Theory uncertainties with theory nuisance parameters and α_S from the $Z\, p_T$

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CERN

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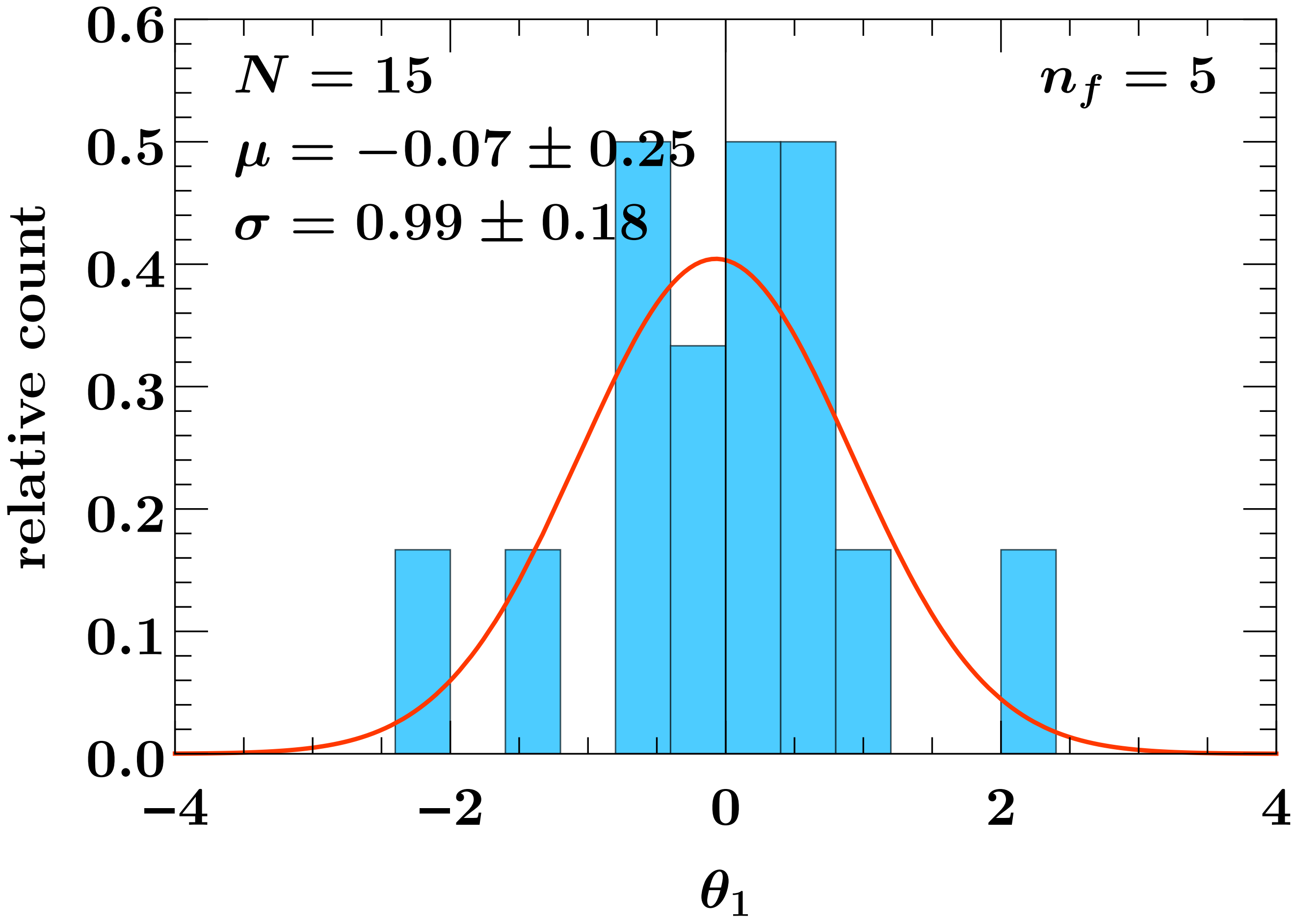
TNPs for Boundary Conditions

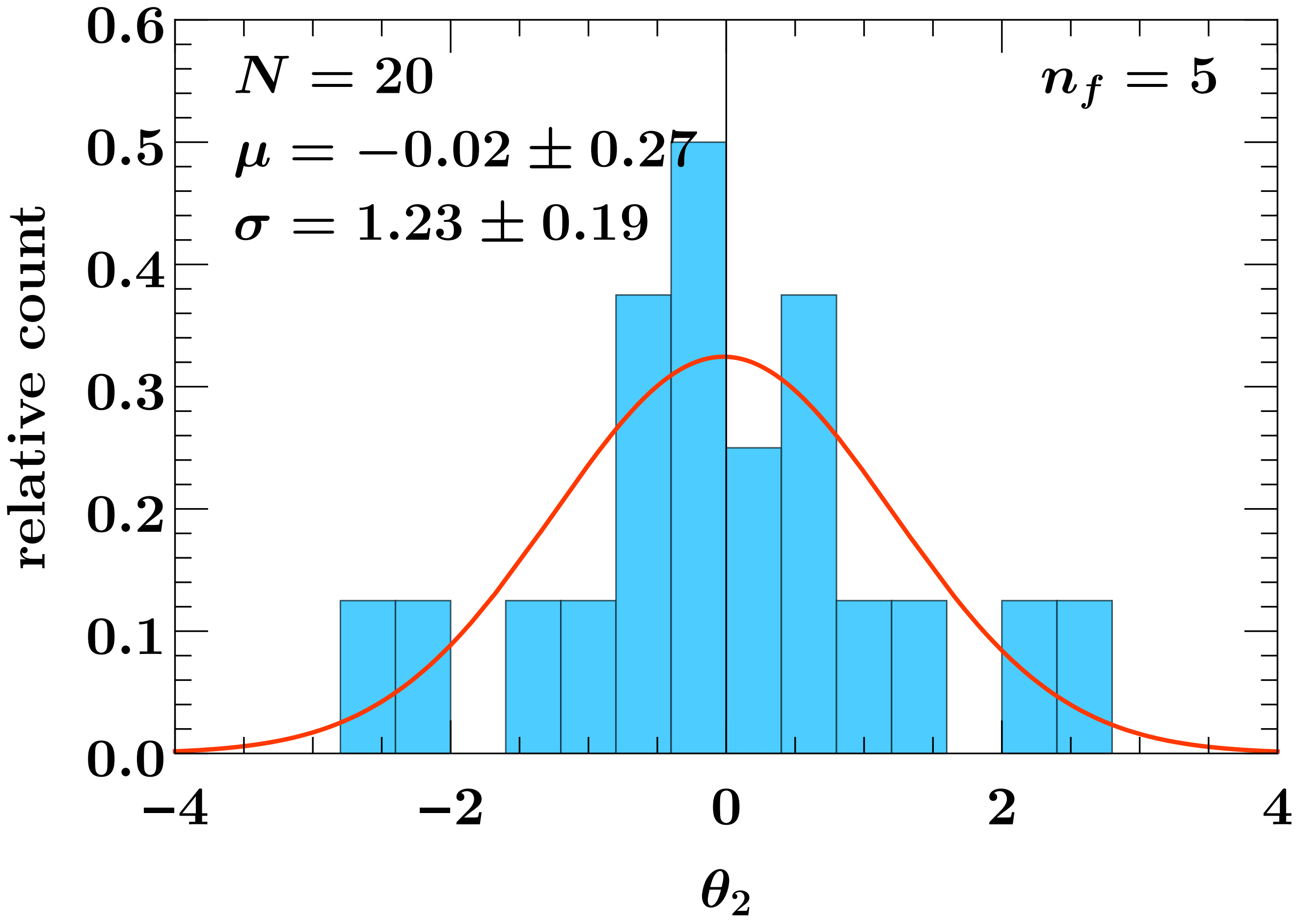
Estimate of $\theta_n^F(n_f)$ from a generic sample of known and independent series

$$F_n(\theta_n) = 4C_r(4C_A)^{n-1}(n-1)!\,\theta_n^F(n_f)$$

1 loop



2 loop



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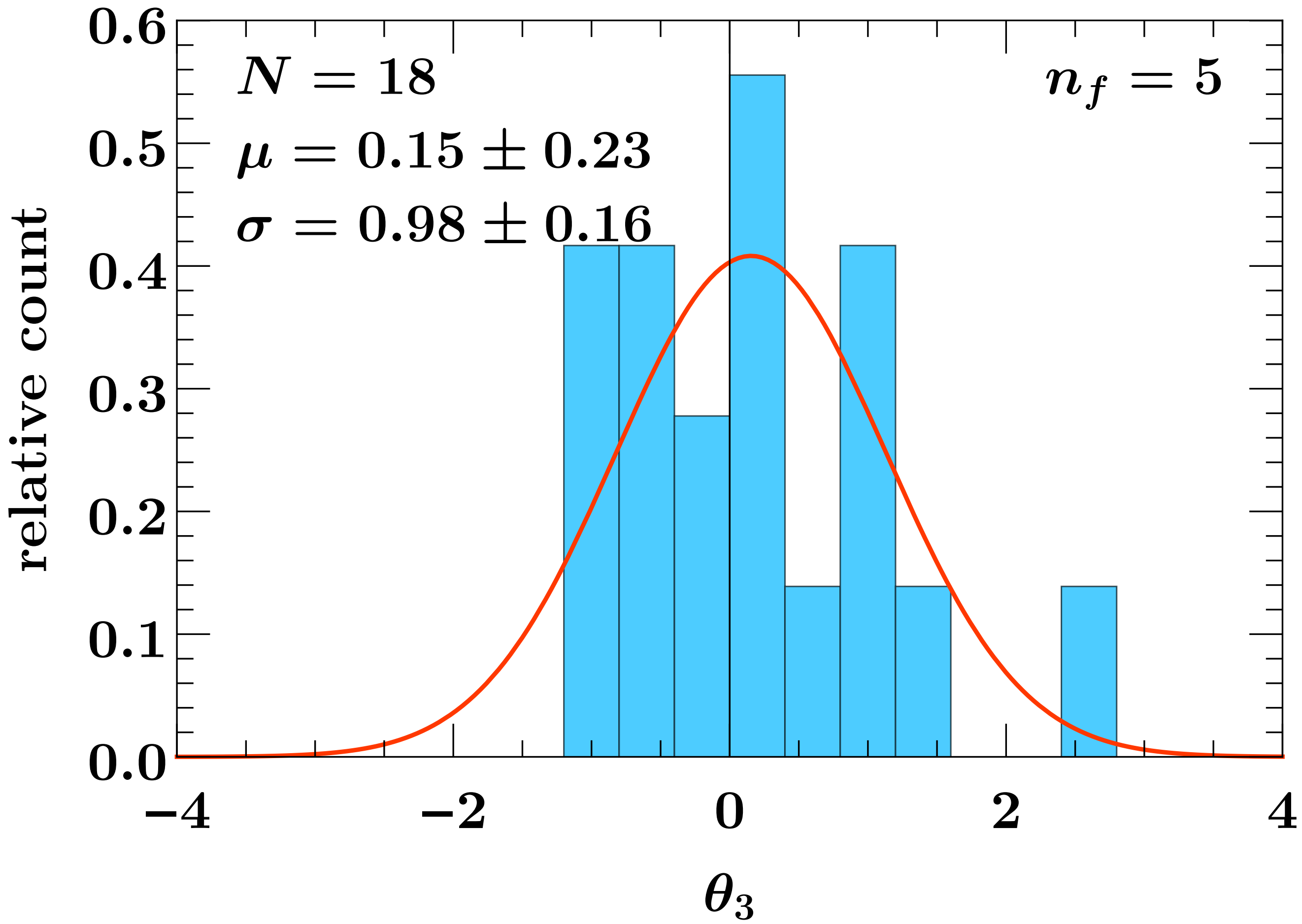
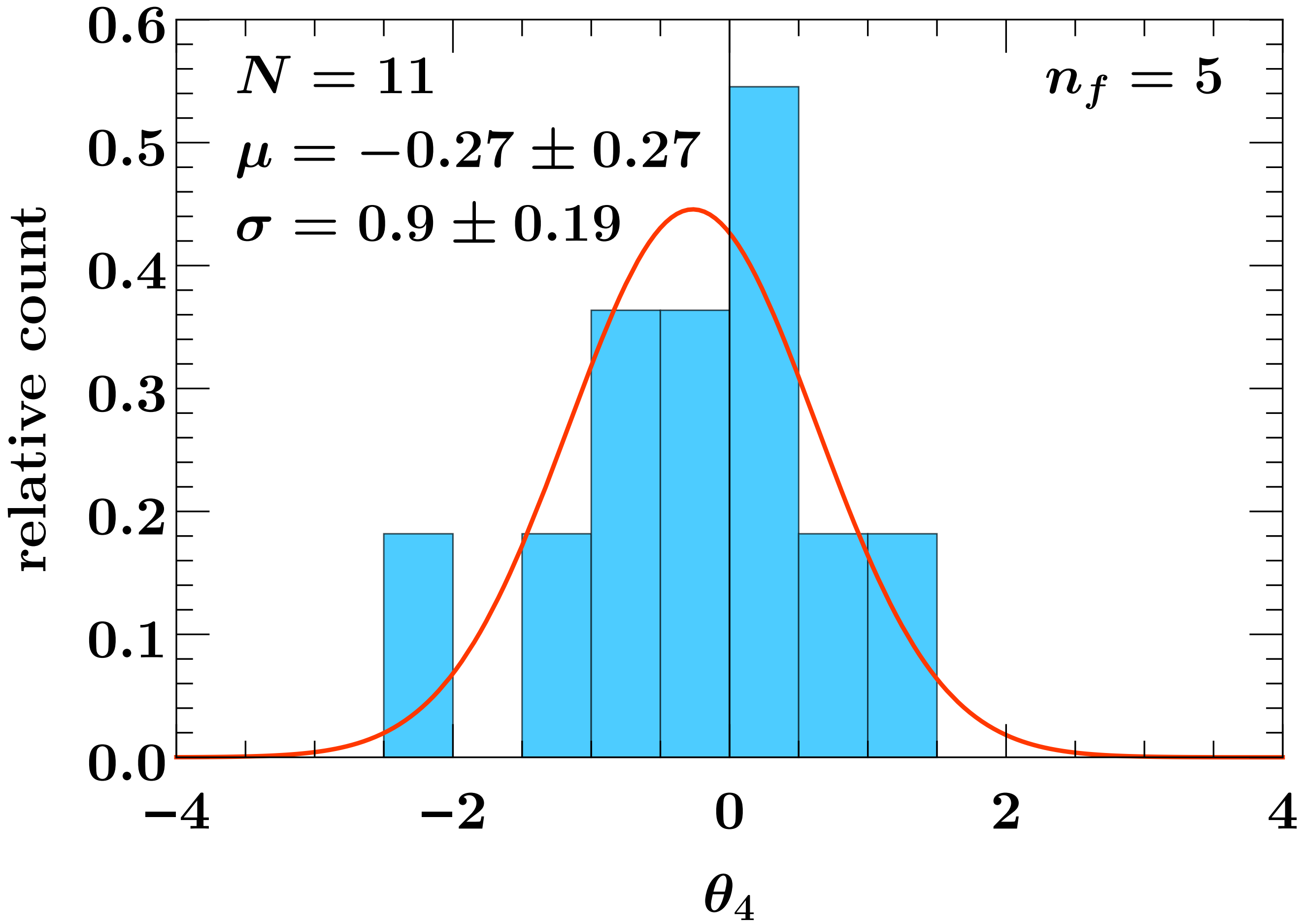


