

REFINEMENT OF THE PION PDF IMPLEMENTING DRELL- YAN EXPERIMENTAL DATA

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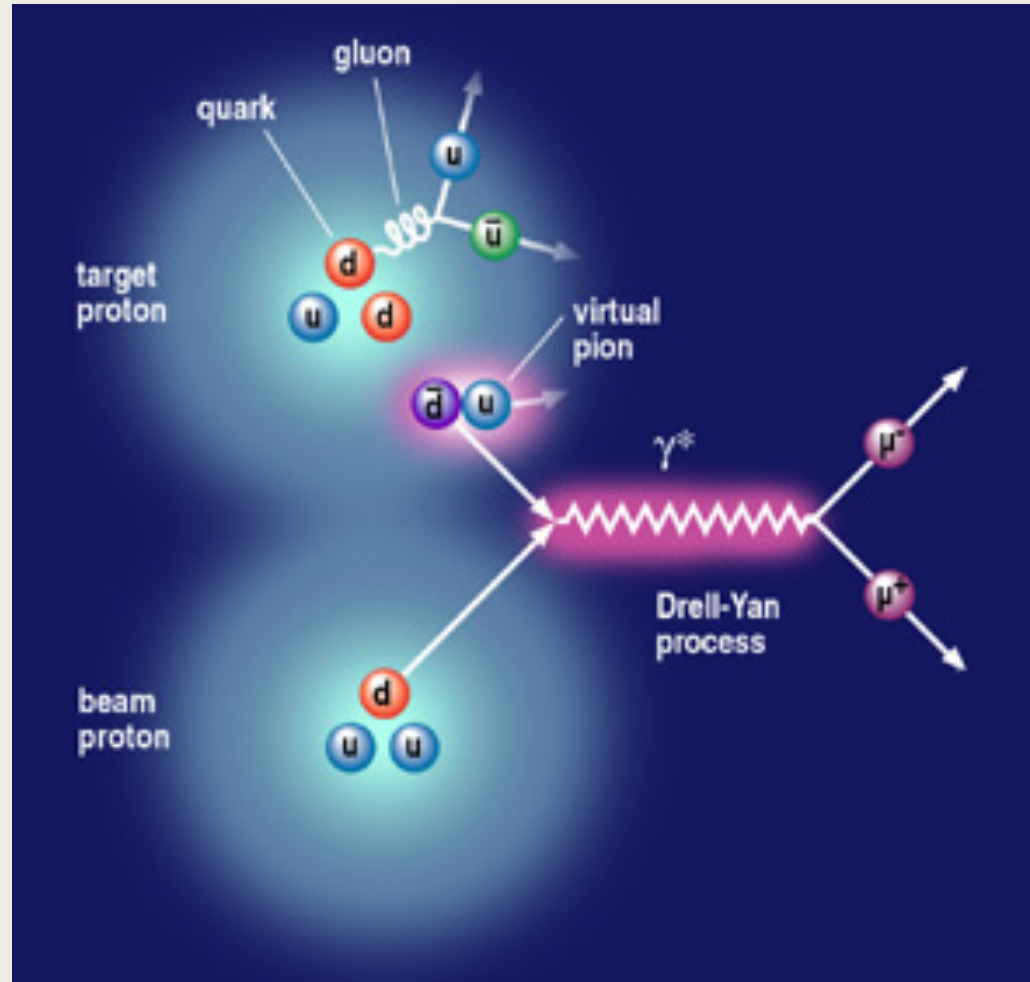
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Drell-Yan process



- Two hadrons collide
 - *Do not need to be protons!*
- One donates a quark, other an antiquark
- Quarks annihilate into a virtual photon
- Dilepton production
- Measure differential cross-section of lepton/antilepton pair

Cross section

$$\frac{d^2\sigma}{dQ^2 dY} = \frac{4\pi\alpha^2}{3N_c Q^2 s} \sum_{i,j} \int dx_1 dx_2 \tilde{C}_{ij}(x_1, x_2, s, M, \mu_f) f_{i/N_1}(x_1, \mu_f) f_{j/N_2}(x_2, \mu_f)$$

- Cross-section differential in invariant mass of lepton pair, Q^2 , and rapidity, Y
- The momentum fractions of the initial hadrons are x_1, x_2
- Parton distribution functions (PDFs) are $f_i(x, Q^2)$
- Sum over all partons

PDFs

- Parameterize the PDF at $Q_0^2 = 1\text{GeV}^2$ as:

$$f(x, \mu^2) = N x^a (1 - x^b)$$

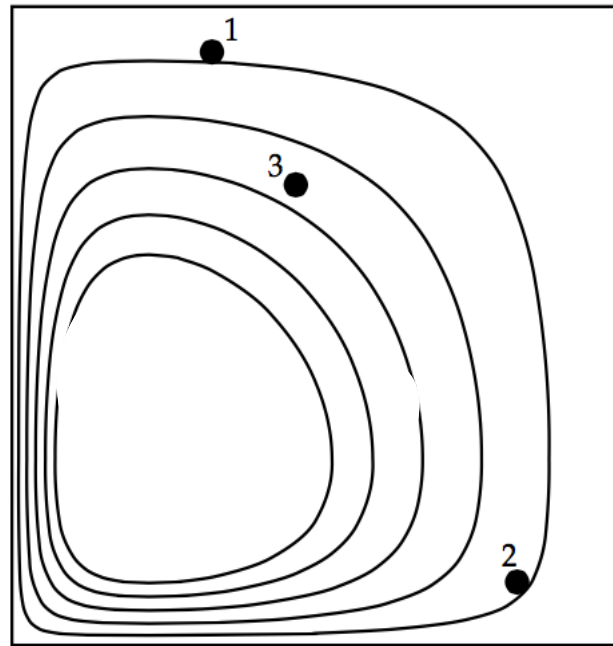
- Definitions: $q_v = \bar{u}_v = d_v$; $q_s = 2(u + \bar{d} + s)$; g
- Use sum rules to fix N_{q_v}, N_g
- We fit a, b for the valence, sea, and gluon, and N for the sea
- PDFs are evolved using DGLAP in Mellin space

