

# Beyond Gaussian Fisher Matrix Forecasts

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# Motivation:

End of the first Golden Age of cosmology:

LSS: PSCz + 2dFGRS + SDSS + ...

CMB: COBE + Boomerang + WMAP + ...

SN Ia: HST + SDSS-II + ...

Shear: CTIO + Combo-17 + COSMOS(1/2) + CFHTLens + ...

Where do we go next?

Plenty of ideas:

DE + MOG + INFLATION+...?

PLANCK+...

LOFAR+  
ALMA+...

Wigglez+  
BOSS+...

DES+  
Panstarrs1+...

CMBPol+...

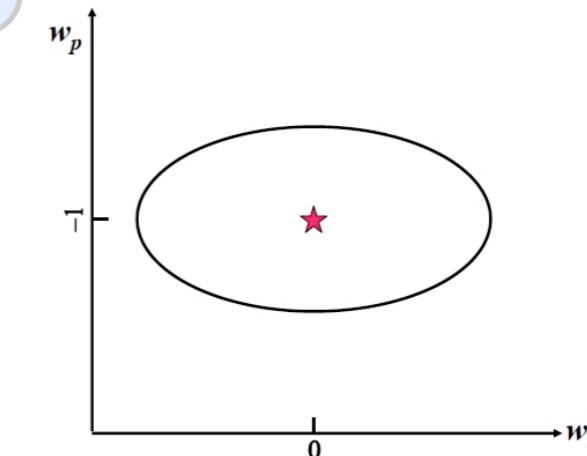
SKA+...

EUCLID+  
JDEM+...

LSST+  
Panstarrs4+...

How do we select the few from the many?  
DE task force figure of merit (FOM) + ...

$$FOM = \frac{1}{\sigma_{w_0} \sigma_{w_a}} \rightarrow F_{w_0 w_a}^{-1}$$



The DETF figure of merit, which is defined to be the reciprocal of the area in the  $w_0 - w_a$  plane that encloses the 95% C.L. region, is also proportional to  $[\sigma(w_p) \times \sigma(w_a)]^{-1}$ .

# Forecasting cosmological parameters:

Fisher matrix formalism: Taylor expand the likelihood around its maximum....

$$F_{\alpha\beta} = - \left\langle \frac{d \log L(\{x_i\} | \{\theta_i\})}{\partial \theta_\alpha \partial \theta_\beta} \right\rangle$$

For Gaussian Likelihood function Fisher matrix becomes (Tegmark, Taylor & Heavens 1997):

$$F_{\alpha\beta} = \frac{1}{2} \text{Tr} [C^{-1} C_{,\alpha} C^{-1} C_{,\beta}] + \mu_{,\alpha} C^{-1} \mu_{,\beta}$$

For LSS the lowest order statistic of interest is the Correlation function or the Power spectrum

$$\xi(r_{12}) = \langle \delta(r_1) \delta(r_2) \rangle \leftrightarrow P(k_1) = V_\mu \langle \delta_{\mathbf{k}_1} \delta_{\mathbf{k}_2} \rangle \delta^K_{k_1, k_2}$$

For the case of the power spectrum and Gaussian Random Field we have:

$$\mu_i = \langle P(k_i) \rangle ; \quad C_{ij} = \langle \delta P(k_i) \delta P(k_j) \rangle = \frac{2}{N_k} P_i^2 \delta^K_{ij}$$

Second term in Fisher matrix grows proportionally to the number of modes

$$\Rightarrow F_{\alpha\beta} \approx \mu_{,\alpha} C^{-1} \mu_{,\beta} = \sum_{i,j} P(k_i) \frac{\partial \log P(k_i)}{\partial \alpha} C^{-1} P(k_j) \frac{\partial \log P(k_j)}{\partial \beta}$$

# Going beyond the Gaussian Fisher matrix....

# Is the likelihood anywhere near a Gaussian?

The power in single mode is given by:

$$P(\mathbf{k}) = V_\mu |\delta(\mathbf{k})|^2$$

For a Gaussian random field we would expect exponential pdf

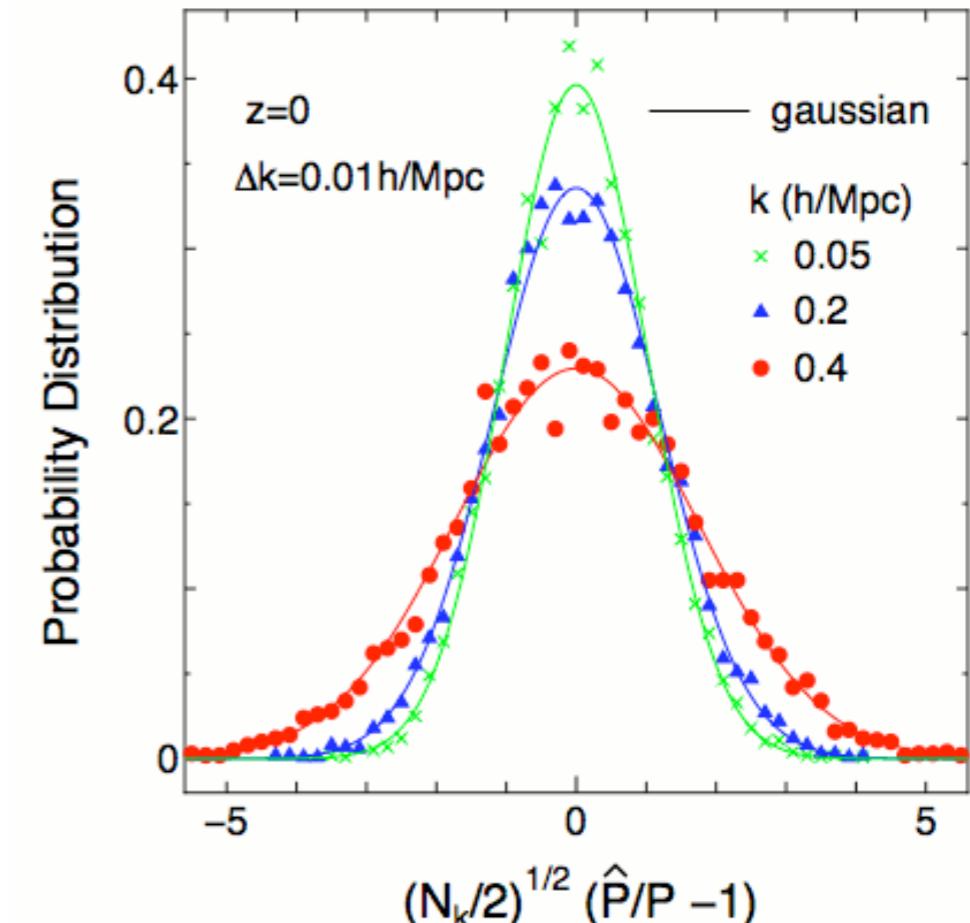
$$p(P)dP = \exp[-P/\langle P \rangle]/\langle P \rangle$$

However, what we measure is the estimator:

$$\hat{P}(k) = \frac{V}{N_k} \sum_i |\delta(k_i)|^2$$

For a Gaussian random field the estimator distribution is, a chi-square:

$$p(\hat{P}) = \frac{1}{\Gamma[N_k/2]} \frac{1}{\hat{P}} \left[ \frac{N_k}{2} \frac{\hat{P}}{\langle P \rangle} \exp \left[ -\frac{\hat{P}}{\langle P \rangle} \right] \right]^{N_k/2}$$



(Takahashi et al 2009)

Gaussian for large N

# Beyond linear theory:

There are two major effects that complicate this simple model

(I) Nonlinear evolution couples Fourier modes and ‘information flows’

(II) Discreteness (sampling) corrections introduce additional terms to the covariance

=> Fully non-Gaussian covariance matrix

$$\begin{aligned}\overline{C}^d[k_i, k_j] = & \frac{1}{V_\mu} \overline{T}[k_i, k_j] + \frac{2}{N_k} \left[ \left( \overline{P}(k_i) + \frac{1}{\bar{n}} \right) \right]^2 \delta_{k_i, k_j}^K \\ & + \frac{4}{N} \overline{B}(k_i, k_j) + \frac{2}{\bar{n}N} [\overline{P}[k_i, k_j] + \overline{P}(k_i) + \overline{P}(k_j)] + \frac{1}{\bar{n}^2 N}\end{aligned}$$

(Scoccimarro et al 99)  
(Meiksin & White 99)  
(Smith 2009)

# The N-body Simulations:

## zHORIZON-I Simulations:

Ensemble of 40 simulations of cubical patch of the LCDM Universe, with cosmological parameters close to WMAP3 cosmology...

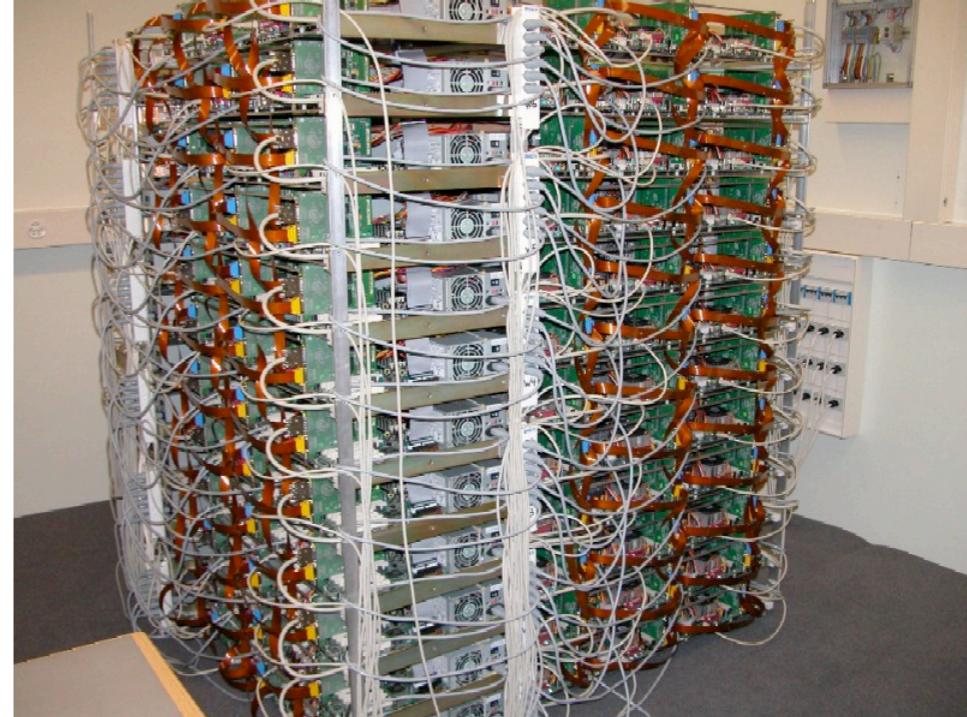
$$V = 1.5^3[\text{Gpc}/h]^3, \quad N = 750^3, \quad \Omega_m = 0.25, \quad \Omega_{\text{DE}} = 0.75, \quad \sigma_8 = 0.8, \quad n_s = 1.0$$

Using: GADGET-2, with 2LPT ICs, and CMBFAST Tfs.

