Simultaneous QCD analysis of collinear distributions

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JAM19 Phys. Rev. D 101, 074020, N. Sato, CA, J.J. Ethier, W. Melnitchouk

Introduction

Introduction

- The d.o.f of QCD, quarks and gluons, cannot be directly measured

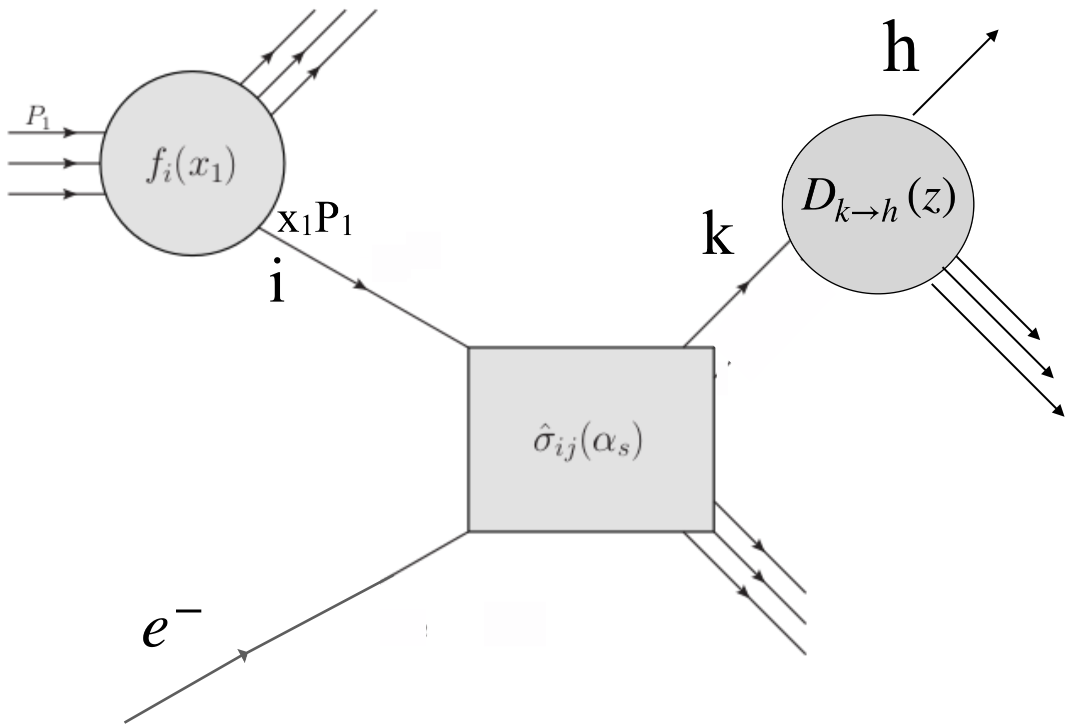
- All we can see are the asymptotic states of QCD, i.e. hadrons

- Experimental data can be interpreted in terms of quarks and gluons

- How? QCD factorization

Collinear Factorization

$$d\sigma^{e^- p \to h X} = \sum_{ik} f_i(x_1, \mu^2) \otimes d\sigma_{i \to k} \otimes D_{k \to h}(z, \mu^2) + \mathcal{O}\left(\frac{\Lambda^2_{QCD}}{\mu^2}\right)$$



Collinear Factorization

pQCD

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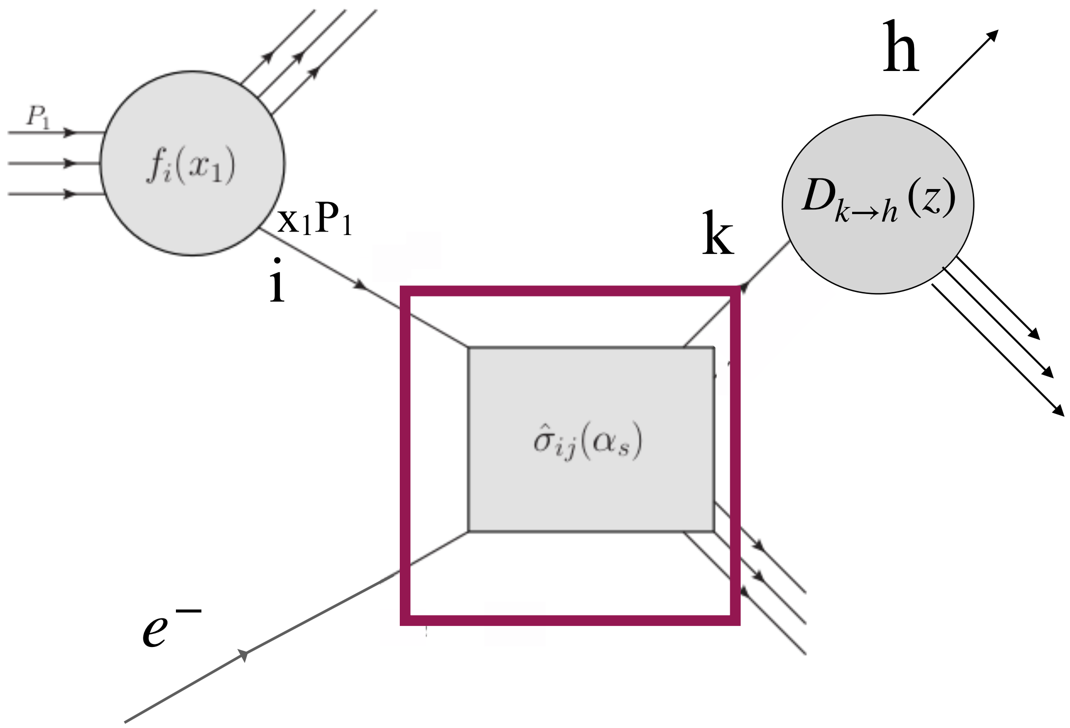
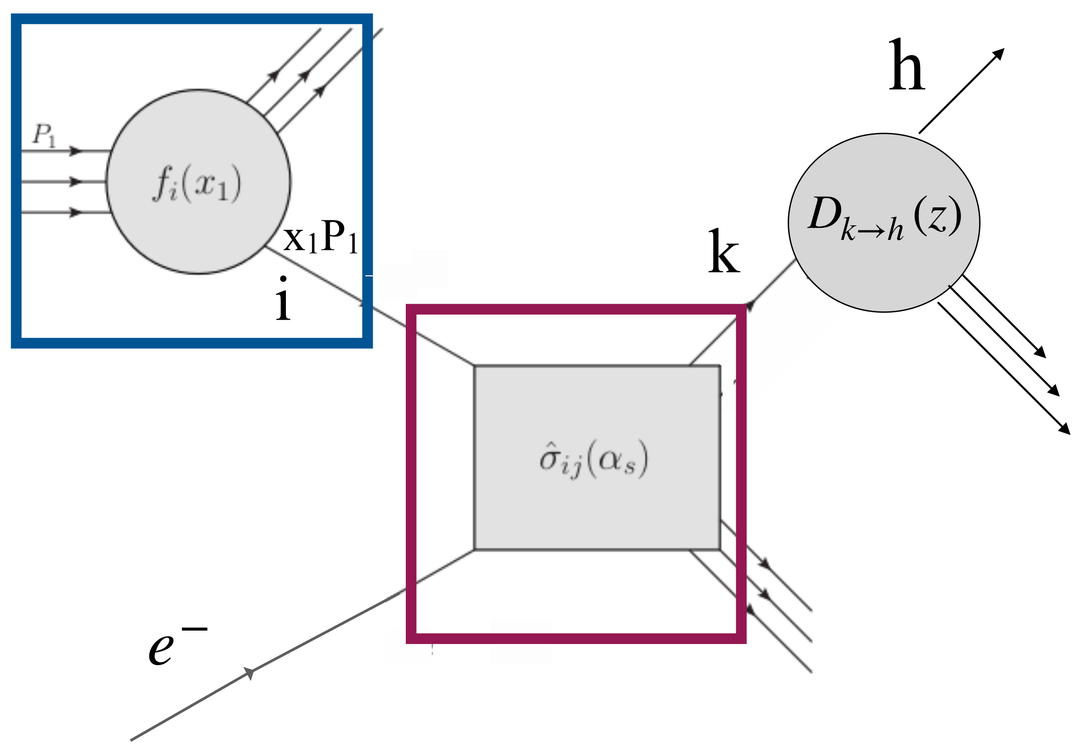


Collinear Factorization

PDFs pQCD

$$d\sigma^{e^- p \to h X} = \sum_{ik} \boxed{f_i(x_1, \mu^2)} \otimes \boxed{d\sigma_{i \to k}} \otimes D_{k \to h}(z, \mu^2) + \mathcal{O}\left(\frac{\Lambda_{QCD}^2}{\mu^2}\right)$$



Collinear Factorization

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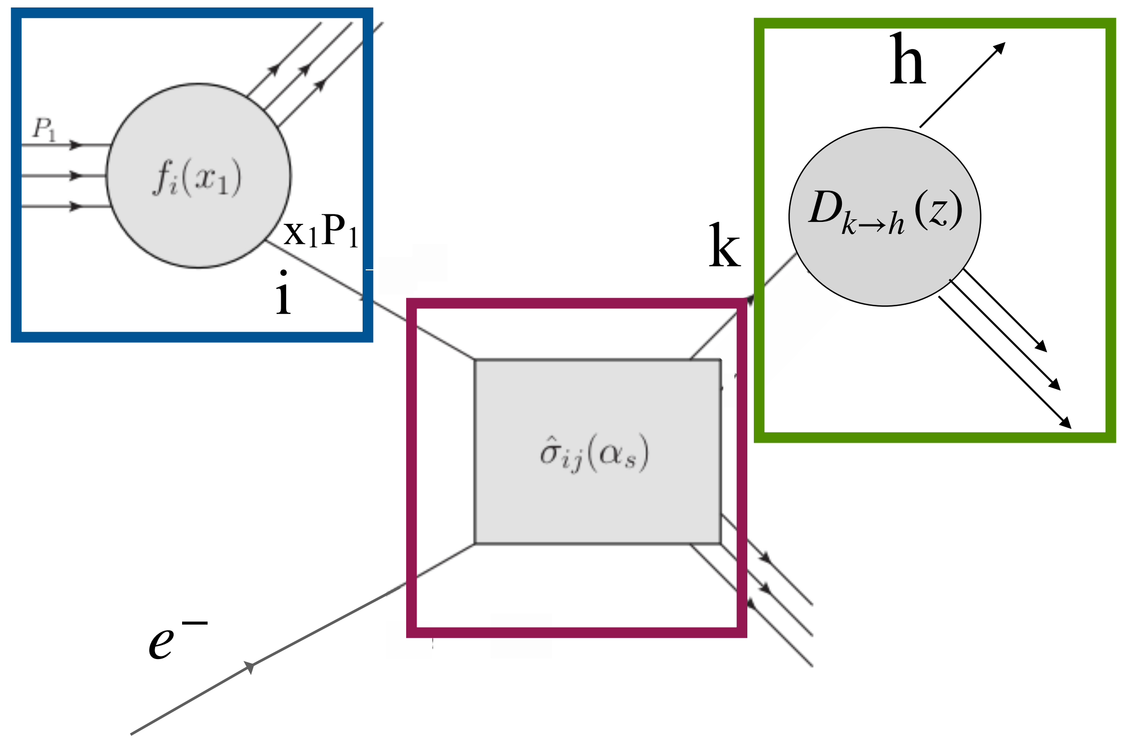

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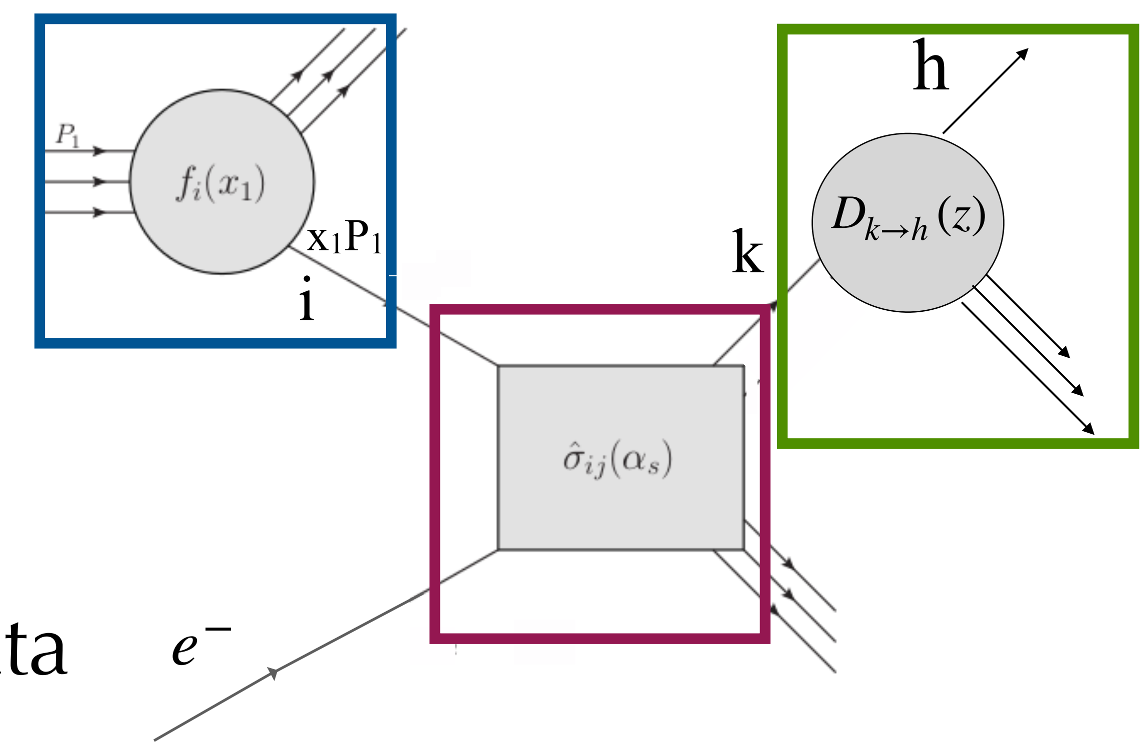
- <u>Non perturbative</u>

- Currently not computable from first principles ⟶ Extract them from data



Universality

- PDFs and FFs are universal

$$\sigma^{exp}_{lp\to lX} = f \otimes \hat{\sigma}_{lp\to lX}$$

$$\sigma^{exp}_{lp\to hX} = f \otimes \hat{\sigma}_{lp\to hX} \otimes d$$

$$\sigma^{exp}_{pp\to l\bar{l}X} = f \otimes f \otimes \hat{\sigma}_{pp\to l\bar{l}X}$$

$$\sigma^{exp}_{l\bar{l}\to hX} = \hat{\sigma}_{l\bar{l}\to hX} \otimes d$$

- Their evolution is perturbative: **DGLAP**

$$Q^2 \frac{\partial f_i(x,Q^2)}{\partial Q^2} = \sum_j \boxed{P_{ij}} \otimes f_j(x,Q^2)$$

Splitting functions (pQCD)

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Splitting functions (pQCD)

Global analysis

- Parametrize the PDFs and FFs at an input scale Q_0

$$f_i(x, Q_0) = N_i \, x^{a_i} \, (1 - x)^{b_i} \, P(x; w_i)$$

$$\overrightarrow{a} = (N_i, a_i, b_i, w_i, \ldots)$$

- Evolve using DGLAP up to the experiment scale
- Compute the experimental cross sections
- Evaluate the χ^2
- Minimize the χ^2 (or maximize the likelihood)

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Bayesian approach

- The probability distribution P is given by

$$P(\vec{a}\,|\,\text{data}) \propto \boxed{\mathscr{L}(\vec{a}\,|\,\text{data})}\,\pi(\vec{a})$$

Likelihood

- Likelihood function

$$\mathscr{L}(\vec{a}\,|\,\text{data}) = exp\left\{-\frac{1}{2}\chi^2(\vec{a})\right\}$$

- Observables and their uncertainties are given by

$$E\left[\mathcal{O}\right] = \frac{1}{N}\sum_k \mathcal{O}\left(\vec{a}_k\right) \qquad V\left[\mathcal{O}\right] = \frac{1}{N}\sum_k \left[E\left[\mathcal{O}\right] - \mathcal{O}\left(\vec{a}_k\right)\right]^2$$

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Maximizing the likelihood

- Maximize P by finding the best fit parameters $\vec{a}_0$ that minimize the χ^2

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$V\left[\mathcal{O}\right]$ given by Hessian Method (expanding around $\vec{a}_0$)

- Used by CT, MMHT, CJ…

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Maximizing the likelihood II

Data resampling method to build the posterior distribution

- Generate N resampled data $\tilde{\sigma}_i$, $i = 1,...N$

Random number

$$\tilde{\sigma}_i = \sigma_i + R_i \alpha_i$$

Quadrature of the sum of uncorrelated uncertainties

- Perform N fits to the resampled data starting with flat priors

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- Used by JAM, NNPDF…

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Why MC?

$$\chi^2 = \sum_{e}^{N_{exp}} \sum_{i}^{N_{data}} \frac{(D_i^e - T_i)^2}{(\sigma_i^e)^2}$$

- Typical PDF parametrization:

$$x\Delta f(x) = N x^a (1-x)^b (1 + c\sqrt{x} + dx)$$

- Perform single χ^2-fit: $\longrightarrow$ Multiple local minima!

Parameters difficult to constrain

Hessian method for uncertainties $\longrightarrow$ Introduces tolerance criteria

Unsuitable for simultaneous analysis of collinear distributions

- Monte Carlo methods:
  - Allows efficient exploration of the parameter space
  - Uncertainties directly obtained from MC replicas

JAM19

What is JAM19?

First **simultaneous** MC analysis of **unpolarized** PDFs and FFs

Why JAM19?

To focus on the study of the **strange** quark distribution

Motivation

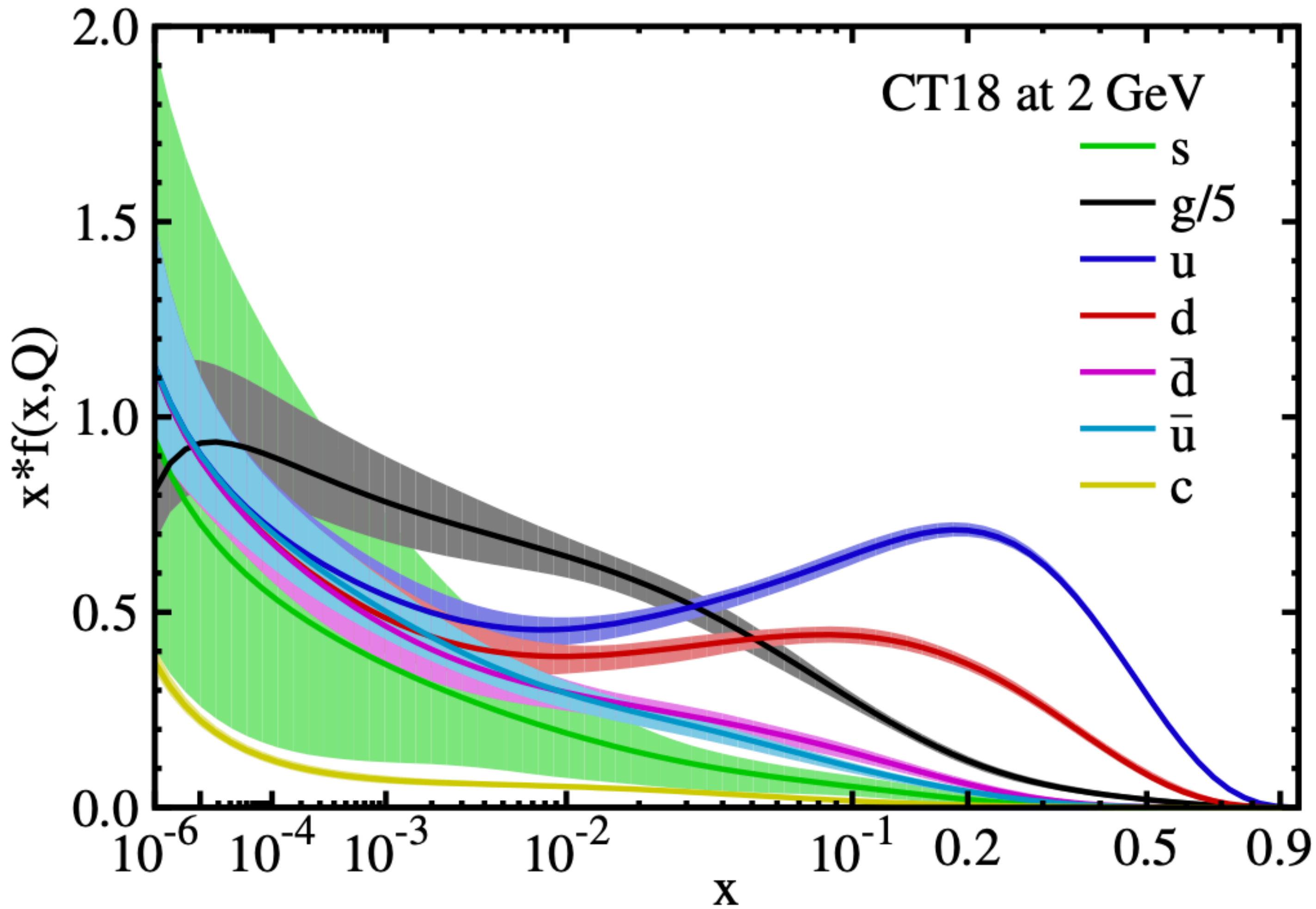
- Testing the universality of PDFs ,FFs…

- All the data must be studied using the **same** theoretical framework

- First step: (first) **simultaneous** analysis of **unpolarized** PDFs and FFs $\longrightarrow$ **Strange** quark distribution

Motivation II

- The strange PDF is less known than the non-strange light flavors



CT18, arXiv:1912.10053 [hep-ph]

Motivation II

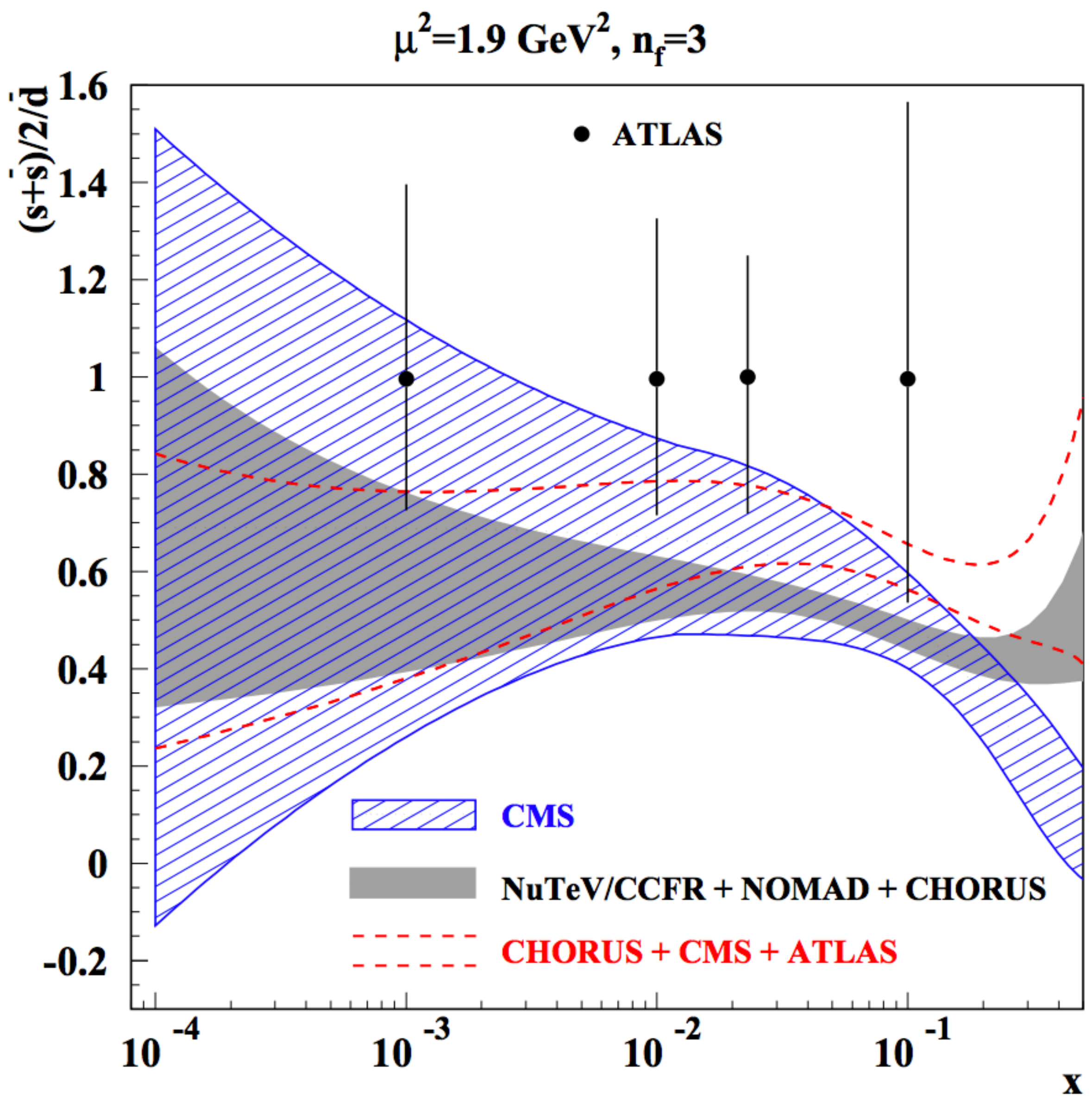
- Traditionally: neutrino-(heavy) nucleus DIS data used to extract the strange PDF.
    - Drawbacks: nuclear effects on PDFs.

- W and Z inclusive production in p-p collisions also sensitive to flavor separation
    - Drawbacks: tension between CMS and ATLAS results?

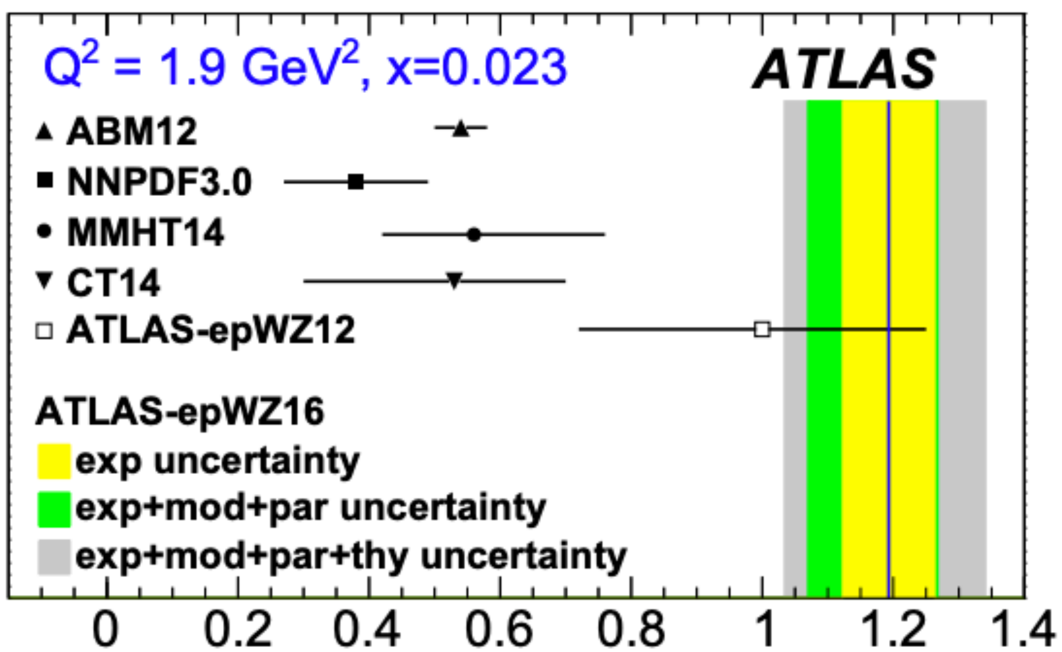
Motivation II

Alhekin et al., arXiv:1404.6469 [hep-ph]

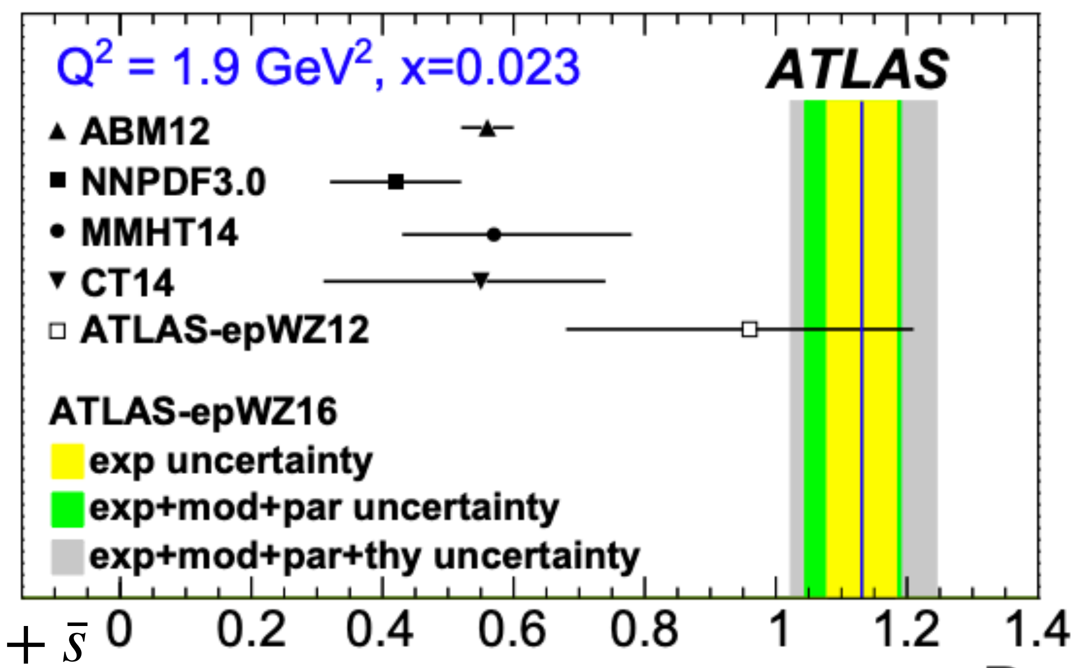
$r_s =$



Motivation II



$$r_s = \frac{s+\bar{s}}{2\bar{d}}$$



$$R_s = \frac{s+\bar{s}}{\bar{u}+\bar{d}}$$

ATLAS Collaboration, arXiv:1612.03016 [hep-ex]

Why don’t we use SIDIS?

Setup: data

$W^2 > 10\,\mathrm{GeV}^2$

$Q^2 > \mathrm{m}_c^2$

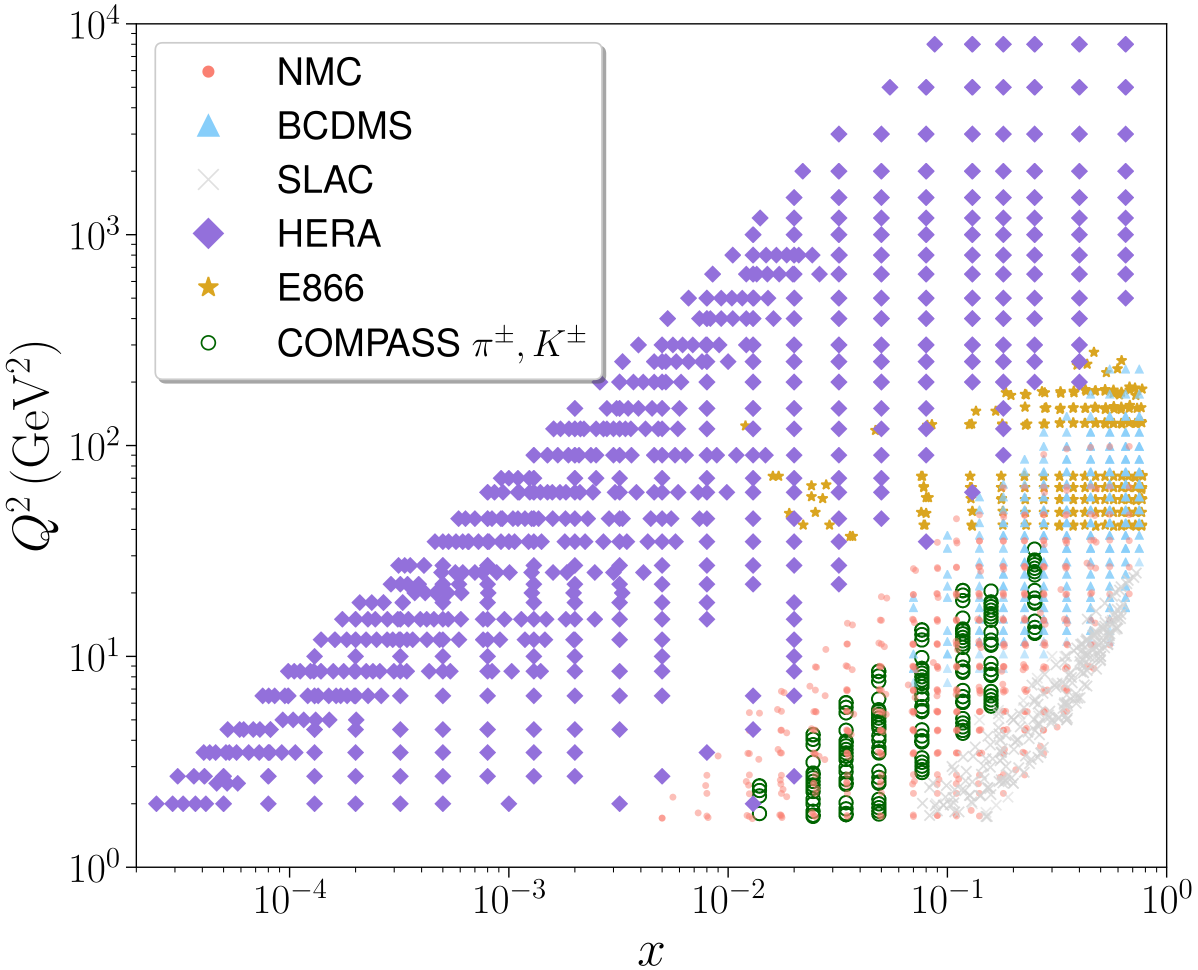
DIS : $l + (p, d) \rightarrow l' + X$

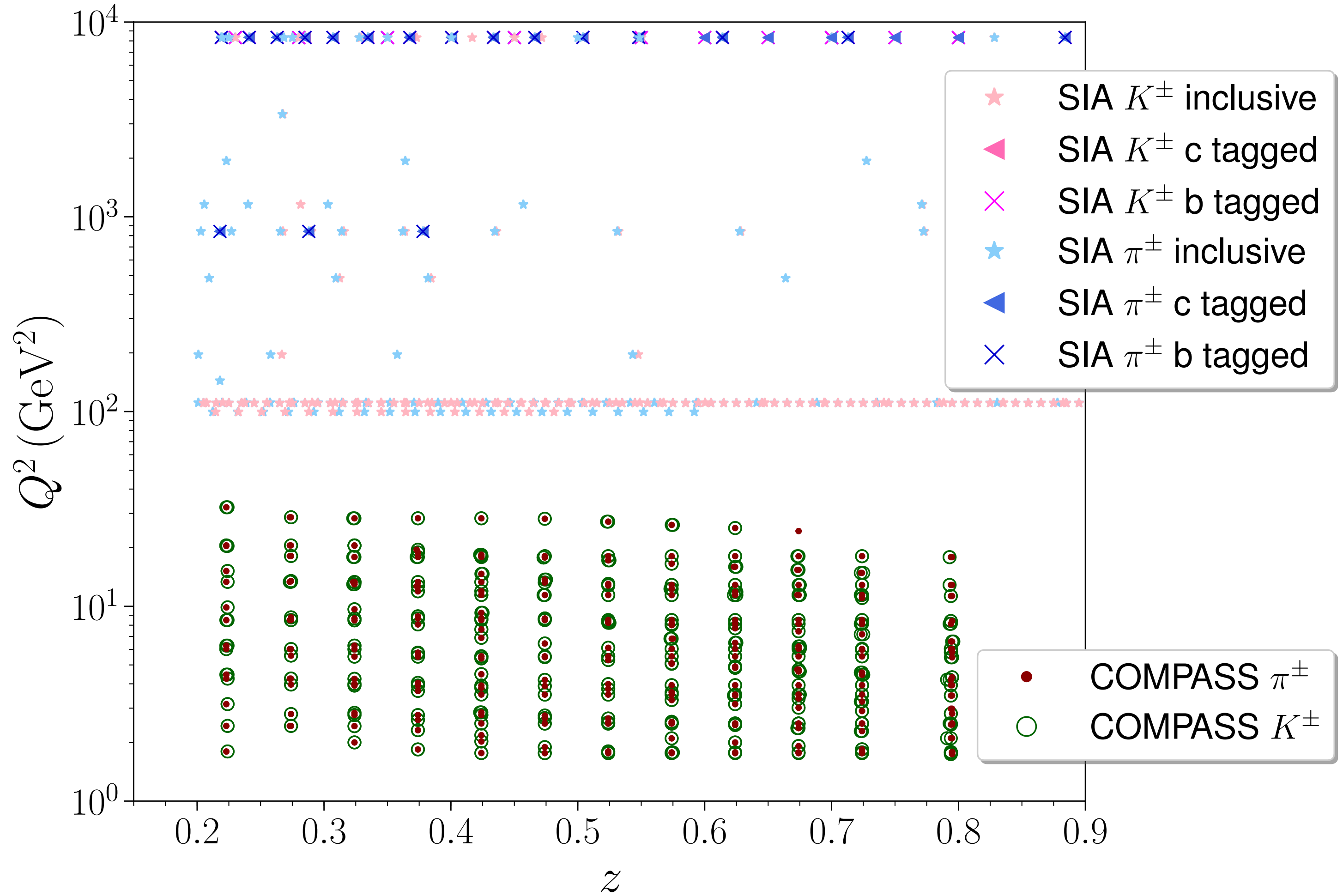
DY : $l + (p, d) \rightarrow l\bar{l} + X$

4366 data points

SIDIS : $l + d \rightarrow l' + h + X$

SIA : $e^+ + e^- \rightarrow h + X$



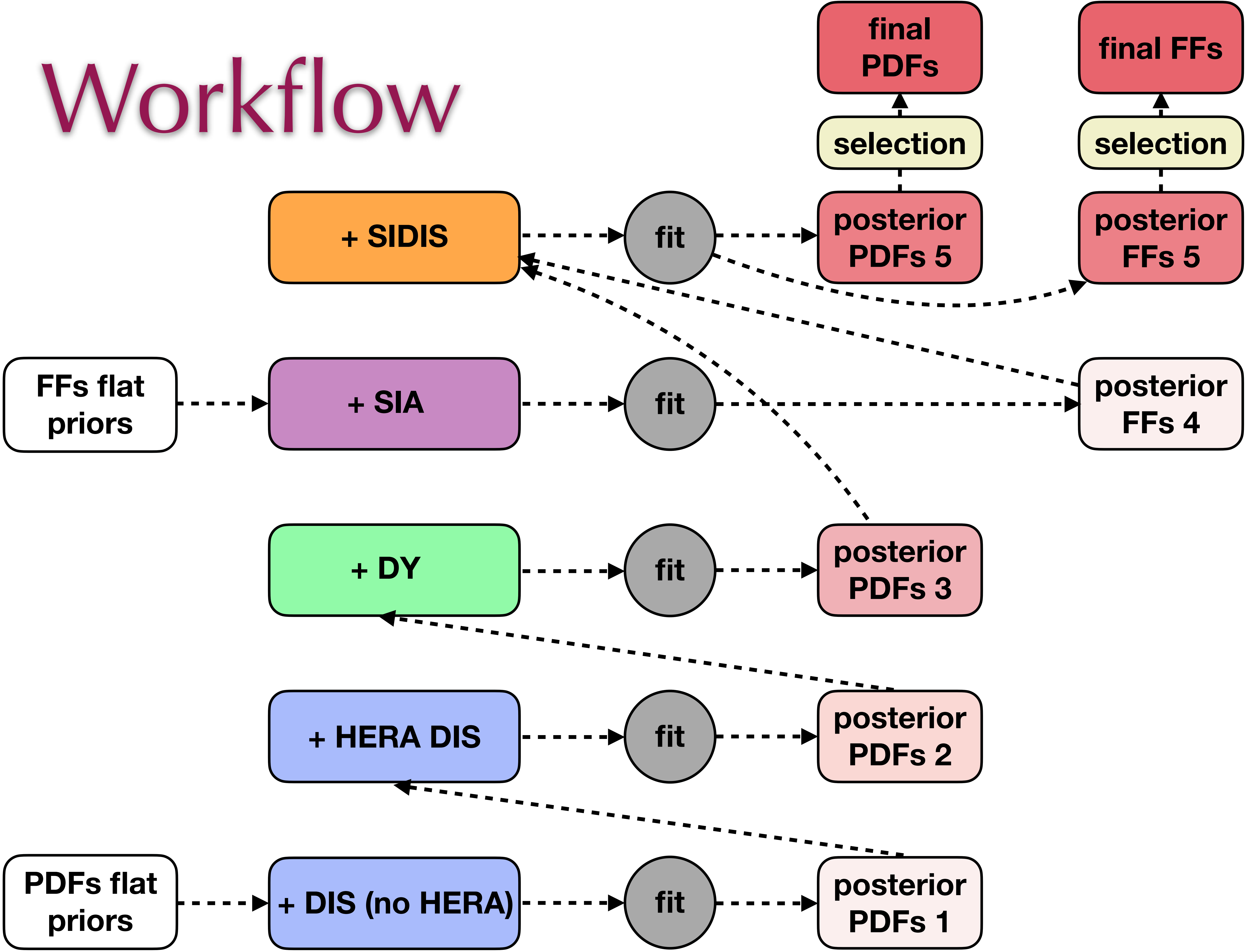


JAM19 methodology

Setup: theory

- All observables computed at NLO in pQCD
- DGLAP truncated evolution at order α_s in Mellin space
- DIS/SIDIS/SIA cross sections computed at leading twist
- Nuclear smearing for deuterium DIS
- Heavy quark treatment : ZM-VFN
- Fitting methodology:
    - MC (multi-steps), k-means clustering, extended reduced χ^2

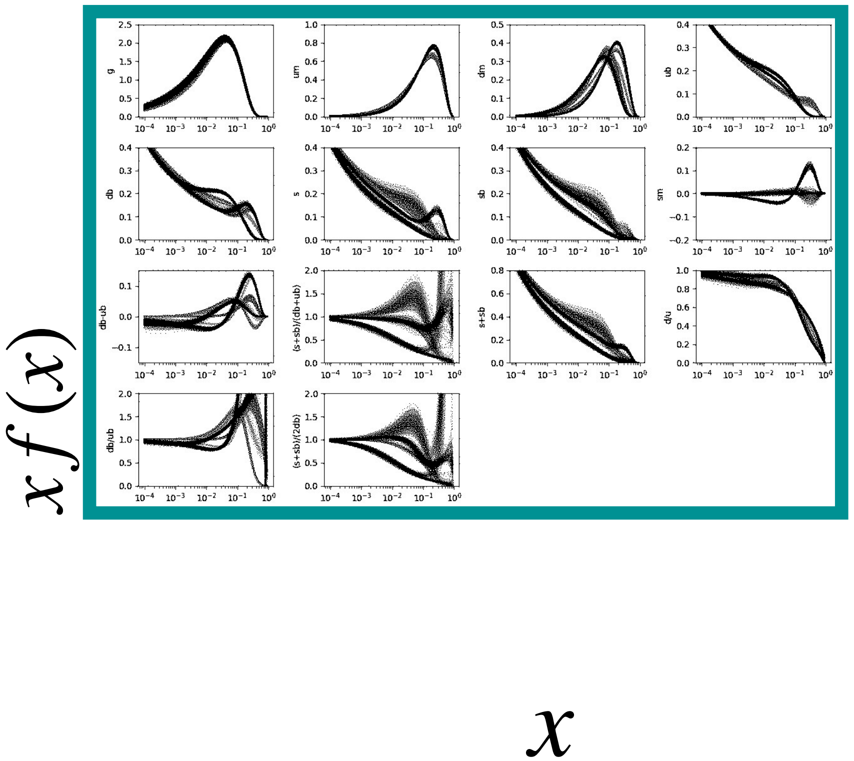
Workflow



final PDFs
final FFs
selection
selection
+ SIDIS
fit
posterior PDFs 5
posterior FFs 5
FFs flat priors
+ SIA
fit
posterior FFs 4
+ DY
fit
posterior PDFs 3
+ HERA DIS
fit
posterior PDFs 2
PDFs flat priors
+ DIS (no HERA)
fit
posterior PDFs 1

