# Large scale clustering with counts-in-cells statistics

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soon: DAMTP Cambridge

**in collaboration with:**
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Advances in Theoretical Cosmology in Light of Data, Stockholm (Sweden), July 2017

# Clustering Statistics



## We can look into the sky

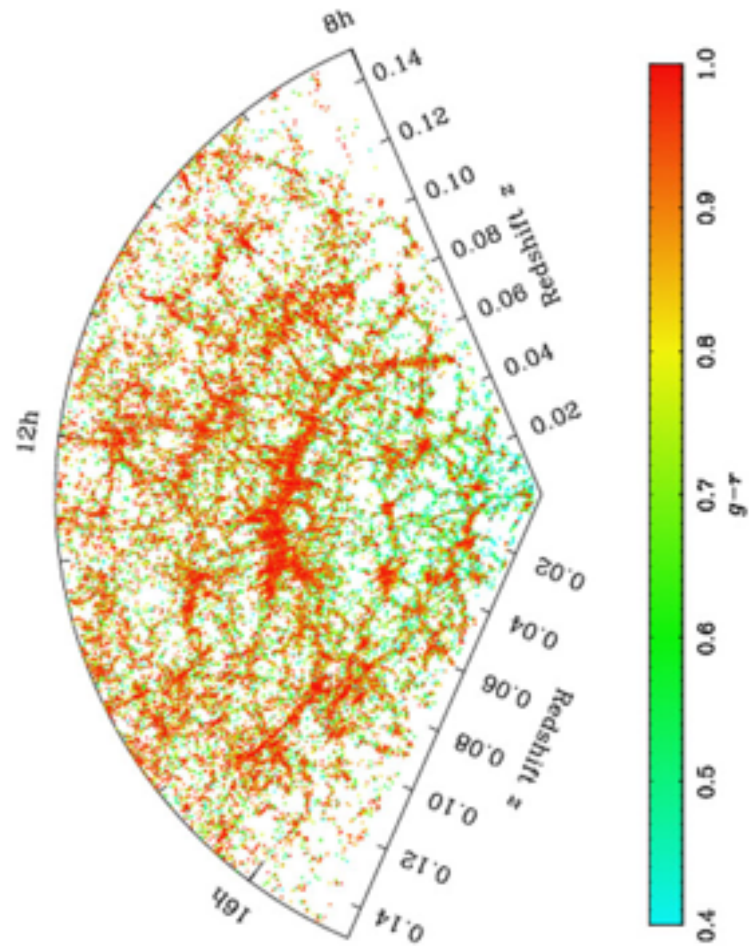
- observe galaxies and clusters
- they form a pattern = **Cosmic Web**

## Learn from and about our past

- structures far away = high redshift
- how structures formed over time

## Clustering pattern constrains cosmology & fundamental physics

- Statistics: quantify what we see
  - mainstream: N-point correlation functions
  - **hipster: counts-in-cells of objects**
- Dynamics: understand gravitational clustering
  - mainstream: perturbation theory for small densities
  - **hipster: spherical collapse for densities in spheres**
- (G)astrophysics: determine relation between dark matter & tracers



## Why you all (should) like counts-in-cells

- **Observational: counts-in-cells**
  - easy to count objects in regions
  - robust against late-time small scale physics
  - contain some information from all higher order N-point correlation functions
  - density-dependent clustering

- **Theoretical: spherical collapse**
  - nonlinear analytical solution
  - densities in spheres = spherical cows

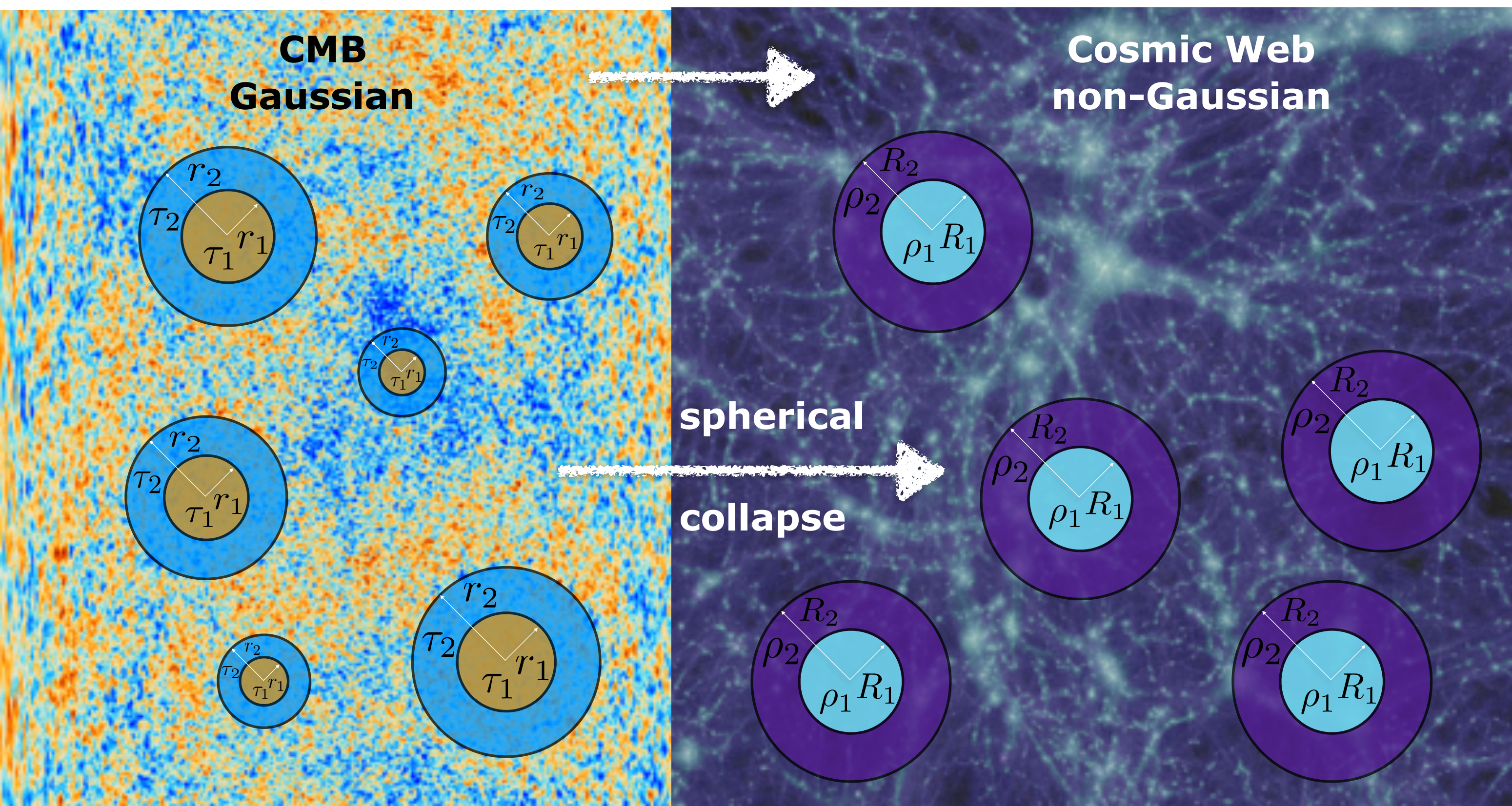
- **What we want**
  - matter in all shapes
    - spectroscopic: spheres
    - photometric: cylinders
    - [weak lensing: cones]
  - cosmology dependence
  - tracer bias & RSD

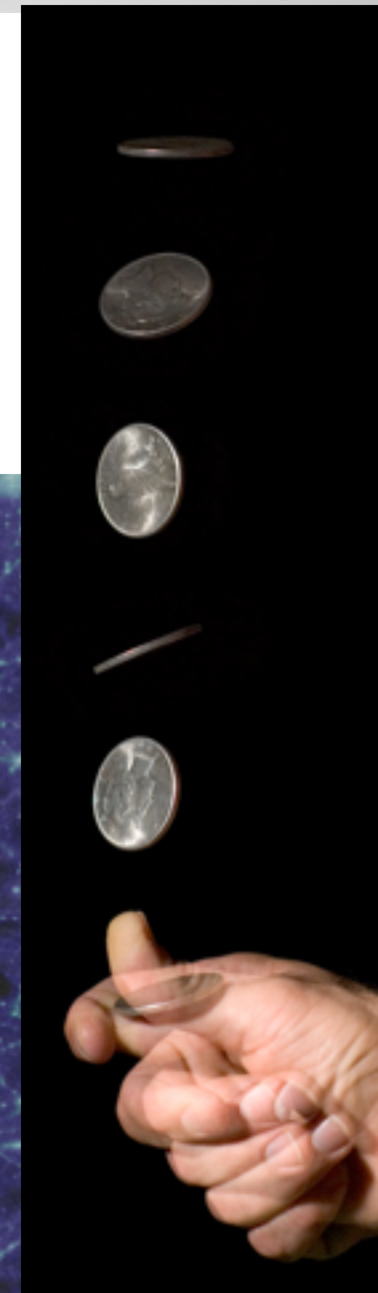
Cora Uhlemann, Universiteit Utrecht

# Clustering Statistics

## What is the most likely way to get a large density fluctuation?

- **Observable: counts-in-cells statistics in spheres**
  - easy to count within data or simulations
- **Large Deviation Theory: spherical collapse**
  - dominant contribution for large deviations



