

Extension of Evolution Mapping to Velocity Statistics

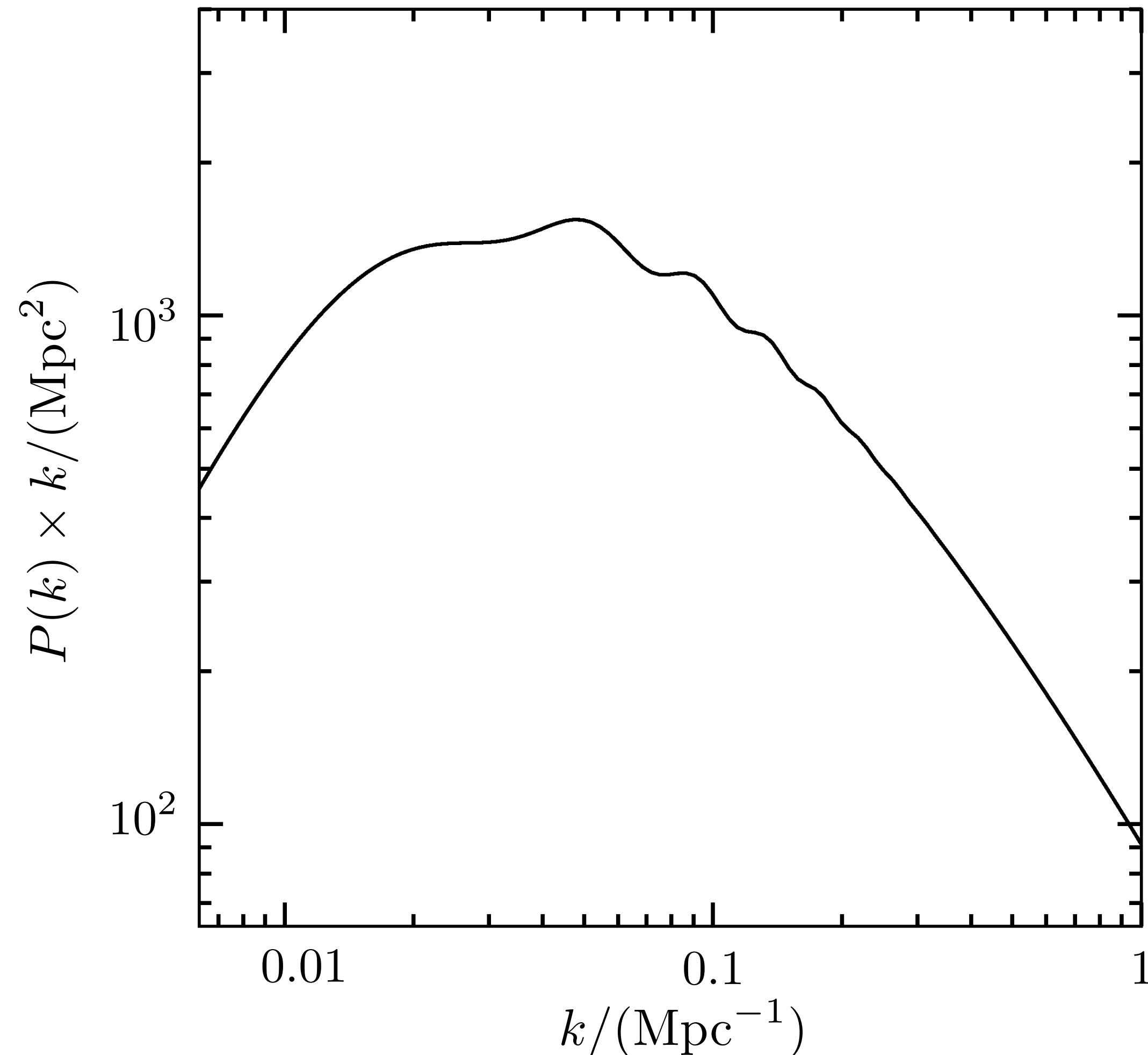
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with *Ariel Sánchez*, *Julien Bel*

