The precision science of **extreme mass-ratio inspirals**

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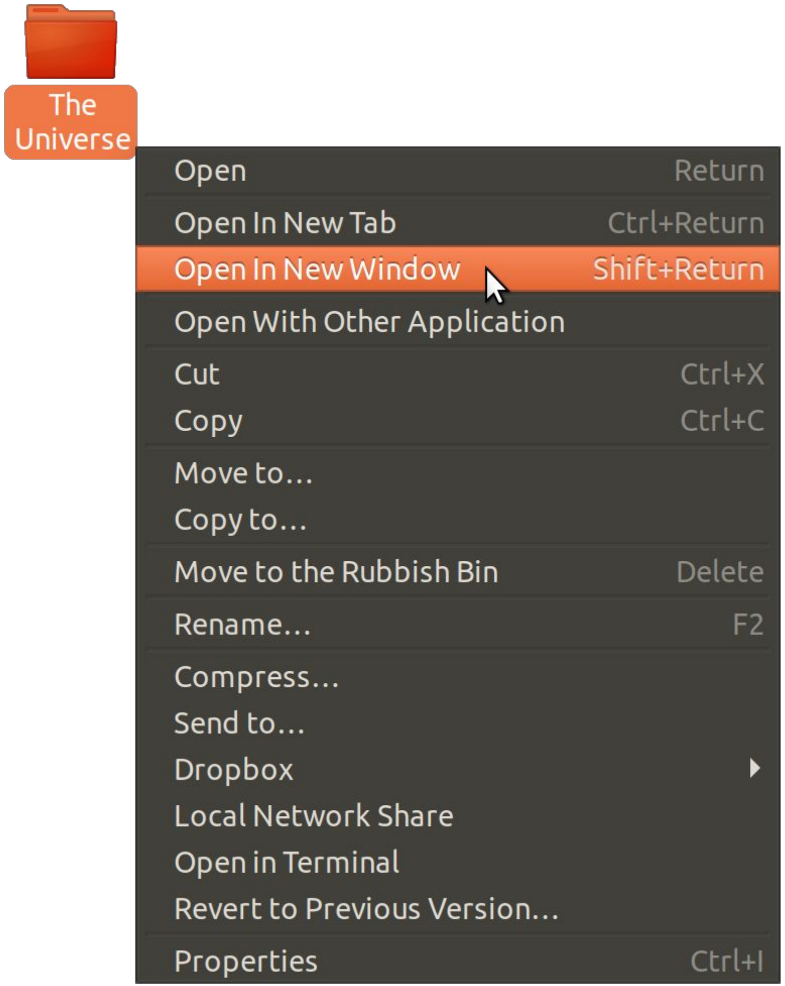
GraSP24 • 24 October 2024 • arXiv:1903.03686 arXiv:2212.06166

University of Glasgow | School of Physics & Astronomy

IGR

UKRI Science and Technology Facilities Council

Image: LIGO/Caltech/MIT/Sonoma State/Aurore Simonnet



An undiscovered source

Massive black holes and stellar companions

Precision measurement

Intricate orbits in the strong field

Black hole astrophysics

Using a population to build understand

An undiscovered source

Spoilers

Signals encode information about their sources

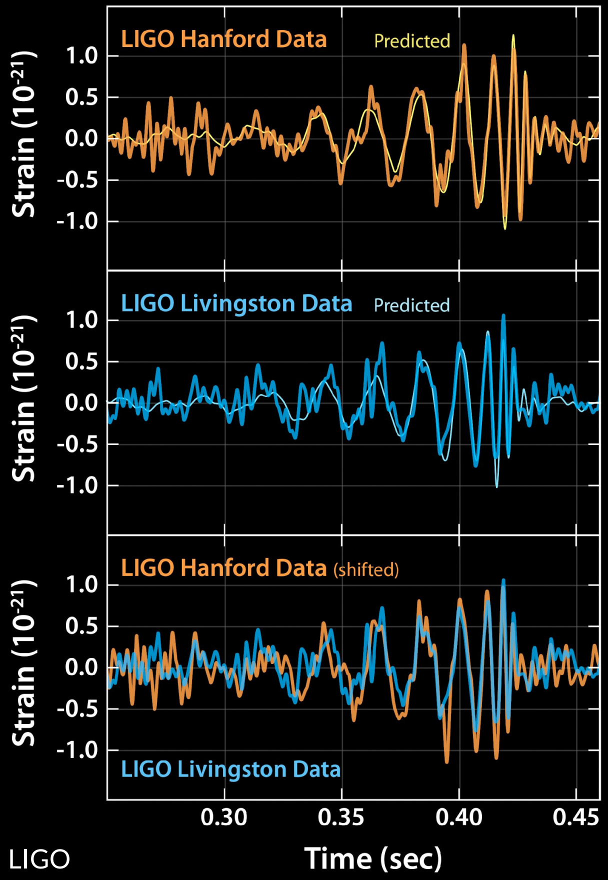
GW150914 parameter estimation
arXiv:1602.03840

GW150914 astrophysical implications
arXiv:1602.03846

14 September 2015 we observed gravitational waves

The signal came from the coalescence of a **near-equal mass** binary black hole

This material is based upon work supported by NSF's LIGO Laboratory which is a major facility fully funded by the National Science Foundation



