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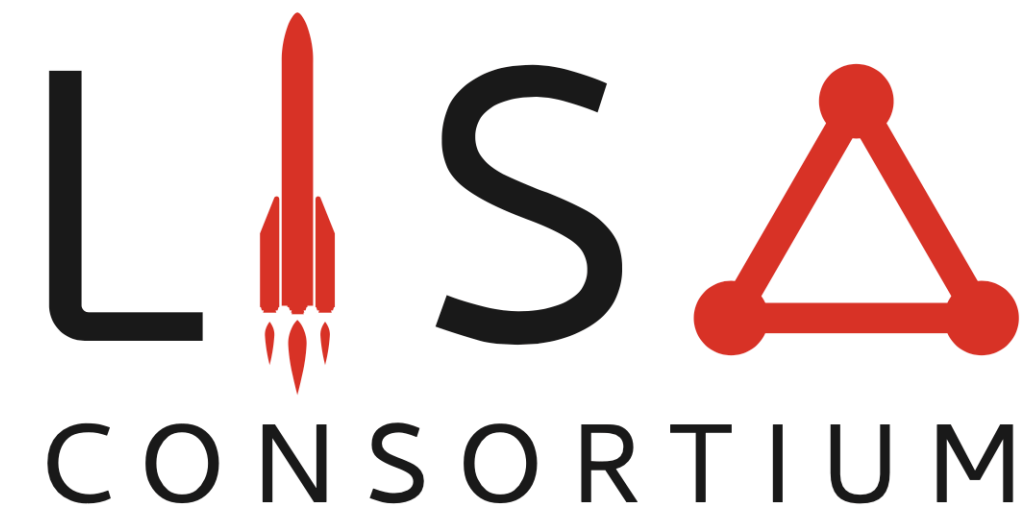
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# Waveform systematics for massive black hole binaries in LISA

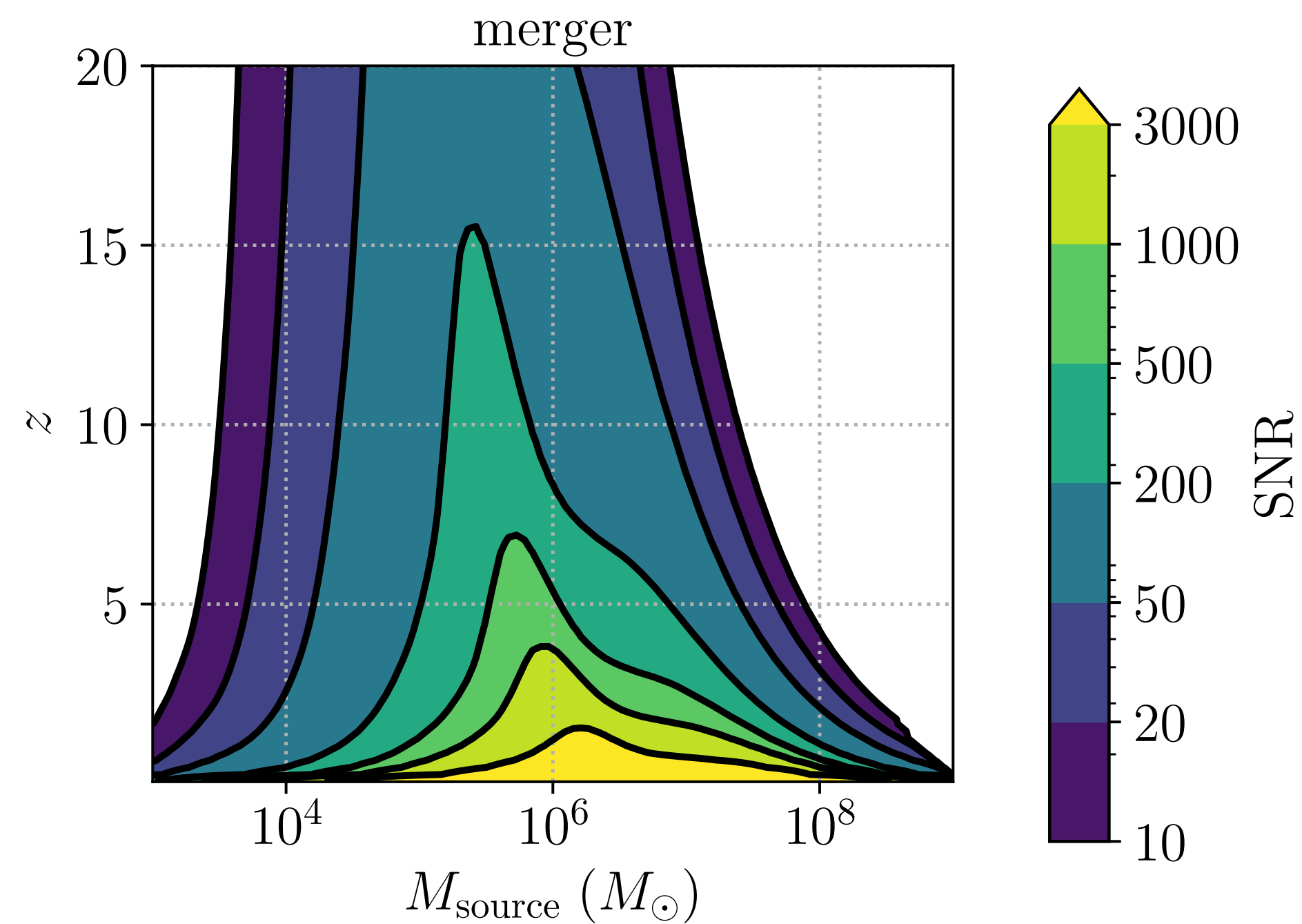
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Sylvain Marsat (L2IT, Toulouse)



# MBHB signals in LISA



## Science case for MBHB systematics

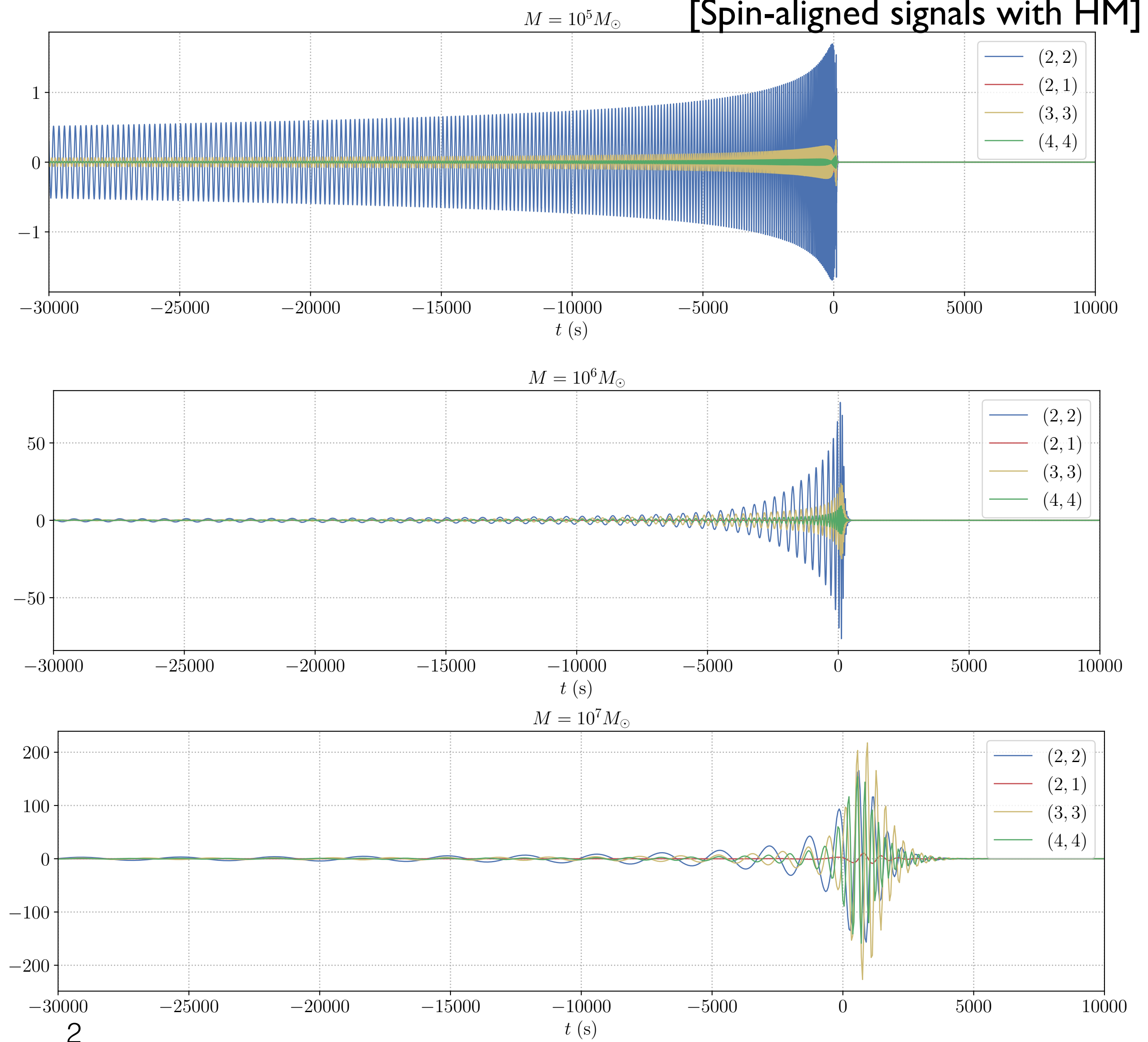
MBHBs high-SNR sources for LISA, waveform systematics crucial for:

- golden events for EM counterparts
- golden events for TGR
- population inference and cosmology
- global fit and residuals

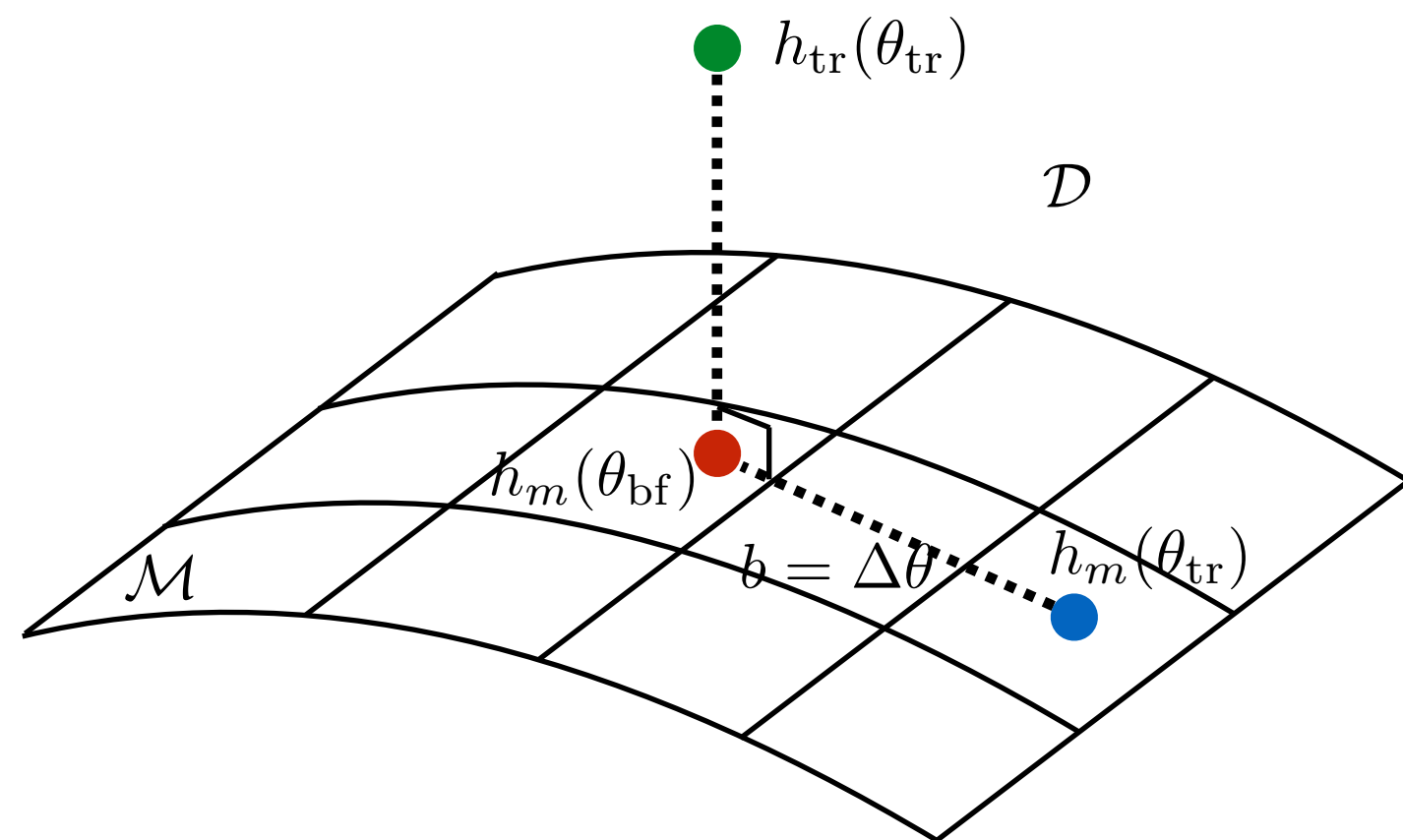
Broader parameter space than LVK: high- $q$ , high-spins, precession, eccentricity

## Whitened time-domain signals

[Spin-aligned signals with HM]



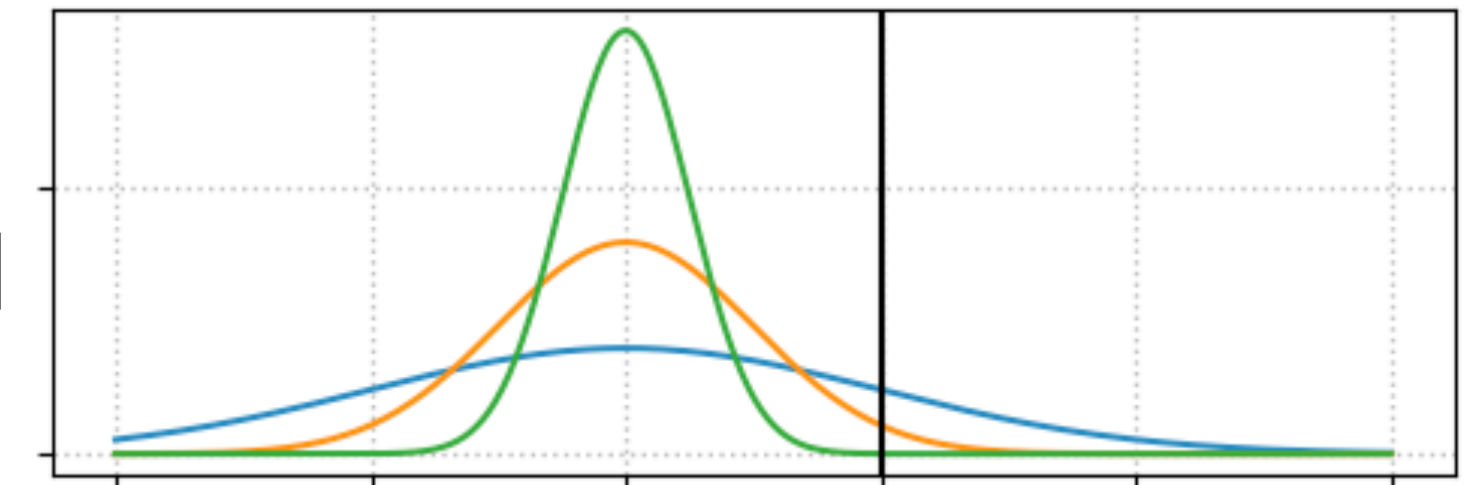
# Waveform systematics and parameter estimation



## Systematic biases:

Ignoring the effect of the noise, bias given by the **best-fit** parameters on the model signal manifold:  $\Delta\theta = \theta_{\text{bf}} - \theta_{\text{tr}}$

- the **bias** is SNR-independent, requires to explore the full parameter space [**expensive**]
- the statistical errors scale with SNR



**Mismatch**, used in waveform modelling. Optimization over time/phase/polarization:

$$\text{MM} = 1 - \max_{t, \varphi, \psi, \dots} \frac{(h_m | h_{\text{tr}})}{\sqrt{(h_m | h_m)} \sqrt{(h_{\text{tr}} | h_{\text{tr}})}}$$

- Computed locally [**fast**]
- SNR-independent
- Different versions: single-detector optimized over sky, combining  $h_+$ ,  $h_\times$

## Indistinguishability criterion:

$$\ln \mathcal{L}(\theta) = -\frac{1}{2} (h(\theta) - h_{\text{tr}} | h(\theta) - h_{\text{tr}})$$

[Lindblom&al 2008]  
[Chatziioannou&al 2019]  
[Toubiana-Gair 2024]

$$\ln \mathcal{L}(\theta_{\text{bf}}) \sim \ln \mathcal{L}(\theta_{1-\sigma})$$

- Constant  $D$ : dimension, approximate
- Scaling  $\text{SNR}^2$  robust

$$\text{MM} < \frac{D}{2} \frac{1}{\text{SNR}^2}$$

SNR  $\sim 10^3$  for LISA !

Is this criterion a good representation of requirements ?

## Linearized biases (Cutler-Vallisneri):

[Flanagan-Hughes 1997]  
[Cutler-Vallisneri 2007]

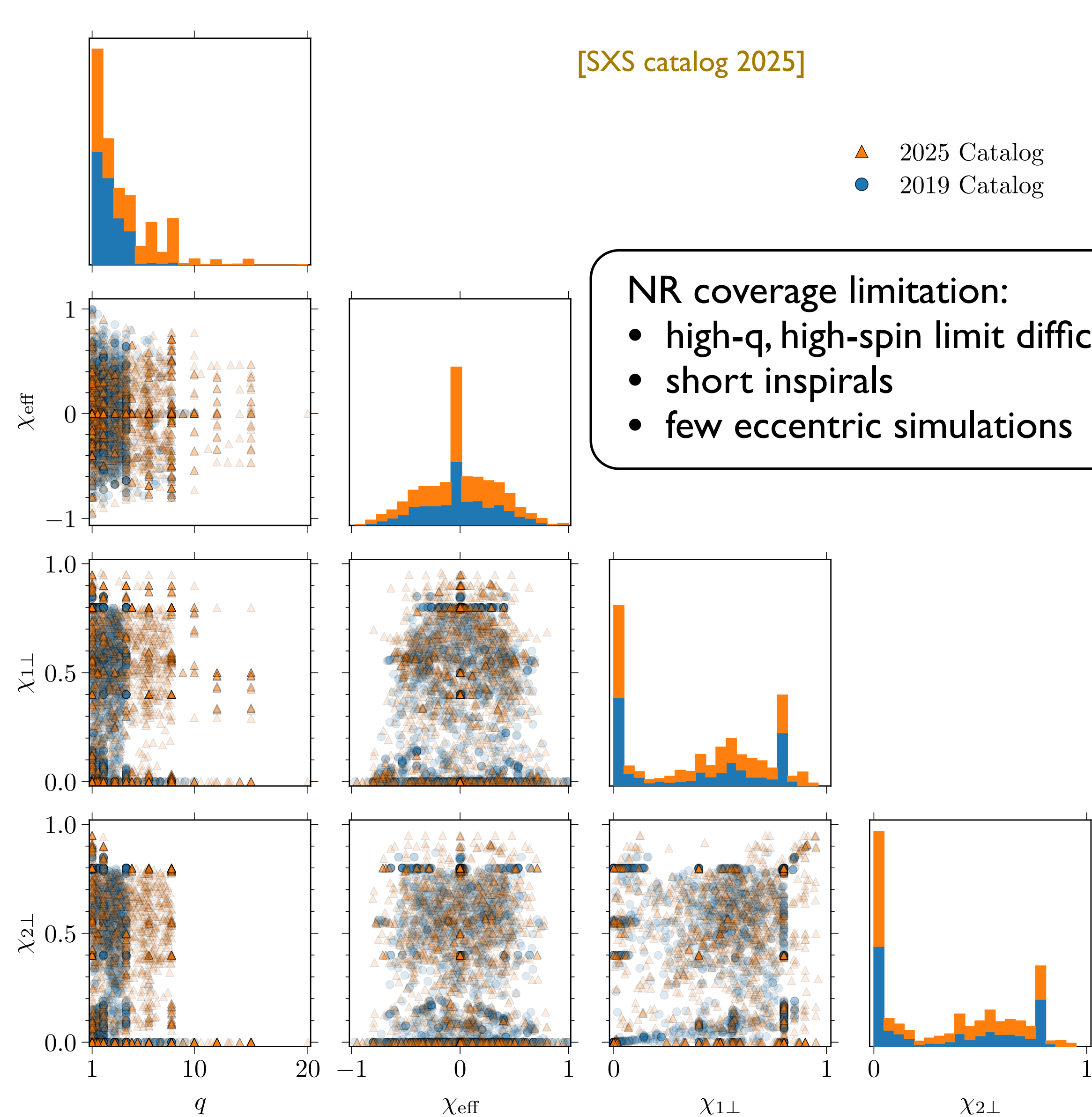
In the linear signal approximation, estimation of bias [**fast**]:

$$F_{ij} = (\partial_i h | \partial_j h)$$

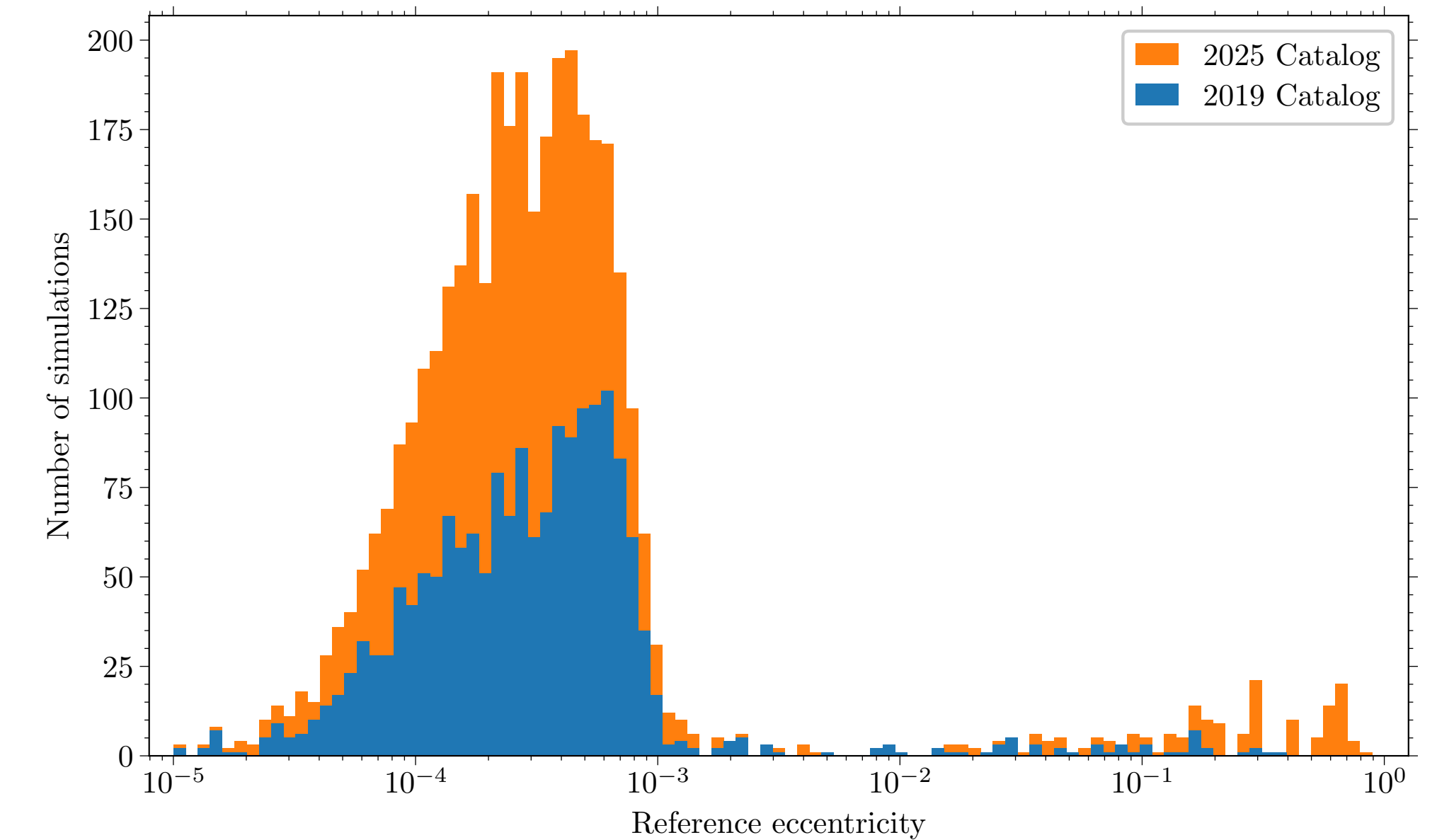
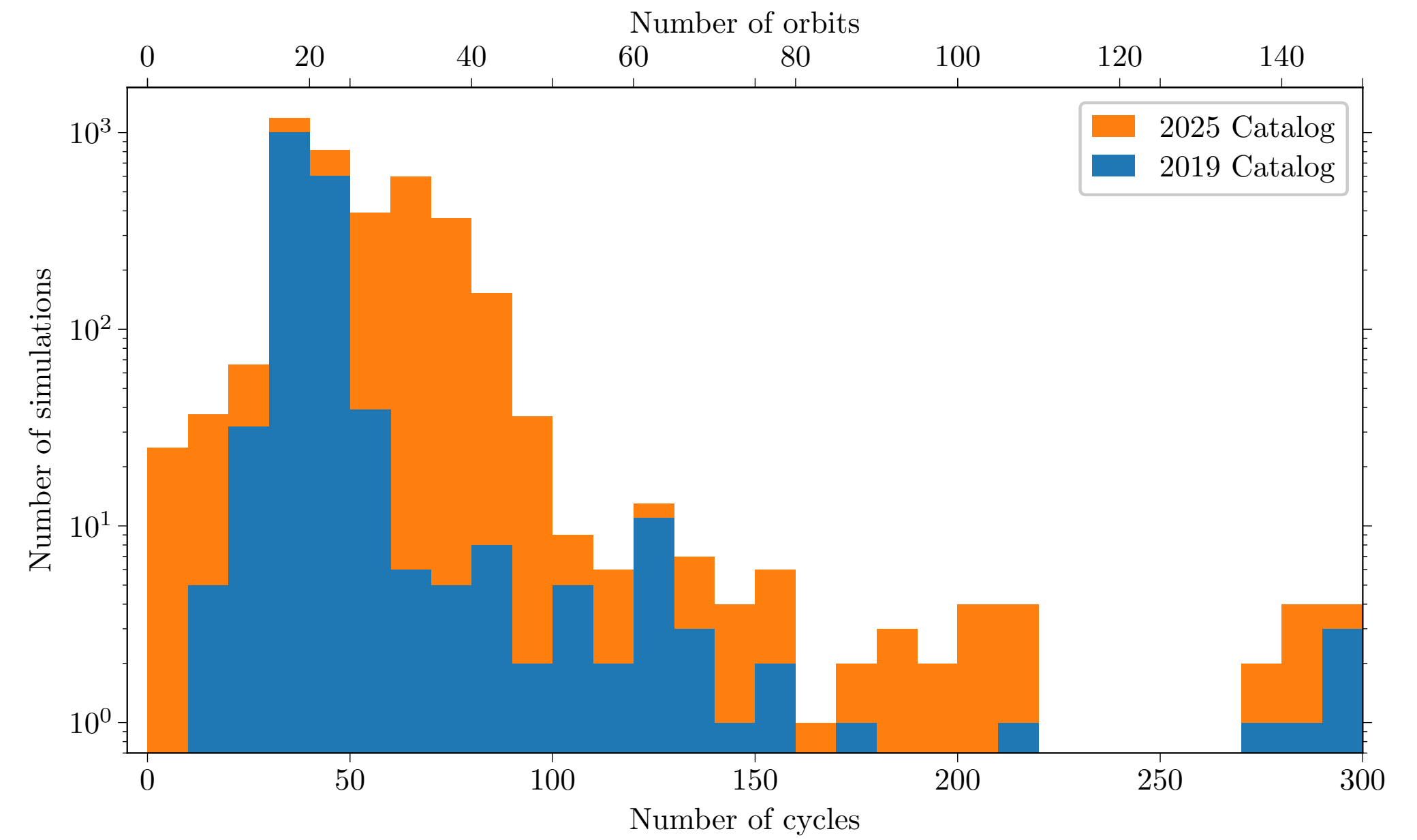
$$\Delta\theta_i = F_{ij}^{-1} (\partial_j h | \delta h)$$

Can we assess biases with efficient tools ?

# Overview of waveform models: NR



4



# Overview of waveform models: Phenom / SEOB / NR Surrogates

## Phenom:

IMRPhenomXPNR [Hamilton+ 2025]

- Fourier-domain, precessing

IMRPhenomTPHM [Estelles+ 2021]

- Time-domain, precessing
- GPU acceleration

IMRPhenomTEHM [Planas+ 2025]

- Time-domain, eccentric

## EOB:

SEOBNRv5PHM [Ramos-Buades+ 2023]

- Time-domain, precessing

SEOBNRv5EHM [Gamboa+ 2024]

- Eccentric, spin-aligned

TEOBResumS-Dali [Nagar+ 2024]

- Spin-precessing, Eccentric

+ \_ROM

- accelerated reduced order models (spin aligned)

## NR surrogates:

NRHybSur3dq8 [Varma+ 2018]

- SXS NR simulations hybridized with long EOB inspirals (covers  $\sim 6$  months for  $M = 10^5 M_\odot$ )
- Surrogate interpolant, time-domain

NRSur7dq4 [Varma+ 2019]

- SXS NR simulations, short
- 7d, fully precessing, with mode asymmetries

+ high-q surrogates

- BH pert. + NR

+ eccentric surrogates

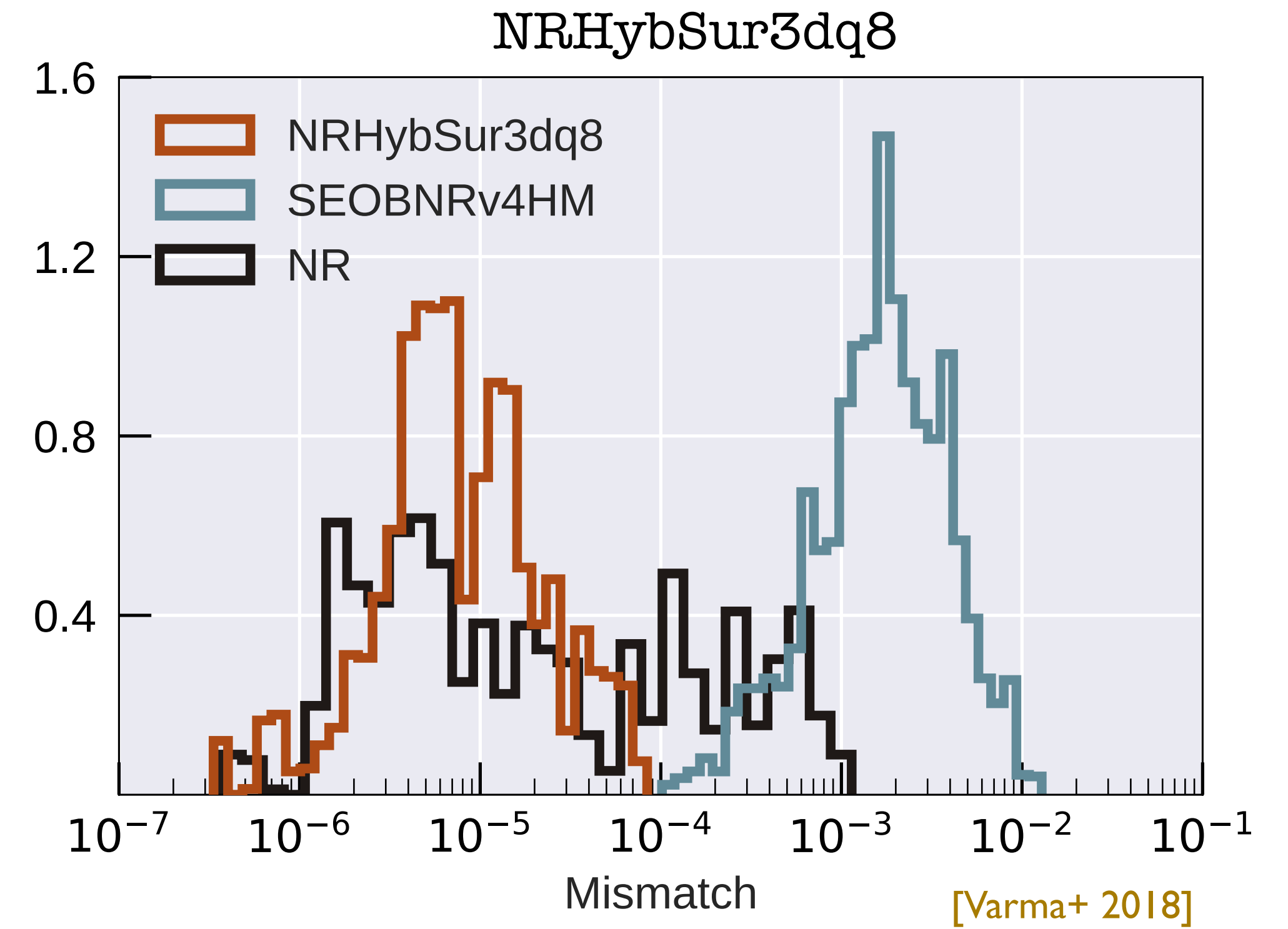
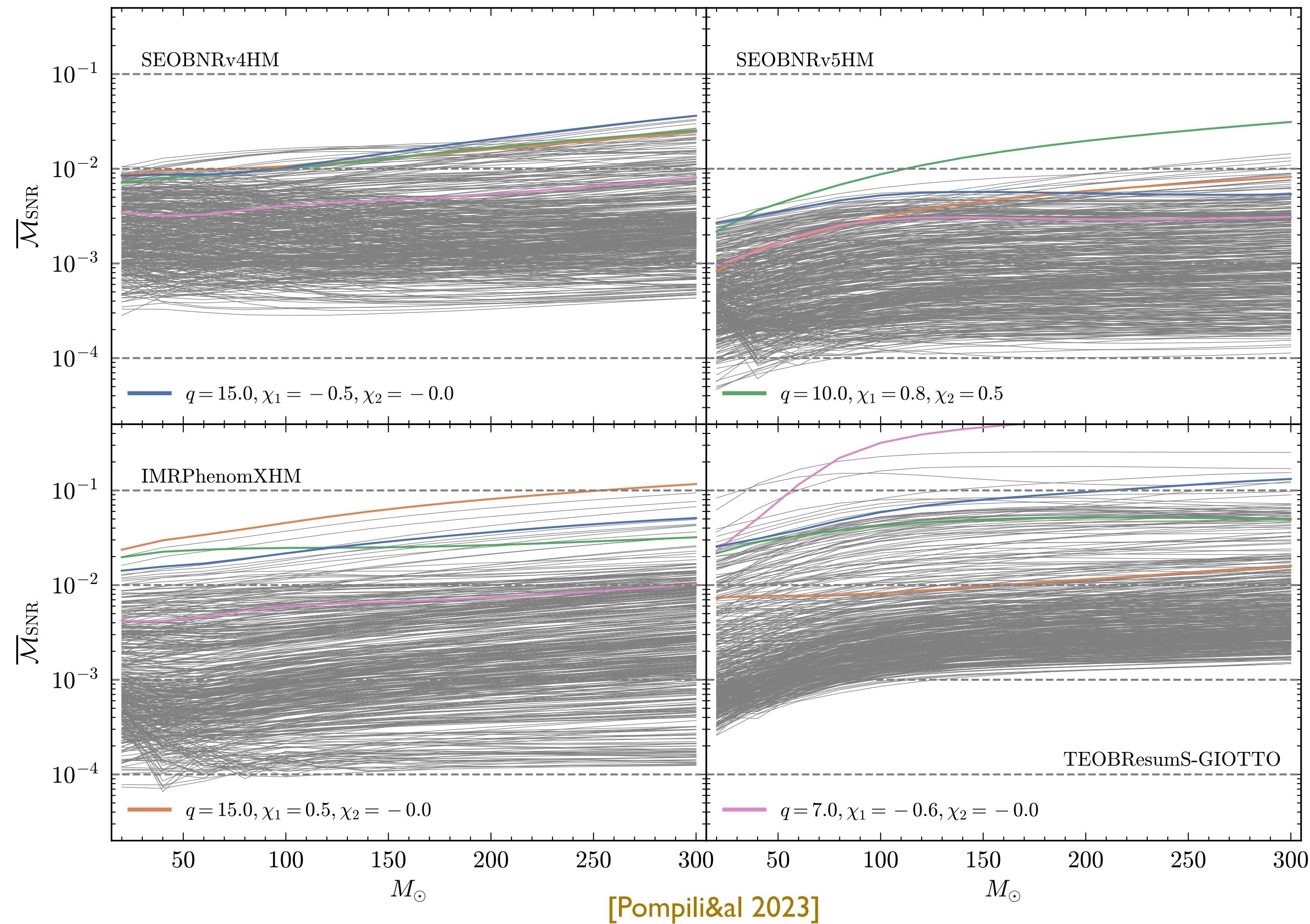
- non-spinning

## Packages:

Moving towards modular codes:

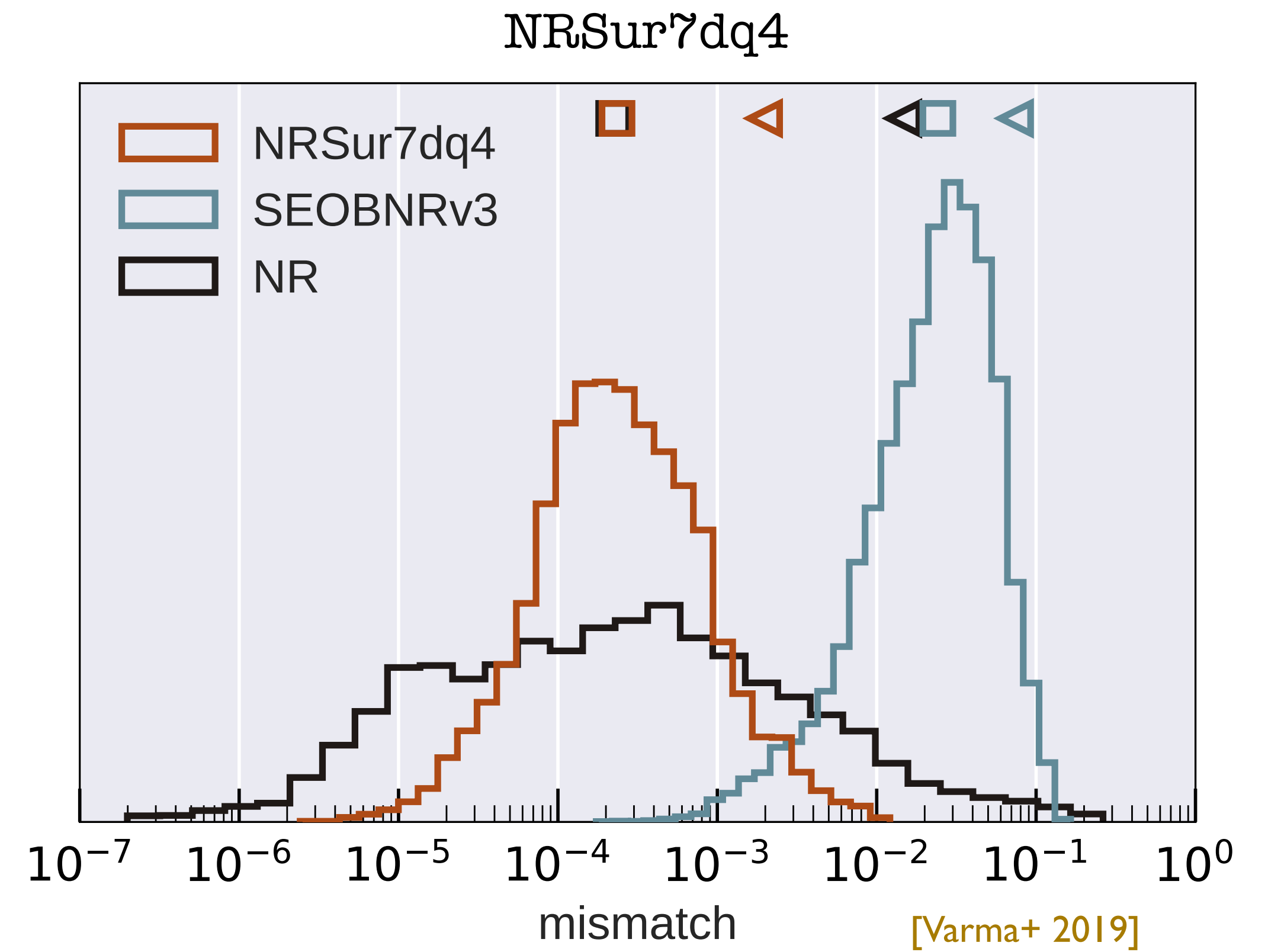
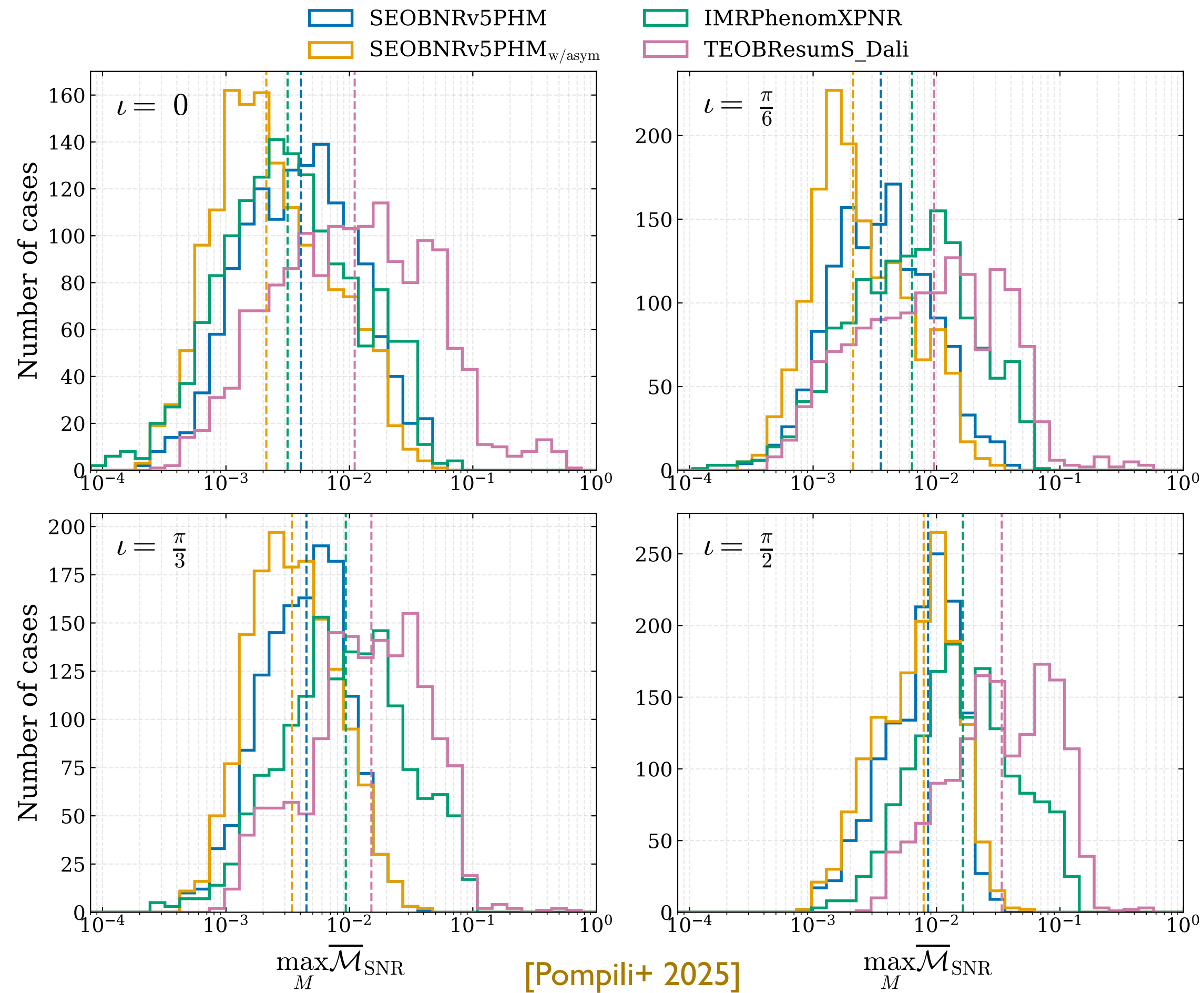
- phenomxpy
- pyseobnr
- gwsurrogate

