

An *Unofficial* DESI Analysis

Turning 5 million galaxies into 3 numbers...

Oliver H. E. Philcox

Junior Fellow @ Simons Foundation

Postdoc @ Columbia

Assistant Prof @ Stanford [from September]

Acknowledgements

Reanalyzing DESI DR1:

1. Λ CDM Constraints from the Power Spectrum & Bispectrum

Anton Chudaykin,^{1,*} Mikhail M. Ivanov,^{2,3,†} and Oliver H. E. Philcox^{4,5,6,7,‡}



Additional thanks

- “**East Coast**” team: Marko Simonovic, Matias Zaldarriaga, Giovanni Cabass, Kazu Akitsu, Stephen Chen
- “**West Coast**” team: Guido D’Amico, Leonardo Senatore, Pierre Zhang, Matt Lewandowski

and, of course, the **DESI collaboration!**

[arXiv:2507.13433](https://arxiv.org/abs/2507.13433)

Galaxy Clustering Experiments

The Past

- BOSS [2009 – 2014]

The Present

- DESI [2021 – 2026]
- Euclid [2024 – 2030]

The Nearly

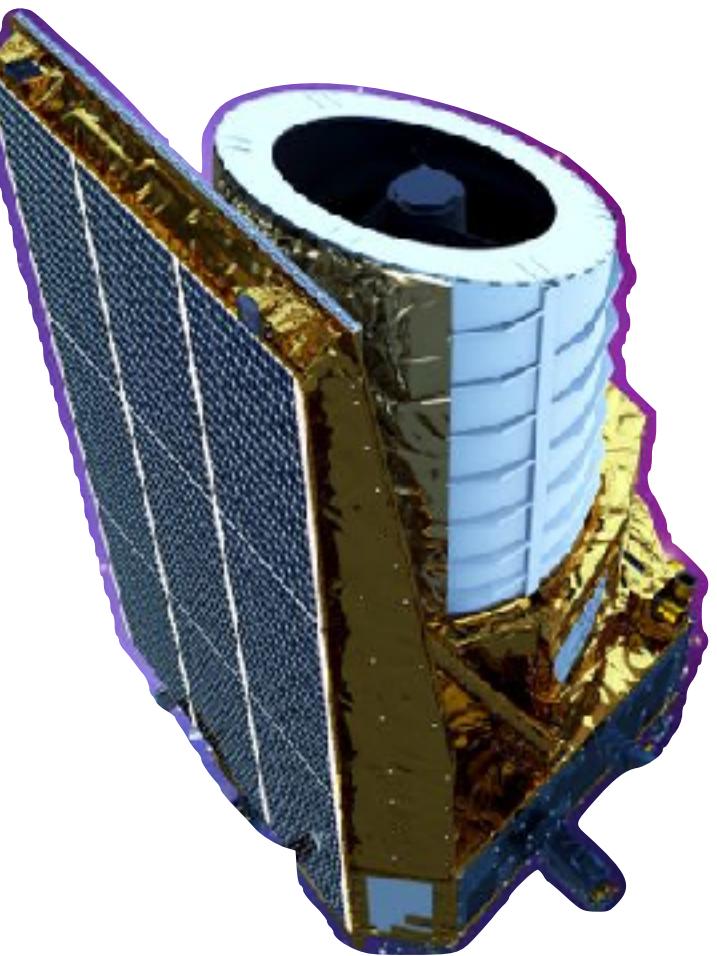
- SphereX [2025 – 2027]
- Rubin [2025 – 2035]
- Roman [launches 2027]

The Future

- Spec-S5? [planning]



SPHEREx



Euclid



DESI



Roman



Rubin

What Do These Probe?

Major Goal: map the distribution of galaxies,
 $\delta_g(\mathbf{x}, z)$ across **space** and **time**

- Surveys range from **low-redshift** ($z \lesssim 0.1$) to high-redshift ($z \lesssim 3$)
 - *Low-z* – magnitude limited
 - *High-z* – large volume
- The surveys range from **ultra-large** to **ultra-deep**
 - *Large* – GR and non-Gaussianity
 - *Deep* – Non-linearities and structure formation



Each blob is a 3D galaxy position!

How to Model A Galaxy Survey

- **Initial Conditions**

- **Gaussian**, with $\zeta \sim \mathcal{N}(0, P_\zeta)$
- (Almost) **Scale-invariant**, with $P_\zeta(k) \sim A_s k^{n_s - 4}$
- **Adiabatic** — all fields have the same initial conditions!

- **Early Universe Physics**

- Standard expansion history including **matter-radiation equality** $k_{\text{eq}} \sim \Omega_m H_0$
- Recombination physics, including **sound horizon** $r_d \sim \Omega_b H_0^2, \Omega_m H_0^2, \dots$

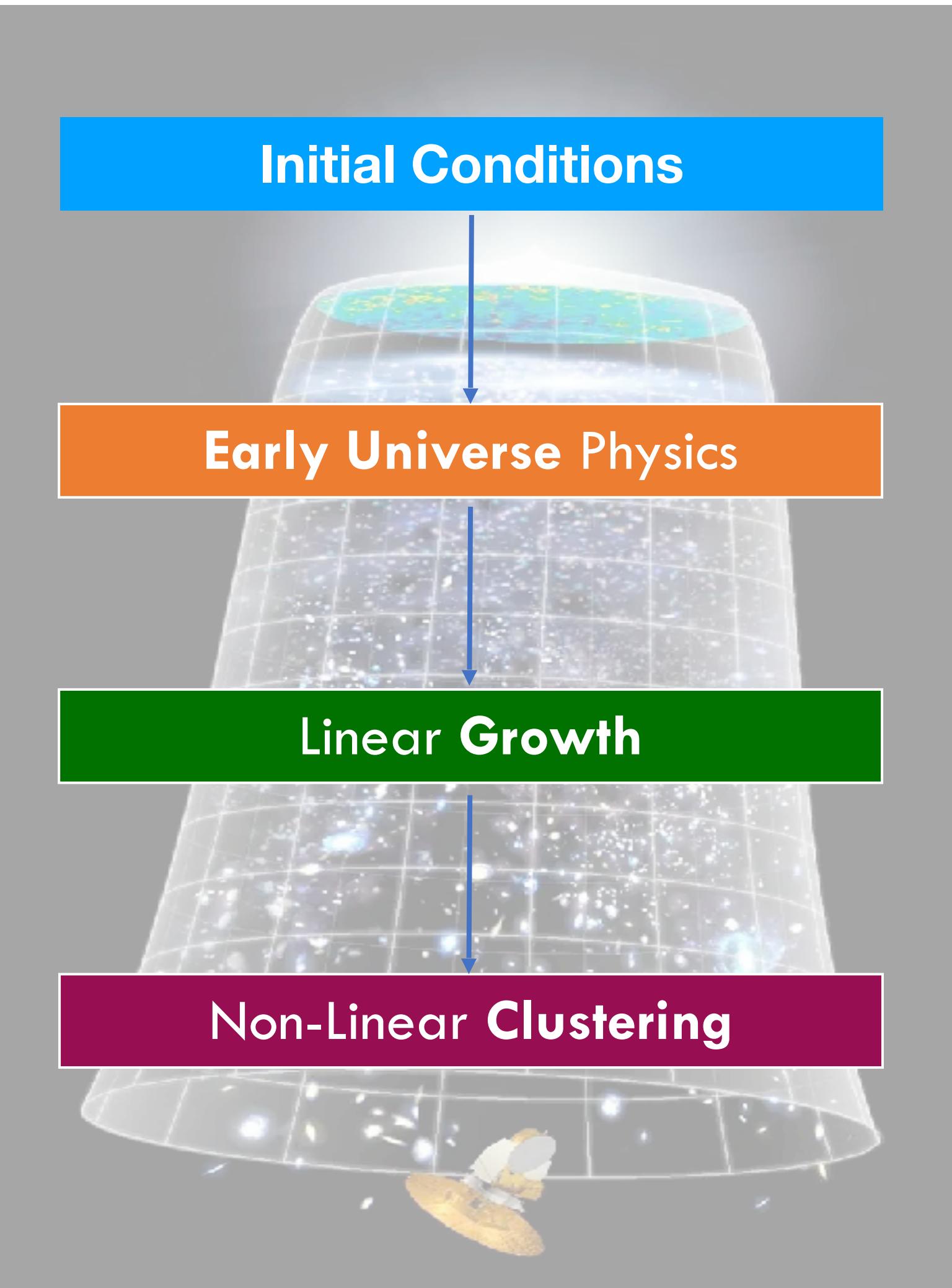
- **Linear Growth**

- Background — $H(z), D_A(z)$ set by $H_0, \Omega_m, \Omega_r, \Omega_\Lambda$
- Perturbations — $D(z), f(z) \sim \Omega_m(z)^\gamma$ set by $\Omega_m, \Omega_r, \Omega_\Lambda + \text{GR}$

- **Non-Linear Clustering**

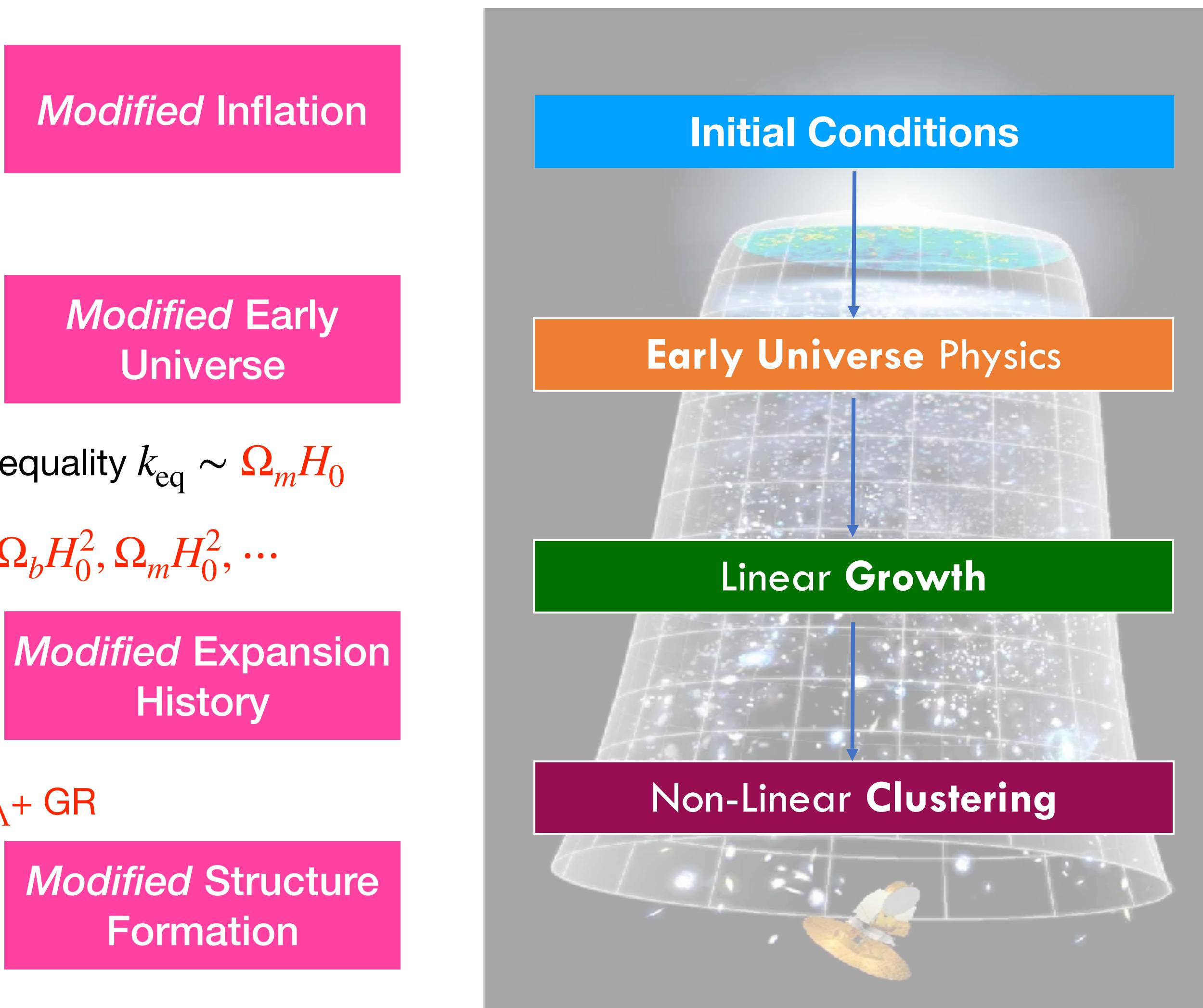
- Collapse of **dark matter** into bound structures
- Formation of **galaxies** around dark matter halos

← ***This is the hard bit!***



How to Model A Galaxy Survey – beyond Λ CDM

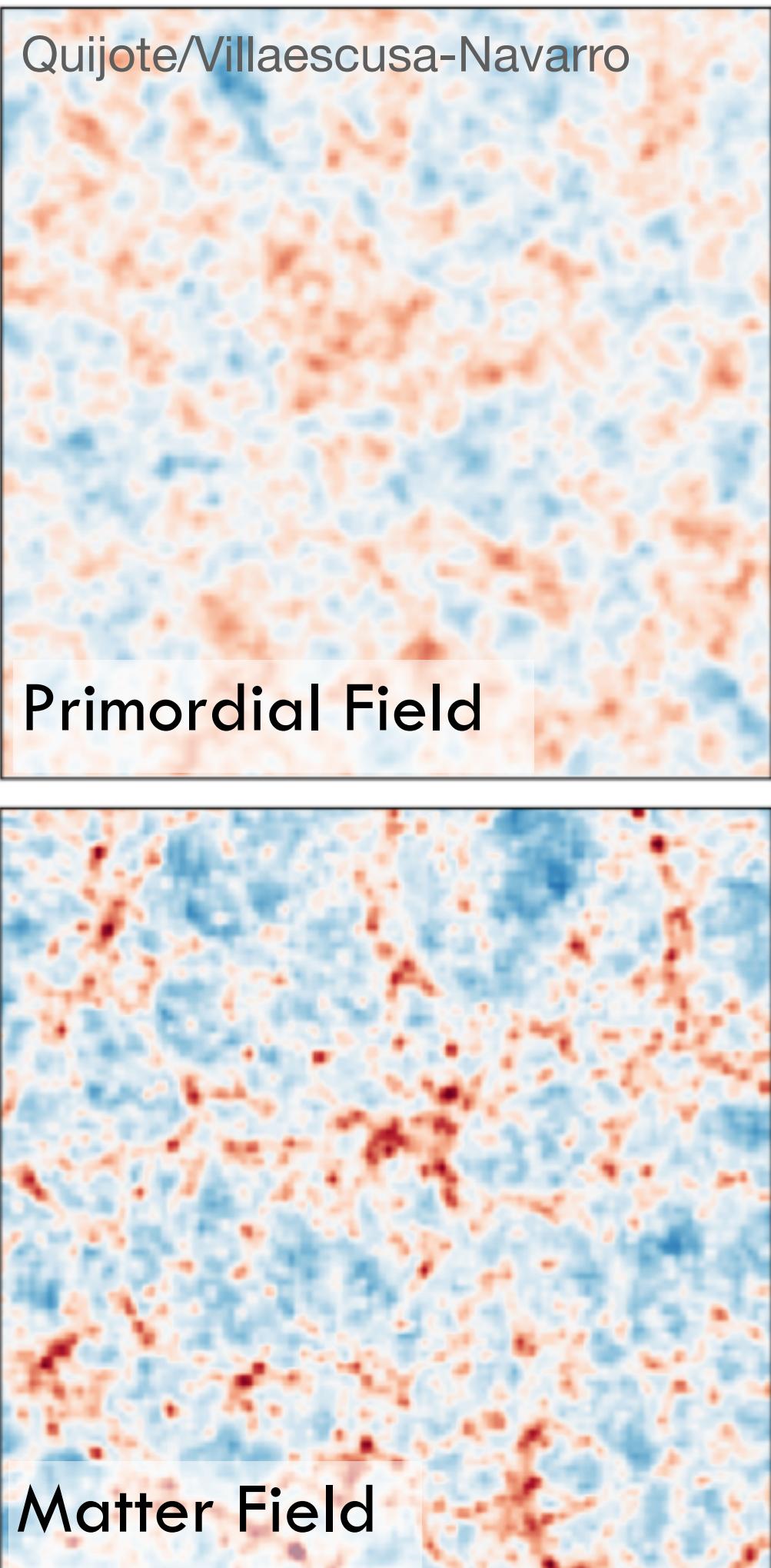
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- **Non-Linear Clustering**
 - Collapse of dark matter into bound structures
 - Formation of galaxies around dark matter halos



Modeling Non-Linearities

Step 1: predict the distribution of dark matter $\delta_m(\mathbf{x}, z)$

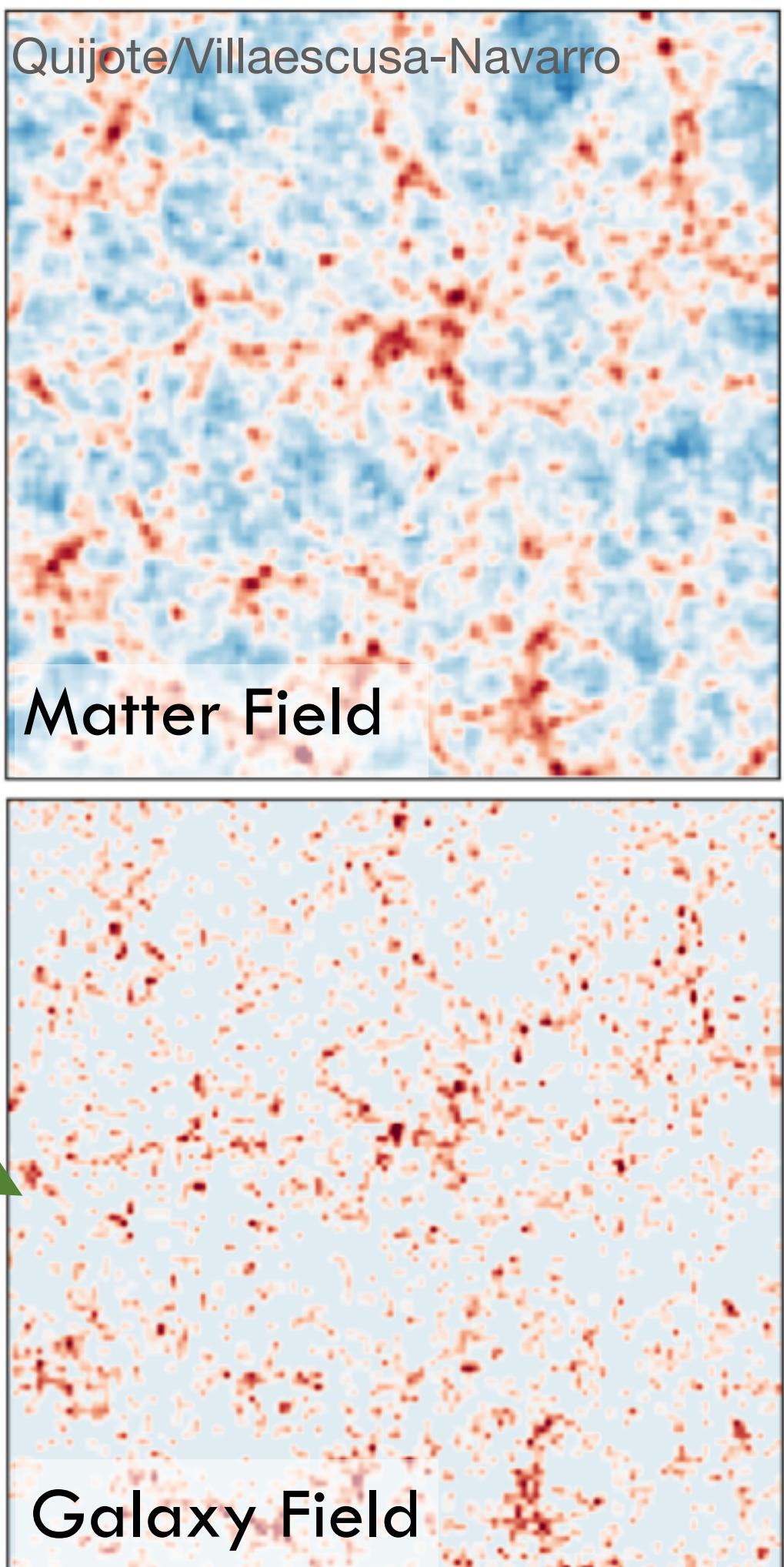
- This can be done either **analytically** or **numerically**
- Most modern analyses use the “**Effective Field Theory of Large-Scale Structure**”
 - This *smoothes* (“coarse-grains”) the dark matter on some scale $R \gtrsim 10 \text{ Mpc}$
 $\delta_m \rightarrow \delta_m \star \text{smoothing}[R]$
 - We can compute δ_m as a **perturbation series** in the **initial conditions**
$$\delta_m \sim K_1 \zeta + \int K_2 \zeta^2 + \int \int K_3 \zeta^3 + \dots$$
 - The **coupling kernels** are set by **gravity**
 - Free **counterterms** account for **small-scale** physics (“renormalization”)
- **Alternative** — run **N-body simulations** and **emulate** the statistics of interest