LIGO

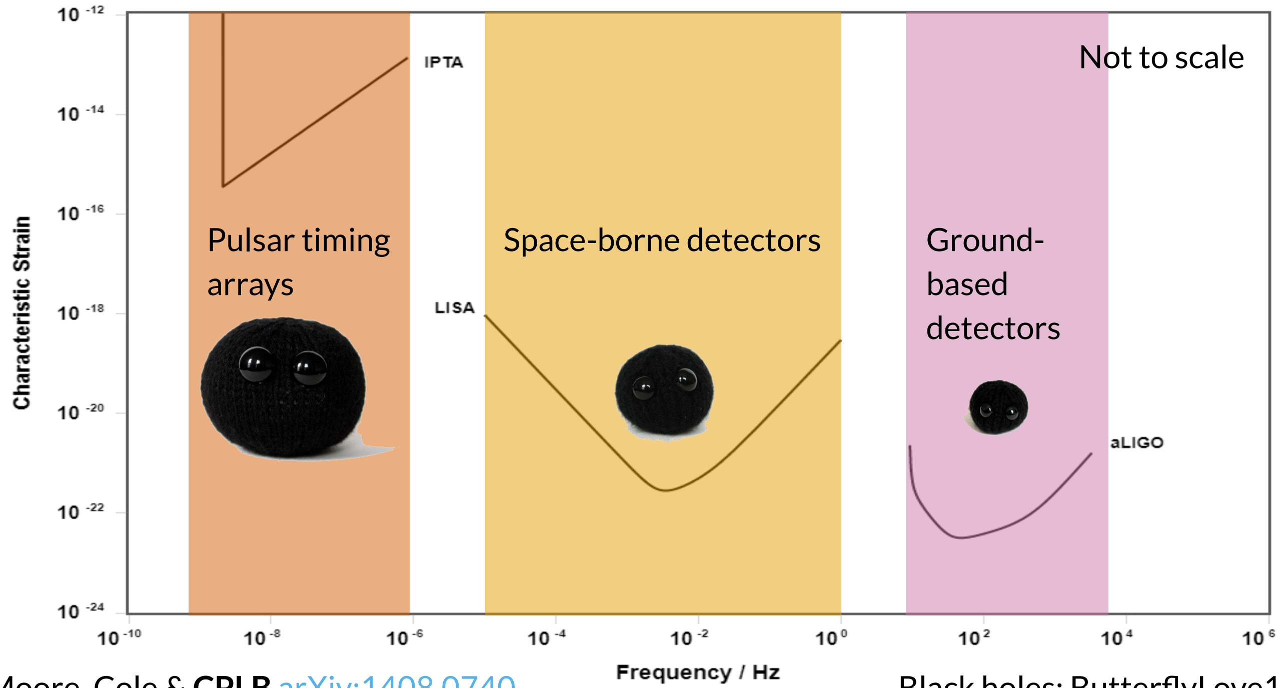
Gravitational-wave spectrum

Different technologies used for different frequency ranges

Currently, LIGO, Virgo and KAGRA observe at highest frequencies

LISA is due for launch in 2030s

Pulsar timing arrays observe at lowest frequencies



Moore, Cole & **CPLB** arXiv:1408.0740

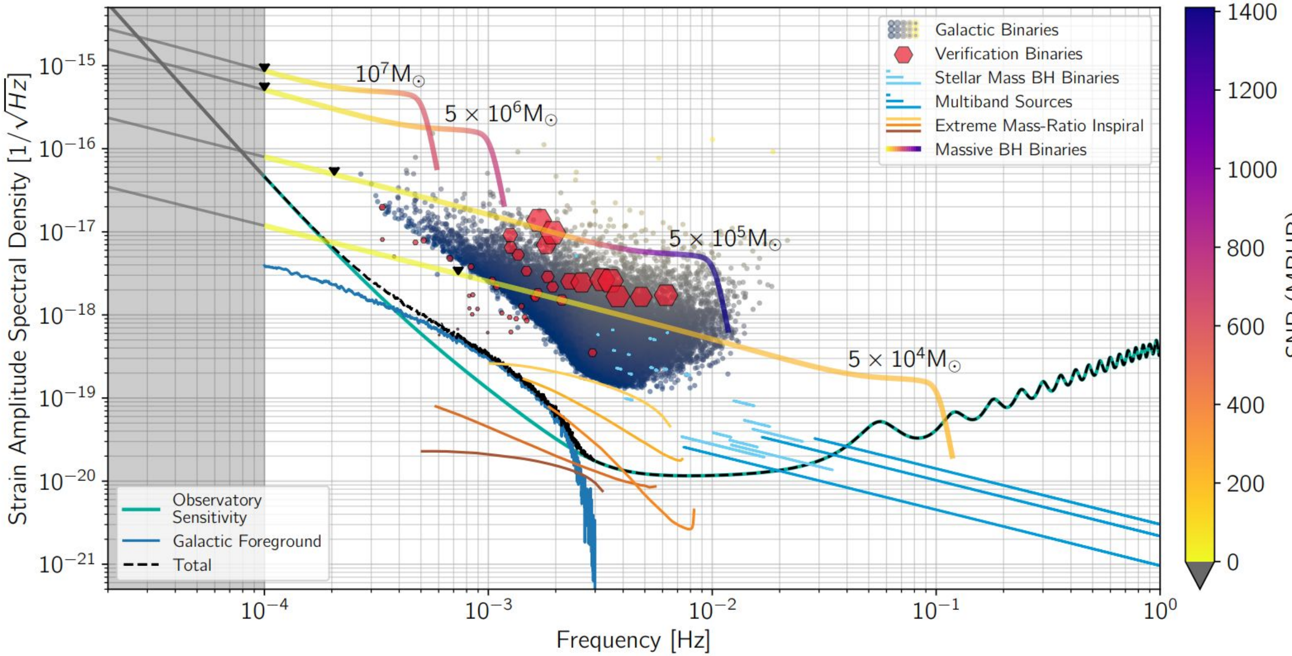
Black holes: ButterflyLove1

LISA

LISA mission accepted by ESA in January, launch planned for 2035

LISA can contribute to a wide range of astrophysics arXiv:2203.06016

Data analysis will be extremely complicated lisa-ldc.lal.in2p3.fr



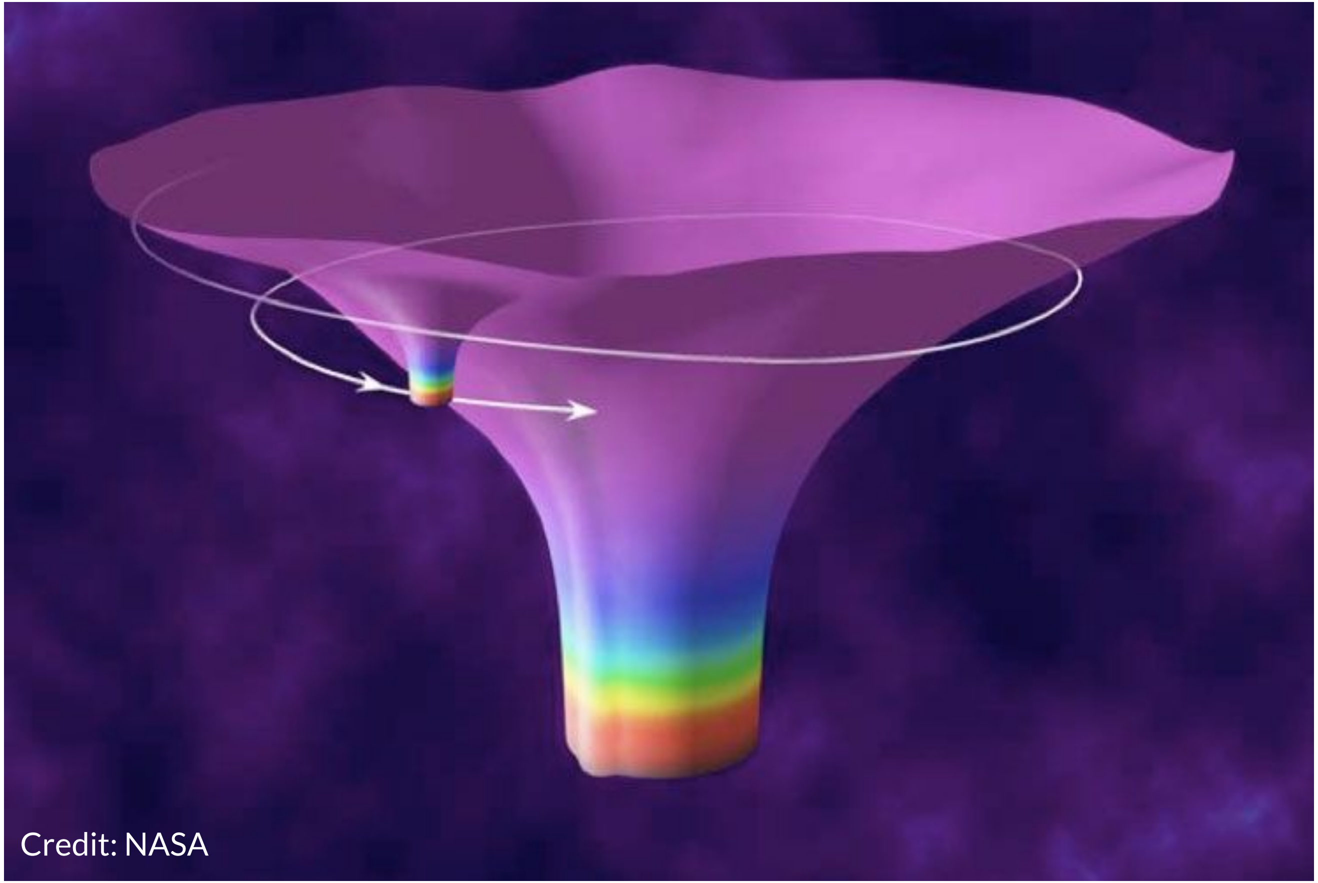
LISA arXiv:2402.07571

Extreme mass-ratio inspirals (EMRIs) source massive black hole + stellar-mass companion. Mass ratio $q \sim 10^{-5}$
arXiv:astro-ph/0703495

Intermediate mass-ratio inspirals (IMRIs) $q \sim 10^{-3}$

Binary extreme mass-ratio inspirals (b-EMRIs) source massive black hole + stellar-mass binary
arXiv:1801.05780

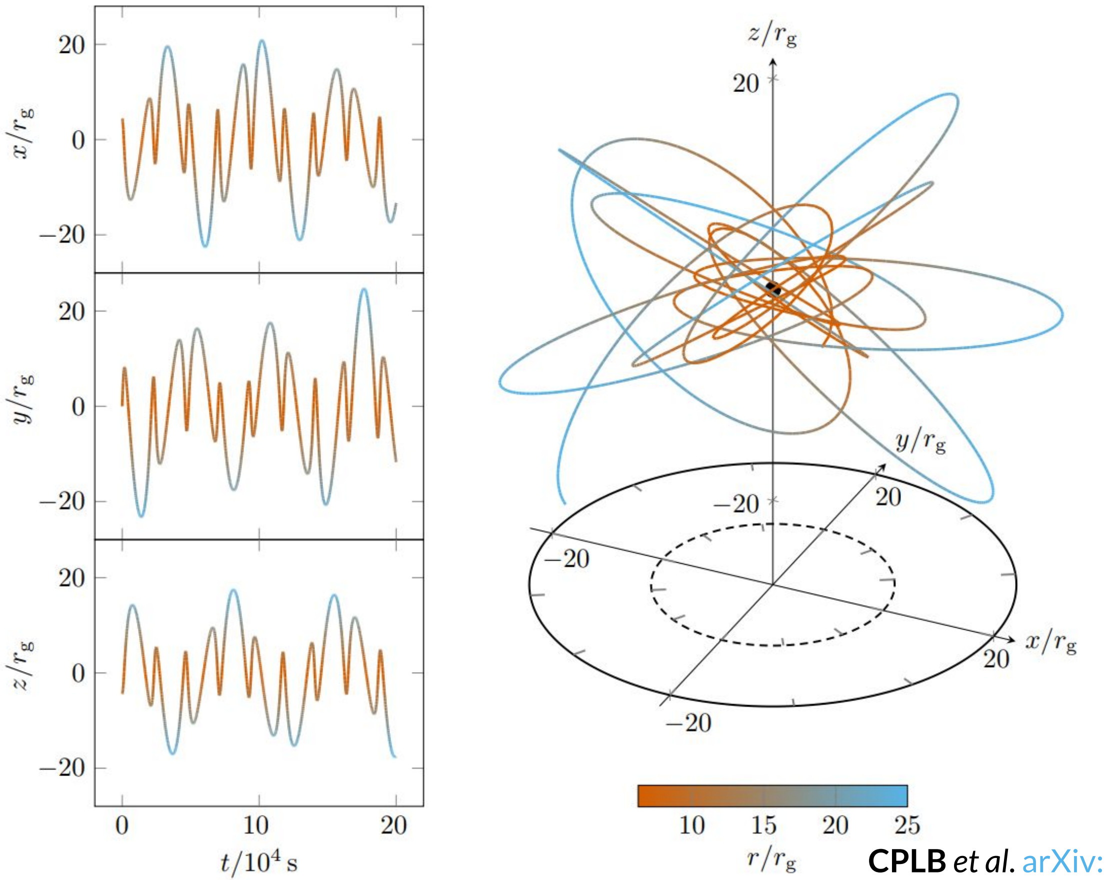
Extremely large mass-ratio inspirals (XMRIs) source massive black hole + subsolar-mass companion $q < 10^{-8}$
arXiv:1903.10871



EMRIs complete many orbits in the strong-field regime. Number of orbits ~$1/q$

Waveforms have a complicated frequency structure, e.g., Speri *et al.* arXiv:2307.12585

Complexity encodes information about the background spacetime, e.g., Barack & Cutler arXiv:gr-qc/0310125