Future Cosmology, IESC - April 24th, 2023

Evolution mapping: linear $P(k)$

We can classify cosmological parameters according to their impact on $P(k)$



$$P_L(k, z) = P(k | \underline{A_s}, n_s) \times T(k) \times \underline{D(z)}$$

Cosmological parameters

Θ_s

ω_c

ω_b

n_s

Θ_e

ω_K

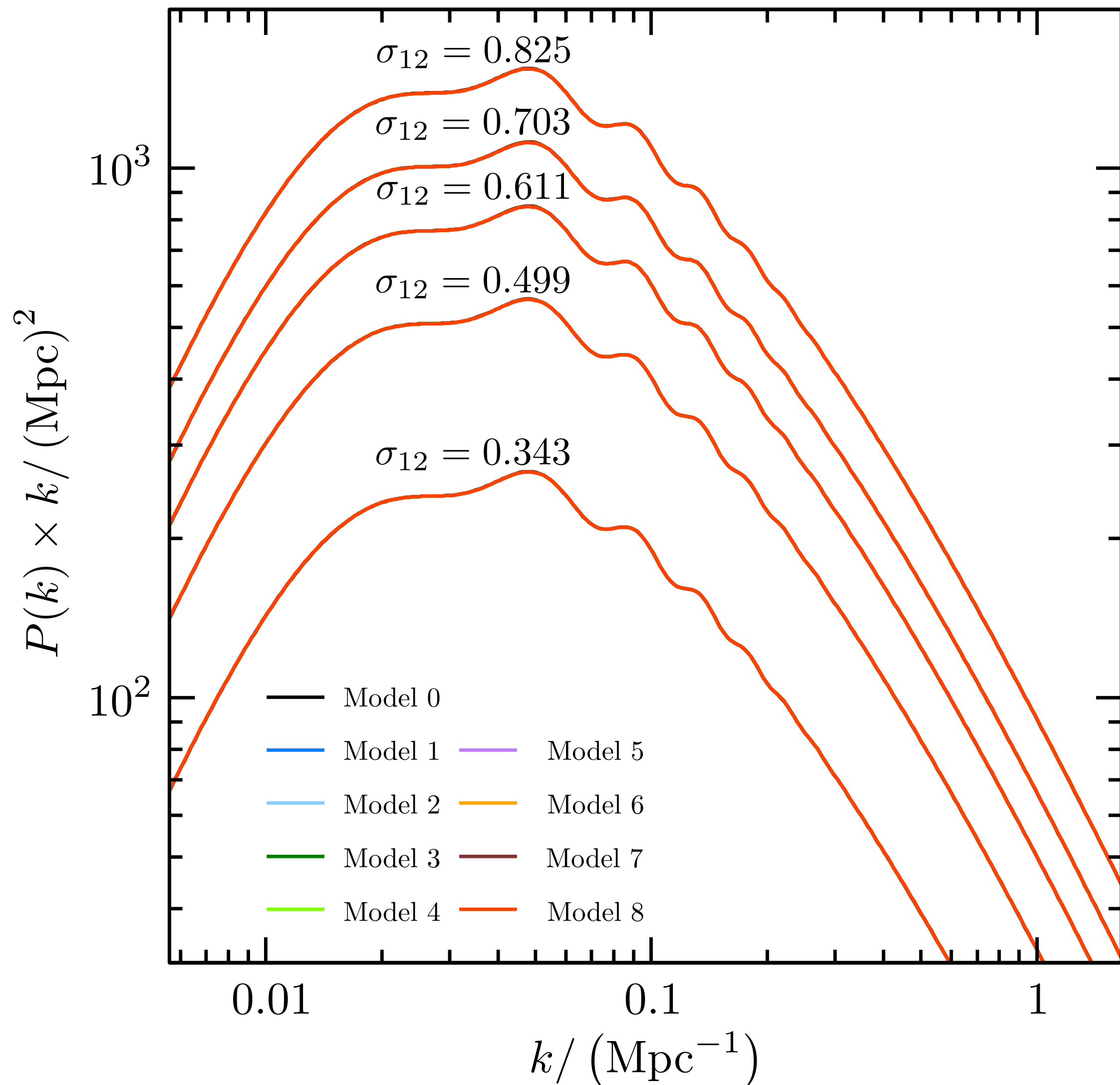
A_s

ω_{DE}

$\omega_{\text{DE}}(a)$

Sánchez (2020)

Evolution mapping: linear $P(k)$

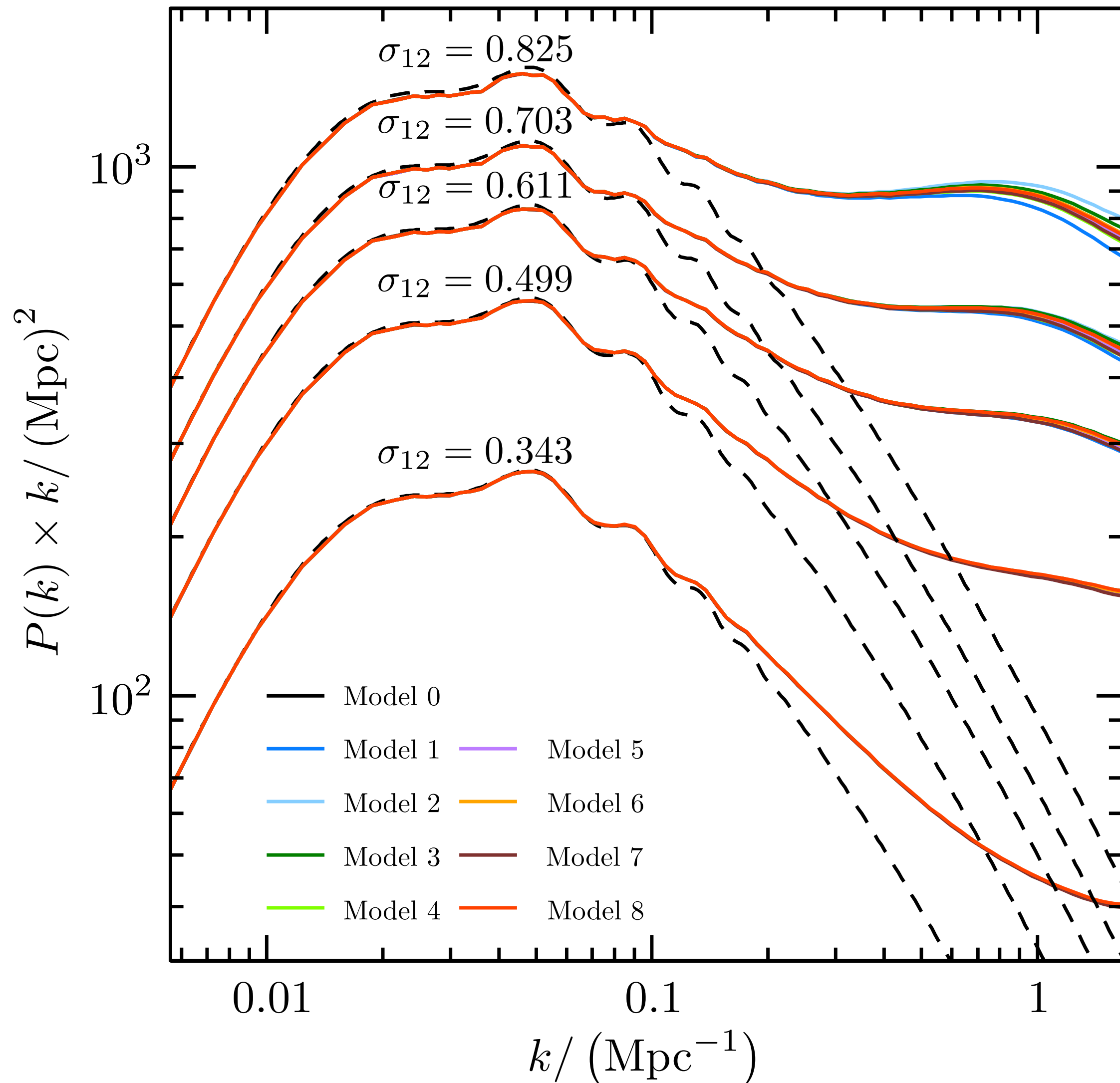


$$P_L(k|z, \Theta_s, \Theta_e) = P_L(k|\Theta_s, \sigma_{12}(z, \Theta_s, \Theta_e))$$

- Impact of evolution parameters on $P(k)$ can be fully described by $\sigma_{12}(z)$, the rms linear variance of the density field in spheres with $R = 12$ Mpc.
- Lost when using quantities that explicitly depend on h (σ_8, Ω_i).

