

Thèse de doctorat

Optimal inference of cosmological parameters in preparation of the Euclid survey

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Soutenue le 15 décembre 2021 devant le jury composé de

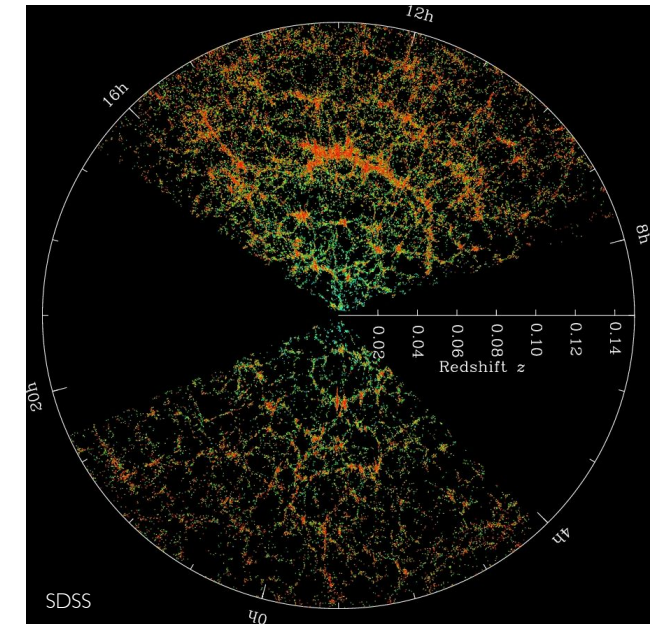
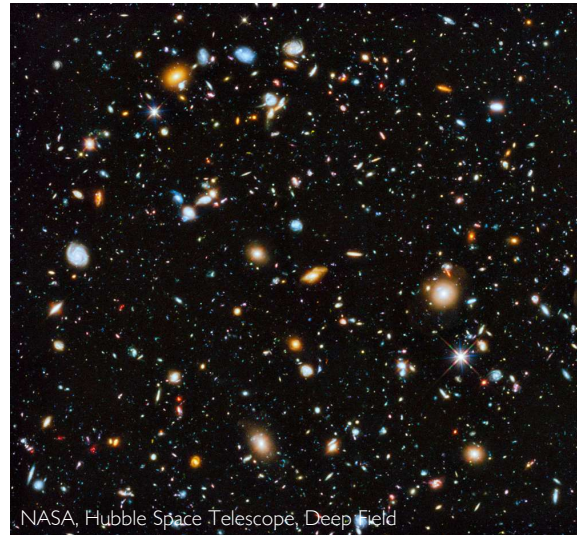
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- Introduction and key concepts
 - I. [State of the art in observational cosmology](#)
 - II. [Parameter inference and covariance matrix](#)
- My work
 - III. [Optimal parameter inference with the power spectrum including massive neutrinos](#)
 - IV. [Impact of Super Sample Covariance on future photometric galaxy surveys](#)

I. State of the art in observational cosmology

- The standard model of cosmology
- The Large Scale Structure and the Euclid survey

The aim of cosmology is to give a scientific description of the content and the evolution of the Universe



Cosmology is a peculiar science as it aims the description of **the Universe as a whole**

On the theory side

Newtonian gravity fails at predicting the behaviour of the Universe

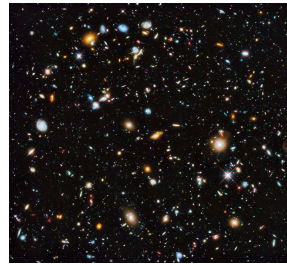
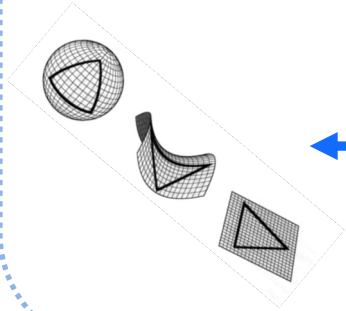
On the observational side

We only have one realisation of the Universe

Theoretical framework

General relativity

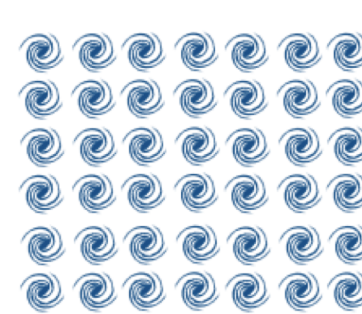
$$\underbrace{R_{\mu\nu} - \frac{1}{2}Rg_{\mu\nu}}_{\text{Geometry}} = 8\pi G \underbrace{T_{\mu\nu}}_{\text{Energy content}}$$



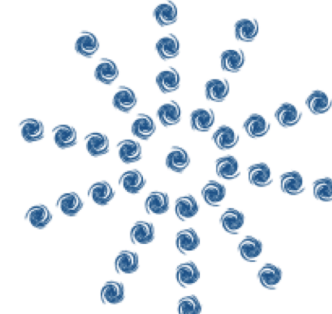
+

The cosmological principle

Homogeneity



Isotropy



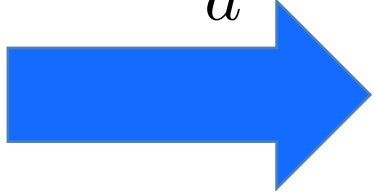
Taken from the PhD thesis of Alice Pisani, 2014

$$g_{\mu\nu}dx^\mu dx^\nu = dt^2 - a(t)^2 [d\chi^2 + S_k^2(\chi)d\Omega^2]$$

Scale factor

Curvature

$$H \equiv \frac{\dot{a}}{a}$$



The expansion rate of the Universe is governed by its content and curvature

$$H(a)^2 = H_0^2 \sum_i \left[\Omega_{i,0} a^{-3(1+w_i)} + \Omega_{k,0} a^{-2} \right]$$

Reduced density $\Omega_i \equiv \rho_i \frac{8\pi G}{3H^2}$ | Equation of state $w_i = p_i/\rho_i$

$\dot{a} = 0$ Static ?

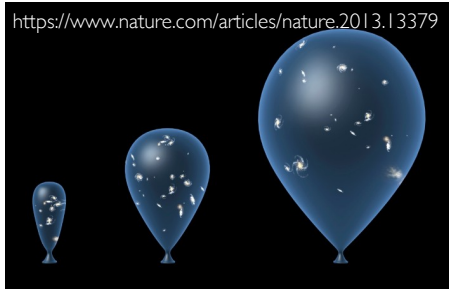
$\dot{a} > 0$ Expanding ?

$\dot{a} < 0$ Contracting ?

An expanding universe

For a universe filled with matter ($\Omega_m = 1$)

$\dot{a} > 0$ The universe is expanding



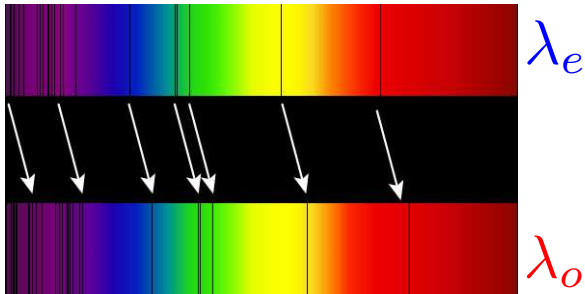
BUT

Einstein introduced the cosmological constant Λ to keep it static :

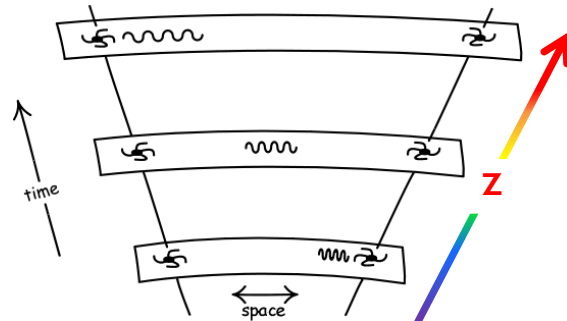
$$R_{\mu\nu} - \frac{1}{2}Rg_{\mu\nu} - \Lambda g_{\mu\nu} = 8\pi GT_{\mu\nu}$$

Observation of the redshift of galaxies (G. Lemaître 1927 and E. Hubble 1929)

<https://en.wikipedia.org/wiki/Redshift>



$$1 + z = \frac{\lambda_o}{\lambda_e}$$



The expansion stretches photon's wavelength $1 + z = \frac{a_0}{a}$

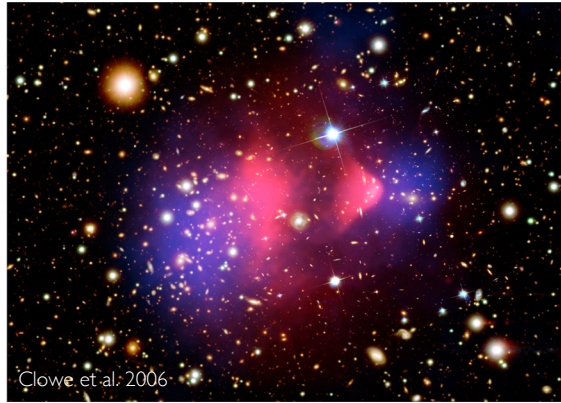
➤ Observational proof of the expansion (Supression of Λ)

➤ Redshift is an indicator of time and distance

Theory
↕
Observation

The understanding of the Universe was built from a combination of observations

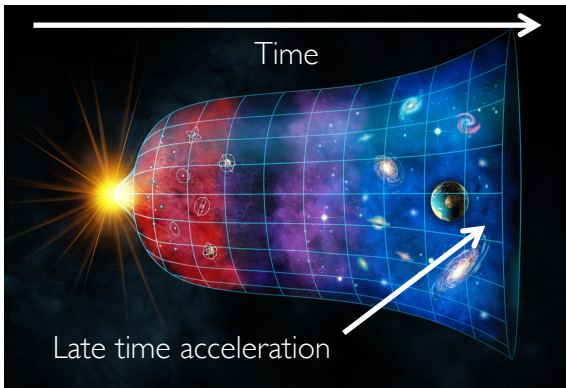
➤ The universe is filled with Cold Dark Matter (CDM)



- Velocity dispersion in Clusters (1933)
- Big Bang Nucleosynthesis (1940)
- Cosmic Microwave Background (1965)
- Galaxy rotation curves (1970)
- Lensing in clusters (2004)

➔ 5% of ordinary matter and 27% of CDM

➤ The expansion of the universe is accelerating

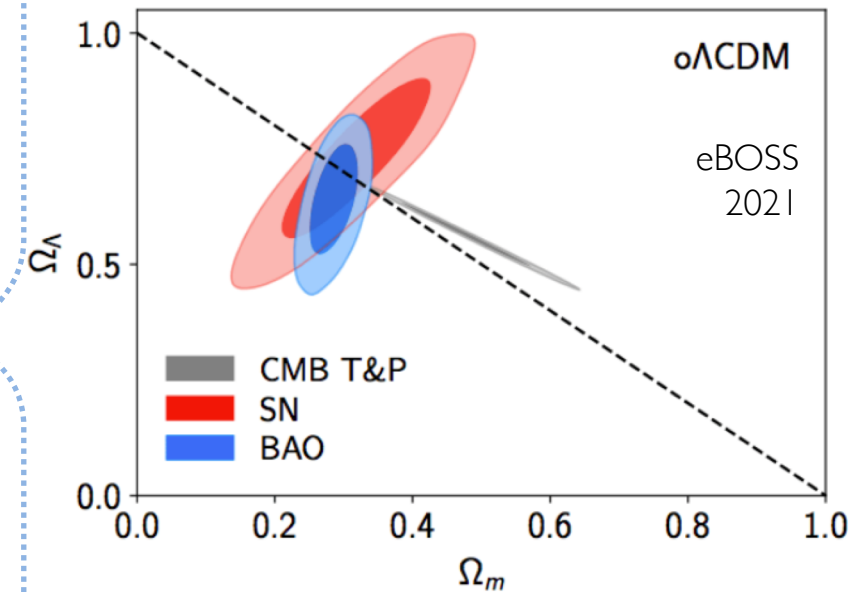


- Type Ia Supernovae (1998)
- Baryon acoustic peak (2005)

➔ 68% of Dark Energy

➔ *Reintroduction of the cosmological constant Λ*

The Λ CDM model



95% of the universe is not understood

<https://newatlas.com/physics/what-is-dark-energy-explained-accelerating-expansion-universe/>

Some issues with Λ CDM

- Explaining the acceleration of the expansion with Λ

120 orders of magnitude difference with the theoretical prediction

- Tension on the measurement of H_0

~ 4 to 5σ tension **within Λ CDM**

Motivations to go
Beyond Λ CDM

Alternatives to Λ CDM

$$R_{\mu\nu} - \frac{1}{2}Rg_{\mu\nu} = 8\pi GT_{\mu\nu}$$

Modified gravity models ?

Look for deviations from Einstein's Field Equations

Additional fluid : Dark energy ?

Look for deviations from $w = -1$

$$w_{\text{DE}}(a) = w_0 + w_a(1 - a)$$

Need precise measurement of cosmological parameters to observe deviations from Λ CDM

$$M_\nu \equiv \sum m_\nu$$

Particle Physics experiment

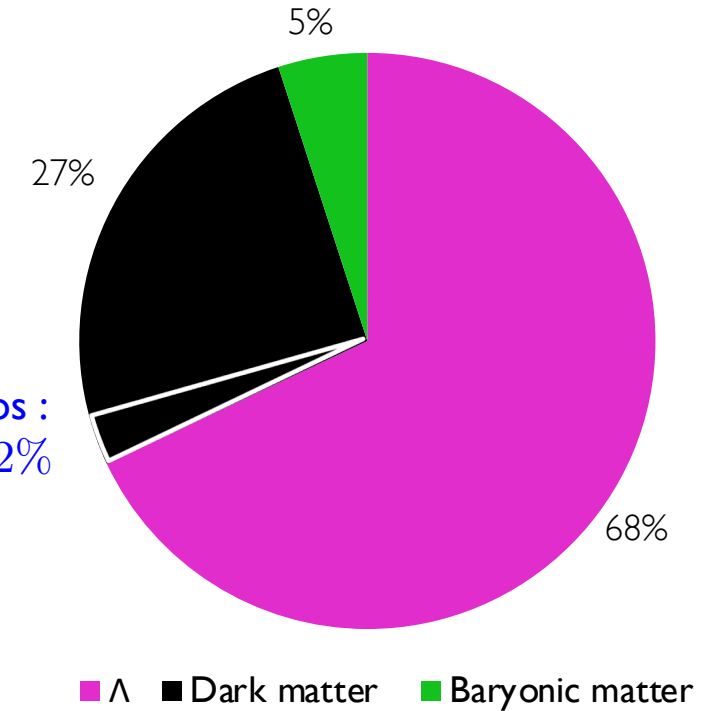
$$\begin{array}{l} \text{NH} \quad 0.056 \text{ eV} \lesssim M_\nu \lesssim 1 \text{ eV} \\ \text{IH} \quad 0.095 \text{ eV} \lesssim \end{array}$$

Reduced density of neutrinos in the universe

$$\Omega_\nu = \frac{M_\nu}{93.14 h^2 \text{ eV}}$$



Neutrinos :
0.1% – 2%



With the expansion of the universe, massive neutrinos undergo a transition from **relativistic** to **non-relativistic**

$$1 + z_{\text{nr}} = 1890 \left(\frac{m_\nu}{1 \text{ eV}} \right)$$



**Need to take this into account to
measure small departures from Λ CDM**

Massive neutrinos in cosmology

$$M_\nu \equiv \sum m_\nu$$

Particle Physics experiment

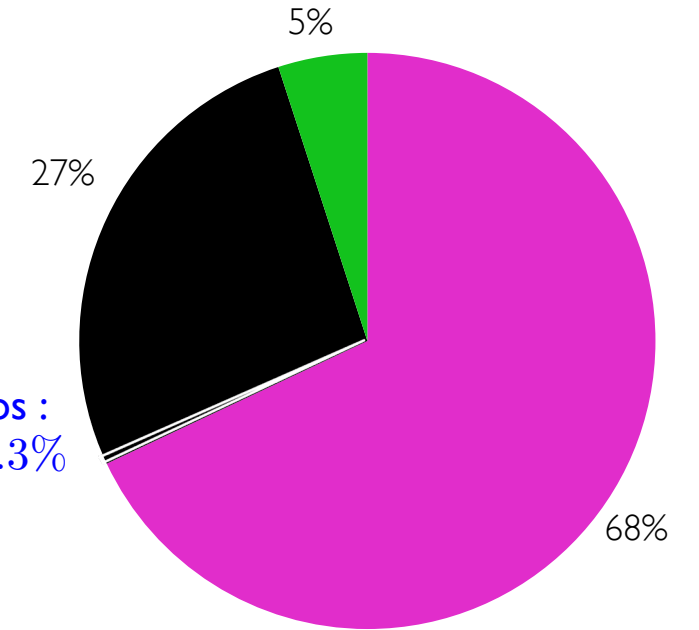
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Reduced density of neutrinos in the universe

$$\Omega_\nu = \frac{M_\nu}{93.14 h^2 \text{ eV}}$$



Neutrinos :
0.1% – 0.3%



■ Λ ■ Dark matter ■ Baryonic matter

With the expansion of the universe, massive neutrinos undergo a transition from **relativistic** to **non-relativistic**

$$1 + z_{\text{nr}} = 1890 \left(\frac{m_\nu}{1 \text{ eV}} \right)$$



Need to take this into account to measure small departures from Λ CDM

Cosmological constraints

CMB + BAO + RSD
+ SNIA

$$M_\nu < 0.1 \text{ eV}$$

[eBOSS collaboration 2020]

The Large Scale Structure is the result of :

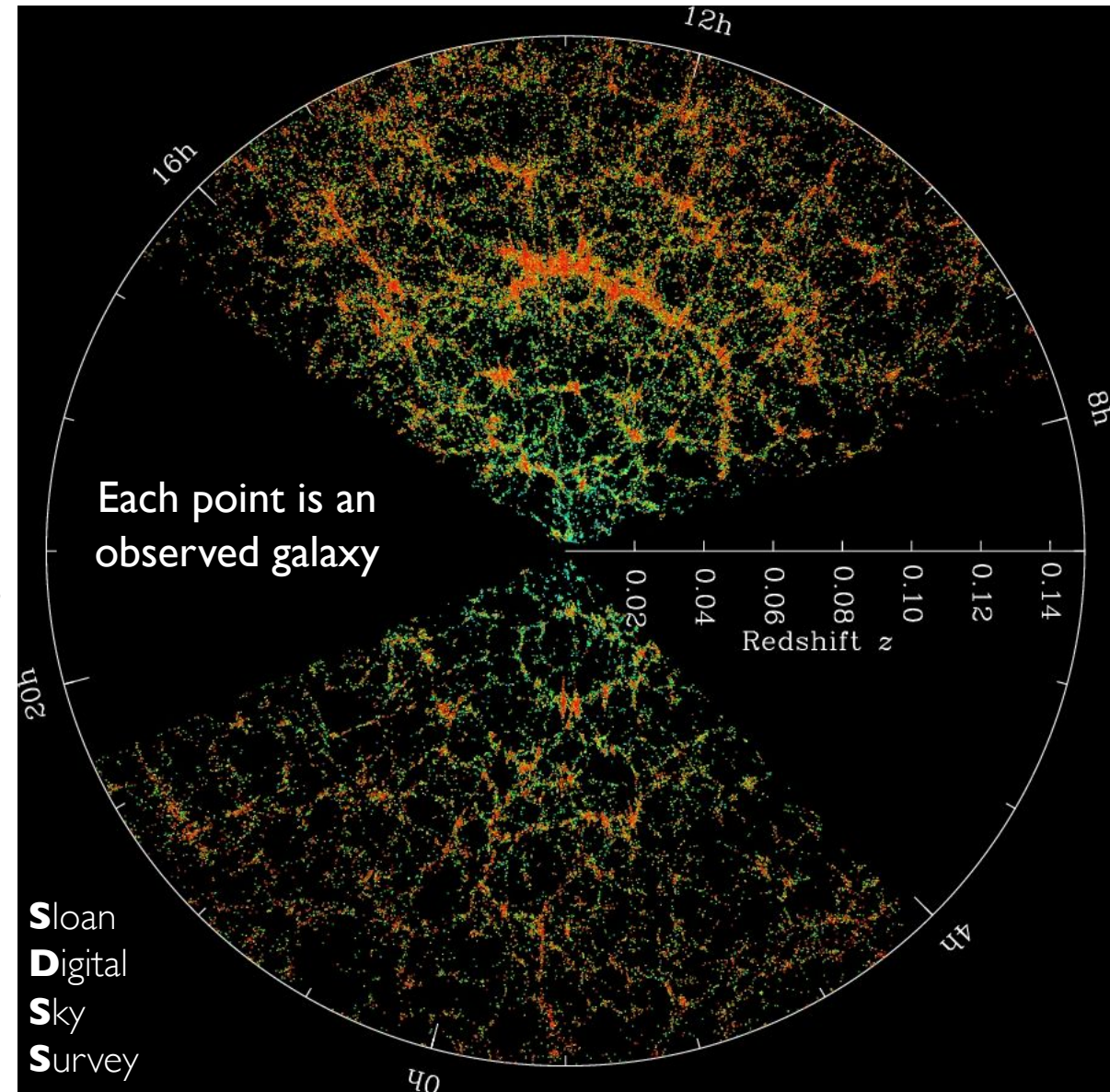
Gravity $\longrightarrow$ Modified gravity

+ Expansion $\longrightarrow$ Dark Energy

+ Interaction between
baryons, photons,
neutrinos, CDM $\longrightarrow$ Nature of Dark Matter,
Total neutrino mass

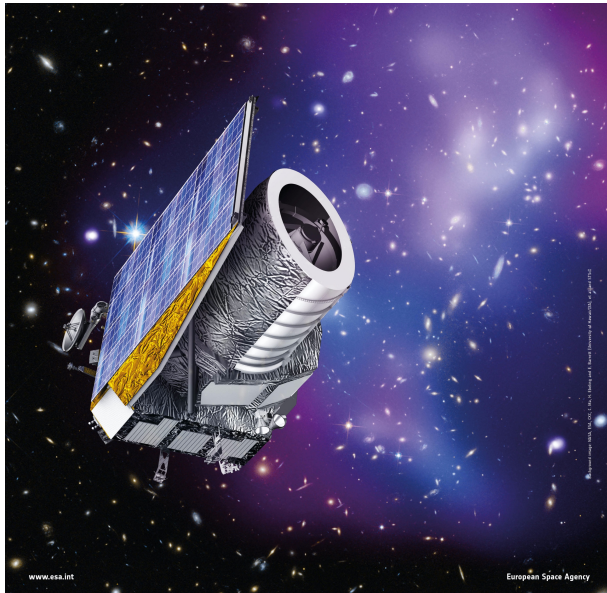
+ Initial conditions $\longrightarrow$ Primordial universe

*Contains a lot of cosmological
information to test models*

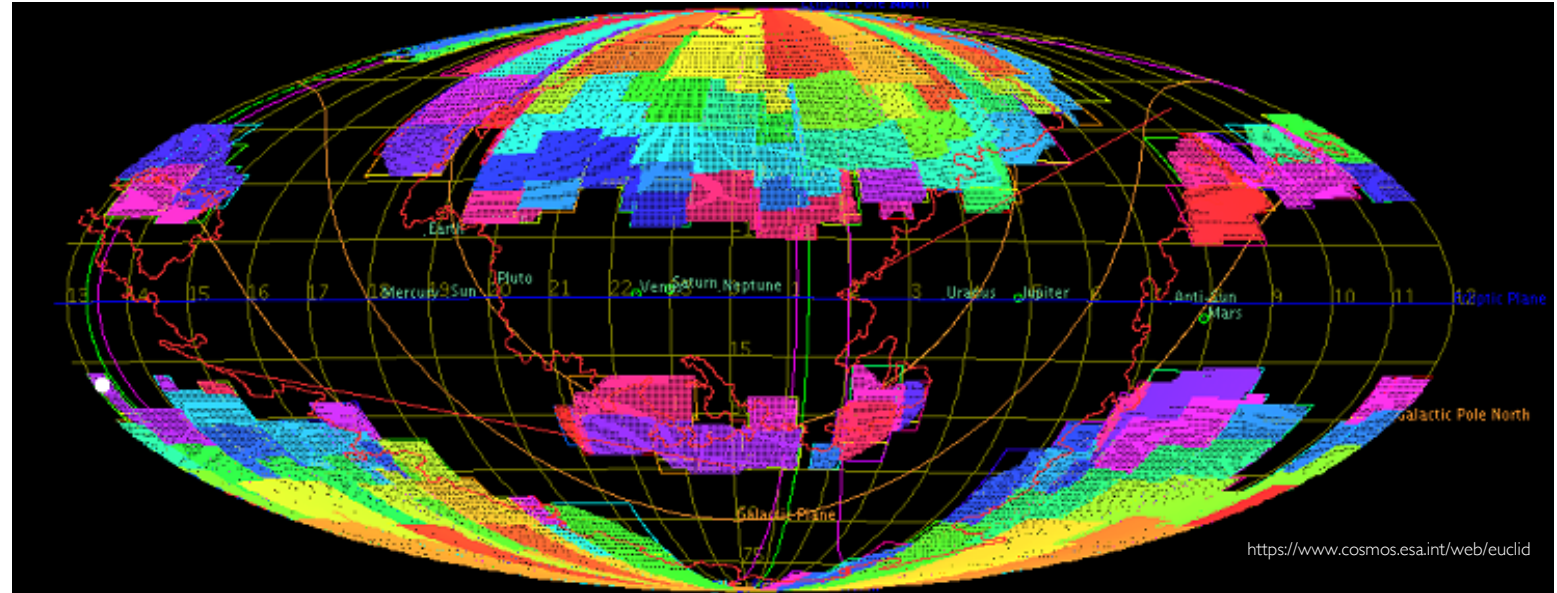


The Euclid galaxy survey

Space telescope : February 5th 2023



Sky coverage of 15 000 deg² for 6 years of observations



2 instruments :

- VIS (visible) : Shapes of 10^9 with **Photo-z** $\in [0.001, 2.5]$
- NISP (infrared) : Spectrum of 50×10^6 galaxies with **Spectro-z** $\in [0.9, 1.8]$

2 main probes :

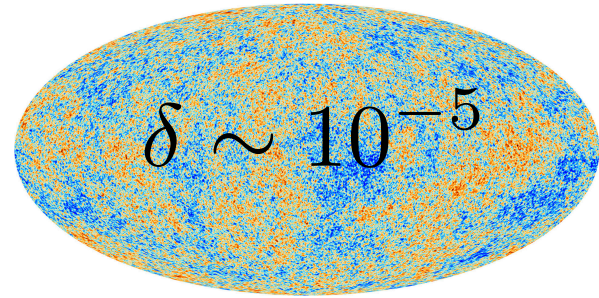
- Weak Lensing
- Galaxy Clustering

II. Cosmological parameter inference with the Large Scale Structure

- Statistics of the Large Scale Structure
- Parameter inference

Statistics of the density field

$z = 1100$

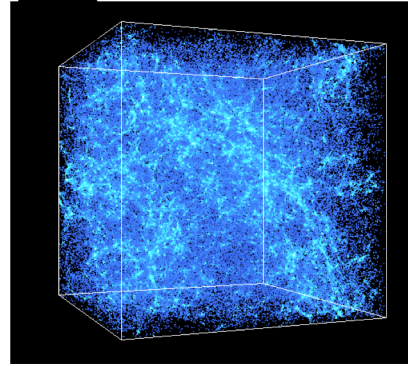


CMB anisotropies = seeds

Linear clustering



$z = 5$

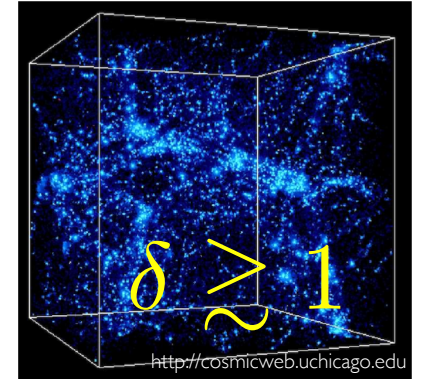


Non-linear clustering



on small scales

$z = 0$

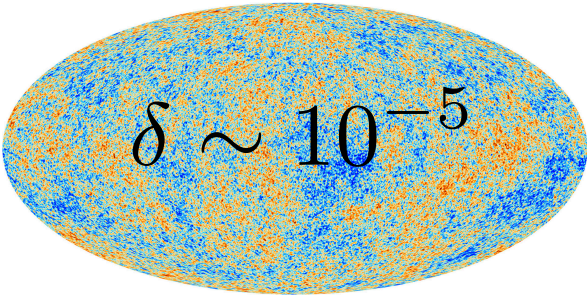


The density contrast field

$$\delta(\mathbf{x}, t) \equiv \frac{\rho(\mathbf{x}, t) - \bar{\rho}(t)}{\bar{\rho}(t)}$$

Statistics of the density field

$z = 1100$



δ follows a **Gaussian** PDF

The density contrast field

$$\delta(\mathbf{x}, t) \equiv \frac{\rho(\mathbf{x}, t) - \bar{\rho}(t)}{\bar{\rho}(t)}$$

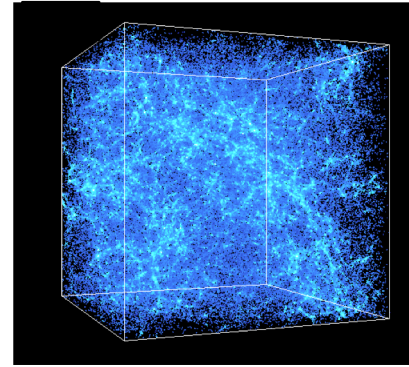
Statistical description

➤ By definition : $\langle \delta(\mathbf{x}) \rangle = 0$

➤ **2-point correlation function** :

$$\langle \delta(\mathbf{x}) \delta(\mathbf{x} + \mathbf{r}) \rangle \equiv \xi(\mathbf{r})$$

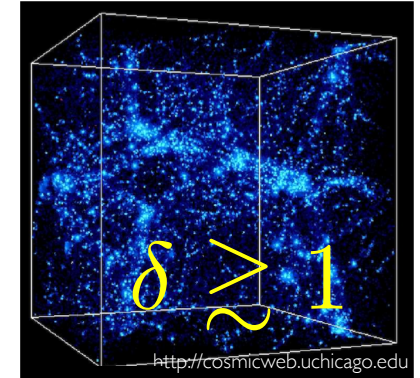
$z = 5$



Linear clustering
→

Non-linear clustering
→
on small scales

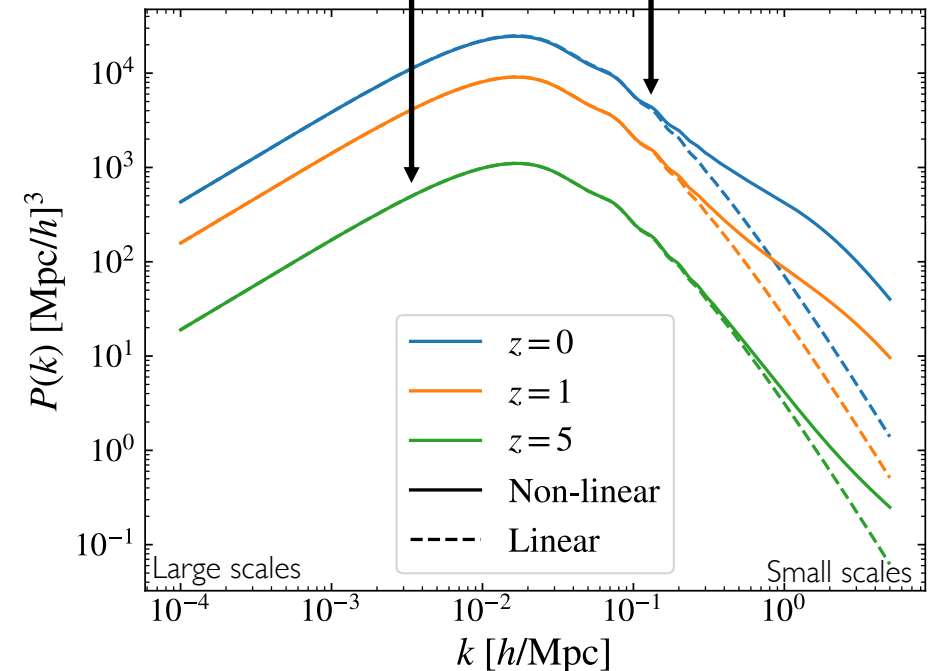
$z = 0$



In Fourier space : **The power spectrum**

$$\langle \delta(\mathbf{k}) \delta(\mathbf{k}') \rangle = \delta_D(\mathbf{k} + \mathbf{k}') P(k)$$

$$k = \frac{2\pi}{r}$$



Parameter inference in cosmology

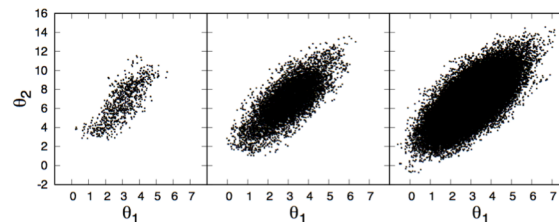
Inference of cosmological parameters from a data set : $\begin{cases} \theta : \Omega_i, H_0, M_\nu \dots \\ \mathbf{D} : P(k), \xi(r) \dots \end{cases}$

Likelihood $\xrightarrow{\quad}$ Prior

$$P(\theta|\mathbf{D}) = \frac{L(\mathbf{D}|\theta)\mathcal{P}(\theta)}{P(\mathbf{D})}$$

Posterior $\xleftarrow{\quad}$ Normalisation

Bayes theorem

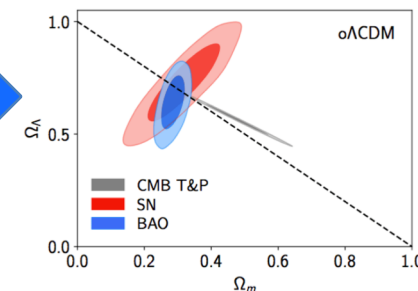


Sample the posterior through statistical processes such as Monte Carlo Markov Chains (MCMC)



Best-fit and errors

$$\theta = \hat{\theta}_{\text{bf}} \pm \hat{\sigma}_\theta$$



For 2-point statistics $[P(k) \text{ or } \xi(r)]$ we generally assume a Gaussian likelihood

$$\chi^2 \equiv -2 \ln L(P(k)|\theta) = [P(k) - P(k; \theta)^{\text{theo}}]^T \mathbf{C}^{-1} [P(k) - P(k; \theta)^{\text{theo}}] + \text{Cst.}$$

Data $\xrightarrow{\quad}$

Model $\xrightarrow{\quad}$

$$C_{ij} \equiv \langle P(k_i)P(k_j) \rangle - \langle P(k_i) \rangle \langle P(k_j) \rangle$$

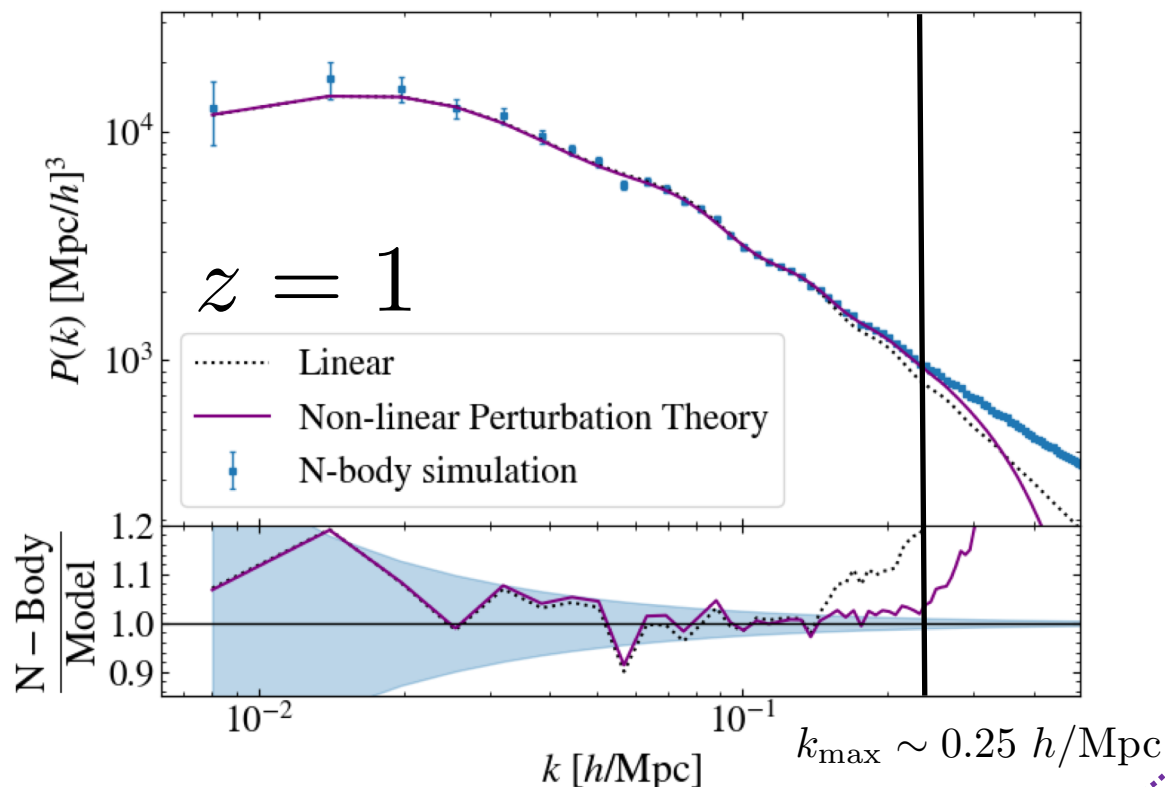
Covariance : Errors and correlations

Non-linear clustering
on small scales

δ becomes non-Gaussian

Simulate non-linear clustering
with N-Body simulations

Test models on
N-body simulations



Covariance : Errors and correlations in the
power spectrum [Scoccimaro et al. 1999]

$$\mathbf{C}(k_i, k_j) = \frac{P(k_i)^2}{N_{k_i}} \delta_{ij} + \bar{T}(k_i, k_j)$$

Trispectrum

$$\langle \delta(\mathbf{k}_1) \delta(\mathbf{k}_2) \delta(\mathbf{k}_3) \delta(\mathbf{k}_4) \rangle_c = \delta_D(\mathbf{k}_1 + \mathbf{k}_2 + \mathbf{k}_3 + \mathbf{k}_4) T(\mathbf{k}_1, \mathbf{k}_2, \mathbf{k}_3)$$

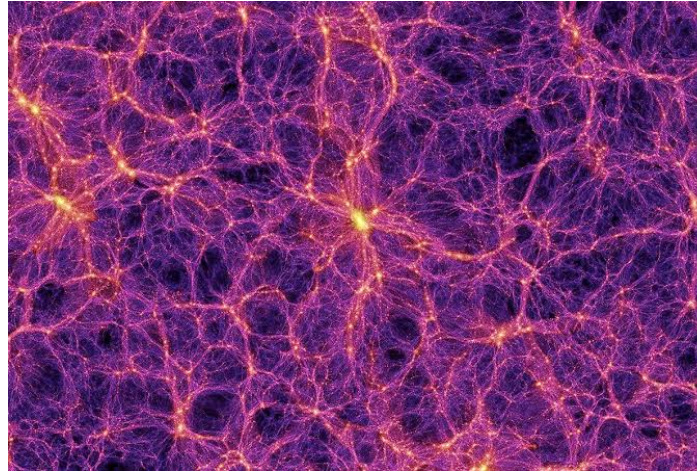
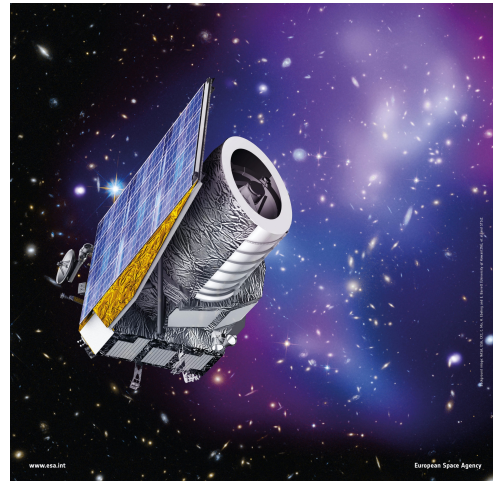
Difficult to predict analytically

Estimate the covariance from simulations

$$\hat{C}_{ij} = \frac{1}{N_m - 1} \left[\sum_n [P^{(n)}(k_i) - \bar{P}(k_i)][P^{(n)}(k_j) - \bar{P}(k_j)] \right]$$

Challenges for precision cosmology

With Euclid we will reach a high precision on LSS observables



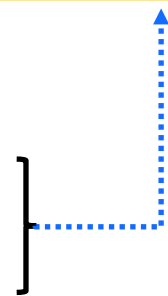
To meet the challenges of modern cosmology :
Test alternative models, neutrino mass, tensions, ...



