

# PNG with *Dark Energy Survey*

## PNG & Beyond workshop

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# Dark Energy Survey (DES)

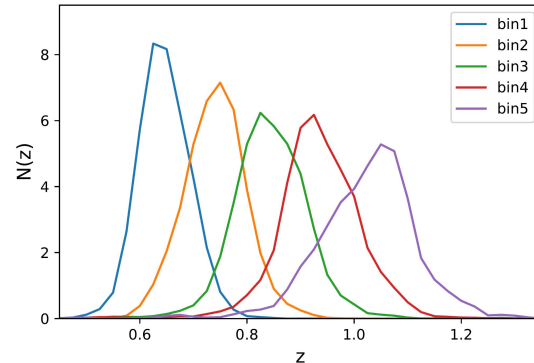
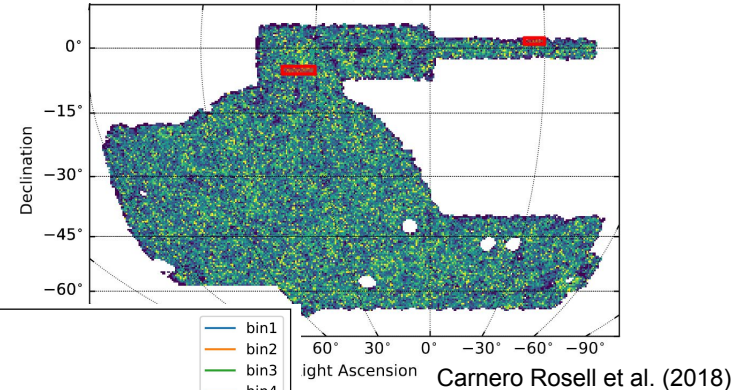
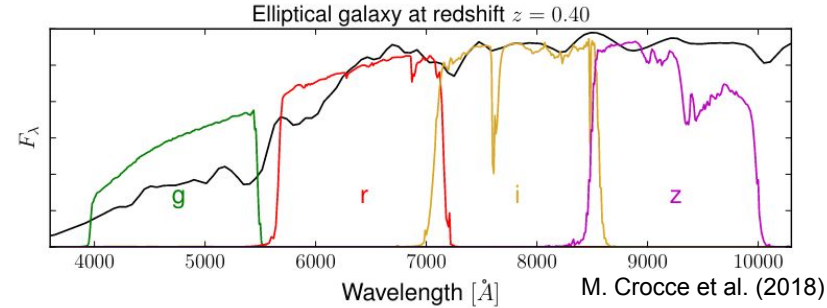


★ Area of  $\sim 5000 \text{ deg}^2$  and **Photometric** in  $\sim 4$  color bands. (similar to VR's LSST) (I. Sevilla-Noarbe et al. 2020)

★ Combination of colors are used to estimate the redshift of galaxies. (for example, De Vicente et al. 2016)

★ Colors selections can be used to define **different galaxy samples:**

- **BAO:** Optimized for BAO... (A. Carnero Rosell et al. 2021)
- **MagLim:** Optimized for weak lensing (A. Porredon et al. 2021)
- **redMagic:** Luminous red galaxies (E. Rozo et al. 2016)



# Primordial non-Gaussianity in DES



## Ongoing projects:

- ★ Angular Power Spectrum.  
H. Camacho et al. Ongoing research
- ★ **Angular Correlation Function methodology (this presentation).**  
**W. Riquelme, S. Avila, J. Garcia-Bellido, et al.**

Other active members: A. Porredon, K. Chan, I. Ferrero, N. Weaverdyck...

## Starting projects :

- Systematics for PNG: N. Weaverdyck, M. R. Monroy
- **Sample optimisation: W. Riquelme, Anna Porredon**

# Primordial non-Gaussianity with Angular correlation function: Integral constraint and validation for DES

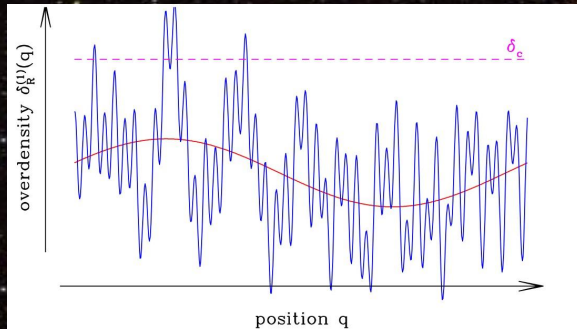
Walter Riquelme,<sup>1,2★</sup> Santiago Avila,<sup>1,2†</sup> Juan García-Bellido,<sup>1,2‡</sup> Anna Porredon,<sup>3</sup> Ismael Ferrero,<sup>4</sup>  
Kwan Chuen Chan,<sup>5</sup> Rogerio Rosenfeld,<sup>6</sup> Hugo Camacho,<sup>7</sup> Adrian G. Adame,<sup>1,2</sup> [-and more-]