Sánchez (2020); Sánchez et al. (2022)

Evolution mapping: non-linear $P(k)$

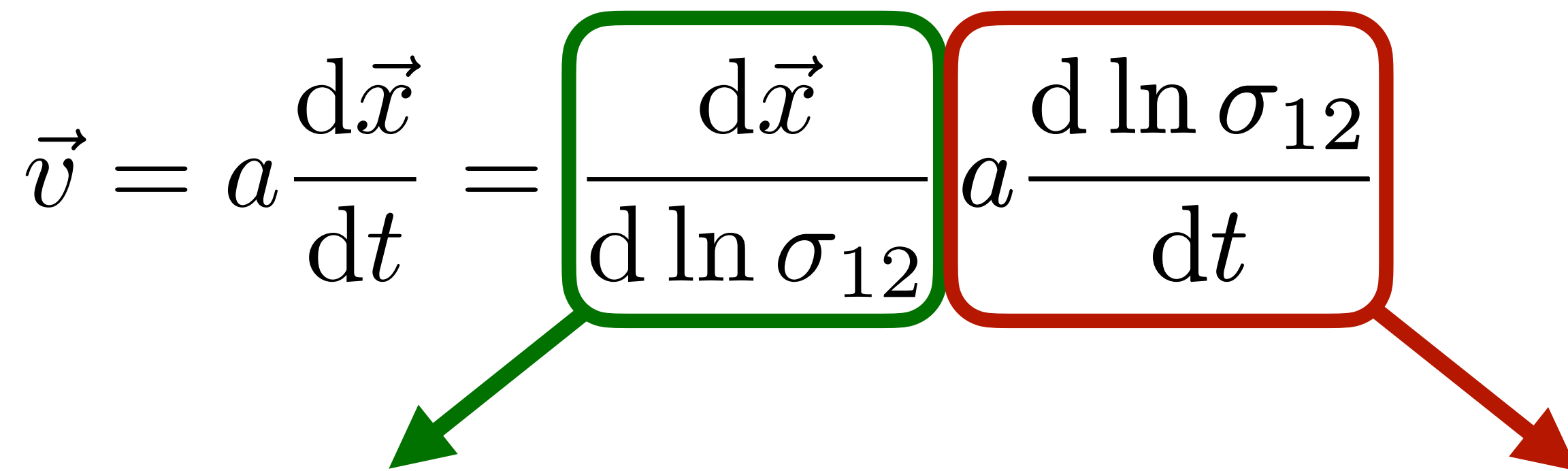


- Given Θ_s , all Θ_e and z leading to the same σ_{12} give indistinguishable $P_L(k)$.
- Evolution mapping is a good approximation also for the $P_{\text{NL}}(k)$.
- Deviations are larger at high k and increase with σ_{12} .

Sánchez (2020); Sánchez et al. (2022)

Evolution mapping: velocity field

- Extend evolution mapping to the statistics of the velocity field which are an essential ingredient for the modelling of the redshift space power spectrum.

$$\vec{v} = a \frac{d\vec{x}}{dt} = \frac{d\vec{x}}{d \ln \sigma_{12}} a \frac{d \ln \sigma_{12}}{dt}$$


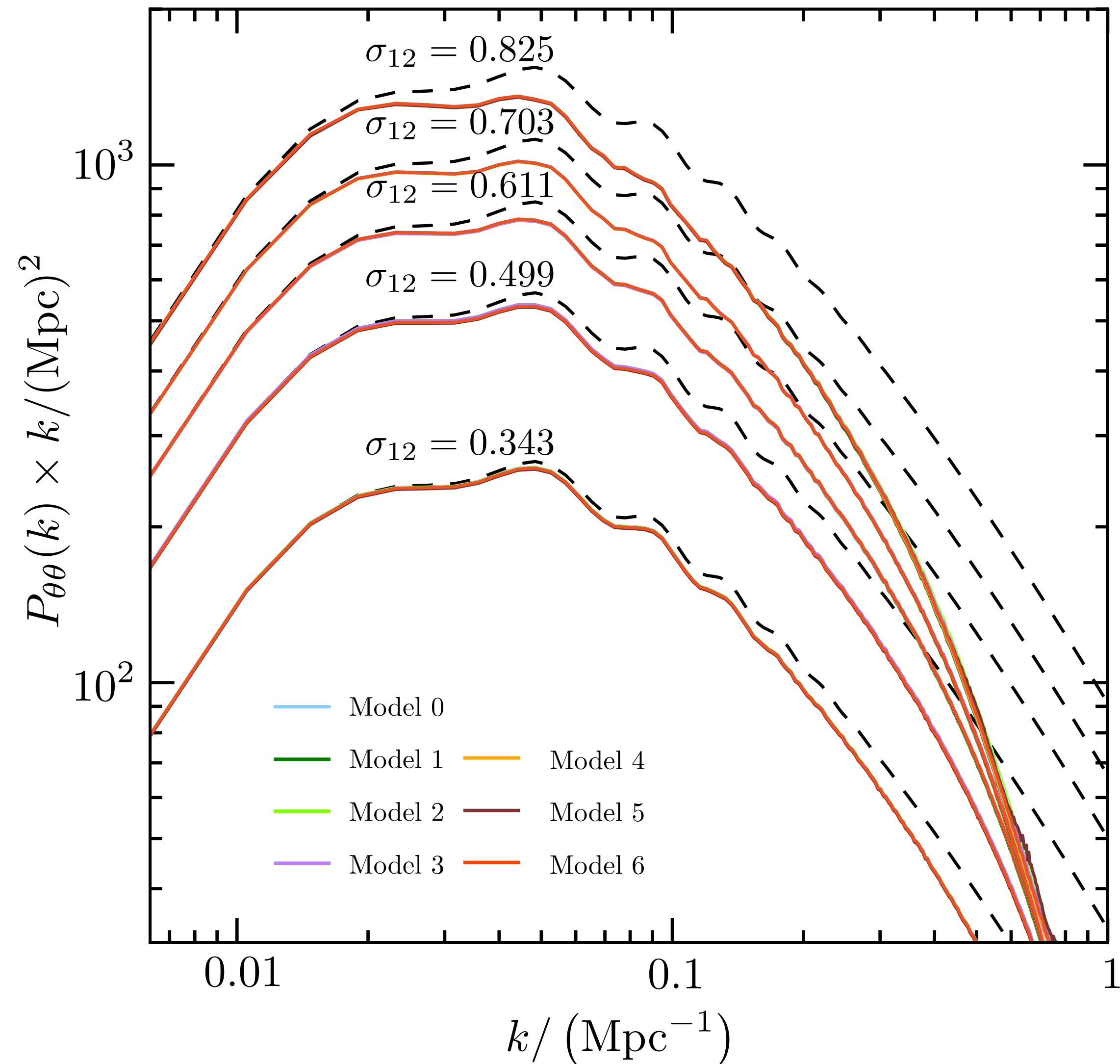
$$a \frac{d \ln \sigma_{12}}{dt} = f a H$$

$$\theta \equiv \frac{\nabla \cdot \vec{v}}{f a H}$$

Trajectories of particles in terms of σ_{12} are almost identical in cosmologies that only differ in shape parameters.

