

# Signatures of primordial NG in CMB and LSS

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# Primordial non-G + observations

1. **CMB:** can we independently constrain every interesting non-Gaussian signal?
2. **Large-scale structure:** what non-Gaussian signals can be constrained, and what are the degeneracies?

# EFT of inflation

$\pi$  = Goldstone boson of spontaneously broken time translations

1-1 correspondence between operators in  $S_\pi$  and  $f_{NL}$ -like parameters  
(Degree-N operator shows up in N-point CMB correlation function)

$$S_\pi = \int d^4x \sqrt{-g} (-\dot{H} M_{\text{pl}}^2) \left[ \frac{\dot{\pi}^2}{c_s^2} - \frac{(\partial_i \pi)^2}{a^2} \right.$$

$$\left. + \frac{A}{c_s^2} \pi_t^3 + \frac{1 - c_s^2}{c_s^2} \frac{\pi_t (\partial_i \pi)^2}{a^2} \right.$$

Equilateral+orthogonal 3-point shapes  
(Senatore, KMS & Zaldarriaga 2009)

$$\left. + B \pi_{ttt}^3 + C \pi_{ttt} \pi_{ijk}^2 + \dots \right.$$

Higher-derivative 3-point shapes  
(Behbahani, Mirbabayi, Senatore & KMS to appear)

$$\left. + D \dot{\pi}^4 + E \dot{\pi}^2 (\partial_i \pi)^2 + F (\partial_i \pi)^2 (\partial_j \pi)^2 + \dots \right.$$

4-point shapes  
(Senatore & Zaldarriaga 2009)

$$\left. + \rho \dot{\pi} \sigma + G \sigma^3 + \dots \right]$$

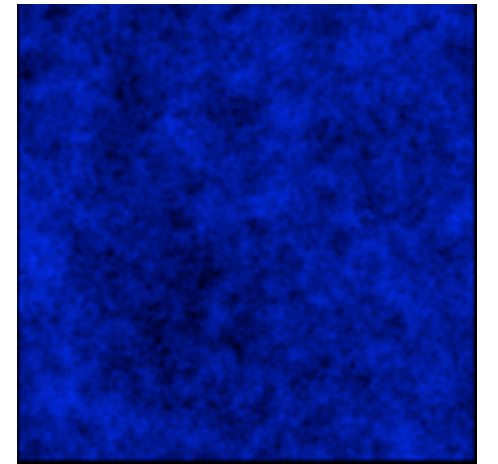
Quasi single-field inflation  
(Chen & Wang 2009)

# CMB data analysis

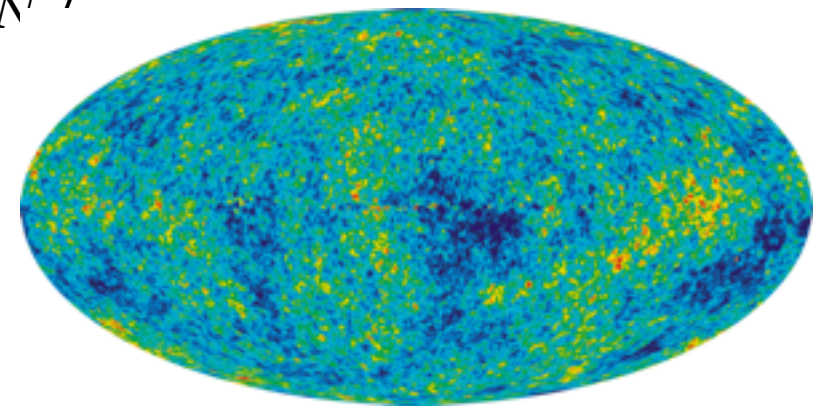
Degree-N operator  $\mathcal{O}$  (e.g.  $\mathcal{O} = \dot{\pi}^3$  or  $\mathcal{O} = \dot{\pi}^4$ )



Curvature N-point function  $\langle \zeta_{\mathbf{k}_1} \zeta_{\mathbf{k}_2} \cdots \zeta_{\mathbf{k}_N} \rangle$



CMB N-point function  $\langle a_{\ell_1 m_1} a_{\ell_2 m_2} \cdots a_{\ell_N m_N} \rangle$



CMB estimator

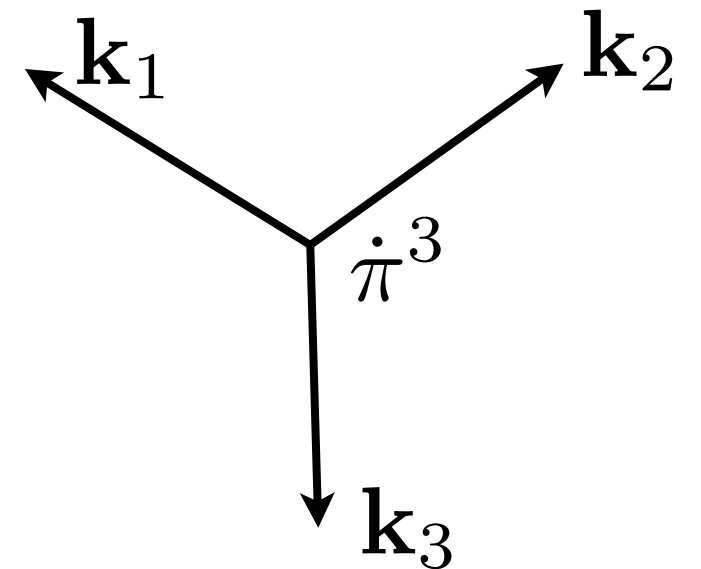
$$\mathcal{E} = \sum_{\ell_i m_i} \langle a_{\ell_1 m_1} a_{\ell_2 m_2} \cdots a_{\ell_N m_N} \rangle \prod_{i=1}^N \tilde{a}_{\ell_i m_i} + \cdots$$

# Computational difficulties

Example:  $\dot{\pi}^3$  interaction

Computing the curvature 3-point function is straightforward...

$$\begin{aligned}\langle \zeta_{\mathbf{k}_1} \zeta_{\mathbf{k}_2} \zeta_{\mathbf{k}_3} \rangle &\propto \int_{-\infty}^0 d\tau \frac{\tau^2 e^{(k_1+k_2+k_3)\tau}}{k_1 k_2 k_3} \\ &= \frac{2}{k_1 k_2 k_3 (k_1 + k_2 + k_3)^3}\end{aligned}$$



# Computational difficulties

...but subsequent steps look intractable in full generality:

**CMB three-point function:** 4D oscillatory integral for each  $(\ell_i, m_i)$

$$\langle a_{\ell_1 m_1} a_{\ell_2 m_2} a_{\ell_3 m_3} \rangle = \sqrt{\frac{(2\ell_1 + 1)(2\ell_2 + 1)(2\ell_3 + 1)}{4\pi}} \begin{pmatrix} \ell_1 & \ell_2 & \ell_3 \\ 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} \ell_1 & \ell_2 & \ell_3 \\ m_1 & m_2 & m_3 \end{pmatrix} \\ \times \int dr dk_1 dk_2 dk_3 \left( \prod_{i=1}^3 \frac{2k_i^2}{\pi} j_{\ell_i}(k_i r) \Delta_{\ell_i}(k_i) \right) \langle \zeta_{\mathbf{k}_1} \zeta_{\mathbf{k}_2} \zeta_{\mathbf{k}_3} \rangle$$

CMB transfer function (computed numerically)

**CMB estimator:** number of terms in sum is  $\mathcal{O}(\ell_{\max}^5)$

$$\mathcal{E} = \sum_{\ell_i m_i} \langle a_{\ell_1 m_1} a_{\ell_2 m_2} a_{\ell_3 m_3} \rangle \tilde{a}_{\ell_1 m_1} \tilde{a}_{\ell_2 m_2} \tilde{a}_{\ell_3 m_3} + \dots$$

observed CMB multiples (appropriately filtered)

# Factorizability = computability

Suppose the curvature 3-point function is **factorizable**

$$\langle \zeta_{\mathbf{k}_1} \zeta_{\mathbf{k}_2} \zeta_{\mathbf{k}_3} \rangle = f_1(k_1) f_2(k_2) f_3(k_3) + 5 \text{ perm.}$$

Define (and precompute)  $\alpha_\ell^{(i)}(r) = \int \frac{2k^2 dk}{\pi} f_i(k) j_\ell(kr)$

**CMB three-point function** is fast to compute:

$$\langle a_{\ell_1 m_1} a_{\ell_2 m_2} a_{\ell_3 m_3} \rangle = \sqrt{\frac{(2\ell_1 + 1)(2\ell_2 + 1)(2\ell_3 + 1)}{4\pi}} \begin{pmatrix} \ell_1 & \ell_2 & \ell_3 \\ 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} \ell_1 & \ell_2 & \ell_3 \\ m_1 & m_2 & m_3 \end{pmatrix} \\ \times \int dr r^2 \alpha_{\ell_1}^{(1)}(r) \alpha_{\ell_2}^{(2)}(r) \alpha_{\ell_3}^{(3)}(r) + 5 \text{ perm.}$$

**CMB estimator** is fast to evaluate:

$$\mathcal{E} = \int r^2 dr \int d^2 \mathbf{n} \prod_{i=1}^3 \left( \sum_{\ell m} \alpha_\ell^{(i)} \tilde{a}_{\ell m} Y_{\ell m}(\mathbf{n}) \right)$$

*Komatsu, Spergel & Wandelt 2003*

*Creminelli, Nicolis, Senatore, Tegmark & Zaldarriaga 2005*

*KMS & Zaldarriaga 2006*

# Making shapes factorizable

Two possibilities for making shape factorizable

$$\text{e.g. } \pi^3 \text{ shape: } \langle \zeta_{\mathbf{k}_1} \zeta_{\mathbf{k}_2} \zeta_{\mathbf{k}_3} \rangle = \frac{2}{k_1 k_2 k_3 (k_1 + k_2 + k_3)^3}$$

1. approximate by a factorizable shape (“template shape”)

$$\langle \zeta_{\mathbf{k}_1} \zeta_{\mathbf{k}_2} \zeta_{\mathbf{k}_3} \rangle \approx \frac{-\sum_i k_i^3 + \sum_{i \neq j} k_i k_j^2 - 2k_1 k_2 k_3}{k_1^3 k_2^3 k_3^3}$$

equilateral template



2. perform an algebraic magic trick, e.g. find integral representation

$$\langle \zeta_{\mathbf{k}_1} \zeta_{\mathbf{k}_2} \zeta_{\mathbf{k}_3} \rangle = \int_{-\infty}^0 t^2 dt \left( \frac{e^{tk_1}}{k_1} \right) \left( \frac{e^{tk_2}}{k_2} \right) \left( \frac{e^{tk_3}}{k_3} \right)$$

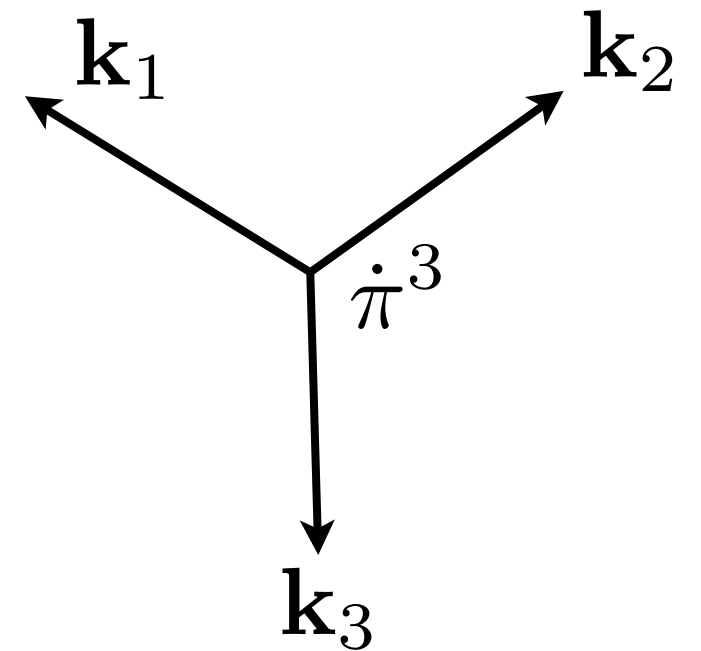
*KMS & Zaldarriaga 2006*



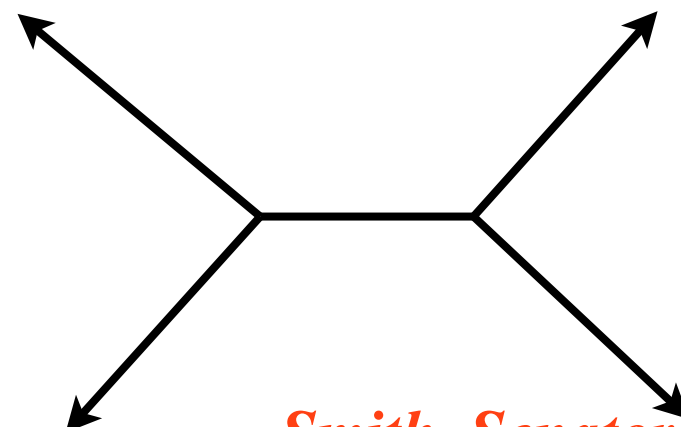
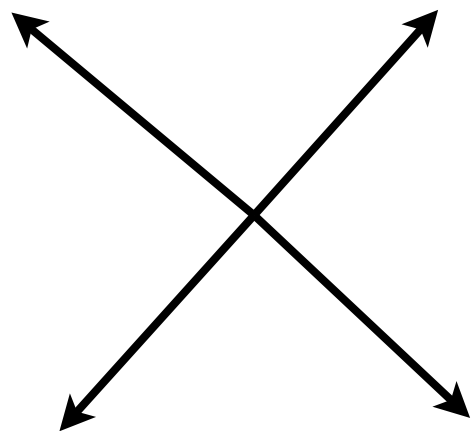
# Factorizability + Feynman diagrams