Nested Sampling

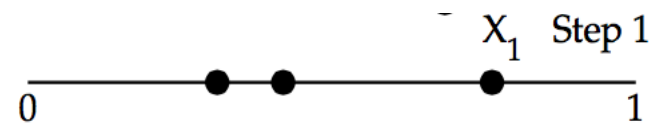
- Monte Carlo fitting method
- Create parameter space to have a uniform prior over a specified range
- Sample points in parameter space closer and closer to the maximum likelihood
- Weights produced with each sample based on proximity to maximum likelihood
- Provides errors without assumption of linear error propagation

$$Var(\mathcal{O}) \propto \sum_k (\mathcal{O}_k - E(\mathcal{O}))^2$$

Nested Sampling



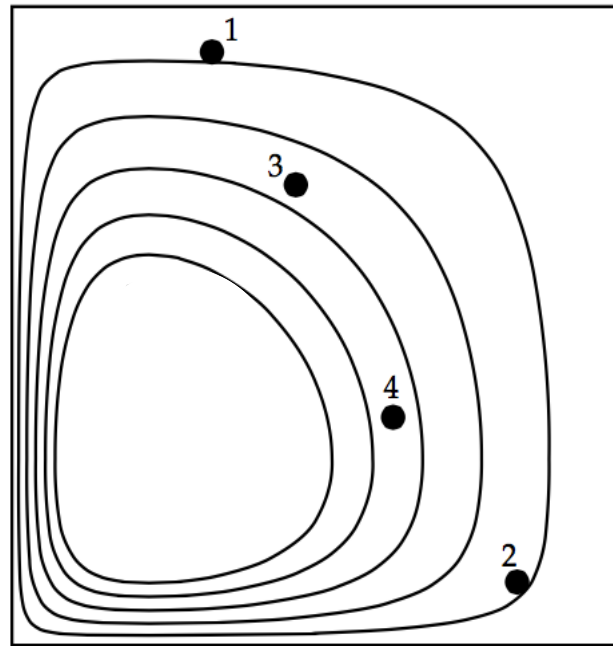
Parameter space



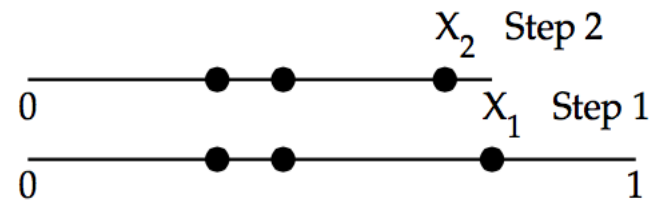
Enclosed prior mass X

- Start with random points on line of $0 < X < 1$.
- $X = 0$ is the point of highest likelihood.

Nested Sampling



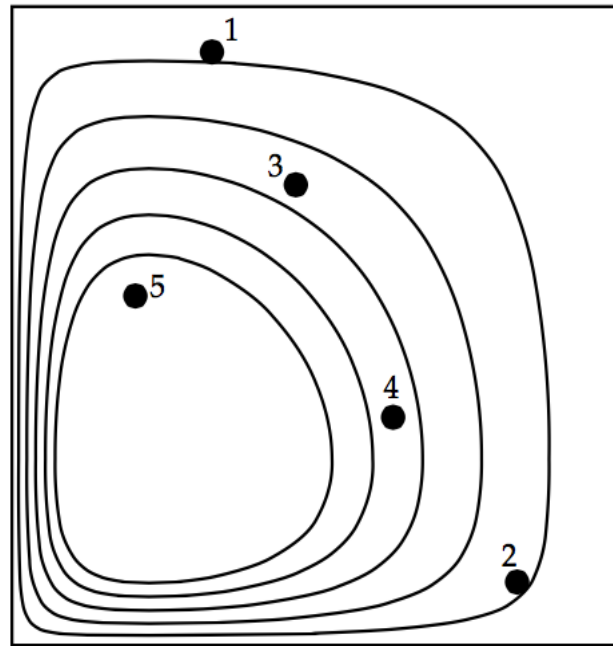
Parameter space



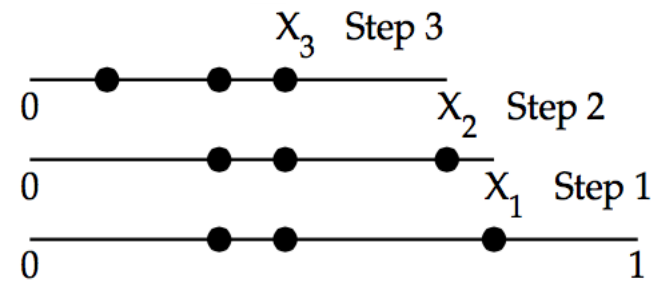
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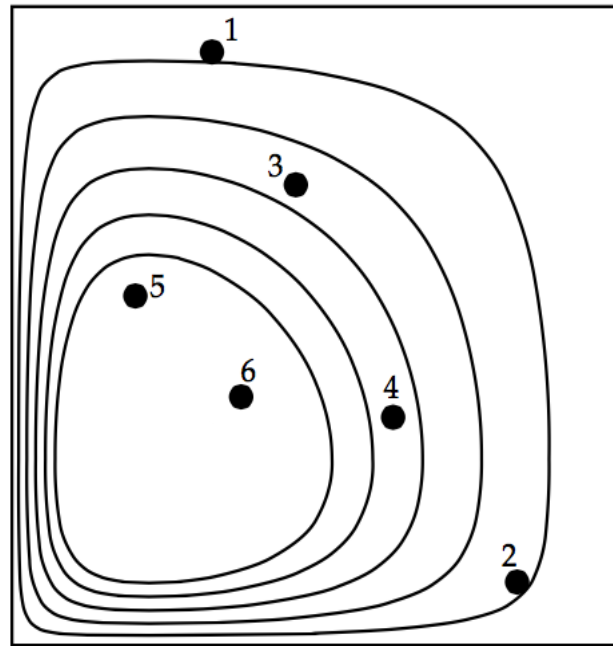
Parameter space



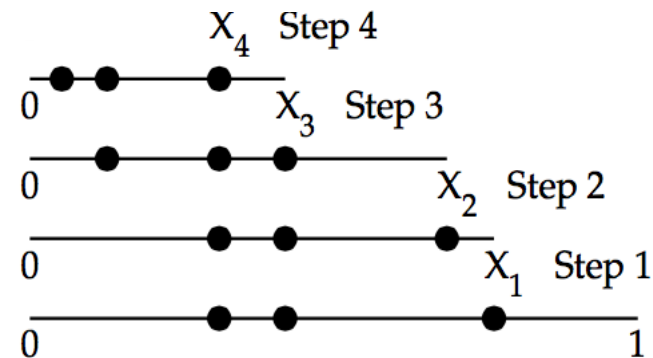
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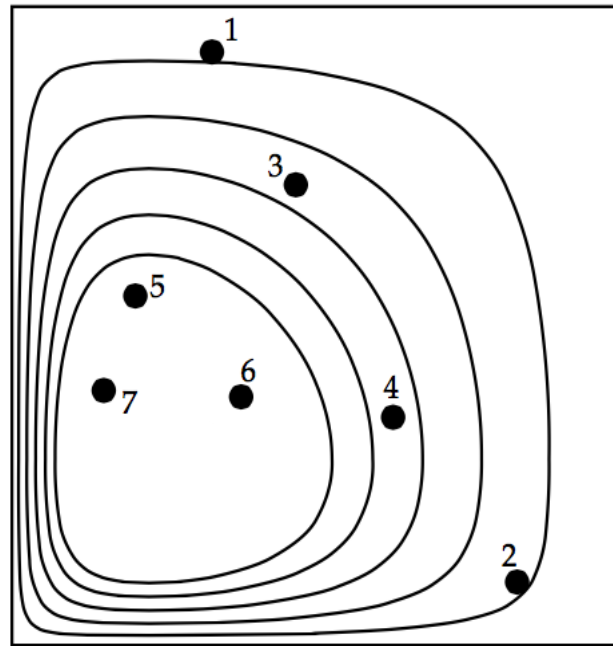
Parameter space



