Dark Matter Searches in the Galactic dwarf spheroidals in the Subaru-PFS era

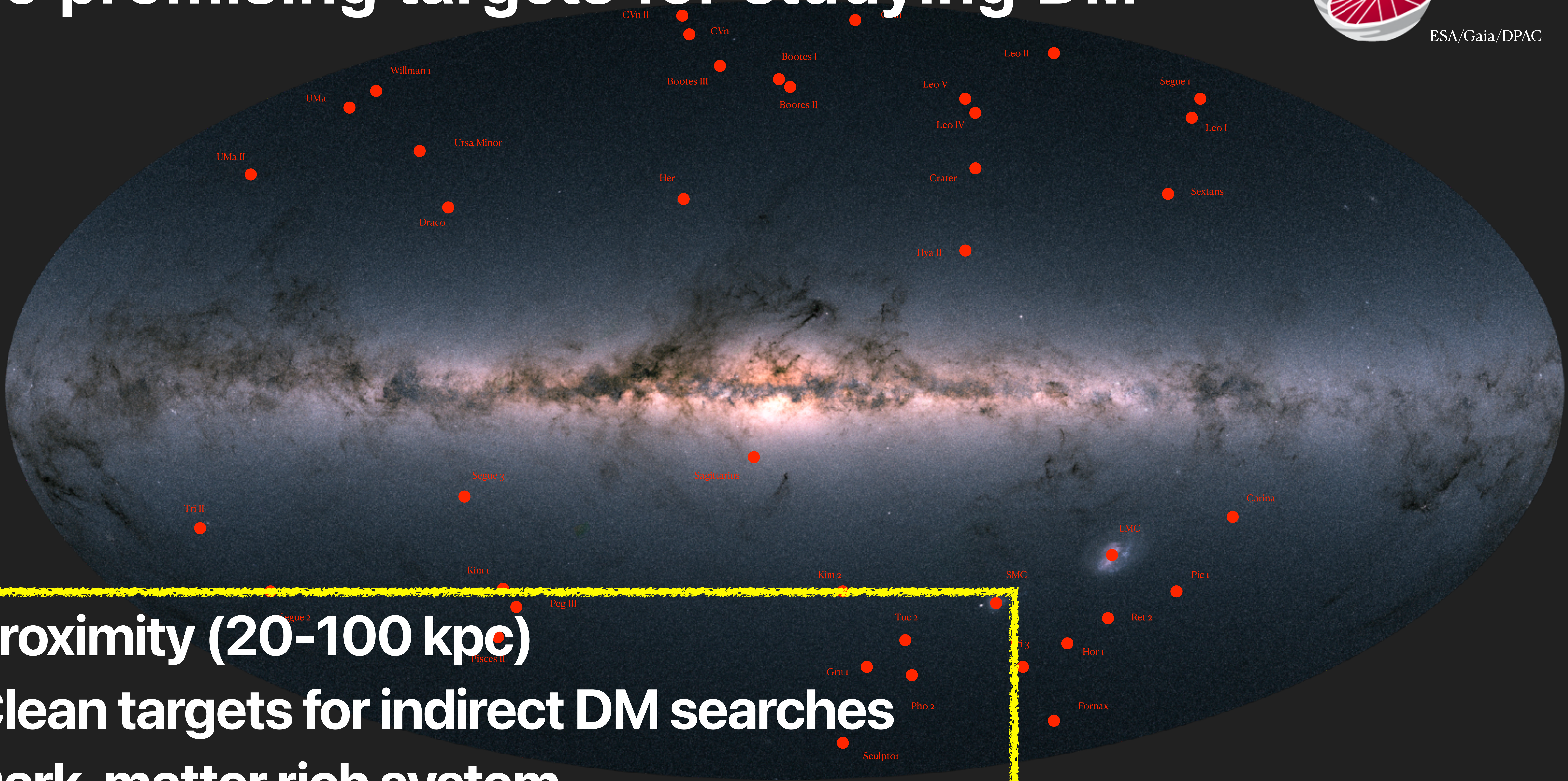
Kohei Hayashi (NIT, Sendai College)

Mar. 8, 2024

FY2023 “What is dark matter?”@YITP

Dwarf spheroidal galaxy (dSph): the promising targets for studying DM

ESA/Gaia/DPAC



- Proximity (20-100 kpc)
- Clean targets for indirect DM searches
- Dark-matter rich system

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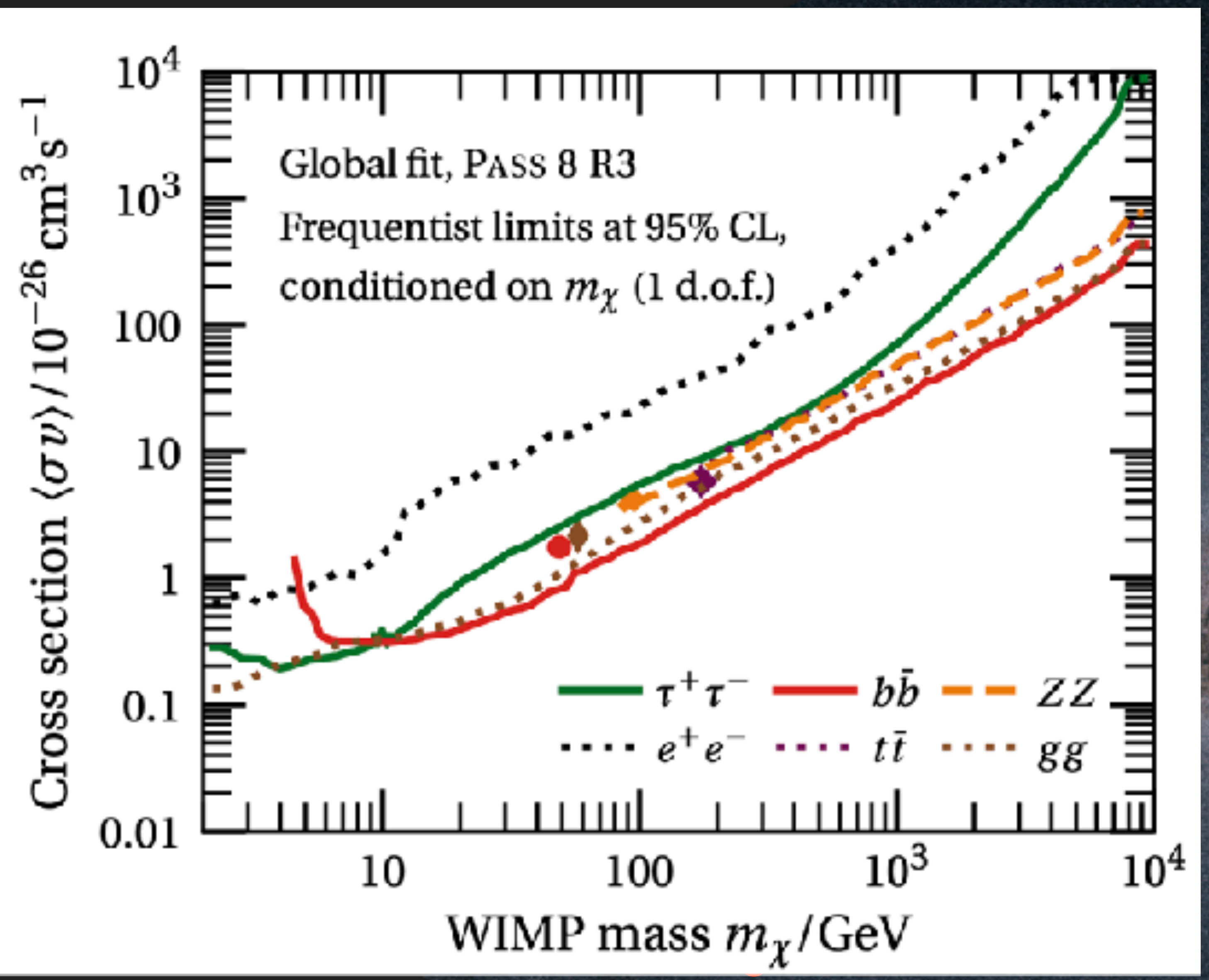
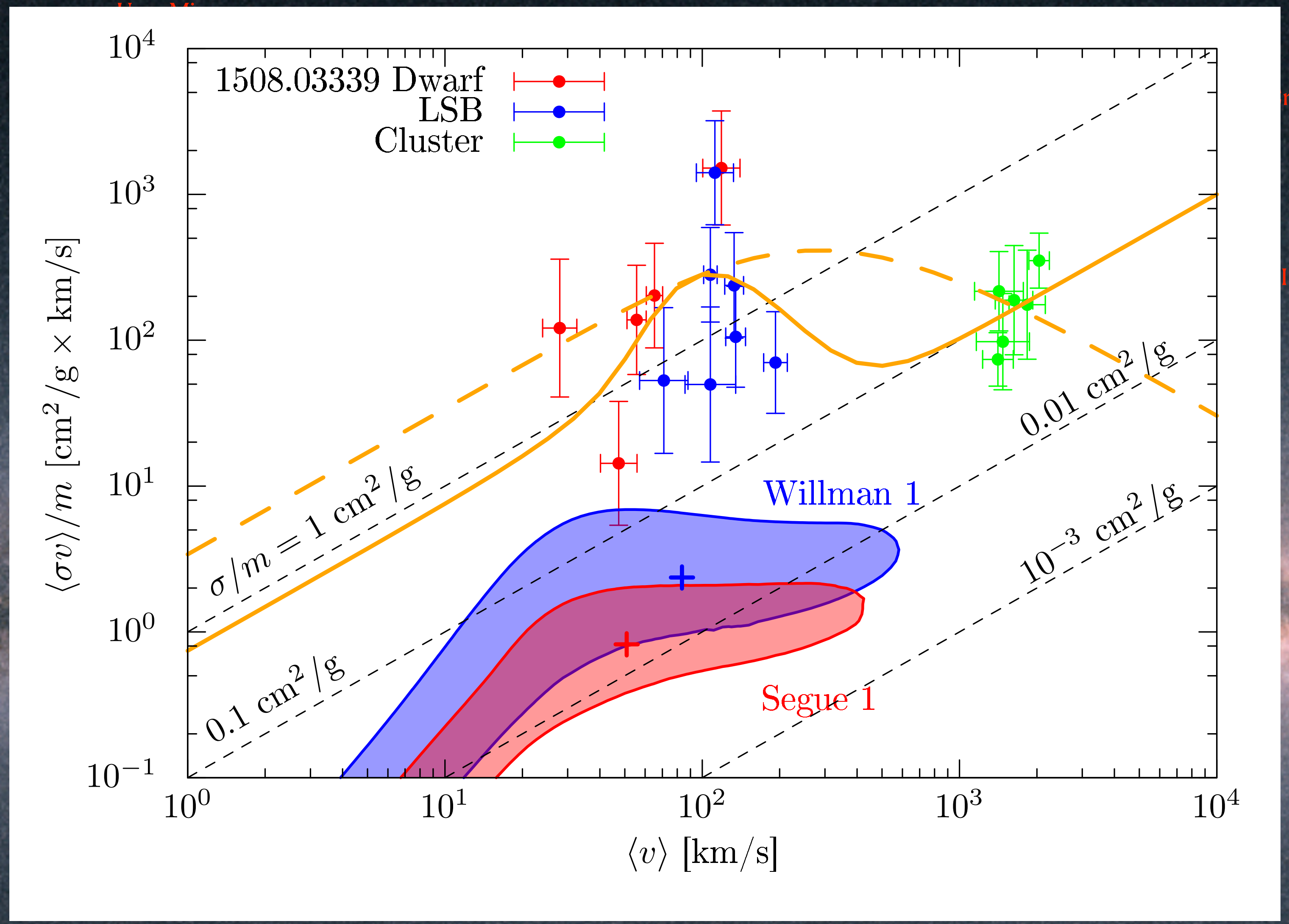
WIMP



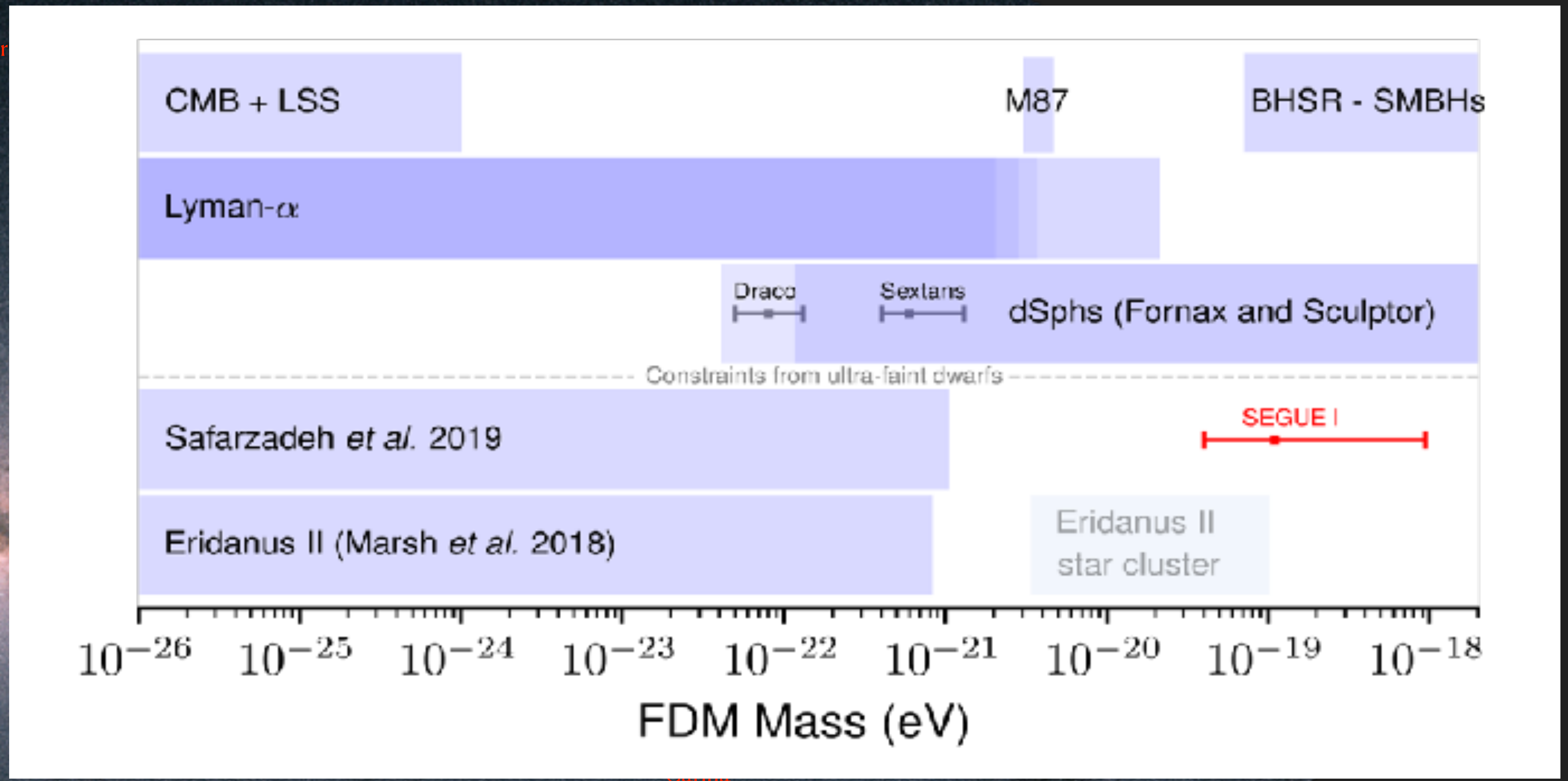
Hoof+ (2020)

SIDM



Hayashi+ (2021)

FDM



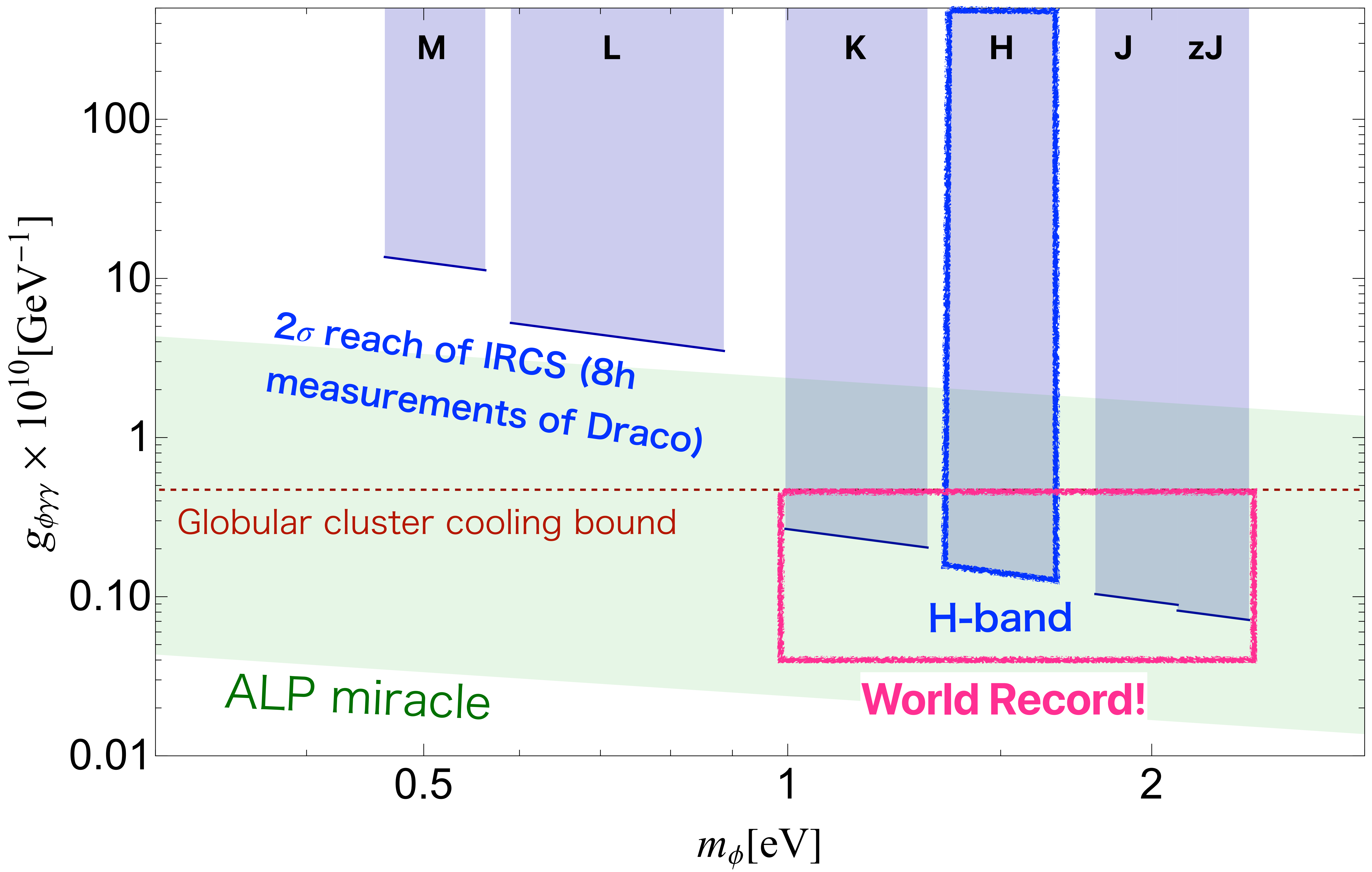
Hayashi+ (2022)

