Center for Astroparticle Physics
GENEVA

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FACULTÉ DES SCIENCES

How well can we constrain primordial non-Gaussianity with Large Scale Structure ?

Vincent Desjacques

Early Universe workshop, CERN, Jan 8, 2015

Local quadratic primordial NG:

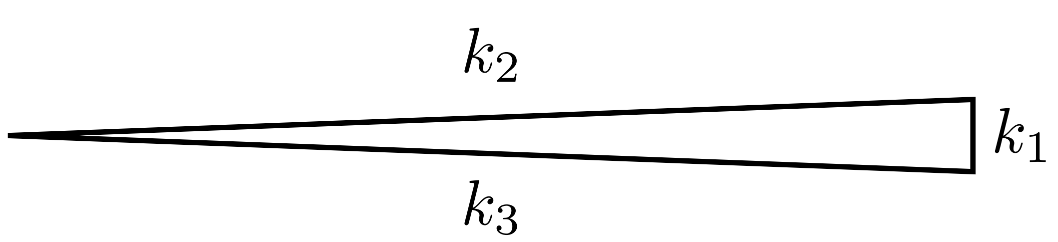
$$\Phi(\mathbf{x}) = \phi(\mathbf{x}) + f_{\rm NL}\phi^2(\mathbf{x})$$

$$|\phi| \sim 10^{-5}$$

$$\langle \Phi(\mathbf{k}_1)\Phi(\mathbf{k}_2)\Phi(\mathbf{k}_3)\rangle_c = (2\pi)^3\delta_D(\mathbf{k}_1+\mathbf{k}_2+\mathbf{k}_3)\,\xi_\Phi^{(3)}(\mathbf{k}_1,\mathbf{k}_2,\mathbf{k}_3)$$

$$\xi_\Phi^{(3)}(\mathbf{k}_1,\mathbf{k}_2,\mathbf{k}_3) = 2f_{\rm NL}\left[P_\phi(k_1)P_\phi(k_2) + 2\ \text{cyc.}\right]$$

$$P_\phi(k) \propto k^{n_s-4} \sim k^{-3}$$



Outline

- *Non-Gaussian bias as a probe of PNG*
- *3 universal truths about non-Gaussian bias*
- *Peak theory: the not so universal truths*
- *Implications for fNL constraints*

Galaxy clustering probes:

- *Cluster counts*

$$S_3 \sim \int d^3\mathbf{k}_1 \int d^3\mathbf{k}_2 \, \xi_\Phi^{(3)}(\mathbf{k}_1, \mathbf{k}_2, -\mathbf{k}_1 - \mathbf{k}_2)$$

- *Galaxy power spectrum*

$$\Delta b_1(k) \sim \int d^3\mathbf{k} \, \xi_\Phi^{(3)}(\mathbf{k}_1, -\mathbf{k}_1, \mathbf{k}), \quad S_3$$

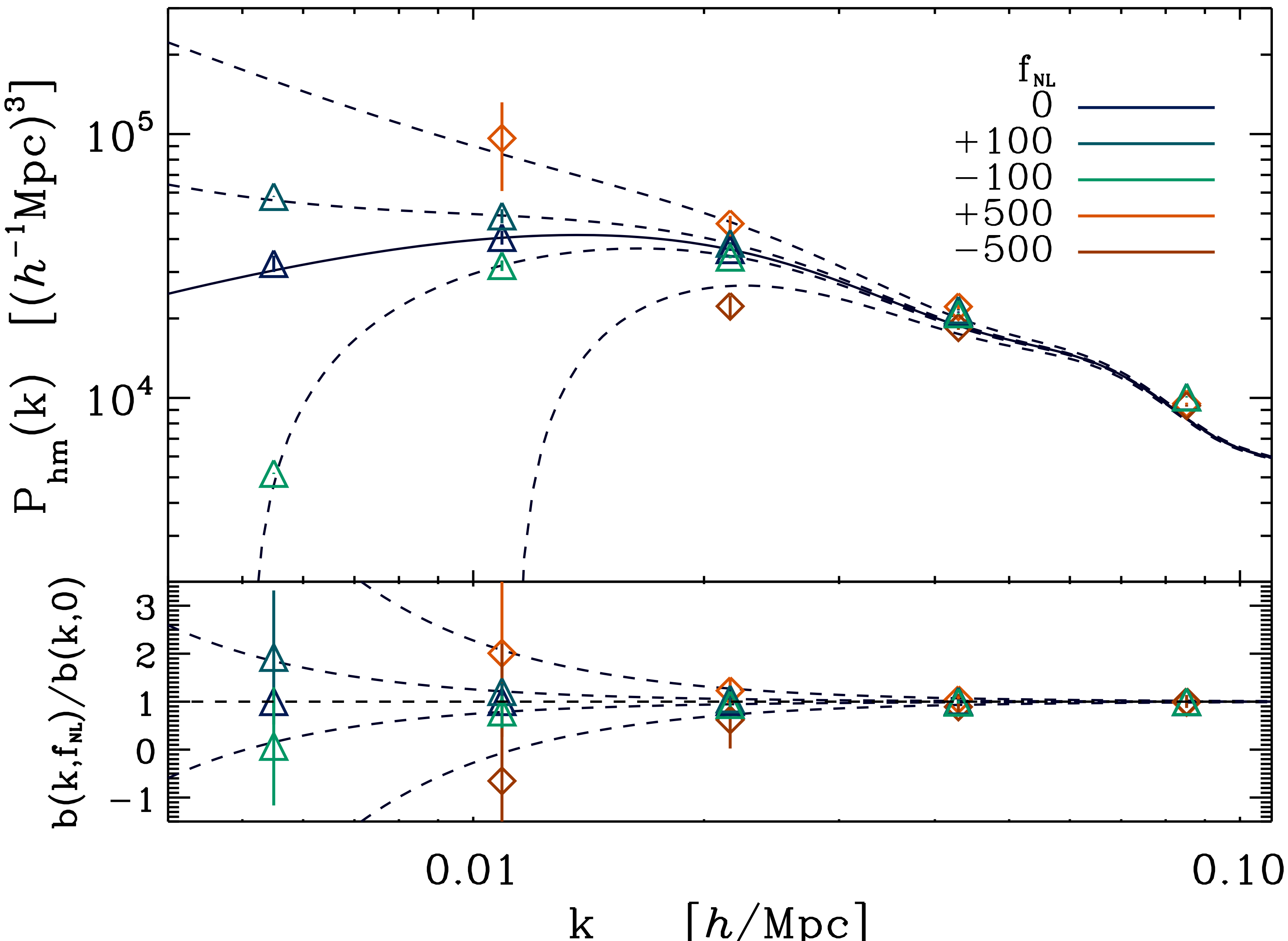
- *Galaxy bispectrum*

$$\xi_\Phi^{(3)}(\mathbf{k}_1, \mathbf{k}_2, -\mathbf{k}_1 - \mathbf{k}_2), \cdots$$

The non-Gaussian bias for local quadratic NG:

$$P_{\rm gg}(k) = \left(b_1 + \Delta b_1^{\rm NG}(k)\right)^2 P_{\rm mm}(k)$$

$$\Delta b_1^{\rm NG}(k) = \frac{2 f_{\rm NL} b_{\rm NG}}{\mathcal{M}(k)} \sim \frac{2 f_{\rm NL} b_{\rm NG}}{k^2}$$



Dalal et al. '08

Most recent constraints:

$$-40 \lesssim f_{\rm NL} \lesssim +40 \quad (95\% \text{ C.L.})$$

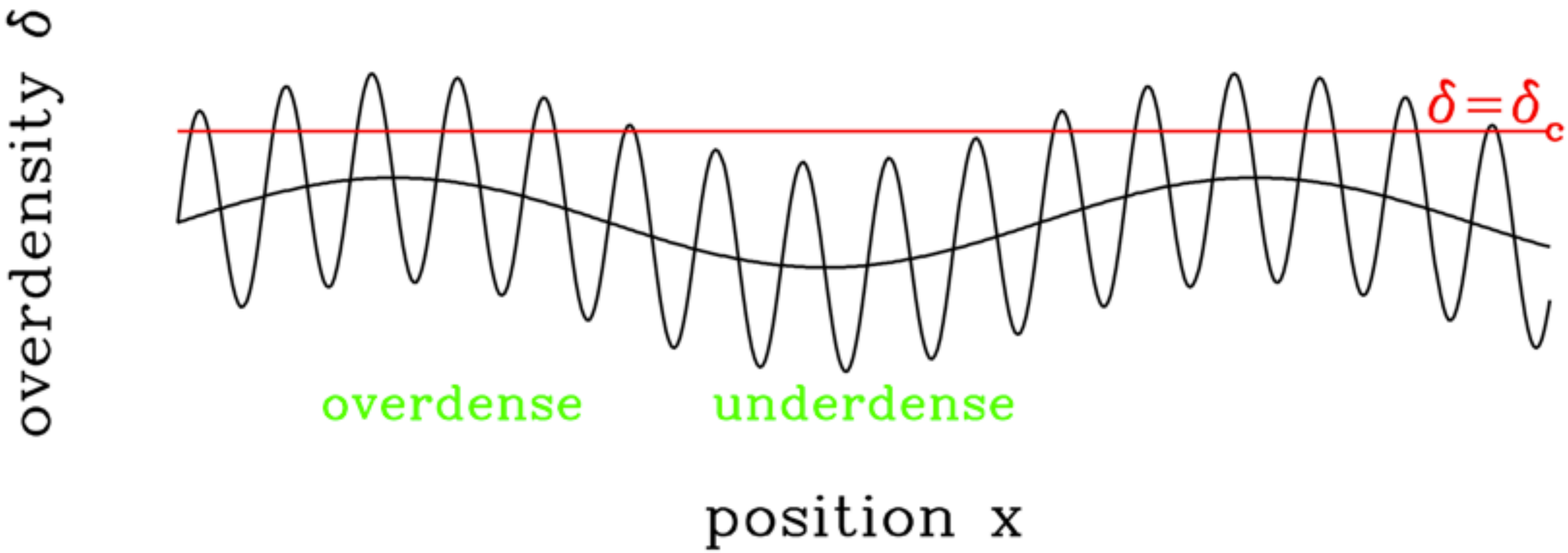
Giannantonio et al. '12, Ho et al. '13, Leistedt et al. '14

Forecast for a Euclid-like survey :

$$\Delta f_{\rm NL} \sim 3$$

Giannantonio et al. '12

Peak-background split (PBS):



$$\delta(\mathbf{x}) = \delta_l(\mathbf{x}) + \delta_s(\mathbf{x})$$

Kaiser '84; Bardeen et al. '86; Cole & Kaiser '89; Mo & White '96; Sheth & Tormen '99; ...

