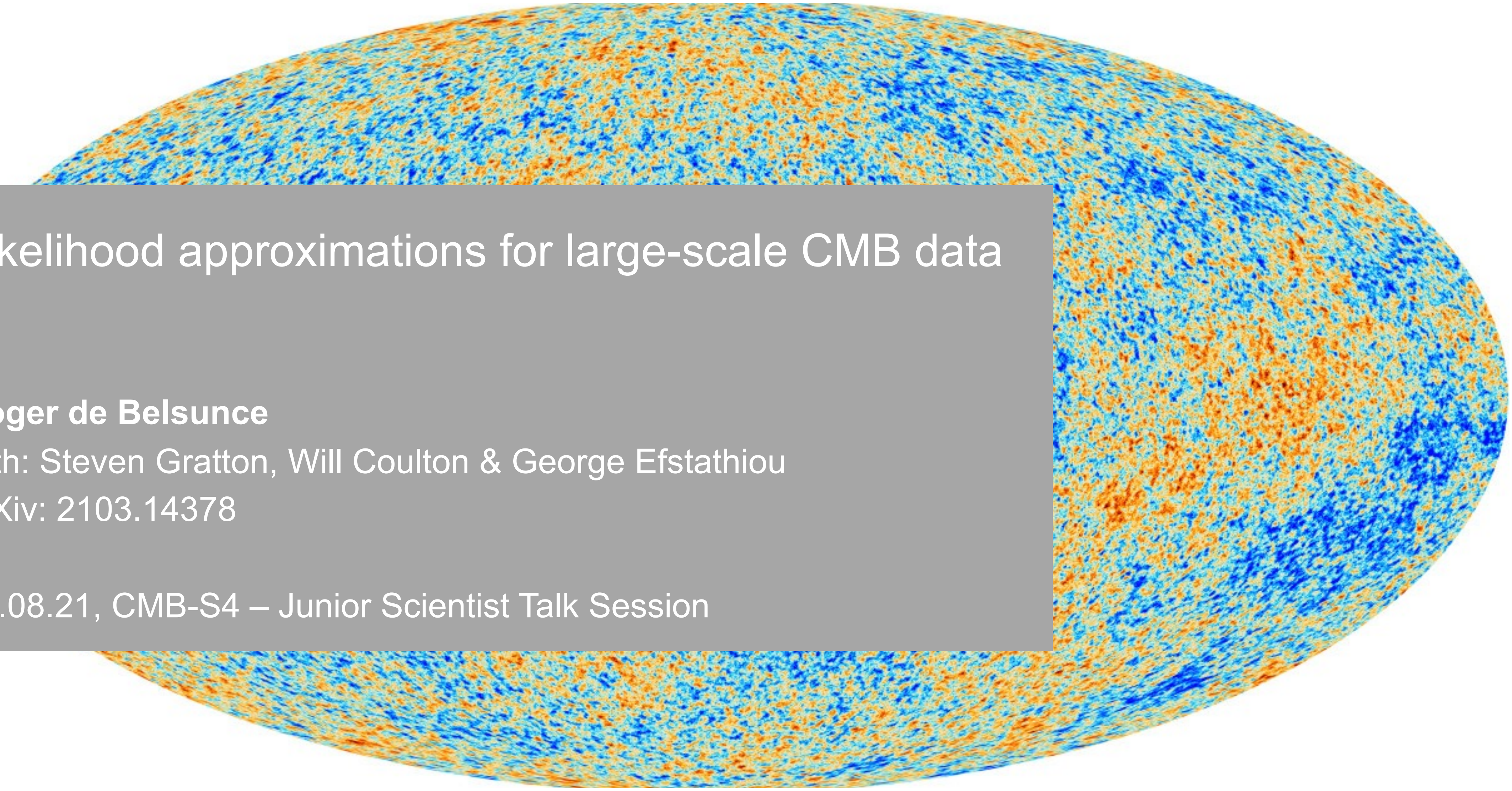


Likelihood approximations for large-scale CMB data

Roger de Belsunce
with: Steven Gratton, Will Coulton & George Efstathiou
arXiv: 2103.14378

13.08.21, CMB-S4 – Junior Scientist Talk Session

Motivation

[1] Pagano et al. (2020)
[2] Gratton (2017)
[3] *Planck* Collaboration XLVI (2016)
[4] Alsing et al. (2018)