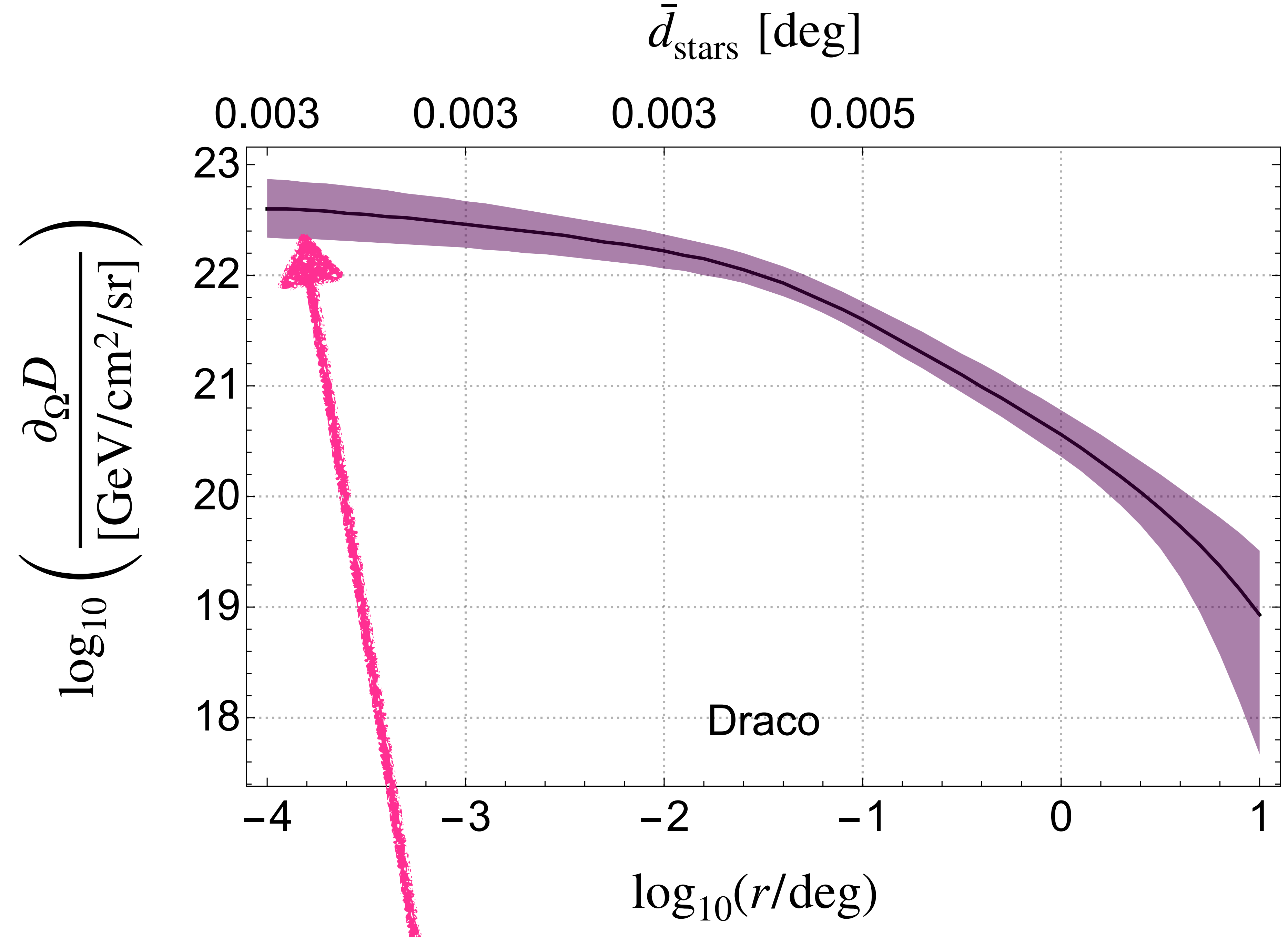
- **Proximity (30-100 kpc)**
- **Clean targets for indirect DM searches**
- **Dark-matter rich system**

Indirect detection of eV DM with Subaru-IRCS

Yin and KH (2024)

Subaru-IRCS observation can place more stringent constraints on $g_{\phi\gamma\gamma}$ of eV DM than the GC cooling.





$$\boxed{\frac{dJ_{\rm decay}}{d\Omega} \sim 10^{22.6}\ [\mathrm{GeV/cm^2/sr}]}$$

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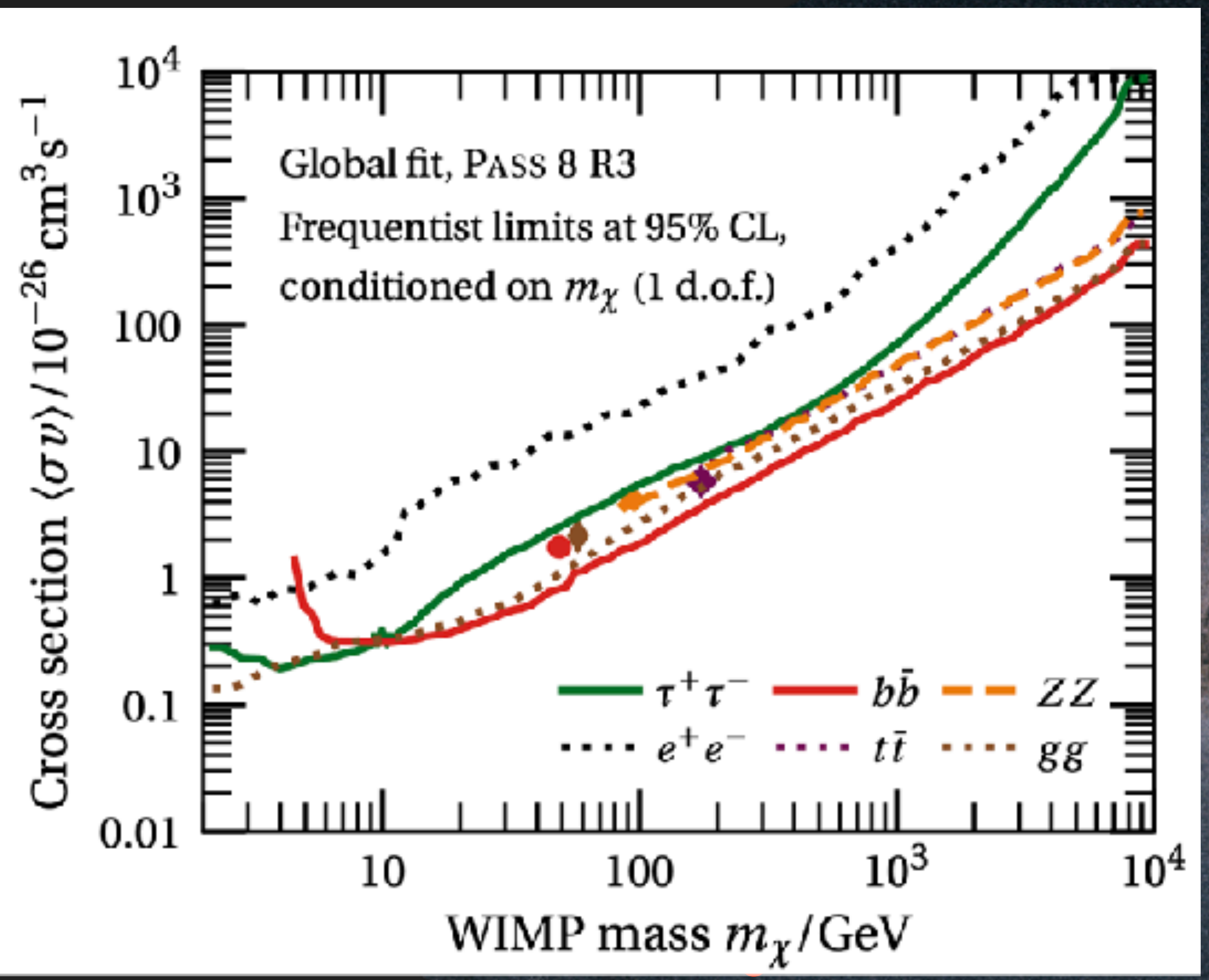

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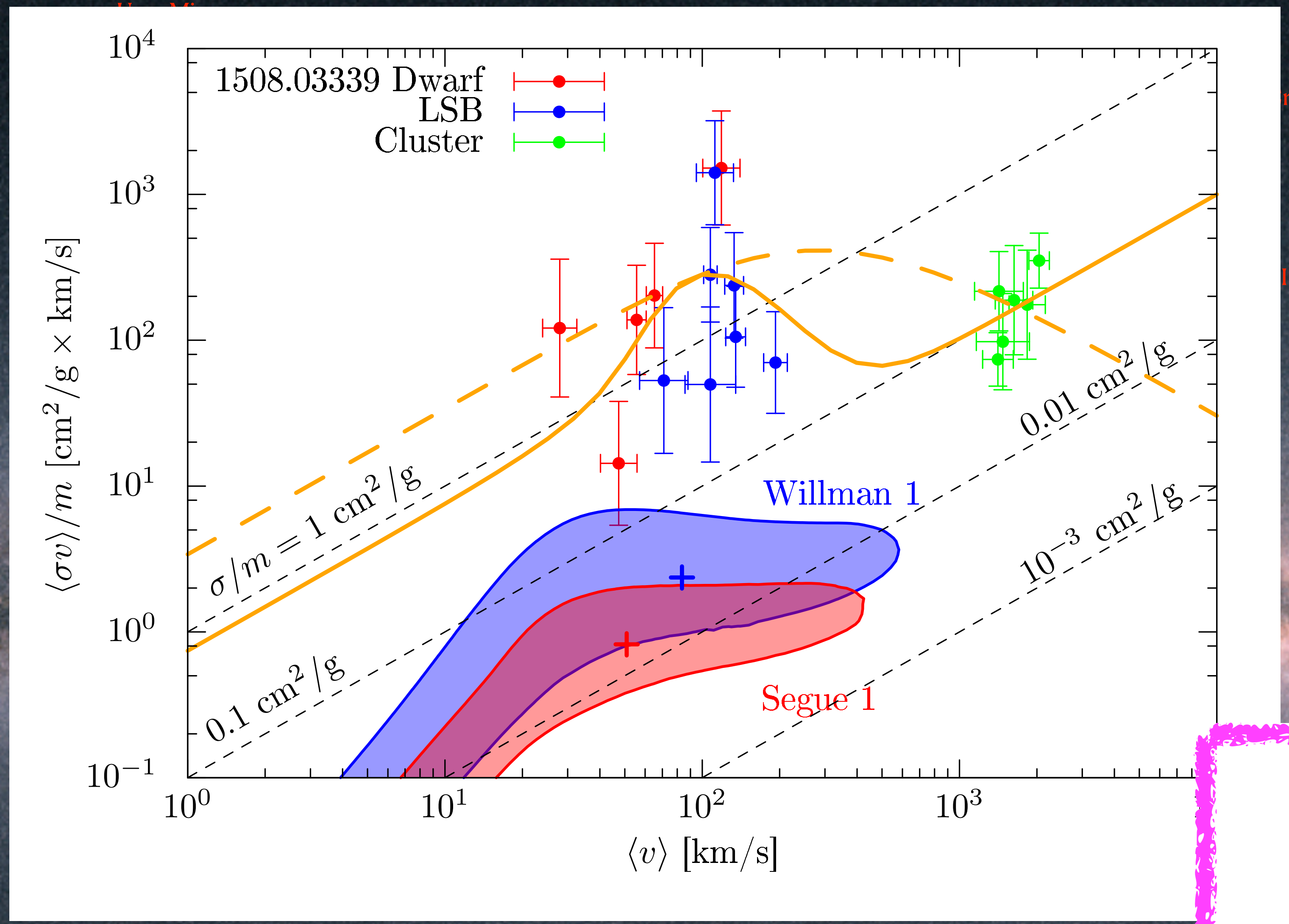
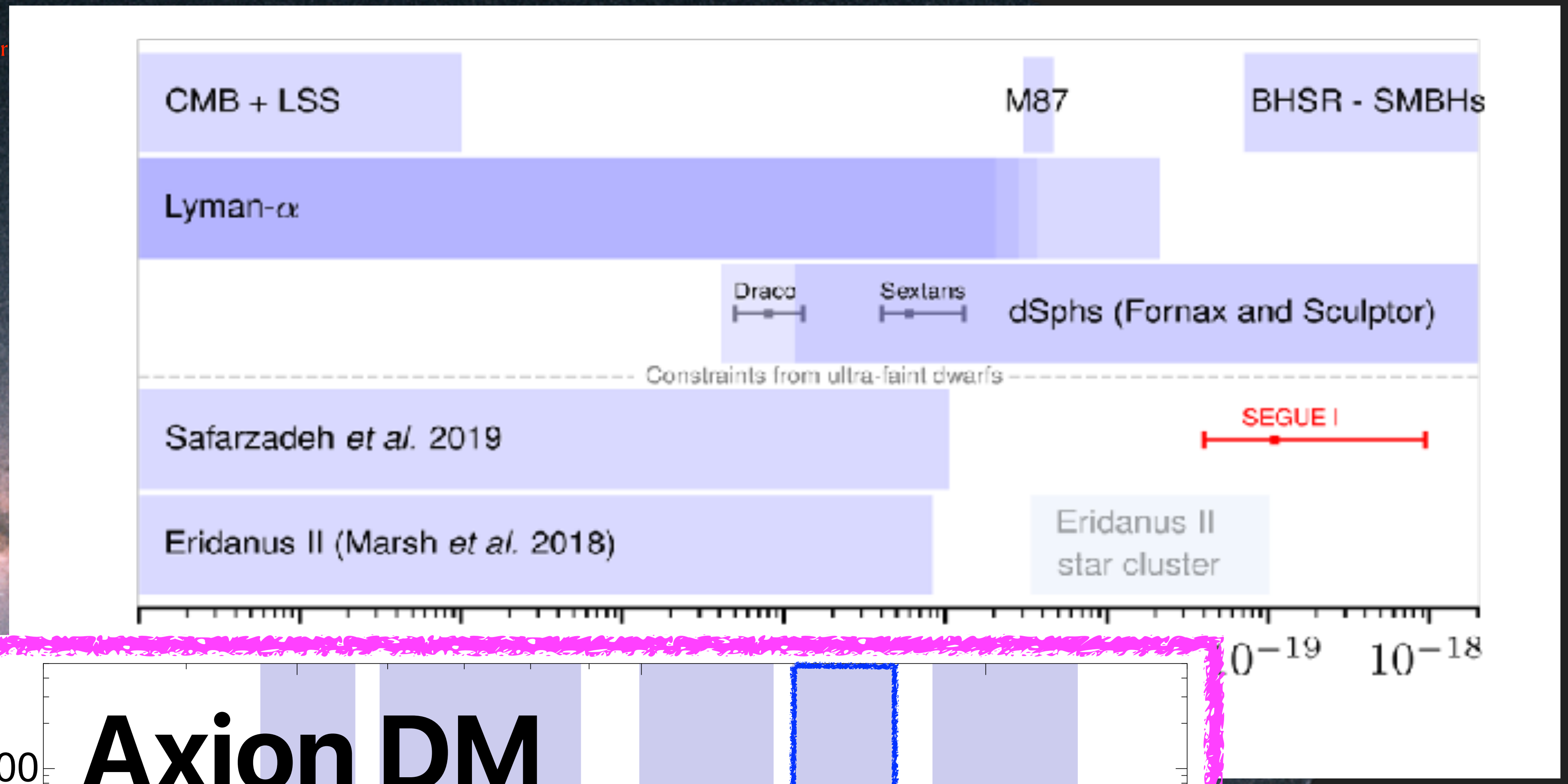
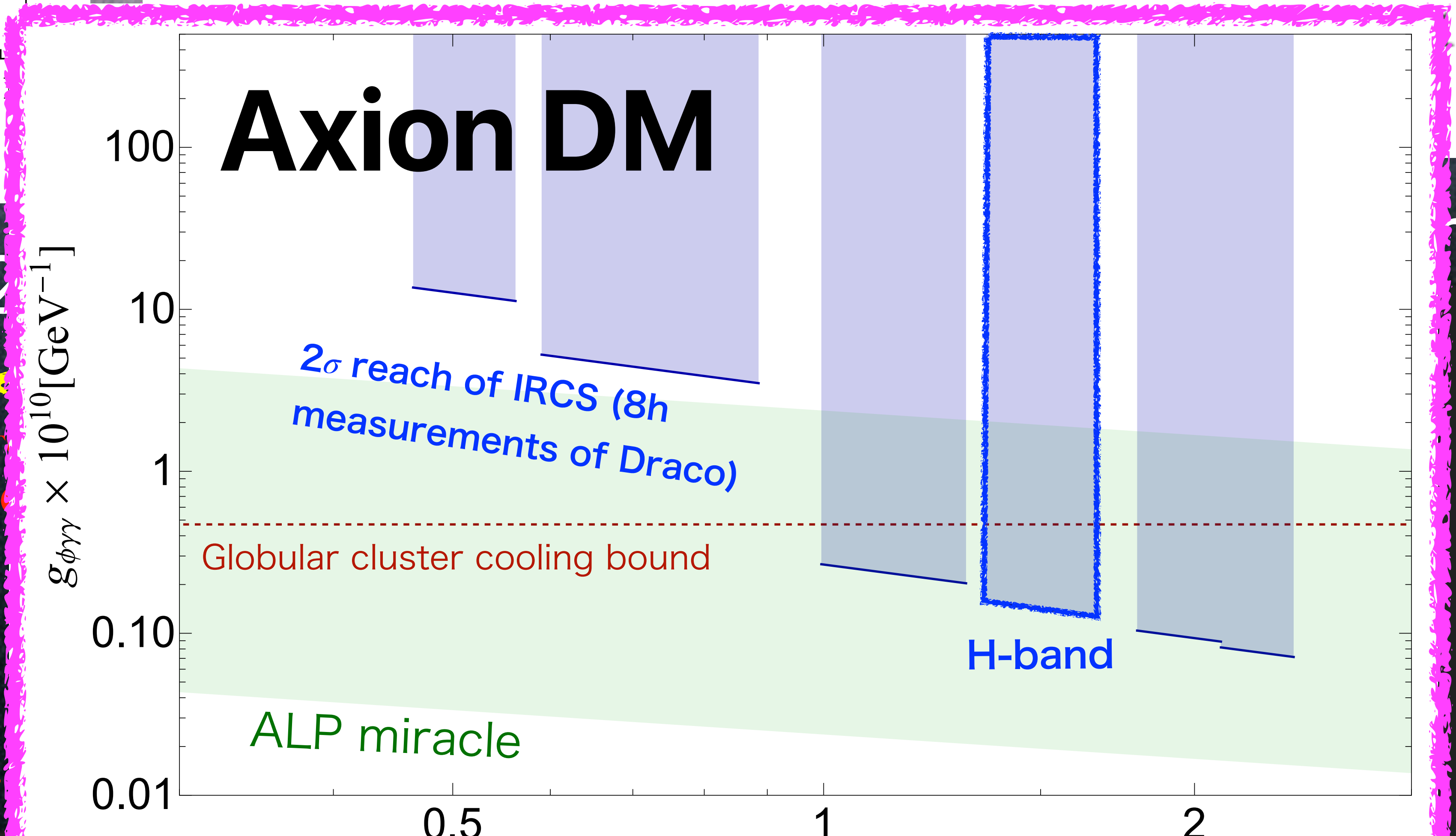


