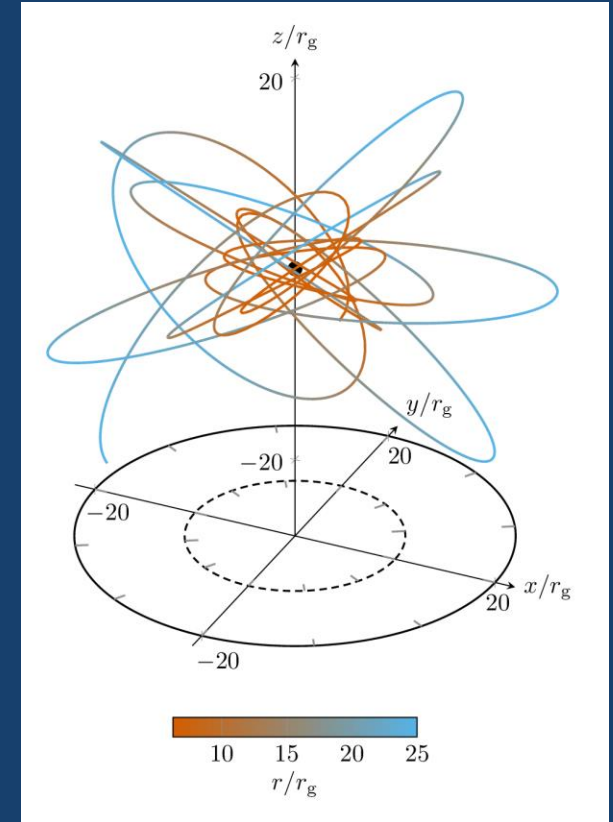
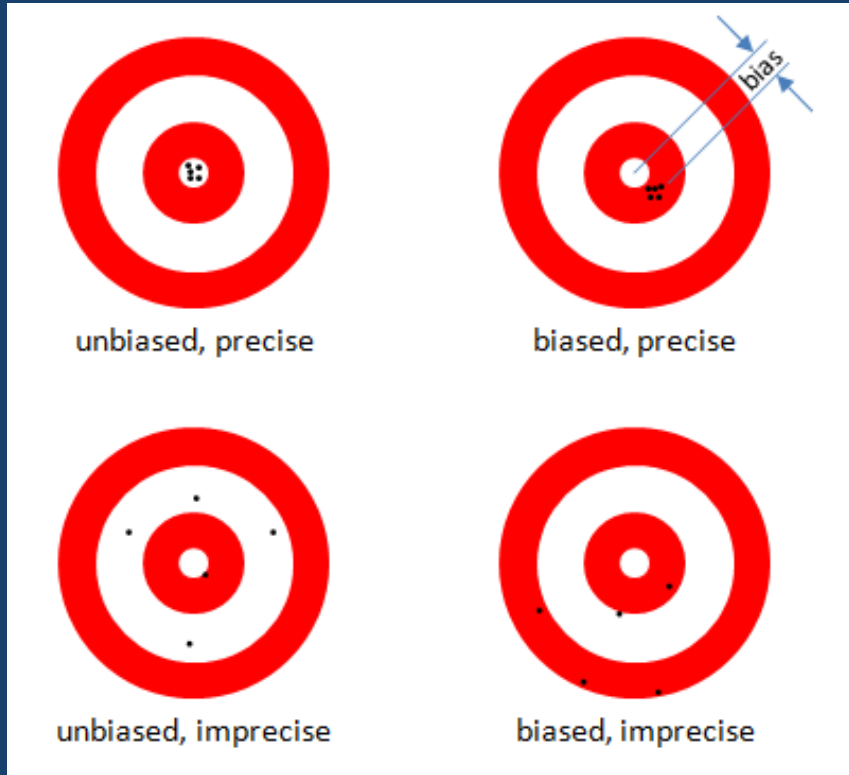




