



# Reweighting the Sivers function with jet data

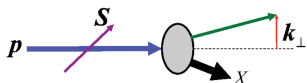
**Carlo Flore**

Laboratoire de Physique des 2 Infinis  
Irène Joliot-Curie (IJCLab), CNRS, Orsay

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M. Boglione, U. D'Alesio, CF,  
J.O. Gonzalez-Hernandez, F. Murgia, A. Prokudin,  
Phys. Lett. B 815 (2021) 136135

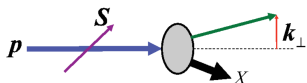
# Introduction - the Sivers function



D.W. Sivers, PRD 41 (1990) 83 & PRD 43 (1991) 261

$$\begin{aligned} & f_{a/p^\dagger}(x, \mathbf{k}_\perp) - f_{a/p^\dagger}(x, -\mathbf{k}_\perp) \\ &= \Delta^N f_{a/p^\dagger}(x, k_\perp^2) \frac{(\hat{\mathbf{p}} \times \mathbf{k}_\perp) \cdot \mathbf{S}}{|\mathbf{k}_\perp|} \quad (\text{TO - CA}) \\ &= -\frac{2|\mathbf{k}_\perp|}{M} f_{1T}^{\perp a}(x, k_\perp^2) \frac{(\hat{\mathbf{p}} \times \mathbf{k}_\perp) \cdot \mathbf{S}}{|\mathbf{k}_\perp|} \quad (\text{Amsterdam}) \end{aligned}$$

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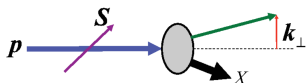


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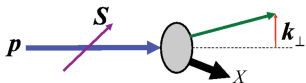


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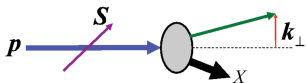


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- extracted from SIDIS azimuthal asymmetries:  $A_{UT}^{\sin(\phi_h - \phi_S)} \equiv \frac{F_{UT}^{\sin(\phi_h - \phi_S)}}{F_{UU,T}} = \frac{c[f_{1T}^{\perp a} D_1^a]}{c[f_1^a D_1^a]}$

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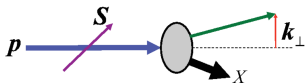


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- in the GPM, Sivers effect generates single spin asymmetries (SSAs) in  $p^\uparrow p \rightarrow \text{jet } X$

# Introduction - formalism

U. D'Alesio, F. Murgia PRD 70 (2004) 074009; M. Anselmino *et al.*, PRD 73 (2006) 014020;  
L. Gamberg, Z.-B. Kang, PLB 696 (2011) 109; U. D'Alesio *et al.*, PRD 96 (2017) 036011 ...

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- a **color gauge invariant formulation of GPM (CGI-GPM)** was developed, with inclusion of initial and final state interaction; **process dependence is recovered**
- $A_N$  in  $p^\uparrow p \rightarrow \text{jet } X$ :

$$A_N \equiv \frac{d\sigma^\uparrow - d\sigma^\downarrow}{d\sigma^\uparrow + d\sigma^\downarrow} \equiv \frac{d\Delta\sigma}{2d\sigma},$$

with

$$d\Delta\sigma^{\text{CGI-GPM}} = \frac{2\alpha_S^2}{s} \sum_{a,b,c,d} \int \frac{dx_a dx_b}{x_a x_b} d^2\mathbf{k}_{\perp a} d^2\mathbf{k}_{\perp b} \left( -\frac{k_{\perp a}}{M_p} \right) f_{1T}^{\perp a}(x_a, \mathbf{k}_{\perp a}) \cos \varphi_a \\ \times f_{b/p}(x_b, \mathbf{k}_{\perp b}) H_{ab \rightarrow cd}^{\text{Inc}} \delta(\hat{s} + \hat{t} + \hat{u})$$

and

$$d\sigma = \frac{\alpha_S^2}{s} \sum_{a,b,c,d} \int \frac{dx_a dx_b}{x_a x_b} d^2\mathbf{k}_{\perp a} d^2\mathbf{k}_{\perp b} f_{a/p}(x_a, \mathbf{k}_{\perp a}) f_{b/p}(x_b, \mathbf{k}_{\perp b}) H_{ab \rightarrow cd}^U \delta(\hat{s} + \hat{t} + \hat{u}).$$

[note:  $d\Delta\sigma^{\text{GPM}} = d\Delta\sigma^{\text{CGI-GPM}} [H_{ab \rightarrow cd}^{\text{Inc}} \rightarrow H_{ab \rightarrow cd}^U]$ ]

# The reweighting method

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Never applied to a fit with actual data...