Run on 128 to 256 processors of the zBox2/3 clusters



zBOX2

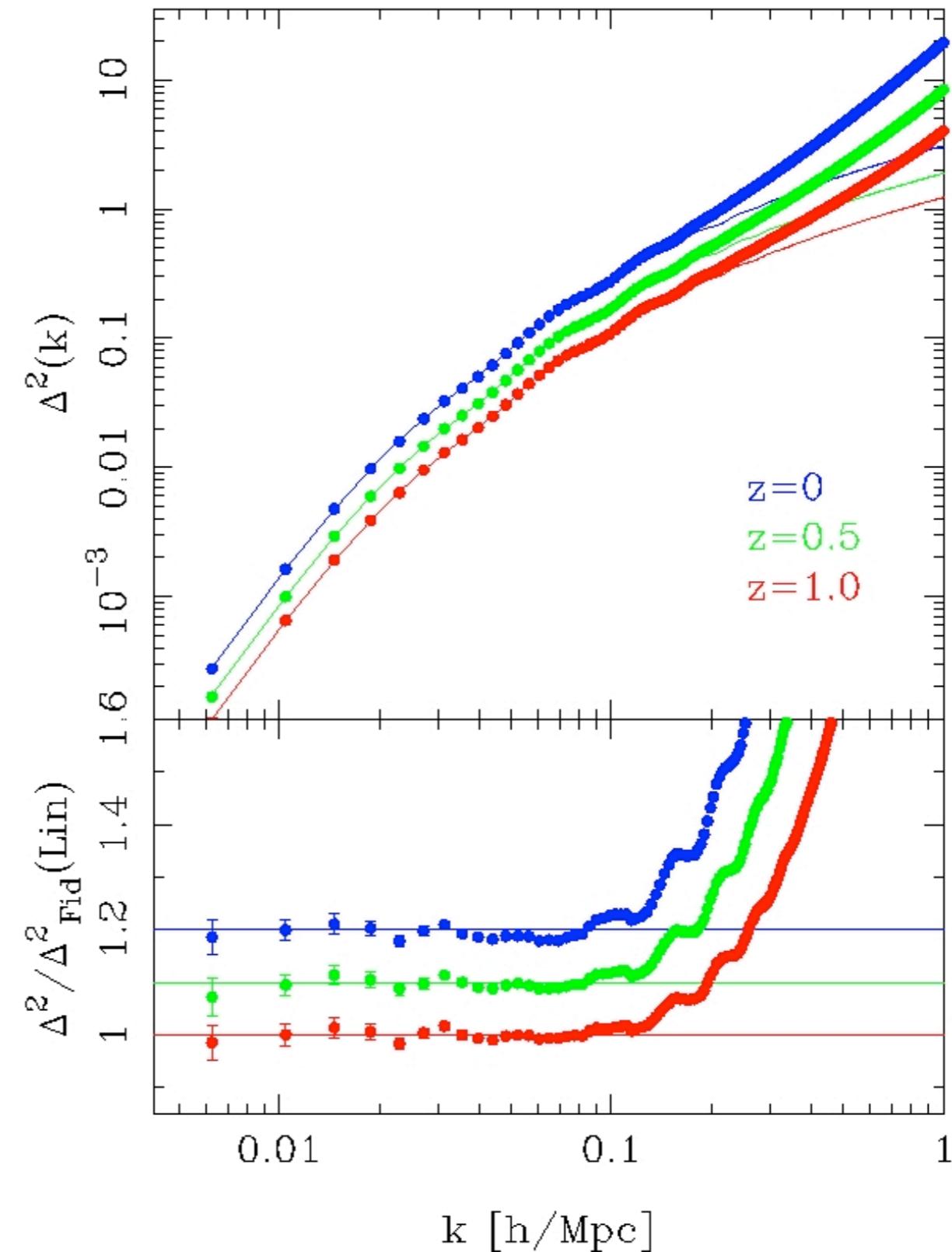


zBOX3

# Evolution of Fiducial model:

Matter power spectrum

$$\Delta^2(k) = \frac{4\pi}{(2\pi)^3} k^3 P(k)$$



# N-body Simulations II:

## zHORIZON-Variants

- : 8 cosmological models, 4 realizations per model.
- : Modification to a single cosmological parameter, all others held fixed
- : Numerical parameters identical
- : Initial Gaussian Random Field matched between models

$$vIa = \{\Omega_m = 0.20, \Omega_{DE} = 0.80, \sigma_8 = 0.8, n_s = 1.00, w_0 = -1.0\}$$

$$vIb = \{\Omega_m = 0.30, \Omega_{DE} = 0.70, \sigma_8 = 0.8, n_s = 1.00, w_0 = -1.0\}$$

$$vIIa = \{\Omega_m = 0.25, \Omega_{DE} = 0.75, \sigma_8 = 0.7, n_s = 1.00, w_0 = -1.0\}$$

$$vIIb = \{\Omega_m = 0.25, \Omega_{DE} = 0.75, \sigma_8 = 0.9, n_s = 1.00, w_0 = -1.0\}$$

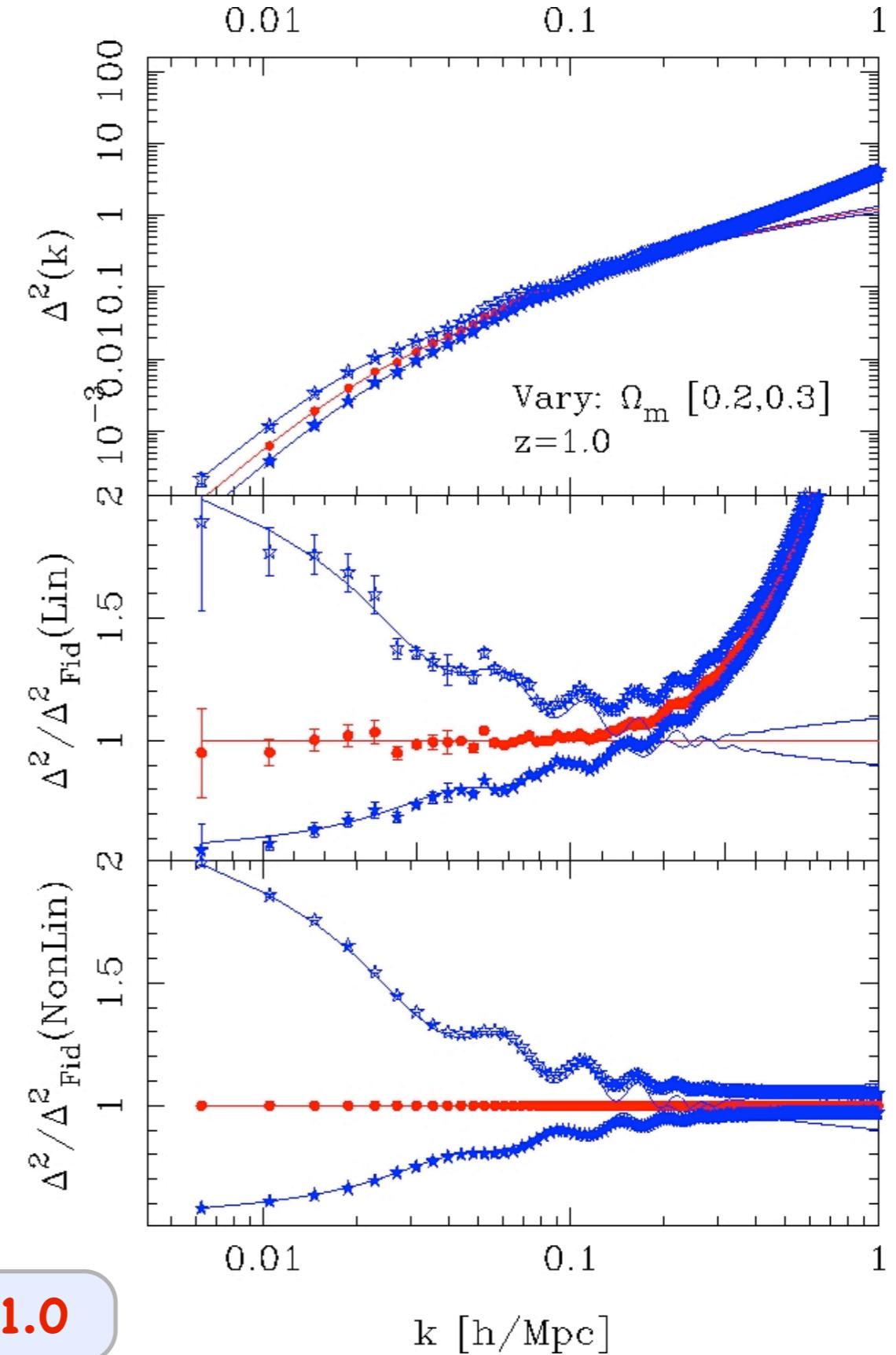
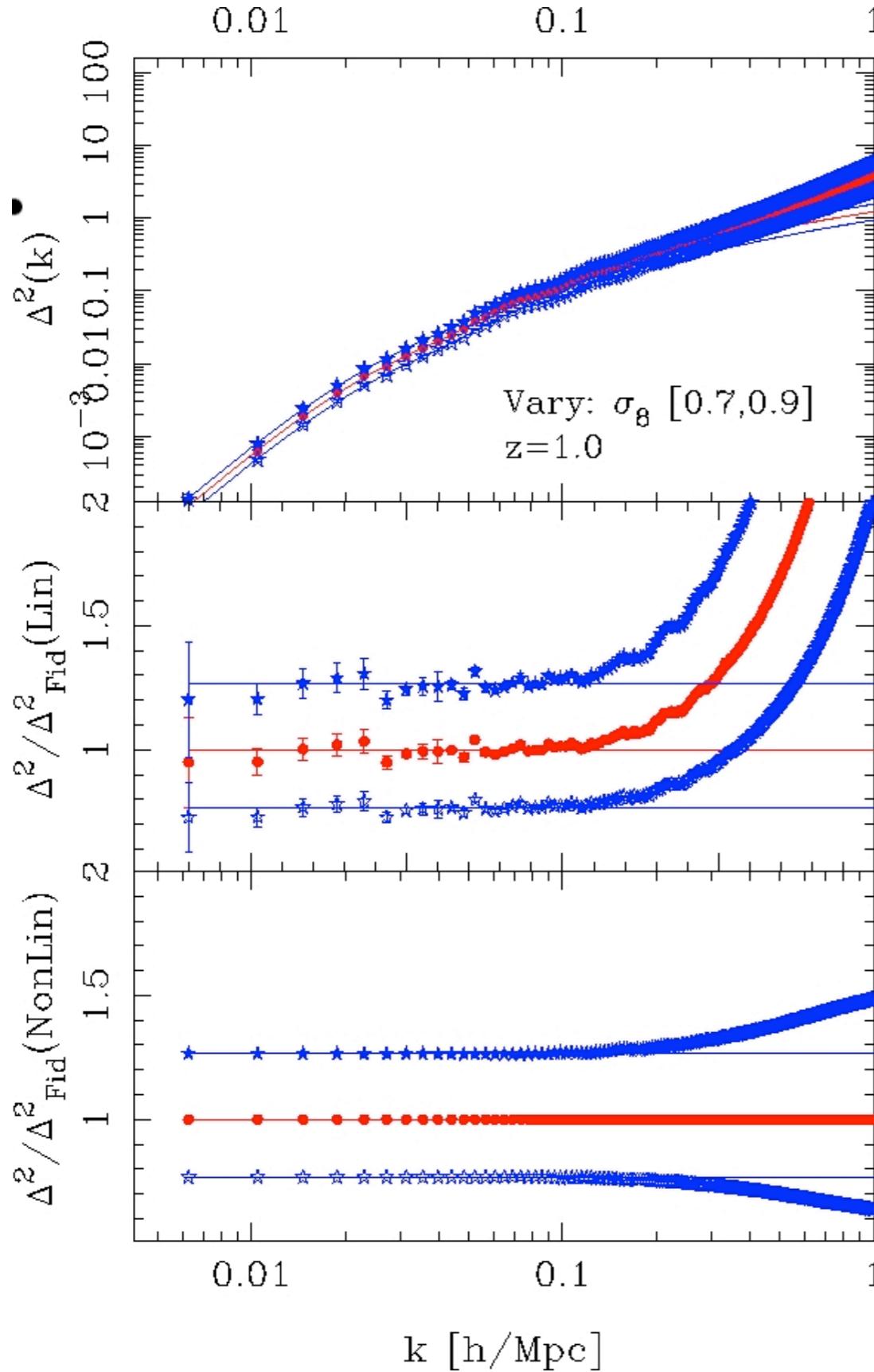
$$vIIIa = \{\Omega_m = 0.25, \Omega_{DE} = 0.75, \sigma_8 = 0.8, n_s = 0.95, w_0 = -1.0\}$$

$$vIIIb = \{\Omega_m = 0.25, \Omega_{DE} = 0.75, \sigma_8 = 0.8, n_s = 1.05, w_0 = -1.0\}$$

$$vIVa = \{\Omega_m = 0.25, \Omega_{DE} = 0.75, \sigma_8 = 0.8, n_s = 1.00, w_0 = -1.2\}$$