# Overview of waveform models: mismatches for the circularized non-precessing case



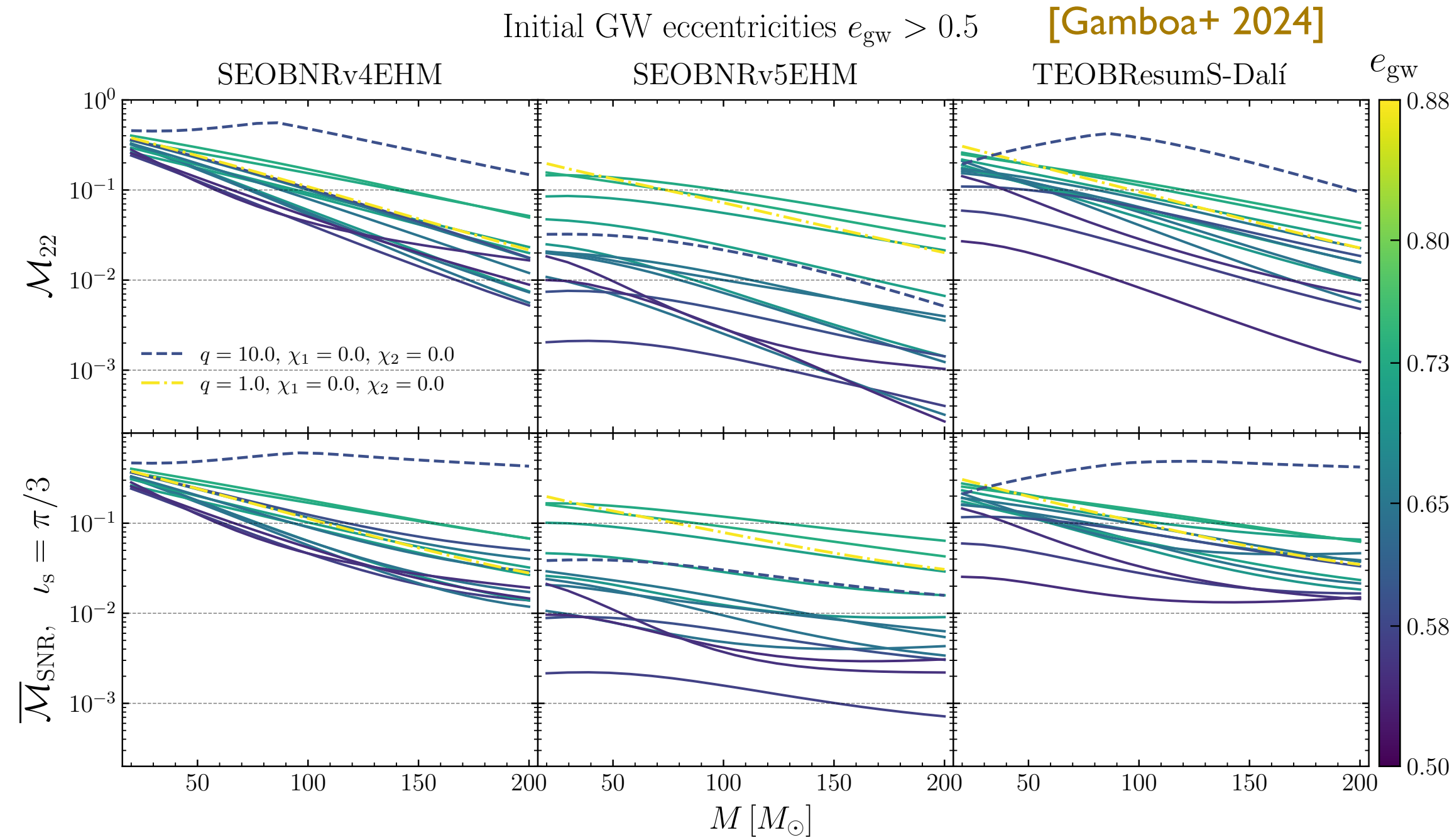
Aligned spin case: mismatch with NR  $\sim 10^{-4} - 10^{-2}$

# Overview of waveform models: mismatches for precession

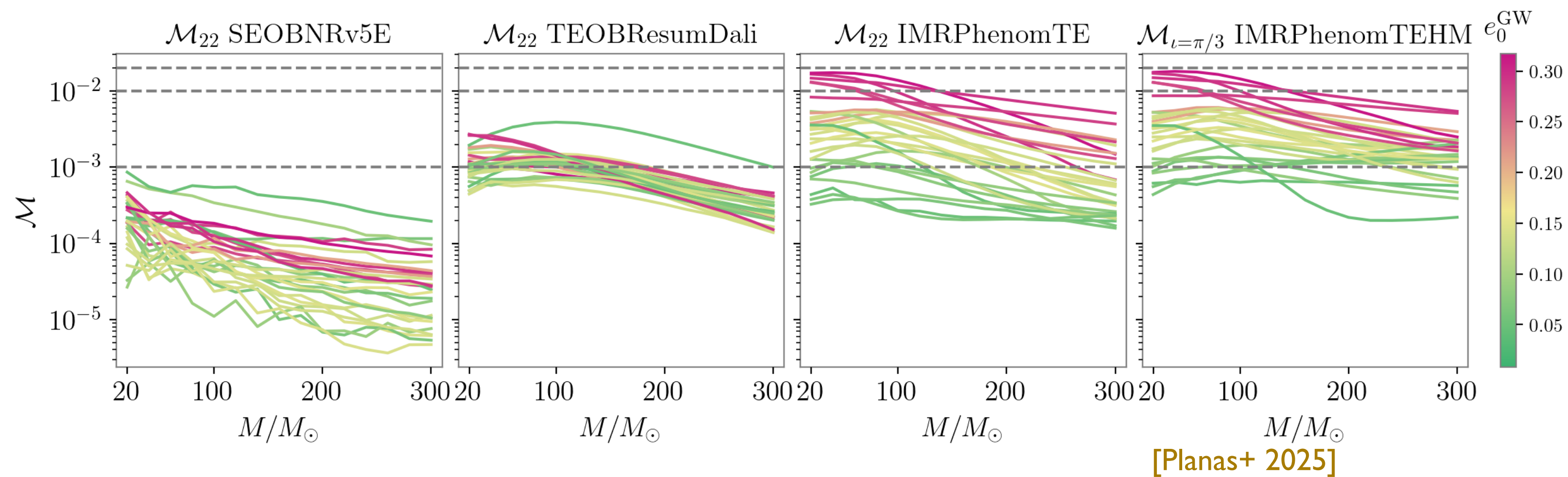


Aligned spin case: mismatch with NR  $\sim 10^{-3} - \text{few } 10^{-2}$

# Overview of waveform models: mismatches for eccentricity



Eccentric case: mismatch with NR  $\sim 10^{-2} - 10^{-1}$



See also:  
 NRSurE\_q4NoSpin\_22  
 [Nee+ 2026]

# Analysis settings

## Injections:

NRHybSur3dq8 [Varma&al 2018]

- SXS NR simulations hybridized with long EOB inspirals (covers  $\sim 6$  months for  $M = 10^5 M_\odot$ )
- Surrogate interpolant, time-domain

## Templates:

Efficient Fourier-domain models from 2 families:

- PhenomHM [London&al 2017]
- PhenomXHM [García-Quirós&al 2020]
- SEOBNRv4HM\_ROM [Cotesta&al 2018]
- SEOBNRv5HM\_ROM [Pompili&al 2023]

Mode content for all: 22, 21, 33, 44

Limitations:

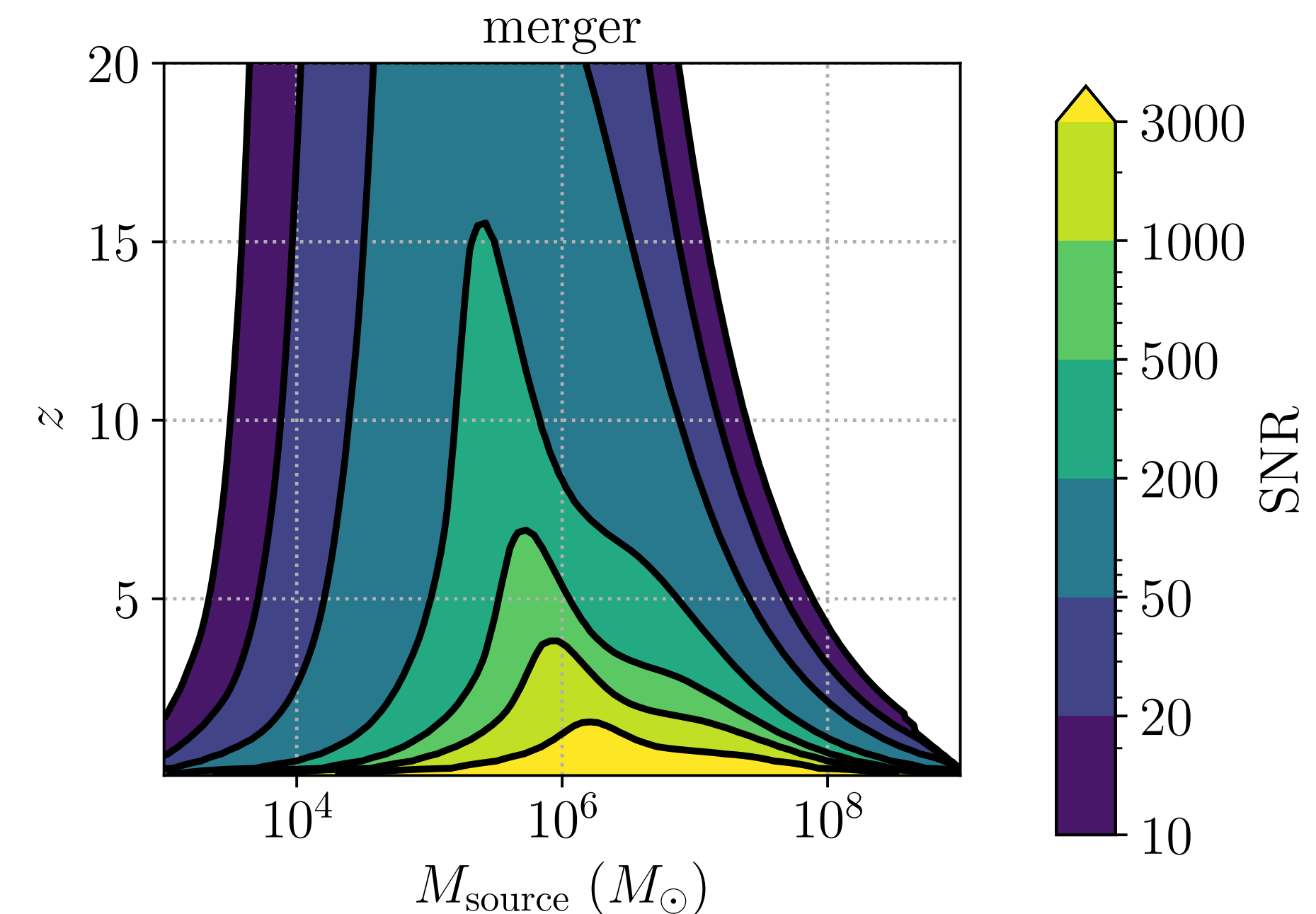
- **aligned spins only**
- in the inspiral, all based on PN/EOB

## Parameter space exploration:

- $M_z = [10^5, 10^6, 10^7] M_\odot$
- $z_{\min} = 1$
- $N = 240$  simulations
- uniform  $q \in [1, 8]$
- uniform  $\chi_1 \in [-0.8, 0.8]$
- uniform  $\chi_2 \in [-0.8, 0.8]$
- randomize orientations

## Analysis:

- Bayesian PE: lisabeta
- Posterior gives statistical uncertainty,  $\max \ln \mathcal{L}$  gives the bias
- Multi-stage tempering to ensure convergence
- Fourier-domain response equal-armlength (same for injection and templates)
- Direct FD Whittle likelihood (no approx.)

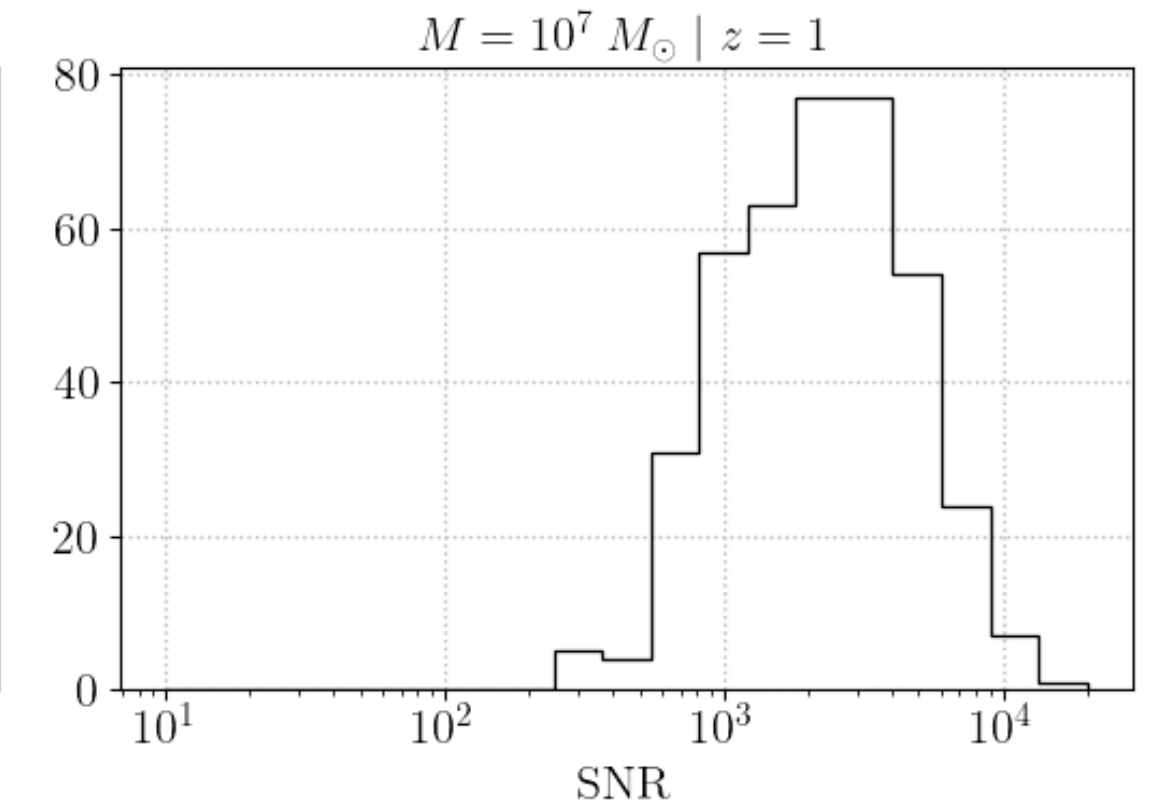
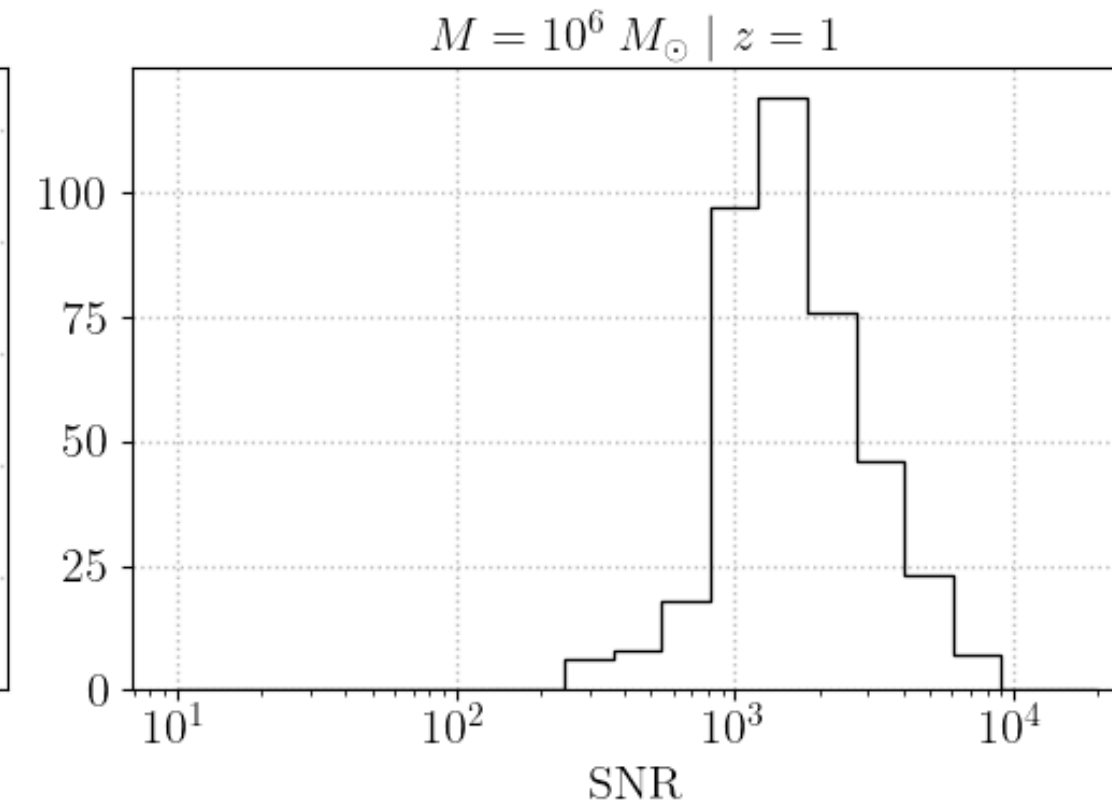
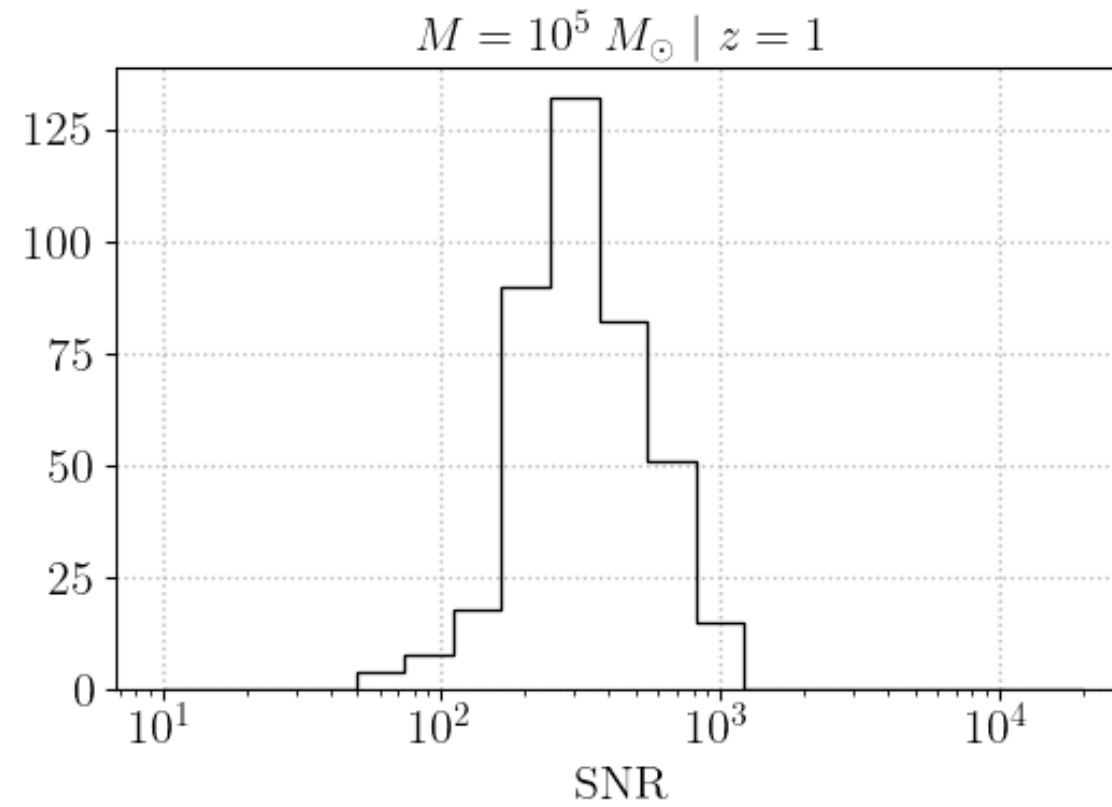


# SNRs and mismatches

Signal-to-noise ratios:

$$\text{SNR}^2 = (h_0|h_0)$$

SNRs up to thousands at  $z = 1$

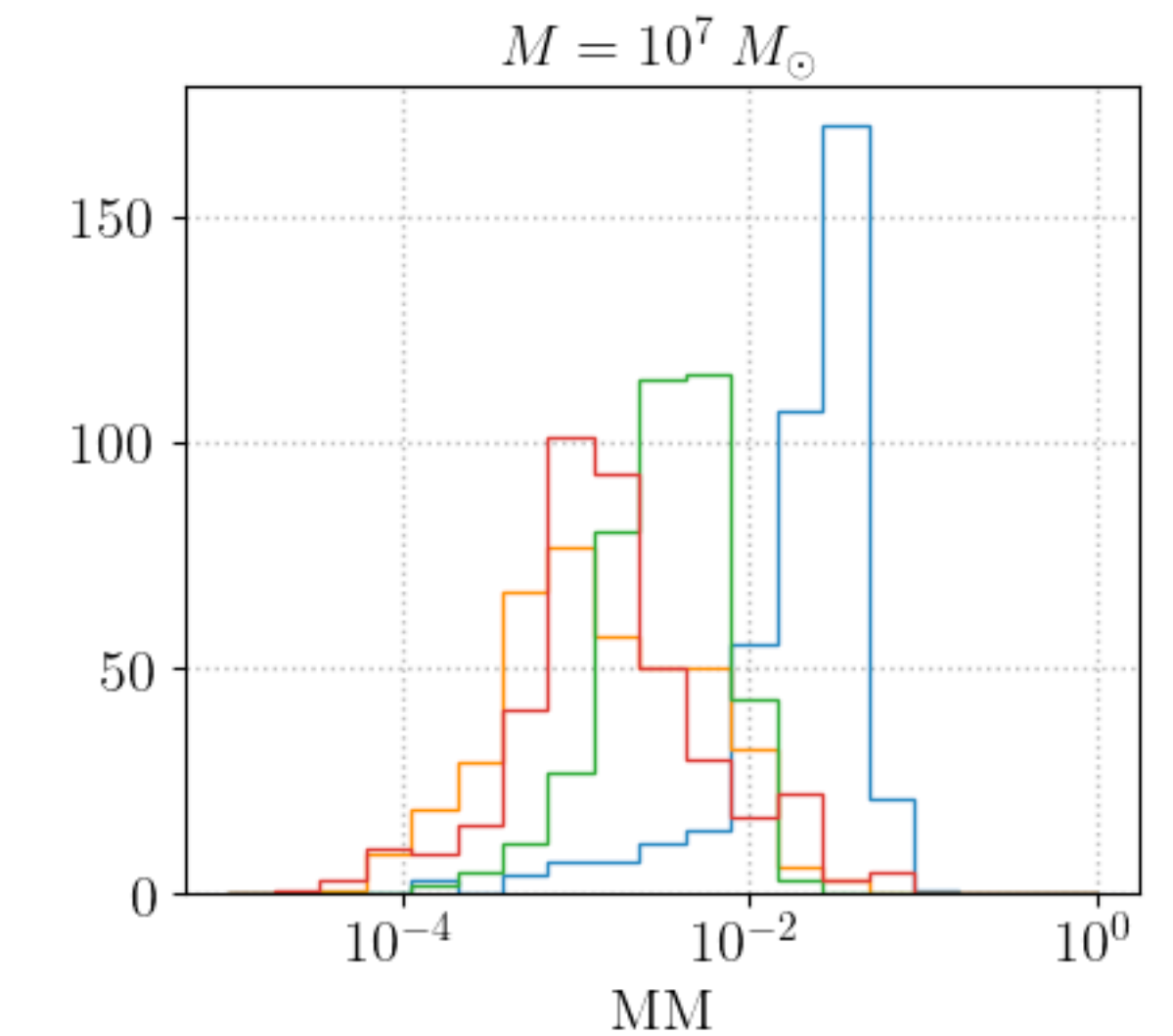
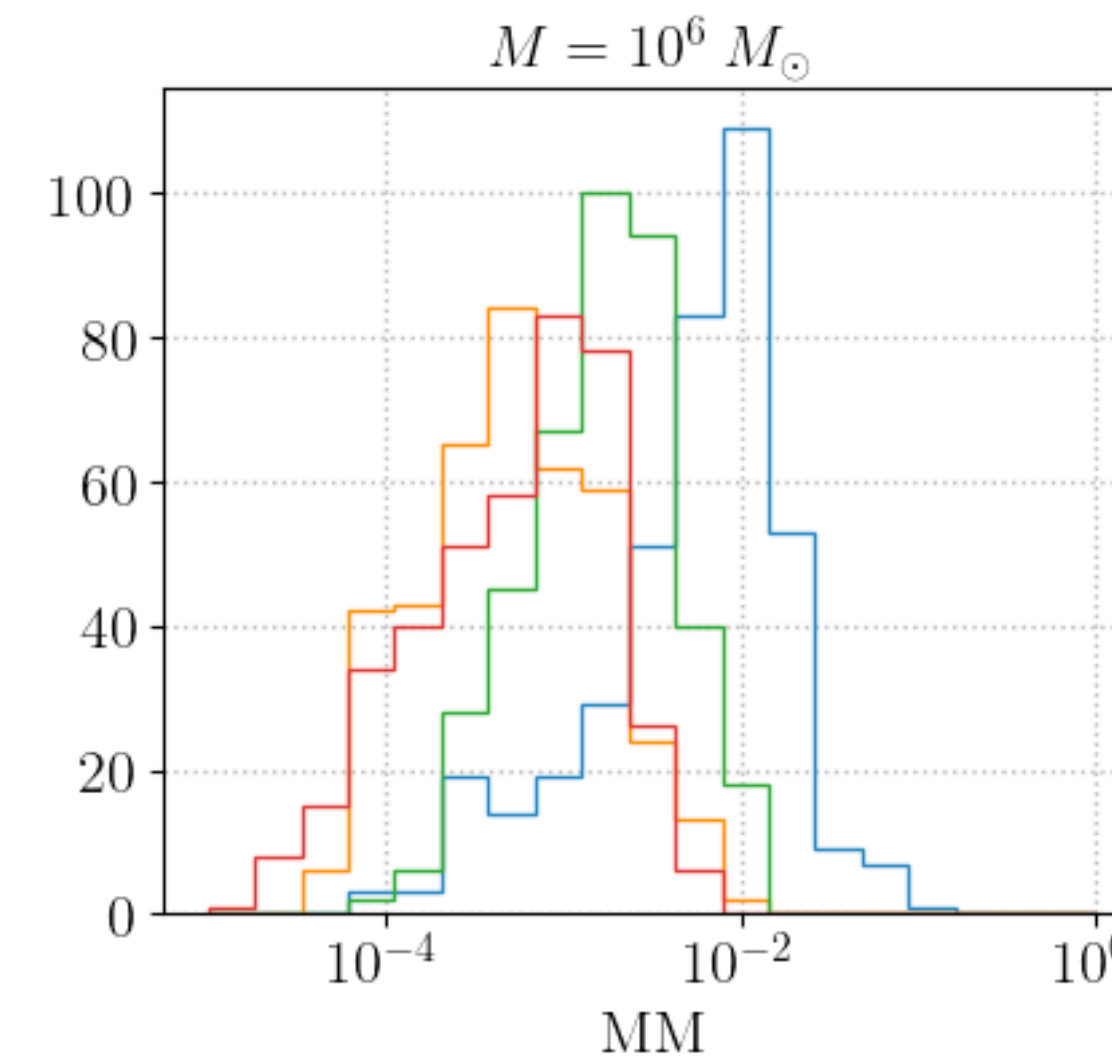
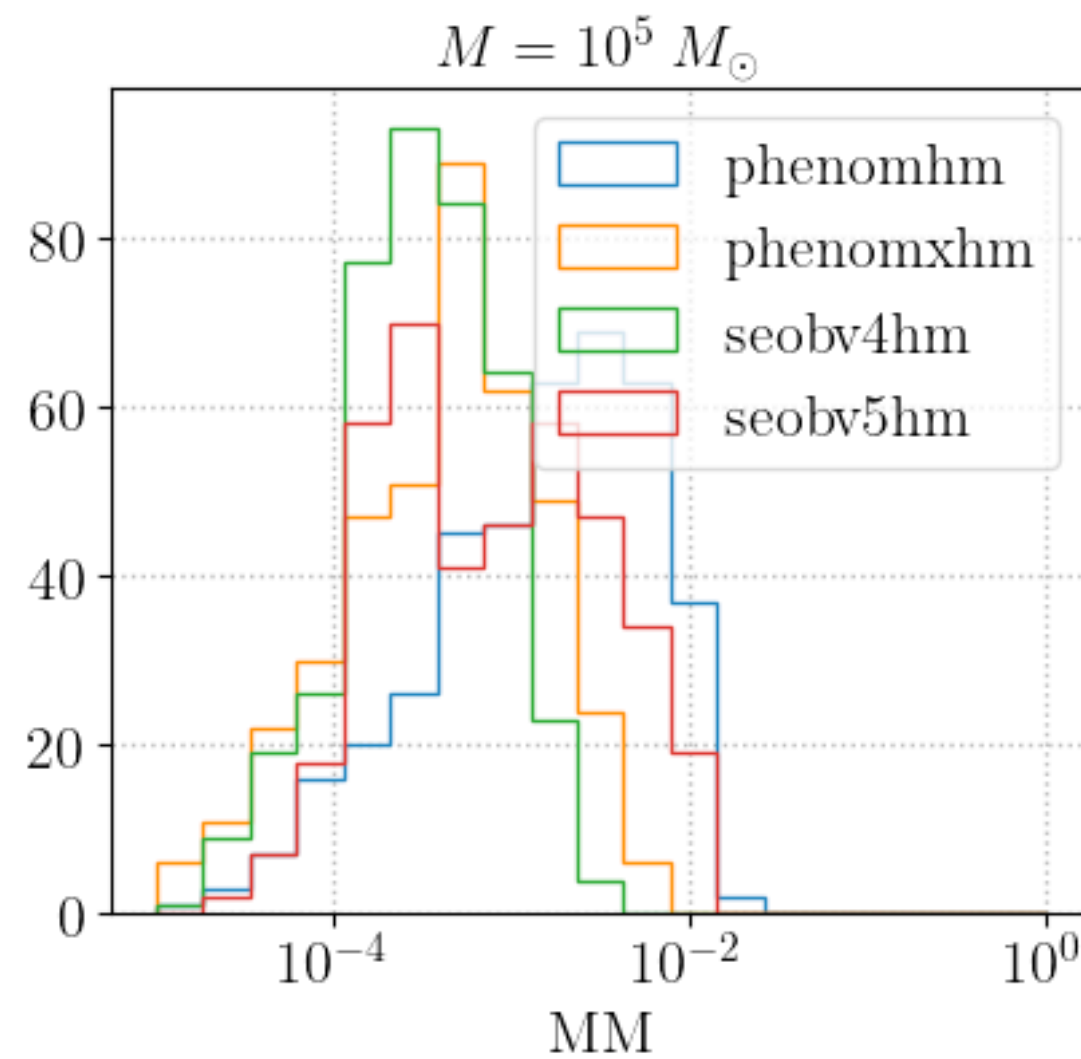


Mismatch:

- averaged response
- single-detector
- optimized: time, phase, polarization, sky

$$\text{MM} = 1 - \max_{t,\varphi,\psi,\dots} \frac{(h_m|h_0)}{\sqrt{(h_m|h_m)}\sqrt{h_0|h_0}}$$

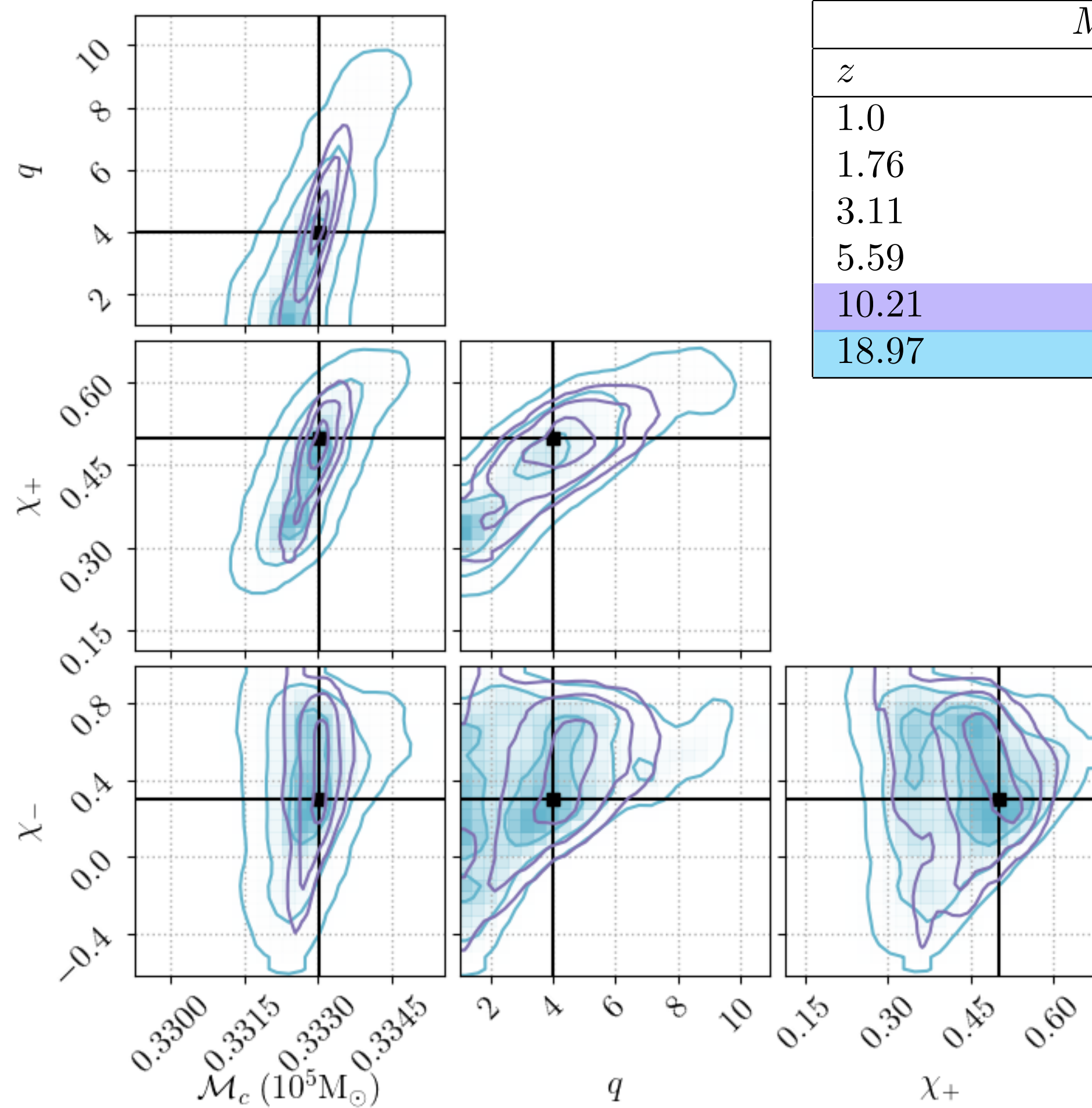
- Mismatches order-of-magnitude similar to LVK
- Improvement for more recent models



# Example Parameter estimation with systematics I

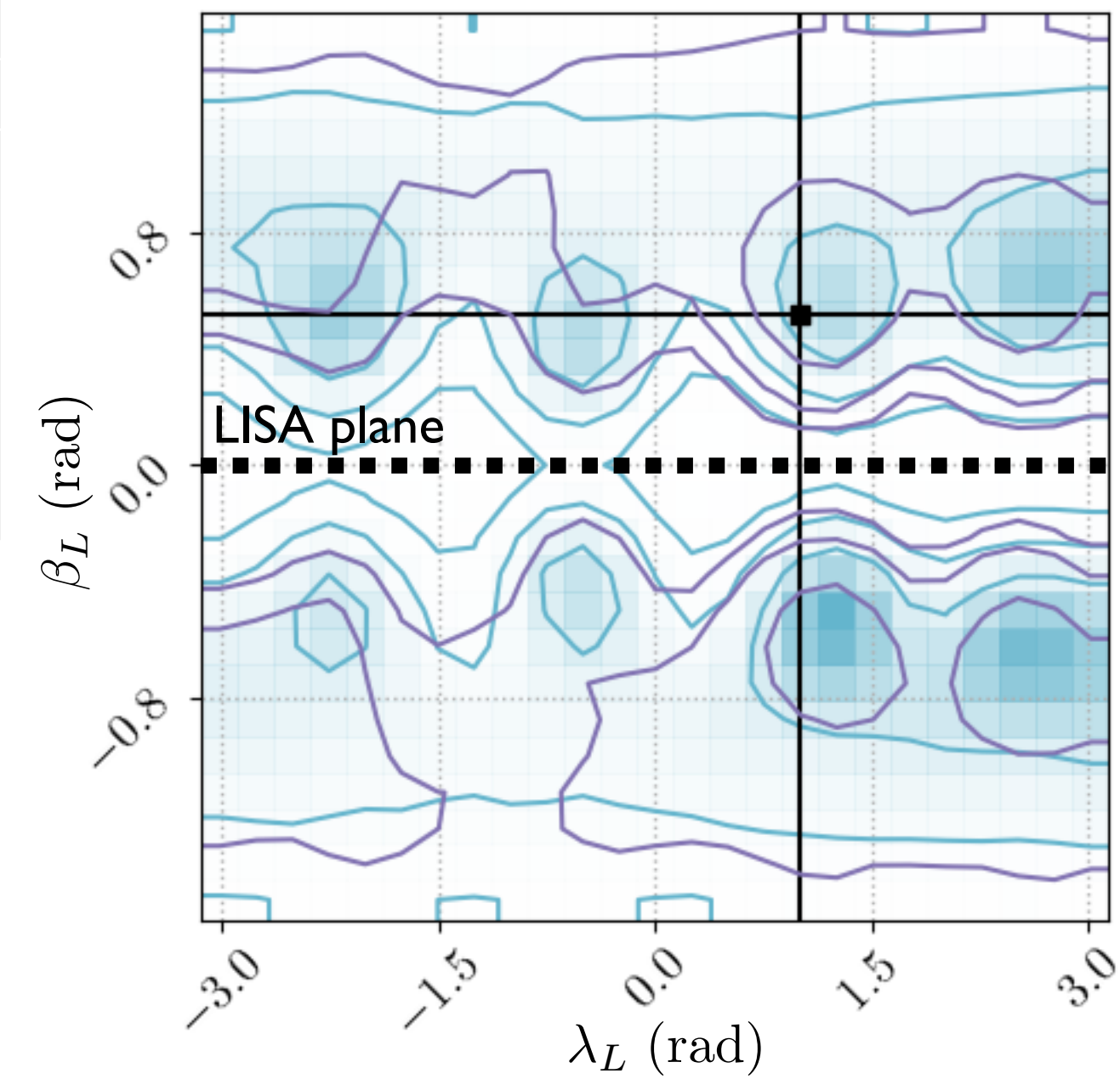
- **Injection:** NRHybSur3dq8  $\{M = 10^5 M_\odot, q = 4, \chi_1 = 0.5, \chi_2 = 0.3\}$
- **Template:** PhenomXHM

Intrinsic params.