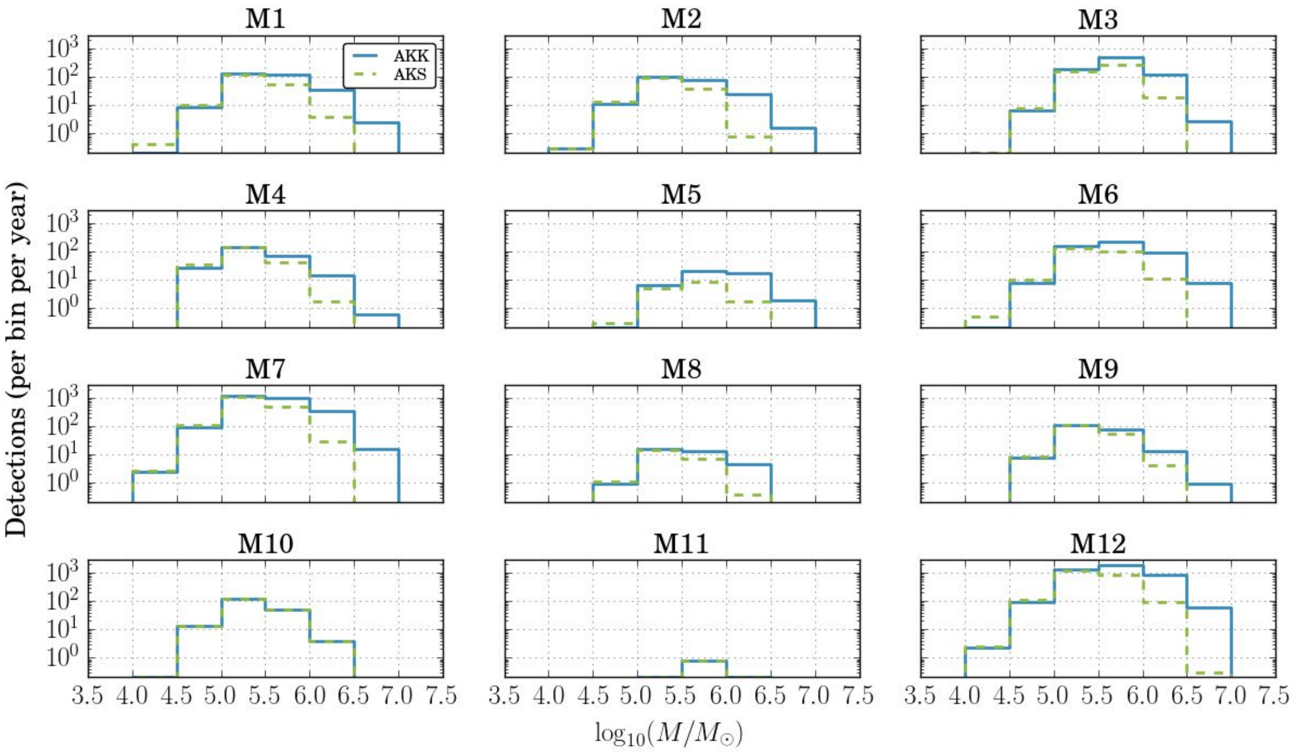
CPLB *et al.* arXiv:1903.03686

Precision measurement

EMRI populations are uncertain. Rates range from ~1 to 10^3 per year

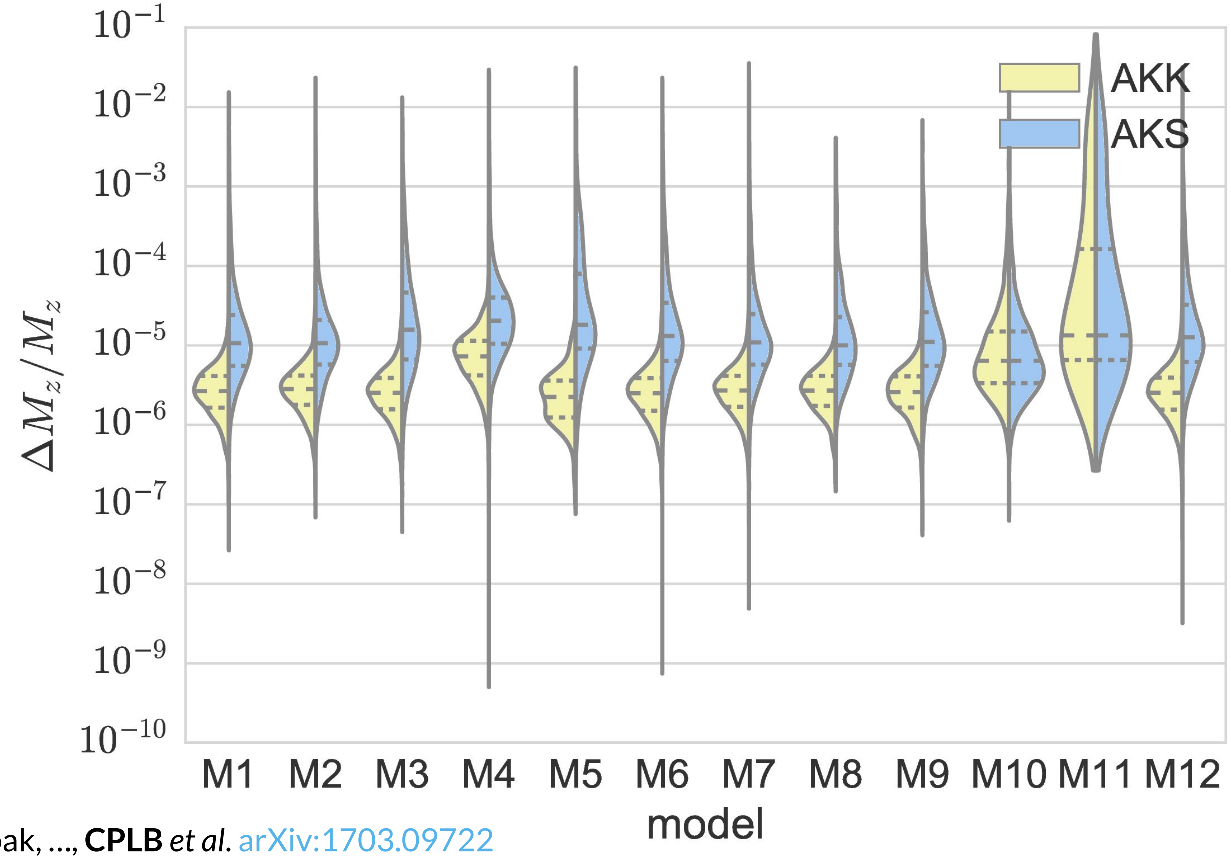
Results are sensitive to choice of waveform

AKK analytic kludge Kerr
AKS analytic kludge Schwarzschild (pessimistic)



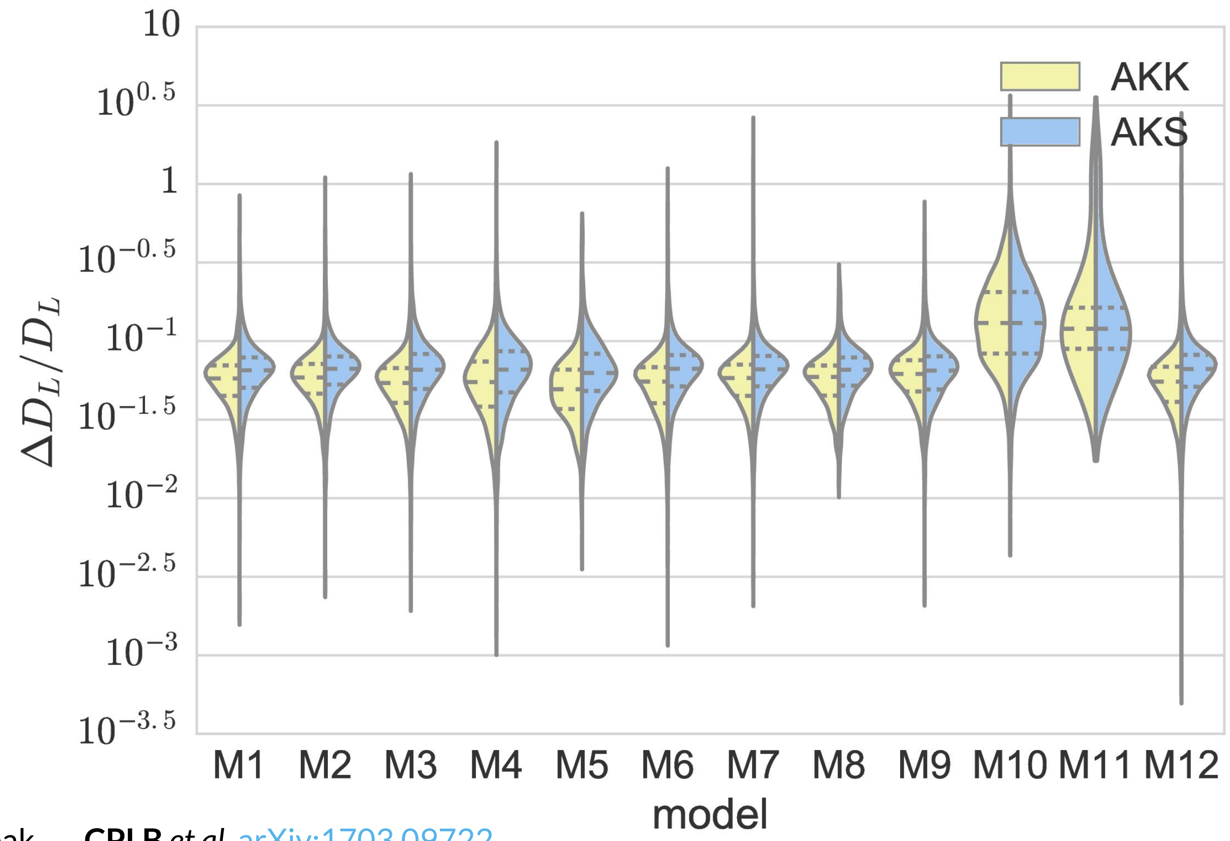
Babak, …, **CPLB** *et al.* arXiv:1703.09722

Massive black hole mass sets orbital frequencies



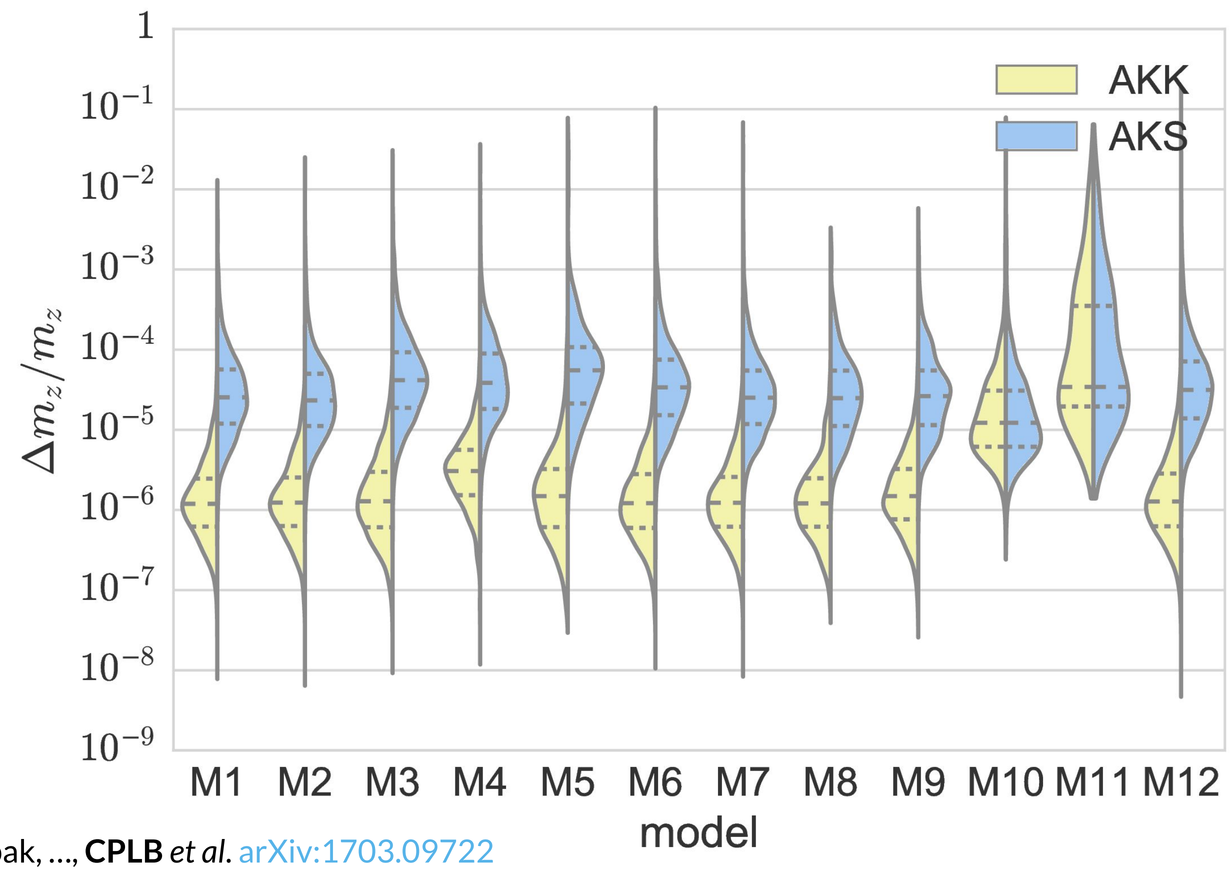
Babak, …, **CPLB** *et al.* arXiv:1703.09722