Modeling Non-Linearities

Step 2: predict the distribution of galaxies $\delta_g[\delta_m](\mathbf{x}, z)$

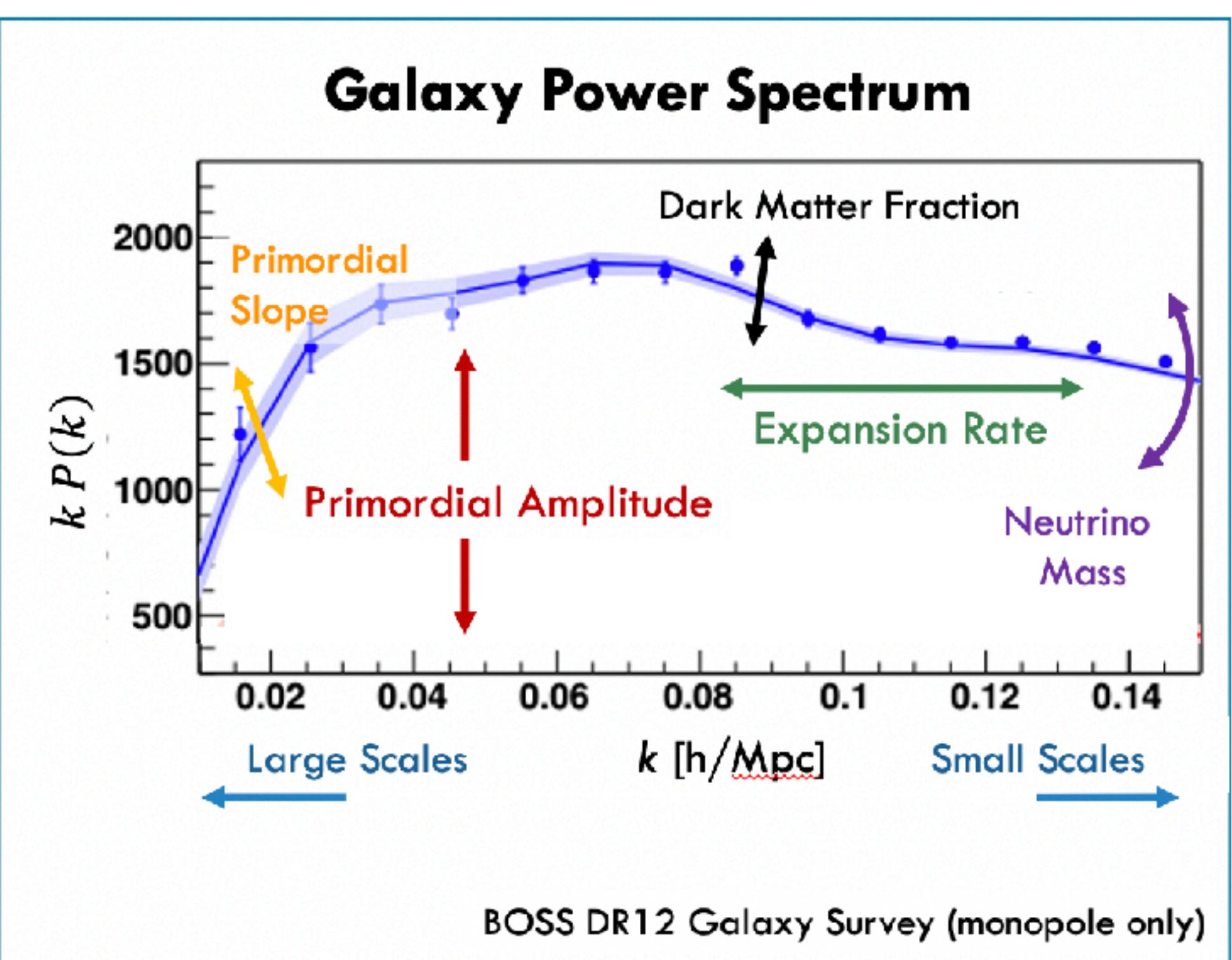
- This can be done **analytically**, **semi-analytically** or **numerically**
- **Effective Field Theory** approach:
 - Compute δ_g as a **perturbation series** in the dark matter density, δ_m
 - Use **symmetries** to account for **any galaxy formation** effects [e.g., homogeneity, isotropy, Galilean invariance]:
$$\delta_g = b_1 \delta + b_2 \delta^2 + b_s s_{ij} s^{ij} + b_\nabla \nabla^2 \delta + \dots$$
 - The **bias parameters** encode galaxy formation physics
 - This is **robust** but limited to large-scales \Rightarrow *loss of information*
 - Can model δ_m either from **theory** or **simulations** (Hybrid EFT)
- **Alternatives:**
 - Post-process **simulations** to add galaxies, with an **HOD** or **Semi-Analytic Model**
 - Perform a full **hydrodynamical simulation!**



What Statistics Should We Use?

Most analyses focus on the simplest statistics

- The **Baryon Acoustic Oscillations** (BAO)
 - Good for tracing the **expansion history** across time
- The **Galaxy Power Spectrum** (or correlation function)
 - This is a **powerful** probe of Λ CDM!



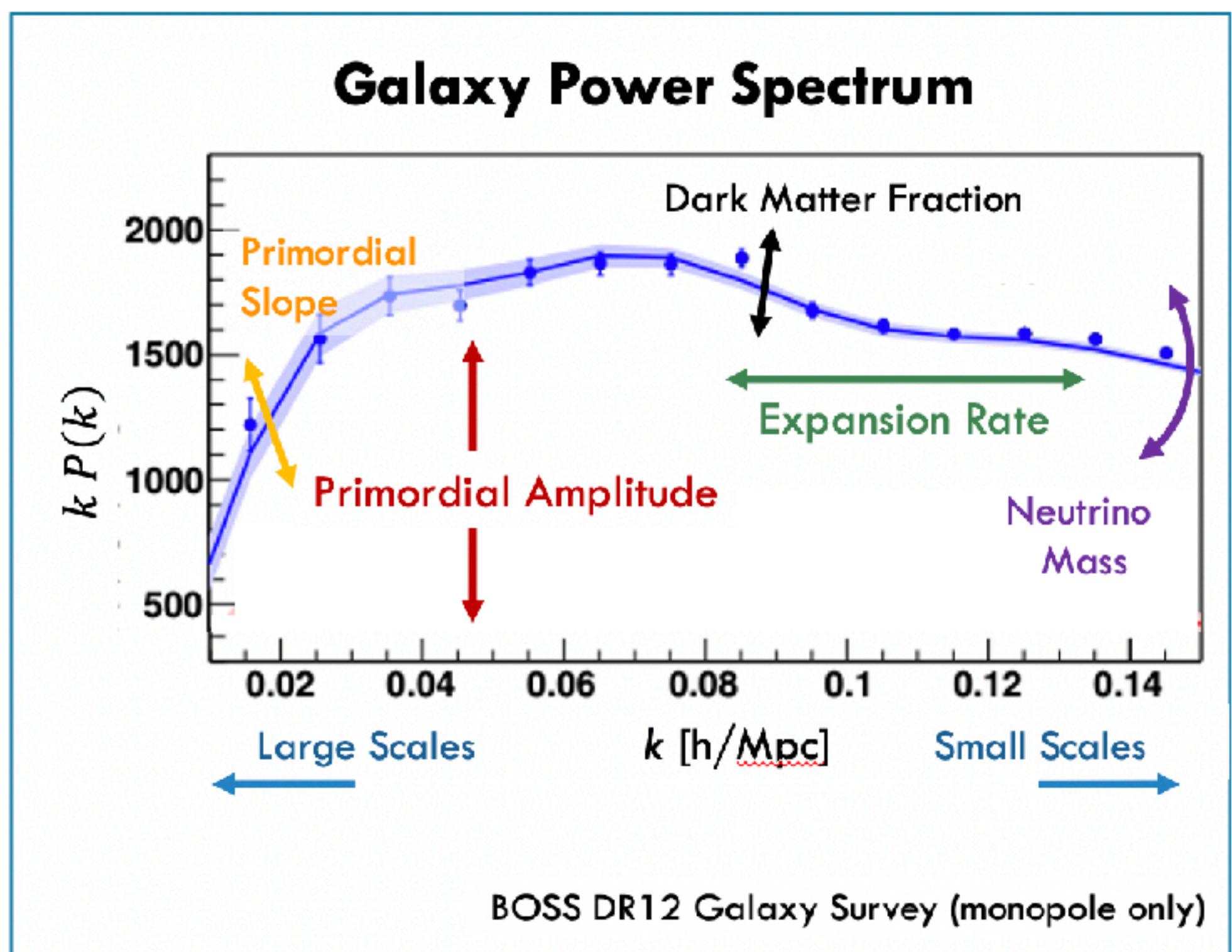
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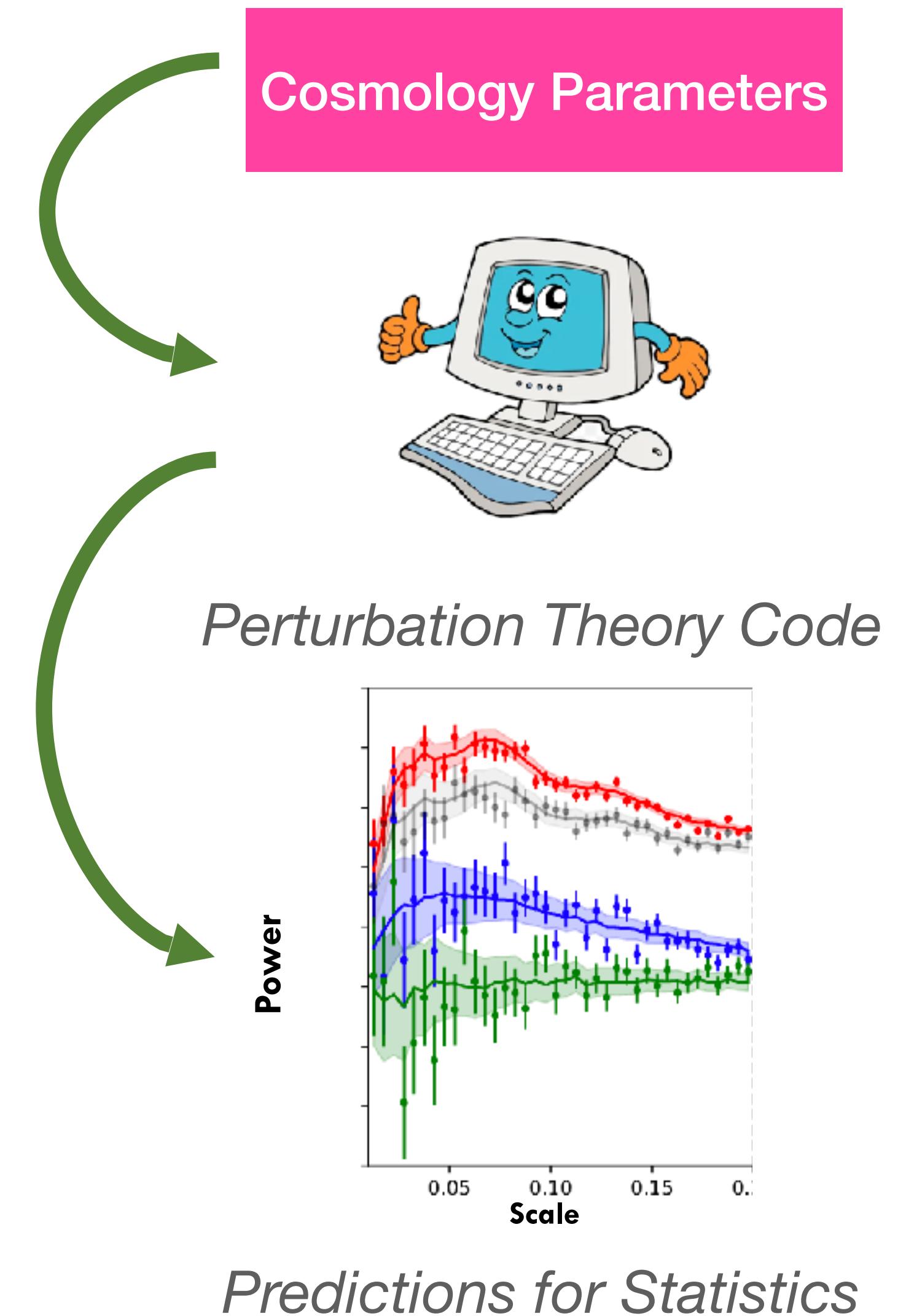
Other options include:

- **Bispectra** and **Trispectra** (3-Point and 4-Point Functions)
 - Traces non-linear information and **inflation** but more expensive!
- **Galaxy bias** and **halo mass functions** $n_{\text{gal}}(M_{\text{halo}})$
 - These probe halo-scale physics ($R \lesssim 10h^{-1}\text{Mpc}$) but are difficult to model!
- **Wavelets, kNNs, CNNs, marked statistics, density-split statistics, ...**
 - These are **non-linear** probes that must be modeled numerically!
- Cross-Correlations with **weak lensing**
 - Strong probes of **gravity**
- Galaxy **spins**, galaxy **shapes**
 - Higher-order physics including **tensors**



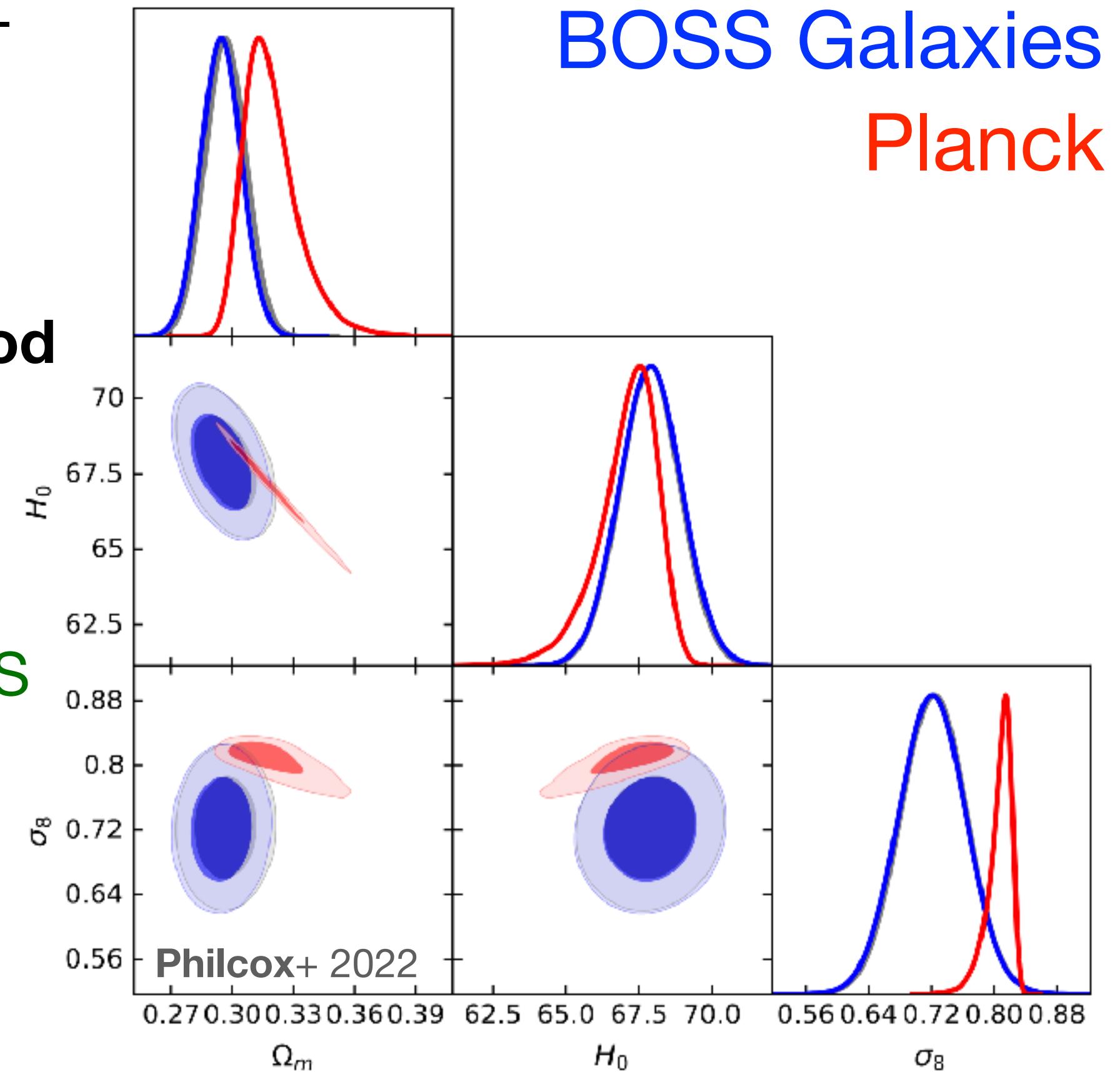
Theory In Practice

- There are **fast codes** implementing the theory predictions:
 - CLASS-PT, Velocileptors, PyBird, PBJ, Class OneLoop, FOLPS- ν ,...
 - These predict the **power spectrum** or **bispectrum** of galaxies
 - By combining with an **observed dataset** and a **Gaussian likelihood** we can constrain any Λ CDM parameter entering the model!



