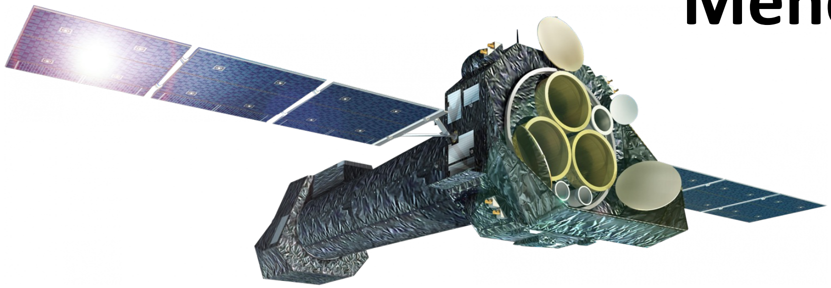
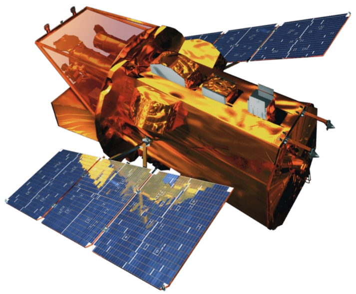
Next generation timing method for irregular light curves of AGN





Mehdy Lefkir – 2nd year PhD student

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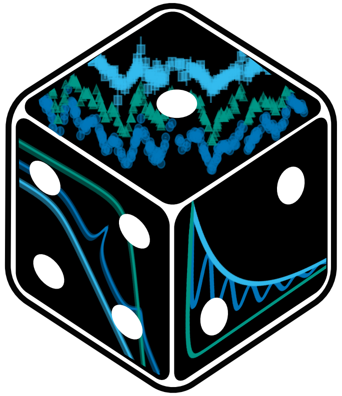


UNIVERSITY OF LEICESTER

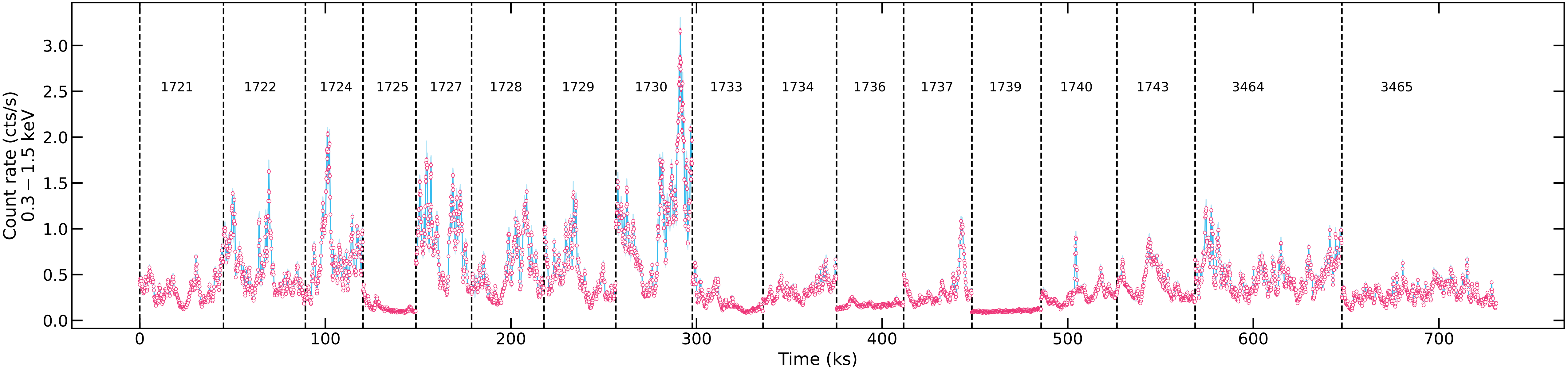
XMM-Newton survey legacy for Athena and beyond- 27th Feb. 2024 - Toulouse

Motivations

- unobscured AGN show a strong variability, what is the physical origin of the variability ?

- Study correlations/delays between wavebands to test models of reprocessing and structure of the engine

XMM-Newton observations of NGC 4051



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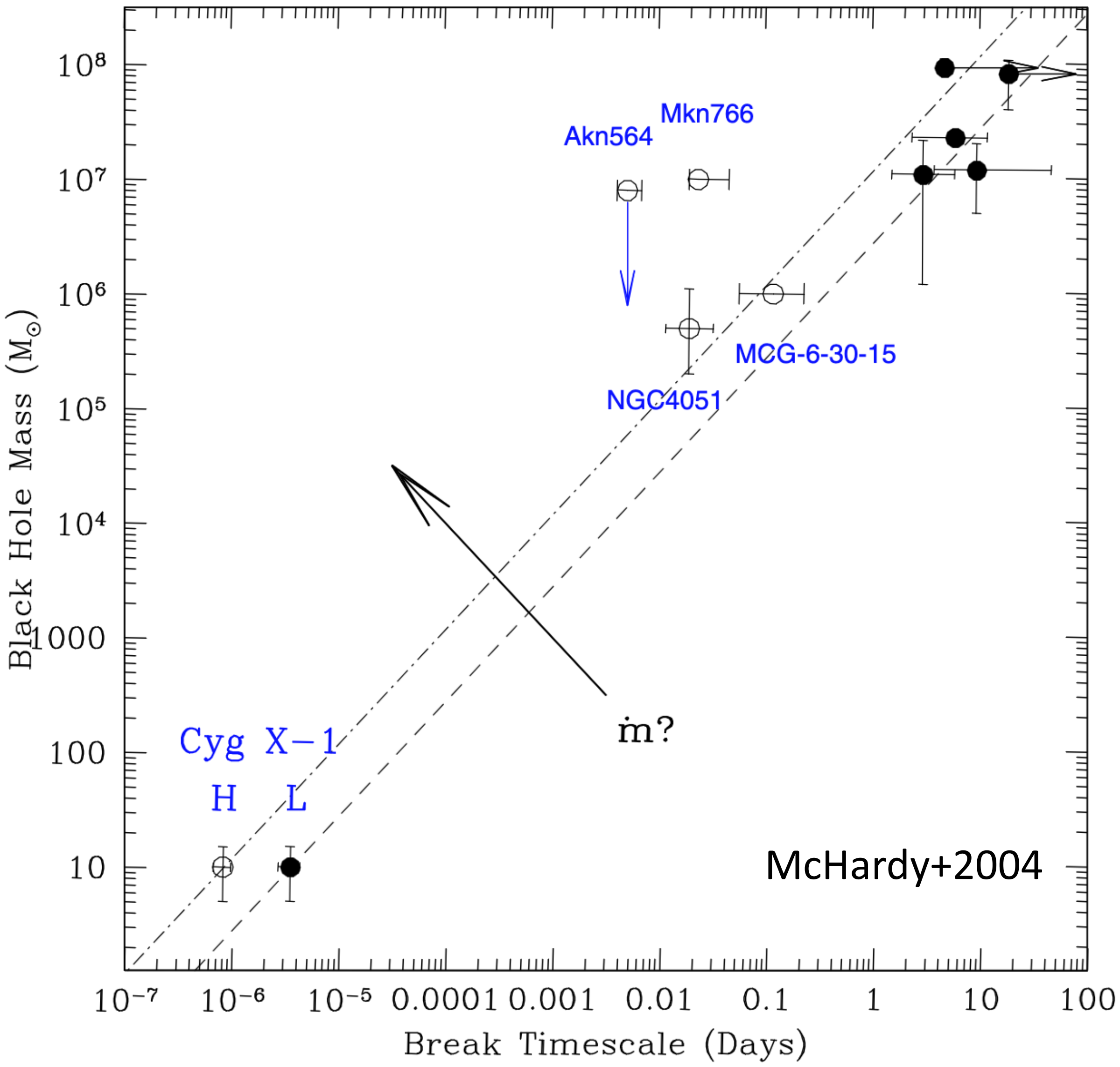

