NNLO interpolation grids for jet production at the LHC

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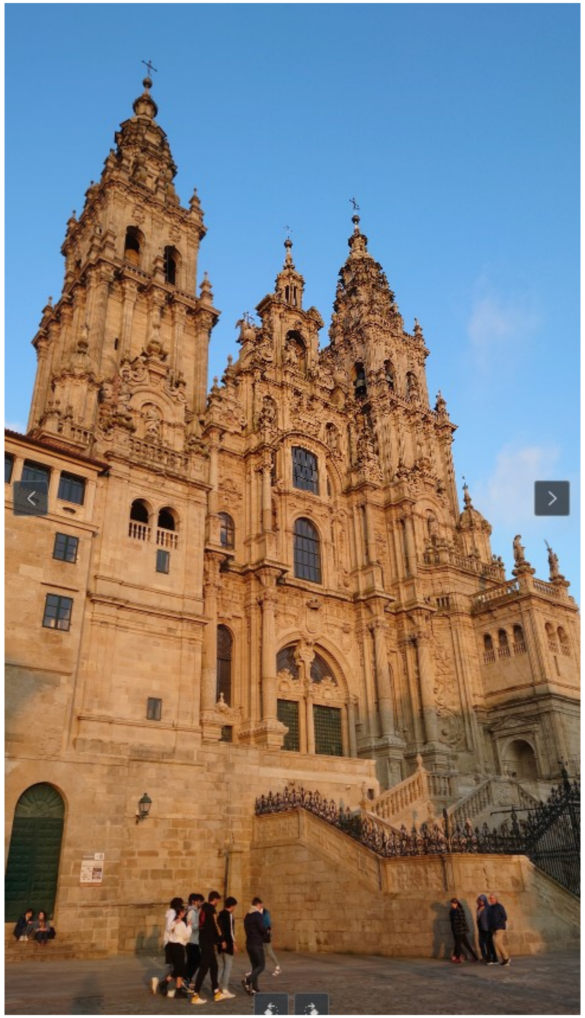
Outline

- **Interpolation grids at NNLO for DIS published**
- **Interpolation grids for numerous jet datasets at LHC computed**
- **Inclusive jets with examples for**
  - **Grid closure**
  - **Scale dependence**
  - **PDF uncertainties**
  - **NNLO K factors**
- **Dijets with application example**
  - **PDF (+α_s) fit**
- **Outlook**



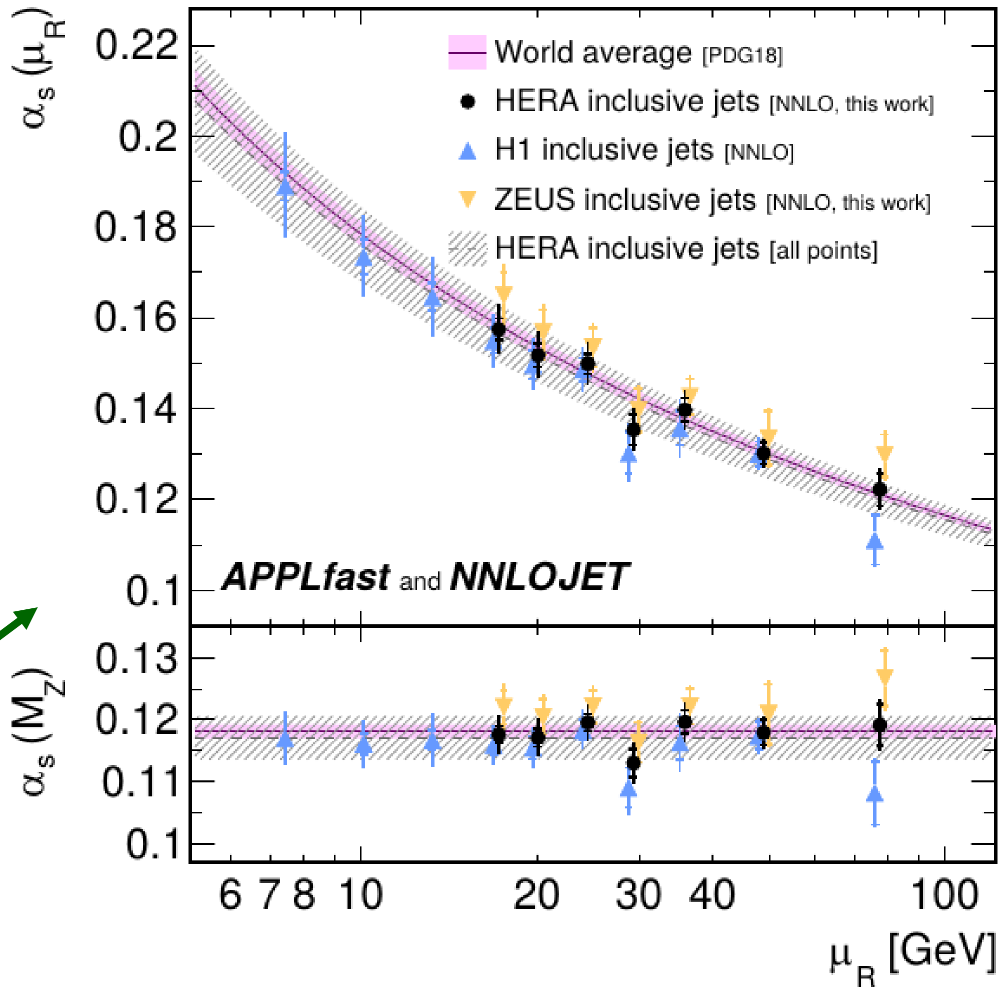
DIS interpolation grids

Successfully used for jets at NNLO in DIS:

- **H1,** **EPJC 77 (2017) 791; Err. EPJC 81 (2021) 738.**
- **APPLfast,** **EPJC 79 (2019) 845; Err. EPJC 81 (2021) 957.**
- **HERAPDF2.0Jets,** **EPJC 82 (2022) 243.**

See also yesterday's talk by Katarzyna Wichmann

Example:
Running of α_s from inclusive jets



Interpolation grids available on:
https://ploughshare.web.cern.ch

Ploughshare

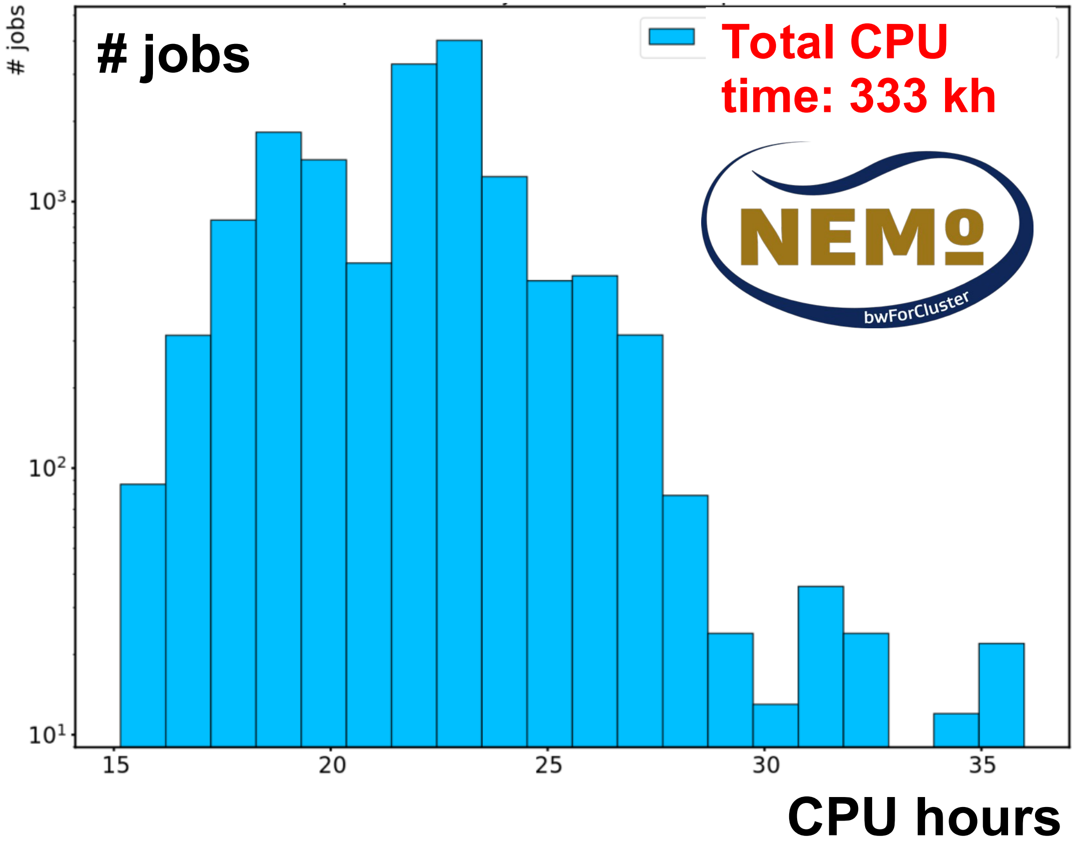
Ingredients

- **Theory:**
  - **NNLOJET:** T. Gehrmann et al., RADCOR2017 PoS (2018) 074, arXiv:1801.06415.
  - **Inclusive jets:** J. Currie et al, PRL 118 (2017) 072002; JHEP 10 (2018) 155.
  - **Dijets:** J. Currie et al., PRL 119 (2017) 152001; A. Gehrmann-de Ridder et al., PRL 123 (2019) 102001.

- **Tools:**
  - **APPLfast interface:** D. Britzger et al., EPJC 79 (2019) 845, arXiv:1906.05303.
  - **fastNLO:** D. Britzger et al., Proc. DIS2012 (2012) 217, arXiv:1208.3641.
  - **APPLgrid:** T. Carli et al., EPJC 66 (2010) 503, arXiv:0911.2985.
  - **xfitter:** S. Alekhin et al., EPJC 75 (2015) 304, arXiv:1410.4412.

