Image from VectorStock.com/7932032

MWL Fitting at the Counts Level

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HELMHOLTZ WEIZMANN RESEARCH SCHOOL MULTIMESSENGER ASTRONOMY

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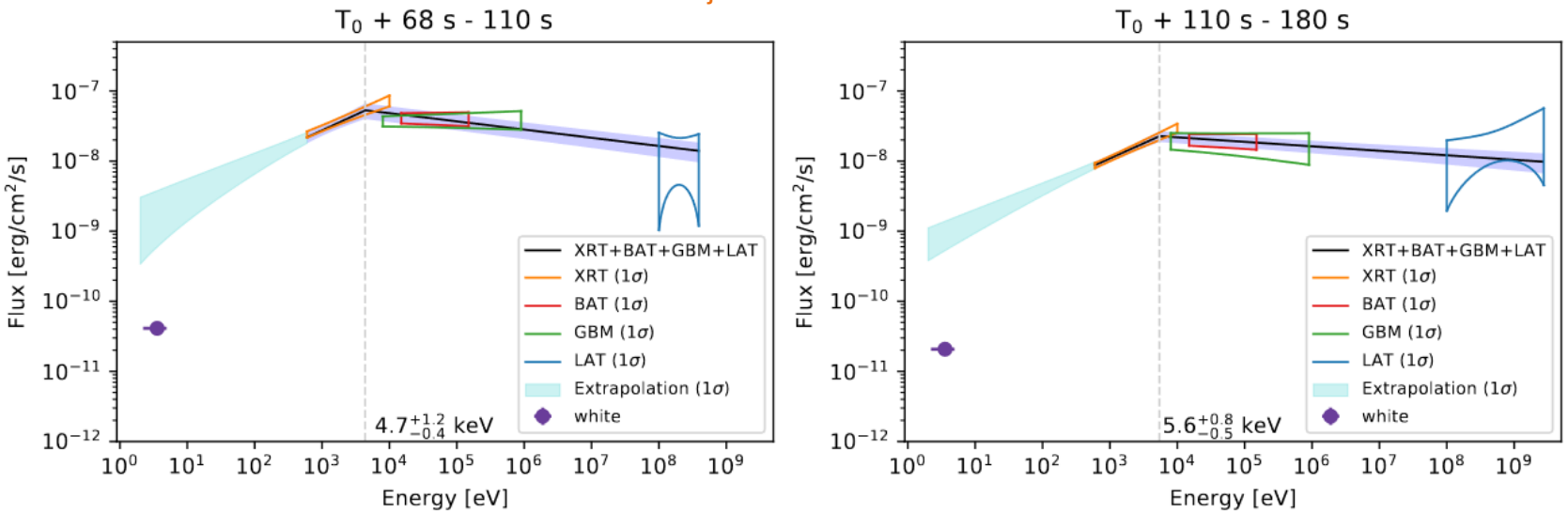
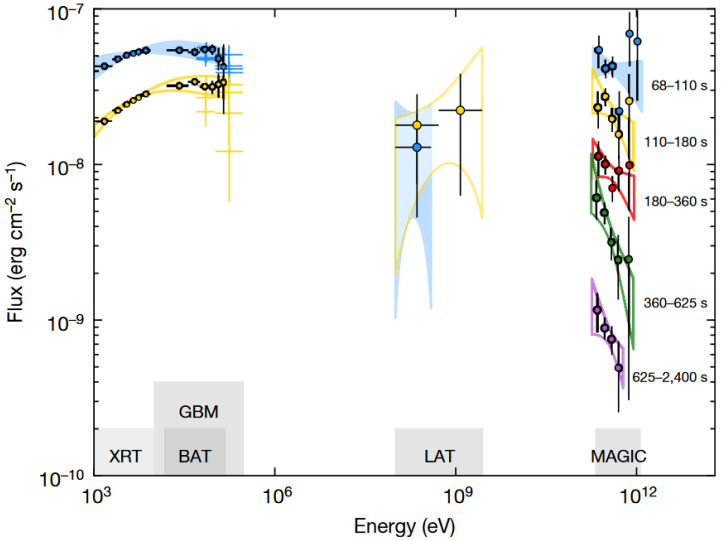
DESY.

Example for this talk: GRB 190114C

Ajello et al. 2020



MAGIC Coll. et al. 2020



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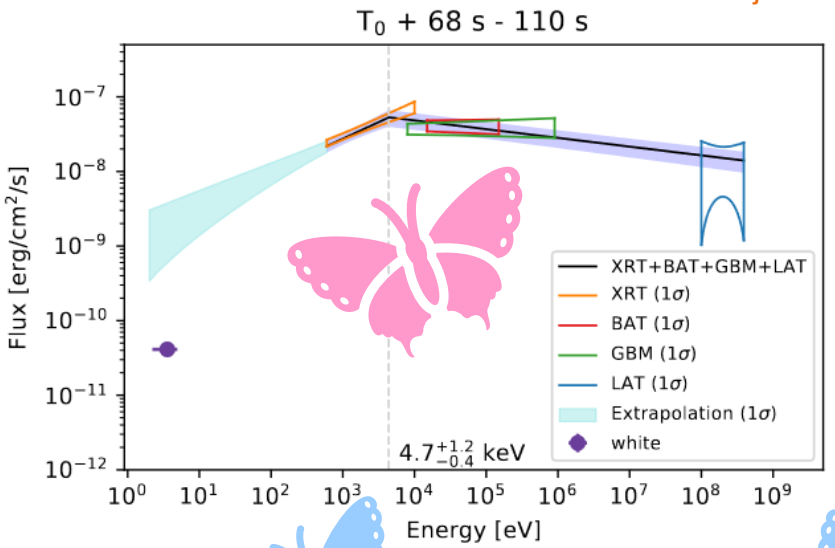

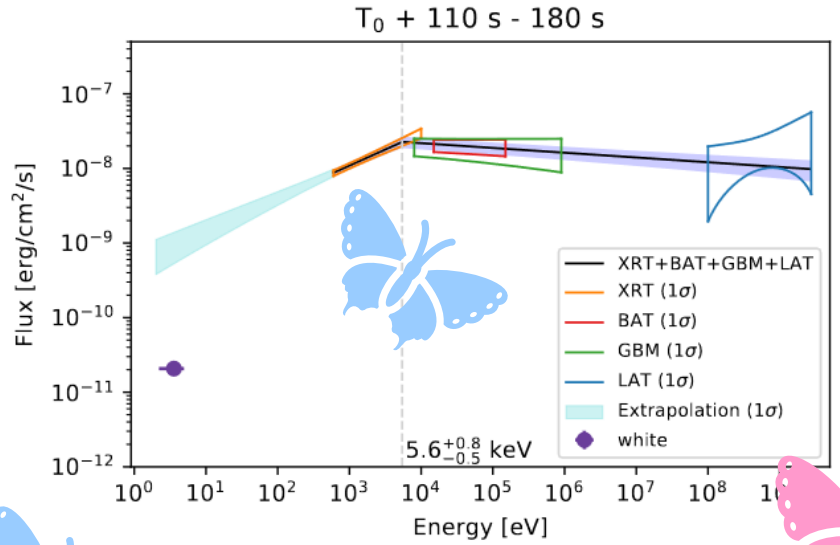

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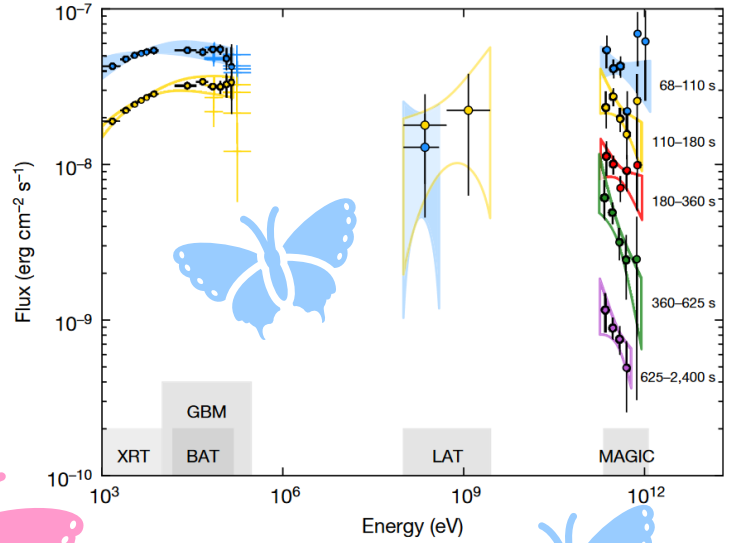

→ pretty to look at these, but scientific suggestiveness requires more than just pretty butterflies!

Fit ?

- Bayesian approach

  → $posterior = \frac{likelihood}{evidence} \cdot prior$

  → (sometimes log) uniform priors

  → evidence: $Z = \int d\vec{\theta}\ likelihood \cdot prior$
  (→ likelihood averaged over parameter space weighted with priors)

- sample posterior

  → detect multiple maxima?

- model comparison via Bayes factor

  → quantitative way of measuring preference of model 1 over model 2

  → metric scale crucial

Fit ?

- Bayesian approach

  → $posterior = \frac{likelihood}{evidence} \cdot prior$

  → (sometimes log) uniform priors

  → evidence: $Z = \int d\vec{\theta}\ likelihood\ prior$
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We need to spend more efforts on this!

- sample posterior

  → detect multiple maxima?

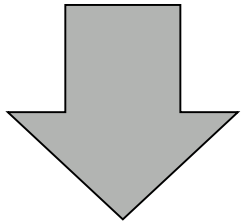
- model comparison via Bayes factor

  → quantitative way of measuring preference of model 1 over model 2

  → metric scale crucial

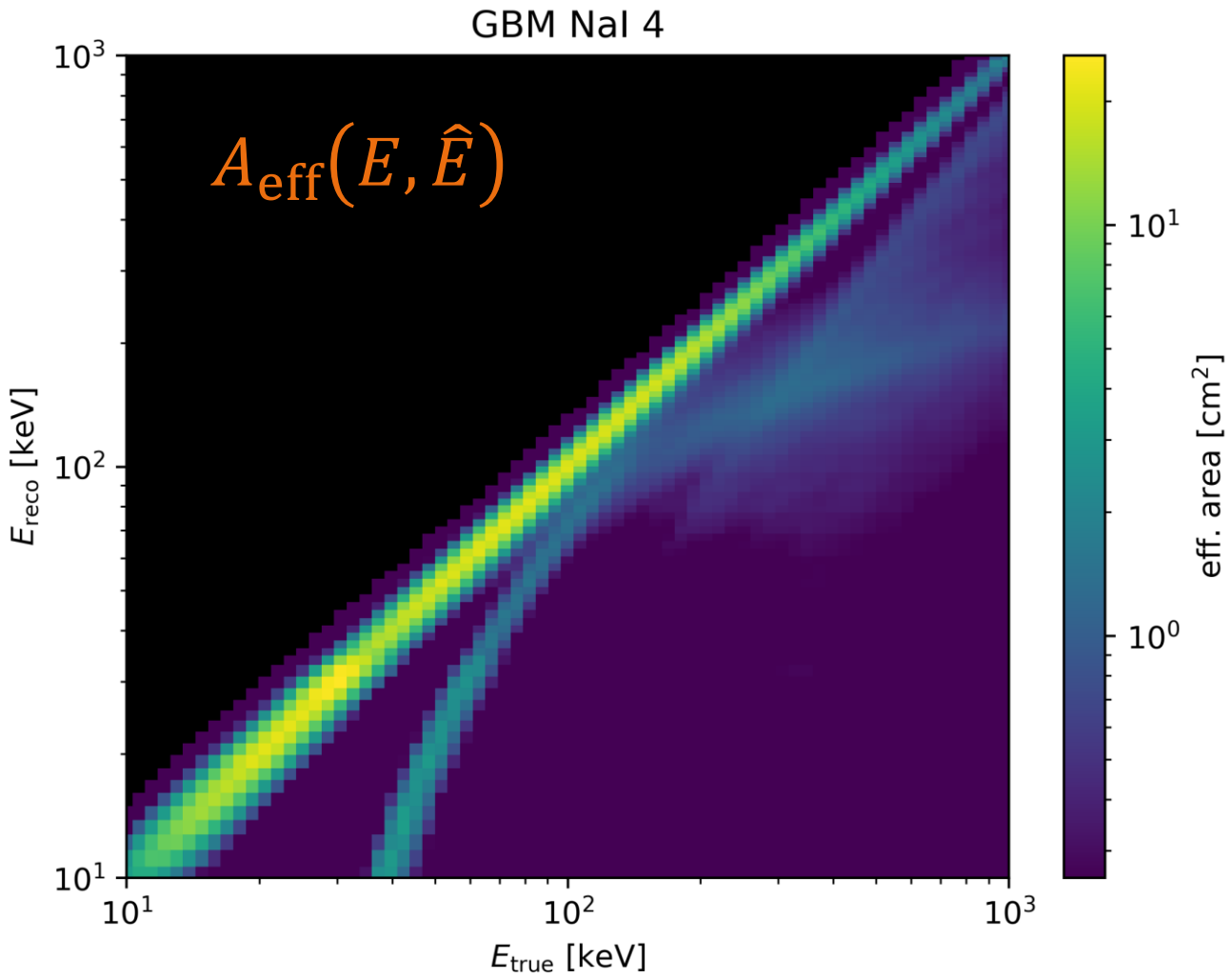
What is the task?

