

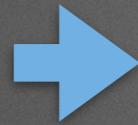
# **Modeling the Universe**

**Interfacing Theory, Simulations, Statistical  
Methods, and Observations**

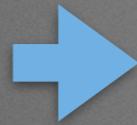
**Tim Eifler**

**(JPL/Caltech, University of Arizona)**

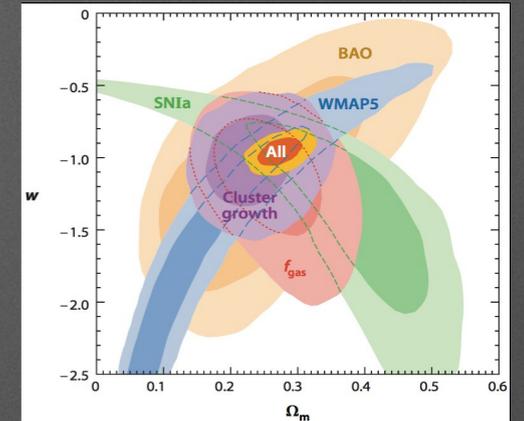
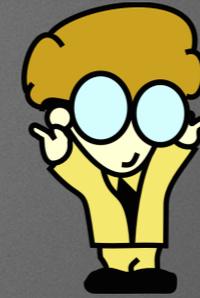
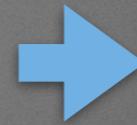
# The Challenge



reduced data  
and catalogs



summary  
statistics



## 1) Independent probes

CMB, SN1a as priors

## 2) Large model vector

Self-consistent modeling of all observables as a function of  
1) cosmological parameters (~10)  
2) nuisance parameters (XXX)

## 3) Enhanced modeling via

- Observations
- Simulations
- Theory

large data vector

$$p(\pi | \hat{\mathbf{d}}) \propto p(\pi) \mathcal{L}(\hat{\mathbf{d}} | \mathbf{m}(\pi), \mathbf{C})$$

posterior probability

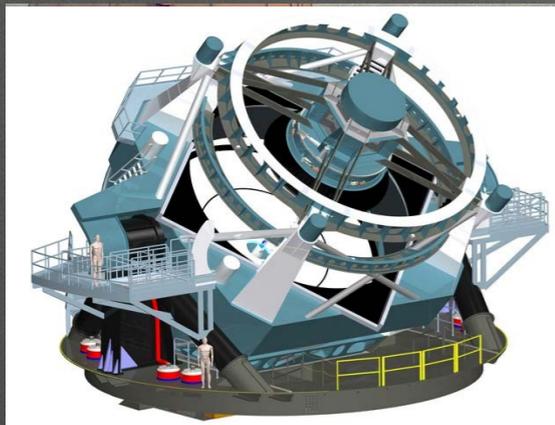
## 4) Statistics I - Likelihood function

- Multivariate Gaussian vs other parameterizations
- Non-parametric forms

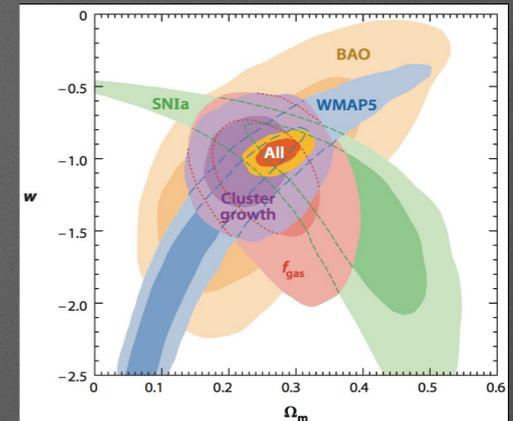
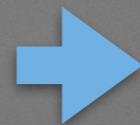
## 4) Statistics II - Covariances

- large and complicated, non-(block) diagonal
- different methods for derivation

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reduced data  
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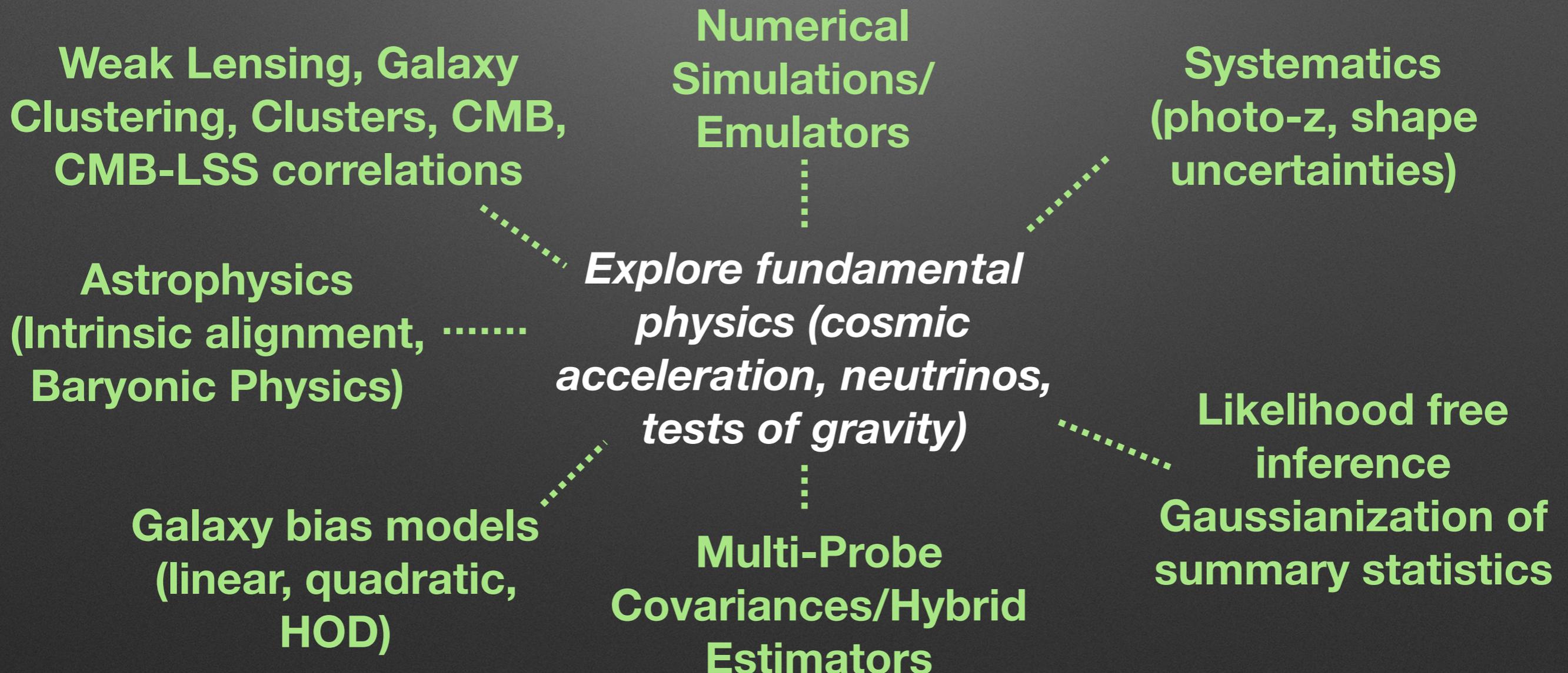
large data vector

$$\text{posterior probability} \rightarrow p(\pi | \hat{\mathbf{d}}) \propto p(\pi) \mathcal{L}(\hat{\mathbf{d}} | \mathbf{m}(\pi), \mathbf{C})$$

# Introducing CosmoLike

Idea: consistent, multi-probe likelihood analysis software framework including

- Realistic statistical error bars (cross-probe covariances)
- Cross-correlations of observables/systematics
- Efficient treatment of nuisance parameters



# Project 1: Simulate a Multi-Probe Likelihood Analysis for LSST

Theory+Sims+Stats -> Obs

*cosmolike - cosmological likelihood analyses for photometric galaxy surveys*

CosmoLike release paper ([www.cosmolike.info](http://www.cosmolike.info))  
Krause & TE 2017

# Example Data Vector and Systematics

- Weak Lensing (cosmic shear)

- 10 tomography bins
- 25 I bins,  $25 < I < 5000$

shear calibration,  
photo-z (sources)  
IA, baryons

- Galaxy clustering

- 4 redshift bins (0.2-0.4, 0.4-0.6, 0.6-0.8, 0.8-1.0)  $b_1, b_2, \dots$
- compare two samples:  $\sigma_z < 0.04$ , redMaGiC **photo-z (lenses)**
- linear + quadratic bias only : I bins restricted to  $R > 10$  Mpc/h
- HOD modeling going to  $R > 0.1$  MPC/h

