FLAVOUR DEPENDENCE OF TMDS

P. Zurita

in collaboration with M. Bury, F. Hautmann, S. Leal-Gómez, I. Scimemi and A. Vladimirov

EINN 2023, Oct. 31st–Nov. 4th 2023
Paphos, Cyprus

OUTLINE

- TMD extraction and flavour dependence: a brief history.
- SV19: PDF uncertainty in TMDPDFs.
- Flavour dependence of TMDs.
- Summary.

A <u>VERY</u> BRIEF HISTORY

Courtesy of previous speakers, I don’t need to introduce the TMDPDFs.

😊 Thanks!

A <u>VERY</u> BRIEF HISTORY

Courtesy of previous speakers, I don't need to introduce the TMDPDFs.

😊 Thanks!

Investigations into the flavor dependence of partonic transverse momentum, A. Signori, A. Bacchetta, M. Radici, G. Schnell. ***JHEP* 11 (2013) 194**

A VERY BRIEF HISTORY

Courtesy of previous speakers, I don't need to introduce the TMDPDFs.

😊 Thanks!

Investigations into the flavor dependence of partonic transverse momentum, A. Signori, A. Bacchetta, M. Radici, G. Schnell. ***JHEP* 11 (2013) 194**

Fit to HERMES data (SIDIS)

$$f_1^a(x, \mathbf{k}_\perp^2; Q^2) = \frac{f_1^a(x, Q^2)}{\pi \langle \mathbf{k}_{\perp,a}^2 \rangle} e^{-\mathbf{k}_\perp^2 / \langle \mathbf{k}_{\perp,a}^2 \rangle}$$

extra x dependence in $\langle \mathbf{k}_{\perp,a}^2 \rangle$

$$D_1^{a\to h}(z, \mathbf{P}_\perp^2; Q^2) = \frac{D_1^{a\to h}(z, Q^2)}{\pi \langle \mathbf{P}_{\perp,a\to h}^2 \rangle} e^{-\mathbf{k}_\perp^2 / \langle \mathbf{P}_{\perp,a\to h}^2 \rangle}$$

extra z dependence in $\langle \mathbf{P}_{\perp,a}^2 \rangle$

A VERY BRIEF HISTORY

Courtesy of previous speakers, I don’t need to introduce the TMDPDFs.

😊 Thanks!

Investigations into the flavor dependence of partonic transverse momentum, A. Signori, A. Bacchetta, M. Radici, G. Schnell. ***JHEP* 11 (2013) 194**

Fit to HERMES data (SIDIS)

$$f_1^a(x, \mathbf{k}_\perp^2; Q^2) = \frac{f_1^a(x, Q^2)}{\pi \langle \mathbf{k}_{\perp,a}^2 \rangle} e^{-\mathbf{k}_\perp^2 / \langle \mathbf{k}_{\perp,a}^2 \rangle}$$

$a = u_v,\ d_v,$ sea

12 parameters in total

$$D_1^{a\to h}(z, \mathbf{P}_\perp^2; Q^2) = \frac{D_1^{a\to h}(z, Q^2)}{\pi \langle \mathbf{P}_{\perp,a\to h}^2 \rangle} e^{-\mathbf{k}_\perp^2 / \langle \mathbf{P}_{\perp,a\to h}^2 \rangle}$$

- Four fits: default, higher Q^2 cut, only pions, flavour independent.

- includes an estimation of the collinear FFs uncertainties in the definition of the χ^2.

χ^2/d.o.f.									**JHEP 11 (2013) 194**
	global	$p \to K^-$	$p \to \pi^-$	$p \to \pi^+$	$p \to K^+$	$D \to K^-$	$D \to \pi^-$	$D \to \pi^+$	$D \to K^+$
Default	1.63 ± 0.12	0.78 ± 0.15	1.80 ± 0.27	2.64 ± 0.21	0.46 ± 0.07	2.77 ± 0.56	1.65 ± 0.20	2.16 ± 0.21	0.71 ± 0.15
$Q^2 > 1.6$ GeV^2	1.37 ± 0.12	0.77 ± 0.14	1.50 ± 0.24	1.91 ± 0.30	0.49 ± 0.07	2.78 ± 0.52	1.28 ± 0.19	1.64 ± 0.25	0.58 ± 0.12
Pions only	2.04 ± 0.16	—	1.68 ± 0.24	2.70 ± 0.22	—	—	1.50 ± 0.18	2.22 ± 0.22	—
Flavor-indep.	1.72 ± 0.11	0.87 ± 0.16	1.83 ± 0.25	2.89 ± 0.23	0.43 ± 0.07	3.15 ± 0.62	1.66 ± 0.20	2.21 ± 0.22	0.71 ± 0.15

TABLE II. 68% confidence intervals of χ^2/d.o.f. values (global result and for every available target-hadron combination $N \to h$) for each of the considered four scenarios.

- Four fits: default, higher Q^2 cut, only pions, flavour independent.

- includes an estimation of the collinear FFs uncertainties in the definition of the χ^2.

	χ^2/d.o.f.								**JHEP 11 (2013) 194**
	global	$p \to K^-$	$p \to \pi^-$	$p \to \pi^+$	$p \to K^+$	$D \to K^-$	$D \to \pi^-$	$D \to \pi^+$	$D \to K^+$
Default	1.63 ± 0.12	0.78 ± 0.15	1.80 ± 0.27	2.64 ± 0.21	0.46 ± 0.07	2.77 ± 0.56	1.65 ± 0.20	2.16 ± 0.21	0.71 ± 0.15
$Q^2 > 1.6$ GeV^2	1.37 ± 0.12	0.77 ± 0.14	1.50 ± 0.24	1.91 ± 0.30	0.49 ± 0.07	2.78 ± 0.52	1.28 ± 0.19	1.64 ± 0.25	0.58 ± 0.12
Pions only	2.04 ± 0.16	—	1.68 ± 0.24	2.70 ± 0.22	—	—	1.50 ± 0.18	2.22 ± 0.22	—
Flavor-indep.	1.72 ± 0.11	0.87 ± 0.16	1.83 ± 0.25	2.89 ± 0.23	0.43 ± 0.07	3.15 ± 0.62	1.66 ± 0.20	2.21 ± 0.22	0.71 ± 0.15

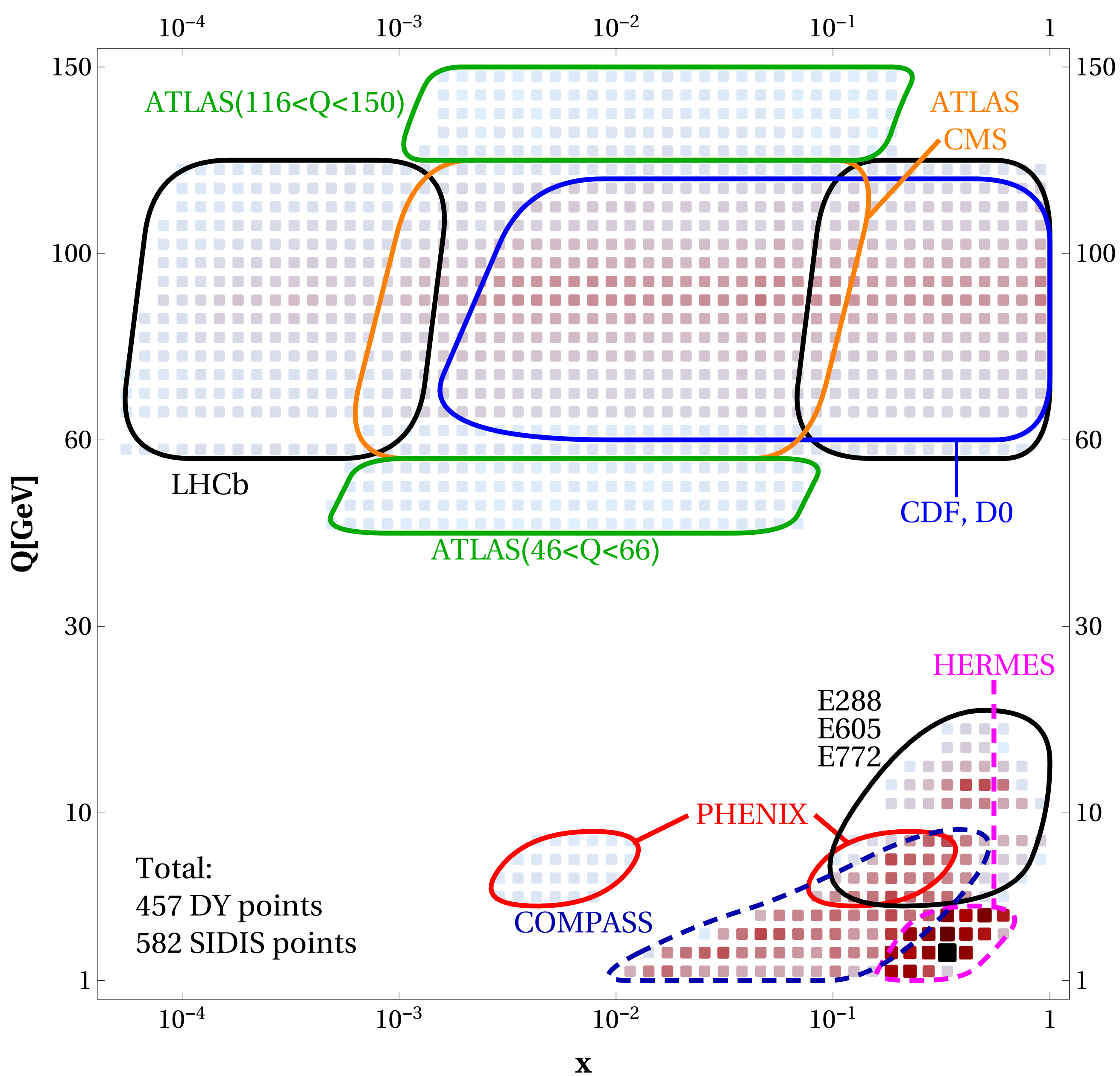
TABLE II. 68% confidence intervals of χ^2/d.o.f. values (global result and for every available target-hadron combination $N \to h$) for each of the considered four scenarios.