4 loop



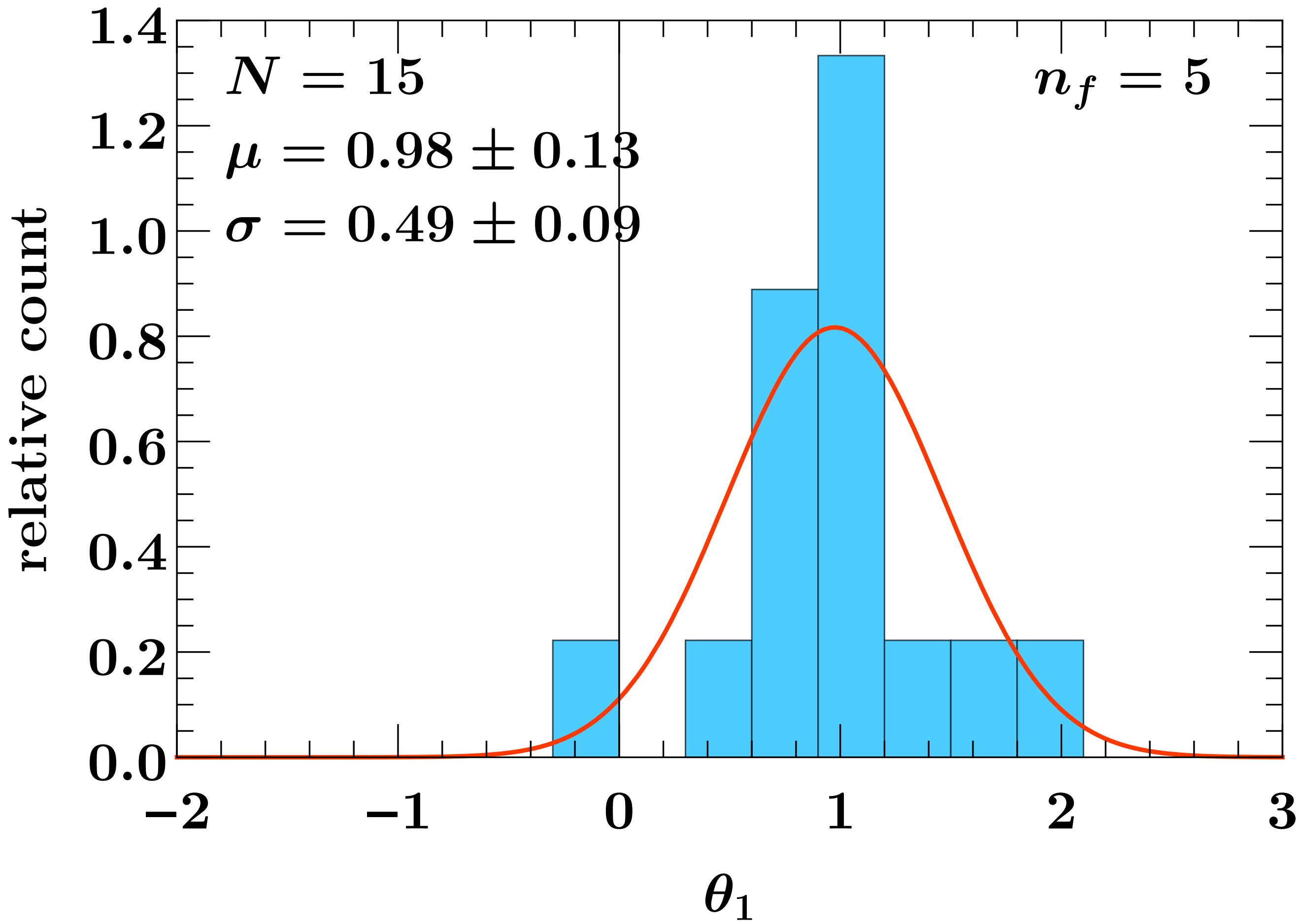
Fit to a Gaussian with $\mu = 0$ and $\sigma = 1$ ✓

TNPs for Anomalous Dimensions

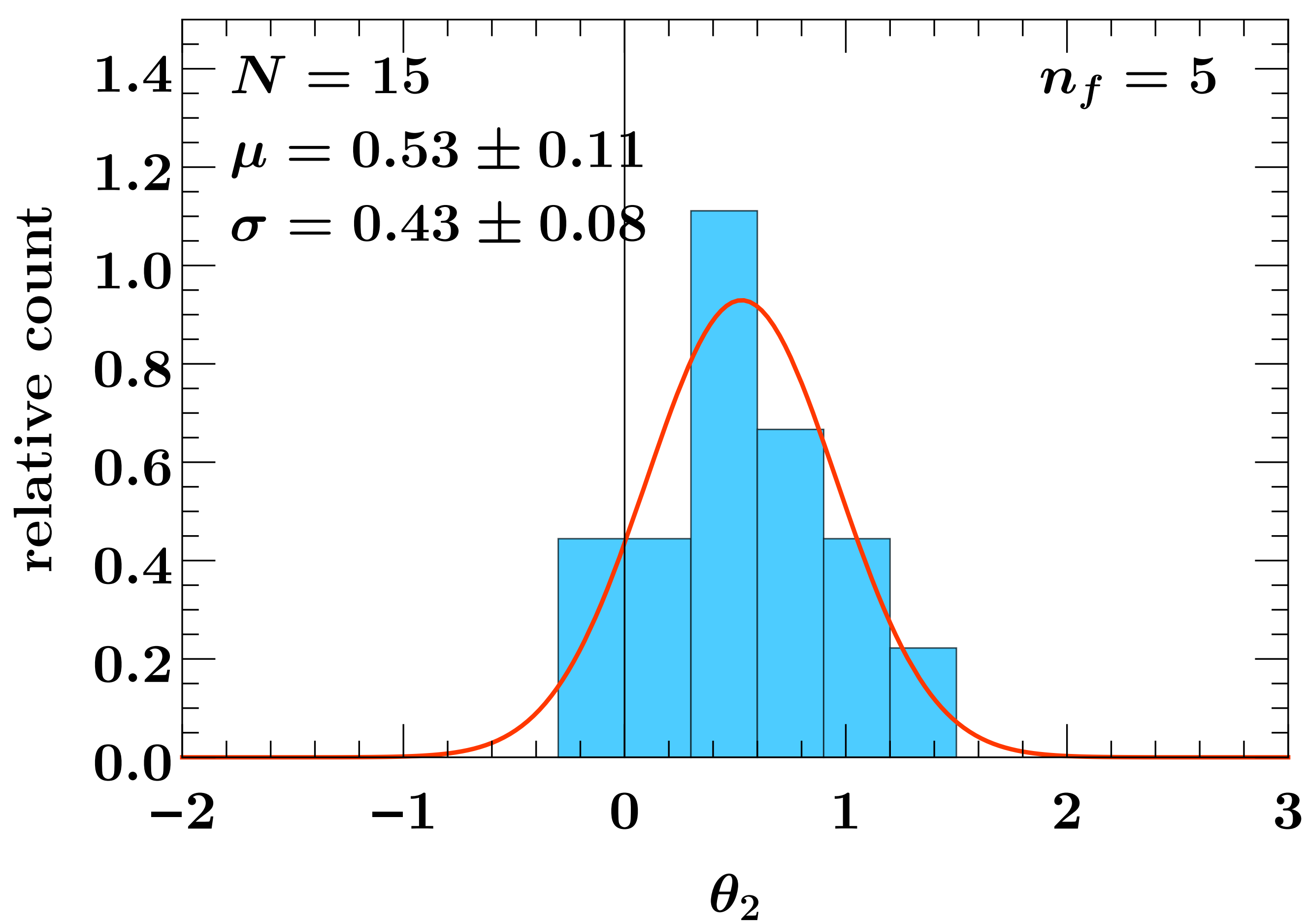
Estimate of $\theta_n^\gamma(n_f)$ from a generic sample of known and independent series

