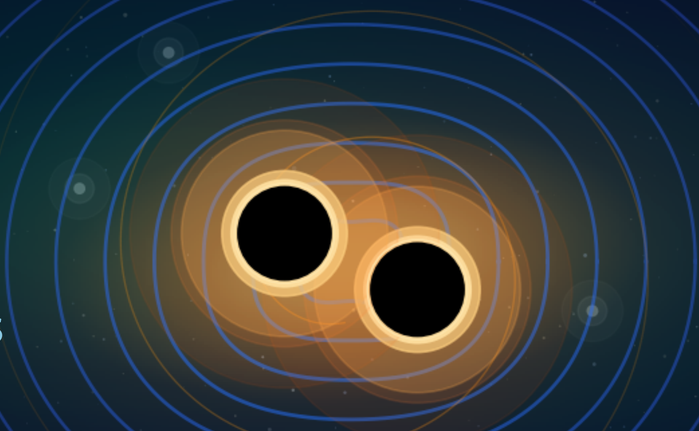
LISA Consortium "Impact of GW Memory" project

Parameter biases induced by omitting GW displacement memory in LISA



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Waveforms and Fundamental Physics
Working Groups of the Consortium

LISA Spain meeting
UIB, 12th November 2026



With Silvia Gasparotto, Milton Ruiz, Henri Inchauspé, Sascha Husa, Jann Zosso and others

Universitat de les Illes Balears
IAC3 Institut d'Aplicacions Computacionals de Codi Comunitari

LISA CONSORTIUM

Introduction: GW memory in LISA

- GW memory: permanent displacement of freely falling test masses after GWs have passed. Sourced by the GW energy itself. The main contribution of the displacement memory is contained in the $(\ell = 2, m = 0)$ mode.

- Why is GW memory relevant for LISA?
  - High SNRs for MBHBs could enable the first single-event detection [Islo+(2019), Inchauspé+(2025)].
  - MBHB population predicts observable memory events within the mission lifetime [Gasparotto+(2023)].

TD waveform with and without memory for a BBH

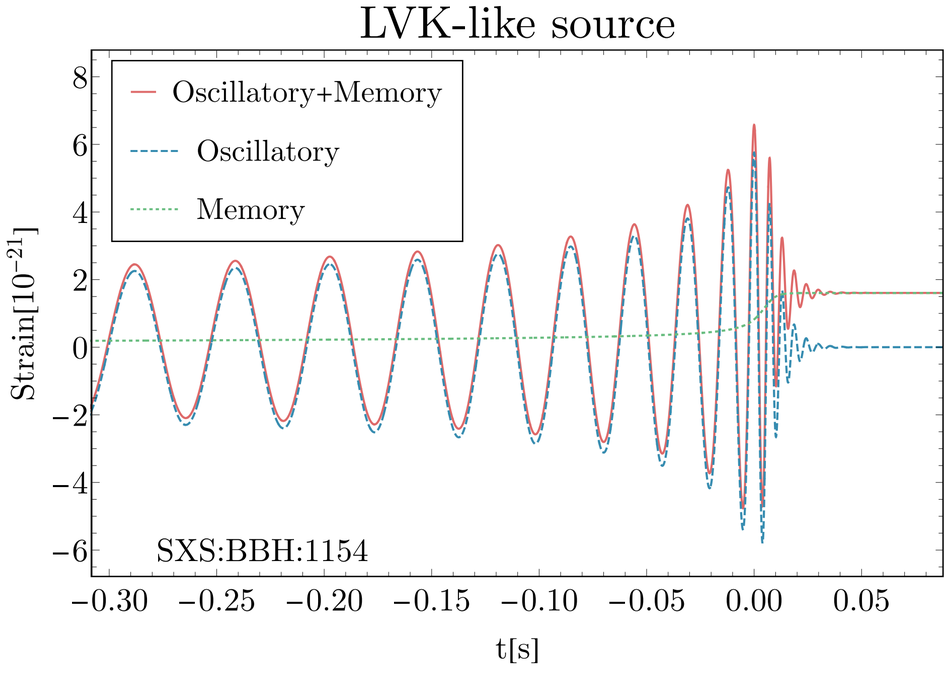


Figure from Rosselló-Sastre+(2024)

GW memory imprint in LISA for a MBHB

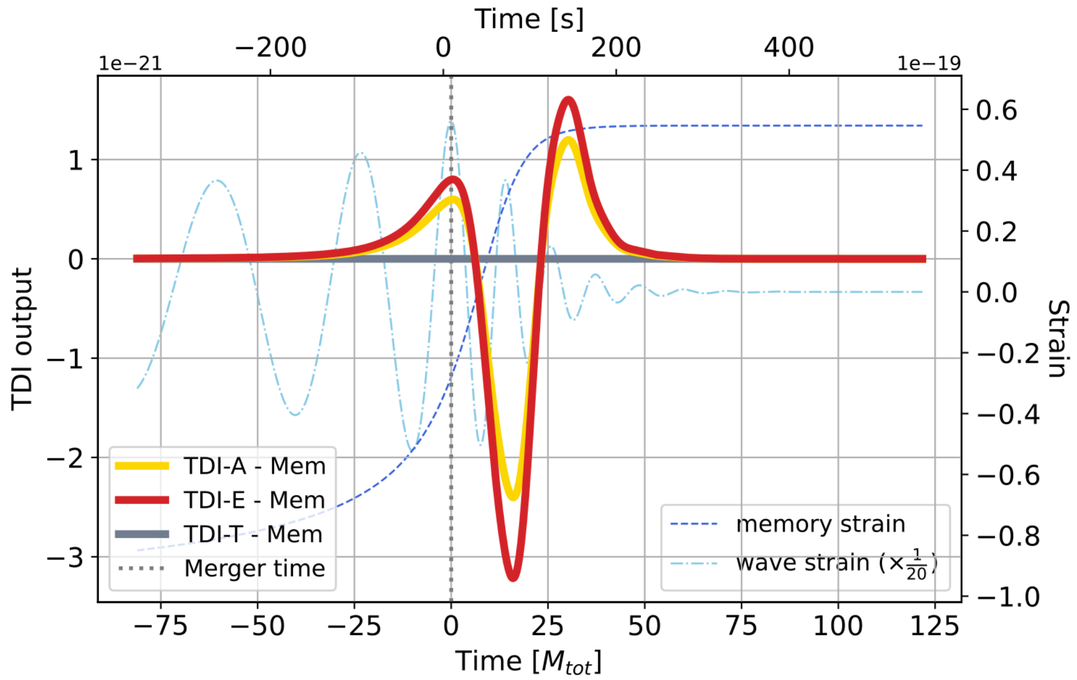


Figure from Inchauspé+(2025)