The investment

Typical total runtime of a grid production



Total # of ~24h jobs: O(15000)

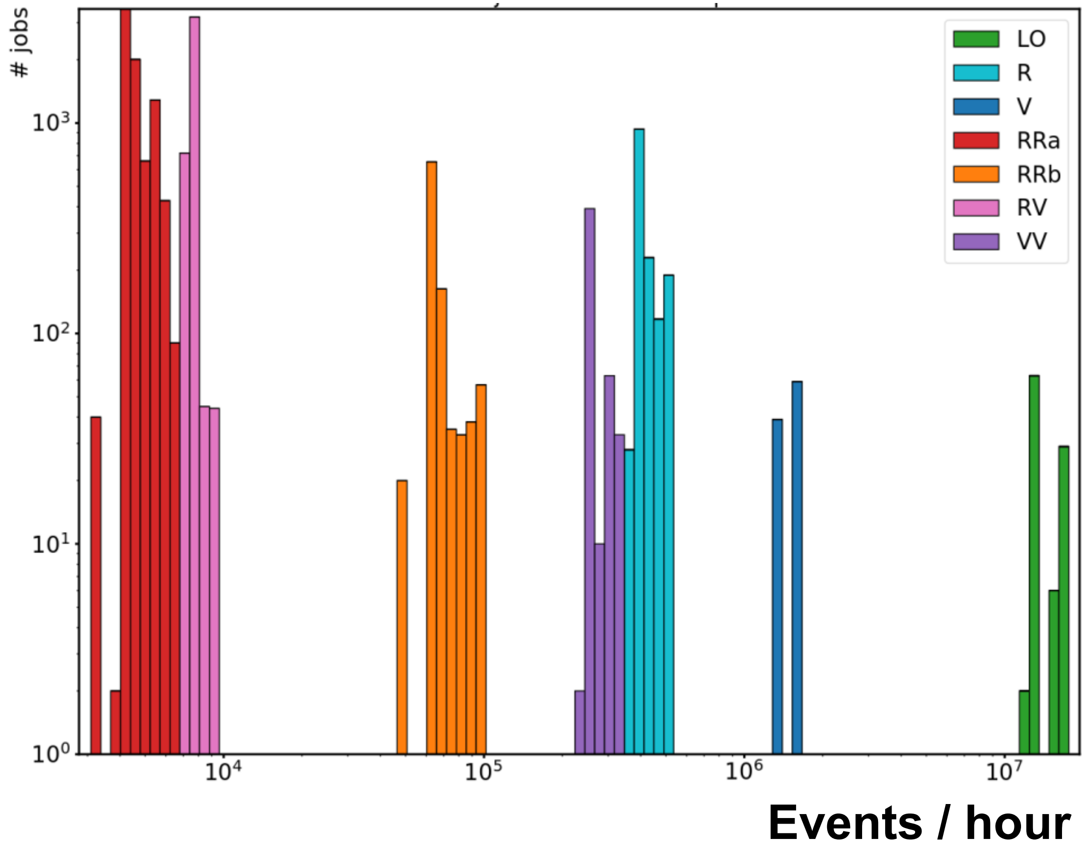
"Events" / hour

RRa, RV: most expensive

LO, NLO, VV: easy

$O(10^3-10^4)$

$O(10^5 - 10^7)$

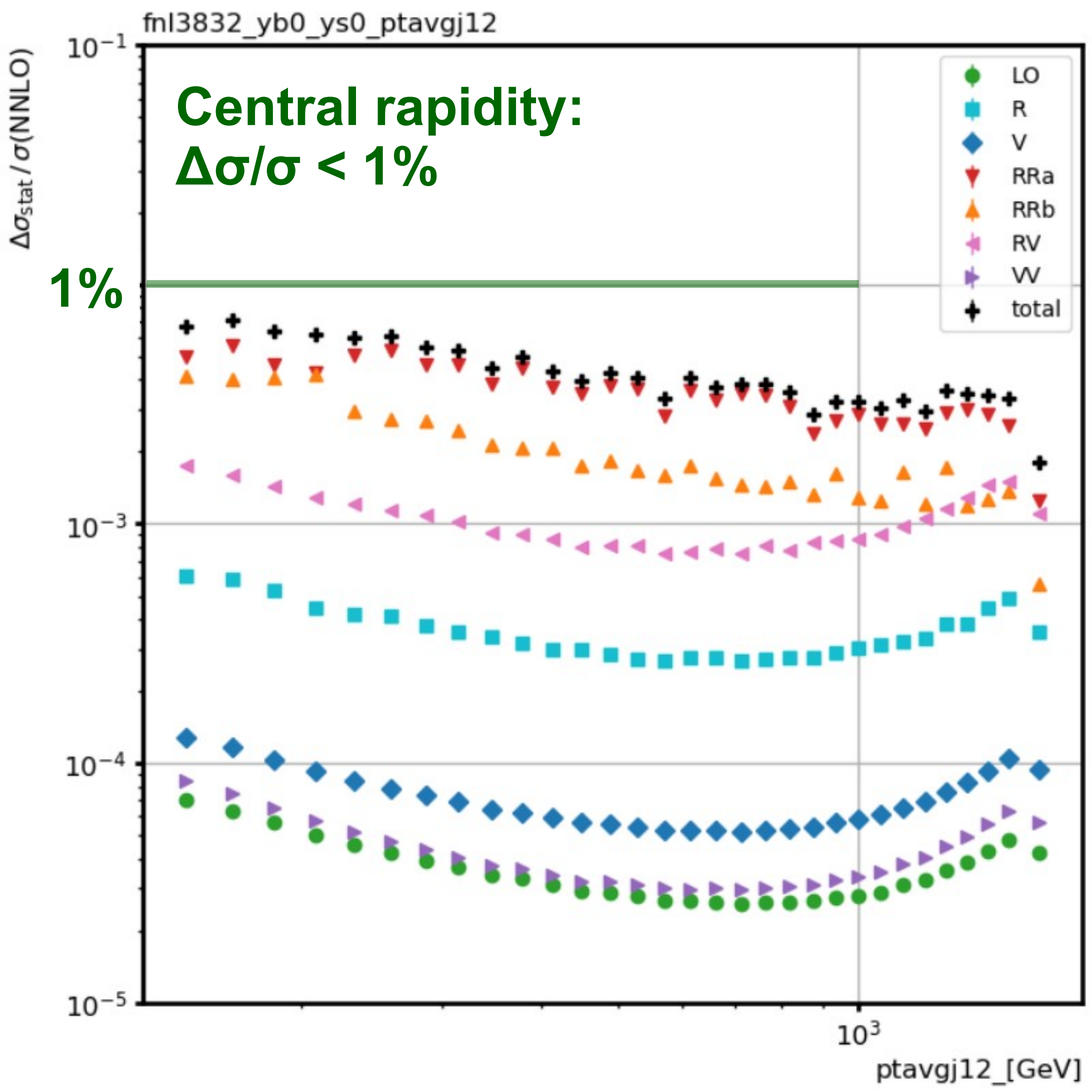


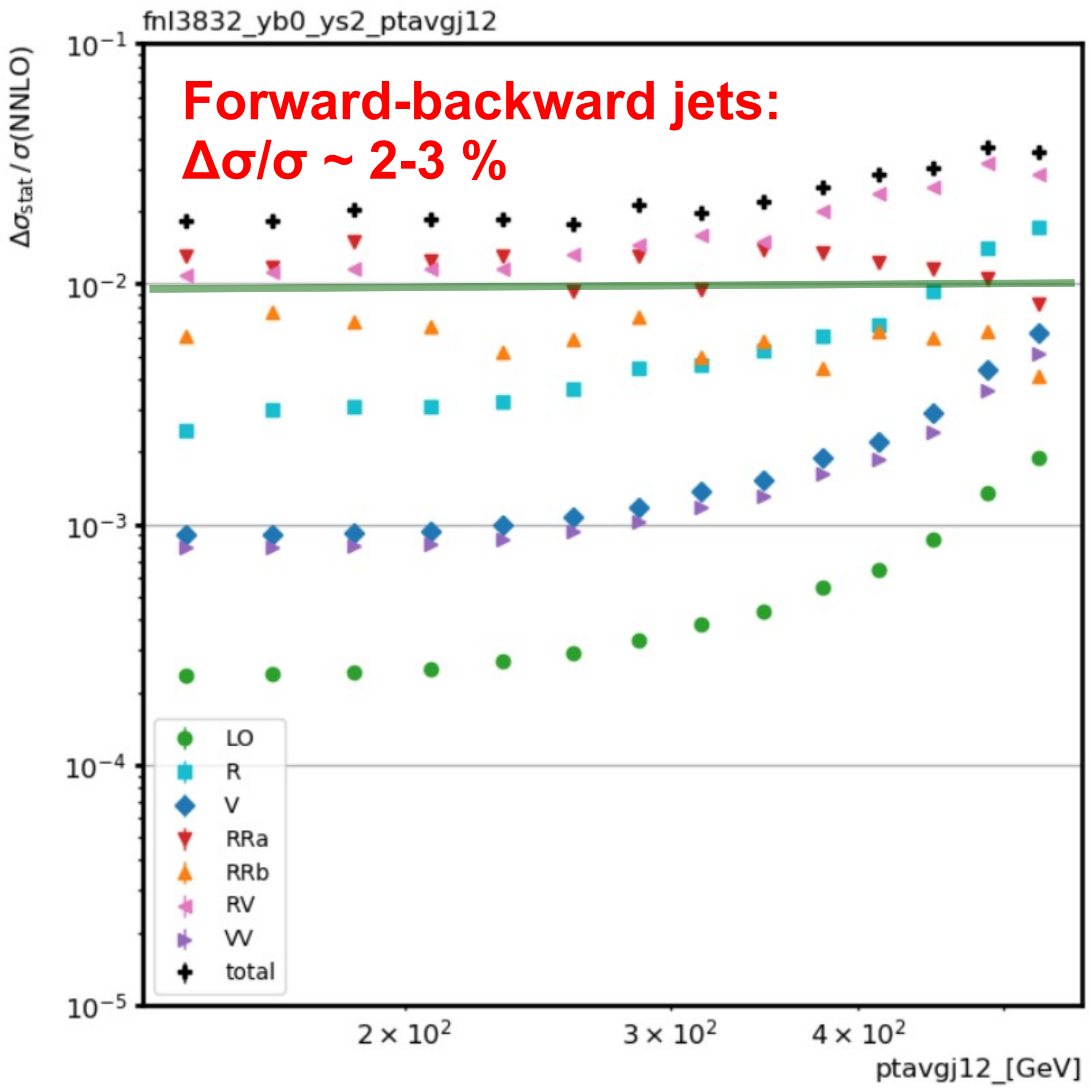
Return on investment

Relative numerical uncertainty of NNLO 3D dijet cross section

Dominated by RRa and RV channels

Numerical uncertainty provided inside grids





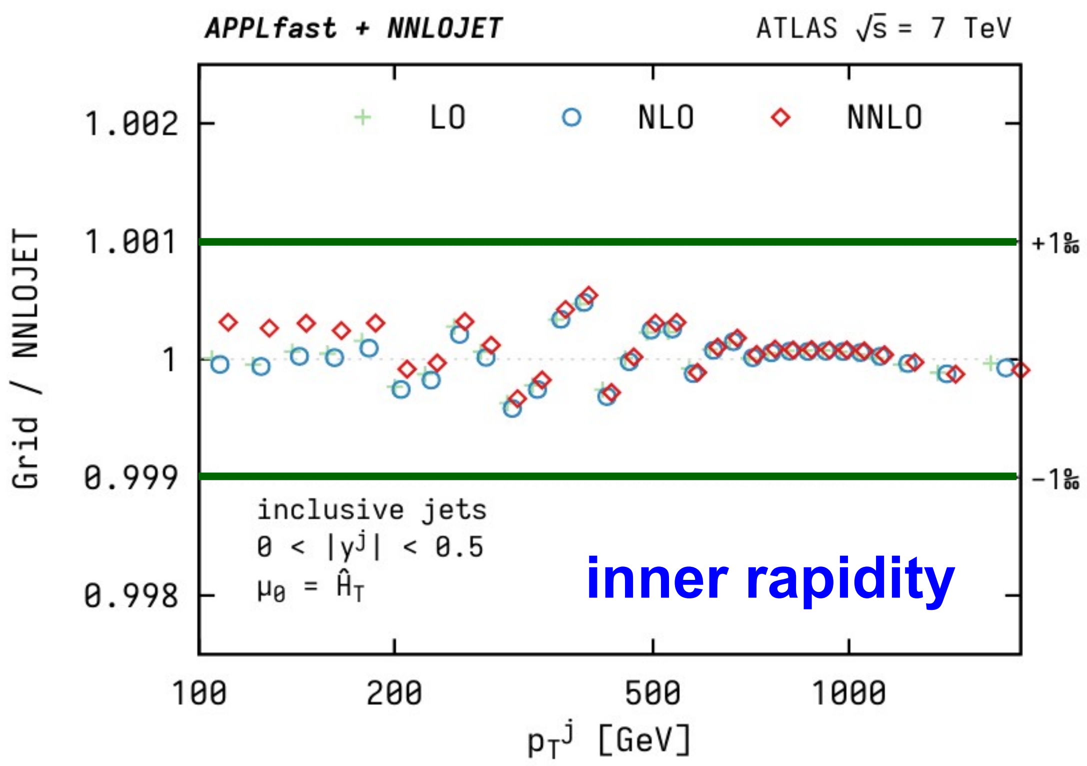
Inclusive jet datasets

- Seven inclusive jet datasets from ATLAS & CMS, 2D in p_T and y
  - Four centre-of-mass energies, three jet radii R
  - Two central scales for $\mu_{R/F}$