$$\gamma_n(\theta_n) = 2C_r(4C_A)^n\,\theta_n^\gamma(n_f)$$

2 loop



3 loop



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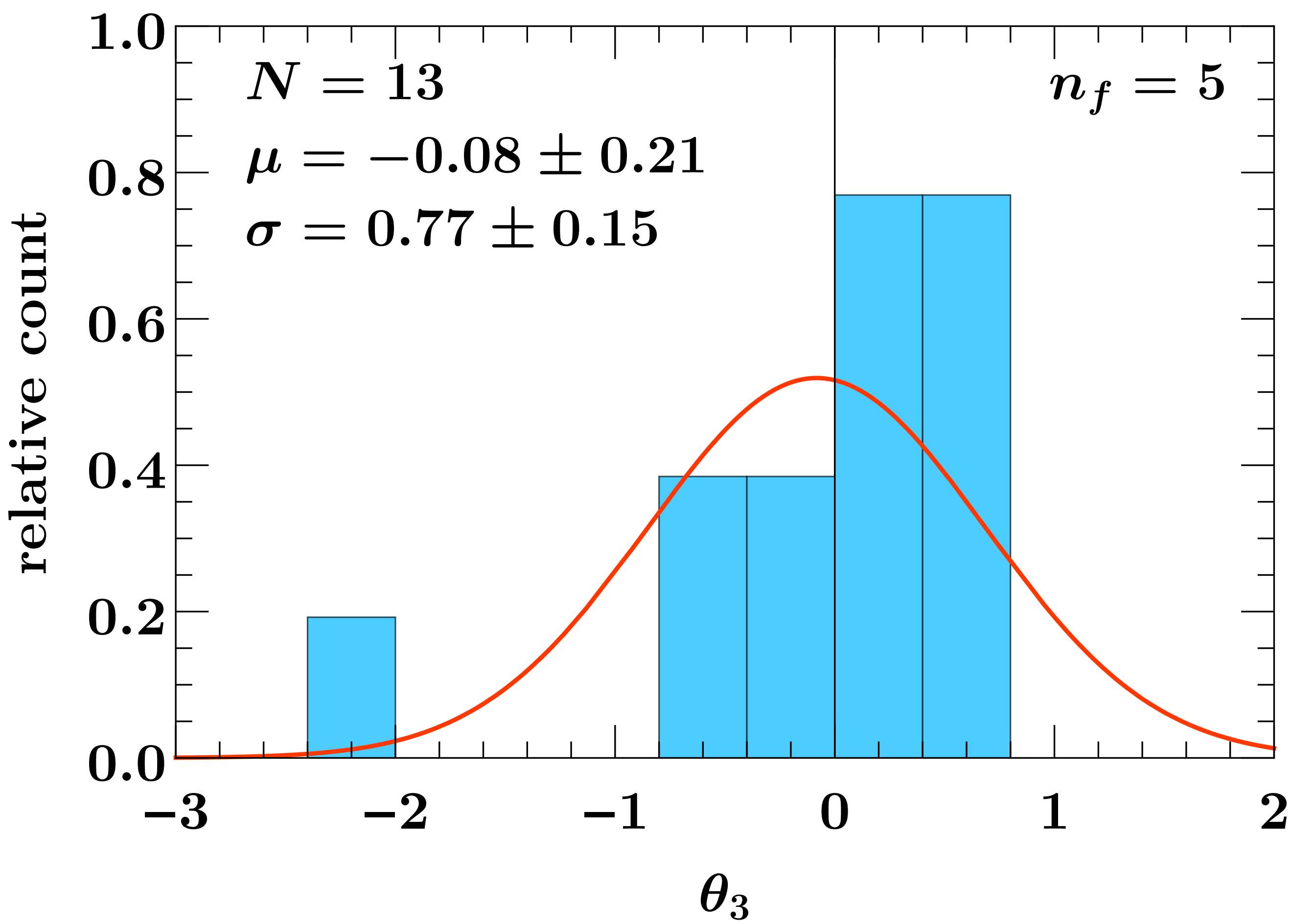
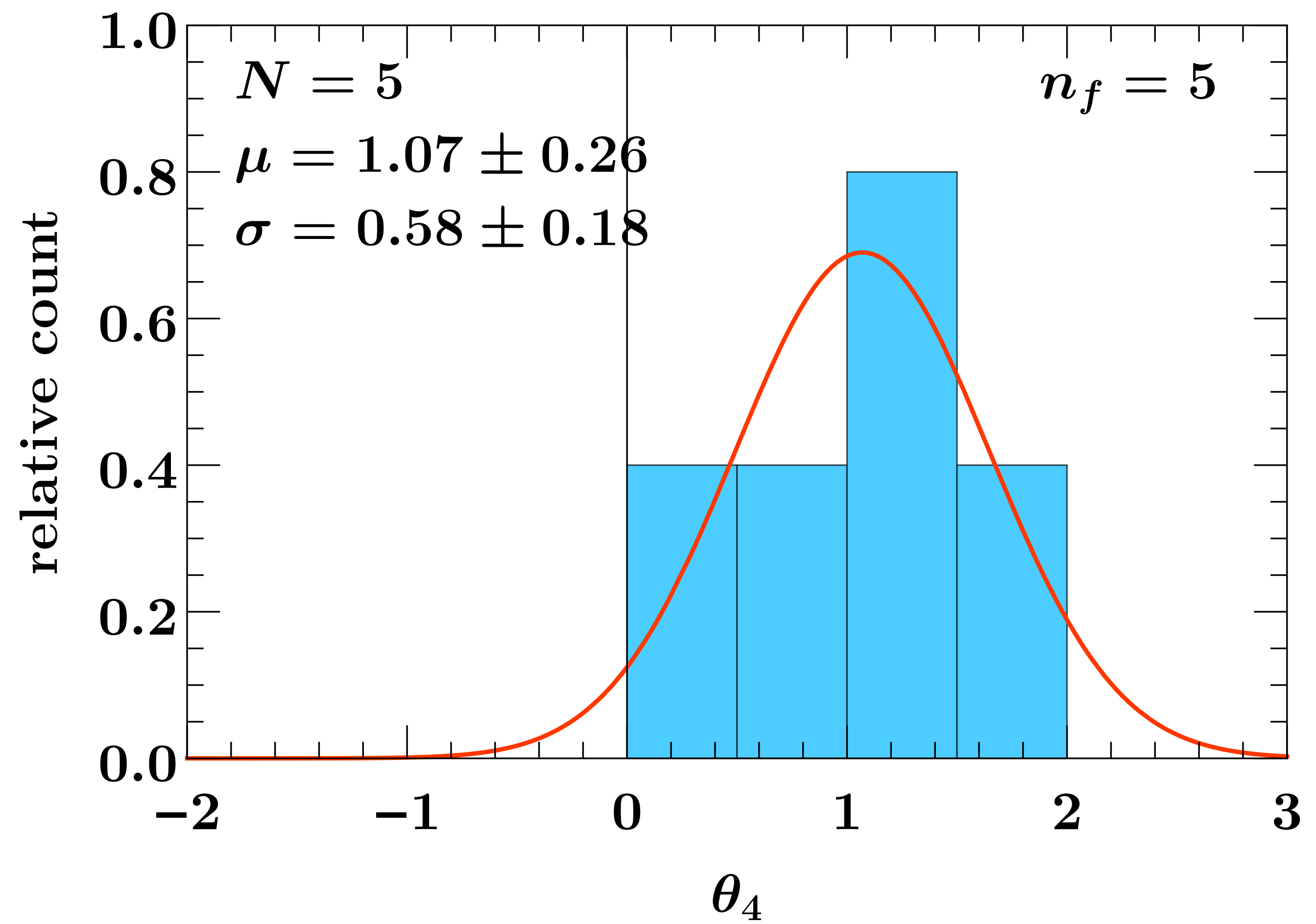


5 loop



Fit to a Gaussian with $\mu \neq 0$ and $\sigma = 0.5$ ✓

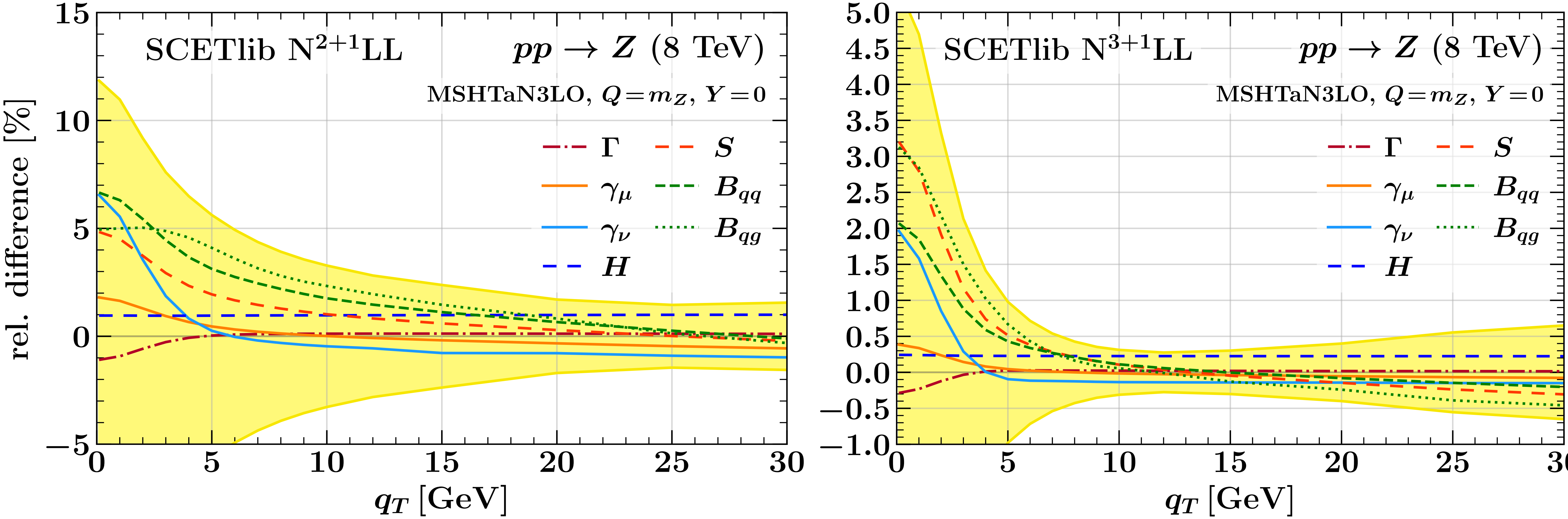
(but using $\mu = 0$ and $\sigma = 1$in what follows for simplicity)

Application of TNPs to Z p_T spectrum

Nomenclature: N^{n+1}LL

N^{n+1}LL resummation + highest-order boundary conditions/anomalous dim. as TNPs

- Varying each θ_i independently
- Add in quadrature for the total uncertainty
- For the beams B_{qj} : $f_n = (0 \pm 1.5) \times f_n^{\text{true}}$, DGLAP splitting functions not varied



Asimov test fitting $\alpha_S(m_Z)$ from $Z\, p_T$

Play with TNPs to study the expected uncertainty/sensitivity on α_S on toy data (**Asimov test**)

- Very precise **ATLAS** measurement at $\sqrt{S} = 8$ TeV: [arXiv 2309.09318 and 2309.12986] based on **N**^{3}**LO**+**N**^{4}**LLa** theoretical predictions from **DYTurbo**;

$$\alpha_S(m_Z) = 0.1183 \pm 0.0009$$

In units of 10^{-3}

Experimental uncertainty	± 0.44	
PDF uncertainty	± 0.51	
Scale variation uncertainties	± 0.42	
Matching to fixed order	0	-0.08
Non-perturbative model	$+0.12$	-0.20
Flavour model	$+0.40$	-0.29
QED ISR	± 0.14	
N^4LL approximation	± 0.04	
Total	$+0.91$	-0.88

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Our theory inputs:

- SCETlib only resummed contribution
  [default central scales and variations, no mass corrections and nonsingular power corrections]

Our toy data:

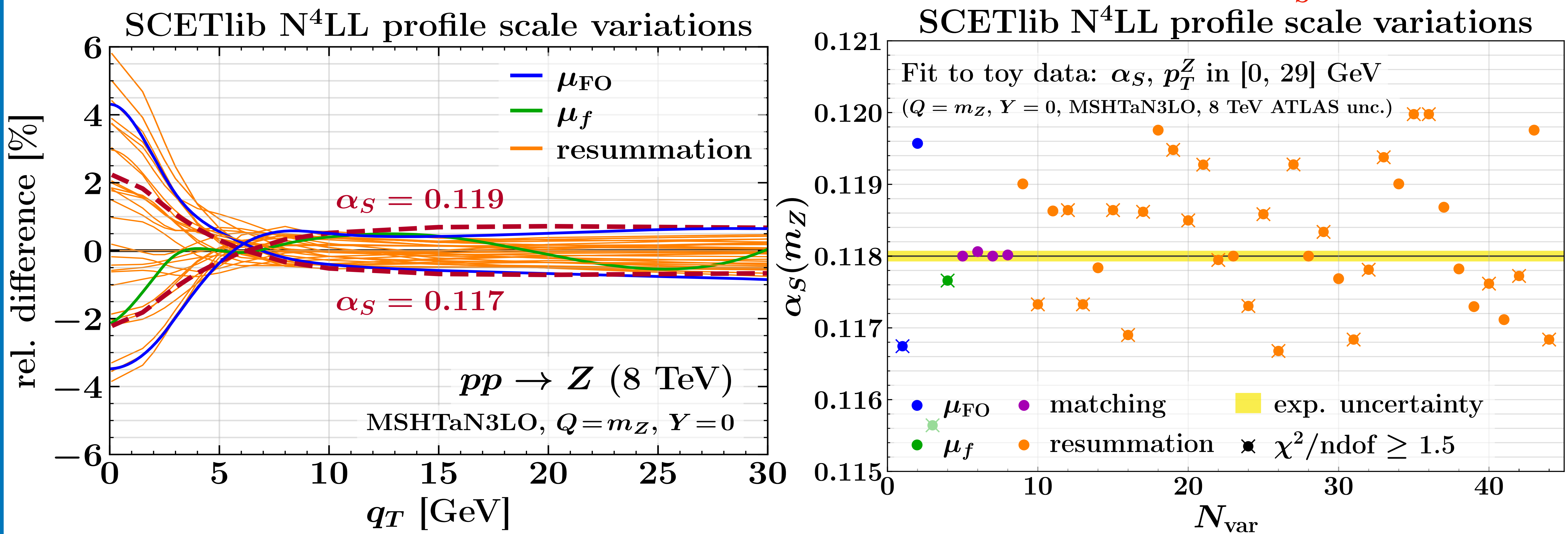
- Data defined as central theory prediction
  [$\alpha_S(m_Z) = 0.118$, fixed nonp. params, MSHT20aN3LO PDF set]

