

# Measuring jet quenching with Bayesian Inference

(and what's next...)

---

**Raymond Ehlers<sup>1</sup>**

Heavy Ion Physics in the EIC Era, INT, Seattle, WA  
23 August 2024

Based on [arXiv:2408.08247](https://arxiv.org/abs/2408.08247)

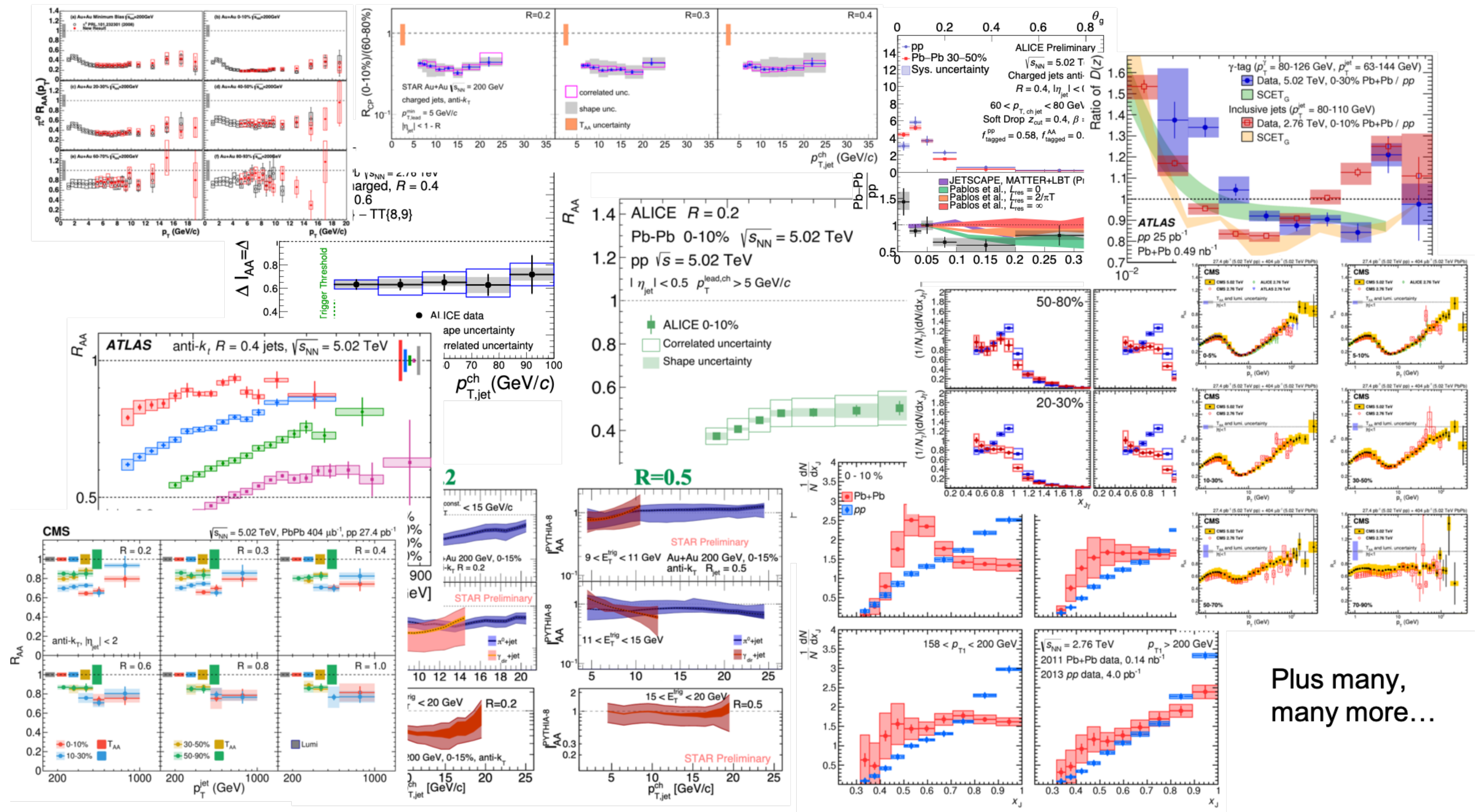
<sup>1</sup>Lawrence Berkeley National Lab/UC Berkeley  
[raymond.ehlers@cern.ch](mailto:raymond.ehlers@cern.ch)



**BERKELEY LAB**

**Berkeley**  
UNIVERSITY OF CALIFORNIA

# Jet quenching measurements



Plus many, many more...

## Bayesian inference + jet quenching

1. How can we make a **consistent picture**?
2. What **physics can we extract**?
3. What **information is contained in each observable**?

## Bayesian inference in the EIC era

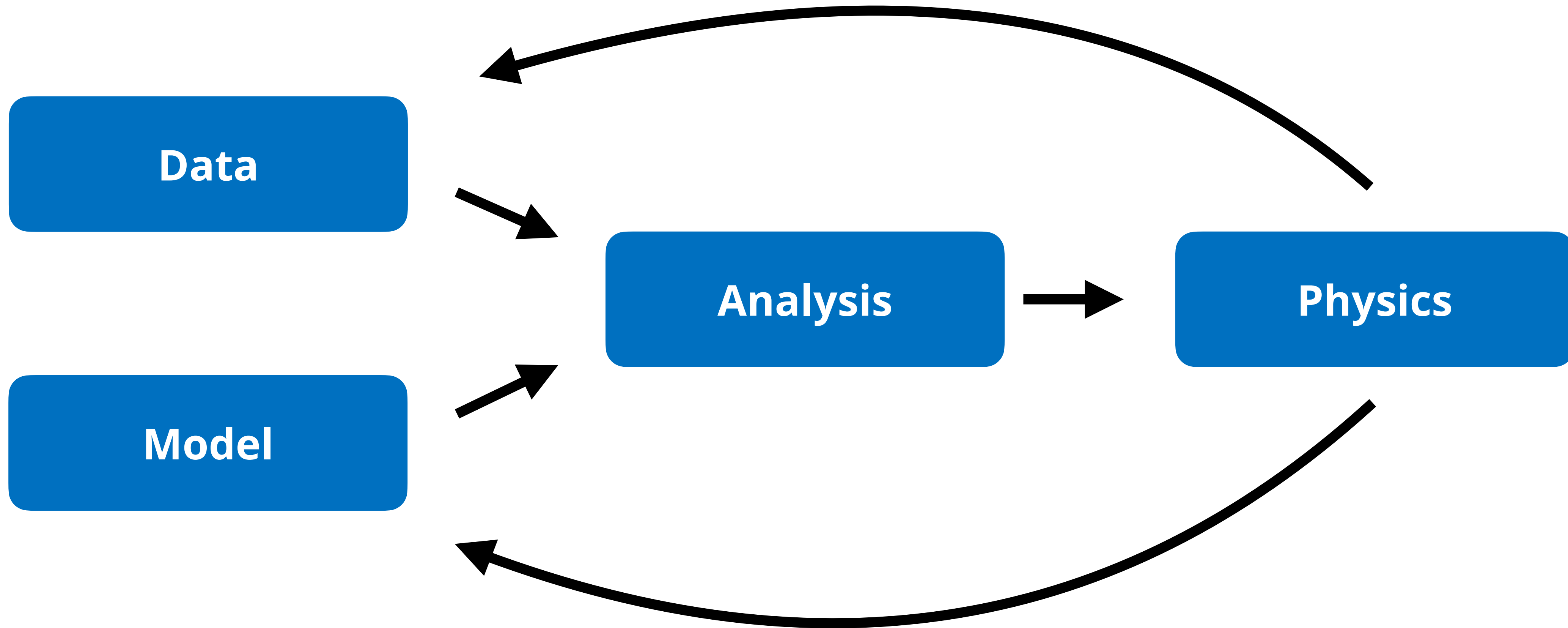
4. **Tools and lessons** from present to future
5. e.g. **EIC + forward LHC/RHIC + Bayesian inference**

# Concept: Bayesian Inference



Insight into physics via **rigorous data-model comparison**

# Concept: Bayesian Inference



Insight into physics via **rigorous data-model comparison**  
and provide **feedback on next generation of measurements and models**

# Bayesian inference

- ◉ **Combine knowledge of theory and experiment** to constrain parameters
- ◉ Given data  $\vec{x}$  and parameters  $\vec{\theta}$ , we can apply **Bayes' theorem**

$$P(\theta|x) = \frac{P(x|\theta)P(\theta)}{P(x)}$$

- ◉  $P(\theta|x)$ : **posterior dist.:**  
prob of  $\theta$  given  $x$
- ◉ Most prob. value  
→ **best description** of data

- ◉  $P(x|\theta)$ : **likelihood**  
 $x$  is described by  $\theta$
- ◉ Depends on covariance,  
**data + theory uncert.**

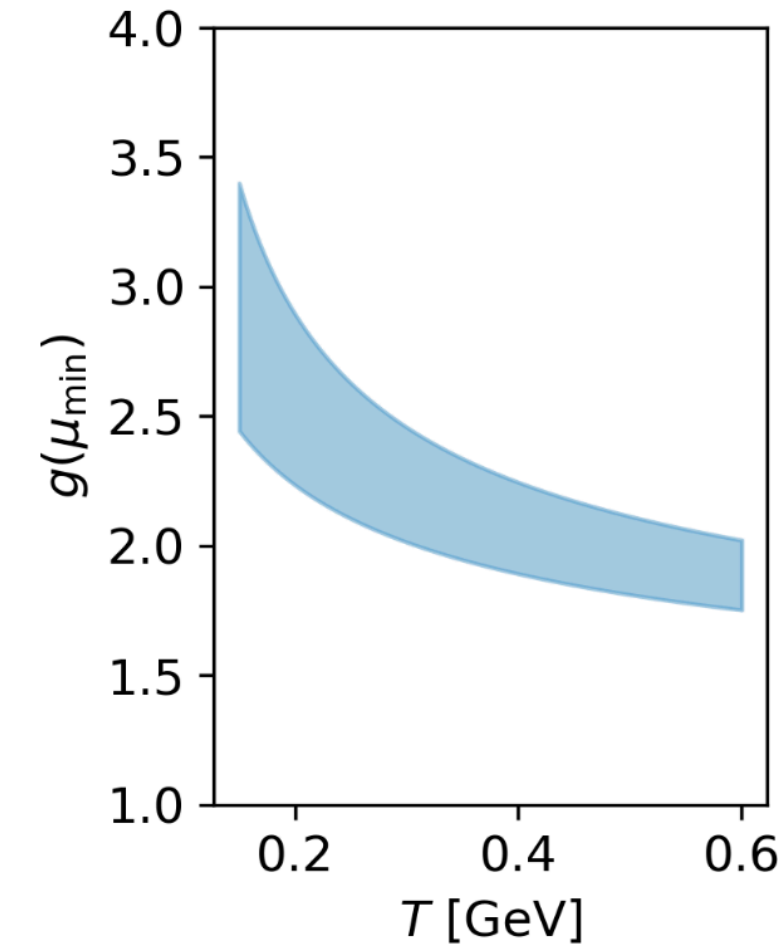
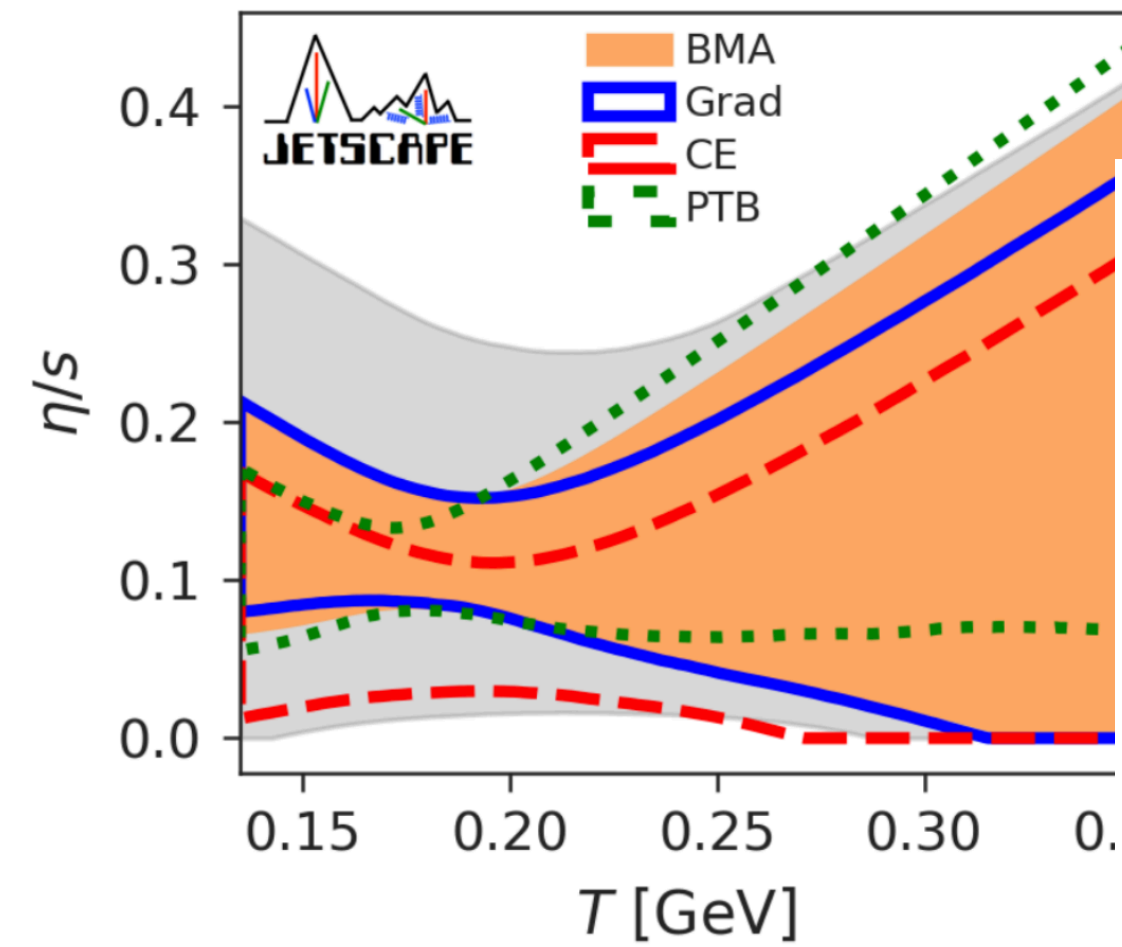
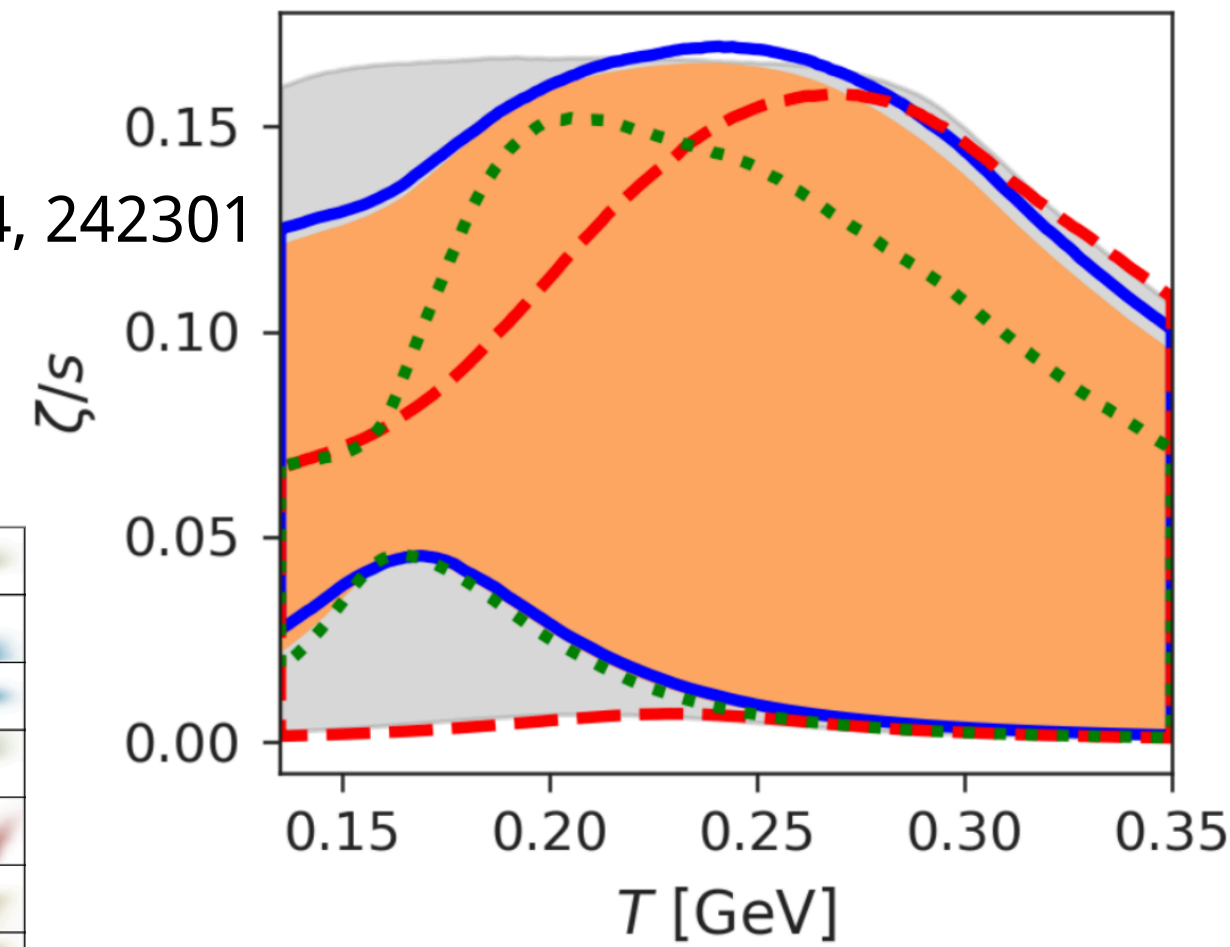
- ◉  $P(\theta)$ : **prior**  
distribution for  $\theta$
- ◉ Choice makes  
assumptions explicit

→ **Posterior encodes everything we want to learn**

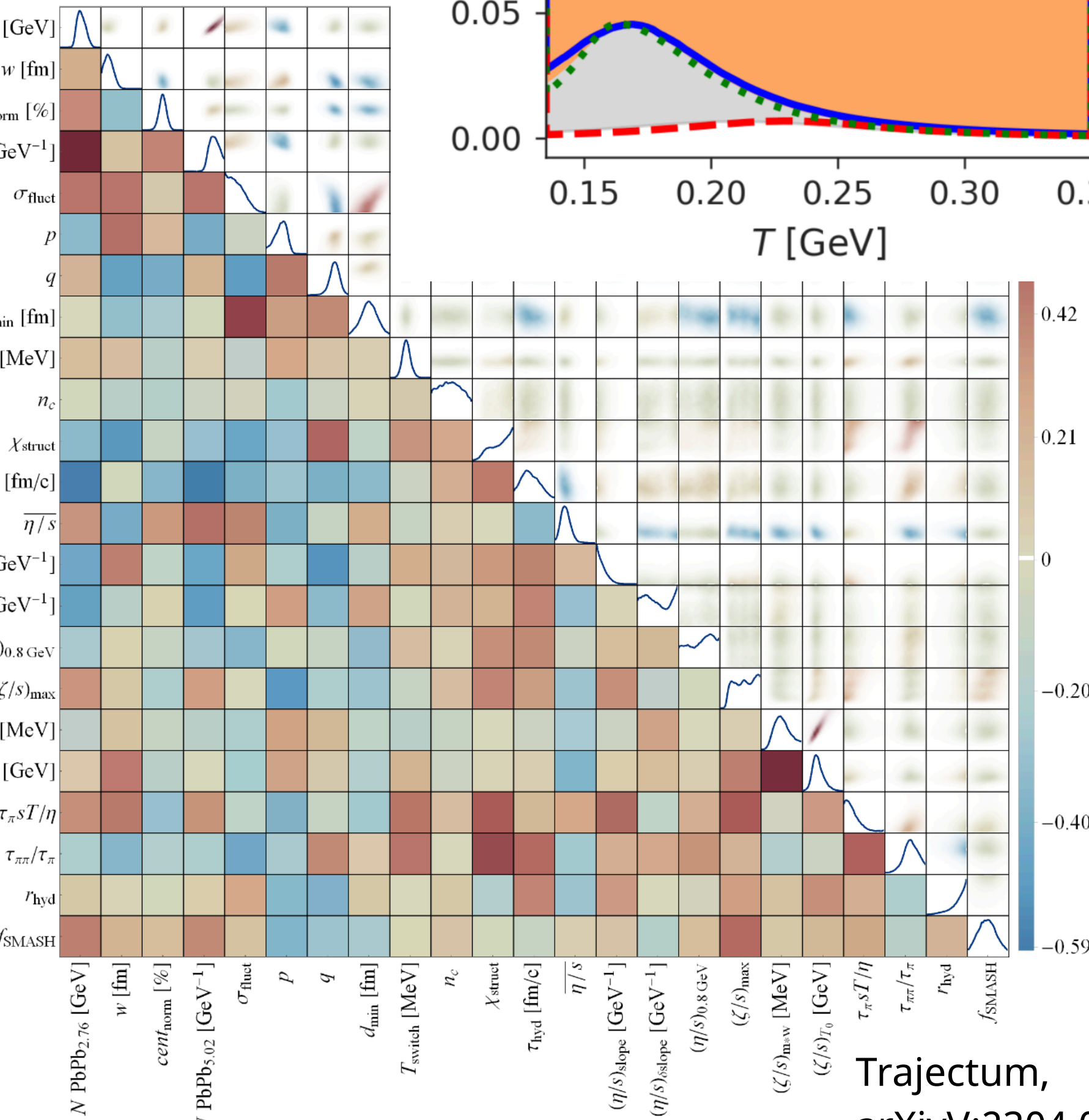
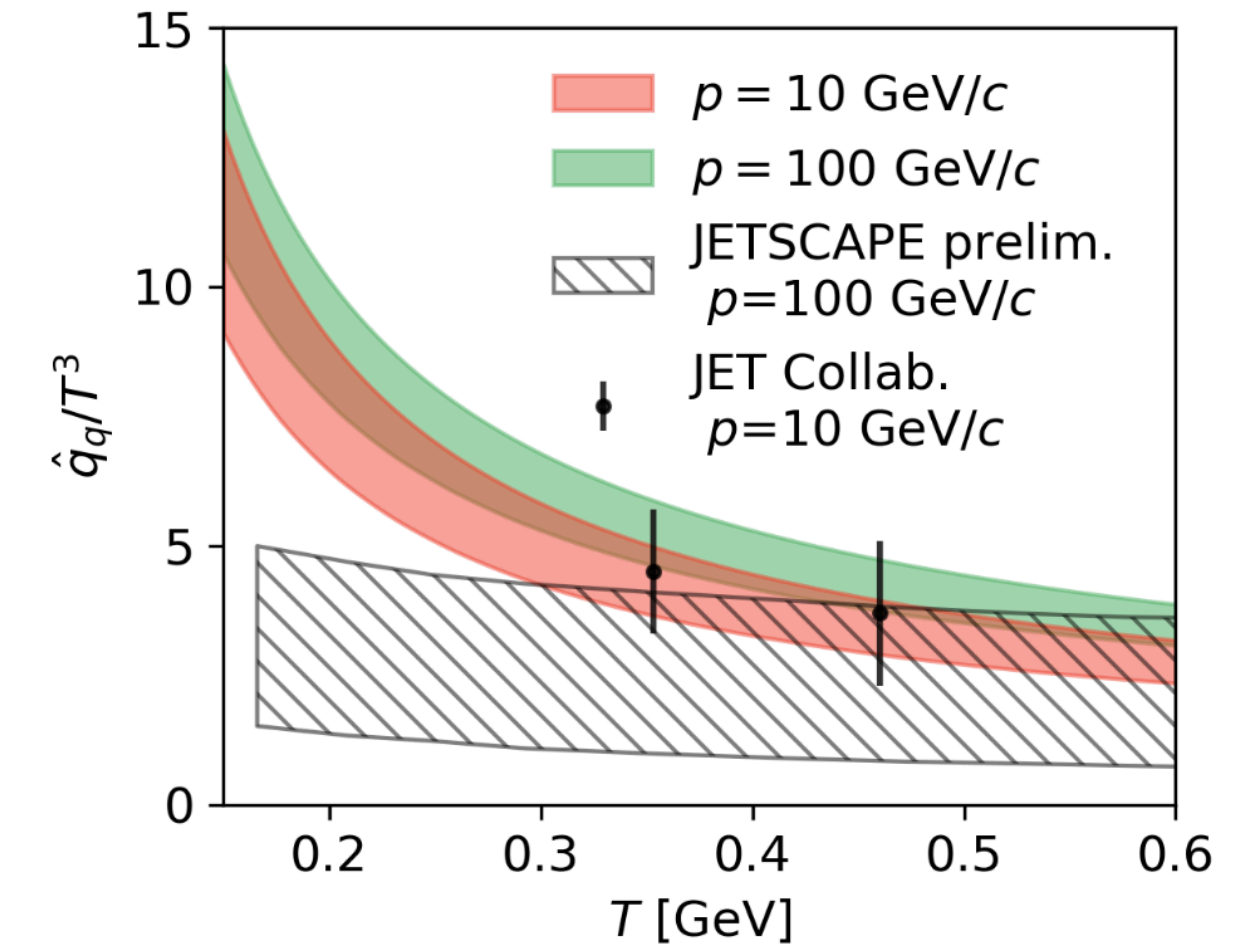
- ◉ Approach enables **computationally tractable approach** to extract parameters
- ◉ Although still CPU intensive!