- Lower χ^2 in the flavour dependent fit.

- Not conclusive due to the limited kinematic span of the data and simplicity of the analysis (e.g. no evolution considered).

SV19: PDF UNCERTAINTY IN TMDPDFS

$$f_{NP}(x,b) = \exp\left(- \frac{\lambda_1(1-x) + \lambda_2 x + x(1-x)\lambda_5}{\sqrt{1+\lambda_3 x^{\lambda_4} \mathbf{b}^2}} \mathbf{b}^2 \right)$$

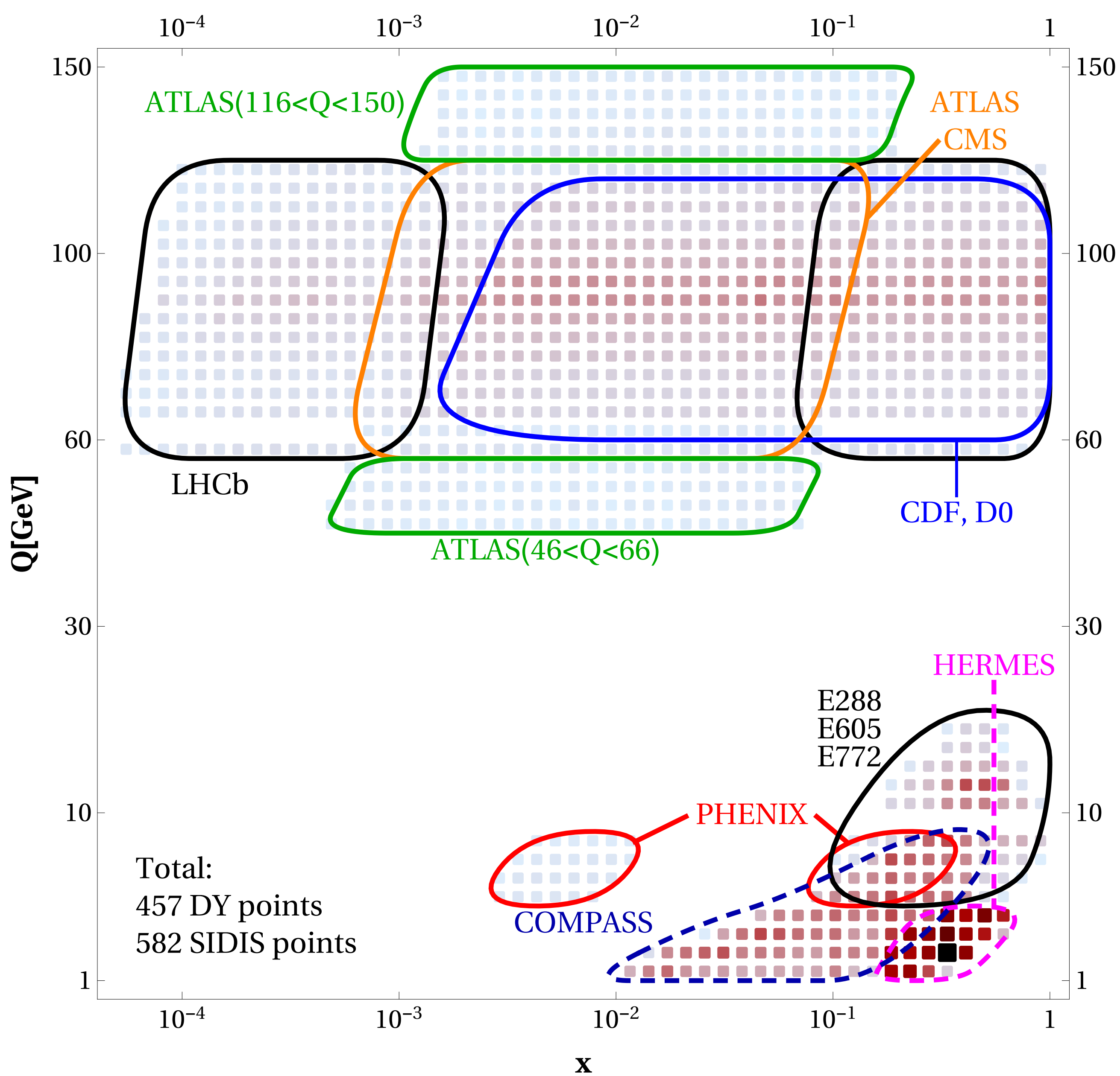


- Drell-Yan and SIDIS data.
- TMD factorisation, N3LL, using the ζ prescription.
- Matching to the collinear PDFs for $b = 0$.

I. Scimemi and A. Vladimirov, **JHEP 06 (2020) 137**

SV19: PDF UNCERTAINTY IN TMDPDFS

$$f_{NP}(x,b) = \exp\left(- \frac{\lambda_1(1-x) + \lambda_2 x + x(1-x)\lambda_5}{\sqrt{1+\lambda_3 x^{\lambda_4} \mathbf{b}^2}} \mathbf{b}^2 \right)$$