Assessing glitch-induced bias and variability in EMRI parameter estimation

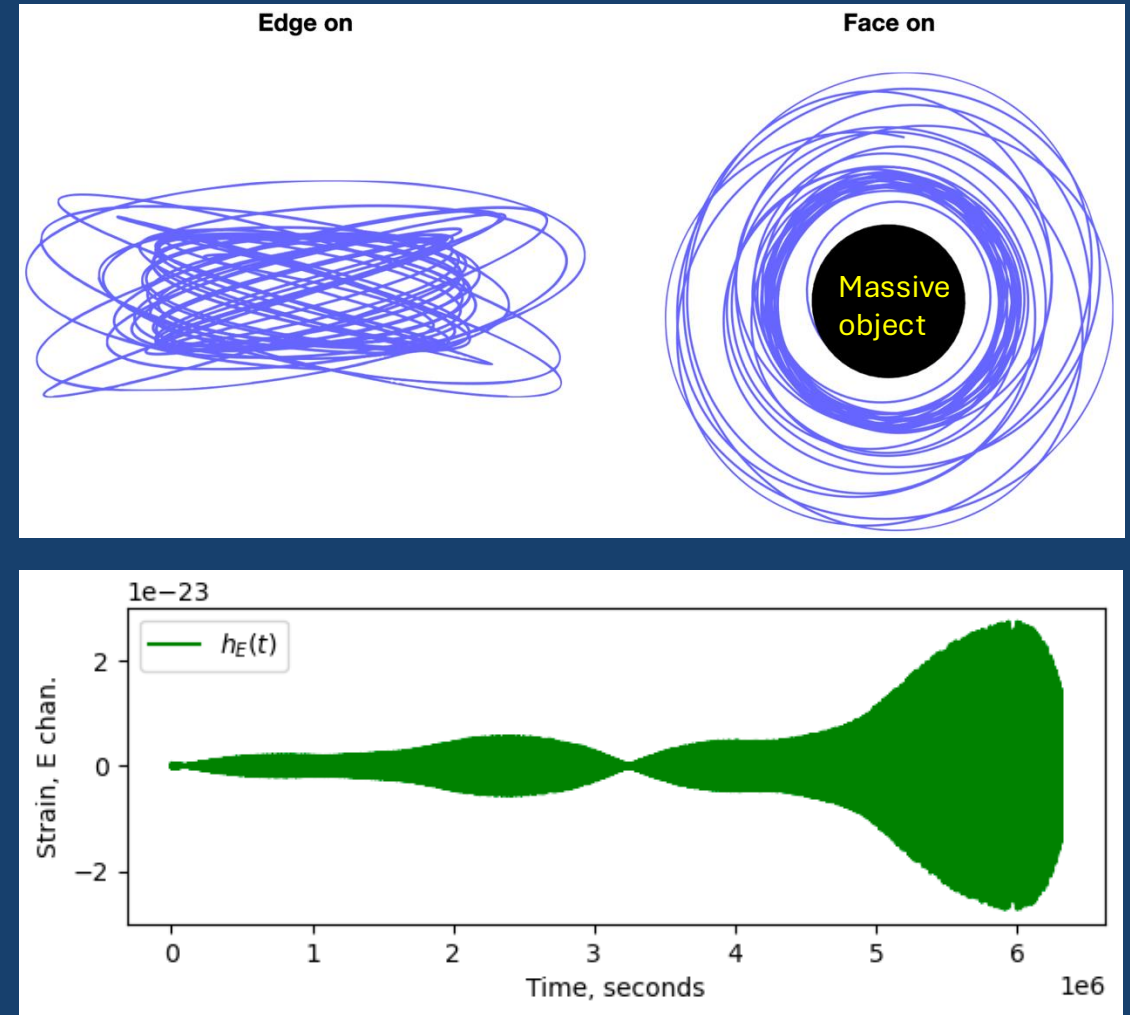
Authors: Amin Boumerdassi, Ollie Burke, Matt Edwards, Avi Vajpeyi



GW source: extreme mass ratio inspiral

- Slow inspiral of **massive** and **compact** object with mass ratio $\frac{M}{\mu} > 10^4$
- Low-amplitude, years-long GW signals
- Successful detection will permit new tests of GR, cosmology etc.

