Impact of Neutron DVCS Measurements on Extraction of Compton Form Factors

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Outline

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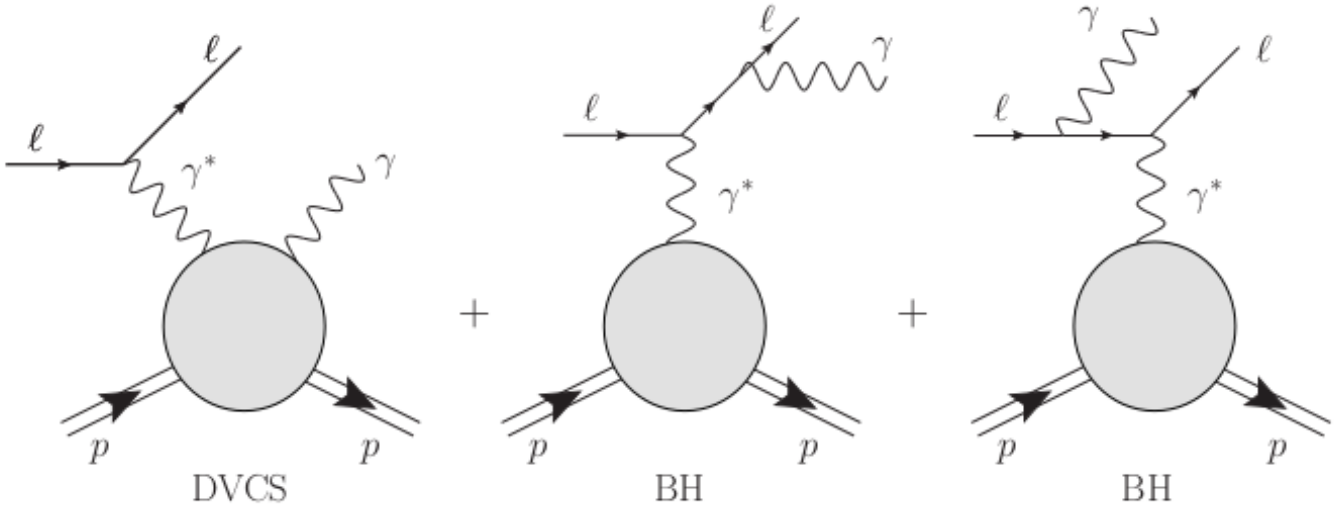
   - Conclusion

Deeply Virtual Compton Scattering

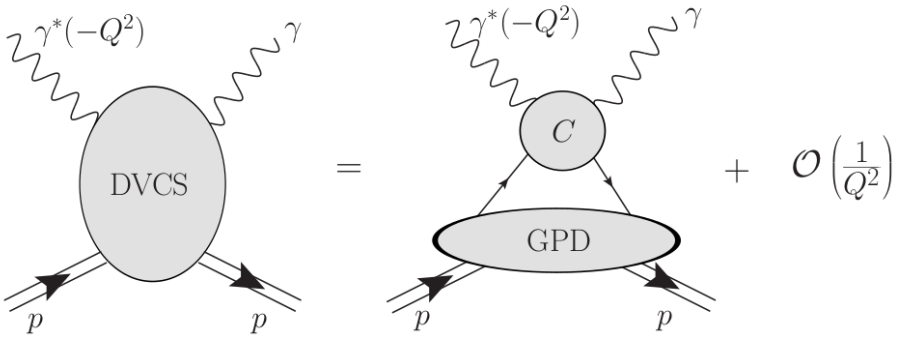
- exclusive process, measured via leptoproduction of a photon



- interference with the Bethe-Heitler process gives unique access to both real and imaginary parts of the DVCS amplitude

Accessing GPDs

- at leading order four complex twist-two Compton form factors $\mathcal{H}\left(\xi, t, Q^2\right), \mathcal{E}\left(\xi, t, Q^2\right), \widetilde{\mathcal{H}}\left(\xi, t, Q^2\right), \widetilde{\mathcal{E}}\left(\xi, t, Q^2\right)$
- factorization theorem [Collins et al. '98]



- CFFs are a convolution [Müller '92, et al. '94, Ji, Radyushkin '96]

$$^a\mathcal{H}\left(\xi, t, Q^2\right) = \int \mathrm{d}x\, C^a\left(x, \xi, \frac{Q^2}{Q_0^2}\right) \underbrace{H^a\left(x, \eta = \xi, t, Q_0^2\right)}_{\text{GPD}}, \; a = q, G$$

Types of models

1. "Physical" GPD (and CFF) model
2. Neural network parametrization of CFFs

Modelling GPDs

GPD evolution

- evolution in x space complicated, we introduce conformal moments

$$F_n(\eta, t) = \int_{-1}^{1} dx c_n(x, \eta) F(x, \eta, t)$$

$$c_n(x, \eta) = \eta^n \frac{\Gamma\left(\frac{3}{2}\right)\Gamma(1+n)}{2^n \Gamma\left(\frac{3}{2}+n\right)} C_n^{\frac{3}{2}}\left(\frac{x}{\eta}\right)$$

- $C_n^{3/2}$ Gegenbauer polynomials
- analytic continuation $n \to j \in \mathbb{C}$
- evolution diagonal in j space at LO

$$\mu \frac{d}{d\mu} F_j^q\left(\eta, t, \mu^2\right) = -\frac{\alpha_s(\mu)}{2\pi} \gamma_j^{(0)} F_j^q\left(\eta, t^2, \mu^2\right)$$

Hybrid model

- valence quarks modelled in x space ($q = u, d$) at crossover line $x = \eta$ (no Q^2 evolution)

$$\mathfrak{Im}\mathcal{H}(\xi, t) \overset{LO}{=} \pi \left[\frac{4}{9} H^{u_{\rm val}}(\xi, \xi, t) + \frac{1}{9} H^{d_{\rm val}}(\xi, \xi, t) + \frac{2}{9} H^{\text{sea}}(\xi, \xi, t) \right]$$

- sea quarks modelled in j space
- $SO(3)$ partial waves expansion
- leading contribution

$$H_j^a(\eta = 0, t) = N^a \frac{\mathrm{B}\left(1 - \alpha^a + j, \beta^a + 1\right)}{\mathrm{B}\left(2 - \alpha^a, \beta^a + 1\right)} \frac{\beta(t)}{1 - \dfrac{t}{\left(m_j^a\right)^2}},$$

$$\left(m_j^a\right)^2 = \frac{1 + j - \alpha^a}{\alpha'^a}, \quad \beta(t) = \left(1 - \frac{t}{M^2}\right)^{-p}, \quad a = \{s, g\}$$

- full NLO QCD Q^2 evolution

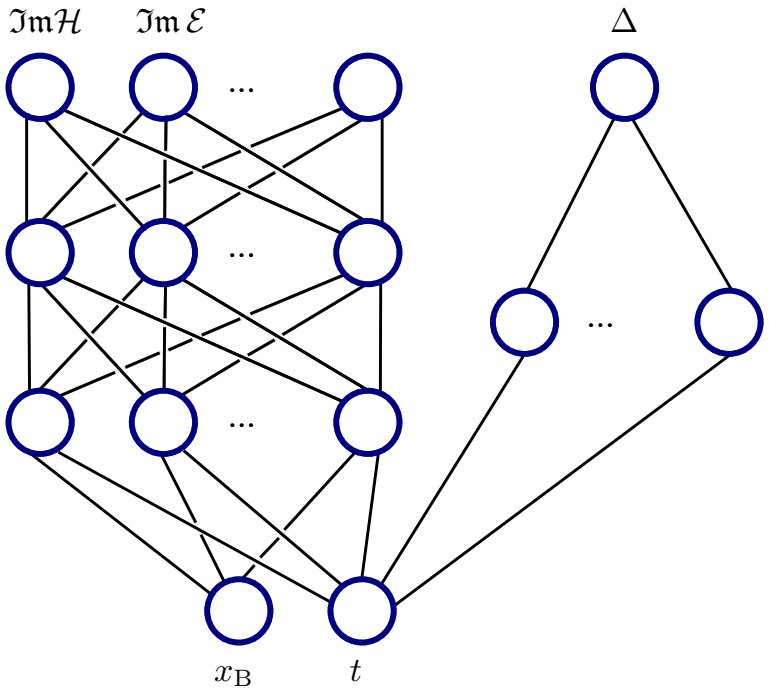
Dispersion relations

- CFFs constrained by dispersion relations

$$\mathfrak{Re}\,\mathcal{H}(\xi,t) \overset{LO}{=} \Delta(t) + \frac{1}{\pi}\mathrm{P.V.}\int_0^1 \mathrm{d}x \left(\frac{1}{\xi - x} - \frac{1}{\xi + x}\right) \mathfrak{Im}\,\mathcal{H}(x,t)$$