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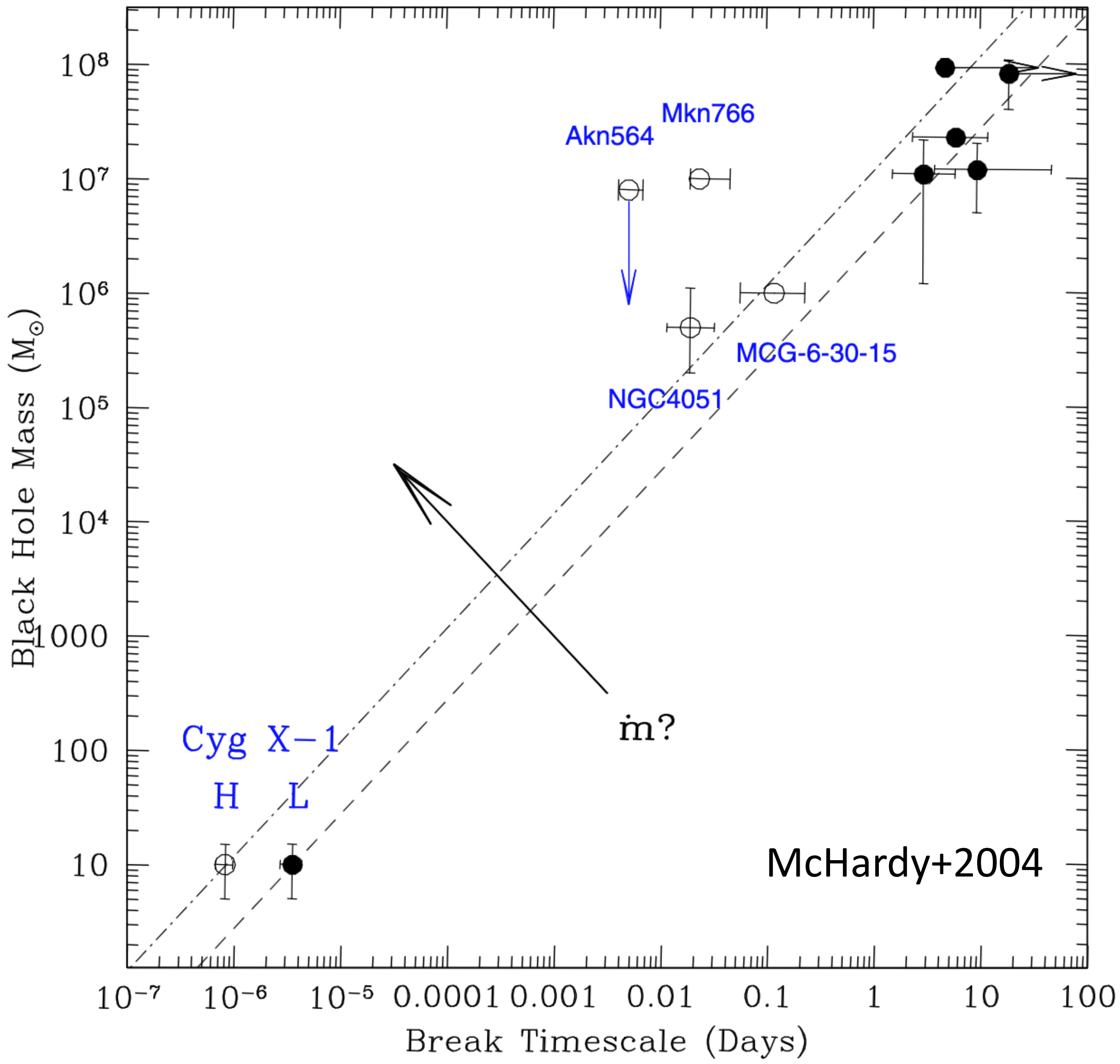
We need a method which can cope with:

- irregular sampling, gaps
- uncertainties on measurement
- leakage and aliasing



Gaussian process regression

Rasmussen & Williams, 2006

A nice and easy way to interpolate points **assuming** the joint probability density function is Gaussian.

A GP is described by a **mean** function and a **covariance** function (or **autocovariance**)

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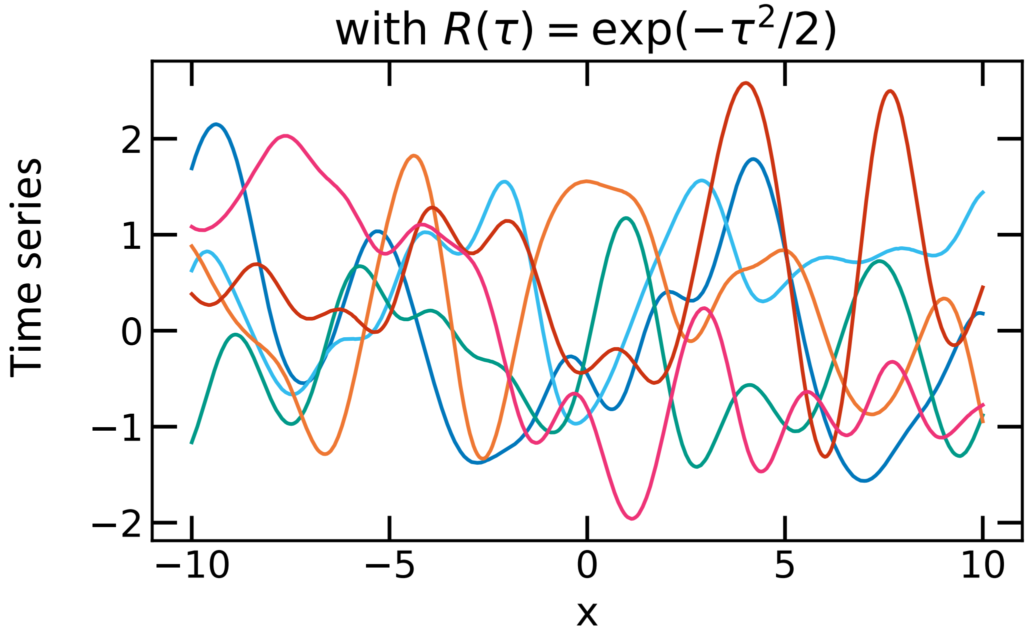

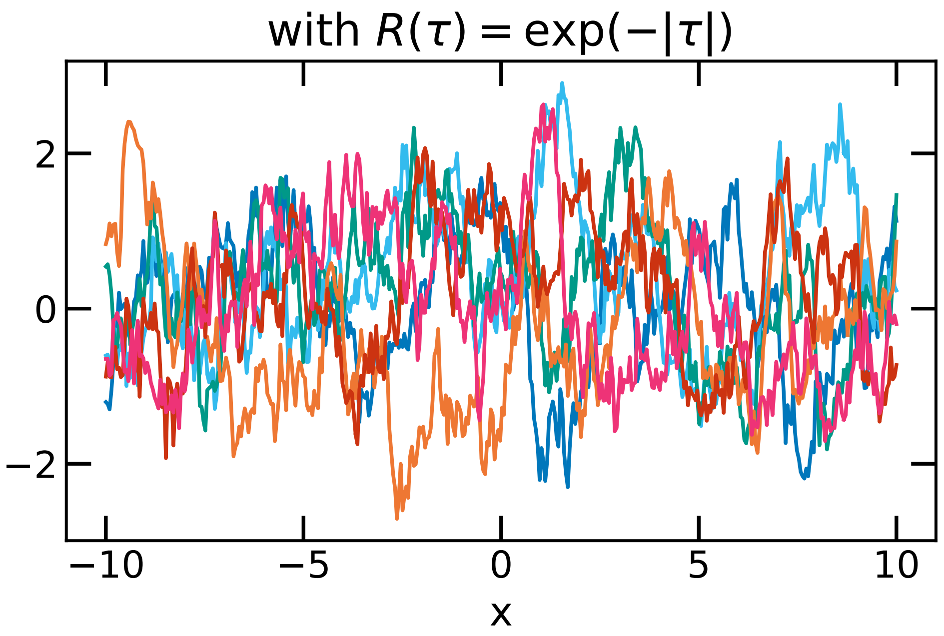

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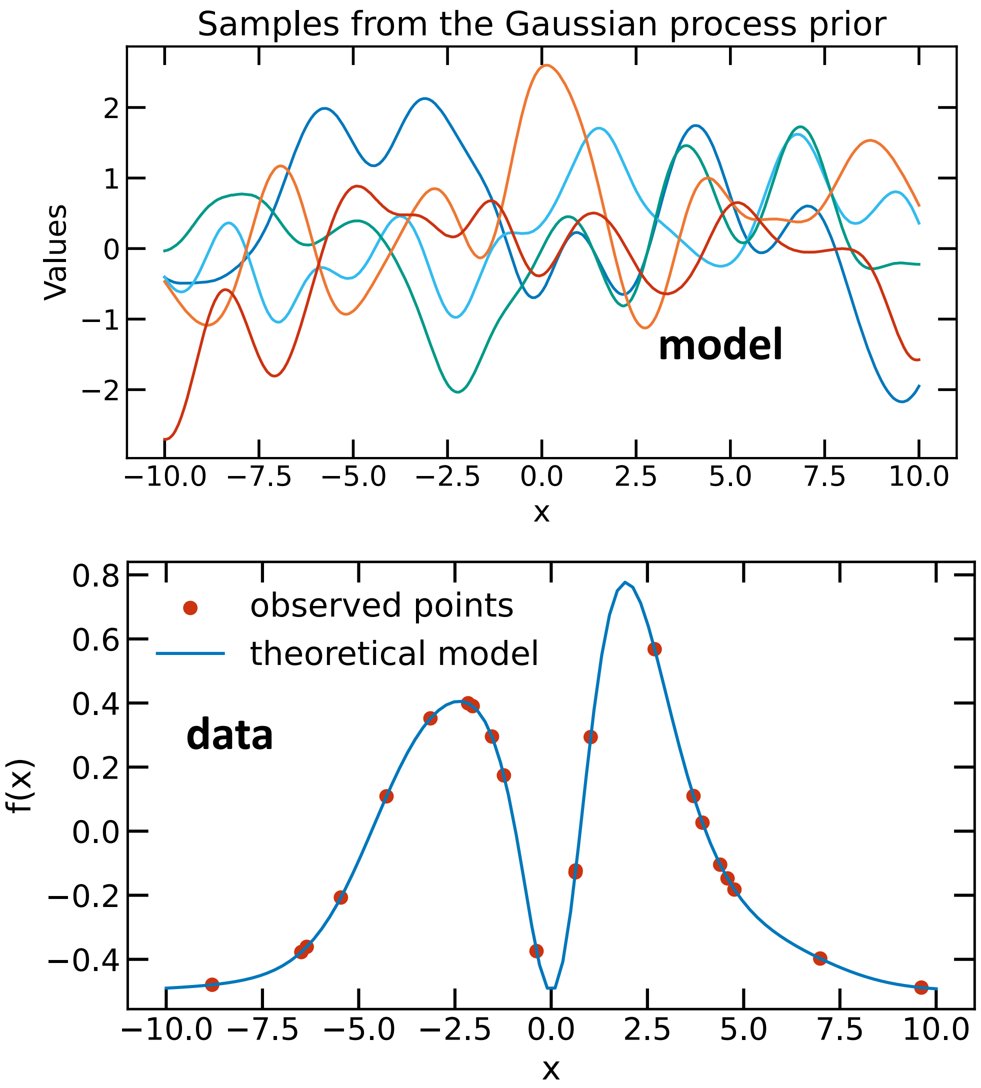

