CMB foregrounds for B-mode studies, Tenerife, Oct 2018
Session VI (cont'). Forecasting future experiments

Forecasting galactic foregrounds cleaning with parametric, pixel-based, max-likelihood approach

Josquin ERRARD

CMB4CAST
GROUNDS

JE, Feeney, Peiris, Jaffe
(JCAP, 2016)

xForecast

Stompor, JE, Poletti
(PRL, 2016)

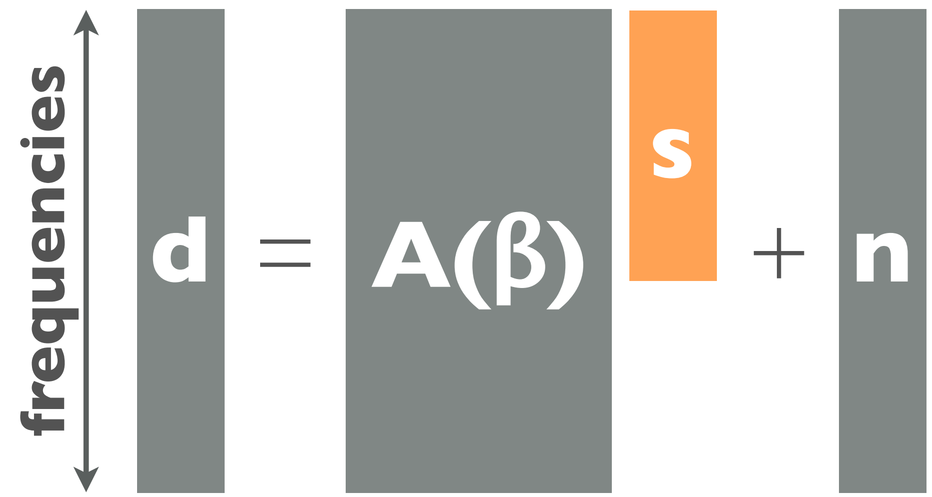
multiPatch

JE et al, in prep

$$d_i(p) = A_{ij}\, s_j(p) + n_i(p)$$

data modeling
for each sky pixel:

[see D. Poletti talk]



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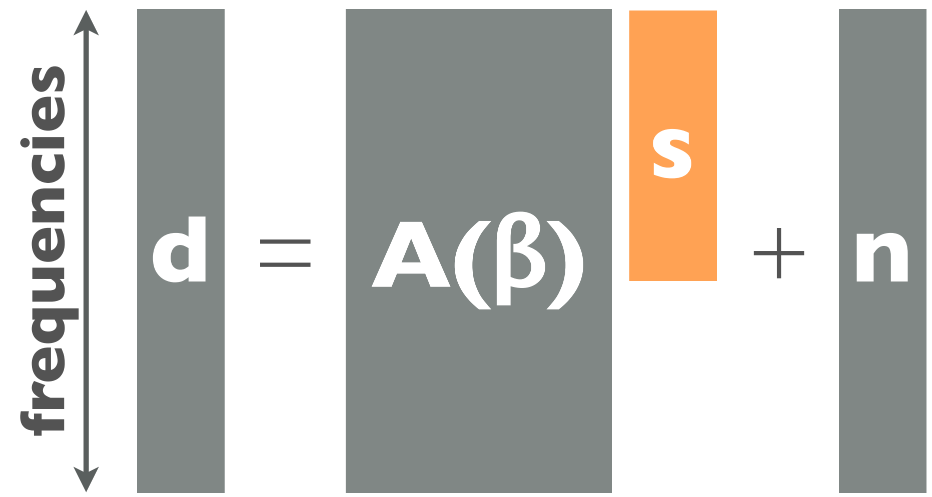

1. estimation of the mixing matrix A

e.g. **Stompor et al. (2009)**

$$A^{\mathrm{raw}}_{\mathrm{sync}}(\nu, \nu_{\mathrm{ref}}) \equiv \left(\frac{\nu}{\nu_{\mathrm{ref}}}\right)^{\beta_s}$$

$$A^{\mathrm{raw}}_{\mathrm{dust}}(\nu, \nu_{\mathrm{ref}}) \equiv \left(\frac{\nu}{\nu_{\mathrm{ref}}}\right)^{\beta_d+1} \frac{e^{\frac{h\nu_{\mathrm{ref}}}{k\,T_d}} - 1}{e^{\frac{h\nu}{kT_d}} - 1}$$

$$\mathbf{A} \equiv \mathbf{A}(\beta = \beta_d, \beta_s, \ldots) \longrightarrow \max\left(\mathcal{L}(\beta)\right)$$

$$-2\,\ln \mathcal{L}_{spec}(\boldsymbol{\beta}) \quad = \quad \mathrm{CONST} - \left(\boldsymbol{A}^t\,\boldsymbol{N}^{-1}\,\boldsymbol{d}\right)^t \left(\boldsymbol{A}^t\,\boldsymbol{N}^{-1}\,\boldsymbol{A}\right)^{-1} \left(\boldsymbol{A}^t\,\boldsymbol{N}^{-1}\,\boldsymbol{d}\right)$$

not perfect recovery of input spectral parameters ➤ foregrounds residuals

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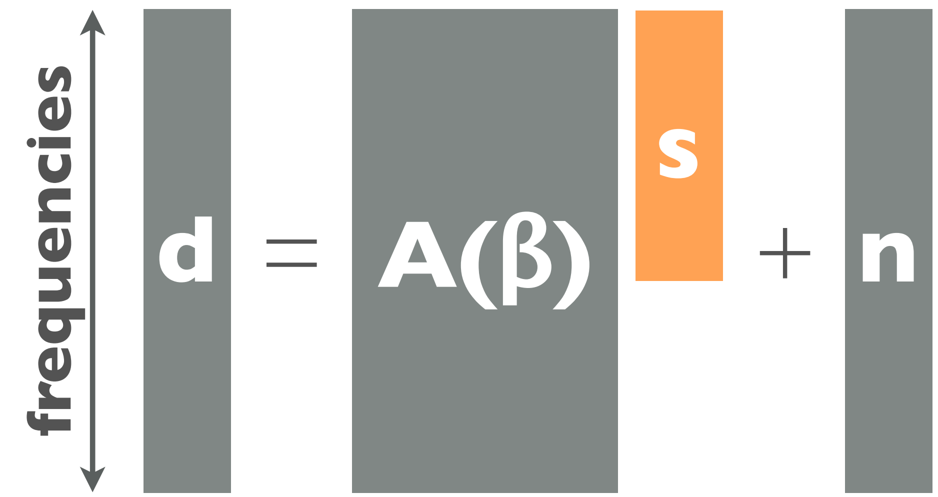
[see D. Poletti talk]



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not perfect recovery of input spectral parameters ➤ foregrounds residuals

2. solve for s [rather general to any comp sep method]

$$\mathbf{s} = \left(\mathbf{A}^T\mathbf{N}^{-1}\mathbf{A}\right)^{-1}\mathbf{A}^T\mathbf{N}^{-1}\mathbf{d}$$

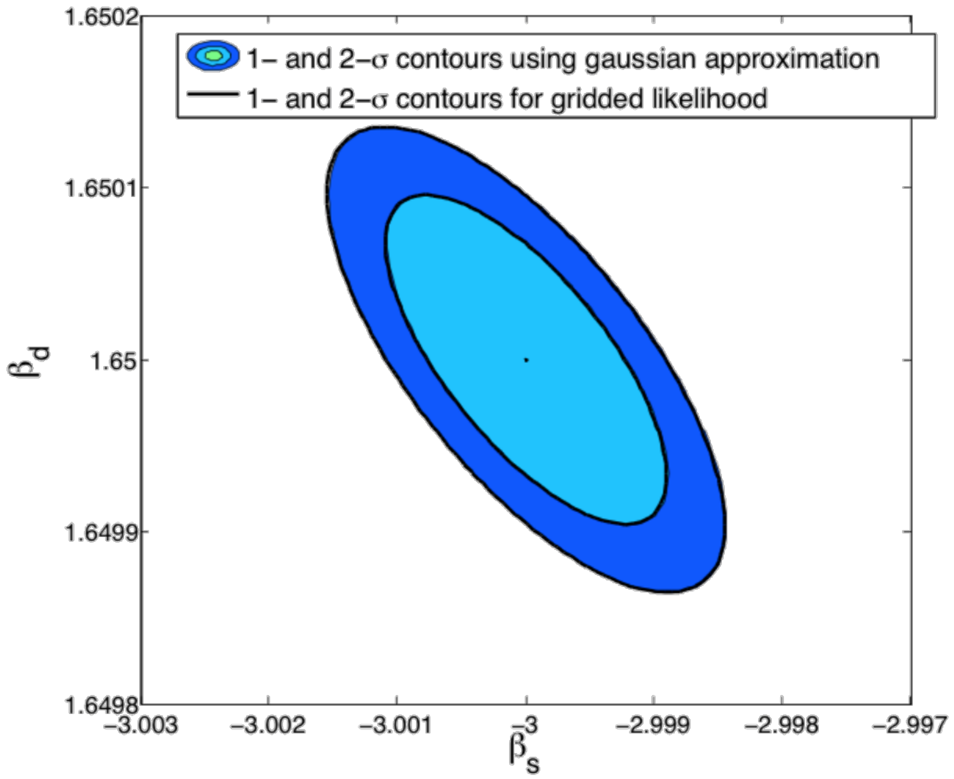
linear combination of various frequency maps ➤ boosted noise

JE, Feeney, Peiris, Jaffe (JCAP, 2016)

CMB4CAST GROUNDS

JE, Feeney, Peiris, Jaffe (JCAP, 2016)

Statistical error bars on spectral parameters:



JE, Stivoli and Stompor (PRD, 2011)

$$\Sigma^{-1} \simeq \quad - \left\langle \frac{\partial^2 \mathcal{L}}{\partial \beta \partial \beta'} \right\rangle_{\rm noise} \Bigg|_{\rm true\ \beta}$$

$$= \mathrm{tr} \left\{ \left[\mathbf{A}^t_{,\beta} \mathbf{N}^{-1} \mathbf{A} \left(\mathbf{A}^t \mathbf{N}^{-1} \mathbf{A} \right)^{-1} \mathbf{A}^t \mathbf{N}^{-1} \mathbf{A}_{,\beta'} - \mathbf{A}^t_{,\beta} \mathbf{N}^{-1} \mathbf{A}_{,\beta'} \right] \sum_p \hat{\mathbf{s}}_p \hat{\mathbf{s}}_p^t \right\}$$

→ **averaged error bars for parametric methods like COMMANDER [see I. Wehus talk]**

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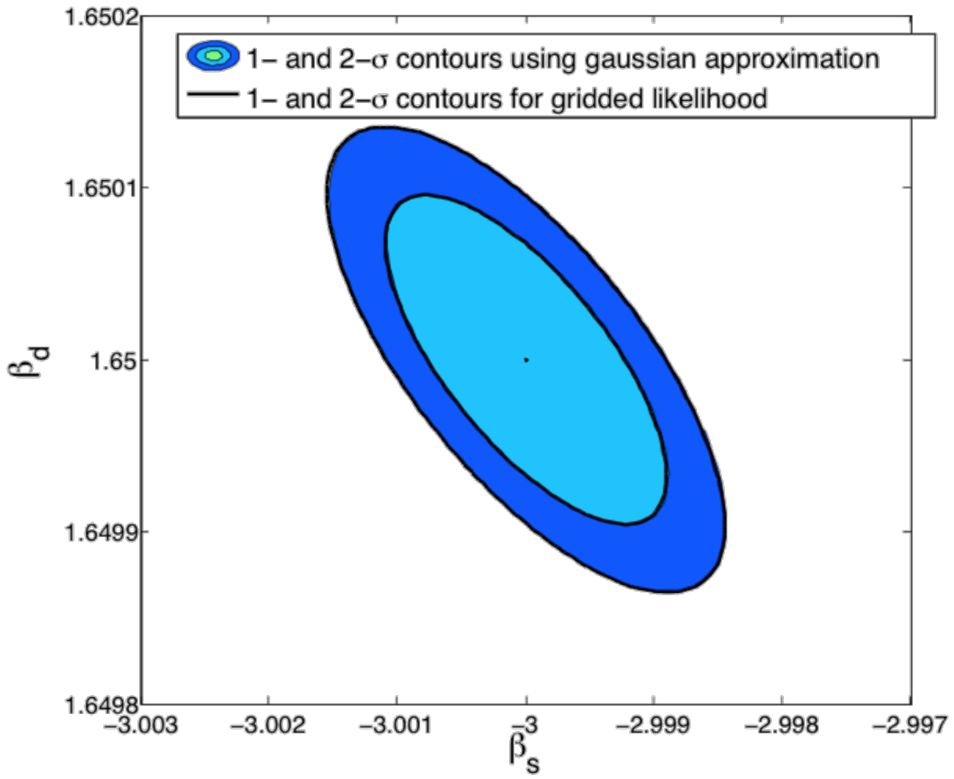

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→ **averaged error bars for parametric methods like COMMANDER [see I. Wehus talk]**

Amplitude of statistical foregrounds residuals:

$$C_\ell^{\rm fg\ res} \equiv \sum_{k,k'} \sum_{j,j'} \Sigma_{kk'} \, \kappa_{kk'}^{jj'} C_\ell^{jj'}$$

Stivoli, Grain, Leach, Tristram, Baccigalupi, Stompor (MNRAS, 2010)

CMB4CAST GROUNDS

JE, Feeney, Peiris, Jaffe (JCAP, 2016)

instrument design

↓

error bars on spectral parameters

↓

level of statistical foregrounds residuals

↓

Fisher analysis for cosmological parameters, including statistical foregrounds residuals, delensing, etc.

optimization

[see M. Abitbol talk]

xForecast

R. Stompor, JE and D. Poletti (PRD 2016, 1609.03807)

[see D. Poletti talk ➔ fgbuster]

simulation of observation with CMB + any foregrounds

↓

spectral analysis using simple scaling laws (e.g. power-law synchrotron and gray body dust)

$$\langle \mathcal{S}_{spec} \rangle = -\mathrm{tr} \sum_p \left\{ (\mathbf{N}_p^{-1} - \mathbf{P}_p) \left(\hat{\mathbf{d}}_p \hat{\mathbf{d}}_p^t + \mathbf{N}_p \right) \right\}$$

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[see D. Poletti talk → fgbuster]

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↓

estimation of statistical and systematic foregrounds residuals

$$C_\ell^{\mathrm{res}} \simeq \otimes_\ell(\tilde{\mathbf{y}}, \tilde{\mathbf{y}}) + \otimes_\ell(\tilde{\mathbf{y}}, \tilde{\mathbf{z}}) + \otimes_\ell(\tilde{\mathbf{z}}, \tilde{\mathbf{y}}) + \mathrm{tr}\left[\mathbf{\Sigma} \otimes_\ell(\tilde{\mathbf{Y}}^{(1)}, \tilde{\mathbf{Y}}^{(1)}) \right]$$

xForecast

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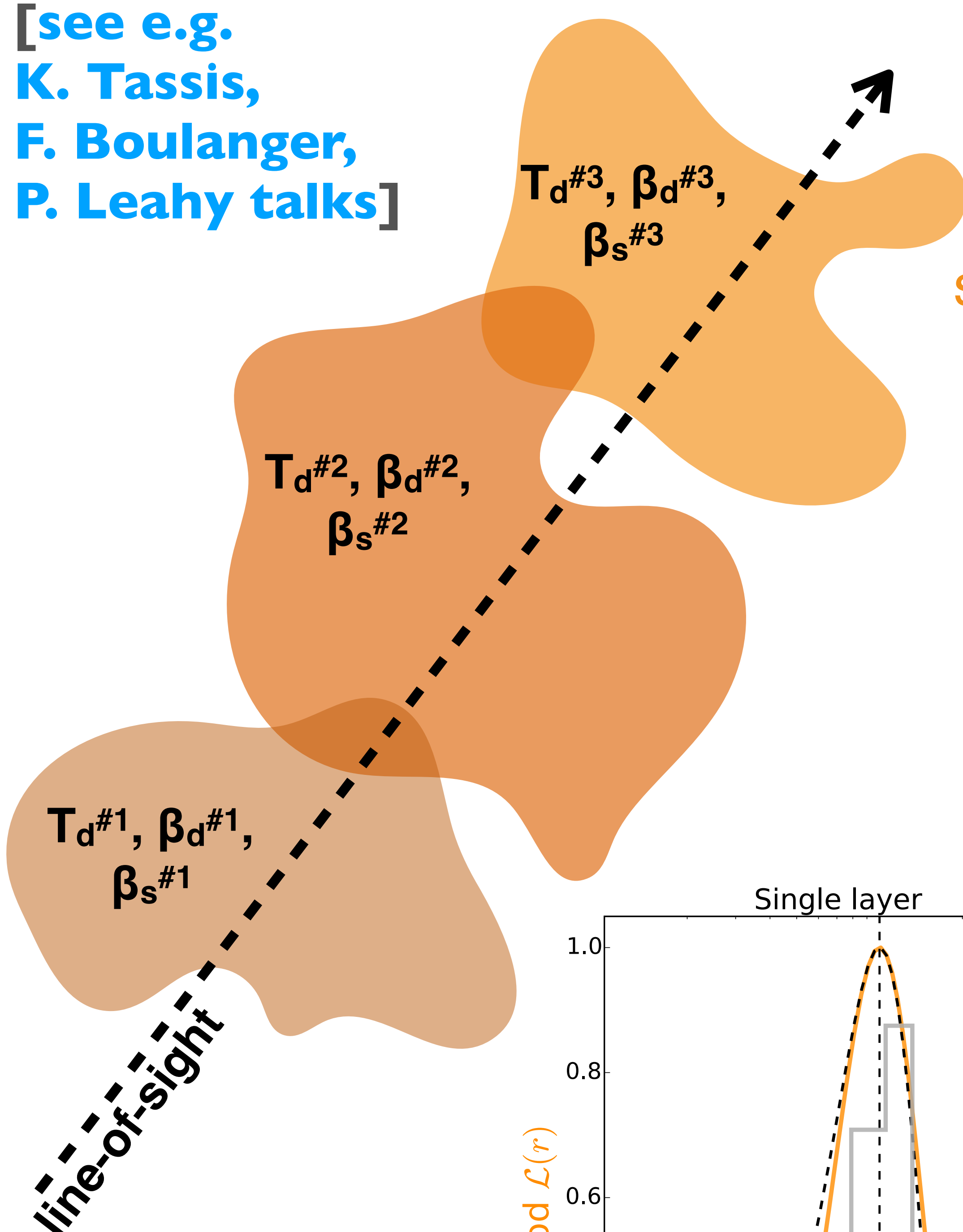
↓

propagation of these to the estimation of tensor-to-scalar ratio *r*

$$\langle \mathcal{S}^{par} \rangle = \mathrm{tr}\, \mathbf{C}^{-1} \mathbf{E} + \ln \det \mathbf{C}$$

[see e.g. K. Tassis, F. Boulanger, P. Leahy talks]

R. Stompor, JE and D. Poletti (PRD 2016, 1609.03807)



Complex foregrounds toy model: N=1,2 or 4 independent foregrounds “layers” along the line-of-sight, with different temperature and spectral indices