PBS: Gaussian bias

$$\delta_{\rm g}(\mathbf{x}) \equiv \frac{\bar{n}_{\rm g}(\mathbf{x})}{\bar{n}_{\rm g}} - 1 = \frac{\bar{n}_{\rm g}\big(\delta_c - \delta_l(\mathbf{x}), \sigma\big)}{\bar{n}_{\rm g}(\delta_c, \sigma)} - 1 = \left(-\frac{1}{\bar{n}_{\rm g}}\frac{d\bar{n}_{\rm g}}{d\delta_c}\right)\delta_l(\mathbf{x}) + \ldots$$

Kaiser '84

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$$\equiv b_1$$

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$$\Phi(\mathbf{x}) = \phi(\mathbf{x}) + f_{\rm NL}\phi(\mathbf{x})^2$$

$$\phi(\mathbf{x}) = \phi_l(\mathbf{x}) + \phi_s(\mathbf{x})$$

$$\Phi = \left(\phi_l + f_{\rm NL}\phi_l^2\right) + \phi_s\left(1 + 2f_{\rm NL}\phi_l\right) + f_{\rm NL}\phi_s^2$$

Slosar et al. '08

$$\sigma_s \rightarrow \sigma_s\left(1 + 2f_{\rm NL}\phi_l\right)$$

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$$\delta_{\mathrm{g}}(\mathbf{x}) = \left(-\frac{1}{\bar{n}_{\mathrm{g}}}\frac{d\bar{n}_{\mathrm{g}}}{d\delta_c}\right)\delta_l(\mathbf{x}) + \left(\frac{1}{\bar{n}_{\mathrm{g}}}\frac{d\bar{n}_{\mathrm{g}}}{d\sigma}\right) 2 f_{\mathrm{NL}} \sigma \phi_l(\mathbf{x}) + \ldots$$

$$= b_1 \delta_l(\mathbf{x}) + 2 f_{\mathrm{NL}} \left(\frac{\partial \ln \bar{n}_{\mathrm{g}}}{\partial \ln \sigma}\right) \phi_l(\mathbf{x}) + \ldots$$

Slosar et al. '08

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$$\equiv \delta_c b_1 \quad \text{iff} \quad \bar{n}_{\rm g} \equiv \bar{n}_{\rm g}(\delta_c/\sigma)$$

Slosar et al. '08

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Local bias approach: $$\delta_{\rm g}(\mathbf{x}) = b_1\delta_l(\mathbf{x}) + \frac{1}{2}b_2\delta_l^2(\mathbf{x}) + \ldots$$

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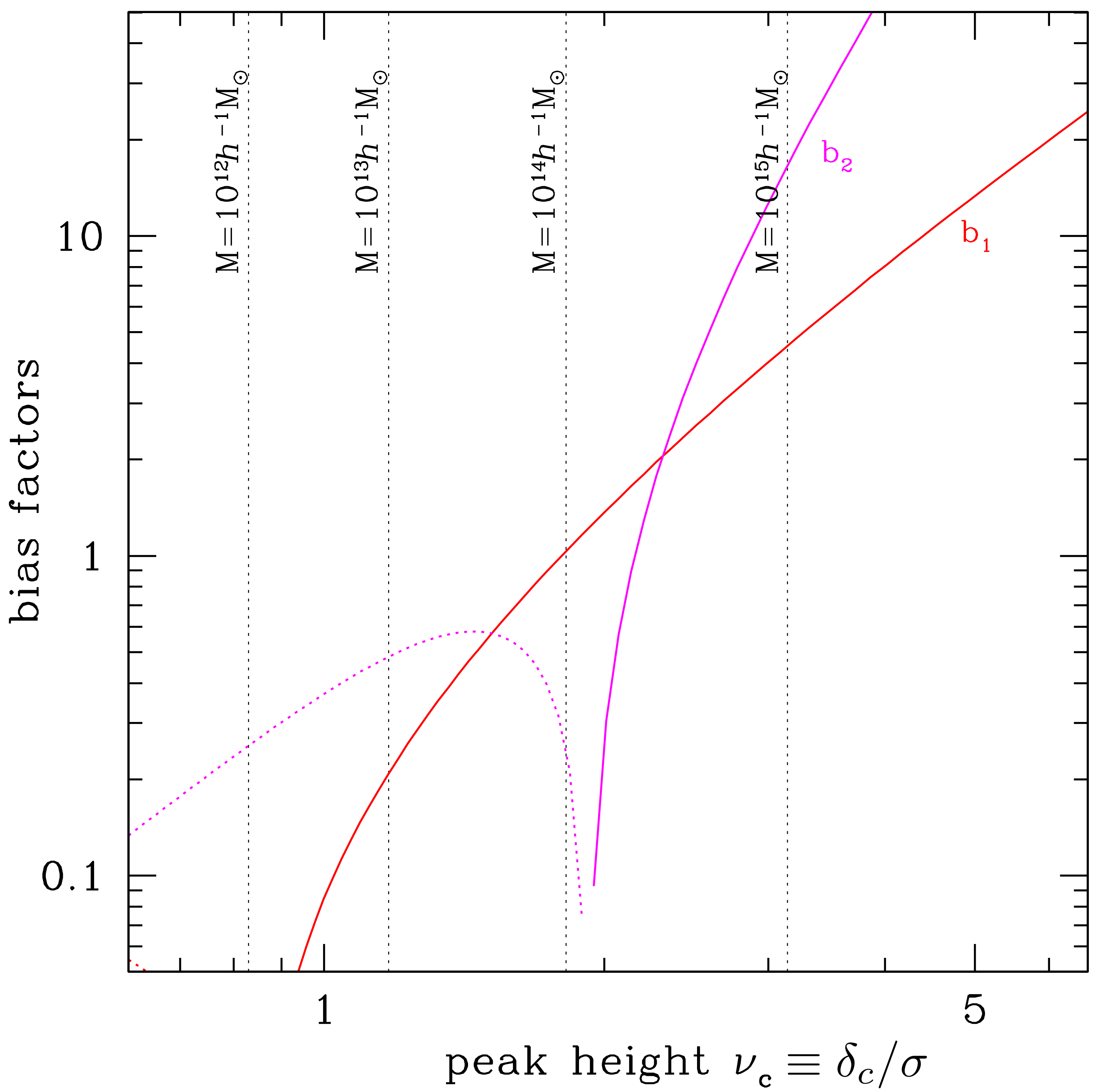
Taruya et al. '08



bias factors
peak height $\nu_c \equiv \delta_c/\sigma$
$M=10^{12}h^{-1}M_\odot$
$M=10^{13}h^{-1}M_\odot$
$M=10^{14}h^{-1}M_\odot$
$M=10^{15}h^{-1}M_\odot$
b_2
b_1
10
1
0.1
1
5

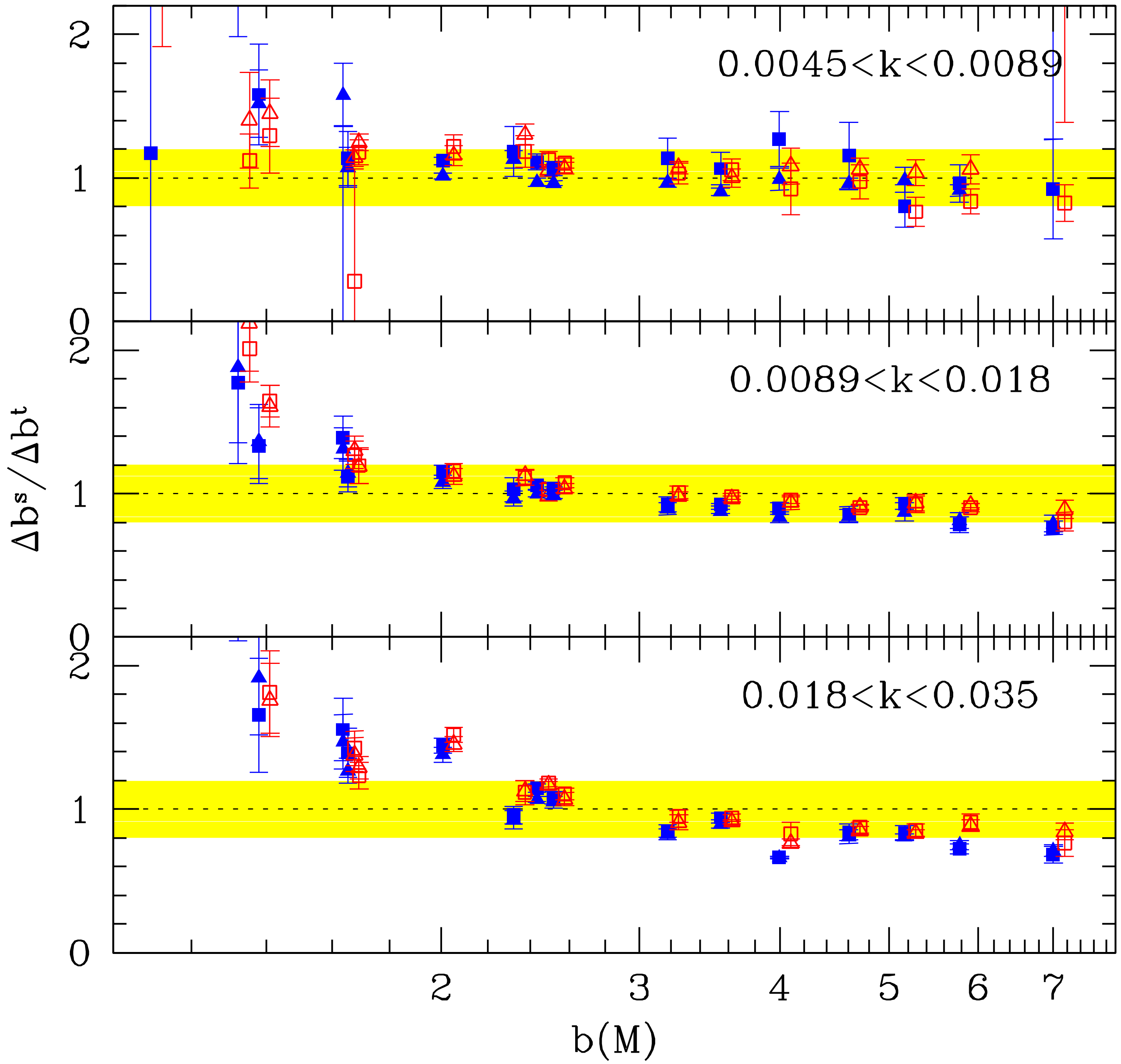
The following three statements are certainly true:

- *The amplitude of the non-Gaussian bias is given by*

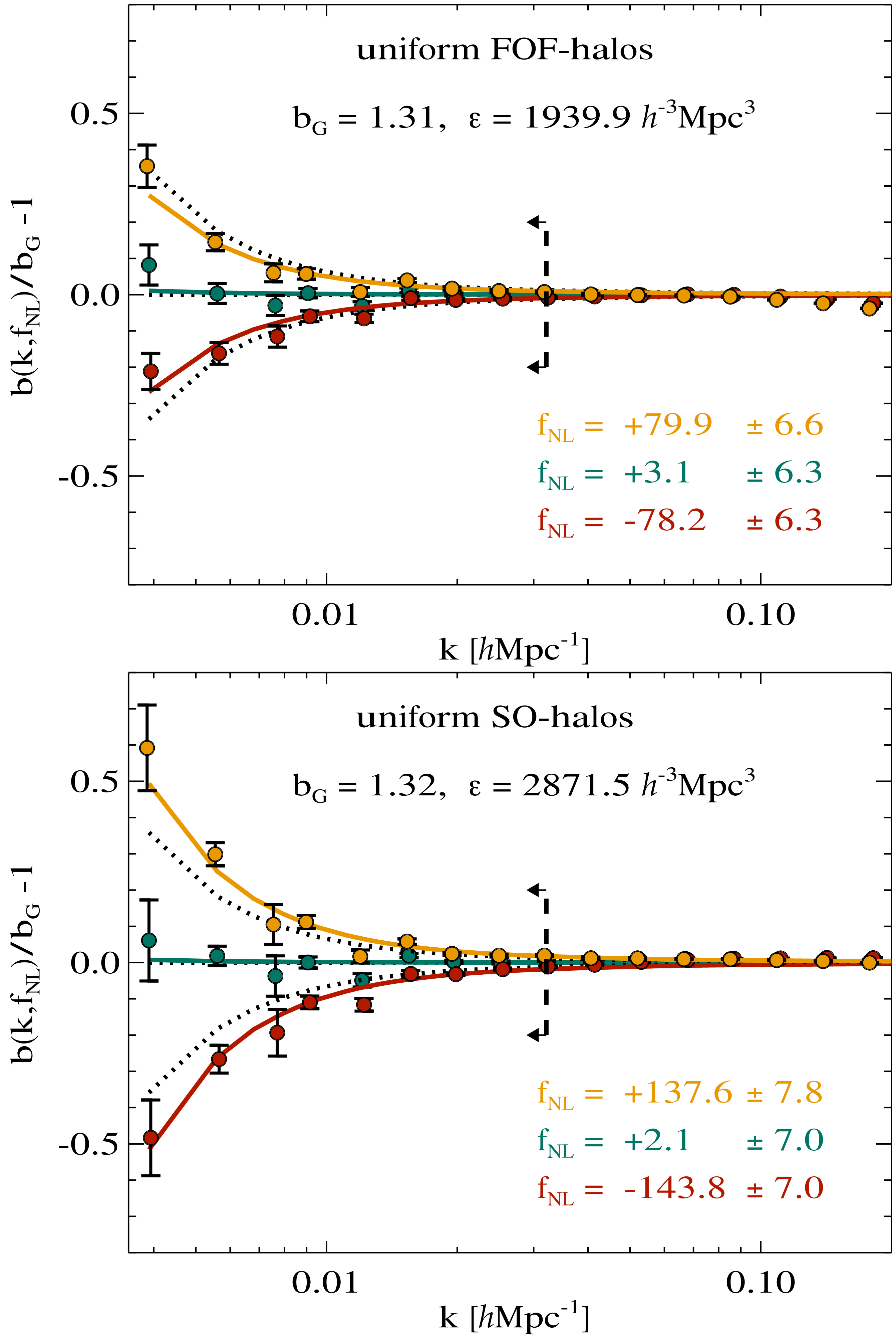
$$\left(\frac{\partial \ln \bar{n}_{\rm g}}{\partial \ln \sigma_8}\right)$$