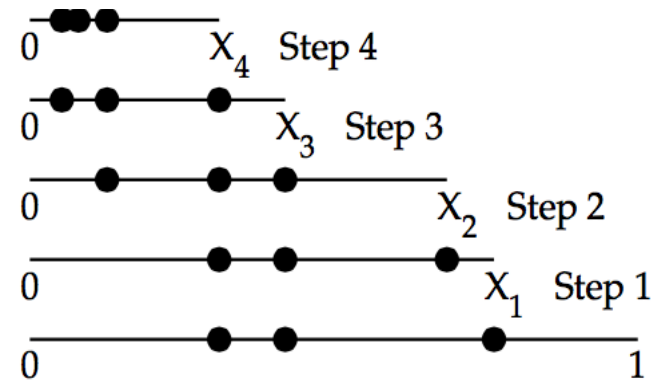
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- Keep randomly sampling until a threshold is reached

Nested Sampling



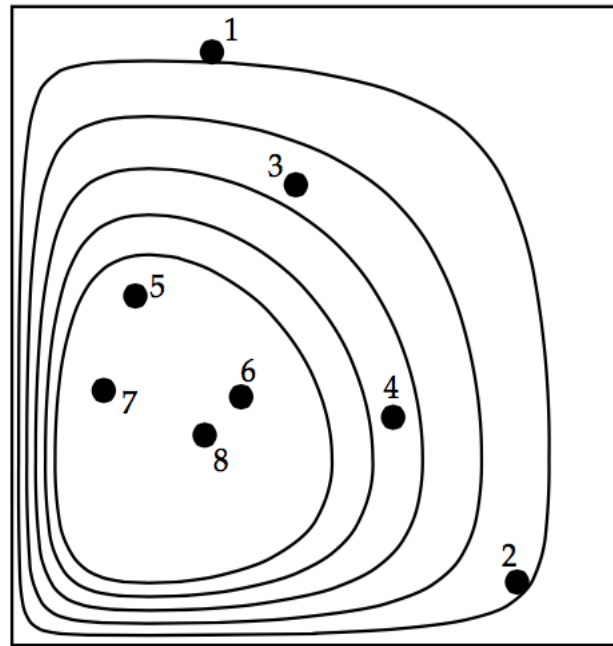
Parameter space



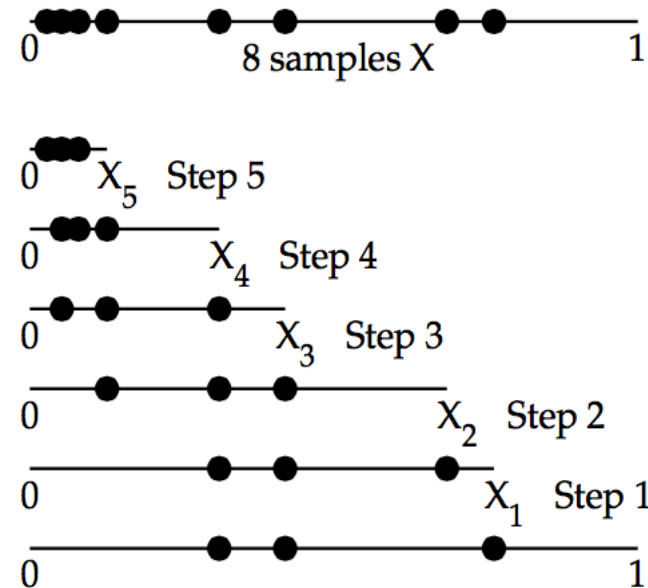
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Parameter space



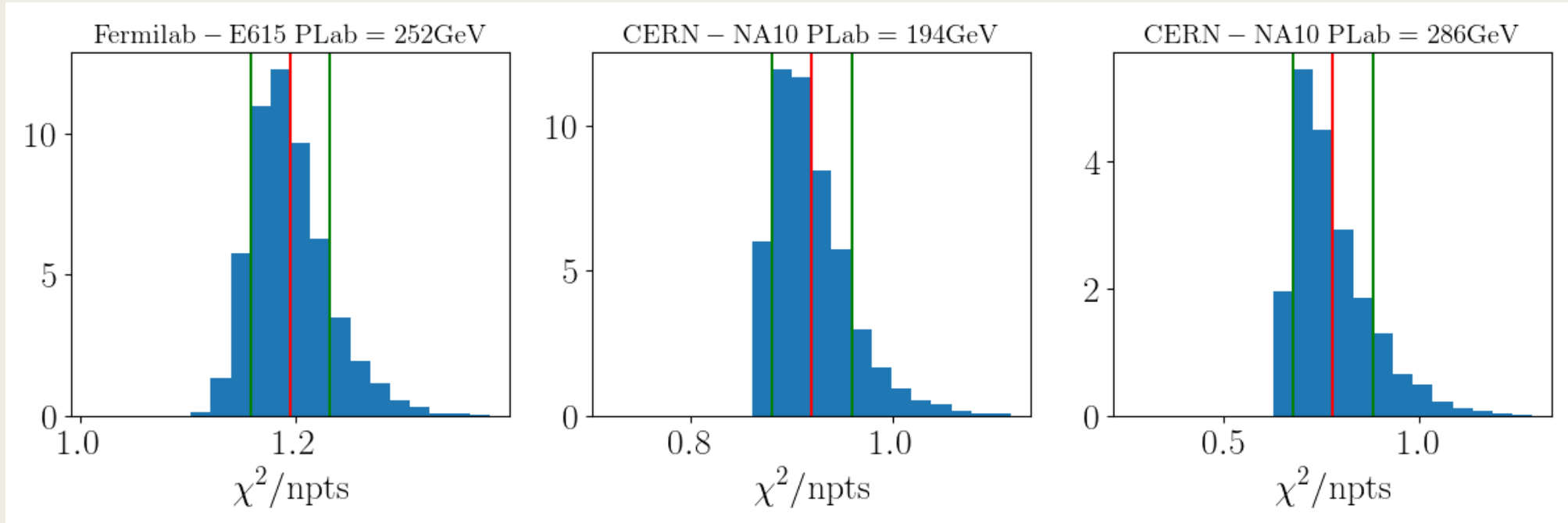
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Datasets & Constrictions