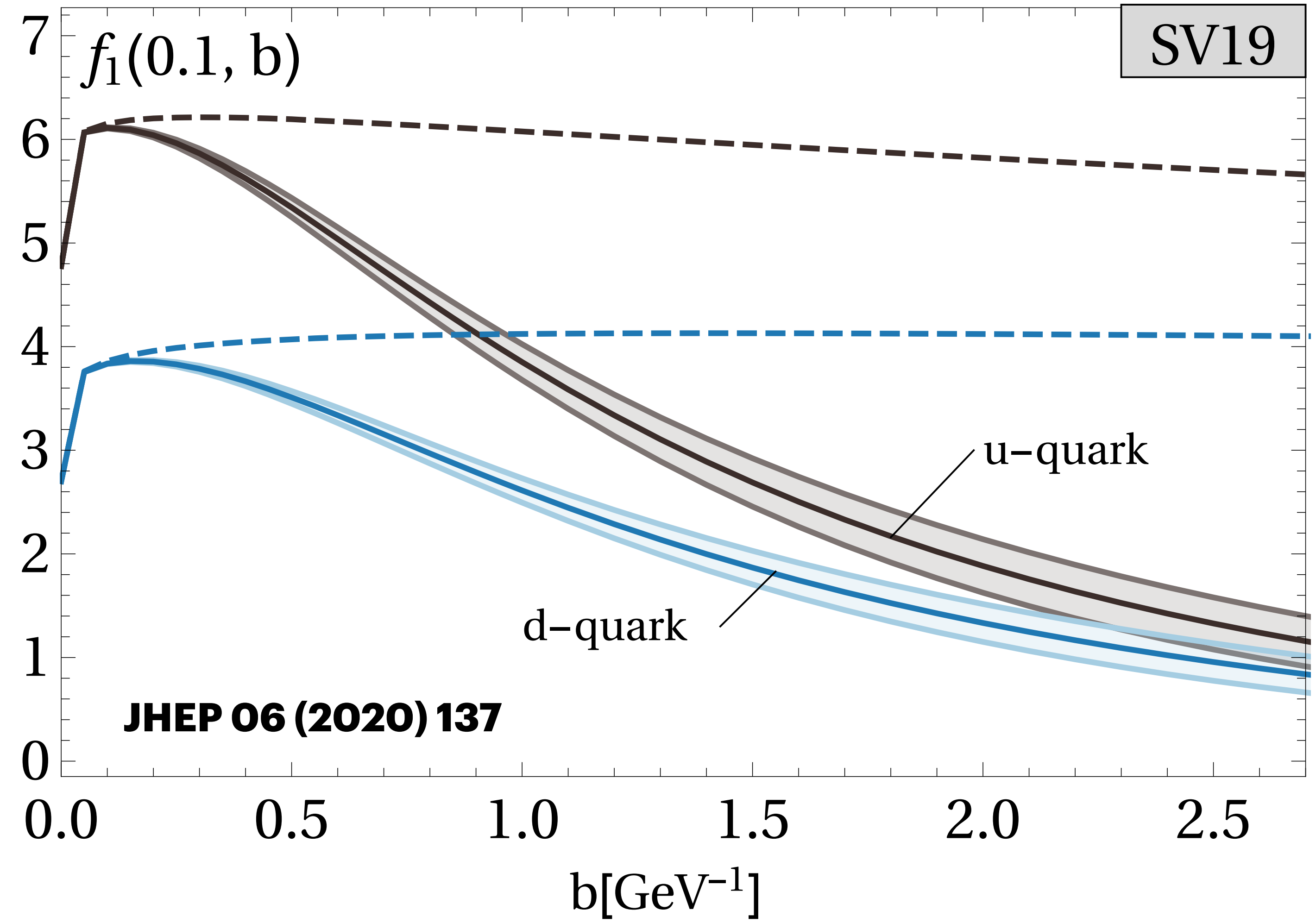


I. Scimemi and A. Vladimirov, **JHEP 06 (2020) 137**

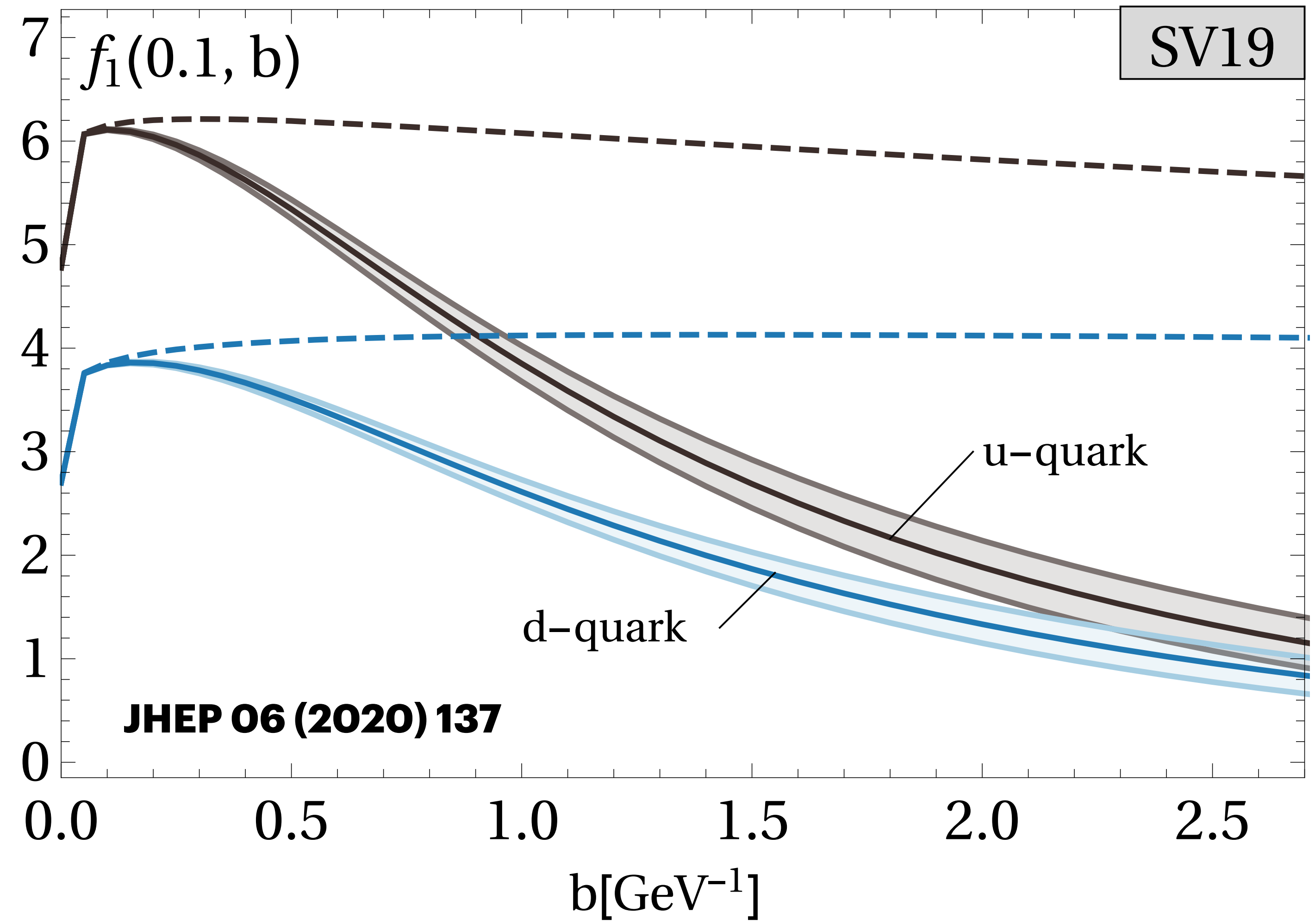
- Drell-Yan and SIDIS data.
- TMD factorisation, N³LL, using the ζ prescription.
- Matching to the collinear PDFs for $b = 0$.
- PDF ***bias***:

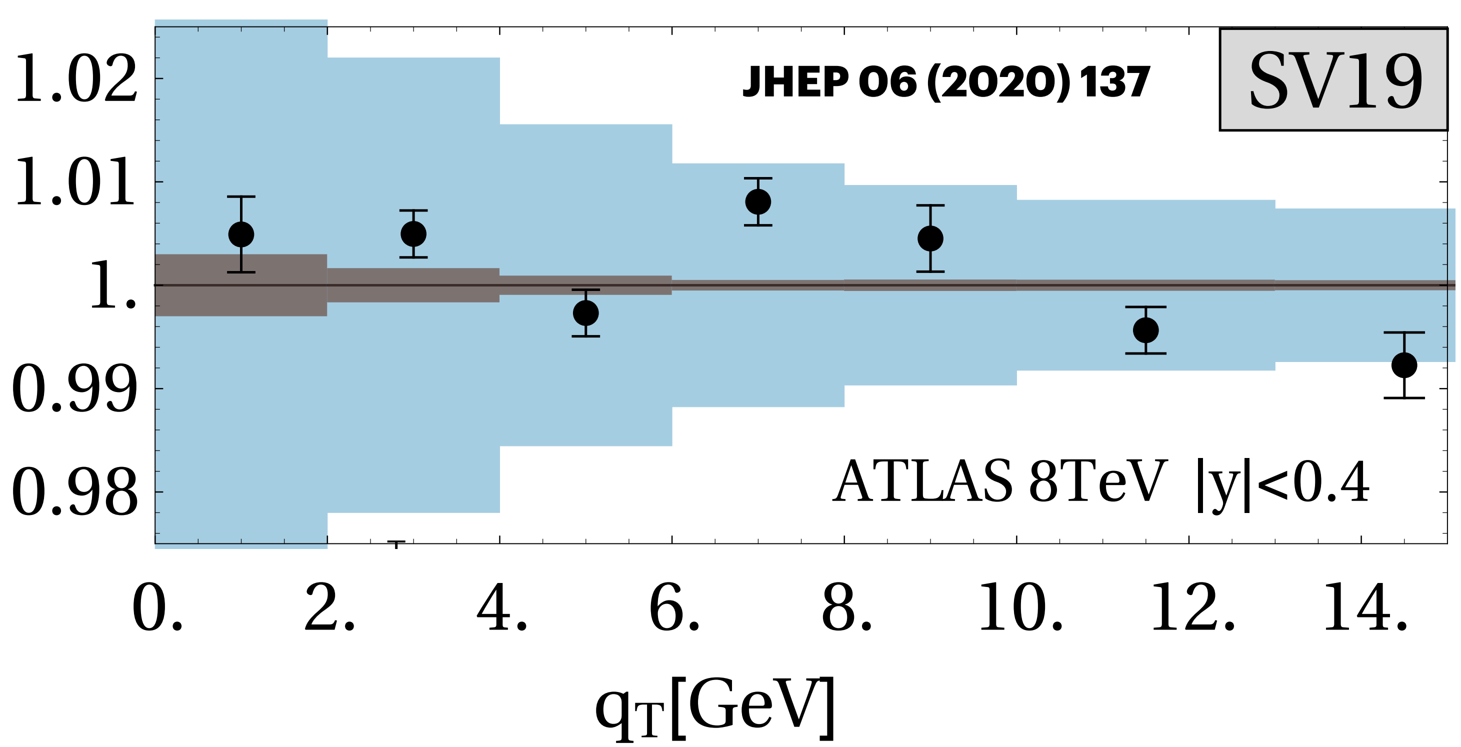
PDF set	χ^2/N_{pt}
CT14	1.59
HERAPDF20	0.97
MMHT14	1.34
NNPDF3.1	1.17
PDF4LHC15	1.53

Also, the TMDPDF uncertainties in SV19 are unrealistically small.

