

Associated to: Project 380 + PubDB 180

Analysis of the weak lensing mass-richness relation of redMaPPer clusters in the LSST DESC DC2 simulations

Constantin Payerne,^{1,2} Zhuowen Zhang,³ Michel Aguena,^{4,5} Céline Combet,² Thibault Guillemin,⁶ Marina Ricci,⁴ Nathan Amouroux,⁶ Eduardo J. Barroso,⁶ Arya Farahi,^{7,8} Eve Kovacs,⁹ Calum Murray,^{4,10} Markus M. Rau,^{11,12} Eli S. Rykoff,^{13,14} Sam Schmidt,¹⁵ and the LSST Dark Energy Science Collaboration

*if anyone has been missed, please claim authorship in PubDB

Cosmology with cluster counts

The abundance of galaxy clusters

- Massive bound systems $M > 10^{14} M_{\odot}$ and detected in λ : X-rays, mm, optical
- Connects proxy-cluster counts to cosmology via a scaling relation:

$$\frac{\partial^2 N_{\text{obs}}^{\text{clusters}}}{\partial \mathcal{O} \partial z} \propto \int dm \frac{\partial^2 N_{\text{th}}^{\text{halo}}(m, z)}{\partial m \partial z} P(\mathcal{O} | m, z) \Phi$$

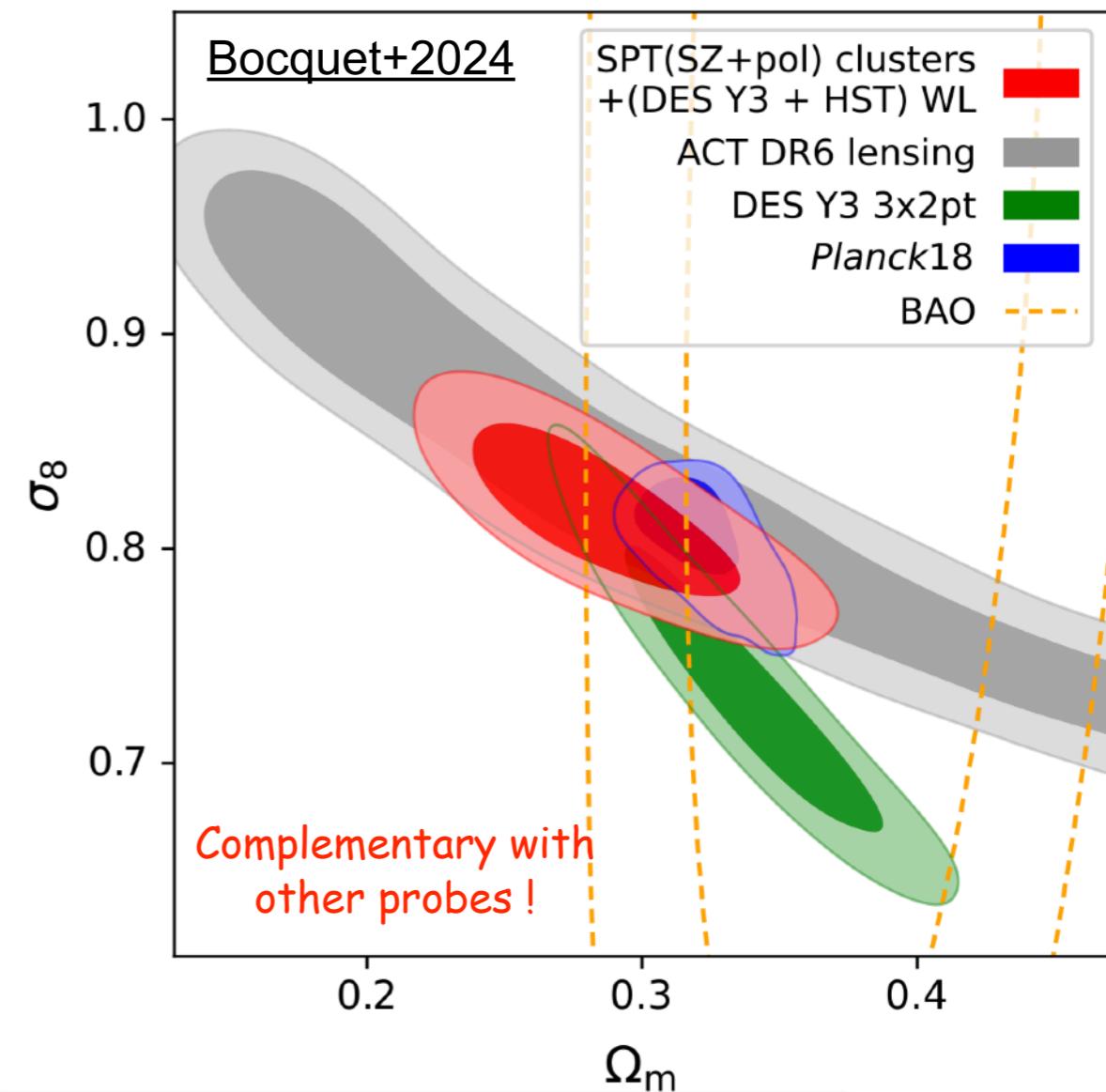
Cosmology with cluster counts

The abundance of galaxy clusters

- Massive bound systems $M > 10^{14} M_{\odot}$ and detected in λ : X-rays, mm, optical
- Connects proxy-cluster counts to cosmology via a scaling relation:

$$\frac{\partial^2 N_{\text{obs}}^{\text{clusters}}}{\partial \mathcal{O} \partial z} \propto \int dm \frac{\partial^2 N_{\text{th}}^{\text{halo}}(m, z)}{\partial m \partial z} P(\mathcal{O} | m, z) \Phi$$

- Privileged probes for structure formation and geometry in Λ CDM (i.e. Ω_m , S_8) + beyond
- Current constraining power: determined by uncertainties on the scaling relation
- Stage IV catalogs (LSST, Euclid, SO) $\sim 100,000$ clusters (x10 current datasets)
- Requires robust modeling of observables, better control of systematics in scaling relations



Weak lensing by galaxy clusters

Weak lensing by galaxy clusters

- Bending of light coming from distant galaxies
- Subtle deformation of galaxy shapes
- Local average $\langle \epsilon \rangle = \langle \epsilon_{\text{int}} \rangle + \gamma$
- Reveals the cluster mass density $\gamma = f(M_{\text{cluster}})$

Weak lensing by galaxy clusters

Weak lensing by galaxy clusters

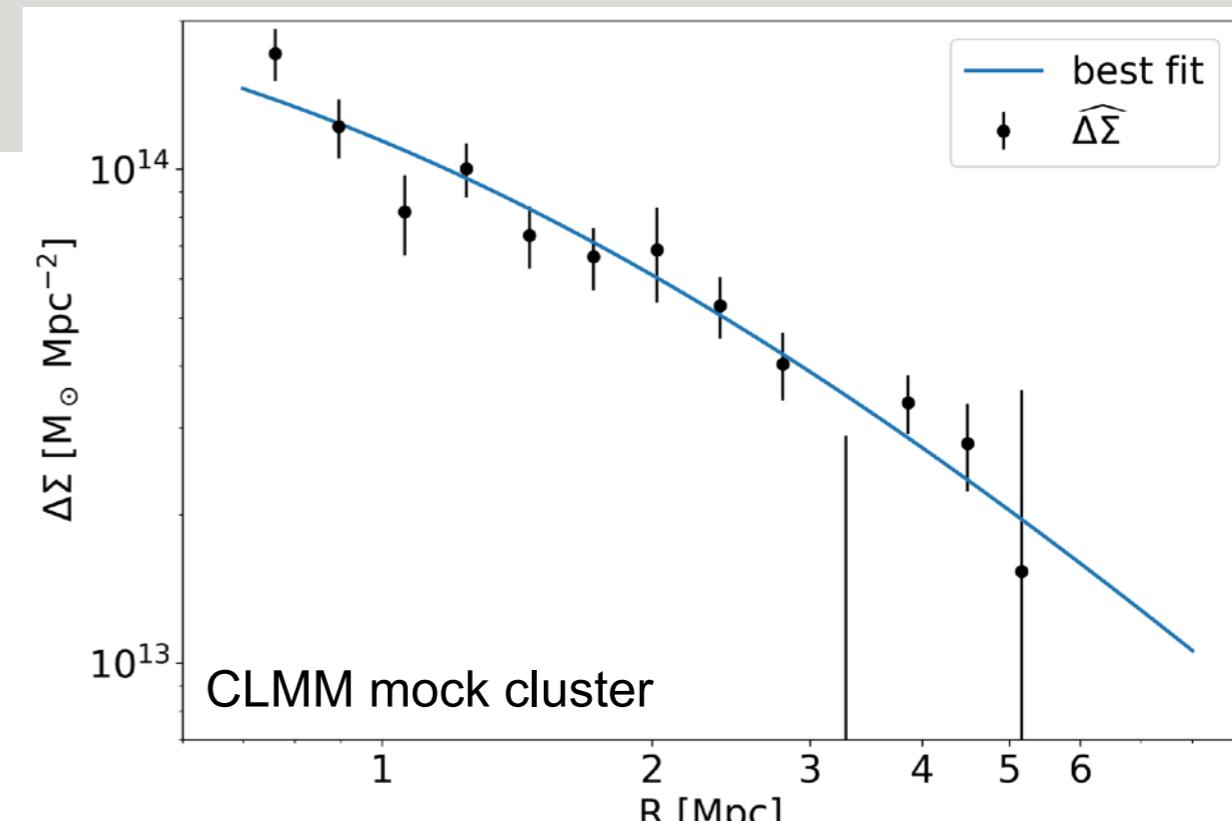
- Bending of light coming from distant galaxies
- Subtle deformation of galaxy shapes
- Local average $\langle \epsilon \rangle = \langle \epsilon_{\text{int}} \rangle + \gamma$
- Reveals the cluster mass density $\gamma = f(M_{\text{cluster}})$

In practice: excess surface density estimator

Data: $\widehat{\Delta\Sigma}(R) = \langle \Sigma_{\text{crit}}(z_{\text{cl}}, z_{\text{gal}}) \epsilon_{+}^{\text{obs}} \rangle$

↑ ↑

Critical surface « tangential »
mass density



Weak lensing by galaxy clusters

Weak lensing by galaxy clusters

- Bending of light coming from distant galaxies
- Subtle deformation of galaxy shapes
- Local average $\langle \epsilon \rangle = \langle \epsilon_{\text{int}} \rangle + \gamma$
- Reveals the cluster mass density $\gamma = f(M_{\text{cluster}})$

In practice: excess surface density estimator

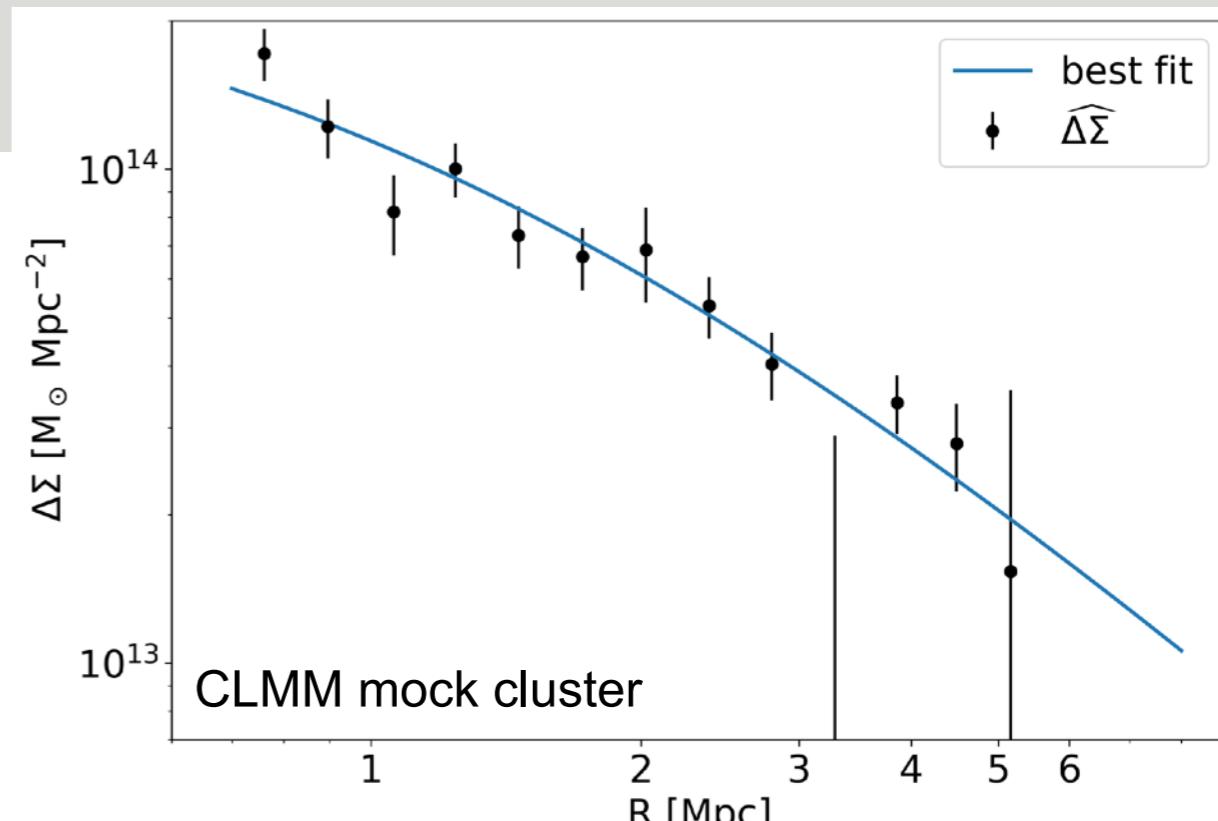
Data: $\widehat{\Delta\Sigma}(R) = \langle \Sigma_{\text{crit}}(z_{\text{cl}}, z_{\text{gal}}) \epsilon_{+}^{\text{obs}} \rangle$

\uparrow \uparrow

Critical surface « tangential »
mass density

Model: $\Delta\Sigma(R) \rightarrow \Sigma(R) = \int d\text{LOS} \boxed{\rho_{3d}(r)}$

Fit $\Delta\Sigma(R) \rightarrow M_{\text{cluster}}$



Weak lensing by galaxy clusters

Weak lensing by galaxy clusters

- Bending of light coming from distant galaxies
- Subtle deformation of galaxy shapes
- Local average $\langle \epsilon \rangle = \langle \epsilon_{\text{int}} \rangle + \gamma$
- Reveals the cluster mass density $\gamma = f(M_{\text{cluster}})$

In practice: excess surface density estimator

Data: $\widehat{\Delta\Sigma}(R) = \langle \Sigma_{\text{crit}}(z_{\text{cl}}, z_{\text{gal}}) \epsilon_{+}^{\text{obs}} \rangle$

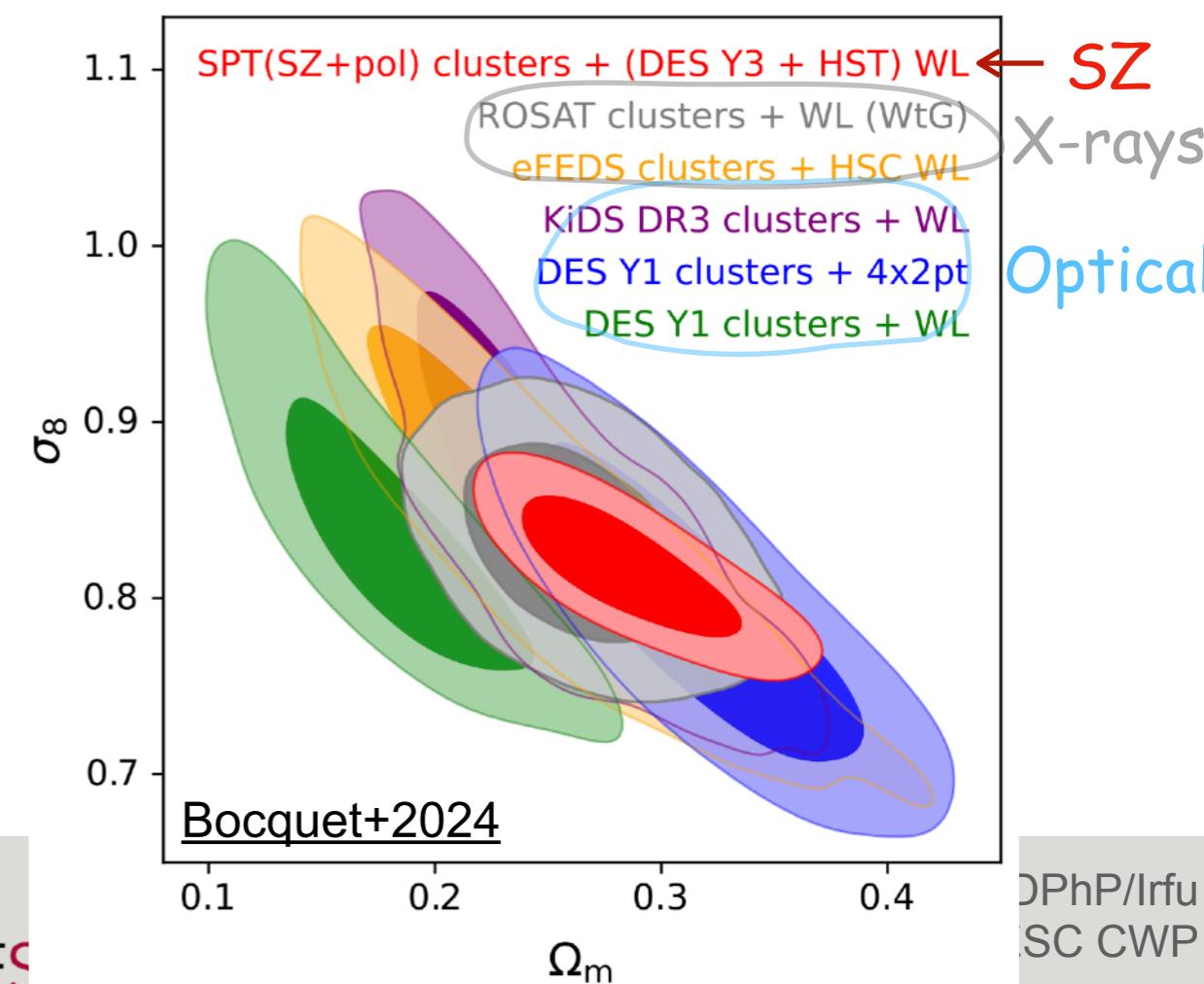
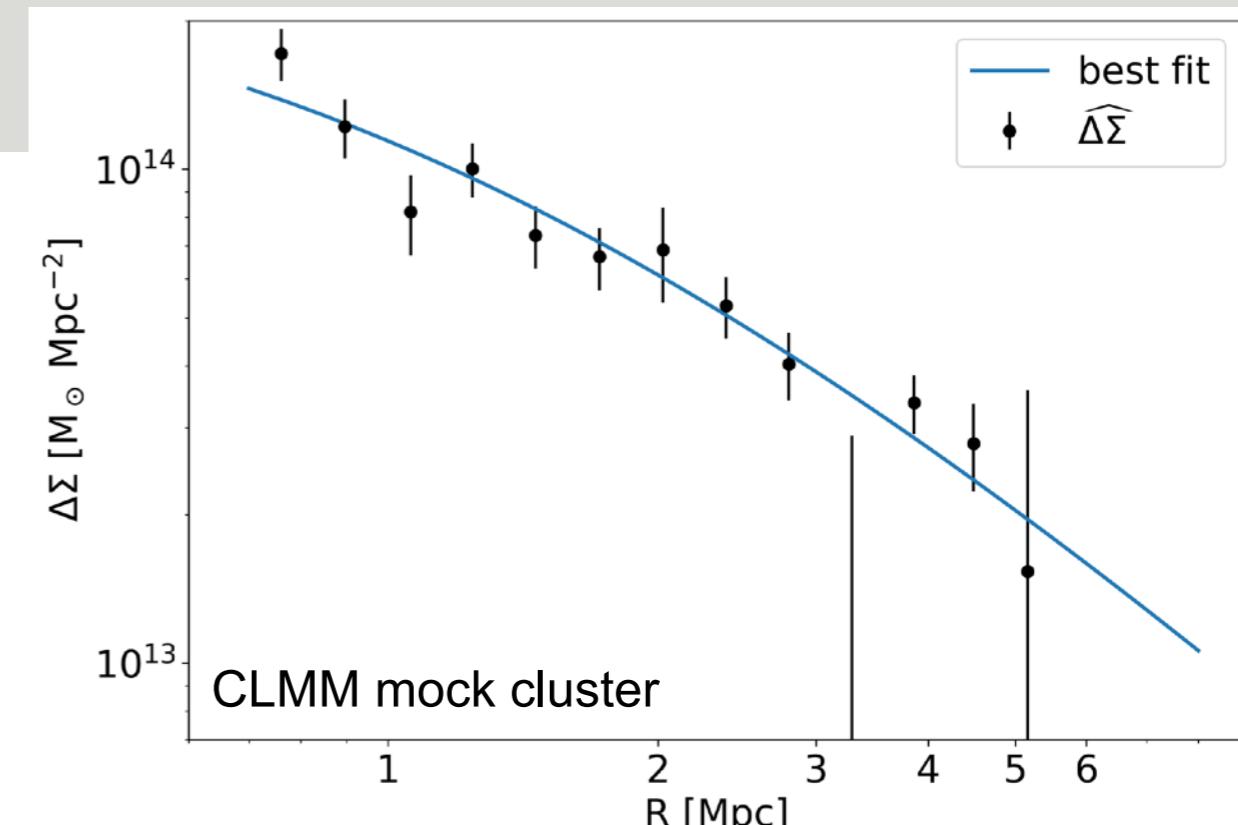
↑ ↑

