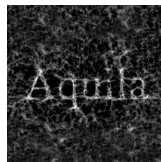# FAST REALISTIC, DIFFERENTIABLE, MOCK HALO GENERATION

FOR WIDE-FIELD GALAXY SURVEYS

Simon Ding, PhD student @ IAP, France

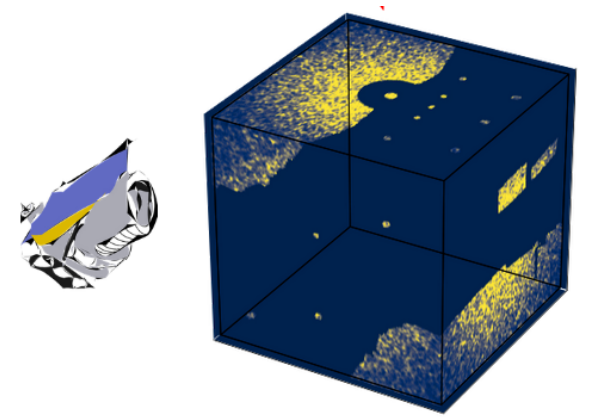supervised by **Guilhem Lavaux (IAP) & Jens Jasche (Stockholm University)**
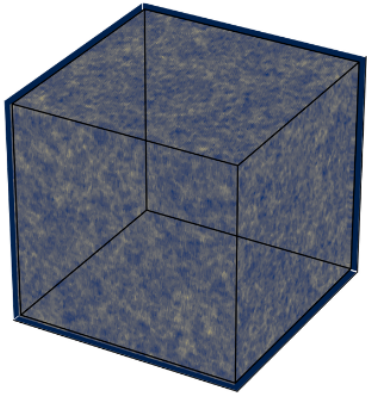
BAYESIAN ORIGIN RECONSTRUCTION FROM GALAXIES (BORG)

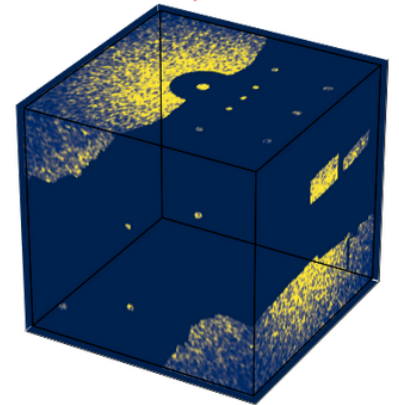# BAYESIAN ORIGIN RECONSTRUCTION FROM GALAXIES (BORG)

Observations

BAYESIAN ORIGIN RECONSTRUCTION FROM GALAXIES (BORG)
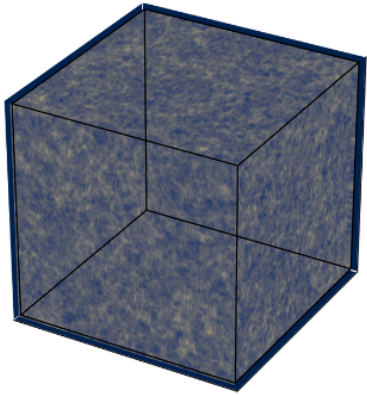

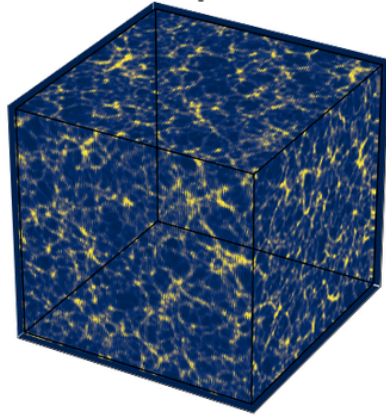Latent parameter space
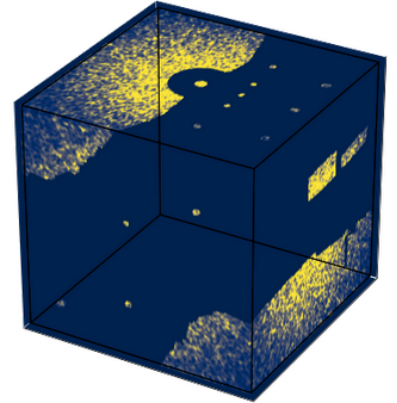(Gaussian prior)

Observations

BAYESIAN ORIGIN RECONSTRUCTION FROM GALAXIES (BORG)

Latent parameter space (Gaussian prior)

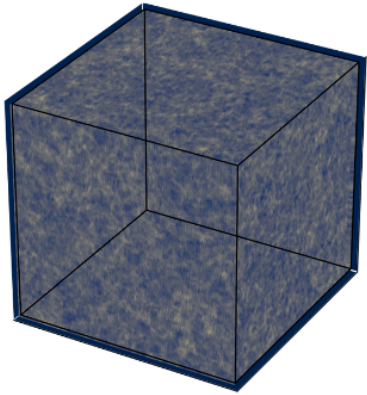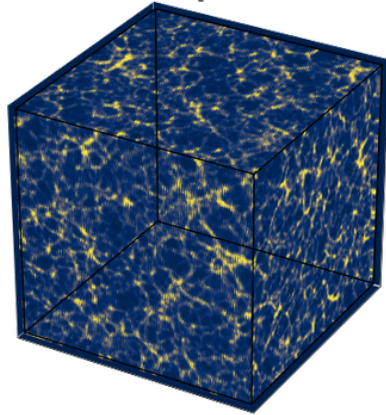Hamiltonian Equation

Observations

BAYESIAN ORIGIN RECONSTRUCTION FROM GALAXIES (BORG)

Latent parameter space (Gaussian prior)

Hamiltonian Equation

Small scale baryonic physics

Observations

BAYESIAN ORIGIN RECONSTRUCTION FROM GALAXIES (BORG)
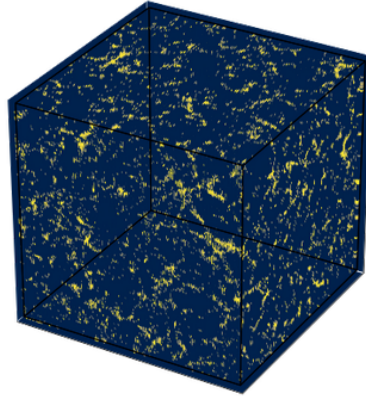

Latent parameter space (Gaussian prior)

Hamiltonian Equation

Small scale baryonic physics

Lightcone + Cosmological expansion

Observations

BAYESIAN ORIGIN RECONSTRUCTION FROM GALAXIES (BORG)

Forward model

| Latent parameter space (Gaussian prior) | Hamiltonian Equation | Small scale baryonic physics | Lightcone + Cosmological expansion | Observations |

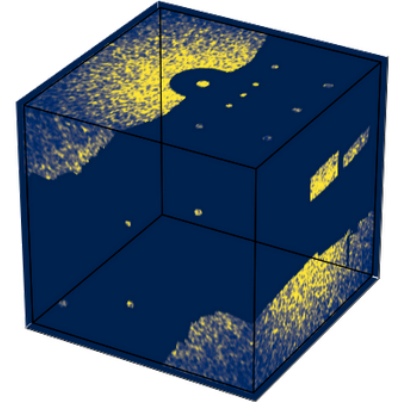# BAYESIAN ORIGIN RECONSTRUCTION FROM GALAXIES (BORG)

Forward model

Likelihood

Latent parameter space (Gaussian prior)

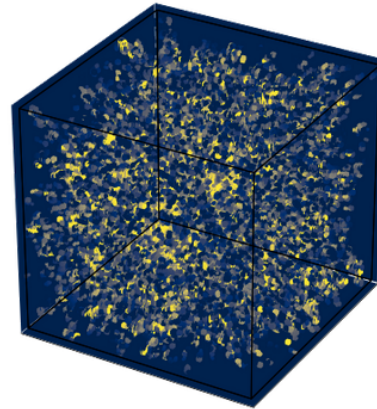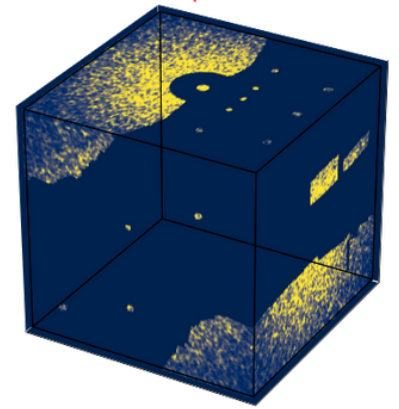Hamiltonian Equation