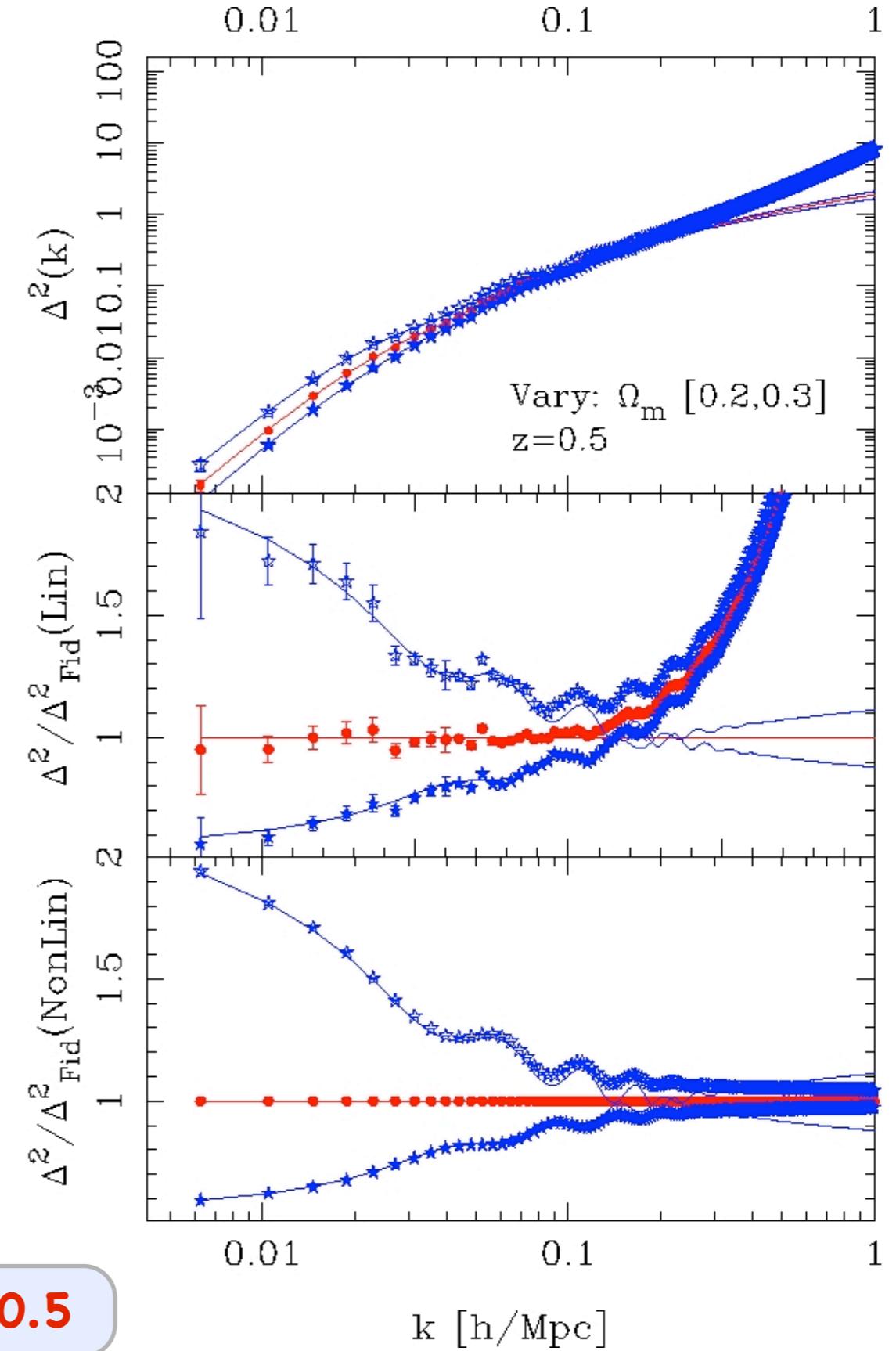
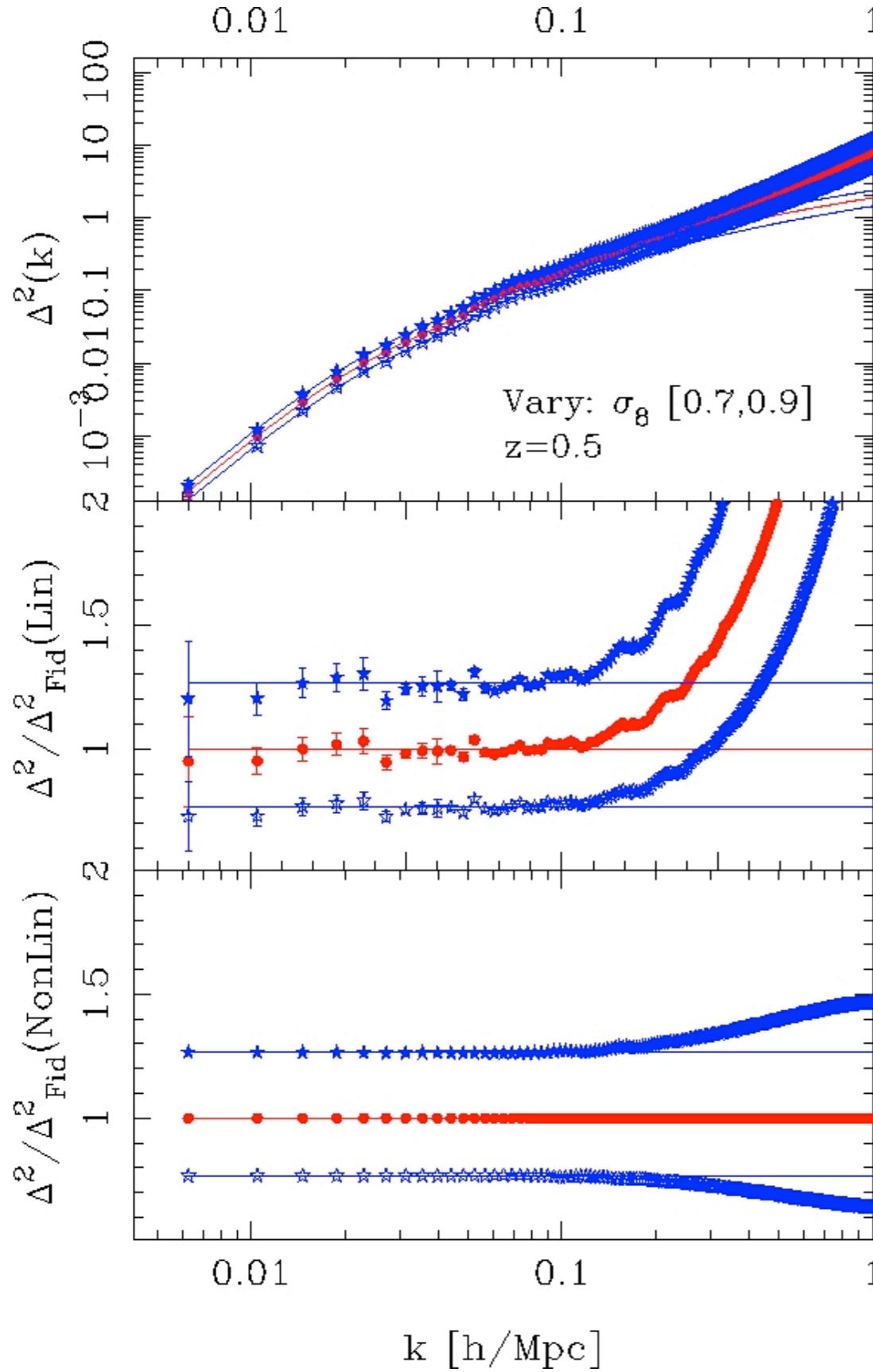
$$vIVb = \{\Omega_m = 0.25, \Omega_{DE} = 0.75, \sigma_8 = 0.8, n_s = 1.00, w_0 = -0.8\}$$

# Evolution of variational cosmologies:



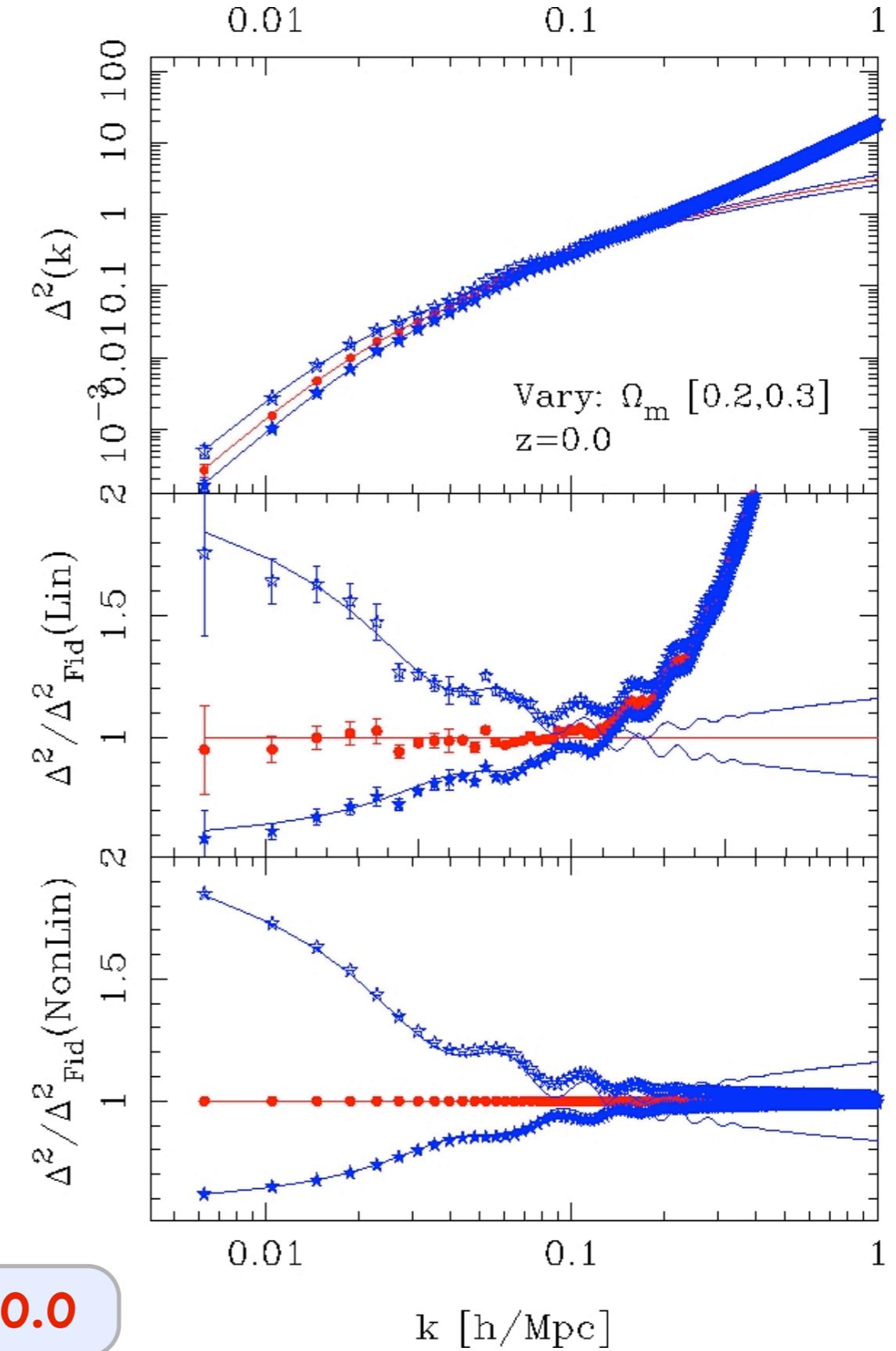
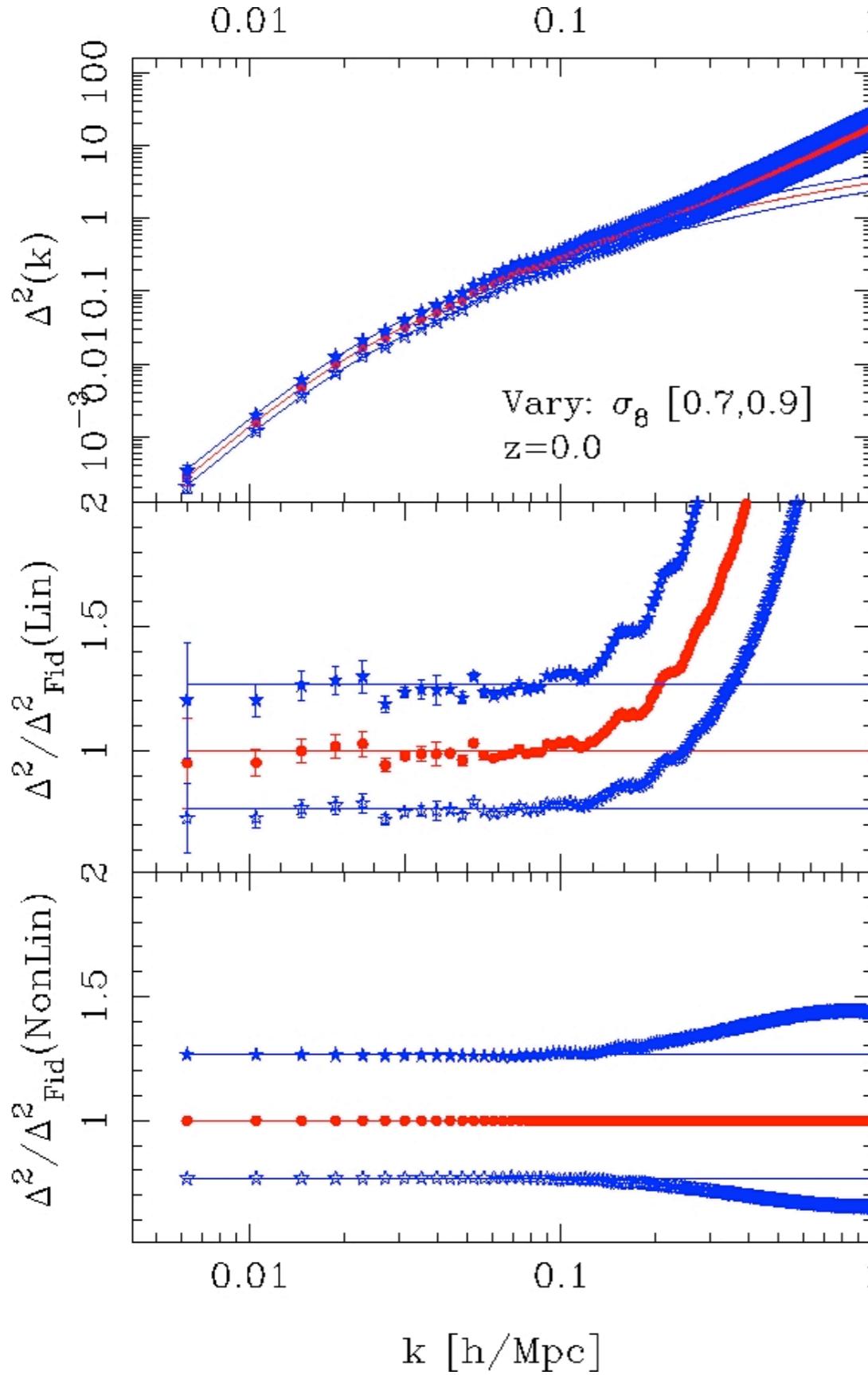
**z=1.0**