Distance sets amplitude



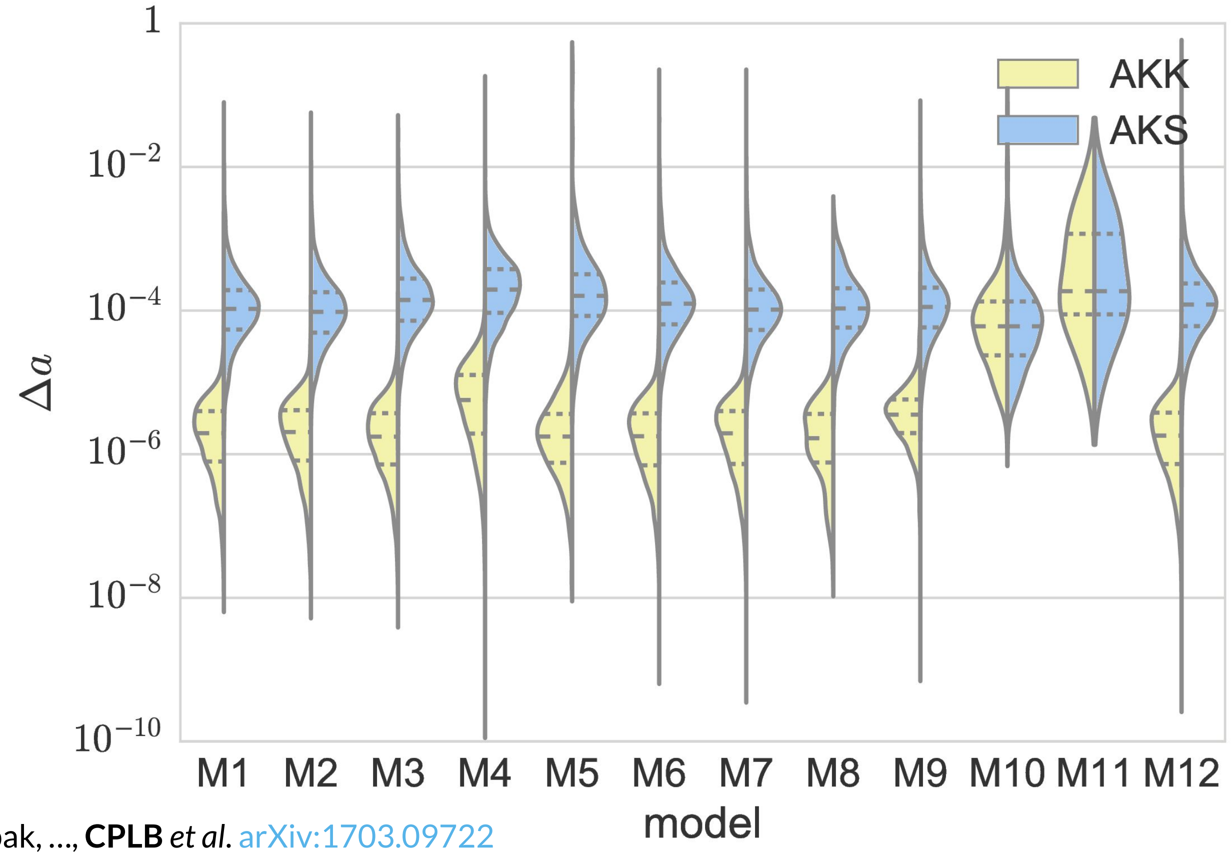
Babak, …, **CPLB** *et al.* arXiv:1703.09722

Companion mass sets inspiral rate and amplitude



Babak, …, **CPLB** *et al.* arXiv:1703.09722

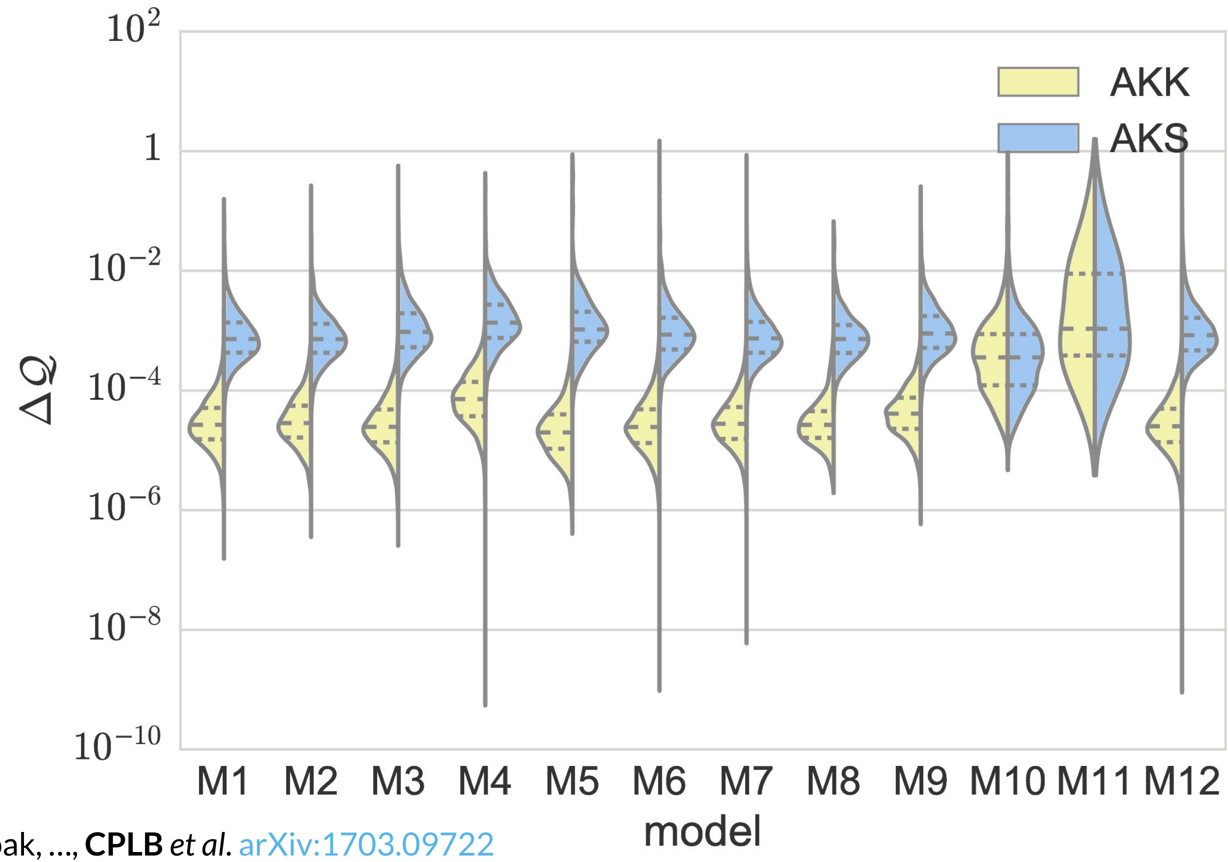
Massive black hole spin influences spacetime close to the black hole



Babak, …, **CPLB** *et al.* arXiv:1703.09722

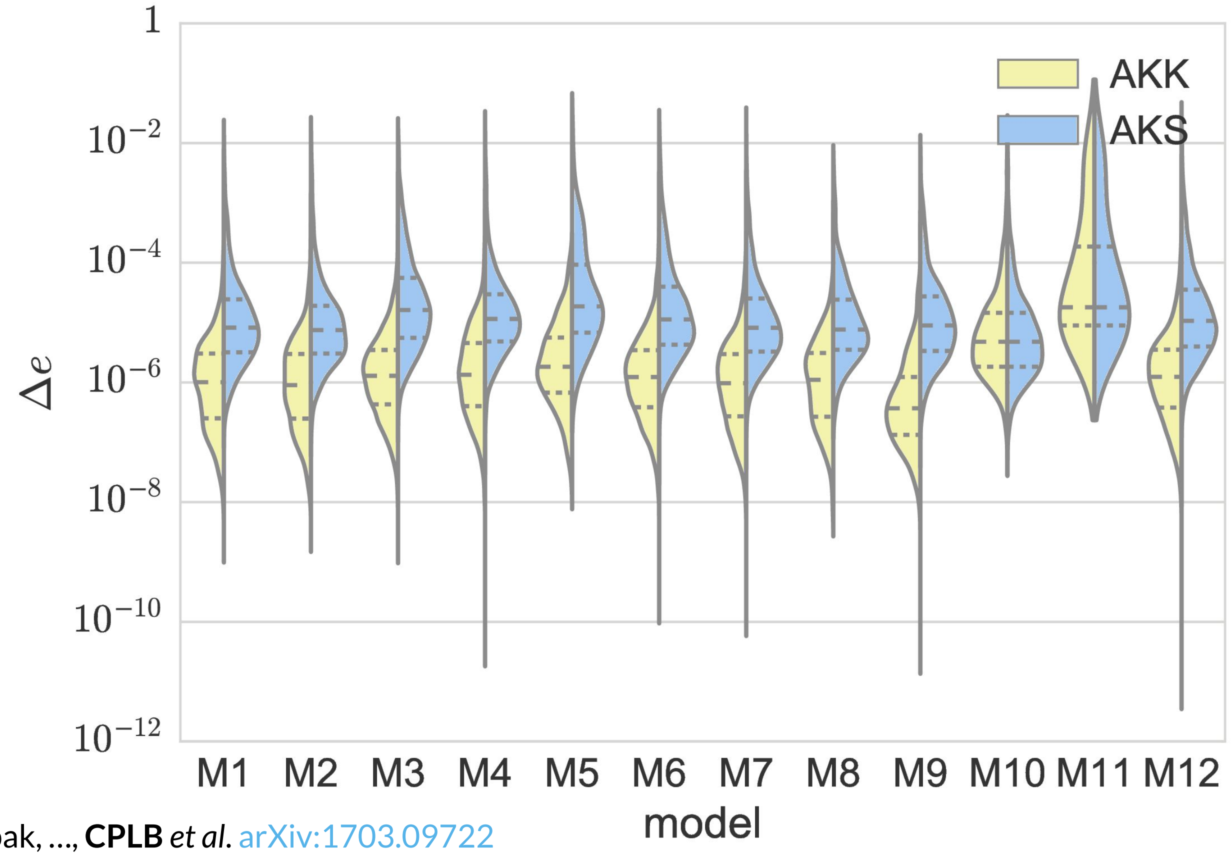
Deviations in the **quadrupole moment** would identify a non-Kerr spacetime