Critical surface « tangential »
mass density

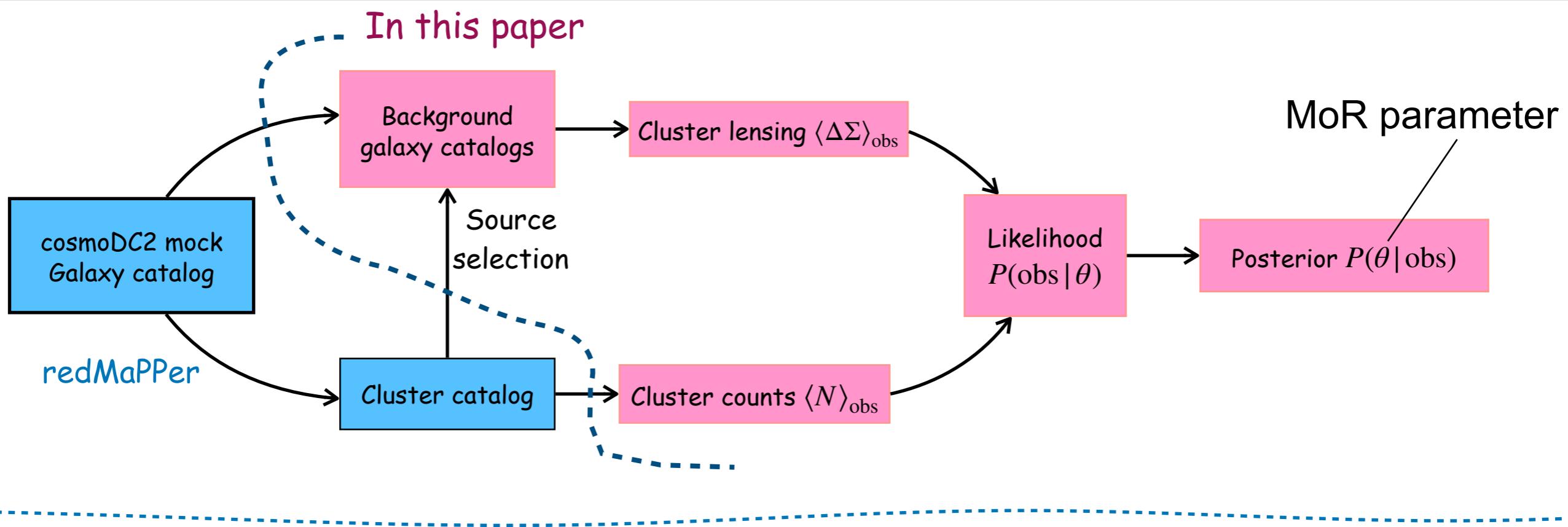
Model: $\Delta\Sigma(R) \rightarrow \Sigma(R) = \int d\text{LOS} \rho_{3d}(r)$

Fit $\Delta\Sigma(R) \rightarrow M_{\text{cluster}}$

Mass-proxy relation !



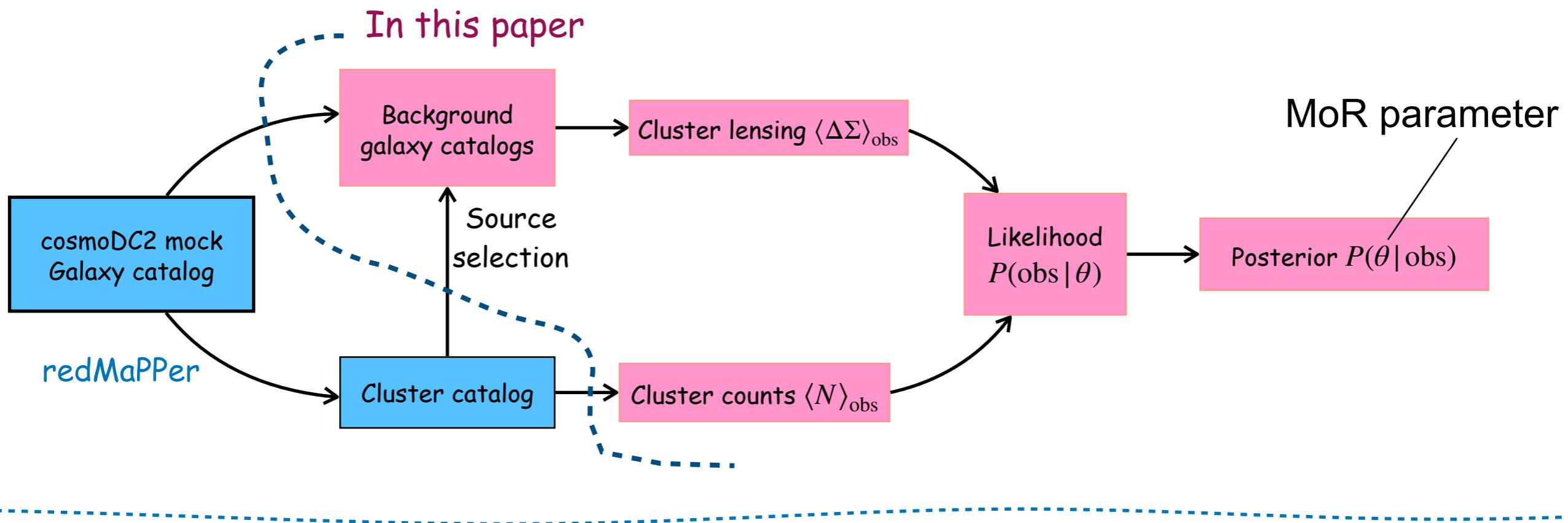
Paper's objectives



« Early » DESC CL end-to-end pipeline

- From galaxies to params.
- With DESC tools ([CLMM](#), [CCL](#), [ClEvaR](#))
- On DESC products (cosmoDC2)
- Combining CC + WL
- Help the design of the [Firecrown](#) likelihood
- [CLCosmo_Sim](#): CC+WL pipeline (public)

Paper's objectives



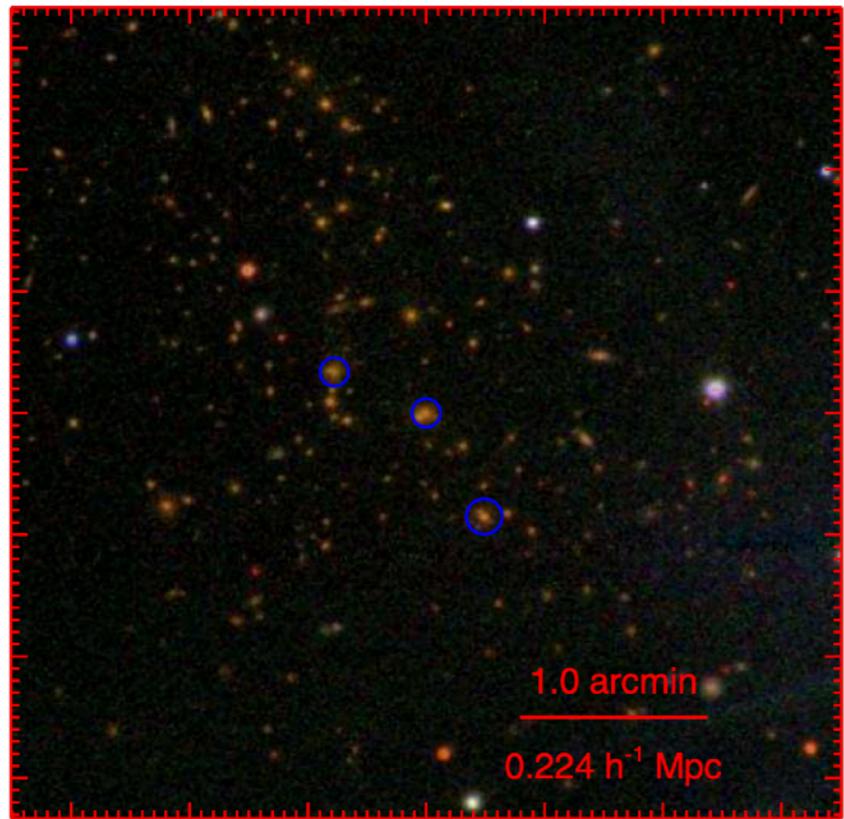
« Early » DESC CL end-to-end pipeline

- From galaxies to params.
- With DESC tools ([CLMM](#), [CCL](#), [ClEvaR](#))
- On DESC products (cosmoDC2)
- Combining CC + WL
- Help the design of the [Firecrown](#) likelihood
- [CLCosmo_Sim](#): CC+WL pipeline (public)

Study the MoR relation in DESC DC2 data

- DC2: Large simulation over 440 deg²
- cosmoDC2: extra-galactic (truth) catalog+PZ *add-ons*
- Cluster catalog: redMaPPer ([Rykoff+13](#))
- [CLCosmo_Sim_database](#): data vectors (only DESC members)

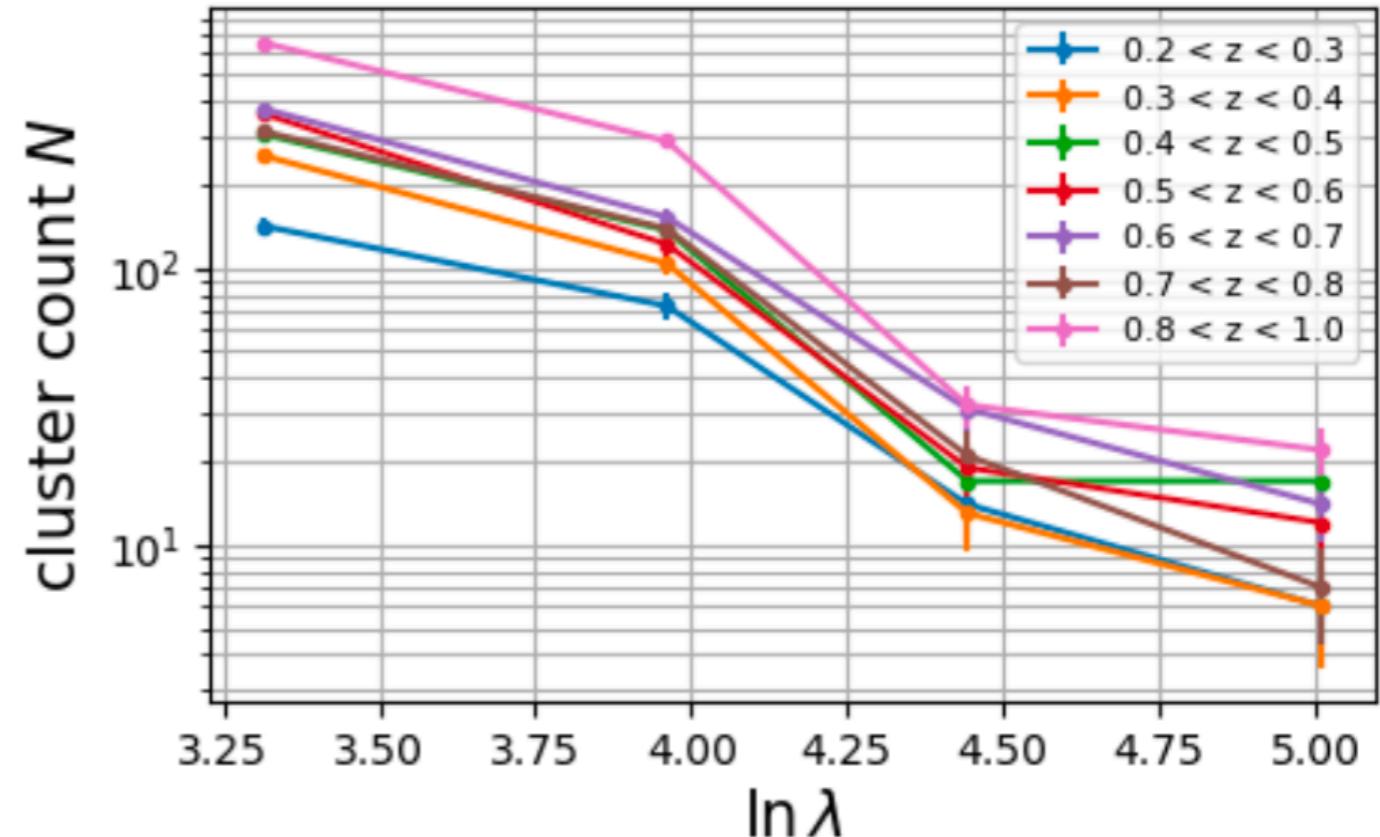
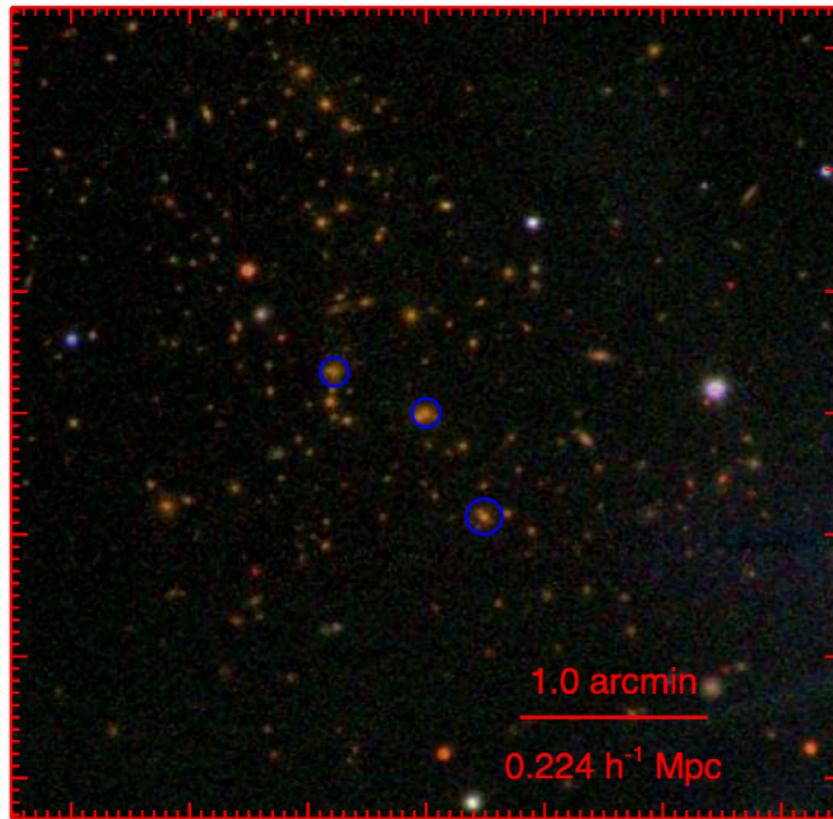
Data: LSST DESC DC2 simulations



Cluster catalog: redMaPPer (Rykoff+13)

- detect over densities of red-sequence galaxies
- For each redMaPPer selected clusters:
 - Assign richness $\lambda \sim \#$ of member galaxies
 - Cluster redshift
- $\sim 880,000$ clusters, $\lambda < 300$, $z < 1.15$
- Other cluster catalogs on DC2 (AMICO, YOLO-CL, WAZP)

Data: LSST DESC DC2 simulations



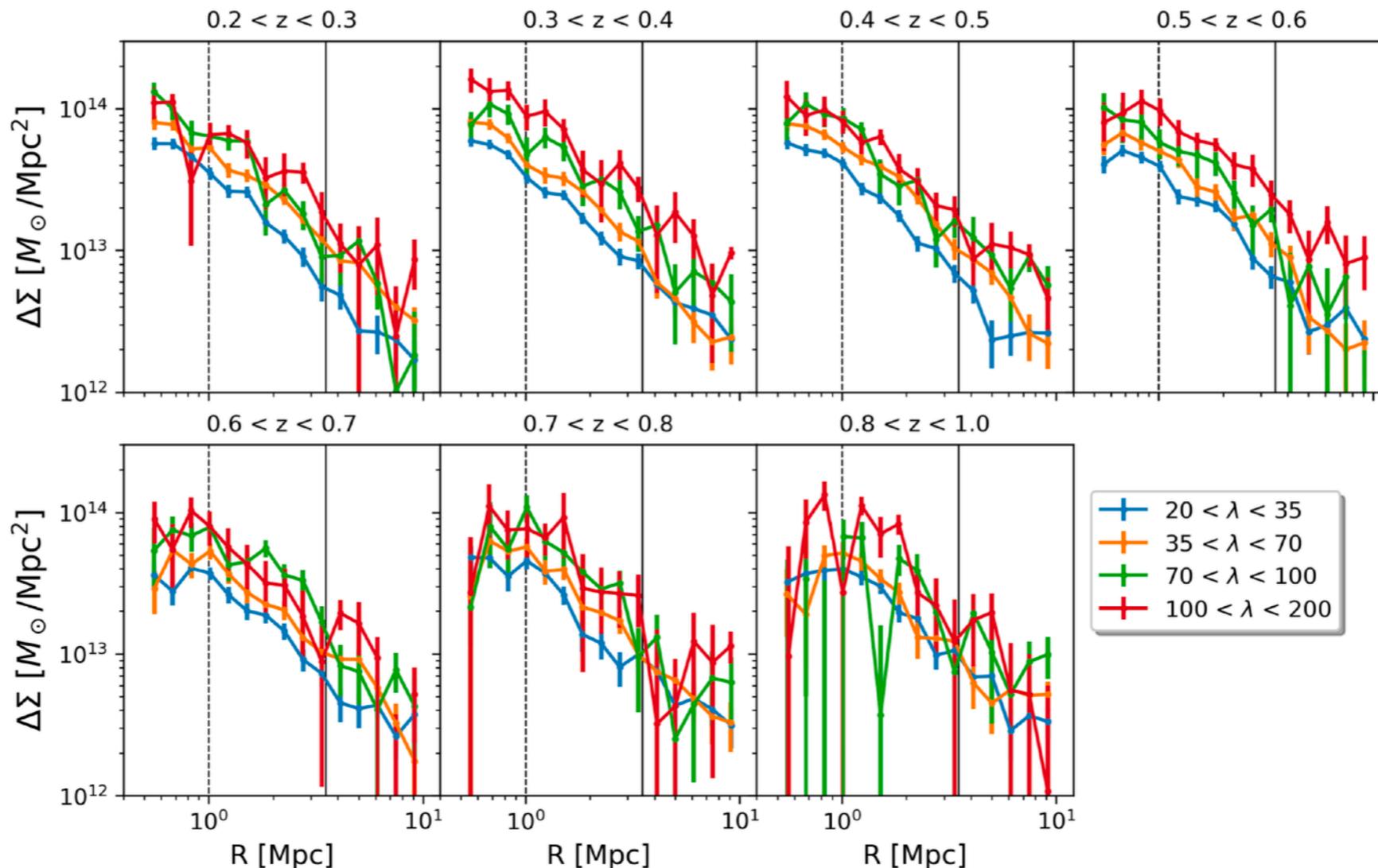
Cluster catalog: redMaPPer (Rykoff+13)