Problem

- noise- & systematics-dominated signal
- No exact analytic likelihood (masked sky)

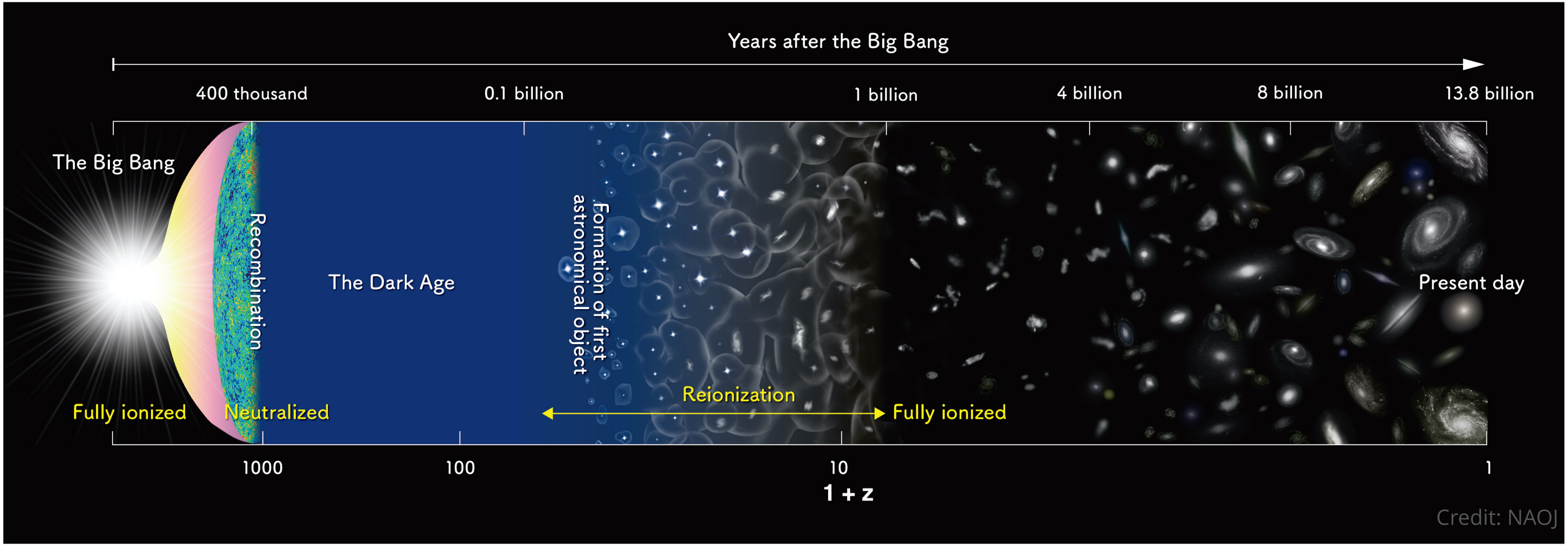
Physical motivation

- τ relevant for M_υ, A_s, n_s, σ_8
- Constraints on reionization models

Solution

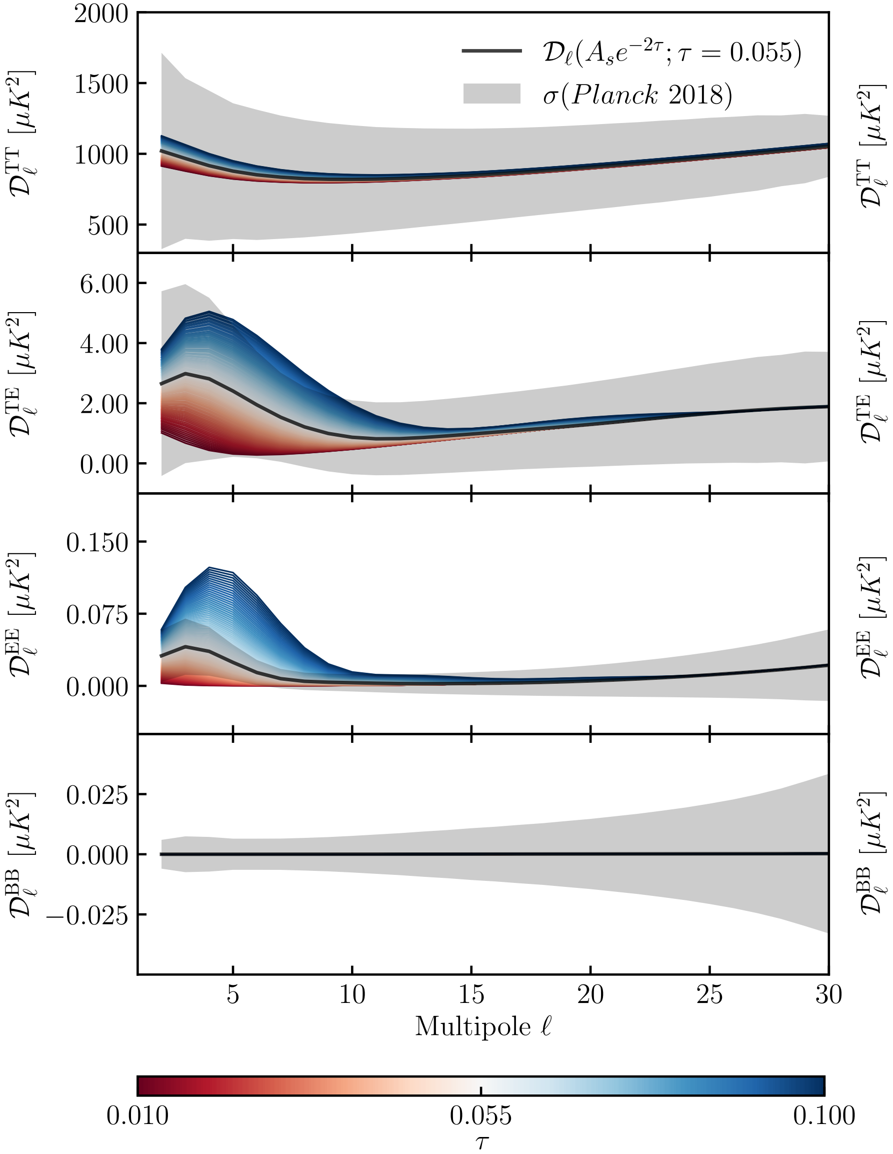
