

# Testing likelihood accuracy for cluster count cosmology

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## **1. Introduction**

1. Cosmology with galaxy cluster abundance
2. Likelihoods for cluster count cosmology

## **2. Framework for testing likelihood accuracy**

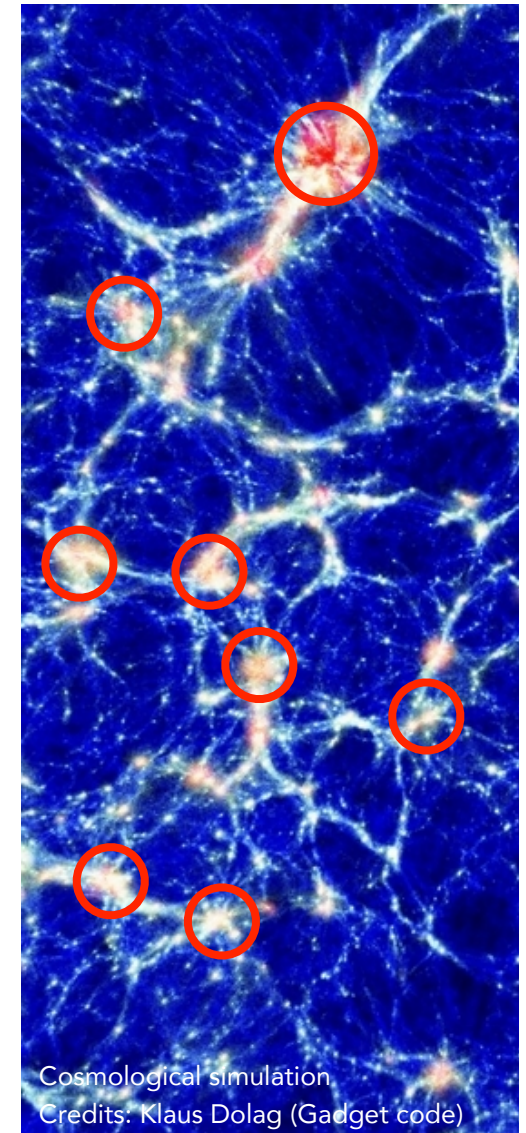
1. The 1000 PINOCCHIO simulations
2. The methodology

## **3. Results**

## **4. Conclusions**

# Galaxy Clusters

- **Describe the latest evolution of the Universe**
  - Most massive bound systems with  $M \in 10^{13} - 10^{15} M_{\odot}$
  - $z < 2$ , last step of hierarchical structure formation process
  - Formed from the growth of small density inhomogeneities
  - By the accretion and merging of smaller structures
- **Good candidates to trace the matter content in the universe**
  - Multi-component systems
    - Dark matter ( $\sim 80\%$ ) and baryonic matter
    - Multi-wavelength objects (optical, near-IR, mm, X-ray)
    - Laboratories to study the co-evolution of the dark and the baryonic matter
  - At larger scales, lie at the intersections of the cosmic web filaments



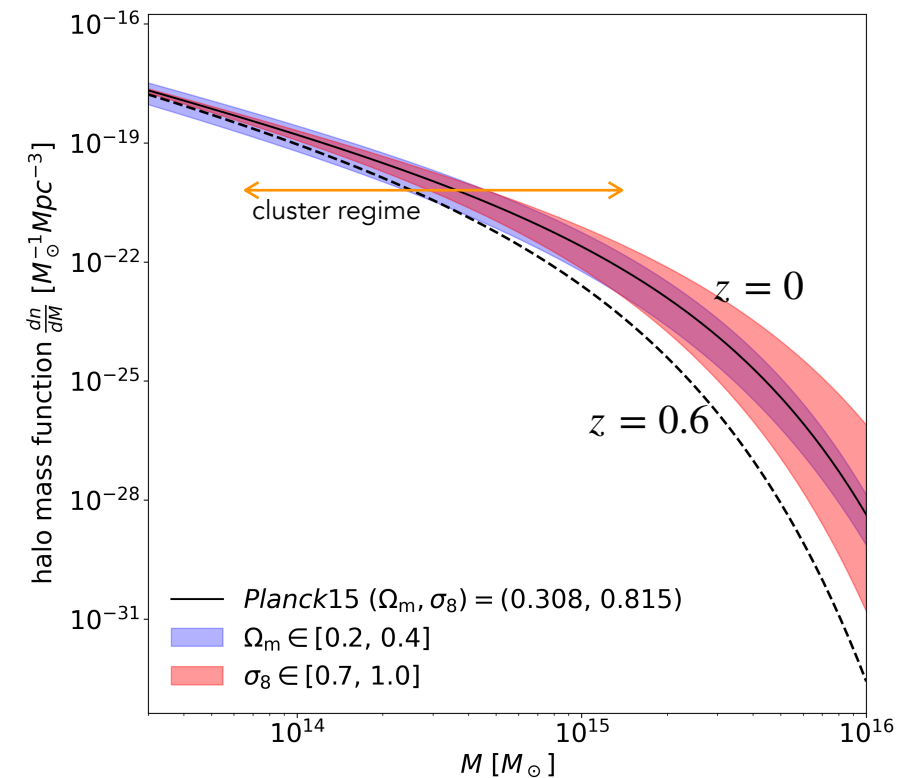
# Cosmology with galaxy cluster abundance

## The abundance of galaxy clusters

- Geometry + growth of structures in the Universe
- Count clusters a function of redshift and mass

$$N_{\text{th}} = \Omega_s \int_{z_1}^{z_2} dz \int_{m_1}^{m_2} dm \frac{dn(m, z)}{dm} \frac{d^2V(z)}{dz d\Omega}$$

- Depends on:
  - **Halo Mass Function**
    - Matter content  $\Omega_m$
    - To the amplitude of matter density fluctuation  $\sigma_8$
    - Formation history : growth rate over cosmological time  $\sigma_8(z)$
  - **Volume**
    - Background cosmology
    - $z < 2$ , sensitive to late time expansion history of the Universe, led by dark energy e.o.s



# Cosmology with galaxy cluster abundance

## Cluster abundance

- Probes  $\Lambda$ CDM ( $\Omega_m, \sigma_8$ ) as well as extensions
  - $w$ CDM
  - Massive neutrinos  $\sum m_\nu$
  - Primordial Non-Gaussianity
  - Testing gravity on large scales  $\rightarrow$  modified gravity scenarios, ...