↓

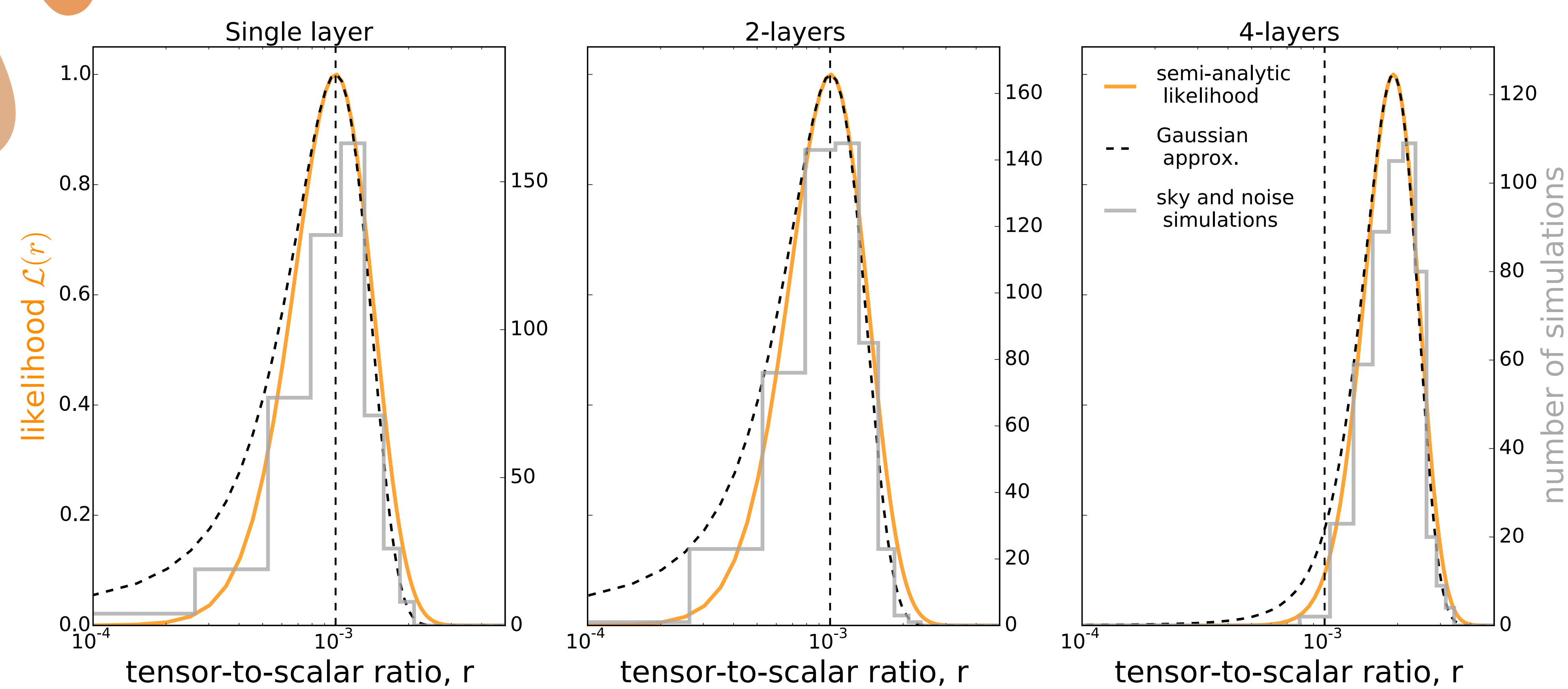
fitting for global parameters {Bd,Bs}

↓

estimate of {Q,U} CMB

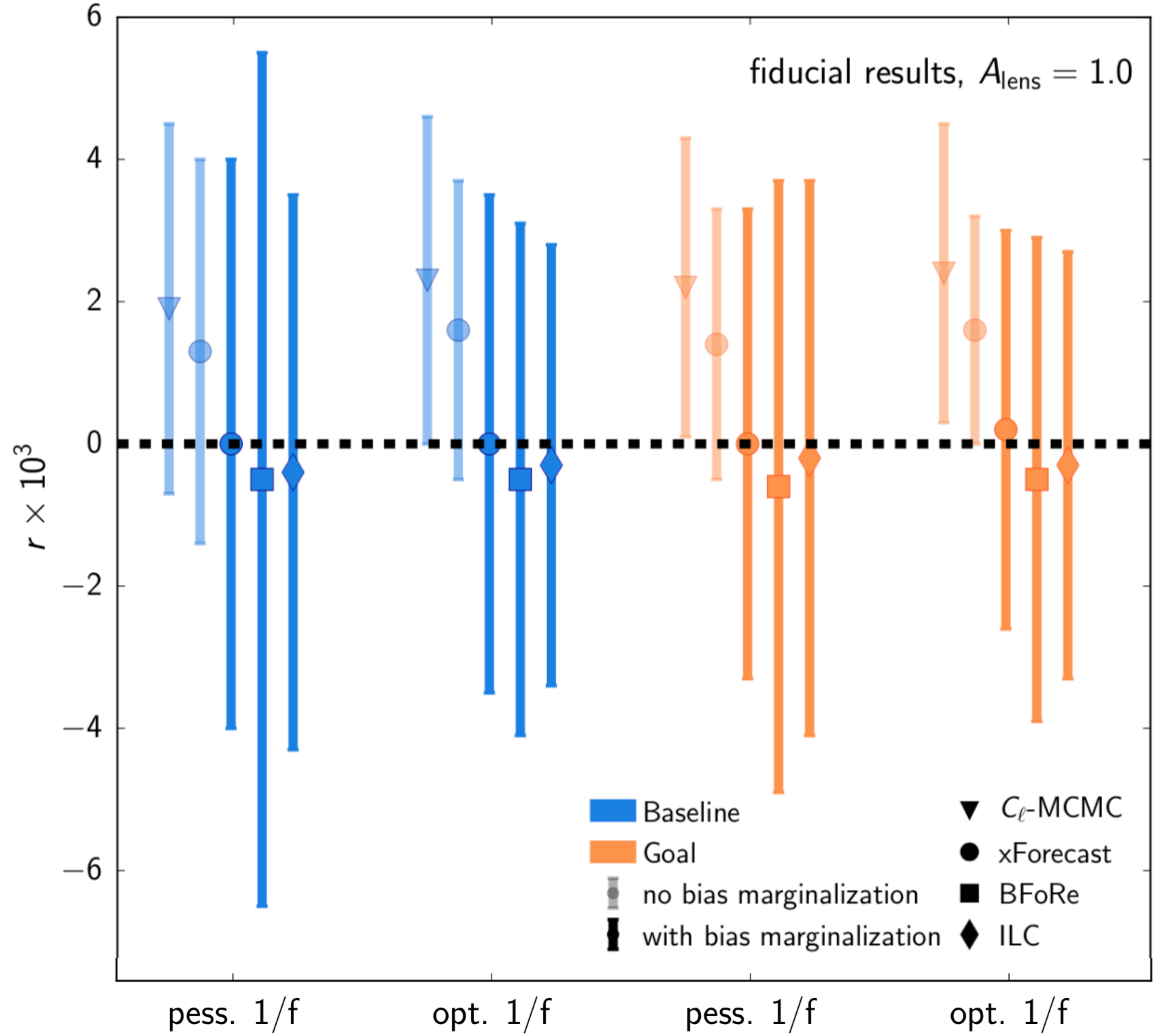
↓

likelihood on r

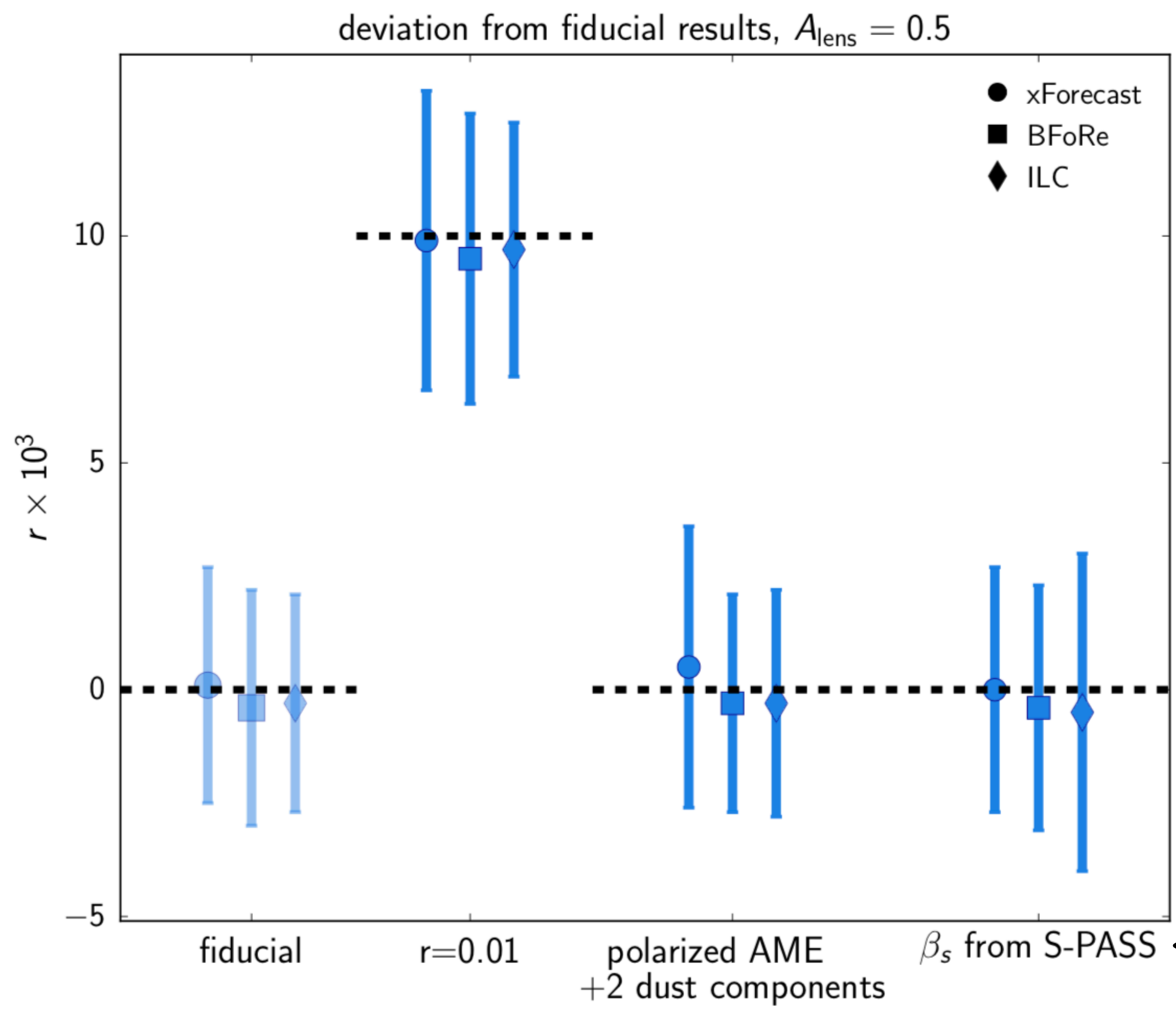


THE SIMONS OBSERVATORY: SCIENCE GOALS AND FORECASTS

arXiv:1808.07445 [talk by C. Hill]



THE SIMONS OBSERVATORY: SCIENCE GOALS AND FORECASTS



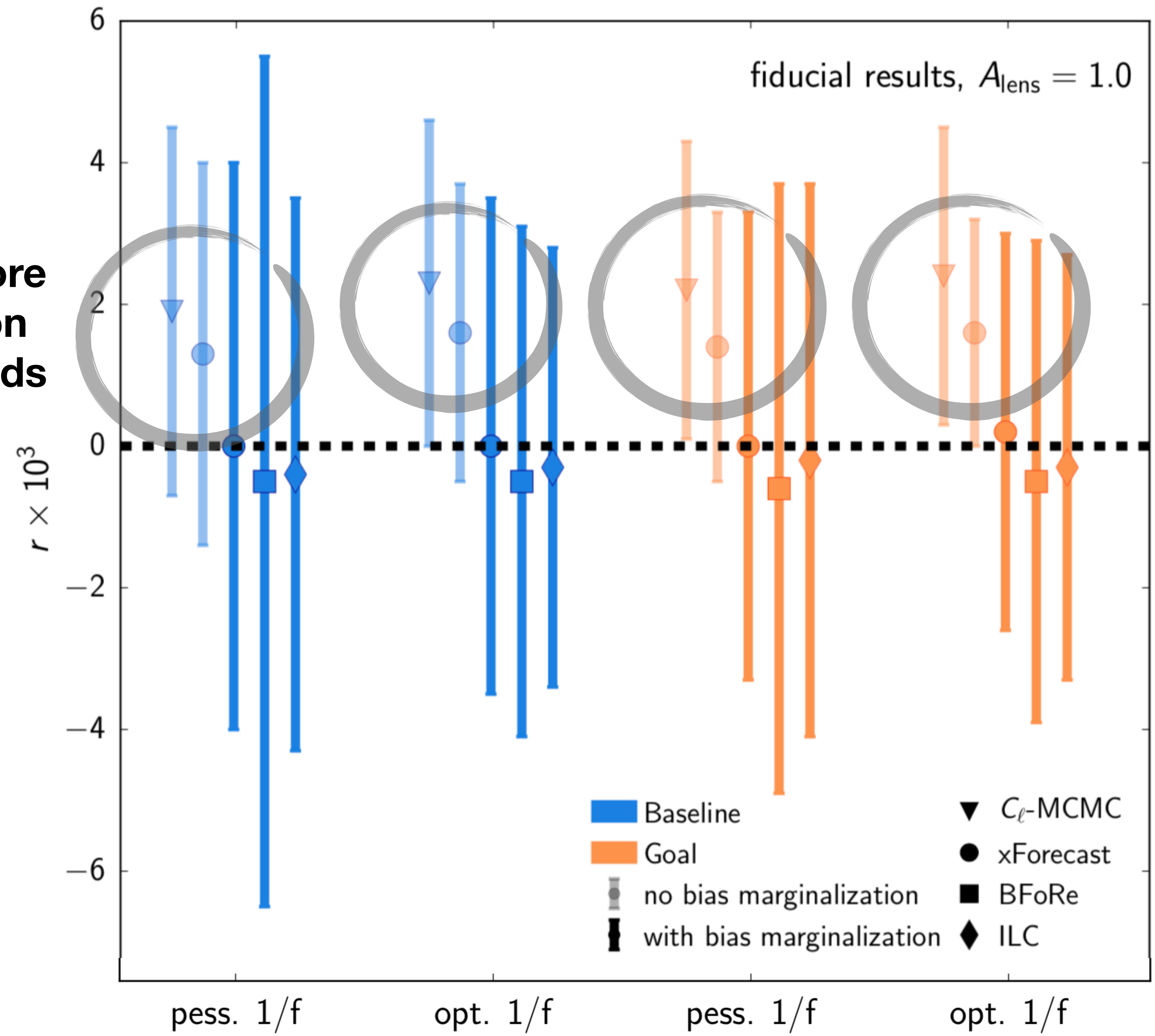
← [see N. Krachmalnicoff talk]

Figure 12. As in Fig. 10, for the cases deviating from the fiducial forecasts. The 'fiducial' points match the second panel of Fig. 10 for baseline sensitivity and optimistic $1/f$. The three other cases assume $r = 0.01$ in the input sky simulations (left), $r = 0.0$ with 2 dust components and polarized AME (middle), and $r = 0.0$ with synchrotron scaling based on a high-resolution β_s template (right). These models are described in Sec. 2.4.4 with forecasts in Table 5.

THE SIMONS OBSERVATORY: SCIENCE GOALS AND FORECASTS

arXiv:1808.07445 [talk by C. Hill]

slight bias before marginalization over foregrounds template



In current simulations, e.g. PySM a1d1s1 [see A. Zonca talk],
how is the bias on tensor-to-scalar ratio sourced?

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➔ from spatial variations of the spectral indices!

(aka decorrelation [see C. Pryke, J. Aumont, ++ talks])

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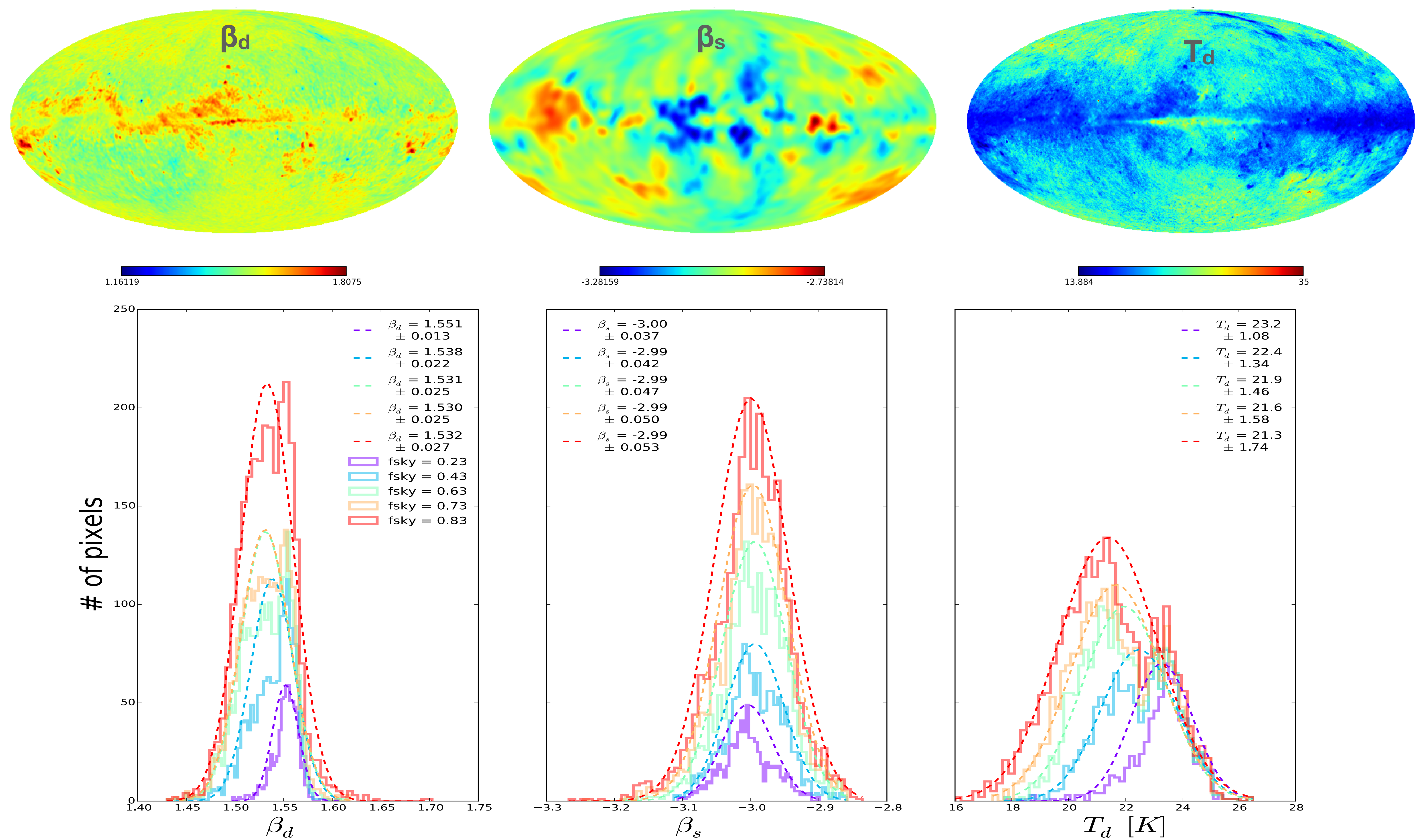
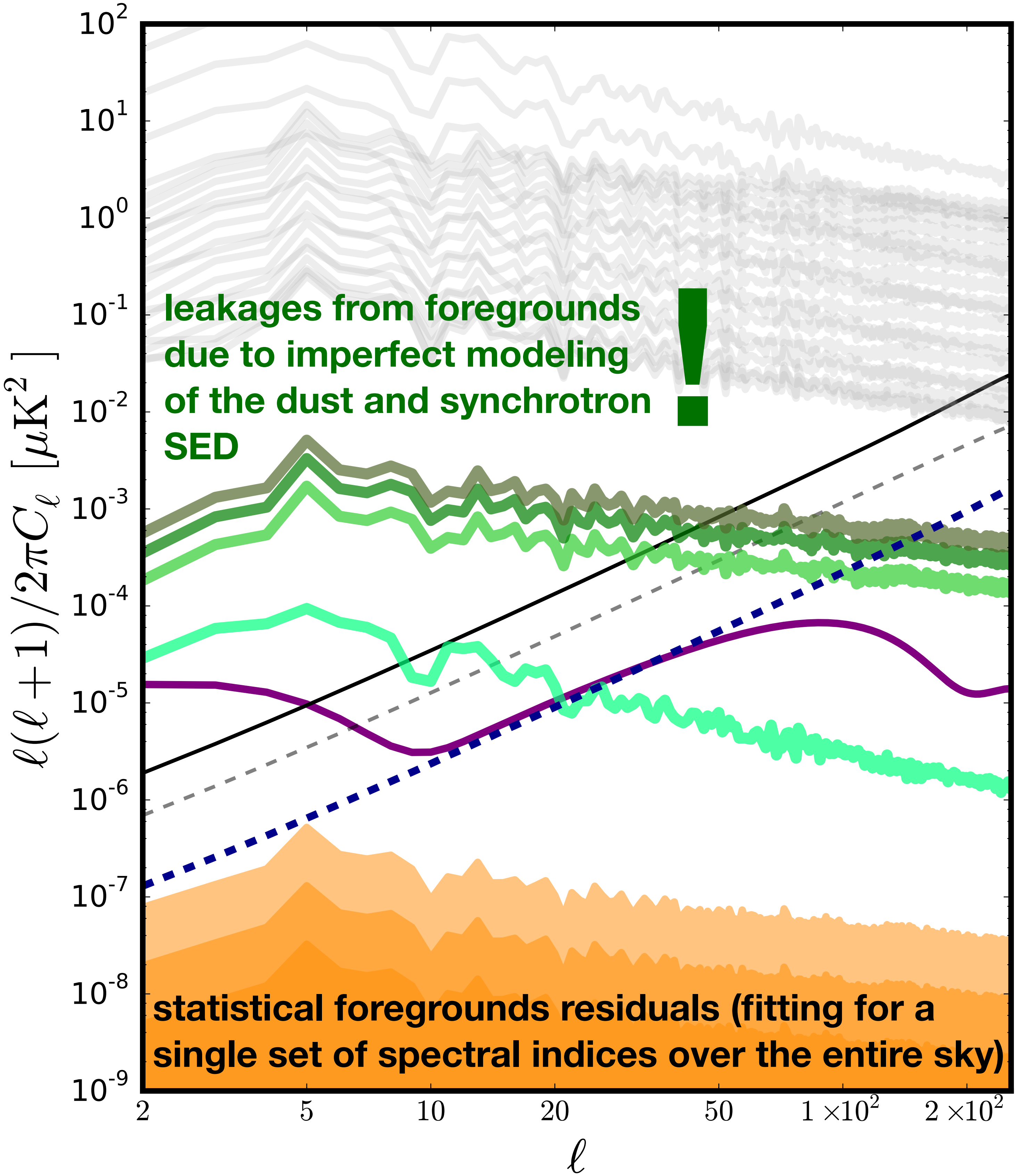
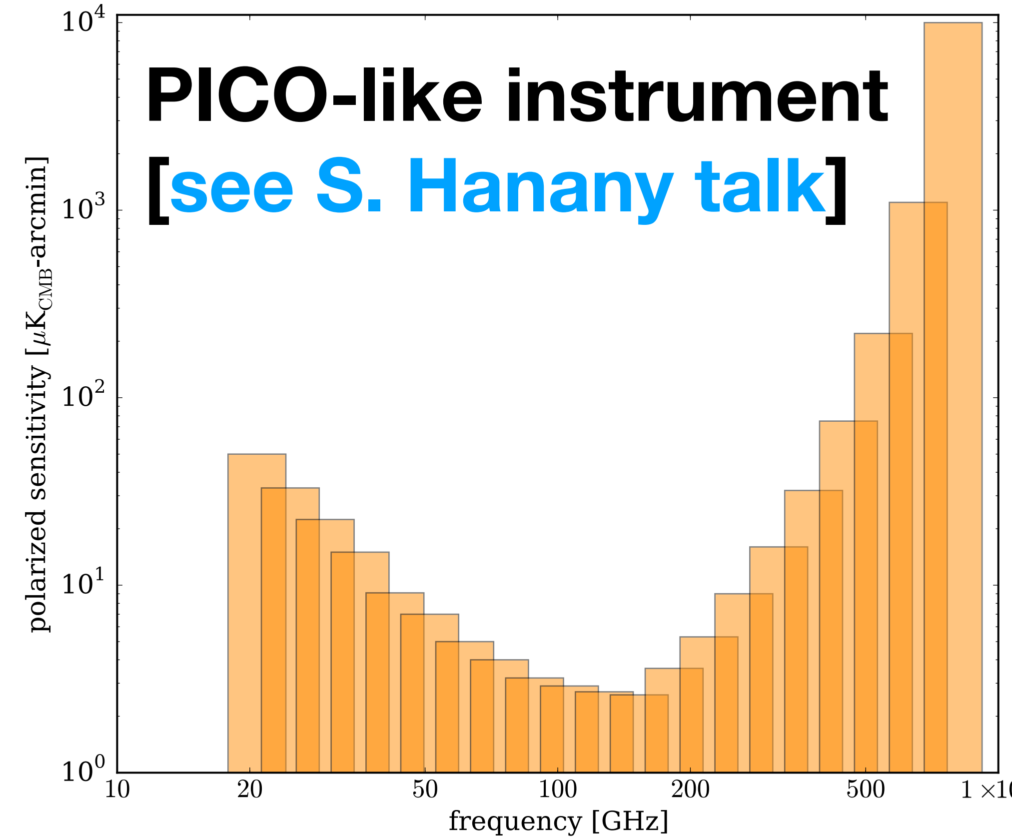