- detect over densities of red-sequence galaxies
- For each redMaPPer selected clusters:
 - Assign richness $\lambda \sim \#$ of member galaxies
 - Cluster redshift
- $\sim 880,000$ clusters, $\lambda < 300$, $z < 1.15$
- Other cluster catalogs on DC2 (AMICO, YOLO-CL, WAZP)

Summary statistics in this analysis

- 4x7 redshift-richness bins
- $20 < \lambda < 200 + 0.2 < z < 1$
- Log-spaced for richness
- $\Rightarrow 3,600$ clusters on 440 deg^2
- Study the mass-redshift dependency of the MoR

Data: LSST DESC DC2 simulations



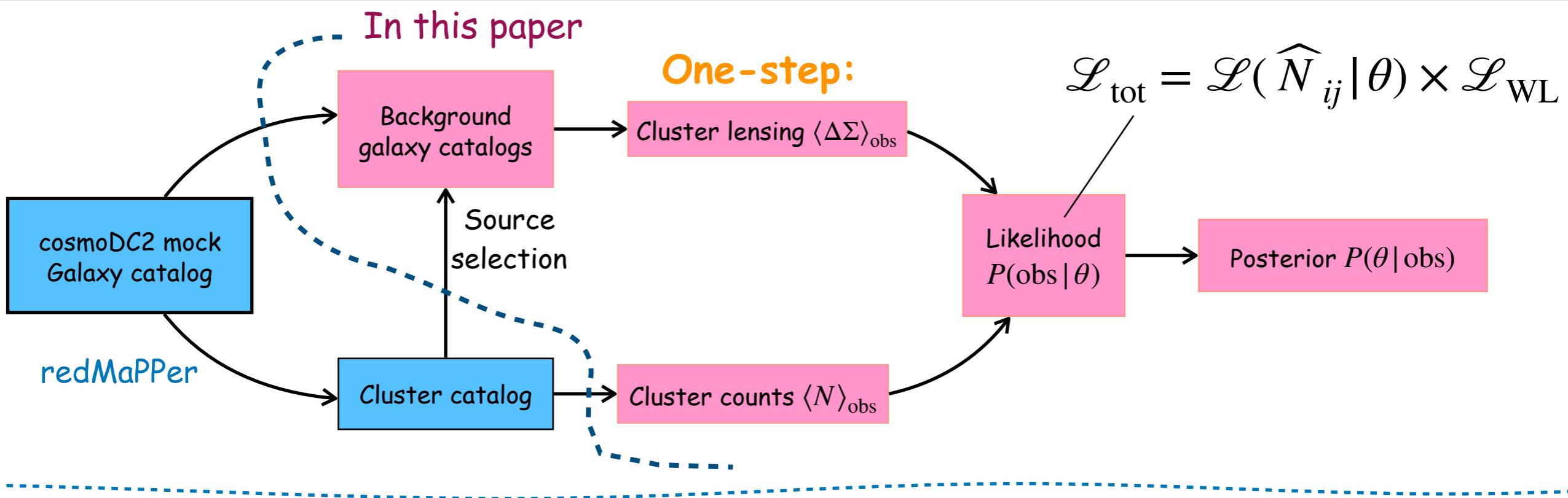
Source selection

- $i < 24.25 + r < 28$
- LSST-like density: 25 gal.arcmin-2
- Behind clusters: $z_{\text{gal}} > z_{\text{cl}} + 0.2$
- Baseline: true redshifts

Stacked cluster lensing profiles

- In richness-redshift bins
- 15 radial bins from 0.7 to 10 Mpc
- $R > 1$ Mpc (ray-tracing resolution, [Kovacs+21](#))
- Baseline: intrinsic shapes+local shear
- $\sigma_{\text{SN}} = 0.25 + \sigma_{\text{meas}} = 0$

Inference from CC+WL

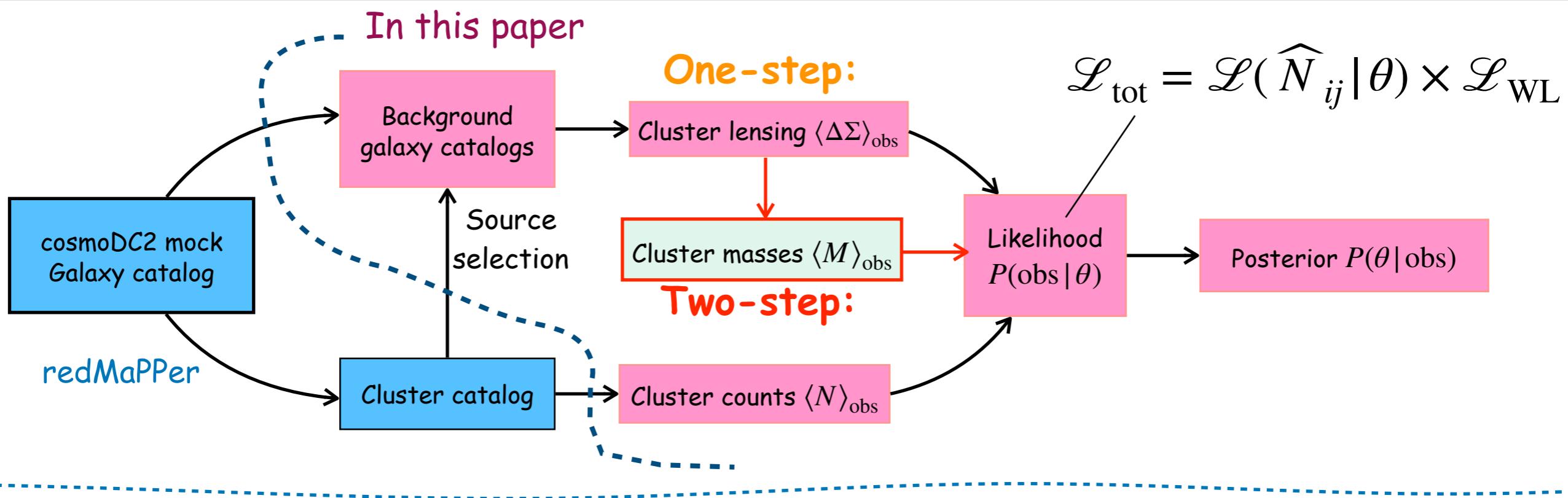


Two alternatives for WL

- **One-step:** use stacked profiles directly
 - flexibility to incorporate several systematic effects (mis-centering, selection biases) *forward* modeling the raw observables.

$$\mathcal{L}_{\text{WL}} = \mathcal{L}(\widehat{\Delta\Sigma}_{ij} | \theta)$$

Inference from CC+WL



Two alternatives for WL

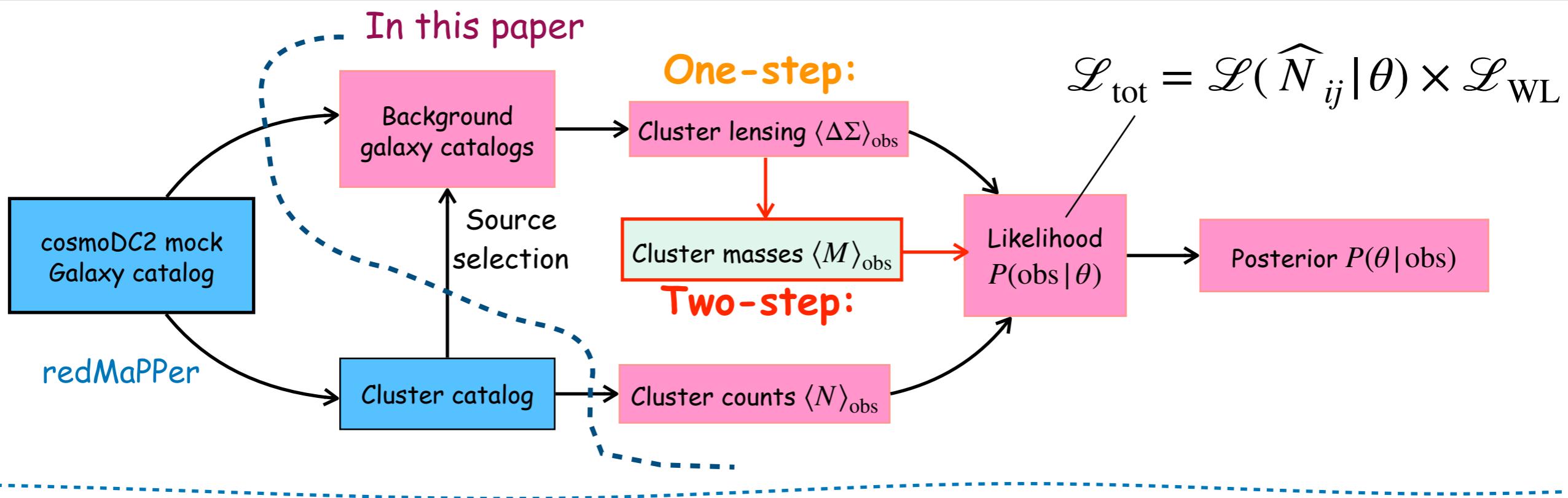
- **One-step:** use stacked profiles directly
 - flexibility to incorporate several systematic effects (mis-centering, selection biases) *forward* modeling the raw observables.
- **Two-step:** First fit the mean mass
 - splitting the problem ! Simplifies integrals and computational times

$$\mathcal{L}_{\text{WL}} = \mathcal{L}(\widehat{\Delta\Sigma}_{ij}|\theta)$$

Or

$$\mathcal{L}_{\text{WL}} = \mathcal{L}(\widehat{M}_{ij}|\theta)$$

Inference from CC+WL



Two alternatives for WL

- **One-step:** use stacked profiles directly
 - flexibility to incorporate several systematic effects (mis-centering, selection biases) *forward* modeling the raw observables.
- **Two-step:** First fit the mean mass
 - splitting the problem ! Simplifies integrals and computational times

$$\mathcal{L}_{\text{WL}} = \mathcal{L}(\widehat{\Delta\Sigma}_{ij}|\theta)$$

Or

$$\mathcal{L}_{\text{WL}} = \mathcal{L}(\widehat{M}_{ij}|\theta)$$

We can now discuss the modeling ...

Modeling for the mass-richness relation

Log-normal distribution

$$P(\ln \lambda | m, z) \propto \exp \left\{ -\frac{[\ln \lambda - \langle \ln \lambda | m, z \rangle]^2}{2\sigma_{\ln \lambda | m, z}^2} \right\}$$

Mean

$$\underline{\ln \lambda_0} + \underline{\mu_z} \log \left(\frac{1+z}{1+z_0} \right) + \underline{\mu_m} \log_{10} \left(\frac{m}{m_0} \right)$$

Variance

$$\underline{\sigma_{\ln \lambda_0}} + \underline{\sigma_z} \log \left(\frac{1+z}{1+z_0} \right) + \underline{\sigma_m} \log_{10} \left(\frac{m}{m_0} \right)$$

Modeling choices

- « Forward » modeling $P(\ln \lambda | m, z)$, parametrization from [Murata+18](#)
- Easier to implement in CC analyses than $P(\ln M | \lambda, z)$
- Log-normal relation, 6 free params.
- $z_0 = 0.5$ and $\log_{10}(m_0/M_\odot) = 14.3$
- Possible redshift evolution μ_z and σ_z

Modeling for cluster count and lensing

Modeling choices

- Fixed [Despali+15](#) halo mass function (fiducial cosmoDC2 cosmology)
- Selection function $\Phi(m, \lambda, z)$:
 - redMaPPer performance (false detection, incompleteness)
 - Calibrated by matching with DM halos
 - Details in Ricci et al. in prep.
- Mass-richness relation
- WL baseline: one-halo regime modeled by a NFW profile, [Duffy+08](#) concentration-mass relation, consider only $R < [1,3.5]$ Mpc

Cluster count

$$N_{ij}^{\text{th}}(\theta) = \int_{z_i}^{z_{i+1}} dz \int_{\lambda_j}^{\lambda_{j+1}} d\lambda \int_{m_{\min}}^{+\infty} dm \times$$
$$\frac{d^2N(m, z)}{dm dz} \Phi(m, \lambda, z) P(\lambda | m, z)$$

HMF selection function Mass-richness
relation

Weak Lensing

$$\Delta\Sigma_{ij}^{\text{th}}(\vec{\theta}) \text{ or } M_{ij}^{\text{th}}(\vec{\theta})$$

Modeling for cluster count and lensing

Modeling choices

- Fixed [Despali+15](#) halo mass function (fiducial cosmoDC2 cosmology)
- Selection function $\Phi(m, \lambda, z)$:
 - redMaPPer performance (false detection, incompleteness)
 - Calibrated by matching with DM halos
 - Details in Ricci et al. in prep.
- Mass-richness relation
- WL baseline: one-halo regime modeled by a NFW profile, [Duffy+08](#) concentration-mass relation, consider only $R < [1,3.5]$ Mpc

Cluster count

$$N_{ij}^{\text{th}}(\theta) = \int_{z_i}^{z_{i+1}} dz \int_{\lambda_j}^{\lambda_{j+1}} d\lambda \int_{m_{\min}}^{+\infty} dm \times \frac{d^2N(m, z)}{dm dz} \Phi(m, \lambda, z) P(\lambda | m, z)$$



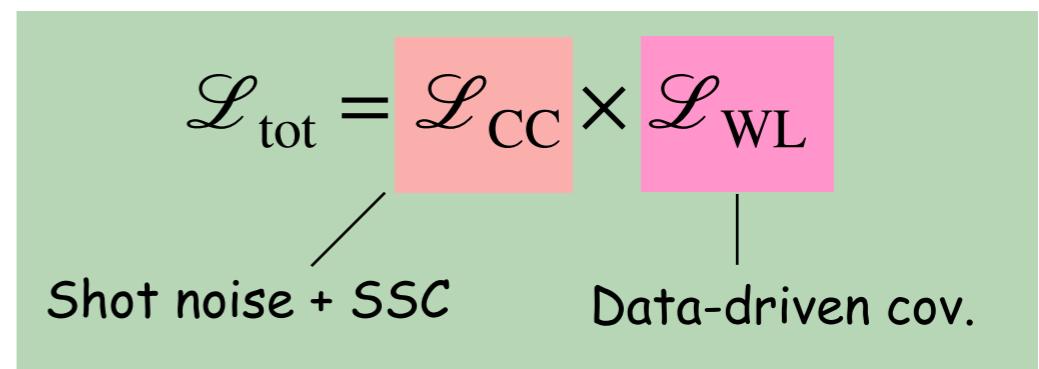
Weak Lensing

$$\Delta\Sigma_{ij}^{\text{th}}(\vec{\theta}) \text{ or } M_{ij}^{\text{th}}(\vec{\theta})$$

Constrain MoR

- Combine likelihoods CC+WL (Gaussian)
- CC: SSC theoretical prediction using [PySSC](#)
- WL profiles: data-driven bootstrap covariance
- Masses: errors from mass measurement

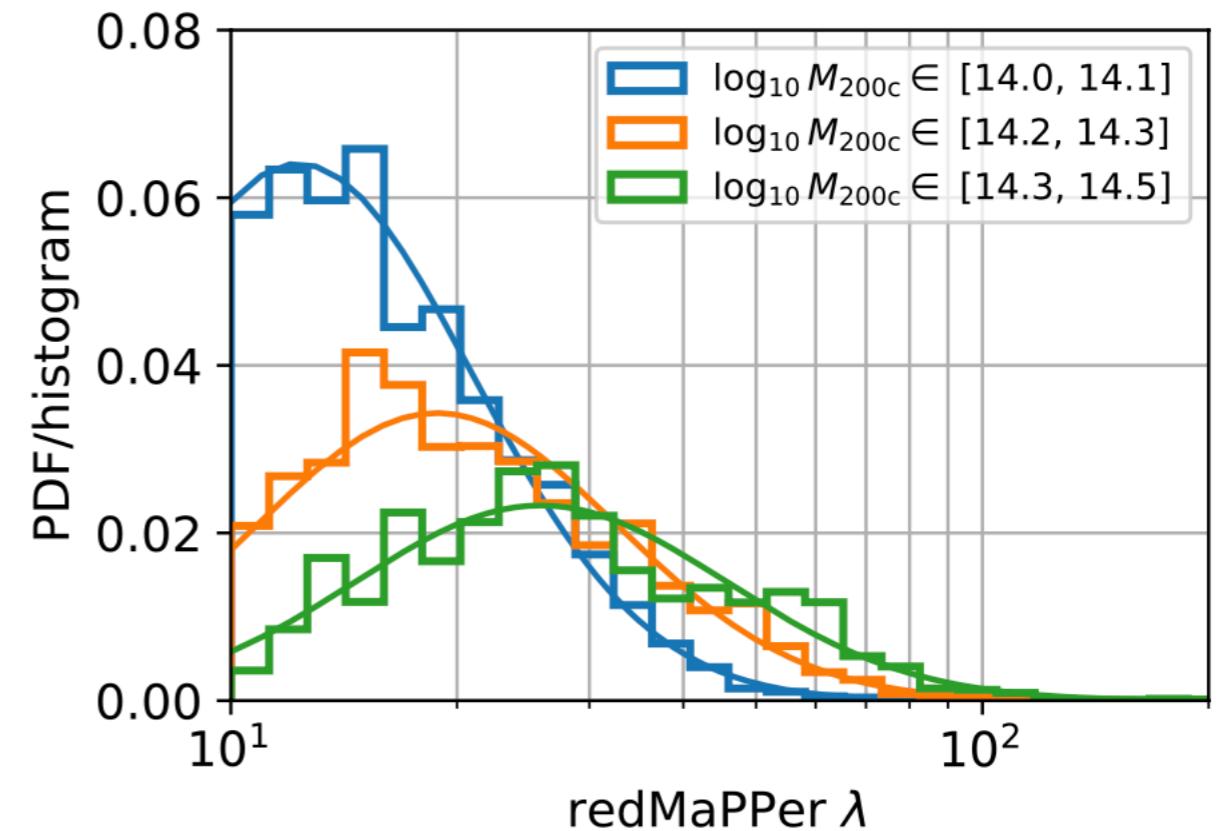
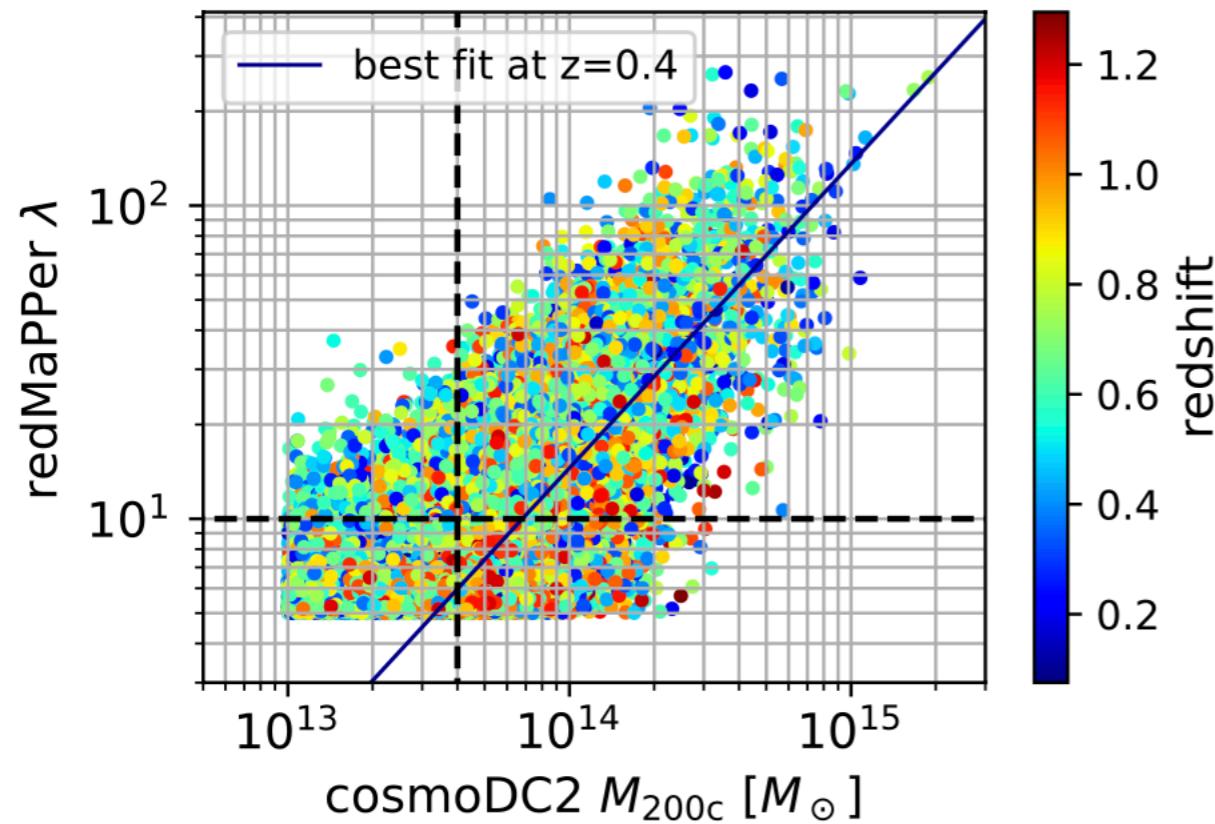
$$\mathcal{L}_{\text{tot}} = \mathcal{L}_{\text{CC}} \times \mathcal{L}_{\text{WL}}$$