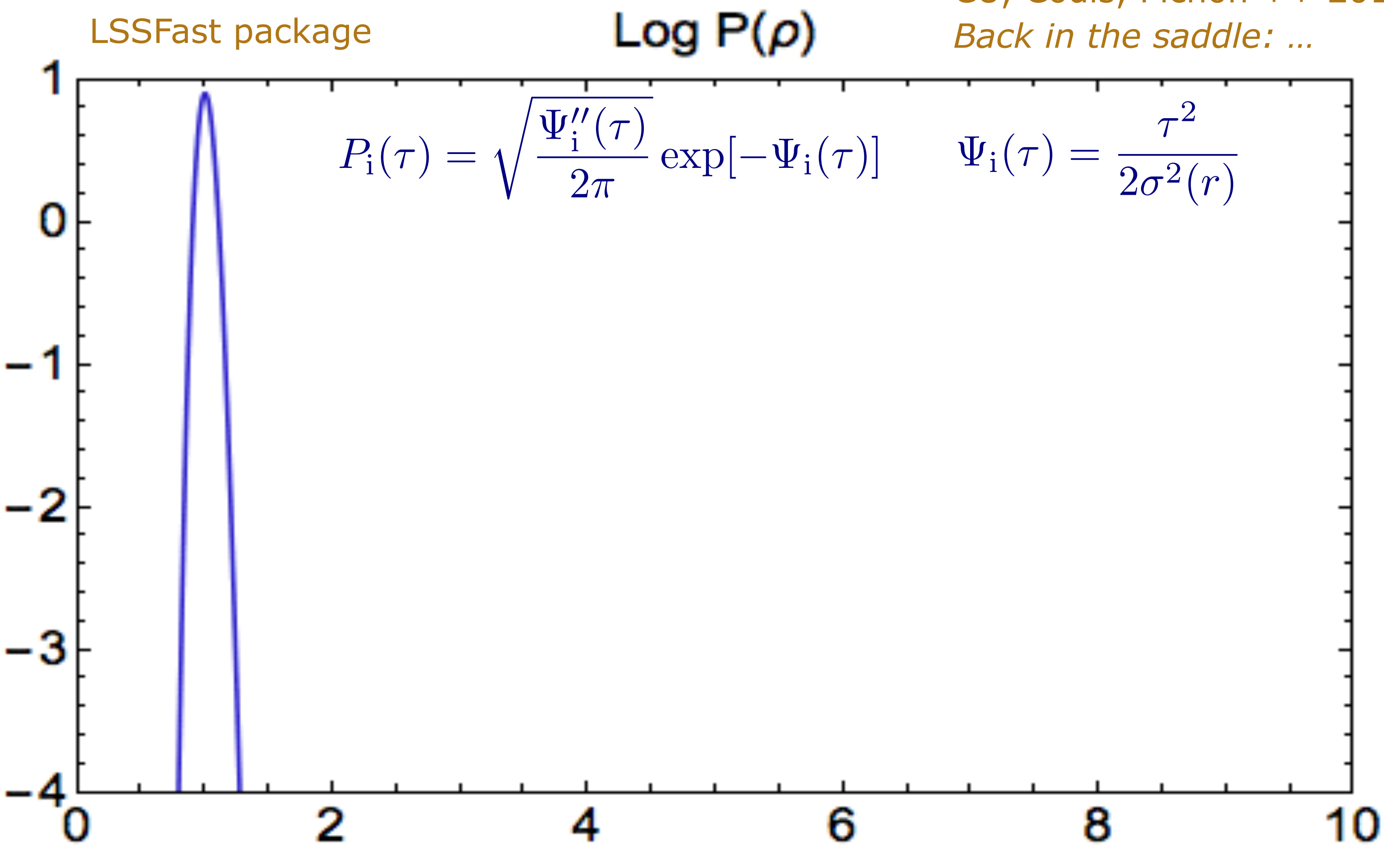



## Dark matter densities-in-spheres: prediction

- simple code LSSFast: needs linear power spectrum & non-linear variance

CU, Codis, Pichon ++ 2016
*Back in the saddle: ...*

LSSFast package




$$P_{\mathrm{i}}(\tau) = \sqrt{\frac{\Psi_{\mathrm{i}}''(\tau)}{2\pi}} \exp[-\Psi_{\mathrm{i}}(\tau)] \qquad \Psi_{\mathrm{i}}(\tau) = \frac{\tau^2}{2\sigma^2(r)}$$