→ fit model to absorbed measurements of multiple detectors



$$\text{Counts rate}\,(E) = \int \mathrm{d}\hat{E}\ \frac{\mathrm{d}N_{\text{source}}}{\mathrm{d}E\ \mathrm{d}t\ \mathrm{d}A}\left(\hat{E}\right)\ \exp\left(-\tau\left(\hat{E}\right)\right)\ A_{\text{eff}}\left(E,\hat{E}\right)\ c_{\text{sys}}$$

Instrument response for single detector



- detector consists of many energy channels

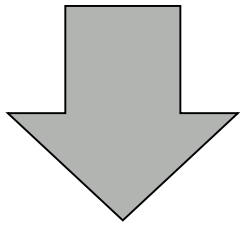
  → **energy dispersion**

- we cannot simply invert (unfold) this matrix

  → **forward folding**

What is the task?

→ fit model to absorbed measurements of multiple detectors



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and

Background rate

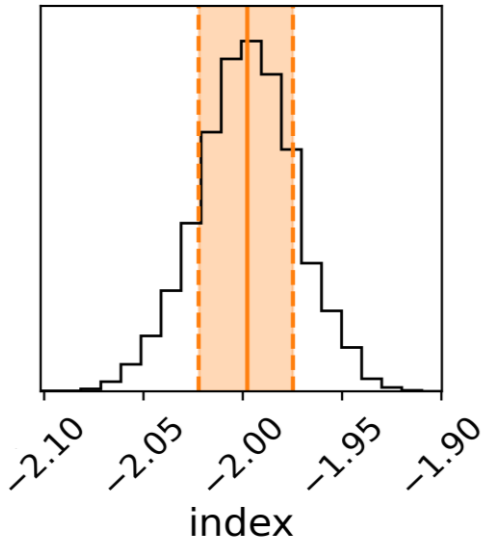
different detectors have different statistics!

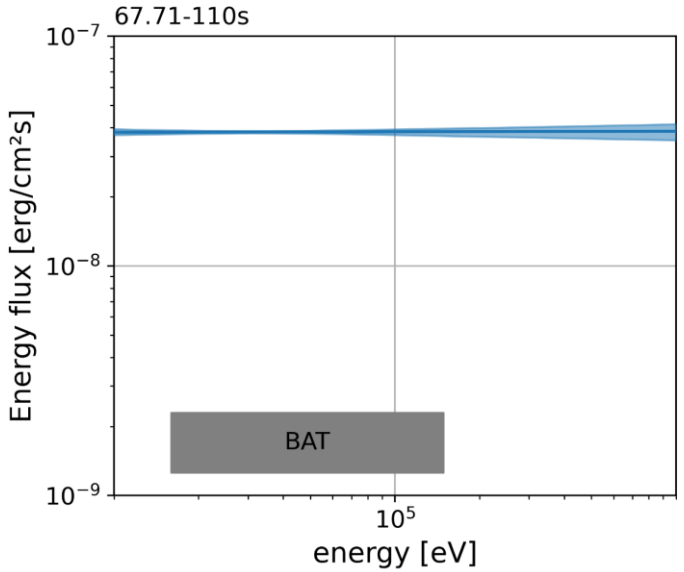
Swift BAT

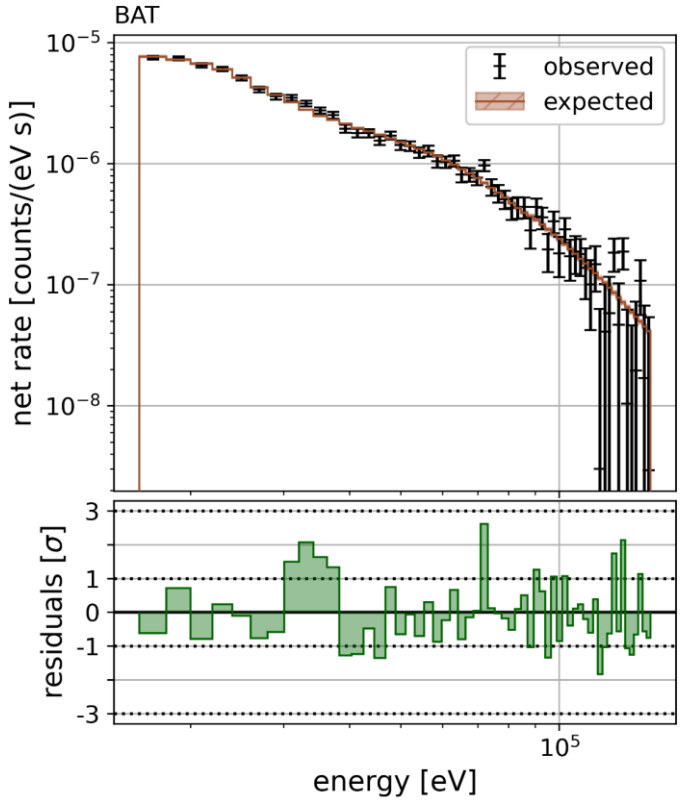
- simplest instrument for us
- ON: Gaussian
- OFF: - (no background, rate fitted)

  → χ^2 (or S statistic)
- good approximation by power law:

  → index = $-1.998^{+0.023}_{-0.024}$







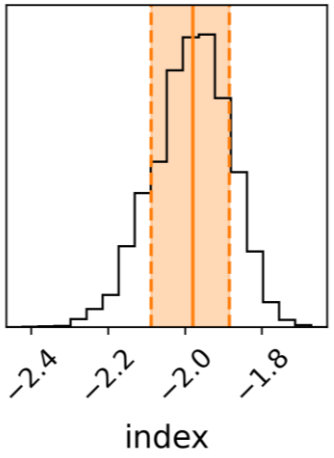
Fermi GBM

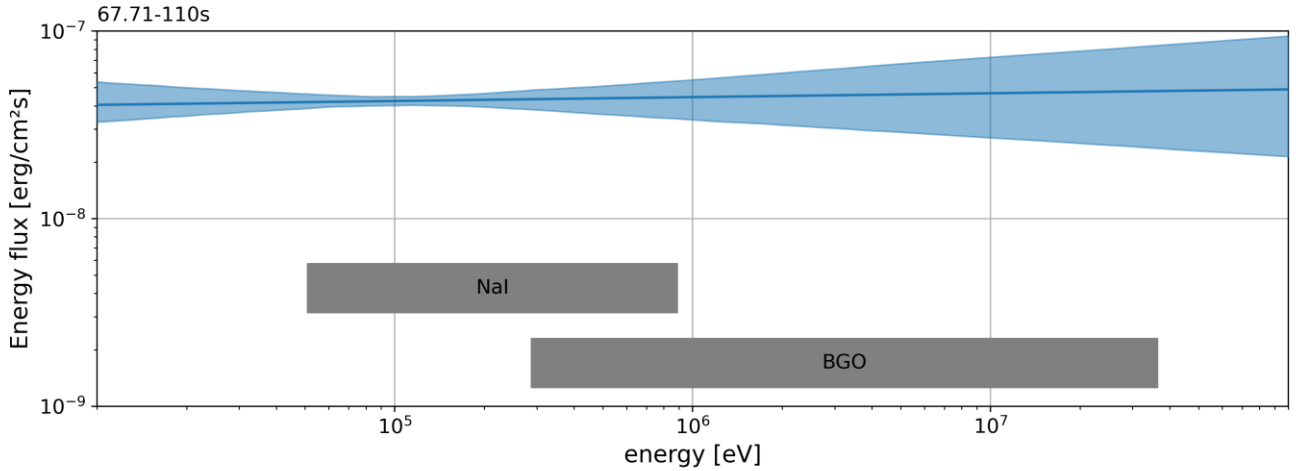
- multiple detectors (12 **NaI** + 2 **BGO**)

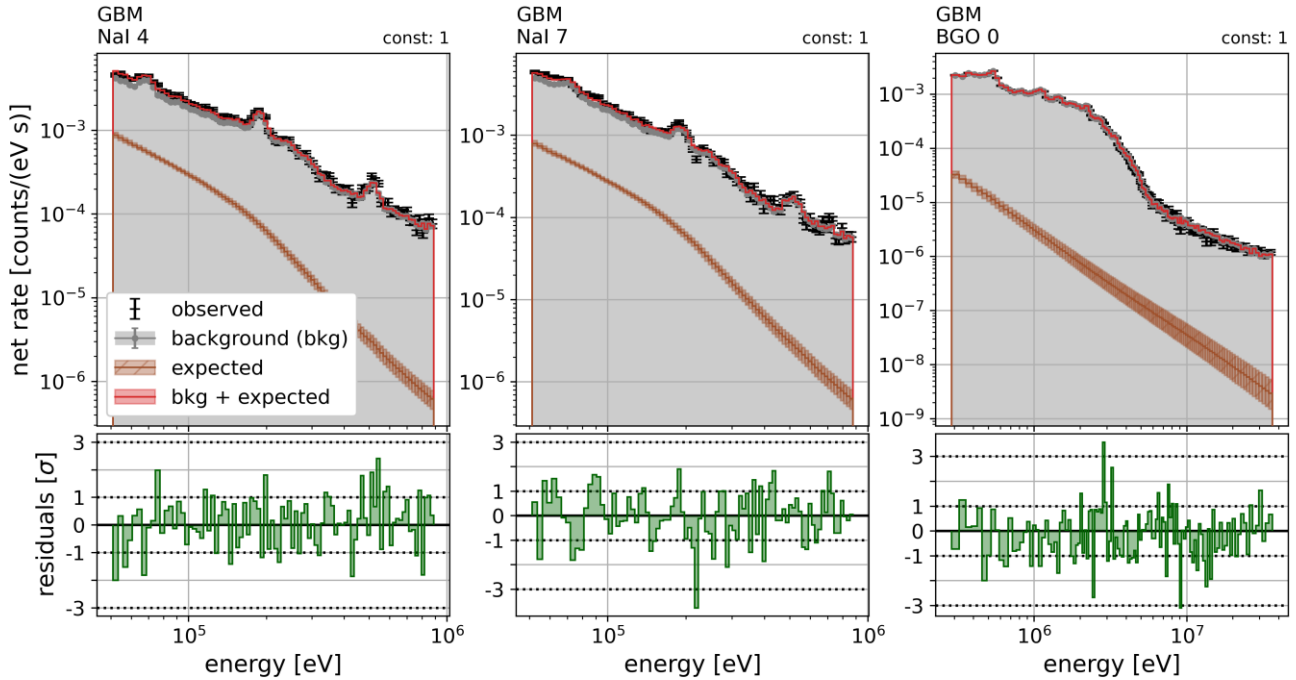
  → properly cross calibrated
- ON: Poisson
- OFF: Gaussian (bkg. fitted)

