Cosmology from CMB & Lyman-α forest

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Outline

Introduction

- Early- and late-time probes of our Universe: CMB, Lyman-α

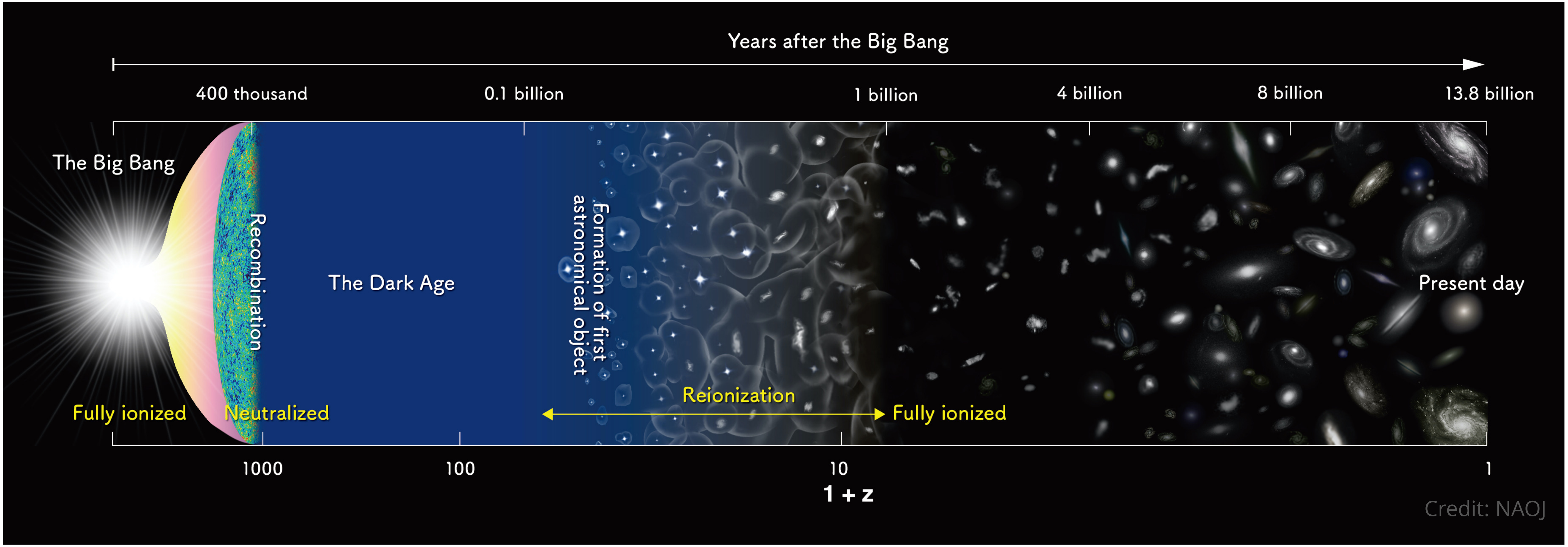
Inference from large-angular scale CMB data

- From likelihood approximations to likelihood-free inference
- Bayesian parametric foreground cleaning

Lyman-α forest

- P1D → CMB lensing x Lyman-α forest → P3D

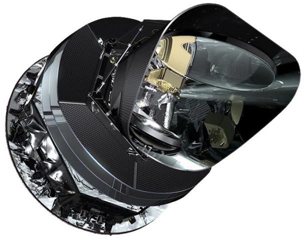
Brief history of the Universe



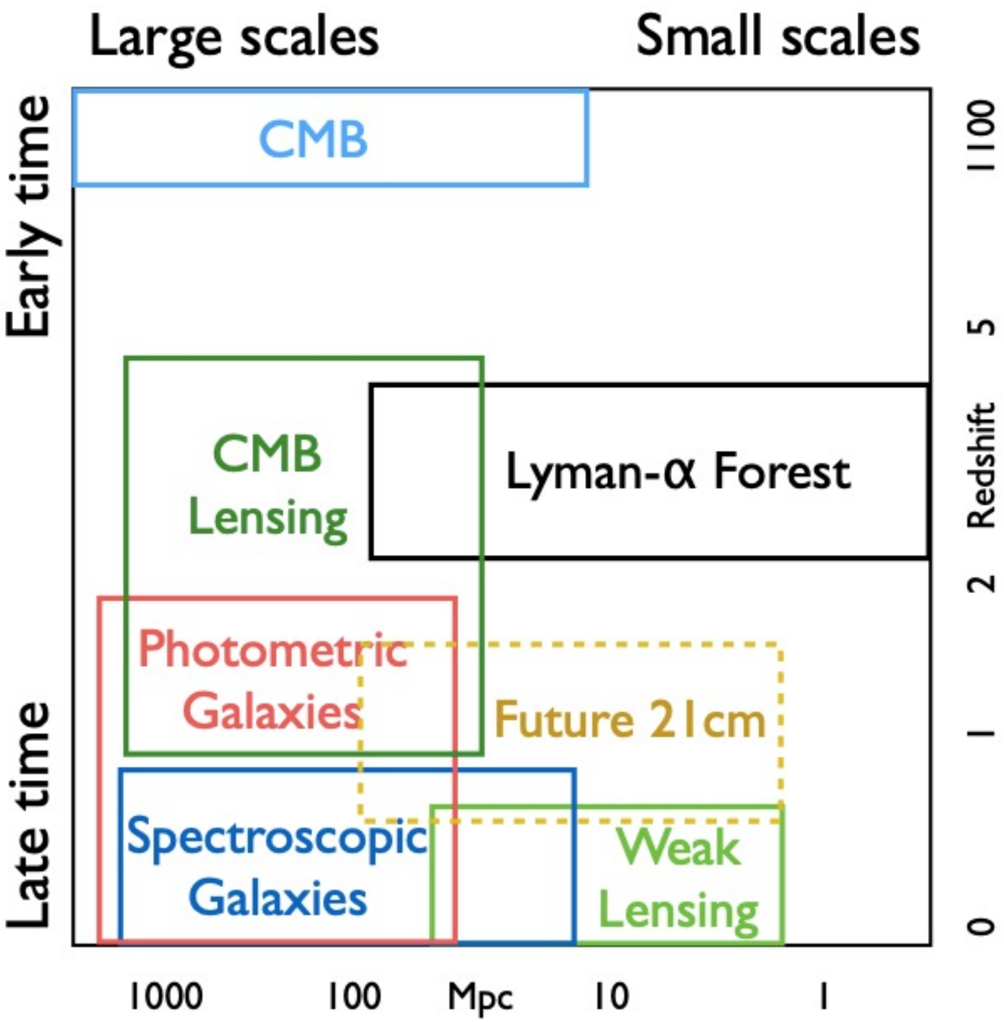
Probing cosmology at different scales

Breaking degeneracies

[1] DESI presentation (Font-Ribera)



Planck

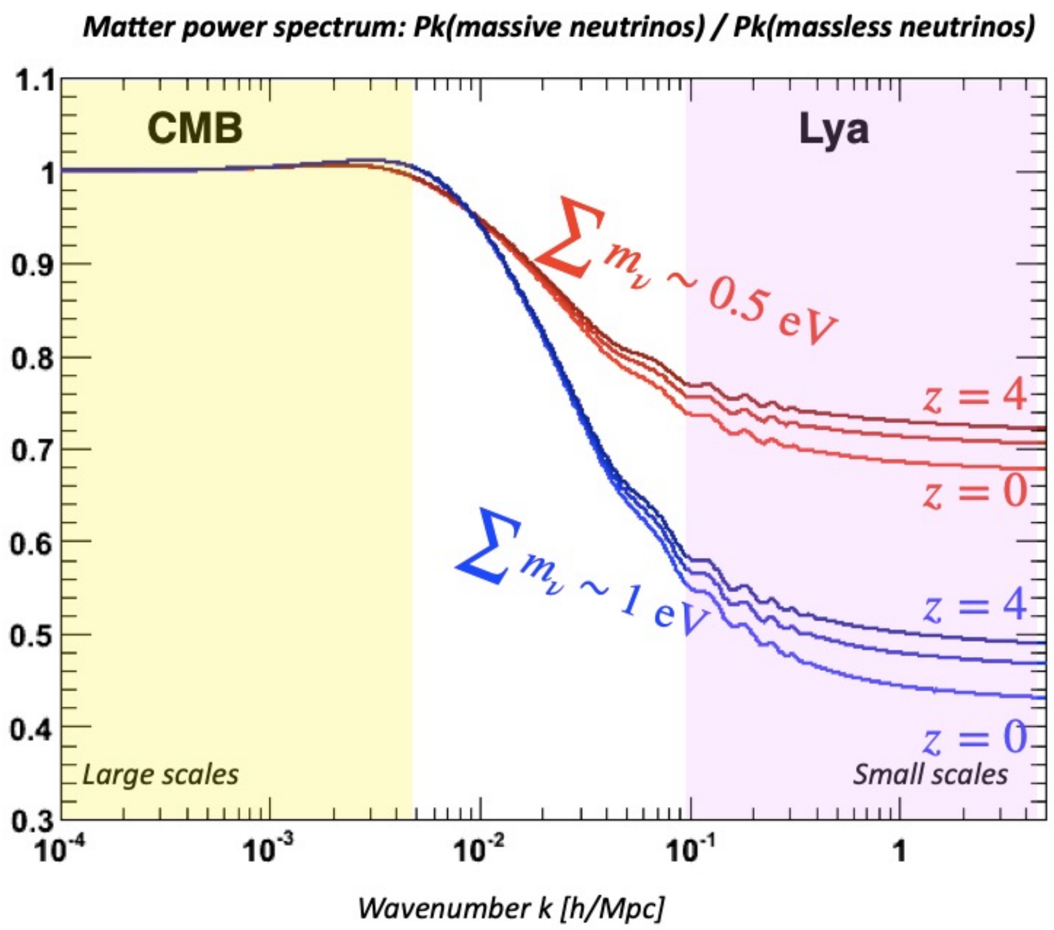


DESI

Probe scales from CMB to Lyman-α

From large to small scales

[1] DESI presentation (Chabanier)



