Bayesian inference and jet quenching

What's new and what's next?

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HP2024
NAGASAKI

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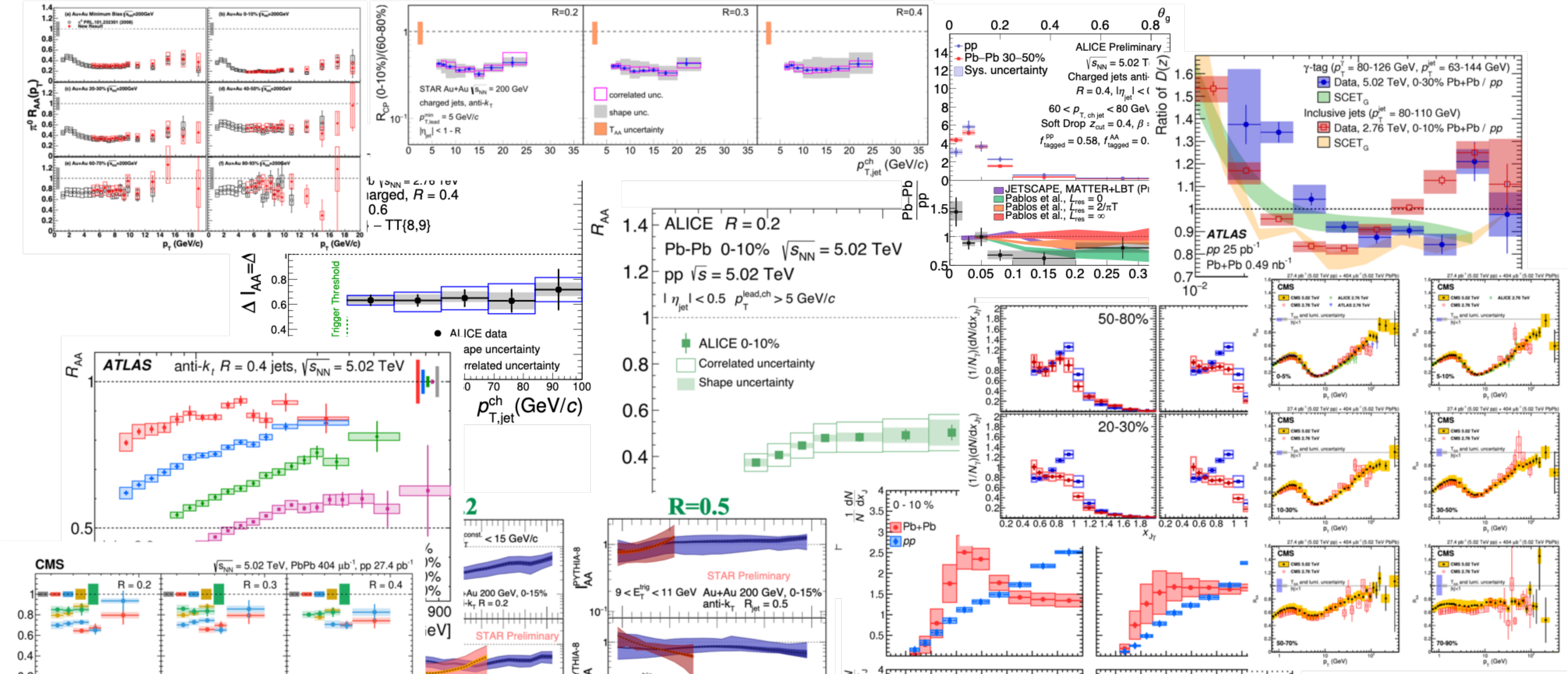
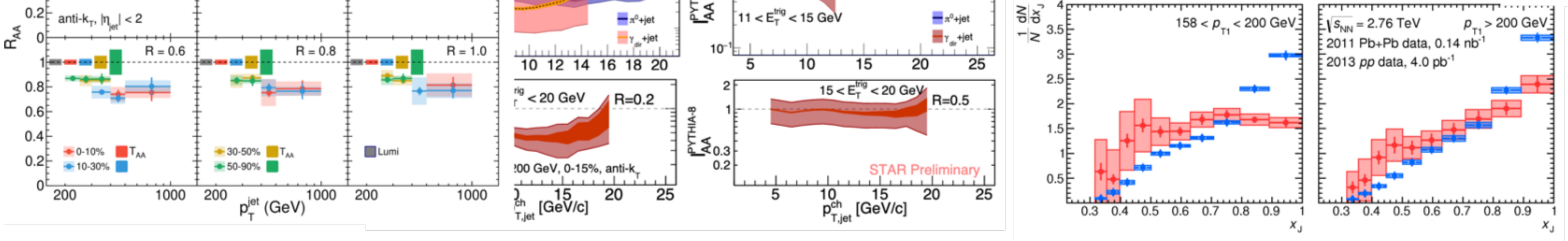
Jet quenching measurements





Plus many, many more…

How do we make sense of this? What can we learn?

1. Why and what of Bayesian inference
2. Bayesian inference in the hard sector
   A. Selection of recent analyses
   B. Current considerations and future questions

Bayesian analysis: Connecting models and data

Analysis | Model | Data

- **For a given model, which parameters are most compatible with exp. measurements**?
- 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 θ given x
  - Most prob. value → **best description** of data
- $P(x|\theta)$: **likelihood** x is described by θ
  - Depends on covariance, **data + theory uncert.**
- $P(\theta)$: **prior** distribution for θ
  - Choice makes assumptions explicit

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

Bayesian analysis: Connecting models and data

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- **Extracting QGP properties is important, but not the only goal!**
- **Broad consistency of model and data**?
  - Search for **regions of tension, areas for improvement**
- **Sensitivity studies + experimental design**
  - **What should we measure next?**

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  - Most prob. value → **best description** of data

data + theory uncert.

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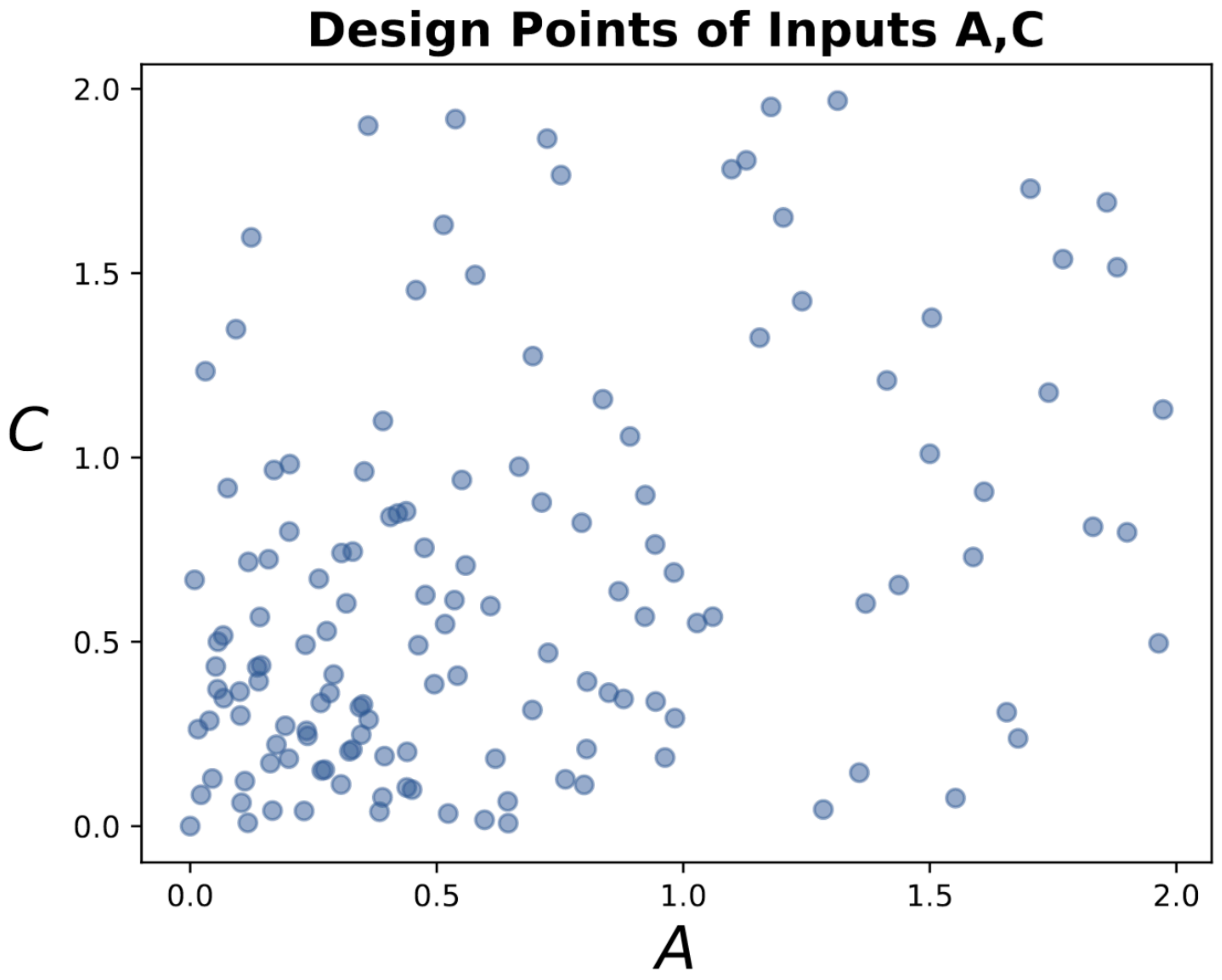
Bayesian analysis: In practice

Analysis | Model | Data

Simplified procedure

1. **Implement parameters to control model (a "parametrization")***
2. **Explore parameter space (w/ bounds from prior)**

- Approach enables **computationally tractable procedure** to extract parameters
  - Calculate limited number of points
  - Interpolate to cover phase space
- **Parameterization + prior choices matter, intertwined with model**



*: Model not necessarily formulated in terms of $\hat{q}$

Bayesian analysis: In practice

Analysis | **Model** | **Data**

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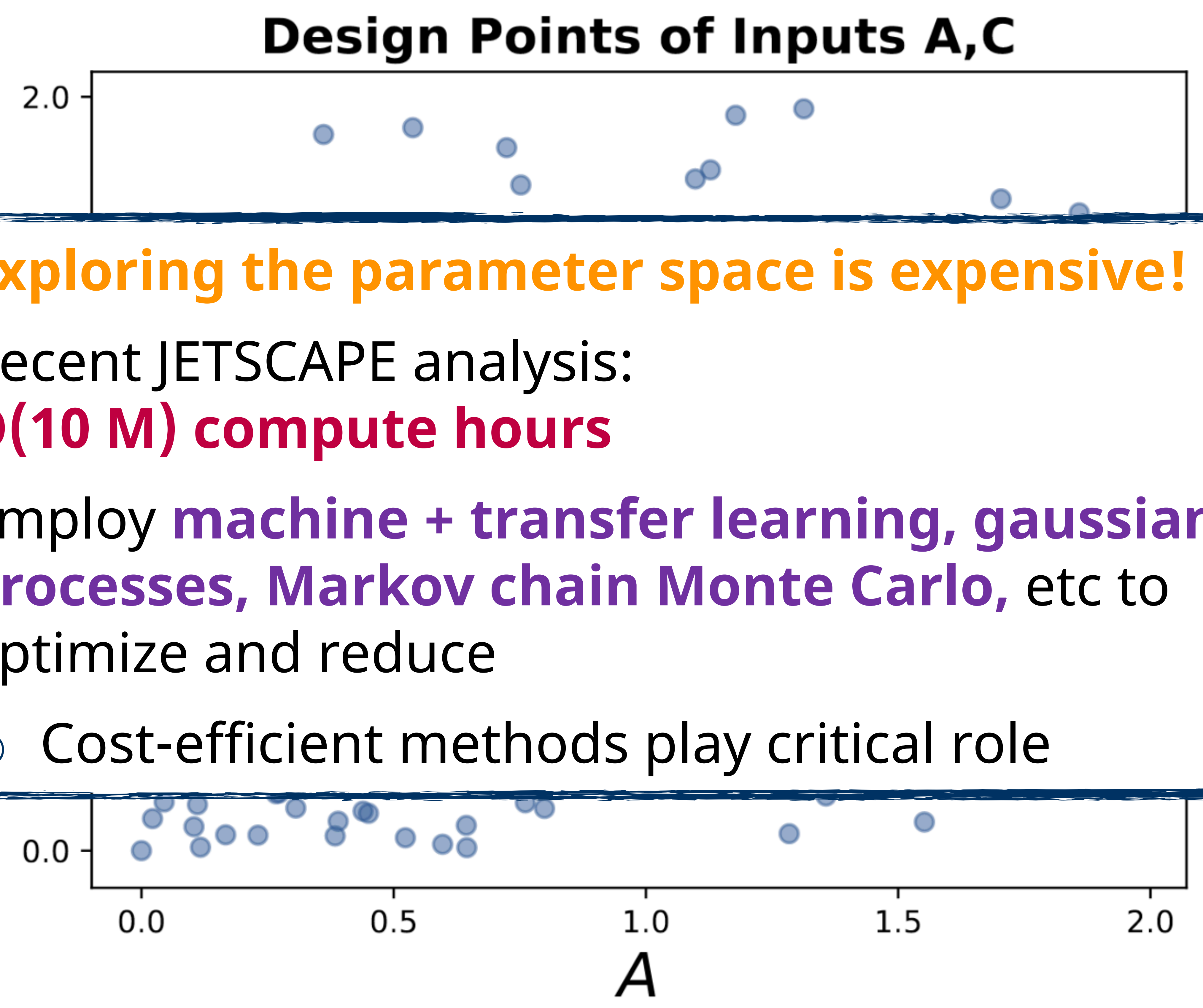


- **Exploring the parameter space is expensive!**
- Recent JETSCAPE analysis: **O(10 M) compute hours**
- Employ **machine + transfer learning, gaussian processes, Markov chain Monte Carlo**, etc to optimize and reduce
  - Cost-efficient methods play critical role

*: Model not necessarily formulated in terms of $\hat{q}$

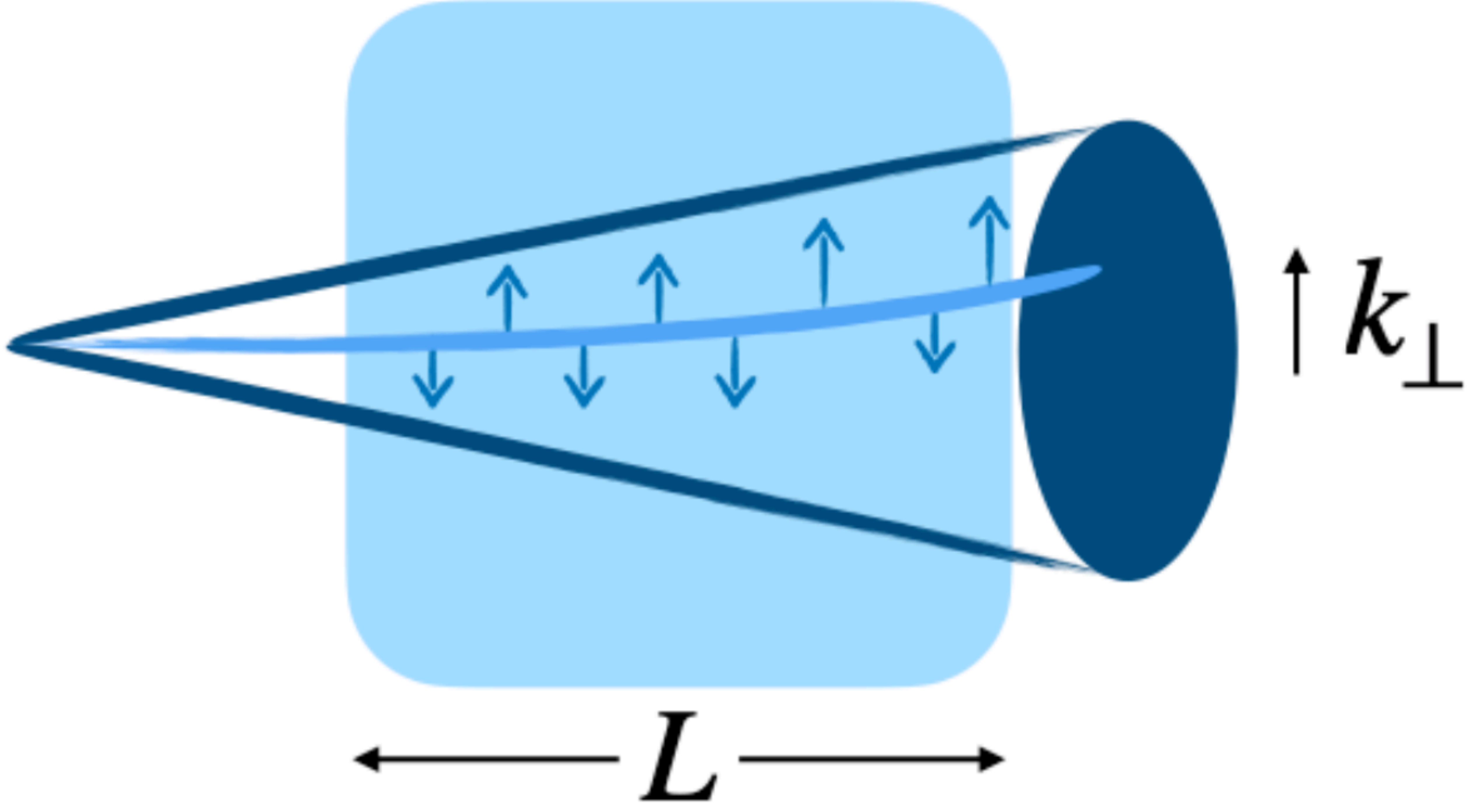
Bayesian analysis: Model*

Analysis | **Model** | Data

- **Pick your favorite Monte Carlo:**
  CUJET, DREENA, Hybrid,
  JETSCAPE (MATTER+LBT), (Co)LBT, LIDO,
  MATTER, MARTINI, …
  - Explore parameter space of these models
- **Model choices matter!**
- **Conclusions may be more general**