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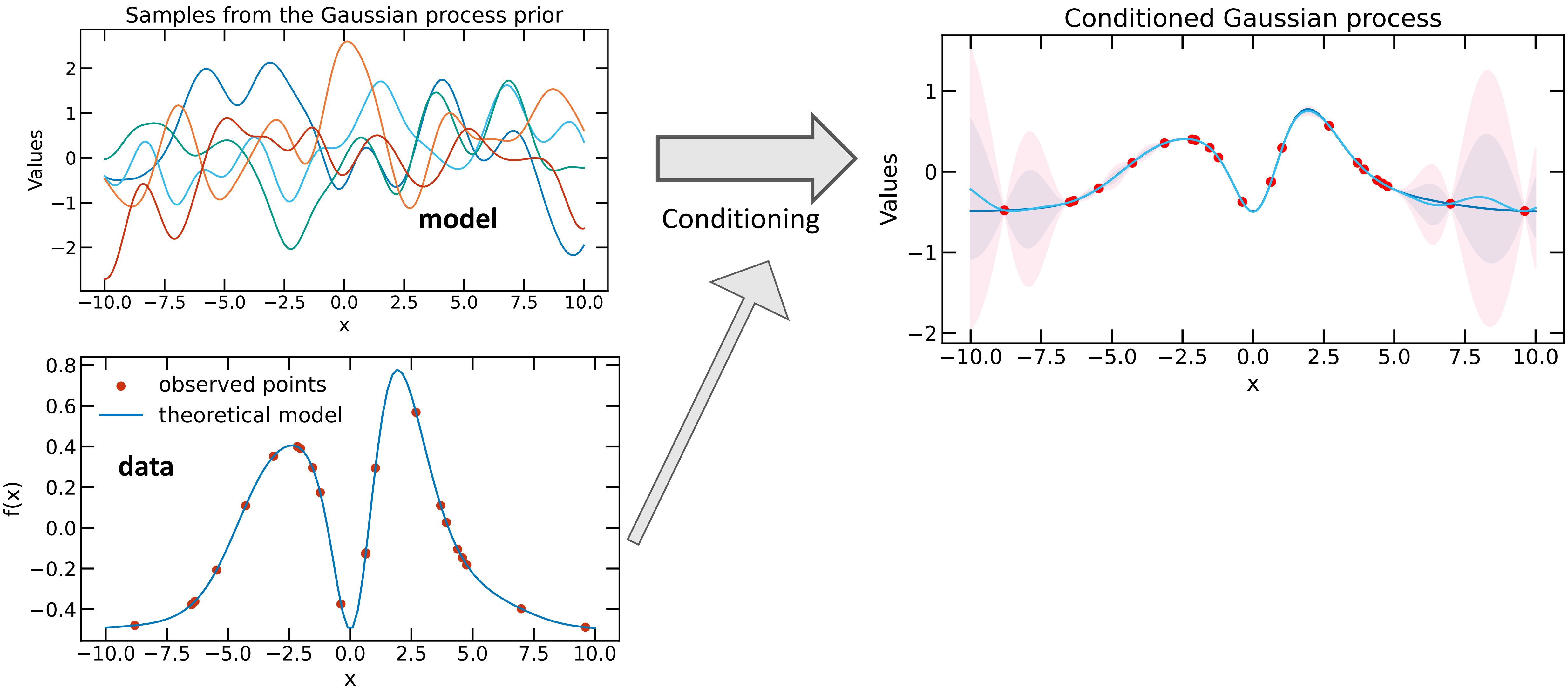

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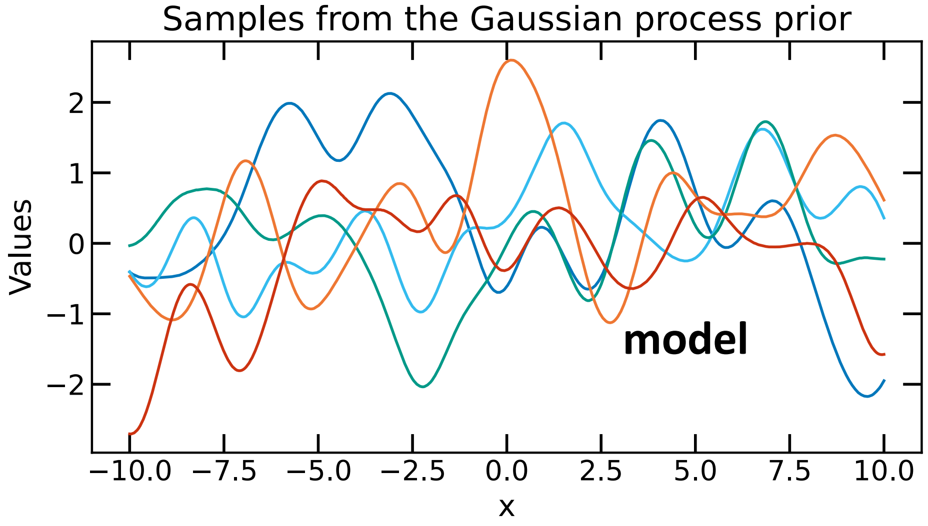

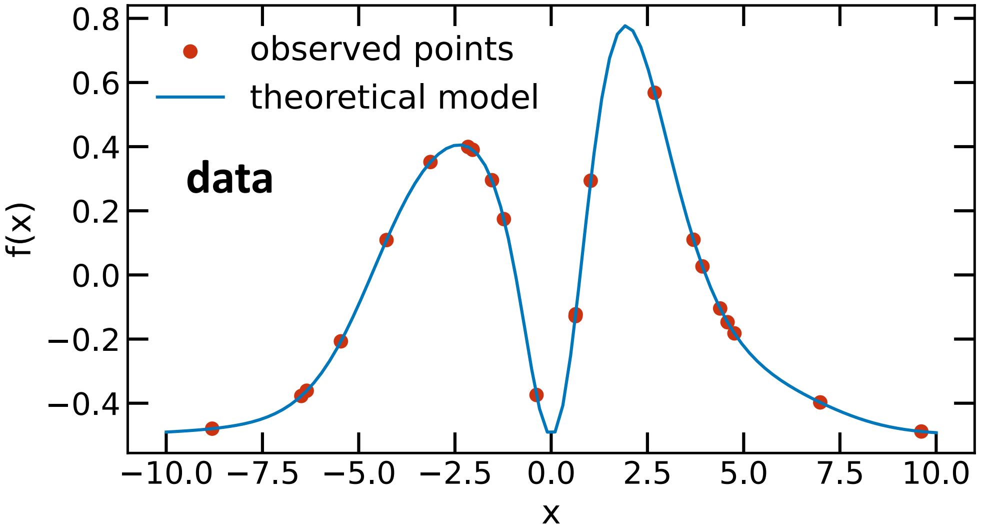

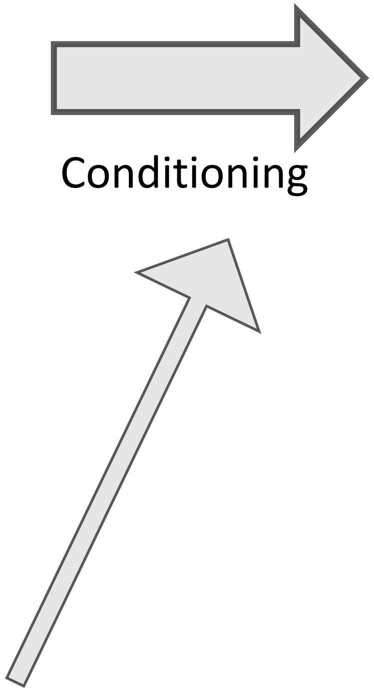

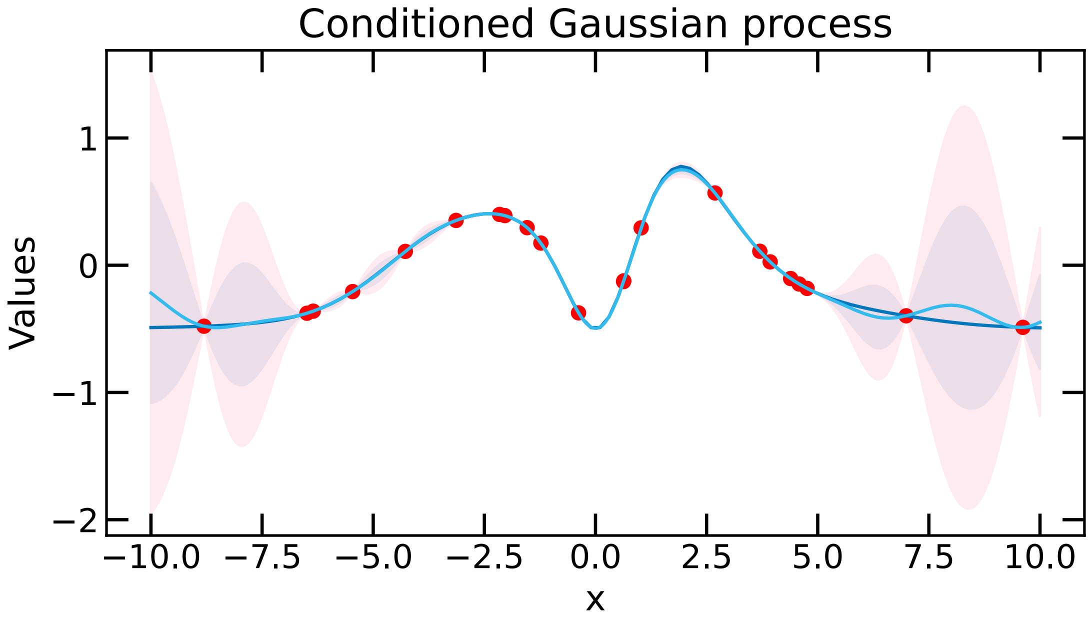

Then, we can find the set of best *hyperparameters* to interpolate the data.