Small scale baryonic physics

Lightcone + Cosmological expansion

Observations

BAYESIAN ORIGIN RECONSTRUCTION FROM GALAXIES (BORG)

Jasche & Wandelt (2013), Jasche, Leclercq & Wandelt (2015), Lavaux & Jasche (2016), Jasche & Lavaux (2019)   Image credit: D.K Ramanah

BAYESIAN ORIGIN RECONSTRUCTION FROM GALAXIES (BORG)

Forward model

Likelihood

My work

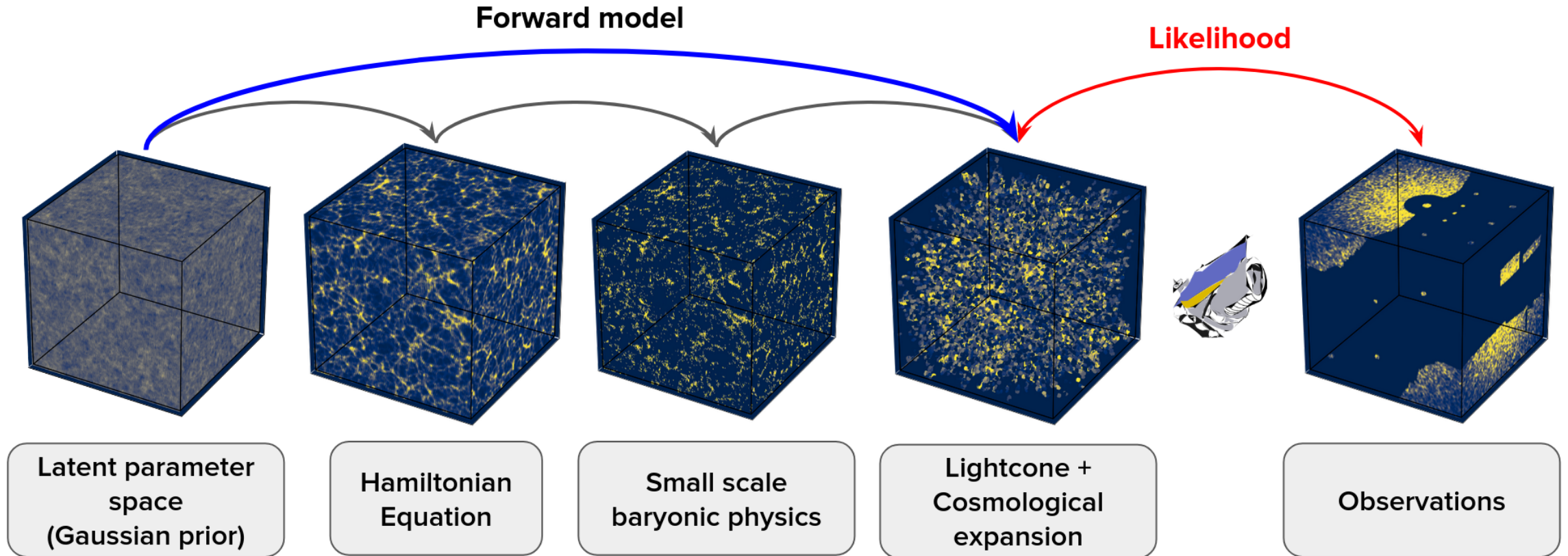| Latent parameter space (Gaussian prior) | Hamiltonian Equation | Small scale baryonic physics | Lightcone + Cosmological expansion | Observations |

Jasche & Wandelt (2013), Jasche, Leclercq & Wandelt (2015), Lavaux & Jasche (2016), Jasche & Lavaux (2019)   Image credit: D.K Ramanah

BAYESIAN ORIGIN RECONSTRUCTION FROM GALAXIES (BORG)

$$\delta_m(x) \rightarrow n_{\mathrm{halo}}\big(M|\delta_m(x)\big)$$

Jasche & Wandelt (2013), Jasche, Leclercq & Wandelt (2015), Lavaux & Jasche (2016), Jasche & Lavaux (2019)

MOCK HALO CATALOGUES FROM NEURAL PHYSICAL ENGINES (NPE)

MOCK HALO CATALOGUES FROM NEURAL PHYSICAL ENGINES (NPE)

dark matter over-density field

From approximate gravity solvers
i.e. 2LPT

MOCK HALO CATALOGUES FROM NEURAL PHYSICAL ENGINES (NPE)

dark matter over-density field → **machine learning + physical contraints**

From approximate gravity solvers i.e. 2LPT

- fast (GPU support)
- differentiable
- Stochastic
- Explainable
- 17-32 parameters

MOCK HALO CATALOGUES FROM NEURAL PHYSICAL ENGINES (NPE)

dark matter over-density field → **machine learning + physical contraints** → **Nbody-like halo catalogues**

From approximate gravity solvers i.e. 2LPT

- fast (GPU support)
- differentiable
- Stochastic
- Explainable
- 17-32 parameters

Validated using:

- Halo mass function
- Power spectrum
- Bispectrum

MOCK HALO CATALOGUES FROM NEURAL PHYSICAL ENGINES (NPE)

dark matter over-density field → **machine learning + physical contraints** → **Nbody-like halo catalogues**
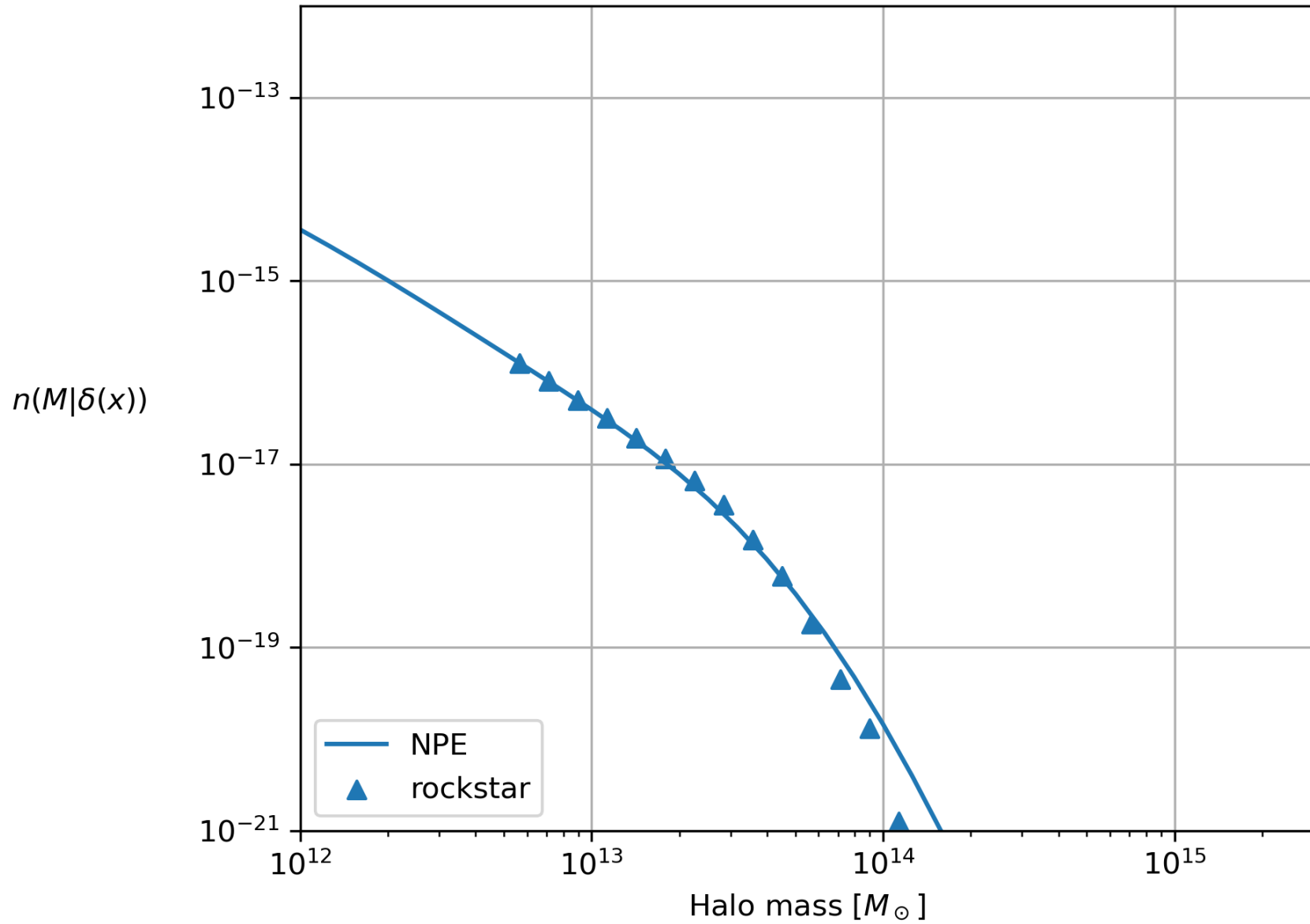
From approximate gravity solvers i.e. 2LPT