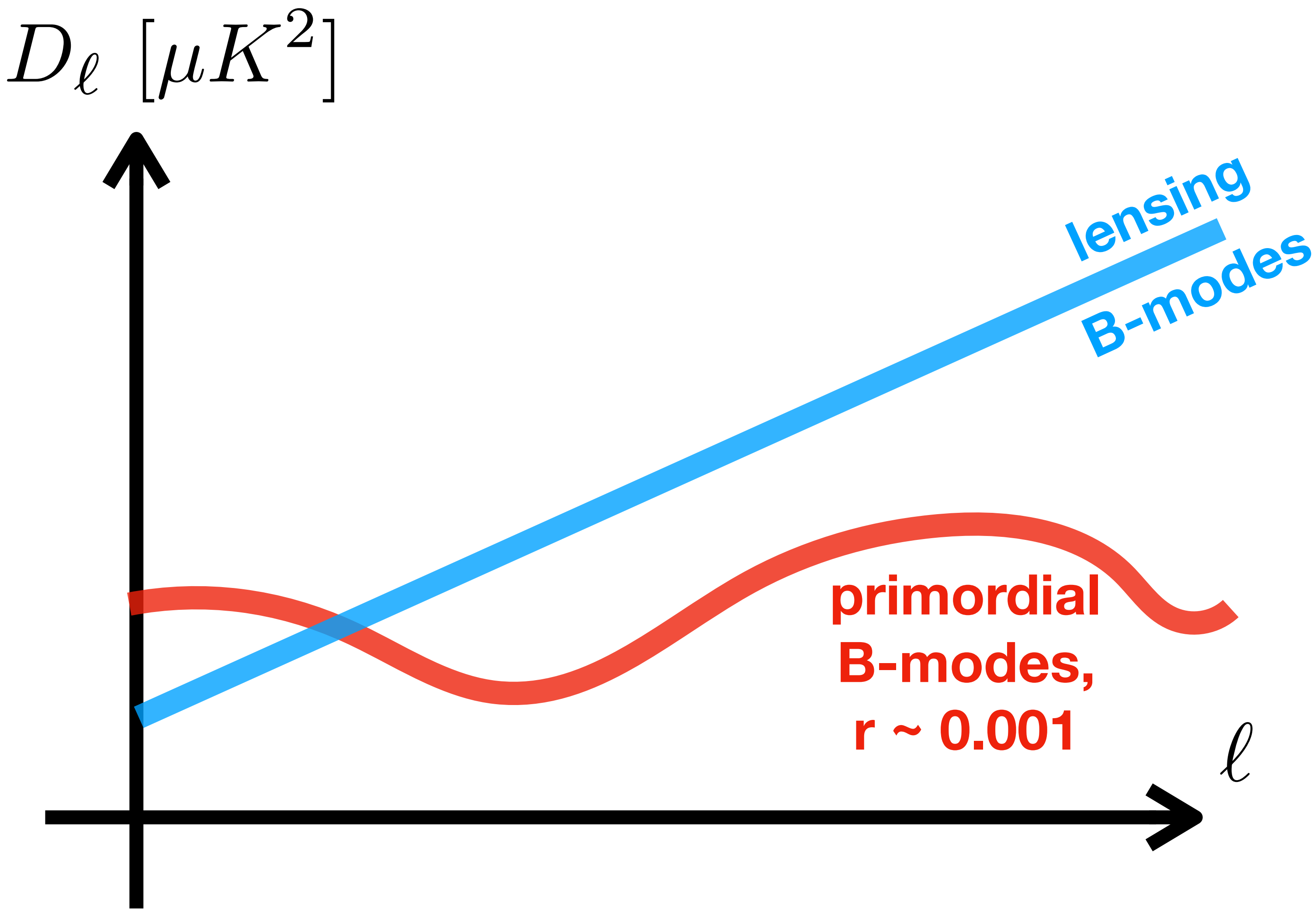




fsky = 60%

- noiseless foregrounds spectra from PySM simulations
- total B-modes
- primordial B-modes (r=0.001, $\tau=0.055$)
- lensing B-modes
- internally delensed B-modes
- xF average residuals $\pm$ 2$-\sigma$
- sys. res. from β_d spat. var.
- sys. res. from β_s spat. var.
- sys. res. from T_d spat. var.
- sys. res. from $\{\beta_d, \beta_s, T_d\}$ spat. var.
- N_ℓ

For a given instrument, there are two extreme solutions for data analysts:



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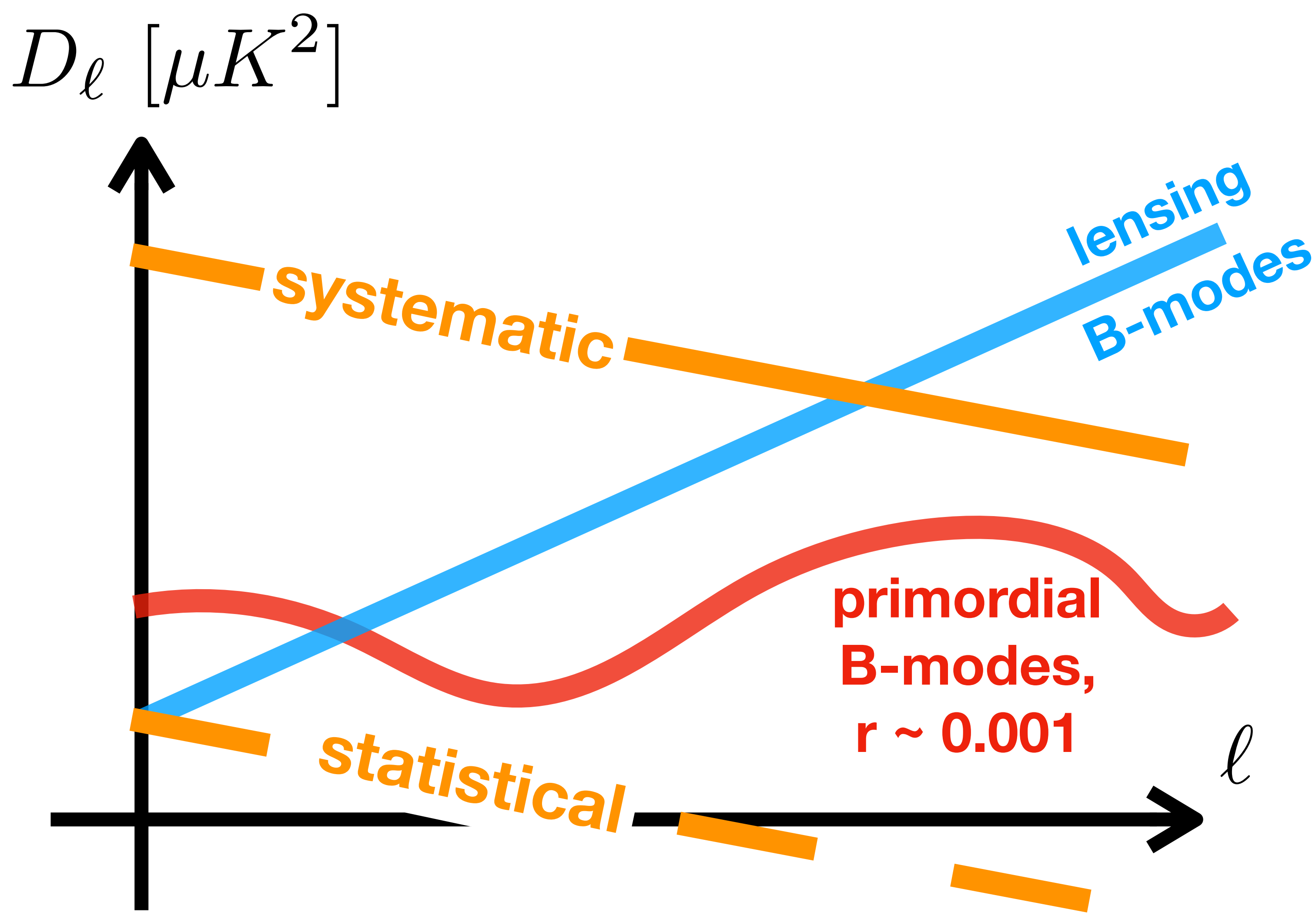

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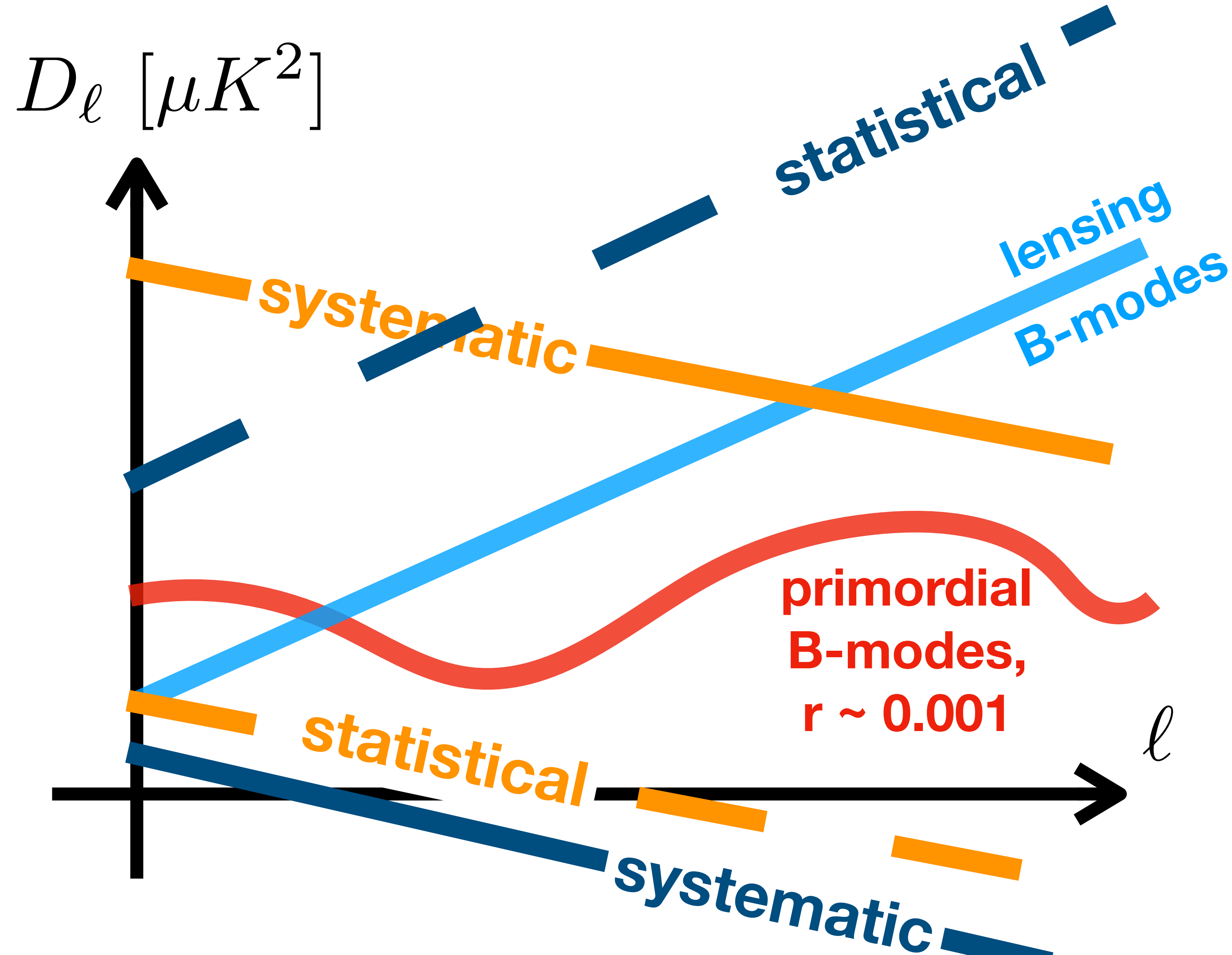

- ◉ fit for a single set of spectral parameters over the entire sky ➔ low level of statistical foregrounds residuals but high level for leakage
- ◉ fit for a as many sets of spectral parameters as sky pixels ➔ high level of statistical foregrounds residuals but small leakage

one should look for a balance between statistical and systematic errors

STATISTICAL error bars on spectral parameters

SYSTEMATIC error bars on spectral parameters

one should look for a balance between statistical and systematic errors

$$\Sigma \equiv \begin{bmatrix} \sigma(\beta_d)^2 & \sigma(\beta_d)\sigma(\beta_s) & \sigma(\beta_d)\sigma(T_d) \\ \star & \sigma(\beta_s)^2 & \sigma(\beta_s)\sigma(T_d) \\ \star & \star & \sigma(T_d)^2 \end{bmatrix}$$

STATISTICAL error bars on spectral parameters

- better signal-to-noise (instrumental sensitivity, etc.)
- few degrees of freedom
- broad frequency range
- large sky area (more pixels!)

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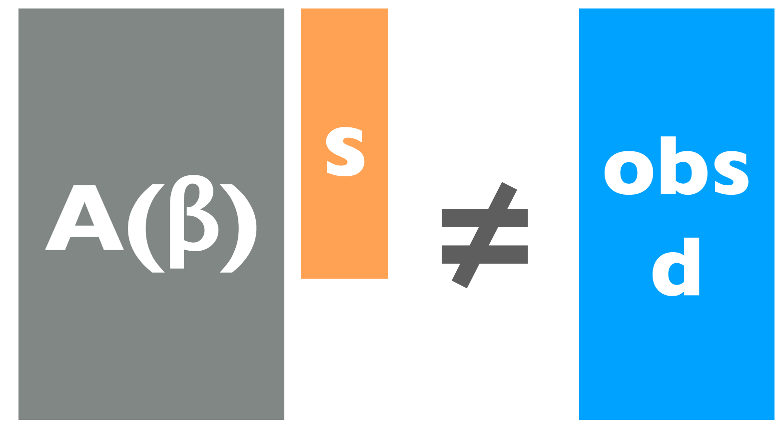
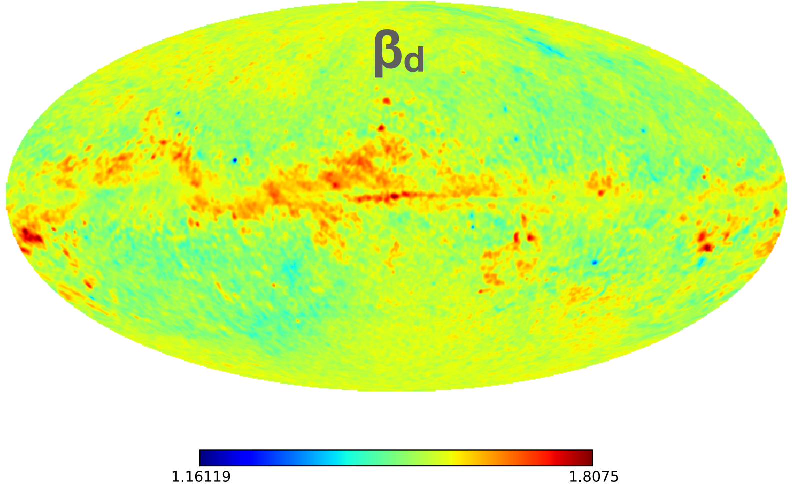
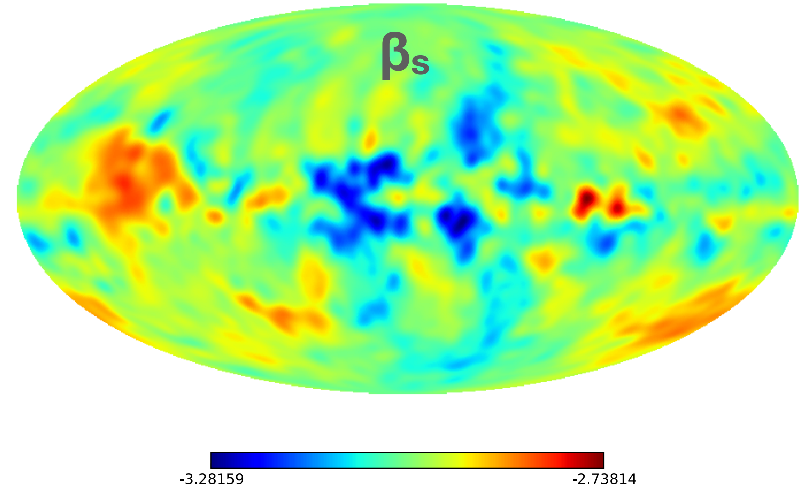
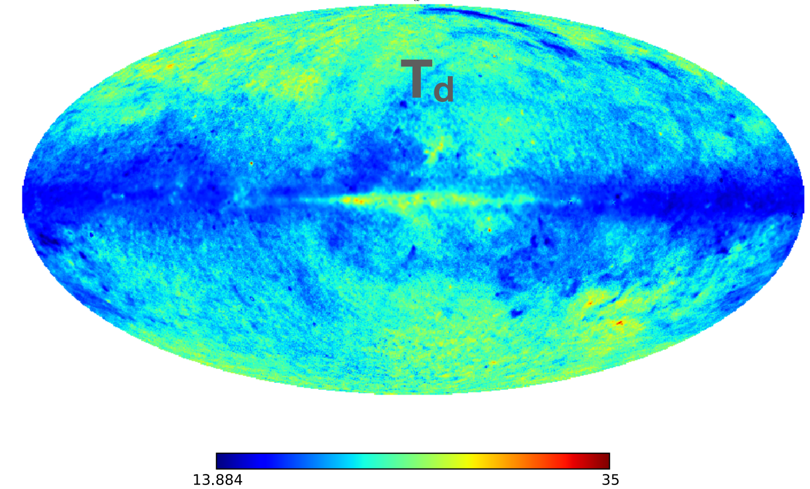


SYSTEMATIC error bars on spectral parameters

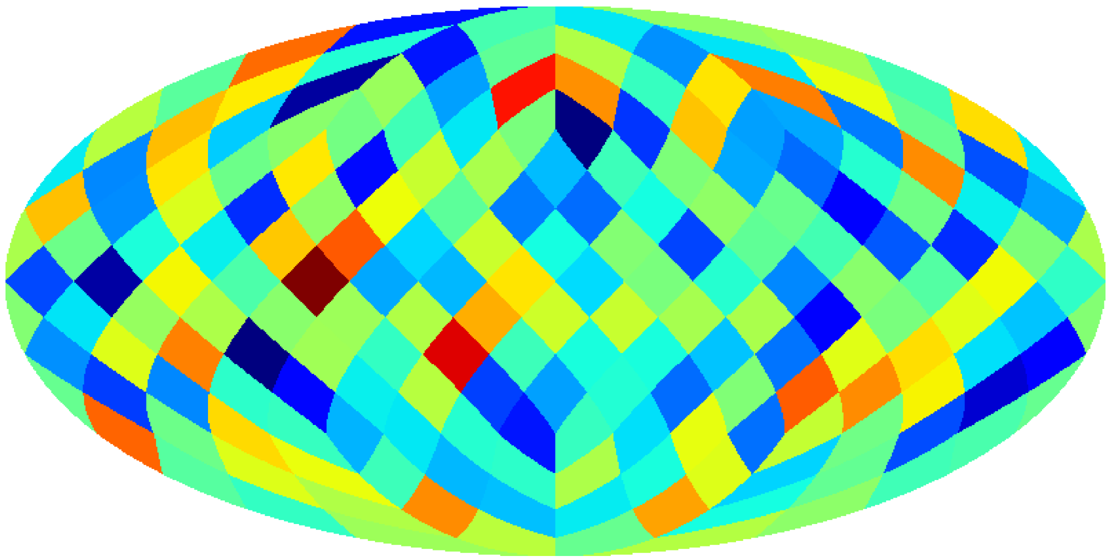
- more internal degrees of freedom (free spectral parameters, sky templates, etc.)
- reduced frequency range
- small sky area (less complexity!)



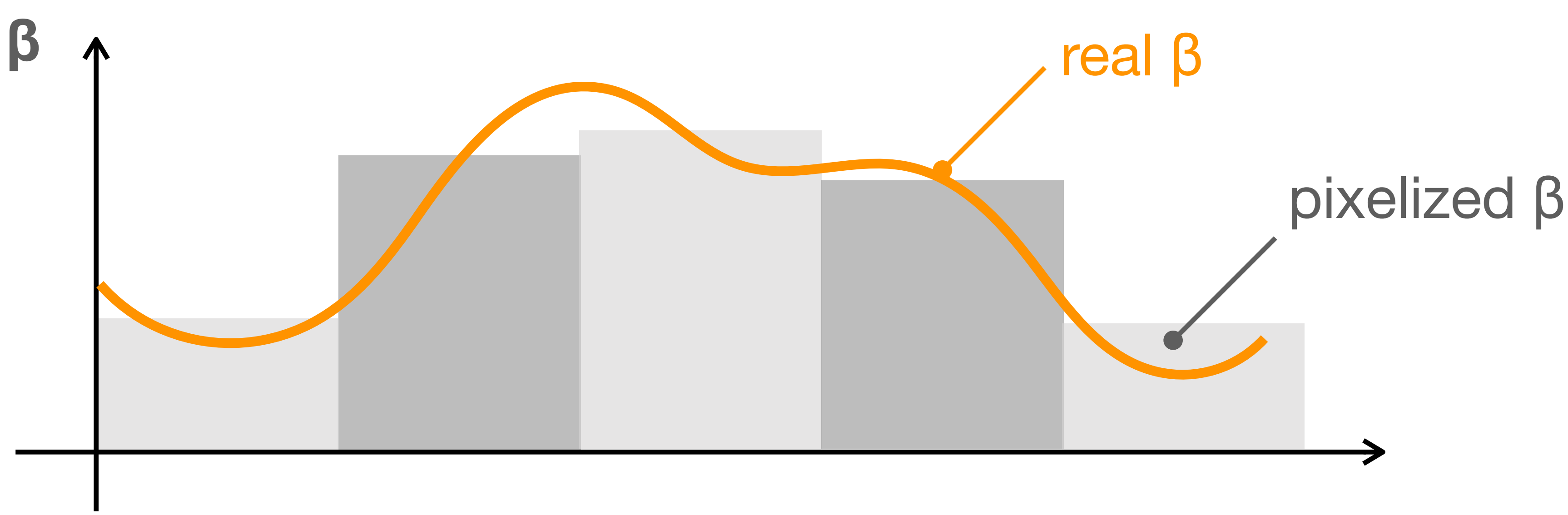




Is “multipatch” the solution?