# Bayesian Inference in heavy-ion collisions (non-exhaustive)

JETSCAPE,  
PRL 126 (2021) 24, 242301

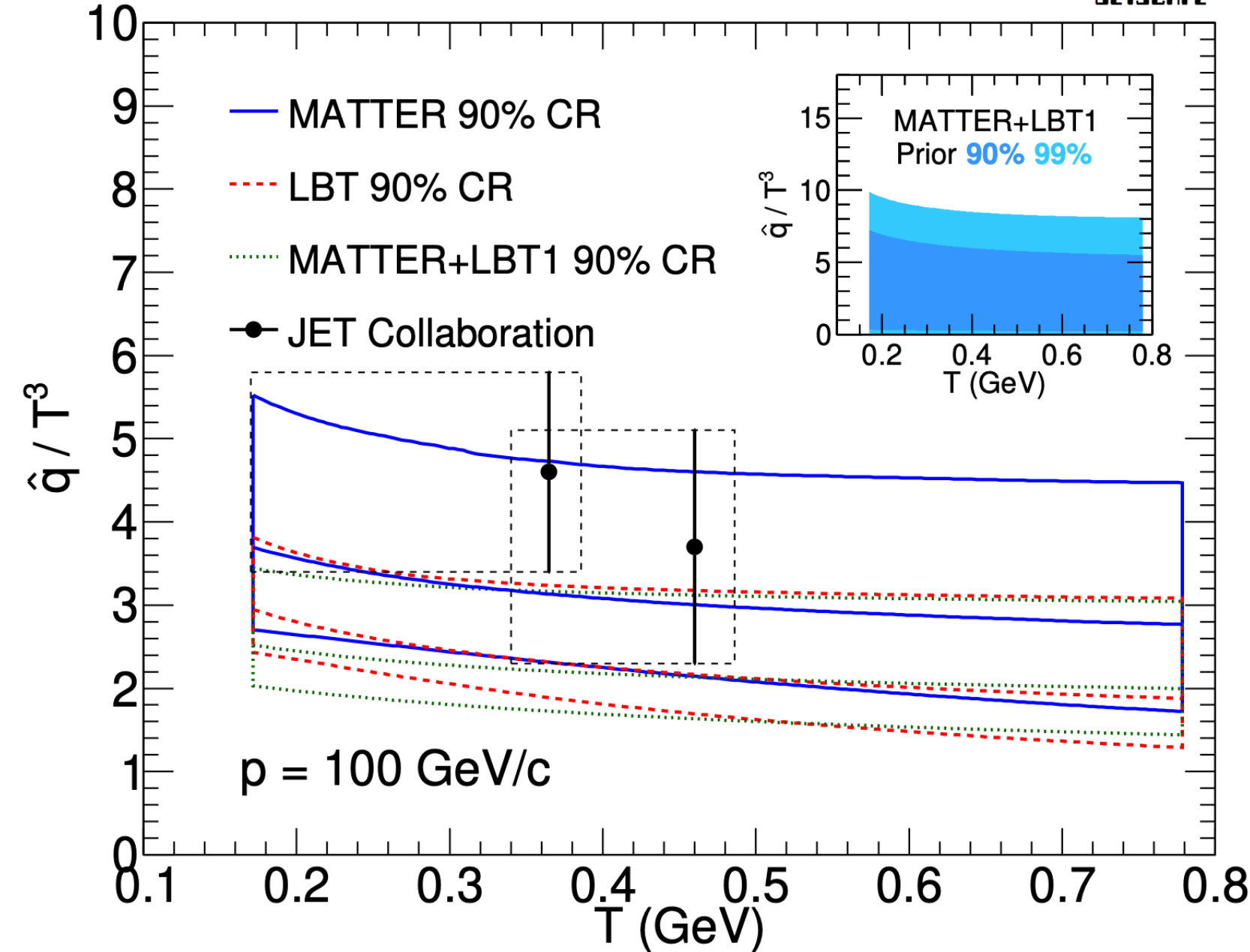


Ke, Wang, JHEP 05 (2021) 041



Trajectum,  
arXivV:2304.06191

JETSCAPE  
(a) PRC 104 (2021) 2, 024905



**Next step in program:**  
**Comprehensive**  
**hadron + jet**  
**calibration...**

# Bayesian inference with inclusive hadron and jet $R_{AA}$

## JETSCAPE, arXiv: 2408.08247

Bayesian Inference analysis of jet quenching using inclusive jet and hadron suppression measurements

R. Ehlers,<sup>1,2</sup> Y. Chen,<sup>3,4,5</sup> J. Mulligan,<sup>1,2</sup> Y. Ji,<sup>6</sup> A. Kumar,<sup>7,8,9</sup> S. Mak,<sup>6</sup> P. M. Jacobs,<sup>1,2</sup> A. Majumder,<sup>9</sup> A. Angerami,<sup>10</sup> R. Arora,<sup>11</sup> S. A. Bass,<sup>12</sup> R. Datta,<sup>9</sup> L. Du,<sup>8,1,2</sup> H. Elfner,<sup>13,14,15</sup> R. J. Fries,<sup>16,17</sup> C. Gale,<sup>8</sup> Y. He,<sup>18,19</sup> B. V. Jacak,<sup>1,2</sup> S. Jeon,<sup>8</sup> F. Jonas,<sup>1,2</sup> L. Kasper,<sup>5</sup> M. Kordell II,<sup>16,17</sup> R. Kunnawalkam-Elayavalli,<sup>5</sup> J. Latessa,<sup>11</sup> Y.-J. Lee,<sup>3,4</sup> R. Lemmon,<sup>20</sup> M. Luzum,<sup>21</sup> A. Mankolli,<sup>5</sup> C. Martin,<sup>22</sup> H. Mehryar,<sup>11</sup> T. Mengel,<sup>22</sup> C. Nattrass,<sup>22</sup> J. Norman,<sup>23</sup> C. Parker,<sup>16,17</sup> J.-F. Paquet,<sup>5</sup> J. H. Putschke,<sup>9</sup> H. Roch,<sup>9</sup> G. Roland,<sup>3,4</sup> B. Schenke,<sup>24</sup> L. Schwiebert,<sup>11</sup> A. Sengupta,<sup>16,17</sup> C. Shen,<sup>9,25</sup> M. Singh,<sup>5</sup> C. Sirimanna,<sup>9,12</sup> D. Soeder,<sup>26</sup> R. A. Soltz,<sup>9,10</sup> I. Soudi,<sup>9,27,28</sup> Y. Tachibana,<sup>29</sup> J. Velkovska,<sup>5</sup> G. Vujanovic,<sup>7</sup> X.-N. Wang,<sup>30,1,2</sup> X. Wu,<sup>8,9</sup> and W. Zhao<sup>9,1,2</sup>  
(The JETSCAPE Collaboration)

<sup>1</sup>Department of Physics, University of California, Berkeley CA 94270.

<sup>2</sup>Nuclear Science Division, Lawrence Berkeley National Laboratory, Berkeley CA 94270.

<sup>3</sup>Laboratory for Nuclear Science, Massachusetts Institute of Technology, Cambridge MA 02139.

<sup>4</sup>Department of Physics, Massachusetts Institute of Technology, Cambridge MA 02139.

<sup>5</sup>Department of Physics and Astronomy, Vanderbilt University, Nashville TN 37235.

<sup>6</sup>Department of Statistical Science, Duke University, Durham NC 27708.

<sup>7</sup>Department of Physics, University of Regina, Regina, SK S4S 0A2, Canada.

<sup>8</sup>Department of Physics, McGill University, Montréal QC H3A 2T8, Canada.

<sup>9</sup>Department of Physics and Astronomy, Wayne State University, Detroit MI 48201.

<sup>10</sup>Lawrence Livermore National Laboratory, Livermore CA 94550.

<sup>11</sup>Department of Computer Science, Wayne State University, Detroit MI 48202.

<sup>12</sup>Department of Physics, Duke University, Durham, NC 27708, USA

<sup>13</sup>GSI Helmholtzzentrum für Schwerionenforschung, 64291 Darmstadt, Germany.

<sup>14</sup>Institute for Theoretical Physics, Goethe University, 60438 Frankfurt am Main, Germany.

<sup>15</sup>Frankfurt Institute for Advanced Studies, 60438 Frankfurt am Main, Germany.

<sup>16</sup>Cyclotron Institute, Texas A&M University, College Station TX 77843.

<sup>17</sup>Department of Physics and Astronomy, Texas A&M University, College Station TX 77843.

<sup>18</sup>Guangdong Provincial Key Laboratory of Nuclear Science, Institute of Quantum Matter, South China Normal University, Guangzhou 510006, China.

<sup>19</sup>Guangdong-Hong Kong Joint Laboratory of Quantum Matter,

Southern Nuclear Science Computing Center, South China Normal University, Guangzhou 510006, China.

<sup>20</sup>Daresbury Laboratory, Daresbury, Warrington, Cheshire, WA44AD, United Kingdom.

<sup>21</sup>Instituto de Física, Universidade de São Paulo, C.P. 66318, 05315-970 São Paulo, SP, Brazil.

<sup>22</sup>Department of Physics and Astronomy, University of Tennessee, Knoxville TN 37996.

<sup>23</sup>Oliver Lodge Laboratory, University of Liverpool, Liverpool, United Kingdom.

<sup>24</sup>Physics Department, Brookhaven National Laboratory, Upton NY 11973.

<sup>25</sup>RIKEN BNL Research Center, Brookhaven National Laboratory, Upton NY 11973.

<sup>26</sup>Department of Physics, Duke University, Durham NC 27708.

<sup>27</sup>University of Jyväskylä, Department of Physics,

P.O. Box 35, FI-40014 University of Jyväskylä, Finland.

<sup>28</sup>Helsinki Institute of Physics, P.O. Box 64, FI-00014 University of Helsinki, Finland.

<sup>29</sup>Akita International University, Yuwa, Akita-city 010-1292, Japan.

<sup>30</sup>Key Laboratory of Quark and Lepton Physics (MOE) and Institute of Particle Physics, Central China Normal University, Wuhan 430079, China.

(Dated: July 26, 2024)

The JETSCAPE Collaboration reports a new determination of the jet transport parameter  $\hat{q}$  in the Quark-Gluon Plasma (QGP) using Bayesian Inference, incorporating all available inclusive hadron and jet yield suppression data measured in heavy-ion collisions at RHIC and the LHC. This multi-observable analysis extends the previously published JETSCAPE Bayesian Inference determination of  $\hat{q}$ , which was based solely on a selection of inclusive hadron suppression data. JETSCAPE is a modular framework incorporating detailed dynamical models of QGP formation and evolution, and jet propagation and interaction in the QGP. Virtuality-dependent partonic energy loss in the QGP is modeled as a thermalized weakly-coupled plasma, with parameters determined from Bayesian calibration using soft-sector observables. This Bayesian calibration of  $\hat{q}$  utilizes Active Learning, a machine-learning approach, for efficient exploitation of computing resources. The experimental data included in this analysis span a broad range in collision energy and centrality, and in transverse momentum. In order to explore the systematic dependence of the extracted parameter posterior distributions, several different calibrations are reported, based on combined jet and hadron data; on jet or hadron data separately; and on restricted kinematic ranges of the jet and hadron data.

### Data

- **Hadron + jet  $R_{AA}$**
- $3\sqrt{s_{NN}}$ , **all eligible data**
- Treat experimental **uncertainty correlations where possible**

### Model

- Multi-stage: MATTER+LBT
- Calibrated 2+1D hydro
- Extract **parametrized  $\hat{q}(T, E, Q)$**
- Goal: **What do jets bring to the analysis?**

### Strategy

- **Active learning** to determine design points
- Significant computing effort:  **$O(10M)$  CPU hours**
- Calculated many **more observables for differential studies**



# Inclusive hadron and jet $R_{AA}$ data

- We adopt an **agnostic approach**: all qualified dataset by a cutoff time (Feb 2022) are included<sup>1</sup>
  - “Qualified” = right category, in target phase space, possible to compare rigorously
- In total **729 data points** used, jump up from previous iteration of analysis of similar nature
- Reported uncertainty sources + estimate for the res

Inclusive hadron $R_{AA}$					
Collab./ref.	System; $\sqrt{s_{NN}}$ [TeV]	Species	Accept.	centr. %	$p_T$ range [GeV/c]
STAR [101]	Au–Au; 0.2	charged	$ \eta  < 0.5$	[0,40]	[9,12]
ALICE [102]	Pb–Pb; 2.76, 5.02	charged	$ \eta  < 0.8$	[0,50]	[9,50]
ATLAS [99]	Pb–Pb; 2.76	charged	$ \eta  < 2$	[0,40]	[9,150]
CMS [103]	Pb–Pb; 2.76	charged	$ \eta  < 1.0$	[0,50]	[9,100]
CMS [100]	Pb–Pb; 5.02	charged	$ \eta  < 1.0$	[0,50]	[9,400]
PHENIX [104]	Au–Au; 0.2	$\pi^0$	$ \eta  < 0.35$	[0,50]	[9,20]
ALICE [105, 106]	Pb–Pb; 2.76	$\pi^0$	$ \eta  < 0.7$	[0,50]	[9,20]
ALICE [107, 108]	Pb–Pb; 2.76	$\pi^\pm$	$ \eta  < 0.8$	[0,40]	[9,20]
ALICE [109]	Pb–Pb; 5.02	$\pi^\pm$	$ \eta  < 0.8$	[0,50]	[9,20]

Inclusive jet $R_{AA}$						
Collab./ref.	System; $\sqrt{s_{NN}}$ [TeV]	type	$R$	Accept.	centr. %	$p_T$ range [GeV/c]
STAR [110]	Au–Au; 0.2	charged	[0.2,0.4]	$ \eta  < 1 - R$	[0,10]	[15,30]
ALICE [111]	Pb–Pb; 2.76	full	0.2	$ \eta  < 0.5$	[0,30]	[30,100]
ALICE [22]	Pb–Pb; 5.02	full	0.2,0.4	$ \eta  < 0.5$	[0,10]	[40,140]
ATLAS [112]	Pb–Pb; 2.76	full	0.4	$ \eta  < 2.1$	[0,50]	[32,500]
ATLAS [113]	Pb–Pb; 5.02	full	0.4	$ \eta  < 2.8$	[0,50]	[50,1000]
CMS [114]	Pb–Pb; 2.76	full	[0.2,0.4]	$ \eta  < 2.0$	[0,50]	[70,300]
CMS [115]	Pb–Pb; 5.02	full	[0.2,1.0]	$ \eta  < 2.0$	[0,50]	[200,1000]

<sup>1</sup>: ATLAS Hadron  $R_{AA}$  @ 5.02 TeV after cutoff date

# $\hat{q}$ parametrization

$$\hat{q}(E, T, Q) = \hat{q}_{\text{HTL}}^{\text{run}} \times f(Q^2)$$

$$\hat{q}_{\text{HTL}}^{\text{run}} = \alpha_{s,\text{fix}} \times \alpha_s(\mu^2) c_a \frac{42\zeta(3)}{\pi} T^3 \log\left(\frac{\mu^2}{6\pi T^2 \alpha_{s,\text{fix}}}\right)$$

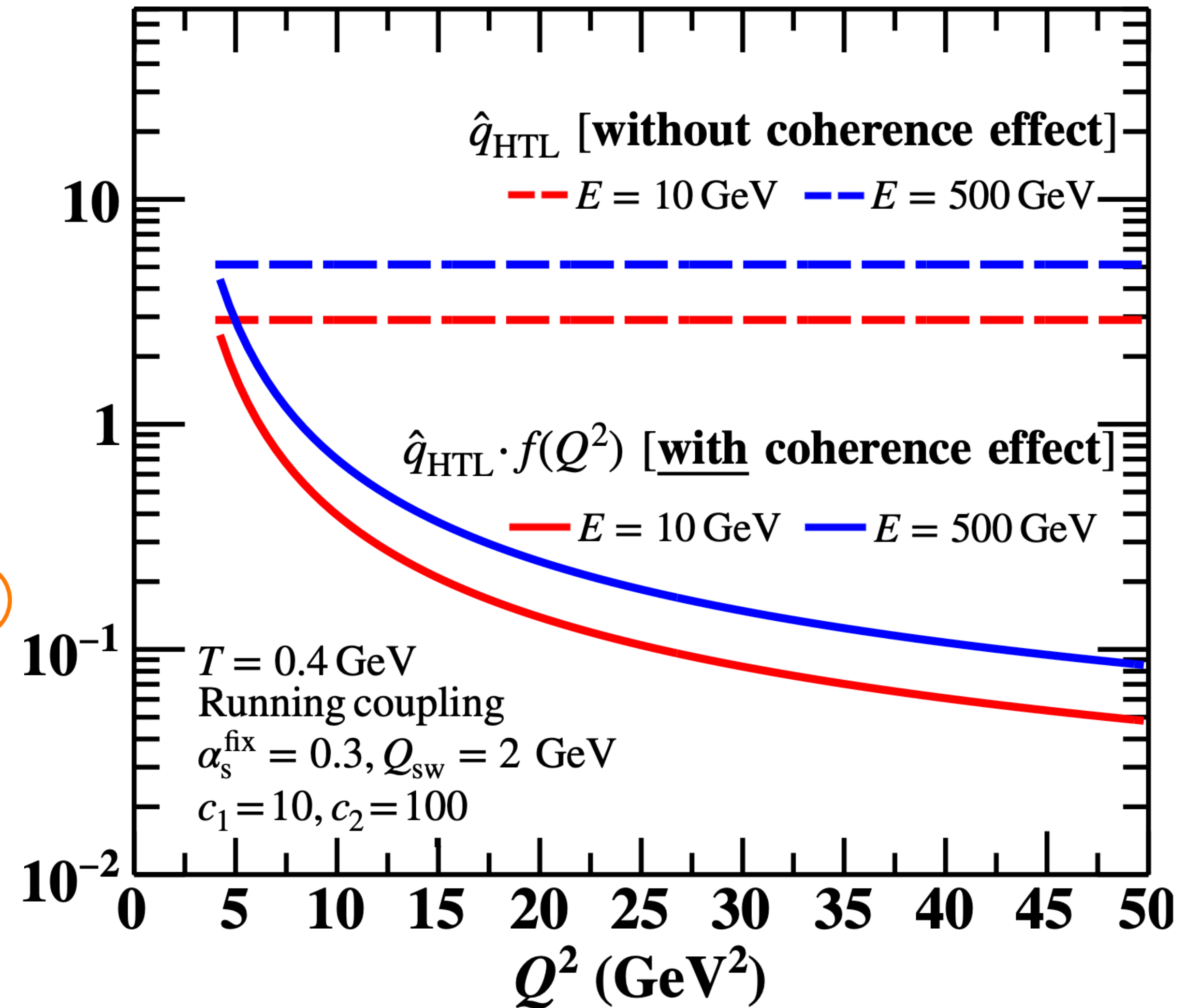
$$f(Q^2) = \frac{N(\exp(c_3(1-x_B)))}{1 + c_1 \ln(Q^2/\Lambda_{\text{QCD}}^2) + c_2 \ln^2(Q^2/\Lambda_{\text{QCD}}^2)} \Big|_{Q \geq Q_0}$$

• 6 total parameters:

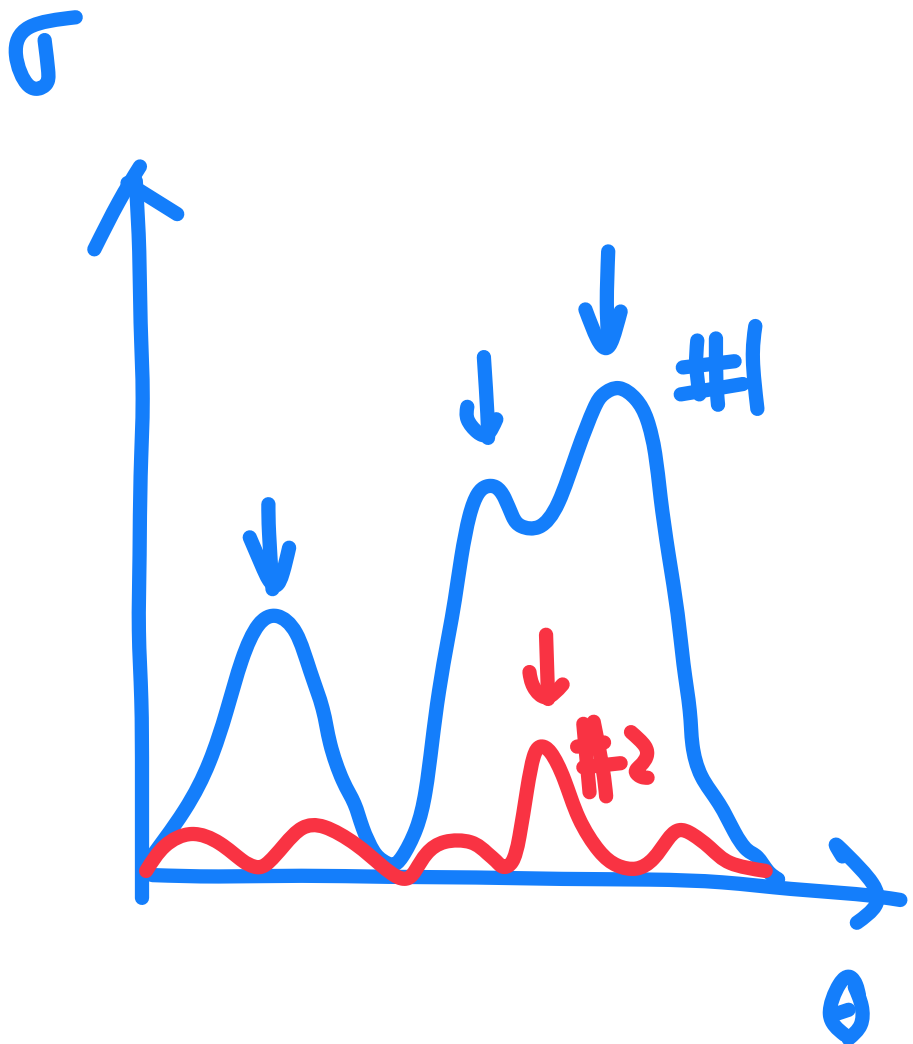
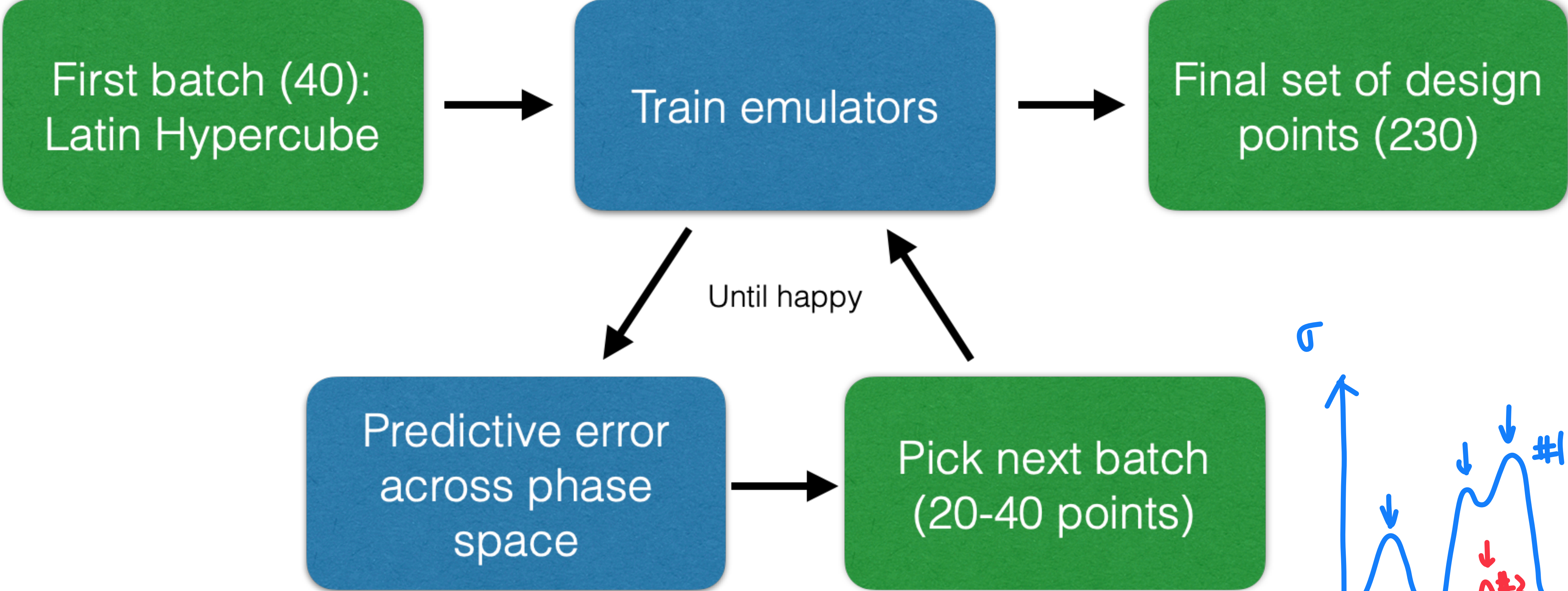
- $\alpha_s$
- $c_1, c_2, c_3$
- $Q_0$  (switching virtuality)
- $\tau_0$  (start time)

• Taken as one possible **candidate** model

• Later: take advantage of JETSCAPE as a modular framework



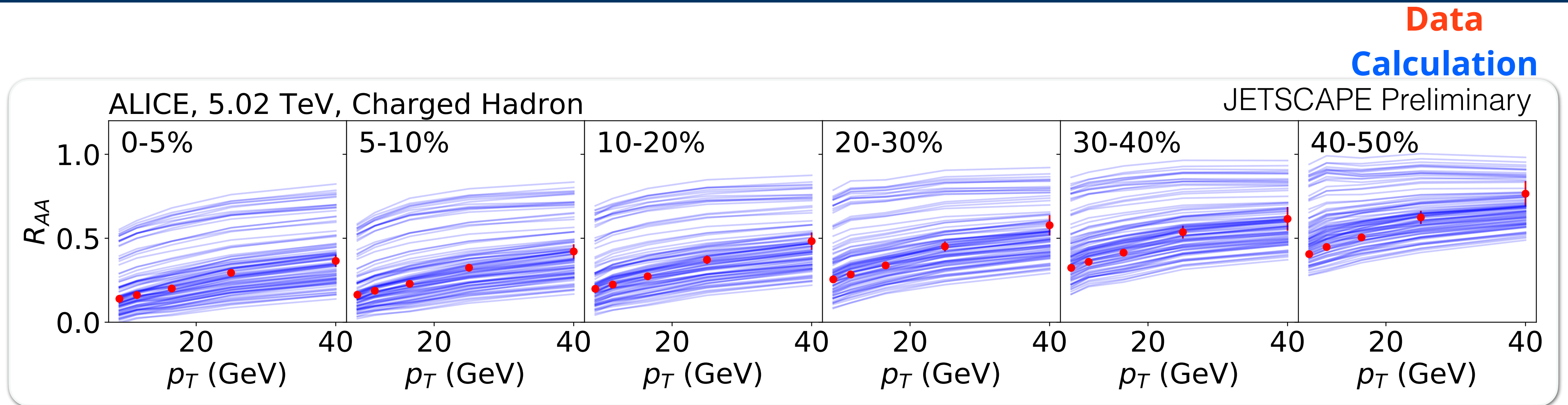
# Active learning design points



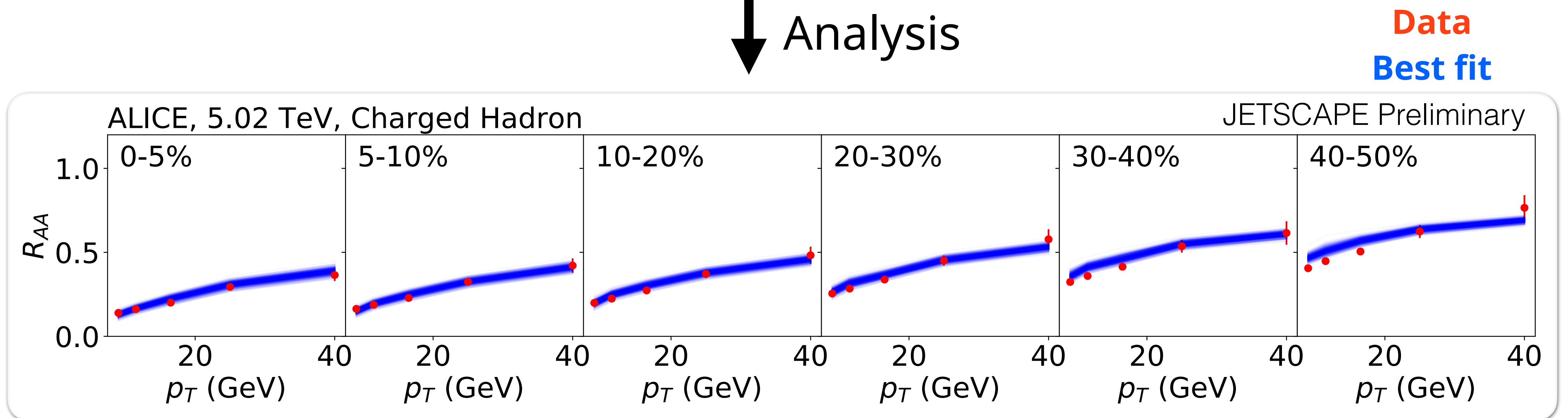
Prioritize **reducing predictive error across the full space**