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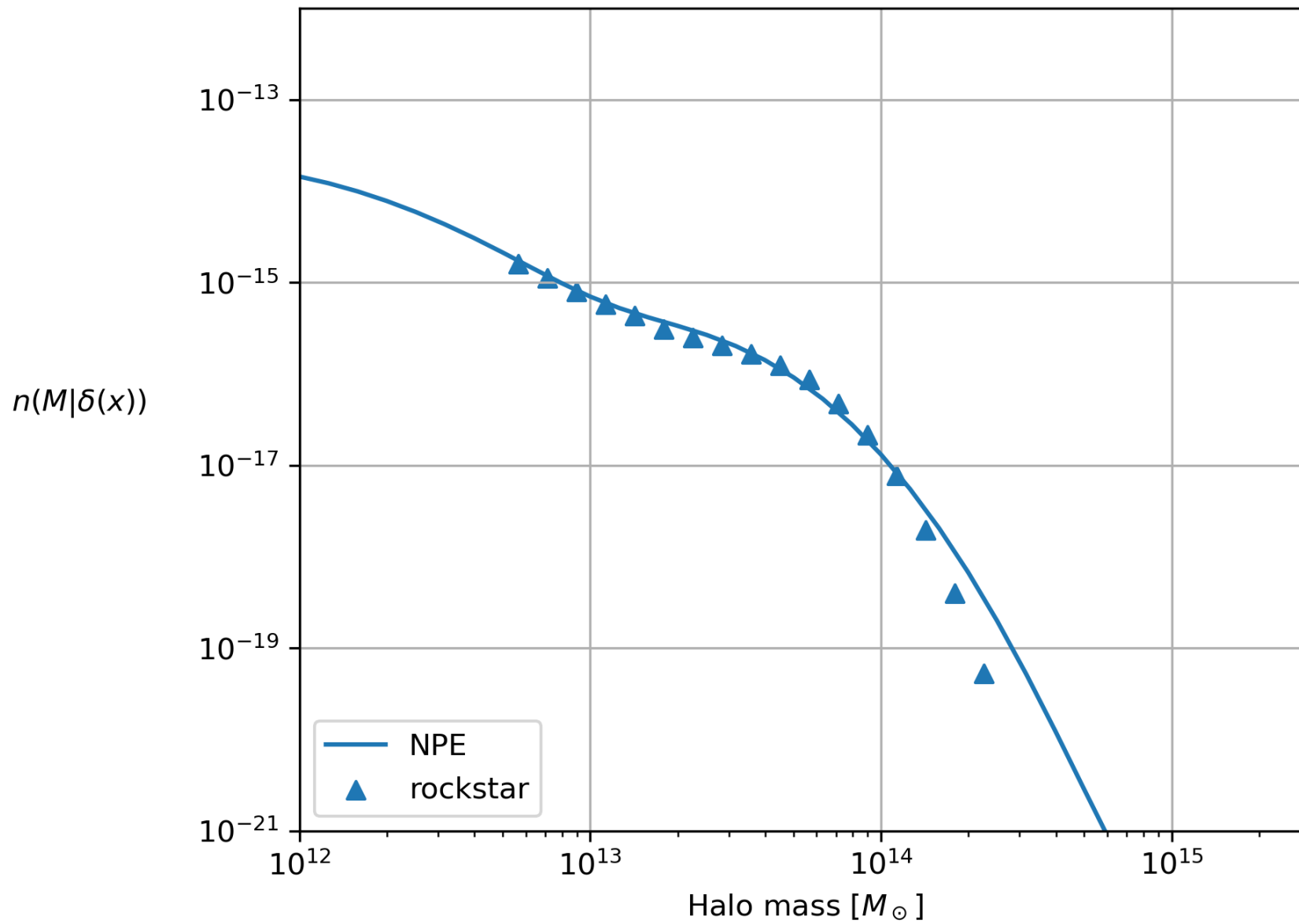- Stochastic
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Validated using:

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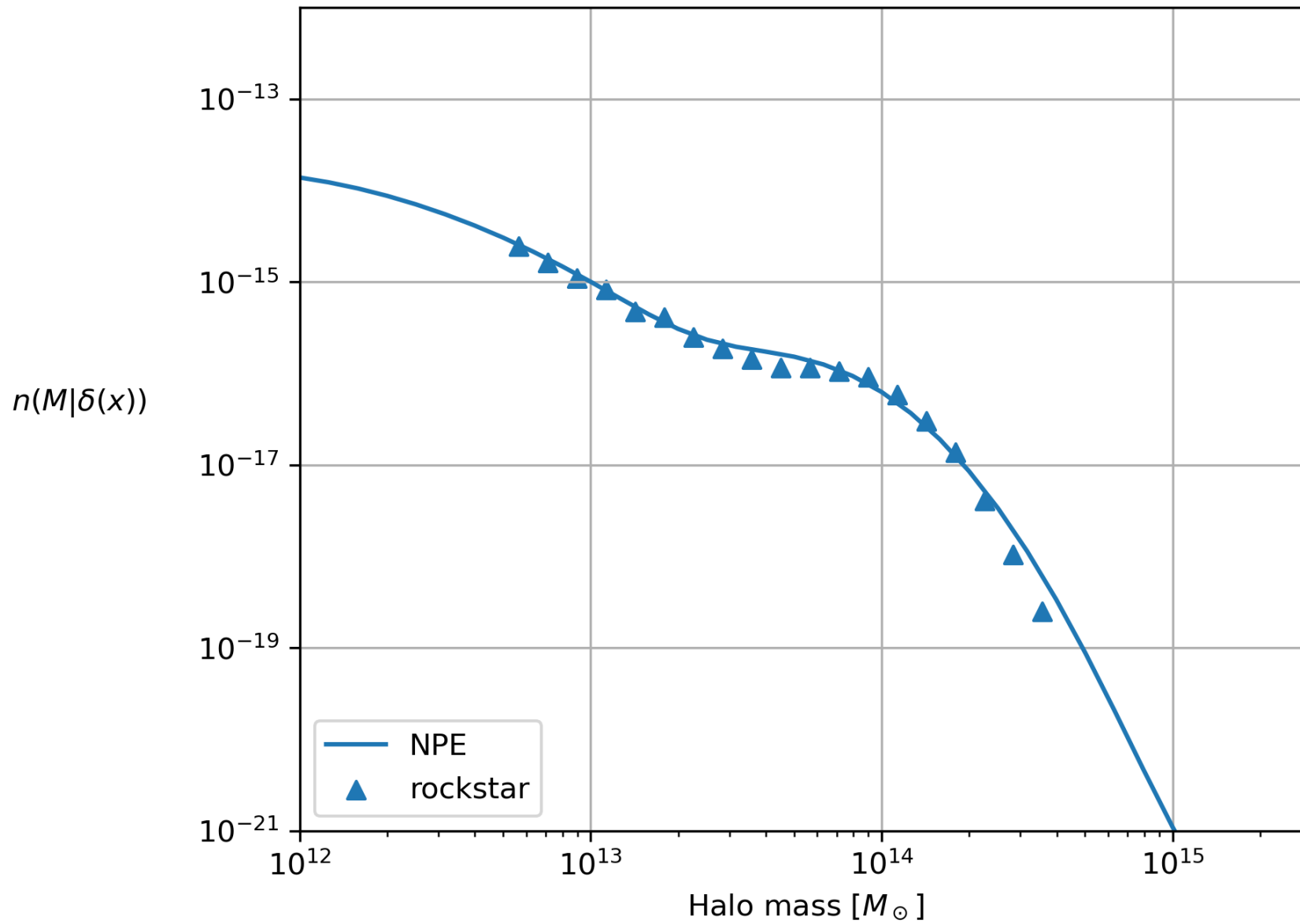- Power spectrum
- Bispectrum