- Ex: **Energy loss in QCD** matter characterized by **jet transport coefficient $\hat{q}$**
  - Path length L, momentum transfer k

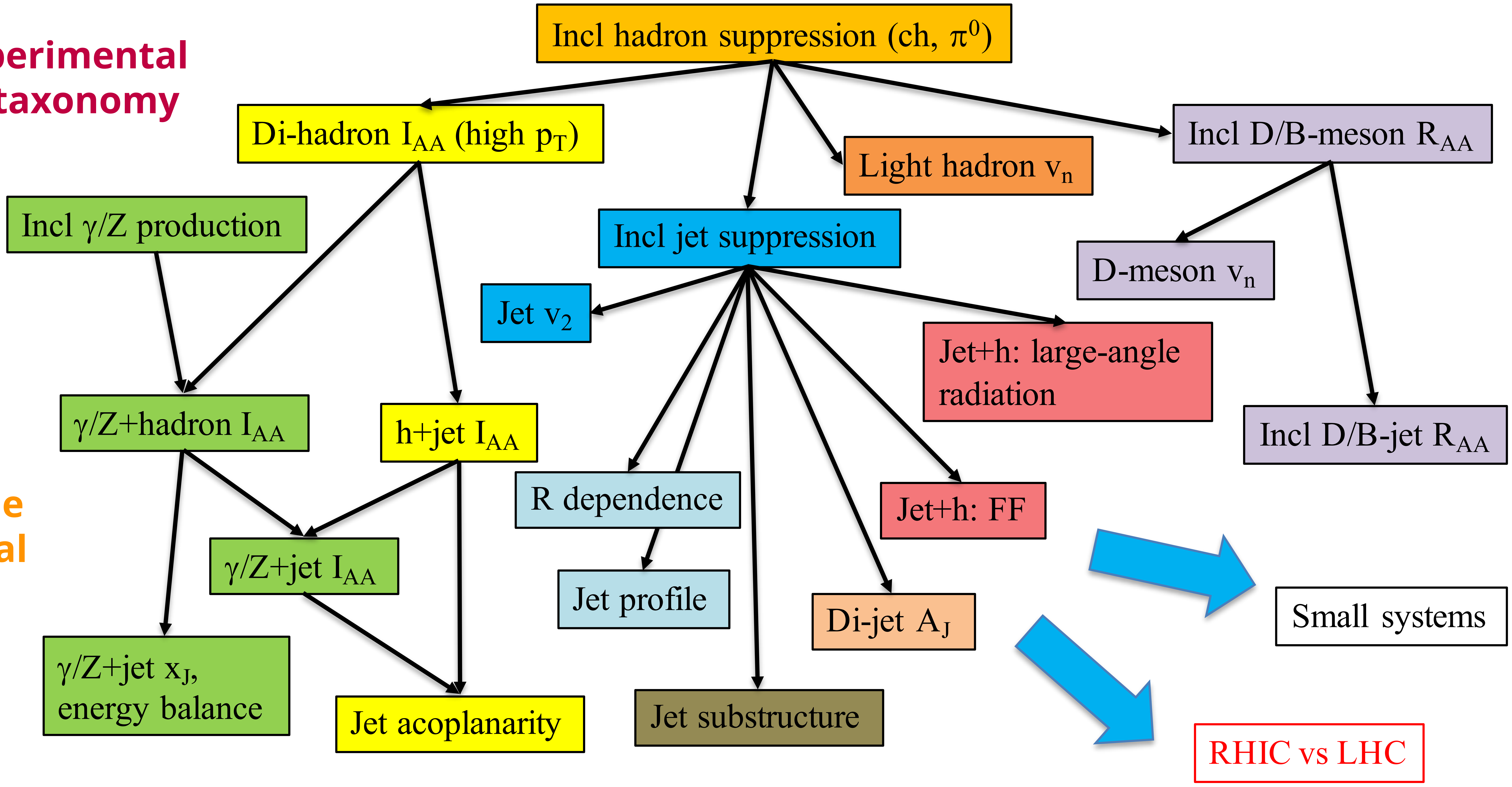
$$\hat{q} \equiv \frac{\langle k_T^2 \rangle}{L} \sim \int k^2 C(k) \mathrm{d}^2 k$$



Bayesian analysis: Data

Analysis | Model | **Data**

Possible experimental observable taxonomy



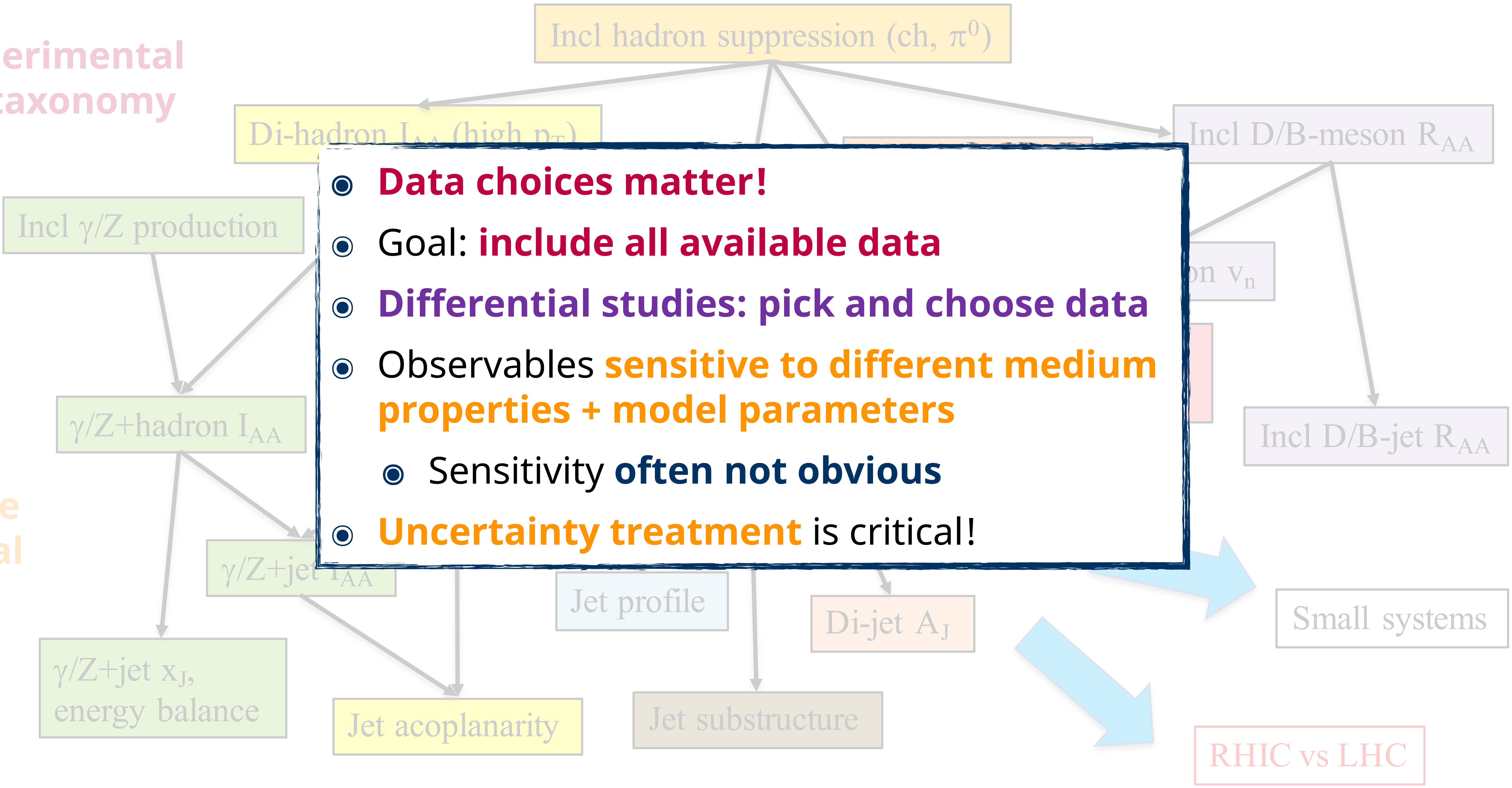
Line adds **one experimental element**

Bayesian analysis: Data

Analysis | **Model** | **Data**

Possible experimental observable taxonomy

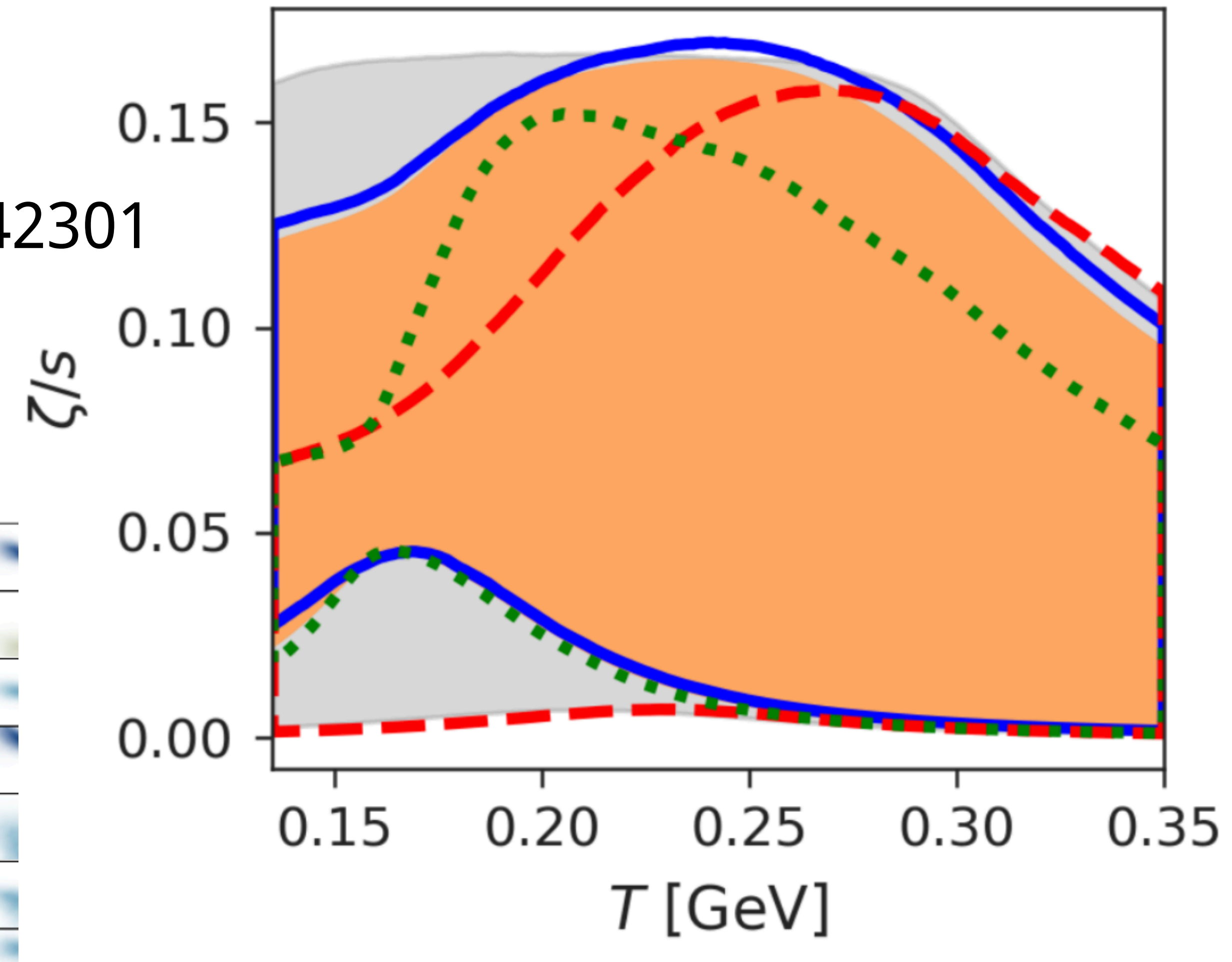
Line adds **one experimental element**

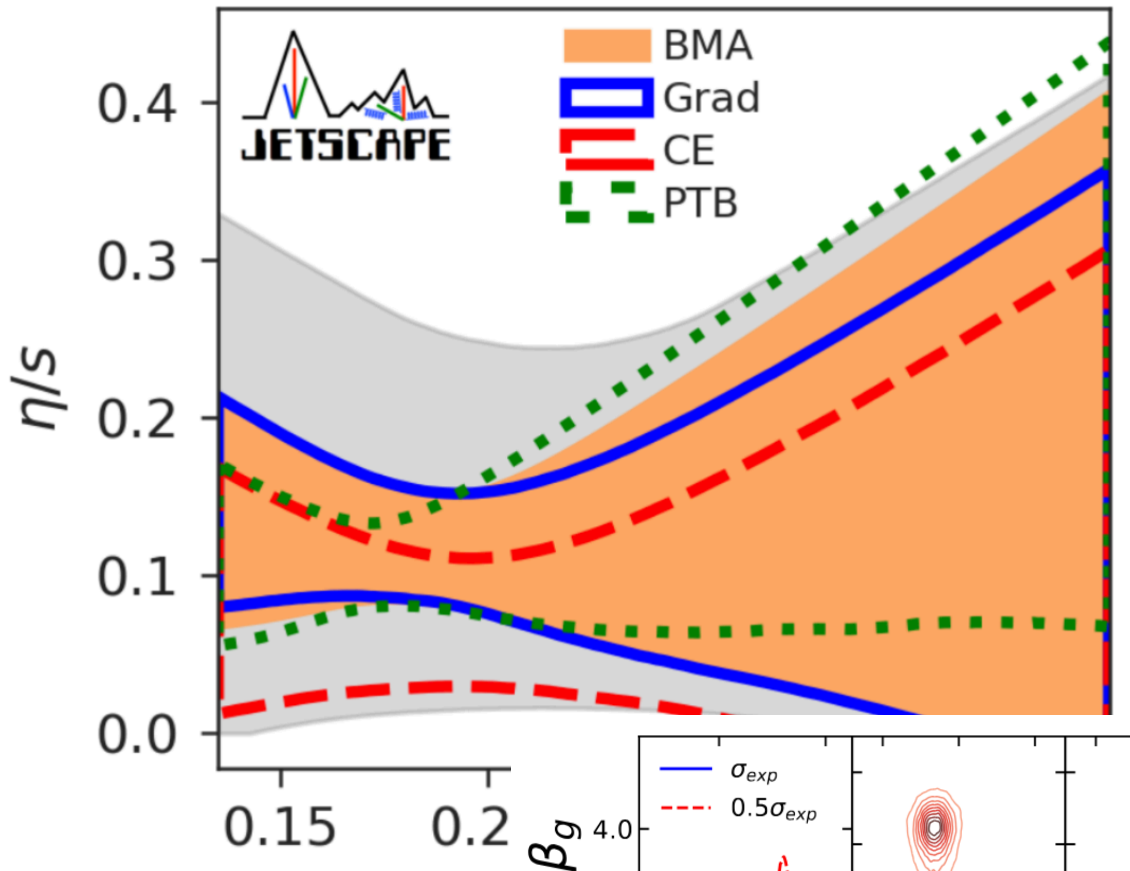


- **Data choices matter!**
- Goal: **include all available data**
- **Differential studies: pick and choose data**
- Observables **sensitive to different medium properties + model parameters**
  - Sensitivity **often not obvious**
- **Uncertainty treatment** is critical!