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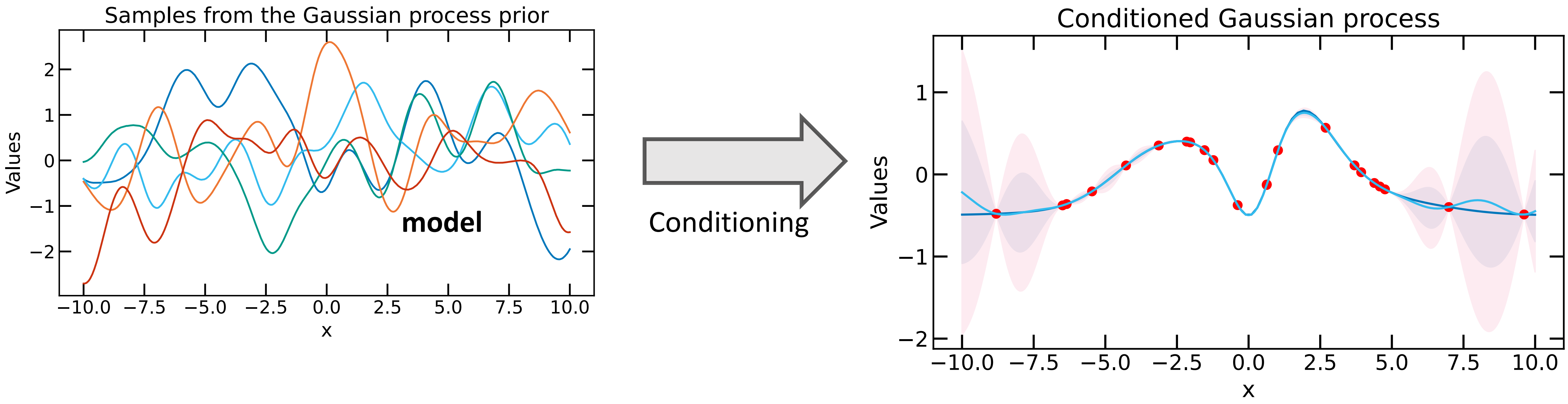

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power spectral density ⟷ Fourier pairs ⟷ **autocovariance**

Similar to

Miller+2010
Zoghbi+2013

Models for the power spectrum

- Analytical ACVF:
  - Damped random walk $P(f) \propto \frac{1}{1+f^2}$ CARMA process, Kelly+2014
  - Celerite $P(f) \propto \frac{1}{1+f^4}$ Foreman−Mackey+2017

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  - Single bending power-law: $P(f) = A\left(\frac{f}{f_b}\right)^{-\alpha_1} \frac{1}{1+\left(\frac{f}{f_b}\right)^{\alpha_2-\alpha_1}}$
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→ **Solution**: approximate the power spectrum with a sum of Celerite ACVF
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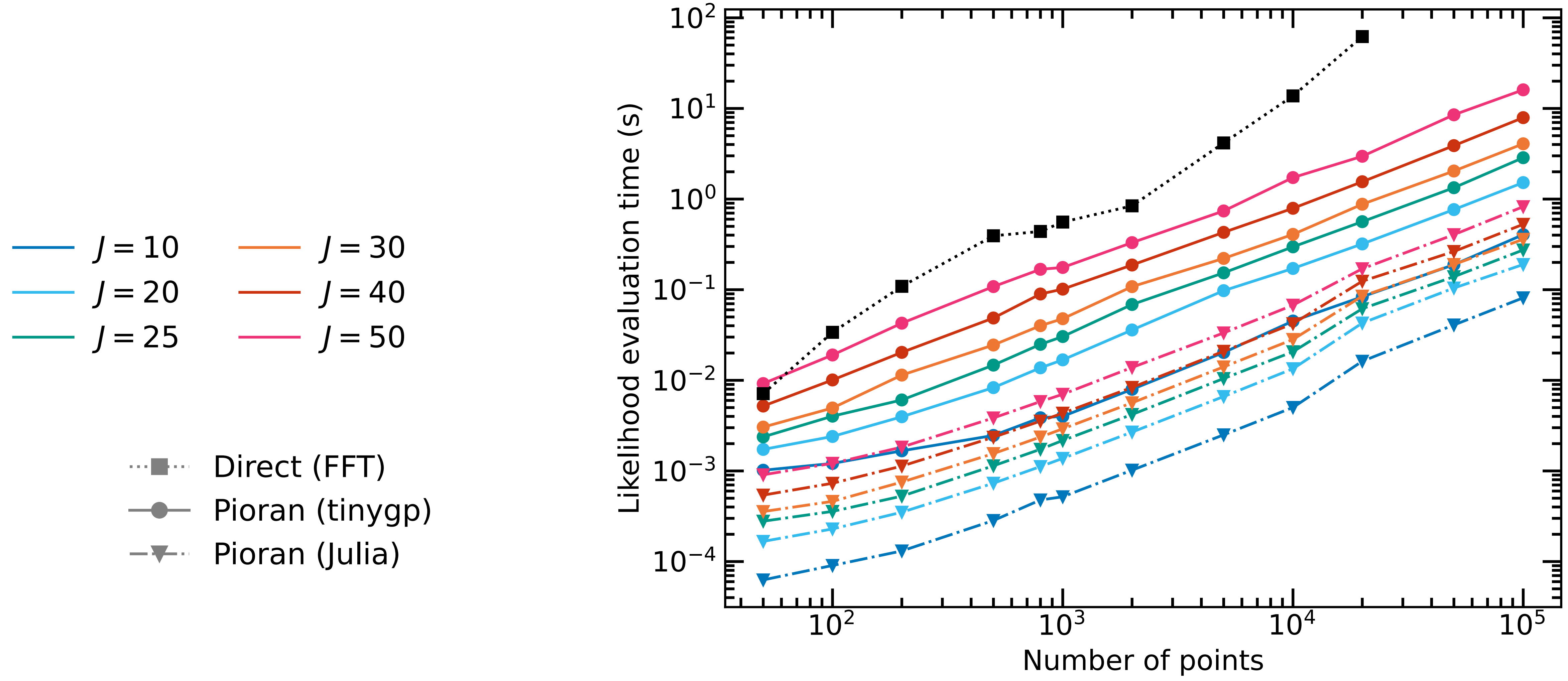

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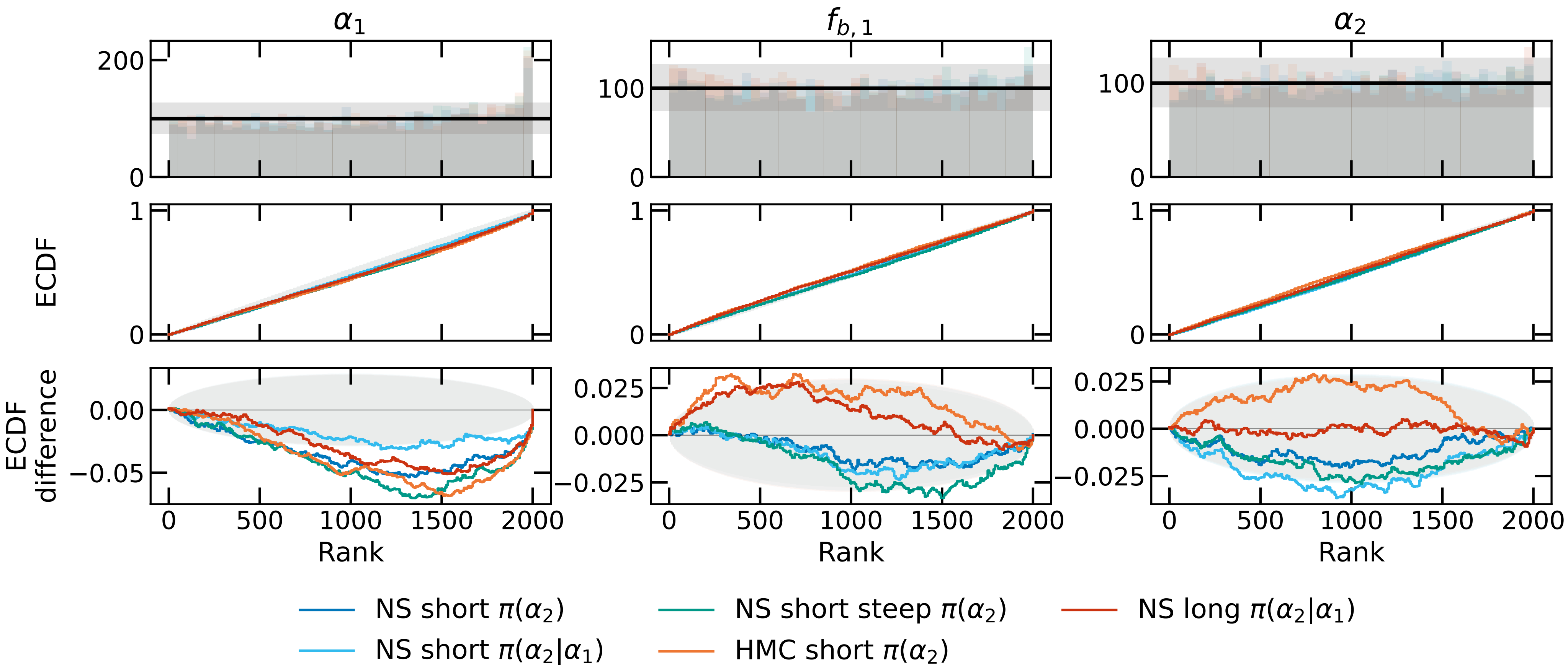
Simulation-based calibration