Overview of the project

Main goal: Provide a comprehensive assessment of WF systematics for the GW memory and guide waveform model improvements.

- Initial focus: aligned-spin, quasi-circular MBHBs to establish a baseline for WF systematics.
- PE studies using current WF models to assess biases and identify SNR thresholds where the (2,0) mode and GW memory become significant.
- Evaluate detectability in LISA.
- Assess the impact of omitting GW memory on residuals for long-duration signals.

Recent work from the Fundamental Physics GW Memory Working Group on the detectability and definition of GW memory: Inchauspé+(2025), Cogez+(2026), Zosso+(2026).

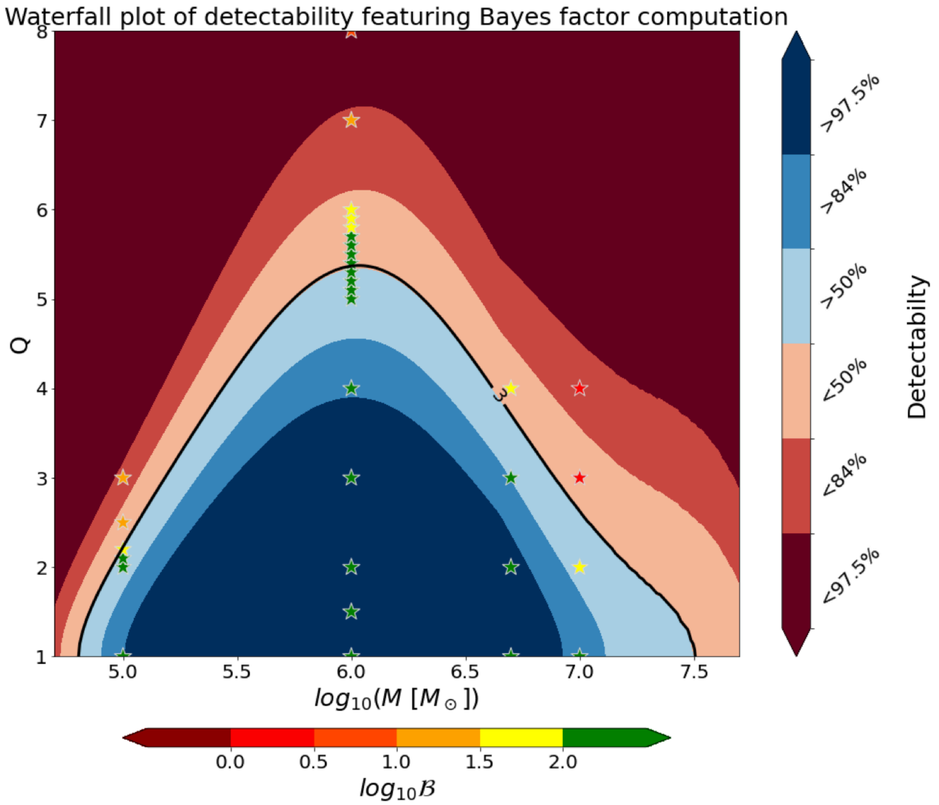


Figure from Cogez+(2026)

How do we measure the parameter biases?

Elements of the Fisher information matrix:

$$\Gamma_{ij} = \left\langle \partial_i h \,|\, \partial_j h \right\rangle,$$

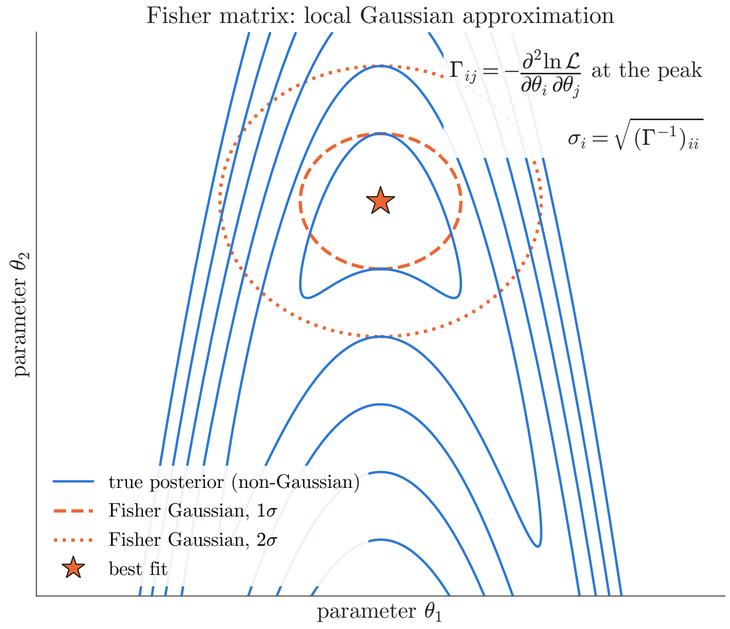
biases in the parameters:

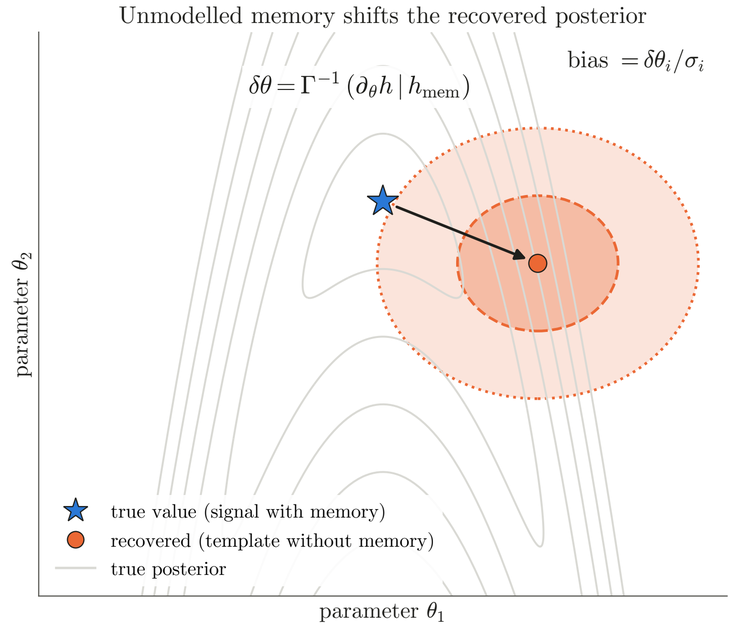
$$\delta\theta_i = \left(\Gamma_{ij}\right)^{-1} \left\langle \partial_j h \,|\, h_{\rm signal} - h \right\rangle.$$

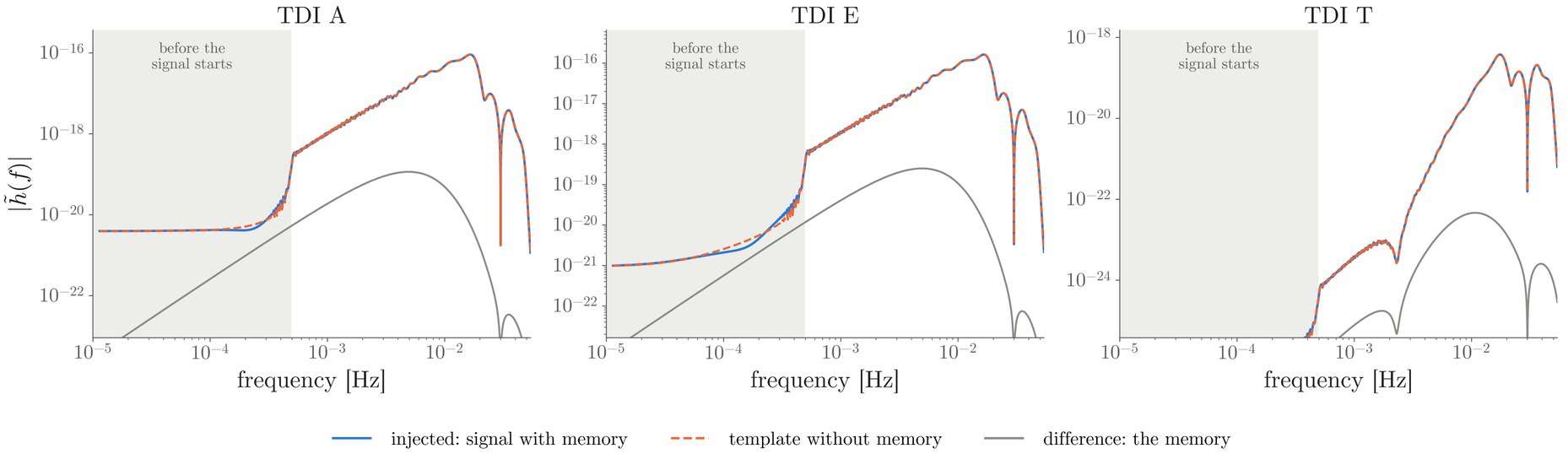
[Cutler+(2007), Völkel+(2025)]

We quote the bias ratio:

$$\frac{\delta\theta}{\sigma} = \frac{\text{recovered value} - \text{true value}}{\text{statistical uncertainty}}$$