Theory In Practice

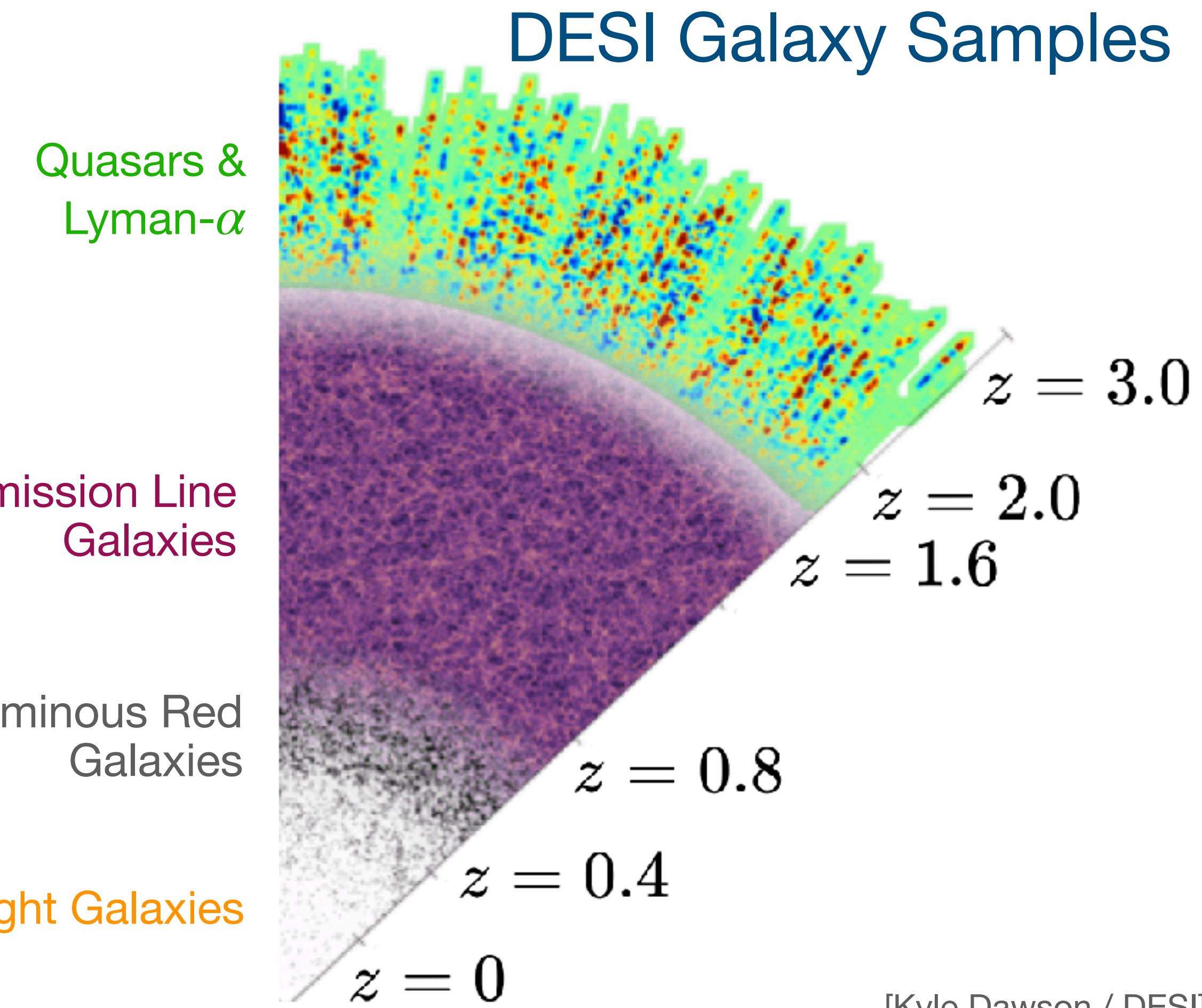
- There are **fast codes** implementing the theory predictions:
 - CLASS-PT, Velocileptors, PyBird, PBJ, Class OneLoop, FOLPS- ν, \dots
- These predict the **power spectrum** or **bispectrum** of galaxies
- By combining with an **observed dataset** and a **Gaussian likelihood** we can constrain any Λ CDM parameter entering the model!
- This has been used to measure $\Omega_m, H_0, \sigma_8, \dots$ from BOSS / eBOSS in **full-shape / direct modeling** analyses
 - (See also *ShapeFit* and $f\sigma_8$ measurements)
- Recently, it has been applied to the **Year 1 DESI dataset**



Can we reproduce this?

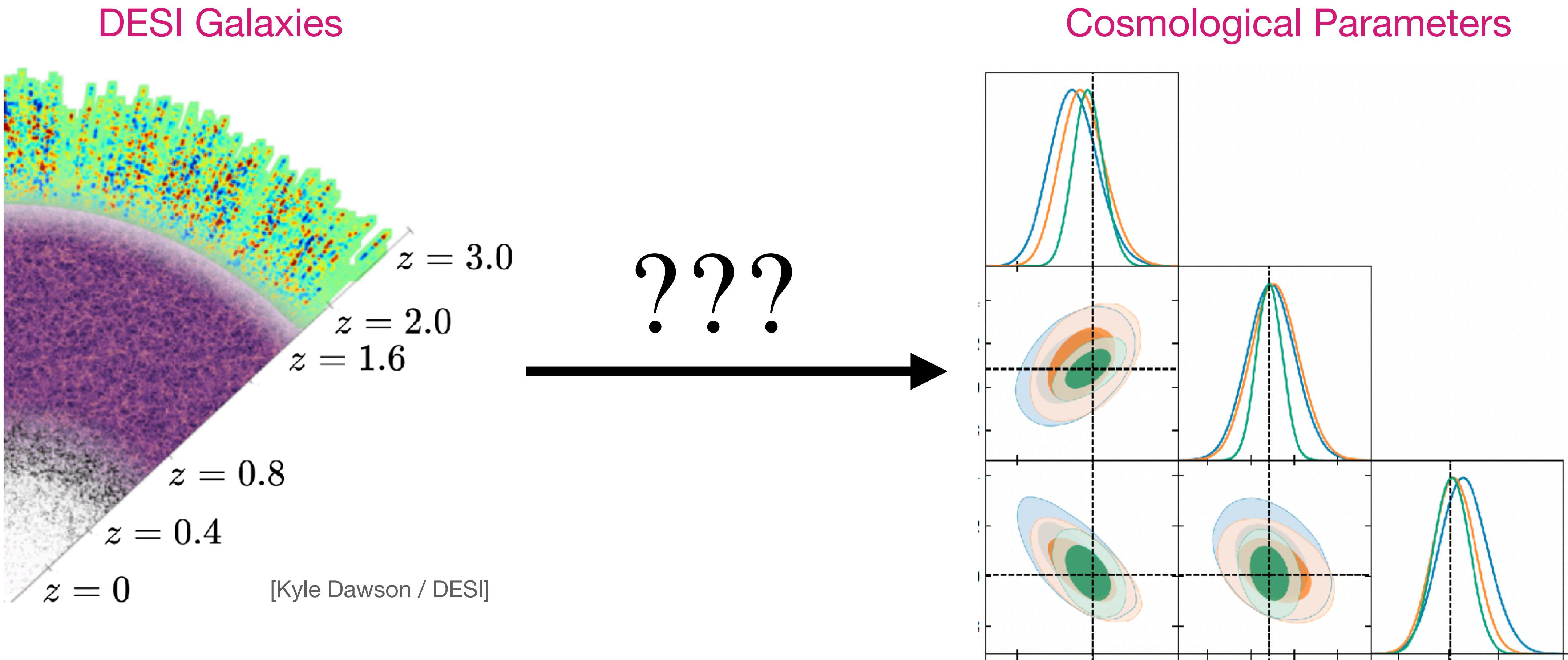
The DESI Universe

- We analyze **six** DESI chunks:
 - **BGS**: Bright Galaxy Sample ($0.1 < z < 0.4$)
 - Low redshift, magnitude limited
 - **LRG**: Luminous Red Galaxies ($0.4 < z < 1.1$)
 - Similar to previous surveys!
 - **ELG**: Emission Line Galaxies ($1.1 < z < 1.6$)
 - Low-redshift tail dropped due to systematic contamination
 - **QSO**: Quasars ($0.8 < z < 2.1$)
 - High redshift, **large** shot-noise
 - **Lyman-alpha** Emission
 - Not included in DR1
 - Each is split into **north** and **south** regions



[Kyle Dawson / DESI]

Reanalyzing DESI



Reanalyzing DESI

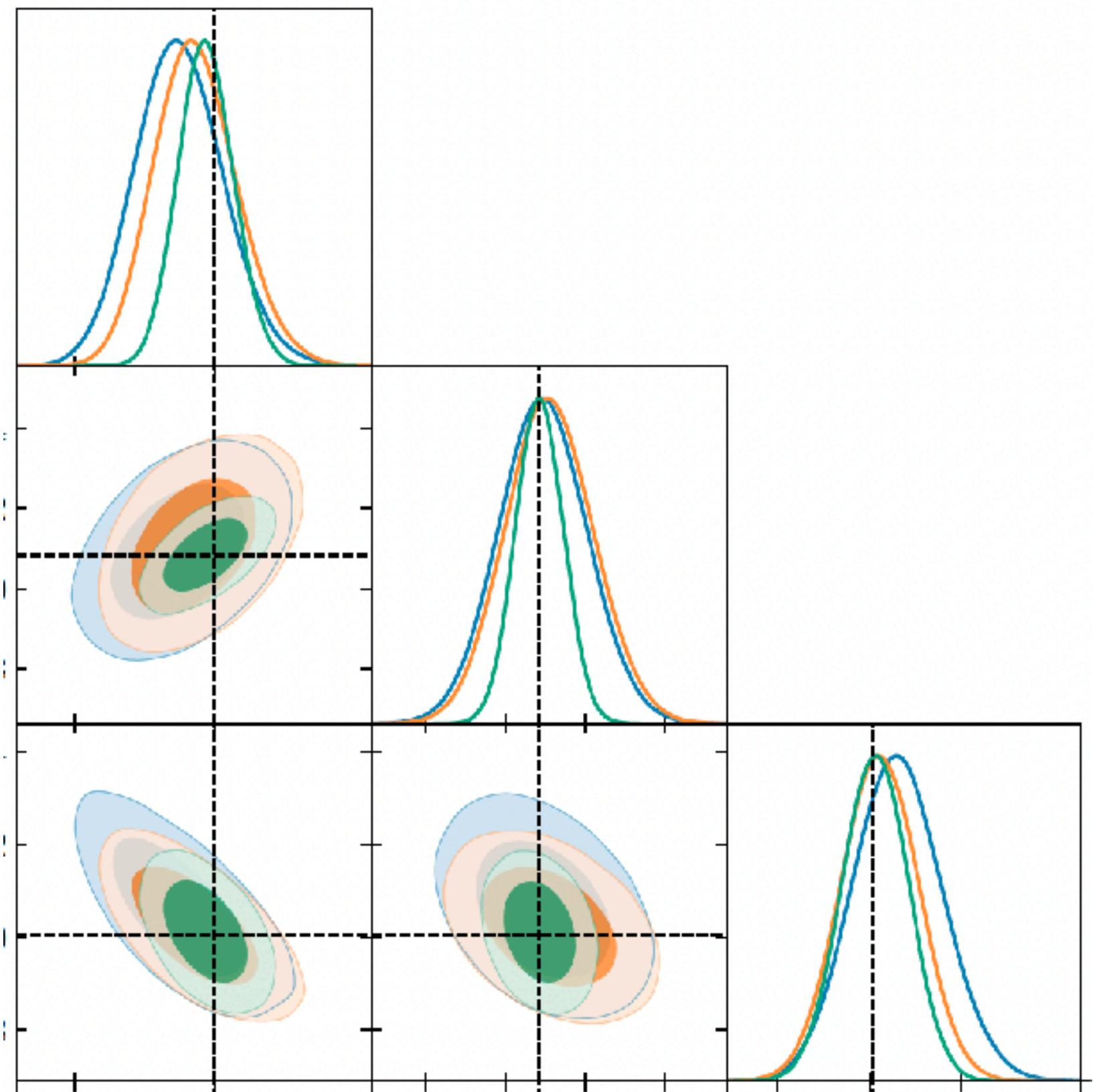
DESI Data Release 1 (LRGs)

TARGETID	Z	NTILE	RA	DEC	...
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39627546840531340	0.9348172077800124	1	158.4799294702238	-9.880343166939232	...
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39627546853115682	0.9274570688680336	1	159.30835543527493	-10.106935803496164	...
...

???



Cosmological Parameters



Reanalyzing DESI

DESI Data Release 1 (LRGs)

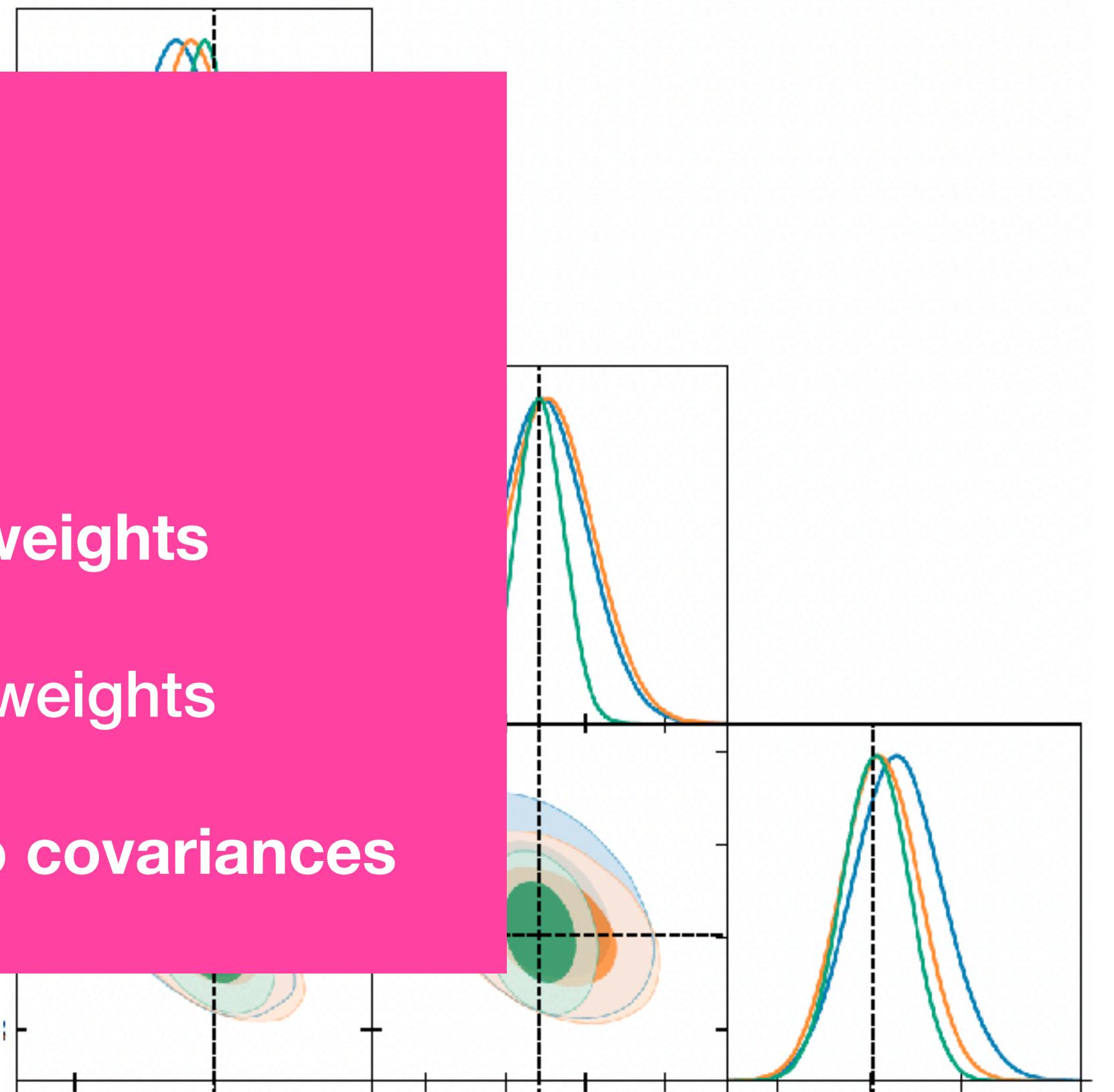
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39627546840534067	0.88129590000311	
39627546840534396	0.6646155566176719	
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39627546853115304	0.5559672054059013	
39627546853115470	0.7147216867384578	
39627546853115682	0.9274570688680336	
...

This is hard

The data release **only** contains:

- Galaxy positions, redshifts and systematic weights
- Random positions, redshifts and systematic weights

There are no simulations, no power spectra and no covariances



Reanalyzing DESI

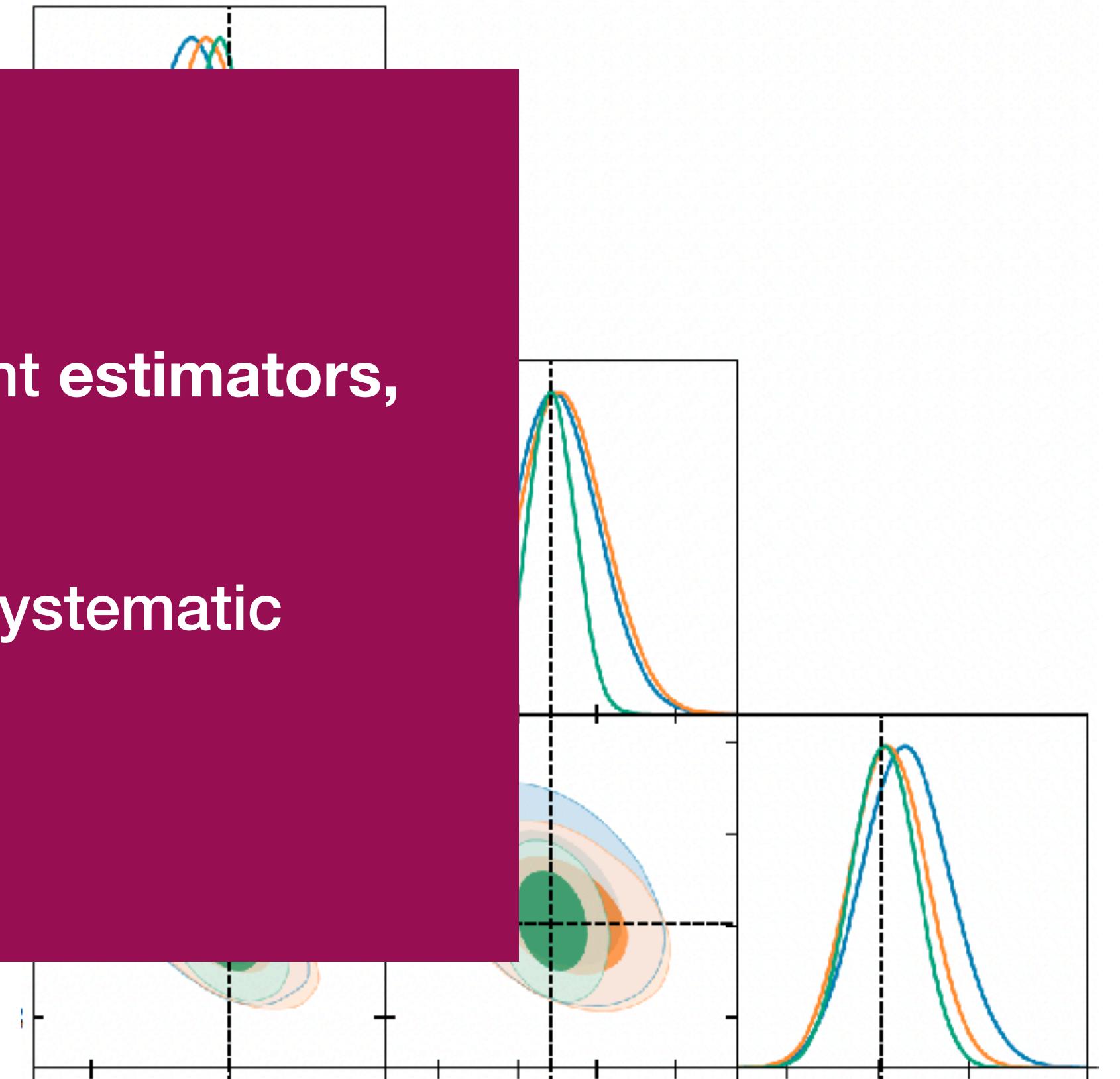
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...