- Only 9 q_T points in [0,29] GeV by ATLAS binning
  [fixed $Q = m_Z$ and $Y = 0$ just for simplicity]

- Using ATLAS exp. uncertainties and correlations, integrated over $|Y| < 1.6$;

Asimov fit result for scale variations

Only fitting α_S



Shape of scale (theory) variation, within the band, strongly effects the result;

uncertainty $\sim \pm 1$ (in units of 10^{-3}) , where 1 means $0.118 \to 0.117$ or 0.119

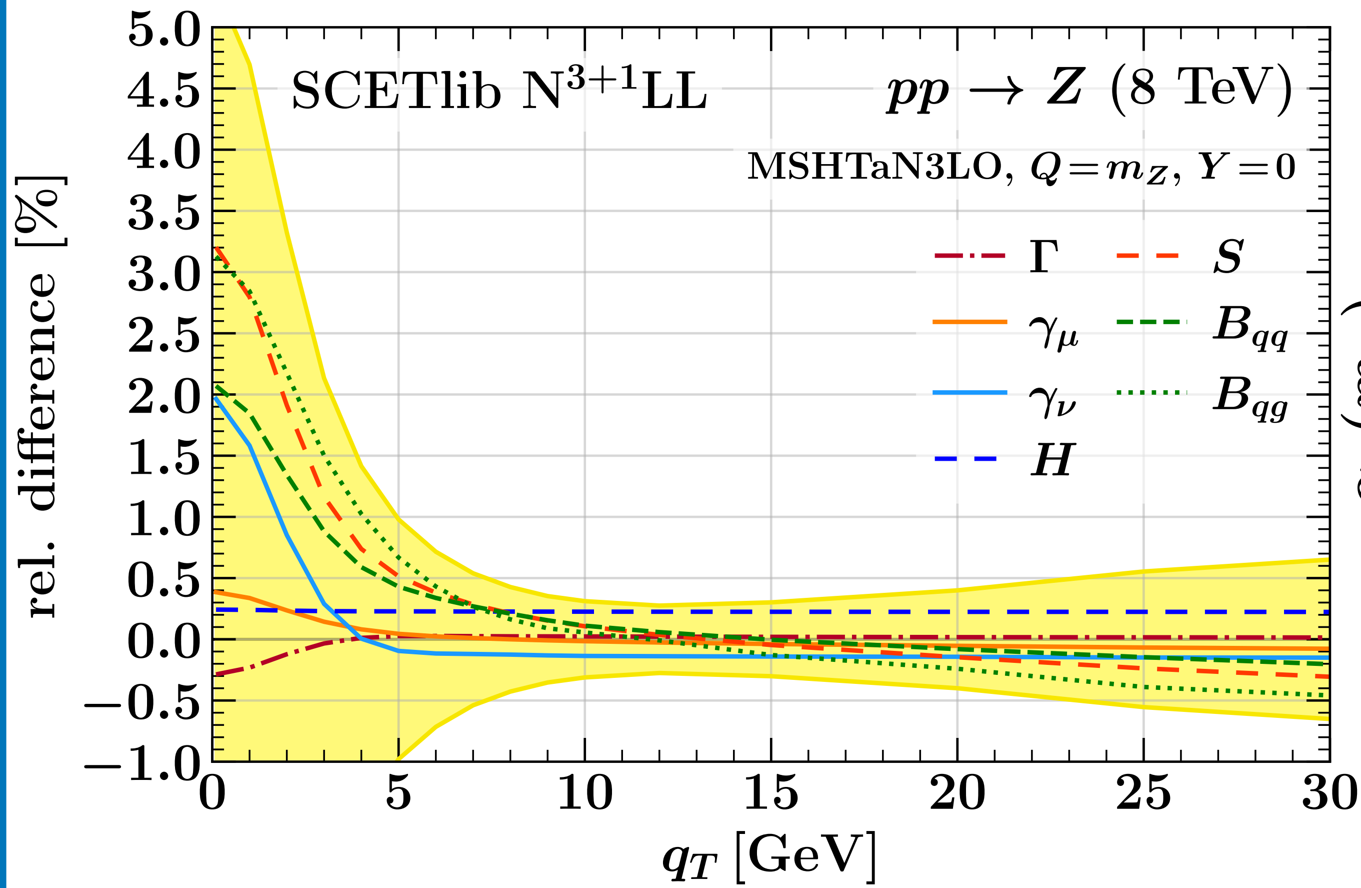
Sum in quadrature: $\Delta_{\mathrm{total}} = \sqrt{\Delta^2_{\mathrm{FO}} + \Delta^2_{\mathrm{resum}} + \Delta^2_{\mathrm{match}}} \sim 2.6$ [neglecting μ_f]

Envelope: $\Delta_{\mathrm{total}} \sim 2.1$

scale variations are not sufficient!

* uncertainties in units of 10^{-3}

Asimov fit result for TNPs



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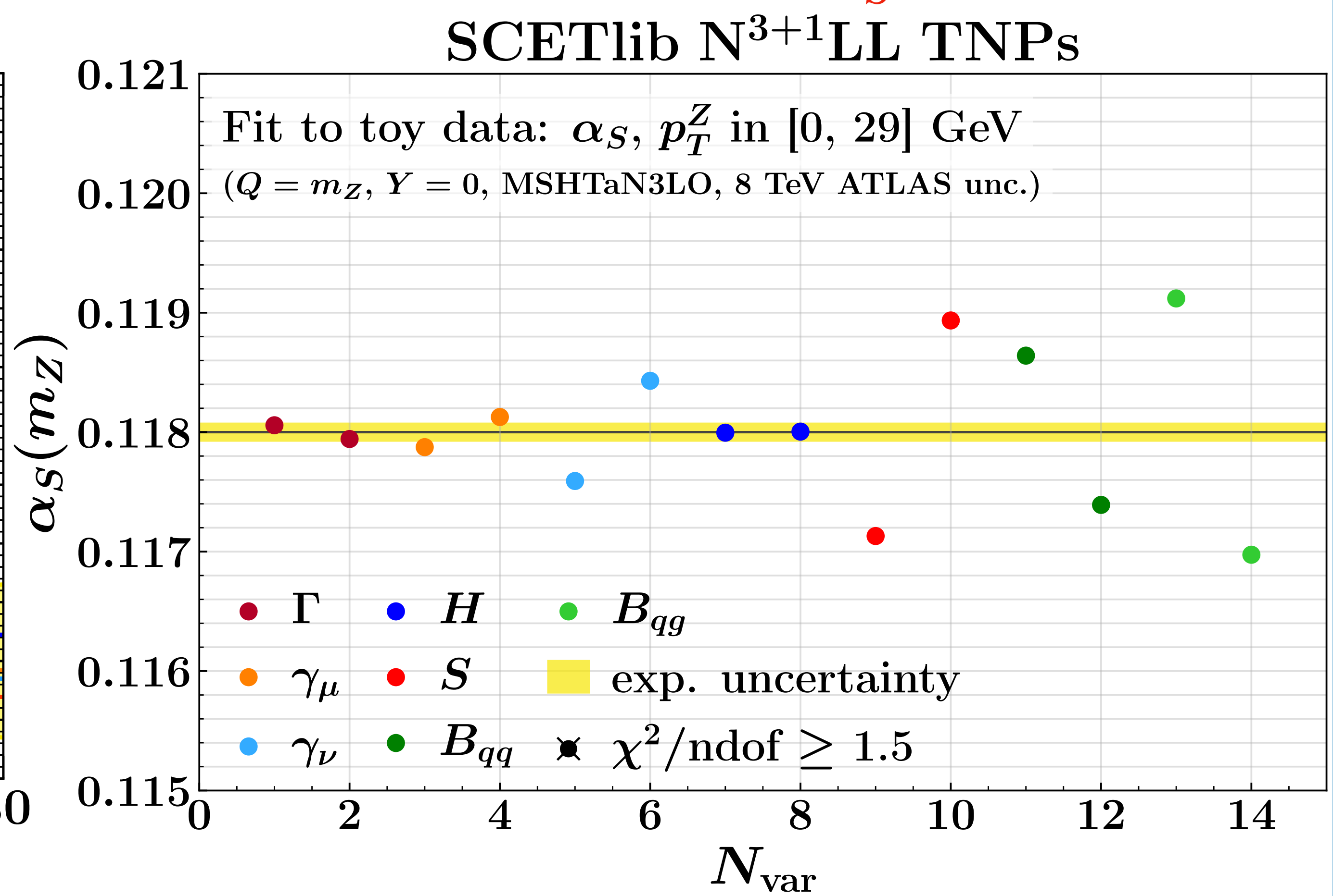

Repeat fit for each TNP variation, using TNPs at N^{3+1}LL;

still does not let the fit decide what to do with α_S (moving the theory or α_S directly?)

TNPs correctly account for their correlations $\Rightarrow$ sum in quadrature: $\Delta_{\text{total}} = 1.6$

* uncertainties in units of 10^{-3}

Playing with the Asimov fit and TNPs

Scanning: vary one TNP at a time and re-fit α_S

Profiling: fitting α_S *together* with all TNPs (allow the fit to decide what to do)

* uncertainties in units of 10^{-3}

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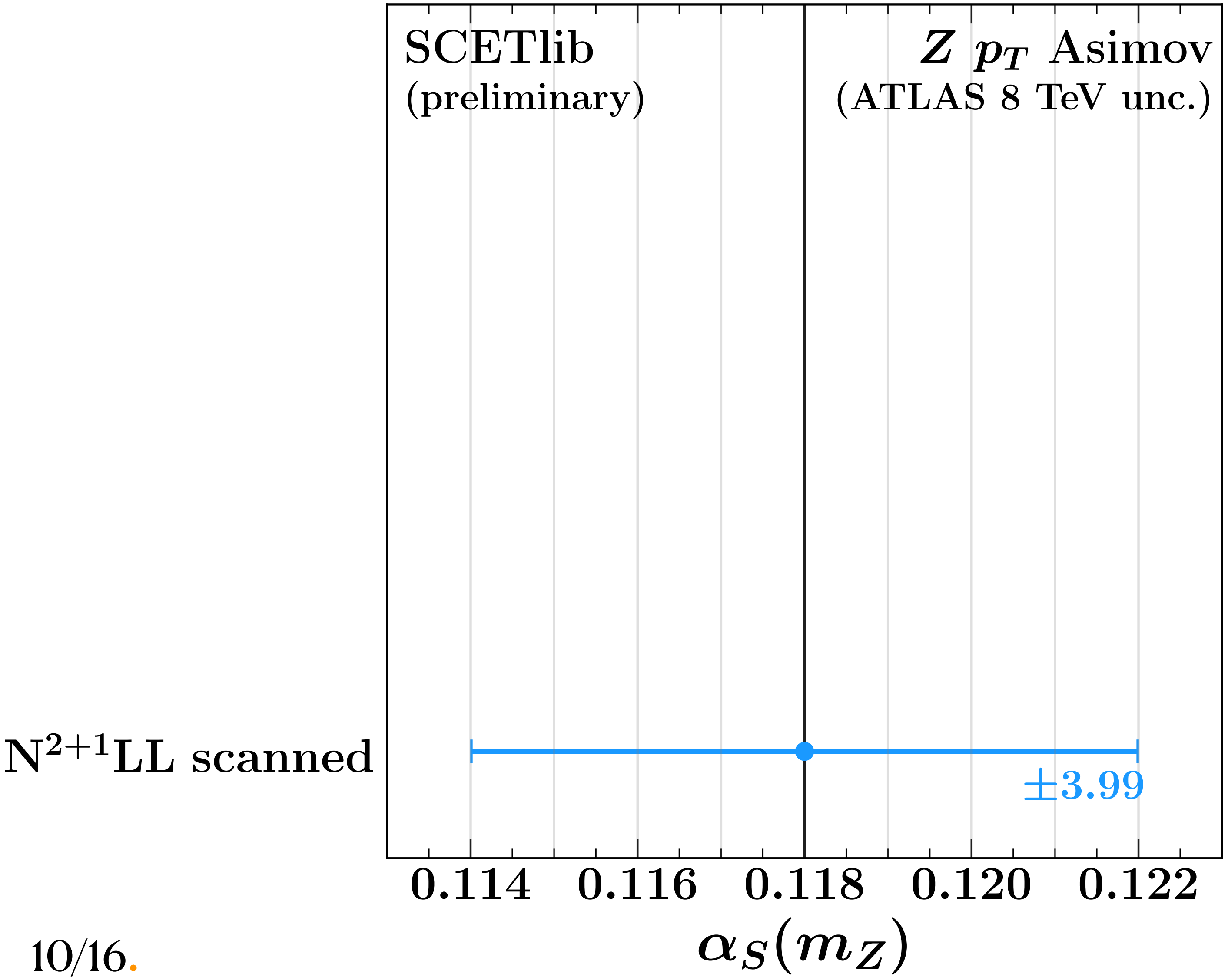
- data = central [$\alpha_S(m_Z) = 0.118$] N^{2+1}LL theory prediction against N^{2+1}LL model