Hayashi+ (202

FDM



hi+ (2022)



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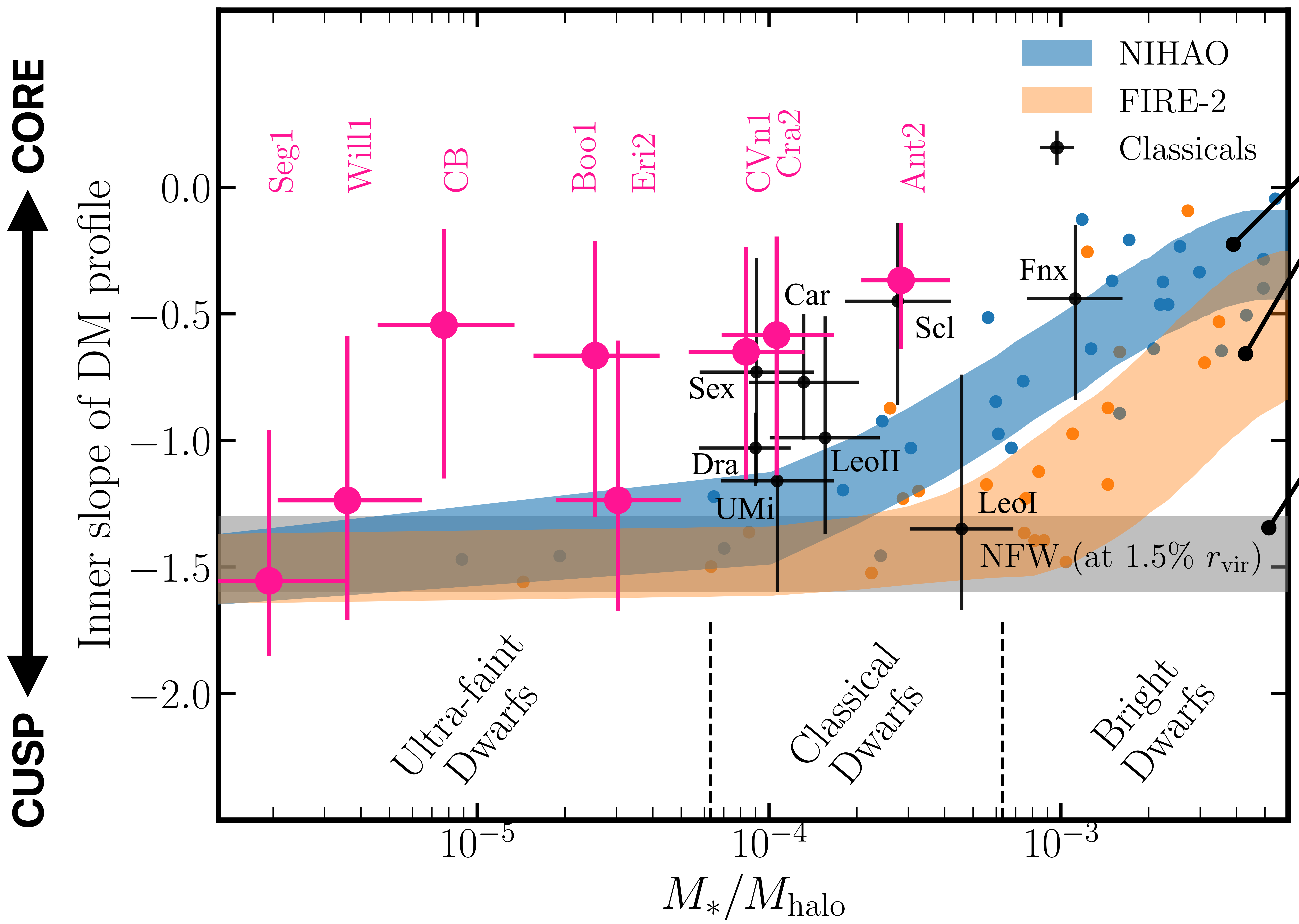
Dwarf spheroidal galaxy (dSph): the promising targets for studying DM

To gain insight into the properties of dark matter from the Galactic dwarf spheroidals

it is *necessary* to place tighter constraints on their *dark matter density profiles.*

Diversity of the DM distributions?

KH, Chiba & Ishiyama (2020)
KH, Hirai, Chiba & Ishiyama (2023)



Prediction from LCDM based N-body+hydro sims.

Prediction from LCDM based pure N-body sims.

- **The diversity of the DM density profiles in the dSphs**.
- There are still **large uncertainties on their inner slopes**.

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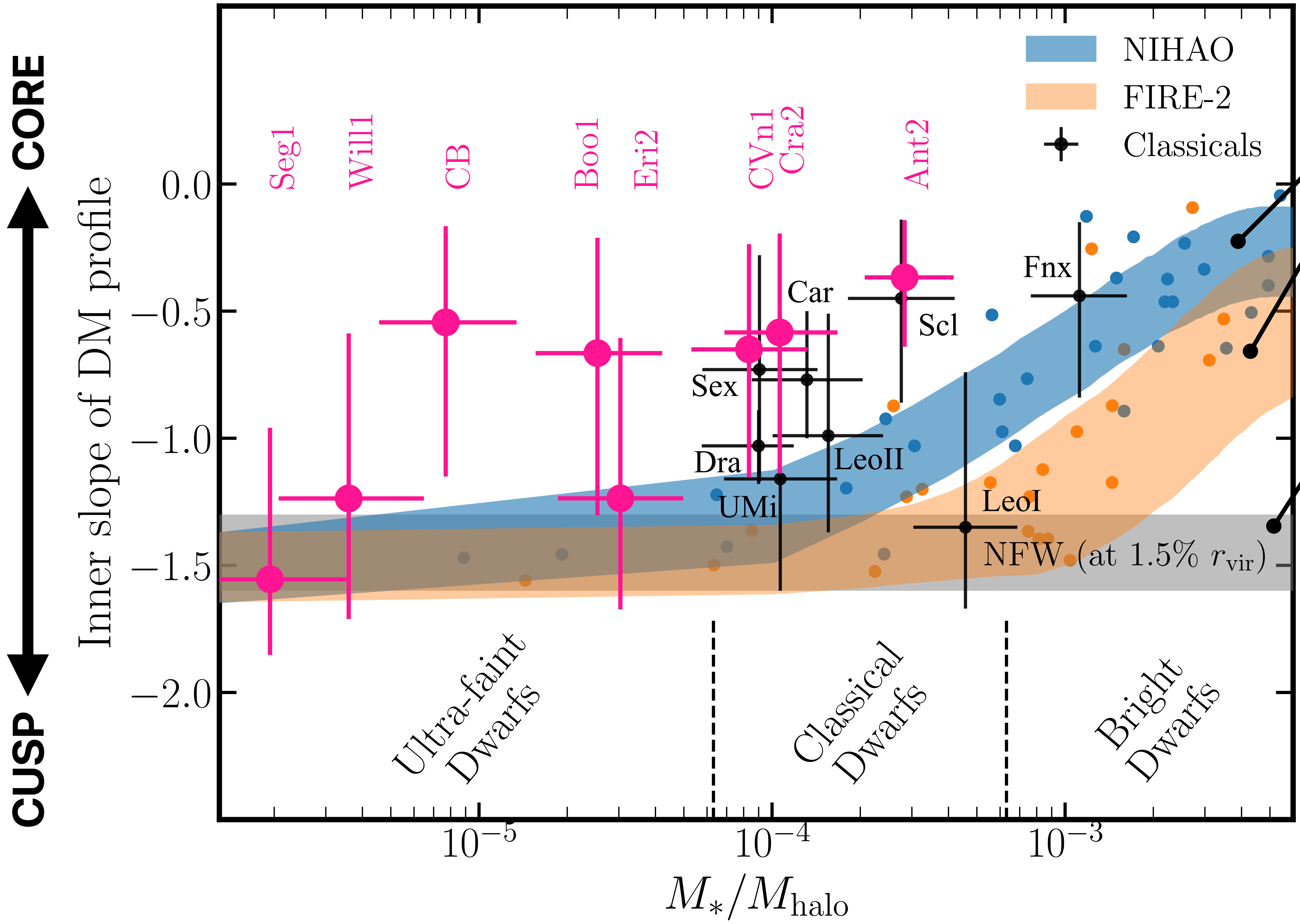

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- **The diversity of the DM density profiles in the dSphs**.
- There are still **large uncertainties on their inner slopes**.

The main reasons:

1. Insufficient number of velocity data
2. Parameter's degeneracy occurs.

ρ_{DM} – β_{ani} degeneracy

Ex. Spherical Jeans eq.

$$\frac{\partial[\nu(r)\sigma_r^2(r)]}{\partial r} + \frac{2\nu(r)\beta_{\mathrm{ani}}(r)\sigma_r^2(r)}{r} = -\nu(r)\frac{GM_{\mathrm{DM}}(r)}{r^2}$$

$$M_{\mathrm{DM}}(r) = \int_0^r 4\pi s^2 \rho_{\mathrm{DM}}(s) ds$$

$$\beta_{\mathrm{ani}}(r) = 1 - \frac{\sigma_t^2(r)}{2\sigma_r^2(r)}$$

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Degeneracy occurs between velocity anisotropy parameter and density distribution.

$\rho_{\rm DM}$ – $\beta_{\rm ani}$ degeneracy

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How to break the degeneracy?

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How to break the degeneracy?

- Higher-order velocity moments
- New observational data such as proper motions of each member star
- ...

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Fourth order velocity moments and kurtosis

Wardana, Chiba, KH (2024, in prep.)

The shape of velocity distribution should be sensitive to velocity anisotropy.

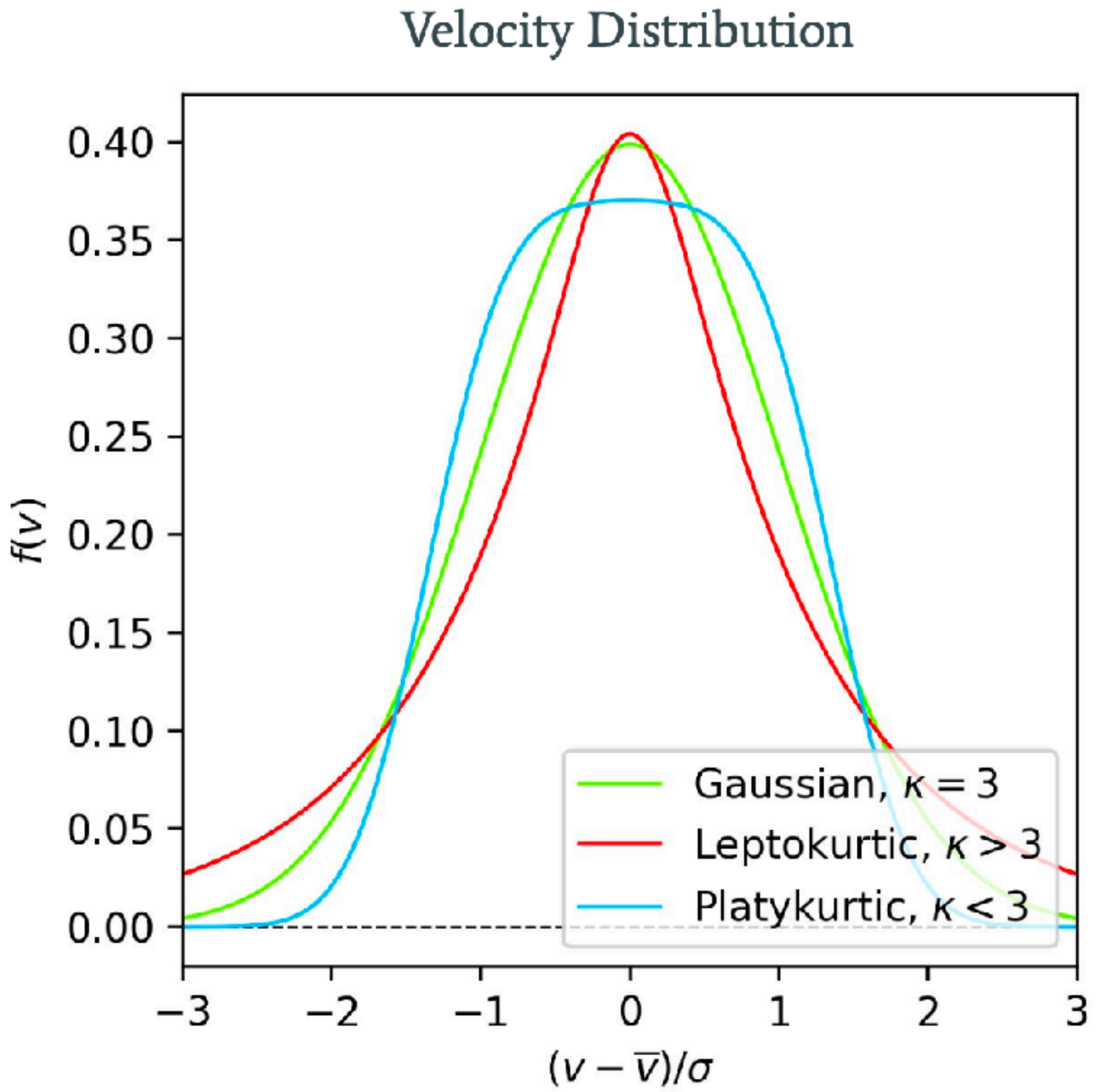
The 4th order velocity moments (spherically symmetry):

$$\overline{v_{\rm los}^4}(R) = \frac{2}{I(R)} \int_R^\infty dr \left[1 - 2\beta\frac{R^2}{r^2} + \frac{1}{2}\beta(1+\beta)\frac{R^4}{r^4}\right] \frac{\nu \overline{v_r^4} r}{\sqrt{r^2 - R^2}}.$$

Kurtosis:

$$\kappa = \frac{\overline{v_{\rm los}^4}}{(\sigma_{\rm los}^2)^2}$$

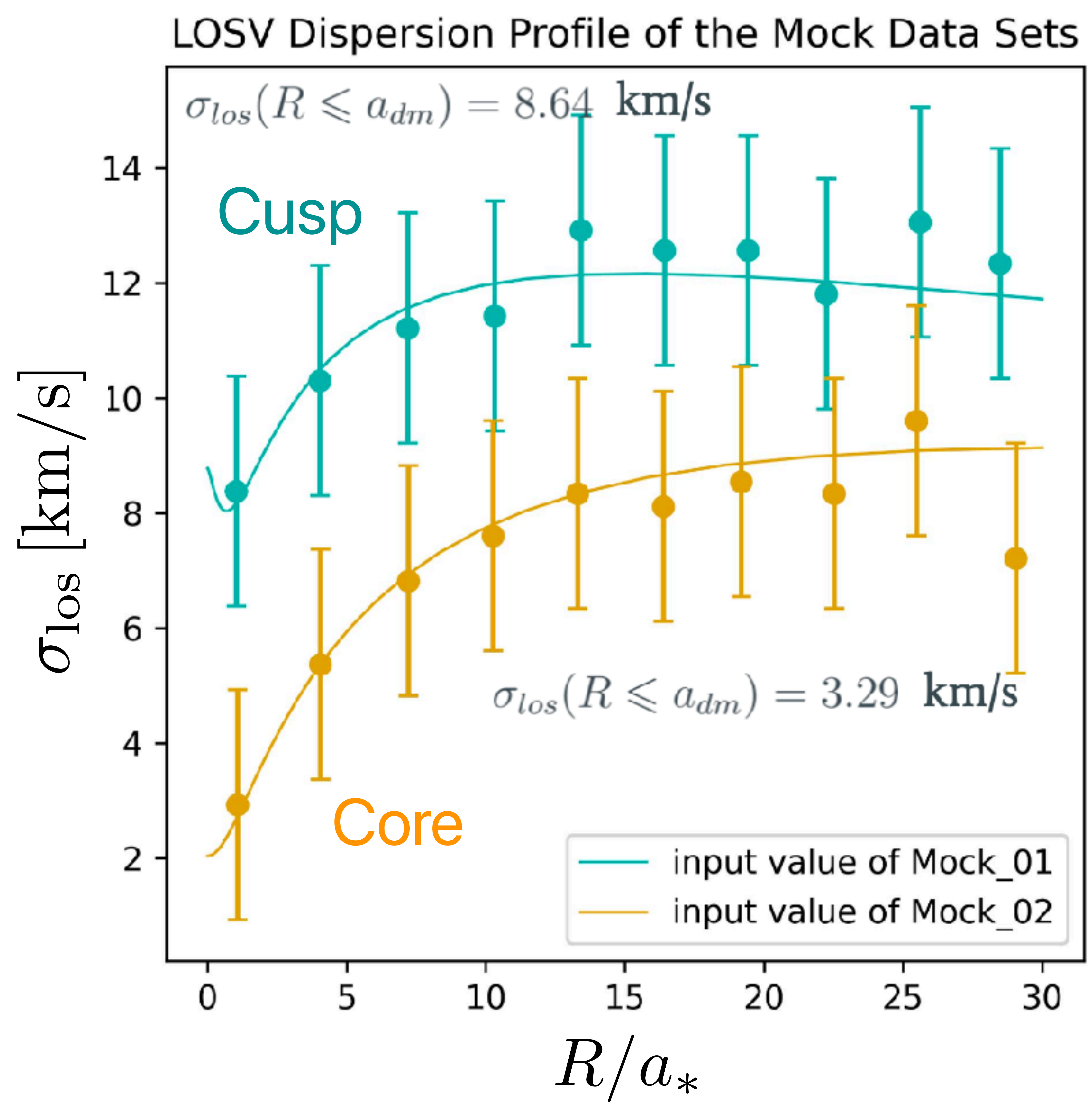
e.g., Lokas (2002), Richardson & Fairbairn (2012)

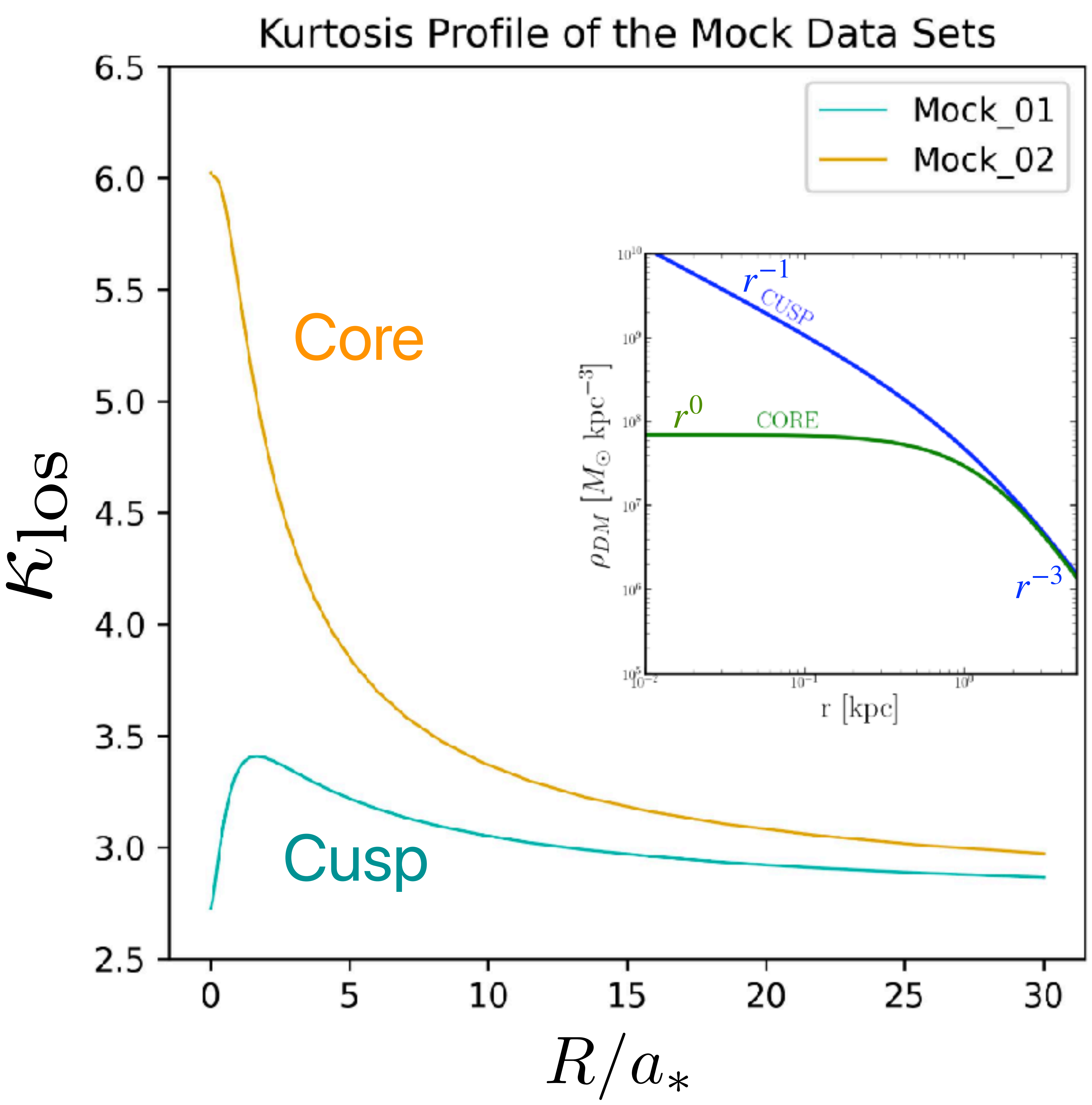


Application to mock data sets

Wardana, Chiba, KH (2024, in prep.)