- Galaxy-galaxy lensing

- galaxies from clustering (as lenses) with shear sources

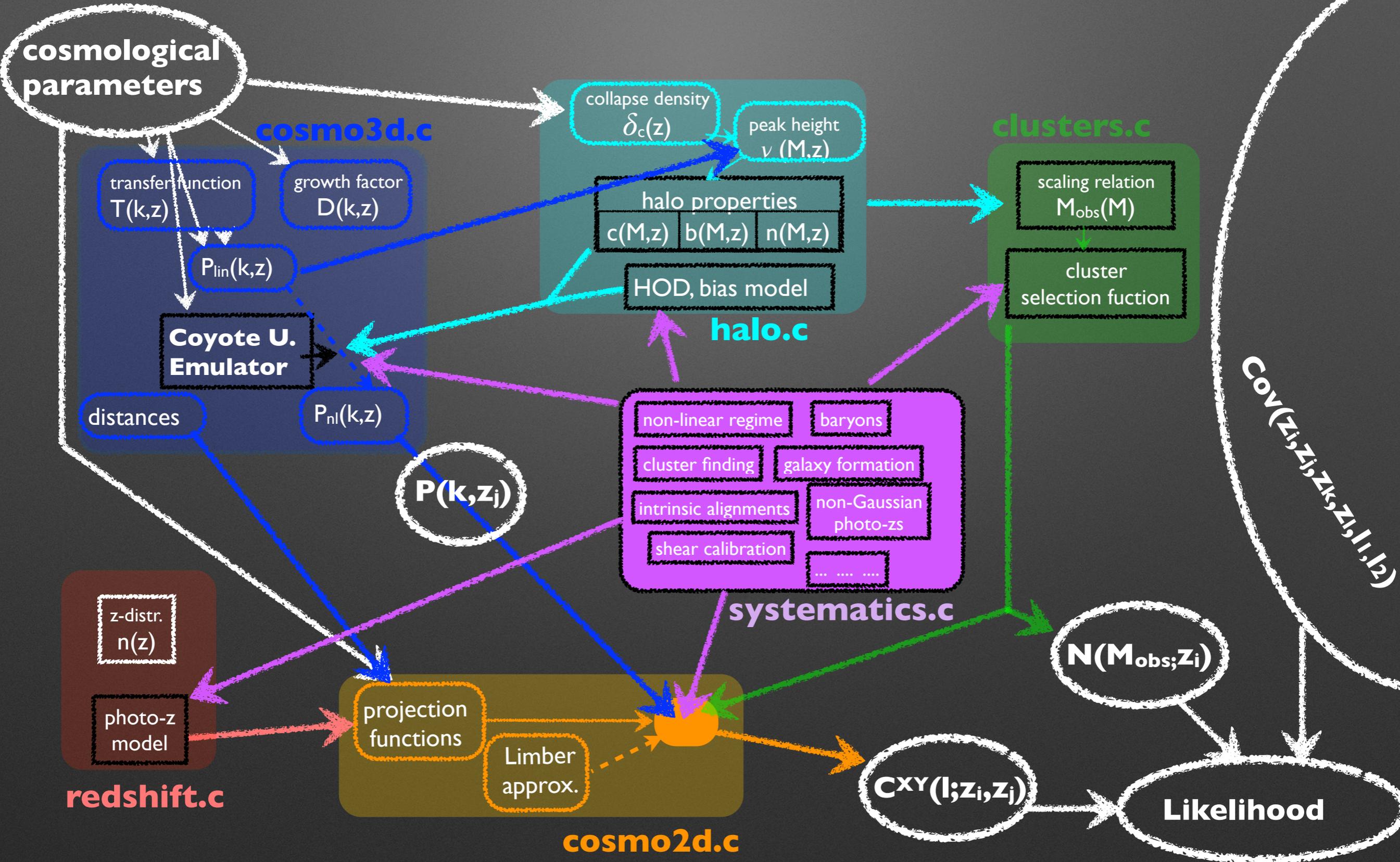
- Clusters - number counts + shear profile

- so far, 8 richness, 4 z-bins (same as clustering)
- tomographic cluster lensing ( $500 < I < 10000$ )

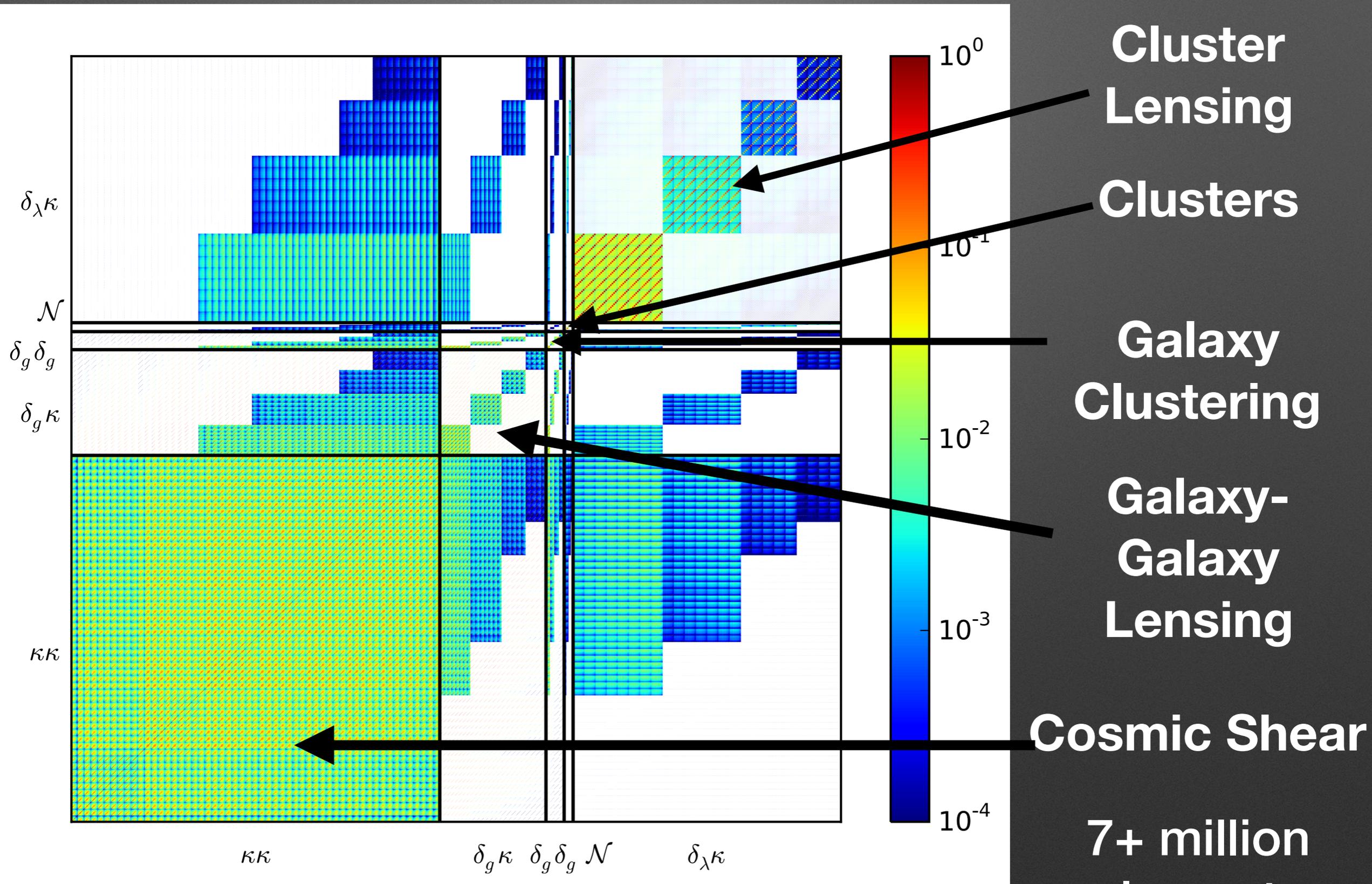
**N-M relation**  
**c-M relation**  
**off-centering**

