Precise Cosmological Constraints from BOSS Galaxy Clustering using the Wavelet Scattering Transform

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A program of SCHMIDT FUTURES

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University of Chicago

Cosmology Seminar
Berkeley Center for Cosmological Physics
Tuesday, March 5, 2024

Background from
Millennium Simulation, 2005

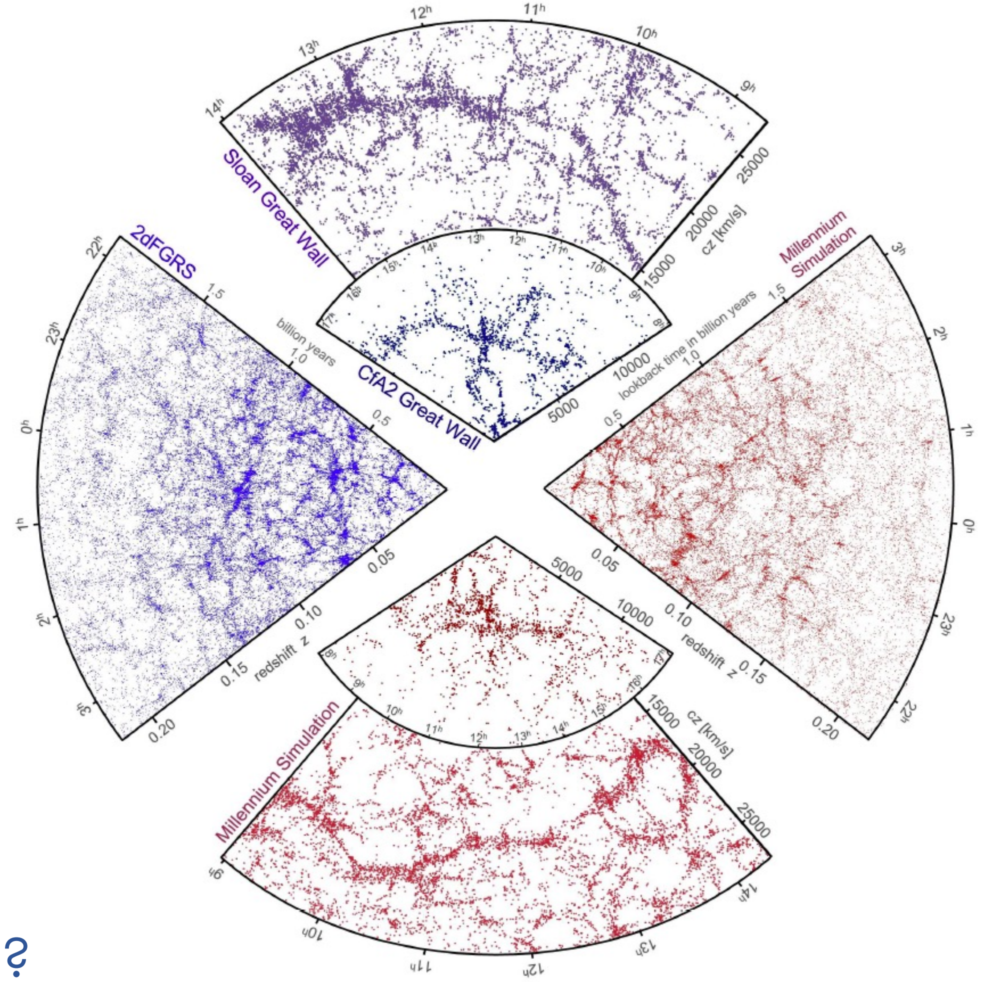
Based on
arXiv: 2310.16116, 2204.13717 & 2108.07821
in collaboration with **Cora Dvorkin & Sandy Yuan**

Challenges in the era of precision cosmology

- Large-Scale Structure (LSS) of the universe a powerful probe of *fundamental physics*
  - Dark energy
  - Dark matter
  - Massive neutrinos
  - Gravity

- Will soon be mapped precisely by:
  - Dark Energy Scientific Instrument (DESI)
  - V. Rubin Observatory LSST
  - Euclid
  - Nancy Grace Roman Space Telescope
  - SPHEREx
  - + Synergies with CMB

- How do we *optimally* extract information from the LSS??



V. Springel et al. (2006)

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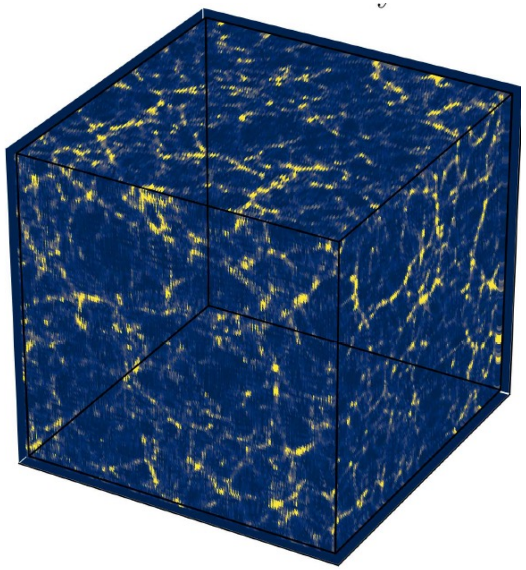
The quest for an ideal estimator

- Attempts to describe the information encoded in the 3D cosmic density field



F. Villaescusa-Navaro et al. (2019)

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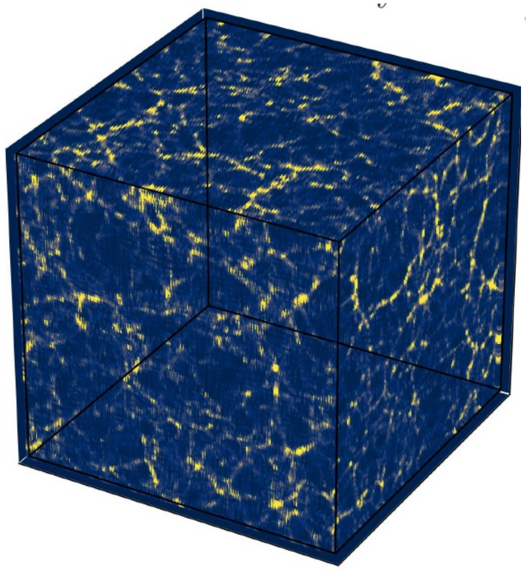
- Attempts to describe the information encoded in the 3D cosmic density field

2-point correlation function/Power Spectrum



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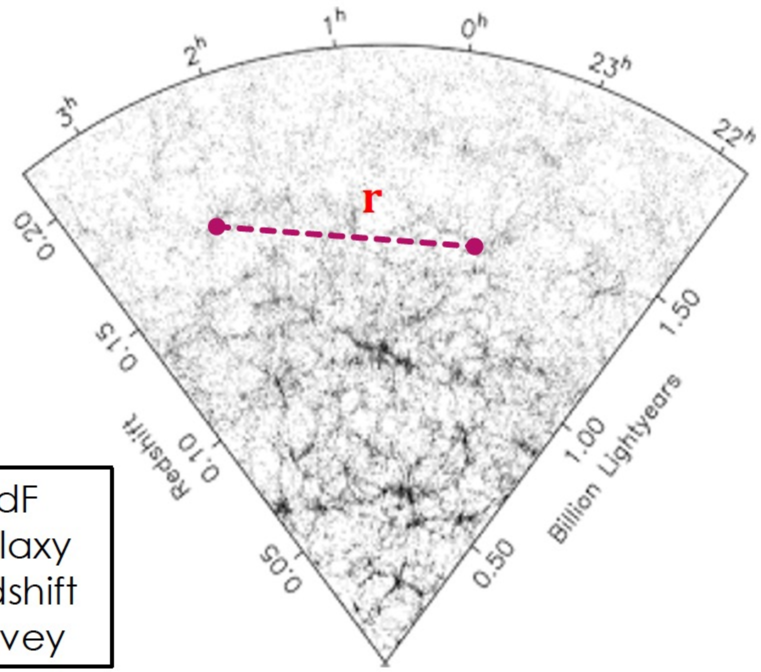

2dF Galaxy Redshift Survey

O. Philcox et al. (2021)

Physical Information

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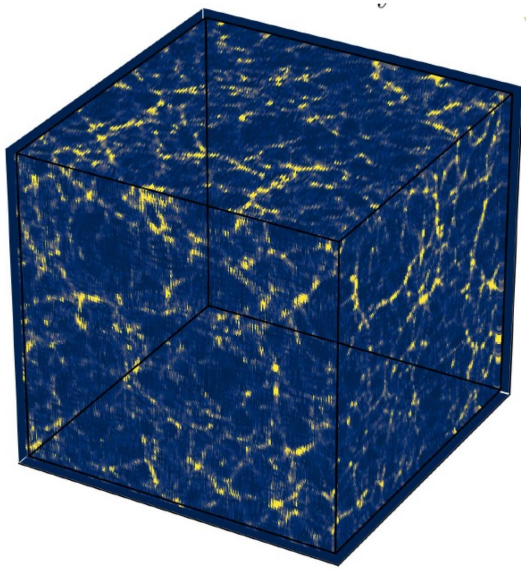
The quest for an ideal estimator

- Attempts to describe the information encoded in the 3D cosmic density field

2-point correlation function/Power Spectrum (Incomplete)



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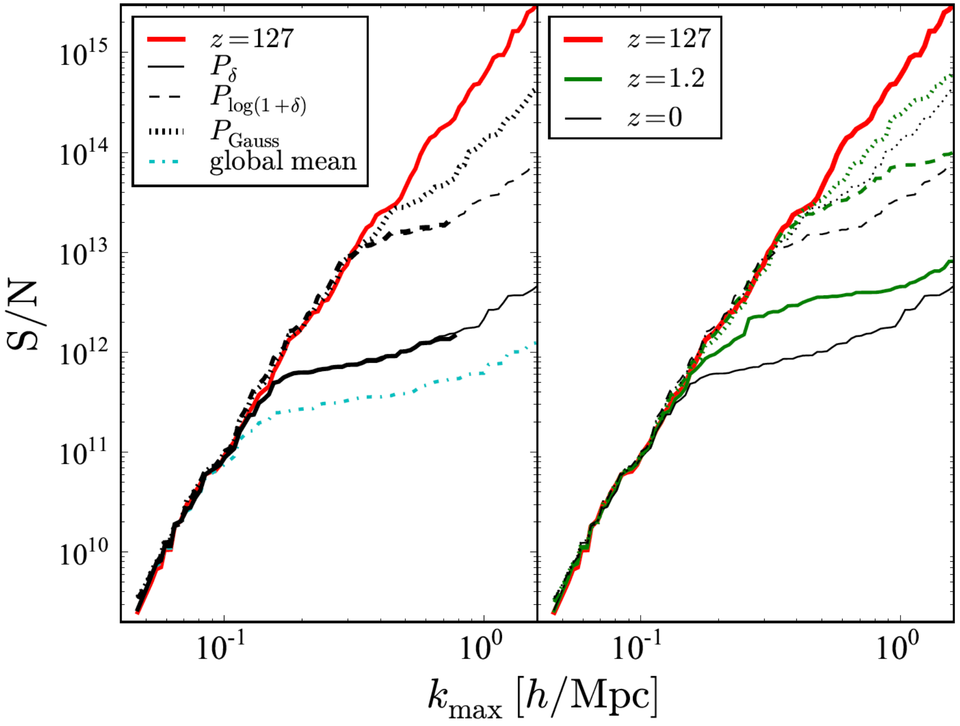

M. Neyrinck et al. (2009)

Power Spectrum information saturates in nonlinear regime. Inadequate!
(Carron 2011,2012)

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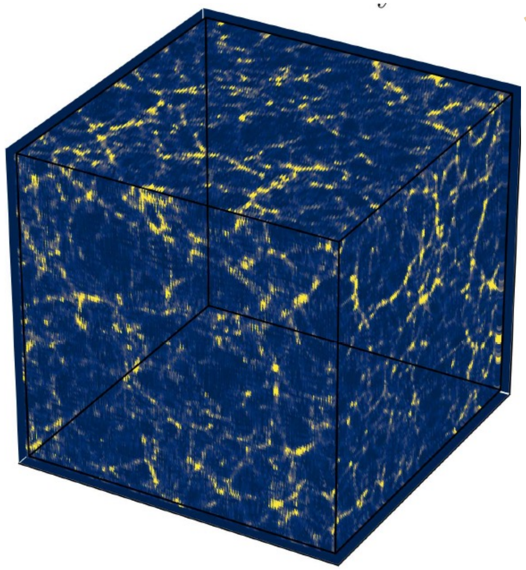
The quest for an ideal estimator

- Attempts to describe the information encoded in the 3D cosmic density field

Power spectrum + Higher order statistics (expensive)



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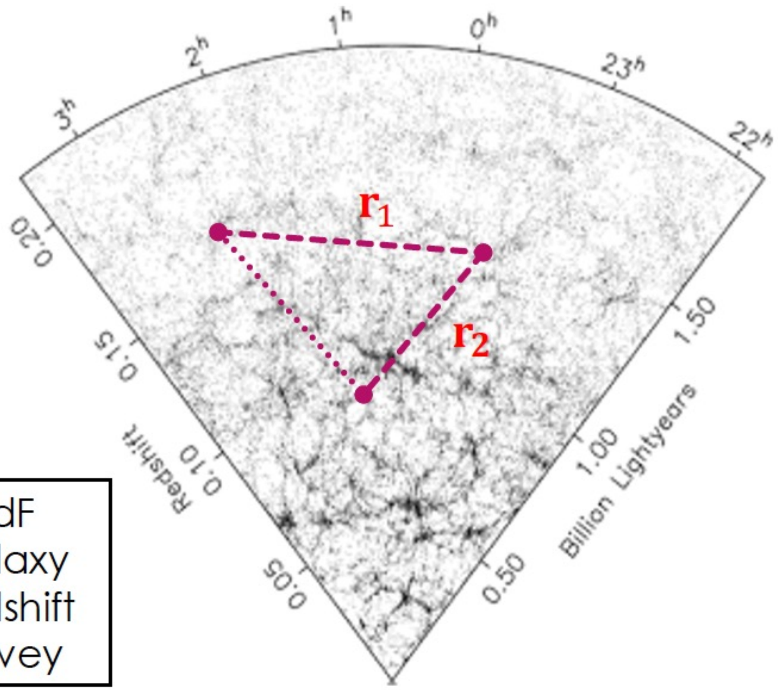
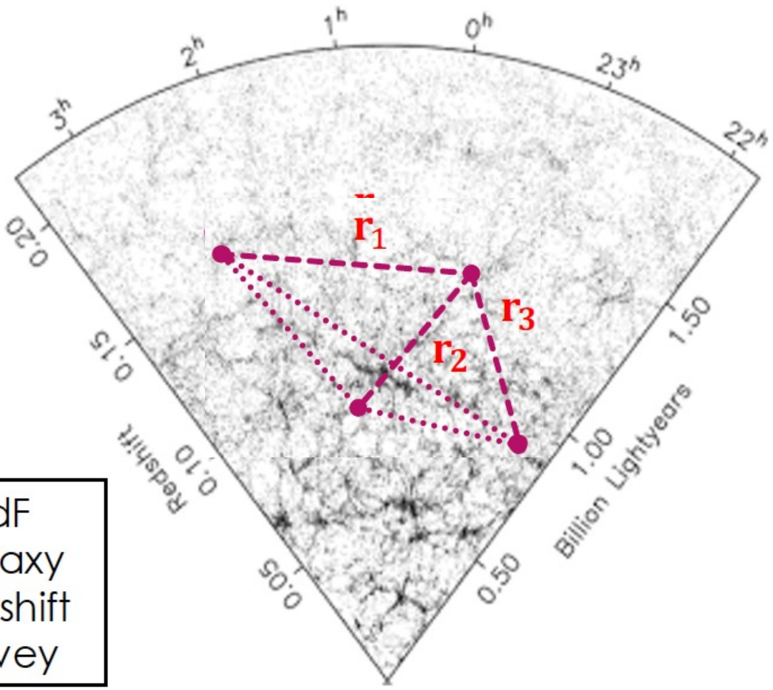
3-point function



2dF Galaxy Redshift Survey

4-point function



2dF Galaxy Redshift Survey

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The quest for an ideal estimator

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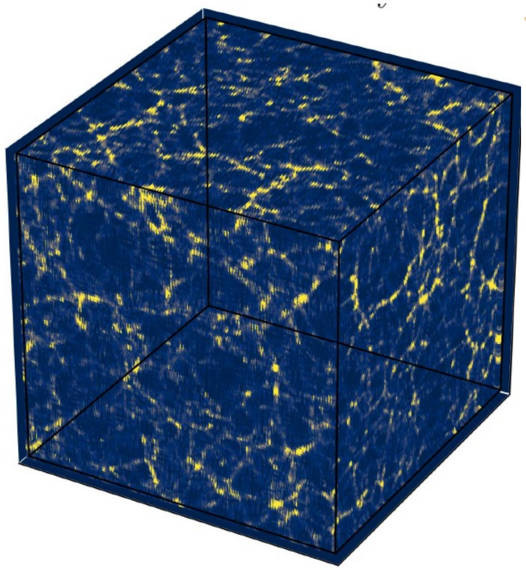


F. Villaescusa-Navaro et al. (2019)

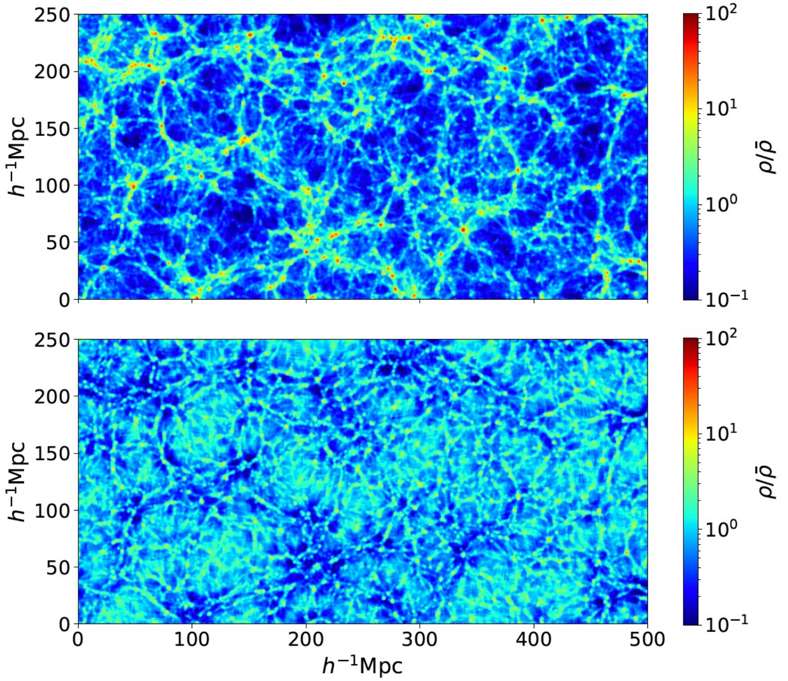
Power spectrum + Higher order statistics

Marked power spectrum, log. transform, skew spectrum
Nearest neighbor distributions, density split, etc

Physical Information

$\delta(x)$

$m(x)$



Massara et al 2020

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The quest for an ideal estimator

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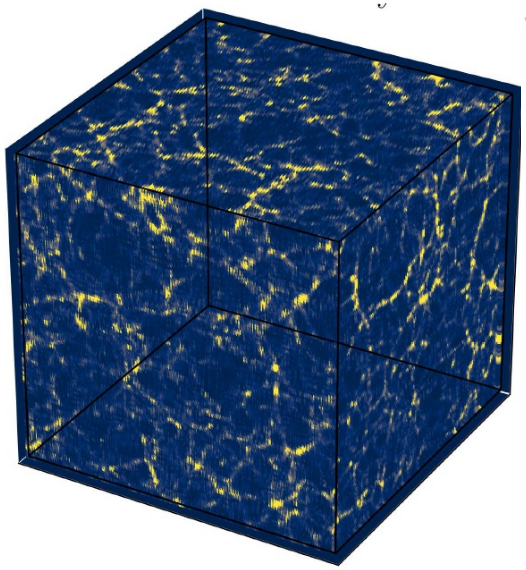

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Physical Information

Artificial Intelligence (e.g. CNNs)
(Training, interpretability)

The quest for an ideal estimator

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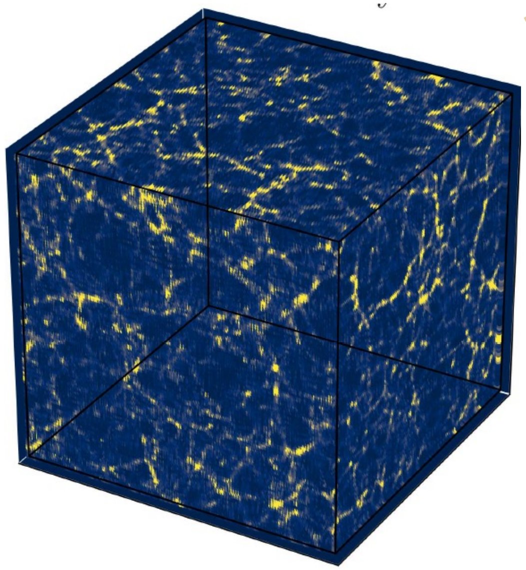

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Power spectrum + Higher order statistics

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Wavelet Scattering Transform (WST)
S. Mallat (2012)

Physical Information

Artificial Intelligence (e.g. CNNs)

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The Wavelet Scattering Transform (WST)

"Scattering Network" image by G. Exarchakis (2018)

Convolution

Modulus

WST: $\langle \left| I_0 \star \psi^{j_1, l_1} \right| \rangle$ → Averaging

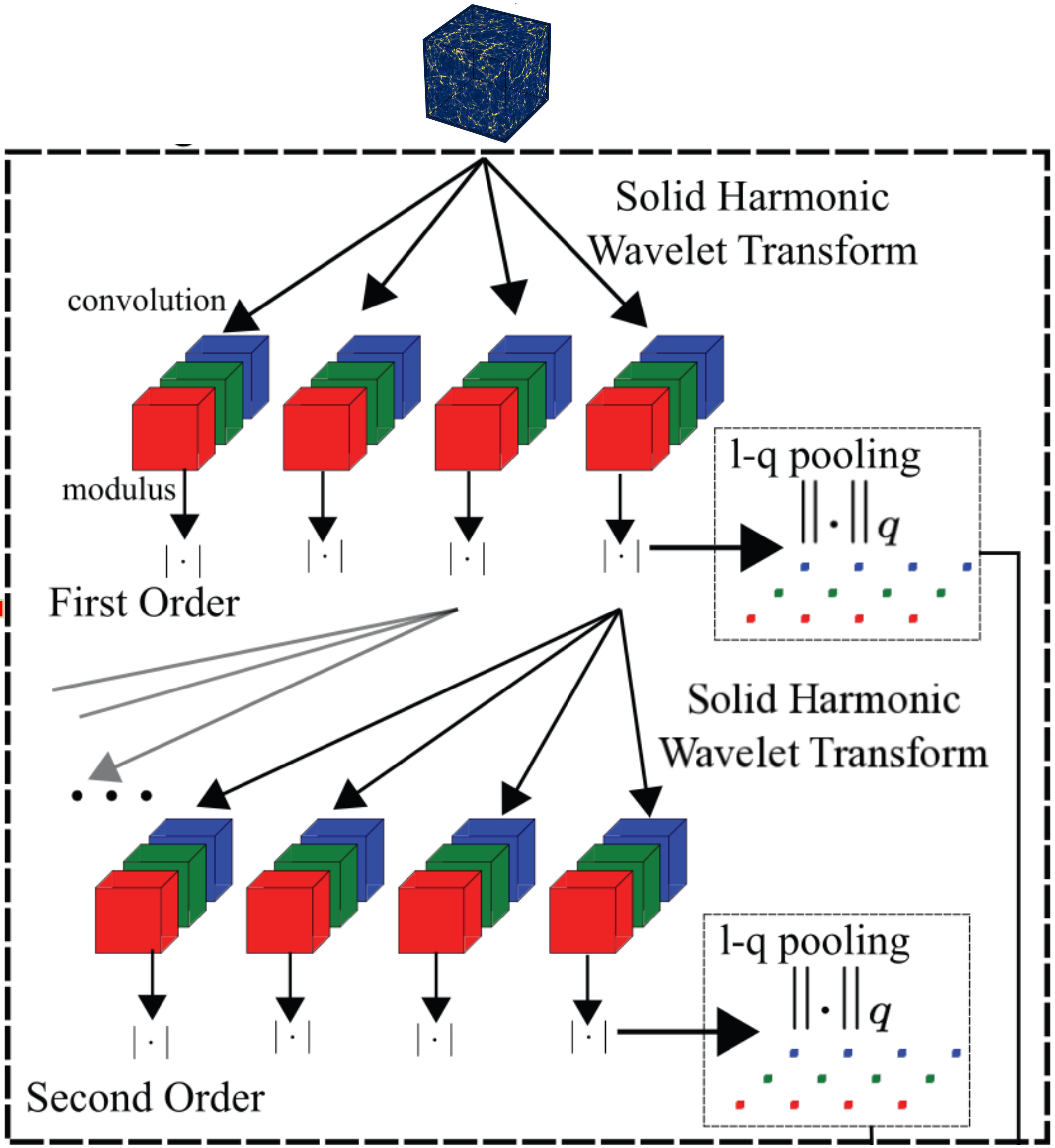
Input field

Family of Wavelets
- Dilated by 2^{j_1} - J scales
- Rotated by l_1 - L orientations

$$\boxed{S_0 = \langle |I_0| \rangle}$$

$$\boxed{S_1^{j_1, l_1} \equiv \langle I_1^{j_1, l_1} \rangle = \langle \left| I_0 \star \psi^{j_1, l_1} \right| \rangle}$$

$$\boxed{S_2^{j_1, l_1, j_2, l_2} \equiv \langle I_2^{j_1, l_1, j_2, l_2} \rangle = \langle \left| |I_0 \star \psi^{j_1, l_1}| \star \psi^{j_2, l_2} \right| \rangle}$$



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The Wavelet Scattering Transform (WST)

Physical interpretation of WST coefficients

- $S_0 = \langle |I_0| \rangle$: Mean field
- $S_1^{j_1,l_1} = \left\langle \left| I_0 \star \psi^{j_1,l_1} \right| \right\rangle$: ~ P(k). In fact, P(k) $\Longrightarrow \langle |I \star e^{-ikx}|^2 \rangle$
- $S_2^{j_1,l_1,j_2,l_2} = \left\langle \left| |I_0 \star \psi^{j_1,l_1}| \star \psi^{j_2,l_2} \right| \right\rangle$: *Non-Gaussian* information (up to 2^2 = 4pcf , for n=2)
- Basis $S_0 + S_1 + S_2$ reflects clustering properties of target field $I_0(x)$
- Retaining all *desirable* properties of regular P(k) ✅ Mallat (2012)

  +
- Compactness ✅ (Anden & Mallat, 2011,2014, Bruna & Mallat, 2013) & Robustness/Stability ✅ (Carron 2011,2012, Cheng & Menard 2021b)
- A CNN with fixed weights, but interpretable! (Bruna & Mallat 2013)
  - Performance on par with a CNN in WL applications! (Cheng et al. 2020b, Cheng & Menard 2021a)
- WST exceeds performance of traditional P(k) in 3D LSS studies **(Valogiannis & Dvorkin 2022a)**
  - Also overperforms marked P(k) (Massara et al., PRL 126, 011301 (2021))