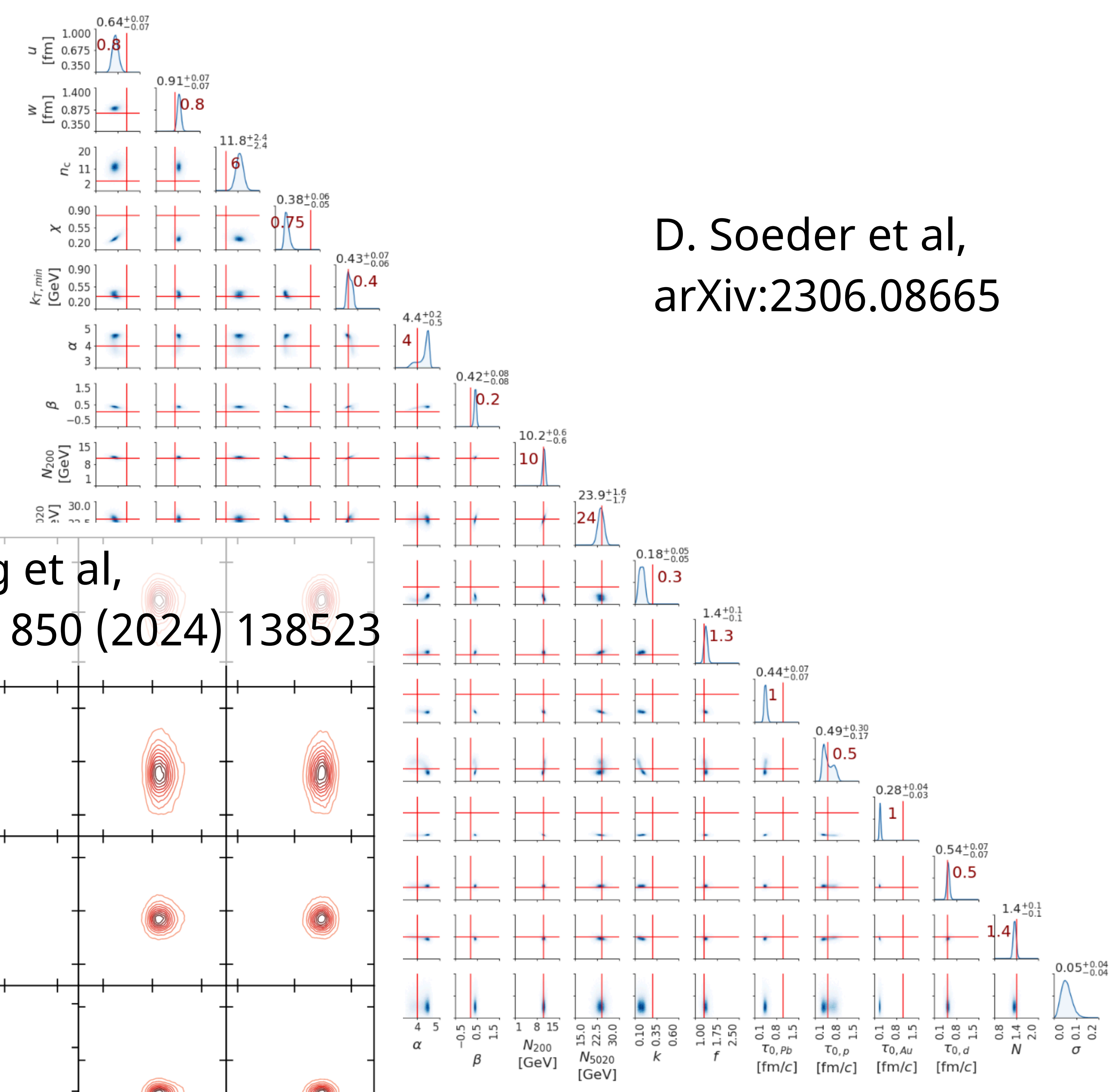
Bayesian Inference in heavy-ion collisions (non-exhaustive)