- only imaginary part of CFFs and one subtraction constant $\Delta(t)$ are modelled

Neural networks constrained by dispersion relations

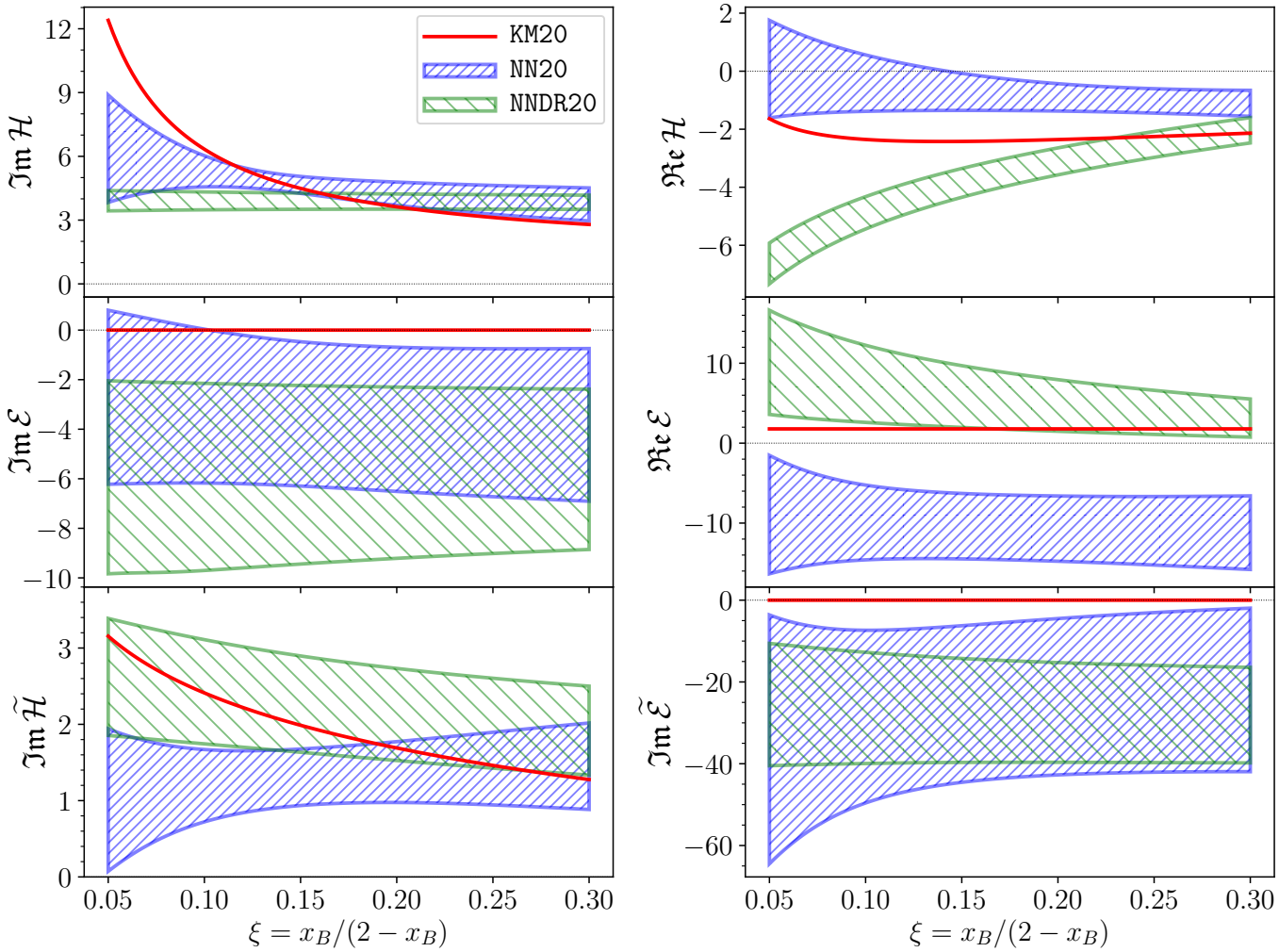


- Only imaginary part of CFFs and one subtraction constant $\Delta(t)$ are parametrized by neural nets

Results

Extraction of 6 CFFs

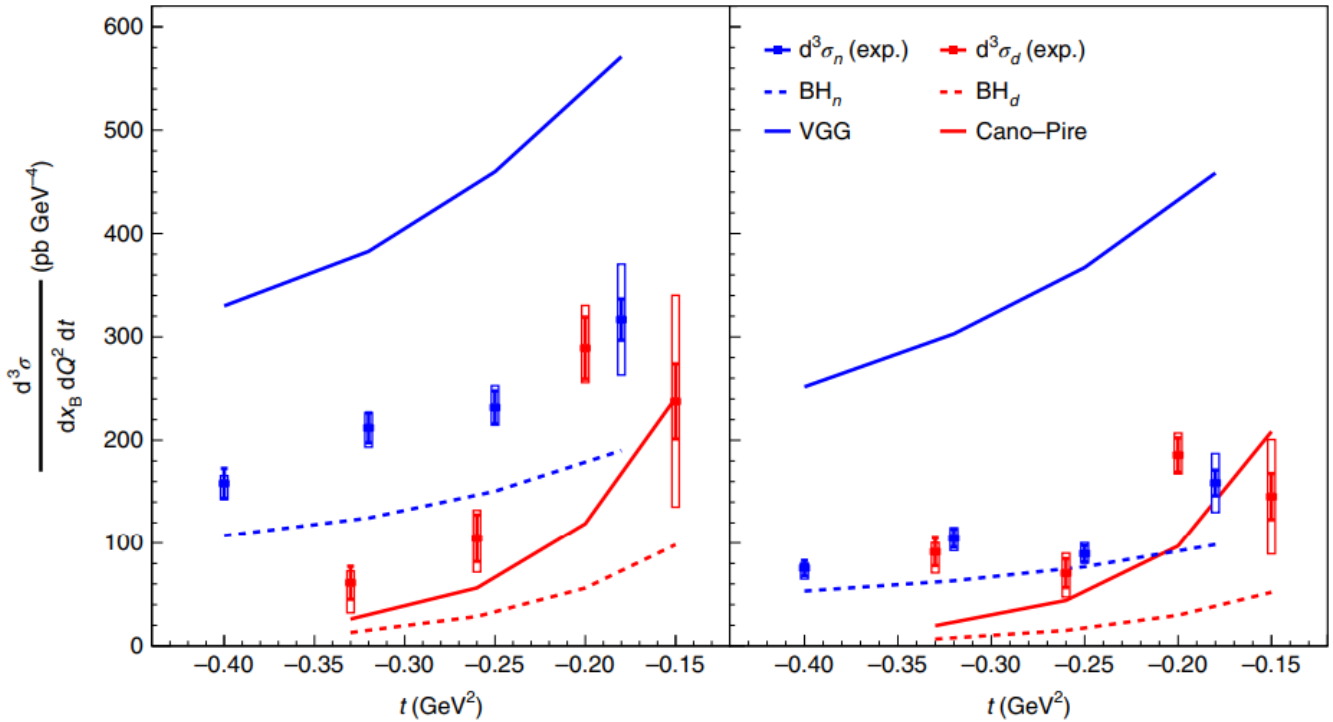
[M. Č., K. Kumerički, A. Schäfer, '20], from JLab Hall A data



