

The Effective Halo Model:

Accurate Models for the Power Spectrum and Cluster Count Covariances

OLIVER PHILCOX (PRINCETON)

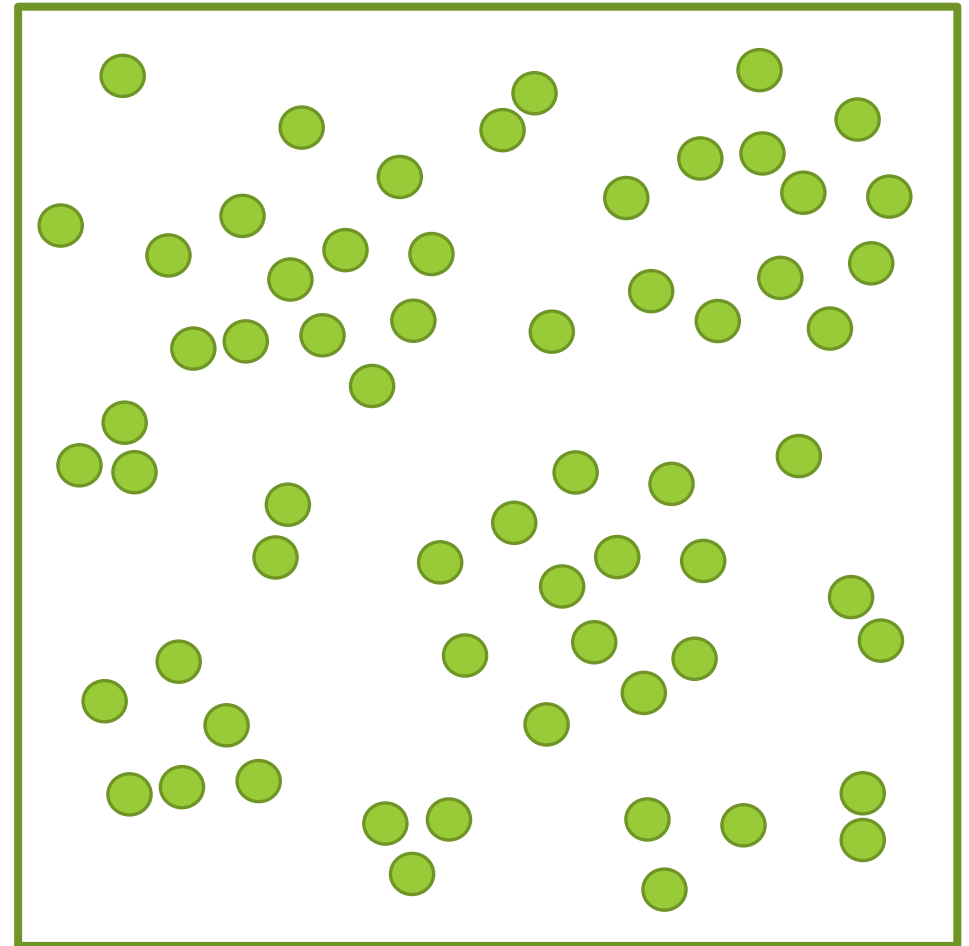
- David Spergel (Princeton / CCA)
- Francisco Villaescusa-Navarro (Princeton / CCA)

May 5, 2020

The Halo Model

- Introduced in **Peebles, 1980**

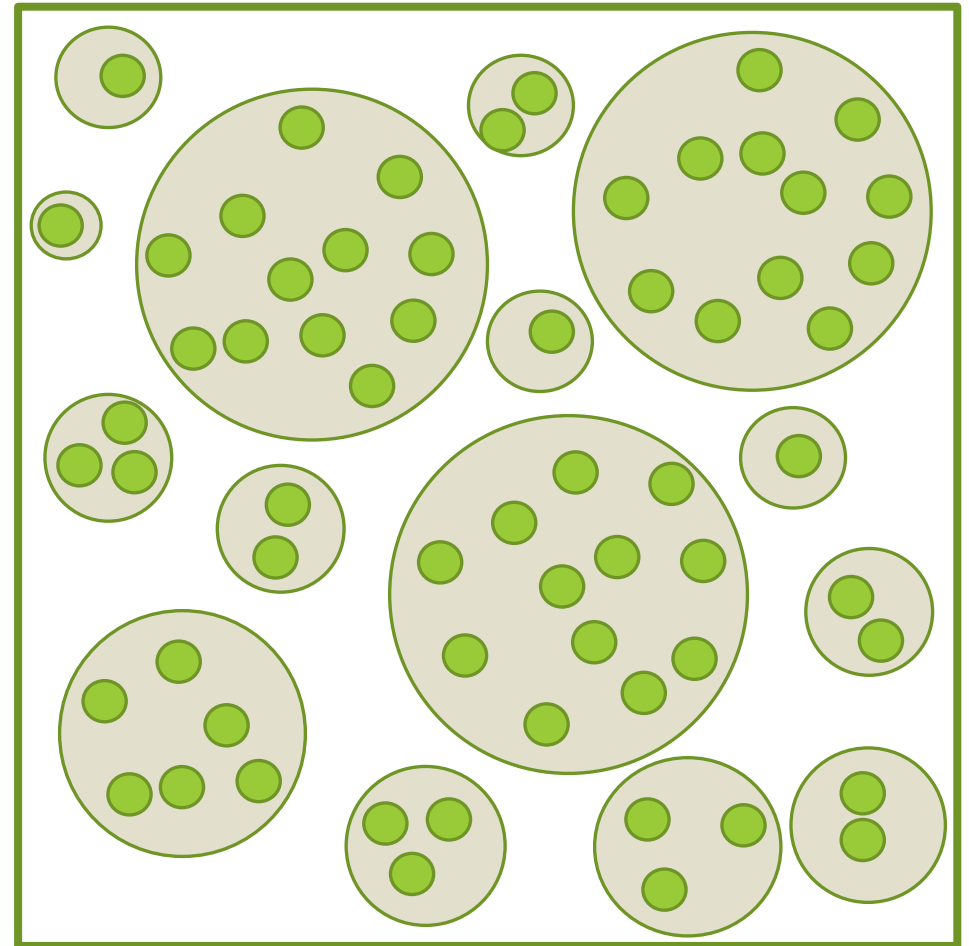
Distribution of Matter Particles



The Halo Model

- Introduced in **Peebles, 1980**
- Assumes that all matter is in **halos**

Distribution of Matter Particles



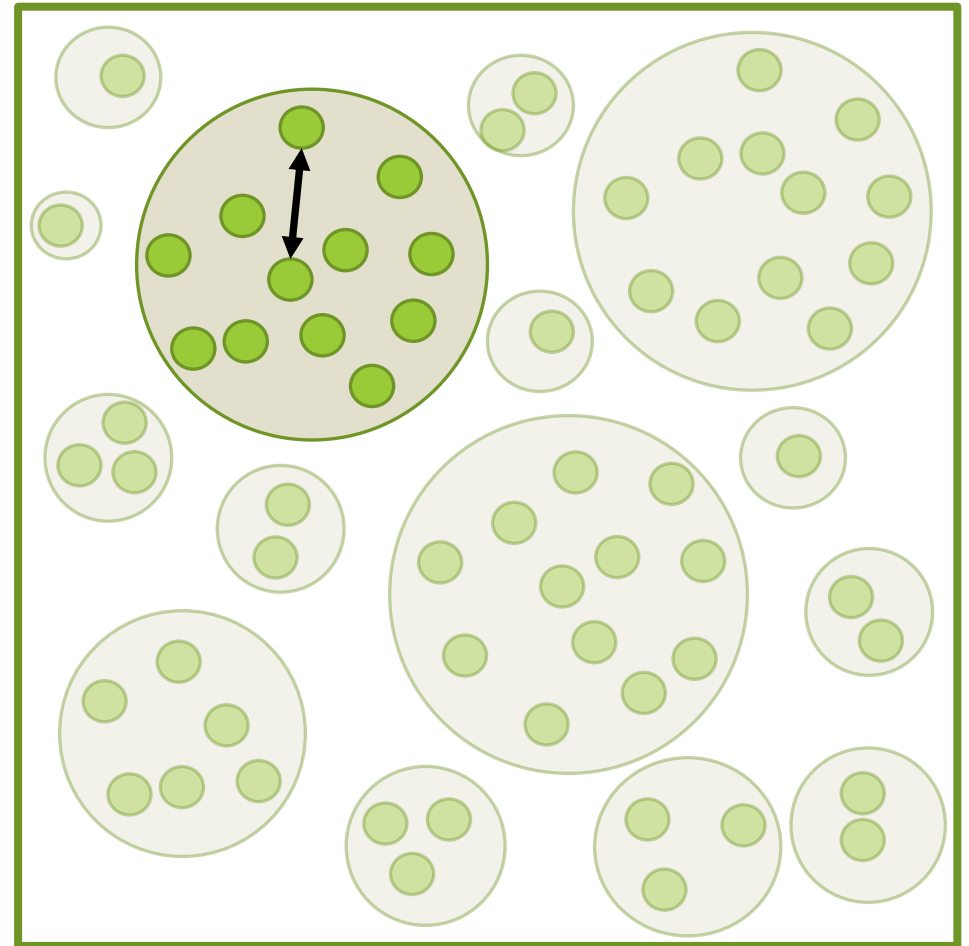
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- Introduced in **Peebles, 1980**
- Assumes that all matter is in **halos**
- Power spectrum composed of **one-halo** and two-halo terms

One-Halo: Particles distributed according to **halo profile**

Two-Halo: Particles distributed according to **halo distributions**

Distribution of Matter Particles



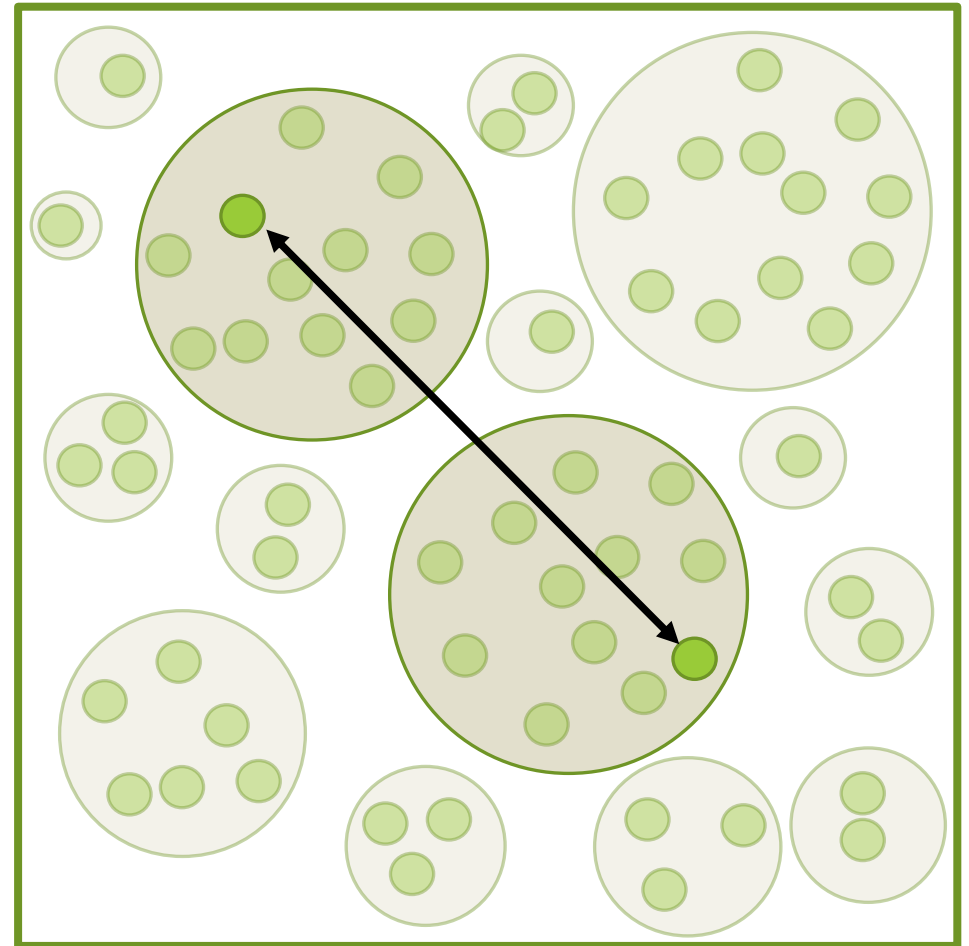
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Distribution of Matter Particles



Standard Halo Model Assumptions

- Halos are **Poisson distributed**

$$\hat{n}(m_1, \mathbf{x}_1)\hat{n}(m_2, \mathbf{x}_2) = n(m_1, \mathbf{x}_1)n(m_2, \mathbf{x}_2) + n(m_1, \mathbf{x}_1)\delta_D(\mathbf{x}_1 - \mathbf{x}_2)\delta_D(m_1 - m_2)$$

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- Position is set by the **linear density field** $\delta_L(\mathbf{x})$