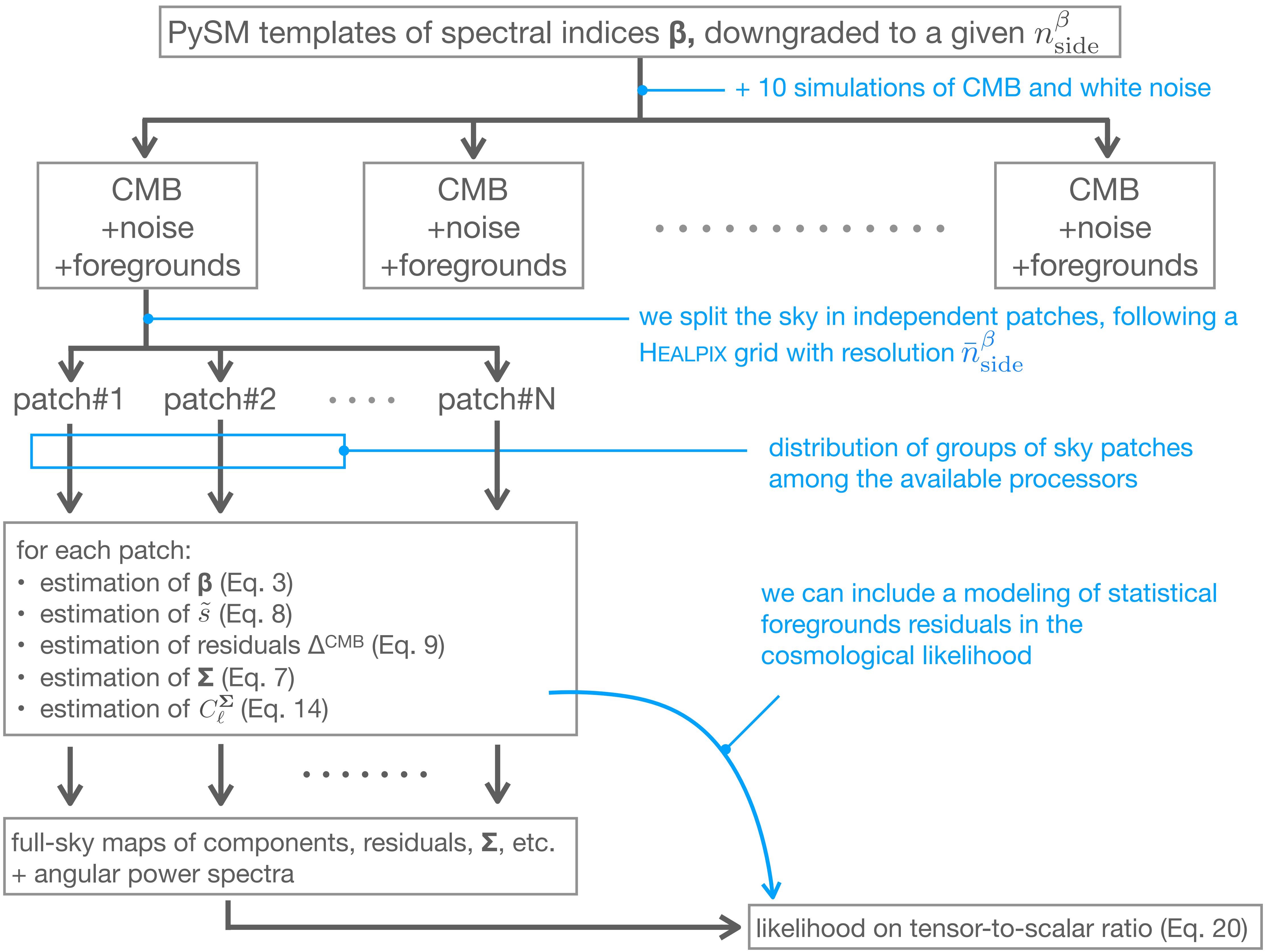


“maximize and minimize” sky area



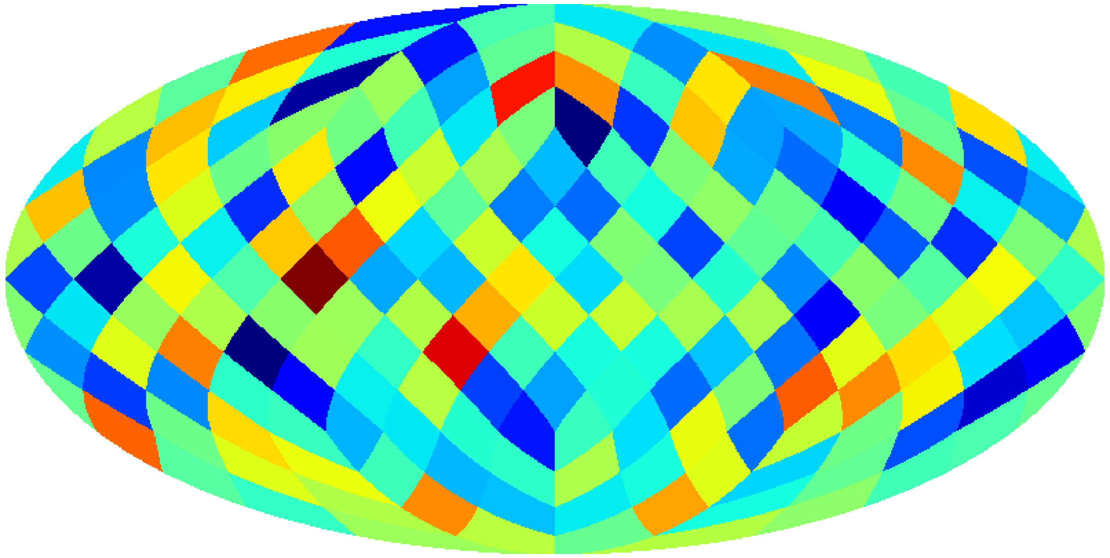
+ only ~3-4 sky components / sky pixel i.e. reduced noise in the reconstructed CMB map

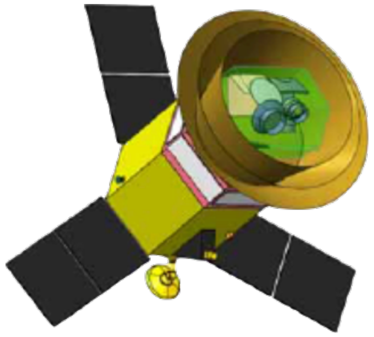
JE et al, in prep — about to be submitted :)



JE et al, in prep

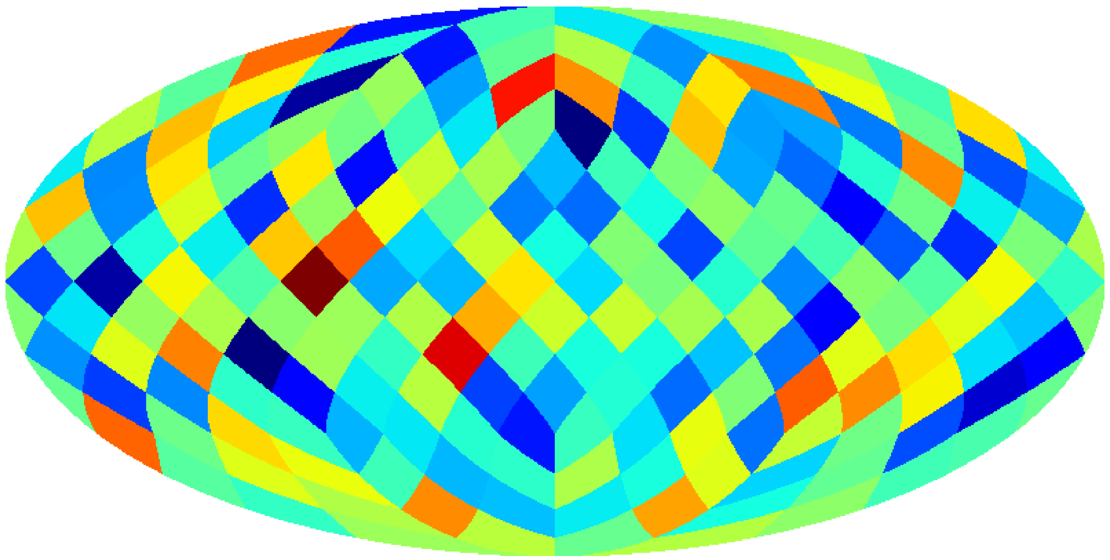
input spectral indices, smoothed and degraded to a Healpix grid n_{side}





[exercise with the international Joint Study Group on foregrounds see M. Hazumi talk]

JE et al, in prep



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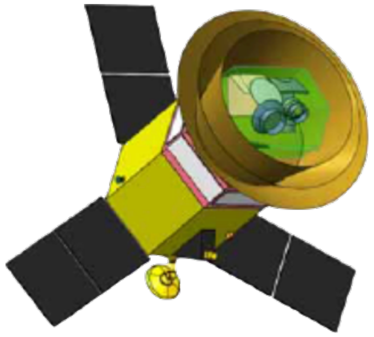

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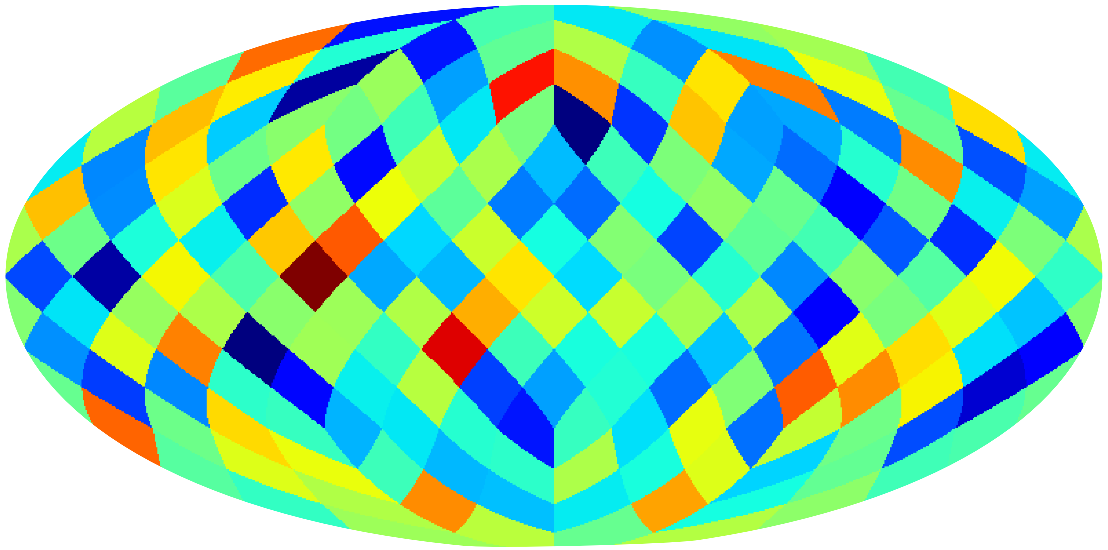
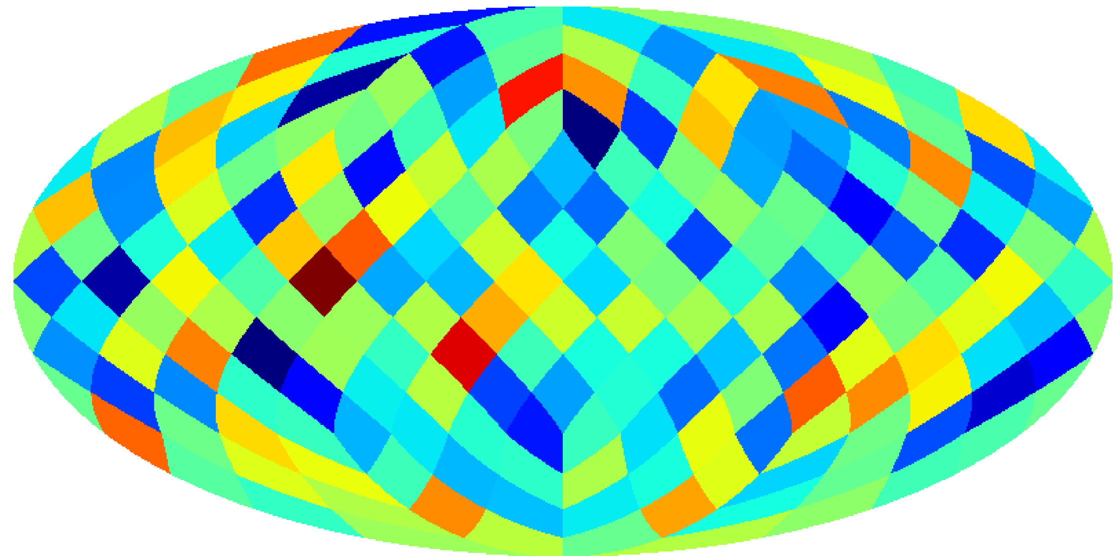
generation of foregrounds frequency maps + CMB + noise simulation

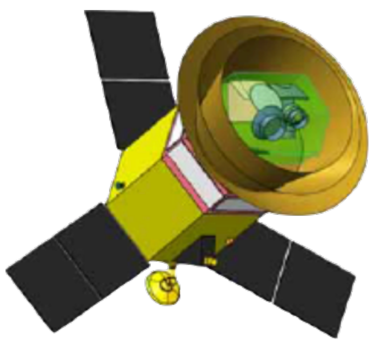


we fit for set of spectral indices for each patch, independently

JE et al, in prep

input spectral indices, smoothed and degraded to a Healpix grid n_{side}





[exercise with the international Joint Study Group on foregrounds see M. Hazumi talk]

generation of foregrounds frequency maps + CMB + noise simulation

let's first assume the input and analysis patches match

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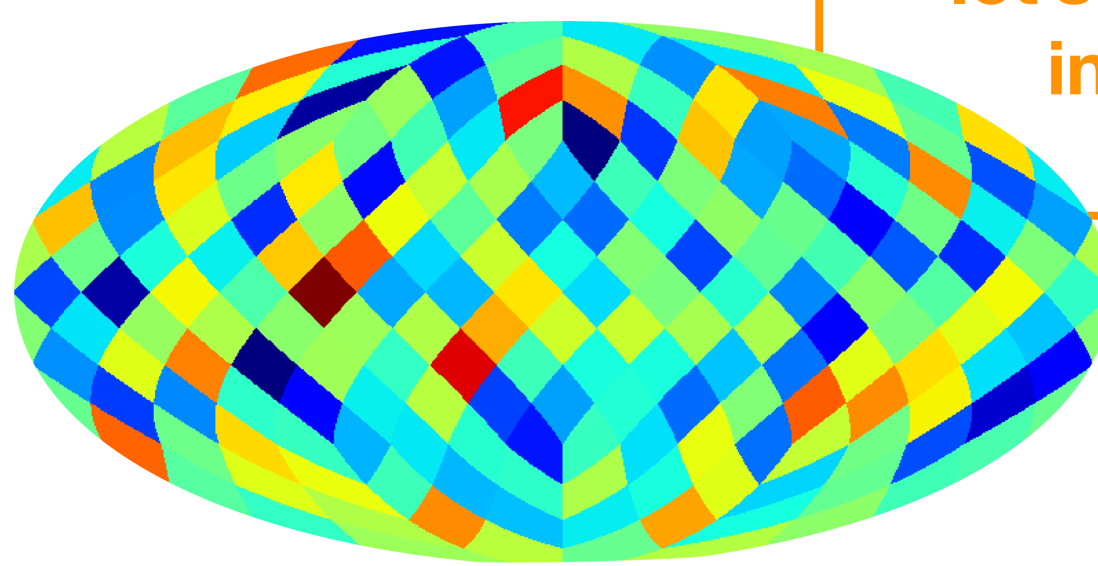

JE et al, in prep

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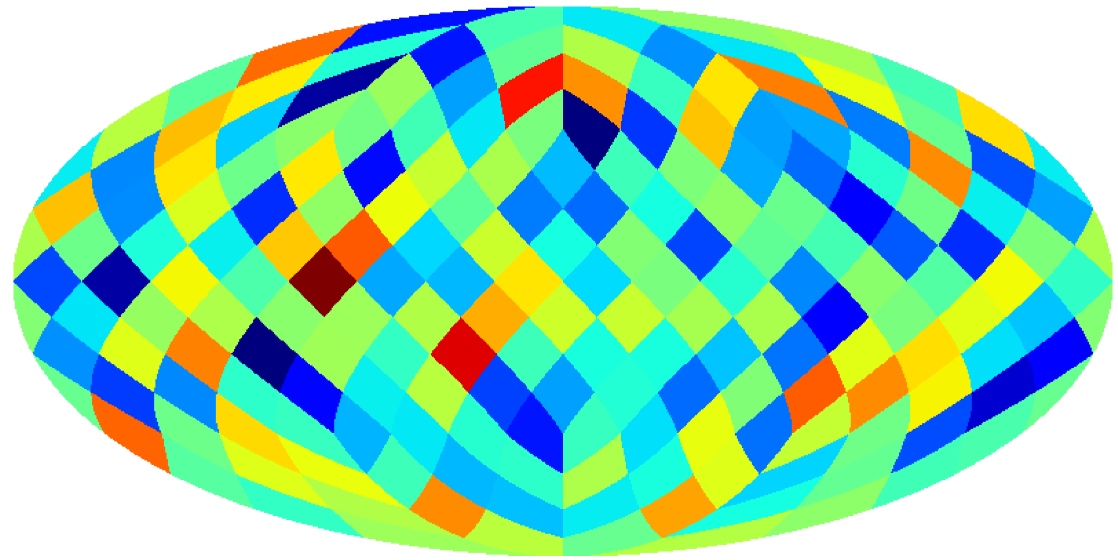

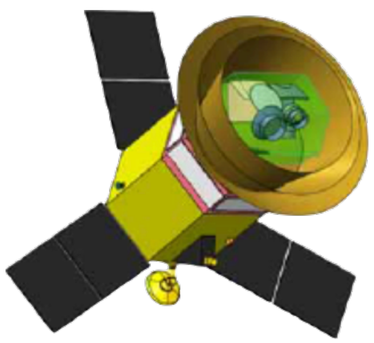

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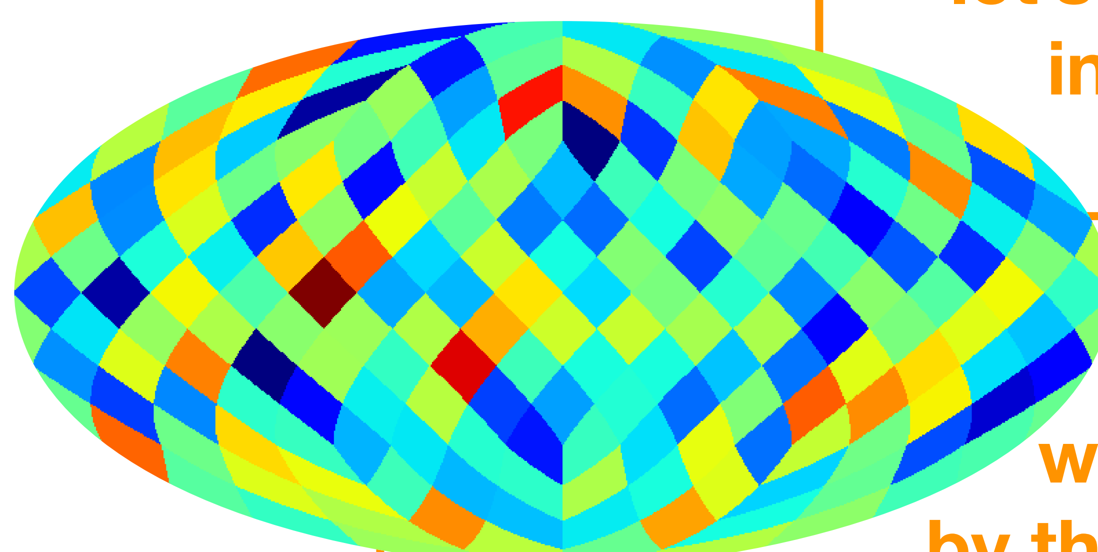
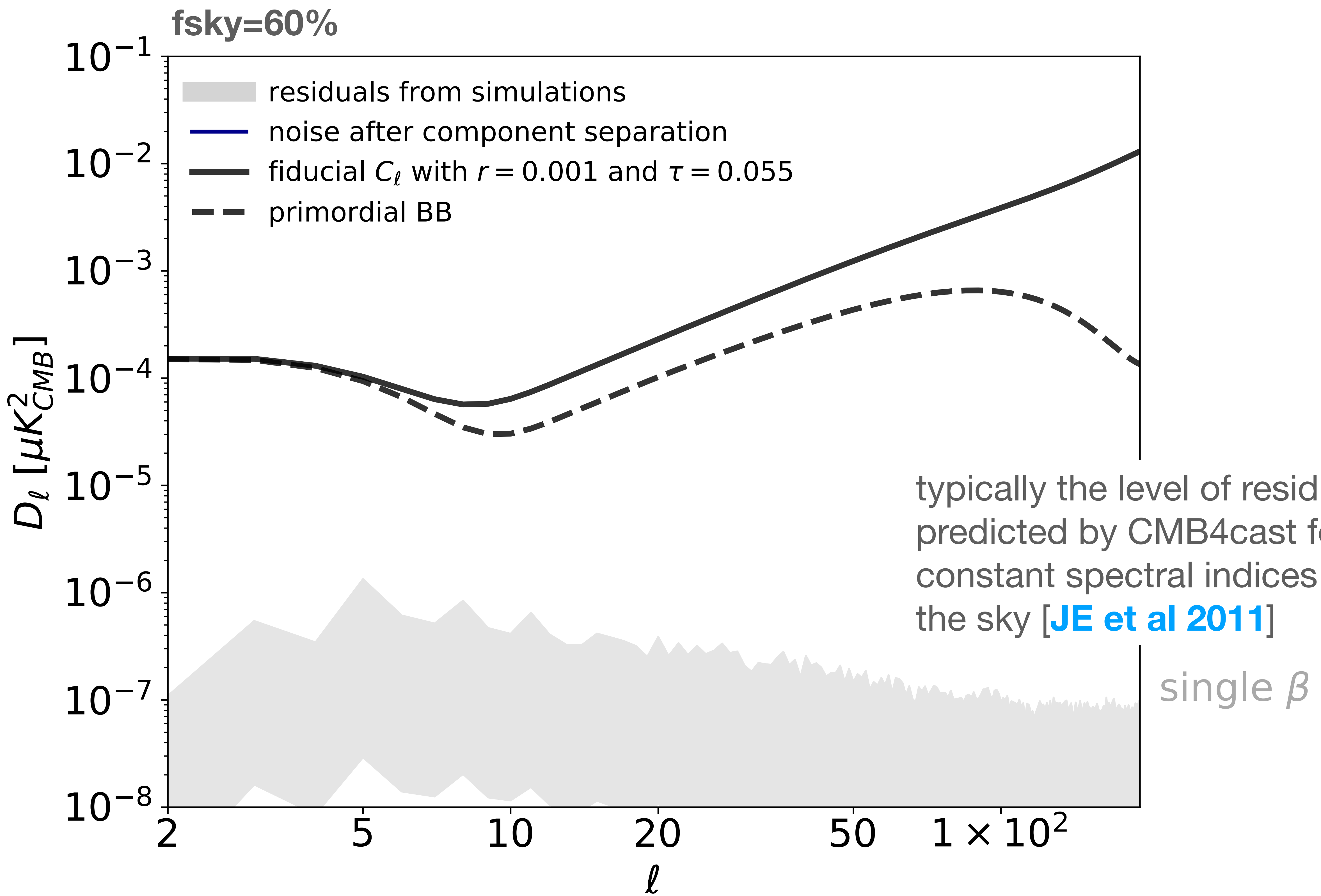
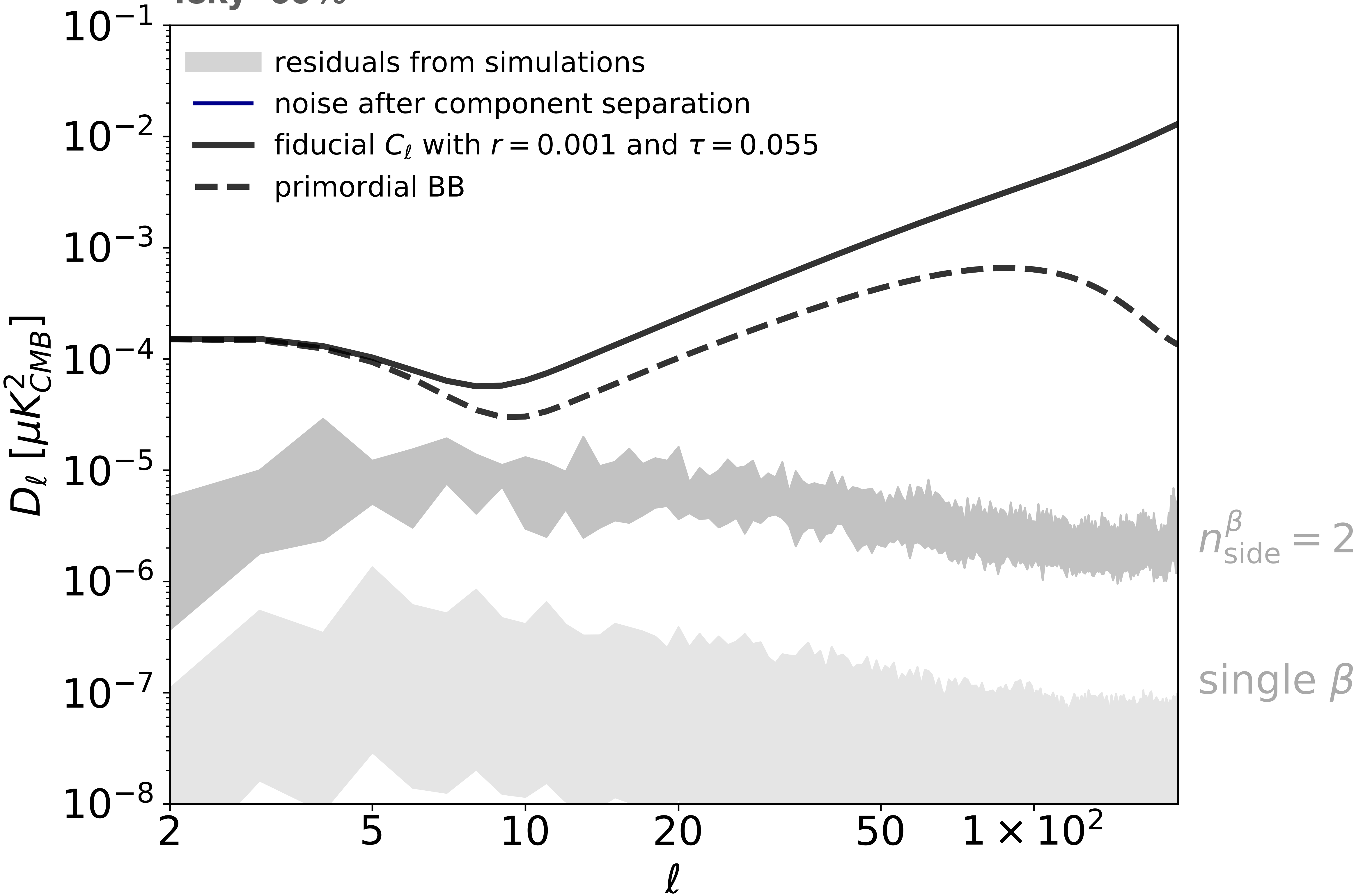


in this case, we are only limited by the statistical error bars on recovered spectral indices