*Important to estimate unbiased **best-fit** and **errors** on cosmological parameters !*

Challenges :

- Combination of probes → **Accurate and precise covariance**
- Non-linear scales → **Accurate modeling**

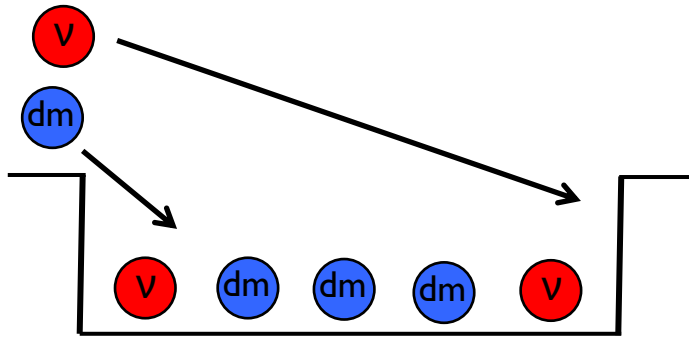


III. Optimal parameter inference with the power spectrum including massive neutrinos

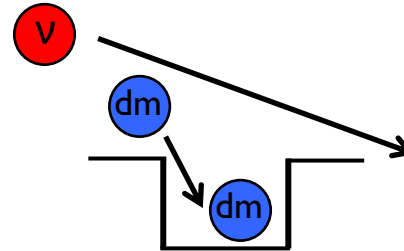
- Parameter inference and sampling noise in the covariance
- Impact of non-Gaussian covariance on cosmological constraints
- Power spectrum non-linear modeling challenge with massive neutrinos

Massive Neutrinos keep a high velocity dispersion

Free streaming: Neutrinos escape from the potential wells on **small scales**

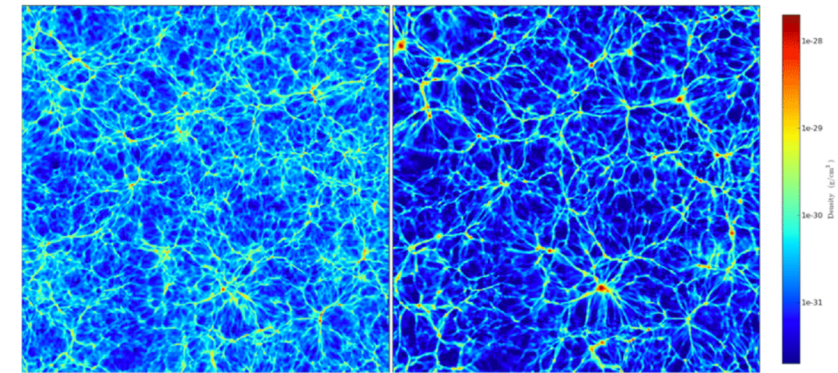


On large scales: Neutrinos behave like CDM



On small scales: Neutrinos do not cluster

Smoothing of density perturbations on small scales

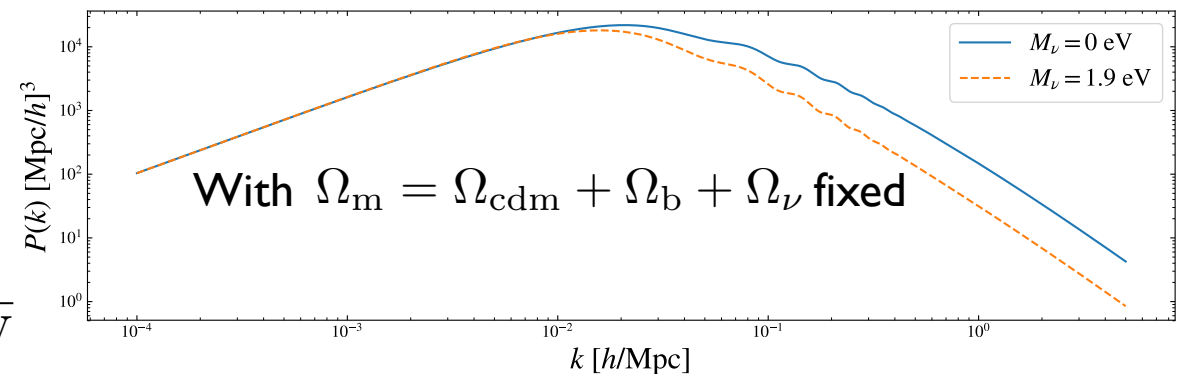


$M_\nu = 1.9 \text{ eV}$

$M_\nu = 0 \text{ eV}$

Imprint on the power spectrum on small scales

$$\Omega_\nu = \frac{M_\nu}{93.14 h^2 \text{ eV}}$$



DEMNUi : Dark Energy and Massive Neutrinos Universe

➤ Cosmologies : 0ν and 16ν

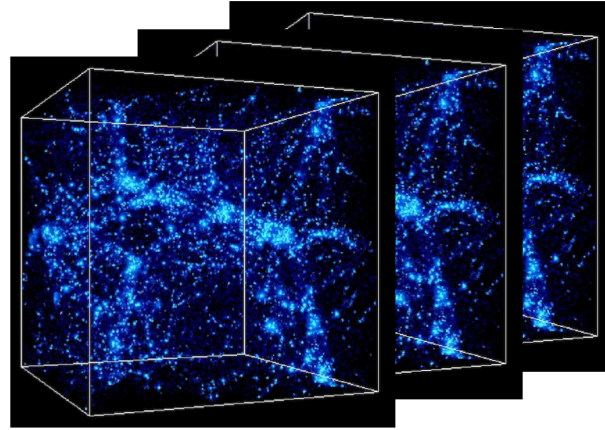
$$\left\{ \begin{array}{l} \Omega_m = 0.32 \\ \Omega_b = 0.05 \\ h = 0.67 \\ n_s = 0.96 \\ A_s = 2.1265 \times 10^9 \\ 3m_\nu = 0 \text{ or } 0.16 \text{ eV} \\ \Omega_{\text{cdm}} = 0.27 \text{ or } 0.2663 \end{array} \right.$$

➤ $V = 1 \text{ [Gpc/h]}^3$

➤ $N_p = 1024^3 (+ 1024^3)$

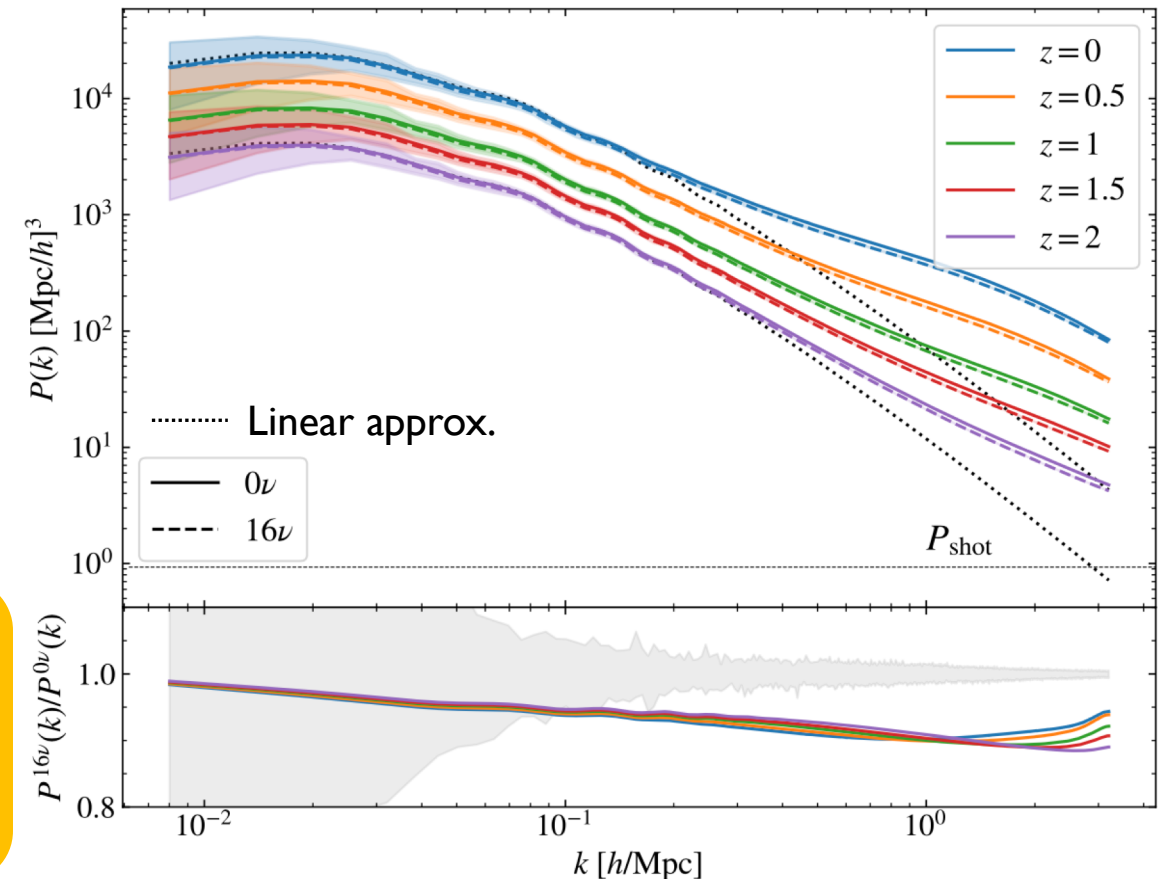
Managed by Carmelita Carbone
[Carbone et al. 2016, Castorina et al. 15]

N-body simulations of **CDM + Massive neutrinos** at $z \approx 0, 0.5, 1, 1.5, 2$



DEMNUi-Cov :
X 50 realisations for each cosmology

Mean CDM power spectrum on 50 DEMNUi-Cov



Estimation of M_ν from the full shape of the power spectrum

Goal ➔

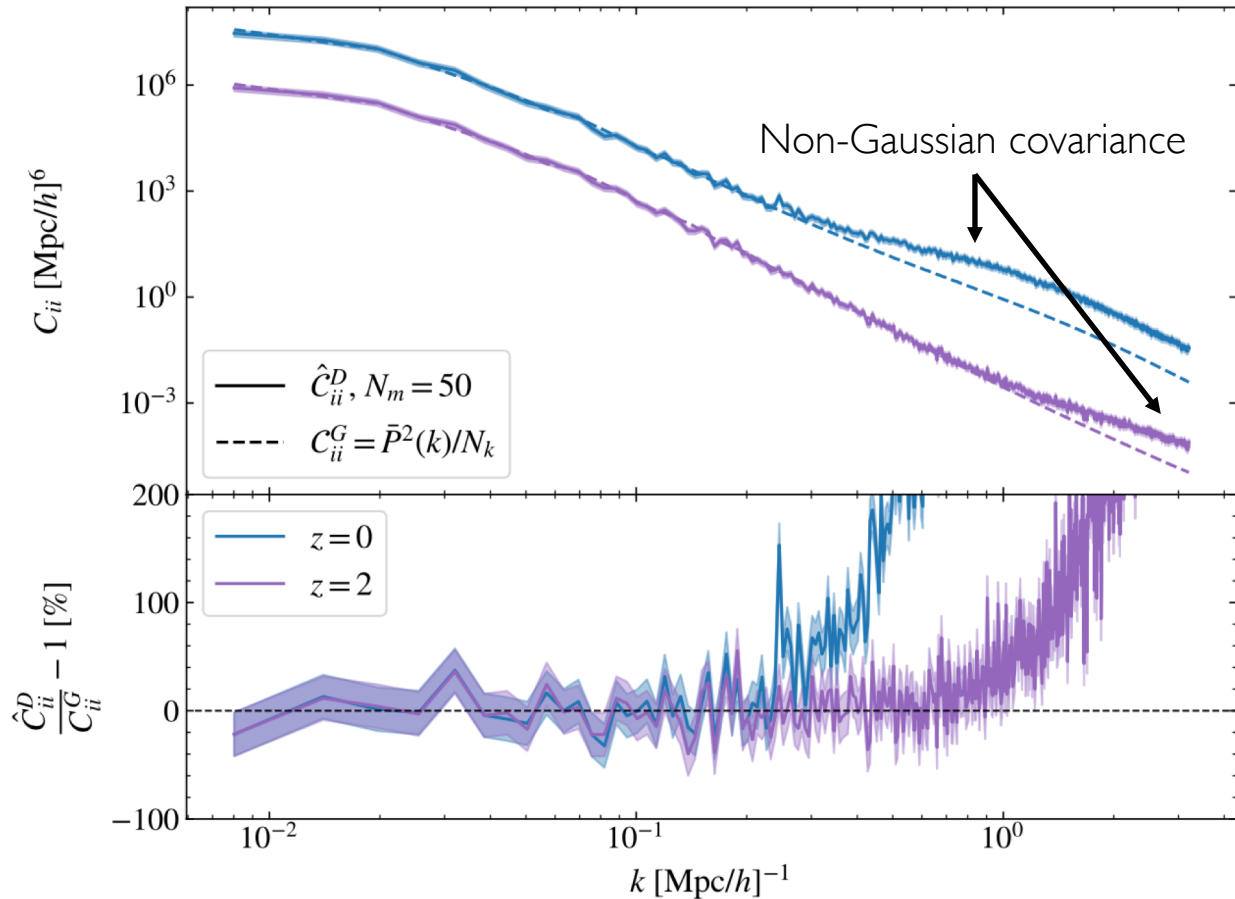
1. Test the covariance
2. Test the non-linear modeling of $P(k)$

The DEMNUni-Cov simulations

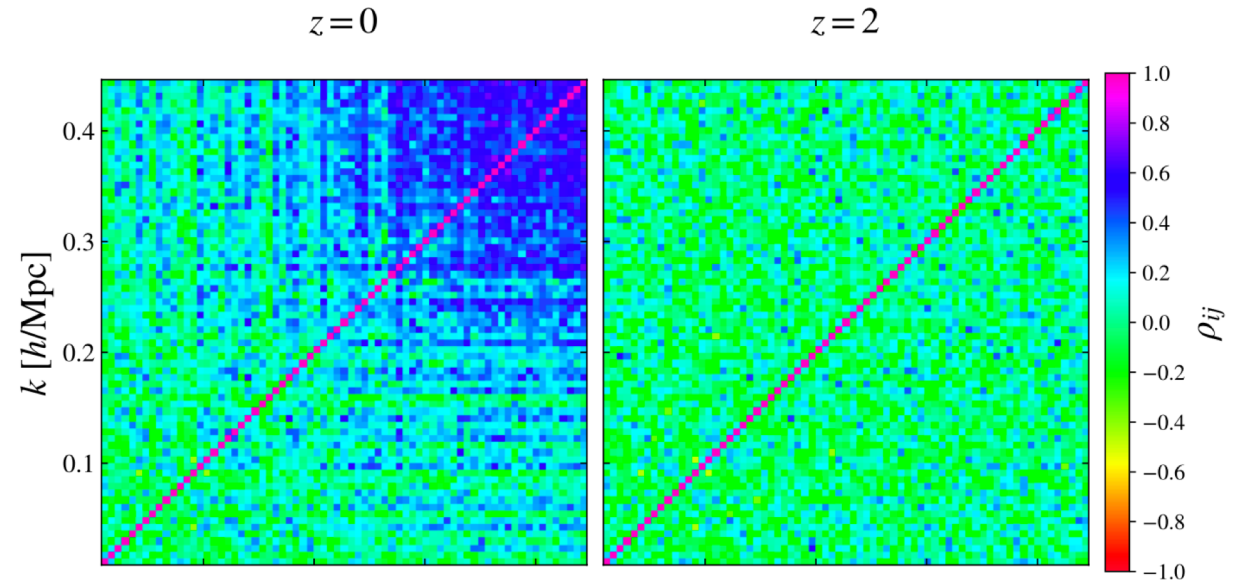
Estimation of the covariance with the 50 realisations

$$\hat{C}_{ij} = \frac{1}{N_m - 1} \left[\sum_n^{N_m} [P^{(n)}(k_i) - \bar{P}(k_i)][P^{(n)}(k_j) - \bar{P}(k_j)] \right]$$

Diagonal of the covariance



Correlation matrix



N-Body simulations = Accurate **non-linearities** and **non-Gaussianities** but CPU-time consuming

With only 50 realisations, the covariance is noisy

Covariance estimation and sampling noise

For N_m realisation of the power spectrum $\hat{C}_{ij} = \frac{1}{N_m - 1} \left[\sum_n^{N_m} [P^{(n)}(k_i) - \bar{P}(k_i)][P^{(n)}(k_j) - \bar{P}(k_j)] \right] \rightarrow$ **Sampling noise**

$$\chi^2 = [[P(k) - P(k; \theta)^{\text{theo}}]^T \mathbf{C}^{-1} [P(k) - P(k; \theta)^{\text{theo}}]] \quad \Psi \equiv \mathbf{C}^{-1}$$

➤ Hartlap bias in the **precision matrix** Ψ
[Wishart 1928, Hartlap 2007]

$$\hat{\Psi} = \hat{\mathbf{C}}^{-1} \rightarrow \langle \hat{\Psi} \rangle = \frac{N_m - 1}{N_m - N_k - 2} \Psi$$

➤ Noise in the estimated precision matrix : $\hat{\Psi} = \Psi + \Delta\Psi$

➔ **Additional variance and bias on the estimated errors and best-fit of parameters**

[Taylor et al. 2013 ; Dodelson & Schneider 2013 ; Percival et al. 2014 ; Taylor & Joachimi 2014]

Solutions to reduce sampling noise effects :

- Create very large sets of mocks : **Covmos** [Baratta et al. 2019, Baratta et al. In prep.]
- Alternative estimators of the covariance : **NERCOME** [Joachimi 2016]

Test of the reliability of these methods

Covmos : Fast mock generation

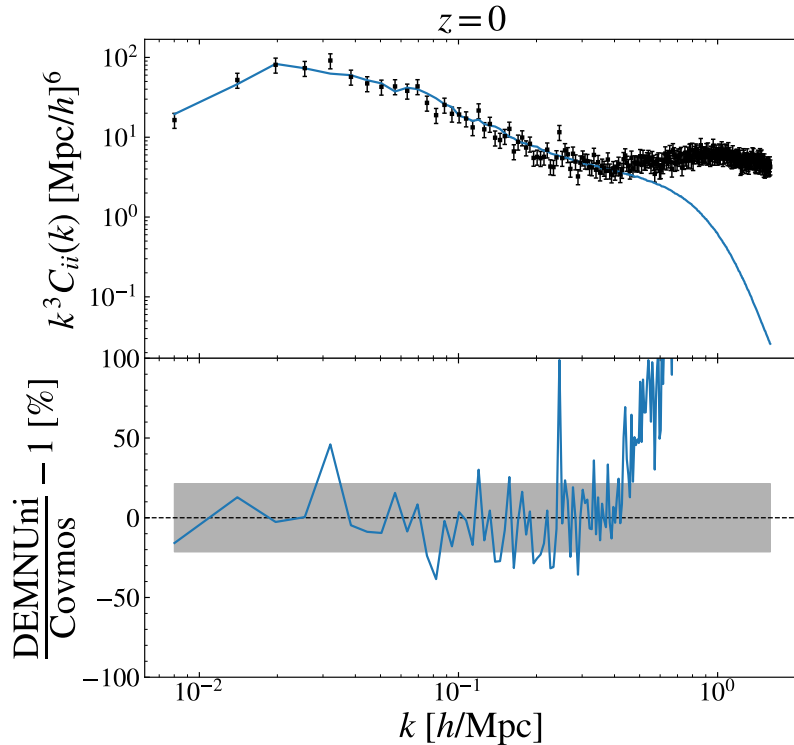
Target $P(k)$ and $\text{PDF}(\delta)$ to [clone DEMNUni-Cov](#)

$$\mathbf{C}(k_i, k_j) = \frac{P^2(k_i)}{N_{k_i}} \delta_{ij} + \bar{T}(k_i, k_j) = \mathbf{C}^G(k_i) + \mathbf{C}^{\text{NG}}(k_i, k_j),$$

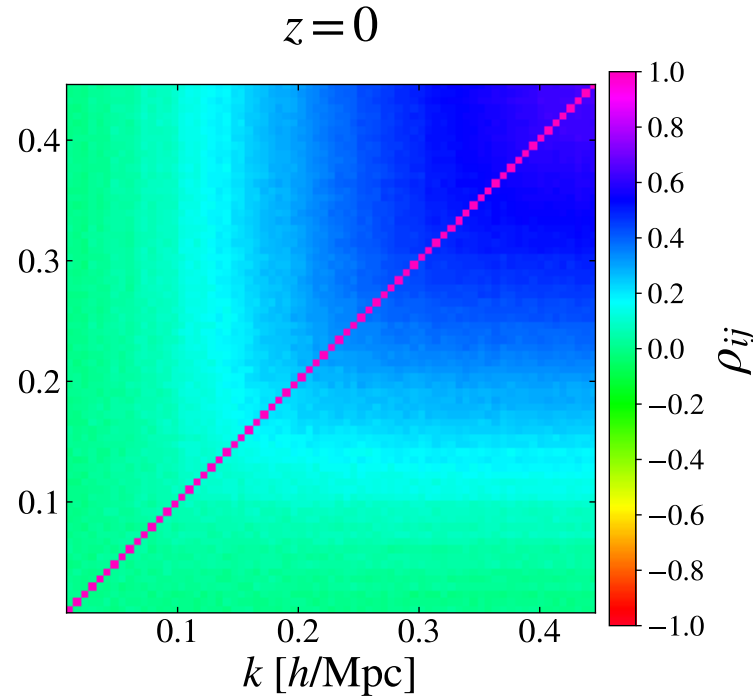
Generate **10 000** catalogs at 5 redshifts ($\sim 24\text{h} \times 5$)

Developed by Philippe Baratta

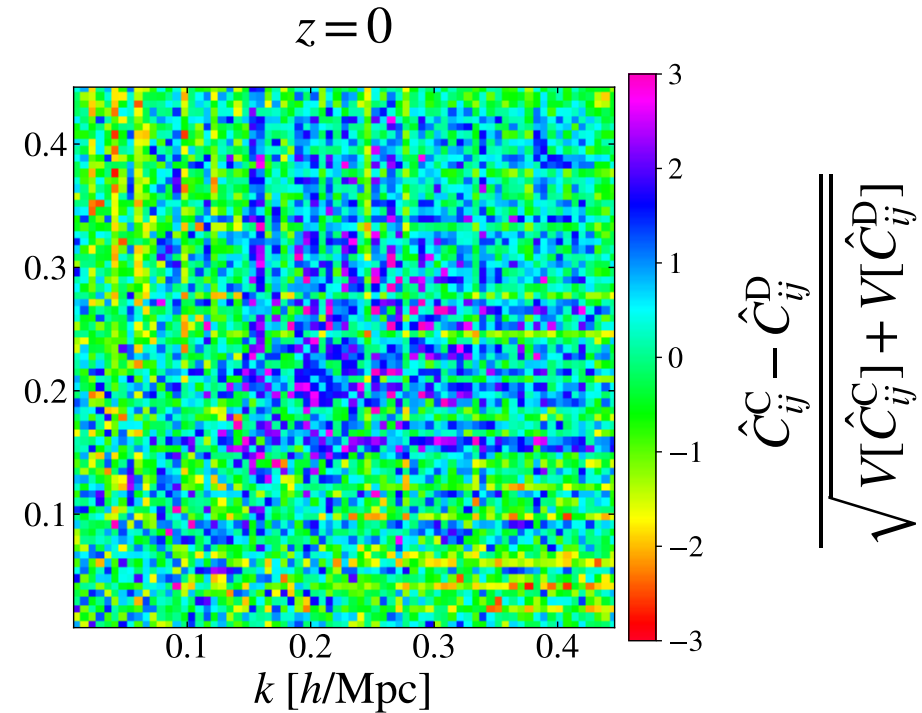
Diagonal of the covariance



Correlation matrix



Deviation with respect to DEMNUni-Cov in σ



NERCOME : Non-parametric Eigenvalue-Regularised COvariance Matrix Estimator

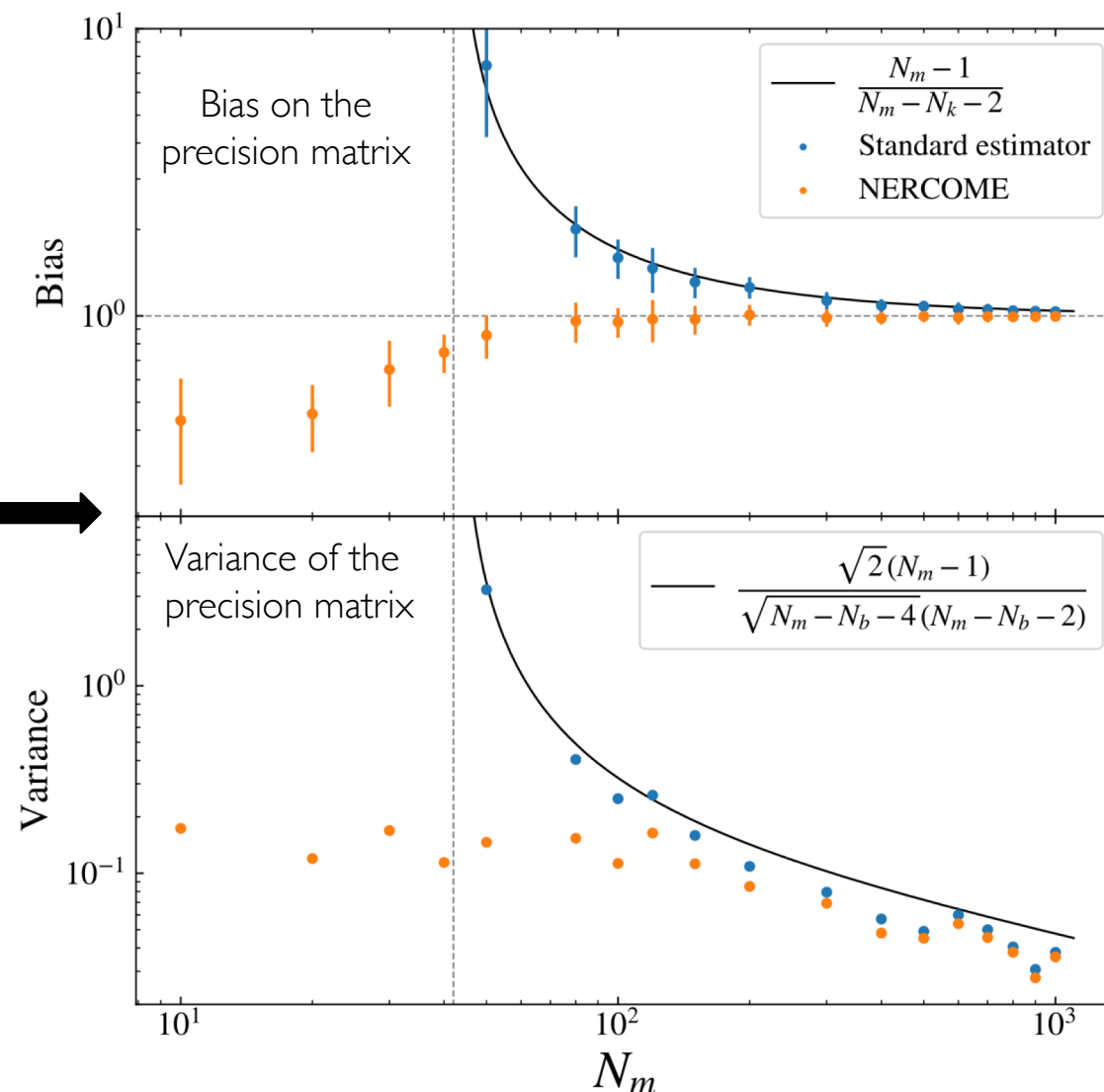
For N_m mocks :

1. Estimate the covariance on 2 subsets of size s and N_m-s : $\hat{S}_1$ and $\hat{S}_2$
2. Eigenvalue Decomposition : $\hat{S}_i = U_i D_i U_i^T$
3. Estimate the new covariance as : $\hat{C}_N = U_1 \text{diag}(U_1^T \hat{S}_2 U_1) U_1^T$

Repeat for 500 random subsets of size s and N_m-s

- Reduces the bias in the precision matrix
- Reduces the variance in the precision matrix

For $N_k = 40$



[Joachimi 2016]

Testing NERCOME on parameter estimation

➤ Tests on the covariance :

- NERCOME : Need a true reference covariance matrix + several realisations of the covariance

- Generate 100 000 + 1 Covmos $P(k)$ x 5 redshifts

For the covariance

For the data-vector

- Divide into 100 subsets with $N_m = 45$

- Estimate the covariance on all subsets with NERCOME and the standard estimator

- Estimate cosmological parameters with MCMC for all the covariance matrices

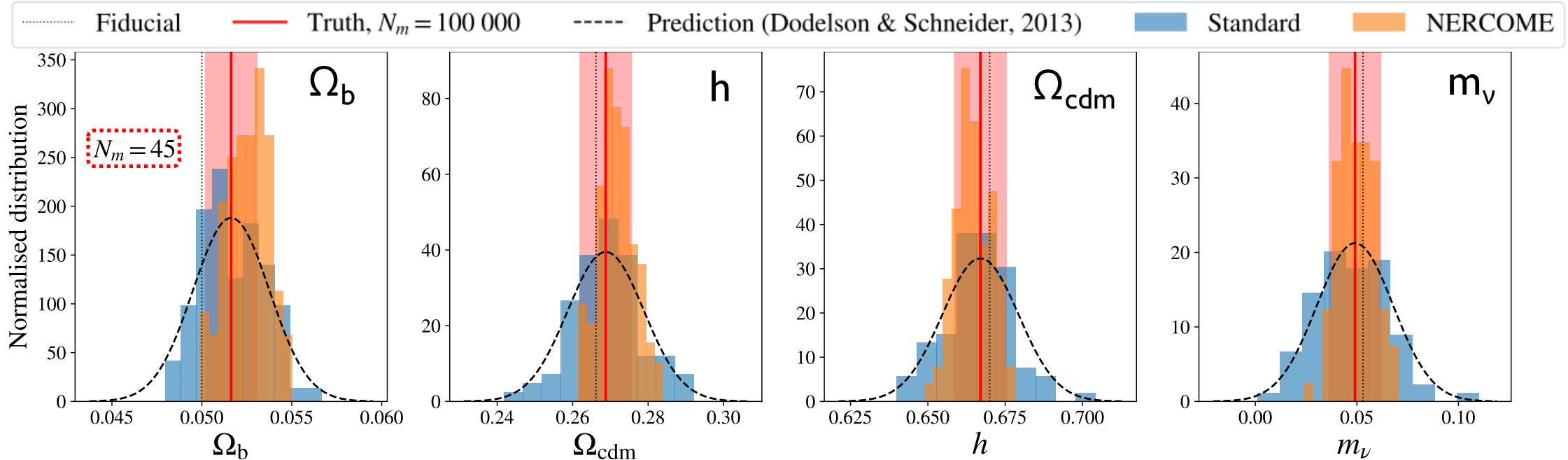
- $k_{\max} = 0.2 \text{ h/Mpc} \rightarrow N_k = 30$

- Non-linear model : Halofit

θ	Priors
Ω_b	[0.01, 0.1]
Ω_{cdm}	[0.01, 0.8]
h	[0.3, 1.5]
$m_\nu \text{ [eV]}$	[0, 1]

Testing NERCOME on parameter estimation

Distribution of **best-fits** for 100 realisations of the covariance

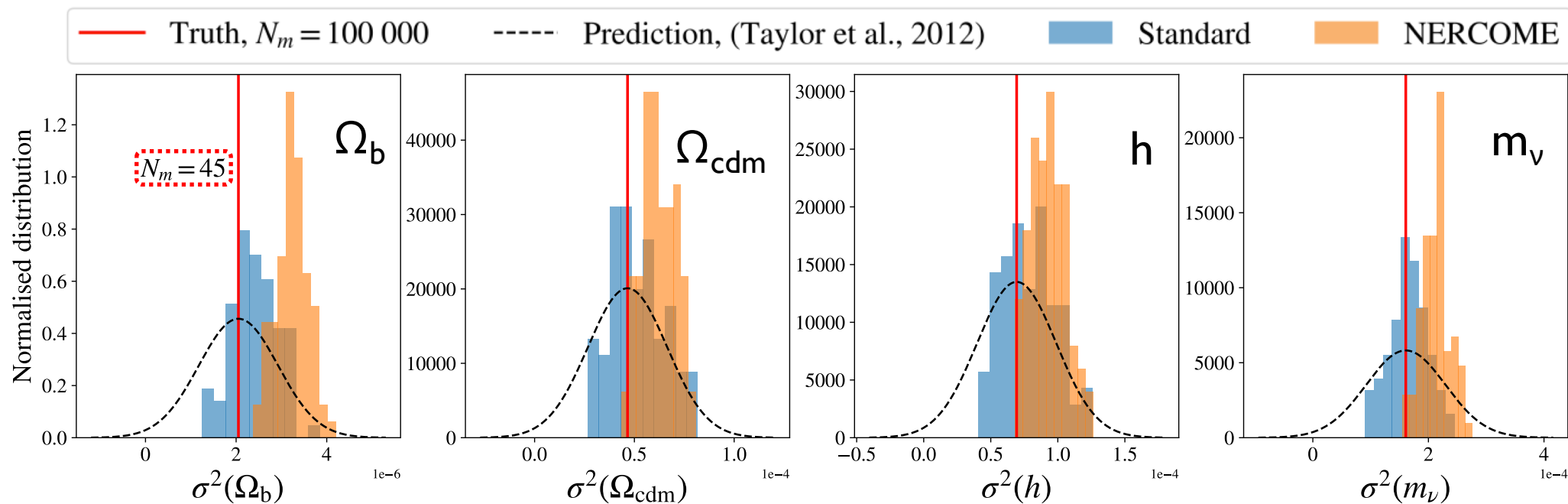


- **Standard estimator** : best-fit dispersion of 1.3σ (larger than the true error)
- **NERCOME** : best-fit dispersion of $\sim 0.7\sigma$ (smaller than the true error)
- Good agreement with the theoretical prediction [Dodelson & Schneider 2013]

NERCOME reduces the dispersion by 50%

Testing NERCOME on parameter estimation

Distribution of errors for 100 realisations of the covariance



- Standard estimator : variance dispersion of 0.25σ
 - NERCOME : variance dispersion of $\sim 0.17\sigma$
- } NERCOME reduces the dispersion by 30%
- NERCOME overestimates the error-bars by $\sim 30\%$ for $N_m = 45$
 - Poor agreement with the theoretical prediction [Taylor et al. 2012]

Testing Covmos on parameter estimation

➤ Tests on the covariance :

- NERCOME 

- With Covmos we can suppress sampling noise. But is the covariance accurate enough ?

 *Test against covariance from DEMNUni-Cov*

Testing Covmos on parameter estimation

➤ Tests on the covariance :

- NERCOME 

- With Covmos we can suppress sampling noise. But is the covariance accurate enough ?