JAM 19: multi-step fitting

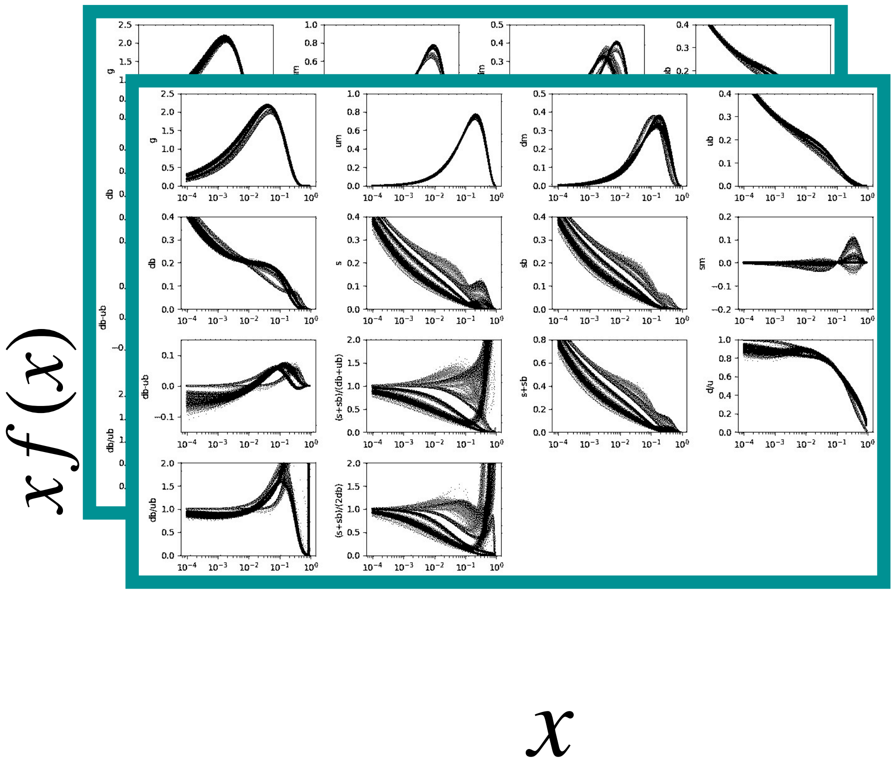
PDFs



+ DIS data

JAM 19: multi-step fitting

PDFs



+ DIS data

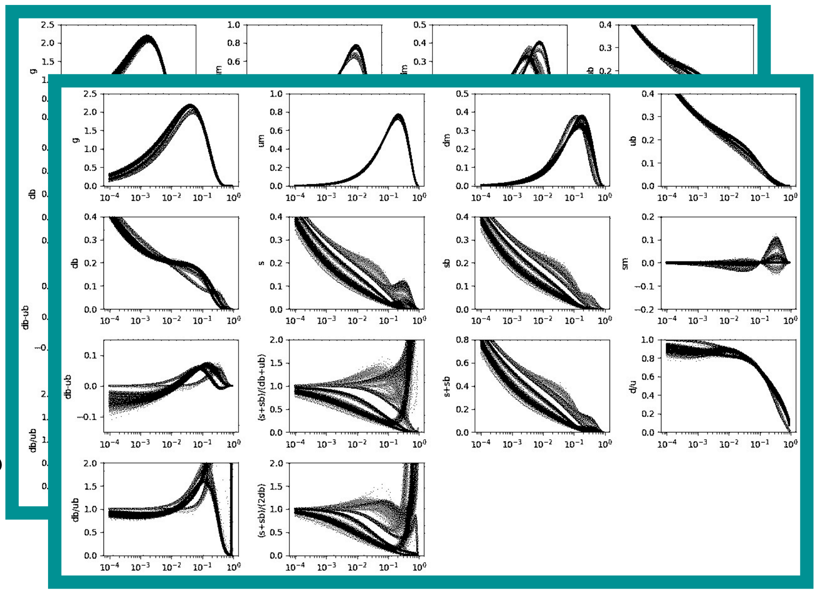
+ DIS + DY data

JAM 19: multi-step fitting

PDFs

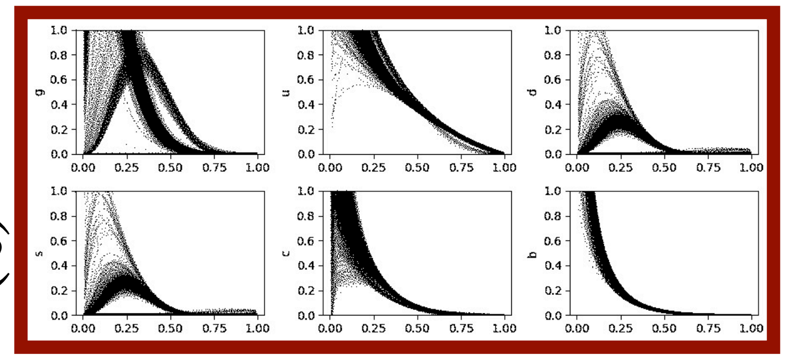
PION FF

$x\,f(x)$



x

$z\,D(z)$



z

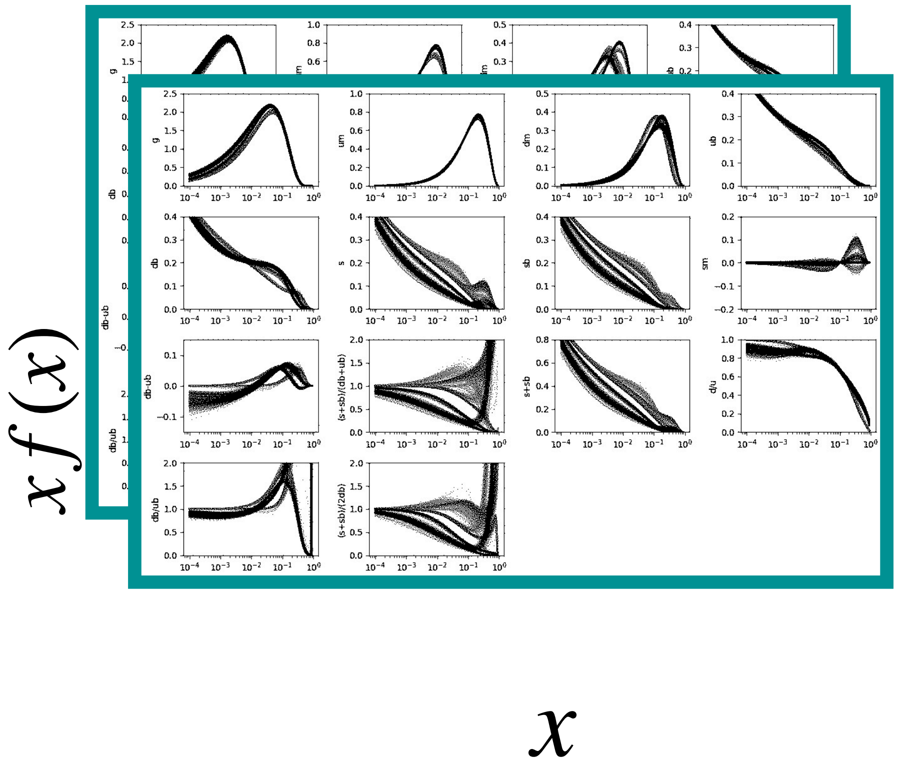
+ DIS data

+ DIS + DY data

+ SIA pion data

JAM 19: multi-step fitting

PDFs



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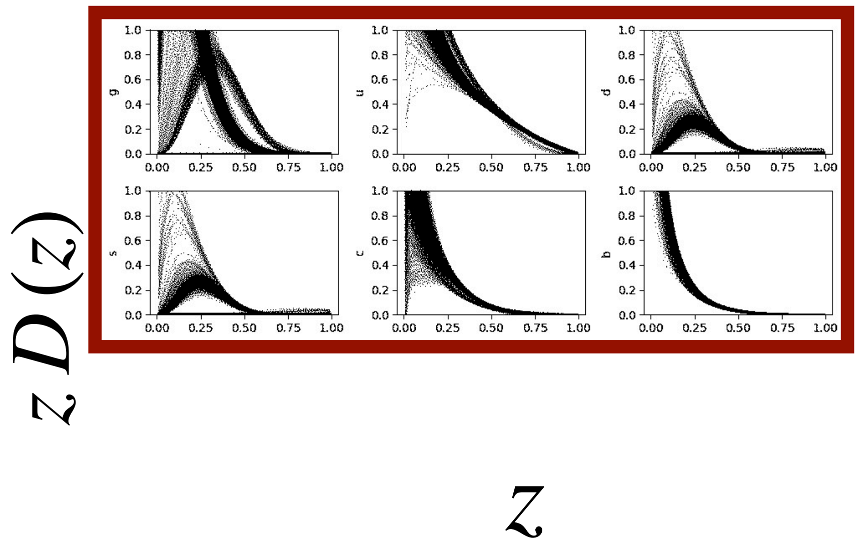
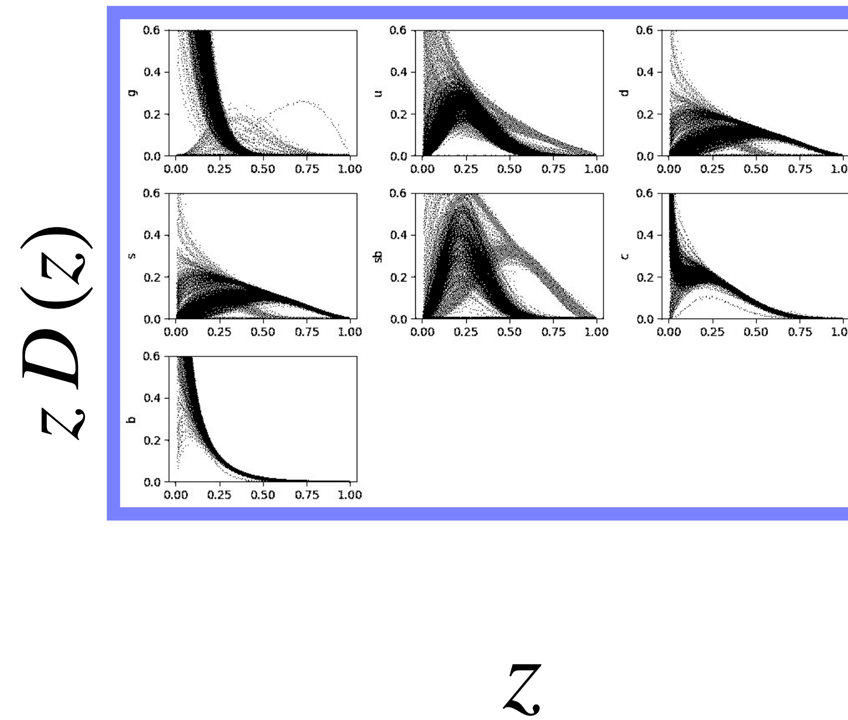


KAON FF



+ DIS data

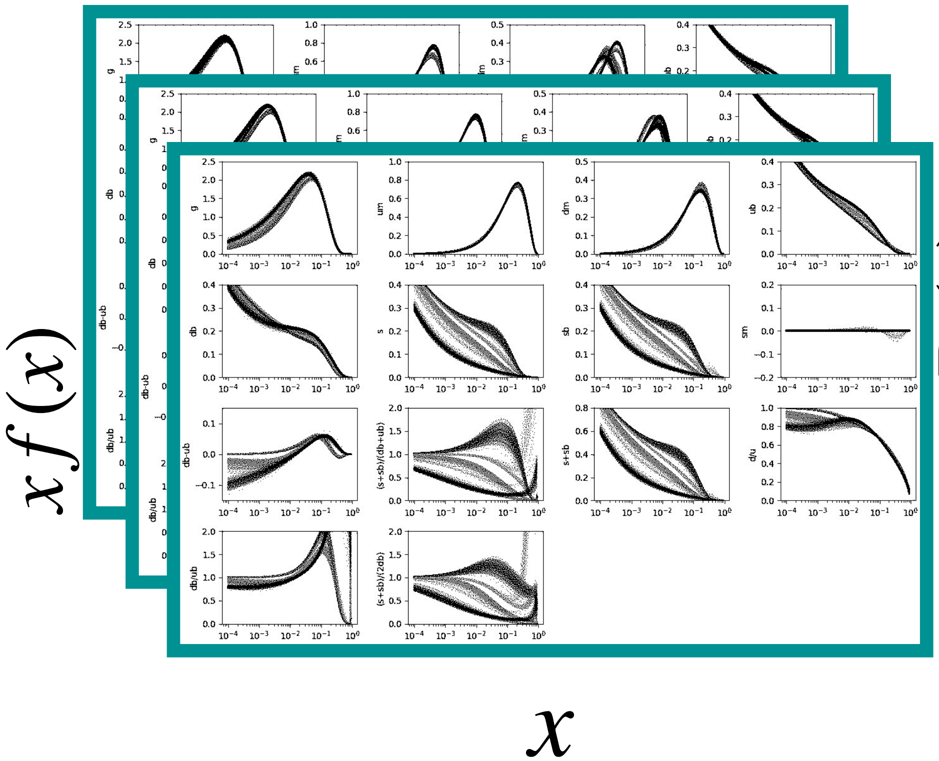
+ DIS + DY data

+ SIA pion data

+ SIA kaon data

JAM 19: multi-step fitting

PDFs



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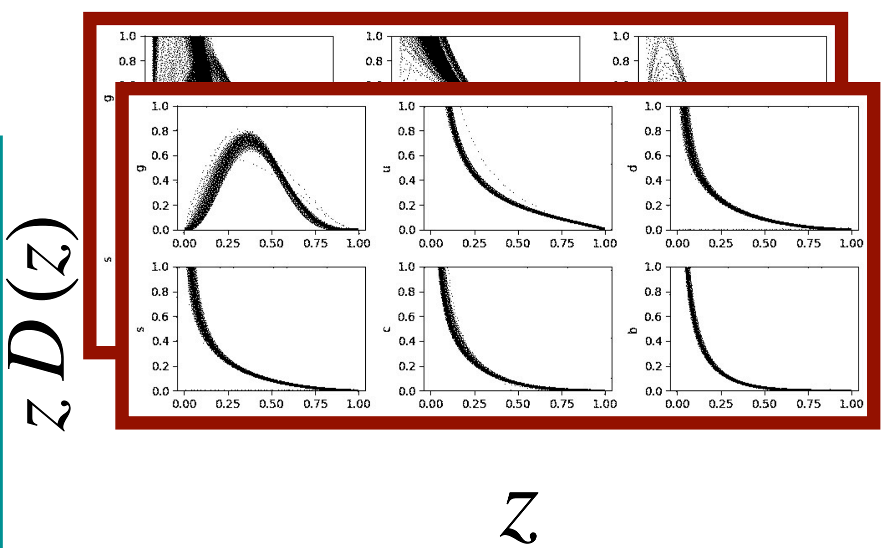

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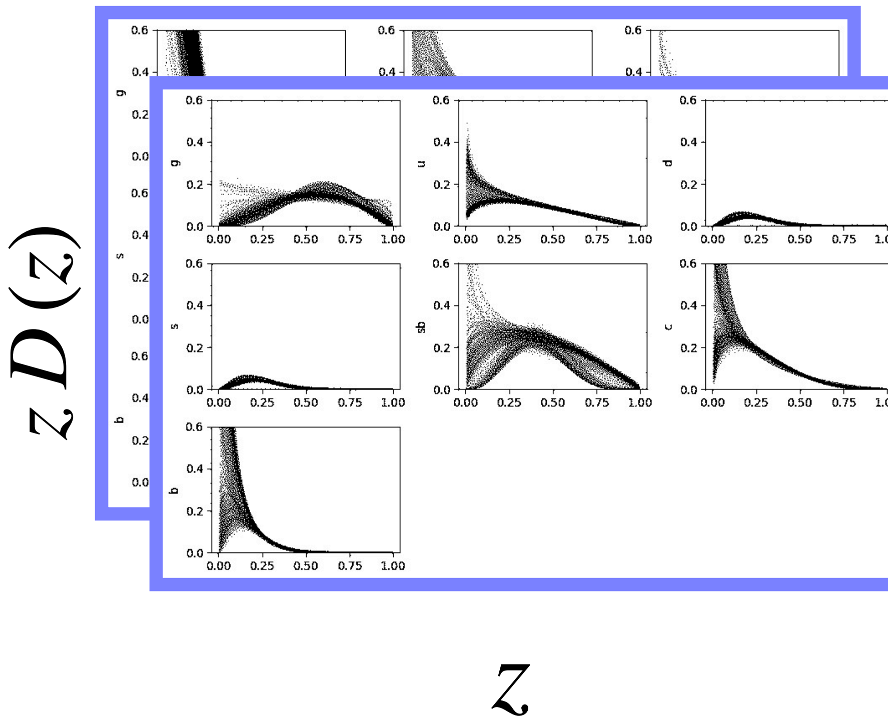

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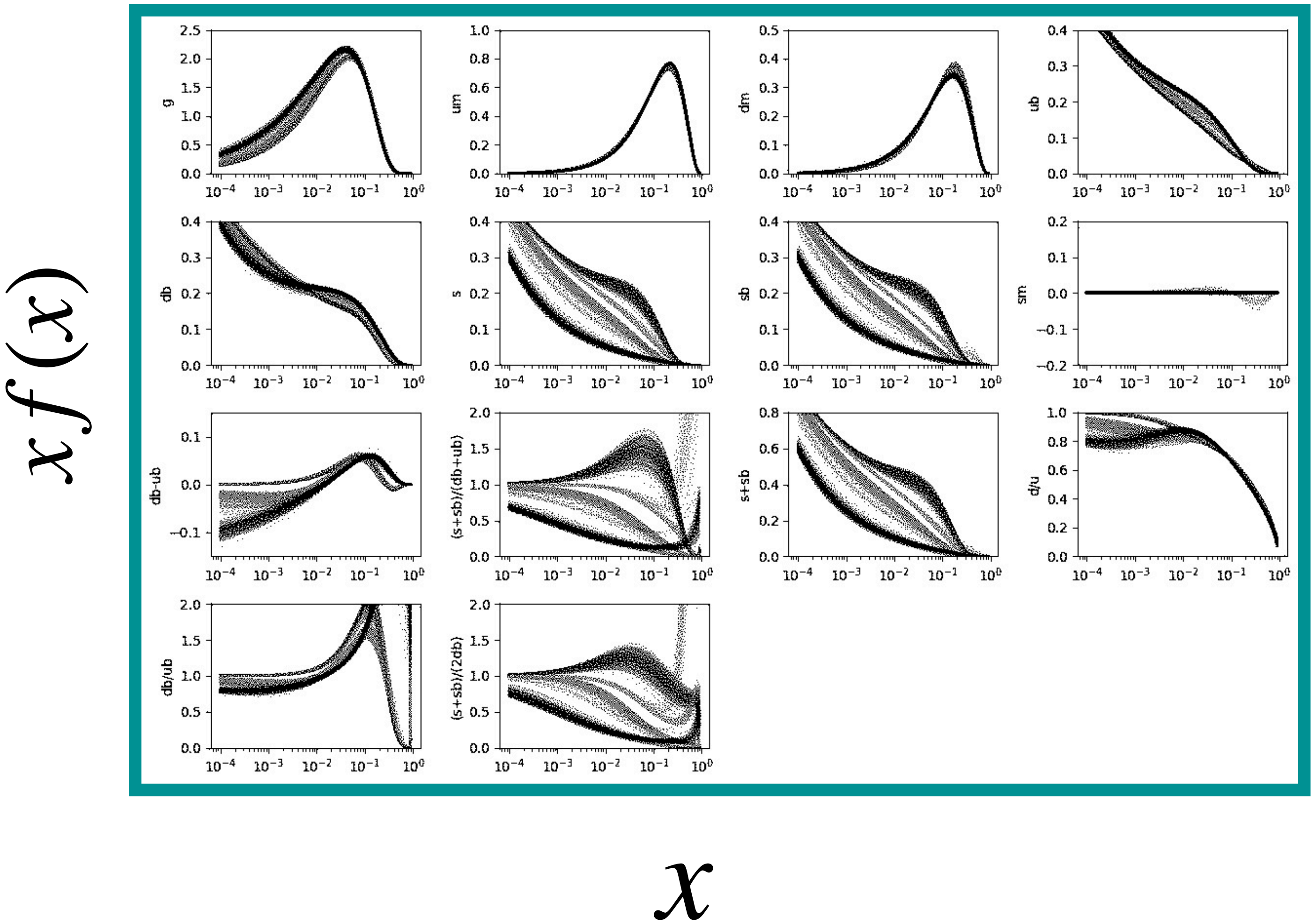
Discrminating multiple solutions



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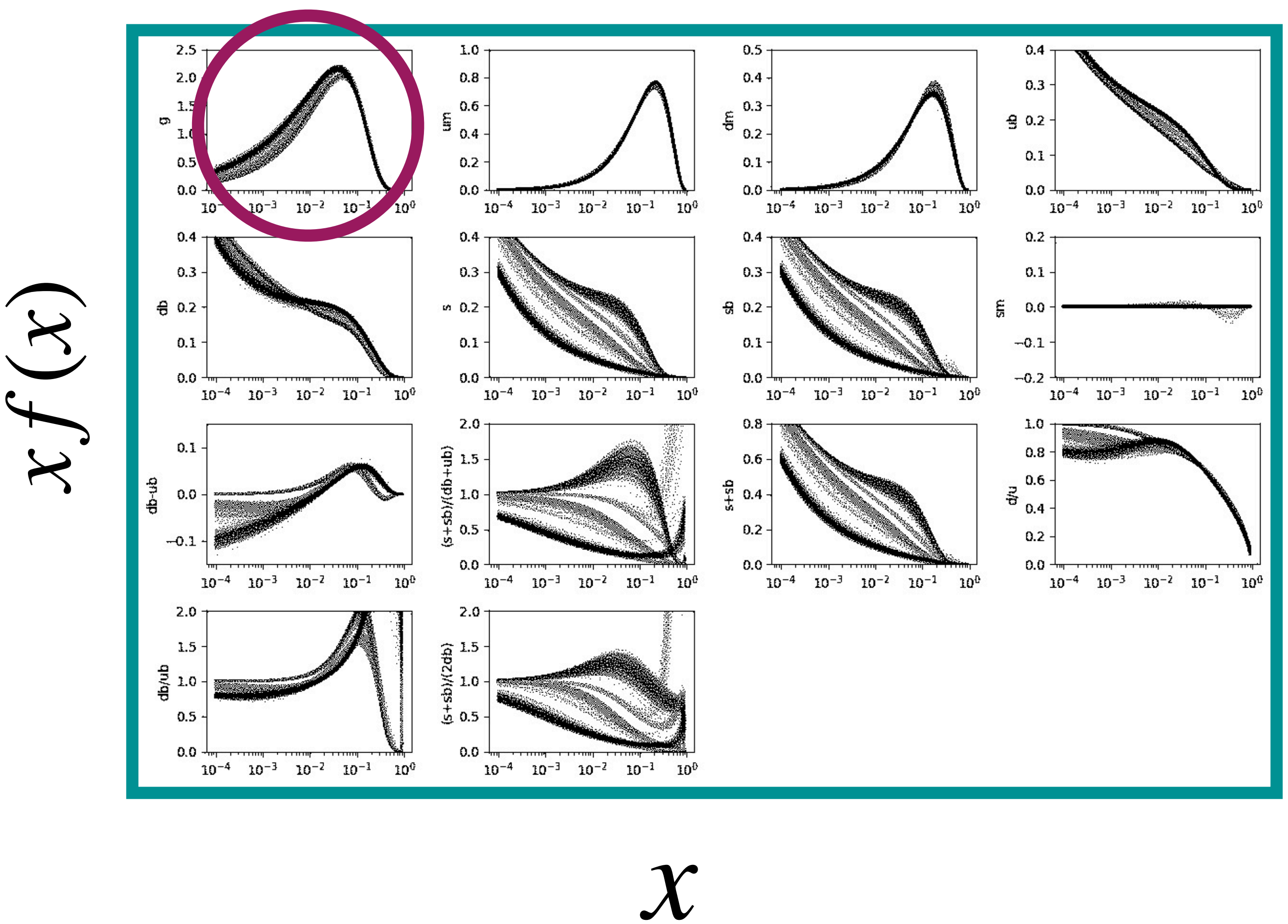

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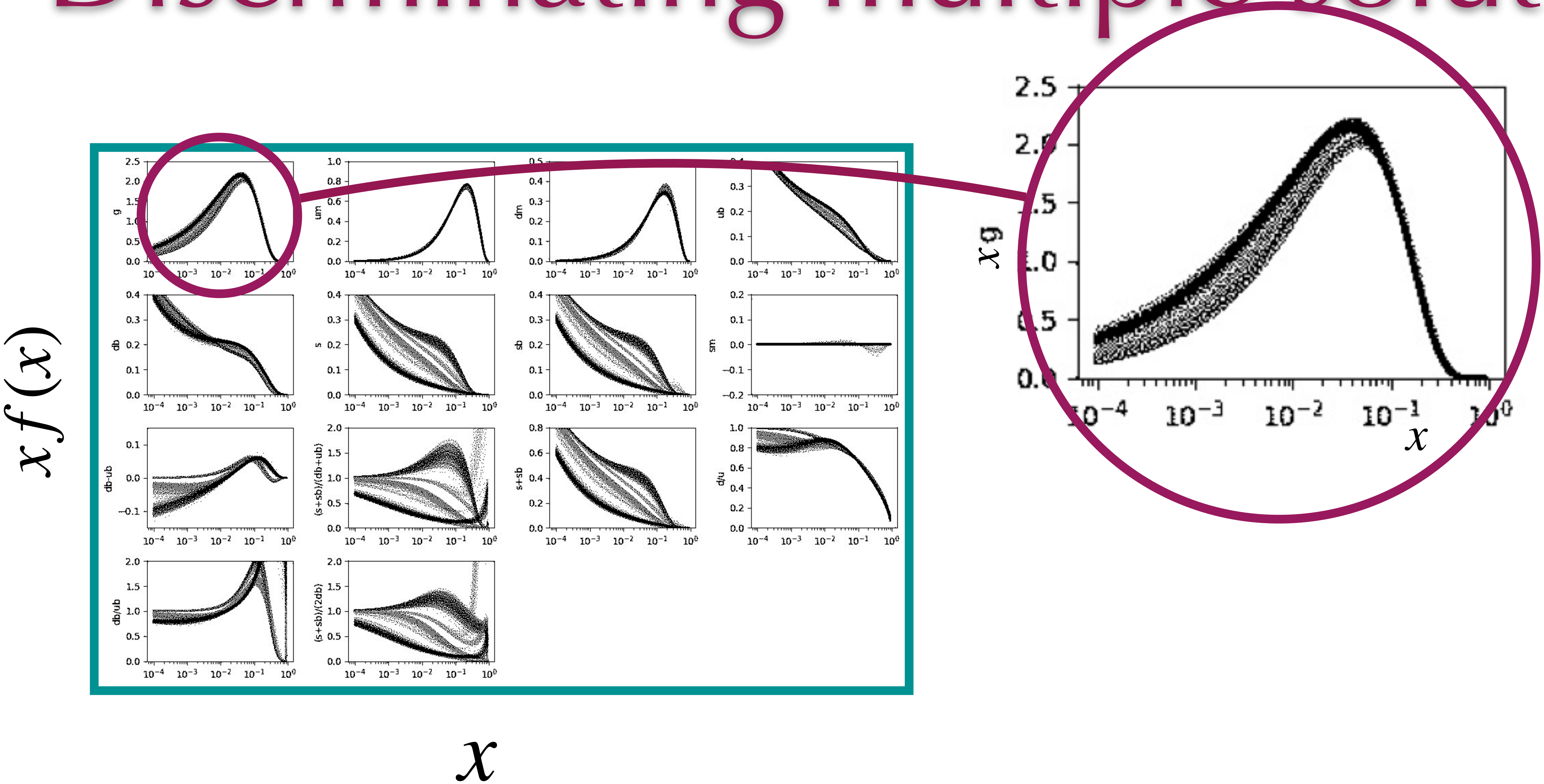

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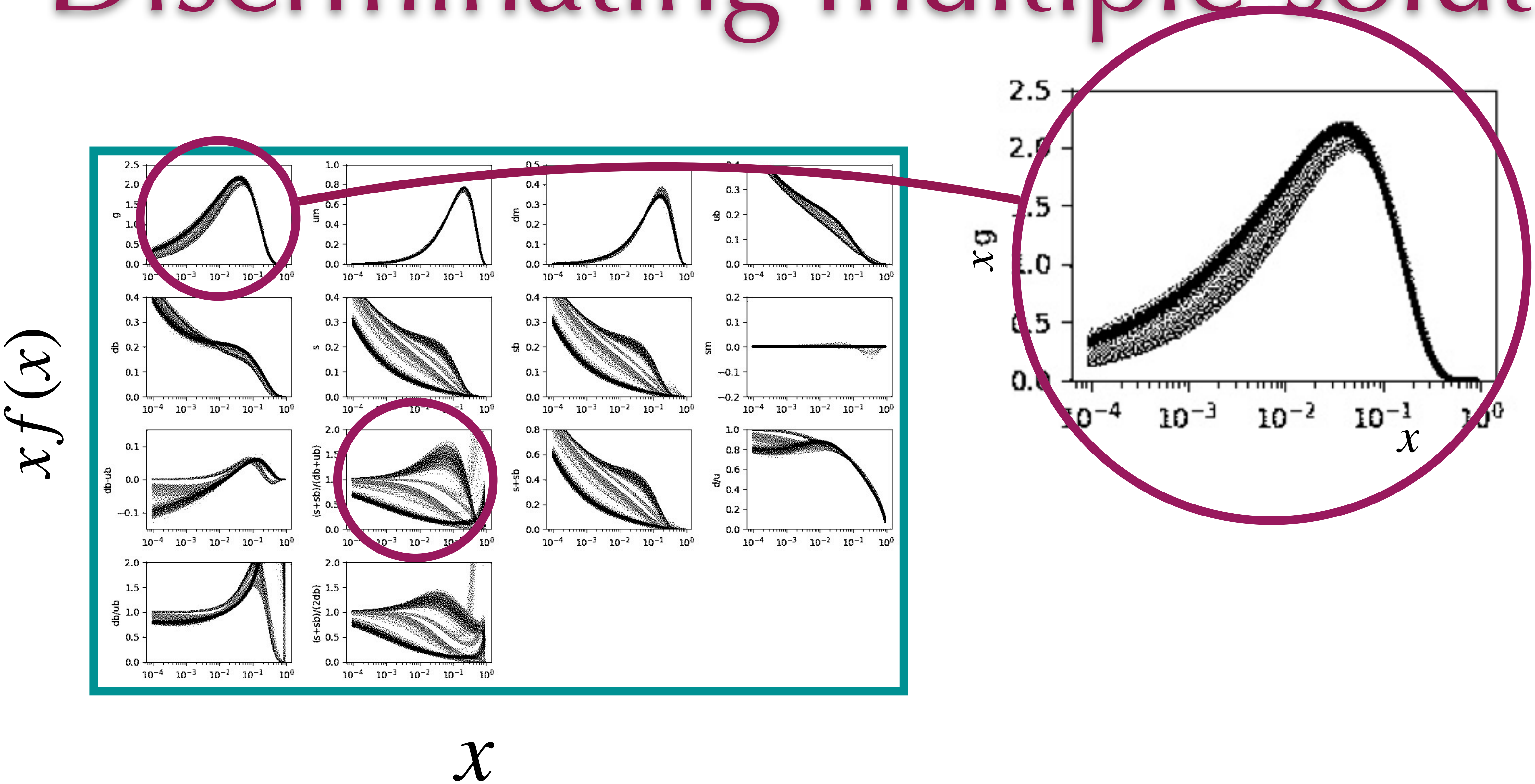

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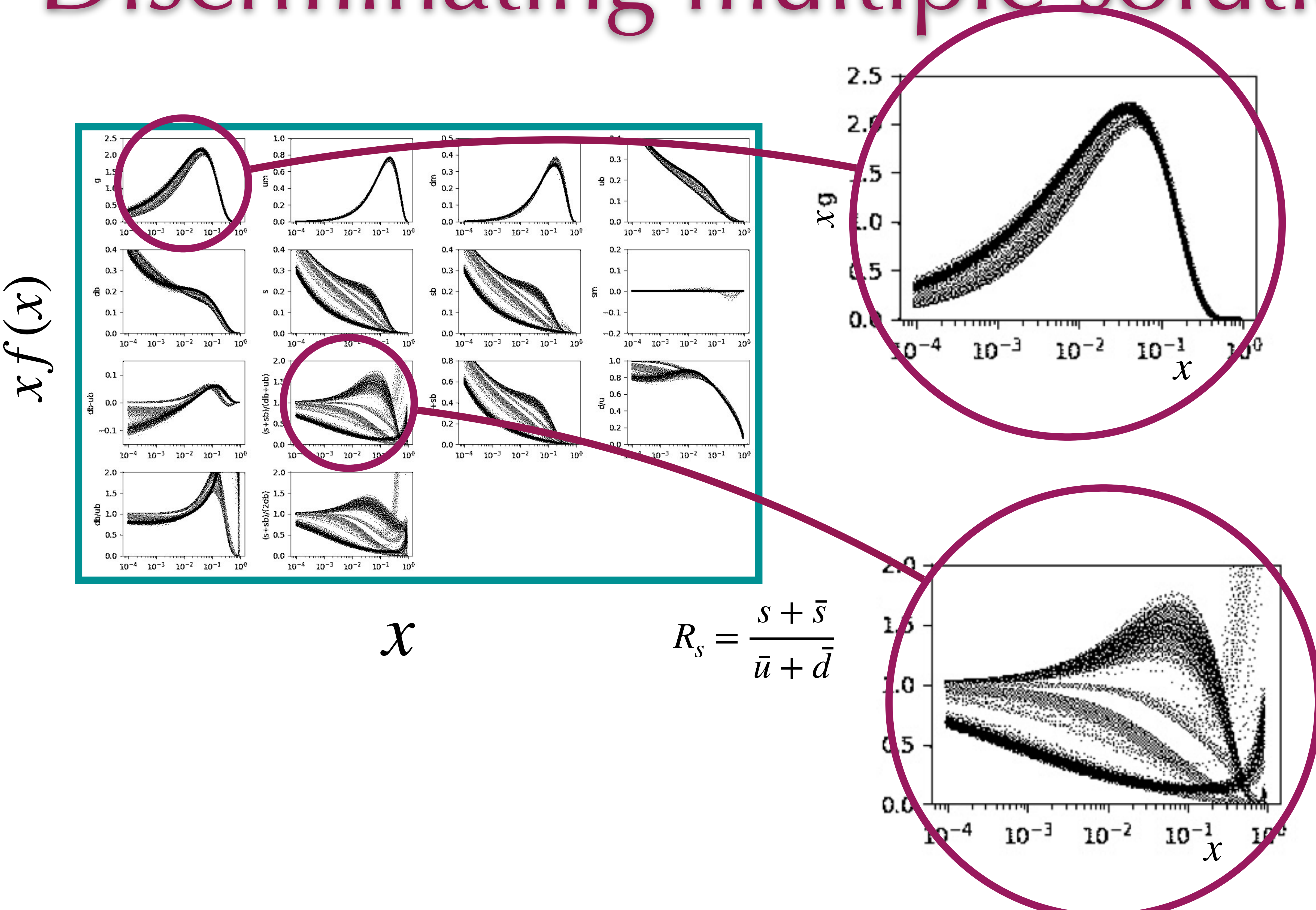
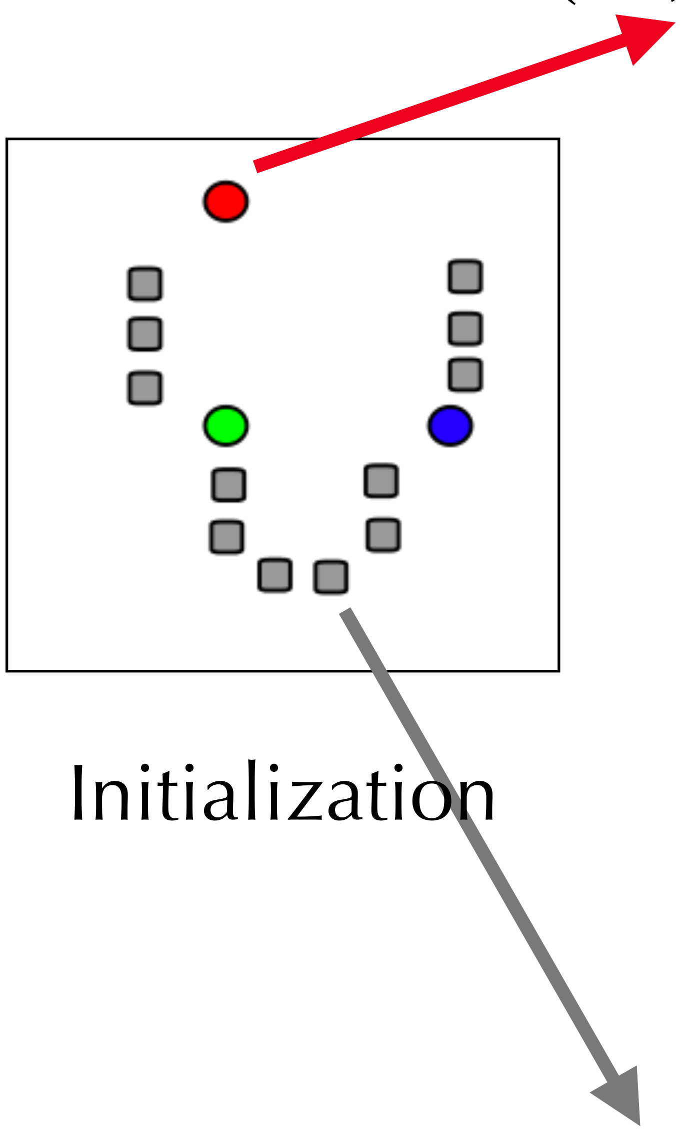


$$R_s = \frac{s+\bar{s}}{\bar{u}+\bar{d}}$$

k-means clustering

E.g. $f(x) = x^{\alpha}(1-x)^{\beta}$



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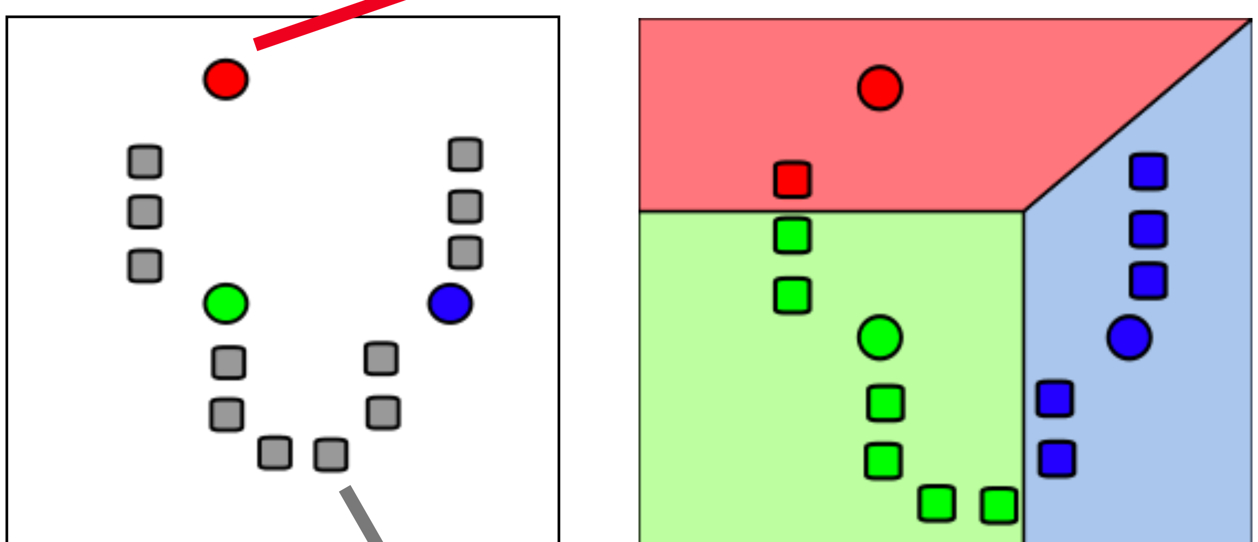
(α^*, β^*) : centroid



Initialization

Assignment

(α_i, β_i) : replica

k-means clustering

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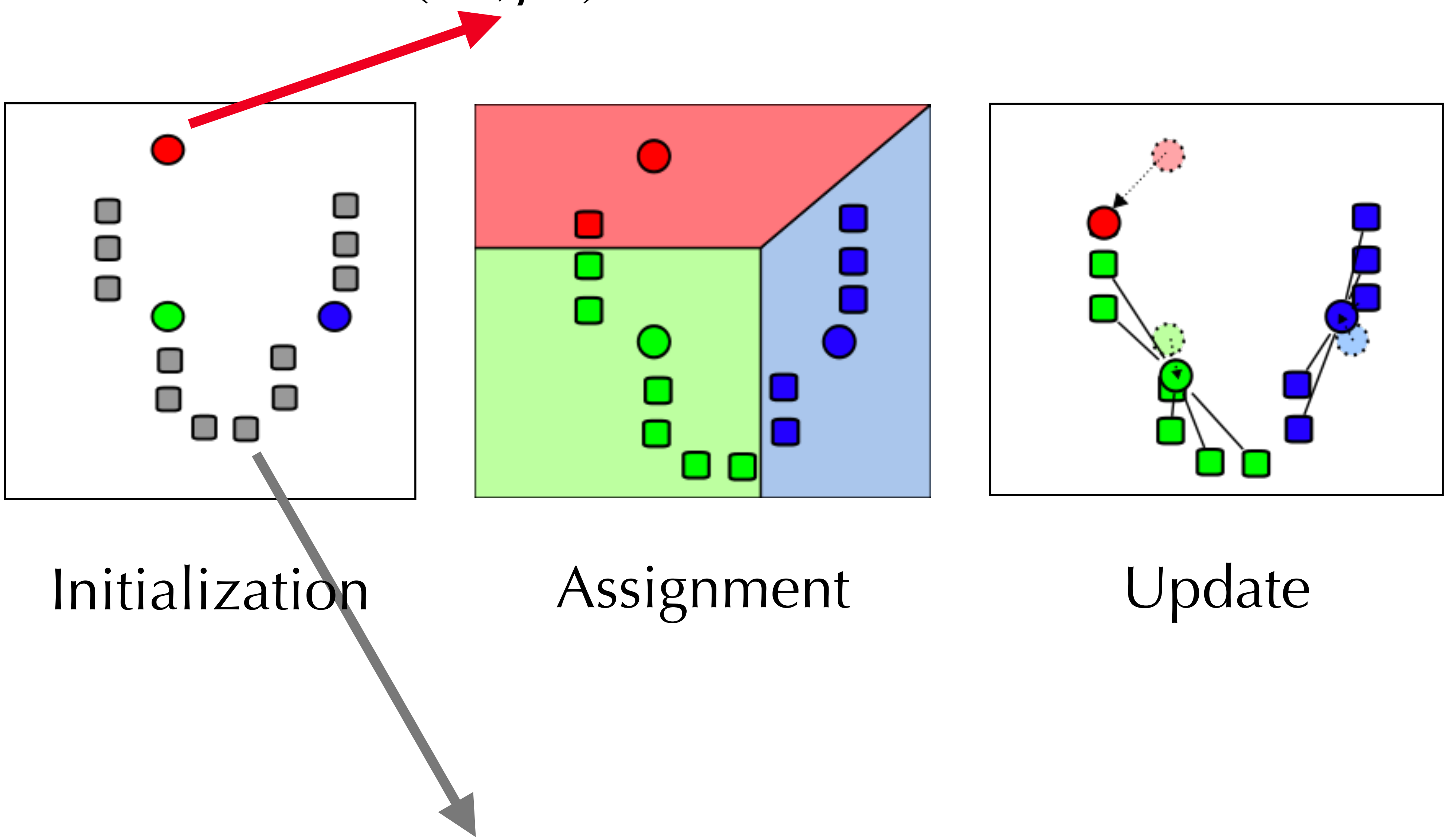