**Observation:** for  $\dot{\pi}^3$  shape, the integral representation is just undoing the last step of the Feynman diagram calculation

$$\begin{aligned} \langle \zeta_{\mathbf{k}_1} \zeta_{\mathbf{k}_2} \zeta_{\mathbf{k}_3} \rangle &\propto \int_{-\infty}^0 d\tau \frac{\tau^2 e^{(k_1+k_2+k_3)\tau}}{k_1 k_2 k_3} \\ &= \frac{2}{k_1 k_2 k_3 (k_1 + k_2 + k_3)^3} \end{aligned}$$



Generalizes to any **tree diagram**, e.g. 4-point estimators:

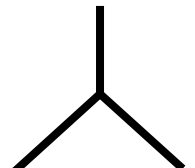


*Smith, Senatore & Zaldarriaga, to appear*

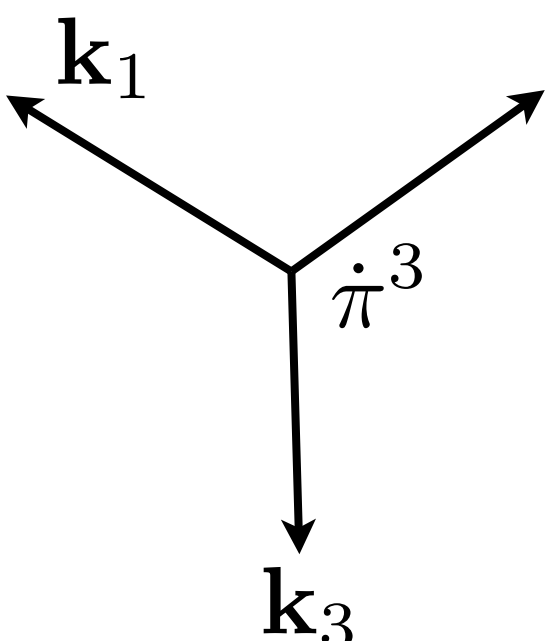
# Factorizability + Feynman diagrams

**Ultimate generalization** of KSW construction: “Estimator” Feynman rules which go directly from the diagram to the CMB estimator

$\longrightarrow$  external line = CMB + harmonic-space factor  $\alpha_\ell(r, t) \tilde{a}_{\ell m}$

 vertex =  $\int r^2 dr dt$  ( N-way real-space product )

$\text{---}$  internal line = harmonic-space factor  $A_\ell(r, t, r', t')$

e.g.   $\mathcal{E} = \int r^2 dr dt \left( \sum_{\ell m} \alpha_\ell(r, t) \tilde{a}_{\ell m} Y_{\ell m}(\mathbf{n}) \right)^3$

# Example: resonant NG

Just an example to illustrate the power of this method in finding a factorizable representation...

$$\langle \zeta_{\mathbf{k}_1} \zeta_{\mathbf{k}_2} \zeta_{\mathbf{k}_3} \rangle \propto \frac{1}{k_1^2 k_2^2 k_3^2} \left[ \sin \left( A \log \frac{k_1 + k_2 + k_3}{k_*} \right) + A^{-1} \sum_{i \neq j} \frac{k_i}{k_j} \cos \left( A \log \frac{k_1 + k_2 + k_3}{k_*} \right) \right]$$

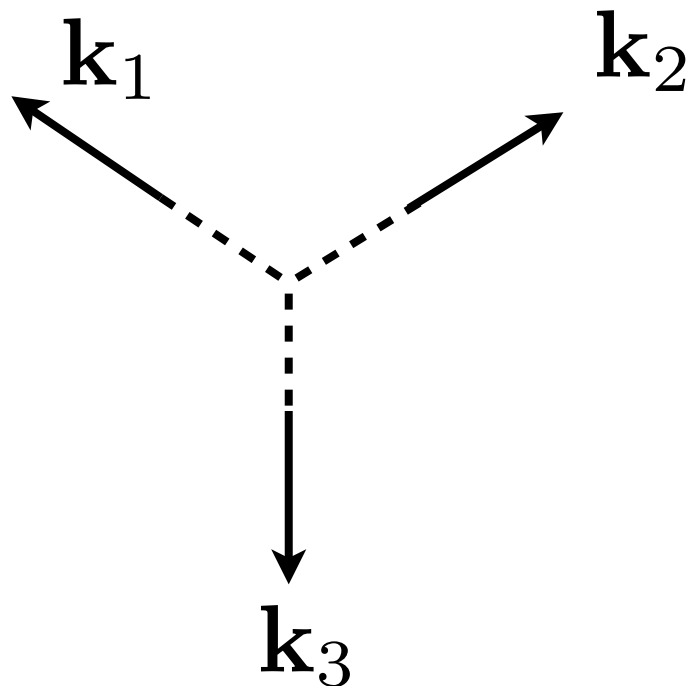
Hard to see how this could ever be made factorizable, but going back to the physics gives the following factorizable representation!

$$\langle \zeta_{\mathbf{k}_1} \zeta_{\mathbf{k}_2} \zeta_{\mathbf{k}_3} \rangle \propto \text{Re} \left[ \frac{e^{(1+iA) \log(i+iA) + iA \log k_*}}{A \Gamma(1+iA)} \int_{-\infty}^{\infty} dx e^{(1+iA)x} g(k_1, x) g(k_2, x) g(k_3, x) \right. \\ \left. \times \left( \left( 1 + \frac{iA}{2} \right) \frac{1}{k_1 k_2^2 k_3^2} + \frac{1}{k_2^2 k_3^3} + \frac{1}{k_1 k_2 k_3^3} + 5 \text{ perm.} \right) \right]$$