  → PGStat
- also flat power law

  → index = -1.98 ± 0.1

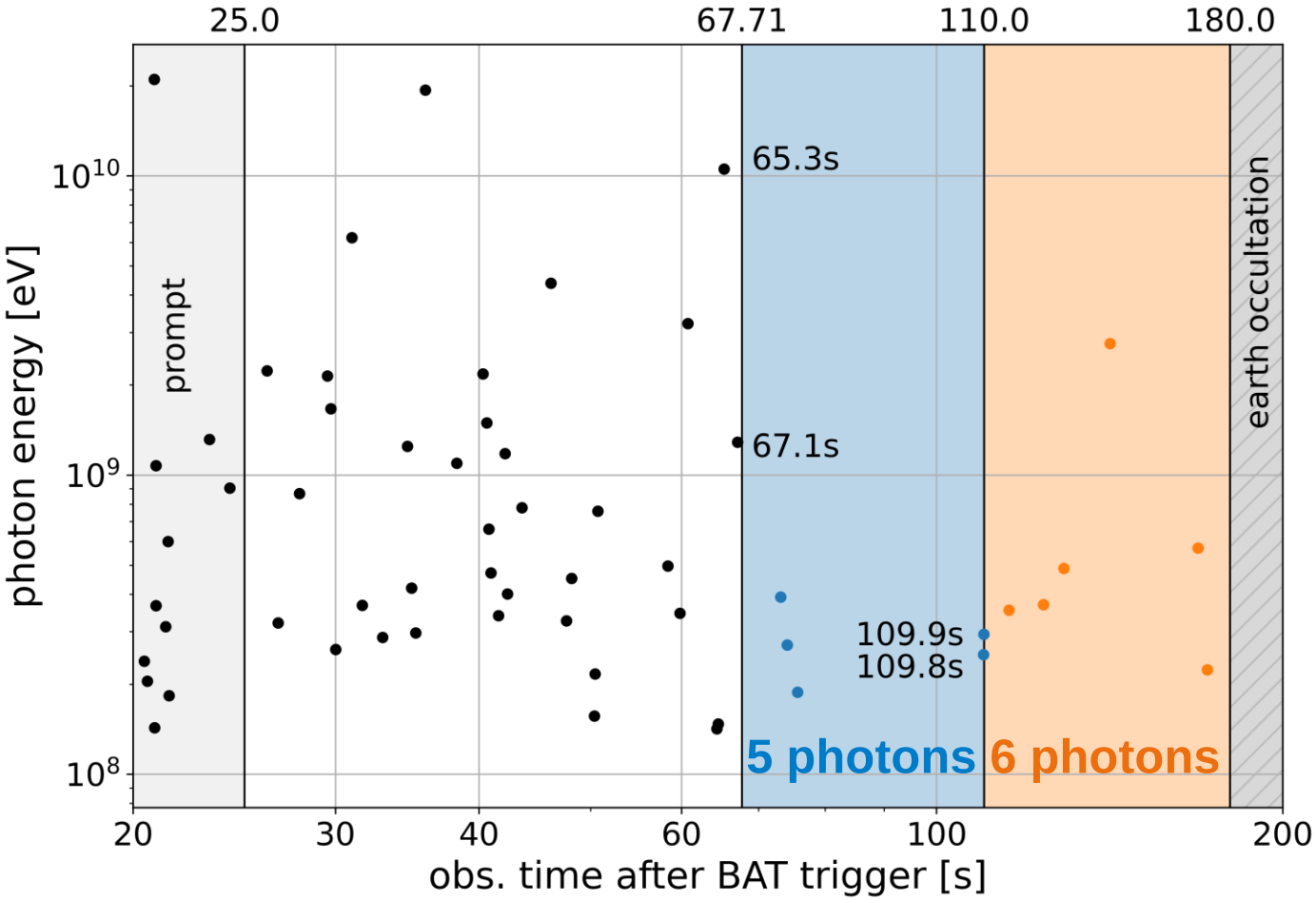






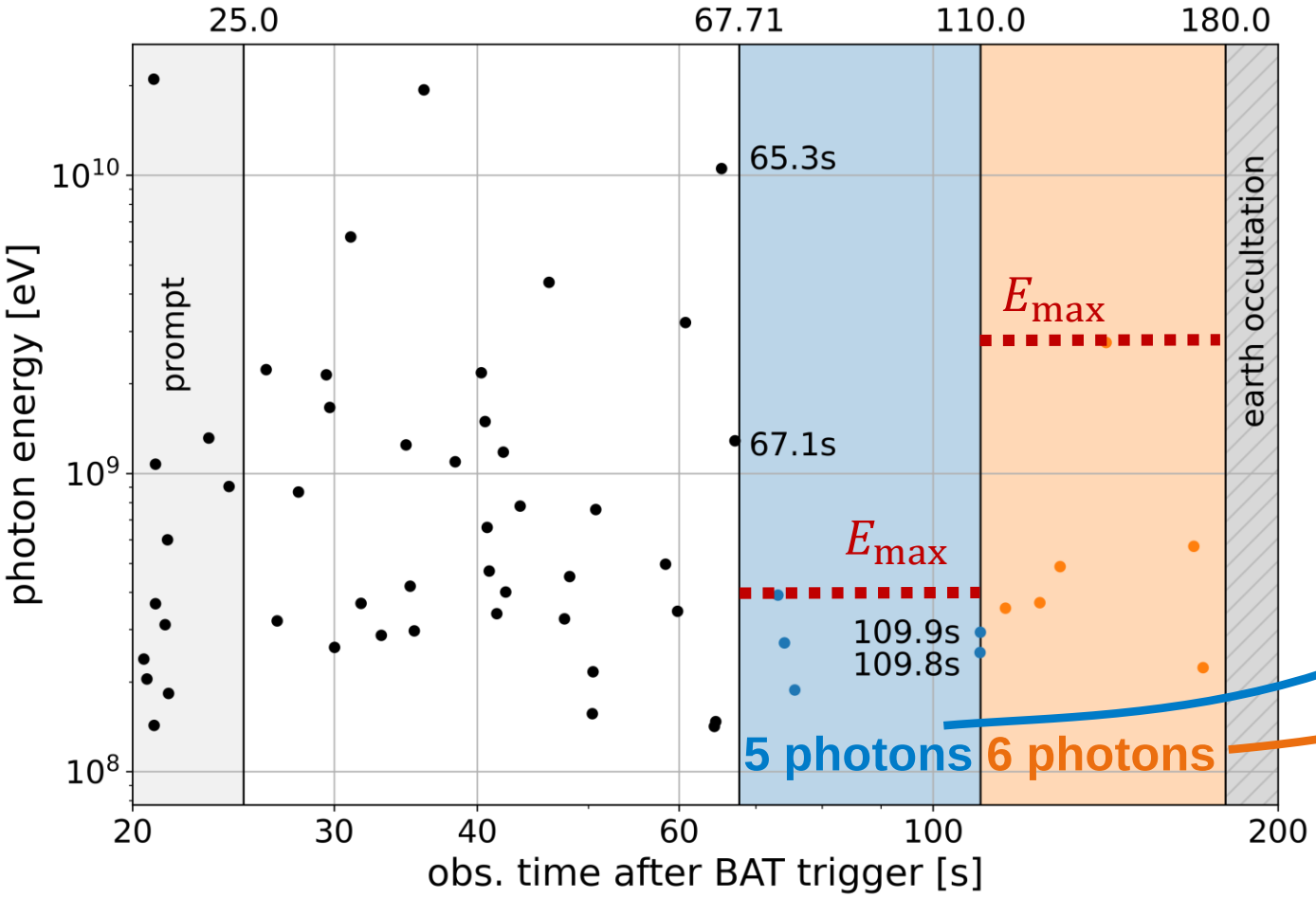
→ background dominated!