**Do not look at experimental data** during this process

# From Prior to Posterior



↓ Analysis



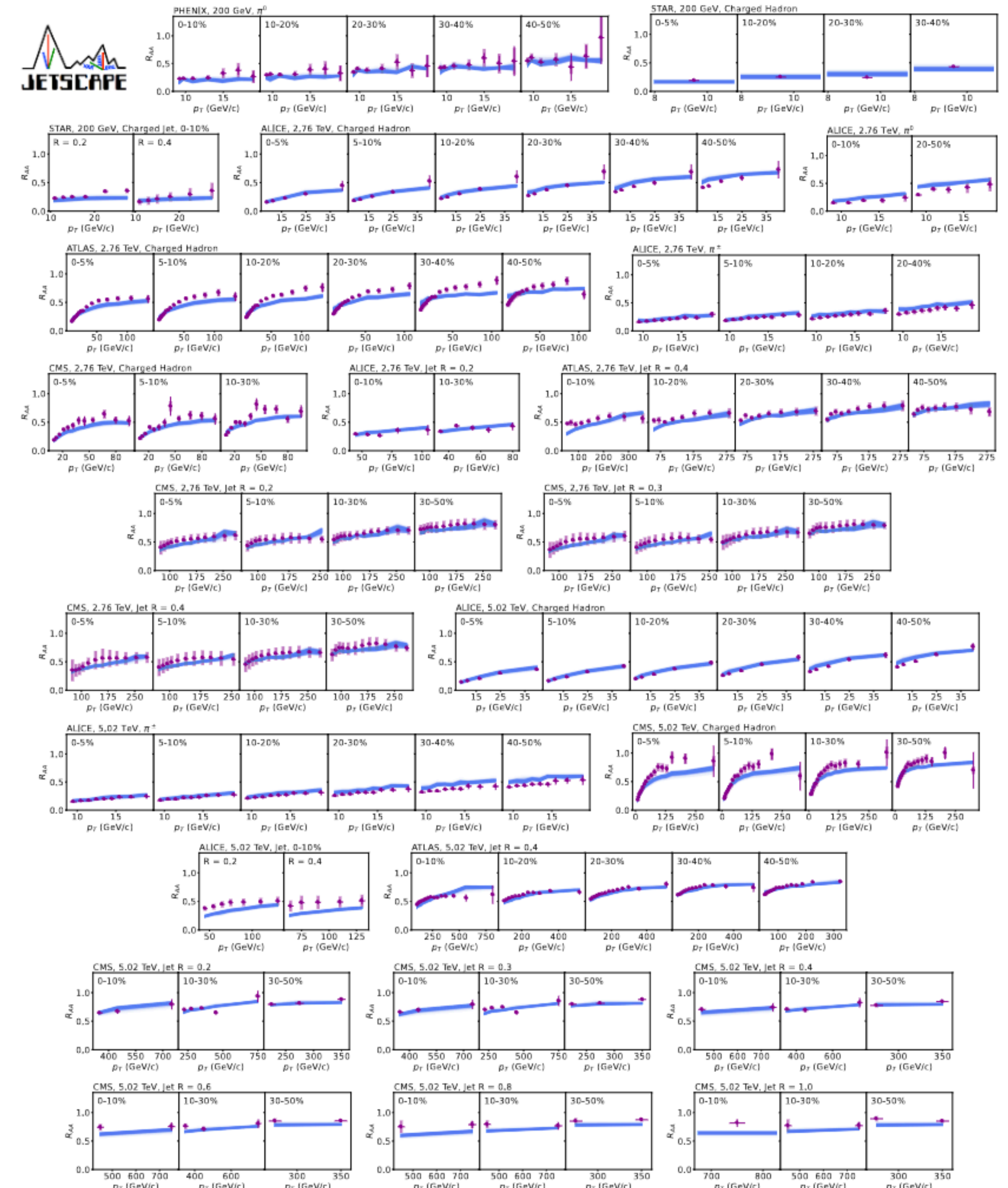
# Data-posterior comparison

Data  
Best fit

Reasonable overall  
agreement

Some tension for  
particular measurements

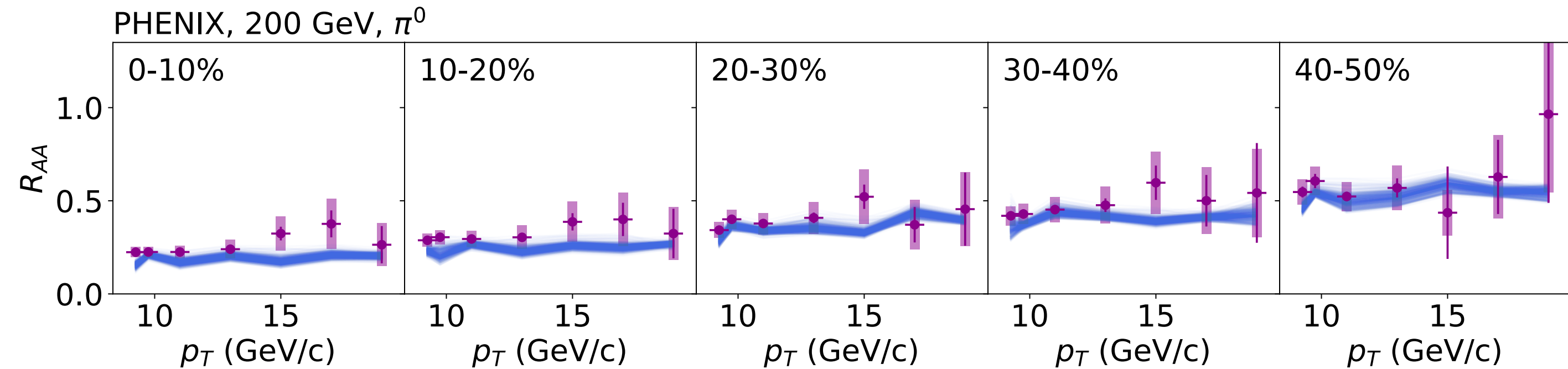
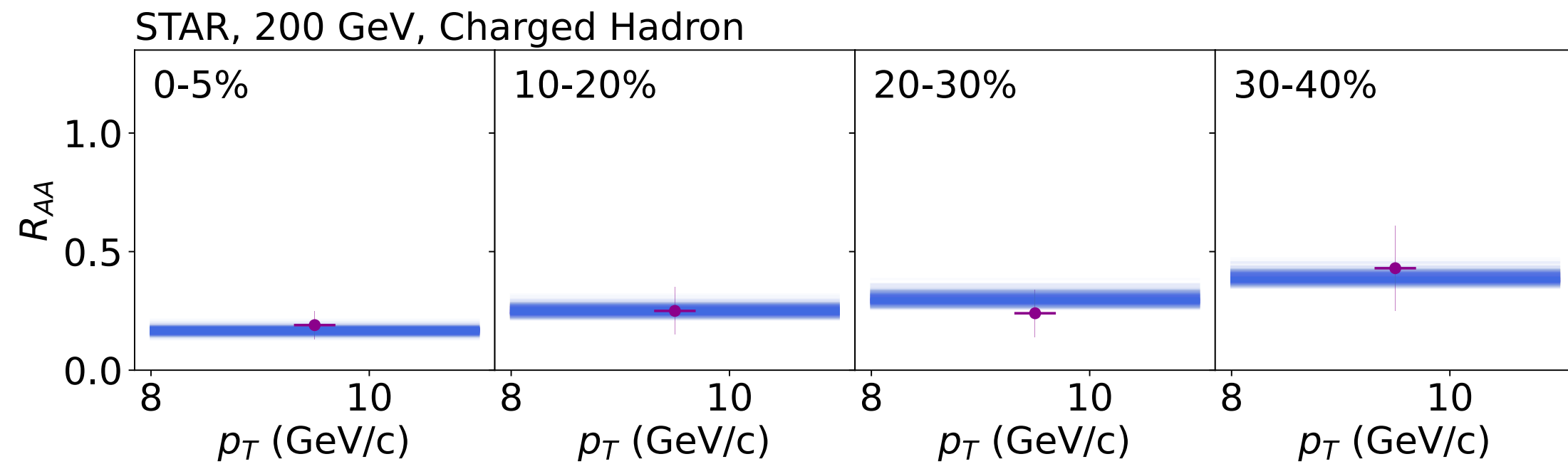
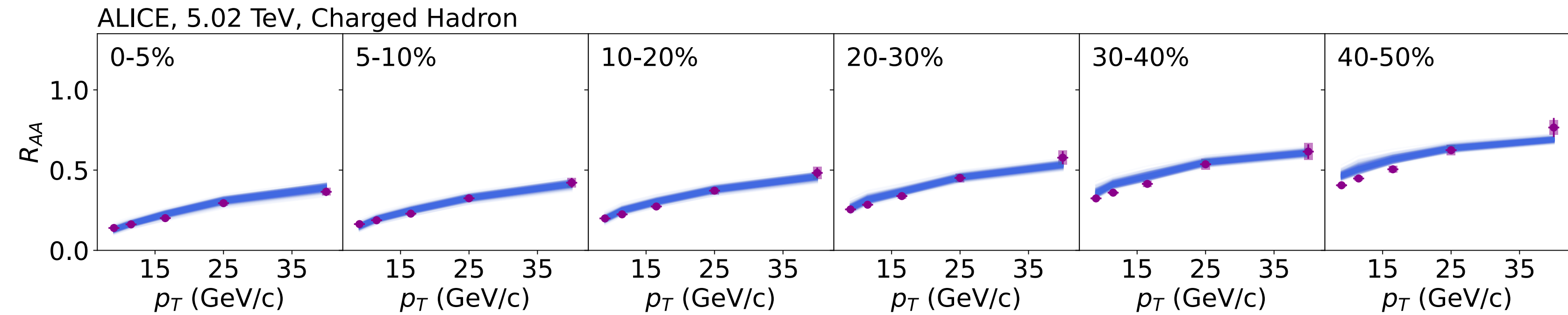
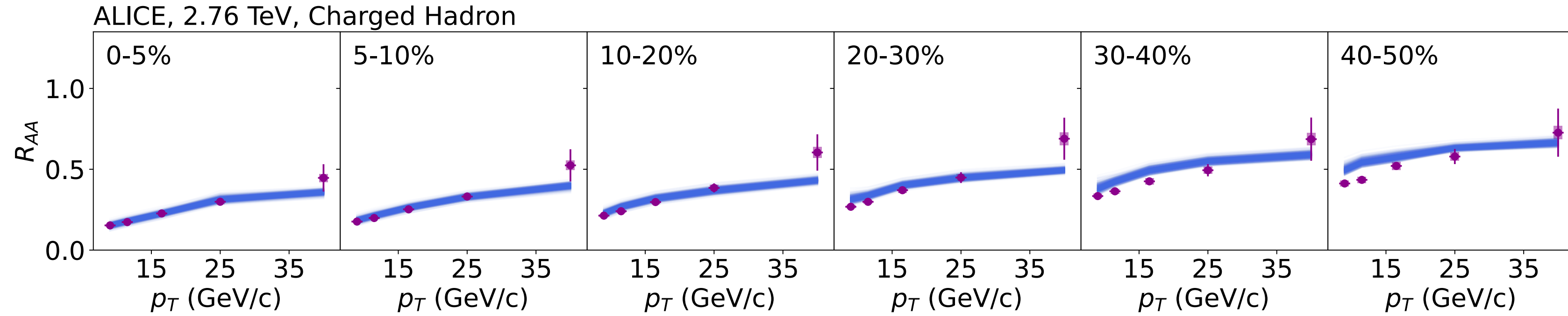
(Don't stare too closely, we'll  
explore zoomed figures)



# Posteriors: hadron $R_{AA}$ at low $p_T$

Good agreement  
at lower  $p_T$

Fairly consistent  
across experiments

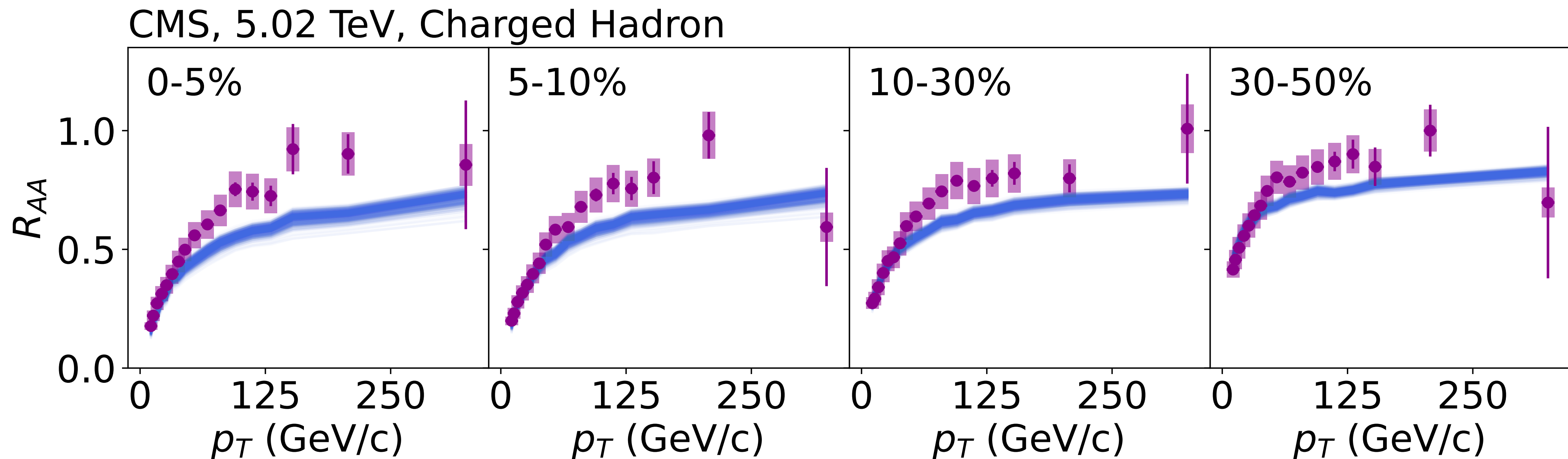


# Posteriors: hadron $R_{AA}$ at high $p_T$

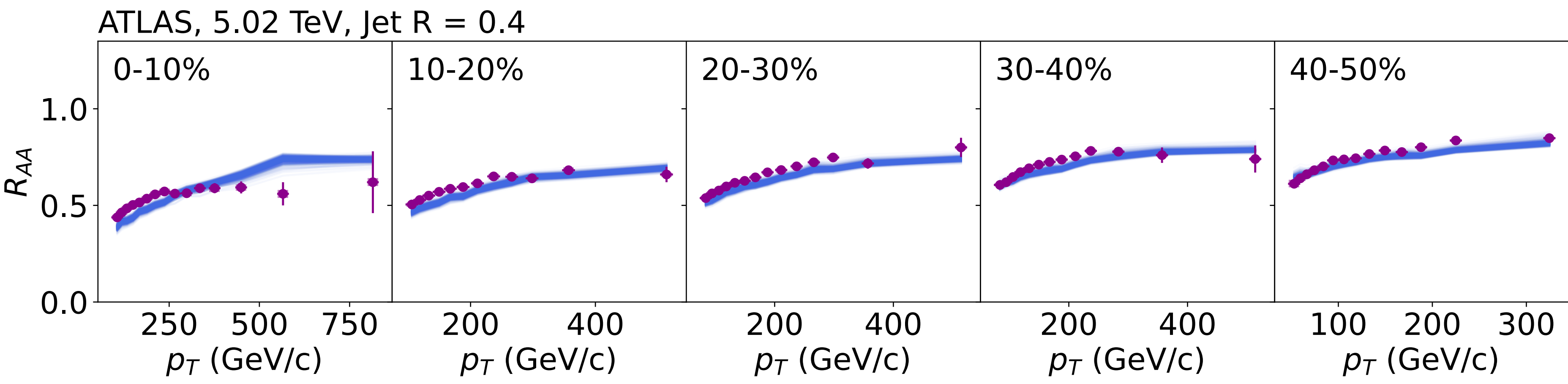
Some **tension** at higher  $p_T$

**Uncertainty smallest at lower  $p_T$**

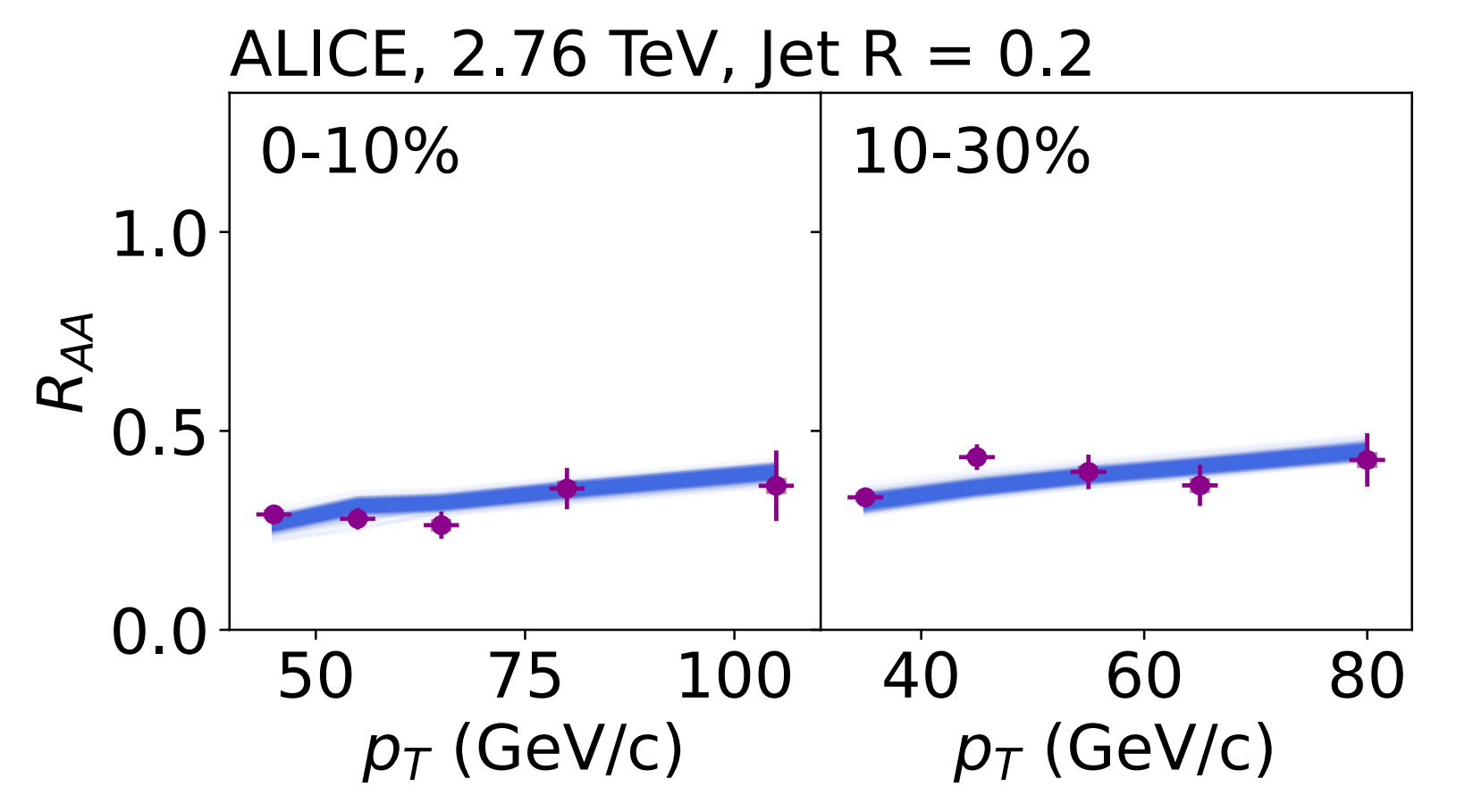
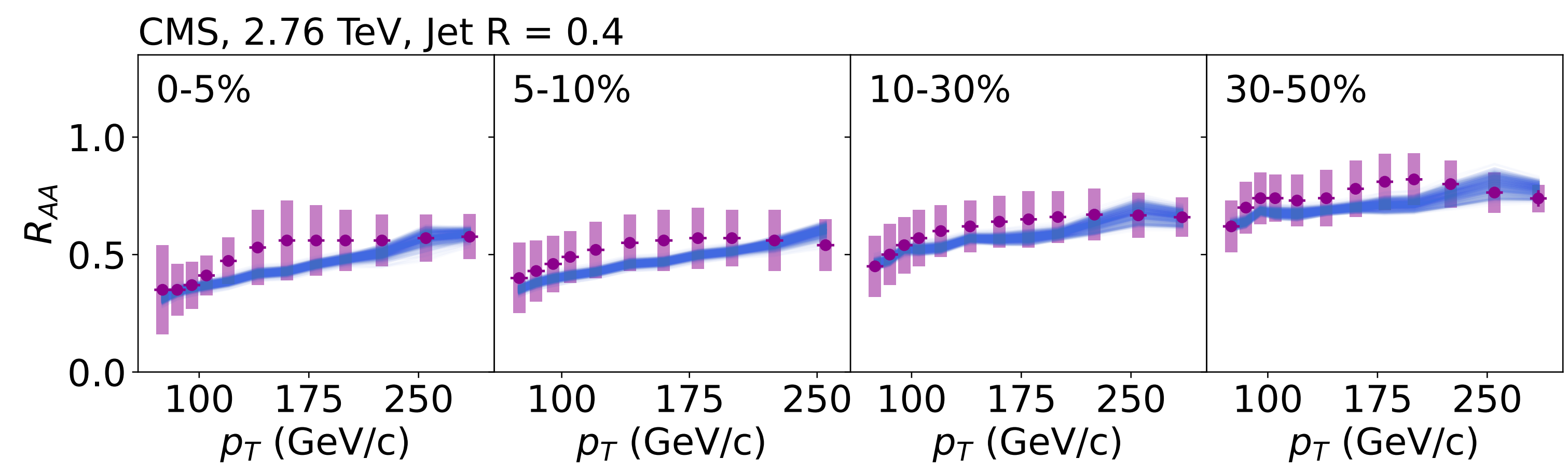
→ drives result



# Posteriors: jet $R_{AA}$

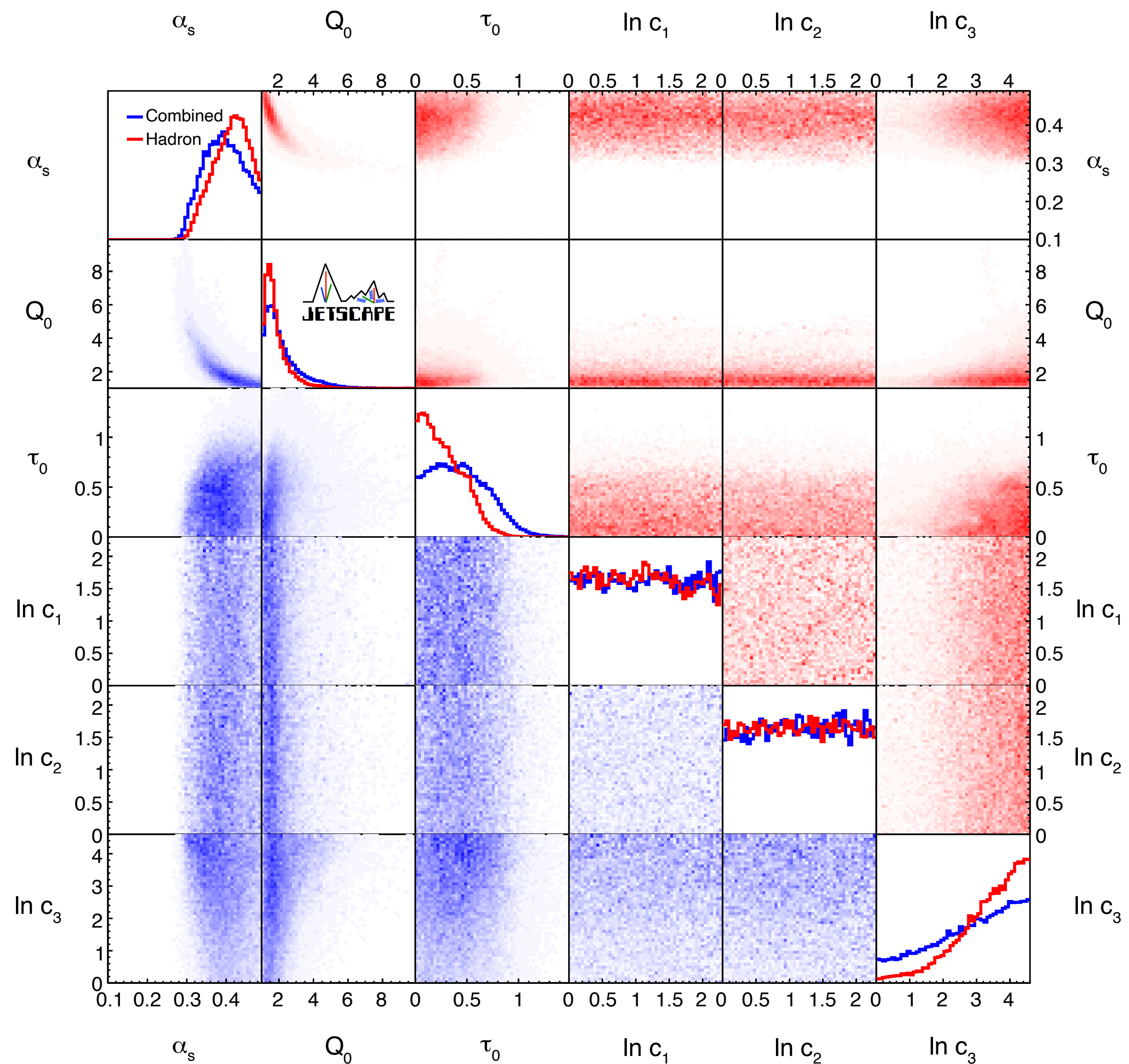


Generally **reasonable agreement**



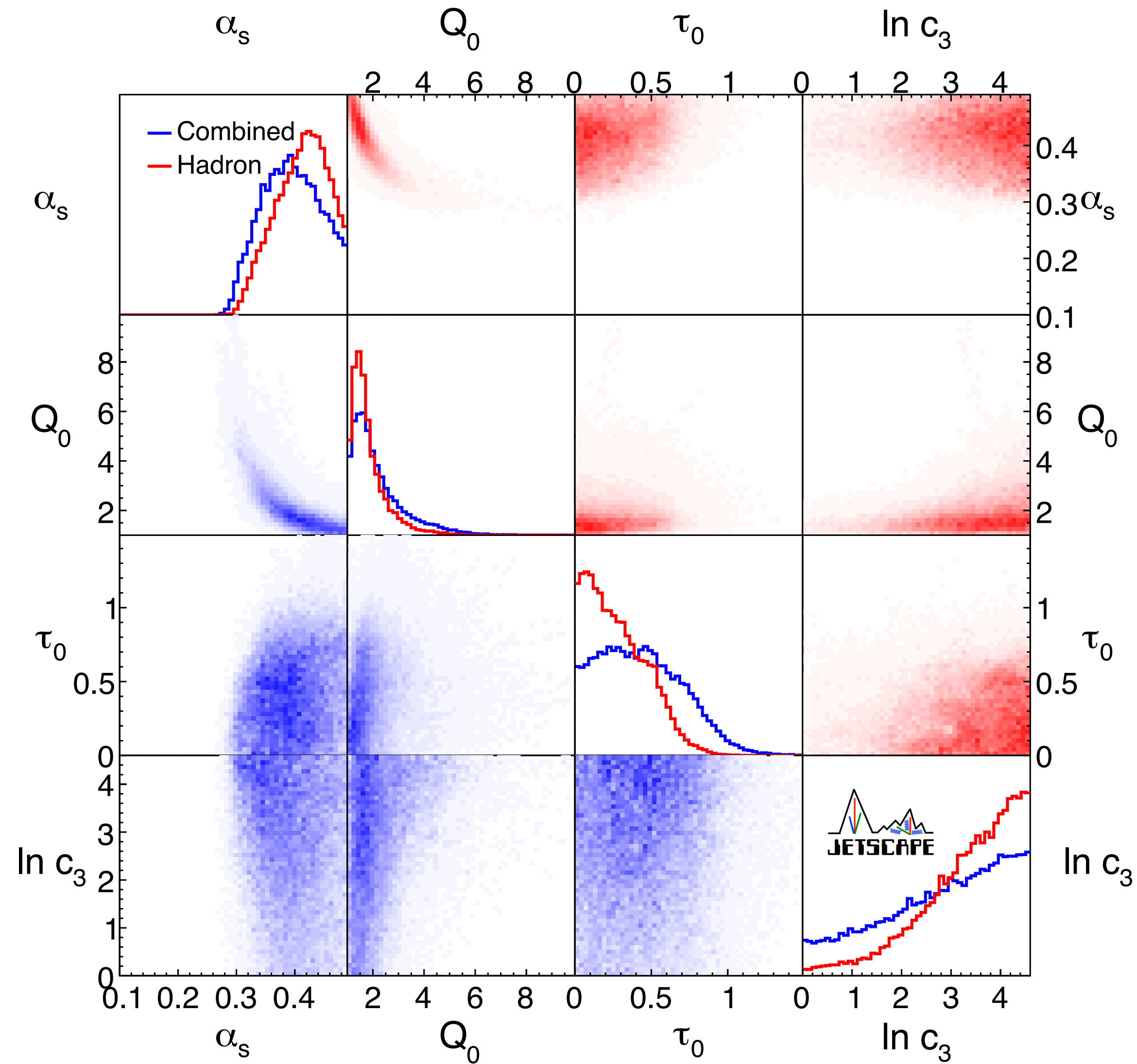


# Parameter posterior distribution



Not much sensitivity  
to  $c_1$  and  $c_2$ .  
→ We'll skip them  
for now

# Parameter posterior distribution



$\alpha_s \sim 0.3-0.4$

Low  $Q_0$  (as expected)