The work has **three** main parts:

1. Angular correlation function with PNG
2. Integral constraint impact
3. Robustness test for DES

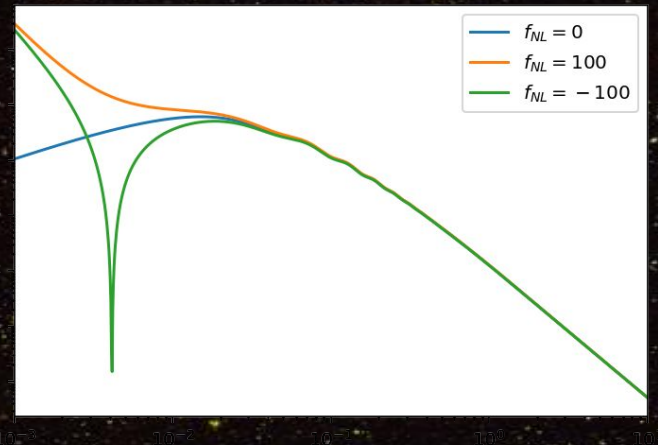
<https://arxiv.org/abs/2209.07187>

# Scale dependent bias



$$P(k, f_{NL}) = b^2(k, f_{NL}) P_{DM}(k)$$

$$b(k) = b_g + \frac{f_{NL}(b_g - p)M(k, z)}{k^2}$$



[Dalal et al. (2008)]  
[Slosar et al. (2008)]

# Angular correlation function (ACF)

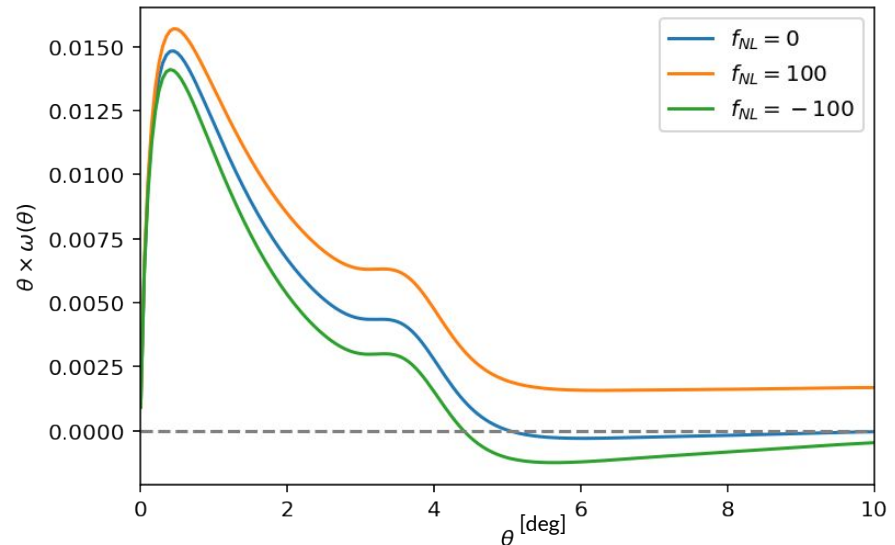
Summary statistic of clustering of galaxies, or other biased tracers.

$$w(\theta, f_{\text{NL}}) = \int dz_1 \int dz_2 n(z_1)n(z_2)\xi(r(z_1, z_2, \theta), f_{\text{NL}})$$

- The ACF is a 2D projection of 2PCF using  $n(z)$  distributions.
- The ACF is *also affected by  $f_{\text{NL}}$*  via scale-dependent bias.

At large scales

$$w(\theta, f_{\text{NL}}) \propto f_{\text{NL}}^2 \cdot \infty$$



# Integral constraint

For limited windowed surveys, the number of galaxies in the universe is estimated from the mean density of the survey, implying:

$$N_g = \bar{n} \int dV_s + \bar{n} \int \xi(r) dV_s$$

$$\int w_{\text{obs}}(\theta) d\Omega = 0$$

$$\sum RR(\theta) w_{\text{obs}}(\theta) = 0$$

Integral  
Constraint  
cond.