Talts+2018, Säilynoja+2021



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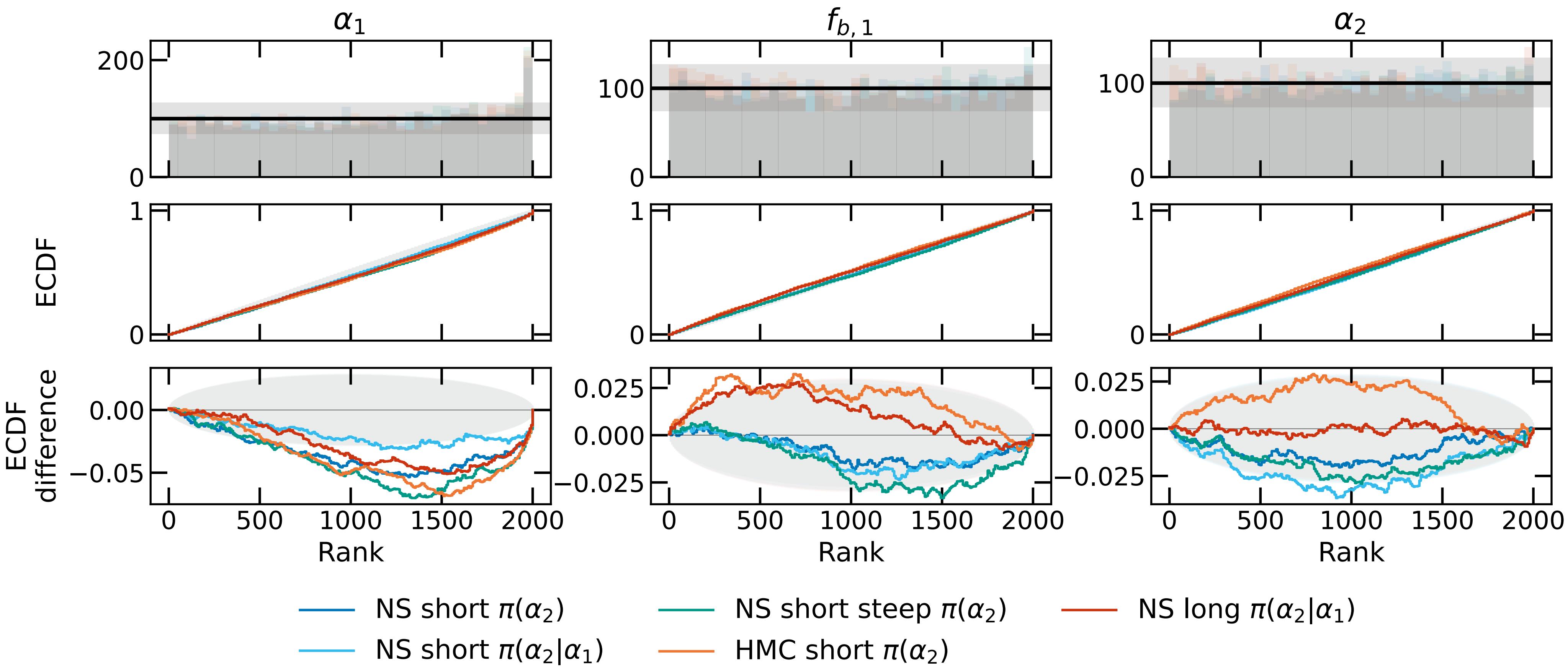


Validation: the method can correctly recover power spectrum parameters
but the low-frequency slope can be **overestimated** if the bend frequency is too small

About the non-linear variability of X-ray light curves and other assumptions

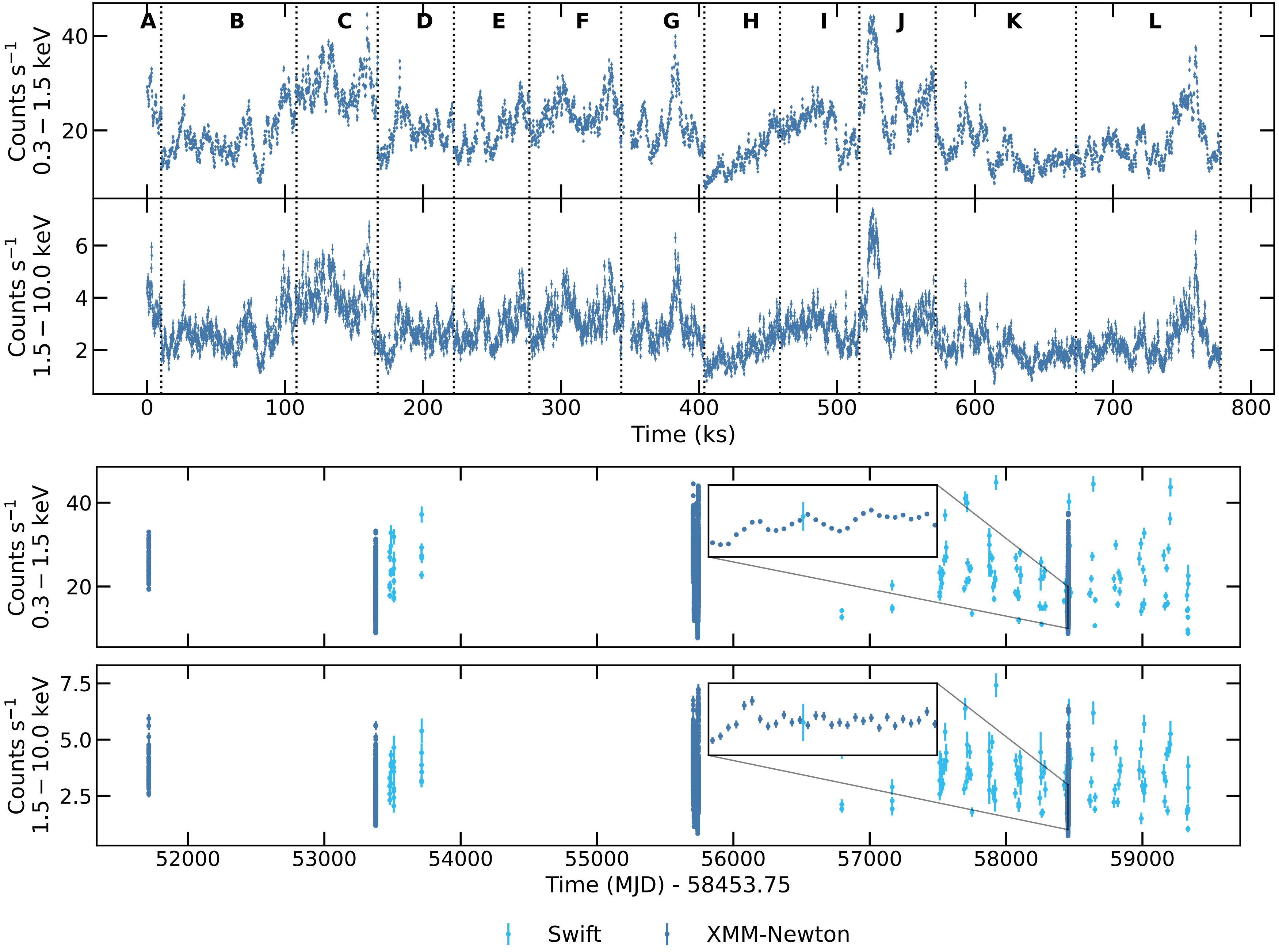
- We assumed Gaussian data ⟵ Lognormal process   Uttley+2005