See Charnock et al. (2020) - arXiv:1909.06379

Conditional halo mass function for $\delta(x) = 2.16$

Conditional halo mass function for $\delta(x) = 8.62$

Conditional halo mass function for $\delta(x) = 15.08$

Conditional halo mass function for $\delta(x) = 21.54$

$n(M|\delta(x))$

Halo mass $[M_\odot]$

NPE

rockstar

Conditional halo mass function for $\delta(x) = 28.00$

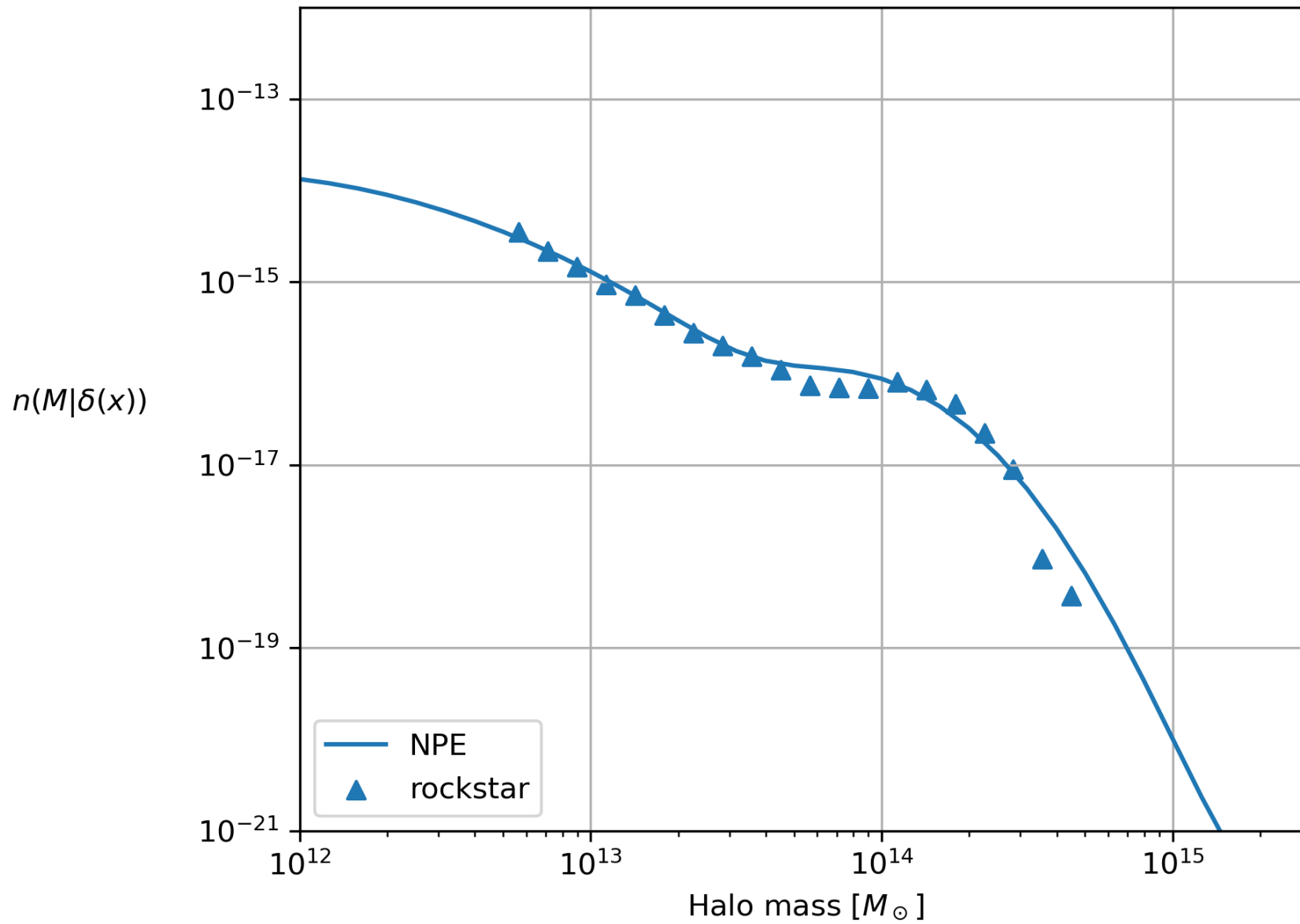Conditional halo mass function for $\delta(x) = 34.46$