Can be calculated from linear theory and used to map one cosmology to another.

Evolution mapping: velocity divergence $P(k)$



- Evolution mapping is a good approximation also for the $P_{\theta\theta}(k)$.
- Deviations on small scales are smaller than for the $P_{\delta\delta}(k)$.
- This approach can be applied in general to the full particle phase-space and thus to all kind of statistics.

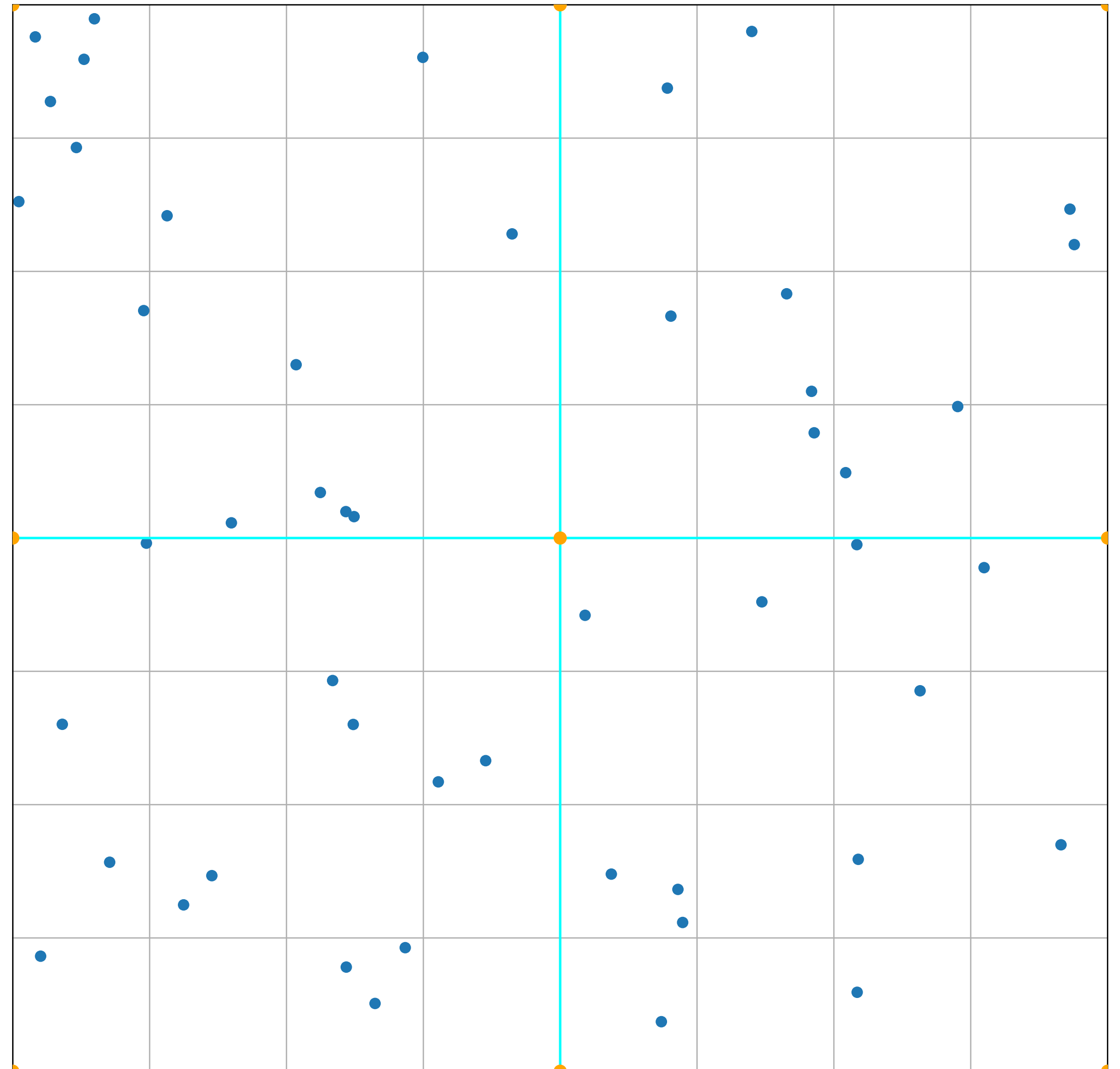


That's all Folks!