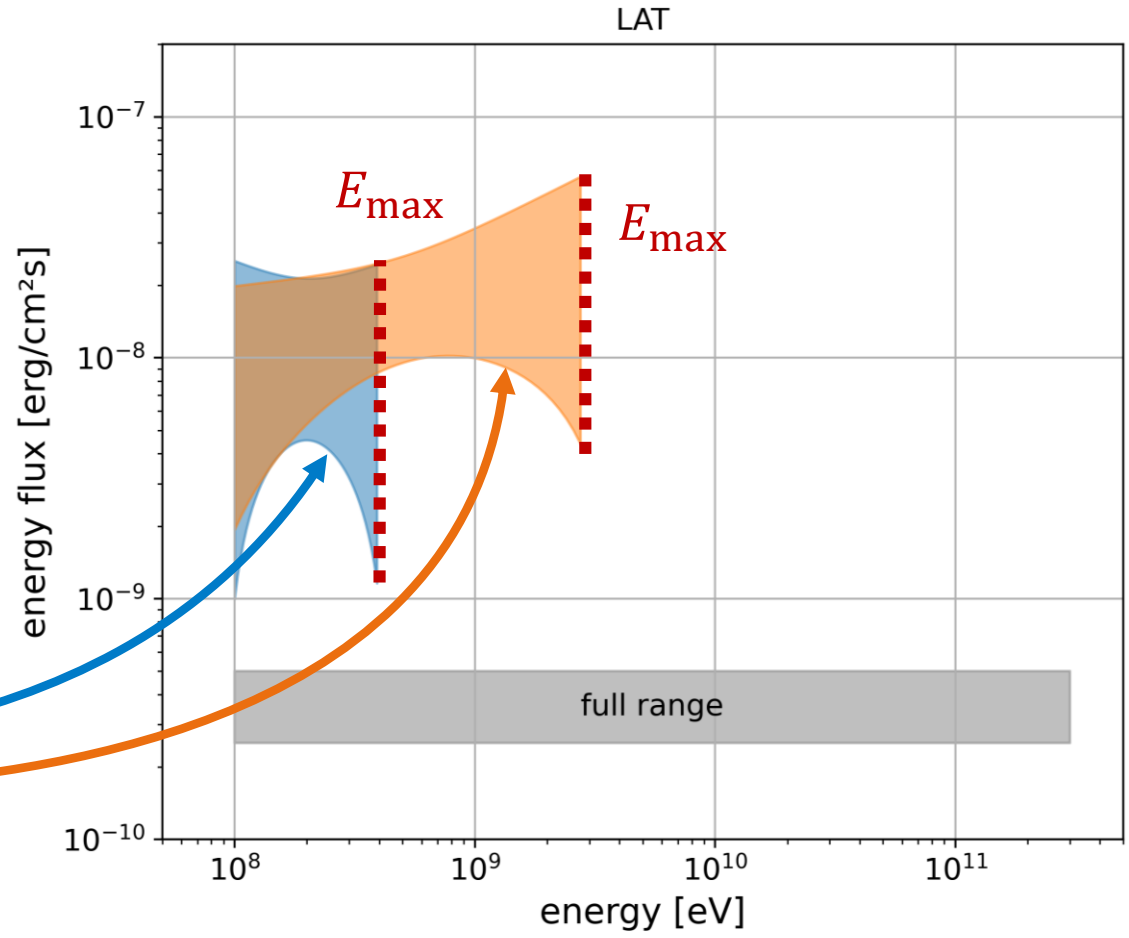
Fermi LAT



→ single photon counter

Fermi LAT





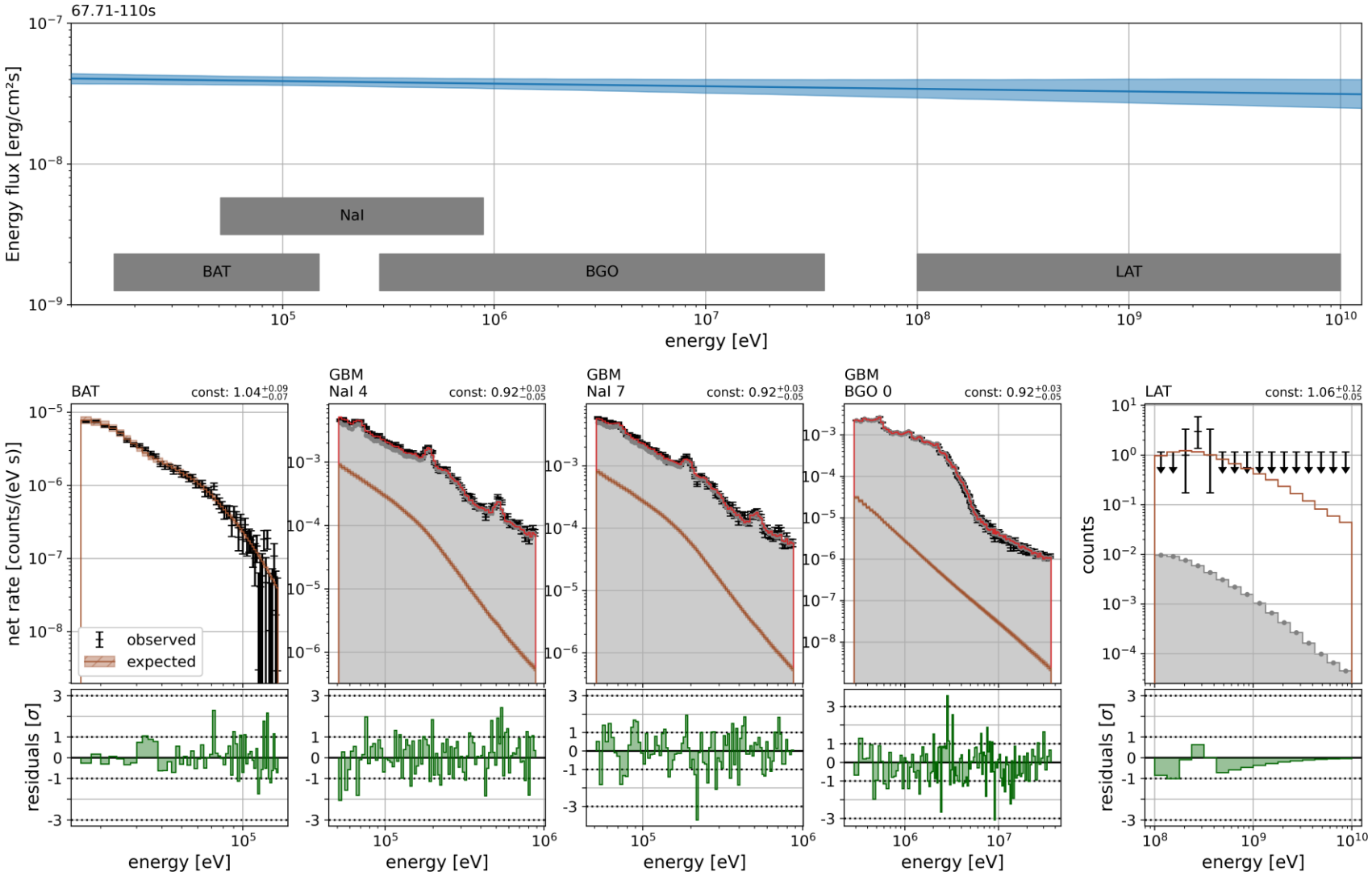
→ single photon counter

→ spectral index not really constrained

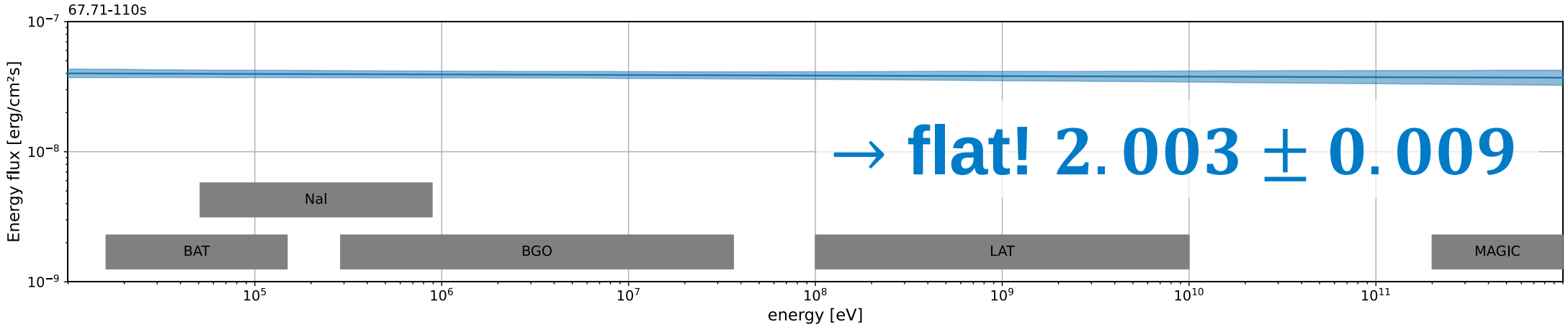
Combined BAT + GBM + LAT

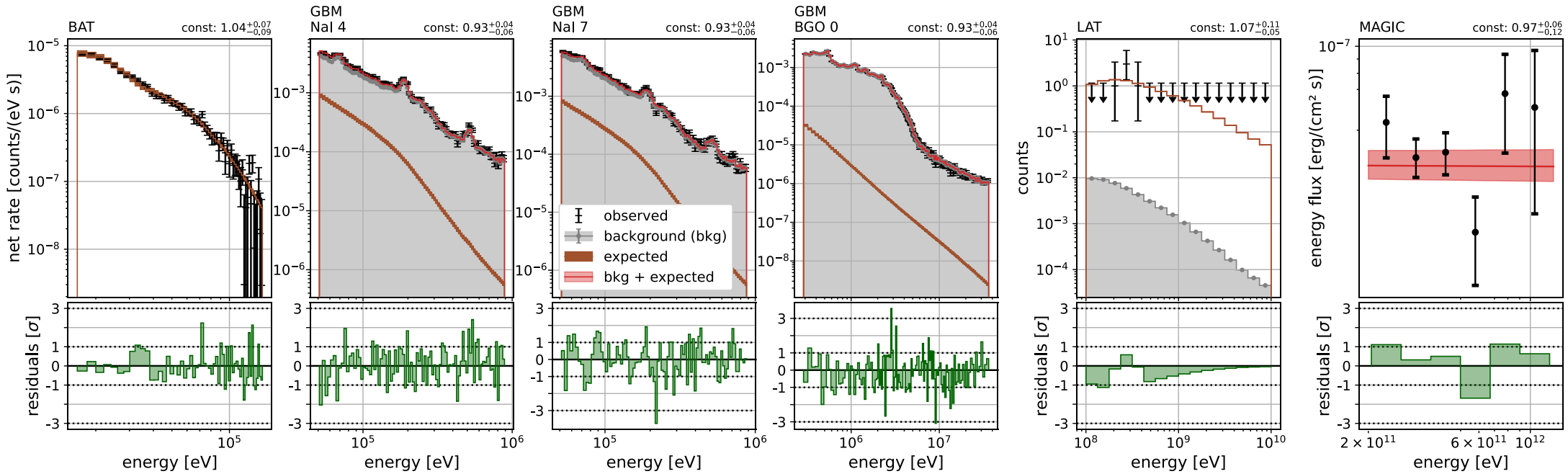
- add additional cross calibration factor of $\pm 15\%$

  → non-trivial, why const? simplest assumption



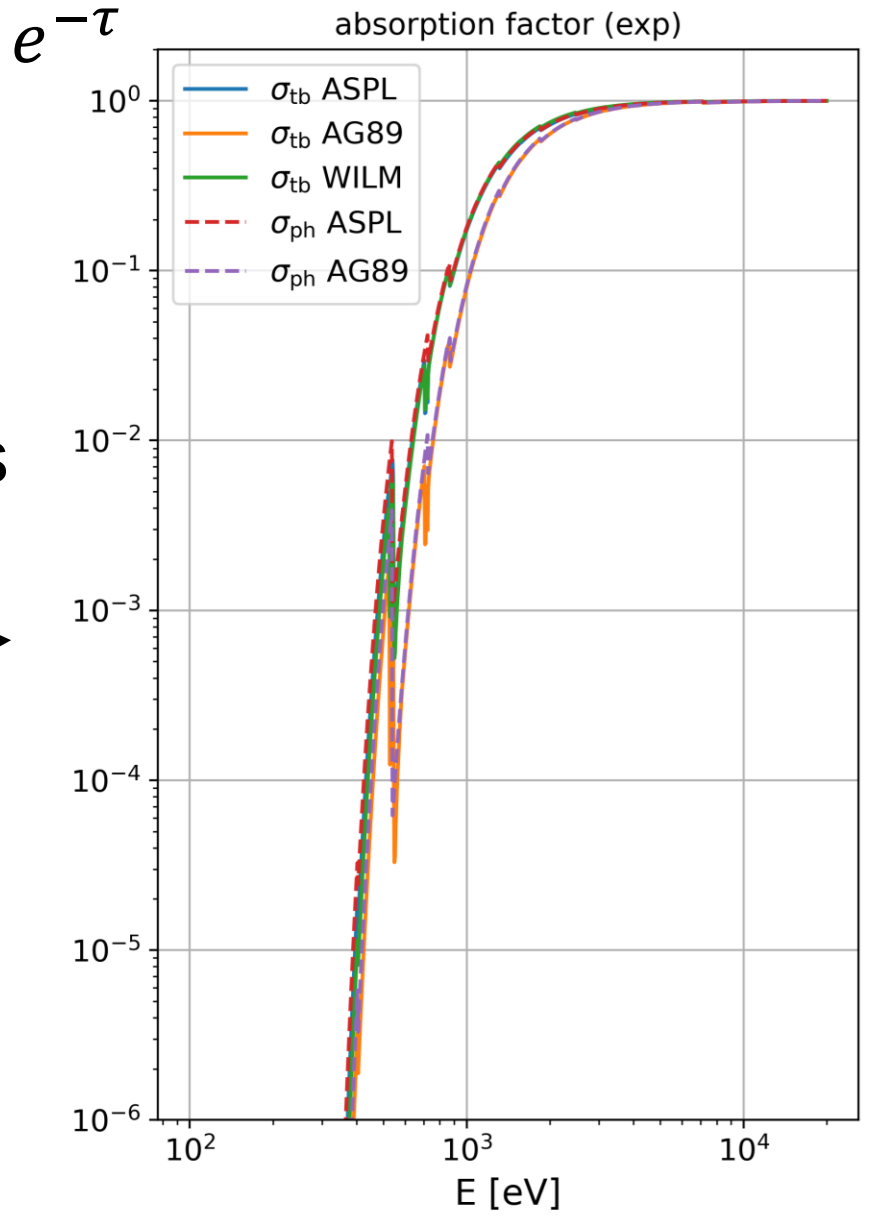
MAGIC? → no public IRF, only χ^2 from data points





Exponential absorption

- we basically fit our box size of useful data
- EBL at high energies
- extinction (dust, photoelectric) at low energies



- Challenges:

  → exponential correction of orders of magnitude

  → curvature

  → steps in cross section introduce steps in correction
  → fit harder breaks than really in data?