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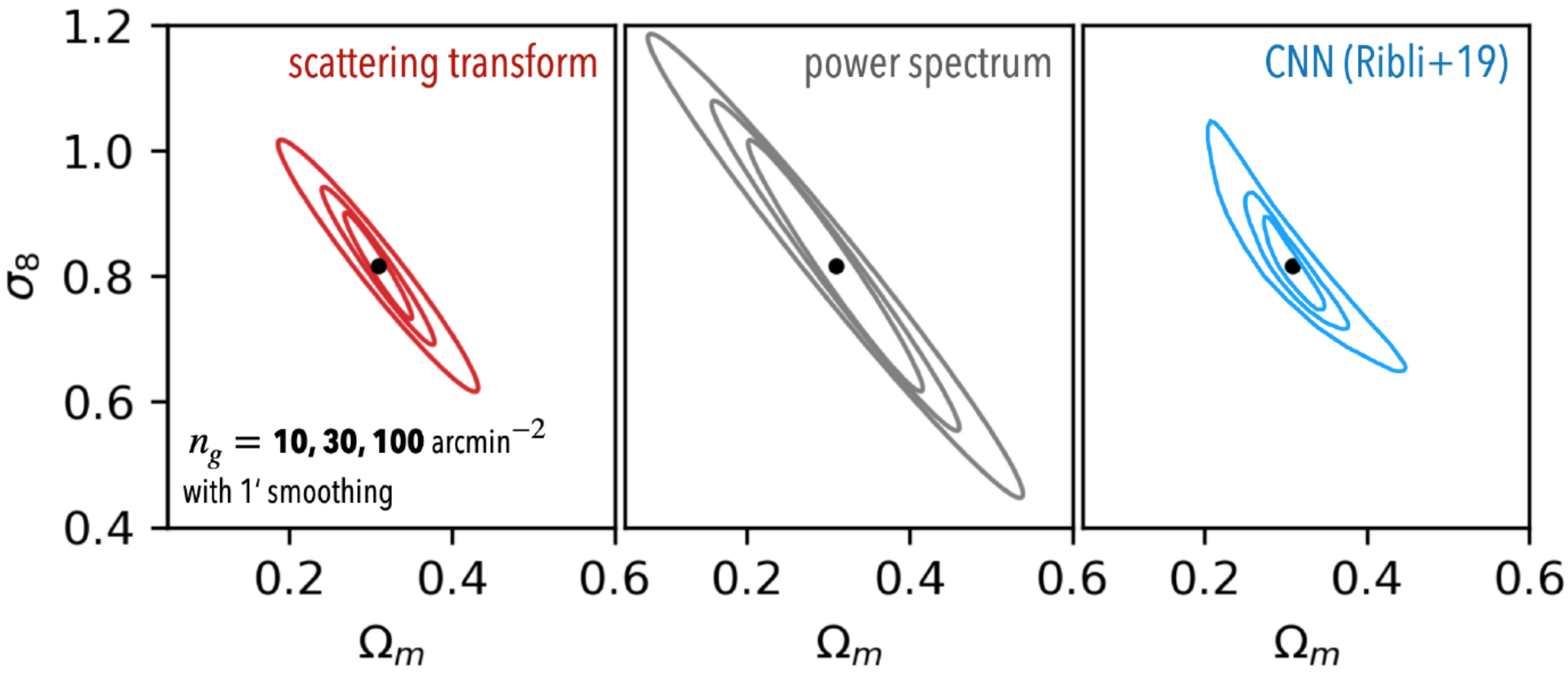
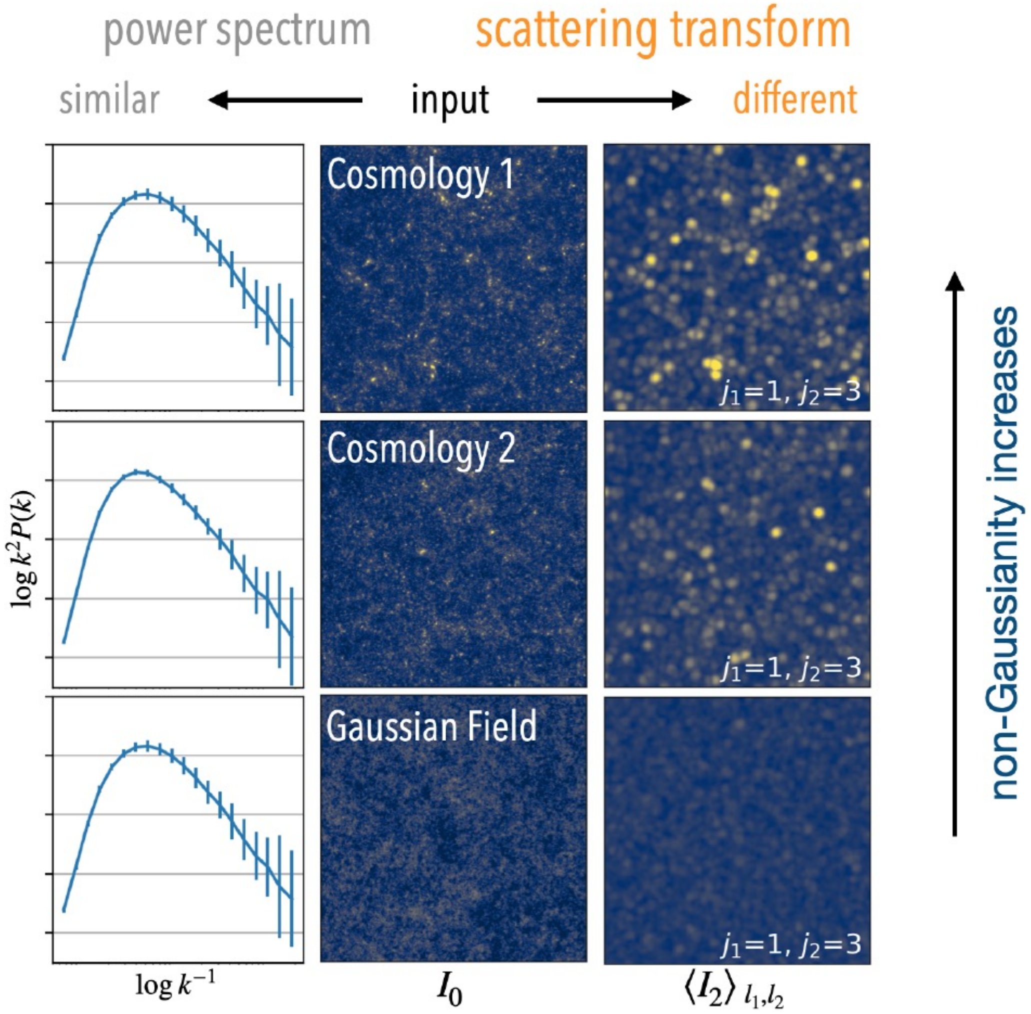
WST application on weak lensing

- Fisher information obtained from 2D simulated WL shear maps
- Performance on par with a state-of-the-art CNN!



Cheng et al. (2020)

WST application on weak lensing



Cheng et al. (2020)

- WST coefficients efficiently identify non-Gaussianity in WL shear maps

The Wavelet Scattering Transform (WST)

- 3-dimensional WST implementation with 'solid harmonic' wavelets (Eickenberg et al. (2018))

$$S_0 = \langle |I(\vec{x})|^q \rangle,$$

$$S_1(j_1, l_1) = \left\langle \left(\sum_{m=-l_1}^{m=l_1} |I(\vec{x}) * \psi^m_{j_1,l_1}(\vec{x})|^2 \right)^{\frac{q}{2}} \right\rangle,$$

$$S_2(j_2, j_1, l_1) = \left\langle \left(\sum_{m=1}^{m=l_1} |U_1(j_1, l_1)(\vec{x}) * \psi^m_{j_2,l_1}(\vec{x})|^2 \right)^{\frac{q}{2}} \right\rangle$$

$$U_1(j_1, l_1)(\mathbf{x}) = \left(\sum_{m=-l_1}^{m=l_1} |I(\mathbf{x}) * \psi^m_{j_1,l_1}(\mathbf{x})|^2 \right)^{\frac{1}{2}}$$

$$\psi_l^m(\mathbf{x}) = \underbrace{\frac{1}{(2\pi)^{3/2}} e^{-|\mathbf{x}|^2/2\sigma^2}}_{\text{Gaussian envelope}} \underbrace{|\mathbf{x}|^l Y_l^m\left(\frac{\mathbf{x}}{|\mathbf{x}|}\right)}_{\text{Solid Harmonics}}$$

- Dilated by dyadic scales 2^{j_1}

$$\psi^m_{j_1,l_1}(\mathbf{x}) = 2^{-3j_1} \psi^{m_1}_{l_1}(2^{-j_1}\mathbf{x})$$

- Wavelets in the literature
  - Bump steerable wavelets (Eickenberg et al, 2022, Allys et al, 2020)
  - Morlet wavelets (Cheng et al. 2020b, Cheng & Menard 2021a)
  - Equivariant wavelets (Saydjari & Finkbeiner, 2021)

- Implemented in KYMATIO package (Andreux et al. 2019)

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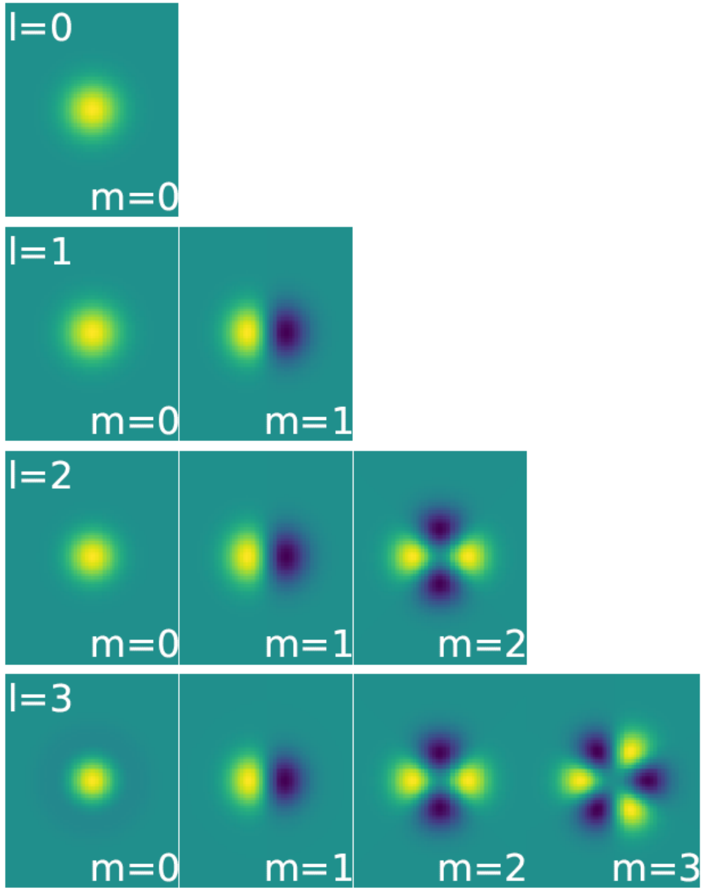

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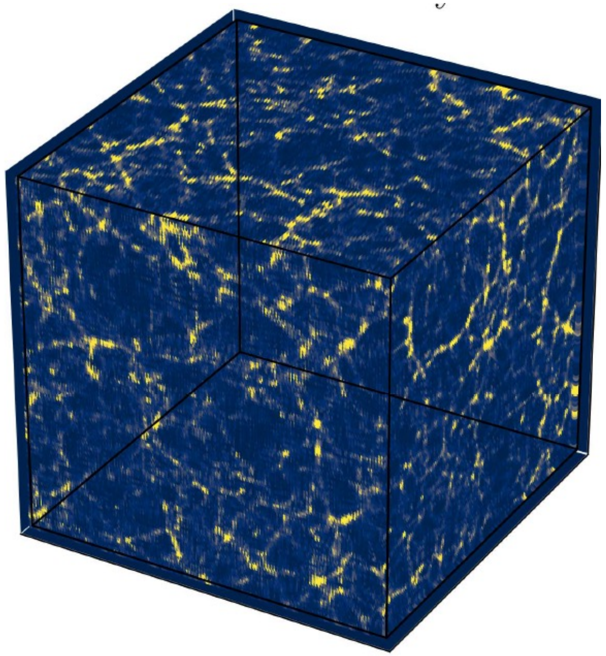
First WST application on 3D LSS

- **First** WST application on 3D matter density field! **(Valogiannis & Dvorkin, 2022a)**

$$\boxed{I(\vec{x}) \equiv \delta_m(\vec{x}) = \frac{\rho_m(\vec{x})}{\bar{\rho}_m} - 1.0}$$, resolution $N_{grid} = 256^3$



- Evaluated from the *Quijote* simulations (F. Villaescusa-Navaro et al., 2019)
- Fiducial cosmology

$$\Omega_\mathrm{m} = 0.3175,\ \Omega_\mathrm{b} = 0.049,\ h = 0.6711$$

$$n_s = 0.9624, \sigma_8 = 0.834, M_\nu = 0.0\,\mathrm{eV}, \text{and } w = -1$$

Box L=1.0 Gpc/h

- In presence of massive neutrinos, trace both:
- $\delta_m = \delta_{CDM} + \delta_b + \delta_\nu$ Total ‘m’ field
- $\delta_{cb} = \delta_{CDM} + \delta_b$ ‘cb’ field

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Fisher forecast

Fisher forecasting

- 15,000 realizations for fiducial cosmology
- 7,000 for linear derivatives in parameters

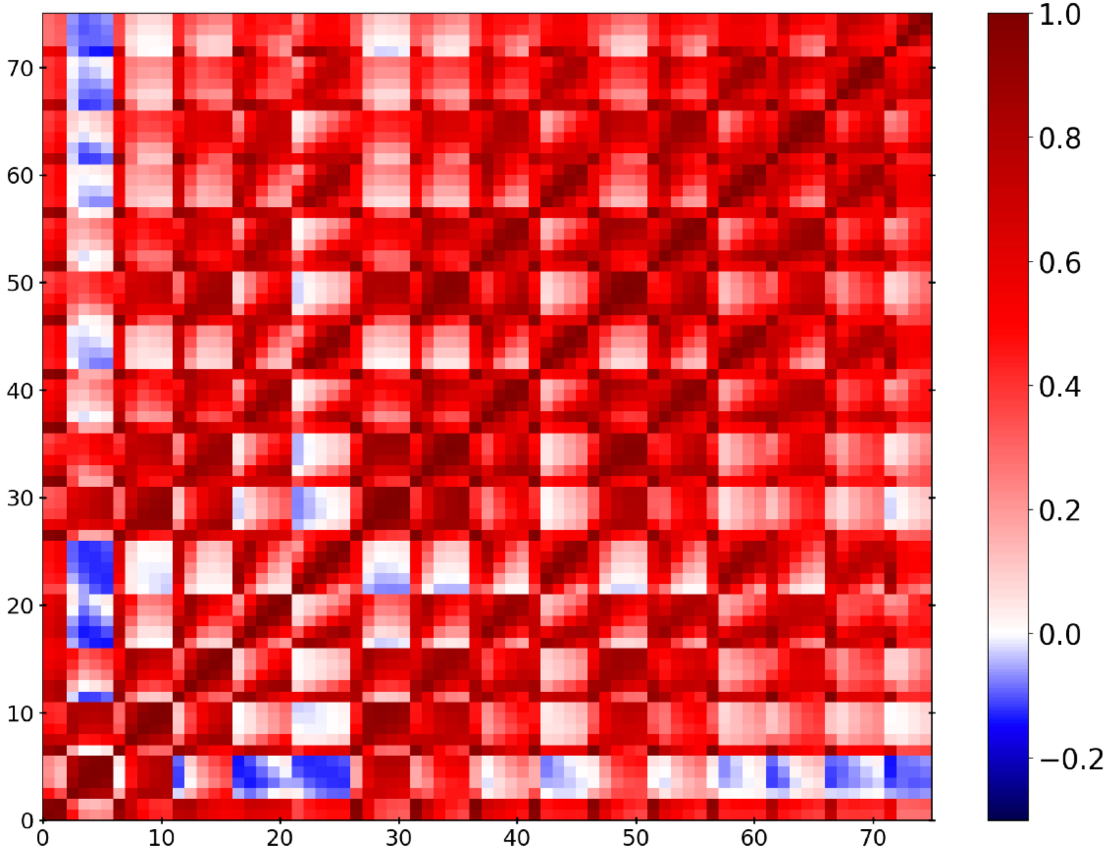
$$F_{\alpha\beta} = \frac{\partial O_i}{\partial \theta_\alpha} C^{-1}_{ij} \frac{\partial O^T_j}{\partial \theta_\beta}$$

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

for $\boxed{\theta_\alpha = \{\Omega_m, \Omega_b, H_0, n_s, \sigma_8, M_\nu\}}$, z=0

Comparing 3 observables O_i:

- Power spectrum **P(k)**
- Marked power spectrum **M(k)**
- $S_0 + S_1 + S_2 = 76$ **WST** coefficients
  Using J=5 scales and L=5 orientations



WST coefficients - correlation matrix
Valogiannis & Dvorkin 2022a

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Marked Power Spectrum

- Marked correlation function generalizes 2-point function

$$\mathcal{M}(r) = \frac{1}{n(r)\bar{m}^2} \sum_{ij} \delta_D(|\mathbf{x}_i - \mathbf{x}_j| - r) m_i m_j = \frac{1 + W(r)}{1 + \xi(r)}$$

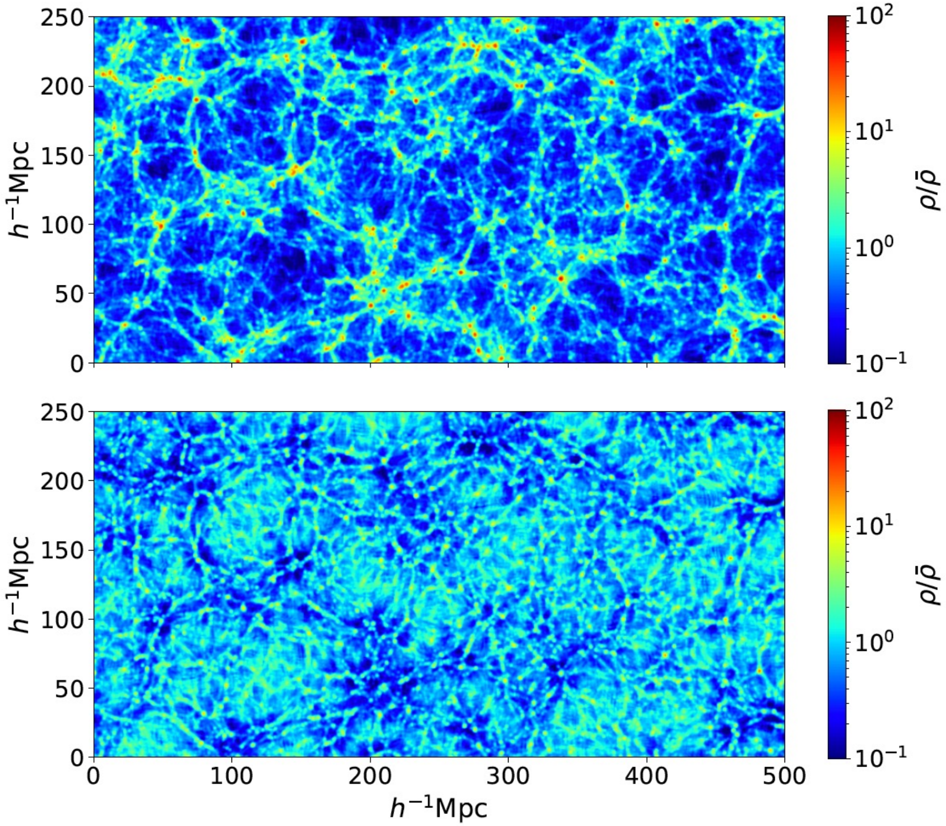
- Each galaxy weighted by mark ‘m’
- Inverse density weighted mark (highlights voids)

$$m\left[\mathbf{x}, R, \delta_s, p\right] = \left(\frac{1 + \delta_s}{1 + \delta_s + \delta_R(\mathbf{x})}\right)^p$$

- Can constrain modified gravity (M. White 2016, **Valogiannis & Bean 2018**, Alam et al., 2021)
- Can constrain neutrino mass (Massara et al, PRL 2020)
- Contains info beyond 2-point function (Philxcox et al., 2020)

$\delta(x)$

m(x)



Massara et al 2020

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WST sensitivity to neutrino mass

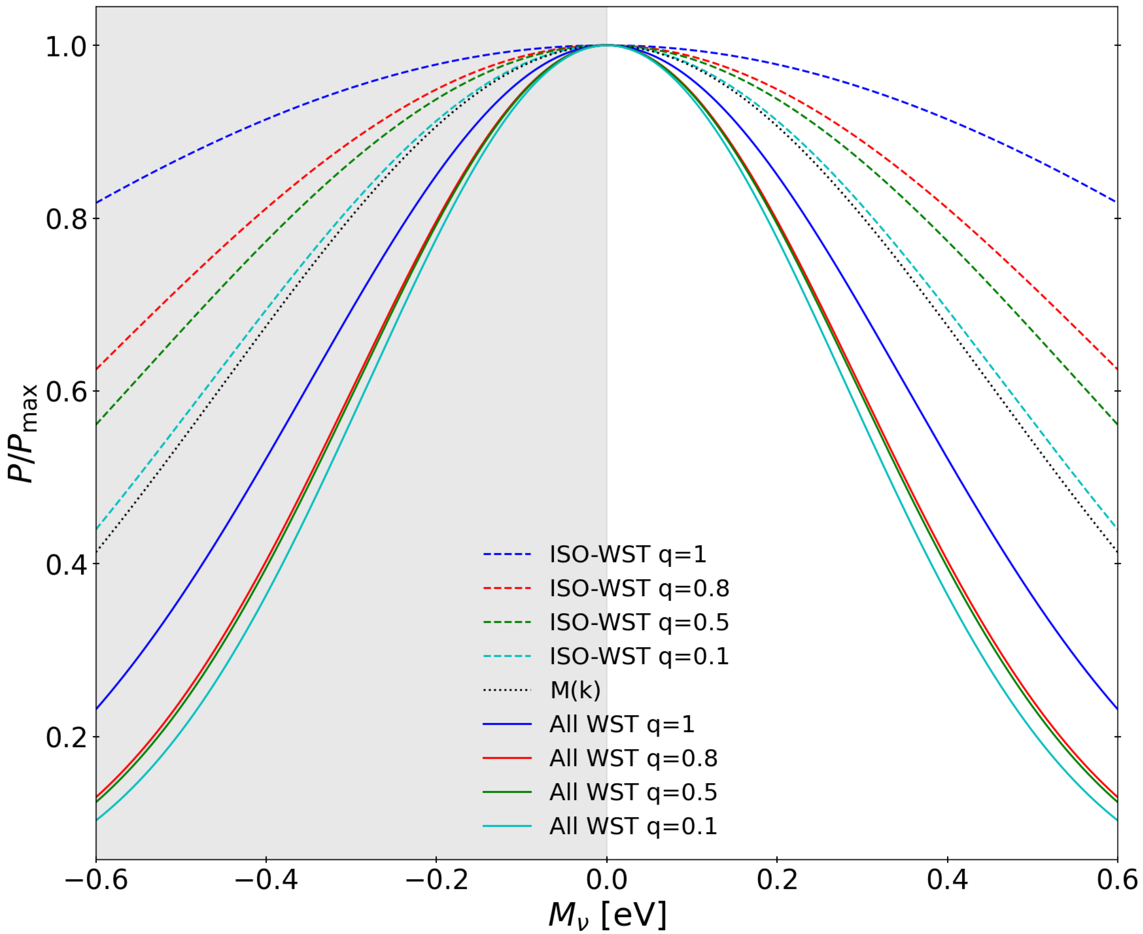
- Raising modulus to powers q<1 emphasizes on cosmic voids (lower overdensity regions)
- Very sensitive to neutrino mass!

$$S_0 = \langle |I(\vec{x})|^q \rangle,$$

$$S_1(j_1, l_1) = \left\langle \left(\sum_{m=-l_1}^{m=l_1} |I(\vec{x}) * \psi^m_{j_1,l_1}(\vec{x})|^2 \right)^{\frac{q}{2}} \right\rangle,$$

$$S_2(j_2, j_1, l_1) = \left\langle \left(\sum_{m=1}^{m=l_1} |U_1(j_1, l_1)(\vec{x}) * \psi^m_{j_2,l_1}(\vec{x})|^2 \right)^{\frac{q}{2}} \right\rangle$$

- q=0.8 found to be optimal



Valogiannis & Dvorkin 2022a

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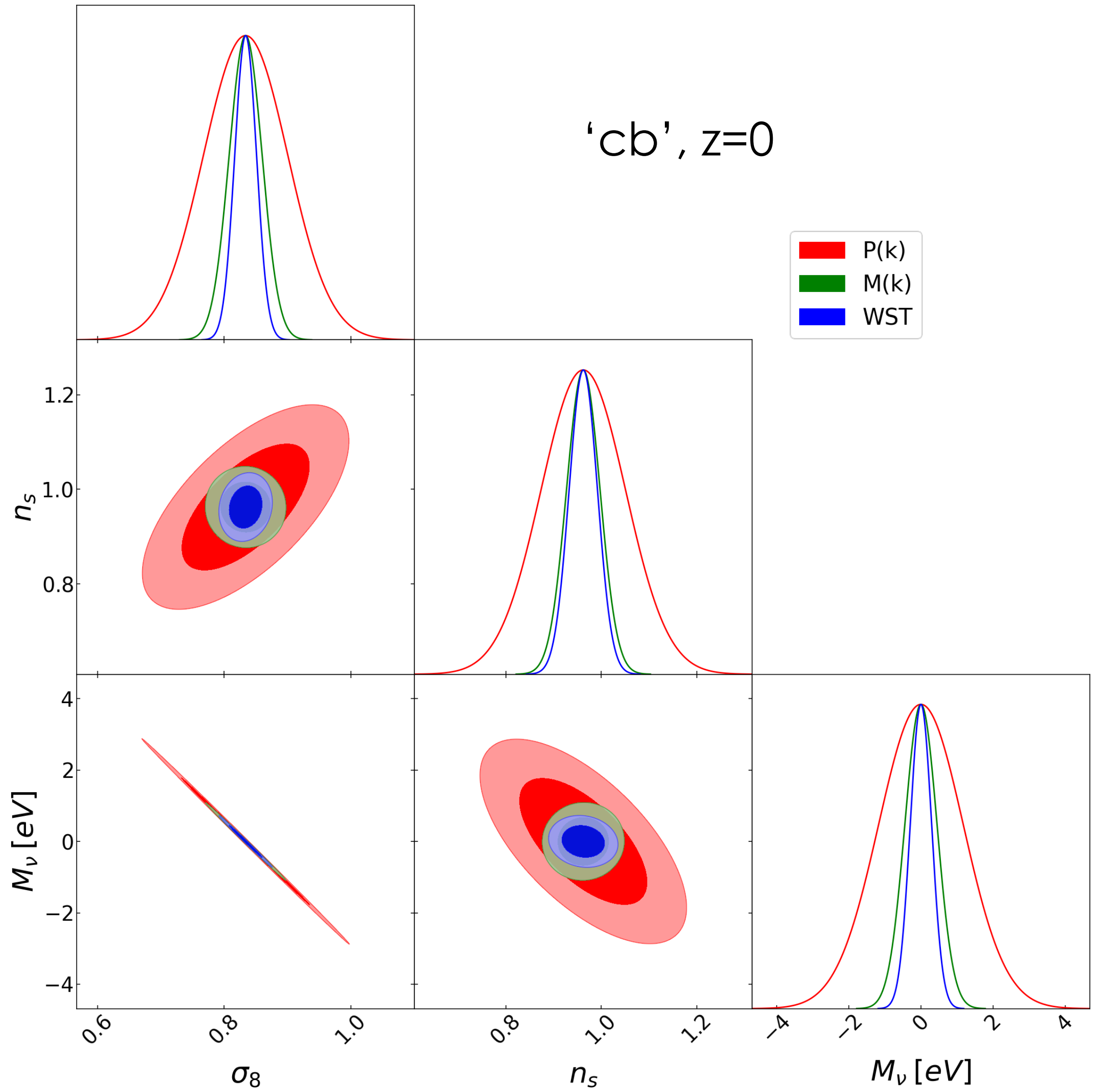
Great improvement over matter P(k)!