# CosmoLike - "Inner Workings"

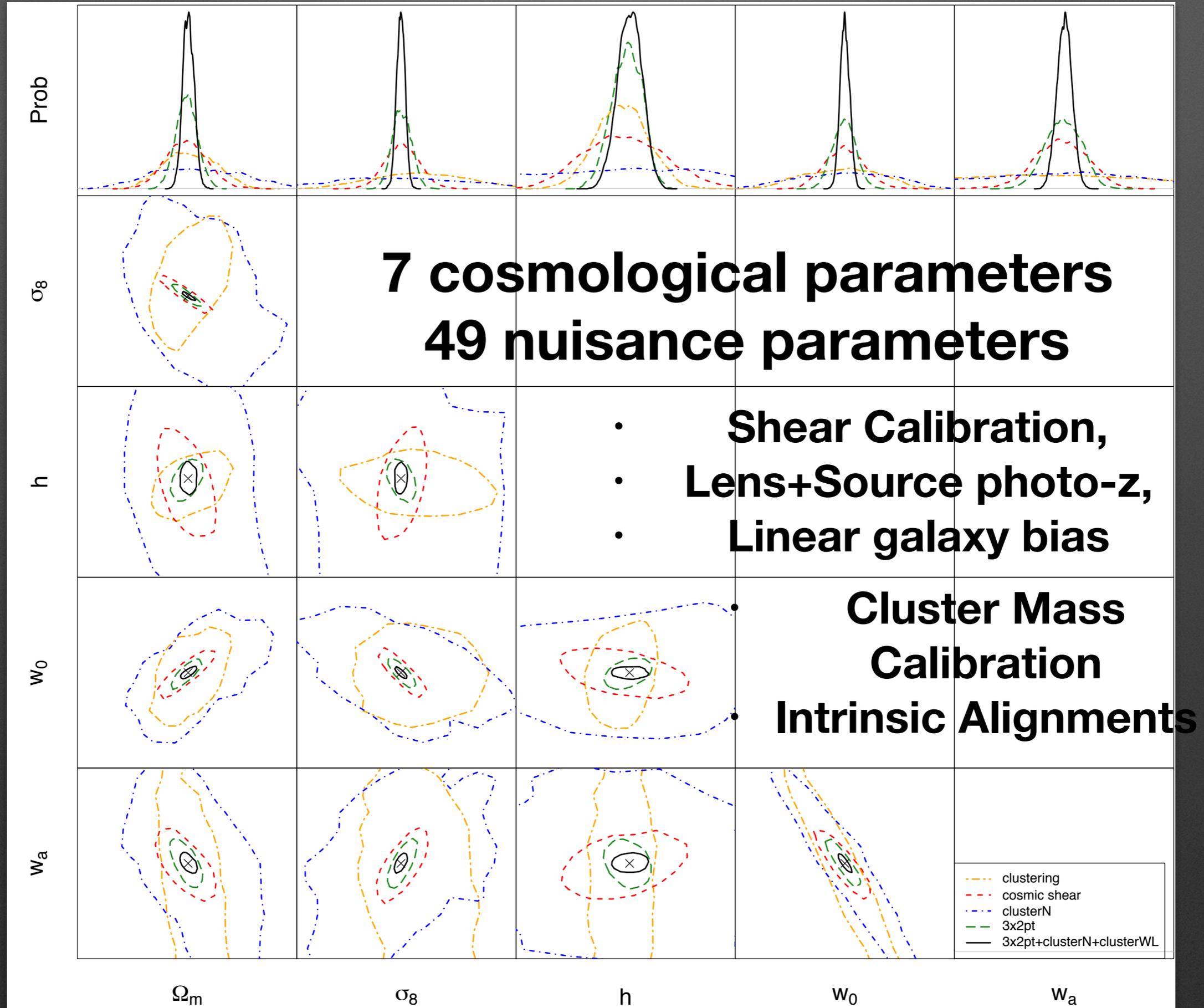
Krause & Eifler 2017



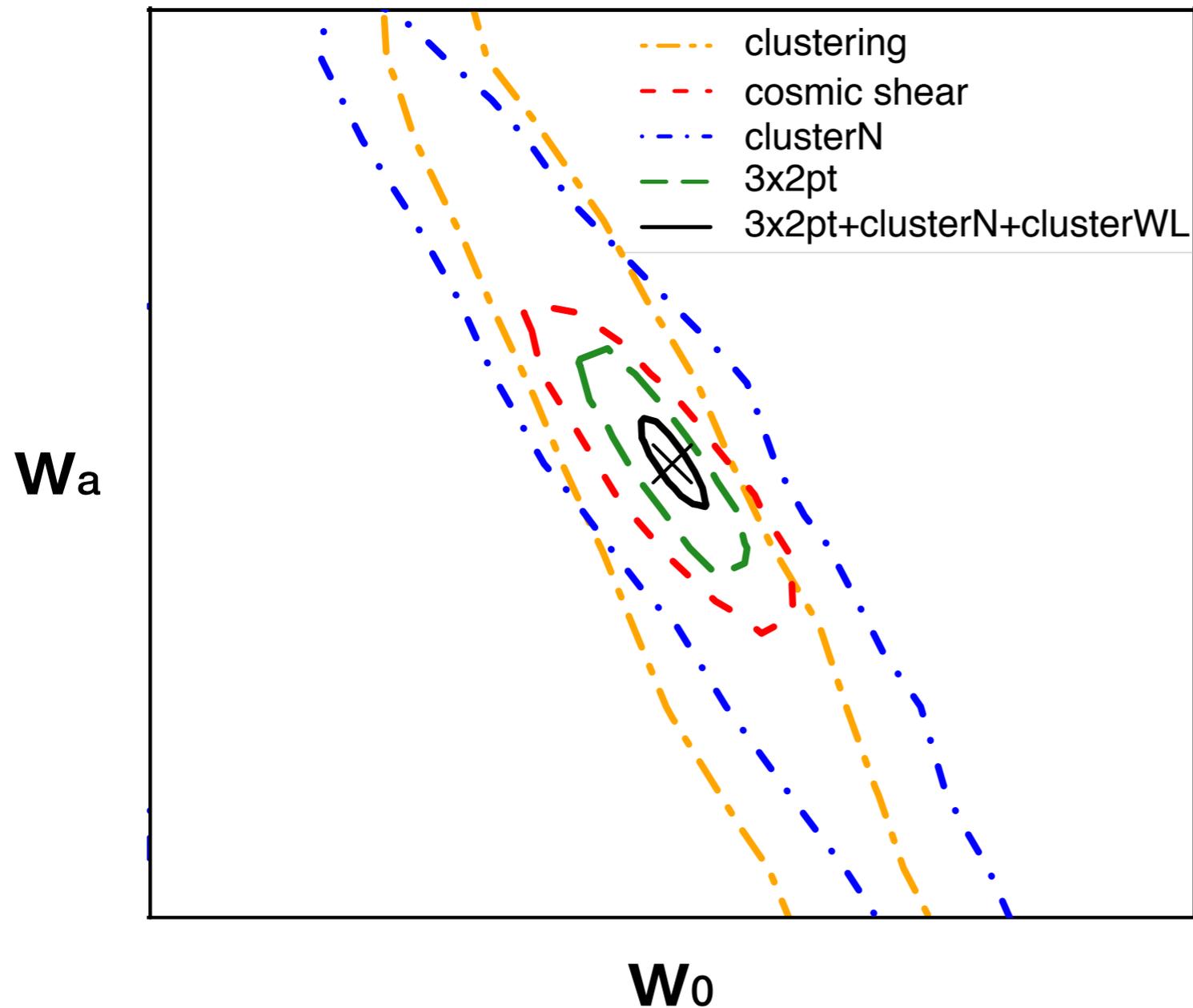
# Multi-Probes Forecasts:



# The Power of Combining Probes



# Zoom into $w_0$ - $w_a$ plane



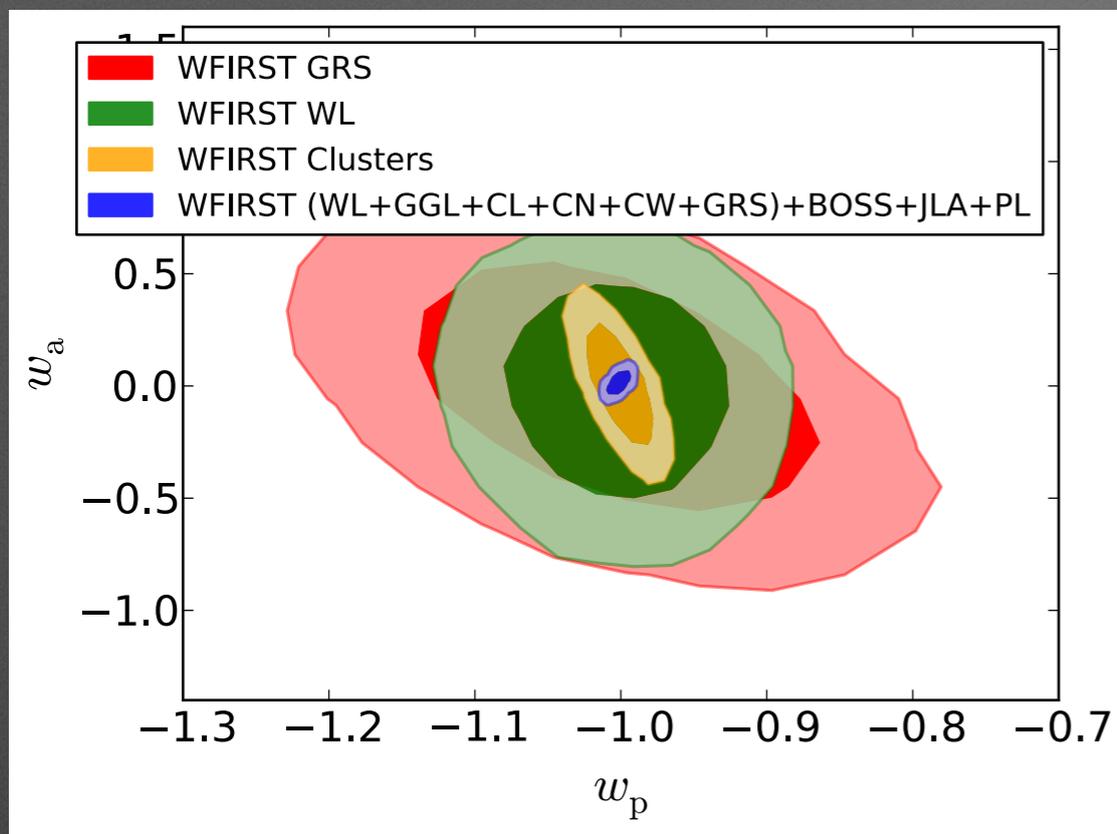
- **Very non-linear gain in constraining power**
- **Most stringent requirements on numerical simulations, photo-z, shear calibration, etc flow from Multi-Probe statistical limits**