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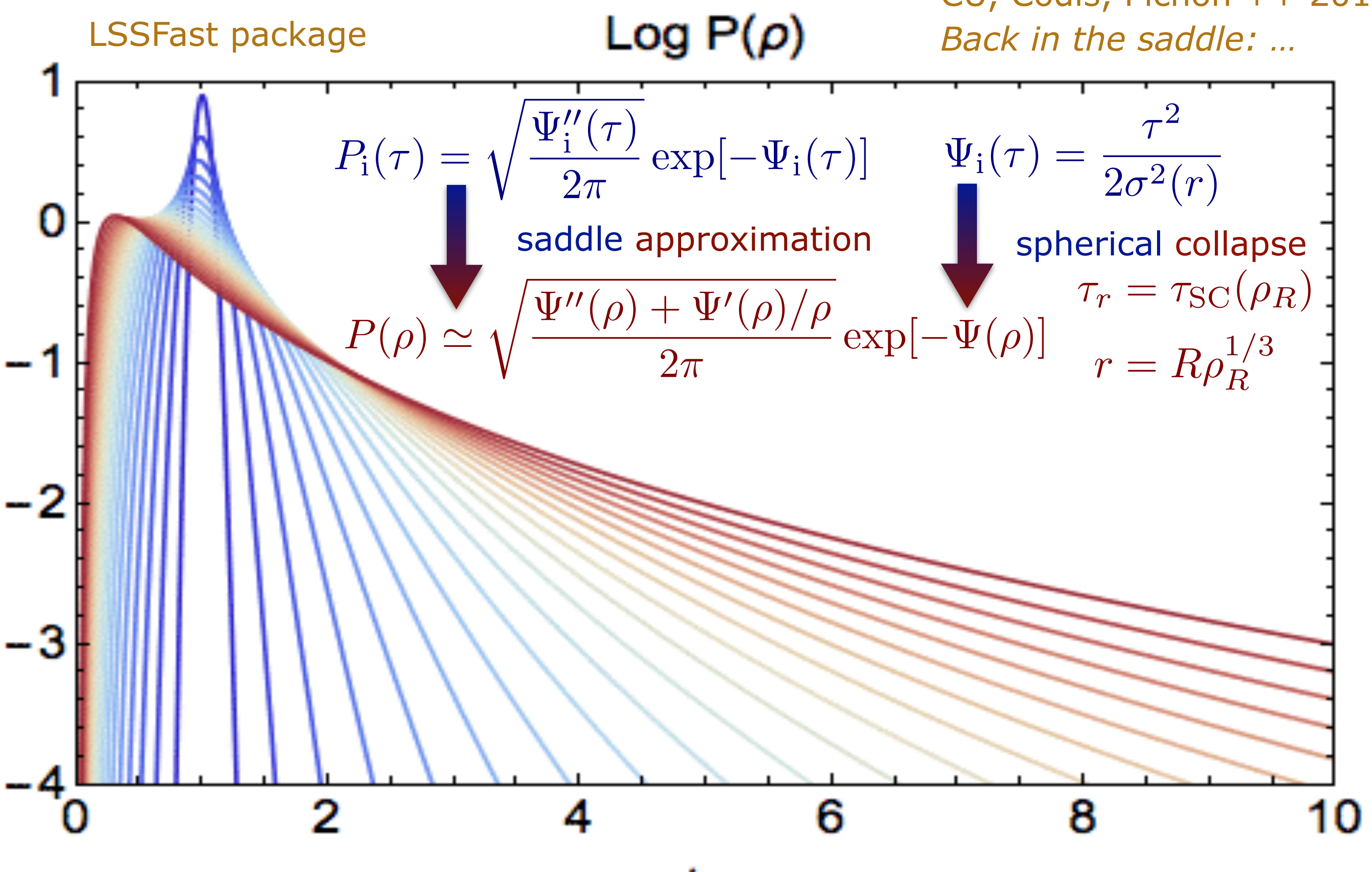
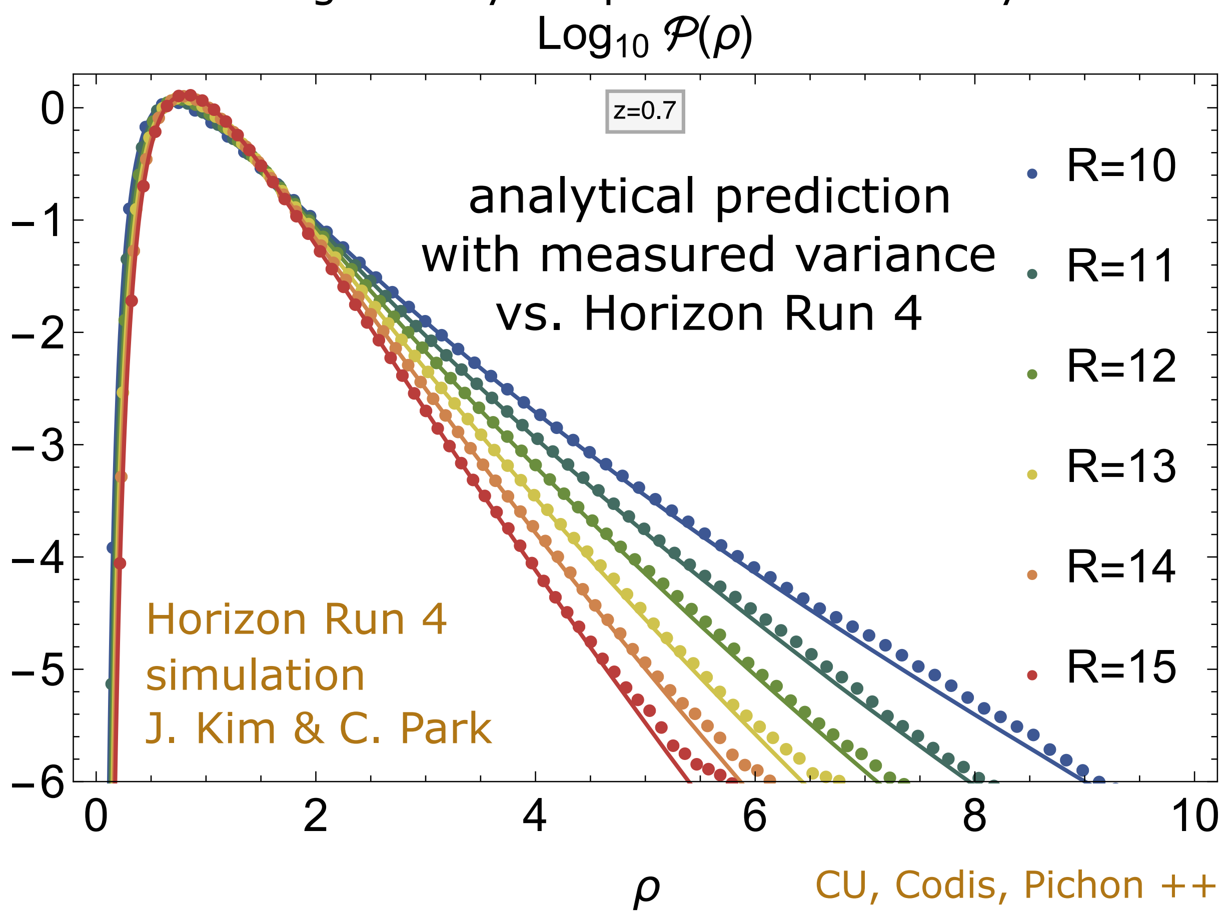


## Dark matter densities-in-spheres: prediction vs. simulation

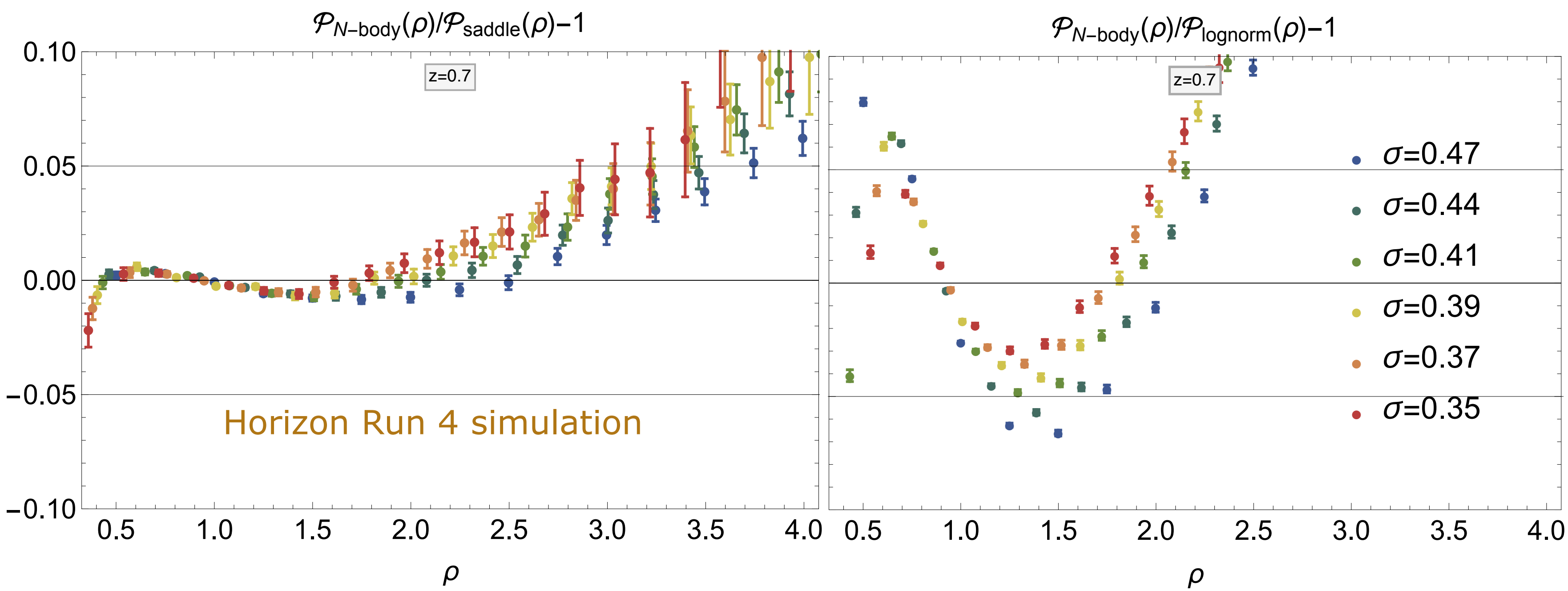
- simple code LSSFast: needs linear power spectrum & non-linear variance
- analytical prediction for regime beyond perturbation theory




CU, Codis, Pichon ++ 2016
*Beyond Kaiser bias: …*

# Dark matter densities-in-spheres: prediction vs. fit

- simple code LSSFast: needs linear power spectrum & non-linear variance
- analytical prediction for regime beyond perturbation theory
- accuracy at the percent level for a wide range of densities




- significant improvement over phenomenological fits with lognormal distribution

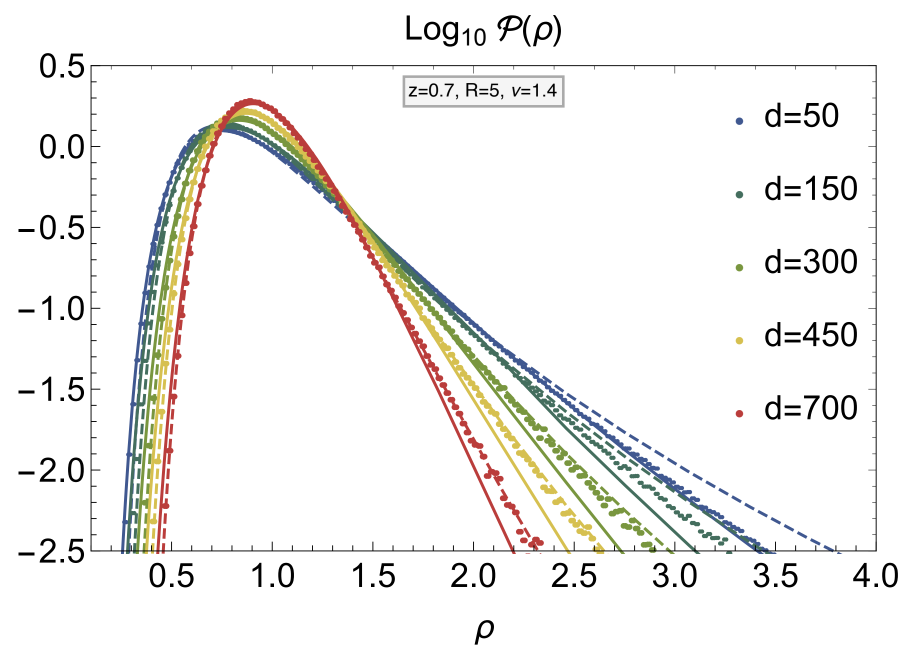
CU, Codis, Pichon ++ 2016
*Beyond Kaiser bias: …*