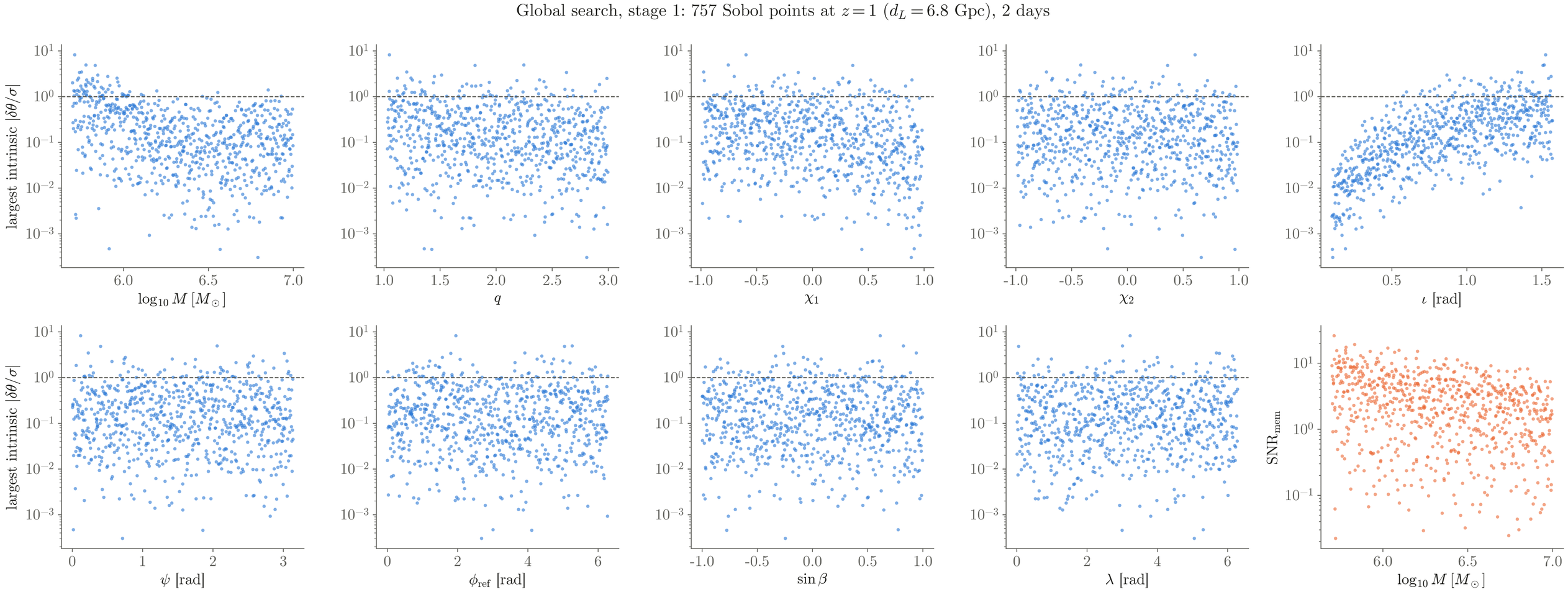


- Injection: Waveform with displacement memory.
- Recovery: Waveform without displacement memory.

Model used: IMRPhenomTHM [Estellés+(2020)] in phenomxpy [García-Quirós+(2025)].

Parameter space: global search to find the sweet spot for memory

1000 configurations across parameter space: total mass, mass ratio, spins, inclination, sky location and polarization.
Main levers: total mass and inclination angle.



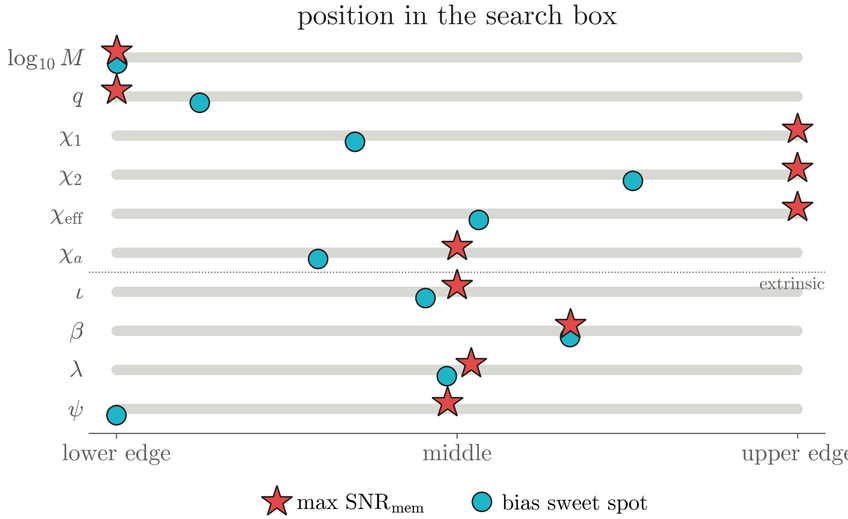
The most memory does not give the largest biases

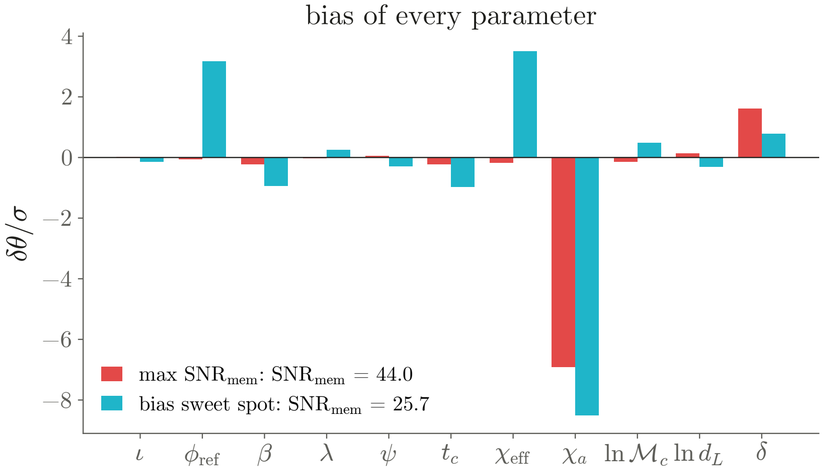
The memory SNR is maximum at equal mass, $q = 1$, with positive, maximal spins $\chi_1 = \chi_2 = 0.99$ ($\mathrm{SNR}_{\mathrm{mem}} \sim 44$), but the bias there is only -6.9σ, against $\sim -8.5\sigma$ at the sweet spot.

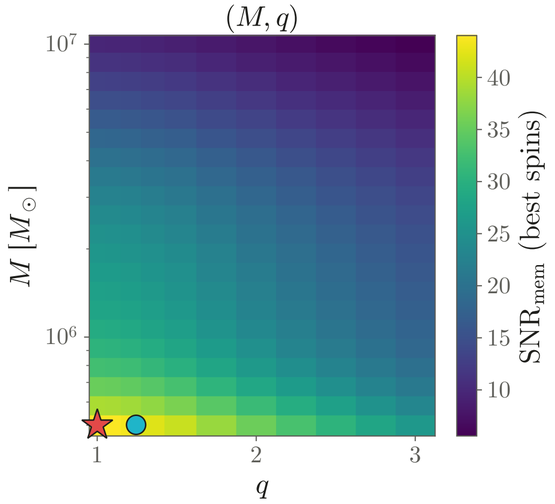
With $M = m_1 + m_2$ and $m_1 \geq m_2$:

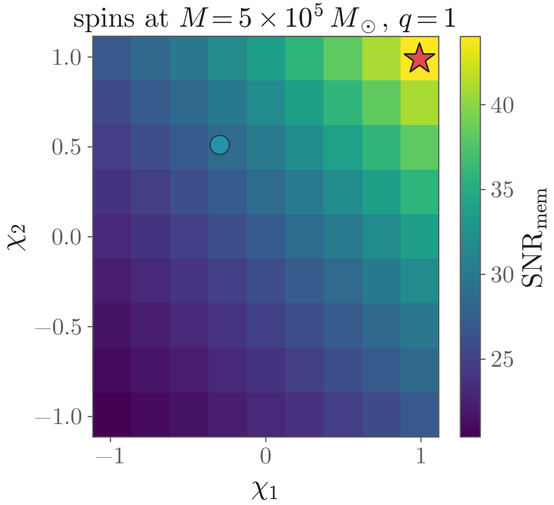
$$\mathcal{M}_c = \frac{(m_1 m_2)^{3/5}}{(m_1 + m_2)^{1/5}}, \delta = \frac{m_1 - m_2}{m_1 + m_2},$$

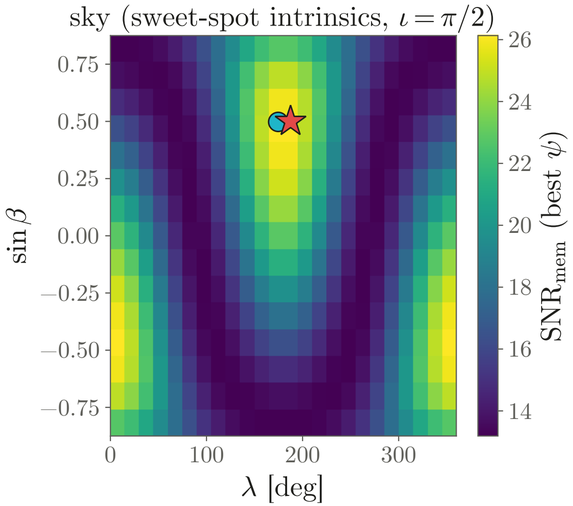
$$\chi_{\mathrm{eff}} = \frac{m_1 \chi_1 + m_2 \chi_2}{m_1 + m_2}, \chi_a = \frac{\chi_1 - \chi_2}{2}.$$









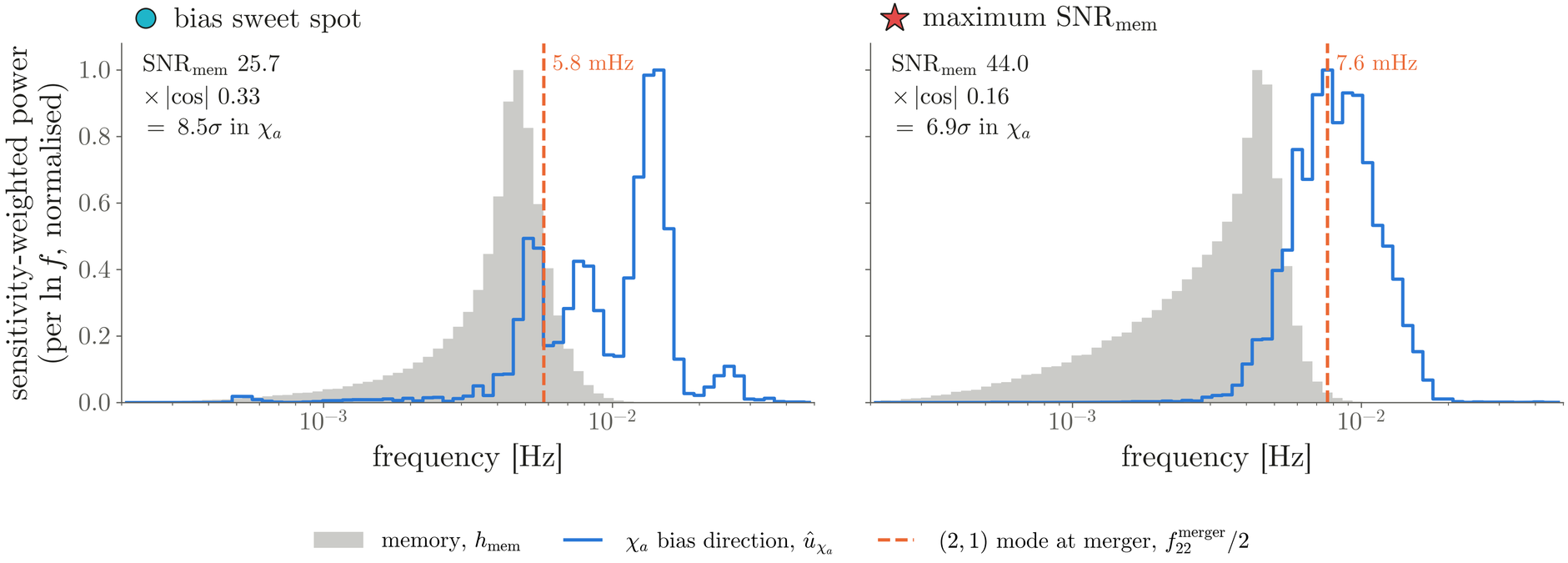


Why the χ_a is the most biased parameter?