Test against covariance from DEMNUni-Cov

Parameter estimation with MCMC :

➤ Data-Vector : DEMNUni-Cov $P(k)$ with 5 redshifts $\times$ 3 independent realisations of the data-vector

➤ For different Covariance :

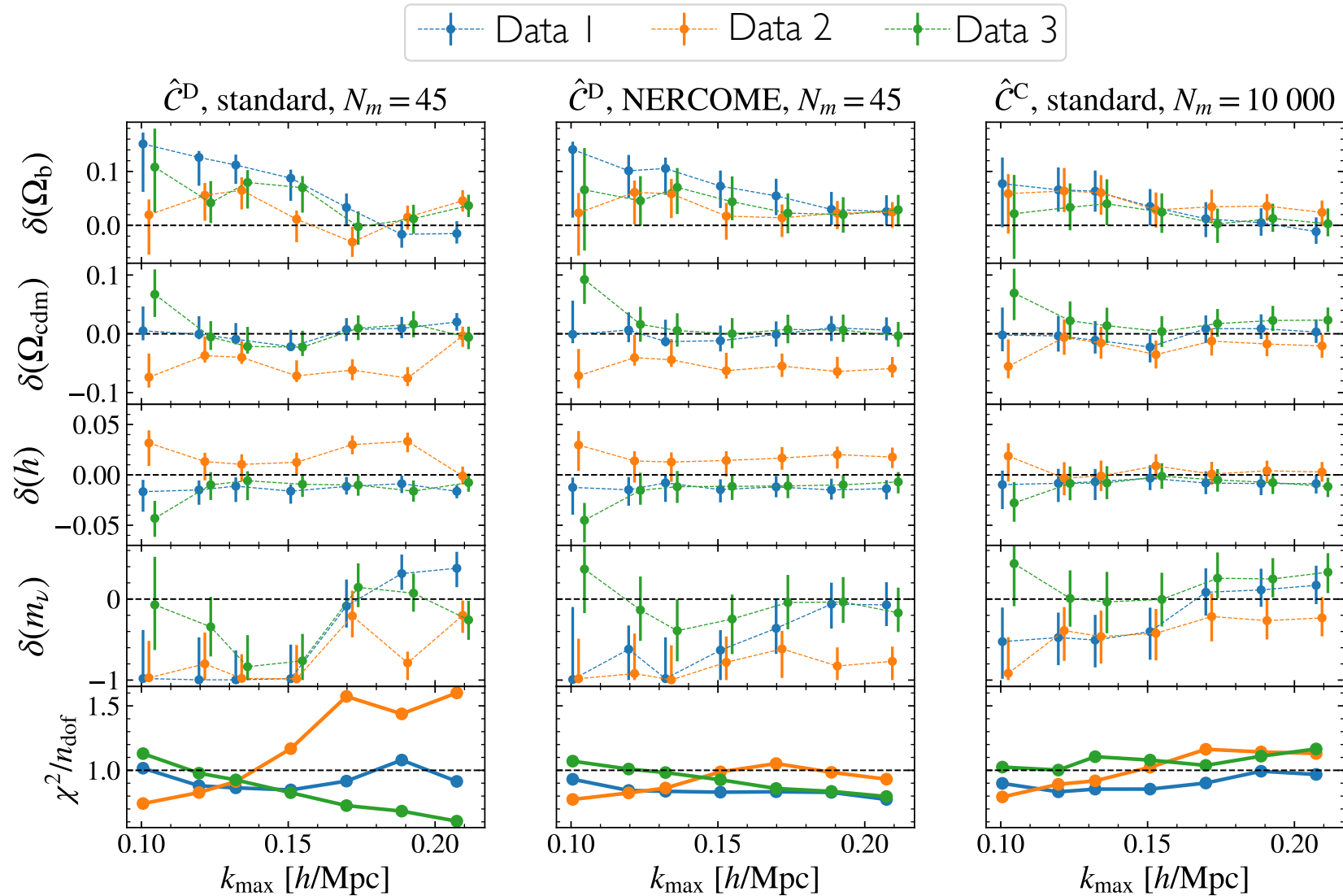
1. DEMNUni-Cov with $N_m=45 \rightarrow$ Accurate but noisy

2. DEMNUni-Cov with $N_m=45$, estimated with NERCOME $\rightarrow$ Accurate and less noisy

3. Covmos, cloned from DEMNUni-Cov, with $N_m = 10\,000 \rightarrow$ No noise but need to test accuracy

➤ $k_{\max} = [0.1, 0.2] \text{ h/Mpc}$

Testing Covmos on parameter estimation



➤ **Standard DEMNUni-Cov (left):**

Large scatter around the fiducial cosmology

➤ **NERCOME DEMNUni-Cov (middle):**

Less scattering, but still systematic deviation for **Data 2**

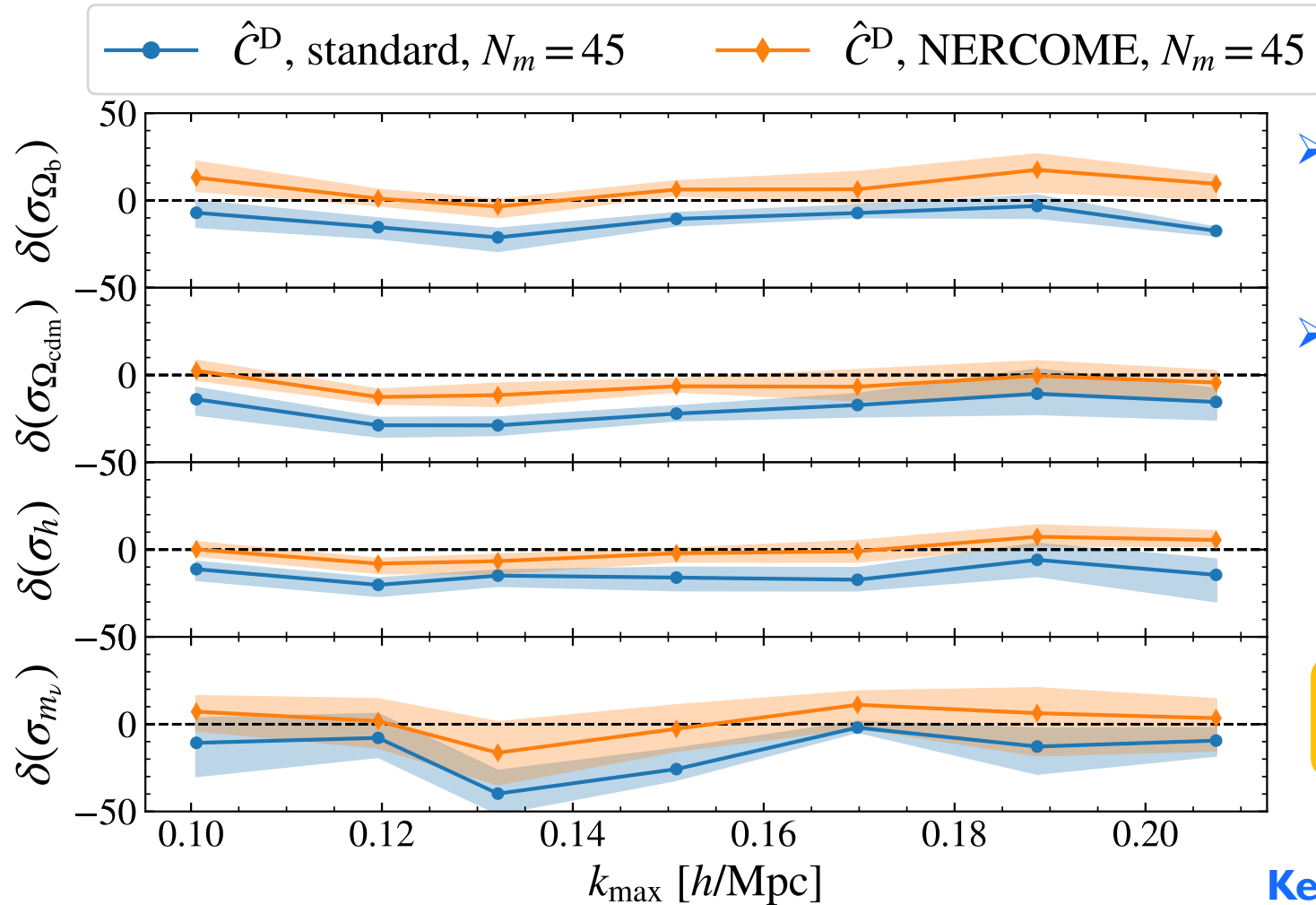
➤ **Covmos (right):**

All data-sets compatible with each other

➔ **Covmos provides unbiased best-fits**

Testing Covmos on parameter estimation

Relative difference with respect to the variance obtained with Covmos $N_m=10\,000$: $\delta(\sigma_\theta) = \sigma_\theta / \sigma_\theta^{\text{Covmos}} - 1 [\%]$



➤ NERCOME $N_m = 45$ give similar error bars than Covmos

➤ We found before that NERCOME leads to $\sim 30\%$ overestimation of errors for $N_m = 45$

Covmos slightly overestimate of error-bars
 ➔ *overestimation the covariance*

Need more N-body realisations to precisely assess bias in error with covmos

Keep covmos with $N_m = 10\,000$ for the following

Impact of trispectrum contribution

➤ Tests on the covariance :

- Sampling noise effects (NERCOME and Covmos) ✓

- Non-Gaussian covariance : $\mathbf{C}(k_i, k_j) = \frac{P^2(k_i)}{N_{k_i}} \delta_{ij} + \bar{T}(k_i, k_j) = \mathbf{C}^G(k_i) + \mathbf{C}^{\text{NG}}(k_i, k_j),$

Should increase the error on cosmological parameters

By how much ?

Impact of trispectrum contribution

➤ Tests on the covariance :

- Sampling noise effects (NERCOME and Covmos) ✓

- Non-Gaussian covariance : $\mathbf{C}(k_i, k_j) = \frac{P^2(k_i)}{N_{k_i}} \delta_{ij} + \bar{T}(k_i, k_j) = \mathbf{C}^G(k_i) + \mathbf{C}^{\text{NG}}(k_i, k_j),$

Should increase the error on cosmological parameters
By how much ?

Compare constraints obtained with the Gaussian covariance only, to quantify the impact of non-Gaussian covariance

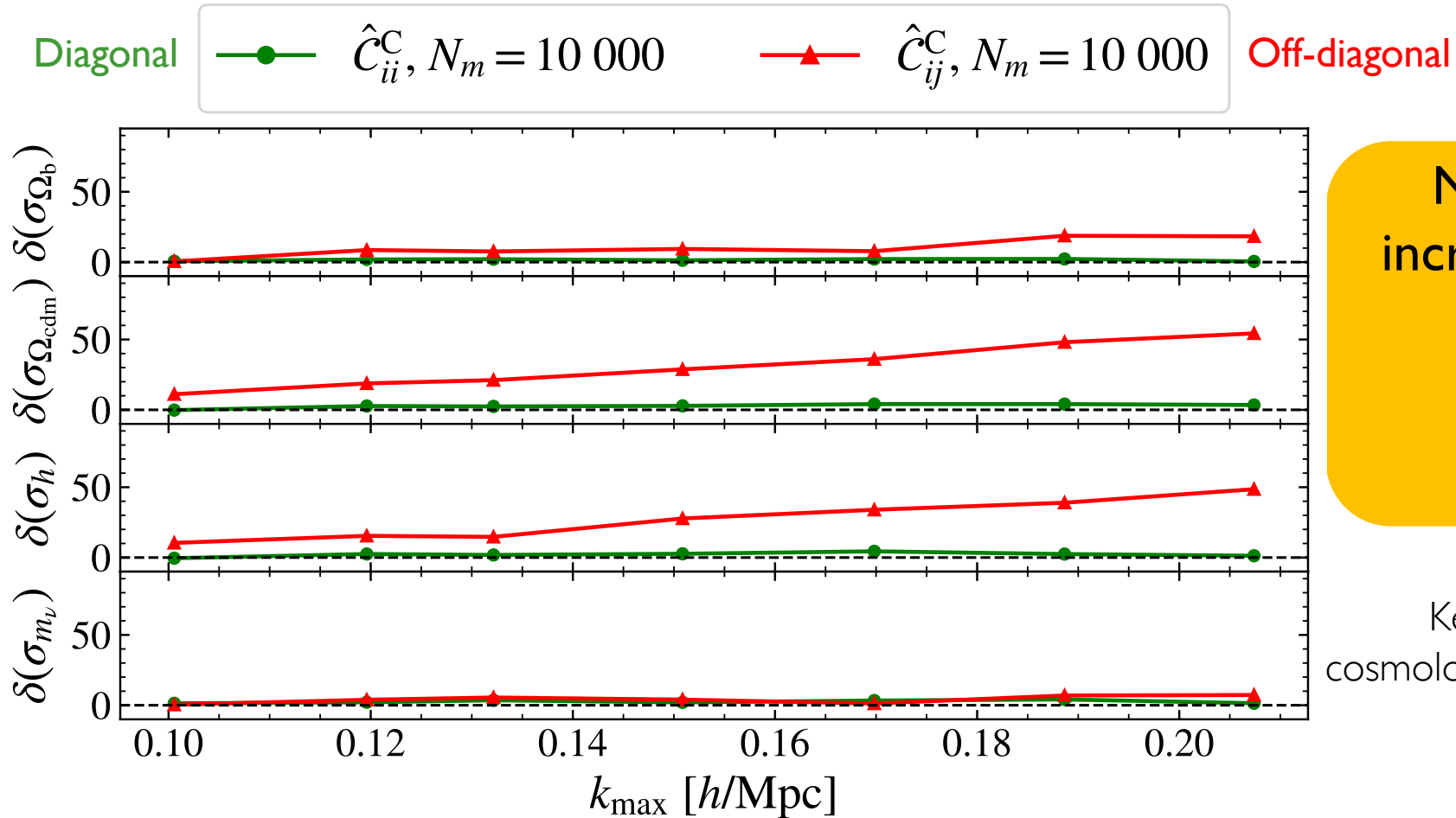
Parameter estimation with MCMC :

- Data-vector : DEMNUni-Cov at 5 redshifts : $z \approx 0, 0.5, 1, 1.5, 2$
- Non-linear model : Halofit
- **Covariance :**
 1. Gaussian only
 2. Covmos $N_m = 10\,000$, diagonal only
 3. Covmos $N_m = 10\,000$, full

Impact of trispectrum contribution

Relative difference with respect to the error obtained with Gaussian only

$$\delta(\sigma_\theta) = \sigma_\theta / \sigma_\theta^G - 1 [\%]$$



Non-Gaussian covariance
increases error bars by $\sim 50\%$
for Ω_{cdm} and h

Error on m_ν is not affected

Keep in mind that we found a slight
cosmological error overestimation with Covmos

Testing non-linear models with massive neutrinos

➤ Tests on the covariance :

- Sampling noise effects ✓
- Non-Gaussian covariance ✓



➤ Test non-linear power spectrum models against DEMNUni-Cov

Testing non-linear models with massive neutrinos

➤ Tests on the covariance :

- Sampling noise effects ✓
- Non-Gaussian covariance ✓



➤ Test non-linear power spectrum models against DEMNUni-Cov

The effect of massive neutrinos is more important on small scales ➔ **Non-linearities**

To model the non-linear power spectrum

➤ Non-linear perturbation theory

Perturbative expansion of the density field

$$\langle (\delta_1 + \delta_2 + \delta_3 + \dots)(\delta_1 + \delta_2 + \delta_3 + \dots) \rangle = P(k) \delta_D(\mathbf{k} + \mathbf{k}')$$

➤ Find appropriate fitting functions

➔ Calibration on N-Body simulations

With massive neutrinos

➤ Non-linear perturbation theory

Difficult to account for neutrino perturbations

➔ **Account for massive neutrinos at the linear level only**

[Castorina et al. 2015]

➤ Fitting functions

➔ **Calibration on N-Body simulations with massive neutrinos**

Non-linear prescriptions for the power spectrum:

- **Halofit**: Empirical fitting functions calibrated on simulations

[Smith et al. 2003, Takahashi et al. 2012]

Calibrated with massive neutrinos [Bird et al. 2011].

- **HMcode**: Physical fitting functions calibrated on simulations

[Mead et al. 2015]

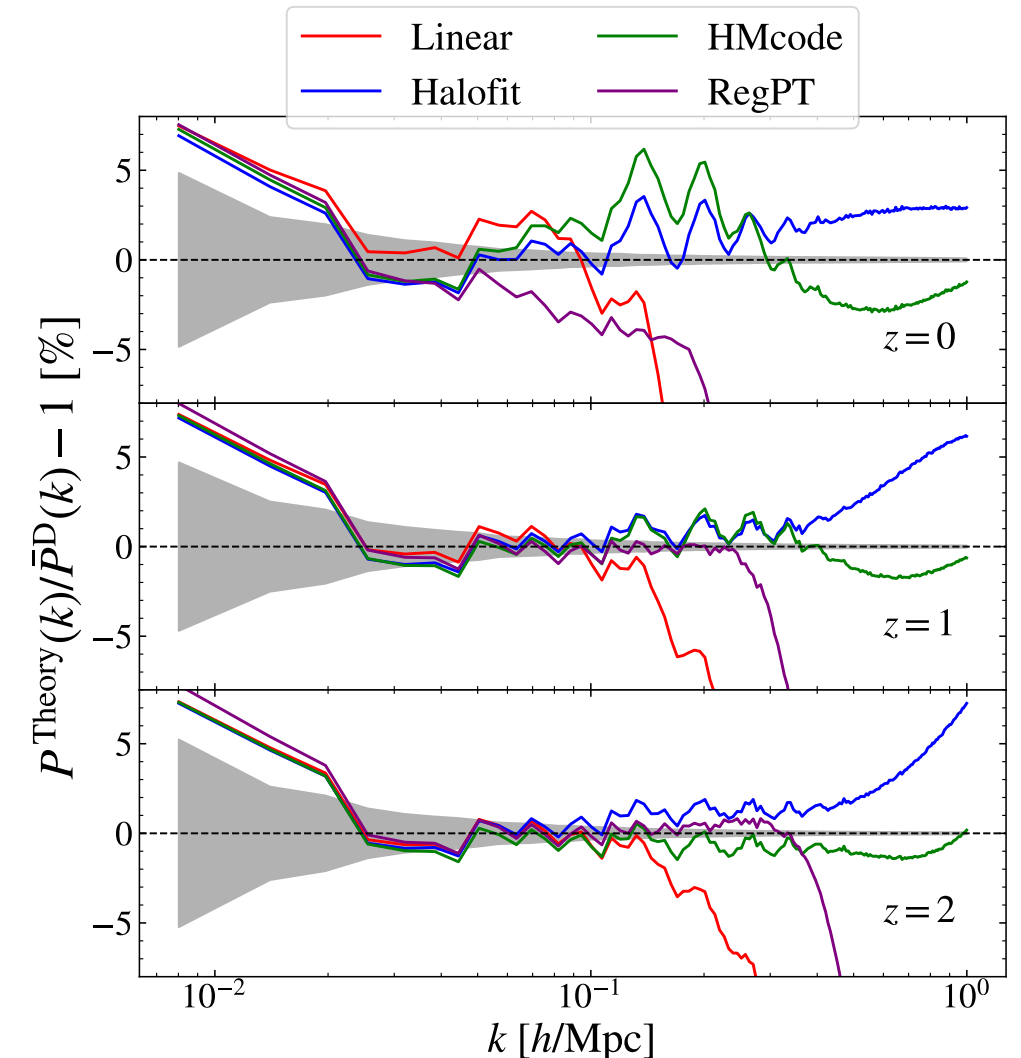
Calibrated with massive neutrinos [Mead et al. 2016].

- **RegPT**: Analytic prediction with Regularised Perturbation Theory

[Taruya et al. 2012]

Account for massive neutrinos at the linear level [Castorina et al. 2015]

Mean DEMNUni-Cov on 50 realisations VS Non-linear model



Parameter estimation with MCMC :

- Data-vector : **Mean DEMNUni-Cov on 12 realisations**
- 4 redshifts : $z \approx 0.5, 1, 1.5, 2$
- Covariance : Covmos Nm = 10 000
- $k_{\text{max}} = [0.1, 0.3] \text{ h/Mpc}$
- **Non-linear models :**
 - Halofit
 - HMCODE
 - RegPT

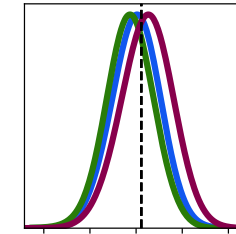
Testing non-linear models with massive neutrinos

Model	$\delta(\omega_b)/\sigma_{\omega_b}$	$\delta(\omega_{\text{cdm}})/\sigma_{\omega_{\text{cdm}}}$	$\delta(h)/\sigma_h$	$\delta(m_\nu)/\sigma_{m_\nu}$
Halofit	-0.28	-0.21	-0.90	0.86
HMcode	-0.46	0.19	2.61	-0.10
RegPT	0.24	0.05	-0.08	-1.20

➤ ω_b and ω_{cdm} : Unbiased for all models up to $k_{\text{max}} = 0.22 \text{ h/Mpc}$

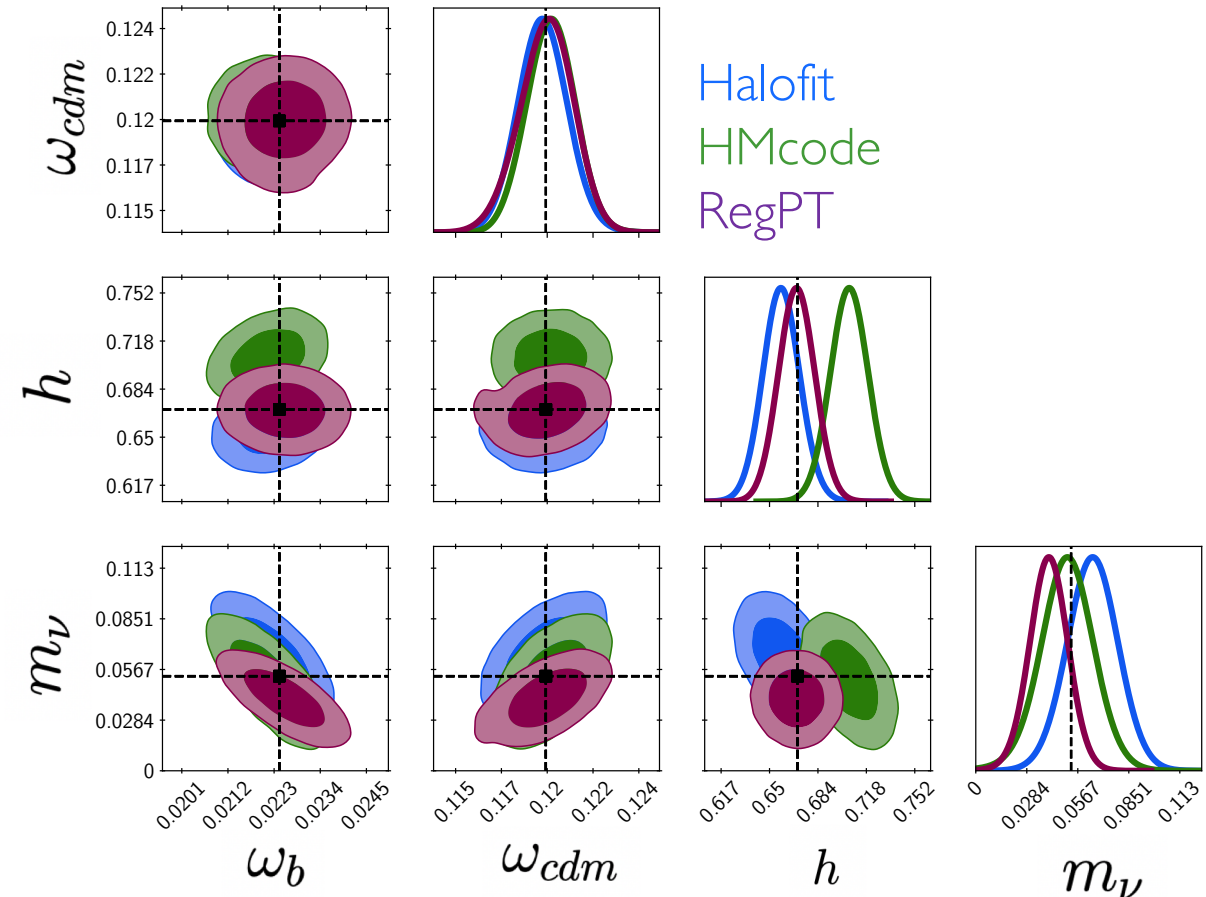
➤ Significant bias on h and m_ν :

- Halofit : $\sim 1\sigma$ bias on h and m_ν
- HMcode : Unbiased estimation of m_ν , but strong bias on h
- RegPT : Lower error-bar on $m_\nu \rightarrow \sim 1\sigma$ bias



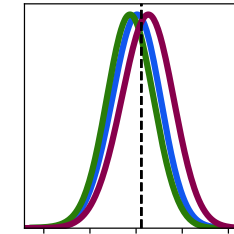
Fit on the mean power spectrum on 12 realisations

$$k_{\text{max}} = 0.2 \text{ h/Mpc}$$



Testing non-linear models with massive neutrinos

Model	$\delta(\omega_b)/\sigma_{\omega_b}$	$\delta(\omega_{\text{cdm}})/\sigma_{\omega_{\text{cdm}}}$	$\delta(h)/\sigma_h$	$\delta(m_\nu)/\sigma_{m_\nu}$
Halofit	-0.28	-0.21	-0.90	0.86
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Fit on the mean power spectrum on 12 realisations

$$k_{\text{max}} = 0.2 \text{ h/Mpc}$$

➤ m_ν and h are correlated

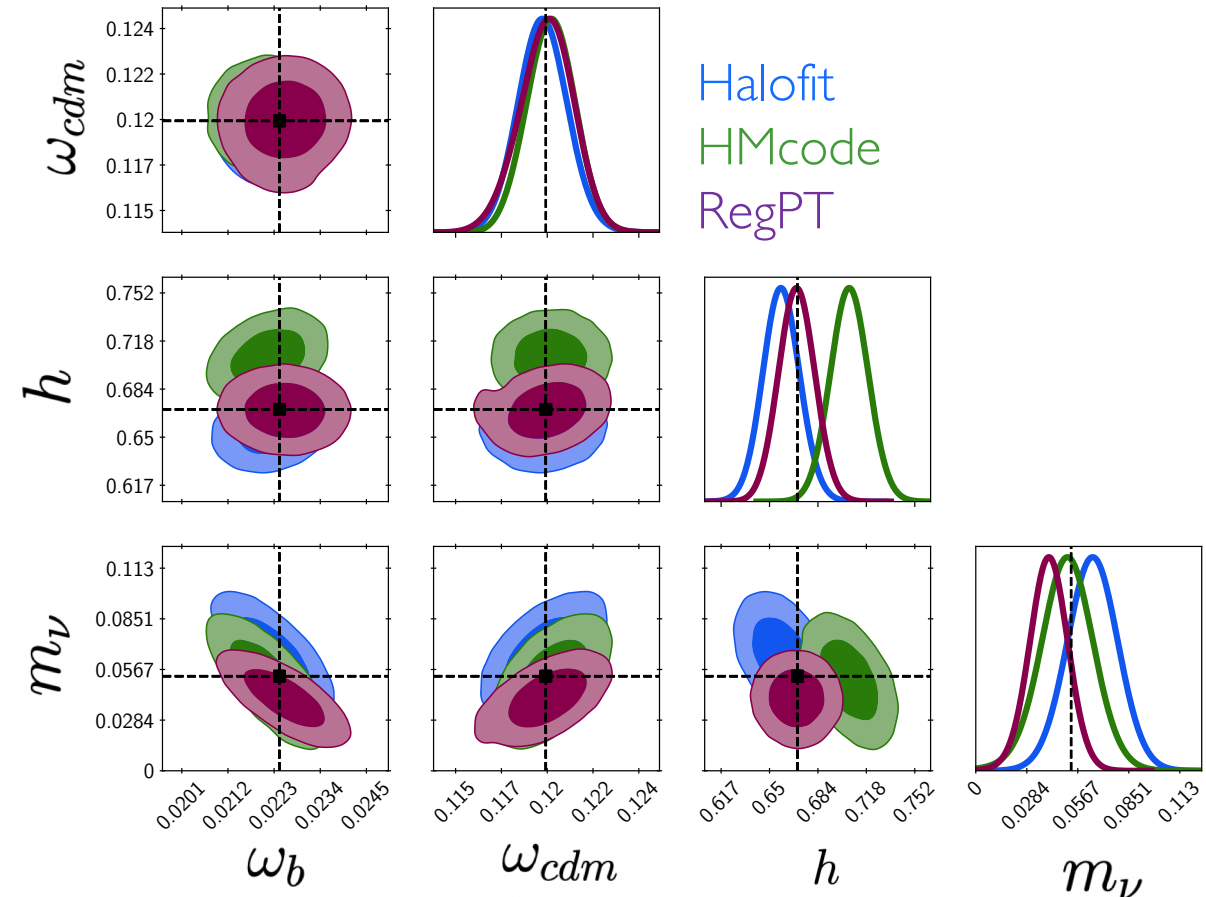
- Both are biased with Halofit
- Surprising that only h is biased with HMcode
- ➔ Test with m_ν fixed

➤ Can come from the treatment of m_ν in :

- The fitting functions (New version of HMcode [Mead et al. 2020])
- The N-Body simulations used for the calibration

➤ With RegPT treatment of m_ν is at the linear level

- Explain the different correlation and error for m_ν ?
- Explain the underestimation of m_ν ?



Non-linear model comparison : Only for real space matter power spectrum

- Limited to $k_{\text{max}} = 0.22 \text{ h/Mpc}$
- Revealed biases : especially for h and m_ν
 - ➔ Different hypothesis to explore to improve the treatment of massive neutrinos for non-linear model

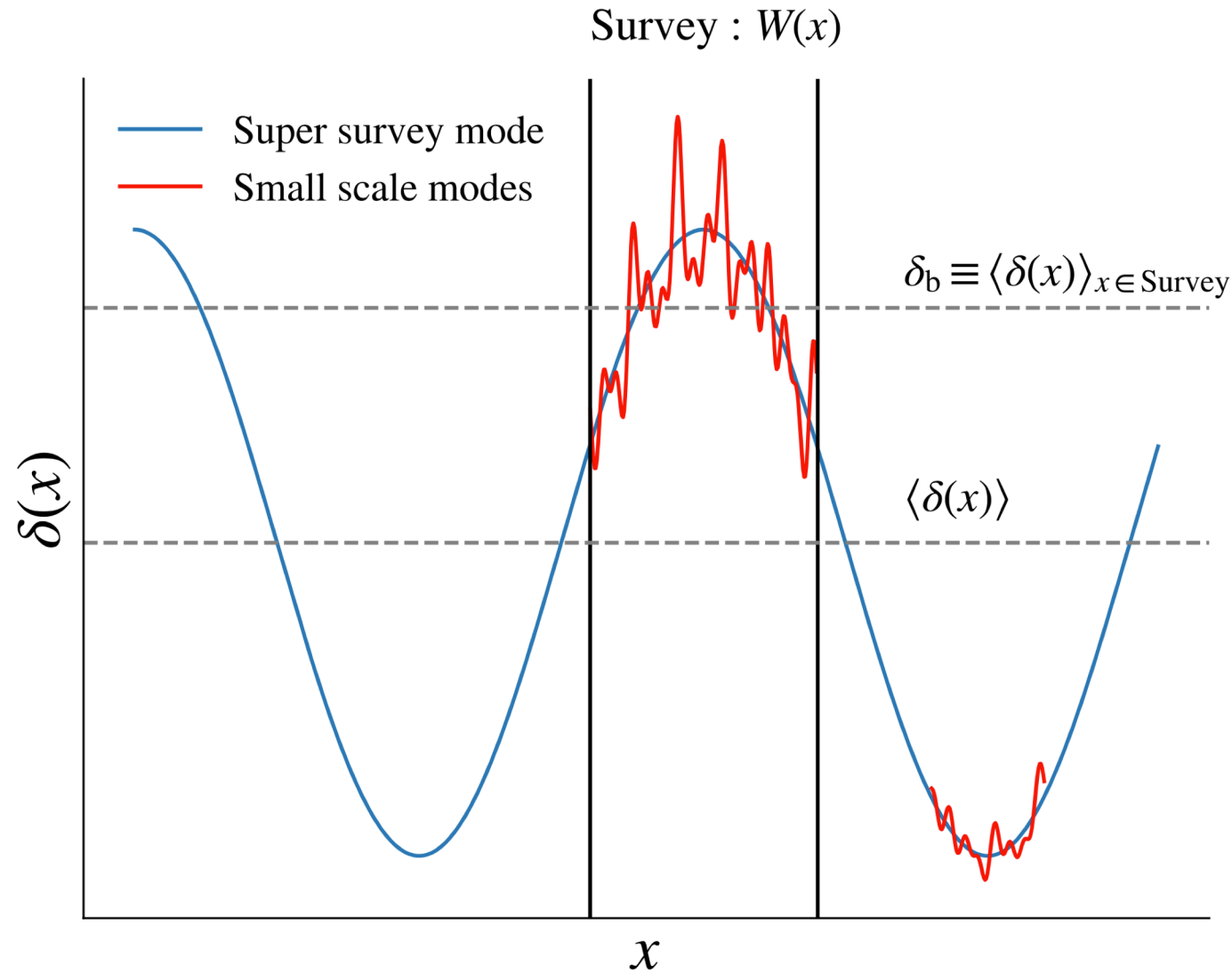
Covariance : Sampling noise and non-Gaussian covariance

- Conclusion on NERCOME : **Handy when N_m is low but conservative in the errors.**
- Conclusion on Covmos : **Suppression of sampling noise but conservative in the errors**
- Non-Gaussian covariance :
 - Significant impact for $k_{\text{max}} > 0.15 \text{ h/Mpc}$
 - The error on m_ν is unchanged

IV. Impact of Super Sample Covariance on future photometric galaxy surveys

- Basics of SSC
- Impact of SSC on Euclid cosmological constraints
- Survey sky coverage and SSC

Super Sample Covariance



If we sit in an over-(under-)density, the clustering is enhanced (damped)

→ **Non-linear coupling between large scales and small scales**

$$\begin{aligned}\sigma^2(z_1, z_2) &= \langle \delta_b(z_1) \delta_b(z_2) \rangle \\ &= \int \frac{d^3 \mathbf{k}}{(2\pi)^3} \tilde{\mathcal{W}}(\mathbf{k}, z_1) \tilde{\mathcal{W}}^*(\mathbf{k}, z_2) P_m(k|z_{12}).\end{aligned}$$

Where $\tilde{\mathcal{W}}$ is the survey window function.

Important source of errors especially for photometric probes

[Barreira et al. 2018, Lacasa 2020]



Forecast of the impact of SSC on Euclid photometric probes :

Photometric Galaxy Clustering (GCph),
Weak Lensing (WL)
and Cross-Correlation (XC)

SSC Depend on the survey window function



Study the impact of the survey footprint in SSC

$$\begin{aligned}\sigma^2(z_1, z_2) &= \langle \delta_b(z_1) \delta_b(z_2) \rangle \\ &= \int \frac{d^3 \mathbf{k}}{(2\pi)^3} \tilde{W}(\mathbf{k}, z_1) \tilde{W}^*(\mathbf{k}, z_2) P_m(k|z_{12}).\end{aligned}$$



The S_{ij} approximation

Observables ($P(k)$, C_l^{GCph} , C_l^{WL} ...)

Response of the observables

Covariance of δ_b

$$\text{Cov}_{\text{SSC}}(O_1, O_2) = \iint dV_1 dV_2 \frac{\partial o_1}{\partial \delta_b}(z_1) \frac{\partial o_2}{\partial \delta_b}(z_2) \sigma^2(z_1, z_2).$$

The S_{ij} approximation

Observables ($P(k)$, C_l^{GCph} , C_l^{WL} ...)

Response of the observables

Covariance of δ_b

$$\text{Cov}_{\text{SSC}}(O_1, O_2) = \iint dV_1 dV_2 \frac{\partial o_1}{\partial \delta_b}(z_1) \frac{\partial o_2}{\partial \delta_b}(z_2) \sigma^2(z_1, z_2).$$

[F. Lacasa & J. Grain 2019] :

In the approximation where the **observable's response vary slowly inside the redshift bins**

$$\text{Cov}_{\text{SSC}}(O_1, O_2) = R_1 O_1 R_2 O_2 \boxed{S_{i_z, j_z}}$$

R is the relative response : $R = \frac{\partial \ln O}{\partial \delta_b}$

SSC for the angular power spectrum

The **angular power spectrum** : $C_{\ell}^{AB}(i_z, j_z) = \int dV W_{i_z}^A(z) W_{j_z}^B(z) P_{AB}(k_{\ell}|z)$ With $k_{\ell} = (\ell + 1/2)/r(z)$

Projection of the 3D power spectrum to the **harmonic space** with
a **kernel** $W(z)$, characteristic of the probe considered

- A and B are the probes : **Photometric Galaxy Clustering** (GCph) or **Weak Lensing** (WL)
- i_z and j_z are the redshift bins



$$\text{Cov}_{\text{SSC}} \left(C_{\ell}^{AB}(i_z, j_z), C_{\ell'}^{CD}(k_z, l_z) \right) \approx R_{\ell}^{AB} C_{\ell}^{AB}(i_z, j_z) \times R_{\ell'}^{CD} C_{\ell'}^{CD}(k_z, l_z) \times S_{i_z, j_z; k_z, l_z}^{A, B; C, D}.$$

Ingredients :

- The $C(l)$
- The non-linear response R_l
- The S_{ijkl} matrix

SSC for the angular power spectrum

The C(l) $C_{\ell}^{AB}(i_z, j_z) = \int dV W_{i_z}^A(z) W_{j_z}^B(z) P_{AB}(k_{\ell}|z)$

Kernels for 10 *Euclid*-like photometric redshift bins

➤ Photometric Galaxy Clustering (GCph)

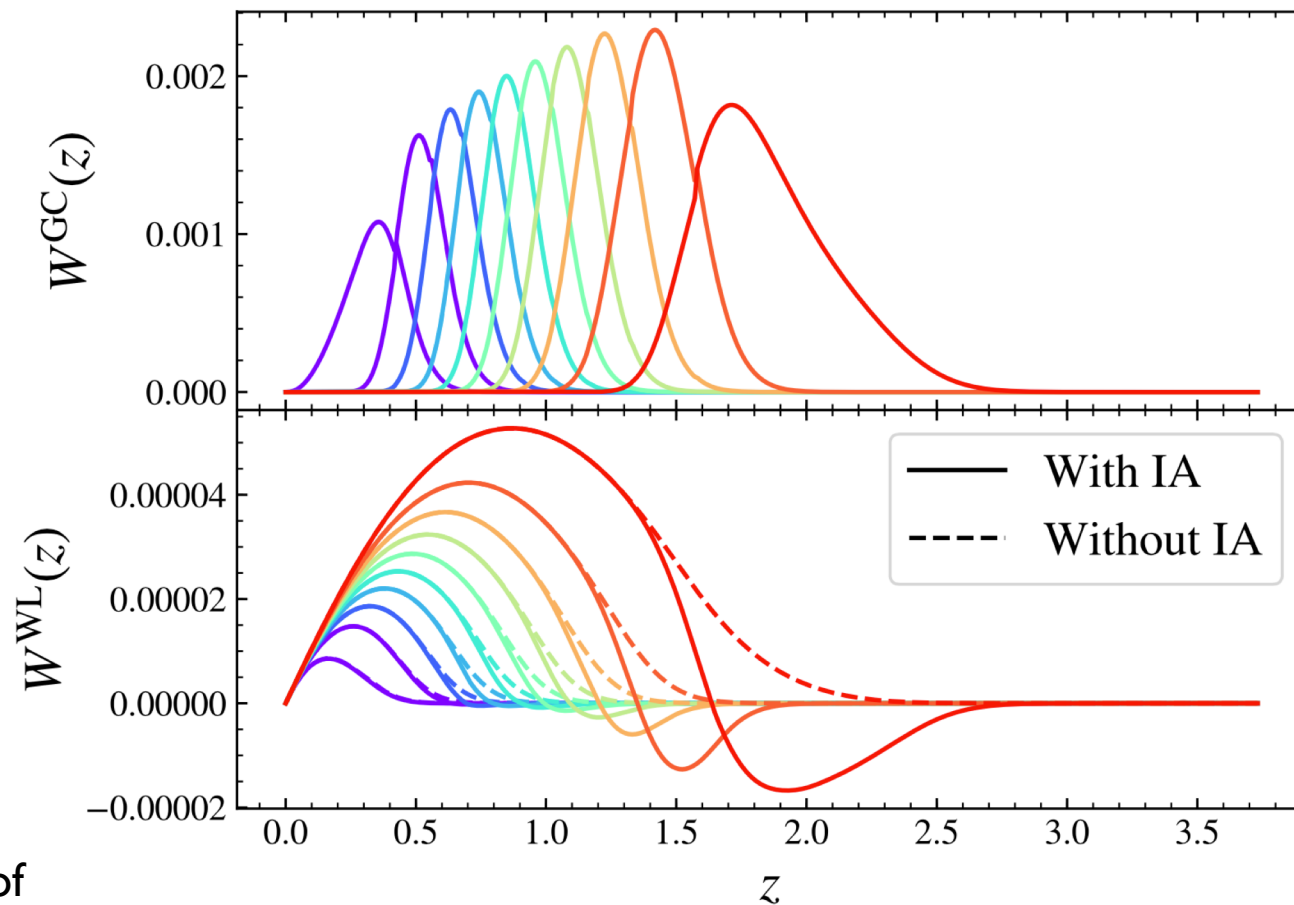
$$W_i^{\text{GC}}(z) = b_i \frac{n_i(z)}{r^2(z)} \frac{H(z)}{c}.$$

➤ Weak Lensing (WL)

$$W^{\text{WL}}(z) = W^{\gamma}(z) + W^{\text{IA}}(z).$$

Cosmic shear

Intrinsic Alignment of galaxies



SSC for the angular power spectrum

The non-linear response R_l

Following [Lacasa & Grain 2019] → Approximation of a constant response : $R_\ell \sim 4$

The S_{ijkl} matrix

$$S_{i_z, j_z; k_z, l_z}^{A, B; C, D} \equiv \int dV_1 dV_2 \frac{W_{i_z}^A(z_1) W_{j_z}^B(z_1)}{I^{AB}(i_z, j_z)} \frac{W_{k_z}^C(z_2) W_{l_z}^D(z_2)}{I^{CD}(k_z, l_z)} \sigma^2(z_1, z_2)$$

C(l) kernels

Covariance of δ_b

Full-sky approximation : $\sigma_{\text{full-sky}}^2(z_1, z_2) = \frac{1}{4\pi} C_\ell^m(z_1, z_2)$ → Rescale by the sky fraction $f_{\text{SKY}} \equiv \Omega_S / 4\pi$

Survey area
↓

Computed with PySSC

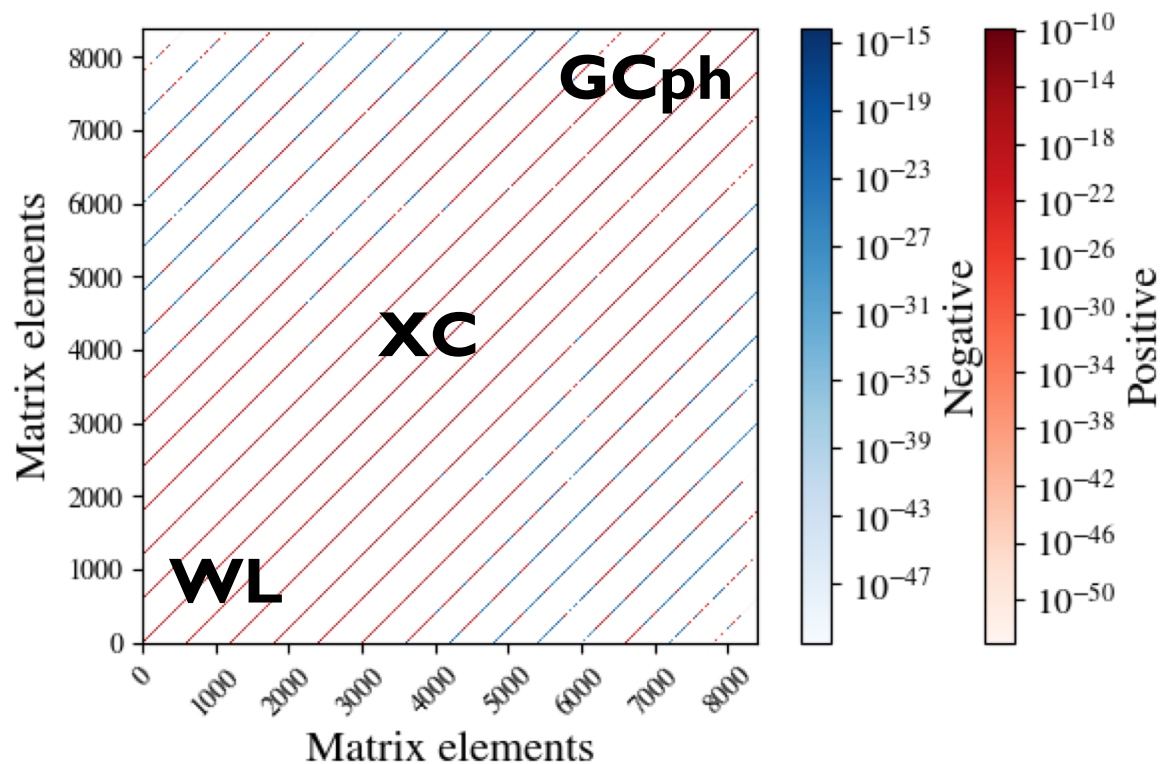
[Lacasa & Grain 2019]

<https://github.com/fabienlacasa/PySSC>

What is the SSC matrix like ?