Imposing integral constraint to theory:

$$w_{th}^*(\theta, f_{\text{NL}}) = w_{th}(\theta, f_{\text{NL}}) - I(f_{\text{NL}}) \implies I(f_{\text{NL}}) = \frac{\sum RR(\theta) w_{th}(\theta, f_{\text{NL}})}{\sum RR(\theta)}$$

# Simulations

In order to test our methods we used two sets of simulations, with and without PNG. From each of these, we compute the ACF.

## ICE-COLA mocks

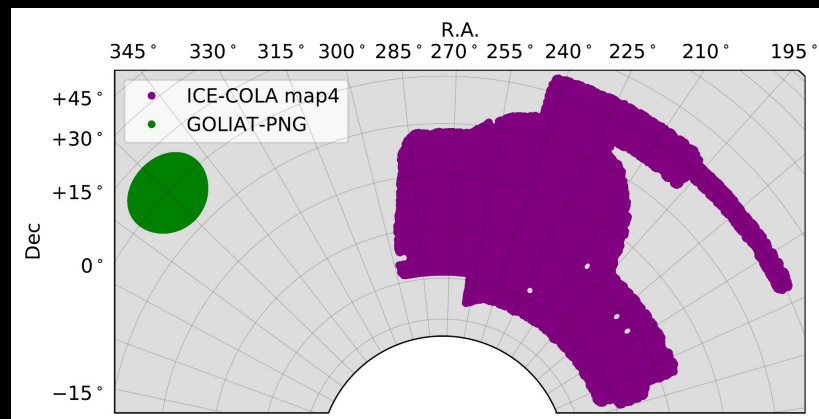
[I. Ferrero et al. 2021]

- 1952 Quasi-NBODY sims.
- $f_{NL} = 0$  ( $p=1$ )
- Redshift  $0.6 < z < 1.1$  divided in 5 redshift bins
- Follows **Y3 BAO** redshift error and angular distribution.

## GOLIAT-PNG mocks

[S. Ávila & A. Adame 2022]

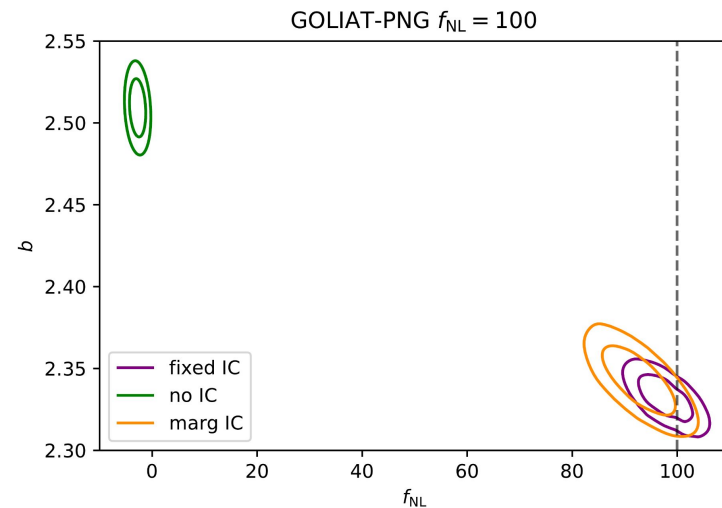
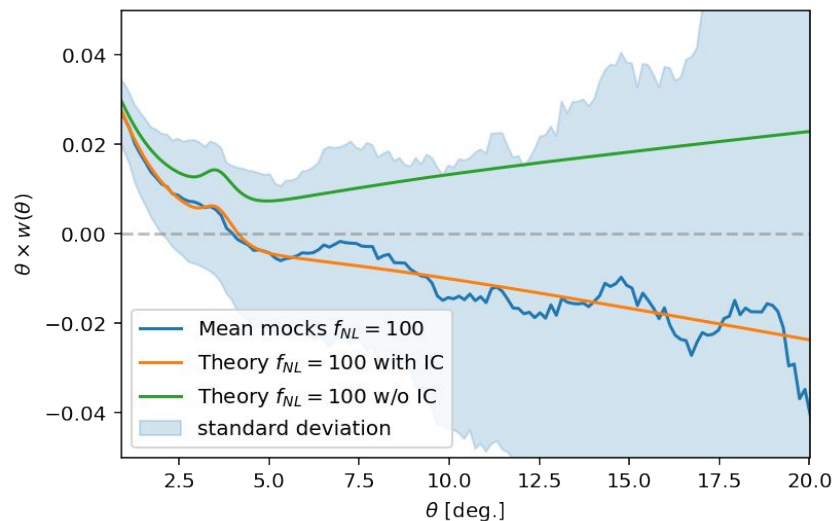
- 246 NBODY sims.
- $f_{NL} = [-100, 100]$  ( $p \sim 0.9$ )
- Semi-aperture of 11.2 deg.
- Survey like redshift dist.  $0.6 < z < 1.1$  in 5 bins