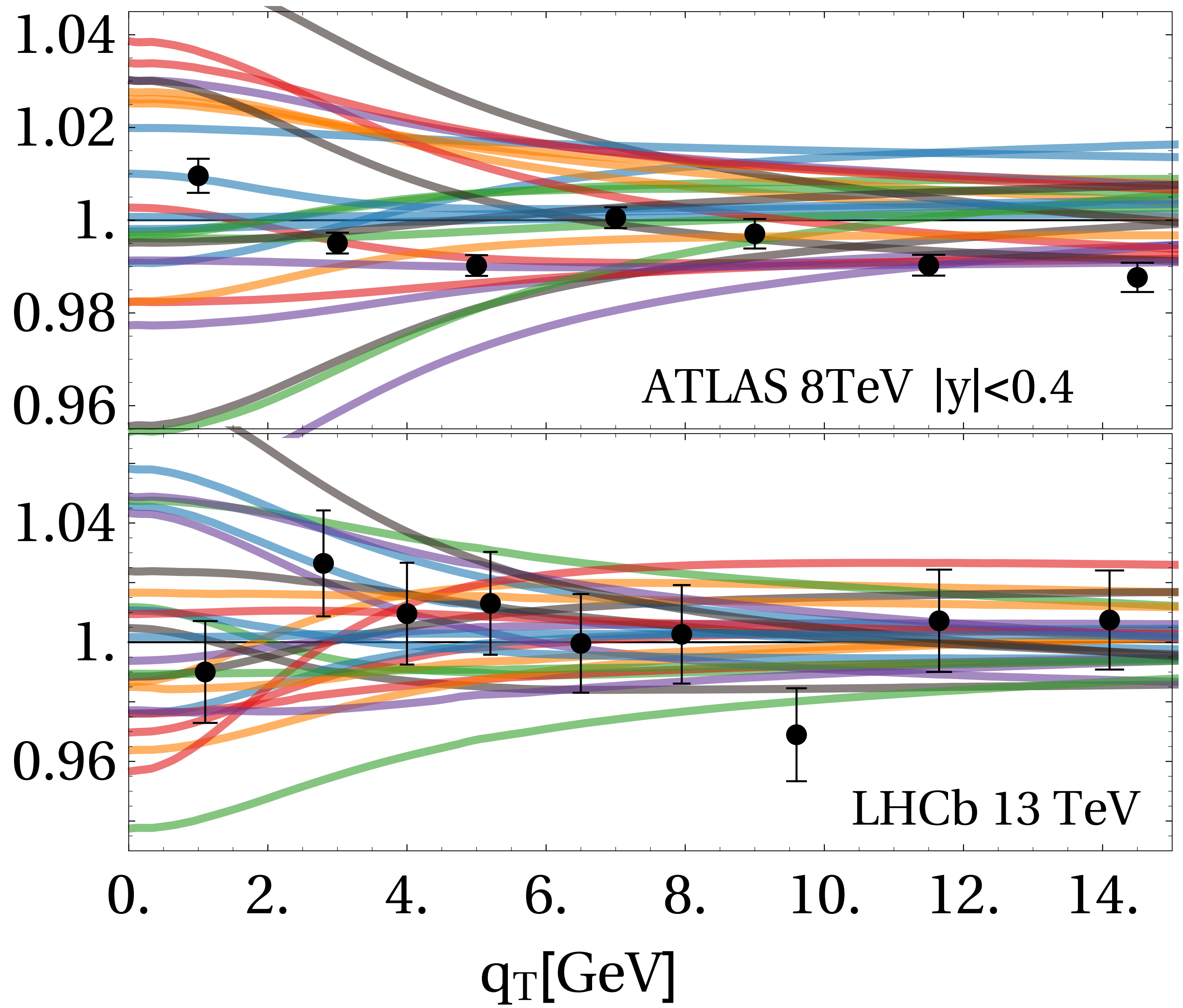


Also, the TMDPDF uncertainties in SV19 are unrealistically small.



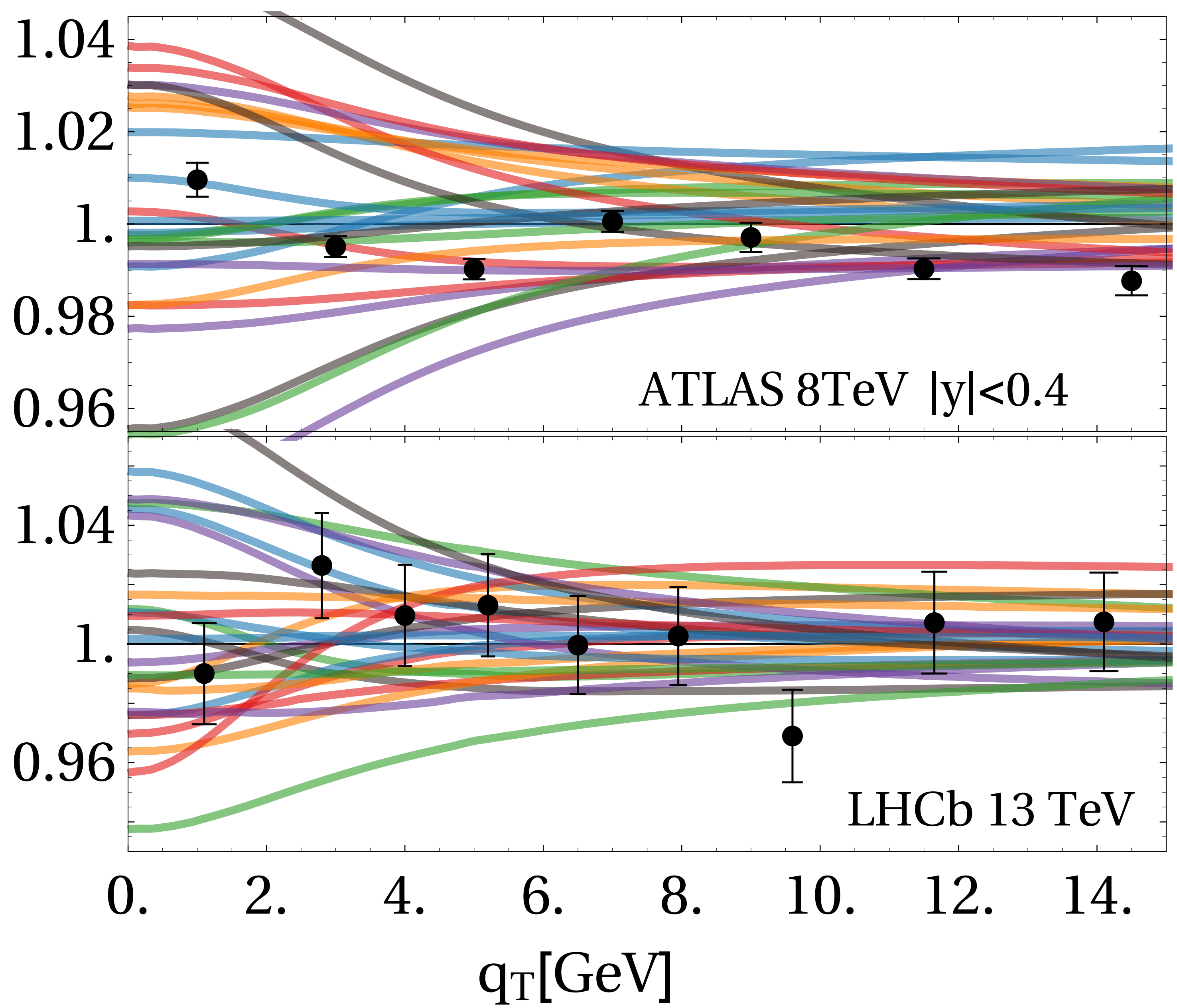


PDF uncertainties dominate the uncertainty bands of the observables.



In SV19 significant part of the replicas give a poor description of the data.