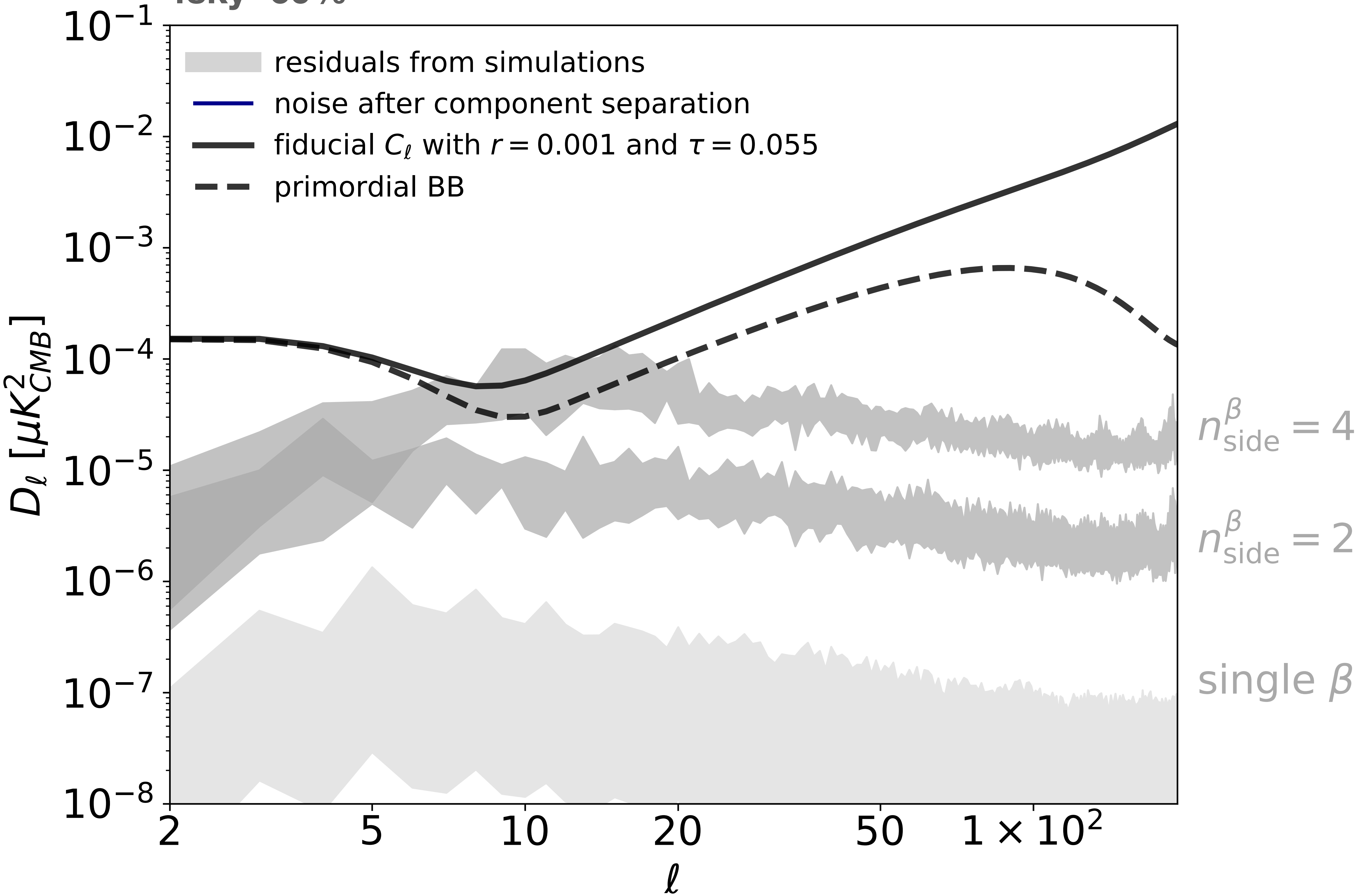
typically the level of residuals predicted by CMB4cast for constant spectral indices over the sky [**JE et al 2011**]

fsky=60%



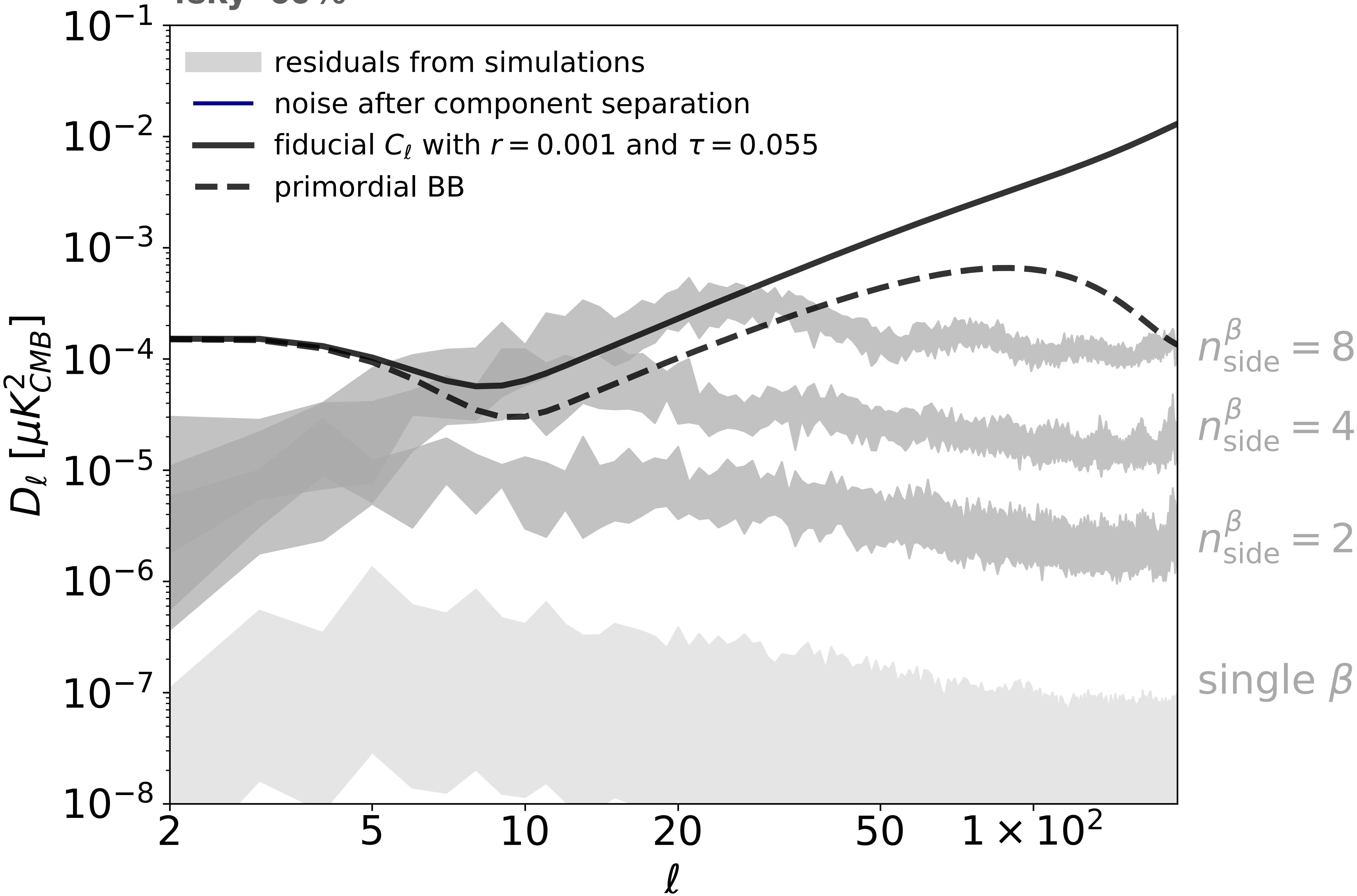
10^{-1}
10^{-2}
10^{-3}
10^{-4}
10^{-5}
10^{-6}
10^{-7}
10^{-8}
$D_\ell\ [\mu K^2_{CMB}]$
residuals from simulations
noise after component separation
fiducial C_ℓ with $r = 0.001$ and $\tau = 0.055$
primordial BB
2
5
10
20
50
1×10^2
ℓ
$n^{\beta}_{\rm side} = 2$
single β

fsky=60%

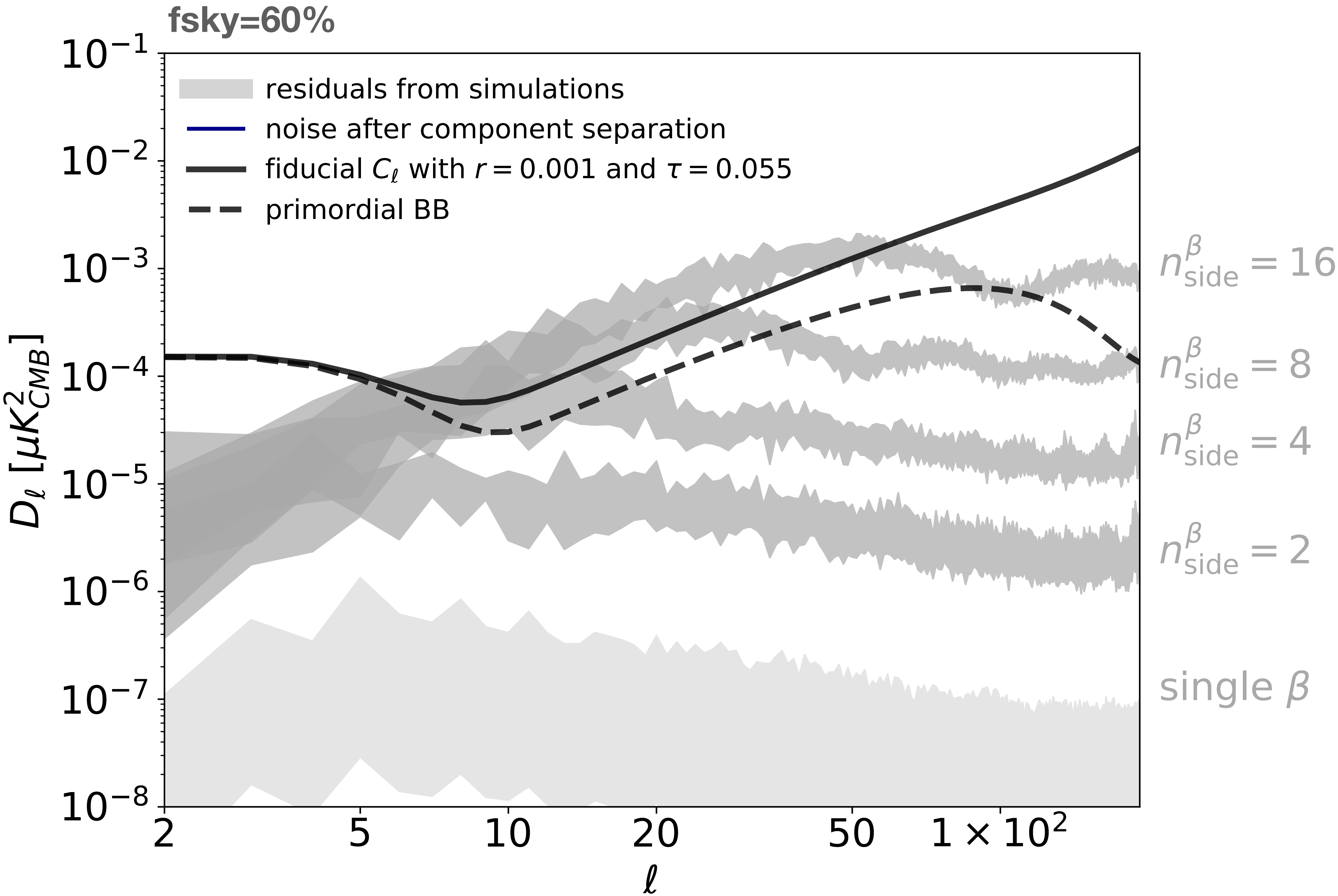


residuals from simulations
noise after component separation
fiducial C_ℓ with $r = 0.001$ and $\tau = 0.055$
primordial BB
$D_\ell\ [\mu K^2_{CMB}]$
ℓ
10^{-1}
10^{-2}
10^{-3}
10^{-4}
10^{-5}
10^{-6}
10^{-7}
10^{-8}
2
5
10
20
50
1×10^2
$n^\beta_{\mathrm{side}} = 4$
$n^\beta_{\mathrm{side}} = 2$
single β

fsky=60%

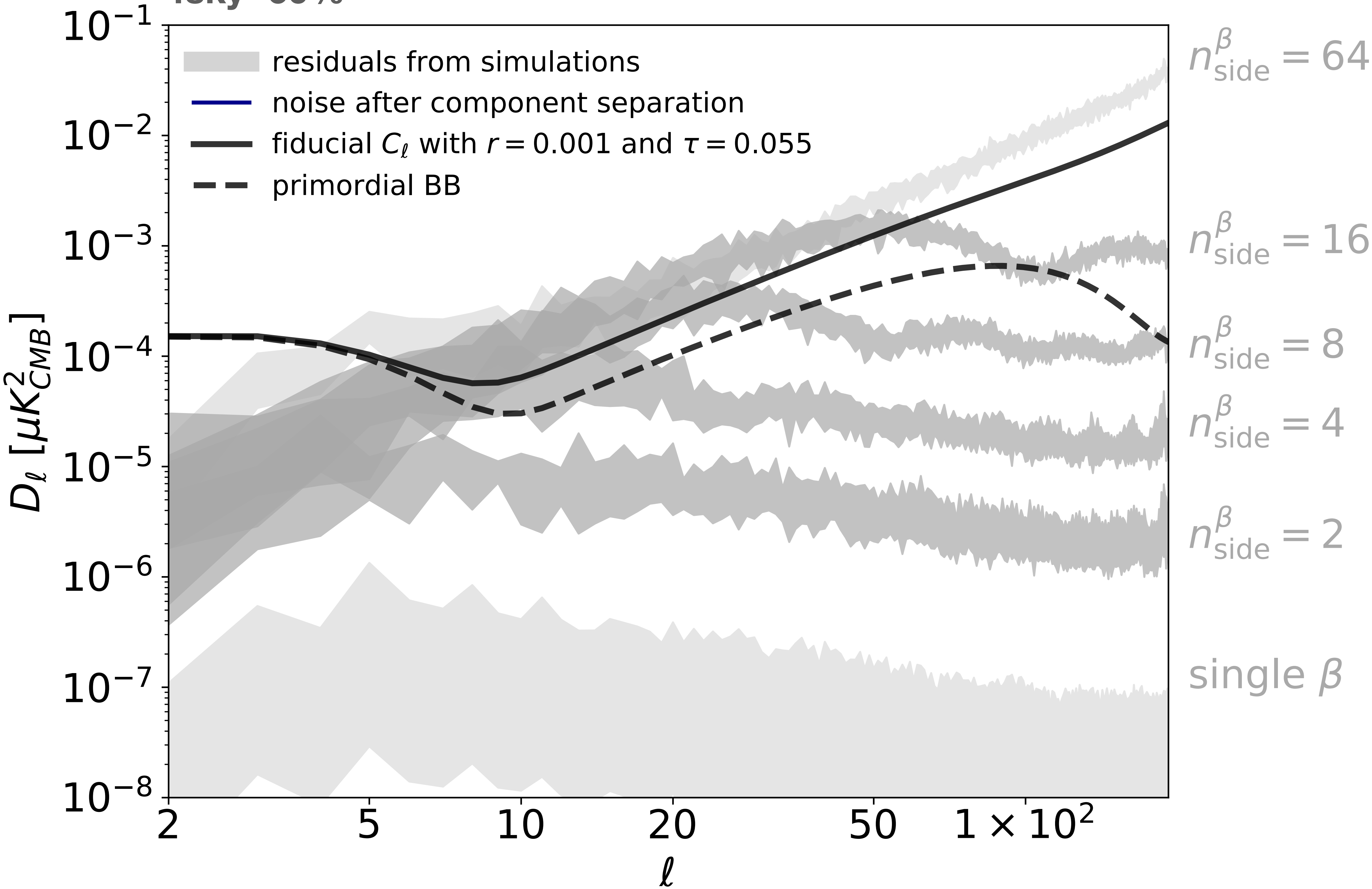


residuals from simulations
noise after component separation
fiducial C_ℓ with $r = 0.001$ and $\tau = 0.055$
primordial BB
10^{-1}
10^{-2}
10^{-3}
10^{-4}
10^{-5}
10^{-6}
10^{-7}
10^{-8}
$D_\ell\ [\mu K^2_{CMB}]$
2
5
10
20
50
1×10^2
ℓ
$n^\beta_{\rm side} = 8$
$n^\beta_{\rm side} = 4$
$n^\beta_{\rm side} = 2$
single β


fsky=60%
residuals from simulations
noise after component separation
fiducial C_ℓ with $r = 0.001$ and $\tau = 0.055$
primordial BB
$n_{side}^{\beta} = 16$
$n_{side}^{\beta} = 8$
$n_{side}^{\beta} = 4$
$n_{side}^{\beta} = 2$
single β
D_ℓ $[\mu K^2_{CMB}]$
ℓ
10^{-1}
10^{-2}
10^{-3}
10^{-4}
10^{-5}
10^{-6}
10^{-7}
10^{-8}
2
5
10
20
50
1×10^2

if not treated, these residuals can generate high bias, cf. Hervías-Caimapo et al, MNRAS, 2017

fsky=60%



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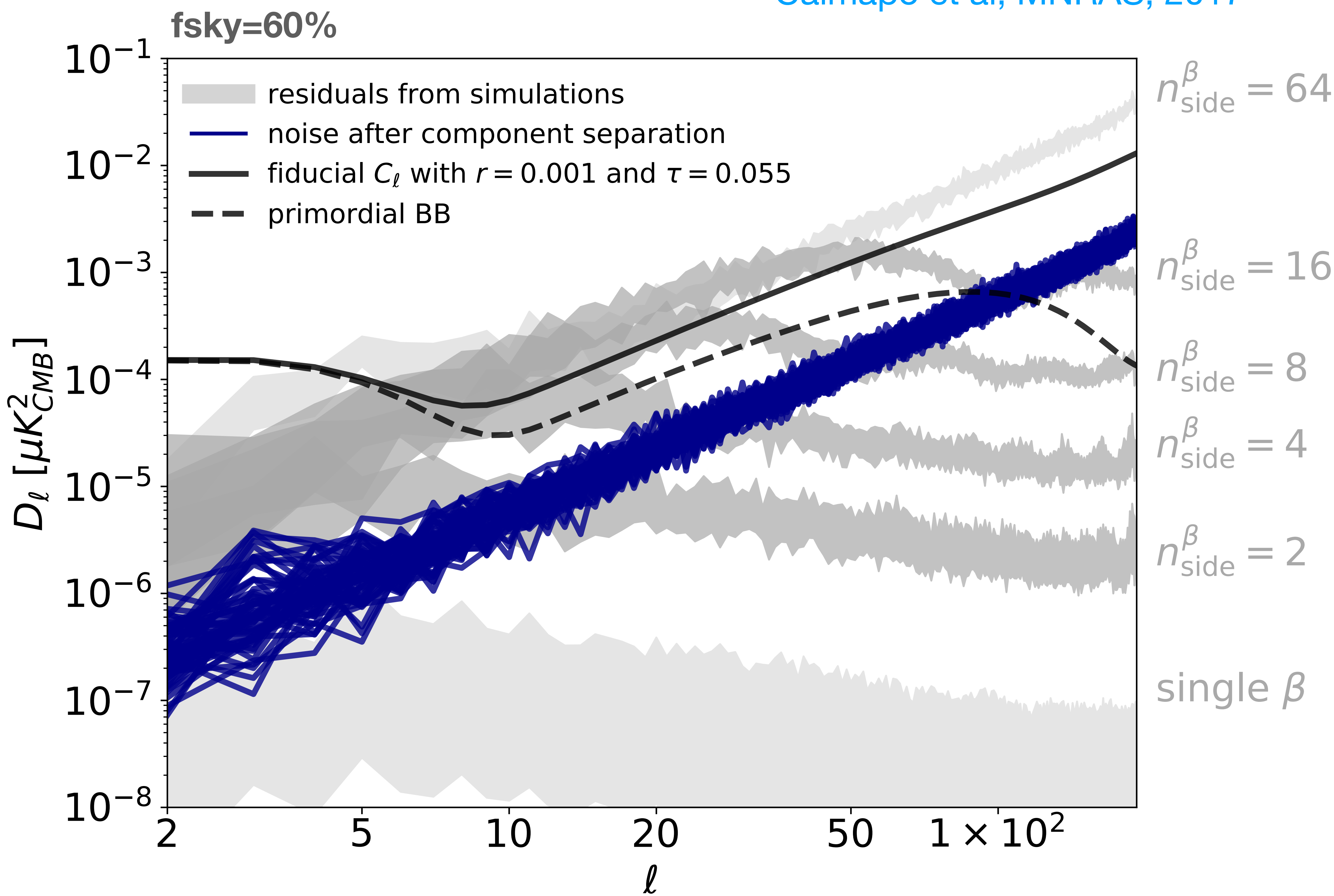
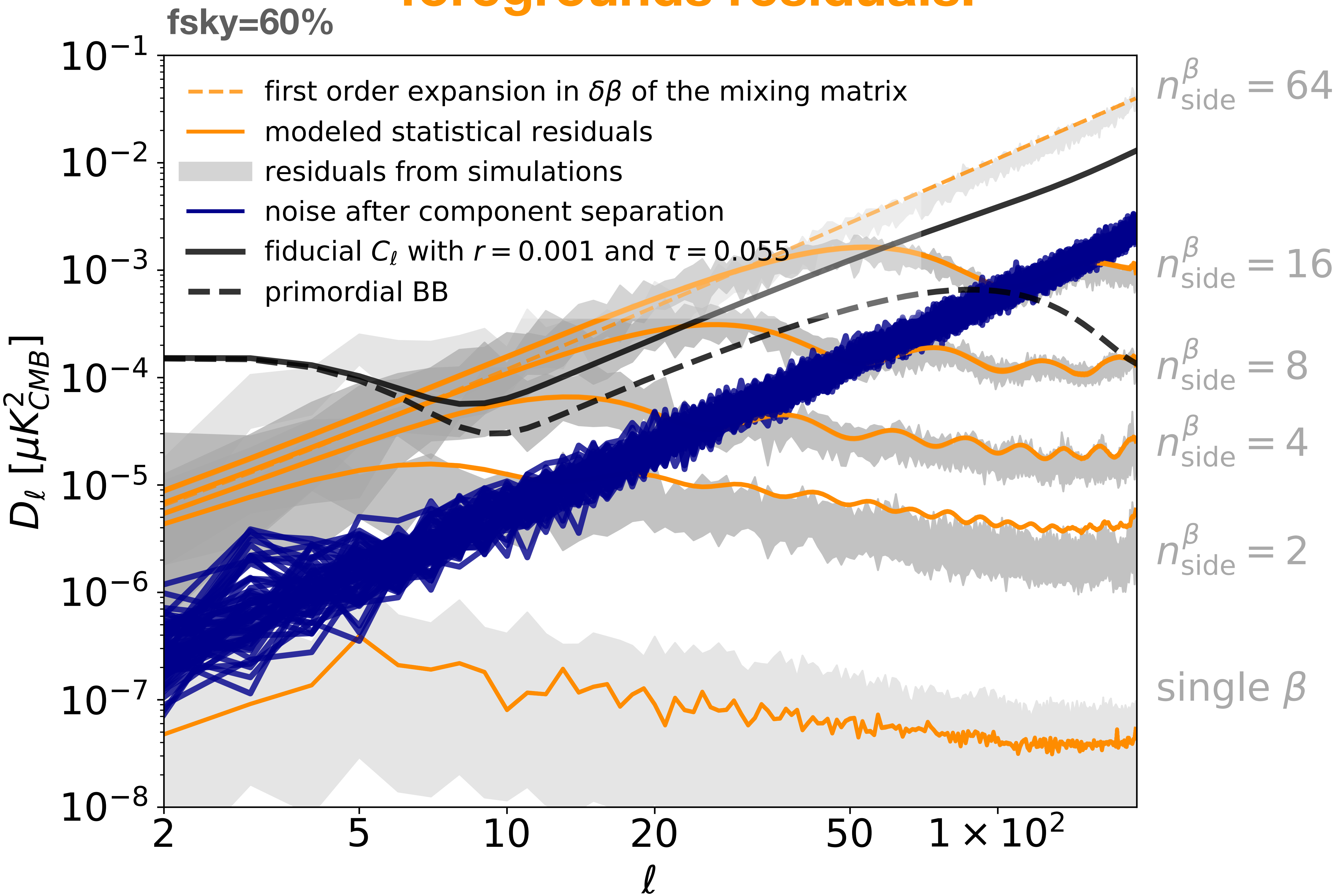


we can semi-analytically model these statistical foregrounds residuals!