EMRIs can provide precision tests of general relativity, e.g., Cárdenas-Avendaño & Sopuerta arXiv:2401.08085



Babak, ..., **CPLB** *et al*. arXiv:1703.09722

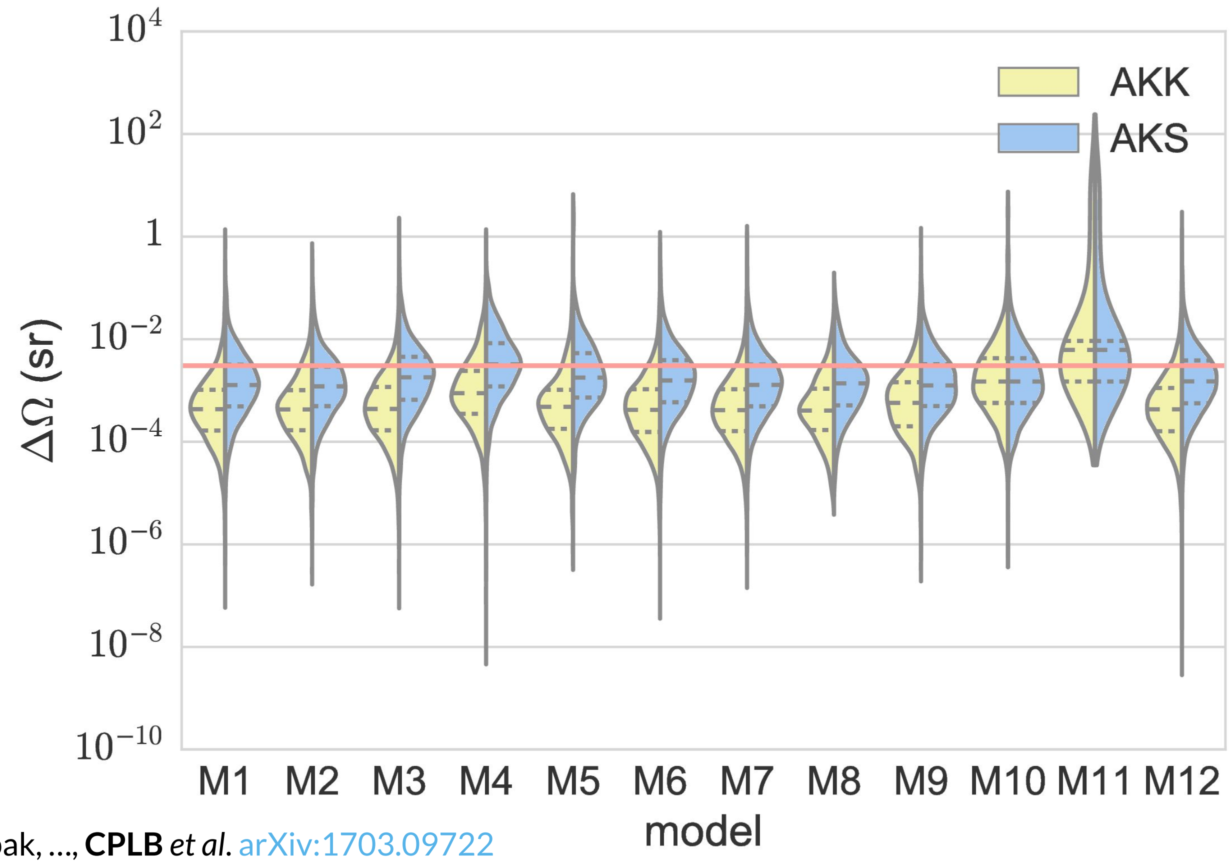
Eccentricity influences set of frequencies



Babak, …, **CPLB** *et al.* arXiv:1703.09722

Sky location important for searching for electromagnetic counterparts and association with host galaxy and cosmology

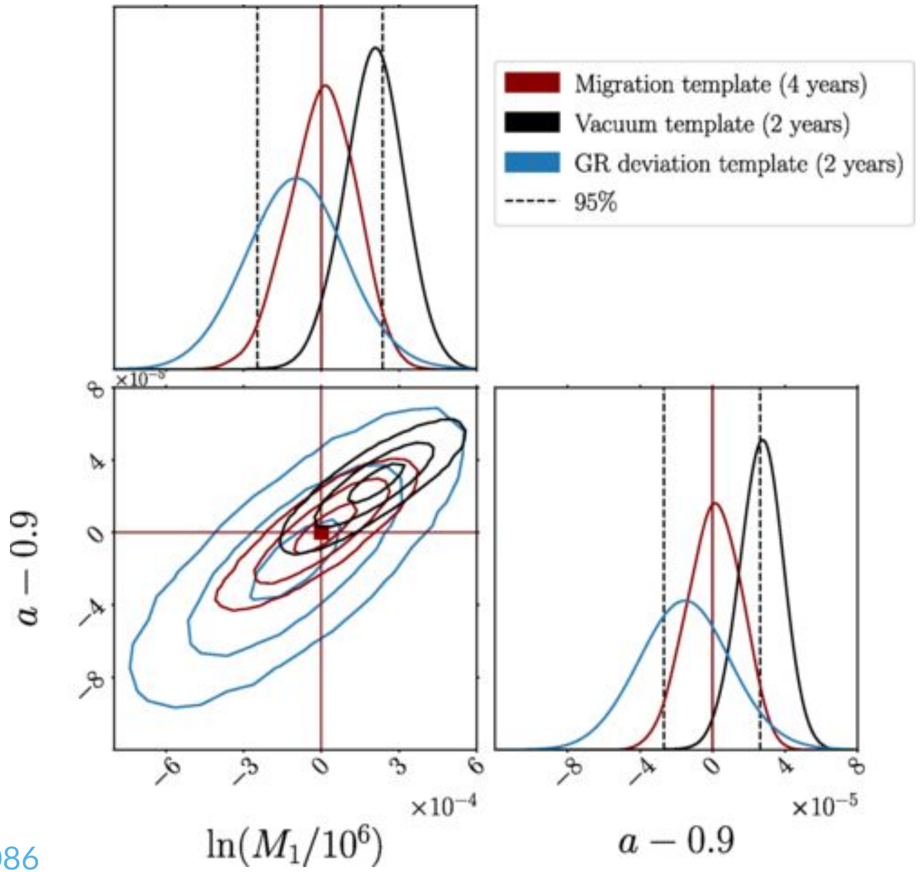
Measurement of the cosmological parameters
Laghi *et al.* arXiv:2102.01708



Babak, …, **CPLB** *et al.* arXiv:1703.09722

Using up-to-date equatorial waveforms

Can measure environmental or non-Kerr effects



Speri *et al.* arXiv:2207.10086

Black hole astrophysics

EMRI formation

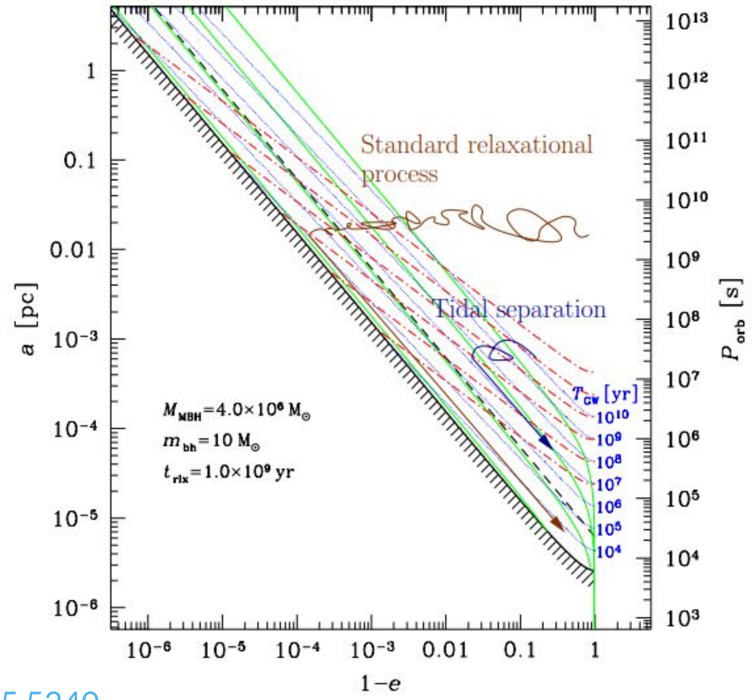
How to get companions close enough?

Dynamical friction and two-body scattering
arXiv:1205.5240

Scattering from cliff-diving orbits
arXiv:2304.13062

Disc-assisted wet EMRIs
arXiv:2104.01208

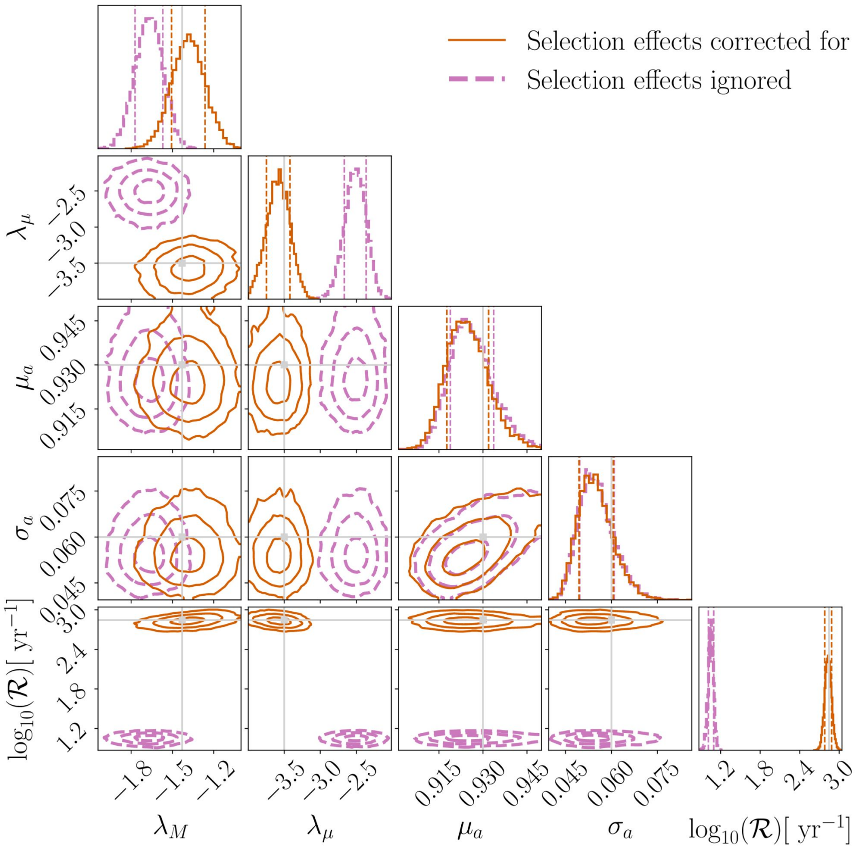
Supernova kicks
arXiv:1902.04581



Amaro-Seoane arXiv:1205.5240

Population inference requires:
1. Parameter estimates for each signal
2. A population model
3. Accounting for selection effects