EMRI's $h(t; \bar{\theta})$ is modelled with 14 parameters e.g. masses **M** and **μ** , spin a , inclination ι , ...



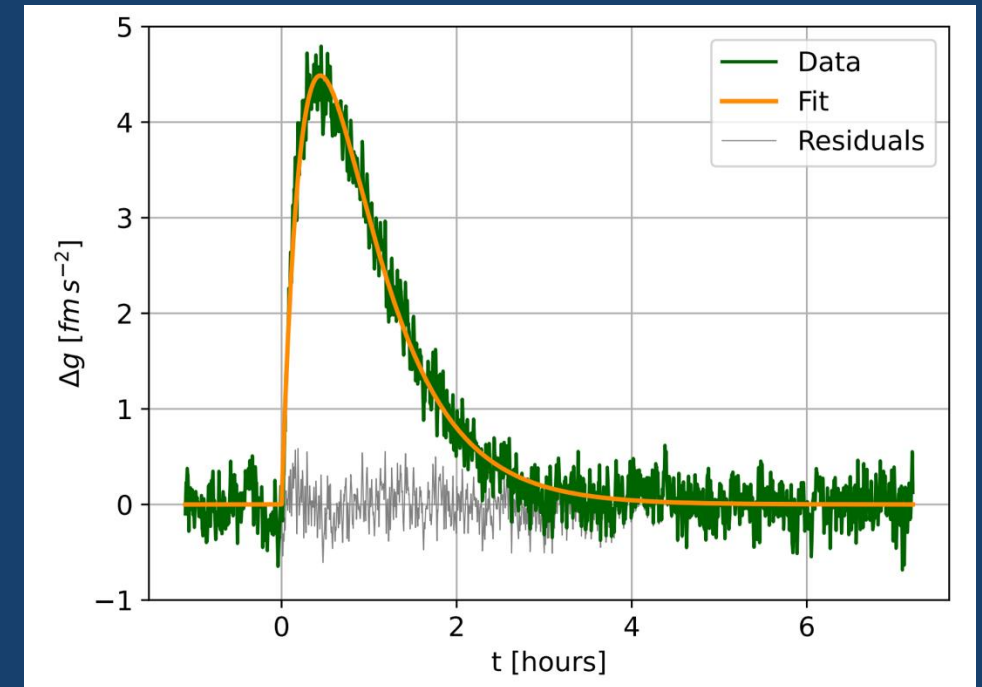
GW noise: glitches

They are:

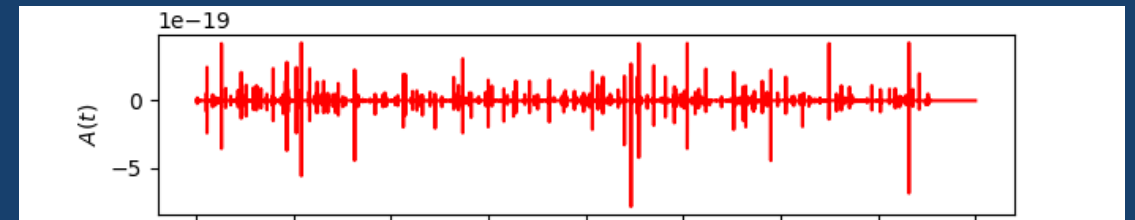
- High-amplitude, short-duration instrumental noise
- NOT astrophysical
- Generally unexplained or coming from local disturbances to the detector

Risks that glitches pose:

- obscure or partially obscure genuine GW events
- mistaken for genuine GW events
- induce biases in GW parameter estimation



Fast Rising Exponential Decay (FRED) glitch



Goals & aims

Investigate the impact that glitch *backgrounds* have on parameter estimation of EMRIs.