## An order of magnitude in observed clusters with next-generation surveys

- From  $10^{3-4}$  to  $10^5$  clusters
- Increase in size + in depth
- Large statistical power + need of significant improvement in control of systematics (e.g. synergy space/ground experiments for WL mass calibration)

Cluster abundance cosmology overview

Surveys	Start	Wavelengths	CL Analysis	Number of clusters
ACT	2007	mm	2013	68 (2020: > 4000)
WtG (ROSAT)	2000	X-rays	2014	224
Planck	2009	mm	2015	439 (all: 1653)
SPT	2007	mm	2016	343
SDSS	2000	Visible	2019	25 000
KiDs	2011	Visible	2020	3 652
DES	2013	Visible	2020	7 000
eROSITA	2019	X-rays	2022	455 (all: 100 000)
Rubin LSST	2023	Visible		> 100 000
Euclid	2023	Visible, near IR		> 100 000
S0	2023	mm		16 000
WFIRST	2026	Visible, near IR		40 000
CMB-S4	2029	mm		100 000
Roman	2027	Blue, near IR		23 000

## Basic recipe for cluster abundance cosmology

- From a galaxy cluster survey with known redshifts, masses
- Count the number  $\vec{N}_{\text{obs}}$  of galaxy clusters within bins of redshift and mass
- Posterior of cosmological parameter

$$p(\vec{\theta} | \vec{N}_{\text{obs}}) = \pi(\vec{\theta}) \mathcal{L}(\vec{N}_{\text{obs}} | \vec{\theta})$$

Likelihood =  $\mathcal{L}(\vec{N}_{\text{obs}} | \vec{\theta})$

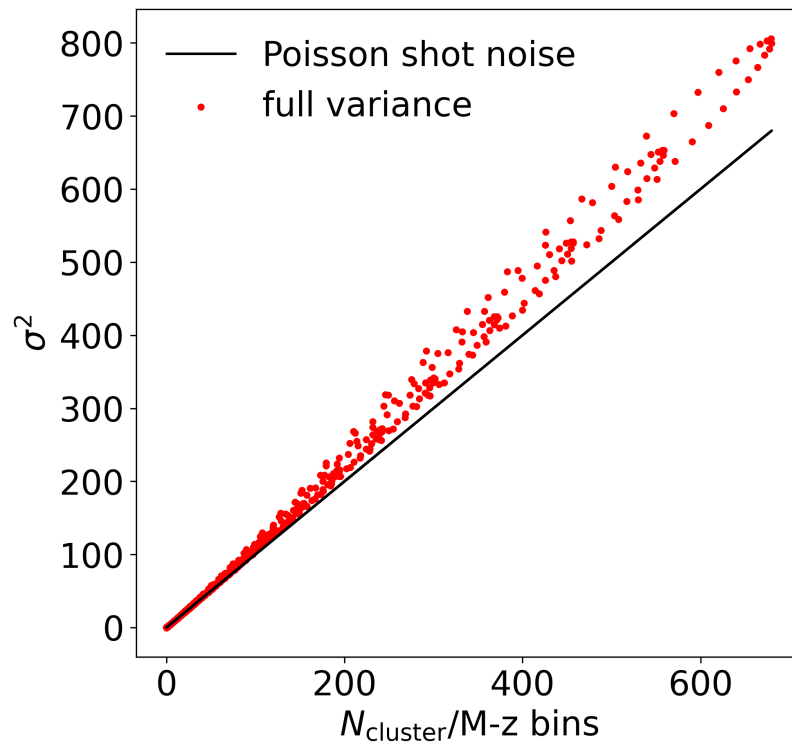
- $\vec{N}_{\text{th}}$  at arbitrary cosmology
- Statistics
  - Count of discrete objects in bins → Poisson sampling
  - Fluctuation + clustering of the matter density field → Gaussian contributions
  - Non-linear physics of halo formation → More complications

# Cluster abundance covariance matrix

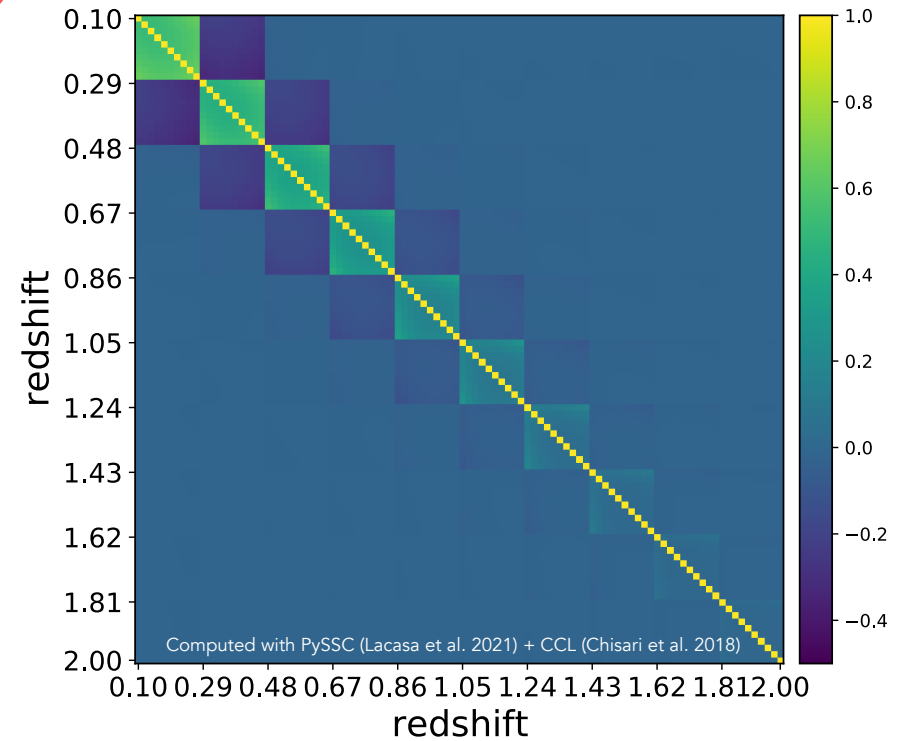
Clustering + fluctuation of matter density field (within/beyond survey volume) = sample covariance