Shot noise + SSC

Data-driven cov.

Fiducial scaling relation?



No « input » mass-richness relation in DC2

- Can be calibrated by matching halos to redMaPPer clusters (CIEVaR)
- Membership matching $\Rightarrow m_k, \lambda_k, z_k$
- We use the unbinned likelihood (truncated gaussians)

→ Used to validate our results !

$$\mathcal{L}_{\text{fid}}(\text{MoR} \mid \text{data}) = \prod_k^{N_{\text{match}}} P(\ln \lambda_k \mid m_k, z_k)$$

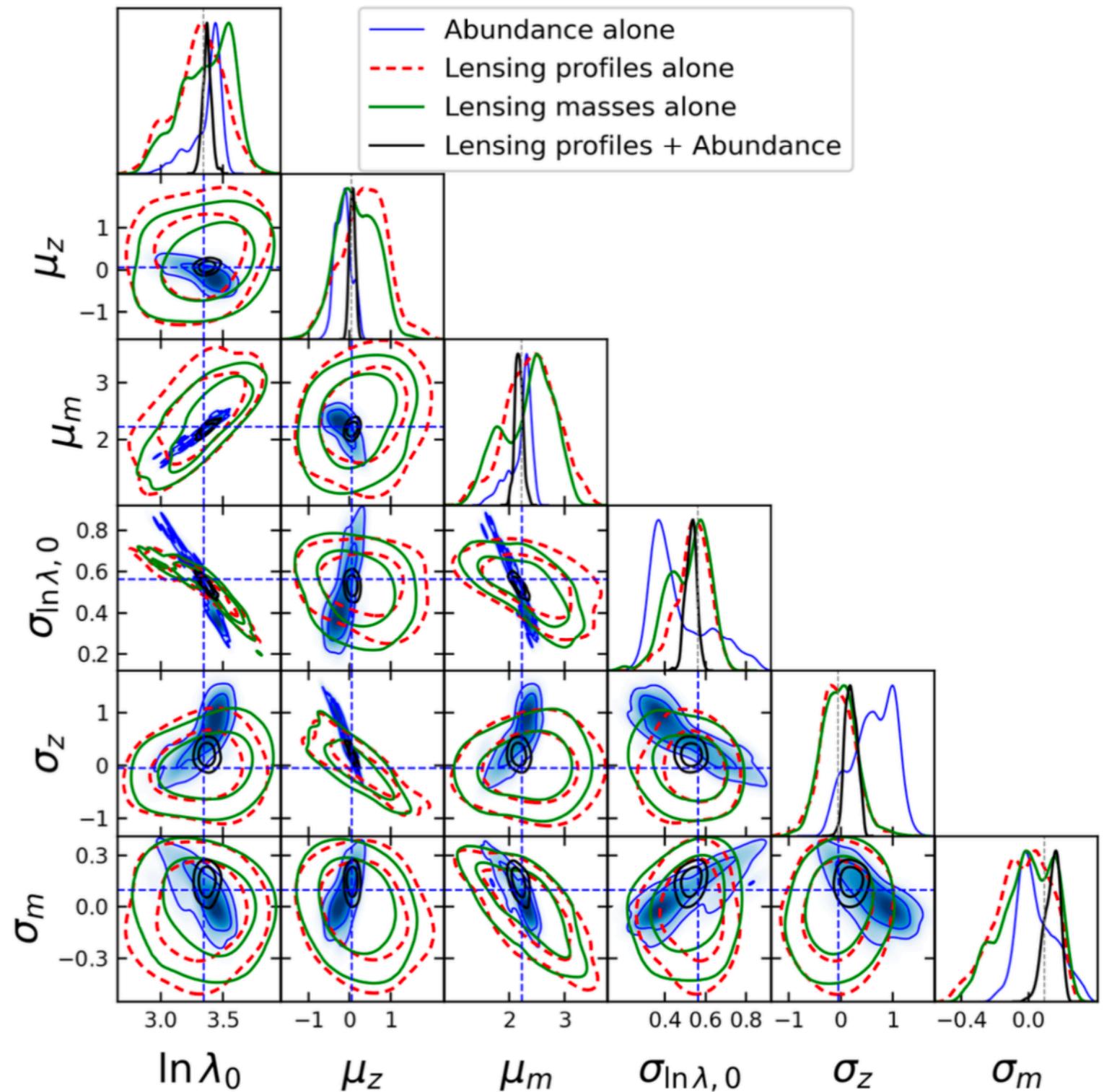
Baseline analysis

Separate Count and lensing

- Different correlations and error
- Compatible constraints at 1σ
- Compatible with « fiducial » relation (using the cluster-halo matched catalog)

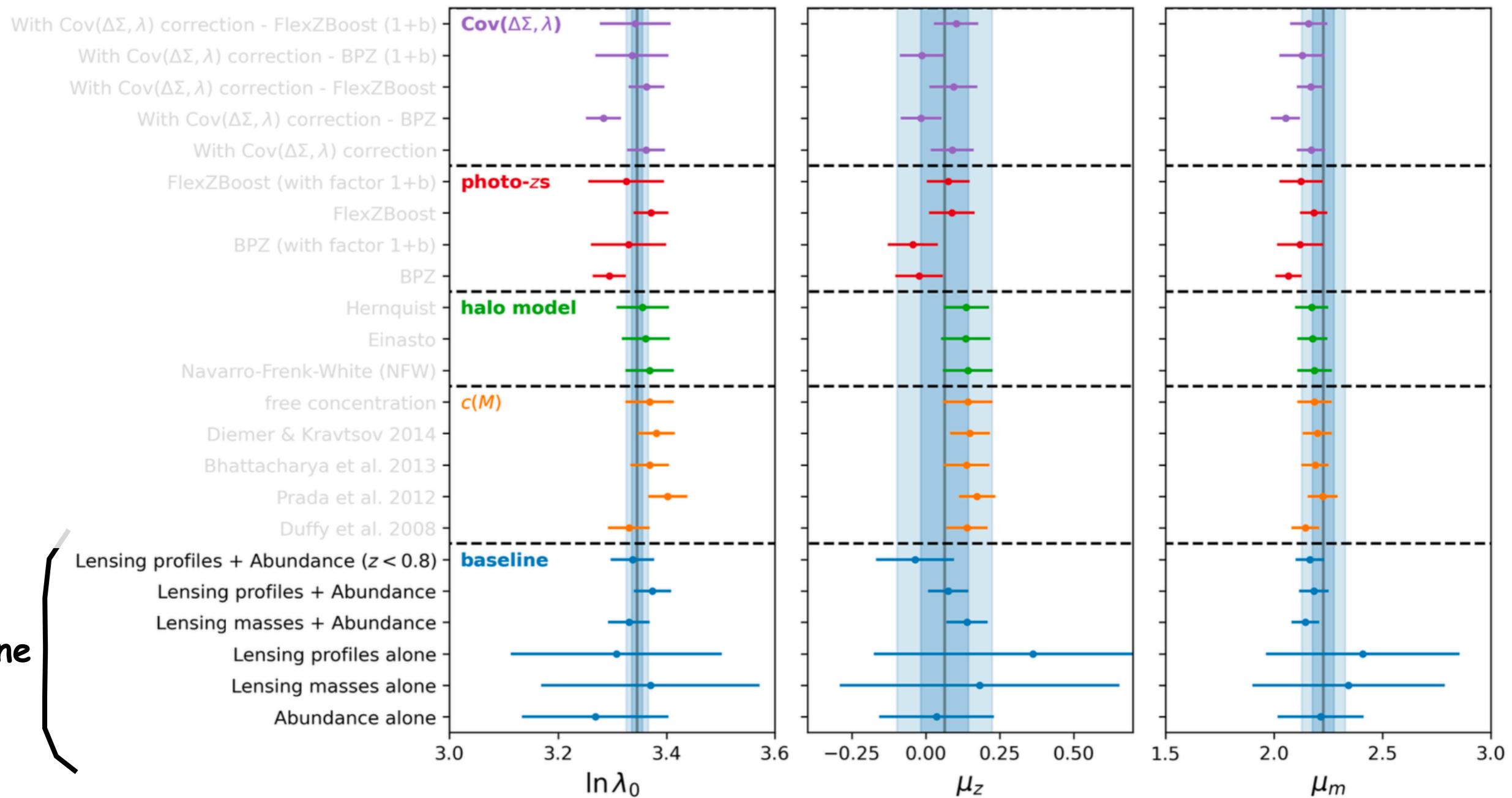
Joint analysis

- Combination breaks degeneracy between params.
- Increase precision significantly
- Recovered fiducial at $< 2\sigma$
- First CC+WL constraints of redMaPPer MoR in DESC DC2 !



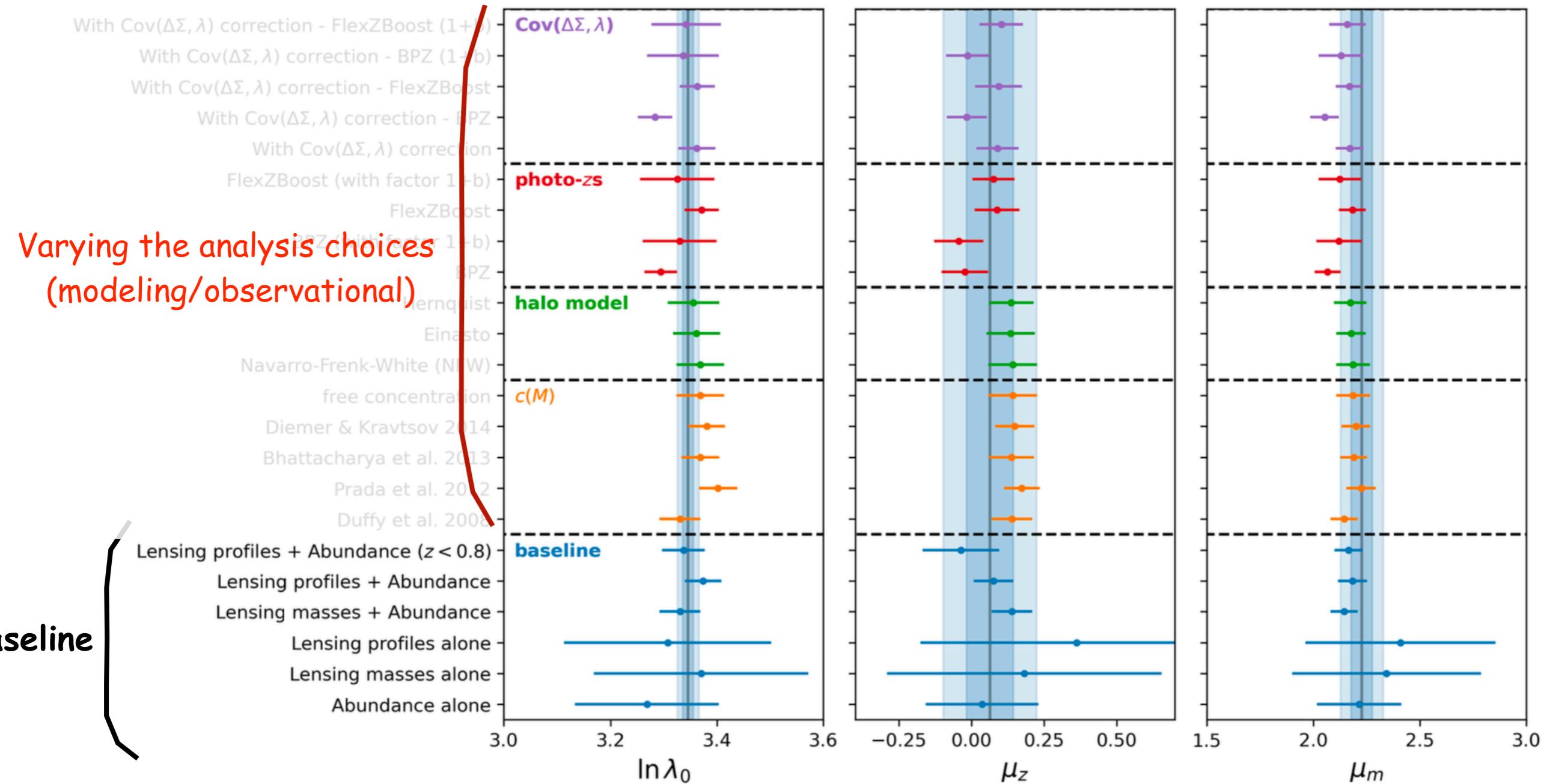
Robustness of MoR in LSST DESC DC2

Goal 2: Test its robustness to modeling choices and observational systematics



Robustness of MoR in LSST DESC DC2

Goal 2: Test its robustness to modeling choices and observational systematics



Robustness of MoR in LSST DESC DC2

Goal 2: Test its robustness to modeling choices and observational systematics

- WL impacted by several systematics (modeling choices, Observational systematics)
- For stage-IV surveys: LSST-like precision of lensing data + large cluster samples, controlling these systematics uncertainties are a big concern

Robustness of MoR in LSST DESC DC2

Goal 2: Test its robustness to modeling choices and observational systematics

- WL impacted by several systematics (modeling choices, Observational systematics)
- For stage-IV surveys: LSST-like precision of lensing data + large cluster samples, controlling these systematics uncertainties are a big concern

Modeling choices: Cluster density

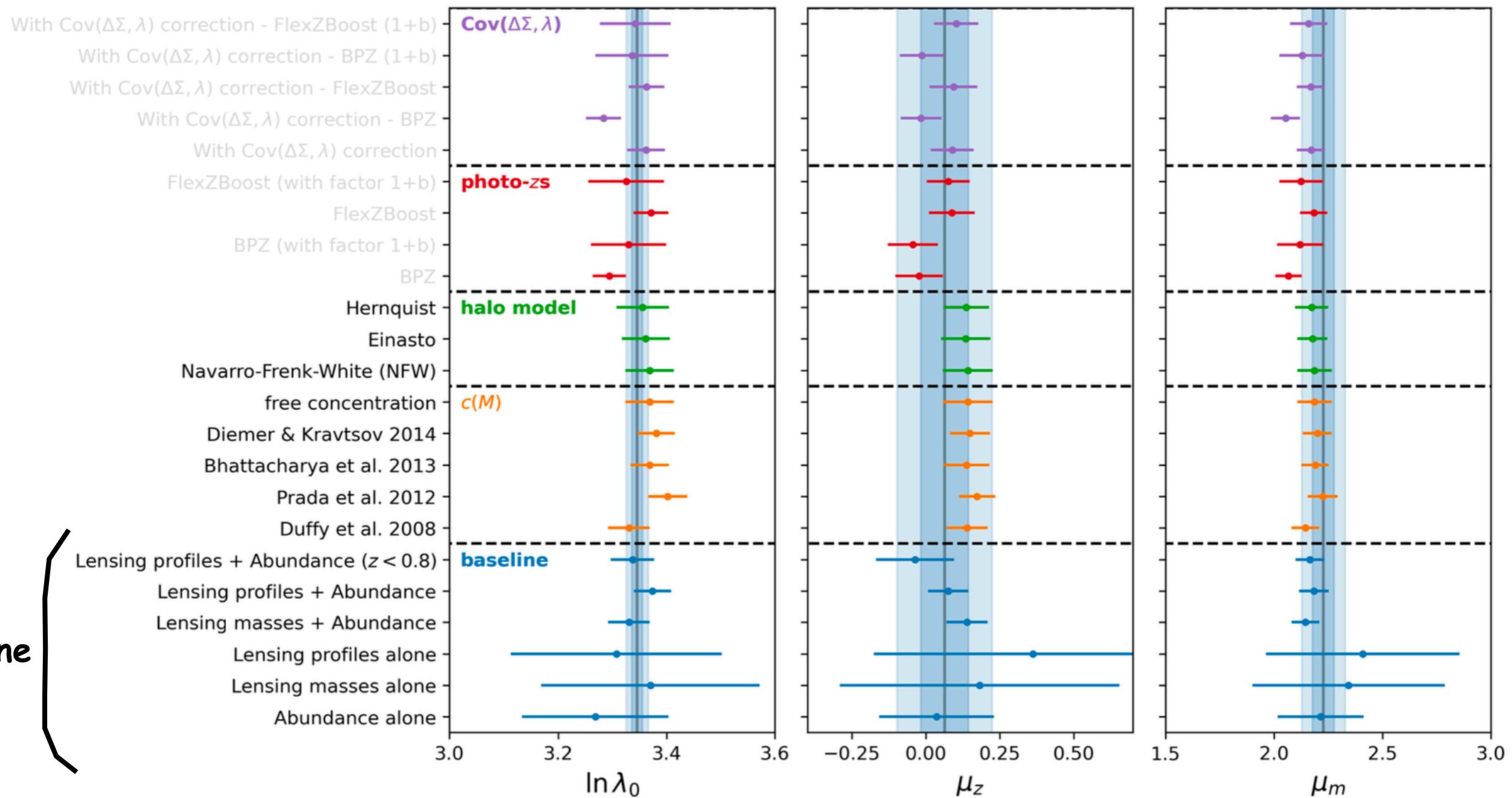
- Different ρ_{3d} exist in the literature (NFW, Einasto, Hernquist)
- Params.: mass M and the concentration c
- M and c appear be correlated in simulations
- c can be set apriori via a $c(M, z)$ relation
- Instead of fitting it jointly with M !
- Again, some $c(M, z)$ exist in the literature