This is important

We develop an **independent pipeline**, using different **estimators**, **covariance estimates**, and **theory codes**

We can include **more data** with **new methods** for systematic corrections



Two-Point Estimators

- The DESI data is a **point cloud** of positions and weights for **galaxies** and **randoms**

$$n_g(\mathbf{x}) \sim \sum_{i=1}^{N_g} w_{g,i} \delta_D(\mathbf{x} - \mathbf{x}_{g,i}), \quad n_r(\mathbf{x}) \sim \sum_{i=1}^{N_r} w_{r,i} \delta_D(\mathbf{x} - \mathbf{x}_{r,i})$$

- We want to turn this into a **power spectrum**

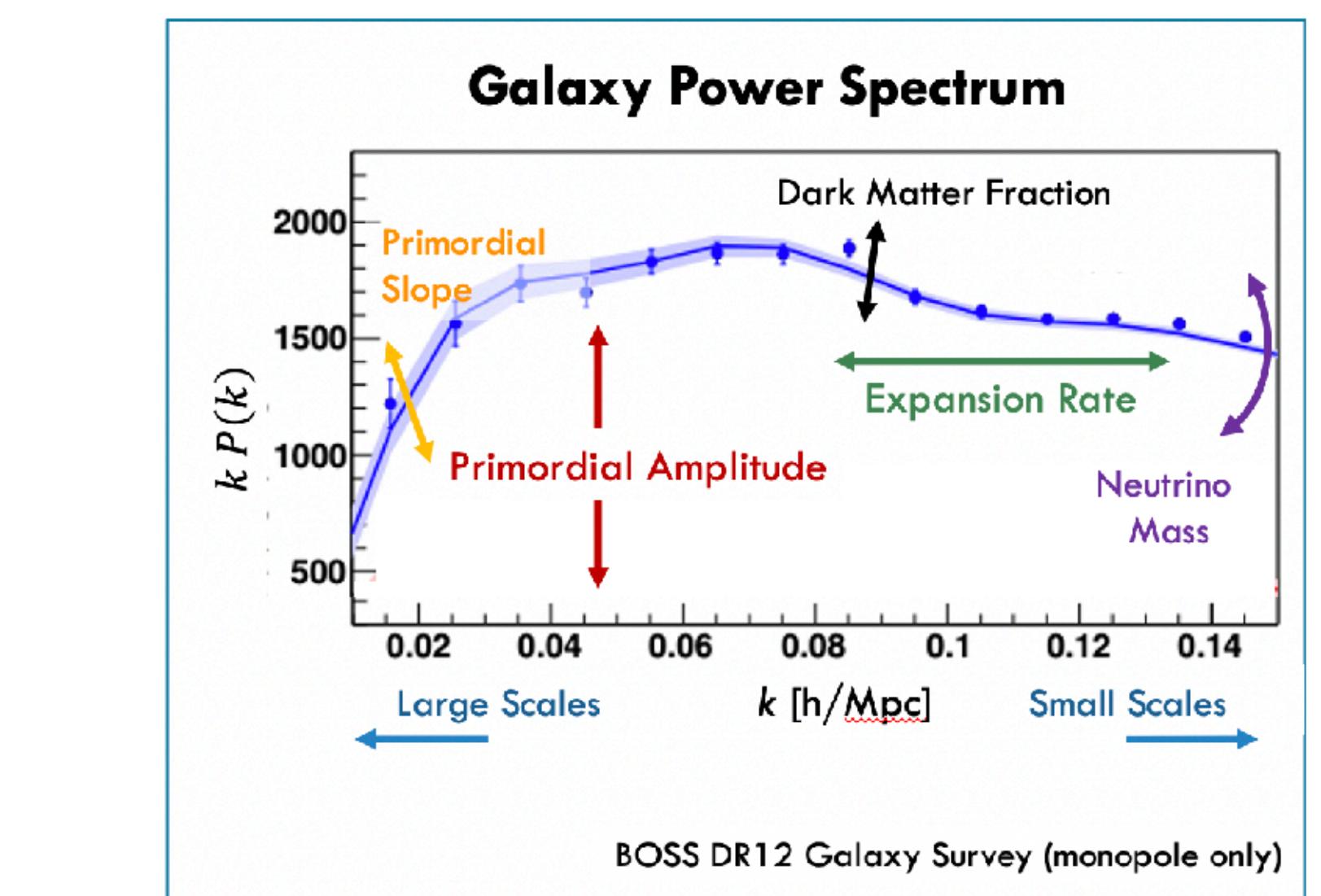
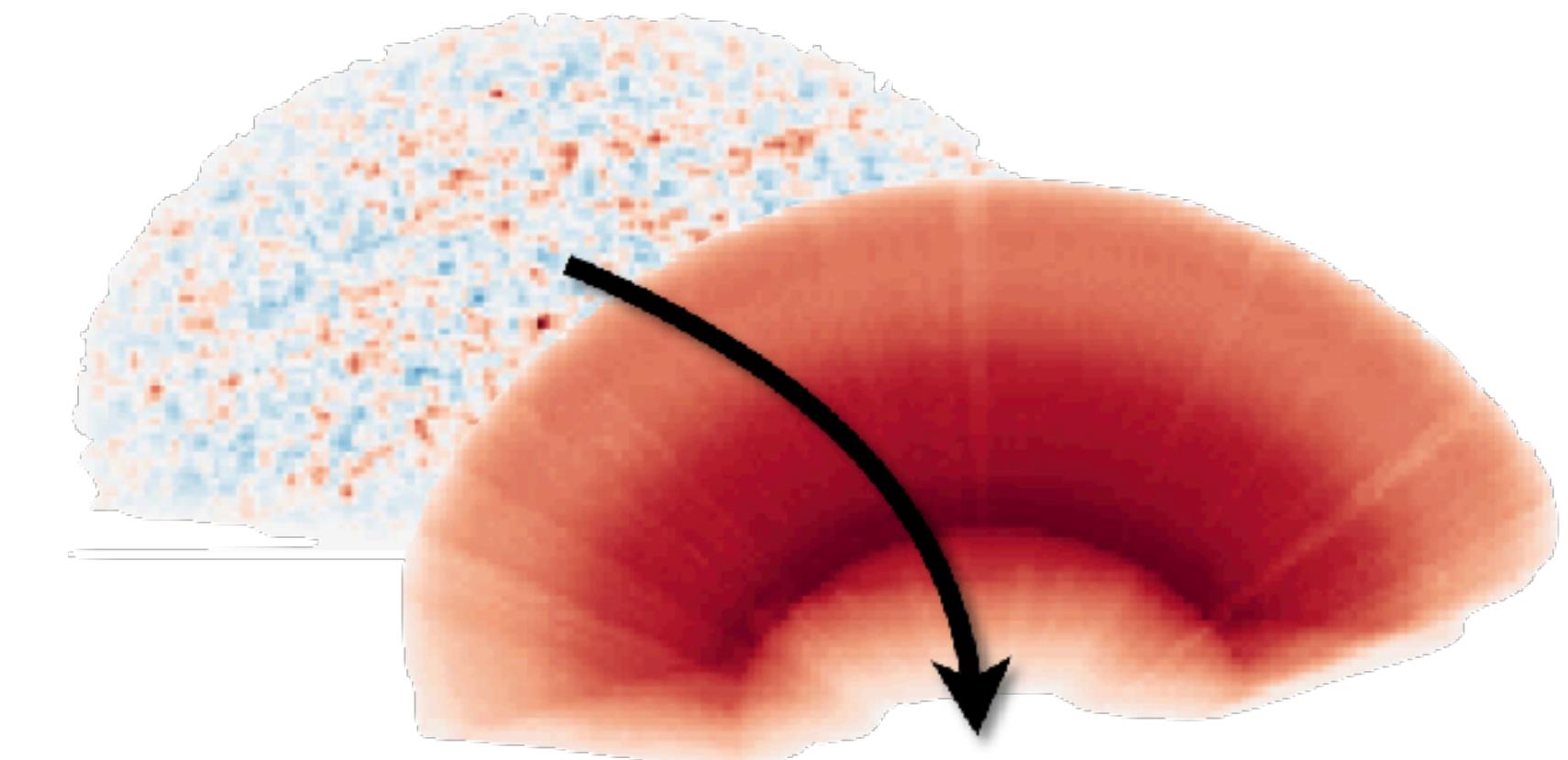
1. FKP estimator

Used by DESI

$$P_{\text{FKP}}(\mathbf{k}) \sim \left| n_g(\mathbf{k}) - \frac{N_g}{N_r} n_r(\mathbf{k}) \right|^2 / \langle n^2 \rangle$$

- This is (almost) optimal
- The output is convolved with the mask:

$$P_{\text{FKP}}(\mathbf{k}) \sim \int d\mathbf{q} \left| n(\mathbf{k} - \mathbf{q}) \right|^2 P_{\text{true}}(\mathbf{q}) / \langle n^2 \rangle$$



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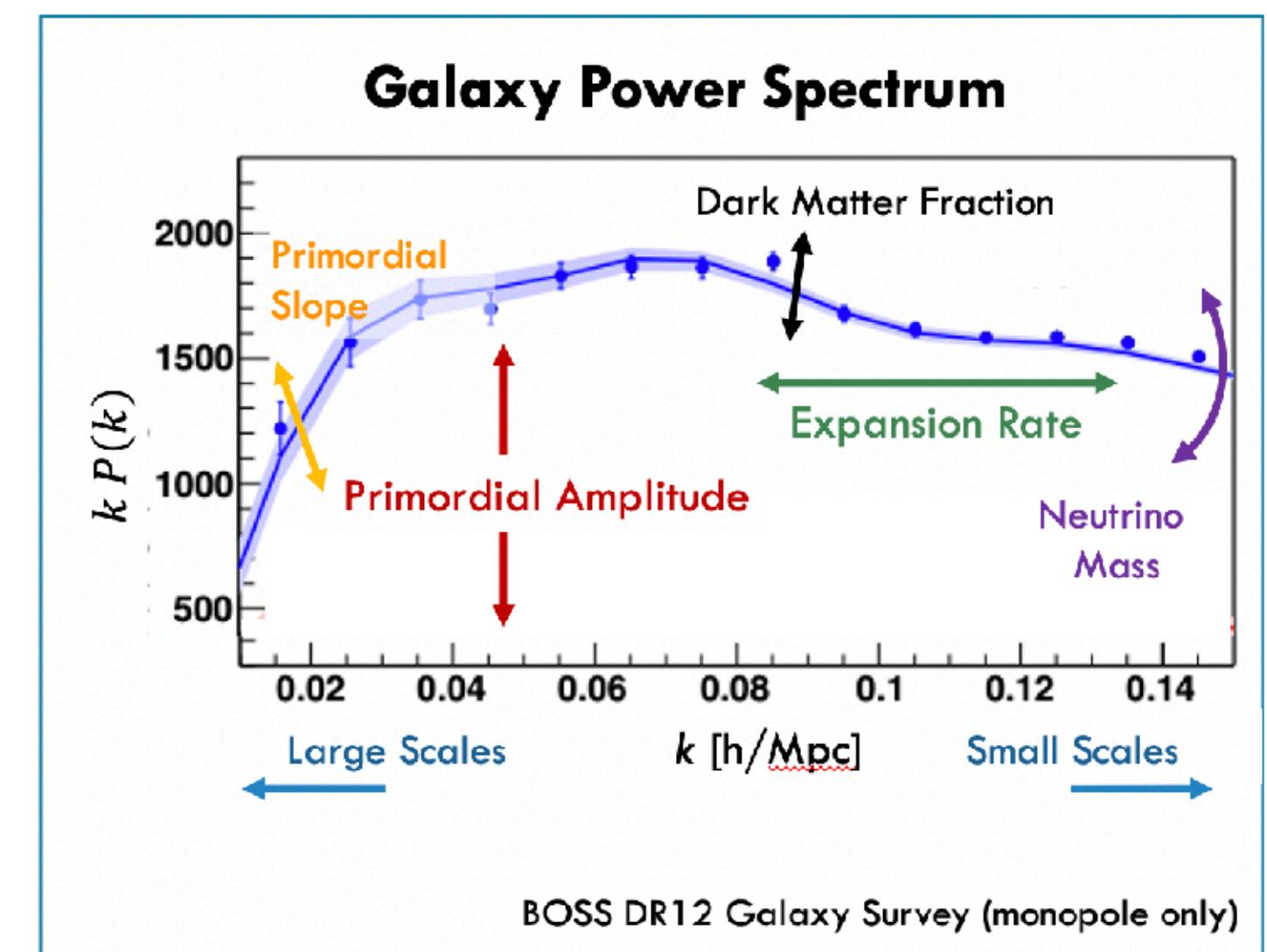
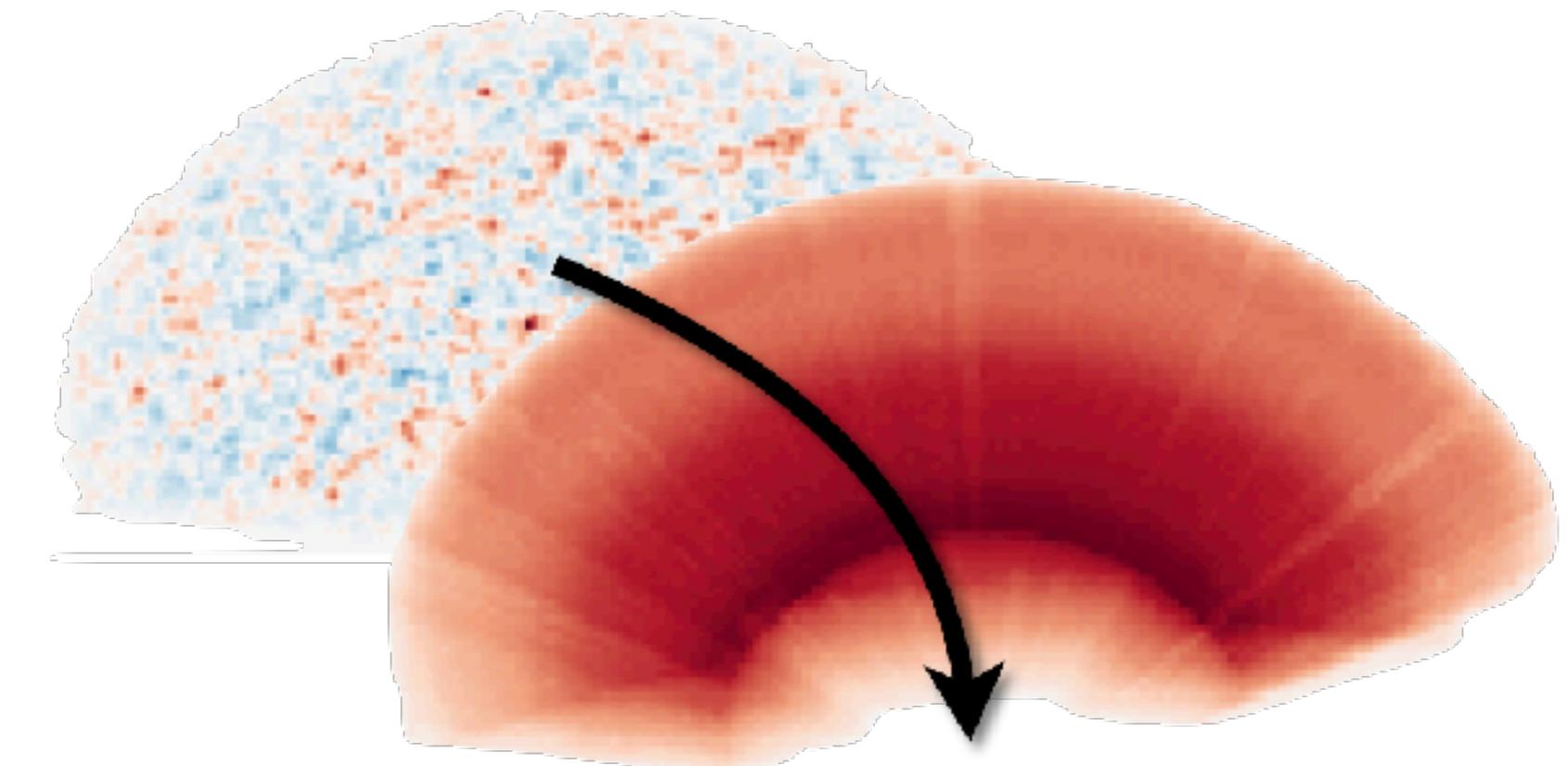
2. Quasi-Optimal “**Unwindowed**” estimator

← Used by us

$$P_{\text{unwin}}(\mathbf{k}) \sim \int d\mathbf{q} \mathbf{W}^{-1}(\mathbf{k}, \mathbf{q}) \left| n_g(\mathbf{q}) - \frac{N_g}{N_r} n_r(\mathbf{q}) \right|^2 / \langle n^2 \rangle$$

- At leading order, the output is **not** convolved with the mask:

$$P_{\text{unwin}}(\mathbf{k}) \sim P_{\text{true}}(\mathbf{k})$$

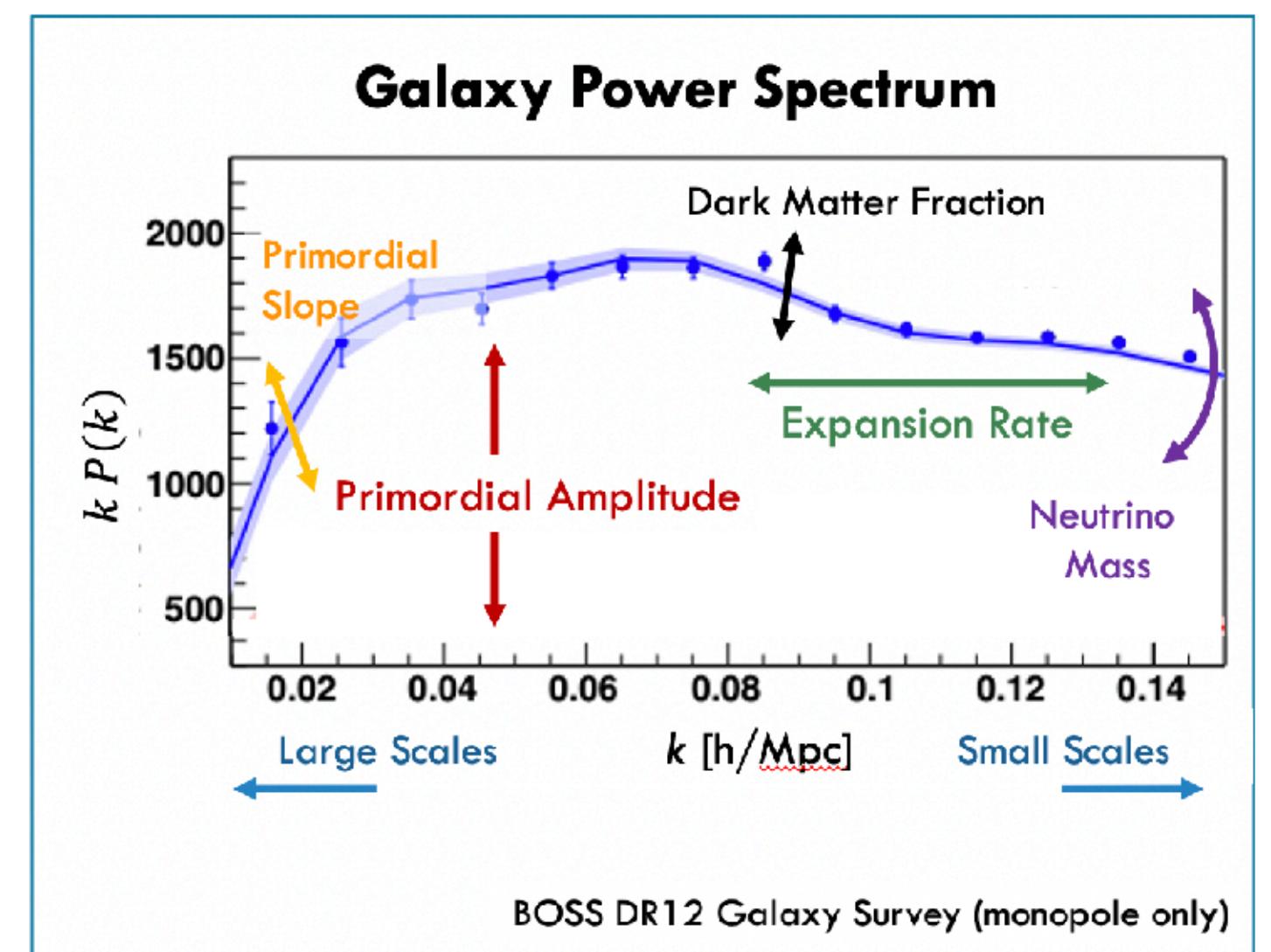
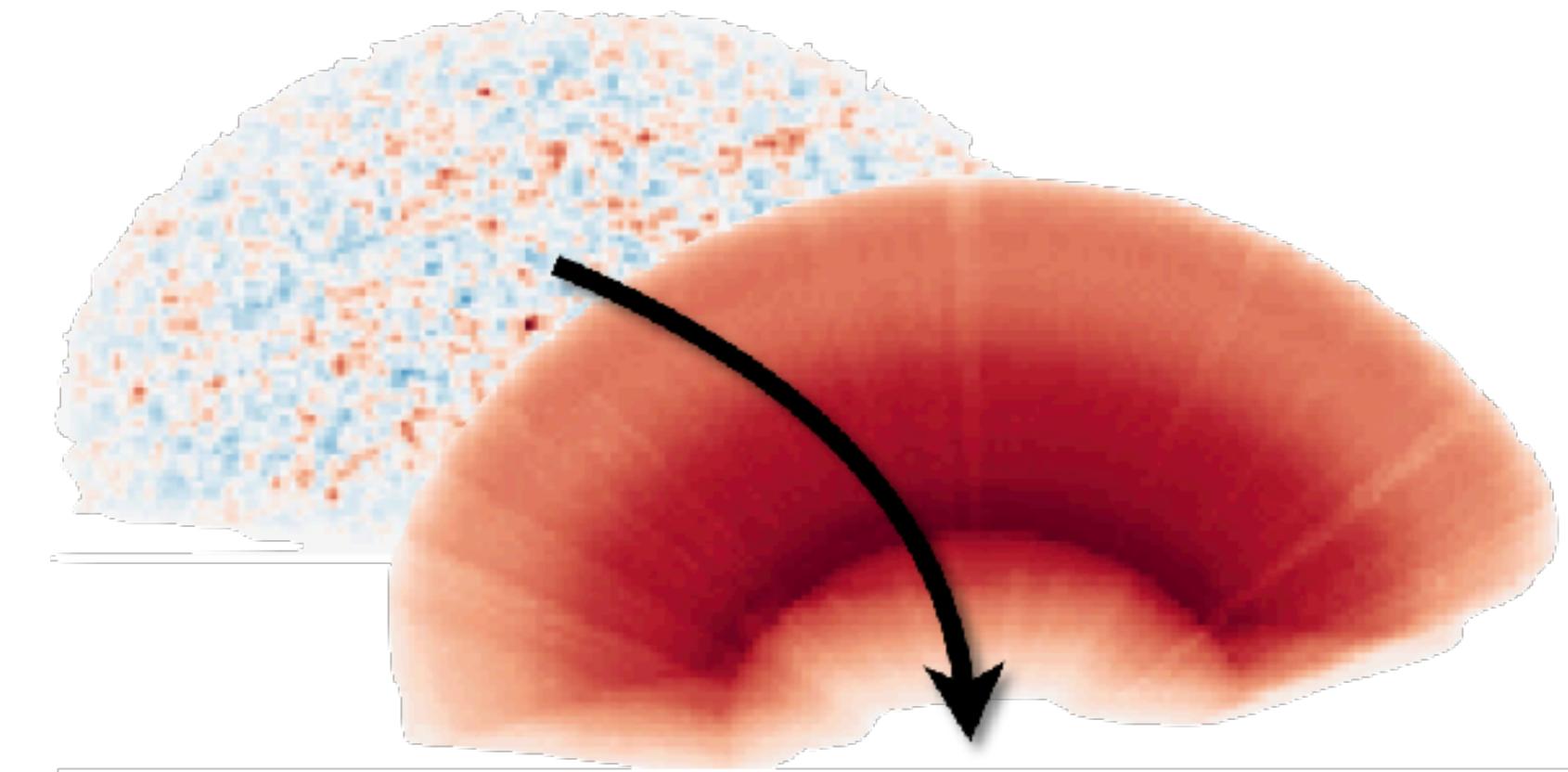