- CMB:
  - Sensitive to large scales
  - Optical depth: $\tau \rightarrow A_s$ & $n_s \rightarrow M_\upsilon$,
  - Tensor-to-scalar ratio: *r*
- Lyman-α forest
  - Sensitive to small scales
  - suppression of matter clustering → M_υ
- CMB x Lyman-α
  - Break degeneracies

[1] de Belsunce et al. (2021)

1.1 Inference from large-angular scale CMB data

Take away:

1. Construct complex likelihoods
2. Novel likelihood techniques

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)
- Limited number of simulations

Physical motivation

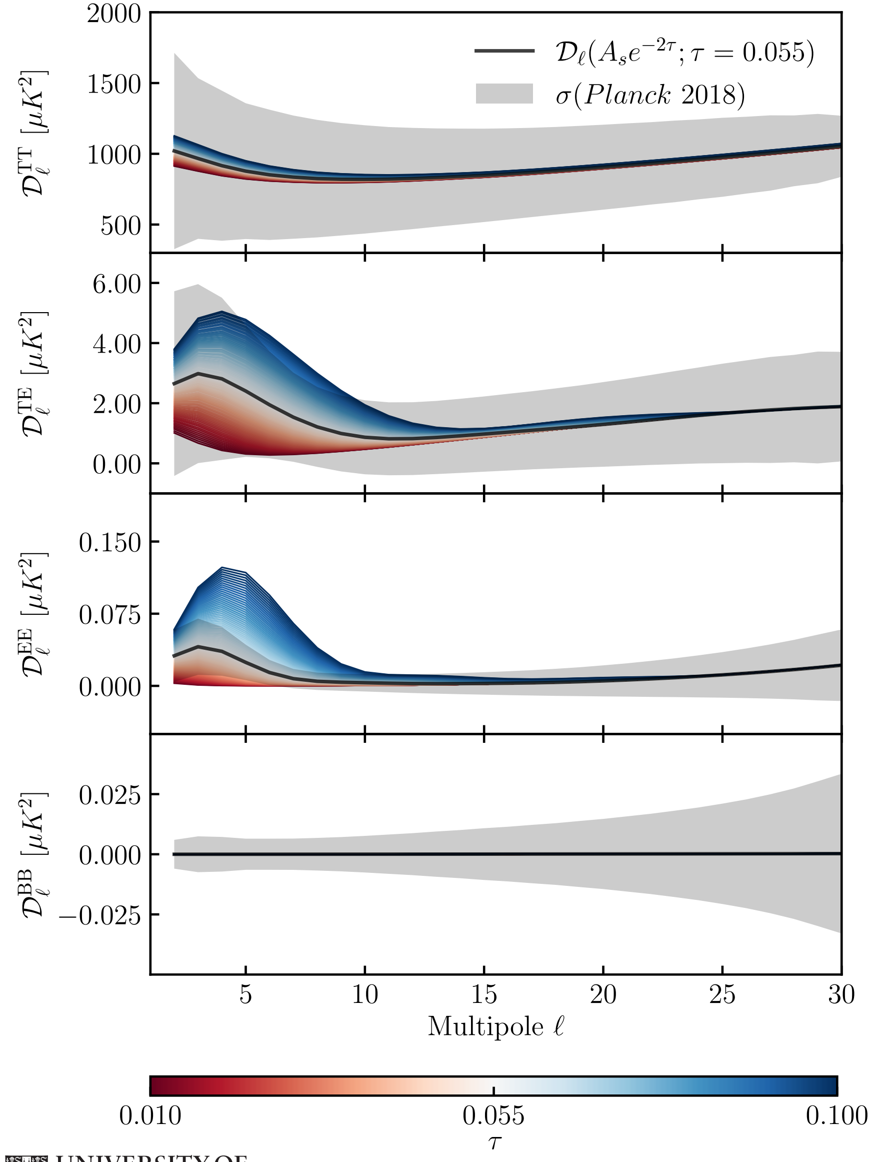
- Optical depth to reionization τ → M_{υ}, A_s, n_s
- Primordial gravitational waves (*r*) → energy scale of inflation
- Constraints on reionization models

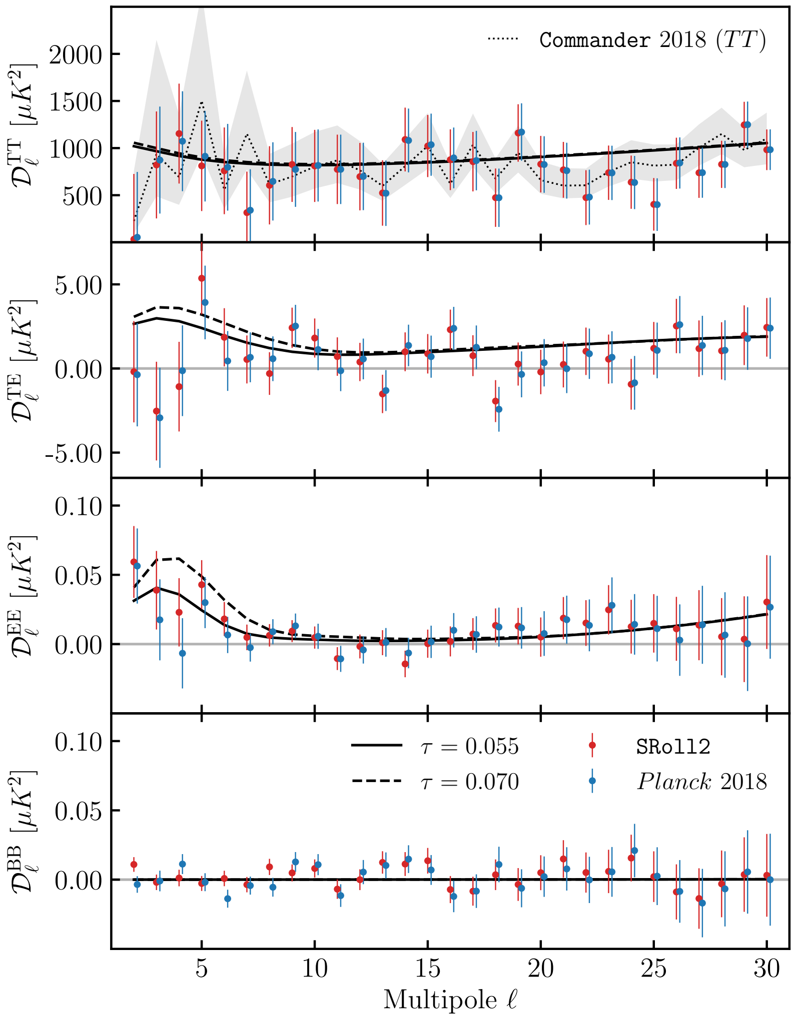
Solution

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

Large-scale CMB data

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





Bayesian inference in a nutshell

1. Compress observed data to a summary statistic $\mathbf{d}_0$ (e.g., power spectrum, NN-based compression)
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 ↓

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

↓

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

↓

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 $C_{\rm fid.} \rightarrow C_{\rm th.}$ to get change in $\ln\mathcal{L}$