$M_z = 10^5 M_\odot$	
$z$	SNR
1.0	317
1.76	158
3.11	79
5.59	40
10.21	20
18.97	10

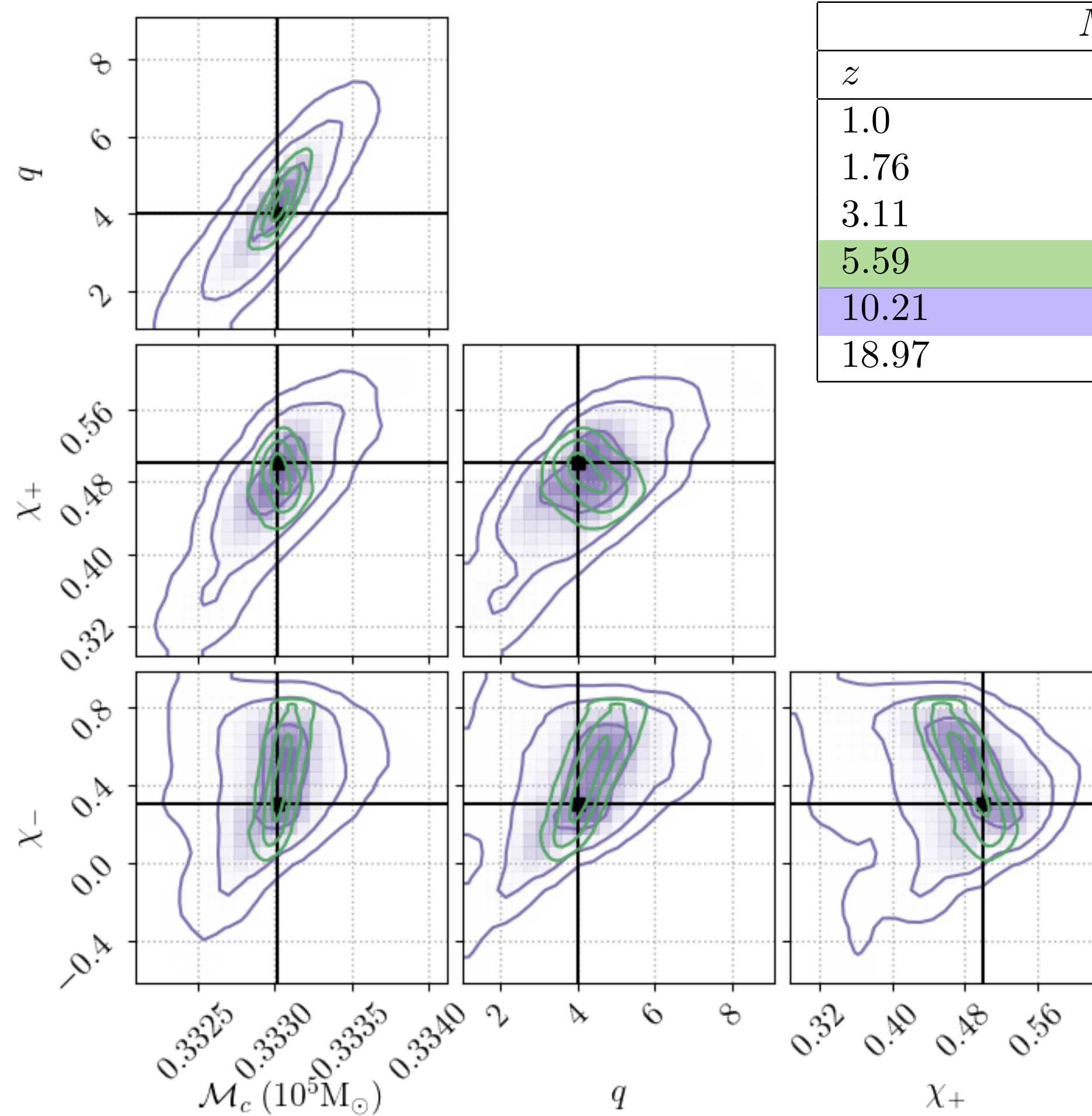
Sky localisation



# Example Parameter estimation with systematics I

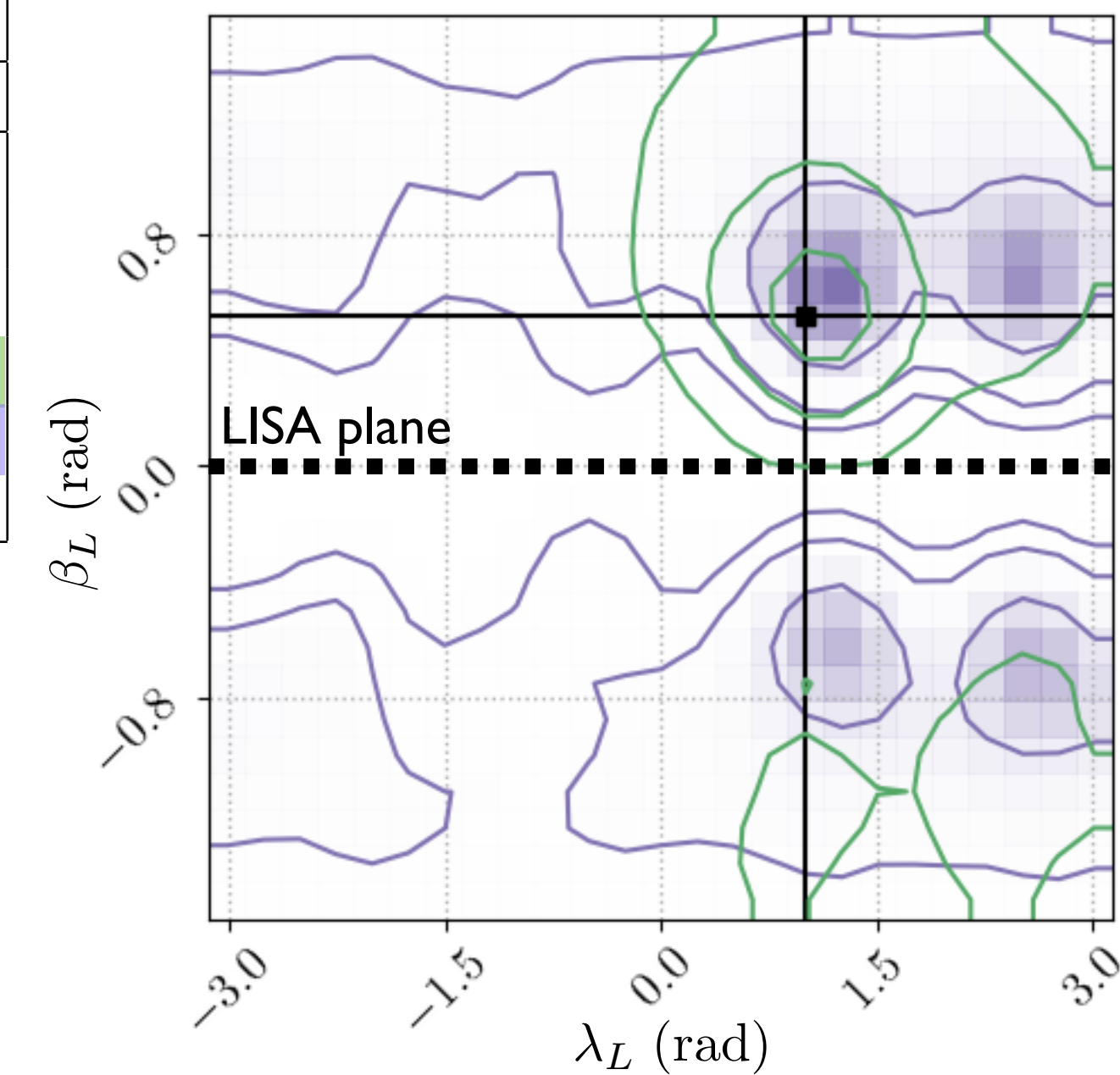
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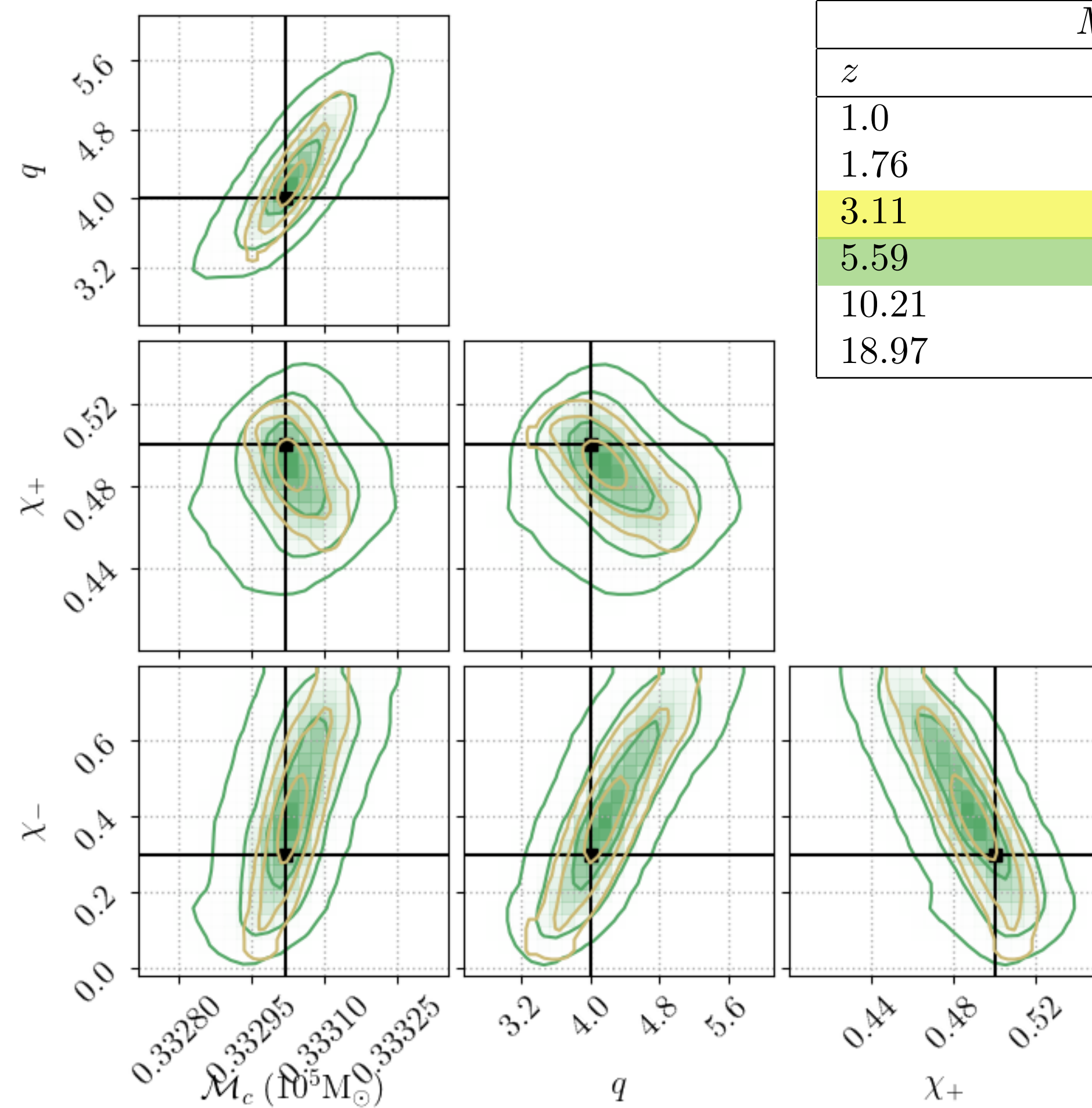
Sky localisation



# Example Parameter estimation with systematics I

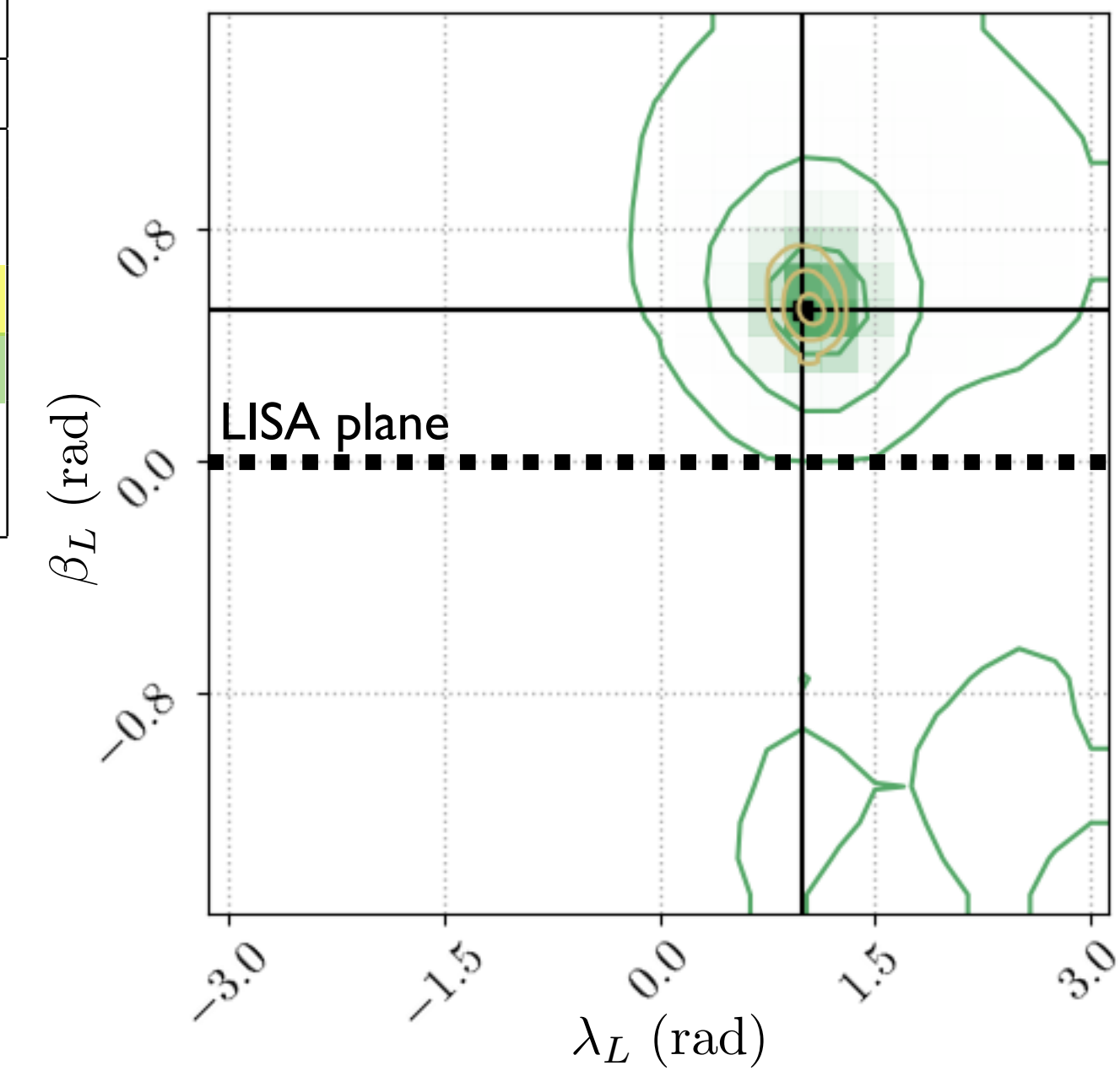
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Intrinsic params.



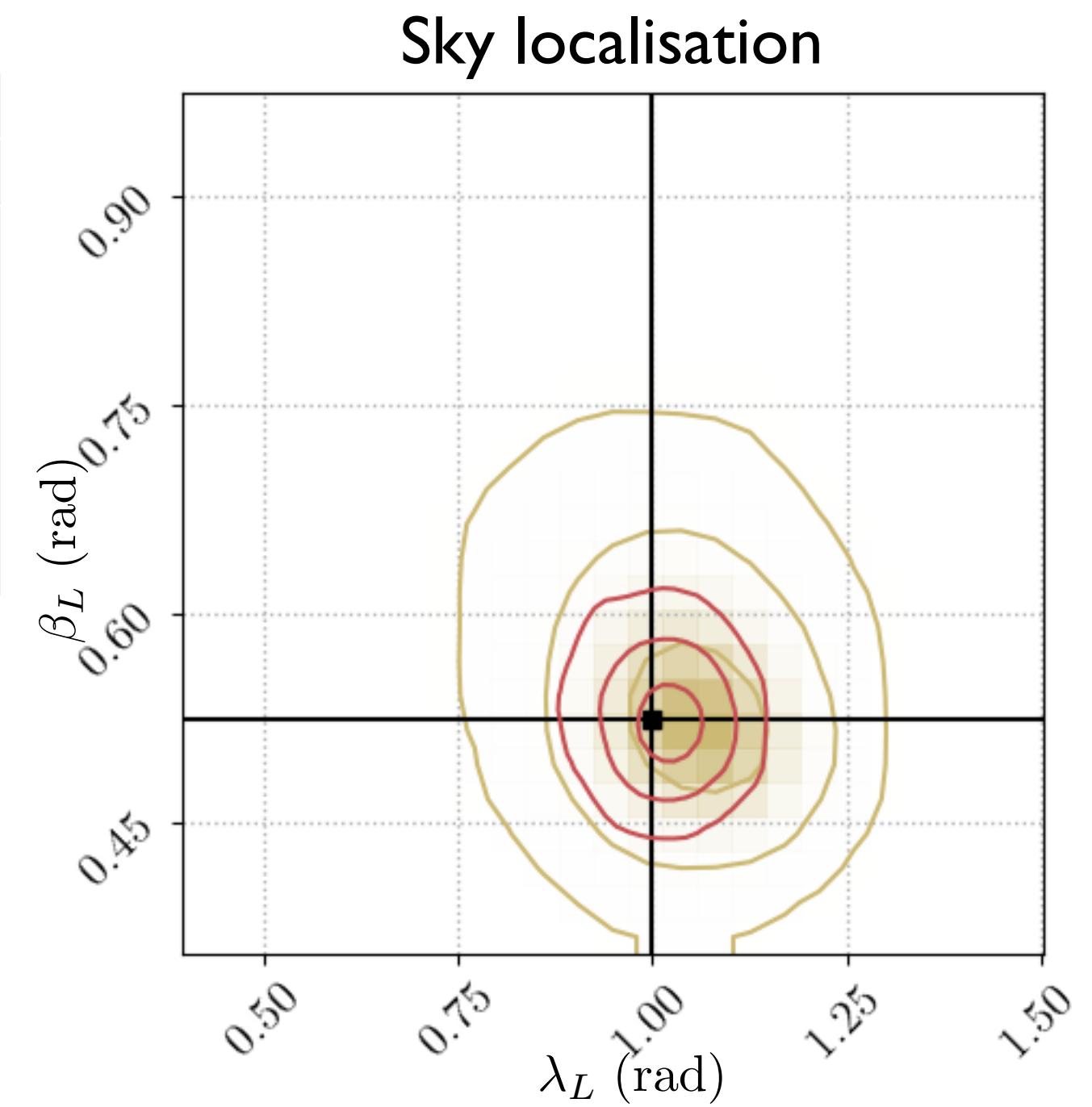
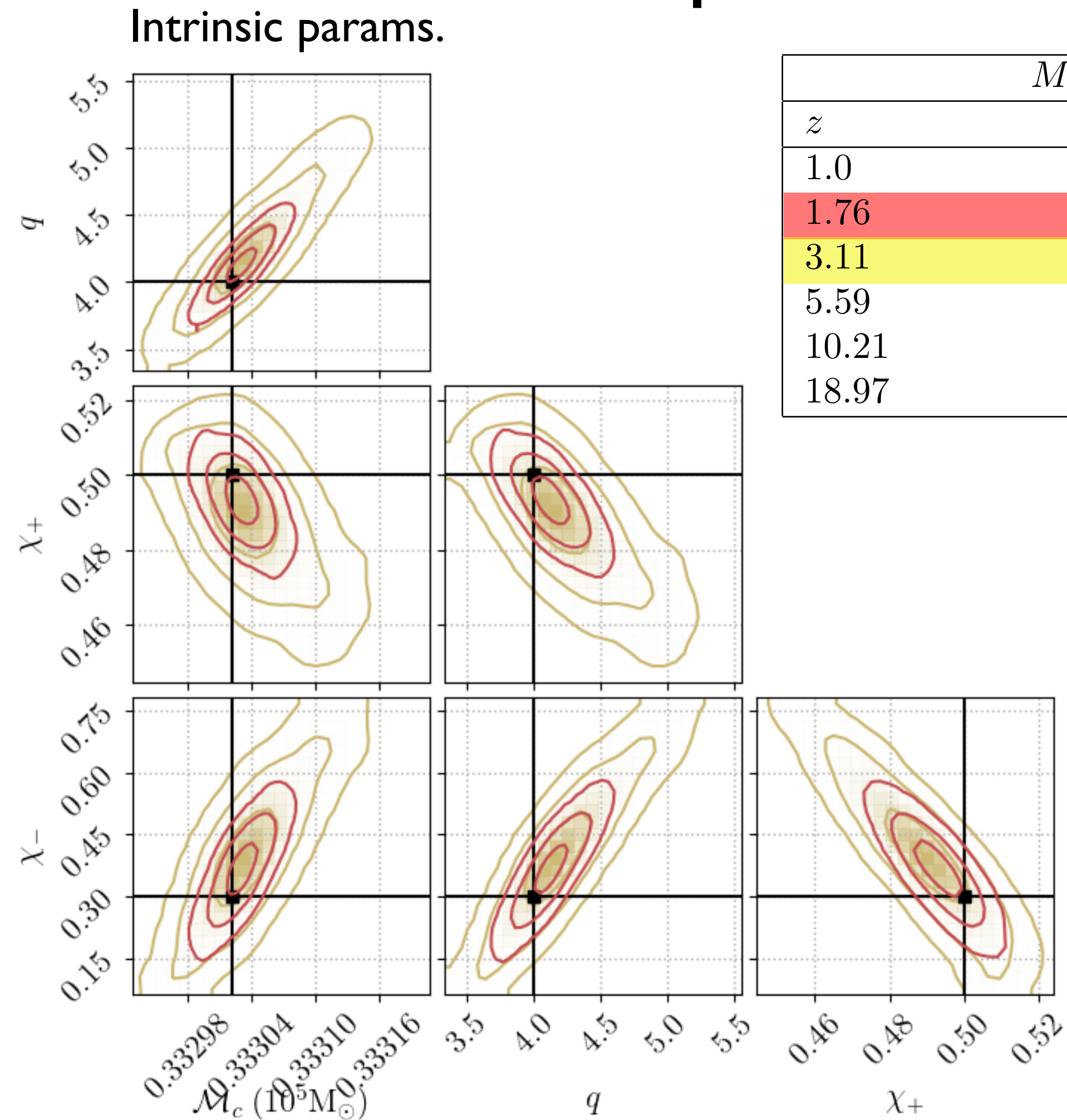
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$z$	SNR
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Sky localisation



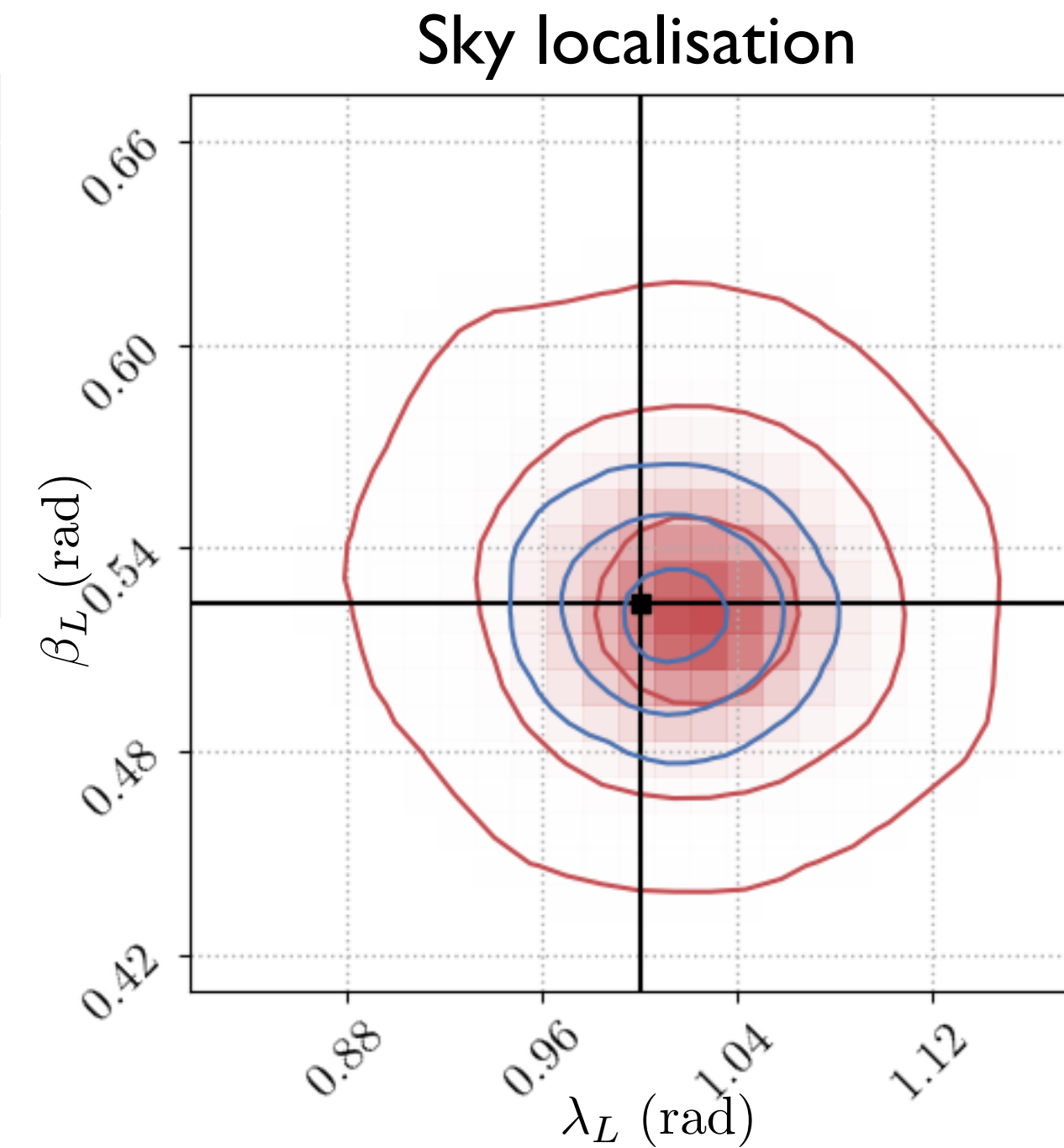
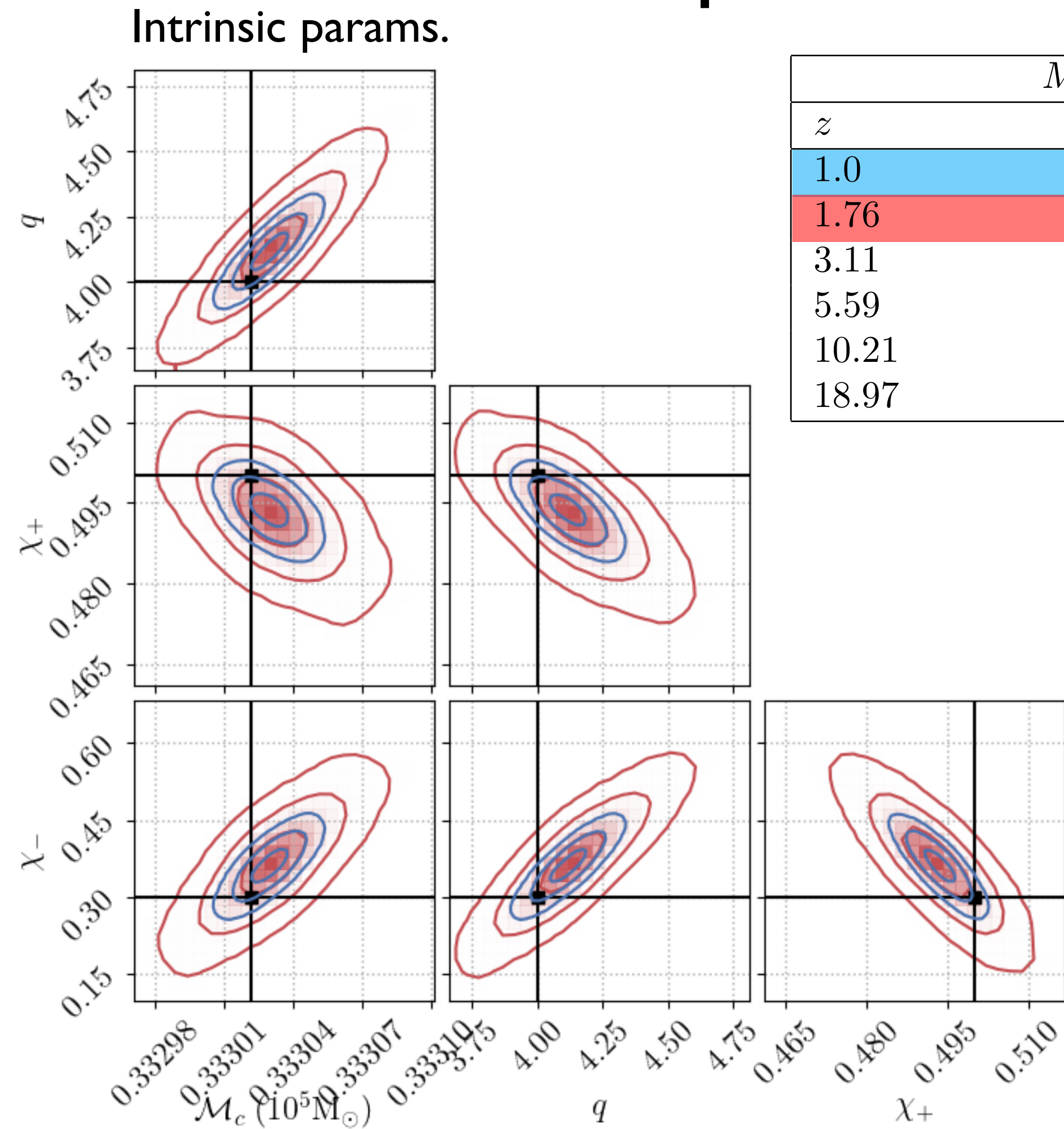
# Example Parameter estimation with systematics I

- **Injection:** NRHybSur3dq8  $\{M = 10^5 M_\odot, q = 4, \chi_1 = 0.5, \chi_2 = 0.3\}$
- **Template:** PhenomXHM



# Example Parameter estimation with systematics I

- **Injection:** NRHybSur3dq8  $\{M = 10^5 M_\odot, q = 4, \chi_1 = 0.5, \chi_2 = 0.3\}$
- **Template:** PhenomXHM



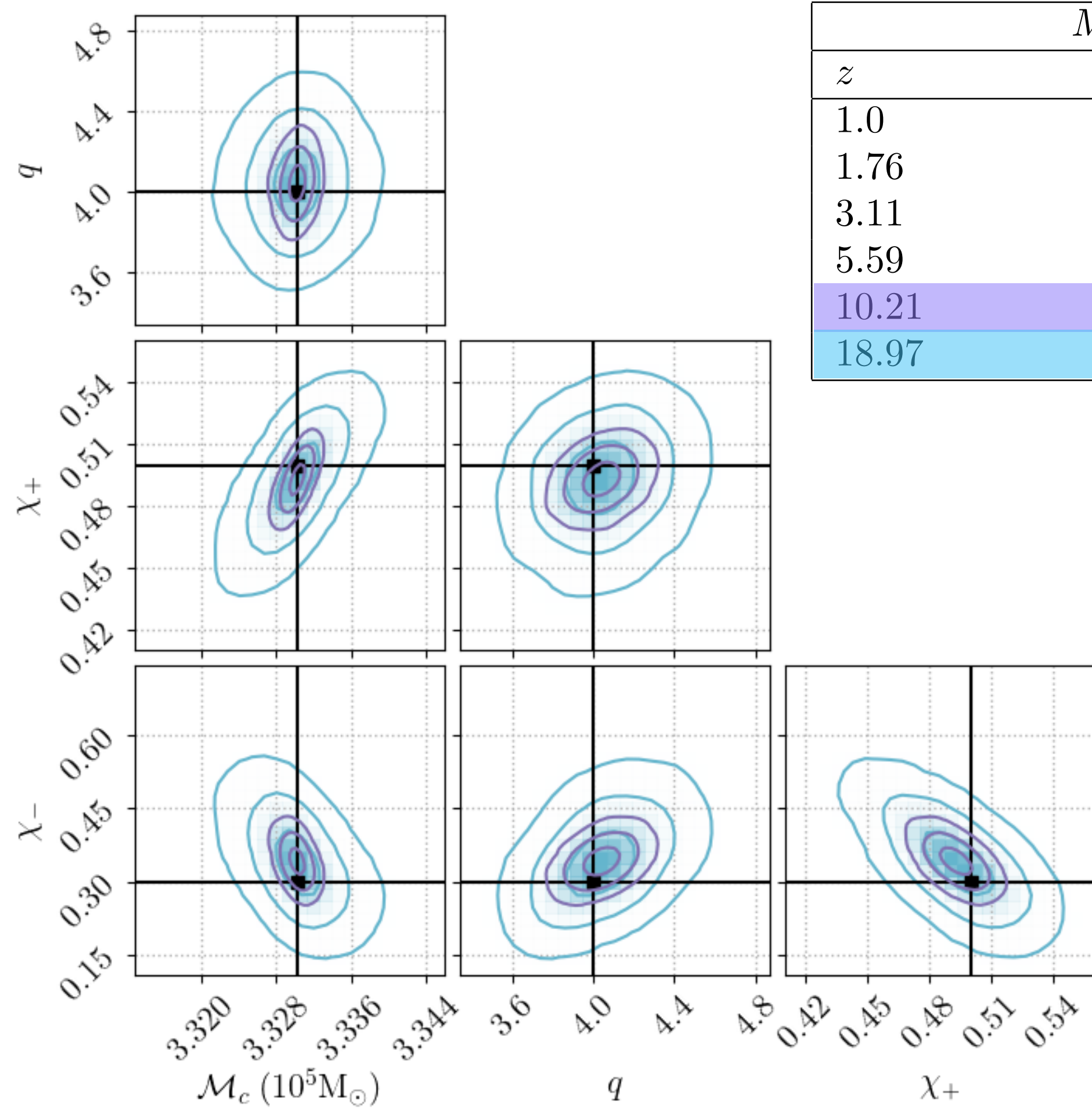
**The good:**

- converges on the true parameters
- mild bias at  $z = 1$ , SNR = 317

# Example Parameter estimation with systematics II

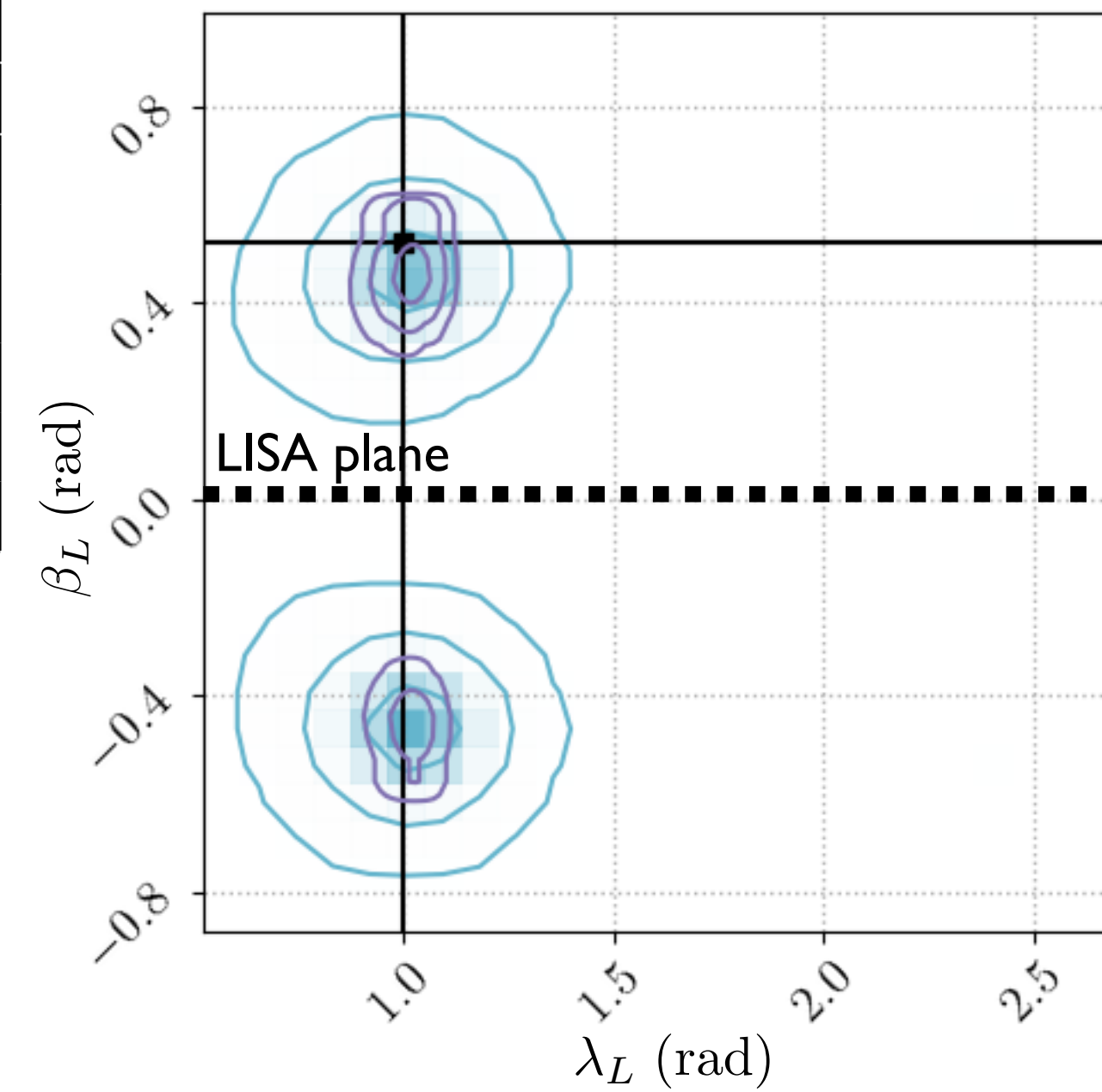
- **Injection:** NRHybSur3dq8  $\{M = 10^6 M_\odot, q = 4, \chi_1 = 0.5, \chi_2 = 0.3\}$
- **Template:** PhenomXHM

Intrinsic params.



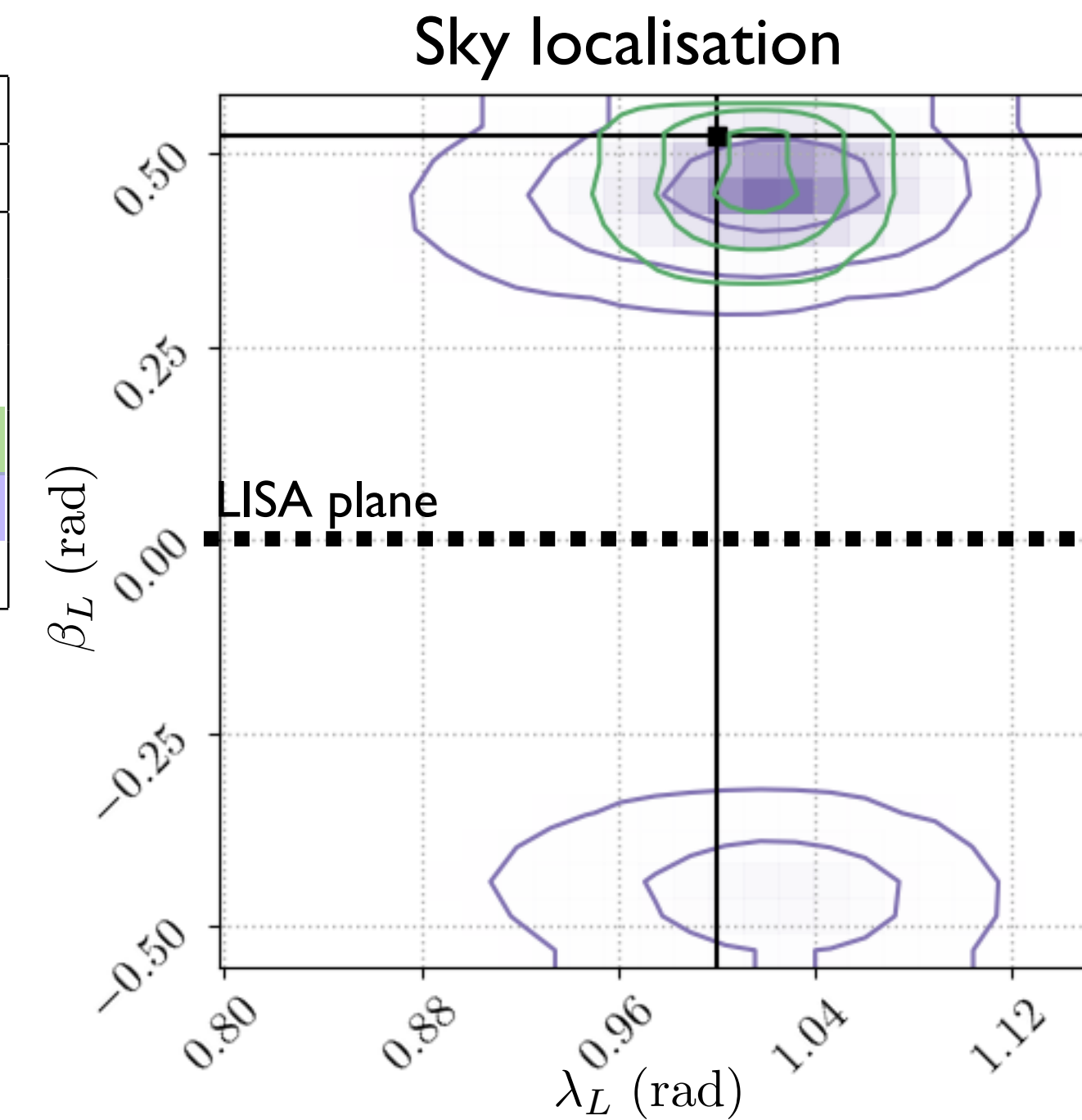
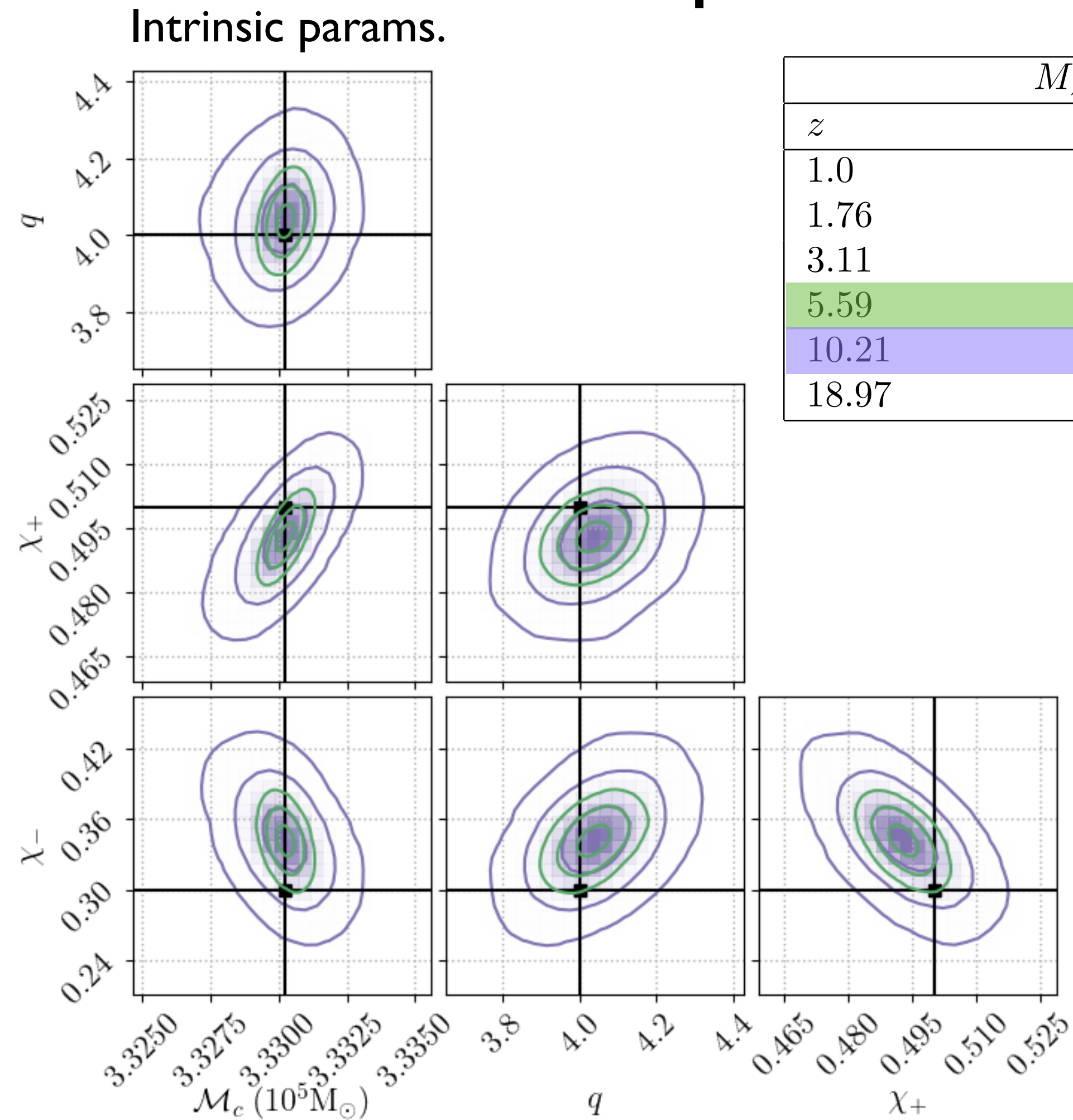
$M_z = 10^6 M_\odot$	
$z$	SNR
1.0	1907
1.76	954
3.11	477
5.59	238
10.21	119
18.97	59