  logarithm of the data

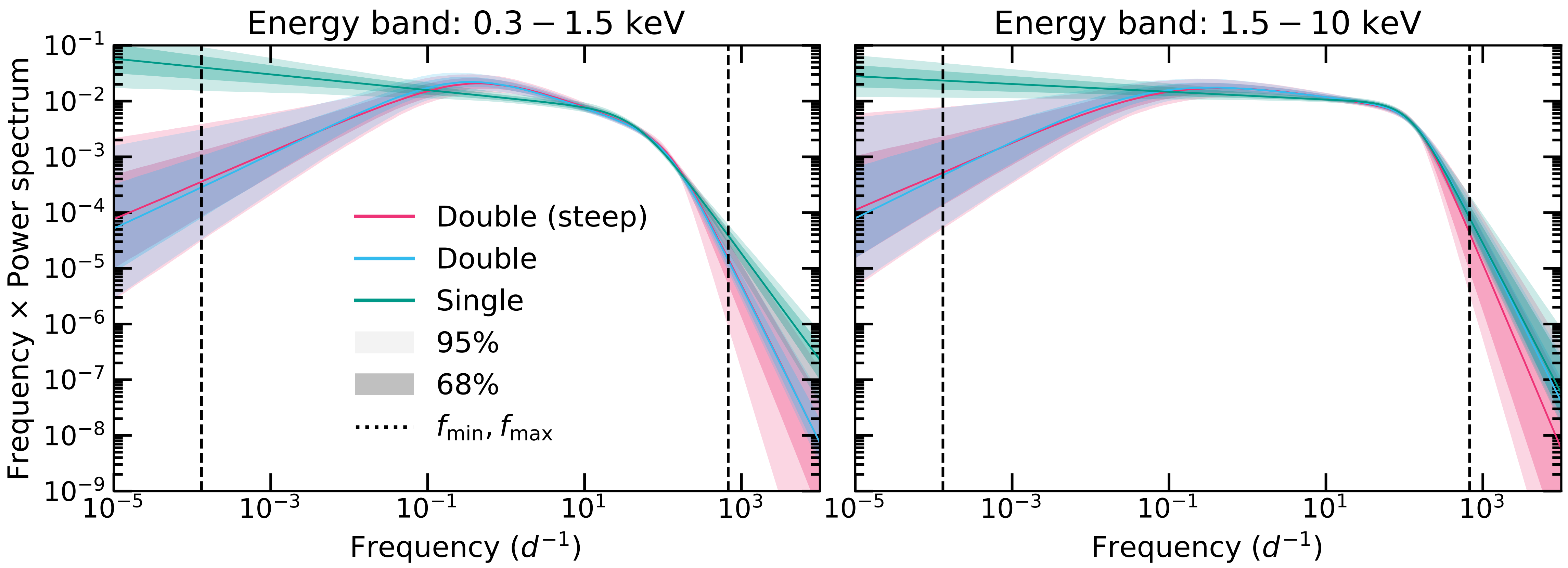
- We also assumed that the time series is weakly stationary

- In fact, it is sampled with a Poisson process (not implemented yet!)

Ark 564 observed by XMM-Newton and Swift

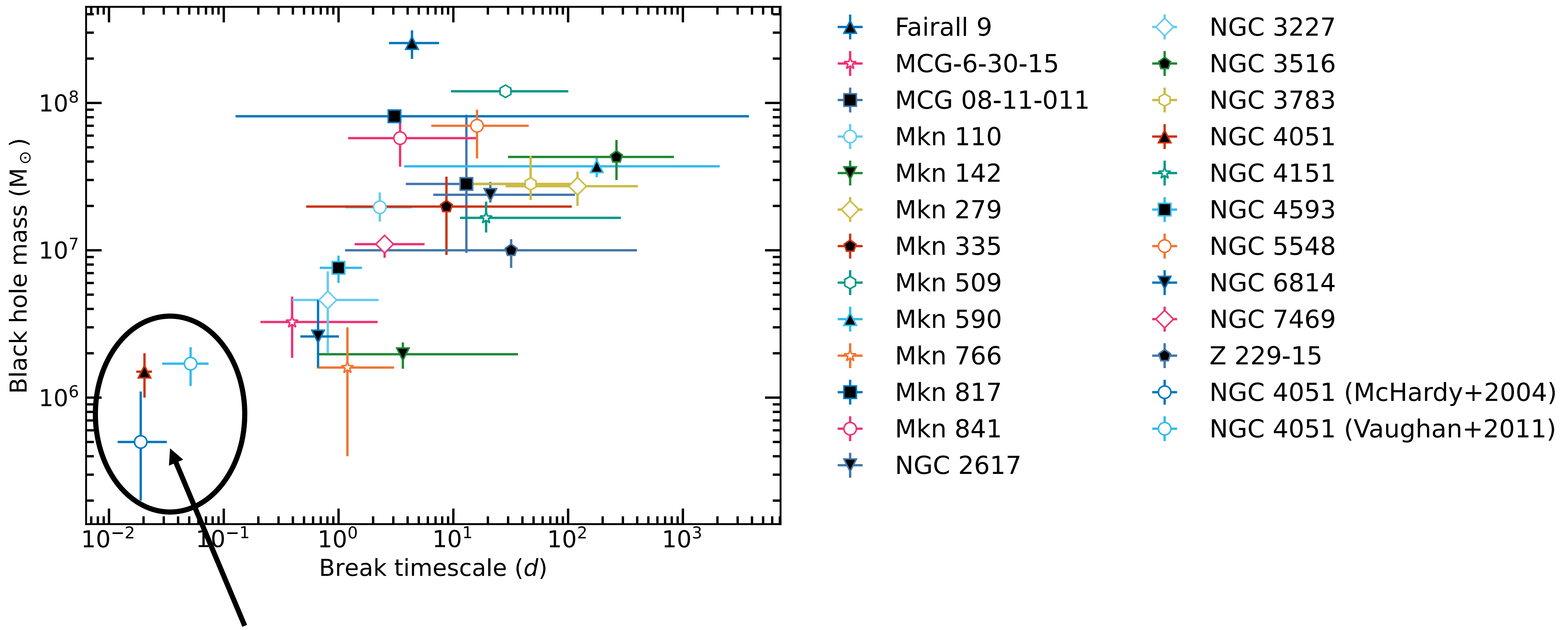


Revisiting the power spectrum of Ark 564



Results consistent with the works of McHardy+2007 using only Swift and XMM-Newton observations

Break time scale – Black hole mass diagram – Work in progress!!