$\mathcal{Q}^2 = 4$ GeV^2
$t = -0.2$ GeV^2

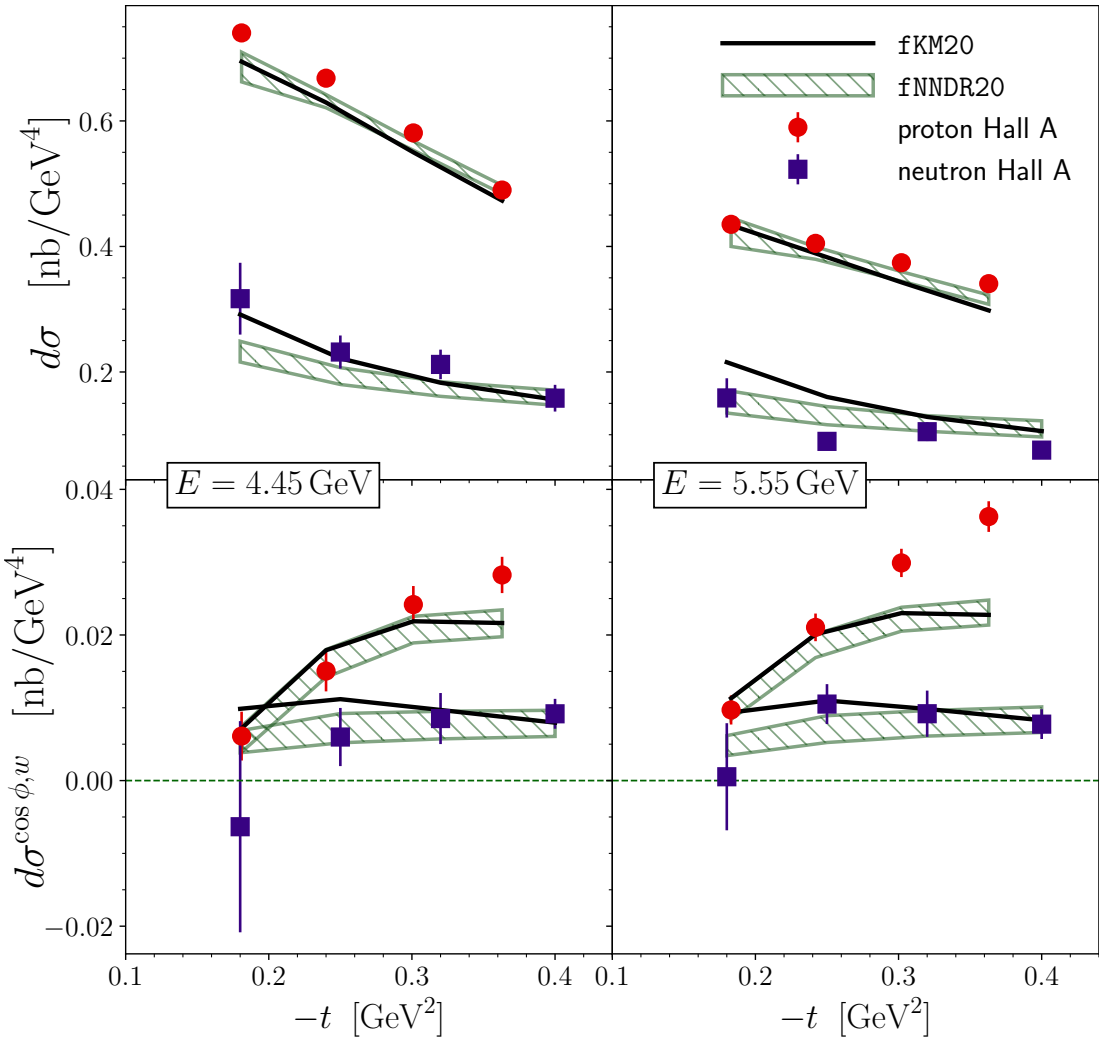
Neutron DVCS

[Benali et al. '20], DVCS off a deuterium target



Using isospin symmetry (e.g. $H^{\text{val}}_{u,\text{proton}} = H^{\text{val}}_{d,\text{neutron}}$) we combine proton and neutron DVCS data to separate up and down quark contributions to CFFs.

- separate model for each flavor CFF: $\mathcal{H}_u$, $\mathcal{H}_d$
- fKM20 "physical" flavored model, fNNDR neural nets and dispersion relations