Two sets of new mock data: cuspy (green) and core (orange) (isotropic: $\beta = 0.$)



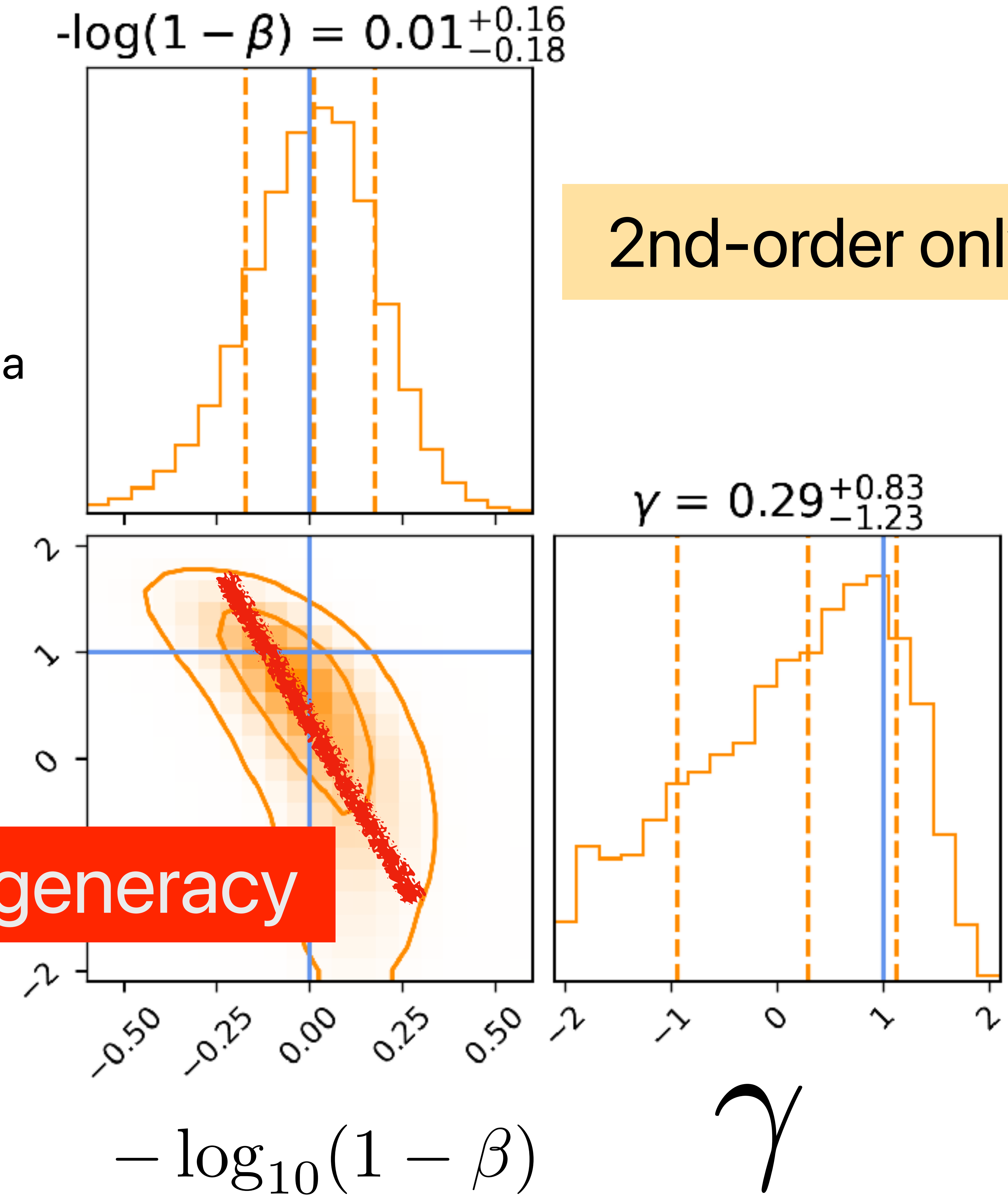


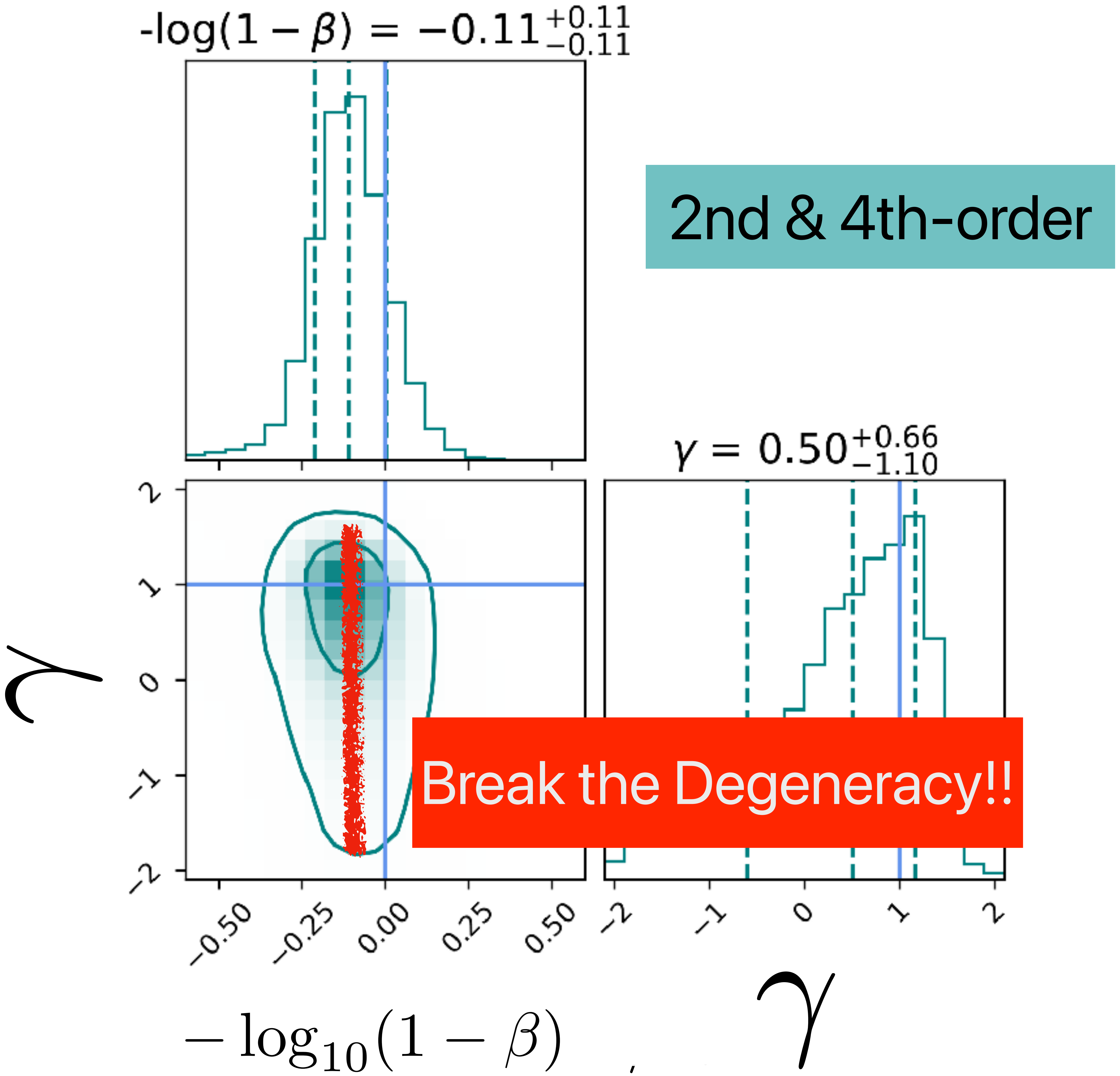
Result: The power of 4th-order moments

Wardana, Chiba, KH (2024, in prep.)

N_{star} = 500 stars, v_{err} = 2 km/s (Similar to the typically available data for MW's dSphs)

Dafa Wardana





Result: Dependance of N_{star}

Wardana, Chiba, KH (2024, in prep.)

2nd & 4th-order moments analysis, v_{err} = 2 km/s is fixed.

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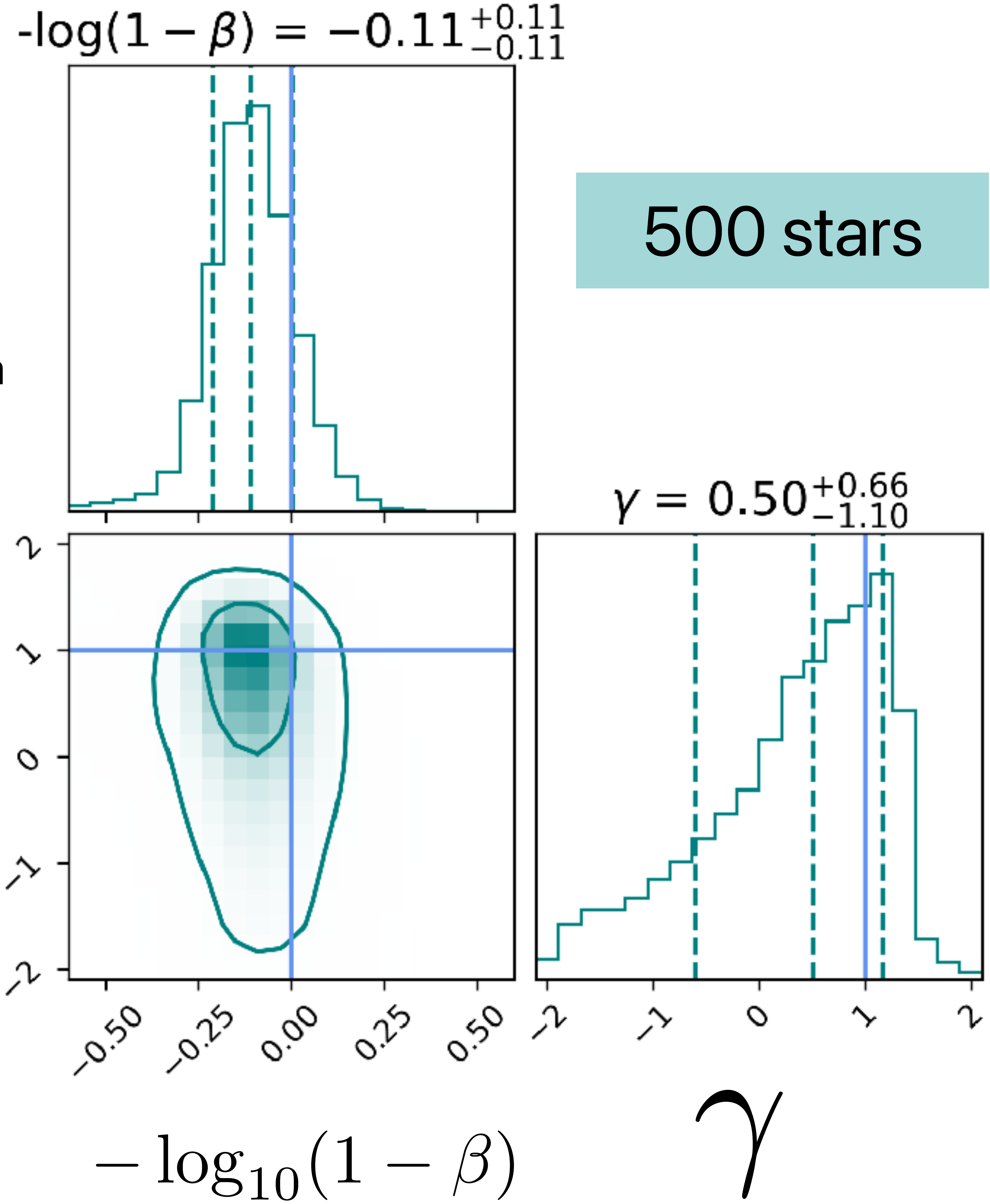
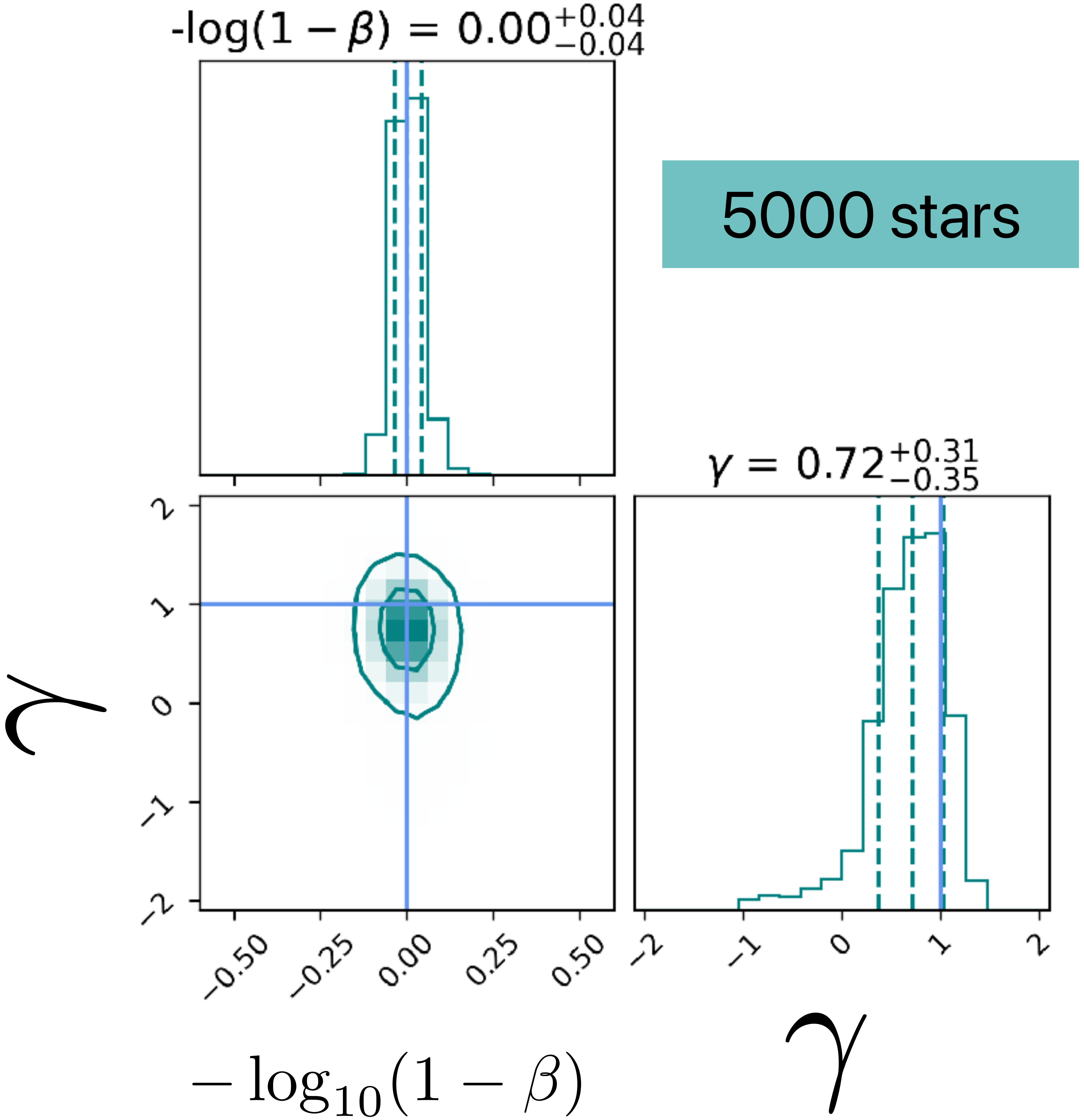