Wide  $\tau_0$  up to  $\sim 1$  fm/c

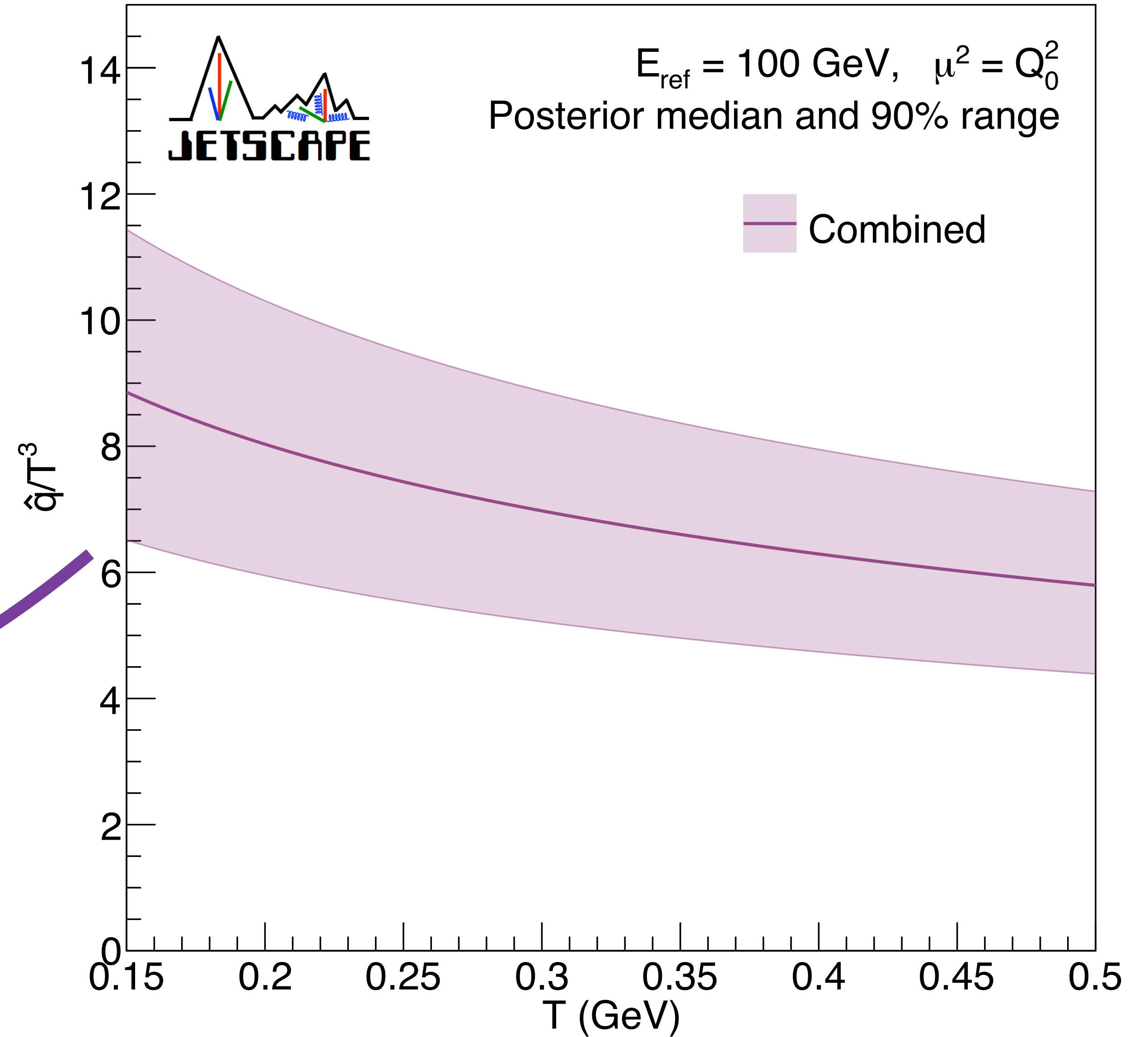
Some preference for larger  $c_3$

# Extracting $\hat{q}$

Put everything together  
to extract  $\hat{q}$

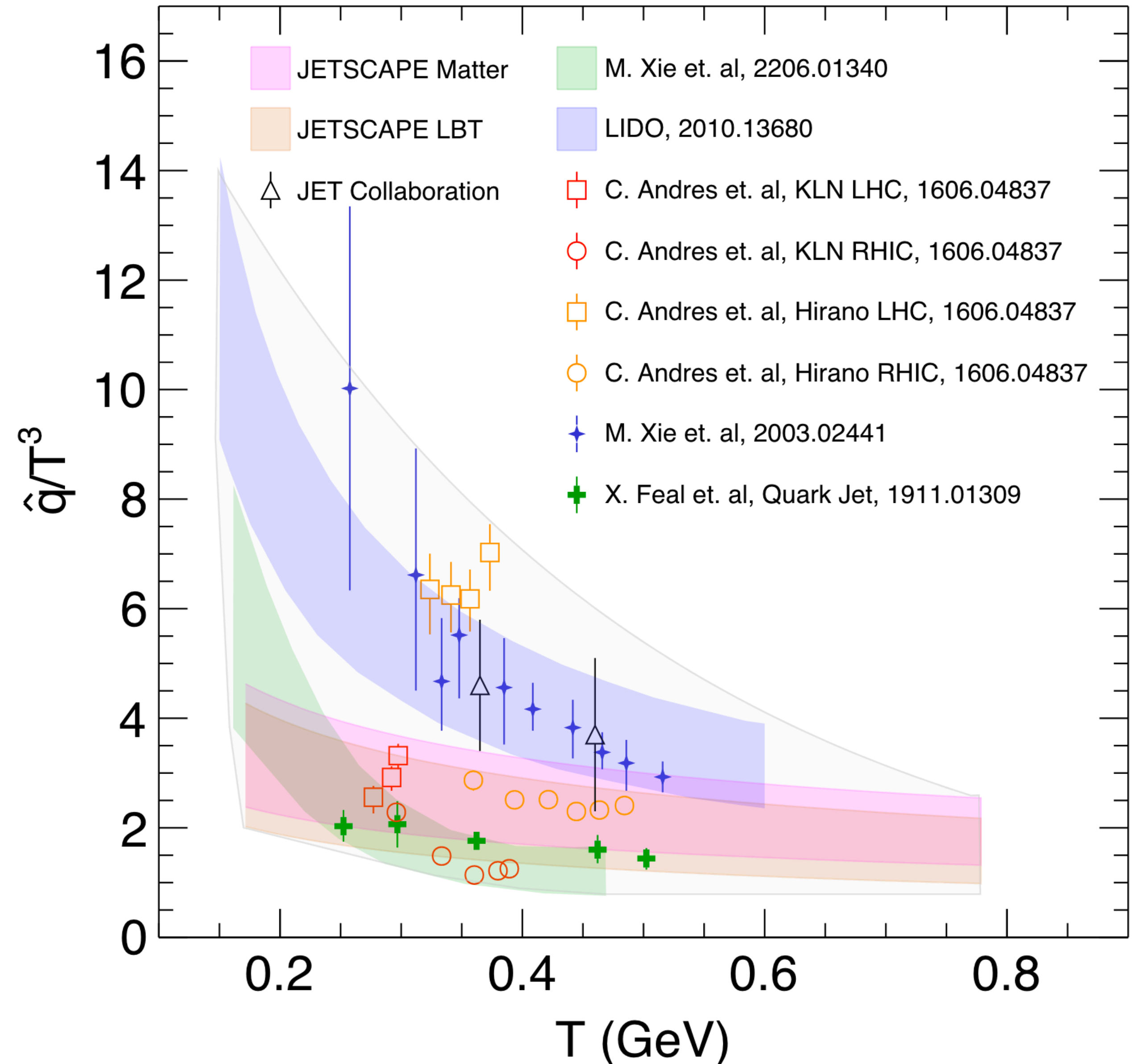
Here we plot the  $\hat{q}$   
when virtuality is low

i.e.,  $\hat{q} = \hat{q}_{HTL}^{run} \times f(Q^2)$



# Not all $\hat{q}$ are equivalent

Details of  $\hat{q}$  extraction  
are important!  
→ **Comparisons may  
not be equivalent**

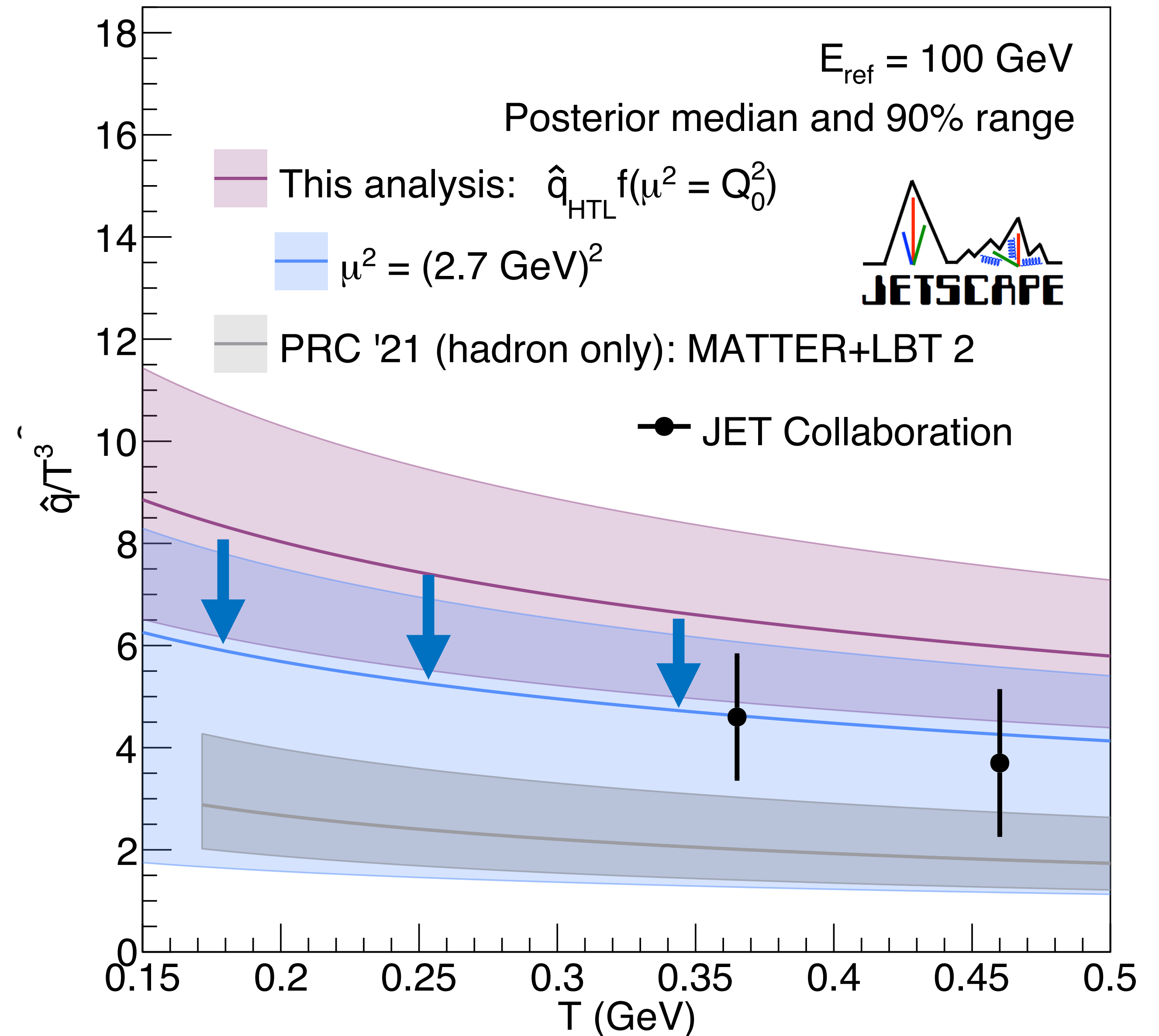


# Not all $\hat{q}$ are equivalent

Details of  $\hat{q}$  extraction are important!

→ **Comparisons may not be equivalent**

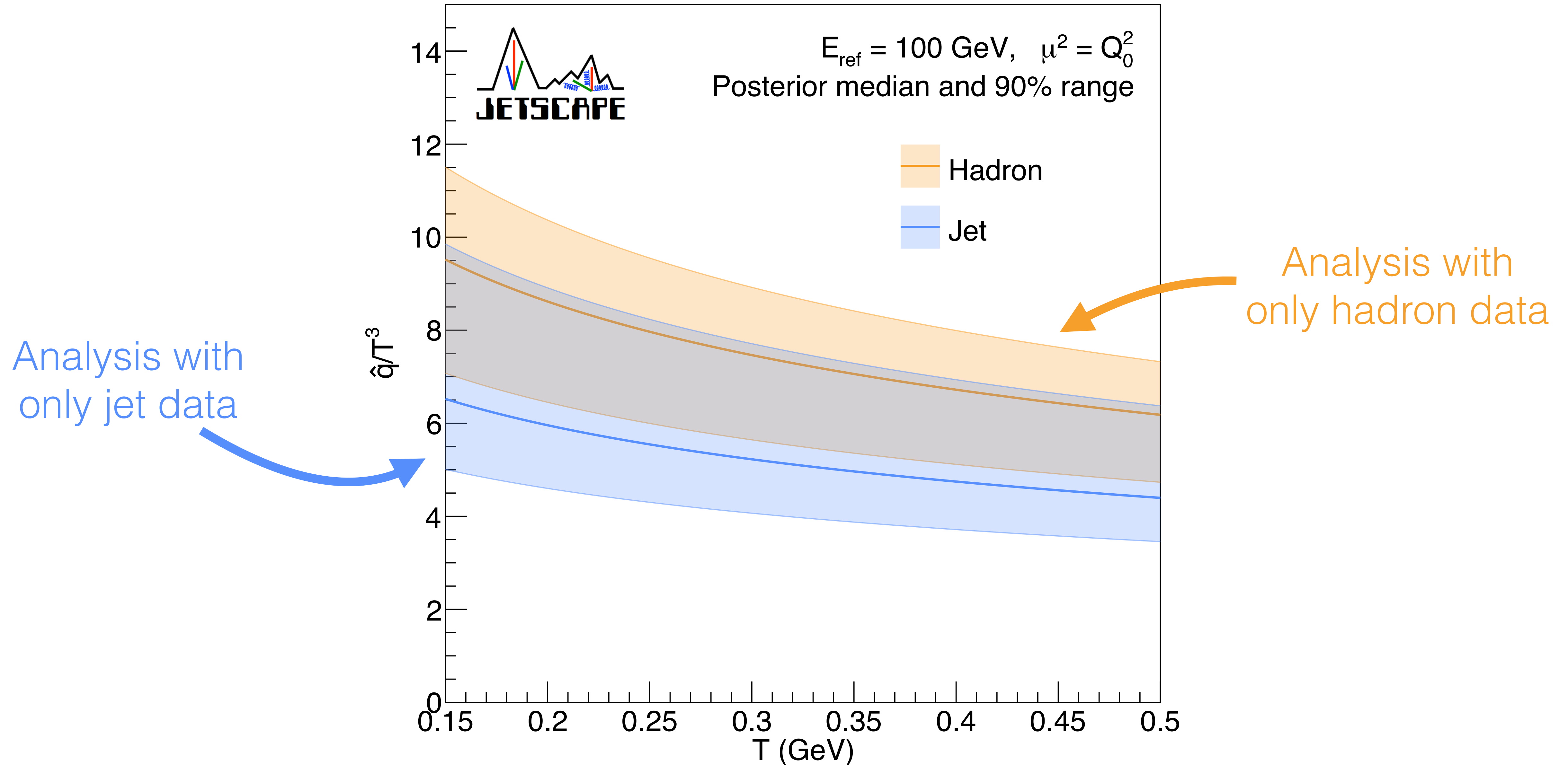
JETSCAPE calibrations are **consistent when evaluated at same  $\mu^2$**



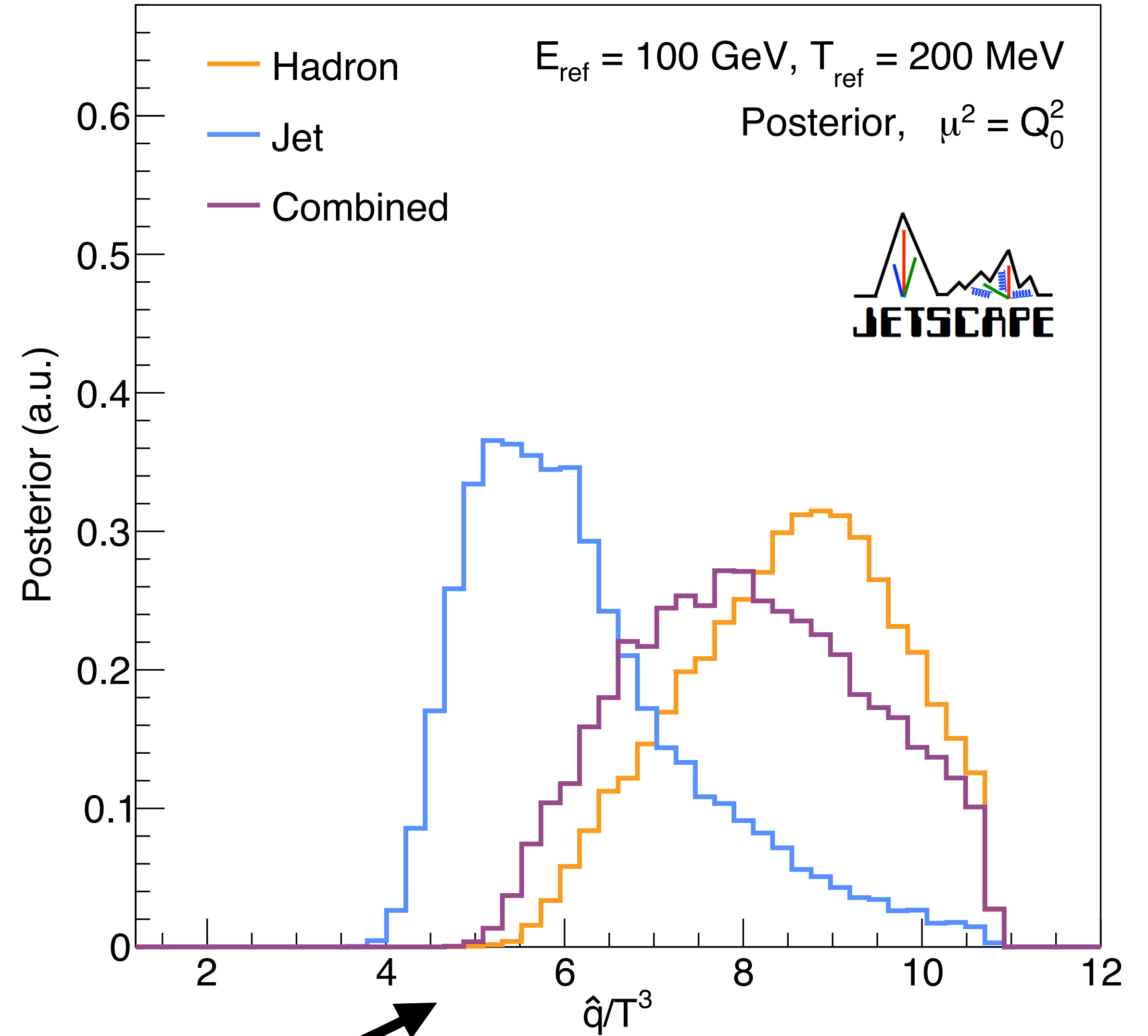
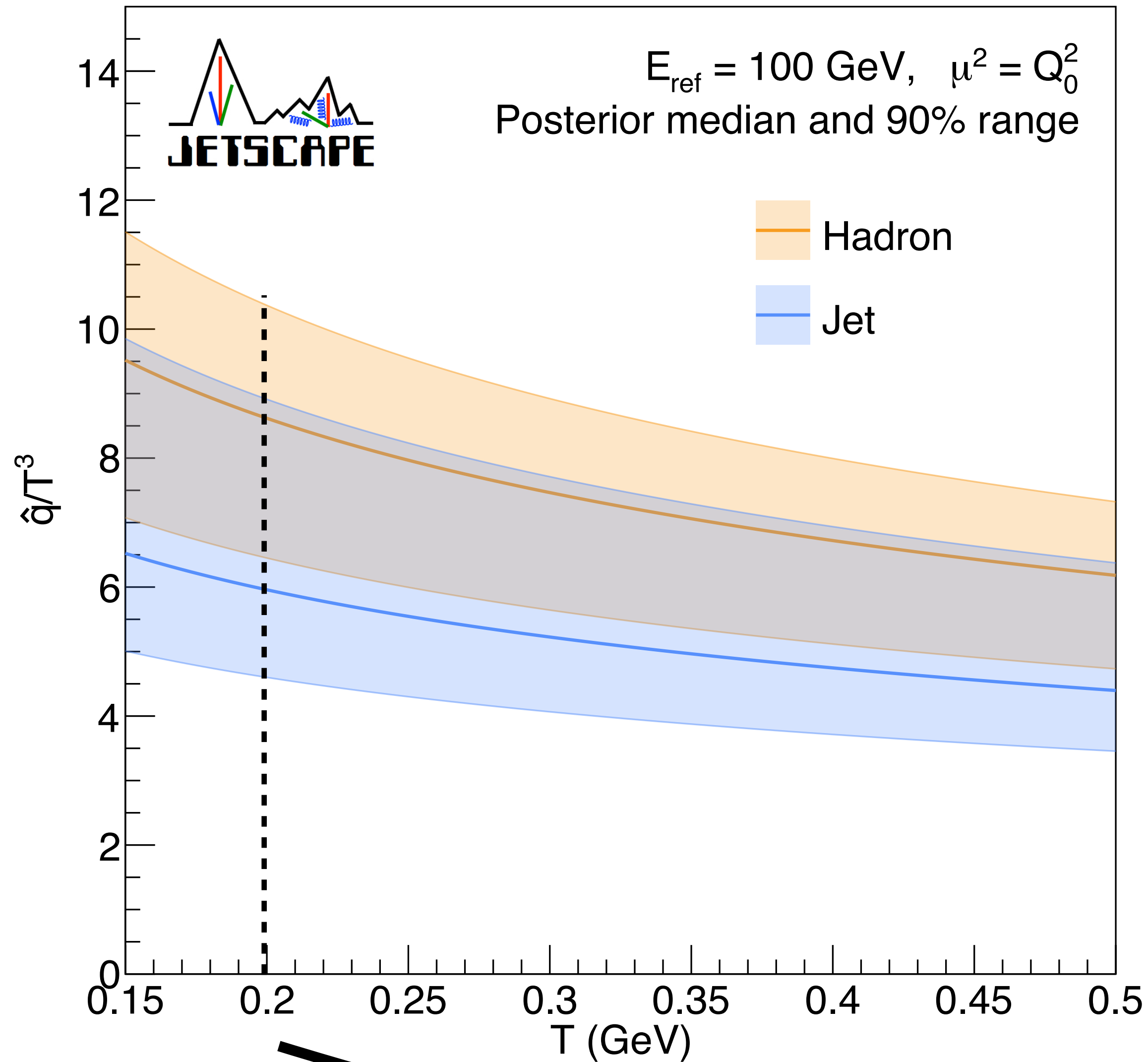
**What's next?**

- 1. Differential studies of model consistency**
- 2. What information is contained in each observable?**

# Hadron vs jet $R_{AA}$

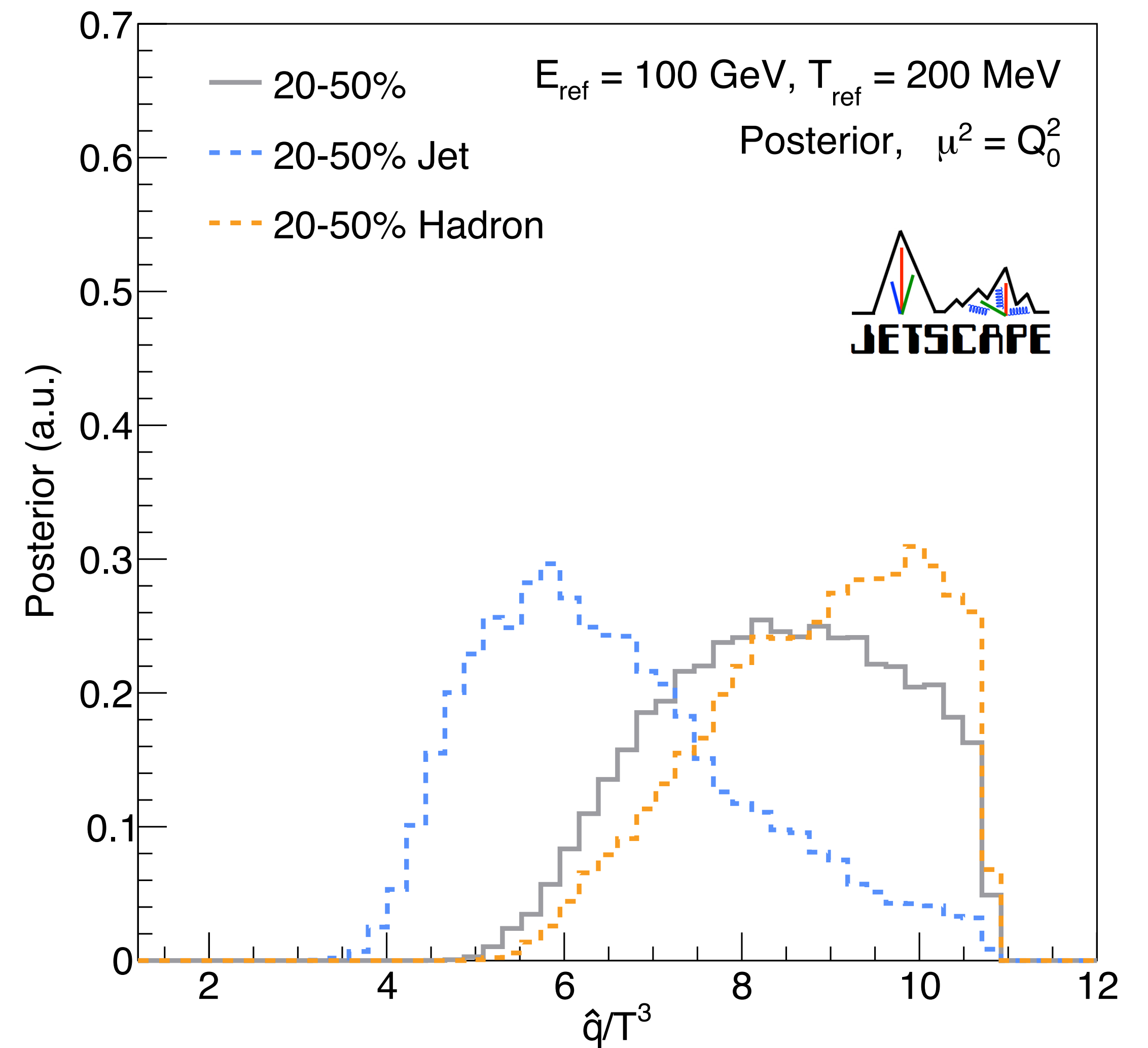
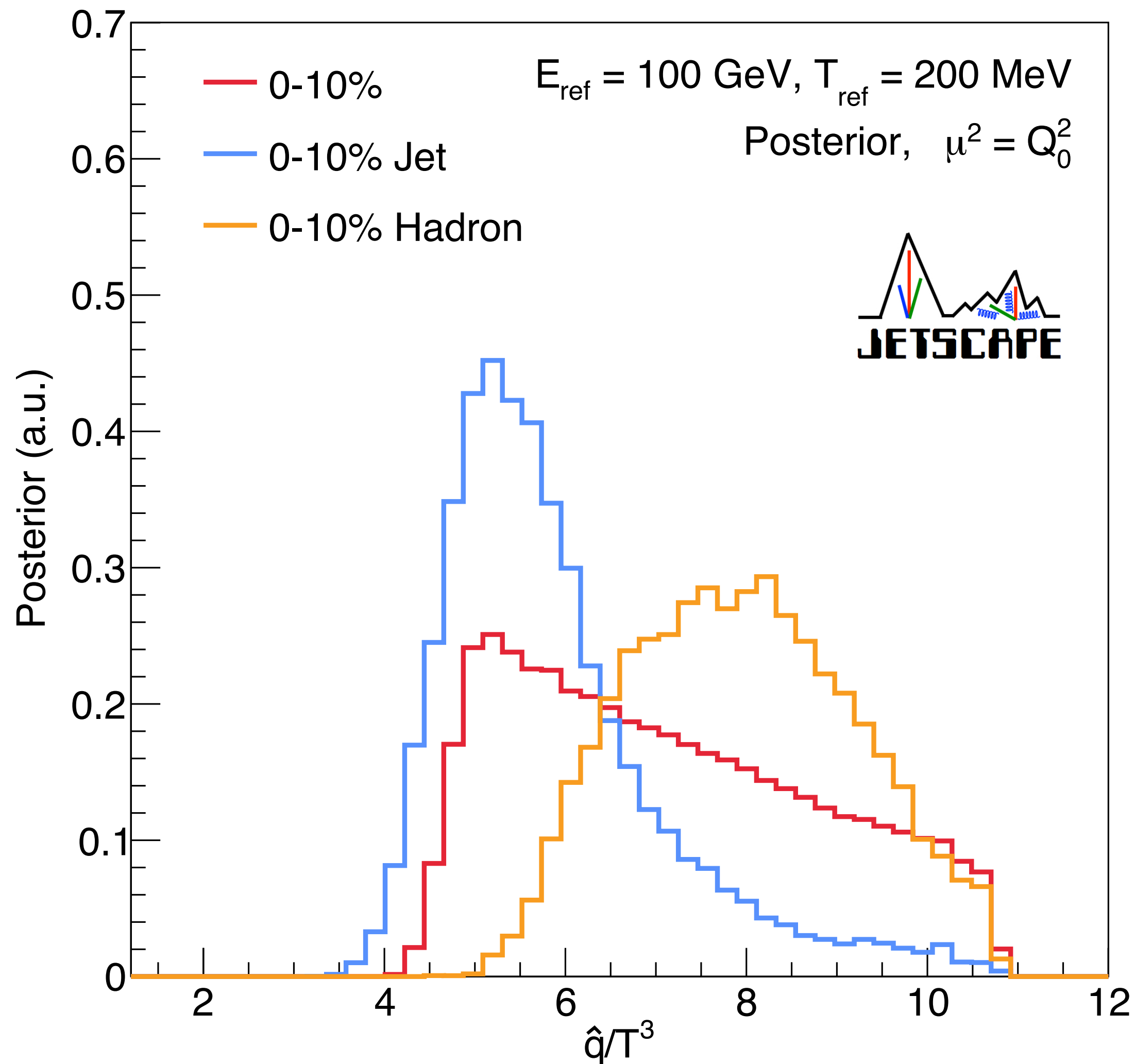