- WST delivers ***significant*** improvement in the 1-σ errors for *all* parameters!
- ~1.2-4x **tighter** errors than from 'cb' P(k)!
- Constrains on neutrino mass:
  - ~4x **tighter** than 'cb' P(k)!
  - ~1.6x **tighter** than 'cb' M(k)!
- ~3x100x **tighter** errors than from 'm' P(k)

Matter type	'm'			'cb'		
Statistic	$P(k)$	$M(k)$	WST	$P(k)$	$M(k)$	WST
$\sigma(\Omega_m)$	0.076	0.013	0.014	0.040	0.016	0.016
$\sigma(\Omega_b)$	0.033	0.010	0.012	0.015	0.009	0.012
$\sigma(\sigma_8)$	0.01	0.002	0.001	0.067	0.026	0.017
$\sigma(n_s)$	0.39	0.044	0.031	0.088	0.035	0.029
$\sigma(H_0)$ [km/s/Mpc]	40.62	9.50	10.34	14.42	8.28	10.32
$\sigma(M_\nu)$ [eV]	0.72	0.016	**0.008**	1.17	0.45	**0.29**

Valogiannis & Dvorkin 2022a

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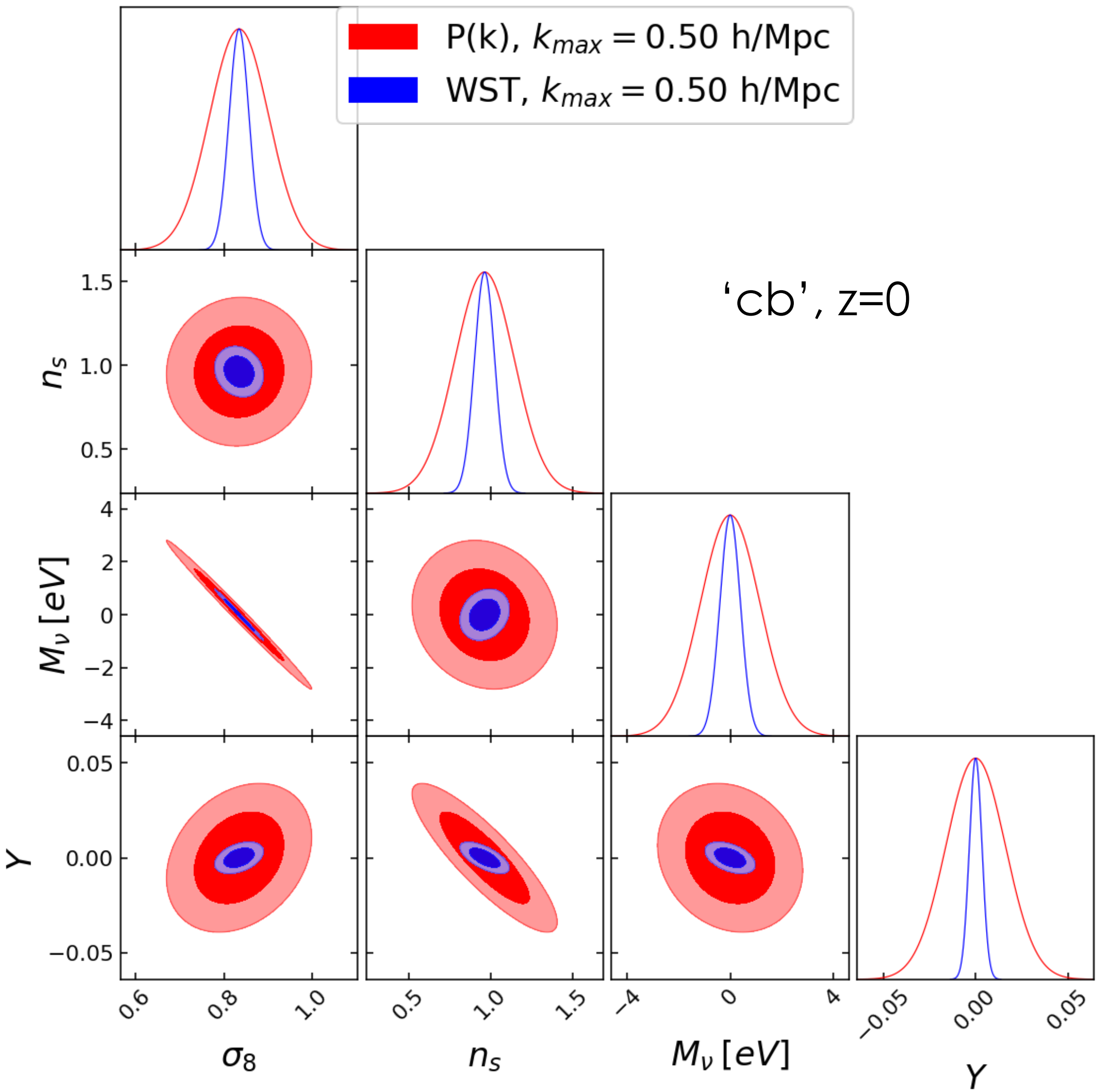
Upcoming MG application



- New WST application on MG in the works, Quijote-MG
- f(R) Hu-Sawicki model application + 6 ΛCDM
- Constrains on MG parameter Y=$f_{R_0}^{\log_2 10}$:
  - ~5x **tighter** than 'cb' P(k)!
- Follows and exceeds neutrino mass trend
  - Parallels between scale-dependent growth in both scenarios
- In collaboration with Francisco Villaescusa-Navarro & Marco Baldi

New column showing contraints on deviations from GR (Y->0)

Valogiannis et al., in prep.

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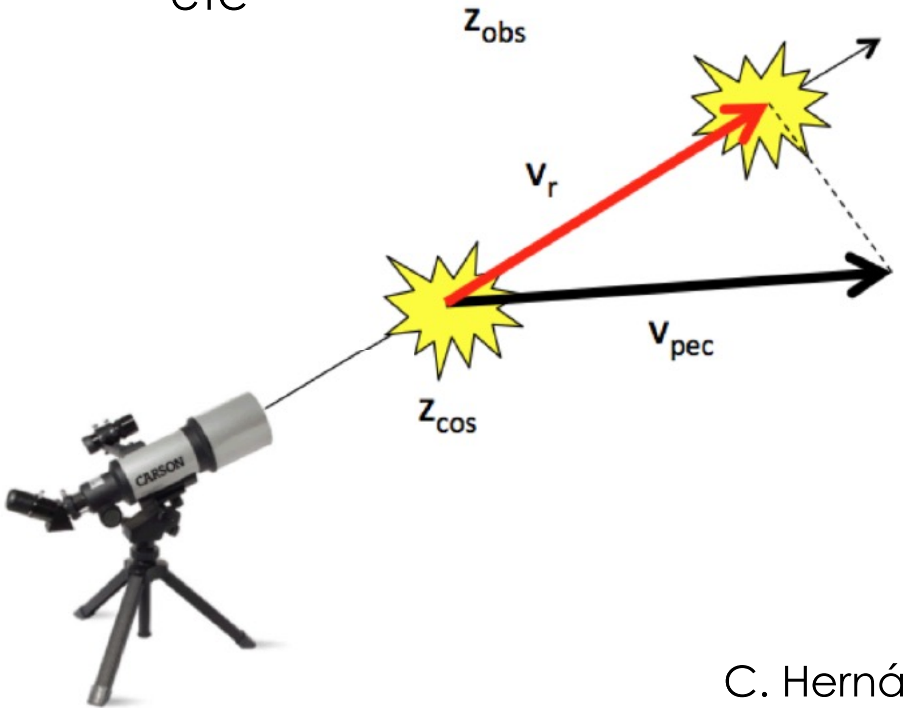
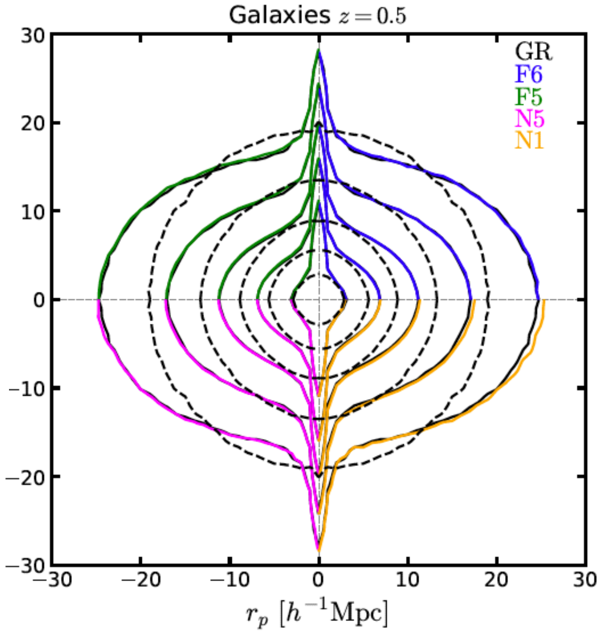
Realistic galaxy survey data

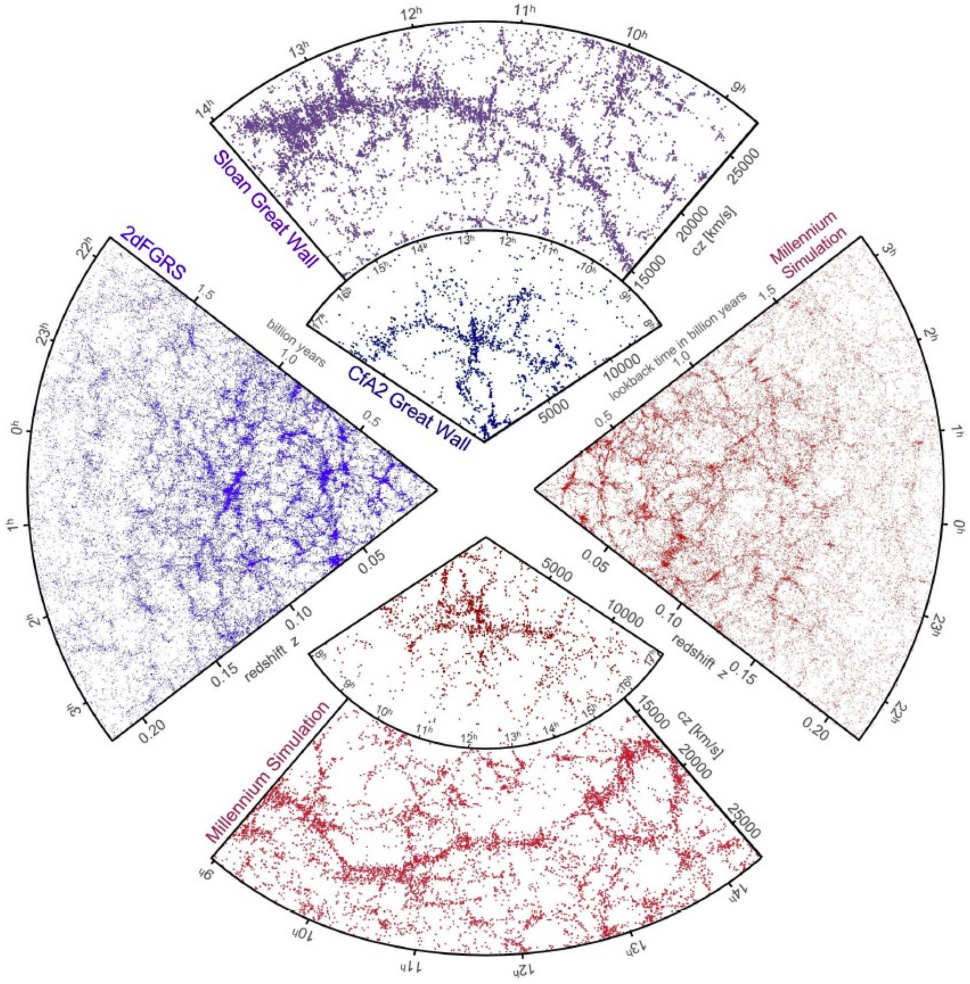
However

- LSS surveys observe *galaxies*:
  - Biased tracers of dark matter field
  - Redshift-Space Distortions (RSD)
  - Systematics (Geometry, fiber collisions, etc..)
  - Lightcone
  - etc





C. Hernández-Aguayo et al., 2018



V. Springel et al. (2006)

Likelihood analysis

- We perform likelihood analysis, sampling from Gaussian likelihood

$$\log \mathcal{L}(\theta|\mathbf{d}) \propto -\frac{1}{2}\left[\mathbf{X}_{\mathbf{d}} - \mathbf{X}_t(\theta)\right]^{\mathrm{T}} C^{-1} \left[\mathbf{X}_{\mathbf{d}} - \mathbf{X}_t(\theta)\right]$$

First WST application on BOSS

- **First** WST application on 3D *redshift-space galaxy* density field! (**Valogiannis & Dvorkin 2022b)**
  - Working with *BOSS CMASS DR12* sample at 0.46<z<0.57
  - Northern + Southern Galactic Cap
- For survey data, fundamental quantity of interest is the *FKP field* (Feldman, Kaiser, Peacock et al., 1994) :

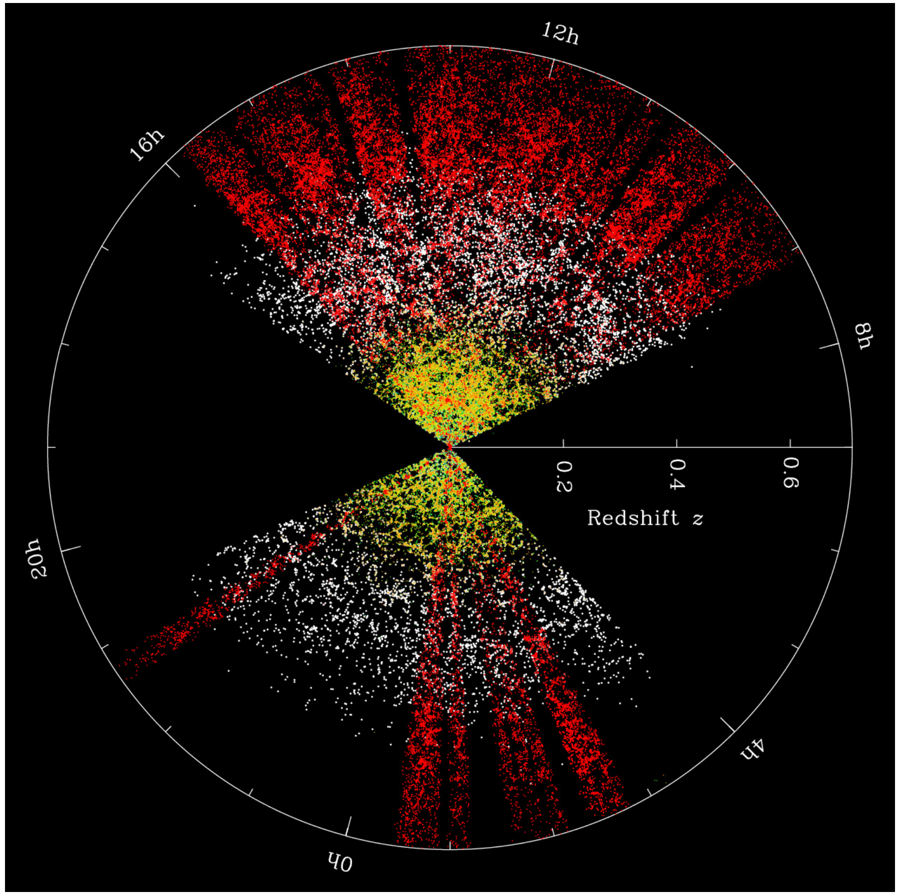
$$F(\mathbf{r}) = \frac{w_{\rm FKP}(\mathbf{r})}{I_2^{1/2}} [\underbrace{w_c(\mathbf{r})n_g(\mathbf{r})}_{\text{Galaxies}} - \alpha_r \underbrace{n_s(\mathbf{r})}_{\text{Randoms}}]$$

- Systematic + FKP weights

$$w_c(\mathbf{r}) = (w_{\rm rf}(\mathbf{r}) + w_{\rm fc}(\mathbf{r}) - 1.0)\, w_{\rm sys}(\mathbf{r})$$

$$w_{\rm FKP}(\mathbf{r}) = [1 + \bar{n}_g(\mathbf{r}) P_0]^{-1}$$

- Serves as input into WST network
  - With $N_{grid} = 270^3$ and $L_{Box} = 2700\ Mpc/h$



SDSS https://blog.sdss.org/

Likelihood analysis

- Data

$$\log \mathcal{L}(\theta|\mathbf{d}) \propto -\frac{1}{2}\left[\mathbf{X_d} - \mathbf{X}_t(\theta)\right]^{\mathrm{T}} C^{-1}\left[\mathbf{X_d} - \mathbf{X}_t(\theta)\right]$$

- Use vector of WST coefficients as observable
- Extracted from BOSS CMASS FKP field, using

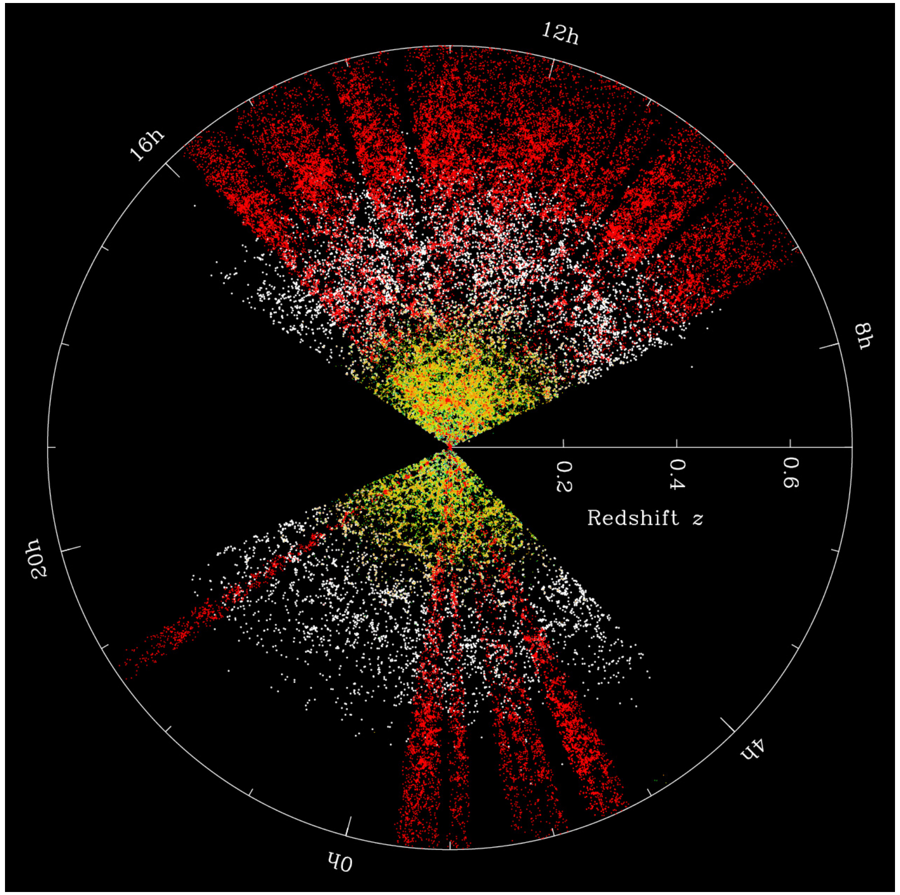
J=5 scales and L=5 orientations

- $\boldsymbol{S_0 + S_1 + S_2 = 76}$ WST coefficients

- Also, use galaxy 2-point correlation function multipoles

$\xi_{l=0,2}(r)$ **($r_{min} = 8$ Mpc/h)**

as benchmark



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Likelihood analysis

- Theory model

$$\log \mathcal{L}(\theta|\mathbf{d}) \propto -\frac{1}{2}\left[\mathbf{X}_{\mathbf{d}} - \mathbf{X}_t(\theta)\right]^{\mathrm{T}} C^{-1}\left[\mathbf{X}_{\mathbf{d}} - \mathbf{X}_t(\theta)\right]$$

- Capture cosmological dependence using

Abacus Summit simulations (Maksimova et al. 2021, Garrison et al. 2019&2021)

HOD tuned to BOSS CMASS at 0.46<z<0.60 with AbacusHOD (**Yuan et al. 2021**)

Box L=2000 Mpc/h, $N_{grid} = 200^3$

- Fiducial cosmology from Planck 2018 $\{\omega_b, \omega_c, n_s, \sigma_8\} = \{0.02237, 0.120, 0.9649, 0.8114\}$
- + Fixed angular size of sound horizon at last scattering. $100\theta_\star = 1.041533$
- + 7 HOD model paramerers (vanilla HOD + velocity bias)

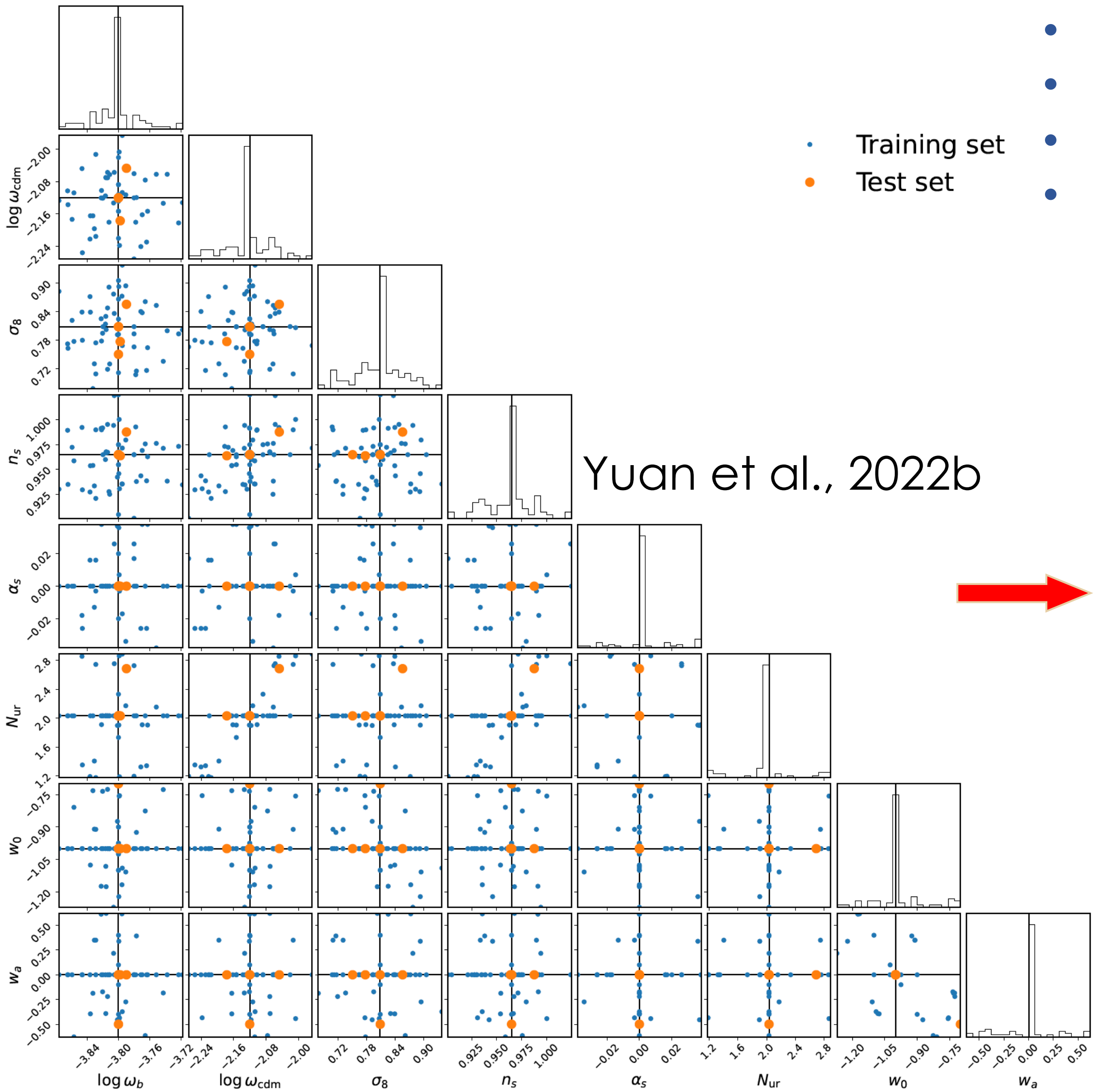
$$\{\alpha, \alpha_{\mathrm{c}}, \alpha_{\mathrm{s}}, \kappa, \log M_1, \log M_{\mathrm{cut}}, \sigma\} = \{0.9022, 0.2499, 1.1807, 0.3288, 14.313, 12.8881, 0.02084\}$$

- We cut Abacus cubic boxes into actual CMASS geometry
  - Using ‘make survey’ (White et al., 2013)

AI in Science
A program of SCHMIDT **FUTURES**

WST emulator

- Construct *full emulator* of WST's cosmological dependence
- Data vector of 76 coefficients up to 2nd order, for J=L=5
- Trained from 151,474 Abacus Summit galaxy mocks!
- 8 cosmo + 7 HOD = 15d space, neural net-based



Yuan et al., 2022b

	Parameter	Bounds
ΛCDM	ω_b	[0.0207, 0.0243]
	ω_c	[0.1032, 0.14]
	σ_8	[0.687, 0.938]
	n_s	[0.901, 1.025]
Extended	a_{run}	[-0.038, 0.038]
	N_{eff}	[2.1902, 3.9022]
	w_0	[-1.27, -0.70]
	w_a	[-0.628, 0.621]
HOD	$\log_{10} M_{\mathrm{cut}}$	[12.4, 13.3]
	$\log_{10} M_1$	[13.0, 15.0]
	σ	[0.001, 1.0]
	α	[0.5, 1.5]
	κ	[0.0, 8]
	α_c	[0.0, 0.8]
	α_s	[0.0, 1.5]