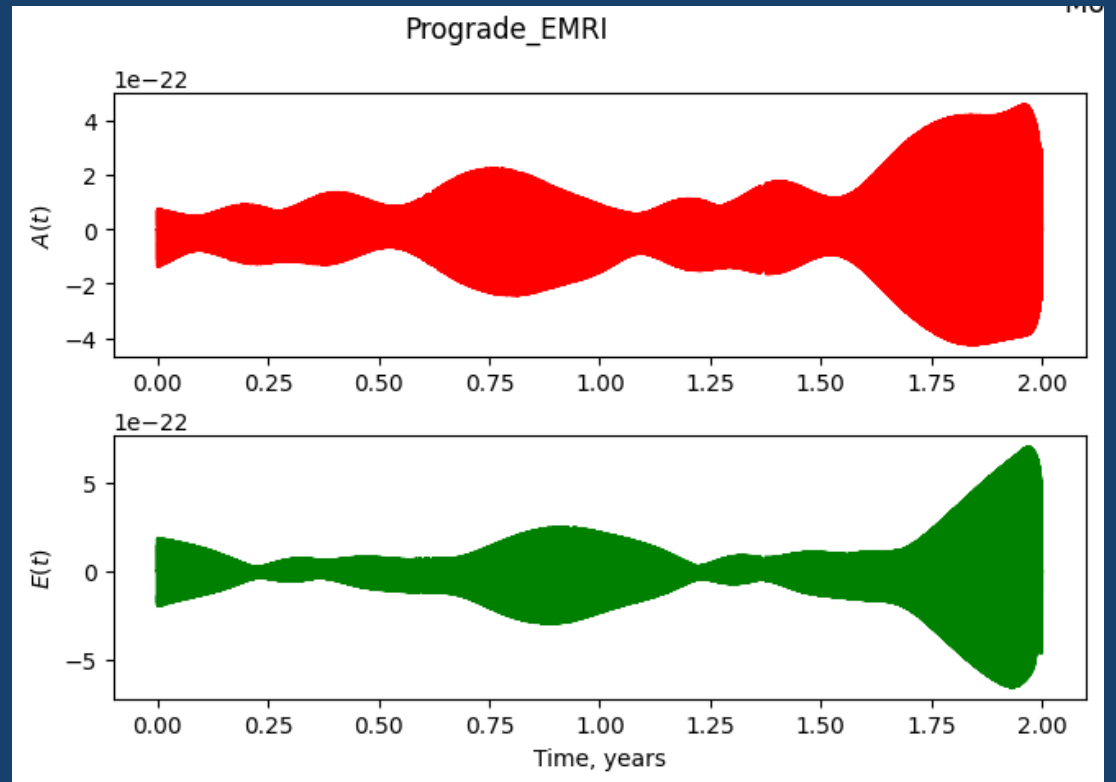
When including glitches in the data, does the posterior distribution become:

- i. significantly biased?
- ii. significantly variable?

Modelling EMRIs

We consider 3 EMRIs all fixed to optimal SNR 80.