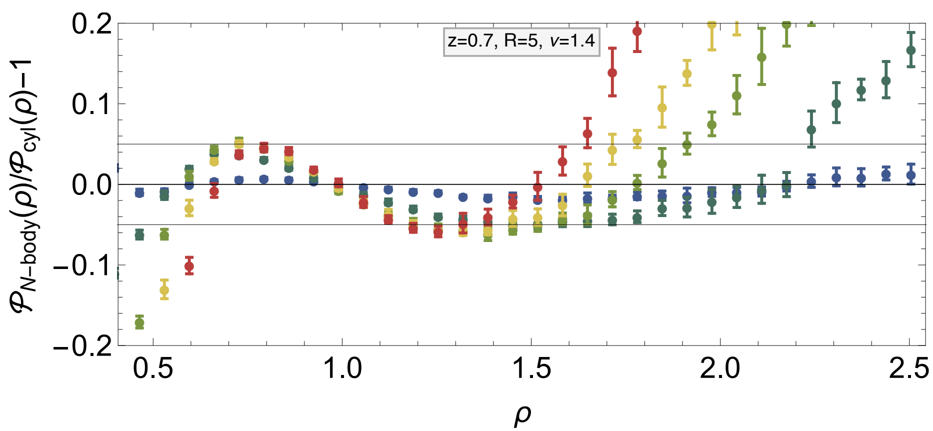
# Dark matter densities-in-cylinders

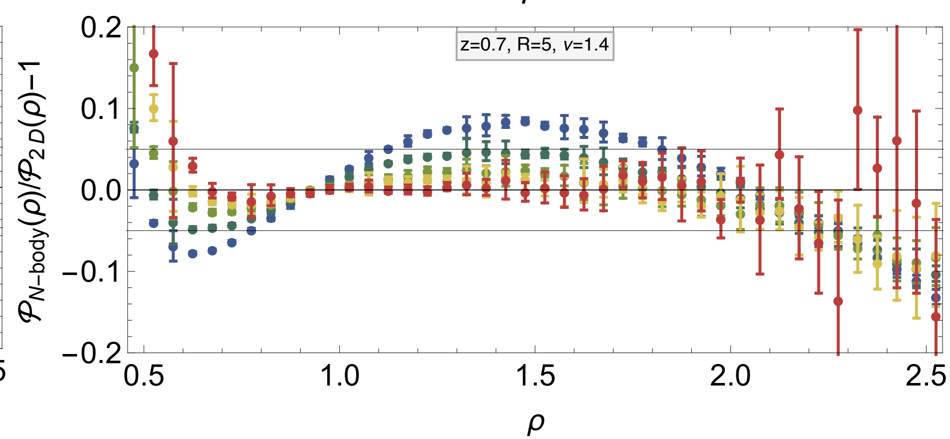
Horizon Run 4 simulation

- for photometric surveys, d>= 50 Mpc/h
- use 2D spherical collapse
- long cylinders R≫d
    - $R_{\rm ini} = R\rho^{1/2}$
- include finite depth
    - $R_{\rm ini} = R\rho^{1/3}$, $d_{\rm ini} = d\rho^{1/3}$

working title:
*Cylinders out of a top-hat*



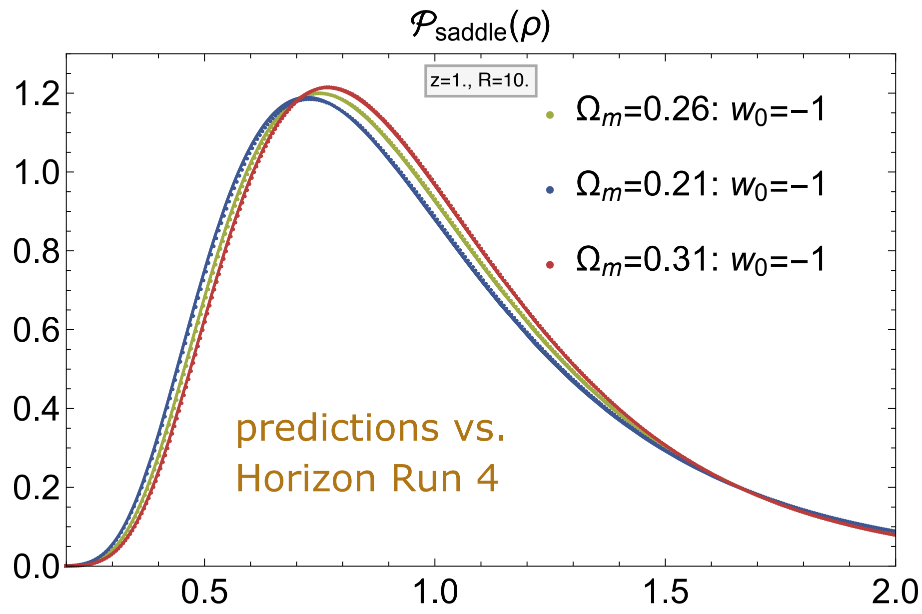
# Why: Constrain Cosmology

## Testing Cosmology with PDFs

**Model for dark matter PDF is sensitive to**
- initial power spectrum: variance(R)
- growth function: variance(z)
- primordial non-Gaussianity: $f_{NL}$ (later)

**Mass density parameter $\Omega_m$**
- changes whole variance(R,z)
- PDF seems to be a good parametrisation

work in progress



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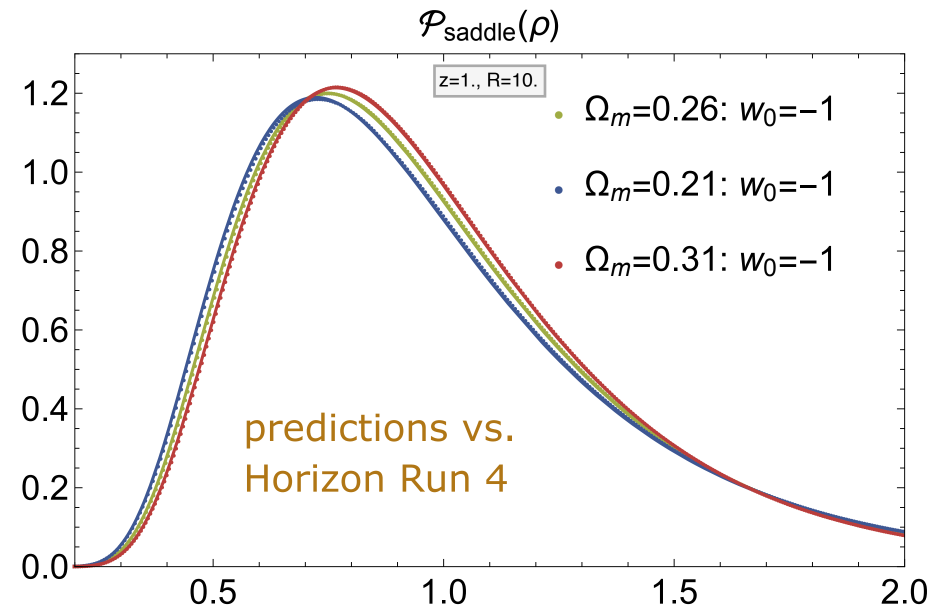


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- changes whole variance(R,z)
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work in progress