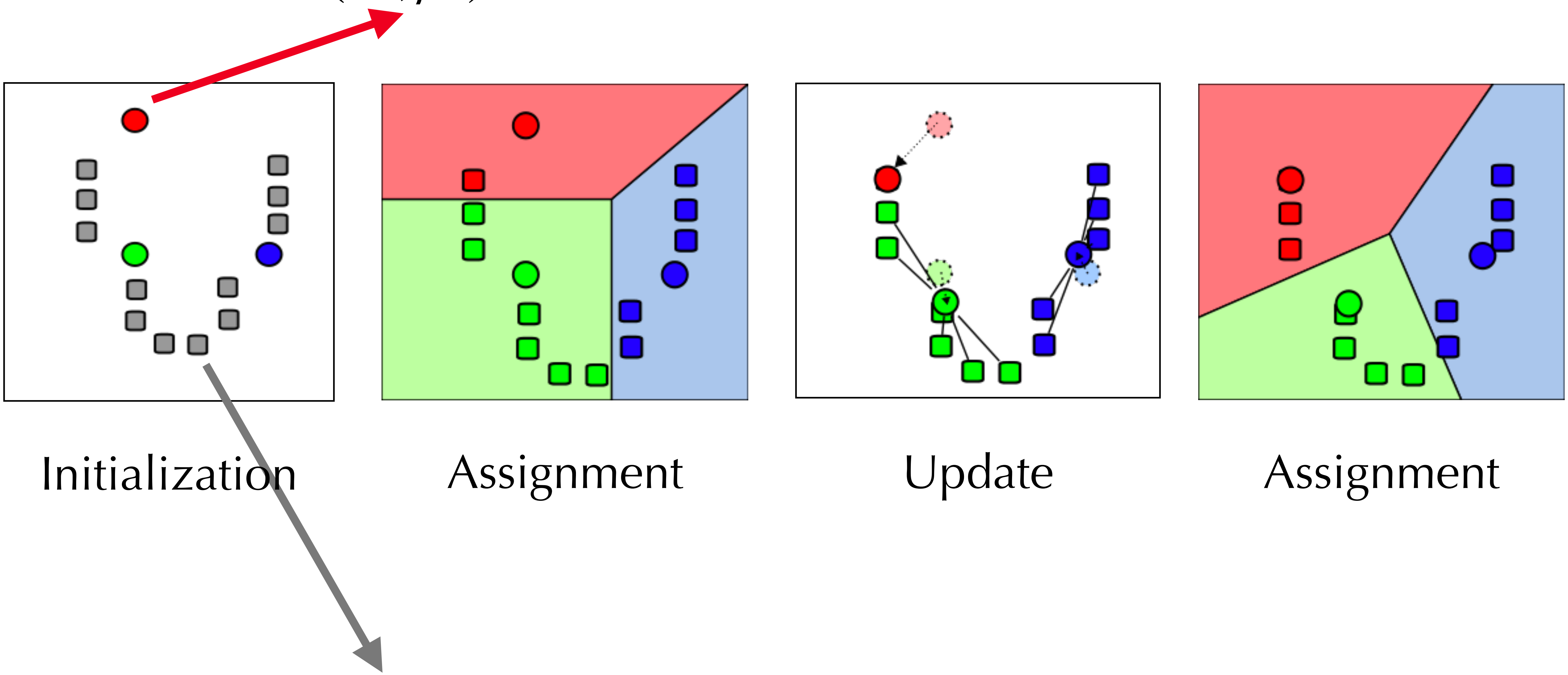
Initialization　　Assignment　　Update

(α_i, β_i) : replica

k-means clustering

E.g. $f(x) = x^{\alpha}(1-x)^{\beta}$

(α^*, β^*) : centroid



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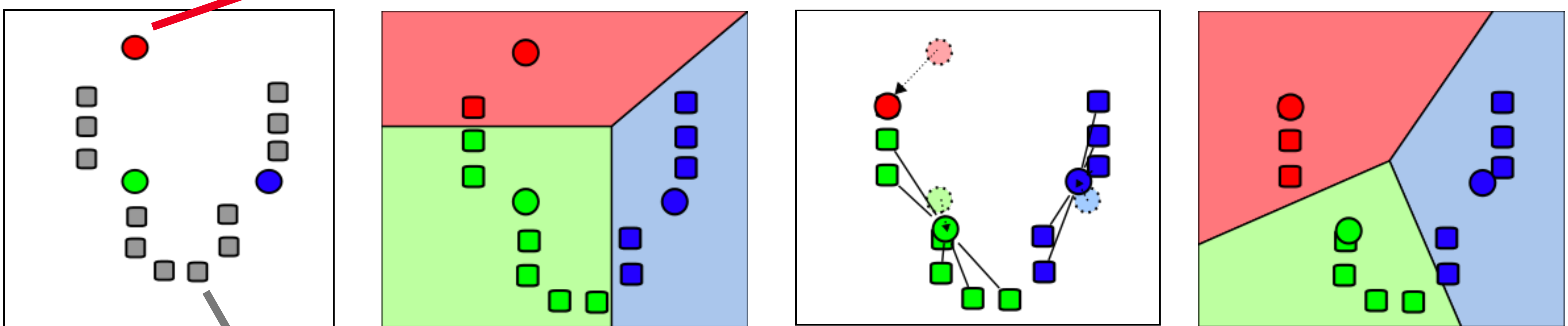
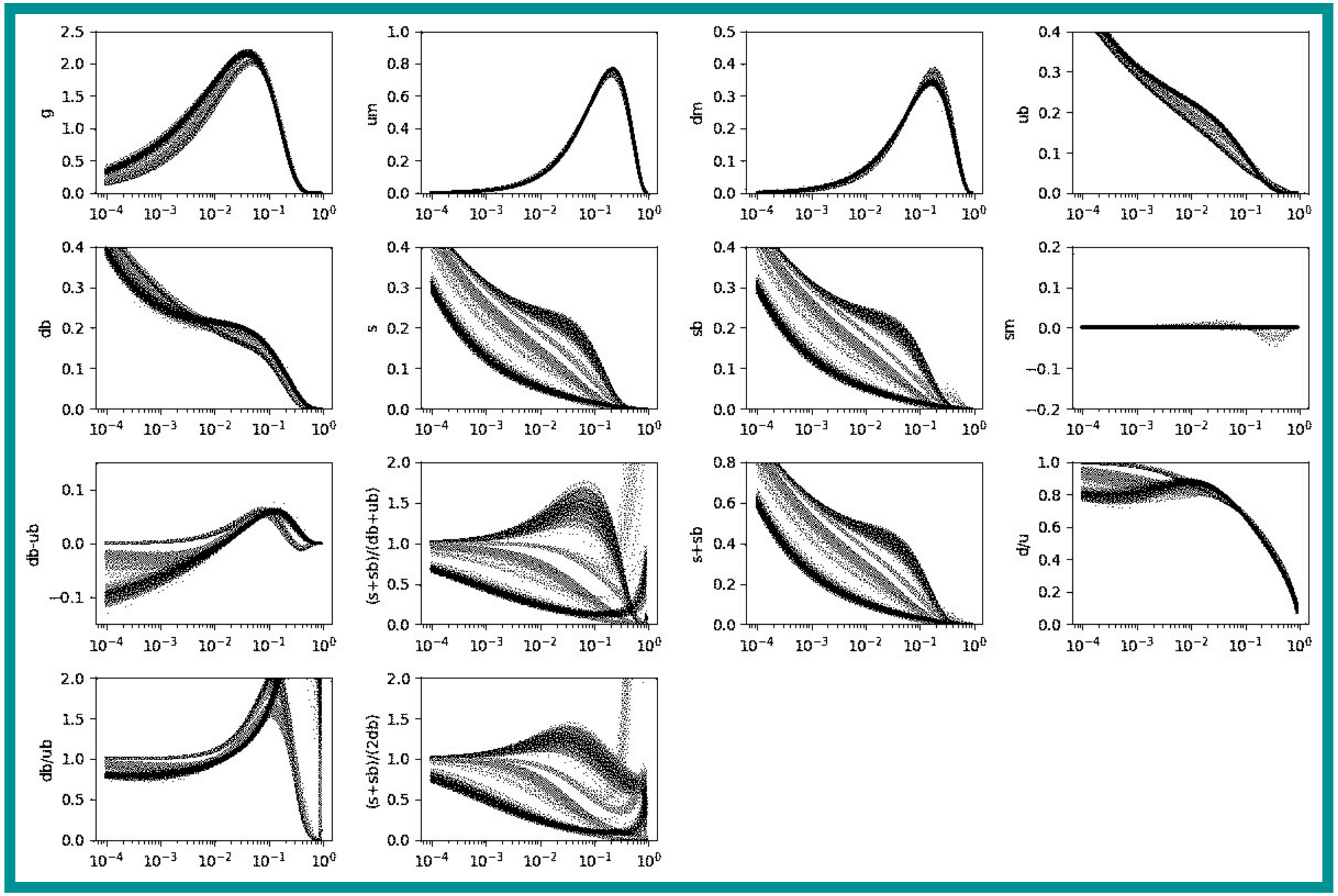


Initialization Assignment Update Assignment

(α_i, β_i) : replica

Repeat until convergence

Discriminating multiple solutions



+ DIS data

+ DIS + DY data

+ SIDIS data

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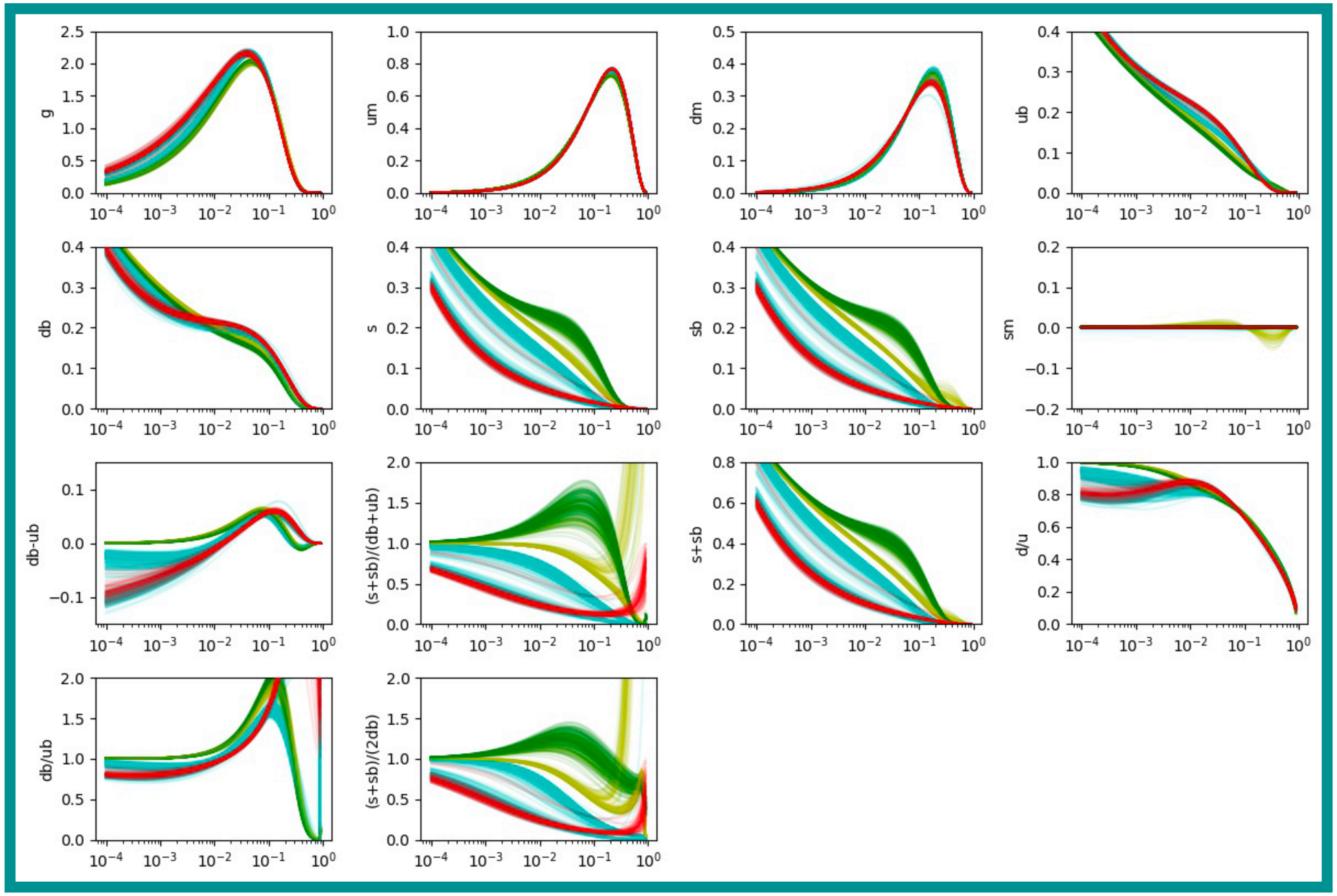

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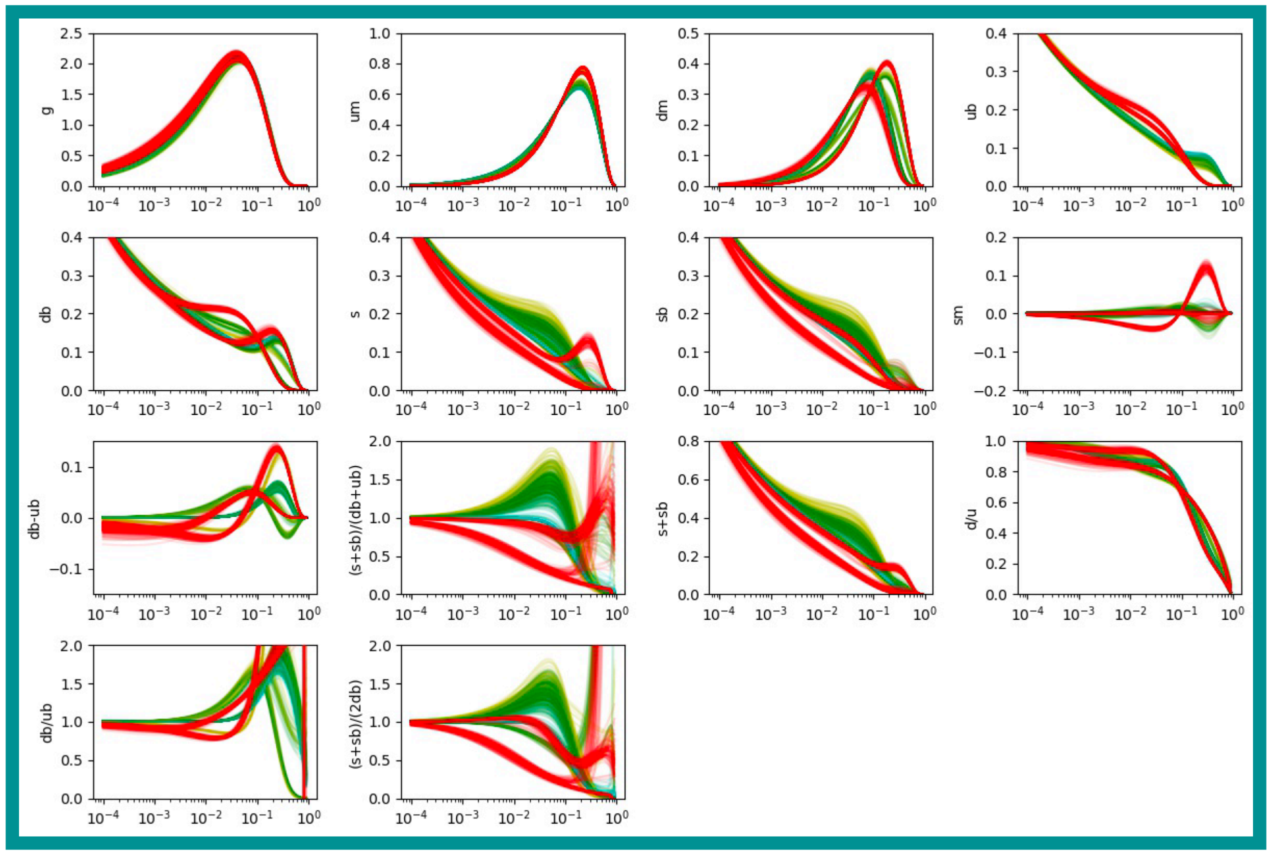
Constraints on Rs

$$R_s = \frac{s + \bar{s}}{\bar{u} + \bar{d}}$$

PDFs

$x\,f(x)$



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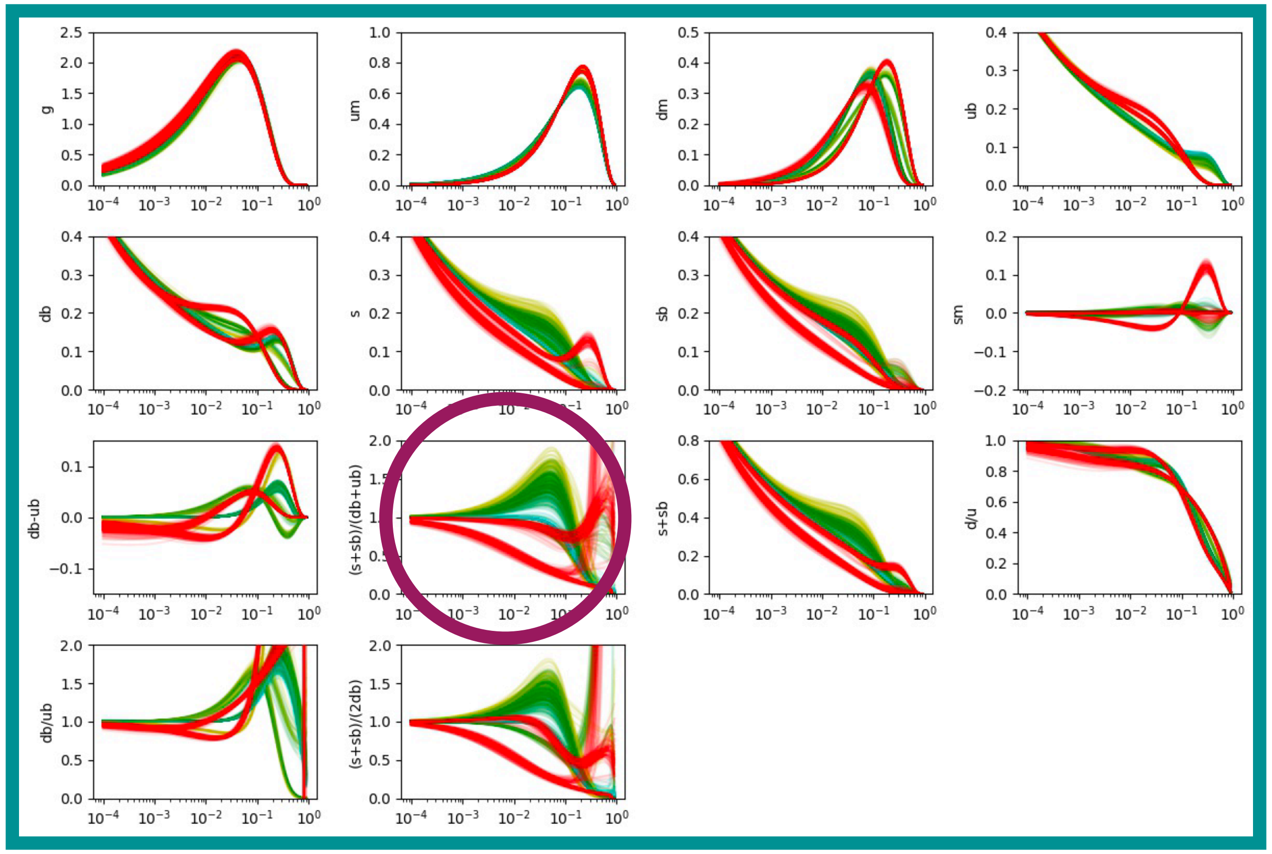

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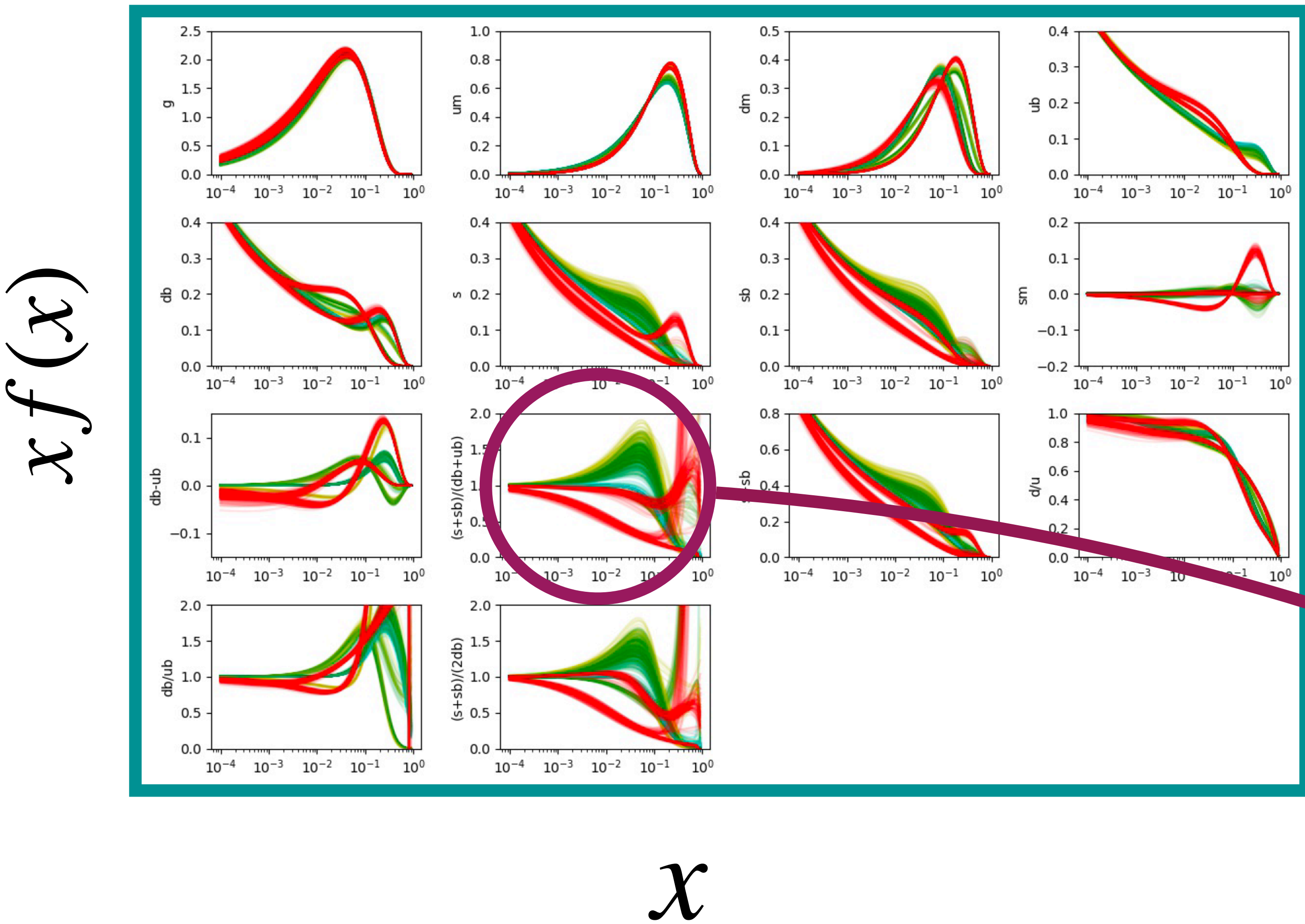

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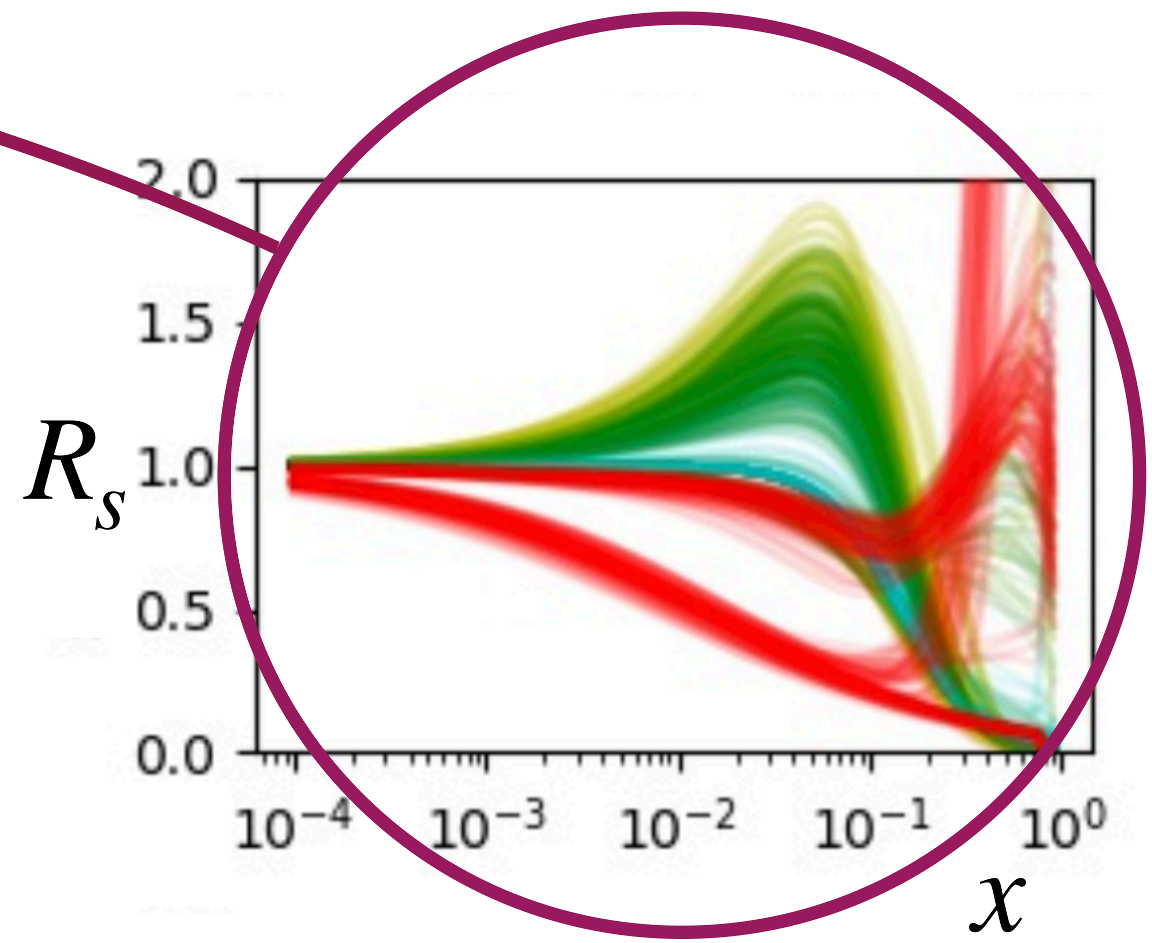

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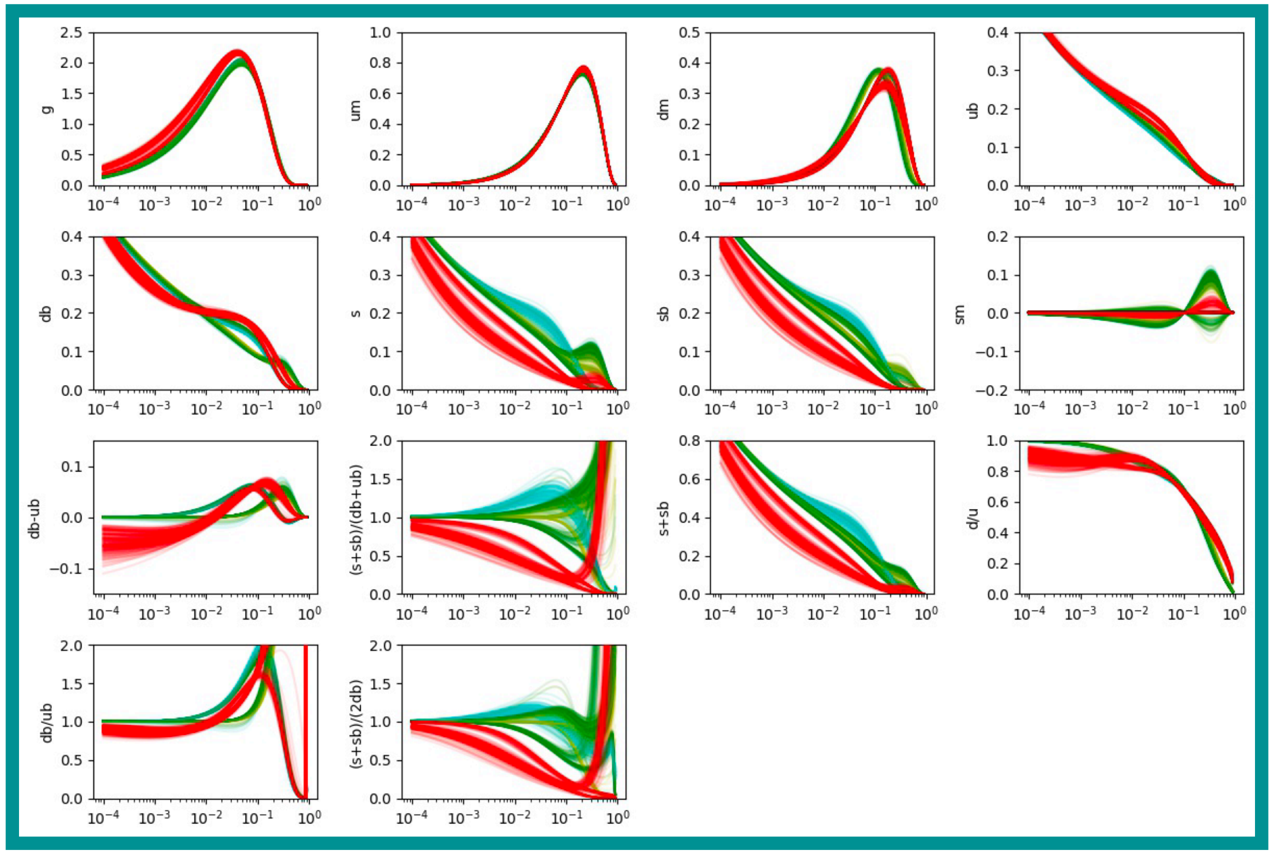
$$R_s = \frac{s + \bar{s}}{\bar{u} + \bar{d}}$$

PDFs

$x\, f(x)$



x

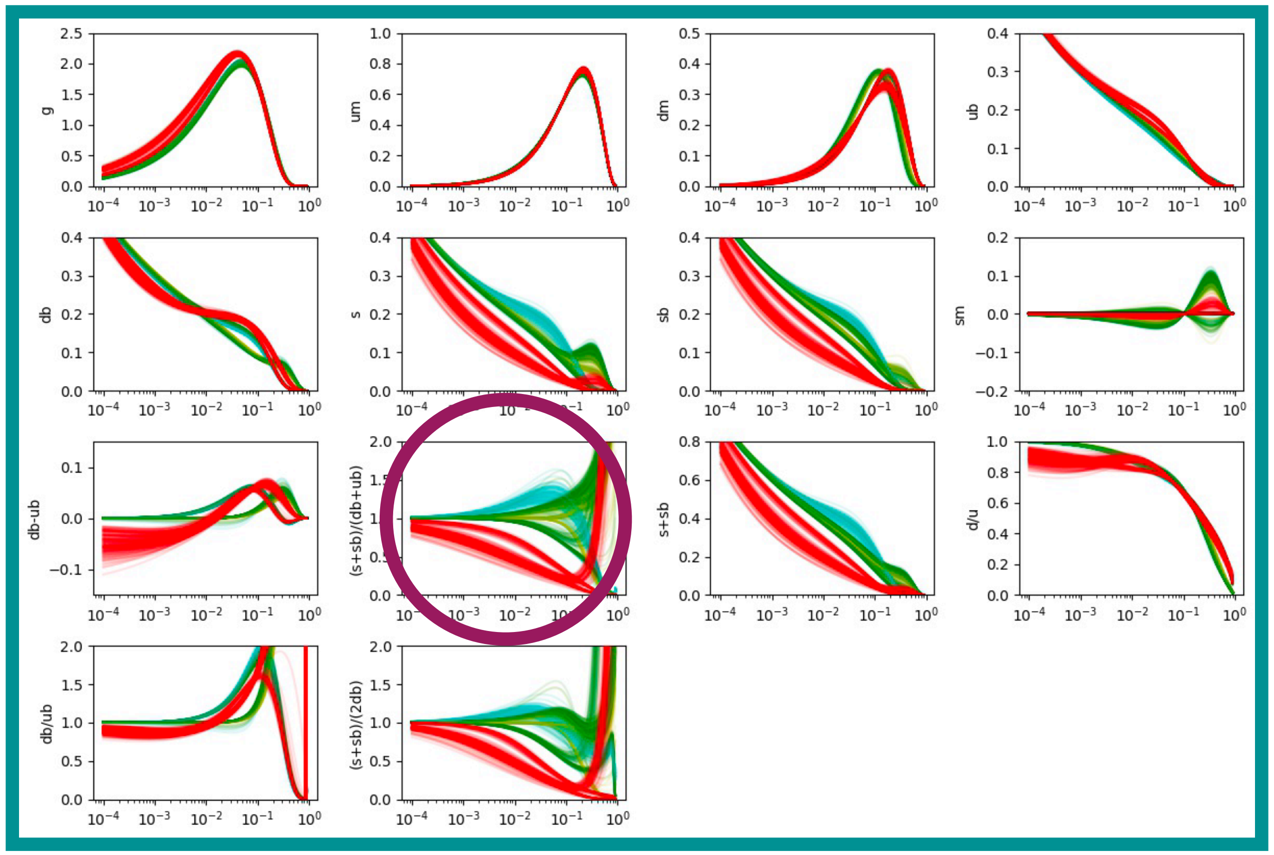
+ DIS data
+ DY data

Constraints on Rs

$$R_s = \frac{s + \bar{s}}{\bar{u} + \bar{d}}$$

PDFs

$x\,f(x)$



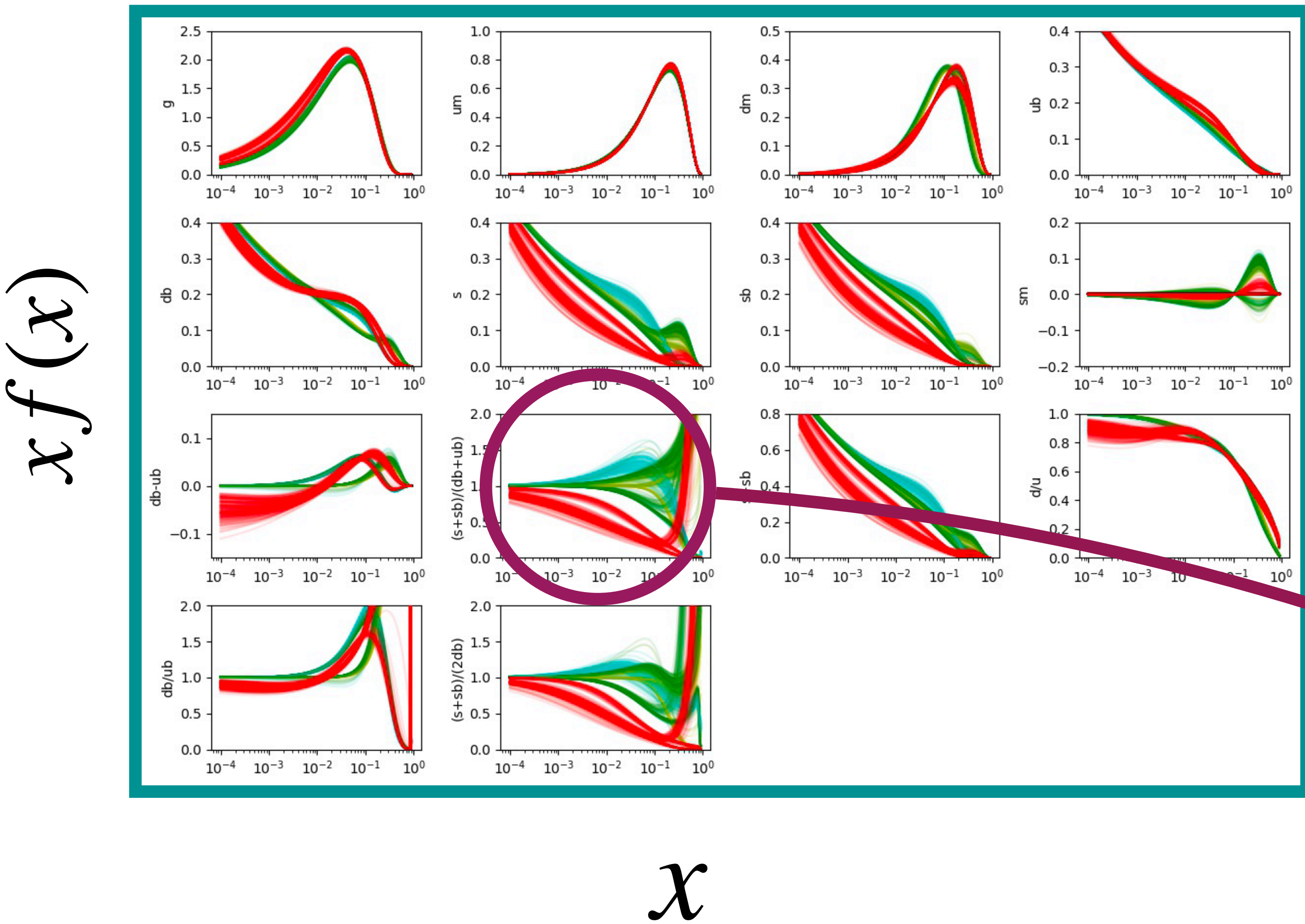
x

+ DIS data
+ DY data

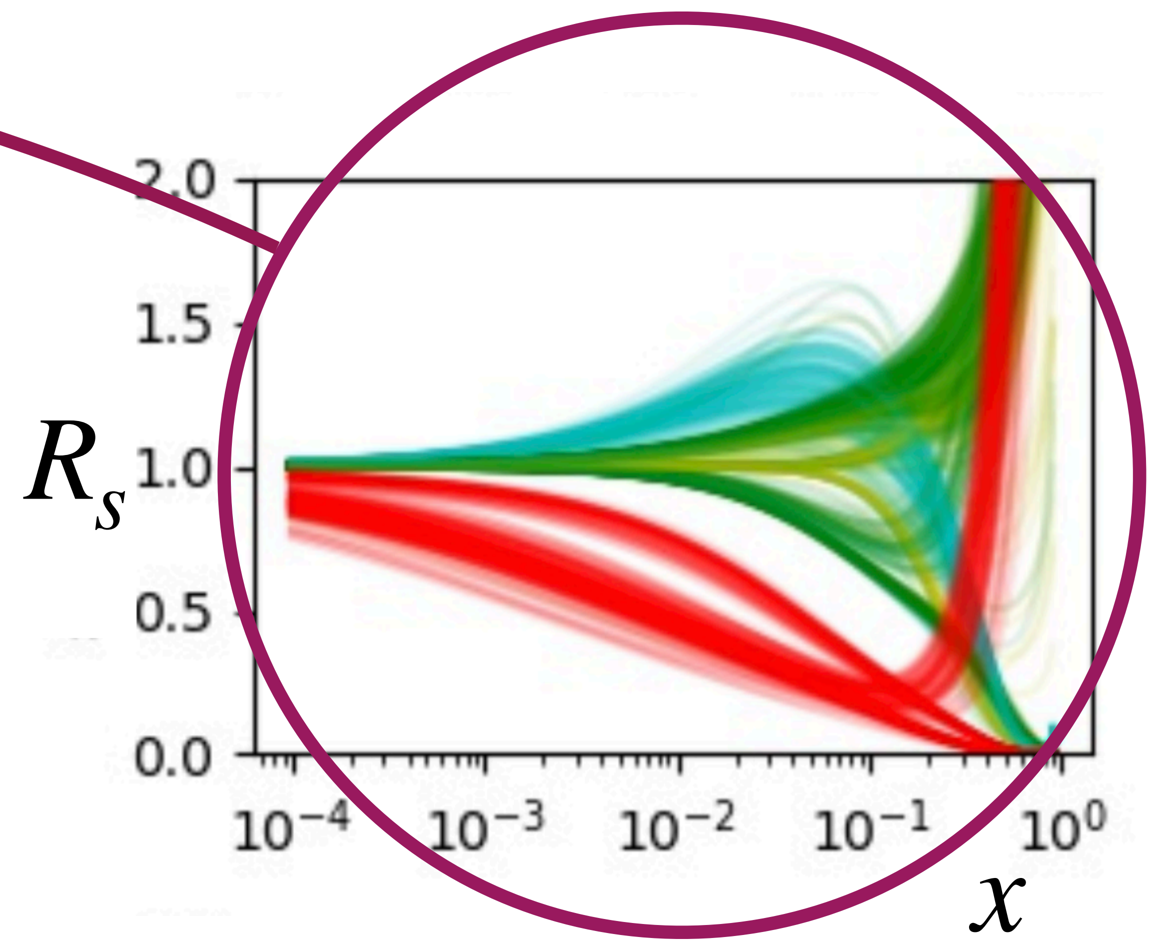
Constraints on Rs

$$R_s = \frac{s + \bar{s}}{\bar{u} + \bar{d}}$$

PDFs



+ DIS data
+ DY data

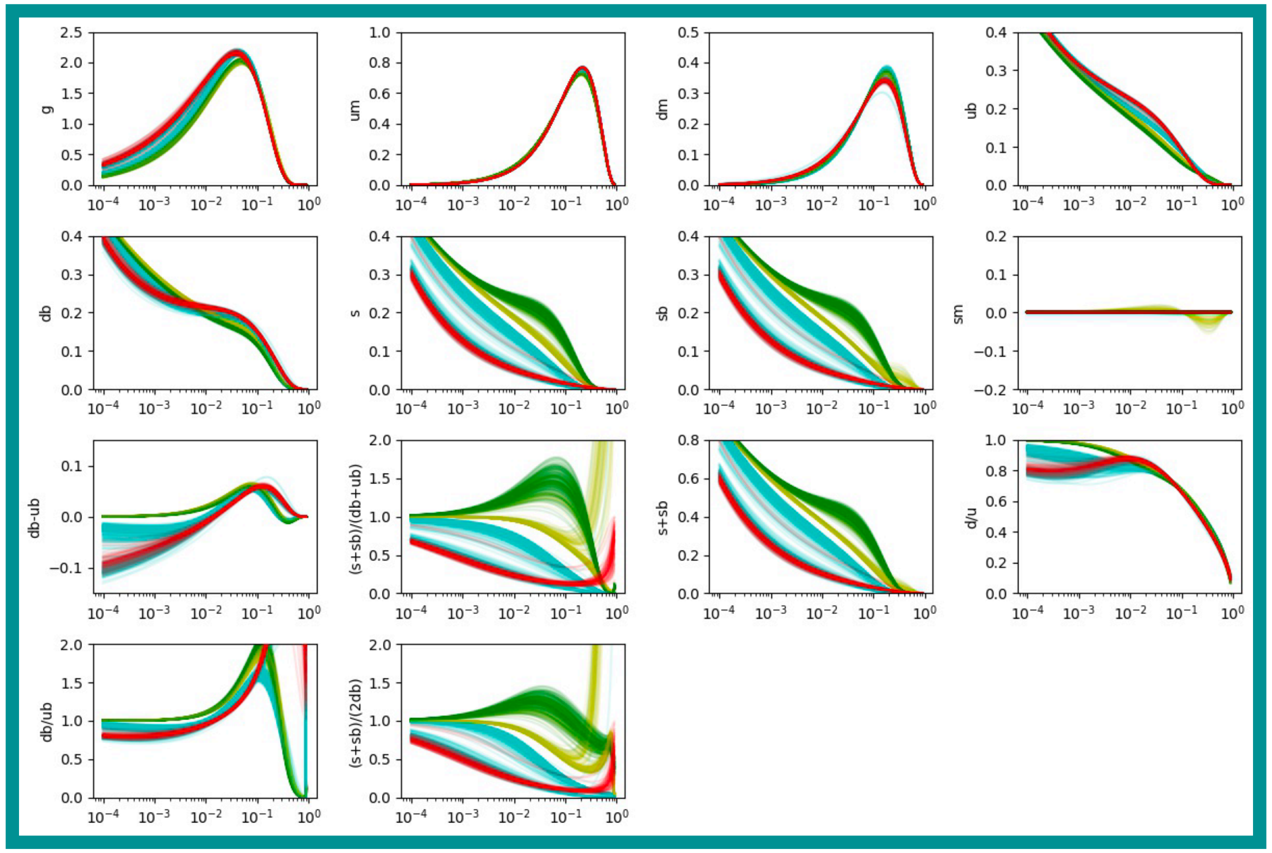


Constraints on R_s

$$R_s = \frac{s + \bar{s}}{\bar{u} + \bar{d}}$$

PDFs

$x\,f(x)$



x

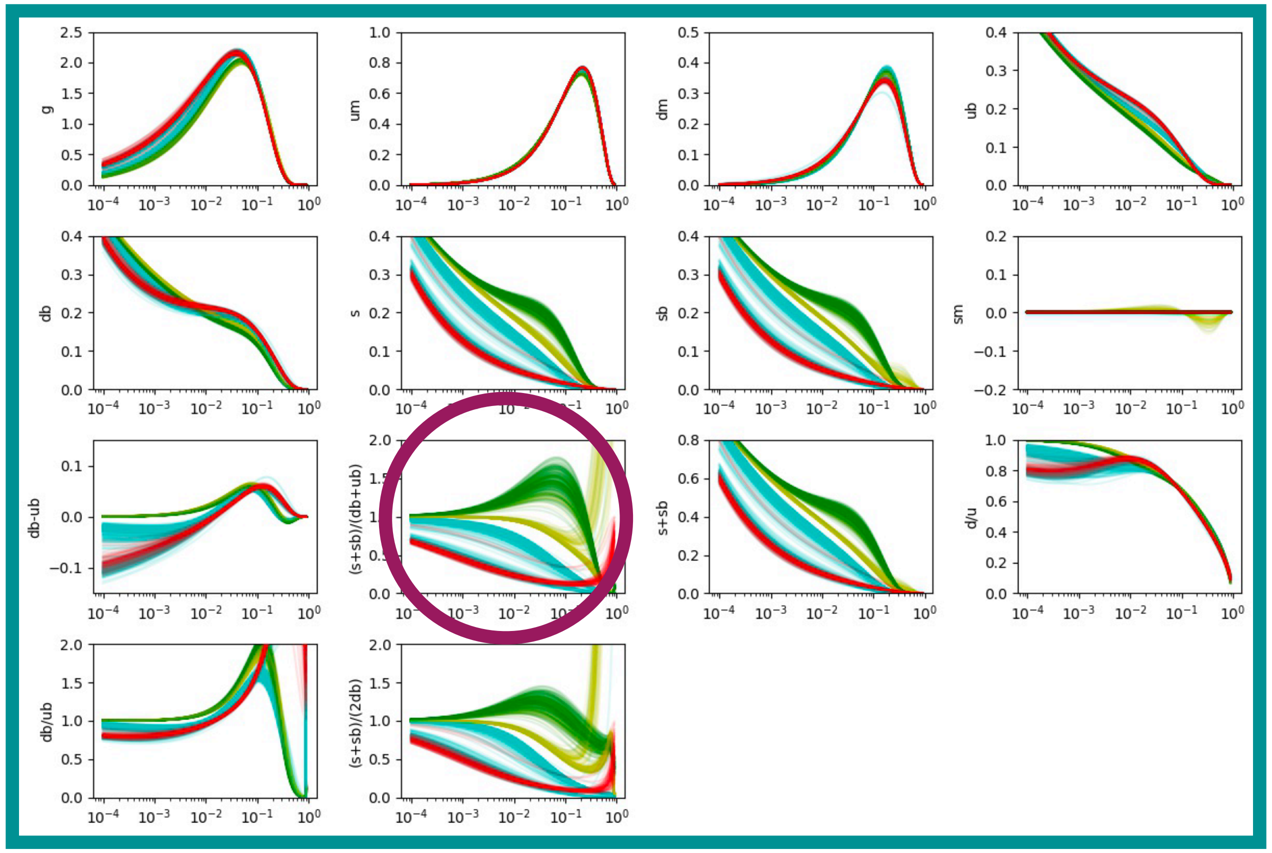
\+ DIS data
\+ DY data
\+ SIA + SIDIS data