Additive variance

$$\sigma^2(\hat{N}) = N + \sigma_{\text{sample}}^2(N)$$



correlation between M-z bins

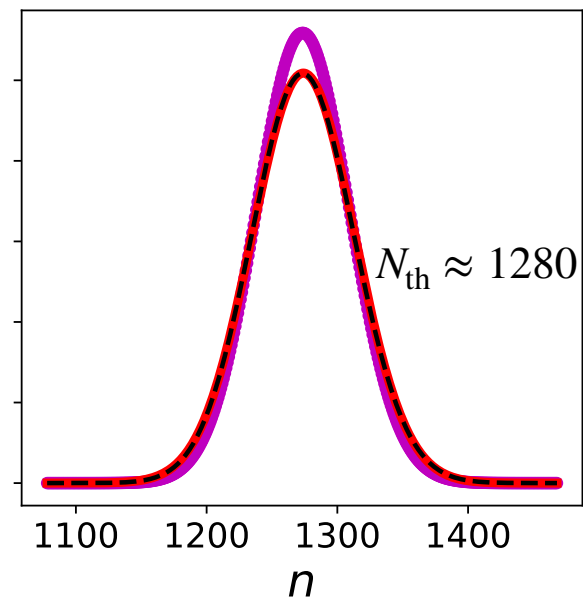
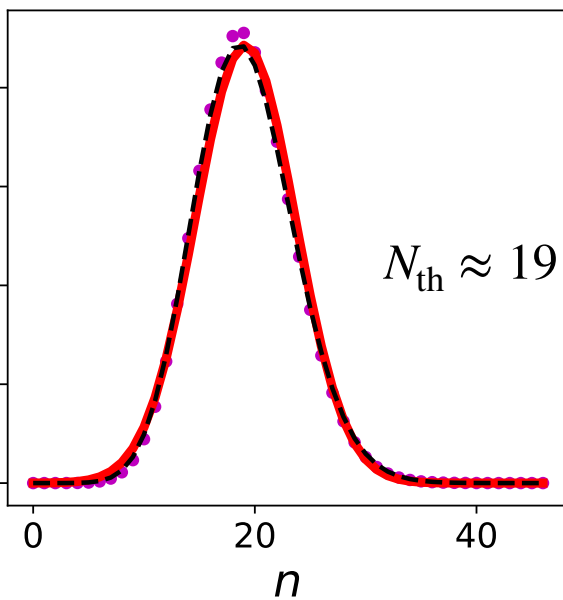
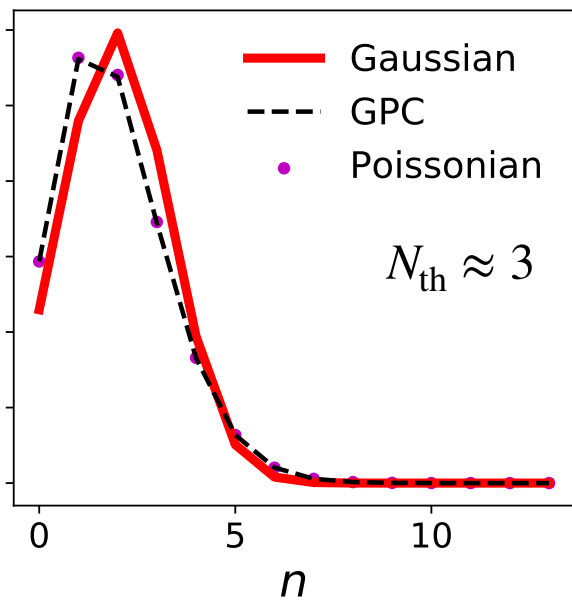


## Likelihoods

- Ideally should describe completely abundance statistics
- There exist approximations
  - **Poisson likelihood** (Planck, 2015  $\sim 500$  clusters)
    - Accounts for Poisson sampling
    - Does not account for sample covariance
    - Valid for low number of clusters, Shot Noise  $>$  Sample variance
  - **Gaussian likelihood** (DES, 2021  $\sim 7000$  clusters)
    - Sample covariance
    - Limited to continuous approximation
    - Valid for high number of clusters, Shot Noise  $\sim$  Sample variance
  - **Gauss-Poisson Compound** (GPC) (KiDS, 2021  $\sim 4000$  clusters)
    - Takes into account both Poisson sampling and sample covariance (Hu & Kravtsov, 2003)
    - Computationally expansive to compute
    - Multidimensional integral  $\mathcal{L}(\hat{N} | \vec{\theta}) \propto \int d\vec{x} \mathcal{N}[\vec{x} | \vec{N}(\theta)] \times \prod_{k=1}^n \mathcal{P}[\hat{N}_k | x_k]$
    - More precise, can we gain cosmological information?



Single variate likelihood  $\mathcal{L}(n|N_{\text{th}})$



\*Dodelson, Schneider 2013, Percival et al. 2022

\*\*Sellentin, Heavens 2018 for cosmic shear

## **Bias on parameter inference**

- Deviation from the latent likelihood may bias results
  - Data covariance matrix is incorrect\*
  - Inferred posteriors will be incorrect
  - The latent likelihood is not Gaussian\*\*
    - Can shift posteriors
- In our case:
  - Latent likelihood is not Poisson, Gaussian, or Gauss-Poisson Compound
  - Halo model is an approximation
- Most robust constraints with analysis likelihood closest to latent one

## **Using simulations to test cluster abundance likelihoods**

- Likelihood: statistical properties of the data at input cosmology
- With multiples simulations, can have access to "true" statistics of abundance

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## → 2. Framework for testing likelihood accuracy