**Dark energy equation of state w**
- changes linear growth
- via Hubble function

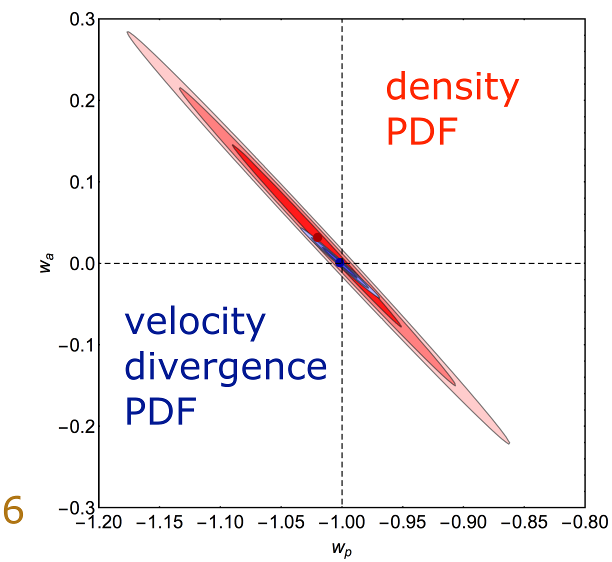
$$\sigma(R,z) \propto D(z|w_0,w_a)$$

$$H^2(z) = H_0^2\left[\Omega_m(1+z)^3 + \Omega_\Lambda \exp\left(\int_0^z \frac{1+\boxed{w(z')}}{1+z'}dz'\right)\right]$$

- dark energy time-dependence

$$w(z) = \boxed{w_0} + \frac{\boxed{w_a}z}{1+z}$$

density: Codis, Pichon ++ 2016
*Encircling the dark: …*
velocity: CU, Codis, Hahn ++ 2016
*Two is better than one: …*




ML estimator

# Reality: Biased tracers

## Combine dark matter with biasing

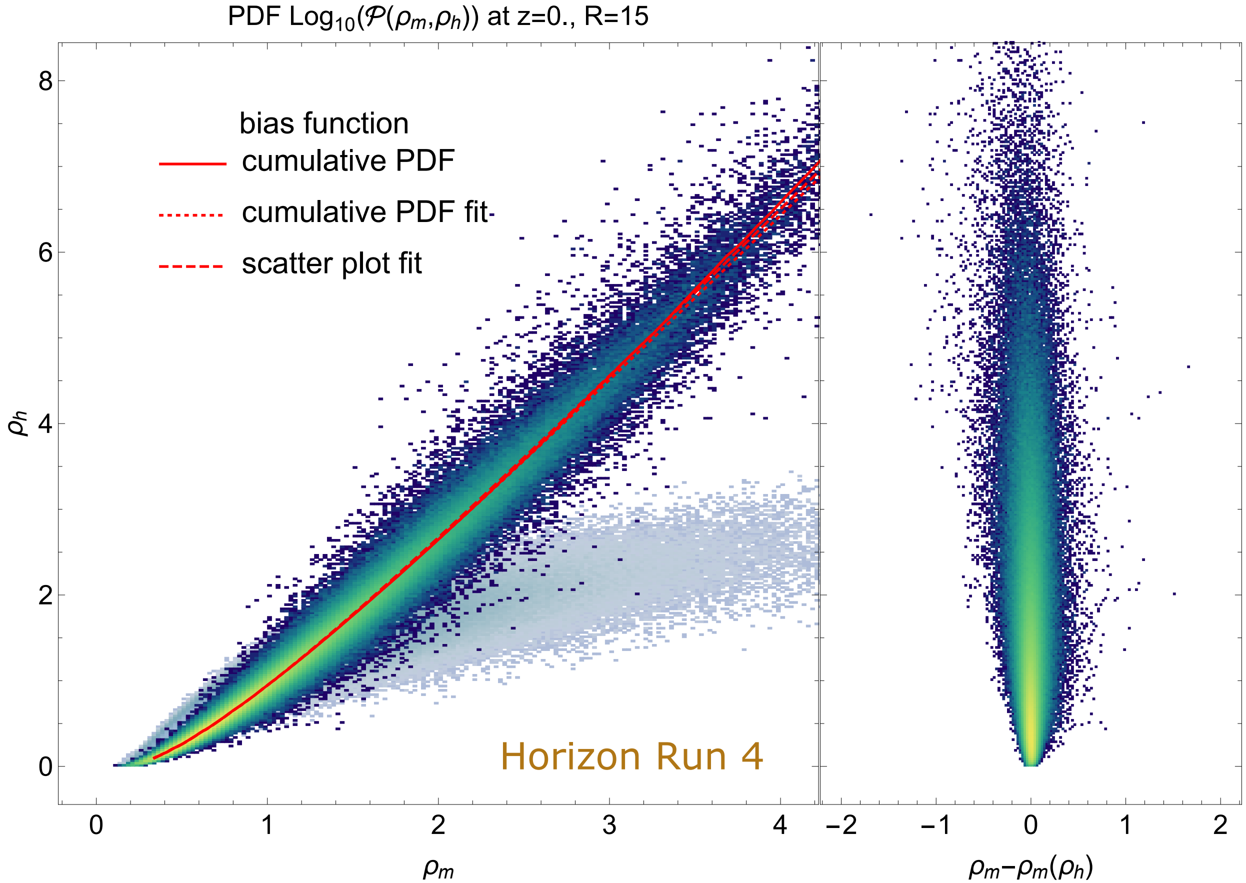
CU, Feix, Codis ++ 2017
*A question of separation: …*

### Describing biased tracers

- tracers: mass-weighted subhalos (real space)
- **average is good enough:** mean bias relation

polynomial bias model for log-densities

$$\log \rho_m = b_0 + b_1 \log \rho_h + b_2 (\log \rho_h)^2$$




mass-weighting of halo densities

Seljak ++ 2009
Hamaus ++ 2010
Jee ++ 2012

# Reality: Biased tracers

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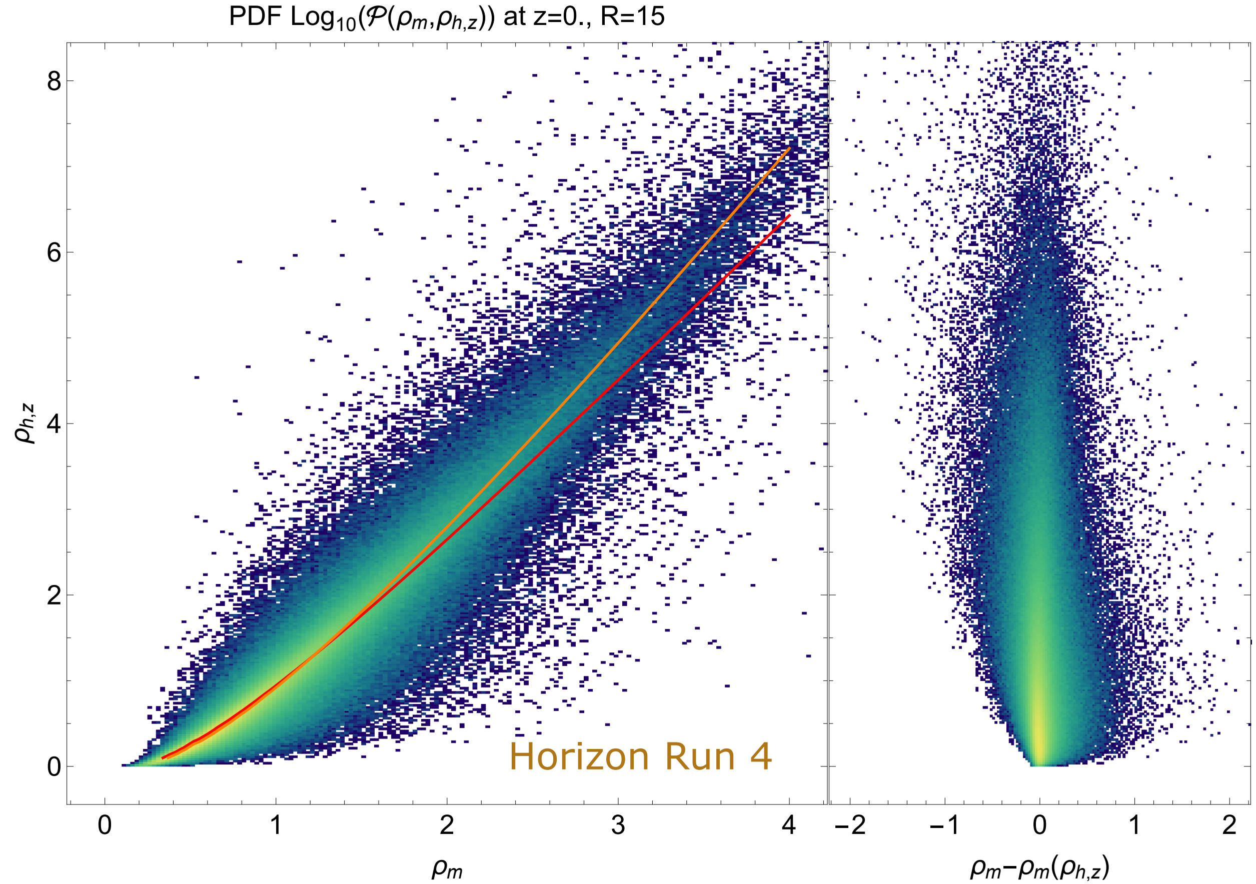
$$\log \rho_m = b_0 + b_1 \log \rho_h + b_2 (\log \rho_h)^2$$