# Project 2: Exploring WFIRST survey strategies

Theory+Sims+Stats -> Obs

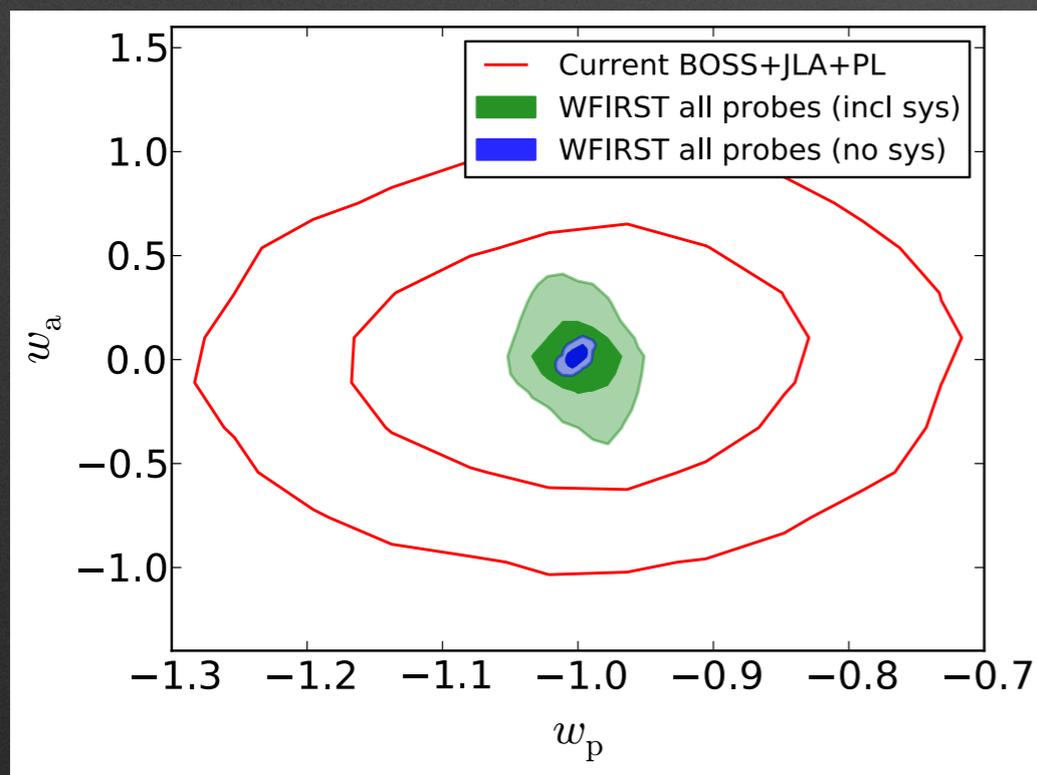
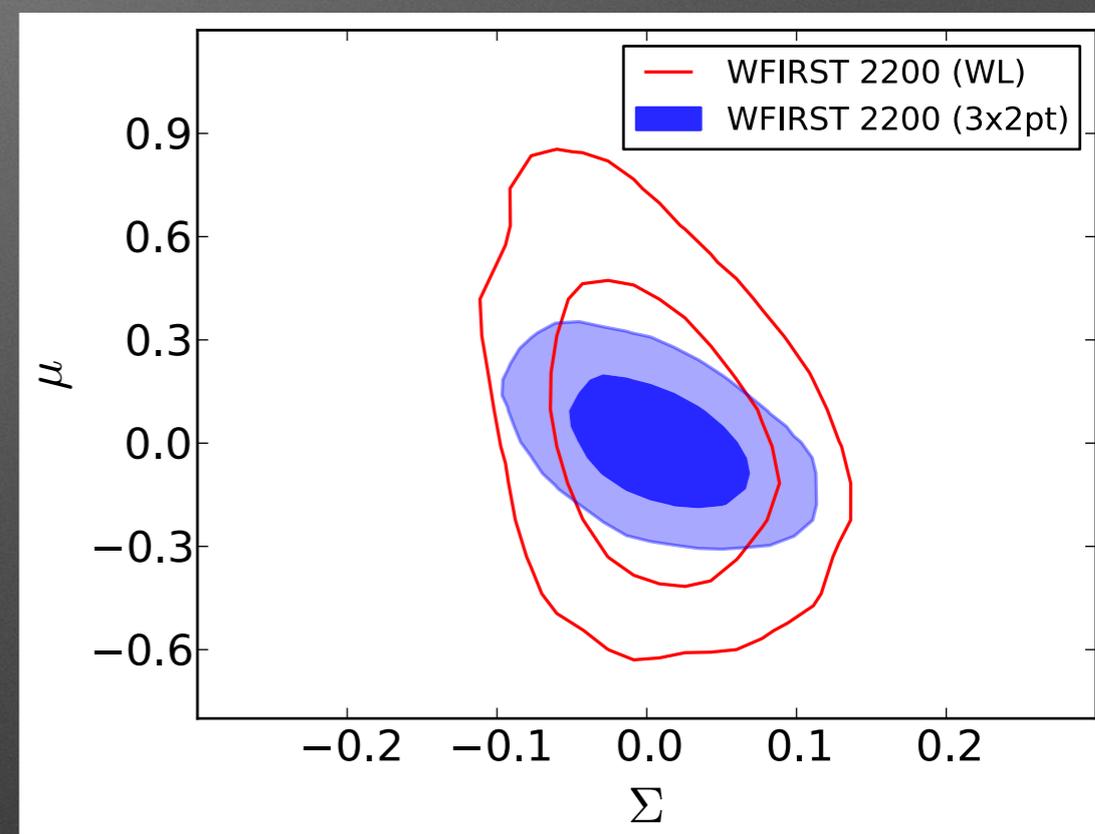
Project within the WFIRST *Cosmology with the  
High Latitude Survey* Science Investigation Team

TE et al in prep



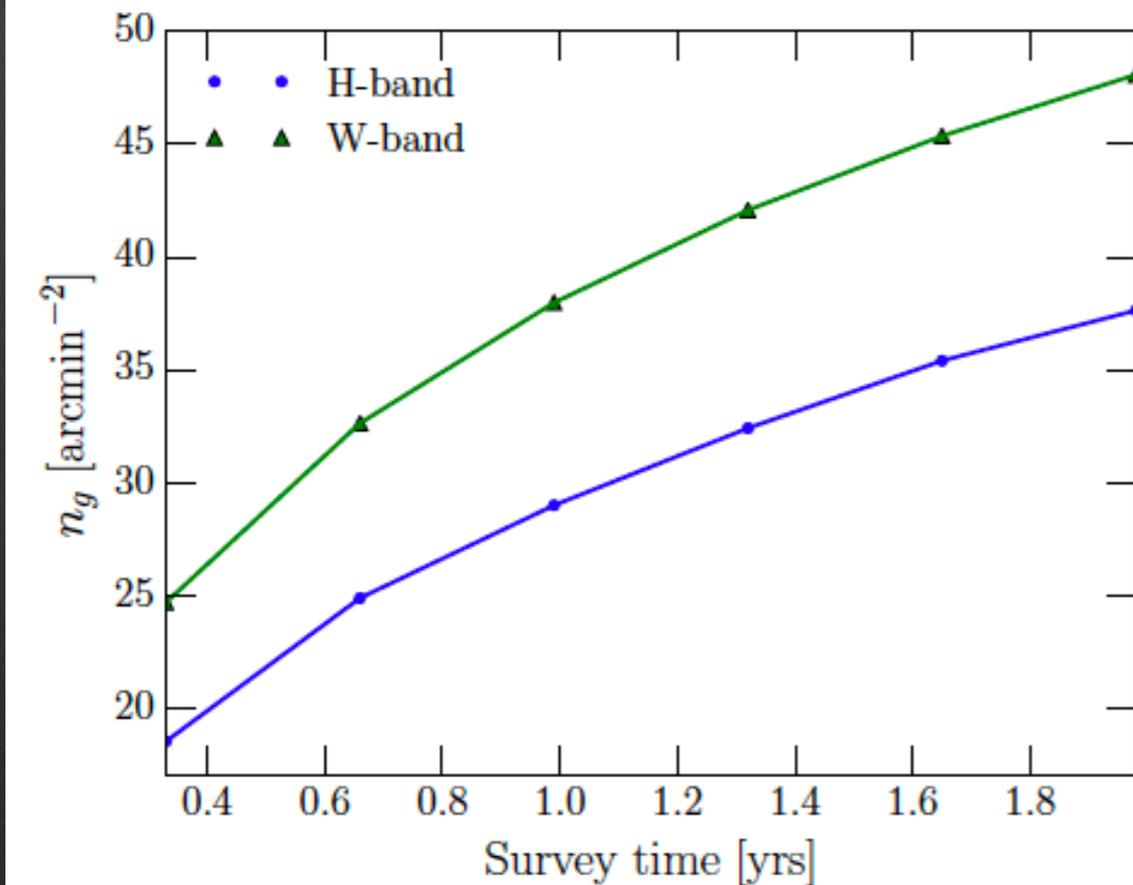
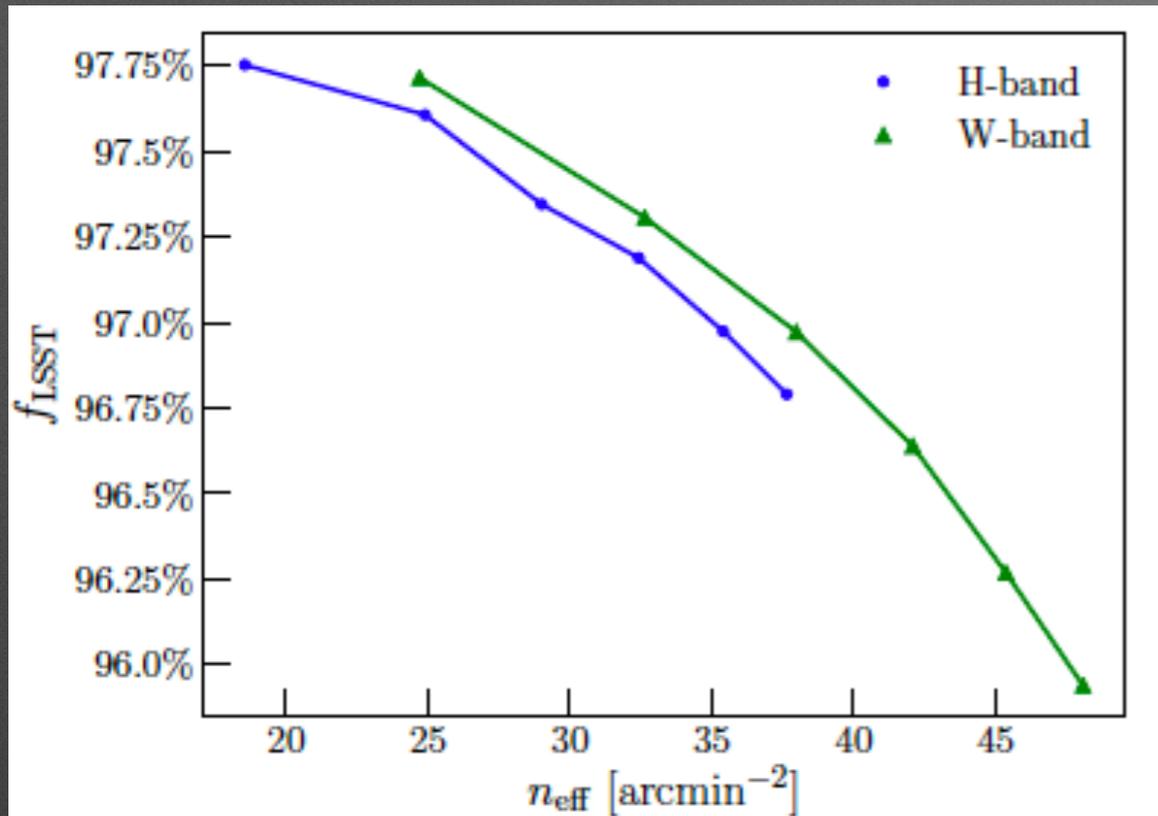
Individual vs multi-probe WFIRST analysis