Sample plots in this talk

Data	$\sqrt{s}$ [TeV]	$\mathcal{L}$ [fb^{-1}]	no. of points	anti-k_T R	kinematic range [GeV]	fiducial cuts	$\mu_{R/F}$-choice
CMS [29]	2.76	0.00543	81	0.7	$p_T^{jet} \in [74, 592]$	$\lvert y\rvert < 3.0$	$p_T^{jet}, \hat{H}_T$
ATLAS [27]	7.0	4.5	2×140	0.4, 0.6	$p_T^{jet} \in [100, 1992]$	$\lvert y\rvert < 3.0$	$p_T^{jet}, \hat{H}_T$
CMS [30]	7.0	5.0	133	0.7	$p_T^{jet} \in [114, 2116]$	$\lvert y\rvert < 3.0$	$p_T^{jet}, \hat{H}_T$
ATLAS [31]	8.0	20.3	2×171	0.4, 0.6	$p_T^{jet} \in [70, 2500]$	$\lvert y\rvert < 3.0$	$p_T^{jet}, \hat{H}_T$
CMS [32]	8.0	5.6 19.7	248	0.7	$p_T^{jet} \in [21, 74]$ $p_T^{jet} \in [74, 2500]$	$\lvert y\rvert < 4.7$	$p_T^{jet}, \hat{H}_T$
ATLAS [33]	13.0	3.2	177	0.4	$p_T^{jet} \in [100, 3937]$	$\lvert y\rvert < 3.0$	$p_T^{jet}, \hat{H}_T$
CMS [34]	13.0	36.3 33.5	2×78	0.4 0.7	$p_T^{jet} \in [97, 3103]$	$\lvert y\rvert < 2.0$	$p_T^{jet}, \hat{H}_T$

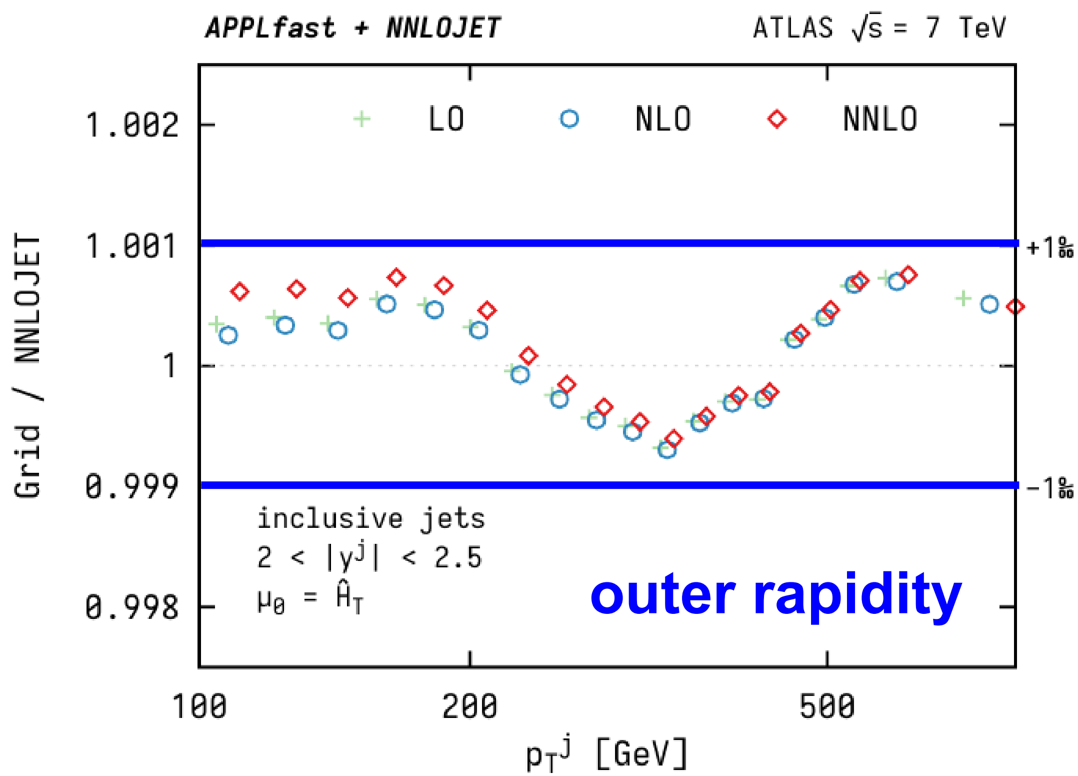
Grid closure vs. NNLOJET



ATLAS inclusive jets at 7 TeV

Generally aim at closure better than 1 ‰

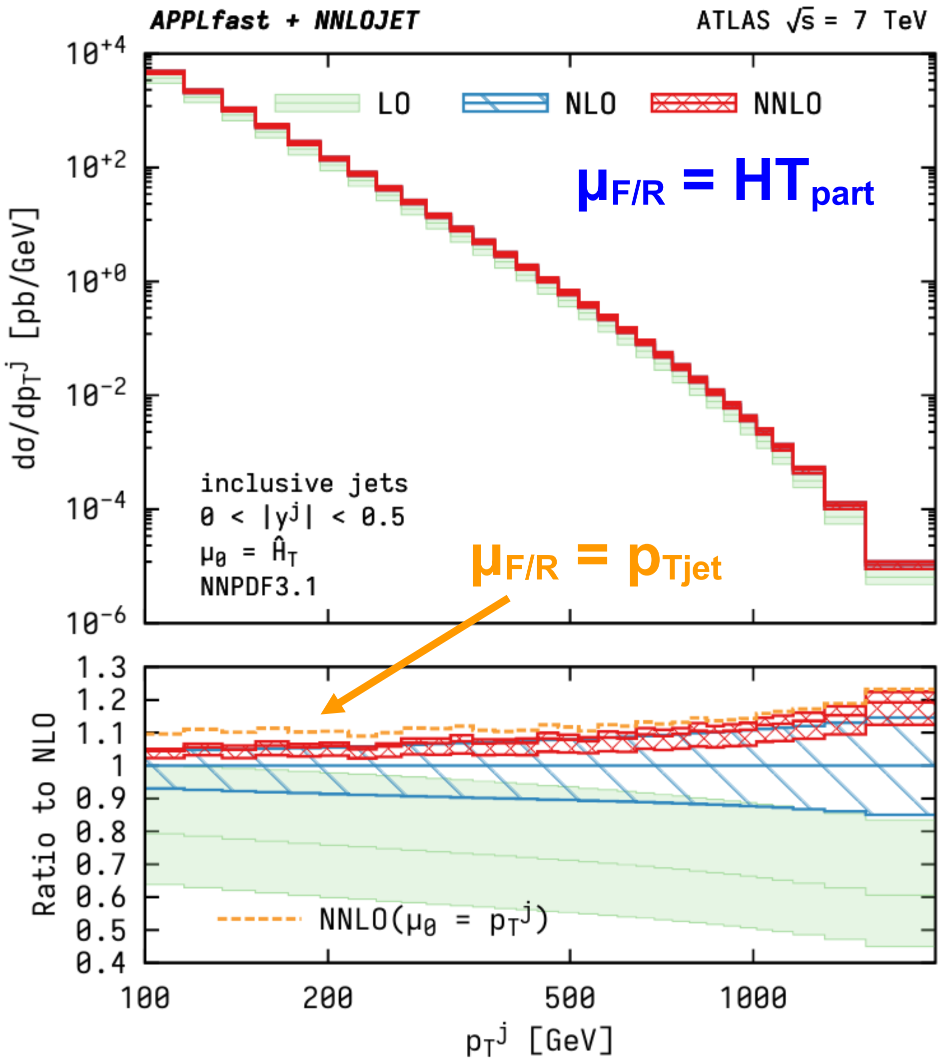
Closure deteriorates somewhat towards phase space limits; exceptionally may exceed 1 ‰ at phase space edges