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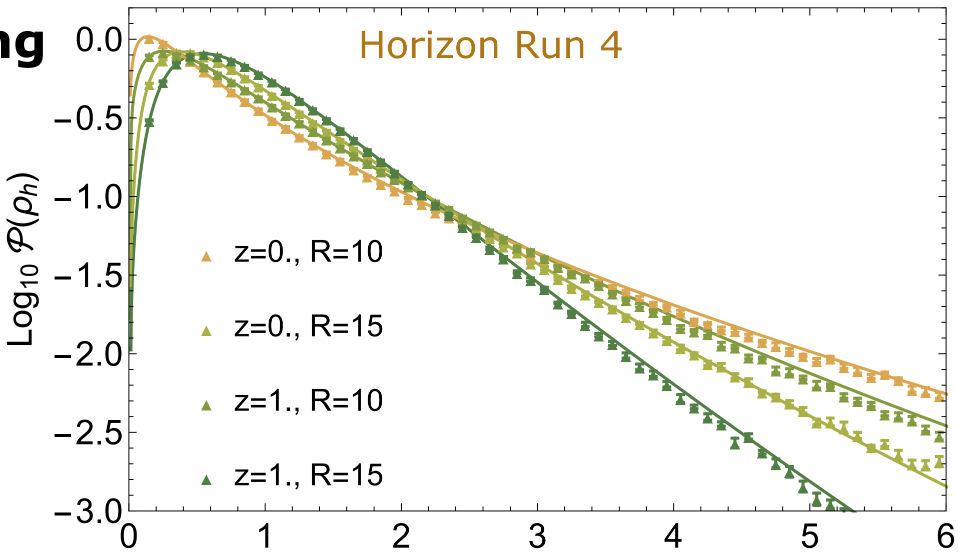


**Counts-in-cells for halos**

- in general: convolve dark matter PDF with joint PDF of dark matter & tracers
- in practice: map with mean bias relation

$$P(\rho_h) = P(\rho_m(\rho_h))\frac{d\rho_m}{d\rho_h}$$

- final parameters: matter variance & bias

CU, Feix, Codis ++ 2017
*A question of separation: …*

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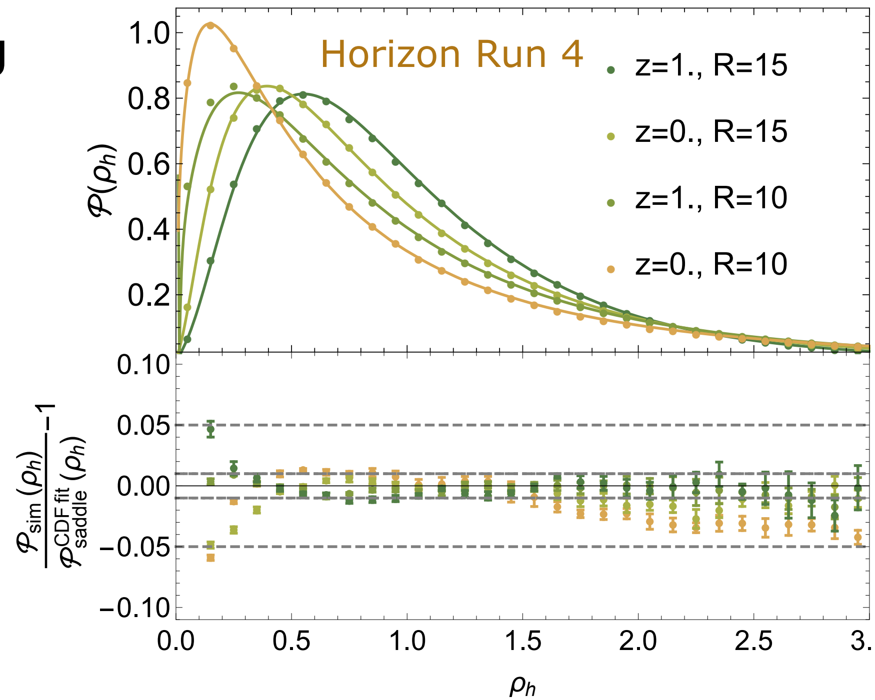


CU, Feix, Codis ++ 2017
*A question of separation: …*

# Reality: Biased tracers

## Combine dark matter with biasing

**Counts-in-cells for halos in z space**

- in general: convolve dark matter PDF with joint PDF of dark matter & tracers
- in practice: map with mean bias relation

$$P(\rho_h) = P(\rho_m(\rho_h))\frac{d\rho_m}{d\rho_h}$$

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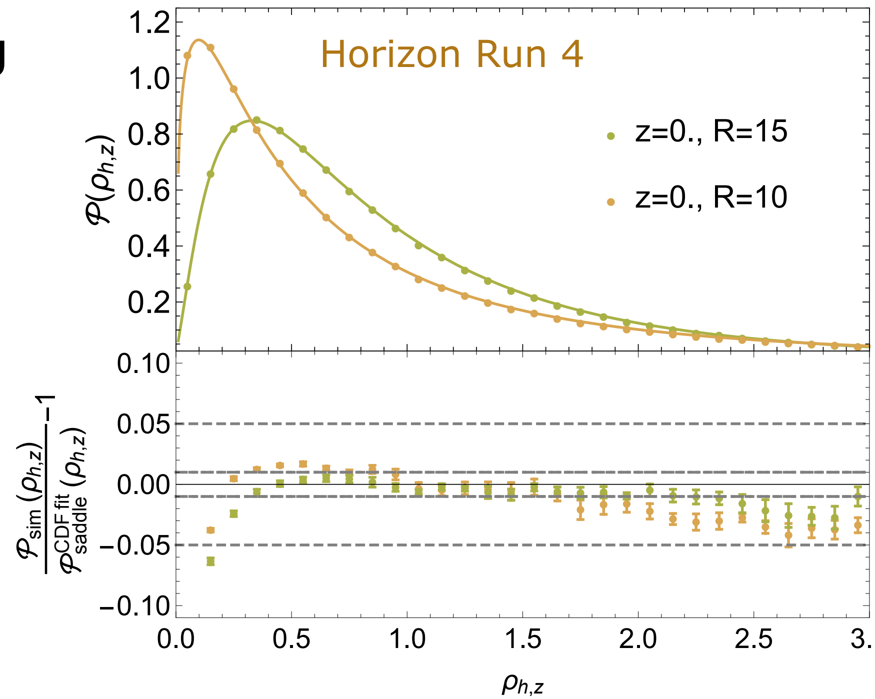
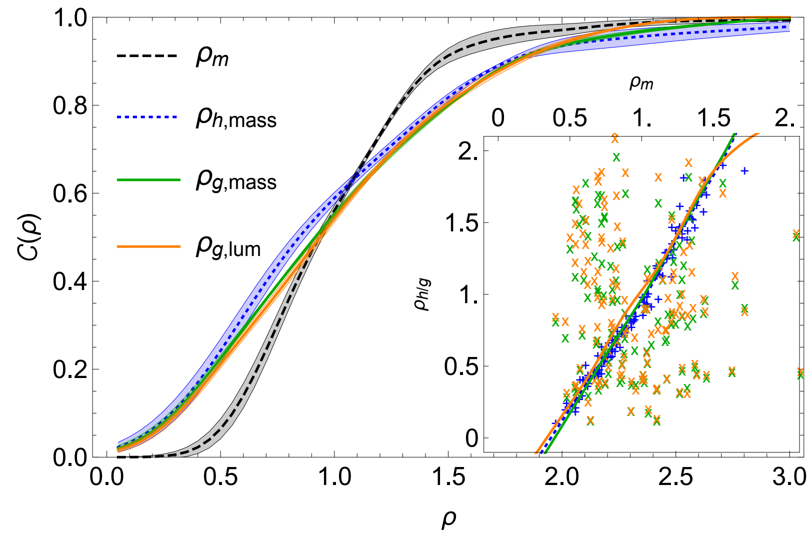



**Counts-in-cells for galaxies**

- model-independent bias-extraction via CDF
- good correspondence between galaxies and mass-weighted subhalos (in real space)

Horizon AGN simulation (with Laigle)