500 stars



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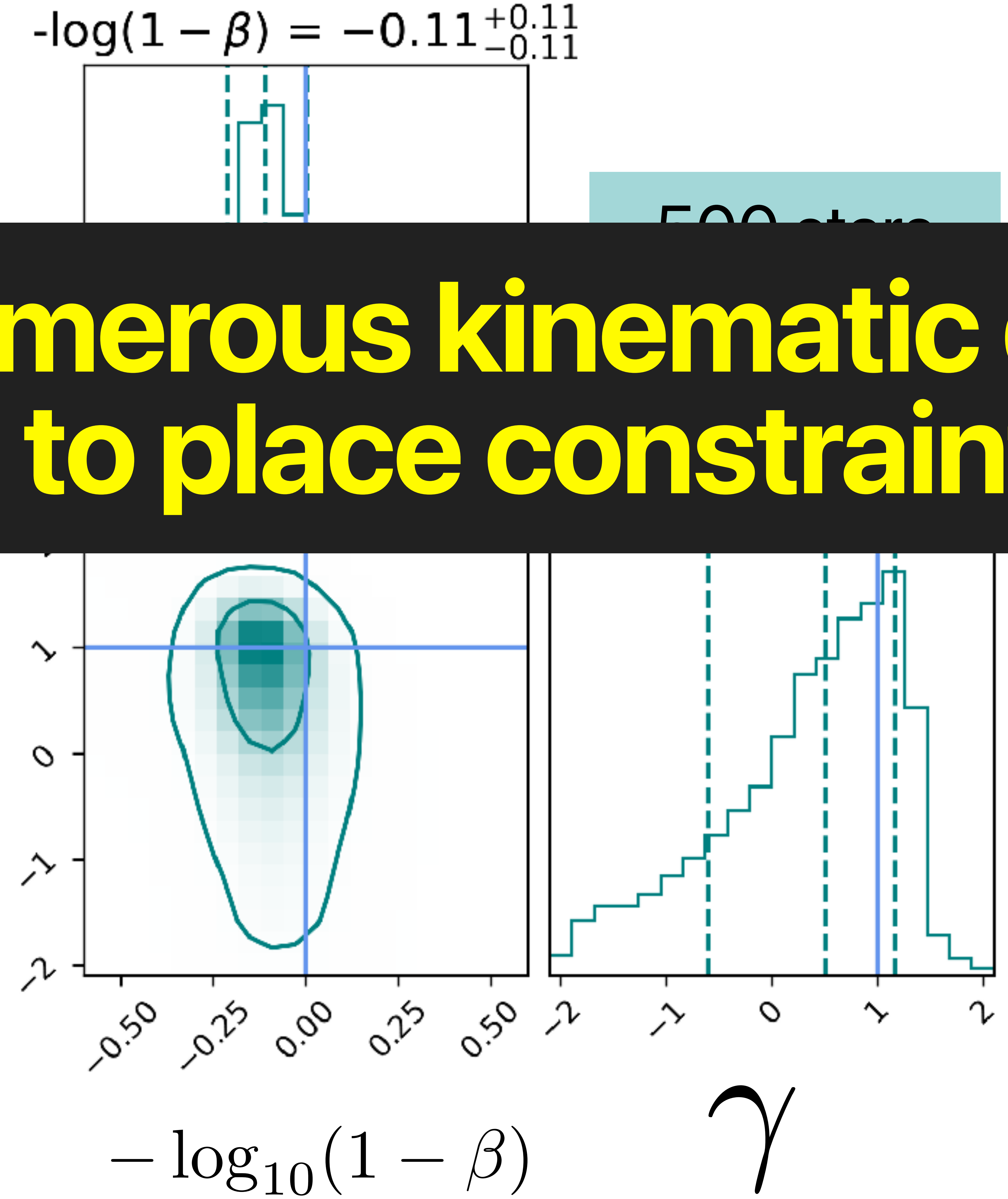
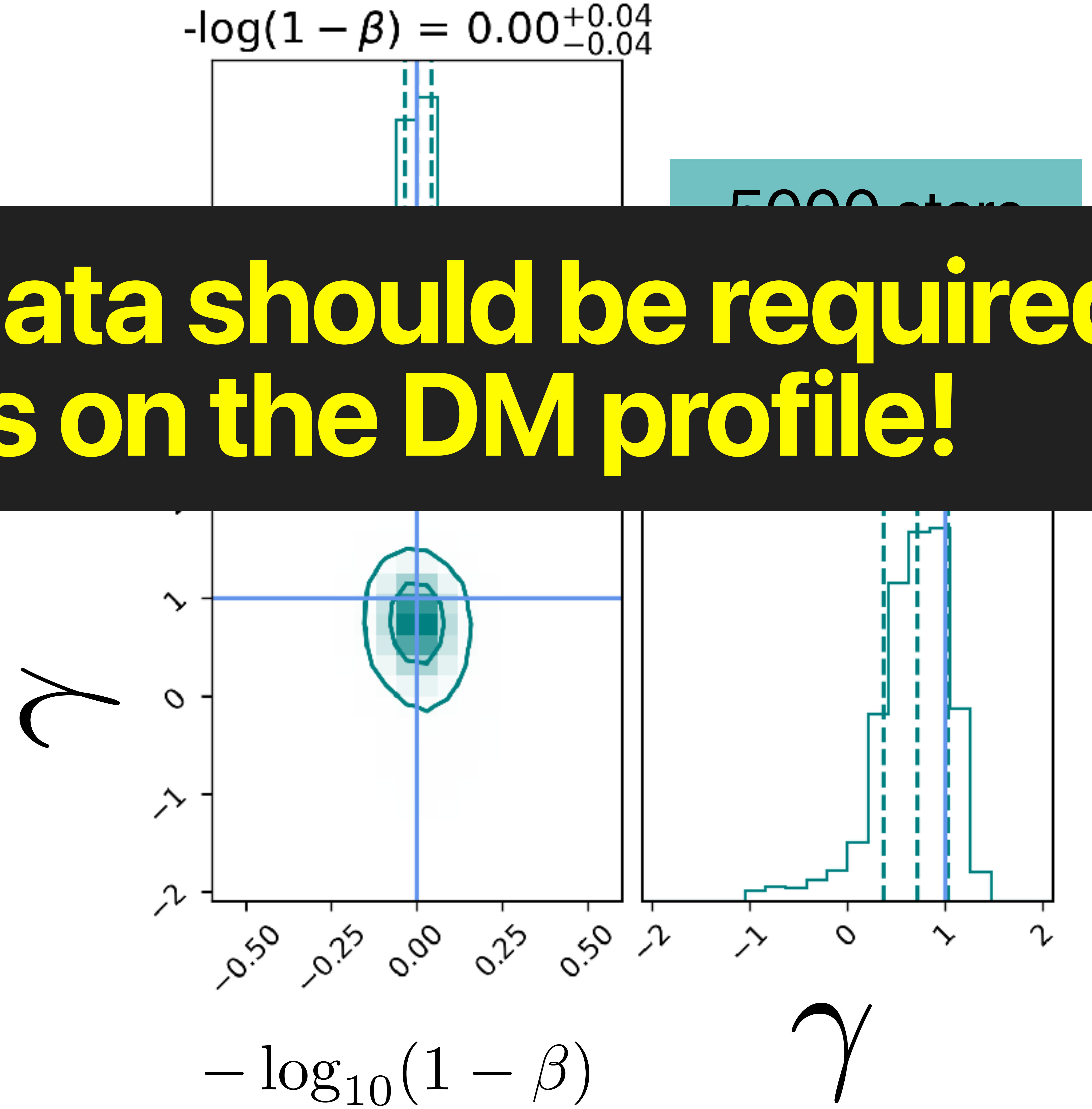




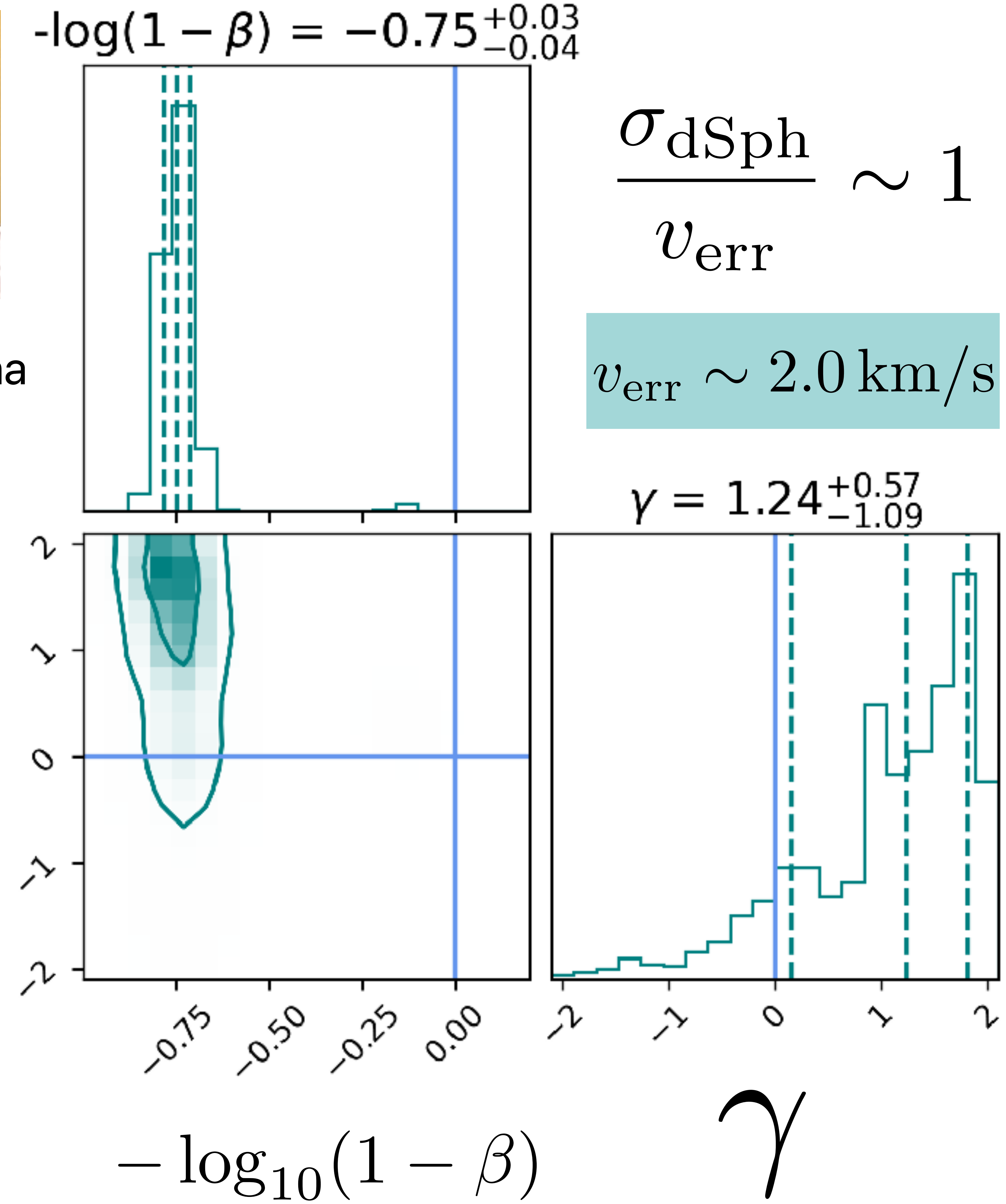
Numerous kinematic data should be required to place constraints on the DM profile!

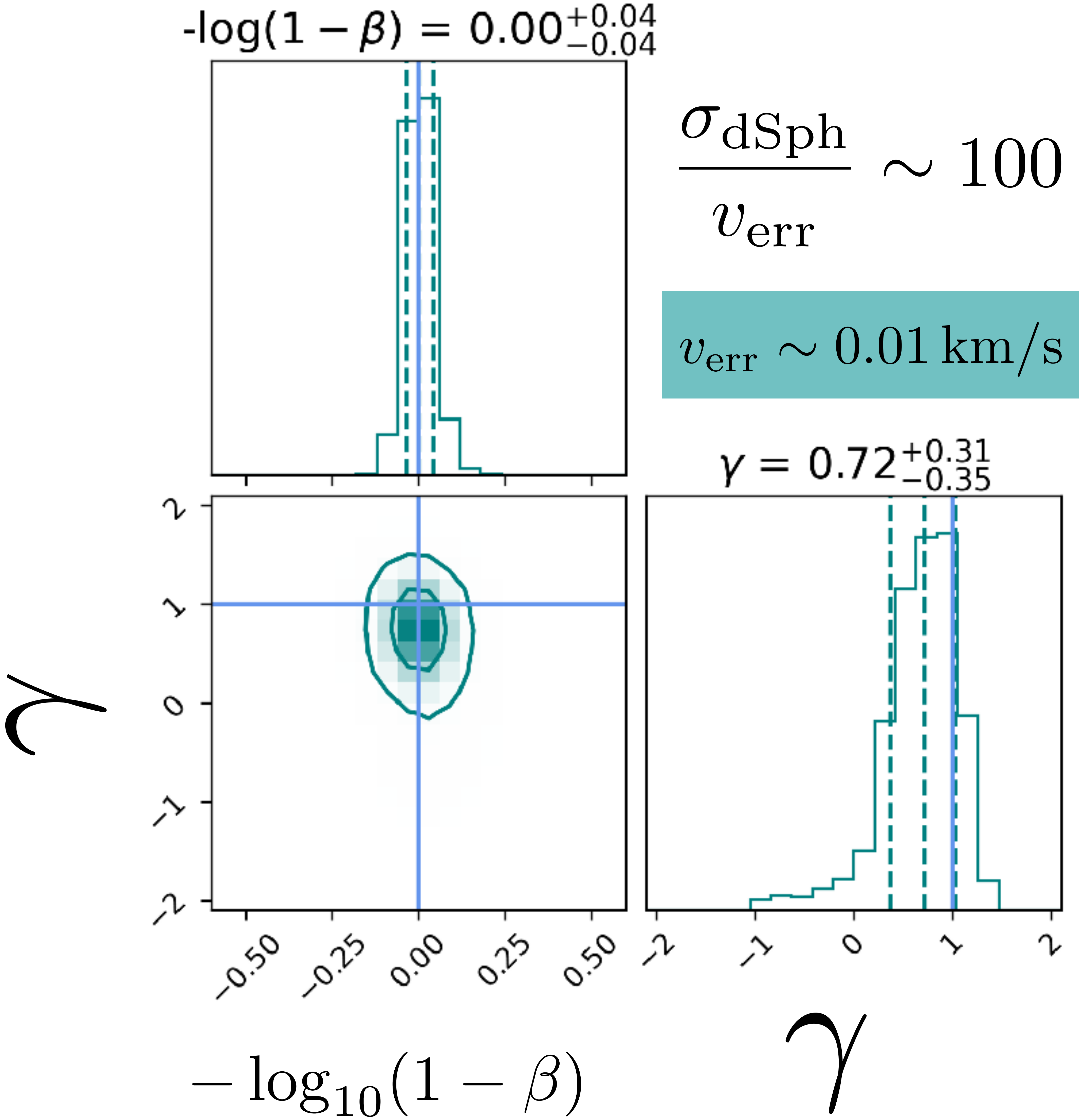
Result: Dependance of v_{err}

Wardana, Chiba, KH (2024, in prep.)

2nd & 4th-order moments analysis, $N_{star} = 5000$.

Dafa Wardana





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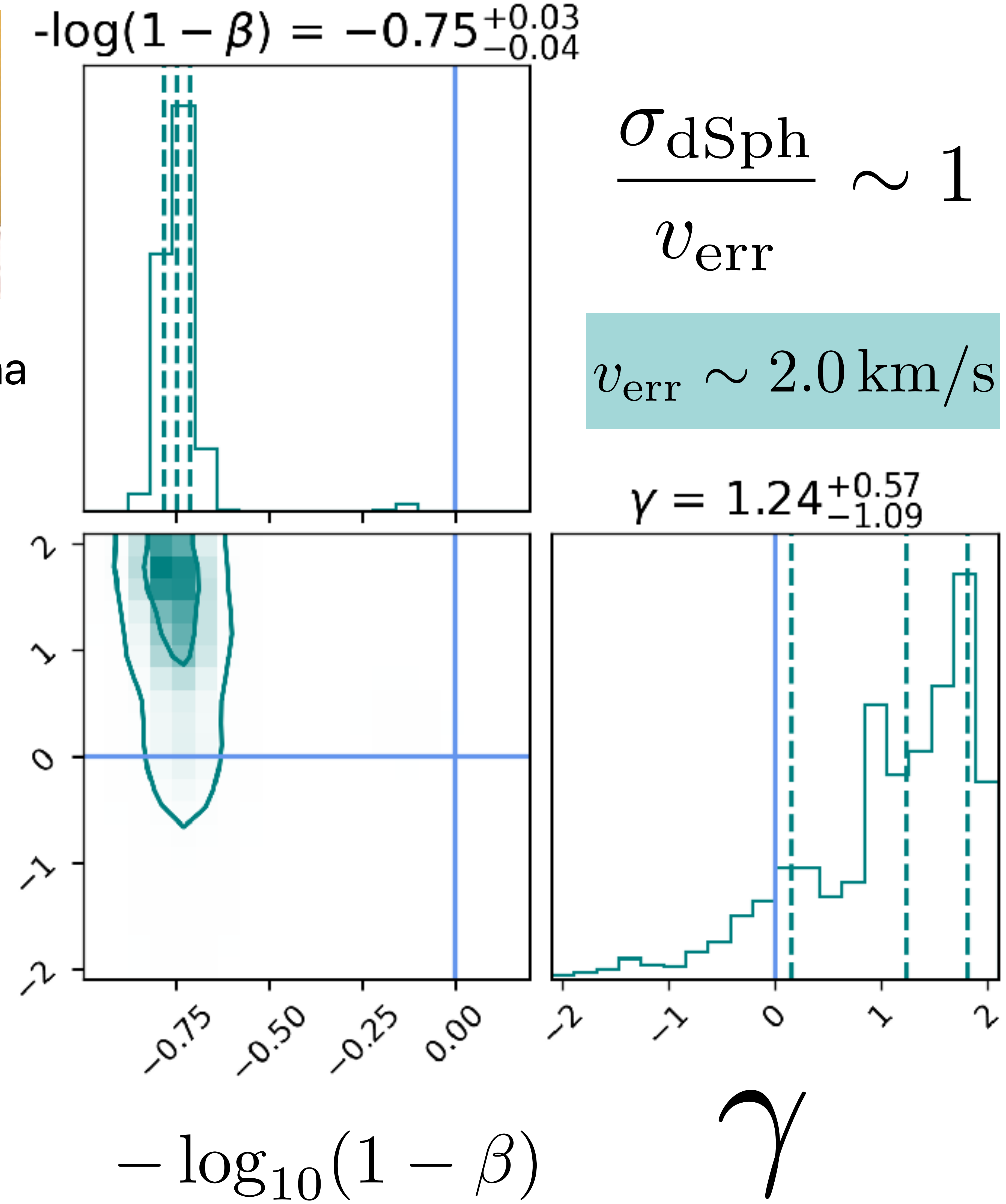
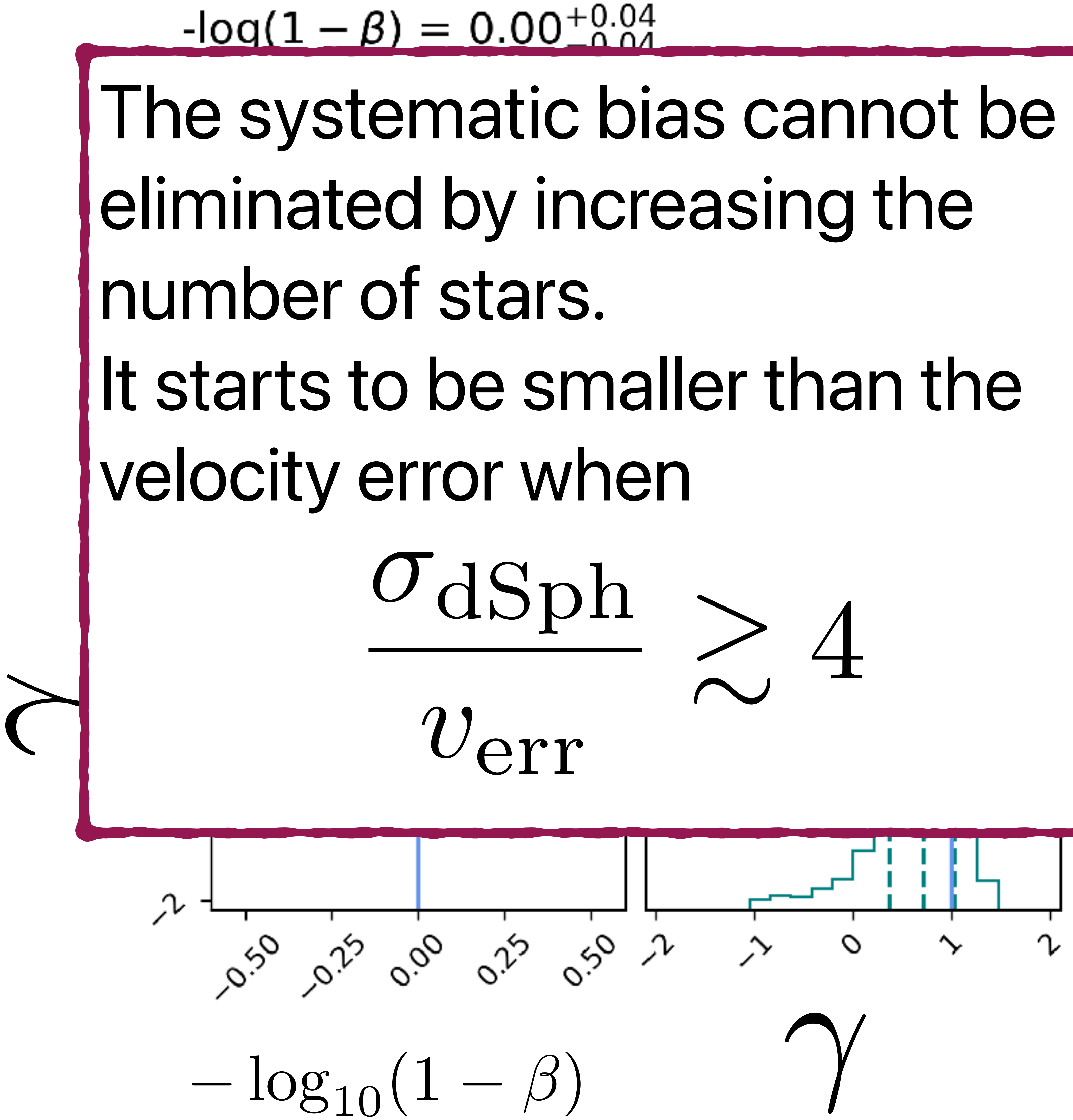


$$\frac{\sigma_{\rm dSph}}{v_{\rm err}} \sim 1$$

$v_{\rm err} \sim 2.0\,{\rm km/s}$



The systematic bias cannot be eliminated by increasing the number of stars.
It starts to be smaller than the velocity error when