# Hadron vs jet $R_{AA}$





# Centrality dependence



**Doesn't change the jet vs hadron picture**

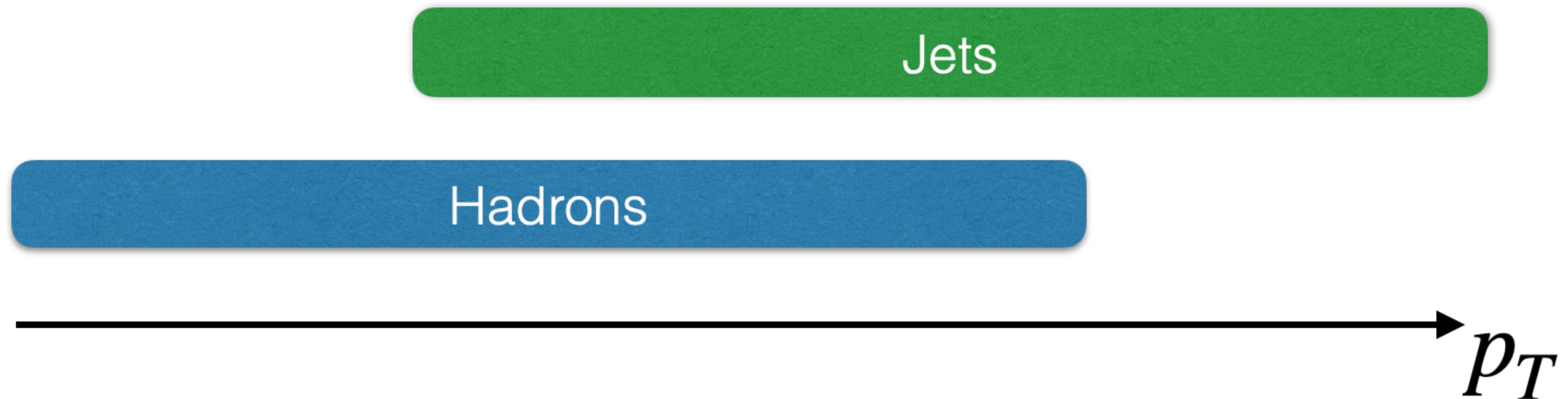
Further investigations in the future

# Kinematic ranges

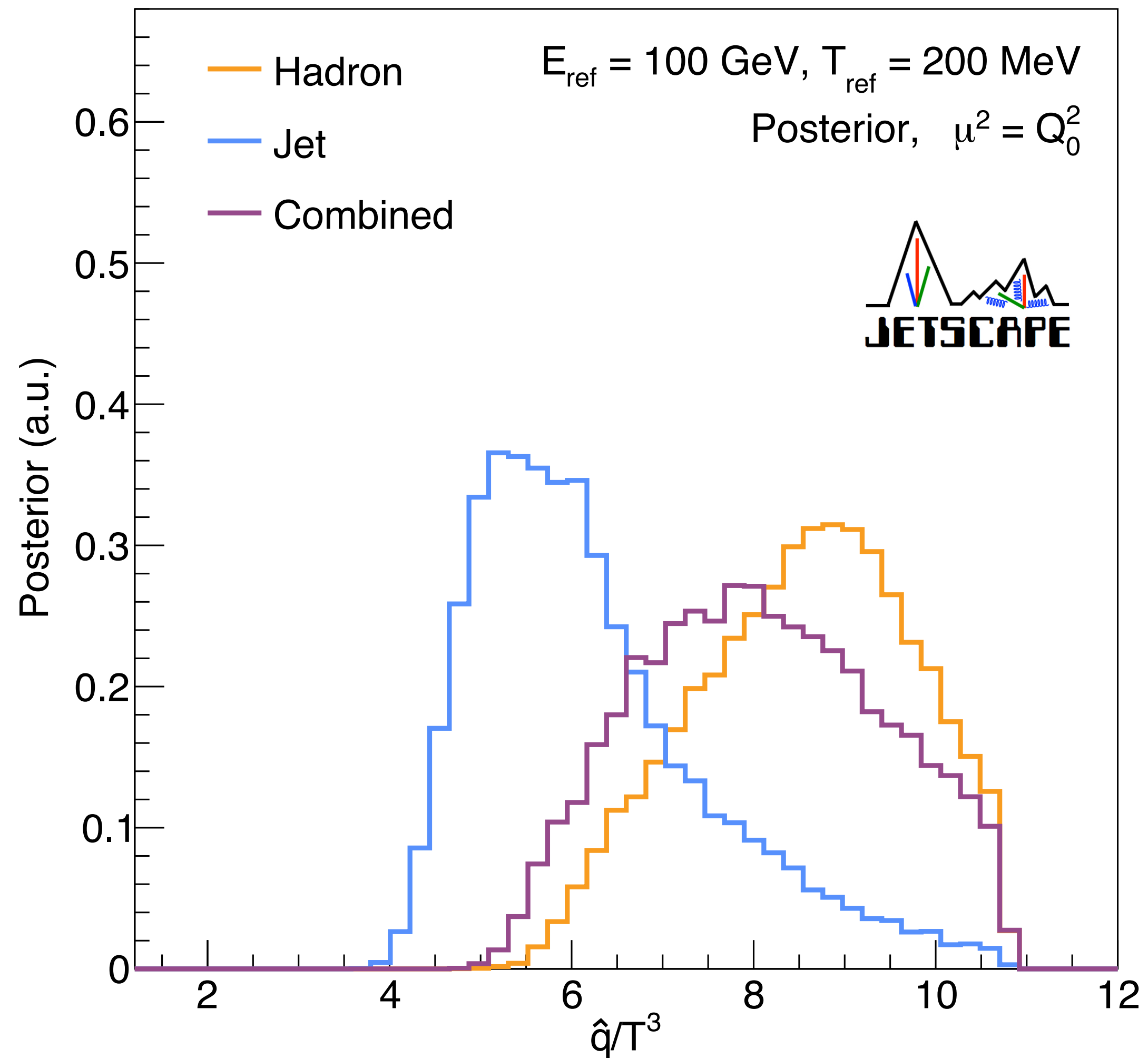
Is the difference we see inherent in the type of observables, or due to another source?

$\hat{q}$  expected to be consistent across observables?

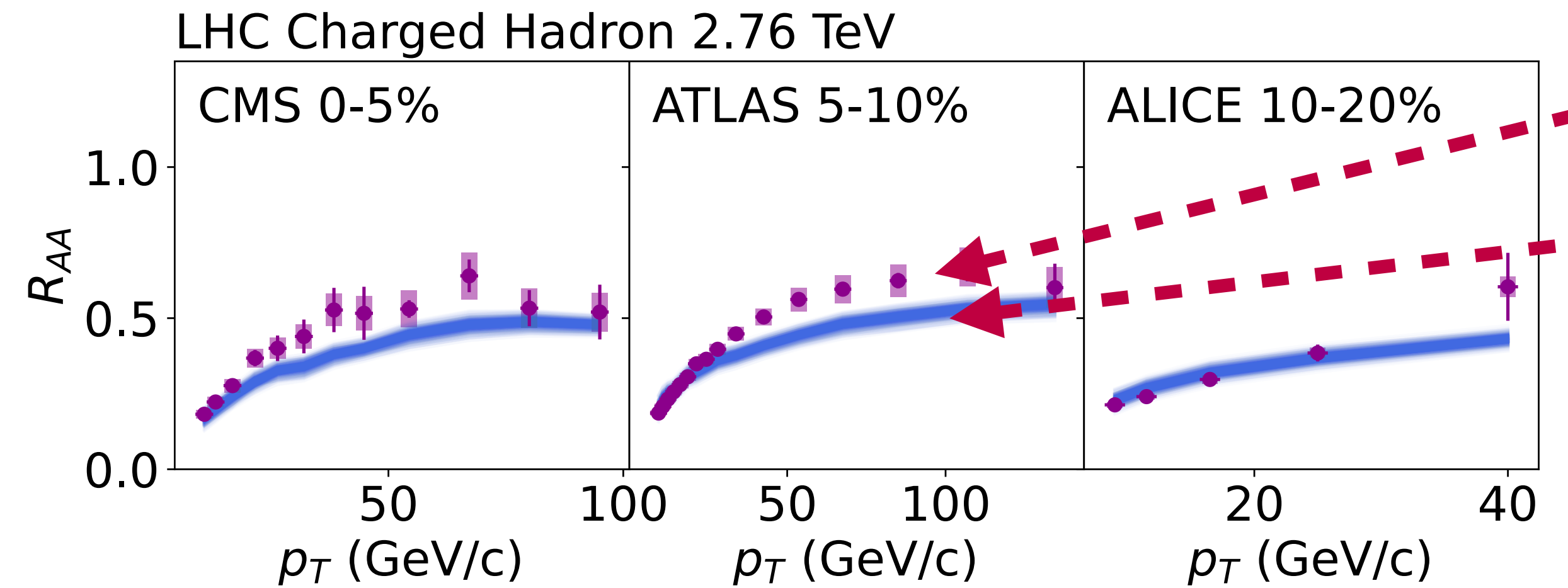
One potential candidate: **kinematic range**



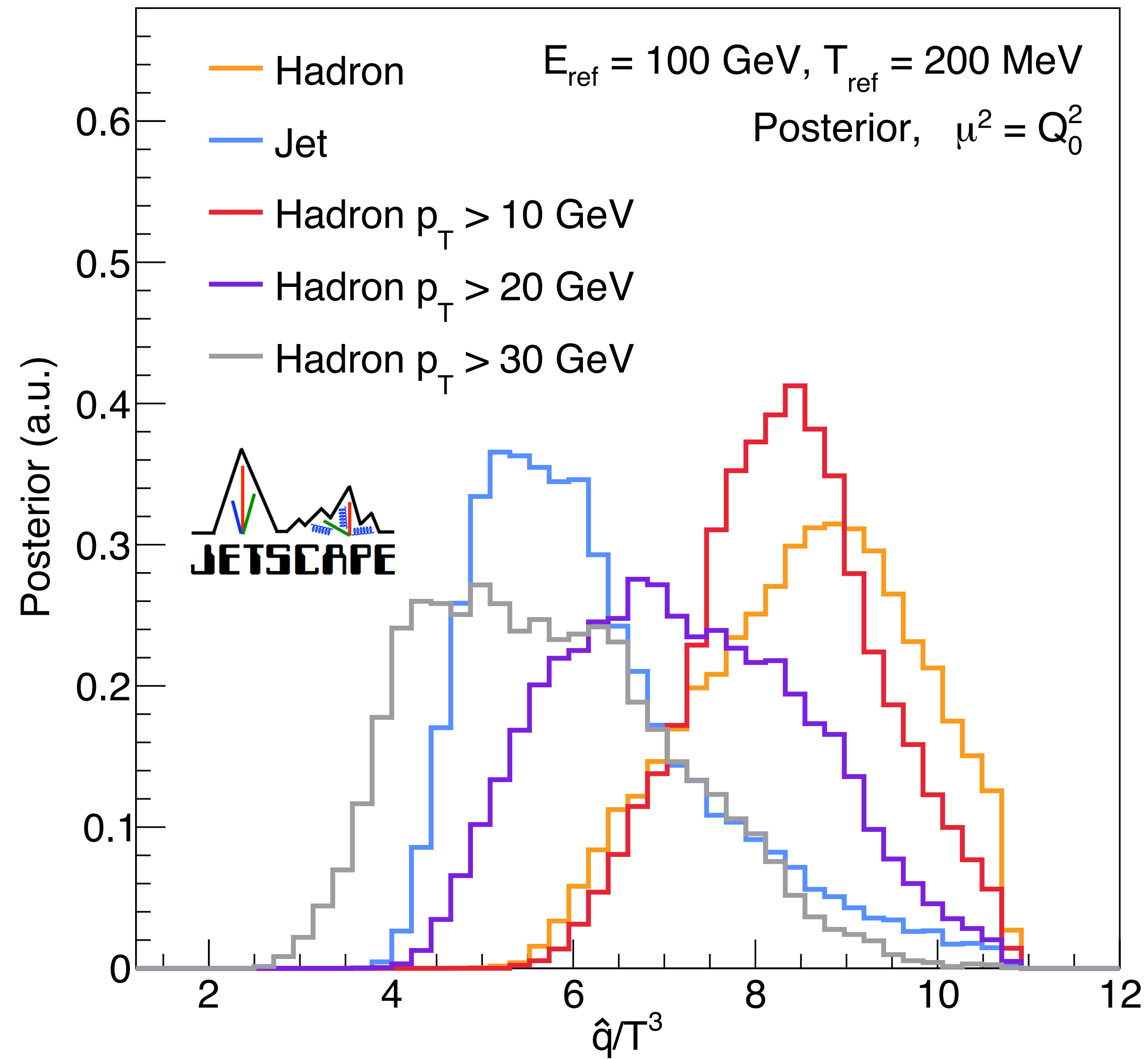
# Calibrating with low vs high $p_T$ hadrons



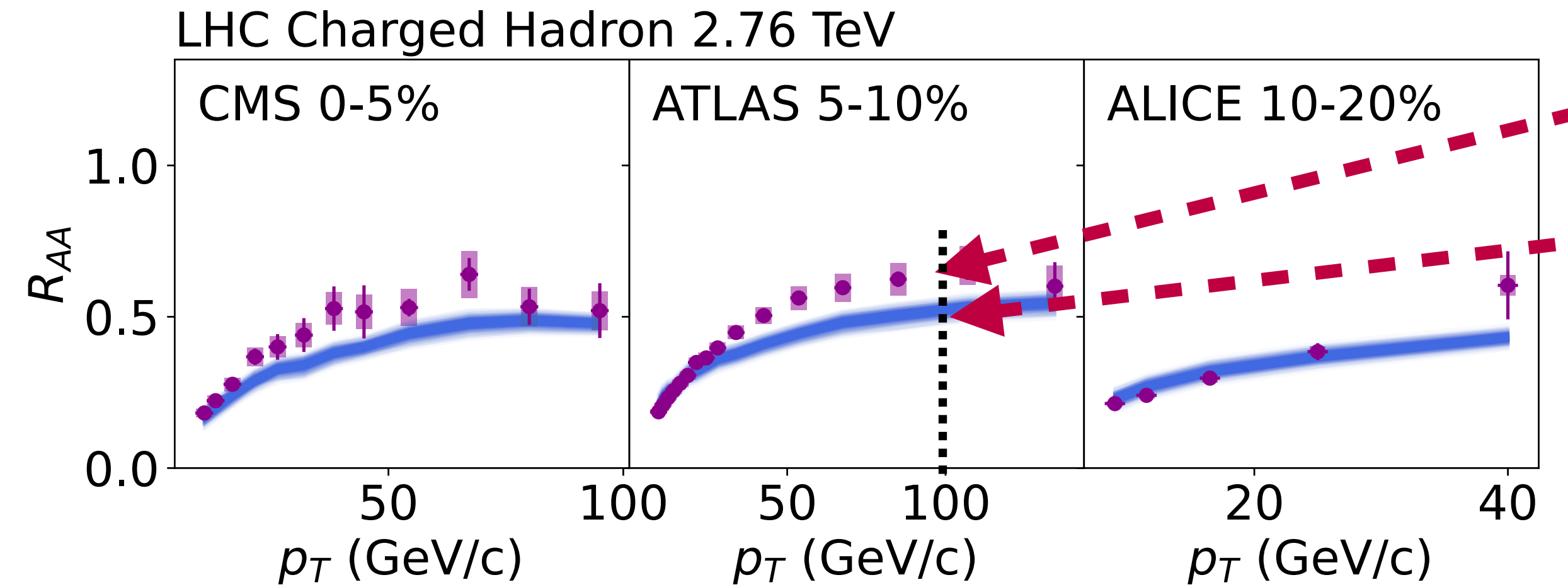
Full  $p_T$  range



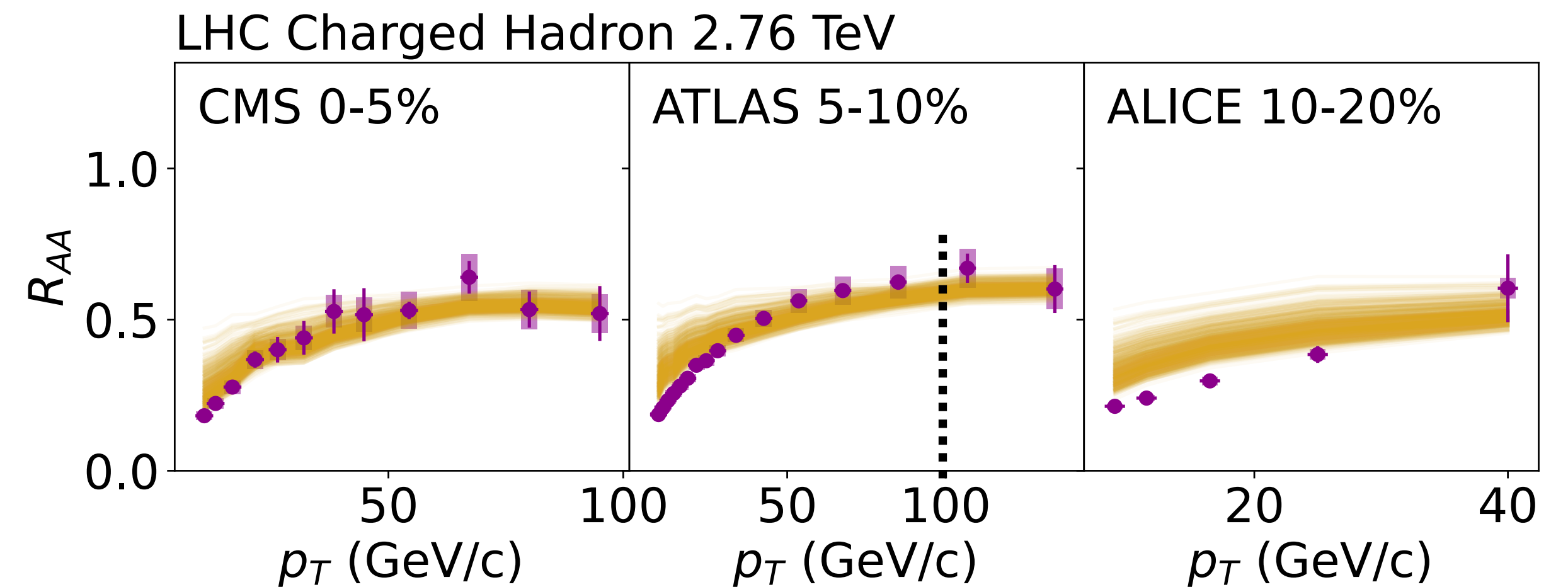
# Calibrating with low vs high $p_T$ hadrons



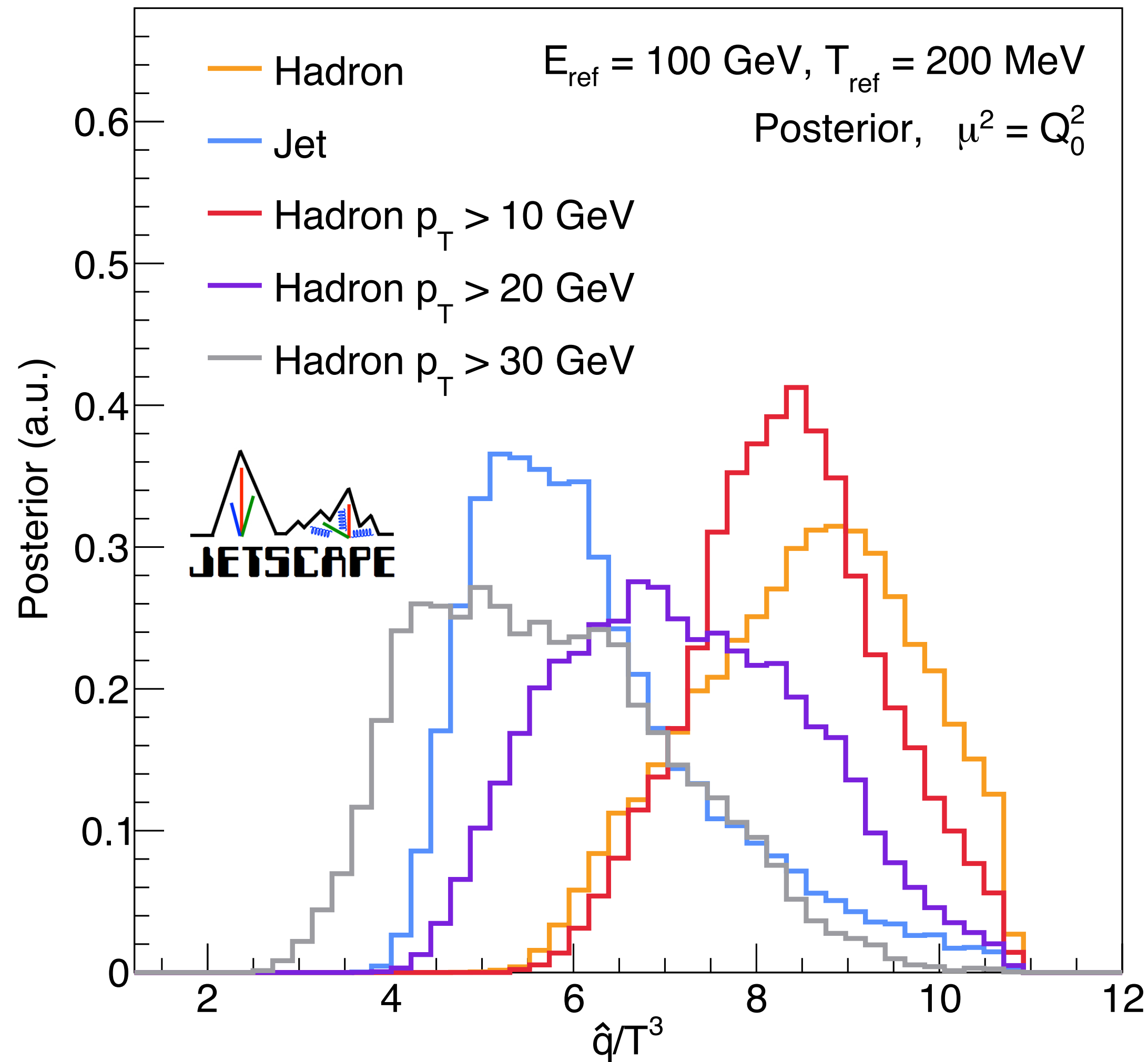
## Full $p_T$ range



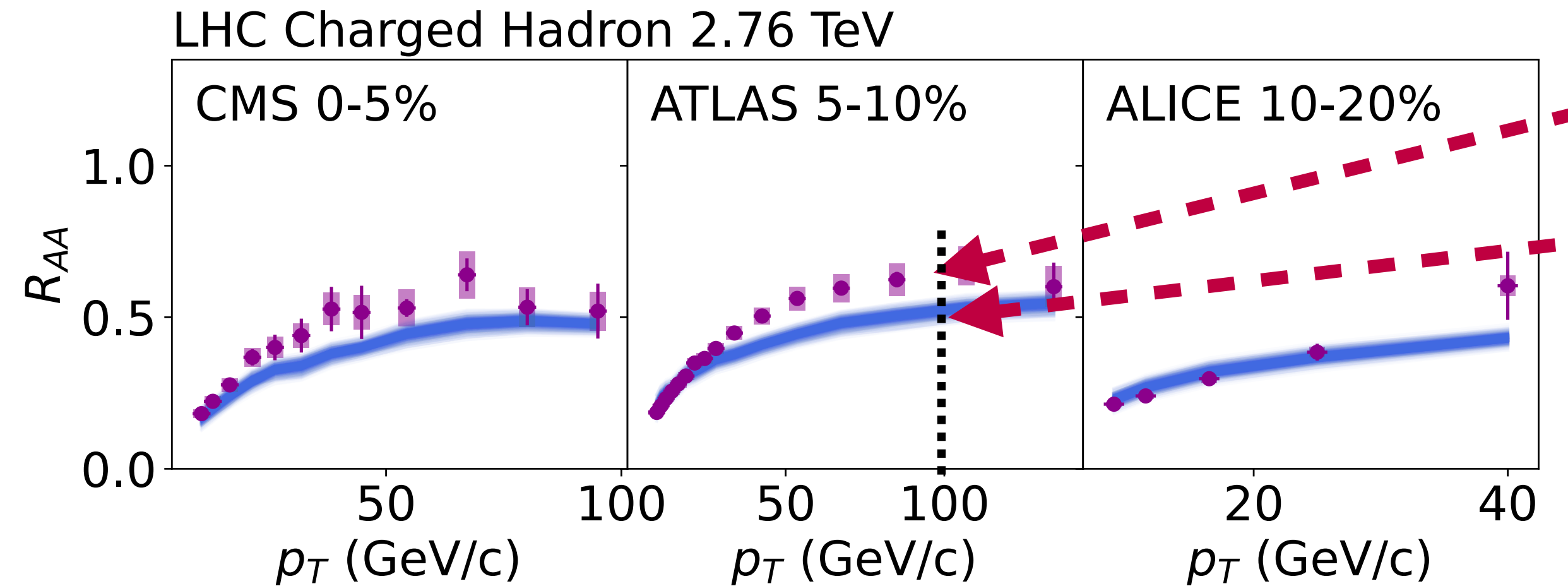
## Only hadrons $p_T > 30 \text{ GeV}$



# Calibrating with low vs high $p_T$ hadrons



## Full $p_T$ range



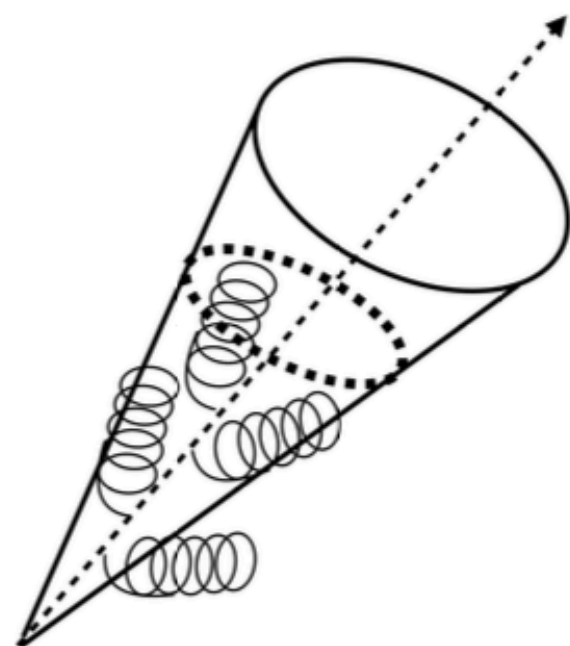
- **Low  $p_T$  dominates** due to small exp. uncert.
- **High  $p_T$**  in line with jet data
- Points to phase space for model improvement
- **Theory uncertainty is important!**
  - eg. No shadowing included
- **Small exp. uncertainty where theory has largest uncertainty**