- Improved noise and systematics modelling
- Three Bayesian frameworks:
  - From likelihood-approximation[1,2] to simulation-based[3,4] schemes

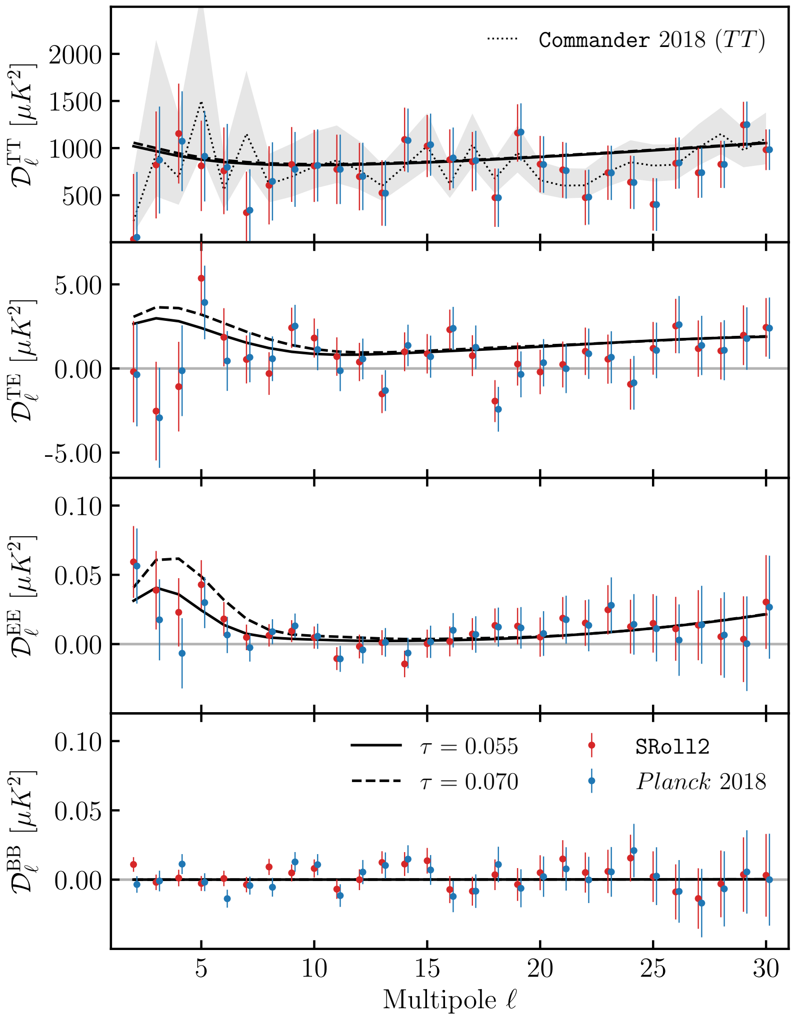
Brief history of the Universe



Optical depth to reionization τ (CMB)