Backup slides

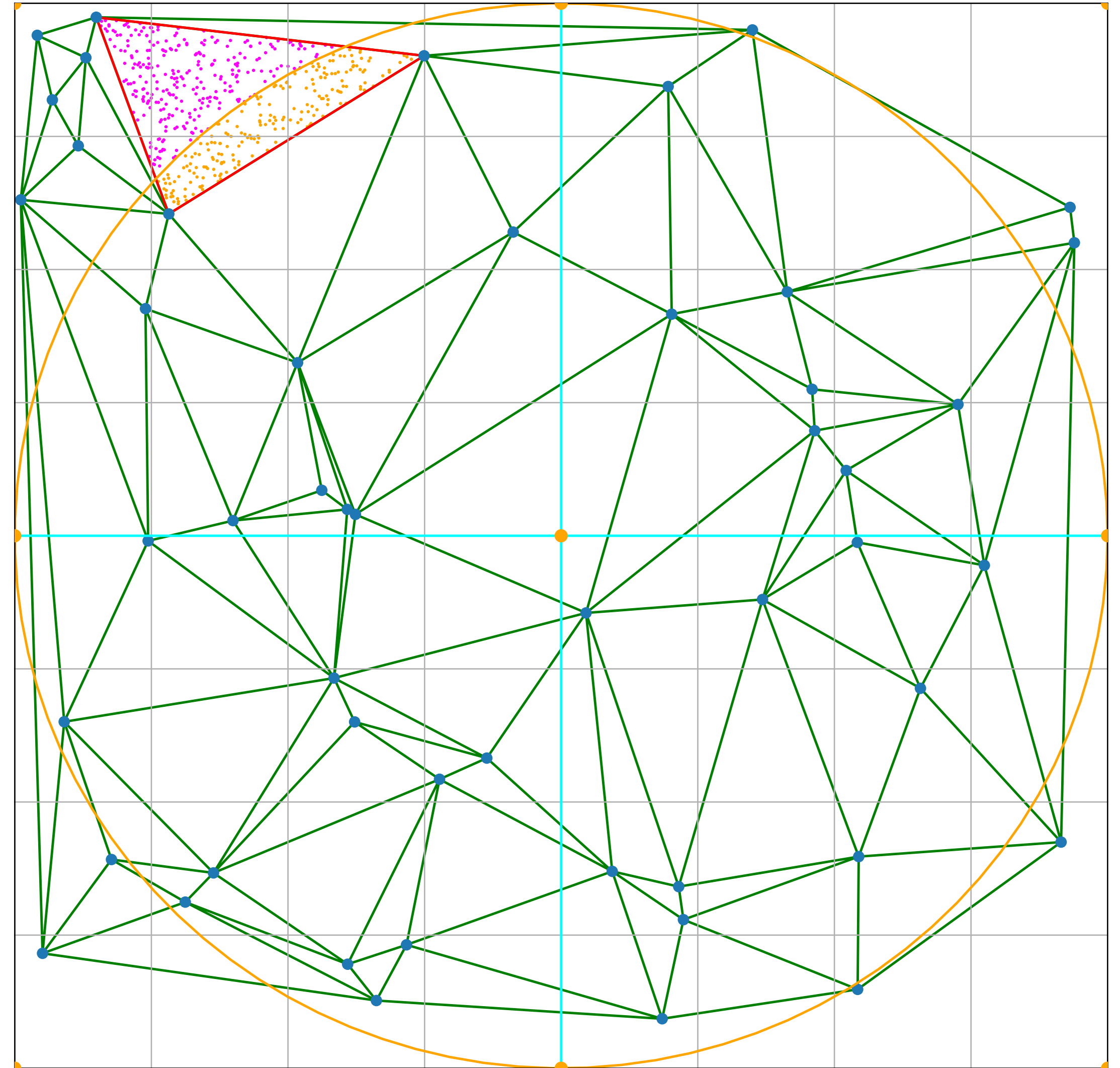
The algorithm

- Assign the particles to cubical cells (green lines) and check if they are:
- Loop over the grid points (orange dots)
 - Fully outside the sphere:
 - skip the step;
 - Center a sphere on the grid point
 - Fully inside the sphere:
 - calculate the mean velocity
 - Gather the particles in the interpolated inside the cubical cells that have the tetrahedron and assign it its center of the sphere as one of their vertices
 - Intersecting the sphere (red triangle):
- Draw a Delaunay tessellation on these particles

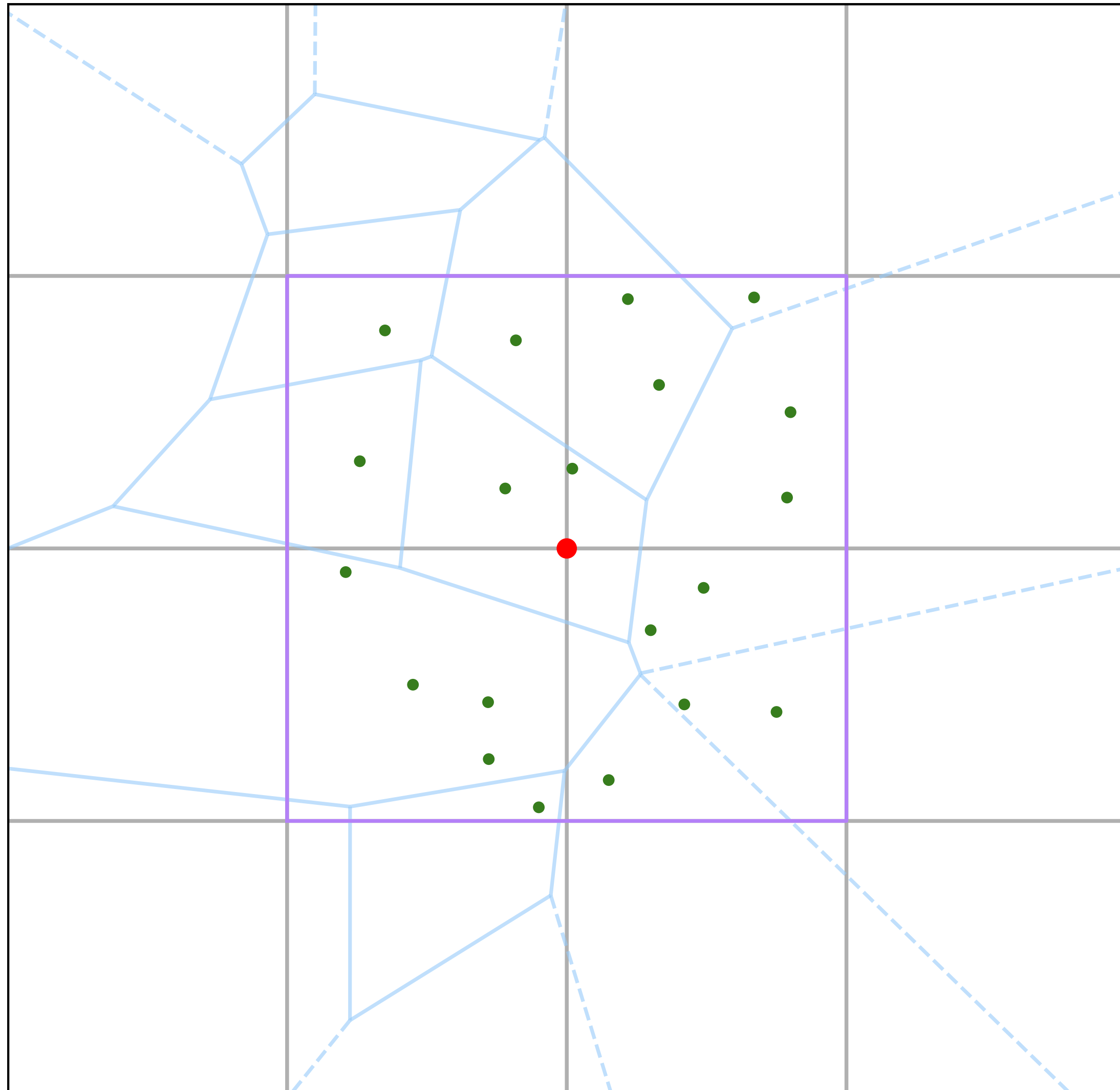


The algorithm

- **Intersecting the sphere (red triangle):**
 - Draw random points inside the tetrahedra
 - Linearly interpolate the velocity for those points that fall inside the sphere (orange dots)
 - Use those points to calculate the average velocity and the volume of the intersection with MC



A simpler approximation



- The Delaunay approach assumes a constant gradient of the field inside each tetrahedron.
- The simplest approximation is to assume the field to be constant inside each Voronoi cell.
- We can use a glass of random points to sample the field in this approximation.
- Faster and comparable results.