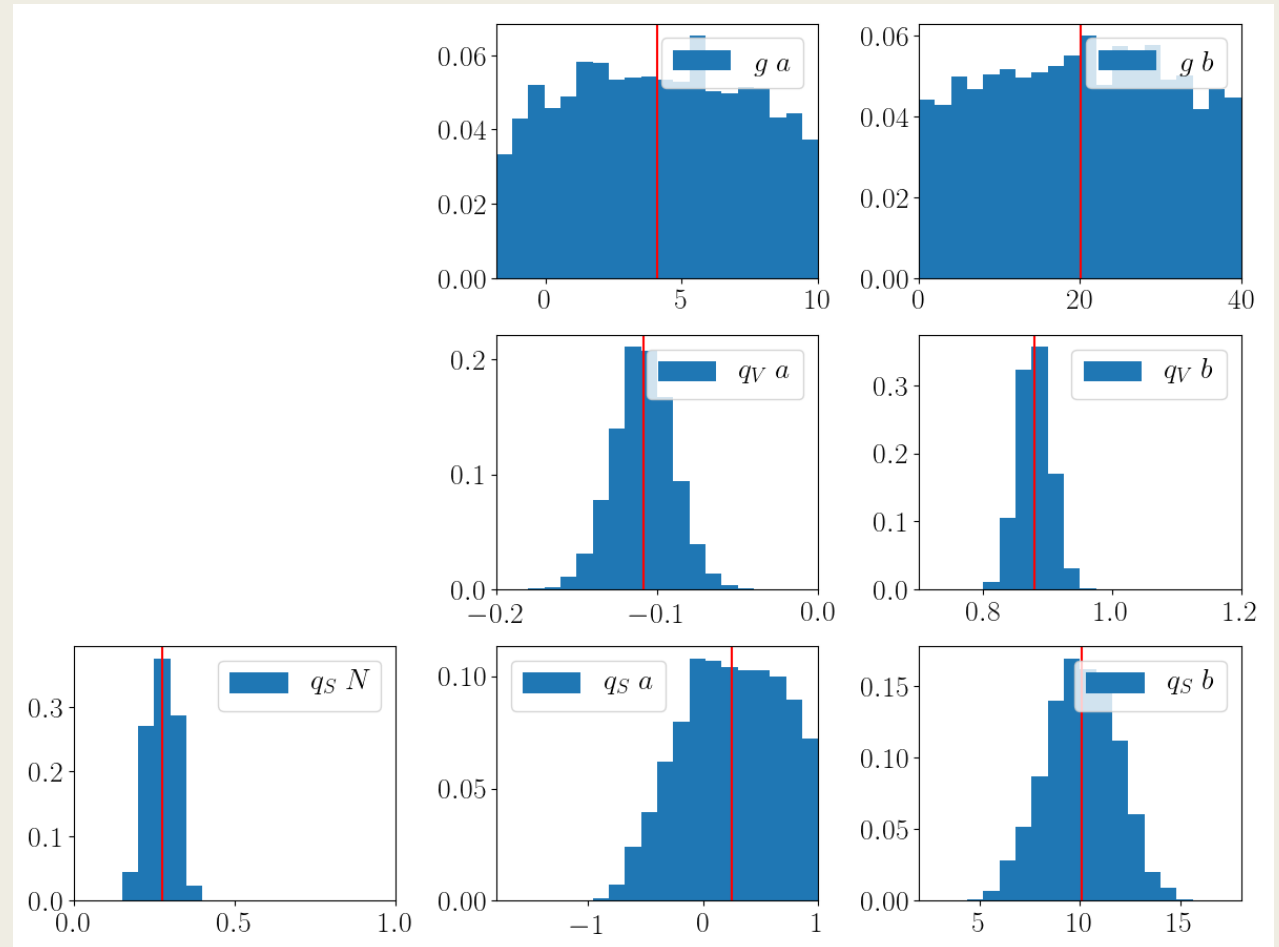
- For Drell-Yan, we use E615 and NA10 datasets
 - π^- beam incident on a Tungsten target
 - Consider only $0 < x_F < 0.9$ and $4.16 < Q < 8.34$ to avoid J/Ψ and Υ production

Drell-Yan fits

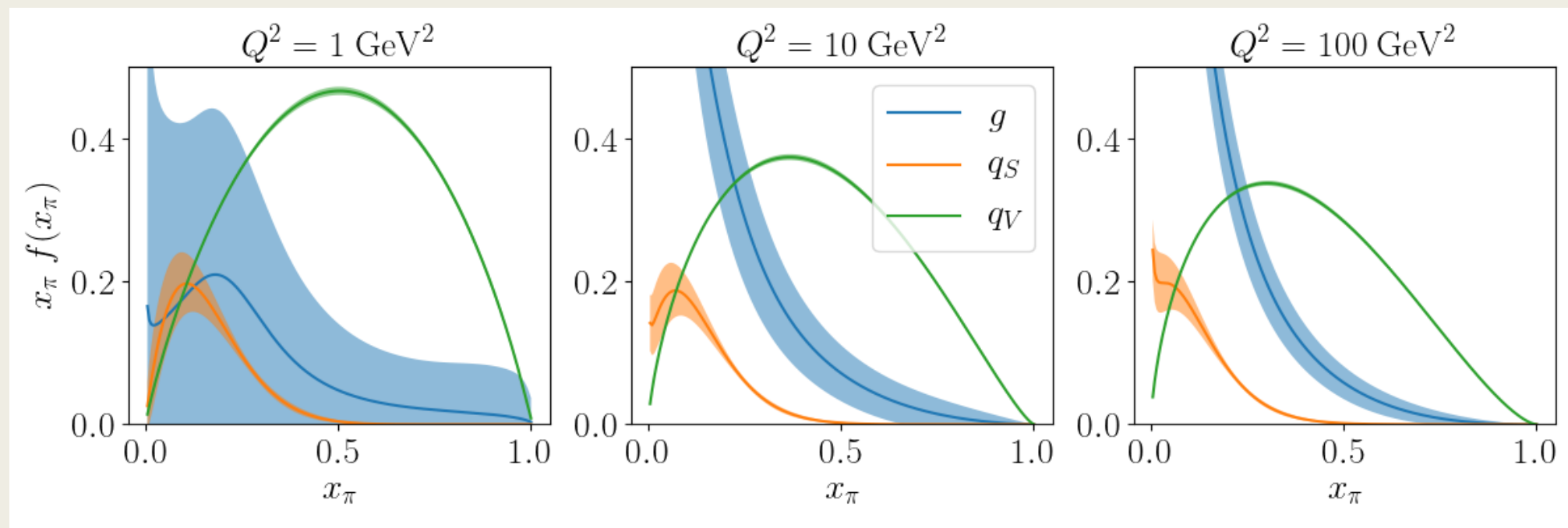


Drell-Yan fits

- q_v is well-constrained by Drell-Yan
- q_s has large spread in parameters
- g has almost not constrain

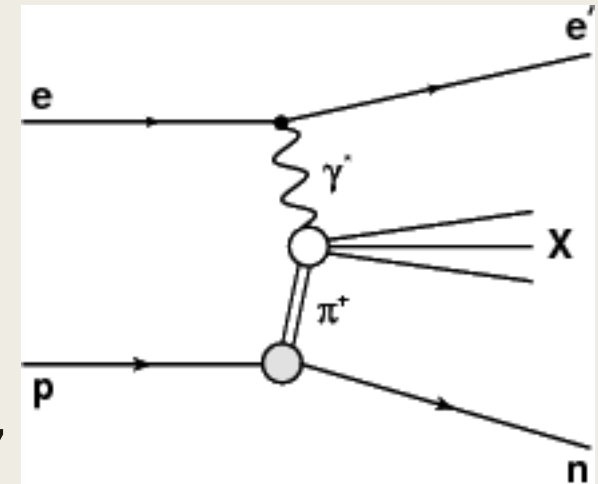


Drell-Yan fits



Leading Neutron

- Add in data from HERA (ZEUS & H1) to perform global fit
- Detect neutrons in coincidence with outgoing electrons:
- Neutron has most of the energy of the proton
- Incoming electron barely strikes the surface of the proton, knocking out a pion from the pion cloud
- Focuses on small x_π , whereas Drell-Yan focuses on large x_π