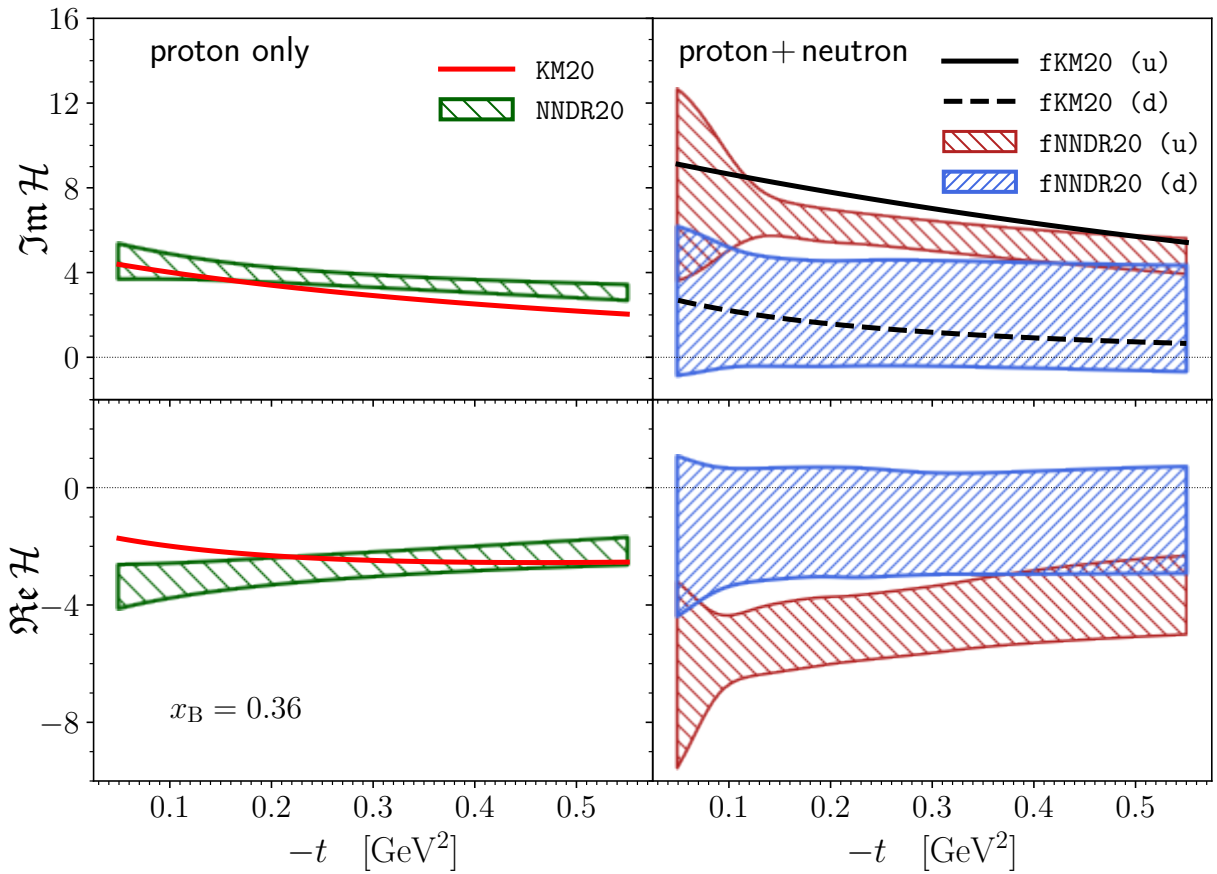


$x_B = 0.36$
$\mathcal{Q}^2 = 1.75$ GeV^2

Flavor CFFs

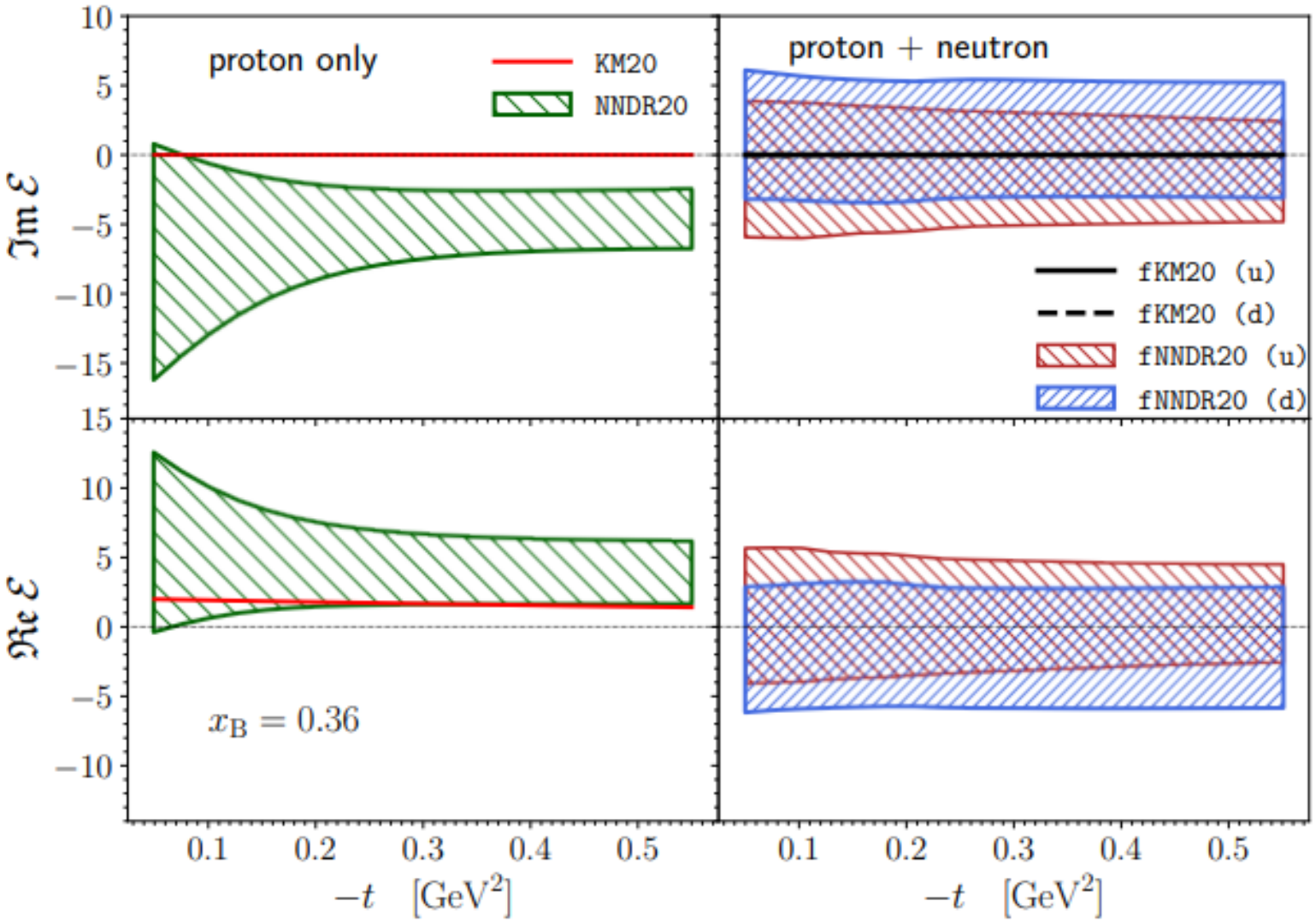
- up and down contributions to CFF $\mathcal{H}$ cleanly separated

$$\mathcal{H} = \frac{4}{9}\mathcal{H}_u + \frac{1}{9}\mathcal{H}_d$$



$x_B = 0.36$
$\mathcal{Q}^2 = 4$ GeV^2

- $\mathcal{E}$ cannot be separated



CLAS 12 GeV predictions

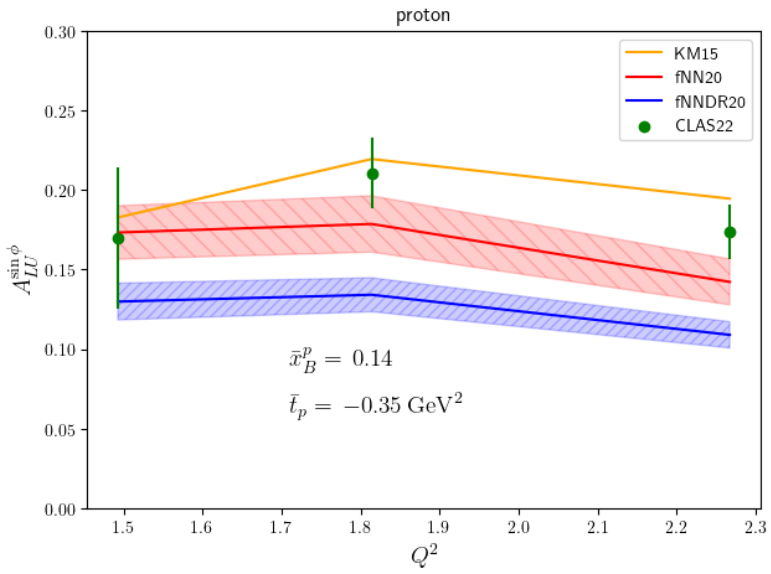
- proton and neutron beam spin asymmetry

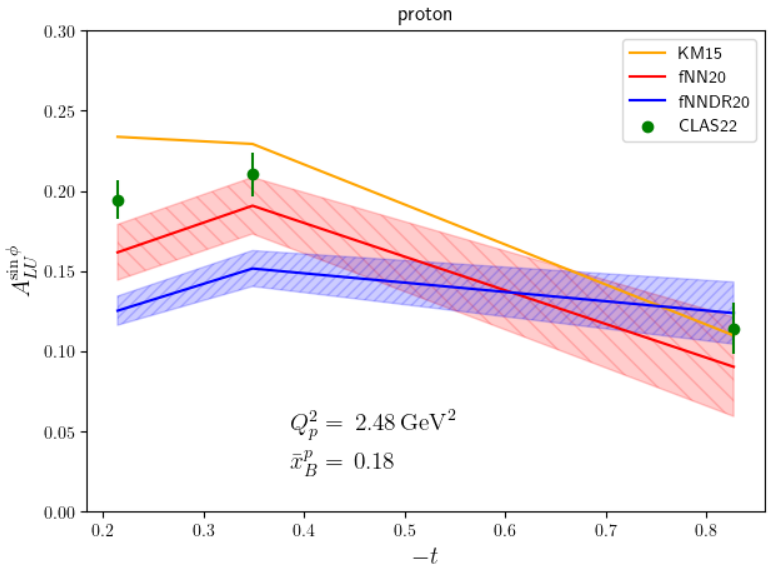
$$A_{LU} = \frac{d\sigma^{\uparrow} - d\sigma^{\downarrow}}{d\sigma^{\uparrow} + d\sigma^{\downarrow}} \propto \mathfrak{Im}\left\{F_1\mathcal{H} + \xi\left(F_1 + F_2\right)\widetilde{\mathcal{H}} - \frac{\Delta^2}{4M^2}F_2\mathcal{E}\right\}\sin(\phi)$$

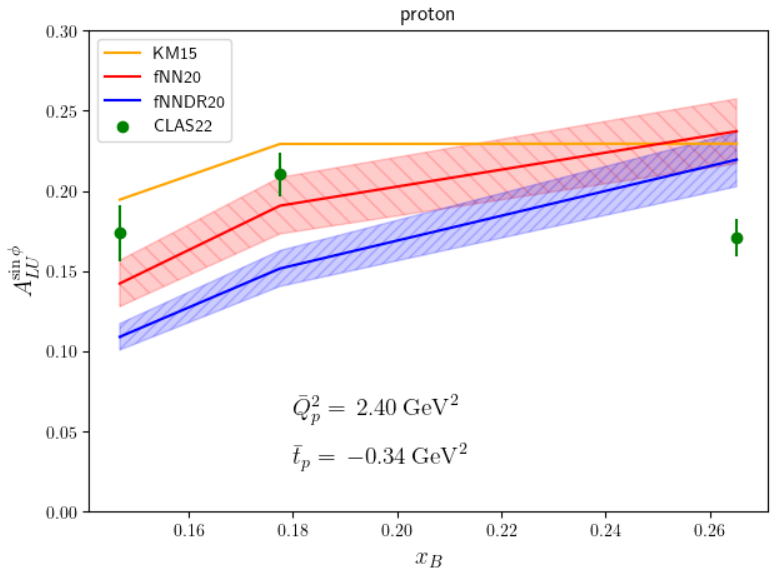
- we analyse harmonics with beam energy 10.4 GeV
- physical model only assumes isospin rotation

$$\mathcal{H}_n^{\mathrm{val}} = \frac{2e_d^2 + e_u^2}{2e_u^2 + e_d^2}\mathcal{H}^{\mathrm{val}} = \frac{2}{3}\mathcal{H}^{\mathrm{val}}\,, \quad \mathcal{H}_n^{\mathrm{sea}} = \mathcal{H}^{\mathrm{sea}}$$