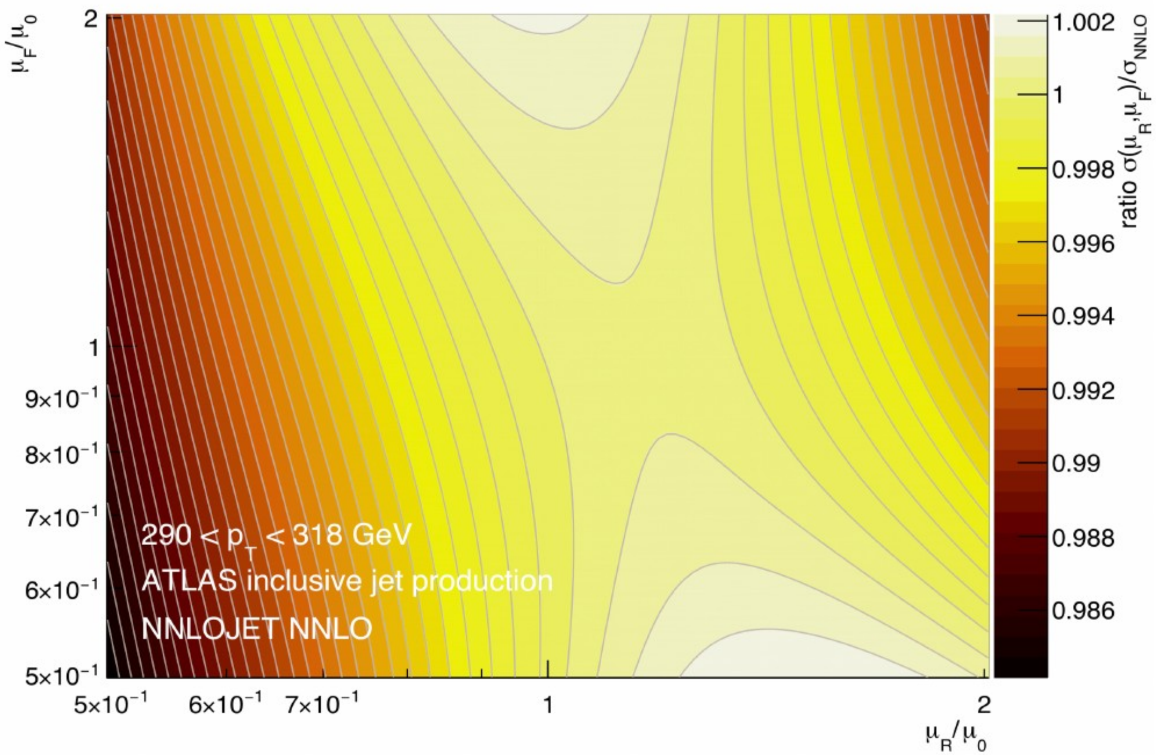
Scale dependence

ATLAS inclusive jets at 7 TeV

Scale uncertainty bands: LO, NLO, NNLO



Full 2-dimensional scale dependence in $\mu_{F/R}$ for each bin



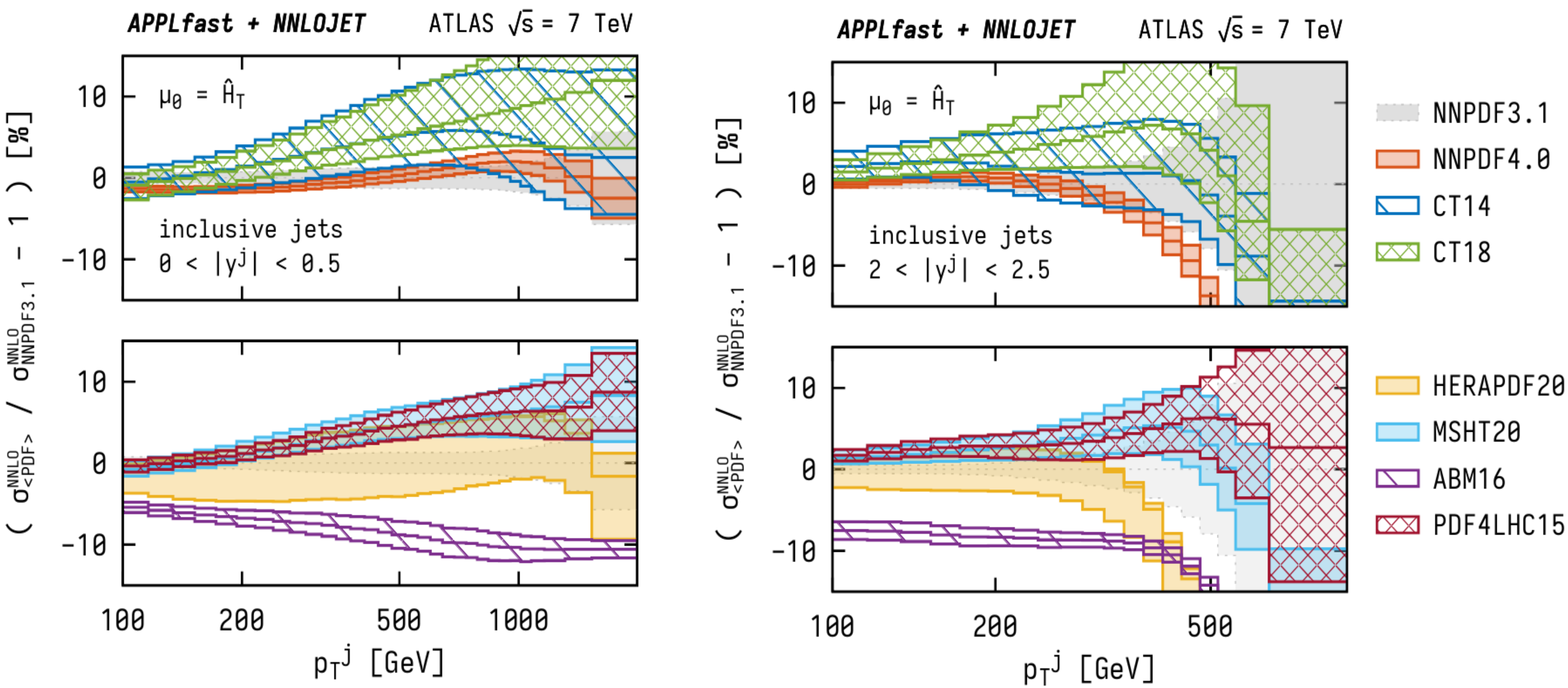
Additional scale: p_{Tjet} instead of HT_{part}

PDF dependence

ATLAS inclusive jets at 7 TeV

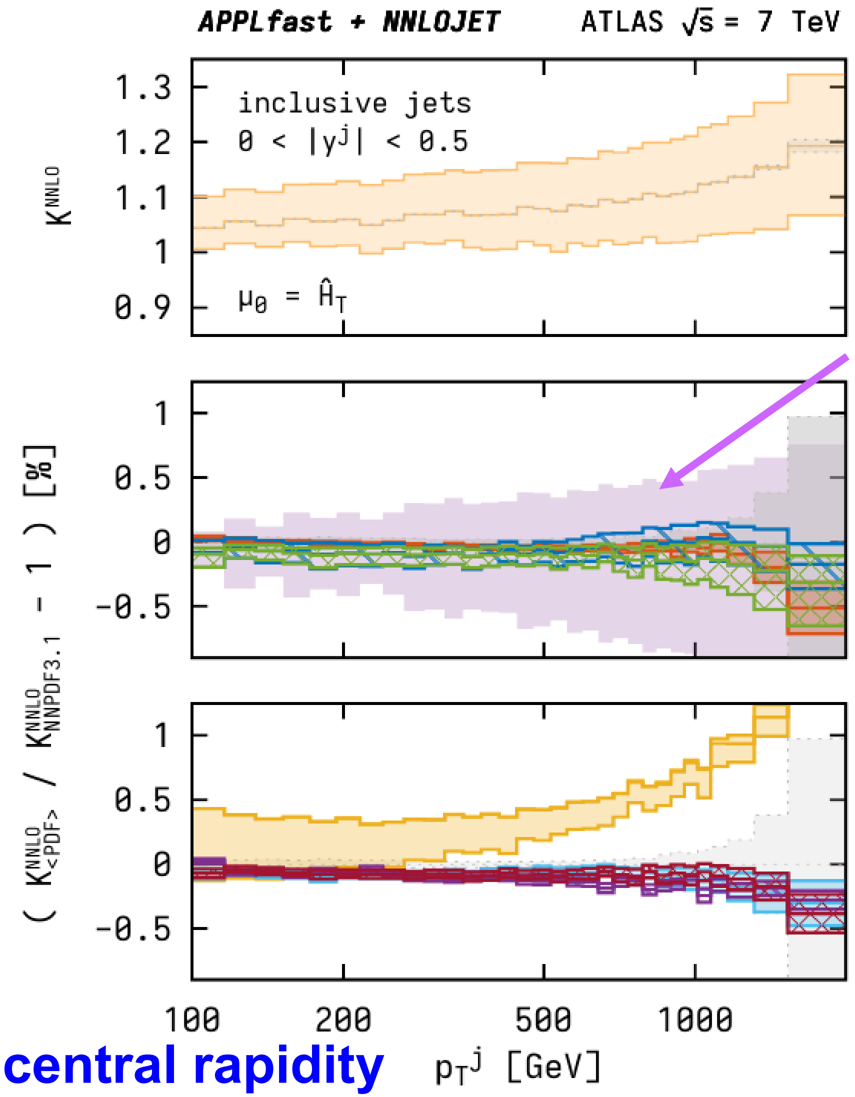
PDF uncertainty bands for selection of 8 PDF sets

central rapidity **outer rapidity**



K factor robustness

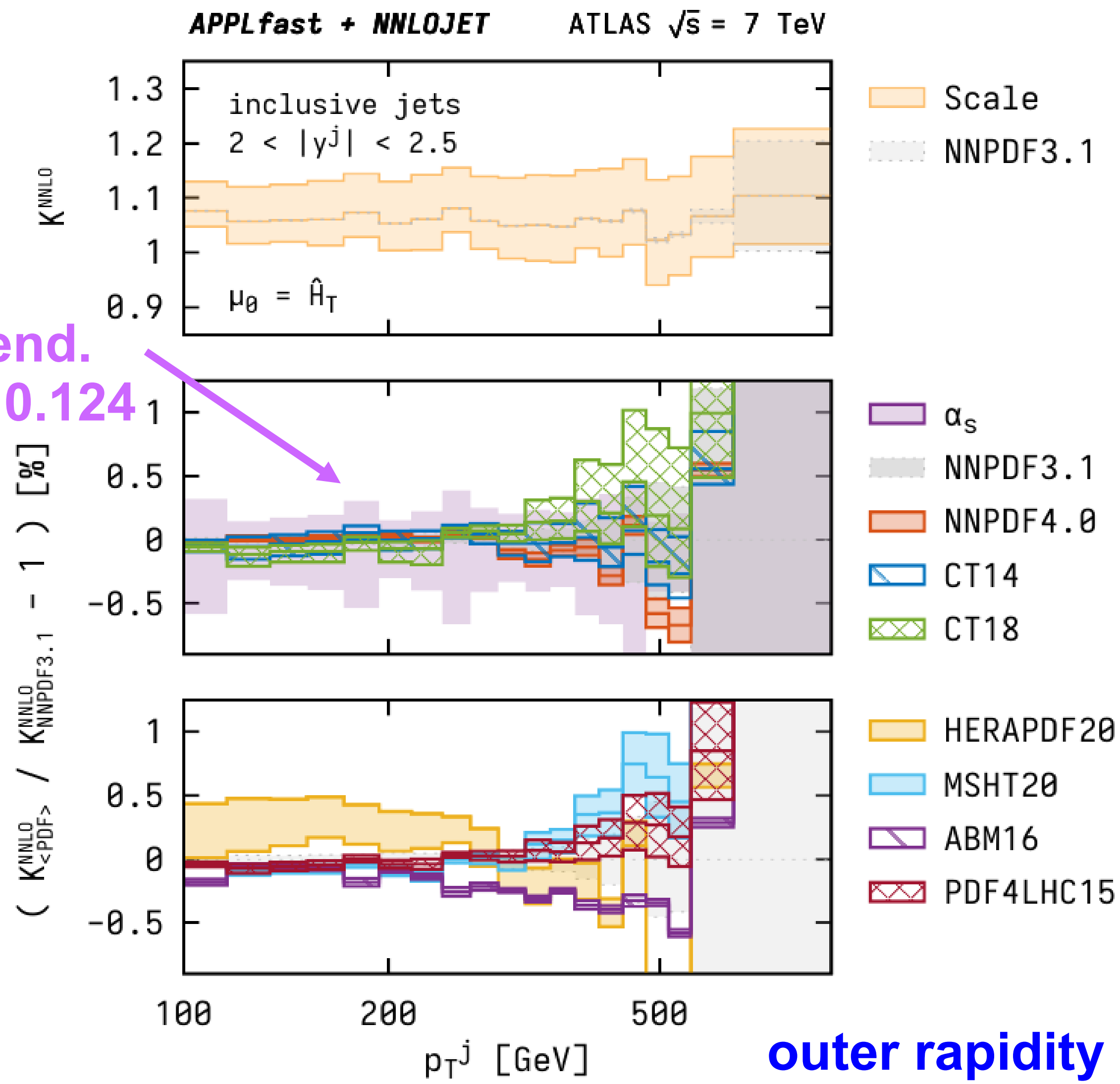
Dependence of K_{NNLO} on: α_s – negligible
most PDF sets – ~ 0.5%
exceptionally (ABM, HERAPDF) – ~ 1%



K_{NNLO}

α_s depend.
0.108 - 0.124

PDF dep.



central rapidity **outer rapidity**

Dijet datasets

- Four dijet datasets from ATLAS & CMS, 2D in m_{12} and y^* or y_{max}, or 3D in $\langle p_{T12} \rangle$, y^*, y_b
  - Three centre-of-mass energies, three jet radii R
  - One central scale for $\mu_{R/F}$, except for 3D data with two