[1] *Planck* Collaboration XLVI (2016)
[2] Delouis et al. (2019)





- Measure τ on 100x143GHz *Planck* low-l HFI maps
  - *Planck* 2018[1] & SRoll2[2] data

Joint likelihood for τ using TT, TE & EE data

Parameter inference in Bayesian framework

1. Compress observed data to a summary statistic $\mathbf{d}_0$ (e.g., power spectrum)
2. Determine unknown parameters θ of a given model $\mathcal{M}$
3. Generate mock data in pairs $\{\mathbf{d}_i, \theta_i\}$ to train models

$$\underbrace{\mathcal{P}(\theta|\mathbf{d}_0, \mathcal{M})}_{\text{Posterior density}} \propto \underbrace{\mathcal{P}(\mathbf{d}_0|\theta, \mathcal{M})}_{\text{Likelihood}} \underbrace{\mathcal{P}(\theta|\mathcal{M})}_{\text{Prior}}$$

Comparison of likelihoods

[1] *Planck* Collaboration XLVI (2016)
[2] Alsing et al. (2018)
[3] Gratton (2017)
[4] Papamakarios (2018)

SimBaL[1] | **DELFI**[2]

Simulation-based likelihoods

Assumption: functional form for distribution of spectra

Fit polynomial

$\mathcal{P}(C_\ell^{\mathrm{sim}}|\ell,\tau,\theta)$

$$\mathcal{L} = \sum_{\ell=2}^{29} \ln \mathcal{P}(C_\ell^{\mathrm{data}};\tau,\theta)$$

C-SimLow

Neural network

$f : C_\ell \mapsto u_\ell : \{u_\ell|\theta \sim \mathcal{N}(0,I)\}$

Normalizing flow[4]

$$\mathcal{P}(C_\ell|\theta) = \mathcal{N}(f^{-1}(C_\ell))\left|\frac{\partial f^{-1}}{\partial C_\ell}\right|$$

pyDELFI[2]

GLASS[3]

Principle of maximum entropy

Only noise covariance matrix

$\mathcal{L}$: compute moments of data
→ analytically (*or* simulations)

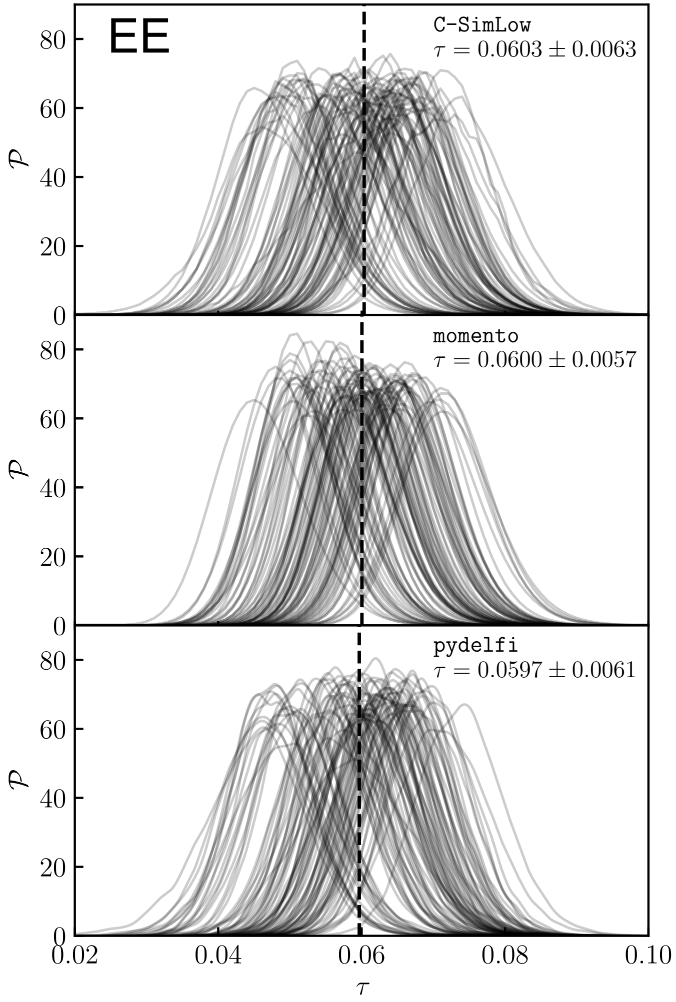
Sampling: integrate along
$C_{\mathrm{fid.}} \rightarrow C_{\mathrm{th.}}$ to get change in $\ln \mathcal{L}$