# GOLIAT-PNG and integral constraint

From all simulations, we perform a joint likelihood measurement of  $f_{NL}$



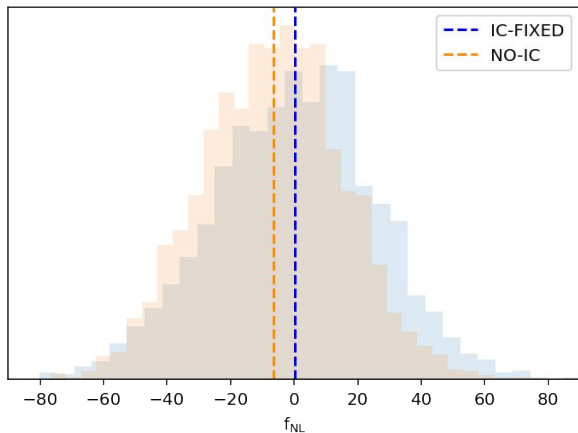
The integral constraint (IC) helps to avoid biased values for  $f_{NL}$

➤ We recover  $f_{NL}=100$  within  $1\sigma$

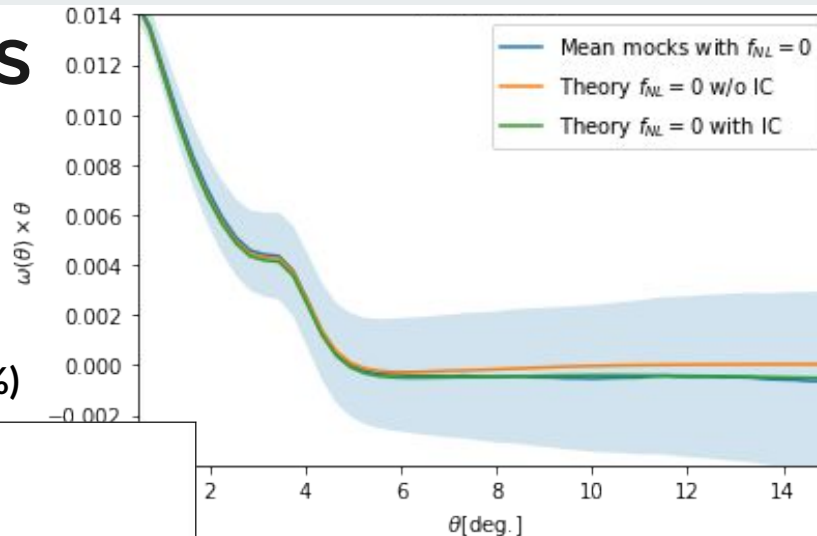
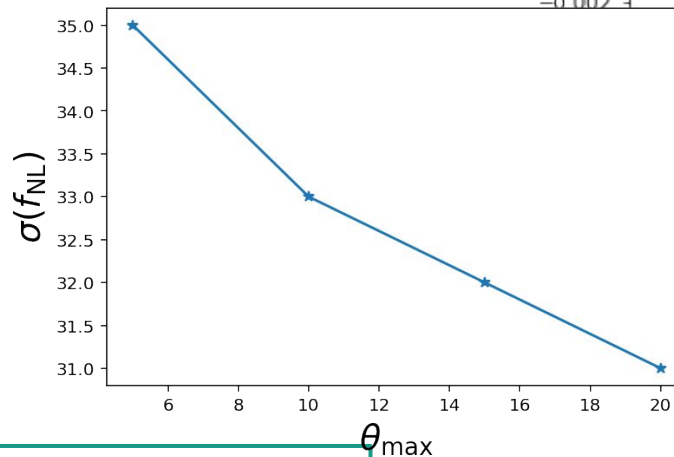
# Robustness and forecast for DES

Using ICE-COLA mocks we test the robustness of our method on a DES-like scenario

1. IC improves accuracy ( $\Delta f_{\text{NL}} \sim 7$ )



2. Large angular scales improves precision (11%)



We forecast  $\sigma(f_{\text{NL}}) \sim 31$   
using the Y3 BAO sample

The ACF with PNG and including the **Integral constraint** can be used to measure  $f_{\text{NL}}$  within DES.