# Jets and jet substructure

- **What (additional) information do jet substructure observables contain?**
- Further **insight into differences** in  $\hat{q}$  from hadron- and jet-only extractions?
- Exploratory investigation with **simplified but consistent** error treatment
  - Focus on 0-10% central data
- **Baseline: Jet  $R_{AA}$  only**

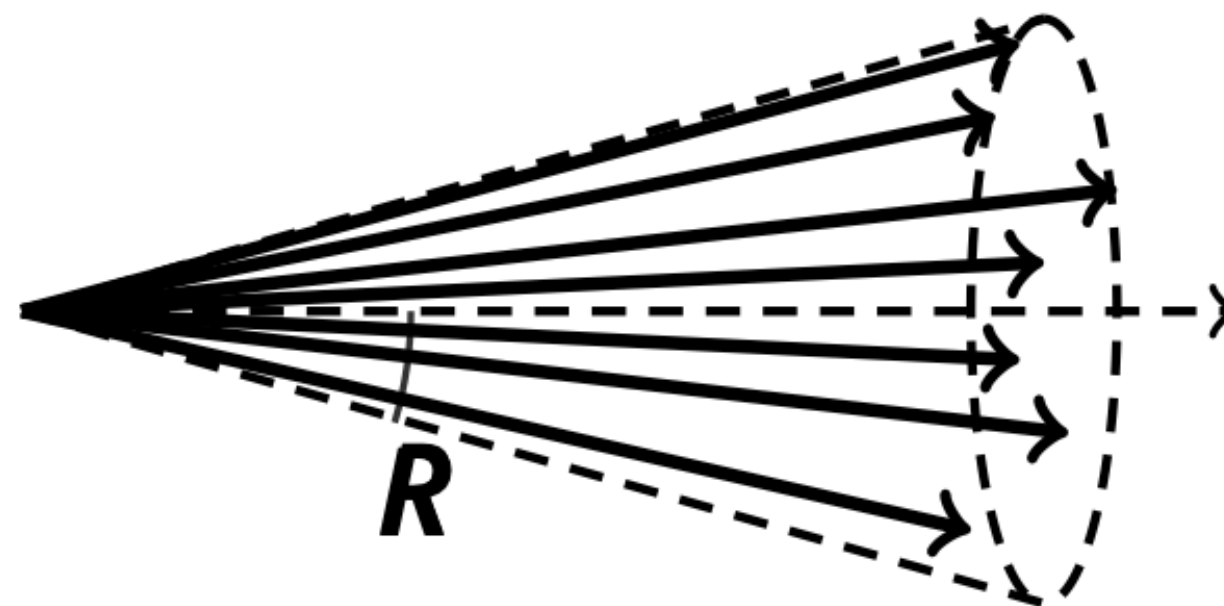
## Jet $R_{AA}$

- ALICE, ATLAS, CMS, STAR



## Fragmentation: $D(z)$

- ATLAS:  $D(z)$
- CMS:  $\xi(z)$



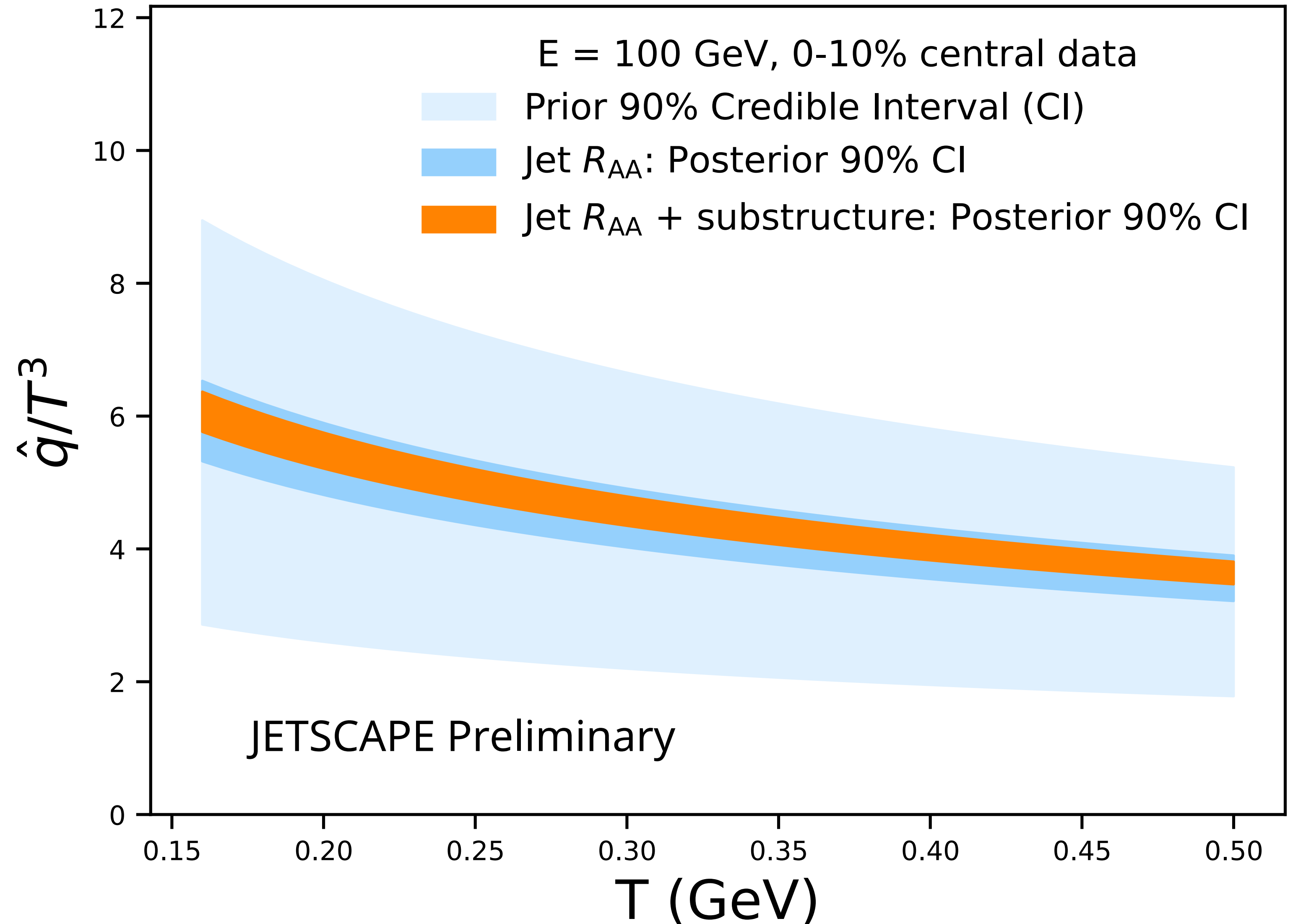
## Groomed jet substructure

- ALICE:  $R_g, z_g$



# Constraints on $\hat{q}$

- **Consistent description of jet  $R_{AA}$  with substructure observables**
- Substructure yields **stronger relative constraint**<sup>1</sup>

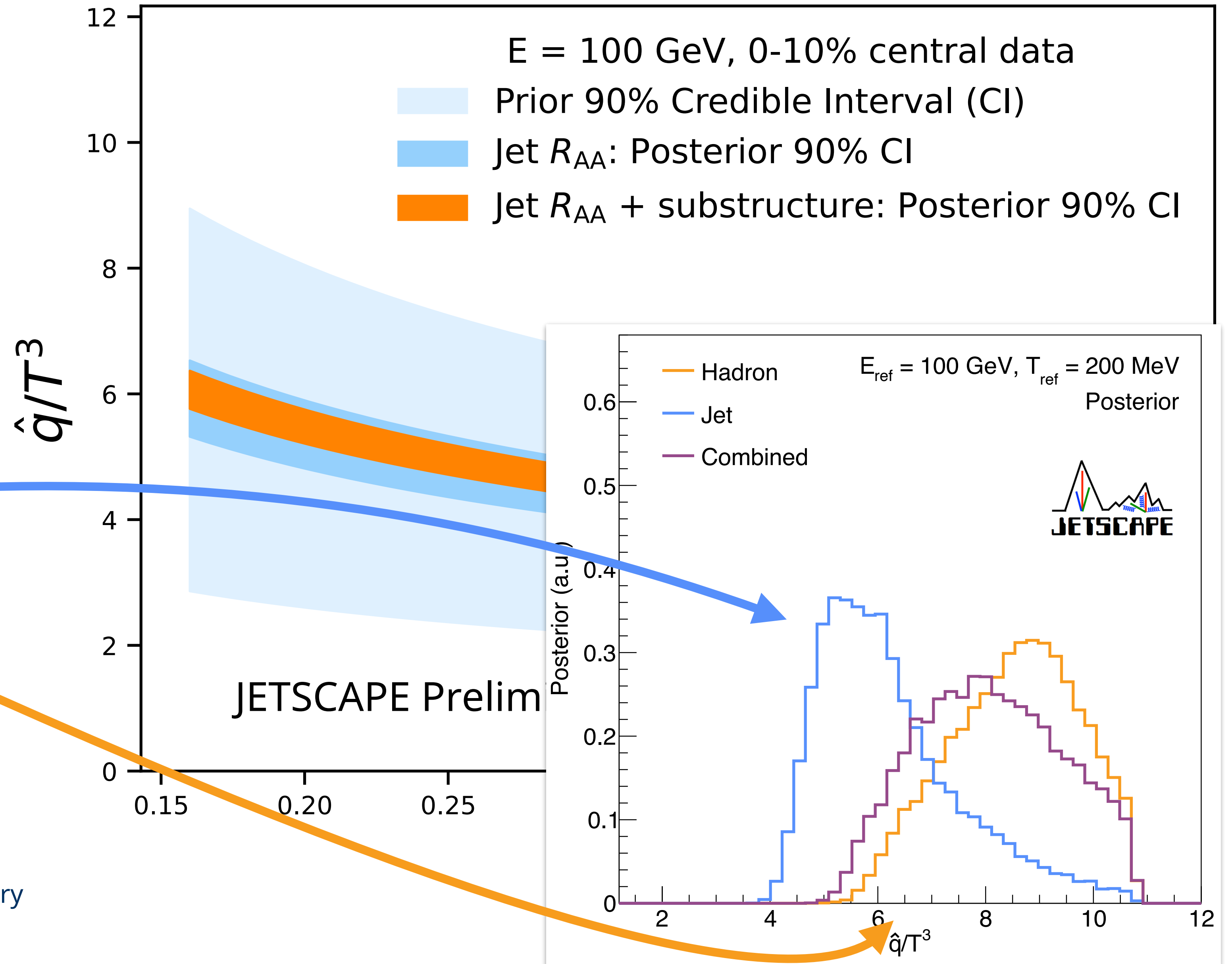


<sup>1</sup>Recent note: relative constraint holds, but y-scale may vary

# Constraints on $\hat{q}$

- Consistent description of jet  $R_{AA}$  with substructure observables
- Substructure yields stronger relative constraint<sup>1</sup>
- Tension between inclusive jets and (low  $p_T$ ) hadrons, but low  $z$  jet fragmentation consistent...?

**Under further investigation**

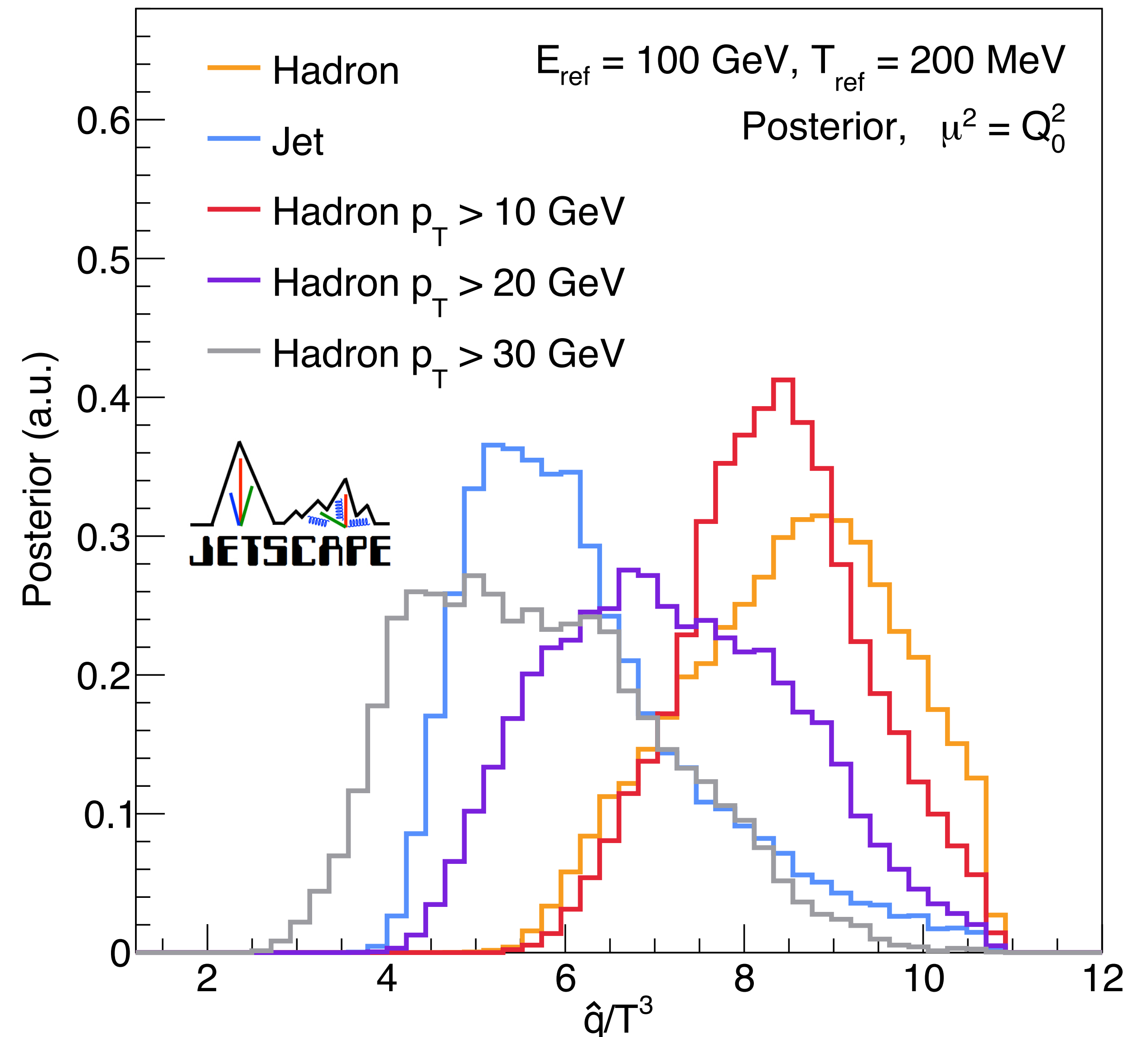


<sup>1</sup>Recent note: relative constraint holds, but y-scale may vary



# Bayesian Inference: Some take-away messages

1. Need fully **apples-to-apples comparison of extracted medium properties**
2. **Estimation of theory uncertainties**
3. **Data agnostic approach**
4. **Experimentalists:** Report **covariance** (harder) or **signed uncertainties** (simpler)!
  - Covariance is important, **especially for precision**
  - See also: Yi Chen, INT 24-88W



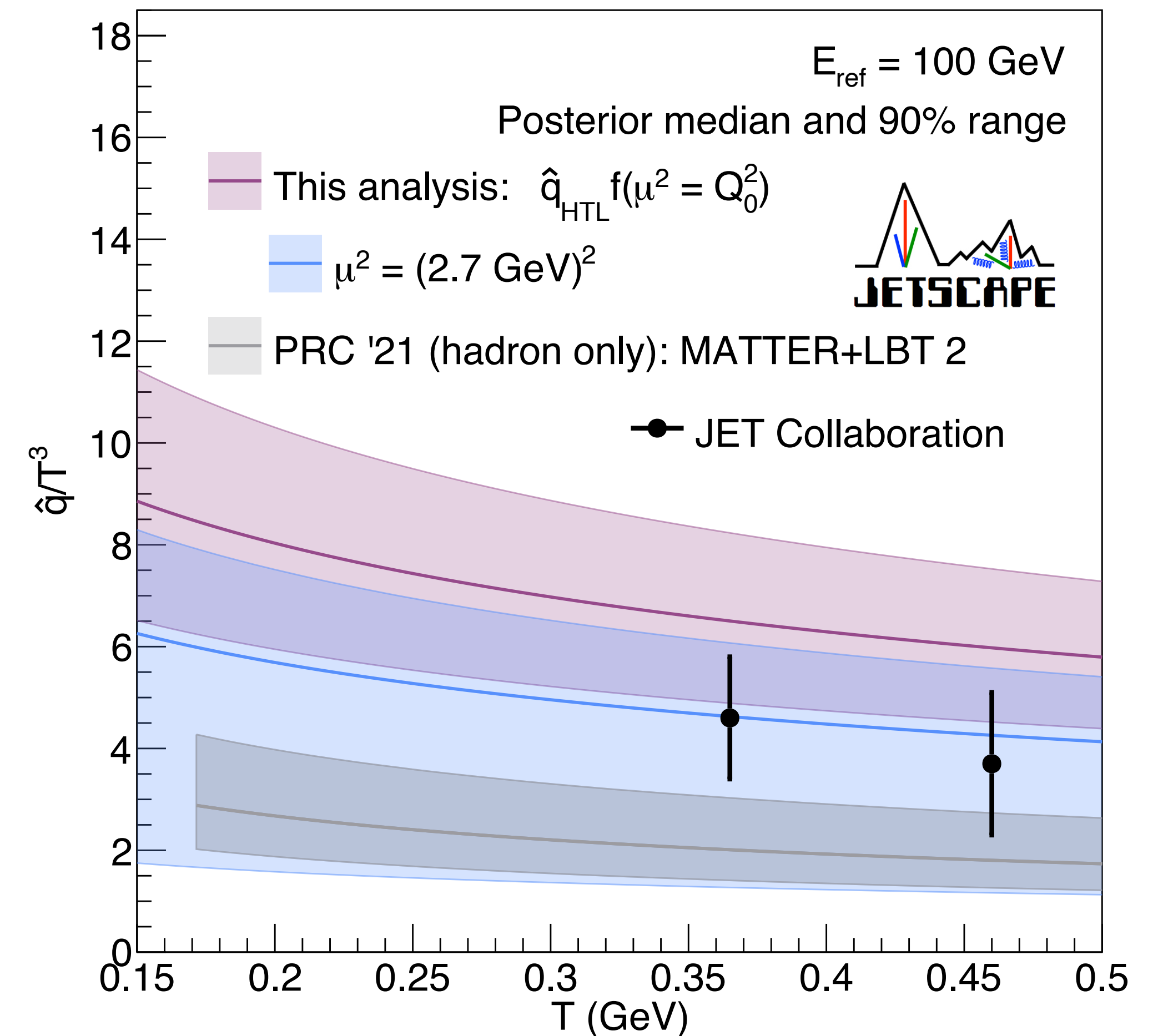
**Towards the future:**

**1. Lessons and tools from present to future**

**2. An example: EIC + forward LHC + Bayesian inference**

# Parametrization choices

- **Parametrization choices significantly impact final extraction**
- **Physics inspired** approach
  - **More constrained, but (often) more interpretable**
- **Information field** approach
  - **More flexible but less interpretable**
- Trade-offs appropriate in different stages of comparison



More physics  
inspired

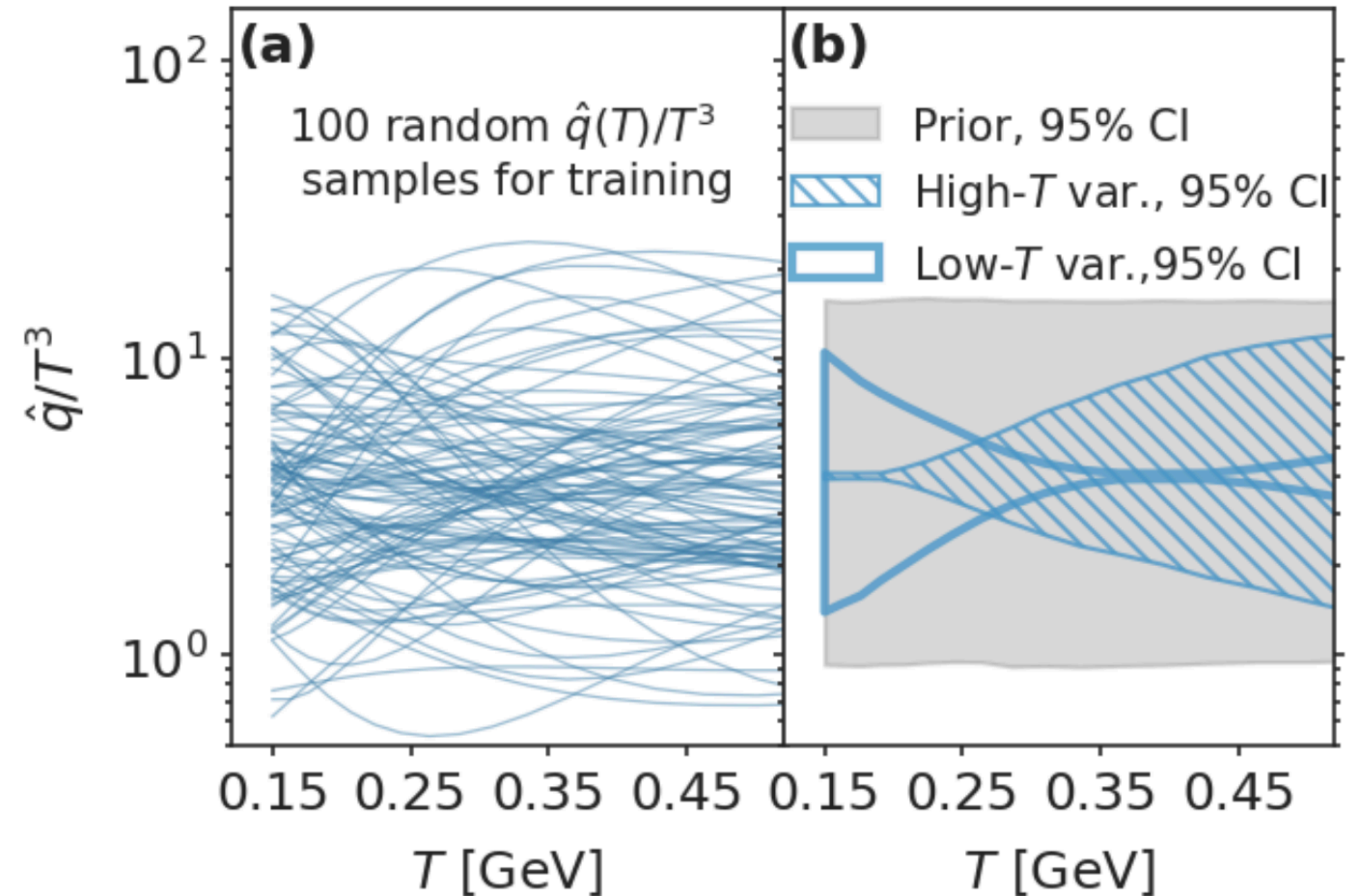


More  
flexible

# Parametrization choices

Xie, Ke, Zhang, Wang, PRC 108 (2023) 1, L011901

- **Parametrization choices significantly impact final extraction**
- **Physics inspired** approach
  - **More constrained, but (often) more interpretable**
- **Information field** approach
  - **More flexible but less interpretable**
- Trade-offs appropriate in different stages of comparison



More physics  
inspired

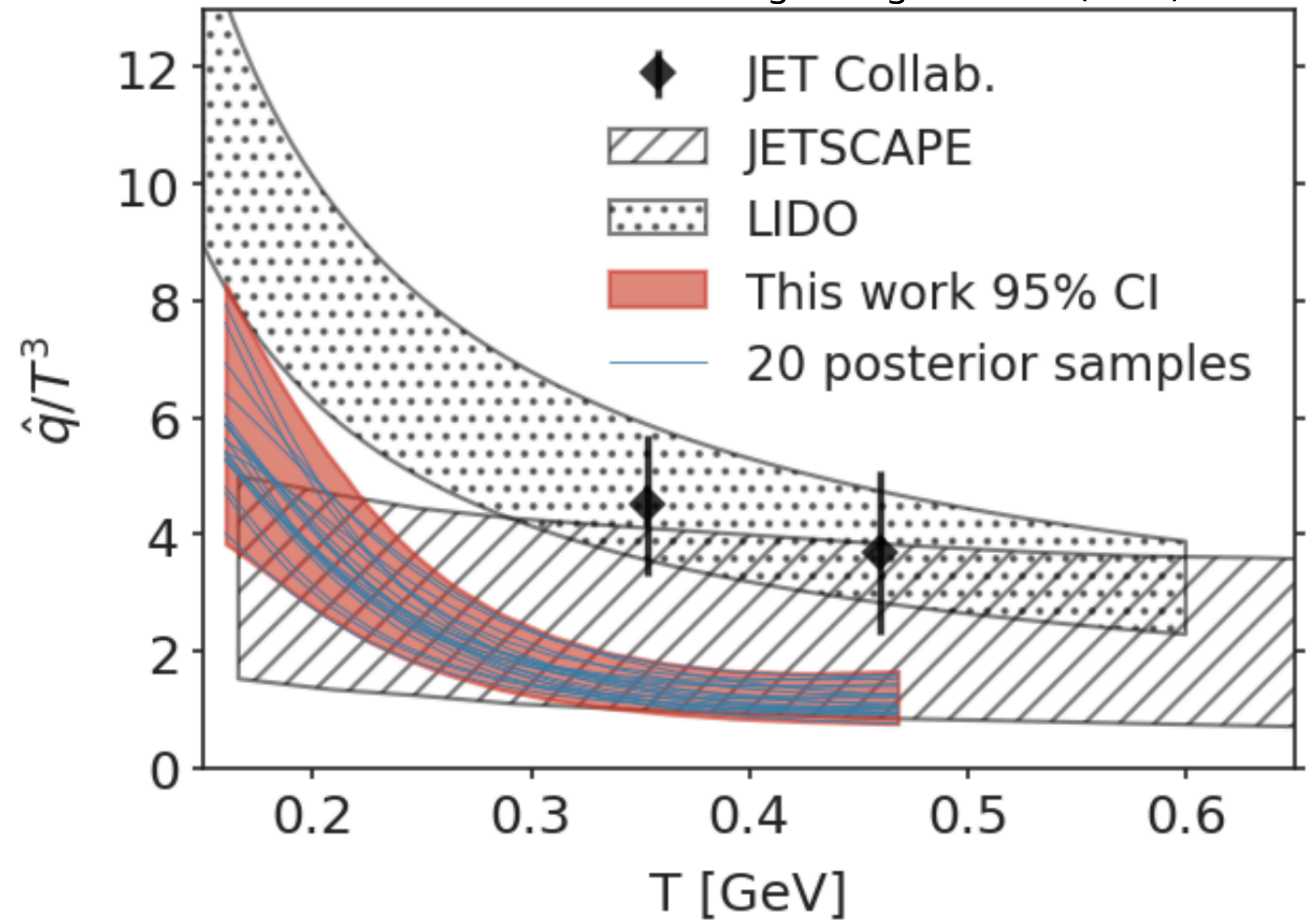


More  
flexible

# Parametrization choices

- **Parametrization choices significantly impact final extraction**
- **Physics inspired** approach
  - **More constrained, but (often) more interpretable**
- **Information field** approach
  - **More flexible but less interpretable**
- Trade-offs appropriate in different stages of comparison