How to account for selection effects
Mandel *et al.* arXiv:1809.02063



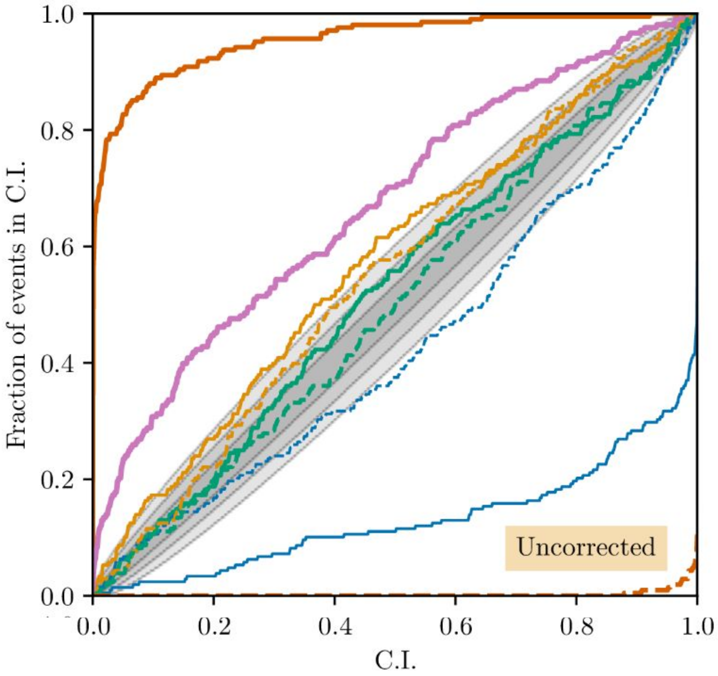
Chapman-Bird, **CPLB** & Woan
arXiv:2212.06166

Validation

Not accounting for selection effects leads to biases

Linear interpolation is insufficient

Our neural network approach works



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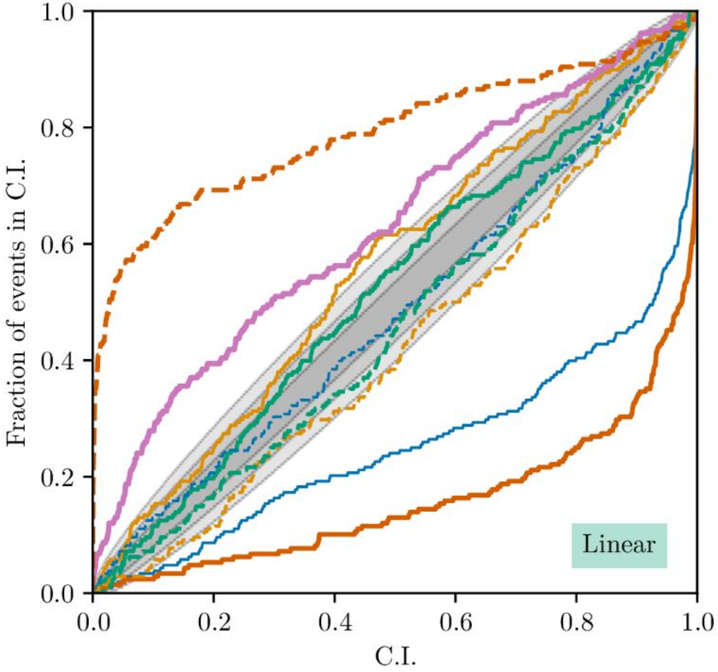


Chapman-Bird, **CPLB** & Woan arXiv:2212.06166

Validation

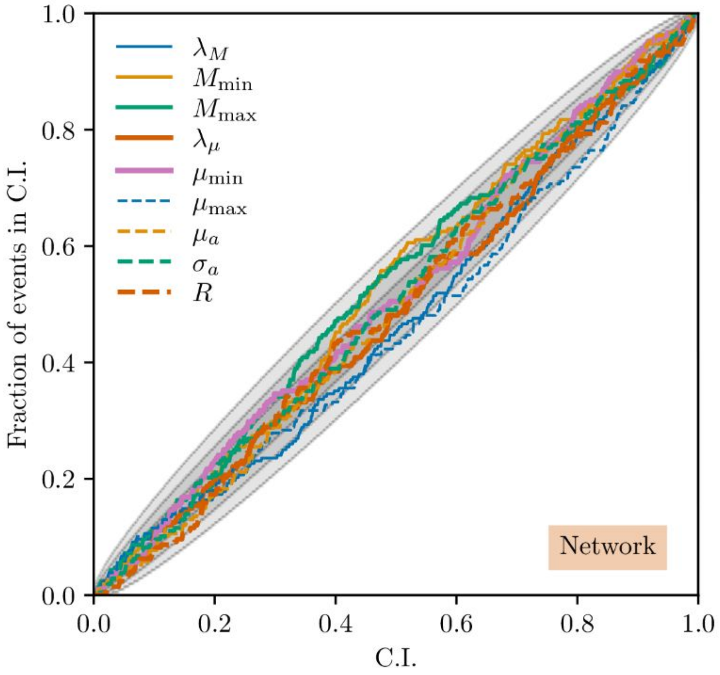
Not accounting for selection effects leads to biases

Linear interpolation is insufficient

Our neural network approach works

And is quick enough to run **hundreds** of population inferences!

poplar code
DOI:10.5281/zenodo.7573034



Chapman-Bird, **CPLB** & Woan arXiv:2212.06166

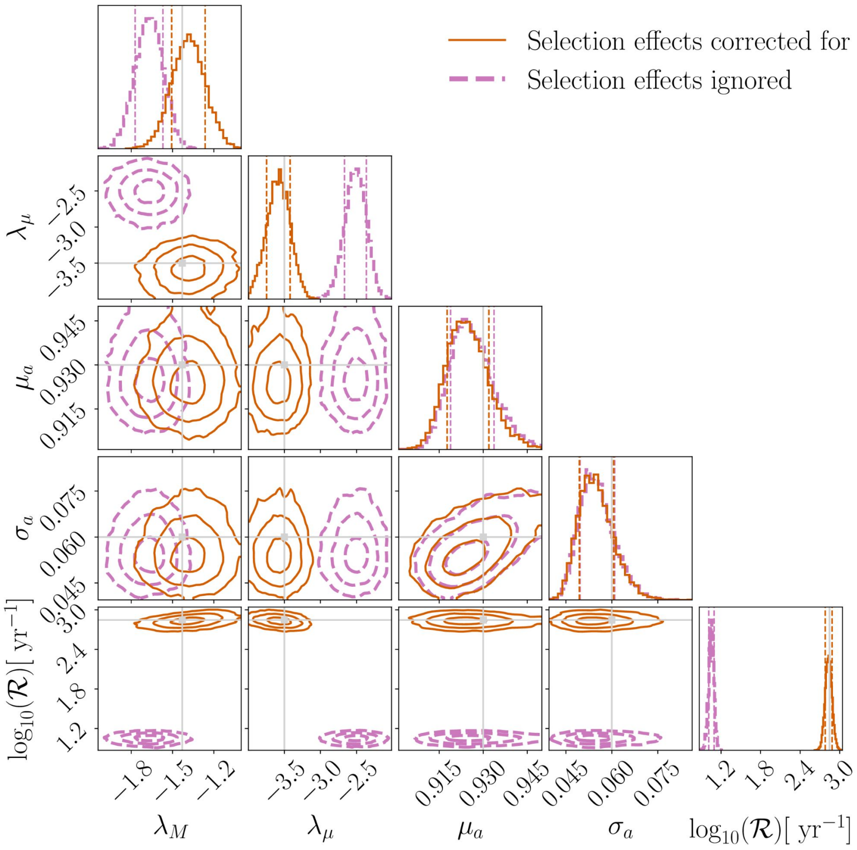
For sources with redshift < 6 and an optimistic event rate

MBH mass function slope: 9%

CO mass function slope 5%

Width of the MBH spin magnitude distribution 10%

Event rate 12%



Chapman-Bird, **CPLB** & Woan
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ButterflyLove1

1. **Extreme mass-ratio inspirals** have intricate waveforms
2. They enable **precision measurements** of individual sources, and a unique insight into the population
3. Significant work is needed to develop LISA data analysis