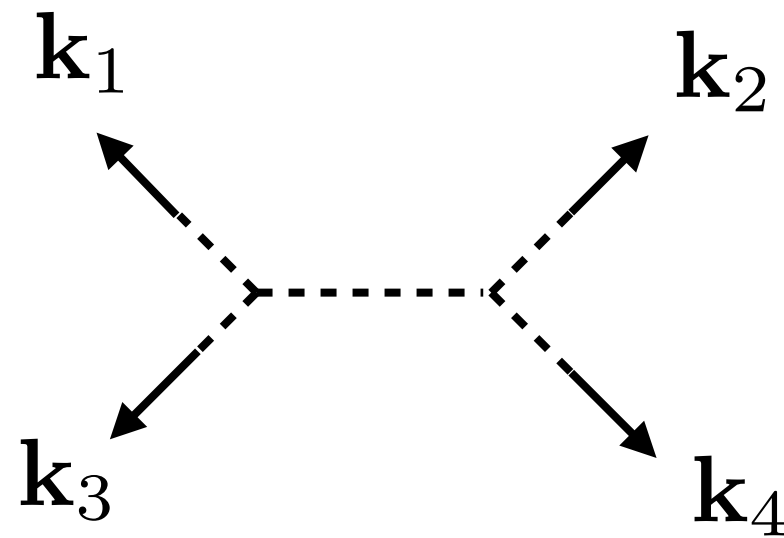
$$g(k, x) = \exp[-(1+iA)ke^x]$$

# Example: quasi single field inflation

$$S_\pi = \int d^4x \sqrt{-g} \left( \frac{1}{2} (\partial\pi)^2 + \frac{1}{2} (\partial\sigma)^2 - \frac{M^2}{2} \sigma^2 + \rho \dot{\pi} \sigma - \frac{g}{3!} \sigma^3 \right)$$



$$\langle \zeta_{\mathbf{k}_1} \zeta_{\mathbf{k}_2} \zeta_{\mathbf{k}_3} \rangle \propto g \rho^3$$



$$\langle \zeta_{\mathbf{k}_1} \zeta_{\mathbf{k}_2} \zeta_{\mathbf{k}_3} \zeta_{\mathbf{k}_4} \rangle \propto g^2 \rho^4$$

Because 3-point function and 4-point function depend on different combinations of parameters, either one can have larger signal-to-noise in different parts of the QSFI parameter space

# Data analysis “to do” list...

For any “physical” shape, current machinery seems to be sufficient to do the analysis! A (possibly incomplete) to do list:

- Higher derivative shapes ( $\ddot{\pi}^3, \ddot{\pi} \pi_{ijk}^2, \dots$ )
- Quartic interactions ( $\dot{\pi}^4, \dot{\pi}^2 \partial_i \pi^2, \partial_i \pi^2 \partial_j \pi^2, \dots$ )
- Quasi single-field inflation
- Solid inflation
- Anything else... ?

# Large-scale structure

Local model:  $\zeta(\mathbf{x}) = \zeta_G(\mathbf{x}) + \frac{3}{5} f_{NL} \zeta_G(\mathbf{x})^2$

Non-Gaussian contribution to **halo bias** on large scales:

$$b(k) \approx b_0 + f_{NL} \frac{b_1}{(k/aH)^2} \quad \text{as } k \rightarrow 0$$