Valogiannis et al., 2023

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WST emulator

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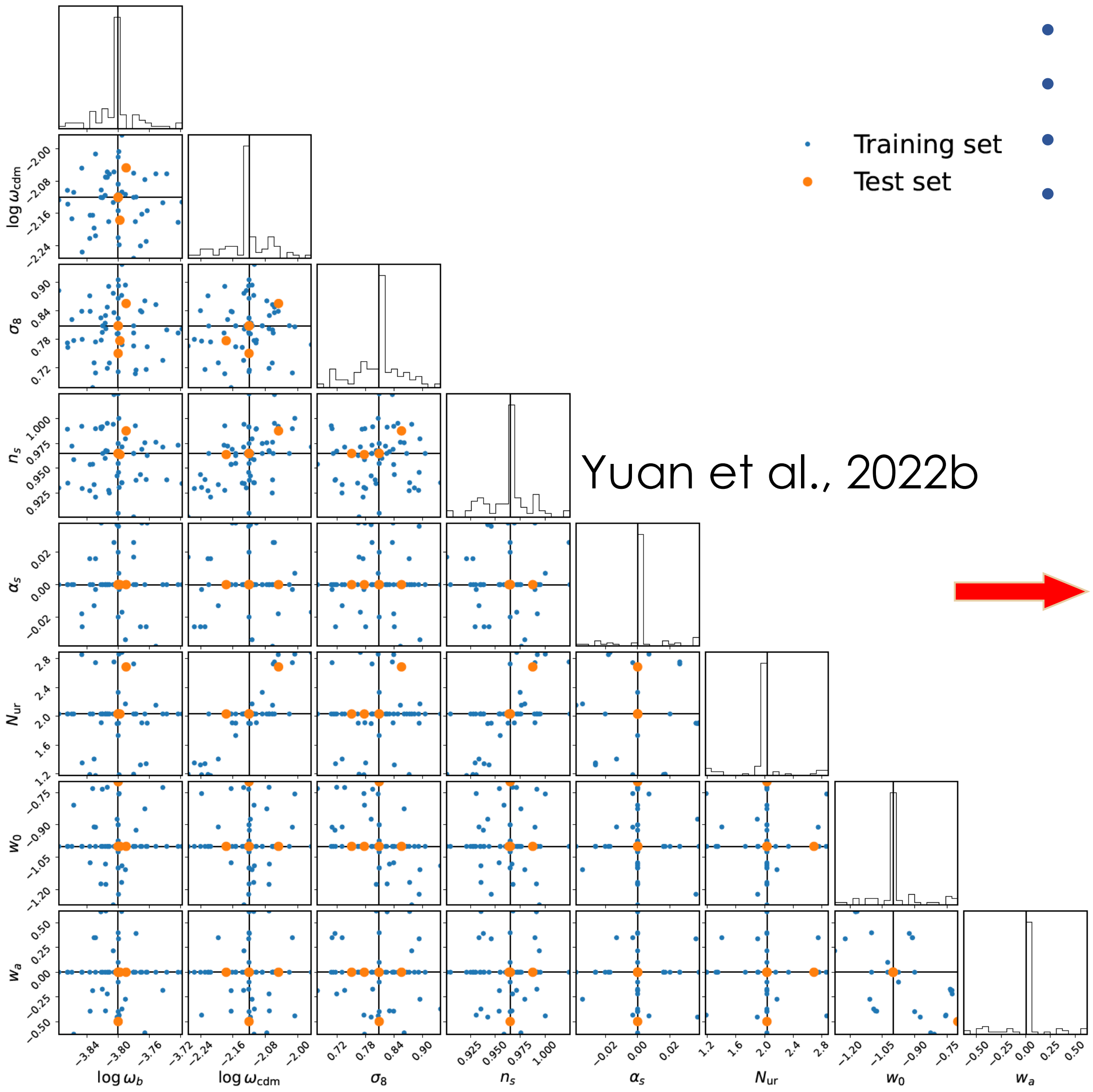
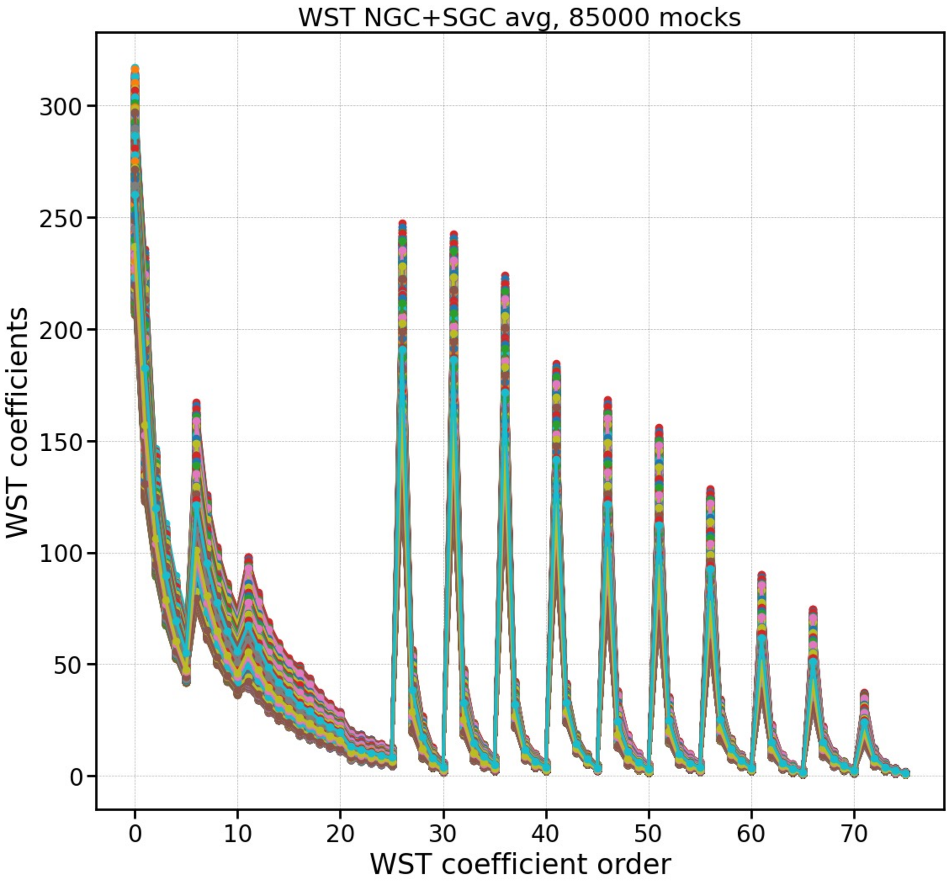


Yuan et al., 2022b



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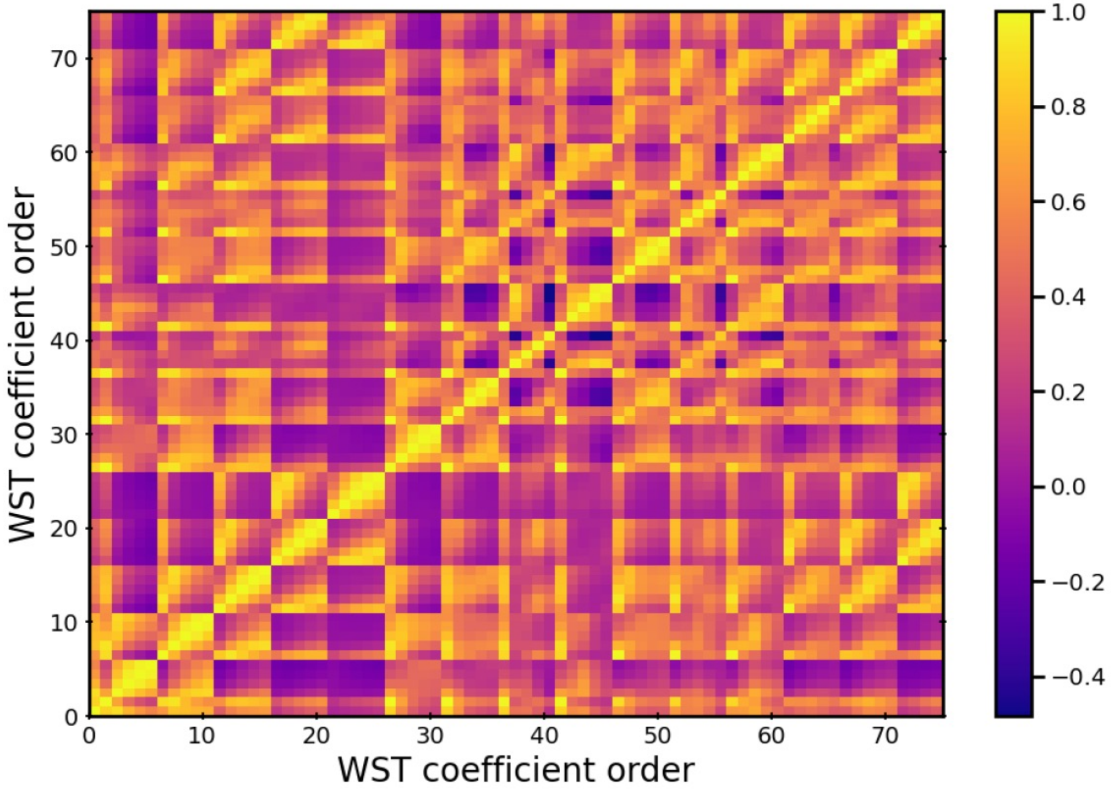
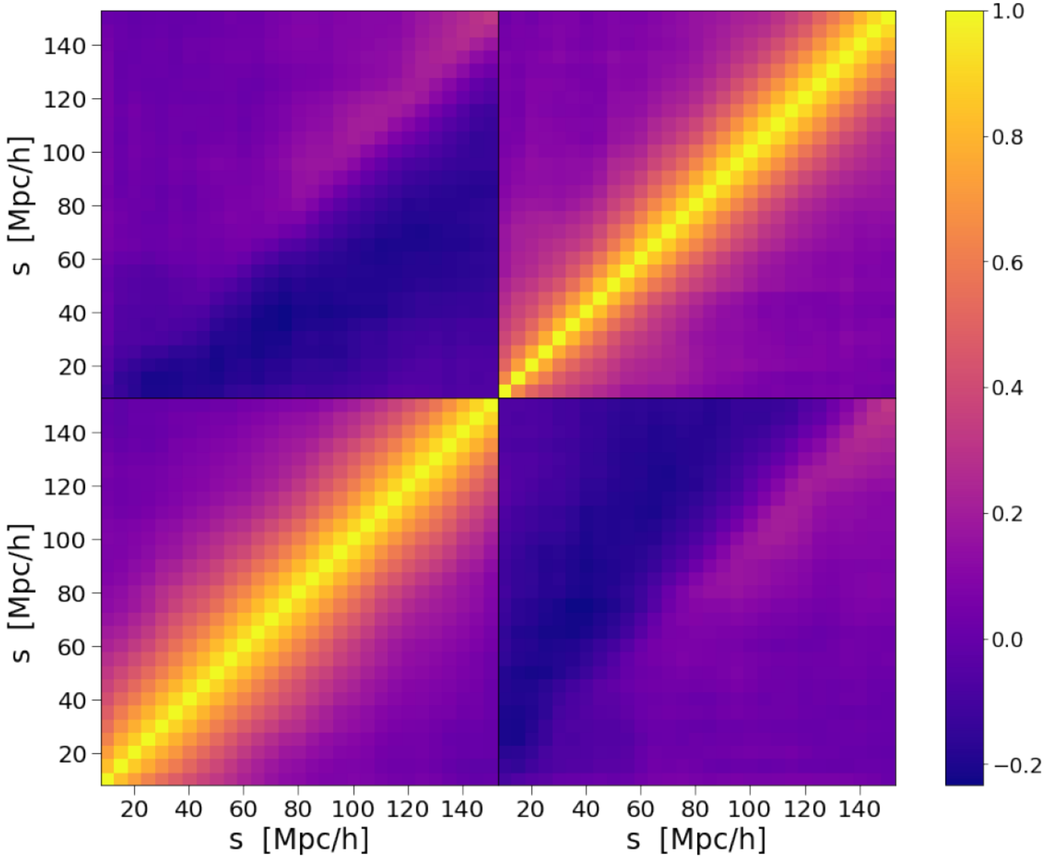
Likelihood analysis

- Covariance matrix obtained from N=2048 *PATCHY* mocks (S. A. Rodriguez-Torres et al., 2016)

$$\log \mathcal{L}(\theta|\mathbf{d}) \propto -\frac{1}{2}\left[\mathbf{X}_\mathbf{d} - \mathbf{X}_t(\theta)\right]^{\mathrm{T}} C^{-1} \left[\mathbf{X}_\mathbf{d} - \mathbf{X}_t(\theta)\right]$$

Valogiannis et al., 2023



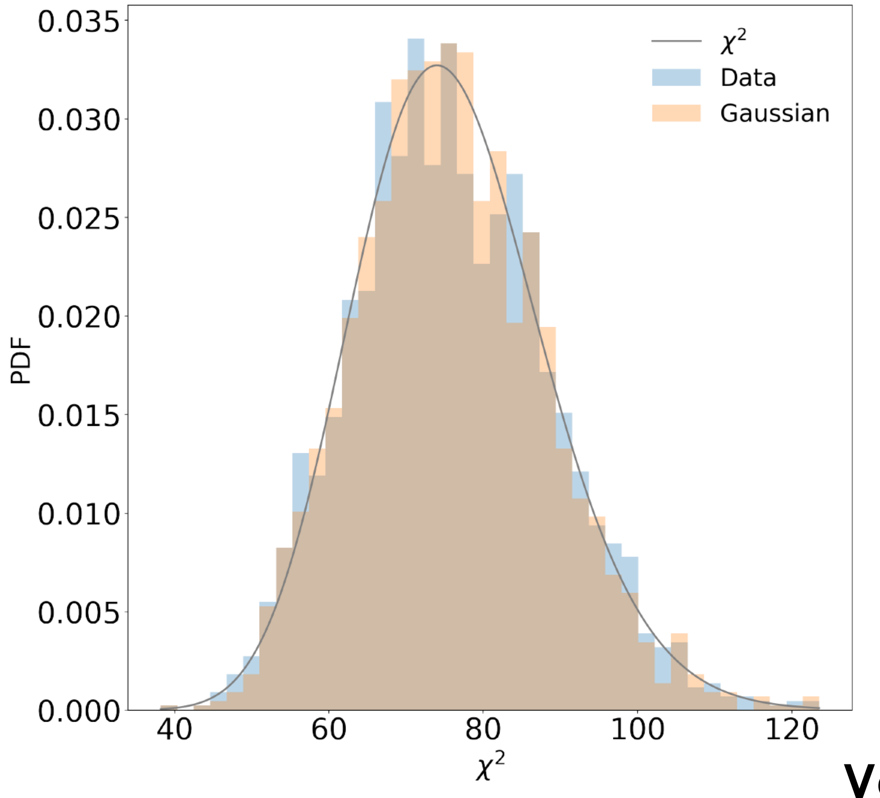


Likelihood analysis

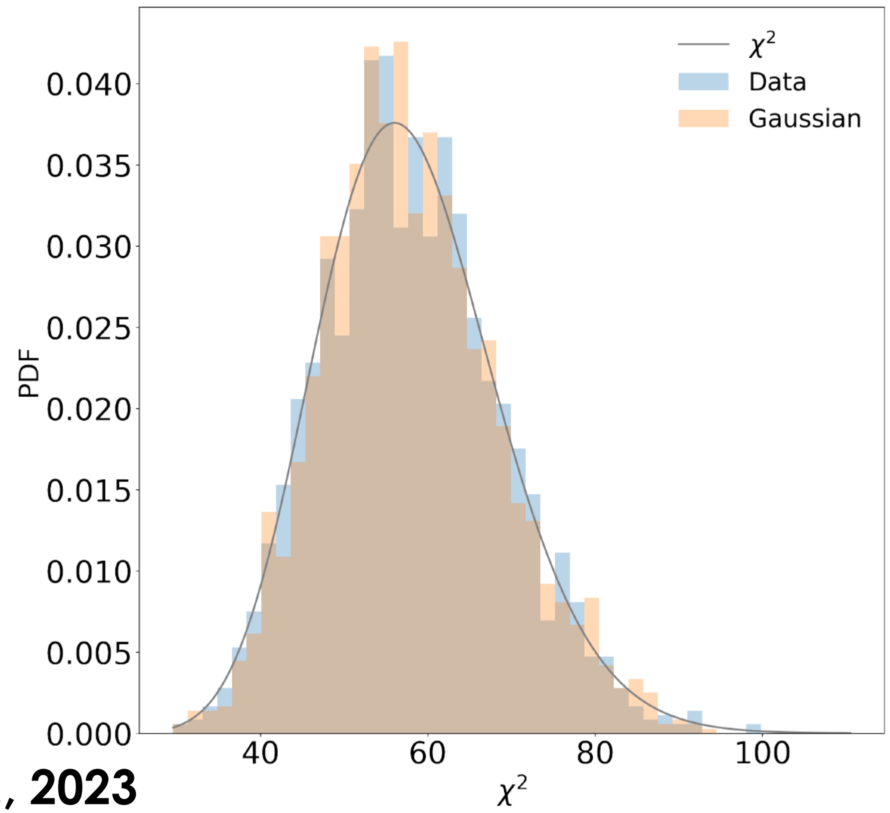
- We perform likelihood analysis, sampling from Gaussian likelihood

$$\log \mathcal{L}(\theta|\mathbf{d}) \propto -\frac{1}{2}\left[\mathbf{X_d} - \mathbf{X}_t(\theta)\right]^{\mathrm{T}} C^{-1} \left[\mathbf{X_d} - \mathbf{X}_t(\theta)\right]$$

WST



Correlation function



Valogiannis et al., 2023

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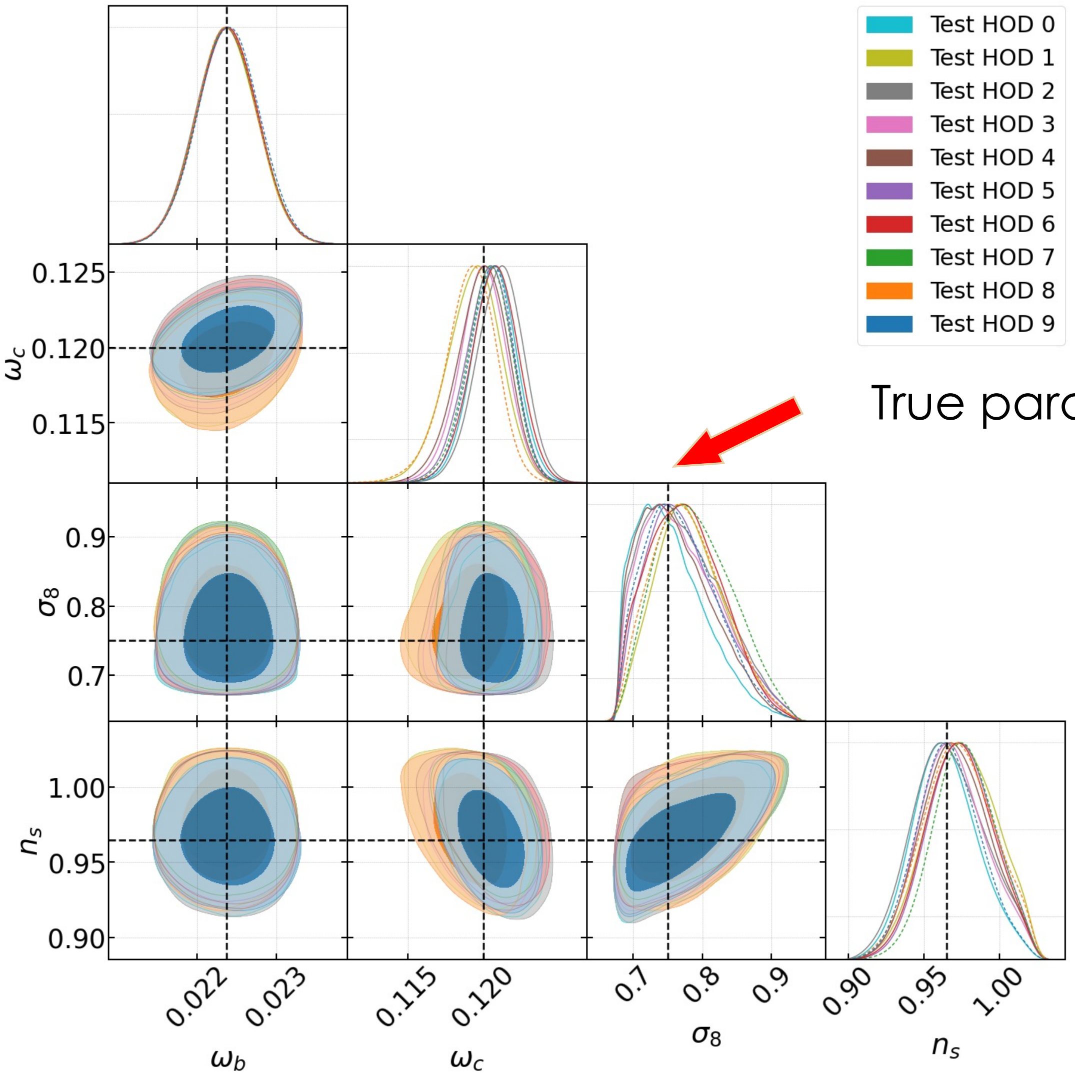
Hold-out tests on Abacus mocks



- Tests against out-sample test set of mocks
- *Successful* parameter recovery in all 40 hold-out tests!!
- Confirms tight 1-σ errors using full likelihood/MCMC!
- Marginalized over 7 HOD nuisance parameters
- In agreement with conclusions of (**Valogiannis** & Dvorkin, 2022b) !

True parameter values

Example of successful parameter recovery from a test mock with low σ_8

Valogiannis et al., 2023

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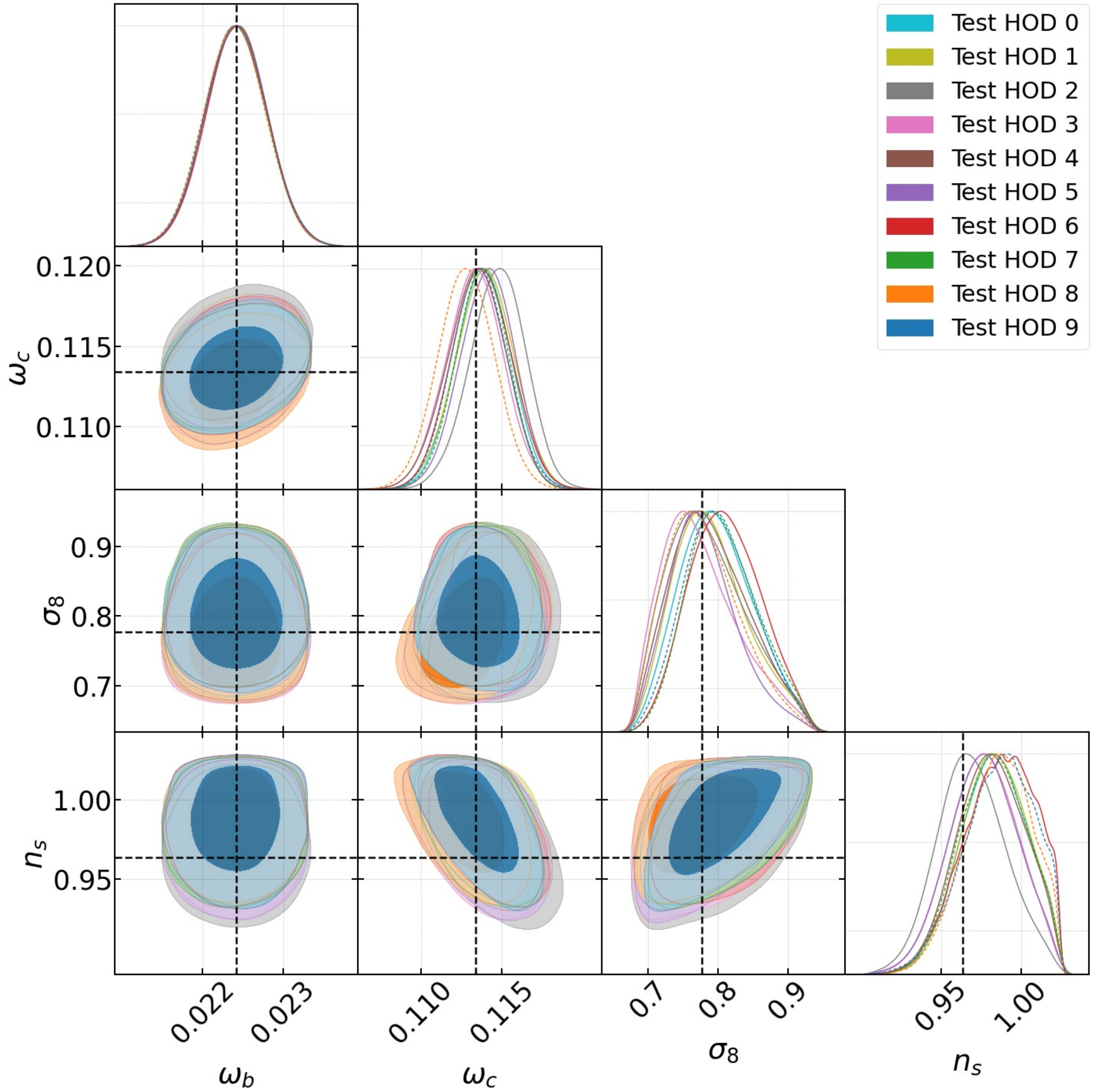
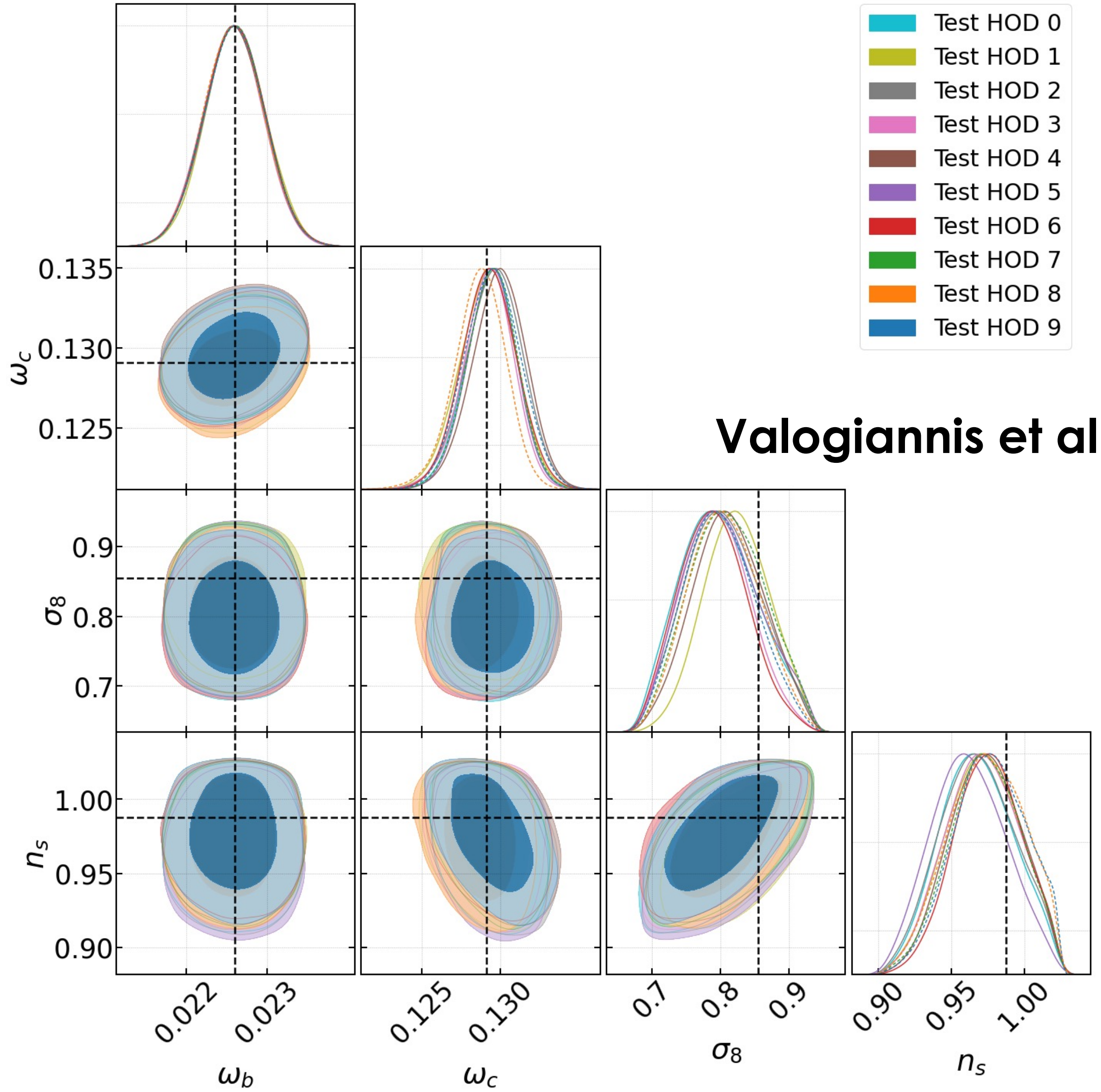
Hold-out tests on Abacus mocks