JE et al, in prep

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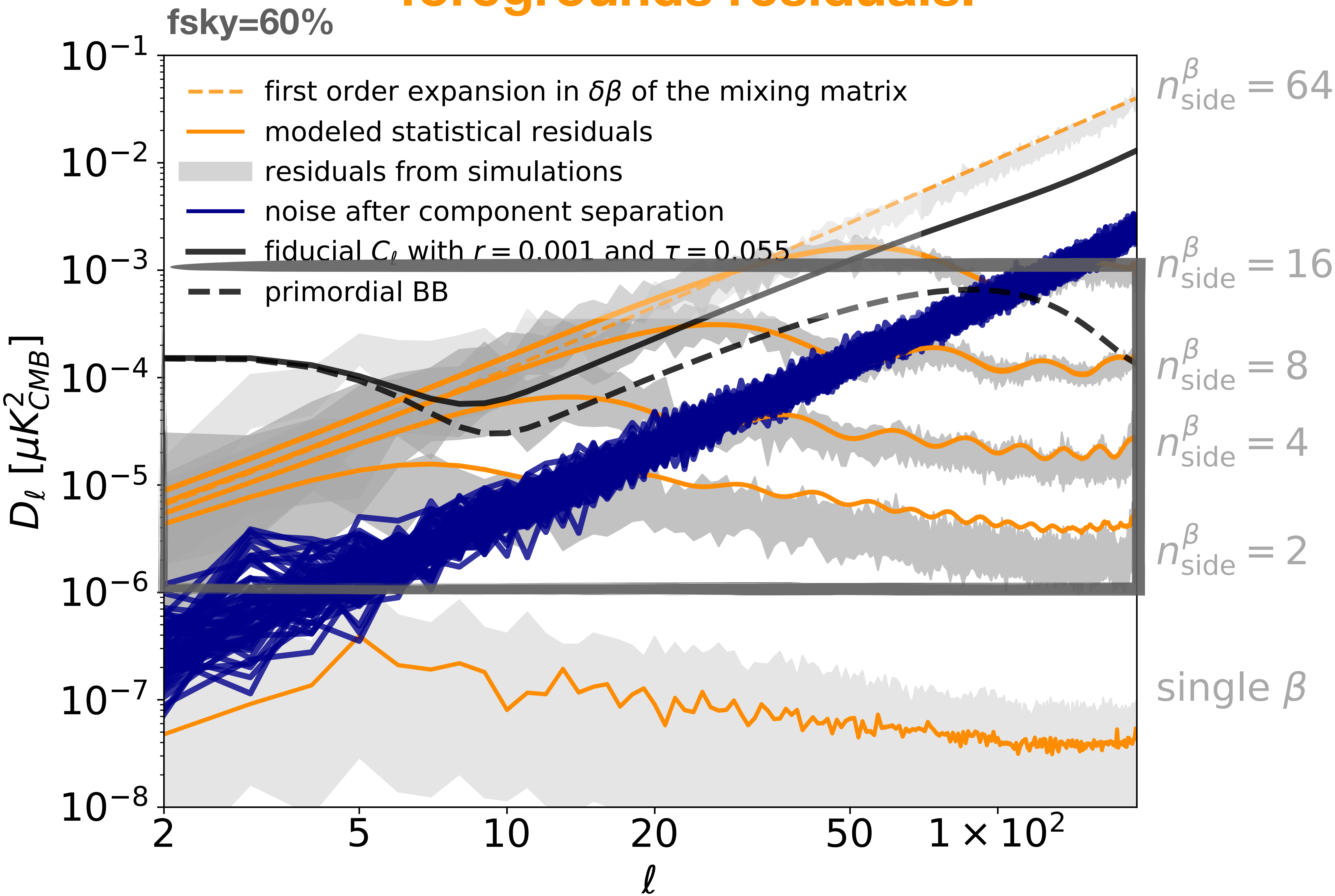
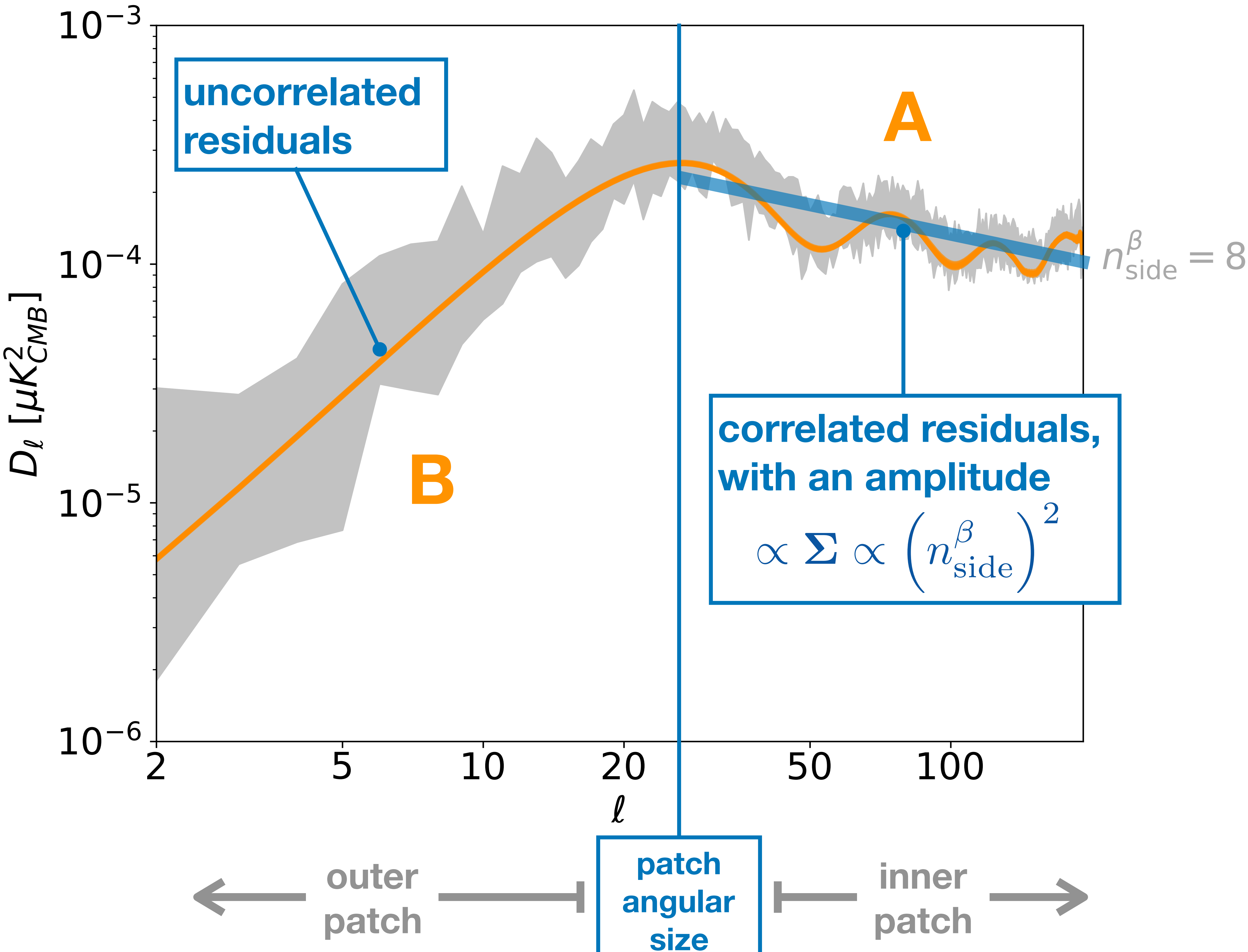
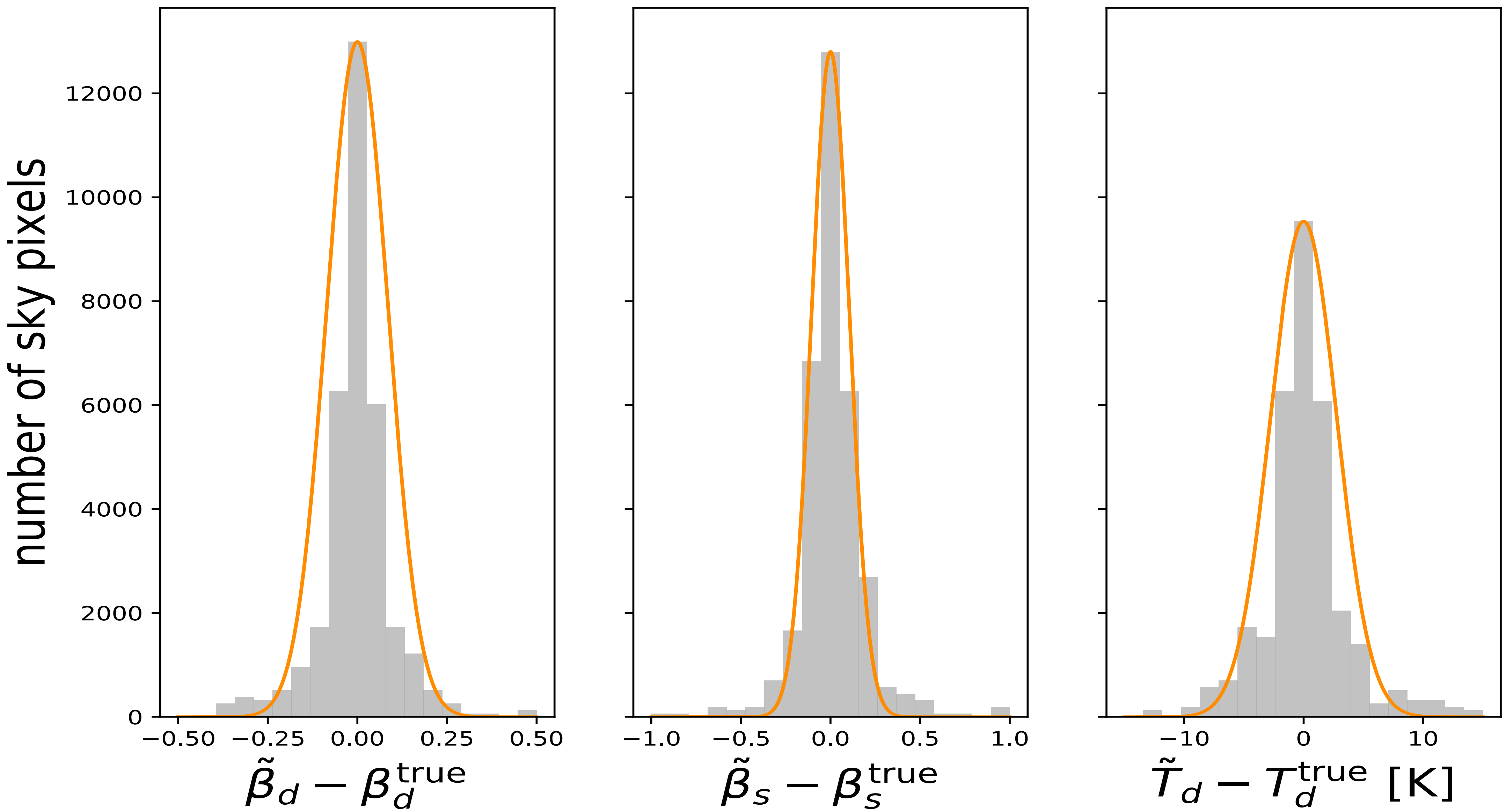


JE et al, in prep



JE et al, in prep

A — we can characterize and model the dispersion of the recovered spectral indices around their “true” values



$$\left[\mathbf{\Sigma}^{-1}_{\rm analytic}\right]_{\beta\beta'} \equiv \left\langle \left.\frac{\partial^2\mathcal{L}}{\partial\beta_i\partial\beta_j}\right|_{\beta\beta'} \right\rangle_{\rm CMB+noise} \simeq -{\rm tr}\left(\left[\left.\frac{\partial\mathbf{A}}{\partial\beta_i}\right|^T_{\beta}\mathbf{N}^{-1}\mathbf{A}\left(\mathbf{A}^T\mathbf{N}^{-1}\mathbf{A}\right)^{-1}\mathbf{A}^T\mathbf{N}^{-1}\left.\frac{\partial\mathbf{A}}{\partial\beta_j}\right|_{\beta'} - \left.\frac{\partial\mathbf{A}}{\partial\beta_i}\right|^T_{\beta}\mathbf{N}^{-1}\left.\frac{\partial\mathbf{A}}{\partial\beta_j}\right|_{\beta'}\right]\sum_p \mathbf{s}_p(\mathbf{s}_p)^T\right)$$

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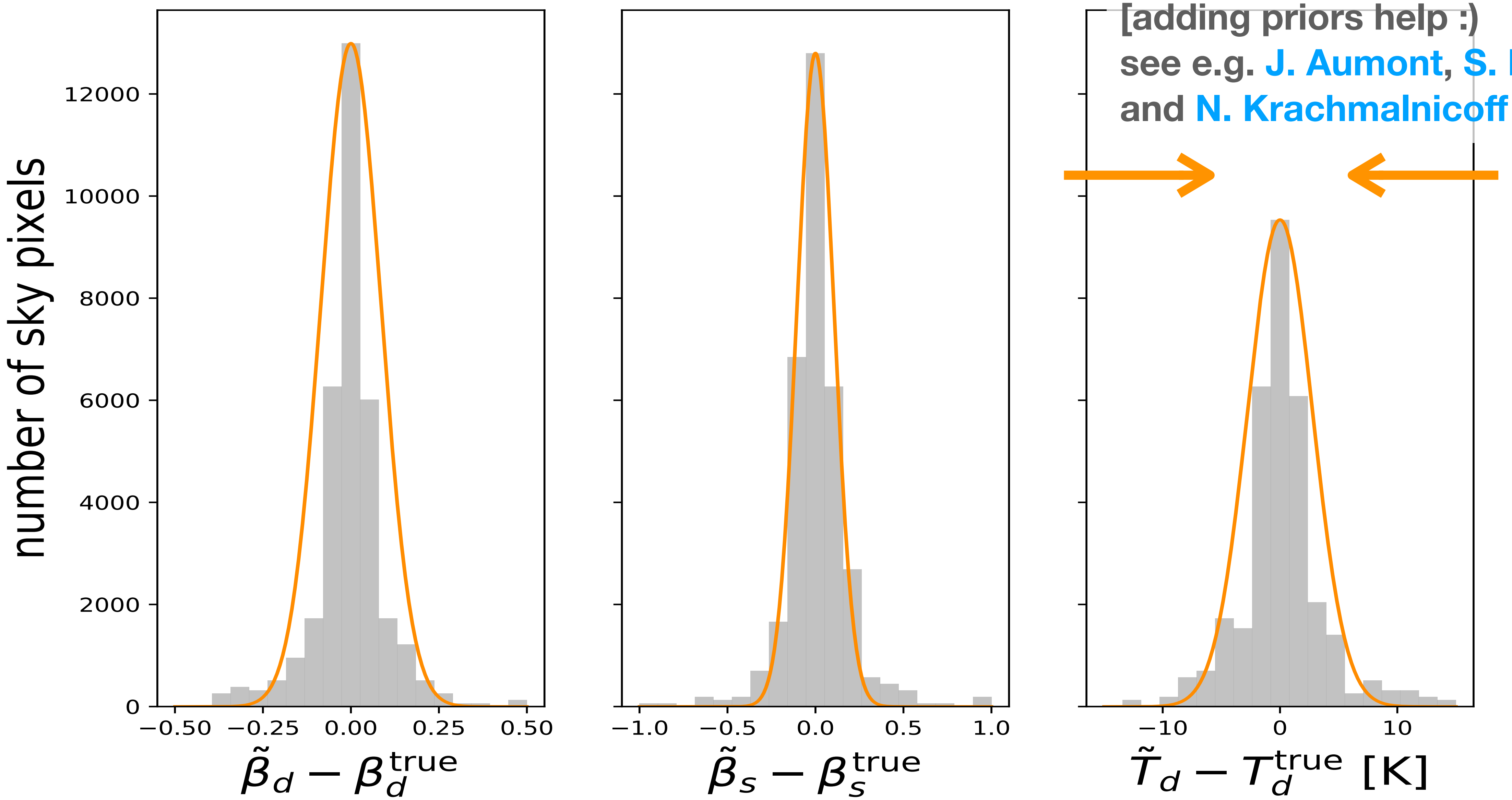

[adding priors help :) see e.g. J. Aumont, S. Hanany and N. Krachmalnicoff talks]

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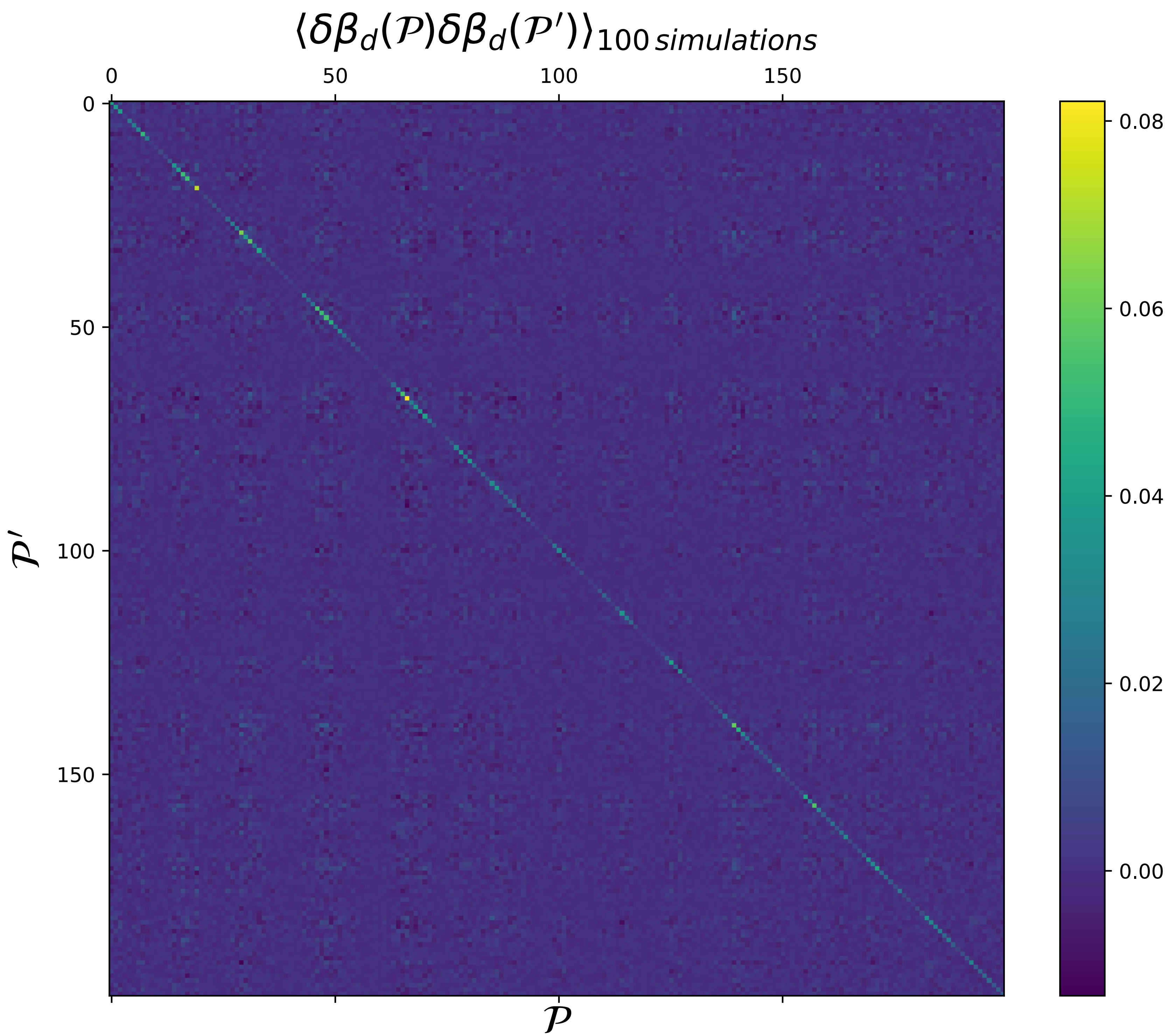
B — we see a decorrelation of statistical foregrounds residuals on large angular scales