NGC 4051 using XMM-Newton observations

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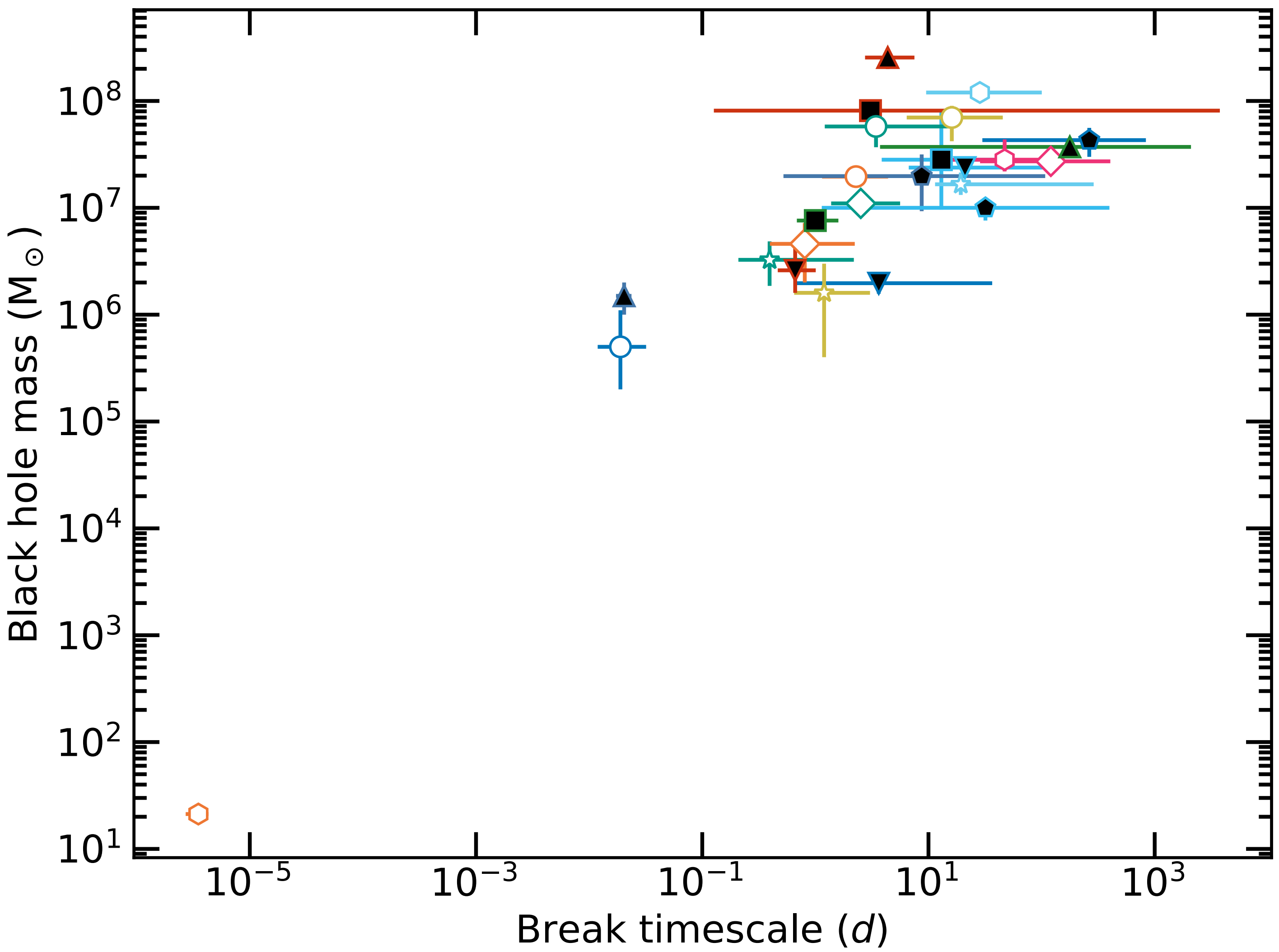
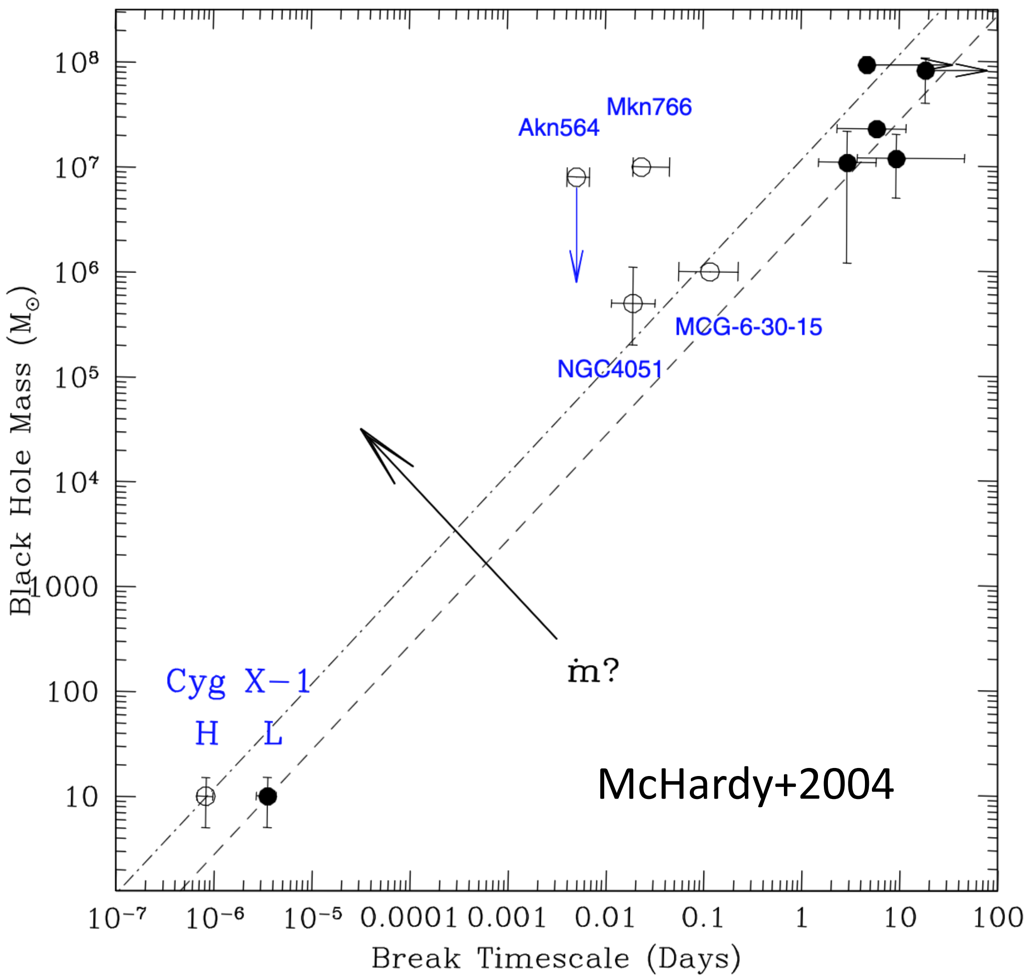
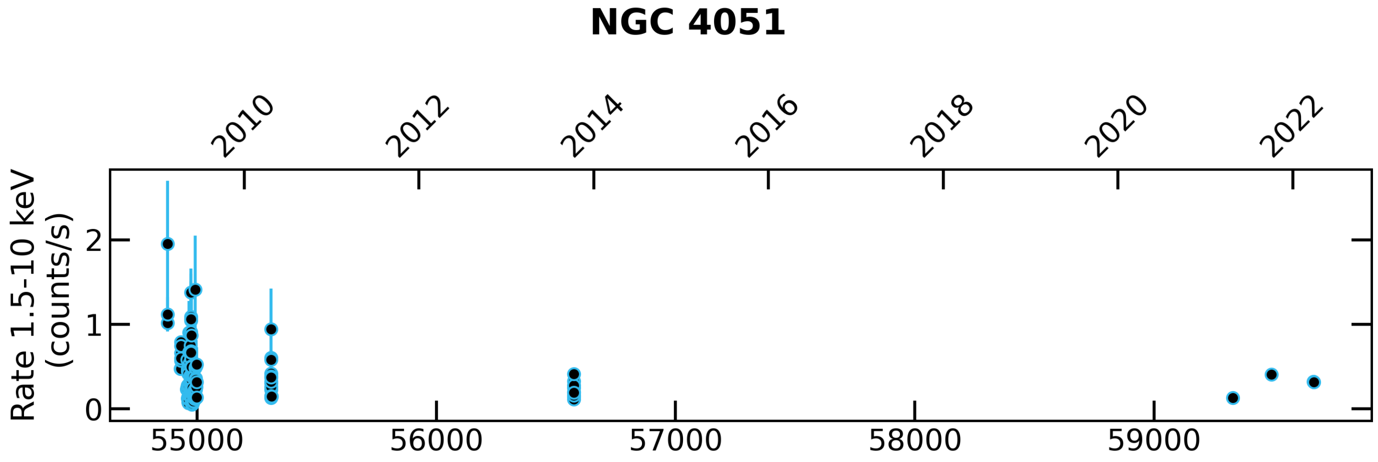


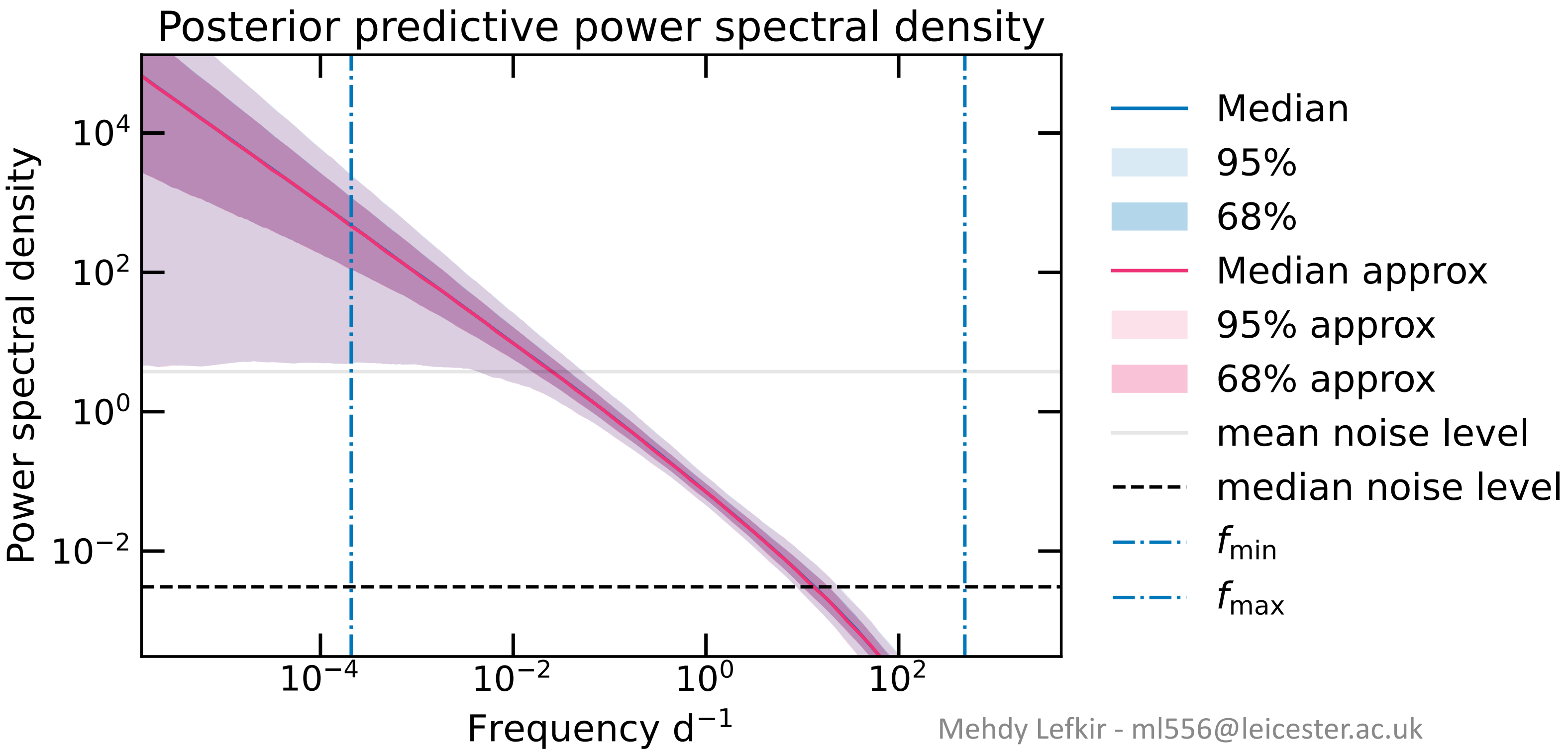


Conclusions

- We have a method to estimate the shape of the power spectrum:
  - Works on irregularly sampled time series
  - Validated with simulations
  - Scales on large datasets
  - Accounts for log-normal distribution
- With Julia and Python (JAX) implementations, currently being integrated in Stingray
- Paper describing the method under internal review
- Next steps:
  - Application to a sample of ~50 AGN with RXTE and Swift+ XMM-Newton data
  - Correlations with other wavelengths, reverberation mapping