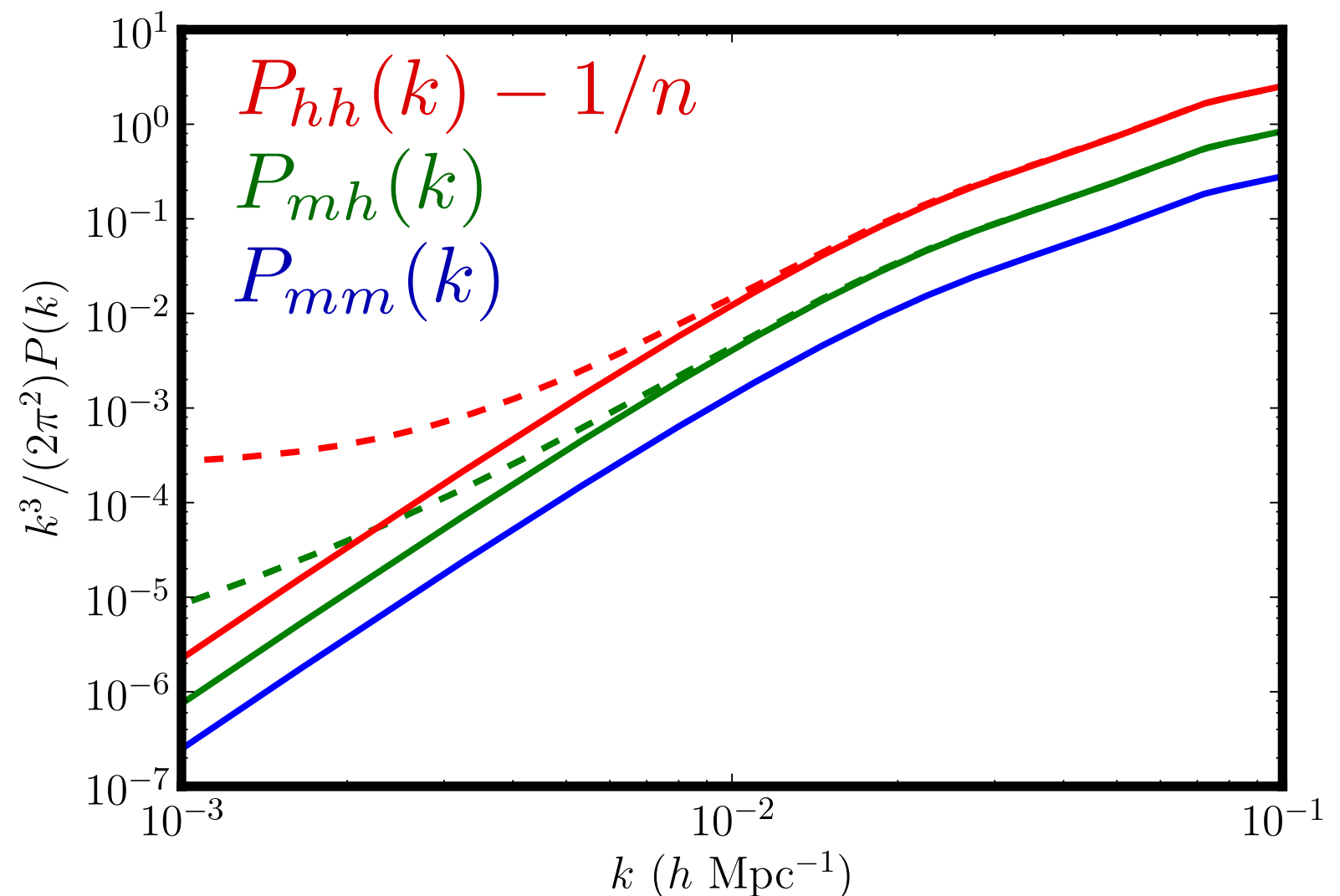
$$P_{mh}(k) \approx b(k) P_{mm}(k)$$

$$P_{hh}(k) \approx b(k)^2 P_{mm}(k)$$

Constraints are ultimately  
**better than the CMB**

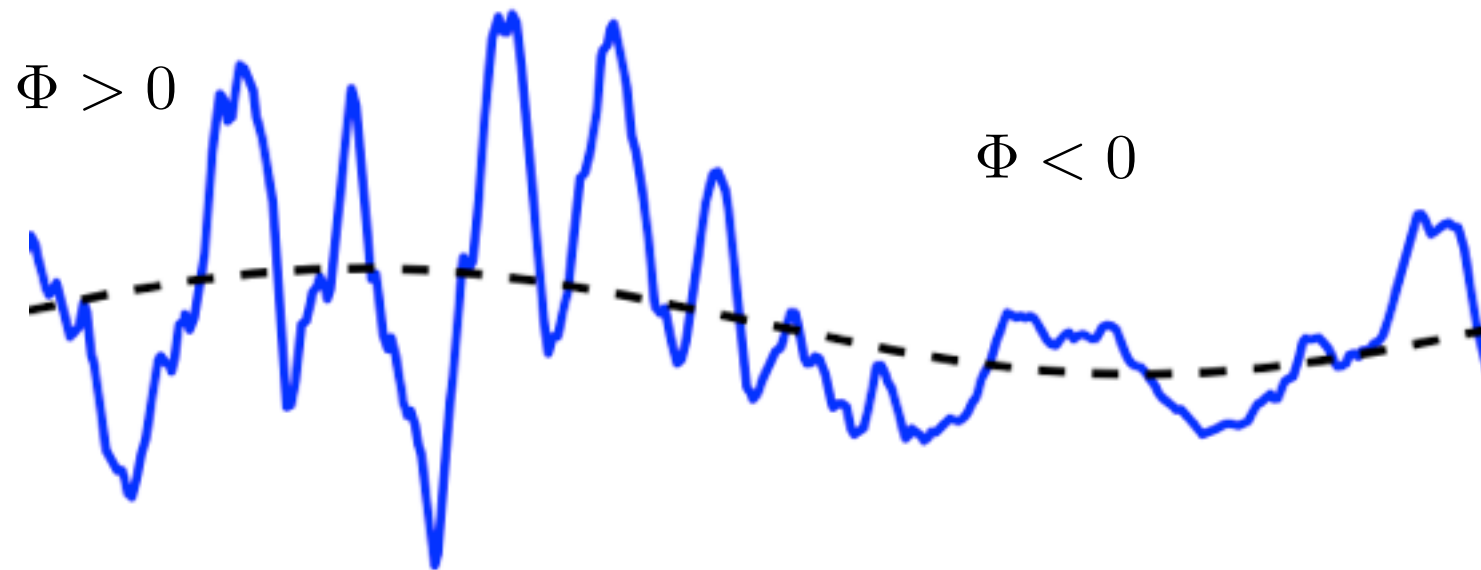
Planck:  $\sigma(f_{NL}) = 5$

LSST:  $\sigma(f_{NL}) \sim 1$



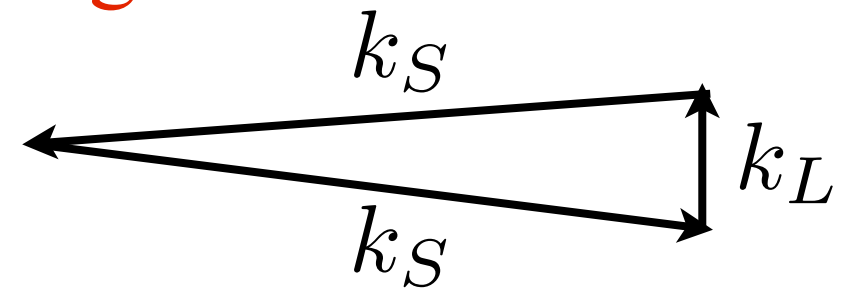
# NG halo bias: interpretation

Correlation between long-wavelength mode and small-scale power



Three-point function is large in **squeezed triangles**

$$\langle \zeta_{\mathbf{k}_L} \zeta_{\mathbf{k}_S} \zeta_{\mathbf{k}_S} \rangle \propto f_{NL} \frac{1}{k_L^3 k_S^3}$$

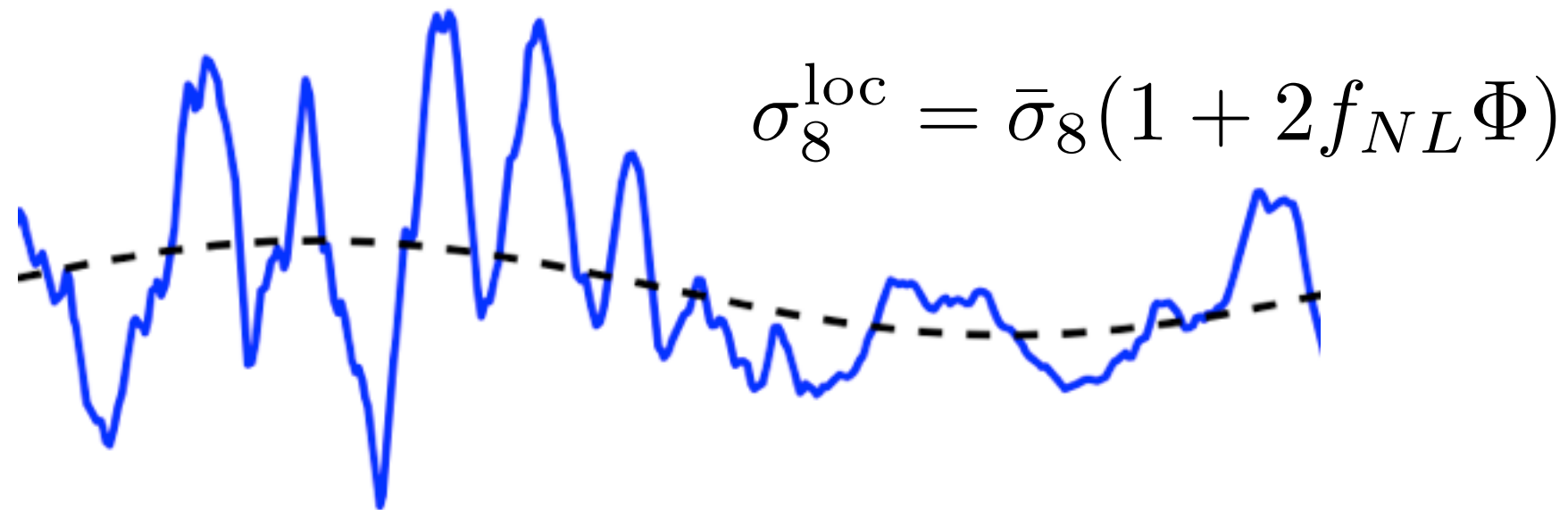


Locally measured fluctuation amplitude  $\sigma_8^{\text{loc}}$  near a point  $\mathbf{x}$  depends on value of Newtonian potential  $\Phi(\mathbf{x})$

$$\sigma_8^{\text{loc}} = \bar{\sigma}_8 (1 + 2f_{NL}\Phi)$$

# NG halo bias: interpretation

This picture naturally leads to **enhanced large-scale clustering**



$$\frac{\delta n_h}{\bar{n}_h} = \underbrace{\frac{\partial \log n_h}{\partial \log \rho_m}}_{b_0} \frac{\delta \rho_m}{\bar{\rho}_m} + \underbrace{\frac{\partial \log n_h}{\partial \log \sigma_8}}_{b_1/2} \frac{\delta \sigma_8}{\bar{\sigma}_8}$$

$$= b_0 \frac{\delta \rho_m}{\bar{\rho}_m} + b_1 f_{NL} \Phi$$

$$= \left( b_0 + b_1 \frac{f_{NL}}{(k/aH)^2} \right) \frac{\delta \rho_m}{\bar{\rho}_m}$$