Leading Neutron

- Observable in H1 data is

$$F_2^{LN(3)}(x, Q^2, y) = f_{\pi+n}(y) F_2^\pi(x_\pi, Q^2)$$

- Where $f_{\pi+n}(y)$ is the splitting function from the proton, and $F_2^\pi(x_\pi, Q^2)$ is the pion structure function (depends on pion PDF)

- Observable in ZEUS is

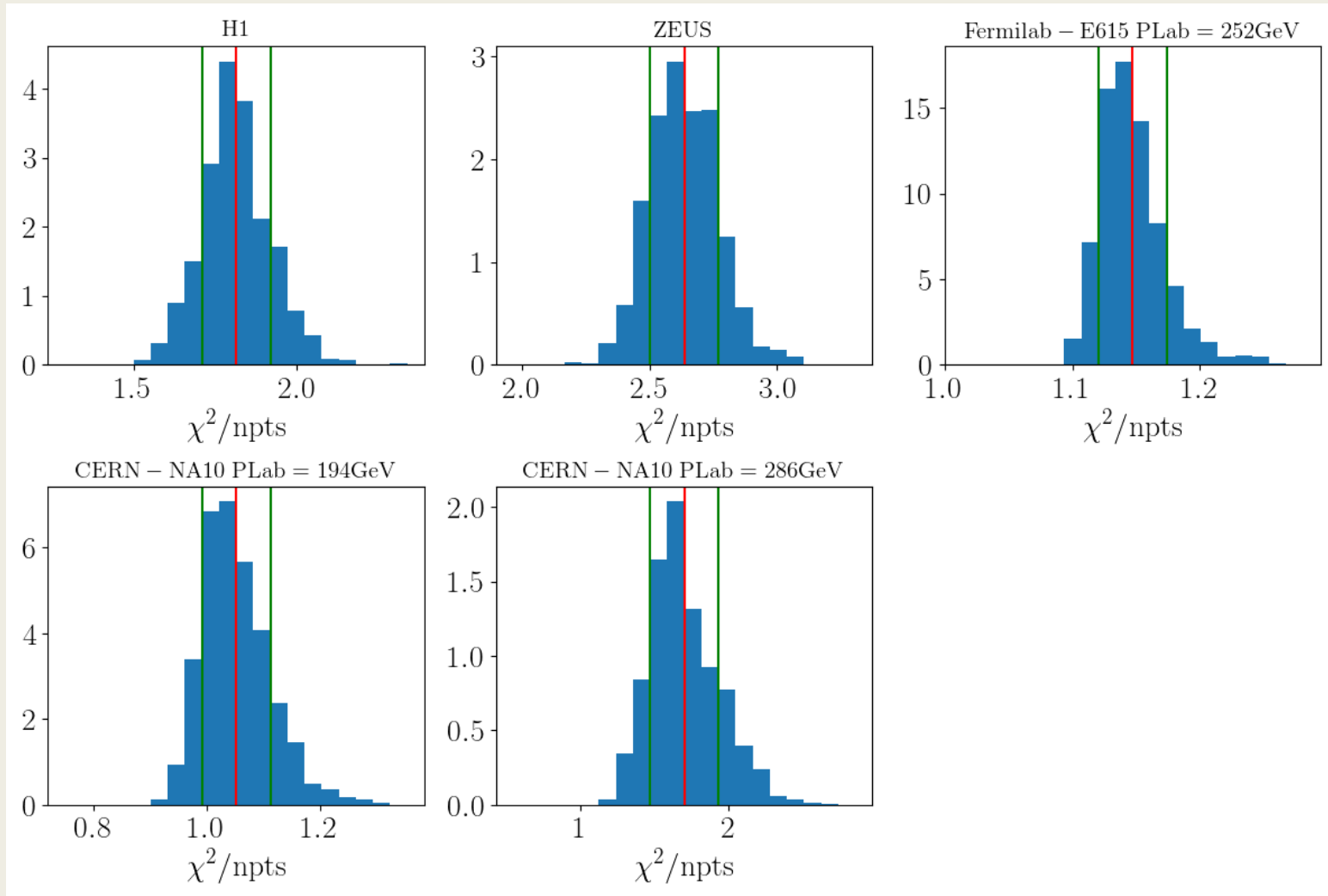
$$r(x_\pi, Q^2, y) = f_{\pi+n}(y) \frac{F_2^\pi(x_\pi, Q^2)}{F_2^p(x, Q^2)} \Delta y$$

- where $F_2^p(x, Q^2)$ is the proton structure function

Datasets & Constrictions

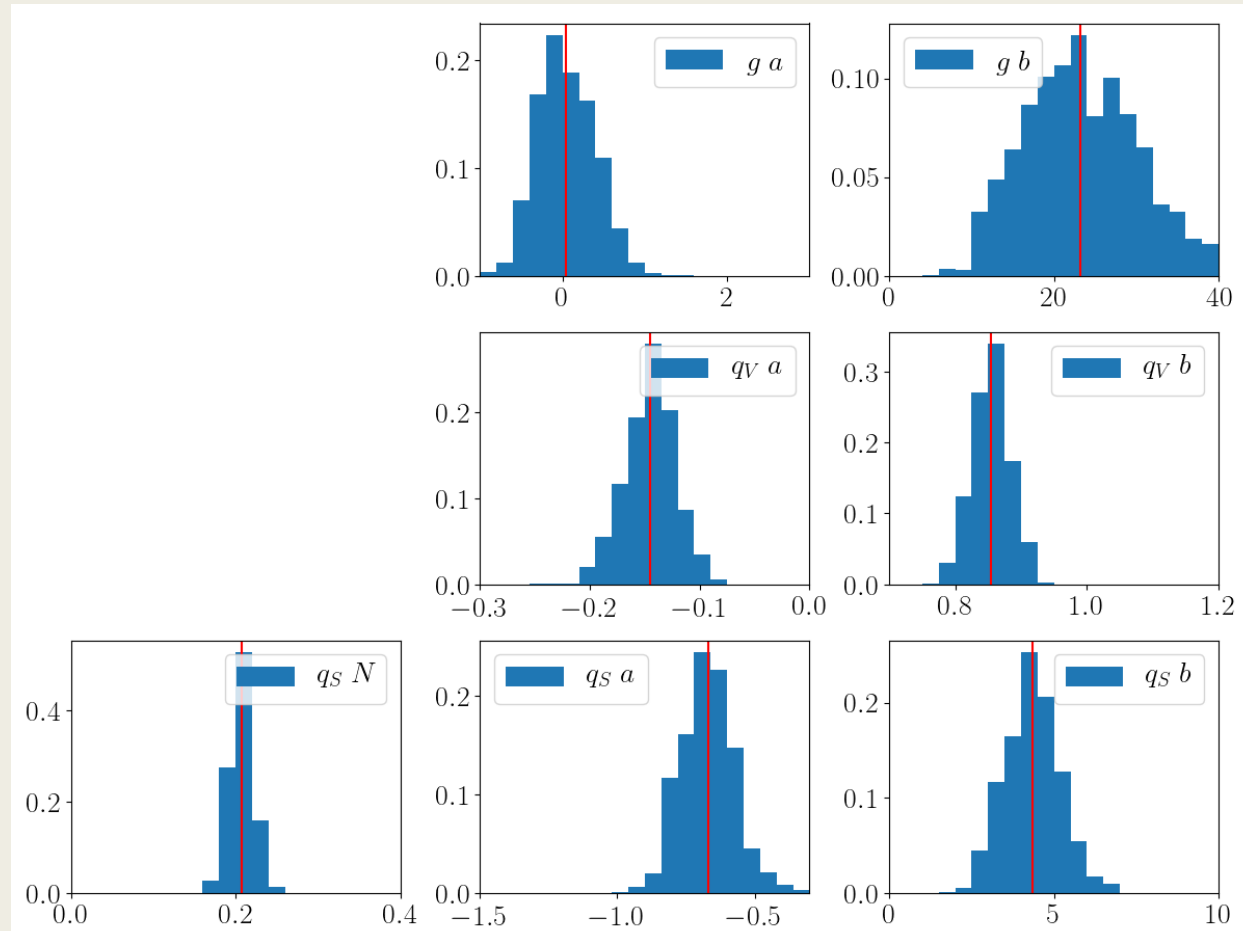
- For Drell-Yan, we use E615 and NA10 datasets
 - π^- beam incident on a Tungsten target
 - Consider only $0 < x_F < 0.9$ and $4.16 < Q < 8.34$ to avoid J/Ψ and Υ production
- For Leading Neutron, we use H1 and ZEUS datasets
 - We consider cuts on data based on maximum $y = x_\pi/x$ values