- $\delta_c b_1$ *is equal to* $\left(\frac{\partial \ln \bar{n}_{\rm g}}{\partial \ln \sigma_8}\right)$ *only if the halo mass function is universal*

- *Local bias expansions cannot correctly predict the amplitude of non-Gaussian bias*



VD, Seljak & Iliev '09



Hamaus, Seljak & VD '11

Toy model: maxima of the linear density field as a proxy for the formation sites of dark matter haloes (Peacock & Heavens '85; BBKS '86)

$$\delta_s(\mathbf{x}) = \delta(\mathbf{x}; R = R_s)$$

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$$\delta_s(\mathbf{x}) = \delta(\mathbf{x}; R = R_s)$$

$$\nu(\mathbf{x}) \equiv \frac{1}{\sigma_0}\delta_s(\mathbf{x}), \qquad \eta_i(\mathbf{x}) = \frac{1}{\sigma_1}\partial_i\delta_s(\mathbf{x}), \qquad \zeta_{ij} \equiv \frac{1}{\sigma_2}\partial_i\partial_j\delta_s(\mathbf{x})$$

$$\sigma_n^2 = \frac{1}{2\pi^2}\int_0^\infty dk\, k^{2(n+1)} P_s(k)$$

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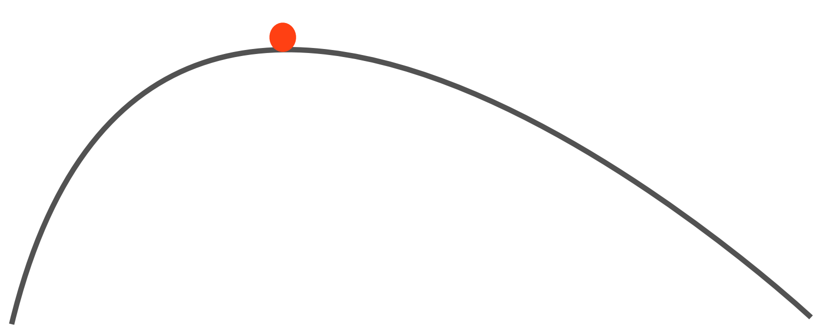
Peak constraint:



(i) $\nu(\mathbf{x}_p) = \frac{\delta_c}{\sigma_0} = \frac{1.68}{\sigma_0} \equiv \nu_c$

(ii) $\eta_i(\mathbf{x}_p) = 0$

(iii) $\lambda_1(\mathbf{x}_p) \geq \lambda_2(\mathbf{x}_p) \geq \lambda_3(\mathbf{x}_p) > 0$

$\lambda_a(\mathbf{x}) = \text{eigenvalues of } -\zeta_{ij}(\mathbf{x})$

"Localized" number density:

$$n_{\rm pk}(\mathbf{x}) = \sum_{\mathbf{x}_p} \delta_D(\mathbf{x} - \mathbf{x}_p) = \frac{(6\pi)^{3/2}}{V_\star} \big|\det\zeta(\mathbf{x})\big| \, \delta_D\big[\boldsymbol{\eta}(\mathbf{x})\big] \, \theta_H\big[\lambda_3(\mathbf{x})\big] \, \delta_D\big(\nu(\mathbf{x}) - \nu_c\big)$$

Kac '43; Rice '51; Bardeen et al. '86

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Reduced N-point correlation is the connected piece of

$$\big\langle n_{\rm pk}(\mathbf{x_1}) \times \cdots \times n_{\rm pk}(\mathbf{x}_N)\big\rangle$$

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So, one ends up computing sth like

$$\int d^{10}\mathbf{y}_1 \ldots \int d^{10}\mathbf{y}_N\, n_{\rm pk}(\mathbf{y}_1)\times\cdots\times n_{\rm pk}(\mathbf{y}_N) P_N(\mathbf{y}_1,\ldots,\mathbf{y}_N)$$

$$\mathbf{y}_\alpha = \Big(\nu(\mathbf{x}_\alpha), \eta_i(\mathbf{x}_\alpha), \zeta_A(\mathbf{x}_\alpha)\Big)$$

Bardeen et al. '86; Regos & Szalay '95; VD '08; VD et al. '10

Local bias approach to discrete density peaks

VD '13

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- *Write down the "effective" bias expansion:*

$$\delta_{\rm pk}(\mathbf{x}) = \sigma_0 b_{10}\nu(\mathbf{x}) + \sigma_2 b_{01} u(\mathbf{x}) + \frac{1}{2}\sigma_0^2 b_{20}\nu^2(\mathbf{x}) + \sigma_0\sigma_2 b_{11}\nu(\mathbf{x})u(\mathbf{x}) + \frac{1}{2}\sigma_2^2 b_{02} u^2(\mathbf{x})$$

$$+\,\sigma_1^2\chi_{10}\eta^2(\mathbf{x}) + \sigma_2^2\chi_{01}\zeta^2(\mathbf{x}) + \dots$$

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$$+\,\sigma_1^2\chi_{10}\eta^2(\mathbf{x}) + \sigma_2^2\chi_{01}\zeta^2(\mathbf{x}) + \dots$$

- Compute the bias factors:

$$\sigma_0^i\sigma_2^j b_{ij} = \frac{1}{\bar{n}_{\rm pk}}\int d^{10}\mathbf{y}\, n_{\rm pk}(\mathbf{y}) H_{ij}(\nu,u) P_1(\mathbf{y})$$

$$\sigma_1^{2k}\chi_{k0} = \frac{1}{\bar{n}_{\rm pk}}\int d^{10}\mathbf{y}\, n_{\rm pk}(\mathbf{y}) L_k^{(1/2)}\!\left(\frac{3\eta^2}{2}\right) P_1(\mathbf{y})$$

$$\sigma_2^{2k}\chi_{0k} = \frac{1}{\bar{n}_{\rm pk}}\int d^{10}\mathbf{y}\, n_{\rm pk}(\mathbf{y}) L_k^{(3/2)}\!\left(\frac{5\zeta^2}{2}\right) P_1(\mathbf{y})$$

χ_{01} : *bias induced by peak profile asphericity*

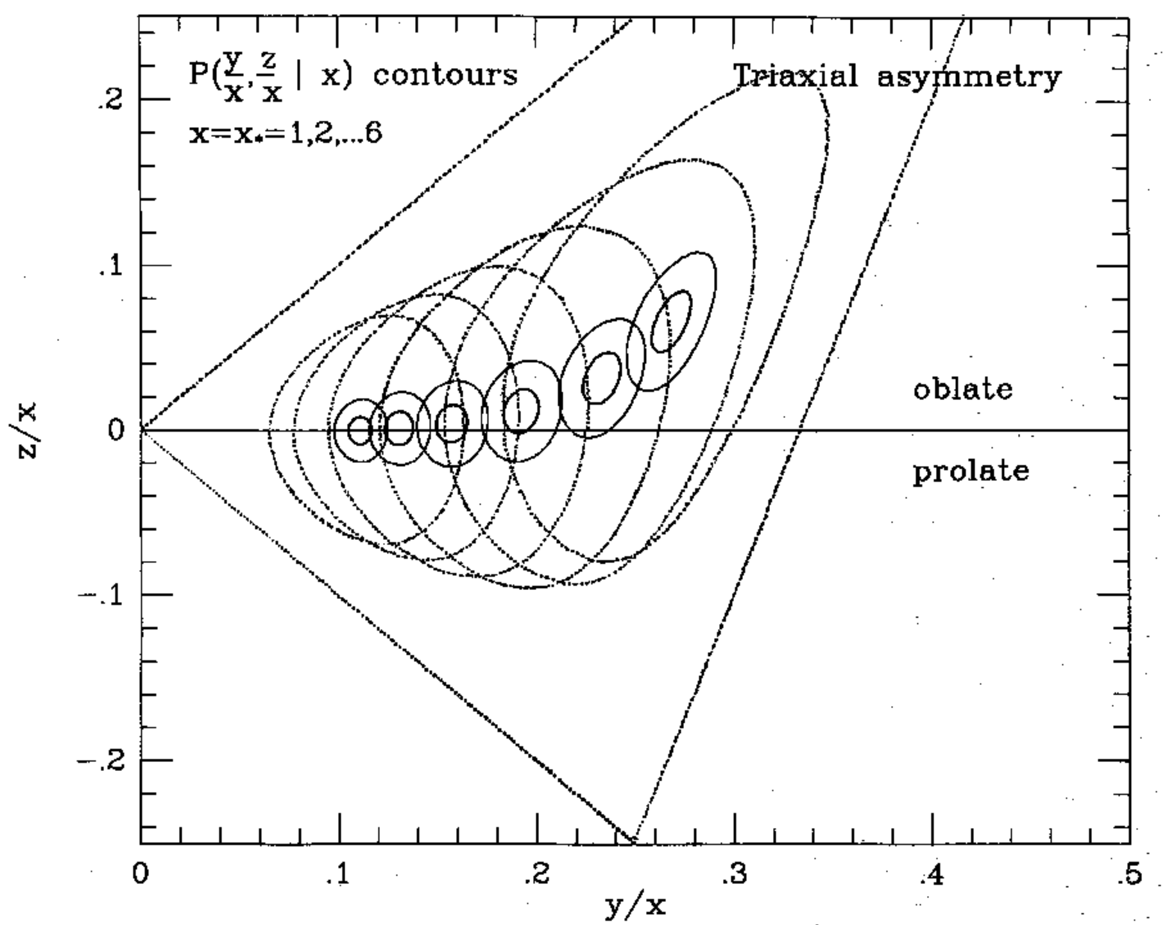

FIG. 7.—The 95%, 90%, and 50% contours of the conditional probability for ellipticity $e = y/x$ and prolateness $p = z/x$ subject to the constraint of given x for peaks (eq. [7.6]). (The x and x_* used here are $1.58 \approx \gamma^{-1}$ times those used in the text, so $\nu = 1, 2, \ldots, 6$ corresponds to the different curves.) This figure demonstrates that, even for high ν, the shapes are triaxial. The values of e and p are constrained to lie in the triangle.