Sample plots in this talk

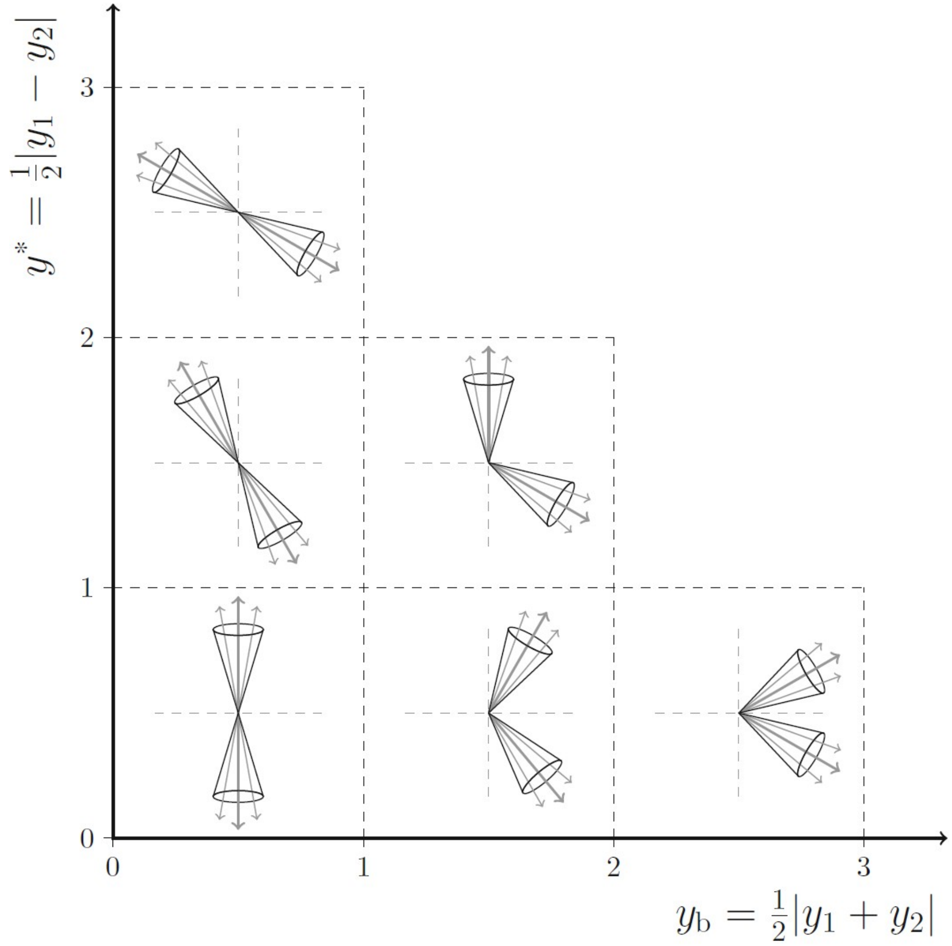
Data	$\sqrt{s}$ [TeV]	$\mathcal{L}$ [fb^{-1}]	no. of points	anti-k_T R	kinematic range [GeV]	fiducial cuts	$\mu_{R/F}$-choice
ATLAS [48]	7.0	4.5	90	0.6	$m_{12} \in [260, 5040]$	$\lvert y_1\rvert, \lvert y_2\rvert < 3.0$ $[p_{T,1}, p_{T,2}] > [100, 50]$GeV $y^* < 3.0$	m_{12}
CMS [30]	7.0	5.0	54	0.7	$m_{12} \in [197, 5058]$	$\lvert y\rvert < 5.0$ $[p_{T,1}, p_{T,2}] > [60, 30]$GeV $\lvert y_{max}\rvert < 2.5$	m_{12}
CMS [47]	8.0	19.7	122	0.7	$\langle p_{T1,2} \rangle \in [133, 1784]$	$\lvert y\rvert < 5.0$ $p_{T,1}, p_{T,2} > 50$GeV $\lvert y_1\rvert, \lvert y_2\rvert < 3.0$	$p_{T,1} \exp(0.3\, y^*)$ m_{12}
ATLAS [33]	13.0	3.2	136	0.4	$m_{12} \in [260, 9066]$	$\lvert y_1\rvert, \lvert y_2\rvert < 3.0$ $p_{T,1}, p_{T,2} > 75$GeV $\langle p_{T1,2} \rangle > 100$GeV $y^* < 3.0$	m_{12}

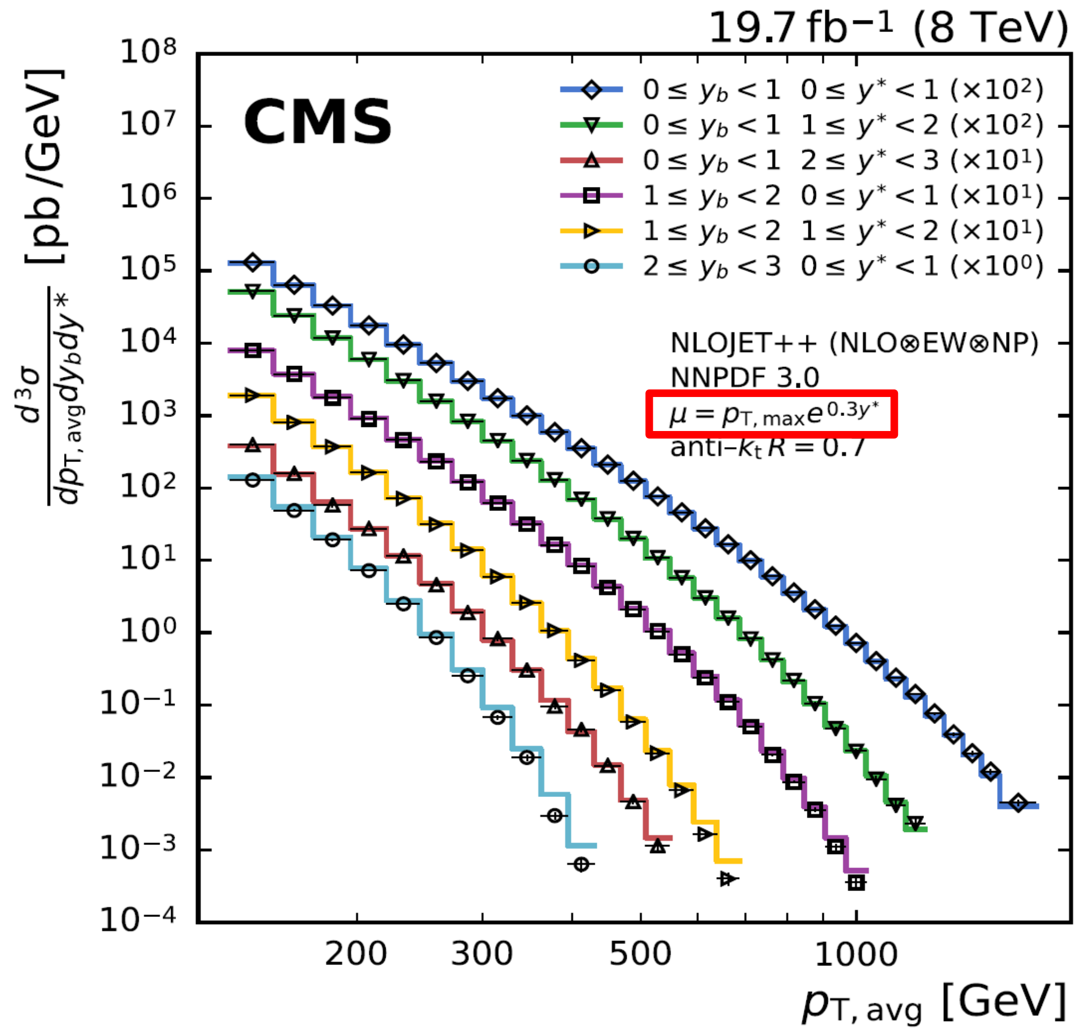
Triple-differential dijets

Most measurements done with respect to dijet mass and either max. rapidity $|y|_{max}$ (CMS) or rapidity separation y^* (ATLAS). One CMS result 3D in p_{T12}, y^*, y_b:

$$\frac{d^3\sigma}{dp_{\mathrm{T,avg}}\,dy_b\,dy^*} \propto \alpha_s^2$$

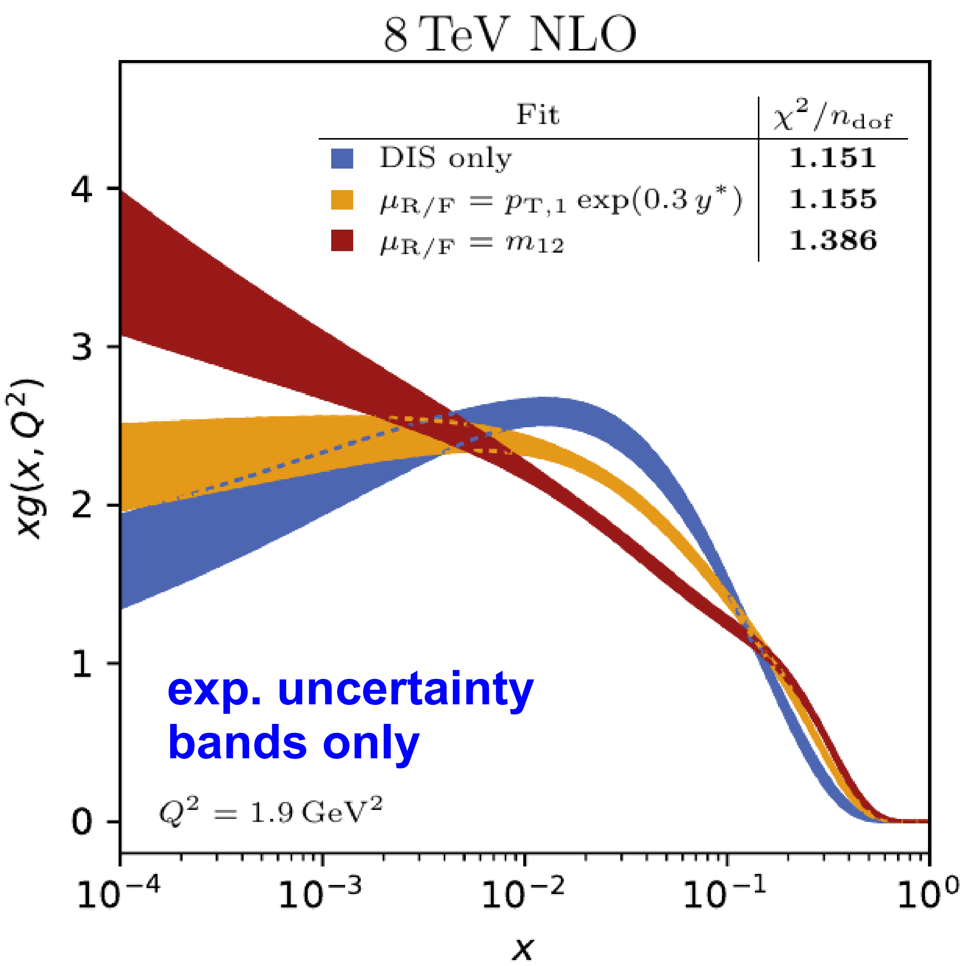
Illustration of dijet event topologies

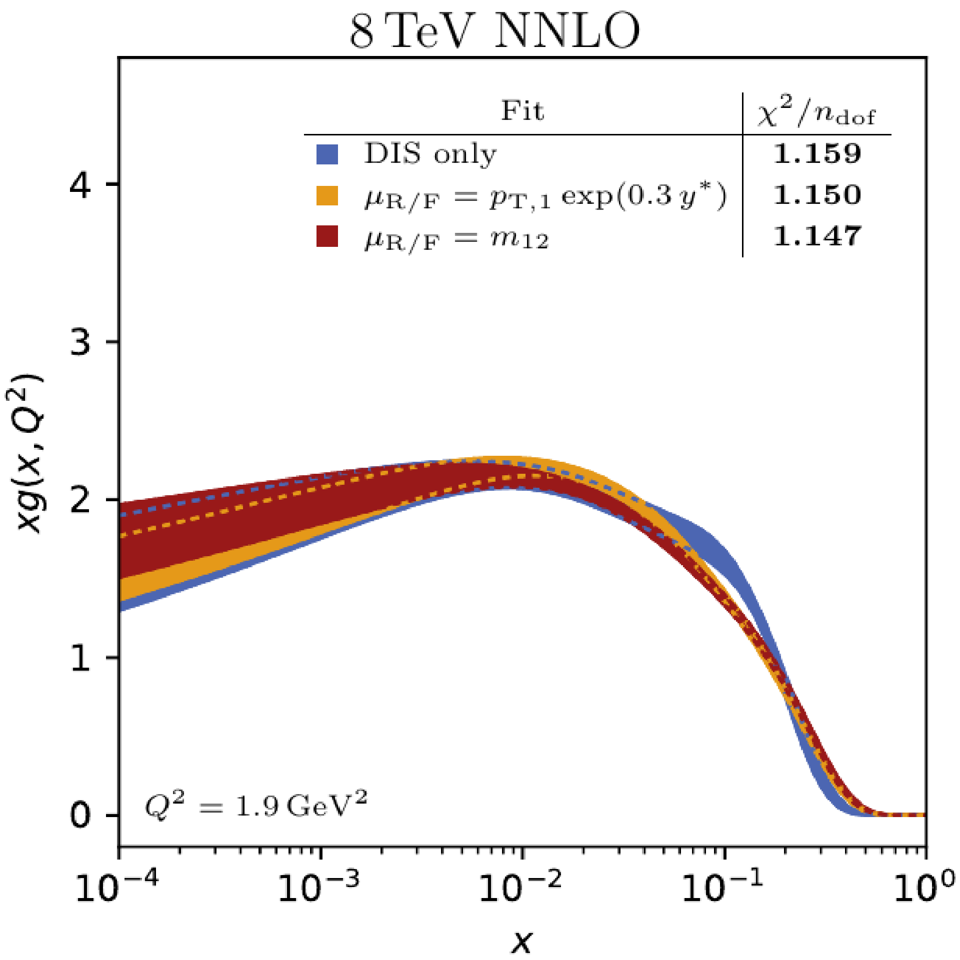




13 parameter fits – NLO vs. NNLO

Gluon from 13-parameter PDF fit with xfitter for two central scale choices



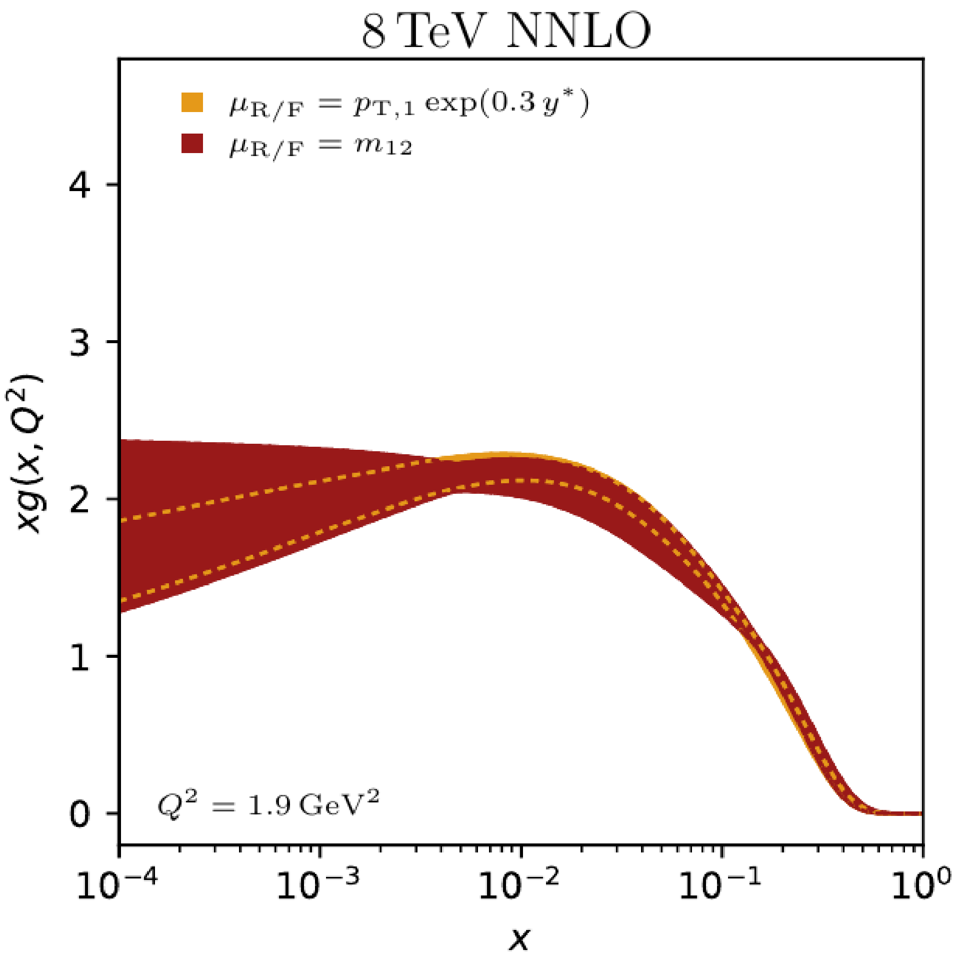


Left: NLO Significant differences between central scale definitions

Right: NNLO Much improved agreement between scales & better fit quality

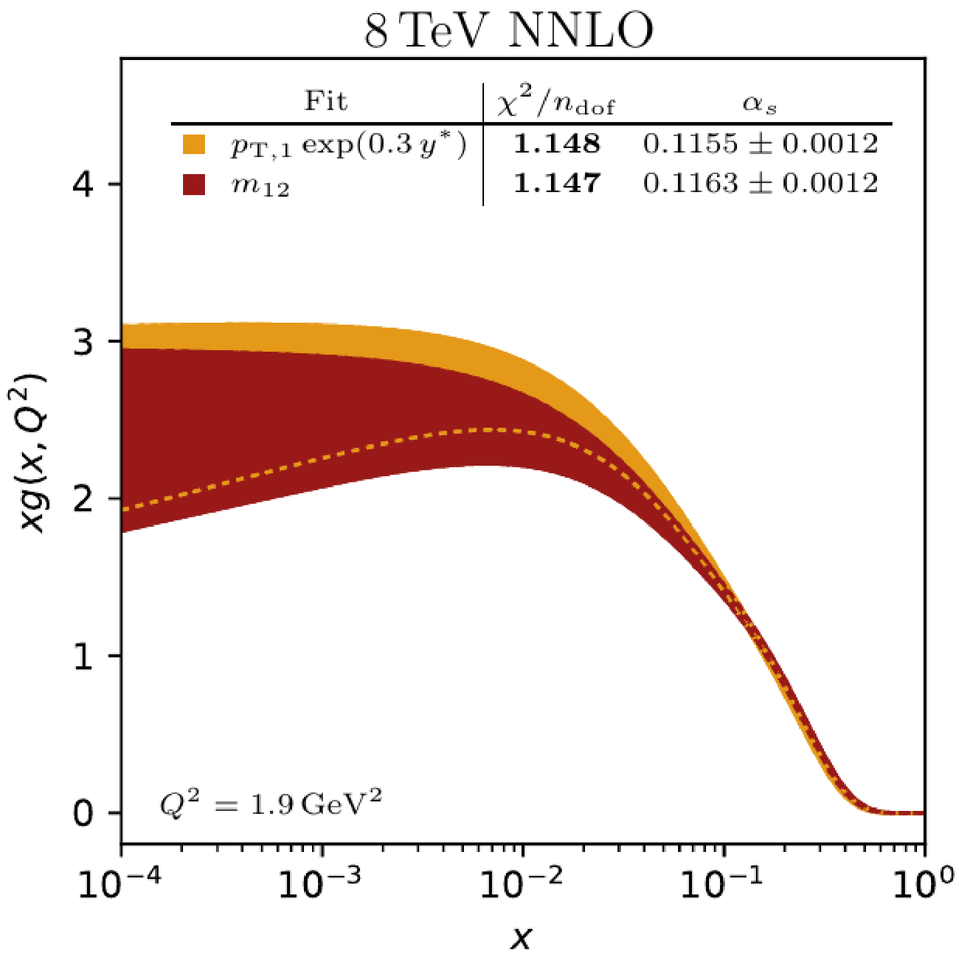
Scale varied fits & PDF+α_s fit

Gluon from 13-parameter PDF fit with scale variation band at NNLO



Much reduced scale dependence

Gluon from 14-parameter PDF fit at NNLO with free α_s



Fit	χ^2/n_{dof}	α_s
$p_{T,1}\exp(0.3\,y^*)$	**1.148**	0.1155 ± 0.0012
m_{12}	**1.147**	0.1163 ± 0.0012

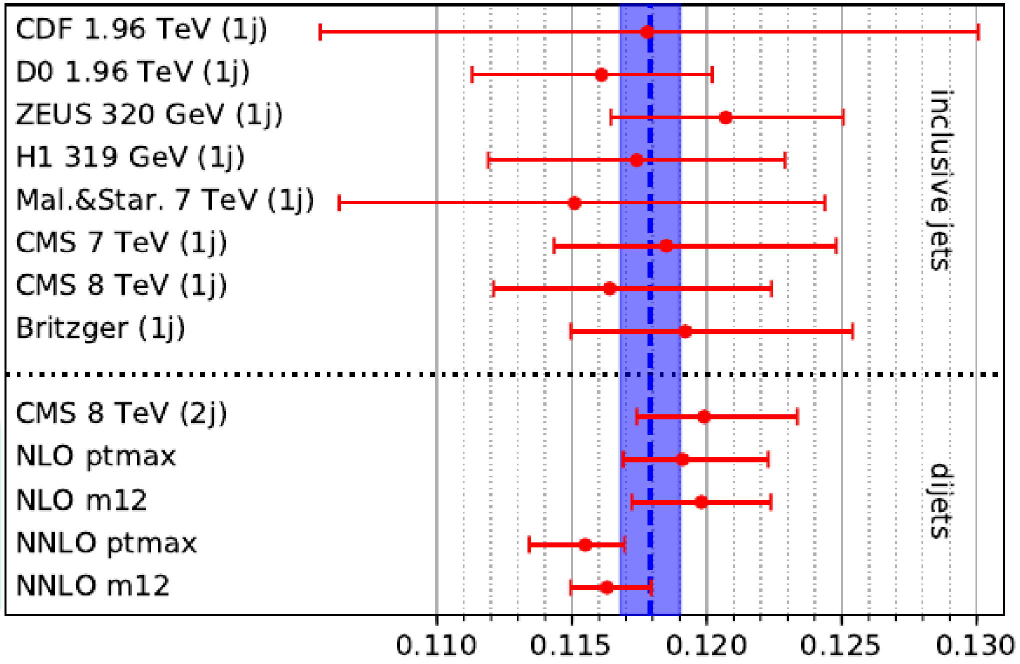
Consistent results between scales

Fitted α_s values

Fitted $\alpha_s(M_Z)$ values

NLO	$\mu = p_{\mathrm{T},1} e^{0.3y^*}$	$0.1191 \pm 0.0015(\mathrm{exp})^{+0.0028}_{-0.0016}(\mathrm{scale})$
	$\mu = m_{12}$	$0.1198 \pm 0.0015(\mathrm{exp})^{+0.0021}_{-0.0021}(\mathrm{scale})$
NNLO	$\mu = p_{\mathrm{T},1} e^{0.3y^*}$	$0.1155 \pm 0.0012(\mathrm{exp})^{+0.0008}_{-0.0017}(\mathrm{scale})$
	$\mu = m_{12}$	$0.1163 \pm 0.0013(\mathrm{exp})^{+0.0010}_{-0.0004}(\mathrm{scale})$