$$\delta\beta_d \equiv \tilde{\beta}_d - \beta_d^{\rm true}$$

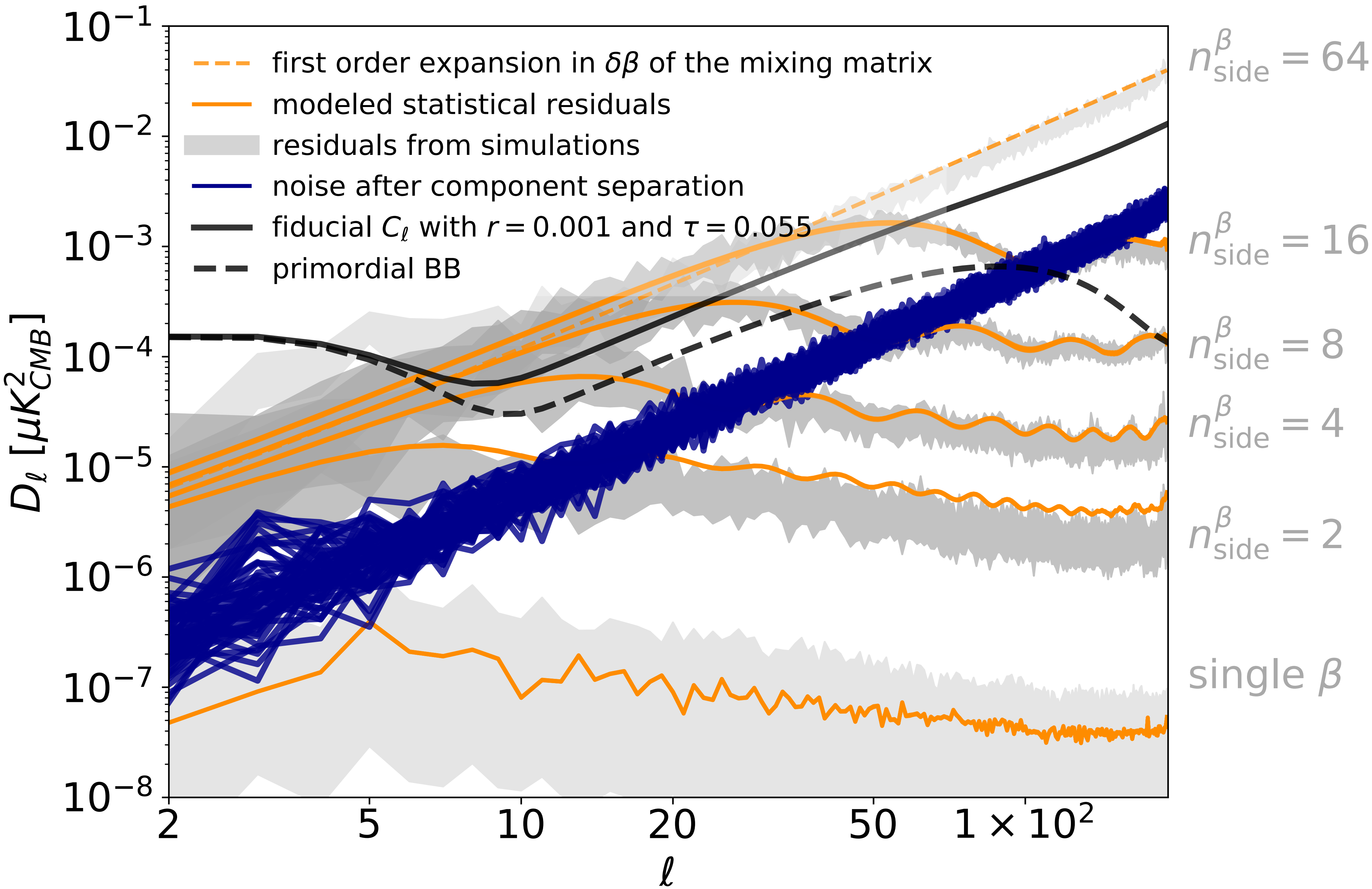


JE et al, in prep

semi-analytical modeling of statistical foregrounds residuals

$$C_\ell^{\boldsymbol{\Sigma}} \equiv \sum_{\mathcal{P}} \sum_{i,j,k,l} \boldsymbol{\Sigma}_{ij}^{\mathcal{P}} \boldsymbol{\kappa}_{kl}^{ij,\,\mathcal{P}} C_\ell^{kl,\,\mathcal{P}}$$

computed from data



JE et al, in prep

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JE et al, in prep

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computed from data

$$\mathbf{C}_\ell^{\rm CMB} \equiv C_\ell^{\rm prim,\,BB}(r) + C_\ell^{\rm lens,\,BB} + N_\ell + C_\ell^{\mathbf{\Sigma}}$$

$$\Big\langle -2\log(\mathcal{L}_{\rm cosmo})\Big\rangle_{\rm CMB+noise} = \sum_\ell \frac{2\ell+1}{2} f_{\rm sky}\left(\mathbf{C}_\ell^{-1}\mathbf{D}_\ell + \log\left[\det(\mathbf{C})\right]\right)$$

JE et al, in prep

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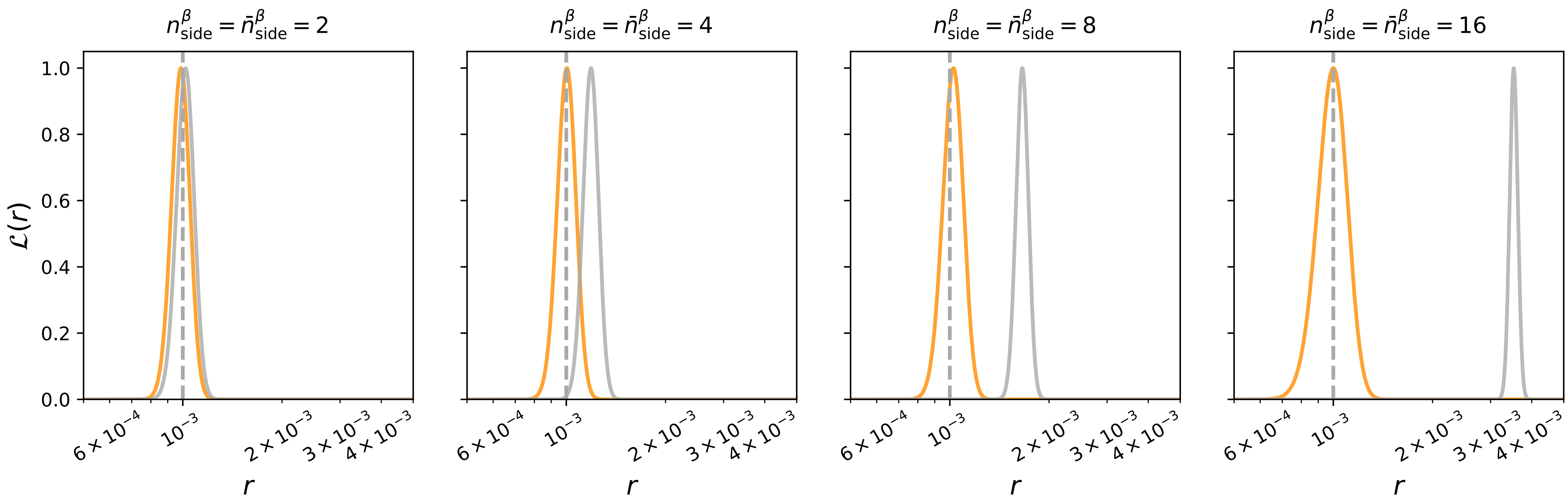

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About more “complex” foregrounds

- sim#1: foregrounds SEDs varying on a resolution (nside=64) >> than the patch size used for the analysis (2<nside<8) ➔ “averaging” effect
- sim#2: a2d6s3 PySM model ➔ polarized AME, dust following Vansyngel et al (2017) and curved synchrotron

JE et al, in prep

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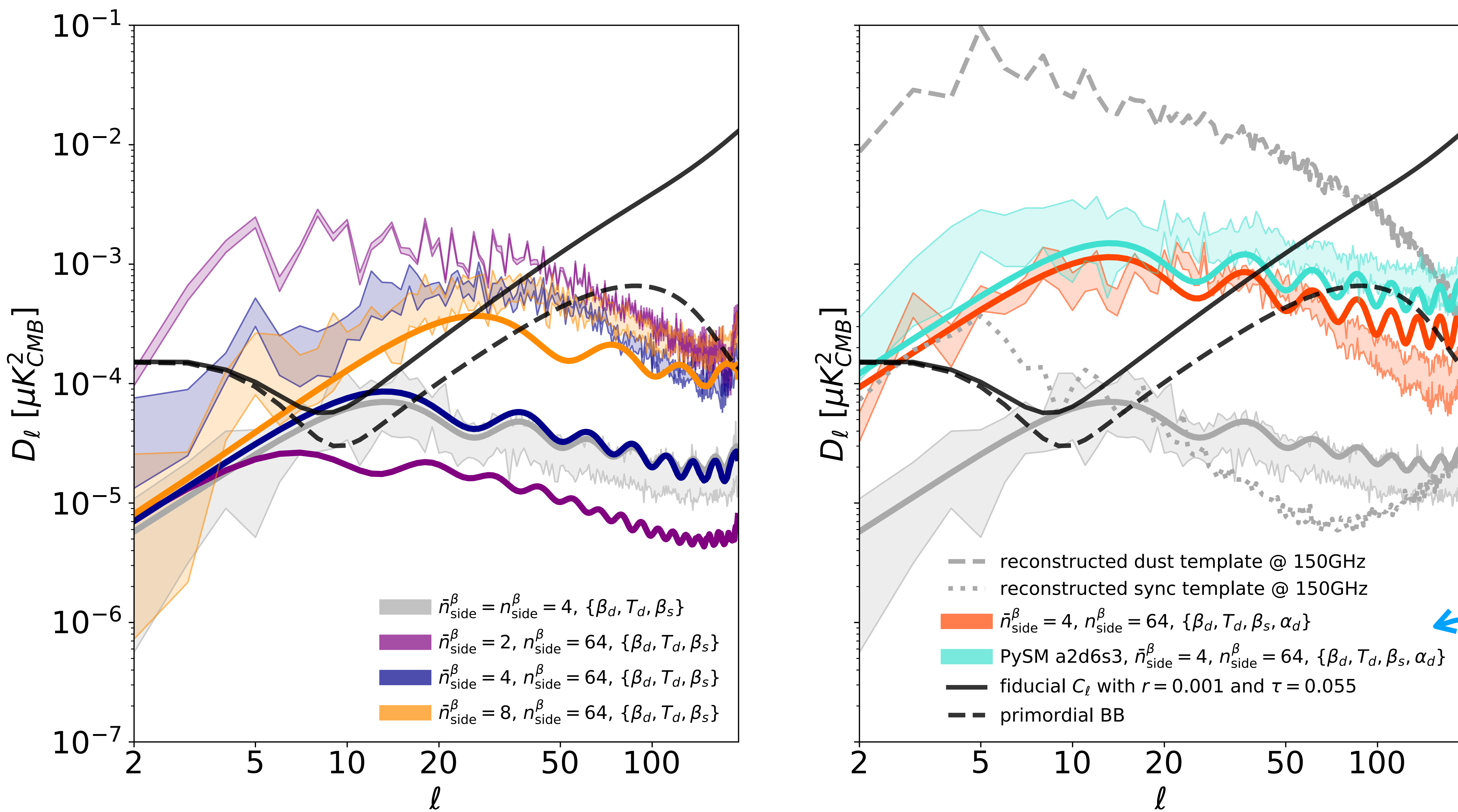

[see A. Mangilli and A. Rotti talks and Chluba et al 2018]

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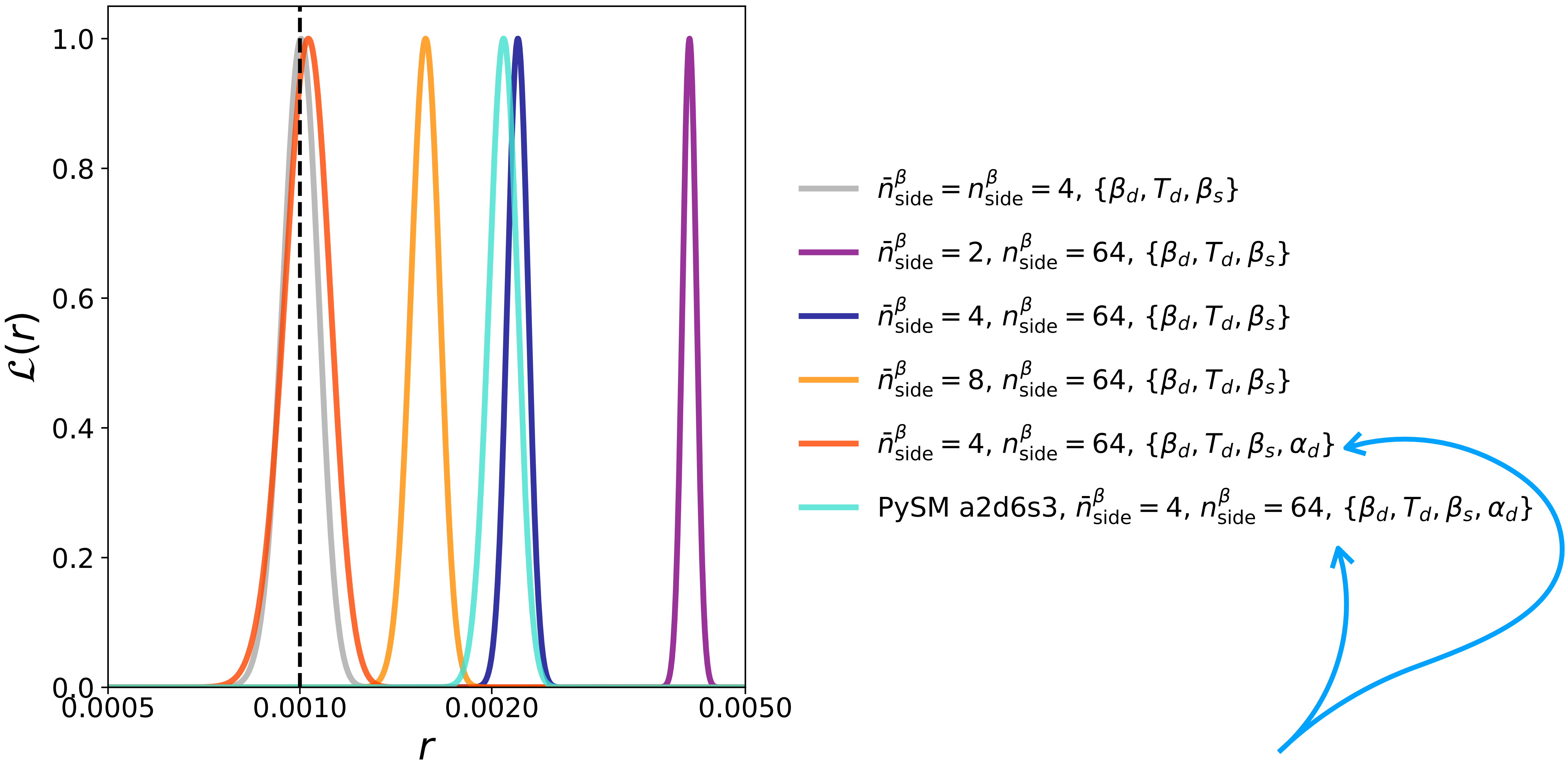

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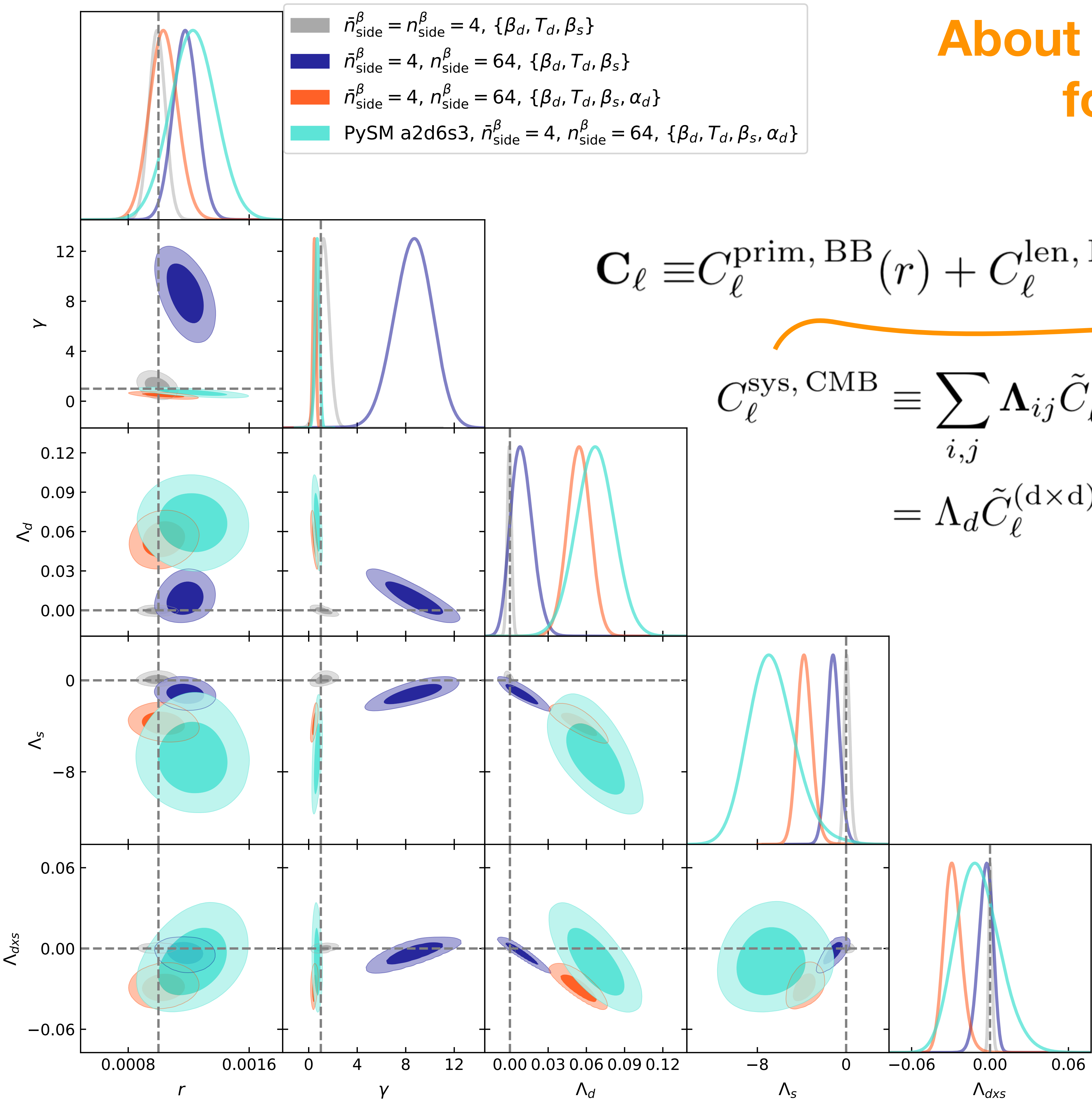

$$\mathbf{C}_\ell \equiv C_\ell^{\rm prim,\,BB}(r) + C_\ell^{\rm len,\,BB} + N_\ell + \gamma\, C_\ell^{\boldsymbol{\Sigma}} + C_\ell^{\boldsymbol{\Lambda}}$$

$$C_\ell^{\rm sys,\,CMB} \equiv \sum_{i,j} \boldsymbol{\Lambda}_{ij} \tilde{C}_\ell^{(i\times j)}$$

$$= \Lambda_d \tilde{C}_\ell^{(\rm d\times d)} + \Lambda_s \tilde{C}_\ell^{(\rm s\times s)} + \Lambda_{d\times s} \tilde{C}_\ell^{(\rm d\times s)}$$

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Conclusions

- **CMB4cast** and **xForecast** are great tools to address specific questions, e.g. the optimization of a focal plane, average performance of an instrument in the case of simple modeling of the SEDs, etc.

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- **Multipatch** approach tries to add the minimum and necessary degrees of freedom to the pixel-based parametric approach in order to deal with these spatial variations
- We show that including an **estimate of statistical foregrounds residuals** in the cosmological likelihood is important to get an unbiased estimate of e.g. tensor-to-scalar ratio, particularly when r ~ 0.001
- We show that adding **moments** to the spectral fit allows the parametric approach to handle spatial averaging of SEDs, and that an extra marginalization of the cosmological likelihood over **systematic leakage** is possible
- There are ways to **lower statistical foregrounds residuals** while keeping the systematic ones under control …

how many moments are necessary?

what are the necessary degrees of freedom?

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what are the necessary degrees of freedom?

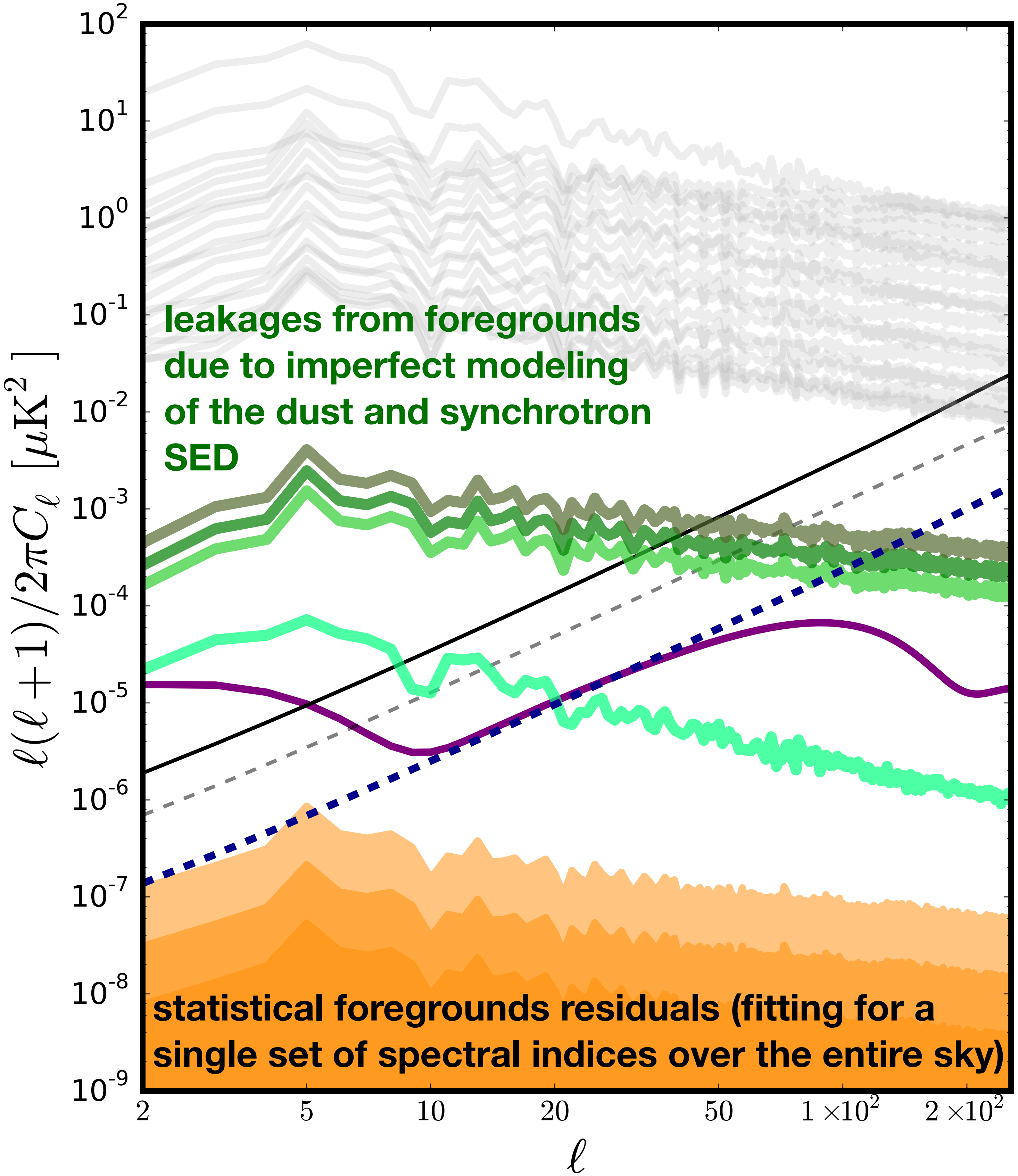
towards an adaptative multipatch?