Modified Gravity

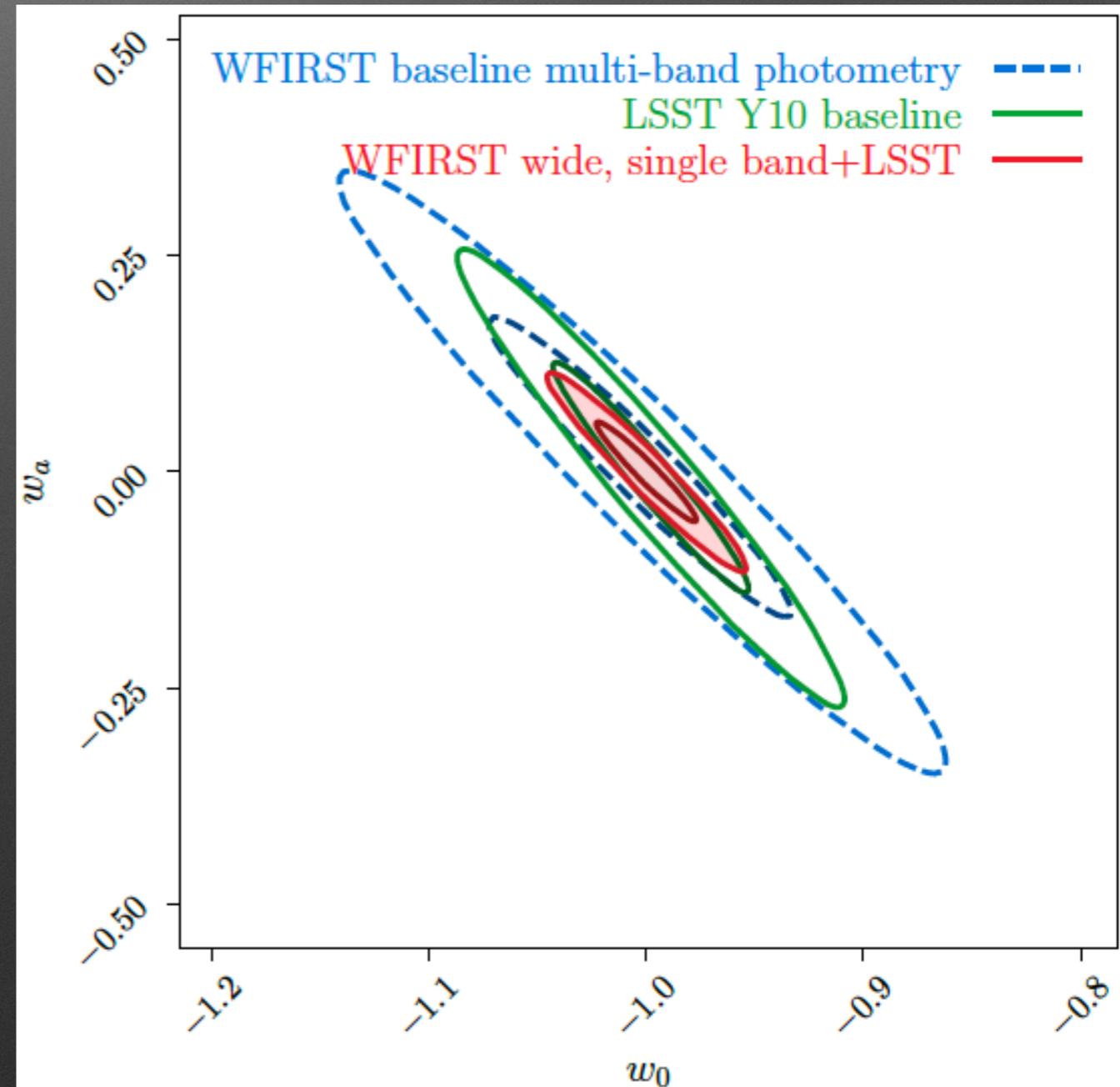


All-In Systematics  
 76 dimensions (7 cosmology, 69 systematics)

# WFIRST - LSST synergies



Possible WFIRST extension of 1.6 years overlapping with LSST



# Project 3:

## New statistical methods to reduce Super-Computing needs

Theory+Stats -> Sims

*Precision matrix expansion - efficient use of numerical  
simulations in estimating errors on cosmological parameters*

Friedrich & TE 2018

# The Problem: Inverse Covariance Estimation

- Analytical covariance model relies on approximations that might be too imprecise for an LSST Y10 data set
- Estimation the covariance from numerical simulations (brute force), requires  $10^5$ - $10^6$  realizations of an LSST Year 10 like survey to shield against noise in the estimator
- Why?
  - The estimated inverse covariance is not the inverse of the estimated covariance
  - High-dimensionality of the data vector  $\rightarrow$  many elements in the covariance

# Idea: Estimate the inverse directly

$$p(\boldsymbol{\pi}|\hat{\boldsymbol{\xi}}) \sim \exp\left(-\frac{1}{2}\chi^2[\boldsymbol{\pi}|\hat{\boldsymbol{\xi}},\mathbf{C}]\right) p(\boldsymbol{\pi})$$

$$\chi^2[\boldsymbol{\pi}|\hat{\boldsymbol{\xi}},\mathbf{C}] = (\hat{\boldsymbol{\xi}} - \boldsymbol{\xi}[\boldsymbol{\pi}])^T \mathbf{C}^{-1} (\hat{\boldsymbol{\xi}} - \boldsymbol{\xi}[\boldsymbol{\pi}])$$

Standard Estimator

$$\hat{\boldsymbol{\Psi}} = \frac{\nu - N_d - 1}{\nu} \hat{\mathbf{C}}^{-1}$$

New idea: Include theory information into estimator

$$\mathbf{C} = \mathbf{A} + \mathbf{B}$$

$$\mathbf{M} = \mathbf{A} + \mathbf{B}_m$$

$$\mathbf{C} = \mathbf{M} + (\mathbf{B} - \mathbf{B}_m)$$

$$\mathbf{X} := (\mathbf{B} - \mathbf{B}_m) \mathbf{M}^{-1}$$

$$\mathbf{C} = (\mathbf{1} + \mathbf{X}) \mathbf{M}$$

Invert and expand as power series

$$\begin{aligned} \hat{\boldsymbol{\Psi}}_{2\text{nd}} = & \mathbf{M}^{-1} + \mathbf{M}^{-1} \mathbf{B}_m \mathbf{M}^{-1} \mathbf{B}_m \mathbf{M}^{-1} \\ & - \mathbf{M}^{-1} (\hat{\mathbf{B}} - \mathbf{B}_m) \mathbf{M}^{-1} \\ & - \mathbf{M}^{-1} \hat{\mathbf{B}} \mathbf{M}^{-1} \mathbf{B}_m \mathbf{M}^{-1} \\ & - \mathbf{M}^{-1} \mathbf{B}_m \mathbf{M}^{-1} \hat{\mathbf{B}} \mathbf{M}^{-1} \\ & + \mathbf{M}^{-1} \frac{\nu^2 \hat{\mathbf{B}} \mathbf{M}^{-1} \hat{\mathbf{B}} - \nu \hat{\mathbf{B}} \text{tr}(\mathbf{M}^{-1} \hat{\mathbf{B}})}{\nu^2 + \nu - 2} \mathbf{M}^{-1} \end{aligned}$$

Build Estimator

$$\begin{aligned} \boldsymbol{\Psi} &= \mathbf{M}^{-1} \left( \sum_{k=0}^{\infty} (-1)^k \mathbf{X}^k \right) \\ &= \mathbf{M}^{-1} (\mathbf{1} - \mathbf{X} + \mathbf{X}^2 + \mathcal{O}[\mathbf{X}^3]) \end{aligned}$$

Only matrix multiplication, no inversion of estimated quantities

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Only matrix multiplication, no inversion of **estimated** quantities

# Standard estimator

$$\hat{\Psi} = \frac{\nu - N_d - 1}{\nu} \hat{\mathbf{C}}^{-1}$$

$$\hat{\mathbf{C}} := \frac{1}{\nu} \sum_{i=1}^{N_s} \left( \hat{\xi}_i - \bar{\xi} \right) \left( \hat{\xi}_i - \bar{\xi} \right)^T$$