Thank you

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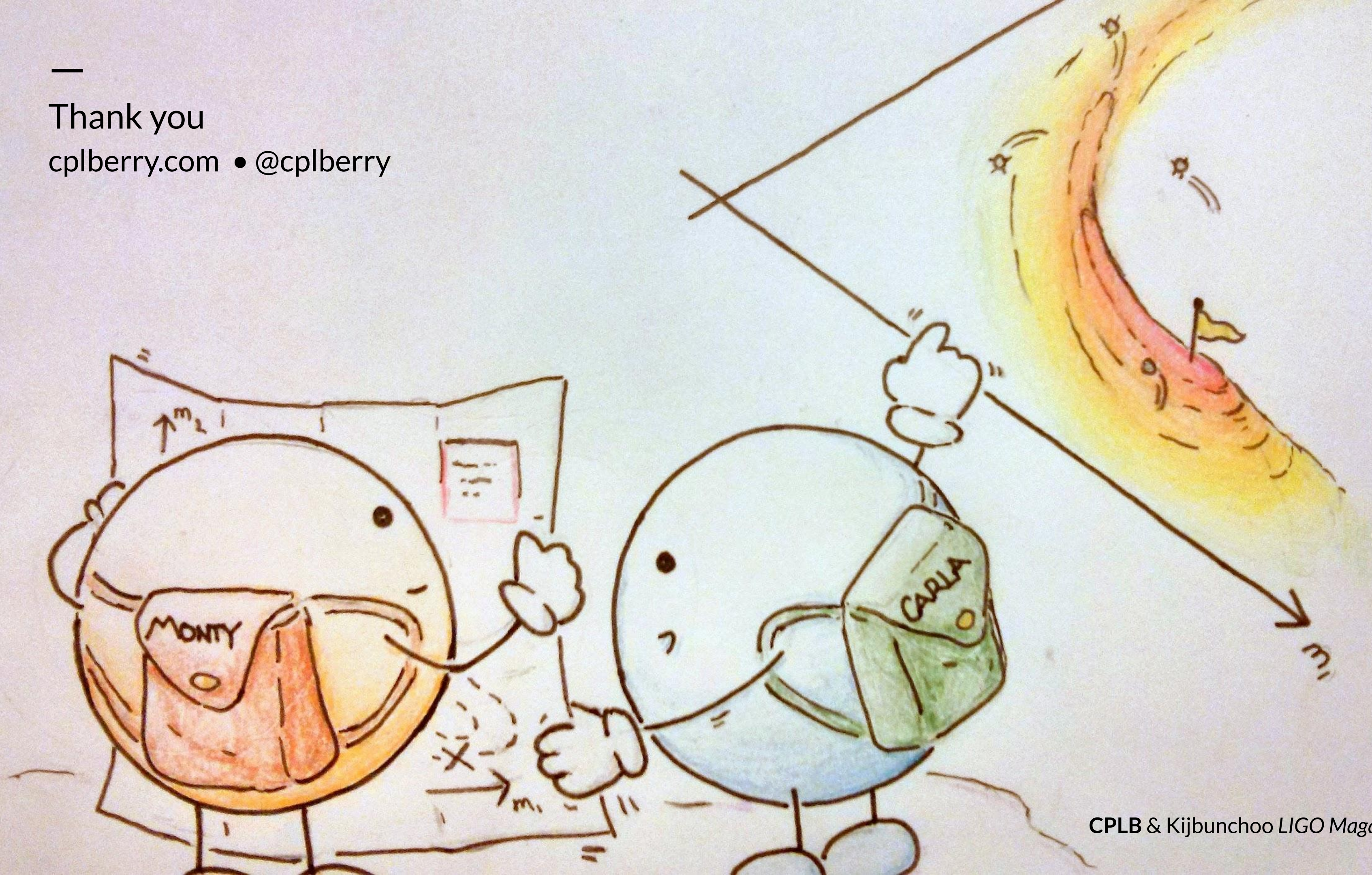
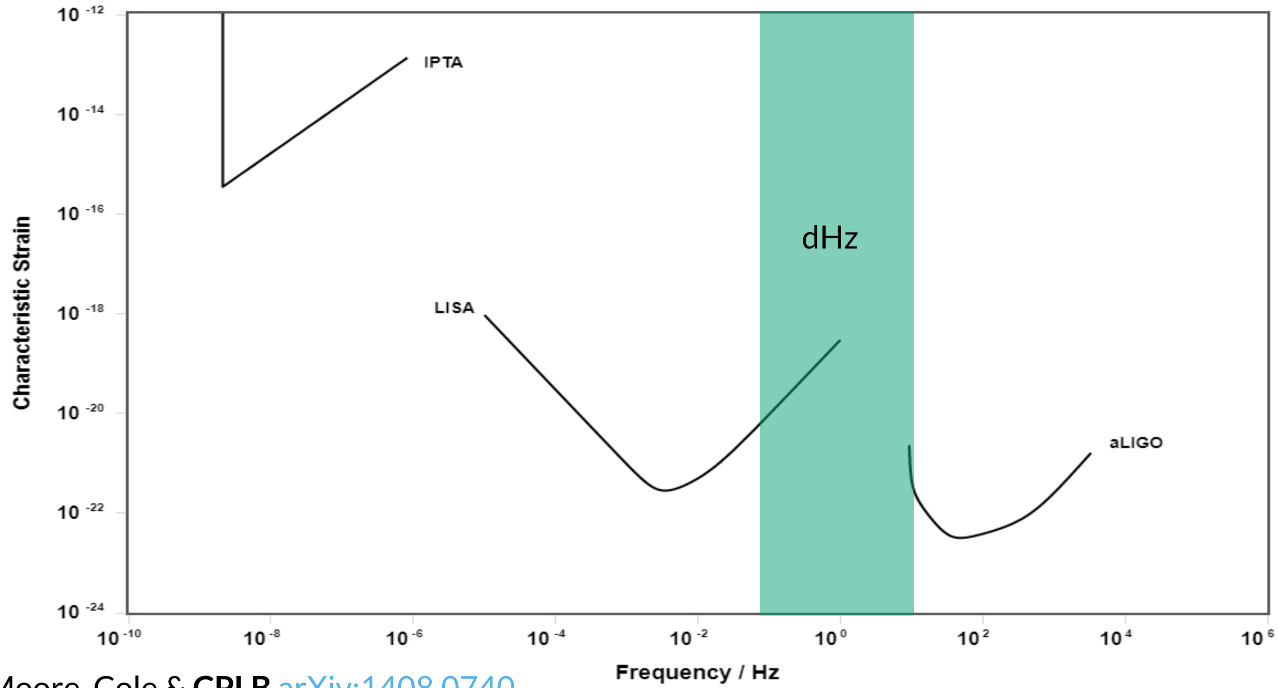


ALIA Bender, Begelman & Gair 2013
TianQin Luo *et al.* arXiv:1512.02076
Taiji Ruan *et al.* arXiv:1807.09495
DECIGO Kawamura *et al.* arXiv:2006.13545
TianGO Kuns *et al.* arXiv:1908.06004
GADFLI McWillians arXiv:1111.3708
gLISA Tinto *et al.* arXiv:1410.1813
SAGE Lacour *et al.* arXiv:1811.04743
MAGIS Graham *et al.* arXiv:1711.02225
AEDGE Abou El-Neaj *et al.* arXiv:1908.00802
Big Bang Observer Crowder & Cornish arXiv:gr-qc/0506015
DO-Conservative & DO-Optimal Arca Sedda, **CPLB** *et al.* arXiv:1908.11375

Gravitational-wave spectrum



Moore, Cole & **CPLB** arXiv:1408.0740

Results depend upon waveforms. Rapid development in recent years
LISA arXiv:2311.01300

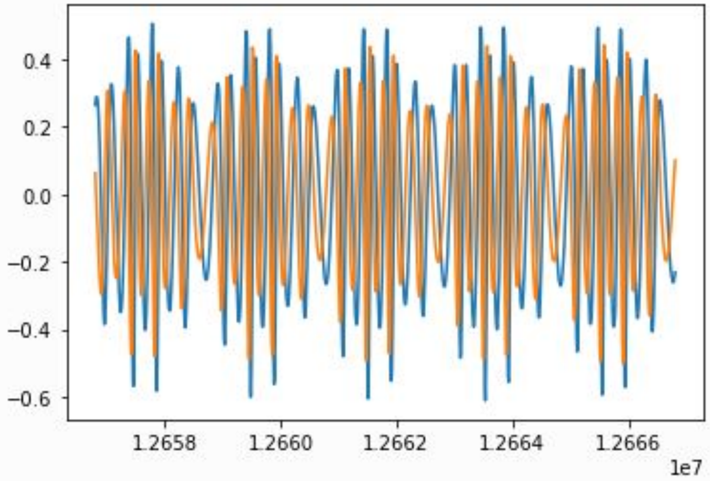
EMRI waveforms calculated using **gravitational self-force**, e.g., Barack & Pound arXiv:1805.10385

Fast EMRI Waveform (FEW) package available
Chua *et al.* arXiv:2008.06071
Katz *et al.* arXiv:2104.04582

FEW package

```
[5]: plt.plot(t[-1000:], wave.real[-1000:])
     plt.plot(t[-1000:], wave.imag[-1000:])

[5]: [<matplotlib.lines.Line2D at 0x7fdf9853f850>]
```

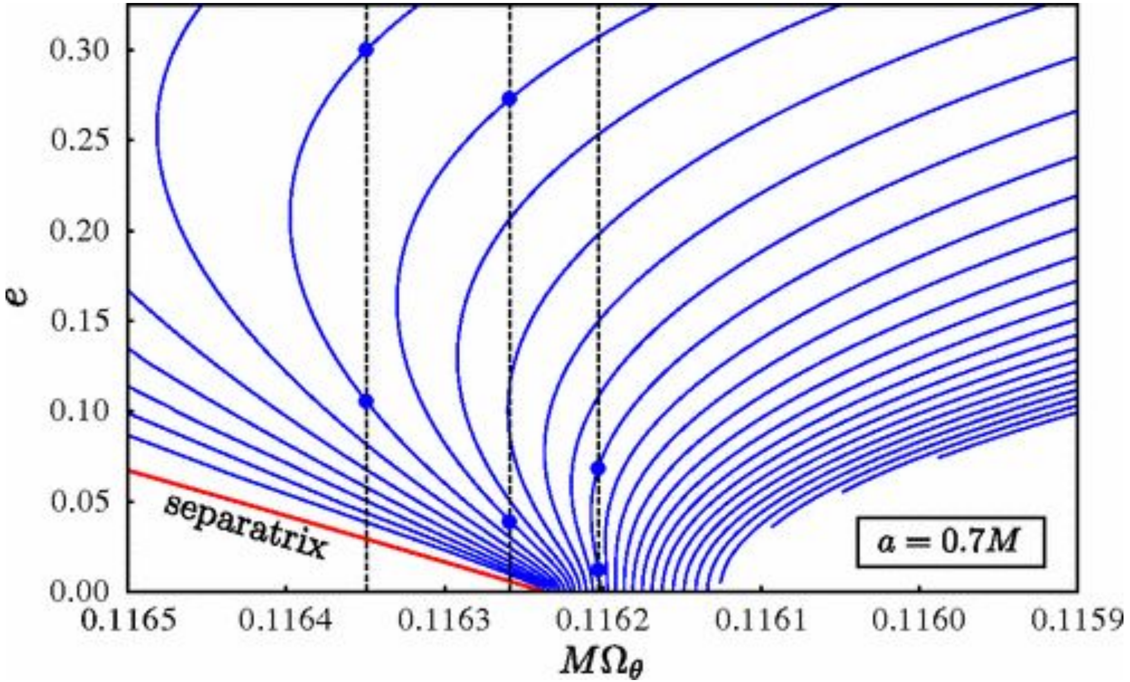


Katz *et al.*
bhptoolkit.org/FastEMRIWaveforms/

EMRI frequencies

EMRIs are typically described by 3 frequencies: radial, polar and azimuthal

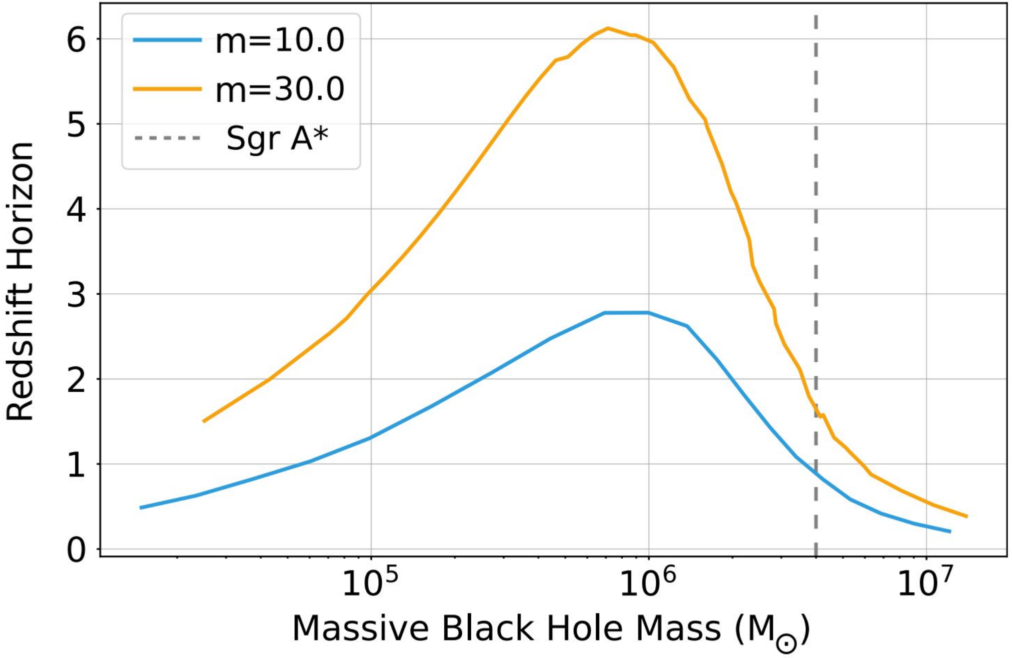
Orbital frequencies in Kerr
Schmidt arXiv:gr-qc/0202090