1. A prograde EMRI (positive spin)
2. A strongfield EMRI ($\frac{M}{\mu} = 10^6$)
3. A retrograde EMRI (negative spin)



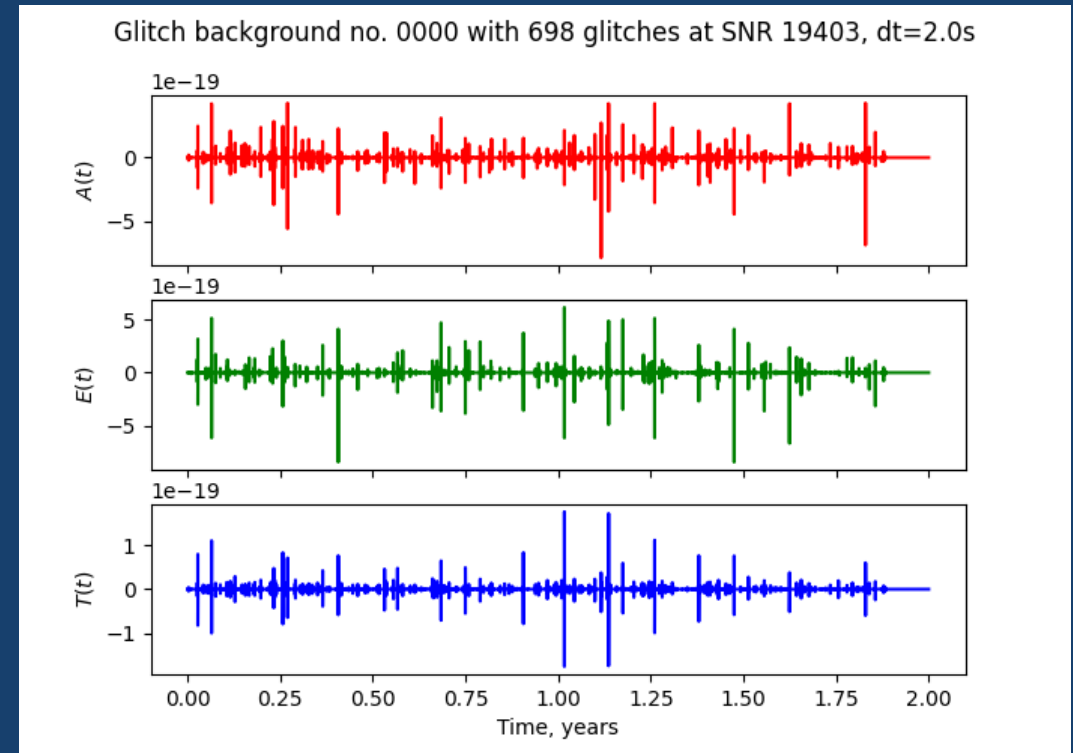
Modelling glitch backgrounds

Borrowing from LISA pathfinder by resampling individual glitches from LPF glitch catalogue.

We allow the following quantities to vary:

- Glitch count (Poisson dist.)
- Amplitude (resampled)
- Duration (resampled)
- Arrival time (exponential dist.)
- Test mass injection point (uniform dist.)

Simulate glitch-mitigated backgrounds by omitting glitches in excess of some maximum SNR.



Modelling the data

The data is a sum of:

1. The true **EMRI** $h(t; \theta_0)$ parameterised by true parameters θ_0
2. Stationary Gaussian **noise** $n(t)$
3. Glitch background $g(t)$ i.e. an ensemble of glitches with variable count, arrival times, amplitudes, durations etc.

Our **data** is:

$$d(t) = h(t; \theta_0) + n(t) + g(t)$$

Estimating EMRI parameters $\bar{\theta} = (M, \mu, a, \dots)$

Using the log Whittle likelihood:

$$L(\textcolor{red}{d}(t) | \bar{\theta}) = (\textcolor{red}{d} - \textcolor{green}{h} | \textcolor{red}{d} - \textcolor{green}{h})$$

A priori:

$$[\bar{\theta}_{bf} | d = h + n] \sim \mathcal{N}(\bar{\theta}_0, \bar{\Sigma}_{noise})$$

And:

$$[\bar{\theta}_{bf} | d = h + n + g] \sim \mathcal{N}(\underbrace{\bar{\theta}_0 + \bar{\beta}_{glitches}}_{\text{Not unbiased}}, \underbrace{\bar{\Sigma}_{noise} + \bar{\Sigma}_{glitches}}_{\text{More variability}})$$

Estimating EMRI biases $\bar{\beta} = (\beta_M, \beta_\mu, \beta_a, \dots)$

We know that $\bar{\theta}_{bf} = \bar{\theta}_0 + \Delta\bar{\theta}$ and bias is a statistic of $\Delta\bar{\theta}$:

$$\bar{\beta} = \mathbb{E}(\Delta\bar{\theta})$$

We can estimate $\bar{\beta}_{glitches}$ by calculating many $\Delta\bar{\theta}_{glitches}$ over many inference runs of distinct data realisations.