Valogiannis et al., 2023

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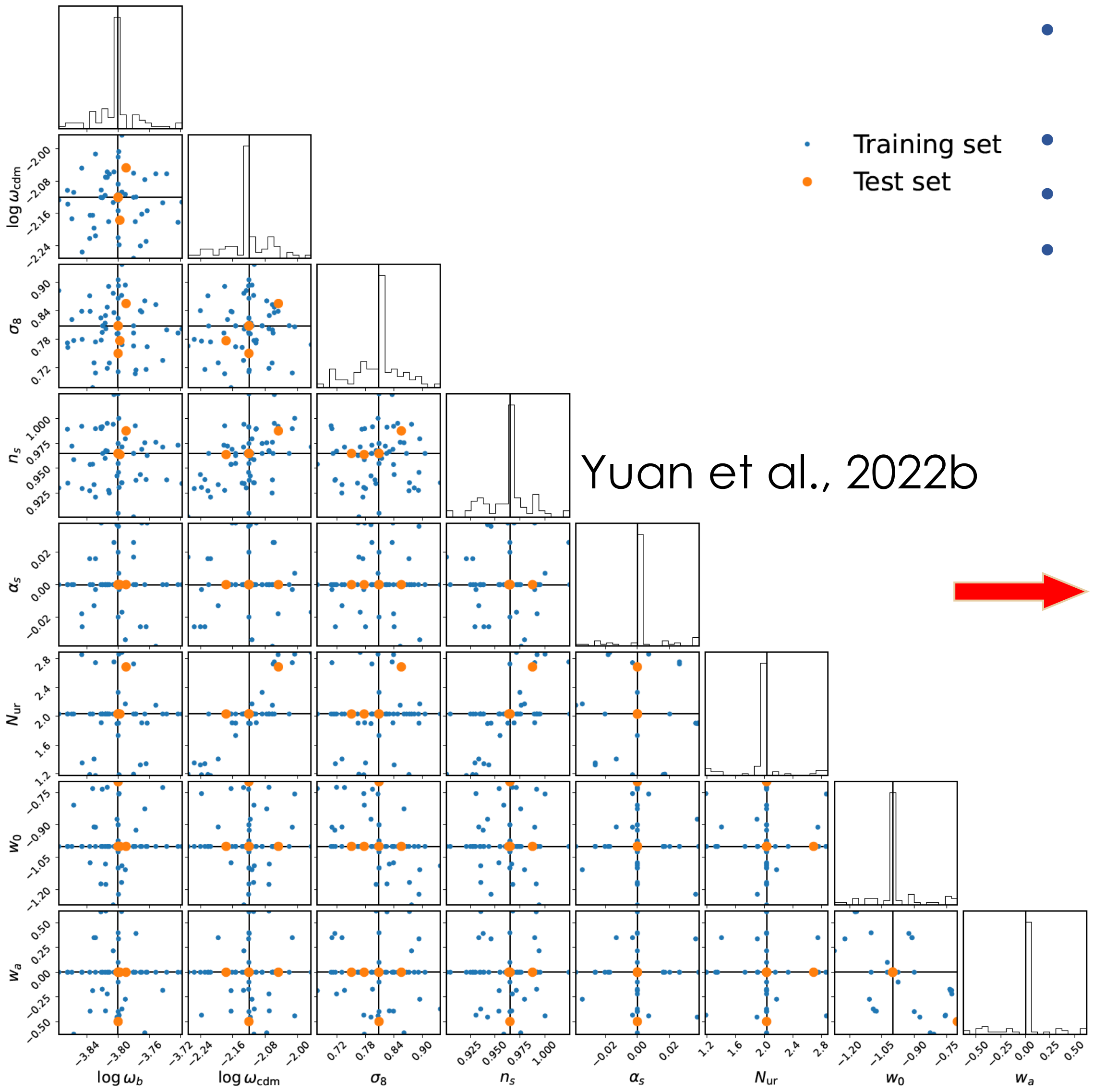
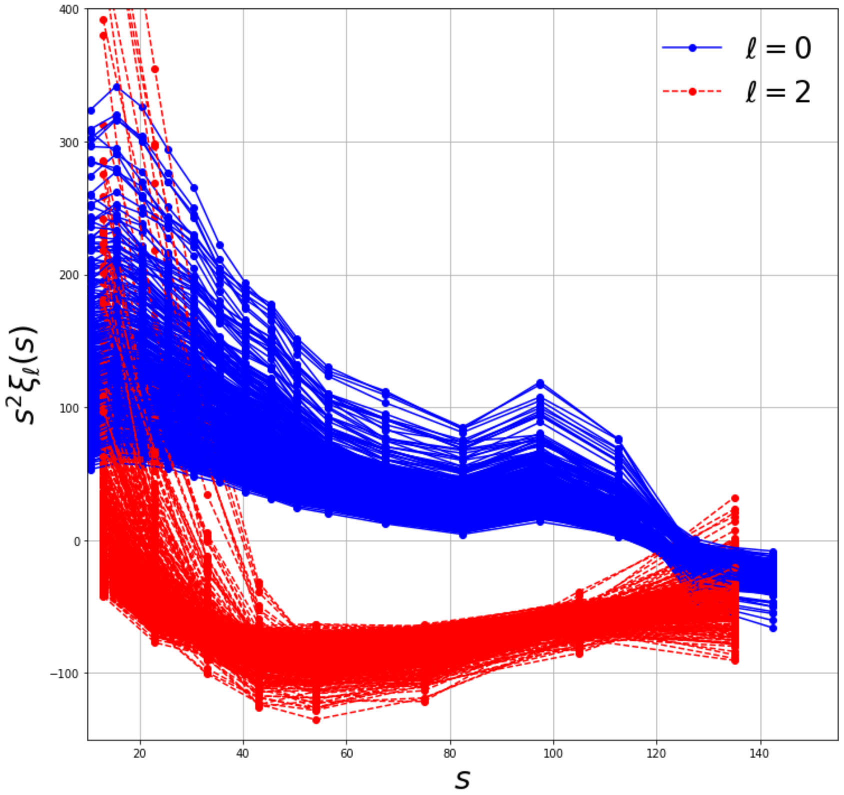
Correlation function emulator

- Construct equivalent emulator for multipoles of galaxy 2-point correlation function (l=0,2)
- Adaptive spatial binning down to r_{min} = 8 Mpc/h
- Trained from 151,474 Abacus Summit galaxy mocks!
- 8 cosmo + 7 HOD = 15d space, neural net-based



Yuan et al., 2022b



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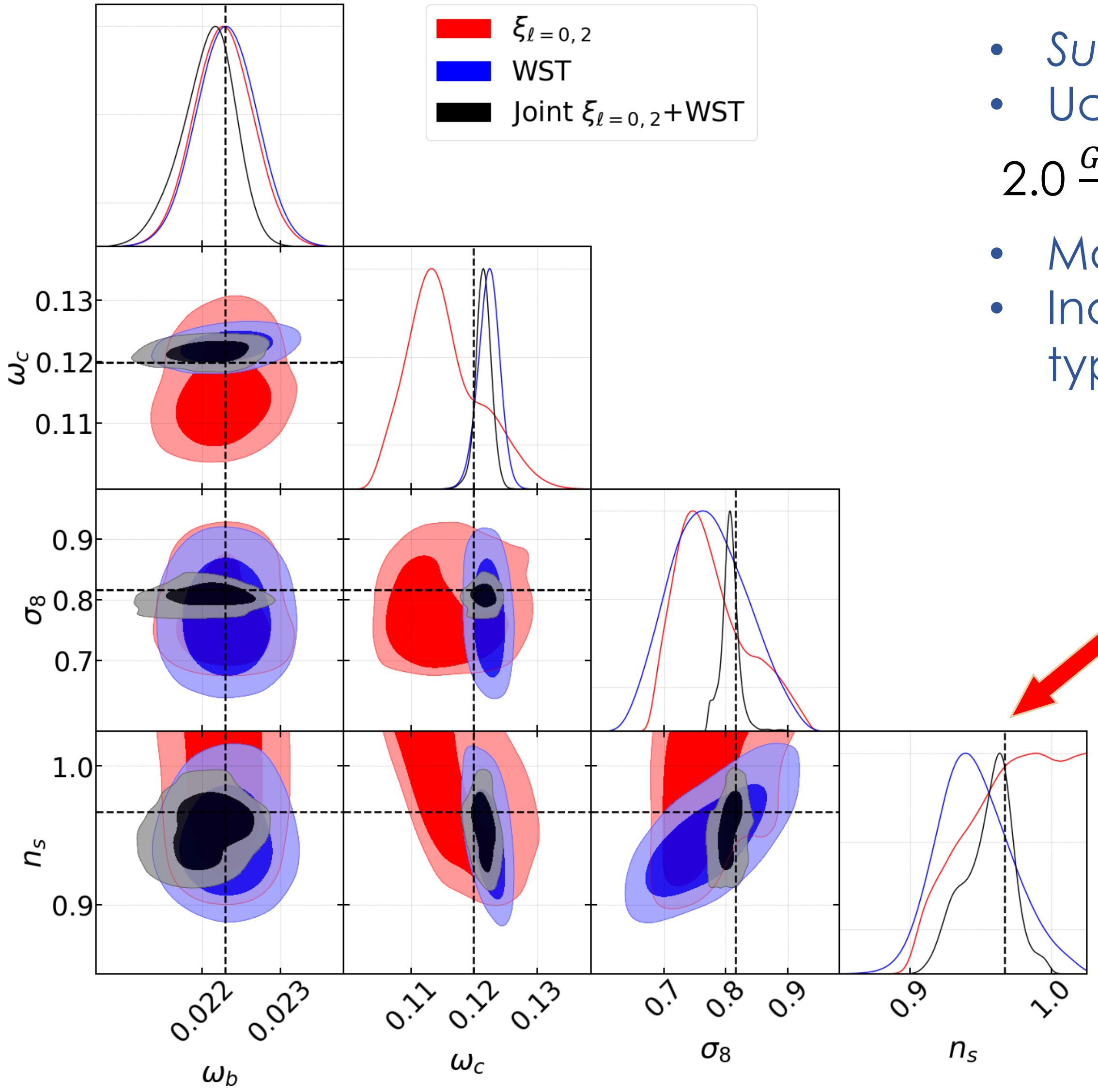
Hold-out tests on external Uchuu mock



- *Successful* parameter recovery in non-HOD mock!!
- Uchuu UniverseMachine mock (T._Ishiyama et al., 2021), $2.0\,\frac{Gpc}{h}$ side box with number density $n_g = 2.9x10^{-4}\,\frac{h^3}{Mpc^3}$.
- More realistic treatment than HOD
- Indicates robustness against different galaxy mock type/model, and also phase!

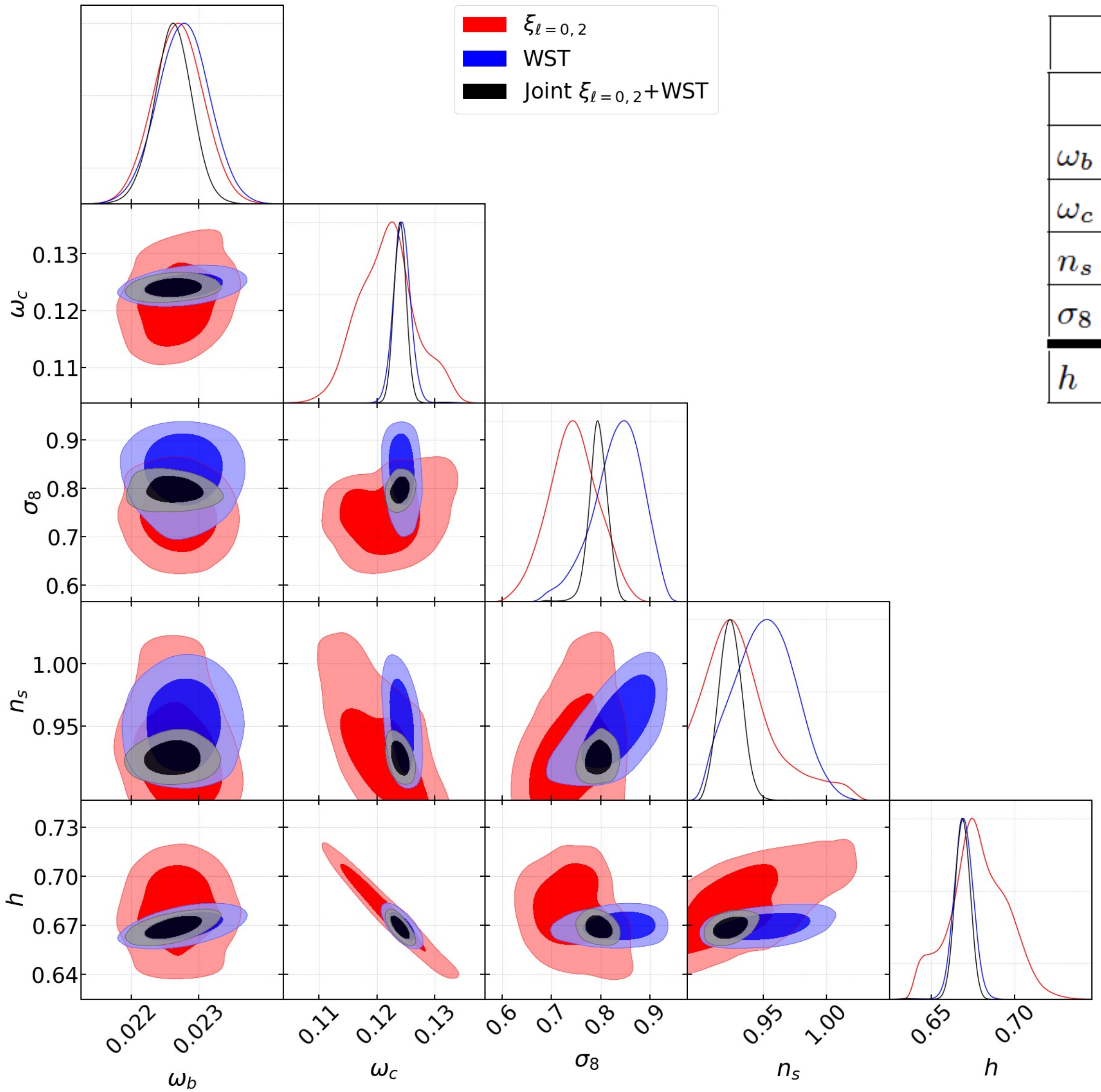
True parameter values

Evidence of successful parameter recovery from Uchuu-SHAM test mock using *abundance matching*

Valogiannis et al., 2023

AI in Science
A program of SCHMIDT **FUTURES**

WST Constraints from BOSS CMASS data!

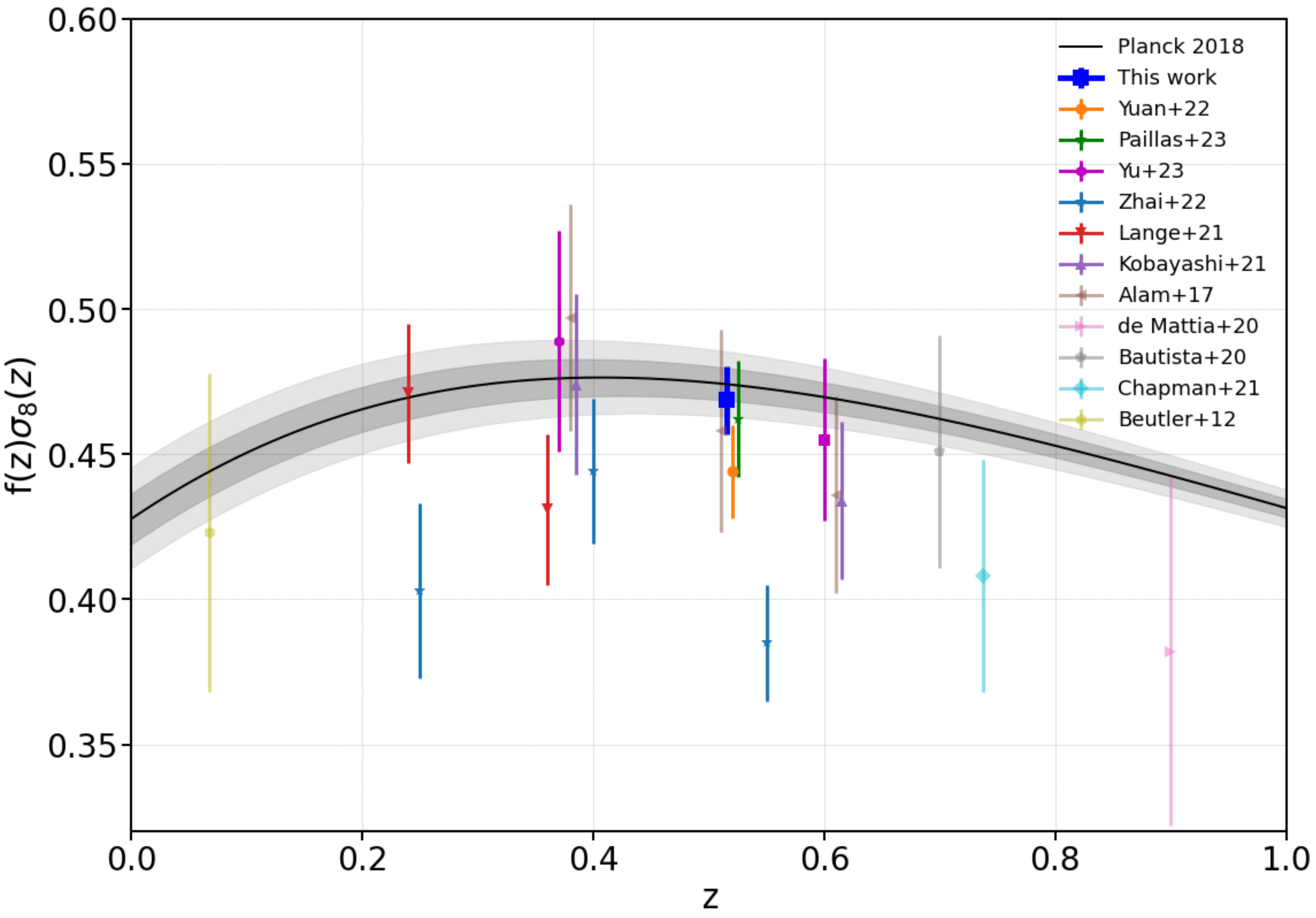


	2-point c.f.		WST		Joint 2-point c.f.+WST	
	Best-fit	Mean$\pm\sigma$	Best-fit	Mean$\pm\sigma$	Best-fit	Mean$\pm\sigma$
ω_b	0.02261	$0.02270^{+0.00037}_{-0.00037}$	0.02274	$0.02277^{+0.00038}_{-0.00038}$	0.0225	$0.02262^{+0.00029}_{-0.00029}$
ω_c	0.1201	$0.1222^{+0.0040}_{-0.0063}$	0.1239	$0.1244^{+0.0015}_{-0.0015}$	0.1238	$0.1241^{+0.0011}_{-0.0011}$
n_s	0.925	$0.922^{+0.037}_{-0.037}$	0.961	$0.951^{+0.023}_{-0.023}$	0.927	$0.924^{+0.01}_{-0.01}$
σ_8	0.742	$0.746^{+0.051}_{-0.051}$	0.860	$0.834^{+0.058}_{-0.039}$	0.793	$0.795^{+0.019}_{-0.019}$
h	0.677	$0.677^{+0.022}_{-0.015}$	0.67	$0.669^{+0.0059}_{-0.0059}$	0.668	$0.669^{+0.0049}_{-0.0049}$

- WST 1σ errors on ω_c& n_s 4.2x & 1.6x *tighter* than ξ(r)
- Joint WST+ξ(r) analysis *improves* 1σ errors by **2.5-6x** compared to ξ(r)-only!
- Joint WST+ξ(r) analysis *improves* 1σ errors by 1.4-2.5x compared to WST-only
- Competitive 0.9%, 2.3% & 1% determination of ω_c, σ_8 & n_s
- 0.7% determination of H_0, as a *derived* parameter from fixed θ_*

Valogiannis et al., 2023

Competitive Constraints on Structure Growth!



- $\mathbf{f\sigma_8(z_{eff} = 0.515)}$**= 0.469** $\pm$ **0.012**
- 2.5% level of determination in agreement with *Planck 2018*
- In 1σ agreement with density-split analysis (Paillas et al., 2023)

- $\boldsymbol{S_8}$ = **0.833** $\pm$ **0.023**, in almost perfect agreement with Planck 2018
  $S_8 = 0.832 \pm 0.013$

Valogiannis et al., 2023

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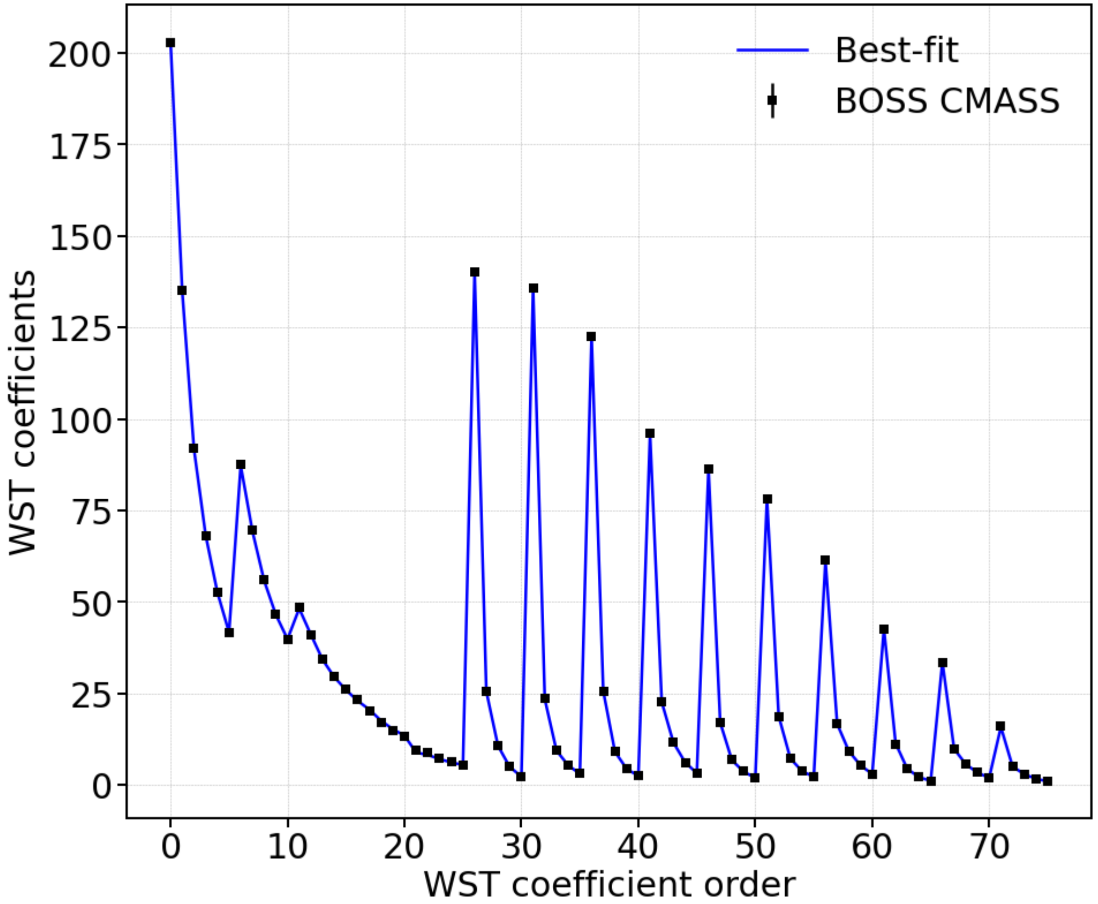
WST Constraints from BOSS CMASS data!



	2-point c.f.		WST		Joint 2-point c.f.+WST	
	Best-fit	Mean$\pm\sigma$	Best-fit	Mean$\pm\sigma$	Best-fit	Mean$\pm\sigma$
ω_b	0.02261	$0.02270^{+0.00037}_{-0.00037}$	0.02274	$0.02277^{+0.00038}_{-0.00038}$	0.0225	$0.02262^{+0.00029}_{-0.00029}$
ω_c	0.1201	$0.1222^{+0.0040}_{-0.0063}$	0.1239	$0.1244^{+0.0015}_{-0.0015}$	0.1238	$0.1241^{+0.0011}_{-0.0011}$
n_s	0.925	$0.922^{+0.037}_{-0.037}$	0.961	$0.951^{+0.023}_{-0.023}$	0.927	$0.924^{+0.01}_{-0.01}$
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Valogiannis et al., 2023

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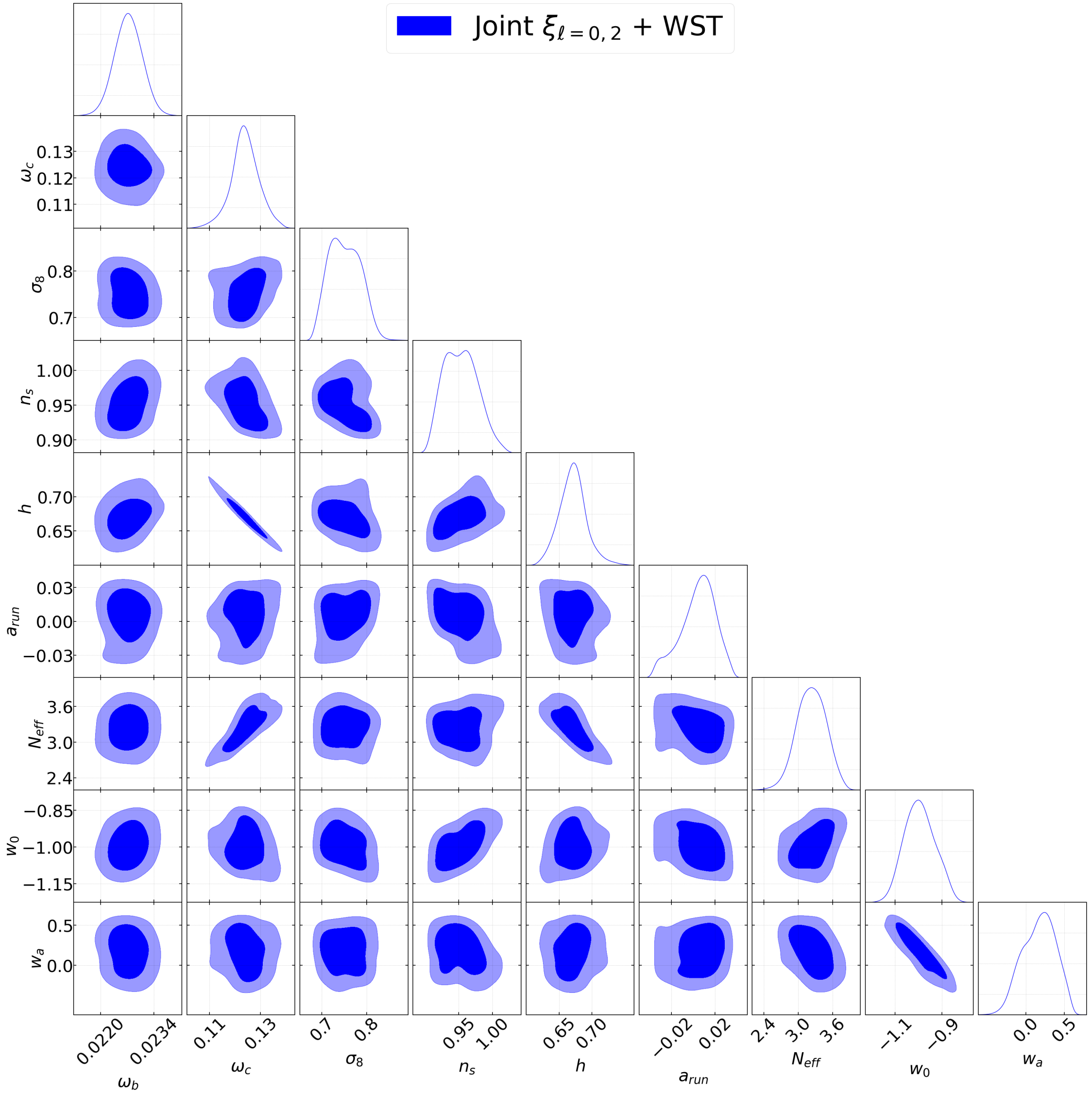
Constraints on ΛCDM extensions