Fig. from Bardeen et al '86

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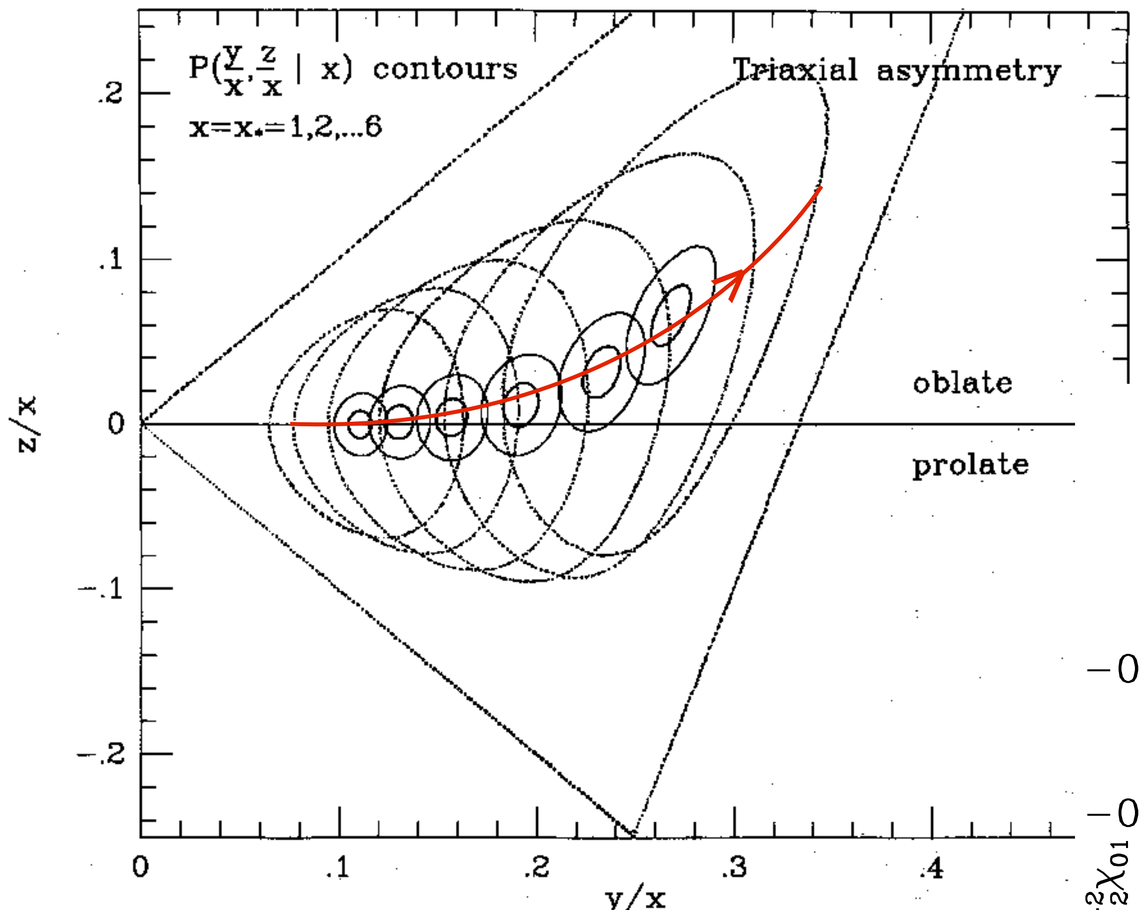

FIG. 7.—The 95%, 90%, and 50% contours of the conditional probability for ellipticity $e = y/x$ and prolateness $p = z/x$ subject to the c[...] peaks (eq. [7.6]). (The x and x_* used here are $1.58 \approx \gamma^{-1}$ times those used in the text, so $\nu = 1, 2, \ldots, 6$ corresponds to the different curves.) T[...] that, even for high ν, the shapes are triaxial. The values of e and p are constrained to lie in the triangle.

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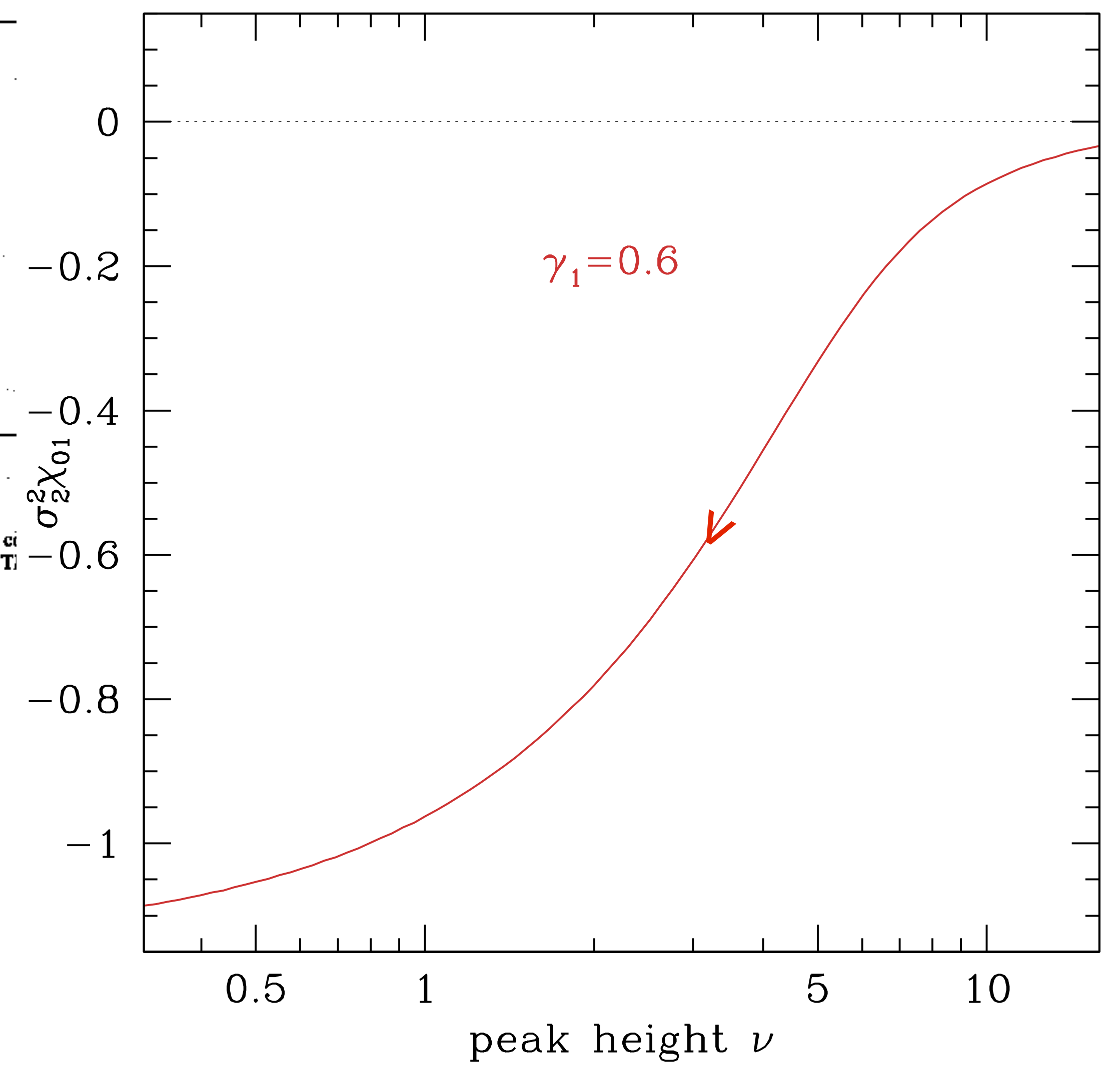

- *N-point connected correlations can be perturbatively computed from*

$$\xi^{(N)}_{\rm pk}(\mathbf{x}_1,\dots,\mathbf{x}_N) \equiv \langle \delta_{\rm pk}(\mathbf{x}_1)\times\cdots\times\delta_{\rm pk}(\mathbf{x}_N)\rangle$$

"Excursion set peaks": combine peak constraint with first-crossing condition

$$\mu(\mathbf{x}) \equiv -\frac{d\delta_s}{dR_s}(\mathbf{x})$$

The "localized" number density of excursion set peaks becomes

$$n_{\rm ESP}(\mu, \mathbf{y}) = \left(\frac{\mu}{\gamma_{\nu\mu}\nu_c}\right) \theta_H(\mu)\, n_{\rm pk}(\mathbf{y})$$

Appel & Jones '91; Paranjape & Sheth '12; Paranjape, Sheth & VD '13

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and the "effective" bias expansion generalizes to

$$\delta_{\rm ESP}(\mathbf{x}) = \sigma_0 b_{100}\nu(\mathbf{x}) + \sigma_2 b_{010} u(\mathbf{x}) + b_{001}\mu(\mathbf{x}) + \ldots$$

VD, Gong & Riotto '13

Consider local quadratic PNG

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$$b_{\rm NG} = \frac{\partial \ln \bar{n}_{\rm h}}{\partial \sigma_8}$$ *Slosar et al '08*

$$b_{\rm NG} = \sigma_0^2 b_2$$ *Taruya et al '08*

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Taruya et al '08

Excursion set peaks:

VD, Gong & Riotto '13

$$b_{\mathrm{NG}} = \sigma_0^2 b_{200} + 2\sigma_1^2 b_{110} + \sigma_2^2 b_{020} + 2\sigma_1^2 \chi_{10} + 2\sigma_2^2 \chi_{01} + \Delta_0^2 b_{002} + 2\gamma_{\nu\mu}\sigma_0 b_{101} + 2\gamma_{u\mu}\sigma_2 b_{011}$$

Consider local quadratic PNG

$$f_{\rm NL}\phi^2: \quad \Delta b_1^{\rm NG}(k) = \frac{2 f_{\rm NL} b_{\rm NG}}{\mathcal{M}(k)}$$

$$b_{\rm NG} = \delta_c b_1$$

Dalal et al '08

$$b_{\rm NG} = \frac{\partial \ln \bar{n}_{\rm h}}{\partial \sigma_8}$$

Slosar et al '08

$$b_{\rm NG} = \sigma_0^2 b_2$$

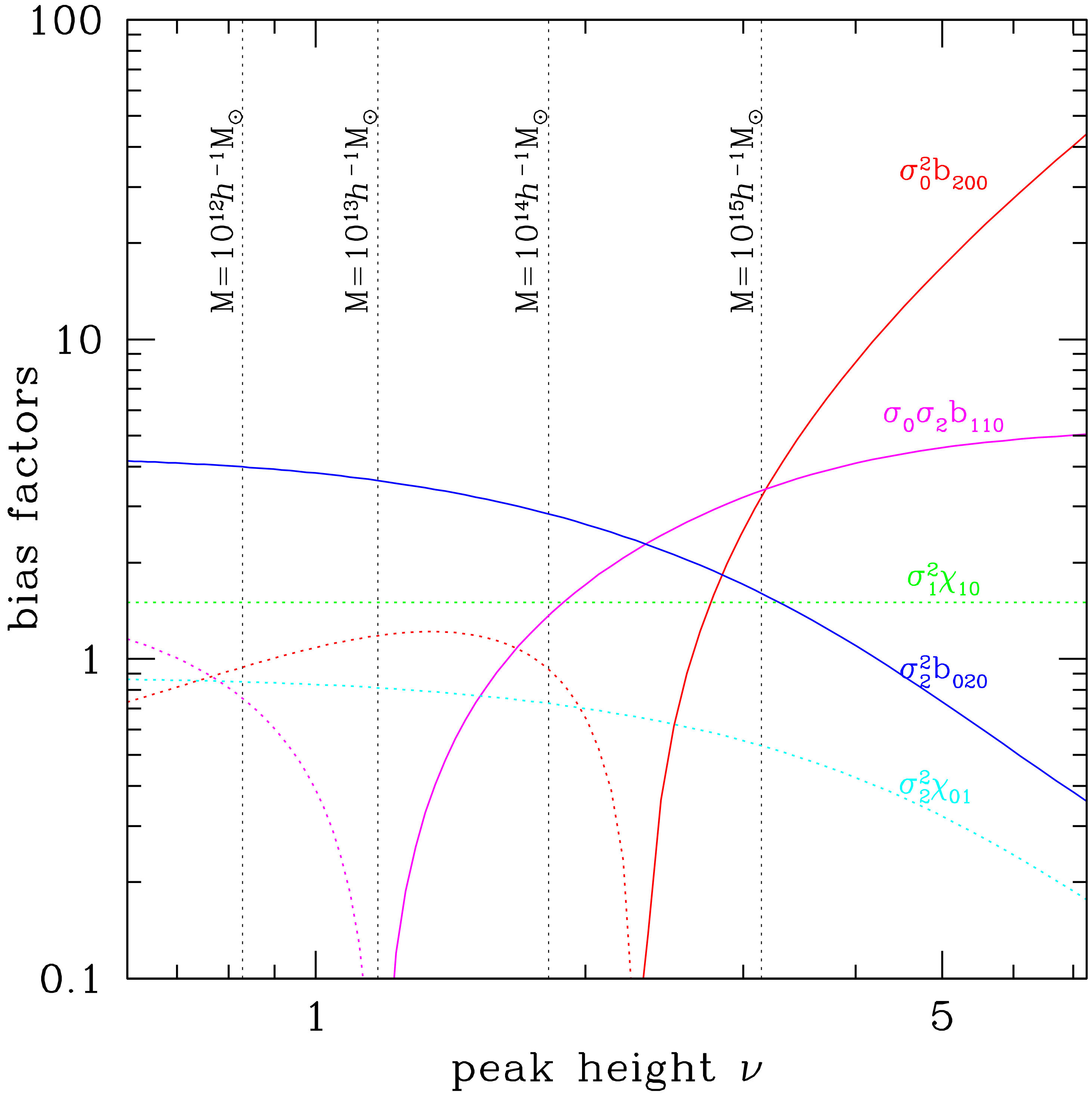
Taruya et al '08

Excursion set peaks:

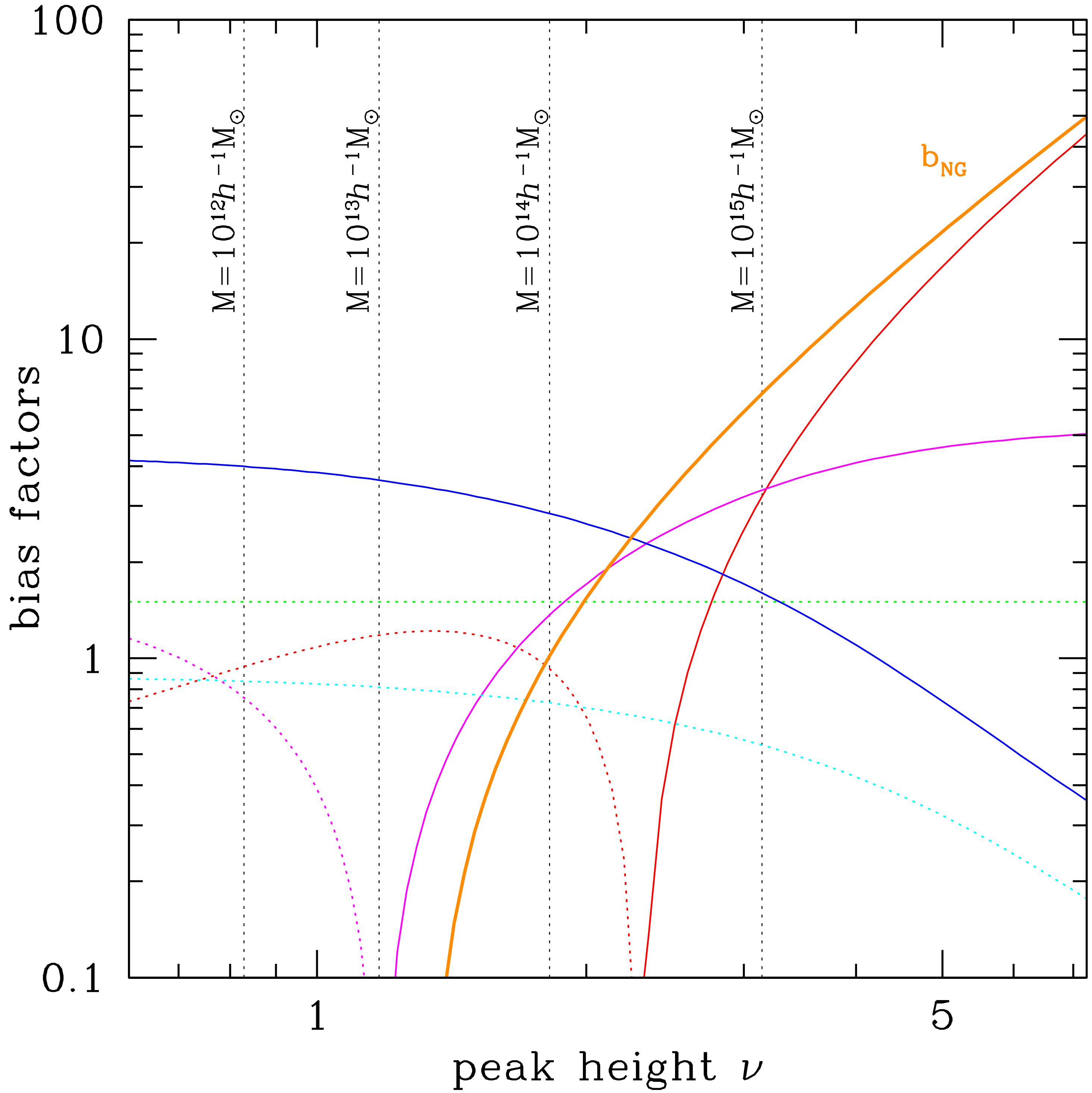
VD, Gong & Riotto '13

$$b_{\rm NG} = \sigma_0^2 b_{200} + 2\sigma_1^2 b_{110} + \sigma_2^2 b_{020} + 2\sigma_1^2 \chi_{10} + 2\sigma_2^2 \chi_{01} + \Delta_0^2 b_{002} + 2\gamma_{\nu\mu}\sigma_0 b_{101} + 2\gamma_{u\mu}\sigma_2 b_{011}$$

$$\equiv \frac{\partial \ln \bar{n}_{\rm h}}{\partial \sigma_8} \qquad !!!$$



100
10
1
0.1
1
5
bias factors
peak height ν
$M=10^{12}h^{-1}M_\odot$
$M=10^{13}h^{-1}M_\odot$
$M=10^{14}h^{-1}M_\odot$
$M=10^{15}h^{-1}M_\odot$
$\sigma_0^2 b_{200}$
$\sigma_0\sigma_2 b_{110}$
$\sigma_1^2\chi_{10}$
$\sigma_2^2 b_{020}$
$\sigma_2^2\chi_{01}$



100
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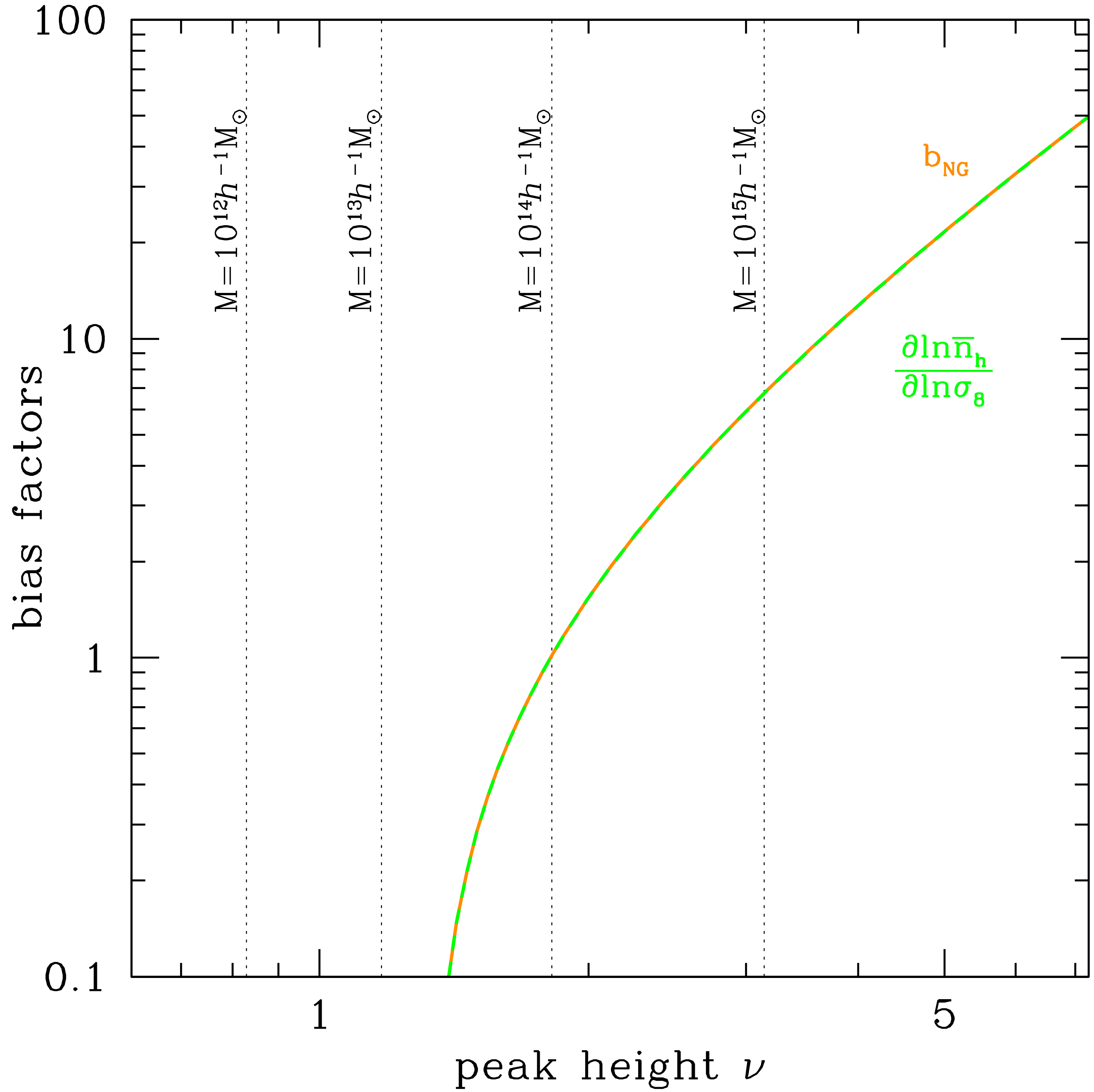
$M=10^{15}h^{-1}M_\odot$
b_{NG}



100
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M=10¹²h⁻¹M⊙
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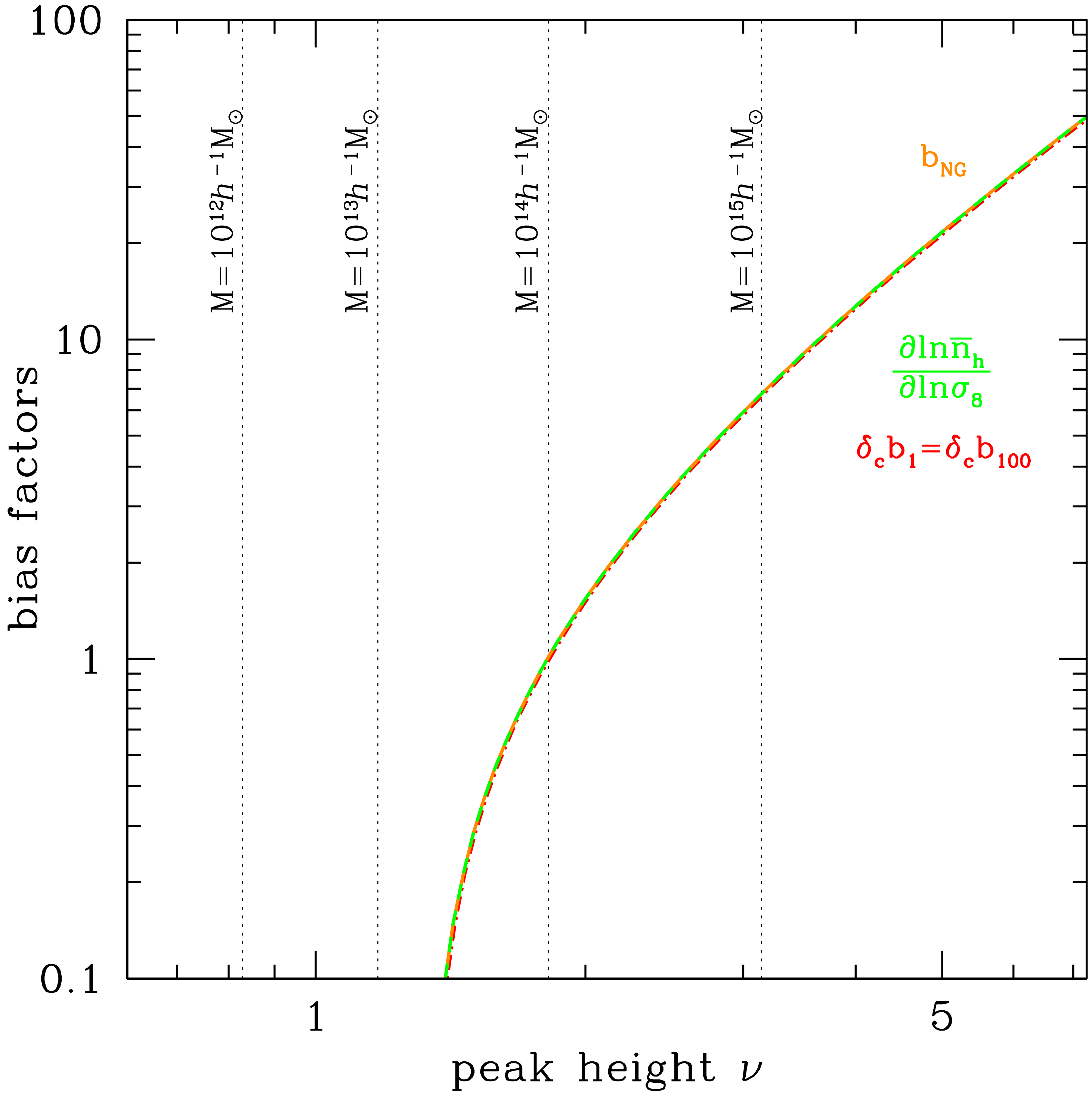
M=10¹⁵h⁻¹M⊙
b_NG
∂ln n̄_h / ∂ln σ_8