JETSCAPE,
PRL 126 (2021) 24, 242301

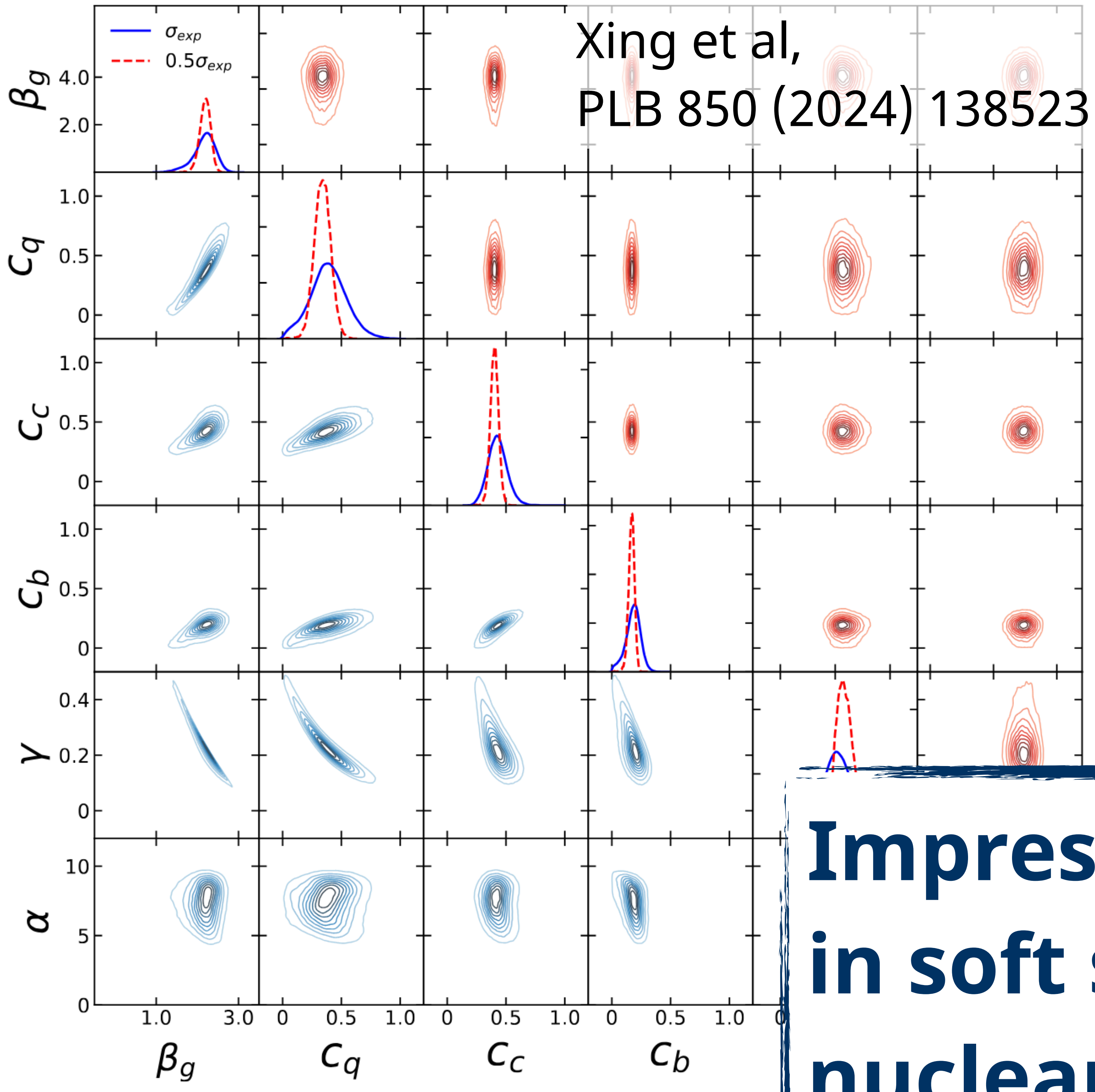


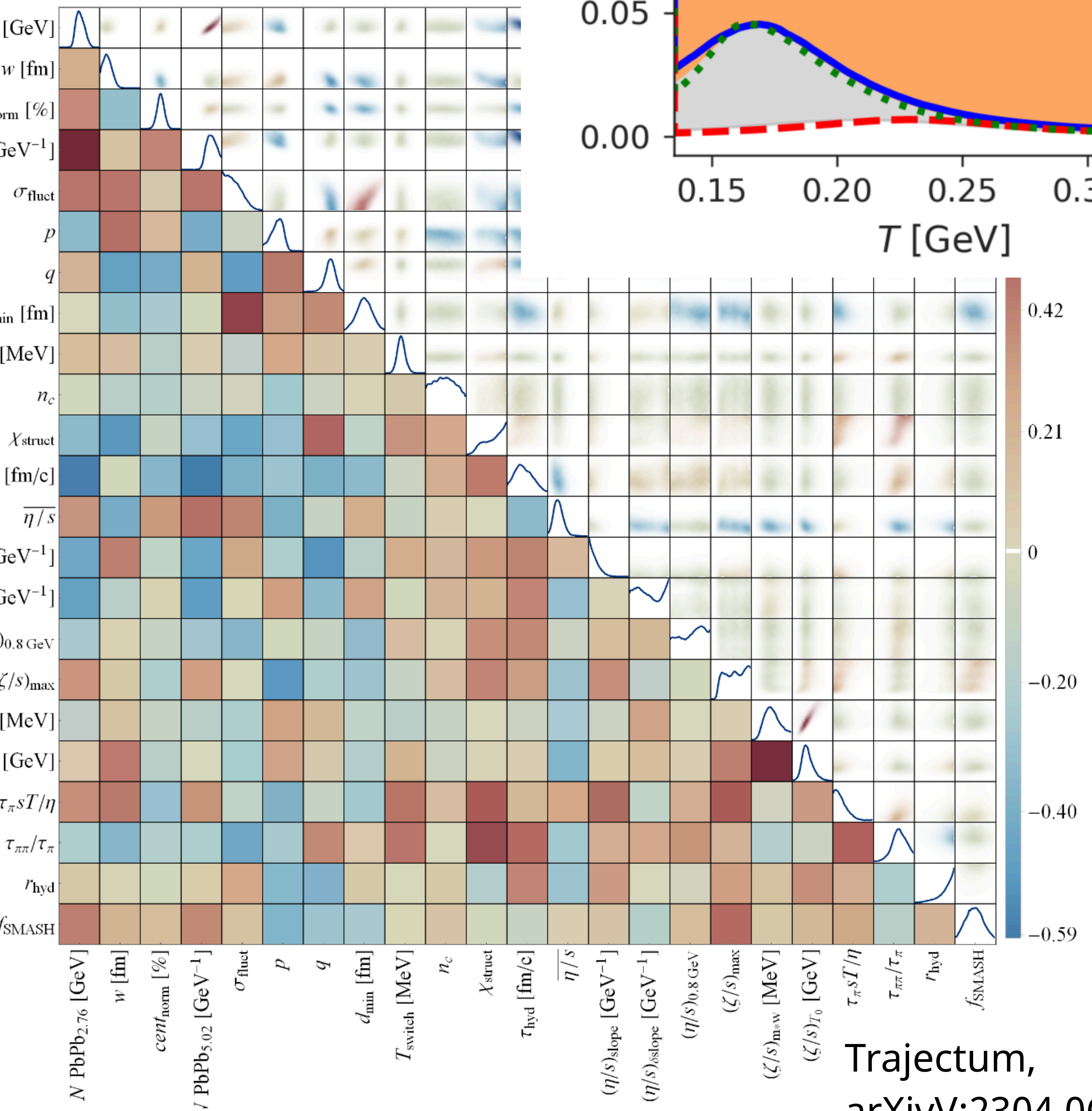


D. Soeder et al,
arXiv:2306.08665



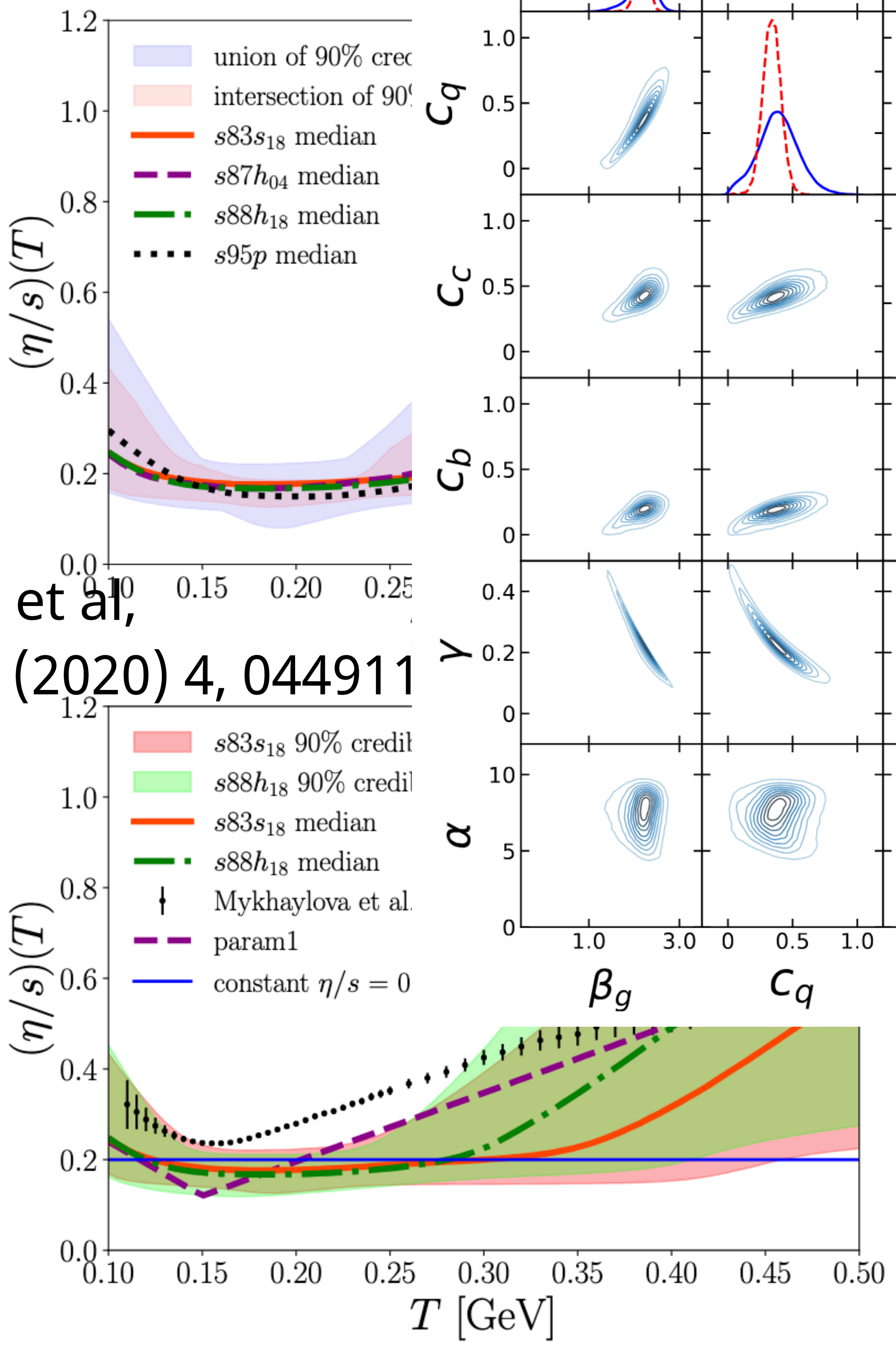
Xing et al,
PLB 850 (2024) 138523





Trajectum,
arXivV:2304.06191

Auvinen et al,
PRC 102 (2020) 4, 044911

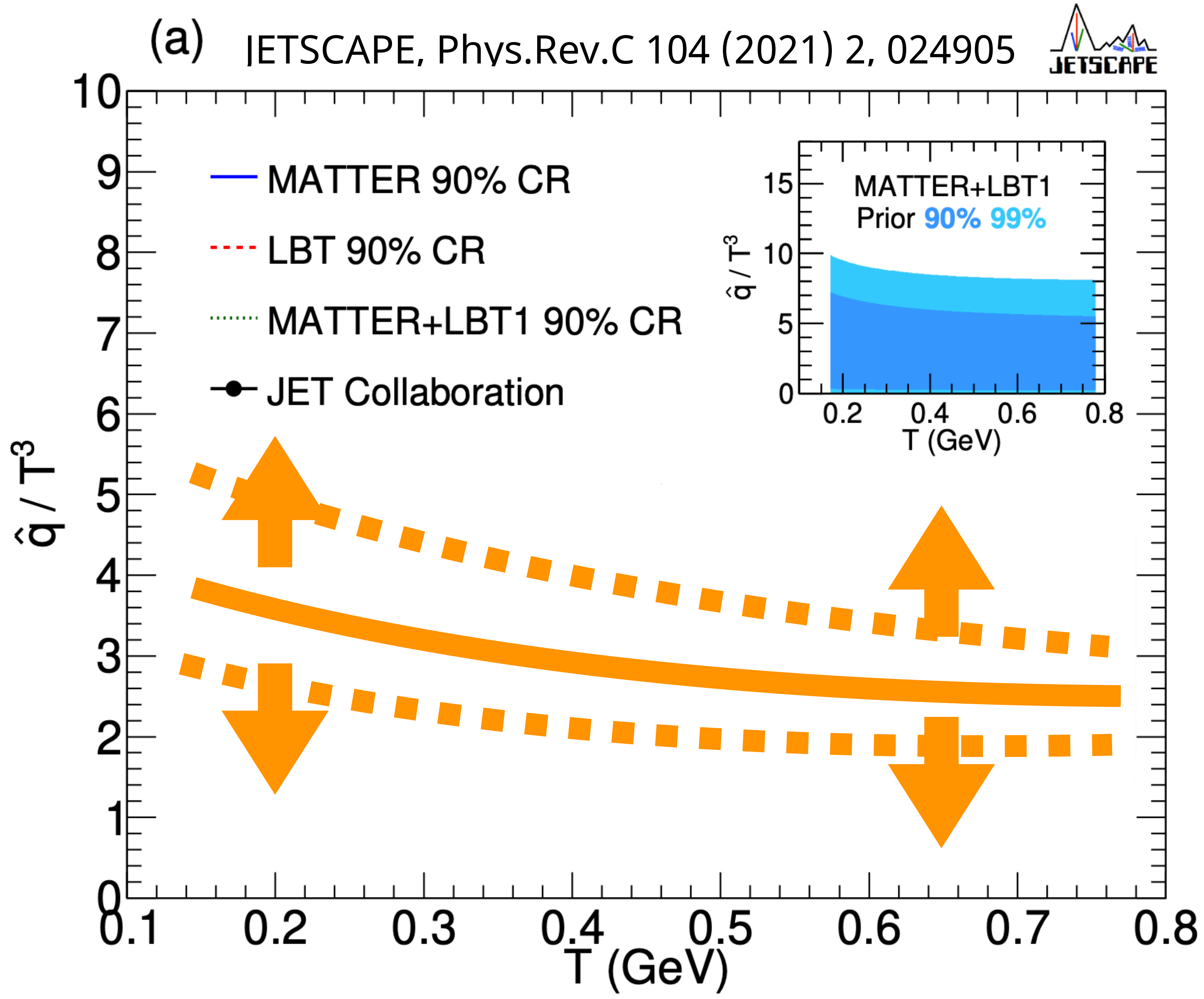


Impressive progress in soft sector, nuclear structure, HF, …
Not covered today

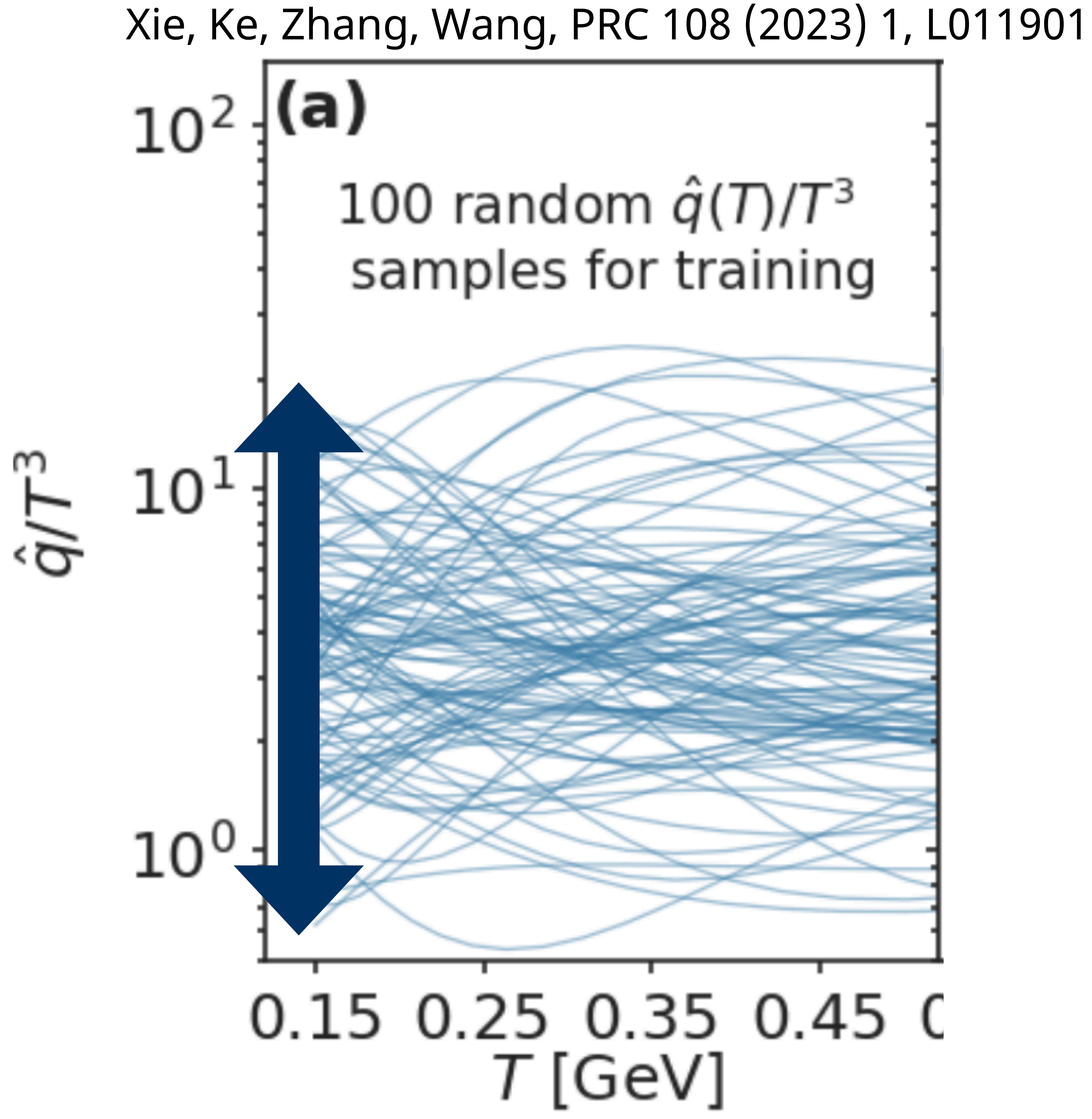
Jet quenching via hadronic observables

Two approaches to $\hat{q}$ parametrization

HTL $\hat{q}$/virtuality dependence: specific analytic form



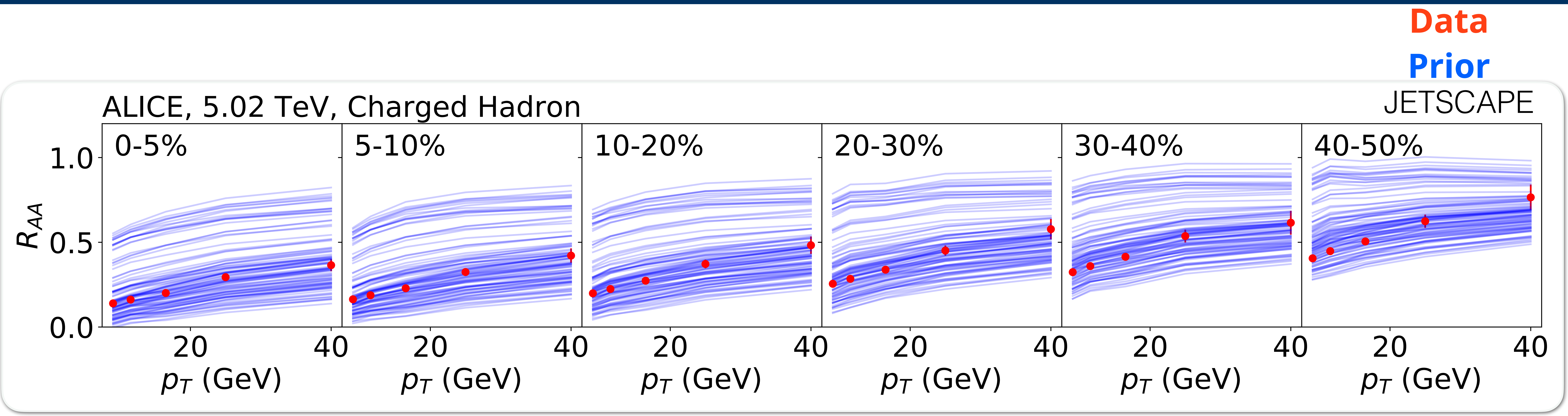
Information field: flexible set of random functions



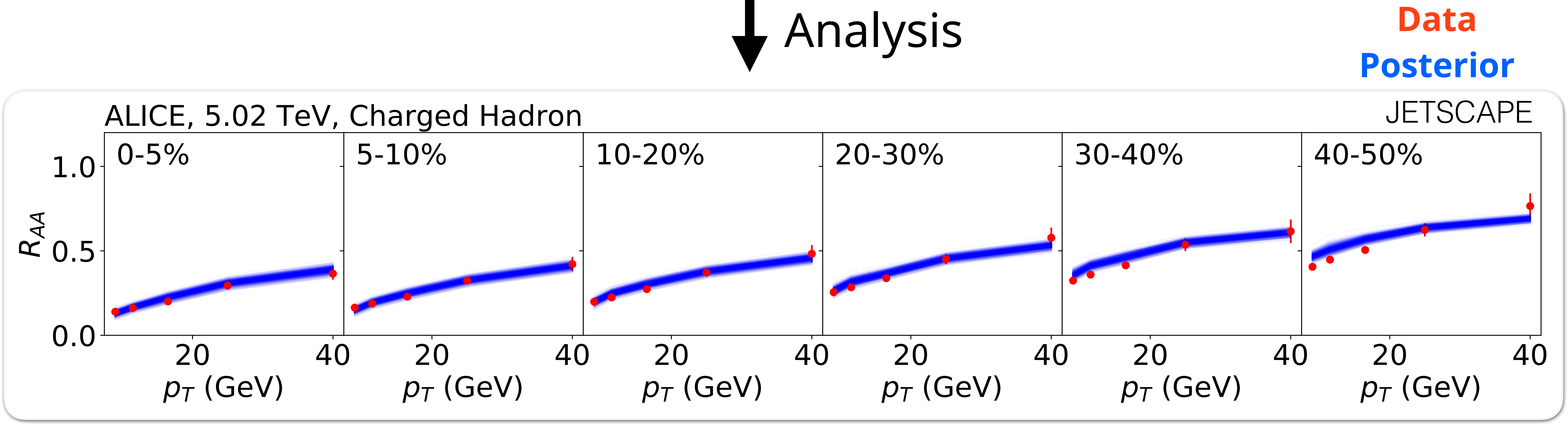
More physics inspired ⟵ **Trade flexibility for interpretability** ⟶ **More flexible**

Parametrization impacts constraints!

From Prior to Posterior: JETSCAPE



Analysis



arXiv:2408.08247

JETSCAPE Inclusive hadron R_{AA}

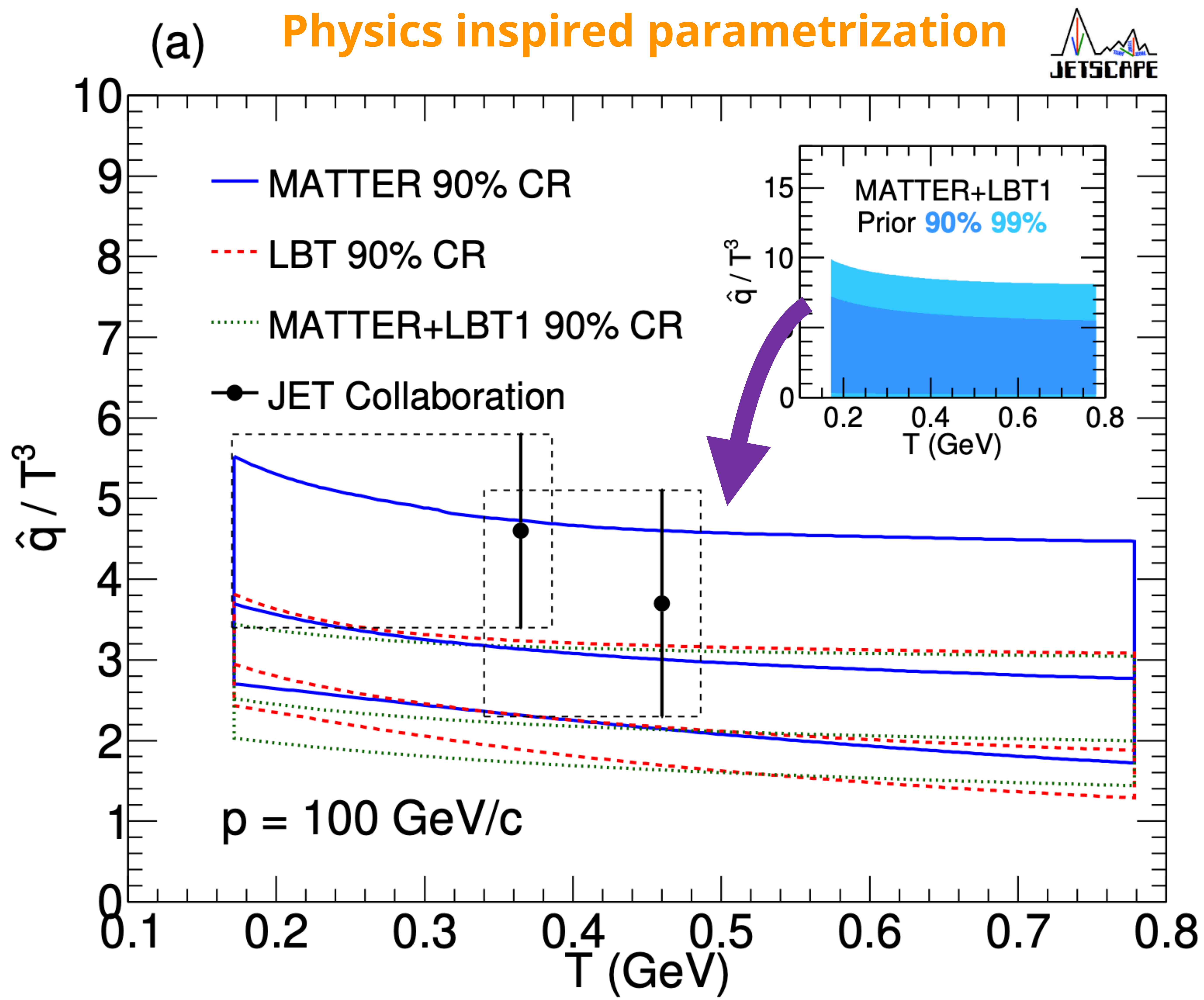
JETSCAPE, 2021

- Proof-of-principle analysis **demonstrating Bayesian inference in the hard sector**
  - Selected inclusive hadron R_{AA}, in terms of centrality, experiments
- **Significant constraints on prior**
- **Consistent $\hat{q}$ for RHIC and LHC**
  Consistent with JET collaboration

Model: JETSCAPE MATTER+LBT (early)

Data: Selection of incl. hadron R_{AA}

Physics inspired parametrization



JETSCAPE, Phys.Rev.C 104 (2021) 2, 024905

Comprehensive hadron analysis: Information field

Xie et al, 2023, 2024

- **First comprehensive analysis with hadron observables**
  - Includes **di-hadron and gamma-hadron correlations** from RHIC, LHC
  - Different sensitivities → additional info

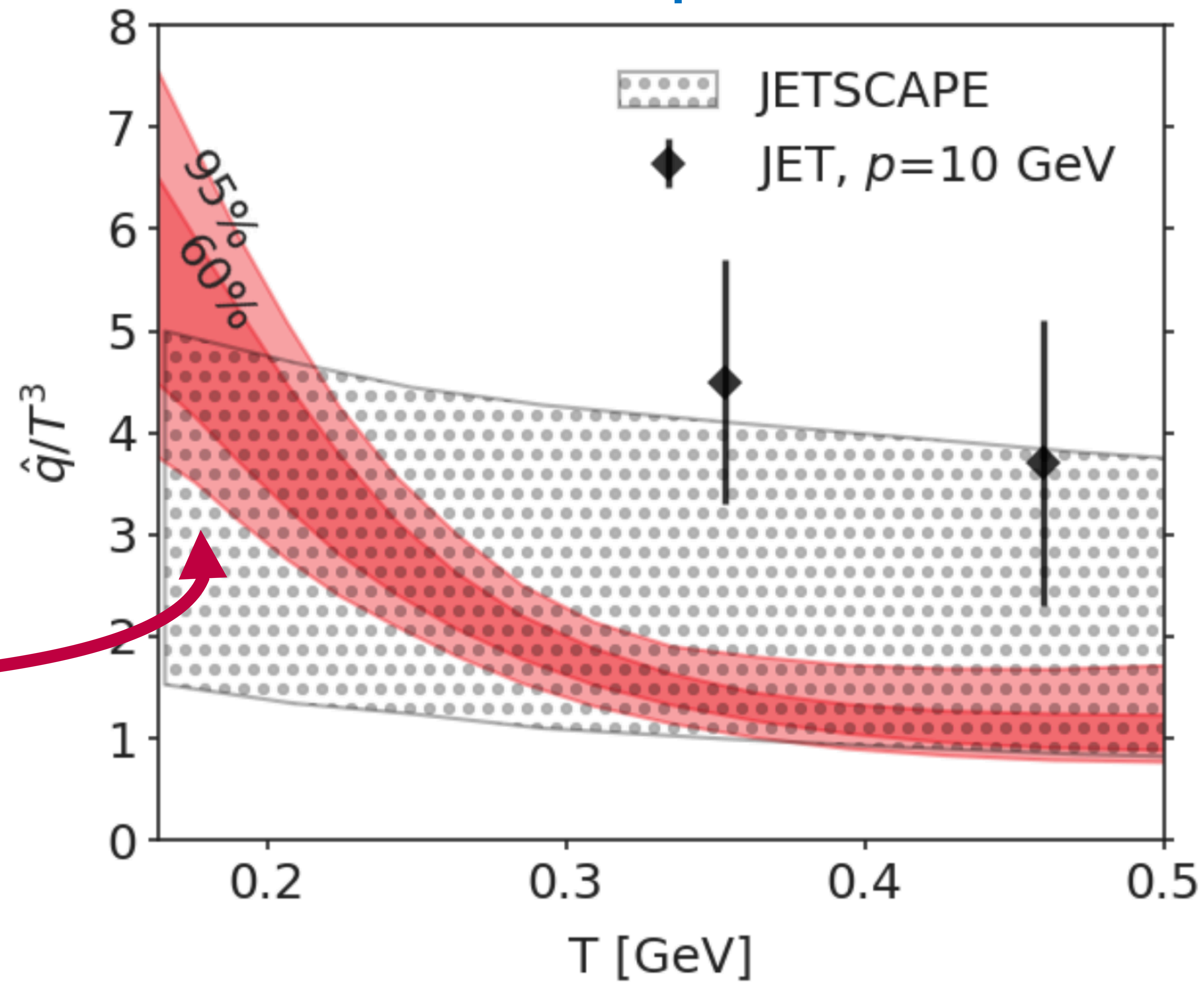
- **Preferred functional form differs from JETSCAPE**
- **Strong increase at low T***