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M. Boglione, U. D'Alesio, CF, J.O. Gonzalez-Hernandez, F. Murgia, A. Prokudin, PLB 815 (2021) 136135

## BAYESIAN REWEIGHTING:

- consider a model for a TMD depending on  $\mathbf{a} = \{a_1, \dots, a_n\}$  parameters with prior probability distribution  $\pi(\mathbf{a})$

[if no prior knowledge exists,  $\pi(\mathbf{a})$  is flat]



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- parameter sets  $\mathbf{a}_k$  produced using Monte Carlo (MC) procedures

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Let's reweight the Sivvers function with STAR data!

# Reweighting the Sivers function (I)

M. Boglione, U. D'Alesio, CF, J.O. Gonzalez-Hernandez, JHEP 07 (2018) 148

- quark Sivers function **parametrization**:

$$\Delta^N f_{q/p^\dagger}(x, k_\perp) = \frac{4M_p k_\perp}{\langle k_\perp^2 \rangle_S} \Delta^N f_{q/p^\dagger}^{(1)}(x) \frac{e^{-k_\perp^2 / \langle k_\perp^2 \rangle_S}}{\pi \langle k_\perp^2 \rangle_S}$$

where  $q = u, d$ , and where  $\Delta^N f_{q/p^\dagger}^{(1)}(x)$  is the **Sivers first  $k_\perp$ -moment**:

$$\begin{aligned} \Delta^N f_{q/p^\dagger}^{(1)}(x) &= \int d^2 \mathbf{k}_\perp \frac{k_\perp}{4M_p} \Delta^N f_{q/p^\dagger}(x, k_\perp) \equiv -f_{1T}^{\perp(1)q}(x) \\ &= N_q (1-x)^{\beta_q} \end{aligned}$$

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M. Boglione, U. D'Alesio, CF, J.O. Gonzalez-Hernandez, JHEP 07 (2018) 148

- quark Sivers function **parametrization**:

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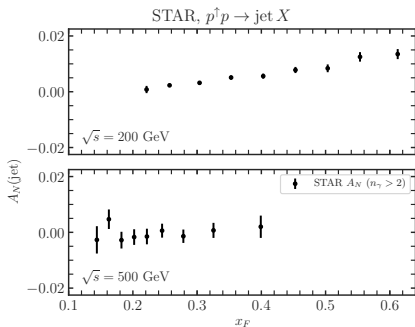
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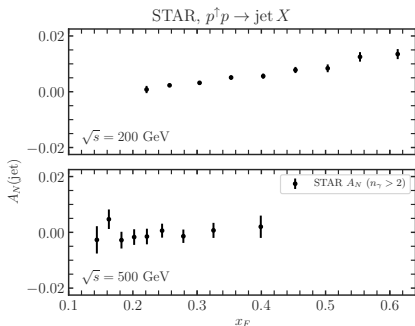
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M. Boglione, U. D'Alesio, CF, J.O. Gonzalez-Hernandez, F. Murgia, A. Prokudin, PLB 815 (2021) 136135;  
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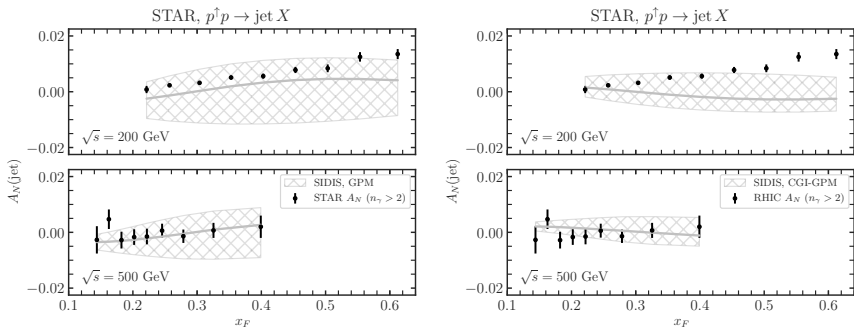
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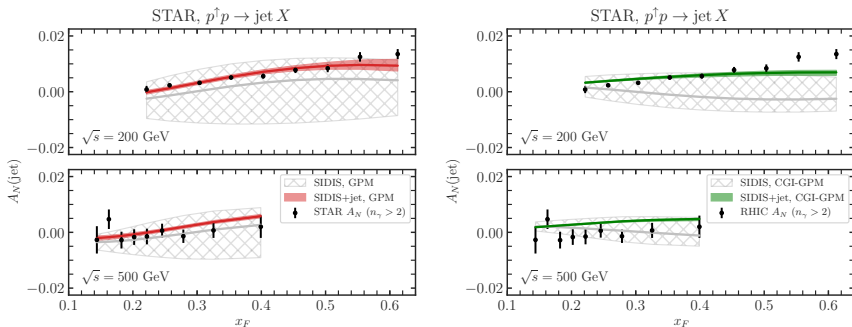