Predictions with SV19 final parameters and different PDF replicas (here NNPDF3.1)

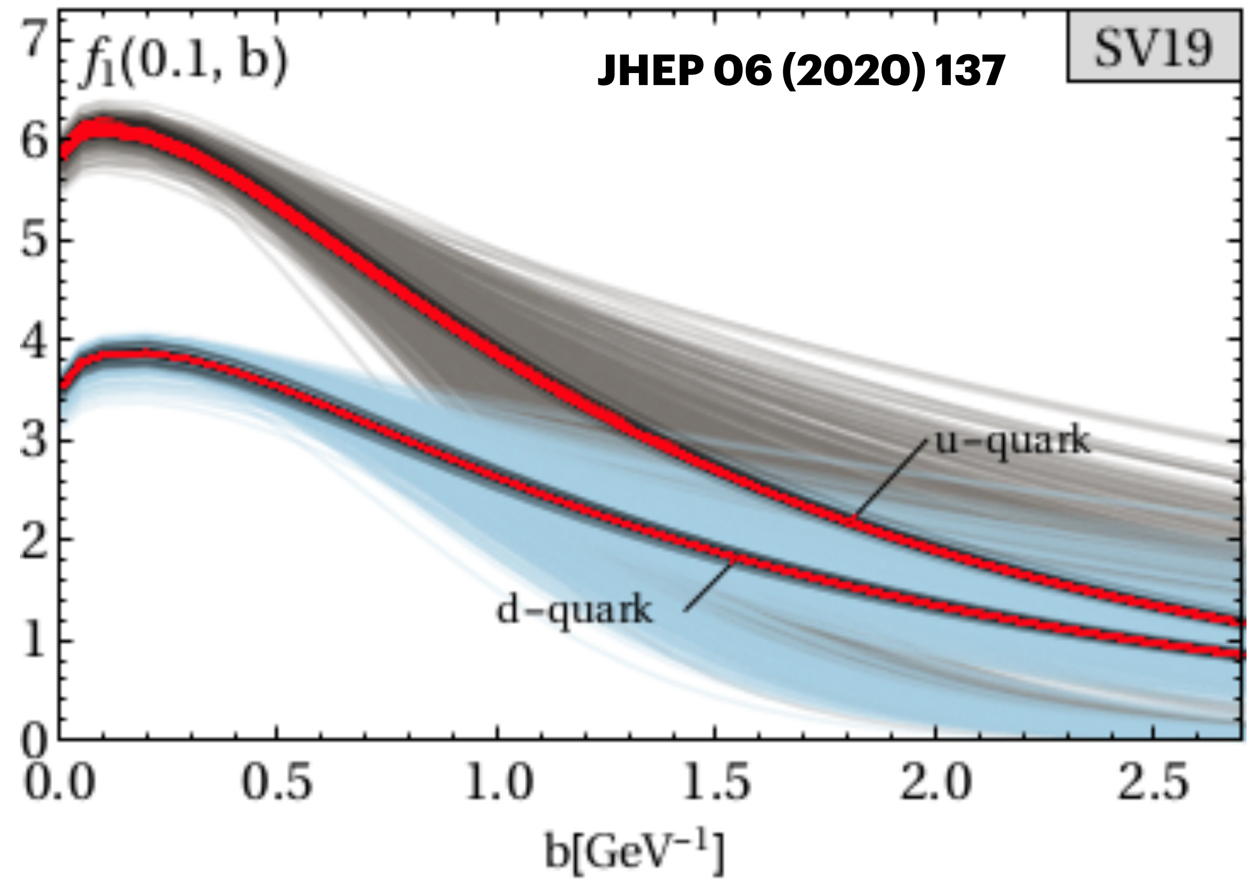


In SV19 significant part of the replicas give a poor description of the data.

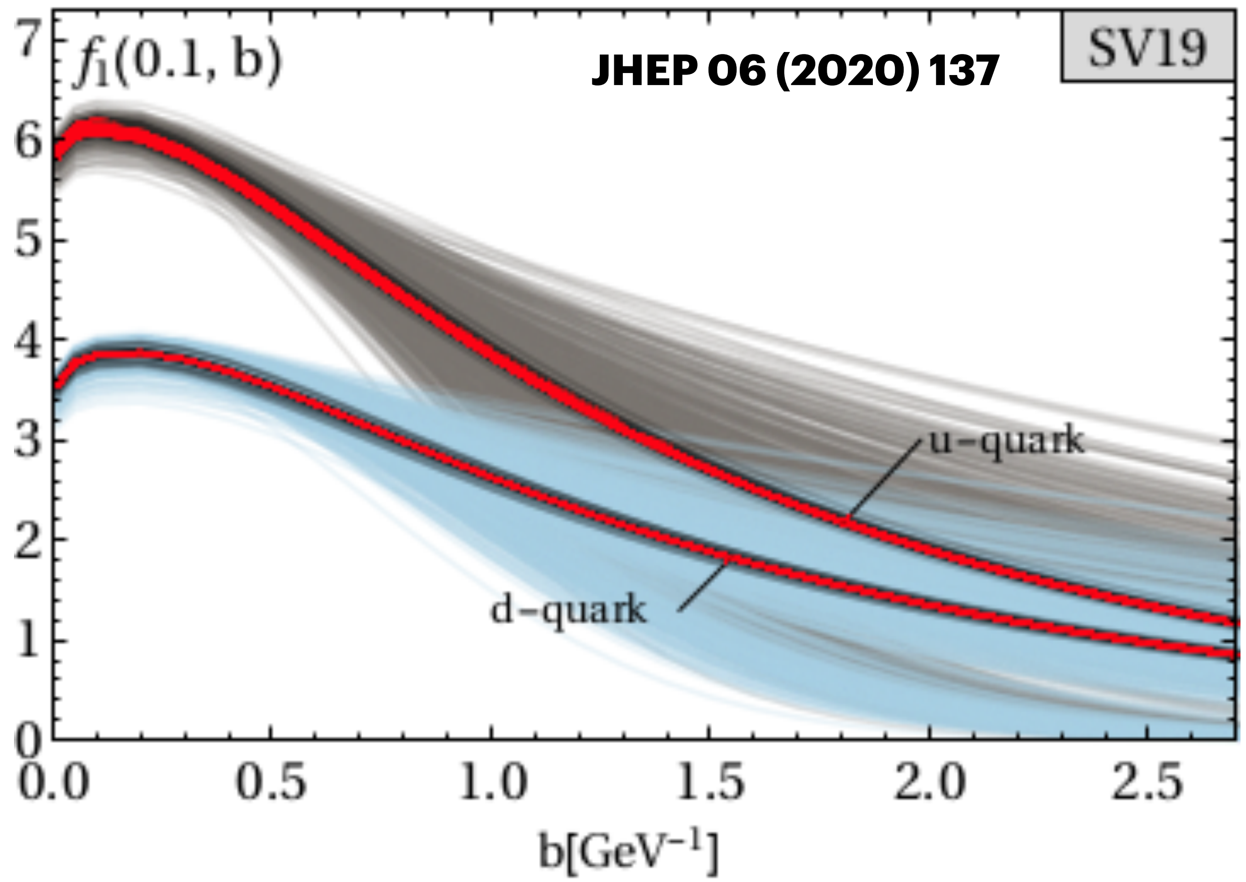
Predictions with SV19 final parameters and different PDF replicas (here NNPDF3.1)

- Similar behaviour for all PDFs considered:
  - CJ15
  - CT14
  - CT18
  - HERAPDF20
  - MMHT14
  - MSHT20
  - NNPDF3.1
  - PDF4LHC15

Solution: include the PDF uncertainties while keeping f_{NP} fixed.