*assumes $\hat{q}$ = 0 below T_C

Model: NLO Parton Model + Higher-twist

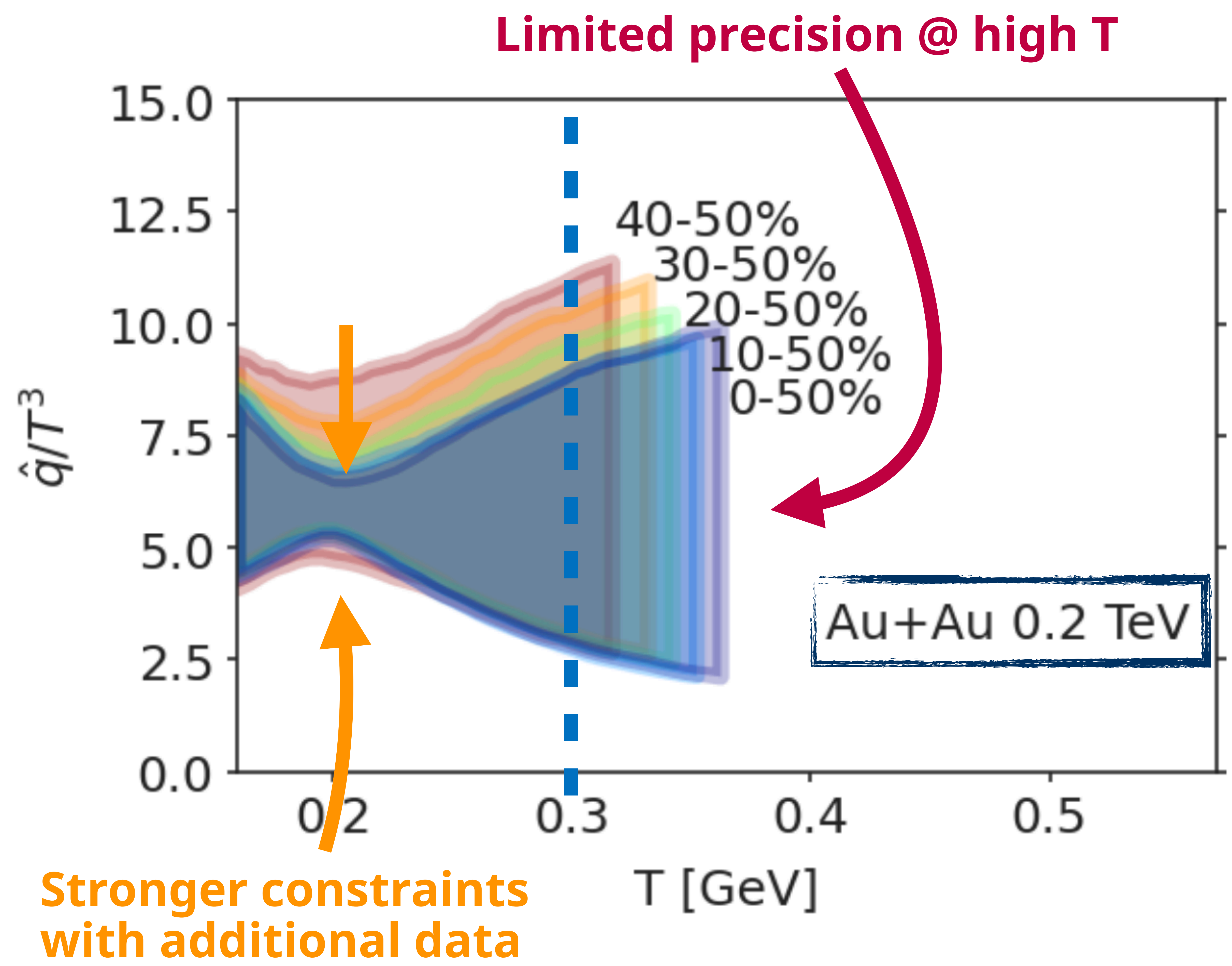
Data: Incl. hadron R_{AA}, di-hadron, γ-hadron corr.

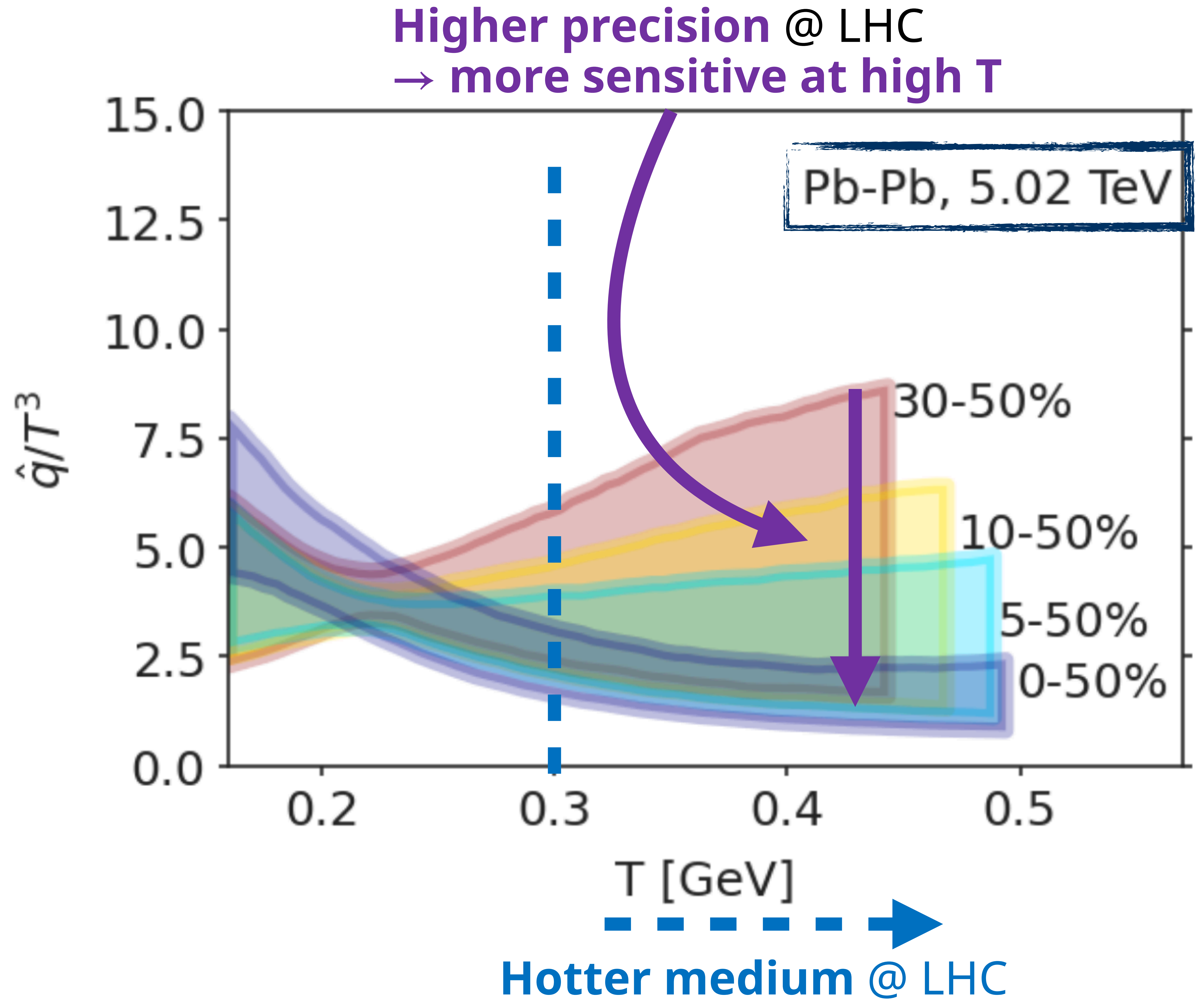
Information field parametrization



Xie, Ke, Zhang, Wang, PRC 108 (2023) 1, L011901
Xie, Ke, Zhang, Wang, PRC 109 (2024) 6, 064917

Information field: centrality + temperature dependence





Model: NLO Parton Model + Higher-twist

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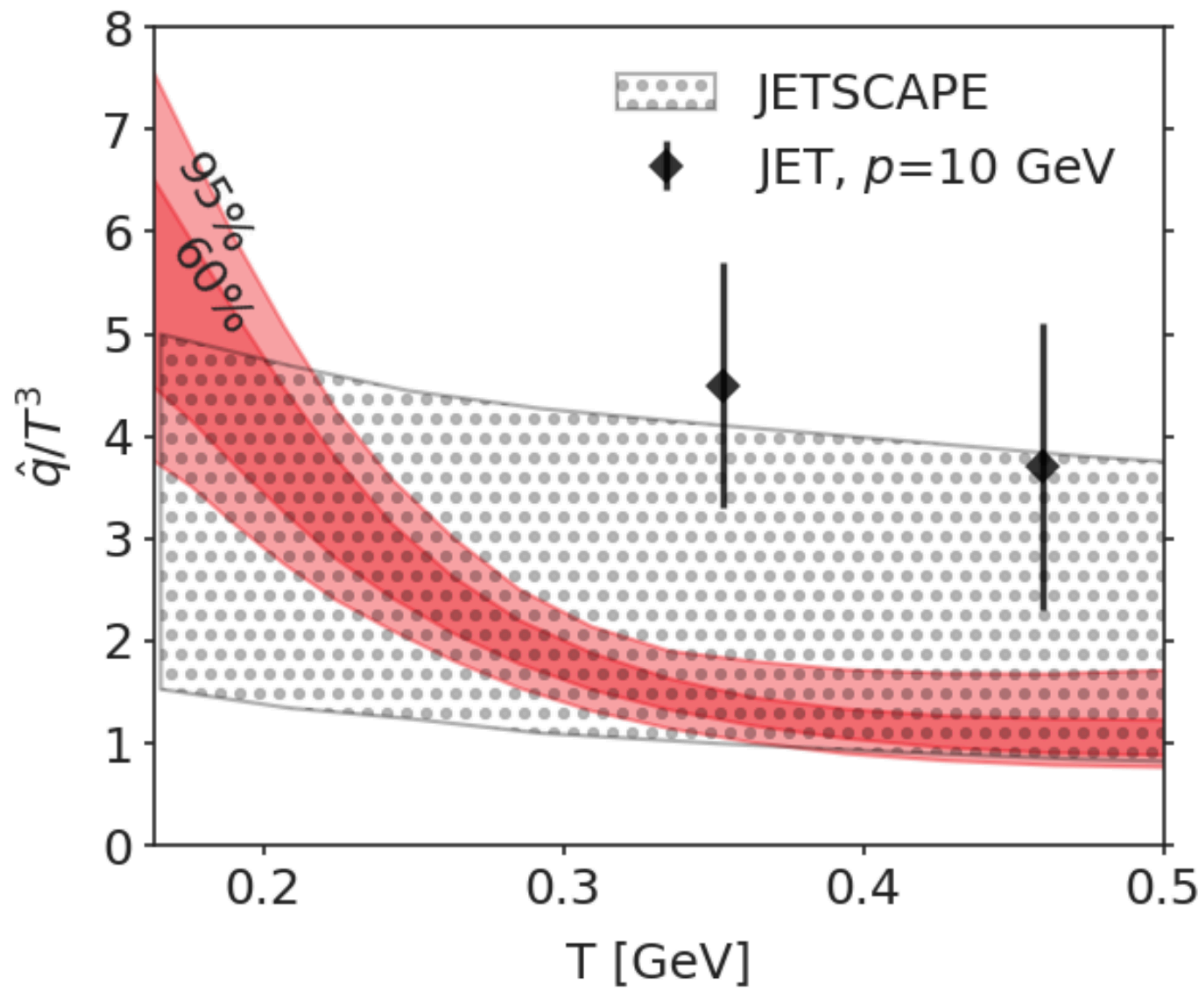
Encodes temperature dependence of data

Xie, Ke, Zhang, Wang, PRC 108 (2023) 1, L011901
Xie, Ke, Zhang, Wang, PRC 109 (2024) 6, 064917

Two approaches to $\hat{q}$ parametrization: What did we learn?

Flexibility vs interpretability:

Highlights influence of model, parametrization, and data choices



Soft-hard correlations

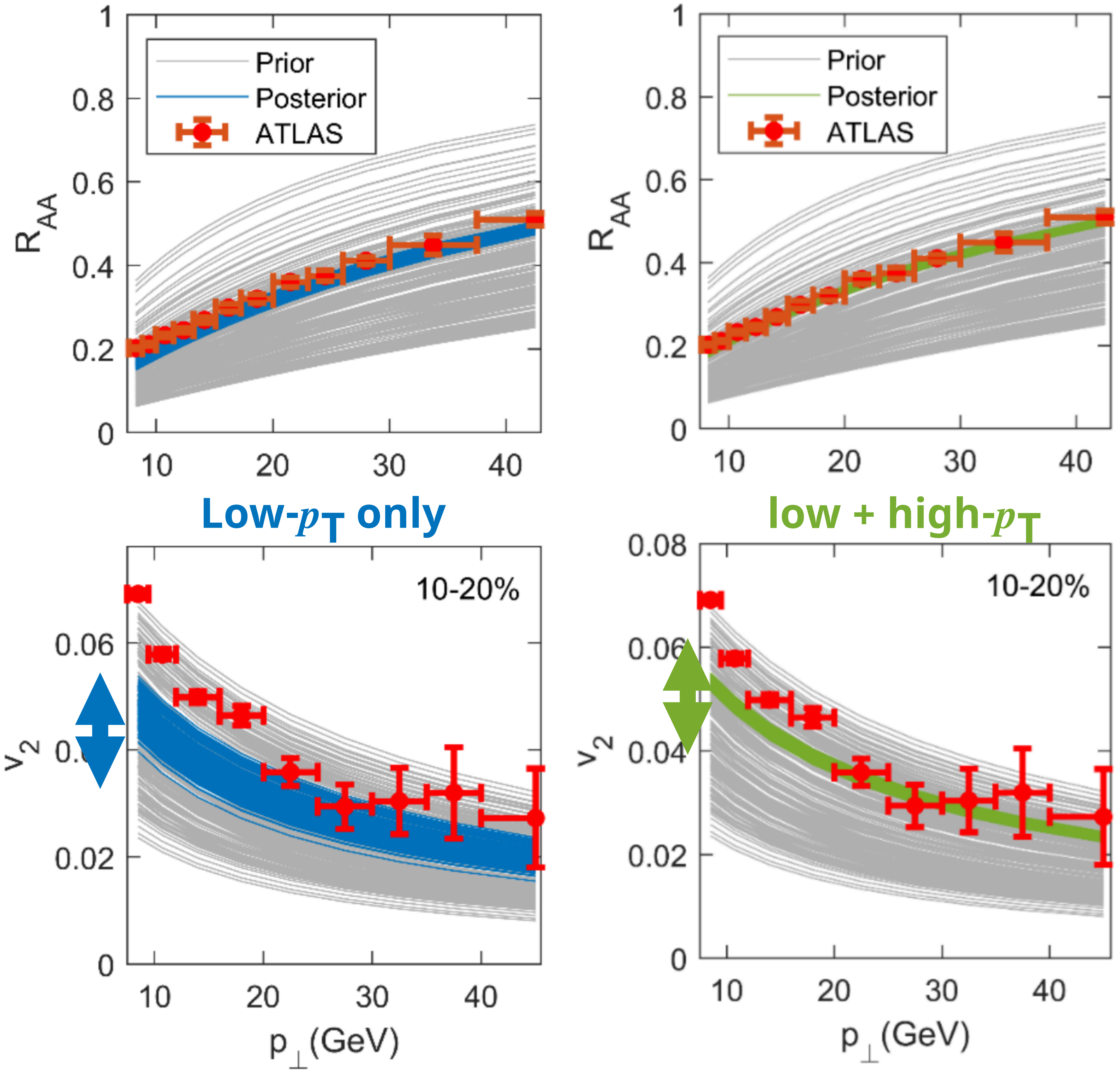
Hard-soft interactions: Bayes-DREENA

DREENA, 2024

- Use **high-p_T observables to explore bulk QGP properties**
  - Expect different η/s at high p_T
- Calibrate with two classes of observables: **only low-p_T** or **low + high-p_T**
  - **Improved description of data** with more data
- **Significantly stronger constraint on parameter posterior** for **low + high-p_T**

➜ **Hard observables impact soft parameters**

First step to further investigations



Model: DREENA-A

Data: Selected ident. part mult., mean p_T, incl., D hadron R_{AA}, v2

Magdalena Djordjevic, Sep 24, 2024, 15:35

Hard-soft interactions: Bayes-DREENA

DREENA, 2024

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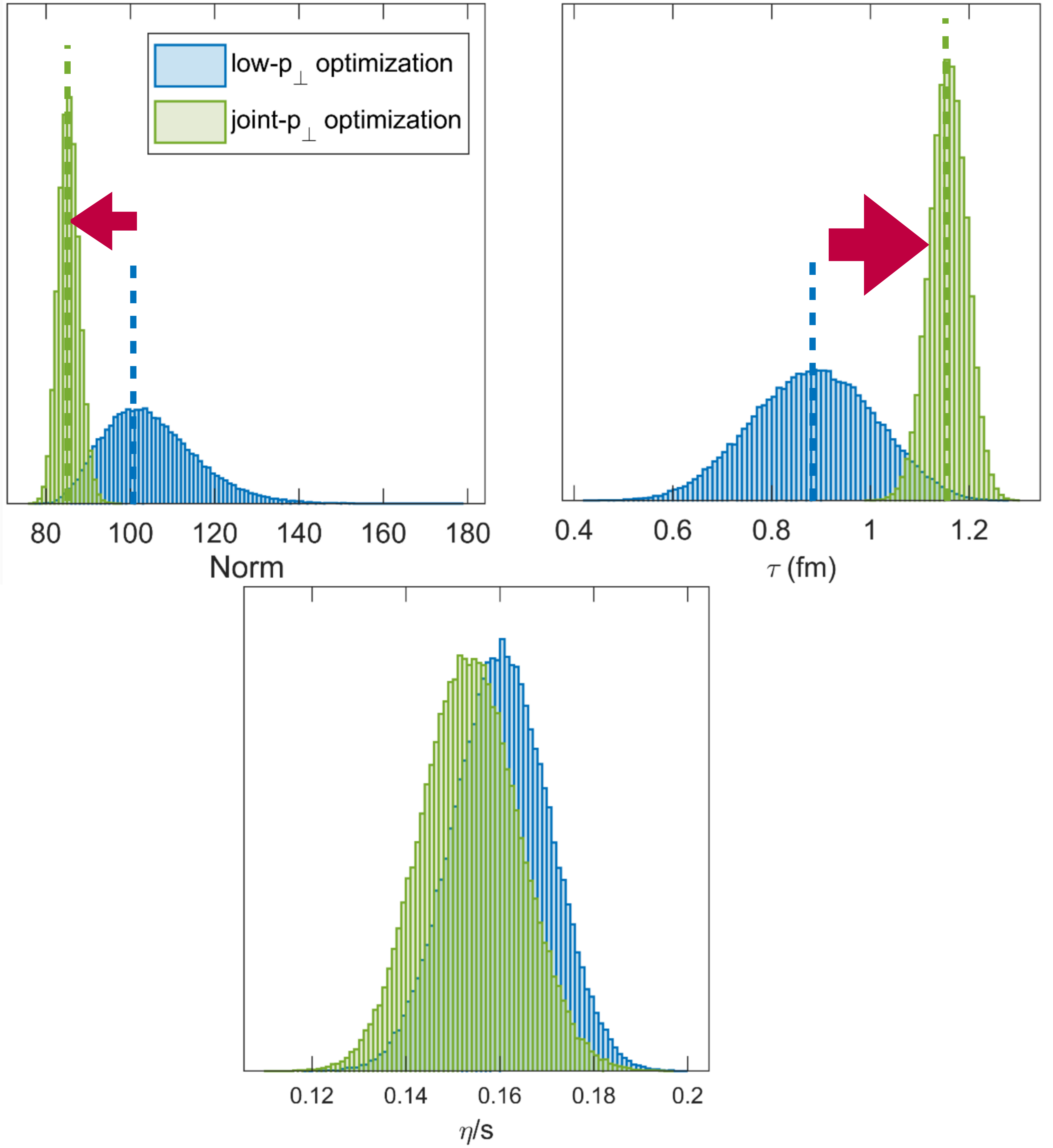