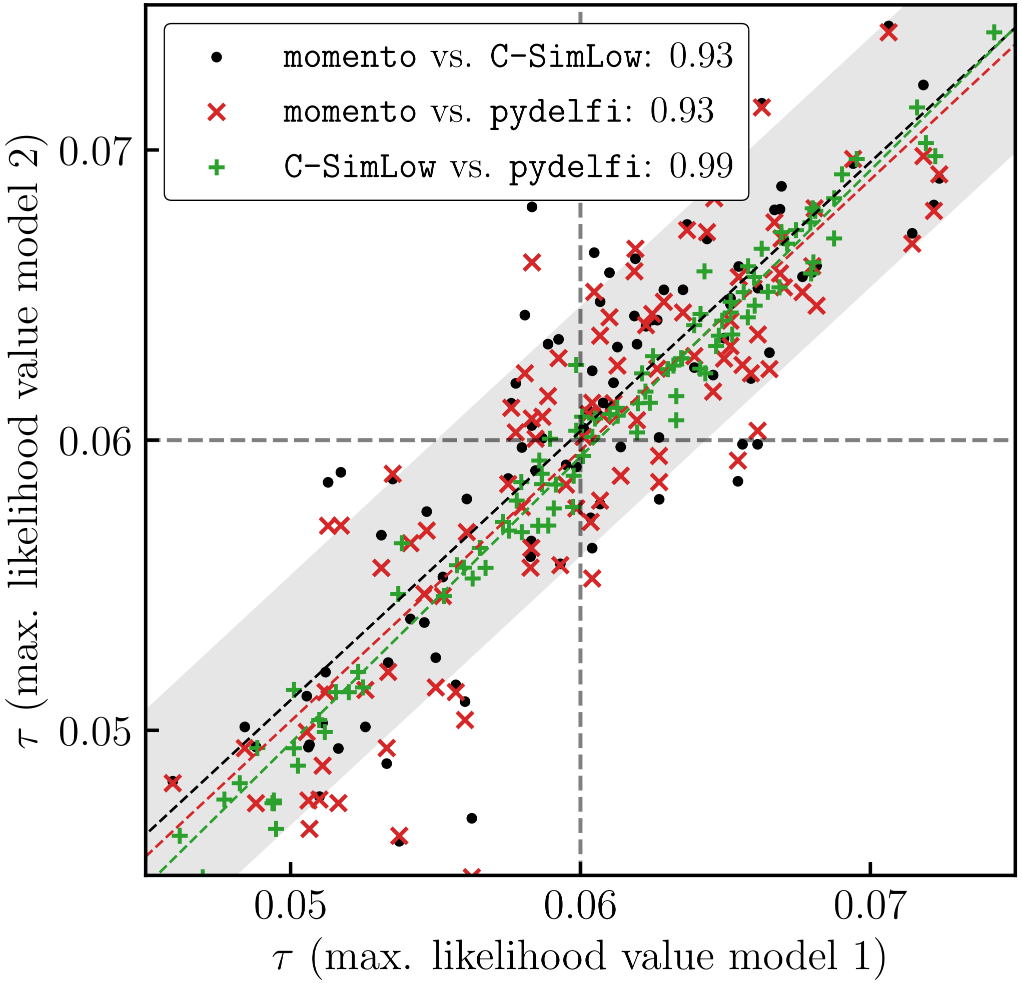
momento

Sounds nice in theory, does it work?