From the bias equation: $$\frac{\delta\theta}{\sigma} = \mathrm{SNR}_{\mathrm{mem}} \times \cos\left(h_{\mathrm{mem}}, \hat{u}_\theta\right)$$

(Memory SNR) × (How well the memory lines up with the waveform change produced by that parameter)

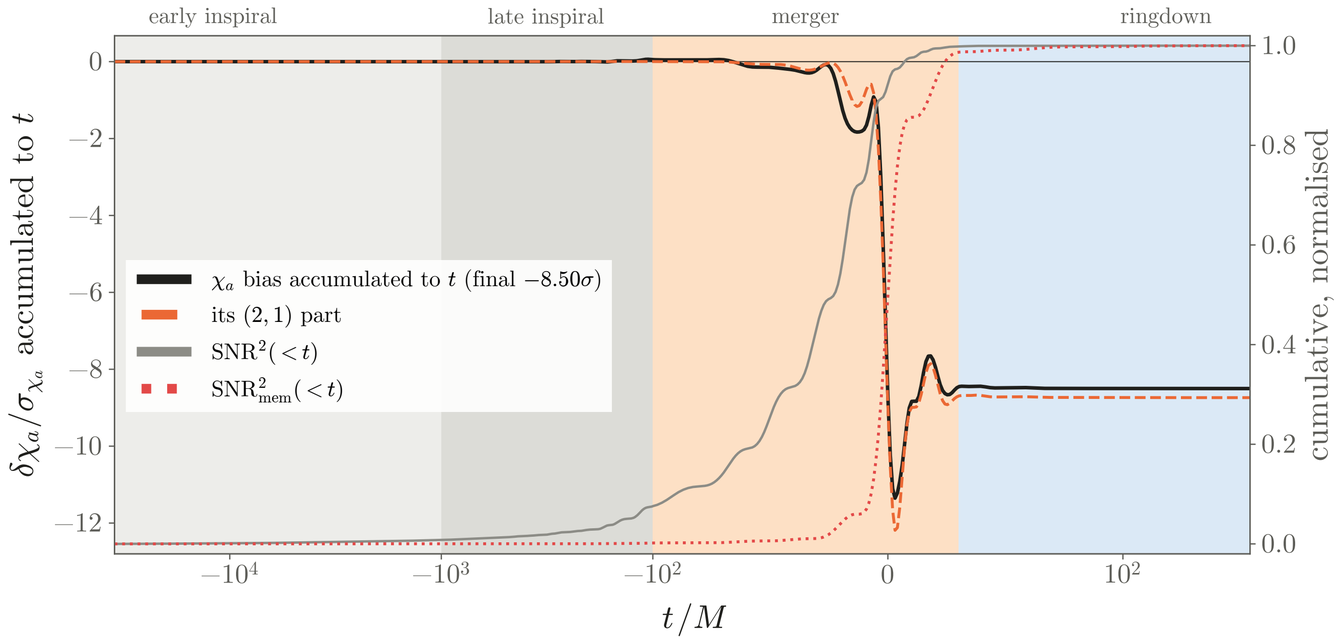
- The memory pulse at the merger, weighted by LISA's sensitivity, has its power at 1-6 mHz.
- In that band, the main mode in the model that can absorb it is the (2,±1) mode ($f_{22}^{\mathrm{merger}}/2$).
- χ_a is the parameter that controls the (2,±1) mode, so the fit uses it to mimic the memory in the template without it.

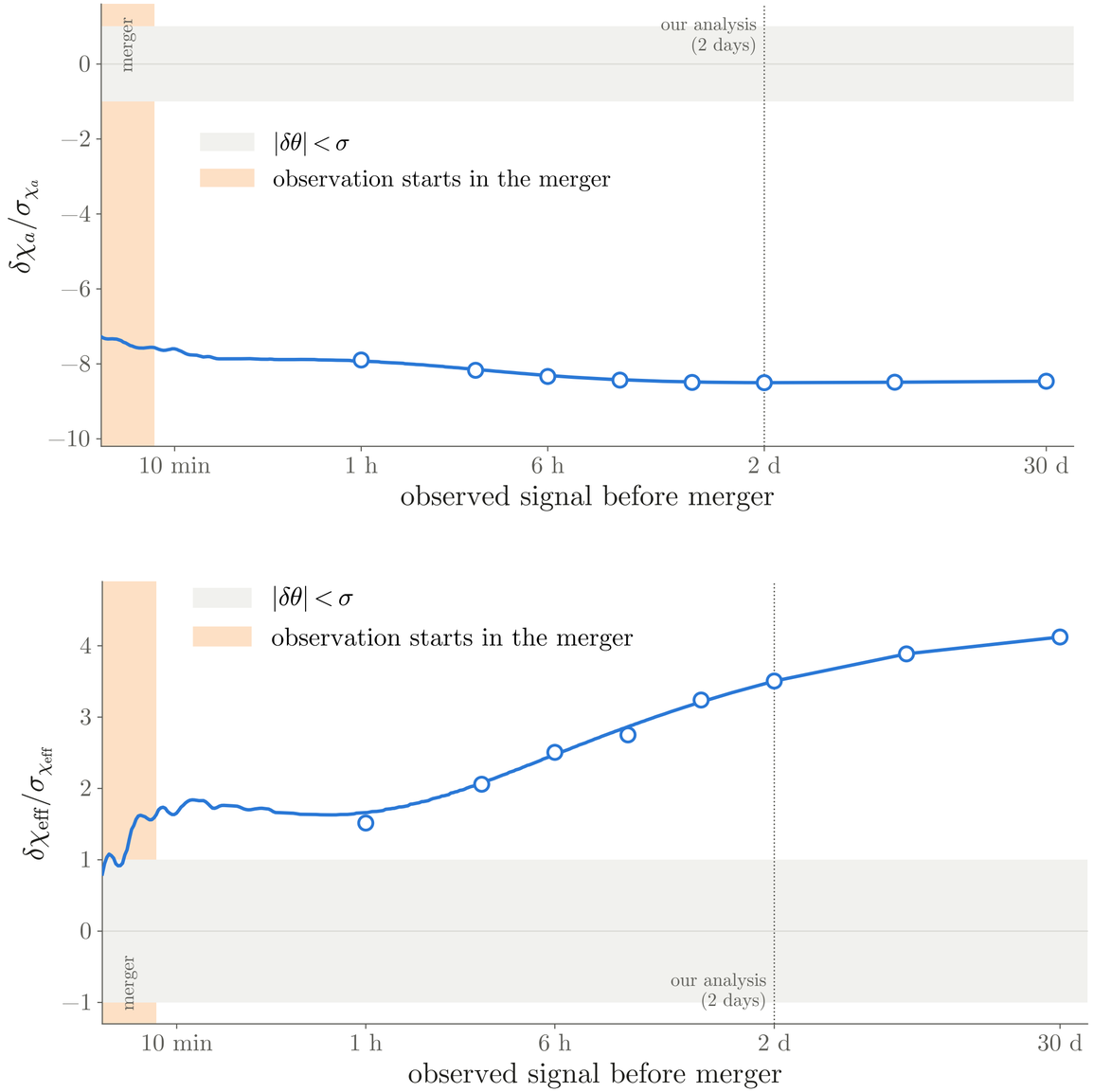


- Sweet spot: the (2,±1) mode is at 5.8 mHz, inside the memory band.
- Maximum memory SNR: large aligned spins push it to 7.6 mHz, above the band, which halves the overlap.