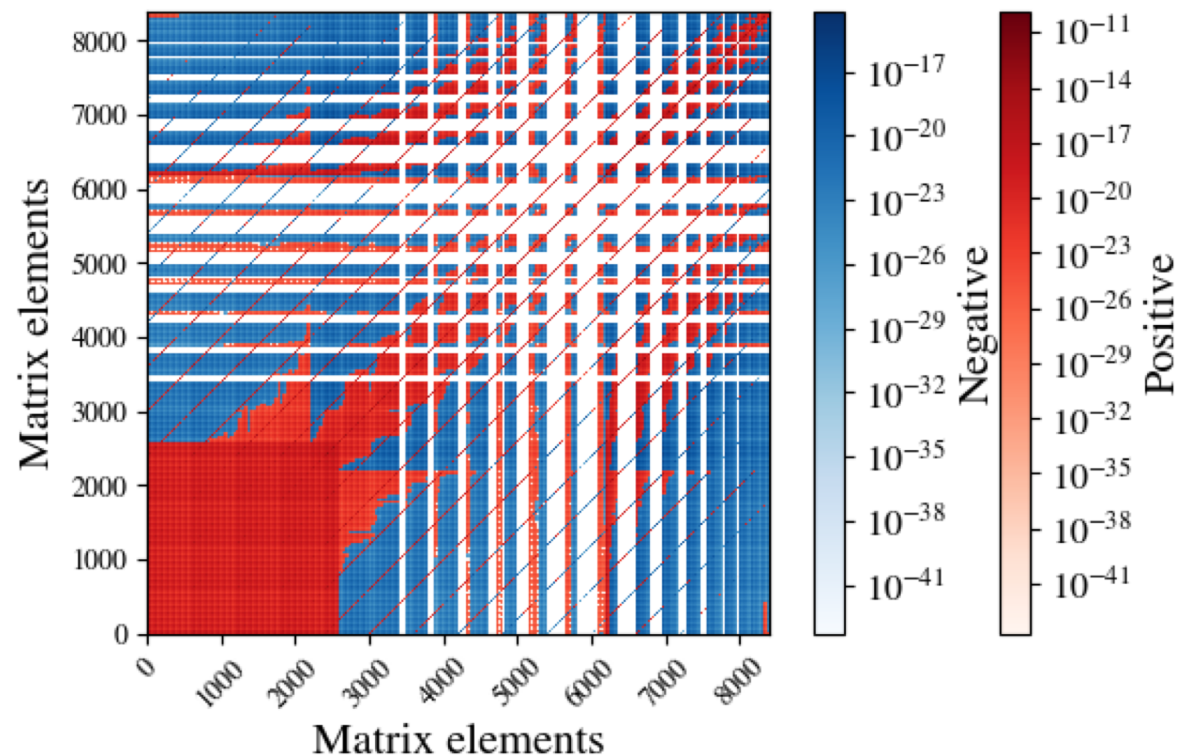
For 3x2-points : GCph+WL+XC, with 10 redshift bins

Gaussian



Diagonal in ℓ

Gaussian + SSC



Non-diagonal

Fisher forecast for 3x2-points

Fisher forecast for Euclid

[Euclid collaboration: Blanchard et al. 2020]

$$F_{\alpha,\beta} = \sum_{i,j,k,l} \sum_{\ell,\ell'} \frac{\partial C_{ij}^{AB}(\ell)}{\partial \theta_\alpha} \text{Cov} \left[C_{ij}^{AB}(\ell), C_{kl}^{CD}(\ell') \right]^{-1} \frac{\partial C_{kl}^{CD}(\ell')}{\partial \theta_\beta},$$

➤ Derivatives : Theoretical $C(\ell)$ for **GCph + WL + XC**

➤ 10 redshift bins :

$$z_i = \{0.0010, 0.42, 0.56, 0.68, 0.79, \\ 0.90, 1.02, 1.15, 1.32, 1.58, 2.50\}.$$

➤ Multipoles : $n_\ell = 40$

$$\ell_{\min} = 10$$

$$\ell_{\max}^{GCph} = \ell_{\max}^{XC} = 3000 \quad \ell_{\max}^{WL} = 5000$$

➤ Covariance :

○ Gaussian

○ Gaussian + SSC

} *Full-sky approximation*

➤ Cosmological parameters : **$w_0 w_a$ CDM scenario**

$$\theta_{\text{cosmo}} = \{\Omega_m, \Omega_b, w_0, w_a, h, n_s, \sigma_8\} \\ = \{0.32, 0.05, -1.0, 0.0, 0.67, 0.96, 0.816\},$$

➤ Nuisance parameters :

○ **Linear galaxy bias** : $\theta_{\text{nuisance}}^{\text{GC}} = \{b_i\}$, for i in $1, \dots, 10$,

○ **Intrinsic alignments** : $\theta_{\text{nuisance}}^{\text{WL}} = \{\mathcal{A}_{\text{IA}}, \eta_{\text{IA}}, \beta_{\text{IA}}\}$,

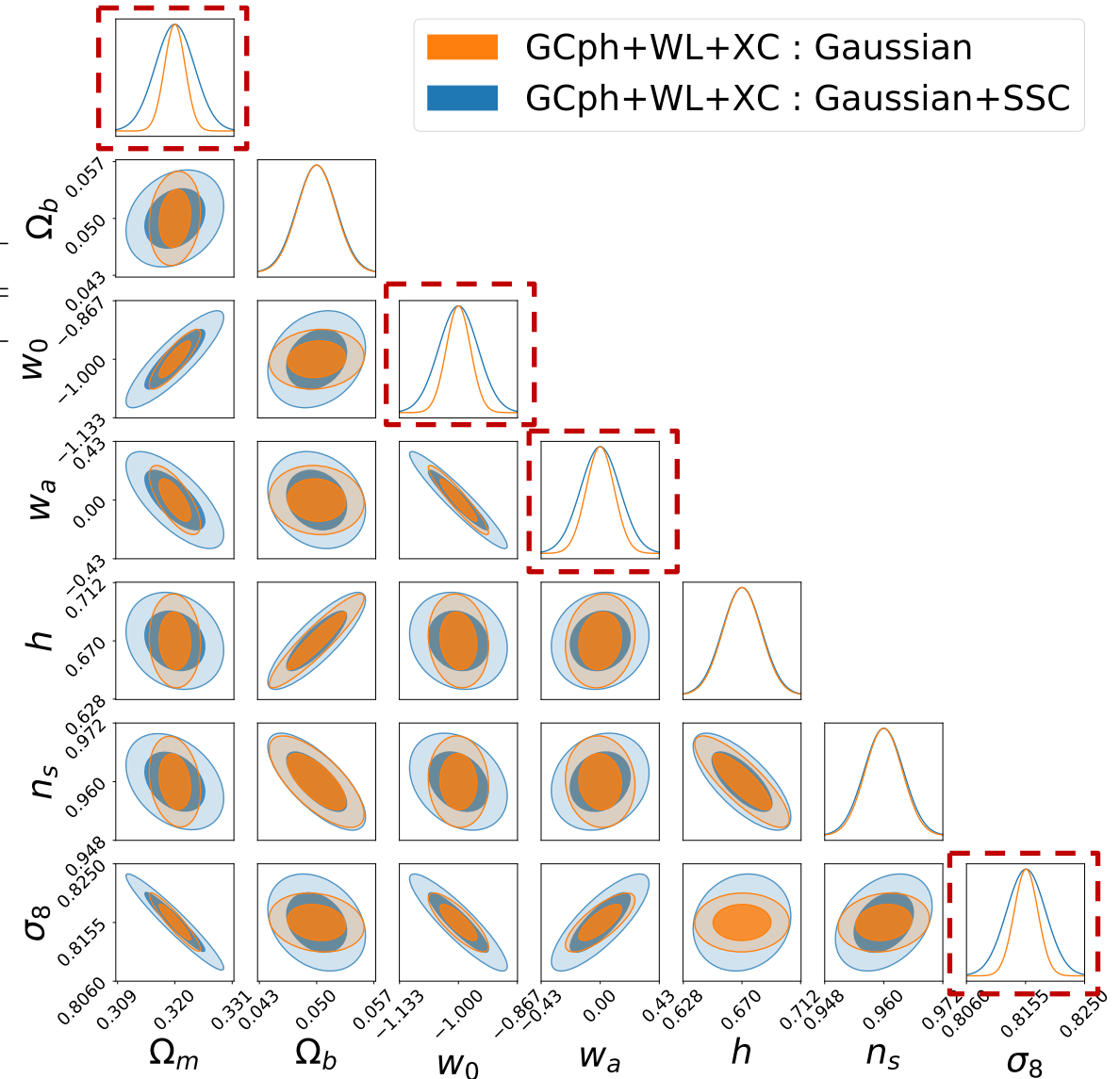
Fisher forecast for 3x2-points : Result

Dark Energy Figure of Merit : $\text{FoM}_{w_0, w_a} = \sqrt{\det(F_{w_0, w_a})}$.

Lower = Worse constraints

Probe	Gaussian	Gaussian+SSC	Decrease due to SSC [%]
GCph+WL+XC	1038.13	454.60	-56.21

- 50% decrease of the Dark Energy FoM
- Ω_m , w_0 , w_a and σ_8 are the most impacted parameters
- ➔ related to the amplitude of the power spectrum



SSC arises from the fact that we observe a limited portion of the universe

What is the impact of the survey footprint ?

For a survey with a mask $\mathcal{M}$ the exact derivation is :

$$\sigma^2(z_1, z_2) = \frac{1}{\Omega_S^2} \sum_{\ell} (2\ell + 1) C_{\ell}(\mathcal{M}) C_{\ell}^{\text{m}}(z_1, z_2),$$



Full-sky VS Partial-sky

Compare the different treatments of the footprint, at the level of parameters



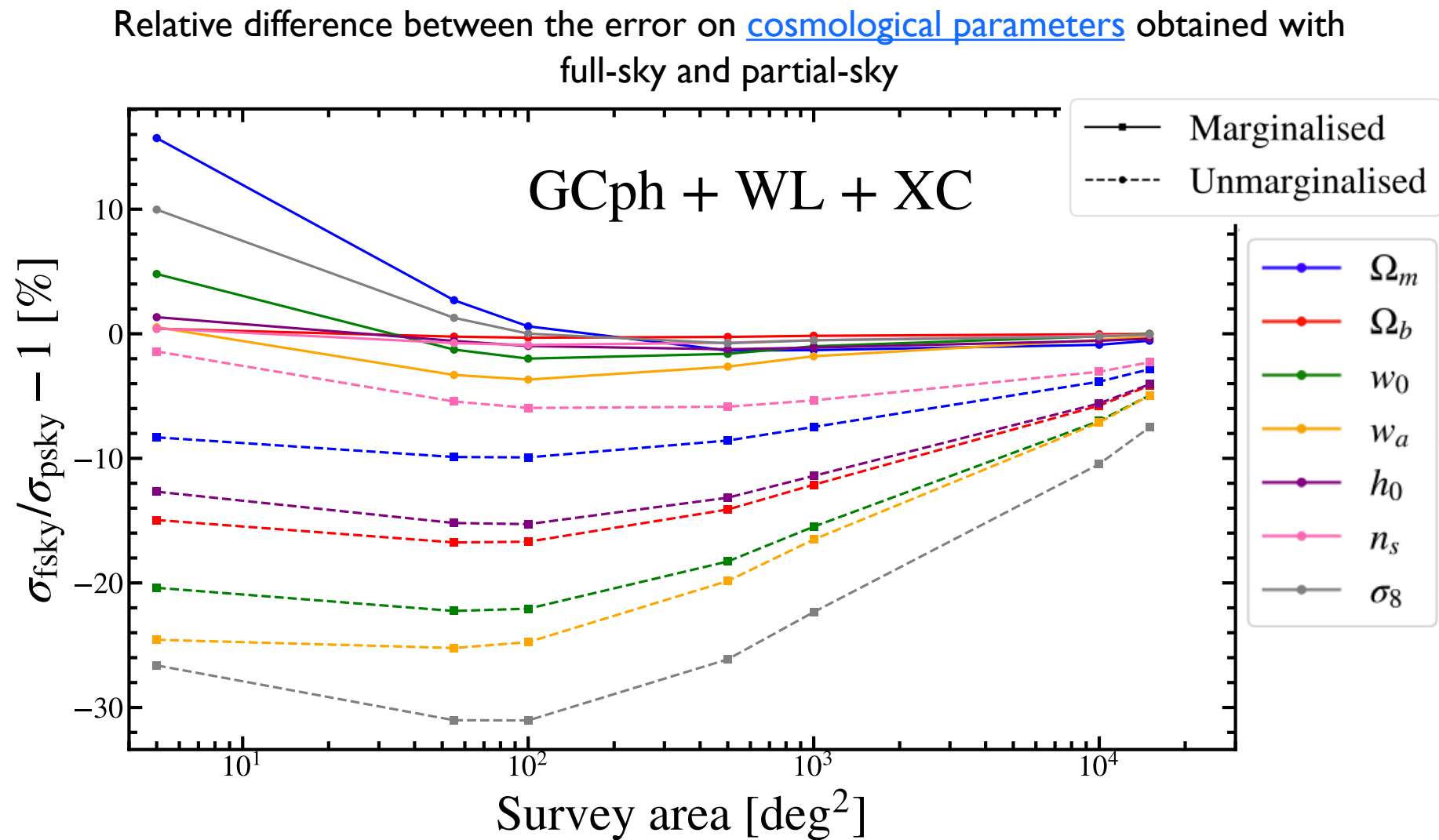
For a simple geometry with varying area



Same forecast setting

Result : Varying survey area

Circular mask with varying area



Result : Varying survey area

Circular mask with varying area



➤ Marginalised error

$$\sigma_{\alpha} = \sqrt{(F^{-1})_{\alpha,\alpha}}.$$

➔ Small difference for wide surveys

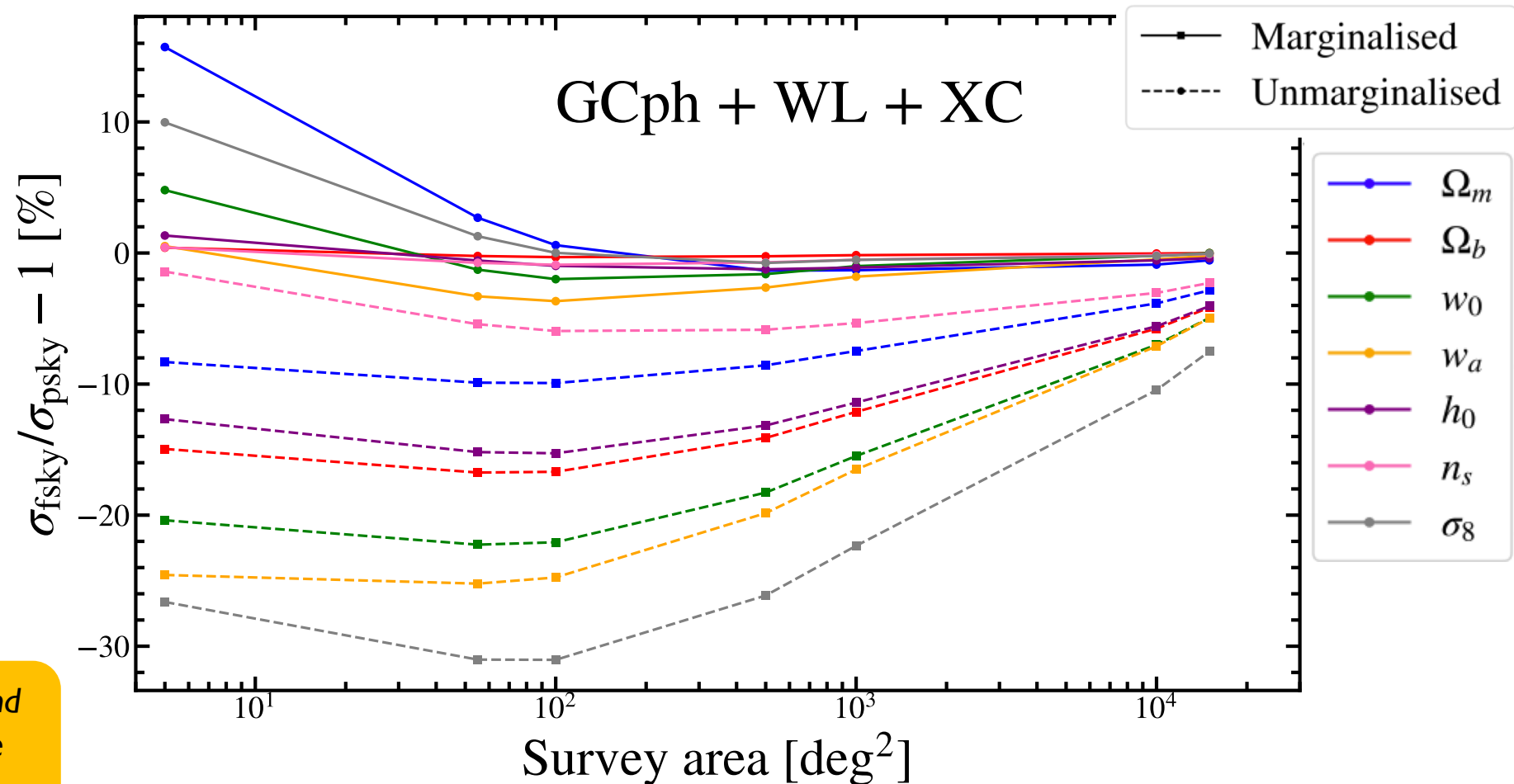
➤ Unmarginalised error

$$\sigma_{\alpha}^U = \sqrt{1/F_{\alpha,\alpha}},$$

➔ Significant difference

➔ Difference between full-sky and partial-sky is absorbed in the marginalisation

Relative difference between the error on [cosmological parameters](#) obtained with full-sky and partial-sky



Result : Varying survey area

Circular mask with varying area

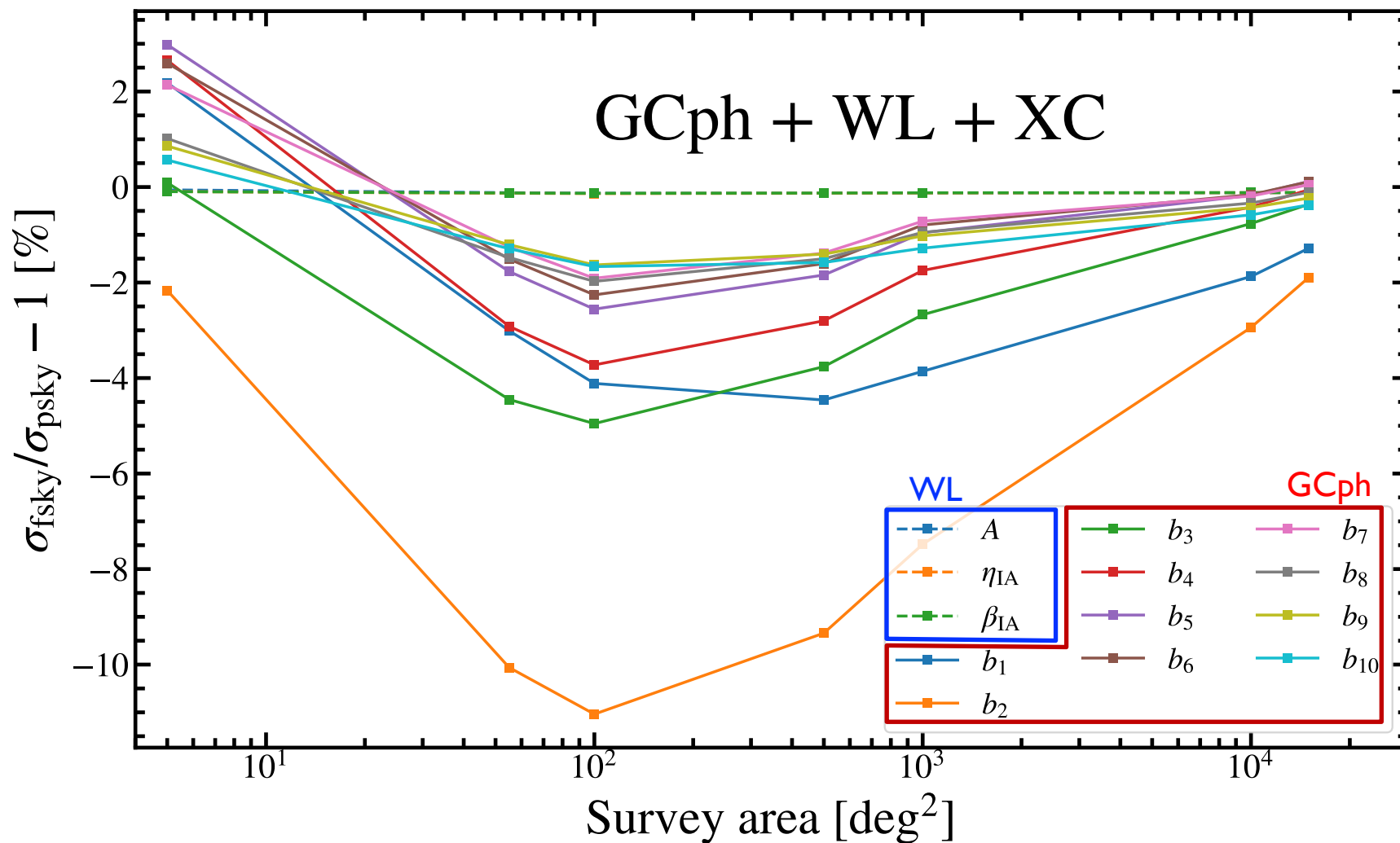


The linear galaxy bias is more sensitive to SSC



The difference is absorbed by the galaxy bias in the marginalisation.

Relative difference between the [marginalised](#) error on [nuisance parameters](#) obtained with full-sky and partial-sky



- Super Sample Covariance has a significant impact on Dark Energy constraints → **-50% on the FoM**

Euclid Key paper : D.Sciotti, S. Gouyou Beauchamps et al. In prep.

- Treatment of the survey footprint for SSC : Accepted paper [Gouyou Beauchamps et al. 2021] in A&A

- Development of a new method to account for the survey footprint :

Soon available at <https://github.com/fabienlacasa/PySSC>

- For marginalised constraints : **Full-sky is sufficient** for area $> 1000 \text{ deg}^2$
- For unmarginalised constraints : **More than 10% difference between full-sky and partial-sky** for all areas between 5 and $15\,000 \text{ deg}^2$

➔ *Might be important if tight priors are applied on nuisance parameters*

Conclusions

With Euclid we will reach a high precision on LSS observables

To exploit cosmological information on small scales and find potential deviations from Λ CDM and accurately measure the total neutrino mass, we need to control :

➤ The covariance :

- Effects of sampling noise can be reduced with NERCOME and Covmos

- Non-Gaussian covariance :

- Trispectrum (Non-linear clustering) : MCMC on N-Body simulations with matter $P(k)$

➔ Significant impact of Fourier mode correlations

- SSC (Survey limited observation) : Theoretical Fisher forecast for 3x2-points

➔ Significant impact on Dark Energy constraints

Which one is the most important ?

➤ The modeling of non-linear scales ➔ Significant bias on the estimation of the neutrino mass

Conclusions

The inference of cosmological parameters involves

➤ The covariance :

- Effects of sampling noise can be reduced with NERCOME and Covmos
- Non-Gaussian covariance :
 - Trispectrum (Non-linear clustering) : MCMC on N-Body simulations with matter $P(k)$
 - ➔ Significant impact of Fourier mode correlations
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Which one is the most important ?

➤ The modeling of non-linear scales ➔ Significant bias on the estimation of the neutrino mass

With Euclid we will reach a high precision on LSS observables

To exploit cosmological information on small scales to find potential deviations from Λ CDM and accurately measure the total neutrino mass, we need to control these effects !

Perspectives

Estimation of the neutrino mass with the power spectrum

- Need **more investigation** for the non-linear modeling challenge
- Extend to **galaxies in redshift space**
- Extend to **non-standard cosmologies**

Super Sample Covariance

- Go beyond the **constant response approximation**
- Estimate the response in N-body simulations

Question the usual assumptions on the Likelihood of 2-point statistics

- Gaussian distribution of data ?
- Cosmological dependence of the covariance

➔ **Additional bias in parameter inference ?**

Euclid Key Papers in progress

We have to be ready for the first Euclid data : 2023 - 2024

Backup

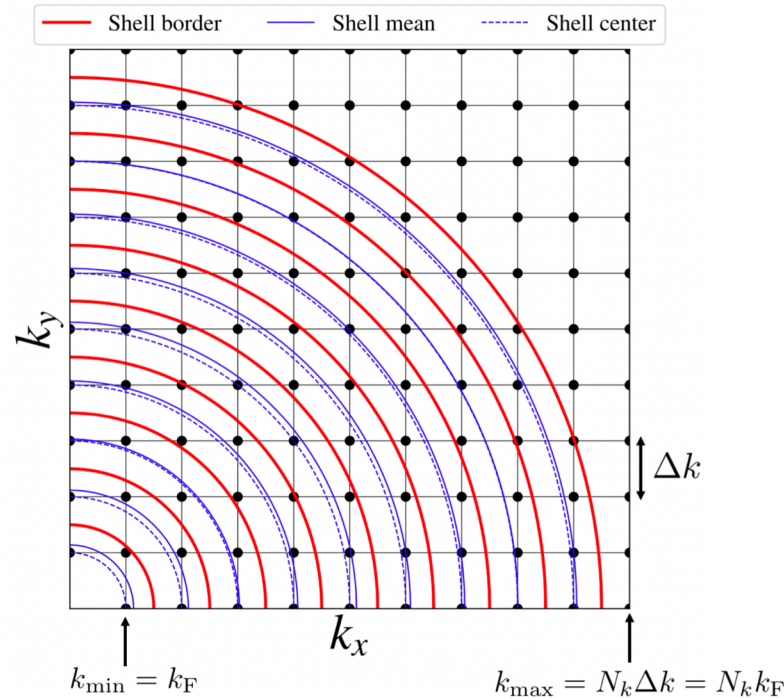
Power spectrum estimation

Estimate the density field on a grid and take the
Fourier Transform

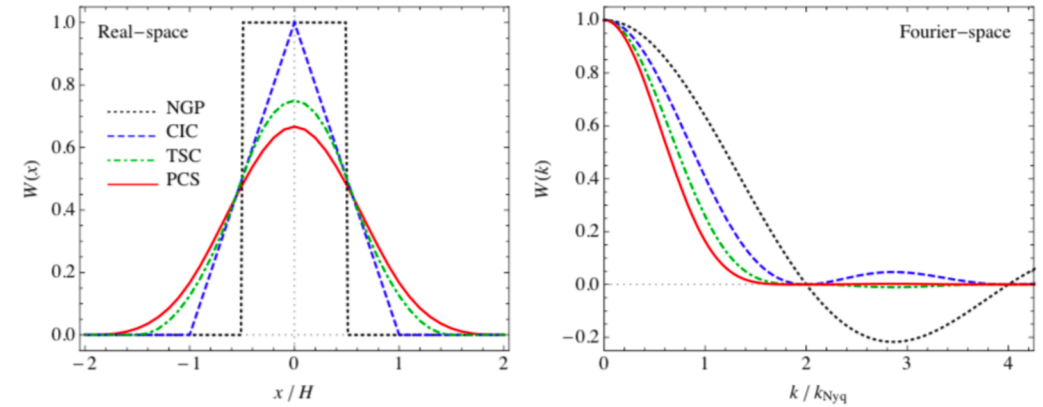
$$\hat{P}(\mathbf{k}_n) \equiv k_F^3 \left[|\delta(\mathbf{k}_n)|^2 - \frac{1}{N_p} \right],$$

Shell average of the 3D $P(k)$

$$\hat{P}(k) = \frac{1}{M_k} \sum_{k < |\mathbf{k}| < k + \Delta k} \hat{P}(\mathbf{k}),$$

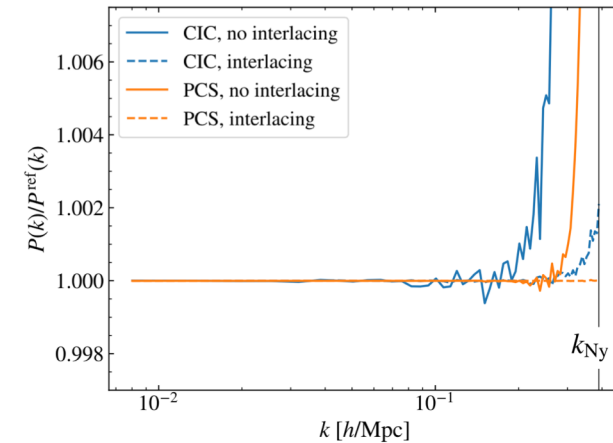


Mass Assignment Scheme

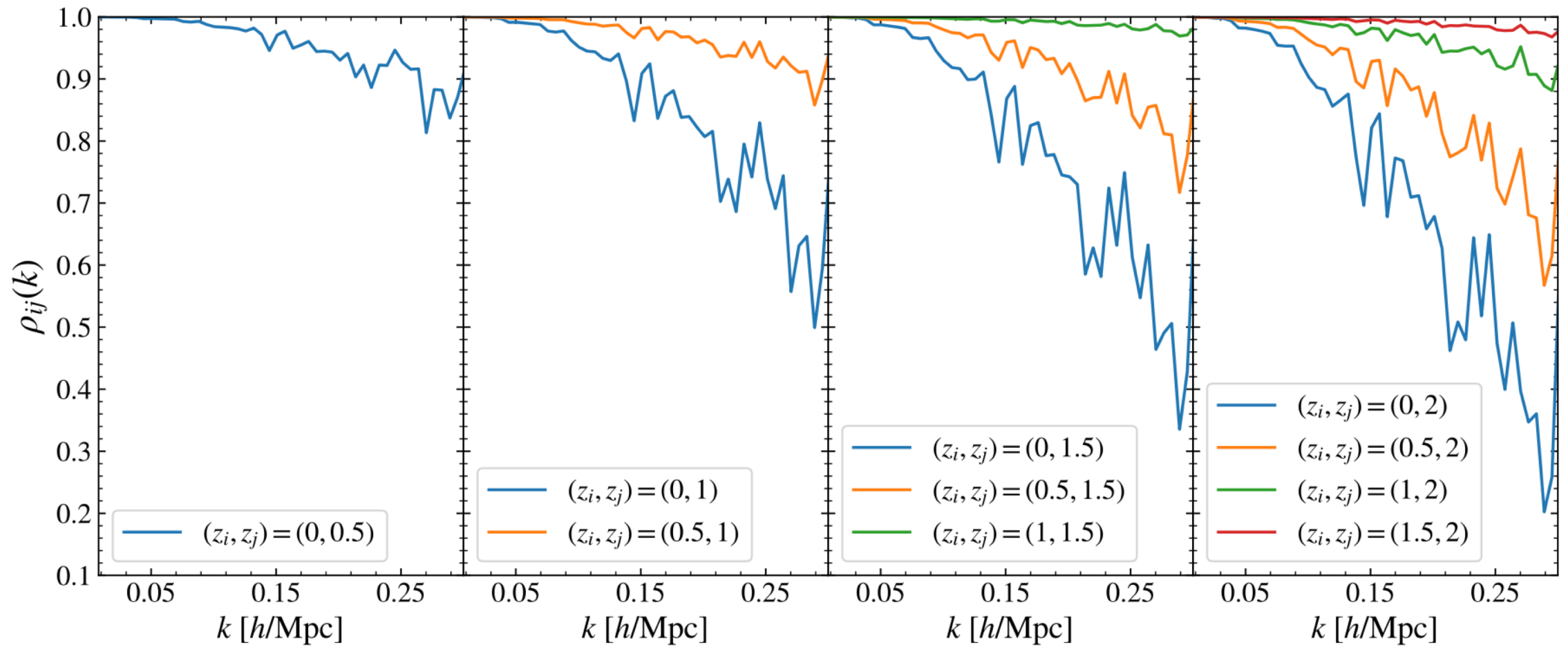


Aliasing and Interlacing

$$P^G(\mathbf{k}) = \sum_{\mathbf{n}} |W(\mathbf{k} - \mathbf{n}k_s)|^2 \left[P(|\mathbf{k} - \mathbf{n}k_s|) + \frac{1}{(2\pi)^3 \bar{n}} \right].$$



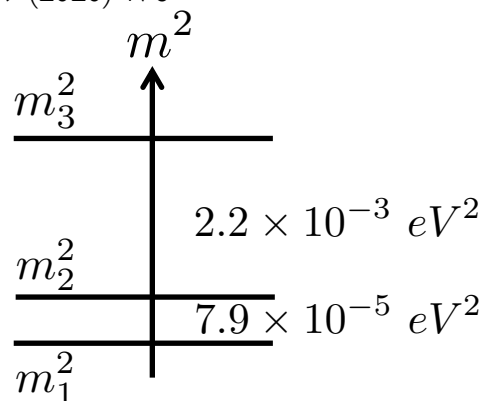
Redshift correlations



Neutrino mass constraints : Particle Physics

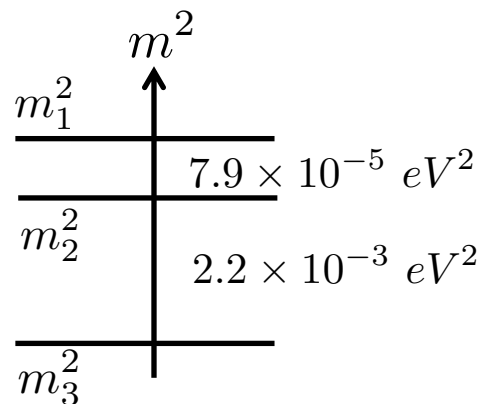
➤ Neutrino oscillations experiments : Super Kamiokande, T2K, KamLand...