1. The 1000 PINOCCHIO simulations
2. The methodology

## 3. Results

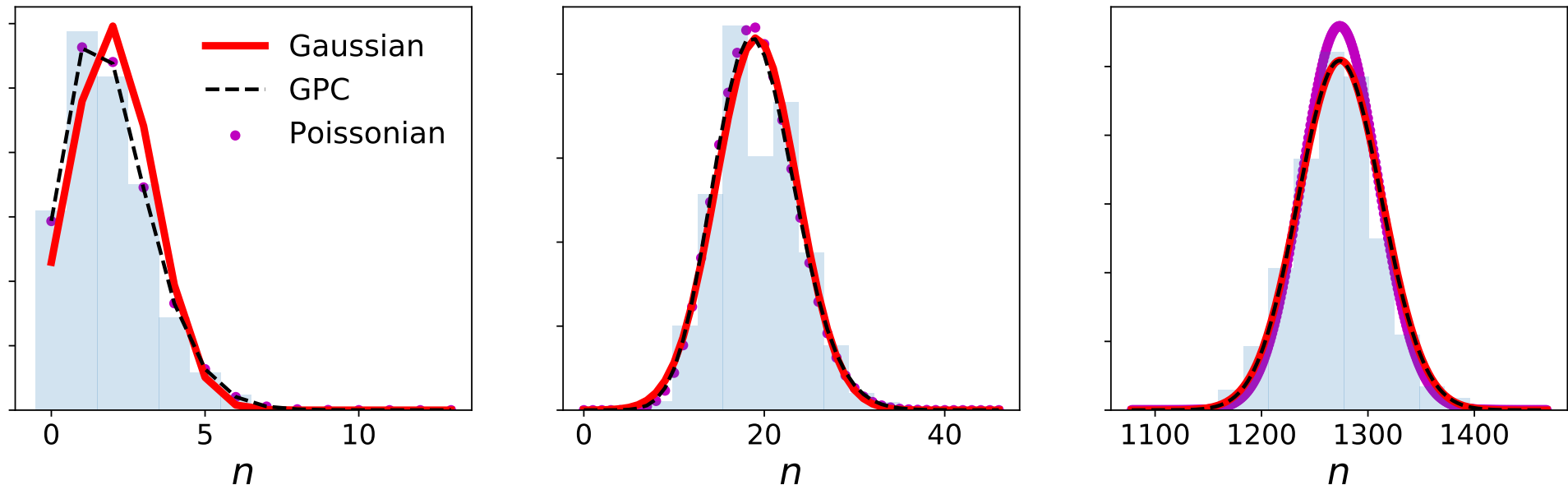
## 4. Conclusions

# Framework for testing the accuracy of likelihoods

## We use a set 1000 simulated dark matter halo catalogs

- PINOCCHIO algorithm (Monaco et al., 2013)
- Planck cosmology
- Masses calibrated on known halo mass function (Despali et al., 2015)
- Euclid-like sky area  $\sim 1/4$  of full-sky
- $\sim 10^5$  halos per simulation
- $M > 10^{14} M_{\odot}$

Abundance likelihood can be estimated from counts over the 1000 cosmological simulations





# Framework for testing the accuracy of likelihoods

## Methodology

- 1. Estimate the posterior for each of the 1000 Pinocchio mocks

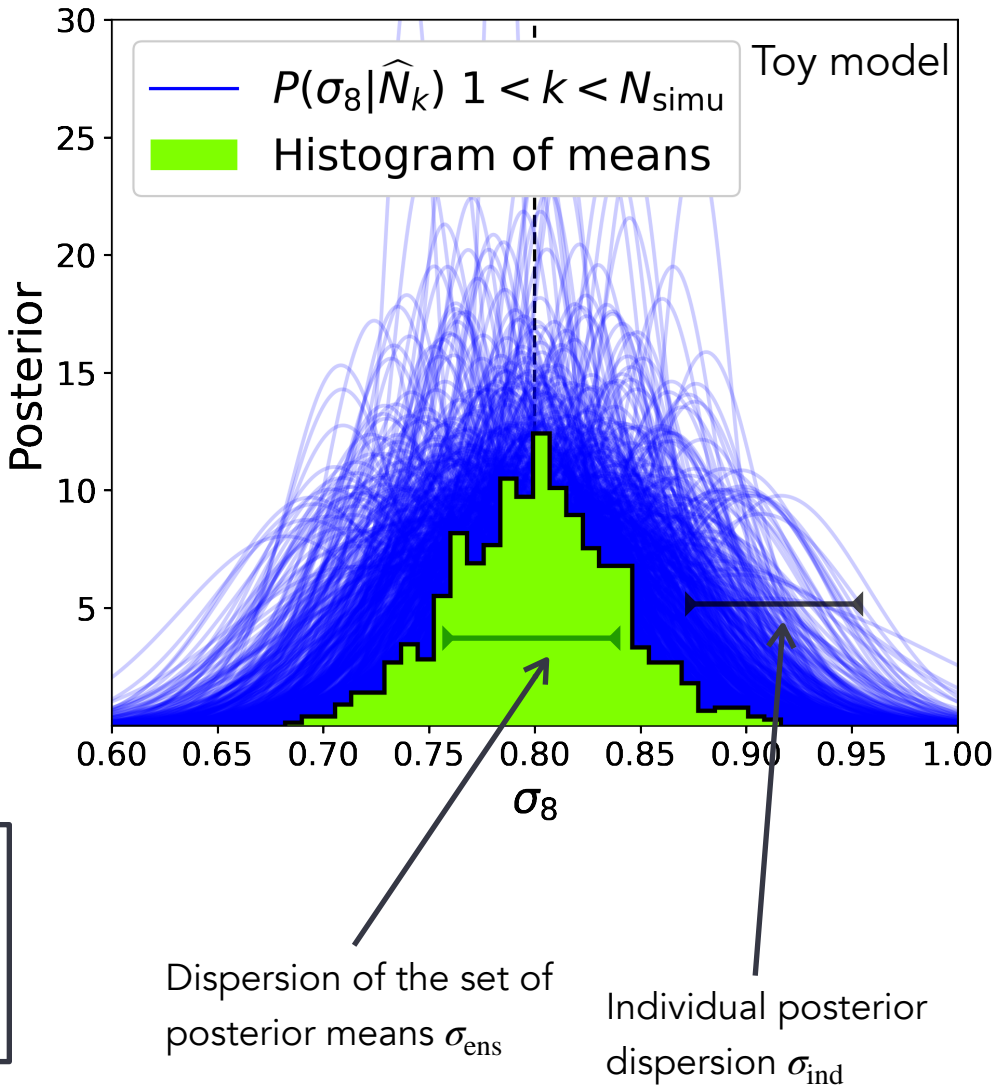
More than 1 parameter: compare covariances