Sky localisation



# Example Parameter estimation with systematics II

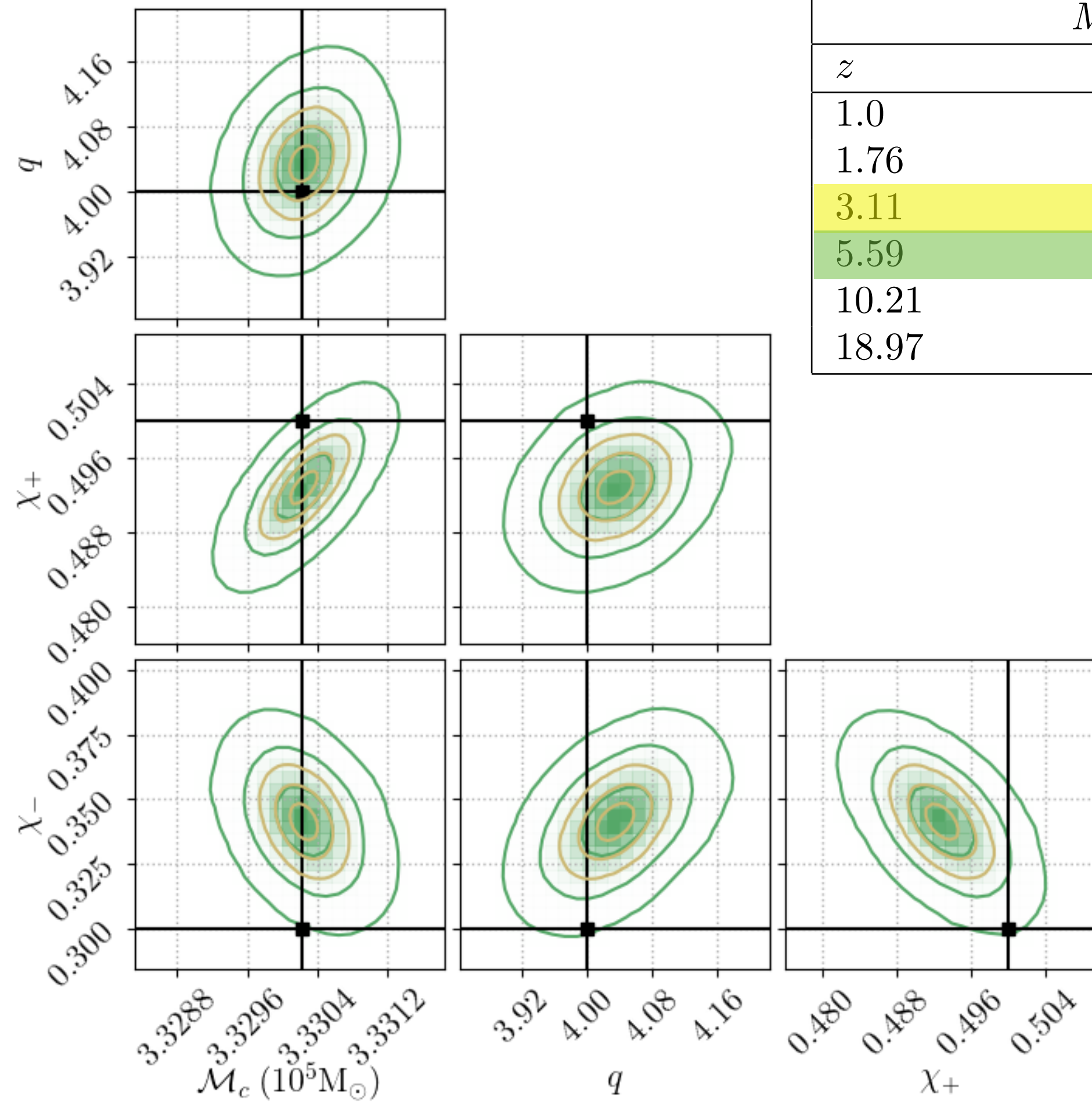
- **Injection:** NRHybSur3dq8  $\{M = 10^6 M_\odot, q = 4, \chi_1 = 0.5, \chi_2 = 0.3\}$
- **Template:** PhenomXHM



# Example Parameter estimation with systematics II

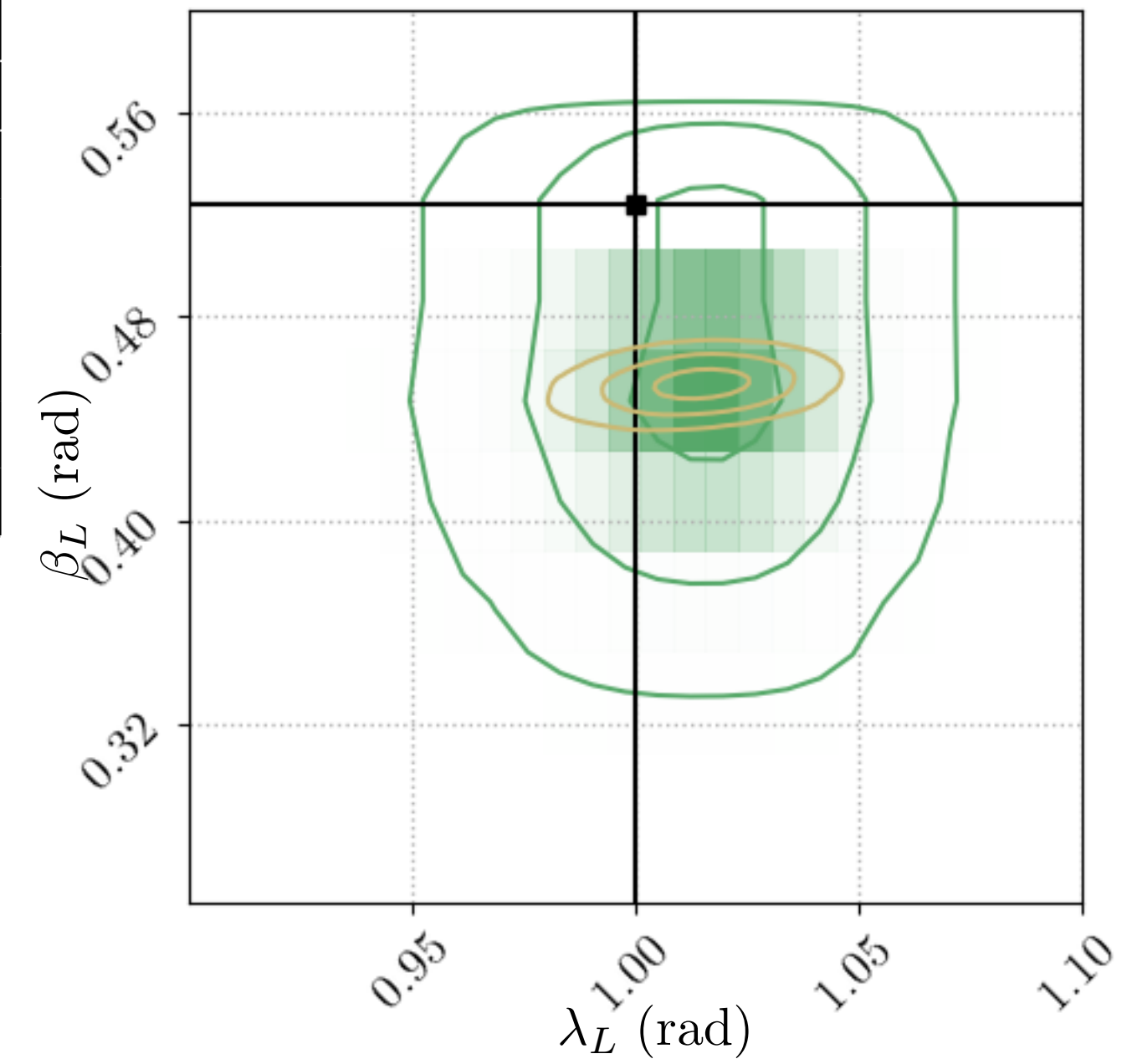
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- **Template:** PhenomXHM

Intrinsic params.



$M_z = 10^6 M_\odot$	
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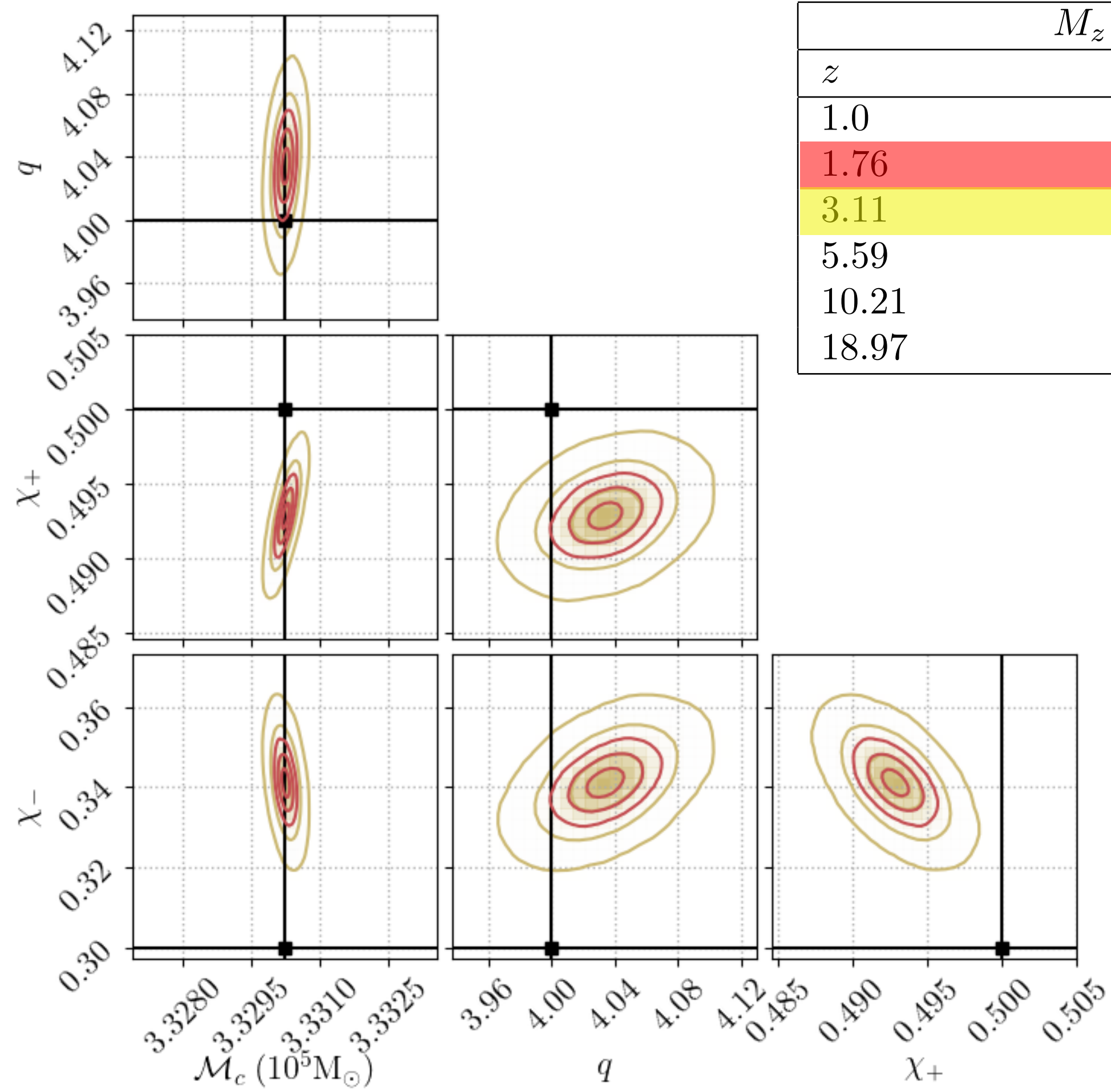
Sky localisation



# Example Parameter estimation with systematics II

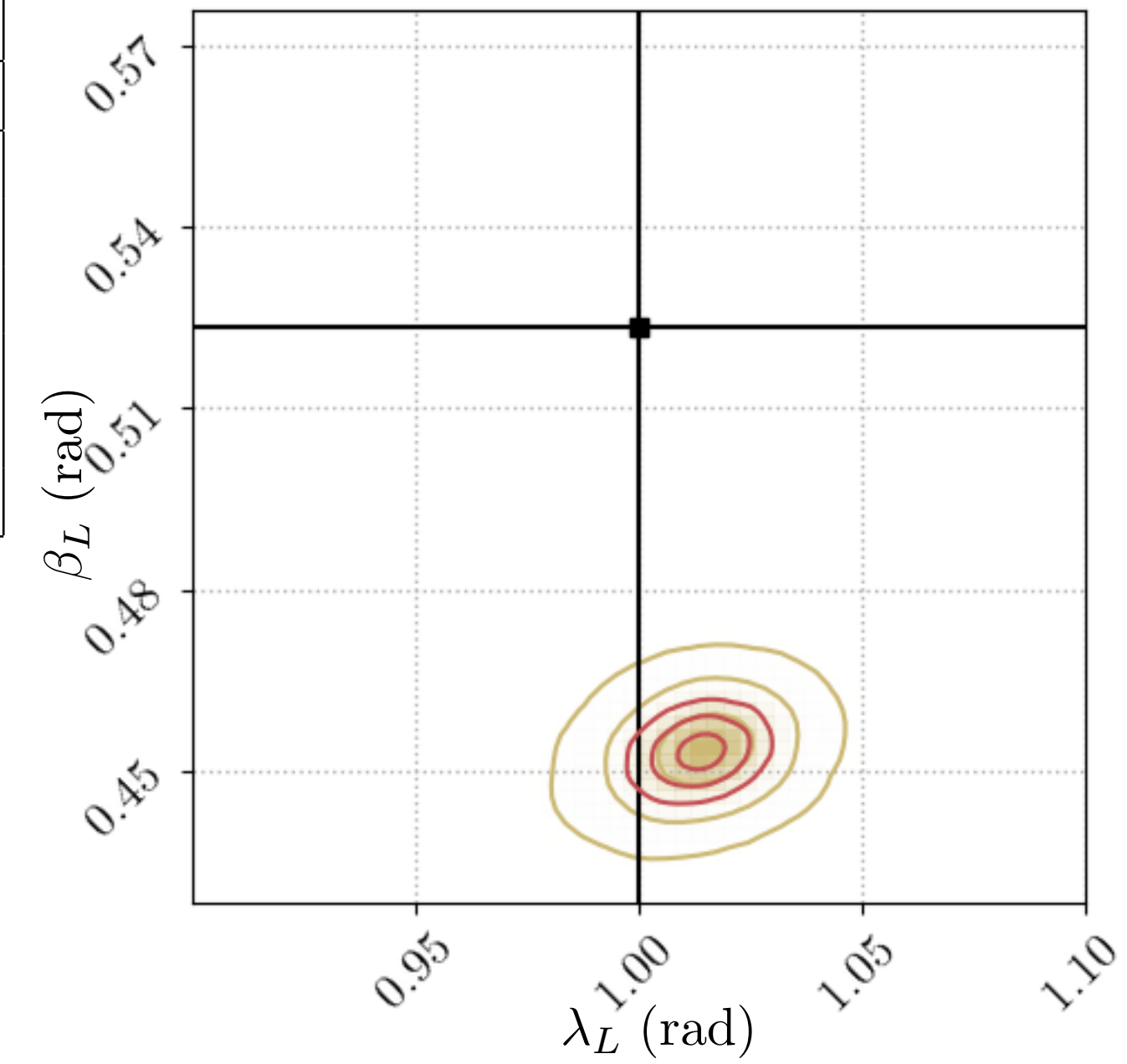
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Intrinsic params.



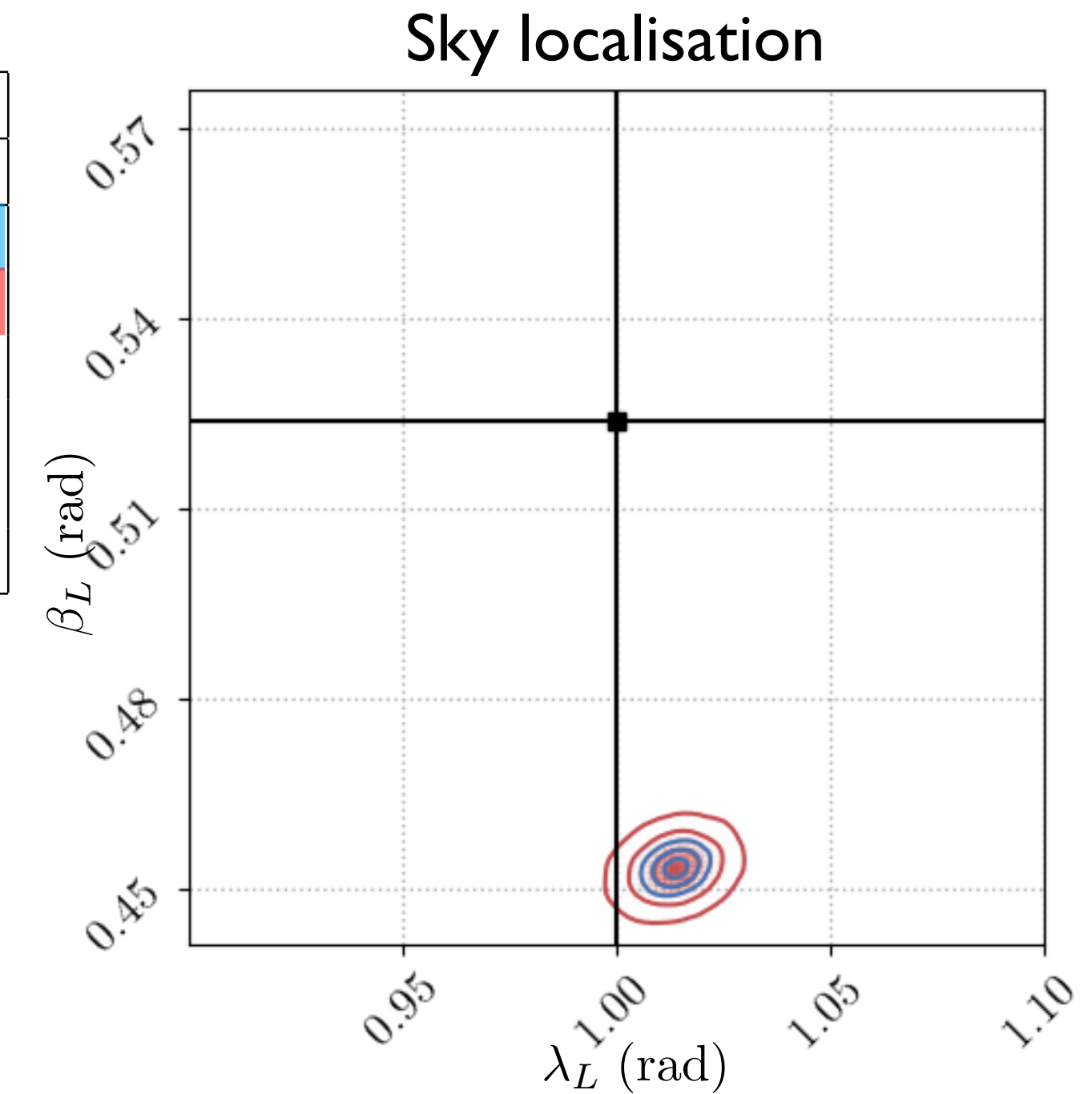
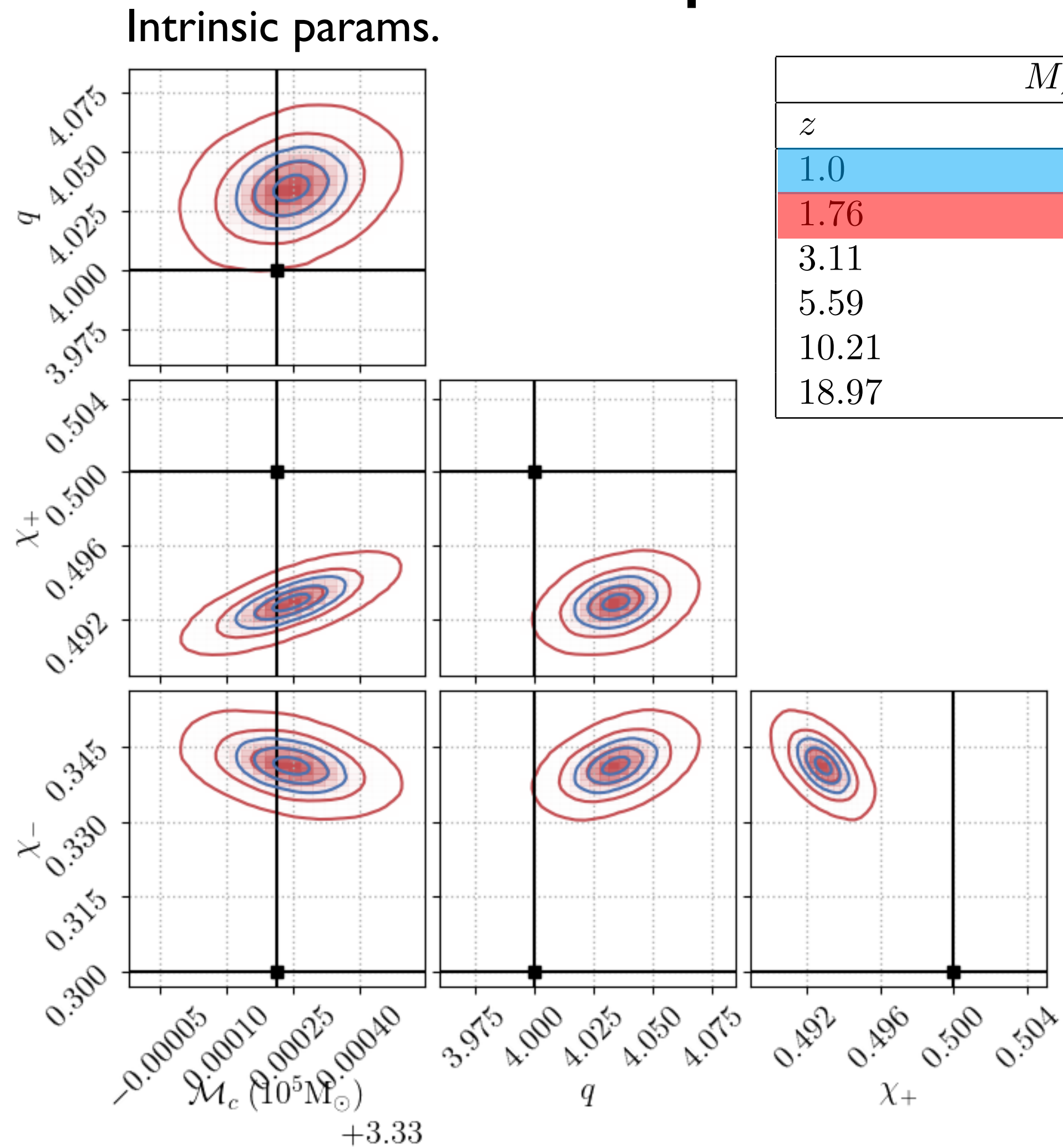
$M_z = 10^6 M_\odot$	
$z$	SNR
1.0	1907
1.76	954
3.11	477
5.59	238
10.21	119
18.97	59

Sky localisation



# Example Parameter estimation with systematics II

- **Injection:** NRHybSur3dq8  $\{M = 10^6 M_\odot, q = 4, \chi_1 = 0.5, \chi_2 = 0.3\}$
- **Template:** PhenomXHM



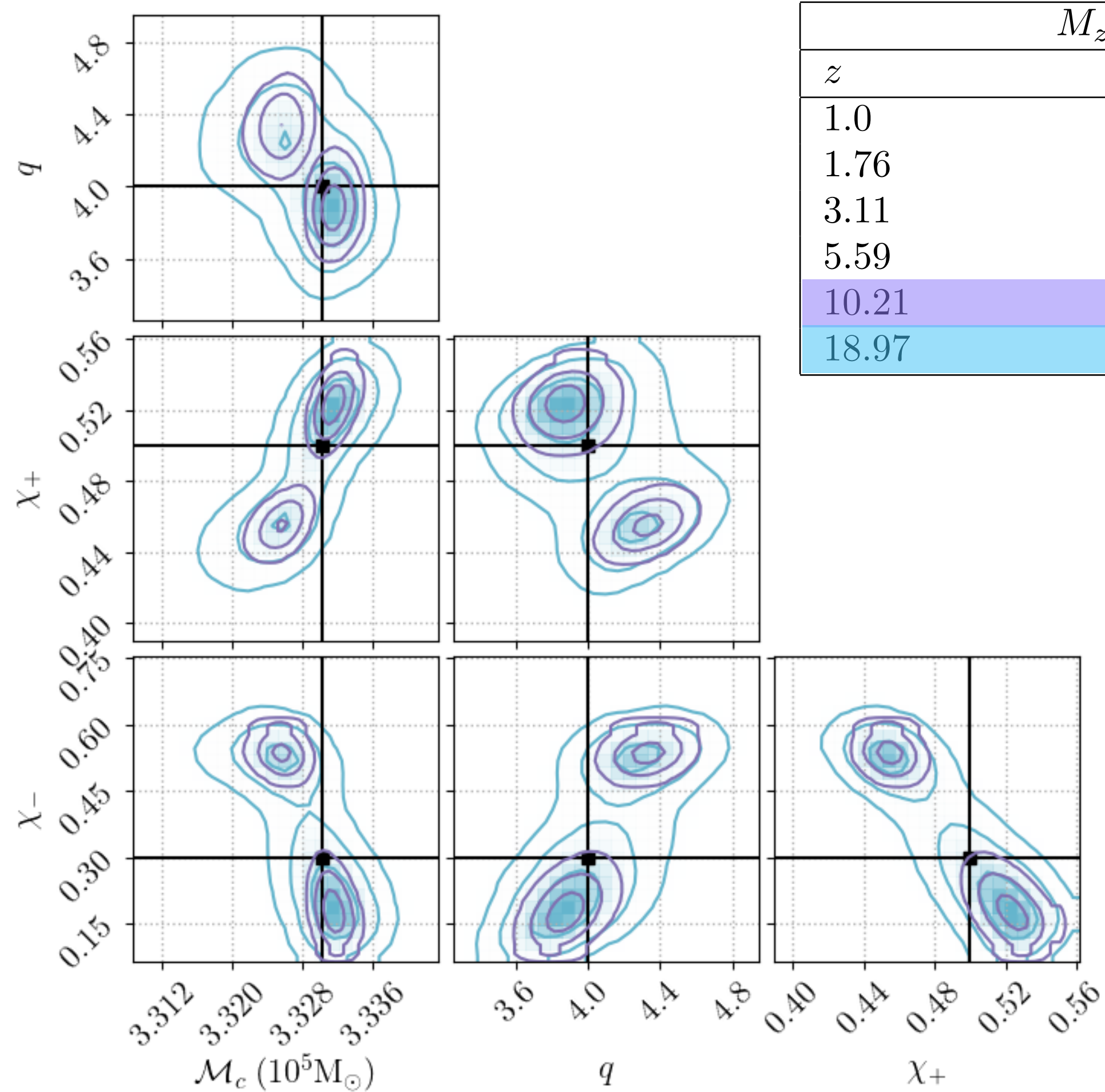
### The bad:

- converges 'near' the true parameters
- significant bias at  $z = 1$ , SNR = 1907

# Example Parameter estimation with systematics III

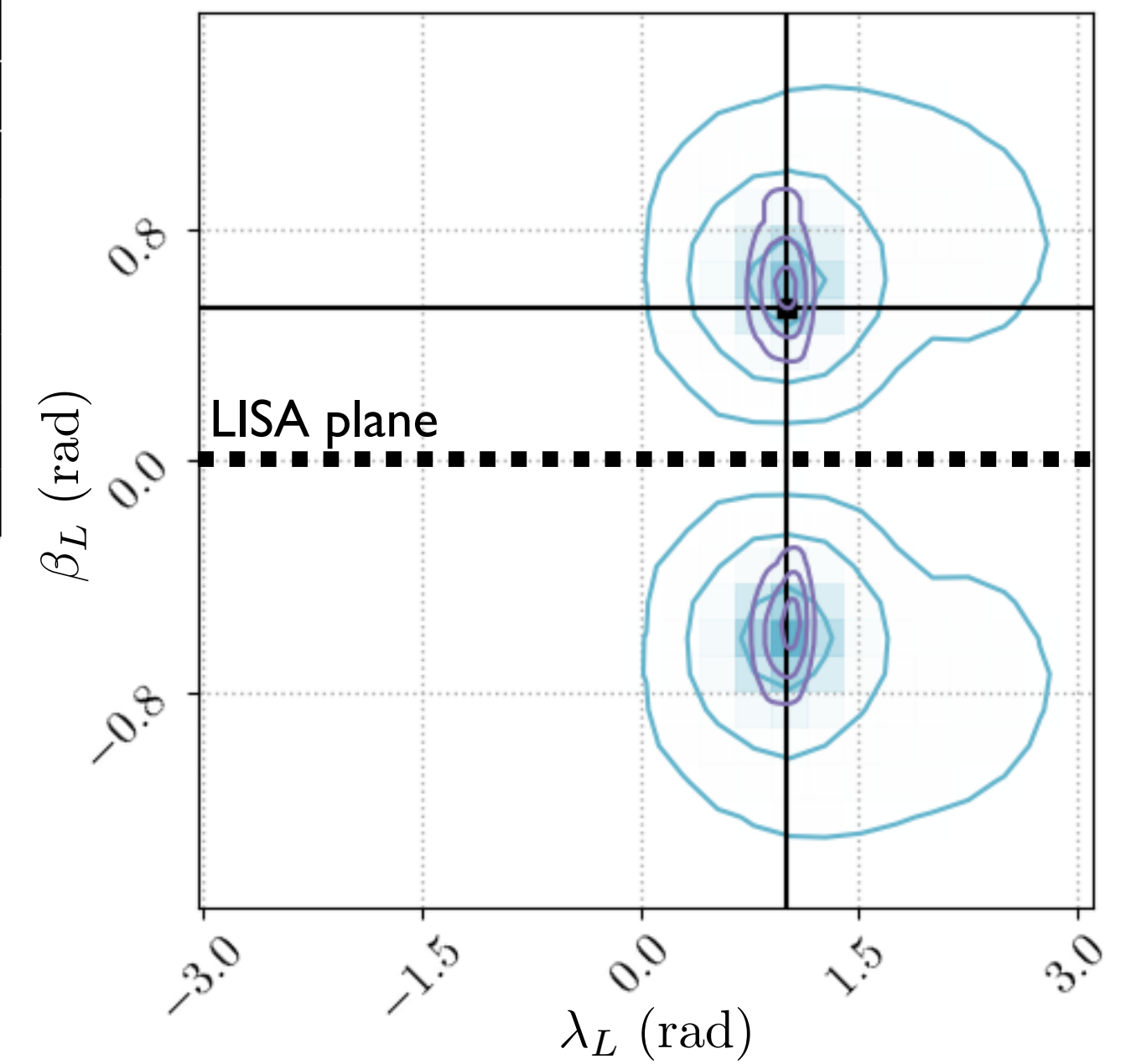
- **Injection:** NRHybSur3dq8  $\{M = 10^6 M_\odot, q = 4, \chi_1 = 0.5, \chi_2 = 0.3\}$
- **Template:** SEOBNRv5HM\_ROM

Intrinsic params.



$M_z = 10^6 M_\odot$	
$z$	SNR
1.0	1907
1.76	954
3.11	477
5.59	238
10.21	119
18.97	59

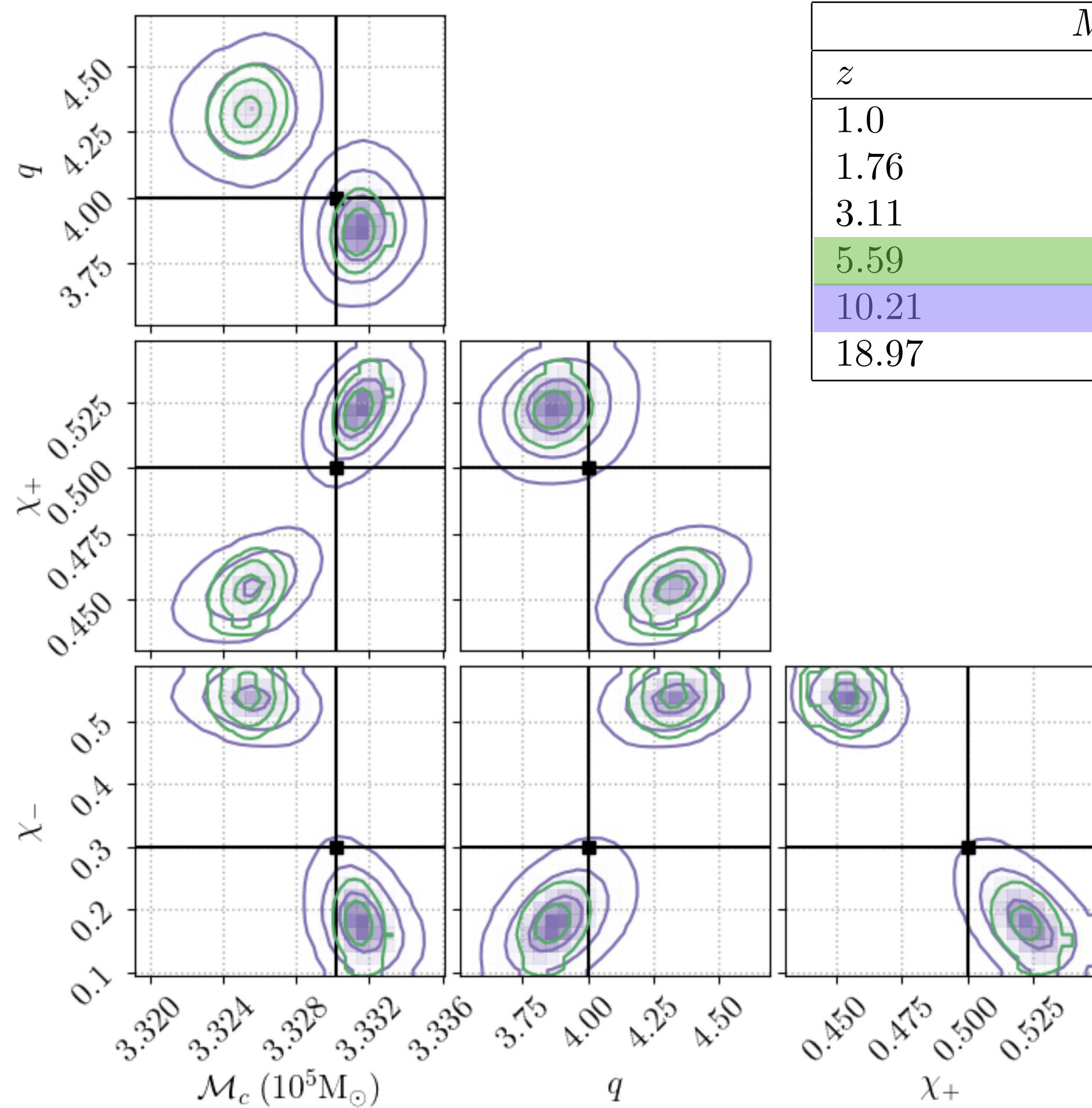
Sky localisation



# Example Parameter estimation with systematics III

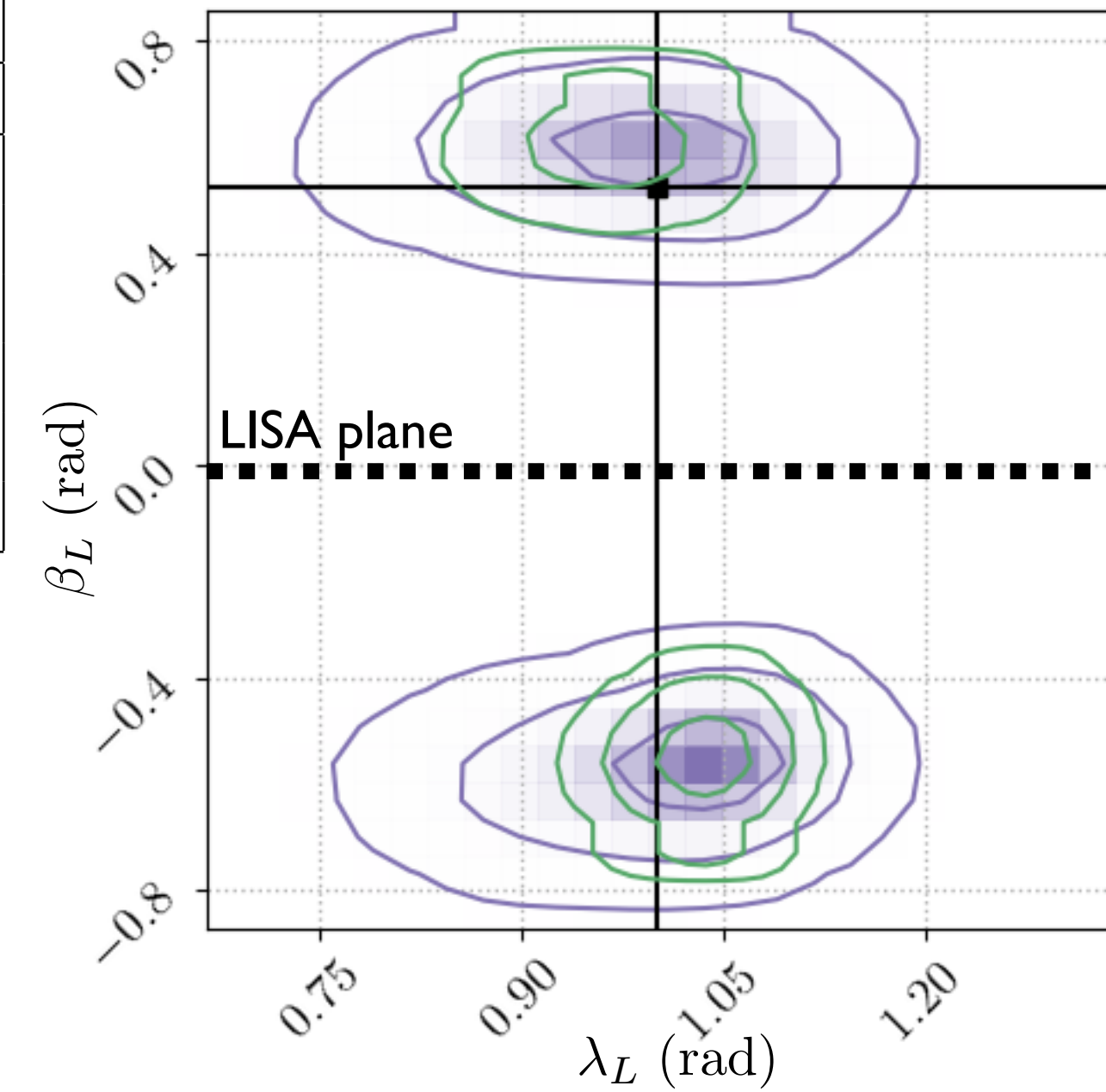
- **Injection:** NRHybSur3dq8  $\{M = 10^6 M_\odot, q = 4, \chi_1 = 0.5, \chi_2 = 0.3\}$
- **Template:** SEOBNRv5HM\_ROM

Intrinsic params.