Test: 100 end-to-end simulations[1] with realistic noise & systematics

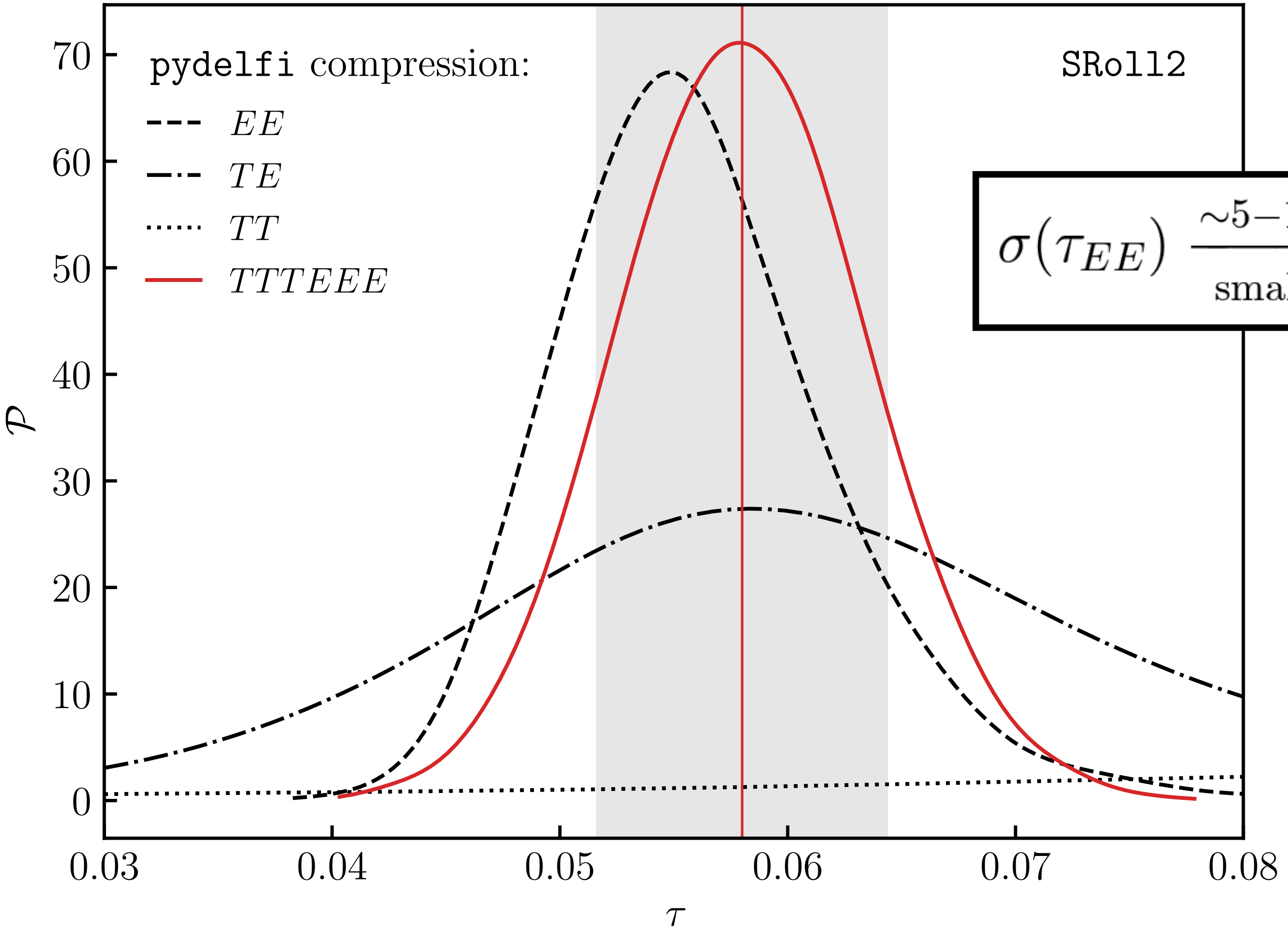
[1] *Planck* Collaboration XLVI (2016)