100
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bias factors
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peak height ν
M=10^12 h^-1 M_⊙
M=10^13 h^-1 M_⊙
M=10^14 h^-1 M_⊙
M=10^15 h^-1 M_⊙
b_NG
∂ln n̄_h / ∂ln σ_8
δ_c b_1 = δ_c b_100

The following three statements are certainly true:

- *The amplitude of the non-Gaussian bias is given by*

$$\left(\frac{\partial \ln \bar{n}_{\rm g}}{\partial \ln \sigma_8}\right)$$

- $\delta_c b_1$ *is equal to* $\left(\frac{\partial \ln \bar{n}_{\rm g}}{\partial \ln \sigma_8}\right)$ *only if the halo mass function is universal*

- *Local bias expansions cannot correctly predict the amplitude of non-Gaussian bias*

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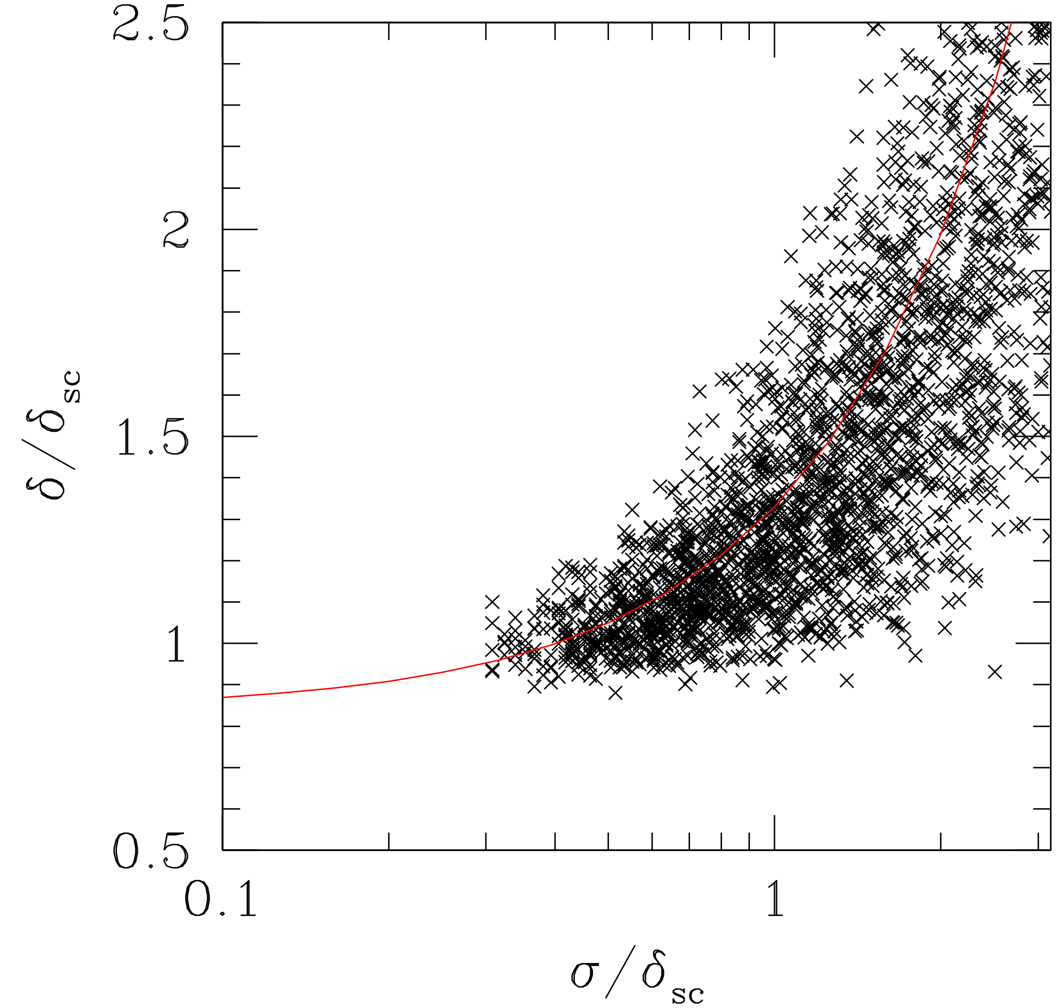
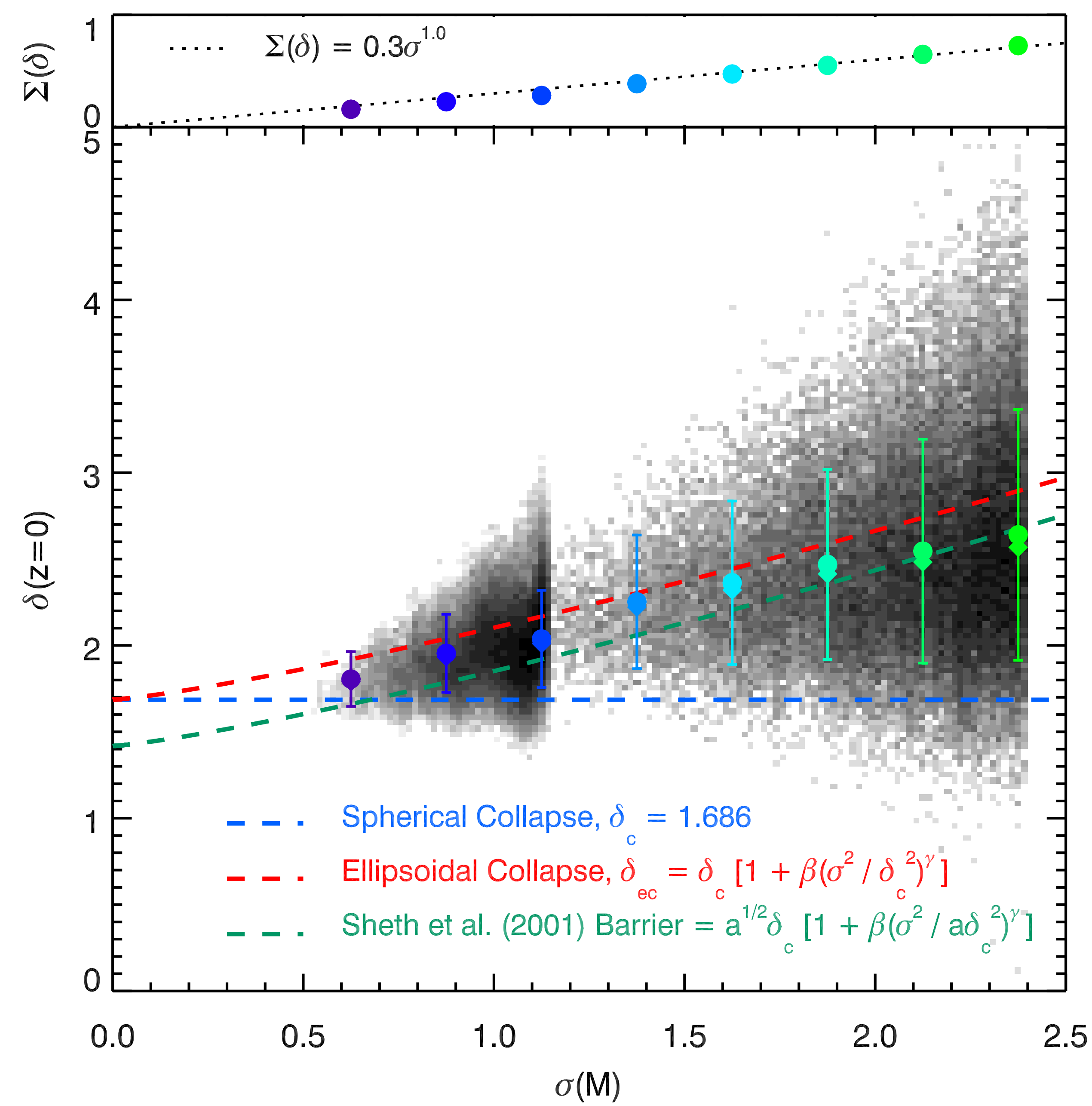
All the results discussed so far have a common denominator: the collapse threshold is assumed to be constant and deterministic while it is in fact moving (e.g. halo mass-dependent) and stochastic