# Sample optimization for fNL

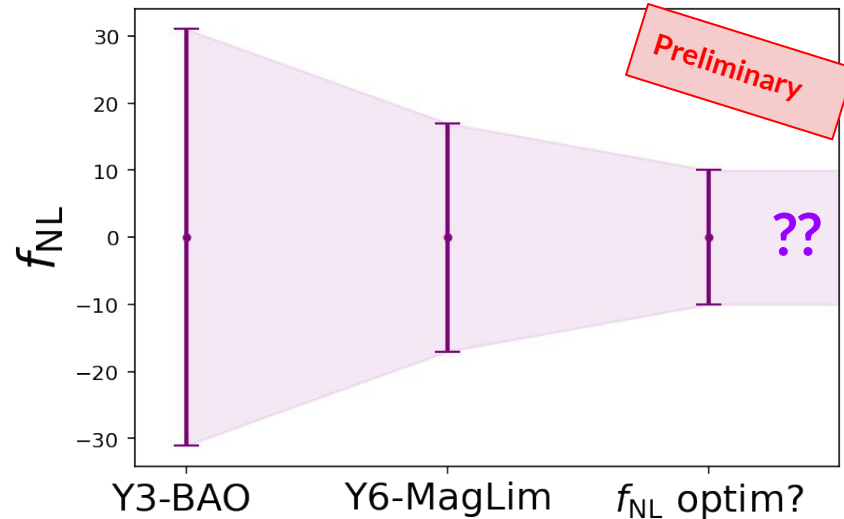
with Anna Porredon (work in progress...)

- Forecast with a theory-data vector

Modifying color cuts in i-band.  
Looking for an optimal sample for fNL.

$$i < az_{\text{phot}} + b$$

Optimize  $a$  and  $b$  to lower fNL errors



- Largest difference between samples?  
**Number density at high redshift...**
  - BAO Y3 sample  $\sim 900\text{k}$  ( $z \sim 1$ )
  - MagLim sample  $\sim 1.4\text{M}$  ( $z \sim 1$ )
  - $f_{\text{NL}}$  optimi1  $\sim 1.6\text{M}$  ( $z \sim 1.2$ )

# Conclusions and prospects

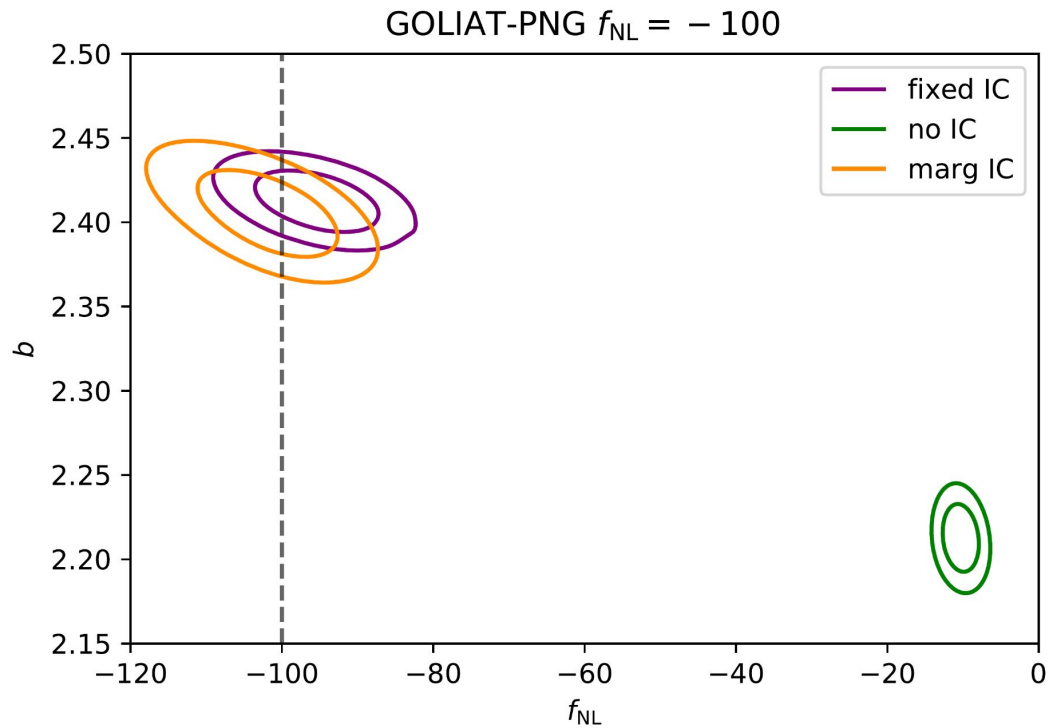
- We presented the methods to use the **Angular correlation function with scale-dep. bias** to measure fNL
- We need to include the **integral constraint** to avoid biased fNL values.
- Using **ICE-COLA** simulations, we have validated the methods to measure **fNL with DES**.
- Some future prospects will include:
  - Systematics impact and mitigation (this is one of the main challenges for fNL)
  - Sample optimization and application to data