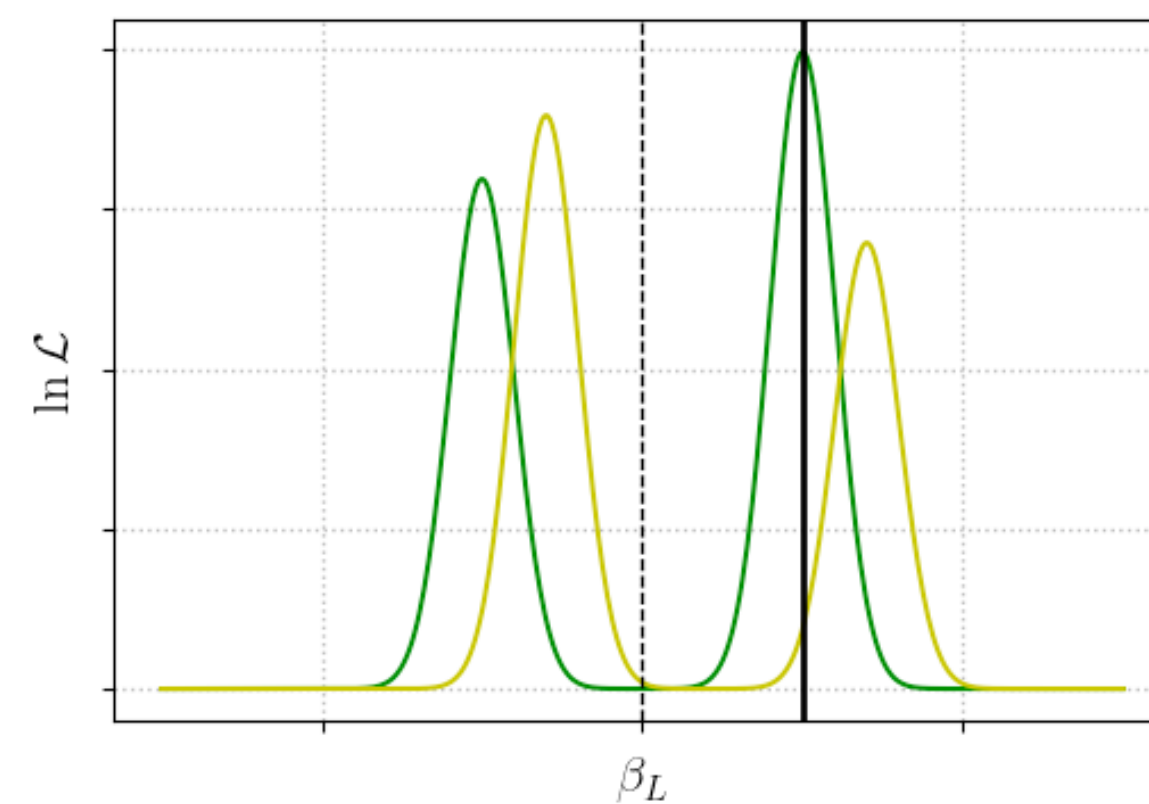
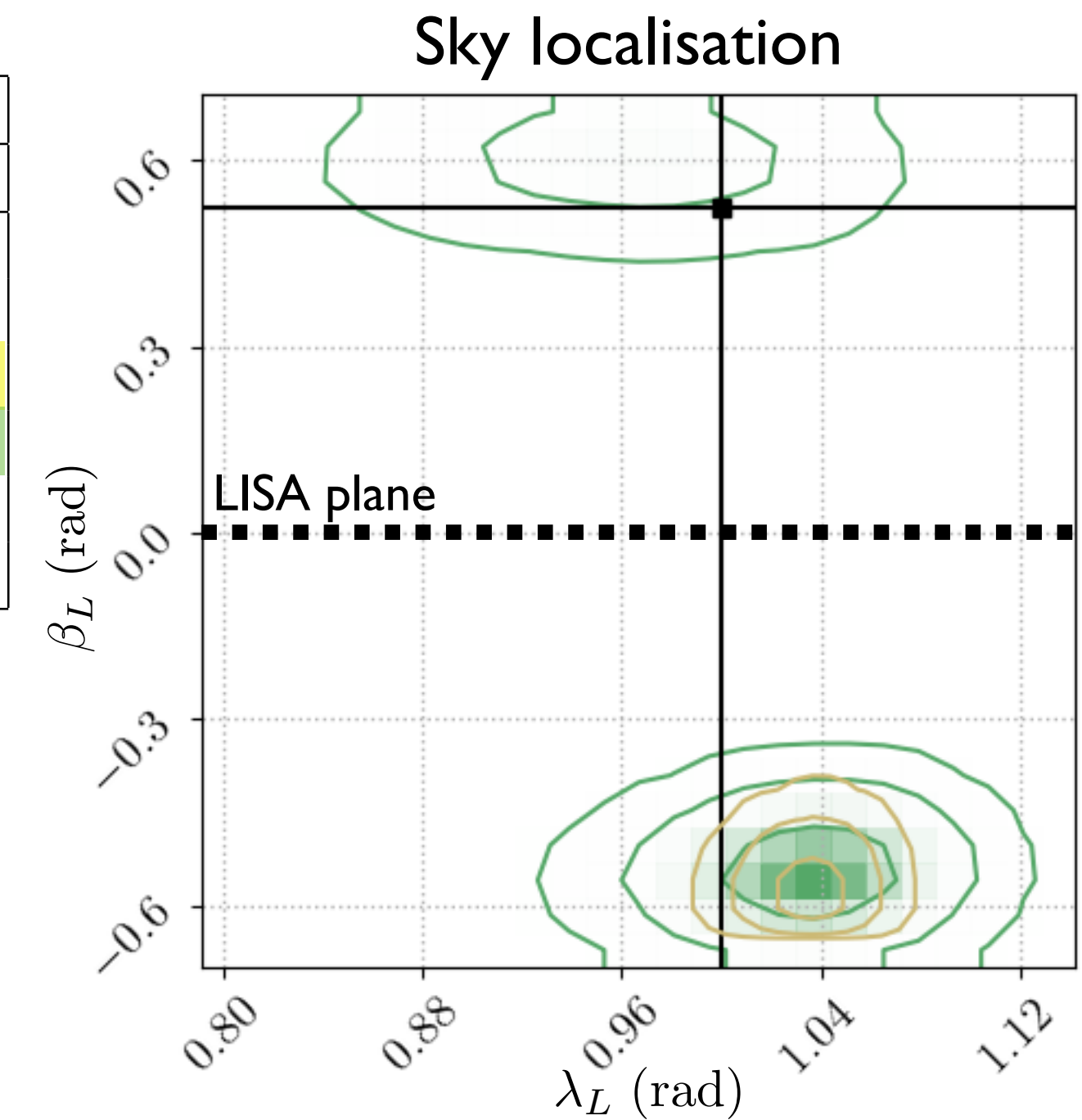
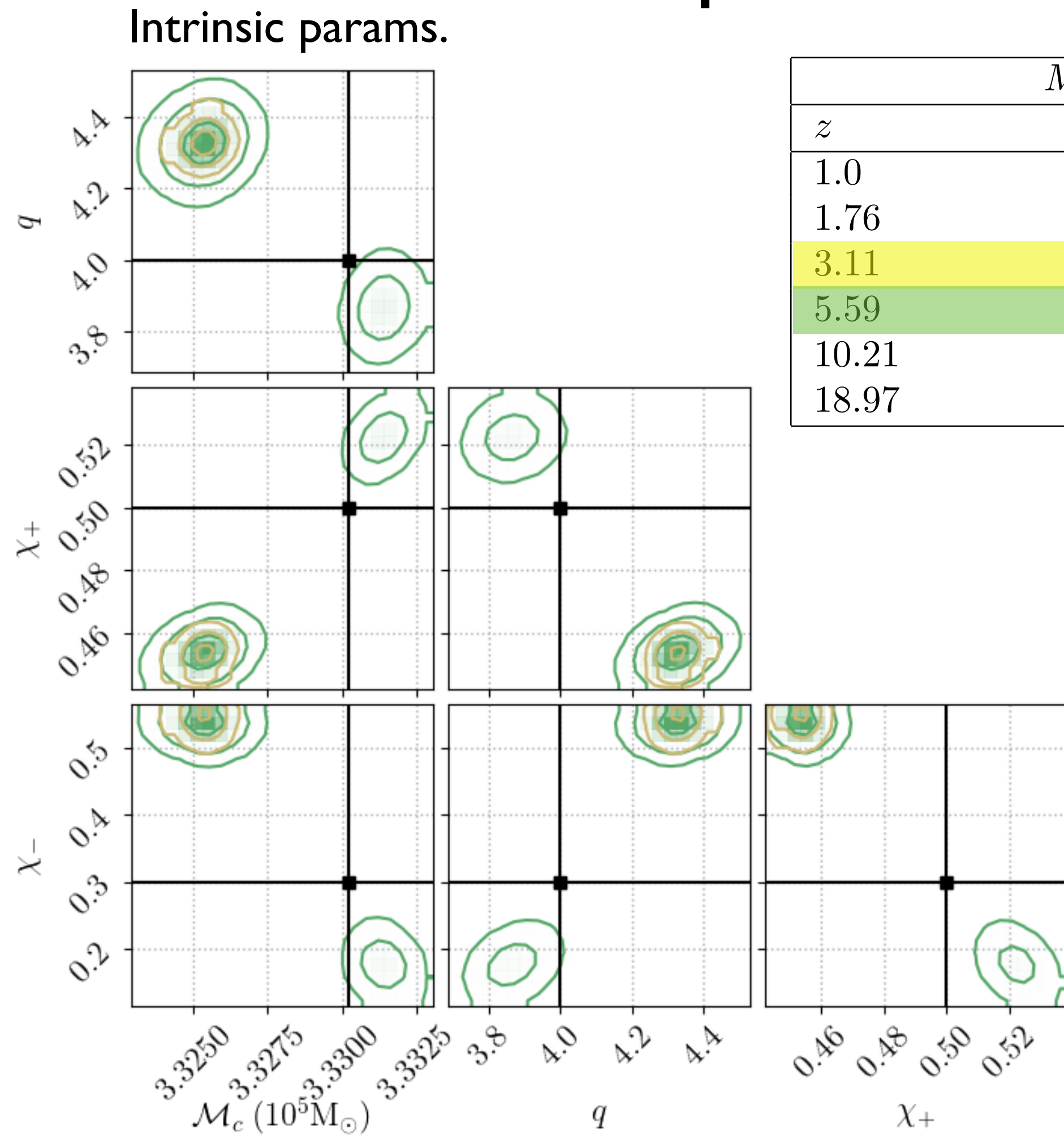
$M_z = 10^6 M_\odot$	
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1.0	1907
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Sky localisation



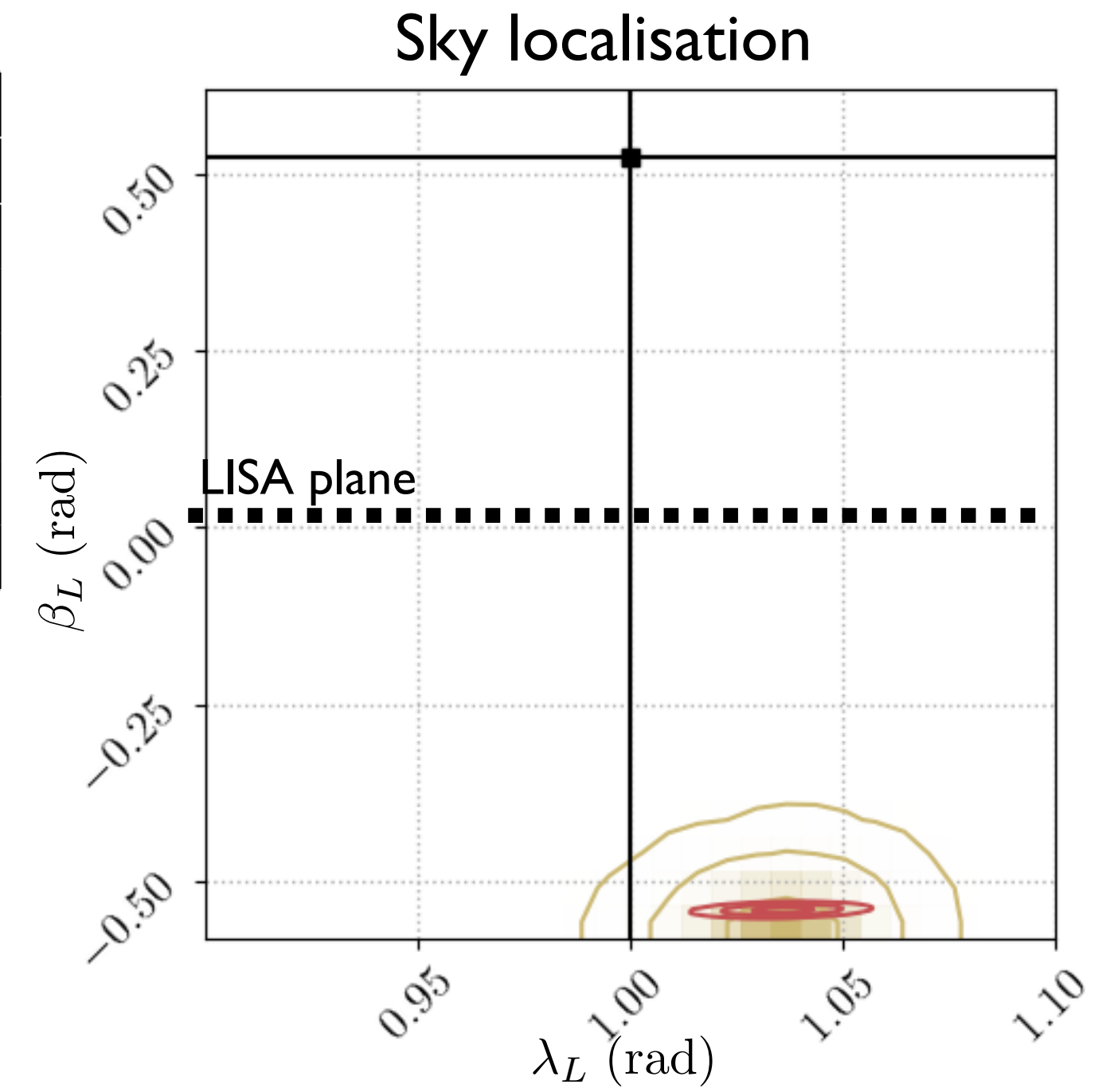
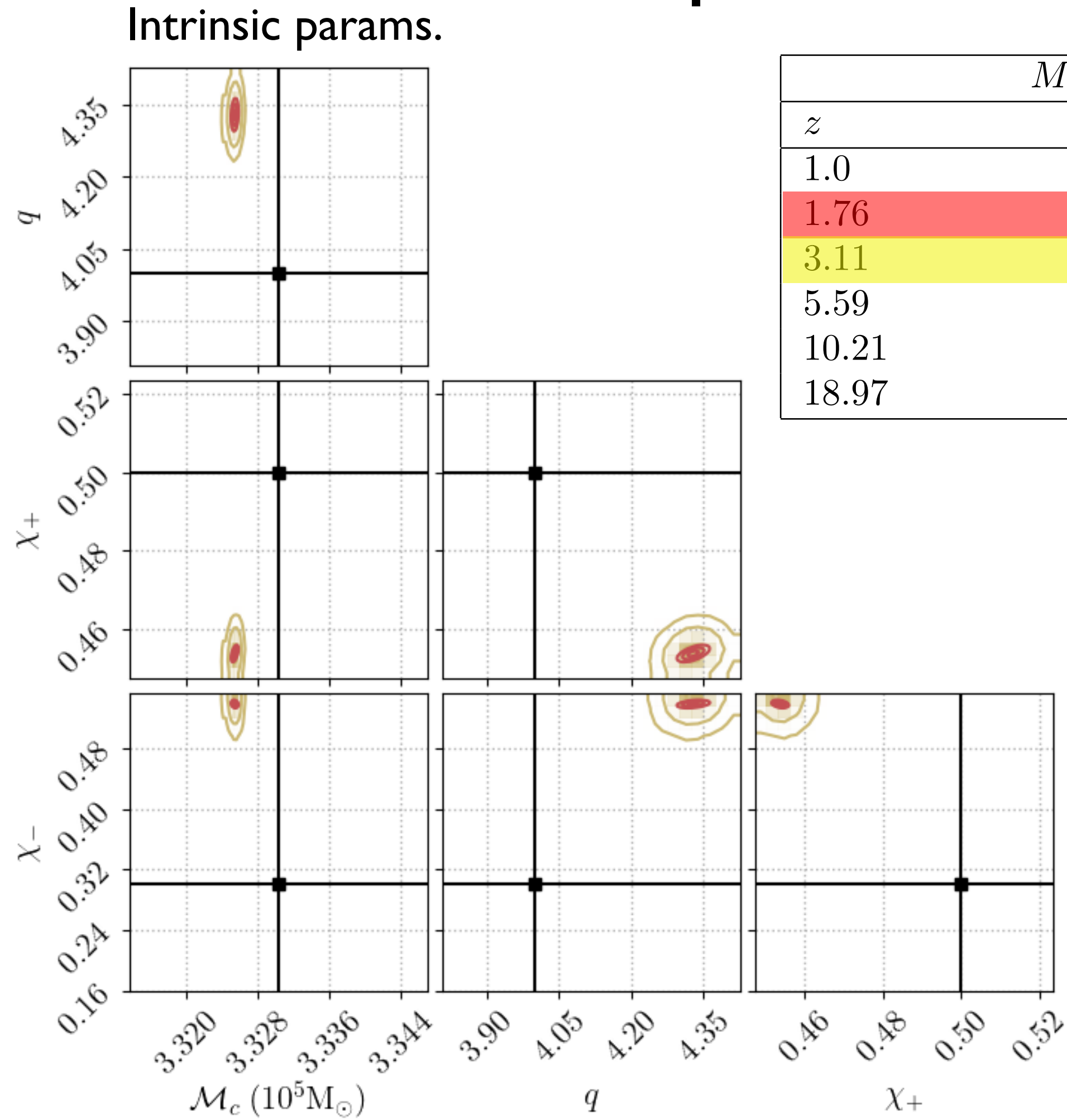
# Example Parameter estimation with systematics III

- **Injection:** NRHybSur3dq8  $\{M = 10^6 M_\odot, q = 4, \chi_1 = 0.5, \chi_2 = 0.3\}$
- **Template:** SEOBNRv5HM\_ROM



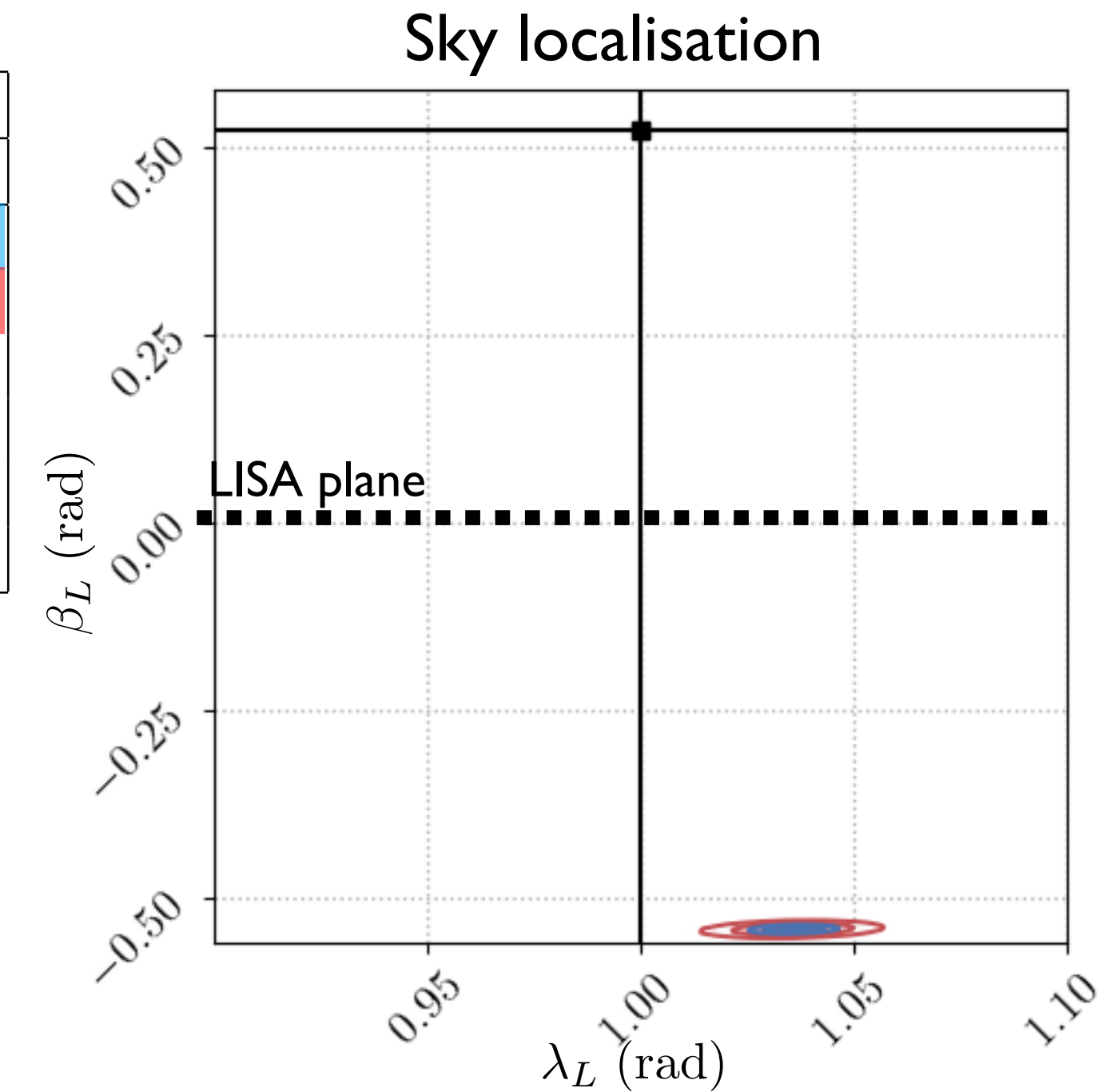
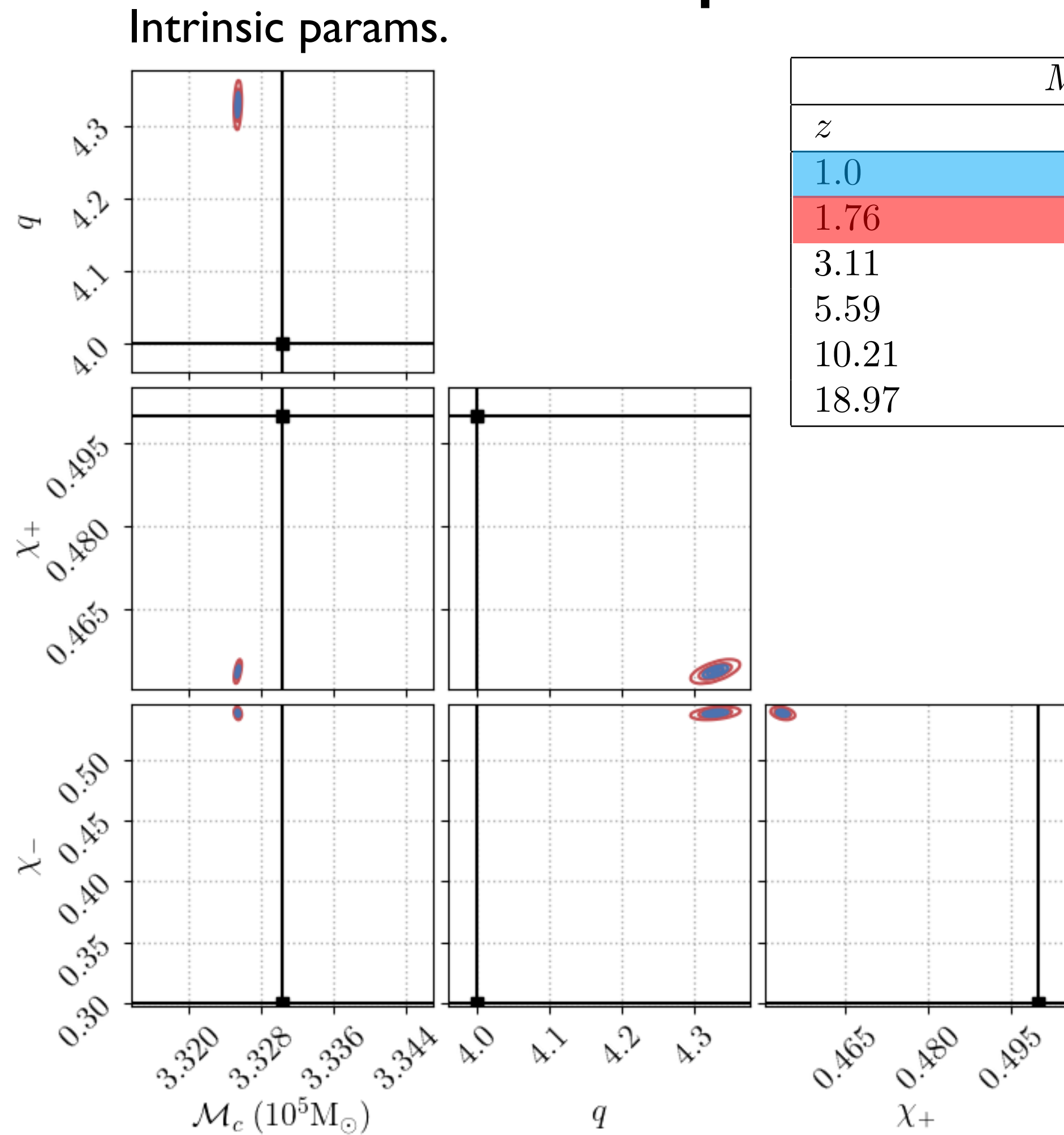
# Example Parameter estimation with systematics III

- **Injection:** NRHybSur3dq8  $\{M = 10^6 M_\odot, q = 4, \chi_1 = 0.5, \chi_2 = 0.3\}$
- **Template:** SEOBNRv5HM\_ROM



# Example Parameter estimation with systematics III

- **Injection:** NRHybSur3dq8  $\{M = 10^6 M_\odot, q = 4, \chi_1 = 0.5, \chi_2 = 0.3\}$
- **Template:** SEOBNRv5HM\_ROM

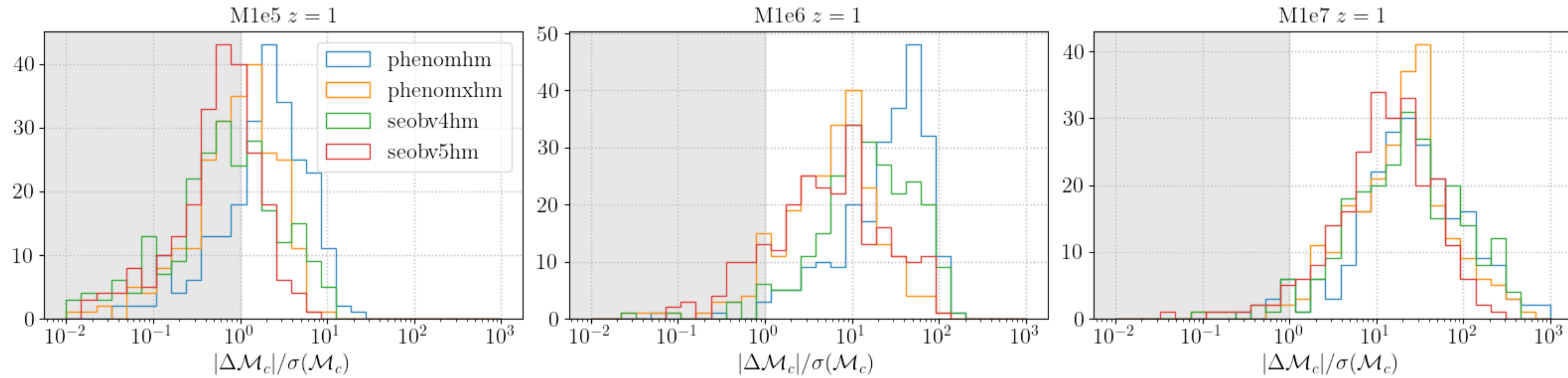


### The ugly:

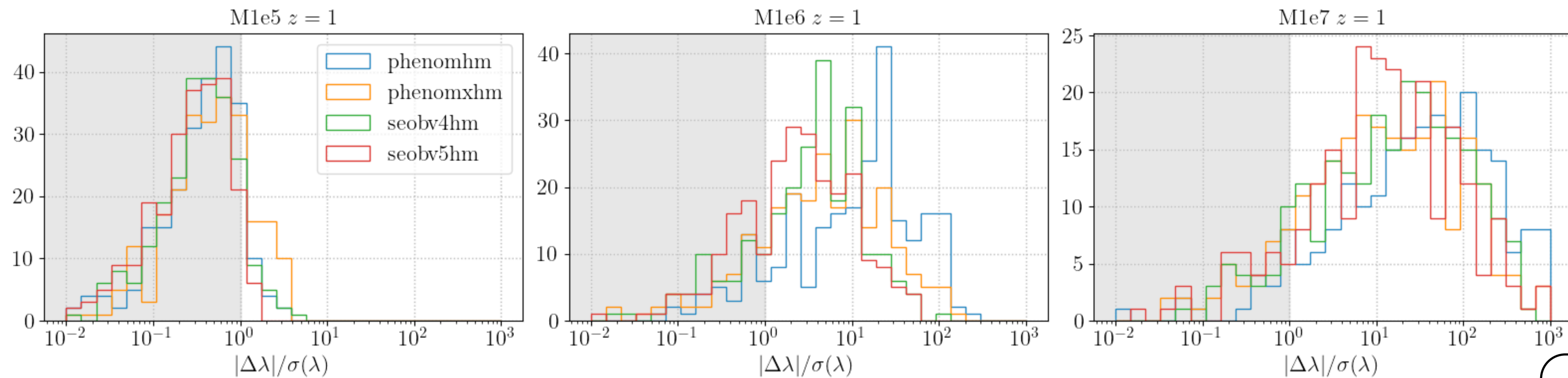
- converges to the **wrong sky mode**
- important bias at  $z = 1$ , SNR = 1907

# Statistical significance of biases

## Bias in chirp mass:



## Bias in longitude (on corrected skymode):

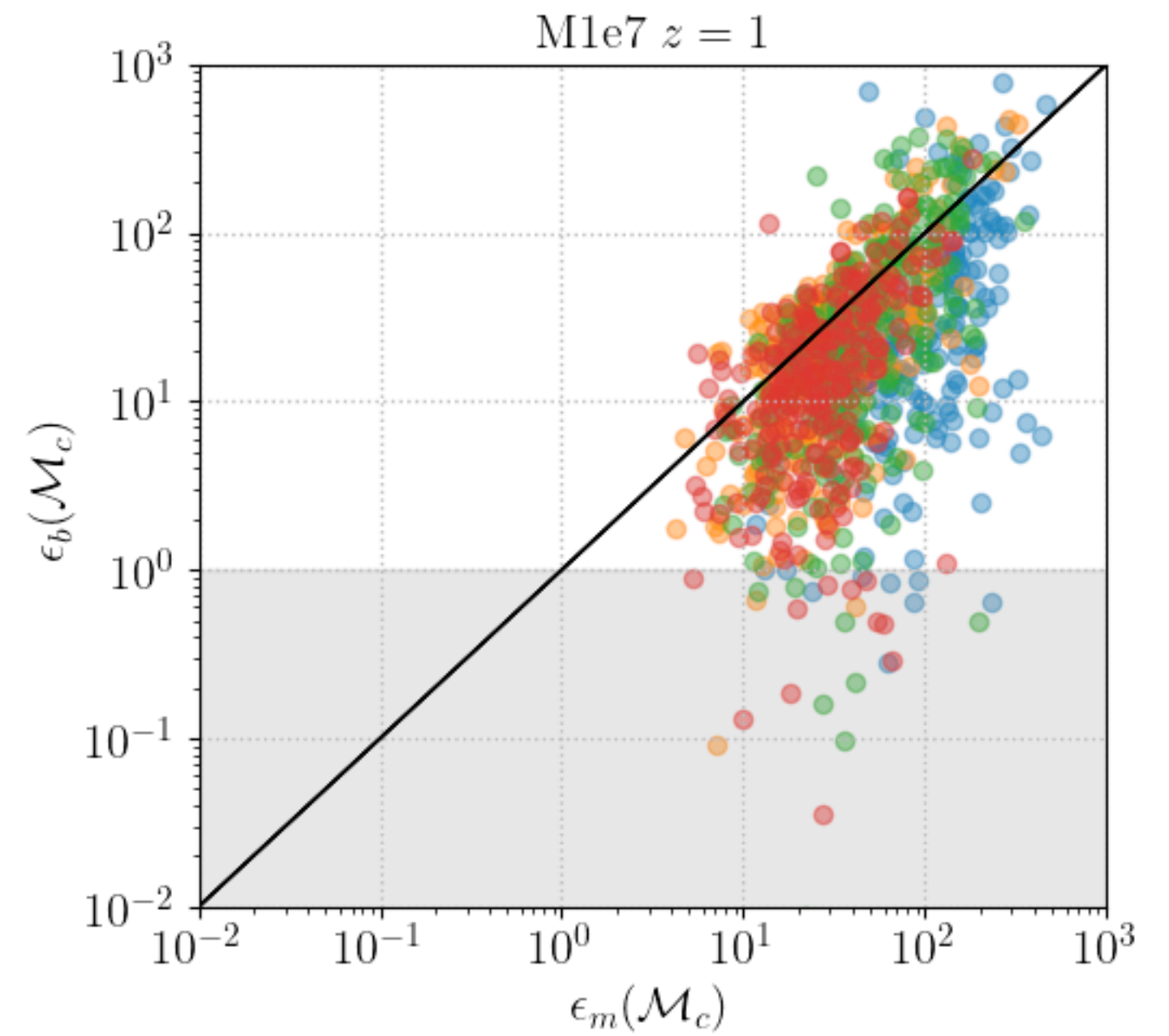
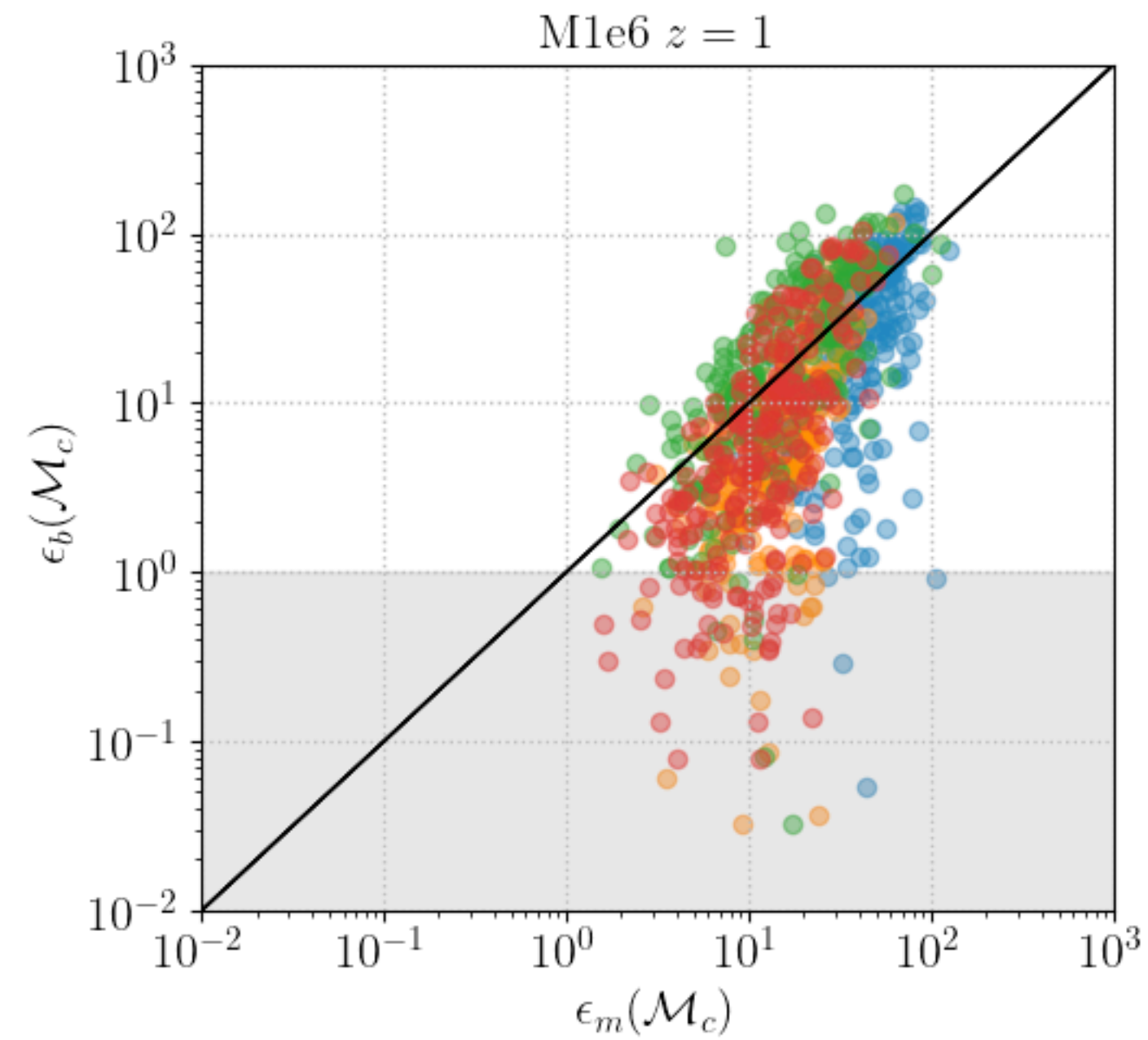
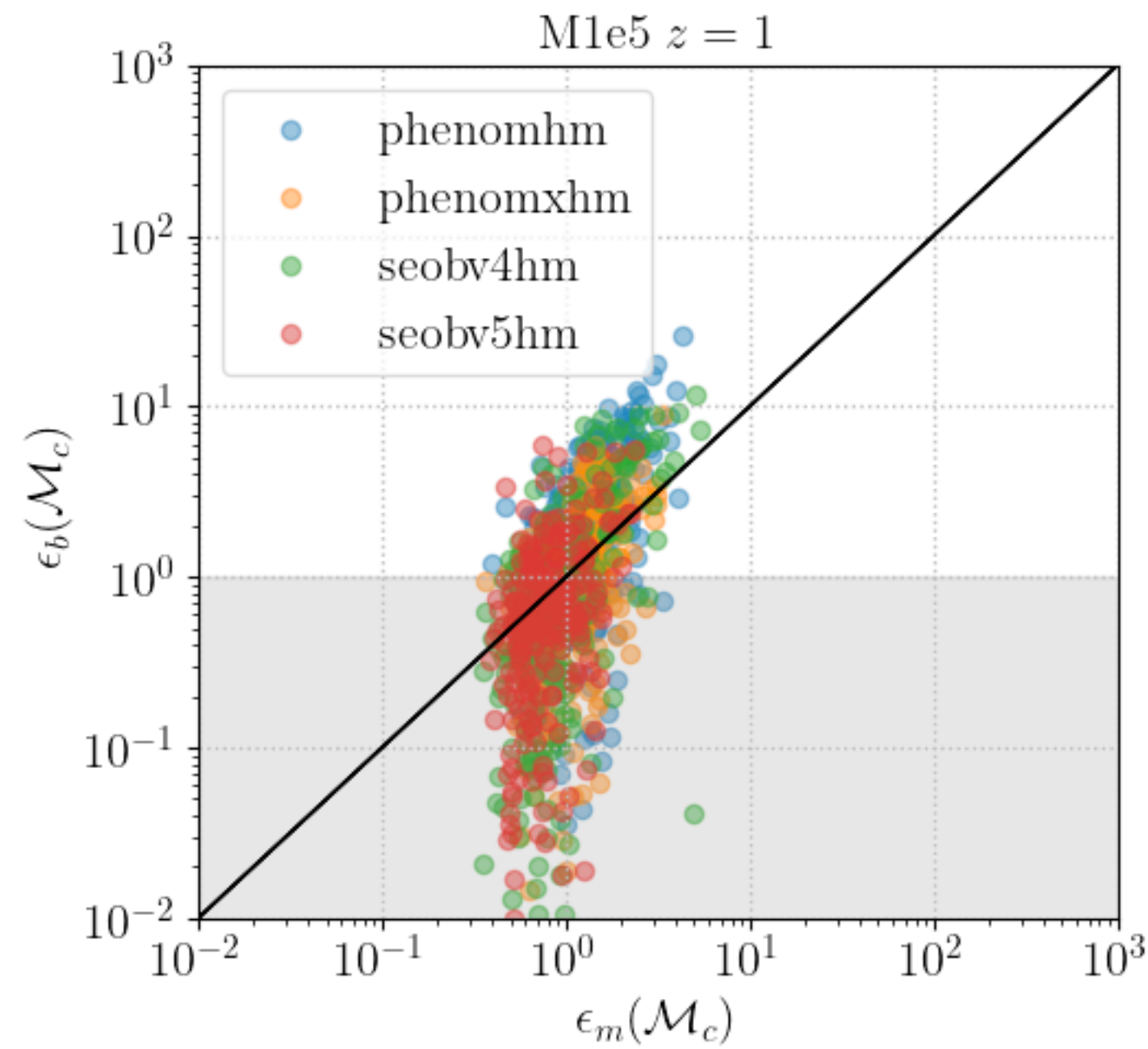


## Wrong skymode recovered:

phenomxhm	
$M_z (M_\odot)$	% wrong
$10^5$	0 %
$10^6$	10 %
$10^7$	54 %

Large biases at high mass  
Wrong skymodes common

# Linking mismatches and biases



From indistinguishability criterion:

$$\text{MM} < \frac{D}{2} \frac{1}{\text{SNR}^2}$$

$$\epsilon_m = \sqrt{\frac{2}{D} \text{SNR}^2 \text{MM}}$$

$\epsilon_m > 1$  means that the mismatch is large enough to indicate a significant bias

From bias measured in PE:

$$\epsilon_b = \frac{\Delta\theta}{\sigma(\theta)}$$

$\epsilon_b > 1$  indicates means that PE measures a significant bias

Both  $\epsilon_b, \epsilon_m \propto \text{SNR}$

Relation between mismatch and bias not straightforward

# Complement: NR vs NR surrogate

## Injections:

NR from SXS catalog

[SXS 2025]

- SXS NR simulations hybridized with long EOB inspirals (covers  $\sim 6$  months for  $M = 10^5 M_\odot$ )
- Surrogate interpolant, time-domain

## Templates:

NRHybSur3dq8

[Varma&al 2018]

- SXS NR simulations hybridized with long EOB inspirals (covers  $\sim 6$  months for  $M = 10^5 M_\odot$ )
- Surrogate interpolant, time-domain

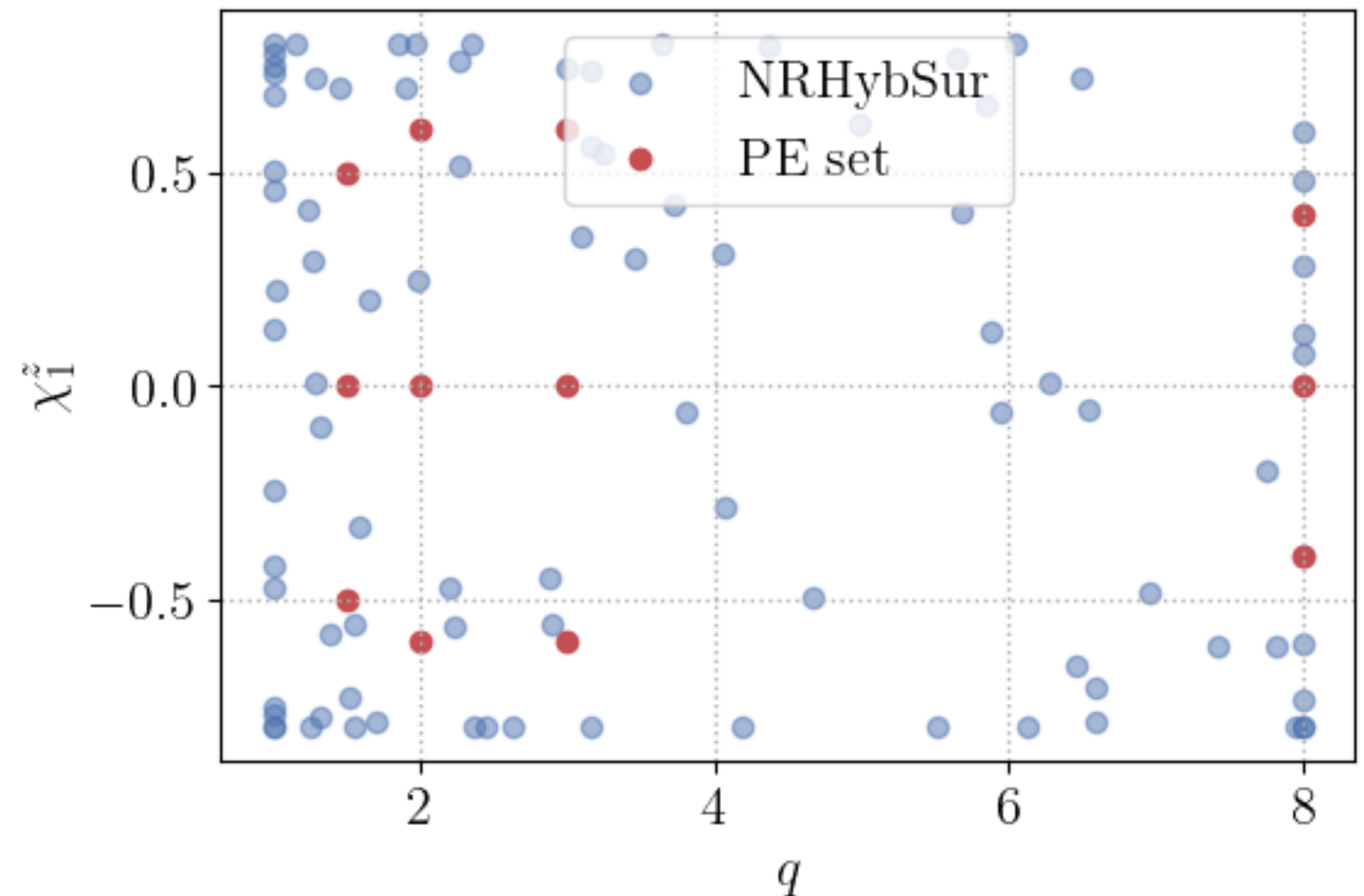
Mode content for all: 22, 21, 33, 44

Time-domain LISA response

Limitations:

- aligned spins only
- $M=1e7$  only, 2 days of signal

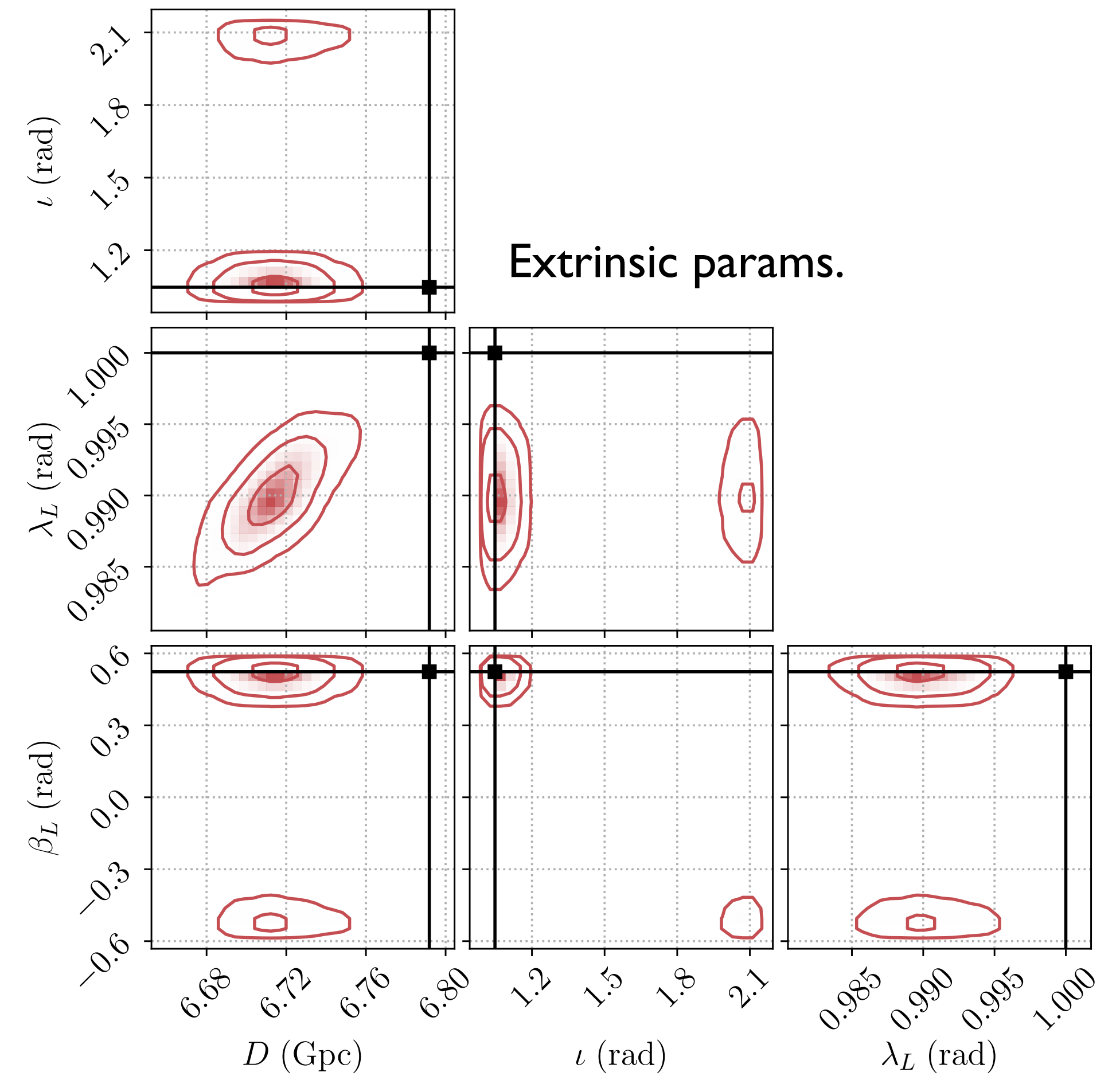
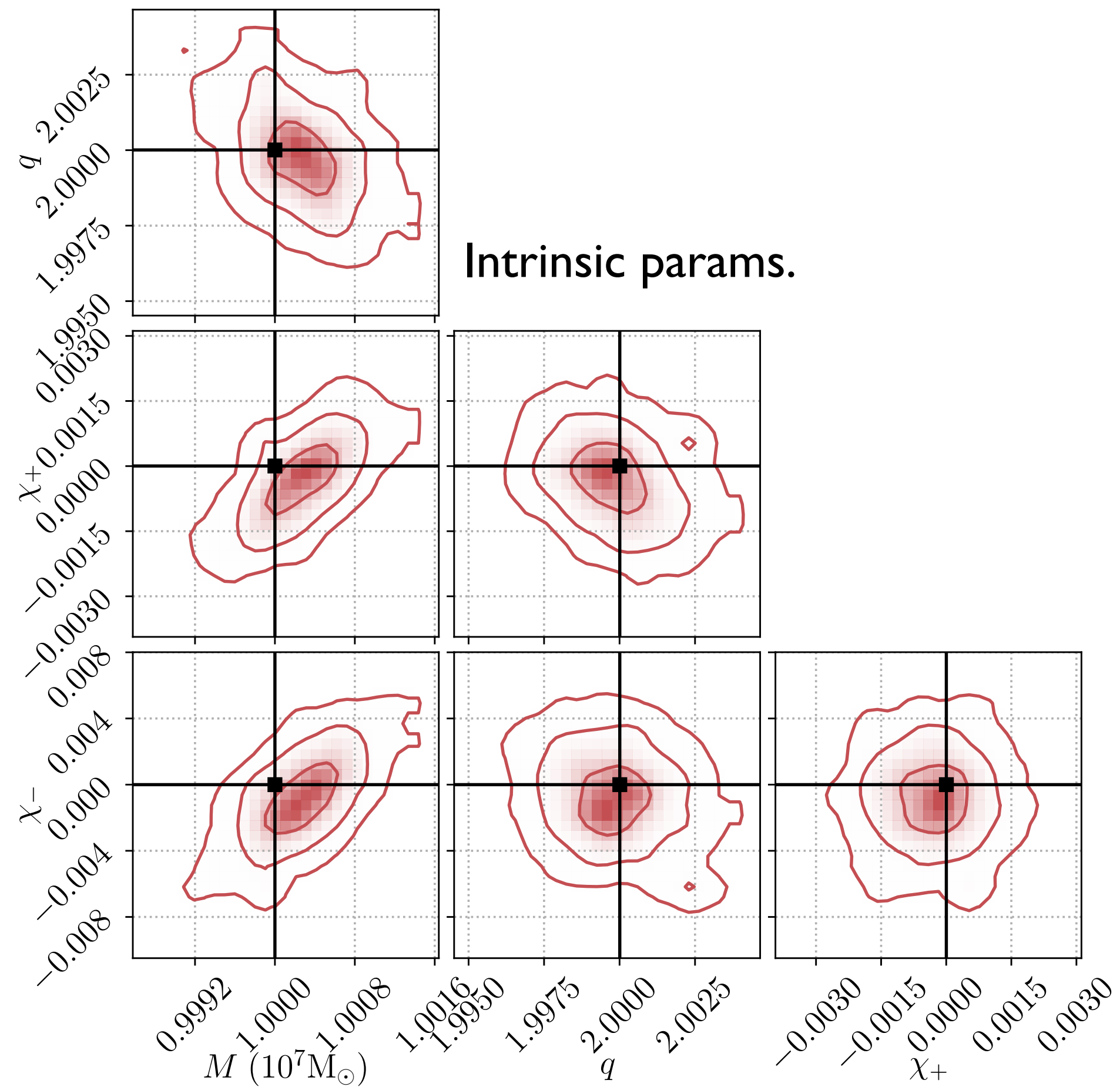
[Preliminary]



# Complement: NR vs NR surrogate

SXS:BBH:2497

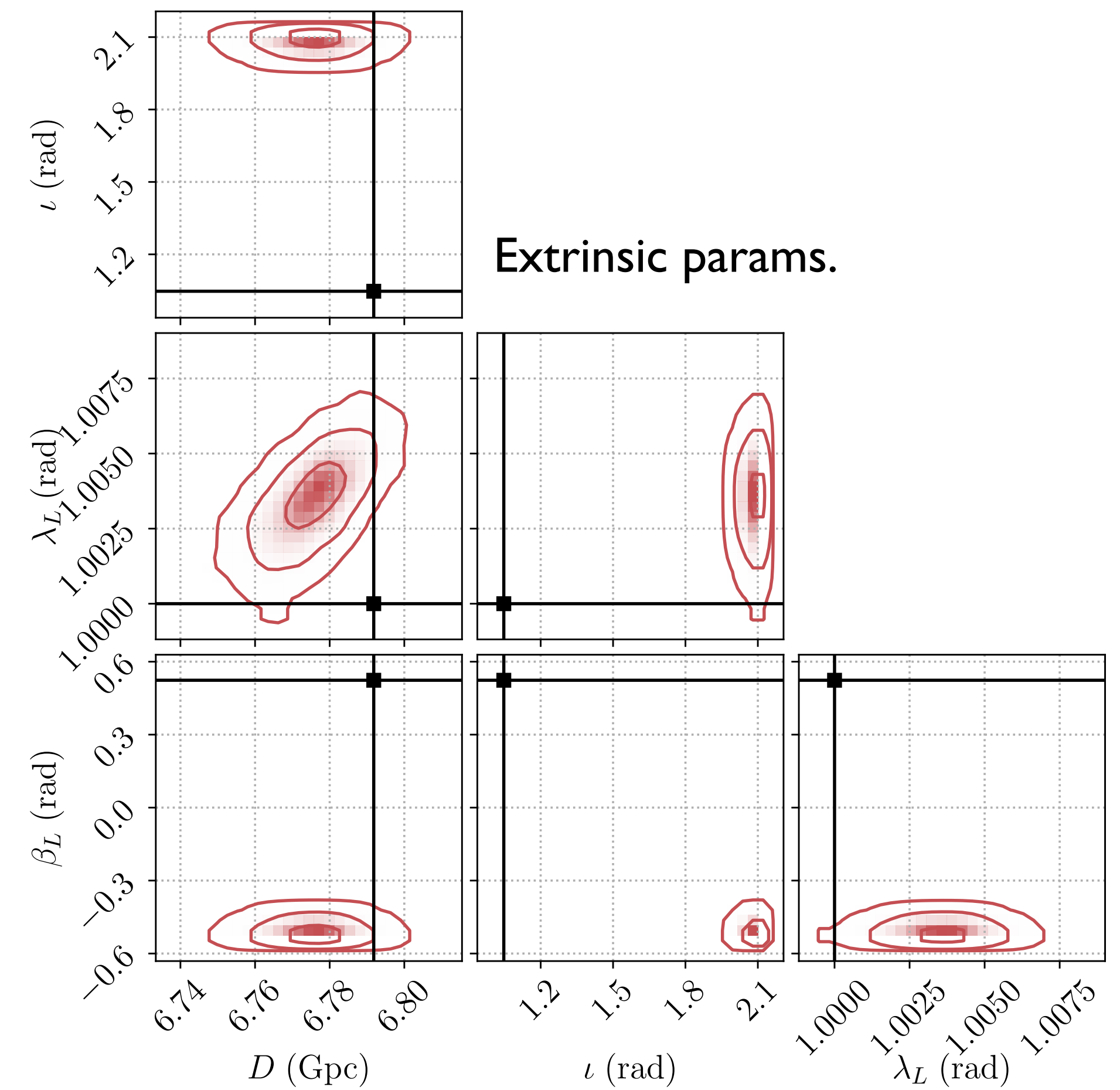
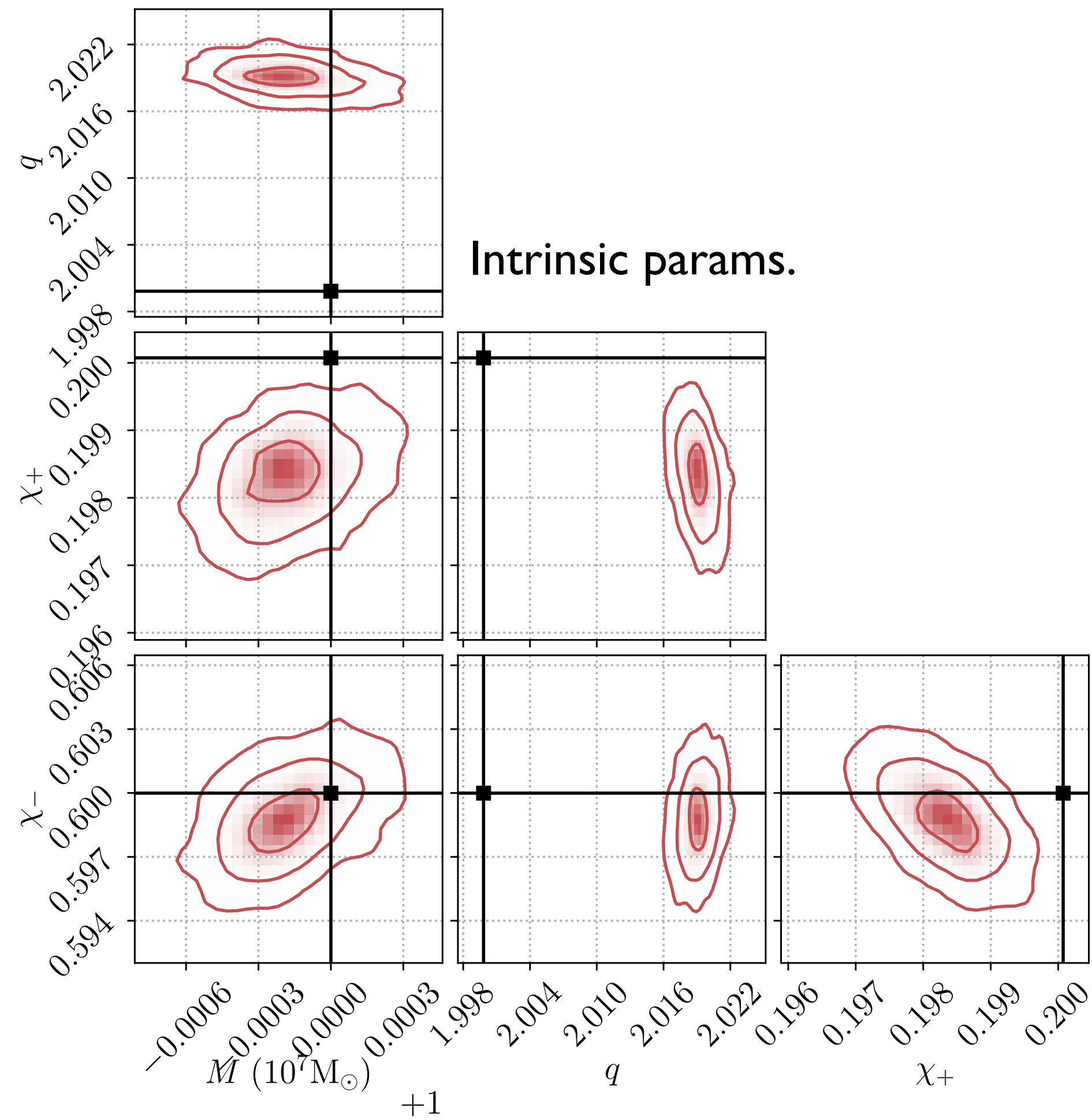
$$M = 10^7 M_{\odot}, q = 2, \chi_1 = 0, \chi_2 = 0, z = 1$$



# Complement: NR vs NR surrogate

SXS:BBH:2128

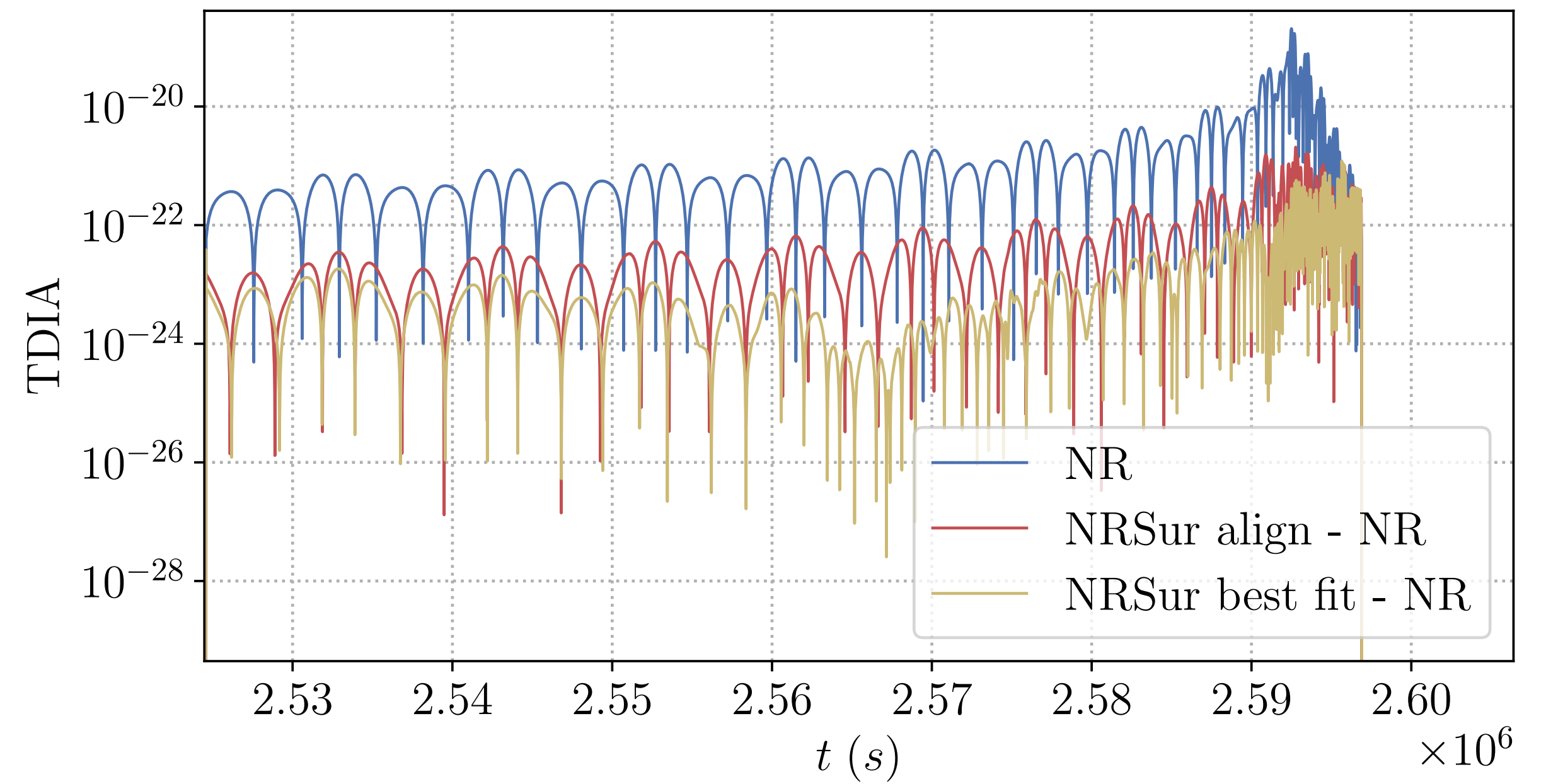
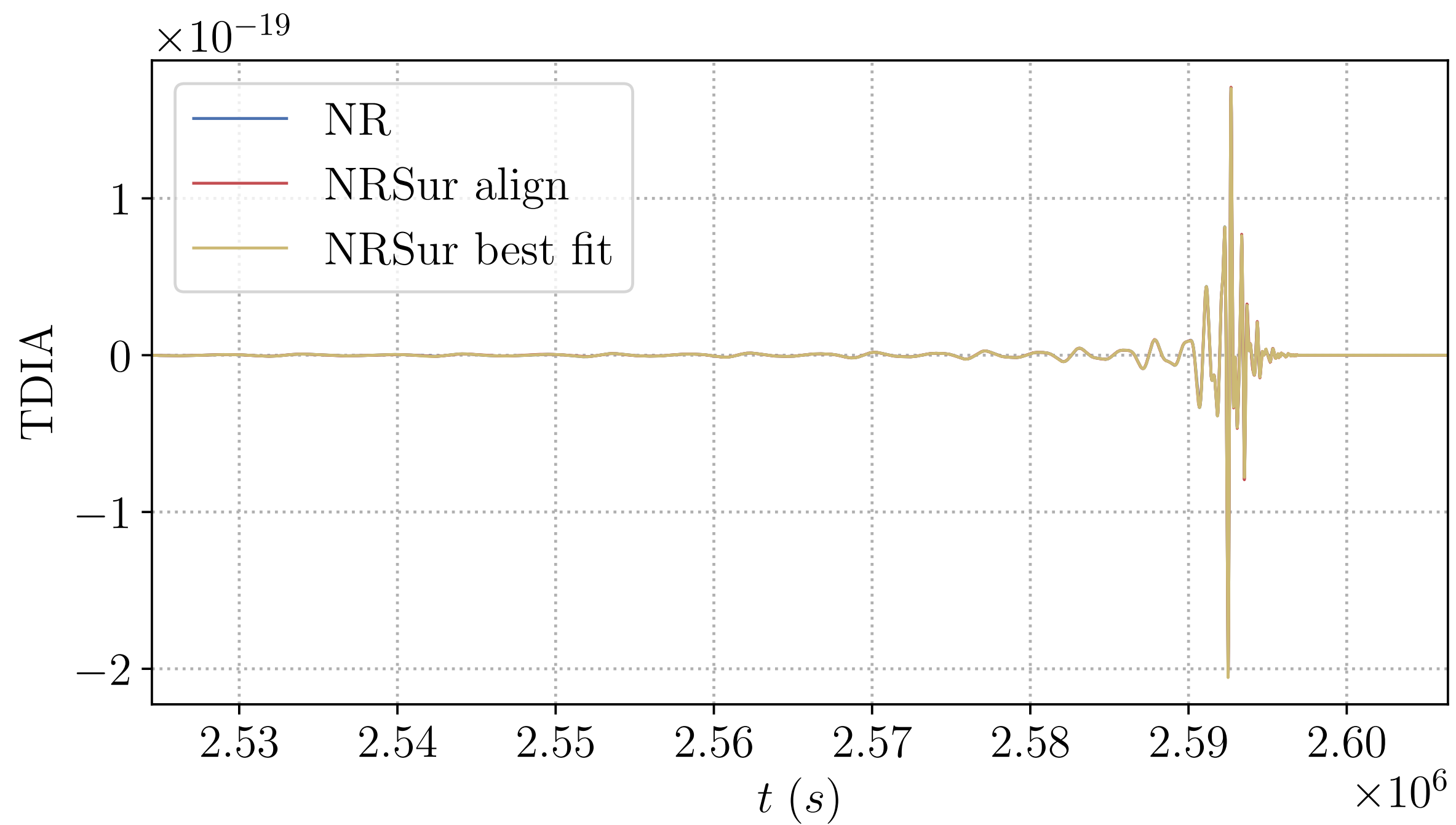
$M = 10^7 M_\odot$ ,  $q = 2$ ,  $\chi_1 = 0.6$ ,  $\chi_2 = -0.6$ ,  $z = 1$



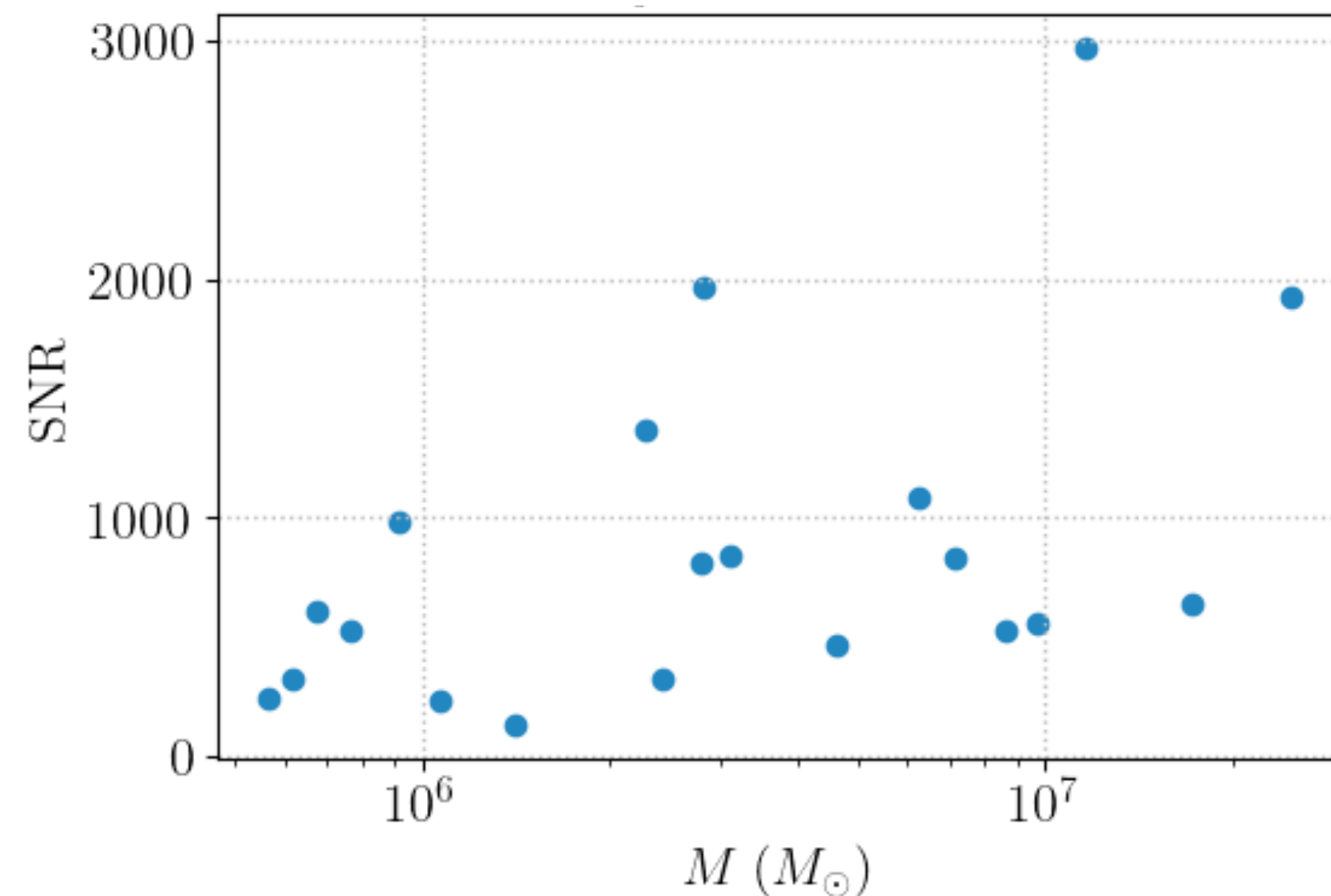
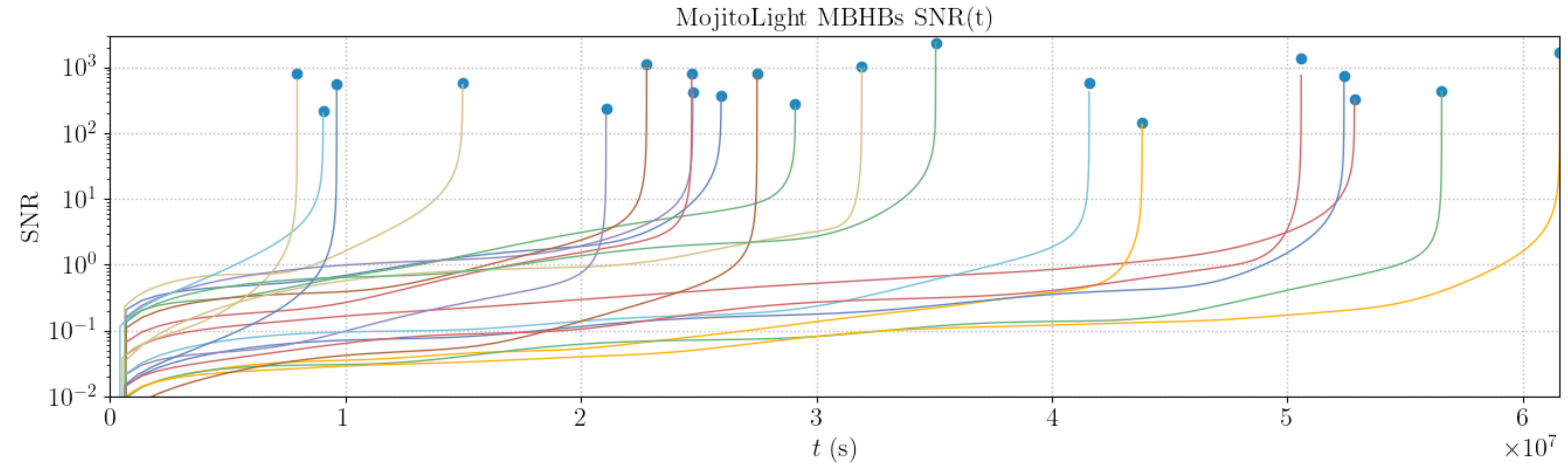
# Complement: NR vs NR surrogate

SXS:BBH:2160

$M = 10^7 M_{\odot}$ ,  $q = 3$ ,  $\chi_1 = 0.6$ ,  $\chi_2 = -0.4$ ,  $z = 1$



# MojitoLight MBHBs: a first look



## MojitoLight sources

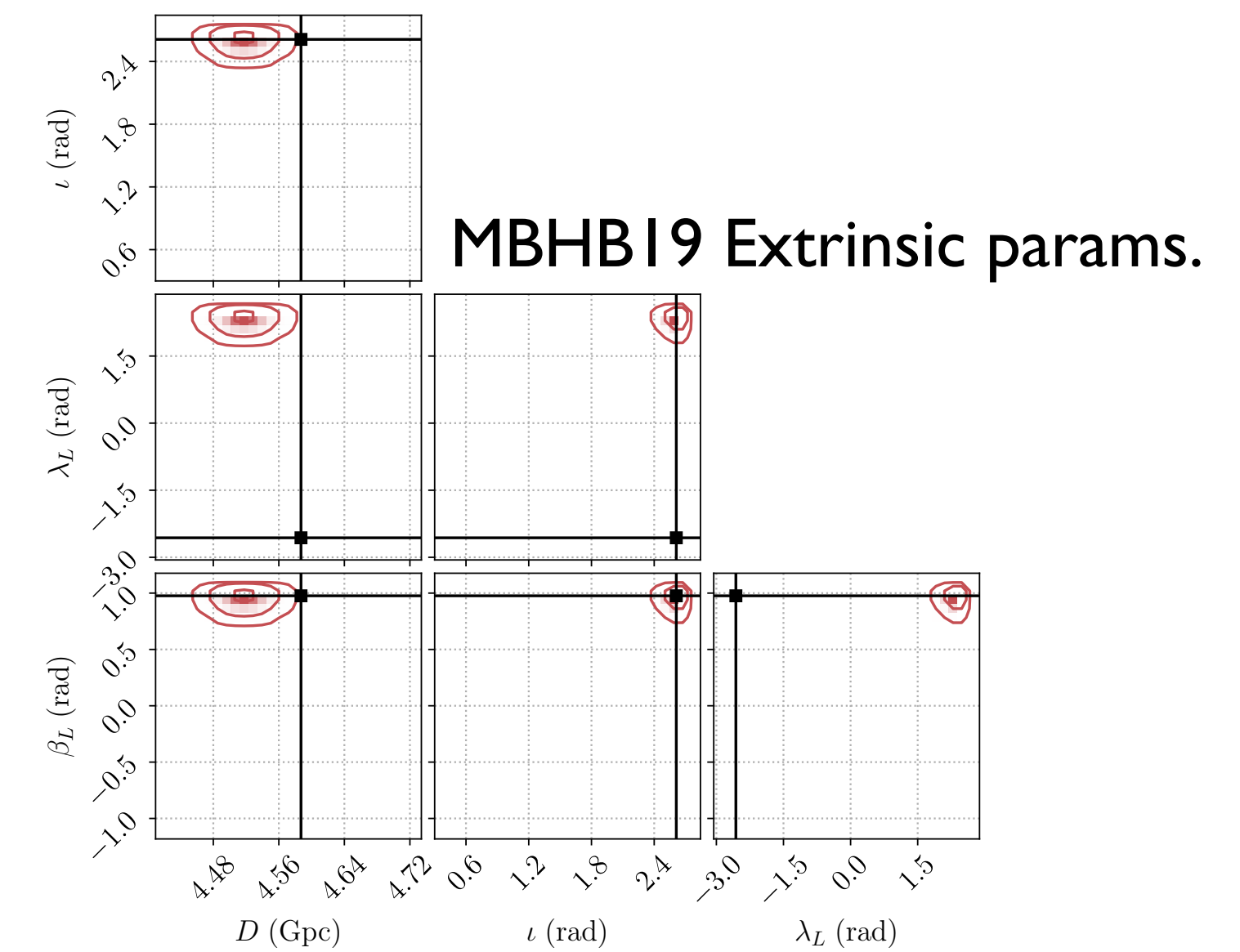
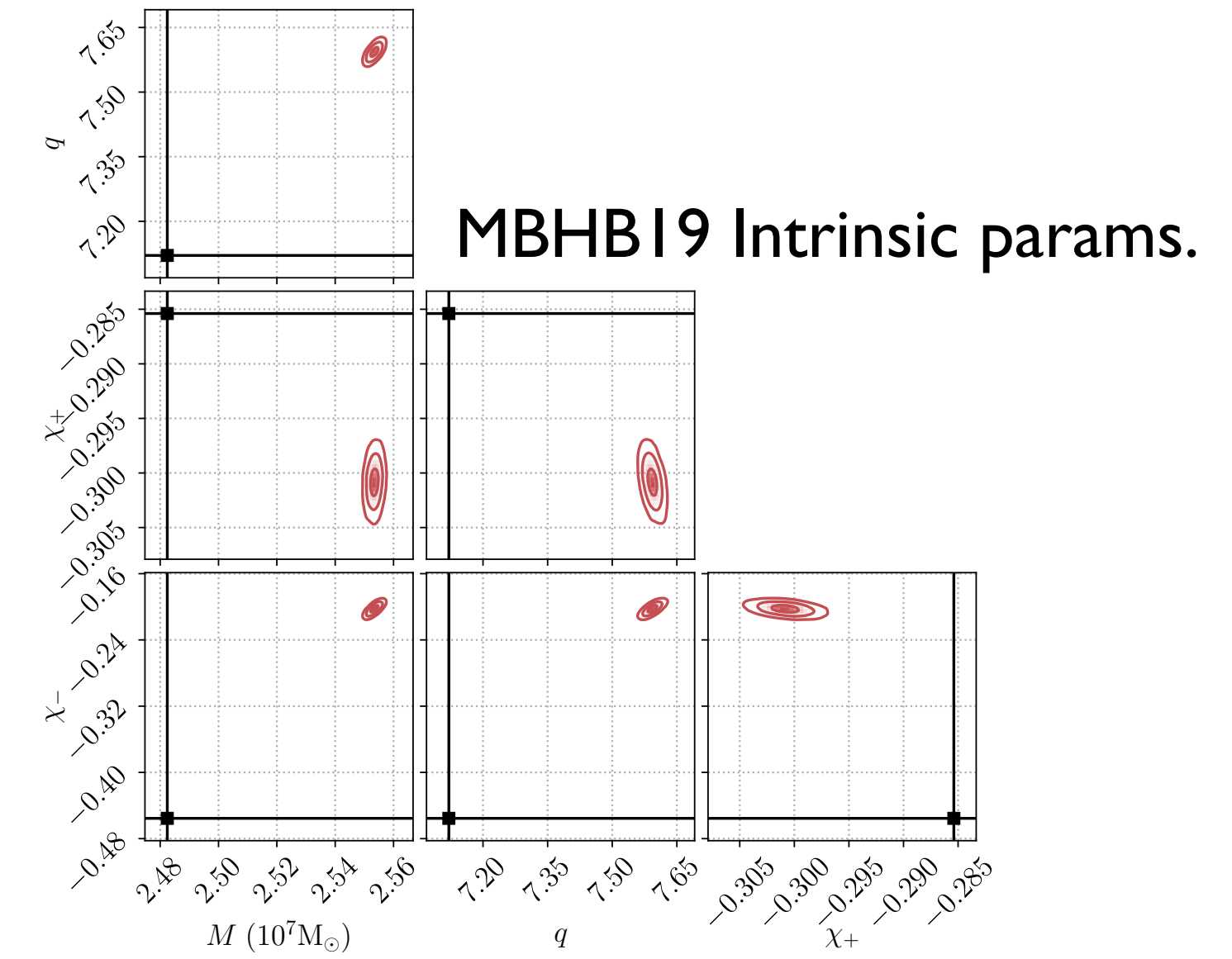
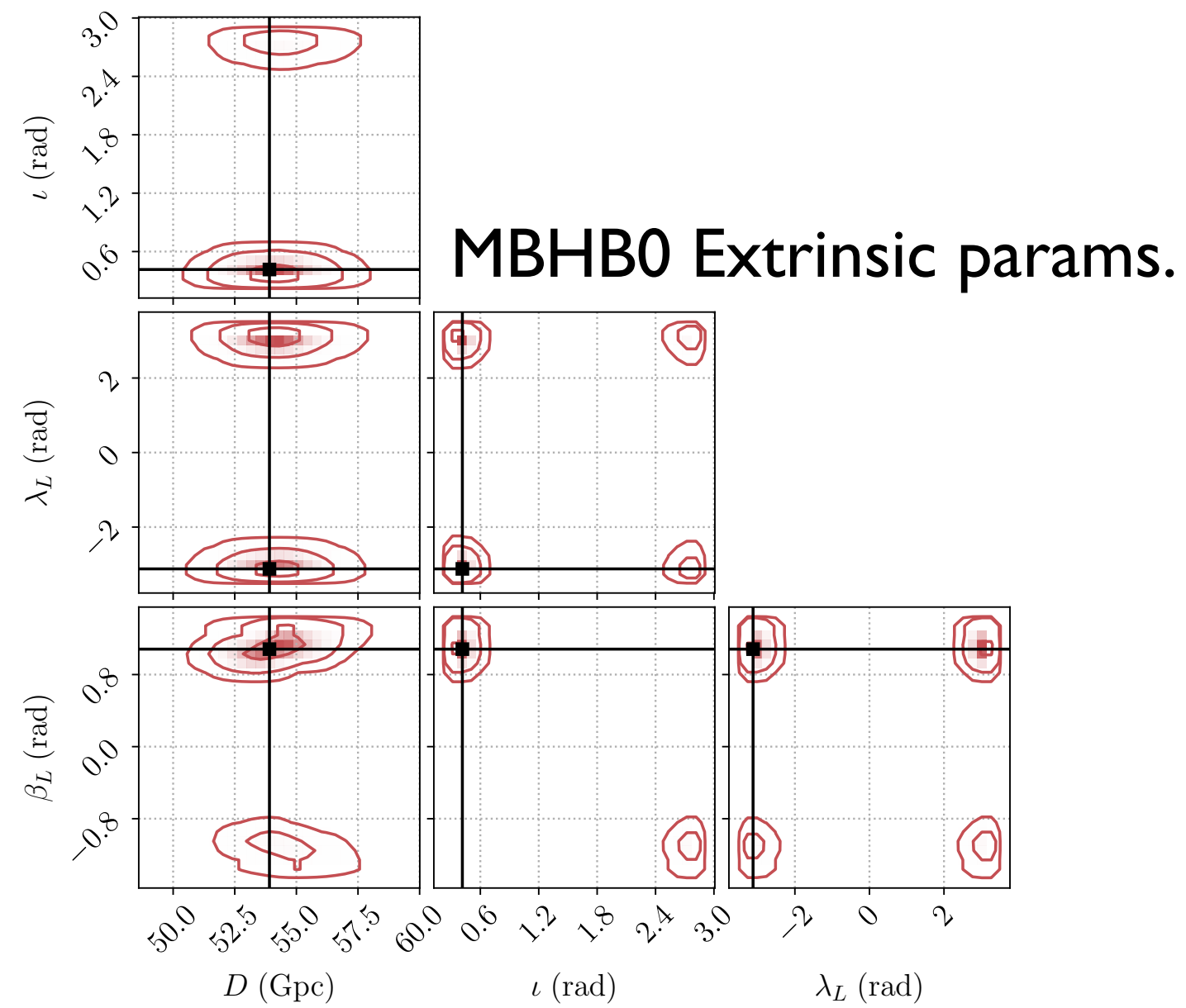
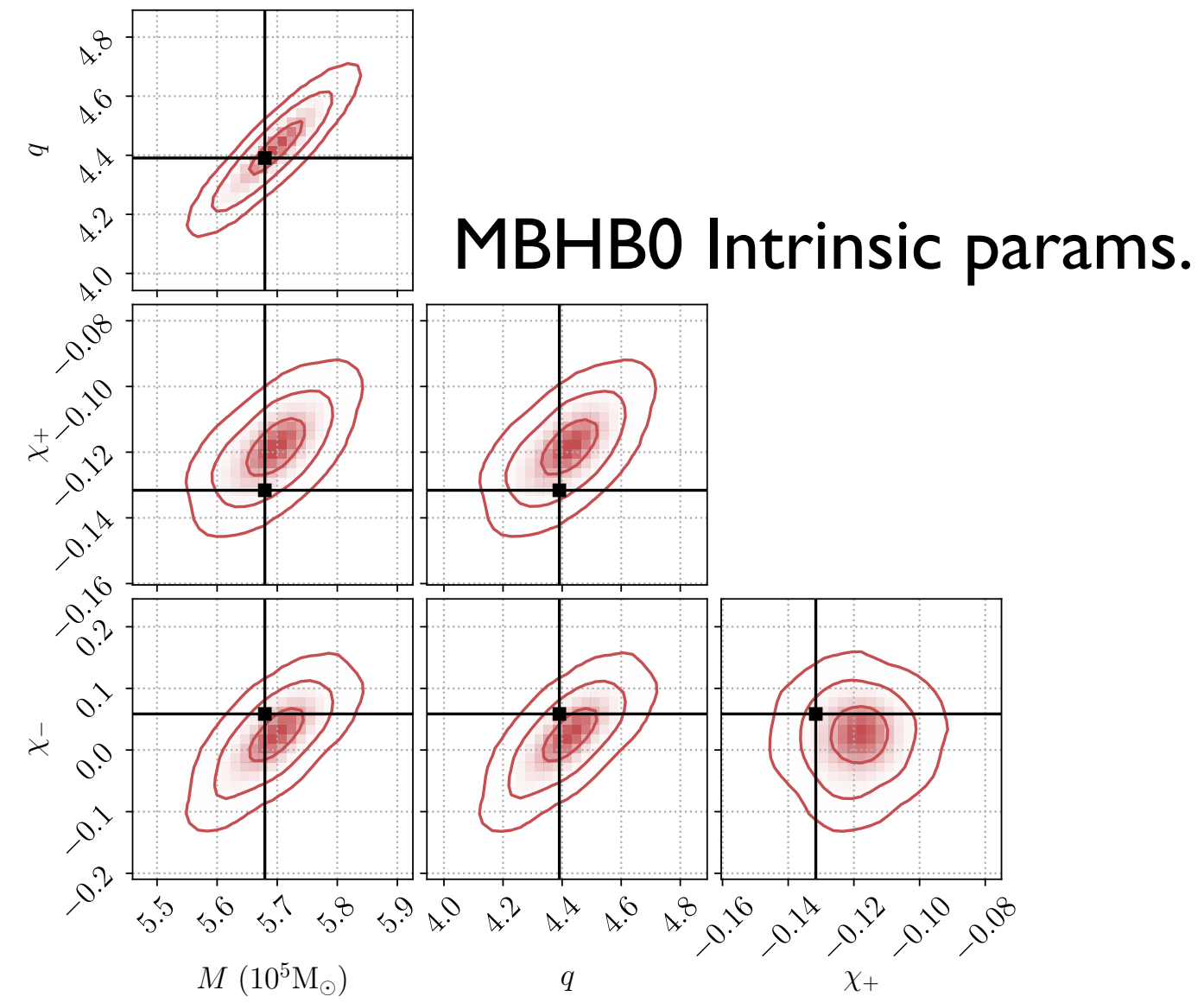
- 20 MBHBs ranging from  $M \sim 5 \cdot 10^5 M_{\odot}$  to  $M \sim 2 \cdot 10^7 M_{\odot}$
- Reaching SNR=10 from <1 day to ~1 month before merger (highest mass happens to be long !)
- Longer signals if looking back in time to SNR=1 threshold
- IMRPhenomTHM waveform model

## Analysis

- IMRPhenomXHM templates
- FD response vs TD response, both for equal-armlength orbits

**[Preliminary]**

# MojitoLight MBHBs: a first look



# MBHB biases caused by missing higher harmonics

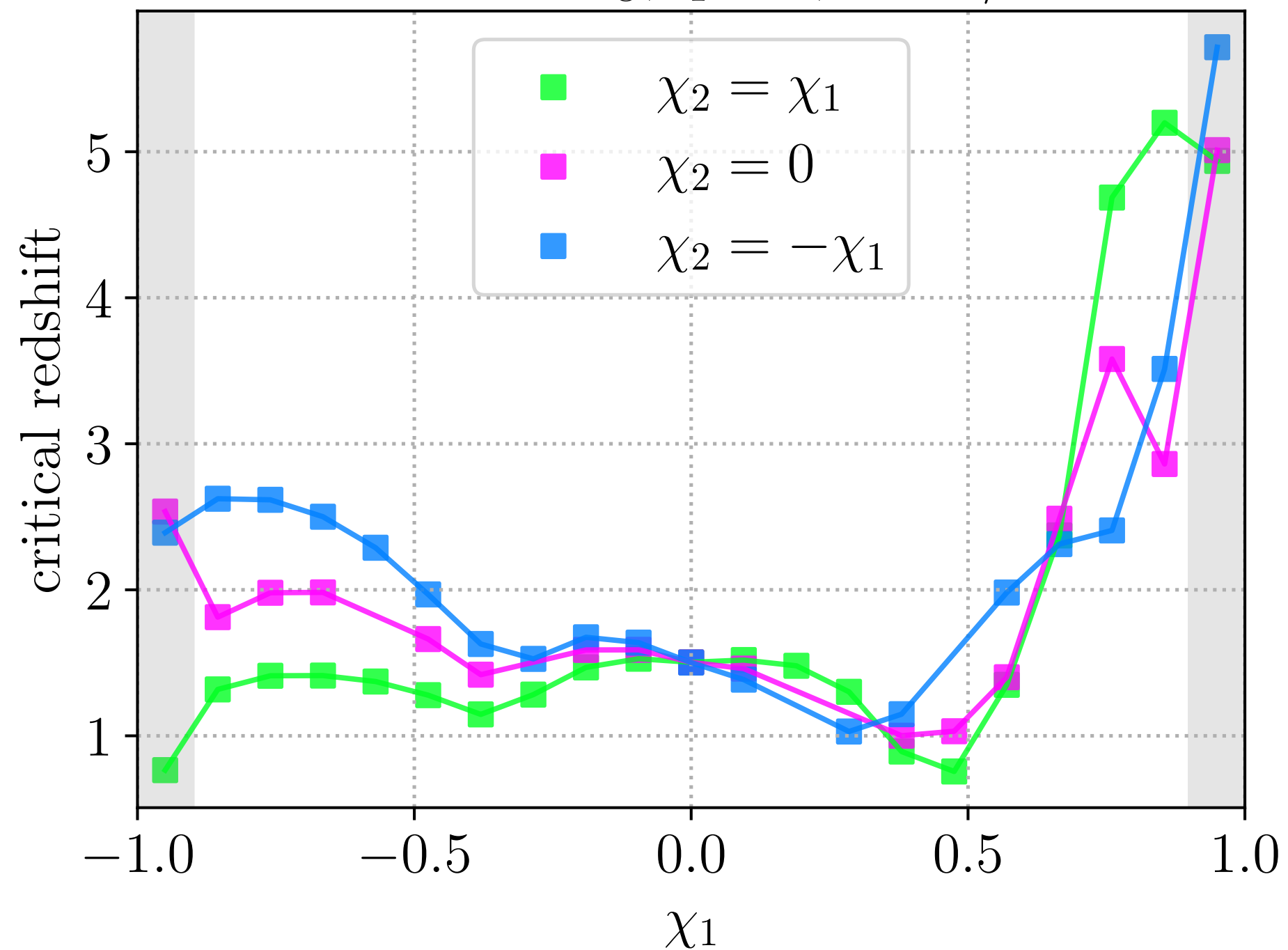
Question: how many  $h_{\ell m}$  should be included in waveform templates ? Current models go up to  $h_{55}$  at most.