Comparison to fitting functions

- Bel et al. (2019) proposed a set of N-body calibrated parametric equations for $P_{\theta\theta}(k, z)$ and $P_{\delta\theta}(k, z)$.

$$P_{\theta\theta}(k) = P_{\theta\theta}^{\text{L}}(k) e^{-k(a_1 + a_2 k + a_3 k^2)}$$

$$P_{\delta\theta}(k) = [P_{\delta\delta}^{\text{NL}}(k) P_{\theta\theta}^{\text{L}}(k)]^{\frac{1}{2}} e^{-\frac{k}{k_\delta} - b k^6}$$

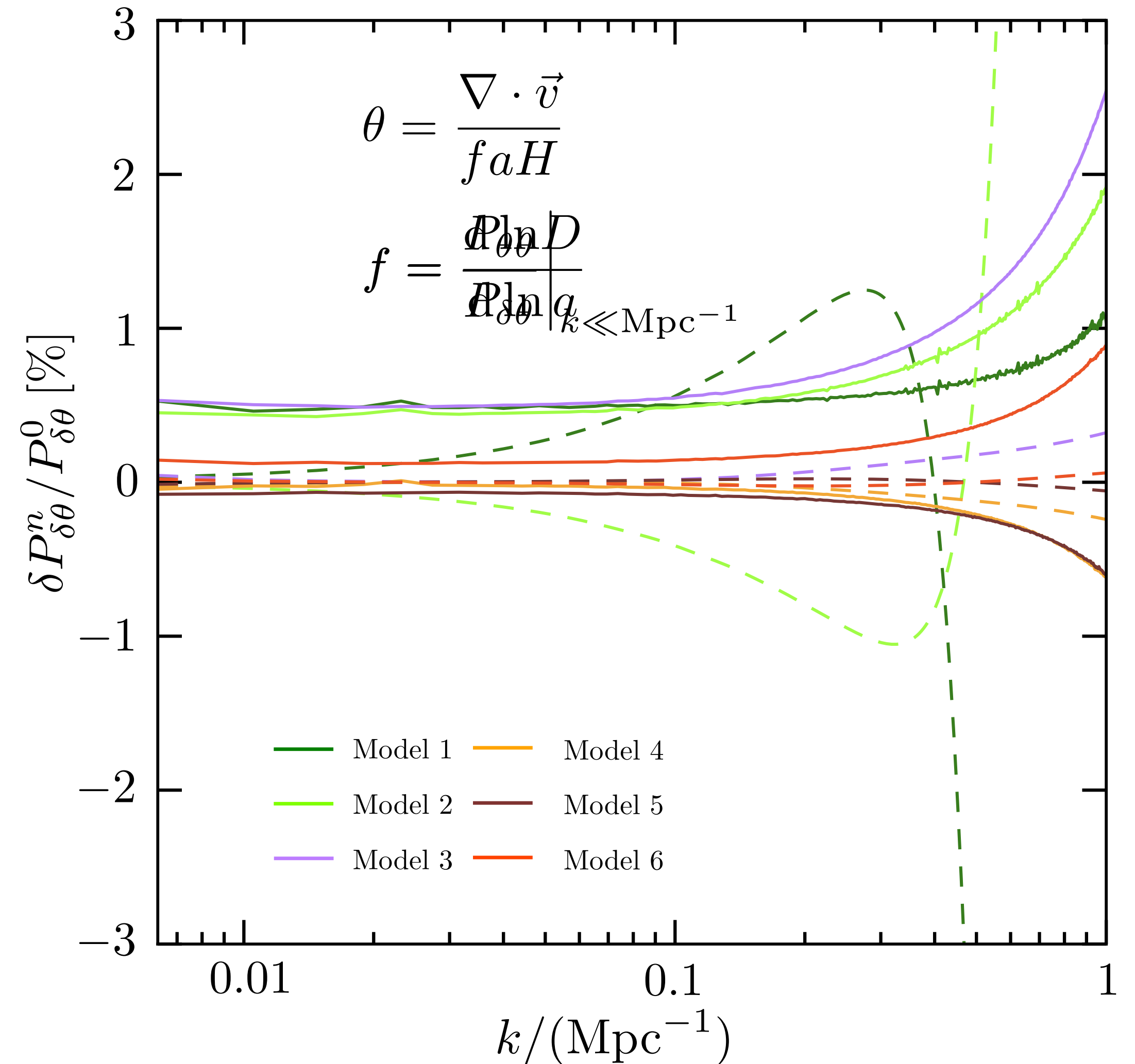
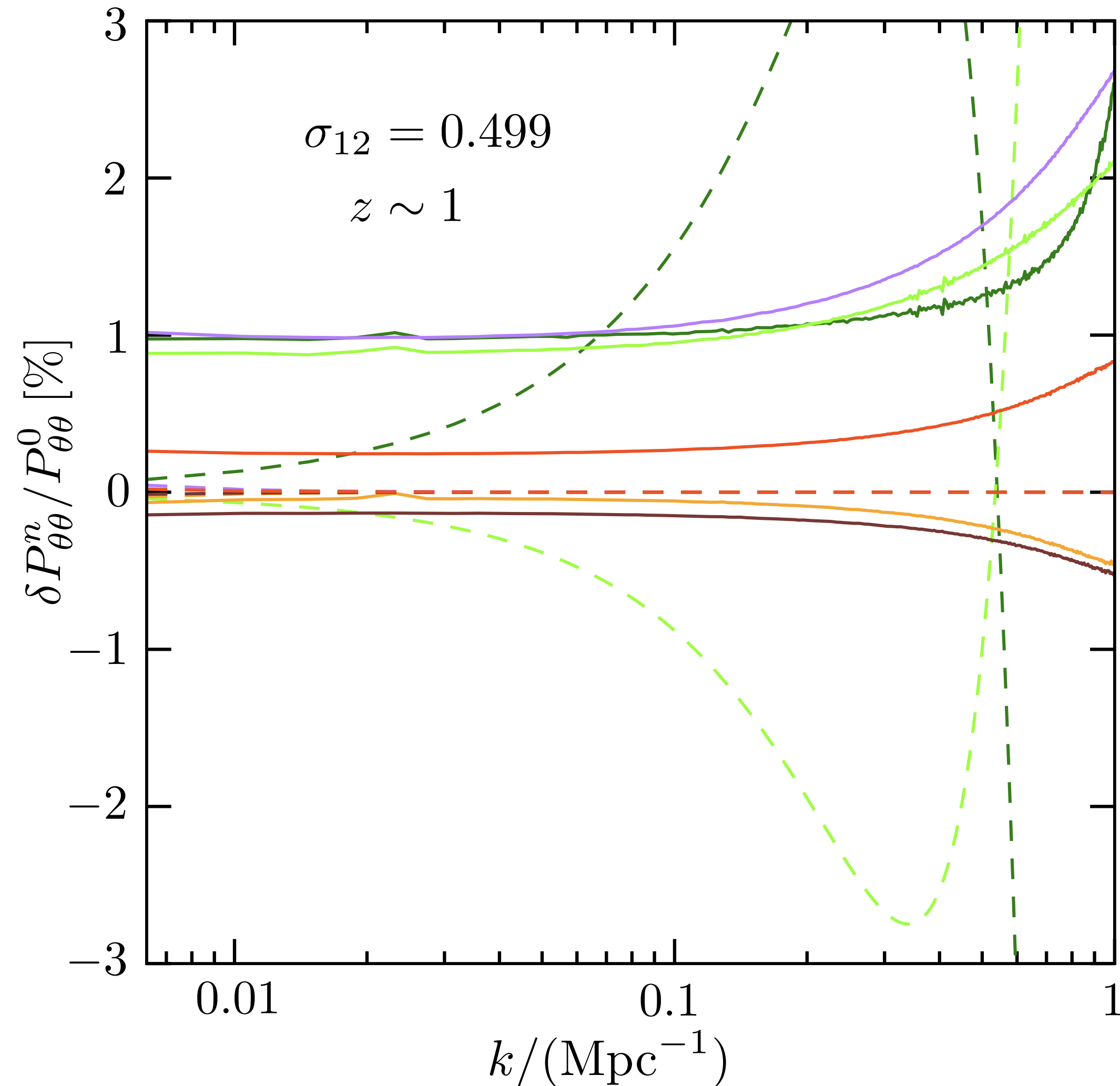
$$\left\{ \begin{array}{l} a_1 = -0.817 + 3.198 \sigma_8(z) \\ a_2 = 0.877 - 4.191 \sigma_8(z) \\ a_3 = -1.199 + 4.629 \sigma_8(z) \\ b = 0.091 + 0.702 \sigma_8^2(z) \\ 1/k_\delta = -0.048 + 1.917 \sigma_8^2(z) \end{array} \right.$$