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Normal

$$\sum m_\nu > 0.056 \text{ eV}$$



Inverted

$$\sum m_\nu > 0.095 \text{ eV}$$

Overall particle physics experiments constraints

NH	$0.056 \text{ eV} \lesssim M_\nu \lesssim 1 \text{ eV}$
IH	0.095 eV

➤ Direct kinematic measurements in tritium β decay : KATRIN

Phys. Rev. Lett. 123, 221802

$$\sum m_\nu < 1 \text{ eV}$$

Neutrino mass constraints : Cosmology

Constraints with the CMB [Planck Collaboration 2020]

- CMB *T&P* (Planck) : $M_\nu < 0.26 \text{ eV}$ (95% C.L.)
- CMB *T&P* (Planck) + Lensing : $M_\nu < 0.24 \text{ eV}$ (95% C.L.)
- CMB *T&P* (Planck) + Lensing + BAO : $M_\nu < 0.12 \text{ eV}$ (95% C.L.) ➔ BAO break degeneracies (Ω_m, H_0)

Constraints with the LSS

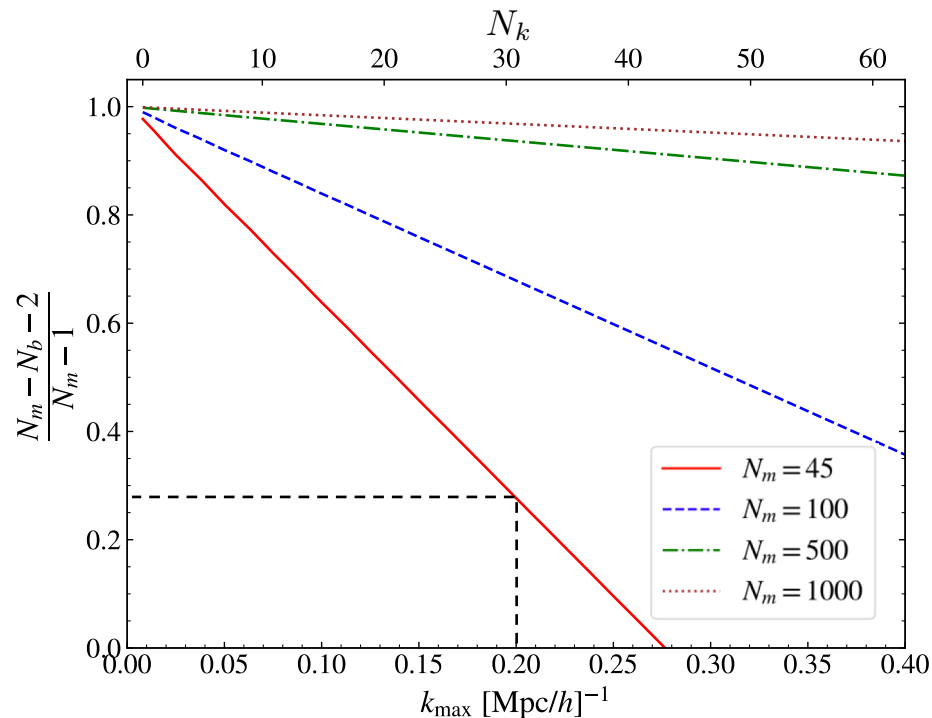
- BAO (BOSS) + CMB *T&P* : $M_\nu < 0.12 \text{ eV}$ (95% C.L.) [Ivanov et al. 2020]
- $P(k)$ (BOSS) + CMB *T&P* : $M_\nu < 0.16 \text{ eV}$ (95% C.L.) [Ivanov et al. 2020]
- Ly- α *ID* $P(k)$: $M_\nu < 0.71 \text{ eV}$ (95% C.L.) [Palanque-Delabrouille et al. 2020]
- Ly- α *ID* $P(k)$ + CMB *T&P* : $M_\nu < 0.1 \text{ eV}$ (95% C.L.) [Palanque-Delabrouille et al. 2020]

Covariance estimation and sampling noise I

For N_m realisation of the power spectrum $\hat{C}_{ij} = \frac{1}{N_m - 1} \left[\sum_n^{N_m} [P^{(n)}(k_i) - \bar{P}(k_i)][P^{(n)}(k_j) - \bar{P}(k_j)] \right] \rightarrow$ **Sampling noise**

➤ Hartlap bias in the **precision matrix** Ψ [Wishart 1928, Hartlap 2007]

$\hat{\Psi} = \hat{C}^{-1}$ Biased estimator of Ψ :
Inverse Wishart distribution $\langle \hat{\Psi} \rangle = \frac{N_m - 1}{N_m - N_k - 2} \Psi \rightarrow$ *Sensitive to the number of simulations and bins*
 N_m and N_k



Hartlap factor to multiply to $\hat{\Psi}$

For example for $N_k = 30$ ($k_{\max} \sim 0.2 \text{ h/Mpc}$) and $N_m = 45 \rightarrow$ **Divide Psi by 3**

First effect of **sampling noise** :

Overestimation of $\Psi \rightarrow$ underestimation of parameter's errors

Covariance estimation and sampling noise II

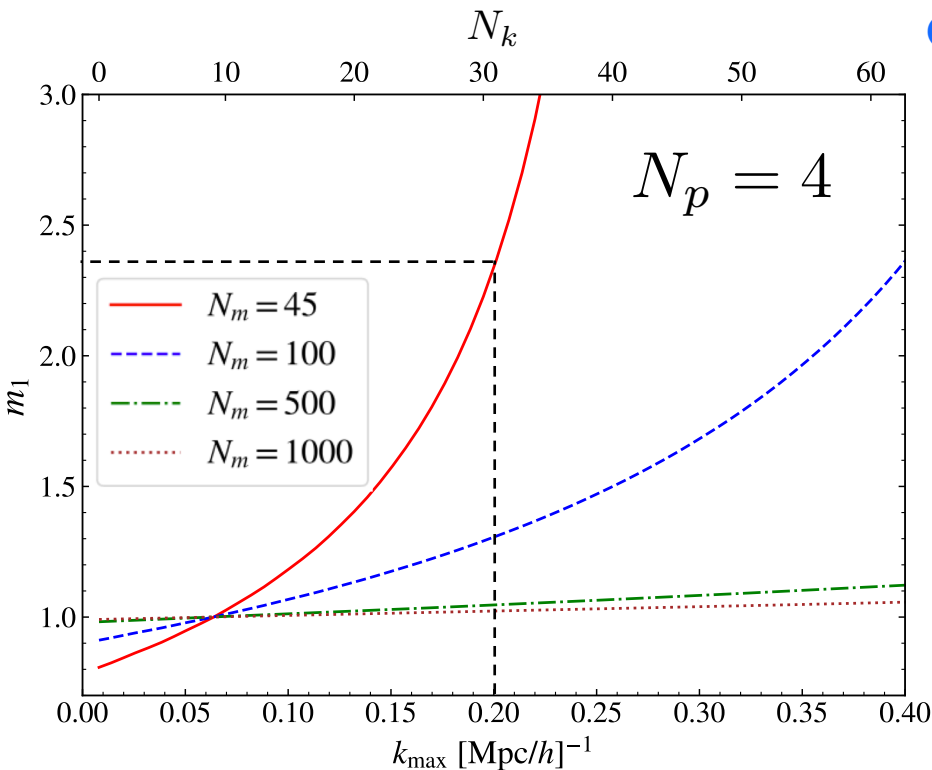
Noise in the estimated precision matrix :

$$\hat{\Psi} = \Psi + \Delta\Psi \quad \text{with} \quad \langle \Delta\Psi_{ij} \Delta\Psi_{kl} \rangle = A(N_m, N_k) \Psi_{ij} \Psi_{kl} + B(N_m, N_k) (\Psi_{ik} \Psi_{jl} + \Psi_{il} \Psi_{jk})$$

[Taylor et al. 2013]

➤ Sampling noise in the precision matrix propagates to the posterior distribution of parameters

[Taylor et al. 2013 ; Dodelson & Schneider 2013 ; Percival et al. 2014 ; Taylor & Joachimi 2014]



Correct by inflating the parameter's covariance matrix Φ

[Percival et al. 2014]

$$\hat{\Phi} \rightarrow m_1 \times \hat{\Phi}$$

For example for
 $N_k = 30$ ($k_{\max} \sim 0.2 \text{ h/Mpc}$)
 and $N_m = 45$

➔ Inflate the error-bars by ~ 50%

$$m_1 = \frac{1 + B(N_b - N_p)}{1 + A + B(N_p + 1)}$$

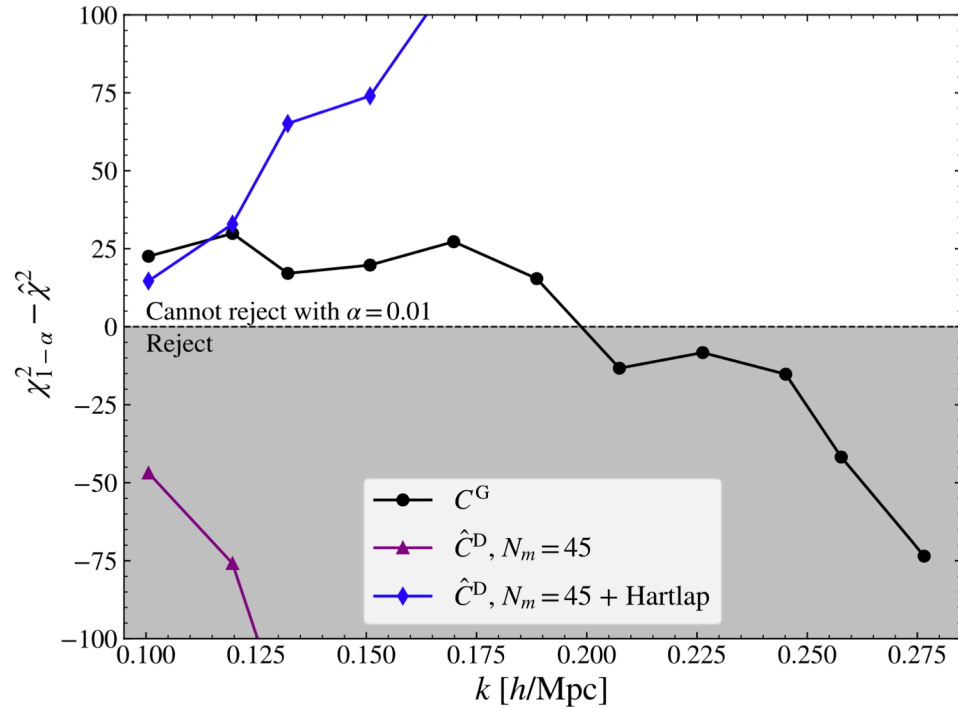
Dispersion on the best-fit

Bias on the estimation of the error

Second effect of sampling noise :

Variance and bias on the estimated variance and best-fit of parameters

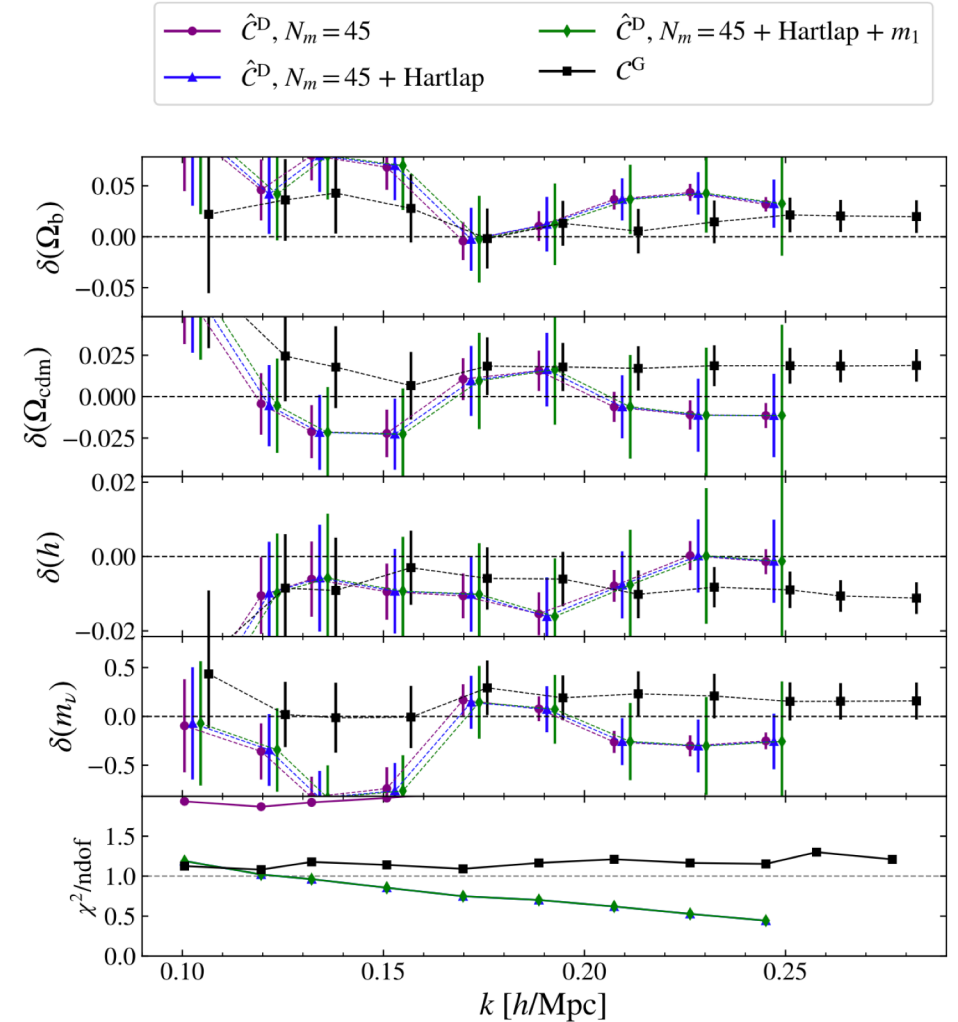
Goodness of fit test



➤ Hartlap bias : $\langle \hat{\Psi} \rangle = \frac{N_m - 1}{N_m - N_k - 2} \Psi$

➤ Sampling noise : $\hat{\Phi} \rightarrow m_1 \times \hat{\Phi} \quad m_1 = \frac{1 + B(N_b - N_p)}{1 + A + B(N_p + 1)}$

Parameter estimation

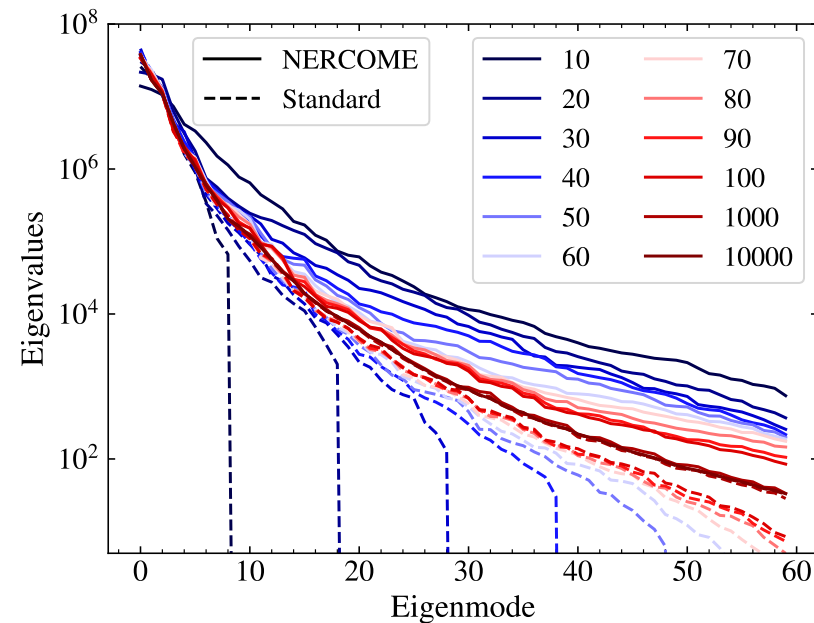


NERCOME : Non-parametric Eigenvalue-Regularised COvariance Matrix Estimator

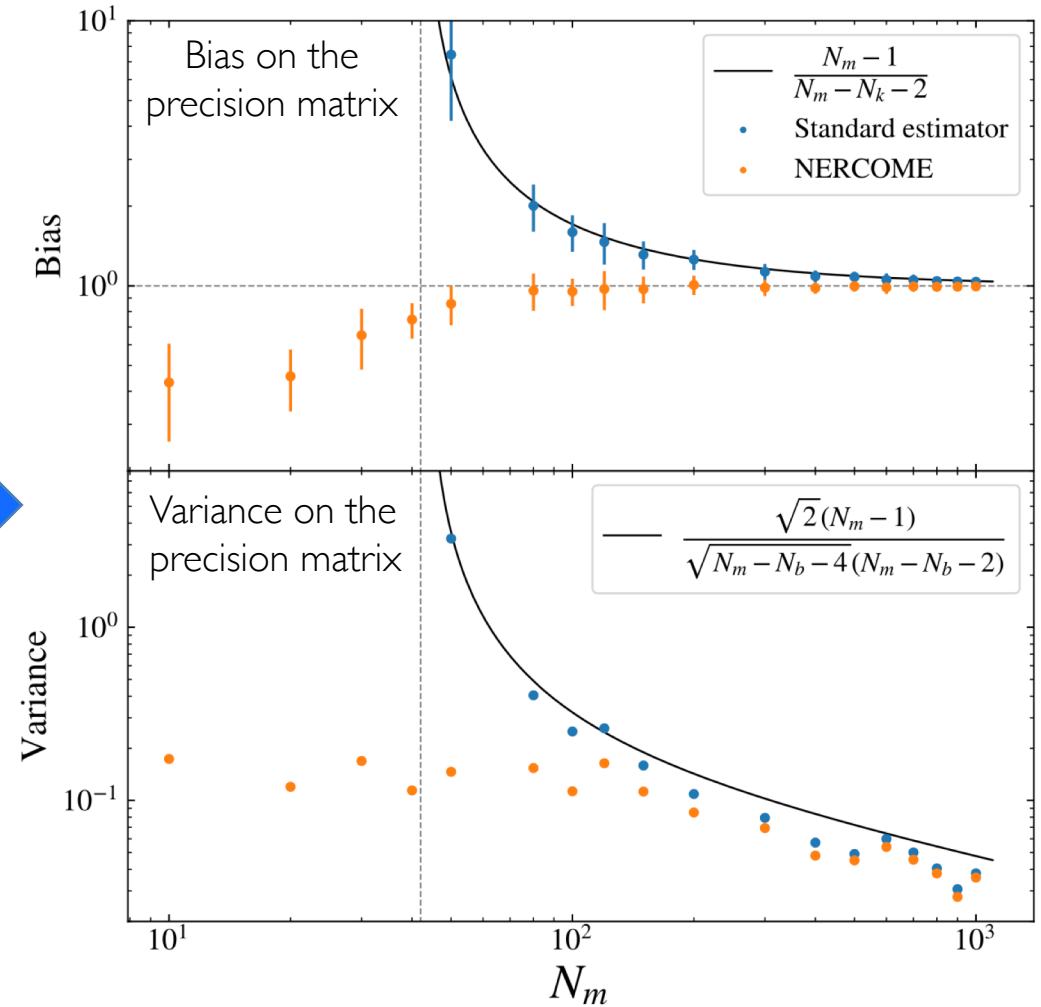
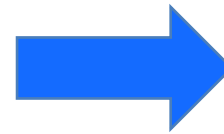
For N_m mocks :

1. Estimate the covariance on 2 subsets of size s and N_m-s : $\hat{S}_1$ and $\hat{S}_2$
2. Eigenvalue Decomposition : $\hat{S}_i = U_i D_i U_i^T$
3. Estimate the new covariance as : $\hat{C}_N = U_1 \text{diag}(U_1^T \hat{S}_2 U_1) U_1^T$

Repeat for 500 random subsets of size s and N_m-s

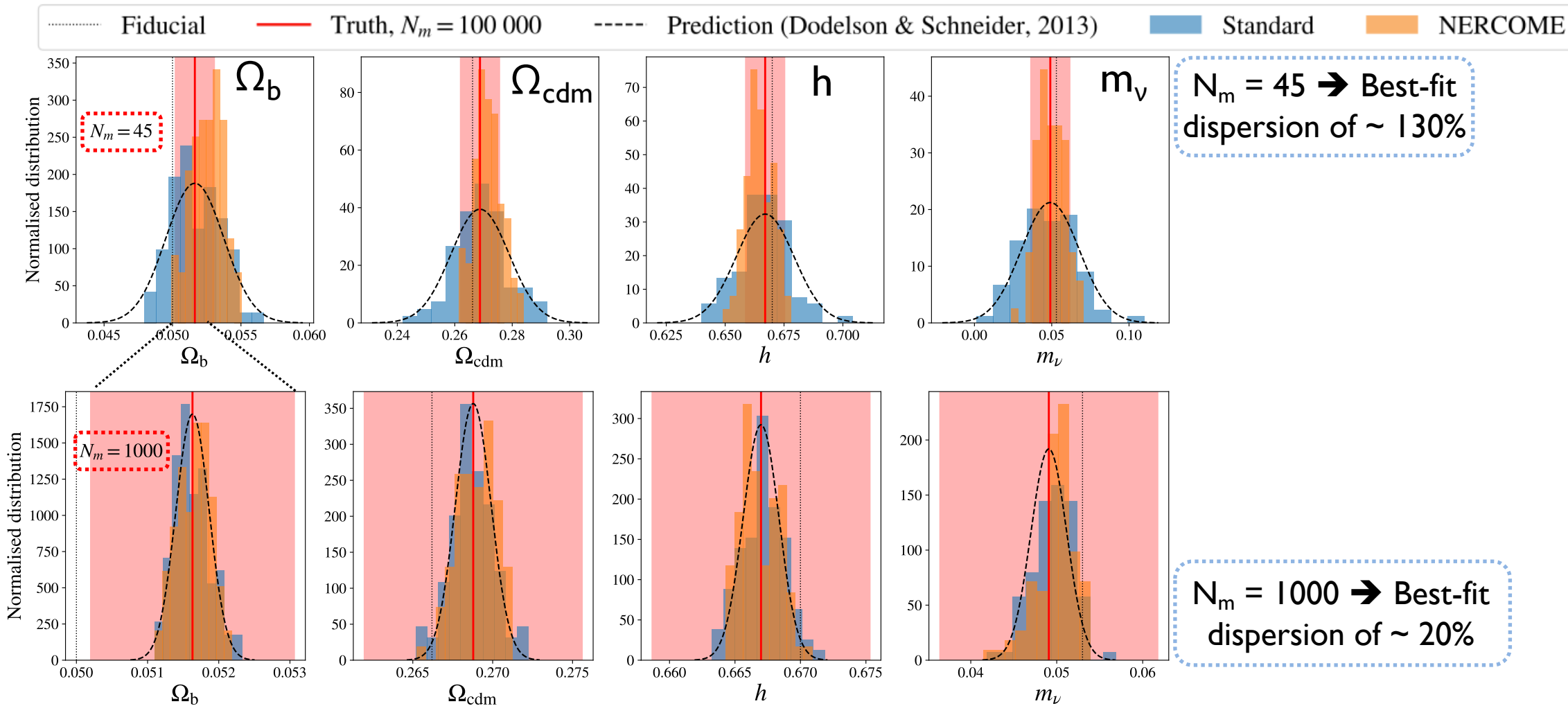


*Non-linear
shrinkage of
low eigenvalues*



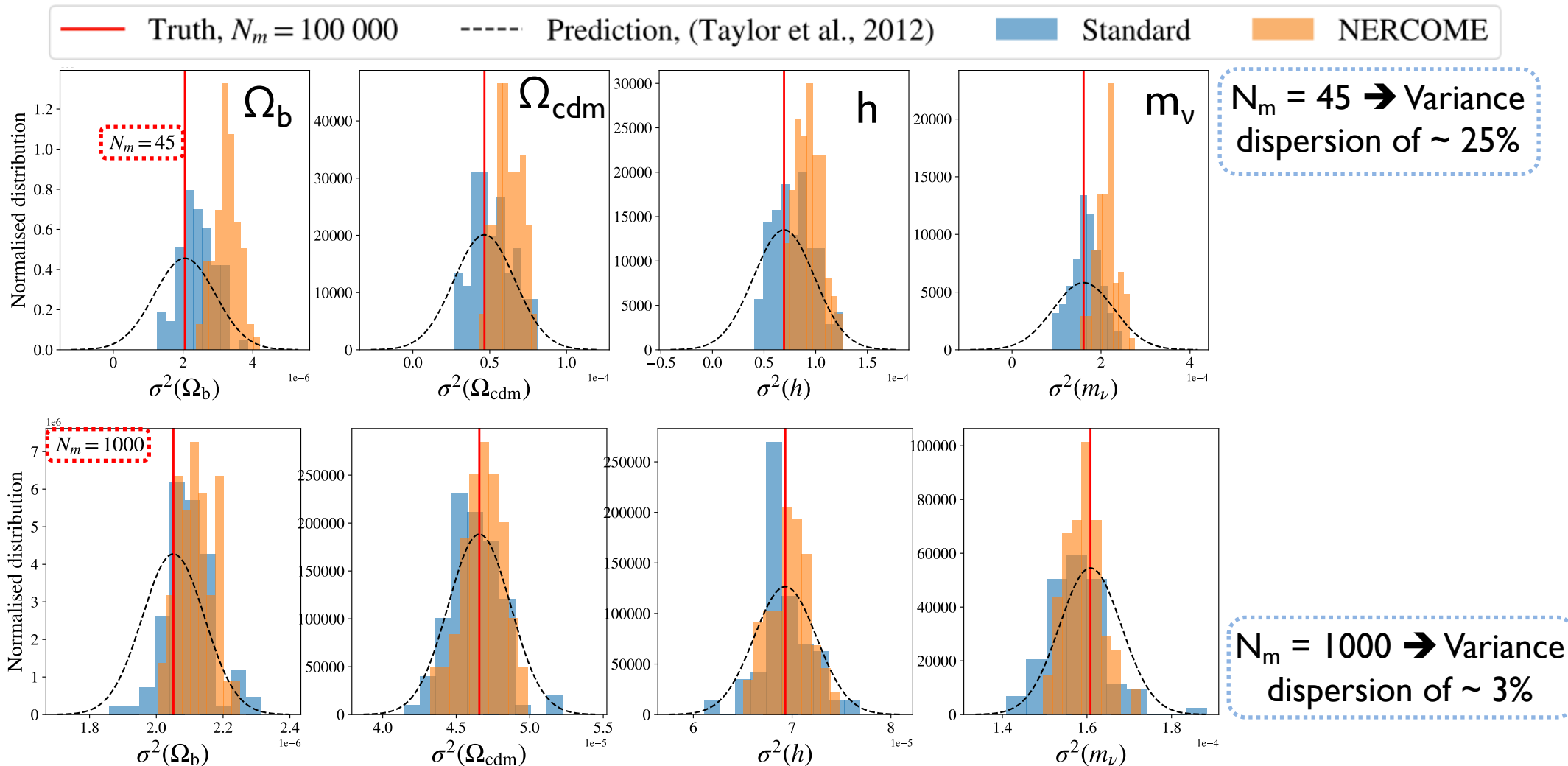
Testing NERCOME on parameter estimation

Distribution of **best-fits** for 100 realisations of the covariance



Testing NERCOME on parameter estimation

Distribution of variances for 100 realisations of the covariance



Testing NERCOME on parameter estimation

Distribution of **best-fits** for 100 realisations of the covariance

$\sqrt{\text{Var}[\theta^{\text{bf}}] / \sigma_{\theta, \text{Truth}}} [\%]$	Ω_b	Ω_{cdm}	h	m_ν	$\sqrt{B(N_b - N_p)} [\%]$
Standard, $N_m = 45$	124.46	134.89	132.63	141.85	148.79 [Dodelson & Schneider 2013]
NERCOME, $N_m = 45$	78.54	69.49	70.16	68.15	
Standard, $N_m = 1000$	17.57	20.00	19.85	19.18	16.40
NERCOME, $N_m = 1000$	16.03	17.56	17.64	17.82	
$\sqrt{\text{Var}[\theta_N^{\text{bf}}] / \text{Var}[\theta_S^{\text{bf}}]} - 1 [\%]$	Ω_b	Ω_{cdm}	h	m_ν	
$N_m = 45$	-38.89	-48.48	-47.11	-51.95	
$N_m = 1000$	-8.79	-12.16	-11.14	-7.09	
$[\langle \theta^{\text{bf}} \rangle - \theta_{\text{Truth}}] / \sigma_{\theta, \text{Truth}}$	Ω_b	Ω_{cdm}	h	m_ν	
Standard, $N_m = 45$	< 0.1	< 0.1	< 0.1	-0.14	
NERCOME, $N_m = 45$	0.60	0.37	-0.26	< 0.1	
Standard, $N_m = 1000$	< 0.1	< 0.1	< 0.1	< 0.1	
NERCOME, $N_m = 1000$	< 0.1	< 0.1	< 0.1	< 0.1	

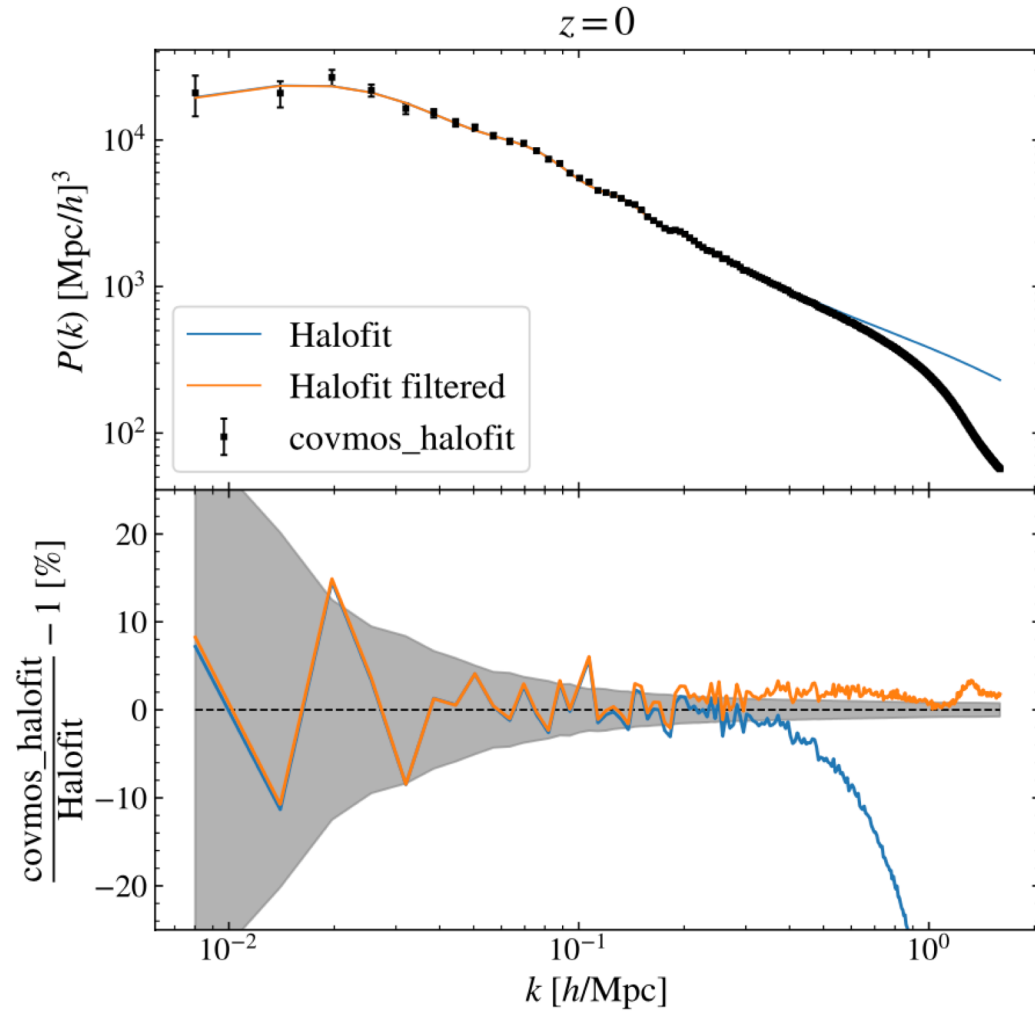
Testing NERCOME on parameter estimation

Distribution of **variances** for 100 realisations of the covariance

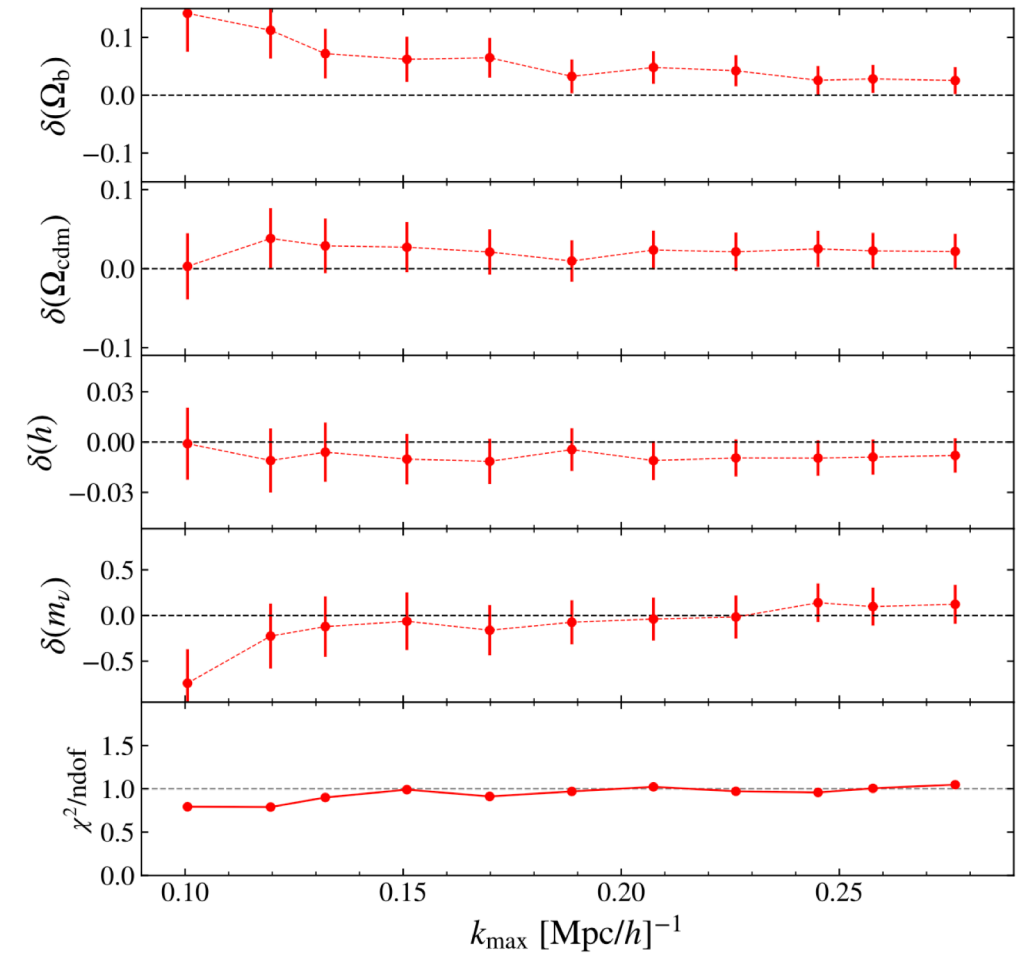
$\sqrt{\text{Var}[\sigma_\theta^2]}/\sigma_{\theta,\text{Truth}}^2$ [%]	Ω_b	Ω_{cdm}	h	m_ν	$\sqrt{2/(N_m - N_b - 4)}$ [%]
Standard, $N_m = 45$	24.86	28.70	28.80	20.27	42.64
NERCOME, $N_m = 45$	17.35	18.17	18.80	14.74	[Taylor et al. 2013]
Standard, $N_m = 1000$	3.58	3.76	3.73	4.30	4.55
NERCOME, $N_m = 1000$	2.64	3.00	3.00	2.71	
$\sqrt{\text{Var}[\sigma_{\theta,N}^2]/\text{Var}[\sigma_{\theta,S}^2]} - 1$ [%]	Ω_b	Ω_{cdm}	h	m_ν	
$N_m = 45$	-30.24	-36.68	-34.72	-27.27	
$N_m = 1000$	-26.34	-20.18	-20.09	-36.97	
$\langle \sigma_\theta^2 \rangle / \sigma_{\theta,\text{Truth}}^2 - 1$ [%]	Ω_b	Ω_{cdm}	h	m_ν	$A + B(N_p + 1)$ [%]
Standard, $N_m = 45$	18.14	11.10	13.60	3.13	43.51
NERCOME, $N_m = 45$	57.84	33.03	33.81	32.36	[Percival et al. 2014]
Standard, $N_m = 1000$	2.21	-0.74	-0.28	-1.93	0.52
NERCOME, $N_m = 1000$	3.32	0.48	0.76	-0.96	

The covmos_halofit data-set

To ensure no bias from the model
→ Target Halofit $P(k)$ with covmos



Parameter inference with
covmos_halofit



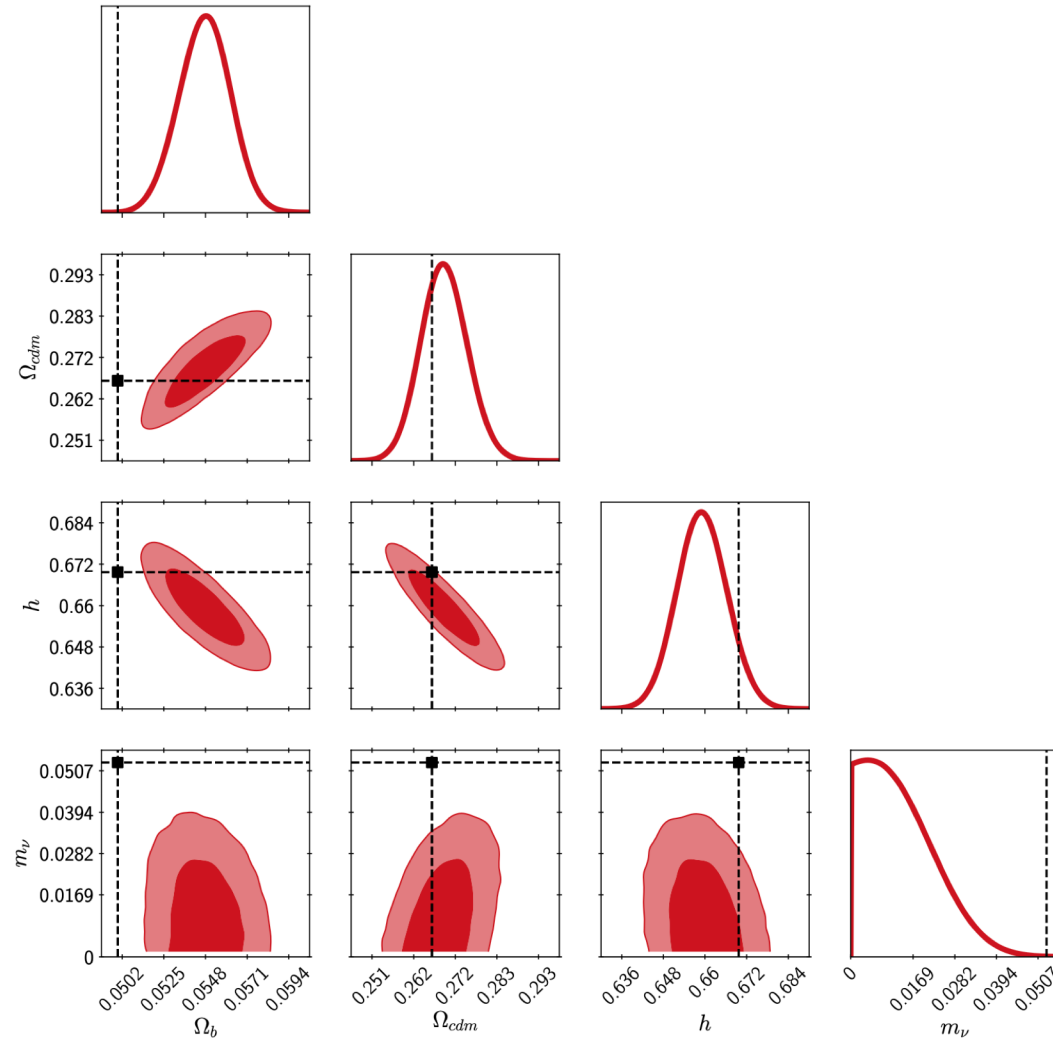
Effect of non-Gaussian posteriors

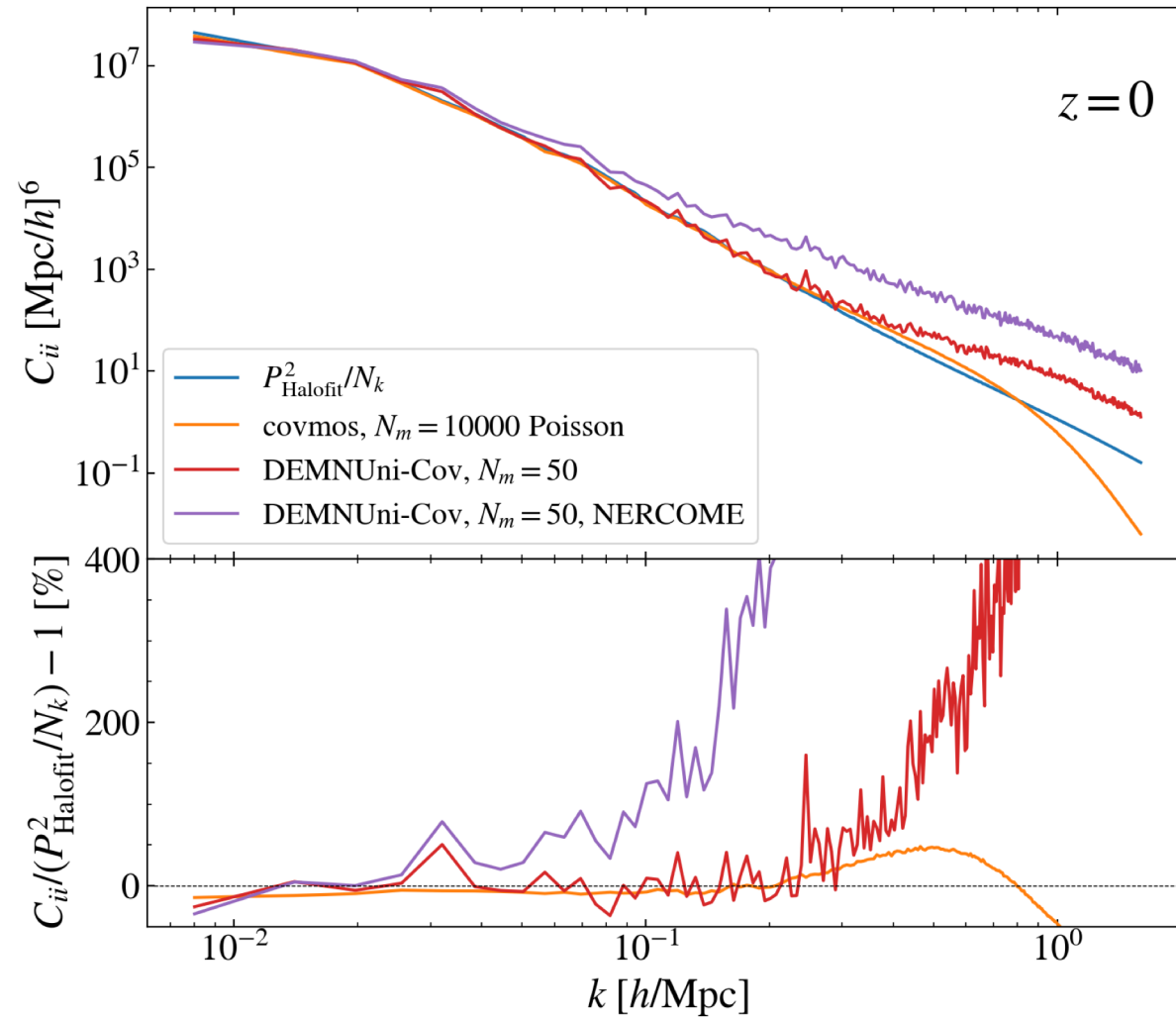
Disagreement between theoretical prediction
and estimation for the **variance on the error and
the bias on the variance**

→ Comes from non-Gaussian posteriors ?