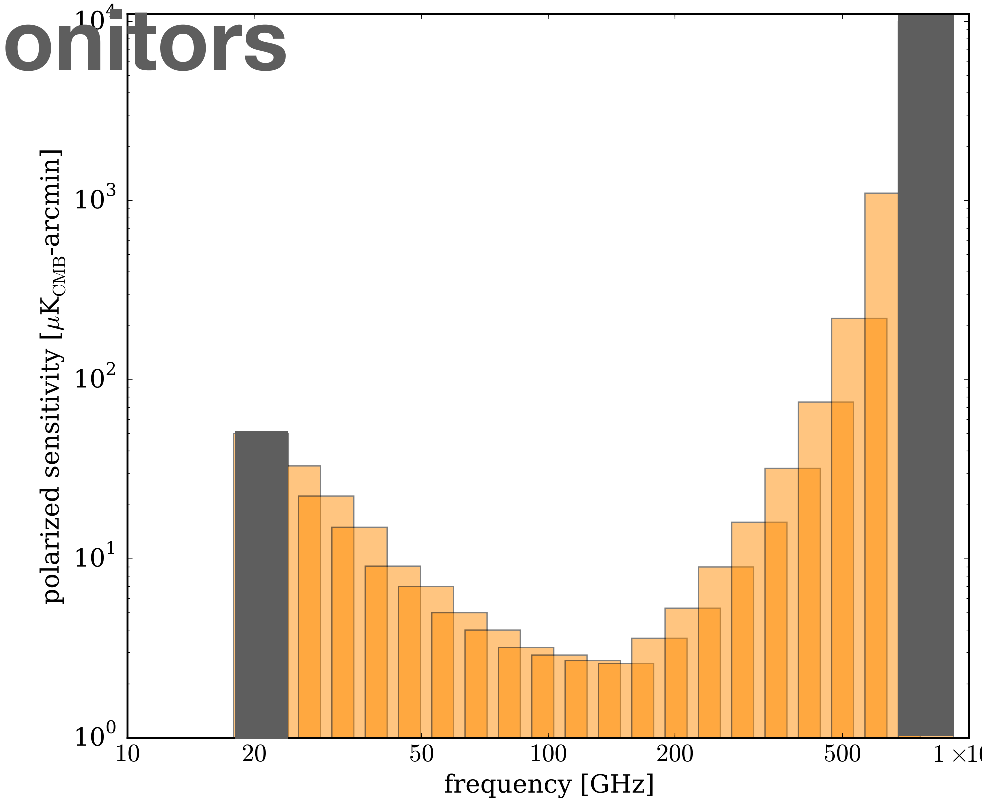
STATISTICAL error bars on spectral parameters ⟷ **SYSTEMATIC error bars on spectral parameters**

finding iteratively independent regions, independently for each spectral index, such that spectral indices can be assumed almost constant → with spatial variations Δβ α σ(β), the statistical error on spectral indices.

BACKUP

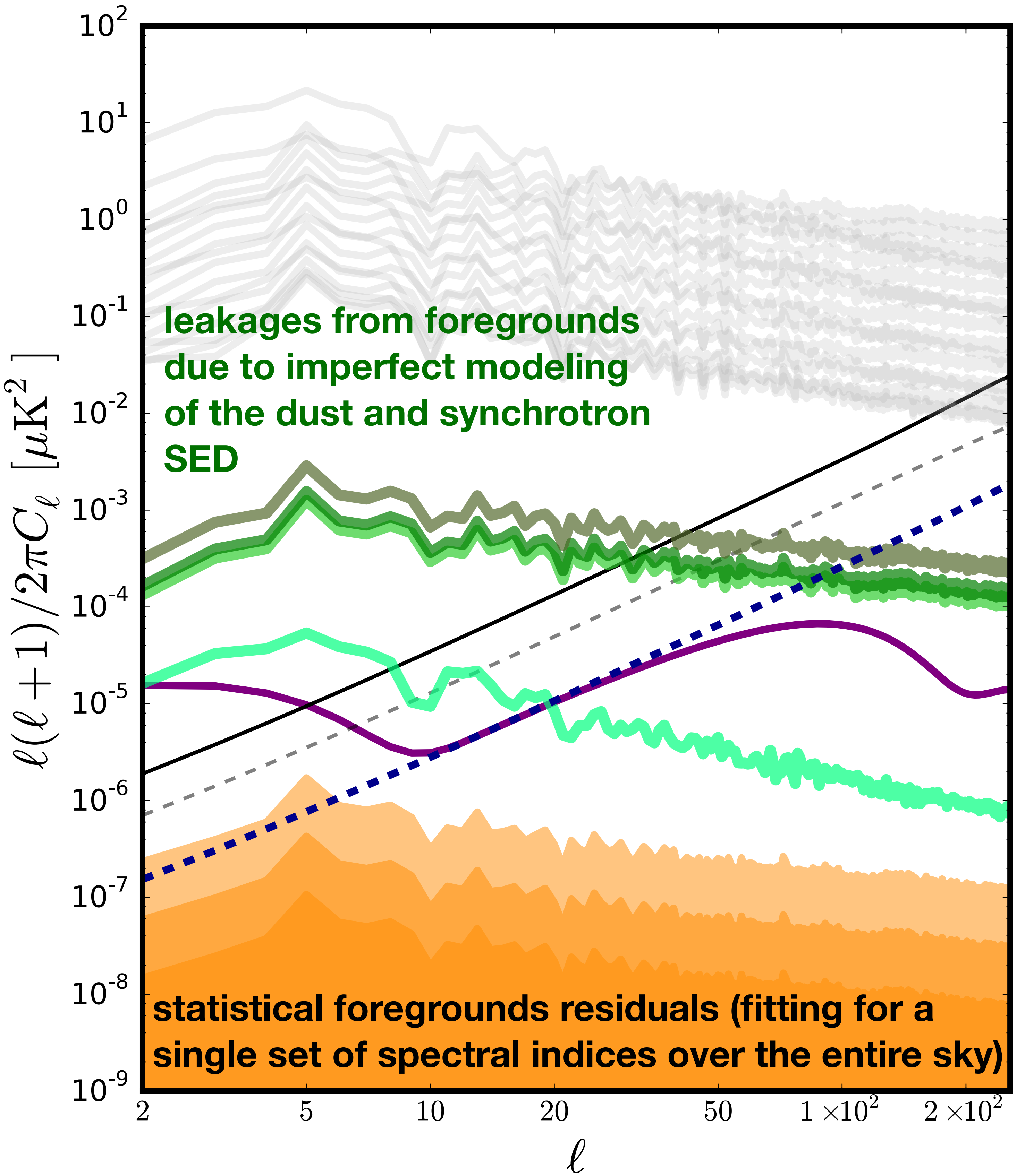
Removing 1 synchrotron and 1 dust monitors

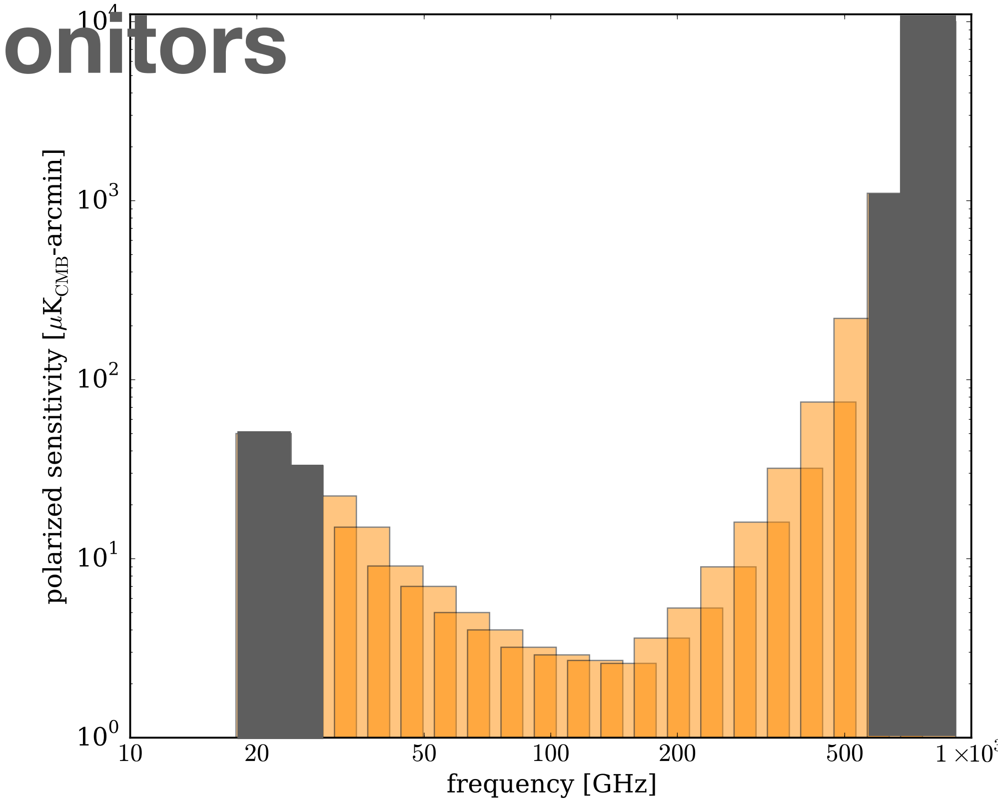




all frequency bands
- 21GHz - 800GHz
60% of the sky

Removing 2 synchrotron and 2 dust monitors

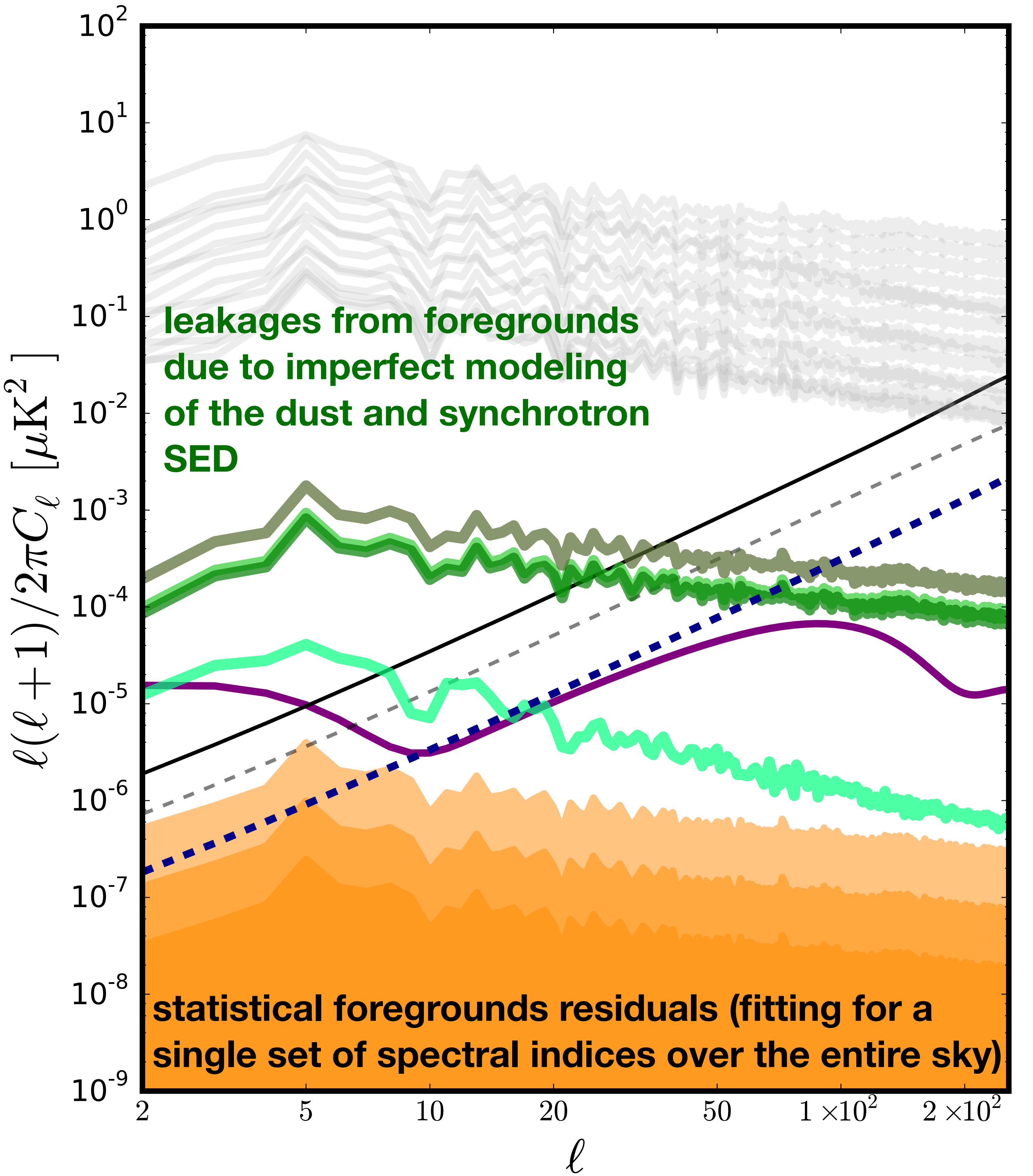


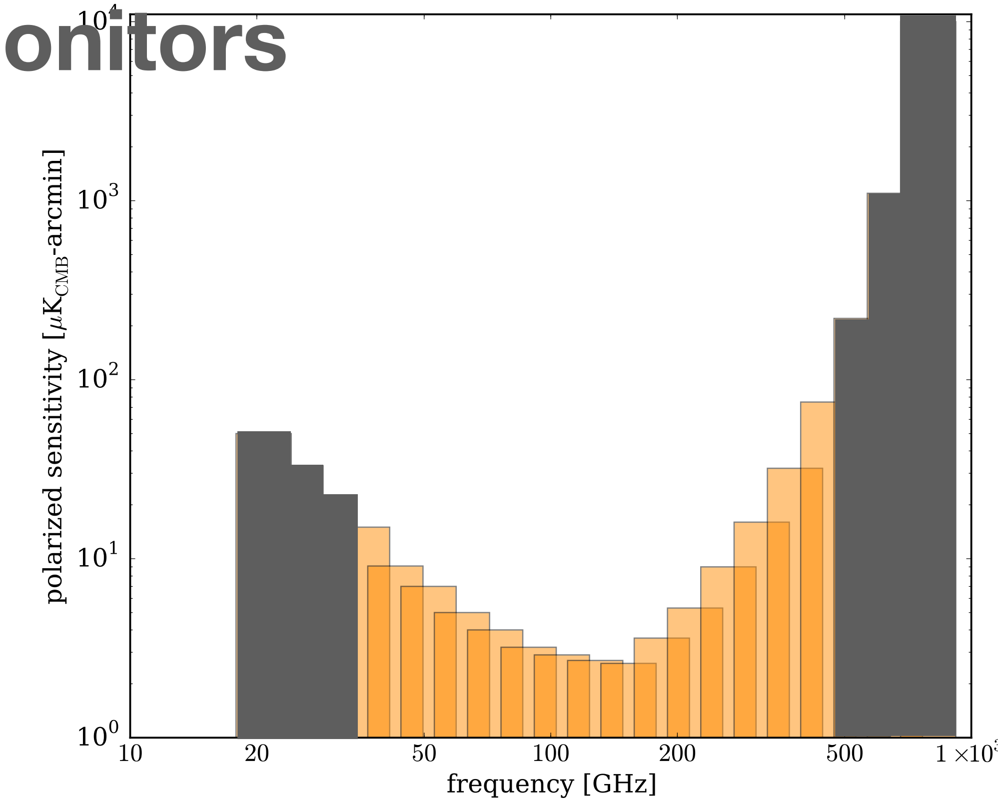


all frequency bands
- **21GHz - 25GHz**
- **665GHz - 800GHz**

60% of the sky

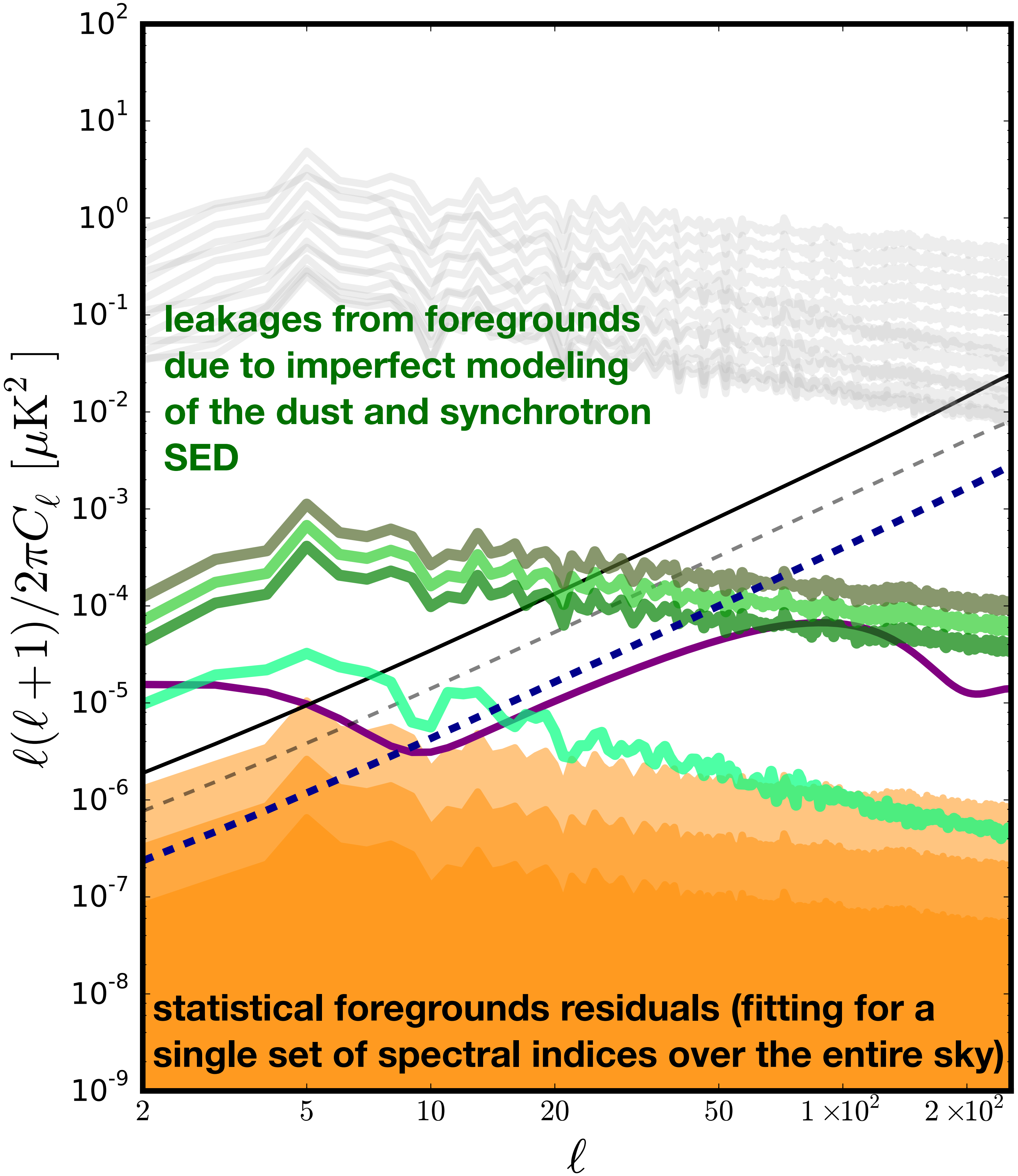
Removing 3 synchrotron and 3 dust monitors

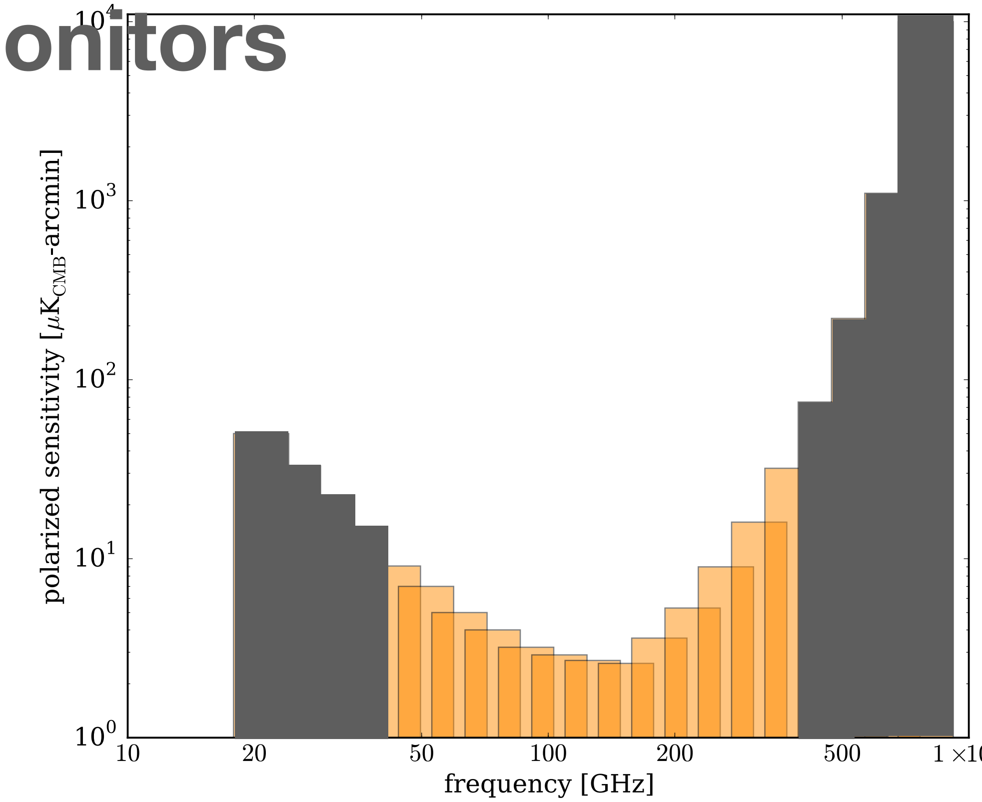




all frequency bands
-21GHz -25GHz -30GHz
-555GHz -665GHz -800GHz
60% of the sky

Removing 4 synchrotron and 4 dust monitors





all frequency bands
-21GHz -25GHz -30GHz -35GHz
-462GHz -555GHz -665GHz -800GHz
60% of the sky