$\sigma_{\text{ind}}^2 \rightarrow C^{\text{ind}}$

Individual parameter covariance

$\sigma_{\text{ens}}^2 \rightarrow C^{\text{ens}}$

Ensemble parameter covariance



# Why comparing individual errors to the spread of means ?

## - Robust constraints ?

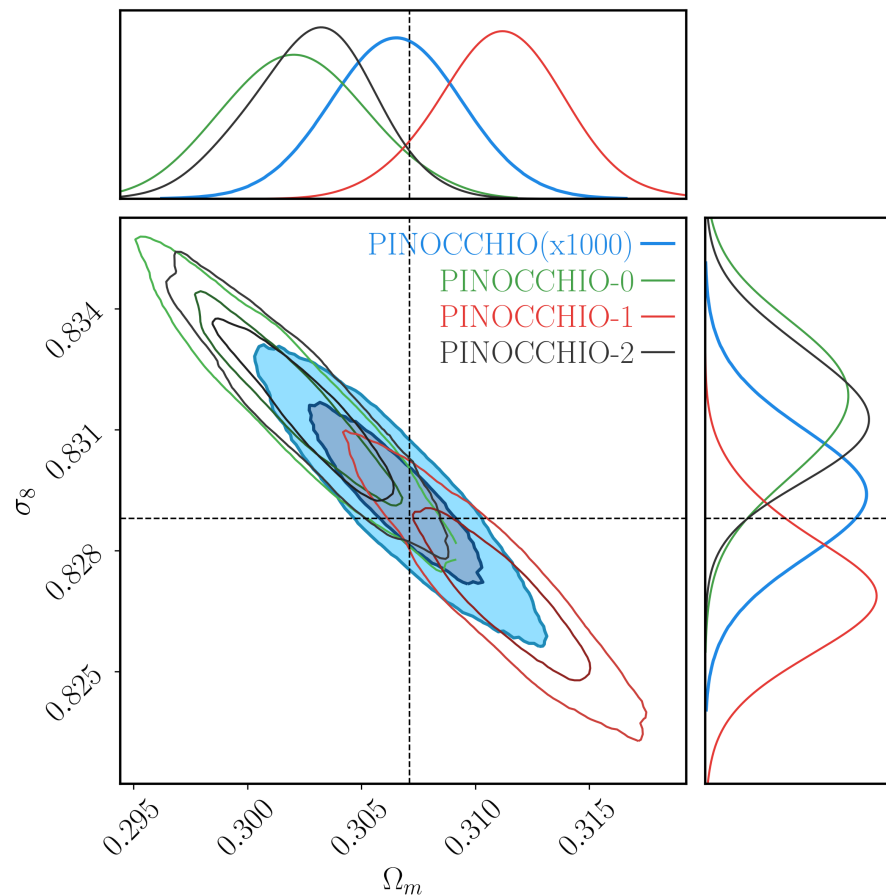
- Reasonable request: For each simulation, the recovered error should be representative of the spread of recovered parameters over many realisations of the "Universe"

## Gaussian likelihood

- Latent likelihood  $\mathcal{L}_X$  and analysis likelihood  $\mathcal{L}_Y$
- Two data covariance matrices  $\Sigma_X$  and  $\Sigma_Y$
- If  $\Sigma_X = \Sigma_Y$ 
  - Then  $C^{\text{ens}} = C^{\text{ind}}$
  - Likelihood accuracy can be forecasted (Fisher formalism)  $\rightarrow C^{\text{Fisher}}$
- If  $\Sigma_X \neq \Sigma_Y$ 
  - Then  $C^{\text{ens}} \neq C^{\text{ind}}$
  - $C^{\text{Fisher}}$  is not sufficient to forecast likelihood accuracy
  - $C^{\text{ens}}$  can be forecasted  $C_{\alpha\beta}^{\text{ens}} = (C^{\text{Fisher}} N)_{\alpha}^T \Sigma_Y^{-1} \Sigma_X \Sigma_Y^{-1} (C^{\text{Fisher}} N)_{\beta} \neq C_{\alpha\beta}^{\text{Fisher}}$
  - Example:  $\Sigma_{Y_{ii}} < \Sigma_{X_{ii}}$  then we have  $C_{\alpha\alpha}^{\text{ind}} < C_{\alpha\alpha}^{\text{correct}} < C_{\alpha\alpha}^{\text{ens}}$
- Likelihood and posterior are not always gaussians
- Rather closeness between individual errors and ensemble error
- Used as a metric to test likelihood accuracy

Using correct likelihood  $C^{\text{ens}} = C^{\text{ind}}$

# Framework for testing the accuracy of likelihoods



Study limited to idealised halos

- Ideal setup: individual “true” masses
- Real data: proxy-selected clusters
- Limited by knowledge of mass-proxy relations + detection efficiency
- Increase error of cosmological parameters

# Cosmological inference setup

- The Poisson, Gaussian and GPC likelihood are approximations
- Valid:
  - At linear scales (clusters are biased tracers of the density field)
  - For given shot noise/sample (co)variance relative importance
    - binning scheme of the mass-redshift plane
    - Sky survey area (Shot noise, sample (co)variance  $\sim \Omega$ )

**Methodology:** Test accuracy of likelihoods for various regimes

For each likelihood

1.  $P(\Omega_m, \sigma_8 | \vec{N}_{\text{obs}})$  for each PINOCCHIO simulation
2. For 3 binning schemes

	Redshift bins	Mass bins	# of bins	Average # N/bin
#1	4	4	16	5000
#2	20	30	600	150
#3	100	100	10 000	10

Poisson sampling  
Sample Variance

$\sim 10^4$  cosmological constraints ! **Importance sampling (efficient for 2 parameters)**