$$\Delta\Sigma(R) \text{ depends on } \int_{-\infty}^{+\infty} dz \rho_{3d}(r)$$

Modelling

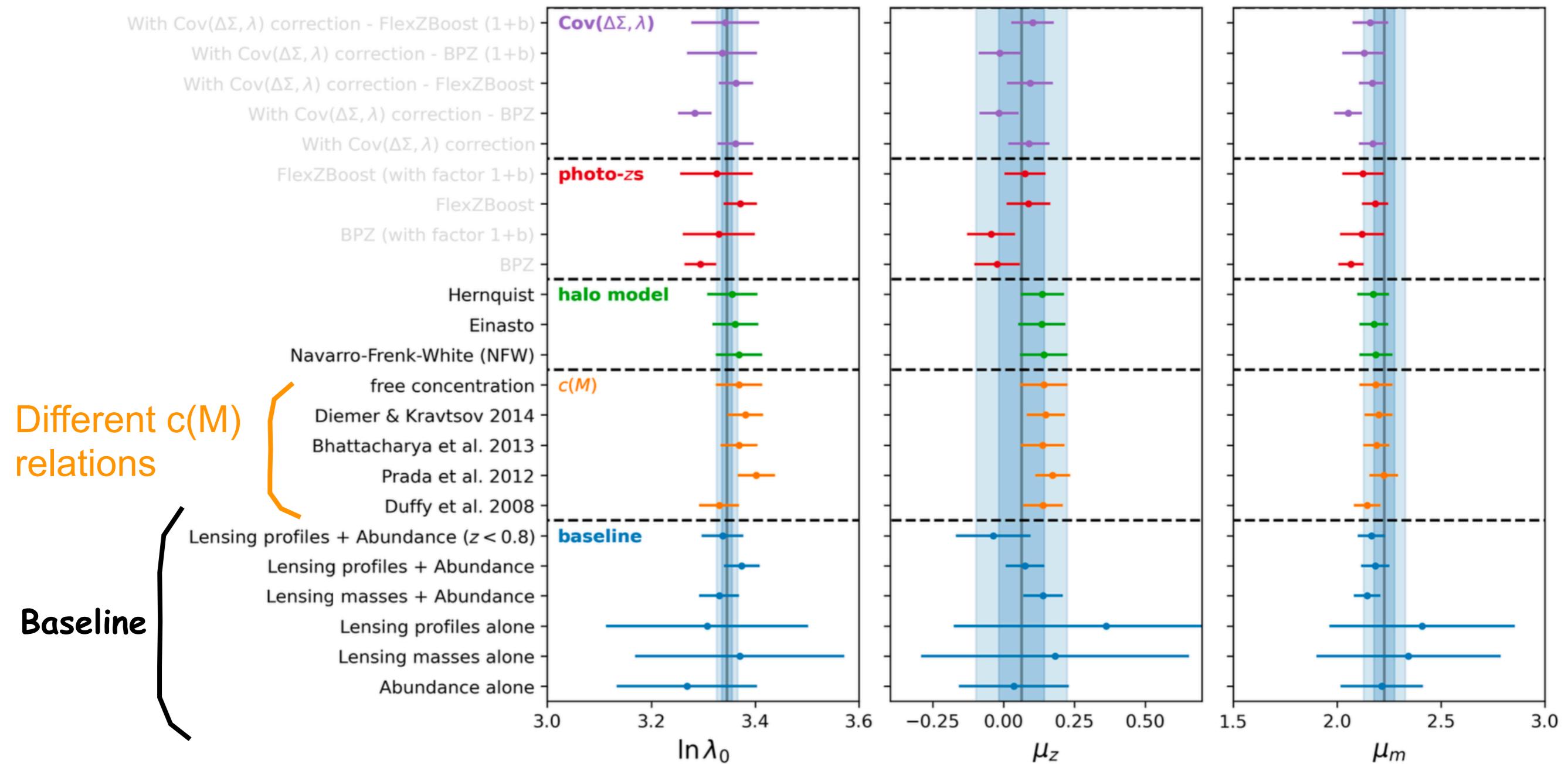
Robustness of MoR in LSST DESC DC2

Goal 2: Test its robustness to modeling choices and observational systematics



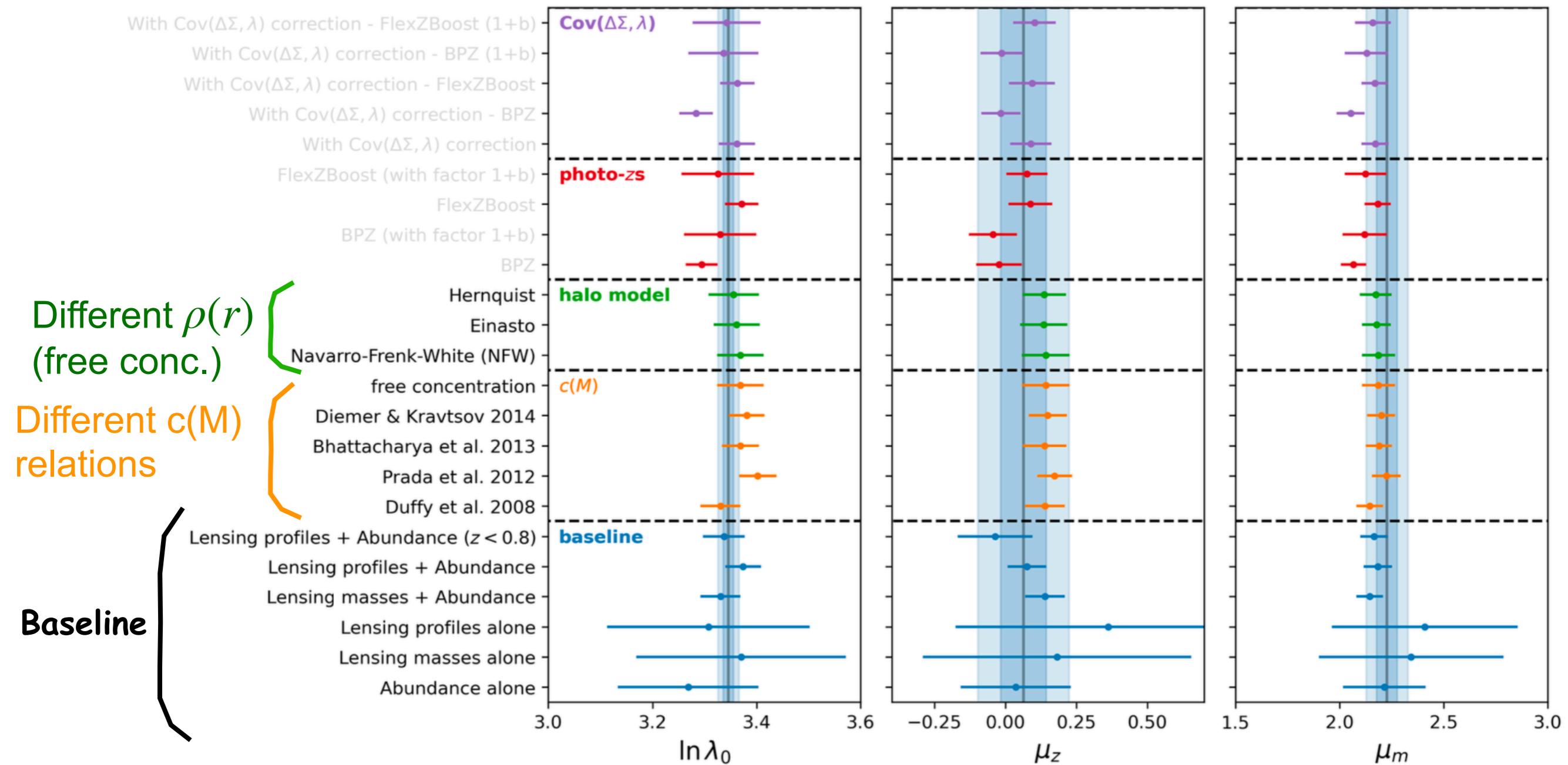
Robustness of MoR in LSST DESC DC2

Goal 2: Test its robustness to modeling choices and observational systematics



Robustness of MoR in LSST DESC DC2

Goal 2: Test its robustness to modeling choices and observational systematics



On the modelling side

$$\Delta\Sigma(R) \text{ depends on } \int_{-\infty}^{+\infty} dz \rho_{3d}(r)$$

Modelling

On the data side

$$\widehat{\Delta\Sigma}(R, z_l) = \langle \Sigma_{\text{crit}}(z_{\text{gal}}, z_l) \epsilon_+^{\text{obs}} \rangle$$

1. Measured redshift

2. Selection biases in cluster finder algorithms

Measured shapes

On the modelling side

$$\Delta\Sigma(R) \text{ depends on } \int_{-\infty}^{+\infty} dz \rho_{3d}(r)$$

Modelling



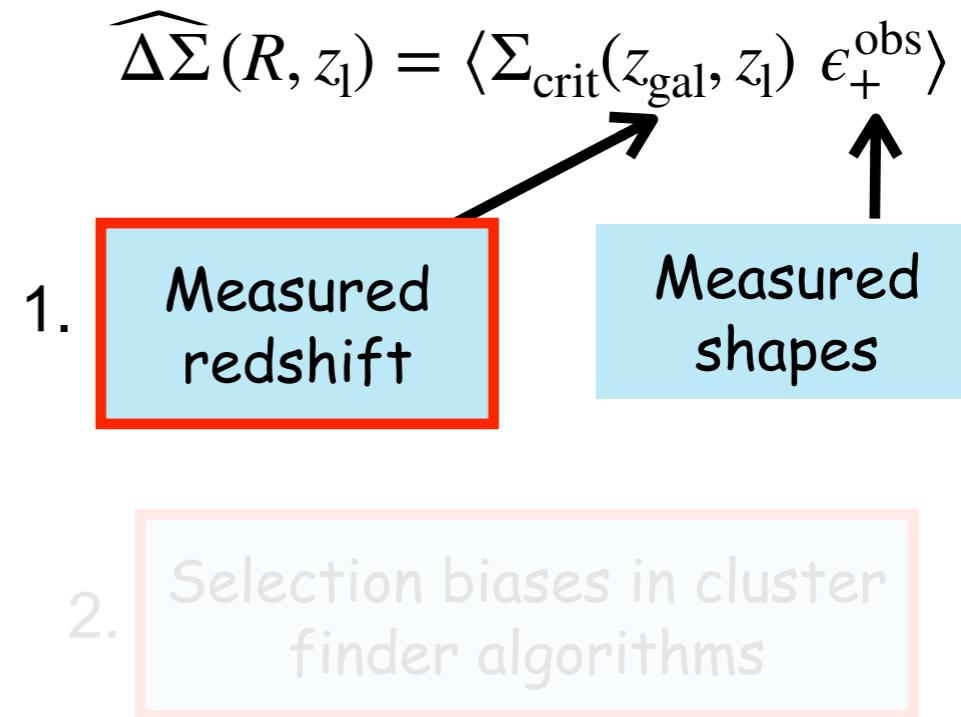
On the data side

$$\widehat{\Delta\Sigma}(R, z_l) = \langle \Sigma_{\text{crit}}(z_{\text{gal}}, z_l) \epsilon_+^{\text{obs}} \rangle$$

1. Measured redshift

2. Selection biases in cluster finder algorithms

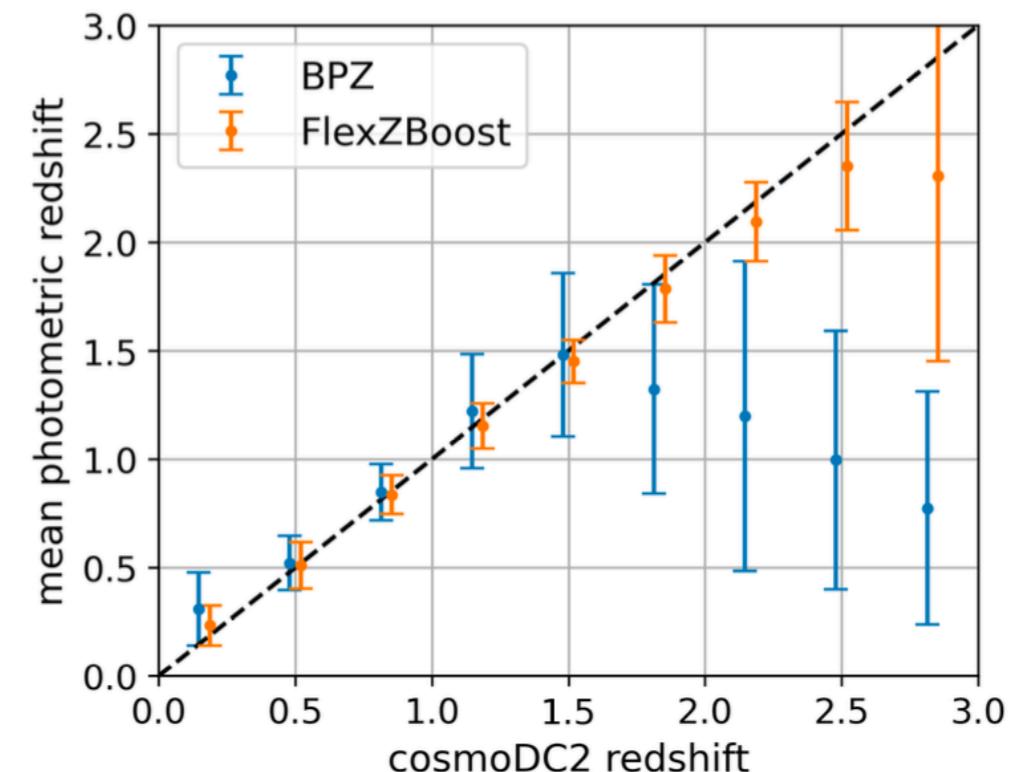
Measured shapes



Photometric redshifts of source galaxies

PZ runs in cosmoDC2

- FlexZBoost: ML-based, will work with deep spectro. datasets => $p(z | m)$
- BPZ: SED template + galaxy type
- We use the first released version
 - Flex: « optimistic » trained with $i < 25$ galaxies
 - BPZ: « discreteness » in the color-redshift space of cosmoDC2 galaxies -> pessimistic
 - No quality cuts applied ! Worst case scenario
- How does it impact WL meas. ?



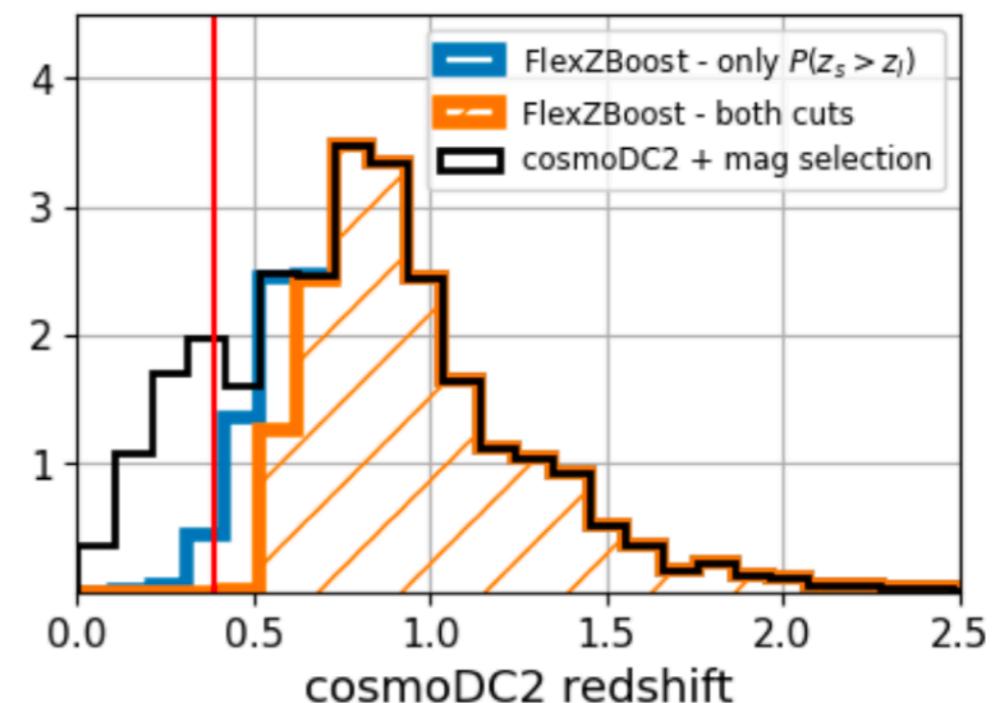
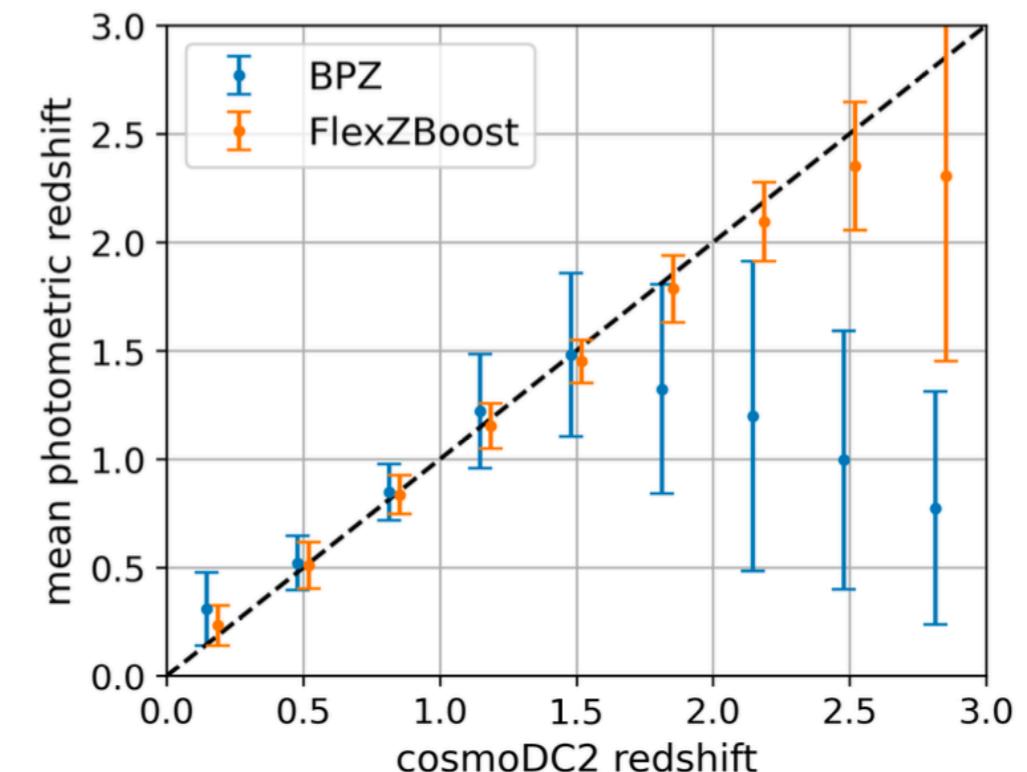
Photometric redshifts of source galaxies

PZ runs in cosmoDC2

- FlexZBoost: ML-based, will work with deep spectro. datasets => $p(z | m)$
- BPZ: SED template + galaxy type
- We use the first released version
 - Flex: « optimistic » trained with $i < 25$ galaxies
 - BPZ: « discreteness » in the color-redshift space of cosmoDC2 galaxies -> pessimistic
 - No quality cuts applied ! Worst case scenario
- How does it impact WL meas. ?