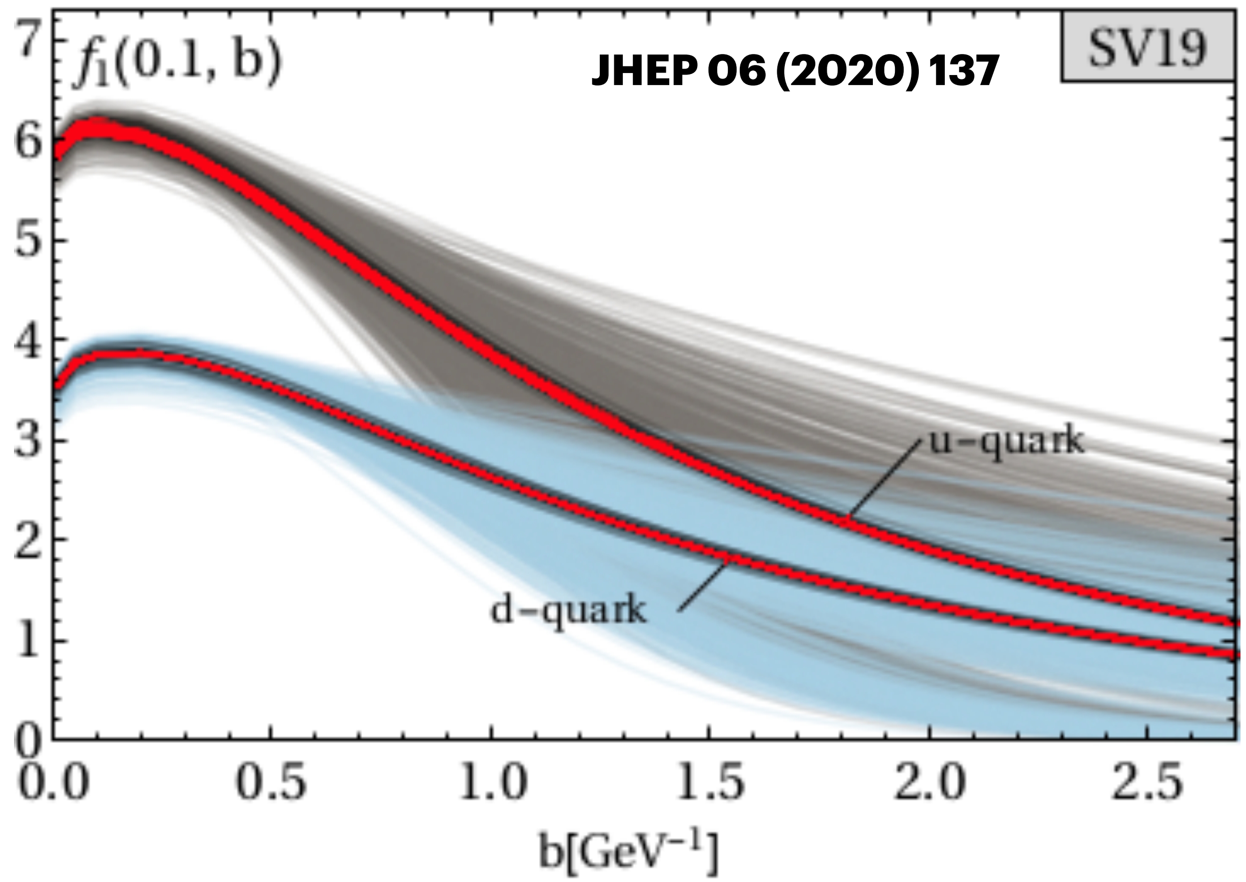


Solution: include the PDF uncertainties while keeping f_{NP} fixed.



This is of course not enough: f_{NP} is not independent of the PDF. A (very time consuming) re-fit for each PDF replica is needed.

Solution: include the PDF uncertainties while keeping f_{NP} fixed.



This is of course not enough: f_{NP} is not independent of the PDF. A (very time consuming) re-fit for each PDF replica is needed.

This mitigates the PDF bias issue.

Flavour dependence of TMDs

- Does the problem lie with the functional form used for f_{NP}?

- We looked for more flexible shapes, larger number of parameters, etc. Nothing changed the picture.

Flavour dependence of TMDs

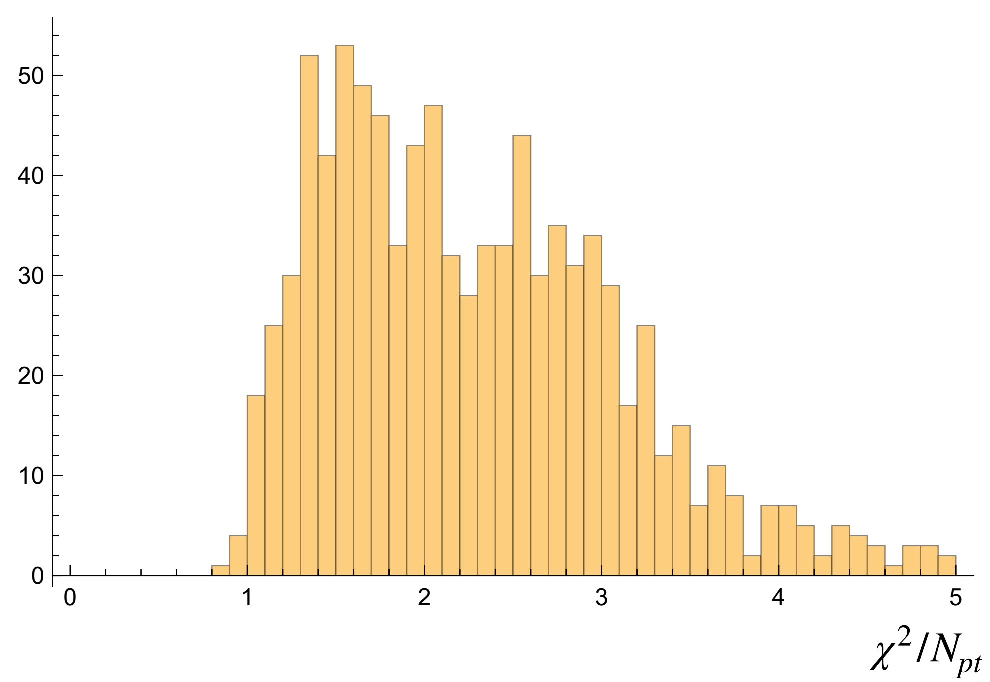
- Does the problem lie with the functional form used for f_{NP}?
- We looked for more flexible shapes, larger number of parameters, etc. Nothing changed the picture. Until we considered the possibility of flavour dependence for f_{NP}:

Flavour dependence of TMDs

Does the problem lie with the functional form used for f_{NP}?

We looked for more flexible shapes, larger number of parameters, etc. Nothing changed the picture. Until we considered the possibility of flavour dependence for f_{NP}:

also seen in ***JHEP* 11 (2013) 194**



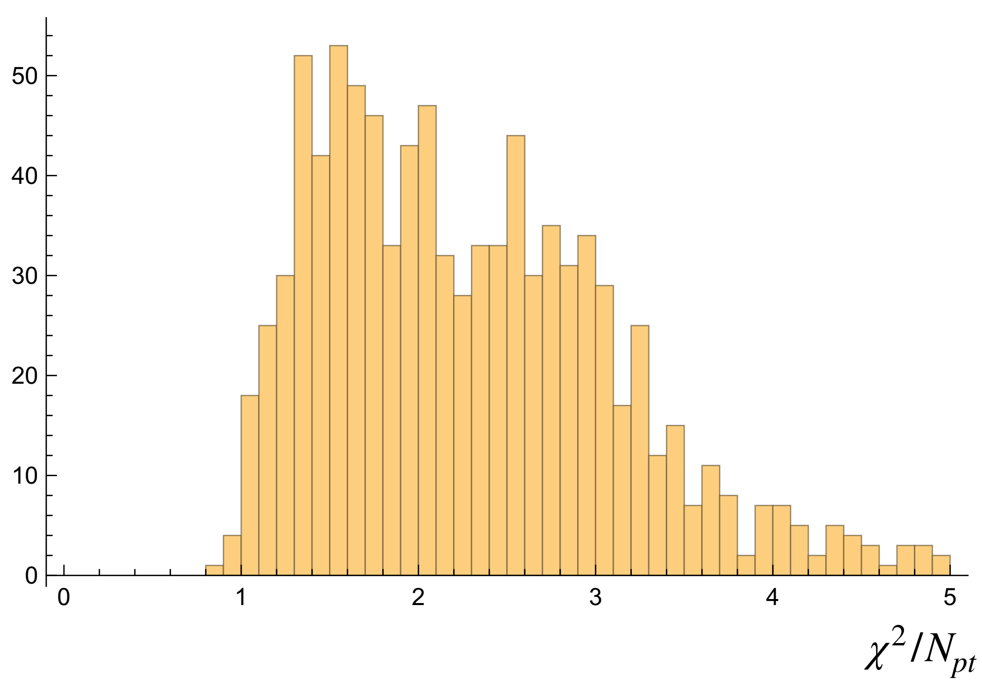
$$f_{NP}(x,b) = \exp\left(-\frac{\lambda_1(1-x)+\lambda_2 x + x(1-x)\lambda_5}{\sqrt{1+\lambda_3 x^{\lambda_4}\mathbf{b}^2}}\mathbf{b}^2\right)$$

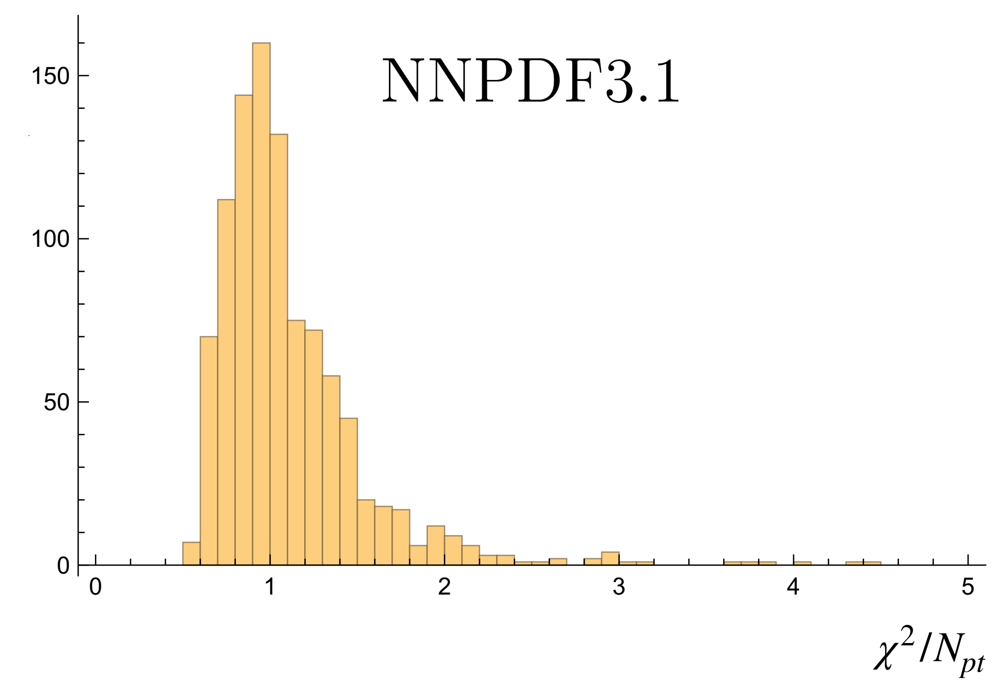
FLAVOUR DEPENDENCE OF TMDS

Does the problem lie with the functional form used for f_{NP}?