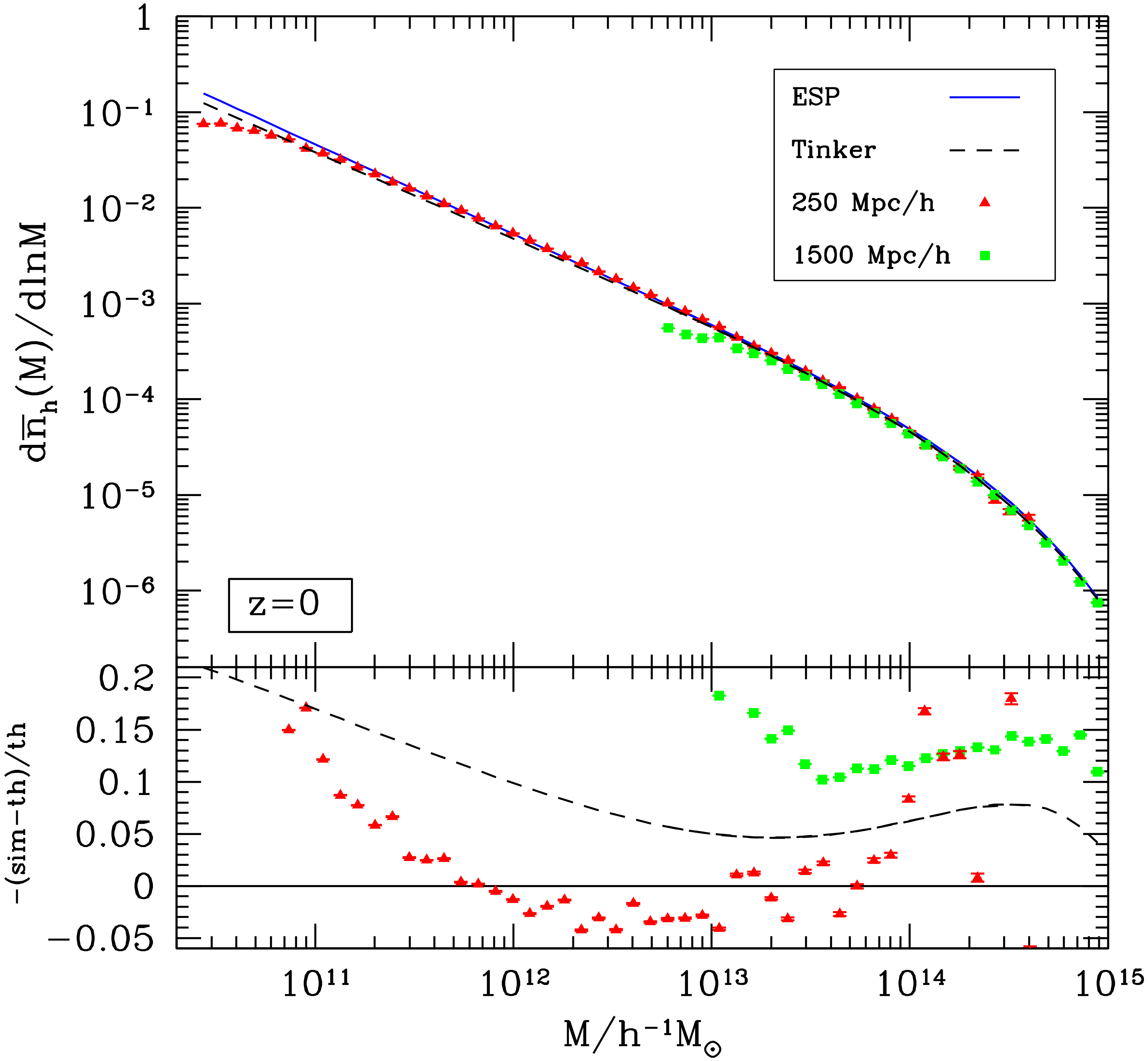
$$B(\sigma) = \delta_c$$



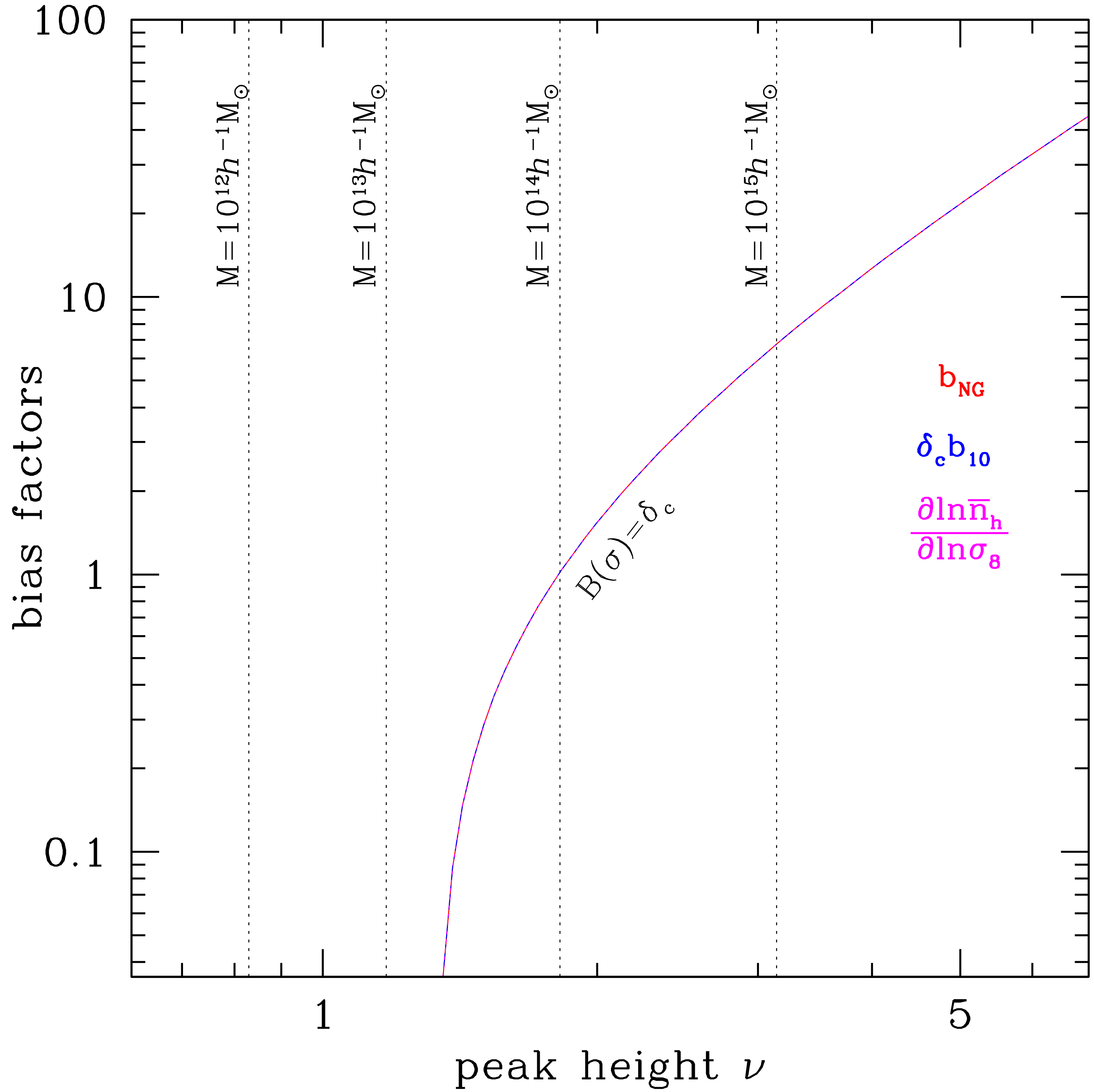
Sheth & Tormen '02



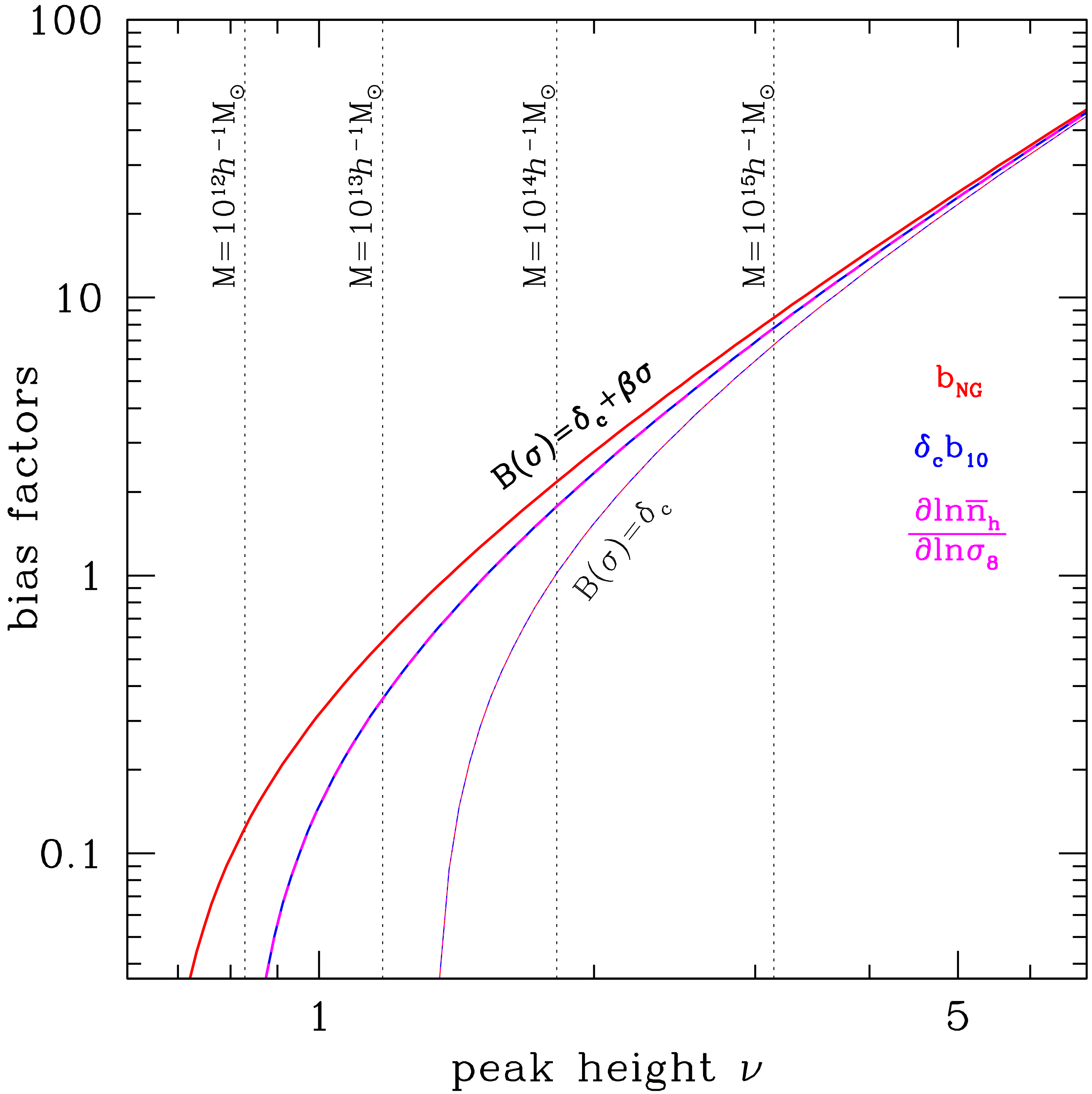
Robertson et al '08



Paranjape, Sheth & VD '13; Biagetti et al '14



Thursday, 8 January 15



100
10
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bias factors
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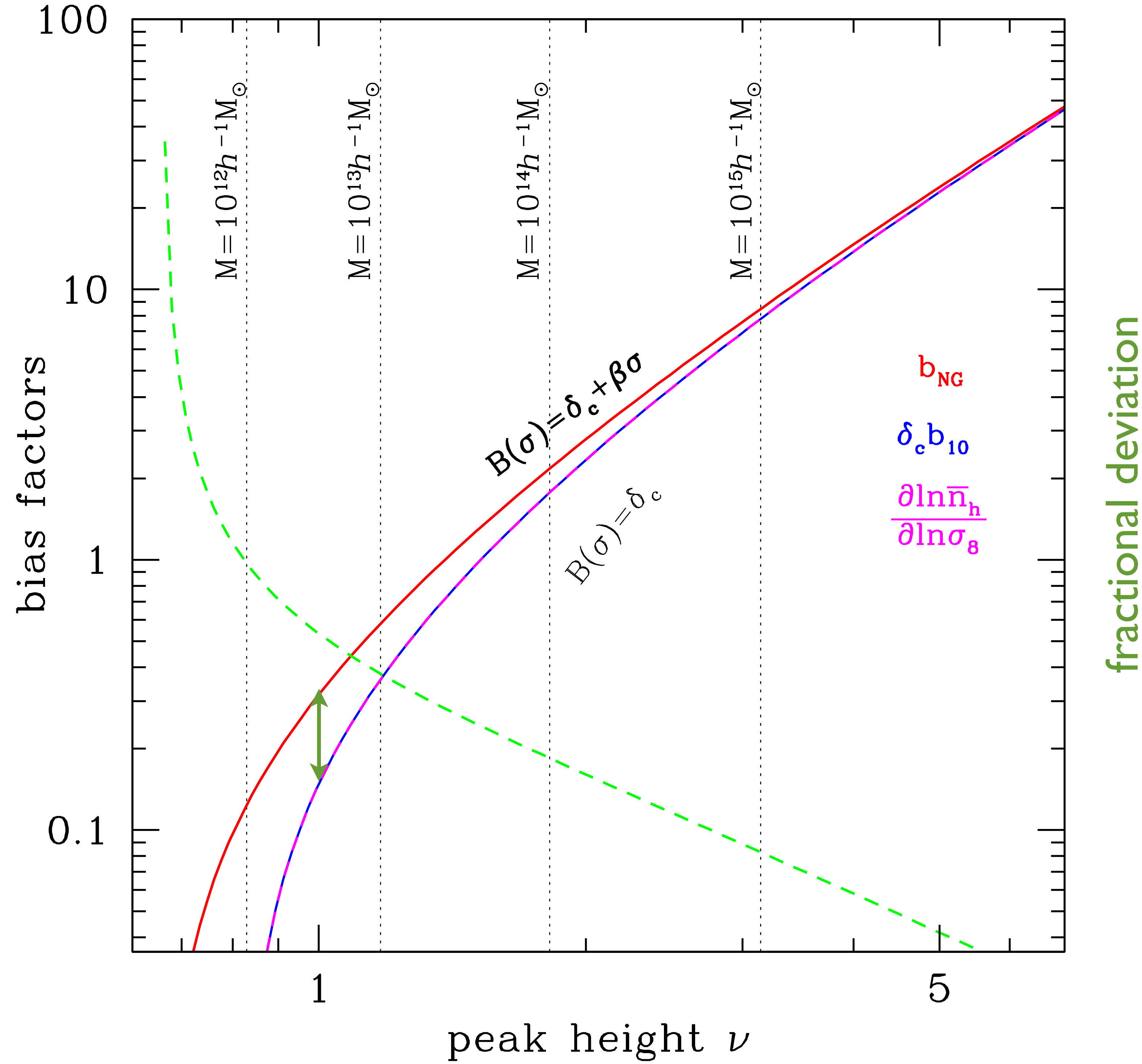
M=10¹²h⁻¹M⊙
M=10¹³h⁻¹M⊙
M=10¹⁴h⁻¹M⊙
M=10¹⁵h⁻¹M⊙
B(σ)=δc+βσ
B(σ)=δc
bNG
δcb10
∂ln n̄h / ∂ln σ8