Inverting quantities with “hats” is dangerous

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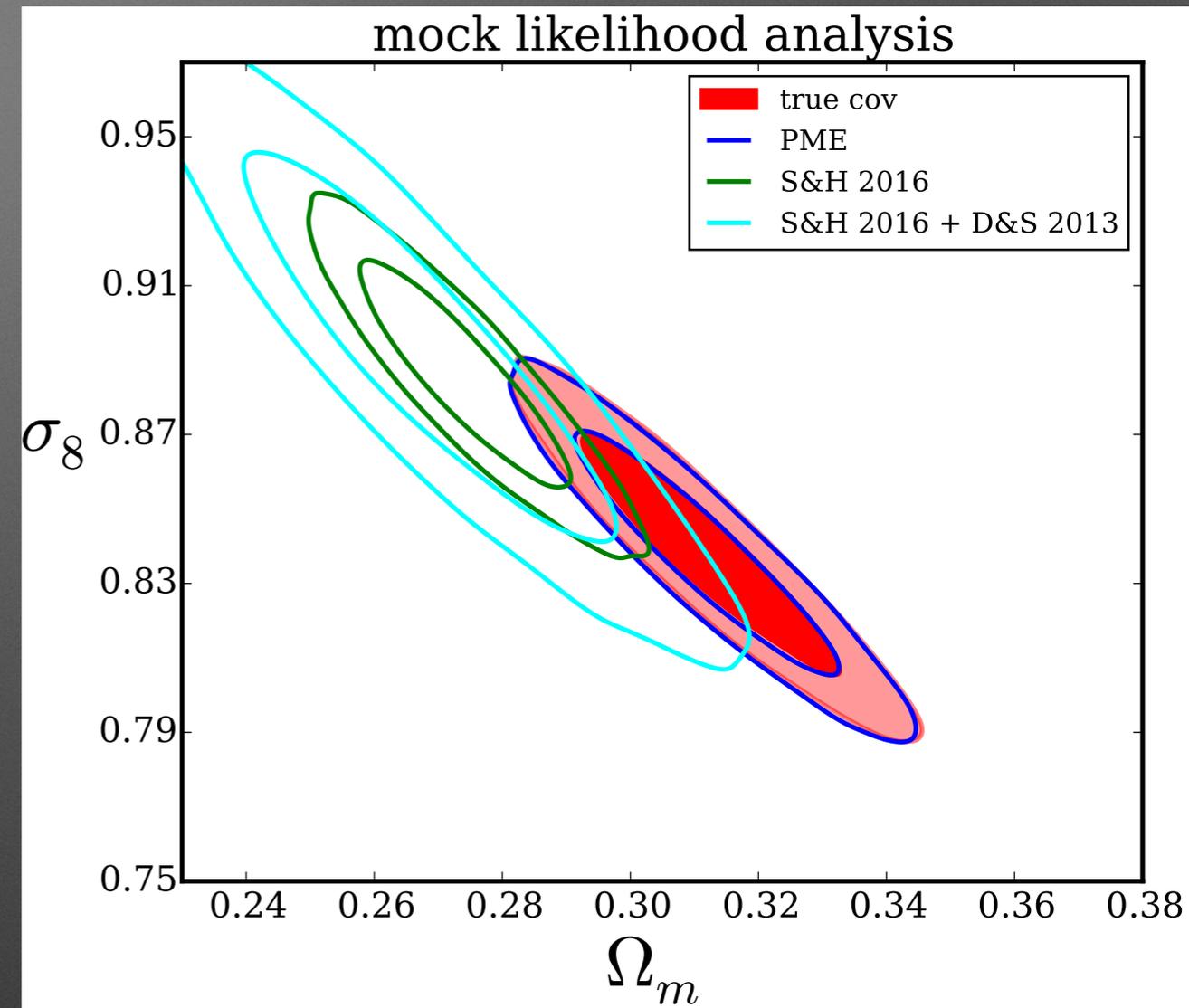
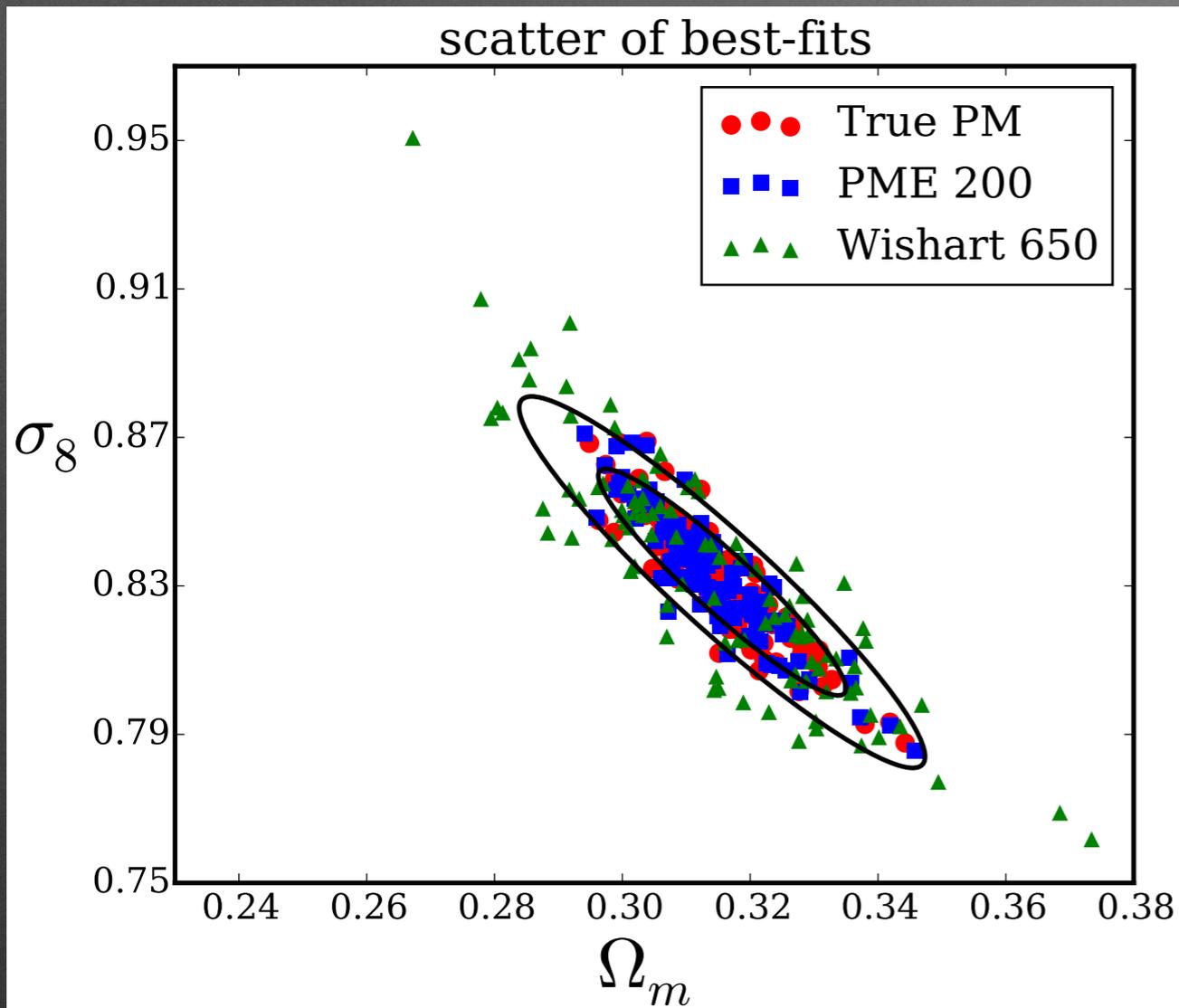
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# New estimator

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No more inversion of “hat quantities”...

# New estimator performance



- Instead of  $>10^5$  our new estimator only requires  $\sim 2000$  numerical simulations (LSST case)
- Given that 1 sim is 1M CPUh, at 1c/CPUh
- New method reduces cost \$1B to \$20M (-> fund theorists!)
- Next step: data compression

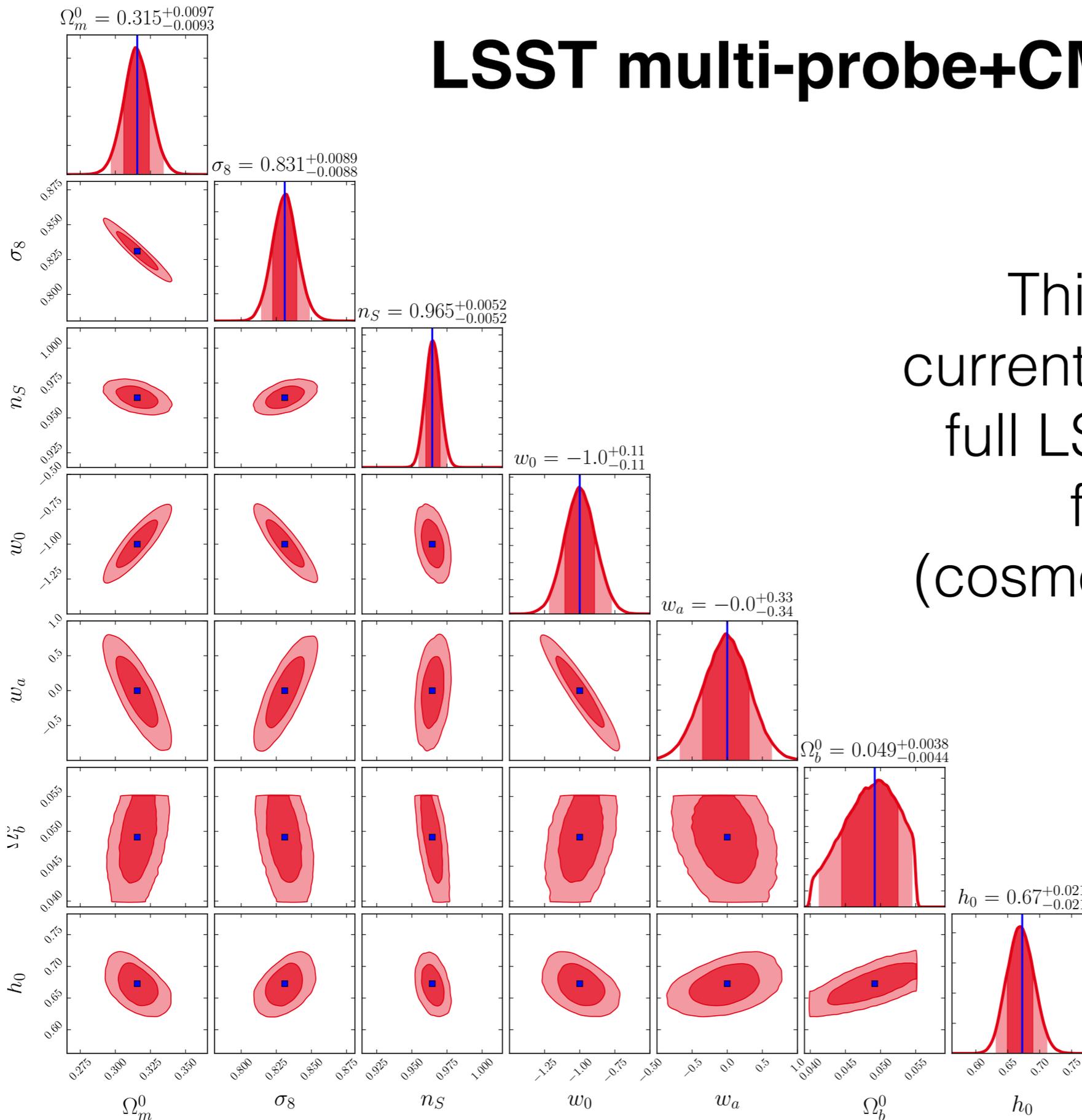
# Project 4: Synergies of CMB-S4 and LSST