We looked for more flexible shapes, larger number of parameters, etc. Nothing changed the picture. Until we considered the possibility of flavour dependence for f_{NP}:

also seen in ***JHEP* 11 (2013) 194**





$$f_{NP}(x,b) = \exp\left(- \frac{\lambda_1(1-x) + \lambda_2 x + x(1-x)\lambda_5}{\sqrt{1+\lambda_3 x^{\lambda_4}\mathbf{b}^2}}\mathbf{b}^2 \right)$$

$$f_{NP}^{f}(x,b) = \exp\left(- \frac{\lambda_1^f(1-x) + \lambda_2^f x}{\sqrt{1+\lambda_0 x^2\mathbf{b}^2}}\mathbf{b}^2 \right)$$

$f = u,\, \bar{u},\, d,\, \bar{d},\, sea$

We repeated the SV19 analysis for the DY case, with recently published data, more modern PDFs and considering two cases:

- EXP: 100 replicas of the data, using the PDF central values.
- PDF: 1000 replicas of the PDFs to fit the data.

- We repeated the SV19 analysis for the DY case, with recently published data, more modern PDFs and considering two cases:

  - EXP: 100 replicas of the data, using the PDF central values.
  - PDF: 1000 replicas of the PDFs to fit the data.

- For each case we obtain a set of parameters which are then combined in a weighted average to give the final result.

- We repeated the SV19 analysis for the DY case, with recently published data, more modern PDFs and considering two cases:

  - EXP: 100 replicas of the data, using the PDF central values.
  - PDF: 1000 replicas of the PDFs to fit the data.

- For each case we obtain a set of parameters which are then combined in a weighted average to give the final result.

- In terms of χ^2:

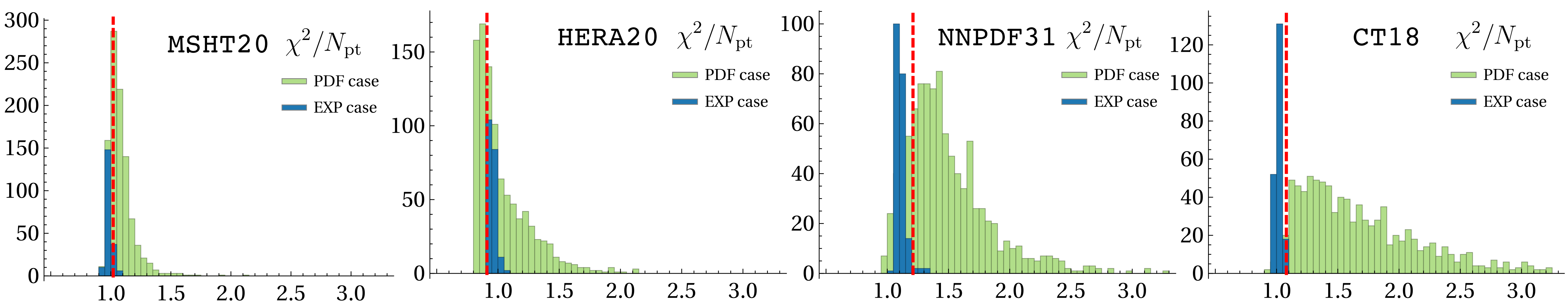
PDF set	χ^2/N_{pt} **in SV19 model**	χ^2/N_{pt} **in flavour dependent model**
CT18	1.26	1.08
HERAPDF2.0	0.97	0.91
MSHT20	1.39	1.12
NNPDF3.1	1.14	1.17

We repeated the SV19 analysis for the DY case, with recently published data, more modern PDFs and considering two cases:

- EXP: 100 replicas of the data, using the PDF central values.
- PDF: 1000 replicas of the PDFs to fit the data.

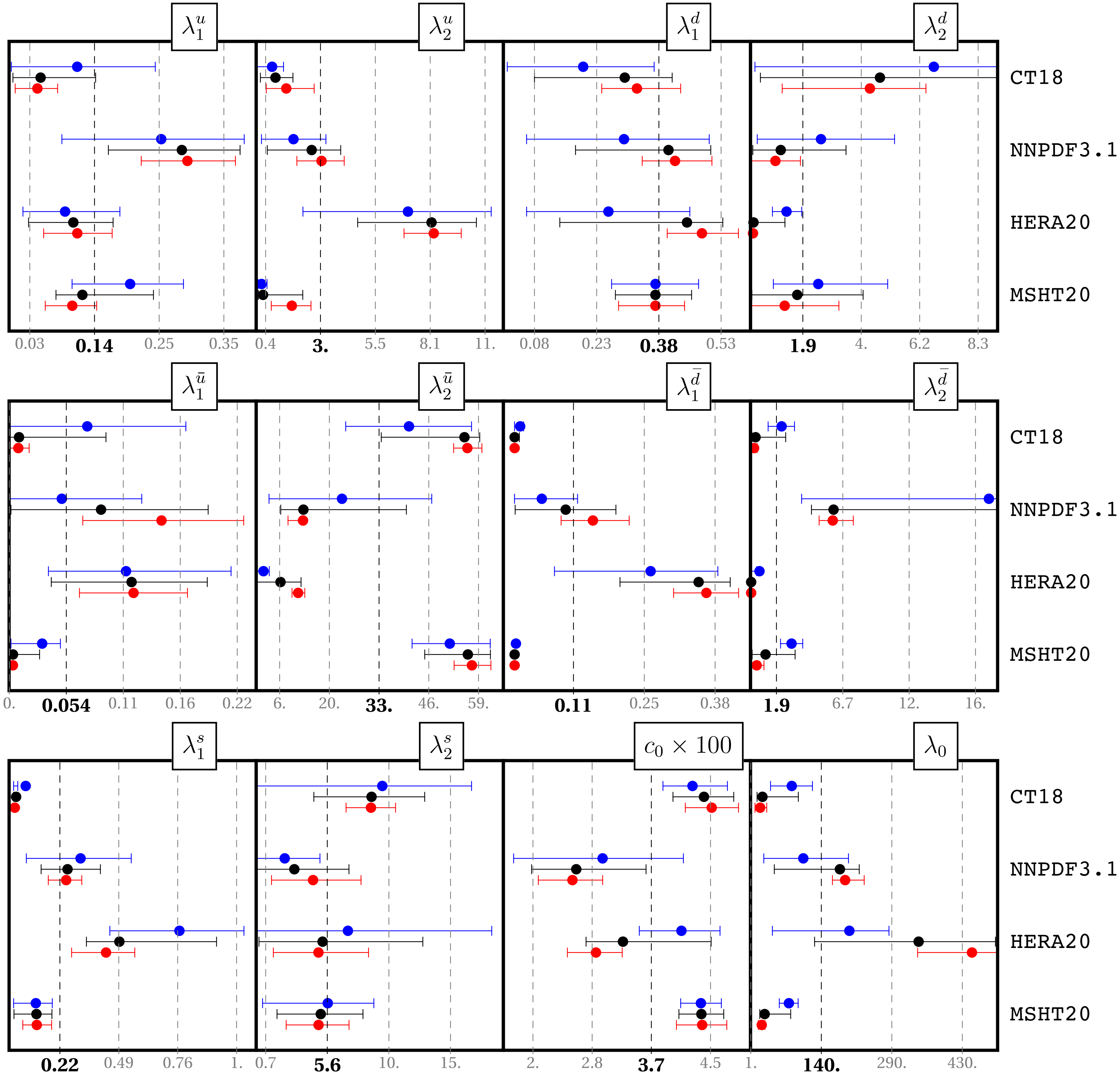
For each case we obtain a set of parameters which are then combined in a weighted average to give the final result.