When does the bias build up?

The biases build up in the last $\sim 100\,M$ before merger. This region plus $\sim 30\,M$ after it holds 97–98% of the memory SNR and all of the bias in χ_a.



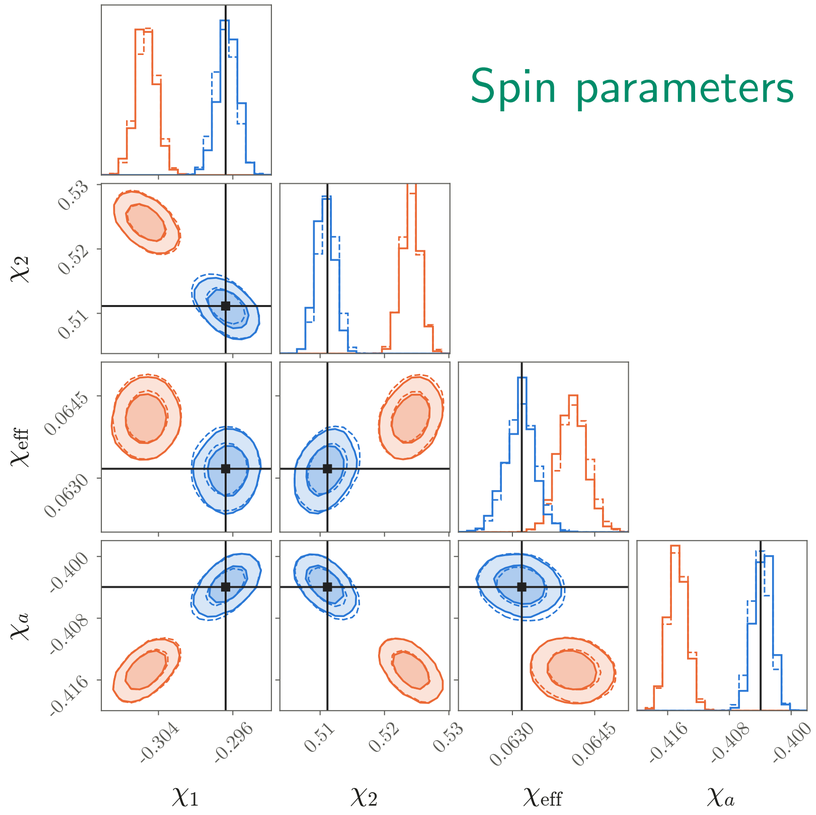


Dependence on the signal duration: SNR and memory SNR are essentially the same from 1 hour to 30 days of data. The bias of every parameter is stable across durations. Only χ_{eff} grows because the long inspiral is what constrains it.

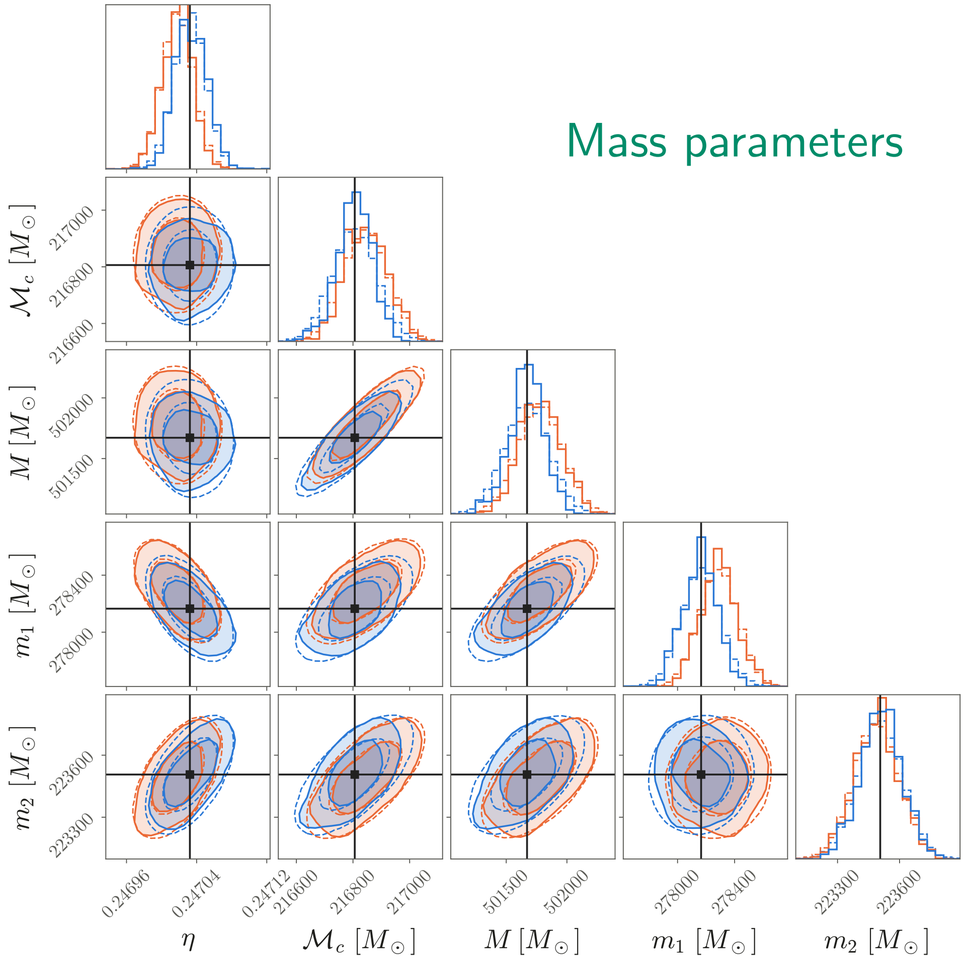
Consistency between Fisher and Bayesian parameter estimation