Obs -> Theory/Sims

*Looking through the same lens: Shear calibration for LSST, Euclid, and WFIRST with stage 4 CMB lensing*

Schaan, Krause, TE et al 2017

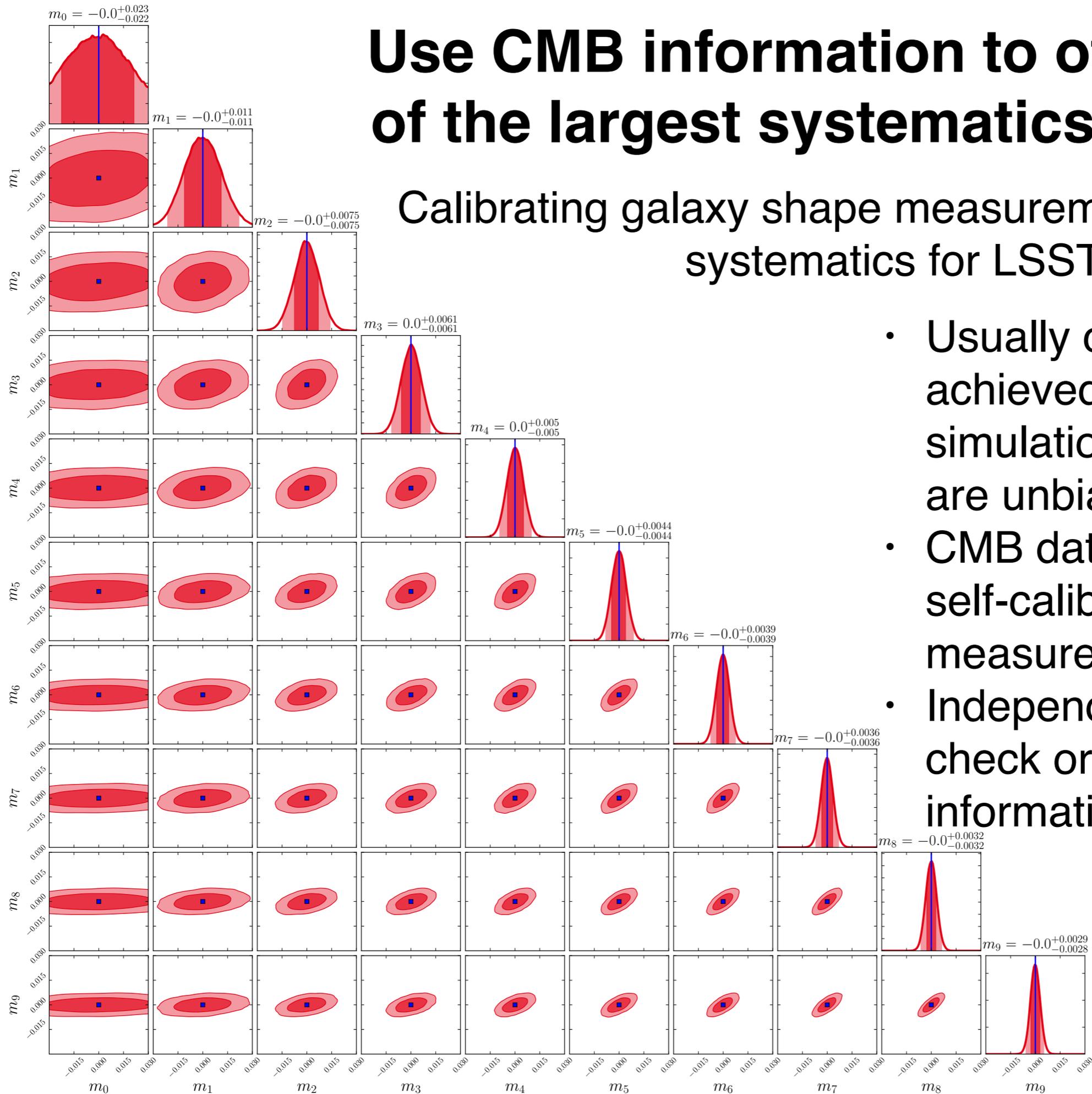
# LSST multi-probe+CMB-S4 Lensing



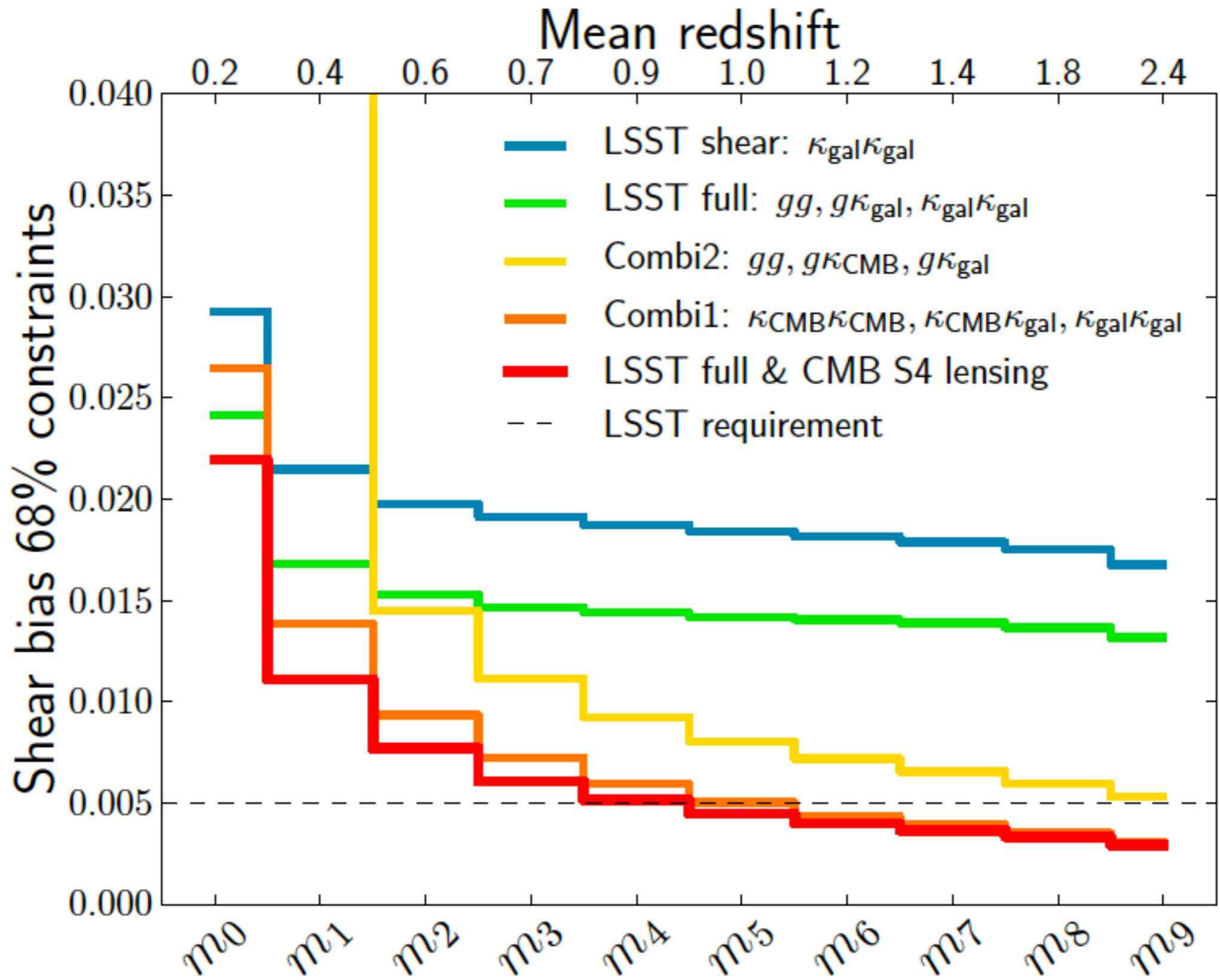
This project is currently evolving into full LSST+CMB-S4 forecasts (cosmology+inflation models)