Two-Point Estimators

- In practice, we compute the **binned power spectrum** in a set of k -bins and redshift-space **multipoles**, plus a (square) **2D normalization matrix**

$$P_\ell^{\text{unwin}}(k) \sim \sum_{\ell' k'} \mathcal{W}_{\ell \ell'}^{-1}(k, k') \left| n_g(\mathbf{k}') - \frac{N_g}{N_r} n_r(\mathbf{k}') \right|^2_{\ell'}$$

- The **numerator** is the standard FKP numerator (up to an user-defined weight)
- The **normalization** can be computed using **Monte Carlo** methods and **FFTs**
(Stochastic Trace Estimation; See Philcox, Floss 2025)
- We account for **residual corrections** using a rectangular **theory matrix** (computed stochastically)
- This is equivalent to the **pseudo- C_ℓ scheme** used in the CMB!
- Up to scale-cuts, it is **equivalent** to the standard estimators



Three-Point Estimators

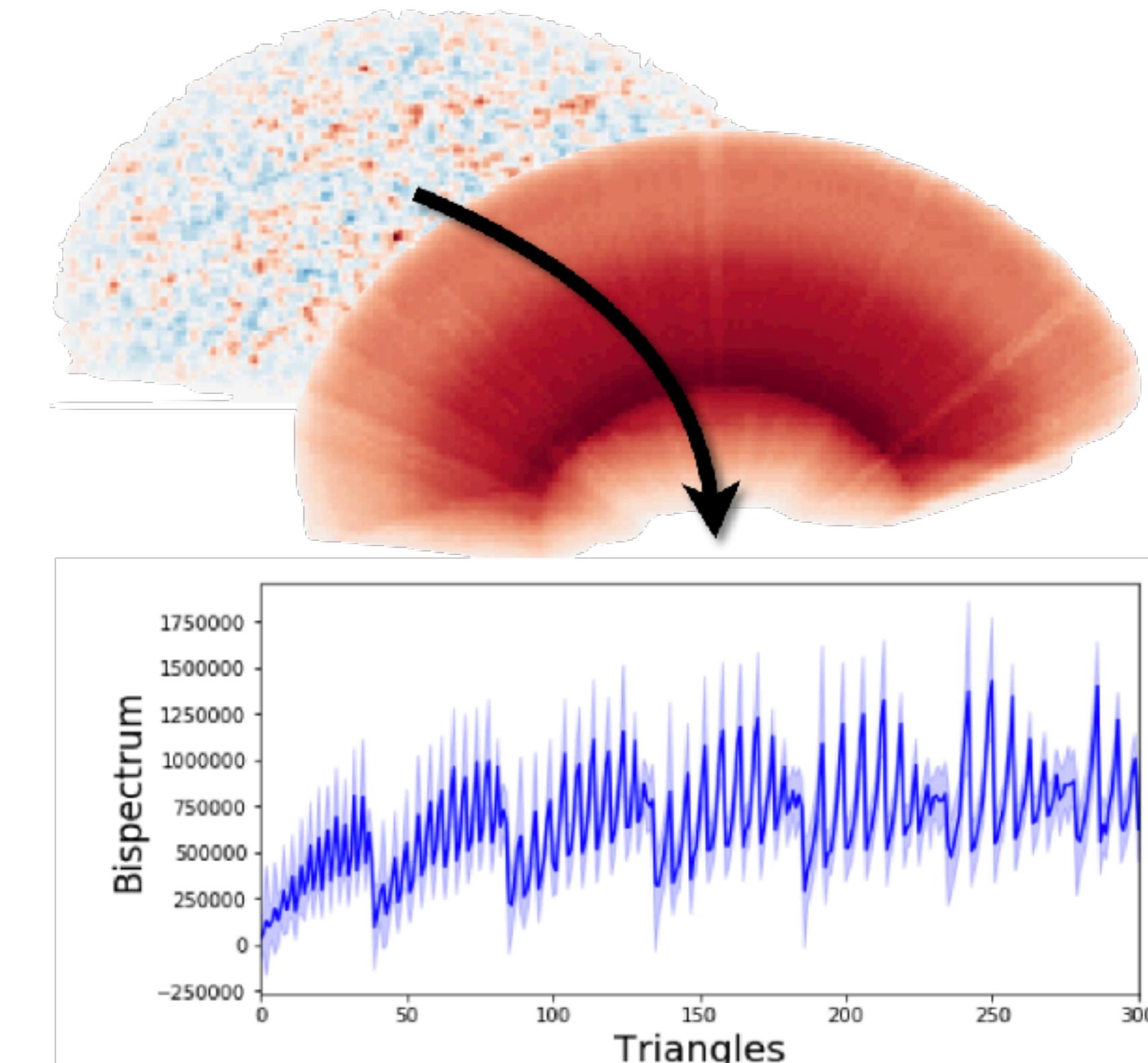
- We also want to compute **bispectra**
- These are usually computed using **FKP-like** estimators:

$$B_{\text{FKP}}(\mathbf{k}_1, \mathbf{k}_2, \mathbf{k}_3) \sim \left\langle \prod_{i=1}^3 \left(n_g(\mathbf{k}_i) - \frac{N_g}{N_r} n_r(\mathbf{k}_i) \right) \right\rangle / \langle n^3 \rangle$$

- The theory needs to be convolved with the **mask**

$$B_{\text{FKP}}(\mathbf{k}_1, \mathbf{k}_2, \mathbf{k}_3) \sim \int_{\mathbf{q}_1 + \mathbf{q}_2 + \mathbf{q}_3 = \mathbf{0}} n(\mathbf{k}_1 - \mathbf{q}_1) n(\mathbf{k}_2 - \mathbf{q}_2) n(\mathbf{k}_3 - \mathbf{q}_3) B_{\text{true}}(\mathbf{q}_1, \mathbf{q}_2, \mathbf{q}_3)$$

- This is a **difficult** 6-dimensional integral to compute at **every** step of the MCMC chain
(See Paredede++)
- Various approximations exist, but they can **break down**
(See Gil-Marín+, Chen+)



Three-Point Estimators

- We compute bispectra using quasi-optimal “unwindowed” estimators:

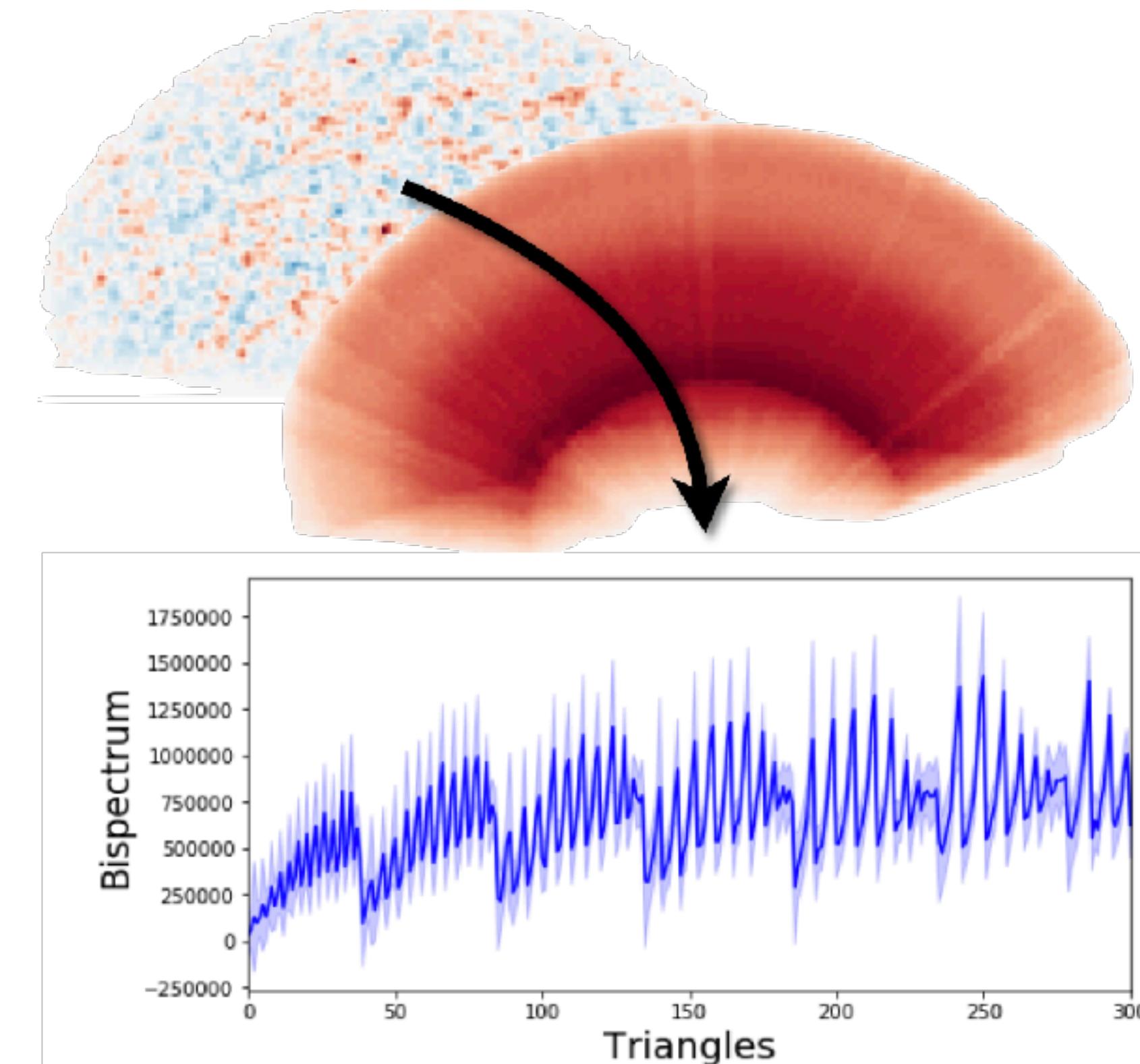
$$B_{\text{bin } a}^{\text{unwin}} \sim \sum_{b \in \text{bins}} \mathcal{W}_{ab}^{-1} \left\langle \prod_{i=1}^3 \left(n_g(\mathbf{k}_i) - \frac{N_g}{N_r} n_r(\mathbf{k}_i) \right) \right\rangle_{\text{bin } b} \quad (+ \text{ linear term})$$

- At leading-order (a good approximation), this does **not** need to be convolved with the mask

$$B_{\text{bin } a}^{\text{unwin}} \sim B_{\text{bin } a}^{\text{true}}$$

- **Plus**, it's almost optimal, even on **large-scales**
- Instead of **mask-convolving** the theory, we **mask deconvolve** the data!
- The **normalization** can be efficiently computed using **Monte Carlo** methods and FFTs
(Philcox, Floss 2025)

Both $P + B$ are computed using the **PolyBin3D** code
(Philcox, Floss 2025)



Accounting for Systematics

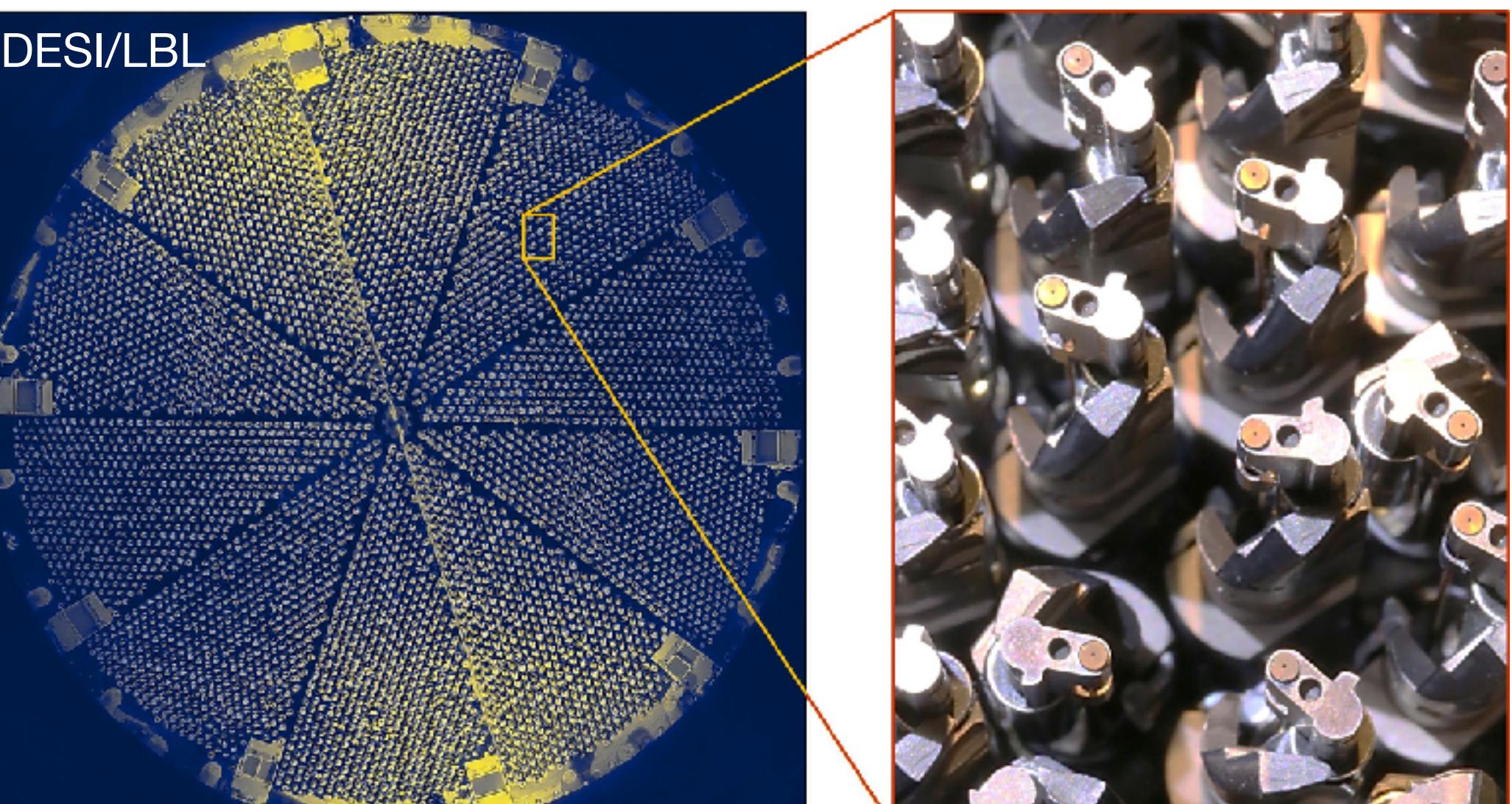
- **Radial integral constraint**
 - [missing line-of-sight fluctuations]
 - Included in **normalization** and **theory matrix**
- **Imaging systematics**
 - [the Galaxy contaminates angular modes]
 - Included in **weights** (as in DESI)
 - Template marginalized out over for ELG2 and QSO
- **Stochasticity**
 - [the sample is discrete]
 - Subtract **Poisson** shot-noise
$$P_{\text{shot}} \sim \bar{n}_g^{-1}, B_{\text{shot}} \sim \bar{n}_g^{-2} + \bar{n}_g^{-1}P(k)$$
- **Wide-angle effects**
 - Included in power spectrum **theory matrix**
$$[\text{Window} \star P_{\ell=1,3}^{\text{WA}}] \sim [\text{Window}' \star P_{\ell}^{\text{true}}]$$

Fiber Collisions

- Small angular scales in DESI are contaminated by observational systematics, i.e. **fiber collisions**
- DESI accounted for this by **removing** pairs of galaxies with small **angular separations**

$$P(\mathbf{k}) \sim \sum_{\text{galaxy } i} \sum_{\text{galaxy } j} w_i w_j e^{i\mathbf{k} \cdot (\mathbf{x}_i - \mathbf{x}_j)} \times \begin{cases} 1 & \text{if } \theta_{ij} > 0.05^\circ \\ 0 & \text{else} \end{cases}$$

- The correction can be computed by explicit **pair-counting**
- We do the same, correcting the **numerator**, the **normalization**, and the **theory matrix** [i.e. residual window]
- DESI applied a **rotation** since the new window is strongly off-diagonal
 - This is **automatically** accounted for in our normalization matrix!



DESI Focal Plane

DESI Fibers

Fiber Collisions

- Fiber collisions are **harder** for the bispectrum
- To remove all close **pairs** (or triplets), we'd need to count all **triplets** of galaxies, which is $\sim 10^6$ times more expensive!