Example of a non-Gaussian posterior

- covmos_halofit
- Standard covariance with $N_m = 45$





Target : P(k) and PDF

With the 1-point PDF all the cumulants should be reproduced

$$\langle \delta^4(\mathbf{x}) \rangle_c = \int d^3\mathbf{k}_1 d^3\mathbf{k}_2 d^3\mathbf{k}_3 T(\mathbf{k}_1, \mathbf{k}_2, \mathbf{k}_3).$$

We hope to reproduce the bin-averaged Trispectrum

$$\bar{T}(k_i, k_j) = \int_{k_i} \frac{d^3 k_1}{V_s(k_i)} \int_{k_j} \frac{d^3 k_2}{V_s(k_j)} T(\mathbf{k}_1, -\mathbf{k}_1, \mathbf{k}_2, -\mathbf{k}_2).$$

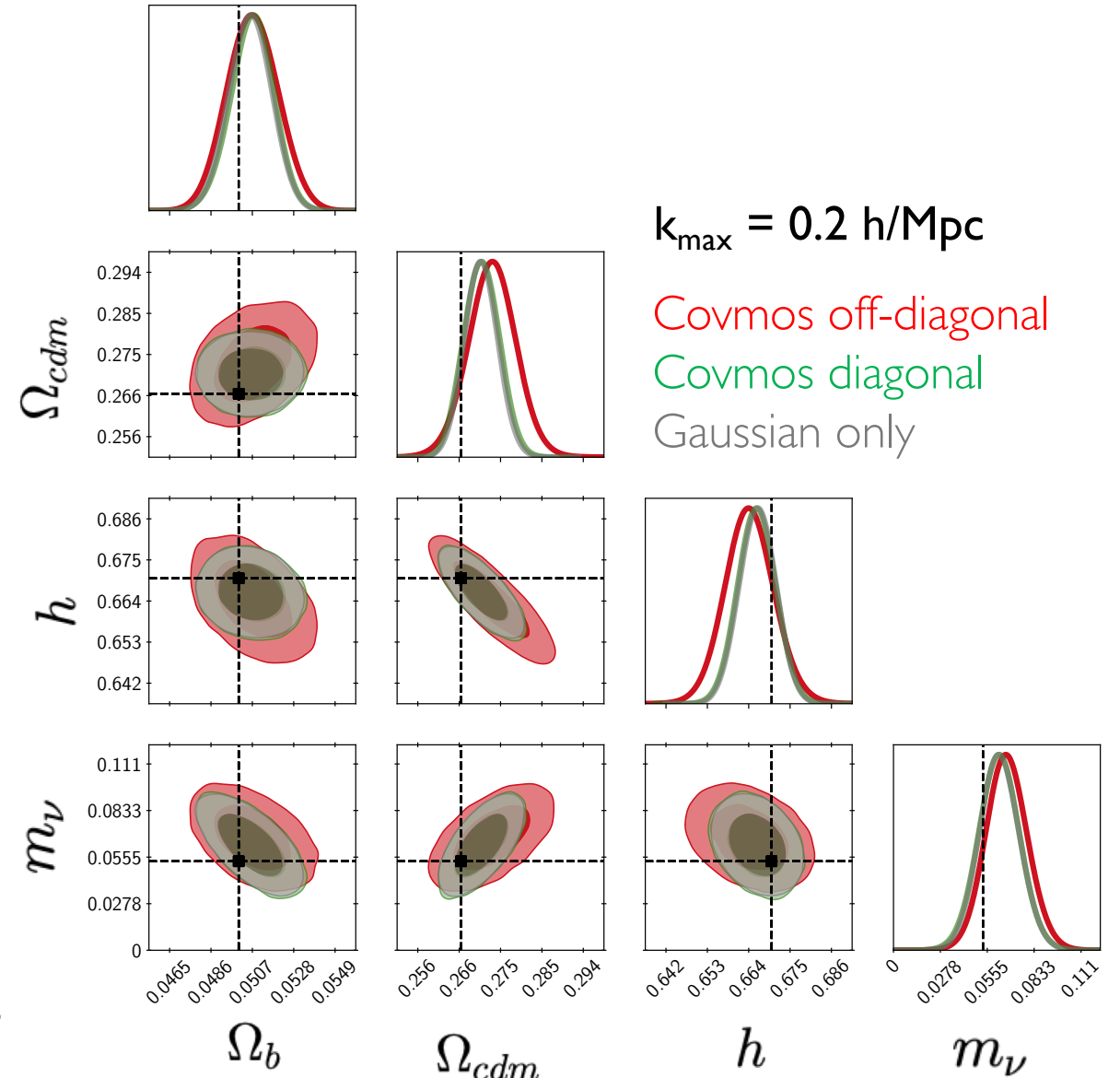
Impact of trispectrum contribution

Compare constraints obtained with the Gaussian covariance only, to quantify the impact of non-Gaussian covariance

$$\mathbf{C}(k_i, k_j) = \frac{P^2(k_i)}{N_{k_i}} \delta_{ij} + \bar{T}(k_i, k_j) = \mathbf{C}^G(k_i) + \mathbf{C}^{\text{NG}}(k_i, k_j),$$

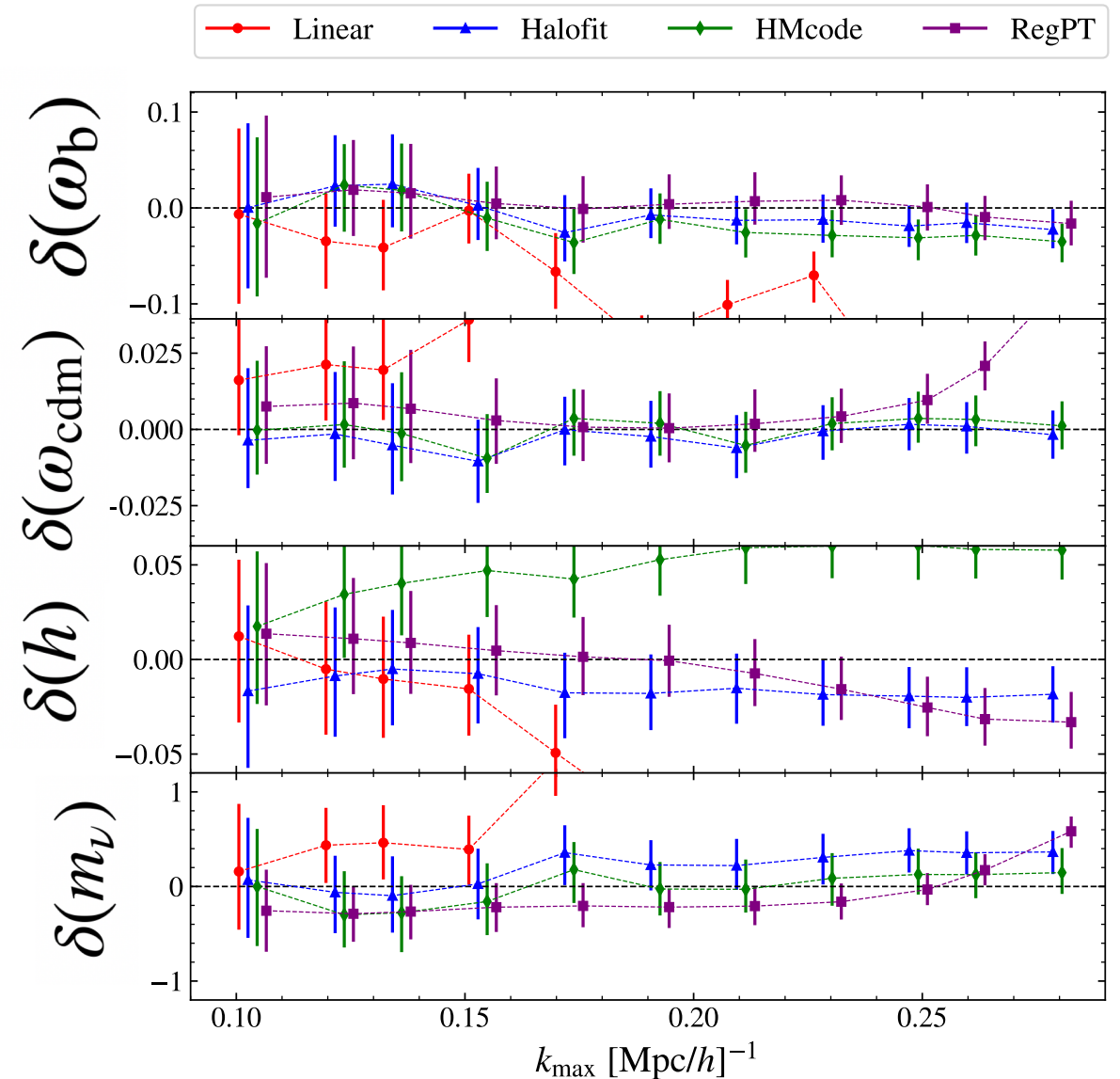
Parameter estimation with MCMC :

- Data : DEMNUni-Cov at 5 redshifts : $z \approx 0, 0.5, 1, 1.5, 2$
 - Non-linear model : Halofit
 - **Covariance :**
 1. Gaussian only
 2. Covmos Nm = 10 000, diagonal only
 3. Covmos Nm = 10 000, full
- Best-fit is unchanged
- Off-diagonal elements are the most important

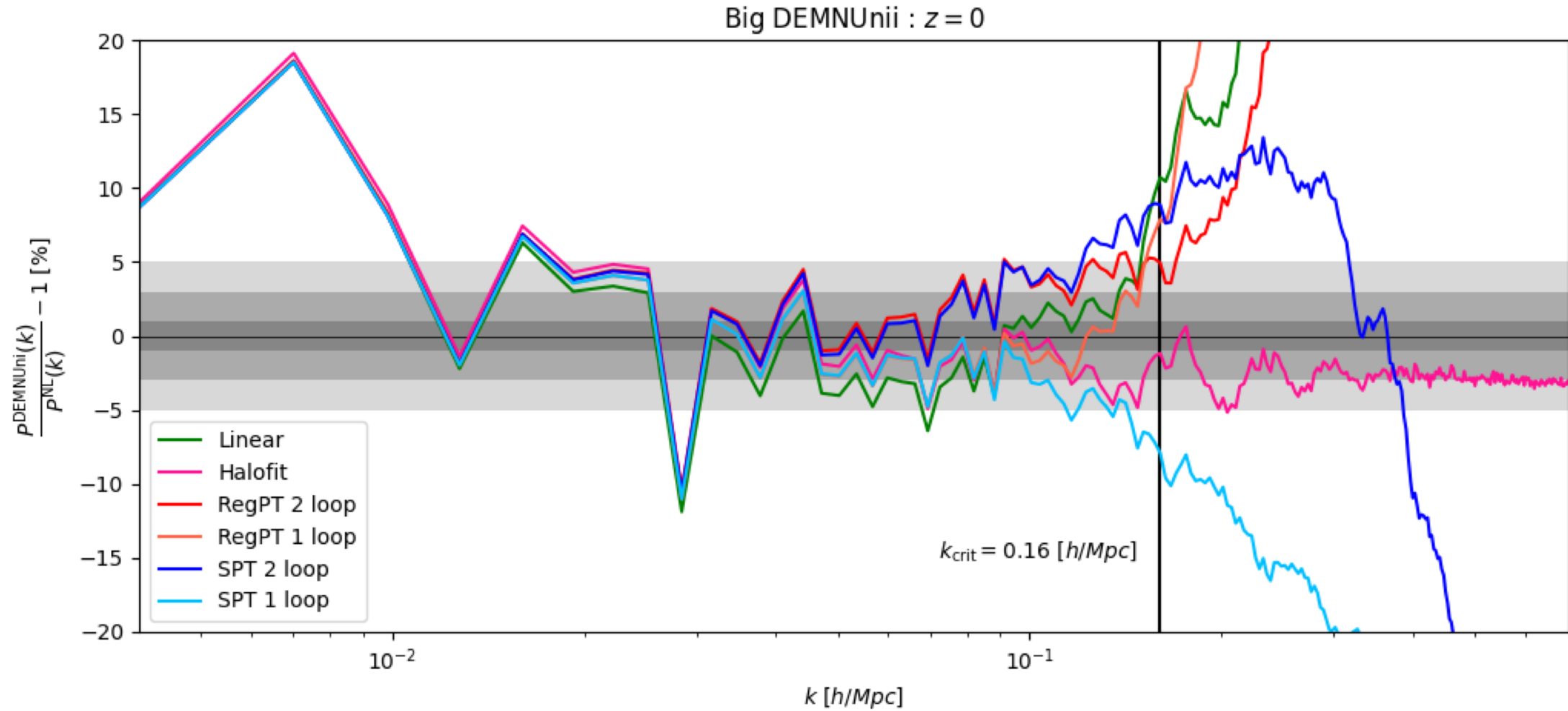


Testing non-linear models with massive neutrinos

- ω_b and ω_{cdm} : Unbiased for all models up to $k_{\text{max}} = 0.22 \text{ h/Mpc}$
- Significant bias on h and m_ν :
 - Halofit : $\sim 1\sigma$ bias on h and m_ν
 - HMcode : Unbiased estimation of m_ν , but strong bias on h
 - RegPT : Lower error-bar on $m_\nu \rightarrow > 1\sigma$ bias

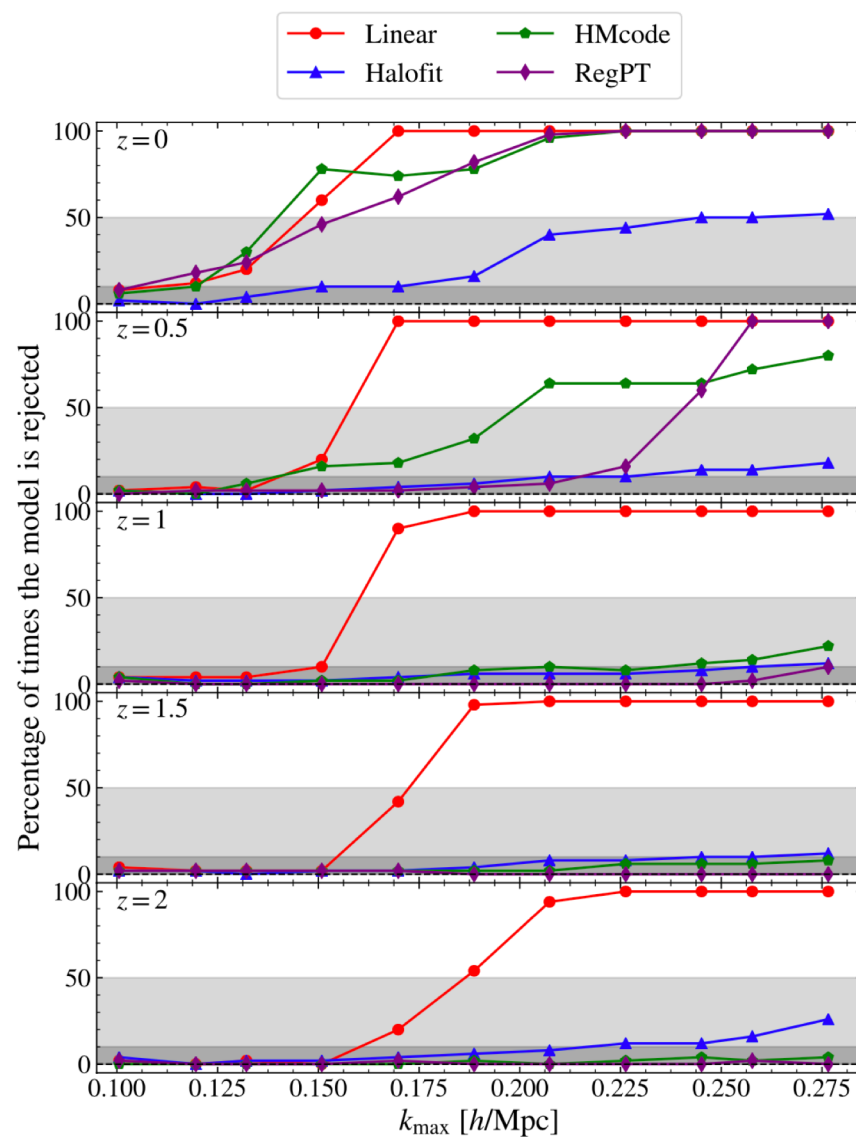


Testing non-linear models with massive neutrinos



Testing non-linear models with massive neutrinos

Goodness of fit test for each
DEMNUi-Cov realisation



Testing non-linear models with massive neutrinos

$$\text{FoM} \equiv \frac{1}{\sqrt{\det(\hat{\Phi})}}.$$

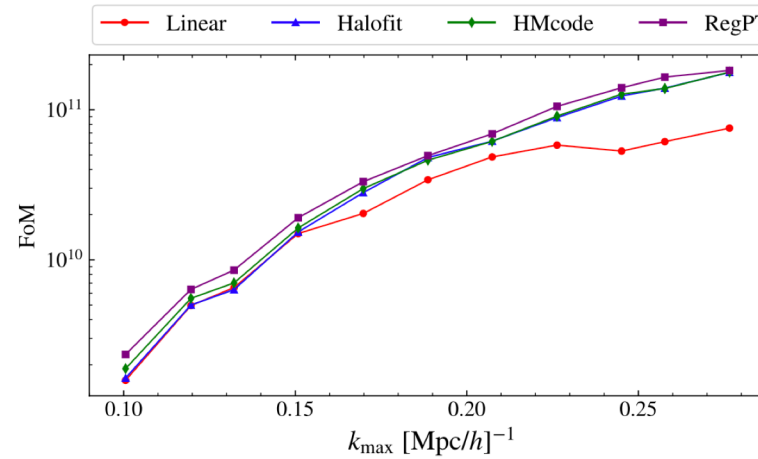


Figure 3.29.: FoM with respect to k_{max} .

$$\text{FoB} \equiv \left[\delta\theta^T \hat{\Phi}^{-1} \delta\theta \right]^{1/2},$$

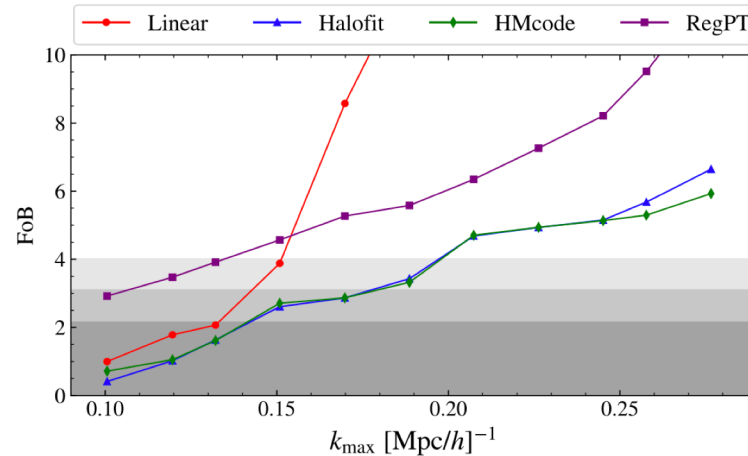
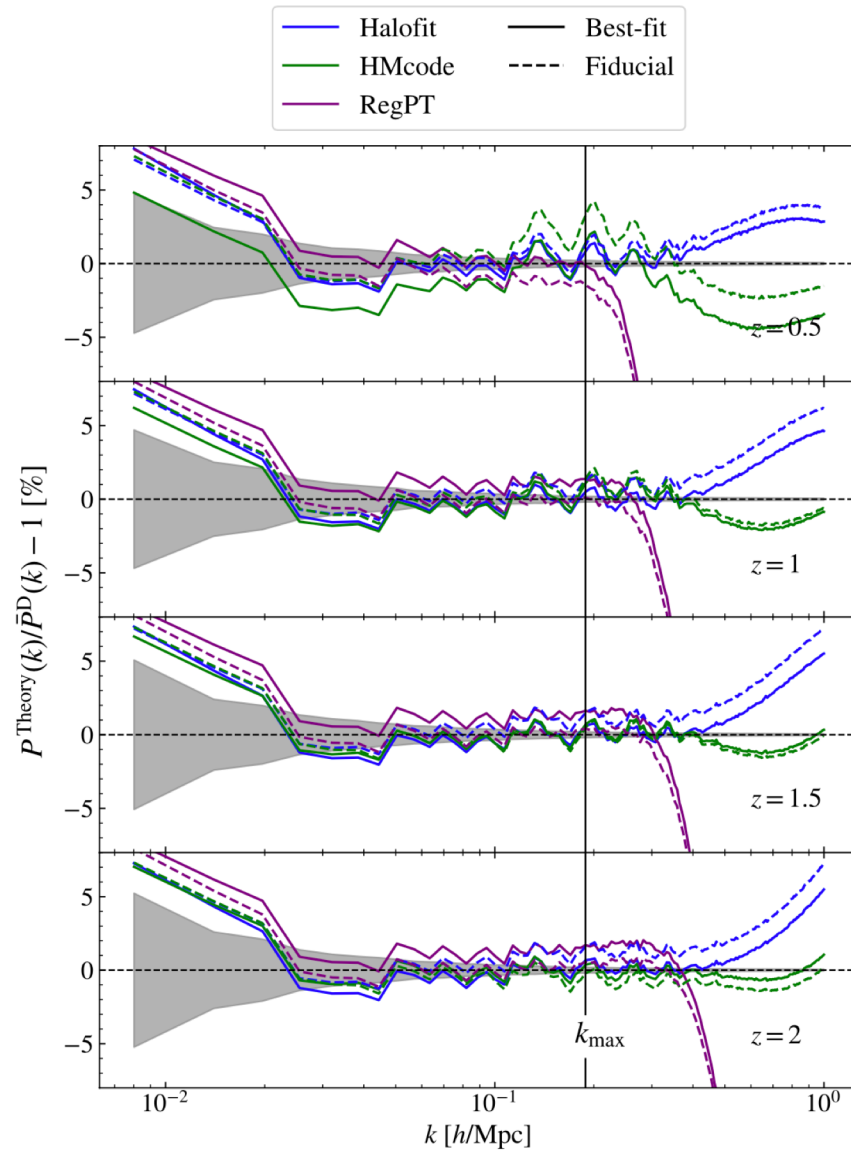


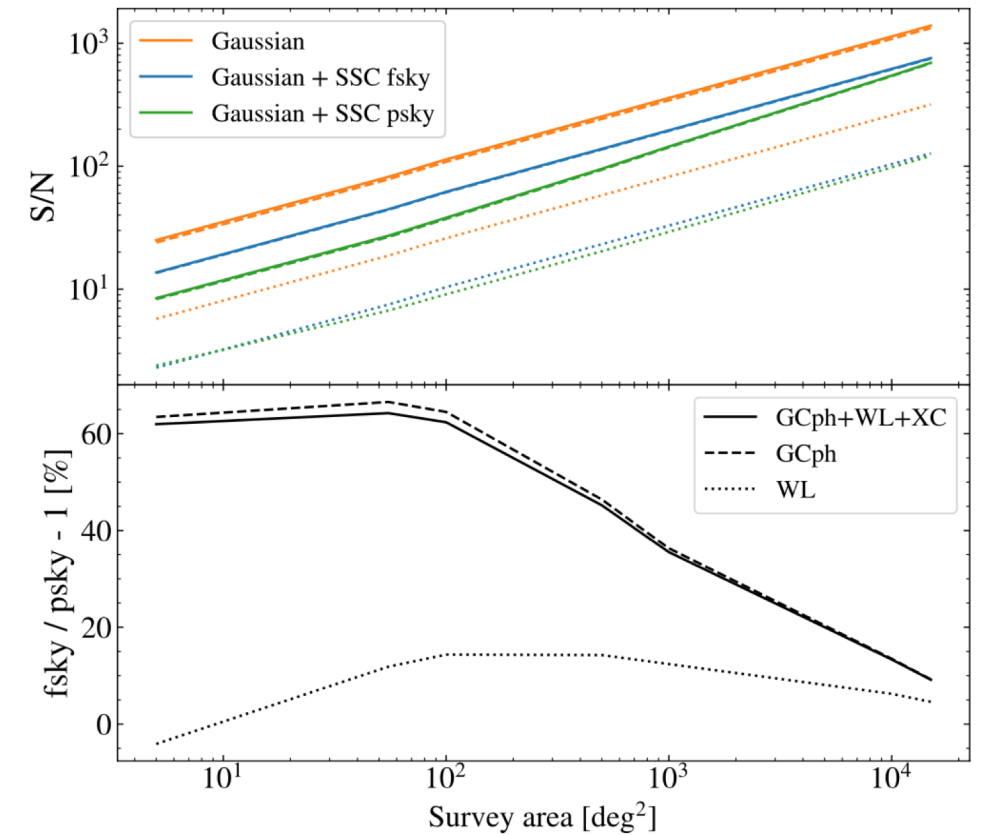
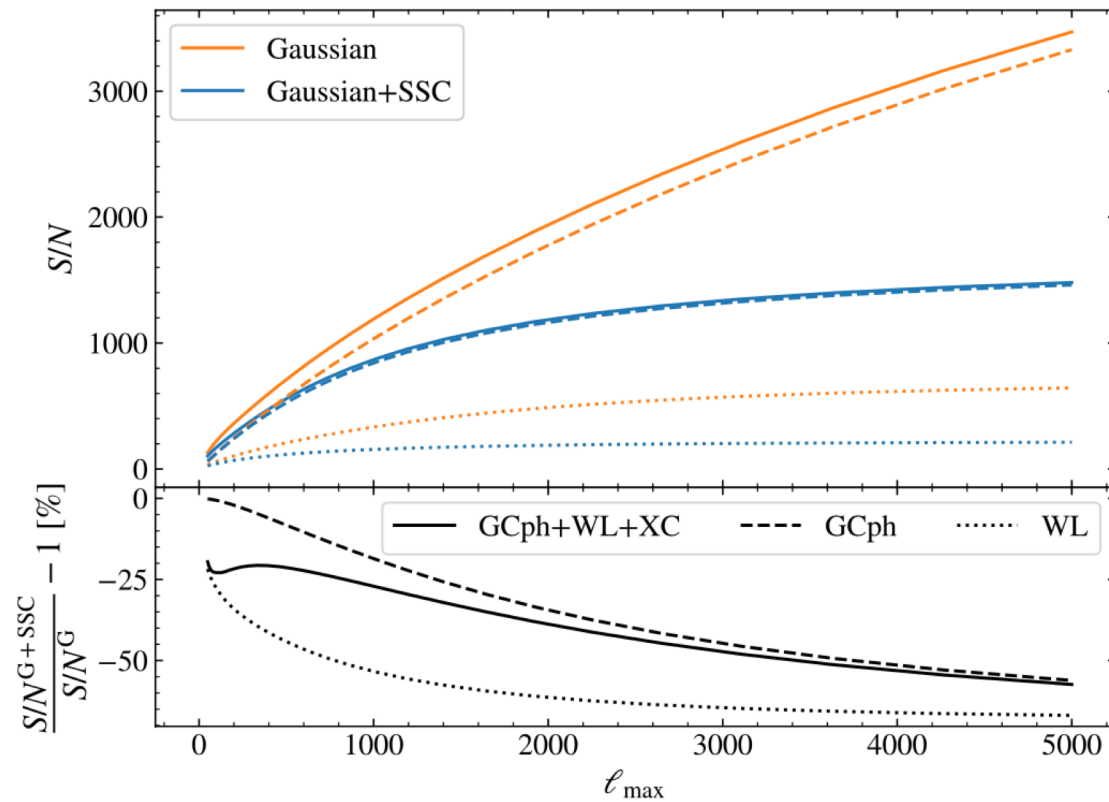
Figure 3.30.: FoB with respect to k_{max} . The grey shaded areas show the 68.3%, 95.5% and 99.7% confidence intervals, corresponding to 1σ , 2σ and 3σ

Testing non-linear models with massive neutrinos



SSC : Signal to noise ratio

$$(S/N)^2 = \sum_{i,j,k,l} \sum_{\ell,\ell'} C_{ij}^{AB}(\ell) \text{Cov} \left[C_{ij}^{AB}(\ell), C_{kl}^{CD}(\ell') \right]^{-1} C_{kl}^{CD}(\ell'),$$



Weak Lensing and Intrinsic Alignments

Observed ellipticities of galaxies :

$$\epsilon = \gamma + \epsilon^{\text{I}}, \quad \Rightarrow \quad W^{\text{WL}}(z) = W^{\gamma}(z) + W^{\text{IA}}(z).$$

Cosmic shear

$$W_i^{\gamma}(z) = \frac{3}{2} \left(\frac{H_0}{c} \right)^2 \Omega_{\text{m},0} \frac{1+z}{r(z)} \int_z^{z_{\text{max}}} \text{d}n_i(z') \left[1 - \frac{r(z)}{r(z')} \right],$$

Intrinsic alignment

$$W_i^{\text{IA}}(z) = -A(z) \frac{n_i(z)}{r^2(z)} \frac{c}{H(z)}.$$

$$A(z) = \frac{\mathcal{A}_{\text{IA}} \mathcal{C}_{\text{IA}} \Omega_m \mathcal{F}_{\text{IA}}(z)}{D(z)},$$

$$\mathcal{F}_{\text{IA}} = (1+z)^{\eta_{\text{IA}}} \left[\frac{\langle L|L \rangle(z)}{L_*(z)} \right]^{\beta_{\text{IA}}},$$

eNLA (extended Non-Linear Alignment) model

$$\text{Cov}_G \left[C_{ij}^{AB}(\ell), C_{kl}^{CD}(\ell') \right] =$$

$$\frac{\delta_{\ell\ell'}^K}{(2\ell+1)f_{\text{SKY}}\Delta\ell} \left\{ \left[C_{ik}^{AC}(\ell) + N_{ik}^{AC}(\ell) \right] \left[C_{jl}^{BD}(\ell') + N_{jl}^{BD}(\ell') \right] \right.$$

$$\left. + \left[C_{il}^{AD}(\ell) + N_{il}^{AD}(\ell) \right] \left[C_{jk}^{BC}(\ell') + N_{jk}^{BC}(\ell') \right] \right\},$$

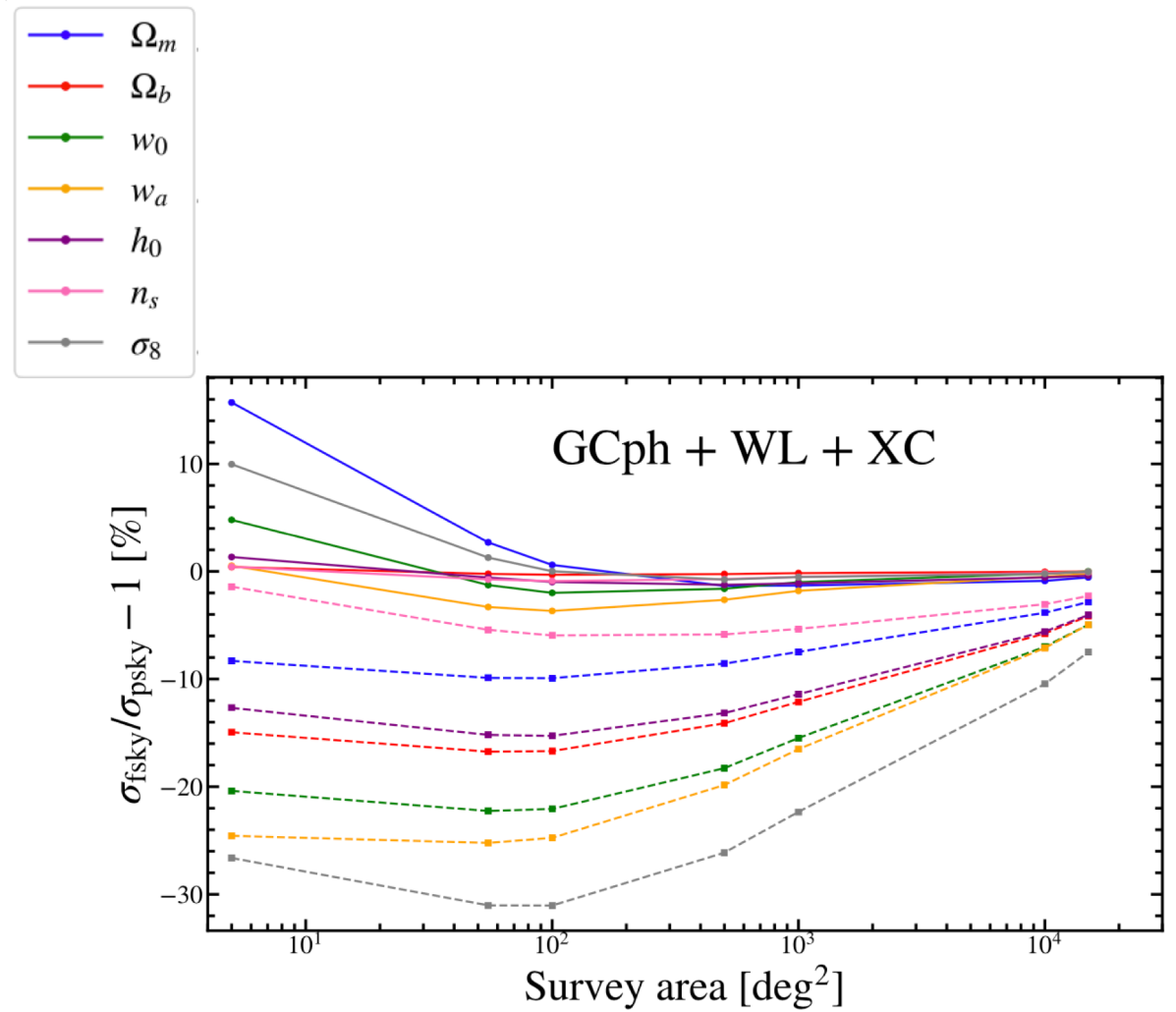
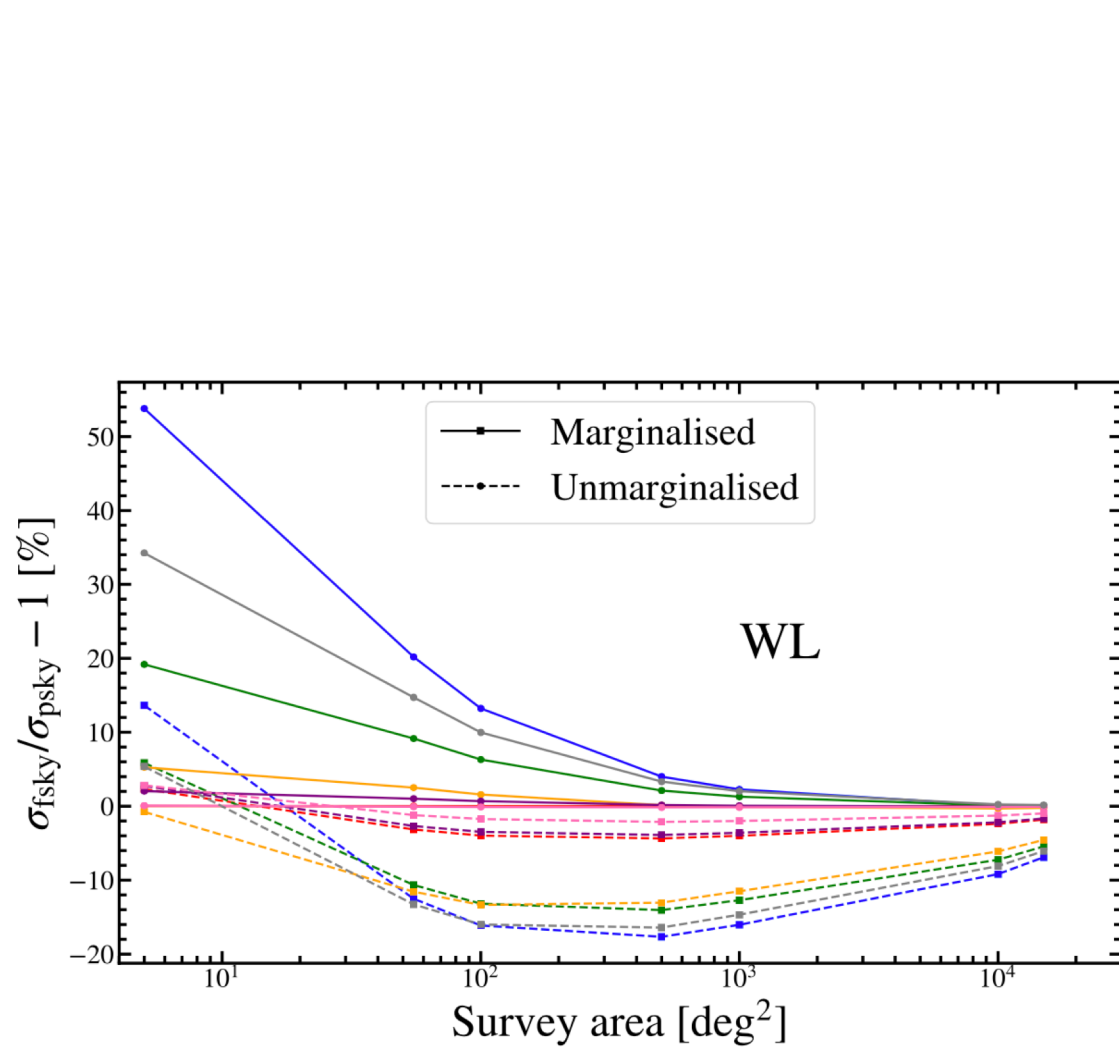
Noise terms N_{ij}