1. Source selection

$$\langle z_{\text{gal}} \rangle > z_{\text{cl}} + \text{offset}$$
$$P(z_{\text{gal}} > z_{\text{cl}}) > \text{offset}'$$



Photometric redshifts of source galaxies

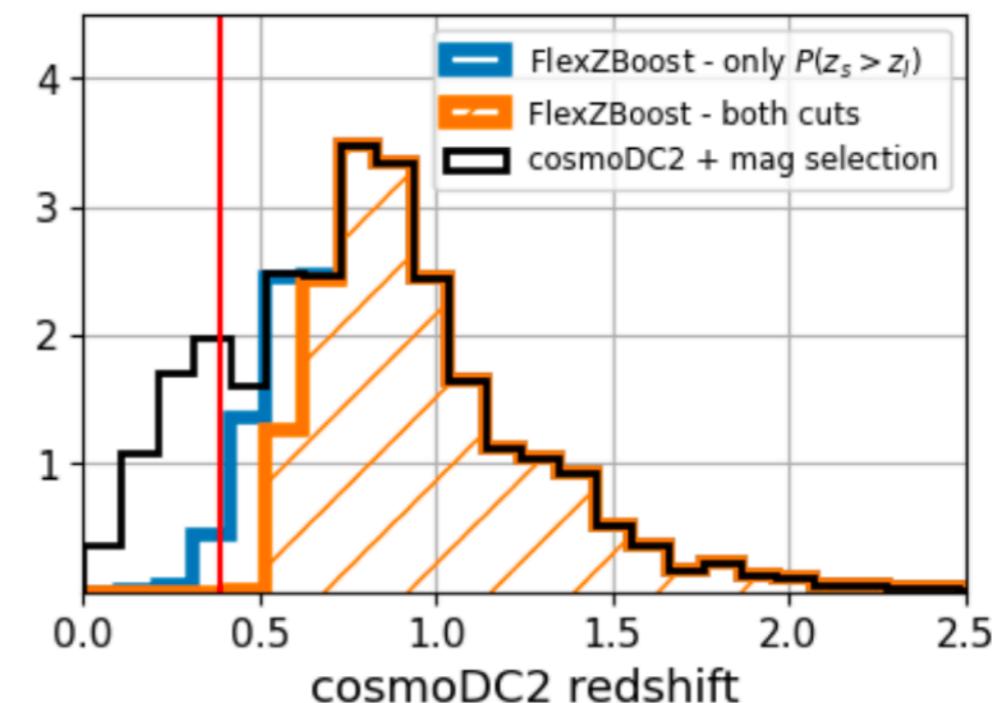
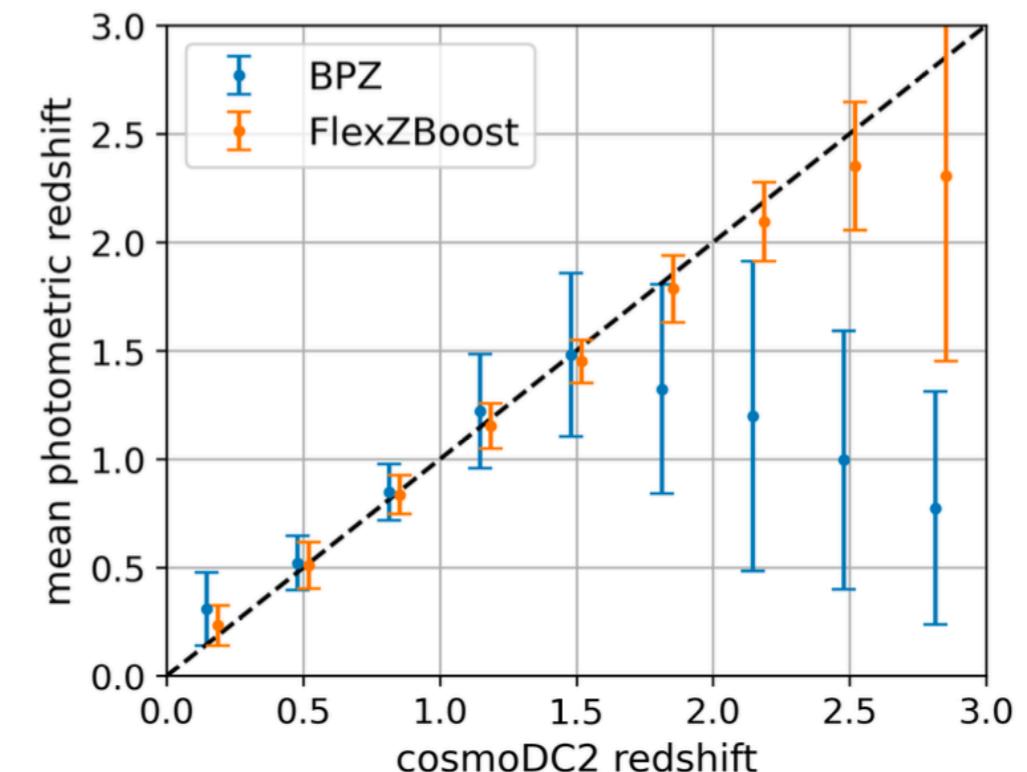
PZ runs in cosmoDC2

- FlexZBoost: ML-based, will work with deep spectro. datasets => $p(z | m)$
- BPZ: SED template + galaxy type
- We use the first released version
 - Flex: « optimistic » trained with $i < 25$ galaxies
 - BPZ: « discreteness » in the color-redshift space of cosmoDC2 galaxies -> pessimistic
 - No quality cuts applied ! Worst case scenario
- How does it impact WL meas. ?

1. Source selection → $\langle z_{\text{gal}} \rangle > z_{\text{cl}} + \text{offset}$
 $P(z_{\text{gal}} > z_{\text{cl}}) > \text{offset}'$

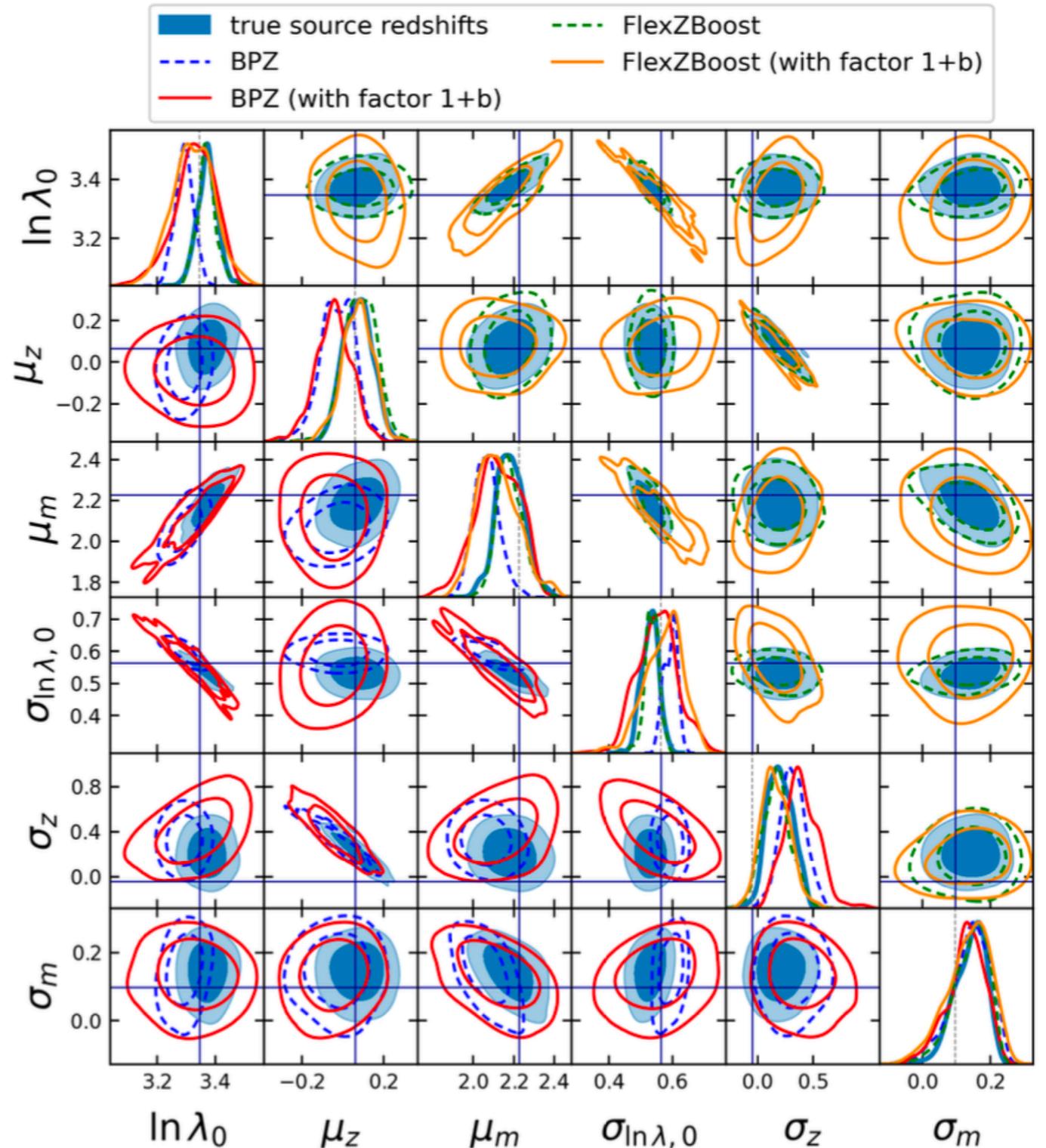
2. WL lens-source weights

$$w_{ls}^{1/2} \propto \int_{z_l}^{+\infty} dz_s \ p(z_s) \Sigma_{\text{crit}}(z_s, z_l)^{-1}$$
$$\propto \frac{D_{ls}}{D_s D_l}$$



Results

- FLEXZBoost: perfect agreement with true redshift case (baseline)
- BPZ: shift at most 1σ in the normalization $\ln \lambda_0$

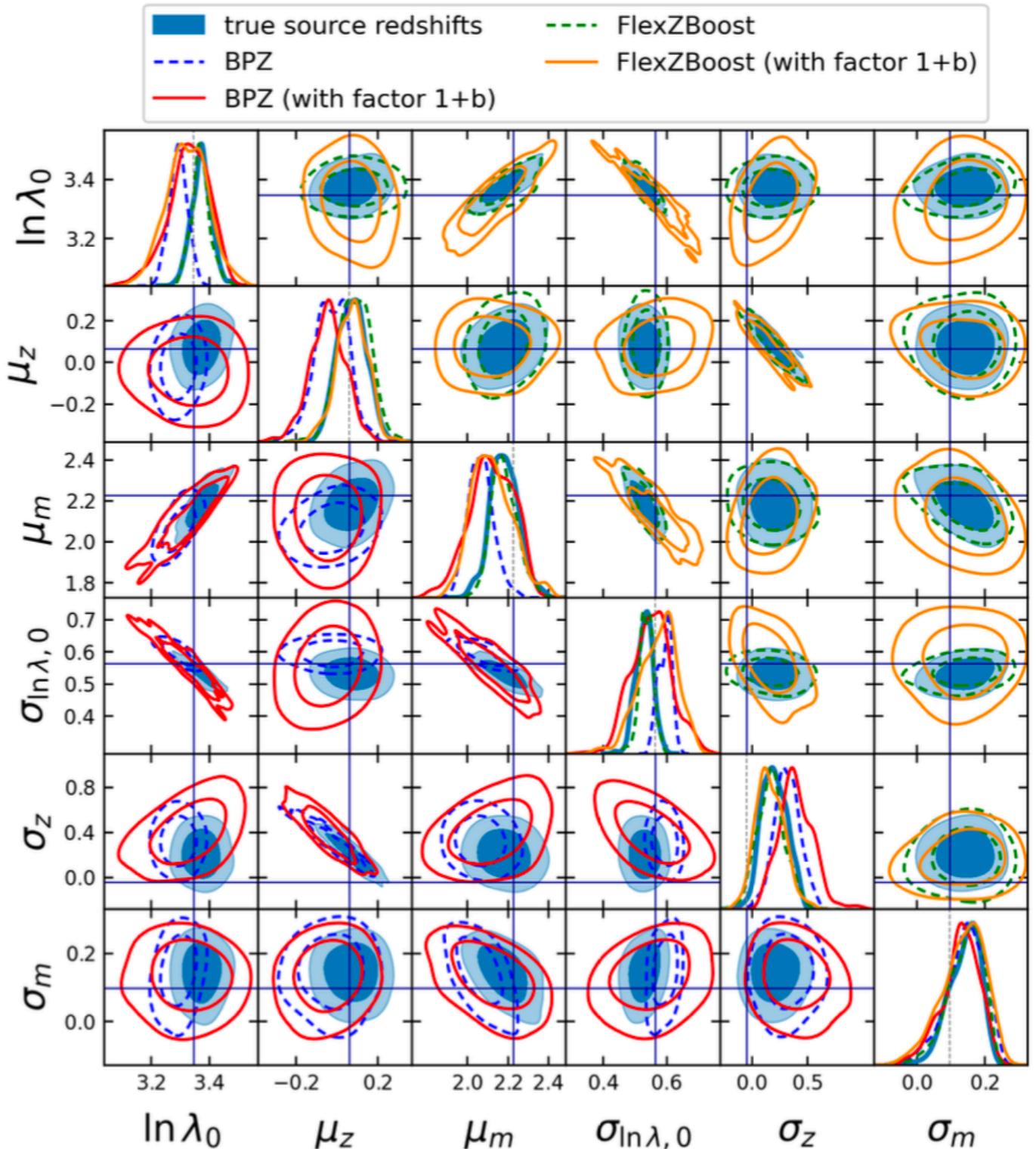


Results

- FFlexZBoost: perfect agreement with true redshift case (baseline)
- BPZ: shift at most 1σ in the normalization $\ln \lambda_0$
- We can correct the model for possible systematic PZ bias $1+b$ ([Simet+16](#))
- And use CC+WL to calibrate this bias

$$\Delta\Sigma_{ij}^{\text{corr}} = (1 + b)\Delta\Sigma_{ij}$$

|
Uncorrected PZ
systematics



Results

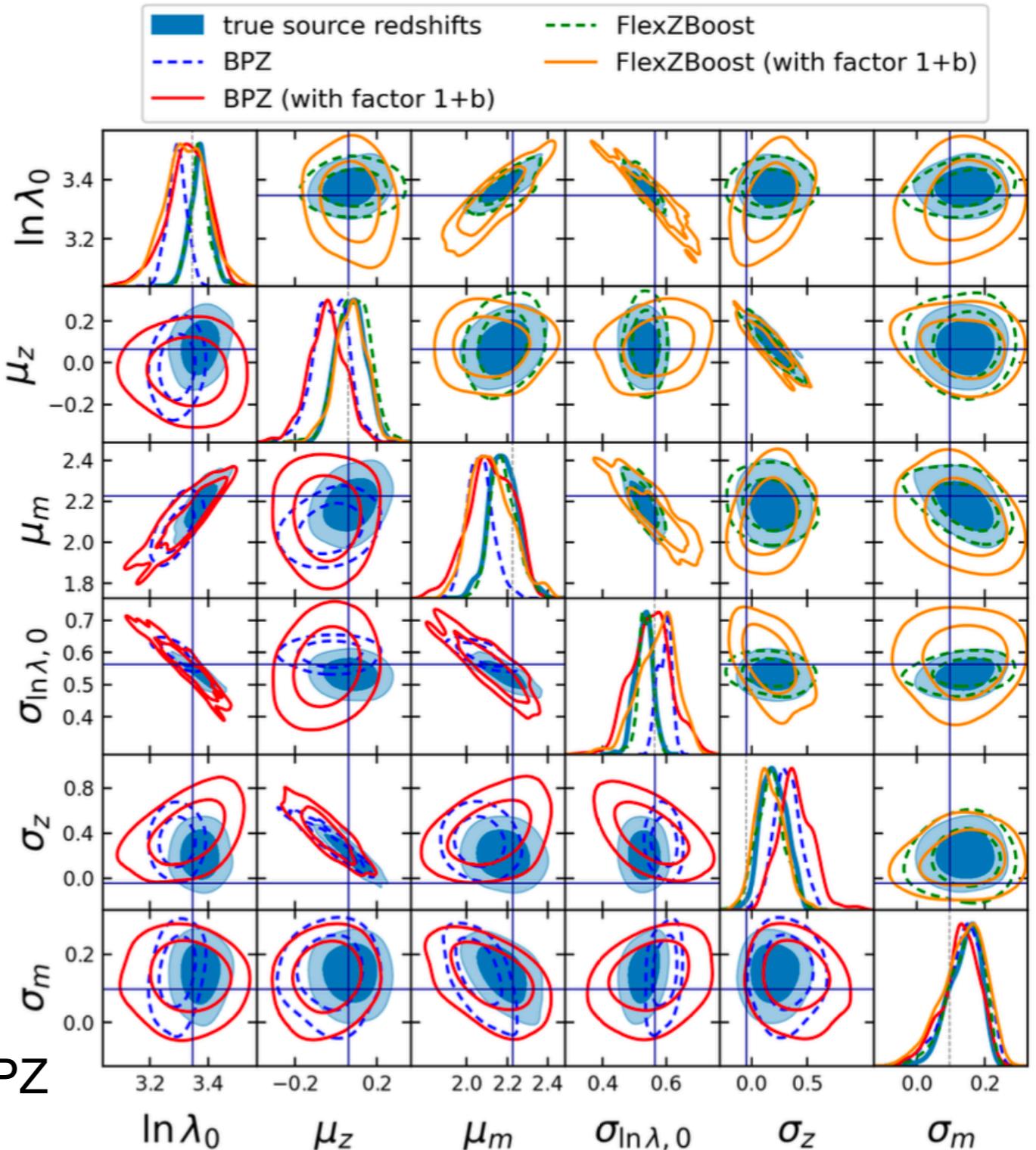
- FFlexZBoost: perfect agreement with true redshift case (baseline)
- BPZ: shift at most 1σ in the normalization $\ln \lambda_0$
- We can correct the model for possible systematic PZ bias $1+b$ ([Simet+16](#))
- And use CC+WL to calibrate this bias

$$\Delta\Sigma_{ij}^{\text{corr}} = (1 + b)\Delta\Sigma_{ij}$$

Uncorrected PZ
systematics

$$b_{\text{flex}} = 0.02 \pm 0.03 \quad b_{\text{bpz}} = -0.02 \pm 0.03$$

- Increase the error bar for both cases
- b compatible with 0 in both cases
- Increase compatibility with baseline for BPZ



On the modelling side

$$\Delta\Sigma(R) \text{ depends on } \int_{-\infty}^{+\infty} dz \rho_{3d}(r)$$

Modelling

On the data side

$$\widehat{\Delta\Sigma}(R, z_l) = \langle \Sigma_{\text{crit}}(z_{\text{gal}}, z_l) \epsilon_+^{\text{obs}} \rangle$$