Highly impractical with MCMC, much faster with Fisher matrices.

Estimating EMRI biases $\bar{\beta} = (\beta_M, \beta_\mu, \beta_a, \dots)$

The Fisher matrix Γ_{ij} has the form:

$$\Gamma_{ij} = (\partial_i h | \partial_j h) \equiv \text{inverse of } \bar{\Sigma}_{noise}$$

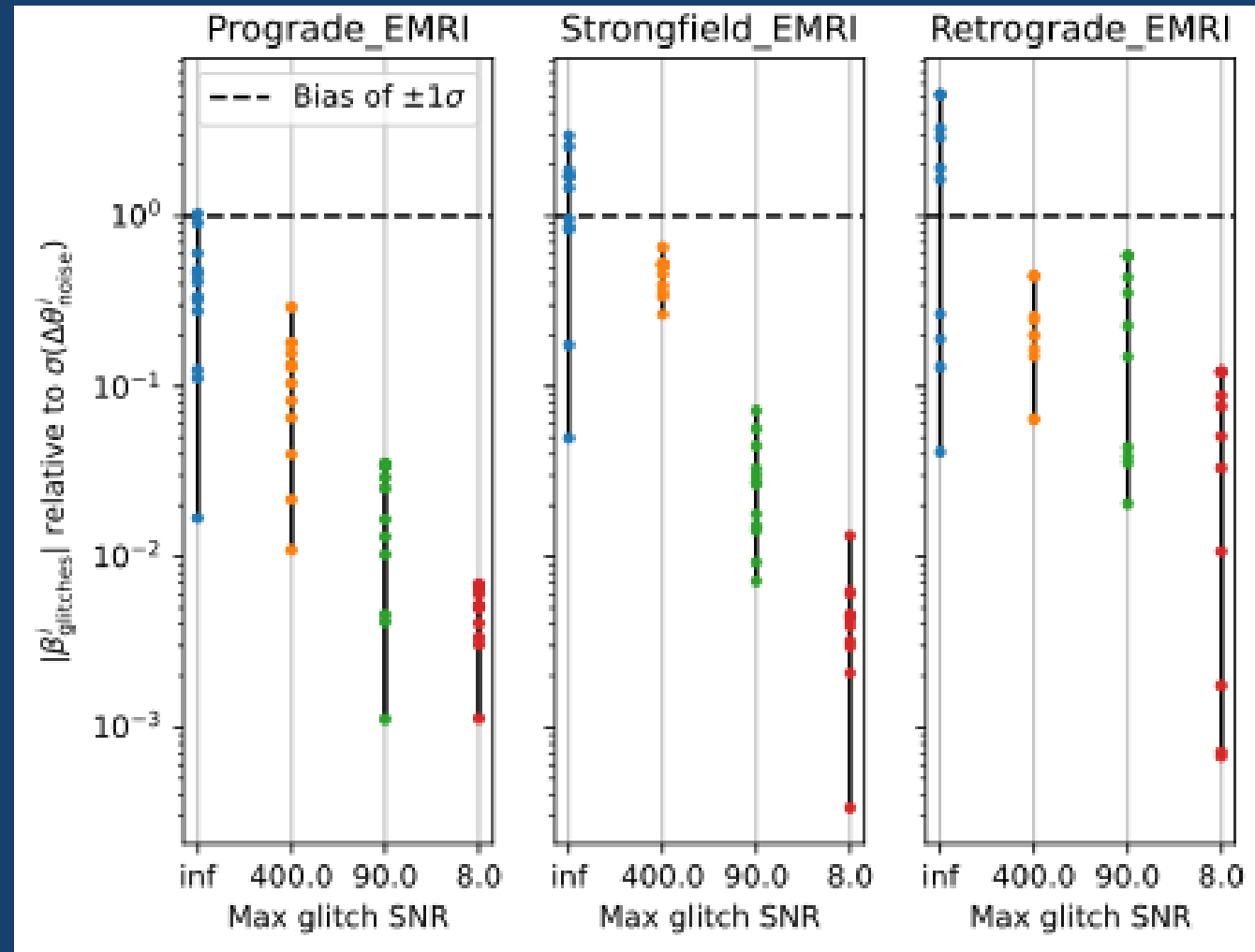
Using perturbation theory, we can express $\Delta\theta$ as:

$$\Delta\theta_{glitches}^i = (\Gamma^{-1})^{ij} (\partial_j h | g)$$

We calculate the above equation for 128 glitch backgrounds!