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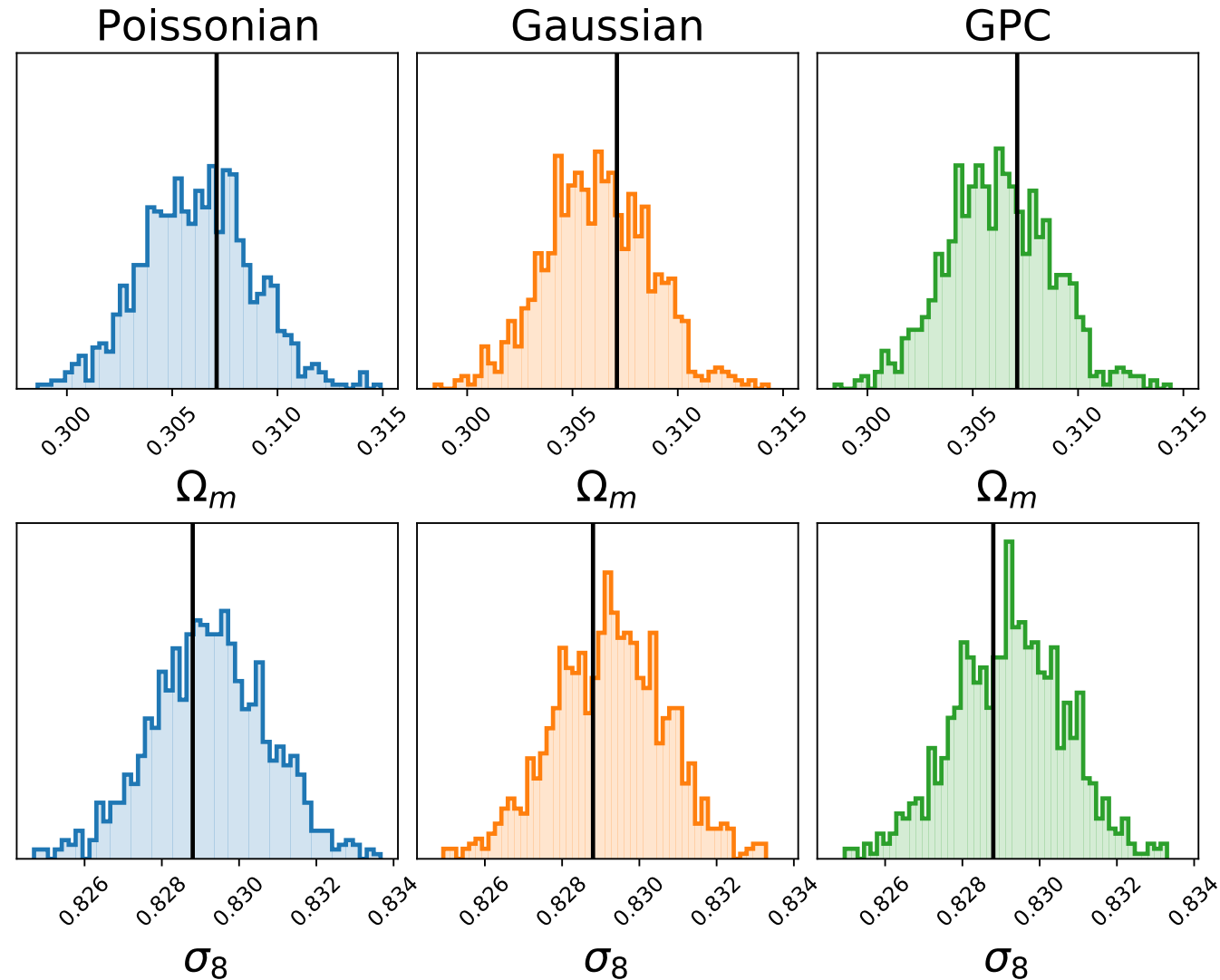
## **3. Results**

## **4. Conclusions**

# Results: (4 redshift bins)x(4 mass bins) case

## Histograms of 1000 means

- Scatter around input cosmology
- Validate the modelling input



# Results: all binning scheme

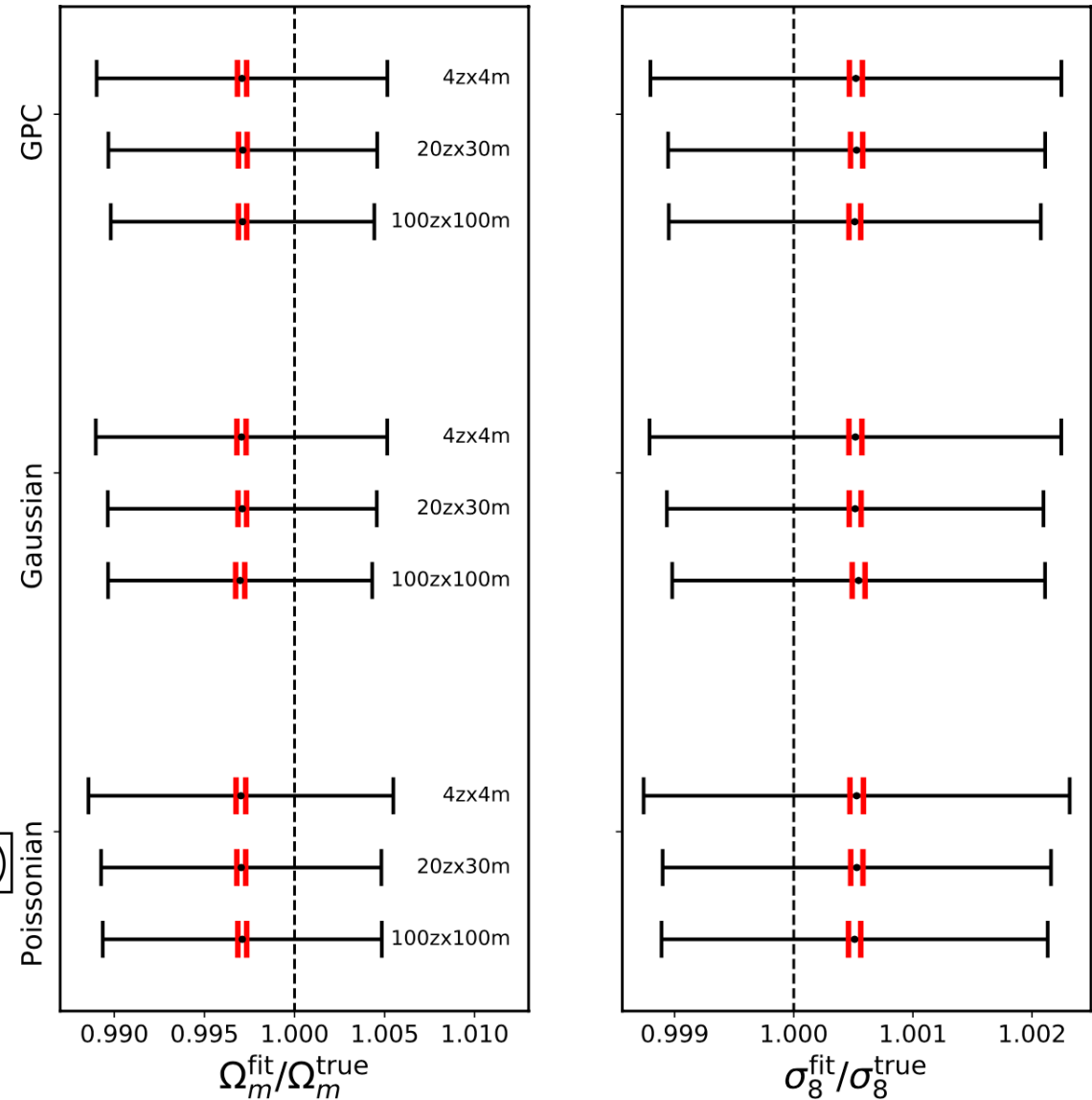
## Bias on the posterior mean

(black) Spread of posterior means

(red) Error on the mean ( $\times 1/\sqrt{1000}$ )