# Evolution of variational cosmologies



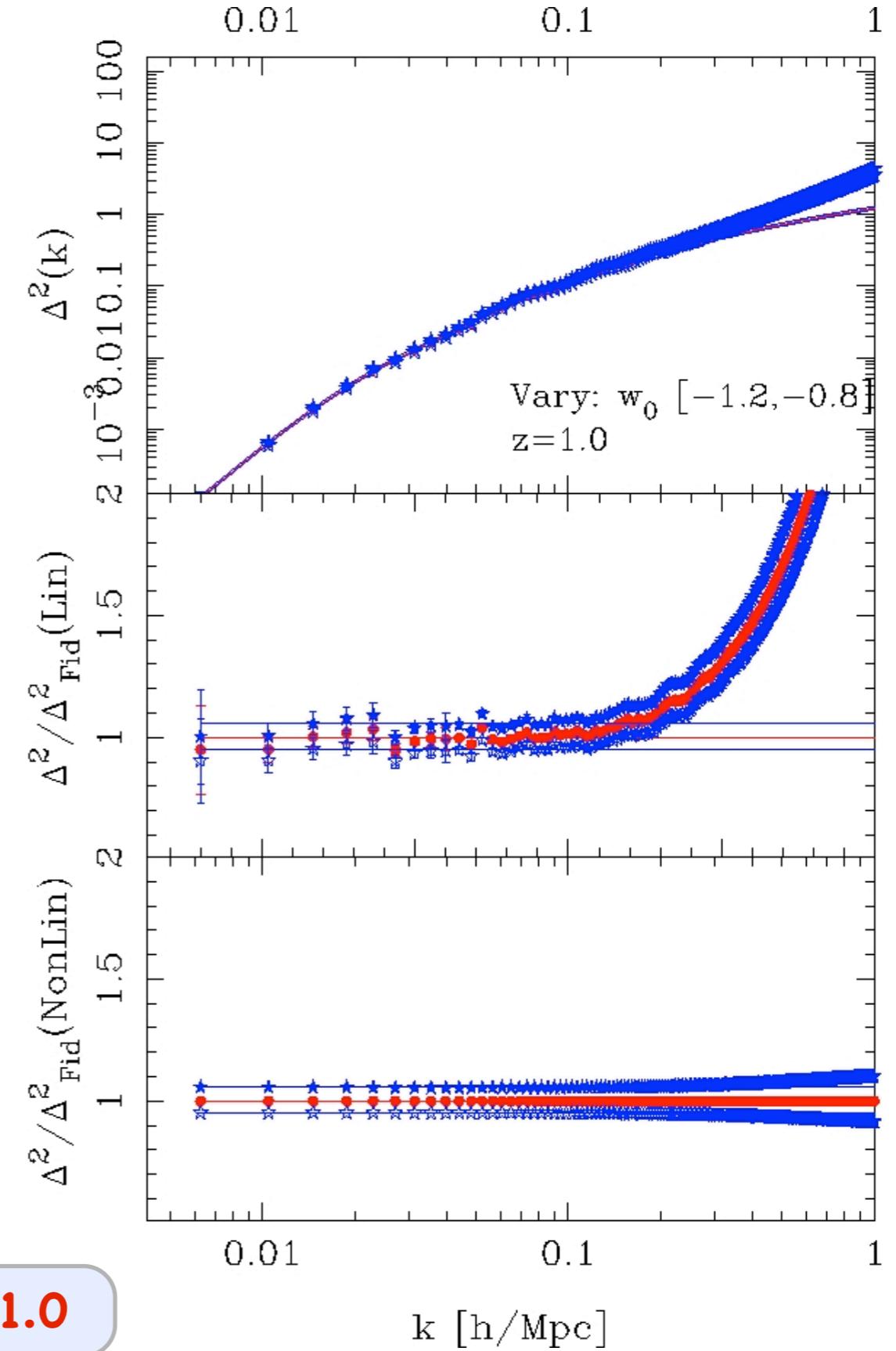
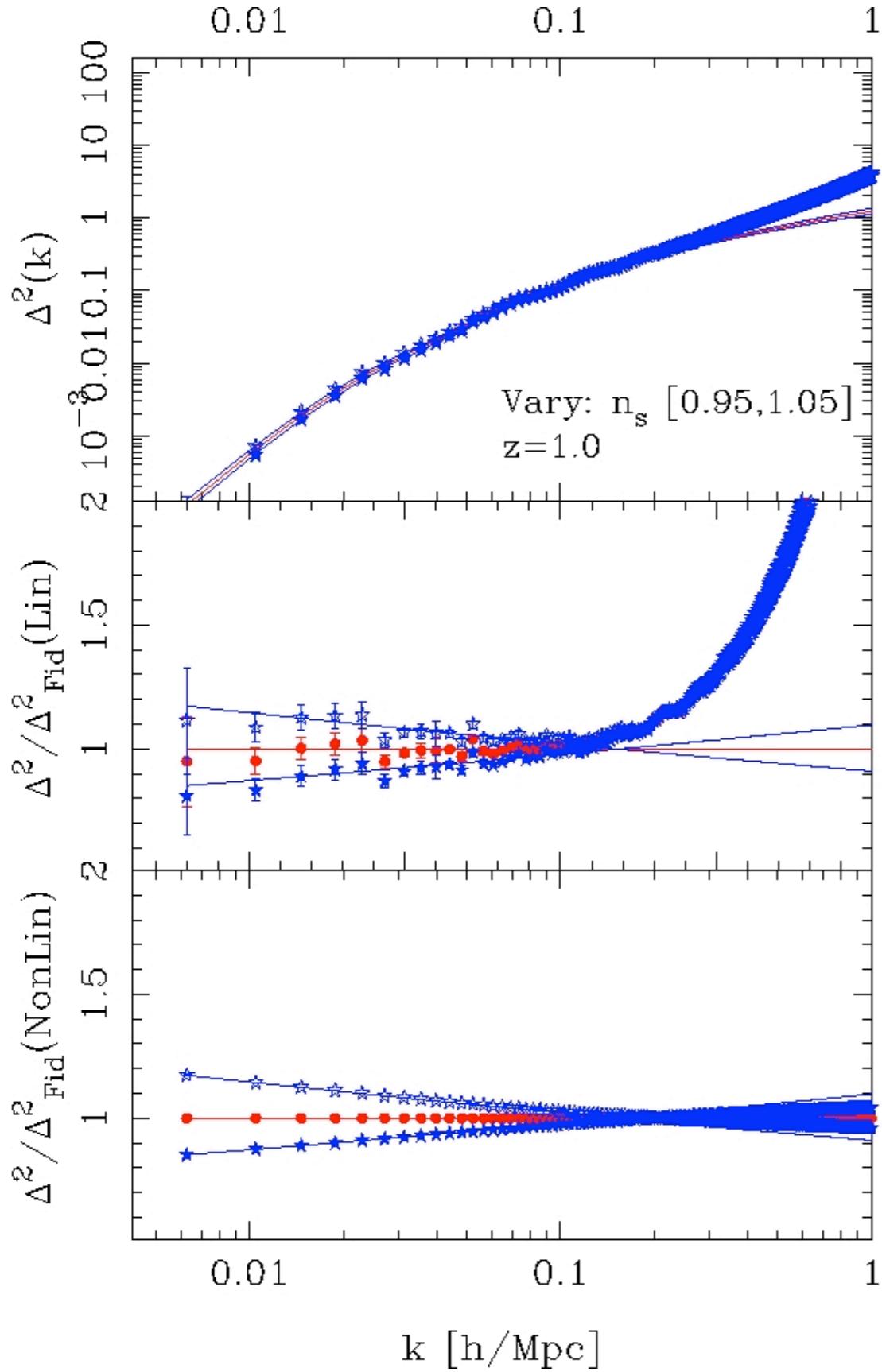
**z=0.5**

# Evolution of variational cosmologies



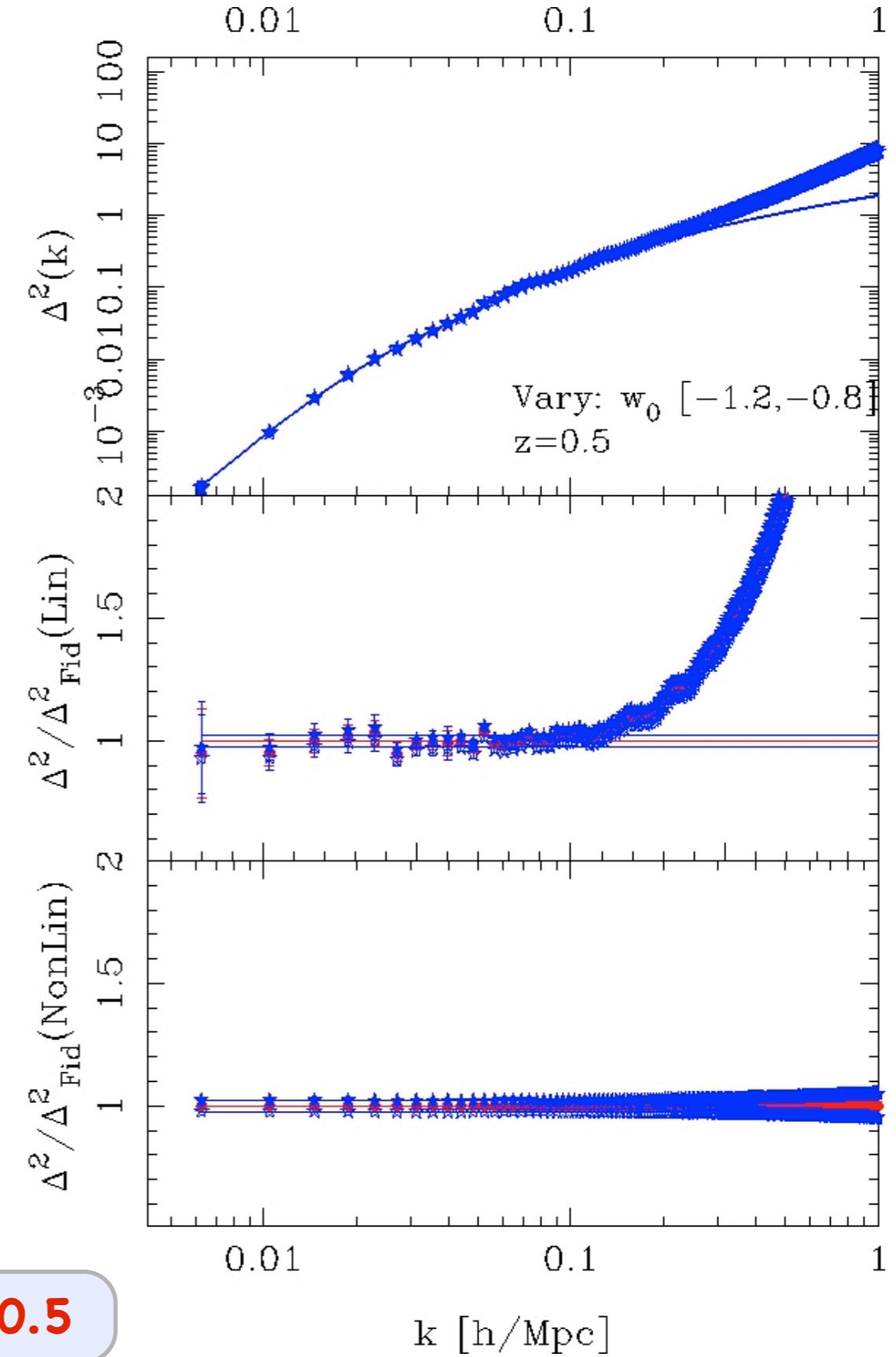
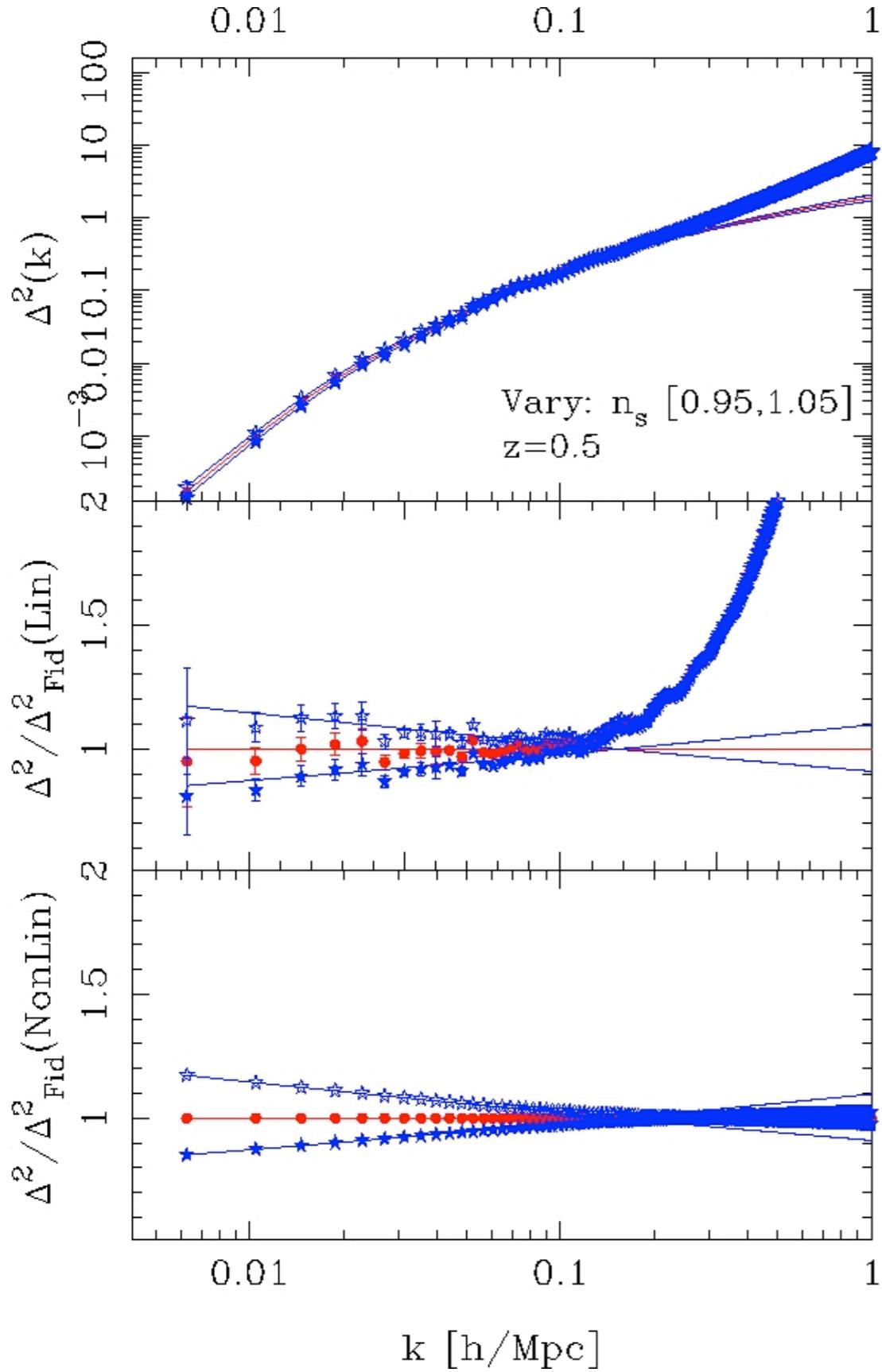
***z=0.0***