Xie, Ke, Zhang, Wang, PRC 108 (2023) 1, L011901



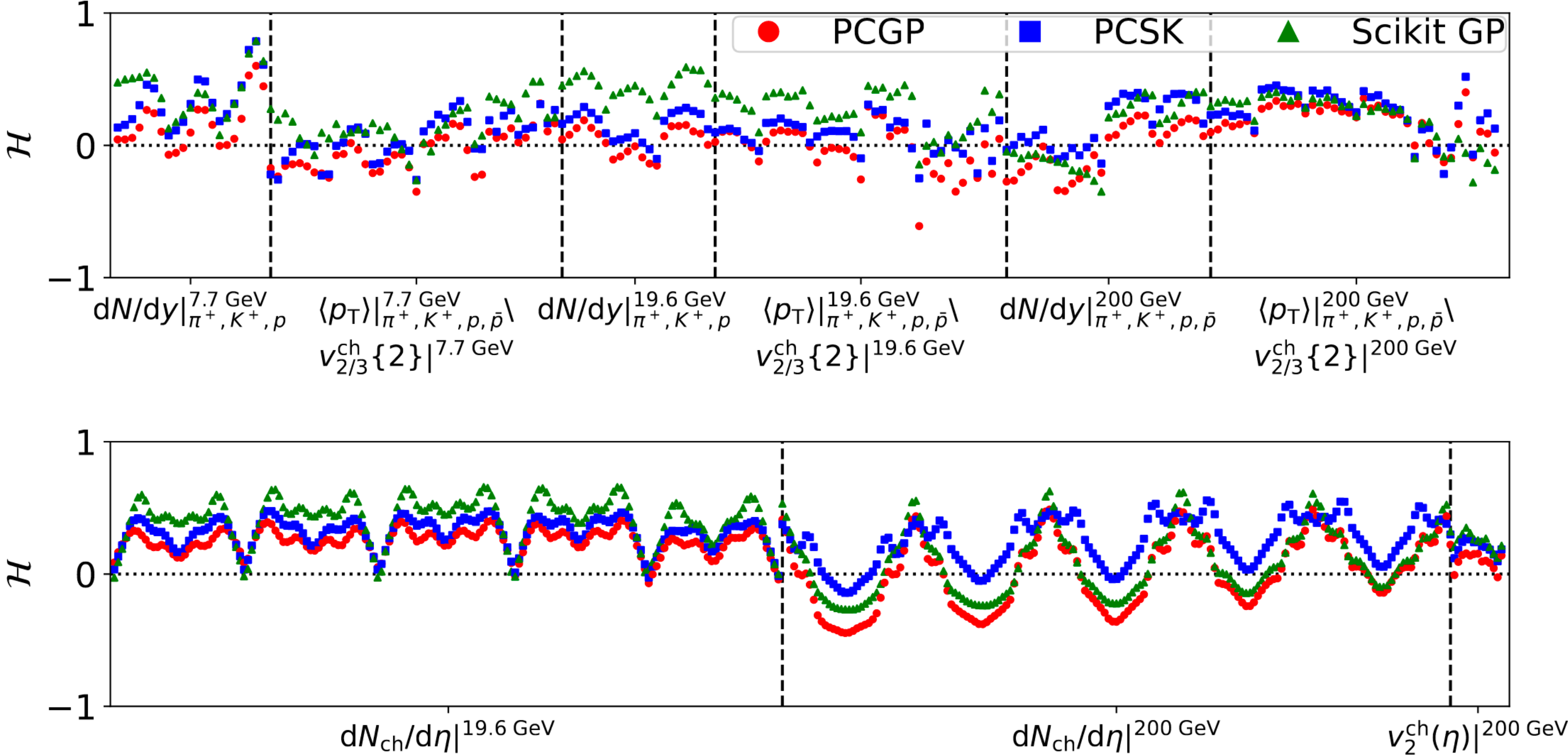
More physics  
inspired



More  
flexible

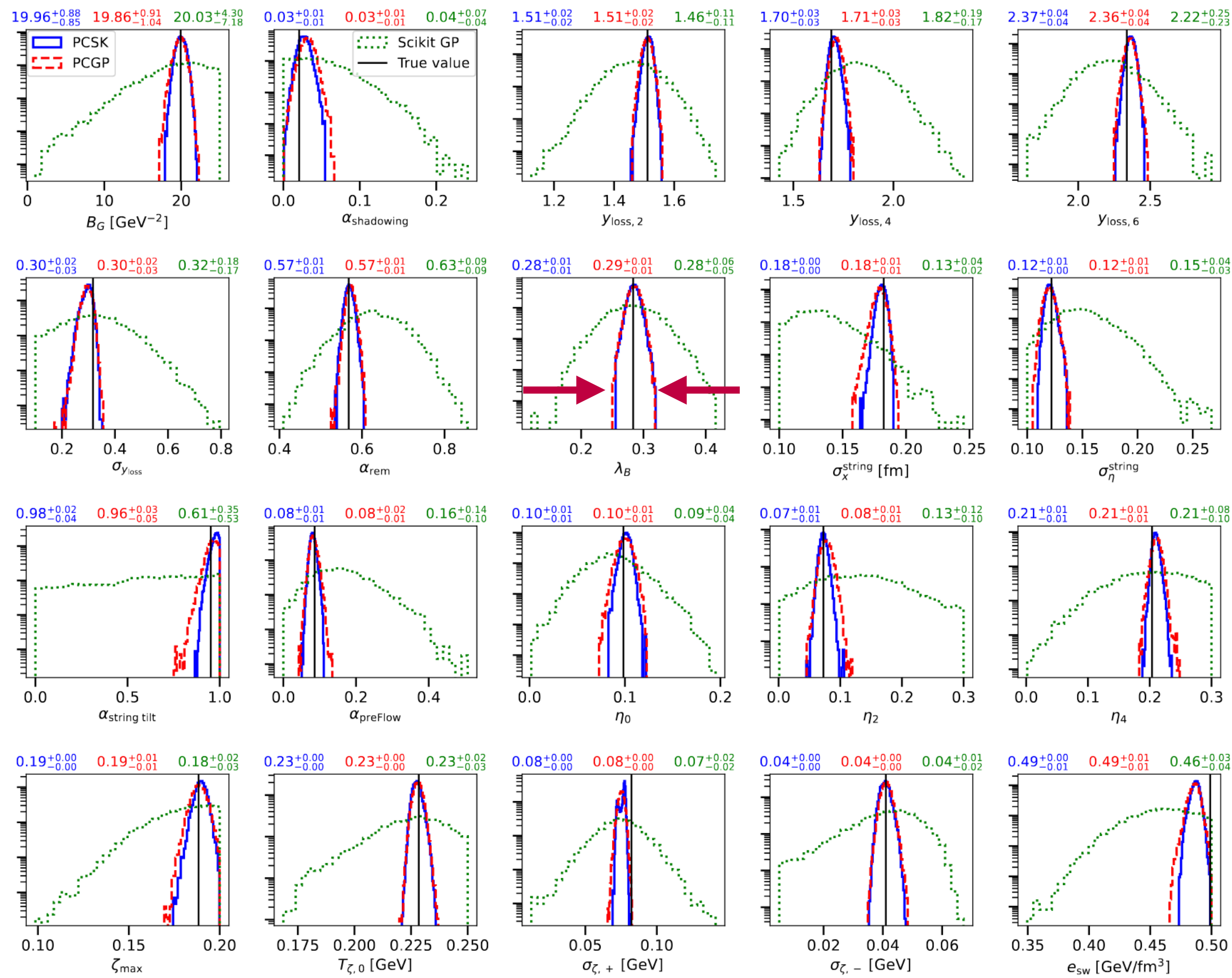
# Improved uncertainty quantification + tools

- **Uncertainty quantification + analysis tools are critical**
- **Expensive forward model**  
→ **emulate the calculation**
- **New emulators with knowledge of uncertainties** show meaningful improvement
- ML: key role to play in Bayesian Inference
  - e.g. Cost-efficient methods



# Improved uncertainty quantification + tools

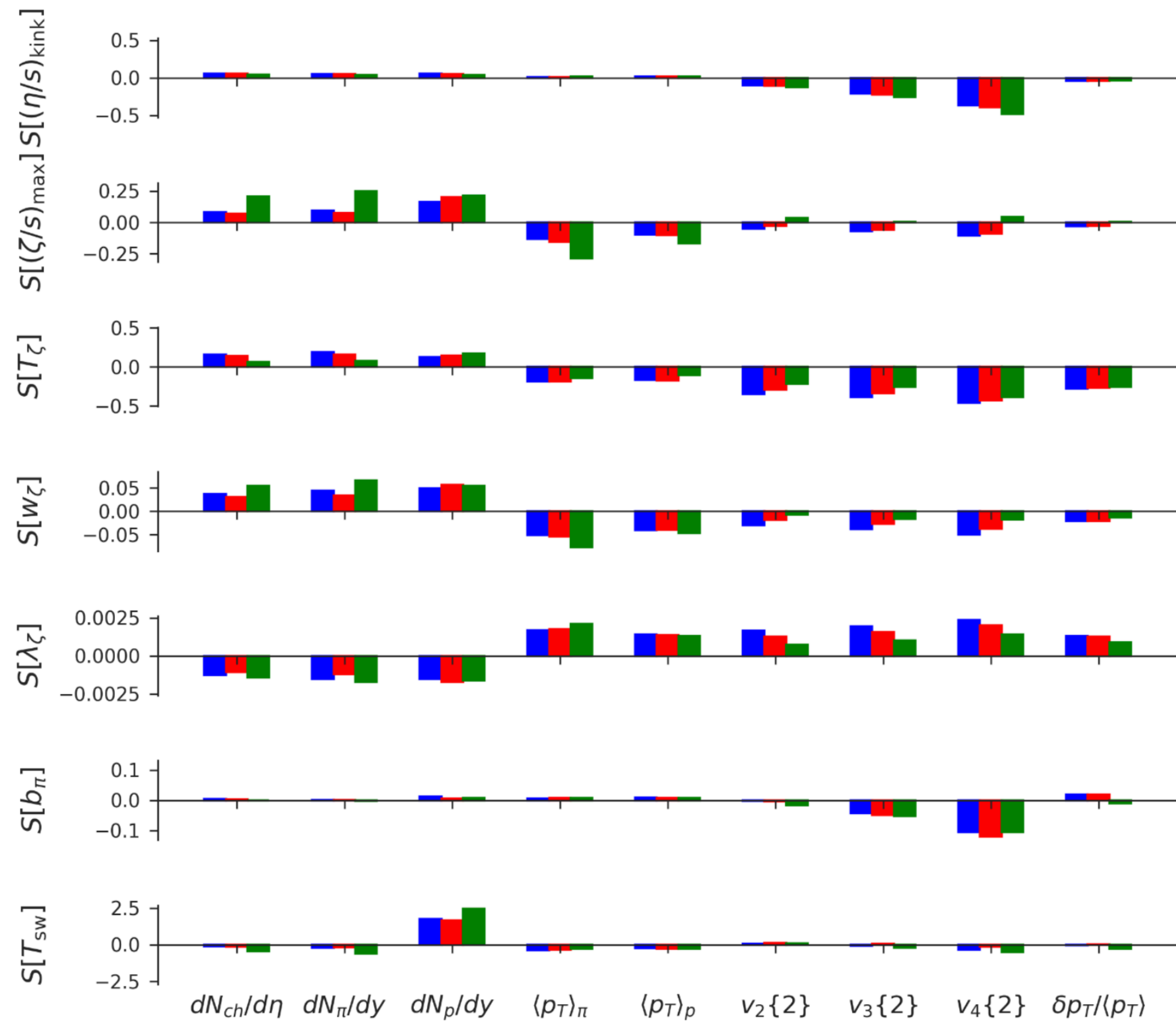
- **Uncertainty quantification + analysis tools are critical**
- **Expensive forward model**  
→ emulate the calculation
- **New emulators with knowledge of uncertainties** show meaningful improvement
- **ML: key role to play** in Bayesian Inference
  - e.g. Cost-efficient methods



# Model sensitivity + experimental design

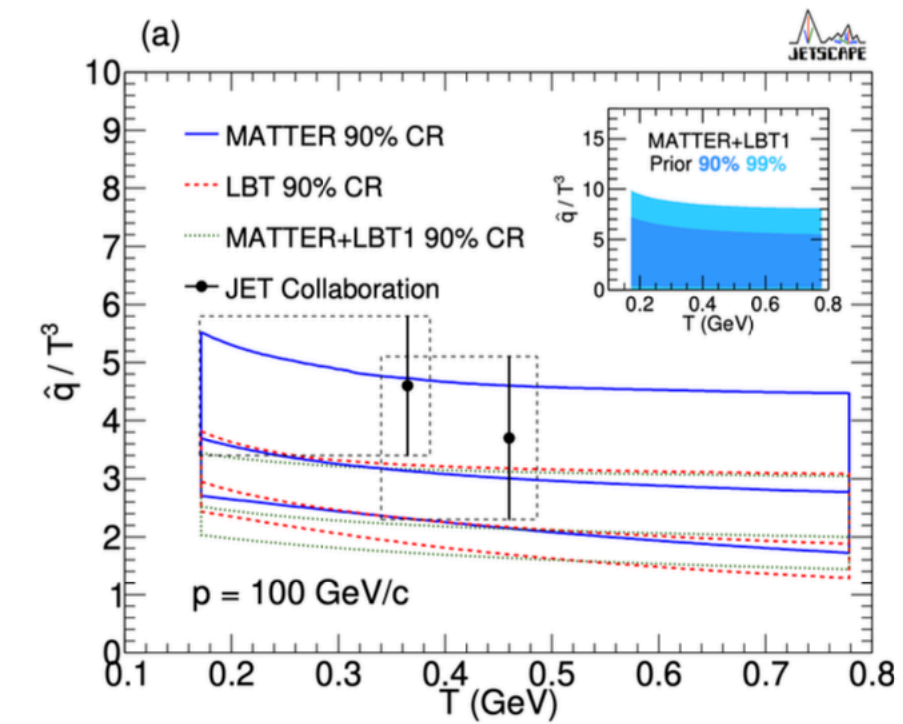
## Observable sensitivity to posterior perturbation

JETSCAPE, PRC.103.054904



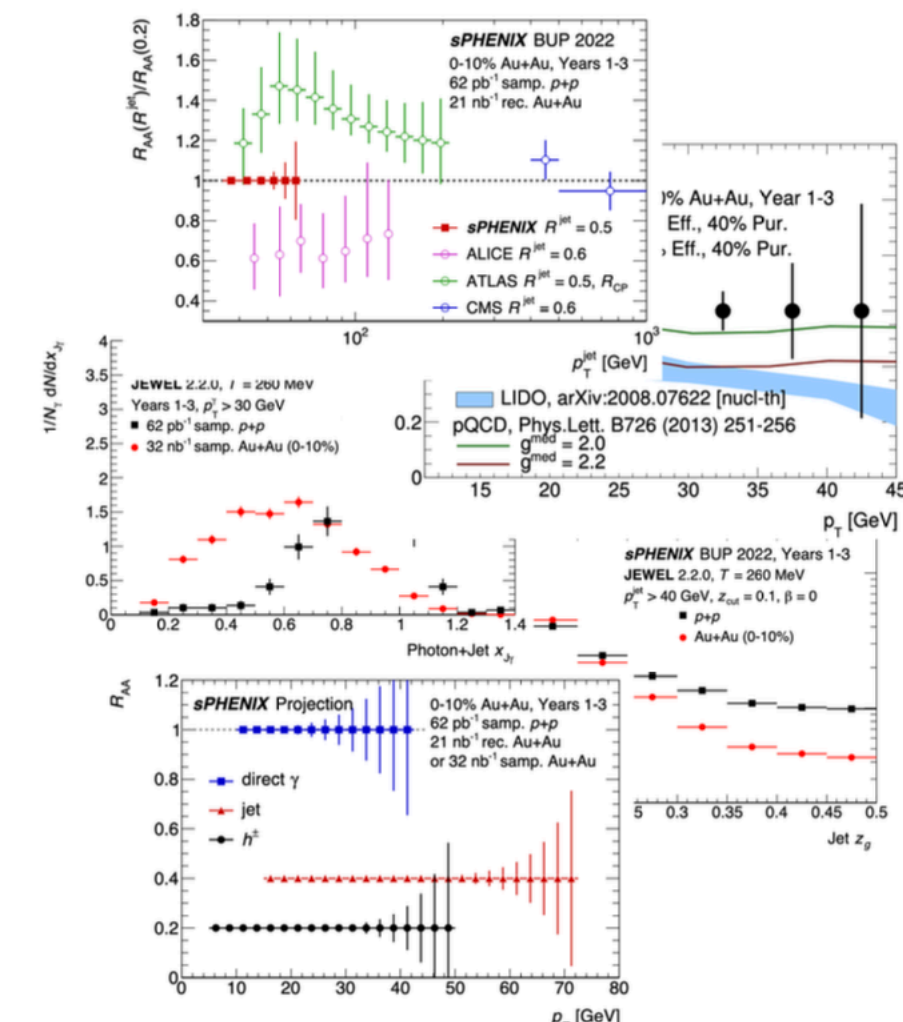
## Identifying new + sensitive observables

e.g. "Bayesian experimental design"



New Bayesian analysis

Further constraints



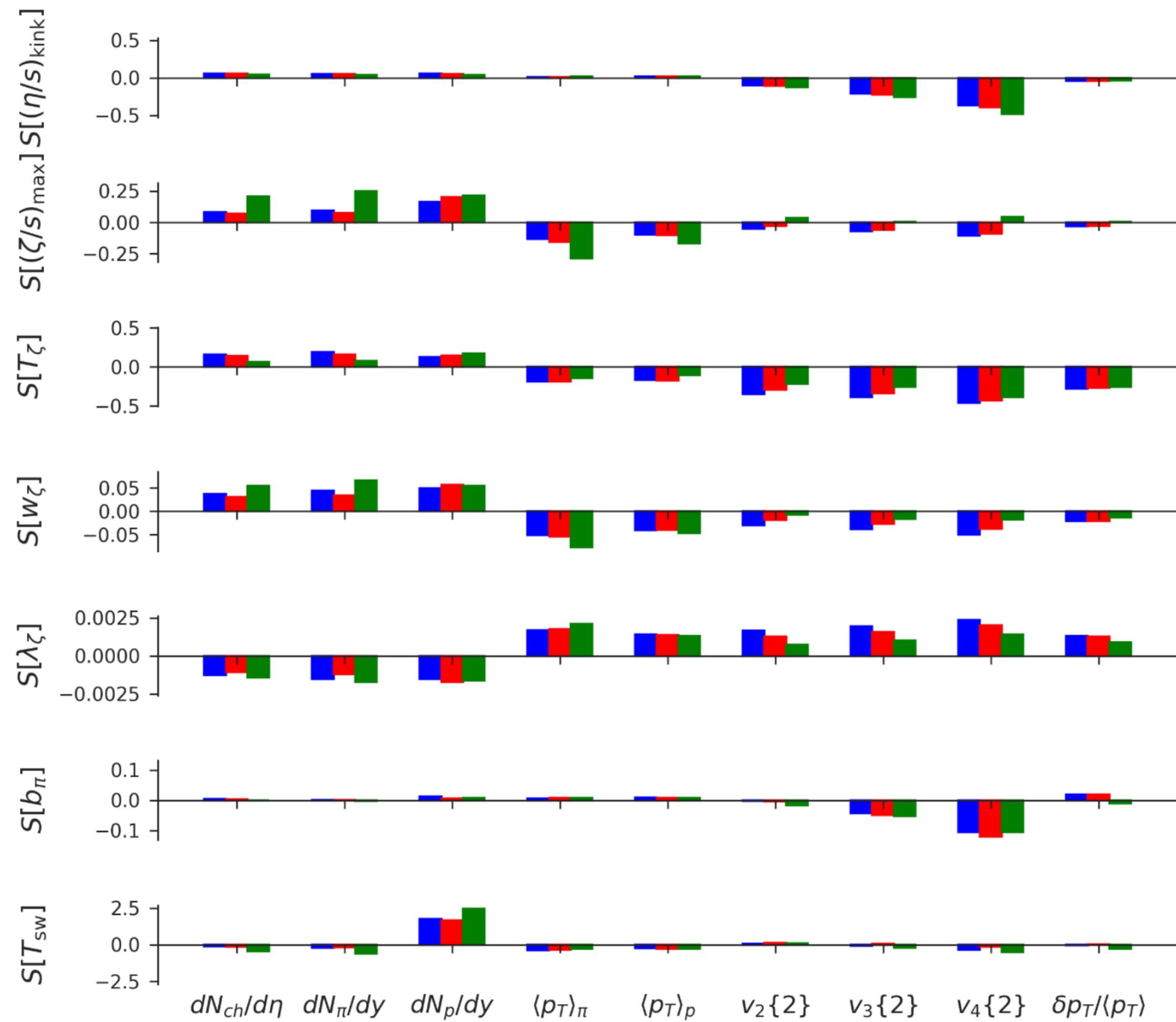
RE, Nucl.Phys.A 1043 (2024) 122821  
(Predictions for the sPHENIX physics program)



# Model sensitivity + experimental design

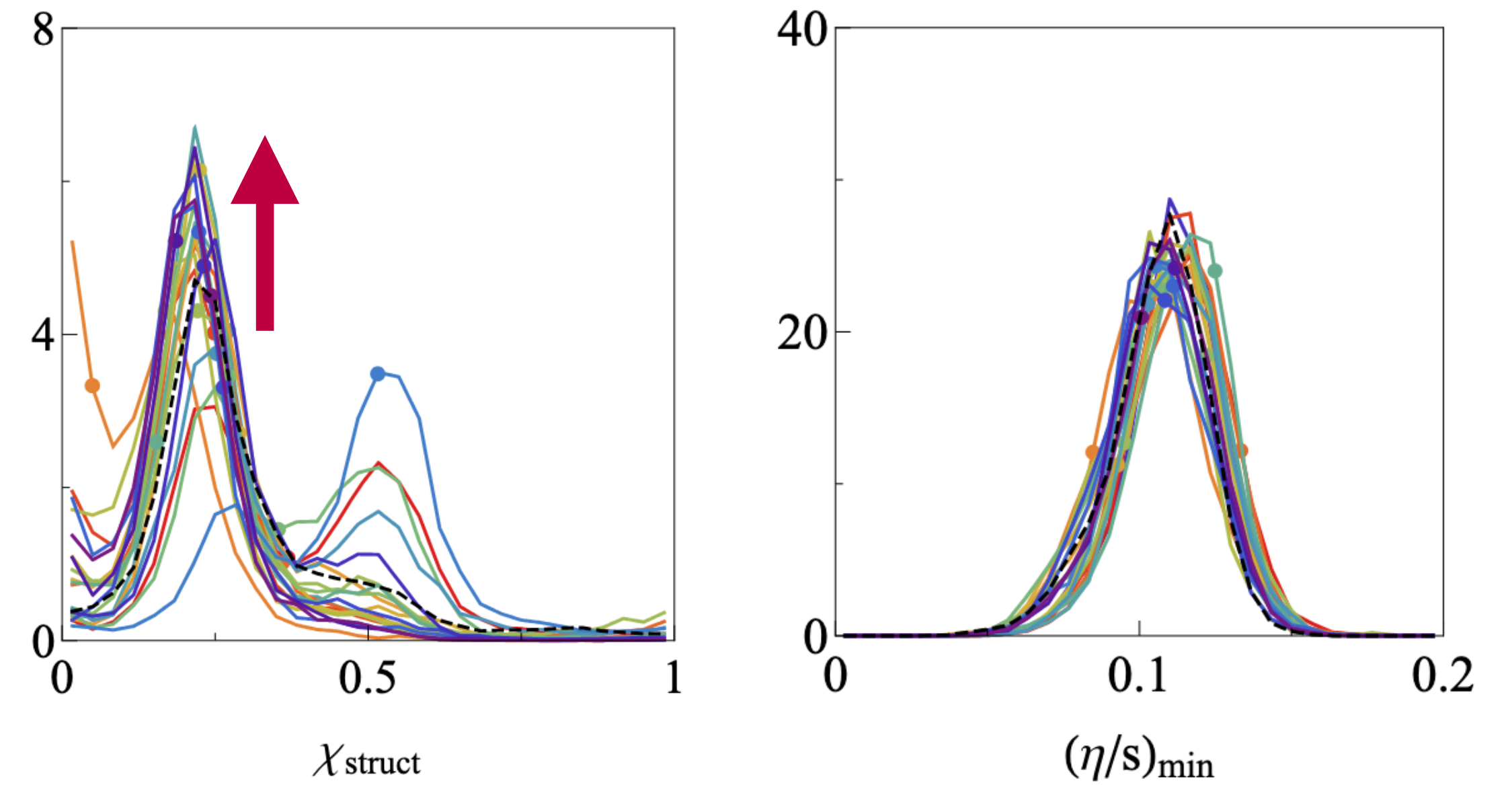
## Observable sensitivity to posterior perturbation

JETSCAPE, PRC.103.054904



## Identifying new + sensitive observables

e.g. "Bayesian experimental design"