- Small constant bias between input and recovered cosmology
  - Accuracy of the underlying halo model
  - Not due to 2-point statistics (Poisson does not depends on it)
  - Numerical error

Small bias on recovered cosmology (sub-percent)

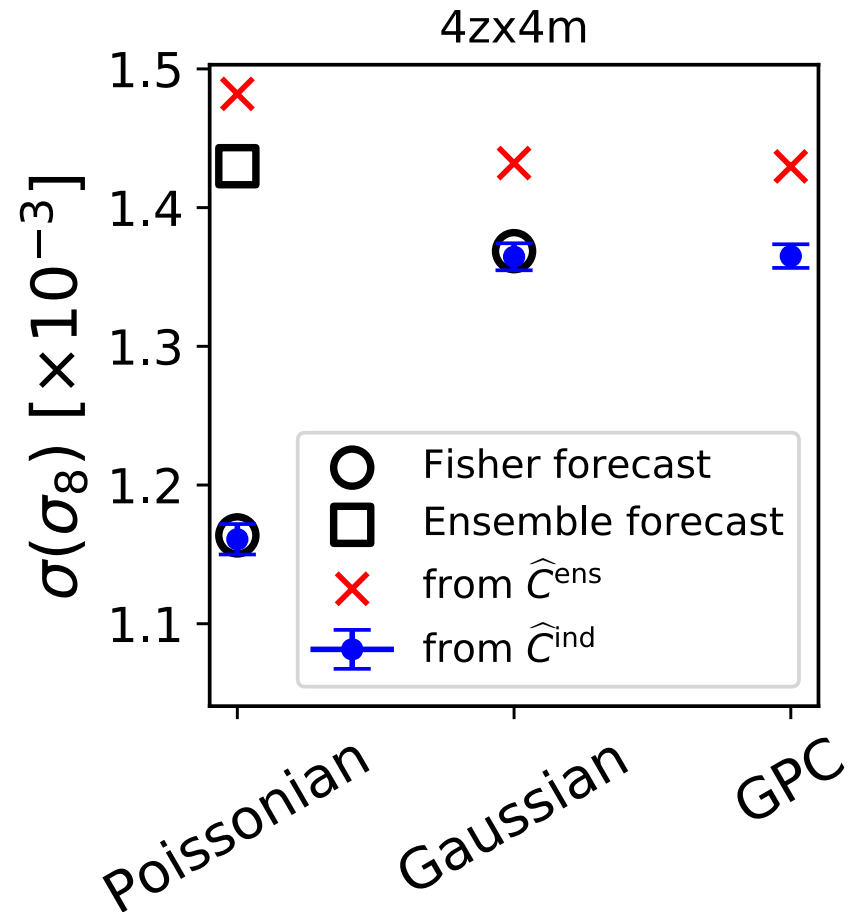


# Results: (4 redshift bins)x(4 mass bins) case

- Individual errors on each simulation (blue)
- Spread of best fits (red)

## Parameter error

- Poisson underestimates the errors, since it not take account of sample variance
  - Gaussian = Gauss-Poisson Compound
    - Slightly underestimate errors, likely due to approximations made for the 2-pt statistics
    - The same level of constraints
- Fisher forecasts (circle) in agreement with individual errors
  - Ensemble forecast (square) for the spread of posterior means





# Results: all binning schemes

## Parameter error

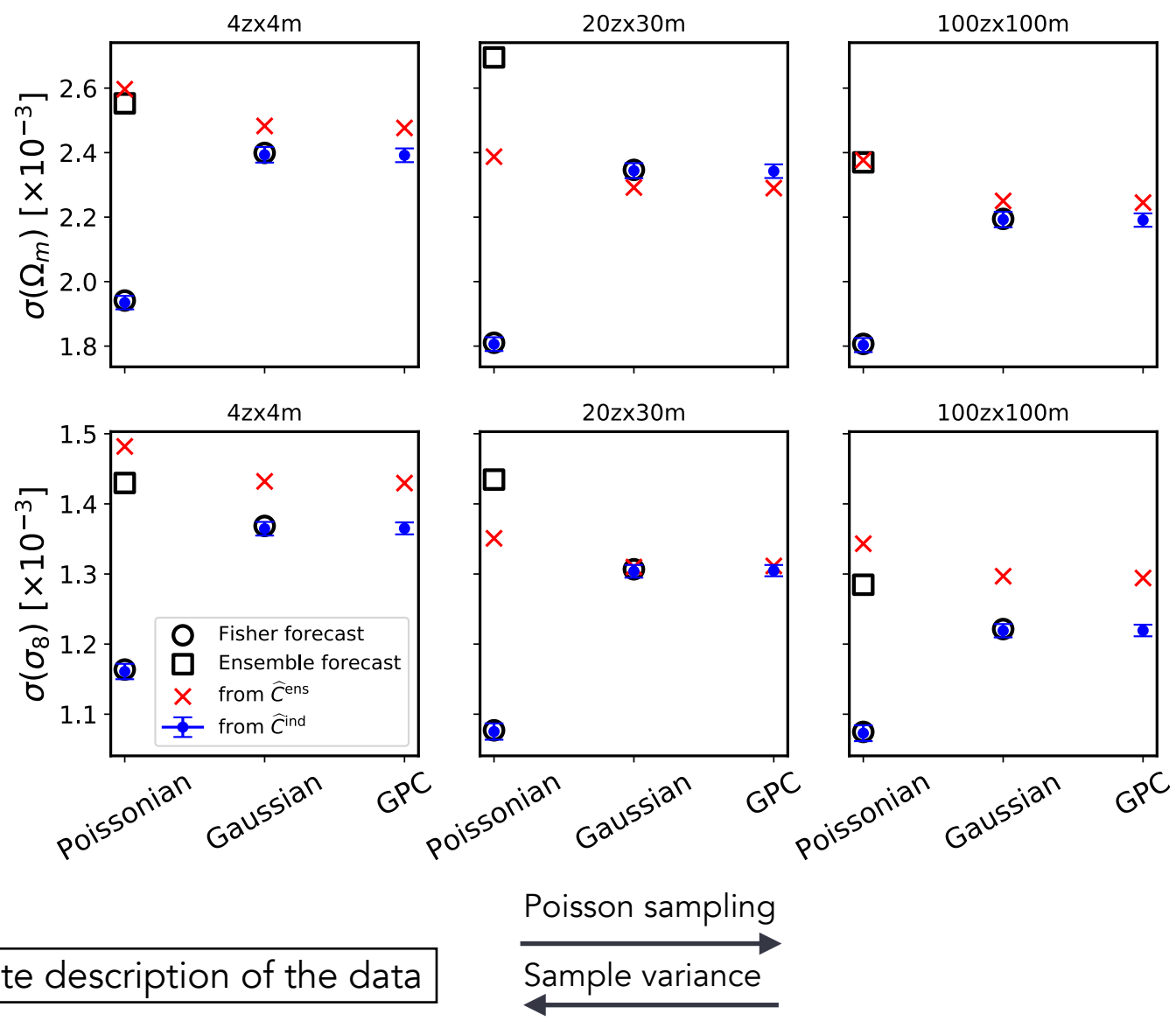
- Errors decreases with the number of bins (10% improvement from 16 to  $10^4$  bins)