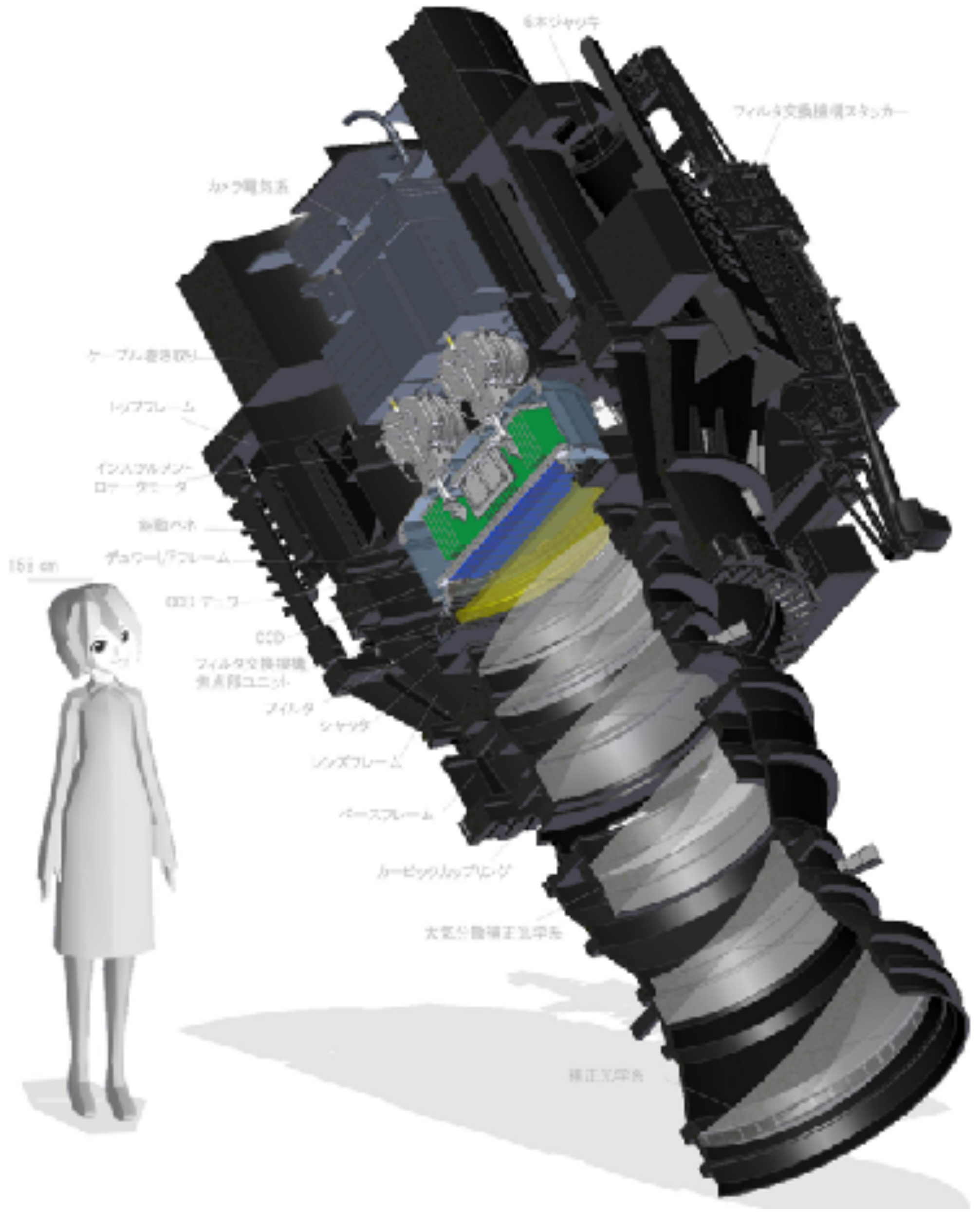
$$\frac{\sigma_{\rm dSph}}{v_{\rm err}} \gtrsim 4$$

Fourth order velocity moments and kurtosis

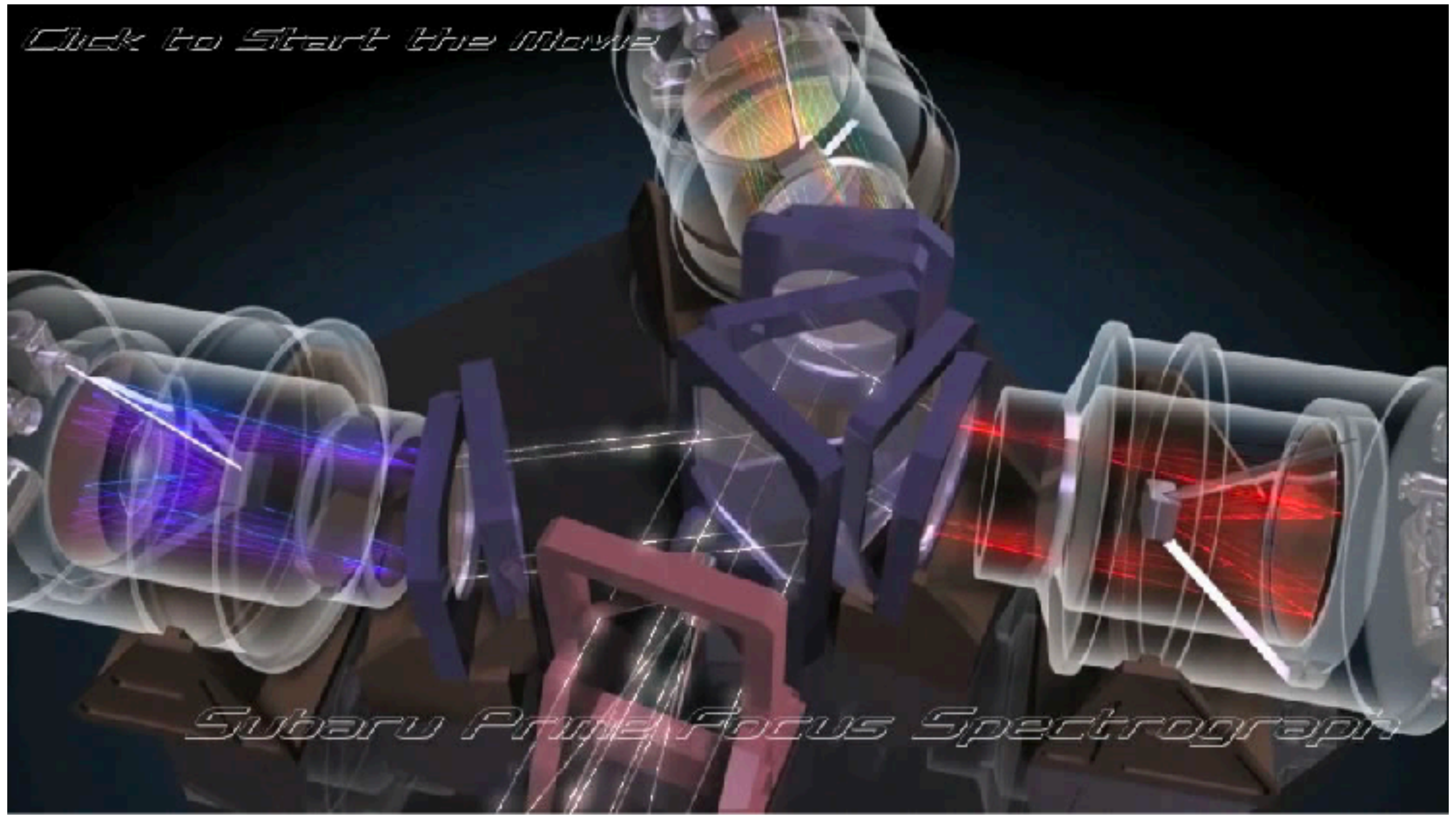
Wardana, Chiba, KH (2024, in prep.)

To place further constraints on DM profiles in the dSphs via 4th order analysis,

- Large number of kinematic data
- Precise velocity measurements



Subaru-HSC



Subaru-PFS

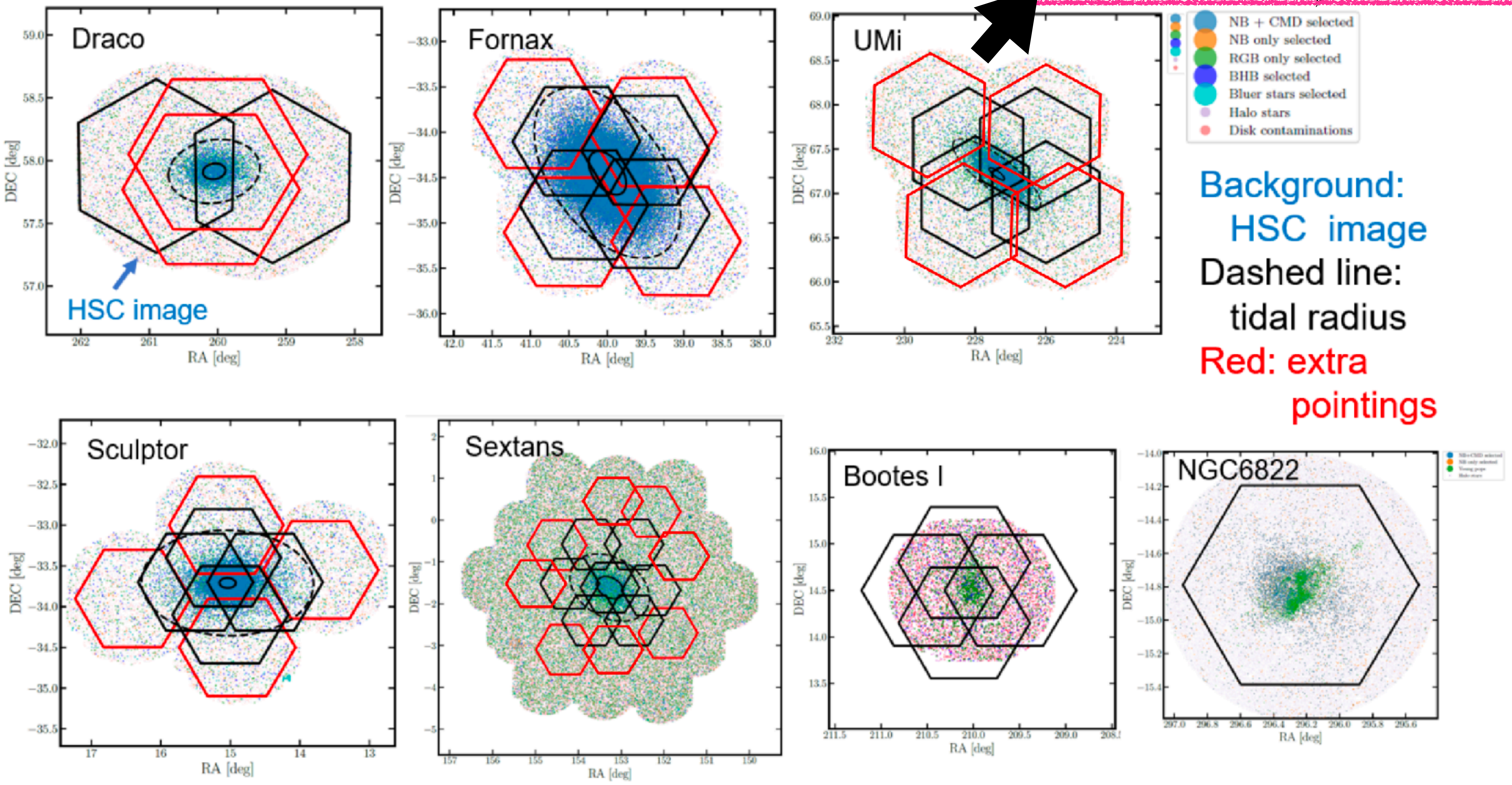
Subaru-PFS is coming soon.

Current

$N_{\mathrm{spec.}} \sim 300$

PFS

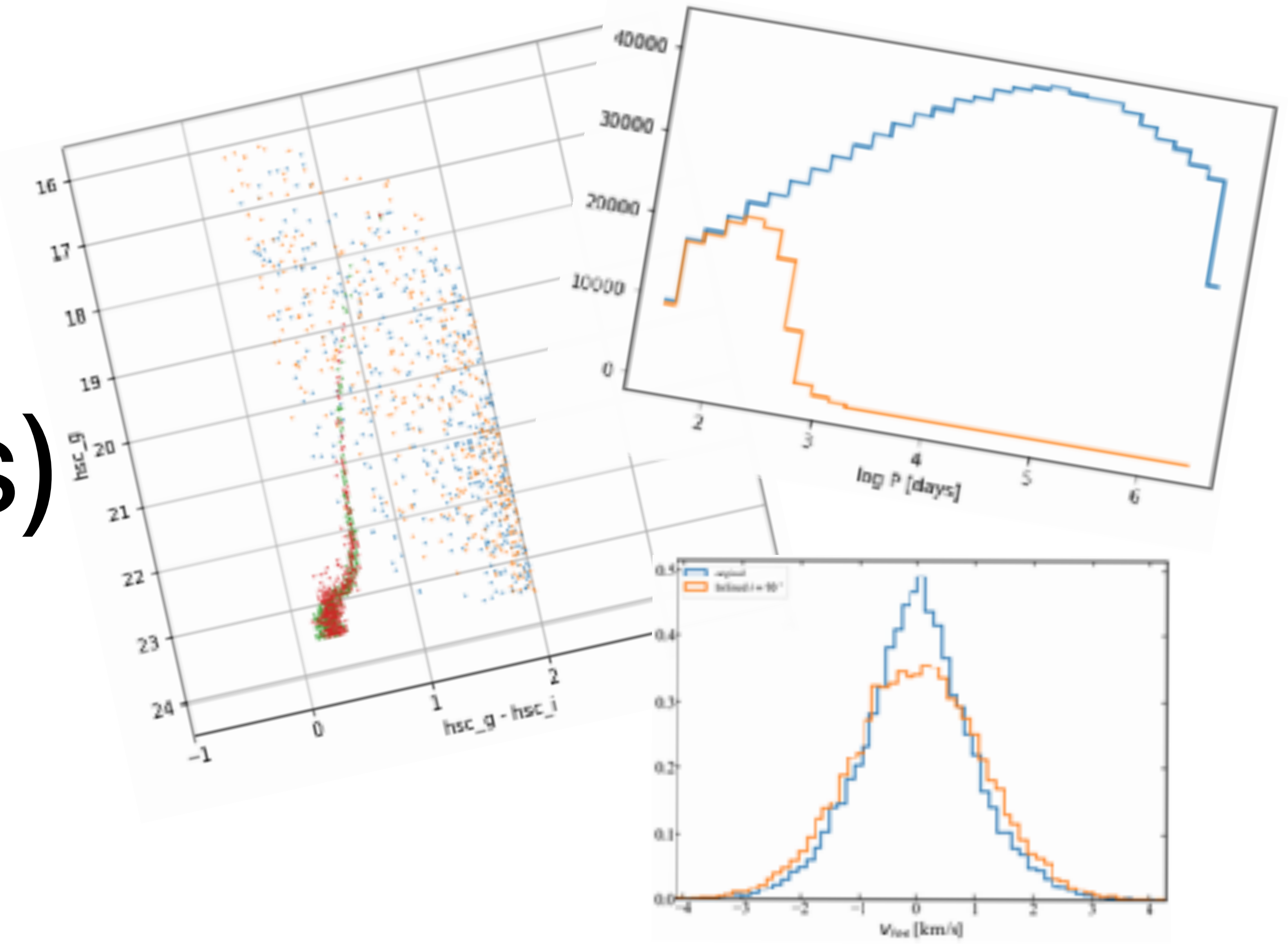
$N_{\mathrm{spec.}} \sim 5000$



Background:
HSC image
Dashed line:
tidal radius
Red: extra
pointings

Non-trivial effects on dynamical analysis should be considered

- Contamination stars (MW think disk, thin disk, and halo stars)
- Binary stars (Binary system can inflate l.o.s velocity dispersions)
- Tidal forces (Deviation from dynamical equilibrium)



Kinematic info. generated by DM potential × Binary stars × Contamination stars

KH

E. Kirby (Notre Dome)

L. Dobos (JHU)

C. Filion (JHU)

PFS-GA science team

DM density profile estimation through normalizing flows

Lim, KH, Nojiri et al. (2024, in prep.)

Observable informations are limited to:

- Celestial coordinate
- Line-of-sight velocity

$$(x, y, z, v_x, v_y, v_z) \longrightarrow (x, y, v_z)$$

Conventional methods introduce in order to simplify the problem and make it solvable only with limited information:

- Symmetry assumptions (e.g., spherical, axisymmetric)
- Parameterized stellar and DM density profiles
- Velocity anisotropy profile
- etc...