Constraints on R_s

$$R_s = \frac{s + \bar{s}}{\bar{u} + \bar{d}}$$

PDFs

$x\,f(x)$



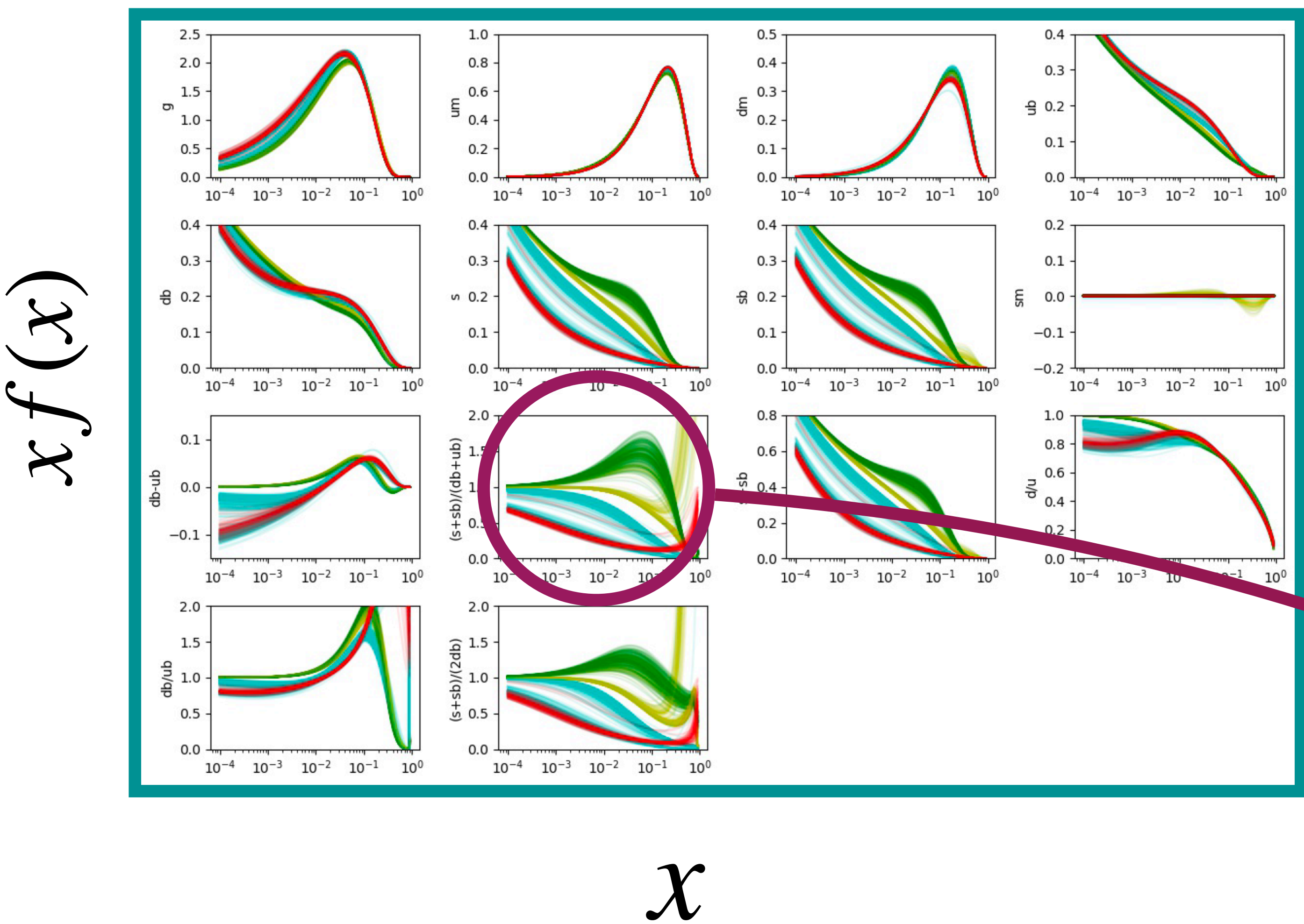
x

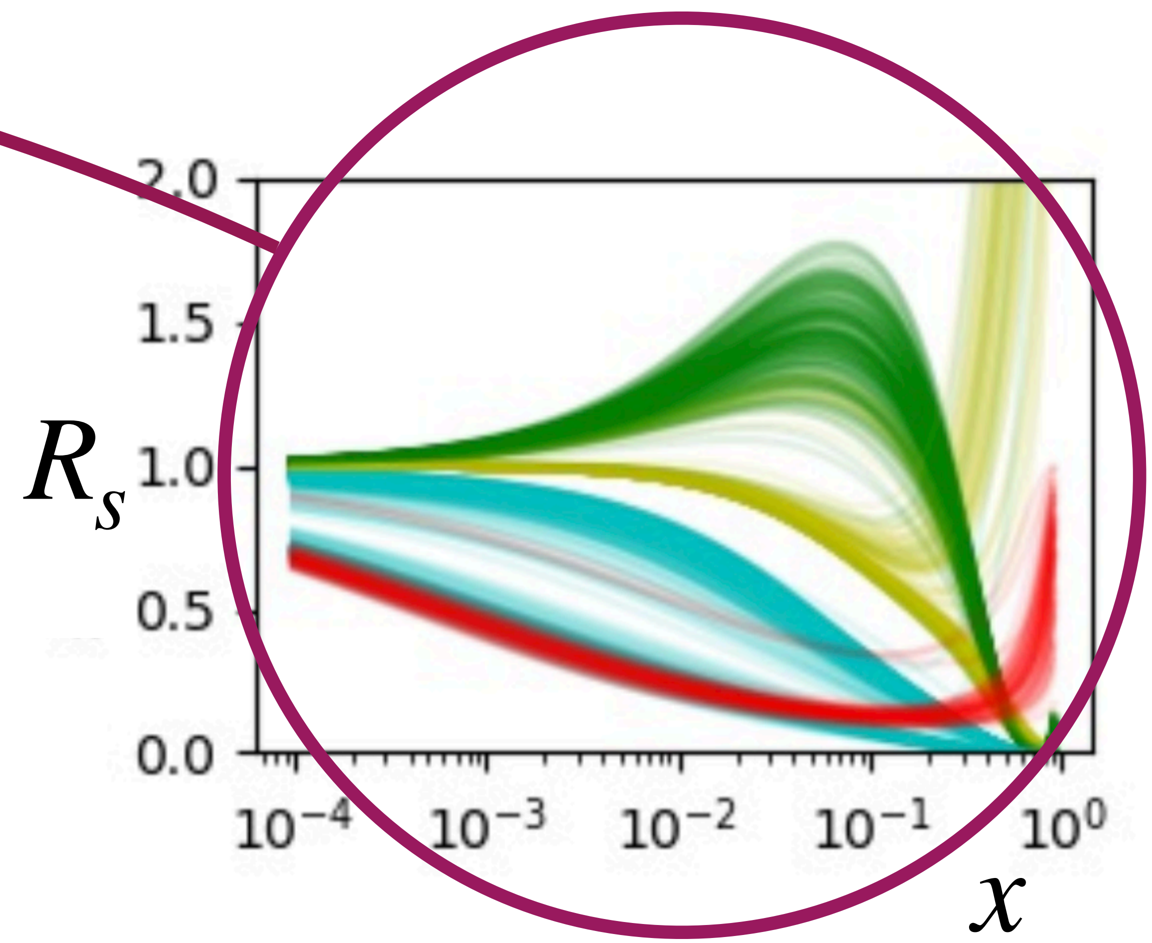
+ DIS data
+ DY data
+ SIA + SIDIS data

Constraints on R_s

$$R_s = \frac{s + \bar{s}}{\bar{u} + \bar{d}}$$

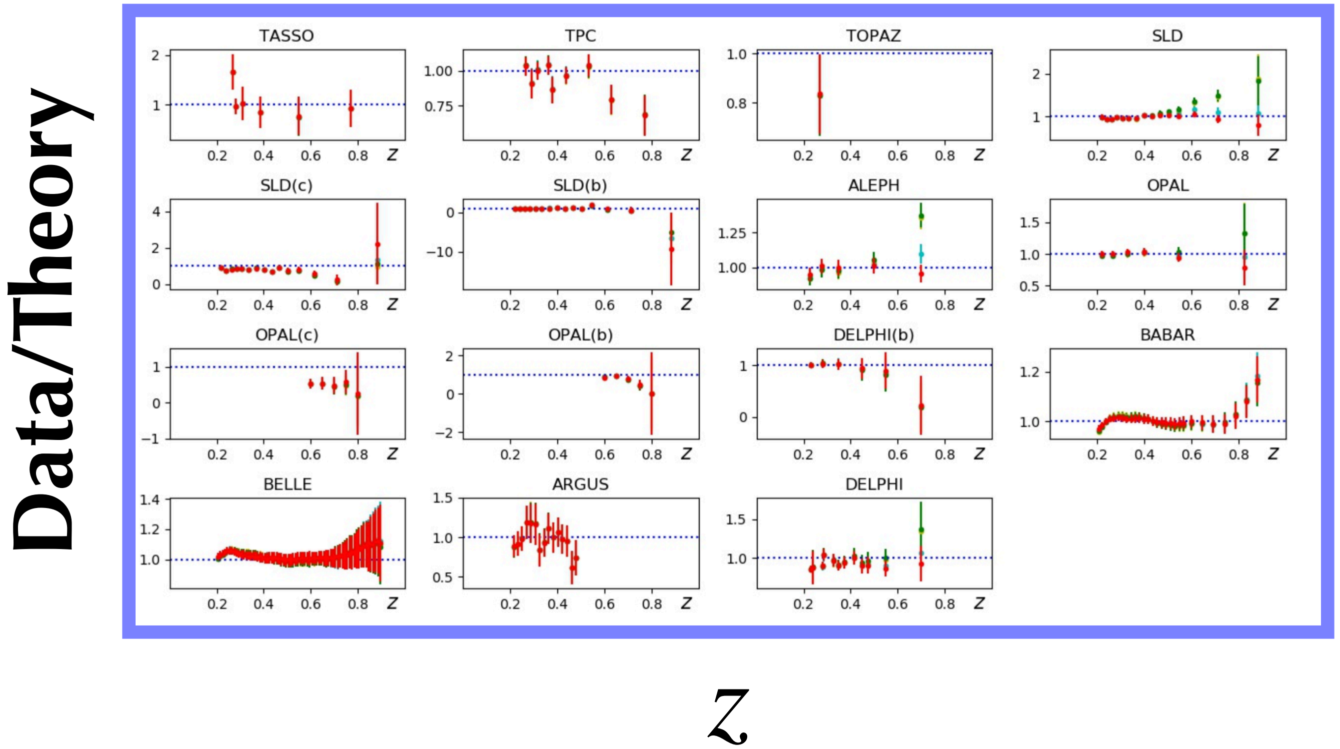
PDFs

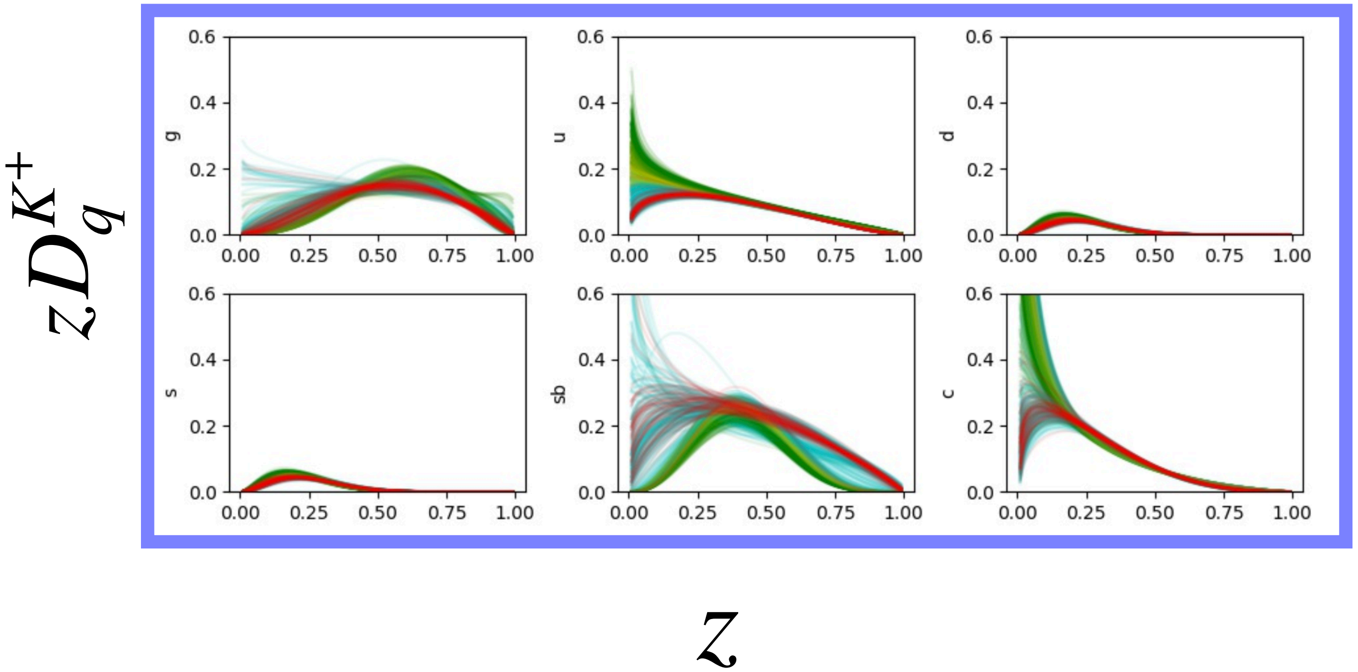




+ DIS data
+ DY data
+ SIA + SIDIS data

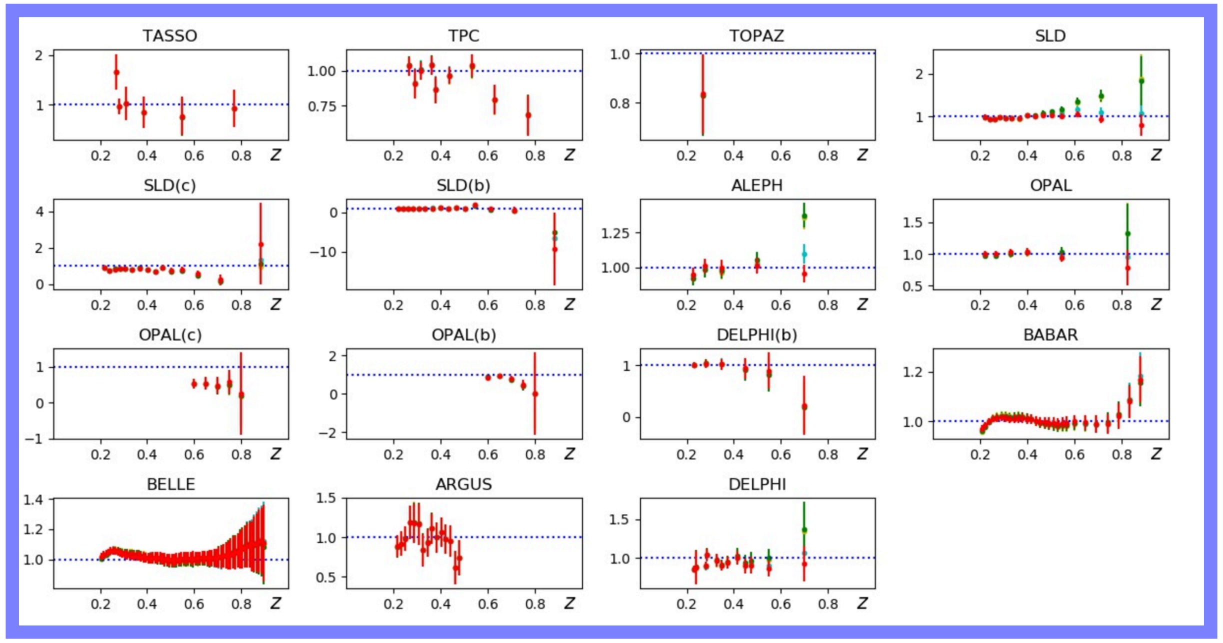
SIA K+/K- data


Data/Theory
TASSO
TPC
TOPAZ
SLD
SLD(c)
SLD(b)
ALEPH
OPAL
OPAL(c)
OPAL(b)
DELPHI(b)
BABAR
BELLE
ARGUS
DELPHI
z


$zD_q^{K^+}$
g
u
d
s
sb
c
z

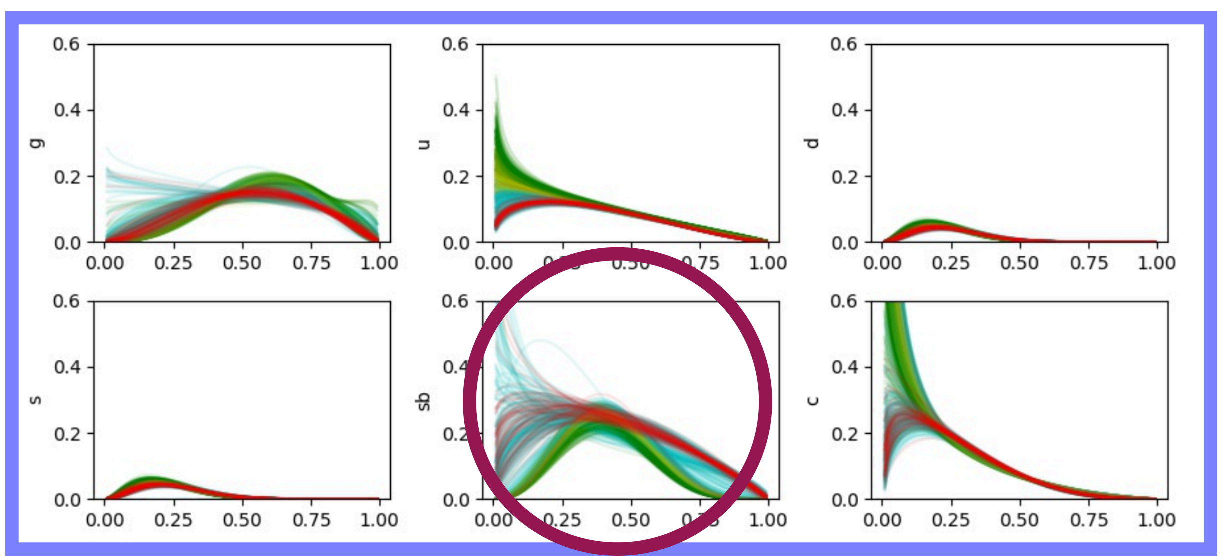
SIA K+/K- data

Data/Theory



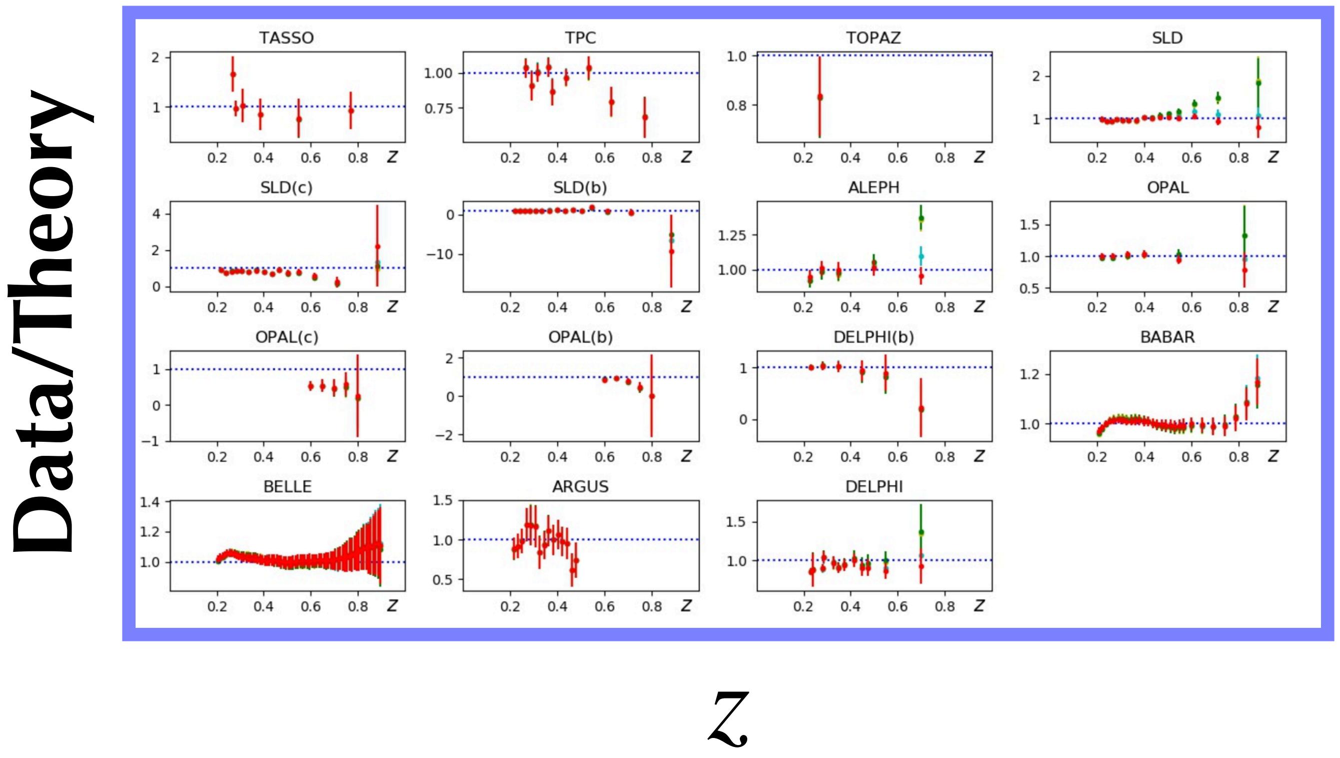
z

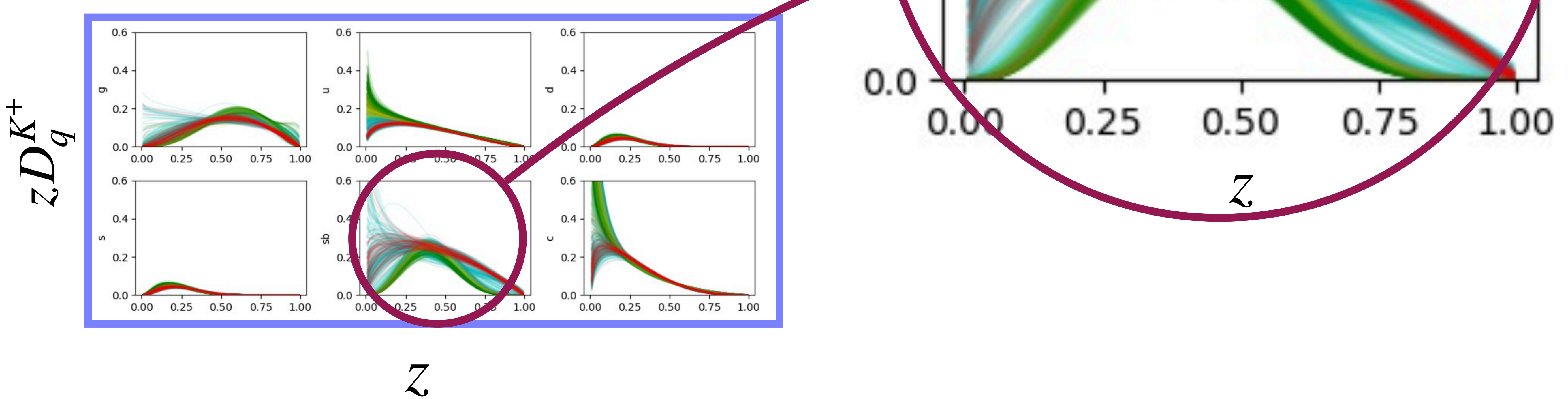
$zD_q^{K^+}$



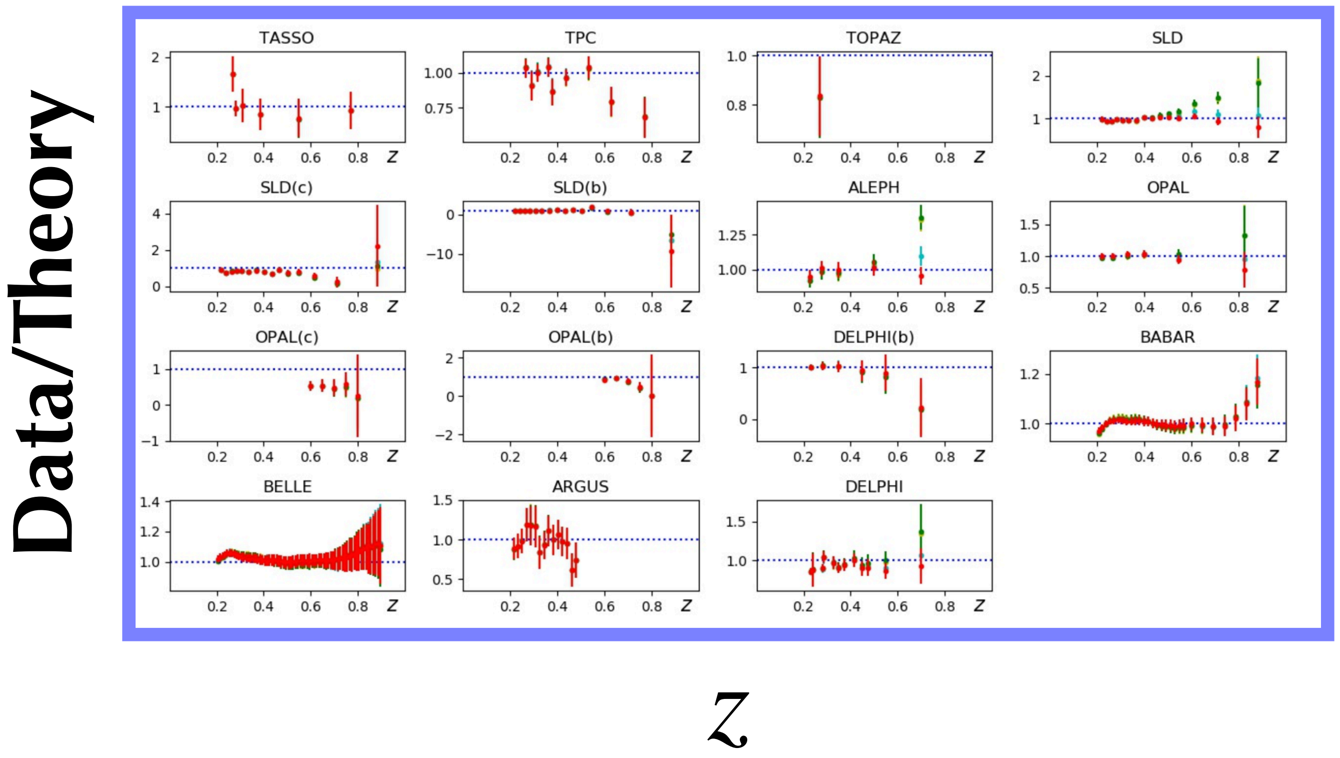
z

SIA K+/K- data

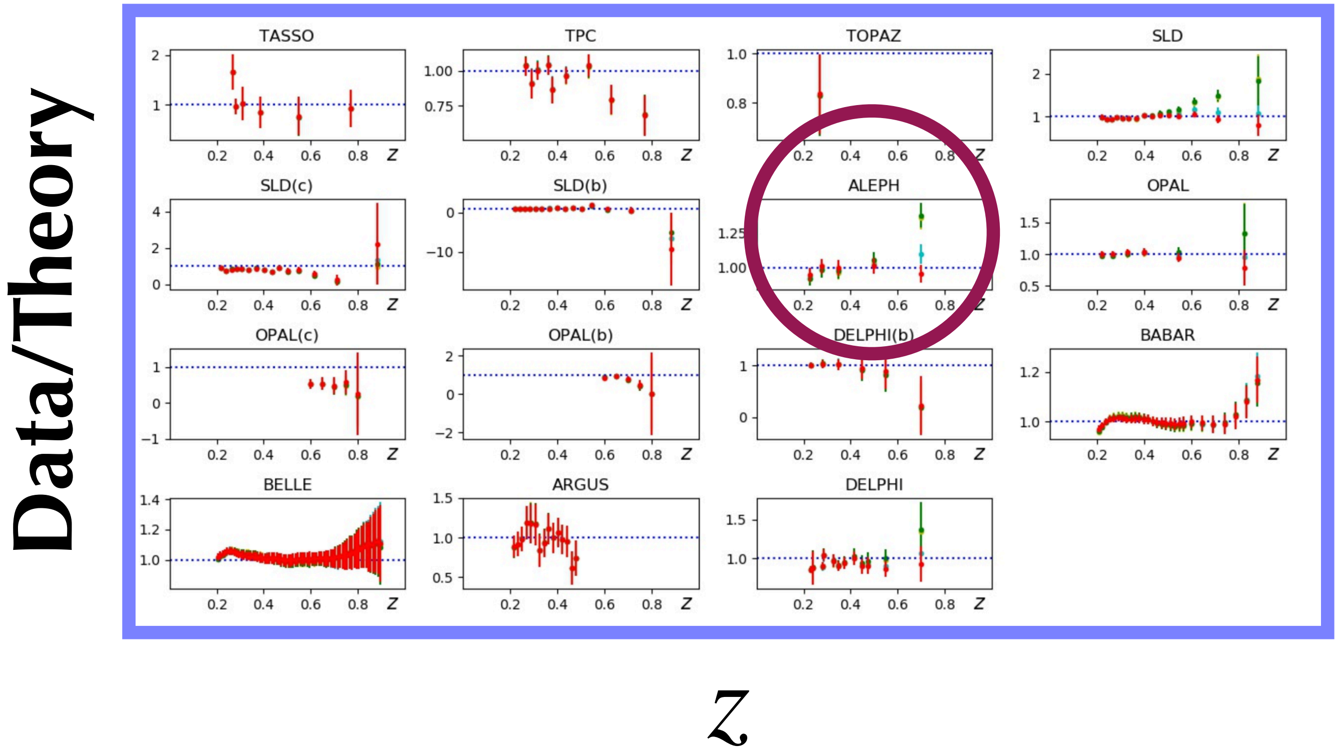

Data/Theory
TASSO
TPC
TOPAZ
SLD
SLD(c)
SLD(b)
ALEPH
OPAL
OPAL(c)
OPAL(b)
DELPHI(b)
BABAR
BELLE
ARGUS
DELPHI
z


$zD_q^{K^+}$
g
u
d
s
sb
c
z
$\bar{s} \to K^+$
$zD_q^{K^+}$
z

SIA K+/K- data

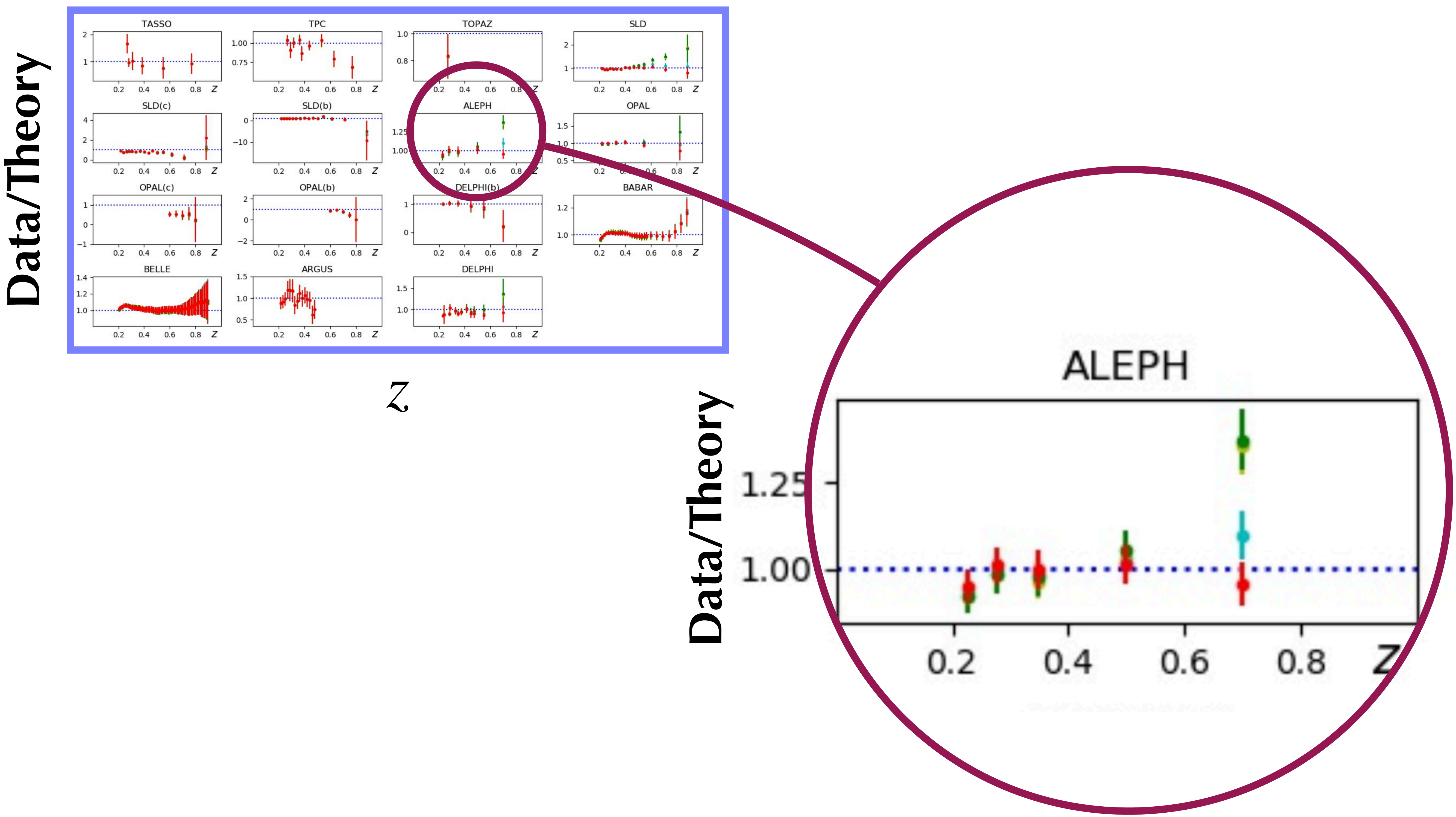

Data/Theory
TASSO
TPC
TOPAZ
SLD
SLD(c)
SLD(b)
ALEPH
OPAL
OPAL(c)
OPAL(b)
DELPHI(b)
BABAR
BELLE
ARGUS
DELPHI
z

SIA K+/K- data



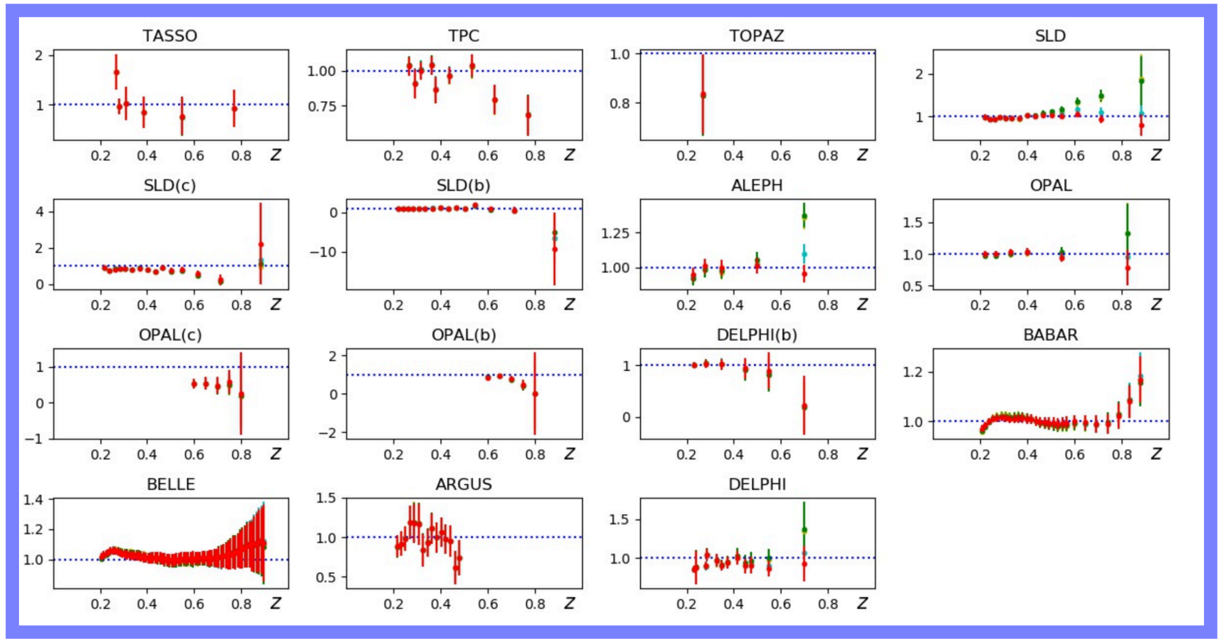
Data/Theory
TASSO
TPC
TOPAZ
SLD
SLD(c)
SLD(b)
ALEPH
OPAL
OPAL(c)
OPAL(b)
DELPHI(b)
BABAR
BELLE
ARGUS
DELPHI
z

SIA K+/K- data


Data/Theory
TASSO
TPC
TOPAZ
SLD
SLD(c)
SLD(b)
ALEPH
OPAL
OPAL(c)
OPAL(b)
DELPHI(b)
BABAR
BELLE
ARGUS
DELPHI
z
ALEPH
1.25
1.00
0.2
0.4
0.6
0.8
Z
Data/Theory

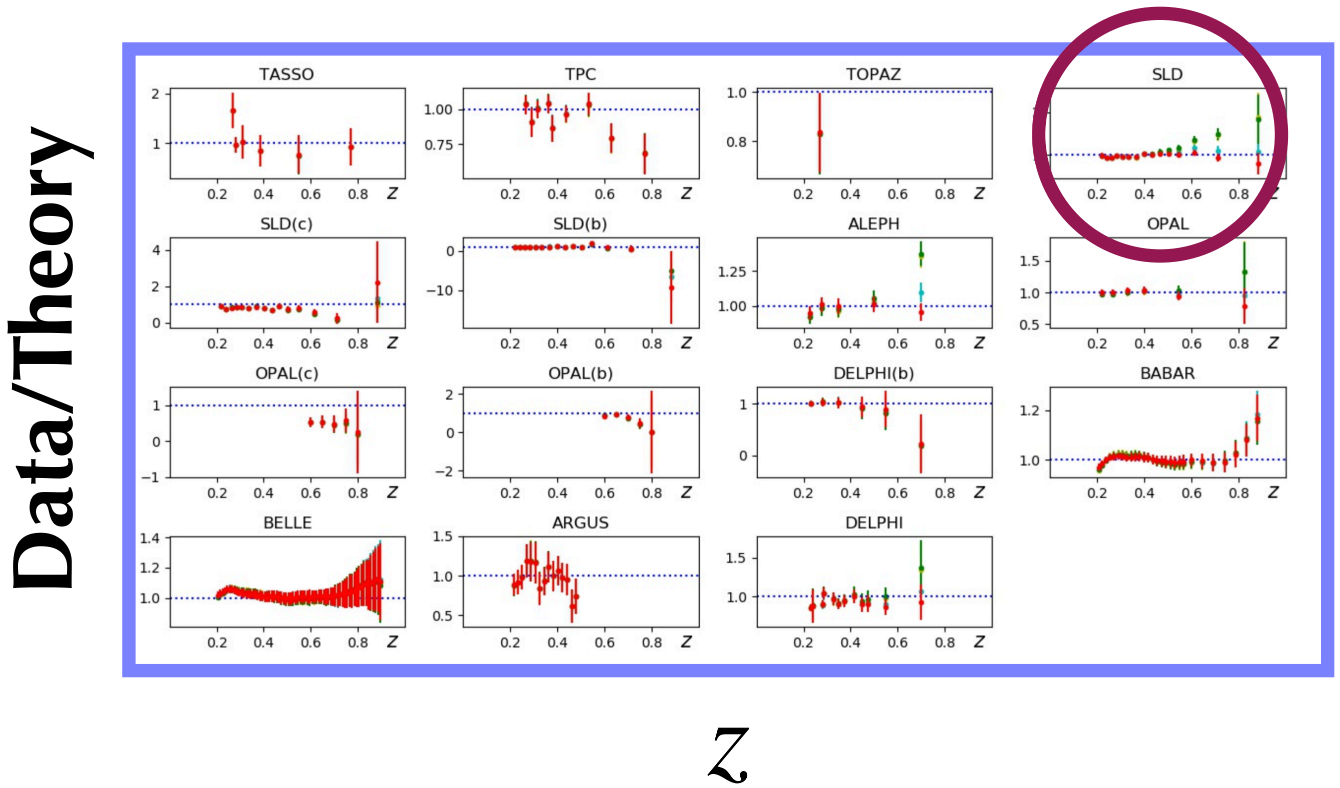
SIA K+/K- data

Data/Theory



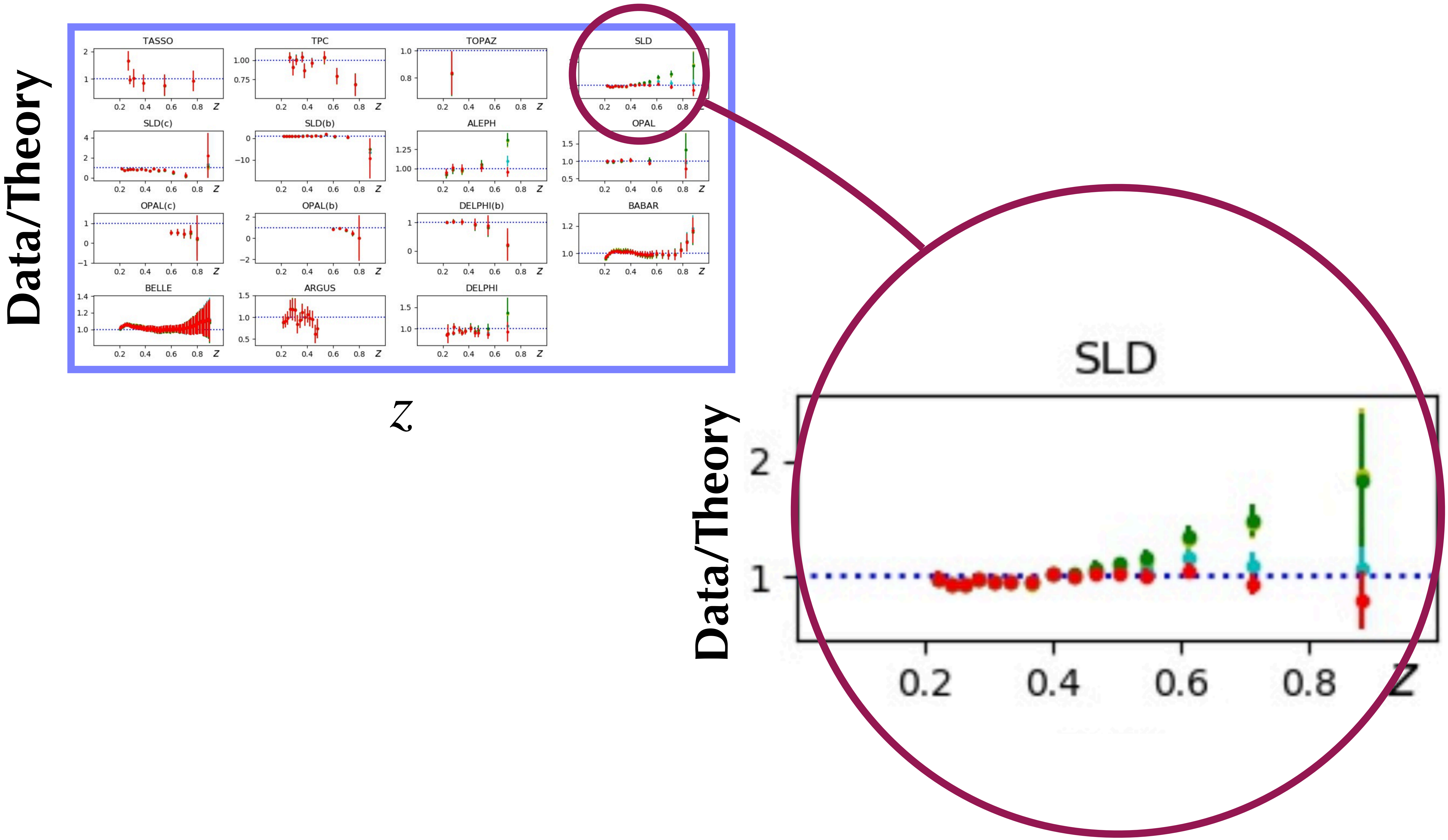
z

SIA K+/K- data



Data/Theory
TASSO
TPC
TOPAZ
SLD
SLD(c)
SLD(b)
ALEPH
OPAL
OPAL(c)
OPAL(b)
DELPHI(b)
BABAR
BELLE
ARGUS
DELPHI
z

SIA K+/K- data


Data/Theory
TASSO
TPC
TOPAZ
SLD
SLD(c)
SLD(b)
ALEPH
OPAL
OPAL(c)
OPAL(b)
DELPHI(b)
BABAR
BELLE
ARGUS
DELPHI
z
SLD
Data/Theory
2
1
0.2
0.4
0.6
0.8
z

