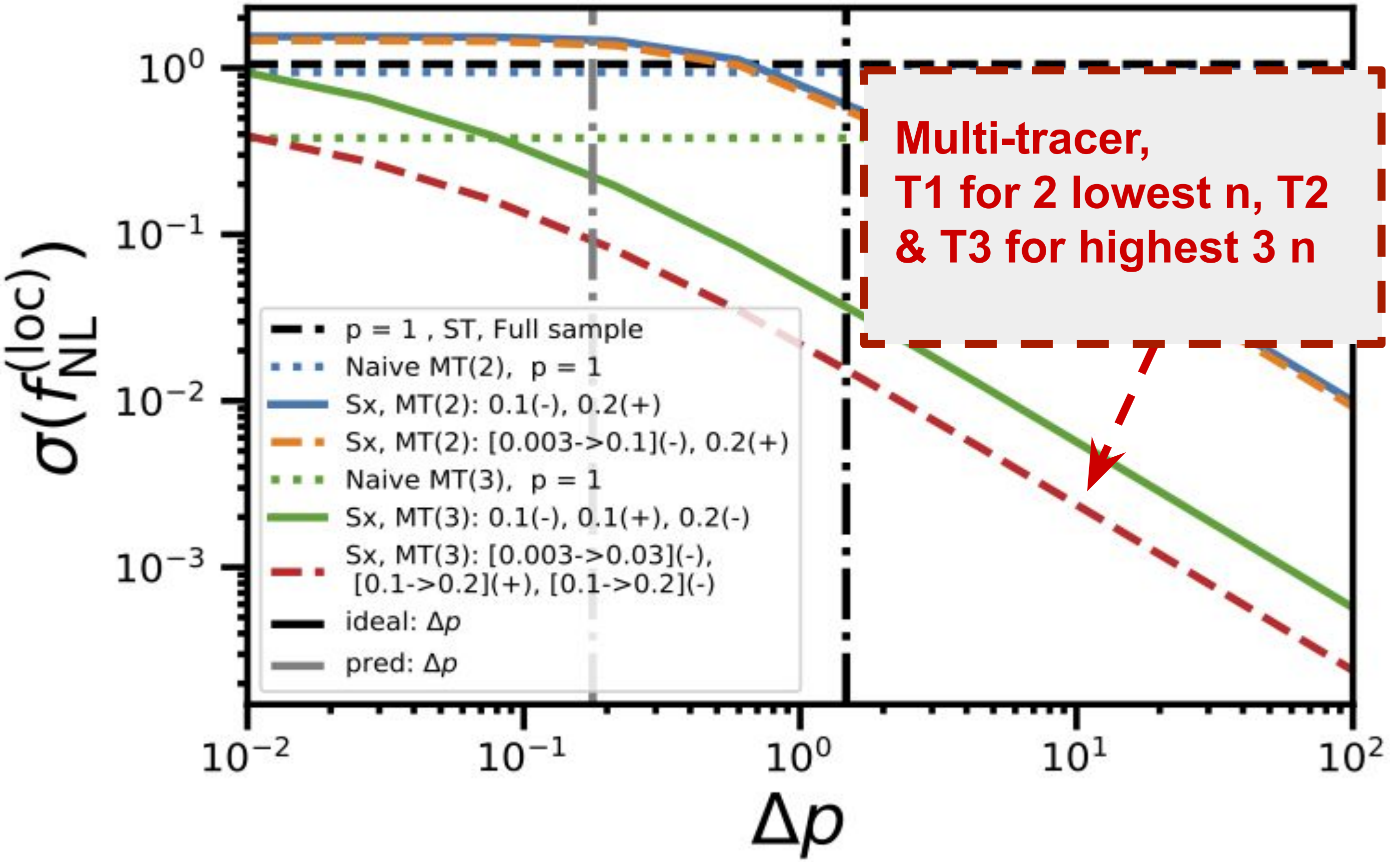
What we might get



3 individual tracers



3-tracer combination



Summary

LPNG with assembly bias underappreciated until recently

Multi-tracer on subsamples can drastically **reduce $\sigma(f_{NL})$**

For DESI, **3x improvement** over single-tracer with ML

Further factor of 2x improvement possible if better model

Future surveys may benefit **by >10x**

Of course, now we need to go **beyond Fisher**!