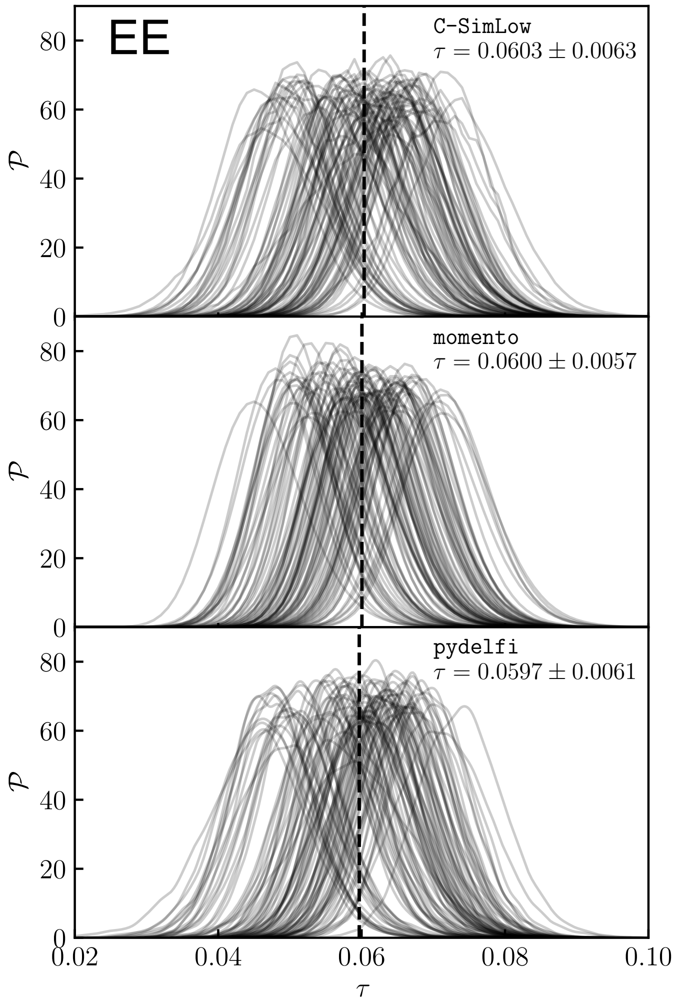
↓

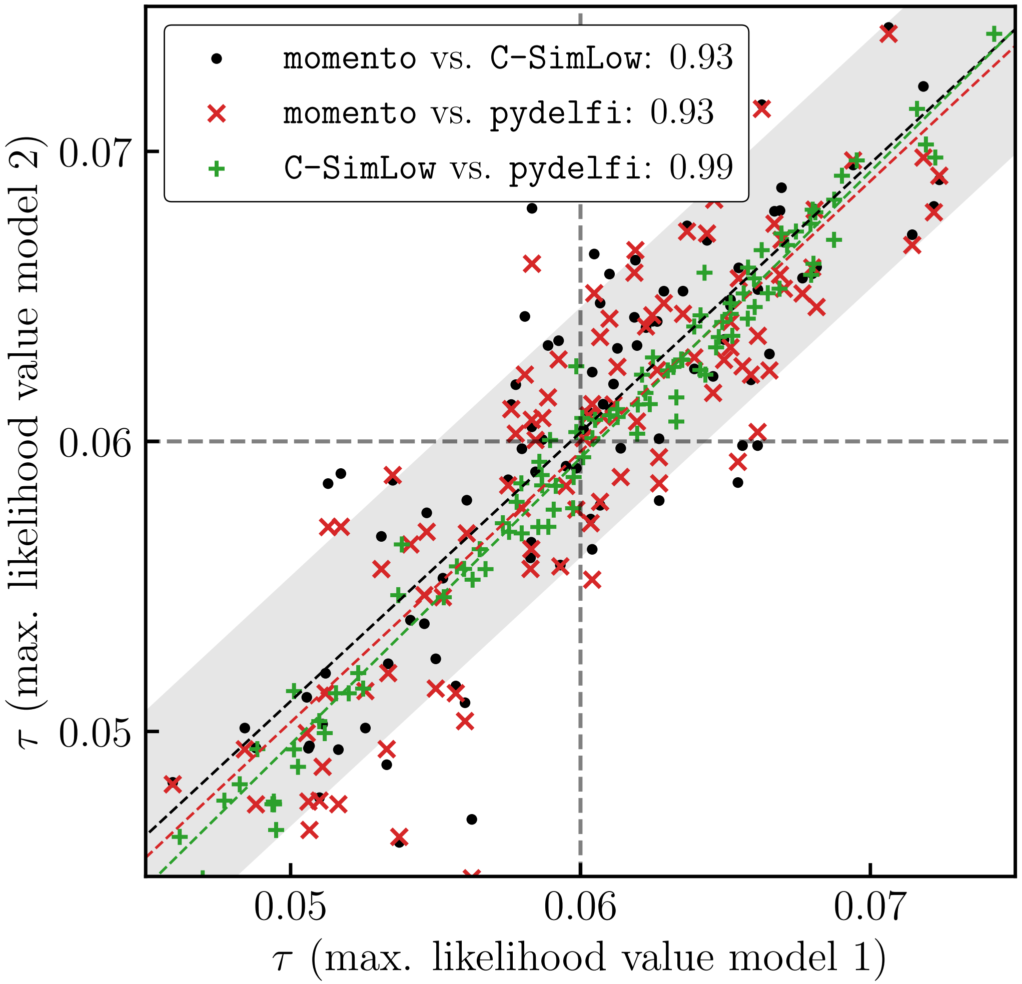
momento

Sounds nice in theory, does it work?

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

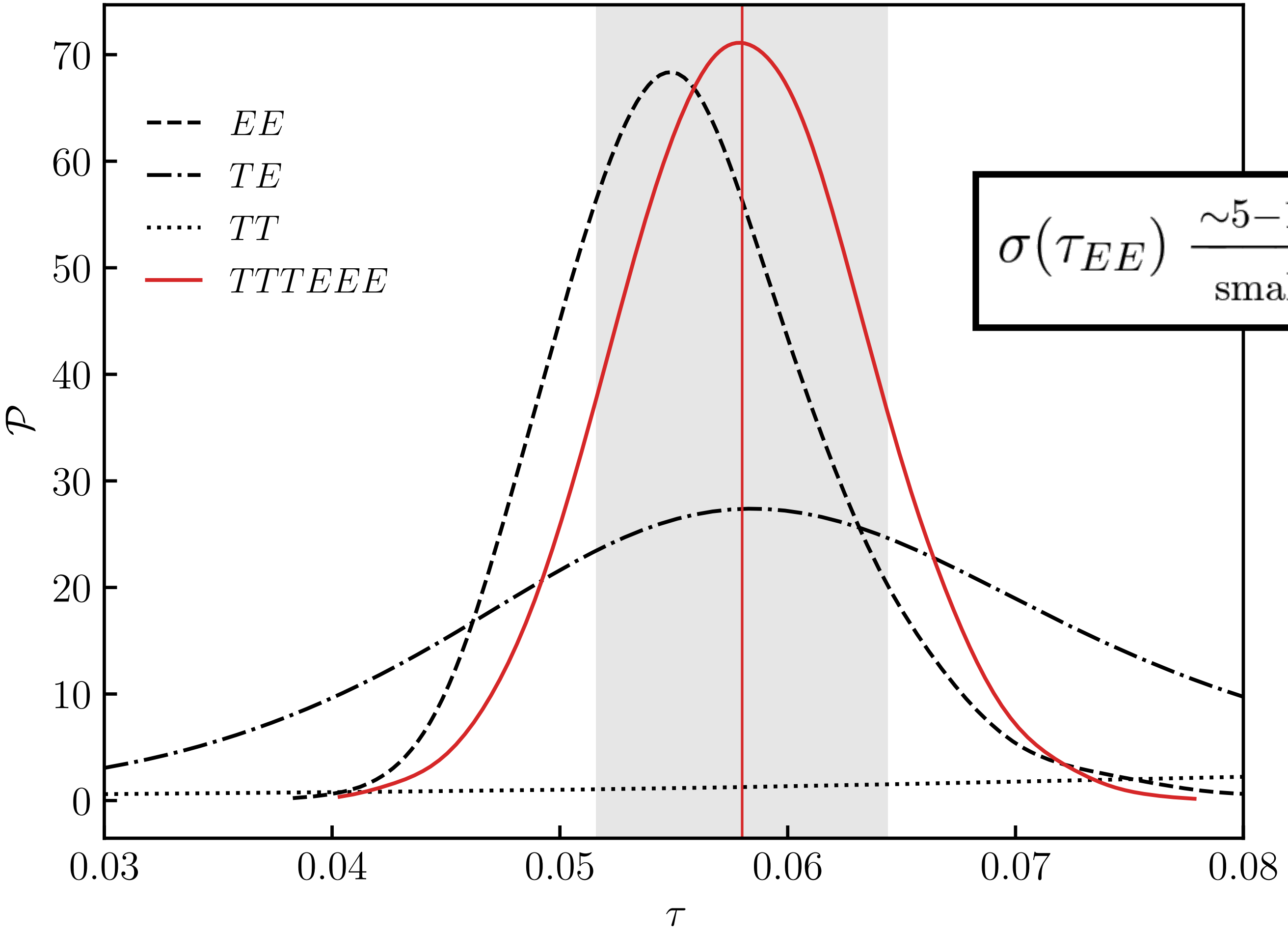
[1] *Planck* Collaboration XLVI (2016)