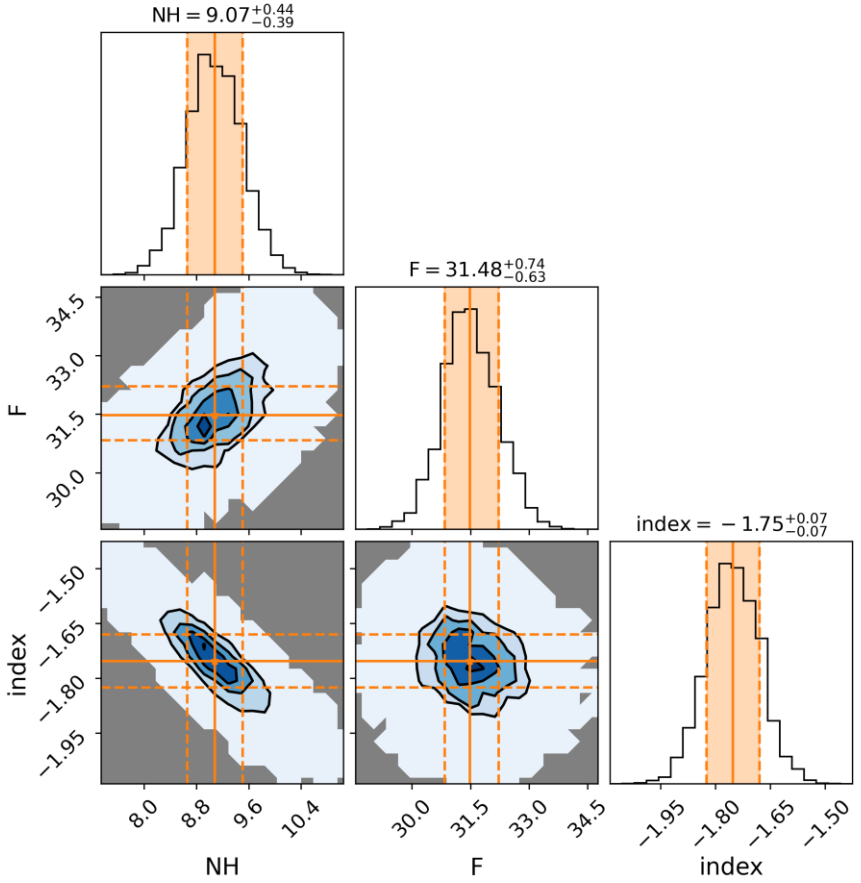
Swift XRT

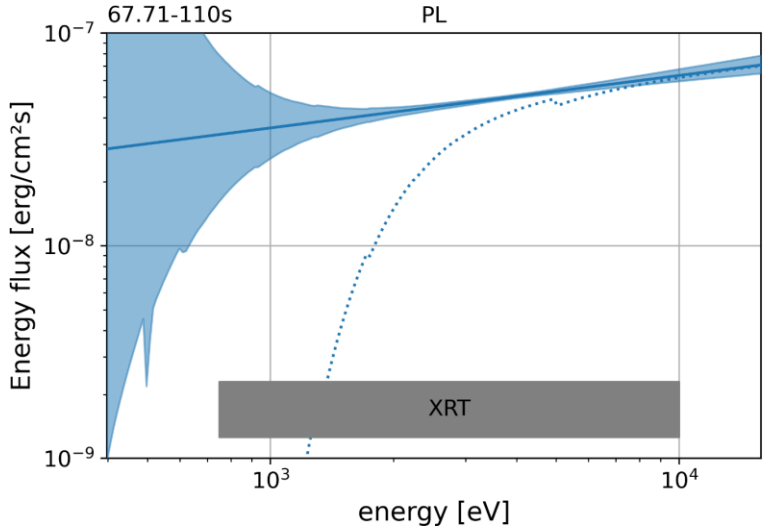
- ON: Poisson
- OFF: Poisson

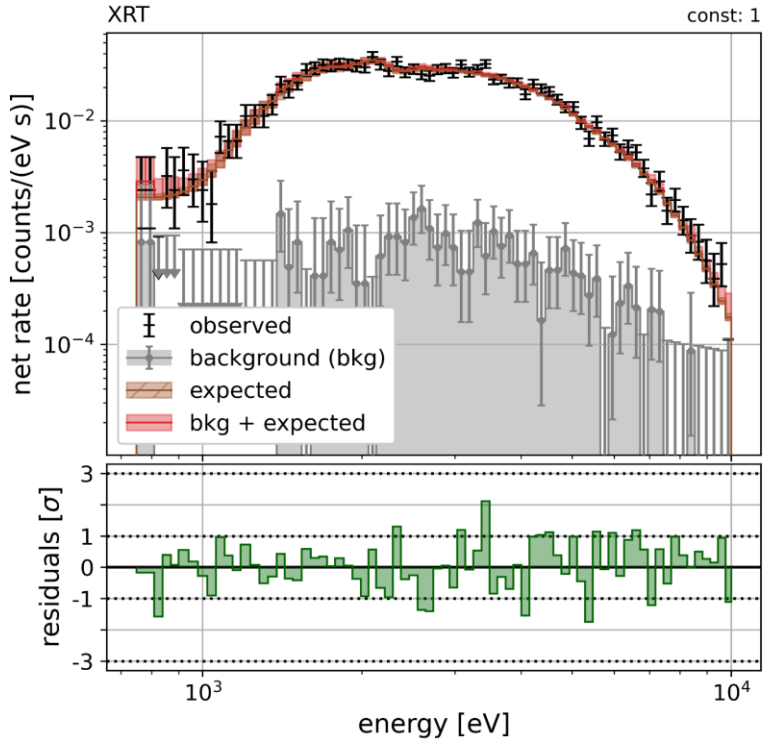
  → CStat
- signal dominated!
- power law + abs:

  → index = -1.75 ± 0.07

  → break!?

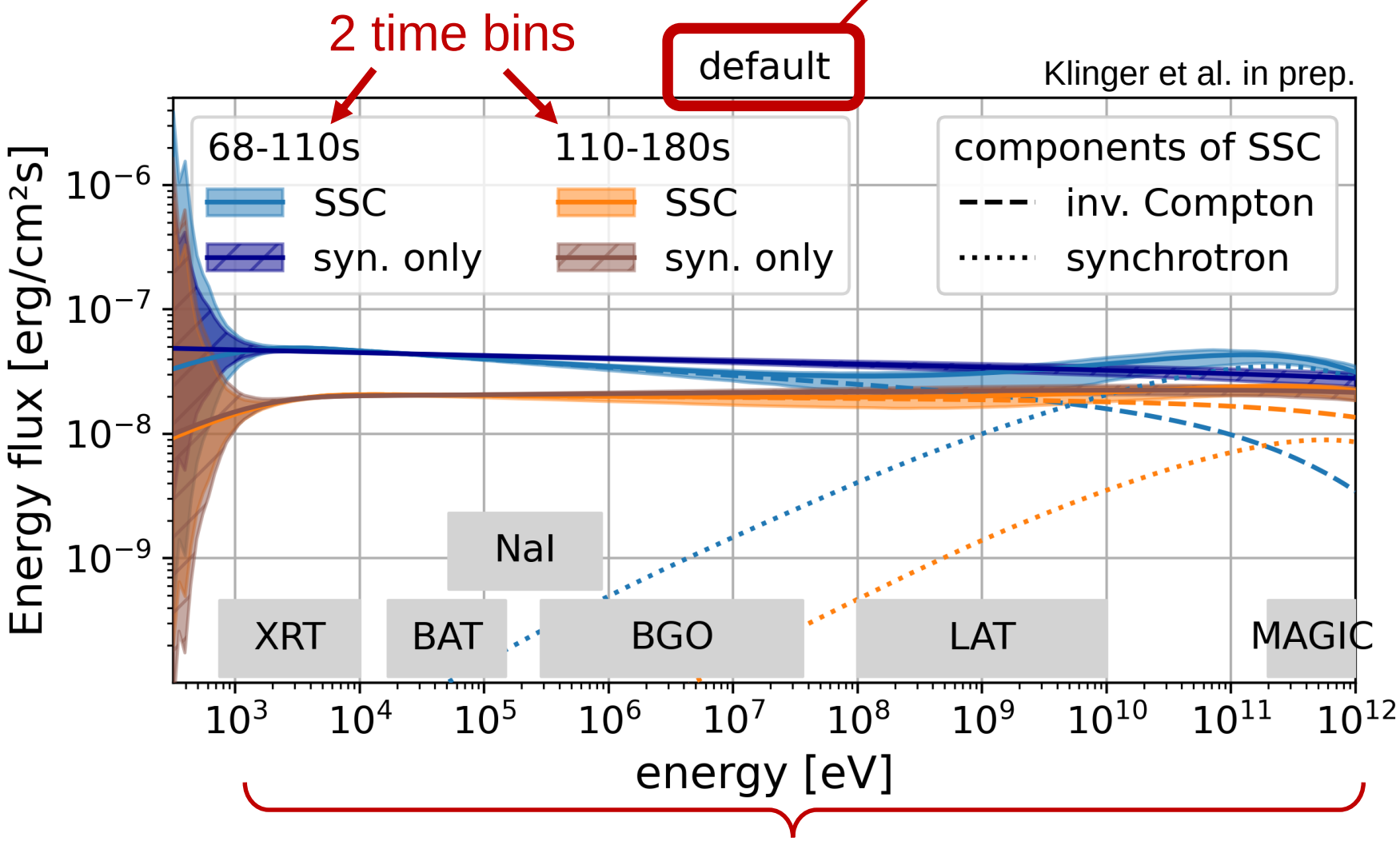






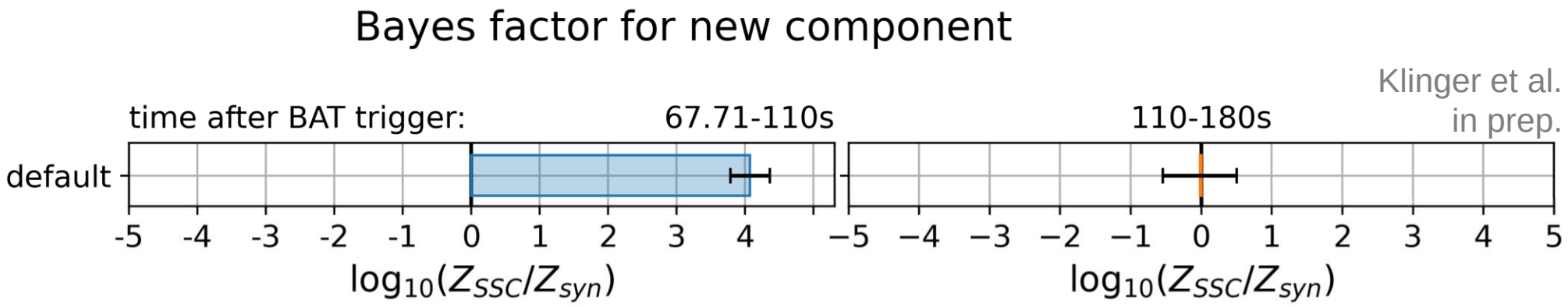
Fitting a reduced SSC model

as in Ajello et al. 2020 (joint Swift+Fermi)
→ only BAT-GBM cross calibration included



flat over 9 orders of magnitude!