CU, Feix, Codis ++ 2017
*A question of separation: …*



# Take home message

## Counts-in-cells are en vogue

**Dark matter densities in spheres & cylinders**

- theory of large deviations: most likely dynamics
- statistics of densities from ***spherical collapse***
- ***%-level analytic predictions*** for R>10 Mpc/h at z=0

**Cosmology dependence**

- initial power spectrum (for $f_{nl}$ also bispectrum)
- nonlinear variance: growth rate & scale-dependence

**Dark matter to tracers for galaxy surveys**

- mean ***local bias*** relation is good enough (also with RSD)
- parametrise with quadratic ***polynomial in log-densities***
- mass-weighted halos ≈ luminosity-weighted galaxies

**Stay tuned!**

- ***Hunting high and low:*** for primordial non-Gaussianity
- ***Cylinders out of a top-hat:*** for photometric surveys

# Reality: Biased tracers

## Combine dark matter with biasing

**Two-point sphere bias**

- density dependence of two-point clustering
- large separation r»R: factorisation

$$\frac{P(\rho(x),\rho'(x+r))}{P(\rho)P(\rho')} = 1 + \xi(r)b(\rho)b(\rho')$$

- Gaussian IC: Kaiser bias + spherical collapse
- can be combined with tracer bias

**Joint parameter estimation**

- PDF template allows to determine parameters (fit or maximising likelihood)
- degeneracy between matter variance and bias

- add 2-pt information to break degeneracy
- demonstrated proof of principle

CU, Feix, Codis ++ 2017
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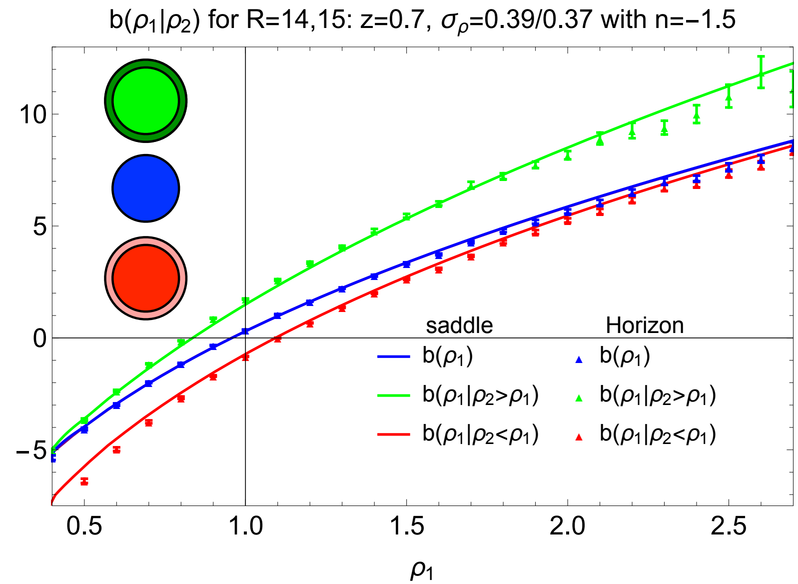


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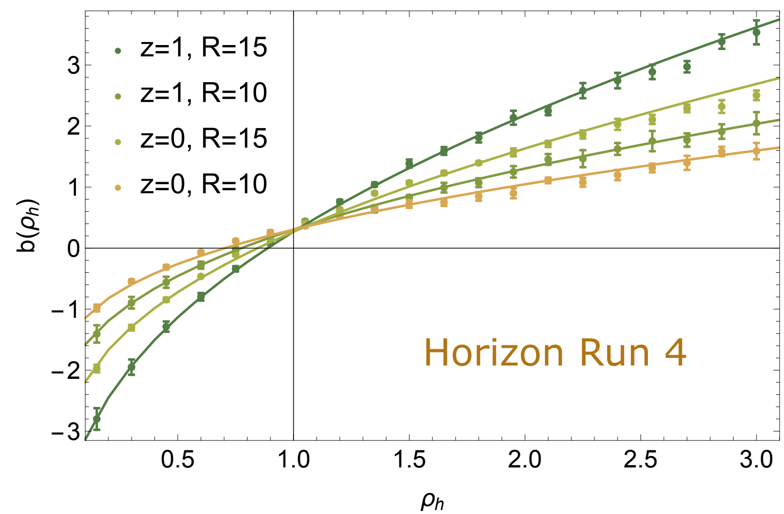
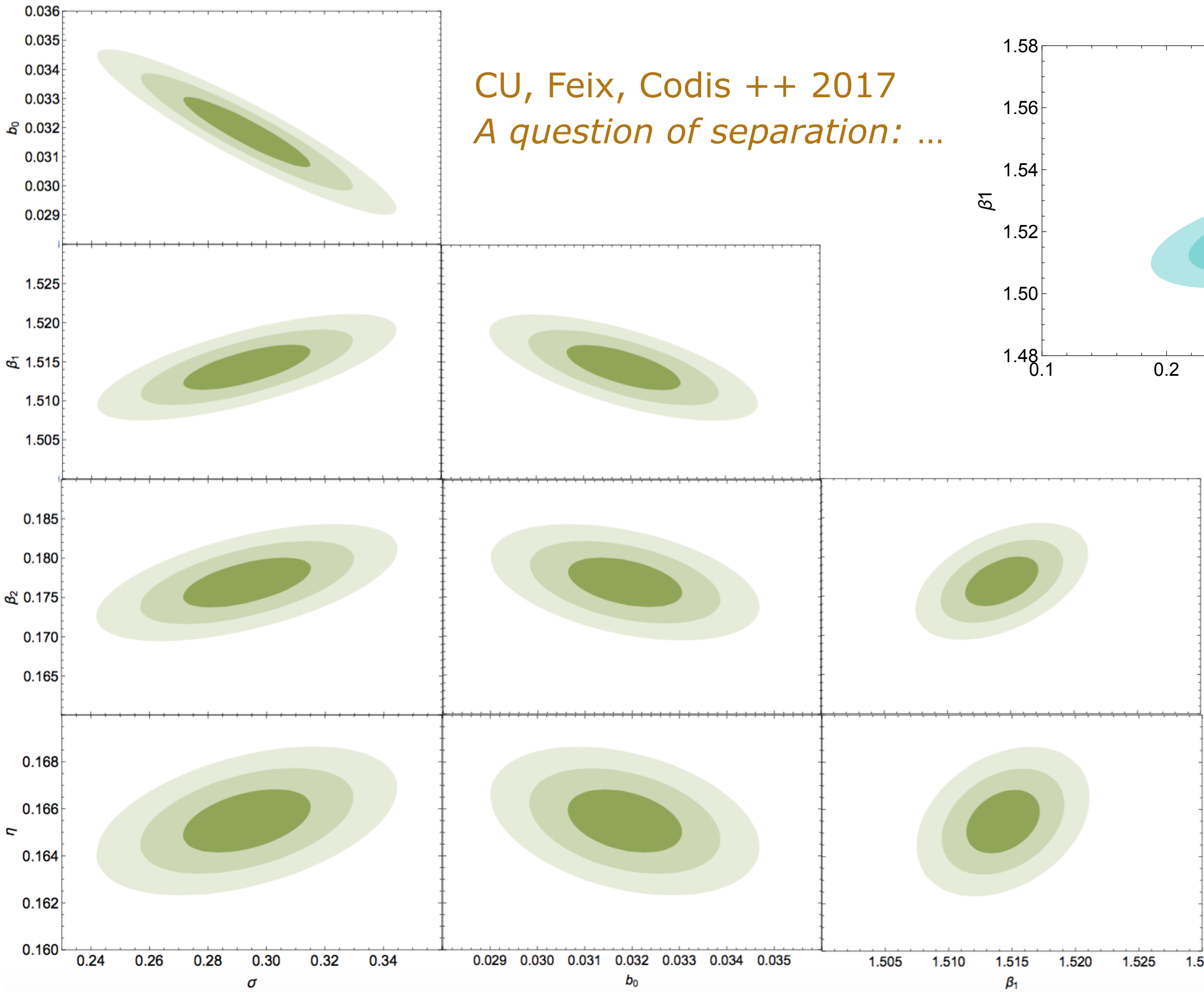