EMRI PE biases

- $\geq 1\sigma$ biases for untreated glitch backgrounds
- $\sim 0.1\sigma$ biases when cutting out glitches of SNRs ≥ 400
- $\sim 0.01\sigma$ biases when cutting out glitches of SNRs ≥ 90

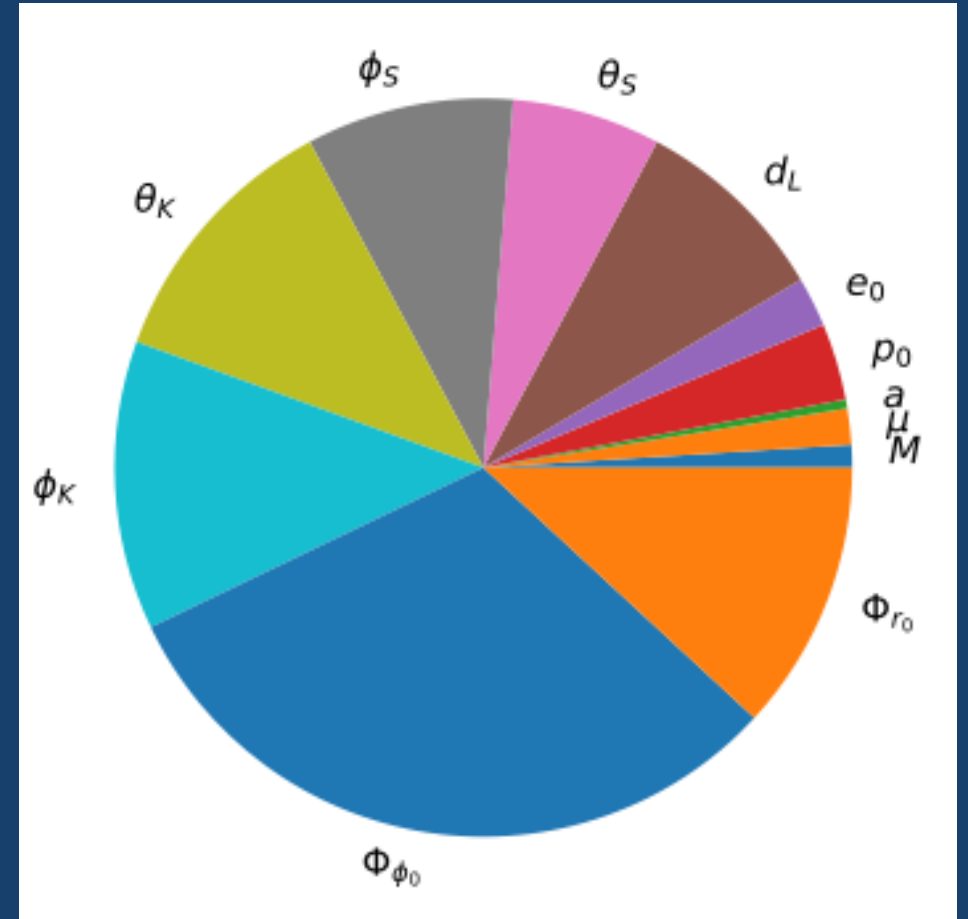


Which parameters had the largest errors?