Magdalena Djordjevic, Sep 24, 2024, 15:35

Hadron and jet observables

Adding in jet suppressions measurements with LIDO

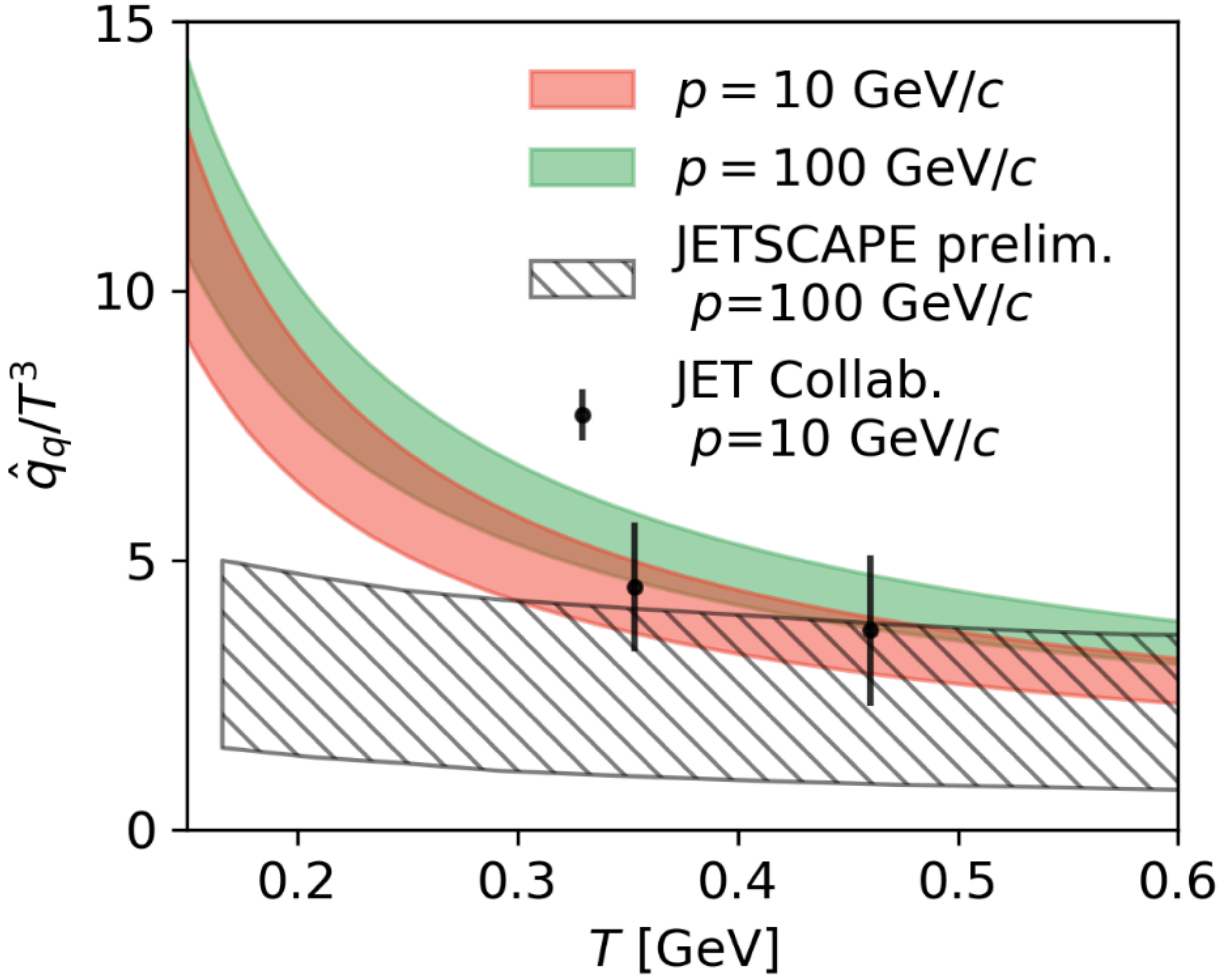
LIDO, 2021

- LIDO first to **calibrate on a subset of jets and hadron R_{AA}** for **initial model calibration**
- Demonstrates that **consistent description is possible**

- Use **calibrated model to predict other datasets**
  - **Fragmentation** well described
  - **R_{AA} R-dependence shows some tension**

Model: LIDO

Data: Selected 0-10% incl. hadron, jet, and D R_{AA}



Ke, Wang, JHEP 05 (2021) 041

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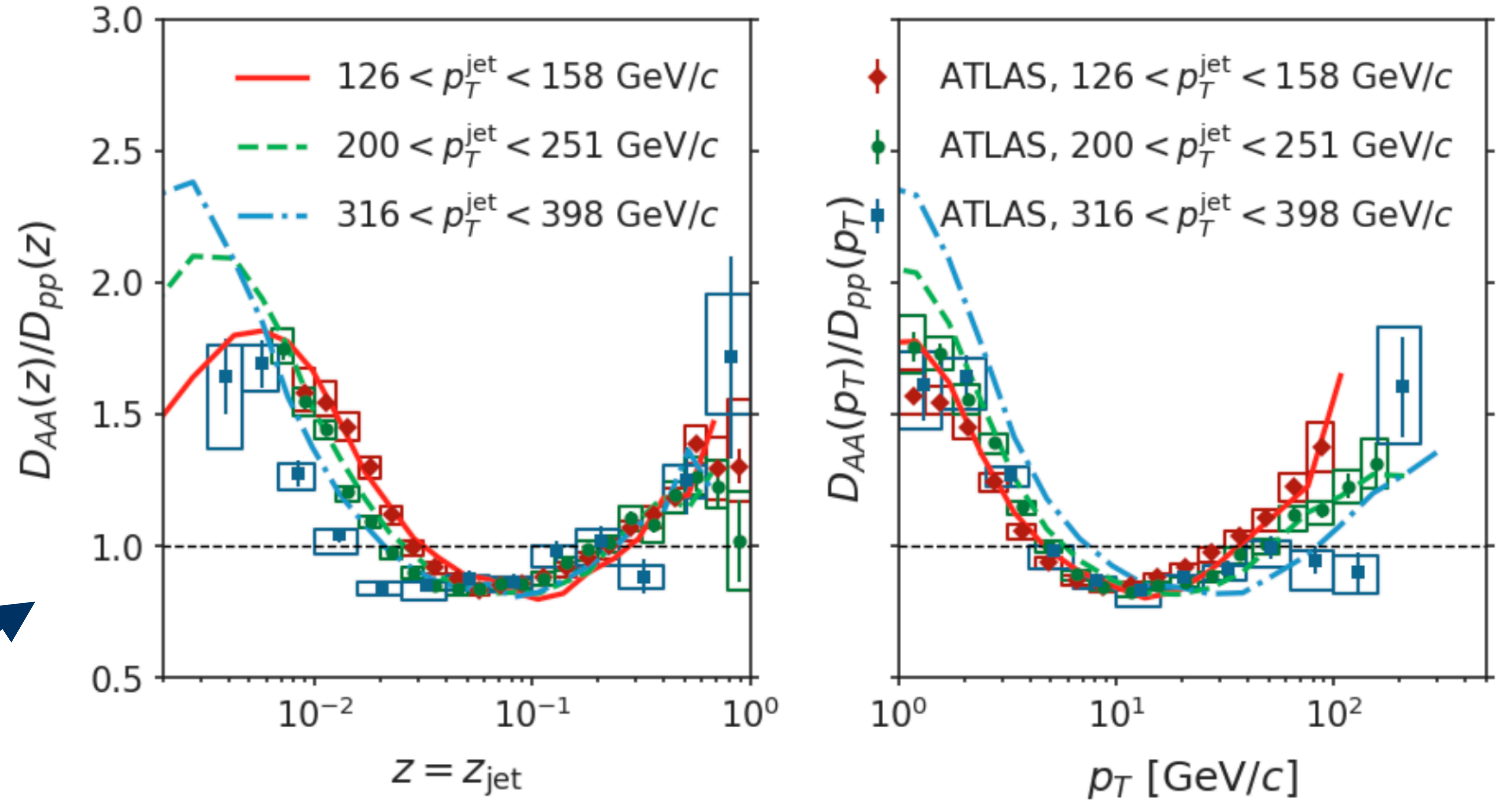

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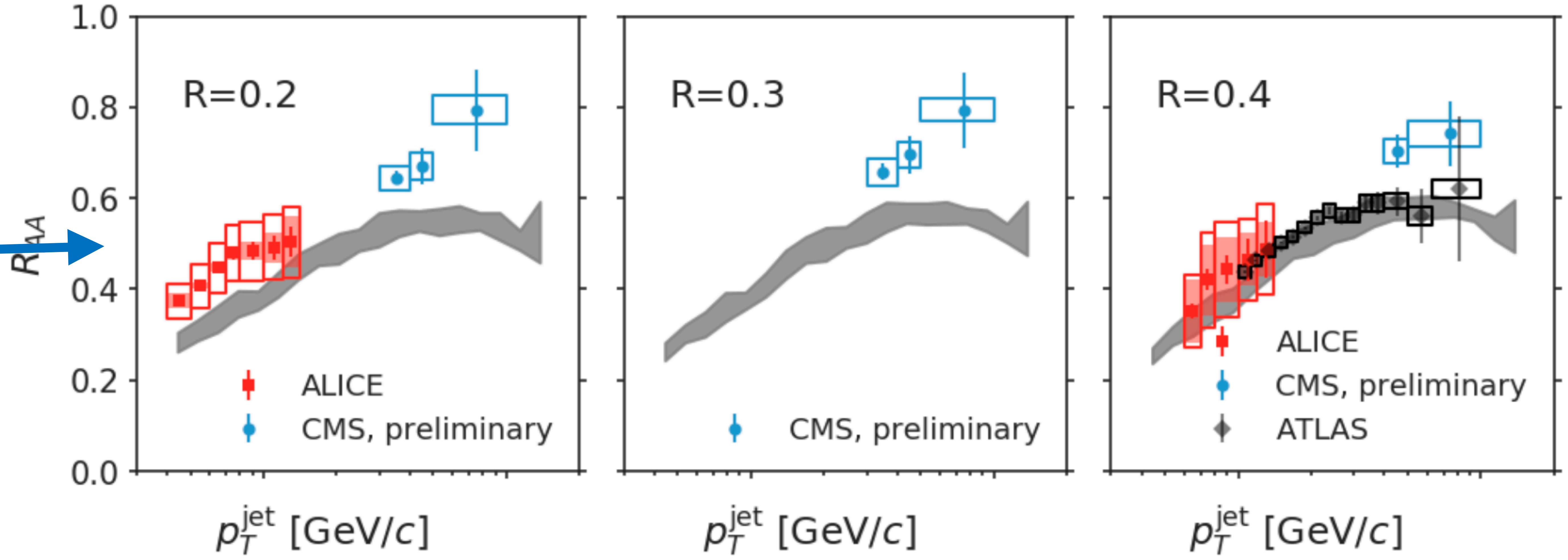


Model: LIDO

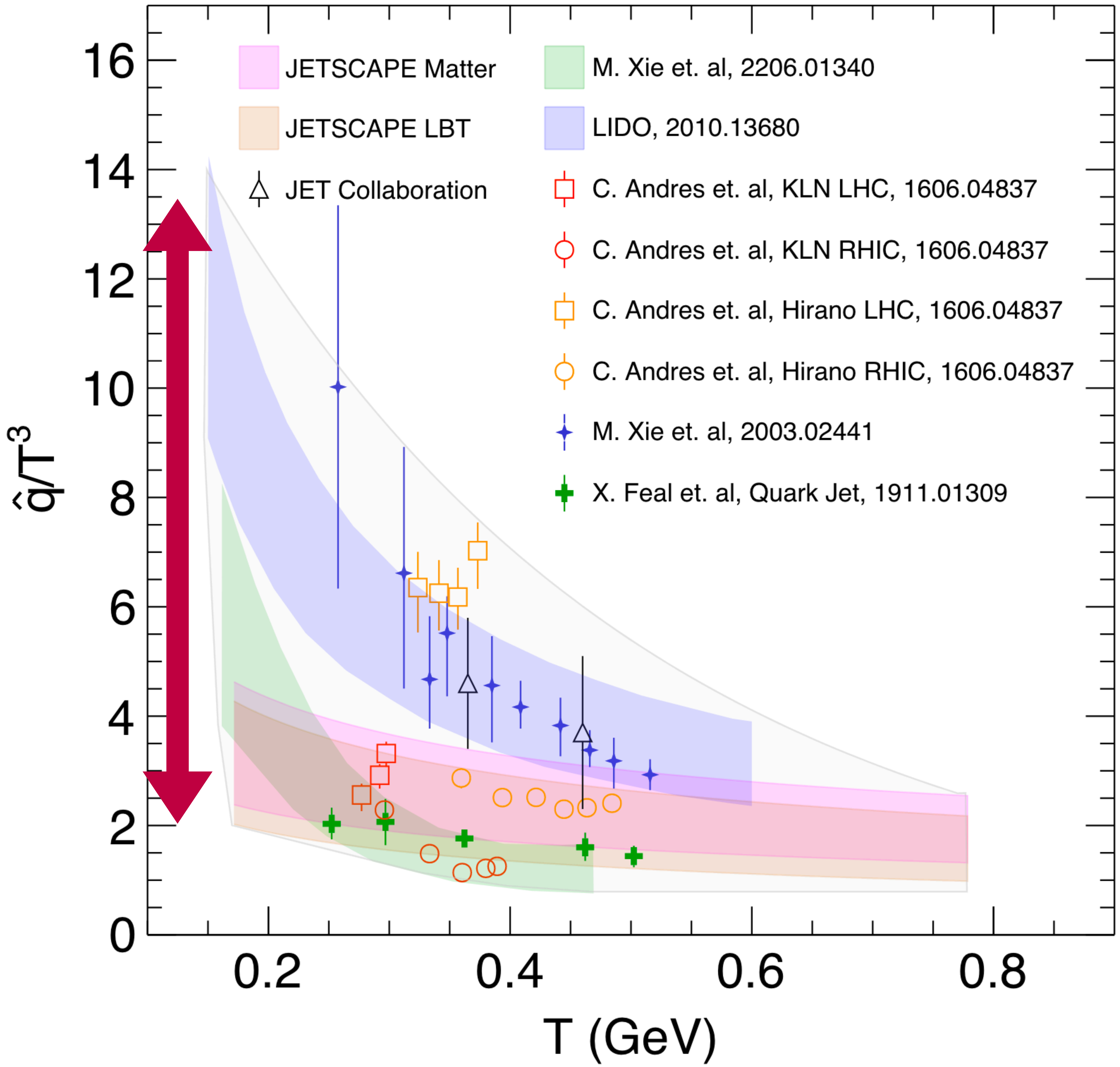
Data: Selected 0-10% incl. hadron, jet, and D R_{AA}