# Back up

## Joint parameter estimation: DM variance + bias params

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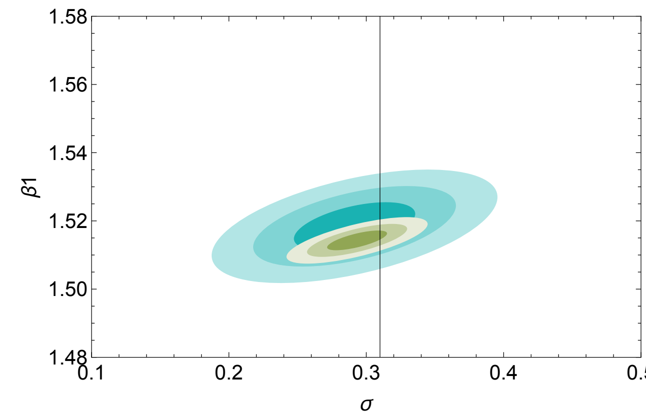
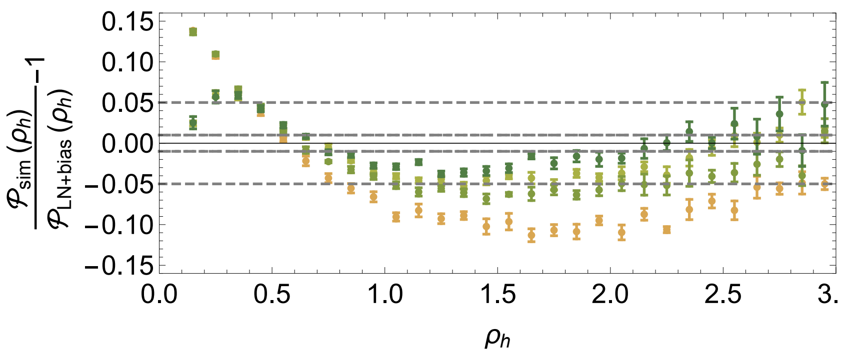
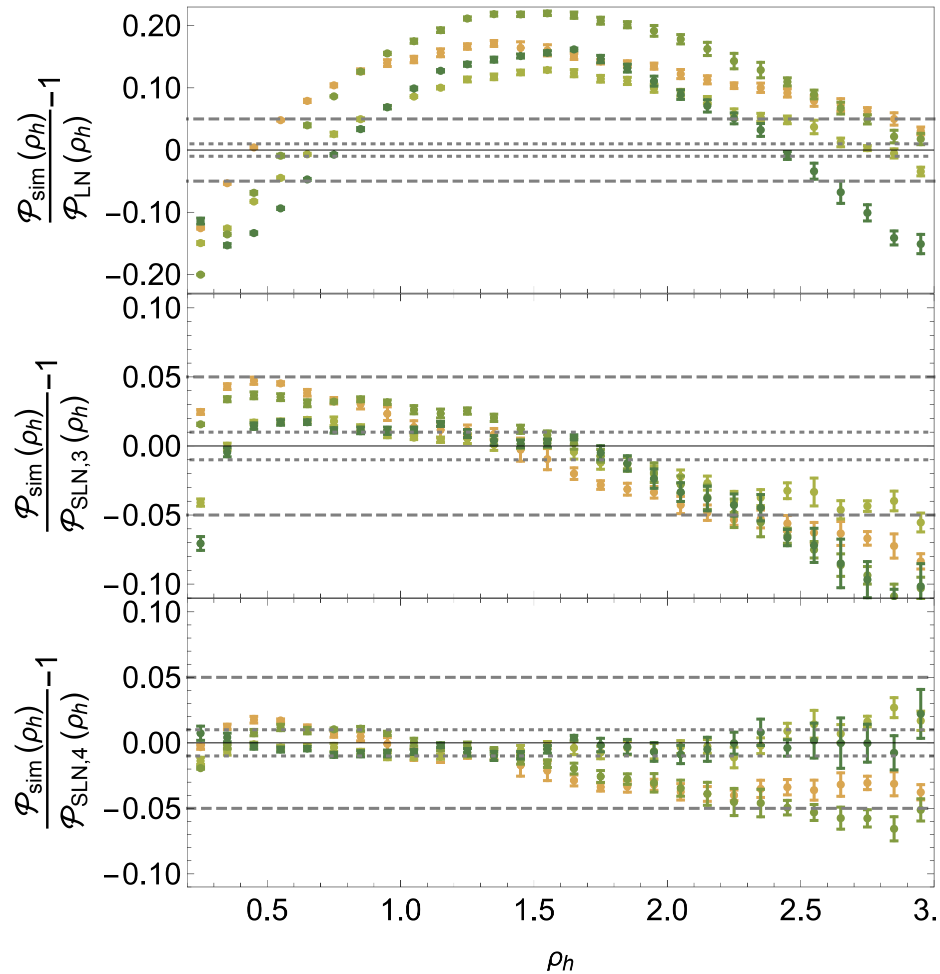
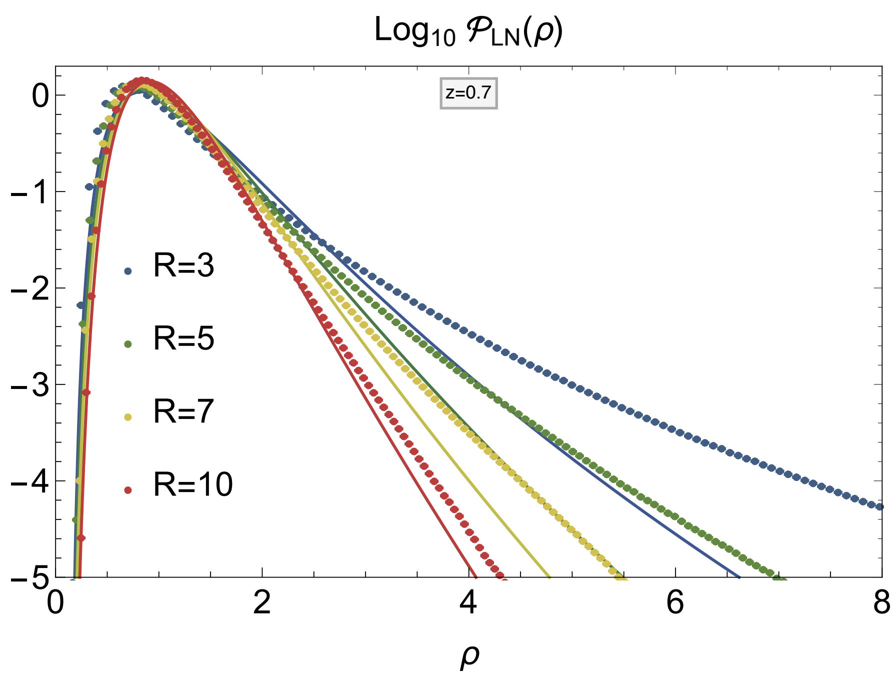


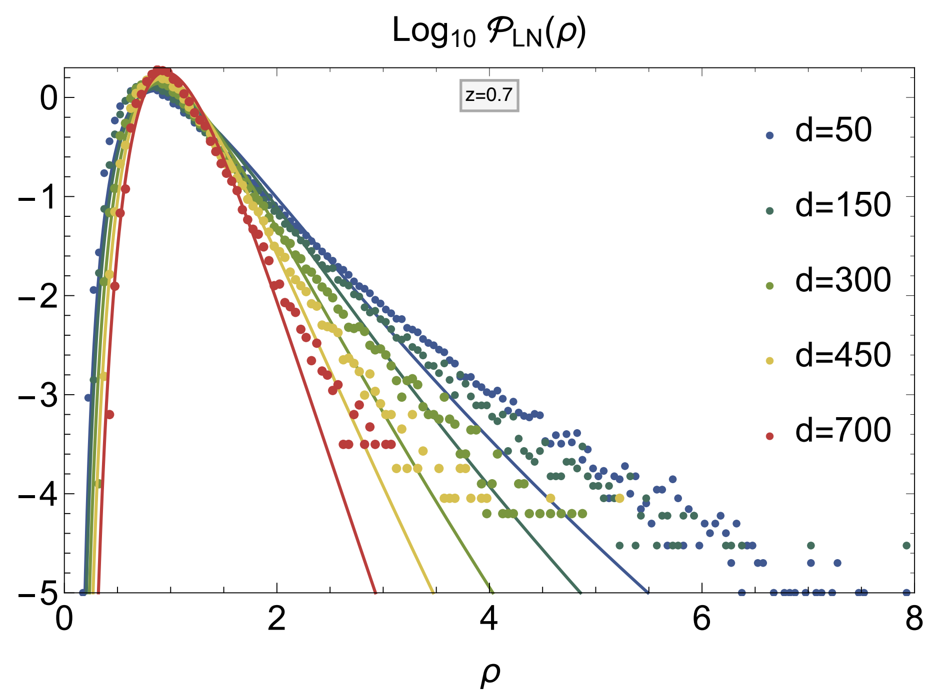
# One-point halo PDF with lognormal



# One-point DM PDF in cylinders with lognormal



# One-point halo PDF & cylinder bias