LN results



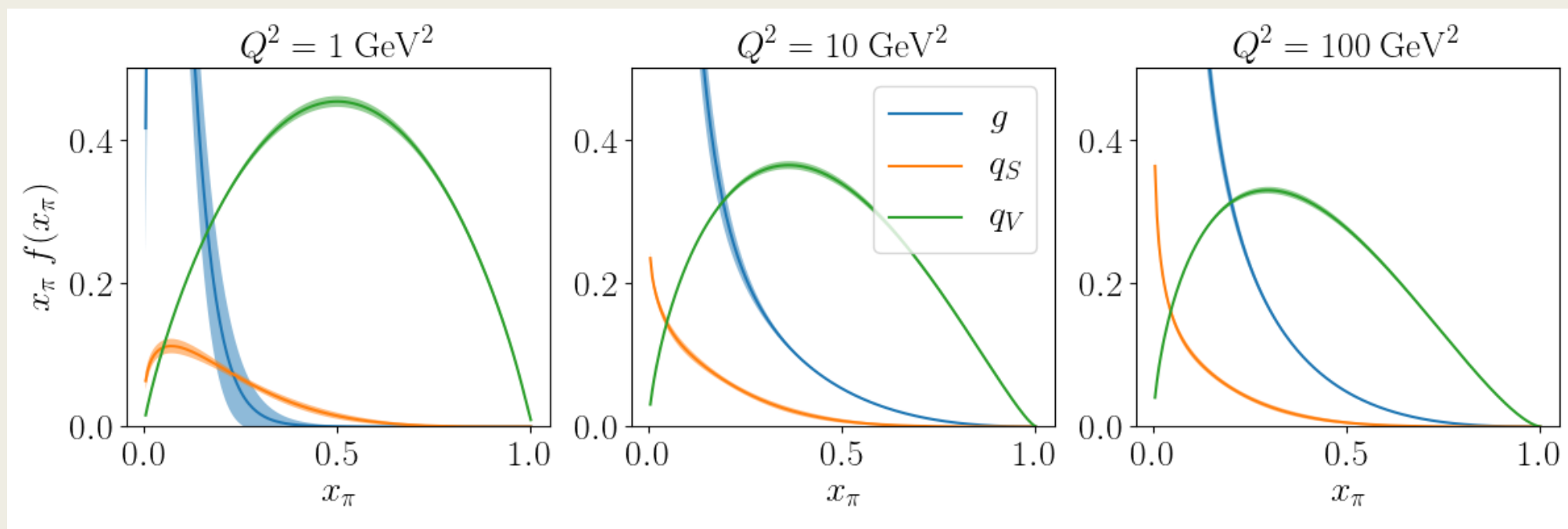
y -cut of 0.2

LN results



y -cut of 0.2

LN results



Conclusion

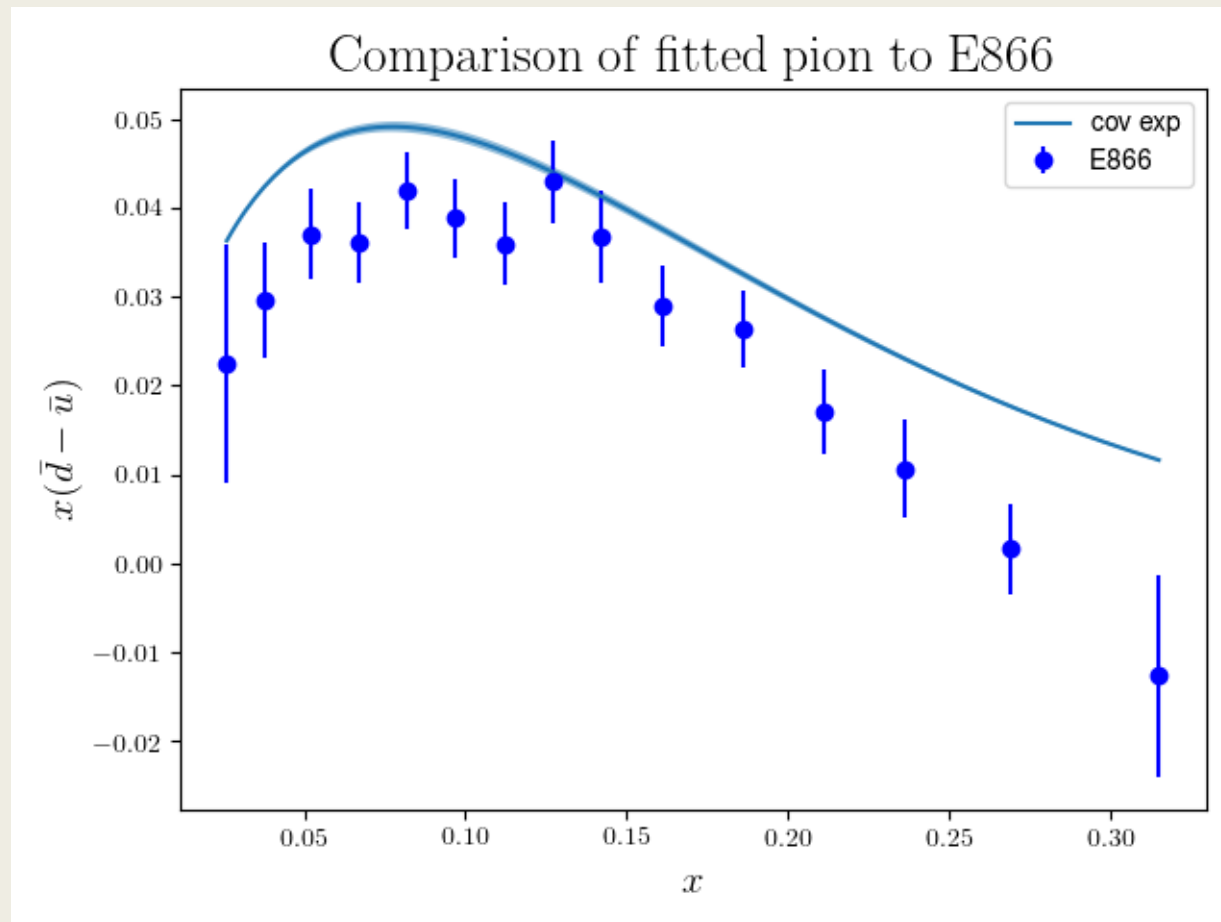
- First attempted fit to both high- x_π and low- x_π regions using Drell-Yan and Leading Neutron data
- Use of nested sampling algorithm to improve errors
- Next steps: to include threshold resummation in our calculation