- GCph : $\delta_{ij}^K / \bar{n}_i$ Shot-noise
- WL : $\sigma_\epsilon^2 \delta_{ij}^K / \bar{n}_i$ Shape-noise

$$\bar{n}_i = 30 \text{ gal/arcmin}^2$$

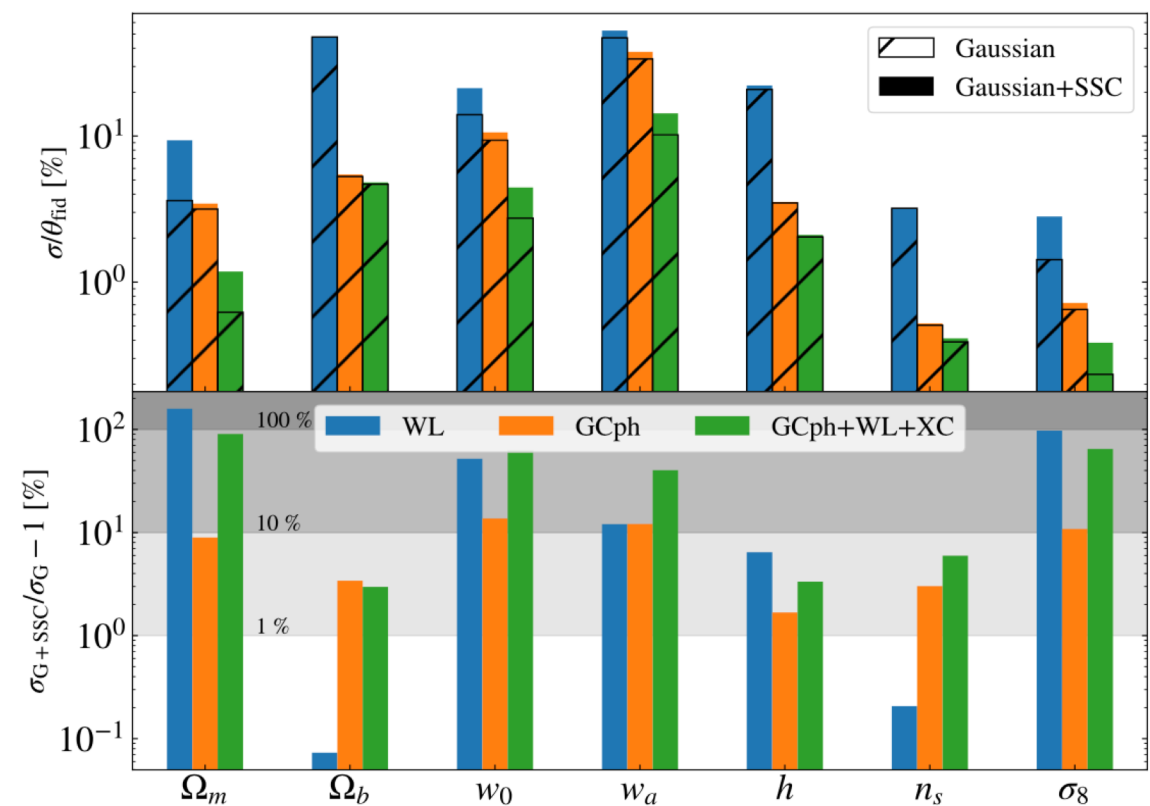
$$\sigma_\epsilon^2 = 0.3$$

Partial sky SSC :WL and GCph

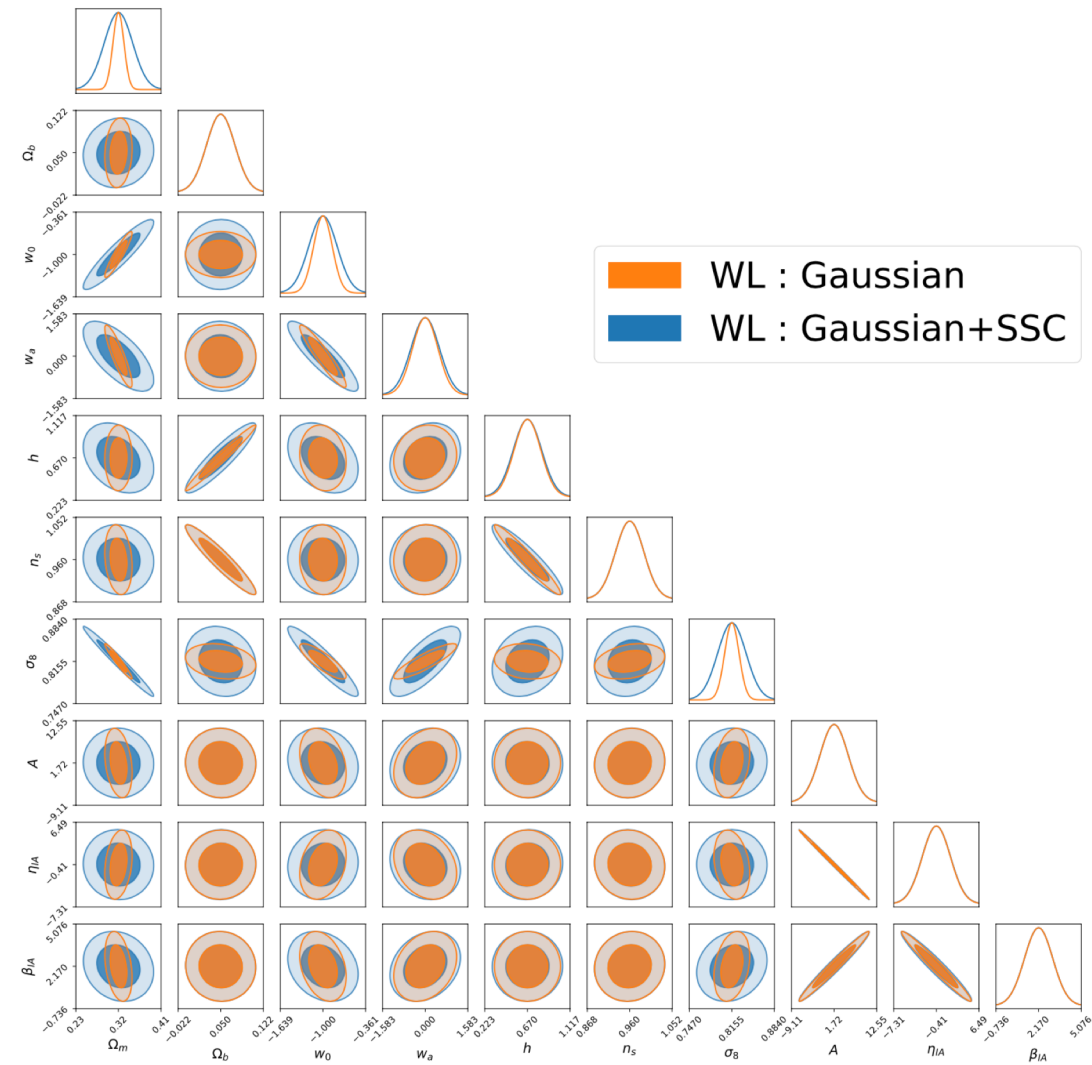


Full-sky SSC : parameters

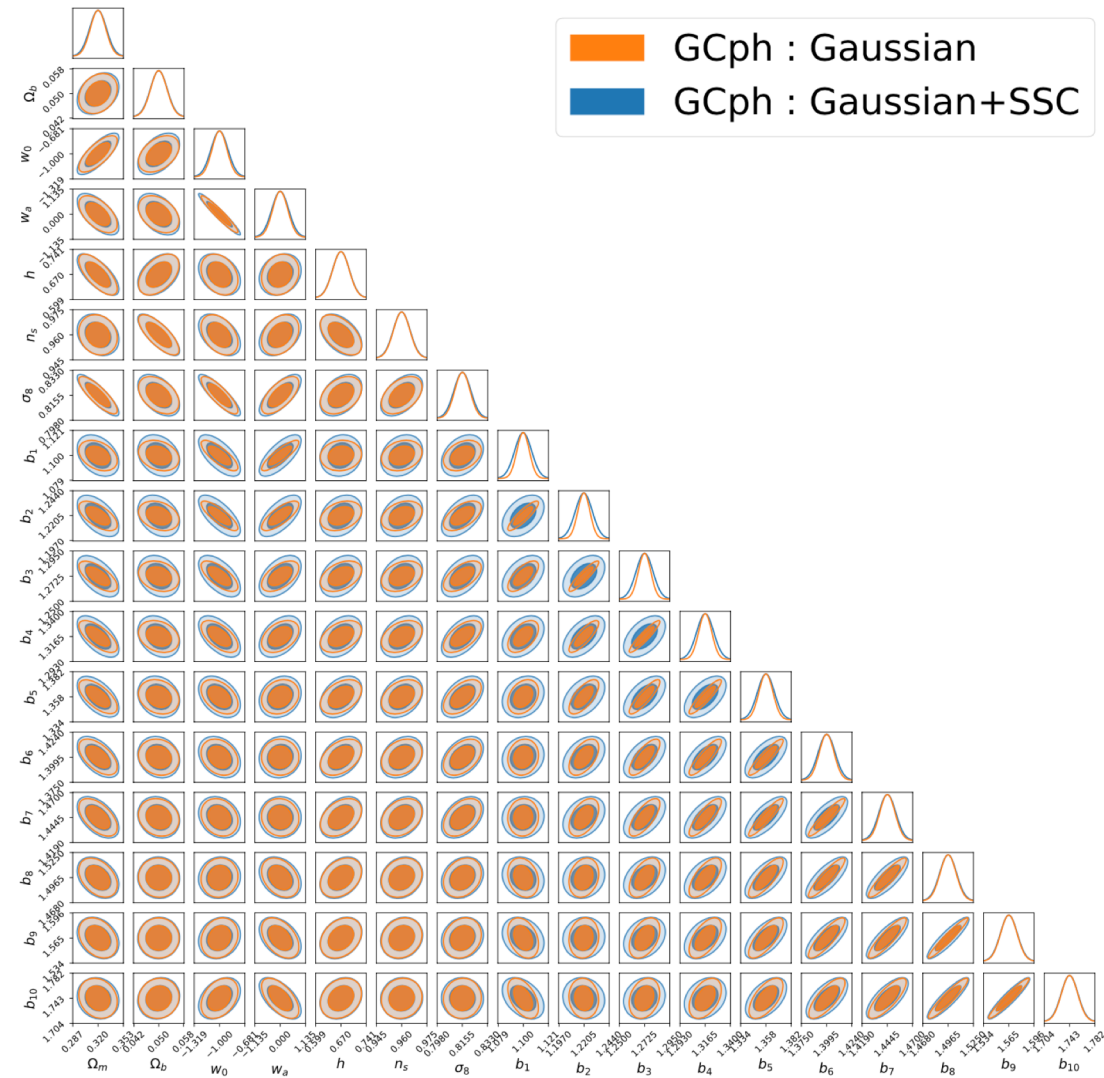
$\sigma/\theta_{\text{fid}} [\%]$	Ω_m	Ω_b	w_0	w_a	h	n_s	σ_8	FoM $_{w_0, w_a}$
GCph, Gaussian	3.16	5.27	9.35	33.76	3.48	0.51	0.65	103.71
GCph, Gaussian+SSC	3.44	5.45	10.64	37.84	3.54	0.52	0.72	89.55
G+SSC/G - 1 [%]	8.96	3.41	13.69	12.10	1.68	3.02	10.84	-13.65
WL, Gaussian	3.61	47.74	14.03	47.11	20.87	3.20	1.42	43.12
WL, Gaussian+SSC	9.34	47.77	21.31	52.78	22.21	3.21	2.81	18.47
G+SSC/G [%]	158.71	0.07	51.90	12.05	6.44	0.21	97.40	-57.16
GCph + WL + XC, Gaussian	0.62	4.68	2.74	10.21	2.04	0.39	0.23	1038.13
GCph + WL + XC, Gaussian+SSC	1.18	4.82	4.45	14.32	2.10	0.41	0.38	490.60
G+SSC/G [%]	90.34	2.97	62.30	40.25	3.34	5.96	64.75	-52.74



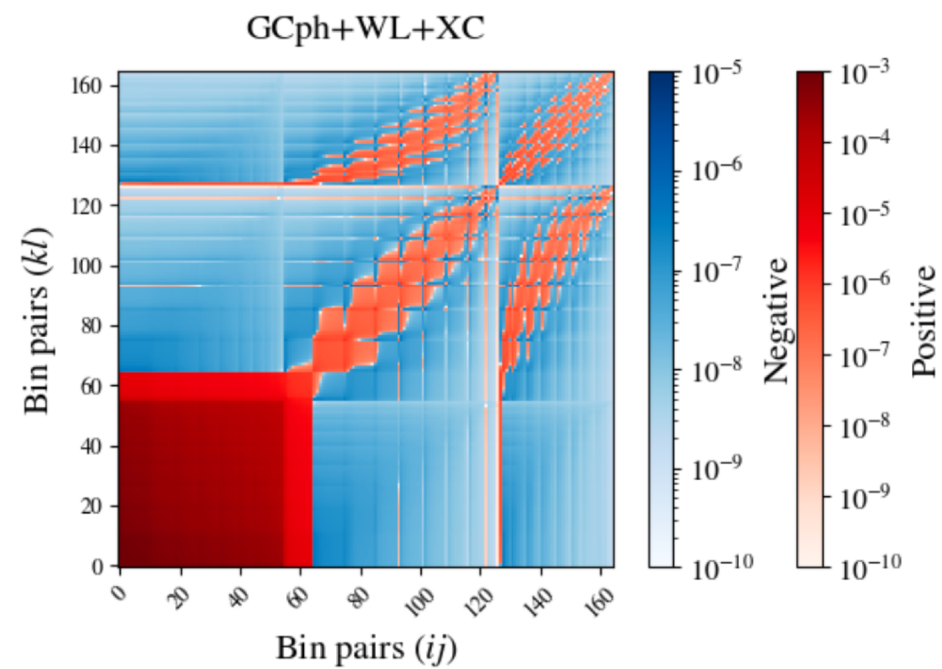
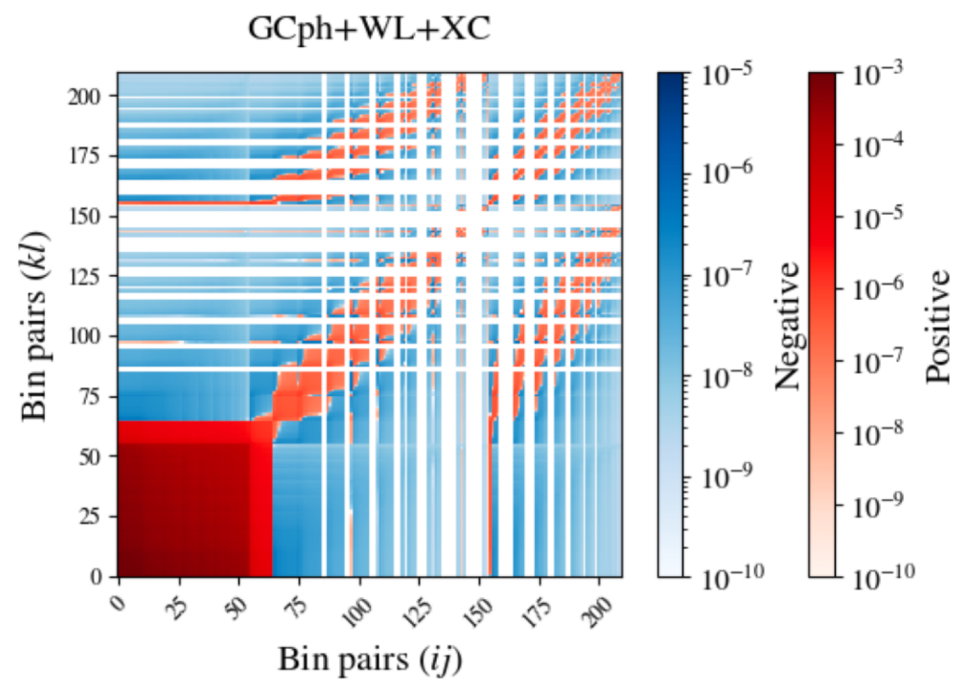
Full-sky SSC :WL



Full-sky SSC : GCph



SSC : S_{ijkl} matrix



SSC : Full-Flat-Partial

Full-sky :

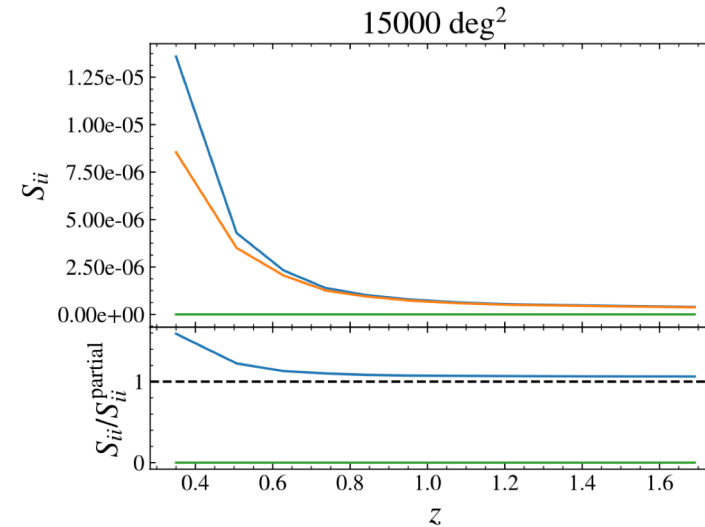
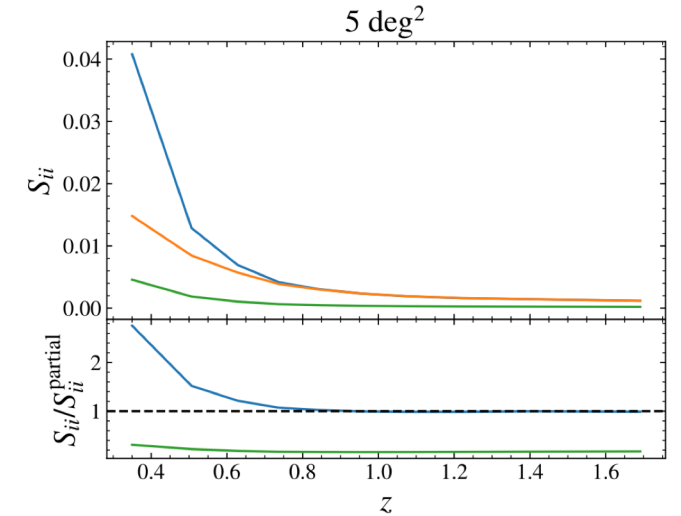
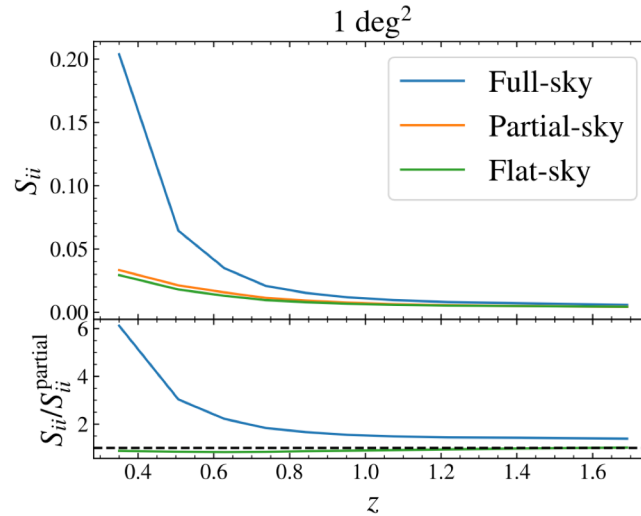
$$\sigma_{\text{full-sky}}^2(z_1, z_2) = \frac{1}{2\pi^2} \int k^2 dk j_0(kr(z_1)) j_0(kr(z_2)) P_m(k|z_{1,2}),$$

Partial-sky :

$$\sigma_{\text{part-sky}}^2(z_1, z_2) = \frac{1}{\Omega_S^2} \sum_{\ell} (2\ell + 1) C^{\mathcal{W}}(\ell) C_{z_{1,2}}^{\mathbf{m}}(\ell),$$

Flat-sky :

$$S_{i,j} = \frac{1}{2\pi^2} \int k_{\perp} dk_{\perp} 4 \frac{J_1(k_{\perp} \theta_S r_1)}{k_{\perp} \theta_S r_1} \frac{J_1(k_{\perp} \theta_S r_2)}{k_{\perp} \theta_S r_2} \\ \times \int dk_{\parallel} j_0\left(\frac{k_{\parallel} \delta r_1}{2}\right) j_0\left(\frac{k_{\parallel} \delta r_2}{2}\right) \cos[k_{\parallel} (r_1 - r_2)] P_m(k|z_{1,2}),$$



Full-sky :

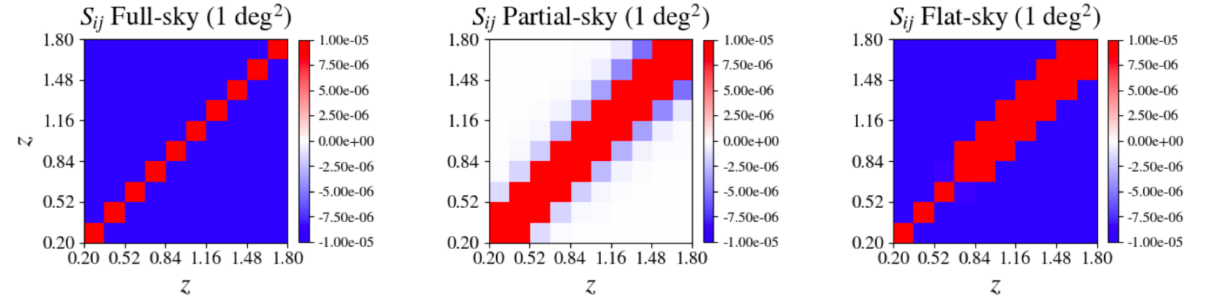
$$\sigma_{\text{full-sky}}^2(z_1, z_2) = \frac{1}{2\pi^2} \int k^2 dk j_0(kr(z_1)) j_0(kr(z_2)) P_m(k|z_{1,2}),$$

Partial-sky :

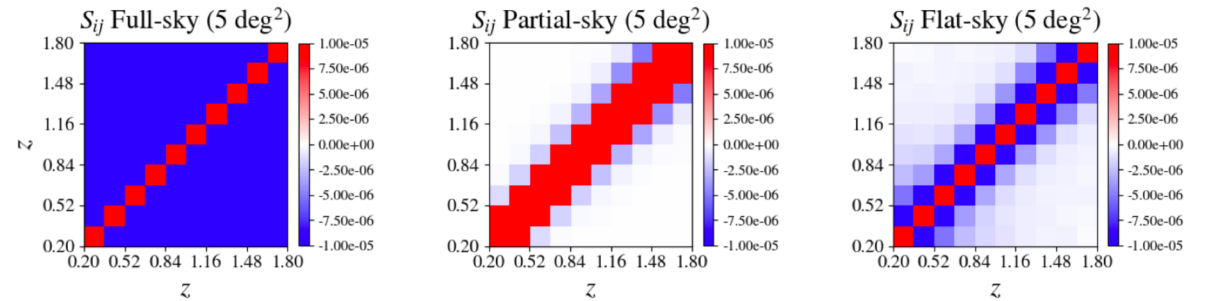
$$\sigma_{\text{part-sky}}^2(z_1, z_2) = \frac{1}{\Omega_S^2} \sum_{\ell} (2\ell + 1) C^{\mathcal{W}}(\ell) C_{z_{1,2}}^{\text{m}}(\ell),$$

Flat-sky :

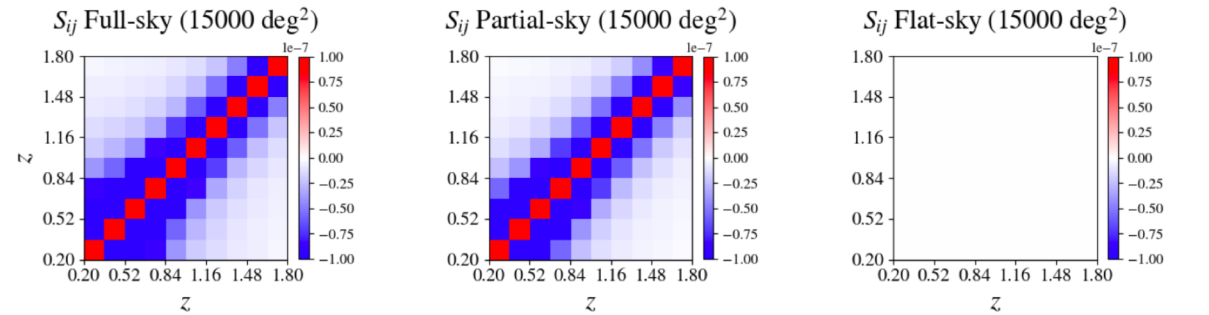
$$S_{i,j} = \frac{1}{2\pi^2} \int k_{\perp} dk_{\perp} 4 \frac{J_1(k_{\perp} \theta_S r_1)}{k_{\perp} \theta_S r_1} \frac{J_1(k_{\perp} \theta_S r_2)}{k_{\perp} \theta_S r_2} \\ \times \int dk_{\parallel} j_0\left(\frac{k_{\parallel} \delta r_1}{2}\right) j_0\left(\frac{k_{\parallel} \delta r_2}{2}\right) \cos[k_{\parallel} (r_1 - r_2)] P_m(k|z_{1,2}),$$



(a)



(b)



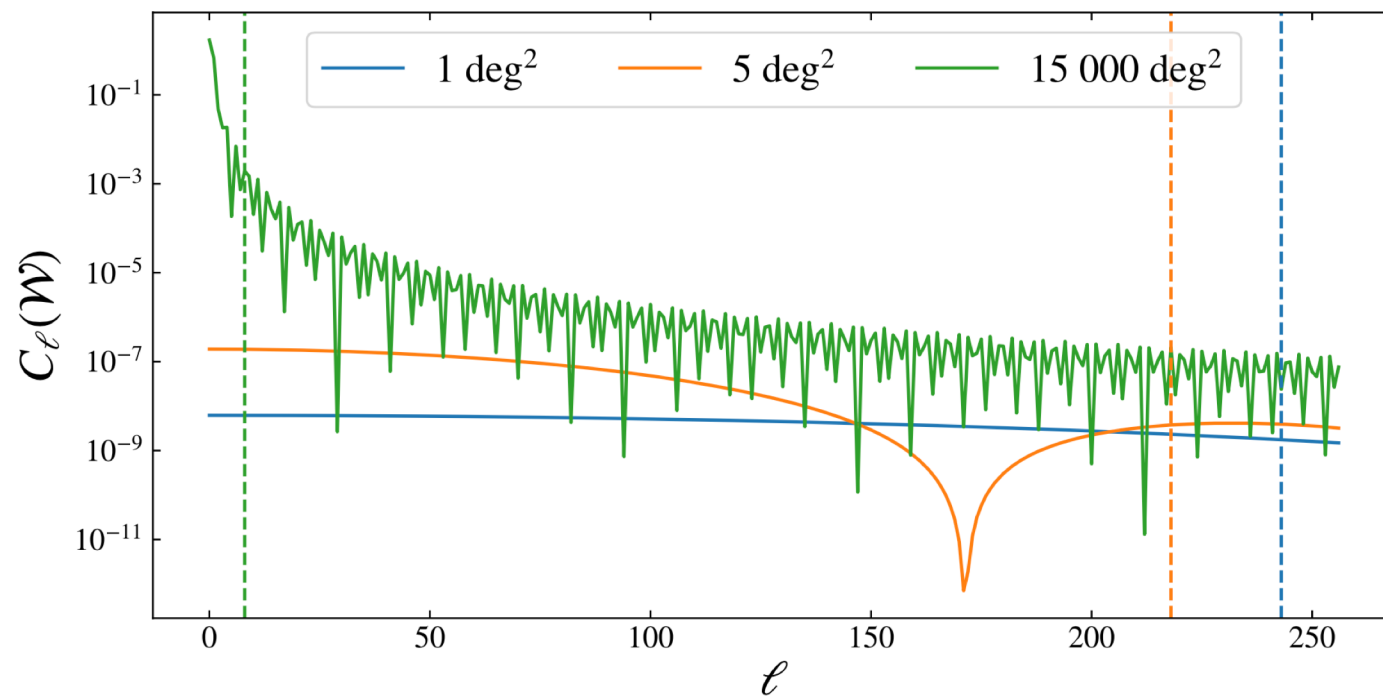
(c)

Survey area [deg ²]	Full-sky	Partial-sky	Flat-sky
1, $f_{\text{SKY}} = 2.42 \cdot 10^{-5}$	6 s	2635 s	165 s
5, $f_{\text{SKY}} = 1.21 \cdot 10^{-4}$	6 s	2371 s	167 s
15 000, $f_{\text{SKY}} = 0.36$	6 s	75 s	166 s

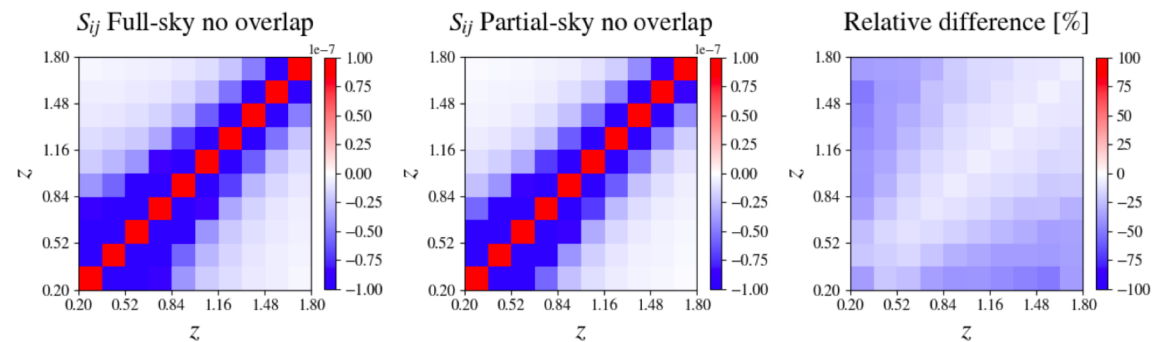
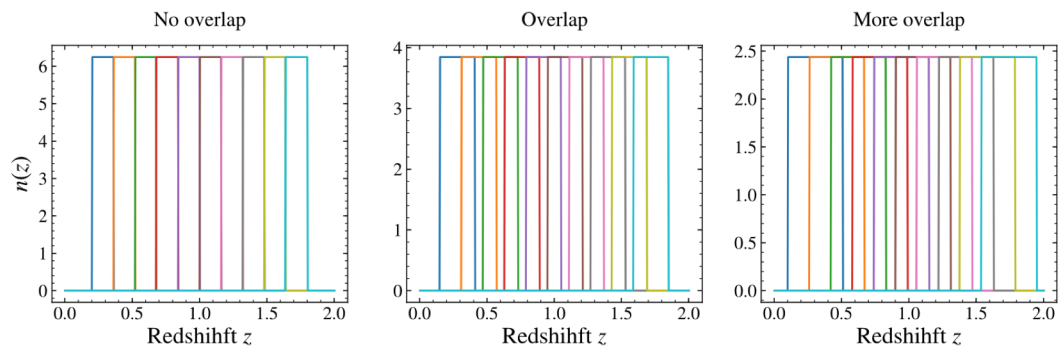
Partial-sky :

$$\sigma_{\text{part-sky}}^2(z_1, z_2) = \frac{1}{\Omega_S^2} \sum_{\ell} (2\ell + 1) C^{\mathcal{W}}(\ell) C_{z_{1,2}}^{\text{m}}(\ell),$$

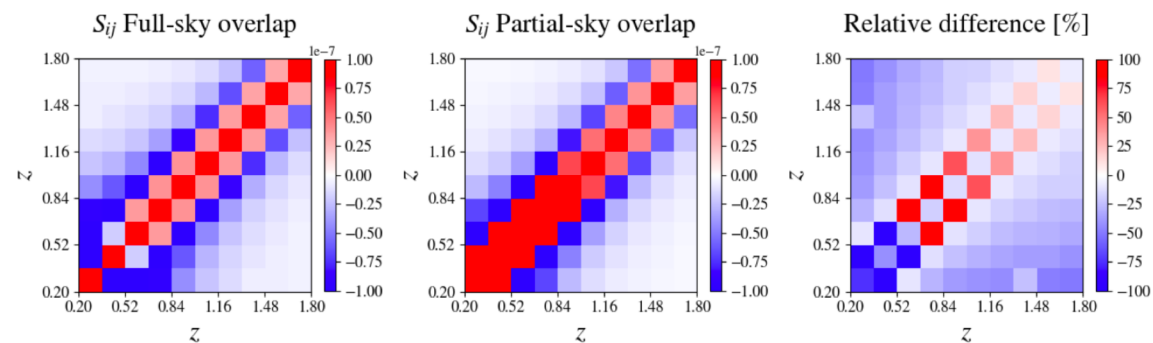
$$\langle \mathcal{W}^2 \rangle = \sum_{\ell} \frac{(2\ell + 1)}{4\pi} C^{\mathcal{W}}(\ell).$$



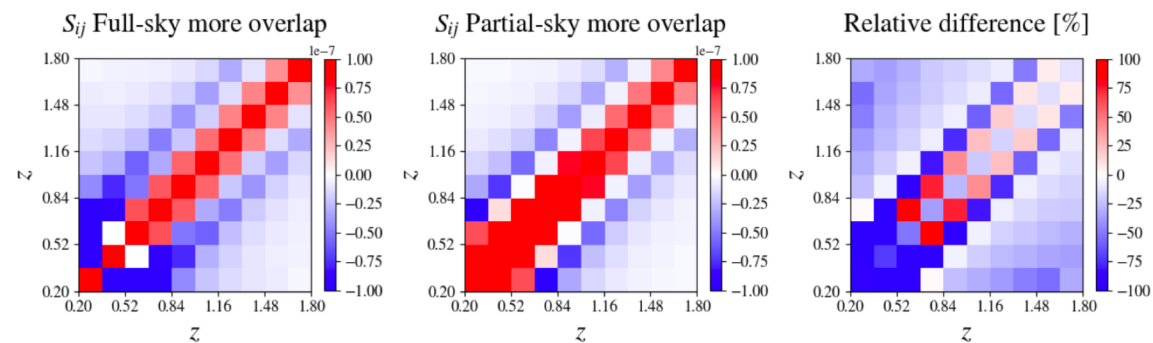
SSC : Redshift overlap



(a)



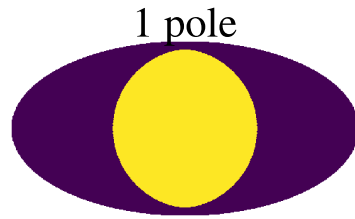
(b)



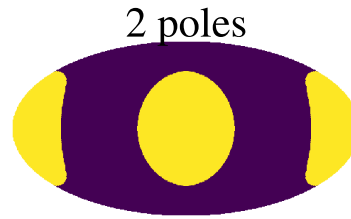
(c)

Partial-sky SSC : varying geometry

Geometry of the survey ?