$$n(m, \mathbf{x}) = n(m) [1 + b(m)\delta_L(\mathbf{x})]$$

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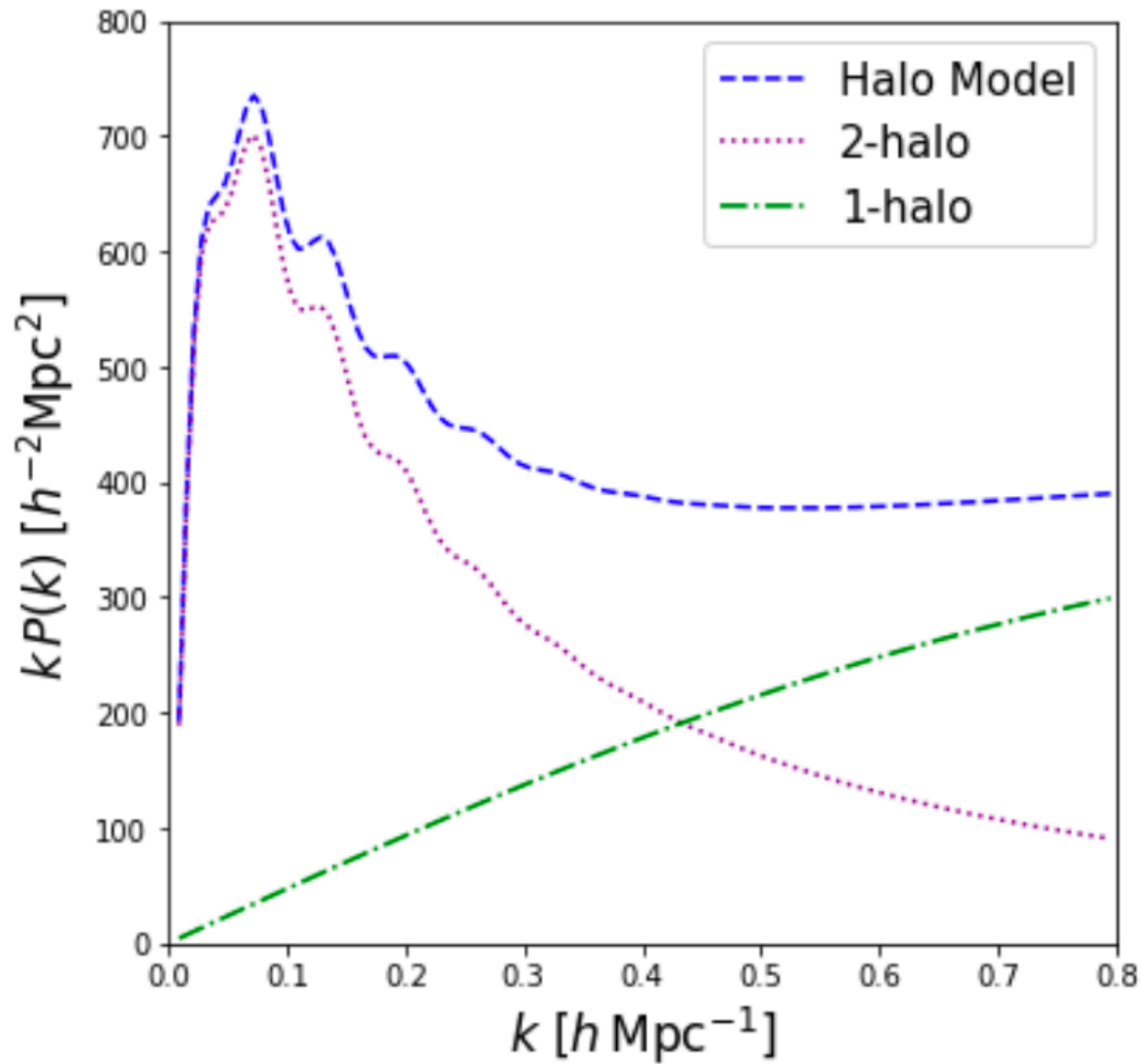
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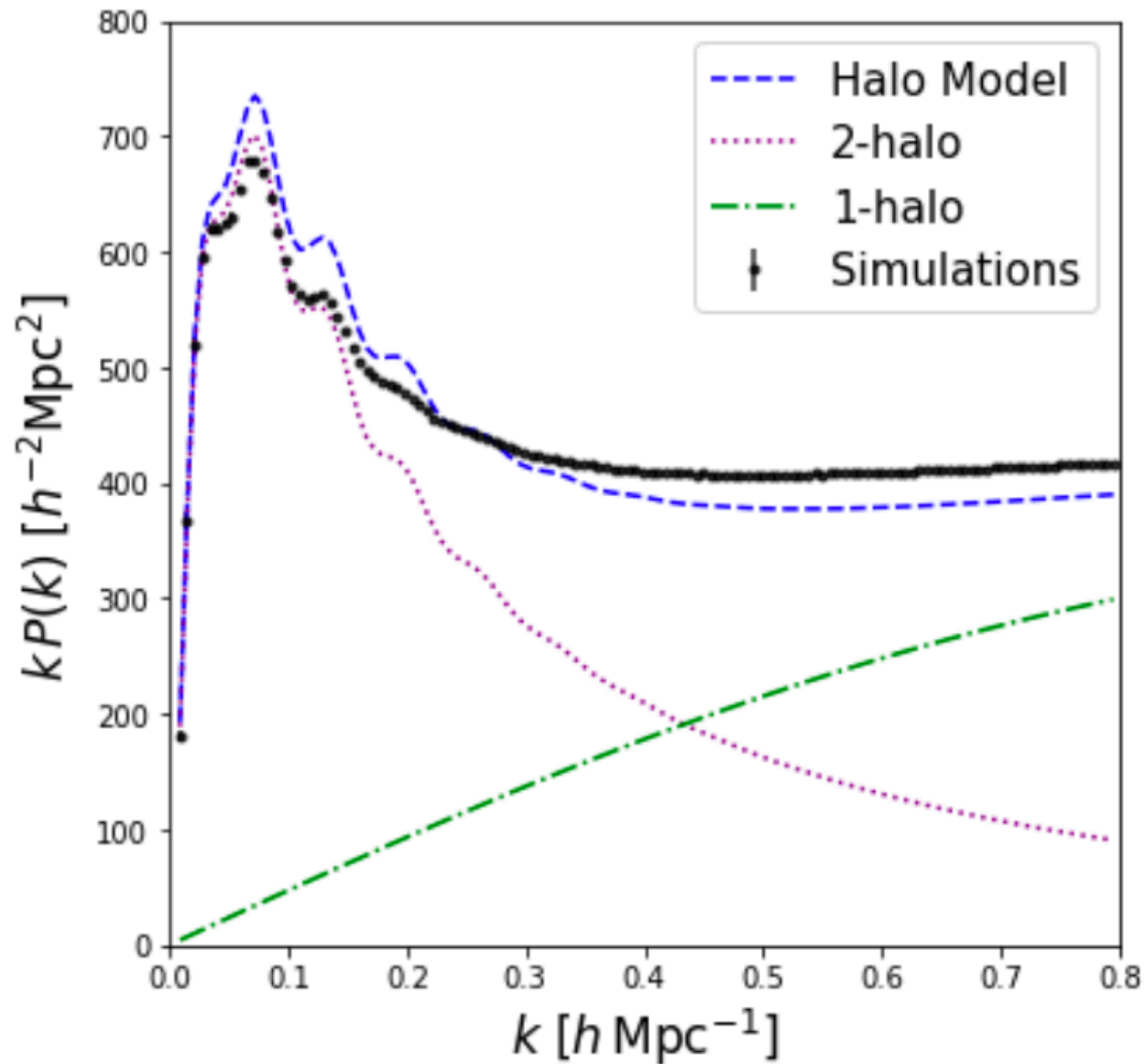
- Leads to a power spectrum;

$$P(k) = \overbrace{[I_1^1(k)]^2 P_L(k)}^{2\text{-halo}} + \overbrace{I_2^0(k)}^{1\text{-halo}}$$

Mass Integrals Linear Power



Standard Halo Model Prediction



N-body Simulations

Standard Halo Model Prediction

Using 100 high-resolution Quijote simulations
(Villaescusa-Navarro+19)

Models computed with *EffectiveHalos* Python code

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Effective Halo Model Assumptions

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- Position is set by the ~~linear density field~~ **smoothed non-linear** density field $\delta_R(\mathbf{x})$

$$n(m, \mathbf{x}) = n(m) [1 + \cancel{b(m)\delta_L(\mathbf{x})} + b(m)\delta_R(\mathbf{x}) + \dots]$$

Effective Halo Model Assumptions

- Halos are **Poisson distributed**

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- **Justification:**

- Halos are well-described by **non-linear** Effective Field Theory models
- Most of halo accretion occurs at **late-times** so needs **Eulerian** description
- Ensures our model is equal to **perturbation theory** on large scales

Effective Halo Model Power

$$P(k) = [I_1^1(k)]^2 P_L(k) + I_2^0(k)$$

Standard Model

Effective Halo Model Power

$$P(k) = [I_1^1(k)]^2 P_L(k) + I_2^0(k) \longrightarrow P(k) = [I_1^1(k)]^2 P_{\text{NL}}(k) W^2(kR) + I_2^0(k)$$

The diagram illustrates the transition from the Standard Model to the Effective Model. The Standard Model equation is $P(k) = [I_1^1(k)]^2 P_L(k) + I_2^0(k)$. The Effective Model equation is $P(k) = [I_1^1(k)]^2 P_{\text{NL}}(k) W^2(kR) + I_2^0(k)$. A large green arrow points from the Standard Model to the Effective Model. Brackets above the Effective Model equation label the terms: $[I_1^1(k)]^2$ and $I_2^0(k)$ are labeled "1-halo", $P_{\text{NL}}(k)$ is labeled "2-halo", and $W^2(kR)$ is labeled "Smoothing Function". A green arrow points from the label "Mass Integrals" to the $[I_1^1(k)]^2$ term. A blue arrow points from the label "Non-Linear Power" to the $P_{\text{NL}}(k)$ term.

Standard Model

Effective Model

$P_{\text{NL}}(k)$ is modelled with **Effective Field Theory**

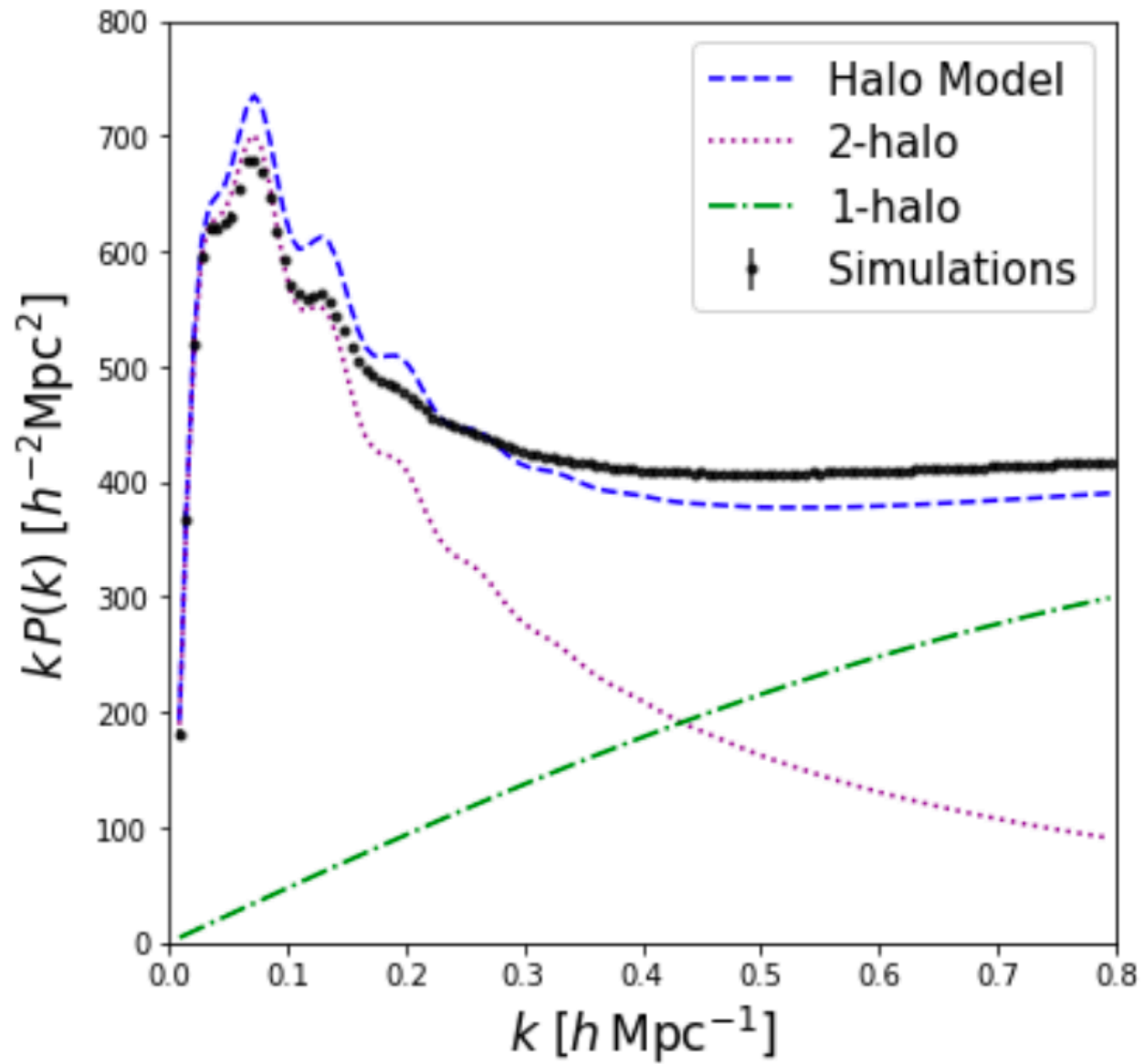
Effective Field Theory

- Evaluate non-linear power with (IR-resummed) 1-loop **Effective Field Theory**

$$P_{\text{NL}}(k) = P_{\text{L}}(k) + P_{1\text{-loop}}(k) - c_s^2 \frac{k^2}{(1+k^2)} P_{\text{L}}(k)$$

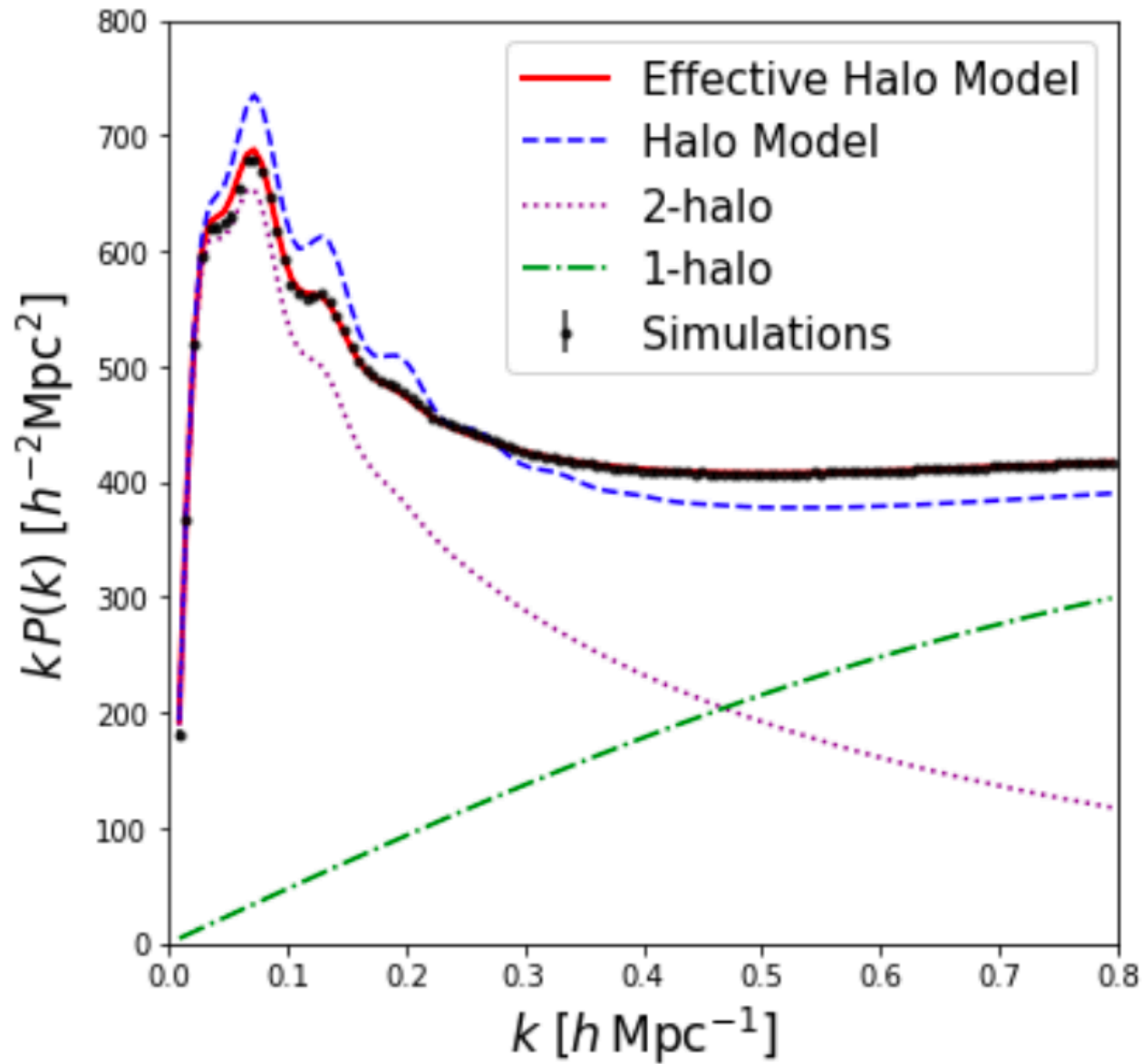
Linear Power 1-loop Power Counterterm

- Counterterm has a **free parameter** c_s^2 and is Pade resummed.
- Percent-accurate up to $k \sim 0.2h \text{ Mpc}^{-1}$