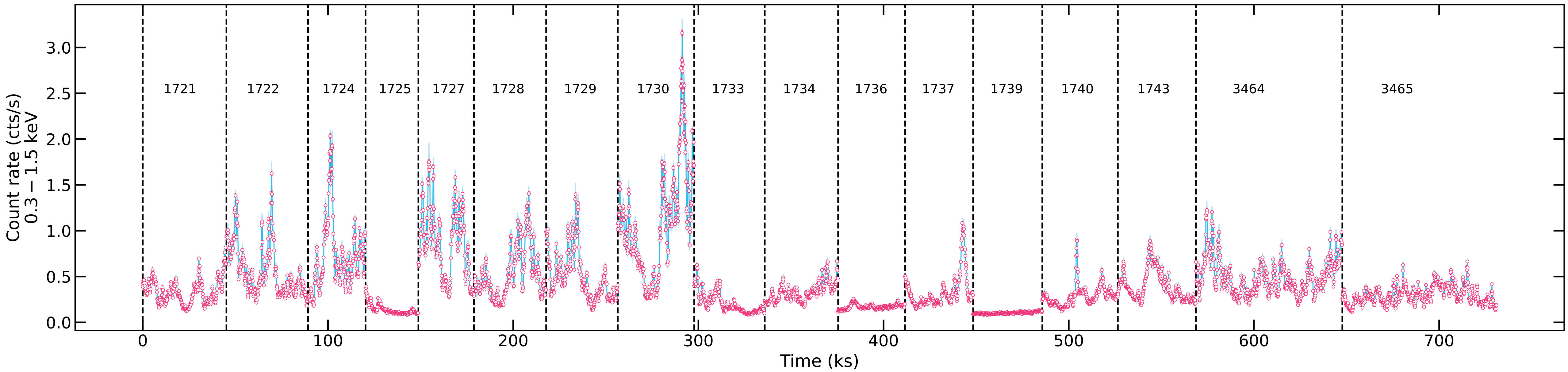
NGC 4051 – a "low" mass AGN: with Swift





- fast variability difficult to see with Swift

NGC 4051 – a “low” mass AGN: with Swift and XMM-Newton

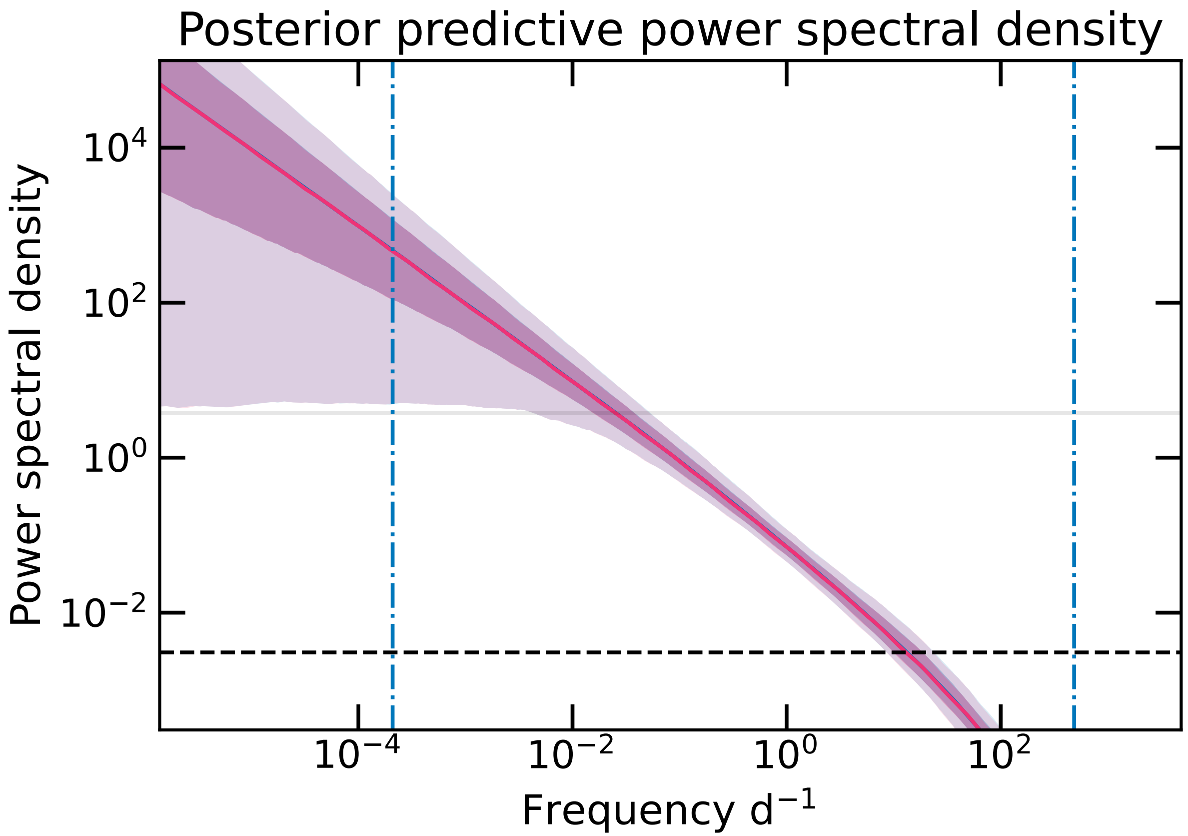


- About 5000 points!
- with a sampling period of 150s

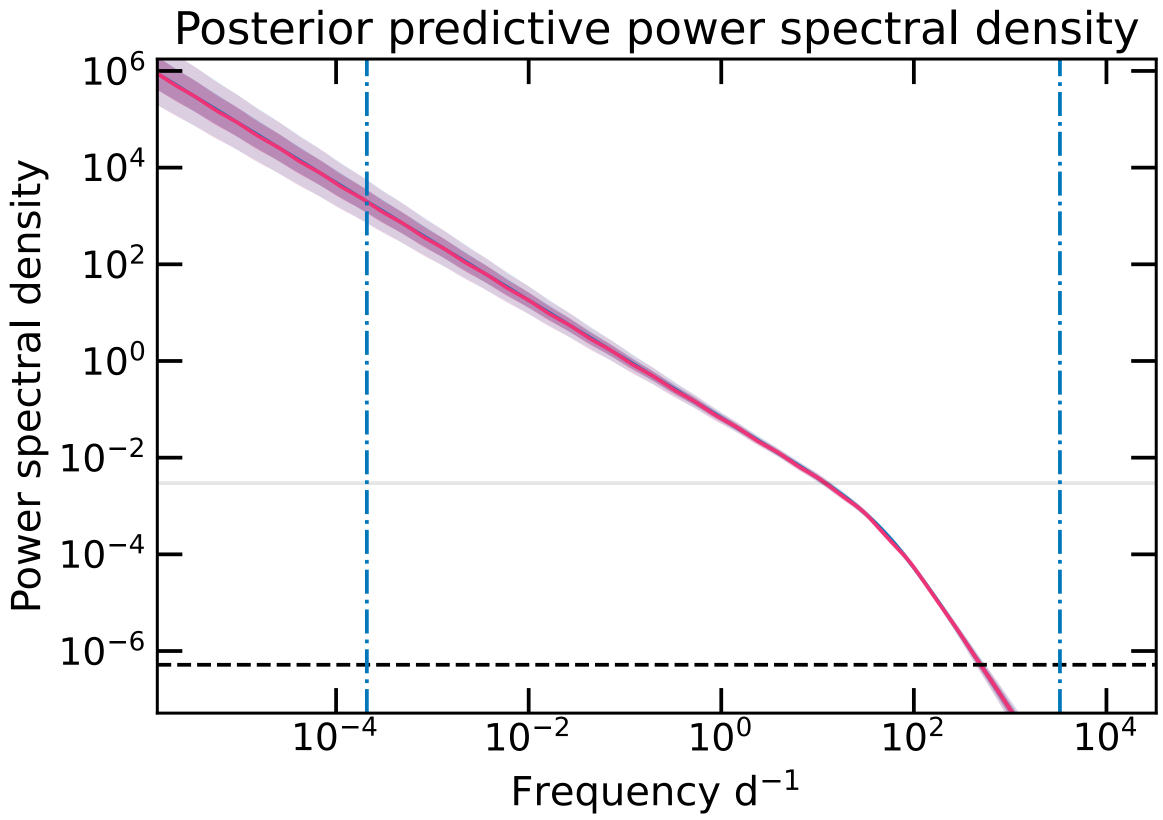
Can we see the fast variability?

NGC 4051 – a “low” mass AGN: with Swift and XMM-Newton

Swift only



Swift and XMM-Newton



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