1. Measured redshift

2. Selection biases in cluster finder algorithms

Measured shapes

On the modelling side

$$\Delta\Sigma(R) \text{ depends on } \int_{-\infty}^{+\infty} dz \rho_{3d}(r)$$

Modelling



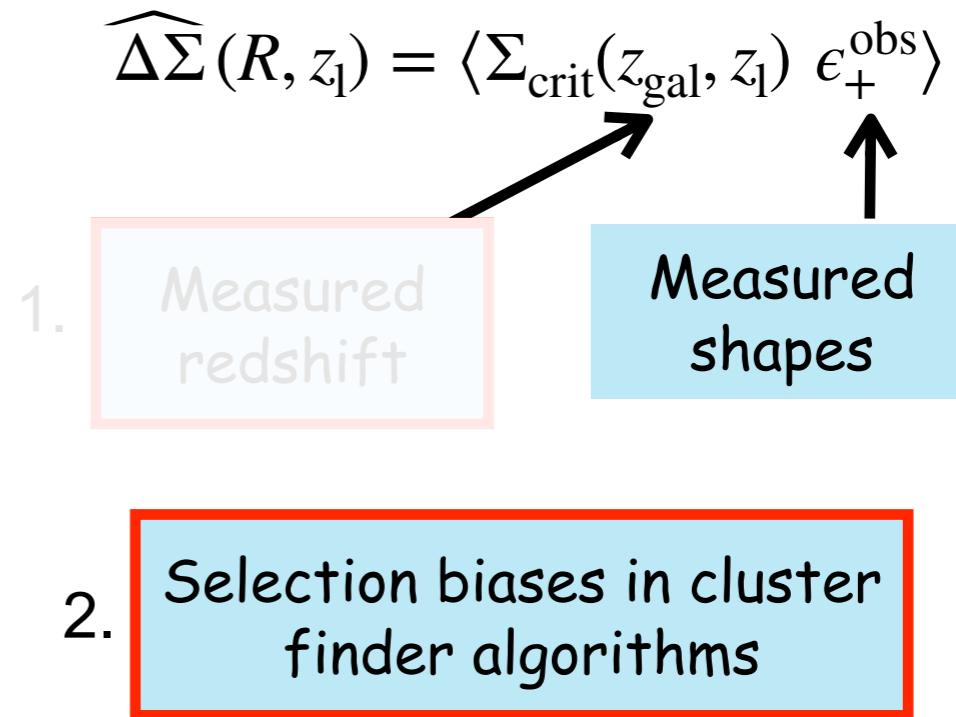
On the data side

$$\widehat{\Delta\Sigma}(R, z_l) = \langle \Sigma_{\text{crit}}(z_{\text{gal}}, z_l) \epsilon_+^{\text{obs}} \rangle$$

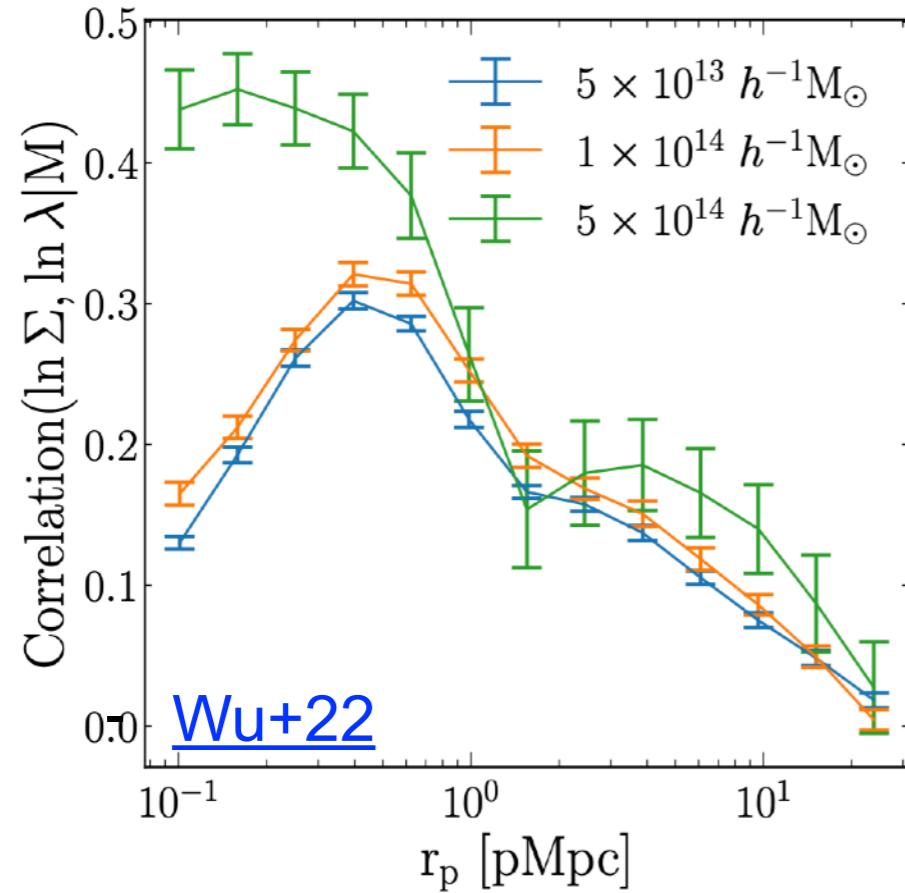
1. Measured redshift

2. Selection biases in cluster finder algorithms

Measured shapes



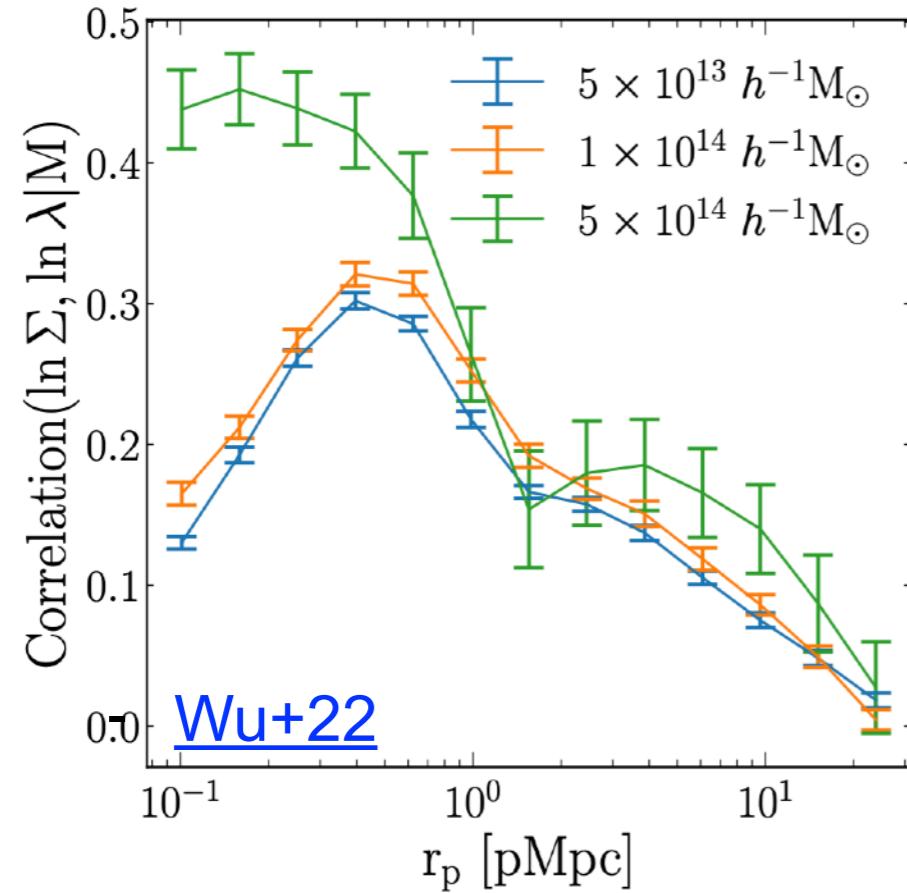
Shear-richness covariance in CL analyses



Shear-richness covariance

- $\text{Corr}(\Delta\Sigma, \ln \lambda)$ arises from halo formation+baryonic physics [Zhang+24](#): property covariance < 0
- +from optically-detected clusters > 0 (e.g. projection effects, [Wu+22](#))
- Plays an increasing role with LSST (see e.g. DES CL Y1)

Shear-richness covariance in CL analyses



$$\Delta\Sigma_{ij}^{\text{corr}} = \Delta\Sigma_{ij} + \frac{[\beta_1]_{ij}}{\mu_m} \langle \text{Cov}(\Delta\Sigma, \ln \lambda | m, z) \rangle_{ij}$$

« standard » prediction

HMF mass slope

MoR mass slope

Shear-richness covariance

Shear-richness covariance

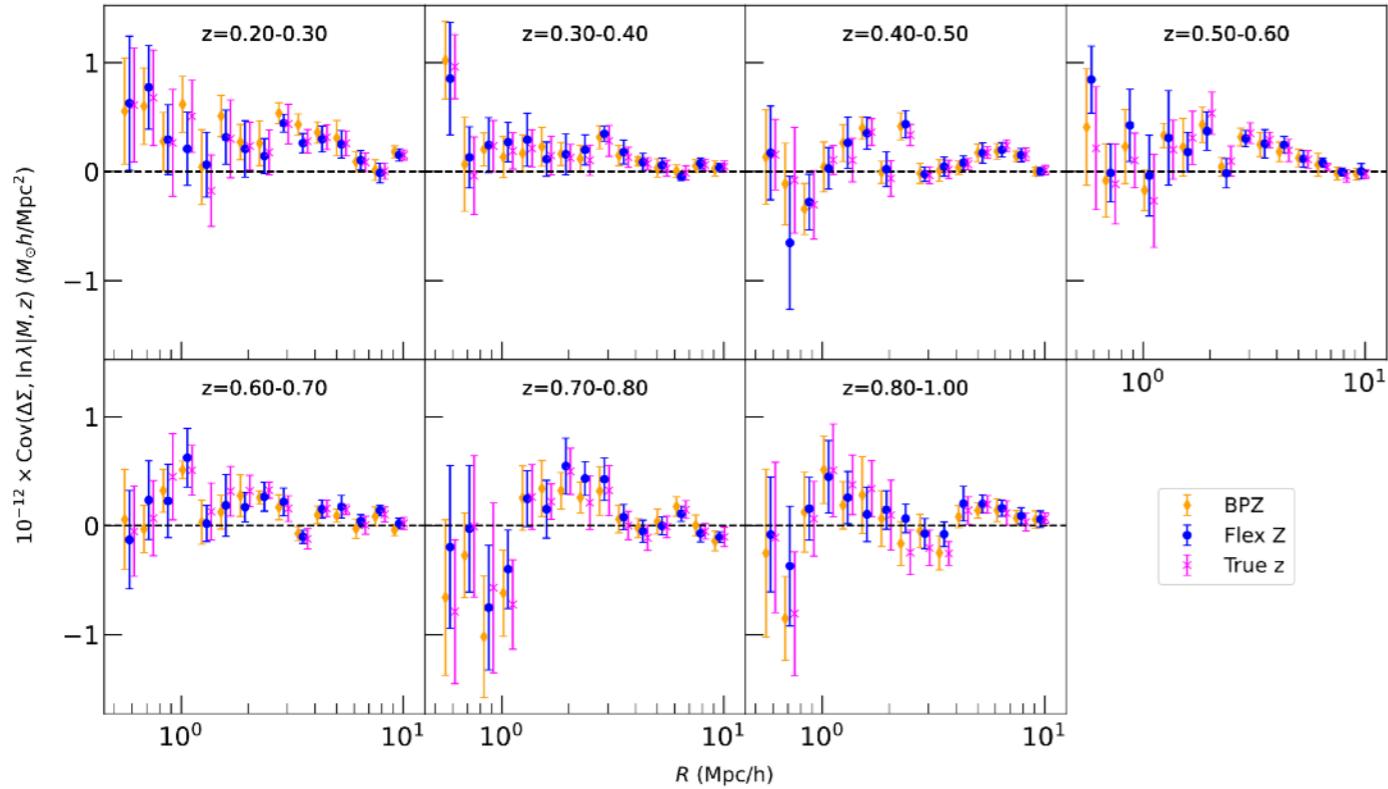
- Corr($\Delta\Sigma, \ln \lambda$) arises from halo formation+baryonic physics [Zhang+24](#): property covariance < 0
- +from optically-detected clusters > 0 (e.g. projection effects, [Wu+22](#))
- Plays an increasing role with LSST (see e.g. DES CL Y1)

Implementation in CL pipeline

- Need to add $P(\Delta\Sigma, \ln \lambda | M)$ relation (see appendix D)
- $\Delta\Sigma$ correcting factor depending on the mass slope of MoR+ « binned » HMF log-slope β_1

Shear-richness covariance in cosmoDC2

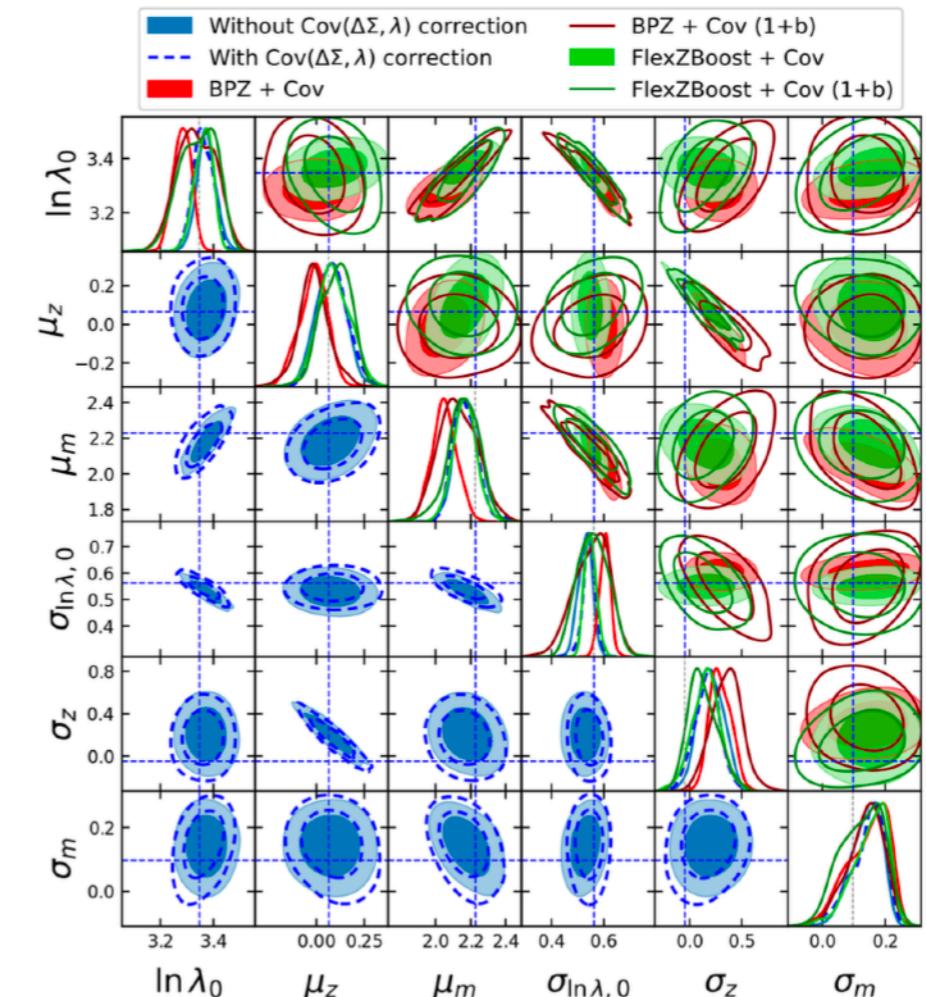
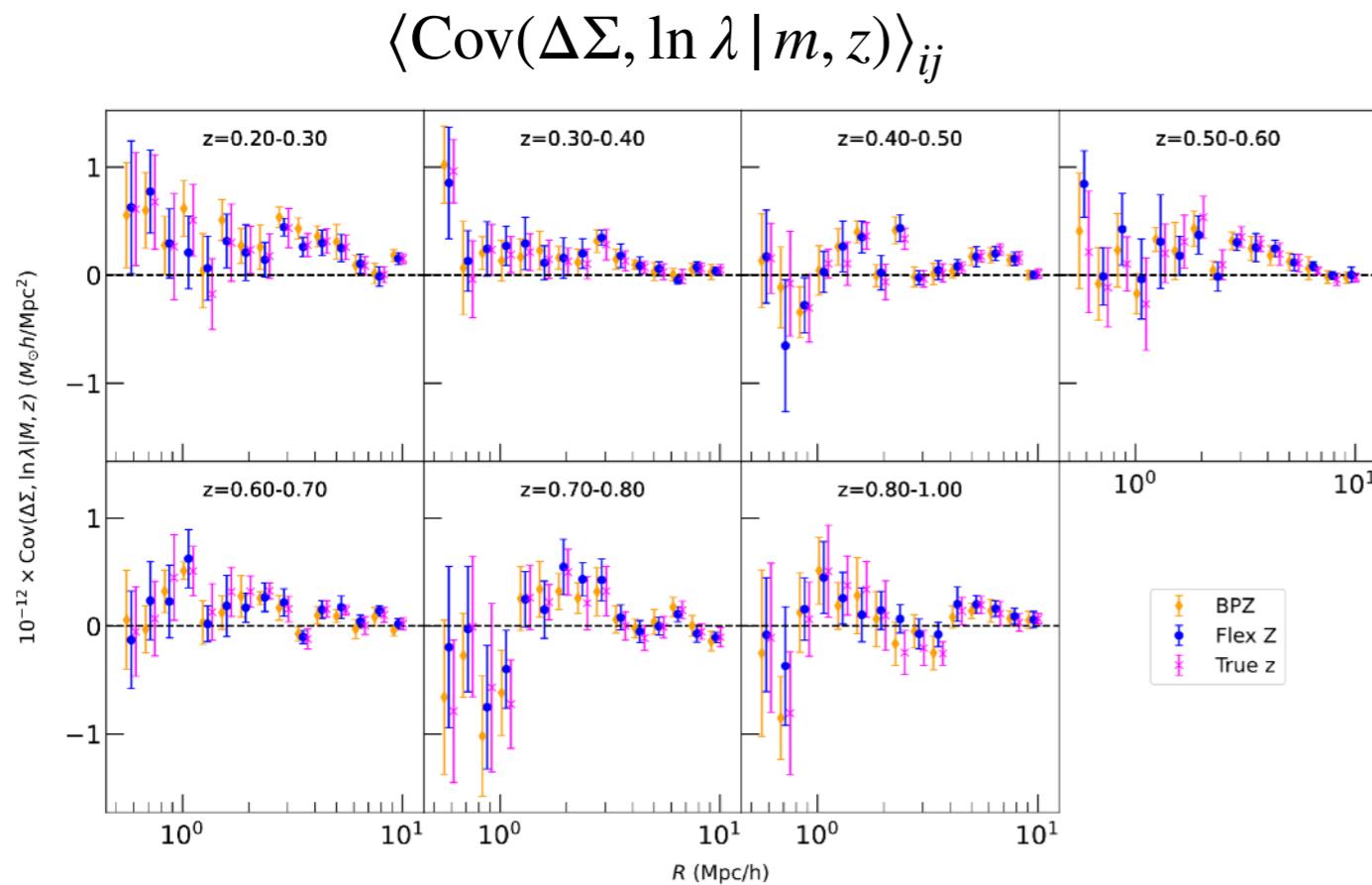
$$\langle \text{Cov}(\Delta\Sigma, \ln\lambda | m, z) \rangle_{ij}$$