N-body Simulations

Standard Halo Model Prediction

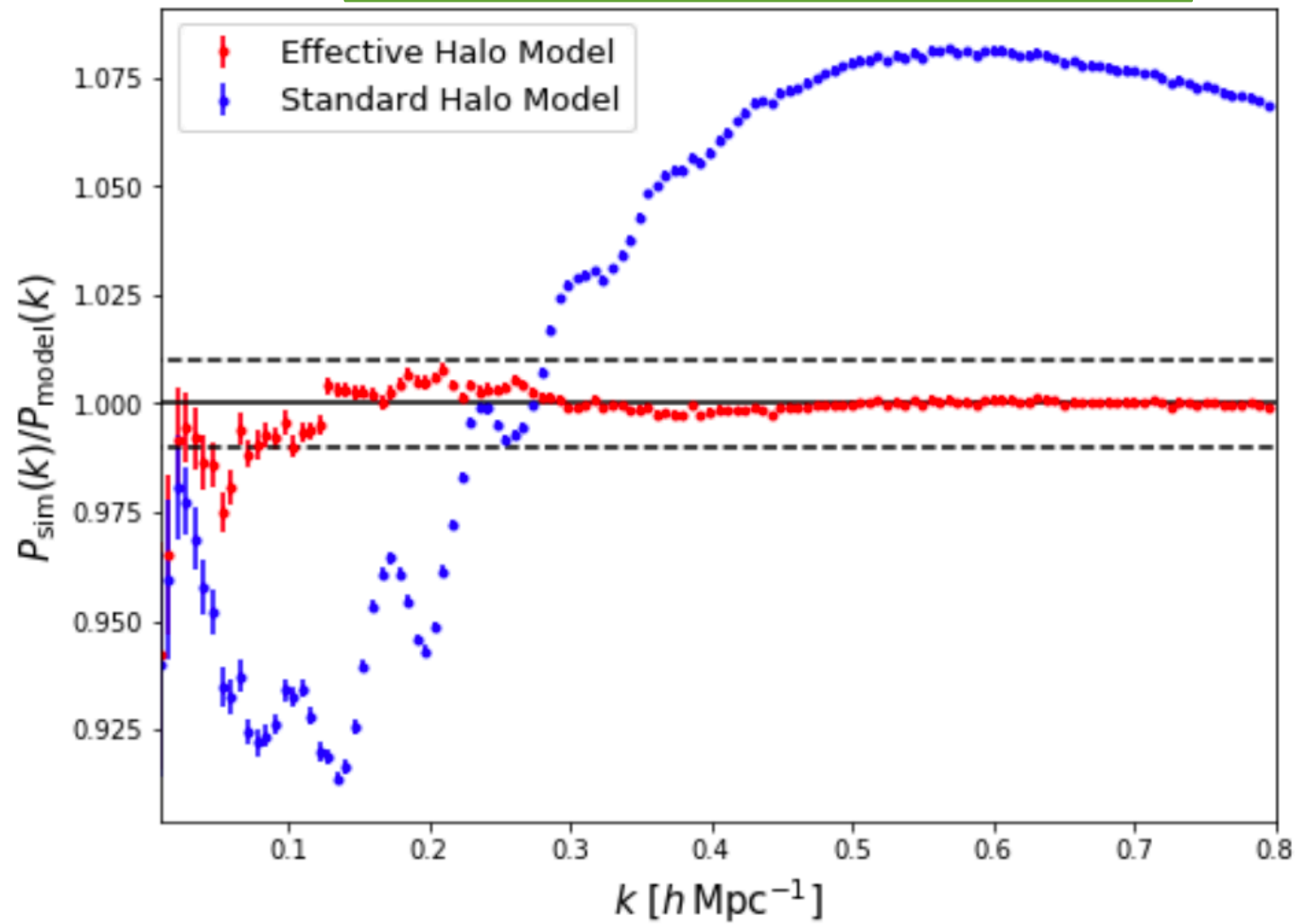


Effective Halo Model

N-body Simulations

Standard Halo Model Prediction

Ratio of Simulation and Model Power



The Effective Halo Model is percent-accurate up to large k !

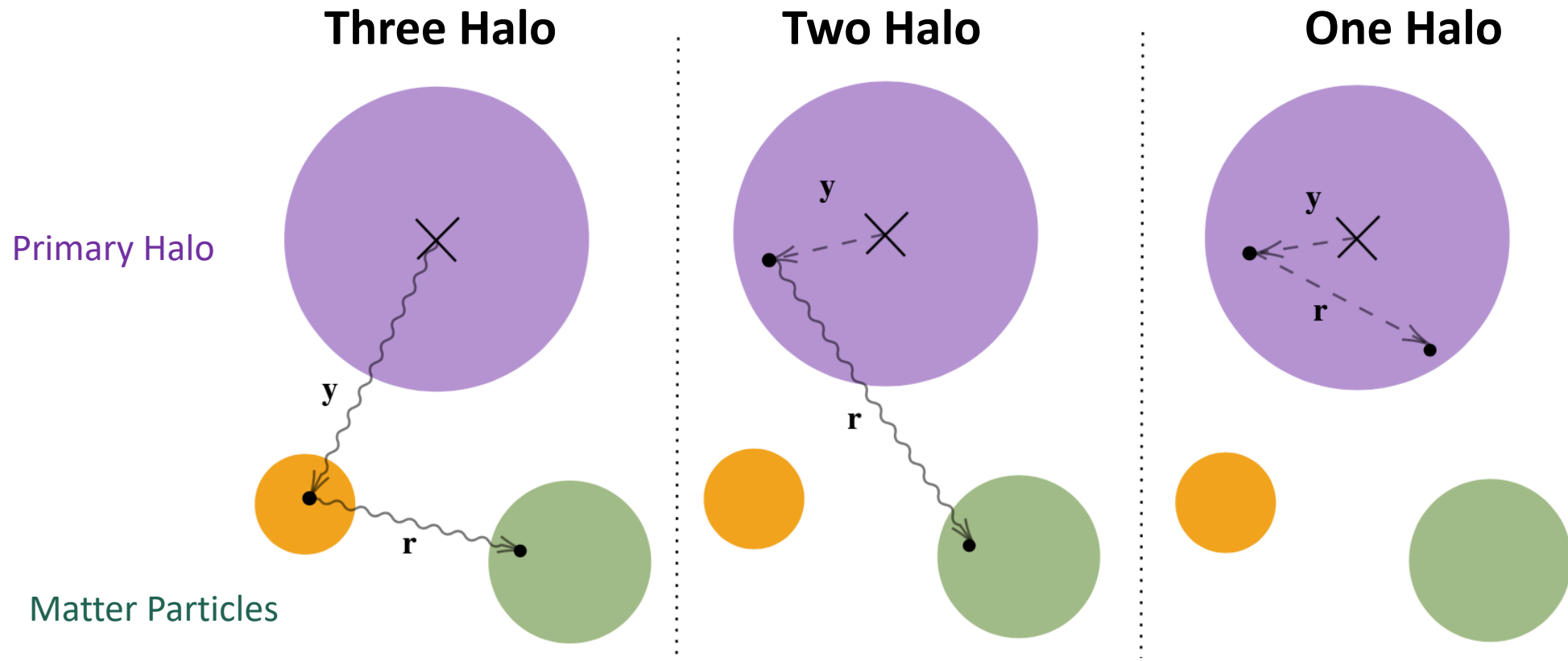
Beyond the Power Spectrum

- The Effective Halo Model can be used to predict **other statistics**, e.g.
 - **Power-spectrum covariance** $\text{cov}(P(k), P(k'))$
 - **Cluster-count covariance** $\text{cov}(N(m), N(m'))$
 - **Power-spectrum x cluster-count covariance** $\text{cov}(N(m), P(k))$
- These are useful for **tSZ** and **weak-lensing** analyses

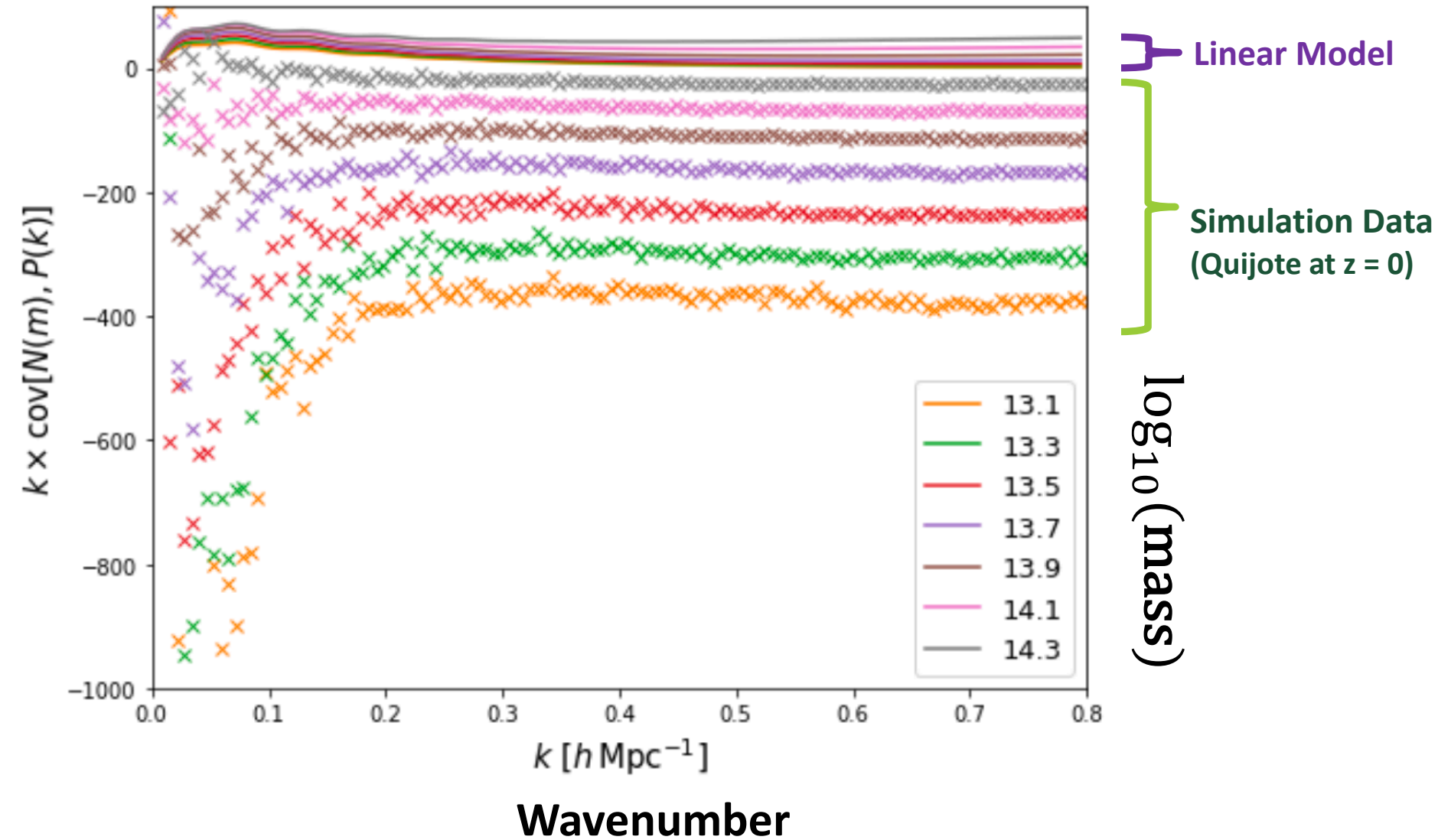
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1) Intrinsic Covariance



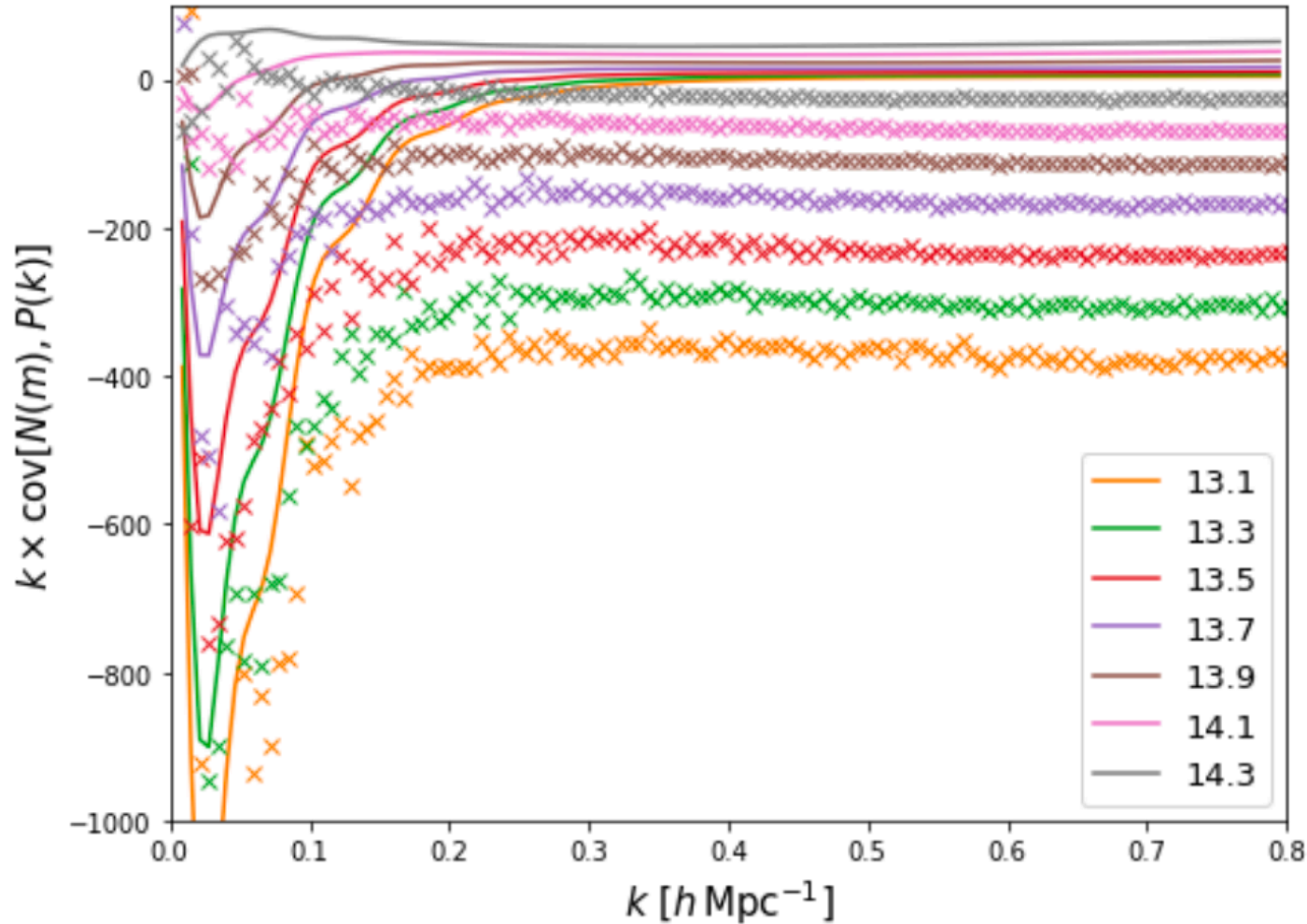
Old Model



Schaan+14, Takada+07,14

Using 15000 Quijote simulations at standard resolution (no super-sample effects)

New Intrinsic Covariance Model



Non-linear model

Simulation Data
(Quijote at $z = 0$)