Conditional halo mass function for $\delta(x) = 40.92$
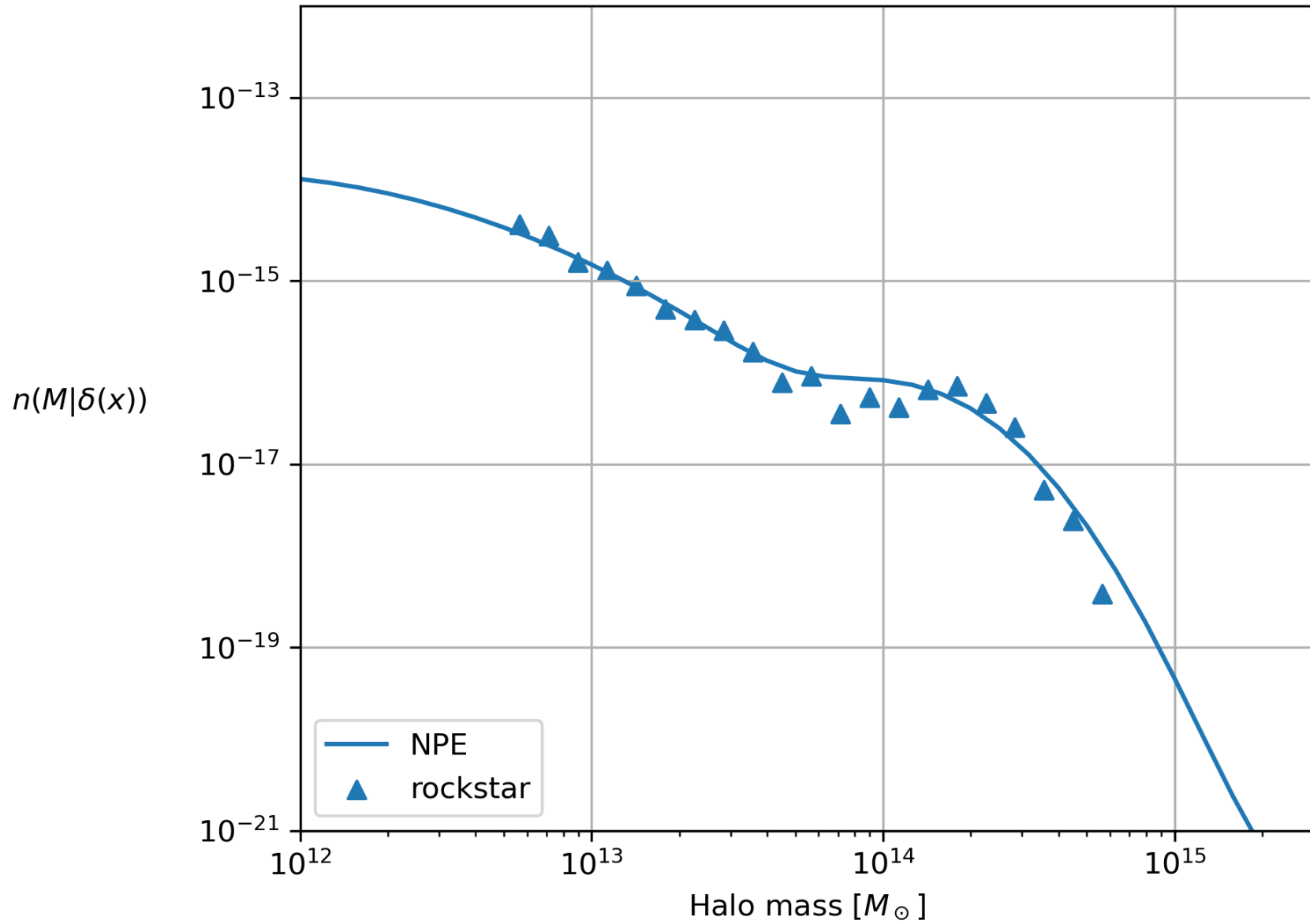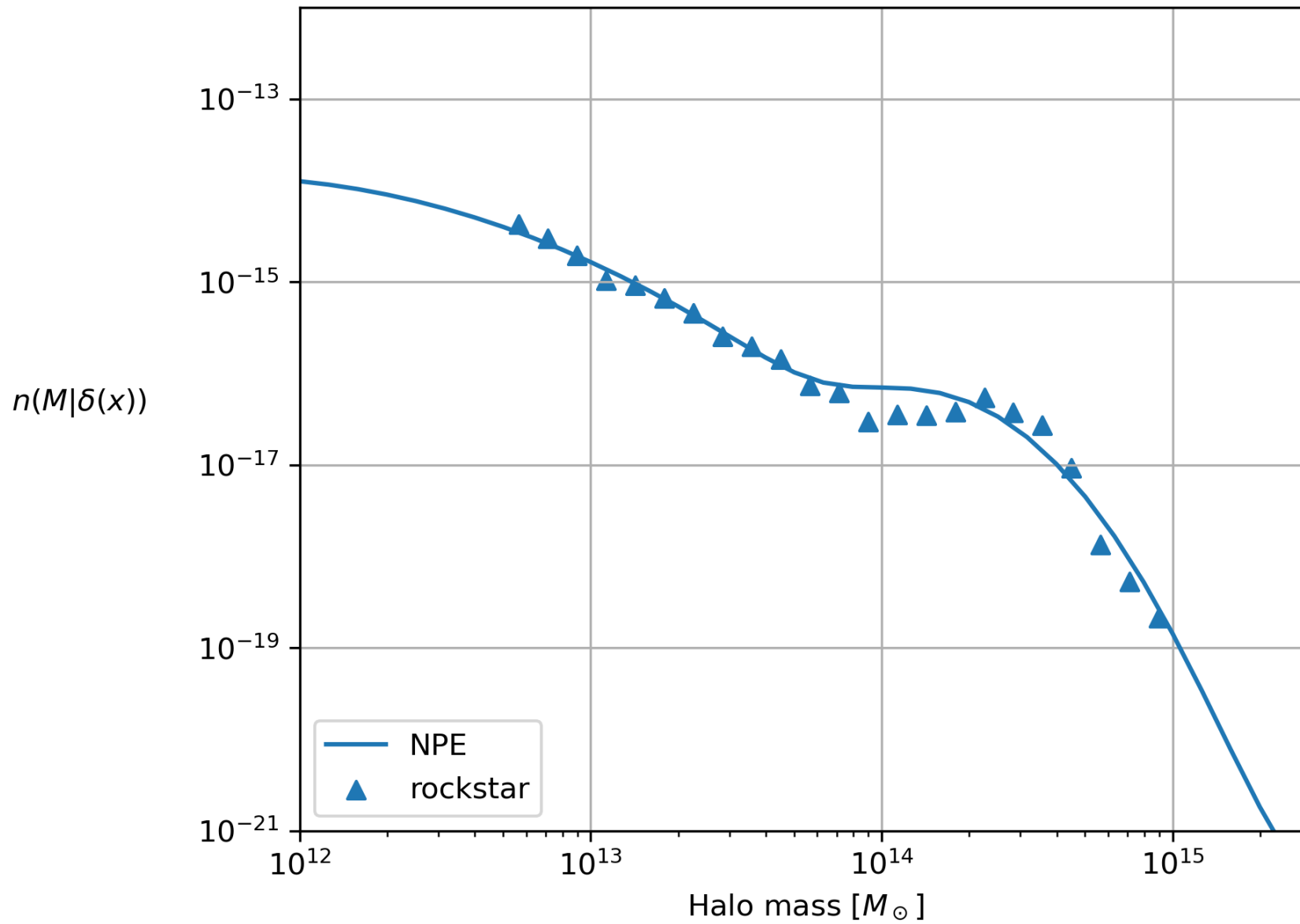