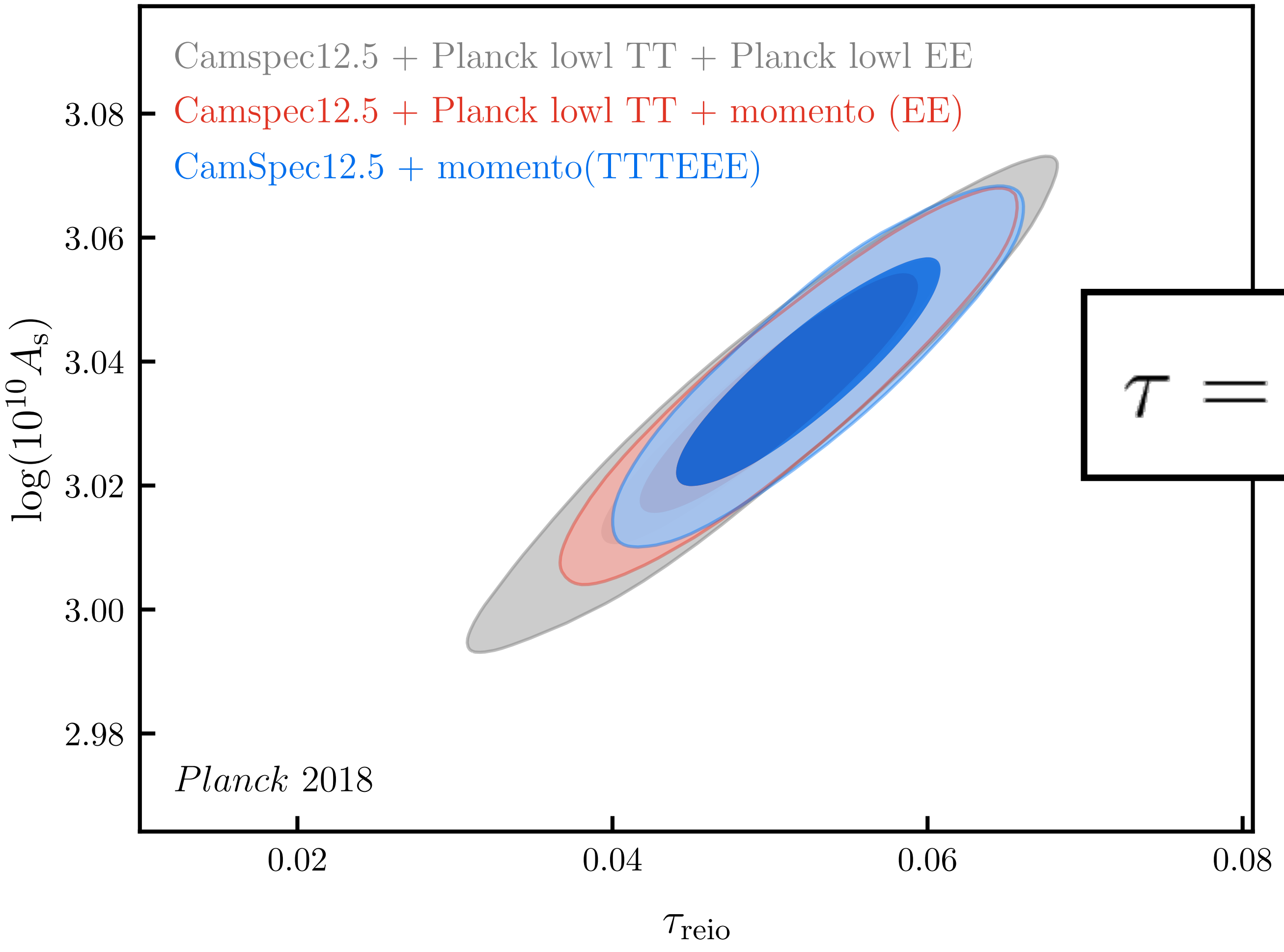
Joint TTTEEE likelihood results

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



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

Exploring cosmological parameter space

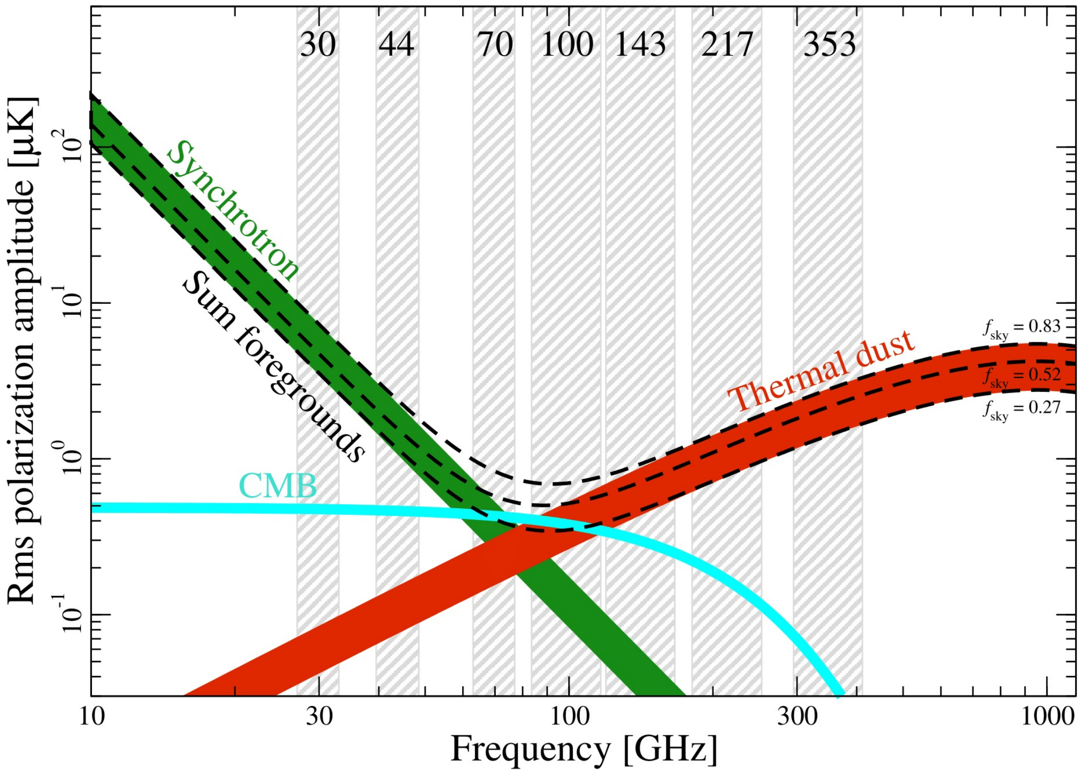


$$\tau = 0.0552^{+0.0056}_{-0.0065}$$

Galactic polarised foregrounds in the CMB

Where can we refine this analysis?

[1] Dunkley et al. (2008)
[2] Eriksen et al. (2008)
[3] Gratton et al. (2008)



- Currently:
  - frequency-dependent template subtraction
- Rethink parametric approach[1,2,3]: $\mathbf{d}_p = \mathbf{A}_p \mathbf{s}_p + \mathbf{n}_p$
  - Spectral index variations across the sky
    - Introduce correlation length

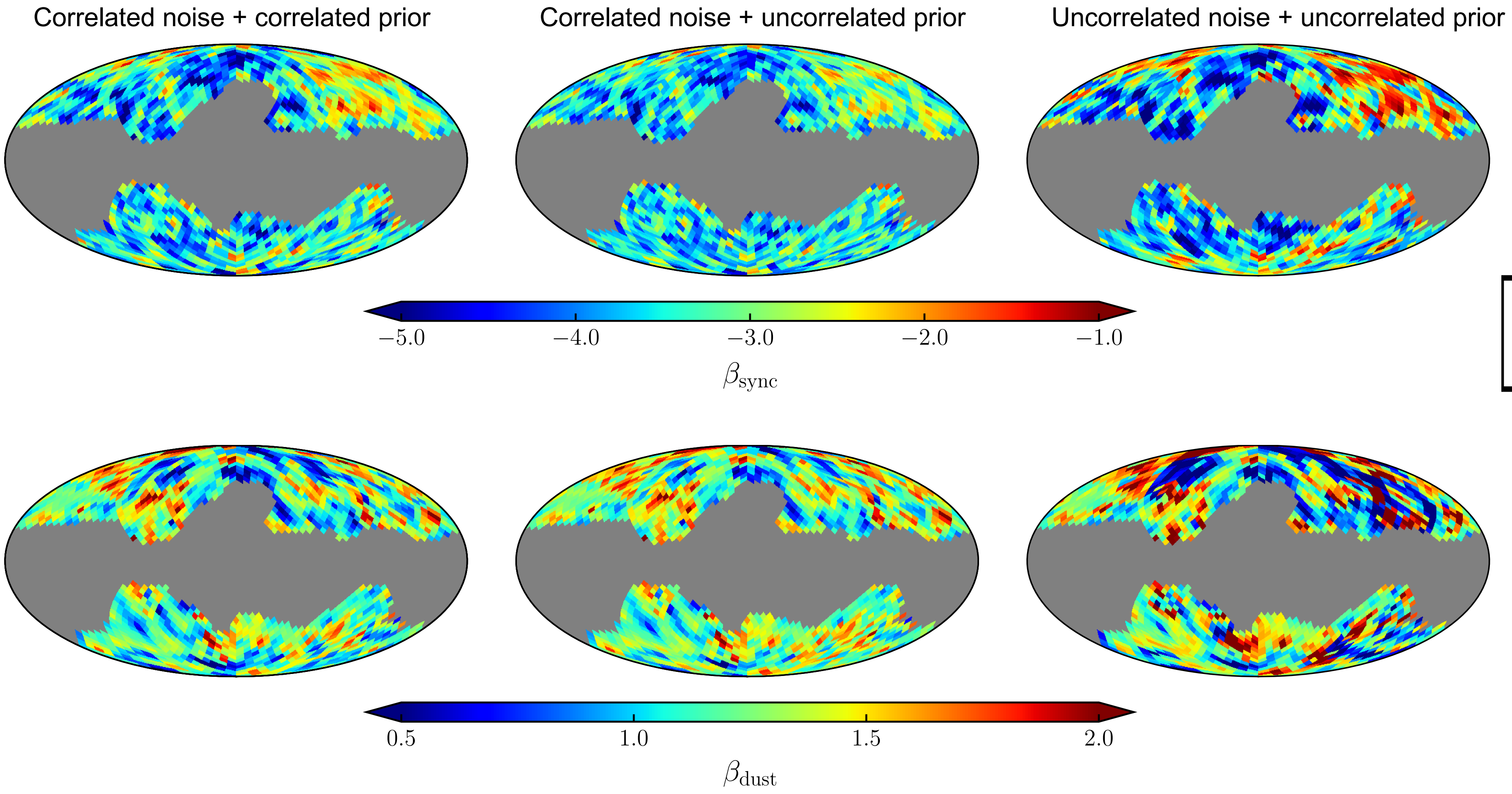
1.2. Bayesian parametric foreground cleaning

Take away:
1. Improved foreground cleaning
2. Prior dependency of result

Galactic polarised foregrounds

Can we observe spectral index variations for synchrotron and thermal dust?