Looking for jobs for next year

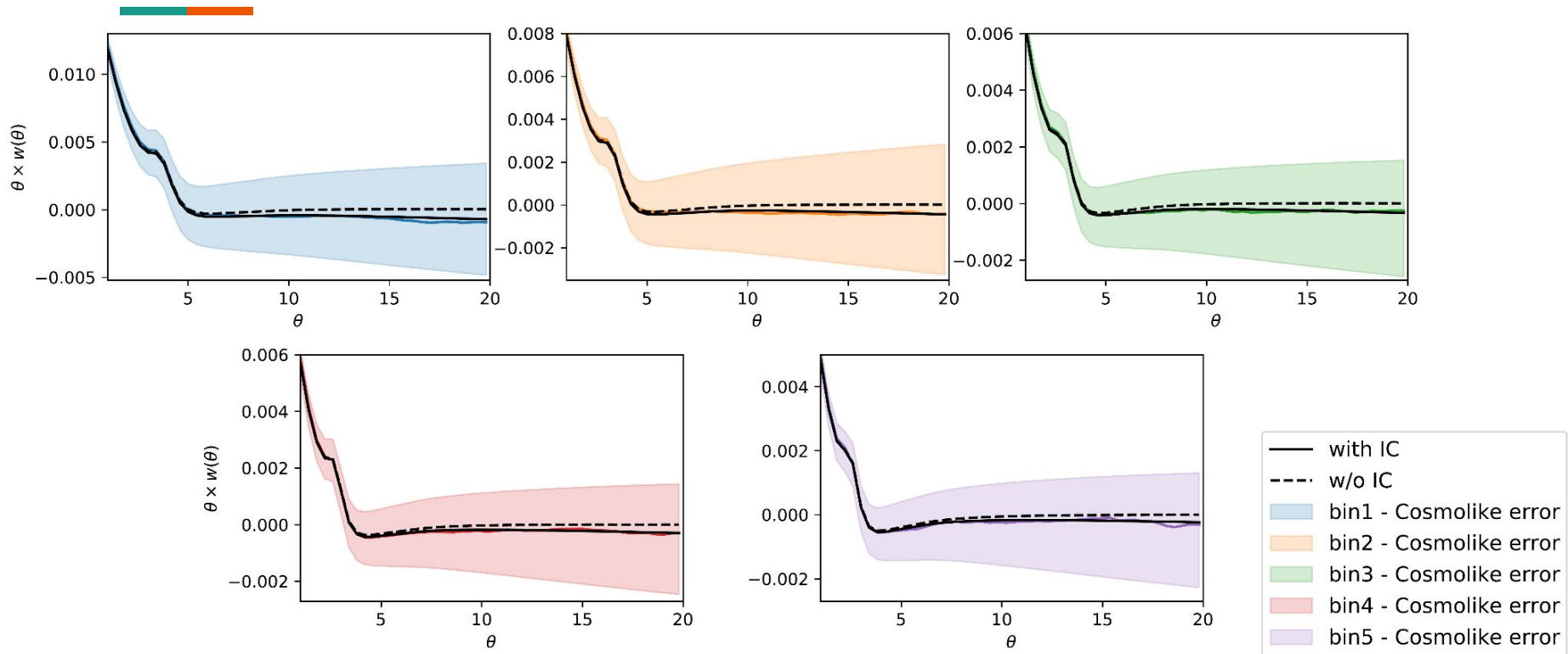


# Extra slides

# fNL=-100 GOLIAT png



# ICE-COLA 5bins



# Impact of p