⚠ Only experimental and scale uncertainties



Comparison with other values obtained from jet cross sections and the world average (blue)

- as expected, smaller α_s values at NNLO
- scale uncertainties: envelope of 6 scale variations
- experimental and especially scale uncertainties smaller at NNLO

Summary & Outlook

- Series of interpolation grids for pp → jets produced for ATLAS & CMS:
  - Inclusive jet & dijet production
  - Several centre-of-mass energies and jet sizes R
  - Numerical accuracy of O(‰) and precision of O(%)
- Will be made public via Ploughshare rather soon'ish

- Continue work on:
  - Other processes in NNLOJET
  - Simplified interface to new NNLOJET version with numerous performance improvements, also for the grid filling
  - Remark concerning arXiv:2204.10173 and leading color:
    - Small effect on inclusive jets or 2D dijets
    - Updated interface also gets full-color result

Data references

- **ATLAS data:**
  - **Inclusive jets:** JHEP 02 153 (2015), JHEP 09 020 (2017), JHEP 05 195 (2018).
  - **Dijets:** JHEP 05 059 (2014), JHEP 05 195 (2018).
- **CMS data:**
  - **Inclusive jets:** EPJC 76(5) 265 (2016), PRD 87 112002 (2013), JHEP 03 156 (2017), JHEP 02 142 (2022).

    Dijets: PRD 87 112002 (2013), EPJC 77(11) 746 (2017).
- **More details on 3D dijet fits:**
  - **G. Sieber, PhD thesis:** IEKP-KA/2016-05, KIT, May 2016.
  - https://publish.etp.kit.edu/record/21328
  - **J. Stark, Master thesis:** ETP-KA/2021-2, KIT, Feb. 2021.
  - https://publish.etp.kit.edu/record/22044

Backup Slides

Interpolation concept

Implemented in APPLgrid & fastNLO

Use interpolation kernel

- Introduce set of n discrete **x-nodes**, x_i's being equidistant in a function f(x)
- Take set of **Eigenfunctions $E_i(x)$** around nodes x_i

→ Interpolation kernels

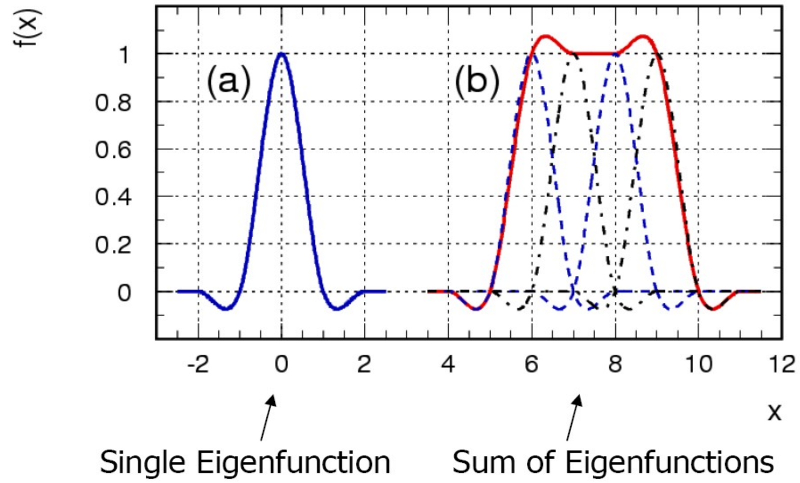
- Actually a rather old idea, see e.g.
  C. Pascaud, F. Zomer (Orsay, LAL), LAL-94-42

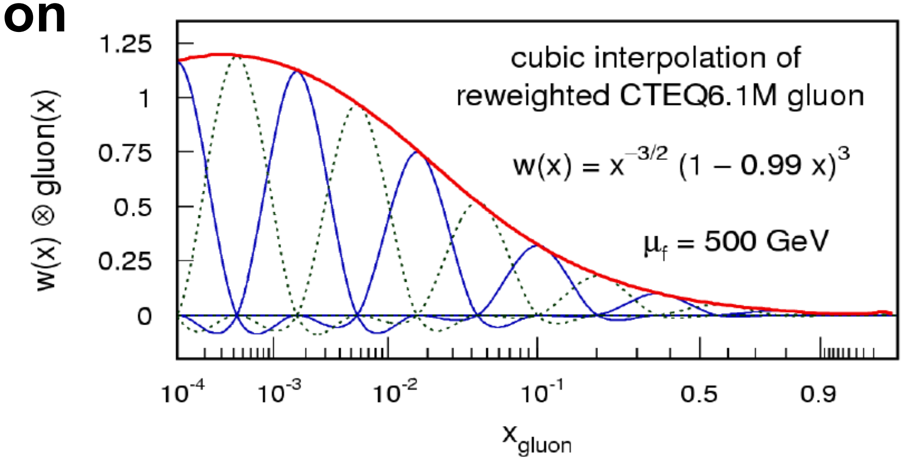
→ Single PDF is replaced by a linear combination of interpolation kernels

$$f_a(x) \cong \sum_i f_a(x_i) \cdot E^{(i)}(x)$$

→ Then the integrals are done only once

→ Afterwards only summation required to change PDF





Tabulate the convolution of the perturbative coefficients with the interpolation kernel

PDF parameterisation

$$xg(x) = A_g\, x^{B_g}\, (1-x)^{C_g}\, (1+E_g x^2)$$
$$xu_v(x) = A_{u_v} x^{B_{u_v}} (1-x)^{C_{u_v}} (1+D_{u_v} x)$$
$$xd_v(x) = A_{d_v} x^{B_{d_v}} (1-x)^{C_{d_v}}$$
$$x\bar{U}(x) = A_{\bar{U}}\, x^{B_{\bar{U}}}\, (1-x)^{C_{\bar{U}}}\, (1+D_{\bar{U}} x)$$
$$x\bar{D}(x) = A_{\bar{D}}\, x^{B_{\bar{D}}}\, (1-x)^{C_{\bar{D}}}$$

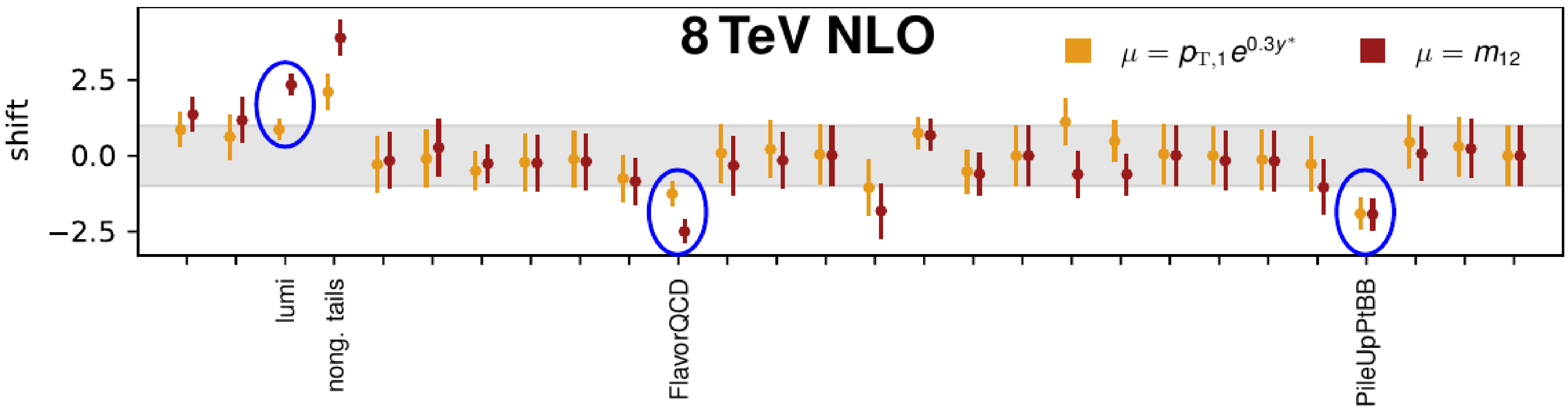
Here:
$f_s = 0.40$

$$A_{\overline{U}} = A_{\overline{D}}(1-f_s)$$

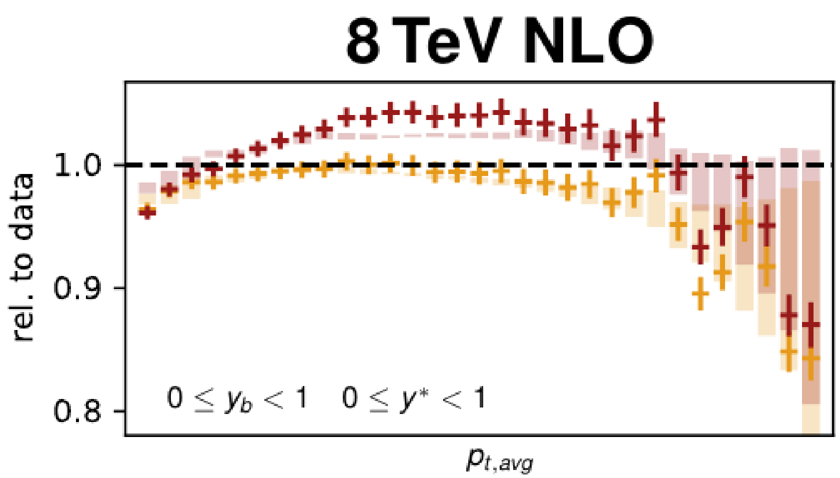
CMS:
$f_s = 0.31$

$$xg(x) = A_g x^{B_g} (1-x)^{C_g} - A'_g x^{B'_g} (1-x)^{C'_g},$$
$$xu_v(x) = A_{u_v} x^{B_{u_v}} (1-x)^{C_{u_v}} (1 + D_{u_v} x + E_{u_v} x^2),$$
$$xd_v(x) = A_{d_v} x^{B_{d_v}} (1-x)^{C_{d_v}} (1 + D_{d_v} x),$$
$$x\overline{U}(x) = A_{\overline{U}} x^{B_{\overline{U}}} (1-x)^{C_{\overline{U}}} (1 + D_{\overline{U}} x),$$
$$x\overline{D}(x) = A_{\overline{D}} x^{B_{\overline{D}}} (1-x)^{C_{\overline{D}}},$$