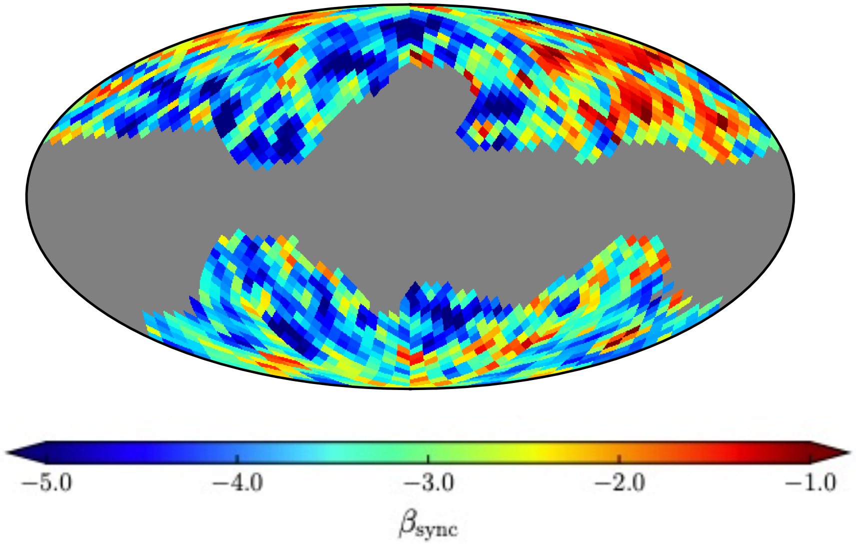
Preliminary

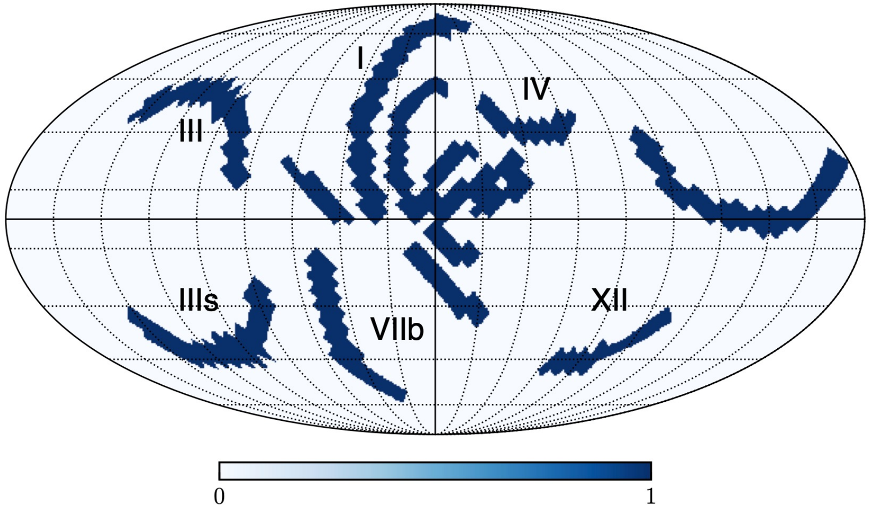


b_{sync} = -2.896 $\pm$ 0.742
b_{dust} = 1.410 $\pm$ 0.309

Evidence for spectral index variations in synchrotron

Uncorrelated noise + uncorrelated prior

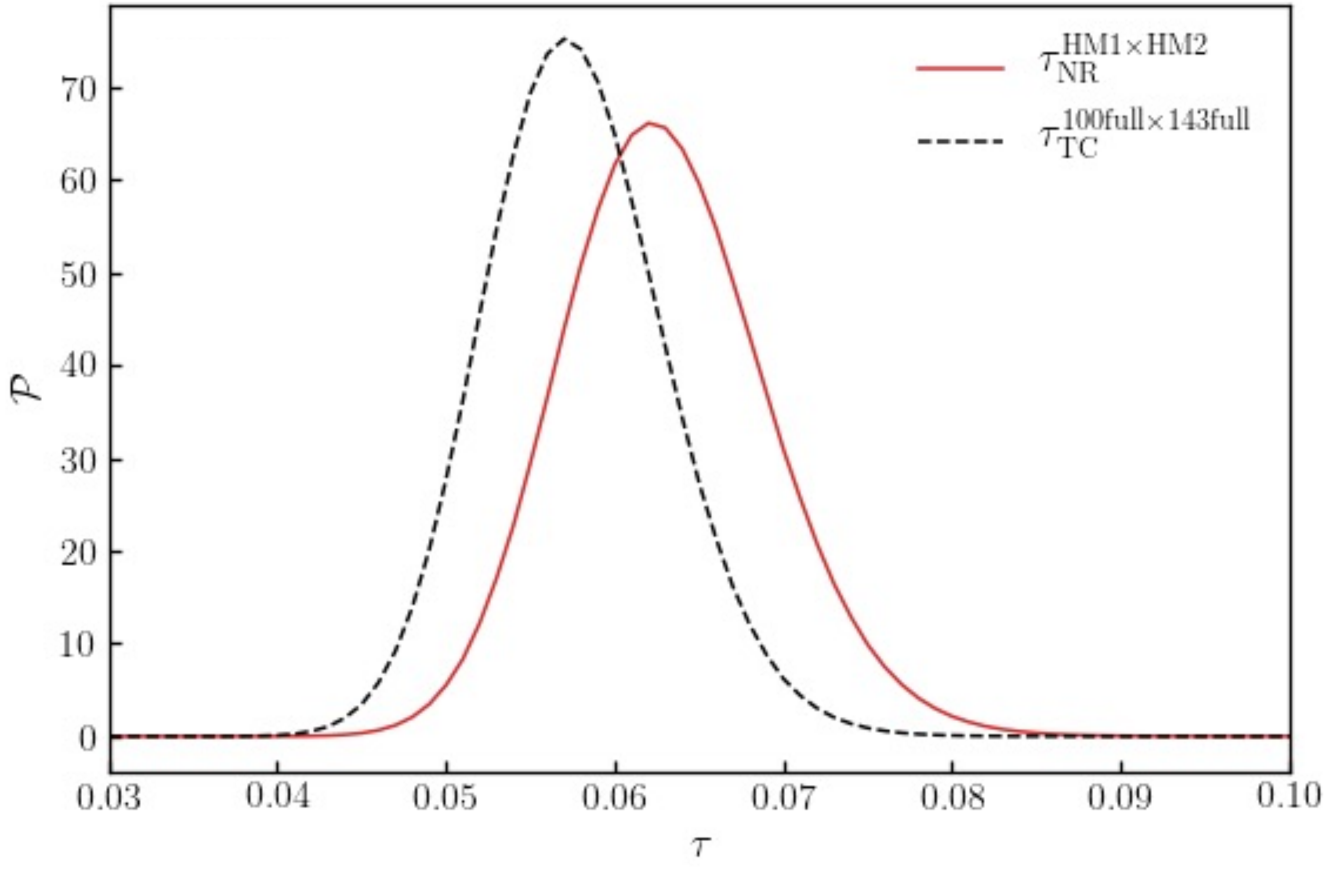




Do we need better CMB foreground cleaning?

[1] Svalheim et al. (2020)
[2] BeyondPlanck Collaboration (2020)
[3] Dunkley et al. (2009)
[4] Eriksen et al. (2008)
[5] Stompor et al. (2009)

Preliminary



τ constraints consistent with template cleaning (<1σ) → limit of Planck data reached

Conclusion

Reached limit of *Planck* data

[1] Sugai et al. (2020)
[2] Ade et al. (2019)

1. Extract science with different statistical frameworks
   – likelihood-approximations & likelihood-free inference

2. Low multipole pipeline relevant for LiteBird[1], Simons Observatory[2]
   – LiteBird sensitive to spectral index variations at low frequencies
     - Optical depth to reionization
     - Primordial gravitational waves (tensor-to-scalar ratio r)

How else could we constrain cosmology, perhaps using late-time probes?