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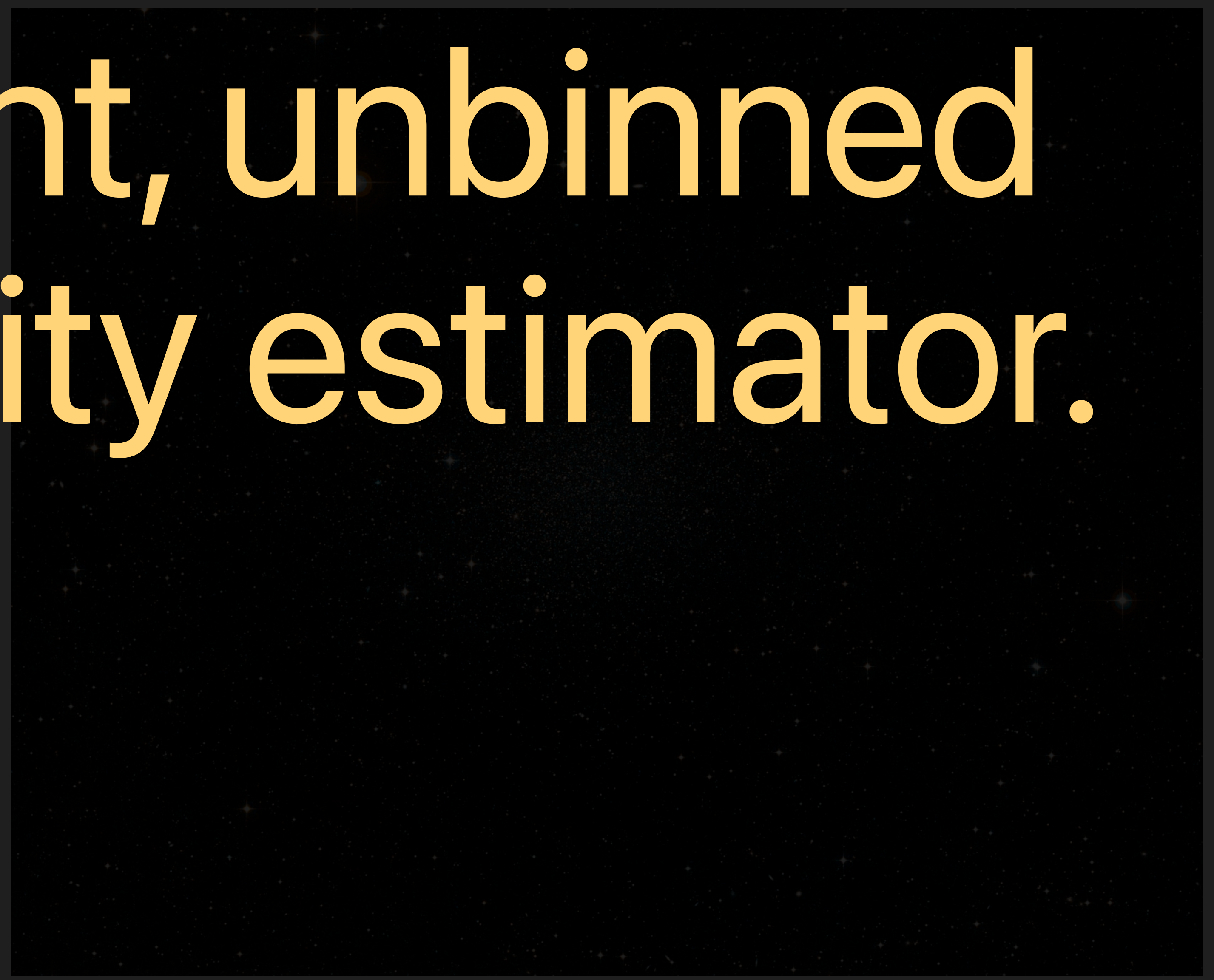

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We introduce model-independent, unbinned Jeans analysis using neural density estimator.

Normalizing flows

$$\nu(r),\ \sigma_r^2(r)$$

Normalizing flows: Neural Density Estimator

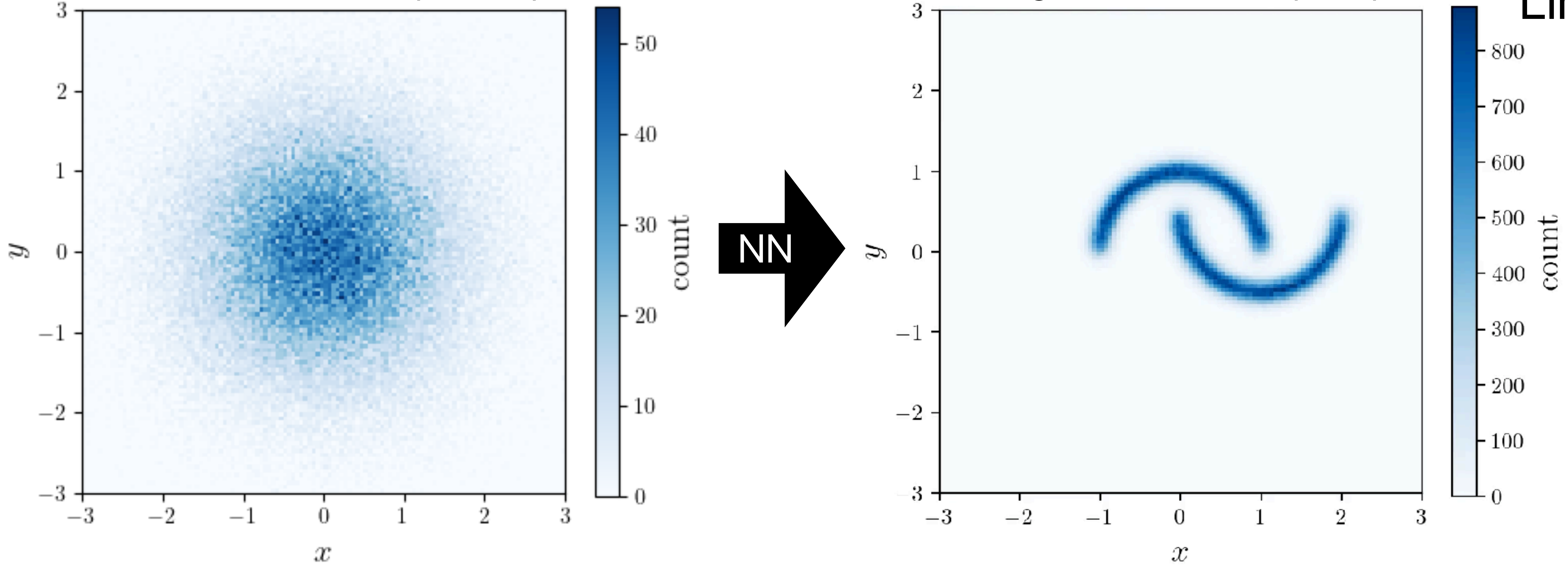
Lim, KH, Nojiri et al. (2024, in prep.)

Lim

Normalizing Flows (NFs) is an artificial neural network that learns a transformation of random variables.

Base distribution (known)

Target distribution (data)

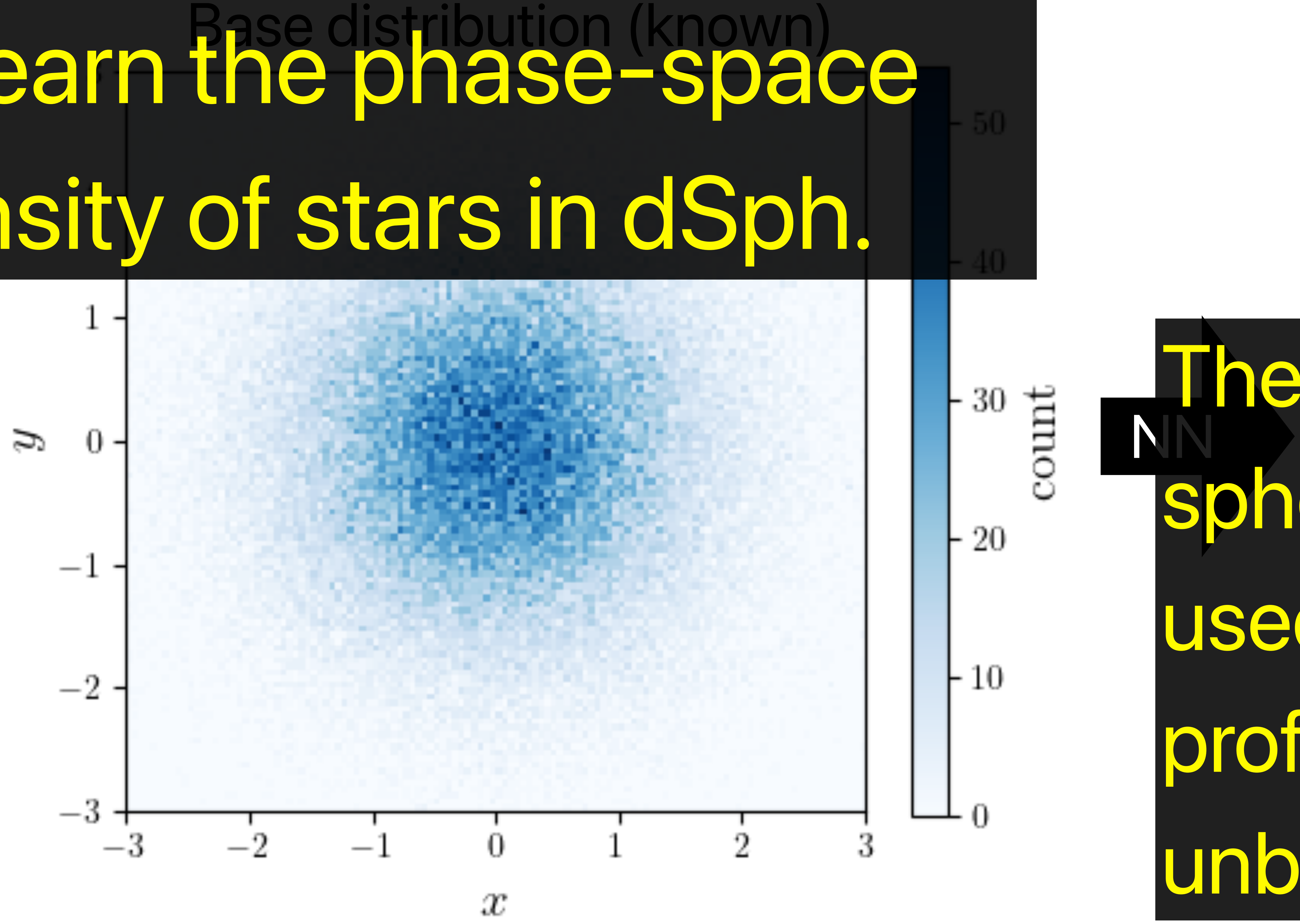


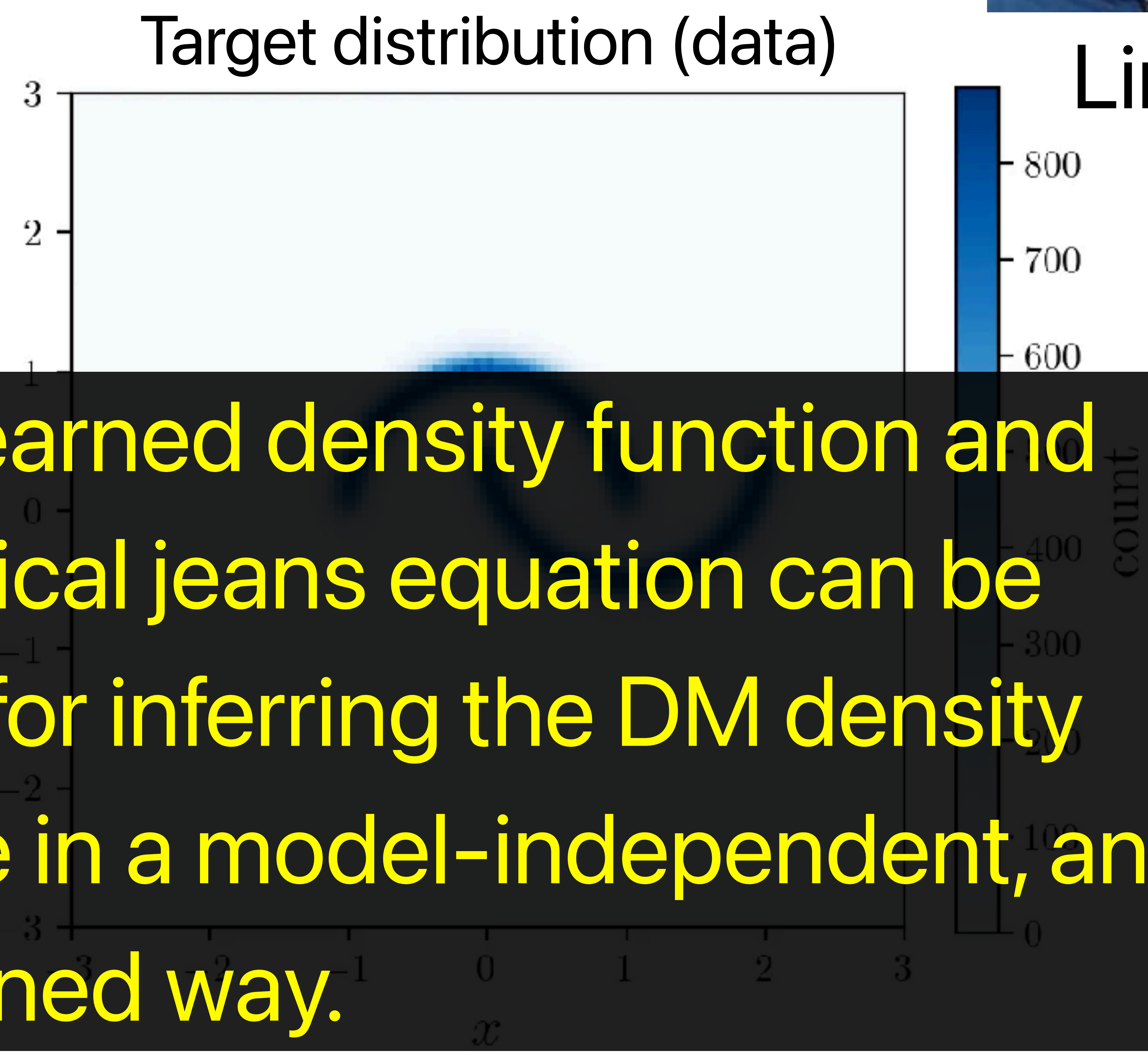
Normalizing flows: Neural Density Estimator

Lim, KH, Nojiri et al. (2024, in prep.)

Normalizing Flows (NFs) is an artificial neural network that learns a transformation of random variables.

We train normalizing flows to learn the phase-space density of stars in dSph.





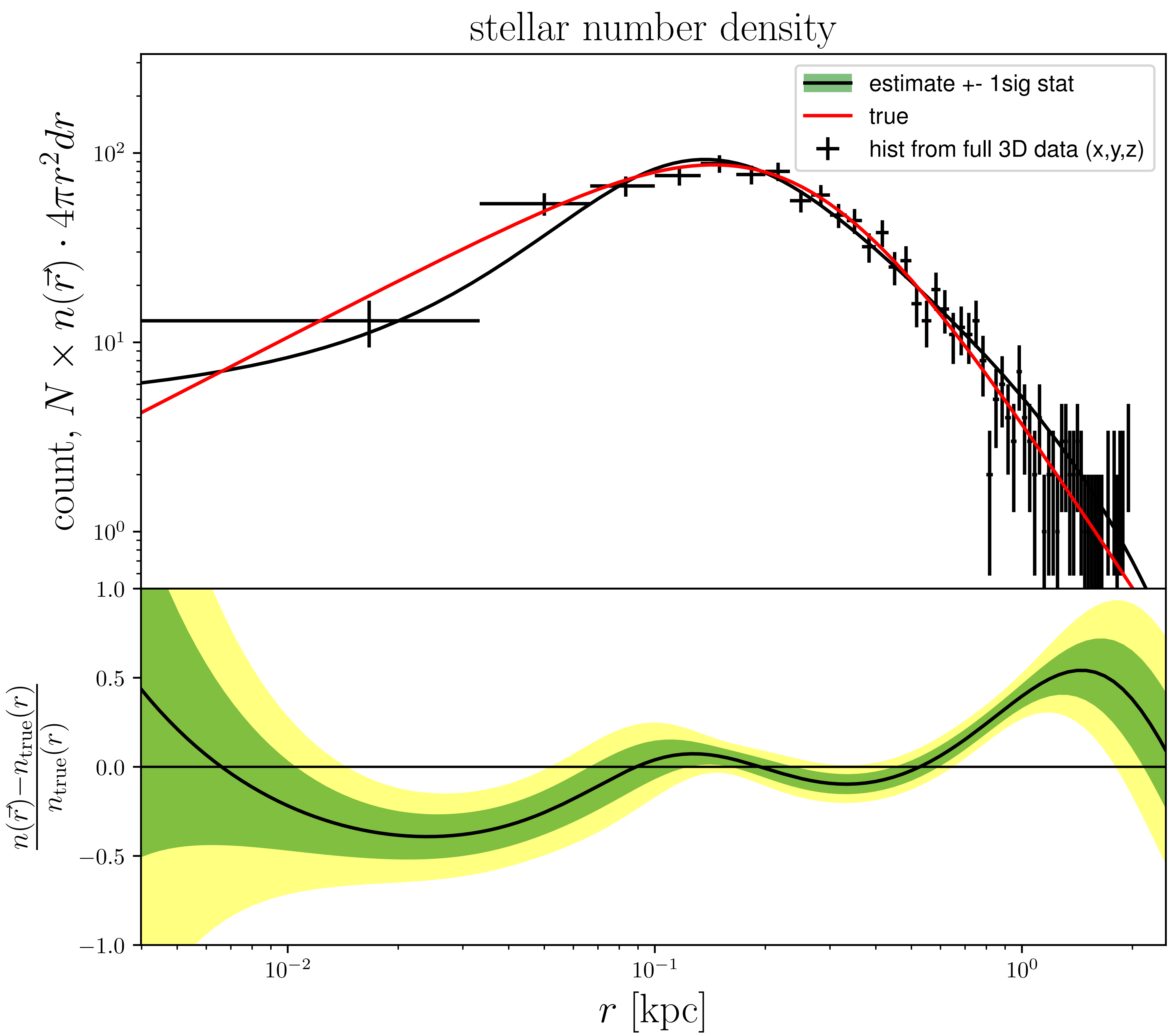
The learned density function and spherical jeans equation can be used for inferring the DM density profile in a model-independent, and unbinned way.