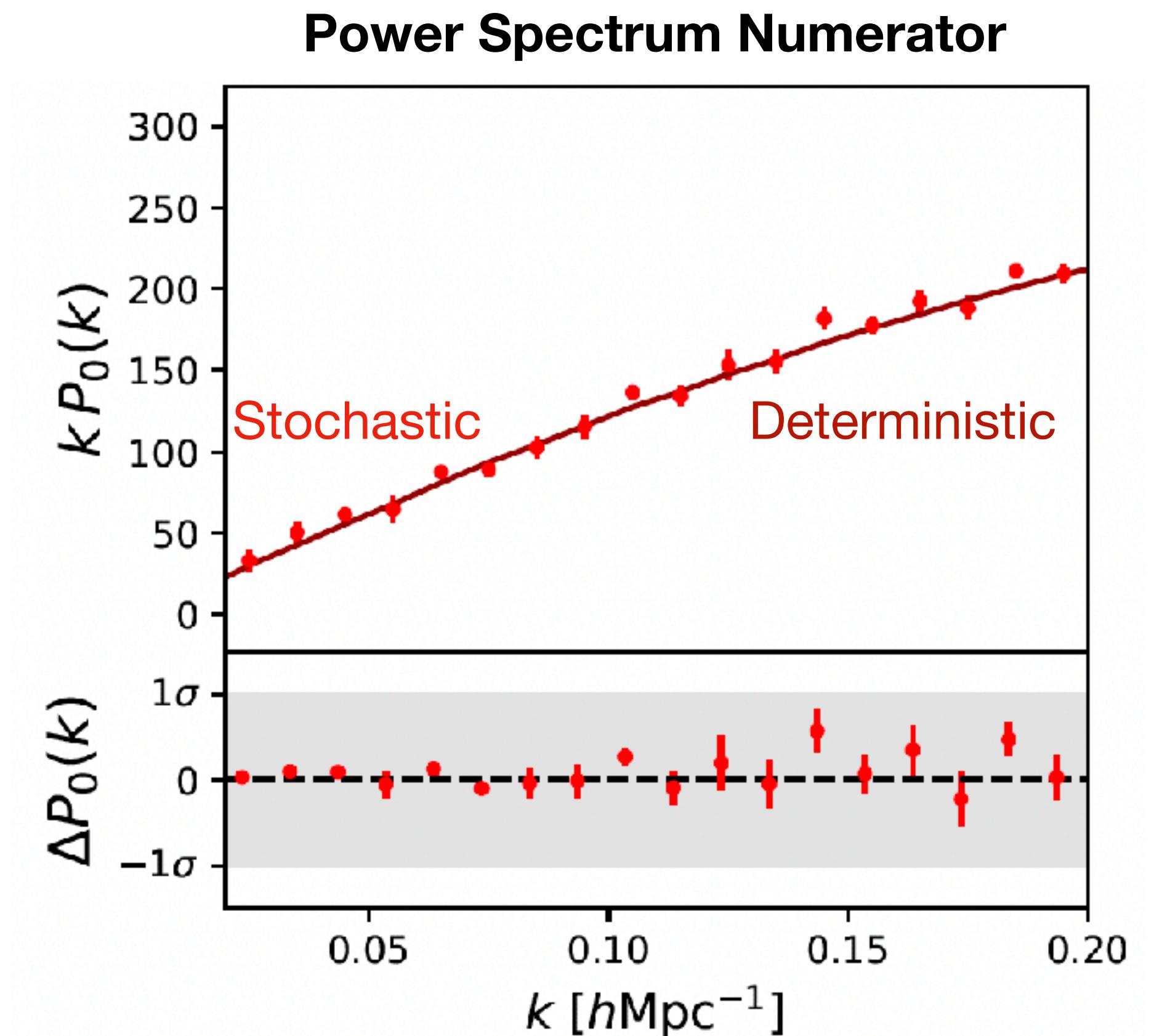
$$B(\mathbf{k}_1, \mathbf{k}_2, \mathbf{k}_3) \sim \sum_{\text{galaxy } i} \sum_{\text{galaxy } j} \sum_{\text{galaxy } k} w_i w_j w_k (\dots) \times \begin{cases} 1 & \text{if } (\theta_{ij} \text{ and } \theta_{jk} \text{ and } \theta_{ki}) > 0.05^\circ \\ 0 & \text{else} \end{cases}$$

- We introduce a novel **stochastic** method for removing these, involving **cross-bispectra**

Power spectrum example:

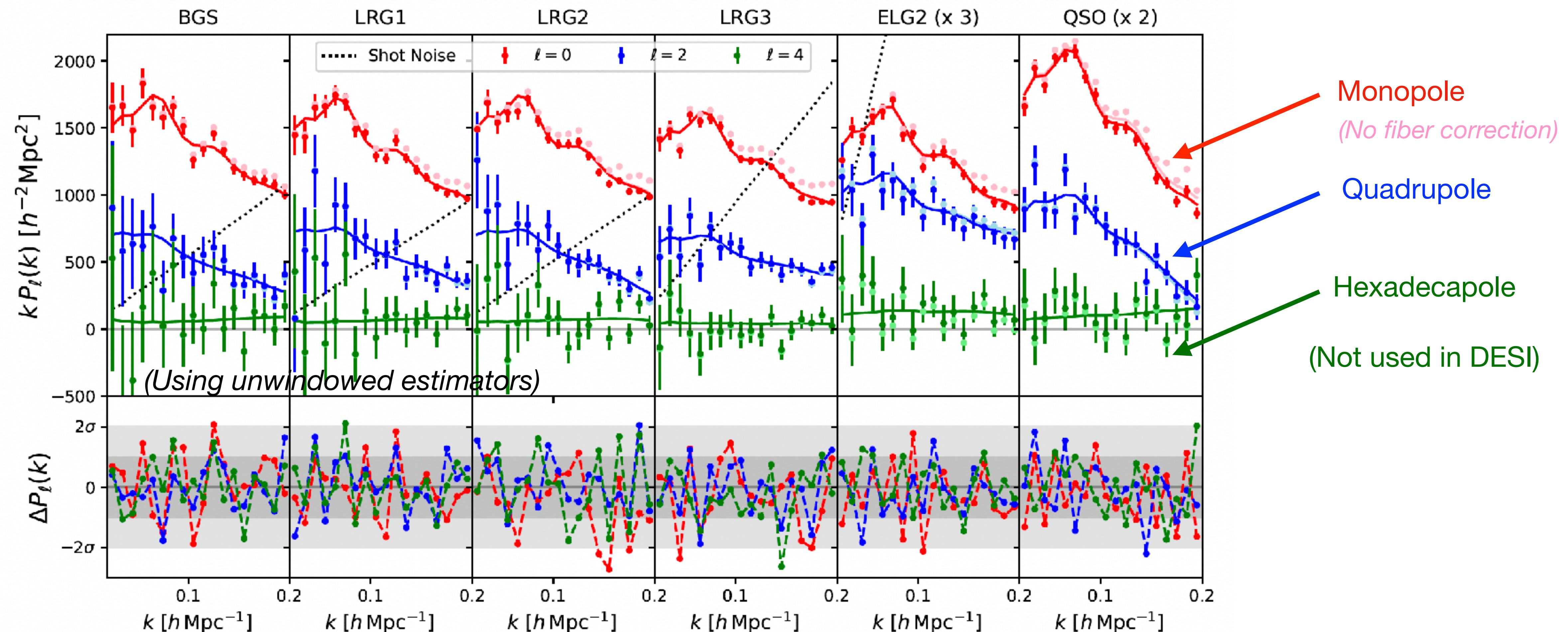
$$\sum_i w_i \epsilon_i \sum_j w_j \sum_k \epsilon_k \begin{cases} 1 & \text{if } \theta_{jk} > 0.05^\circ \\ 0 & \text{else.} \end{cases} \Rightarrow \sum_i w_i \sum_j w_j \begin{cases} 1 & \text{if } \theta_{ji} > 0.05^\circ \\ 0 & \text{else.} \end{cases}$$

average over $\epsilon_i \sim \mathcal{N}(0,1)$



Power Spectrum Data-Set

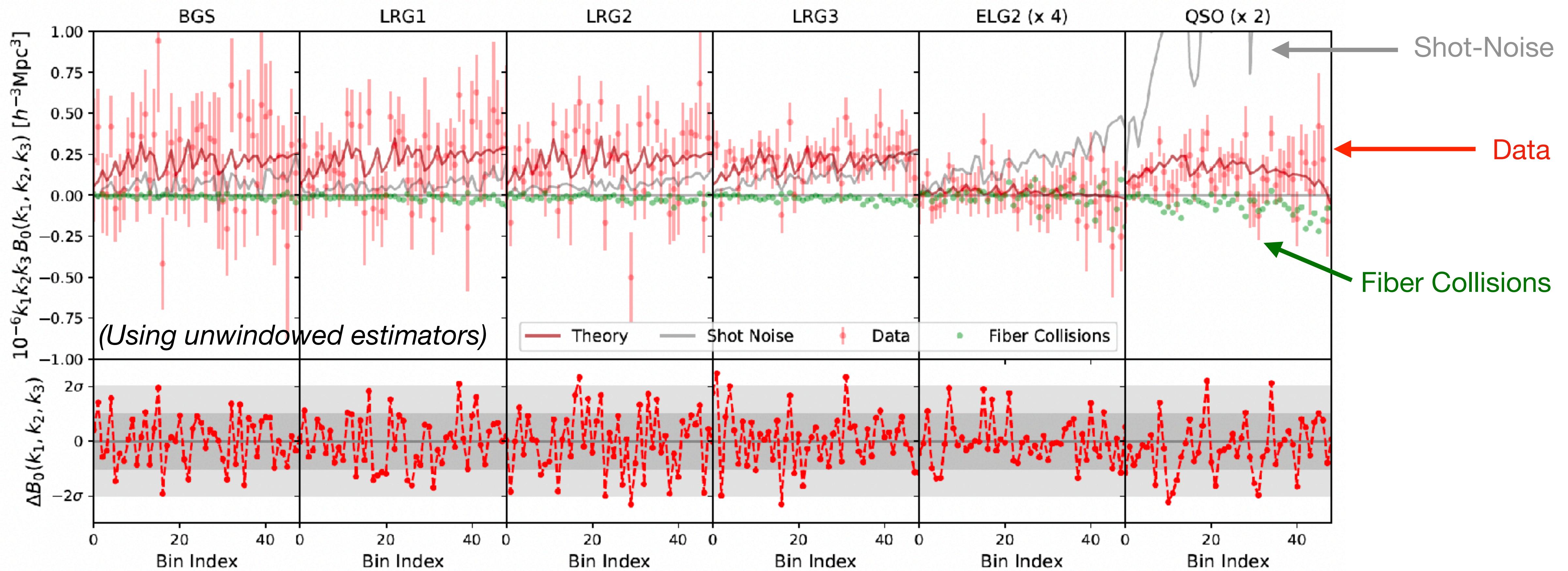
$P_\ell(k)$ for $\ell = 0, 2, 4$ and $0.02 \text{ } h\text{Mpc}^{-1} \leq k \leq 0.20 \text{ } h\text{Mpc}^{-1}$



(Maximum SNR: 230σ)

Bispectrum Data-Set

$$B_0(k) \text{ for } 0.02 \text{ } h\text{Mpc}^{-1} \leq k \leq 0.08 \text{ } h\text{Mpc}^{-1}$$



(Maximum SNR: 9σ)

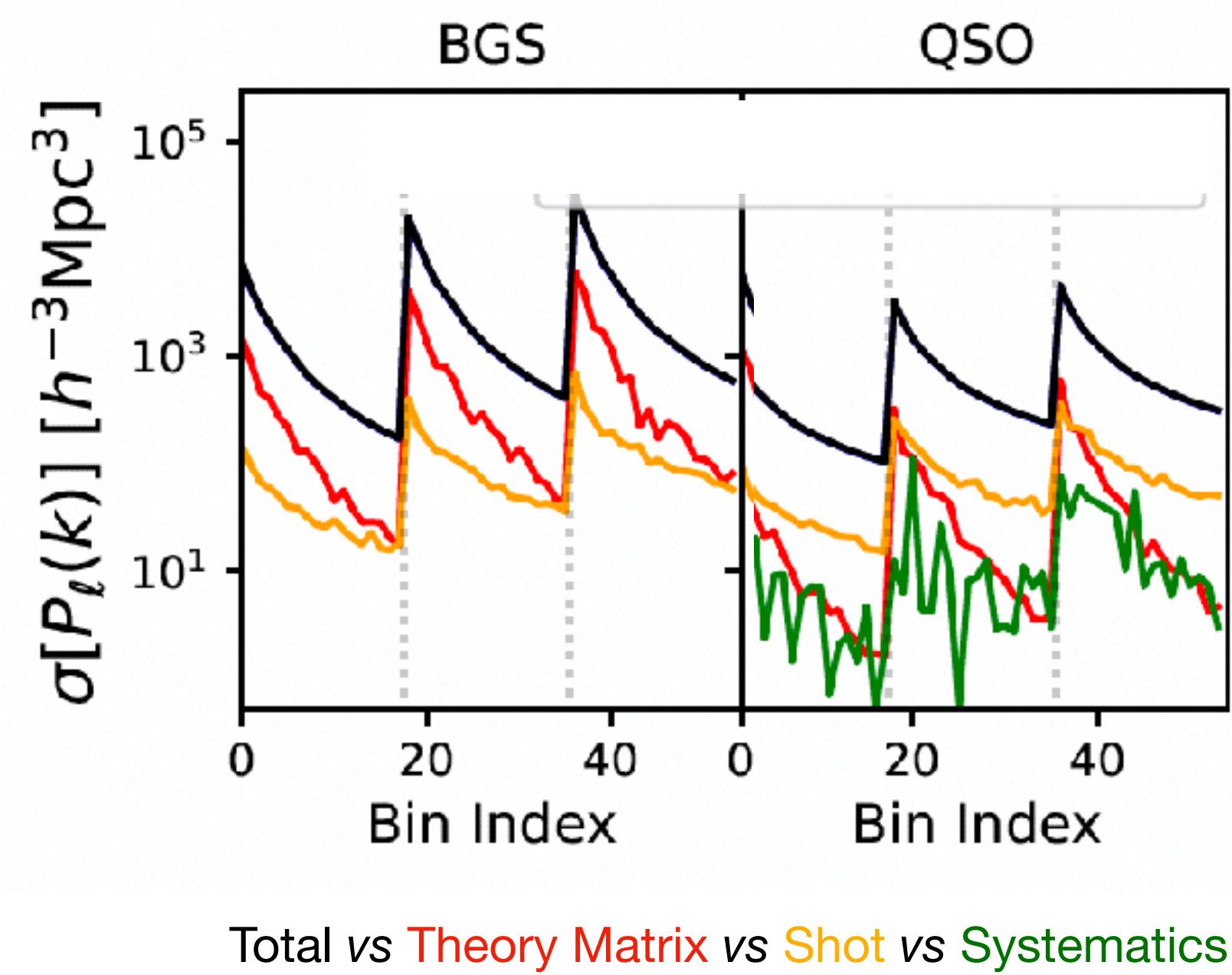
Covariance Matrix

- DESI computed the covariances using **simulations**
- We compute covariance **analytically**

$$\text{cov}[\mathbf{P}] \sim P^2(k) \star \text{mask}^4, \quad \text{cov}[\mathbf{B}] \sim P^3(k) \star \text{mask}^6$$

- This is computed on a **grid**, accounting for the **mask**
- **PolyBin3D** measures this similarly to the **normalization** and **theory matrix**
- This depends on a power spectrum **model** fit from the **data**
- **Note:** we do not include non-Gaussian terms...
- DESI rescaled the **simulation** covariance to match a **data-calibrated** theory covariance — we do not need to do this! (It also does not make a difference)
- We **inflate** covariance to include various **sources of noise**

DESI $P(k)$ Covariance



Theoretical Model

- We fit the data with the **Effective Field Theory of Large Scale Structure at one-loop** for P and **tree-level** for B
- **Parameters** (assuming Λ CDM):
 - Cosmology: free $(H_0, \omega_{\text{cdm}}, \log A_s)$, plus priors on (ω_b, n_s)
 - Bias: free $(b_1, b_2, b_{\mathcal{G}_2}, b_{\Gamma_3})$
 - Stochasticity: free $P_{\text{shot}}, B_{\text{shot}}, A_{\text{shot}}, a_0, a_2$
 - Counterterms: free $c_0, c_2, c_4, \tilde{c}, c_1$
- Most parameters are **analytically marginalized**
- We rescale parameters by σ_8 according to degeneracies

89 Parameters

CLASS-PT

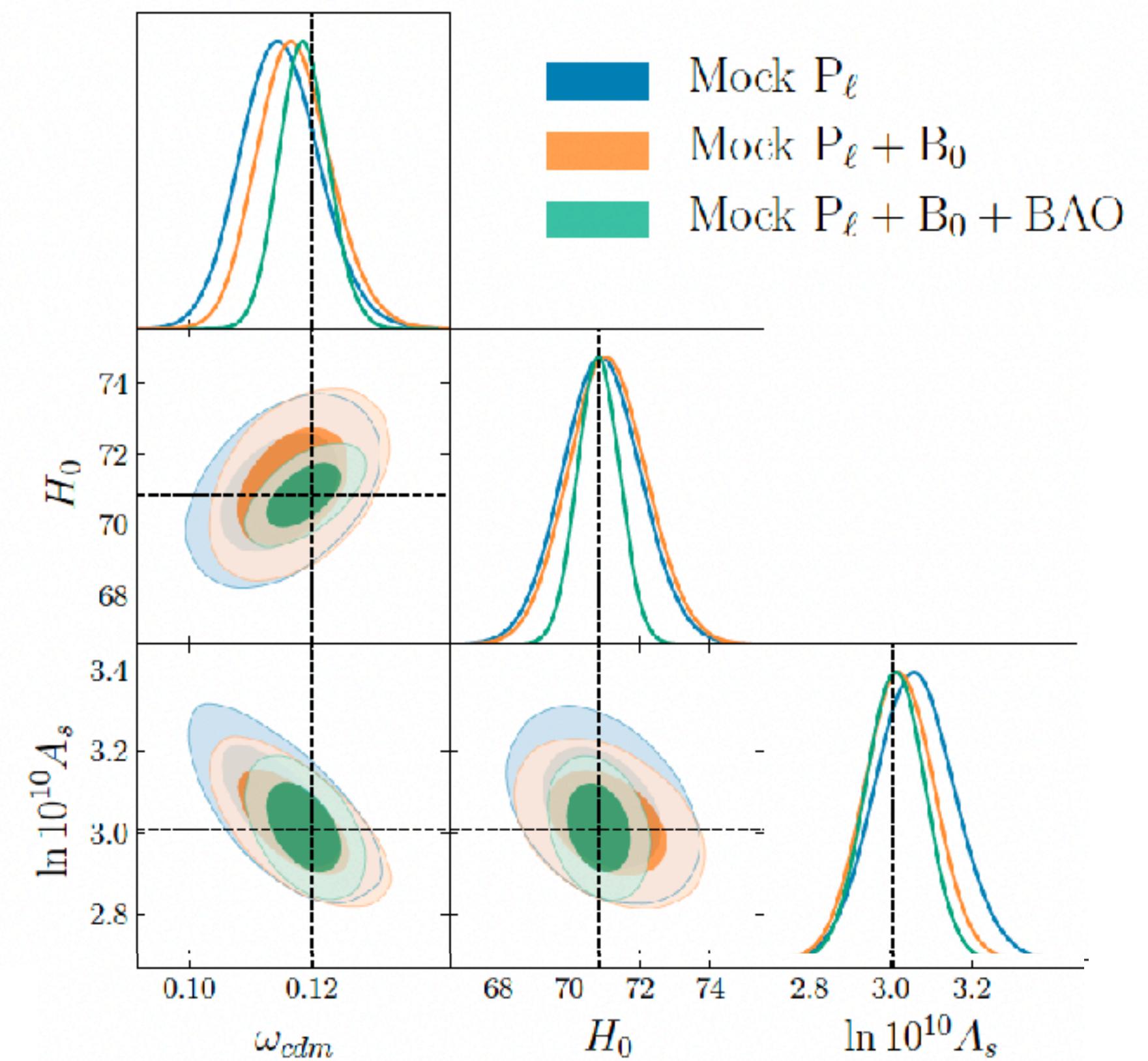
Theory $P_\ell(k)$

Theory $B_0(k_1, k_2, k_3)$

Likelihood

Projection Effects

- When analyzing synthetic data, do we recover the input cosmology?
 - The best-fit can be shifted due to **non-Gaussian posteriors** and **parameter degeneracies**
 - This is a consequence of **Bayes' theorem**, but minimizing these helps to interpret **posteriors**
- We find **good consistency** with inputs, particularly when **extra data** is added ($< 0.4\sigma$)
- The **rescaled biases** (e.g., $b_1 \rightarrow b_1\sigma_8$) help a lot!
e.g. Maus+24