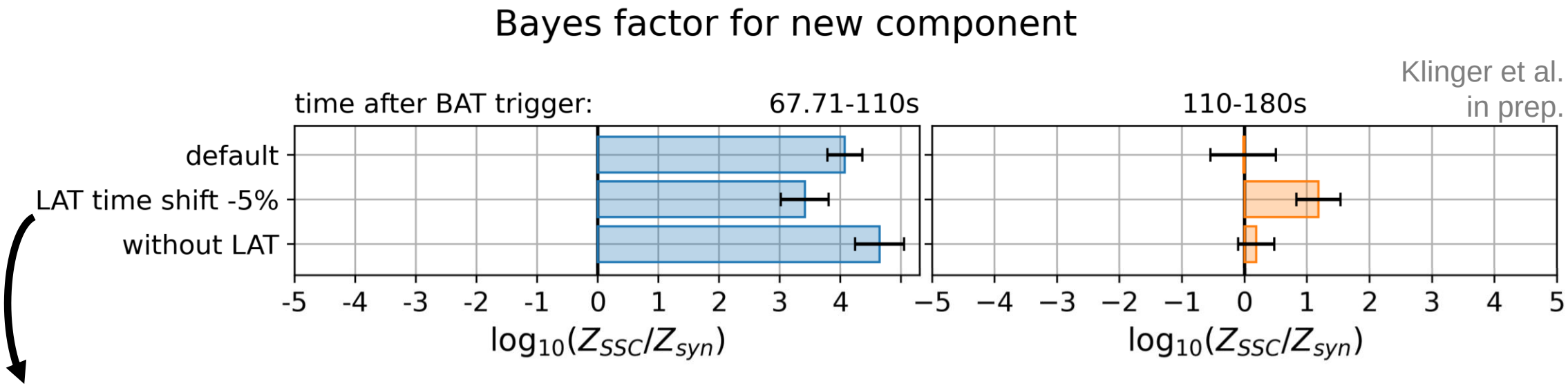
Preference for new component?



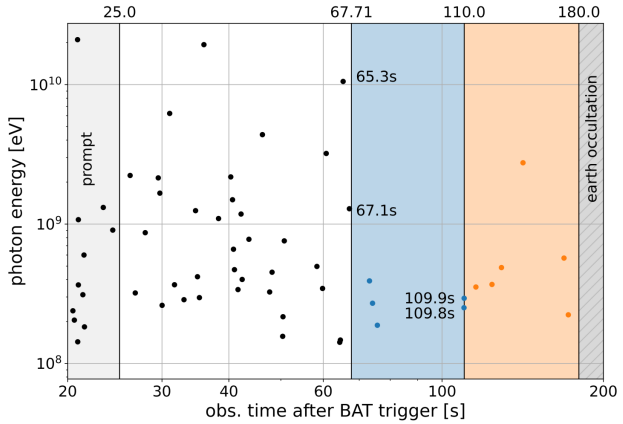
yes

no

Stability of Preference: LAT



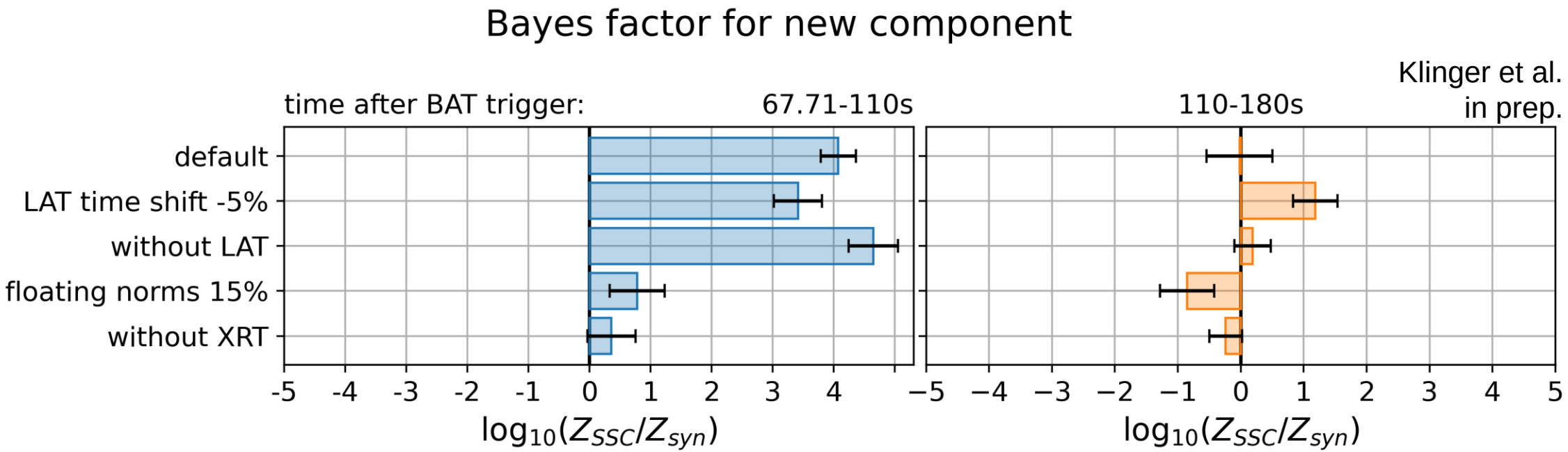
Klinger et al. in prep.



- shift LAT time selection window by 5% (2.1s)
- leave out LAT completely

→**LAT not very strong**

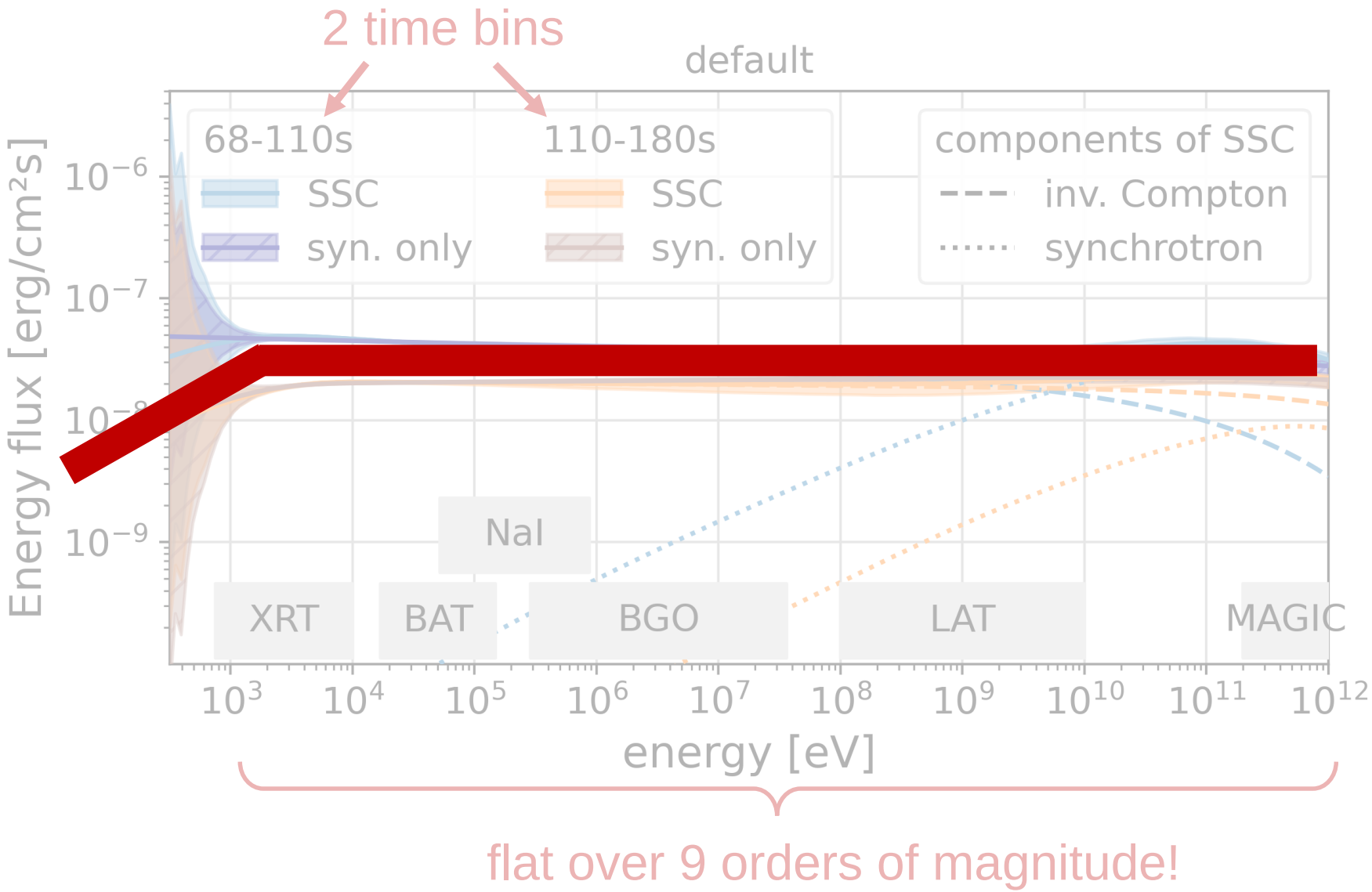
Stability of Preference: XRT



- systematic cross calibration uncertainty of 15%
  (a.k.a. floating norm or effective area correction)
- leave out XRT completely

  → **XRT drives new component!**

Fitting a reduced SSC model



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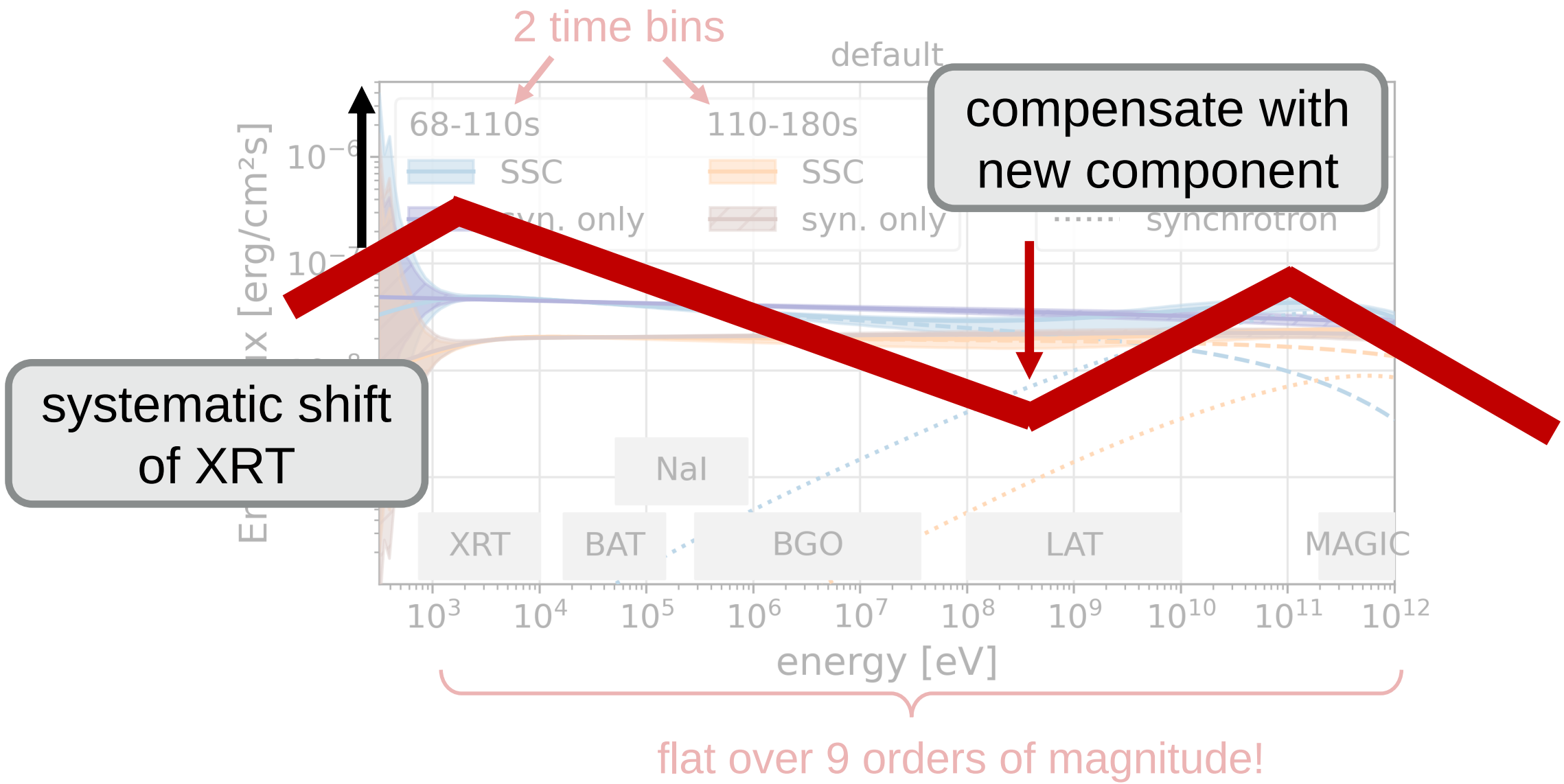