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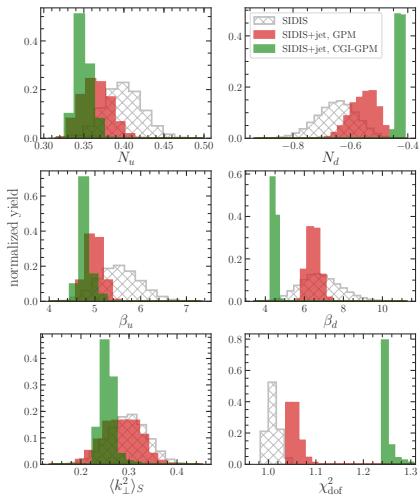
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# Reweighting the Sivers function (II)

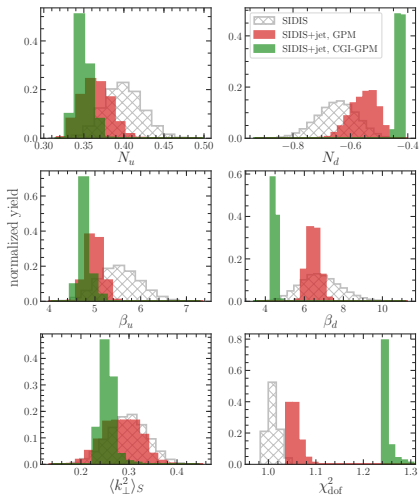
M. Boglione, U. D'Alesio, CF, J.O. Gonzalez-Hernandez, F. Murgia, A. Prokudin, PLB 815 (2021) 136135



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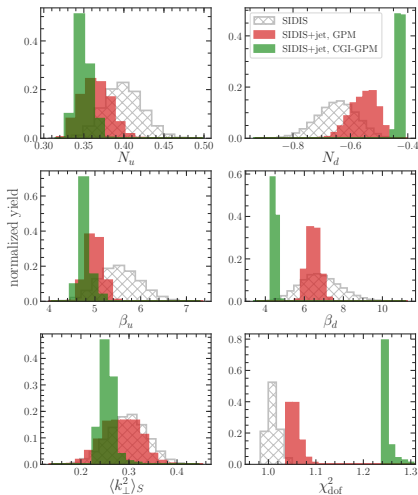