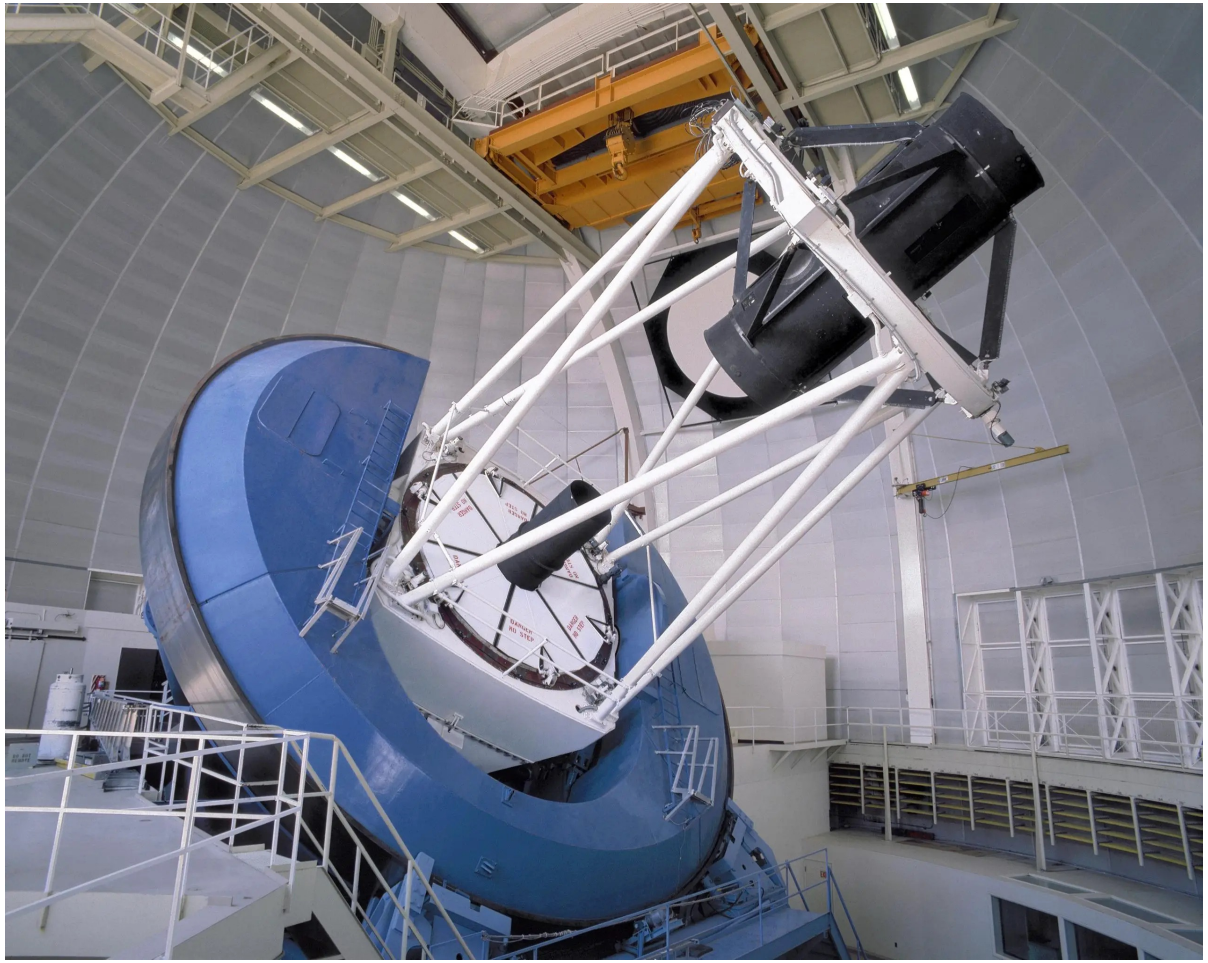
- Joint WST+ξ(r) analysis allows simultaneous constraints on 4 extensions to ΛCDM
- 1σ consistency with ΛCDM limits

$$w_0 = -1, w_a = 0, a_{\rm run} = 0, N_{\rm eff} = 3.046$$

	Joint 2-point c.f.+WST	
	Best-fit	Mean±σ
ω_b	0.02280	$0.02273^{+0.00036}_{-0.00036}$
ω_c	0.1227	$0.1239^{+0.0056}_{-0.0056}$
σ_8	0.748	$0.751^{+0.034}_{-0.040}$
n_s	0.928	$0.953^{+0.022}_{-0.030}$
h	0.675	$0.671^{+0.021}_{-0.021}$
$a_{\rm run}$	0.002	$0.004^{+0.019}_{-0.012}$
$N_{\rm eff}$	3.048	$3.23^{+0.26}_{-0.26}$
w_0	−1.039	$-0.995^{+0.061}_{-0.073}$
w_a	0.29	$0.17^{+0.24}_{-0.21}$

Valogiannis et al., 2023

WST Constraints from DESI Y1 data!



Dark Energy Spectroscopic Instrument (DESI)

Alternative Summary Statistics in DESI

- **Wavelet scattering transform**
- Void-galaxy cross-correlation function
- DT spheres/voids
- Void size function
- kNN statistics
- Lensing Cumulants
- Minkowski functionals
- Density-split clustering
- Linear point distance scale
- Void lensing

Etc

Two-point correlation functions of DESI tracers from DESI Y1 blinded catalogs (without reconstruction). The circle indicates the location of the BAO features. (Credits to by Ashley Ross & DESI collaboration)

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Conclusions

- Wavelet Scattering Transform: a novel statistic that efficiently extracts non-Gaussian information from physical fields. *Ideal* middle ground between CNN and traditional estimators
- *First* WST application to actual spectroscopic data **(Valogiannis et al., 2023, arXiv: 2310.16116 , Valogiannis & Dvorkin , arXiv: 2204.13717, Phys. Rev. D 105, 103534, 2022)**
  - Worked with BOSS CMASS galaxy sample at 0.46<z<0.57
  - **Substantial** improvement in the 1σ errors over traditional galaxy ξ(r) multipoles
- Ongoing & future improvements (in progress)
  - Can more accurately capture lightcone evolution, fiber collision/systematic effects in galaxy mocks (Eg. see Yuan et al. 2022c)
  - Design wavelets tailored for cosmological/RSD applications (public package under construction!)
  - Blind mock challenges
- Future applications
  - Application to DESI – Project #255 (& Euclid)
  - Constrain neutrino mass (Eg. as in **Valogiannis & Dvorkin, arXiv: 2108.07821, Phys. Rev. D 105, 103534, 2022**)
  - Constrain fundamental physics (theories of gravity, primordial non-Gaussianity, parity violation)
  - Weak lensing & cross-correlations (DES, future applications to Rubin LSST & Euclid, DESI-II)
  - Recent applications also to Lyman-a, 21cm cosmology, axion string-induced effects

Thank you!

WST emulator

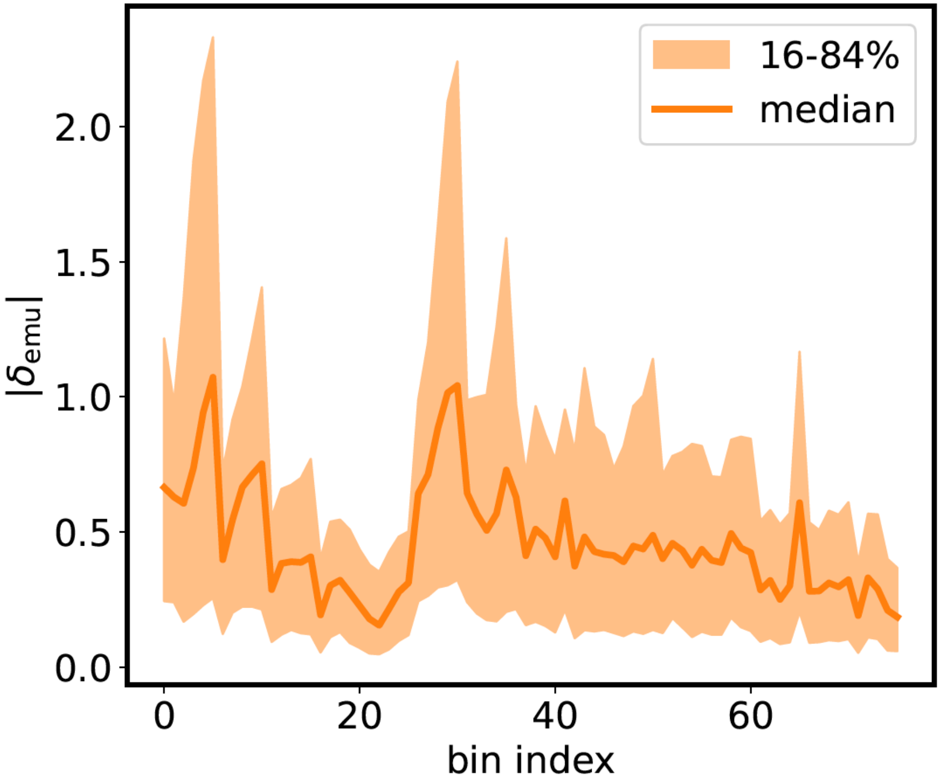
- Quantify emulator error using test Abacus mocks
  - Test c001-c004 cosmologies
  - 1000 hod configurations for each, 4x1000=4000 test mocks
- Obtain total WST covariance

$$C = C_{\rm data} + C_{\rm emulator} + C_{\rm mock,sample}$$

Data covariance obtained from 2048 Patchy mocks

Covariance contribution from emulator error

Phase correction



Valogiannis et al., 2023

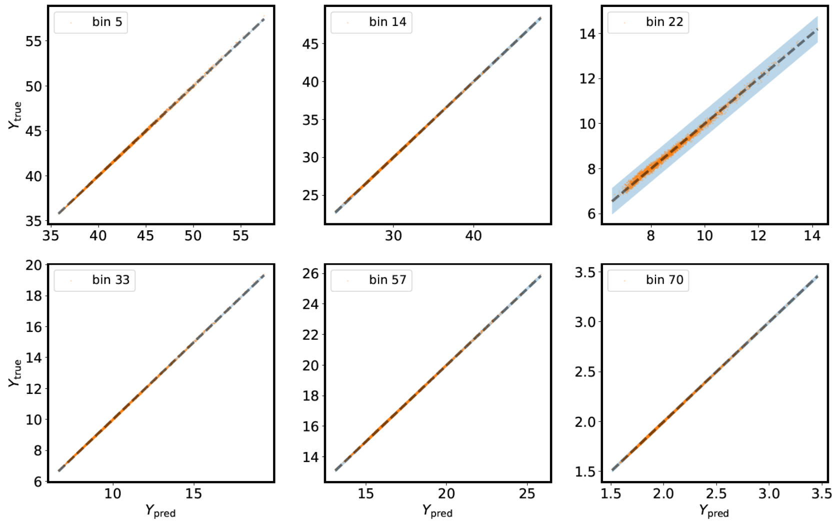


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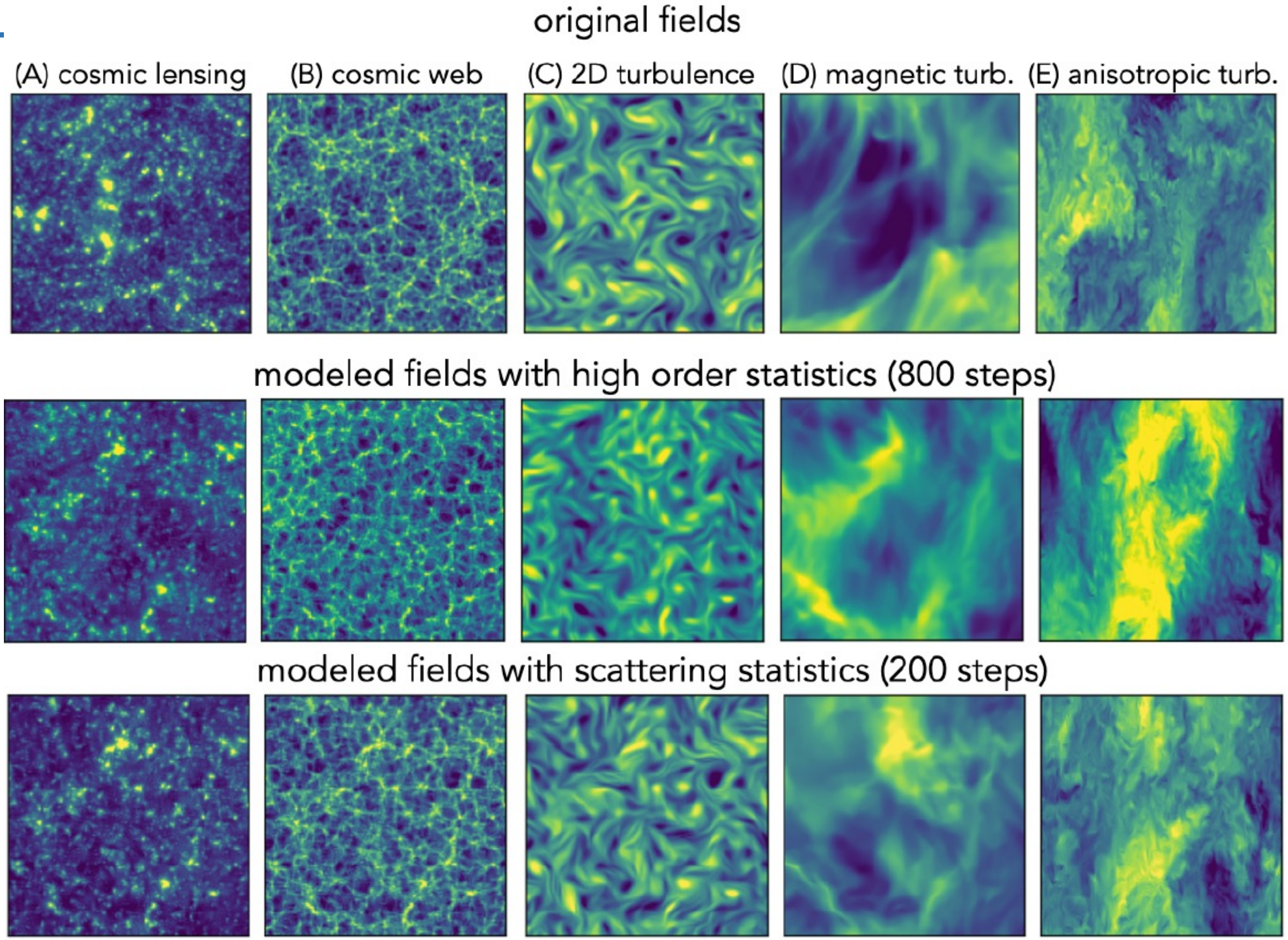
Image Synthesis/Generation

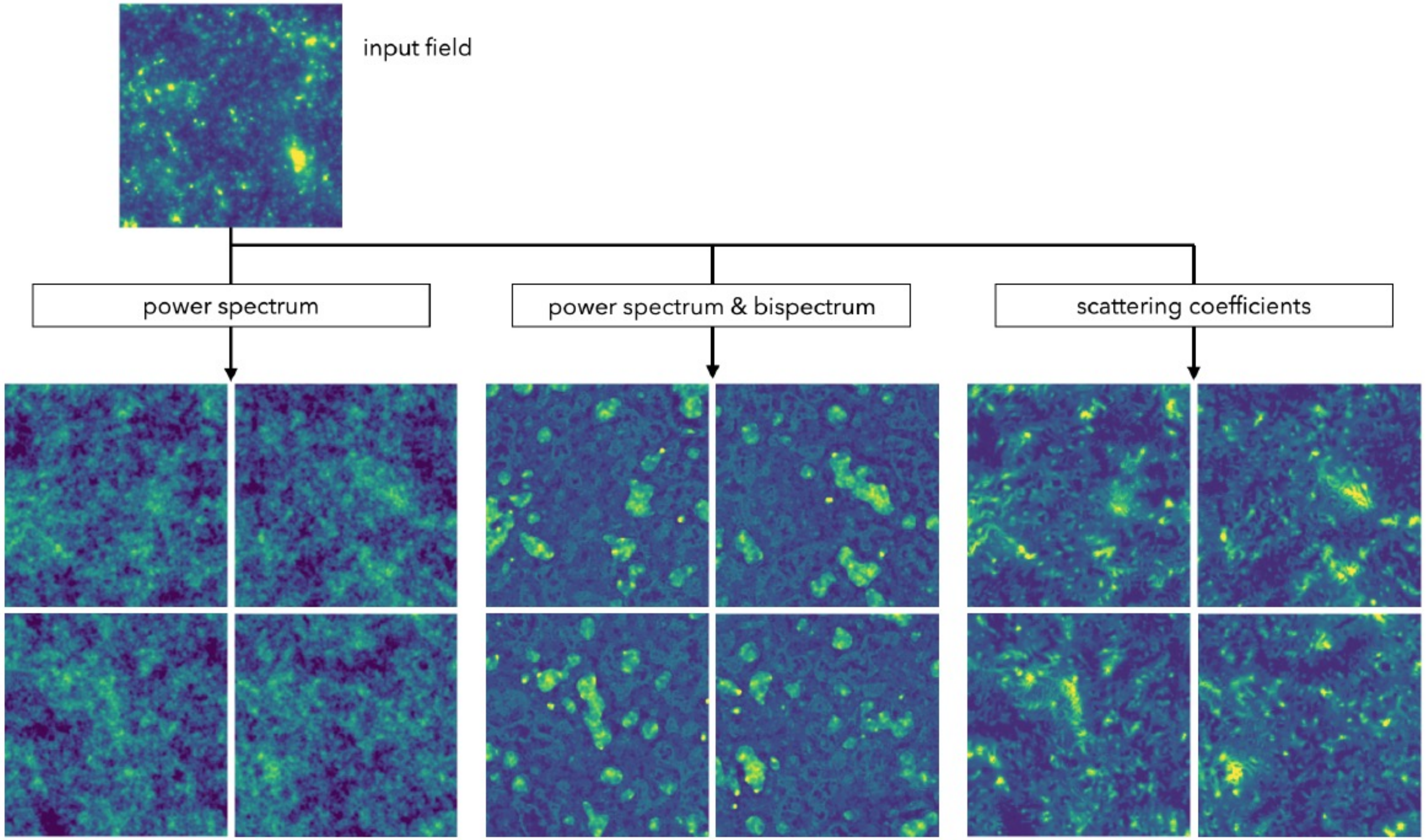


Cheng et al. (2023)

Image Synthesis/Generation

- WST coefficients can also be used to generate fields with similar properties/texture

Weak Lensing map



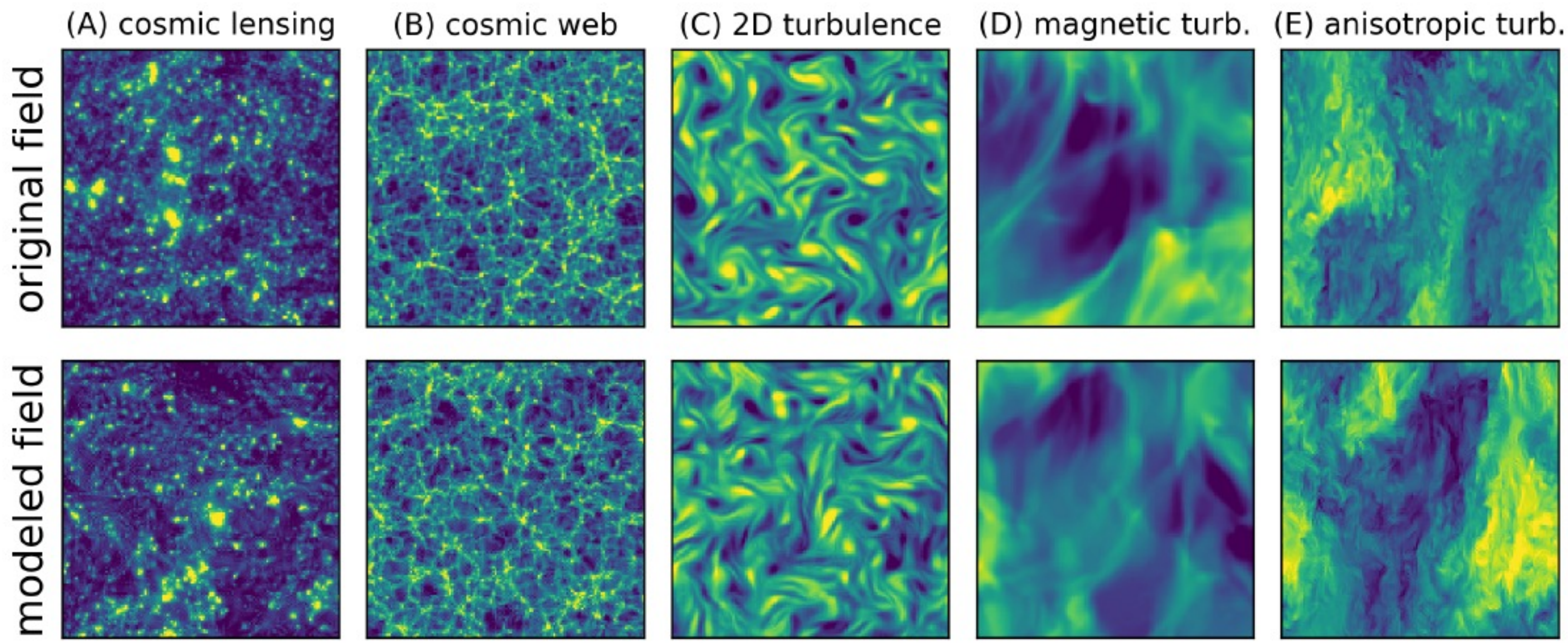
Cheng & Benard (2021a)

Image Synthesis/Generation

- Application to various physical fields

Input

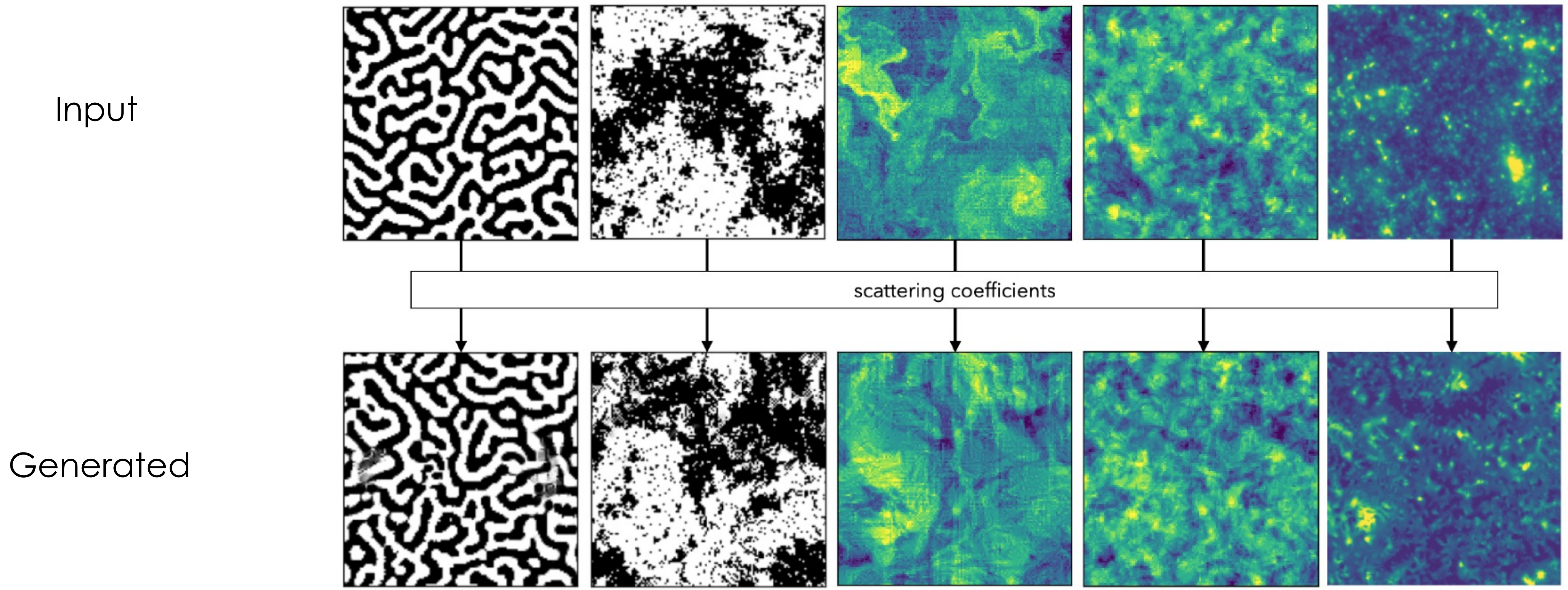
Generated



Cheng et al. (2023)

Image Synthesis/Generation

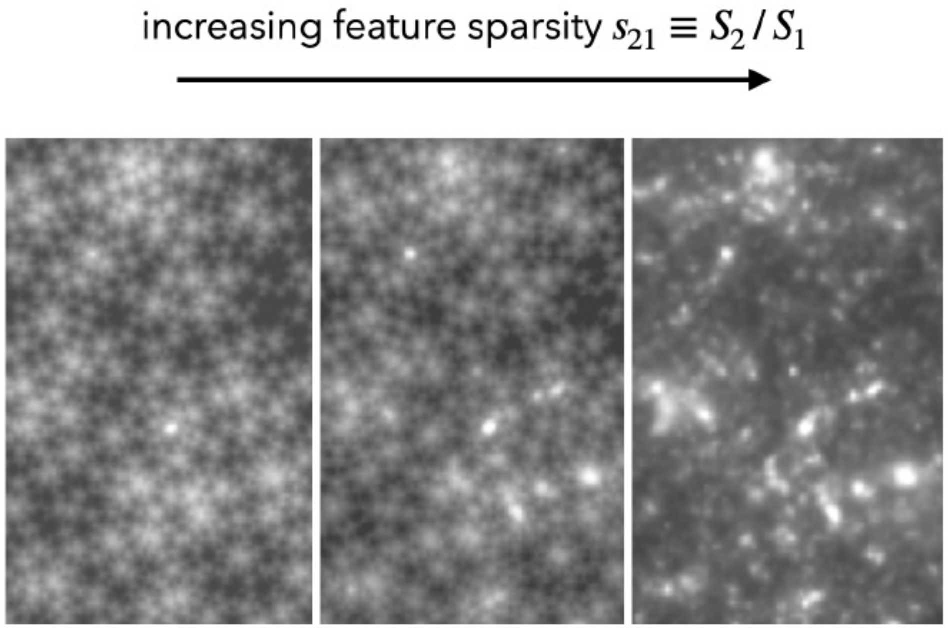
- Application to various physical fields