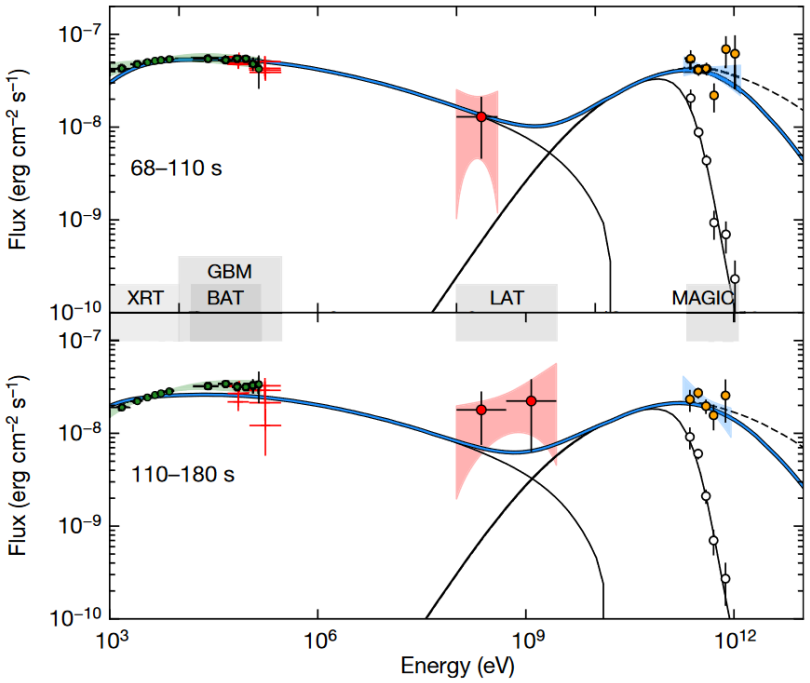
More general remarks to stimulate discussion

Common approaches to compare models to data

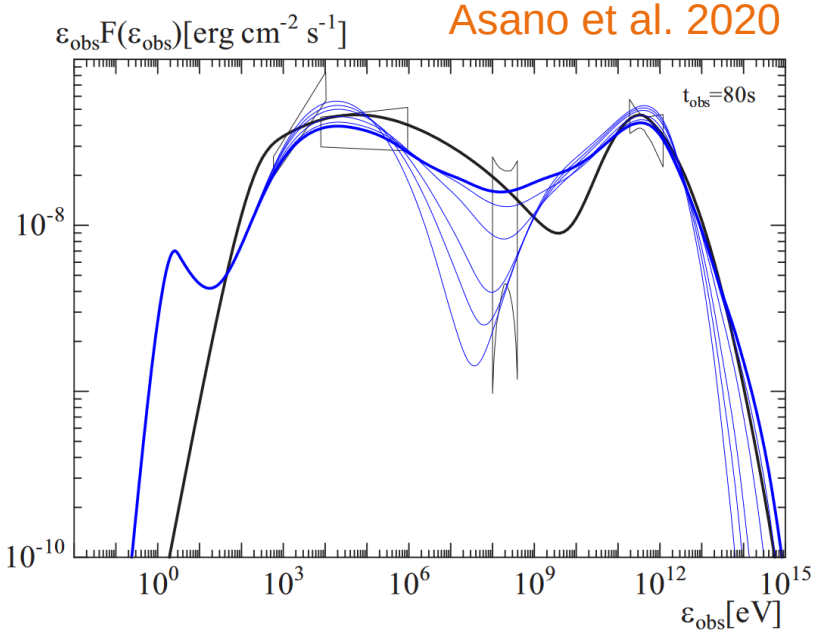
- tune parameters by hand such that they roughly can explain the data

  → no fit, thus statistically not meaningful

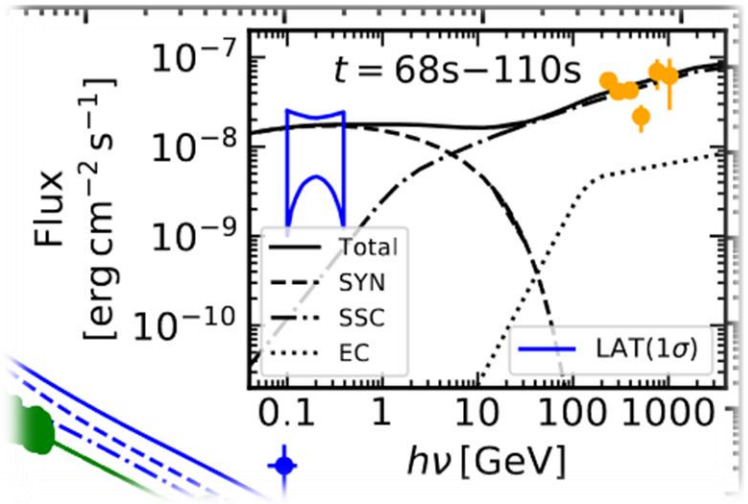
MAGIC Coll. et al. 2020



Asano et al. 2020



Zhang et al. 2020



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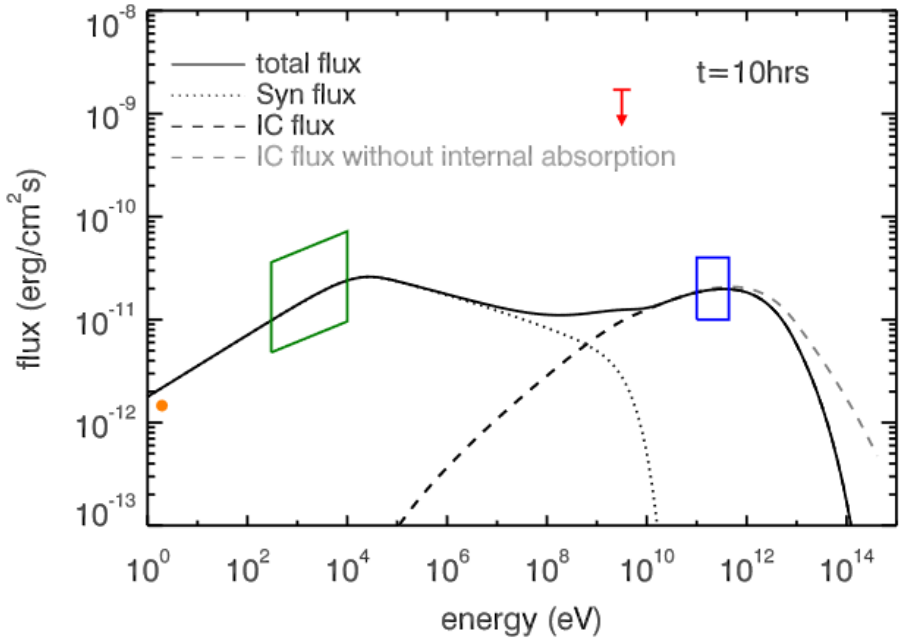
Wang et al. 2019



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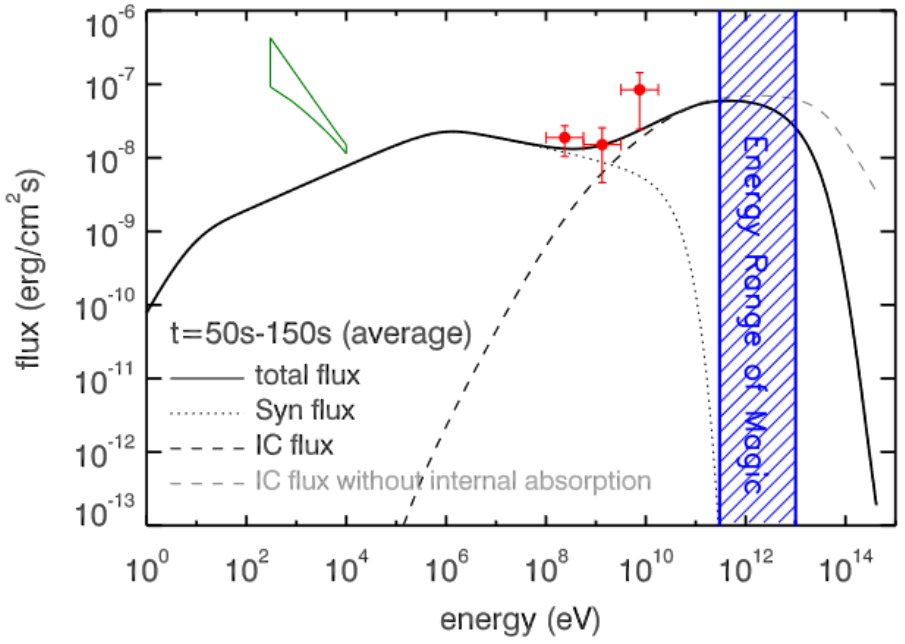


Common approaches to compare models to data

- tune parameters by hand such that they roughly can explain the data

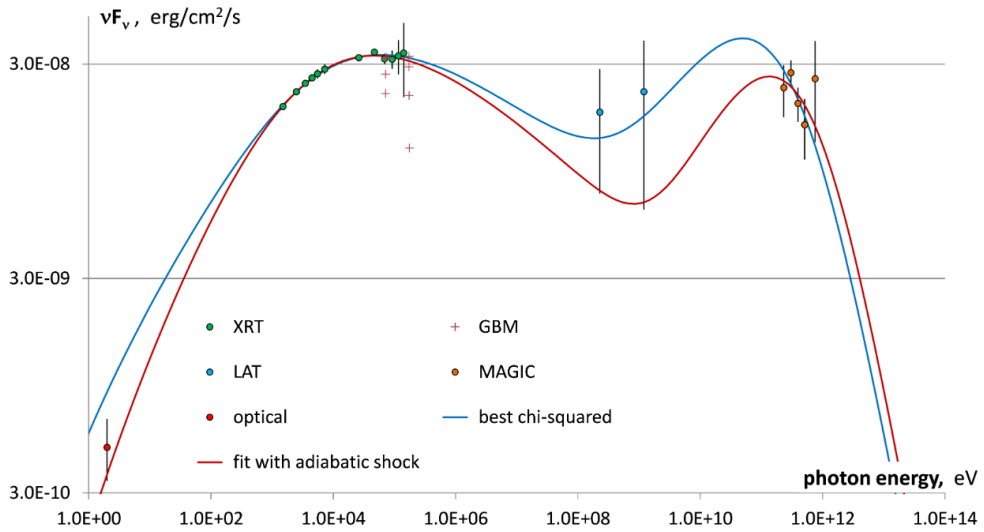
  → no fit, thus statistically not meaningful

- take data points from publications and calculate (minimize) a χ^2

  → proper statistics? cross calibration? systematics? absorption?..

  → Why do we waste or energy to understand the instruments to ignore it in the fit?