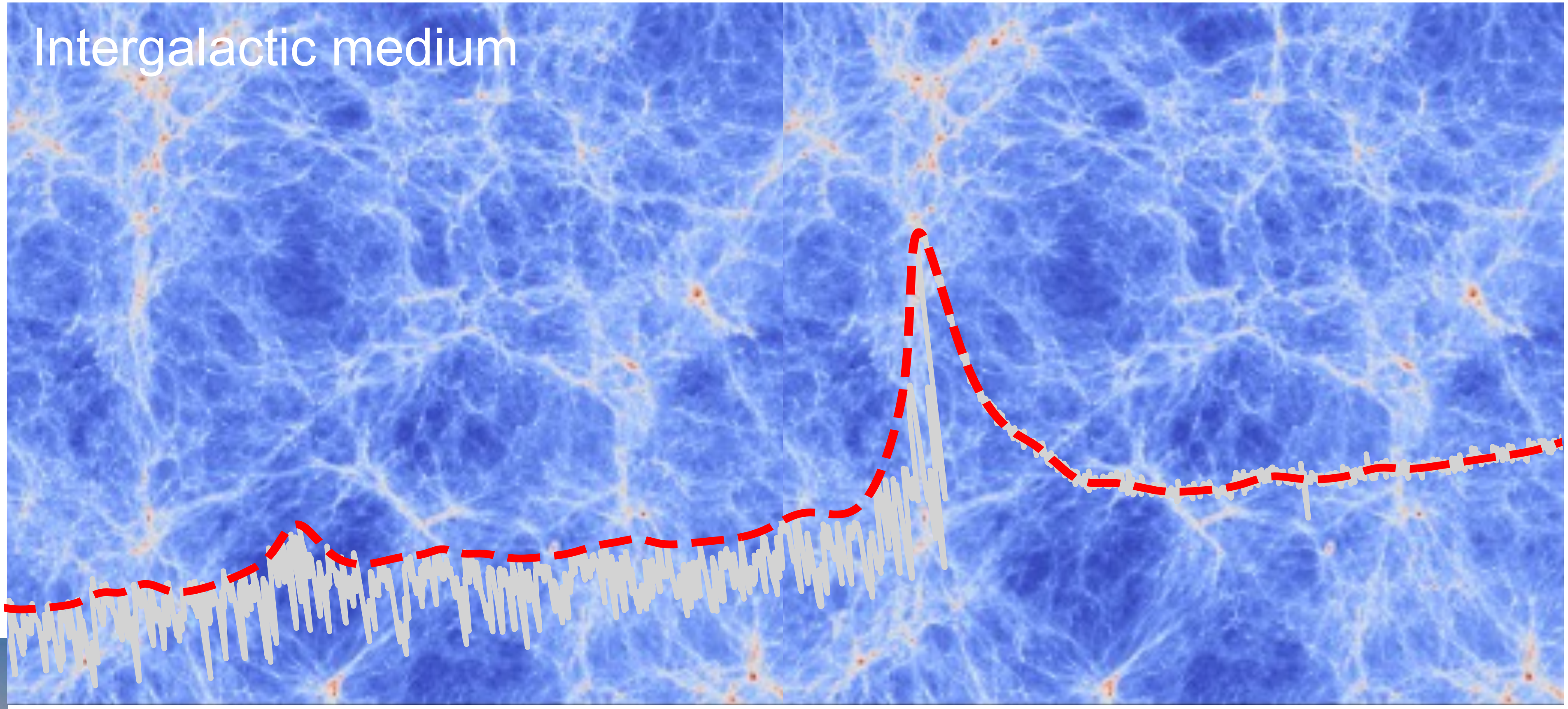
2. Lyman-α forest – road to full-shape measurement

Take away:
1. High z → high k
2. Access full-shape information

The Lyman-α forest

High redshift dark matter tracer into the mildly non-linear regime

[1] Cambridge IGM group (Iršič)

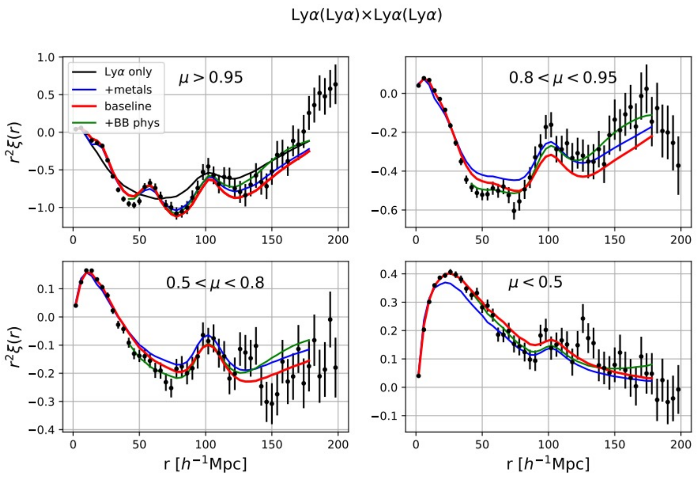


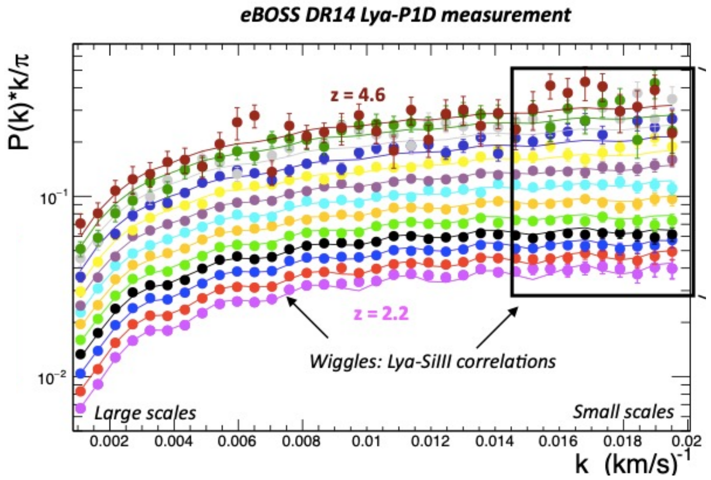
DESI

The Lyman-α forest

Probe scales from ~100 Mpc/h down to ~100 kpc/h

[1] du Mas des Bourboux et al. (2020)
[2] Palanque-Delabrouille et al. (2013)
[3] Chabanier et al. (2018)
[4] Doux et al. (2017)
[5] Chiang & Slosar (2017)
[6] Font-Ribera et al. (2017)





~100 Mpc/h — ~10 Mpc/h — ~1 Mpc/h — ~100 kpc/h

BAO[1]
- Expansion history

P3D[6]
- Full-shape info
- Amplitude (σ_8) & matter ($\Omega_m h$)

CMB x Ly-α [4,5]
- Amplitude & shape of matter clustering

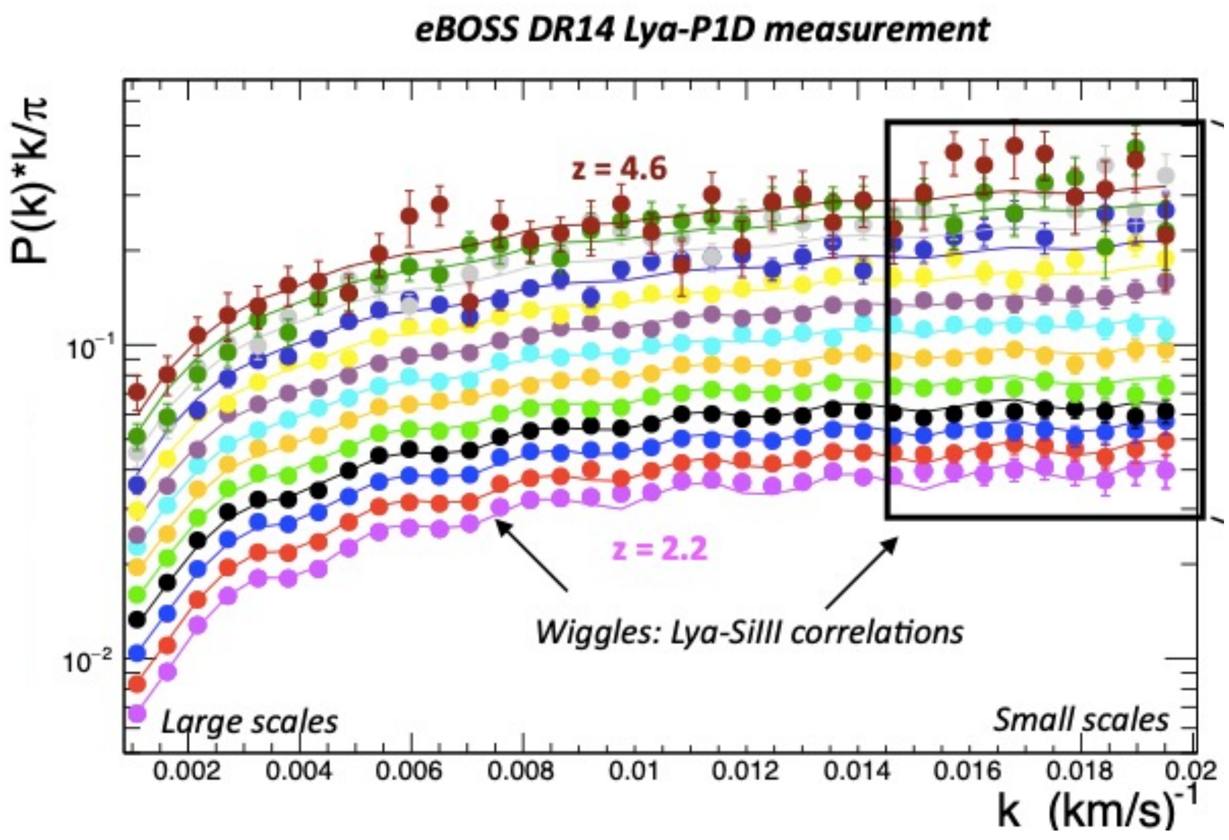
P1D[2,3]
- Neutrino mass
- IGM thermal parameters
- DM models

Key systematics:
1. Continuum
2. DLA / BAL
3. Metals

P1D from Lyman-α forest

How do we propagate uncertainties through to the final P1D?