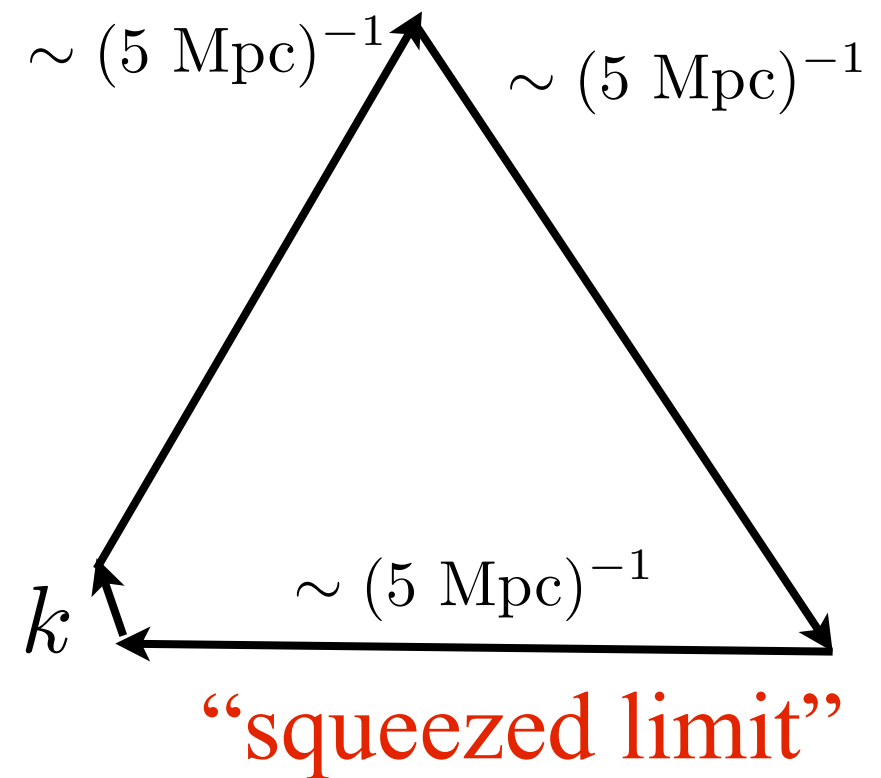


# General expression for non-Gaussian clustering

Schematic form:

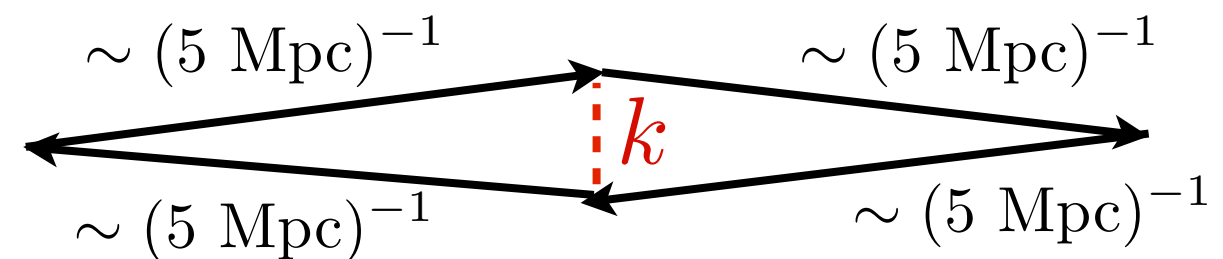
$$P_{mh}(k) = \left( b_0 + \sum_{N=1}^{\infty} b_N f_{N+2}(k) \right) P_{mm}(k)$$

$$f_N(k) = \int_{\mathbf{k}_i} \langle \zeta_{\mathbf{k}} \zeta_{\mathbf{k}_1} \cdots \zeta_{\mathbf{k}_{N-1}} \rangle$$



$$P_{hh}(k) = \left( b_0^2 + 2 \sum_{N=1}^{\infty} b_0 b_N f_{N+2}(k) + \sum_{MN} b_M b_N g_{M+1, N+1}(k) \right) P_{mm}(k)$$

$$g_{MN}(k) = \int_{\substack{\sum \mathbf{k}_i = \mathbf{k} \\ \sum \mathbf{k}'_j = -\mathbf{k}}} \langle \zeta_{\mathbf{k}_1} \cdots \zeta_{\mathbf{k}_M} \zeta_{\mathbf{k}'_1} \cdots \zeta_{\mathbf{k}'_N} \rangle$$

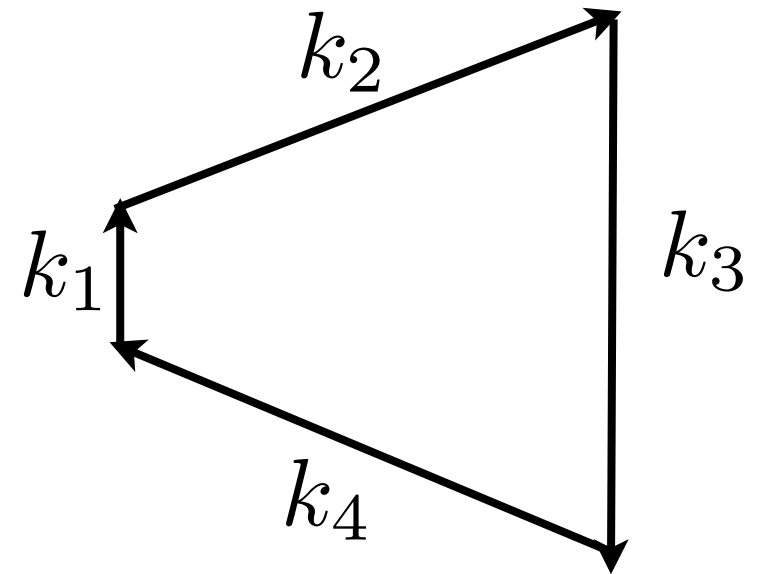


# Example 1: bias from squeezed 4-point function

$g_{NL}$  model:

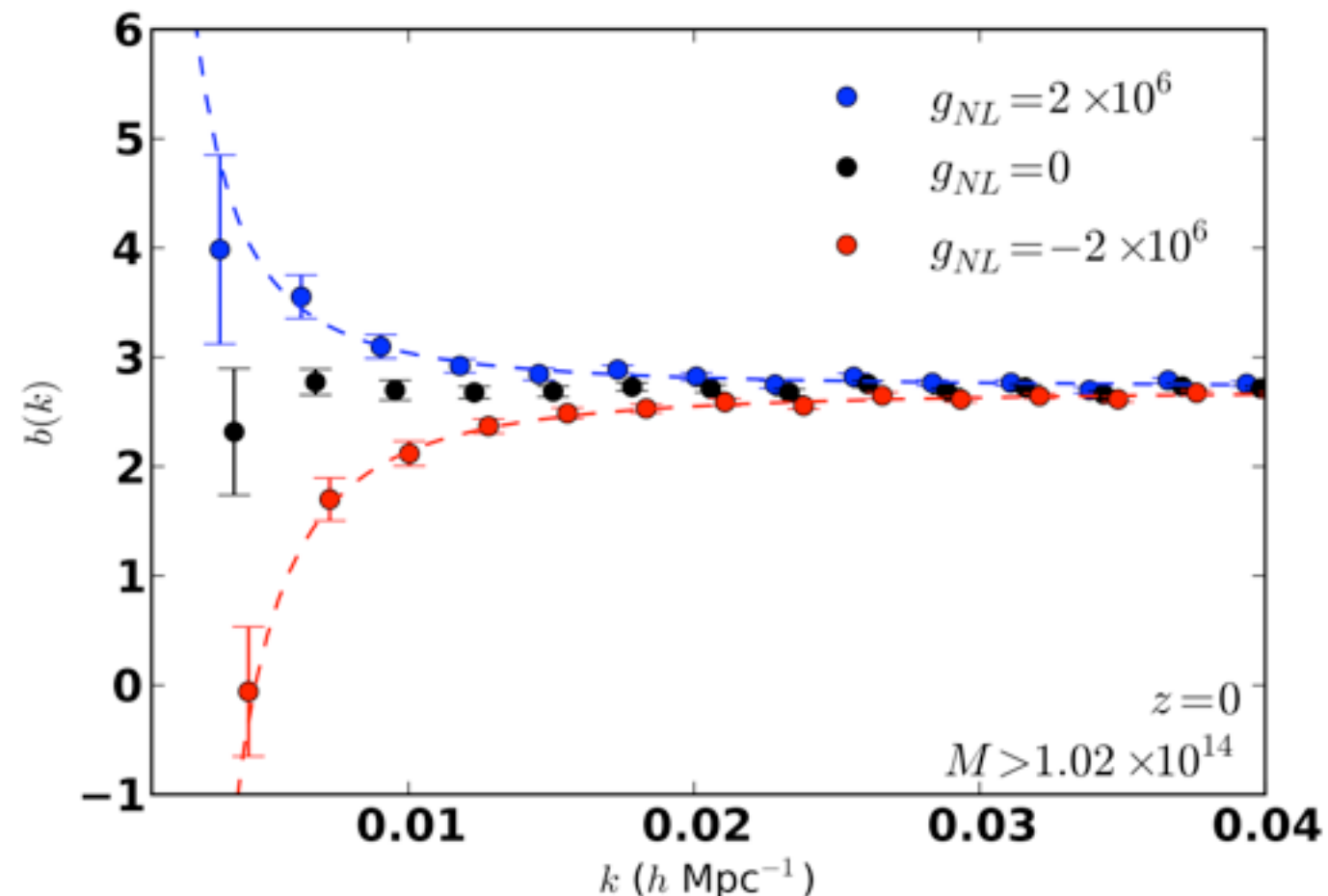
$$\zeta = \zeta_G + g_{NL} \zeta_G^3$$

Simple example of non-Gaussian model whose 4-point function  $\langle \zeta_{\mathbf{k}_1} \zeta_{\mathbf{k}_2} \zeta_{\mathbf{k}_3} \zeta_{\mathbf{k}_4} \rangle$  is large in the squeezed limit  $k_1 \rightarrow 0$ .



Scale dependence of bias is same as  $f_{NL}^{\text{loc}}$  model

Mass and redshift dependence are different, but hard in practice to discriminate  $f_{NL}^{\text{loc}}$  and  $g_{NL}$



*Smith, Ferraro & LoVerde 2011*

# Example 2: stochastic bias from collapsed 4-pt

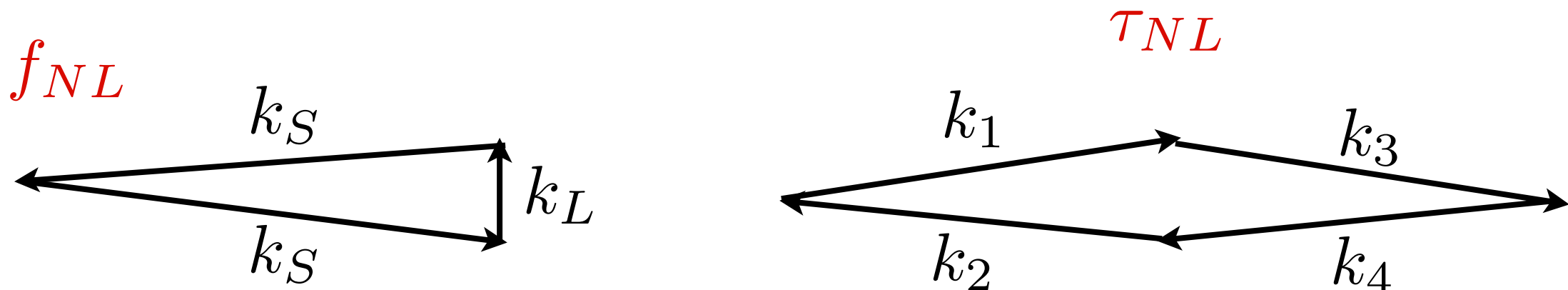
$\tau_{NL}$  model:

$$\langle \zeta_{\mathbf{k}_1} \zeta_{\mathbf{k}_2} \zeta_{\mathbf{k}_3} \rangle = \frac{6}{5} f_{NL} (P_\zeta(k_1) P_\zeta(k_2) + 2 \text{ perm.})$$

$$\langle \zeta_{\mathbf{k}_1} \zeta_{\mathbf{k}_2} \zeta_{\mathbf{k}_3} \zeta_{\mathbf{k}_4} \rangle = 2\tau_{NL} \left[ P_\zeta(k_1) P_\zeta(k_2) P_\zeta(|\mathbf{k}_1 + \mathbf{k}_3|) + 23 \text{ perm.} \right]$$