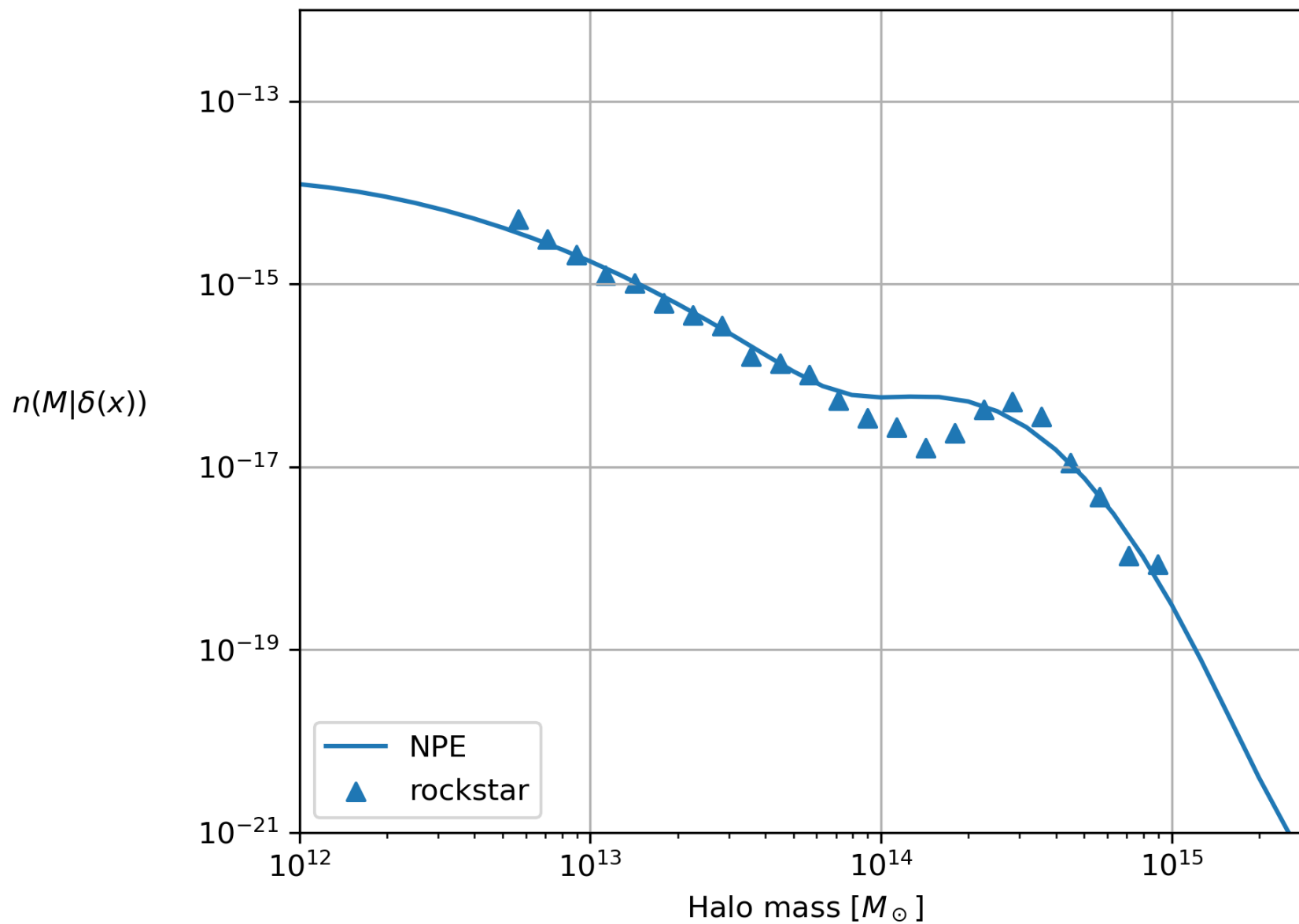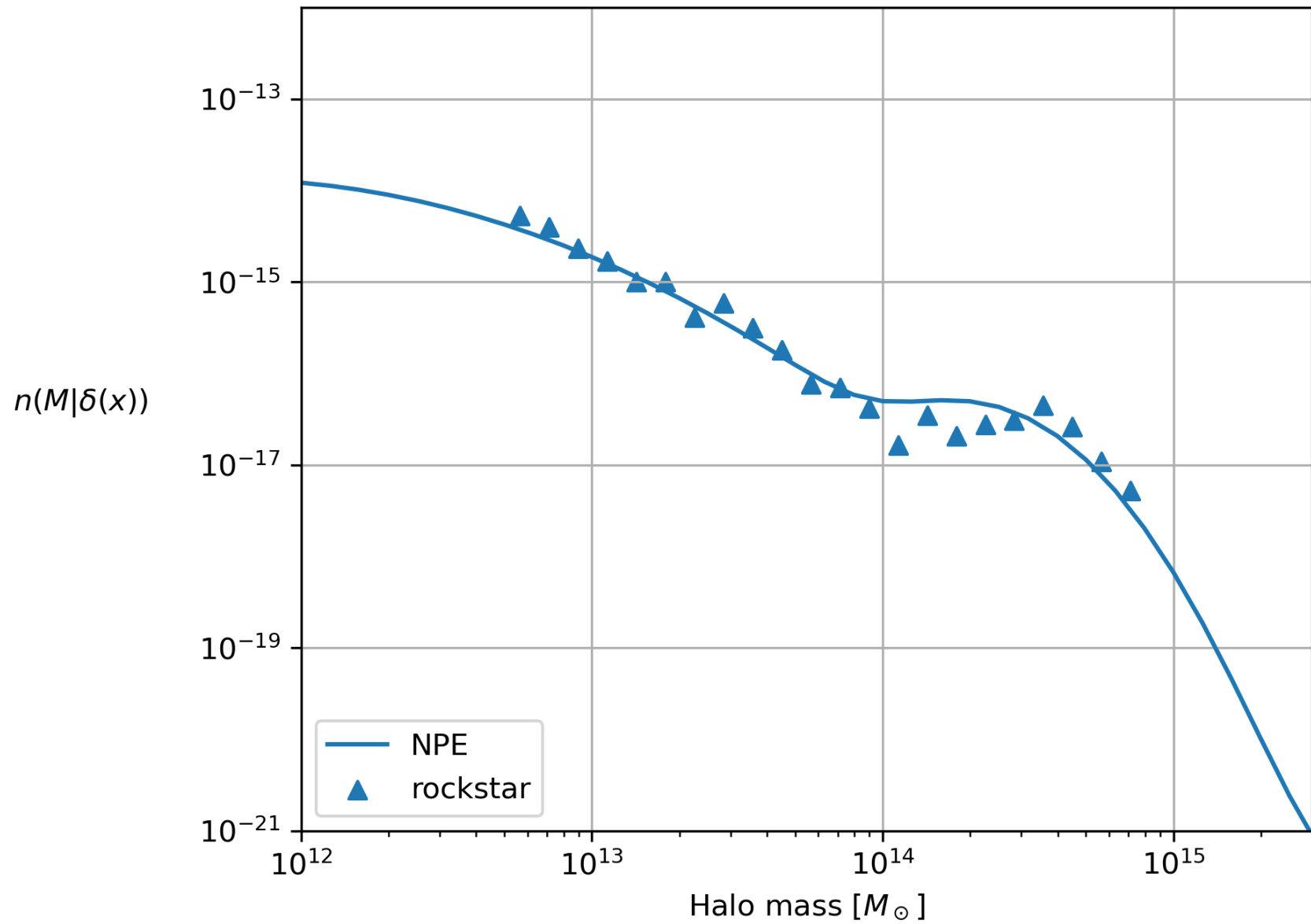