1 pole



2 poles



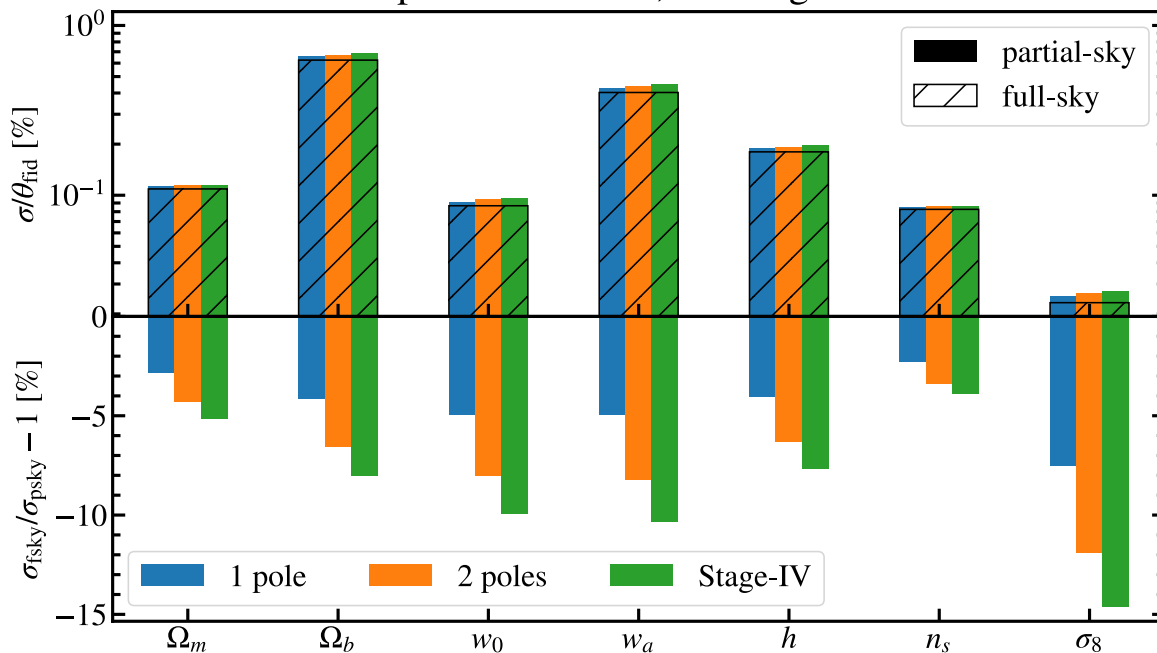
Stage-IV

For a fixed survey area of 15 000 deg²

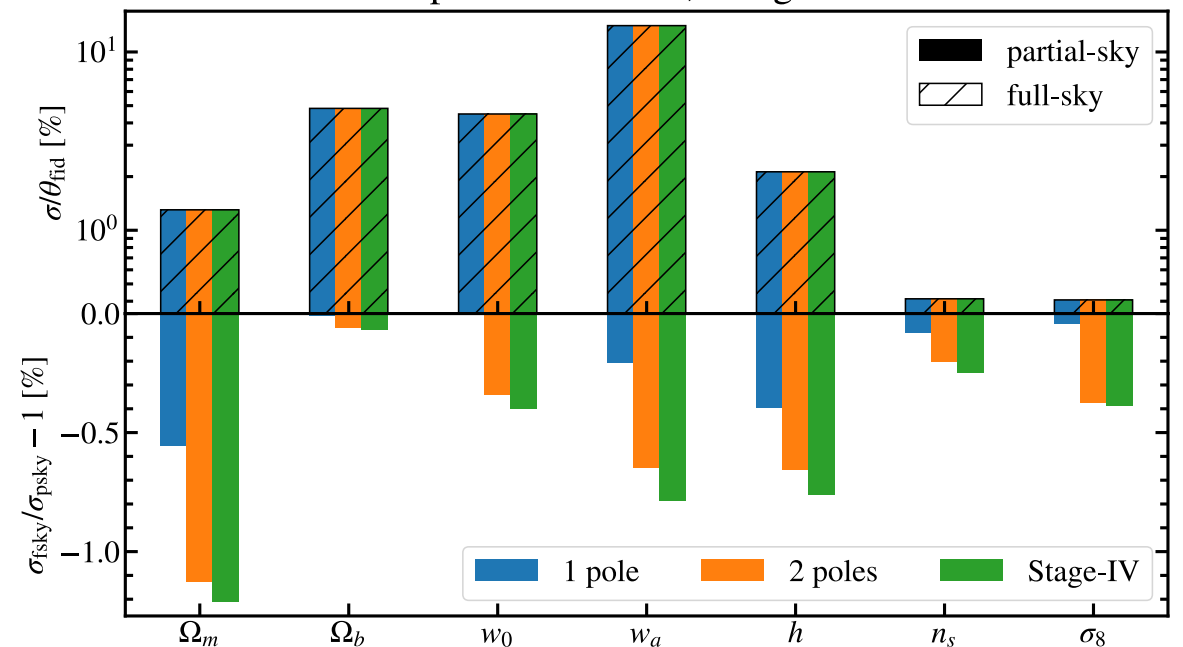
- **Top** : Relative error for full-sky and partial-sky
- **Bottom** : Relative difference between the two

- Difference increases for a more complex footprint
- Negligible difference for marginalised errors

GCph + WL + XC, Unmarginalised



GCph + WL + XC, Marginalised



$$n^{\text{true}}(z) \propto \left(\frac{z}{z_0}\right)^2 \exp\left[-\left(\frac{z}{z_0}\right)^{3/2}\right],$$

$$n_i(z) = \frac{\int_{z_i^-}^{z_i^+} dz_p n^{\text{true}}(z) p_{ph}(z_p|z)}{\int_{z_{\min}}^{z_{\max}} dz \int_{z_i^-}^{z_i^+} dz_p n^{\text{true}}(z) p_{ph}(z_p|z)},$$

$$p_{ph}(z_p|z) = \frac{1 - f_{out}}{\sqrt{2\pi}\sigma_b(1+z)} \exp\left\{-\frac{1}{2}\left[\frac{z - c_b z_p - z_b}{\sigma_b(1+z)}\right]^2\right\} +$$

$$+ \frac{f_{out}}{\sqrt{2\pi}\sigma_o(1+z)} \exp\left\{-\frac{1}{2}\left[\frac{z - c_o z_p - z_o}{\sigma_o(1+z)}\right]^2\right\}.$$

$n(z)$	c_b	z_b	σ_b	c_o	z_o	σ_o	f_{out}
Wide, $f_{out} = 0.1$	1.0	0.0	0.05	1.0	0.1	0.05	0.1
Wide, $f_{out} = 0.25$	1.0	0.0	0.05	1.0	0.1	0.05	0.25
Tight, $f_{out} = 0.1$	1.0	0.0	0.02	1.0	0.1	0.02	0.1

$$\bar{n}_i = 30 \text{ gal/arcmin}^2$$

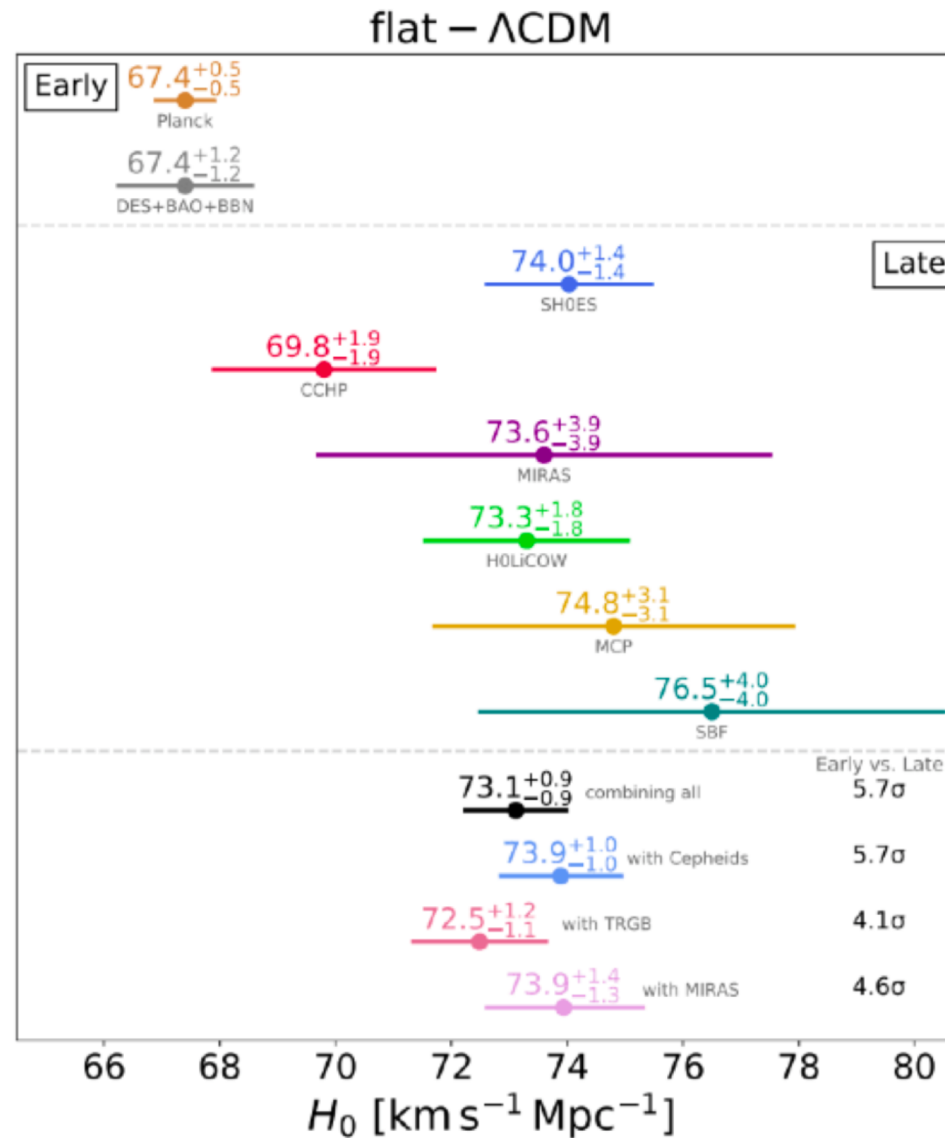
H_0 tension

$H_0 \sim 67 \pm 0.5$ VS 73 ± 1 km/s/Mpc

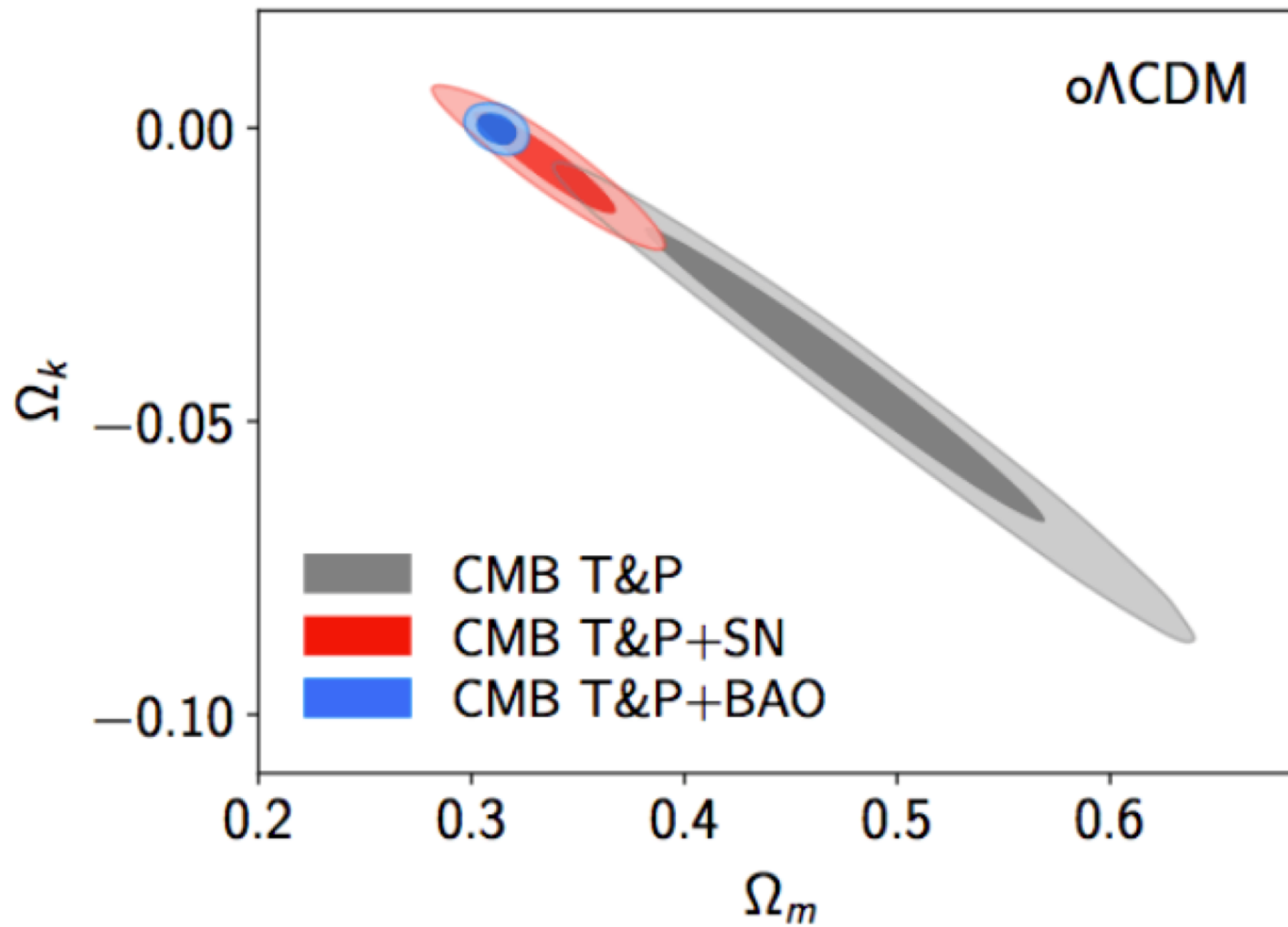
Late time probes
(CMB, BAO+BBN)

Early time probes
(Cepheids, TGRB)

~ 4 to 5σ tension within Λ CDM



Spatial curvature of the Universe



eBOSS 2021

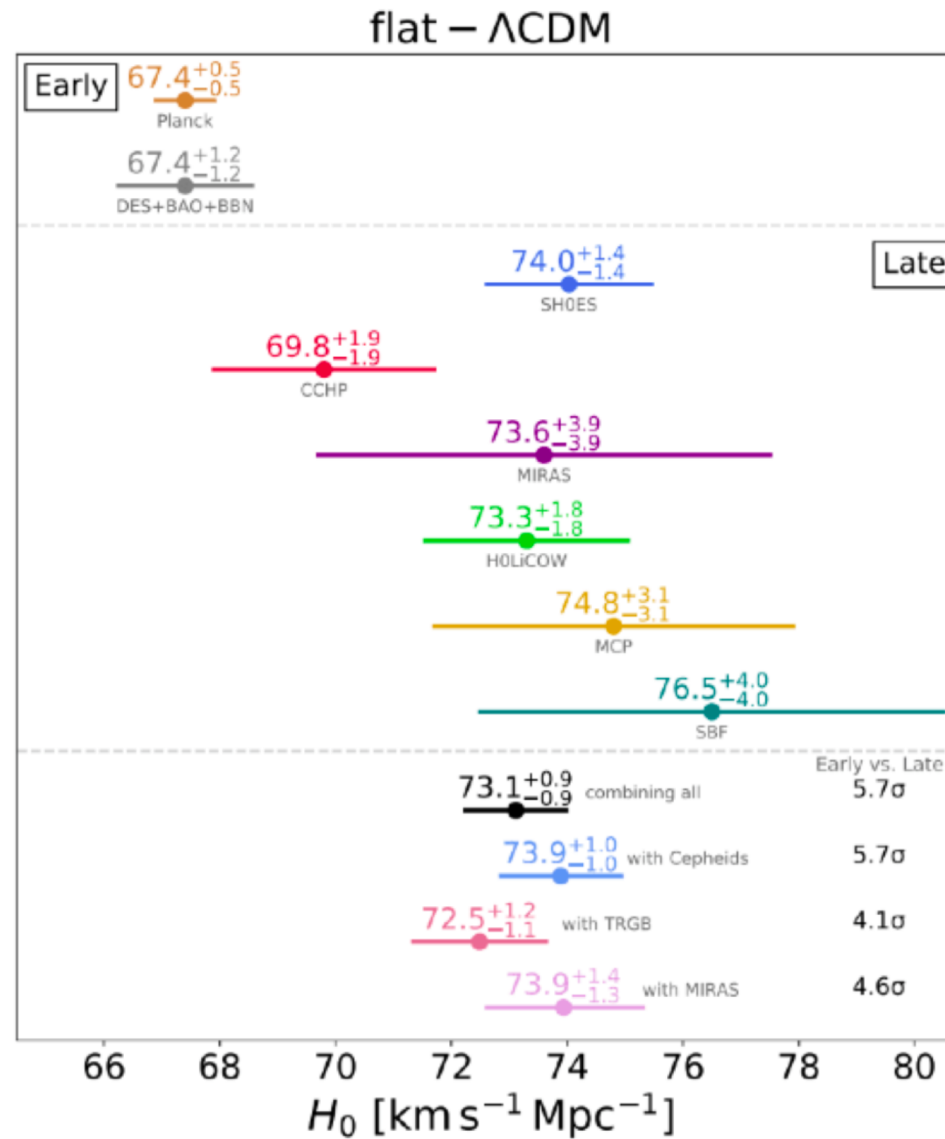
H_0 tension

$H_0 \sim 67 \pm 0.5$ VS 73 ± 1 km/s/Mpc

Late time probes
(CMB, BAO+BBN)

Early time probes
(Cepheids, TGRB)

~ 4 to 5σ tension within Λ CDM



Observational pillars of Λ CDM

➤ Redshift of galaxies $1 + z \equiv \frac{\lambda_0}{\lambda} = \frac{a_0}{a}$

➤ Big Bang Nucleosynthesis (BBN)

➤ Cosmic Microwave Background (CMB)

➤ Galaxy rotation curves
Velocity dispersion in clusters + Lensing

➤ Type Ia Supernovae (SNIa)

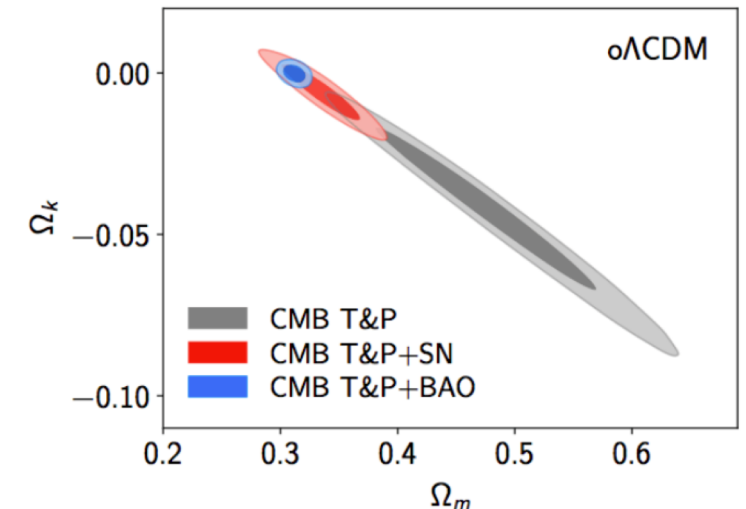
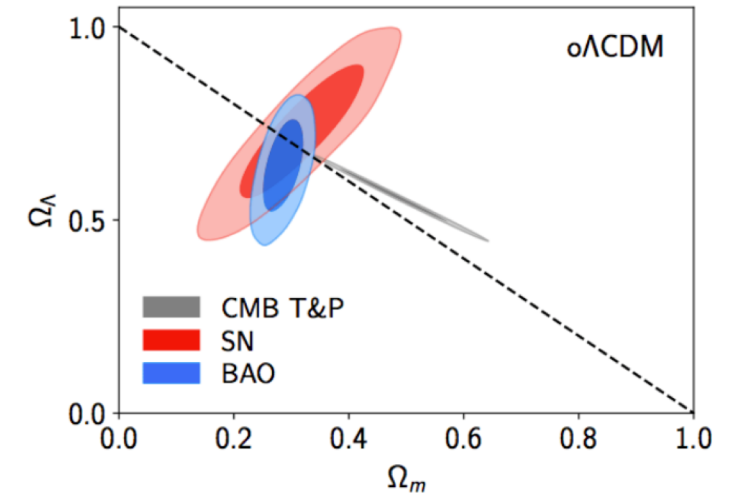
➤ Baryon acoustic peak (BAO)

Expansion of the universe
from a Big Bang
Suppression of Λ

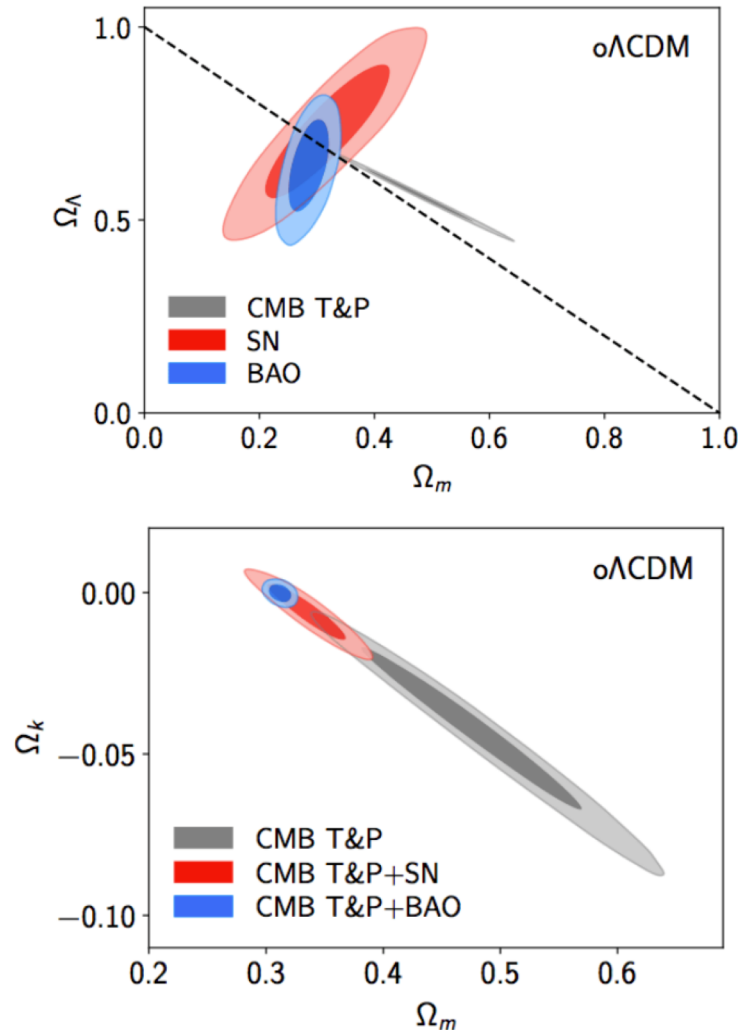
Cold Dark Matter (CDM)

Accelerated expansion
Reintroduction of Λ

The Λ CDM model



The Λ CDM model

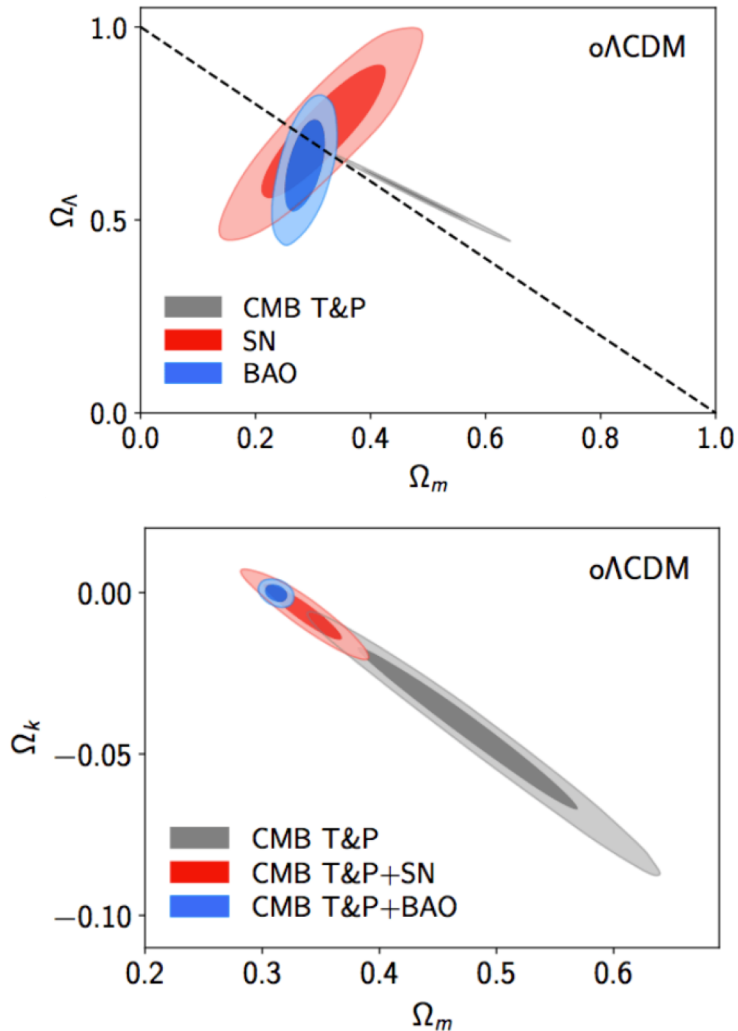


- 5 % of baryonic matter, well described by Particle Physics
- 25 % of CDM : Non standard matter
- 70 % of Λ or Dark Energy or Modified Gravity ?
- Spatially flat ? Not with CMB alone
- $H_0 = 67$ or 73 km/s/Mpc ? Early VS Late time probes
- What about massive neutrinos ? Important role for cosmology
- Inflation theory ? No observational signature

Still interesting physics to explore and understand !

The concordance model : Λ CDM

eBOSS collaboration 2021

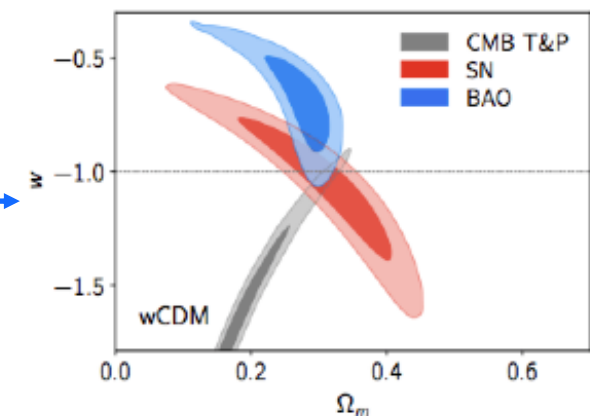
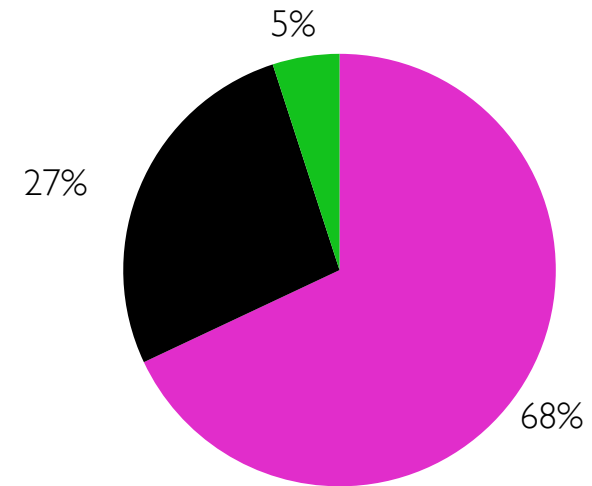


The universe is

- 5% of baryonic matter
Well described by Particle Physics
- 27% of Cold Dark Matter
Non standard matter
- 68% of Λ or Dark Energy
Responsible for the acceleration
- Spatially Flat
For CMB + SN + BAO

Dominated by
the dark sector

■ Λ
■ Dark matter
■ Baryonic matter



All probes are
compatible
with $w = -1$
→ Λ

- Explaining the acceleration of the expansion

The energy of vacuum does not fit Λ
120 orders of magnitude difference with theoretical prediction

- Tension on today's expansion rate

$H_0 \sim 67 \pm 0.5$ VS 73 ± 1 km/s/Mpc

Late time probes
(CMB, BAO+BBN)

Early time probes
(Cepheids, TGRB)

~ 4 to 5σ tension within Λ CDM

Motivation to go

Beyond Λ CDM

$$R_{\mu\nu} - \frac{1}{2}Rg_{\mu\nu} = 8\pi GT_{\mu\nu}$$

Modified gravity models ?

Look for deviations from Einstein's Field Equations

Additional fluid : Dark energy ?

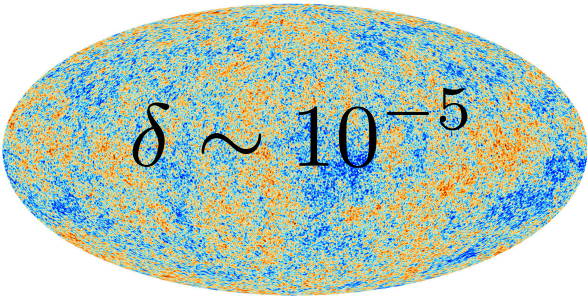
Look for deviations from $w = -1$

$$w_{\text{DE}}(a) = w_0 + w_a(1 - a)$$

Need precise measurement of cosmological parameters to observe deviations from Λ CDM

Statistics of the density field

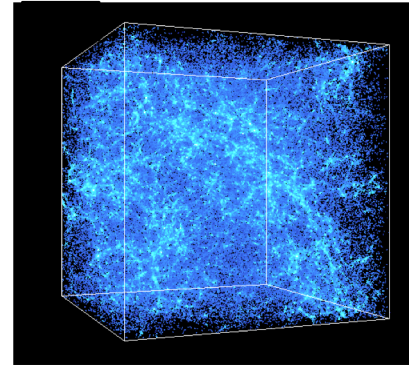
$z = 1100$



CMB anisotropies = seeds

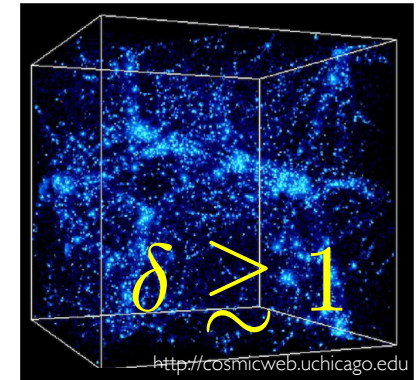
Linear clustering

$z = 5$



Non-linear clustering
on small scales

$z = 0$



The density contrast field

$$\delta(\mathbf{x}, t) \equiv \frac{\rho(\mathbf{x}, t) - \bar{\rho}(t)}{\bar{\rho}(t)}$$

In Fourier space : **The power spectrum**

$$\langle \delta(\mathbf{k}) \delta(\mathbf{k}') \rangle = \delta_D(\mathbf{k} + \mathbf{k}') P(k)$$

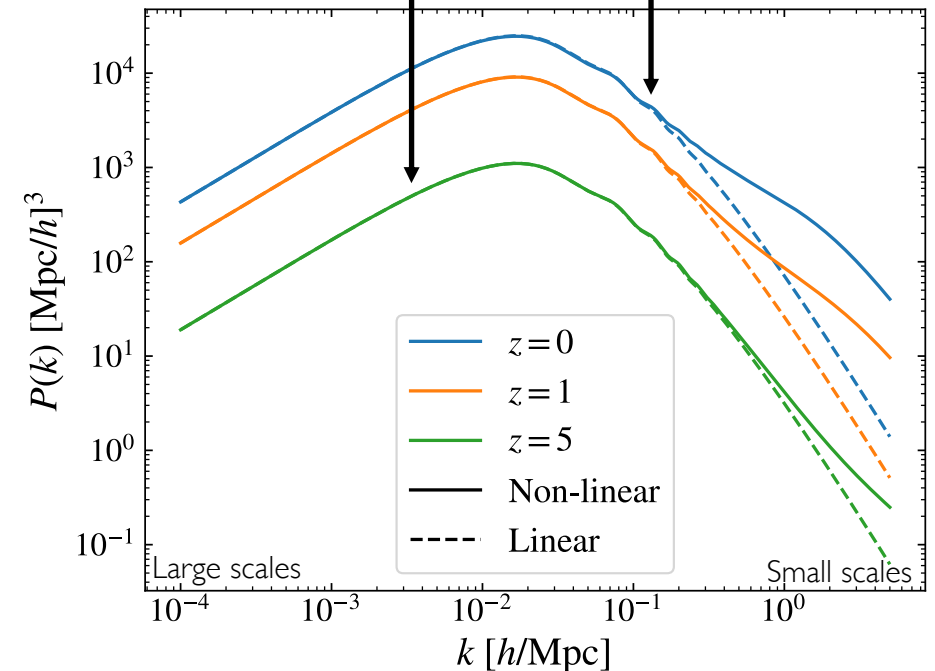
Statistical description

➤ By definition : $\langle \delta(\mathbf{x}) \rangle = 0$

➤ 2-point correlation function :

$$\langle \delta(\mathbf{x}) \delta(\mathbf{x} + \mathbf{r}) \rangle \equiv \xi(\mathbf{r})$$

$$k = \frac{2\pi}{r}$$



Non-linear clustering and non-Gaussian covariance

Non-linear clustering

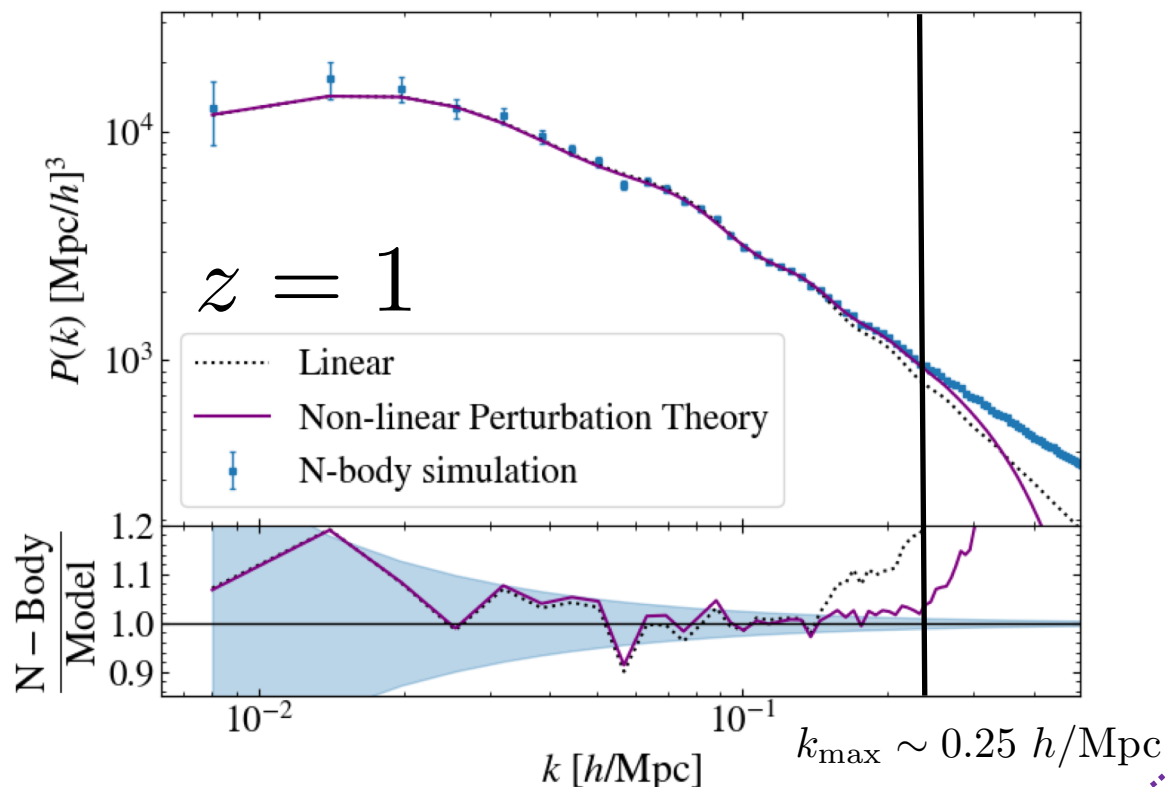
on small scales

δ becomes non-Gaussian

CMB $\rightarrow \delta$ follows a Gaussian PDF

Simulate non-linear clustering
with N-Body simulations

Test models on
N-body simulations



Covariance : Errors and correlations in the
power spectrum [Scoccimaro et al. 1999]

$$\mathbf{C}(k_i, k_j) = \frac{P(k_i)^2}{N_{k_i}} \delta_{ij} + \bar{T}(k_i, k_j)$$

Trispectrum

$$\langle \delta(\mathbf{k}_1) \delta(\mathbf{k}_2) \delta(\mathbf{k}_3) \delta(\mathbf{k}_4) \rangle_c = \delta_D(\mathbf{k}_1 + \mathbf{k}_2 + \mathbf{k}_3 + \mathbf{k}_4) T(\mathbf{k}_1, \mathbf{k}_2, \mathbf{k}_3)$$

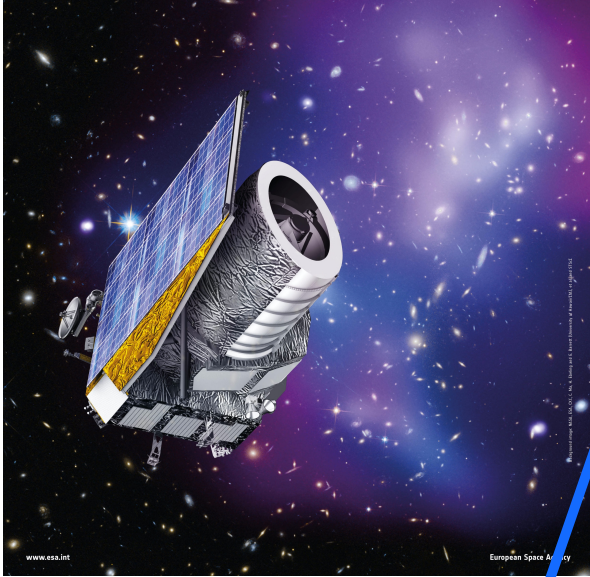
Difficult to predict analytically

Estimate the covariance from simulations

$$\hat{C}_{ij} = \frac{1}{N_m - 1} \left[\sum_n [P^{(n)}(k_i) - \bar{P}(k_i)][P^{(n)}(k_j) - \bar{P}(k_j)] \right]$$

The Euclid galaxy survey

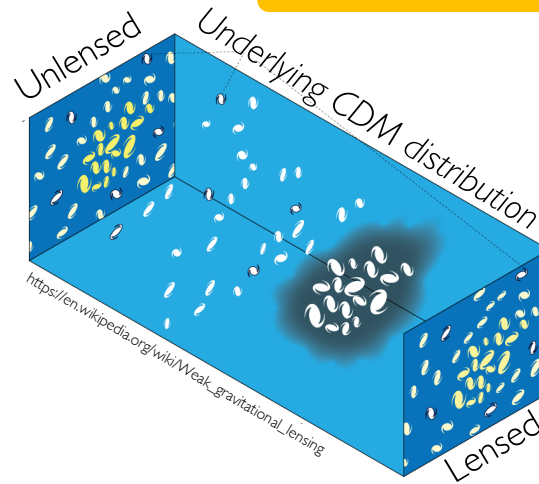
The Euclid mission



- **VIS (visible)** : Shapes of 10^9 with **Photo-z** $\in [0.001, 2.5]$
- **NISP (infrared)** : Spectrum of 50×10^6 galaxies with **Spectro-z** $\in [0.9, 1.8]$

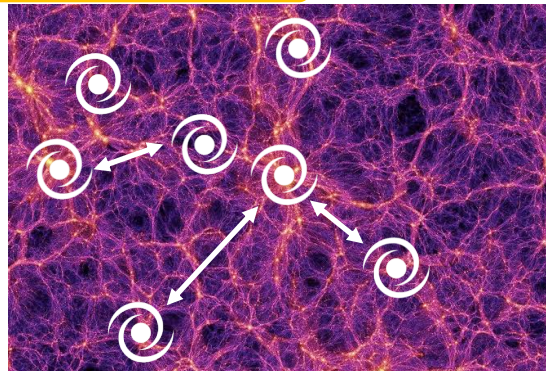
Main Probes of the LSS

Shape of galaxies : ➤ **Weak Lensing**



3D map of the position of galaxies

➤ **Galaxy Clustering**



Scientific objectives

- Time dependence of Dark Energy
 $w_{\text{DE}}(a) = w_0 + w_a(1 - a)$
- Modifications of gravity through the growth of structures

- Measuring the total neutrino mass

$$M_\nu \equiv \sum m_\nu$$

- **Early universe** (Inflation, primordial non-Gaussianities)

Euclid IST:Forecast : [Euclid Collaboration 2019]

Table 3: Expected number density of observed H α emitters for the *Euclid* spectroscopic survey. This number has been updated since the Red Book (Laureijs et al. 2011) to match new observations of number densities and new instrument and survey specifications. The first two columns show the minimum, $z_{\min}$, and maximum, $z_{\max}$, redshifts of each bin. The third column is the number of galaxies per unit area and redshift intervals, $dN(z)/d\Omega dz$. The fourth column shows the number density, $n(z)$. The fifth column lists the total volume. Finally, in the sixth column we list the galaxy bias evaluated at the central redshift of the bins, $z_{\text{mean}} = (1/2)(z_{\max} + z_{\min})$.

$z_{\min}$	$z_{\max}$	$dN(z_{\text{mean}})/d\Omega dz [\text{deg}^{-2}]$	$n(z_{\text{mean}}) [h^3 \text{Mpc}^{-3}]$	$V_s(z_{\text{mean}}) [\text{Gpc}^3 h^{-3}]$	$b(z_{\text{mean}})$
0.90	1.10	1815.0	6.86×10^{-4}	7.94	1.46
1.10	1.30	1701.5	5.58×10^{-4}	9.15	1.61
1.30	1.50	1410.0	4.21×10^{-4}	10.05	1.75
1.50	1.80	940.97	2.61×10^{-4}	16.22	1.90

Table 4: Specifications for the *Euclid* photometric weak lensing survey.

	Parameter	<i>Euclid</i>
Survey area in the sky	A_{survey}	15 000 deg^2
Galaxy number density	n_{gal}	30 arcmin^{-2}
Total intrinsic ellipticity dispersion	σ_{ϵ}	0.30
Number of redshift bins	N_z	10