Model assumes:

- Quadratic bias
- Non-Linear power

Philcox+20

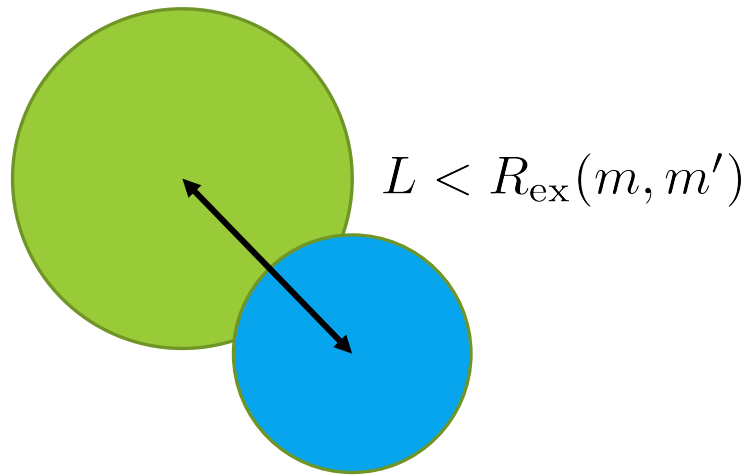
Using 15000 Quijote simulations at standard resolution (no super-sample effects)

2) Exclusion Covariance

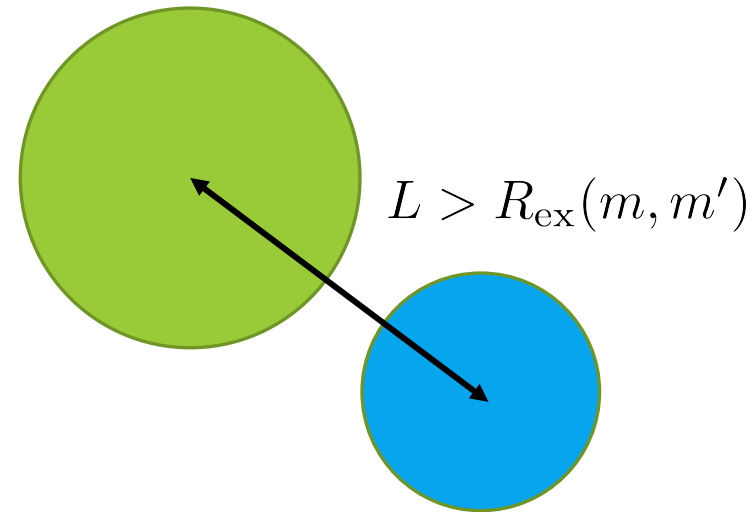
- Halos cannot overlap!
- For halo mass m , there must be **no halos** with $m' > m$ within some **exclusion radius** $R_{\text{ex}}(m, m')$

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Overlapping Halos: Classified as One Object



Separate Halos: Classified as Two Objects

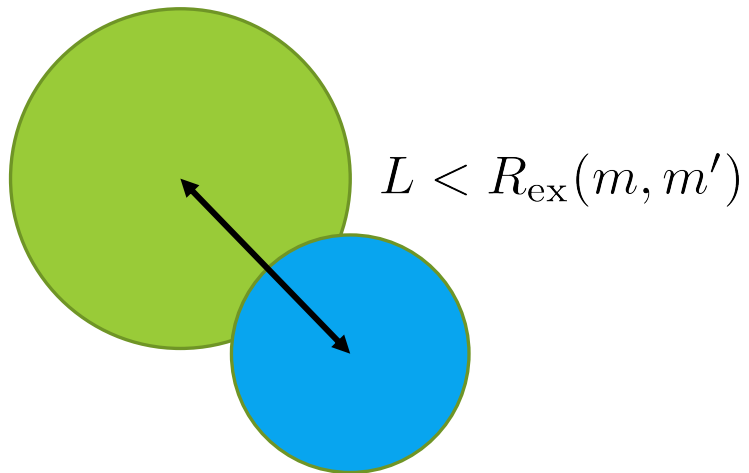
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○ Halos cannot overlap!

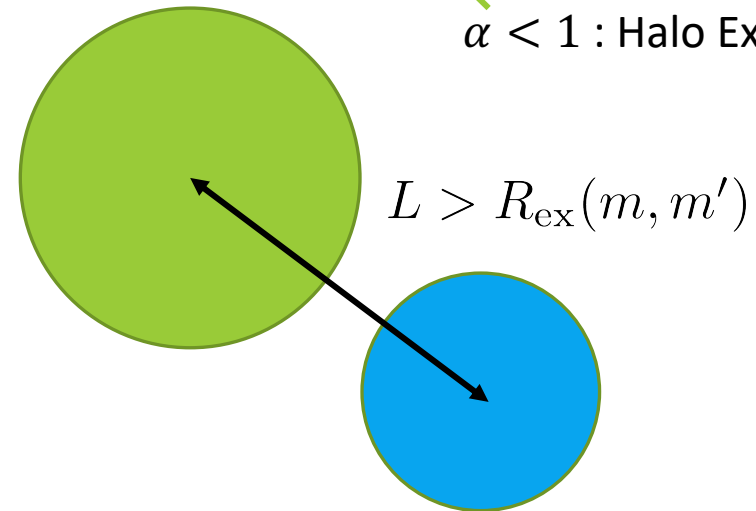
○ For halo mass m , there must be **no halos** with $m' > m$ within some **exclusion radius** $R_{\text{ex}}(m, m')$

$$R_{\text{ex}}(m, m') = \alpha [R_{\text{Lag}}(m) + R_{\text{Lag}}(m')]$$

$\alpha < 1$: Halo Exclusion Scale

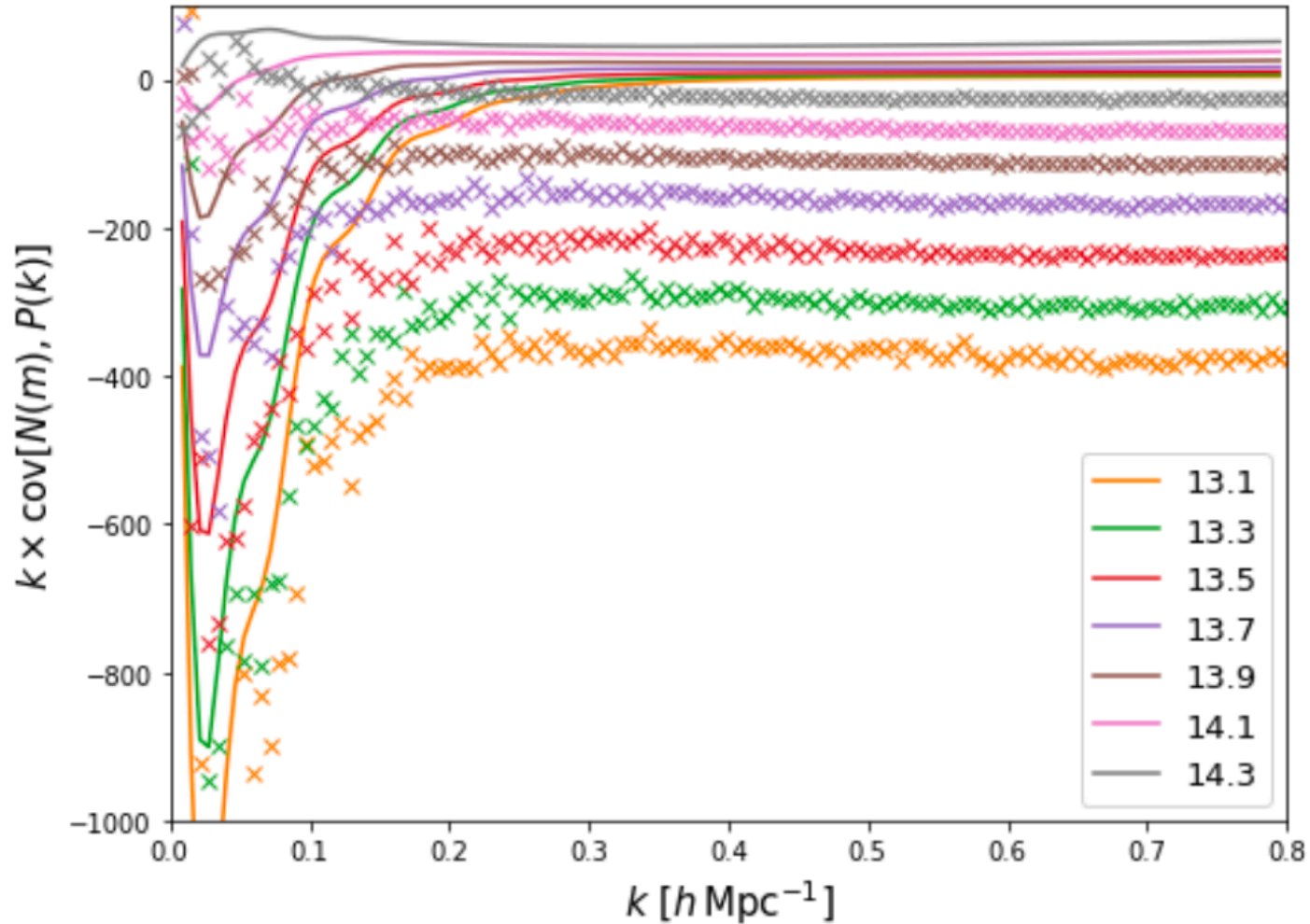


Overlapping Halos: Classified as One Object



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New Intrinsic Covariance Model



Non-linear model

Simulation Data
(Quijote at $z = 0$)

$\log_{10}(\text{mass})$

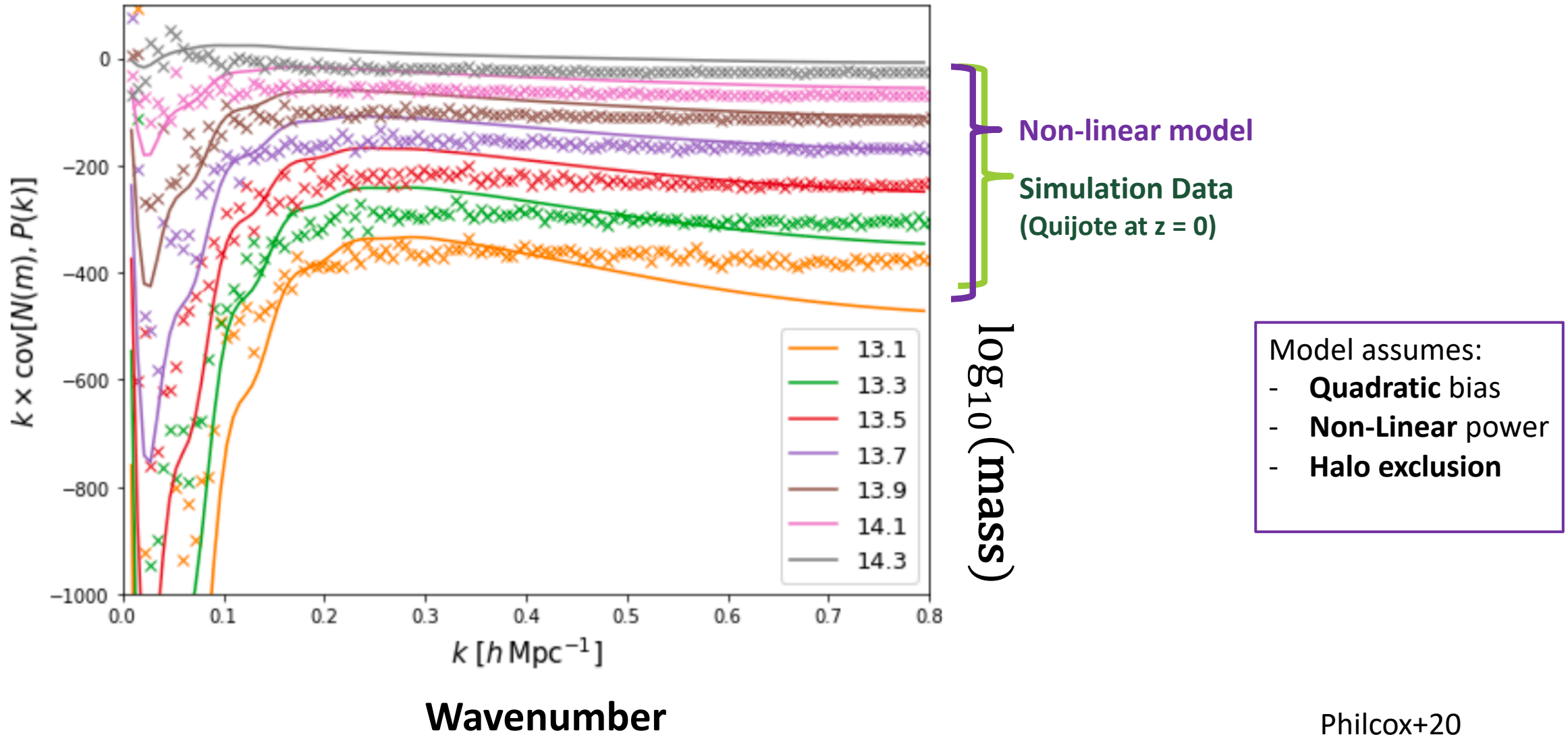
Model assumes:
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Wavenumber

Philcox+20

Using 15000 Quijote simulations at standard resolution (no super-sample effects)

New Intrinsic + Exclusion Covariance Model



Using 15000 Quijote simulations at standard resolution (no super-sample effects)

Philcox+20

3) Super-Sample Covariance

- Density modes δ_b on scales comparable to the survey width modulate the background density

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- This causes an **extra covariance**

$$\text{cov}(N(m), P(k)) \rightarrow \text{cov}(N(m), P(k)) + \frac{\partial N(m)}{\partial \delta_b} \frac{\partial P(k)}{\partial \delta_b} \sigma^2(V)$$