Calculated:

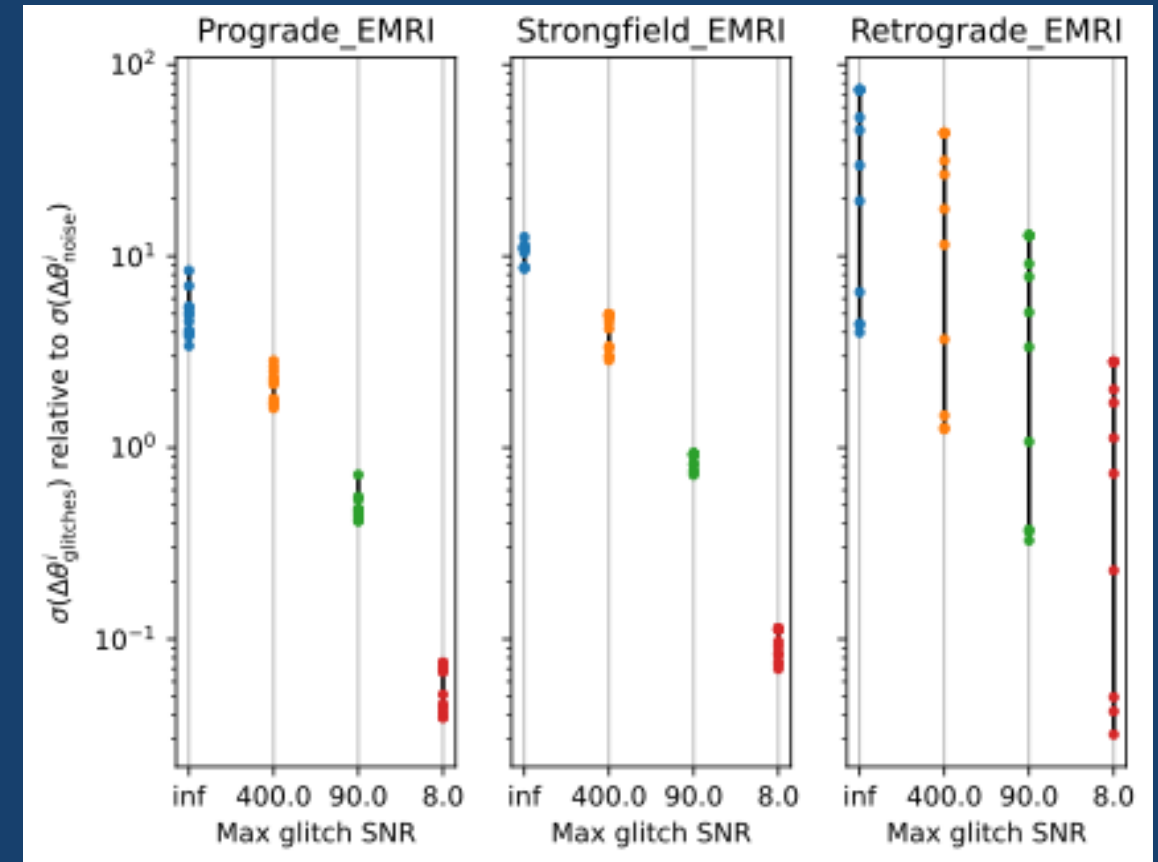
$$\arg \max \left| \frac{\Delta \bar{\theta}_{\text{glitches}}}{\sigma(\Delta \theta_{\text{noise}})} \right|$$

- Extrinsic parameters are overwhelmingly likely to have the largest parameter errors



EMRI PE variability

- 3-8x increase in uncertainty of $\bar{\theta}_{bf}$ for untreated glitch backgrounds
- 2-3x increase in uncertainty of $\bar{\theta}_{bf}$ when cutting out glitches of SNRs ≥ 400
- Otherwise negligible changes in uncertainty



Conclusions & next steps

Findings:

- EMRIs are surprisingly robust to glitch backgrounds (though not immune!)
- We can be quite lax with glitch mitigation and still have relatively unbiased and precise PE
- Extrinsic parameters are more likely to have the largest errors than intrinsic ones

Potential future work:

- Experiment with actual glitch mitigation tools
- More granular levels of glitch mitigation