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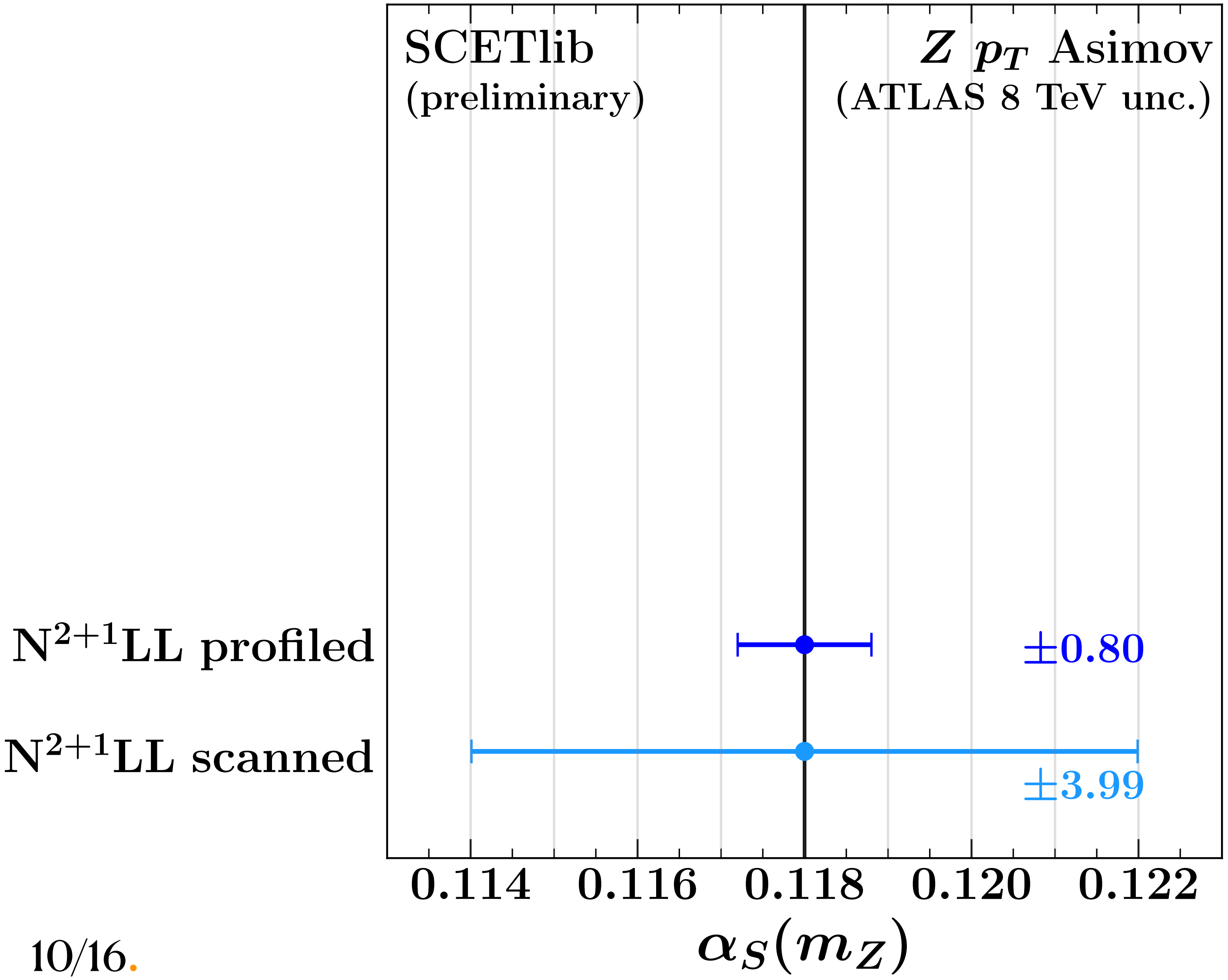

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- data = central N^{3+1}LL theory prediction against N^{2+1}LL model

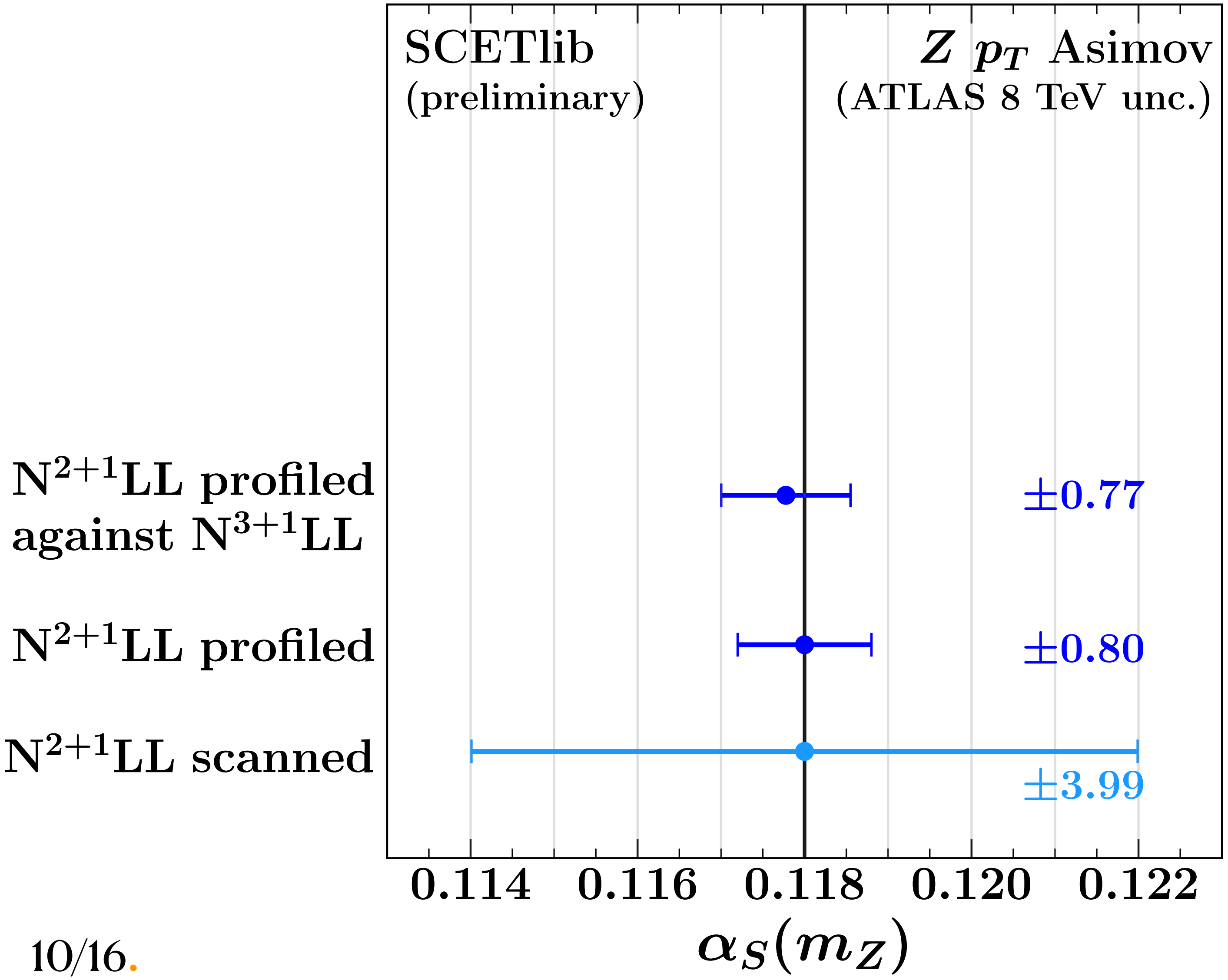
This test is very interesting: simulation of what will happen using the real data for the fit

↓

data constraining TNPs a lot, reducing the uncertainty on α_S

↓

N^{2+1}LL order may **not** be enough!



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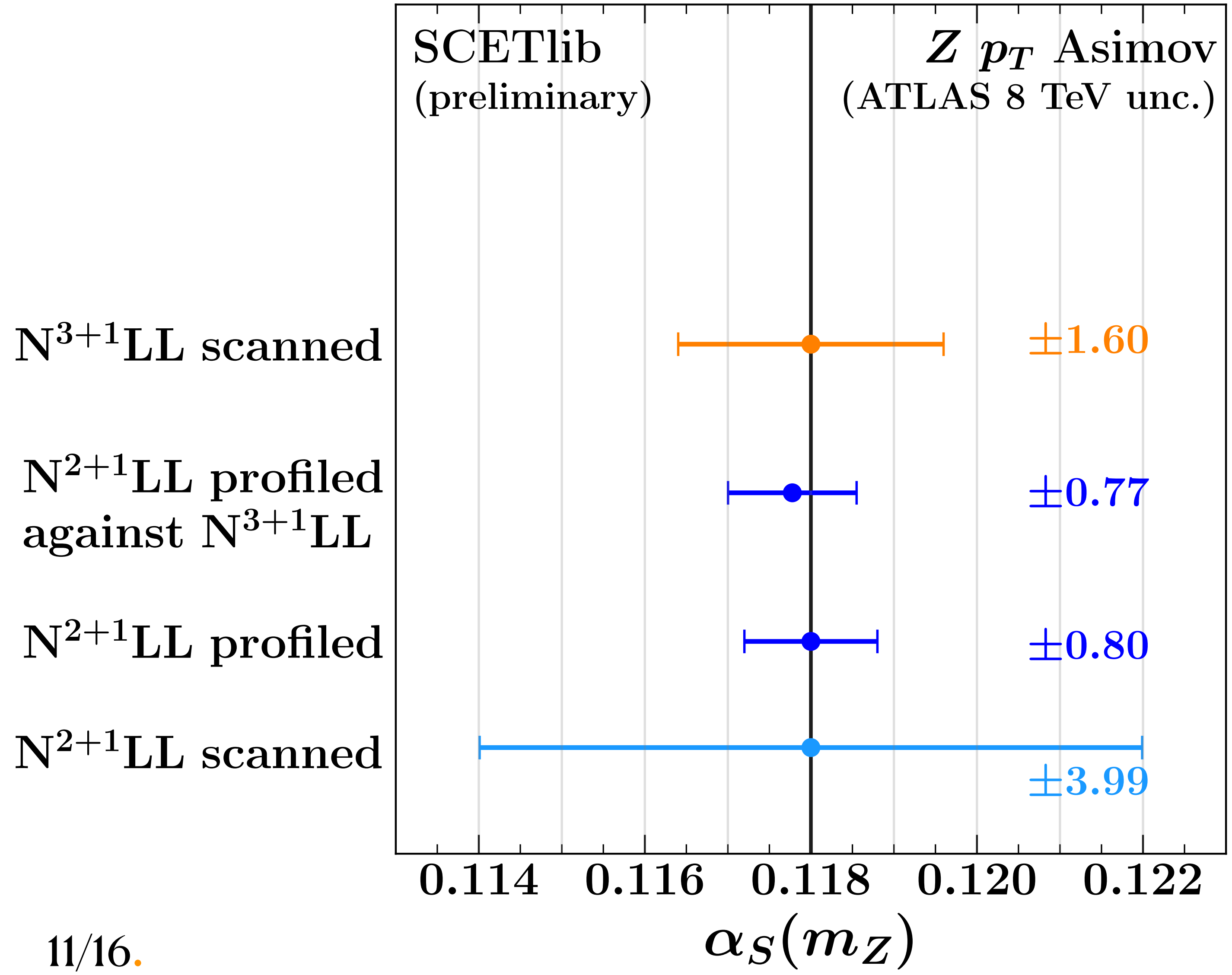