SIDIS K-

Unfavored solutions

Large $s(x)$

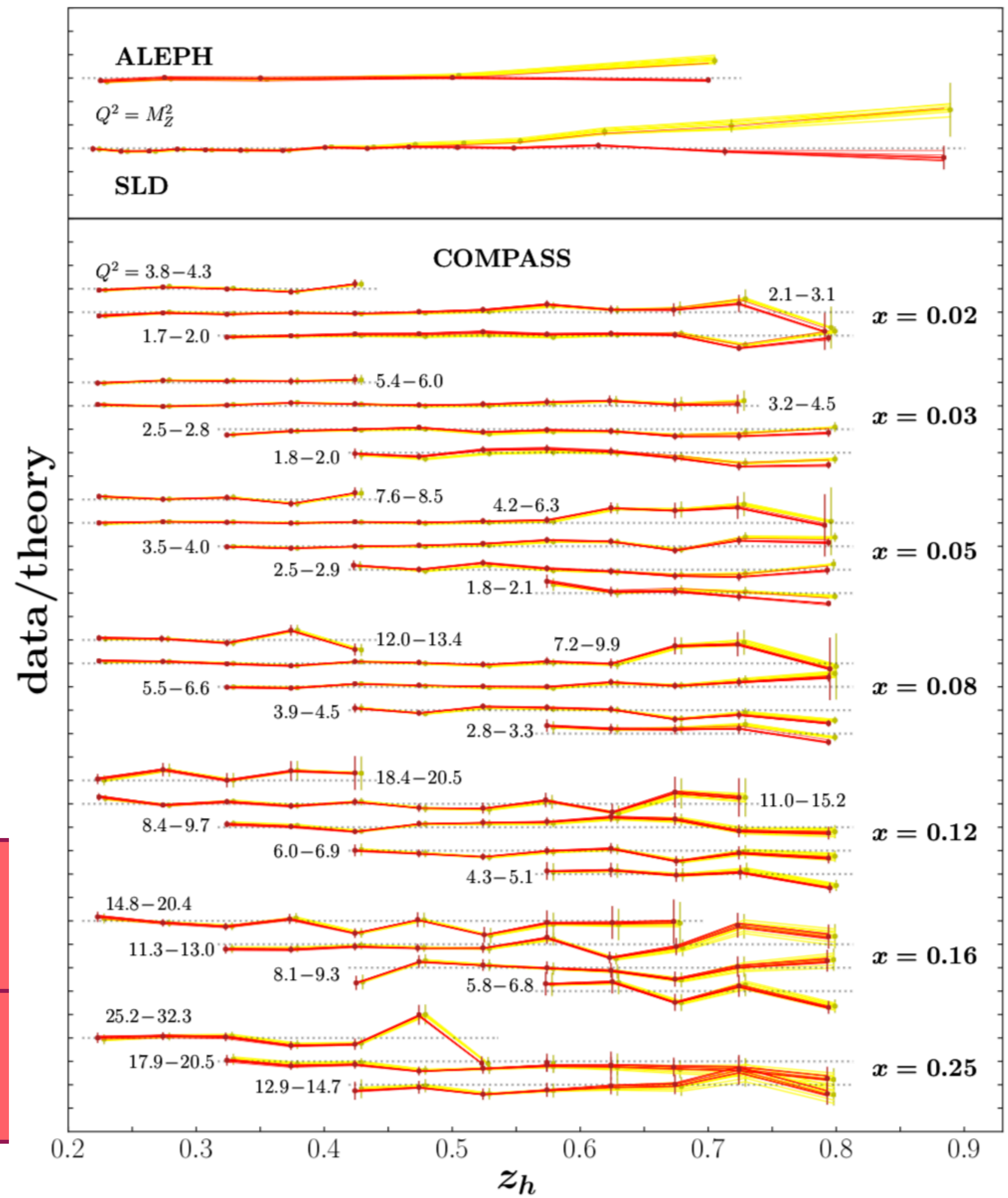
Small $D_{s^\pm}^{K^\pm}(z)$

Favored solutions

Large $D_{s^\pm}^{K^\pm}(z)$

Small $s(x)$

$\chi^2_{\mathrm{SLD}} = 4.10$	$\chi^2_{\mathrm{SLD}} = 1.38$
$\chi^2_{\mathrm{ALEPH}} = 4.62$	$\chi^2_{\mathrm{ALEPH}} = 0.34$

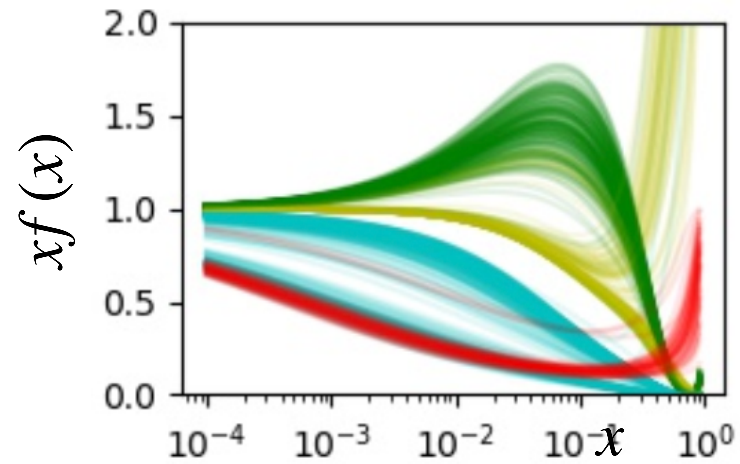


SIA

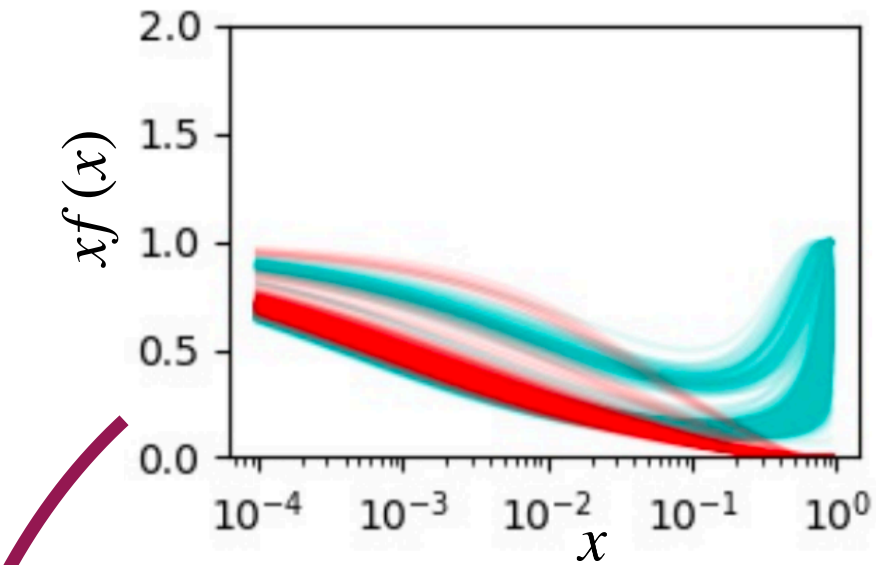
SIDIS

JAM19: Selection Criteria

- Apply k-means clustering

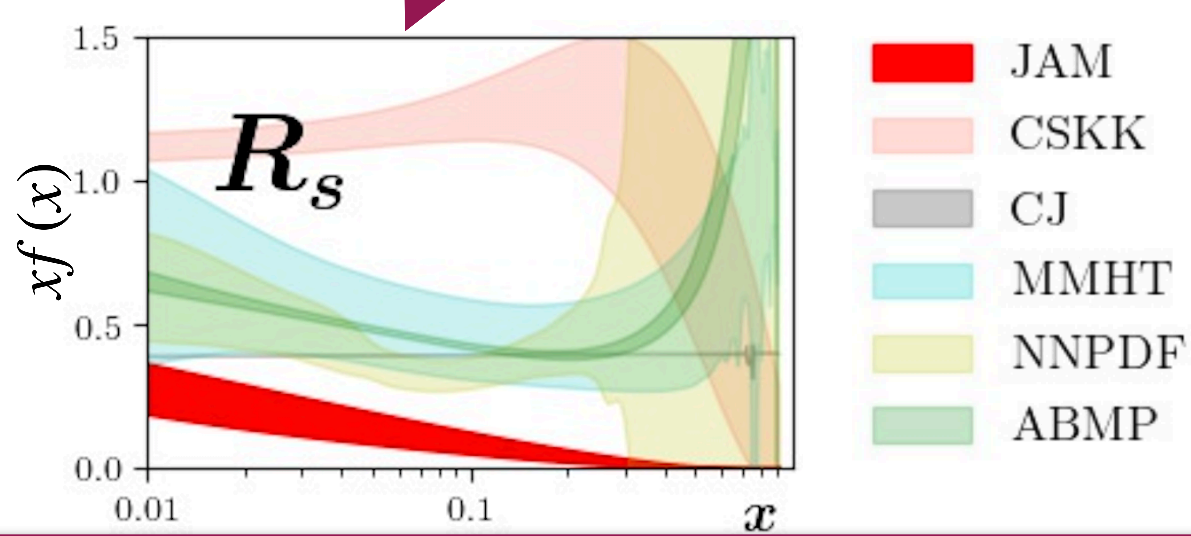


- Classify clusters by increasing order in 'extended' reduced χ^2



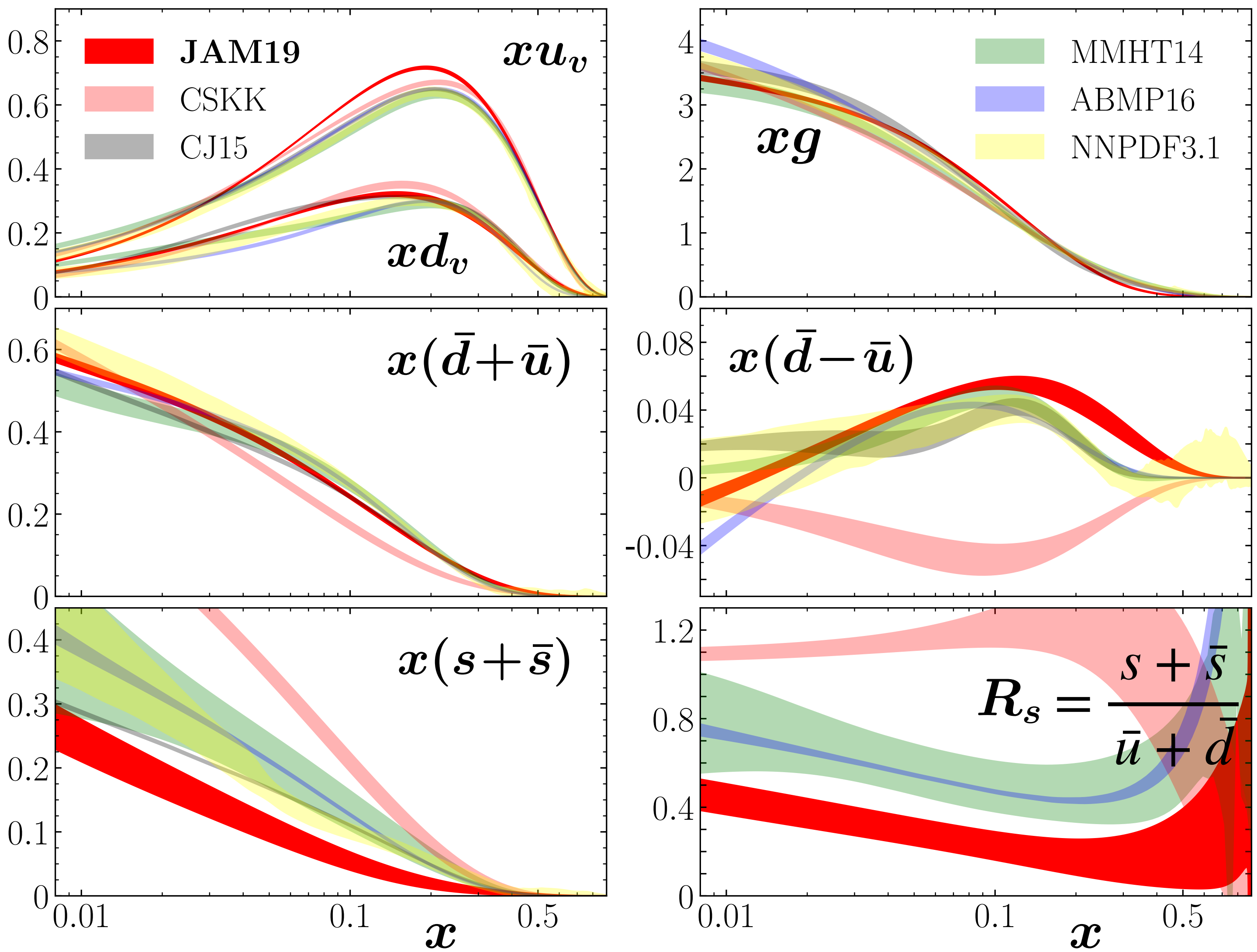
$$\frac{\chi^2}{N_{\text{tot}}} + \sum_{exp} \frac{\chi^2_{\text{exp}}}{N_{\text{exp}}}$$

- Perform a new sampling with flat priors around the best cluster



PDF results

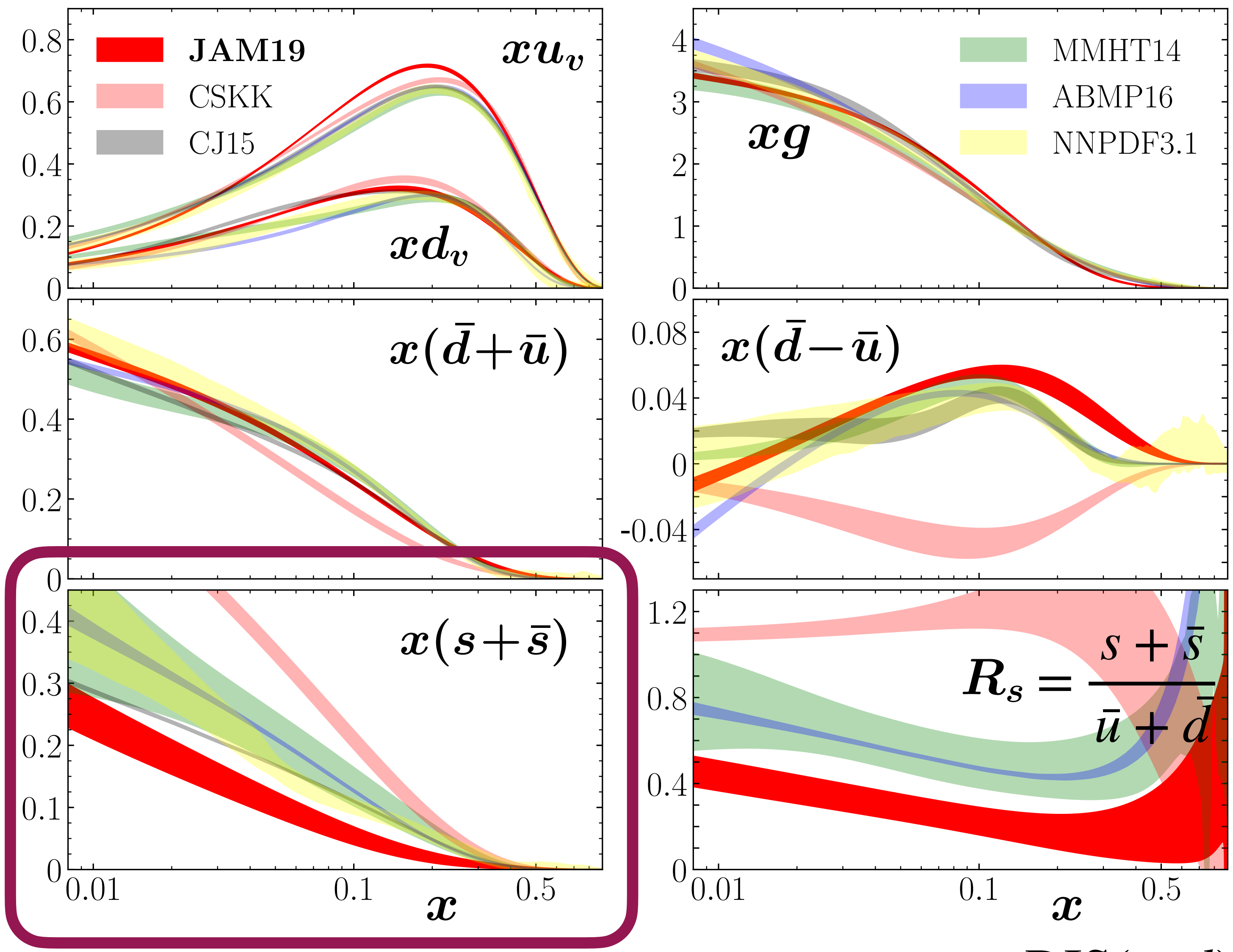
JAM19 PDFs



DIS(p, d)
DY(pp, pd)
SIA$(\pi^\pm, K^\pm)$
SIDIS$(\pi^\pm, K^\pm)$

Q = 2 GeV

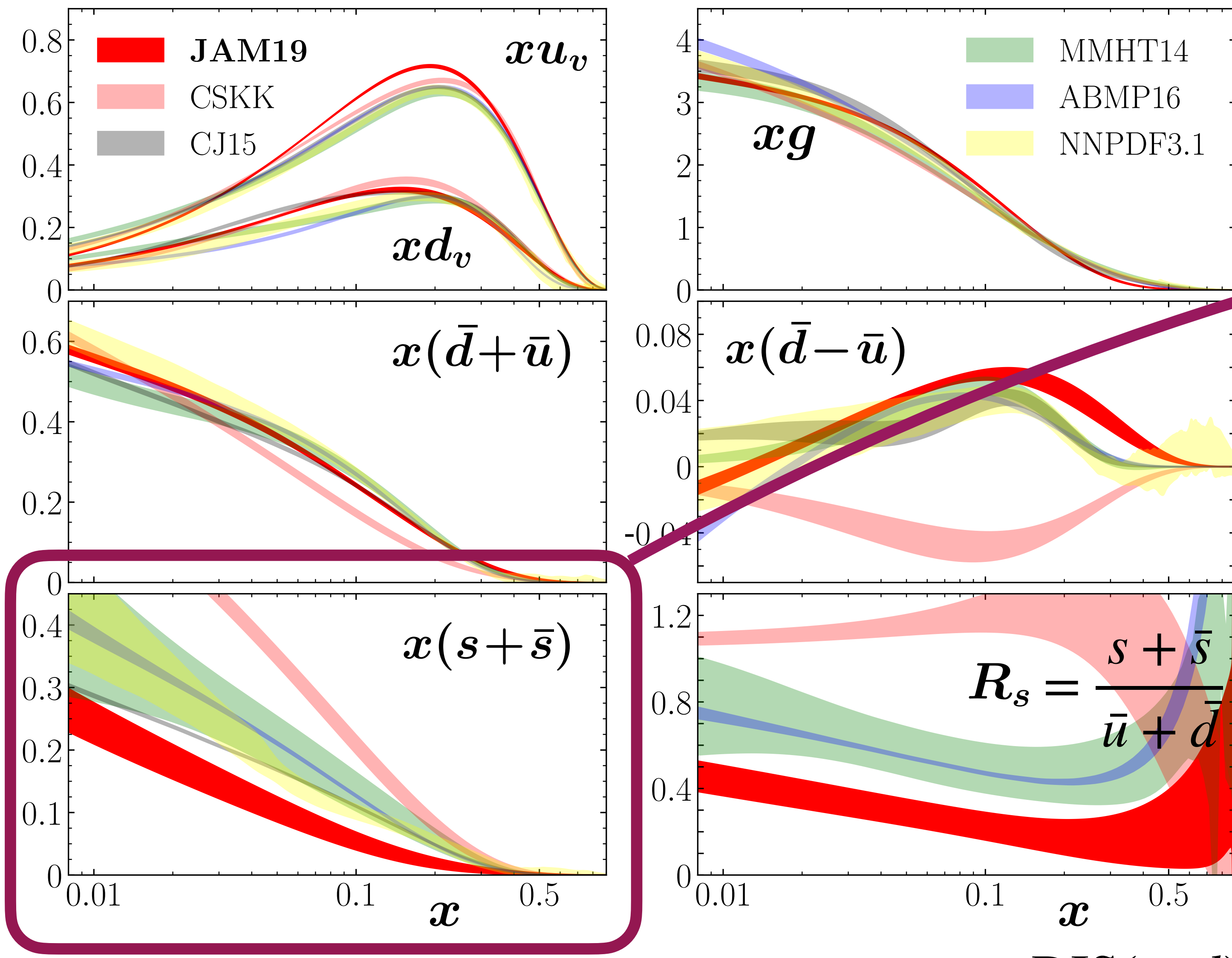
JAM19 PDFs

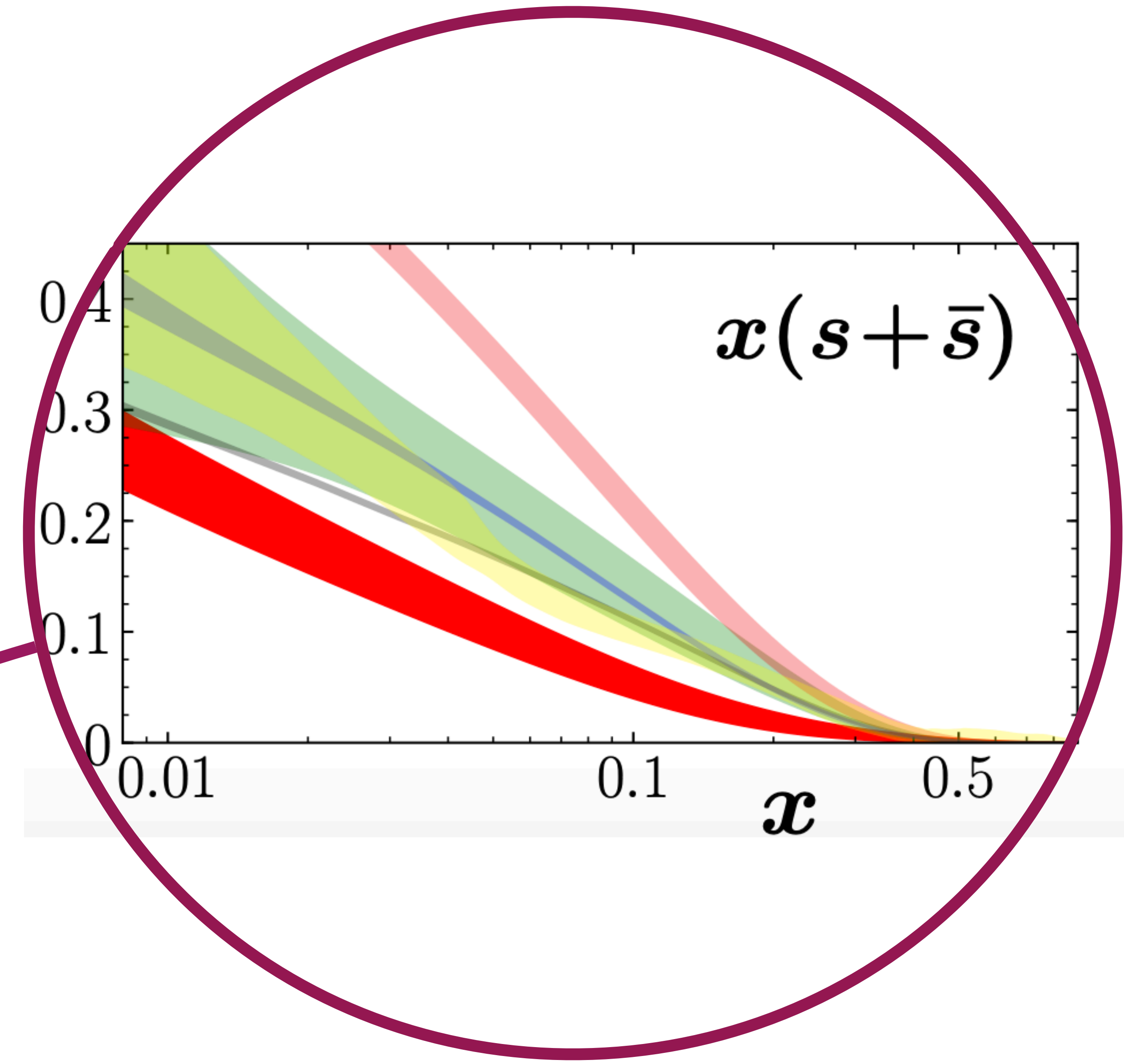


Q = 2 GeV

DIS(p, d)
DY(pp, pd)
SIA$(\pi^{\pm}, K^{\pm})$
SIDIS$(\pi^{\pm}, K^{\pm})$

JAM19 PDFs



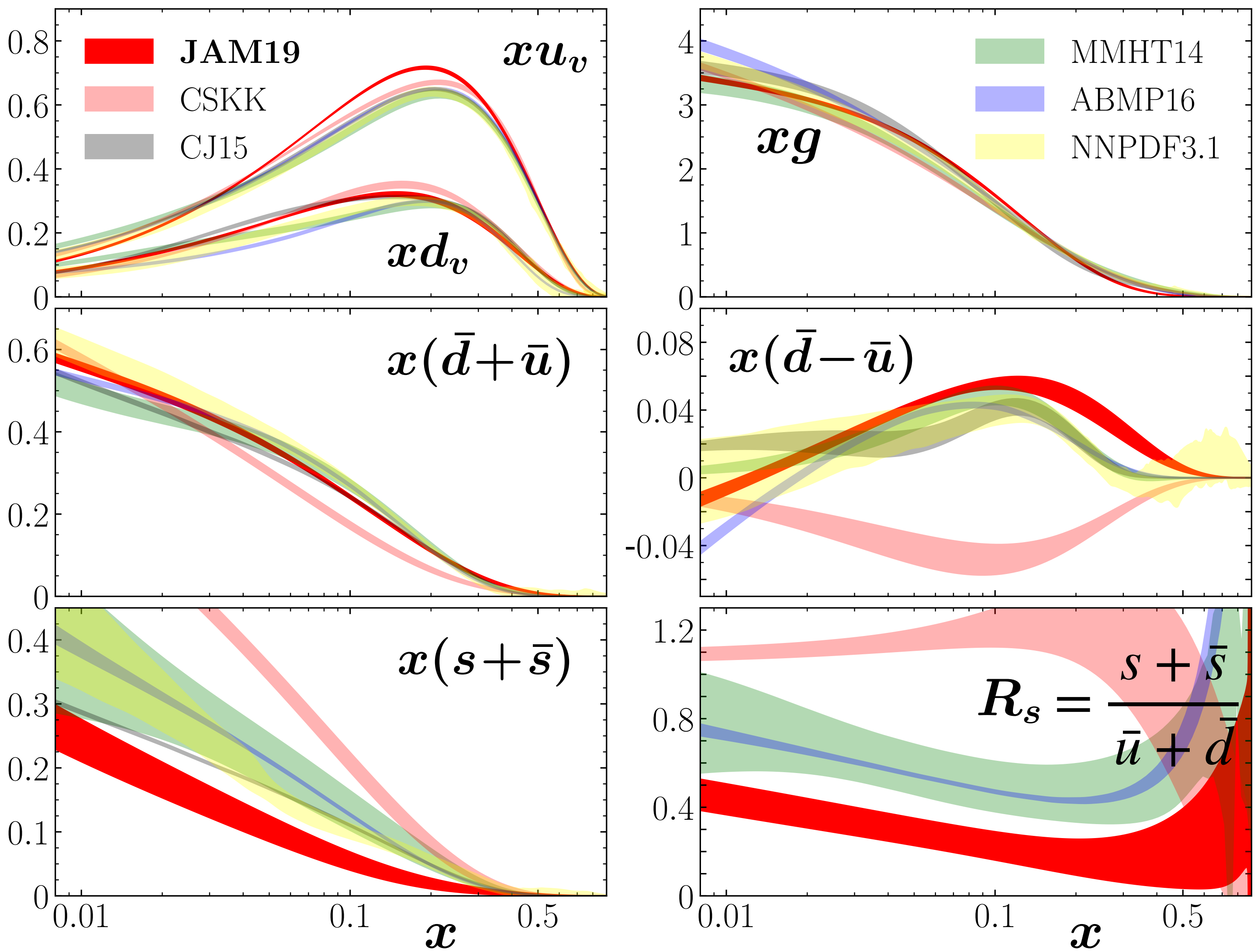


Strong strange suppression

Q = 2 GeV

DIS(p, d)
DY(pp, pd)
SIA$(\pi^{\pm}, K^{\pm})$
SIDIS$(\pi^{\pm}, K^{\pm})$

JAM19 PDFs



$\mathrm{DIS}(p, d)$

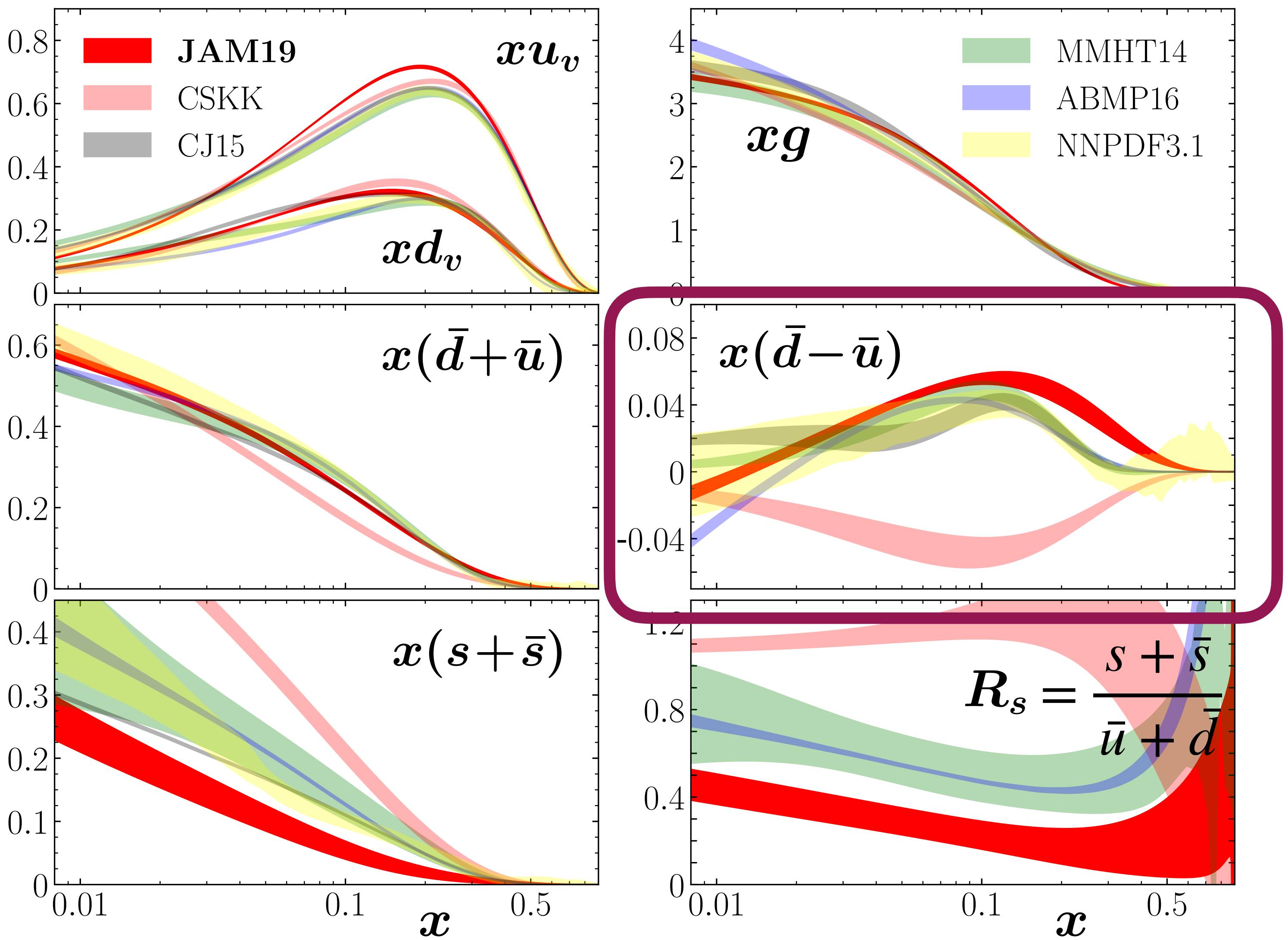
$\mathrm{DY}(pp, pd)$

$\mathrm{SIA}(\pi^{\pm}, K^{\pm})$

$\mathrm{SIDIS}(\pi^{\pm}, K^{\pm})$

Q = 2 GeV

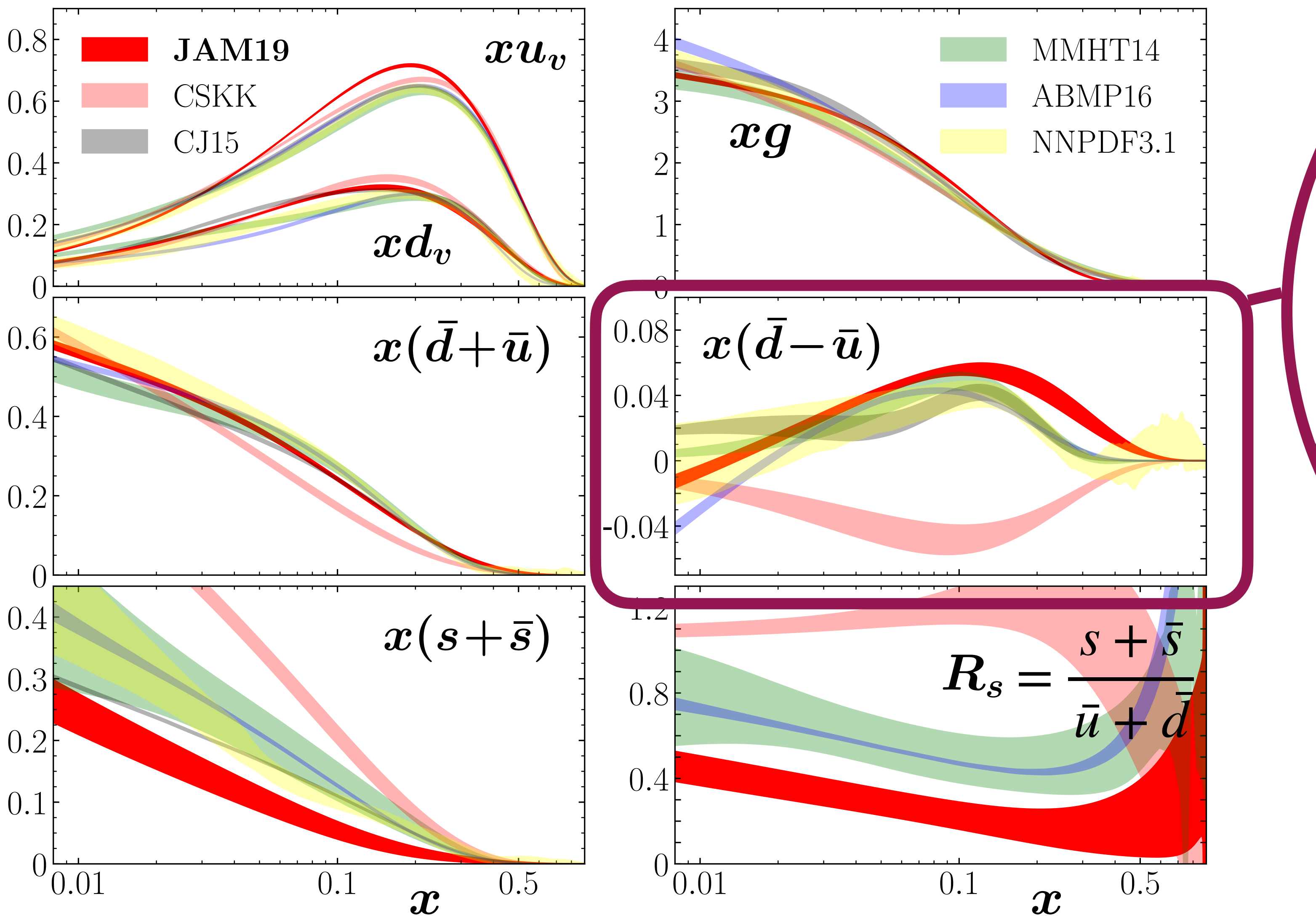
JAM19 PDFs

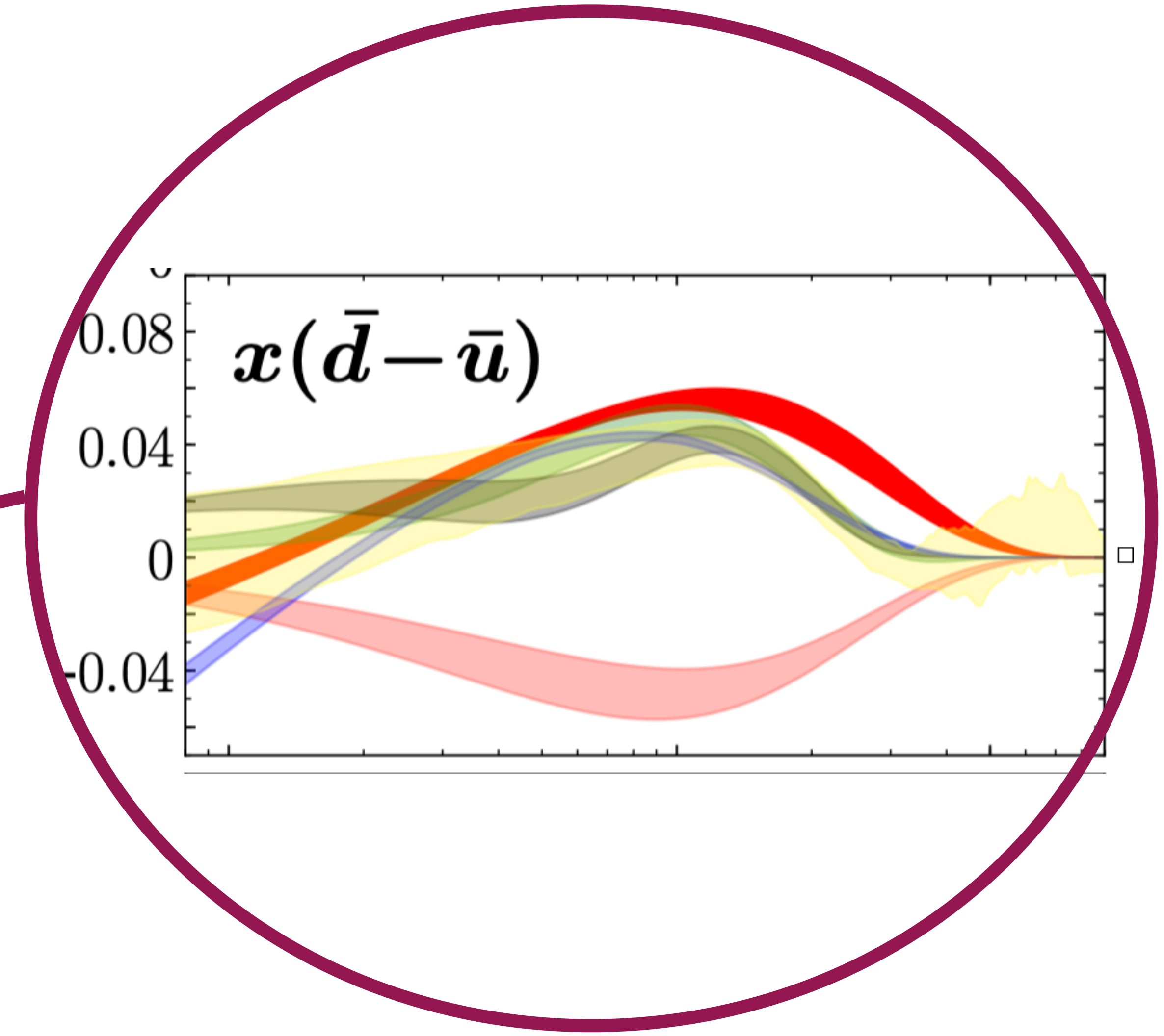


DIS(p, d)
DY(pp, pd)
SIA$(\pi^{\pm}, K^{\pm})$
SIDIS$(\pi^{\pm}, K^{\pm})$

Q = 2 GeV

JAM19 PDFs





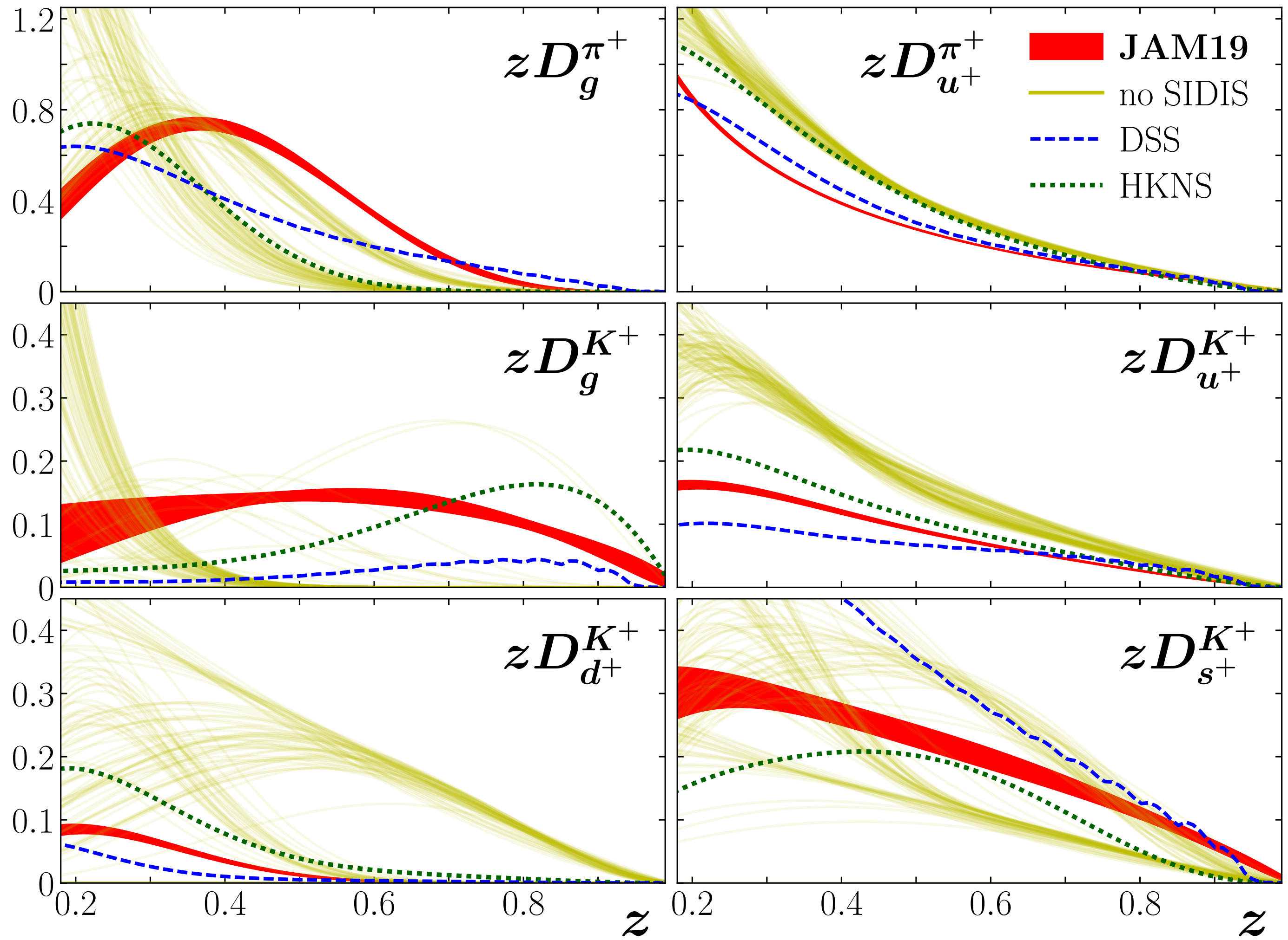
$\bar{d} - \bar{u} > 0$ at x $\sim 0.1 - 0.2$