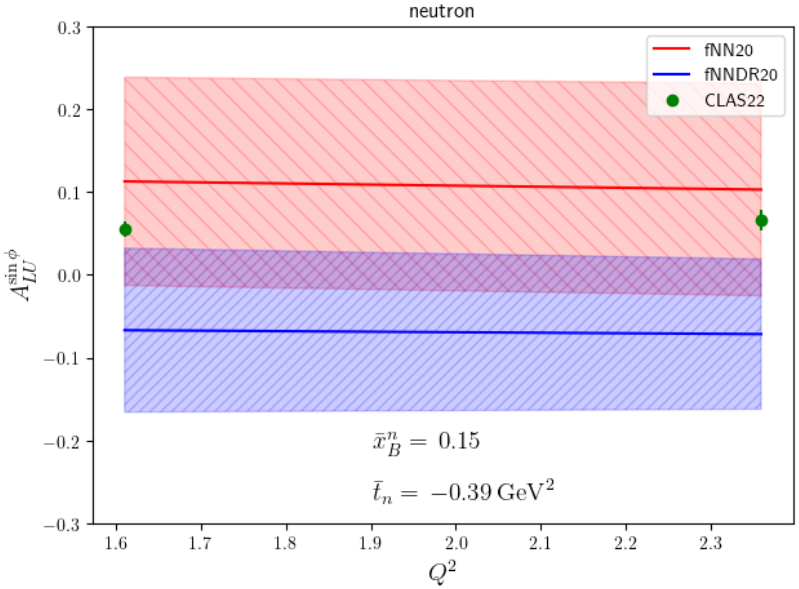
2020 models predictions

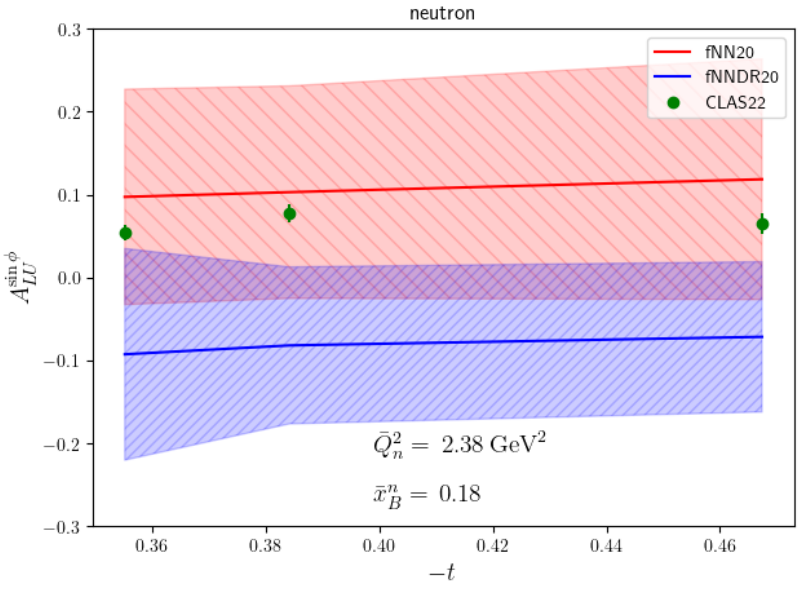


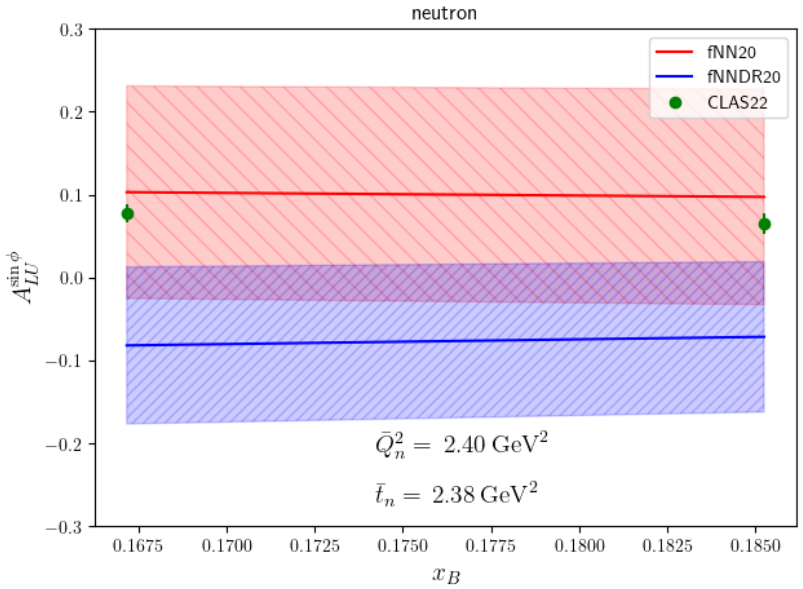




CLAS22 predictions







Reweighting

- reweighting neural nets according to their χ^2
- for the 2020 paper we had 20 neural nets in each model. Now we generated additional 80 nets (same training procedure, same old data) to "improve statistics"
- most χ^2 were still too large, formal reweighting yields just one "best" net
- hand selecting the best nets still yields too few nets
- it seems that reweighting procedure is appropriate for the situation where new data is just a refinement of the old data, and not when completely new observables are being measured

New fits with CLAS 2022 data

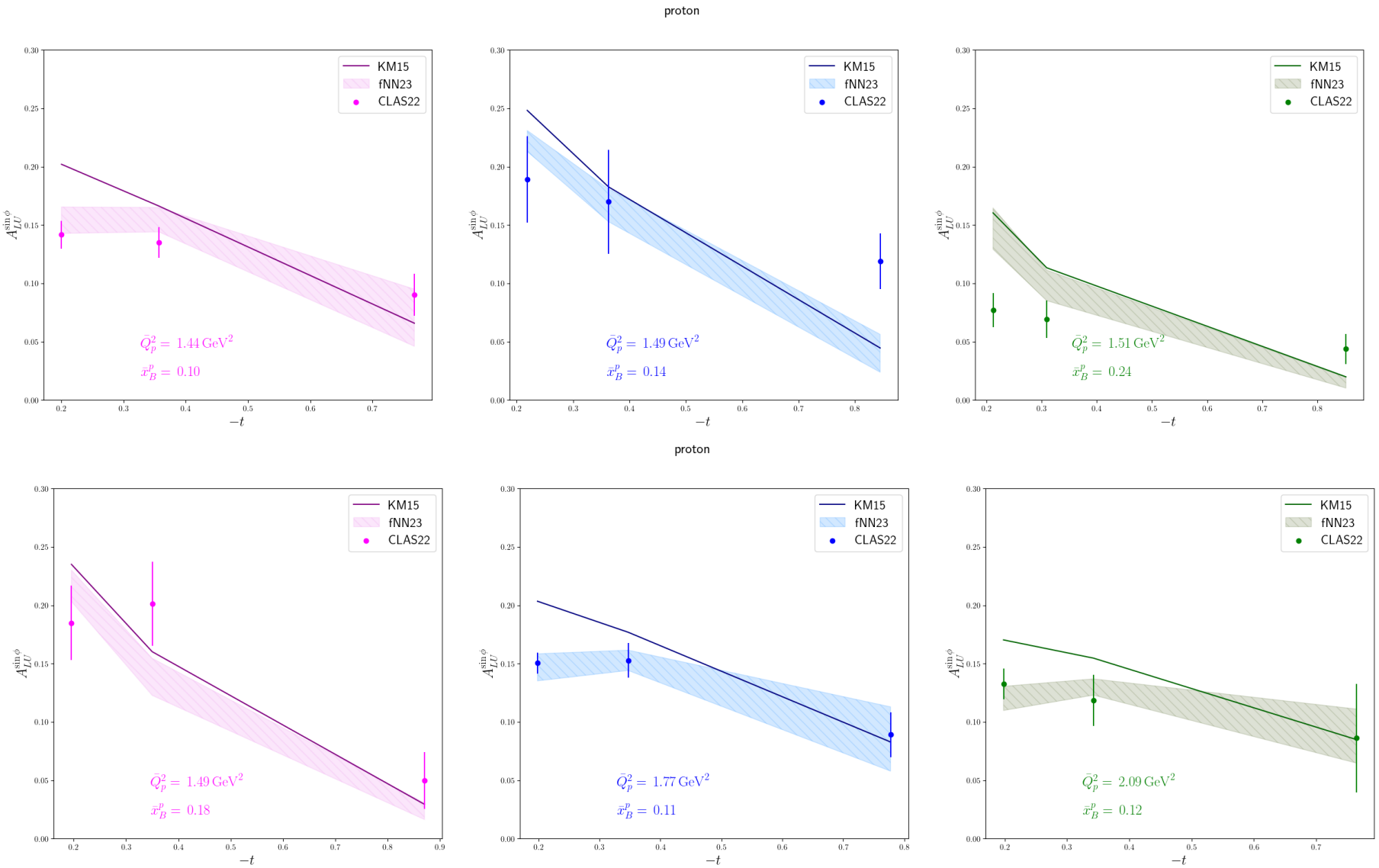
- We performed new NN and NNDR fits on harmonics with new CLAS 2022 data (39 points with $-t < 0.5$ GeV^2) and previously available JLab data (257 points)