- Zero-noise injection.
- Recovery with IMRPhenomTHM with and without memory.
- Full TDI-2 LISA response [Baghi(2022)].
- Sampler: `ptemcee` [Vousden+(2015)].
- Walkers initialized from the Fisher prediction.
- SNR of the full signal: 4001.
- SNR of the memory signal: 25.7.

Spin parameters



Mass parameters



Full PE, template with memory
Fisher, template with memory
Full PE, template without memory
Fisher, template without memory
injected value (signal with memory)

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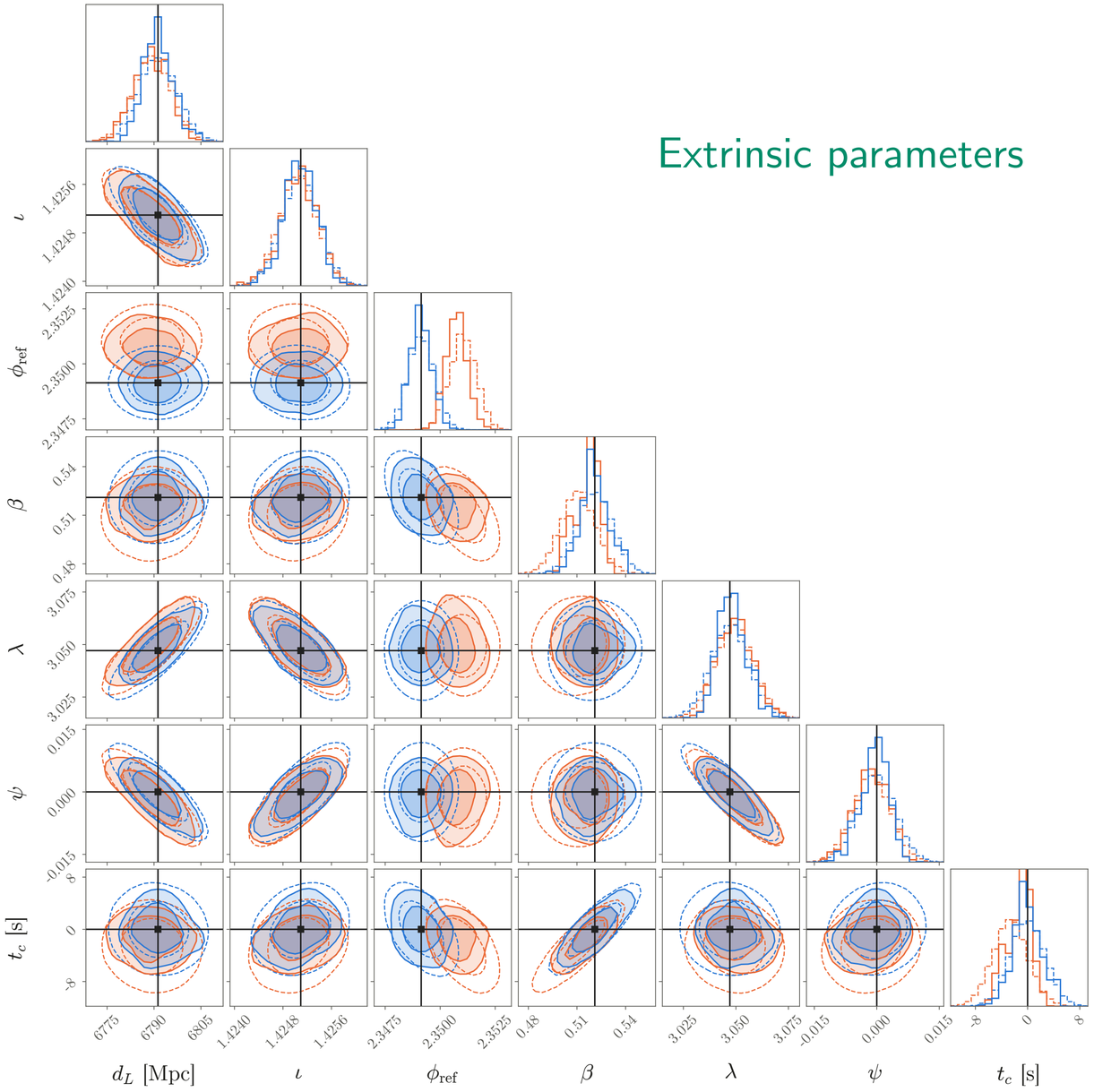

Conclusions

- Omitting the GW displacement memory can bias LISA MBHB parameters significantly. The largest effect is in the spin difference χ_a.
- Most memory ≠ most bias: what matters is how well the memory lines up with the (2,±1) mode.
- The biases form around the merger, and they do not depend on the signal duration.
- Full Bayesian PE agrees well with Fisher estimates in the cases we have tested.

Future work

- Compute SNR thresholds and evaluate detectability.
- Perform injections with noise, rather than only zero-noise injections.
- Perform full PE runs without Fisher initialization.
- Go beyond quasi-circular, aligned-spin systems using eccentric and/or precessing waveform models.

Take-home🏠 message: For loud, low-mass, edge-on MBHBs, waveform models need to include GW displacement memory. Leaving it out leads to biases, which can be quite large, especially for the spin parameters.

Acknowledgements

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