Warburton, Barack & Sago arXiv:1301.3918

EMRI horizon

EMRIs can be seen to cosmological redshifts

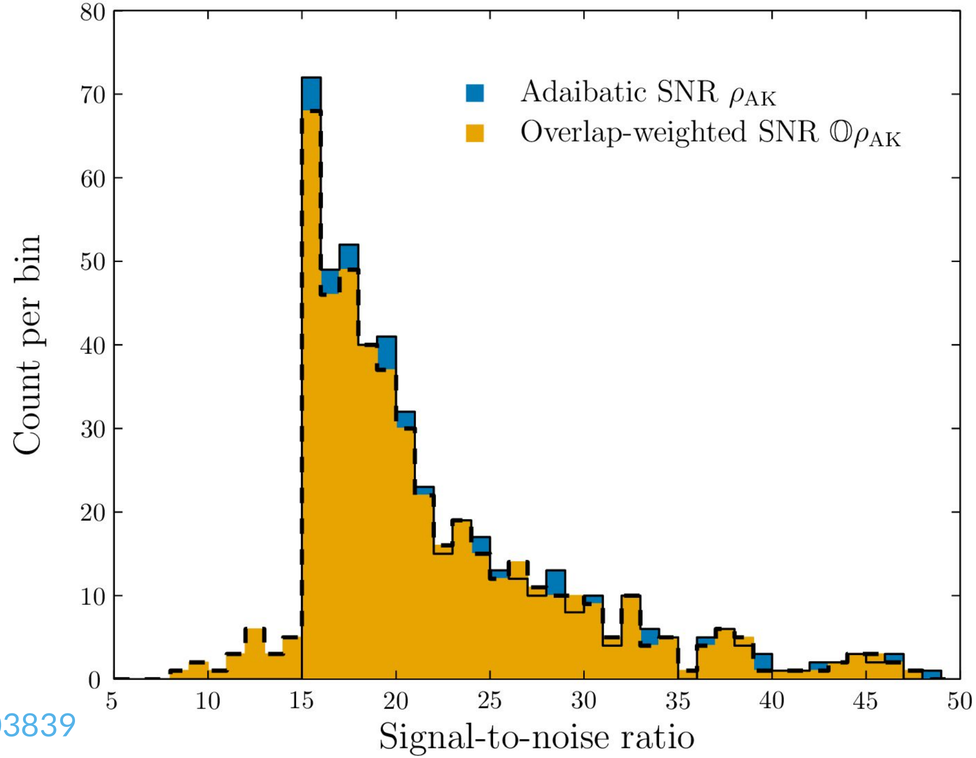


LISA arXiv:2402.07571

Resonances

Transient resonances need to be accounted for in evolution
Flanagan & Hinderer arXiv:1009.4923

Most resonances are late in inspiral, and less important for low eccentricity orbits



CPLB *et al.* arXiv:1602.03839

Population models

EMRI populations are uncertain. Rates range from ~1 to 10^3 per year

Results are sensitive to choice of waveform

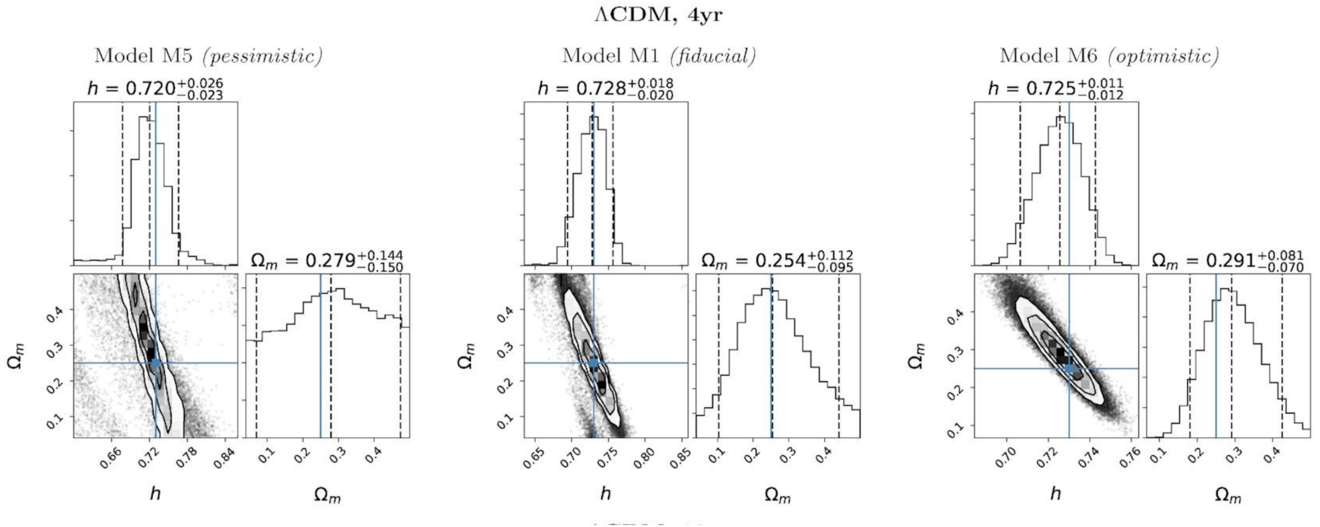
AKK analytic kludge Kerr
AKS analytic kludge Schwarzschild (pessimistic)

Model	Mass function	MBH spin	Cusp erosion	M–σ relation	N_p	CO mass $[M_\odot]$	EMRI rate $[\mathrm{yr}^{-1}]$ Total	Detected (AKK)	Detected (AKS)
M1	Barausse12	a98	yes	Gultekin09	10	10	1600	294	189
M2	Barausse12	a98	yes	KormendyHo13	10	10	1400	220	146
M3	Barausse12	a98	yes	GrahamScott13	10	10	2770	809	440
M4	Barausse12	a98	yes	Gultekin09	10	30	520 (620)	260	221
M5	Gair10	a98	no	Gultekin09	10	10	140	47	15
M6	Barausse12	a98	no	Gultekin09	10	10	2080	479	261
M7	Barausse12	a98	yes	Gultekin09	0	10	15800	2712	1765
M8	Barausse12	a98	yes	Gultekin09	100	10	180	35	24
M9	Barausse12	aflat	yes	Gultekin09	10	10	1530	217	177
M10	Barausse12	a0	yes	Gultekin09	10	10	1520	188	188
M11	Gair10	a0	no	Gultekin09	100	10	13	1	1
M12	Barausse12	a98	no	Gultekin09	0	10	20000	4219	2279

Babak, …, **CPLB** *et al.* arXiv:1703.09722

Cosmological parameter measurements from **dark siren** analysis

Initially suggested in MacLeod & Hogan arXiv:0712.0618



Laghi *et al.* arXiv:2102.01708

Machine learning

Two levels of emulation:
1. Signal SNRs to learn detection threshold as a function of source parameters
2. Population detection probability as a function of population hyperparameters

poplar code
DOI:10.5281/zenodo.7573034

Setting	SNR MLP	$\alpha(\lambda)$ MLP
Number of (hidden) layers	10	8
Neurons per layer	128	128
Activation function	SiLU	SiLU
Rescaling	Unit normal	Unit normal
Optimiser	Adam	Adam
Learning rate	5×10^{-4}	5×10^{-4}
Batch size	10^4	10^5
Max epochs	10^5	10^3
Loss function	L1	L1

Chapman-Bird, **CPLB** & Woan arXiv:2212.06166

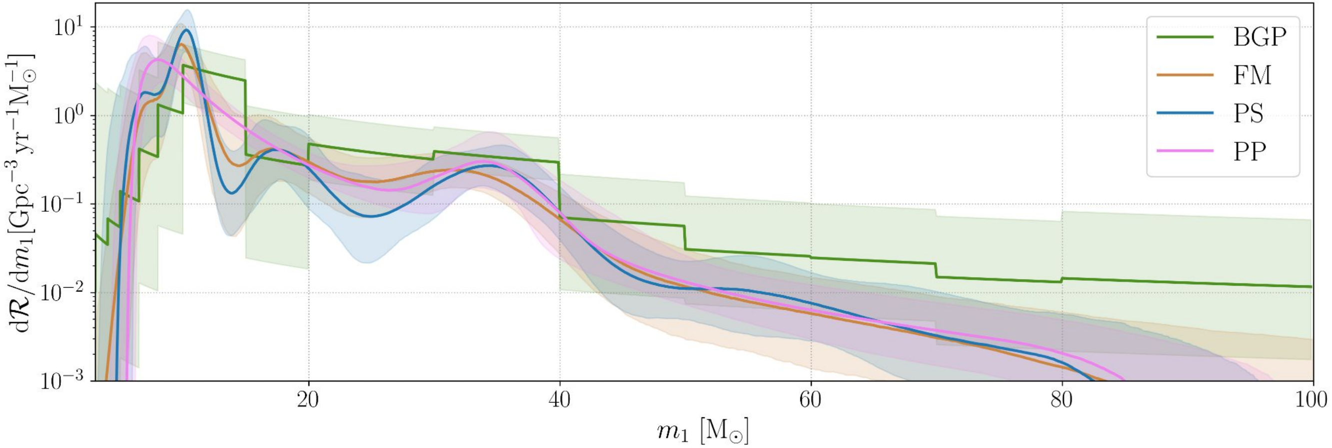
Astrophysical distribution

BGP = binned Gaussian process

FM = flexible mixtures Gaussian kernels

PS = power-law plus spline

PP = power-law plus (Gaussian) peak



LVK arXiv:2111.03634