Q = 2 GeV

DIS(p, d)
DY(pp, pd)
SIA$(\pi^{\pm}, K^{\pm})$
SIDIS$(\pi^{\pm}, K^{\pm})$

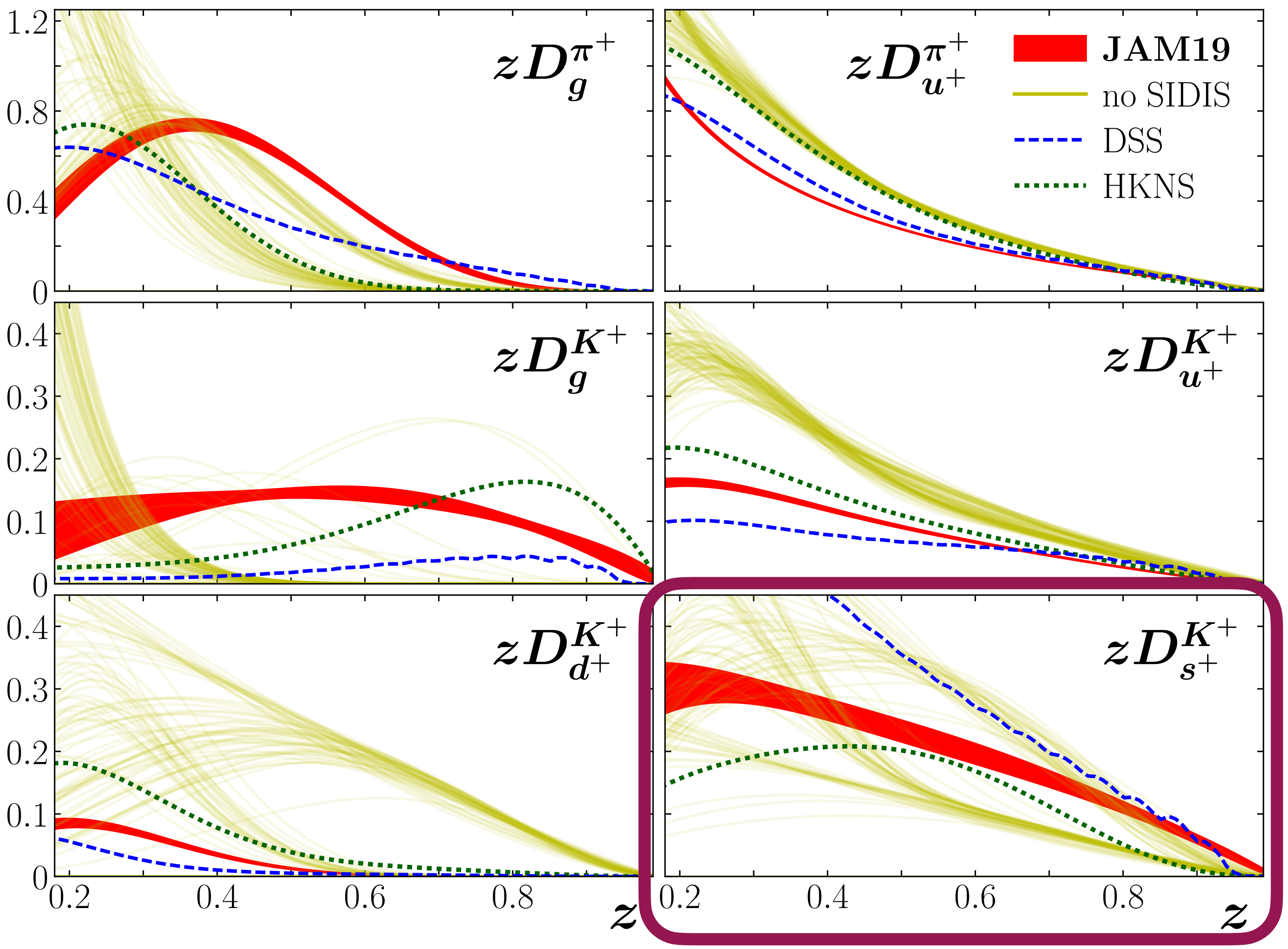
FF results

JAM19: FF



Q = m$_c$

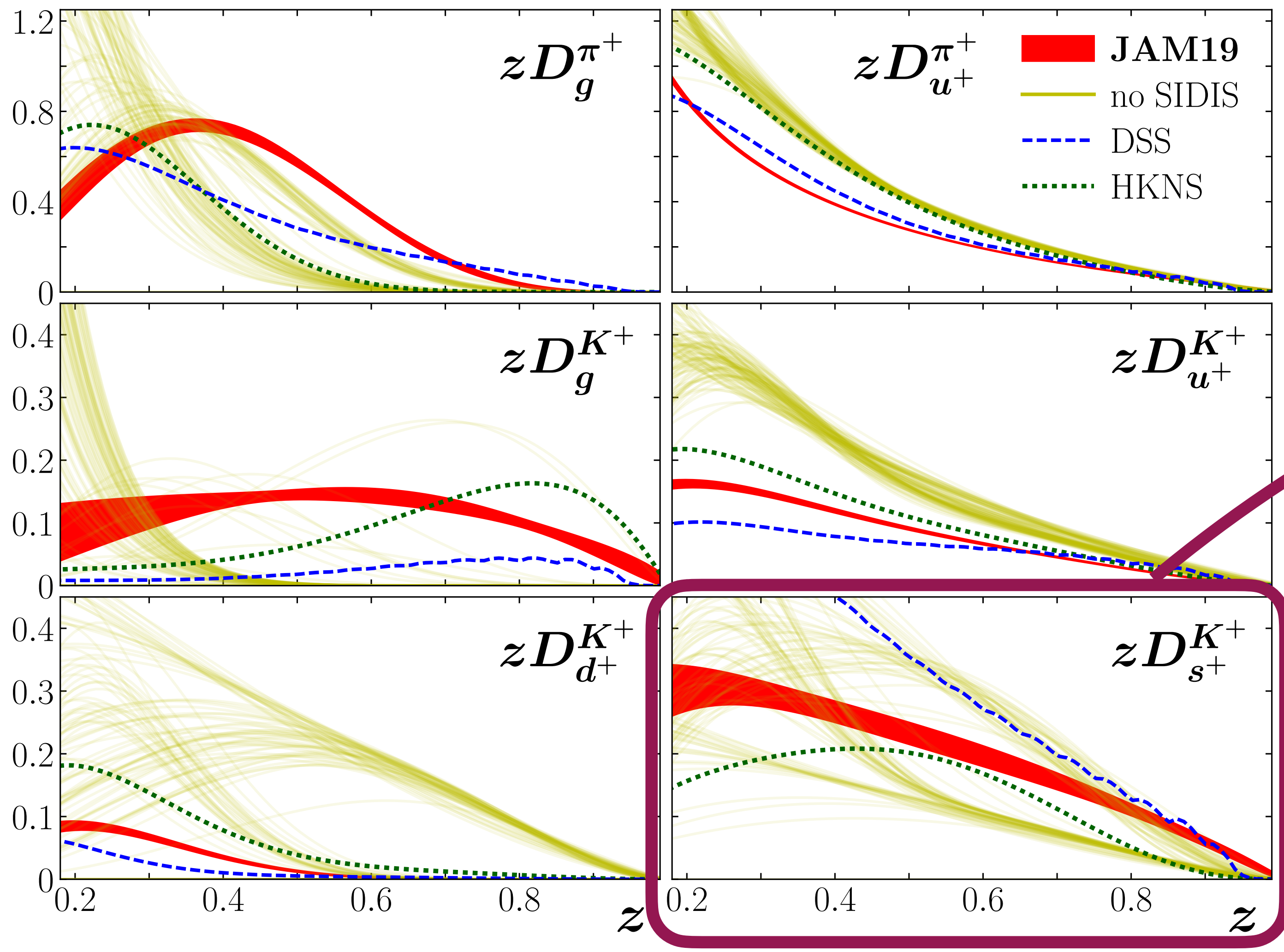
JAM19: FF

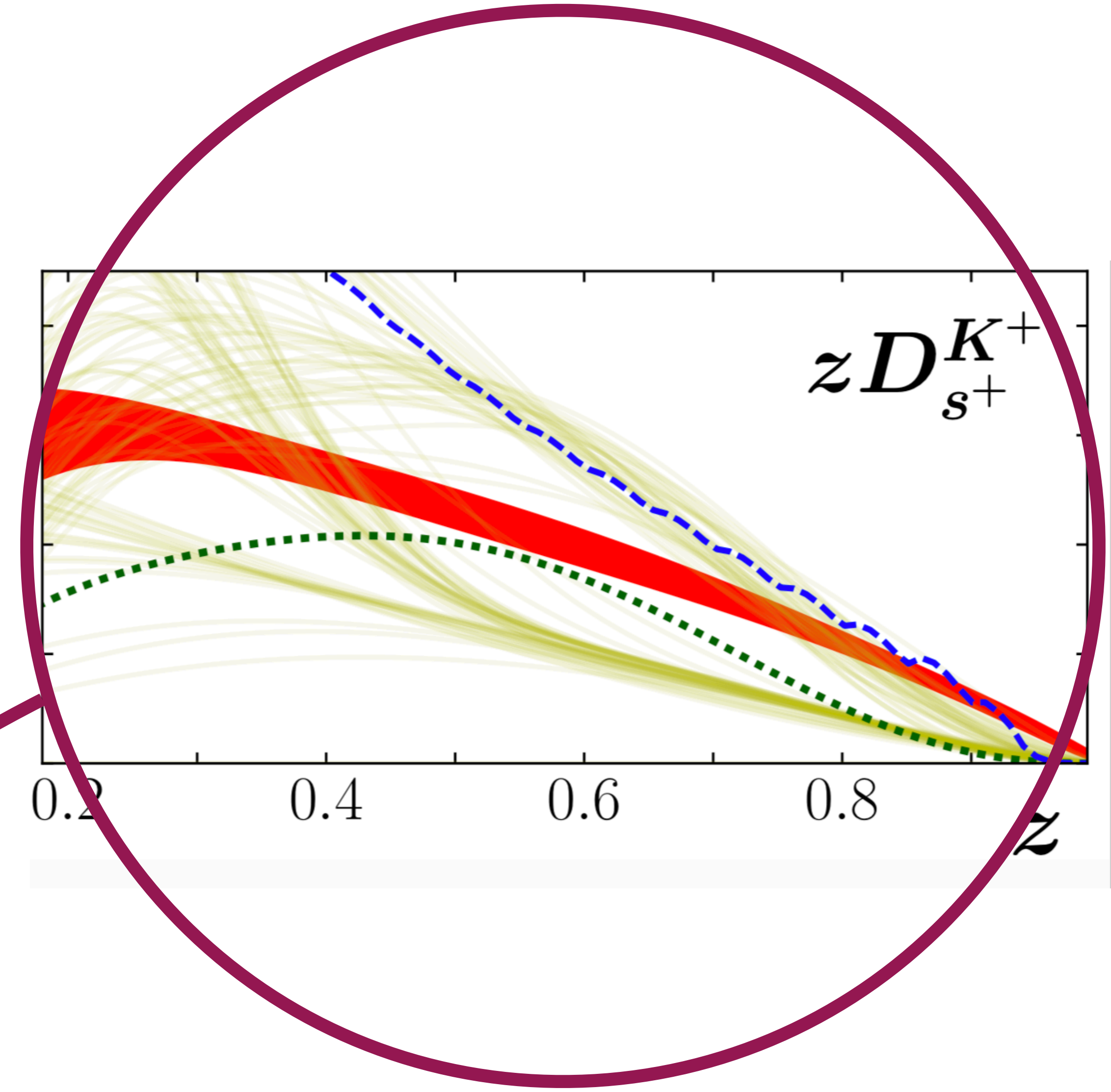


$zD_g^{\pi^+}$
$zD_{u^+}^{\pi^+}$
JAM19
no SIDIS
DSS
HKNS
$zD_g^{K^+}$
$zD_{u^+}^{K^+}$
$zD_{d^+}^{K^+}$
$zD_{s^+}^{K^+}$
1.2
0.8
0.4
0
0.4
0.3
0.2
0.1
0
0.4
0.3
0.2
0.1
0
0.2
0.4
0.6
0.8
z
0.2
0.4
0.6
0.8
z

Q = m_c

JAM19: FF

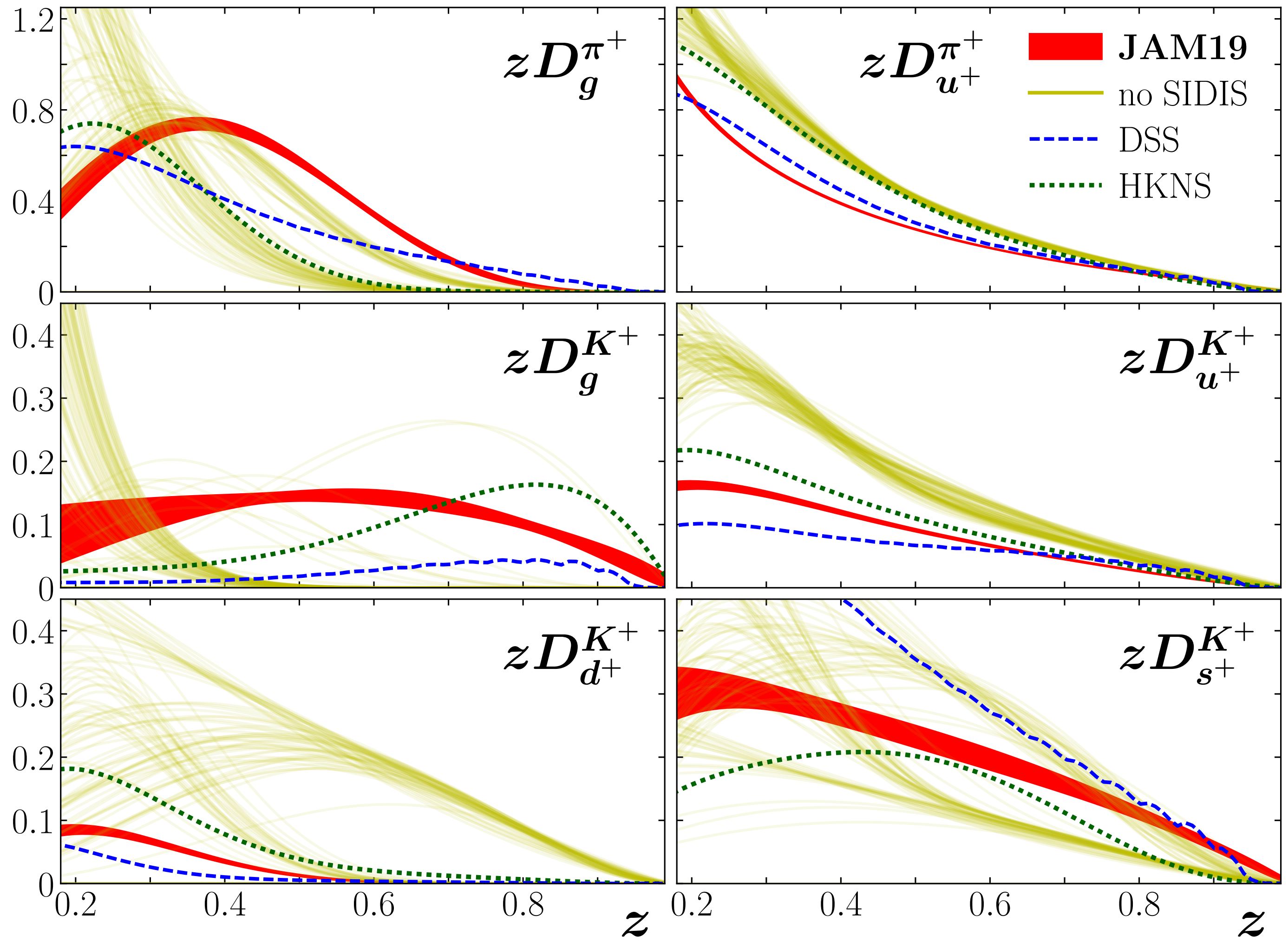




Large $\bar{s} \rightarrow K^+$

$Q = m_c$

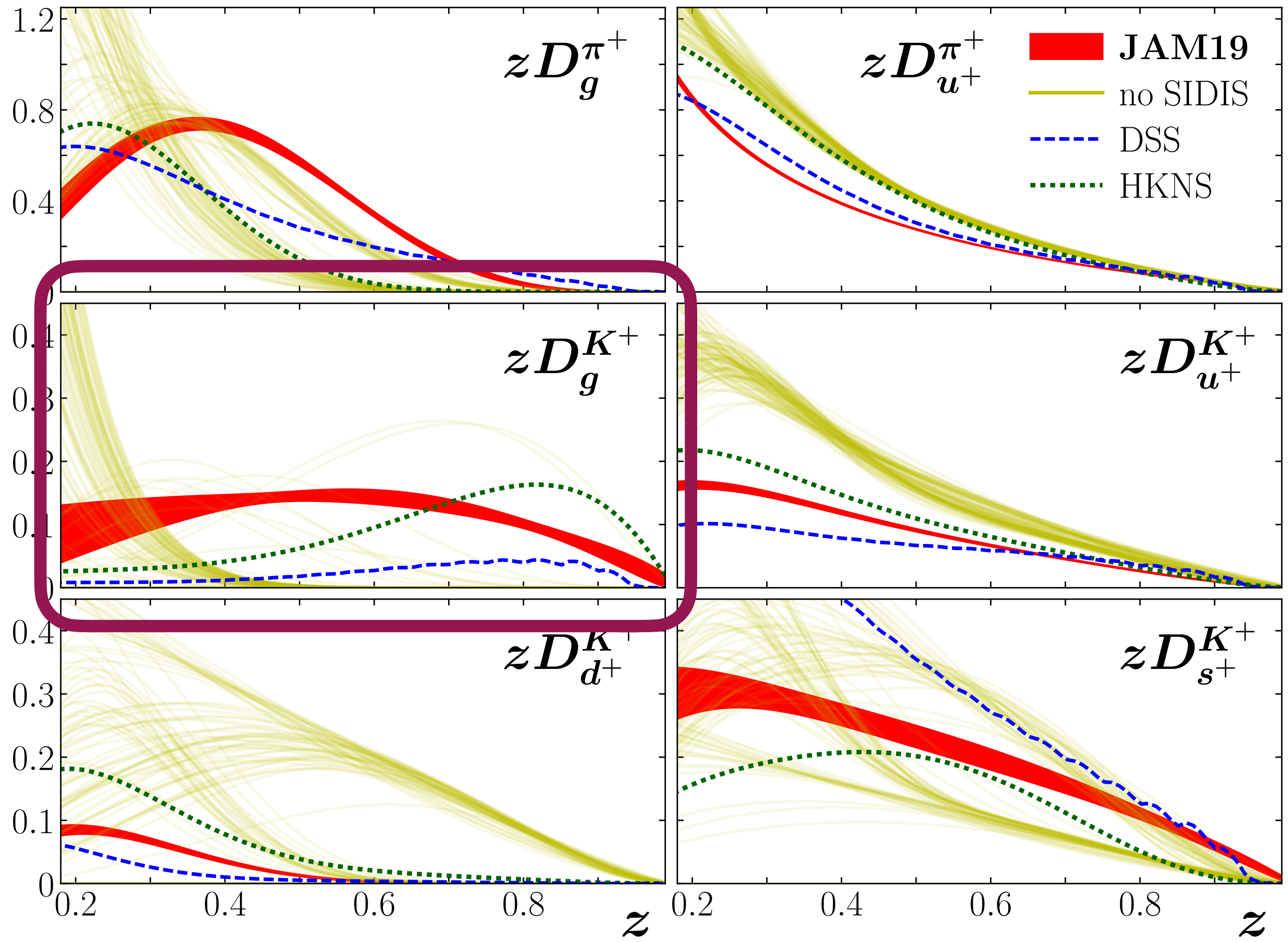
JAM19: FF



$zD_g^{\pi^+}$
$zD_{u^+}^{\pi^+}$
JAM19
no SIDIS
DSS
HKNS
$zD_g^{K^+}$
$zD_{u^+}^{K^+}$
$zD_{d^+}^{K^+}$
$zD_{s^+}^{K^+}$
1.2
0.8
0.4
0
0.4
0.3
0.2
0.1
0
0.4
0.3
0.2
0.1
0
0.2
0.4
0.6
0.8
z
0.2
0.4
0.6
0.8
z

$Q = m_c$

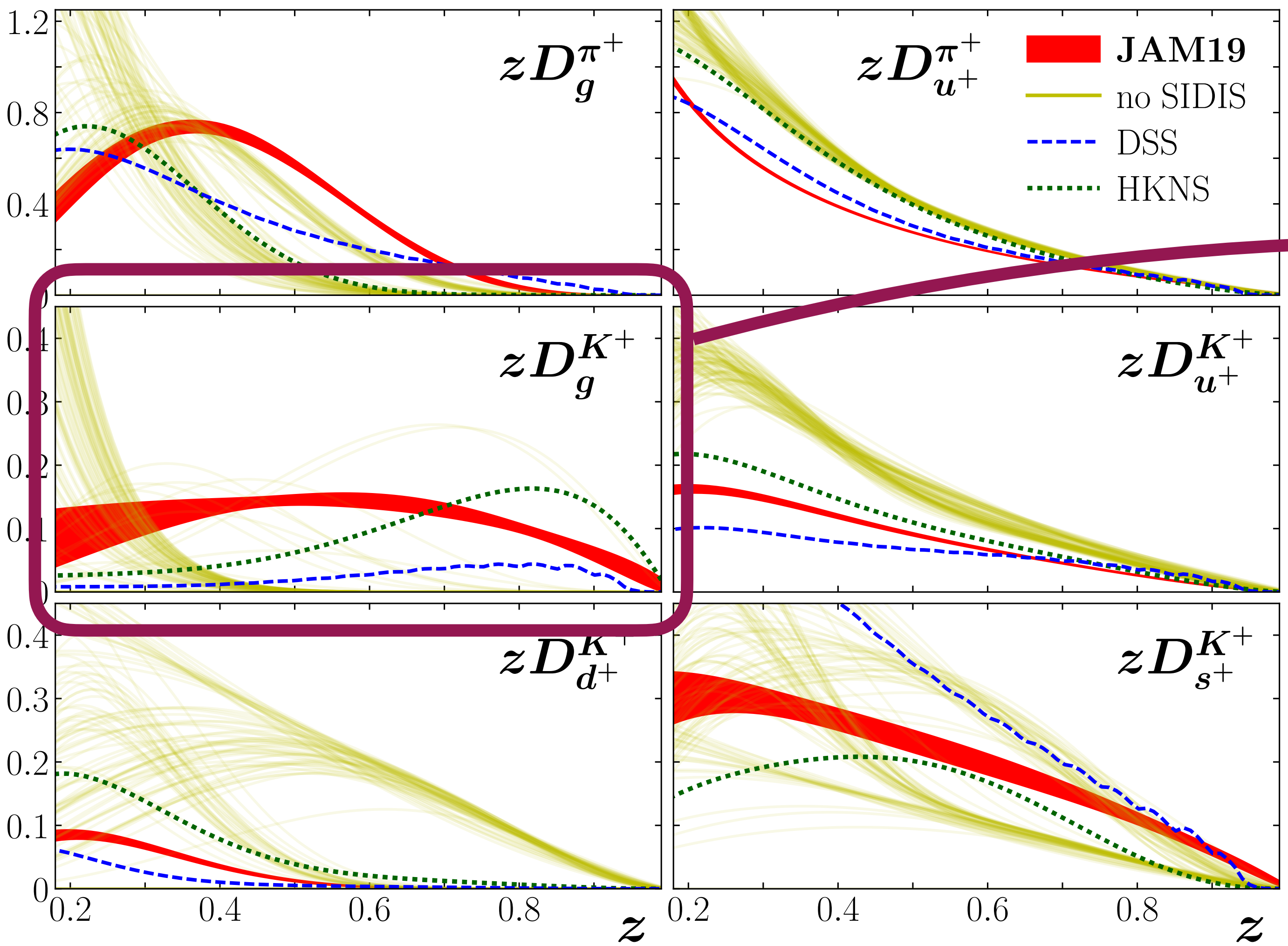
JAM19: FF

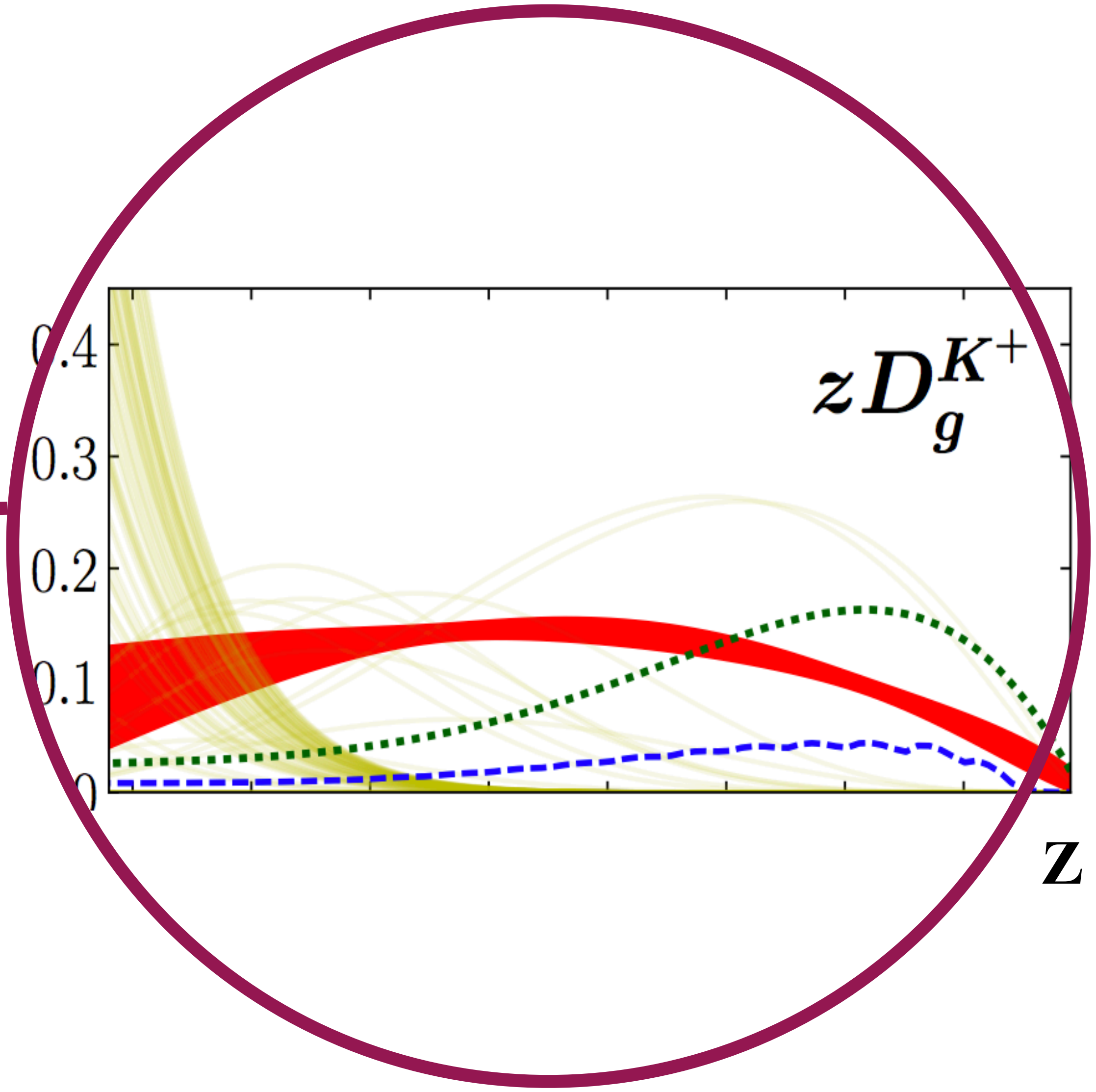


$zD_g^{\pi^+}$
$zD_{u^+}^{\pi^+}$
JAM19
no SIDIS
DSS
HKNS
$zD_g^{K^+}$
$zD_{u^+}^{K^+}$
$zD_{d^+}^{K^+}$
$zD_{s^+}^{K^+}$
1.2
0.8
0.4
0.4
0.3
0.2
0.1
0
0.2
0.4
0.6
0.8
z

Q = m$_c$

JAM19: FF

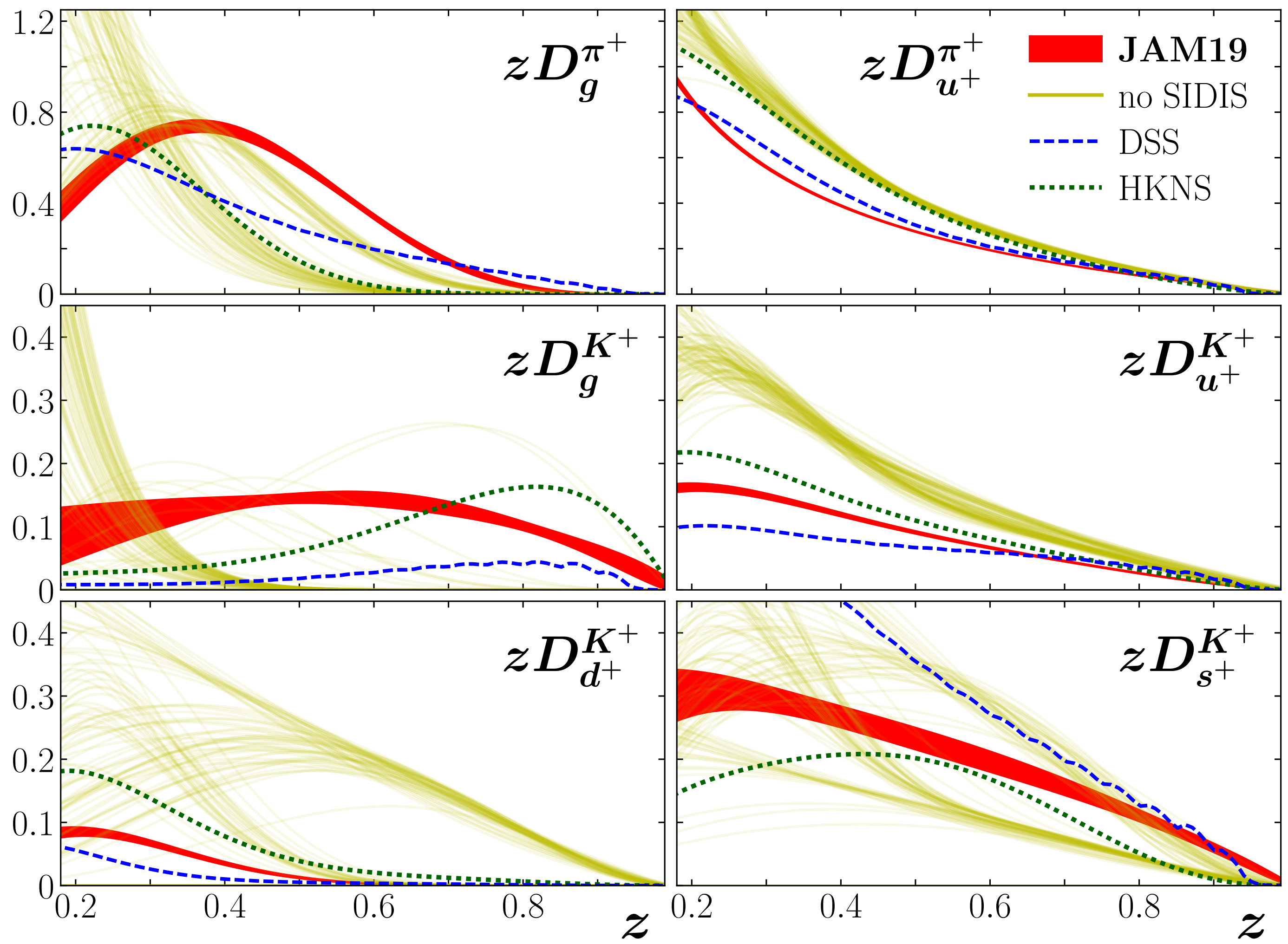




Q = m$_c$

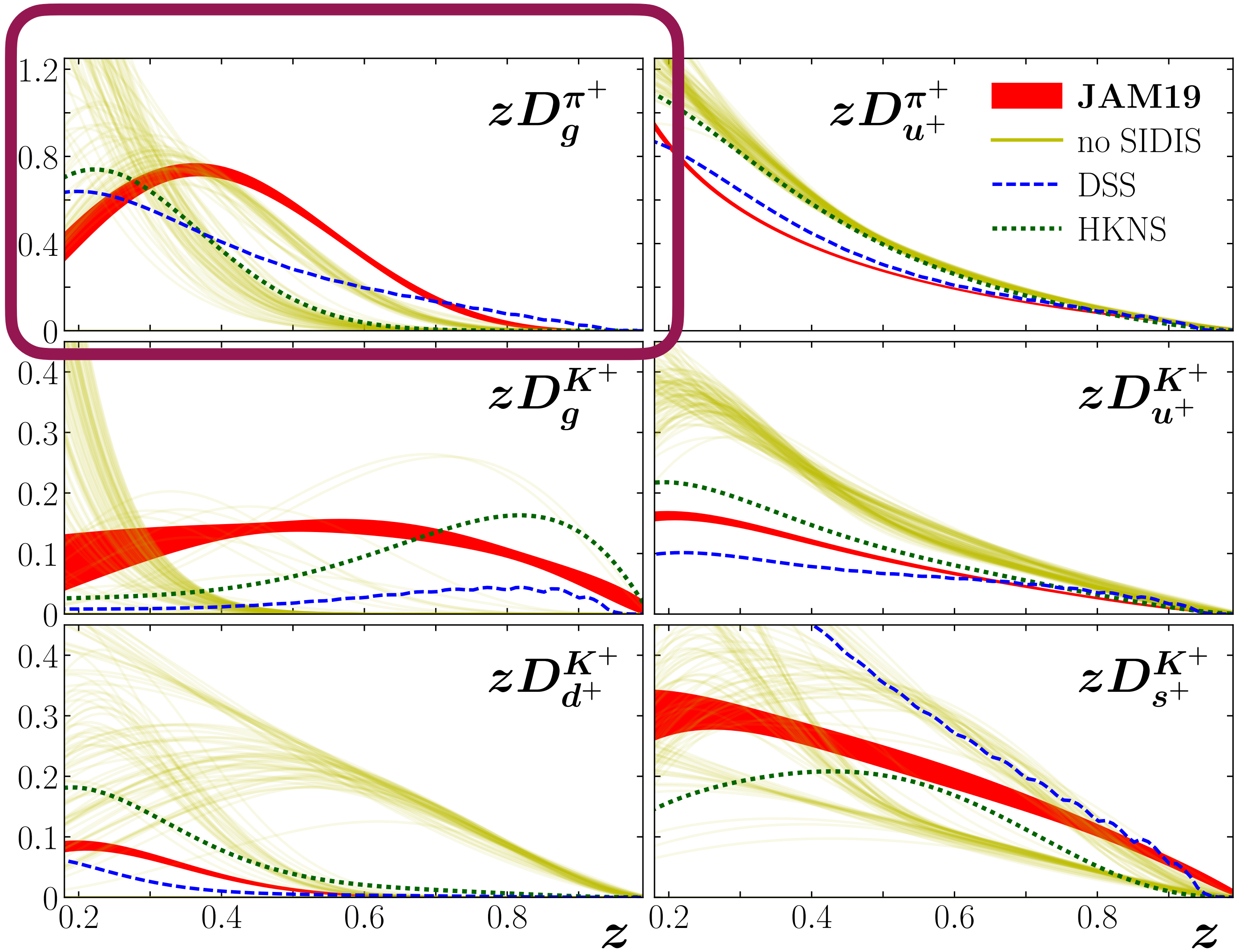
Constraints on
$g \rightarrow K^+$

JAM19: FF



Q = m$_c$

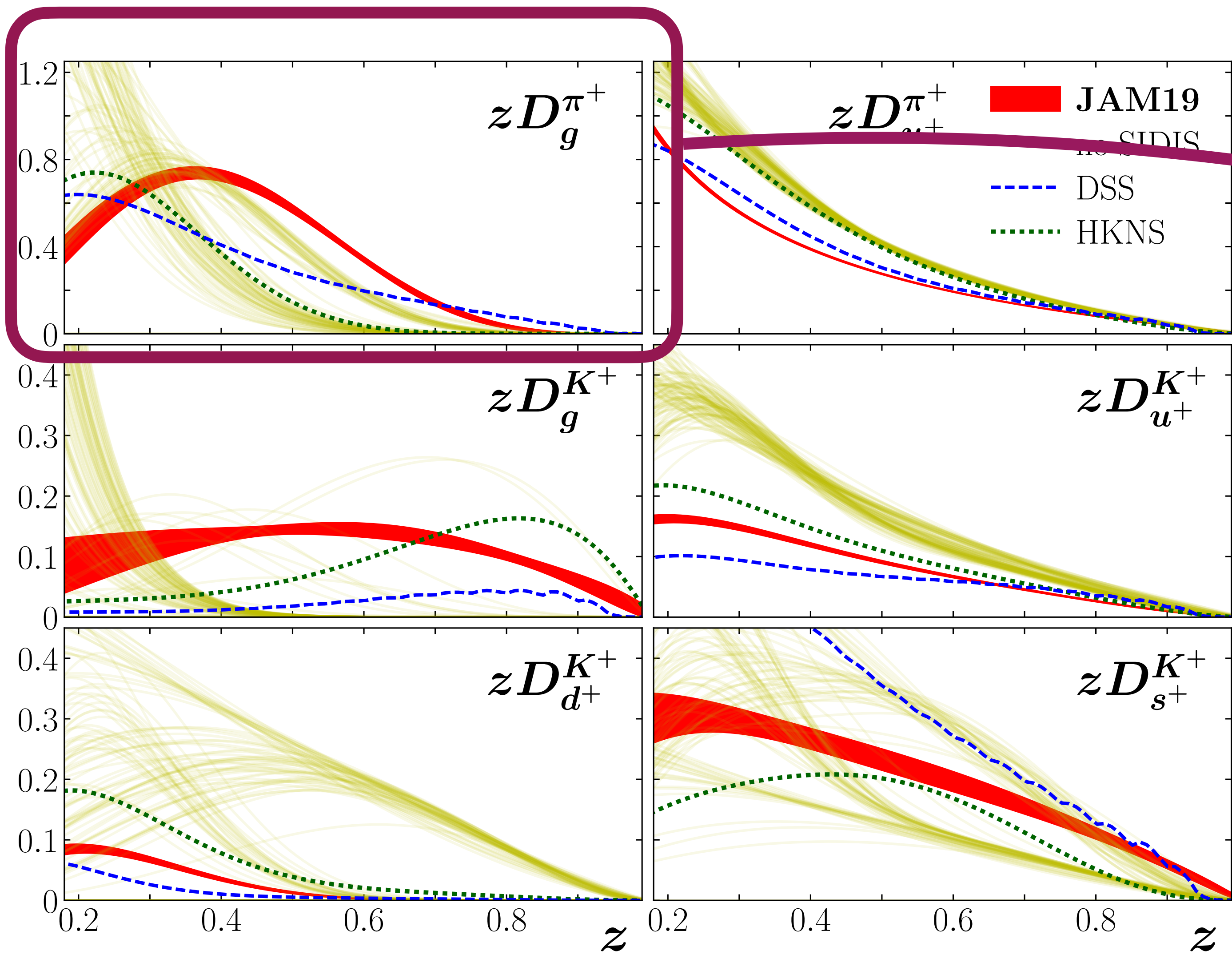
JAM19: FF



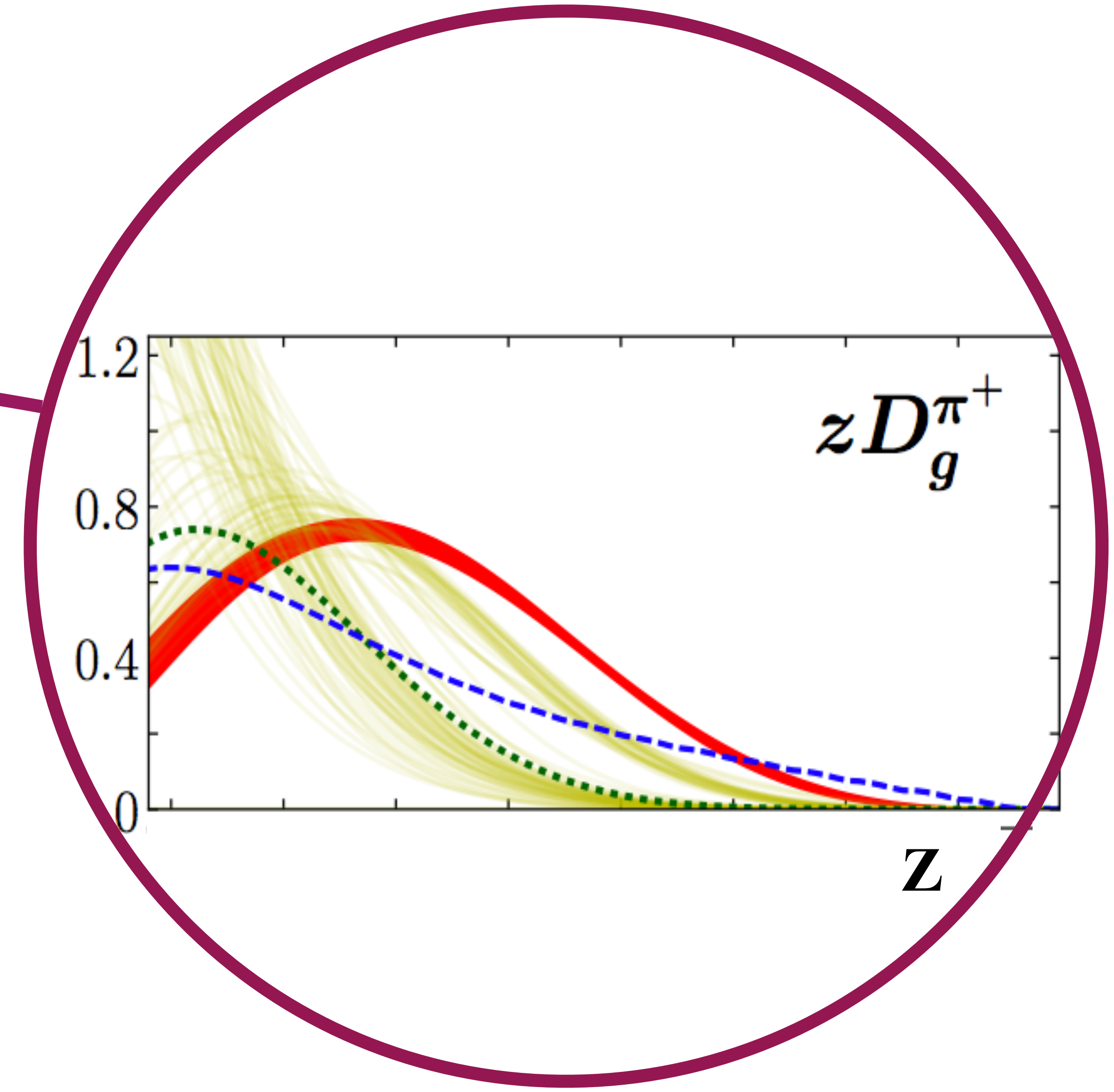
1.2
0.8
0.4
0
$zD_g^{\pi^+}$
$zD_{u^+}^{\pi^+}$
JAM19
no SIDIS
DSS
HKNS
0.4
0.3
0.2
0.1
0
$zD_g^{K^+}$
$zD_{u^+}^{K^+}$
0.4
0.3
0.2
0.1
0
$zD_{d^+}^{K^+}$
$zD_{s^+}^{K^+}$
0.2
0.4
0.6
0.8
z
0.2
0.4
0.6
0.8
z