- Usage of Mpc/ h units in σ_8 , introduces an implicit dependence on h , making the fitting functions unreliable when varying this parameter.

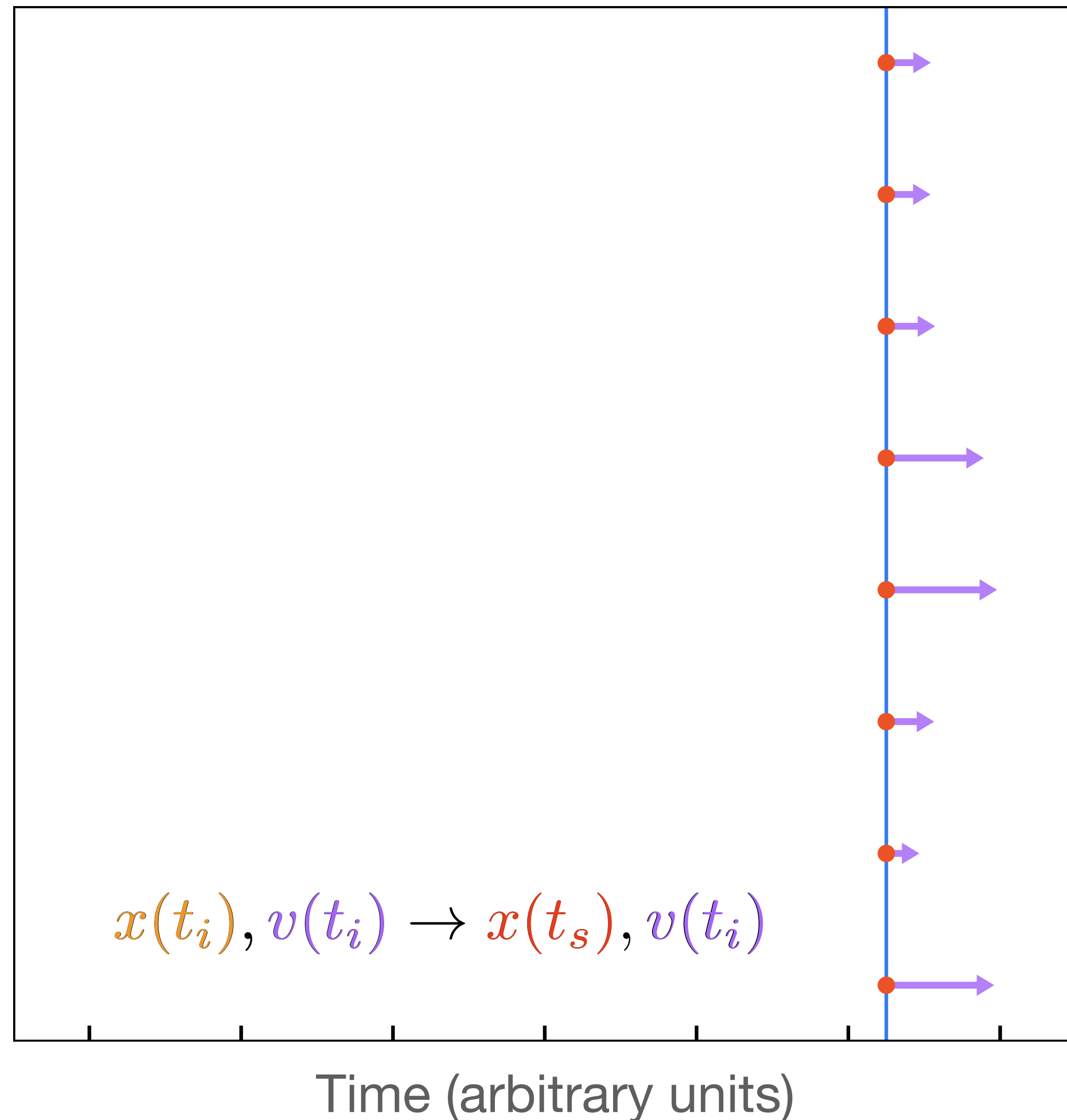
Comparison to fitting functions

$$P_{\theta\theta}(k) = P_{\theta\theta}^L(k) e^{-k(a_1 + a_2 k + a_3 k^2)}$$

$$P_{\delta\theta}(k) = [P_{\delta\delta}^{\text{NL}}(k) P_{\theta\theta}^L(k)]^{\frac{1}{2}} e^{-\frac{k}{k_\delta} - b k^6}$$