# Evolution of variational cosmologies



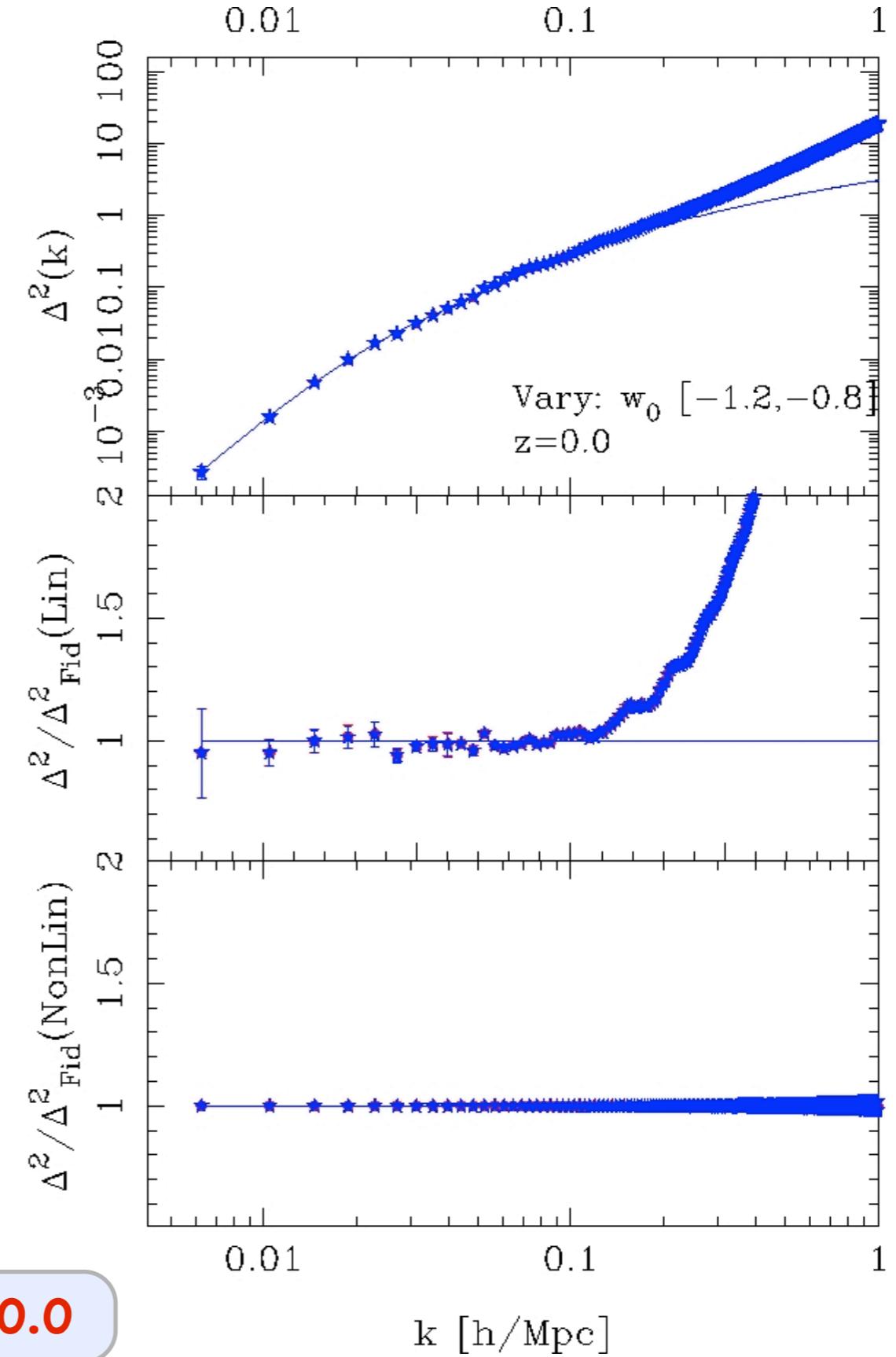
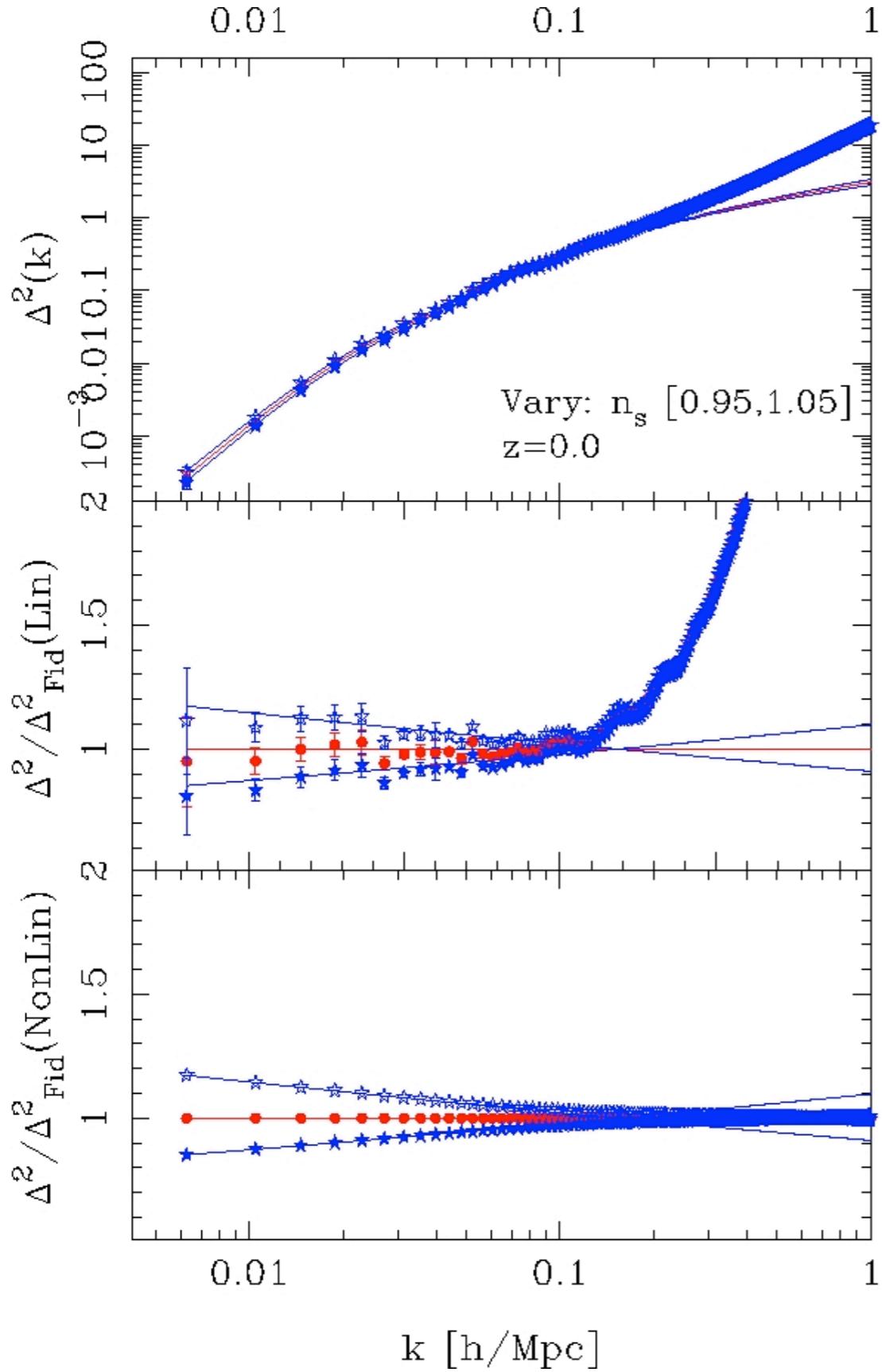
**$z=1.0$**