$Q = m_c$

JAM19: FF



Q = m$_c$

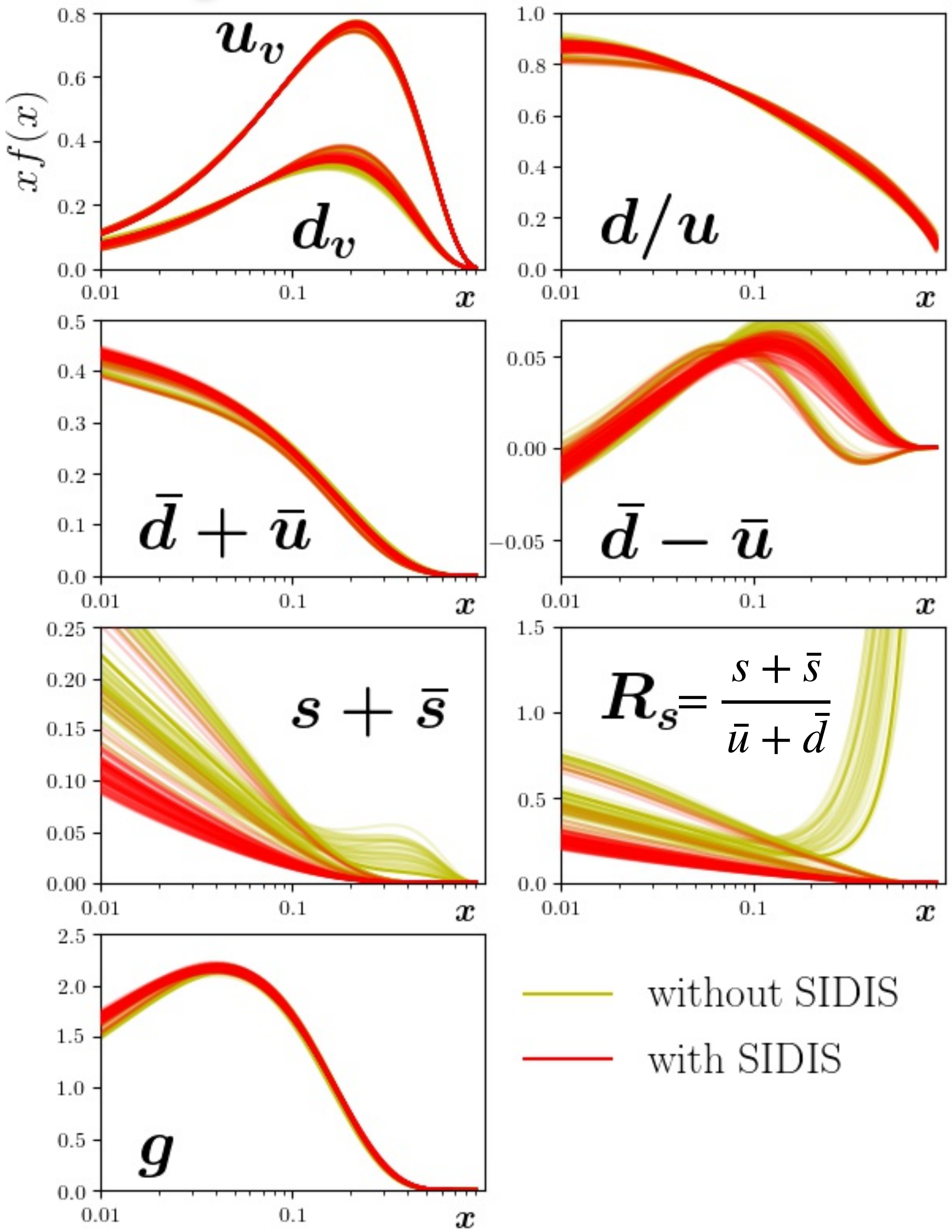


Constraints on

$g \to \pi^+$

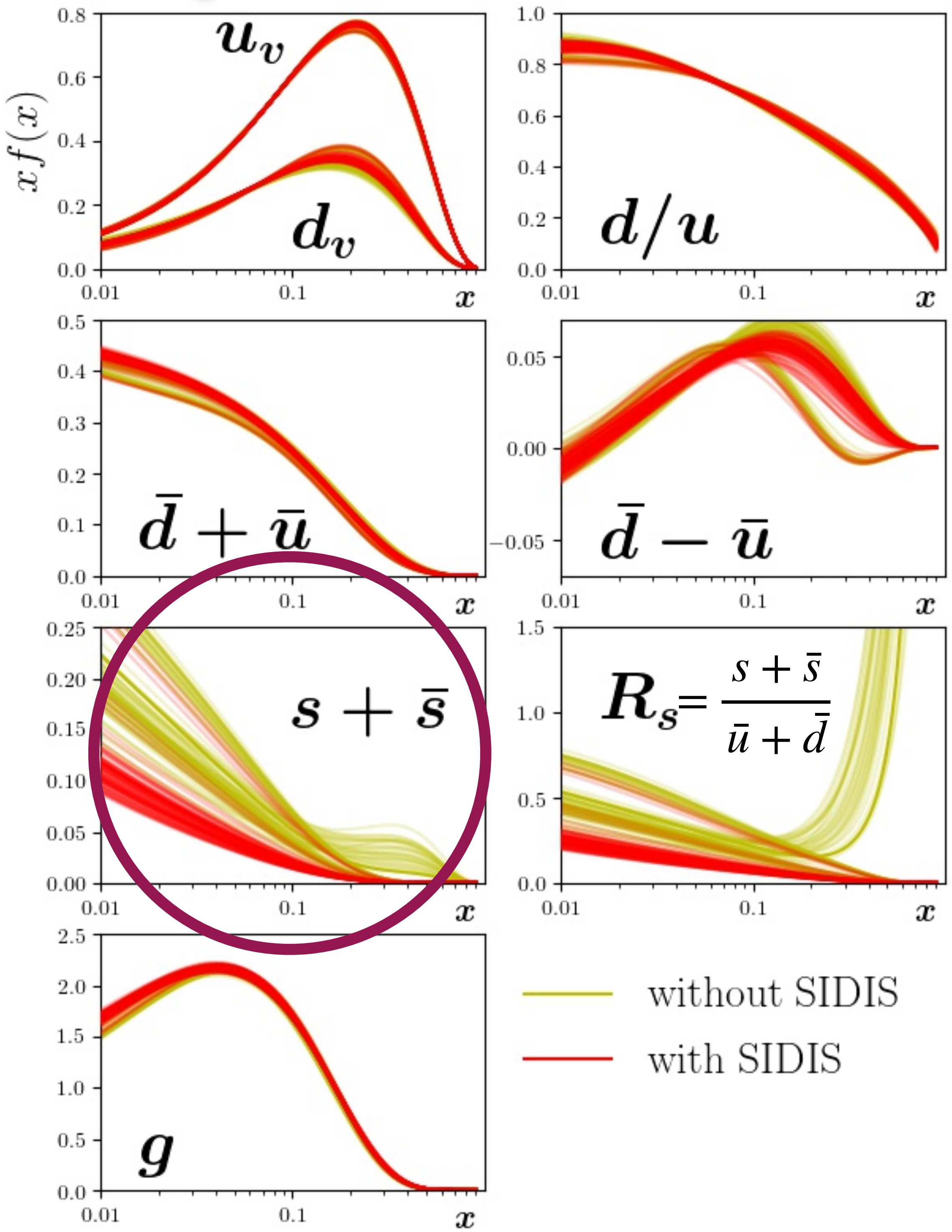
Impact of SIDIS data

Impact of SIDIS data on PDFs



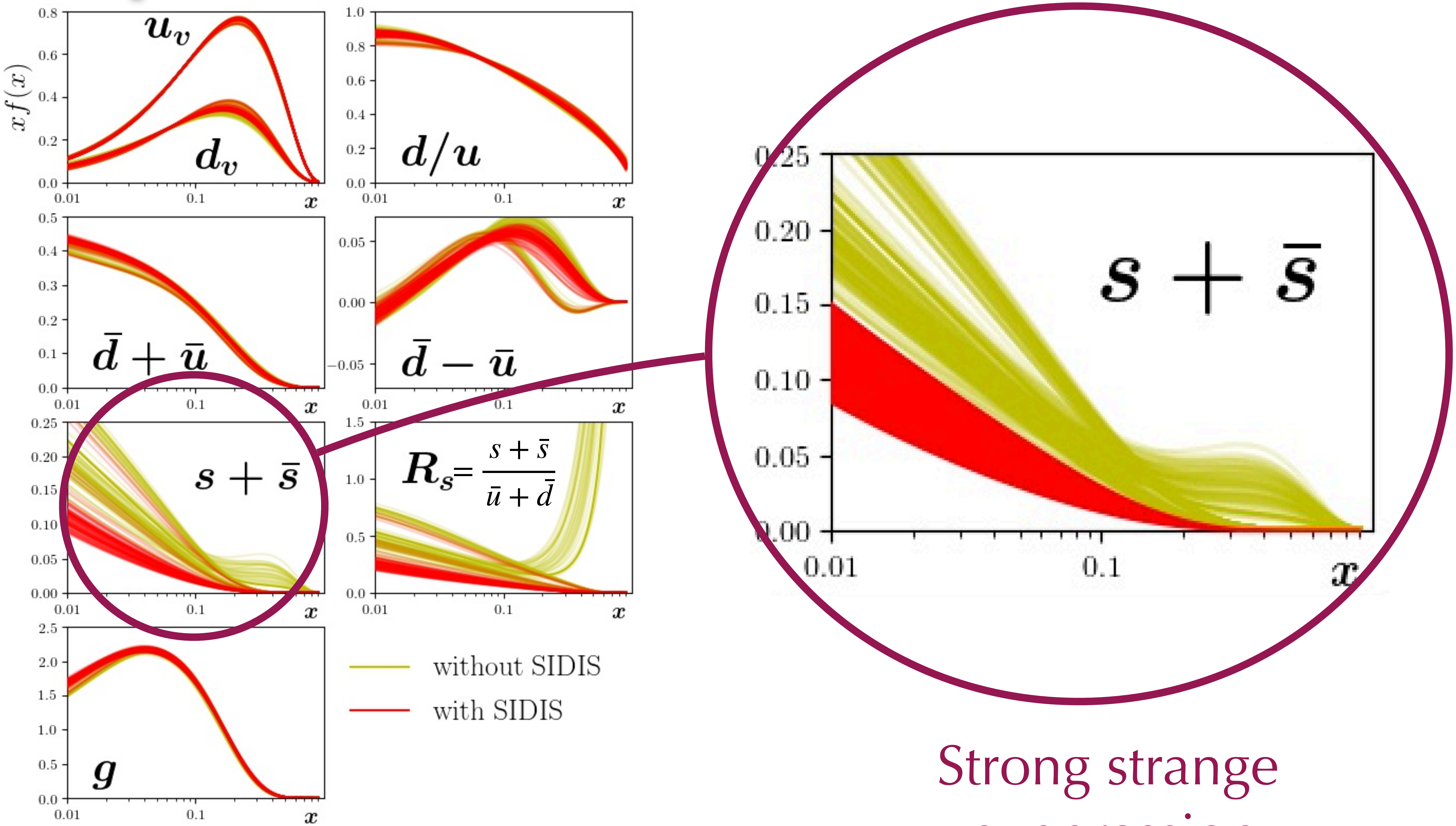
Q = m_c

Impact of SIDIS data on PDFs



Q = m$_c$

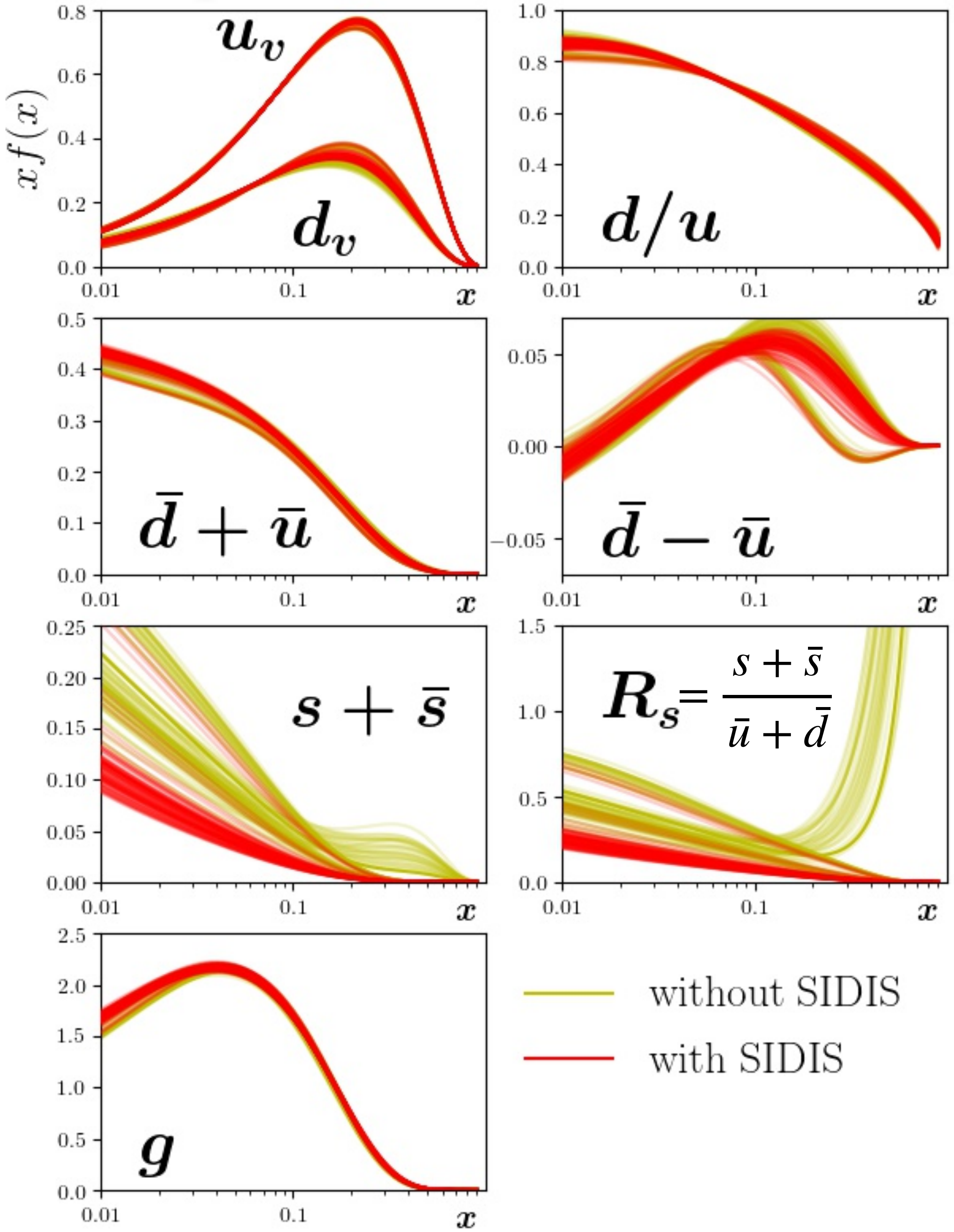
Impact of SIDIS data on PDFs



Q = m$_c$

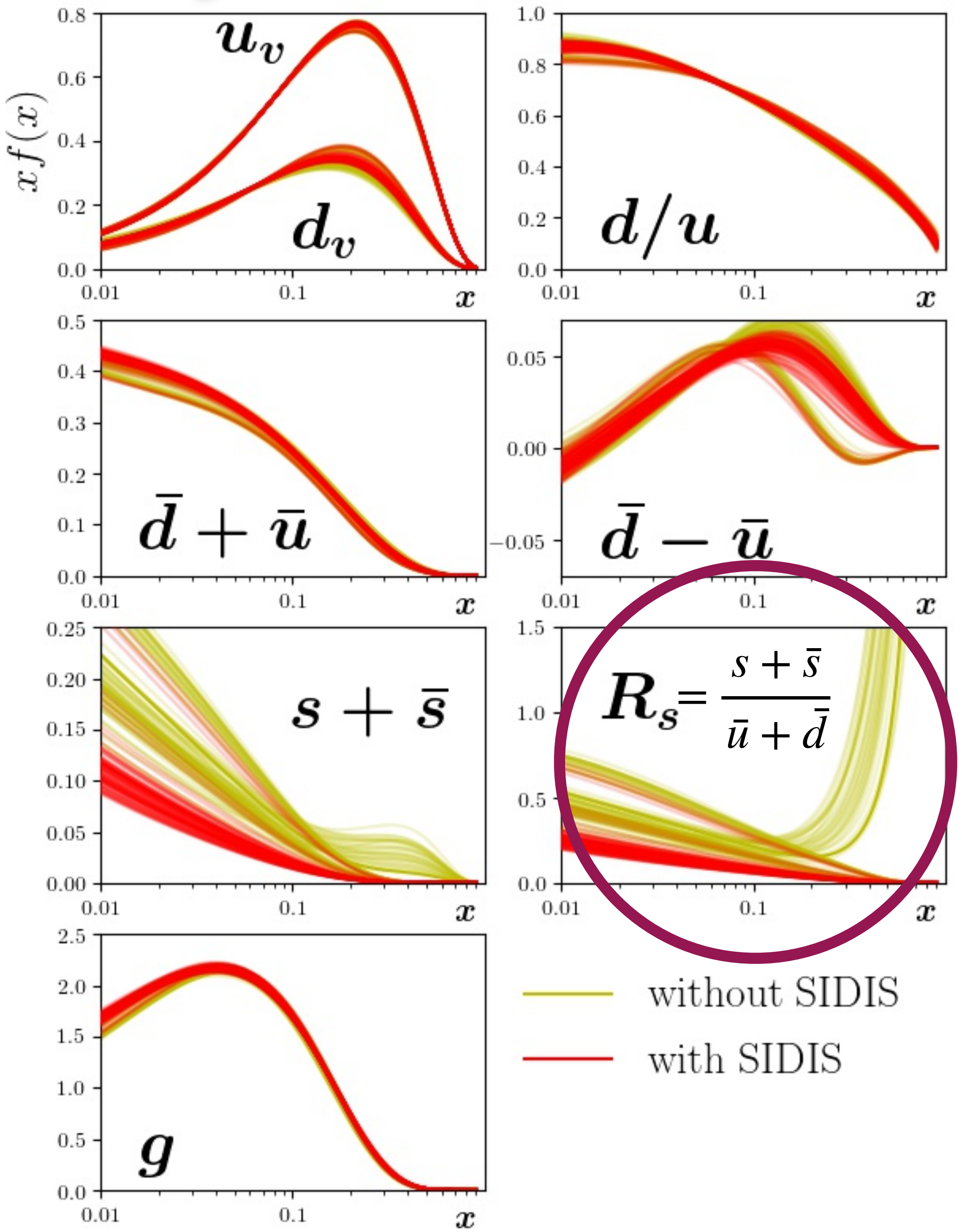
Strong strange suppression

Impact of SIDIS data on PDFs



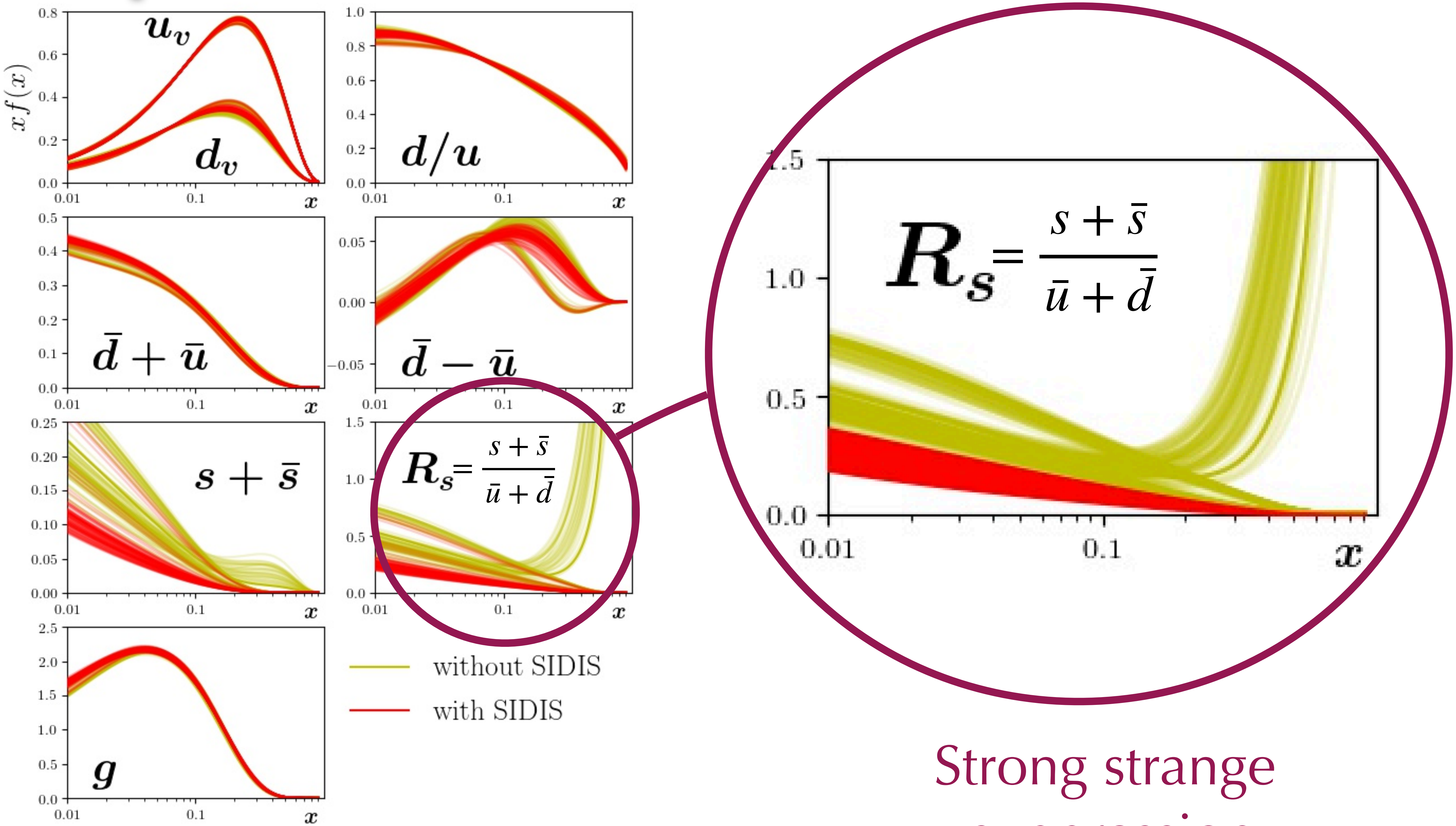
Q = m$_c$

Impact of SIDIS data on PDFs



$Q = m_c$

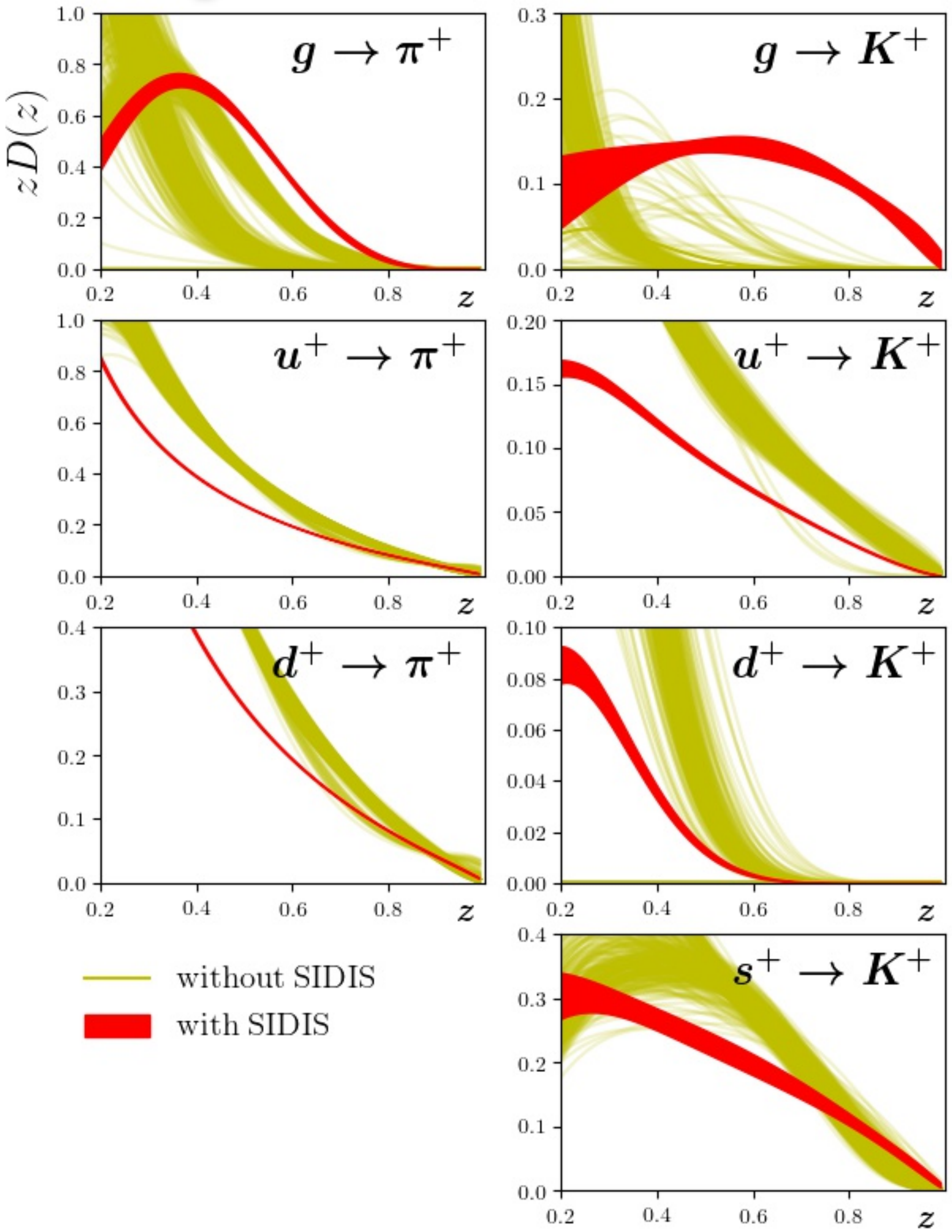
Impact of SIDIS data on PDFs



$\mathbf{Q = m_c}$

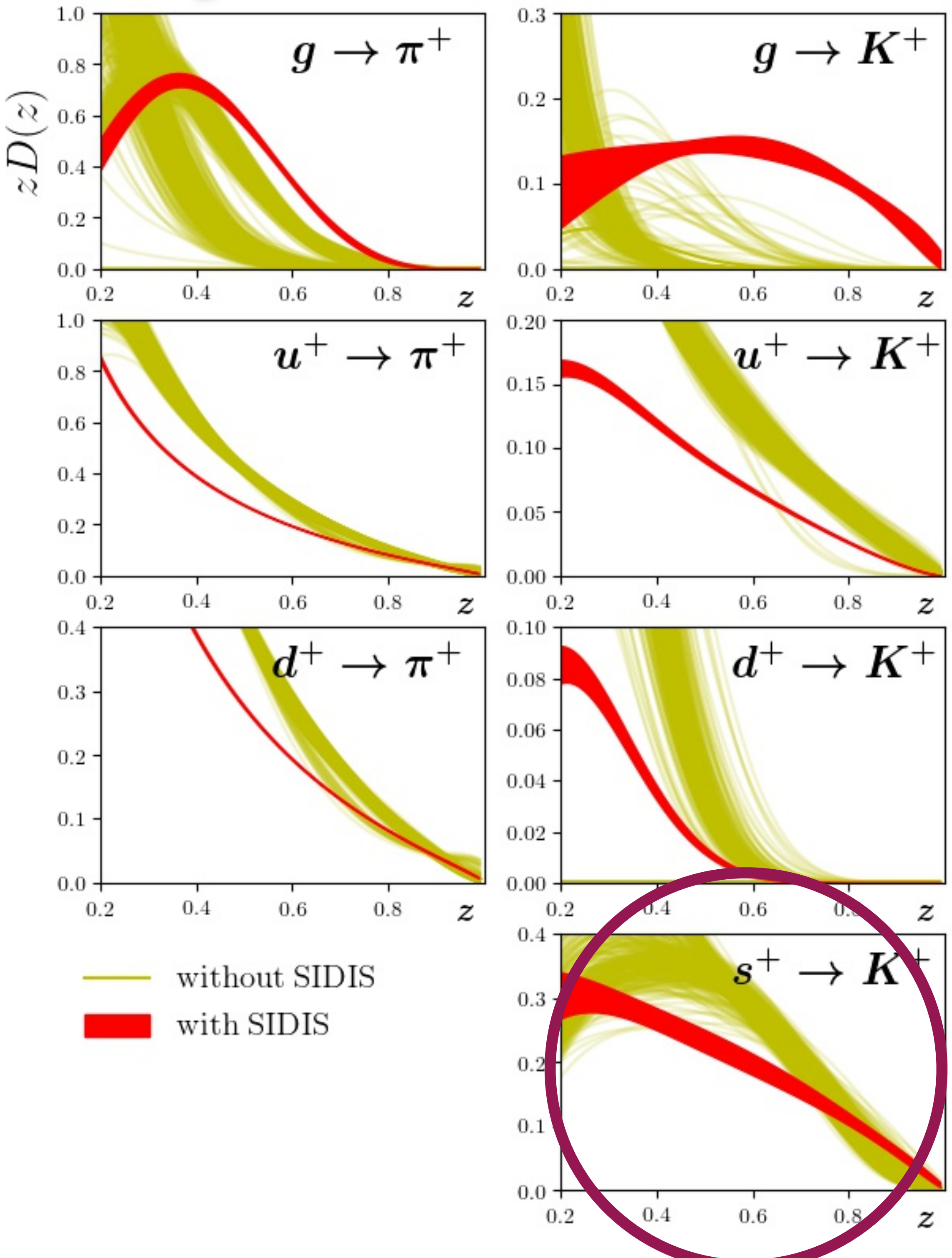
Strong strange suppression

Impact of SIDIS data on FF



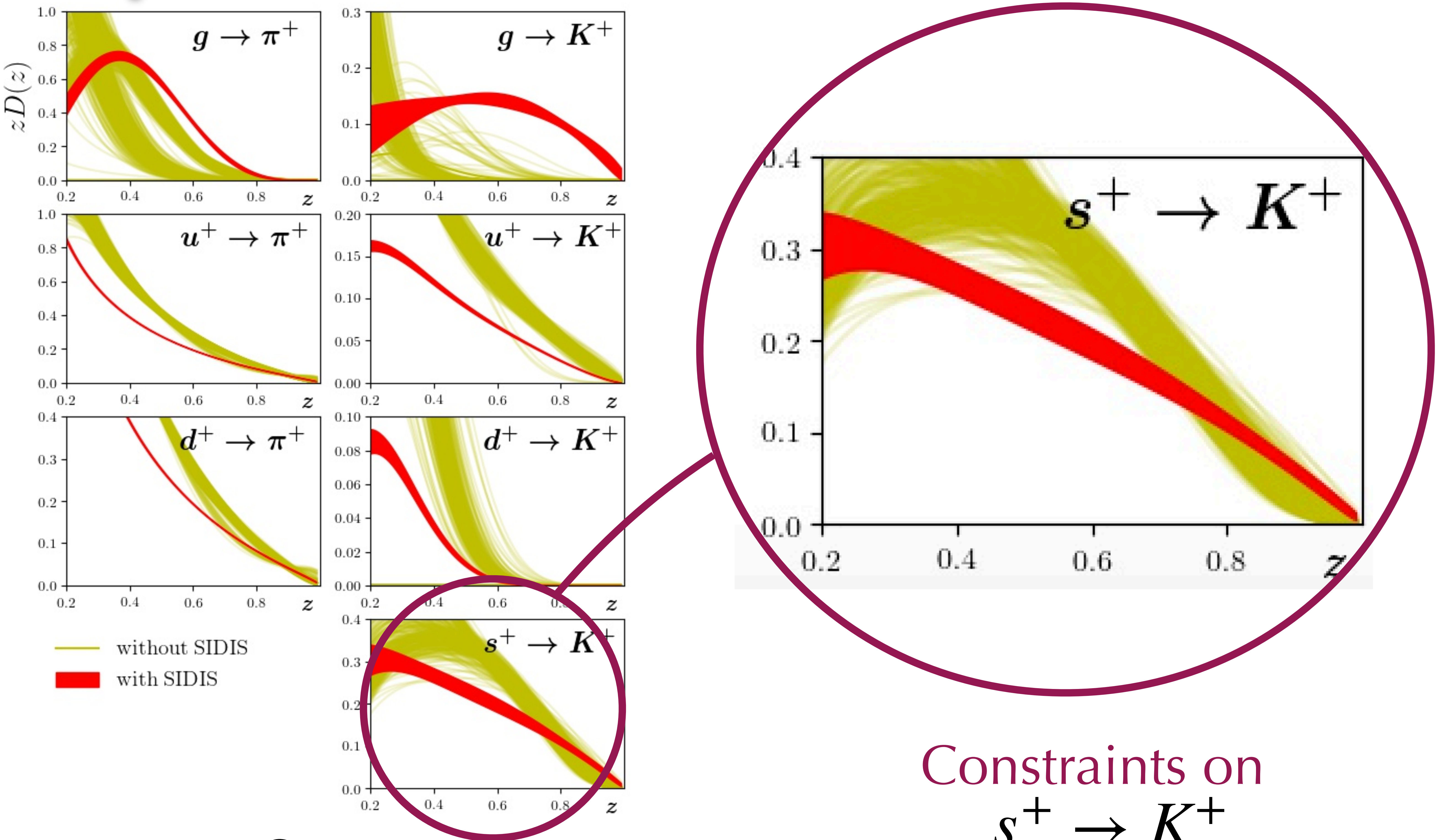
Q = m$_c$

Impact of SIDIS data on FF



Q = m$_c$

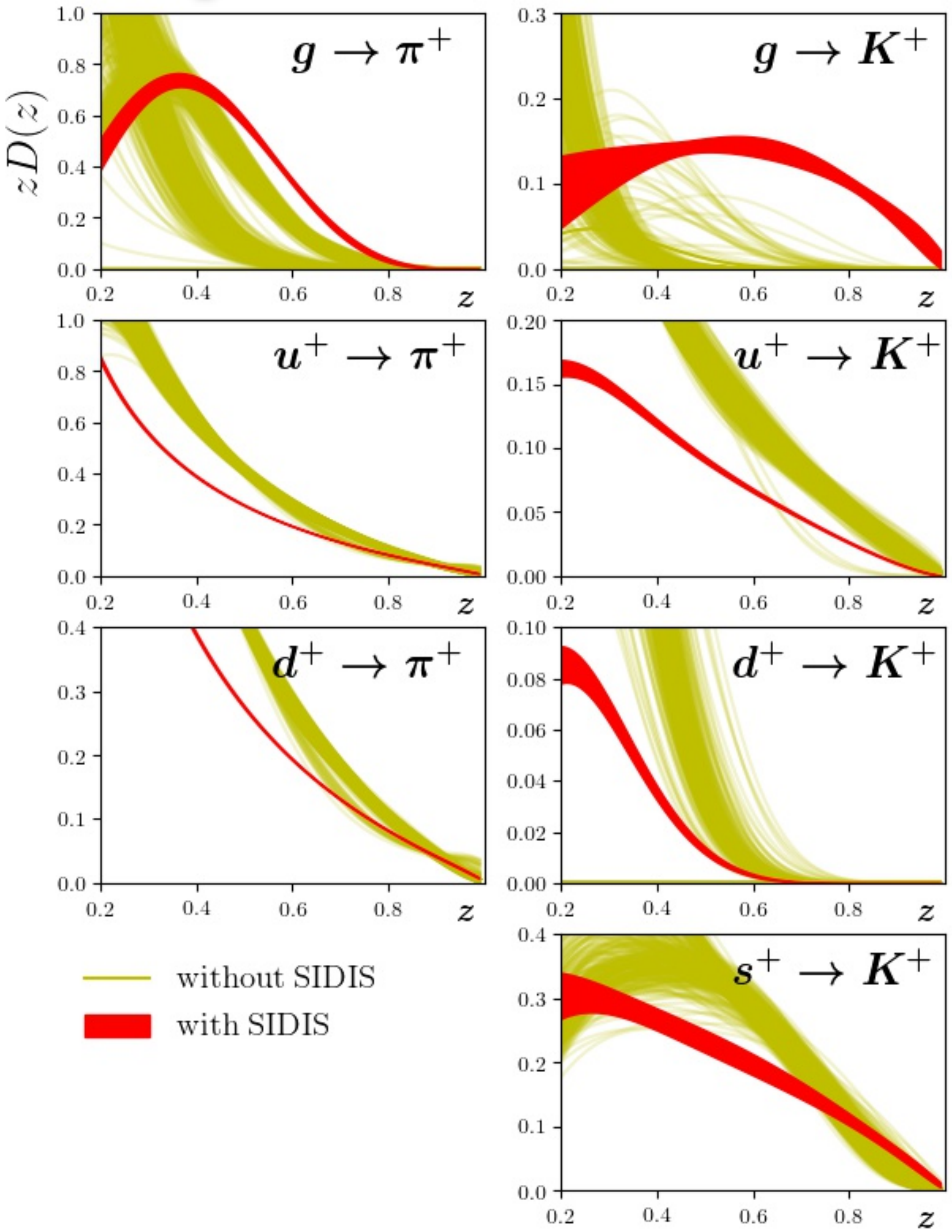
Impact of SIDIS data on FF



Q = m$_c$

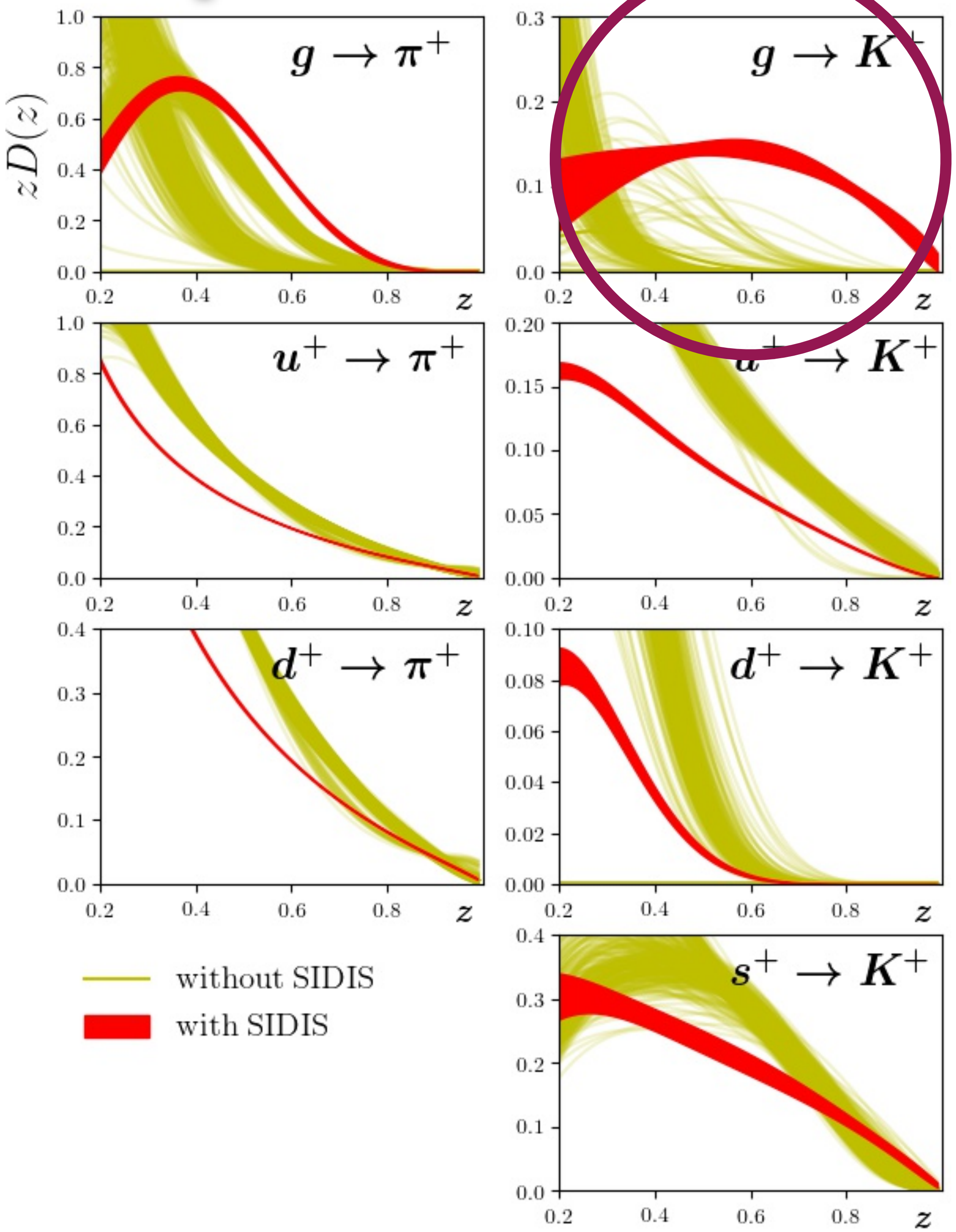
Constraints on
$s^+ \to K^+$

Impact of SIDIS data on FF



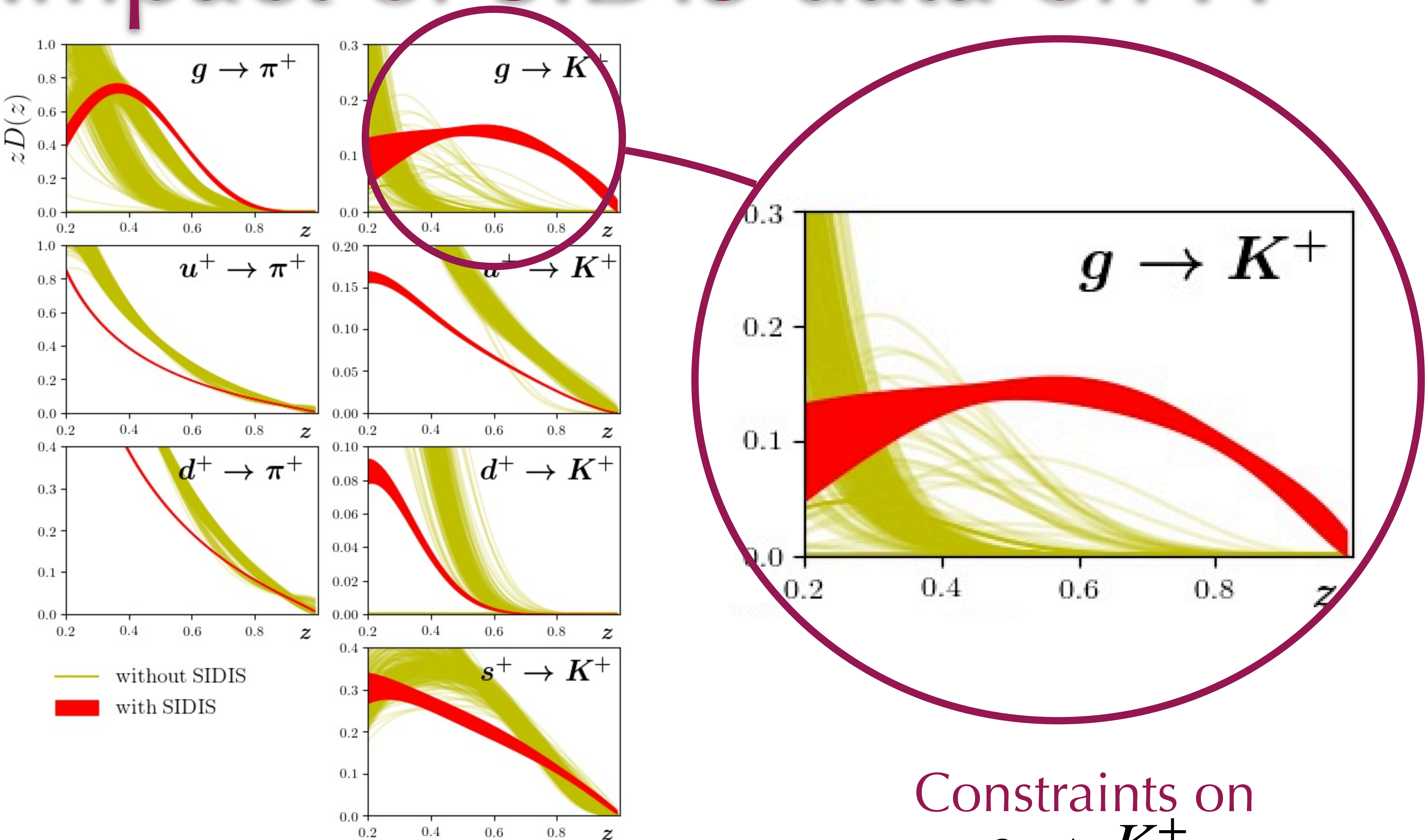
Q = m$_c$

Impact of SIDIS data on FF



Q = m$_c$

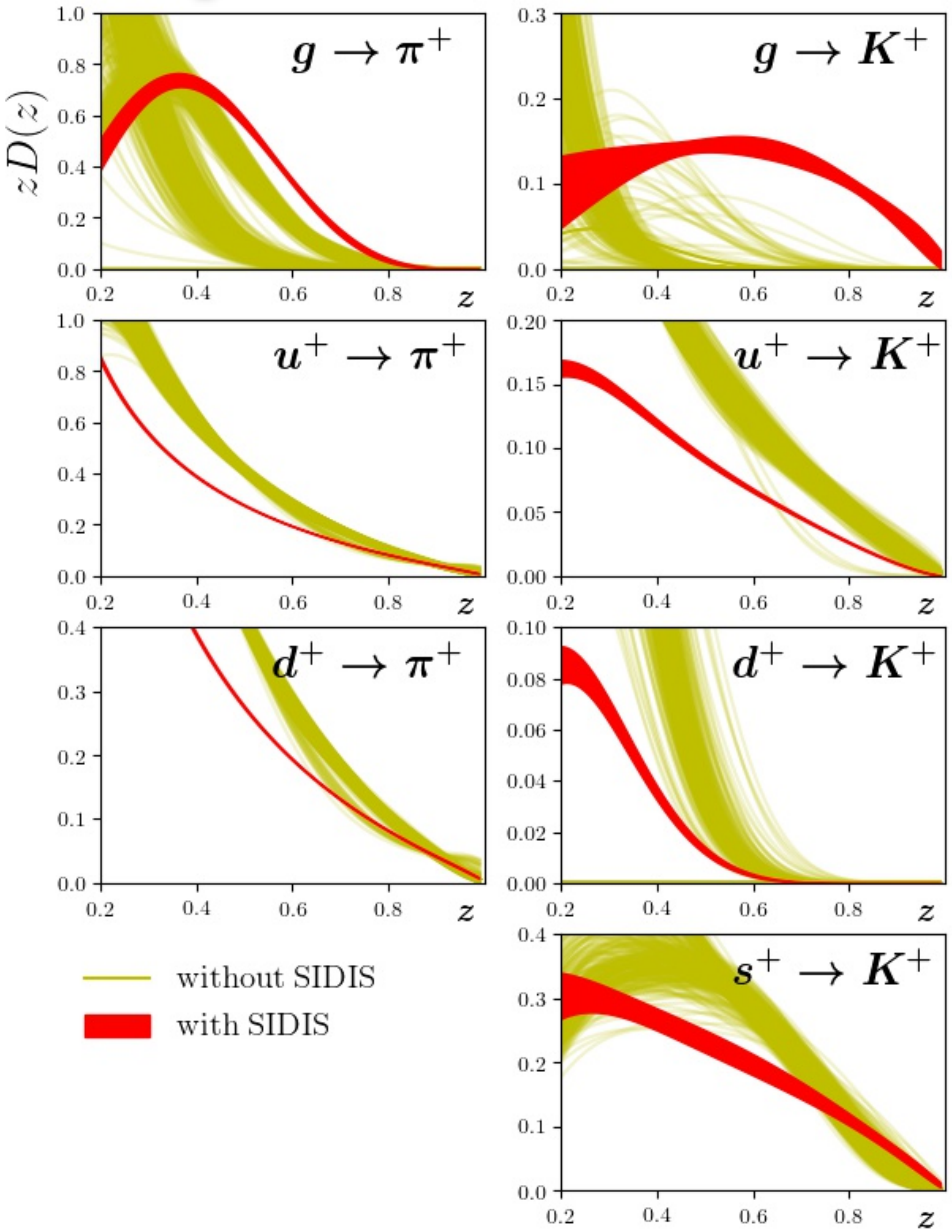
Impact of SIDIS data on FF



Q = m$_c$

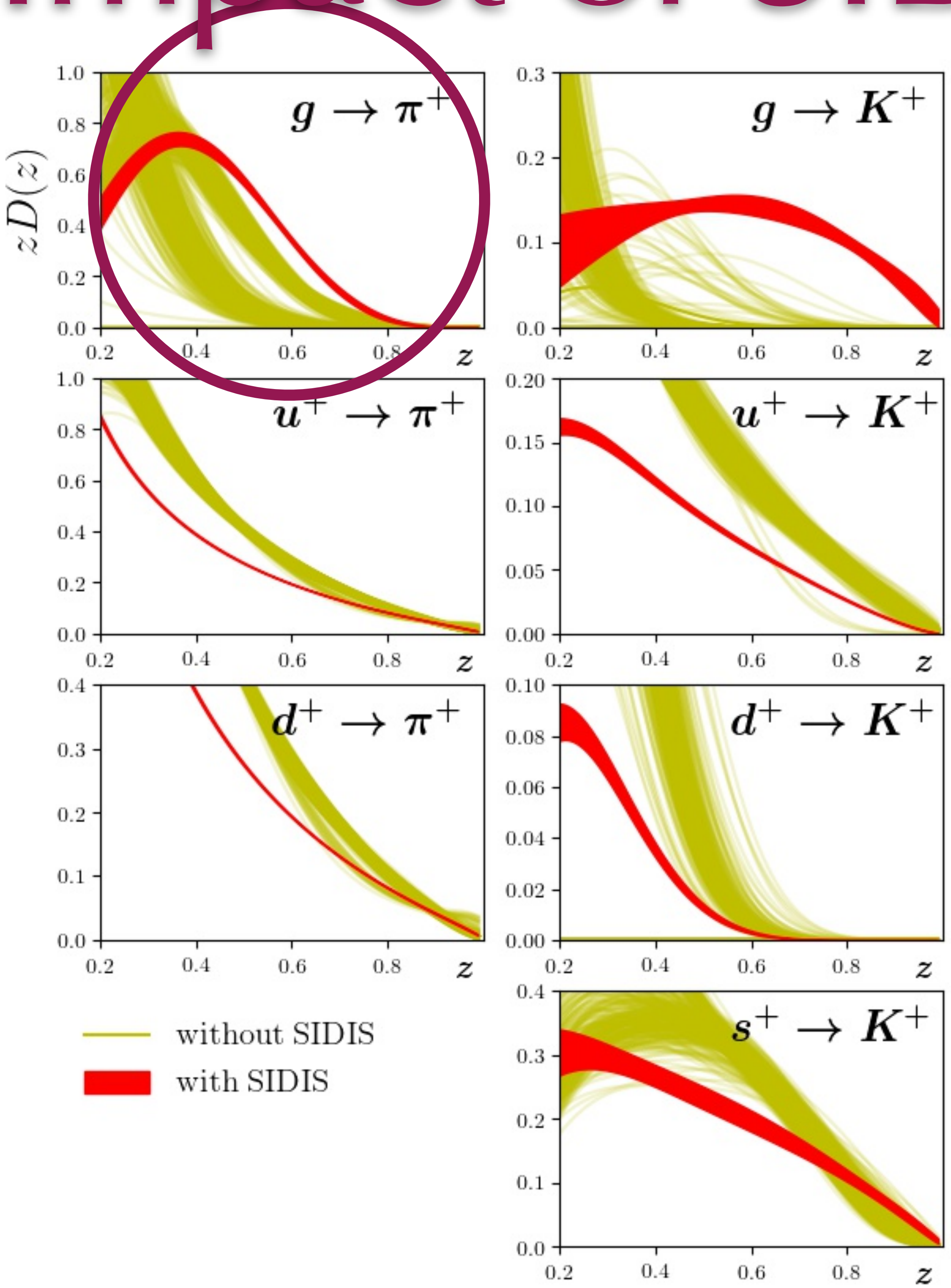
Constraints on $g \to K^+$

Impact of SIDIS data on FF



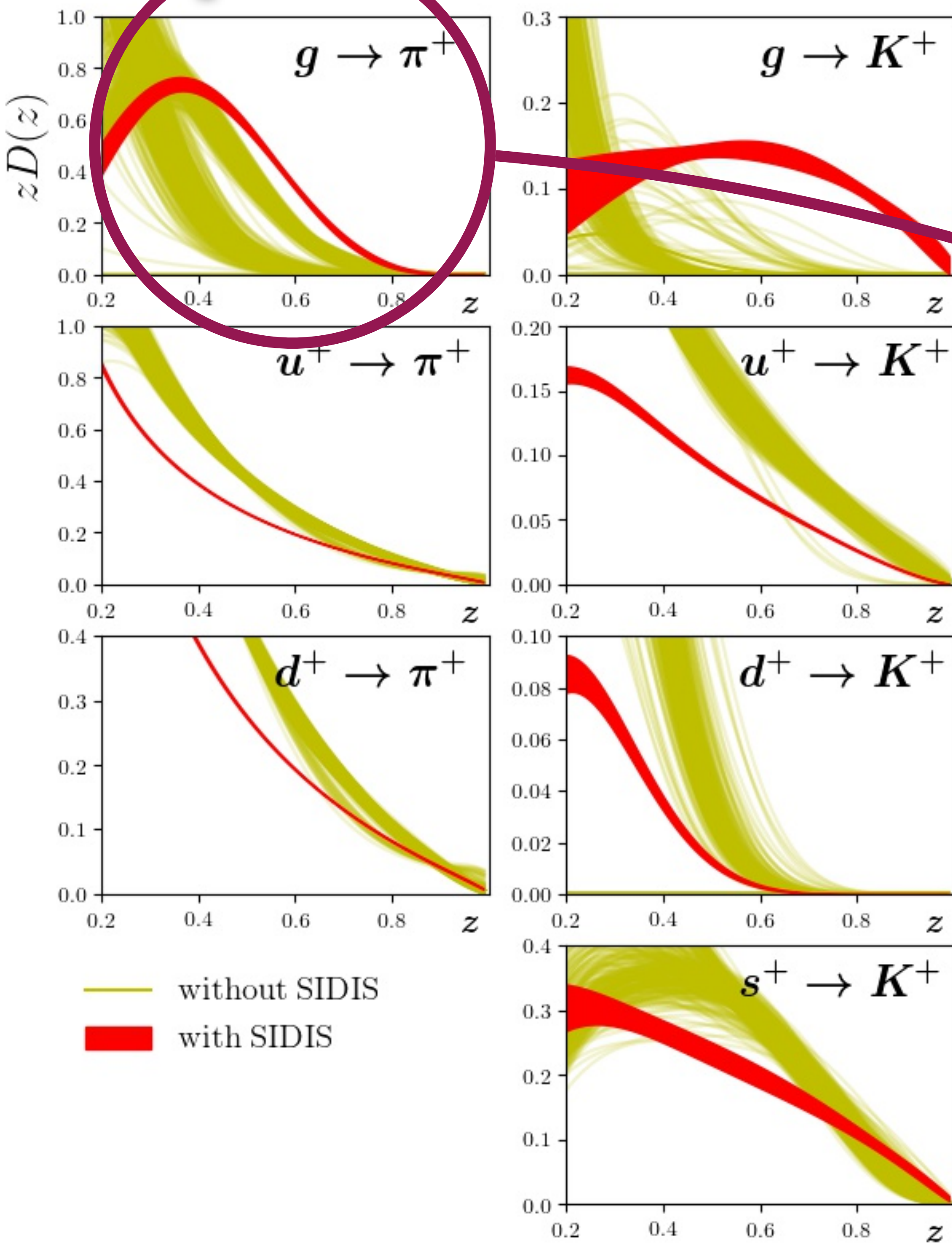
Q = m$_c$

Impact of SIDIS data on FF

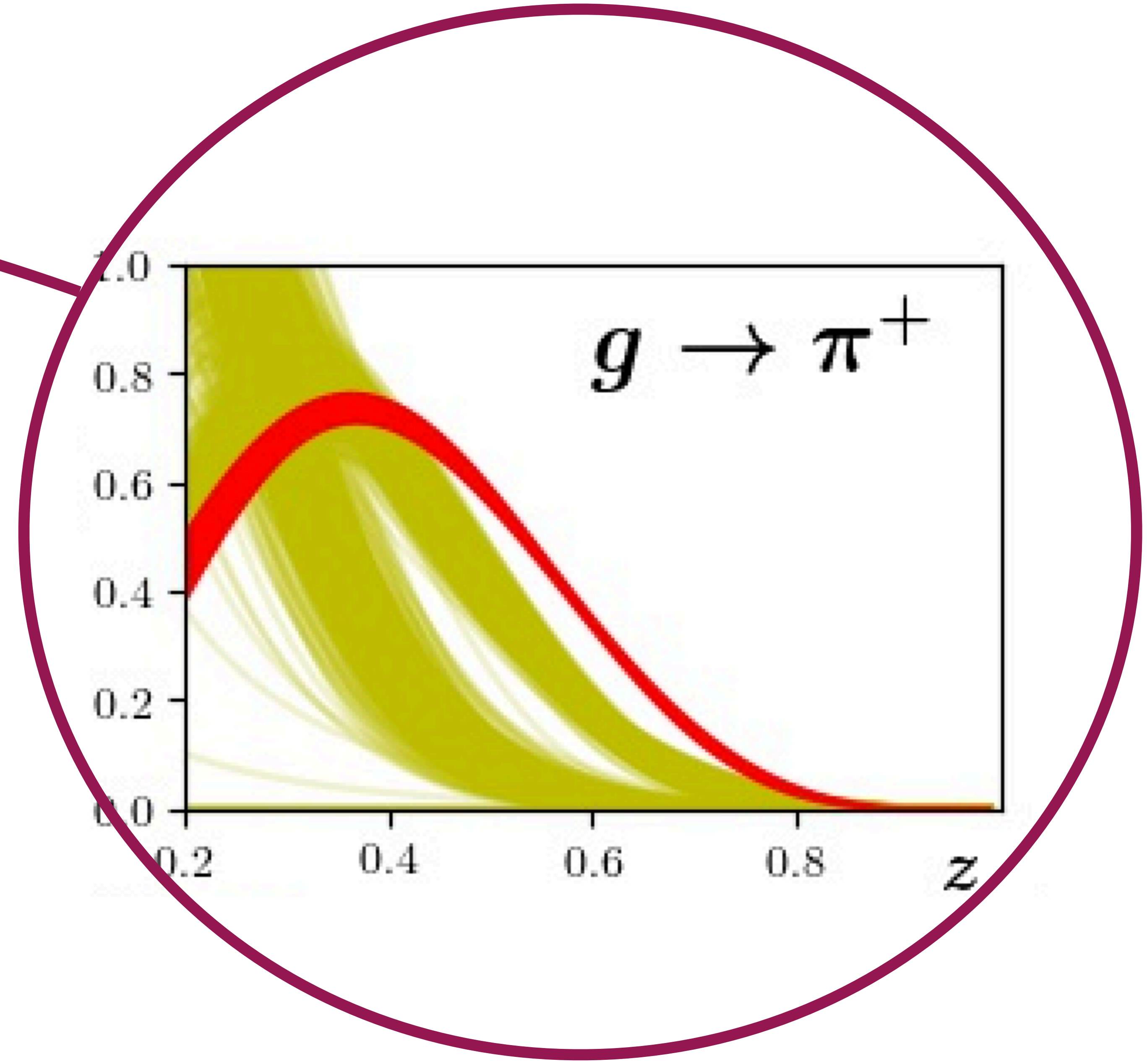


$Q = m_c$

Impact of SIDIS data on FF



Q = m$_c$



Constraints on

$g \to \pi^+$

Summary

- First MC fit of PDFs and FFs using DIS, DY, SIDIS and SIA data

- MC statistical methods are important for a robust extraction of non-perturbative collinear distributions

- JAM19 Methodology: MC (multi-steps), k-means clustering, 'extended' reduced χ^2

- Strange PDF strongly suppressed

Thanks

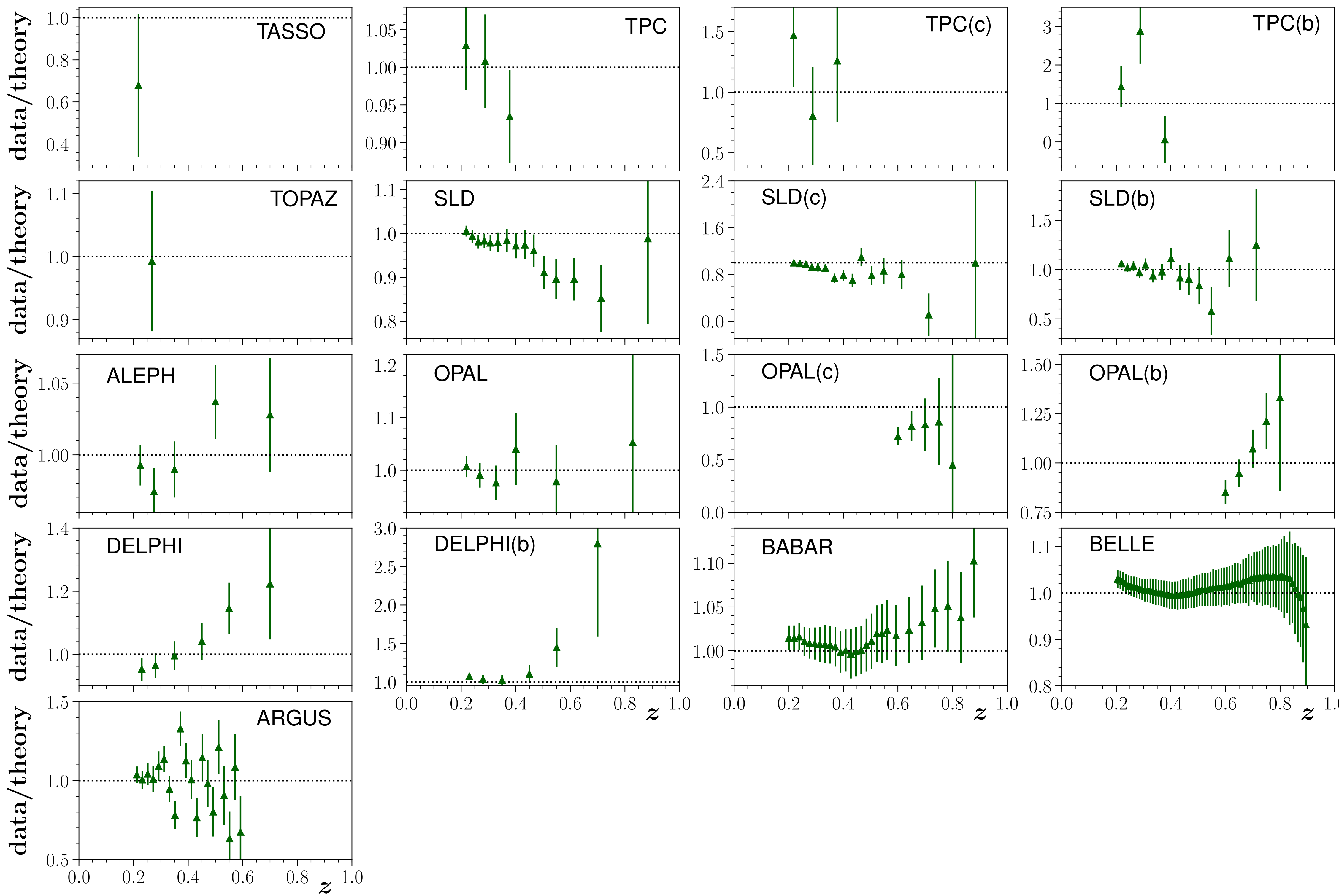
Chi2

Reaction	N_{dat}	χ^2	χ^2/N_{dat}
SIDIS	992	1243.12	1.25
SIA	444	562.80	1.27
DIS	2680	3437.96	1.28
DY	250	416.29	1.67

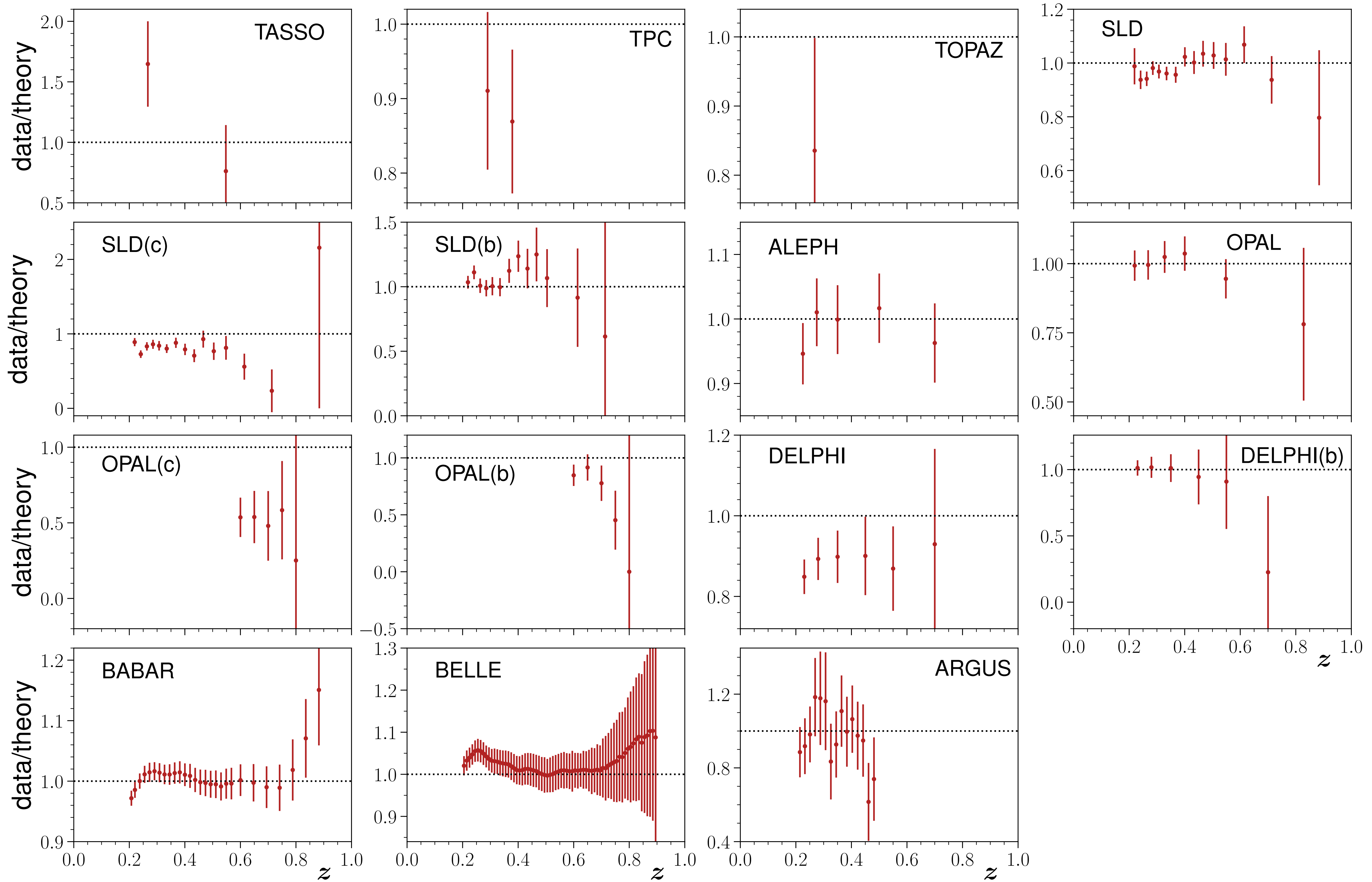
Reaction	N_{dat}	χ^2	χ^2/N_{dat}
SIDIS ($\pi^\pm$)	498	585.48	1.18
SIDIS($K^\pm$)	494	657.64	1.33
SIA($\pi^\pm$)	231	247.27	1.07
SIA ($K^\pm$)	213	315.53	1.48

Experiment	target	hadron	N_{dat}	χ^2/N_{dat}
COMPASS	d	π^+	249	1.26
COMPASS	d	π^-	249	1.09
COMPASS	d	K^+	247	1.24
COMPASS	d	K^-	247	1.43

SIA: pions

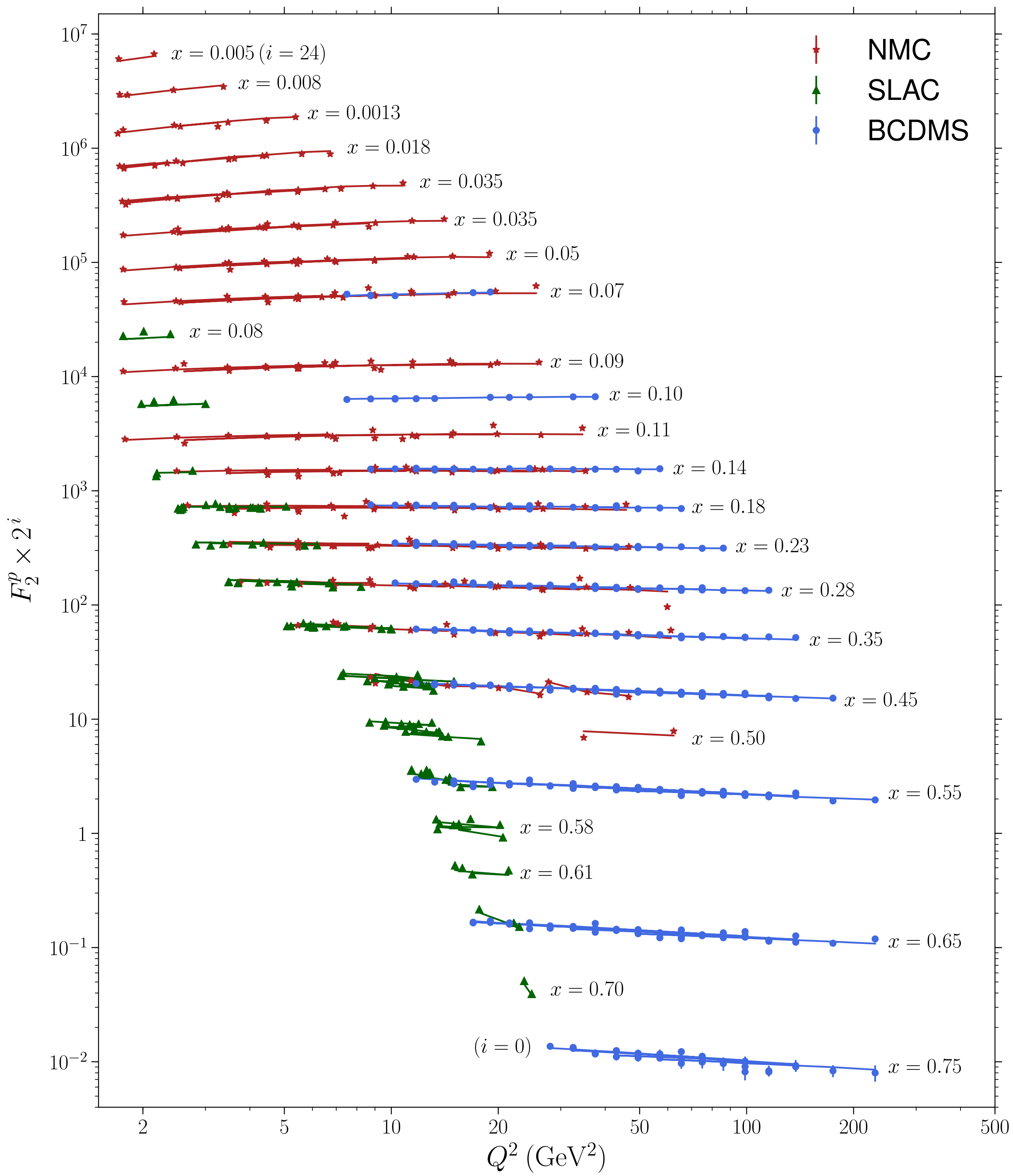

TASSO
TPC
TPC(c)
TPC(b)
TOPAZ
SLD
SLD(c)
SLD(b)
ALEPH
OPAL
OPAL(c)
OPAL(b)
DELPHI
DELPHI(b)
BABAR
BELLE
ARGUS
data/theory
z

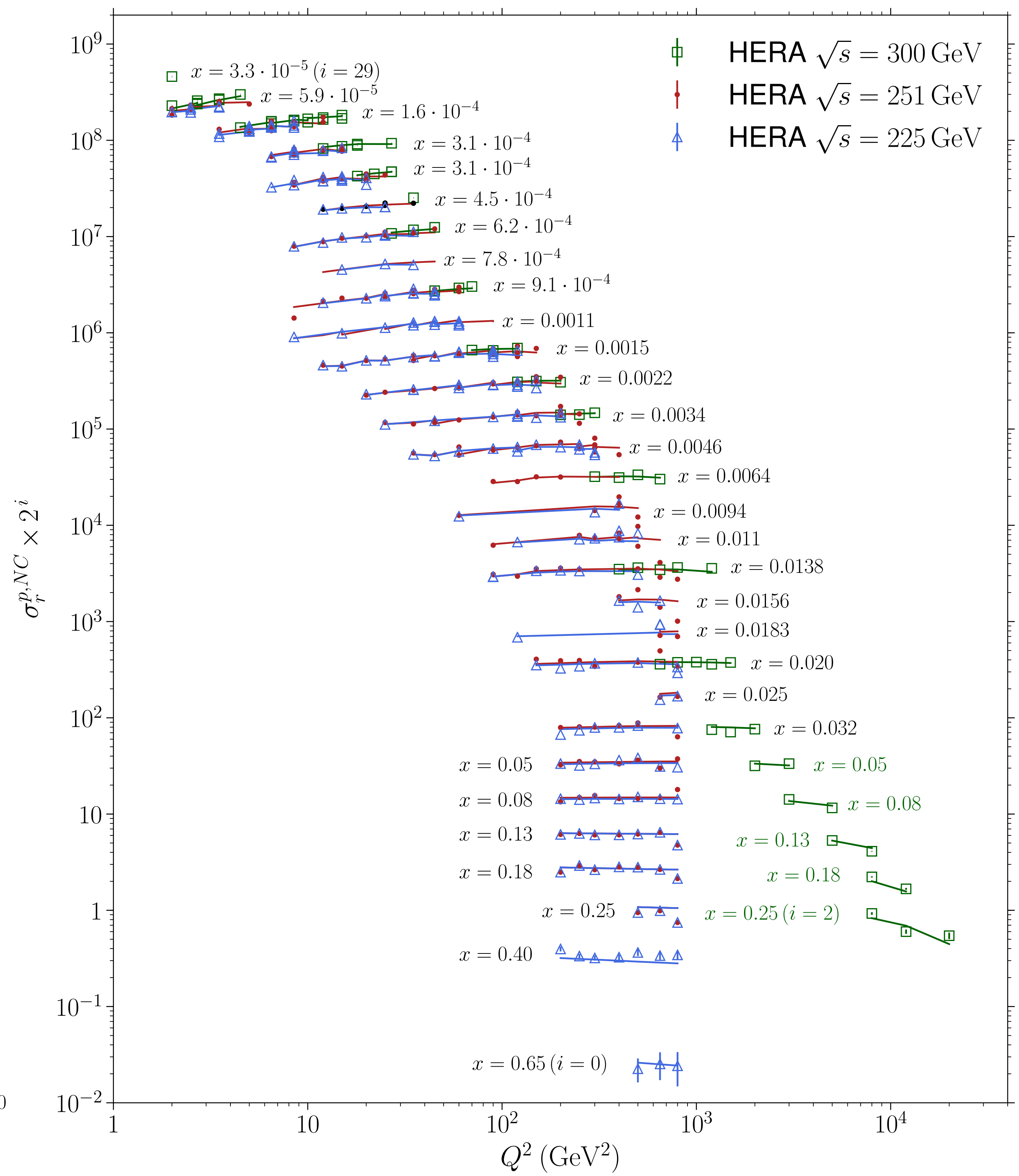
SIA: kaons



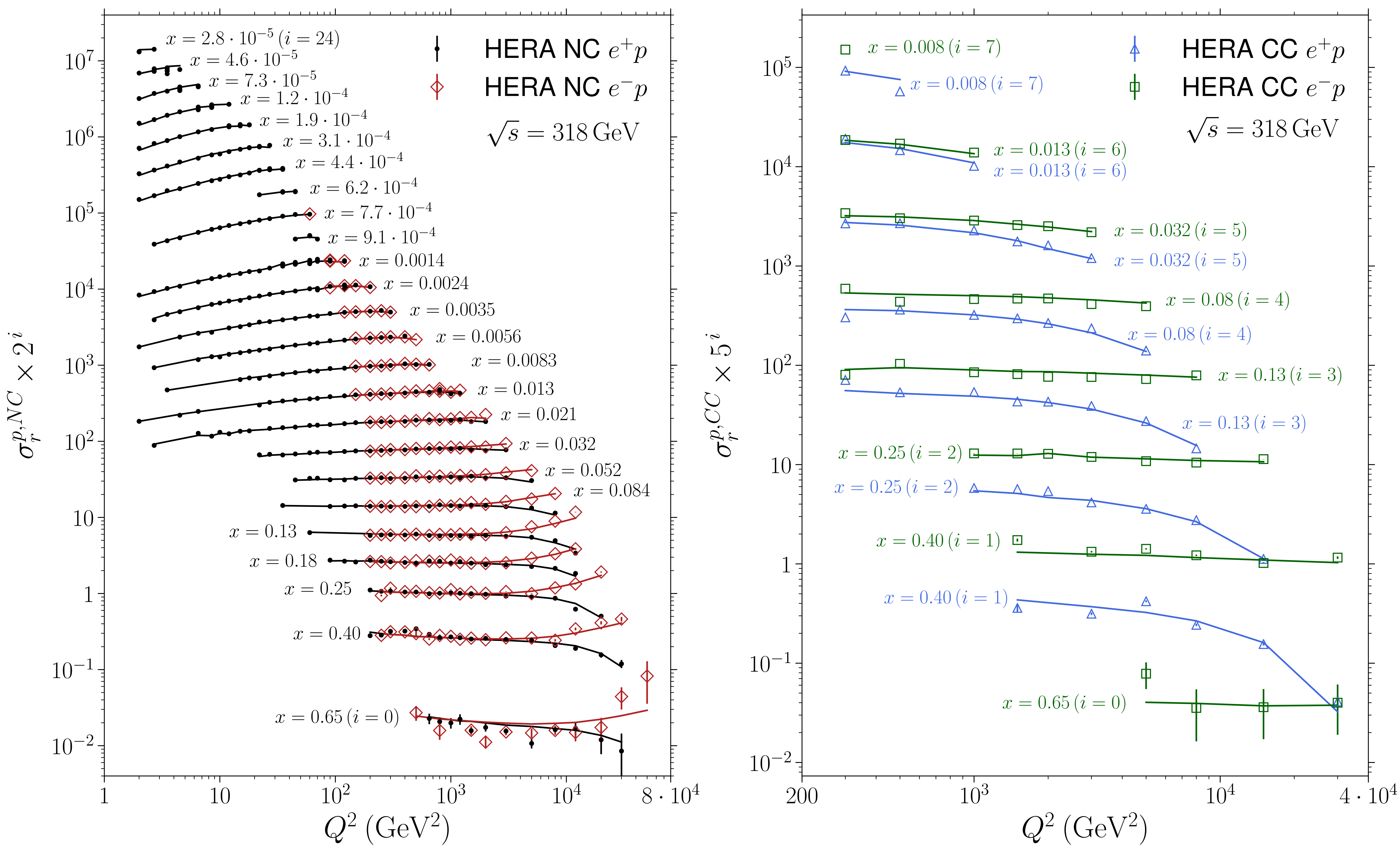