[1] McDonald et al. (2006)
[2] Palanque-Delabrouille et al. (2013)
[3] Chabanier et al. (2018)



- P1D Lyman-a $P_{1D}\left(z, k_{\parallel}\right) = \int \frac{d\boldsymbol{k}_{\perp}}{(2\pi)^2} P_{3D}(z, \boldsymbol{k}_{\perp}, k_{\parallel})$
- Flux density field $\delta_F(\mathbf{x}) = \frac{F(\mathbf{x}) - \bar{F}}{\bar{F}}$
- Lyman-a P1D

$$P_{raw}(k) = [P_{Ly\alpha}(k) + P_{correlated}(k) + P_{uncorrelated}(k)] \cdot W^2(k) + P_{noise}(k)$$

Sources of uncertainty in analysis:
1. Continuum fit
2. Noise estimate

Continuum fitting - PCA

Tests on eBOSS DR16 data

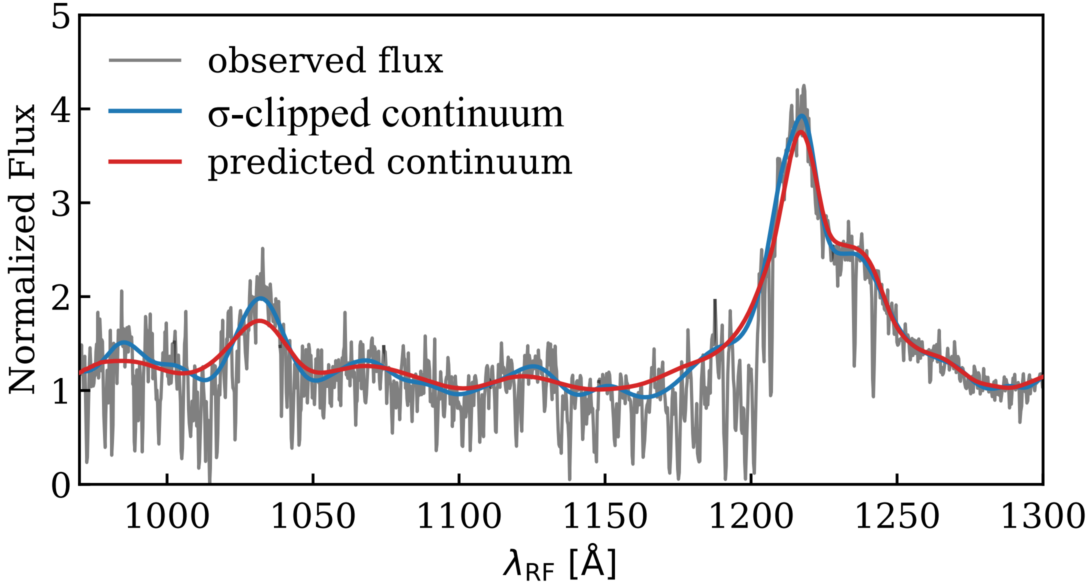
Preliminary

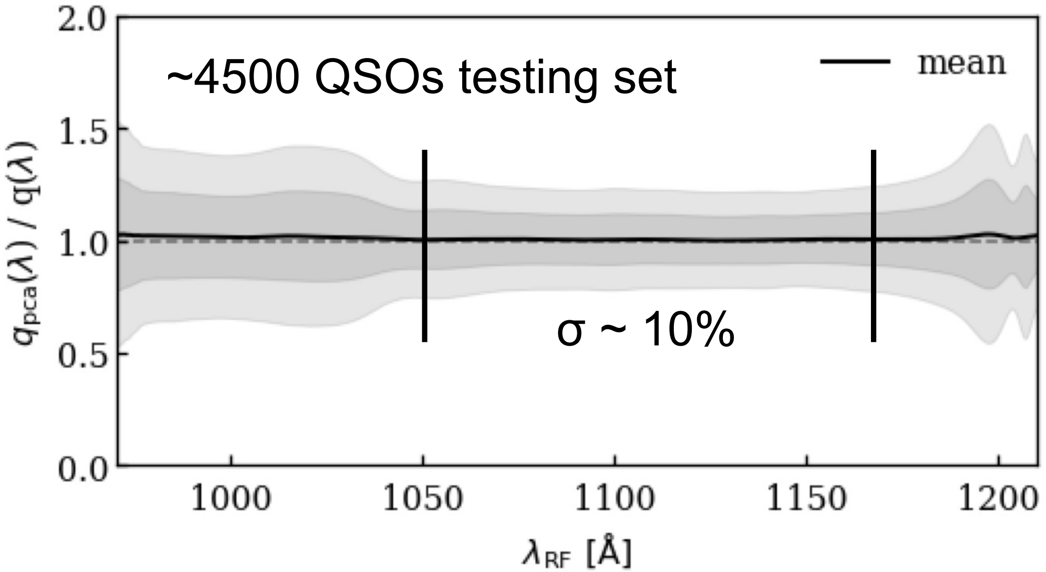
[1] Dall'Aglio et al. (2008)
[2] Bosman et al. (2020)

- Train PCA method on high S/N eBOSS sample
  - ~9000 QSOs
  - 2 < z < 2.5
  - SNR > 7

- Measure continuum redwards of Ly-α peak
  - σ-clipped continuum[1]
  - Less noisy and fewer absorption features
  - Project bluewards[2] to measure continuum in low SNR regime

- Propagate uncertainty from continuum fitting to δ_F





Unbiased & accurate continuum fitting

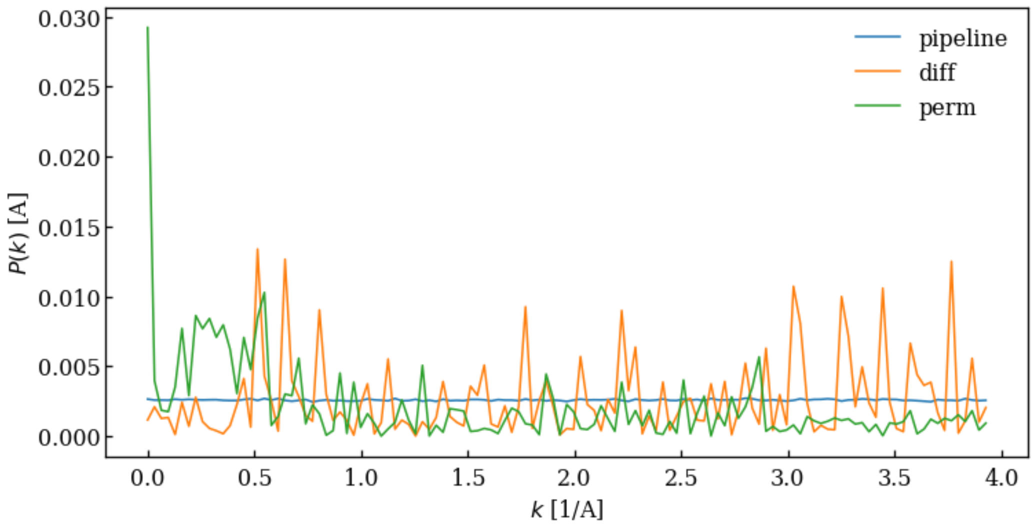
Noise estimation

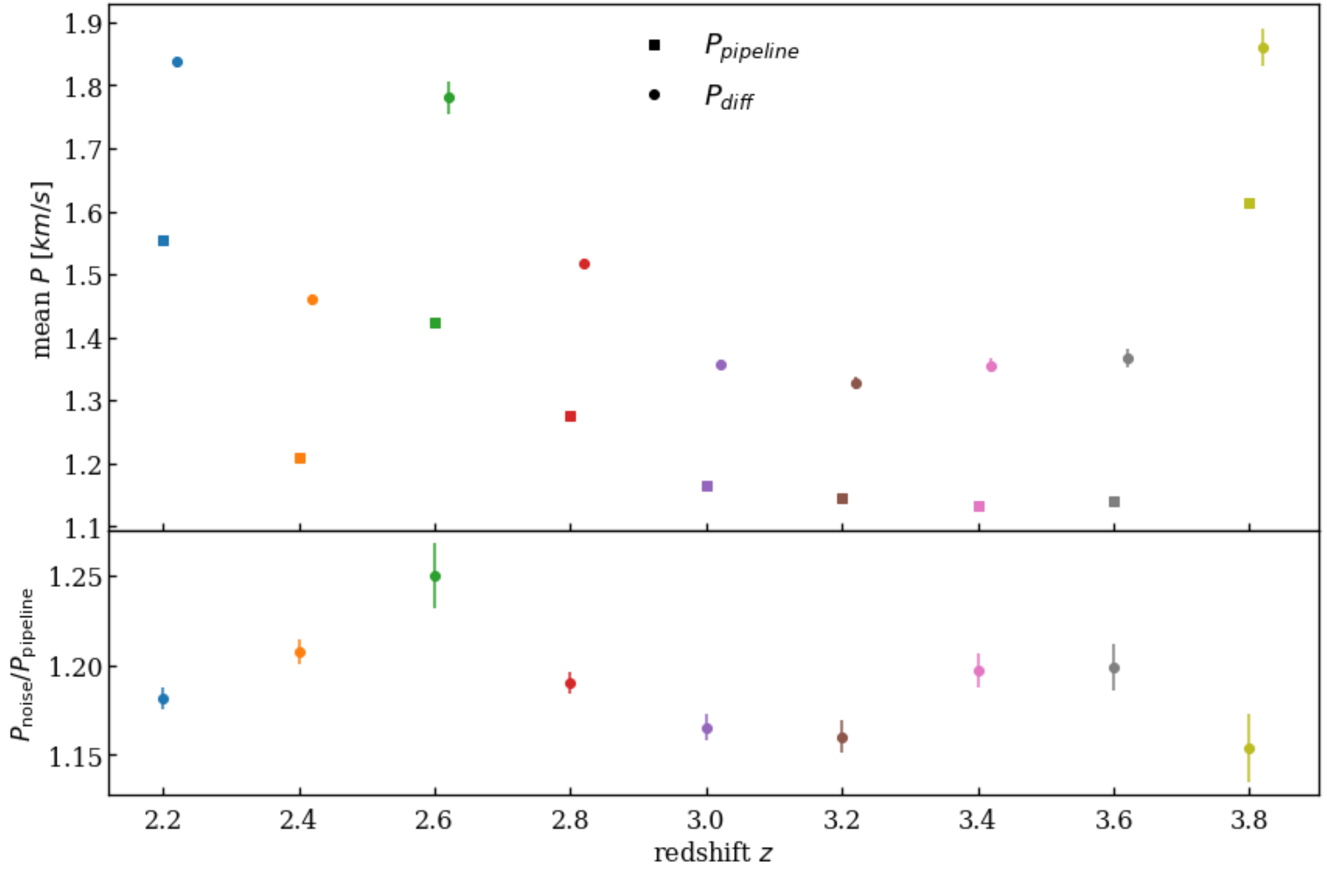
Analysis of DESI Science Verification (Everest) data