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Playing with the Asimov fit and TNPs

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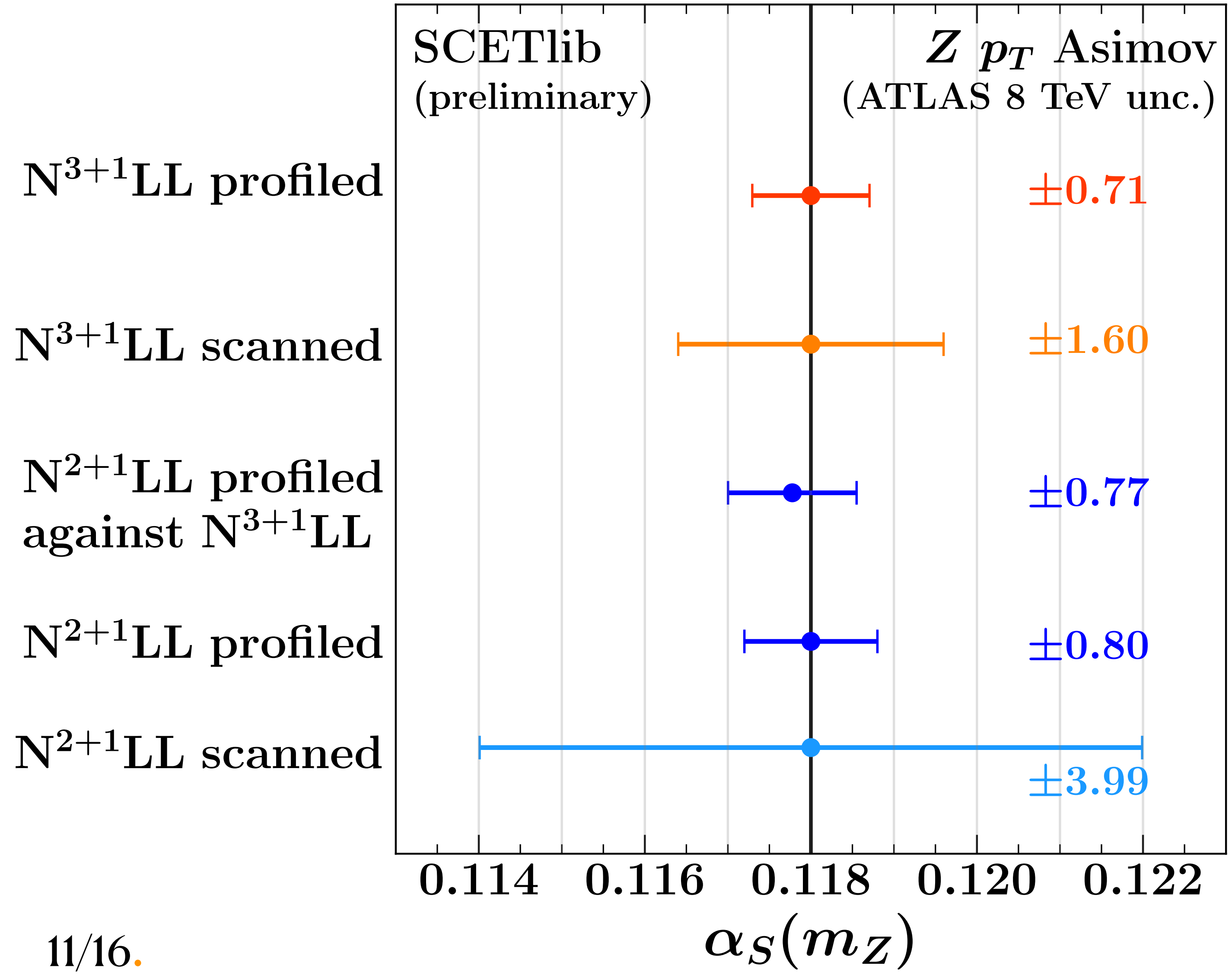
- data = central $N^{3+1}LL$ theory prediction against $N^{2+1}LL$ model
- data = central $N^{3+1}LL$ theory prediction against $N^{3+1}LL$ model

Profiling constraints the TNPs allowing data to reduce the theory uncertainty!



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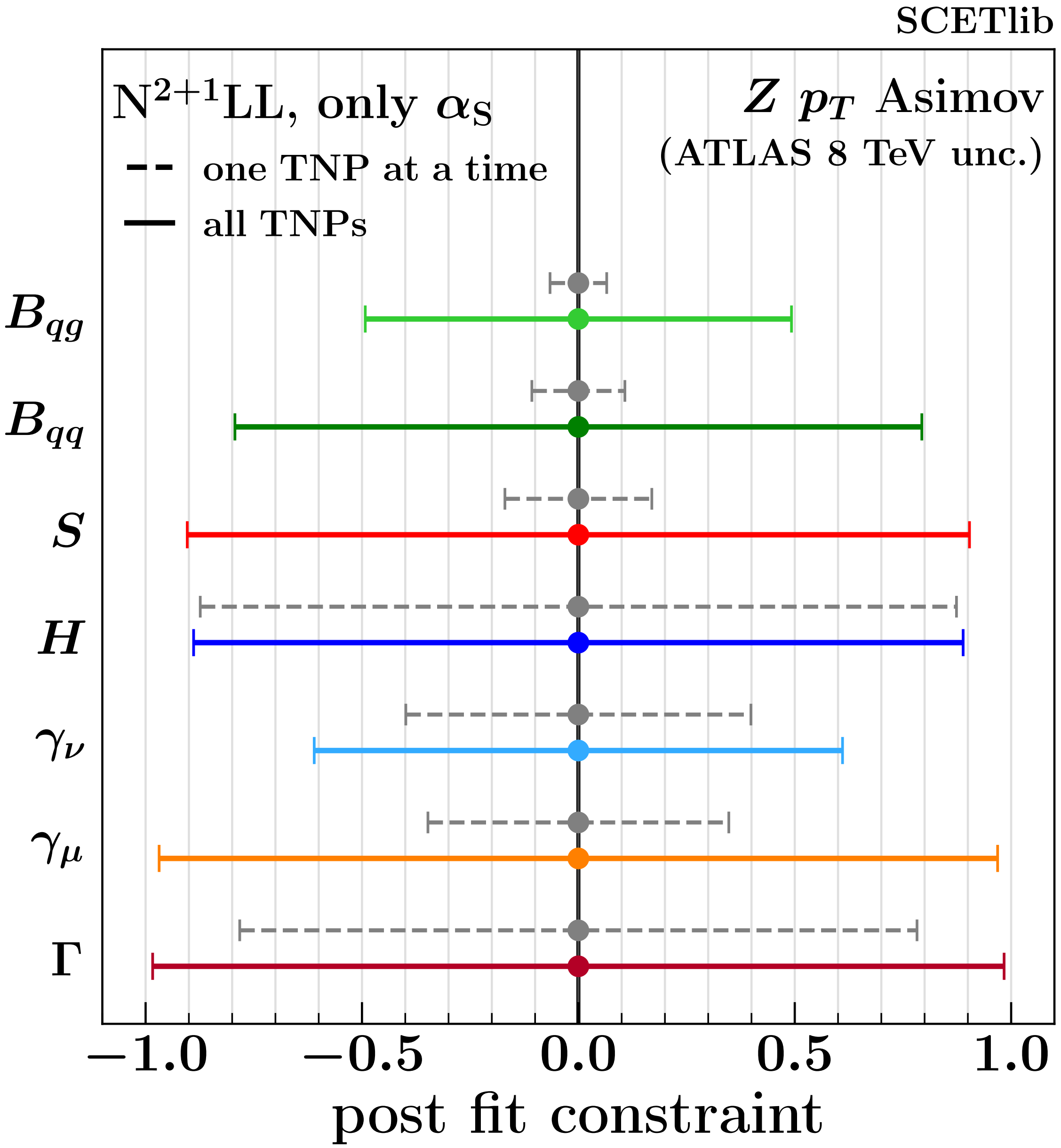
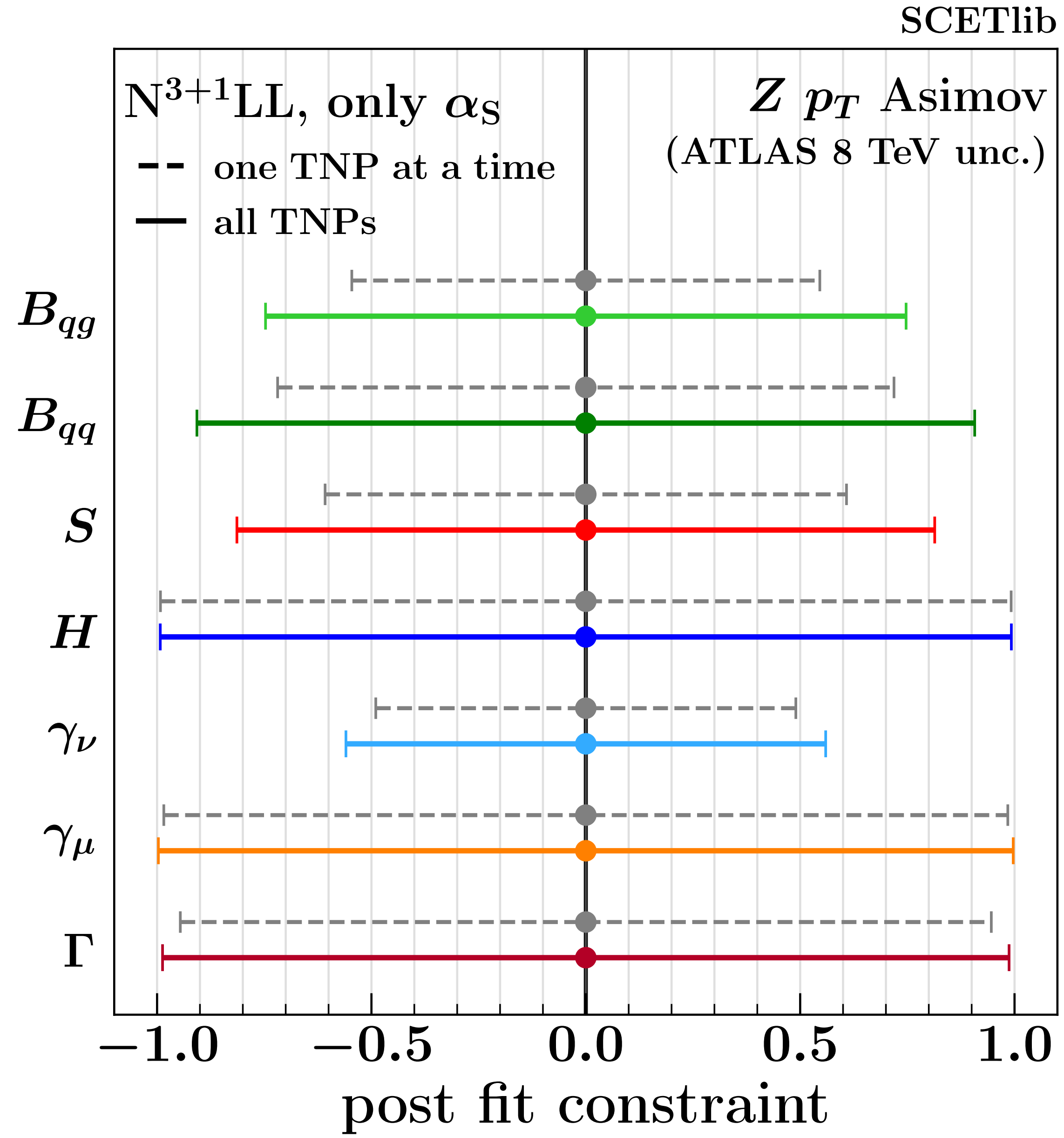
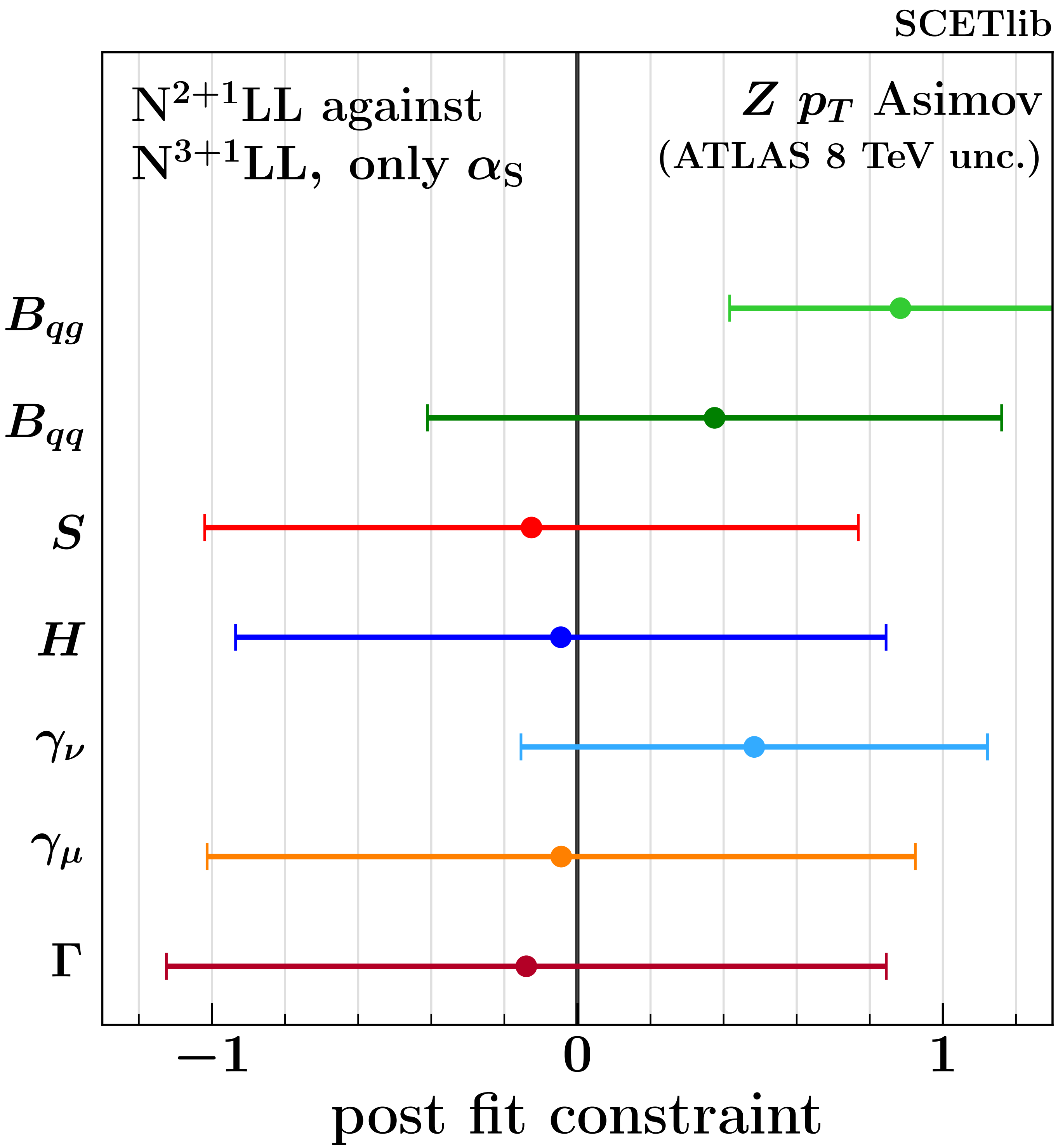
Constraints on TNPs