Nijs, van der Schee, PRC 106 (2022) 4, 044903

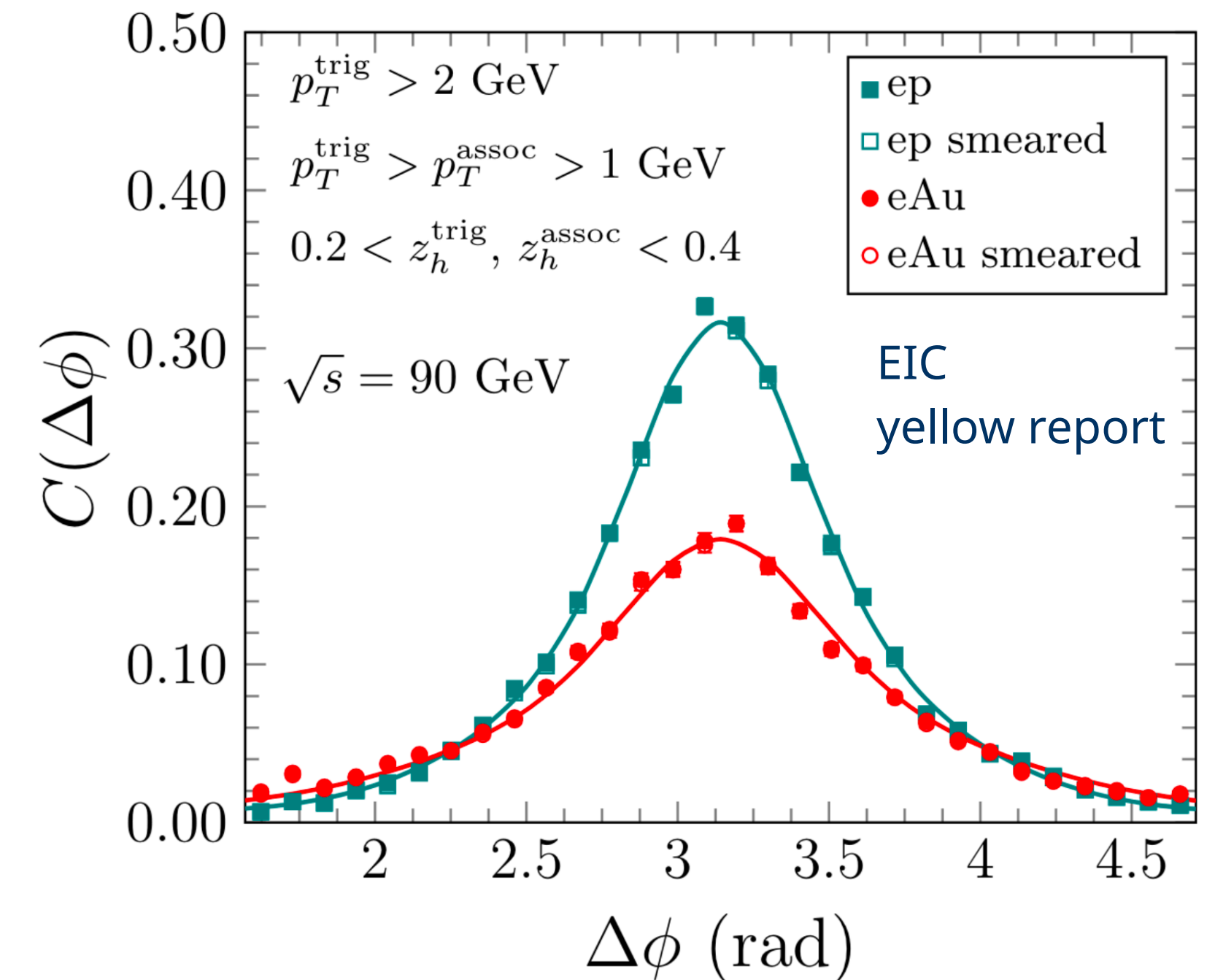
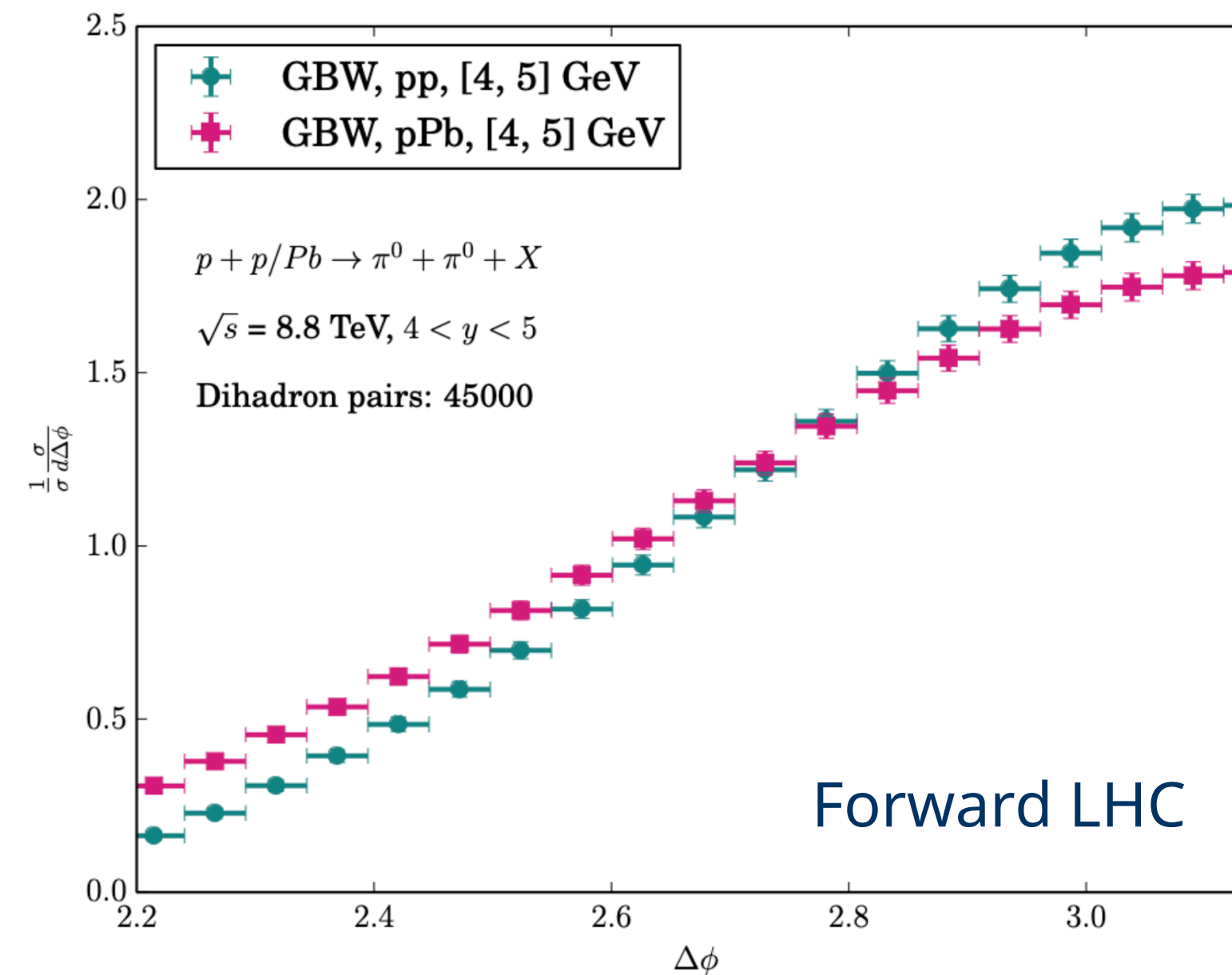
# Connecting Forward LHC + EIC

- Complementarity between forward LHC/RHIC + EIC
- Bayesian inference: essential for comprehensive analysis of heterogeneous datasets (EIC, fLHC, fRHIC) with rigorous theory to explore linear/non-linear QCD evolution

	Inclusive DIS	SIDIS	DIS dijet	Inclusive in $p+A$	$\gamma$ +jet in $p+A$	dijet in $p+A$
$xG_{WW}$	–	–	+	–	–	+
$xG_{DP}$	+	+	–	+	+	+

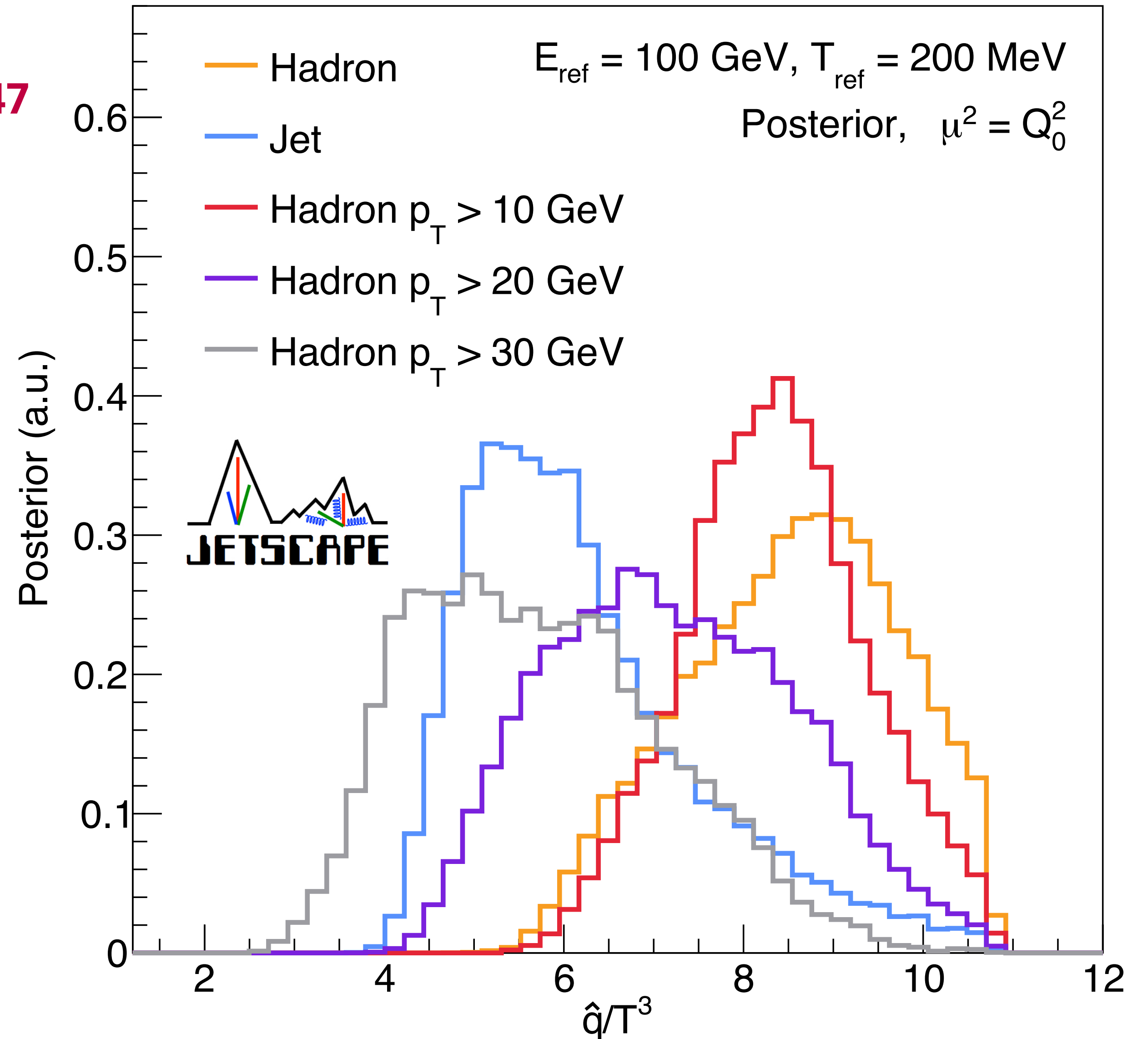
**Table 7.2:** The process dependence of two gluon distributions (i.e., the Weizsäcker-Williams (WW for short) and dipole (DP for short) distributions) in  $e+A(e+p)$  and  $p+A$  collisions. Here the + and – signs indicate that the corresponding gluon distributions appear and do not appear in certain processes, respectively.

- Model consistency with data
- Models which best describe data (Bayes evidence)
- Observable sensitivity studies



# Summary

- New  $\hat{q}$  extraction including **jet  $R_{AA}$** : [arXiv:2408.08247](https://arxiv.org/abs/2408.08247)
  - Includes **all applicable experimental data**
  - Overall reasonable description of data
- Studies on **hadron vs jet, jet substructure** point to regions of **agreement, tension**
- **General tool** to investigate models
- Pinpoint regions of interest, **provide important feedback for models**
- Many **lessons learned and tools developed, to be applied in era of HIC + EIC**



# Bonus: So, you want to run JETSCAPE or X-SCAPE?

- Start with the JETSCAPE summer school: <https://indico.cern.ch/event/1282714/>
- Information, documentation, hands-on exercises
- Recorded on [YouTube](#)
- If you want to get going right away, start with the hands-on session and see below

## TLDR (many caveats apply)

```
docker run -it jetscape/jetscape_full /bin/bash
cd <BUILD_DIRECTORY>; ./runjetscape ../config/jetscape_user_PP19.xml # Runs PP19 tune
```

## Bulk medium calculations

- Start with Bayesian soft-sector tune:  
PRL 126 (2021) 24, 242301, PRC 103 (2021) 5, 054904
  - [XML configuration file \(on GitHub\)](#)
- Configuration corresponds to MAP parameters
- Read the paper and README carefully, as some tweaks on the configuration may be necessary

## Jet energy loss calculations

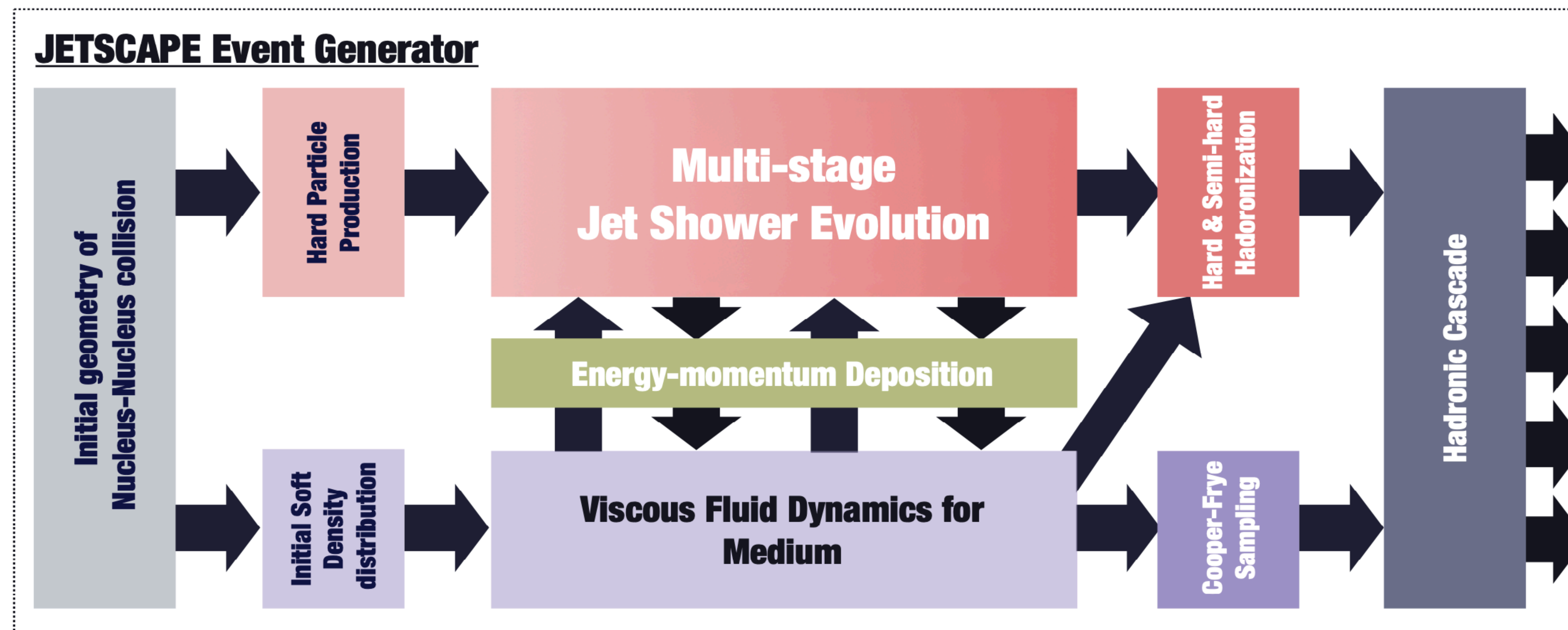
- Start with AA22 tune: PRC 107 (2023) 3, 034911
  - [XML configuration file \(on GitHub\)](#)
- Currently requires pre-computed hydro events, which you need to request from JETSCAPE
  - Tuned on-the-fly hydro may be possible soon
- MAP (presented here) available soon

**Backup**

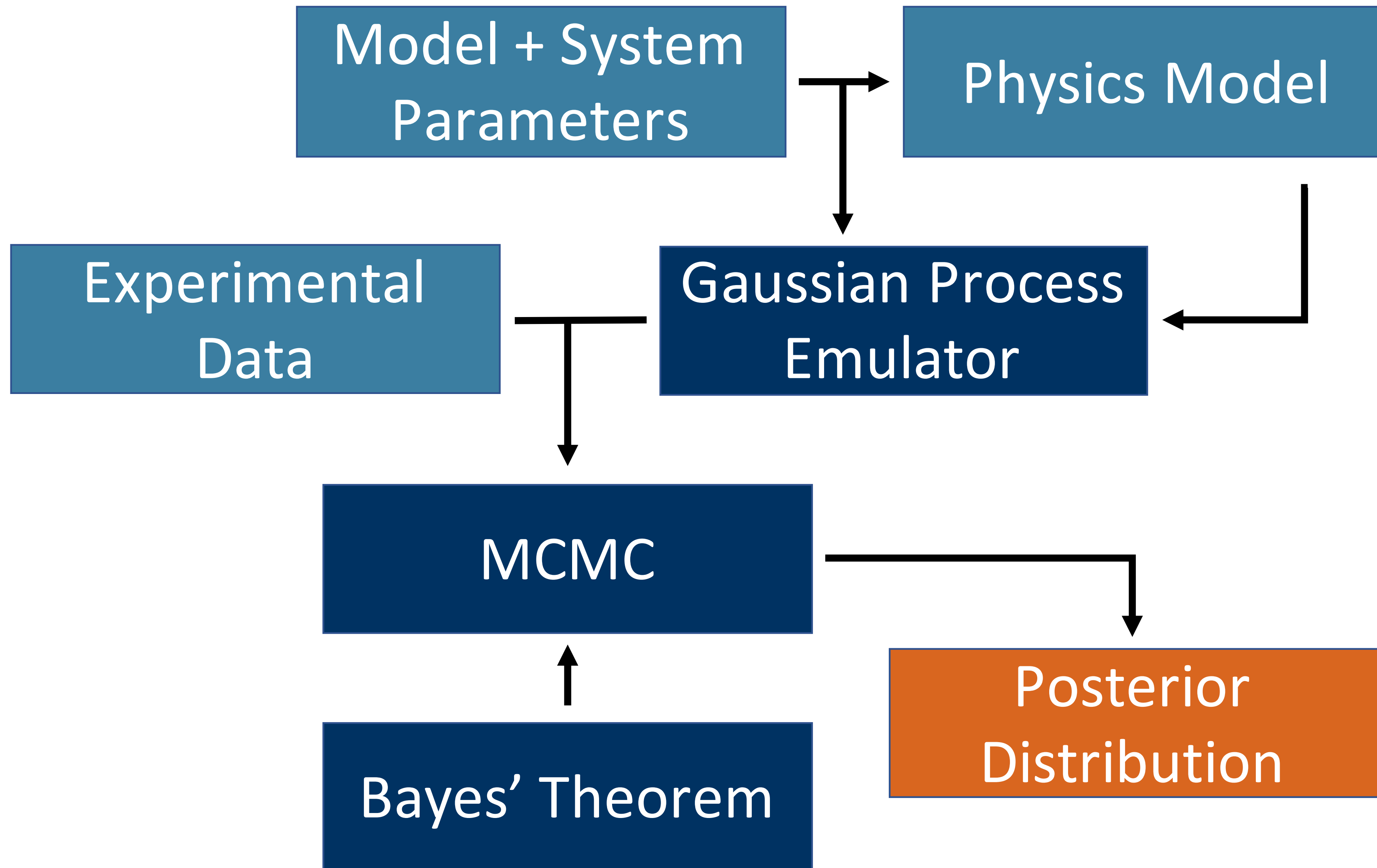
# JETSCAPE Framework

- **MC event generator package for heavy ion collisions**

- General, modular and extensible
- Communication between modules
- Available on  **GitHub** [github.com/JETSCAPE](https://github.com/JETSCAPE)

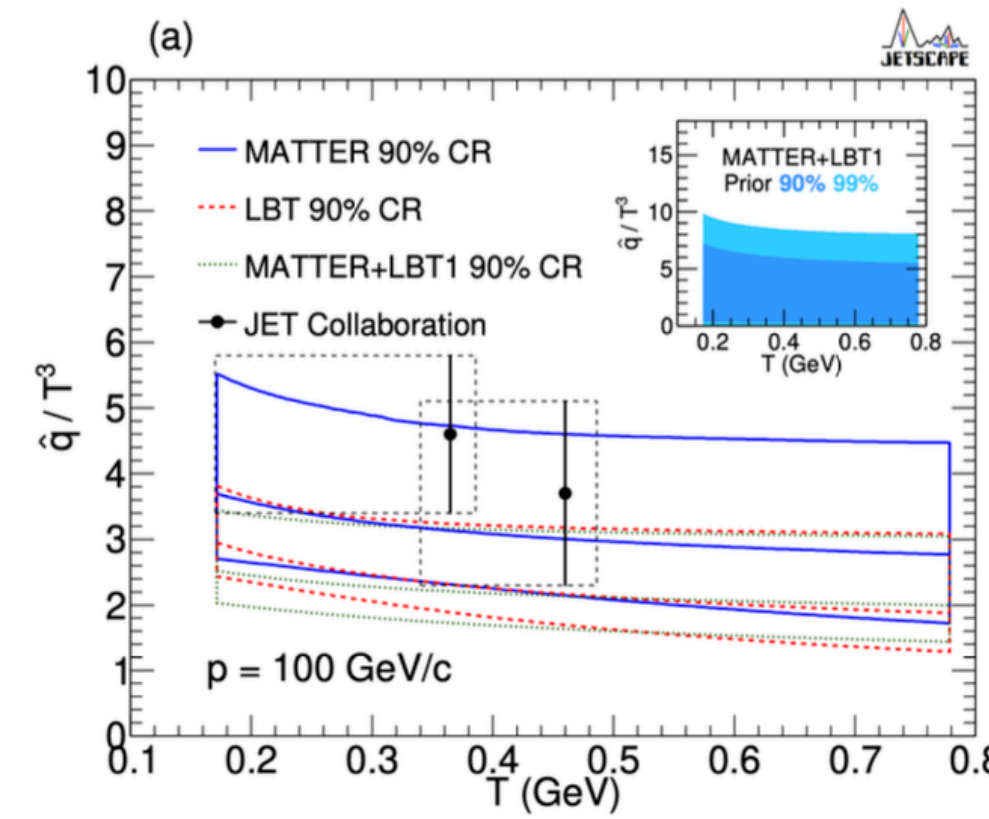


# Bayesian Inference workflow

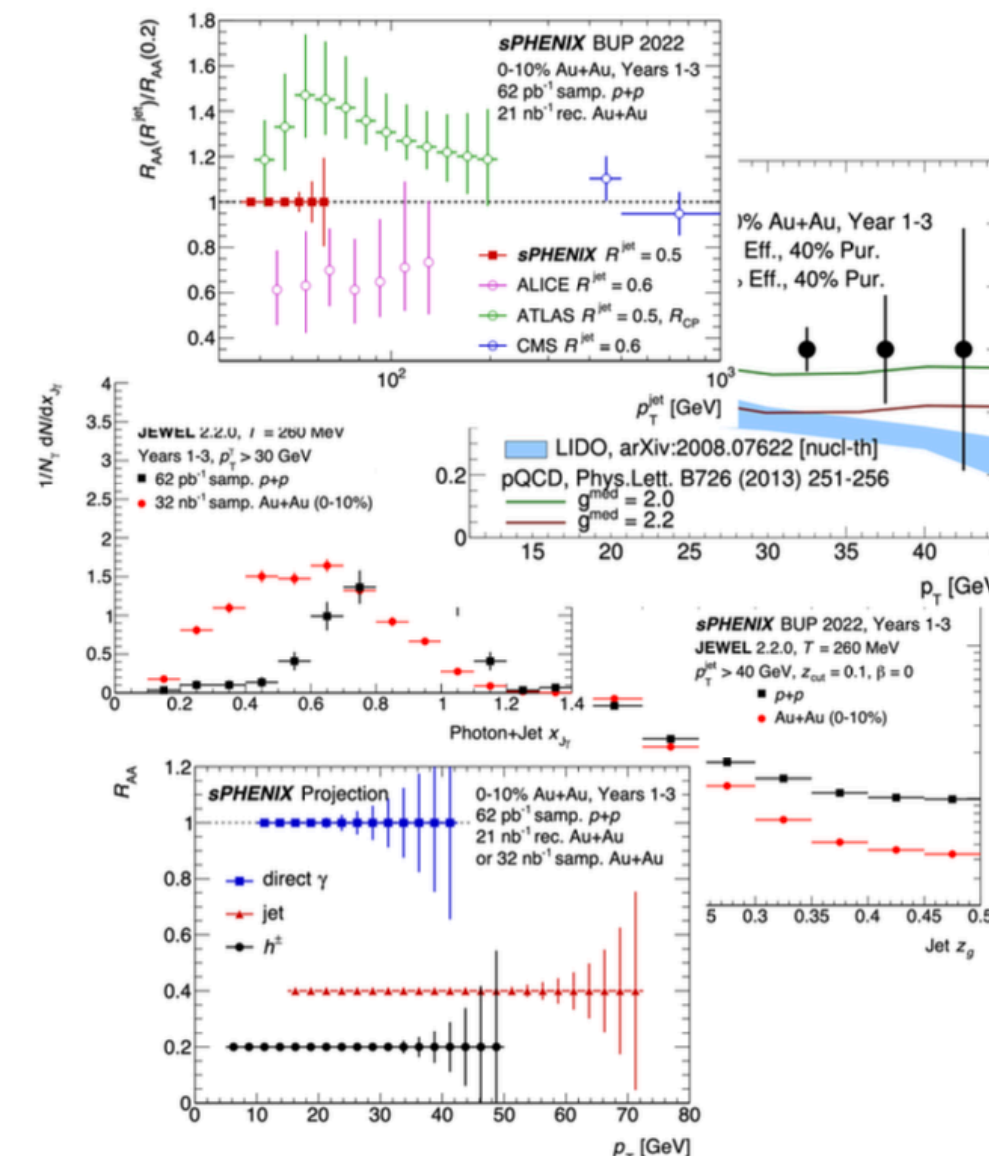


# Bayesian experimental design

- **Quantify impact** of new sPHENIX data (to prioritize measurements?)
  - eg. Neutrino physics: [Phys.Rev.C 103 \(2021\) 6, 065501](#)
  - eg. OO w/ Trajectum: [arXiv:2110.13153](#)
- 1. **Calibrate model** to existing data (ie. Bayesian analysis)
  - eg. JETSCAPE hard sector calibration
- 2. **Generate pseudo-data** with expected sPHENIX uncertainties
  - Can sample posterior dist. for parameters
- 3. Re-run Bayesian Inference, and **observe impact on new posterior**
  - Further vary observables included



New Bayesian analysis



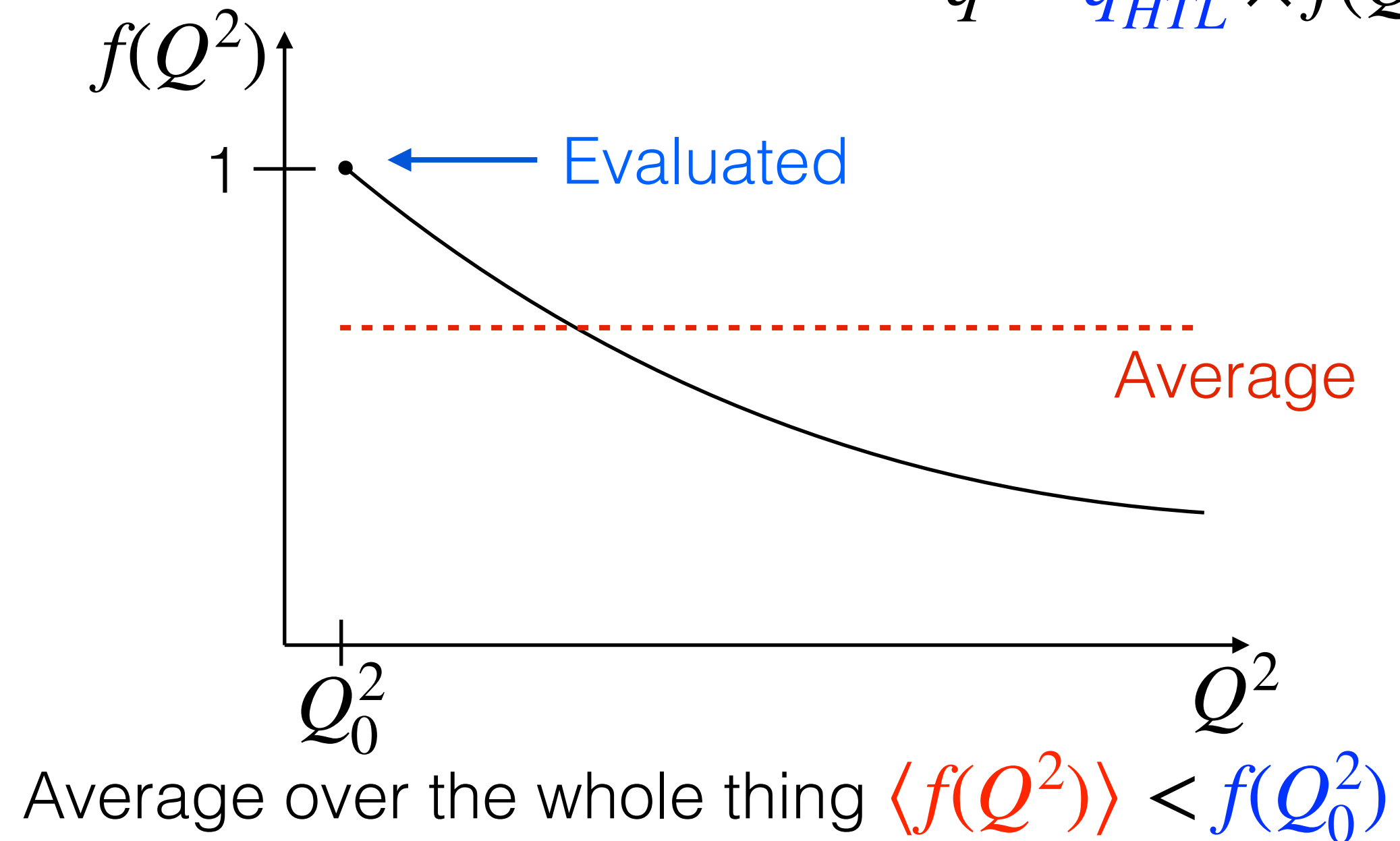
Further constraints



# Evaluating virtuality dependence for $\hat{q}$

Imagine for now we stay with latest analysis

$$\hat{q} = \hat{q}_{HTL}^{run} \times f(Q^2)$$



# Virtuality dependence: $f(Q^2)$