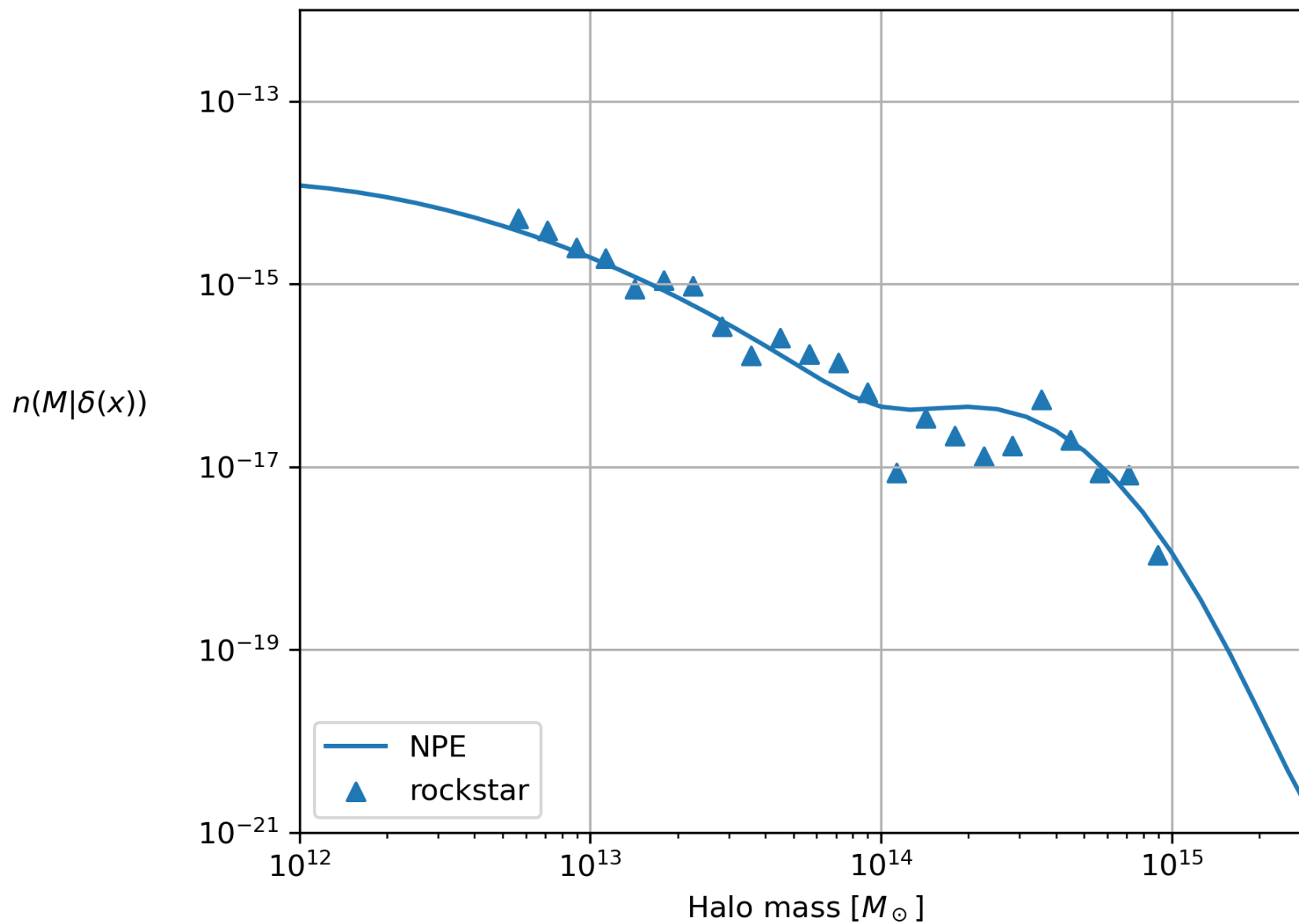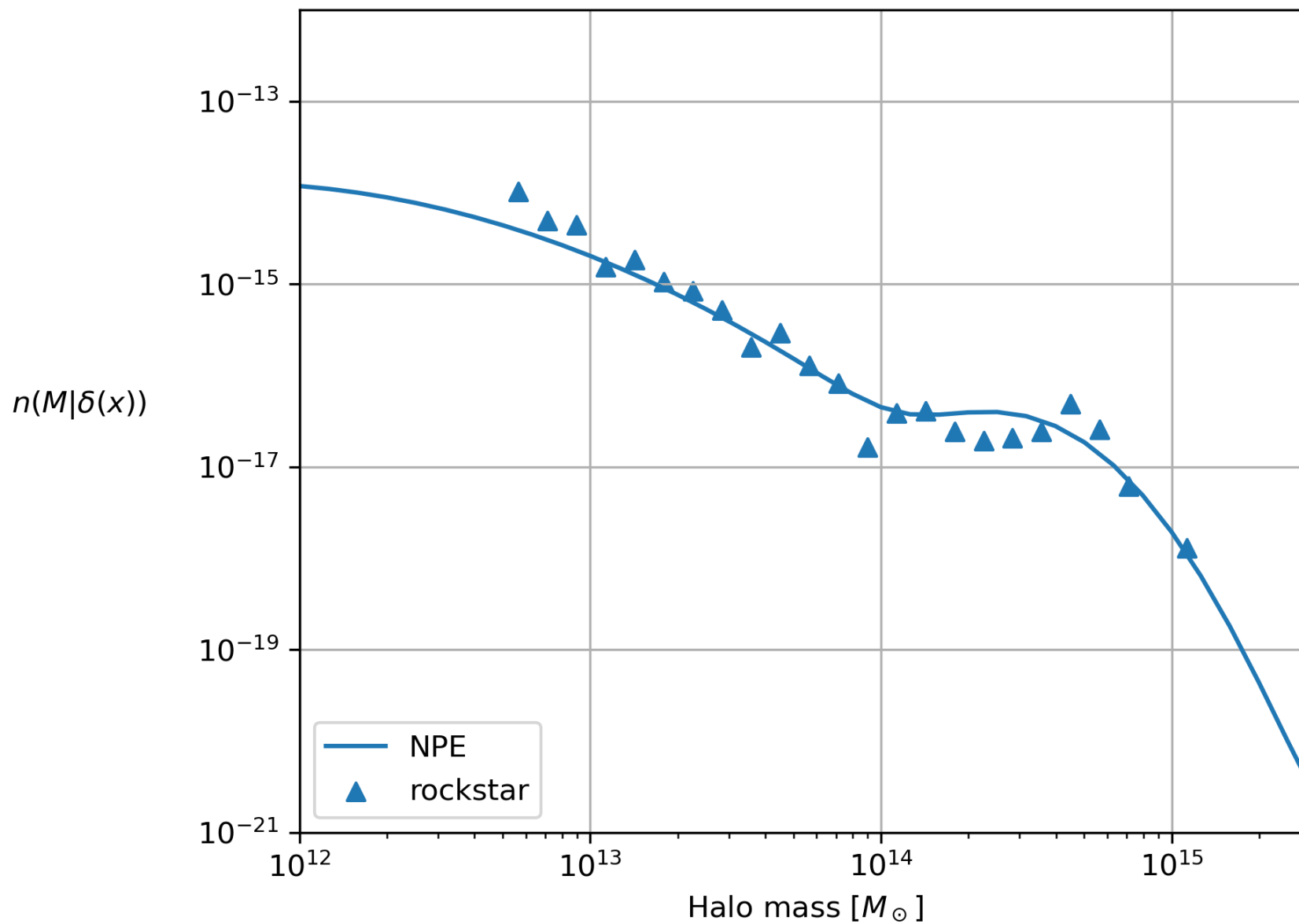
Conditional halo mass function for $\delta(x) = 47.38$