## - Poisson

- Underestimates the error, even for fine binning, does not account for sample variance

## - Gaussian = Gauss-Poisson Comp.

- Over/under estimate constraints (approximation for computing the covariance matrix)
- The same level of constraints



Gaussian likelihood remains an accurate description of the data

# Pushing toward the Poisson regime?

For all binning setups

- Gaussian is more accurate than Poisson
- Gaussian misses Poisson sampling

Find where Poisson and Gauss-Poisson

Compound are valid and the Gaussian is not valid ?

- Force shot noise dominant regime

1. Use only high mass halos  $M > 5.10^{14} M_{\odot}$
2. Reducing survey sky area  $\times 1/10$

## 1. High mass sample

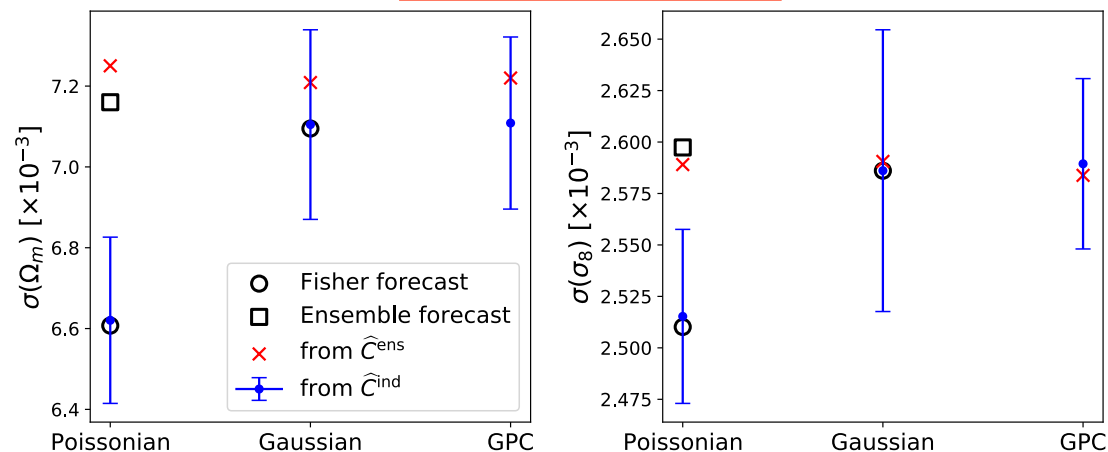
Poisson underestimates error by 20 - 30 %

GPC and Gaussian: closer to ensemble error

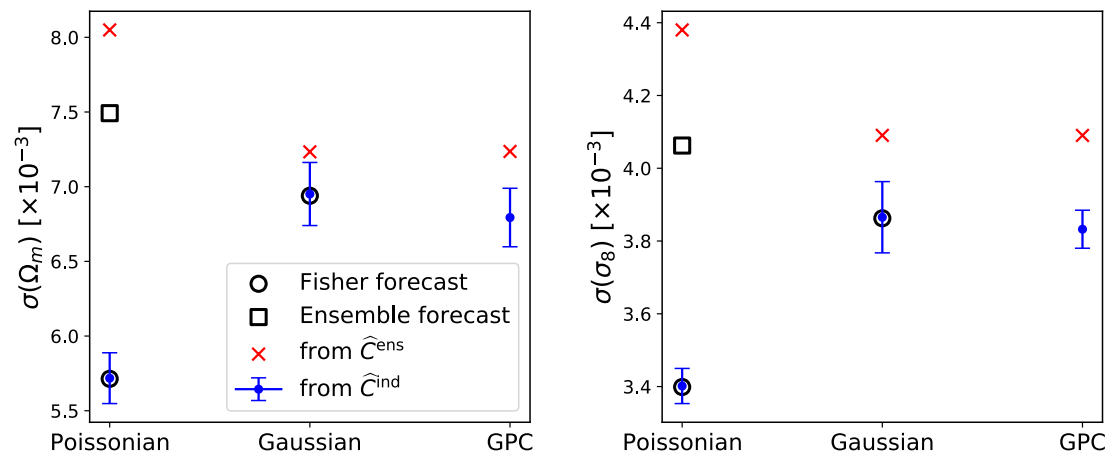
## 2. Reduced volume sample

Poisson underestimates error by 5 - 20 %

## 1. High mass sample



## 2. Reduced volume sample



## Recap

- We tested the accuracy of cluster likelihoods with
  - 1000 simulated dark matter halo catalogs
  - By comparing posterior variances to spread of means over the 1000 simulations
  - Sensitive to analysis likelihood and latent likelihood properties

## Conclusions: For future Euclid or Rubin-like surveys

- Gaussian gives robust constraints over a wide range of inference setup
- No gain in using Gauss-Poisson Compound (same level of constraints but computationally expansive)
- Gauss-Poisson Compound = Gaussian (under/overestimating errors at most 5%)
- Poisson likelihood always underestimates errors