BACKUP SLIDES

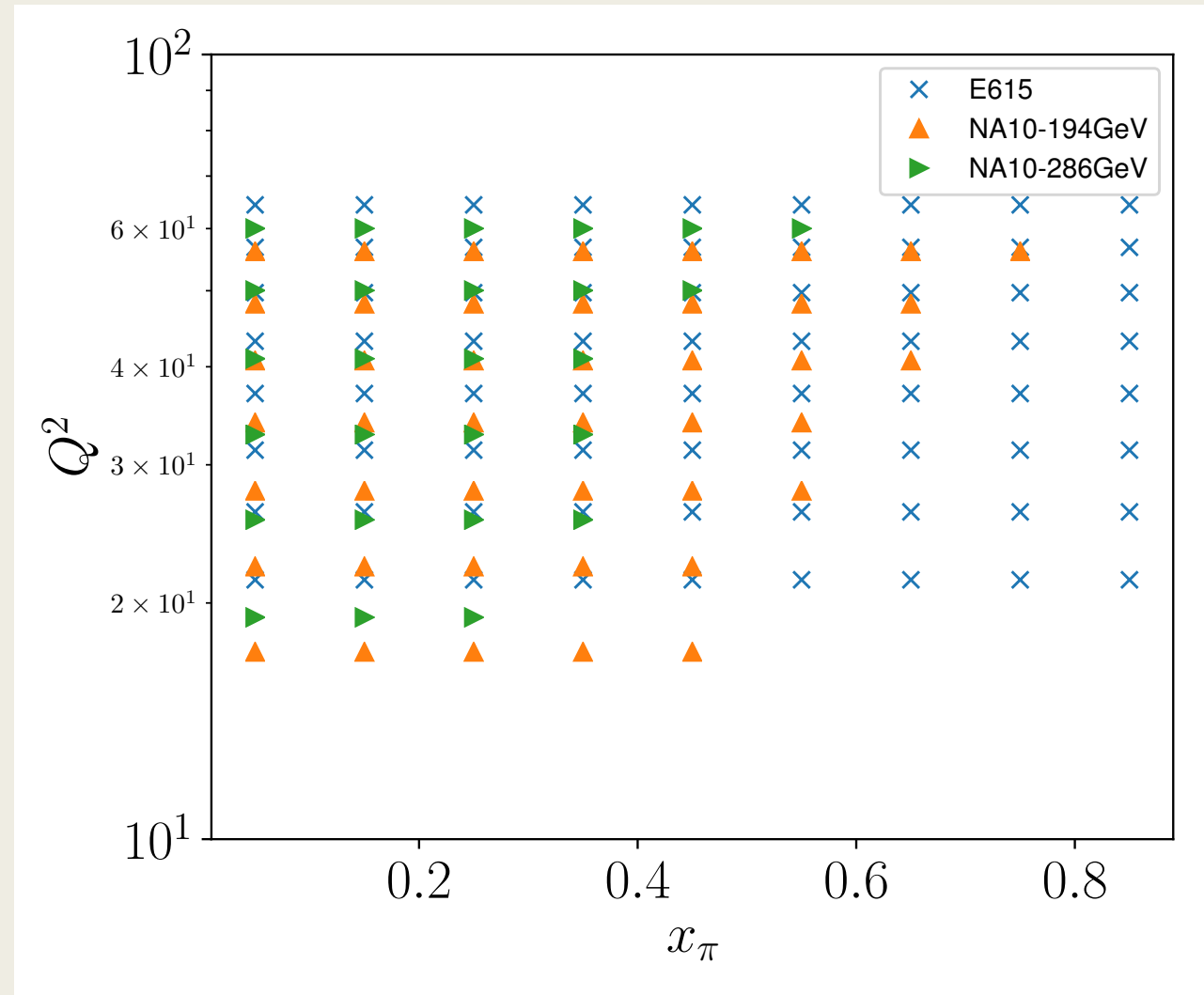
Prediction of E866

- Can make a prediction of E866 data for $\bar{d} - \bar{u} = (f_{\pi^+n} - \frac{2}{3}f_{\pi^-\Delta^{++}}) \otimes \bar{q}_v^\pi$ using our valence π PDF, where f_{π^+n} and $f_{\pi^-\Delta^{++}}$ are the splitting functions from the proton