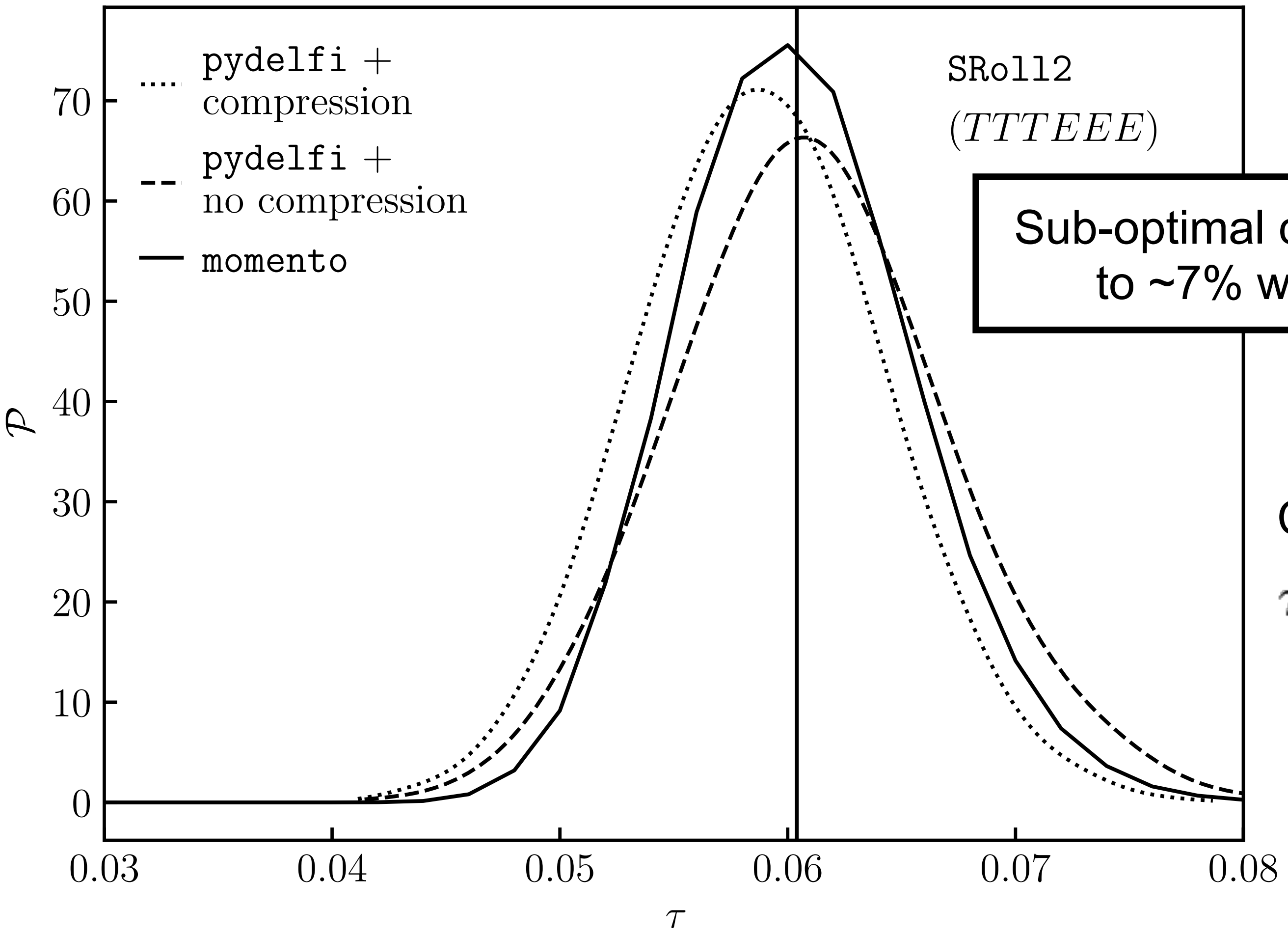
Joint TTTEEE likelihood results

Cross-correlations between TT, TE, EE pull posterior upwards



$$\boxed{\sigma(\tau_{EE}) \xrightarrow[\text{smaller}]{\sim 5\text{–}10\%} \sigma(\tau_{TTTEEE})}$$