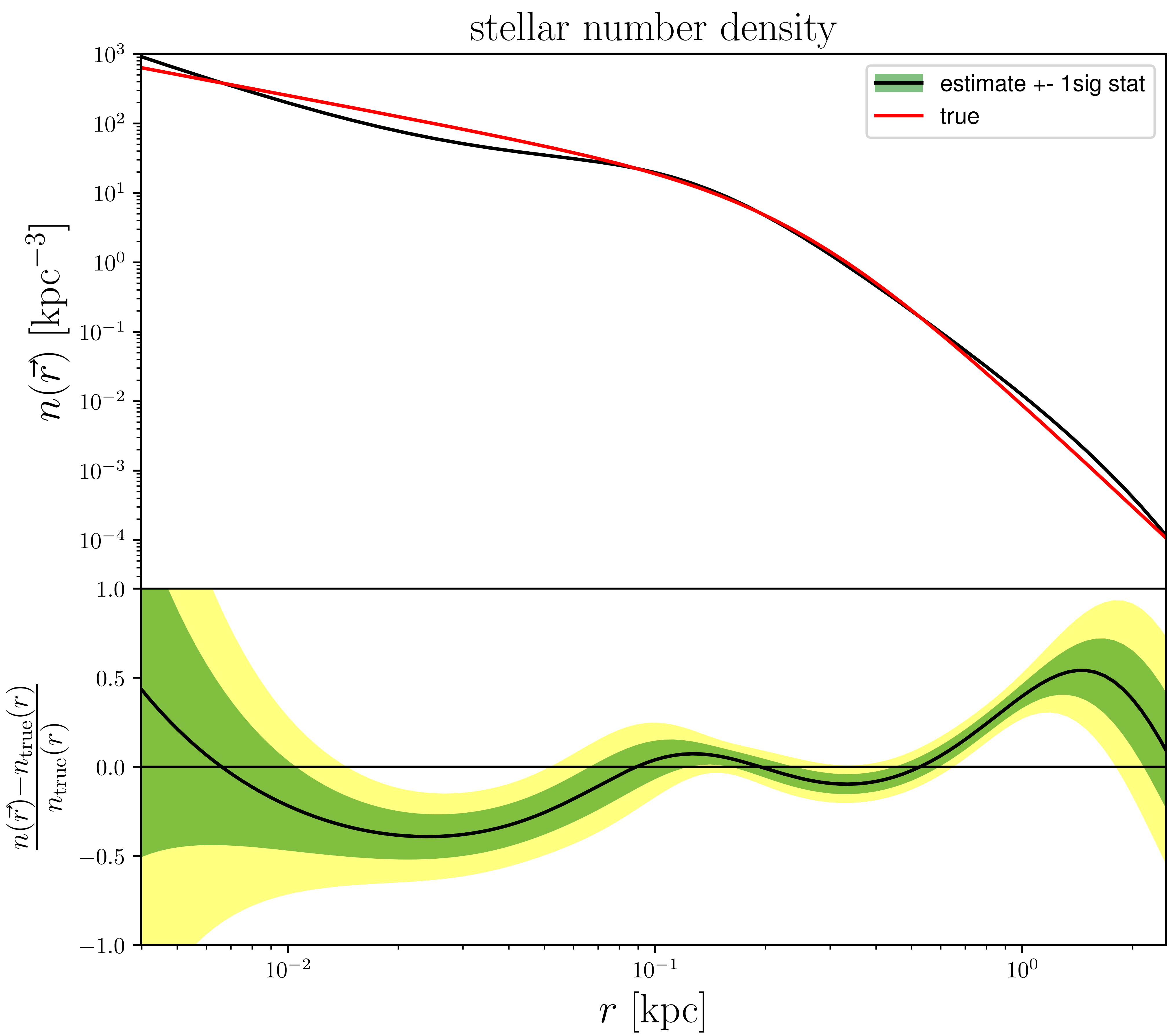
Results: Stellar number density

Lim, KH, Nojiri et al. (2024, in prep.)

Inferred stellar number density trained on 2D position (x,y).

Mock 1000 stars are taken from GaiaChallenge with cusp DM, isotropic: $\beta = 0$.



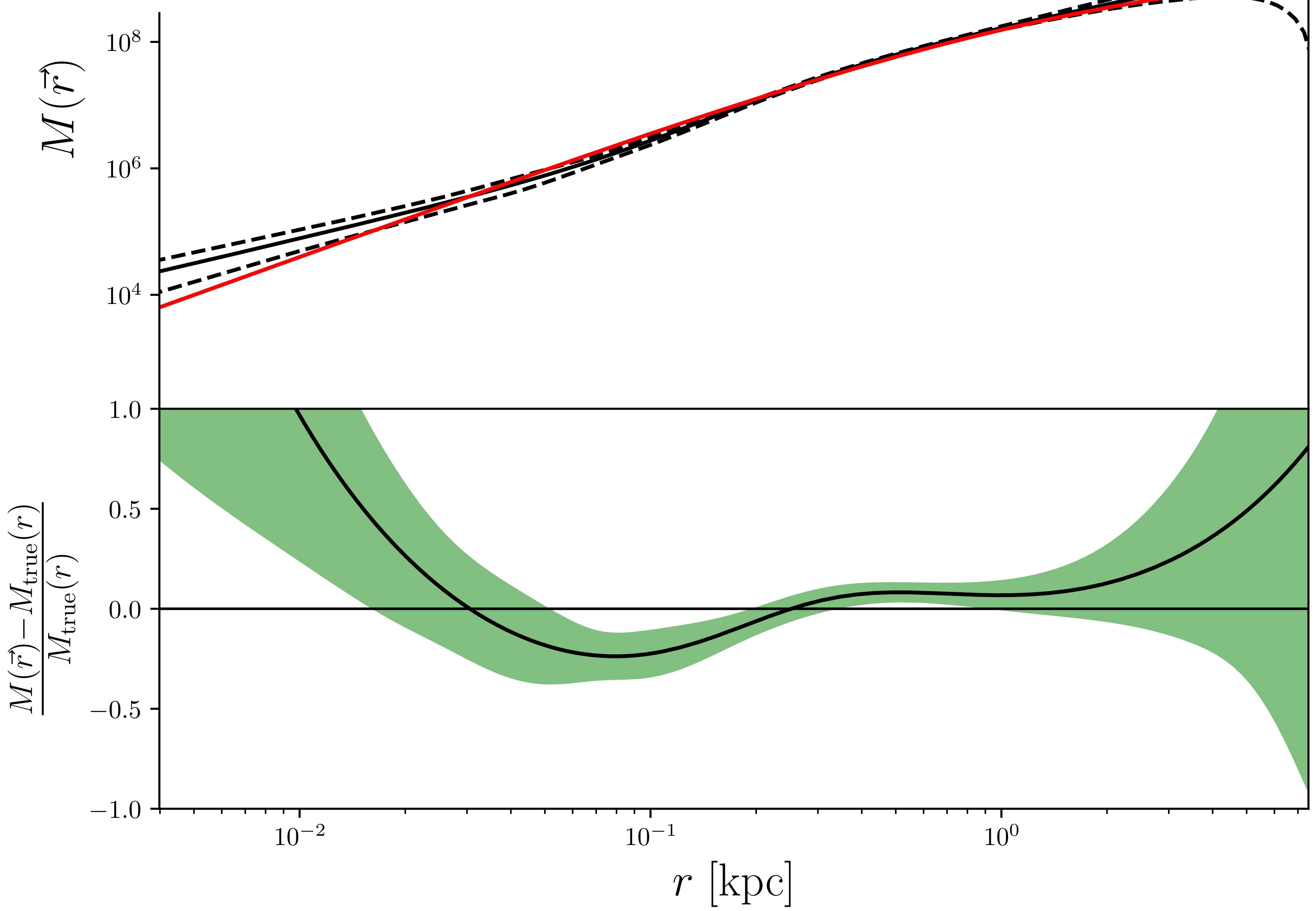


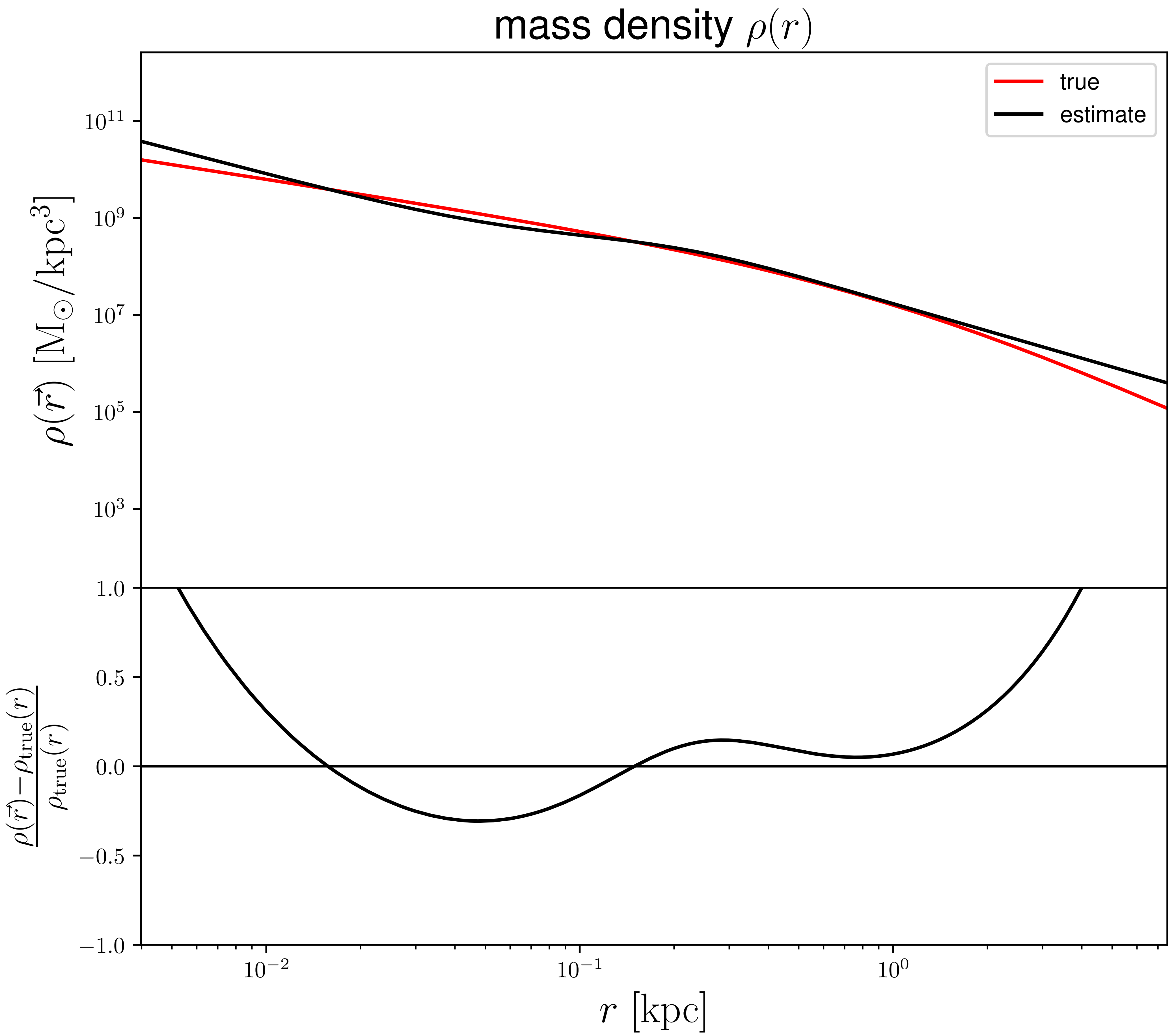
Results: Dark matter density

Lim, KH, Nojiri et al. (2024, in prep.)

Inferred mass density calculated from stellar density and velocity dispersion trained on 3D infomation (x,y, vz).

$$M(<r) = -\frac{r\sigma_r^2}{G}\left(\frac{d\log\nu}{d\log r} + \frac{d\log\sigma_r^2}{d\log r} + 2\beta\right)$$





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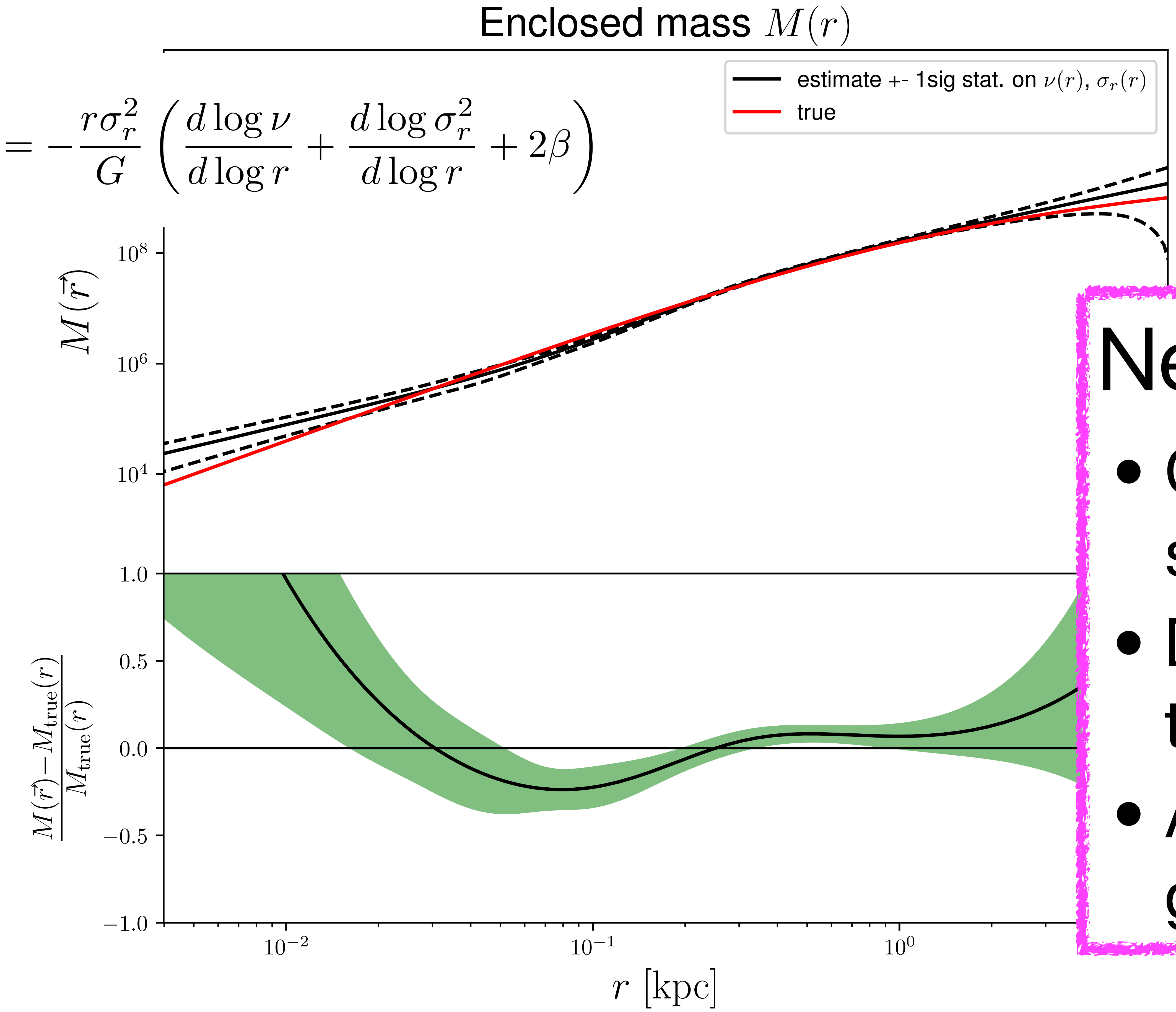

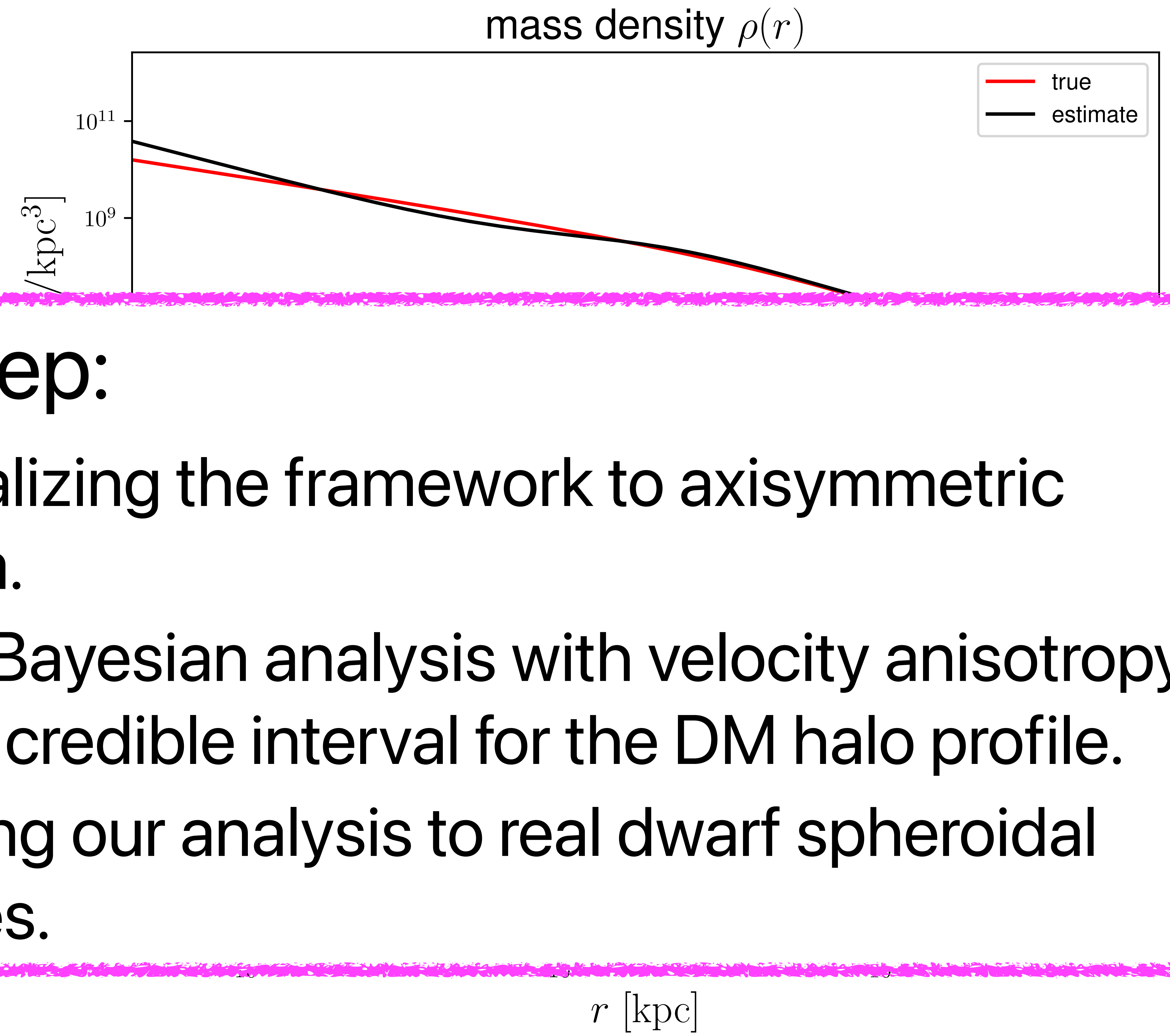

Next step:

- Generalizing the framework to axisymmetric system.
- Doing Bayesian analysis with velocity anisotropy to give credible interval for the DM halo profile.
- Applying our analysis to real dwarf spheroidal galaxies.

Take Home Message

- The Galactic dwarf spheroidal galaxies are ideal target for studying the basic properties of dark matter.
- The current constraints on their DM density profiles still have large uncertainties, even though several dSphs favor cusped DM halo.
- Our teams are now developing new dynamical analysis to place further constraints on dSph’s DM density profile.
- **Subaru HSC/PFS** enable us to hunt a huge number of dSph’s stars out to their outskirts, and thereby placing tighter constraints on their DM density profiles.