Constraints on Λ CDM

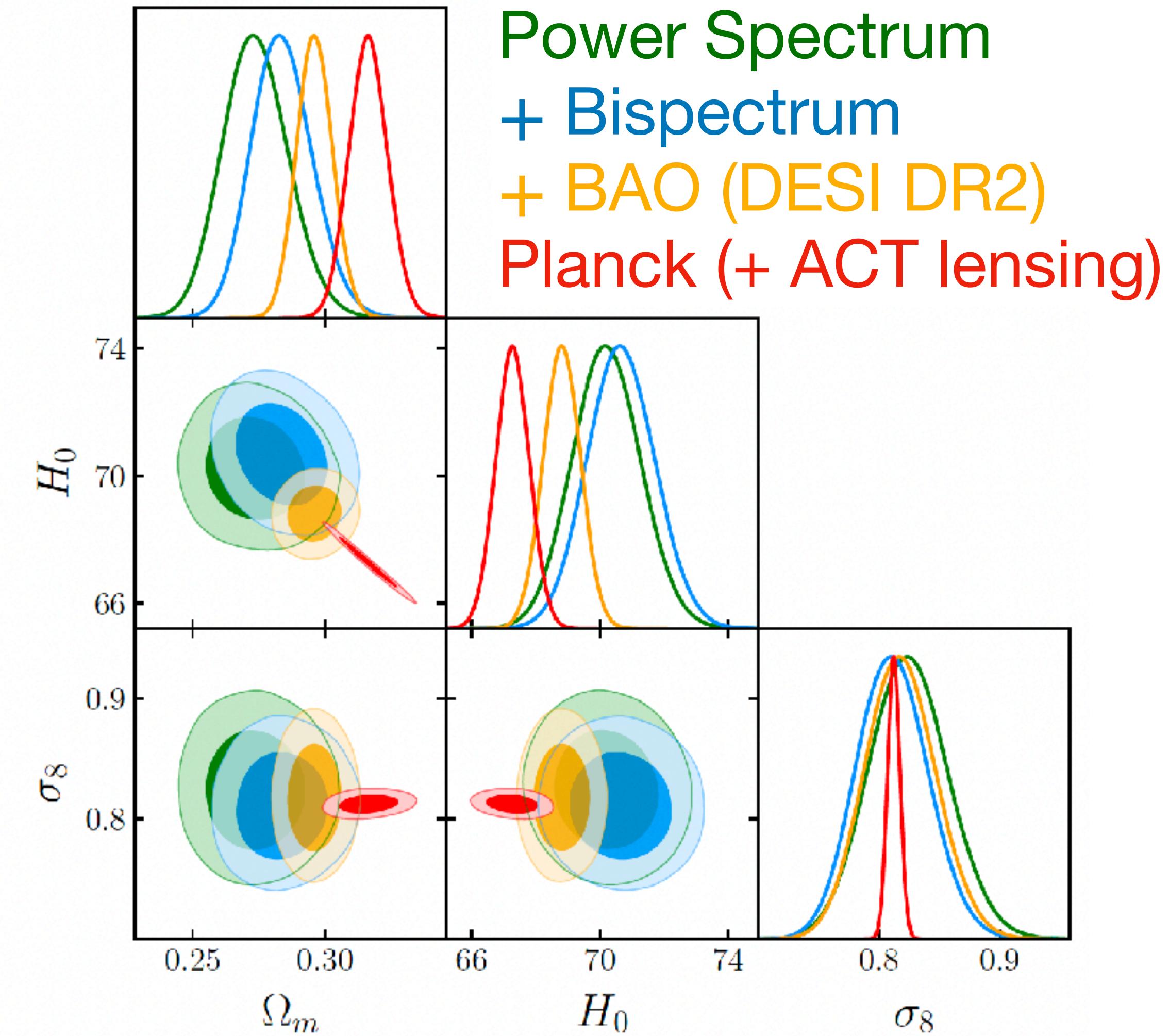
DESI alone finds **strong constraints** on Ω_m, H_0, σ_8

- Adding the **bispectrum** improves constraints by $\sim 10\%$
- Adding the (official) DESI DR2 BAO gives **significant** improvements in Ω_m, H_0
- No evidence for H_0 tension or S_8 tension ($S_8 = 0.813 \pm 0.031$)

Our constraints are **broadly consistent** with Planck

- $P + B + \text{BAO}$ dataset matches CMB to 2σ (1.8σ with PR4)

Dataset	Ω_m	H_0	σ_8
$P_\ell(k)$	$0.274^{+0.012}_{-0.013}$	$70.22^{+1.06}_{-1.06}$	$0.825^{+0.033}_{-0.033}$
$P_\ell(k) + B_0(k)$	$0.284^{+0.010}_{-0.012}$	$70.67^{+1.05}_{-1.05}$	$0.811^{+0.028}_{-0.031}$
$P_\ell(k) + B_0(k) + \text{BAO}$	$0.296^{+0.007}_{-0.007}$	$68.82^{+0.58}_{-0.58}$	$0.818^{+0.029}_{-0.029}$
CMB	$0.316^{+0.007}_{-0.007}$	$67.28^{+0.53}_{-0.53}$	$0.812^{+0.005}_{-0.005}$

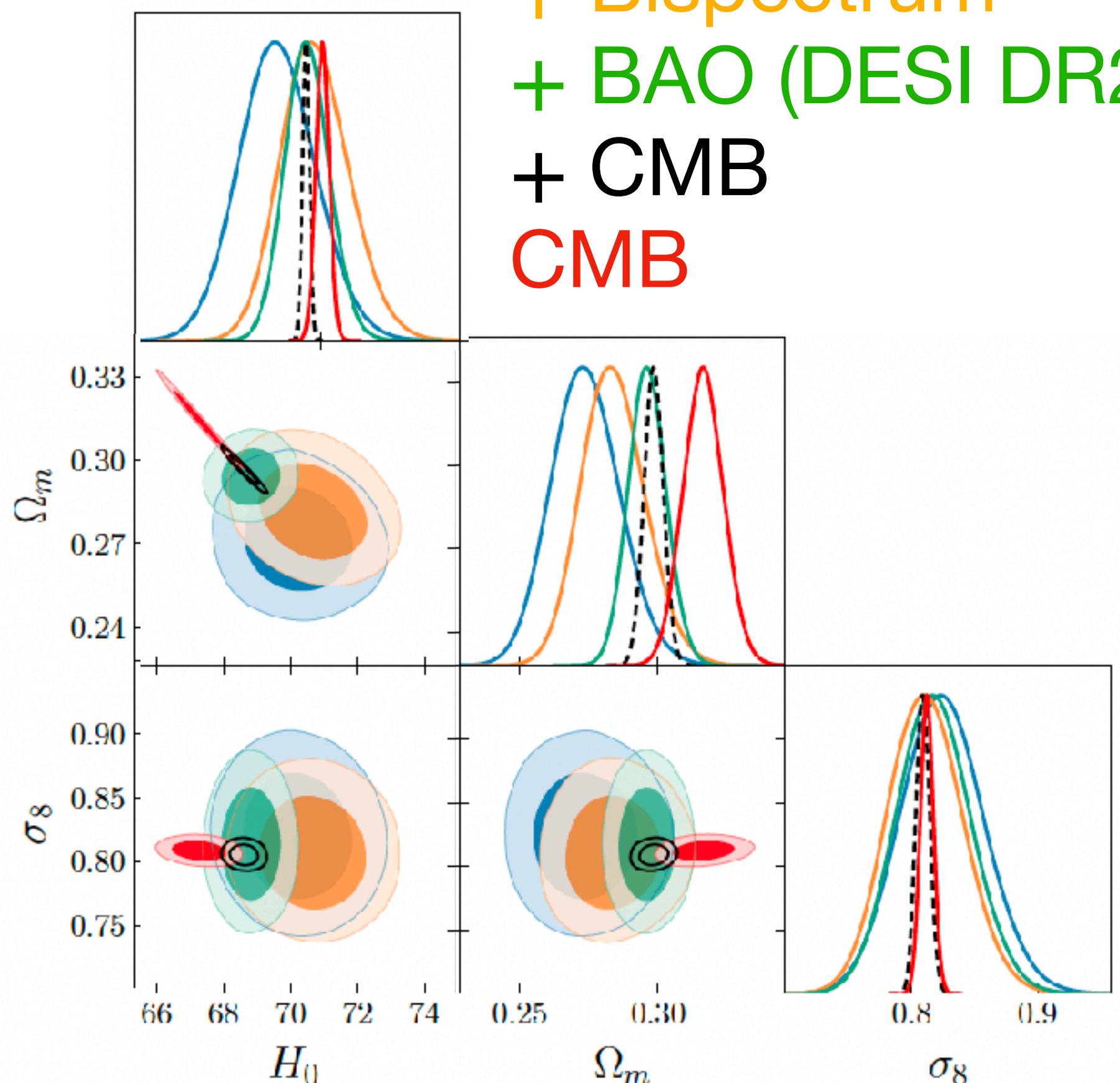


Constraints on Λ CDM

We find even **stronger** constraints combining with the CMB:

- DESI **enhances** Planck constraints up to $2 \times$
 - $\Omega_m = 0.298 \pm 0.003$
 - $H_0 = 68.61 \pm 0.28$
 - $\sigma_8 = 0.809 \pm 0.005$
- Ω_m is still a **bit low** but it **shifts towards Planck** as more data is added

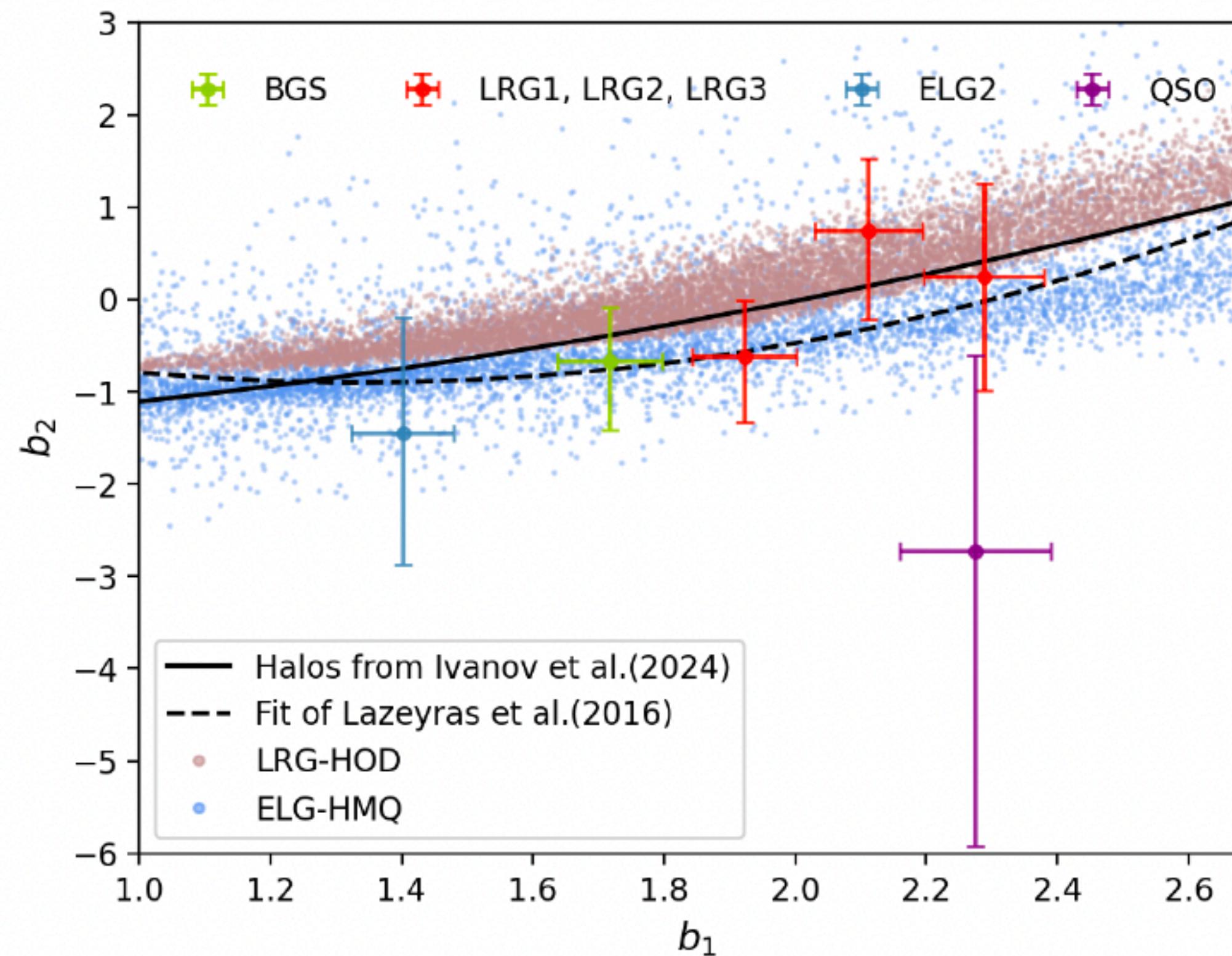
Power Spectrum
+ Bispectrum
+ BAO (DESI DR2)
+ CMB
CMB



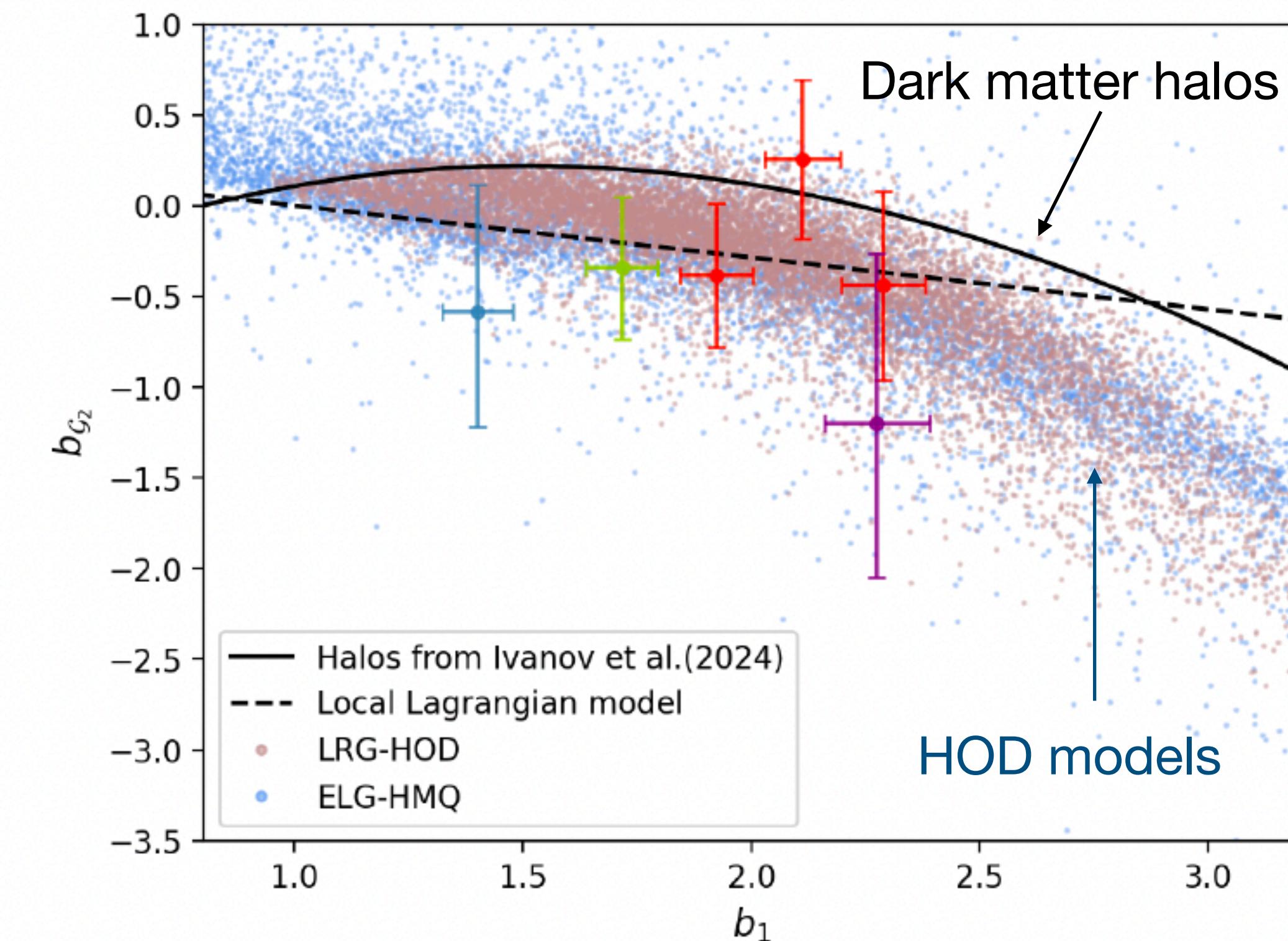
Constraints on Bias Parameters

- Adding the **bispectrum** leads to strong constraints on **bias parameters**
- These agree with HOD predictions, but not with **dark matter** predictions