The world's knowledge of $\hat{q}$

State-of-the-field from 2022

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

→ **Comparisons may not be equivalent**



Apolinário, Lee, Winn: Prog.Part.Nucl.Phys. 127 (2022) 103990

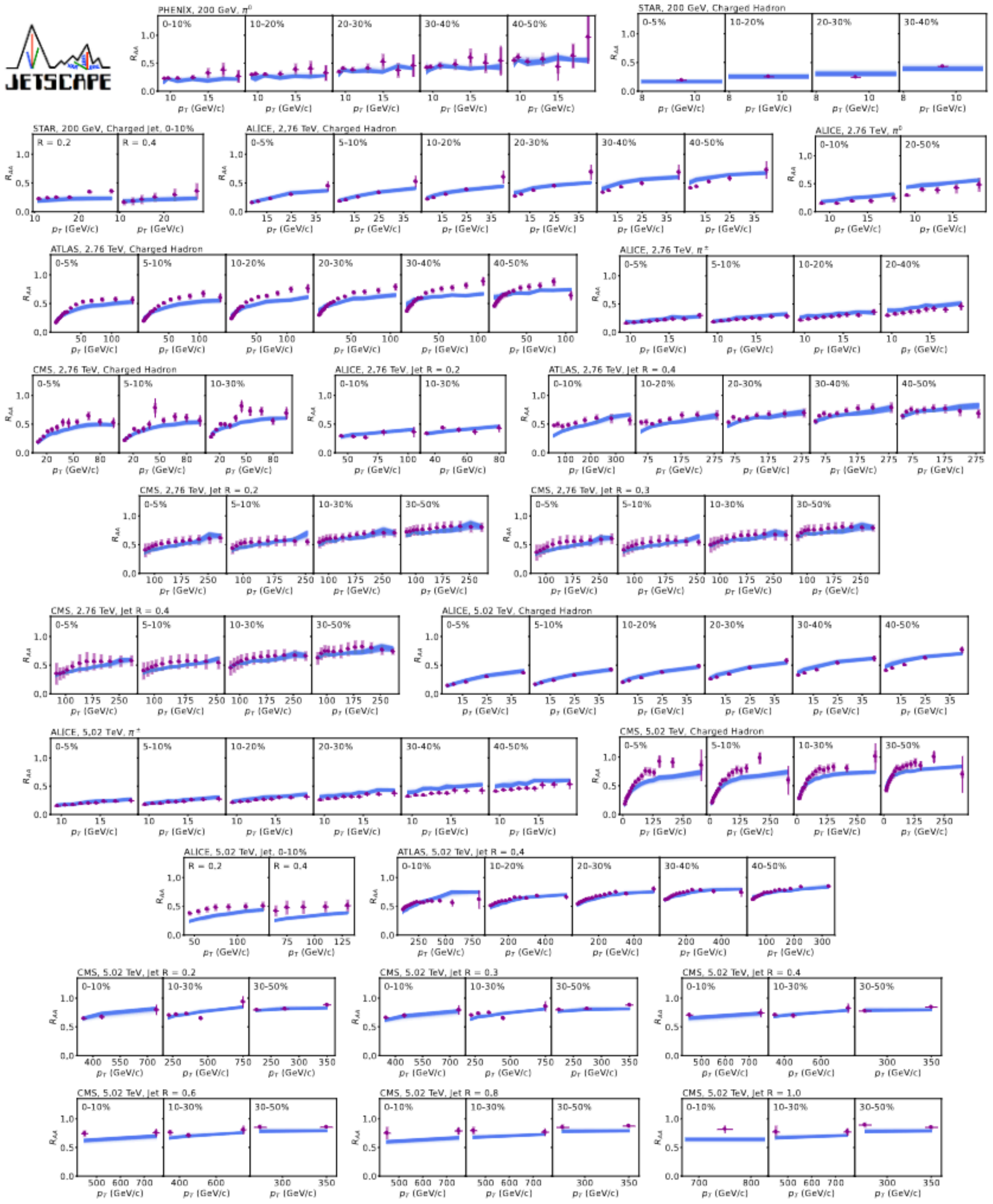
Comprehensive hadron and jet R_{AA} analysis: JETSCAPE

JETSCAPE, 2024

- Comprehensive study: **what do jets bring to the analysis**?
  - Include **all available inclusive hadron and jet R_{AA} measurements**
- **Reasonable overall description of data**, with **some tension for particular measurements**

Data

Best fit



Model: JETSCAPE MATTER+LBT

Data: Inclusive hadron and jet R_{AA}

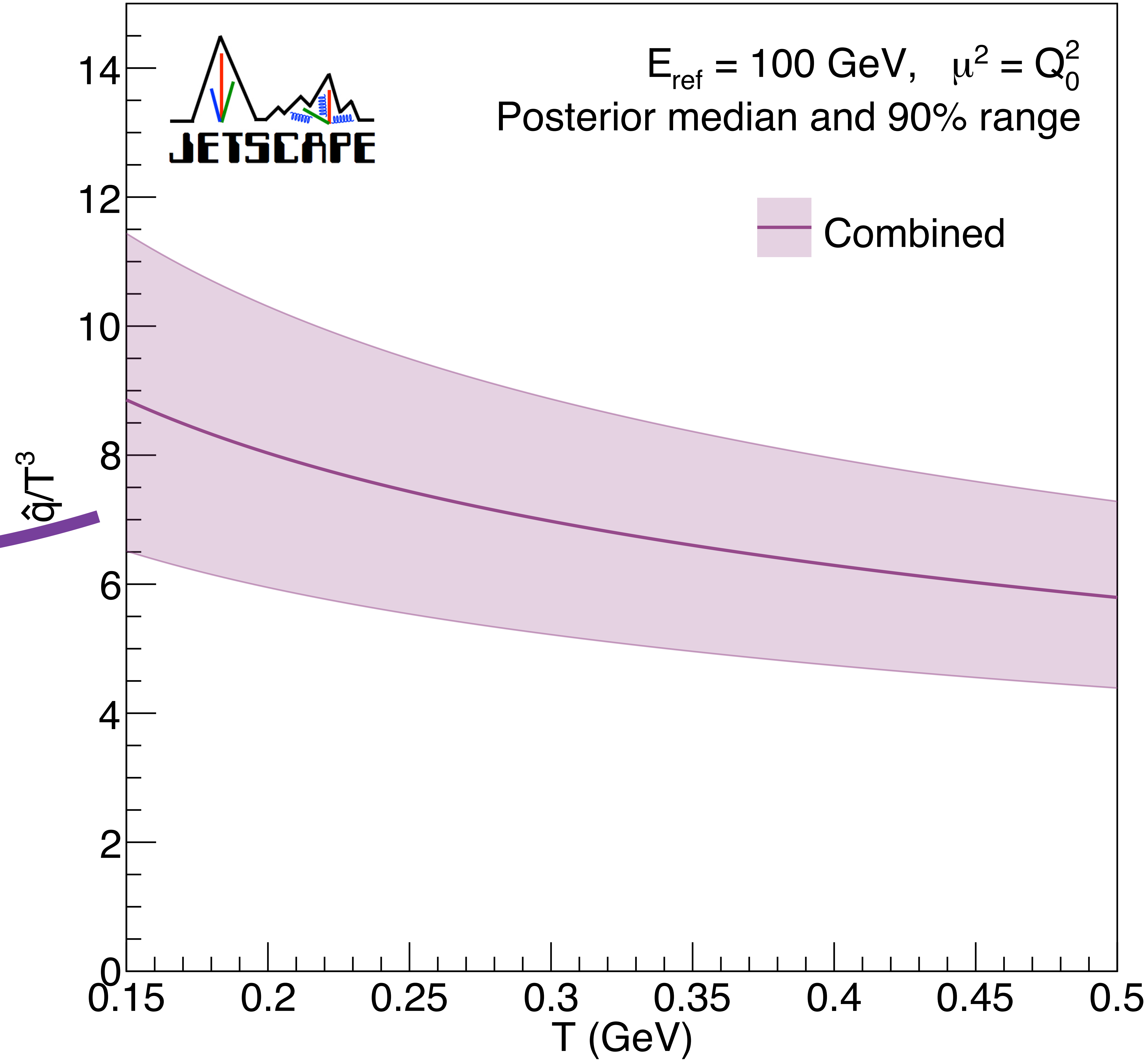
JETSCAPE, arXiv:2408.08247

Peter Jacobs, Sep 23, 2024, 15:40

Not all $\hat{q}$ are equivalent

JETSCAPE reports $\hat{q}$
when virtuality is low
i.e., $\hat{q} = \boxed{\hat{q}^{run}_{HTL}} \times f(Q^2)$

Explore differentially with fixed framework



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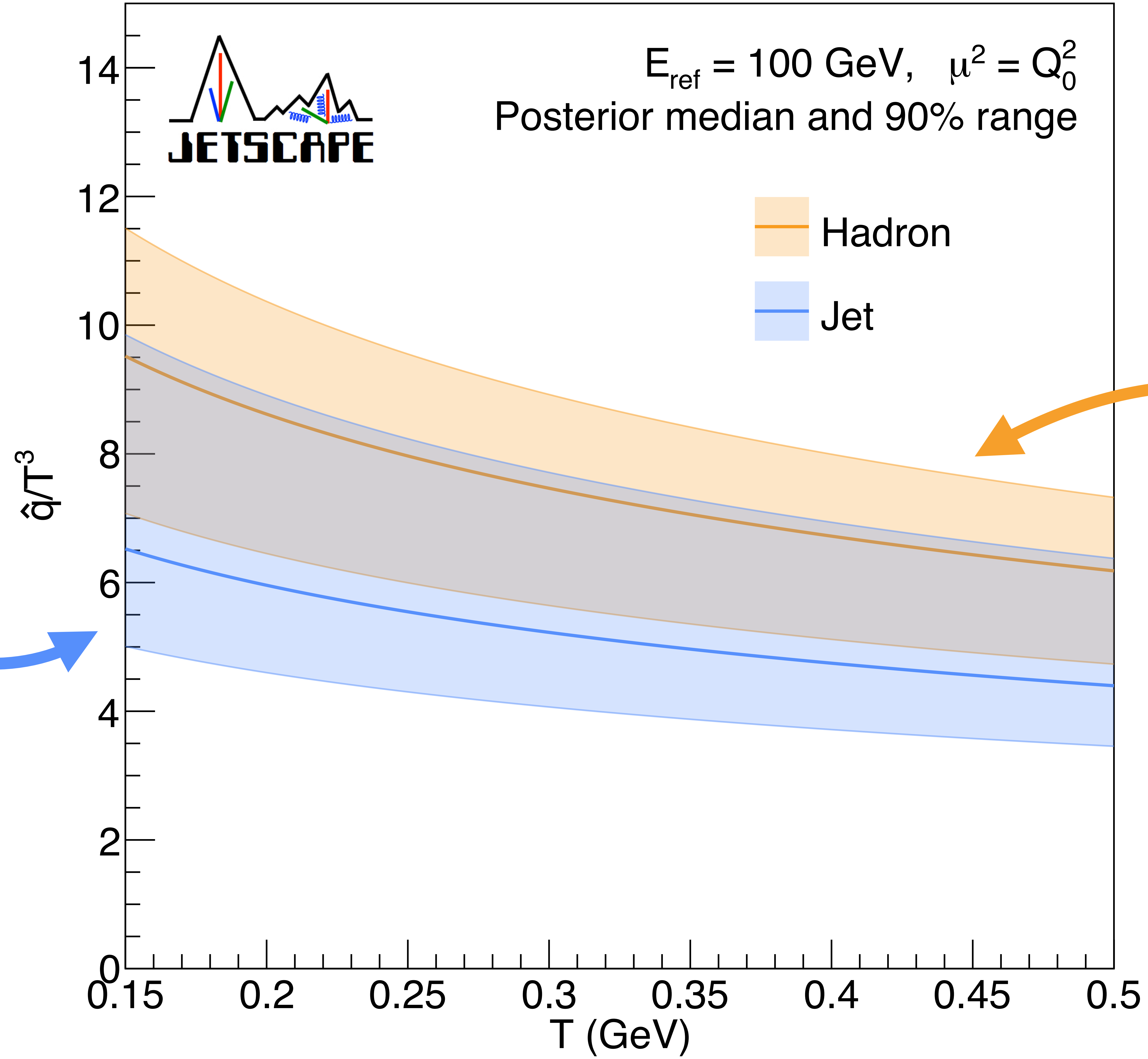
arXiv:2408.08247

Differential studies of hadron vs jet R_{AA}

Analysis with only jet data



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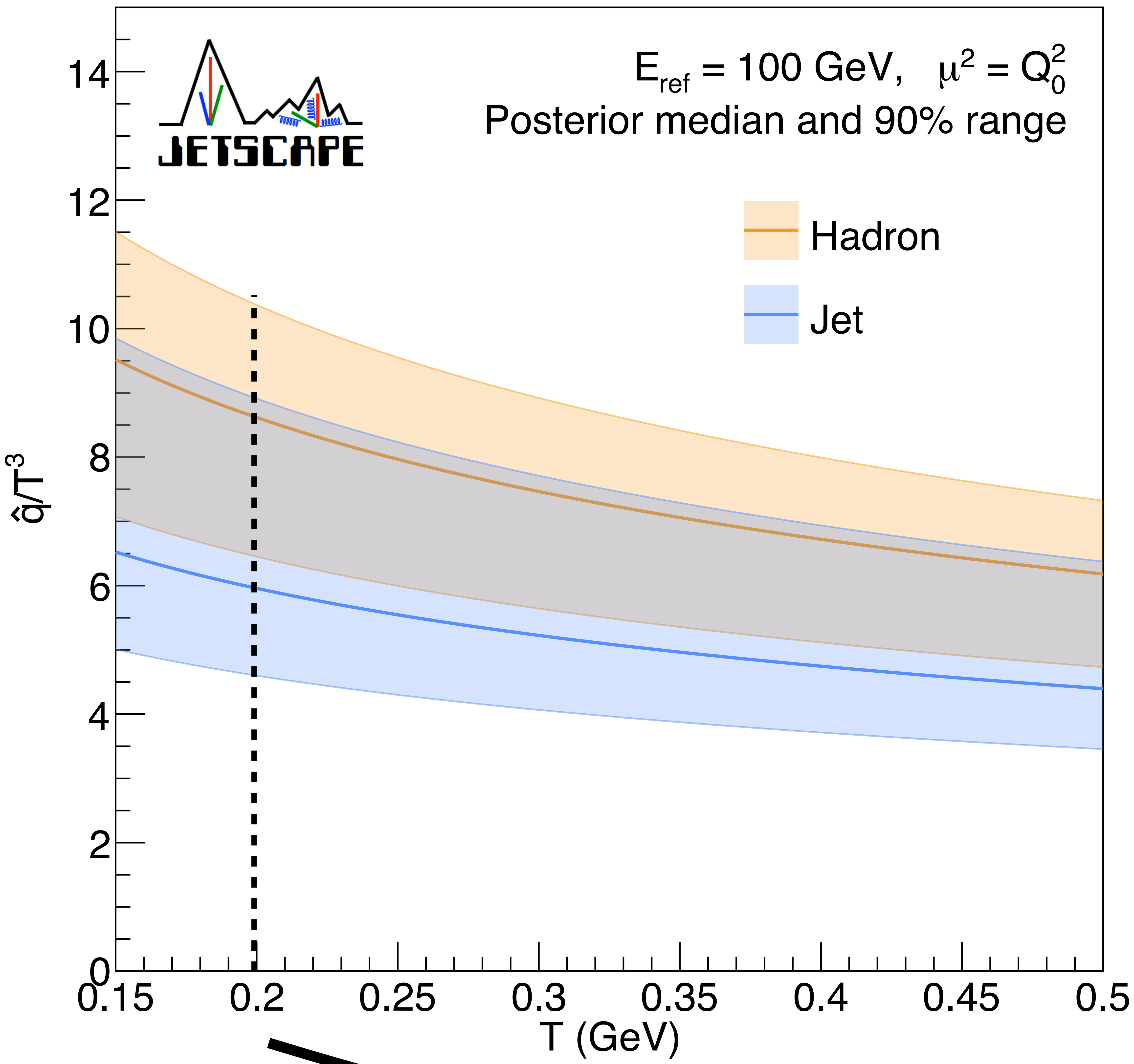
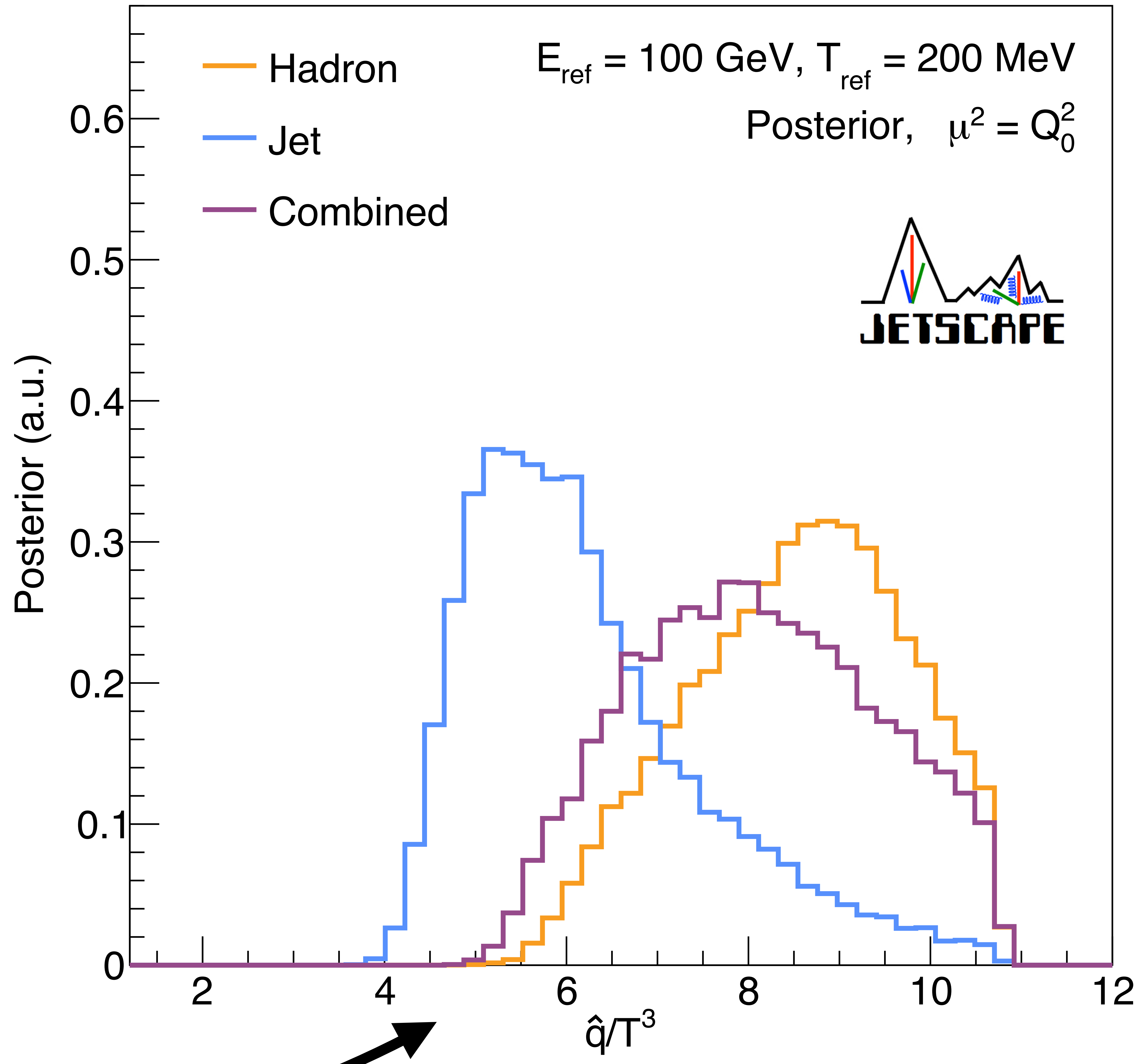
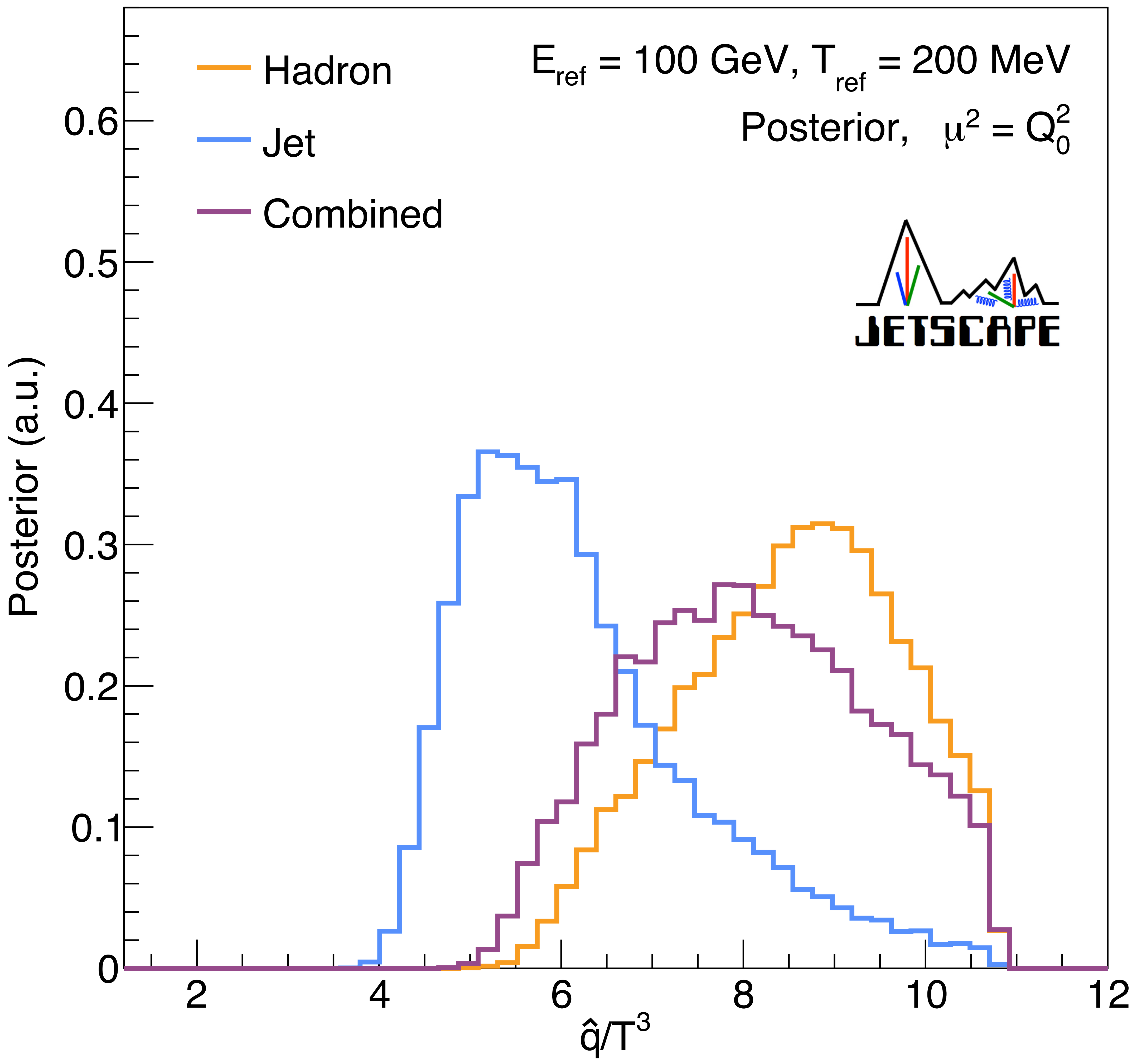