# Evolution of variational cosmologies



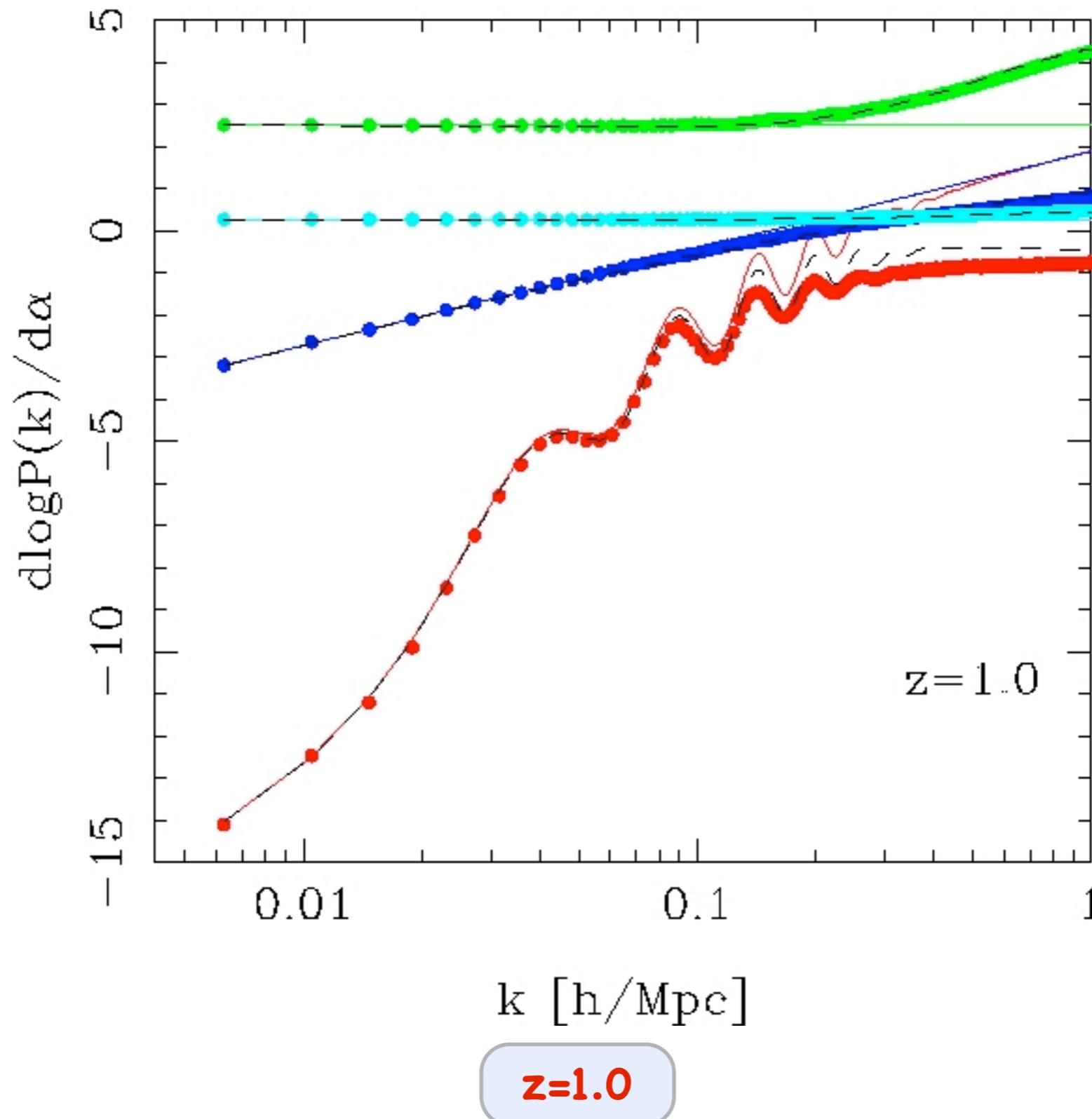
**z=0.5**

# Evolution of variational cosmologies

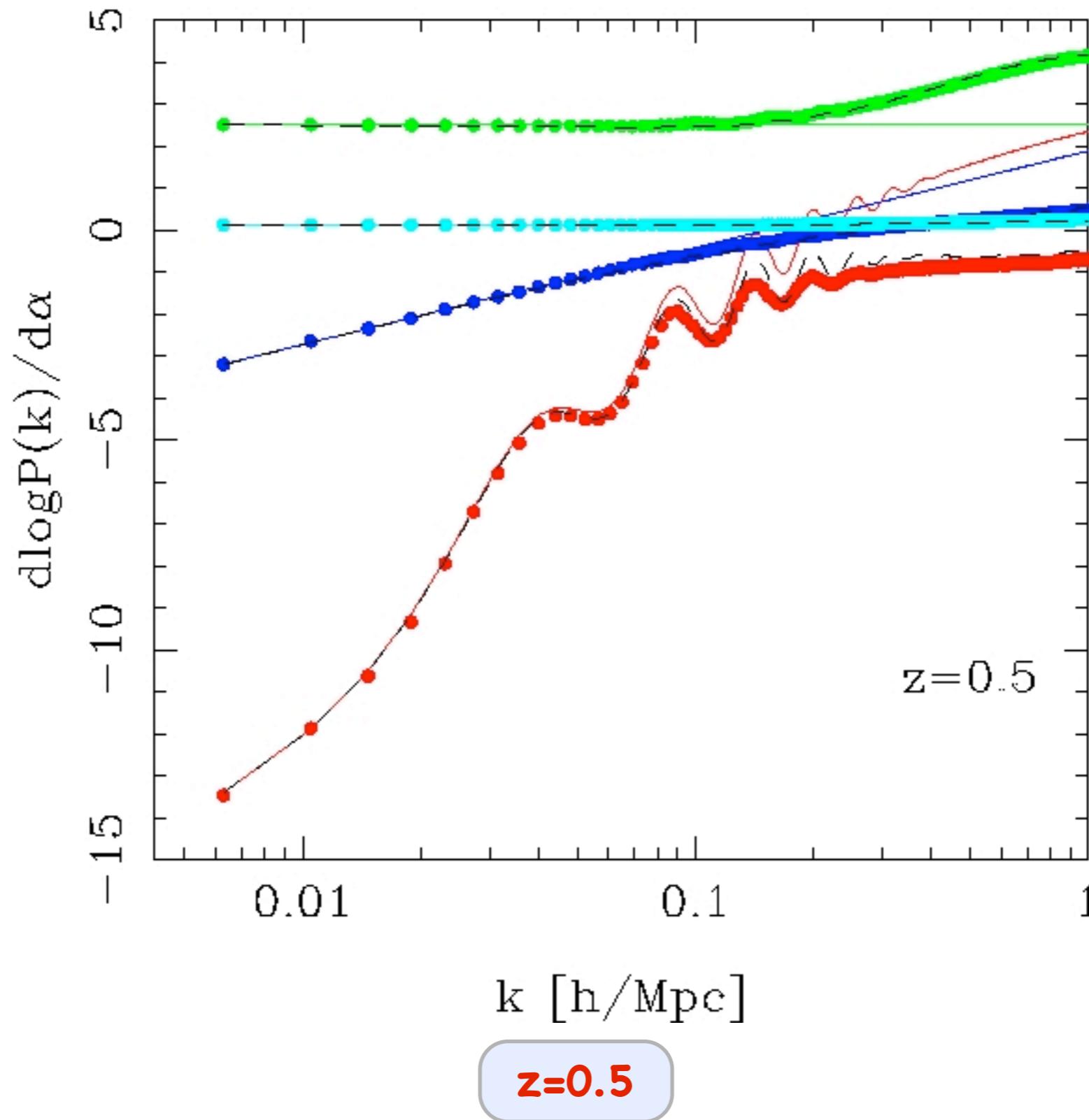


**z=0.0**

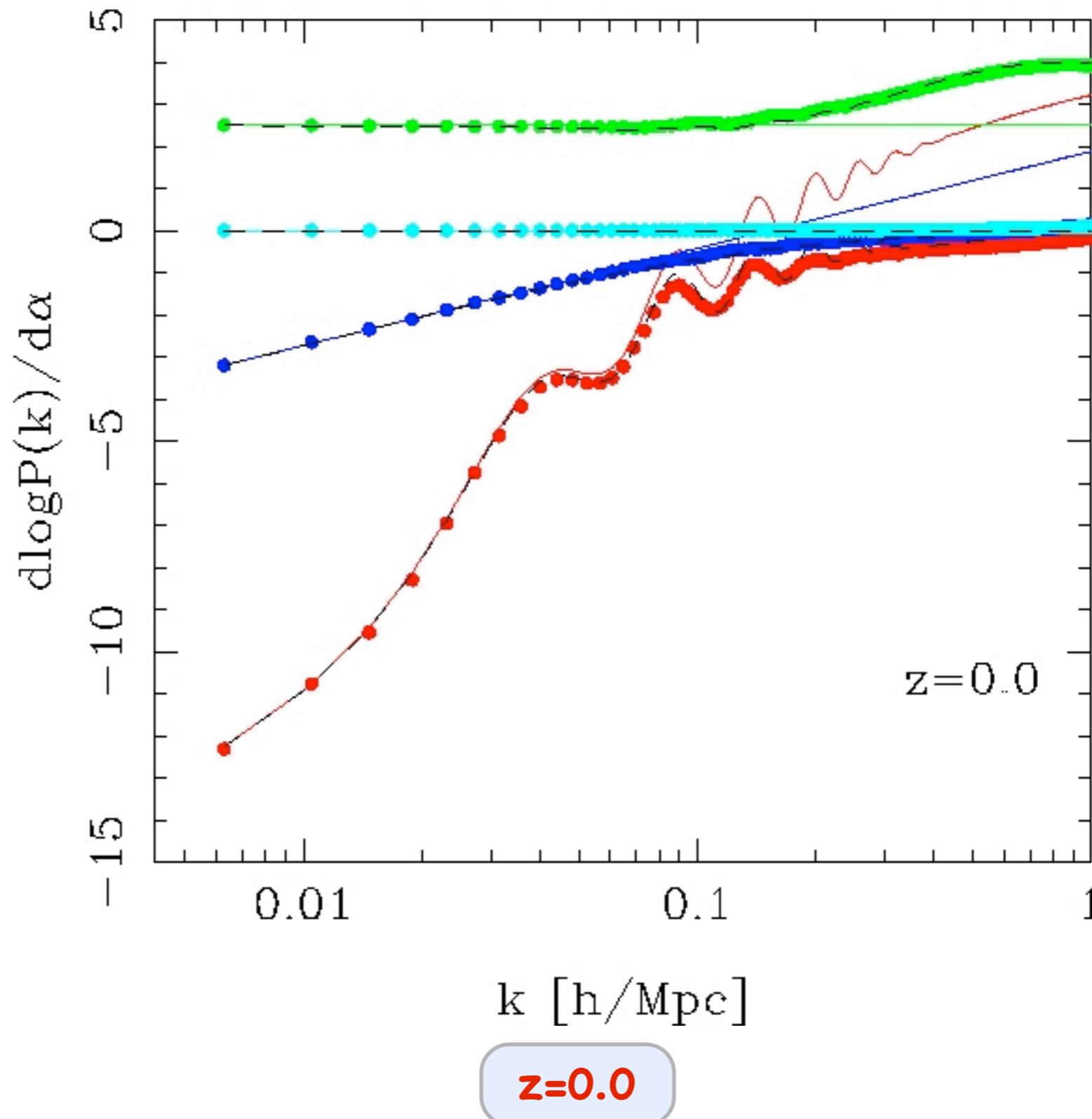
# Fisher matrix derivatives:



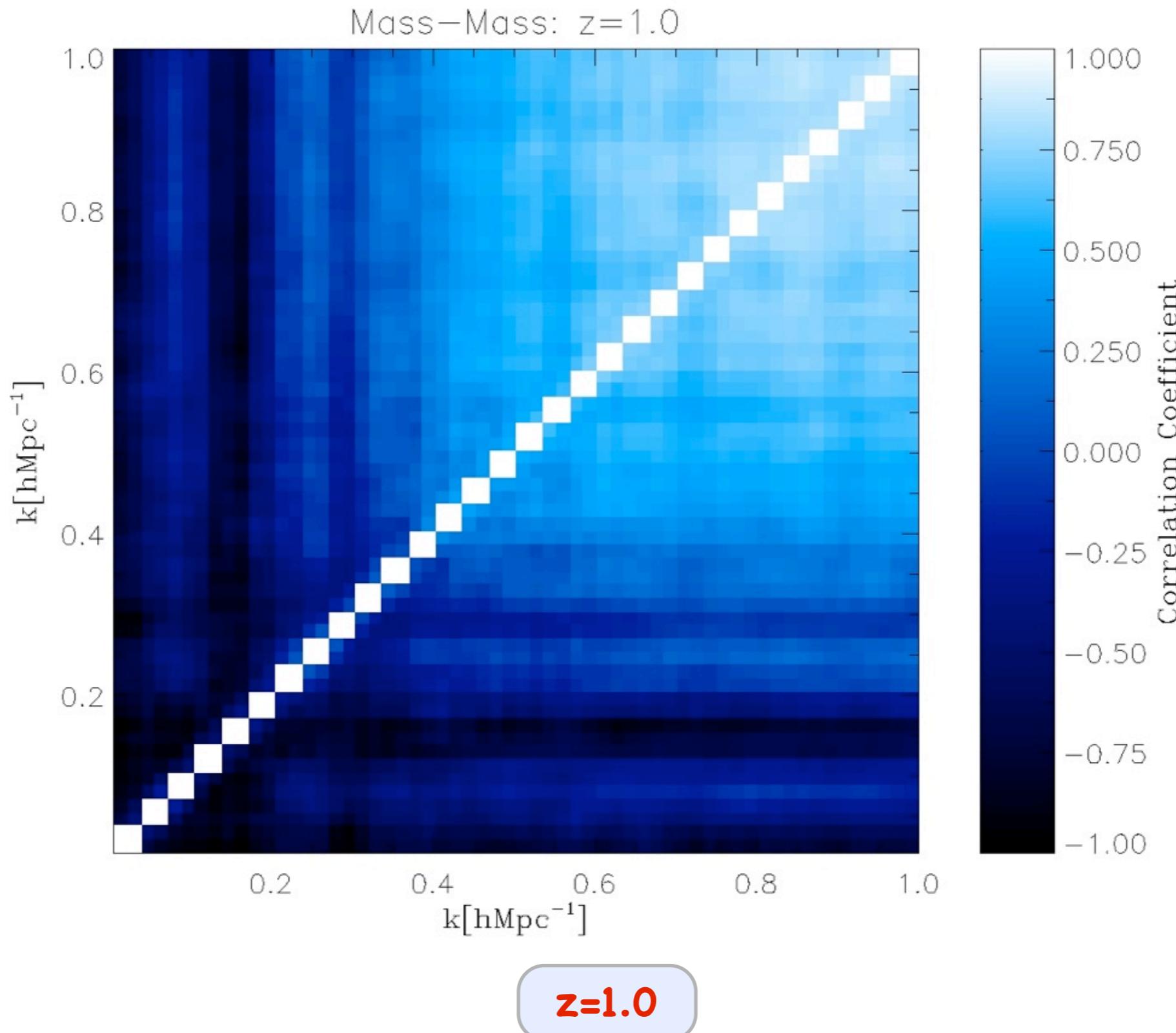
# Fisher matrix derivatives:



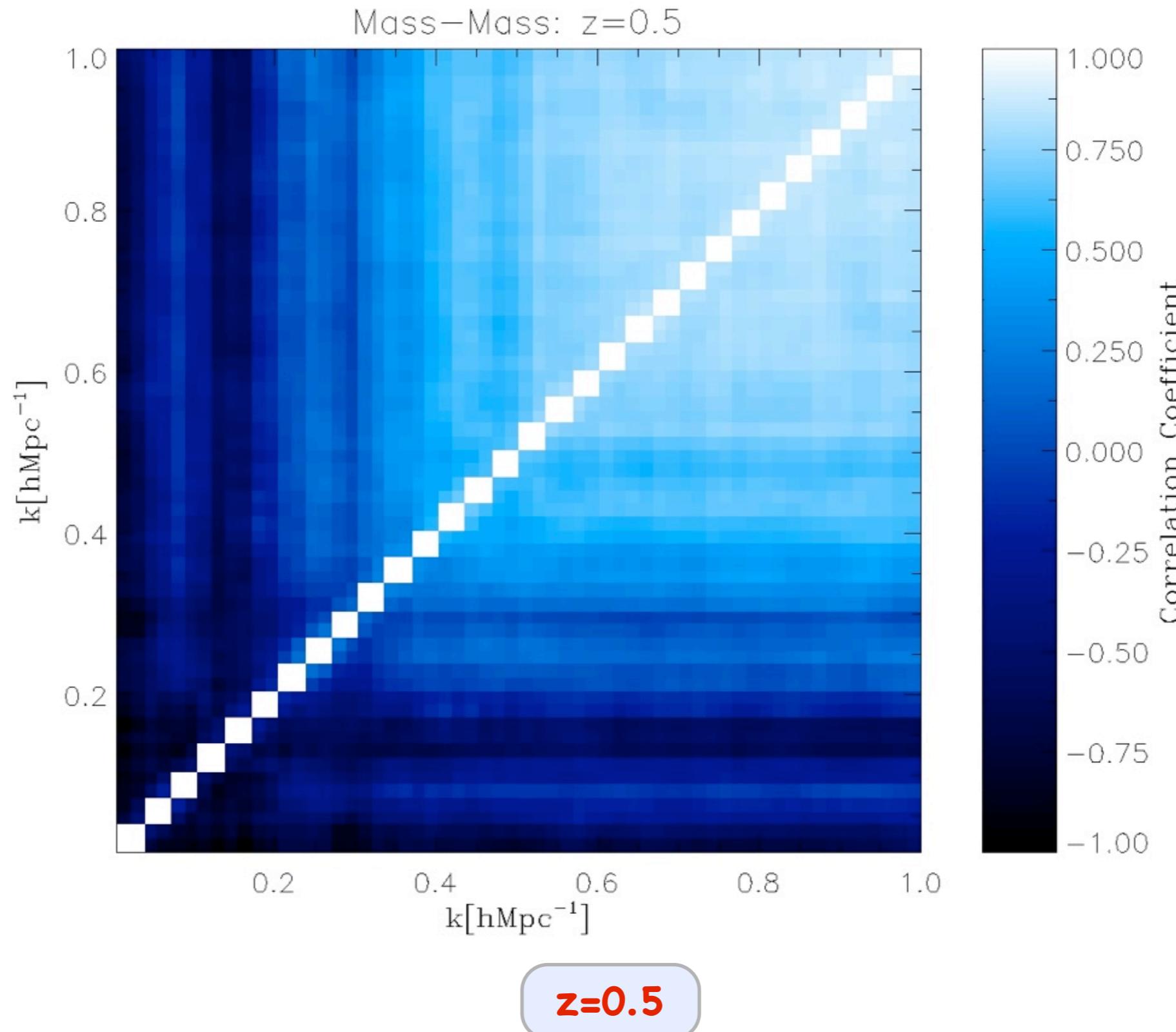
# Fisher matrix derivatives:



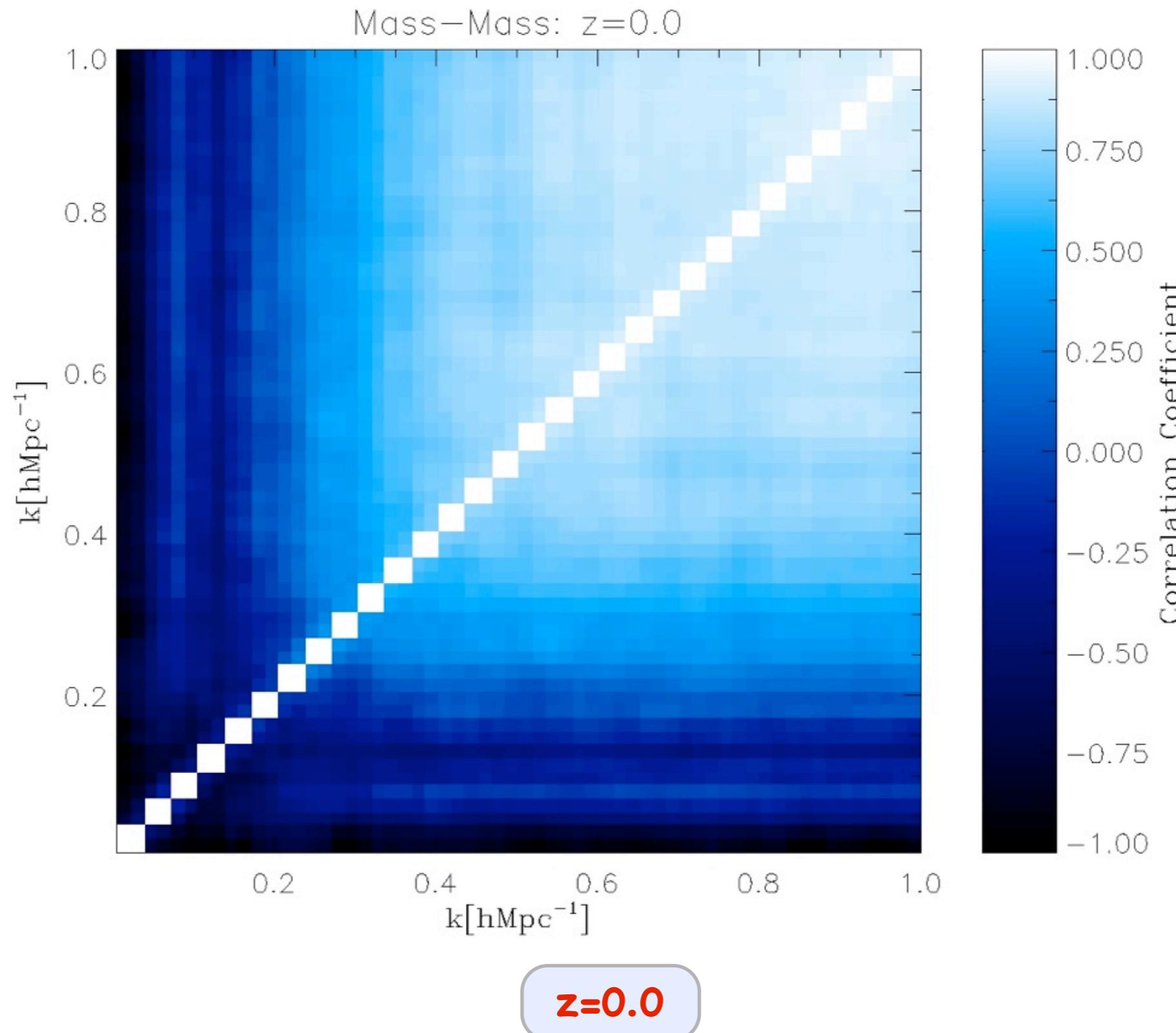
# Power spectrum Correlation matrices:



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# Power spectrum Correlation matrices:



# What about the Fisher information?

# Simple survey case:

- 1: Suppose we have 3 galaxy surveys tracing structure at:  
low ( $z=0$ ) + intermediate ( $z=0.5$ ) + high redshift ( $z=1$ )
- 2: Suppose all surveys cover same volume:  $V=3 \text{ [Gpc/h]}^3$  &  
galaxies are densely sampled (galaxy bias=1 &  $nP \gg 1$ )
- 3: We measure 4 parameters from the data:  $\{\Omega_m, \sigma_8, n_s, w_0\}$

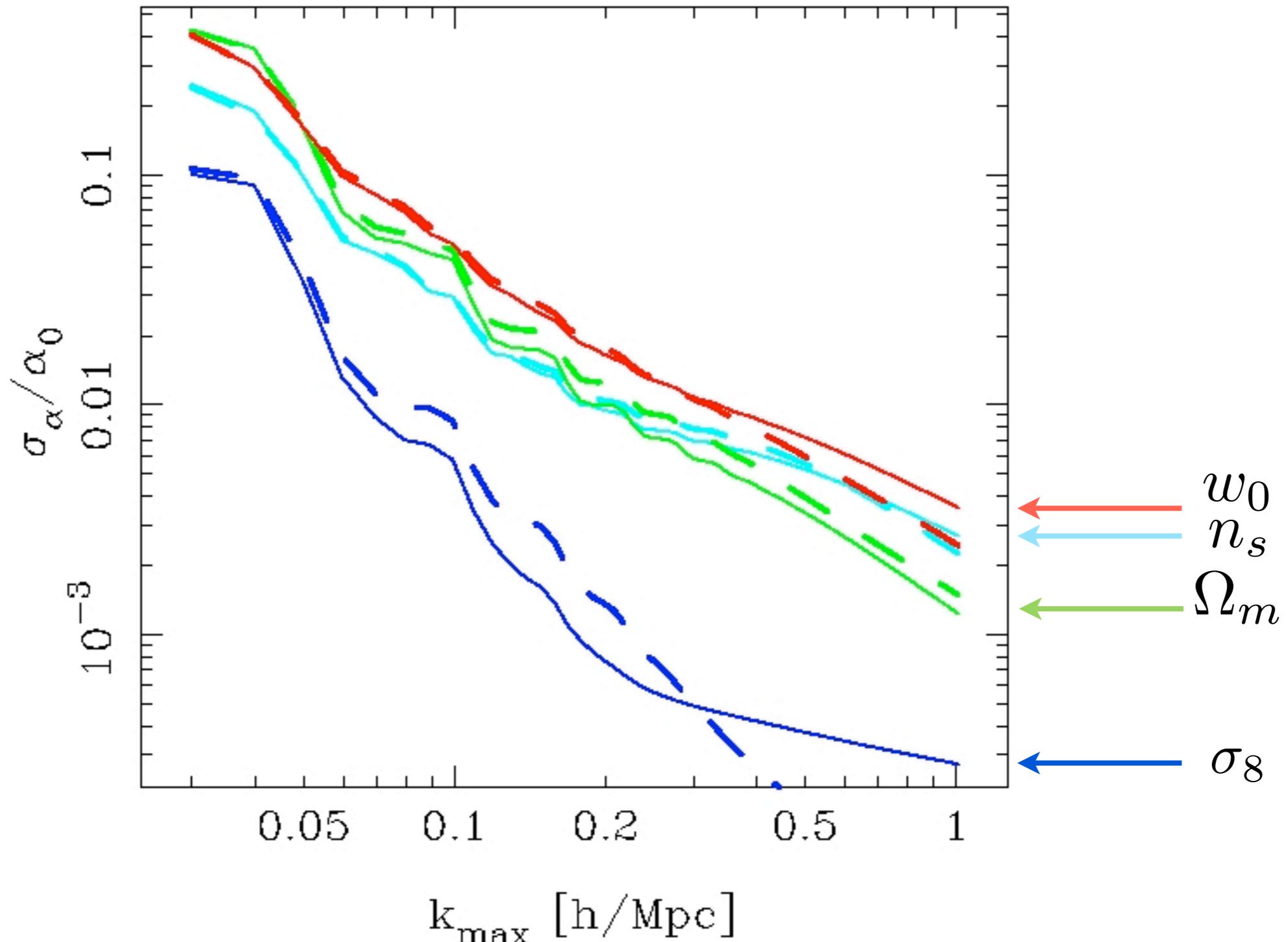
Assuming survey volumes are uncorrelated, then we add Fisher matrices  
=> Total Fisher information (Important for constraining Dark Energy!)

$$F_{\alpha\beta}^{\text{TOT}} = F_{\alpha\beta}(z = 0.0) + F_{\alpha\beta}(z = 0.5) + F_{\alpha\beta}(z = 1.0)$$