Number count response Power spectrum response Variance of δ_b

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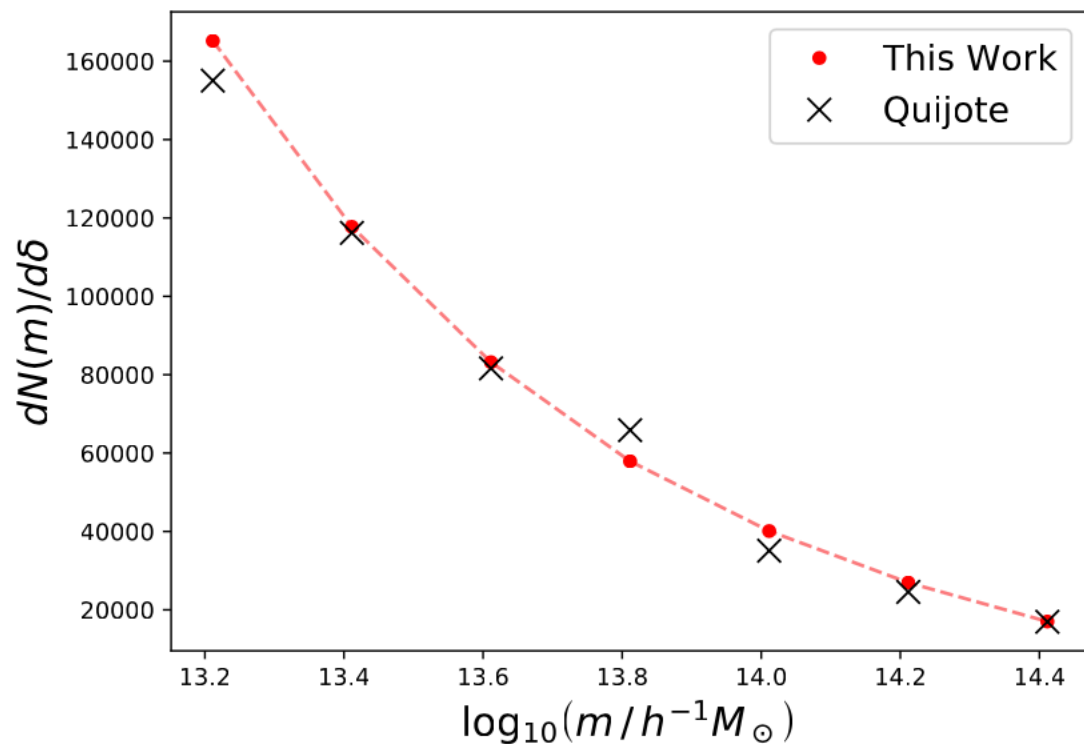
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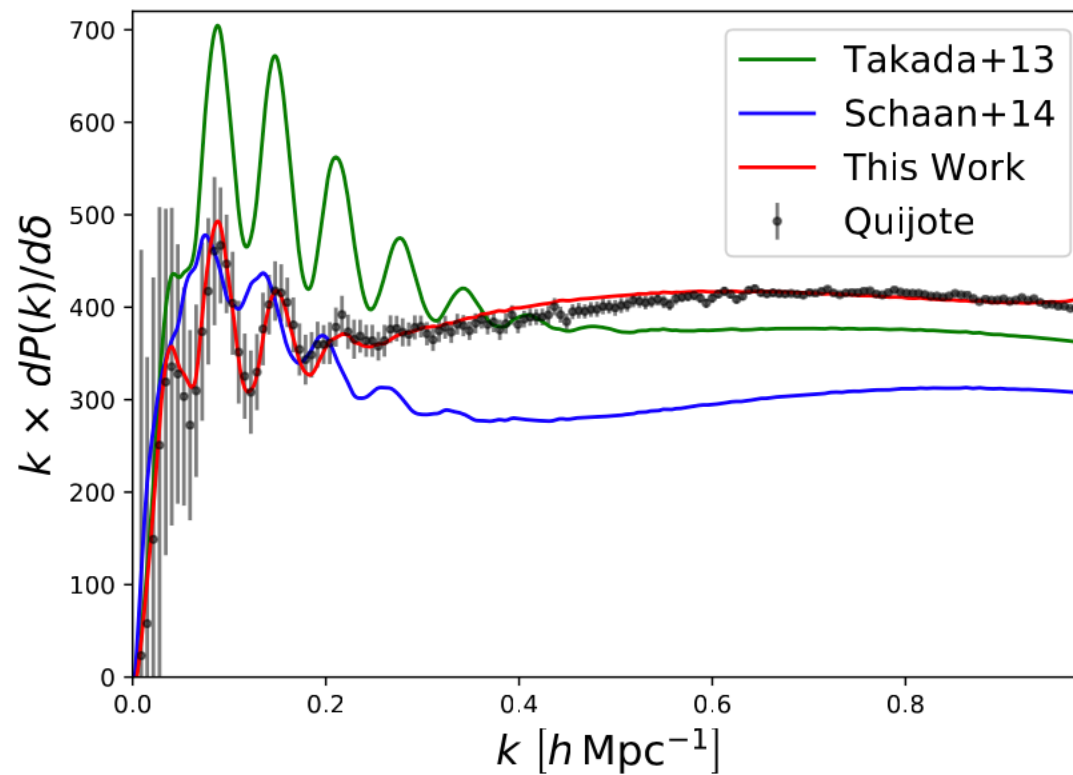
- But not normally found in N-body simulations
 - Use **separate universe** simulations [Li+14], and **sub-box** simulations

Response Terms

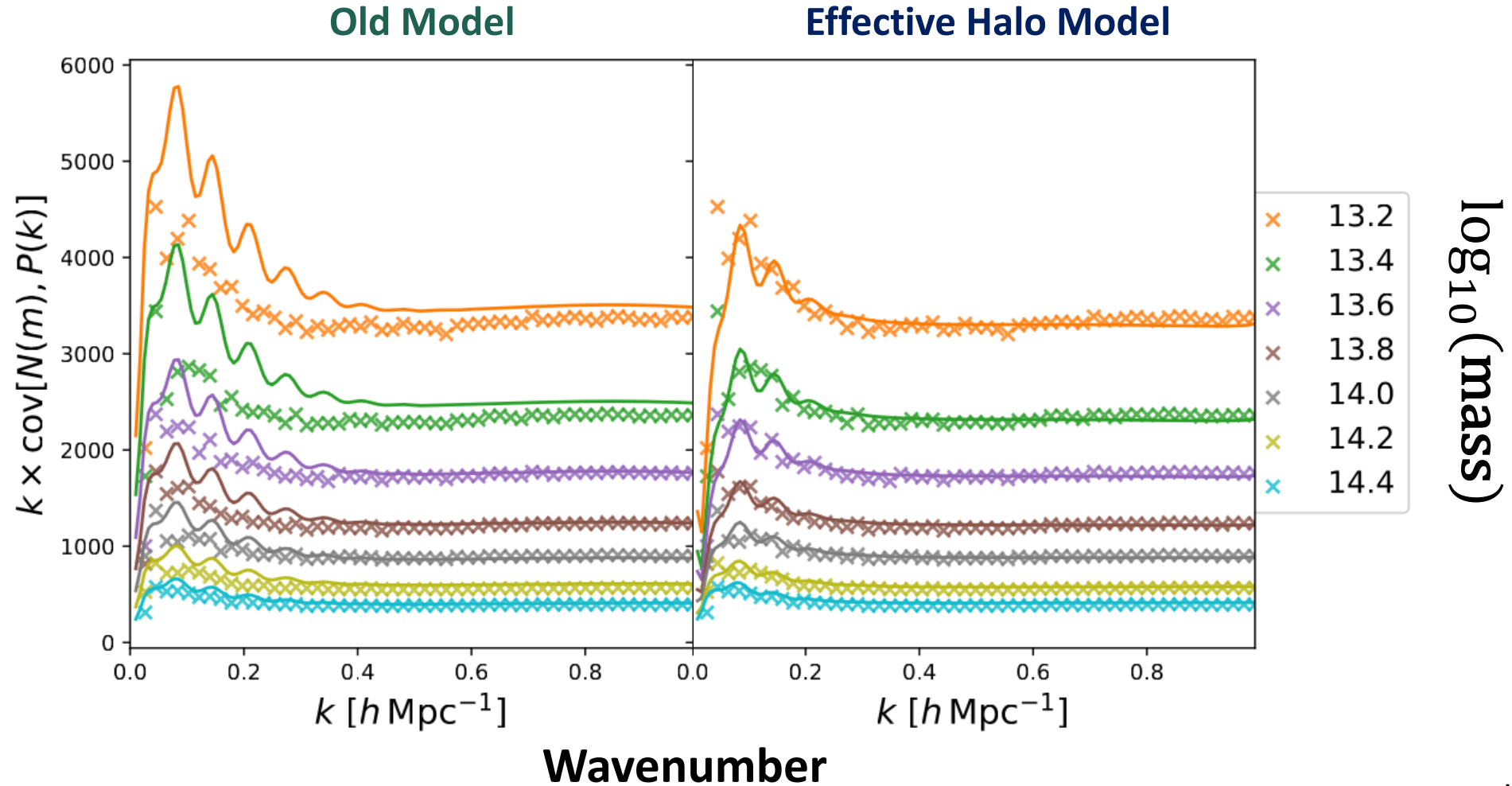
Number count response



Power spectrum response



Full Covariance using sub-box Simulations



Conclusions

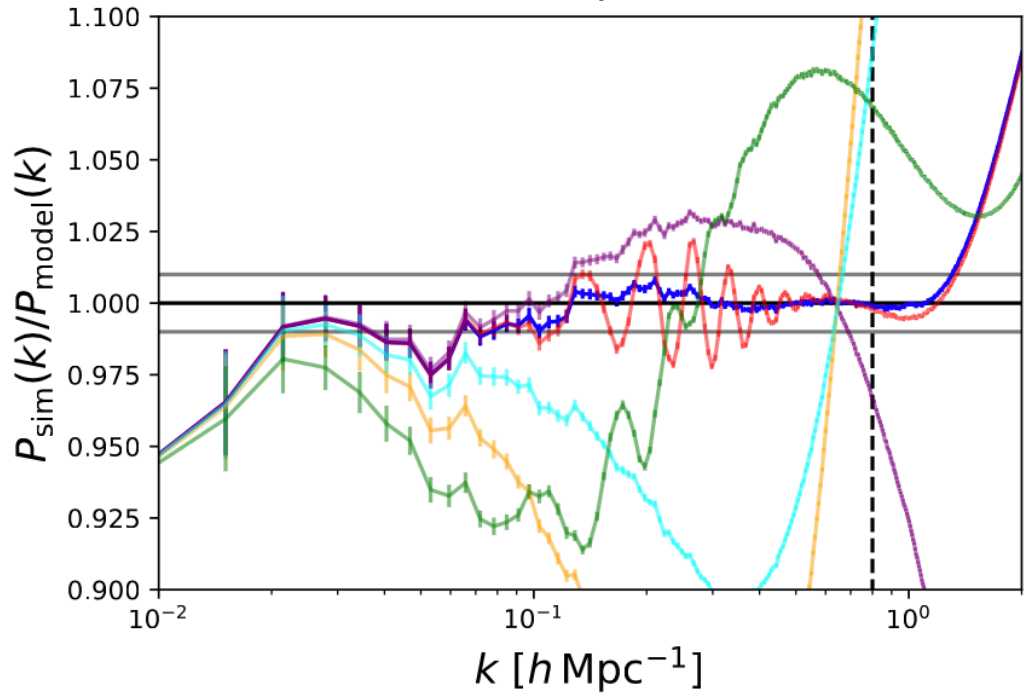
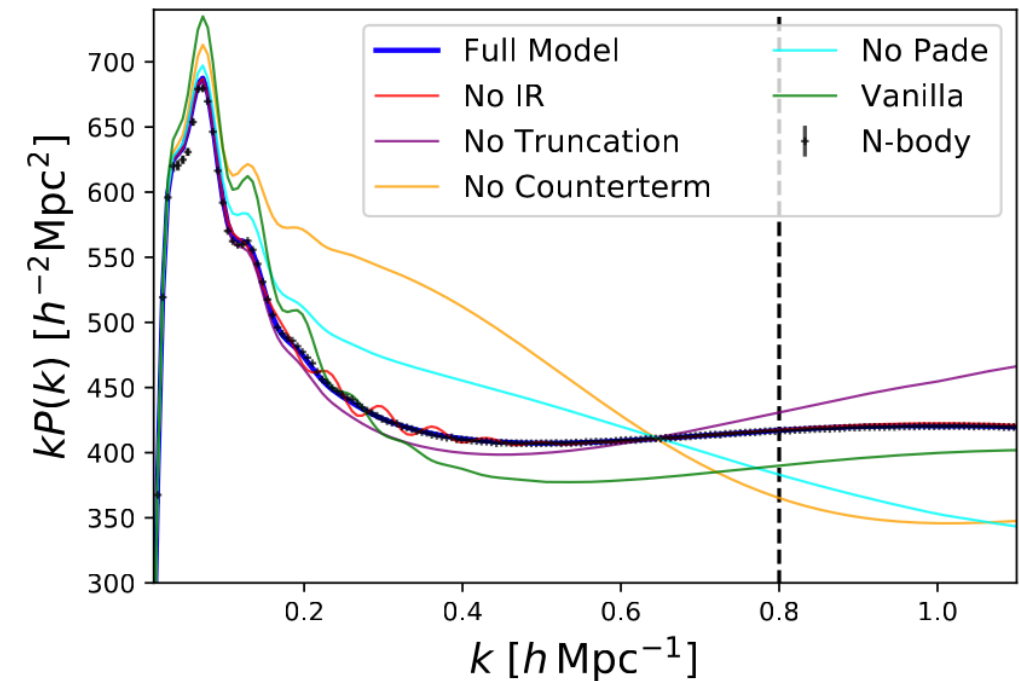
(arXiv: 2004.09515)

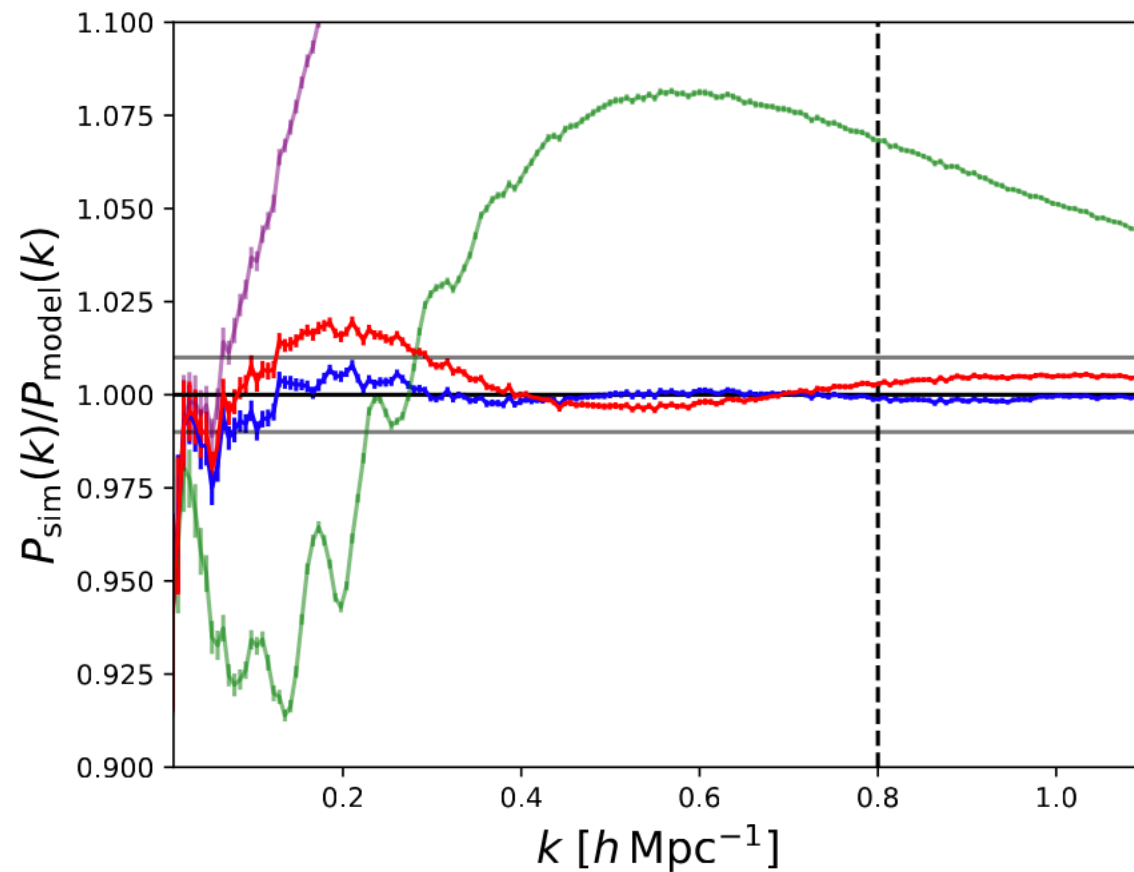
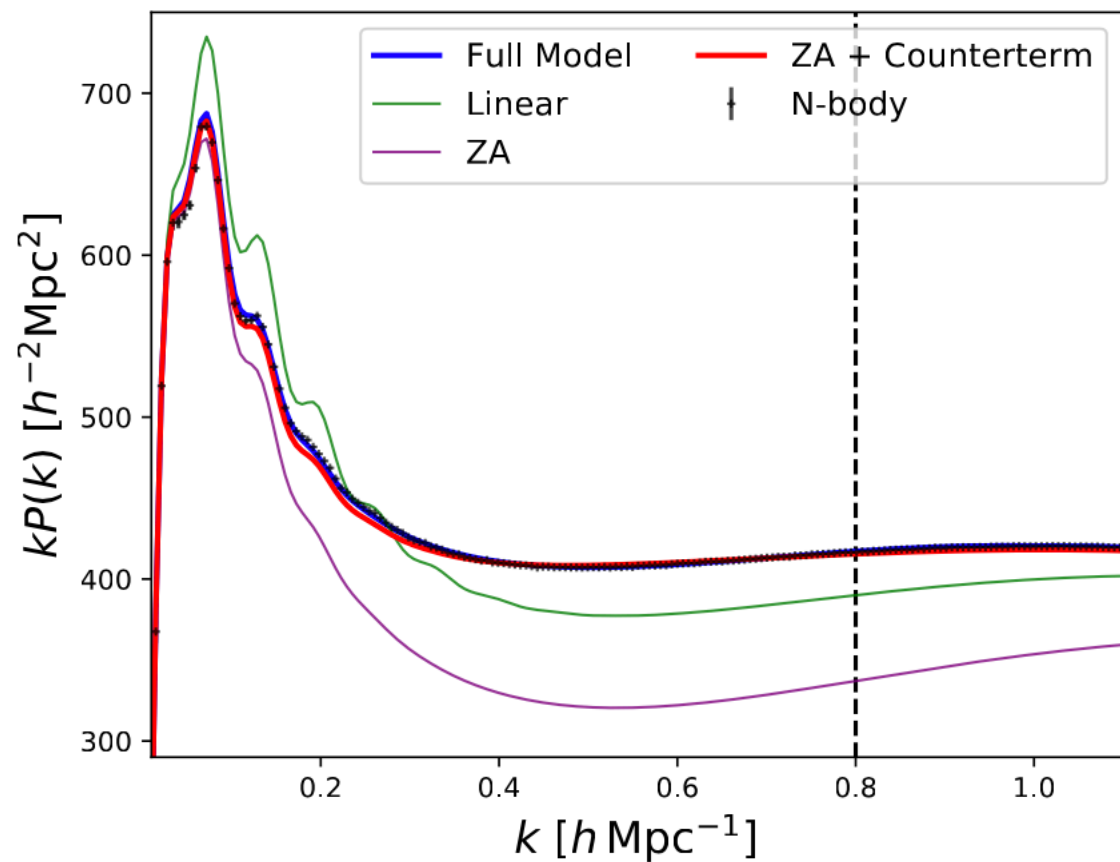
- Using the **Halo Model** and **Effective Field Theory** we get 1% accurate matter power spectra to $k \sim 1h \text{ Mpc}^{-1}$
- Can extend this to other statistics, e.g. **cluster count covariances**, but we must consider **halo exclusion**
- Includes a **fast** and **easy-to-use** Python package: [EffectiveHalos.readthedocs.io](https://effectivehalos.readthedocs.io)