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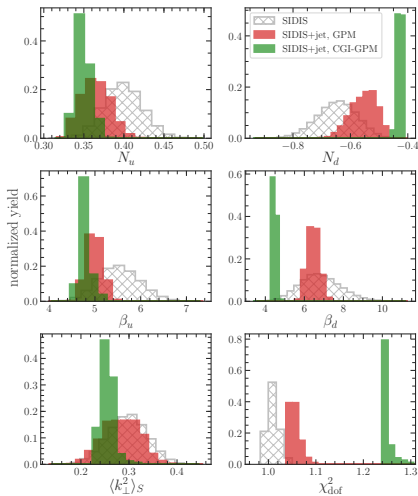


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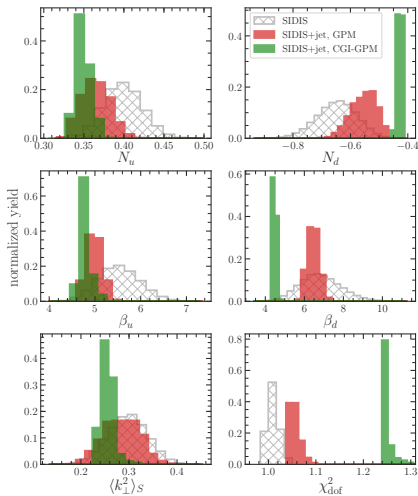


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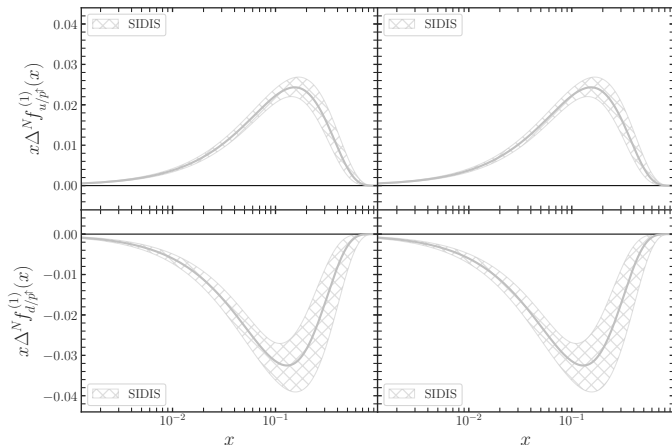


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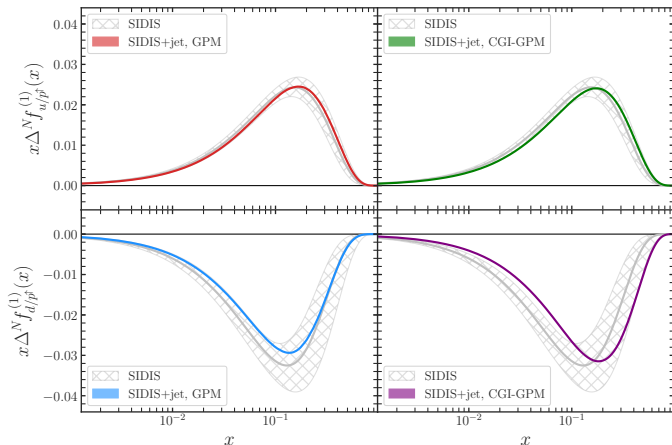
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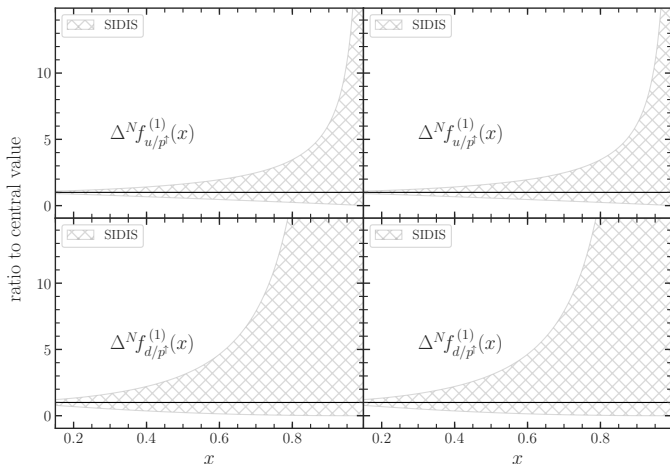