A problem with velocities



- Gadget4 produces snapshots at the closest synchronisation point to the required z .
- An optional setting forces snapshots at a specific z at the cost of biased velocities.
- The particle positions get synchronised with a drift to the required redshift while velocities remain unchanged.
- This produces (at first order) an overall shift in the amplitude of the $P_{\theta\theta}(k, z)$.

Emulating the non-linear $P(k)$

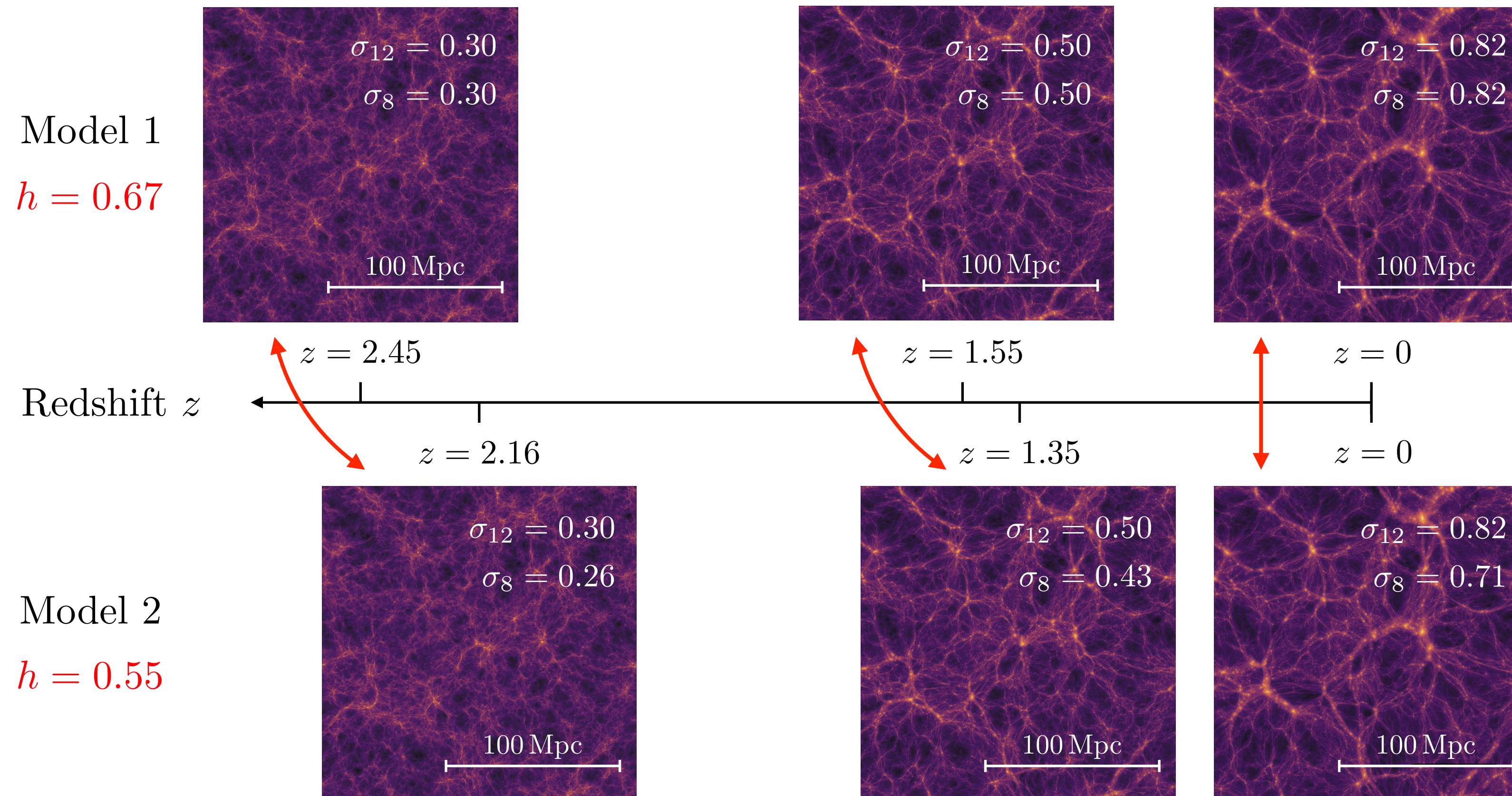
Standard approach: $\Theta = (\underbrace{\omega_c, \omega_b, n_s}_{\text{shape}}, \underbrace{\omega_K, \omega_{\text{DE}}, w_0, w_a, \dots}_{\text{evolution}}, z)$

Evolution mapping: $\Theta = (\omega_c, \omega_b, n_s, \sigma_{12})$

CASSANDRA

Evolution mapping reduces the required number of parameters to describe $P(k|z)$.

Emulator results must be corrected by $\Delta g(\sigma_{12})$



Linear level

$$v_j(k, a) = i \frac{k_j}{k^2} \mathcal{H} f(a) \delta_m(k, a). \quad \Theta_k \equiv \frac{ik_j v_j(k, a)}{Ha}$$

$$P_{\Theta\Theta}(k, a) = f^2 P_m(k, a)$$

$$\frac{d\sigma_{12}}{dt} = \sigma_{12}(z) \frac{dD(z)}{da} \frac{da}{dt} = f(a) H(a) \sigma_{12} \quad v = a \frac{dx}{dt} = a \frac{dx}{d\sigma_{12}} \frac{d\sigma_{12}}{dt} = \tilde{v} \sigma_{12} f a H$$

$$\tilde{\Theta}_k \equiv ik_j \tilde{v}_j(k, a) = - \frac{\delta_m(k, a)}{\sigma_{12}}$$

$$P_{\tilde{\Theta}\tilde{\Theta}}(k, a) = \frac{P_m(k, a)}{(\sigma_{12})^2}$$