Extensions

- Baryonic Physics
- Joint likelihoods of **tSZ cluster counts** and **weak lensing**

Power Spectrum Model Components



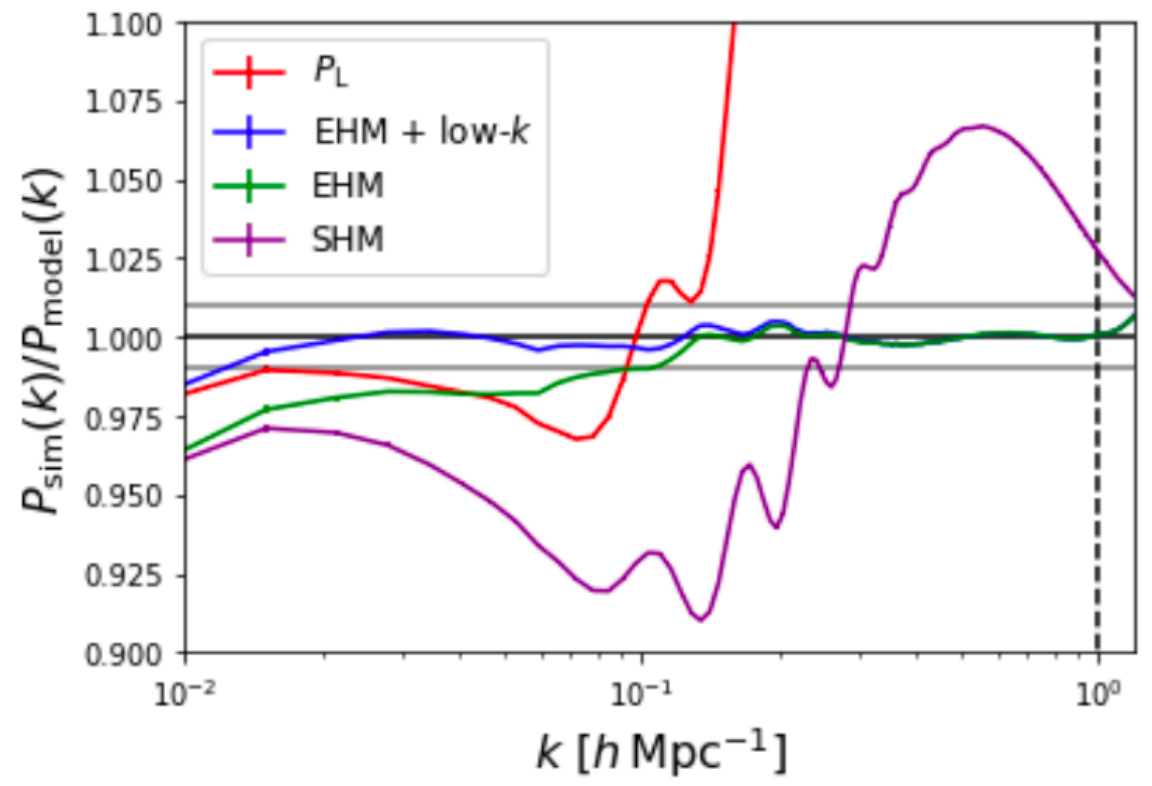
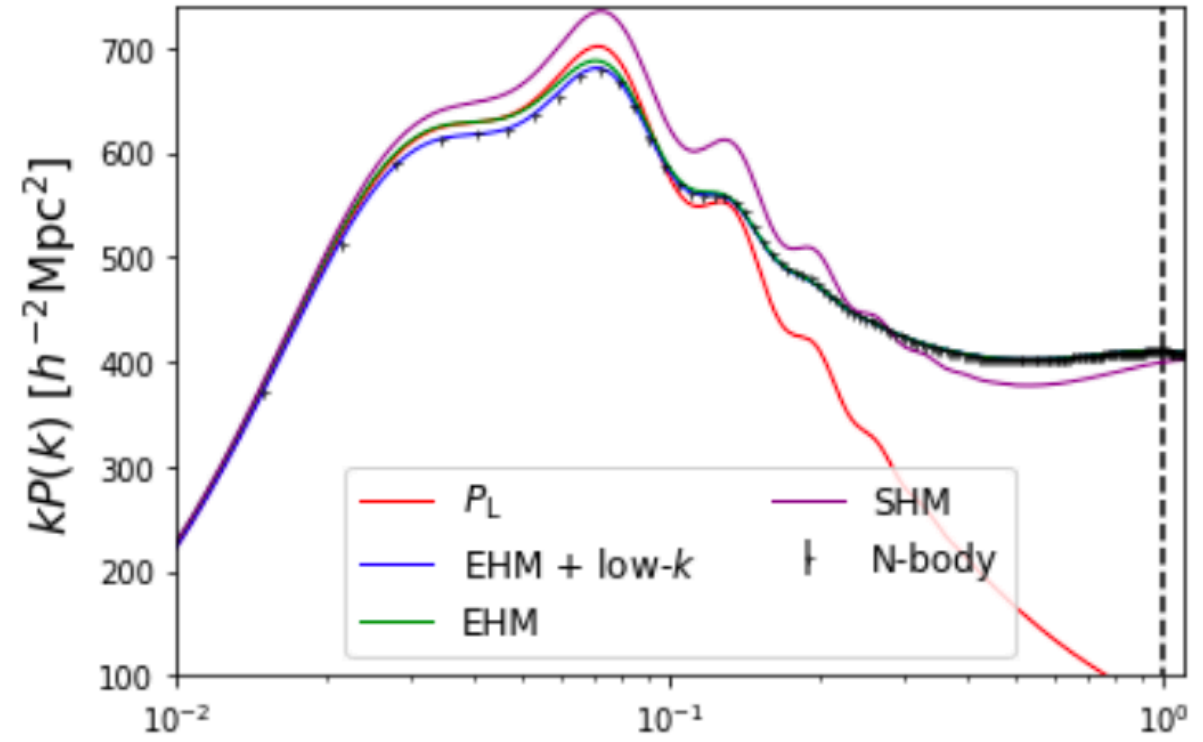


Zel'dovich Approximation vs EFT

Schmidt (2016) Correction

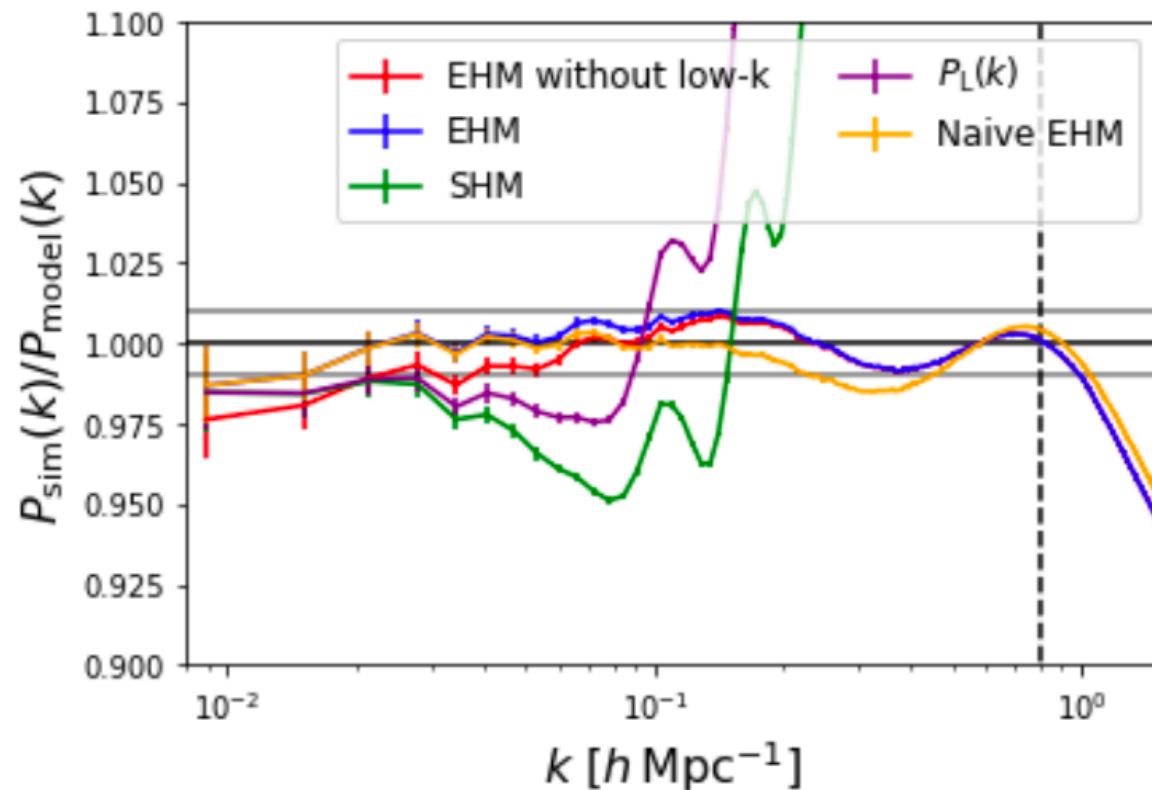
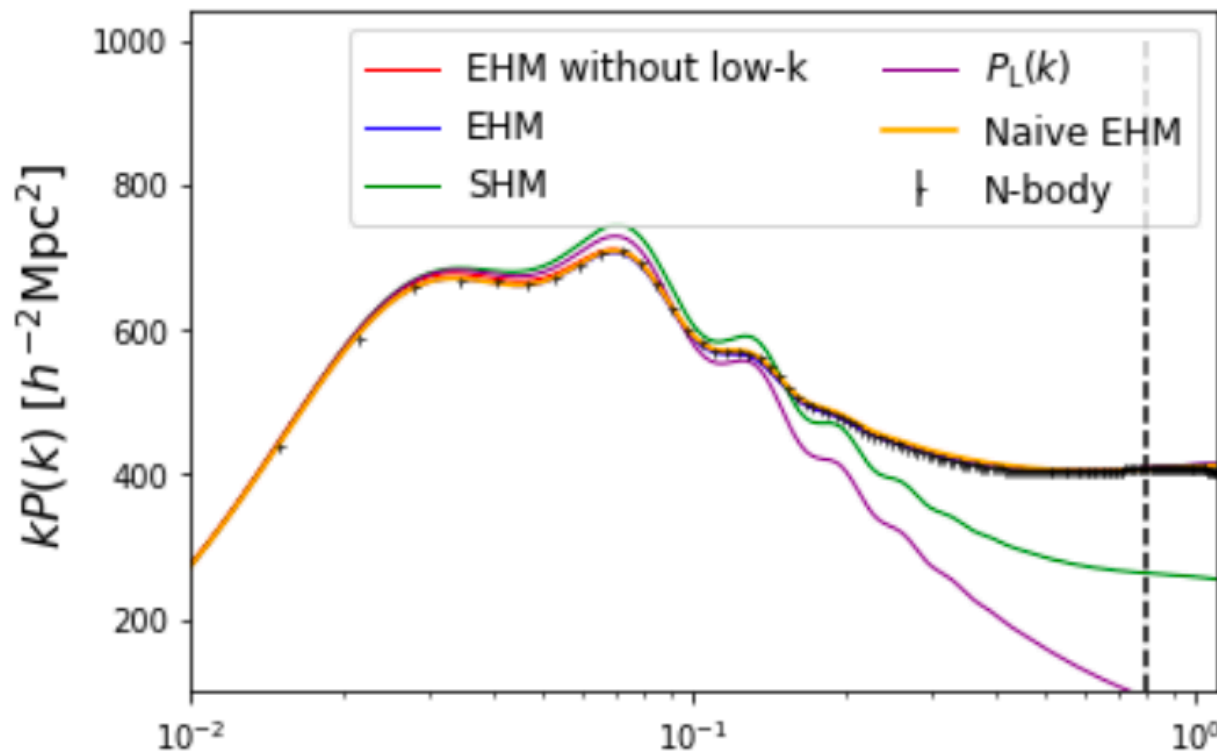
$$P^{1h}(k) \rightarrow P^{1h}(k) - \frac{1}{\bar{\rho}\langle m \rangle} \int dm_1 dm_2 \frac{m_1^2}{\bar{\rho}} \frac{m_2^2}{\bar{\rho}} n(m_1)n(m_2)u(k|m_1)u(k|m_2)\Theta(k|m_1, m_2)$$

$$\Theta(k|m_1, m_2) = \frac{1}{1 + [k (R_L(m_1) + R_L(m_2))]^4}$$



Low-k Effects

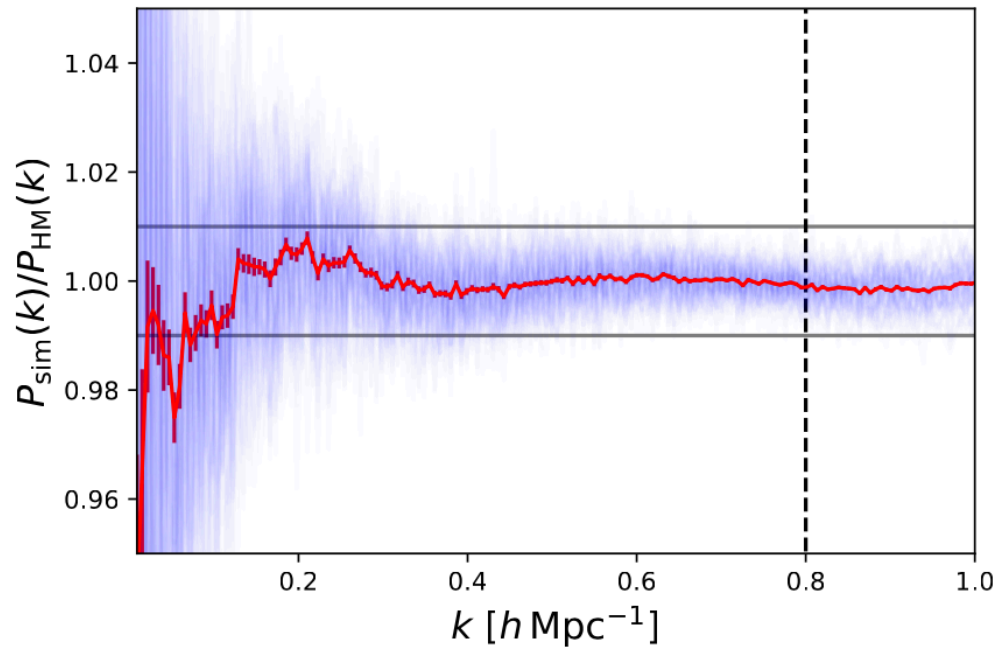
Following Massara et al. (2014), treat CDM+baryons with the halo model and assume **linear theory** for the neutrino correlators:



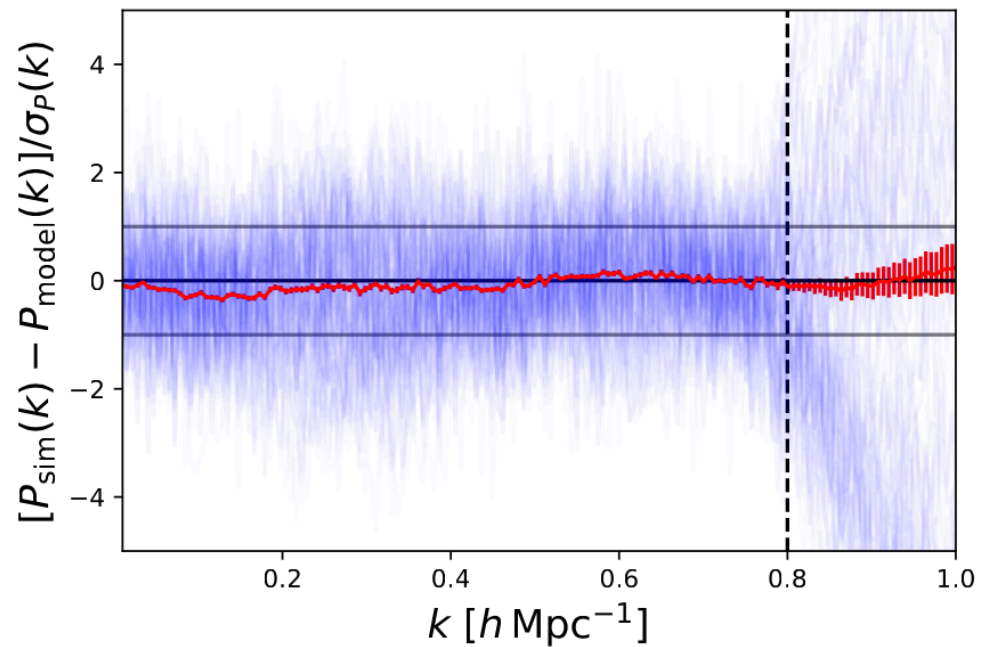
From 500 Quijote Simulations at $\sum m_\nu = 0.4 \text{ eV}$

Massive Neutrinos

Philcox+ (in prep)



Fitting Individual Simulations



Fitting for non-standard cosmologies

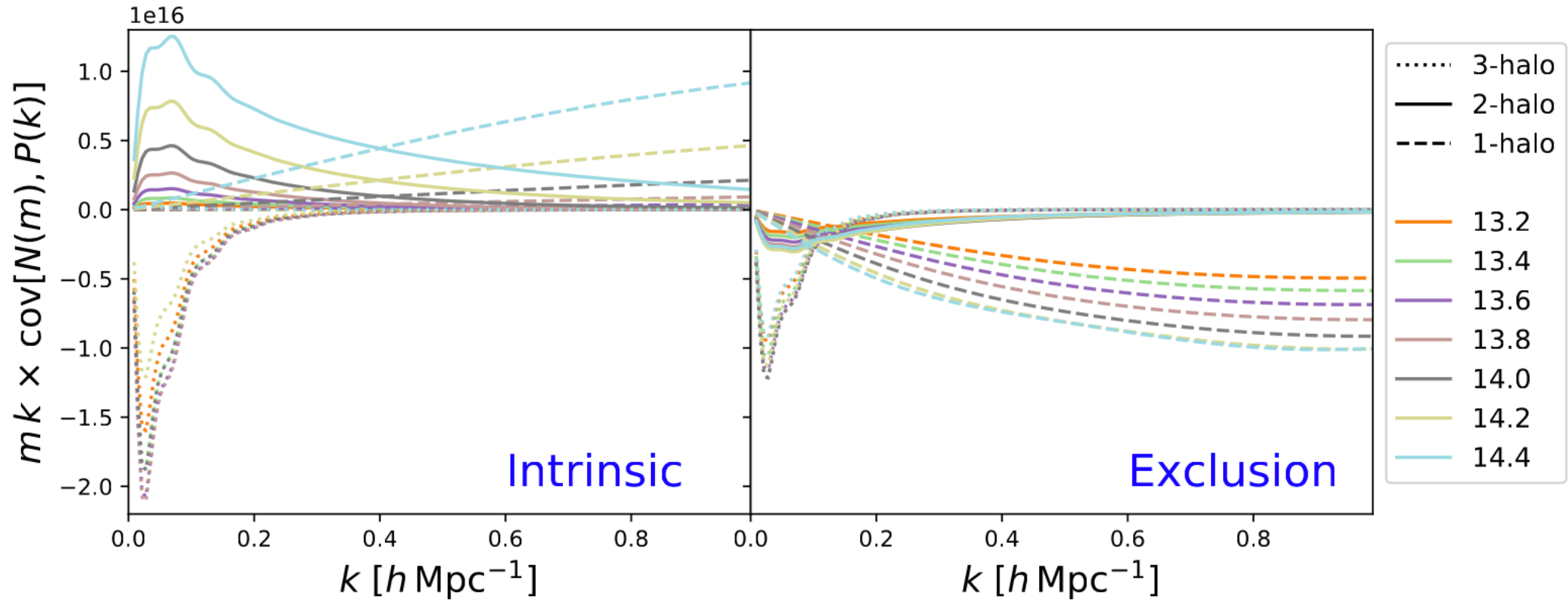
$$\begin{aligned} \frac{dP_{\text{HM}}(k)}{d\delta_b} = & 2I_1^2(k)I_1^1(k)W^2(kR)P_{\text{NL}}(k) + I_2^1(k, k) \\ & + \left[I_1^1(k) \right]^2 W^2(kR)P_{\text{NL}}(k) \left(\frac{68}{21} + \frac{26}{21} \frac{P_{\text{SPT}}(k) + P_{\text{ct}}(k)}{P_{\text{NL}}(k)} \right) \\ & - \frac{1}{3} \frac{d \log k^3 P_{\text{NL}}(k)}{d \log k} P_{\text{HM}}(k), \end{aligned}$$

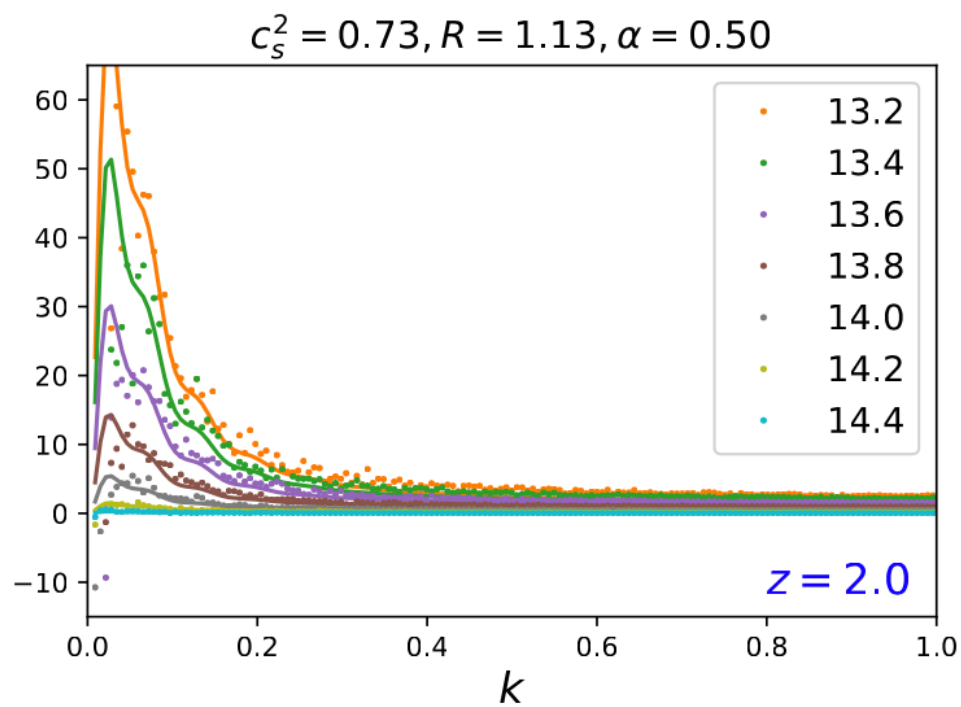
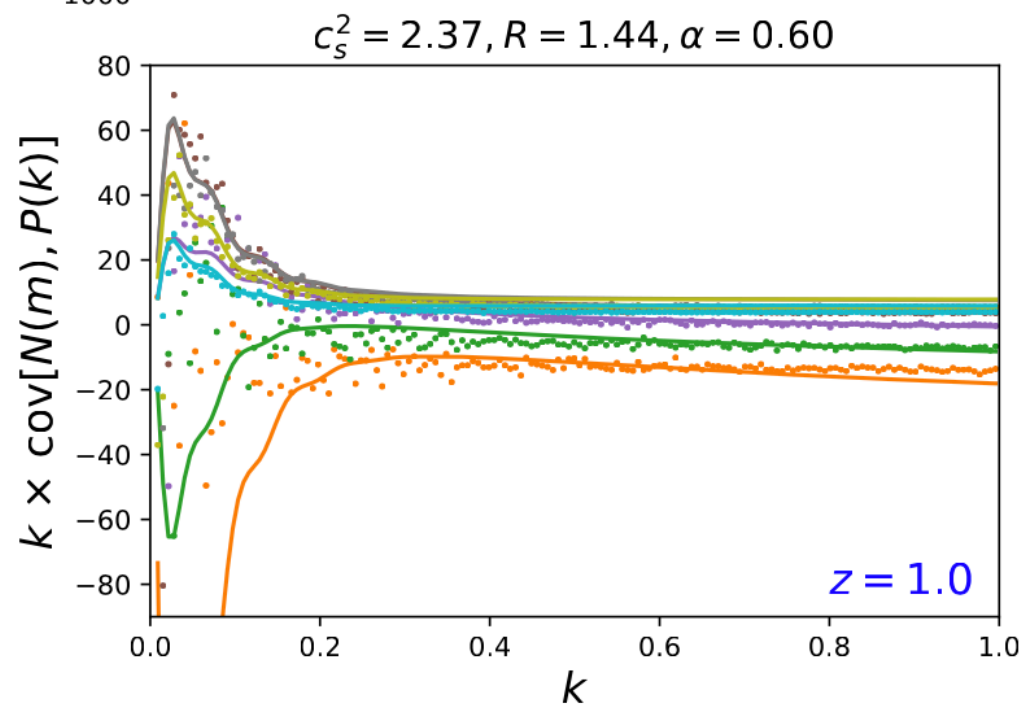
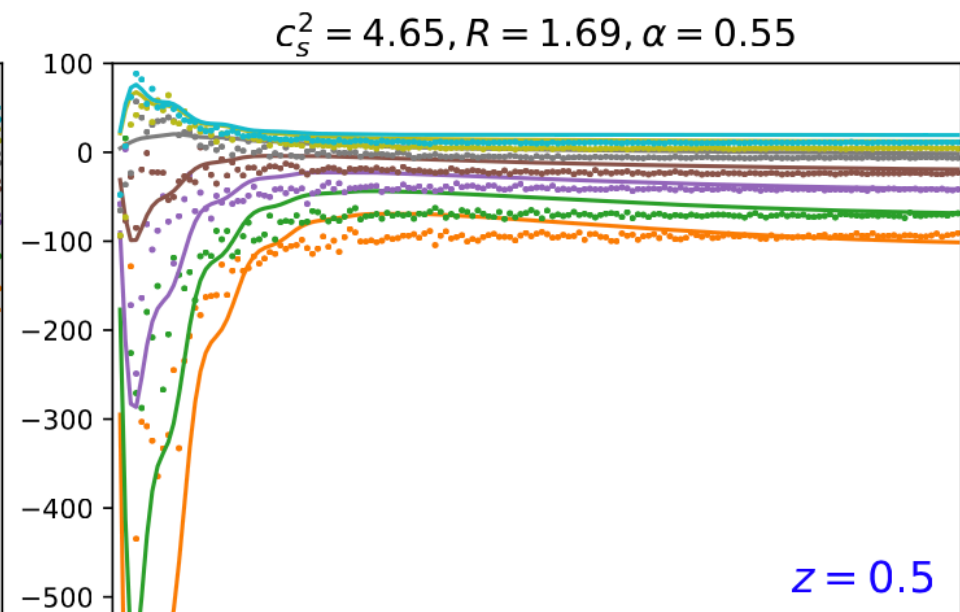
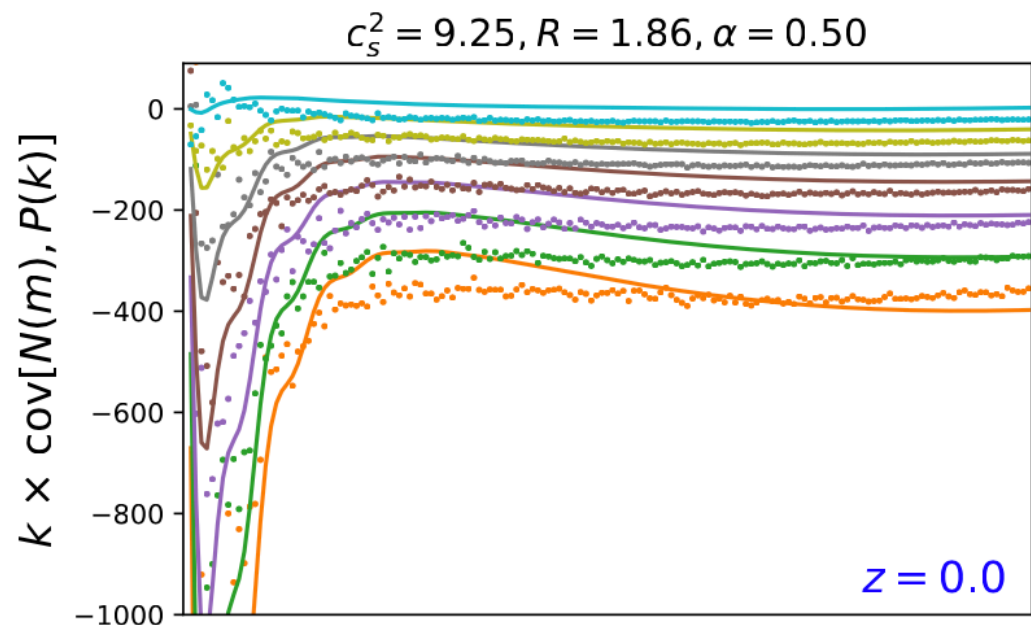
Power Spectrum Response

$$\frac{\partial N(m)}{\partial \delta_b} \equiv \frac{\partial}{\partial \delta_b} \int d\mathbf{x} n(m) = Vn(m)b^{(1)}(m),$$