100
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bias factors
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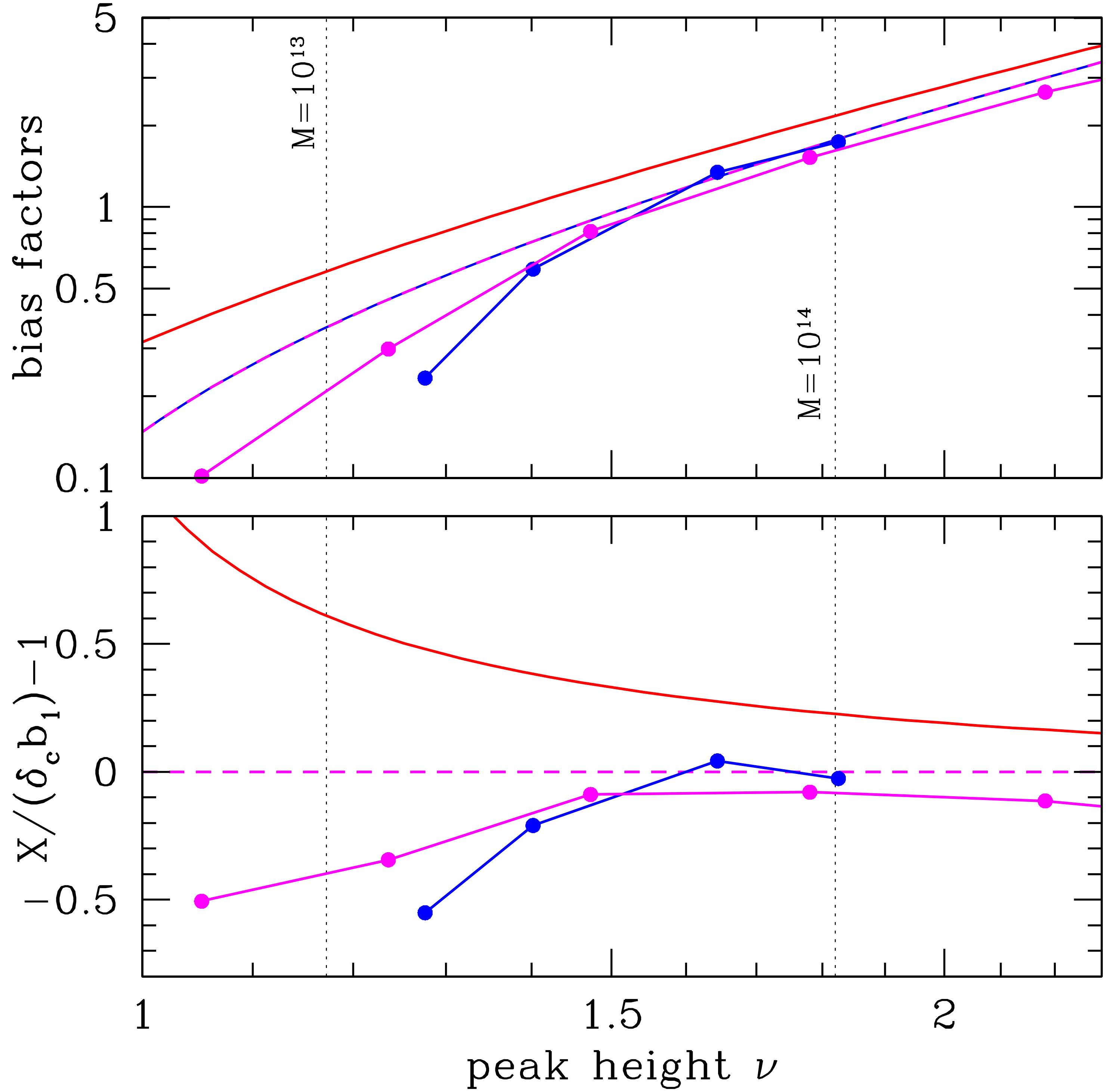
peak height ν
M=10¹²h⁻¹M⊙
M=10¹³h⁻¹M⊙
M=10¹⁴h⁻¹M⊙
M=10¹⁵h⁻¹M⊙
B(σ)=δc+βσ
B(σ)=δc
bNG
δcb10
∂ln n̄h / ∂ln σ8
fractional deviation

Preliminary ! work in progress with Matteo Biagetti



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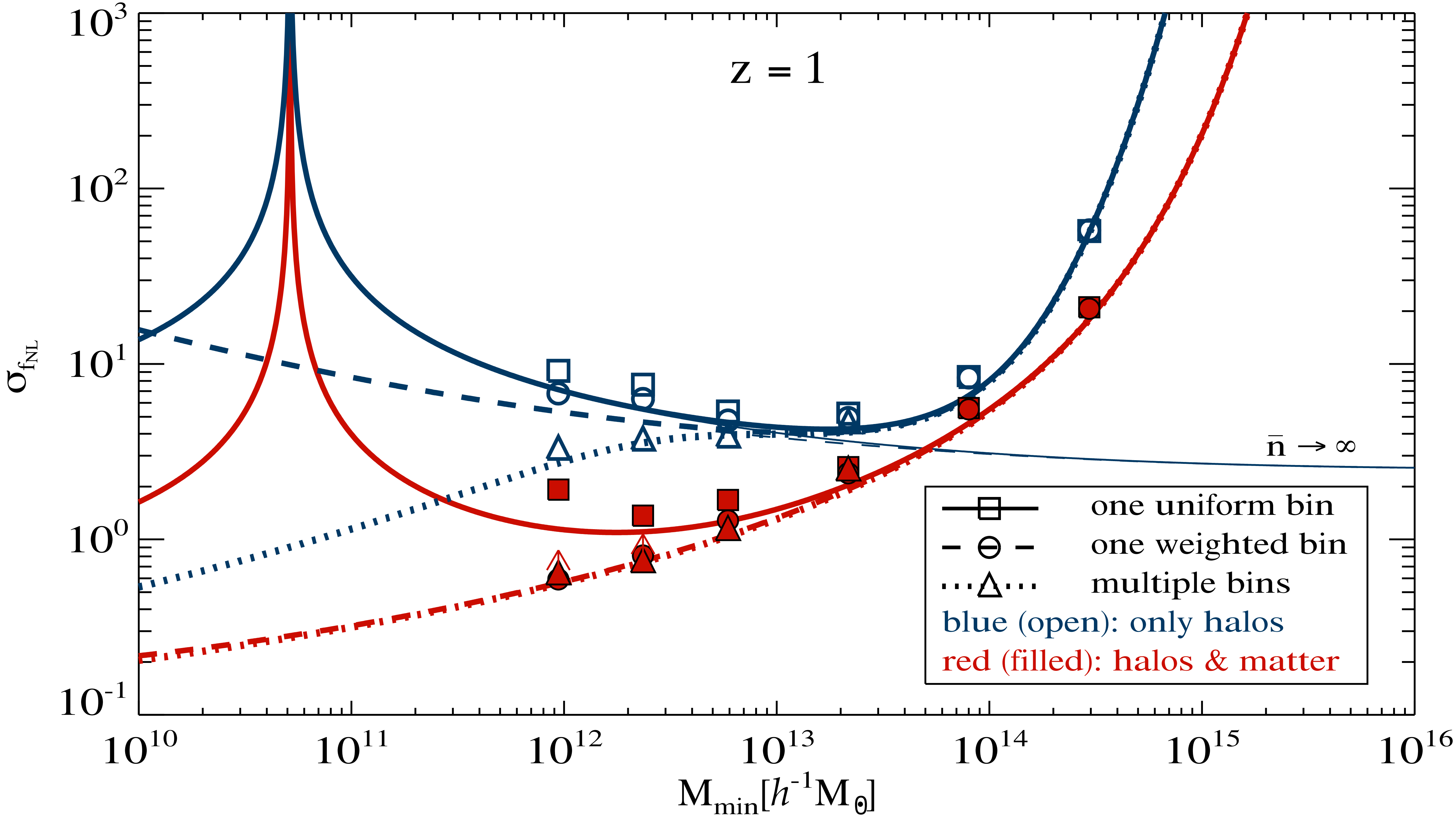
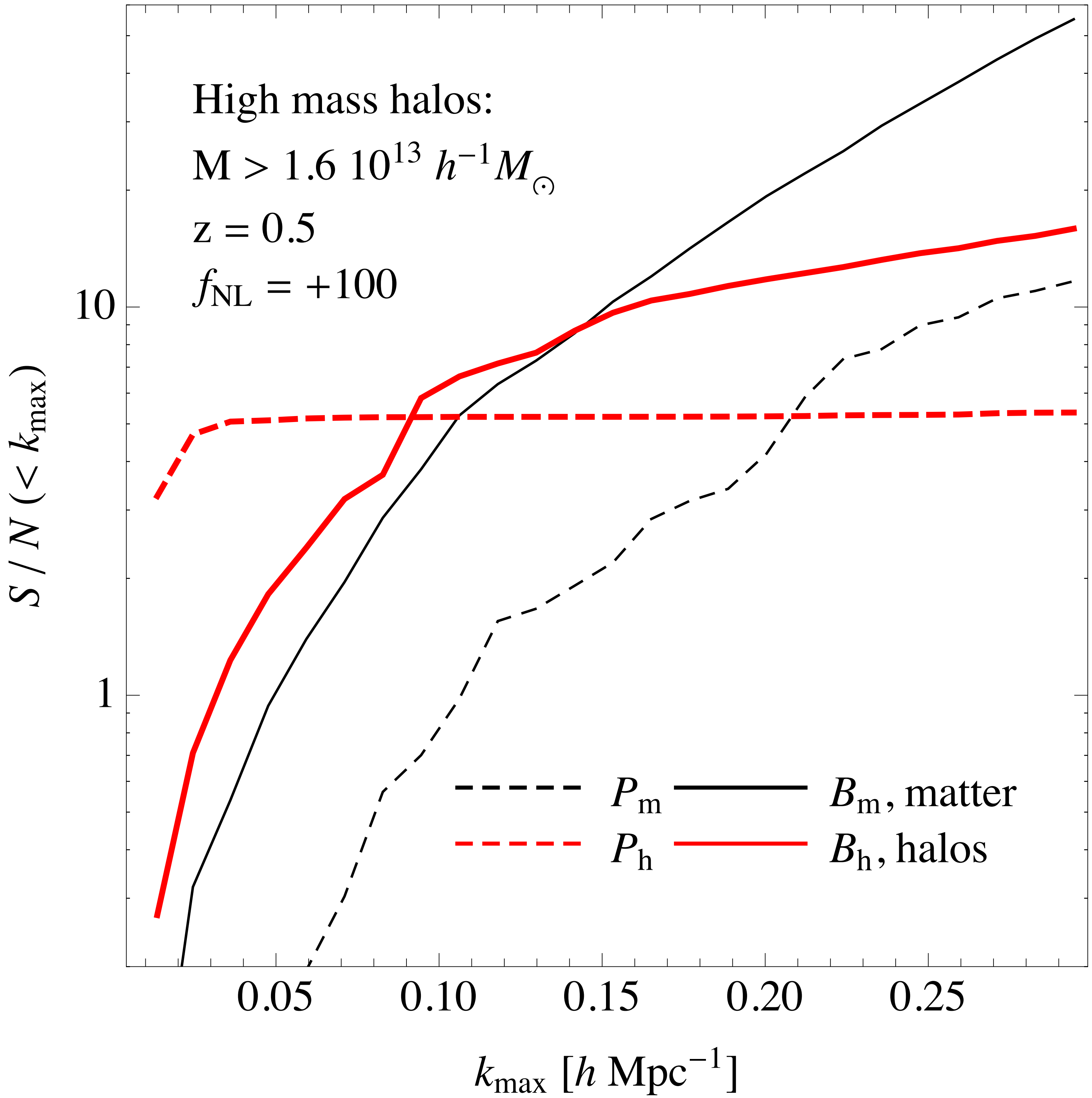


Hamaus, Seljak & VD '11

Beyond galaxy power spectrum: galaxy bispectrum and matter statistics



Sefusatti, Crocce & VD '12

Conclusion

- *Non-Gaussian bias is subtle: peak-background split may not work*
- *If confirmed, many of the current constraints and forecasts are in need of revision*
- *Peak theory is a powerful approach to understand the nitty-gritty details of galaxy bias*