drastic reduction of uncertainties



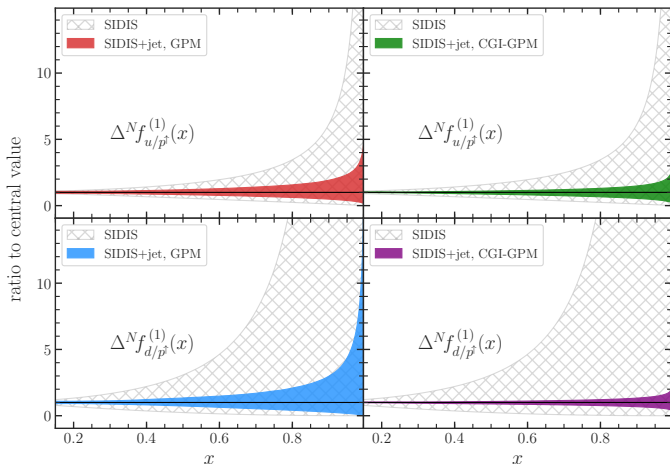
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STAR data allows to constrain the Sivers function at large  $x$ !

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- Forthcoming measurements from **COMPASS, JLab** and **the EIC** will play a **crucial role in unravelling the nucleon structure in its full complexity**

**Thank you**



**Backup**

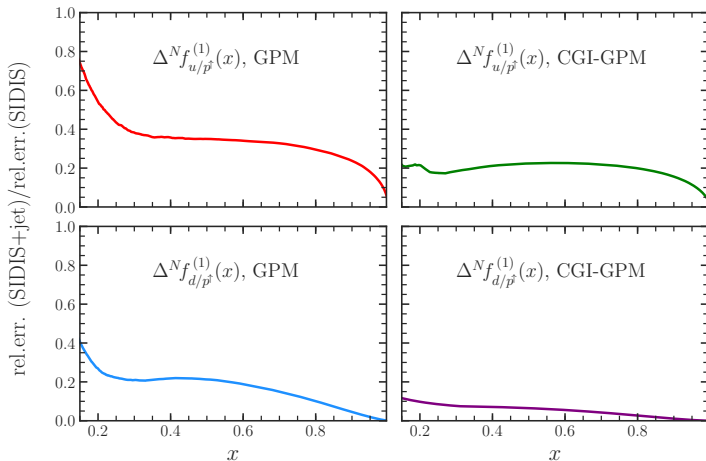
# Reweighting the Sivers function - parameters

M. Boglione, U. D'Alesio, CF, J.O. Gonzalez-Hernandez, F. Murgia, A. Prokudin, PLB 815 (2021) 136135

	SIDIS	SIDIS+jet, GPM	SIDIS+jet, CGI-GPM
$N_u$	$0.40^{+0.05}_{-0.04}$	$0.36^{+0.04}_{-0.03}$	$0.35^{+0.02}_{-0.01}$
$N_d$	$-0.65^{+0.13}_{-0.15}$	$-0.55^{+0.07}_{-0.10}$	$-0.43^{+0.01}_{-0.02}$
$\beta_u$	$5.52^{+0.93}_{-0.83}$	$4.98^{+0.34}_{-0.30}$	$4.79^{+0.28}_{-0.19}$
$\beta_d$	$6.77^{+2.29}_{-1.85}$	$6.45^{+0.63}_{-0.52}$	$4.48^{+0.17}_{-0.13}$
$\langle k_{\perp}^2 \rangle_S$	$0.30^{+0.08}_{-0.08}$	$0.28^{+0.07}_{-0.07}$	$0.26^{+0.03}_{-0.02}$
$\chi_{\text{dof}}^2$	$1.01^{+0.03}_{-0.02}$	$1.05^{+0.03}_{-0.01}$	$1.25^{+0.04}_{-0.01}$

# Reweighting the Sivvers function - relative errors

M. Boglione, U. D'Alesio, CF, J.O. Gonzalez-Hernandez, F. Murgia, A. Prokudin, PLB 815 (2021) 136135



Ratio of relative errors