Quadratic Bias

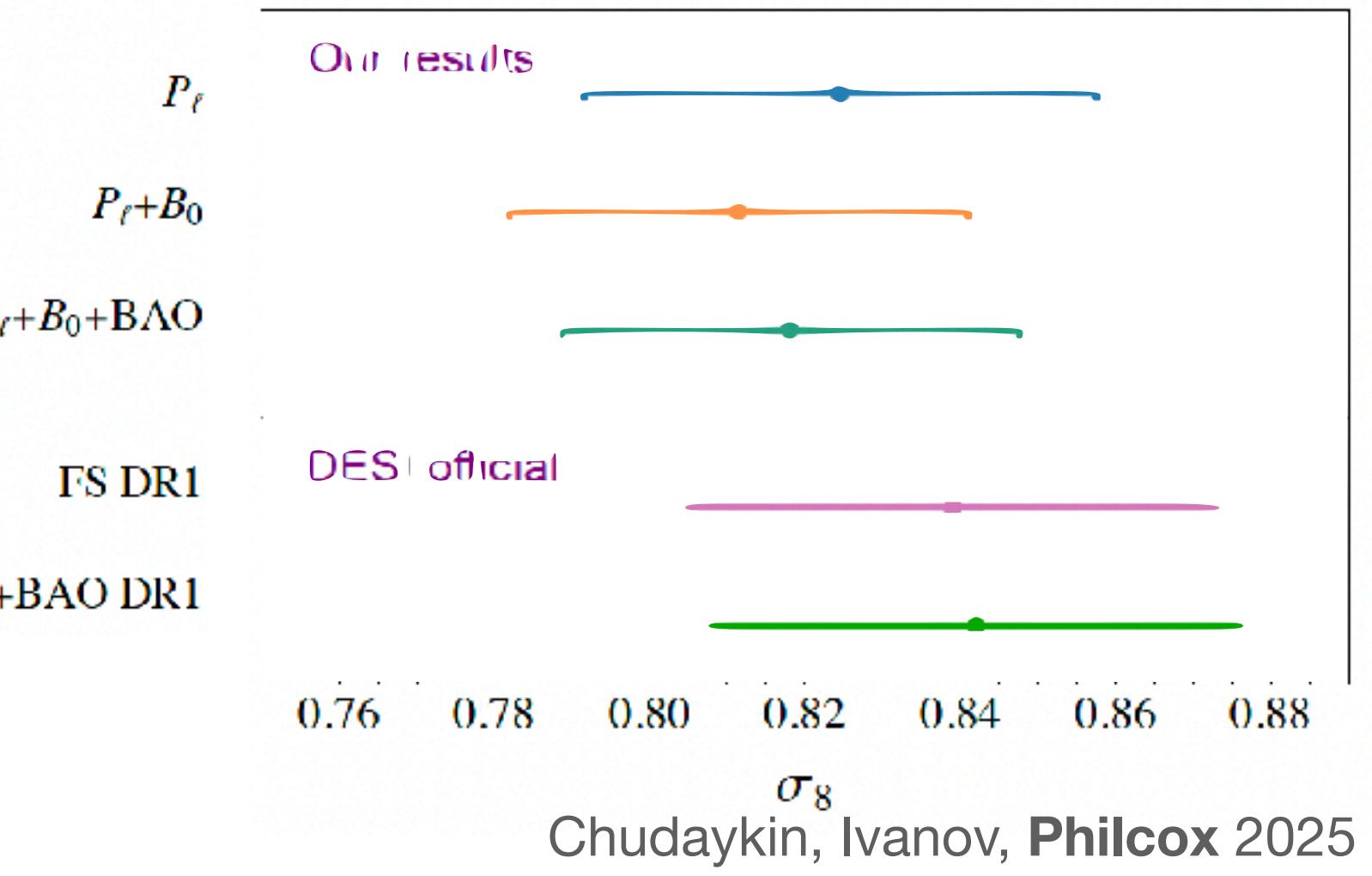
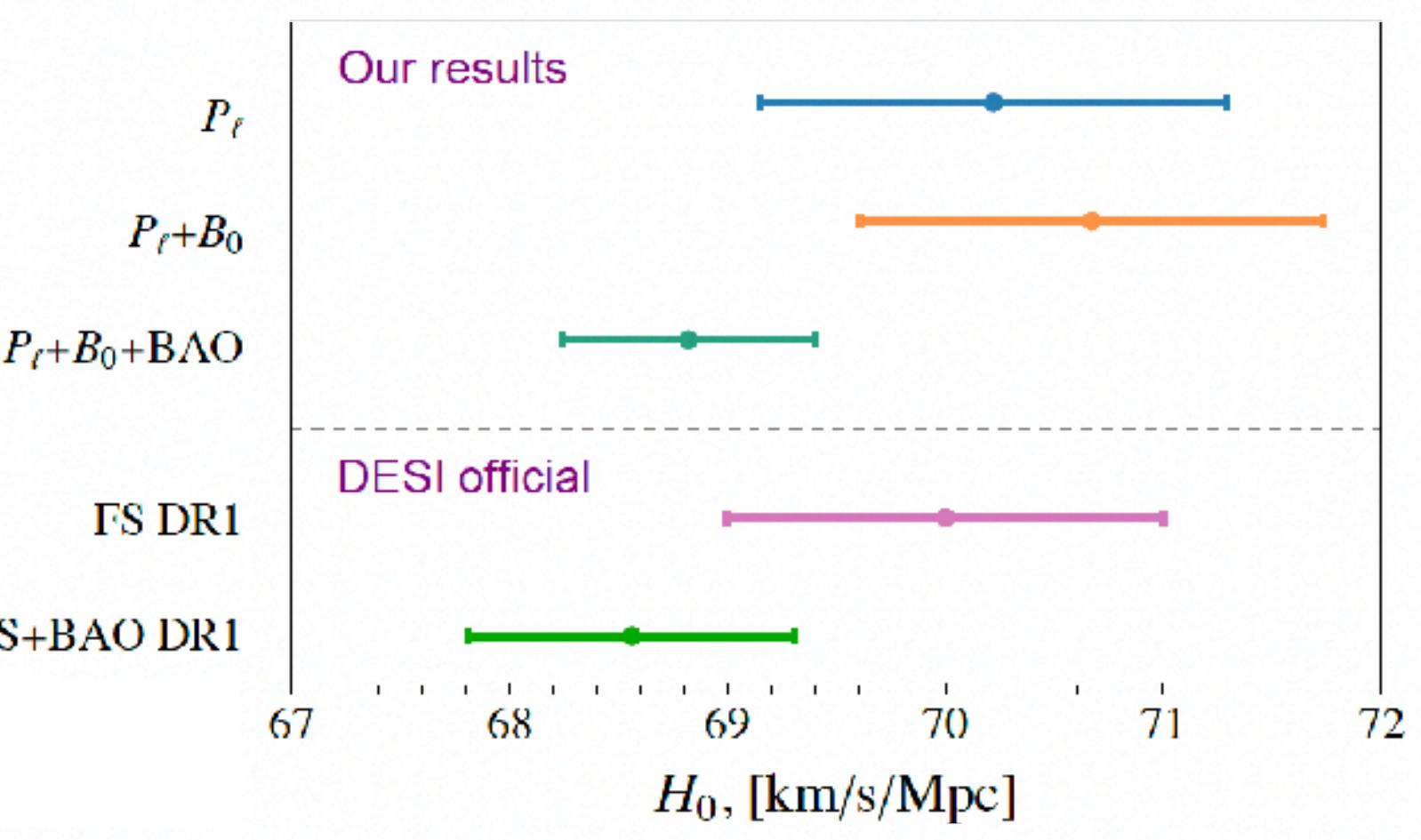
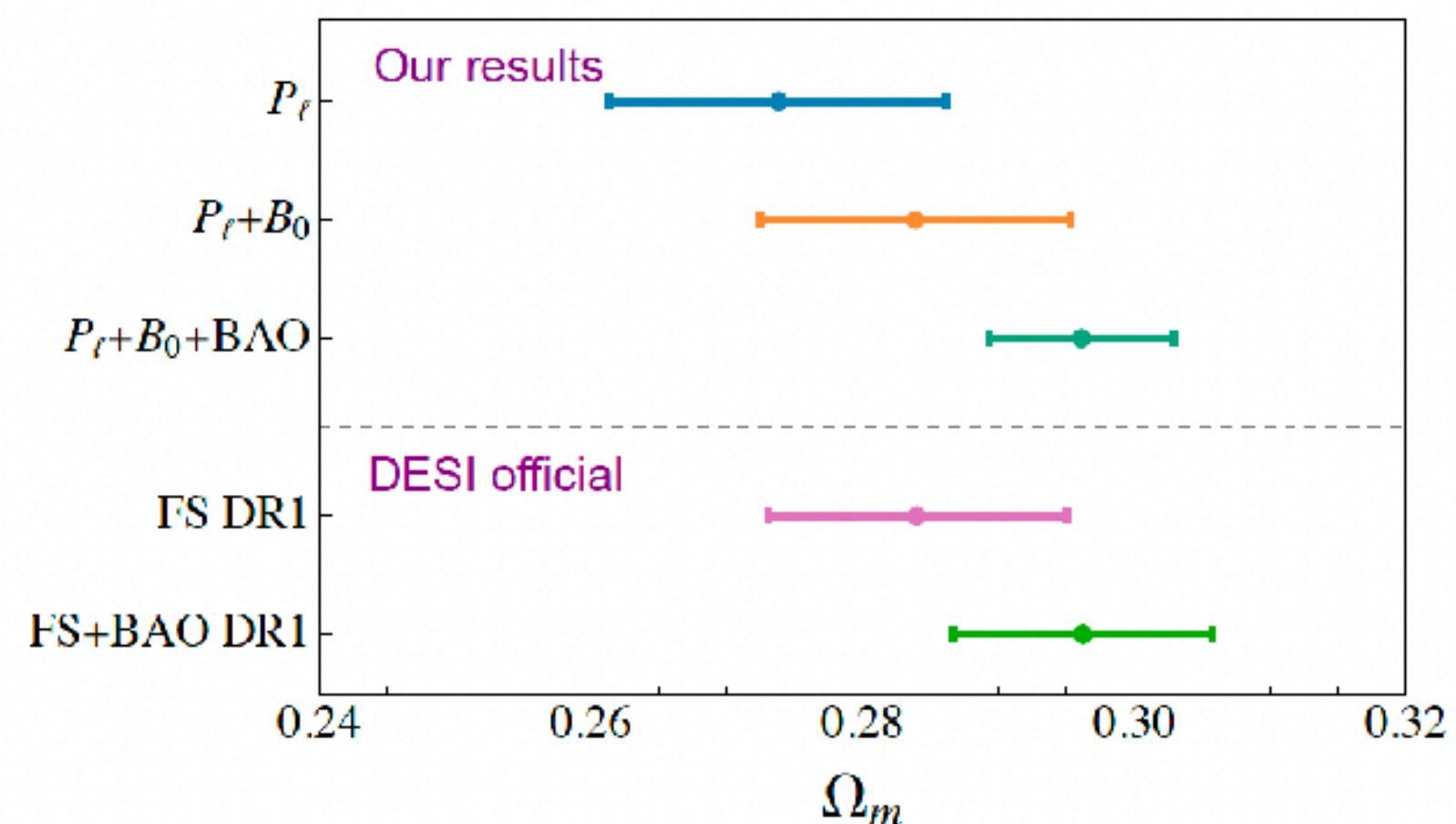


Tidal Bias



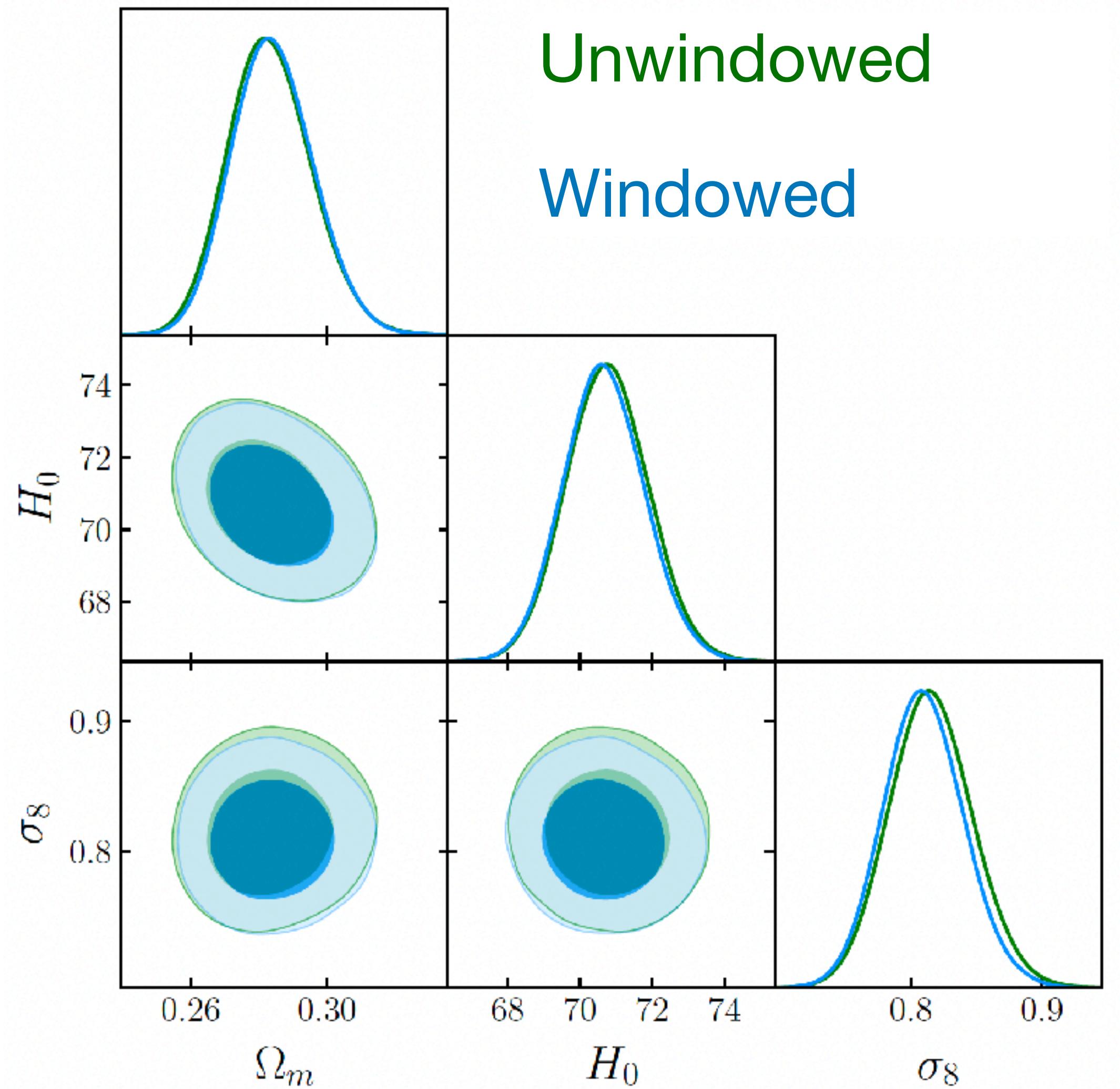
Comparison to Official Results

- We find **fairly good** agreement with DESI with
 $\Delta\Omega_m = -0.8\sigma, \Delta H_0 = +0.2\sigma, \Delta\sigma_8 = -0.4\sigma$
- The main differences are due to:
 - Addition of the **hexadecapole** (P_4)
 - Free **scale-dependent** shot-noise ($P \supset \frac{1}{\bar{n}} [1 + a_0 k^2]$)
 - Free higher-order **fingers-of-God** counterterm (\tilde{c})
 - Free cubic bias (b_{Γ_3})
 - Analytic covariance
 - And of course, the addition of the **bispectrum** and **DR2 BAO**



Other Systematic Checks

- Results are **stable** ($< 0.5\sigma$ shifts) under changes to the bias model
 - i.e. fixing $a_0, b_{\Gamma_3}, \tilde{c}$
 - Or removing the hexadecapole
- Results are **stable** under switching from **unwindowed** to (conventional) **windowed** estimators
 - (Windowed are much slower however!)

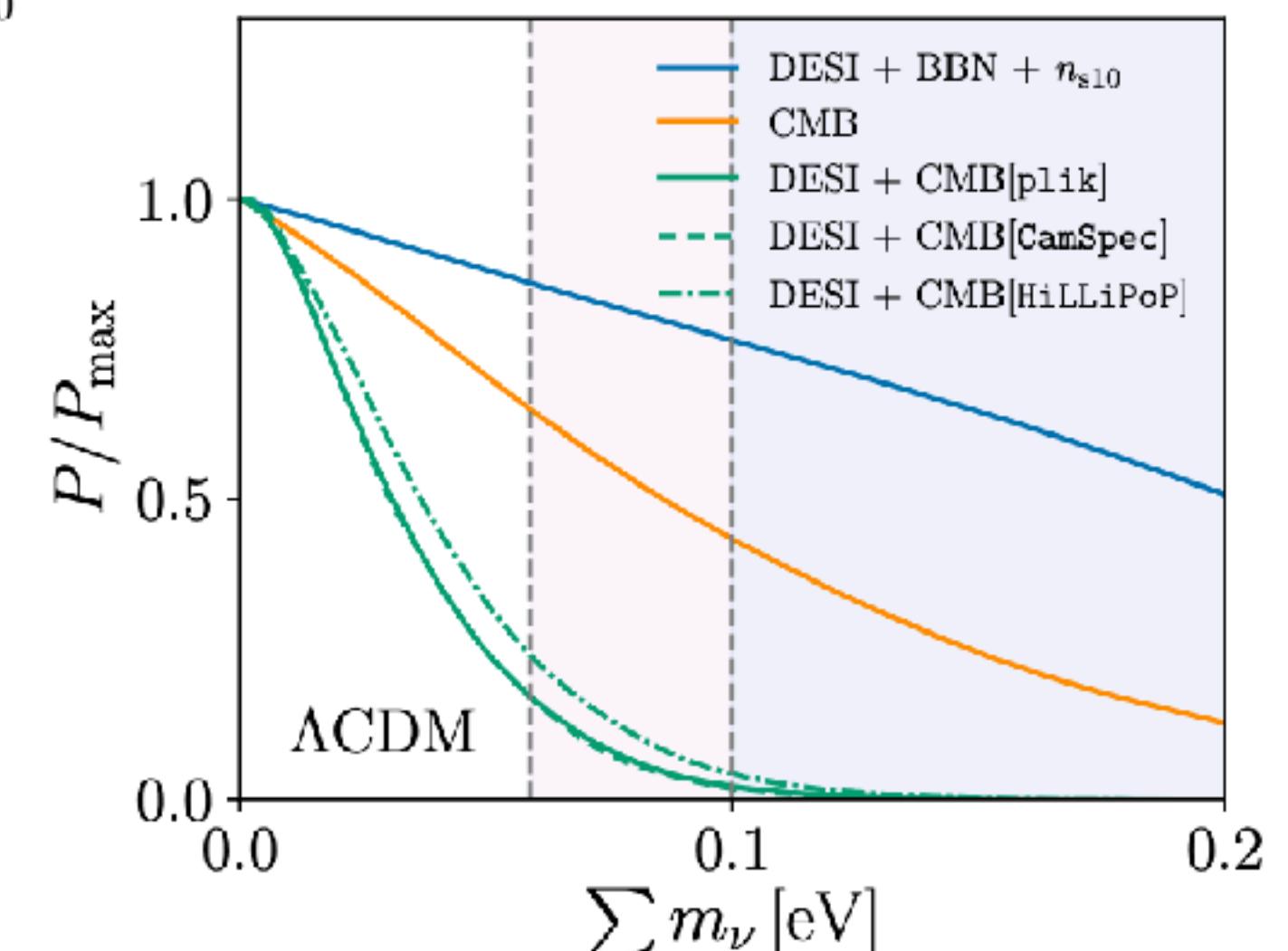
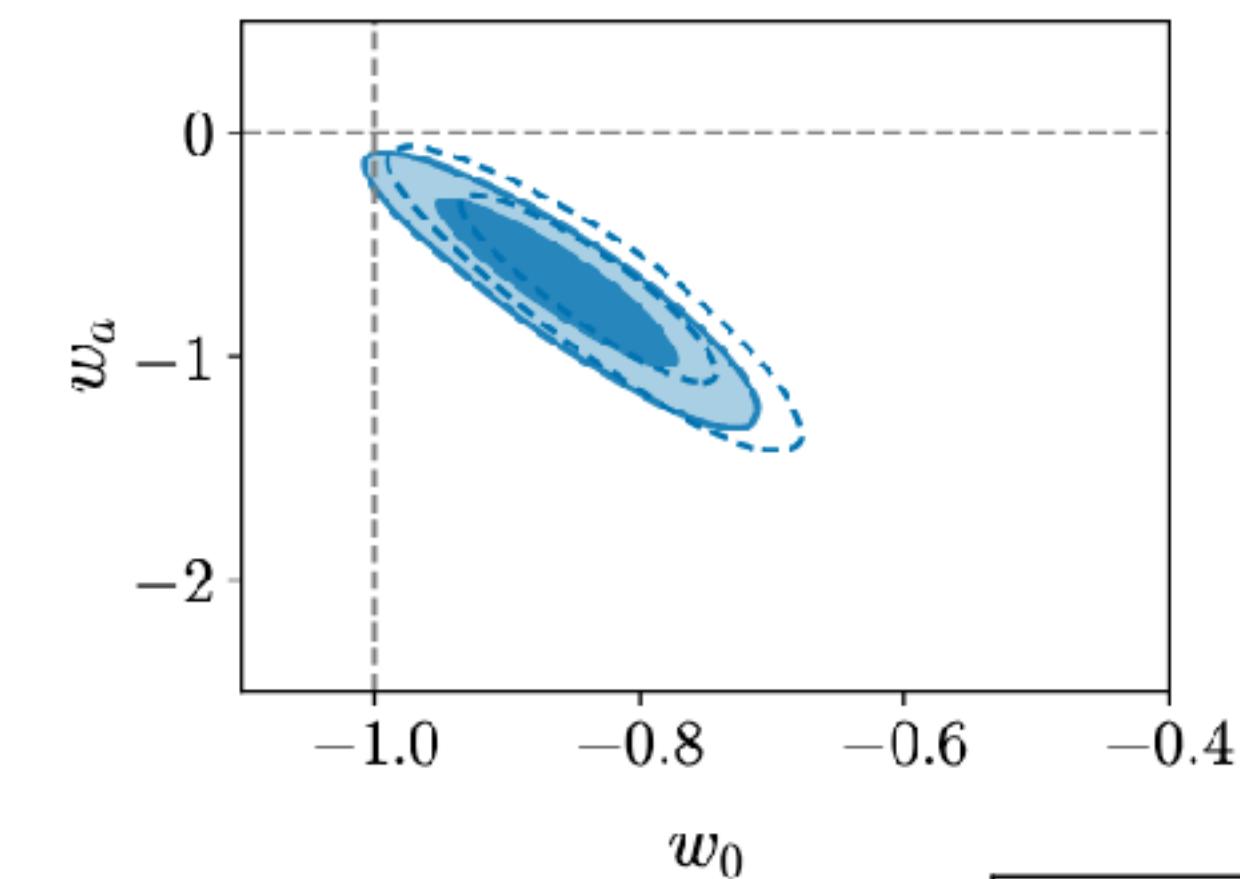


Next works

- There are **many** more models to explore, e.g.,
 - Curvature Ω_k
 - Dark Energy $w(a)$
 - Neutrinos $\sum m_\nu$
 - Primordial non-Gaussianity, $f_{\text{NL}}^{\text{loc, eq, orth}}$
- There are **many** more datasets to explore, e.g.,
 - Combined BAO and full-shape data
 - Bispectrum multipoles, B_ℓ
 - Smaller scale bispectra (one-loop)

Can we independently reproduce these?

— DESI (BAO) + CMB + PantheonPlus
— DESI (FS+BAO) + CMB + PantheonPlus



Summary

- We perform a **full renalysis** of the **public** DESI DR1 (full-shape), using **independent estimators, theory codes, and covariances!**
- We find **consistency** within $\approx 0.5\sigma$, and we add **new data** ($P_4 + B_0$)
- There's a lot more to explore with the data!