In DC2 data

- Using the matched cluster-halo catalog and individual profiles
- Measure the total (intrinsic+extrinsic) cov
- Low amplitude: $0.1-0.01 \times$ standard profile
- Expected: HOD model for cosmoDC2 halos, idealistic run for redMaPPer (true magnitudes)

Shear-richness covariance in cosmoDC2



In DC2 data

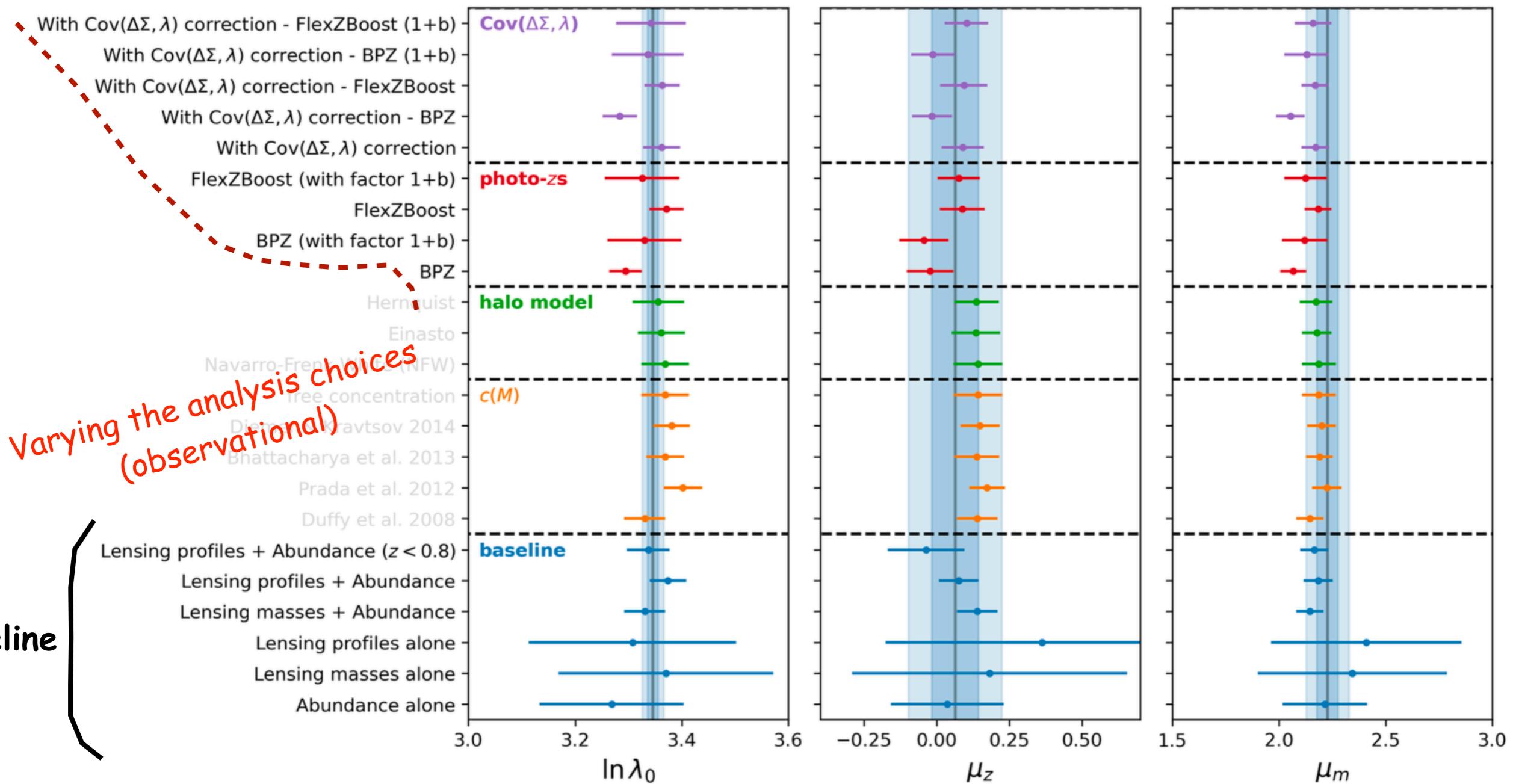
- Using the matched cluster-halo catalog and individual profiles
- Measure the total (intrinsic+extrinsic) cov
- Low amplitude: $0.1-0.01 \times$ standard profile
- Expected: HOD model for cosmoDC2 halos, idealistic run for redMaPPer (true magnitudes)

Impact on MoR

- Small impact $< 1\sigma$, as expected
- Assess PZ+shear-richness covariance by using PZ data vectors, and (1+b) factor

Robustness of MoR in LSST DESC DC2

Goal 2: Test its robustness to modeling choices and observational systematics



Summary

Context

- Clusters are important cosmological probes of the Universe formation history
- Well-calibrated MoR are crucial for cluster-based analyses
- WL probes the mass distribution around clusters, asset to constrain MoR

Summary

Context

- Clusters are important cosmological probes of the Universe formation history
- Well-calibrated MoR are crucial for cluster-based analyses
- WL probes the mass distribution around clusters, asset to constrain MoR

This work

- Build « Early » CL pipeline for DESC with DESC tools (CLMM, CCL, CIEVAR)
- Analysis of the redMaPPer MoR
 - CC+WL MoR, improve the precision when combining probes
 - Account for redMaPPer selection function
 - Robustness tests (non exhaustive list) wrt to modeling choices
 - Wrt to observational systematics: PZ, shear-richness covariance
 - Compatible with the baseline choices and fiducial constraints
- Contribues to the analysis/validation of the cosmoDC2 dataset for CL studies

Summary

Context

- Clusters are important cosmological probes of the Universe formation history
- Well-calibrated MoR are crucial for cluster-based analyses
- WL probes the mass distribution around clusters, asset to constrain MoR

This work

- Build « Early » CL pipeline for DESC with DESC tools (CLMM, CCL, CIEVAR)
- Analysis of the redMaPPer MoR
 - CC+WL MoR, improve the precision when combining probes
 - Account for redMaPPer selection function
 - Robustness tests (non exhaustive list) wrt to modeling choices
 - Wrt to observational systematics: PZ, shear-richness covariance
 - Compatible with the baseline choices and fiducial constraints
- Contribues to the analysis/validation of the cosmoDC2 dataset for CL studies

Plan for analyzing the LSST

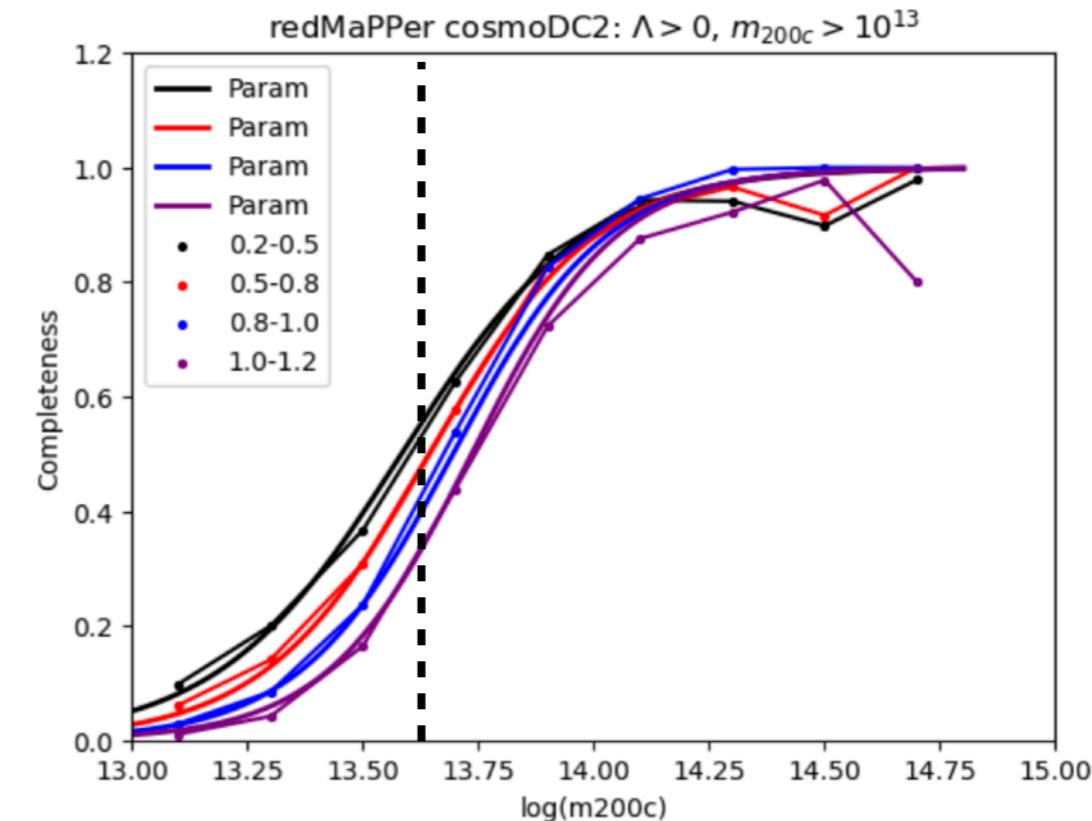
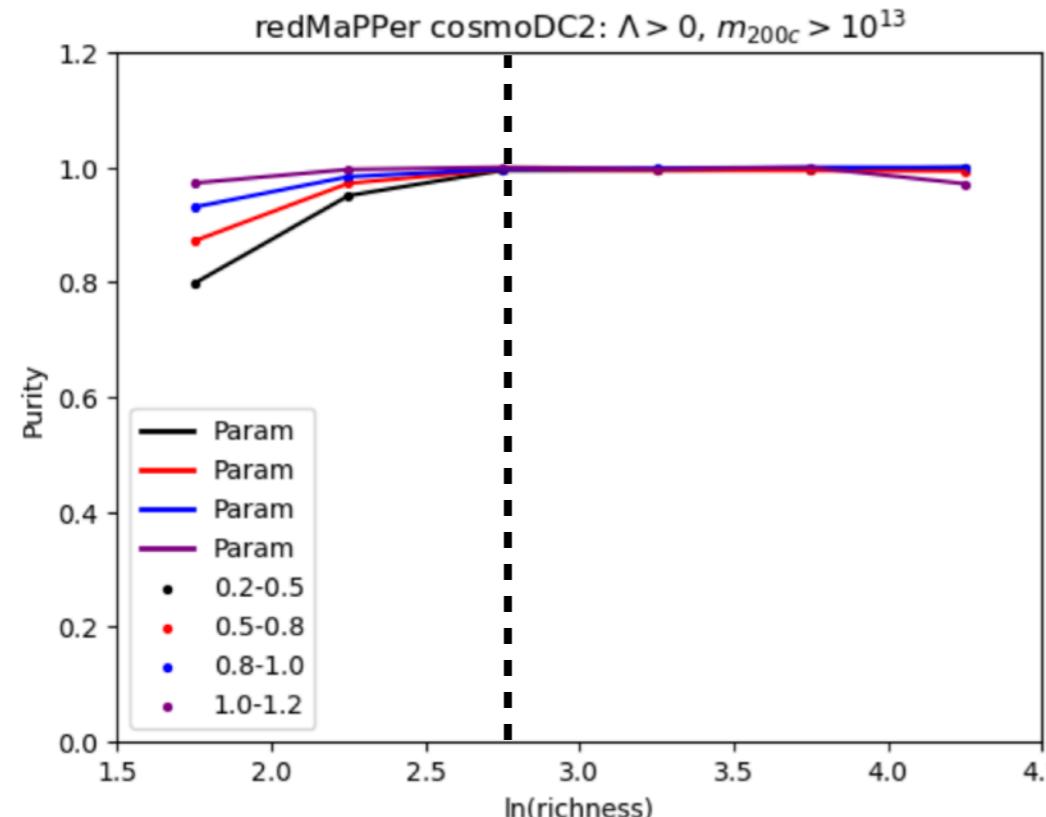
- Hope it paves the way for the LSST CL DESC pipeline ! Active discussions in prep. of ComCam data
- **Precision $\times 6.4$ with « idealistic » LSST** (e.g. true mag./shapes), work is needed to estimate the budget of shape measurement.

Thank you!



redMaPPer selection function

Figures by Thibault Guillemin et al.



Principle

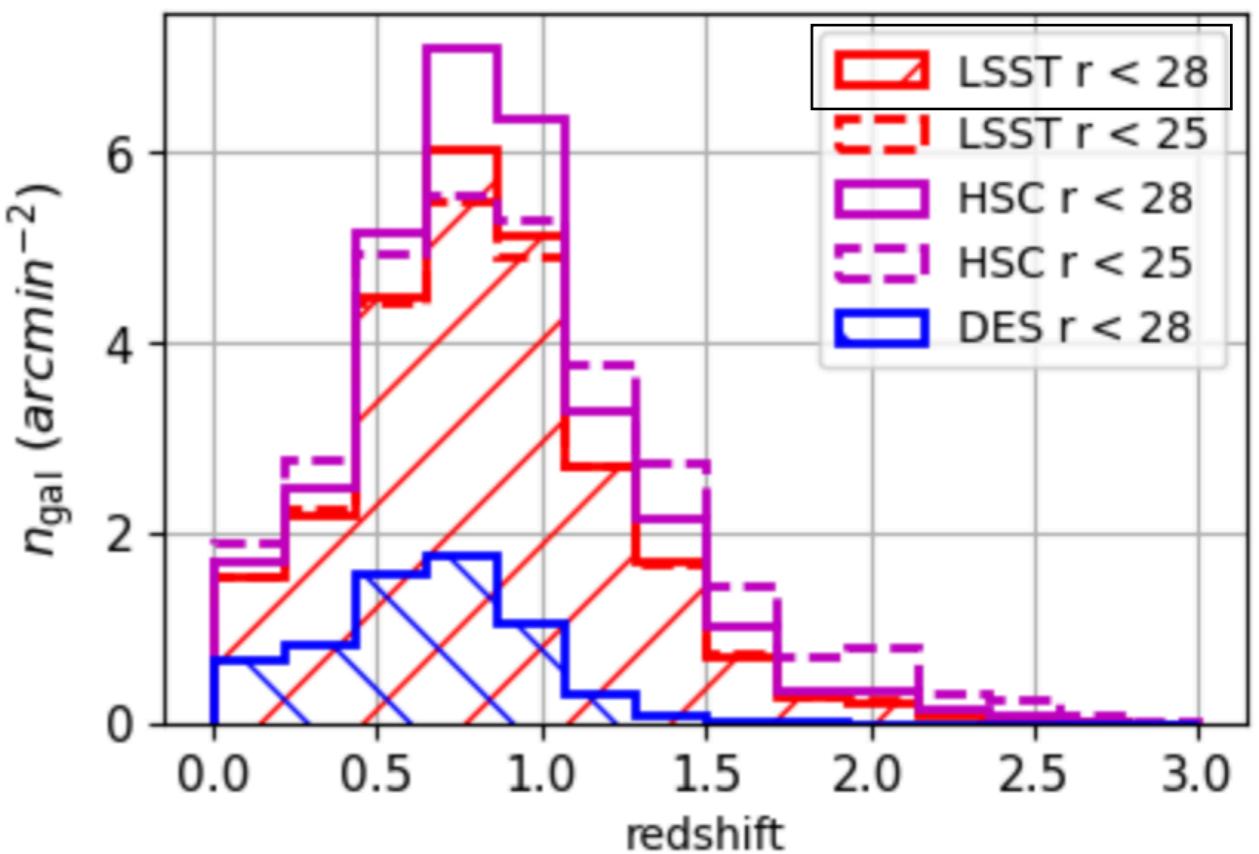
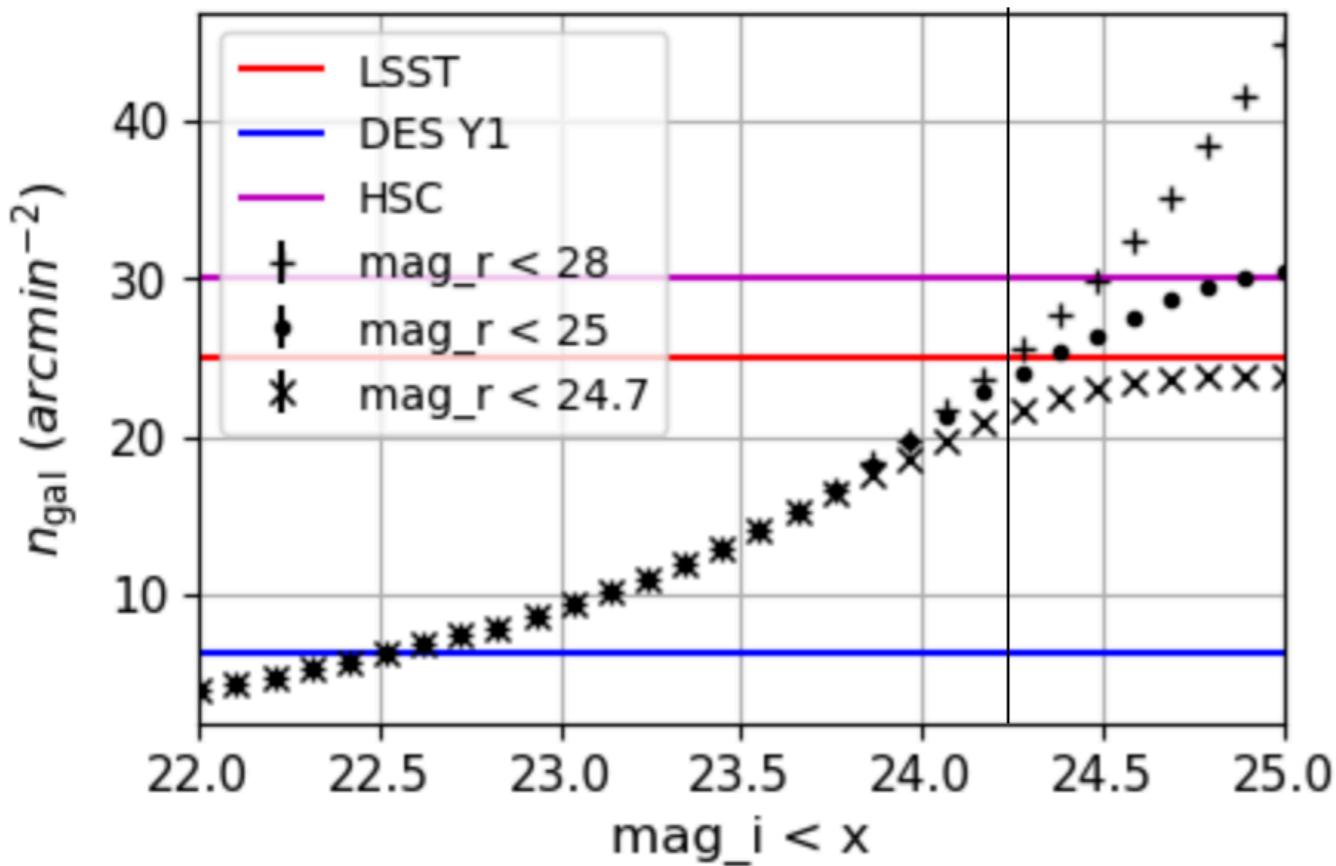
- Geometrical match between RM clusters to DC2 halos (CIEvaR)
- Membership matching
- Selection function

$$\Phi(m, \lambda, z) = \frac{c(m, z)}{p(\lambda, z)}$$

Completeness ————— Purity

Results

- RM cat. is pure for $\lambda \geq 20$ is pure
- RM cat. is $> 80\%$ complete for $M \geq 10^{14} M_\odot$
- We fit « smooth » functions to be used in the CL+WL prediction modules



Choices:

- $i < 24.25$
- $r < 28$