[Pitte+ 2023]  
[Yi+ 2025]  
[Yi+ 2026]

LISA consortium project [Waveform Working Group] coordinator: Sophia Yi (Johns Hopkins U.)

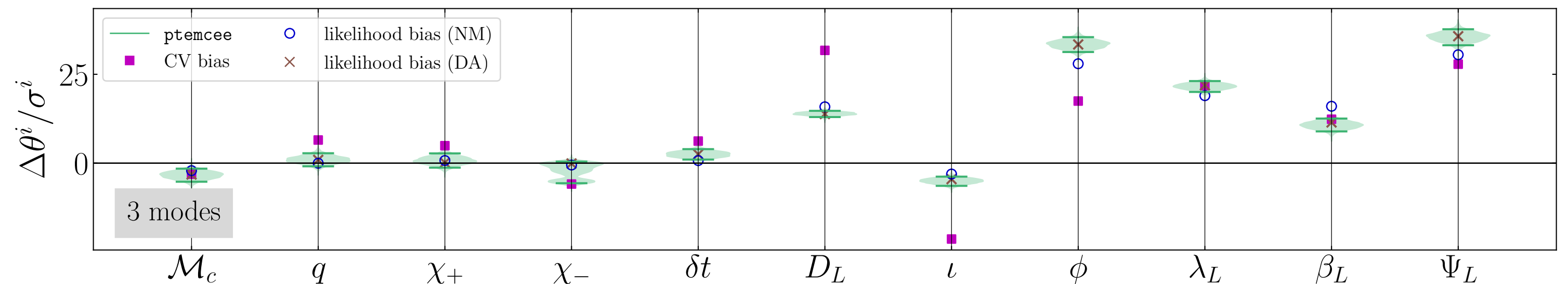
Min. redshift unbiased when ignoring (3,2) mode:

$M = 10^6 M_{\odot}$ ,  $q = 4$ ,  $\iota = \pi/3$  [Yi+ 2026]



Estimating biases: Cutler-Vallisneri (can fail), direct Nelder-Mead

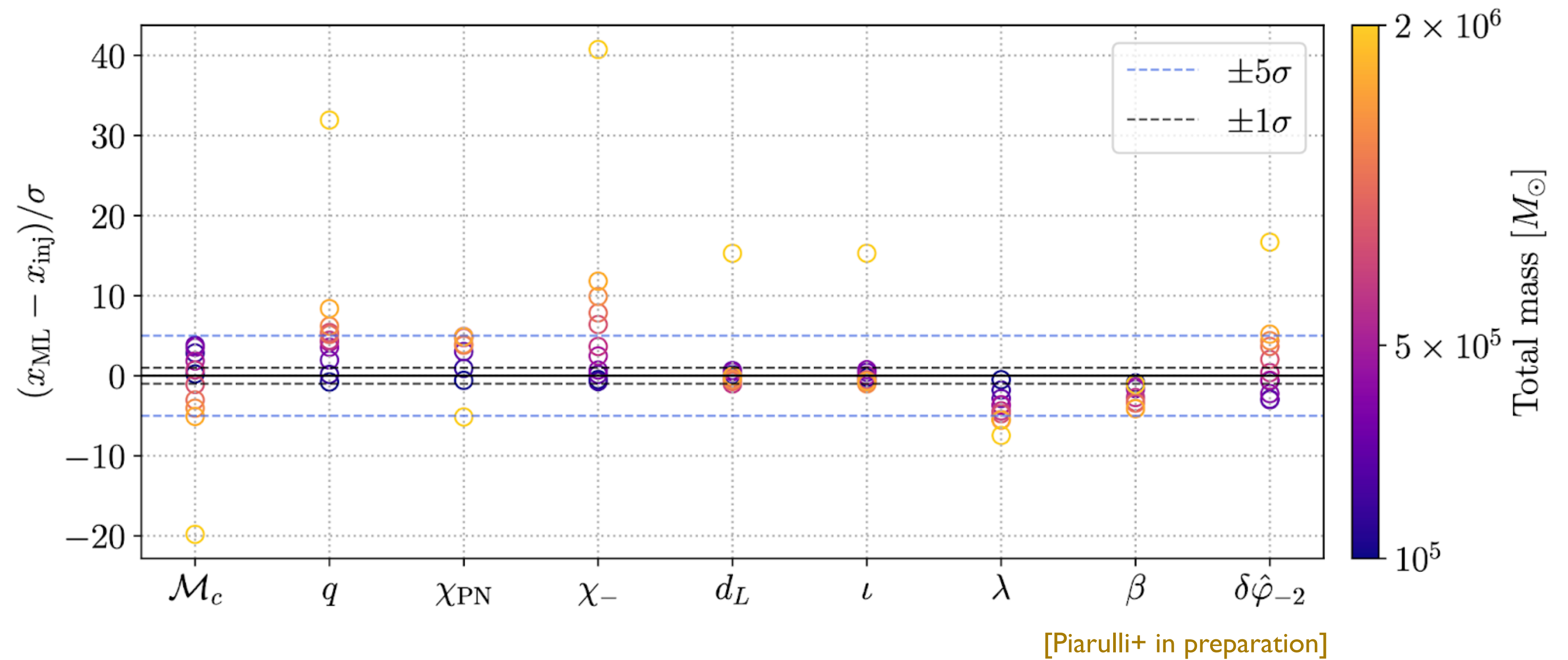
$M = 10^6 M_{\odot}$ ,  $q = 1.1$ ,  $\iota = \pi/3$  [Yi+ 2026]



# MBHB biases: impact on tests of GR

Question: how does waveform inaccuracy affect tests of GR, and can waveform errors be mistaken for false deviations from GR ?

LISA consortium project [Fundamental Physics Working Group] coordinators: Manuel Piarulli (L2IT), Elisa Maggio (La Sapienza, Roma)



# Conclusion and outlook

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## Highlights

- Even for the simpler case of aligned spins + HM, significant systematic biases at high masses
- Strong progressivity: worse at higher masses, for merger-dominated signals
- Systematics can also mislead us towards the wrong sky mode

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## Outlook

- Expectation: systematics could be even worse in presence of precession and eccentricity...
- Mitigation: waveforms should come with uncertainties ! How to determine the error envelopes ? The LISA science case could require revisiting with a marginalization over waveform uncertainty.
- Mitigation: targeted a posteriori improvement of waveform models for golden events ?

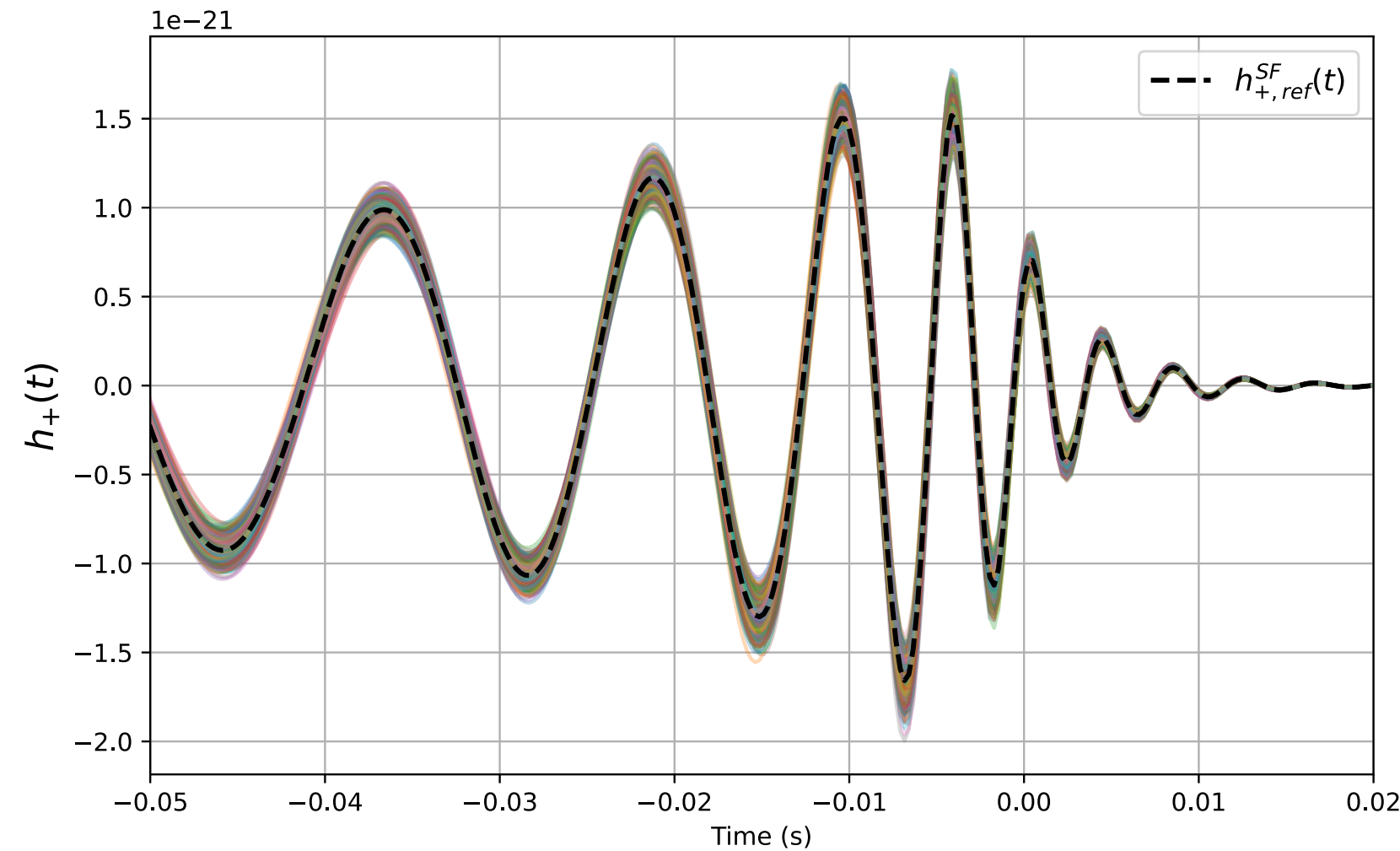






# Dealing with waveform errors

## Marginalization over waveform errors:



## Probabilistic waveforms:

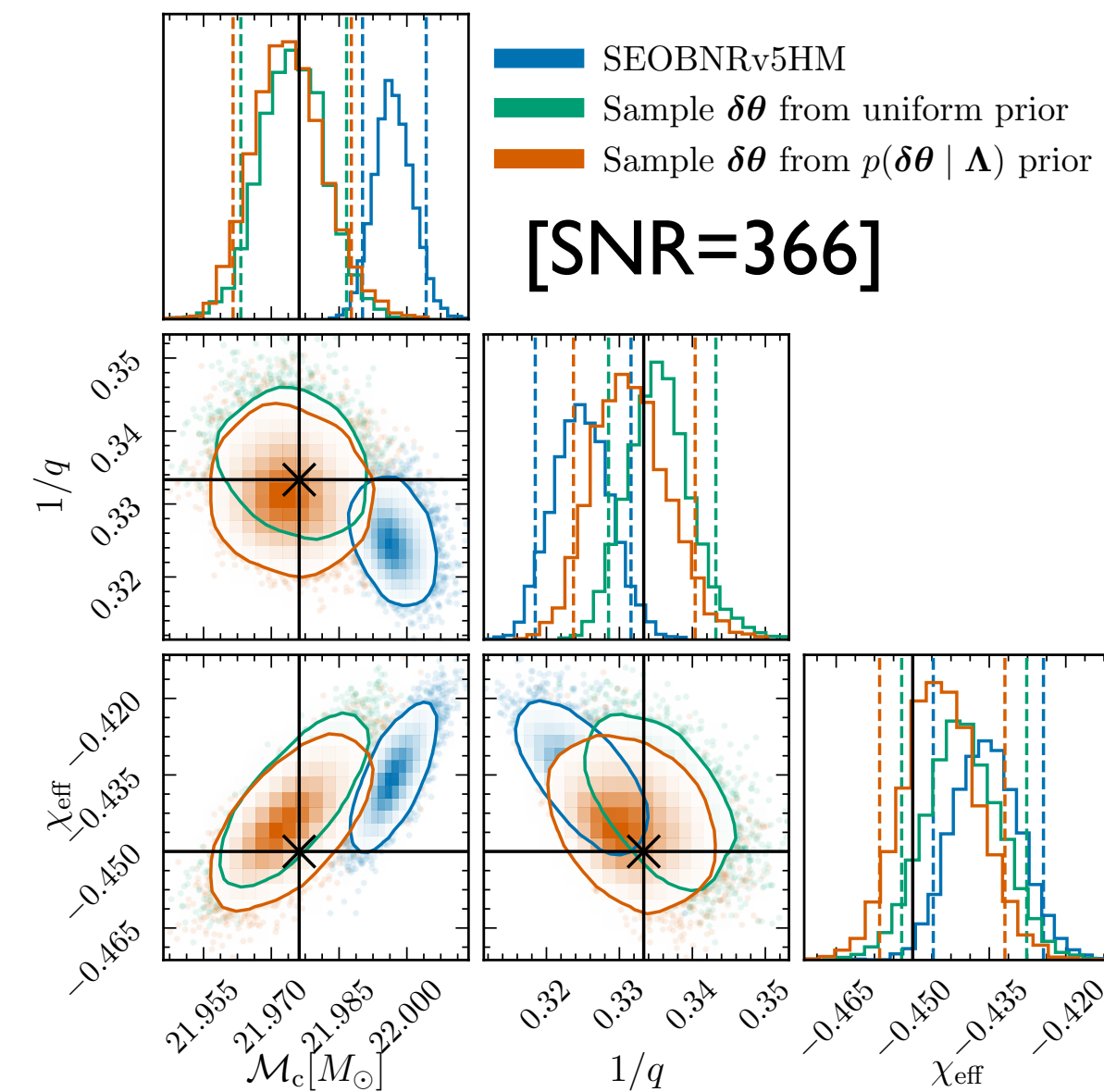
- amplitude/phase envelopes, as in detector calibration

$$h(f) = (A + \delta A)e^{i(\phi + \delta\phi)} \quad [\text{Kumar+ 2025}]$$

- constructed as Gaussian Process Regression (also guides next simulations)

[Moore-Gair 2014]  
[Williams+2019]  
[Bachhar+ 2024]

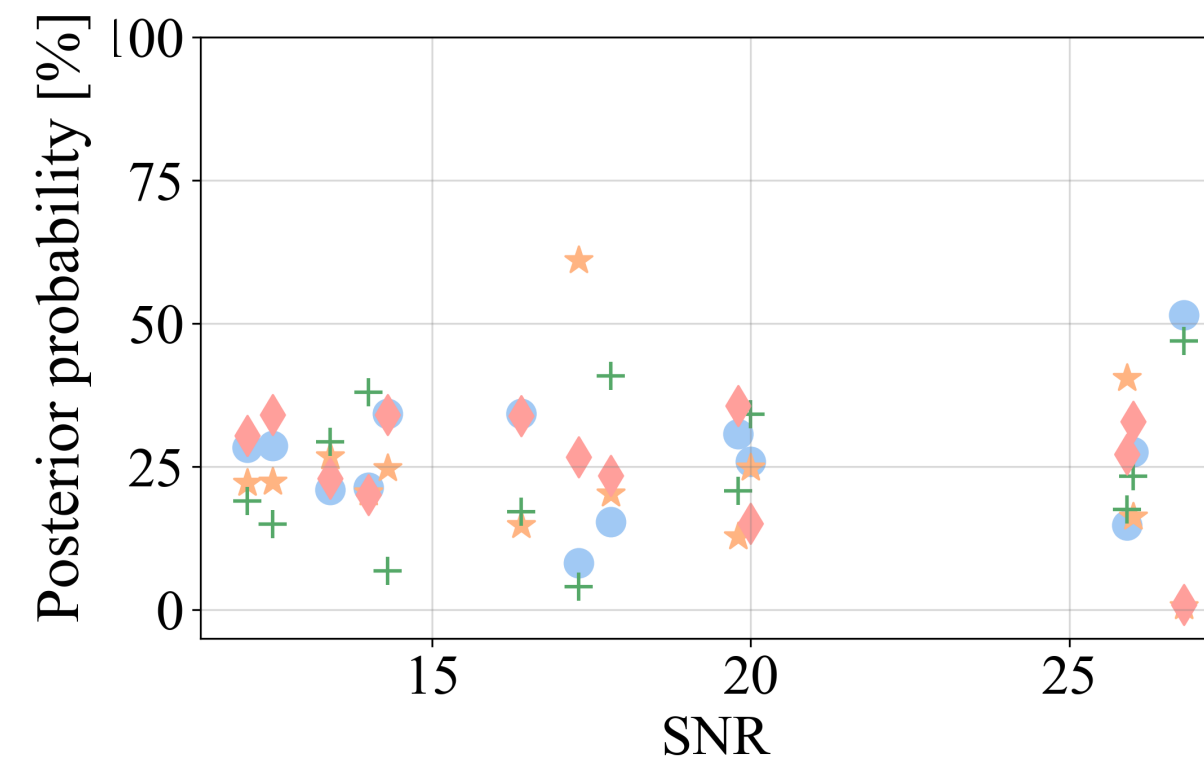
## Marginalization over SEOB NR calibration:



Calibration params  
 $\theta \sim p(\theta | \text{NR})$

[Pompili+ 2024]

## Hypermodels:



$$\Omega = \{\Omega_0, \Omega_1, \dots, \Omega_{n-1}\}$$

$$\mathcal{O}_B^A = \frac{p_A}{p_B} = \frac{n_A}{n_B}$$

- NRSur7dq4
- SEOB NR v4 PHM
- IMRPhenomXPHM
- IMRPhenomTPHM

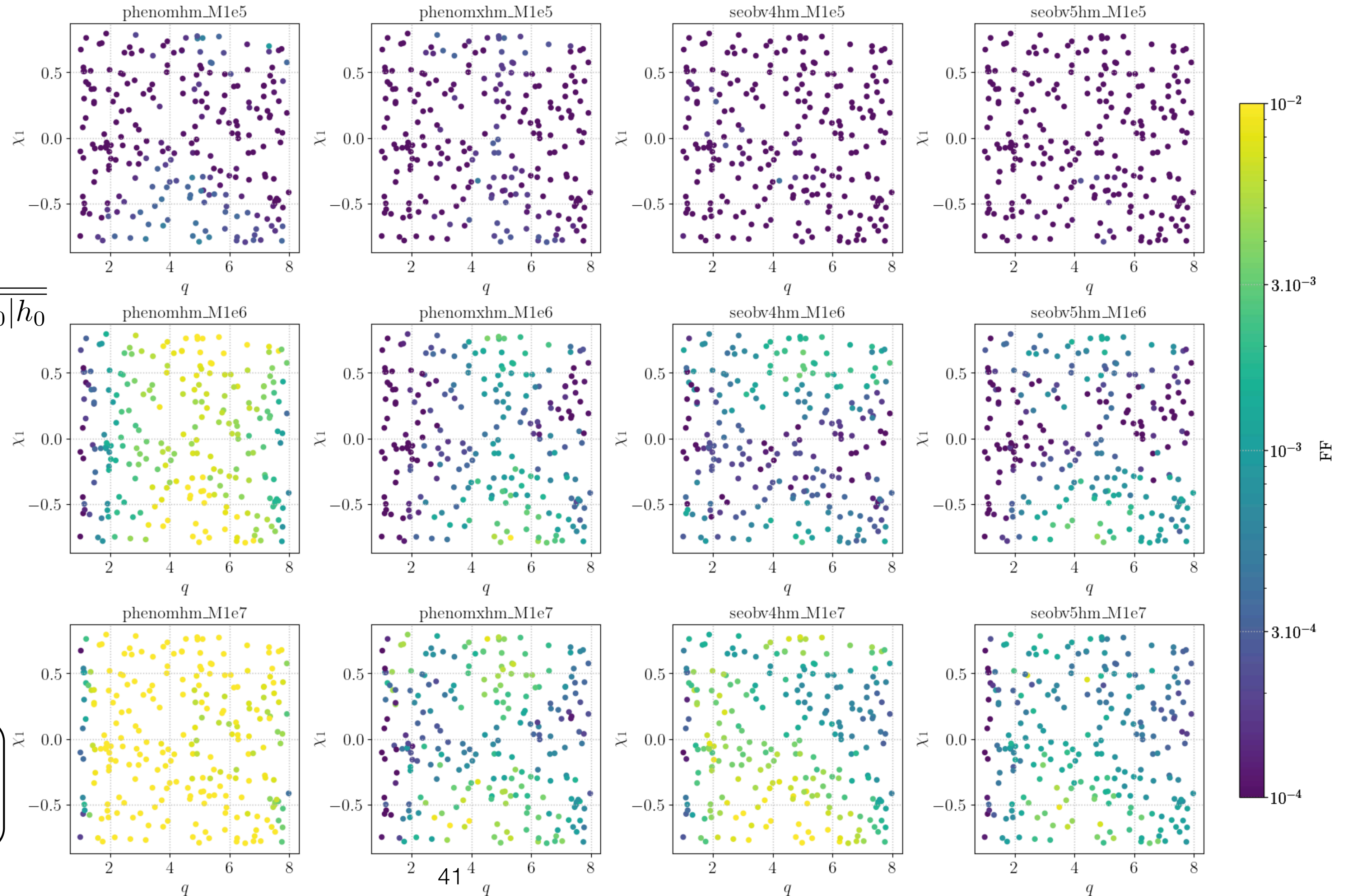
[Puecher+ 2023]  
[Hoy+ 2024]  
[Ashton+ 2019]

# Fitting factors in parameter space

Fitting factor, computed at best-fit params (optimization over all parameters):

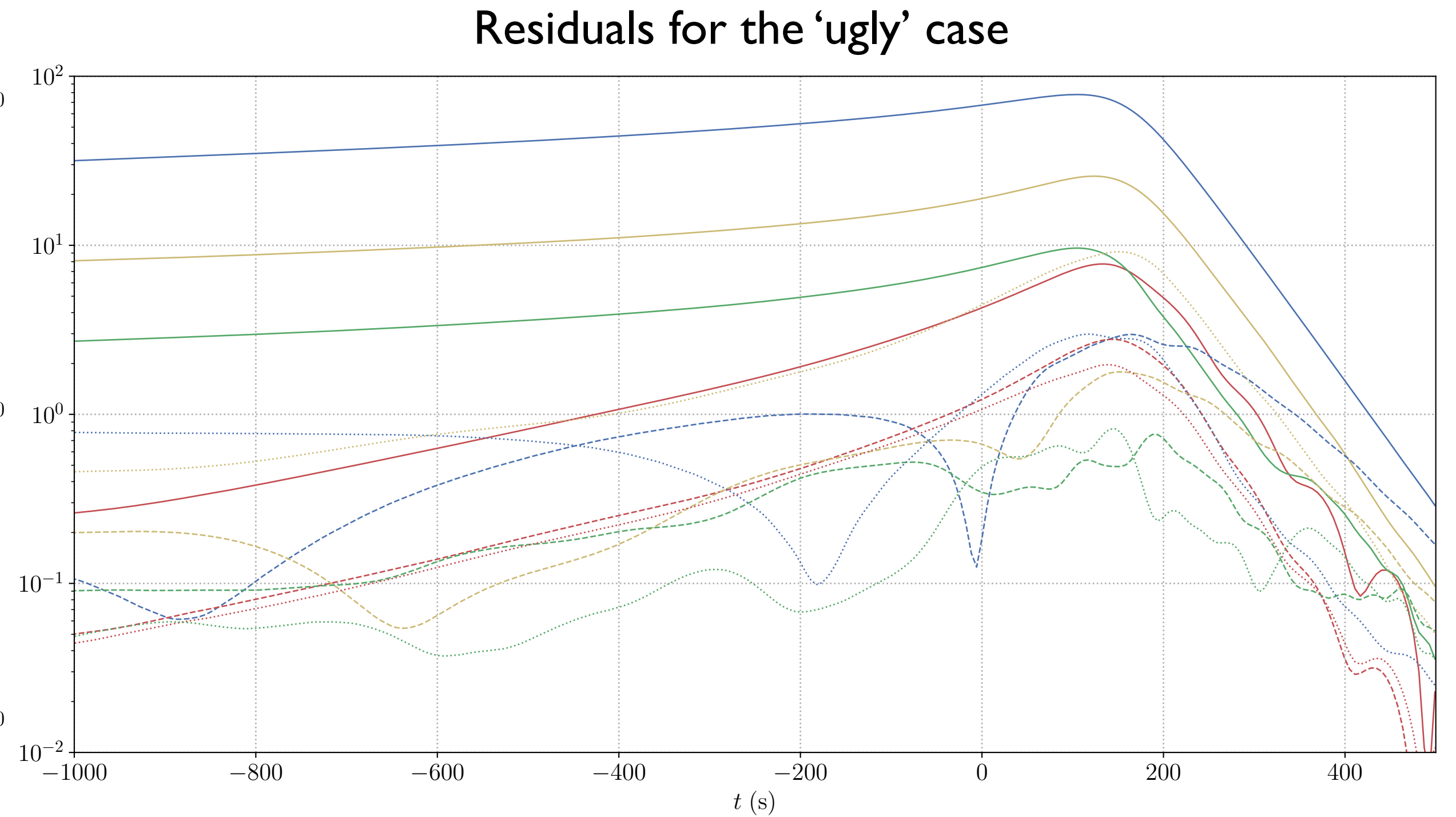
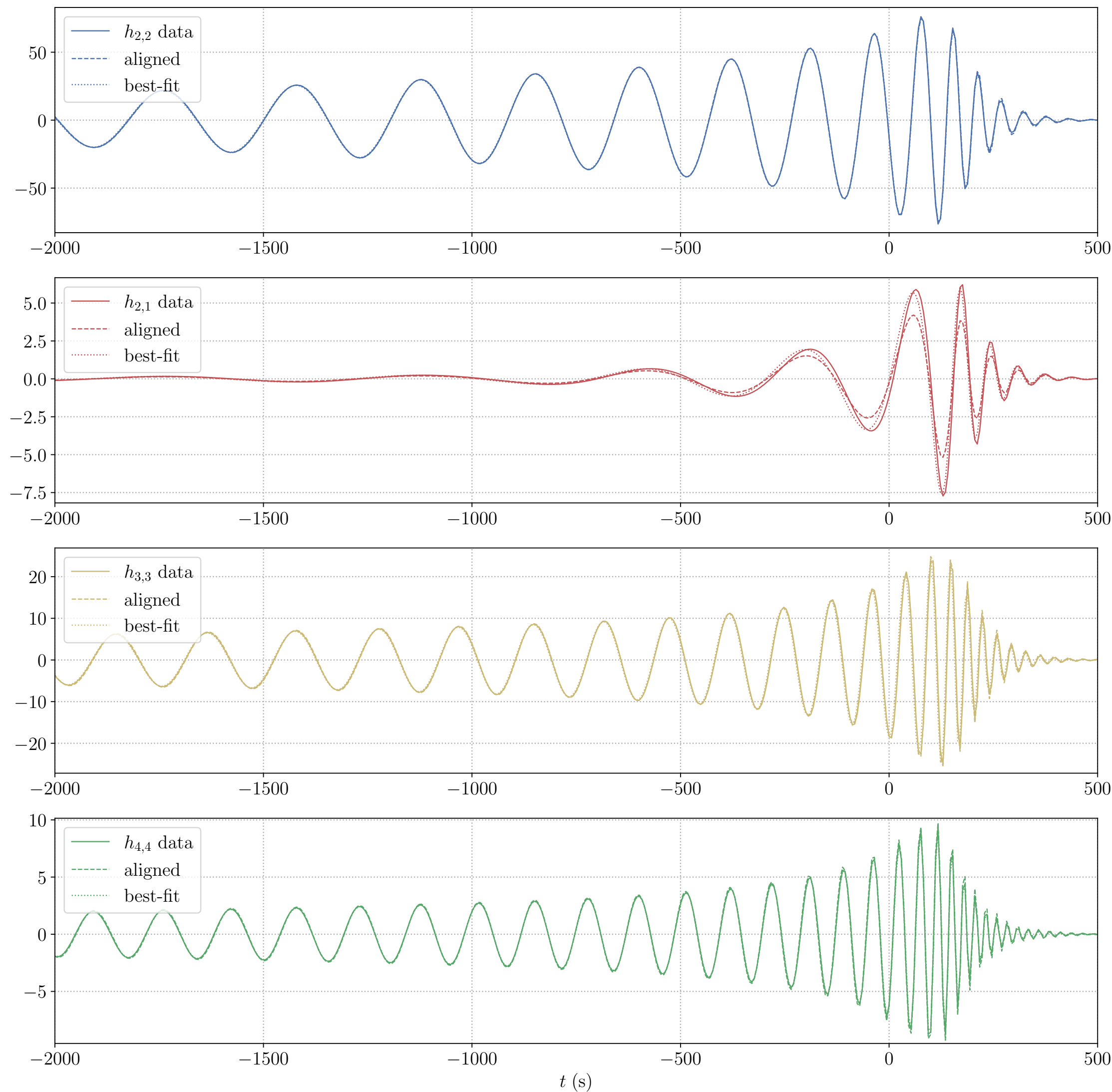
$$FF = 1 - \max_{\theta} \frac{(h_m | h_0)}{\sqrt{(h_m | h_m)} \sqrt{h_0 | h_0}}$$

$$\ln \mathcal{L}_{\max} = -\text{SNR}^2 \times FF$$



Trend: strong dependence on M  
 Trend: larger errors at large spins  
 Trend in q ?

# Example Parameter estimation with systematics III: TD signals and residuals

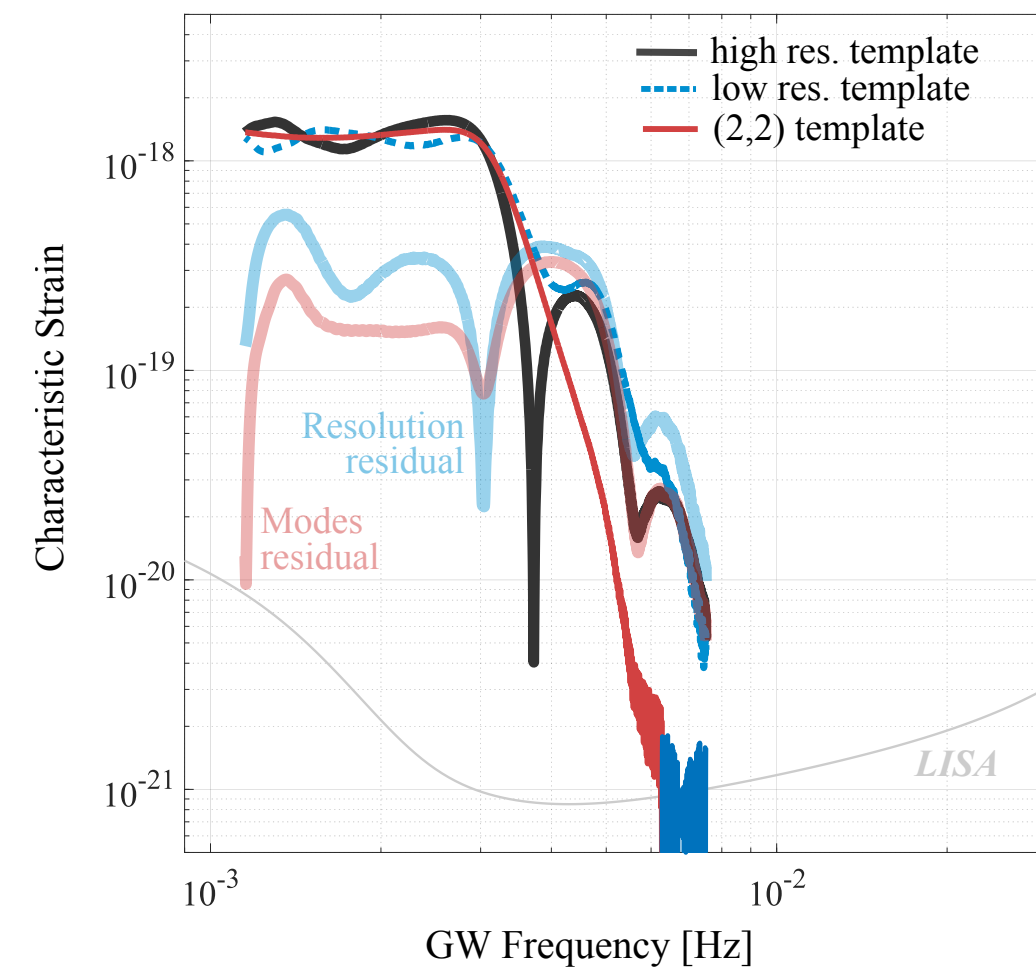


- Residuals are 'visually' small...
- Details of HM at merger are important

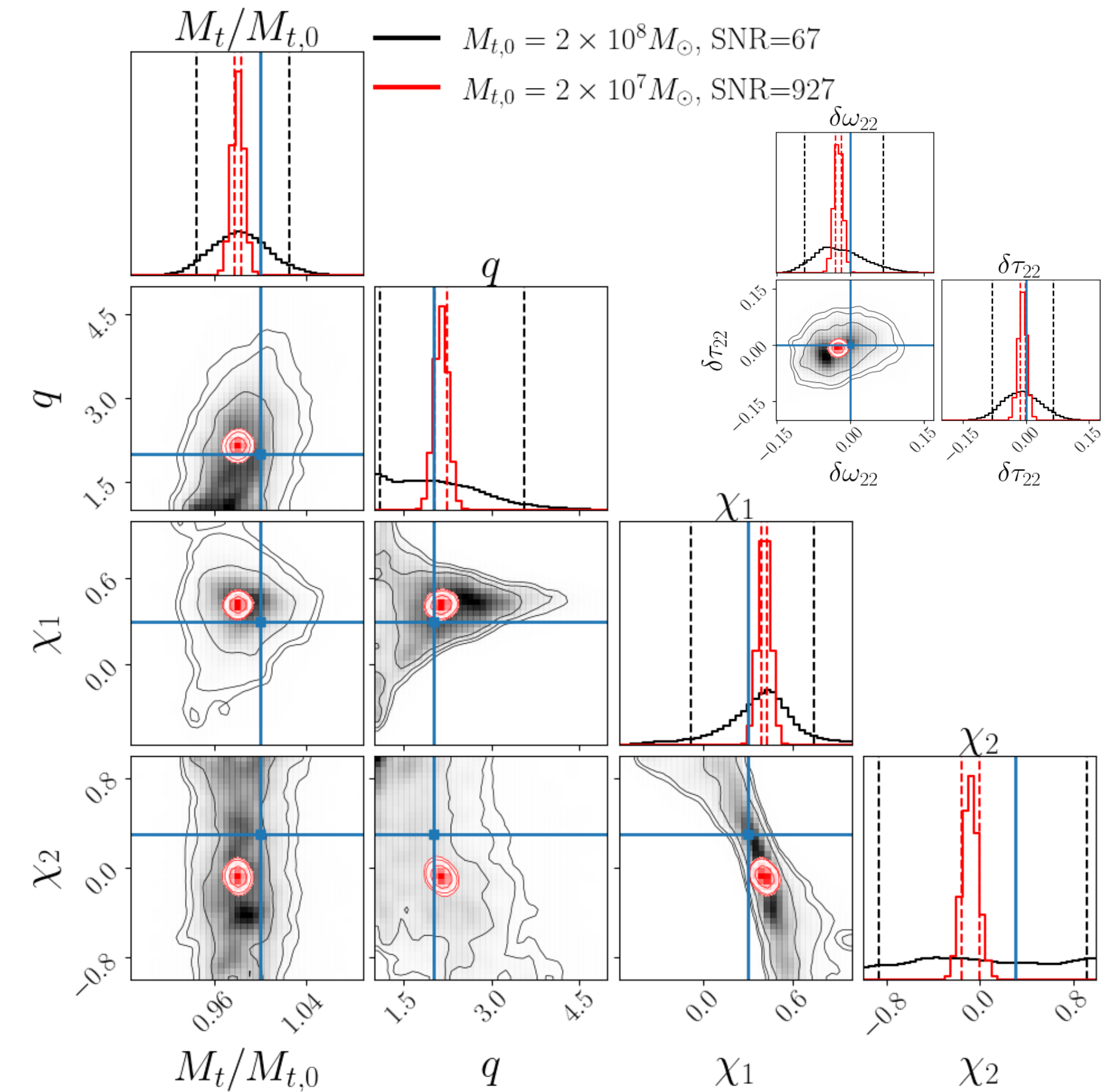
# Waveform systematics studies for LISA MBHBs

## NR residuals (Maya code):

[Ferguson+ 2020]