Number Count Response

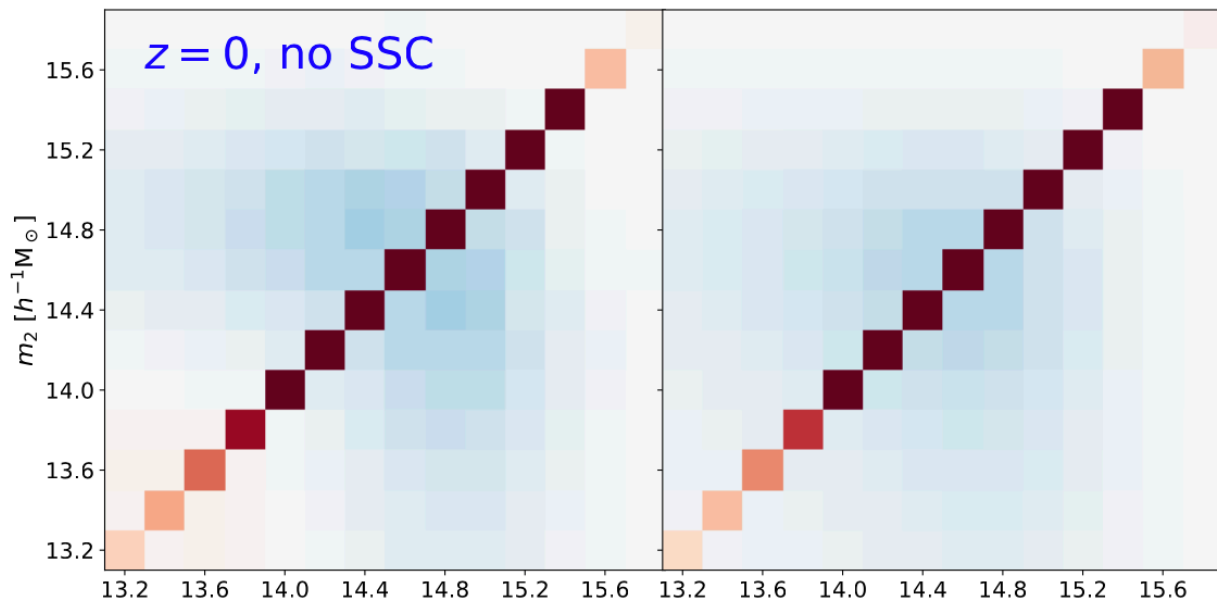
Covariance Components





Quijote Simulations

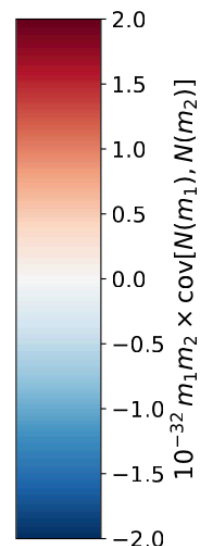
This Work



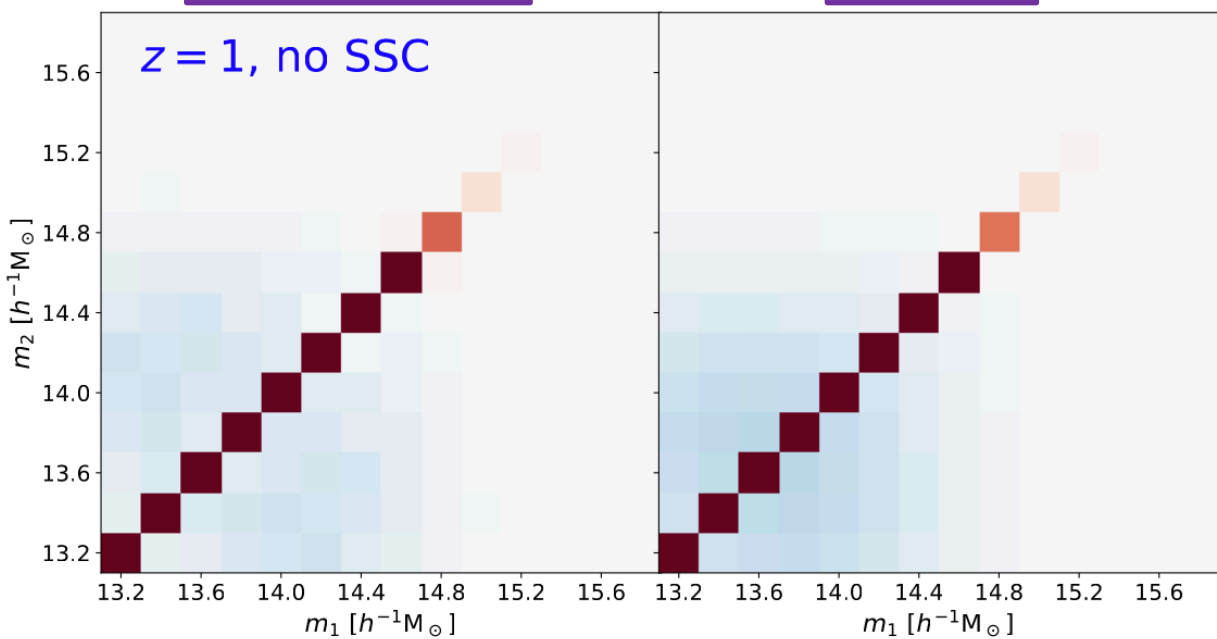
$z = 0$, no SSC

Simulations

Model



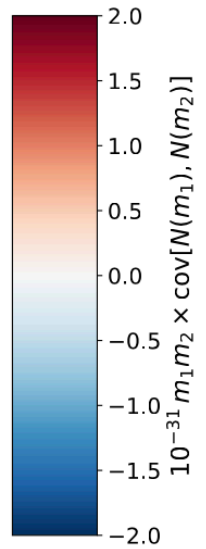
Halo Covariance



$z = 1$, no SSC

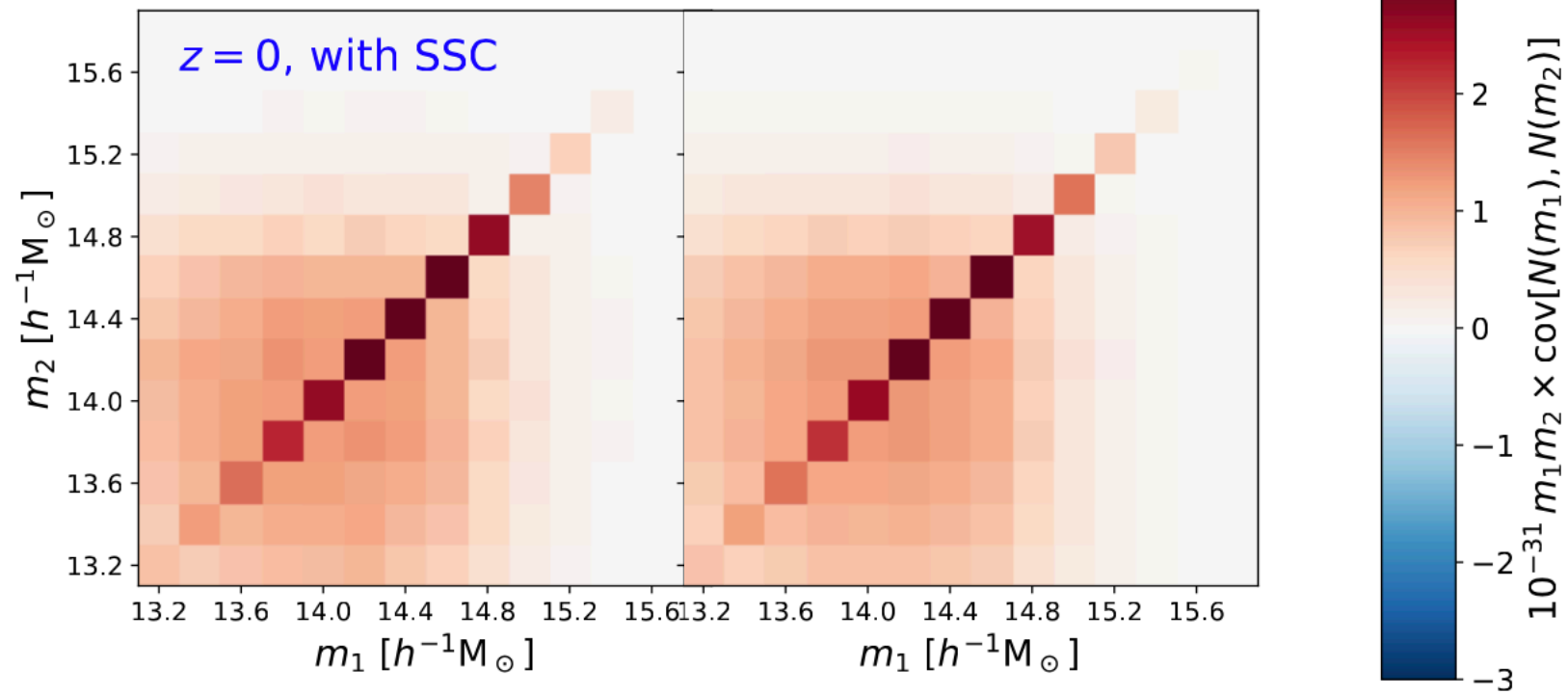
Simulations

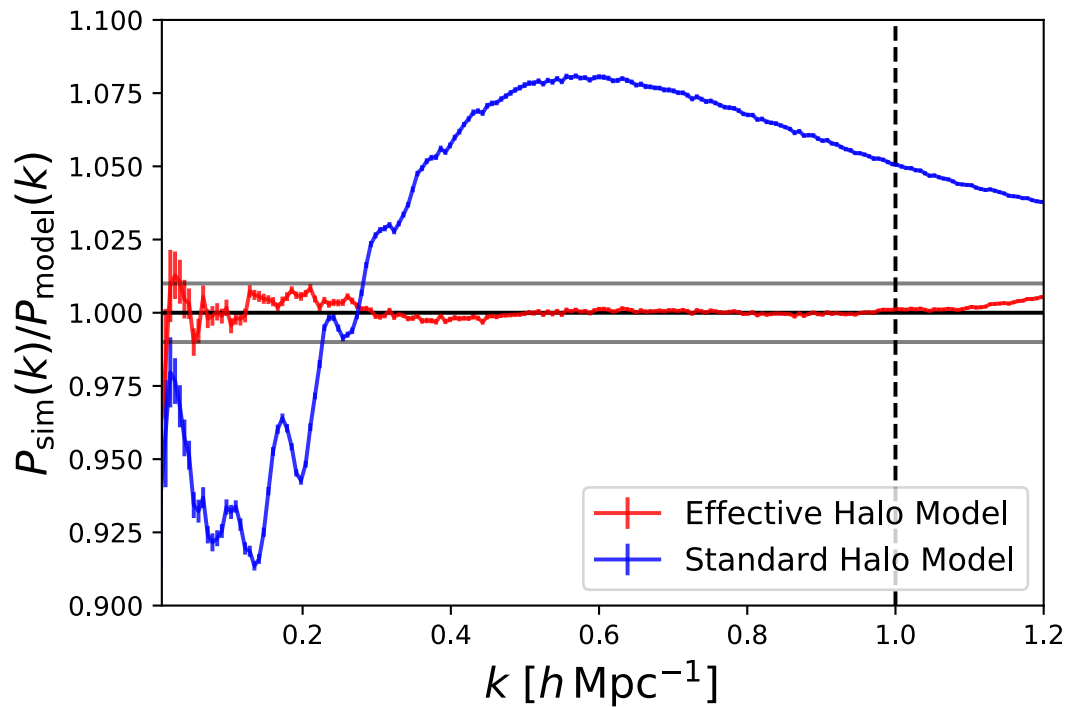
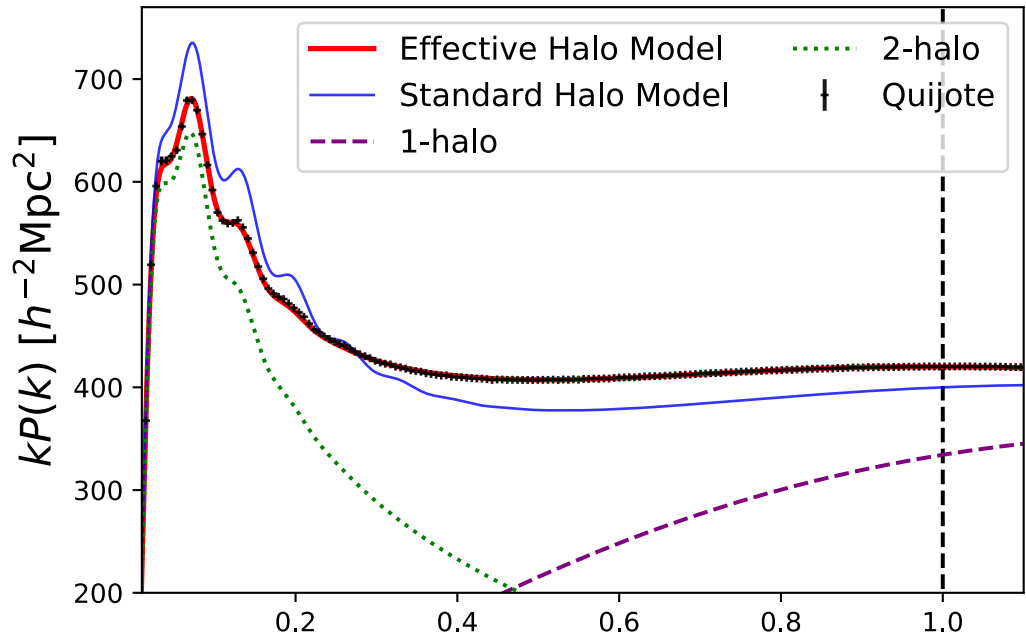
Model



Simulations

Model





The Effective Halo Model

- Combine the Halo Model and Perturbation Theory
- One Assumption:
 - **Halos are distributed according to the smoothed non-linear density field**
- Gives **accurate** predictions for matter power spectra and covariances with halo counts
- Test with **Quijote** simulations

**1% Accuracy to
k = 1 h/Mpc**