data/theory
TASSO
TPC
TOPAZ
SLD
SLD(c)
SLD(b)
ALEPH
OPAL
OPAL(c)
OPAL(b)
DELPHI
DELPHI(b)
BABAR
BELLE
ARGUS
z

DIS: proton


NMC
SLAC
BCDMS
$x = 0.005\,(i = 24)$
$x = 0.008$
$x = 0.0013$
$x = 0.018$
$x = 0.035$
$x = 0.035$
$x = 0.05$
$x = 0.07$
$x = 0.08$
$x = 0.09$
$x = 0.10$
$x = 0.11$
$x = 0.14$
$x = 0.18$
$x = 0.23$
$x = 0.28$
$x = 0.35$
$x = 0.45$
$x = 0.50$
$x = 0.55$
$x = 0.58$
$x = 0.61$
$x = 0.65$
$x = 0.70$
$(i = 0)$
$x = 0.75$
$F_2^p \times 2^i$
Q^2 (GeV^2)

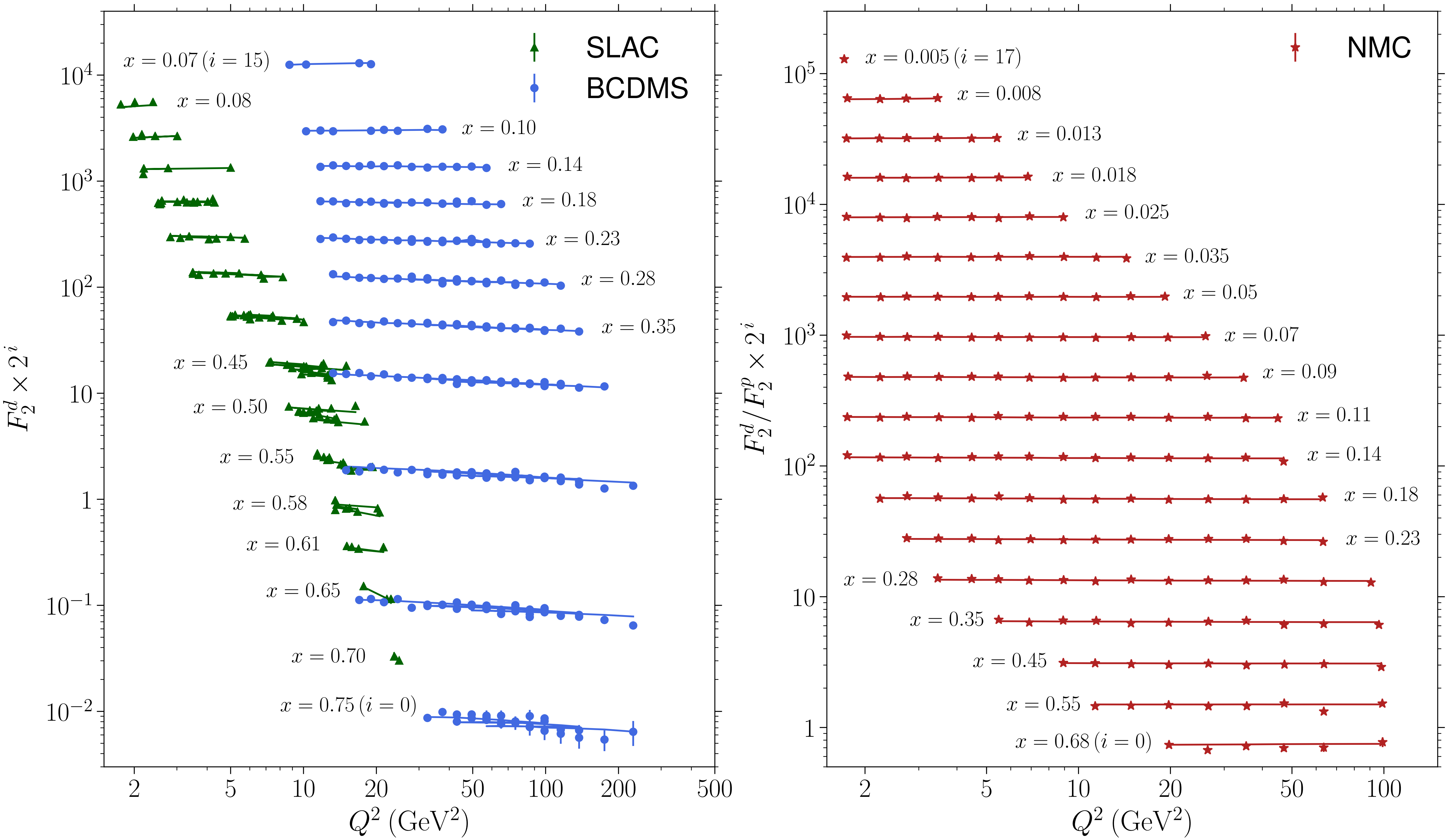

HERA $\sqrt{s} = 300$ GeV
HERA $\sqrt{s} = 251$ GeV
HERA $\sqrt{s} = 225$ GeV
$x = 3.3 \cdot 10^{-5}\,(i = 29)$
$x = 5.9 \cdot 10^{-5}$
$x = 1.6 \cdot 10^{-4}$
$x = 3.1 \cdot 10^{-4}$
$x = 3.1 \cdot 10^{-4}$
$x = 4.5 \cdot 10^{-4}$
$x = 6.2 \cdot 10^{-4}$
$x = 7.8 \cdot 10^{-4}$
$x = 9.1 \cdot 10^{-4}$
$x = 0.0011$
$x = 0.0015$
$x = 0.0022$
$x = 0.0034$
$x = 0.0046$
$x = 0.0064$
$x = 0.0094$
$x = 0.011$
$x = 0.0138$
$x = 0.0156$
$x = 0.0183$
$x = 0.020$
$x = 0.025$
$x = 0.032$
$x = 0.05$
$x = 0.05$
$x = 0.08$
$x = 0.08$
$x = 0.13$
$x = 0.13$
$x = 0.18$
$x = 0.18$
$x = 0.25$
$x = 0.25\,(i = 2)$
$x = 0.40$
$x = 0.65\,(i = 0)$
$\sigma_r^{p,NC} \times 2^i$
Q^2 (GeV^2)

DIS: proton

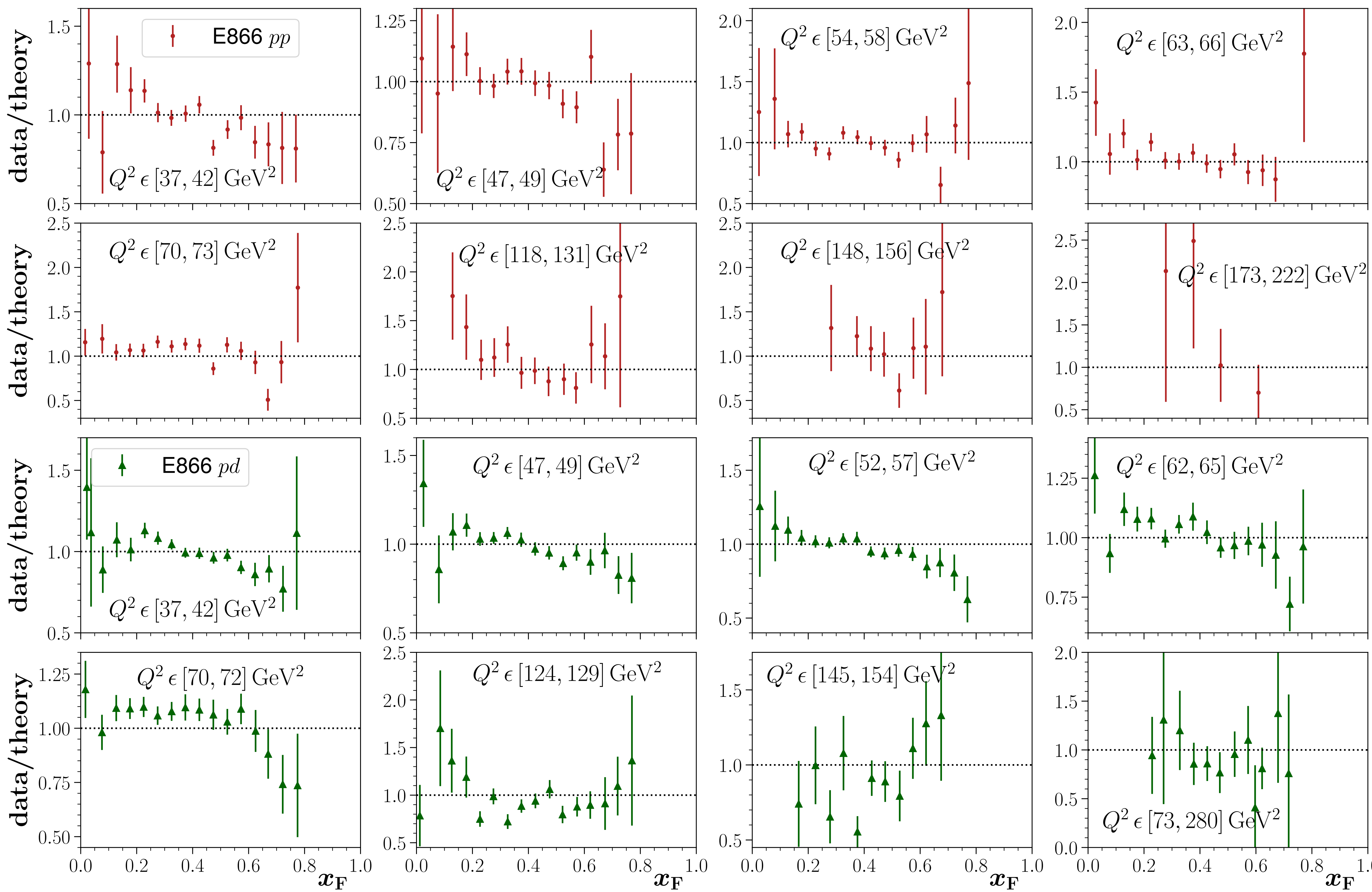


HERA NC e^+p
HERA NC e^-p
$\sqrt{s} = 318\,\text{GeV}$
$\sigma_r^{p,NC} \times 2^i$
Q^2 (GeV^2)
$x = 2.8 \cdot 10^{-5}$ $(i = 24)$
$x = 4.6 \cdot 10^{-5}$
$x = 7.3 \cdot 10^{-5}$
$x = 1.2 \cdot 10^{-4}$
$x = 1.9 \cdot 10^{-4}$
$x = 3.1 \cdot 10^{-4}$
$x = 4.4 \cdot 10^{-4}$
$x = 6.2 \cdot 10^{-4}$
$x = 7.7 \cdot 10^{-4}$
$x = 9.1 \cdot 10^{-4}$
$x = 0.0014$
$x = 0.0024$
$x = 0.0035$
$x = 0.0056$
$x = 0.0083$
$x = 0.013$
$x = 0.021$
$x = 0.032$
$x = 0.052$
$x = 0.084$
$x = 0.13$
$x = 0.18$
$x = 0.25$
$x = 0.40$
$x = 0.65$ $(i = 0)$
HERA CC e^+p
HERA CC e^-p
$\sqrt{s} = 318\,\text{GeV}$
$\sigma_r^{p,CC} \times 5^i$
Q^2 (GeV^2)
$x = 0.008$ $(i = 7)$
$x = 0.013$ $(i = 6)$
$x = 0.032$ $(i = 5)$
$x = 0.08$ $(i = 4)$
$x = 0.13$ $(i = 3)$
$x = 0.25$ $(i = 2)$
$x = 0.40$ $(i = 1)$
$x = 0.65$ $(i = 0)$

DIS: deuteron



DY



E866 pp
E866 pd
data/theory
x_F
$Q^2 \epsilon$ [37, 42] GeV^2
$Q^2 \epsilon$ [47, 49] GeV^2
$Q^2 \epsilon$ [54, 58] GeV^2
$Q^2 \epsilon$ [63, 66] GeV^2
$Q^2 \epsilon$ [70, 73] GeV^2
$Q^2 \epsilon$ [118, 131] GeV^2
$Q^2 \epsilon$ [148, 156] GeV^2
$Q^2 \epsilon$ [173, 222] GeV^2
$Q^2 \epsilon$ [37, 42] GeV^2
$Q^2 \epsilon$ [47, 49] GeV^2
$Q^2 \epsilon$ [52, 57] GeV^2
$Q^2 \epsilon$ [62, 65] GeV^2
$Q^2 \epsilon$ [70, 72] GeV^2
$Q^2 \epsilon$ [124, 129] GeV^2
$Q^2 \epsilon$ [145, 154] GeV^2
$Q^2 \epsilon$ [73, 280] GeV^2