# Use CMB information to offset one of the largest systematics in LSST

Calibrating galaxy shape measurements is a major systematic for LSST



- Usually calibration is achieved through costly simulations, which we hope are unbiased
- CMB data can be used to self-calibrate LSST shape measurements
- Independent consistency check or additional information



Allows for independent LSST shear calibration at level of LSST requirements in highest z-bins (hard to achieve otherwise)

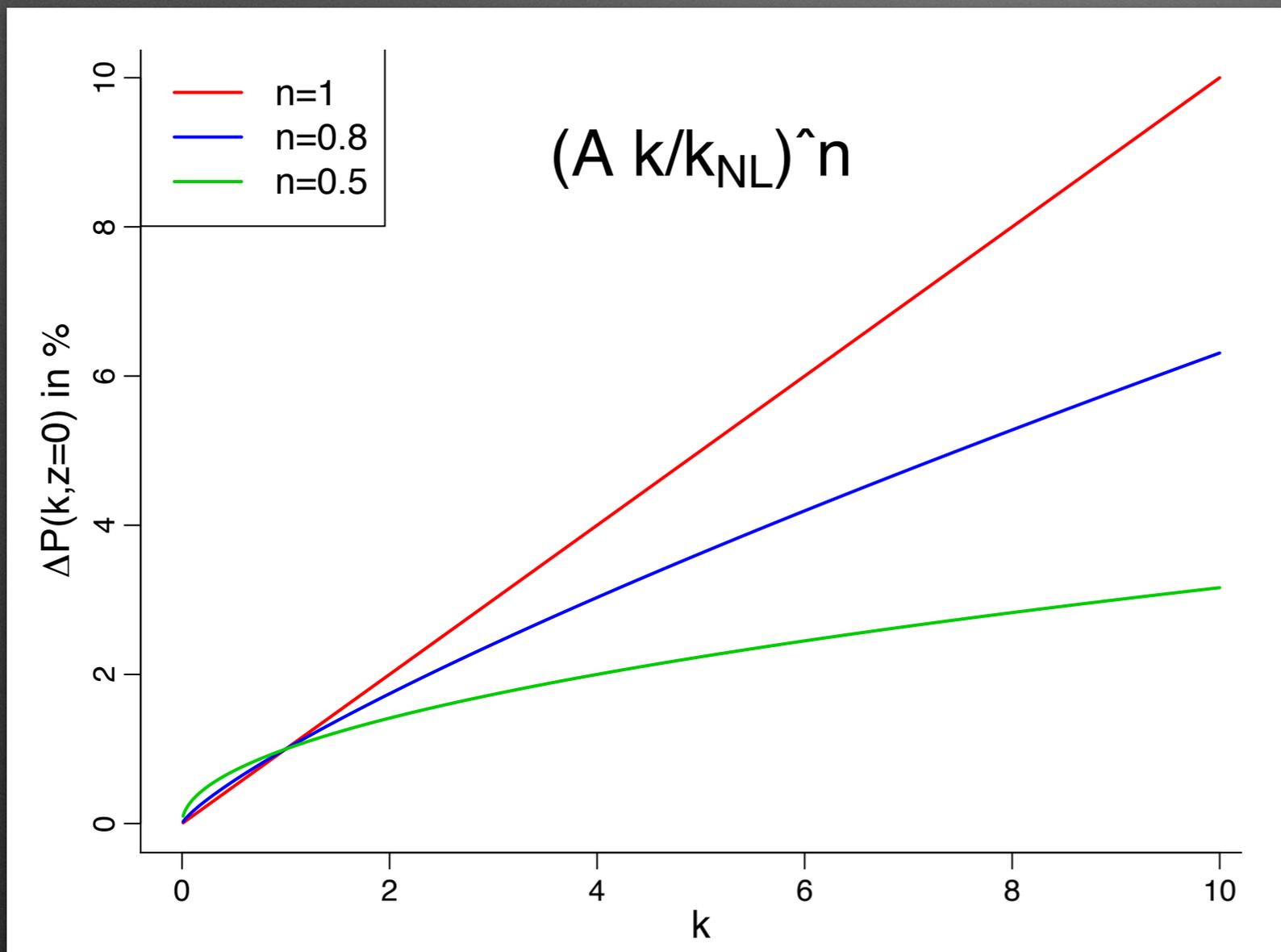
# Project 5: Test Accuracy in Numerical Simulations

Theory -> Sims

Project in some shelf... might never  
see daylight...

# Numerical simulations have uncertainties

## Matter Power Spectrum Error Models

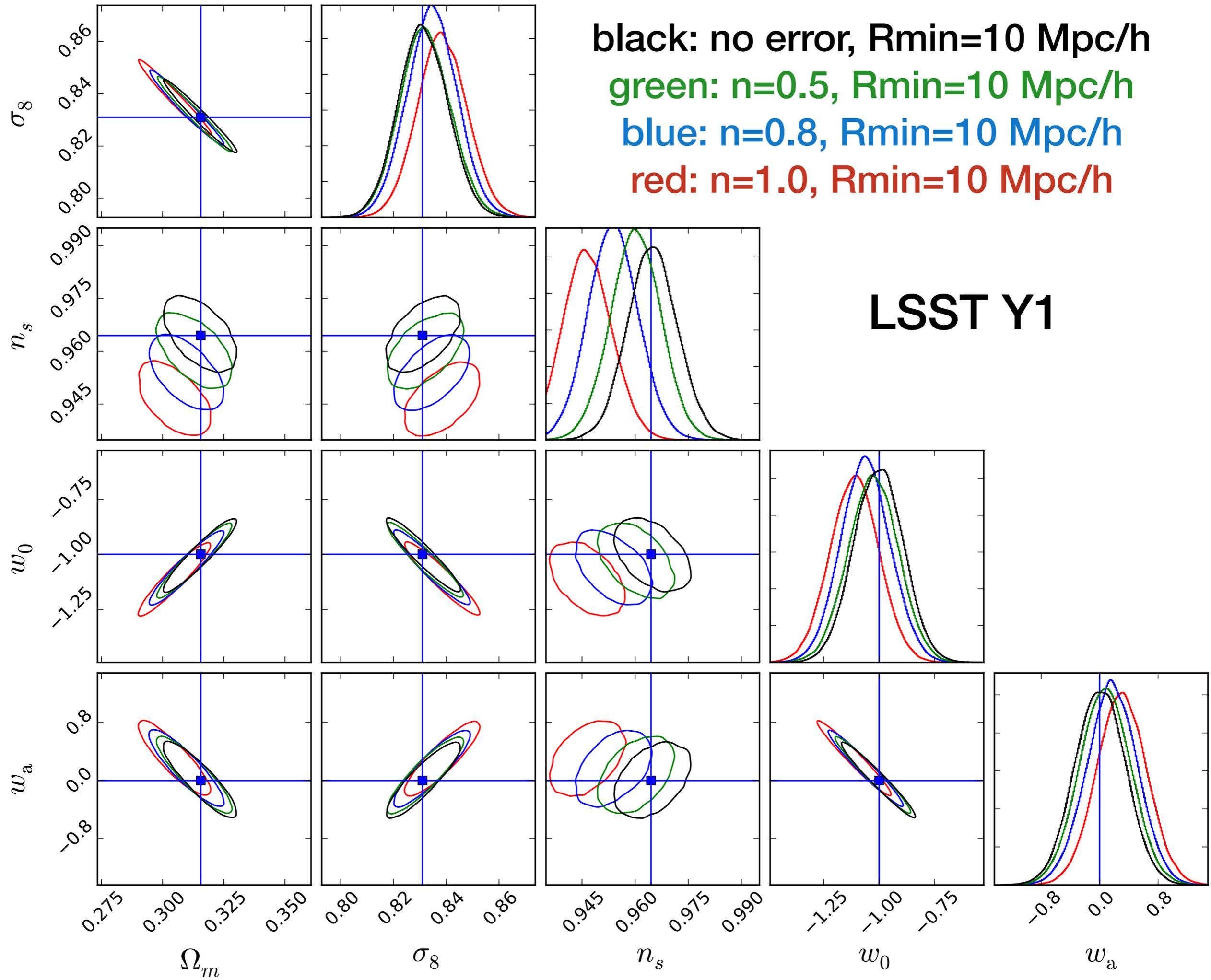


## Joint data vector details (LSST Y1, 18000 deg<sup>2</sup>)

- **WL Source Sample:**
  - 5 tomographic bins [0:2.5]
  - 25 l-bins [30:5000]
  - $n_{gal}=13$  gal/arcmin<sup>2</sup>
- **Clustering Lens Sample:**
  - 4 tomographic bins [0:1.0]
  - 25 l-bins [30:5000]
  - red sequence sample
  - $k_{max}$  cut-off,  $R=[2,5,10]$  Mpc/h to justify linear galaxy bias models
- **Galaxy galaxy lensing using lens and source sample**

**black: no error, Rmin=10 Mpc/h**  
**green: n=0.5, Rmin=10 Mpc/h**  
**blue: n=0.8, Rmin=10 Mpc/h**  
**red: n=1.0, Rmin=10 Mpc/h**

**LSST Y1**



# Conclusions

Future of cosmology is very exciting  
and very complex

- Exciting because of the enormous amount of cosmological data from a variety of surveys
- Complex because smart+precise multi-probe and multi-data set analyses are hard
- We need creative research on systematics mitigation, precise error calculation, model building, data inference
- Critical to interface expertise in simulations, observations, analytical modeling, statistical methods