Preliminary

[1] Ravoux et al. (in prep)

- Compare DESI SV noise estimates:
  1. DESI pipeline
  2. Difference of exposure sets[1]
     - e.g.: (a+c+e)-(b+d+f)
  3. Permutations of exposures
     - e.g.: a-b, a-c, a-d, b-c, c-d
- New noise estimate important for P1D



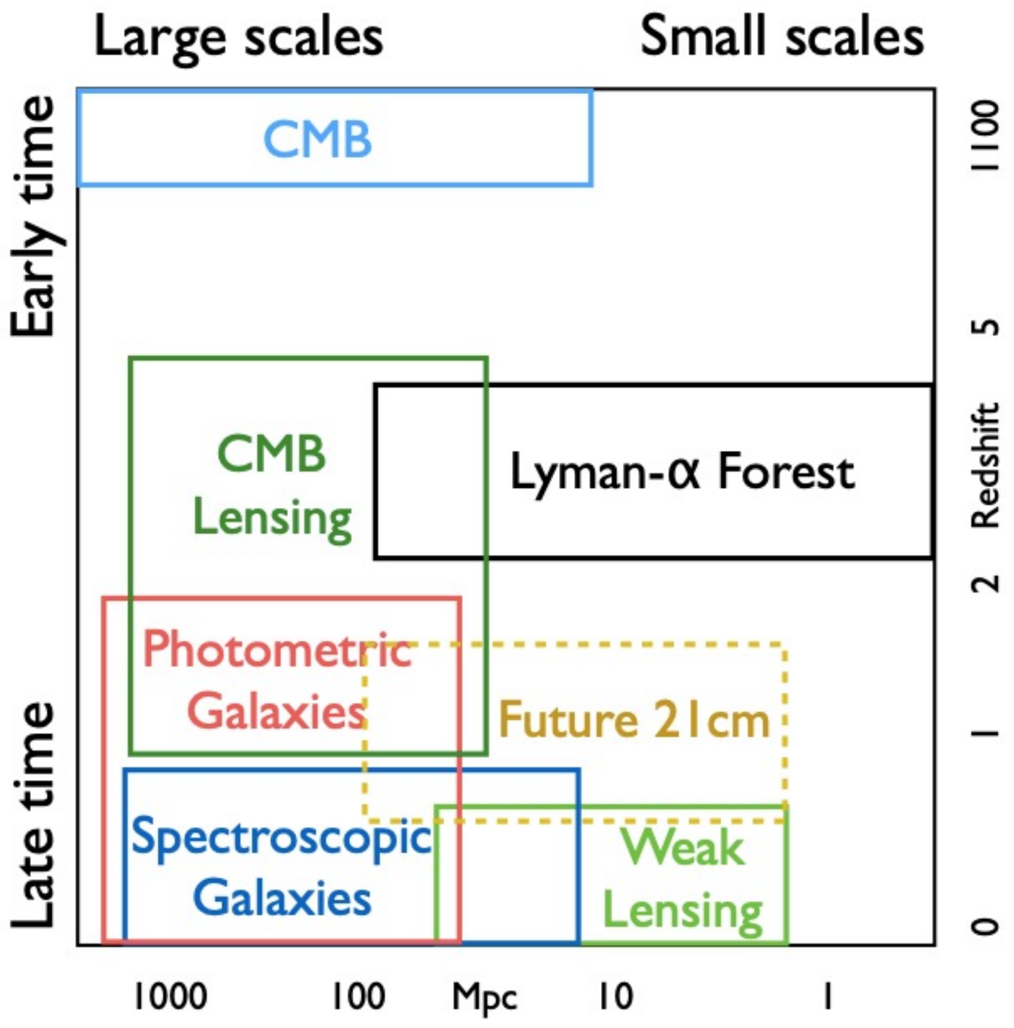


DESI pipeline underestimates the noise by ~20%

Next steps for Lyman-α: CMB x Lyman-α

Postdoc project I: Why is lensing "low"?

[1] Doux et al. (2017)
[2] Chiang & Slosar (2017)
[3] DESI presentation (Font-Ribera)



- Lyman-α forest probes:
  - small scale clustering
  - High redshift: $2 < z < 5$
- Opportunity:
  - Cross-correlate δ_{lensing} x $\delta_{\text{Ly-}\alpha}$
    - 2pt correlation instead of 3pt[1,2] at field level

➢ shape of primordial P(k)
➢ Ω_m at z=3
➢ neutrino mass

Lyman-α: high z → high k

Next steps for Lyman-α: P3D

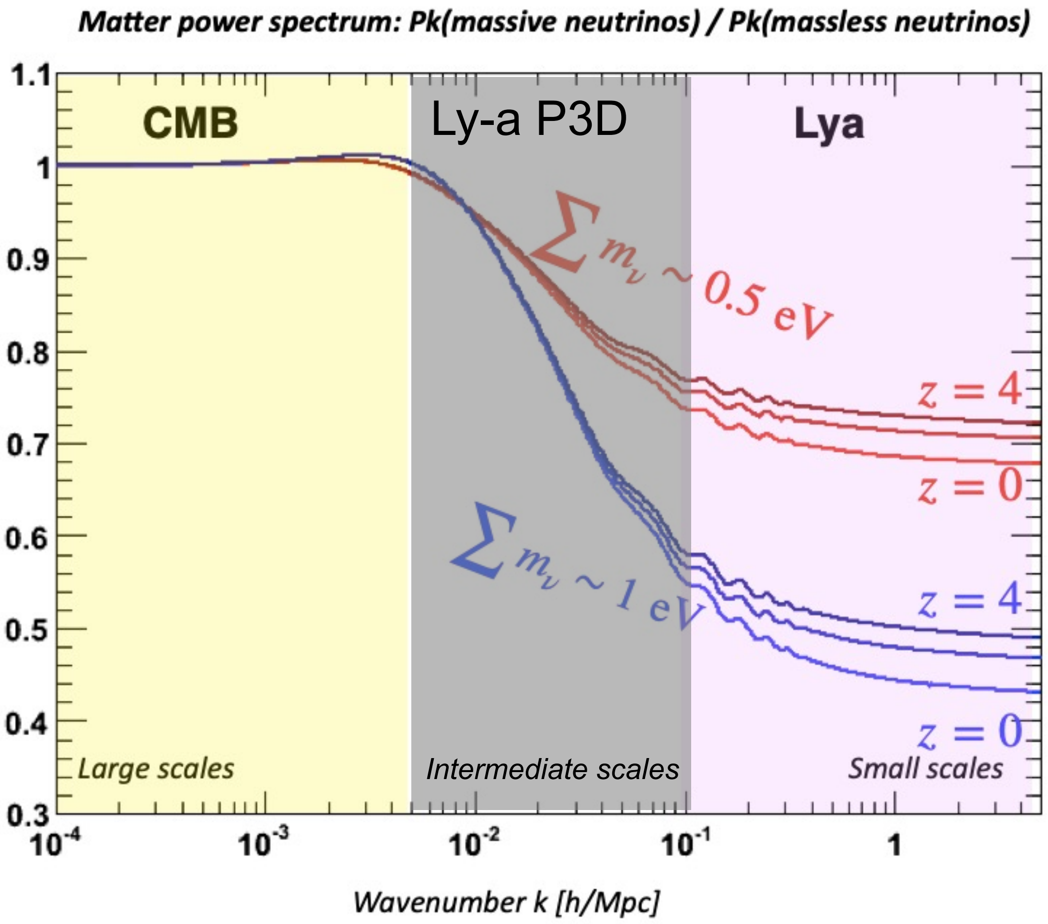
Postdoc project II

[1] Font-Ribera et al. (2017)

- Access information stored in broadband shape
  - Ω_m, n_s, σ_8

- Break amplitude-slope degeneracy

- systematics have negligible effect on BAO but important for P3D measurement



Lyman-α P3D: consistently access different scales

Conclusion

Please get in touch if you want to chat more!

[1] Sugai et al. (2020)
[2] Ade et al. (2019)

1. Low multipole inference pipeline → LiteBird[1], Simons Observatory[2]
   - Complex likelihoods with systematics (**τ**, ***r***)
   - CMB foregrounds (priors)

2. Lyman-α → DESI
   - Exciting data
   - Understand main systematics in analysis (continuum)
   - P1D as test case
     - Continuum fitting crucial to keep long modes → CMB x Lyman-α
     - Propagate errors through to P(k)
   - From P1D to P3D

How can we exploit efficiently (all) the information from cosmological data sets?