	2020	2023
fNN	1.5	1.25
fNNDR	1.5	>3

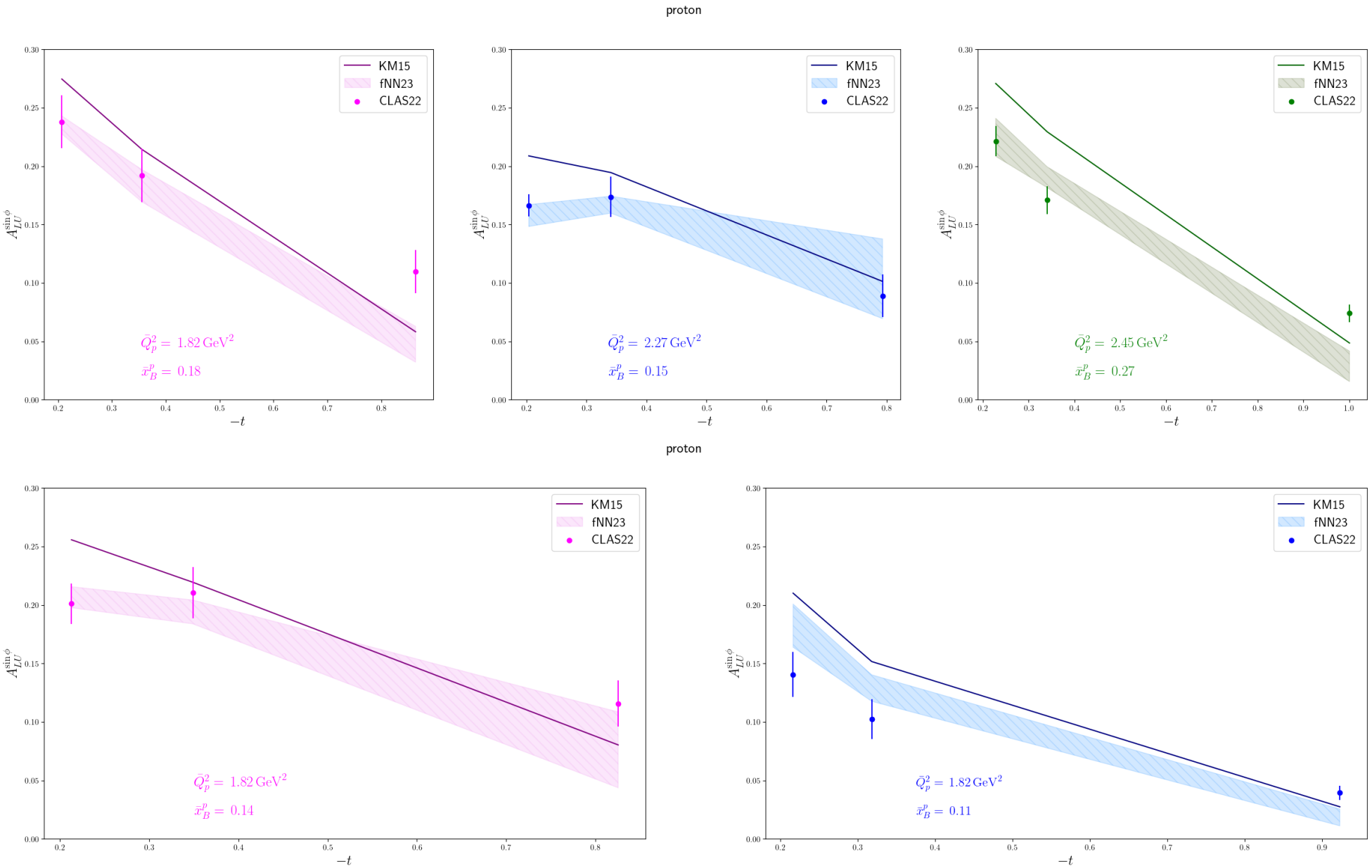
Table: χ^2/N_{pts}

- new data clearly exclude the fNNDR model
- we also trained NN and NNDR models on only CLAS data (excluding Hall A data): fNNC23 and fNNDRC23 models
- fNNC23 behaves better than fNNDRC23, just like fNN23 outperforms fNNDR23, but fNN23 still outperforms all of them

Proton data

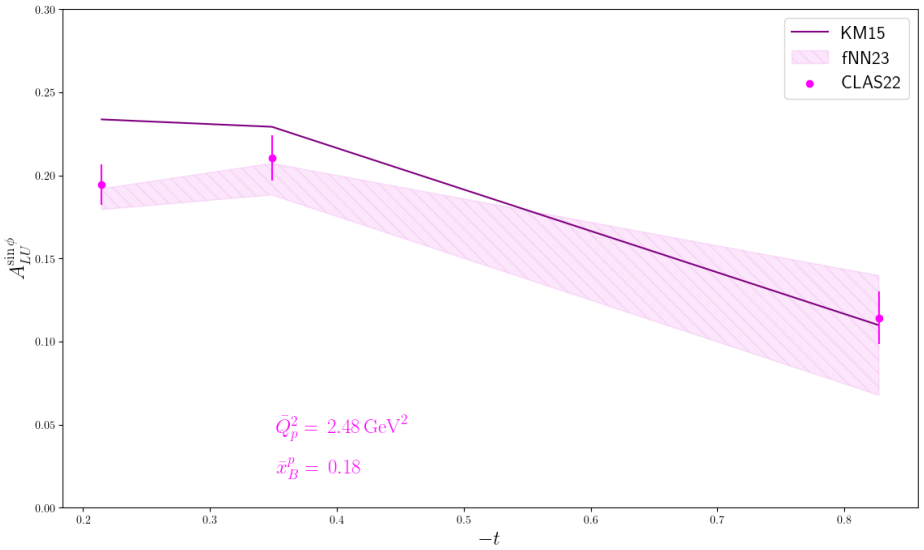

proton
KM15
fNN23
CLAS22
$\bar{Q}_p^2 = 1.44\,\mathrm{GeV}^2$
$\bar{x}_B^p = 0.10$
$\bar{Q}_p^2 = 1.49\,\mathrm{GeV}^2$
$\bar{x}_B^p = 0.14$
$\bar{Q}_p^2 = 1.51\,\mathrm{GeV}^2$
$\bar{x}_B^p = 0.24$
proton
$\bar{Q}_p^2 = 1.49\,\mathrm{GeV}^2$
$\bar{x}_B^p = 0.18$
$\bar{Q}_p^2 = 1.77\,\mathrm{GeV}^2$
$\bar{x}_B^p = 0.11$
$\bar{Q}_p^2 = 2.09\,\mathrm{GeV}^2$
$\bar{x}_B^p = 0.12$
$A_{LU}^{\sin\phi}$
$-t$