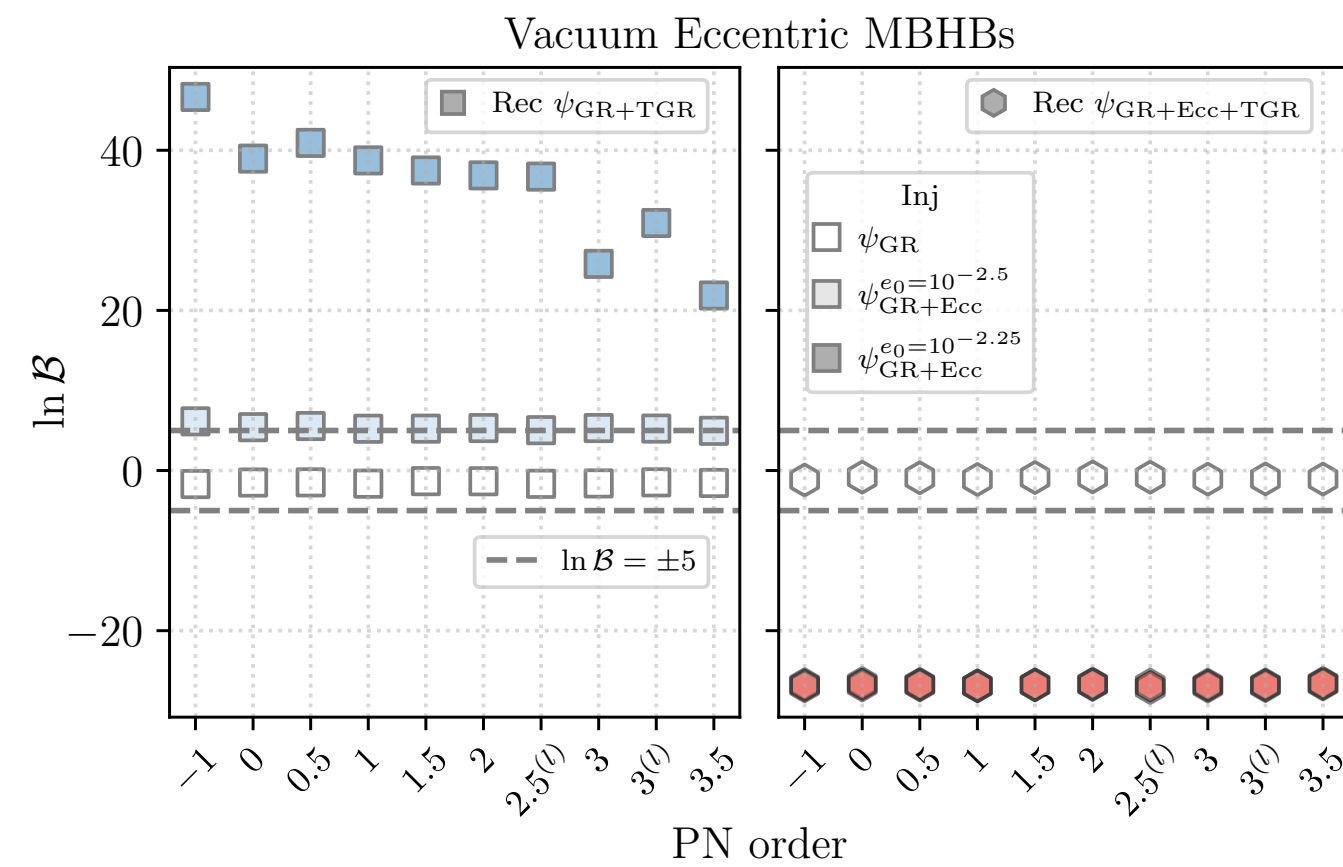


## pSEOBNR vs NR:



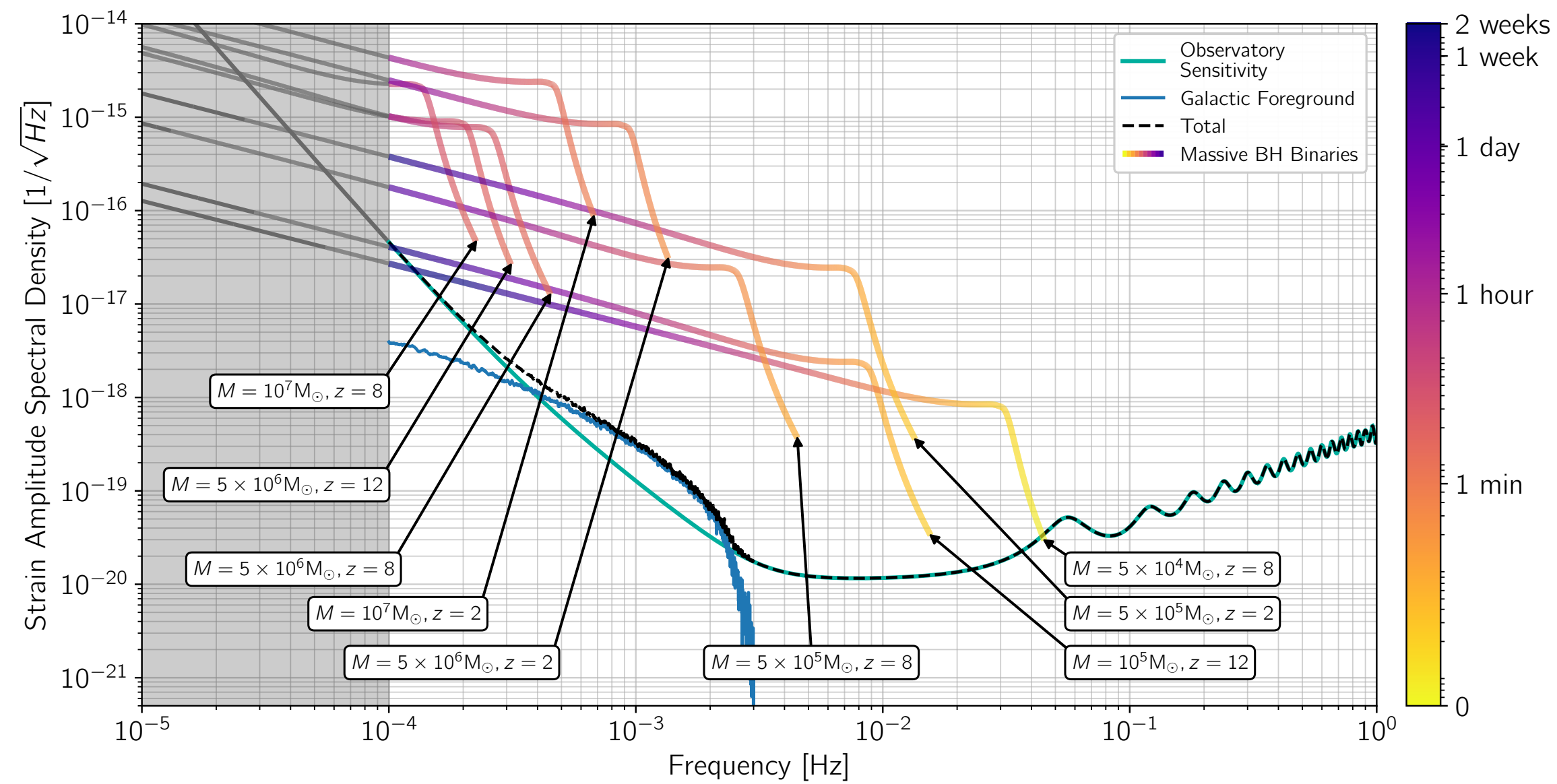
## TGR systematics when ignoring ecc/env.:

[Garg+ 2024]



[Toubiana+ 2023]

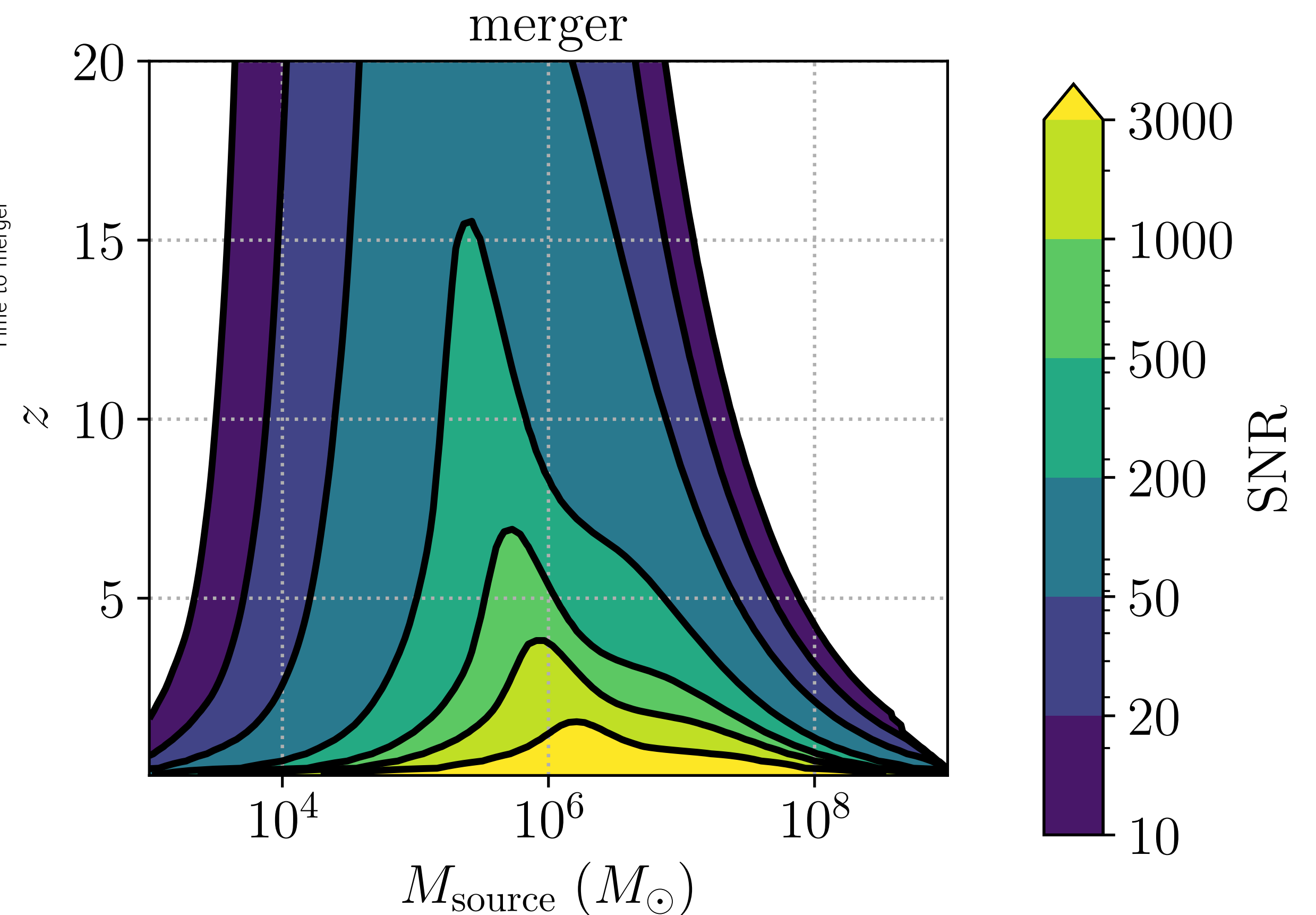
# Massive black hole binaries for LISA



## Science case

MBHBs cardinal sources for LISA, waveform systematics crucial for:

- golden events for EM counterparts
- golden events for TGR
- population inference and cosmology
- global fit and residuals

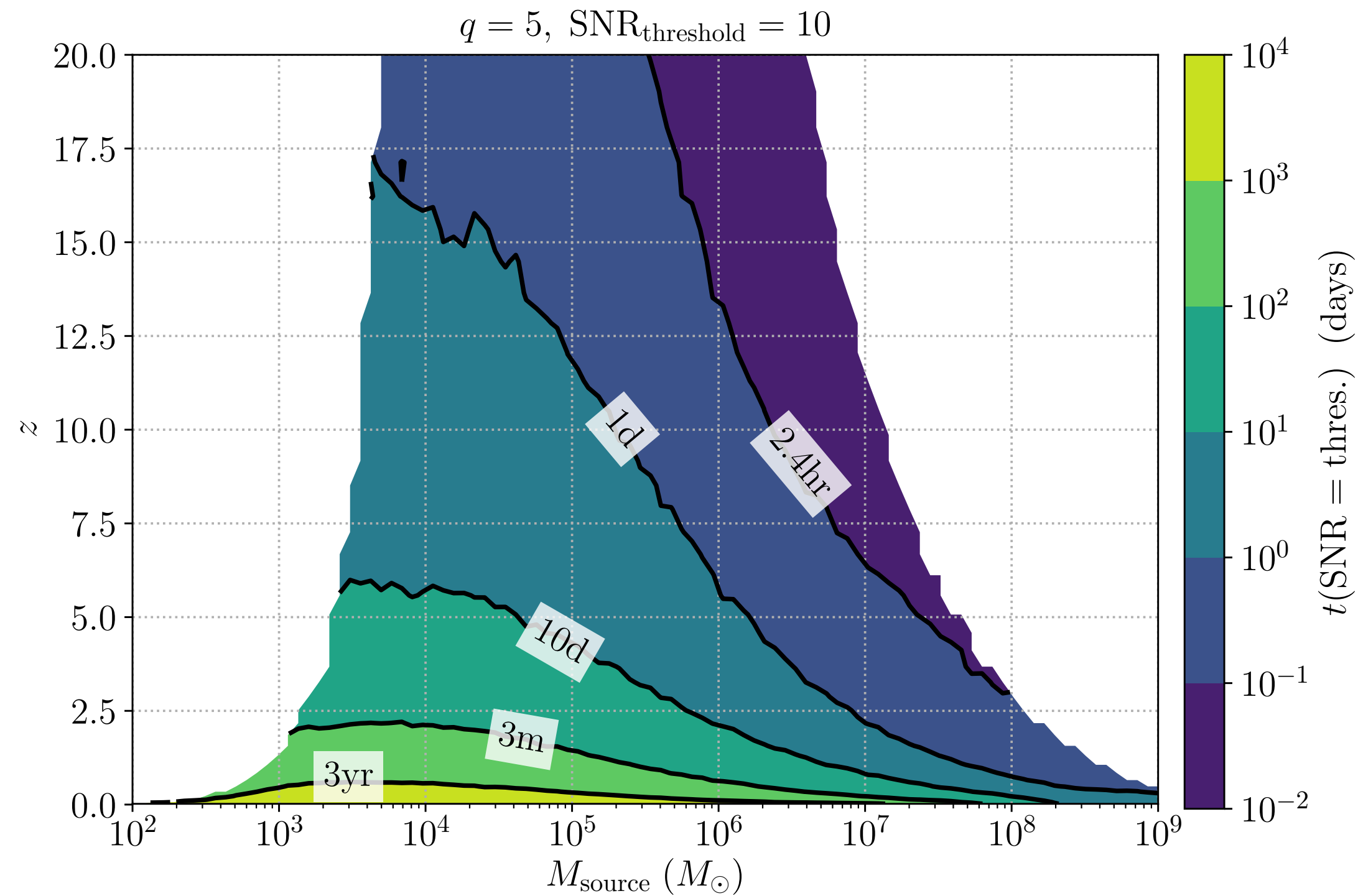


Extremely loud mergers...

Broader parameter space than LVK: high- $q$ , high-spins, precession, eccentricity

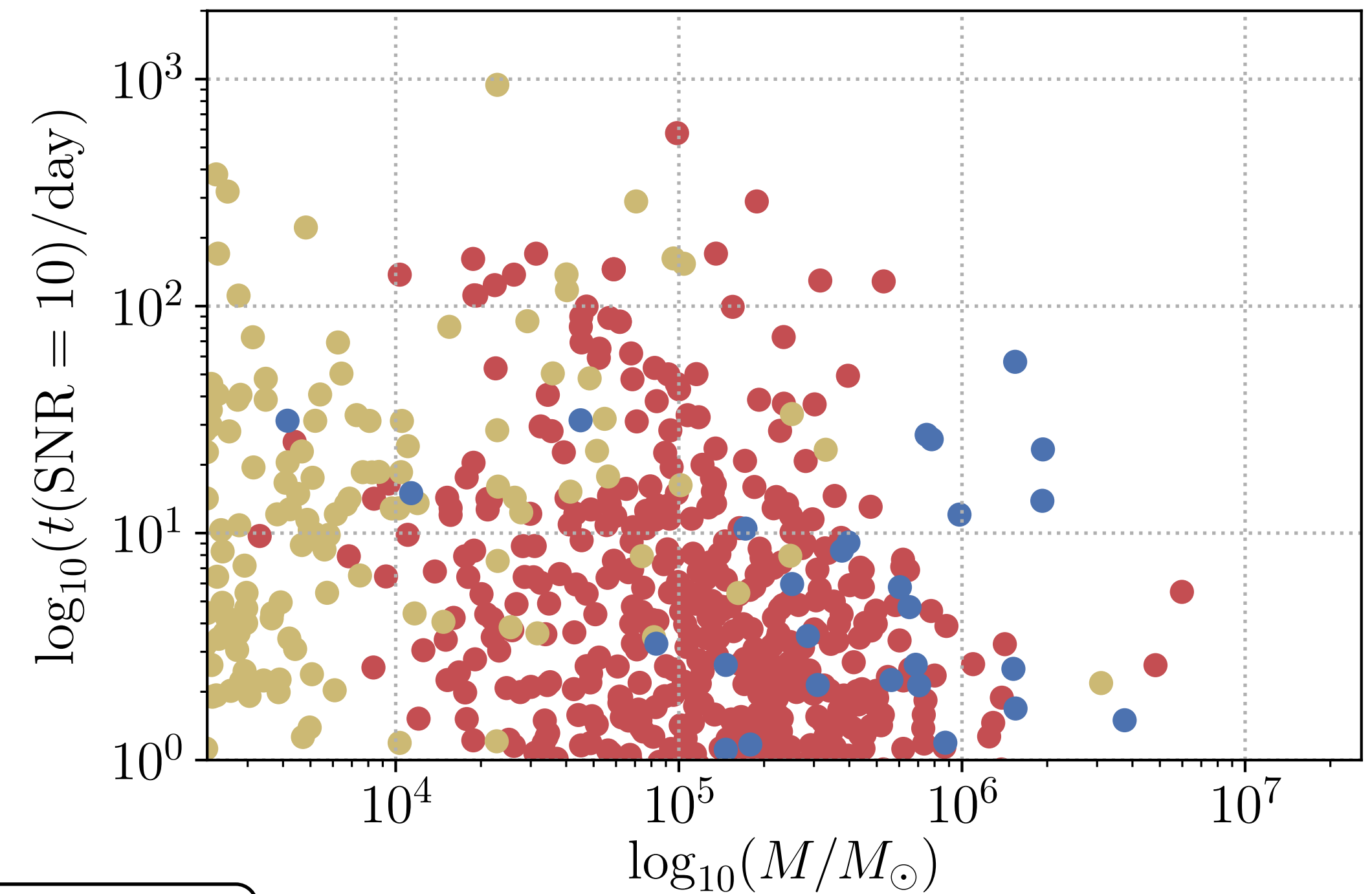
# The length of MBHB signals

- How long before merger can we detect the signal ?
- SNR=10 to claim detection



Astrophysical models [Barausse 2012]:

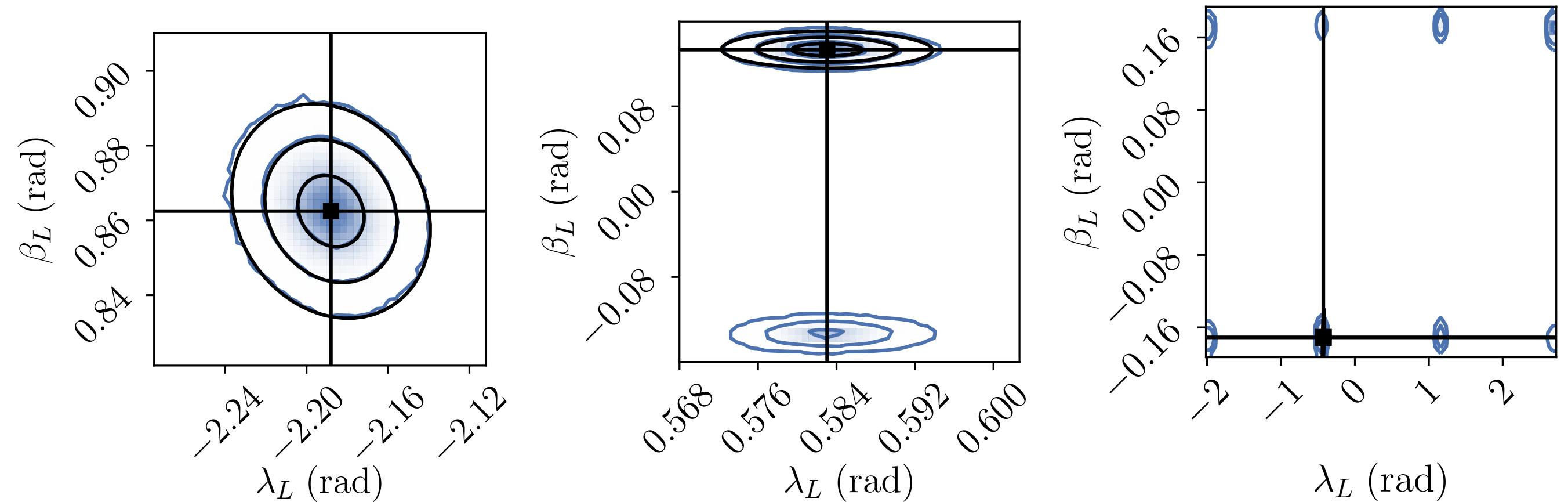
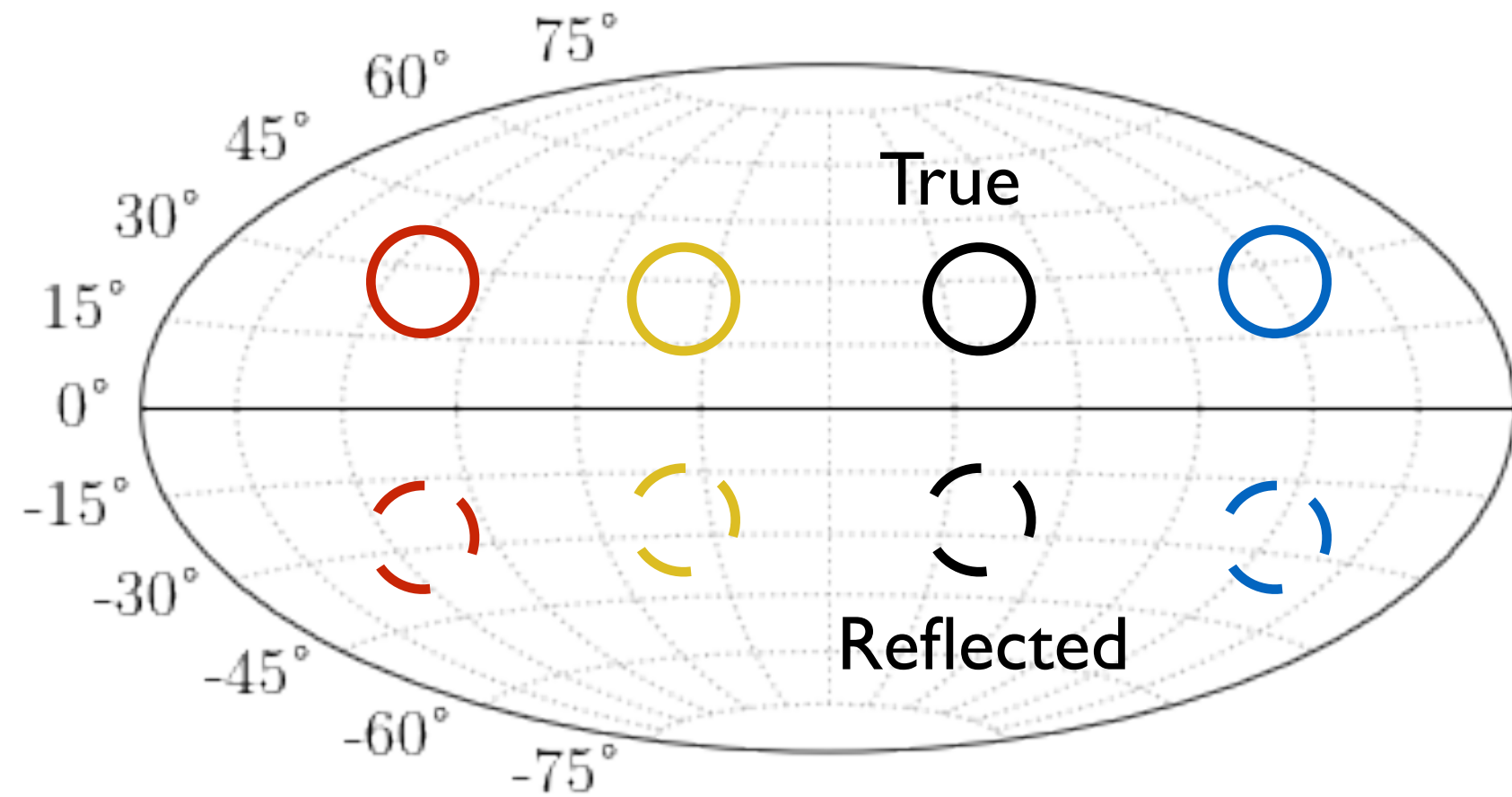
- Heavy seeds - delay
- Heavy seeds - no delay
- PopIII seeds - delay



MBHB detected signals:  
Bulk shorter than ~10days  
Tail extending to ~3months

# LISA response and multimodality in the sky

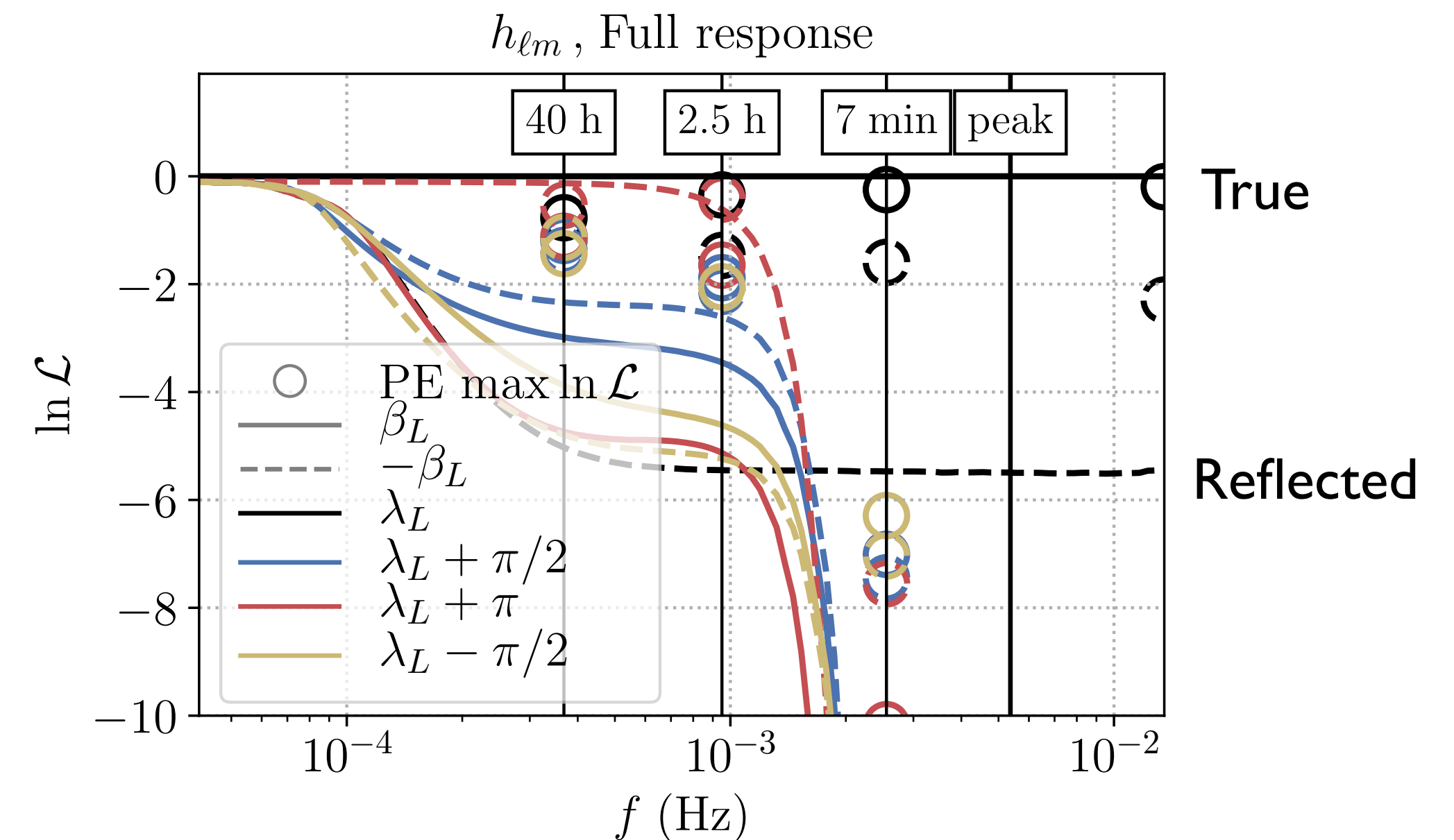
## Multimodality pattern:



## Degeneracy breaking:

- motion of LISA: eliminates all modes but the antipodal, weak for short high-mass signals
- high-frequency effects in the response: eliminates all modes but the reflected, only at high frequencies

- Multimodality broken by subdominant effects in response (motion, high-f)

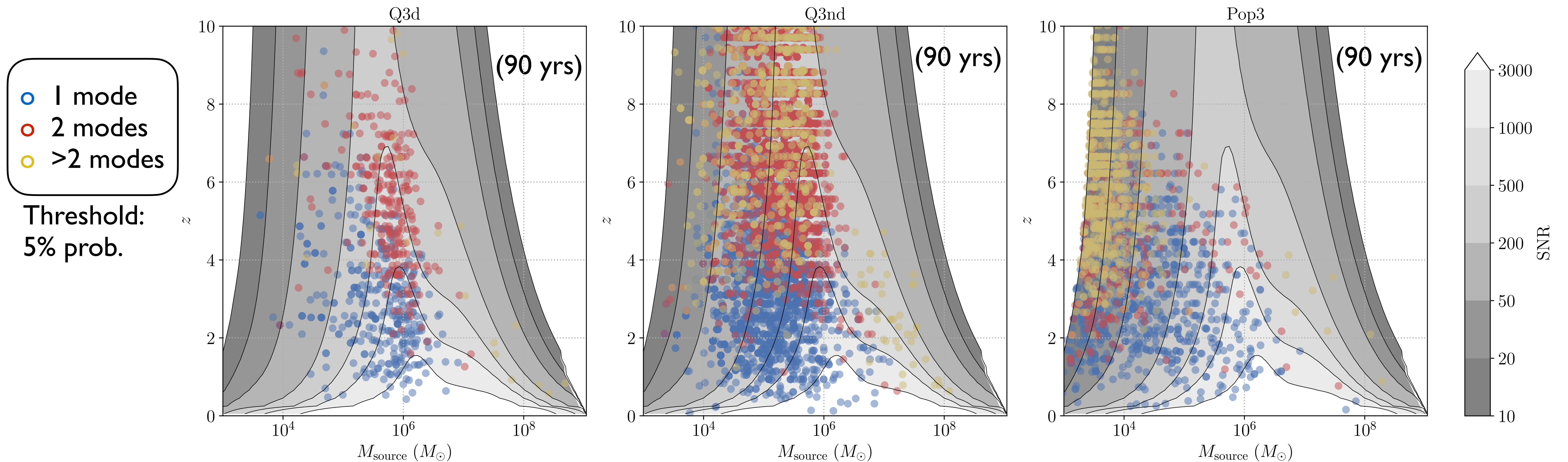


# Sky multimodalities for LISA MBHBs

- **Bayesian PE** required to explore multimodal posteriors
- Simulation of 90yrs catalogs
- Custom proposals for degeneracies

Astrophysical models [Barausse 2012]:

- Heavy seeds - delay (Q3d)
- Heavy seeds - no delay (Q3nd)
- PopIII seeds - delay (Pop3)



Applications: EM counterparts and cosmological inference  
[Mangiagli&al 2022, Mangiagli&al 2023]

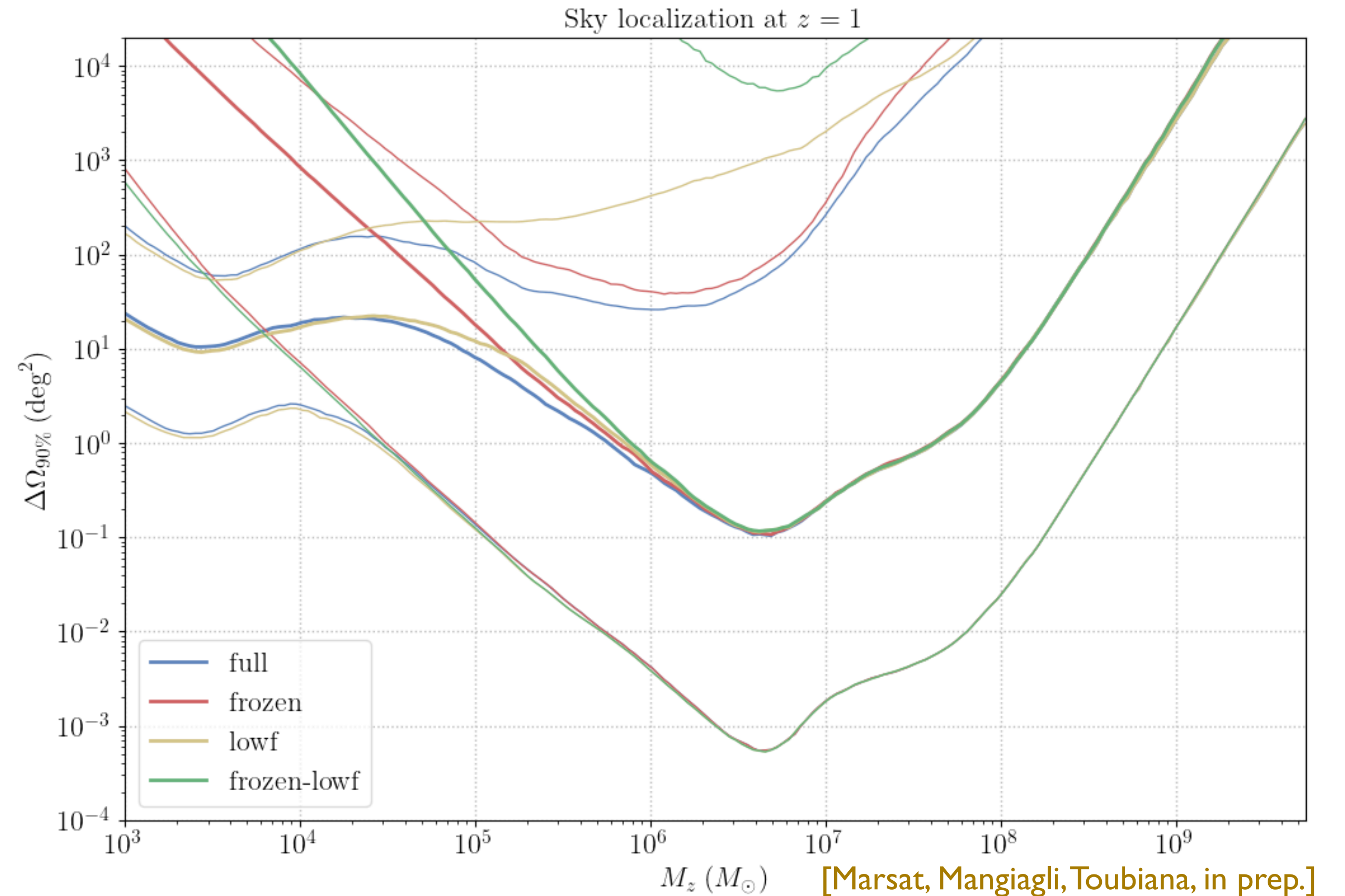
Multimodality in the sky present, but rare for counterpart candidates post-merger

# Fisher localization: which part of the response is important ?

## Analysis settings:

- Fisher matrix localization: sky area of the main mode of the posterior
- Randomization over 1000 orientations, mass ratios, spins
- Change the response model: keep or ignore the motion and high-f effects

- ‘Pattern function’ response is the main source of main-mode localization at high mass, from subdominant HM
- Multimodality broken in turn by subdominant effects in response (motion, high-f)

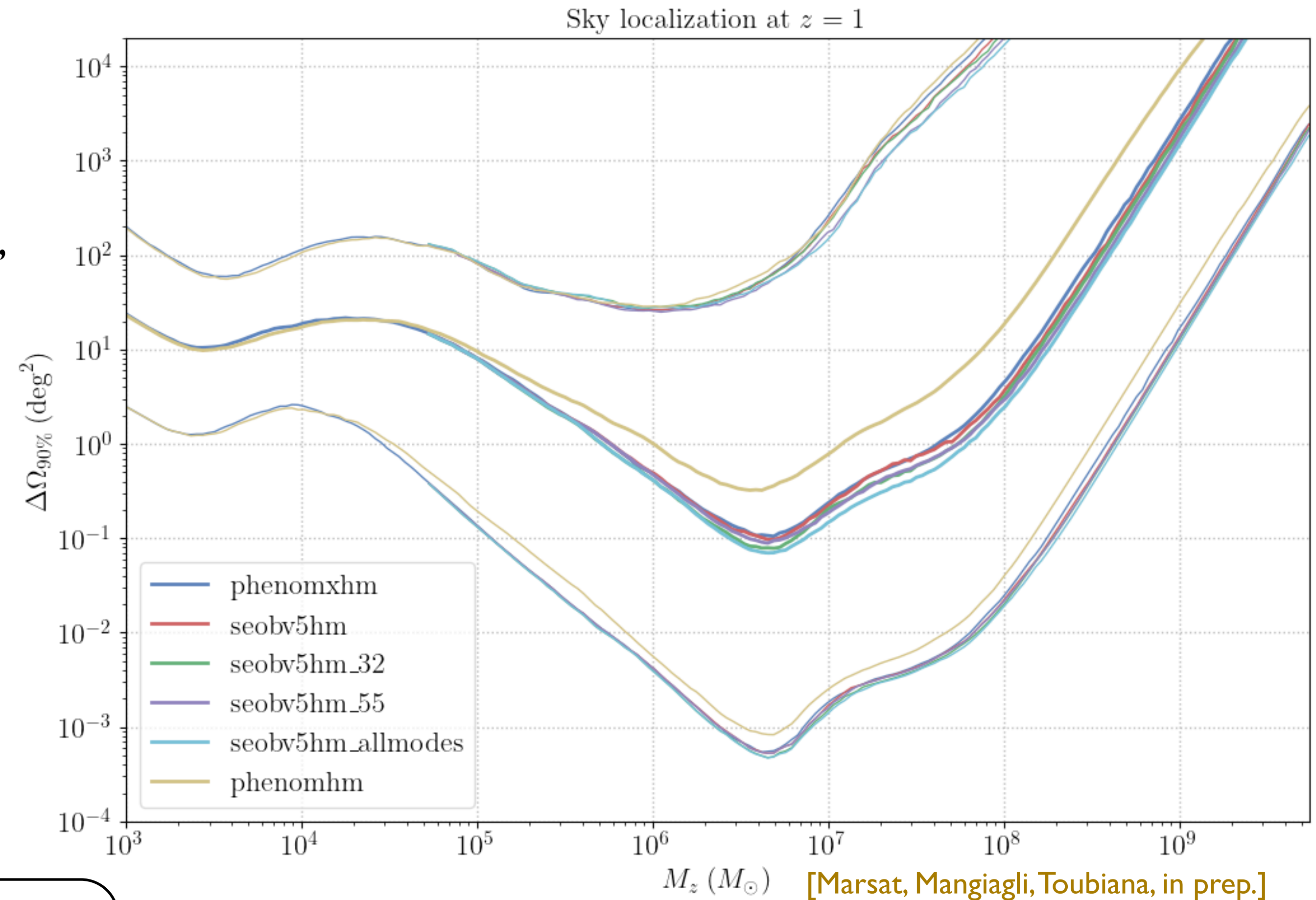


- Sky localization at high mass: weak effects, high SNR
- Unlike LVK localization from triangulation, LISA localization potentially vulnerable to systematics

# Fisher localization: do waveform models agree on prospective ?

## Analysis settings:

- Fisher matrix localization: sky area of the main mode of the posterior
- Randomization over 1000 orientations, mass ratios, spins
- Change the waveform model: PhenomHM, PhenomXHM, SEOBNRv5HM\_ROM



- In the high-mass range (HM important), older waveform models can be inaccurate also for prospective PE
- Modern waveform models agree well for prospective

# Example Parameter estimation with systematics II: Cutler-Vallisneri bias

## Linearized biases (Cutler-Vallisneri):

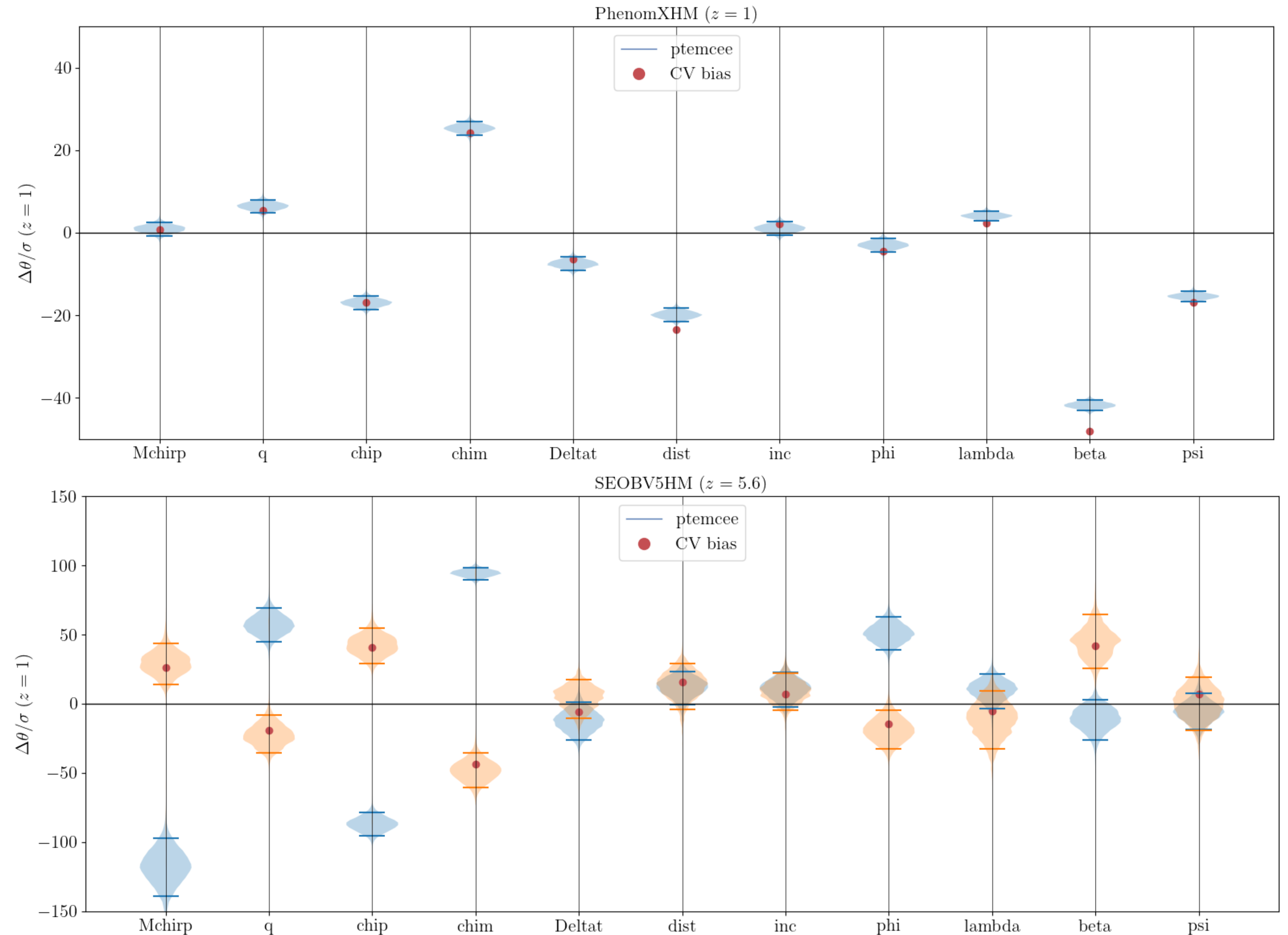
[Flanagan-Hughes 1997]  
[Cutler-Vallisneri 2007]

In the linear signal approximation, estimation of bias:

$$F_{ij} = (\partial_i h | \partial_j h)$$

$$\Delta\theta_i = F_{ij}^{-1} (\partial_j h | \delta h)$$

- Cutler-Vallisneri biases give reasonable estimates in mild cases
- Fail to capture distant secondary mode — needs to be adapted
- Can fail for severe biases



# Biases caused by missing higher harmonics

## Estimating the bias is an optimization problem

- Cutler Vallisneri is one step of Newton's gradient descent, approximating the Hessian with the Fisher matrix
- Are there better optimization algorithms ? (e.g. simplex method)
- One simple idea is to repeat CV as iterated gradient descent

$$\Delta\theta = H^{-1} \cdot \nabla \ln \mathcal{L}$$
$$H_{ij} = \partial_i \partial_j \ln \mathcal{L} \sim (\partial_i h | \partial_j h)$$

[Preliminary]

There should be better bias estimators than CV - robustness ?

[Sophia Yi &al, in prep.]

Mode config: [(2, 2), (3, 3), (2, 1)]