- $N^{2+1}LL$: TNPs much more constrained than at $N^{3+1}LL$
- If TNPs get strongly constrained, the next order becomes relevant for the uncertainty correlations!

Constraints on TNPs



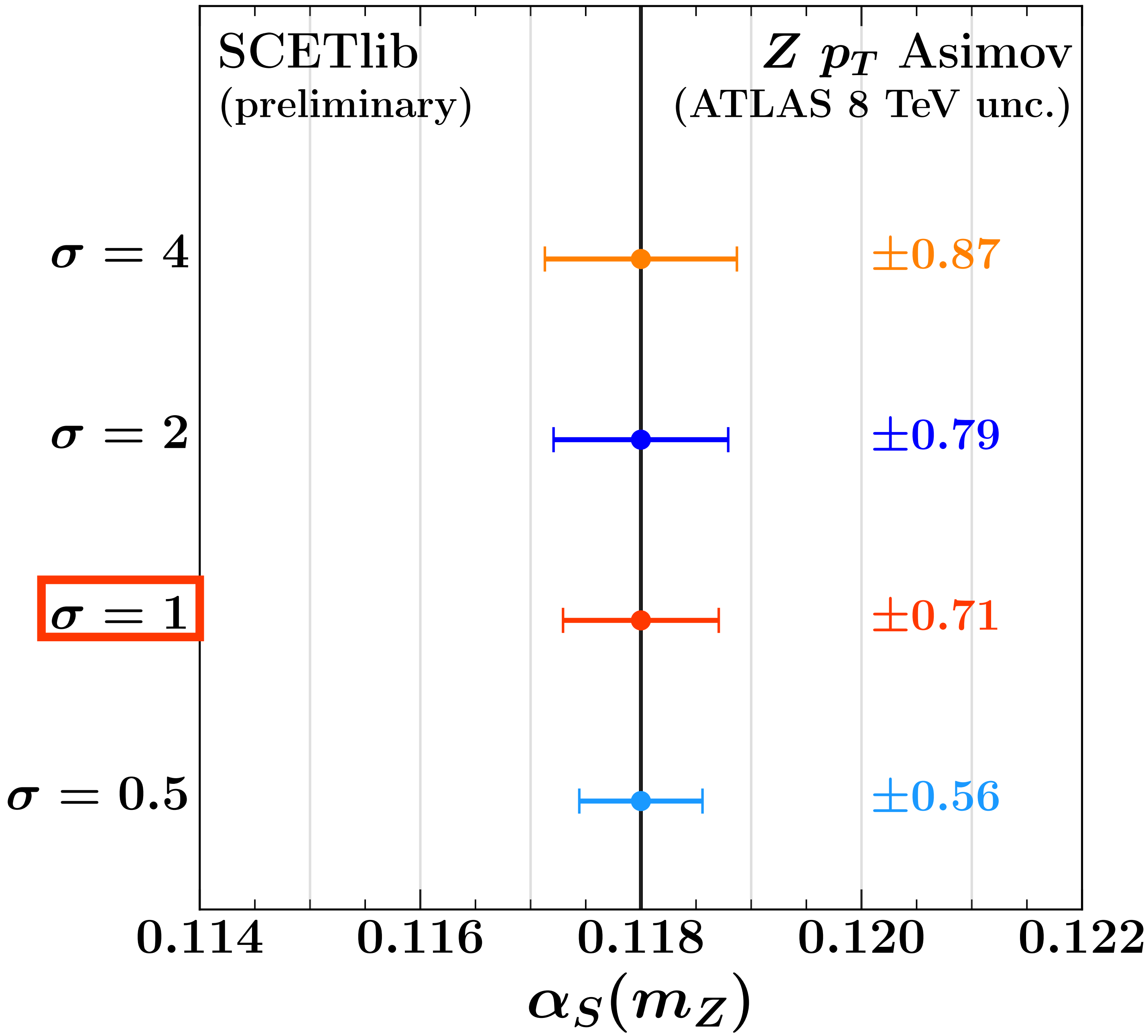
data = central $\mathrm{N}^{3+1}\mathrm{LL}$ theory prediction against $\mathrm{N}^{2+1}\mathrm{LL}$ theory model

As expected, some TNPs are strongly pulled

this is another indication that $\mathrm{N}^{2+1}\mathrm{LL}$ is just not enough

Different constraints on TNPs

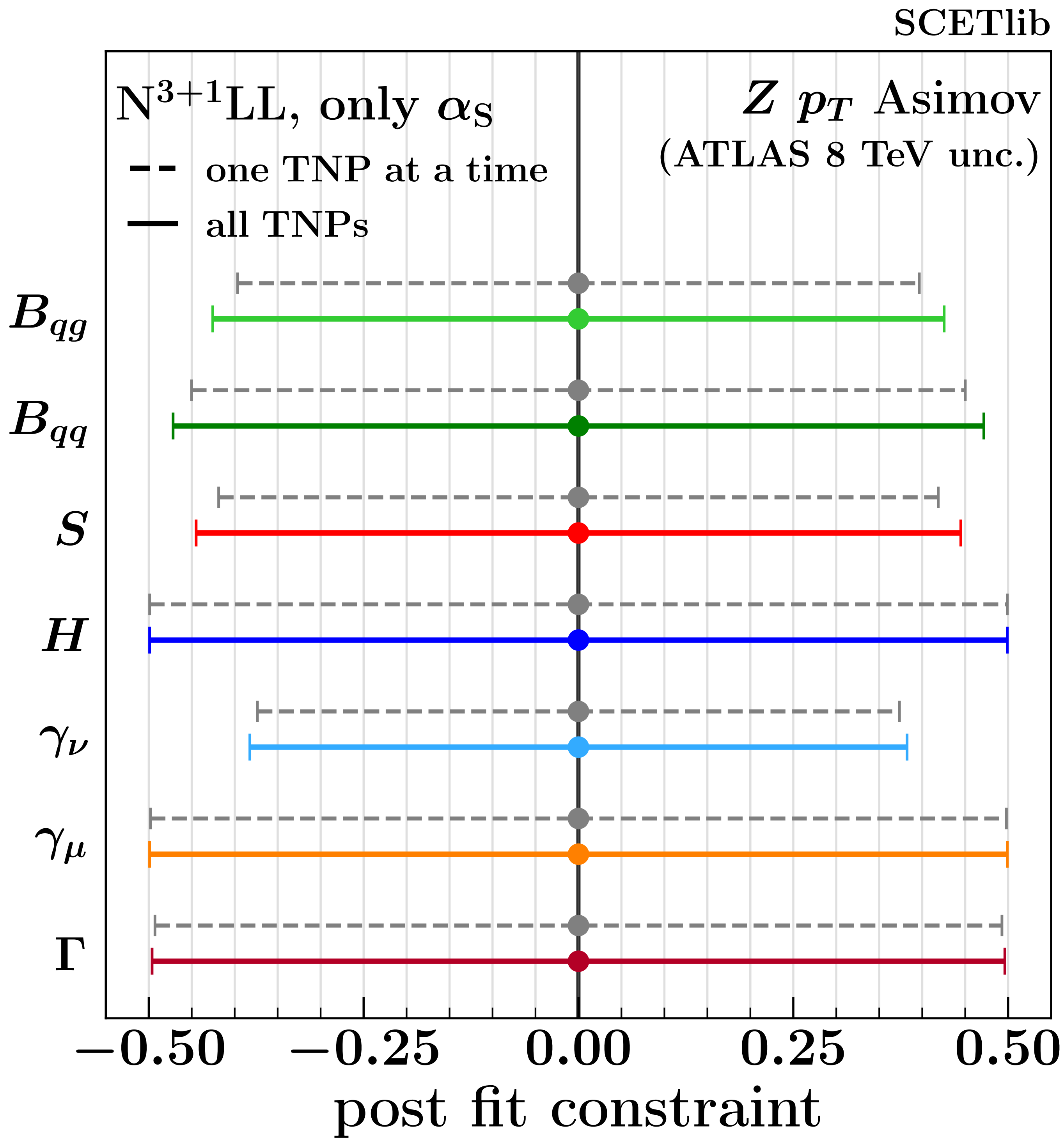
Using now $\mu = 0$ but $\sigma = 0.5, 1, 2, 4$:



- Similar increase in the uncertainties when relaxing the TNPs constraint
- Further reducing the uncertainty worth it!
  [exp. uncertainty ~ theo. uncertainty]

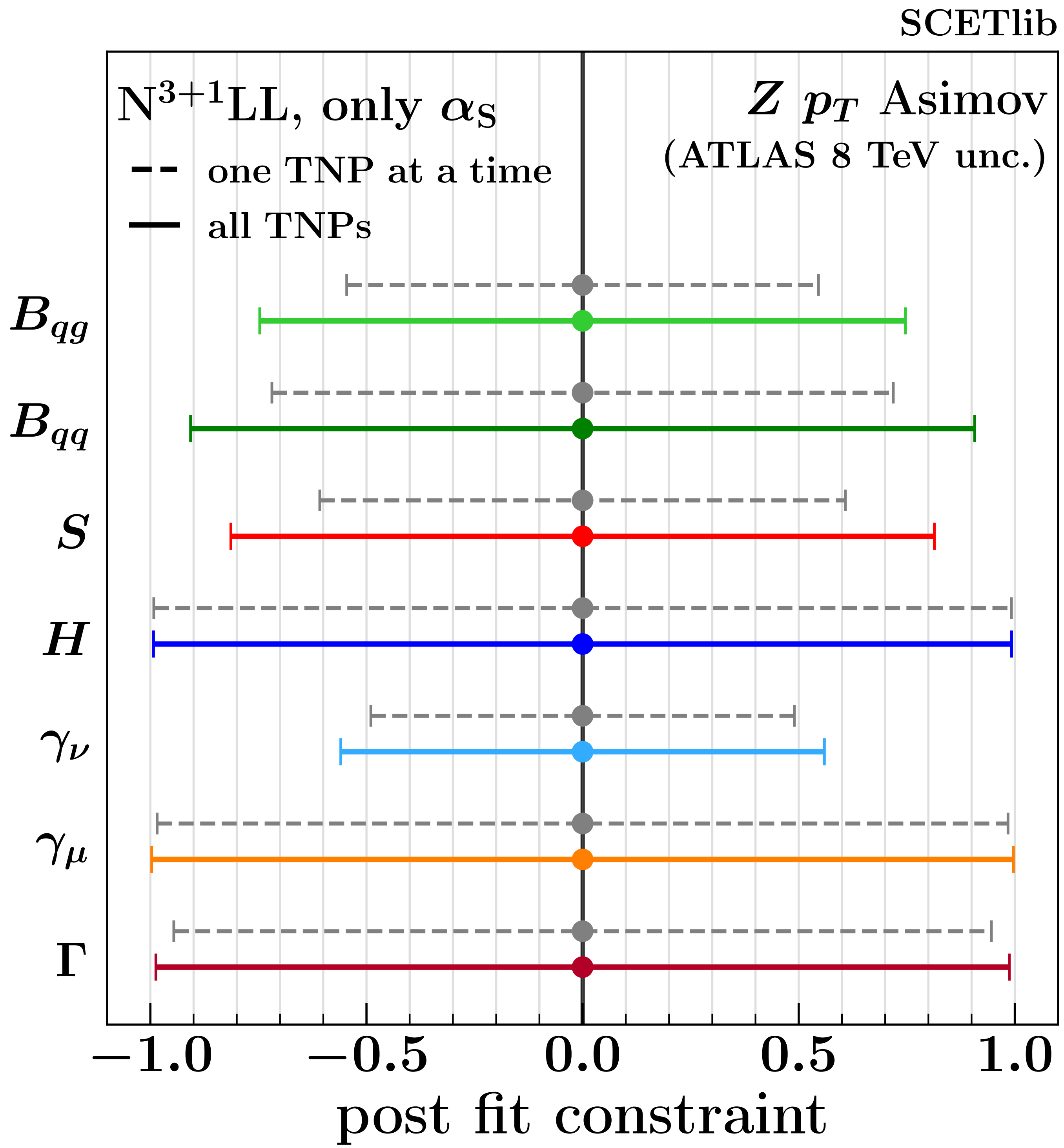
Different constraints on TNPs

Using now $\mu = 0$ but $\sigma = 0.5$:



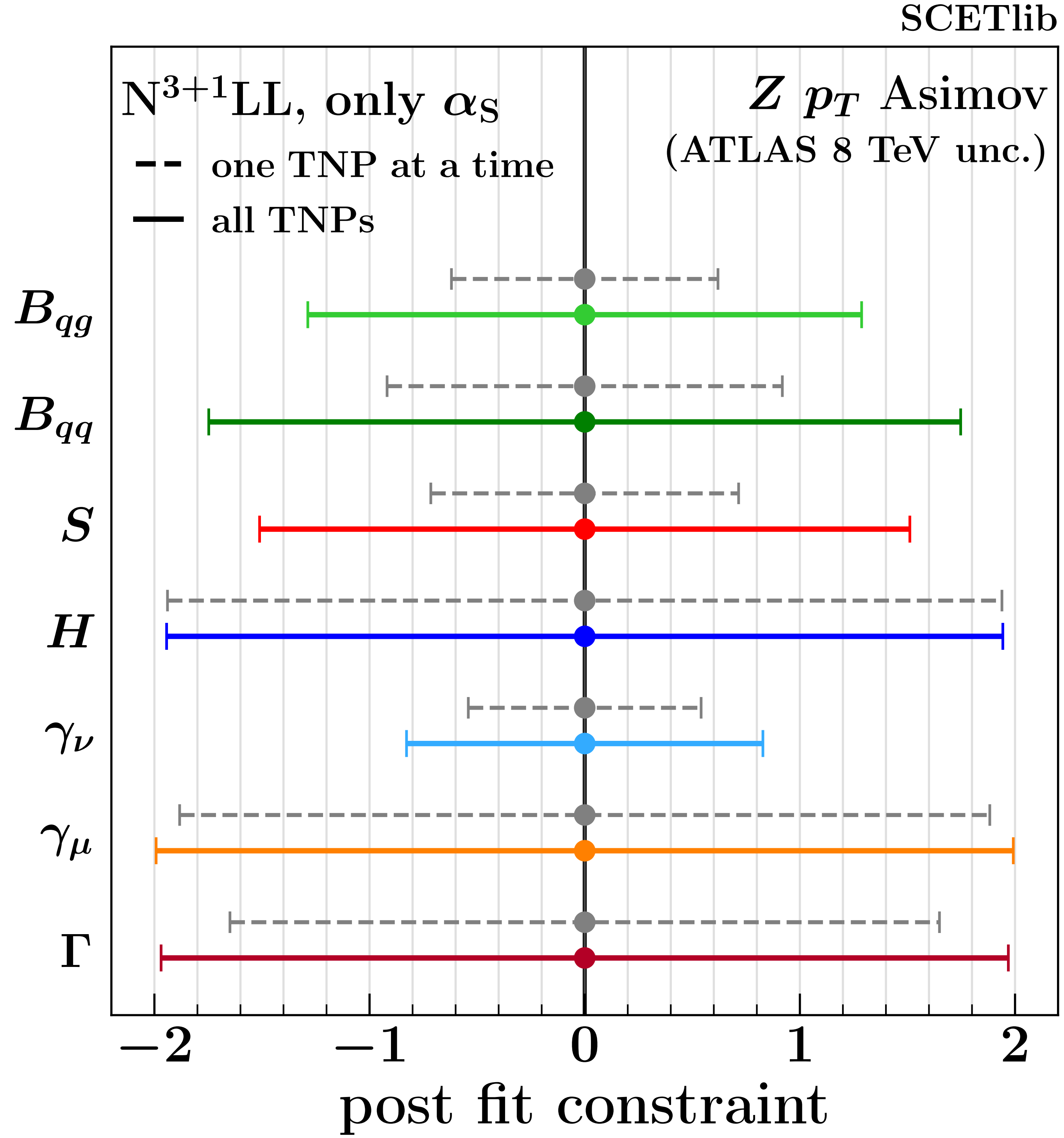
Different constraints on TNPs

Using now $\mu = 0$ but $\sigma = 1$:



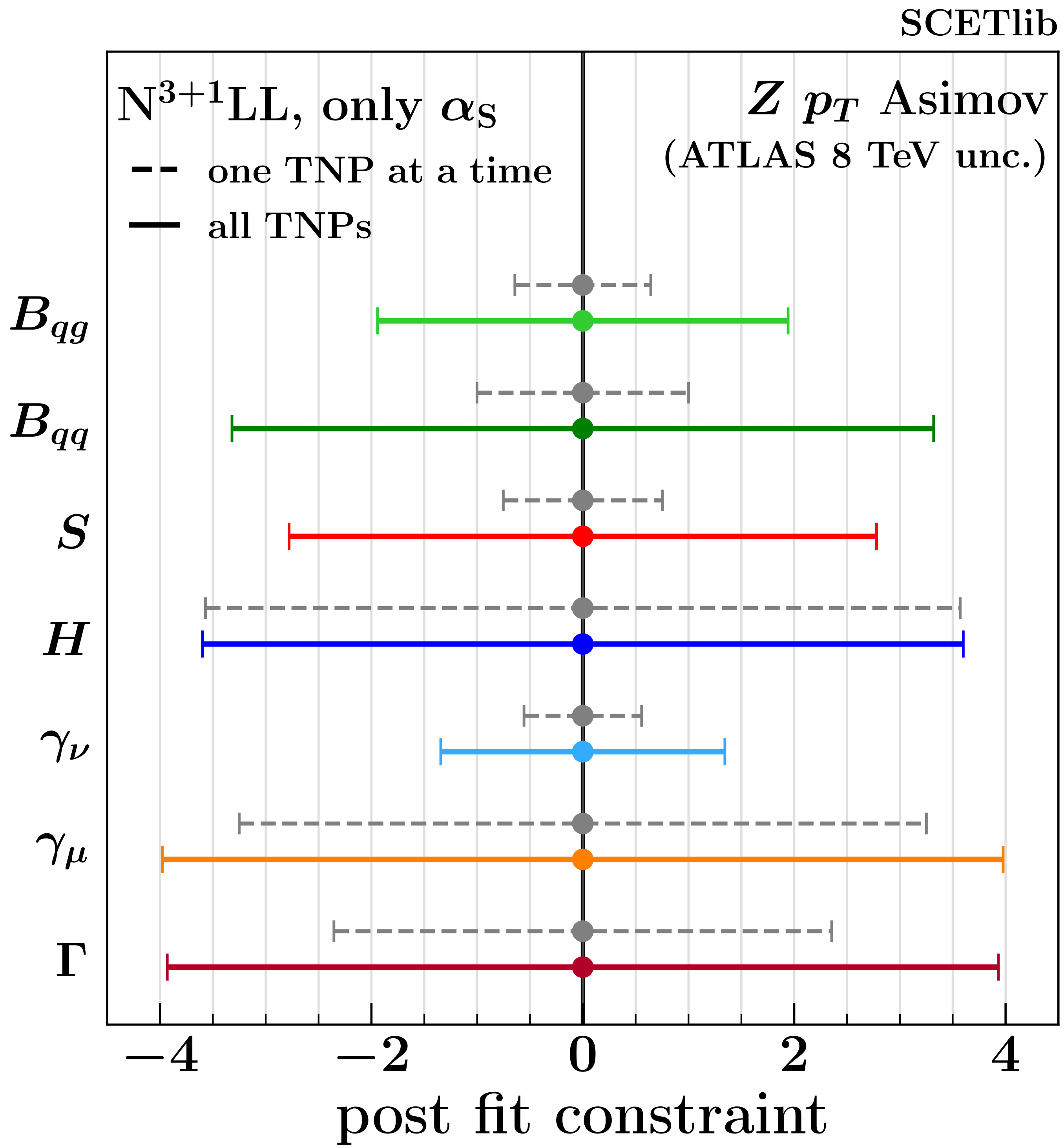
Different constraints on TNPs

Using now $\mu = 0$ but $\sigma = 2$:



Different constraints on TNPs

Using now $\mu = 0$ but $\sigma = 4$:



Summary

Need for theoretical predictions with reliable uncertainties including correlations for interpretation of LHC precision measurements:

Theory Nuisance Parameters perfect candidate

- include correct correlations across the p_T spectrum
- can be constrained by data reducing theory uncertainty
- value of σ doesn't really matter once profiling and exp. uncertainty sufficiently small
- so far work as advertised for Asimov tests

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