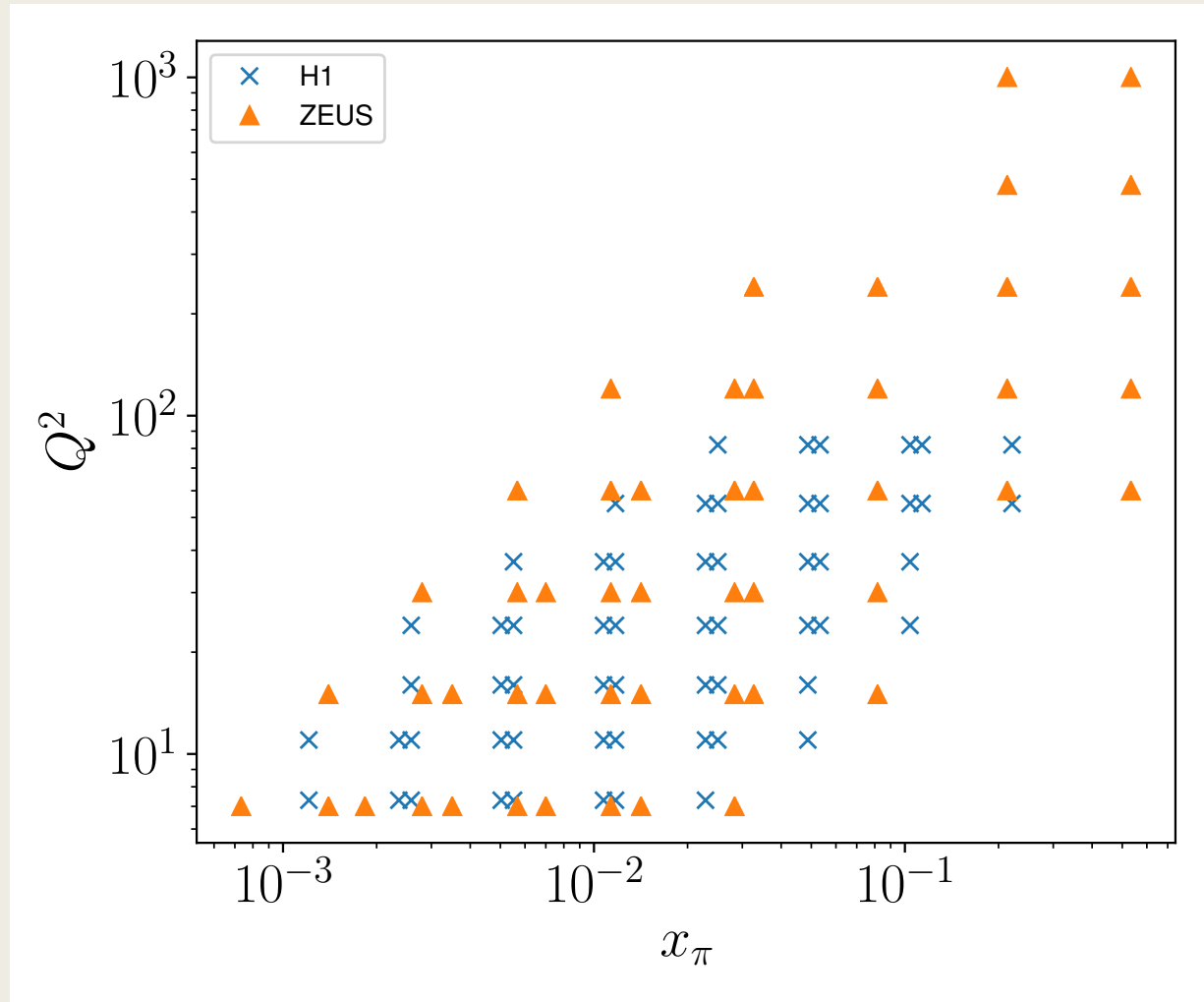
Kinematics - DY

- Hard cut-offs for $4.16^2 < Q^2 < 8.34^2$
- More available data for large- x_π



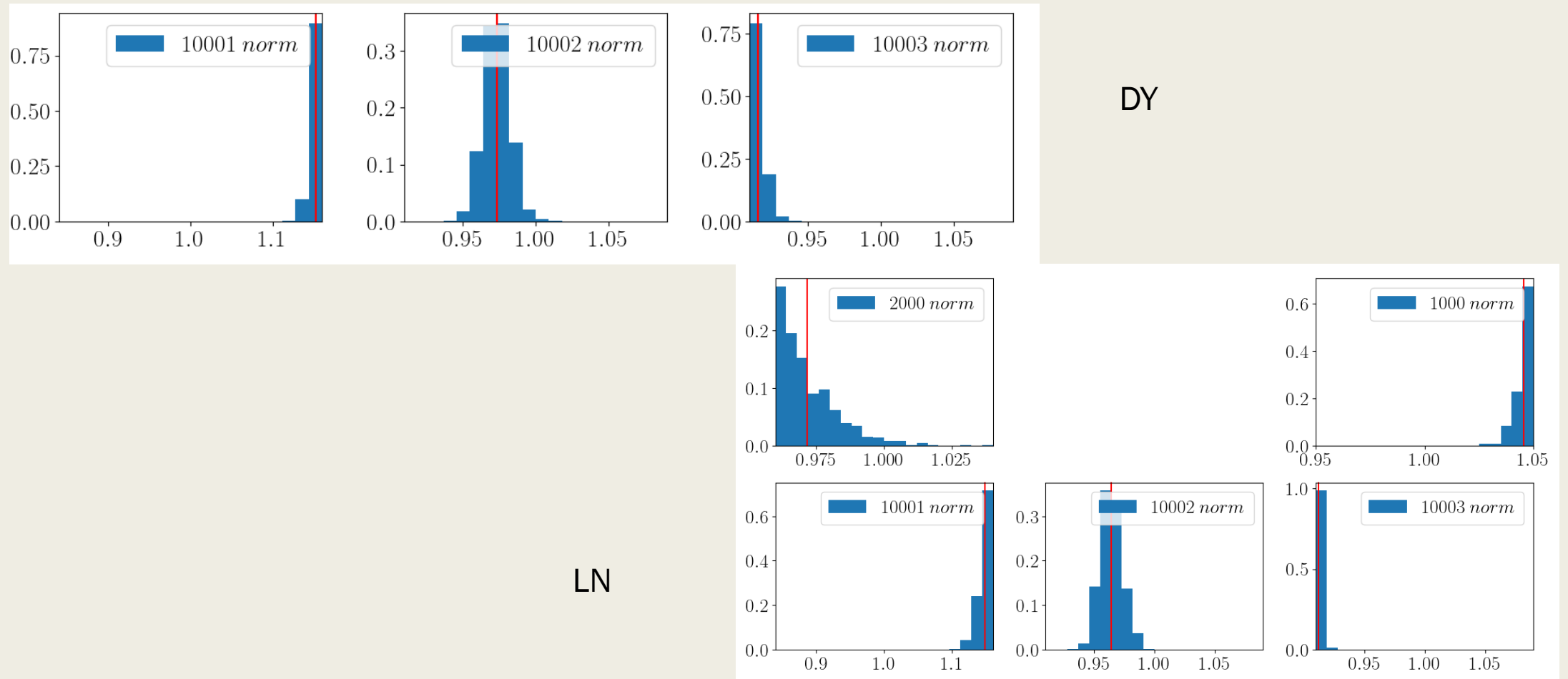
Kinematics - LN

- y -cut of 0.2



Normalization Parameterization

- For all datasets with overall normalization uncertainty, we fit to within the reported percentage around 1.



Mellin Transformation

$$f_i^n(\mu) \equiv \int_0^1 dx x^{n-1} f_i(x, \mu)$$

- Analogous to the Fourier transform
- Transform from x-space to Mellin space (exponents of x)

WHY??

- We know how PDFs evolve in scale based on DGLAP:

$$\frac{\partial f_i(\mu_f^2)}{\partial \ln(\mu_f^2)} = DGLAP$$

Mellin Inversion

- After evolution, invert back into x-space

$$f_i(x, \mu) = \frac{1}{2\pi i} \int_{C_n} dn x^{-n} f_i^n(\mu)$$

- For each value on the contour, we do the DGLAP evolution
- At large enough contour radius, integrand converges