More importantly:



M. Bury, F. Hautmann, S. Leal-Gómez, I. Scimemi, A. Vladimirov, PZ, JHEP 10 (2022) 118

Differences between flavours are clear:

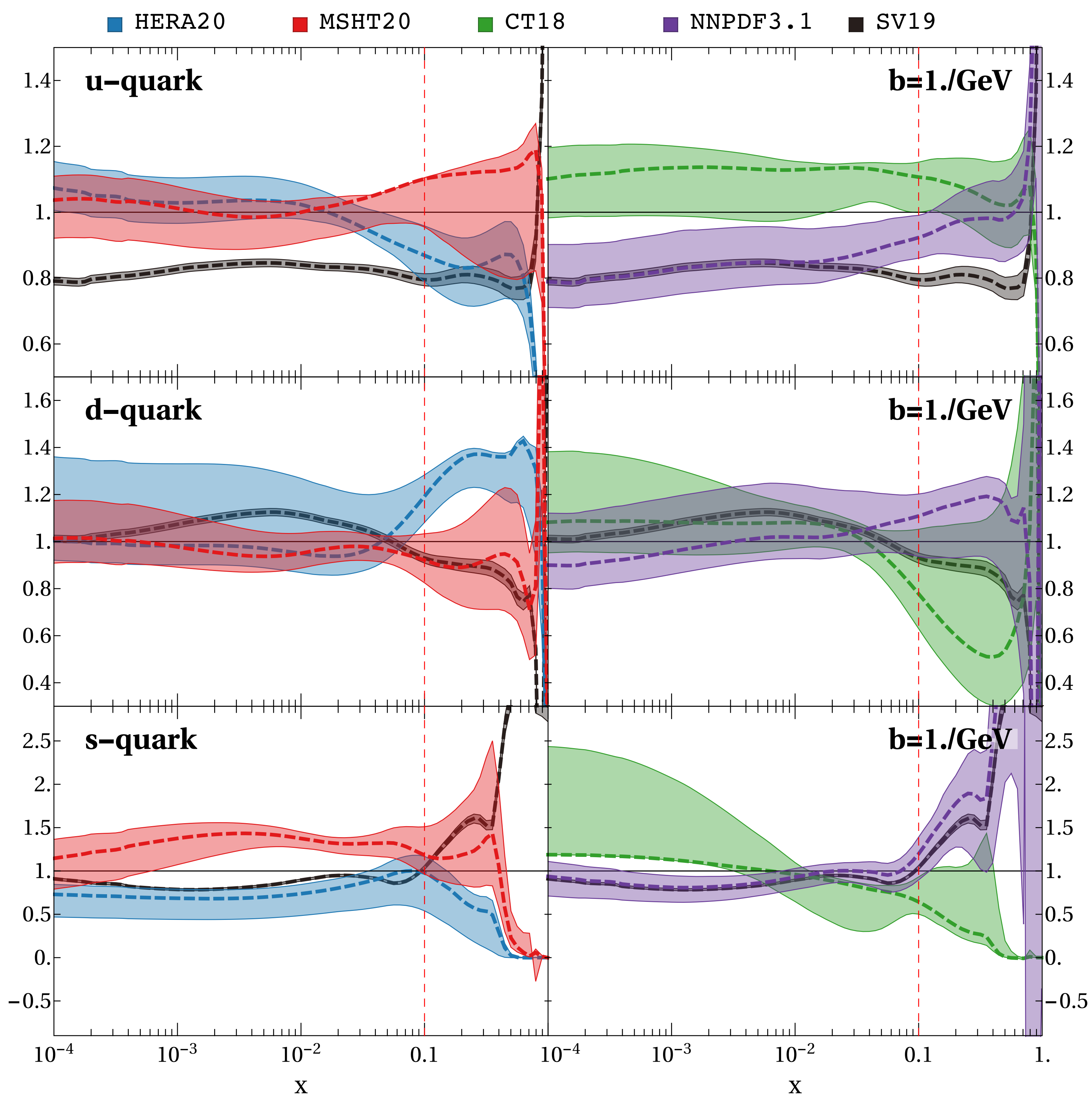


Red: fit of **EXP** replicas.

Blue: fit of **PDF** replicas.

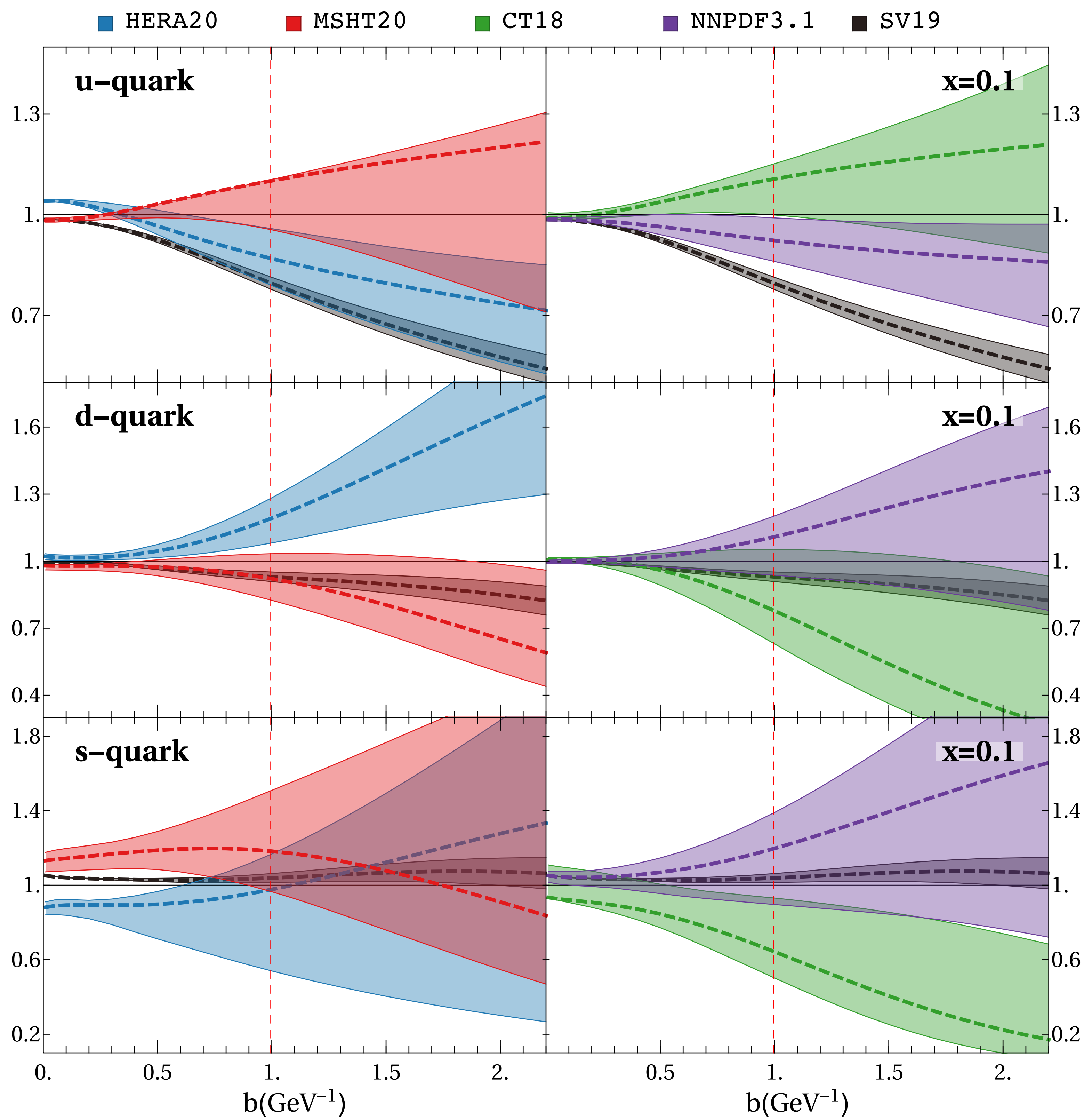
Black: final result.

We obtain more realistic uncertainty bands for the TMDPDFs:



JHEP 10 (2022) 11

We obtain more realistic uncertainty bands for the TMDPDFs:



JHEP 10 (2022) 11

SUMMARY

- The main source of uncertainty for TMD predictions come from the PDFs.

- The issue of the PDF bias in unpolarised TMDPDFs can be improved by considering the PDF uncertainties in the fit.

- Introducing a flavour dependence in the f_{NP} model is crucial to obtain "good" fits for all replicas.

- We have now a full fit of TMDPDFs done in this framework (V. Moos, I. Scimemi, A. Vladimirov and PZ, **arXiv:2305.07473 [hep-ph]**, see V. Moos' talk earlier today).

- We are currently working in a TMDFF extraction.

SUMMARY

- The main source of uncertainty for TMD predictions come from the PDFs.

- The issue of the PDF bias in unpolarised TMDPDFs can be improved by considering the PDF uncertainties in the fit.

- Introducing a flavour dependence in the f_{NP} model is crucial to obtain "good" fits for all replicas.

- We have now a full fit of TMDPDFs done in this framework (V. Moos, I. Scimemi, A. Vladimirov and PZ, **arXiv:2305.07473 [hep-ph]**, see V. Moos' talk earlier today).

- We are currently working in a TMDFF extraction.

Is this flavour dependence truly a TMD requirement?

THANK YOU FOR YOUR ATTENTION!