# 1-D Marginalized errors:

(Solid lines) => Linear  $P(k)$  + Gaussian Covariance matrix

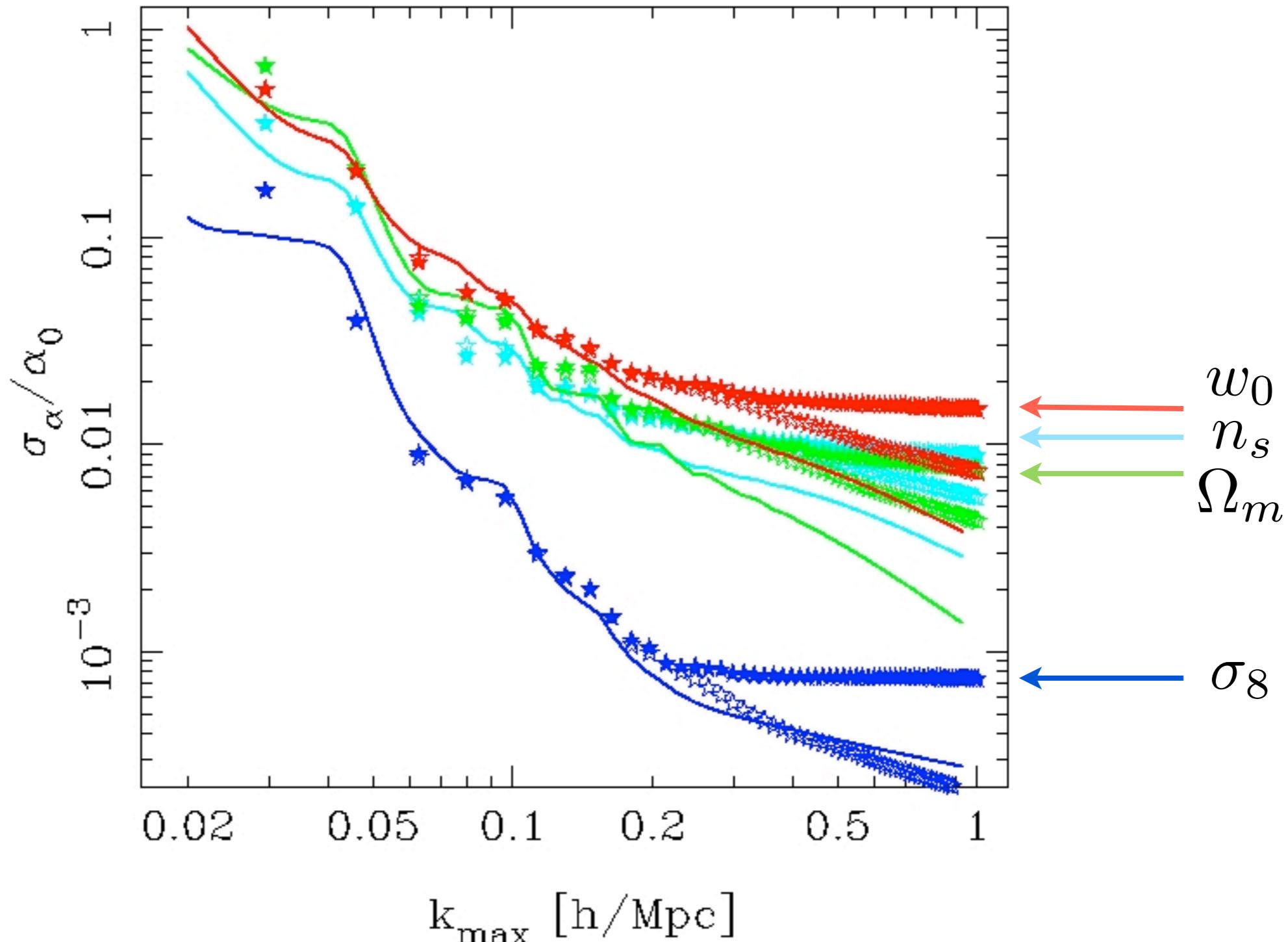
(Dash lines) => halofit  $P(k)$  + Gaussian Covariance matrix



# 1-D Marginalized errors:

(Solid points) => measured  $P(k)$  + derivatives + Non-Gaussian Covariance matrix

(Open points) => measured  $P(k)$  + derivatives + Diagonal elements of Non-Gaussian Covariance matrix



# Dark Energy: 2-D Marginalized errors:

Sim+NonGauss:

kmax=1.0

kmax=0.1

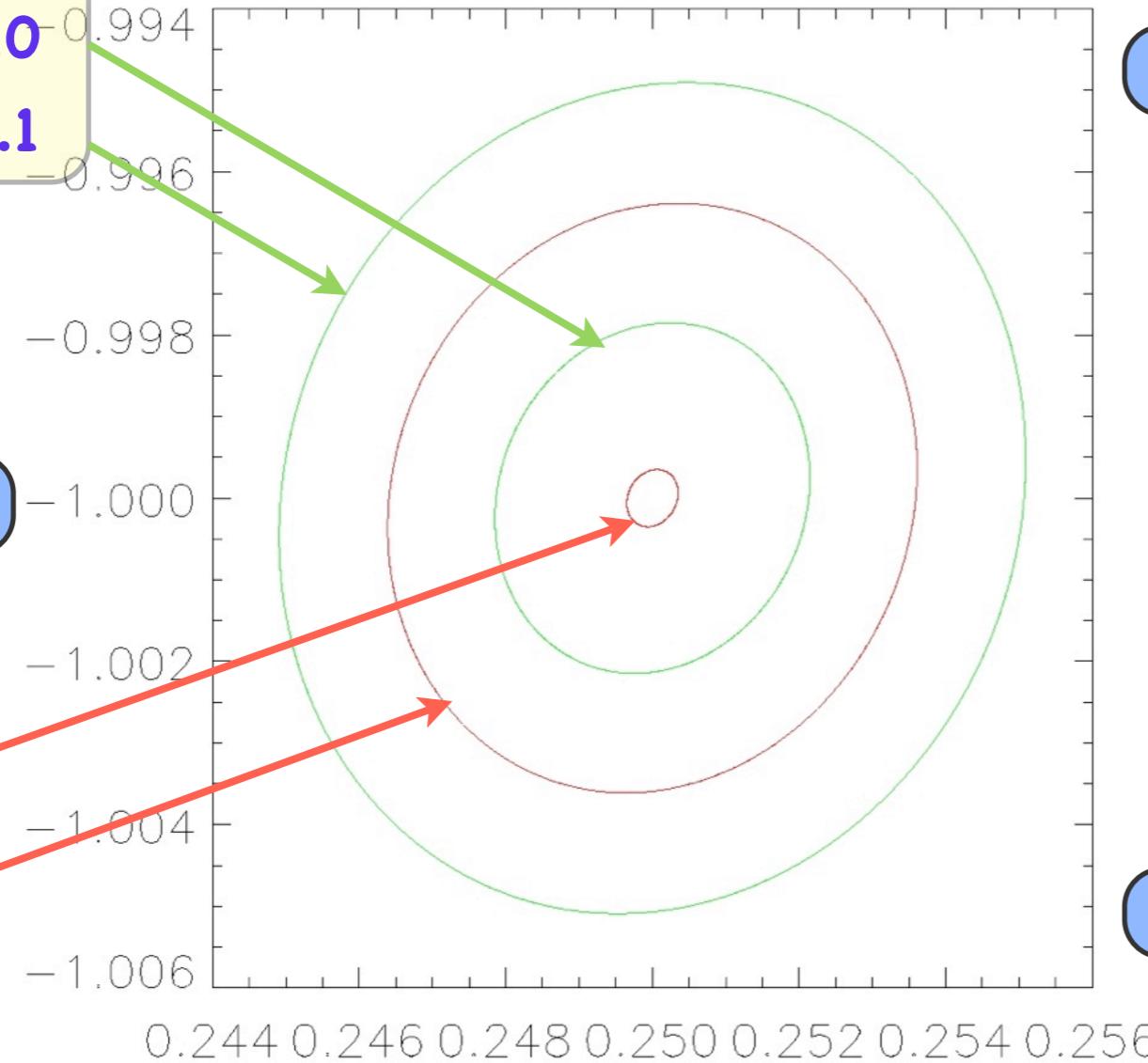
$w_0$

Lin+Gauss:

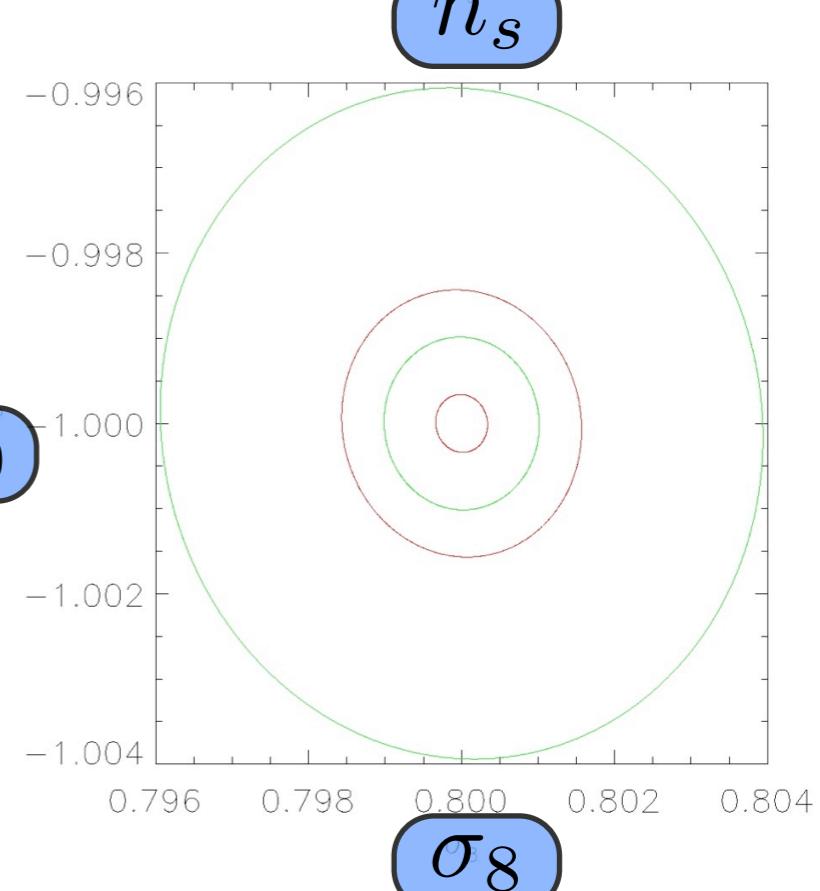
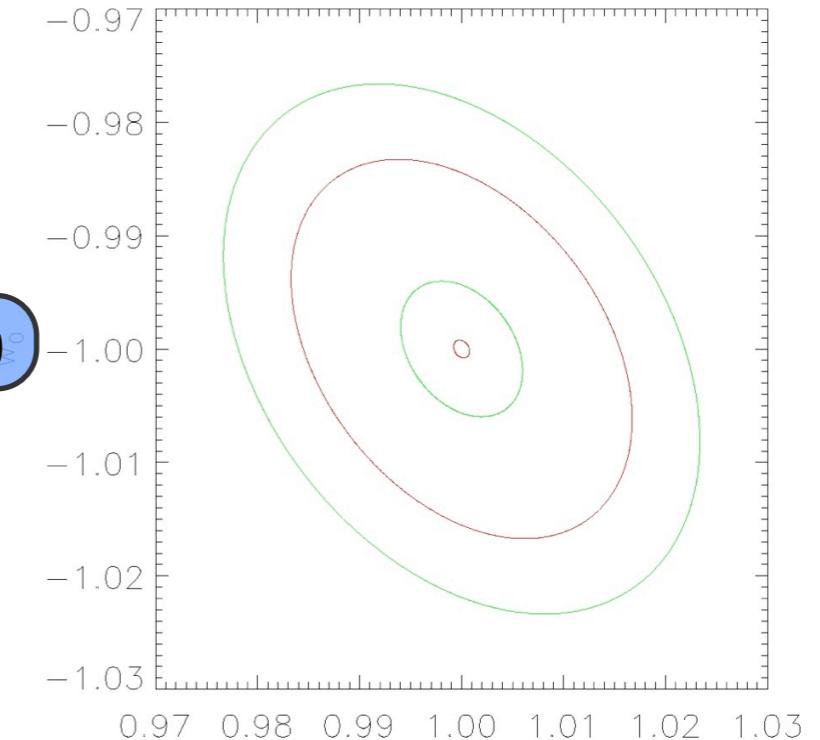
kmax=1.0

kmax=0.1

$\Omega_m$



$w_0$



# Summary & Conclusions:

- 1: Fisher matrix formalism allows us to optimize future galaxy surveys
- 2: One must explore assumptions
- 3: We modeled Fisher matrix using simulations
- 4: Nonlinear evolution can erode information in  $P(k)$ 
  - => non-Gaussian covariance matrix
  - => nonlinear  $P(k)$  derivatives
- 5: Parameter errors saturated at much lower  $k$  than currently thought  
(see also, Takada & Jain 2009, Takahashi et al 2009, Sato et al 2010)

Future directions: => Information flows into the higher order moments!

# Forecasting cosmological parameters:

Linear Theory + Gaussian Case:

$$\begin{aligned}\Rightarrow F_{\alpha\beta} &\approx \sum_{i,j} P(k_i) \frac{\partial \log P(k_i)}{\partial \alpha} C^{-1} P(k_j) \frac{\partial \log P(k_j)}{\partial \beta} \\ &= \frac{1}{2} \sum_i N(k_i) \left[ \frac{\bar{n}P(k_i)}{1 + \bar{n}P(k_i)} \right]^2 \frac{\partial \log P(k_i)}{\partial \alpha} \frac{\partial \log P(k_i)}{\partial \beta} \\ &= \frac{1}{2} \frac{V_\mu}{(2\pi)^3} \int d^3k \left[ \frac{\bar{n}P(k)}{1 + \bar{n}P(k)} \right]^2 \frac{\partial \log P(k)}{\partial \alpha} \frac{\partial \log P(k)}{\partial \beta} \quad (\text{Tegmark 1997})\end{aligned}$$

Predictions for the marginalized errors on parameters,  
and their covariances can then be obtained by inverting the Fisher matrix:

$$\text{MVB} \Rightarrow \begin{cases} \sigma_{\alpha\alpha} = \sqrt{[F^{-1}]_{\alpha\alpha}} \\ \sigma_{\alpha\beta} = \sqrt{[F^{-1}]_{\alpha\beta}} \end{cases}$$

(For a great review see Heavens 2009)