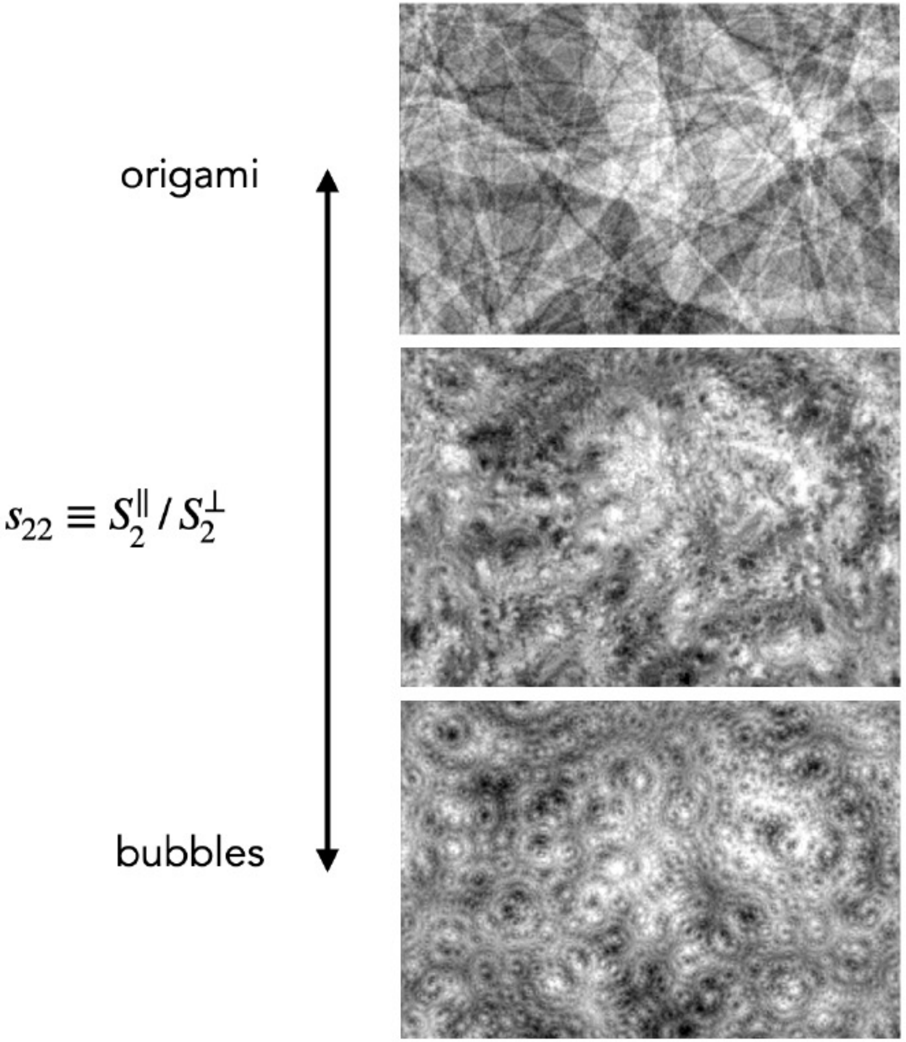


Cheng & Benard (2021b)

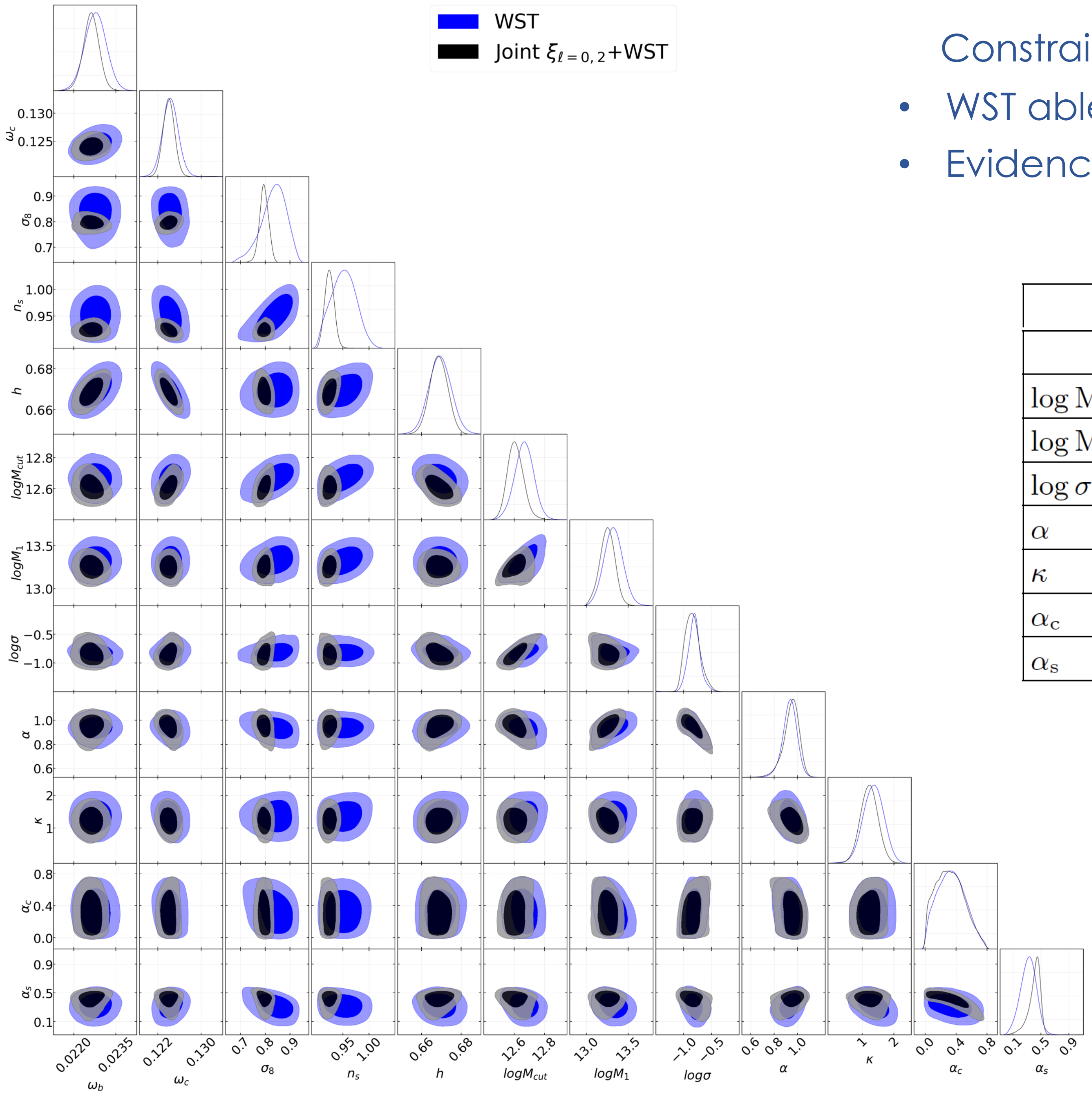
Image Synthesis/Generation

- Application to various physical fields





Cheng & Benard (2021b)



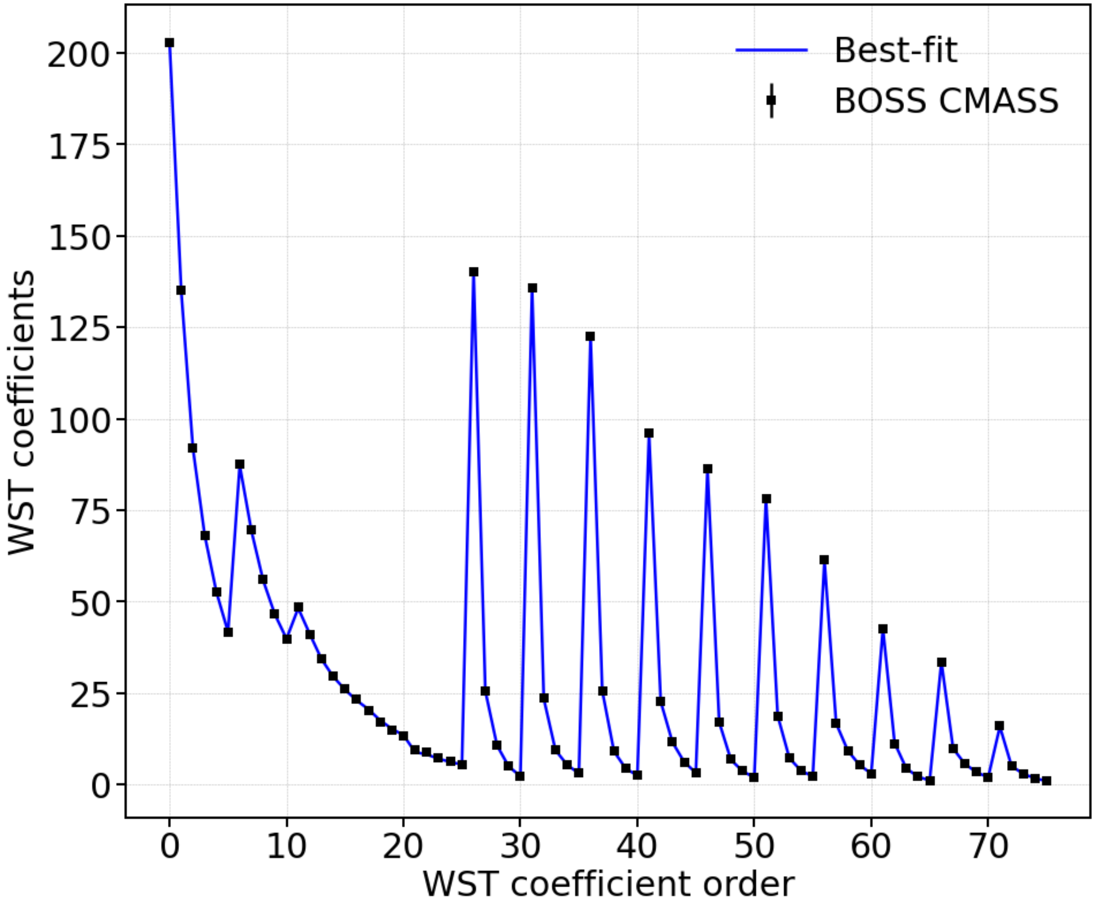
Constraints on full set of parameters, including HOD

- WST able to constrain HOD parameters
- Evidence of non-zero velocity bias

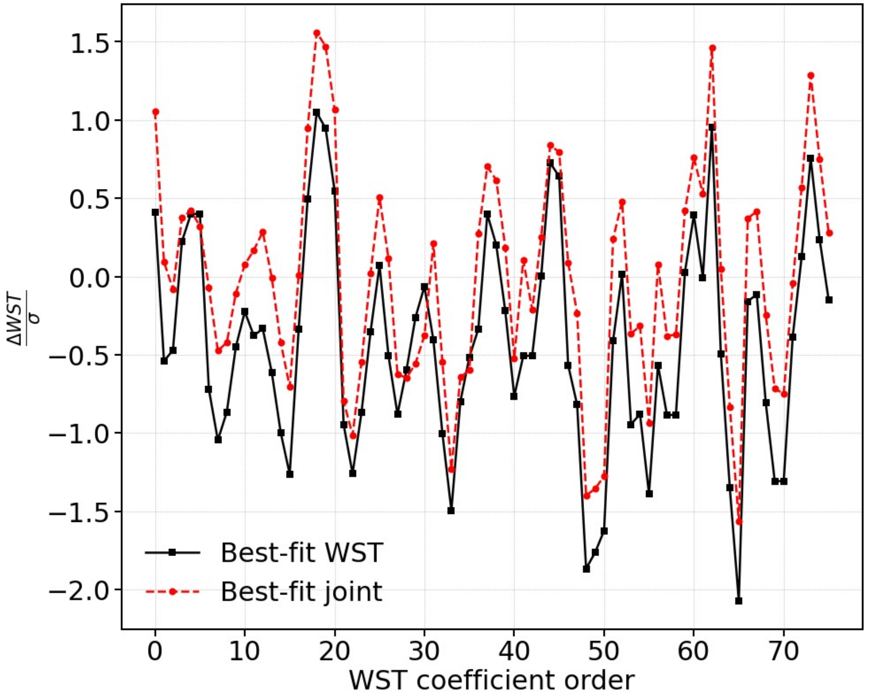
	WST		Joint 2-point c.f.+WST	
	Best-fit	Mean$\pm\sigma$	Best-fit	Mean$\pm\sigma$
$\log \mathrm{M_{cut}}$	12.681	$12.668^{+0.068}_{-0.068}$	12.608	$12.613^{+0.045}_{-0.060}$
$\log \mathrm{M_1}$	13.34	$13.33^{+0.13}_{-0.13}$	13.252	$13.25^{+0.11}_{-0.11}$
$\log \sigma$	-0.783	$-0.823^{+0.11}_{-0.097}$	-0.829	$-0.87^{+0.25}_{-0.25}$
α	0.921	$0.934^{+0.064}_{-0.054}$	0.943	$0.944^{+0.077}_{-0.049}$
κ	1.336	$1.36^{+0.32}_{-0.32}$	1.236	$1.22^{+0.28}_{-0.28}$
α_c	0.322	$0.34^{+0.17}_{-0.20}$	0.367	$0.32^{+0.16}_{-0.22}$
α_s	0.306	$0.32^{+0.12}_{-0.11}$	0.411	$0.408^{+0.099}_{-0.049}$

Valogiannis et al., 2023

WST Constraints from BOSS CMASS data!



	2-point c.f.		WST		Joint 2-point c.f.+WST	
	Best-fit	Mean±σ	Best-fit	Mean±σ	Best-fit	Mean±σ
ω_b	0.02261	$0.02270^{+0.00037}_{-0.00037}$	0.02274	$0.02277^{+0.00038}_{-0.00038}$	0.0225	$0.02262^{+0.00029}_{-0.00029}$
ω_c	0.1201	$0.1222^{+0.0040}_{-0.0063}$	0.1239	$0.1244^{+0.0015}_{-0.0015}$	0.1238	$0.1241^{+0.0011}_{-0.0011}$
n_s	0.925	$0.922^{+0.037}_{-0.037}$	0.961	$0.951^{+0.023}_{-0.023}$	0.927	$0.924^{+0.01}_{-0.01}$
σ_8	0.742	$0.746^{+0.051}_{-0.051}$	0.860	$0.834^{+0.058}_{-0.039}$	0.793	$0.795^{+0.019}_{-0.019}$
h	0.677	$0.677^{+0.022}_{-0.015}$	0.67	$0.669^{+0.0059}_{-0.0059}$	0.668	$0.669^{+0.0049}_{-0.0049}$



Valogiannis et al., 2023

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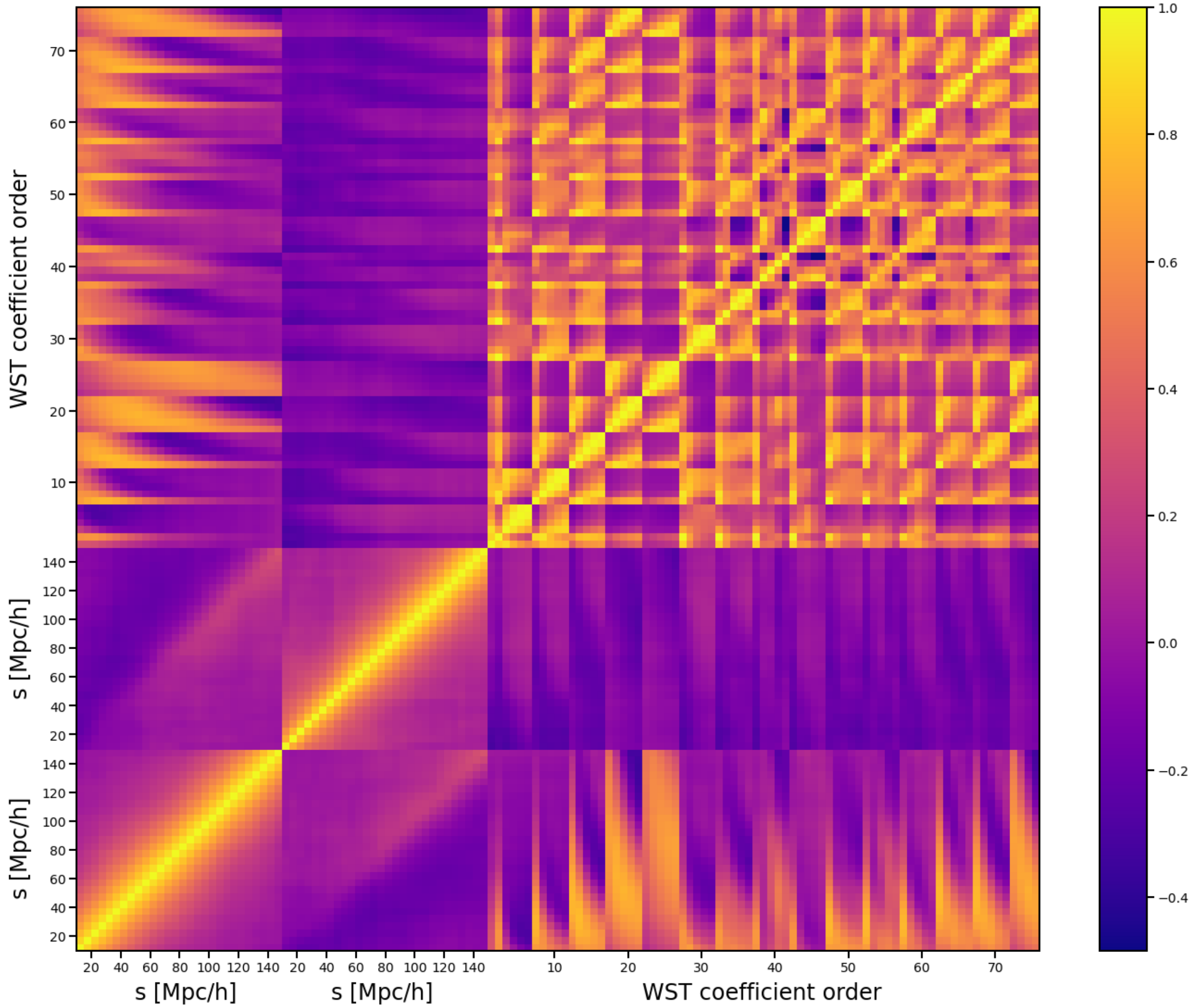
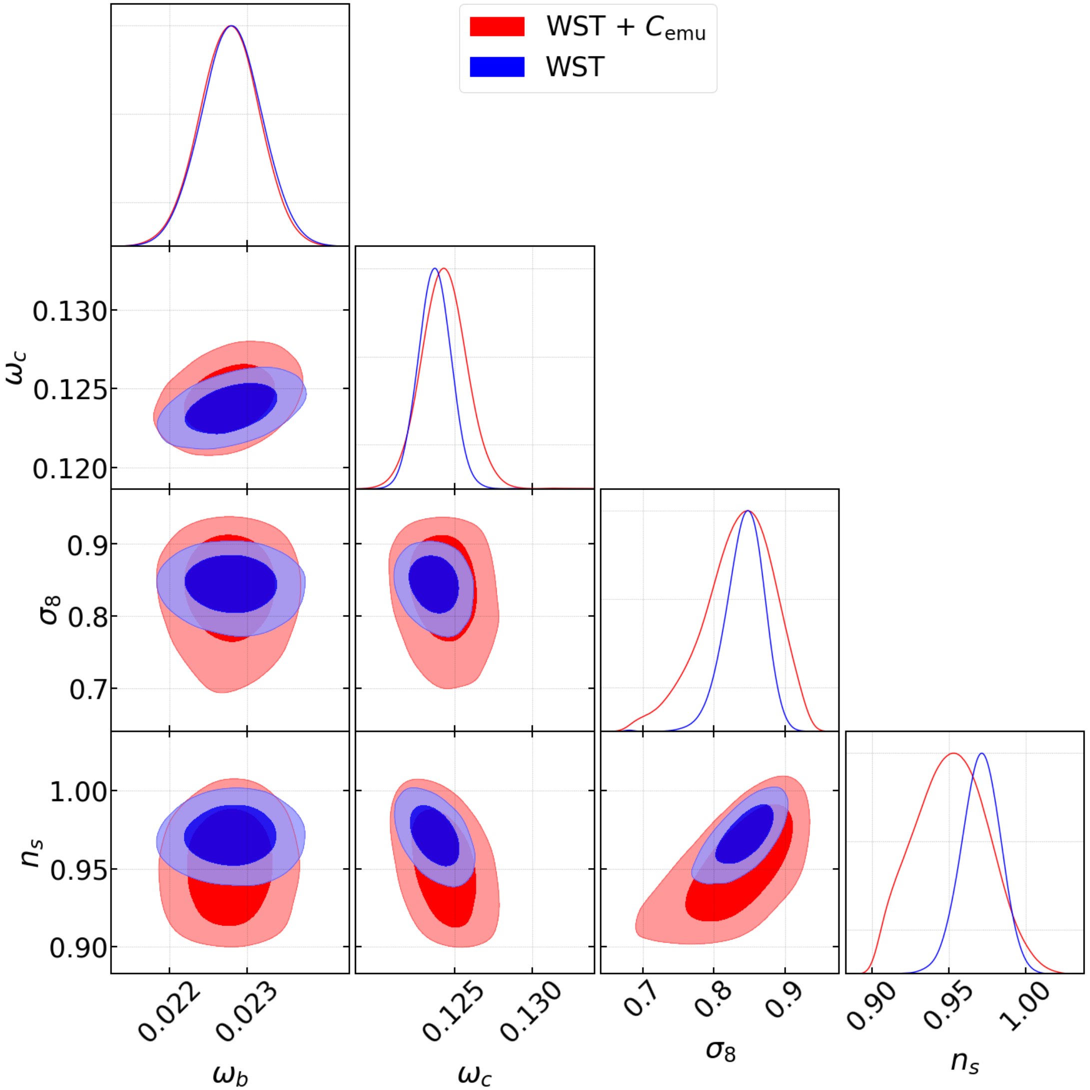
Likelihood analysis

- Covariance matrix obtained from N=2048 *PATCHY* mocks (S. A. Rodriguez-Torres et al., 2016)



Valogiannis et al., 2023

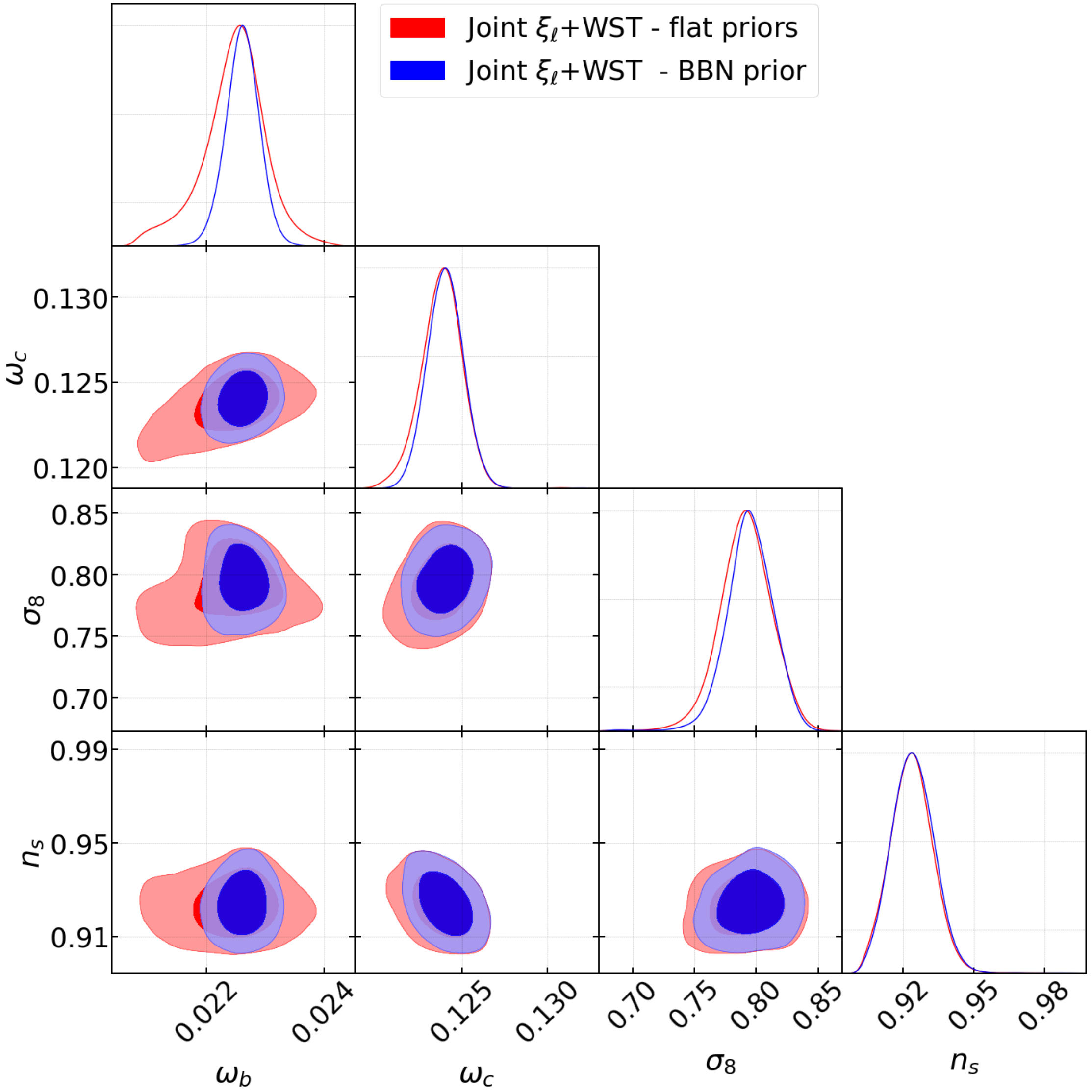
Impact of emulator error



- Addition of emulator error increases 1σ errors disproportionally for WST (vs ξ(r))
- In some cases (e.g. σ_8) this effect almost completely masks the gains compared to ξ(r)

Valogiannis et al., 2023

Impact of ω_b prior

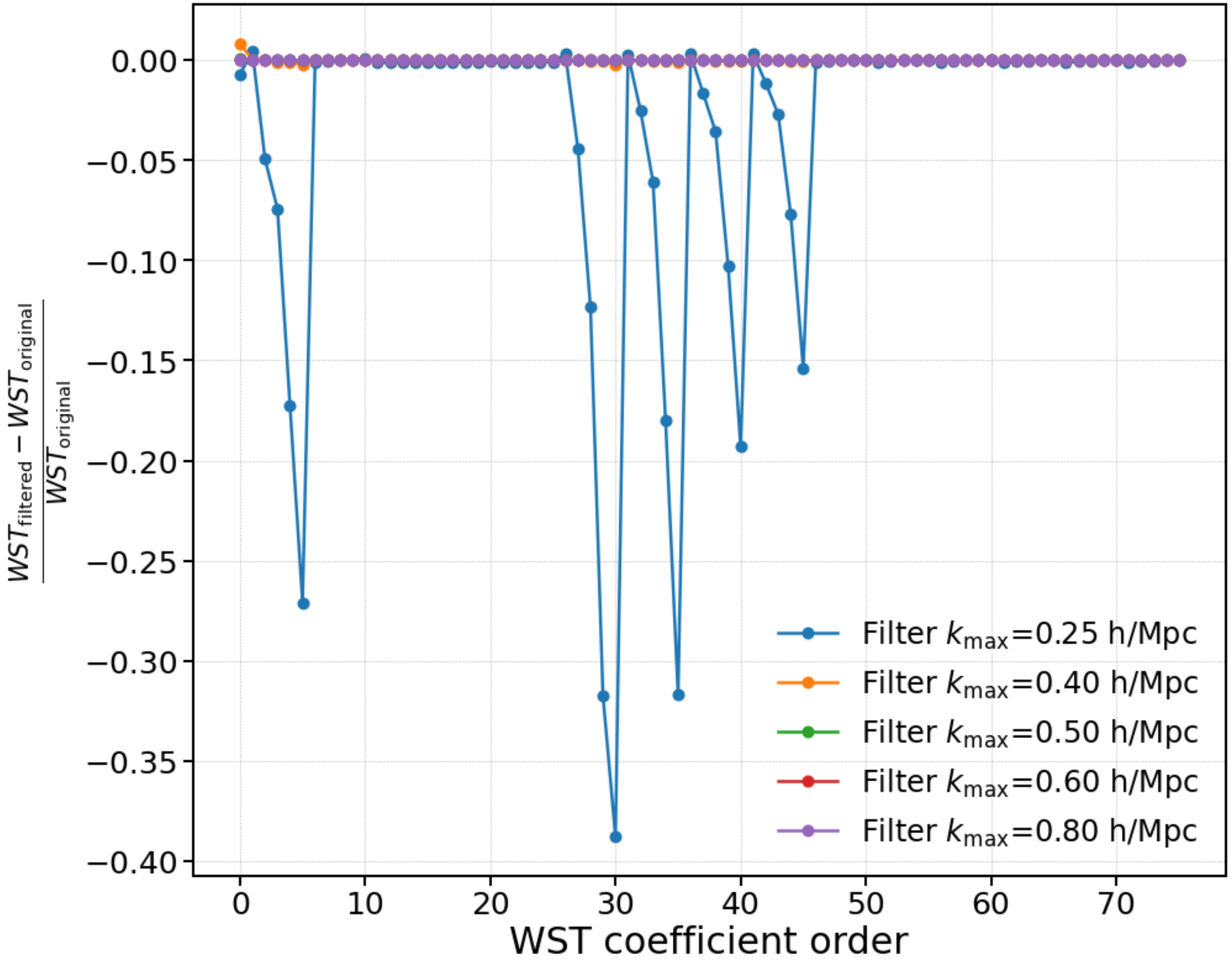


- Joint analysis results robust against choice of ω_b prior !