Effect of score compression on posterior

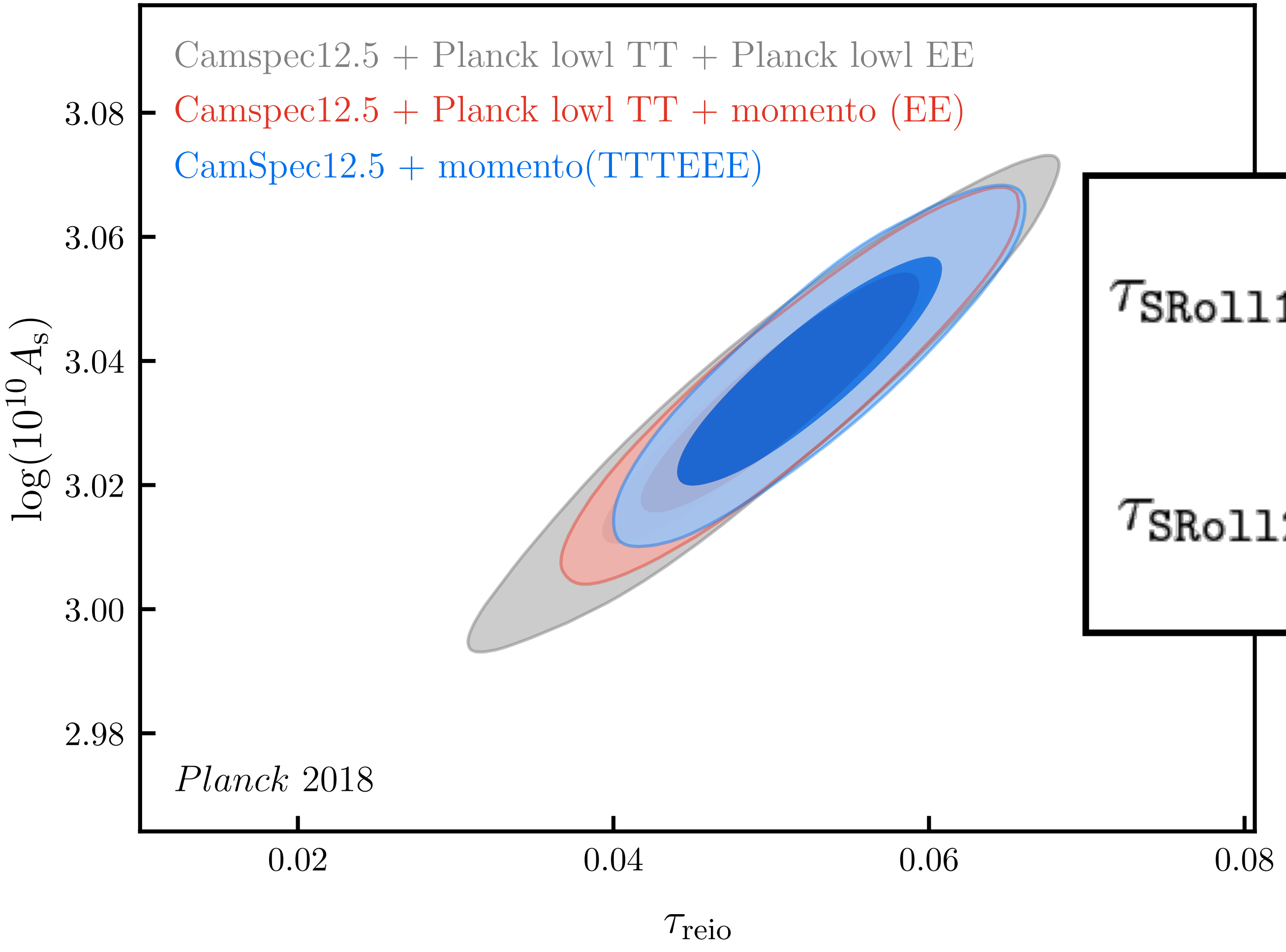


Sub-optimal compression leads to ~7% wider posteriors

Compression:

$$\tau_c = \nabla_\tau \ln \mathcal{P}(\hat{\mathcal{C}}_\ell^{XY})\Big|_{\theta^\star}$$

Exploring cosmological parameter space



$$\tau_{\texttt{SRoll1}} = 0.0552^{+0.0056}_{-0.0065}$$

$$\tau_{\texttt{SRoll2}} = 0.0627^{+0.0050}_{-0.0058}$$

Next steps

Please get in touch if you want to chat more!

Applying for postdocs this fall!

rmvd2@cam.ac.uk

- Consistent results for three Bayesian methods
  - momento uses most physical information
- Tighter constraints than *Planck* 2018/SRoll2:
  - Improved noise & systematics modelling
  - Quadratic cross-spectrum estimation
  - First joint likelihood TT, TE, EE for τ
- relevant for future large-scale CMB surveys such as LiteBIRD
  - Measure tensor-to-scalar ratio r