Derishev & Piran 2021



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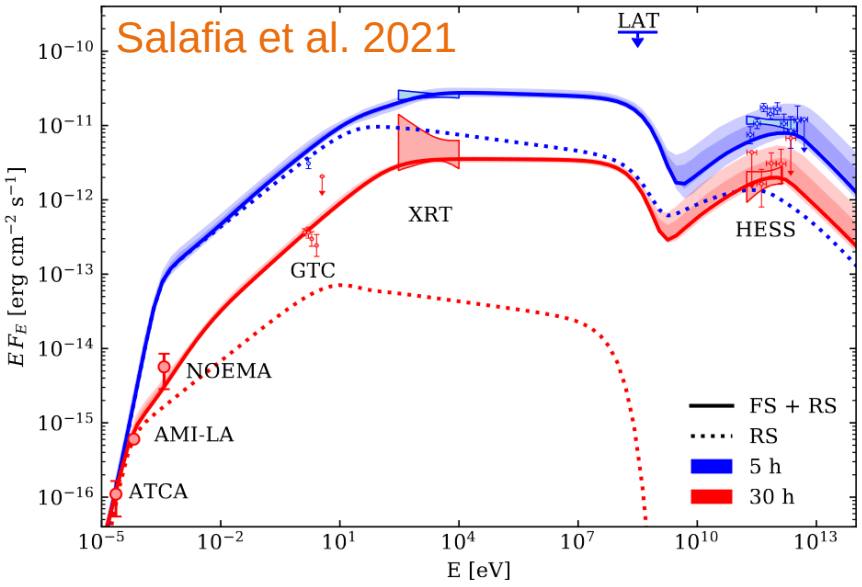

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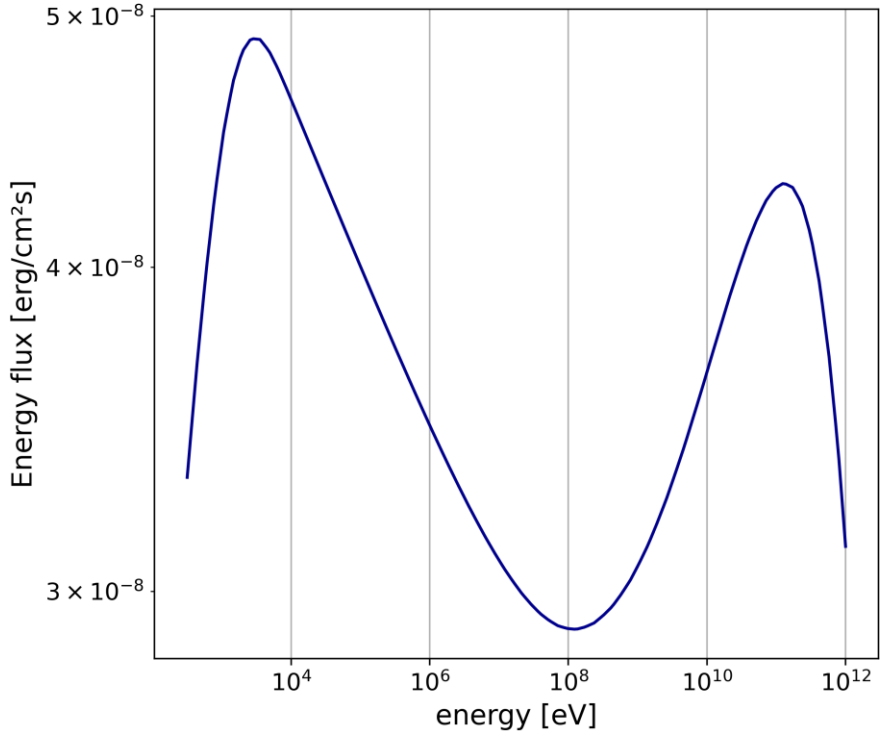
  → Why do we waste or energy to understand the instruments to ignore it in the fit?

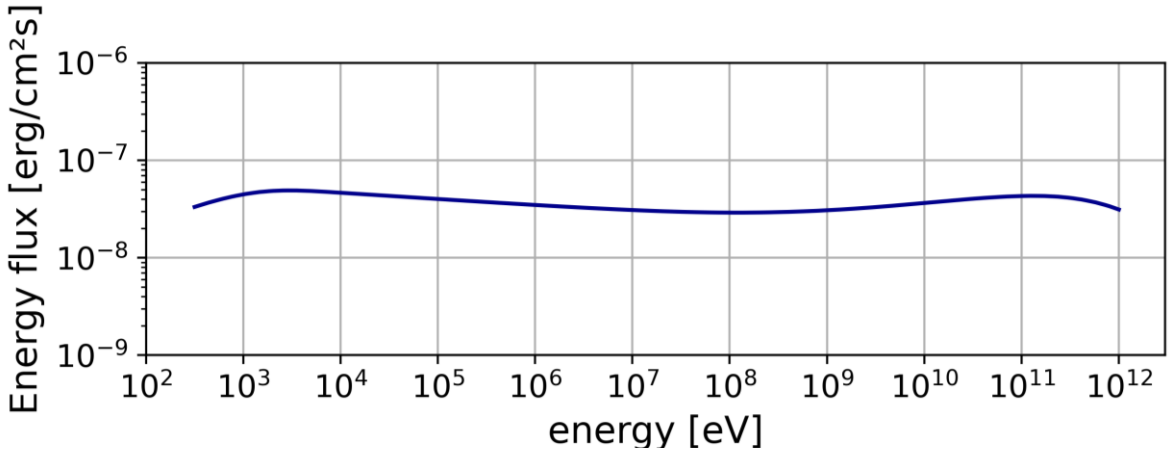
- integrate an entire instrument to a flux and a slope and include this in the total likelihood

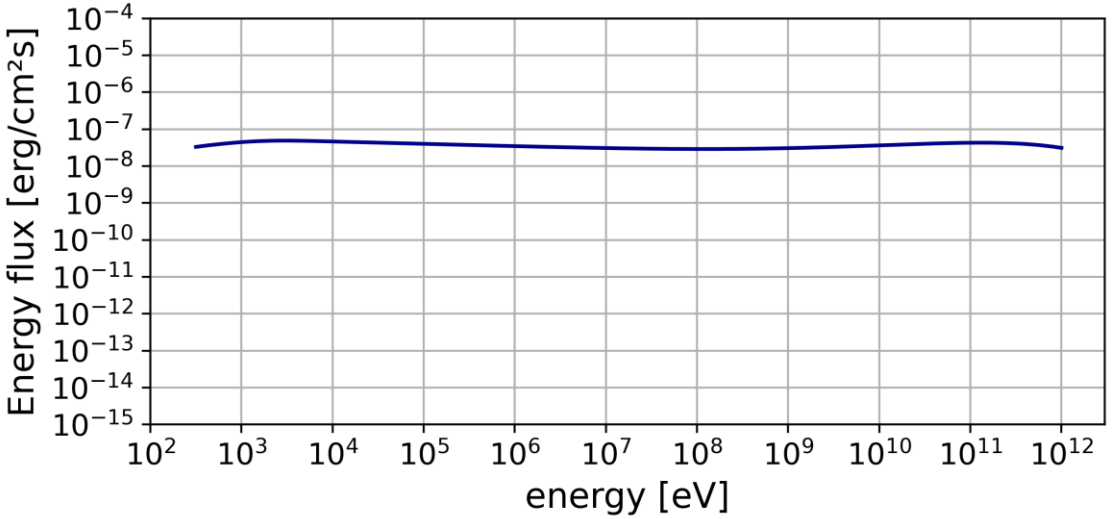
- include 1 or 2 instruments

Reminder

- aspect ratio makes new components





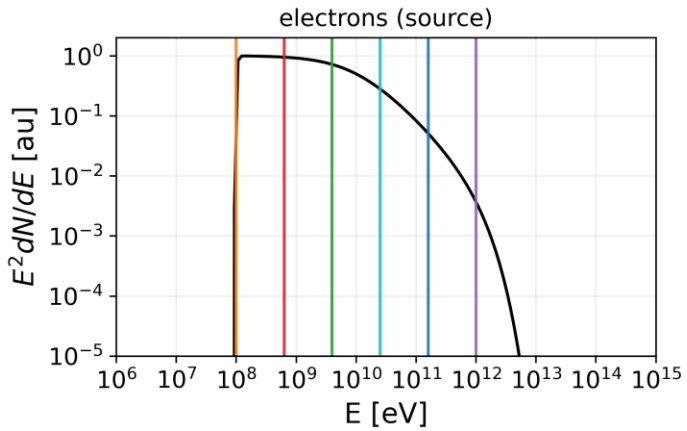


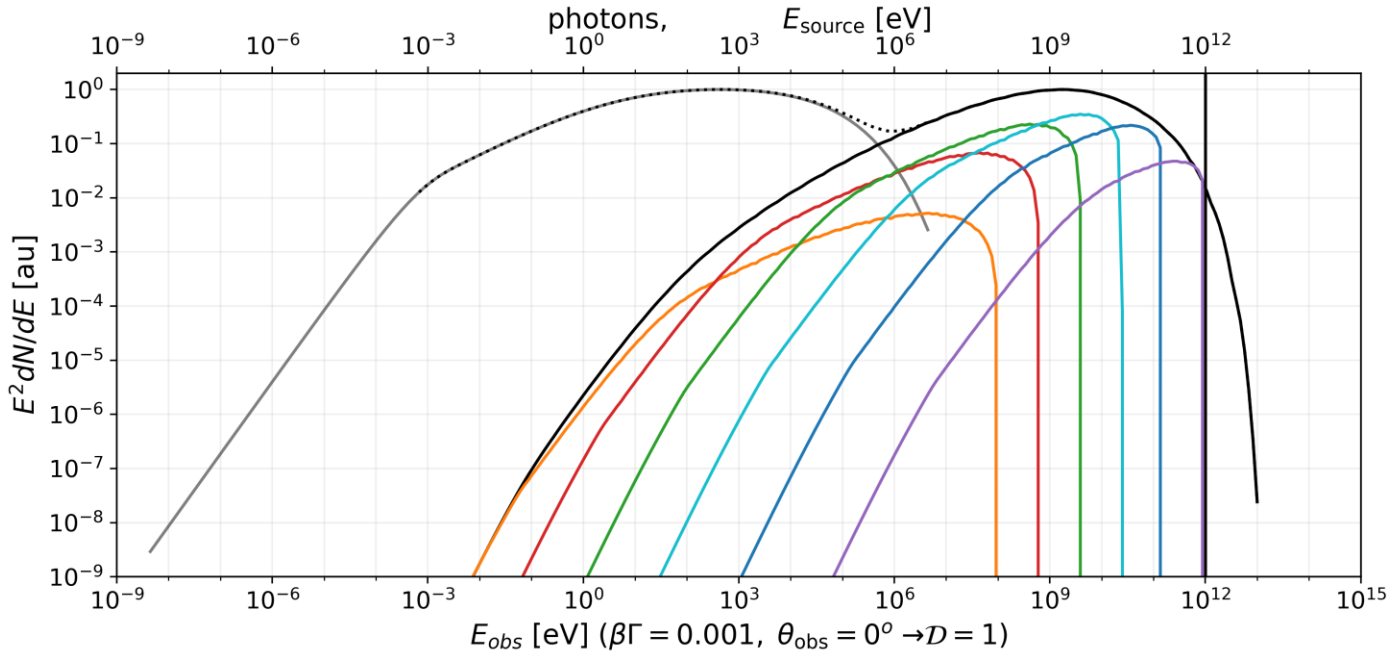
Reminder

- aspect ratio makes new components
- we don’t expect a bunch of power laws

  → power laws are good for intuition, but not for comparison to data

  → kernels are smooth, observations are the result of several convolutions!





Reminder

- aspect ratio makes new components
- we don’t expect a bunch of power laws

  → power laws are good for intuition, but not for comparison to data

  → kernels are smooth, observations are the result of several convolutions!
- open source software for proper fitting is already there

  → Multi-Mission Maximum Likelihood framework (3ML, https://threeml.readthedocs.io/en/stable/index.html#)

  → Gammapy (https://gammapy.org/)