Valogiannis et al., 2023

AI in Science
A program of SCHMIDT **FUTURES**

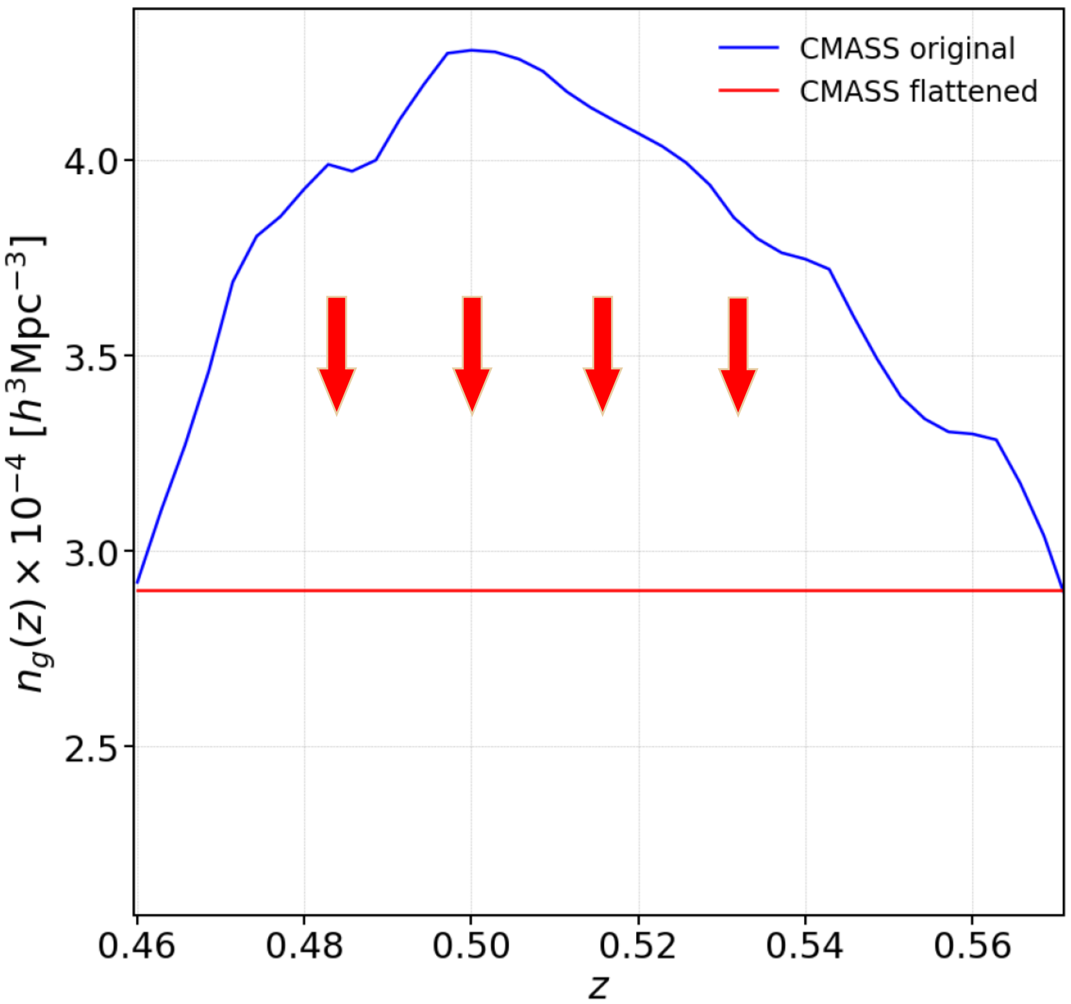
Sensitivity to small scales



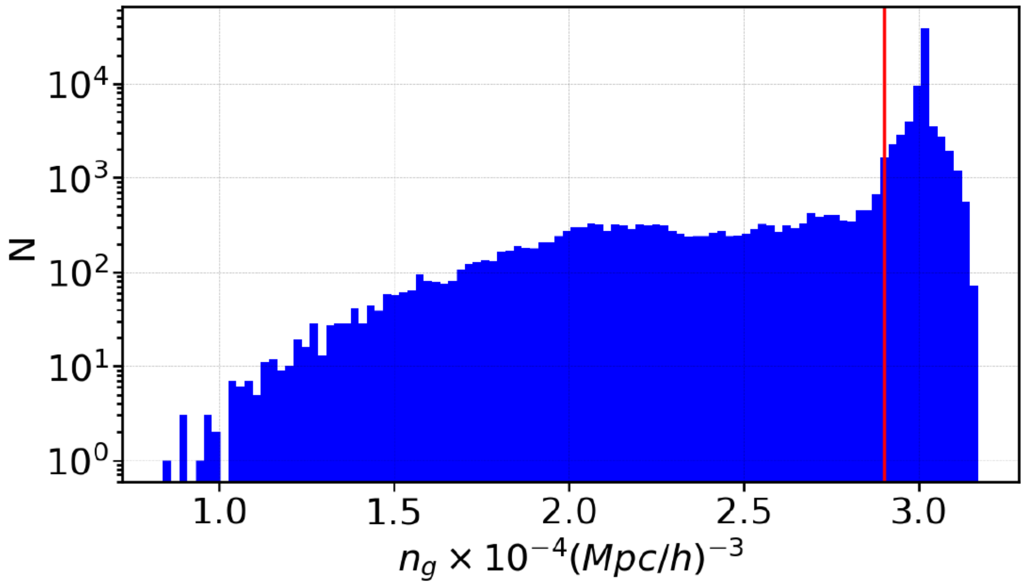
- Sharp top hat-k filter confirms that we are not sensitive to modes k>0.8 h/Mpc

Valogiannis et al., 2023

Effect of n(z) on wst estimator



- BOSS CMASS sample has varied n(z)
- Clustering approximated using Abacus mock of constant $n(z) = 2.9\mathrm{x}10^{-4}\,\frac{h^3}{\mathrm{Mpc}^3}$.
- Good enough approximation for 2-point function Yuan et al., 2022b)
- Not sure for WST, density-dependent/field-level statistic
- Downsample to match constant $n(z) = 2.9\mathrm{x}10^{-4}\,\frac{h^3}{\mathrm{Mpc}^3}$

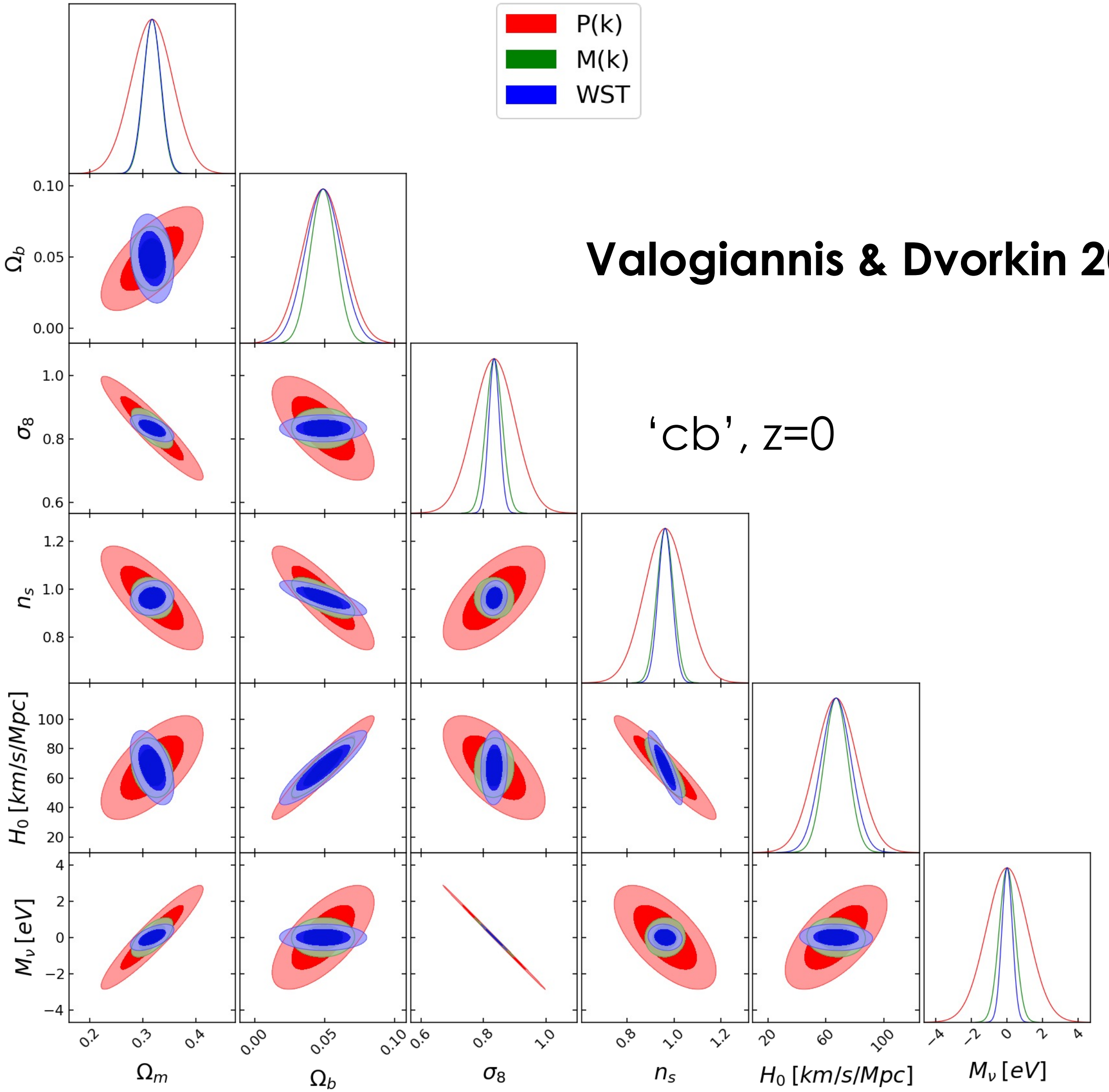


Valogiannis et al., 2023

Great improvement over P(k)!

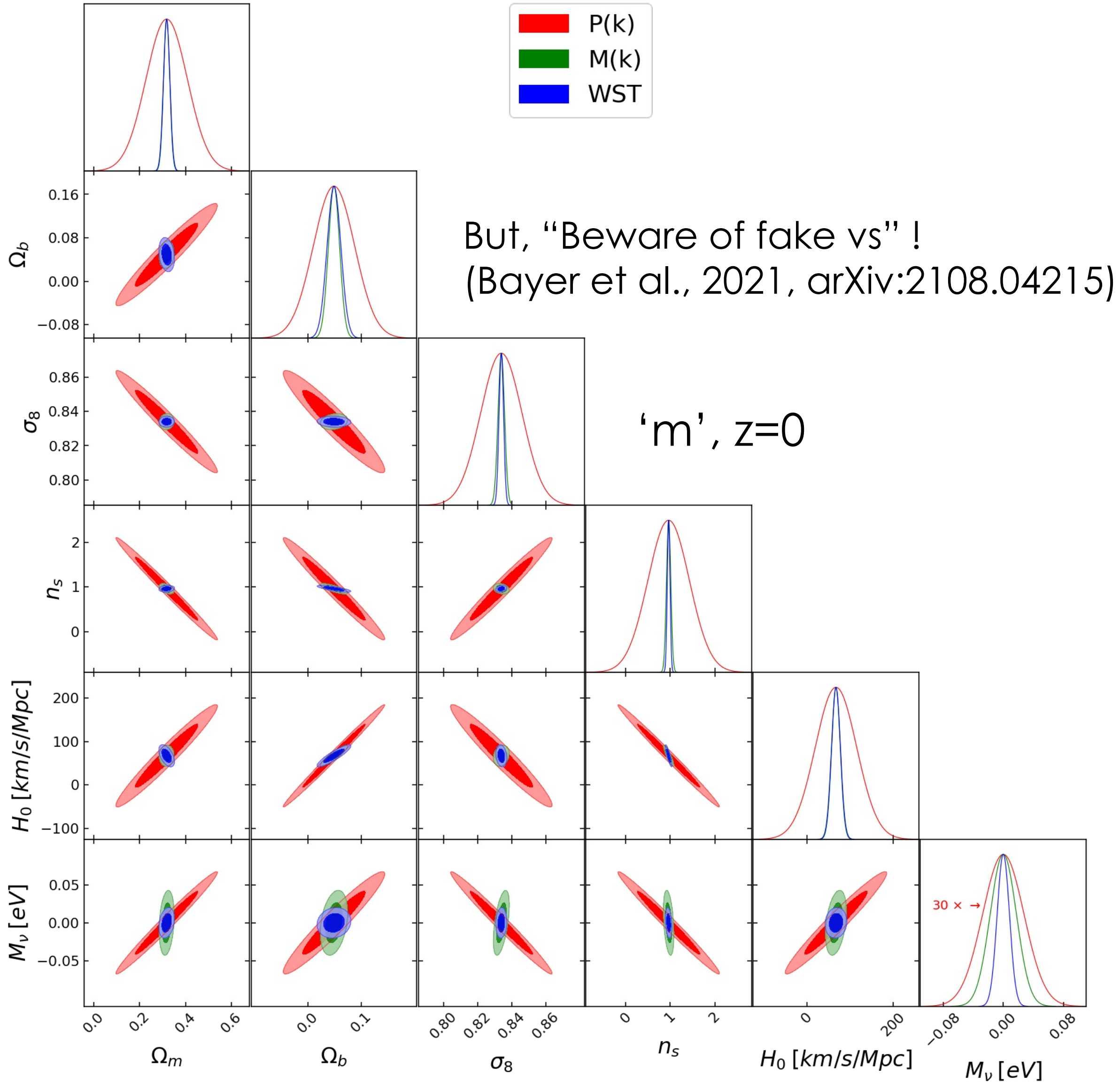
Valogiannis & Dvorkin 2022a

‘cb’, z=0



But, “Beware of fake νs” !
(Bayer et al., 2021, arXiv:2108.04215)

‘m’, z=0



Likelihood analysis

- Theory model

$$\log \mathcal{L}(\theta|\mathbf{d}) \propto -\frac{1}{2}\left[\mathbf{X_d} - \mathbf{X}_t(\theta)\right]^{\mathrm{T}} C^{-1}\left[\mathbf{X_d} - \mathbf{X}_t(\theta)\right]$$

- To model WST (and P(k)) cosmological dependence, we use the *approximation:*

$$\mathbf{X}_t(\theta) = \mathbf{X}_t(\theta_{\mathrm{fid}}) + (\theta - \theta_{\mathrm{fid}})\nabla_\theta \mathbf{X}$$

Prediction for fiducial cosmology

Constructed from 'Linear derivative grid' of cosmologies

ω_b	ω_c	n_s	σ_8
0.02237	0.1200	0.9649	0.8114
0.02282	0.1200	0.9649	0.8114
0.02193	0.1200	0.9649	0.8114
0.02237	0.1240	0.9649	0.8114
0.02237	0.1161	0.9649	0.8114
0.02237	0.1200	1.0249	0.8114
0.02237	0.1200	0.9049	0.8114
0.02237	0.1200	0.9649	0.8698
0.02237	0.1200	0.9649	0.7532

- + Additional derivative steps in the 7 HOD parameters

Valogiannis & Dvorkin 2022b

Physical explanation of results

Why does the WST work so well??

WST key physical properties

- Successive WST layers pick up information >2-point function ✅
  - Known to encode additional information (eg. Hahn et al. 2020 & 2021)

+

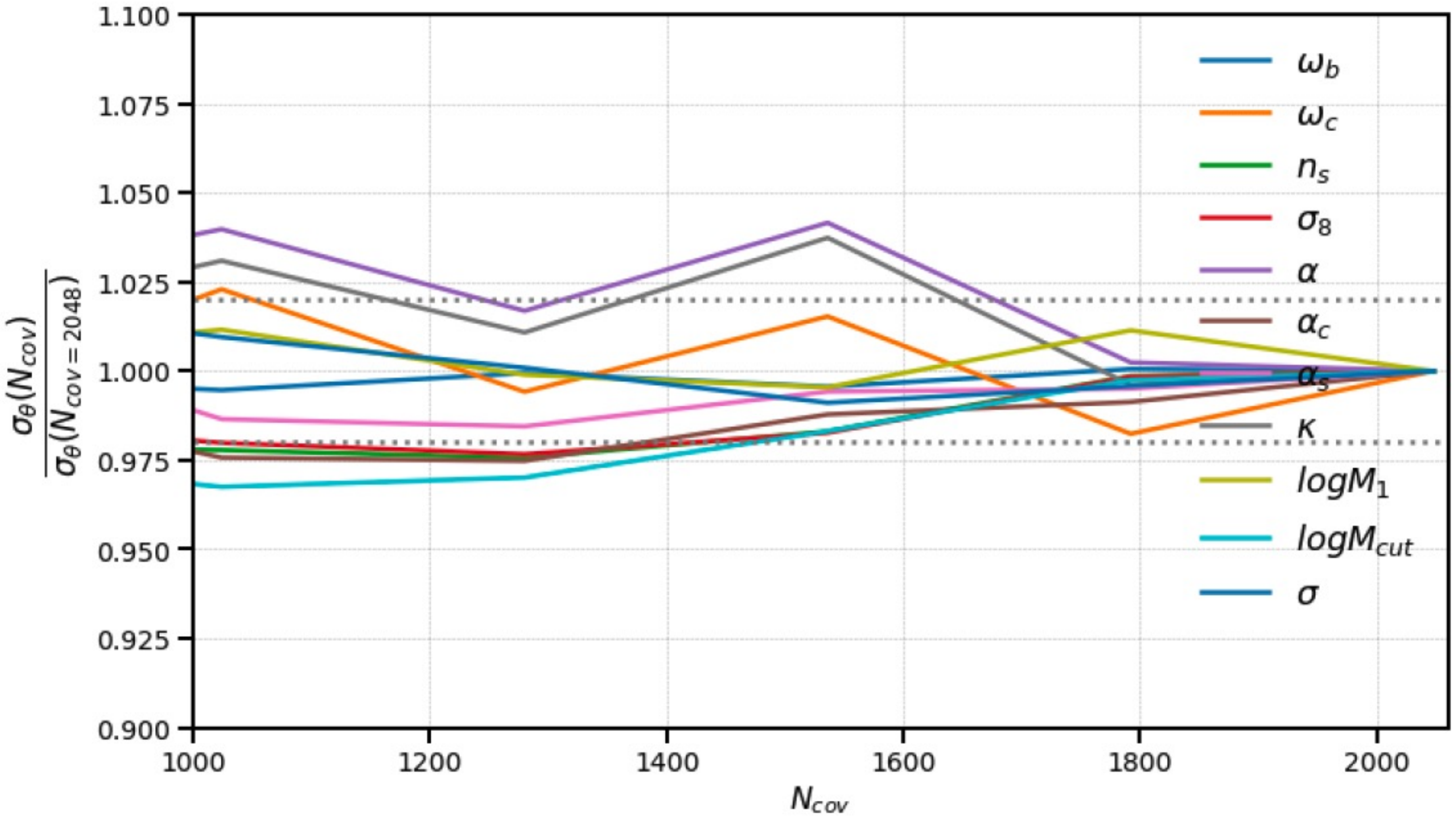
- Choice of q<1 highlights cosmic voids (under-densities) ✅
  - Sensitive cosmological probe (eg. Massara et al, 2020)

↓

Enhanced cosmological information

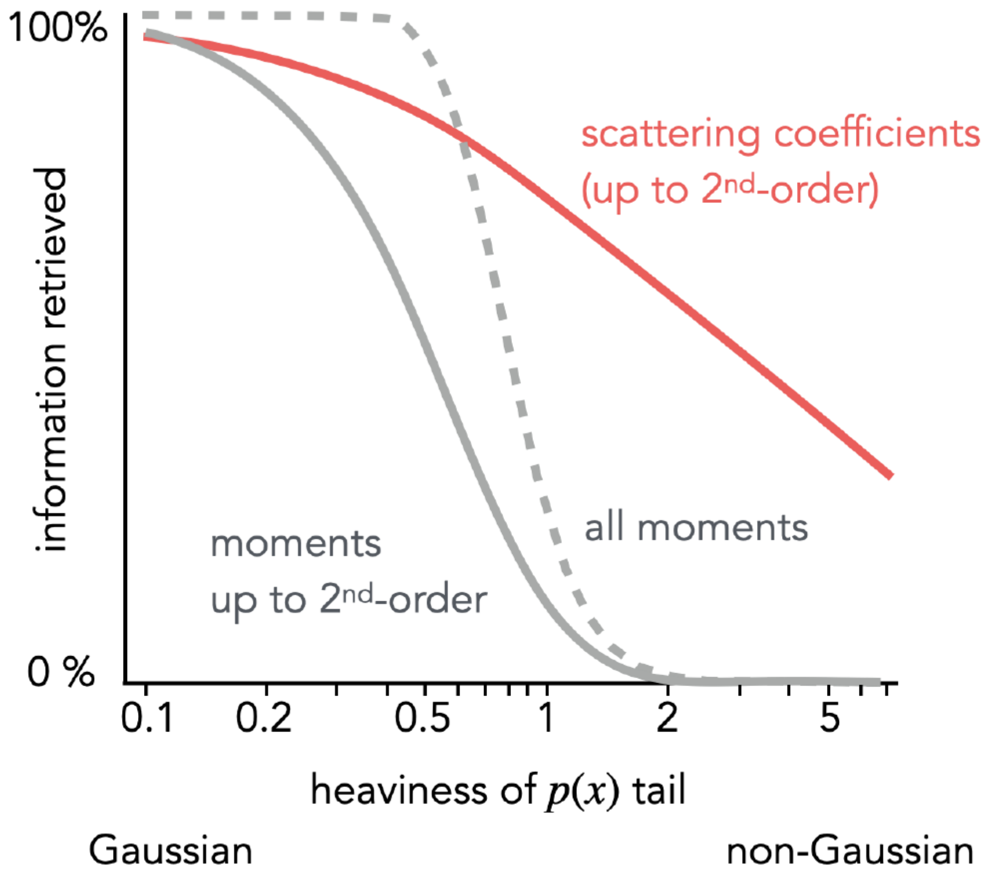
- Parallels to marked M(k) (Massara et al, 2020)

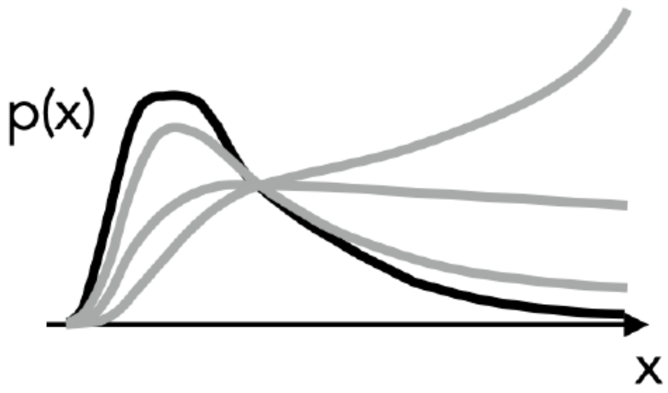
Convergence



Valogiannis & Dvorkin 2022

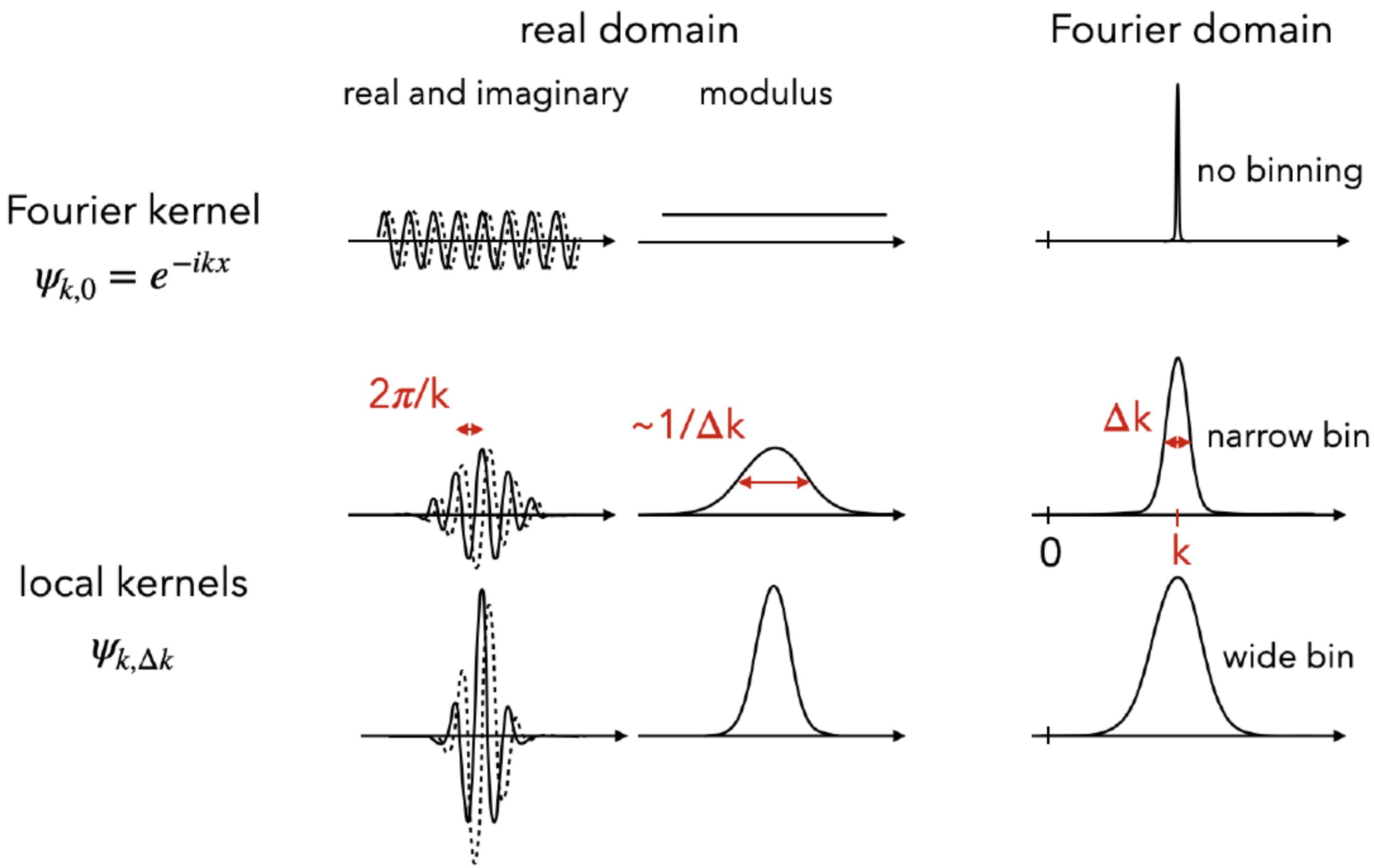
Advantages of low-order statistics





Cheng & Menard, 2021

Localized Wavelets



Cheng & Menard, 2021