Conditional halo mass function for $\delta(x) = 53.83$

Conditional halo mass function for $\delta(x) = 60.29$

$$3 \cdot 10^{12} \leq M_{\mathrm{vir}}[M_\odot] < 1 \cdot 10^{13}$$

ground truth

prediction (mean)

$P(k) \; [h^{-3}\mathrm{Mpc}^3]$

$k \; [h \; \mathrm{Mpc}^{-1}]$

S. Ding et al. (in prep.)

$$3 \cdot 10^{12} \leq M_{\mathrm{vir}}[M_\odot] < 1 \cdot 10^{13}$$

ground truth

prediction (mean)

$B_{k_1,k_2}(\theta)$ $[h^{-6}\mathrm{Mpc}^6]$

$k_1 = 0.1h\ \mathrm{Mpc}^{-1}$
$k_2 = 0.2h\ \mathrm{Mpc}^{-1}$

Angle θ

S. Ding et al. (in prep.)

$w_0^{CNN} = -0.3995^{+0.0009}_{-0.0008}$

$w_1^{CNN} = 0.0385^{+0.0002}_{-0.0002}$

$w_2^{CNN} = -0.0031^{+0.0001}_{-0.0001}$

$w_3^{CNN} = -0.0006^{+0.0001}_{-0.0001}$

S. Ding et al. (in prep.)
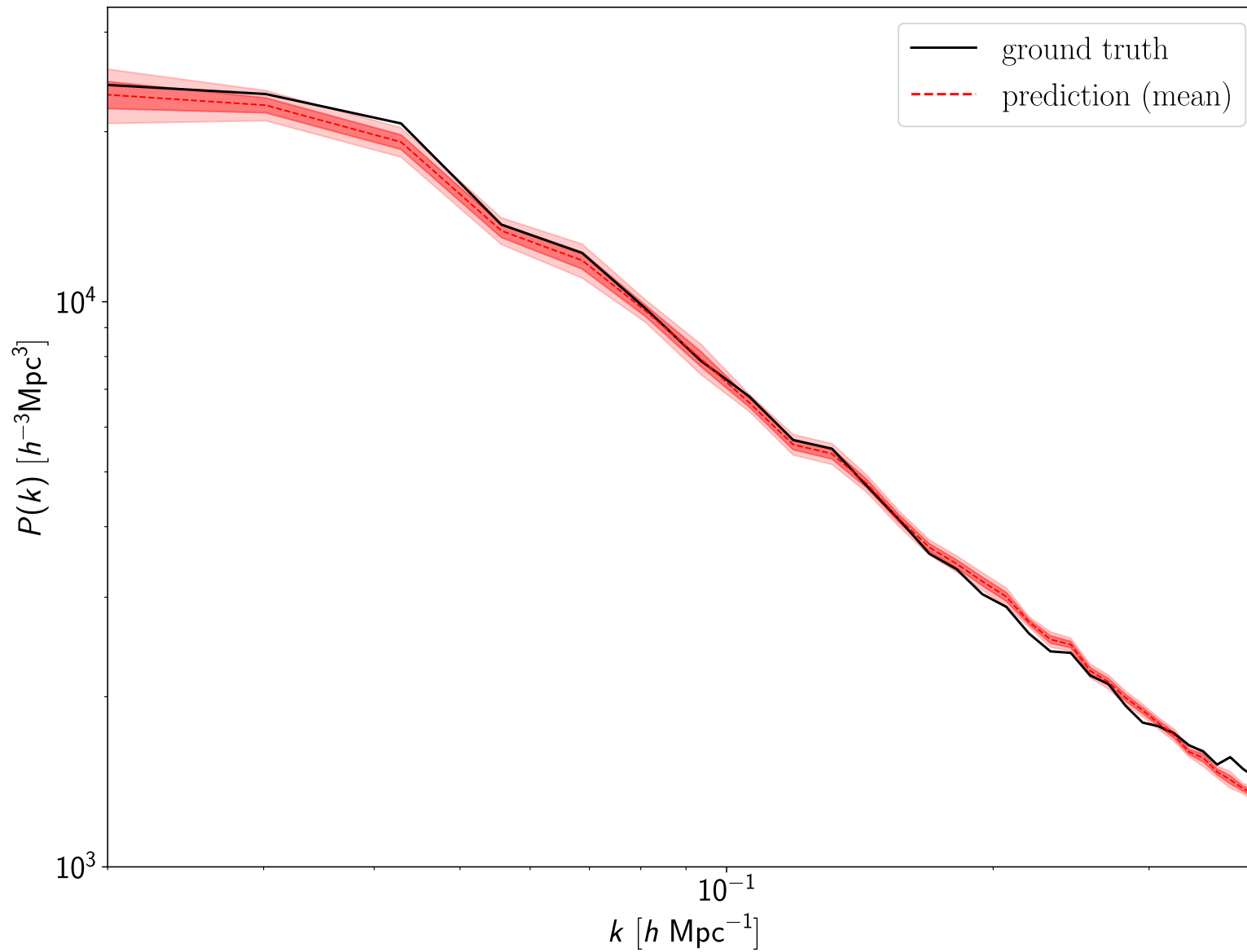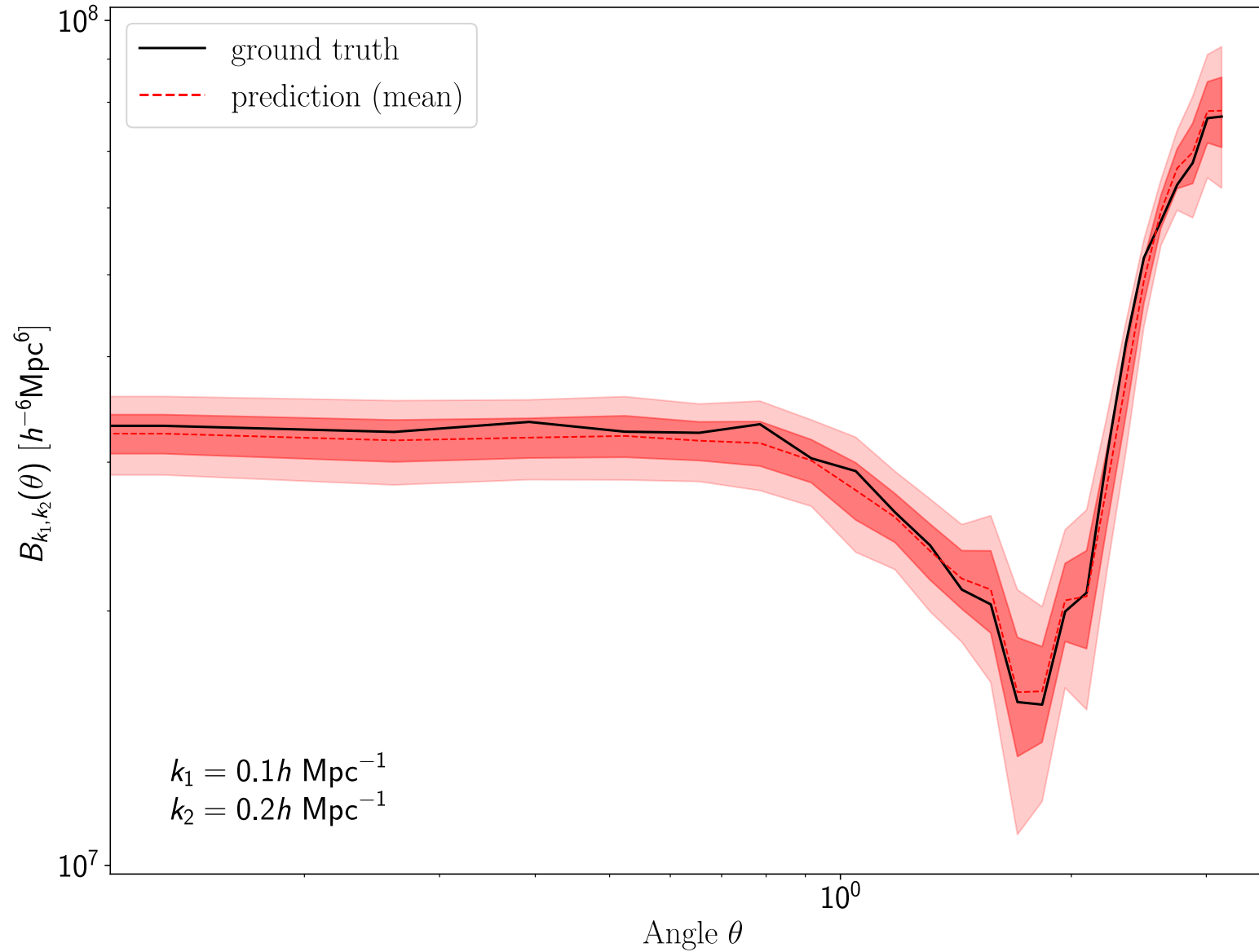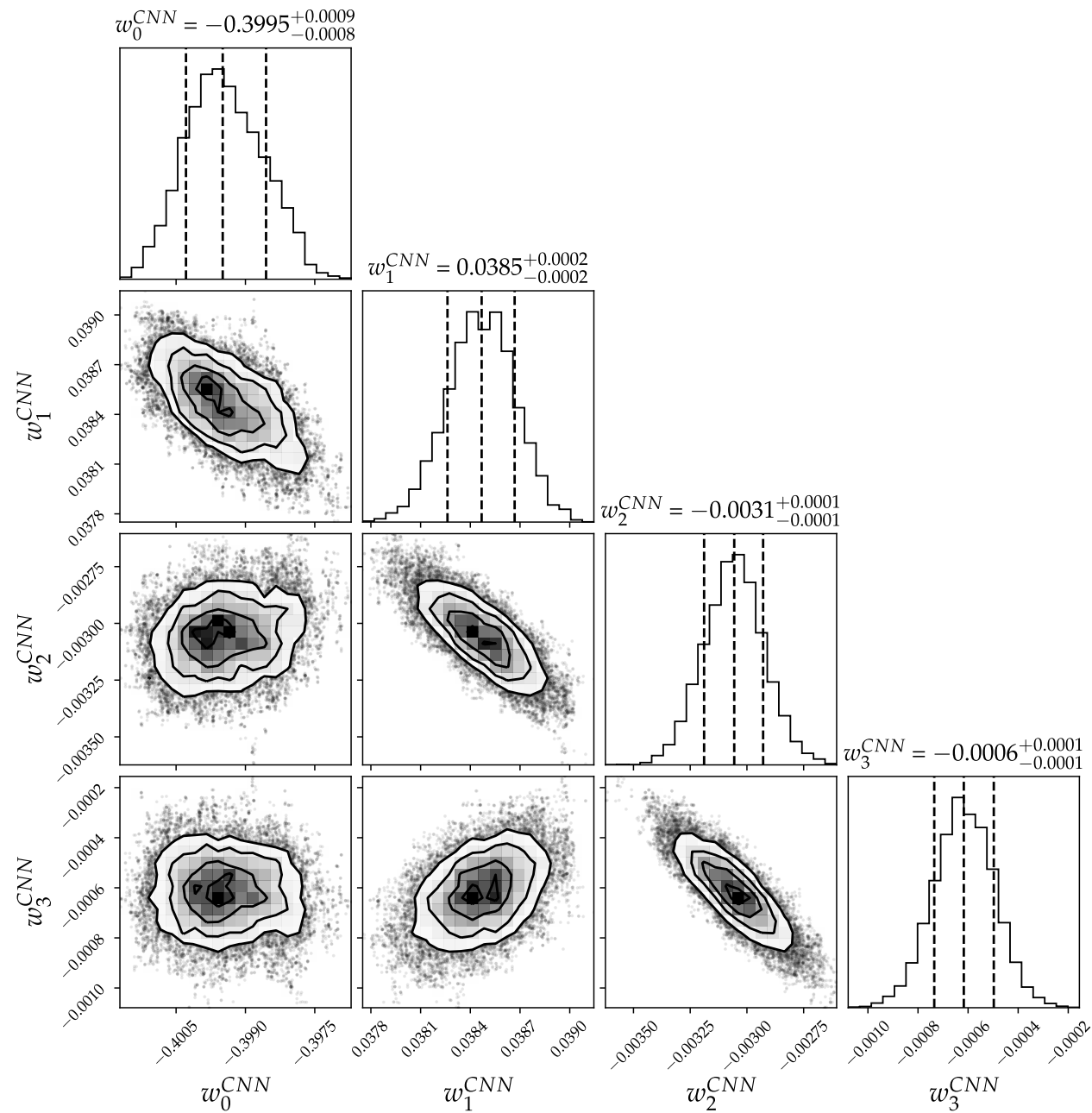
dark matter over-density field	→	**Neural Physical Engine**	→	**Nbody-like halo catalogues**

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Happy to chat in person, Slack or via simon.ding@iap.fr
I'm looking for a postdoctoral position starting **January 2025**!