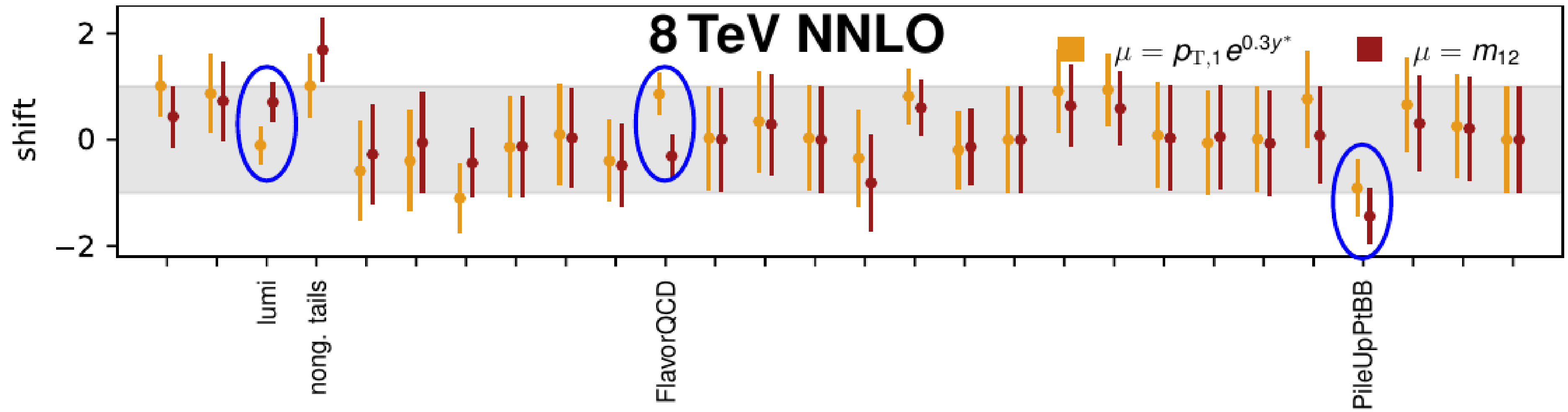
Pulls of fitted nuisance parameters



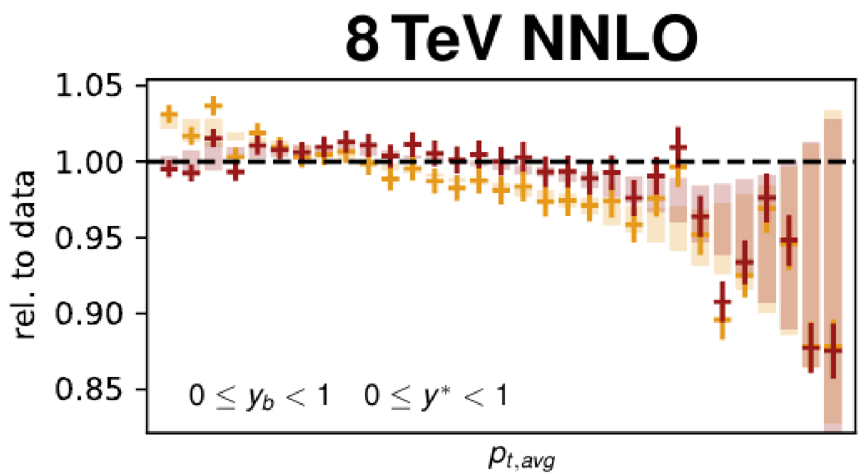
- curved distortion between prediction (crosses) and central data (black line)
- data is shifted towards predition (transparent bars)
- outliers in shifts produce distortion, lumi globally shifts data



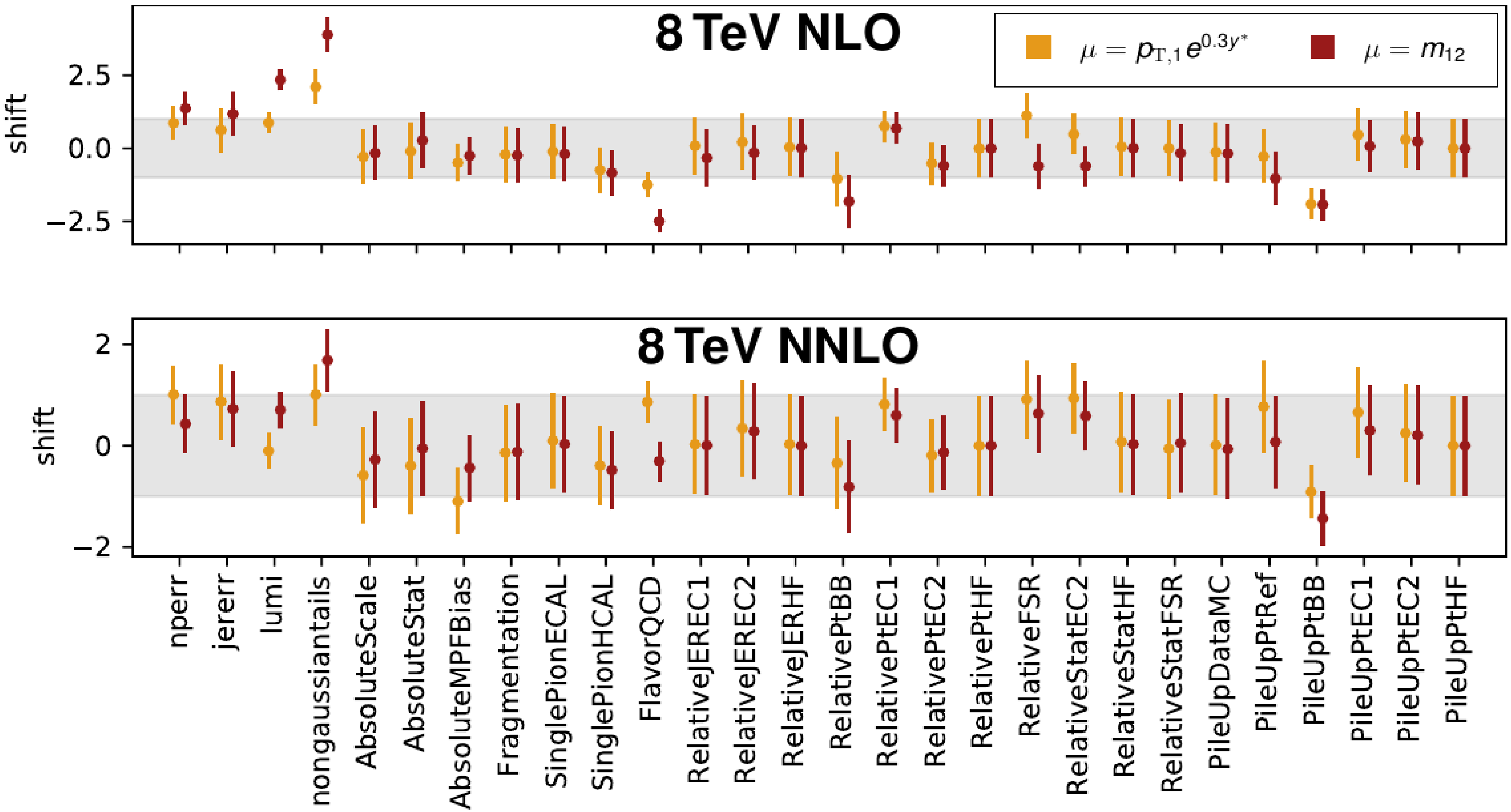
Pulls of fitted nuisance parameters



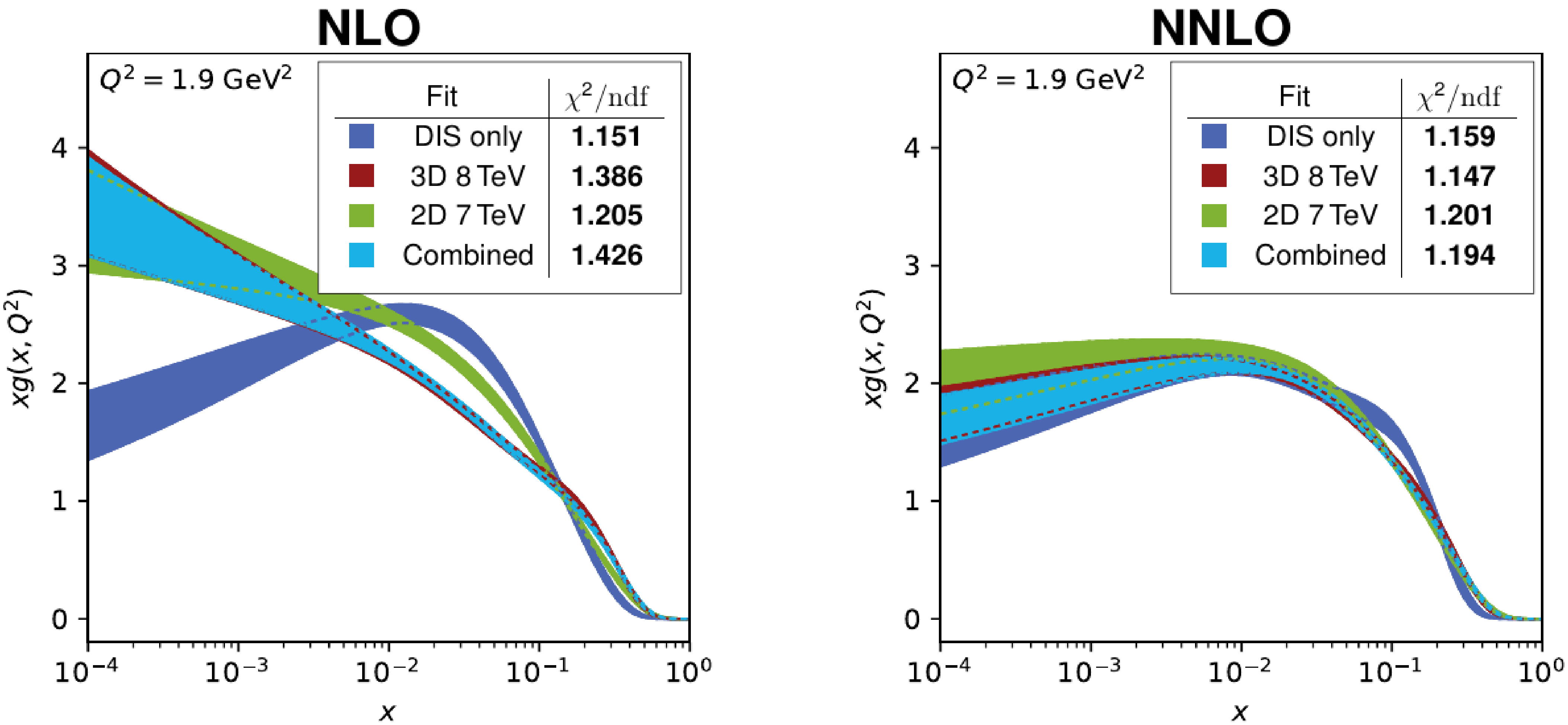
- curved distortion drastically reduced in NNLO
- previous outliers in shifts almost back in the gray 1-sigma region



Pulls of fitted nuisance parameters



Including 7 TeV 2D dijet data



- use $\mu = m_{12}$ (dijet mass) scale for both datasets
- 7 & 8 TeV data compatible, 3D 8 TeV data dominates the combined fit
- NNLO results much more consistent

Grid distribution – Ploughshare