In simple local model ( $\zeta = \zeta_G + \frac{3}{5} f_{NL} \zeta_G^2$ ) one has

$\tau_{NL} = \left(\frac{6}{5} f_{NL}\right)^2$  but in general  $f_{NL}$ ,  $\tau_{NL}$  can be independent



# Example 2: stochastic bias from collapsed 4-pt

Our general expression predicts the following:

$$P_{mh}(k) = \left( b_0 + b_1 \frac{f_{NL}}{(k/aH)^2} \right) P_{mm}(k)$$

$$P_{hh}(k) = \left( b_0^2 + 2b_0b_1 \frac{f_{NL}}{(k/aH)^2} + b_1^2 \frac{\frac{25}{36} \tau_{NL}}{(k/aH)^4} \right) P_{mm}(k)$$

Qualitative prediction of  $\tau_{NL}$  model: “stochastic” halo bias

Matter and halo fields are not proportional on large scales

Gives some scope for **distinguishing**  $f_{NL}$ ,  $\tau_{NL}$ :

- Different bias values inferred from  $P_{mh}(k)$ ,  $P_{hh}(k)$
- Different tracer populations are not 100% correlated
- Even with a single population, can separate  $k^{-2}$ ,  $k^{-4}$  terms

# Example: quasi-single field inflation

$$S_\pi = \int d^4x \sqrt{-g} \left( \frac{1}{2} (\partial\pi)^2 + \frac{1}{2} (\partial\sigma)^2 - \frac{M^2}{2} \sigma^2 + \rho \dot{\pi} \sigma - \frac{g}{3!} \sigma^3 \right)$$

Squeezed/collapsed limits (where  $\alpha = \frac{3}{2} - \sqrt{\frac{9}{4} - \frac{M^2}{H^2}}$ )

$$\lim_{k_L \rightarrow 0} \langle \zeta_{\mathbf{k}_L} \zeta_{\mathbf{k}_S} \zeta_{\mathbf{k}_S} \rangle \propto g\rho^3 \left( \frac{1}{k_L^{3-\alpha} k_S^{3+\alpha}} \right)$$

$$\lim_{|\mathbf{k}_1 + \mathbf{k}_2| \rightarrow 0} \langle \zeta_{\mathbf{k}_1} \zeta_{\mathbf{k}_2} \zeta_{\mathbf{k}_3} \zeta_{\mathbf{k}_4} \rangle \propto g^2 \rho^4 \left( \frac{1}{|\mathbf{k}_1 + \mathbf{k}_2|^{3-2\alpha} k_1^{3+\alpha} k_3^{3+\alpha}} \right)$$

**Prediction:** non-Gaussian bias has spectral index given by

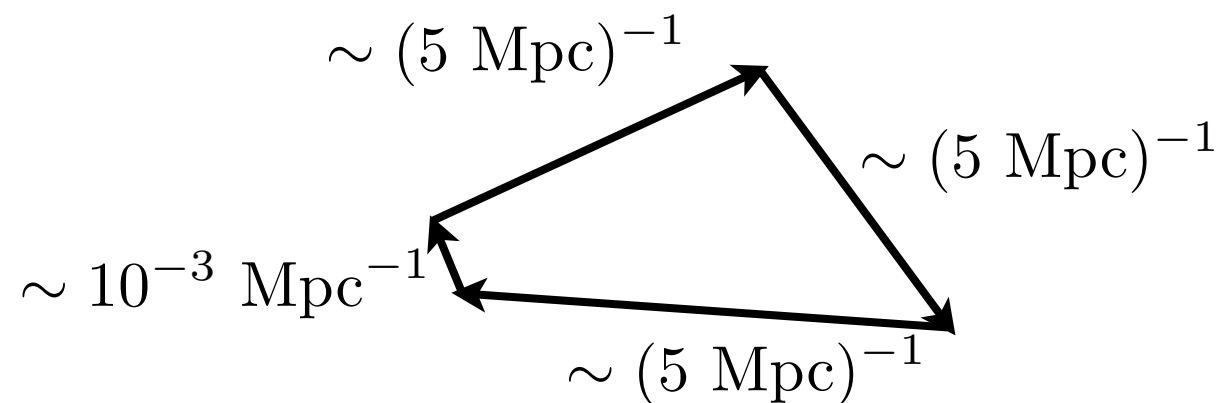
$$b(k) = b_0 + b_1 \frac{g\rho^3}{(k/aH)^{2-\alpha}}$$

**Prediction:** bias is mostly stochastic (“ $\tau_{NL}$ ” =  $g^2 \rho^4$  is enhanced relative to the square of “ $f_{NL}$ ” =  $g\rho^3$ )

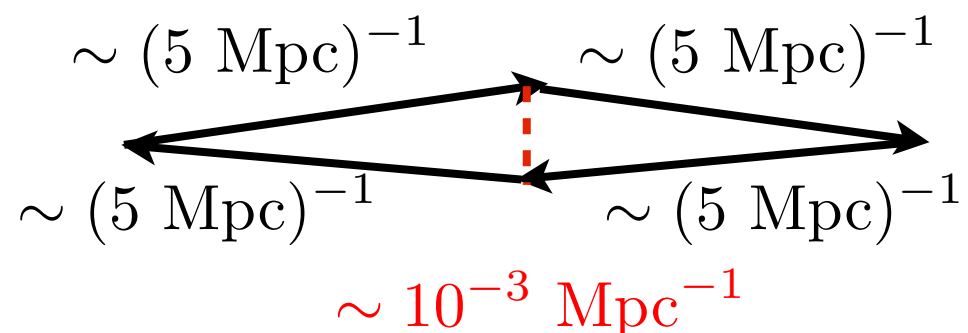
# Large-scale structure: general picture

Large-scale structure constraints are best understood as precise tests of **statistical homogeneity of the universe on large scales**

Non-Gaussian models with large squeezed limits can be interpreted as **large-scale inhomogeneity in statistics of small-scale modes**, e.g:



large-scale correlation between **density** and **small-scale skewness**



large-scale inhomogeneity in **small-scale power**, uncorrelated to density (“stochastic”)

# Conclusions and future outlook

## CMB:

Can measure N-point correlation function  $\langle T_{l_1} T_{l_2} \cdots T_{l_N} \rangle$  with full shape discrimination. “One estimator per diagram”

Statistical machinery is mature but many shapes unanalyzed!

## Large-scale structure:

Future constraints on some models (e.g.  $f_{NL}^{\text{loc}}$ ) better than CMB

Models without squeezed limits (e.g. single field) **unconstrained**

Difficult to separate different N-point shapes (or different values of N) but some scope for discriminating models based on **spectral index of the halo bias** and **stochastic vs non-stochastic bias**