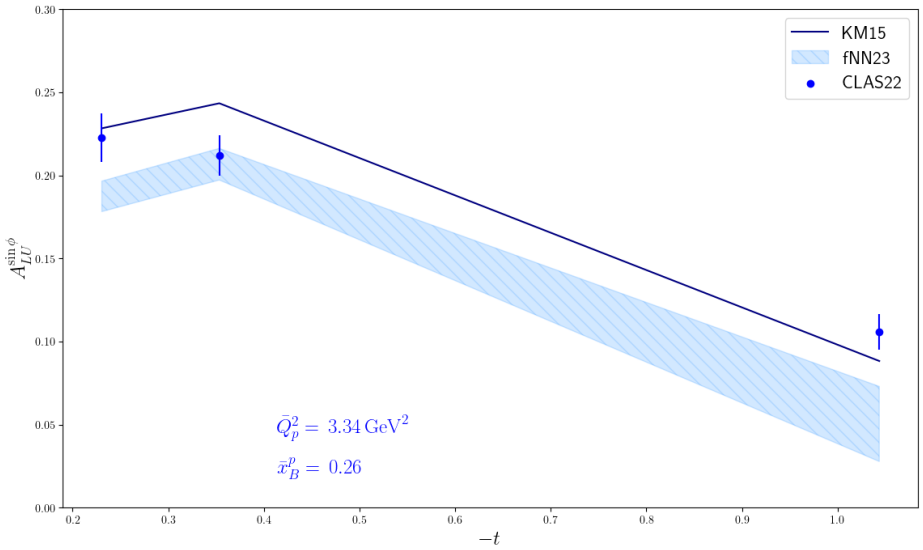
CLAS22 predictions



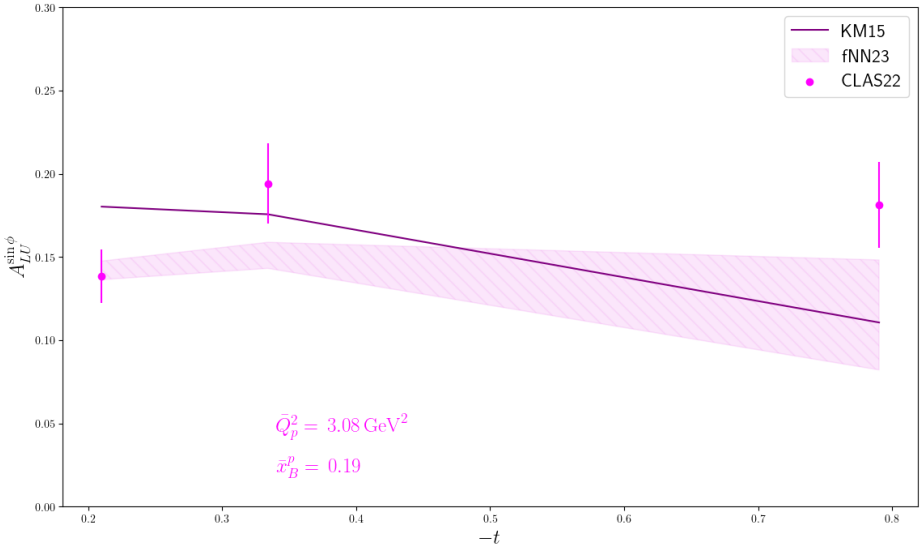
CLAS22 predictions

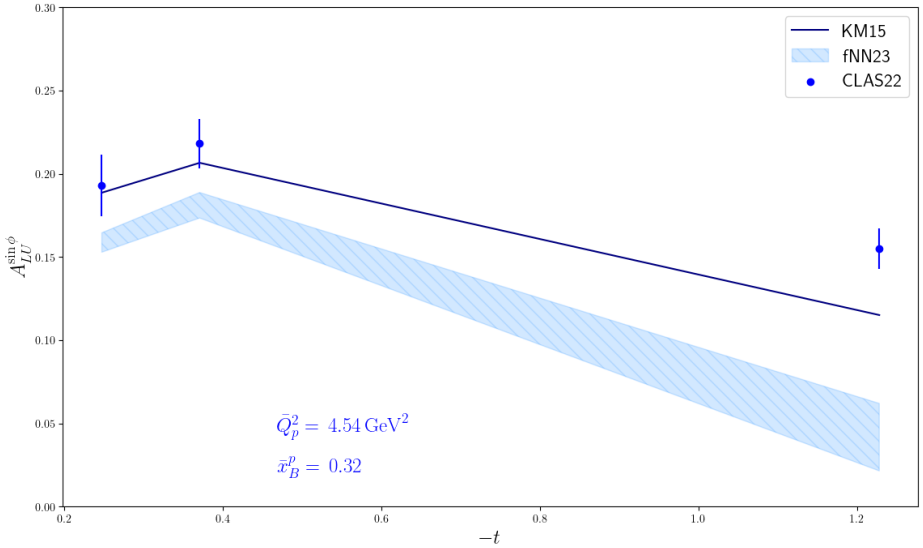
proton



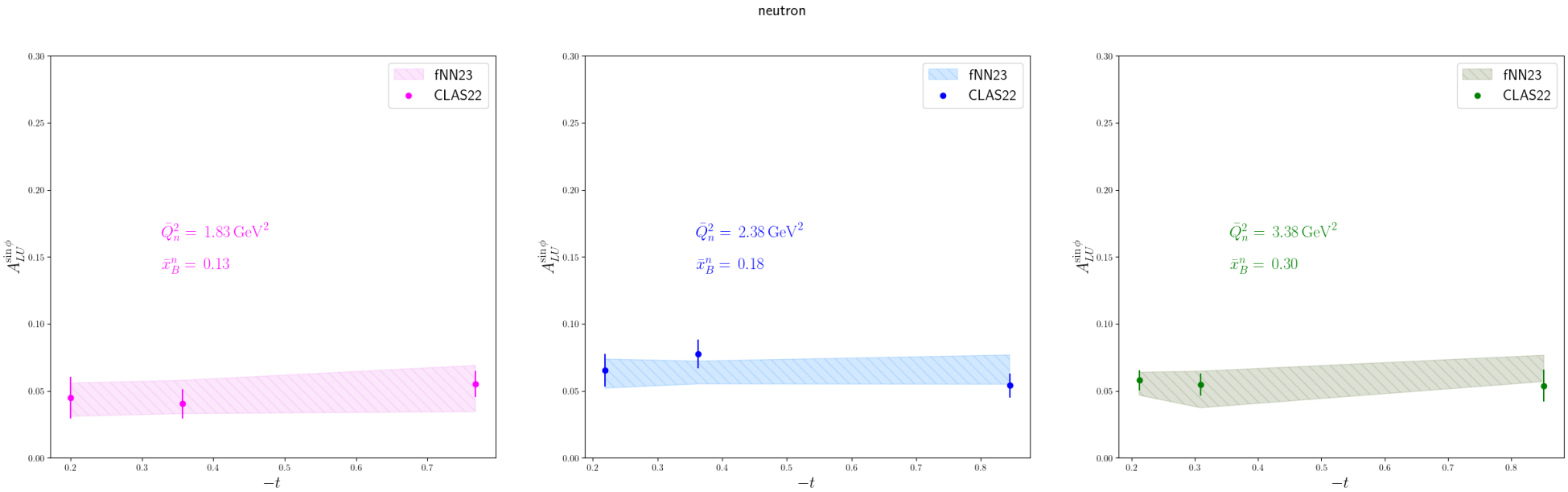


proton

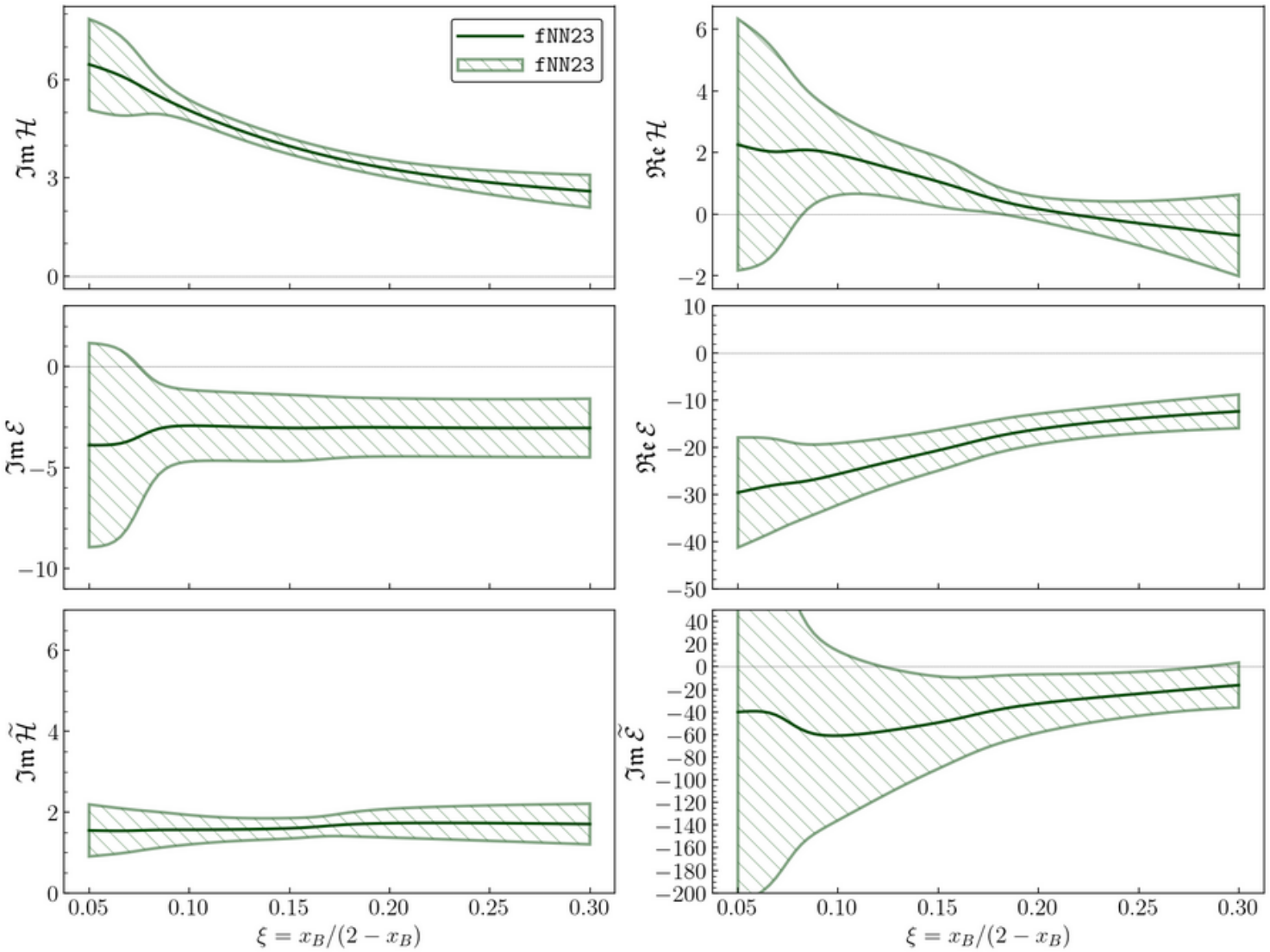




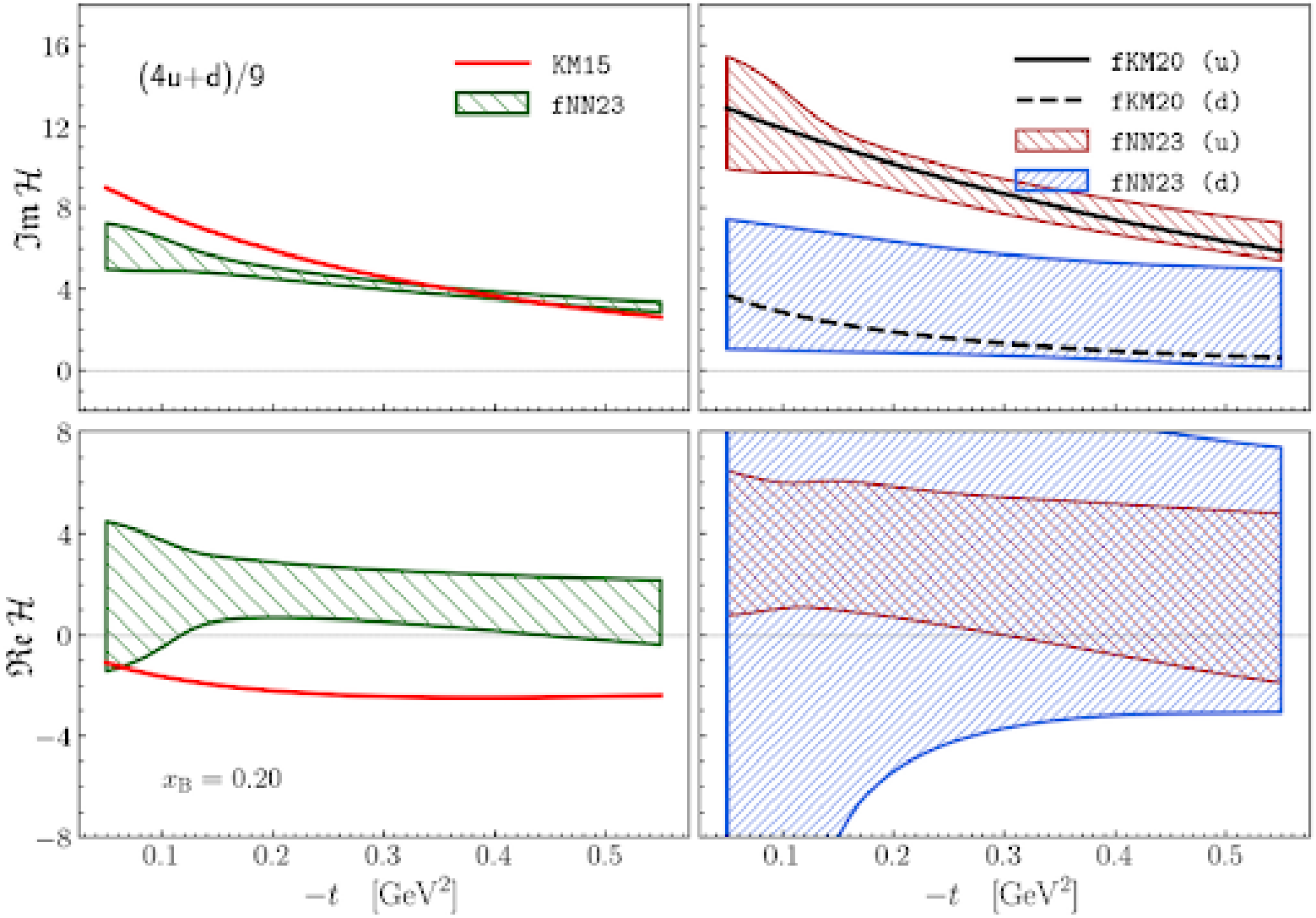
Neutron data



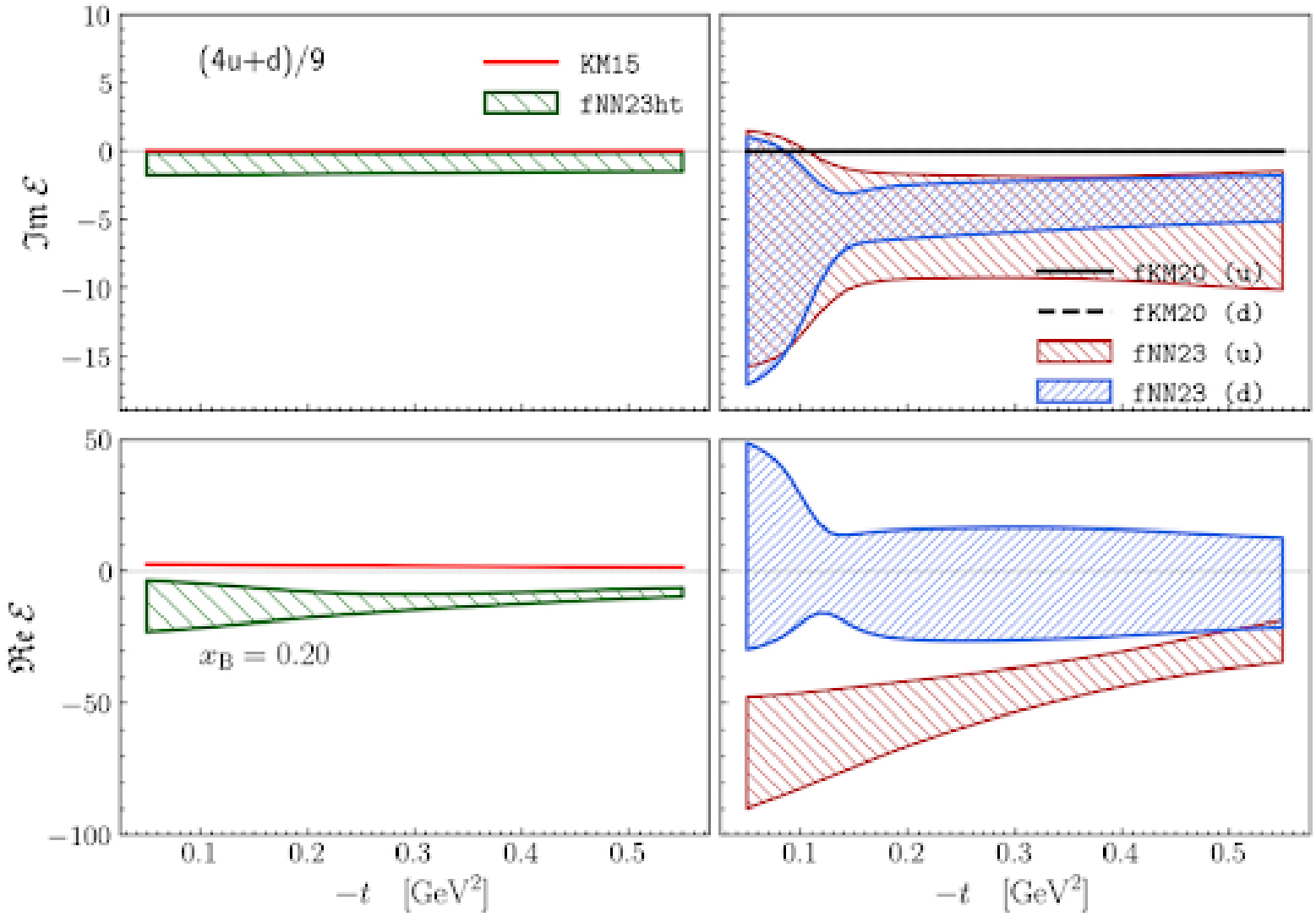
New CFF extraction



Flavor separation of CFF $\mathcal{H}$



Flavor separation of CFF $\mathcal{E}$



Conclusion

- new data favours models without dispersion relations
- 2020 data allows for flavour separation of CFF $\mathcal{H}$, but not $\mathcal{E}$
- 2022 data allows for flavour separation of $\mathfrak{Im}\,\mathcal{H}$ and $\mathfrak{Re}\,\mathcal{E}$