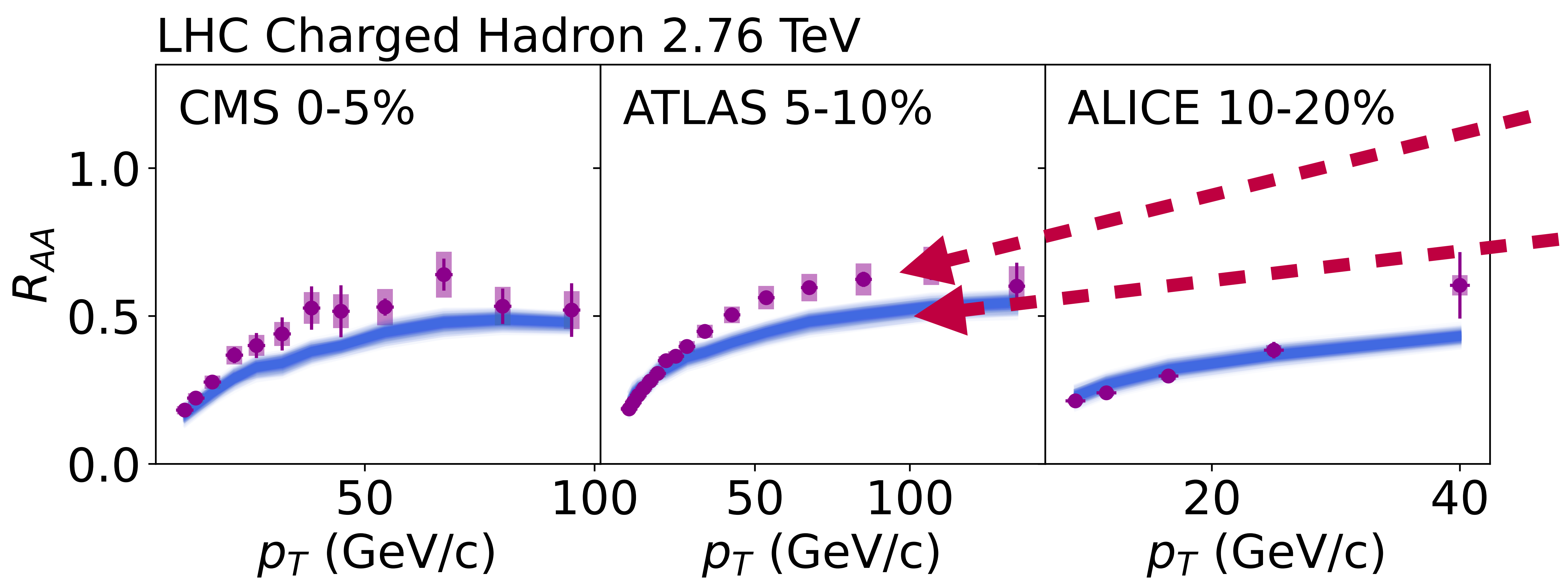


Peter Jacobs, Sep 23, 2024, 15:40 arXiv:2408.08247

Calibrating with low vs high p_T hadrons



Full p_T range



Peter Jacobs, Sep 23, 2024, 15:40 arXiv:2408.08247

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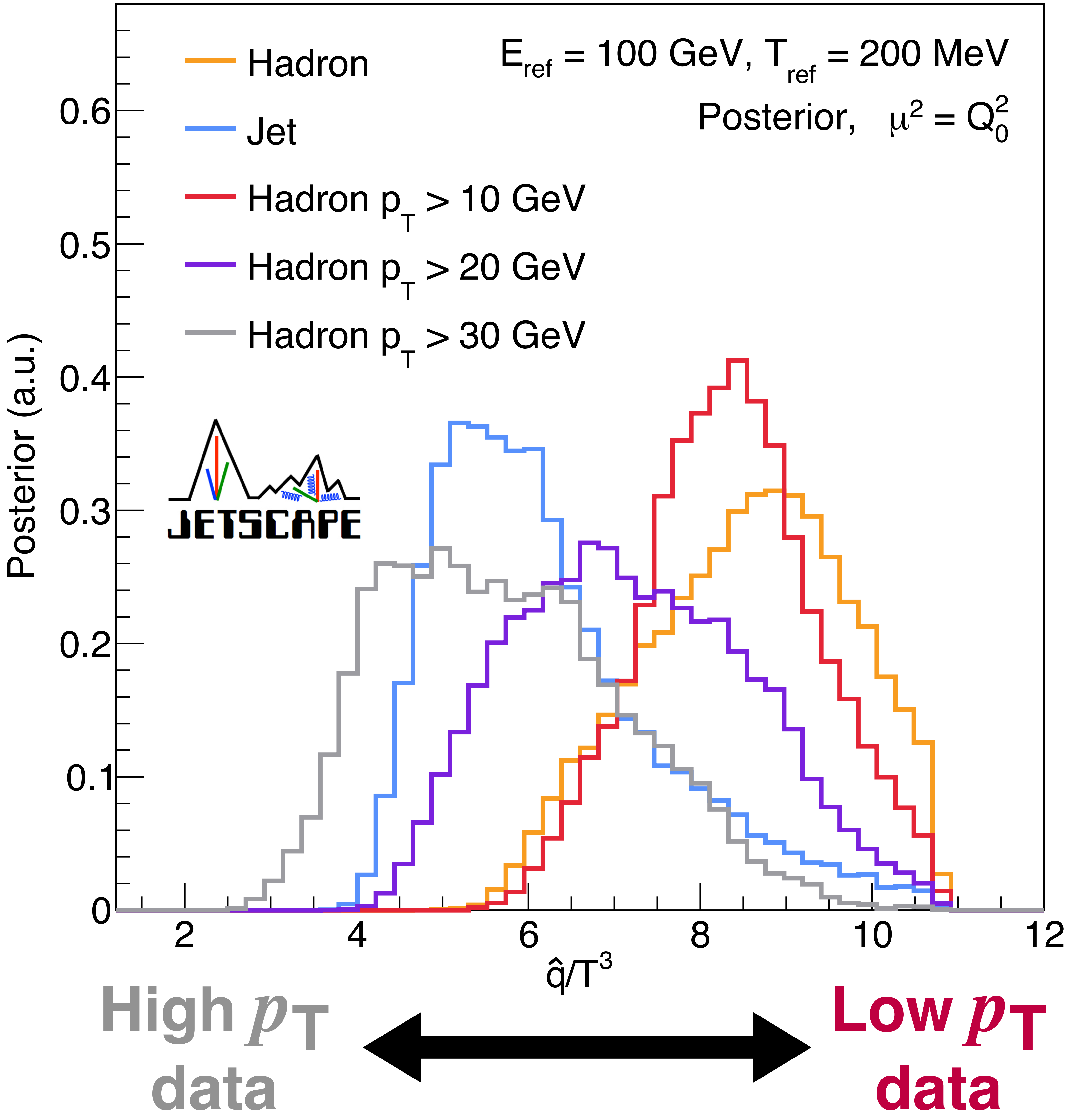
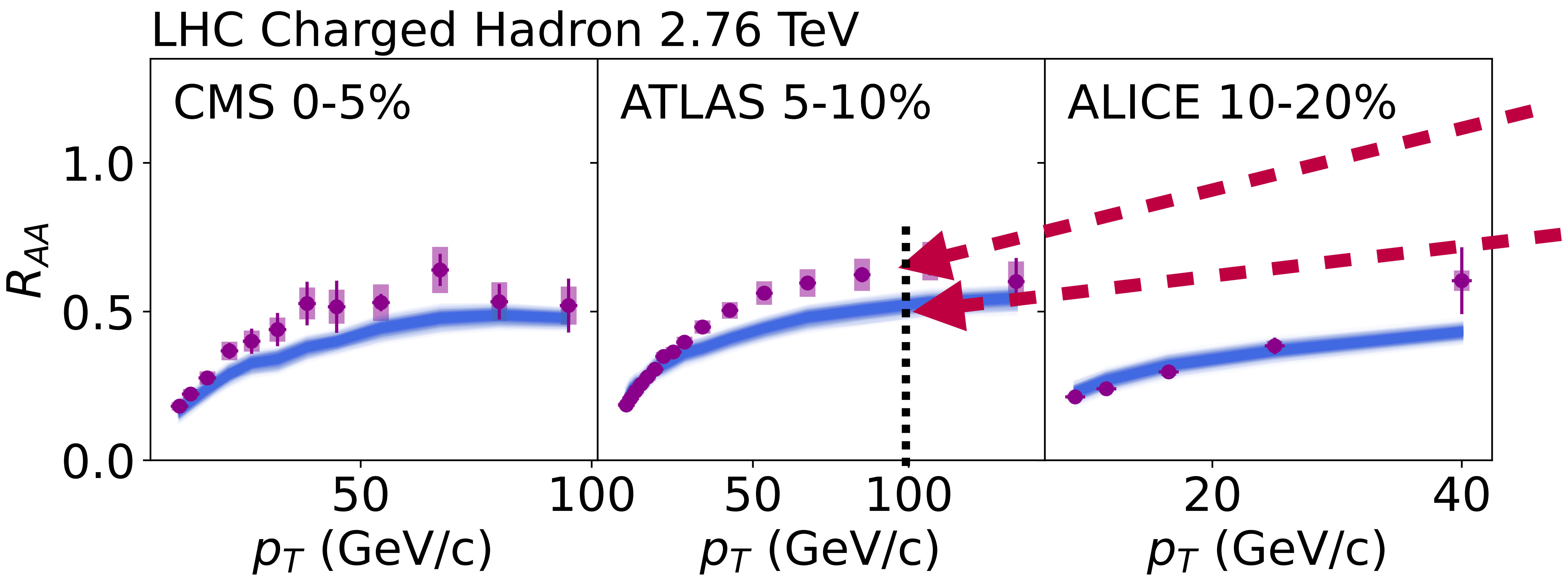
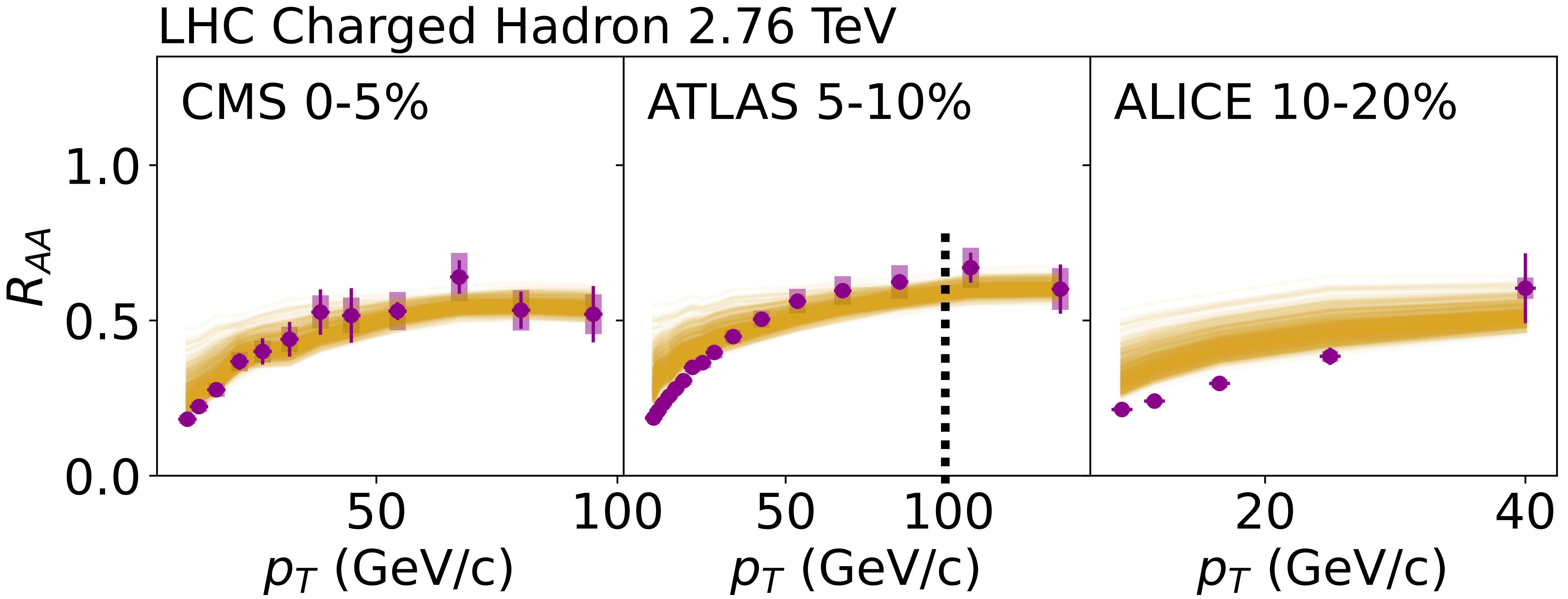


Full p_T range



Only hadrons $p_T > 30$ GeV



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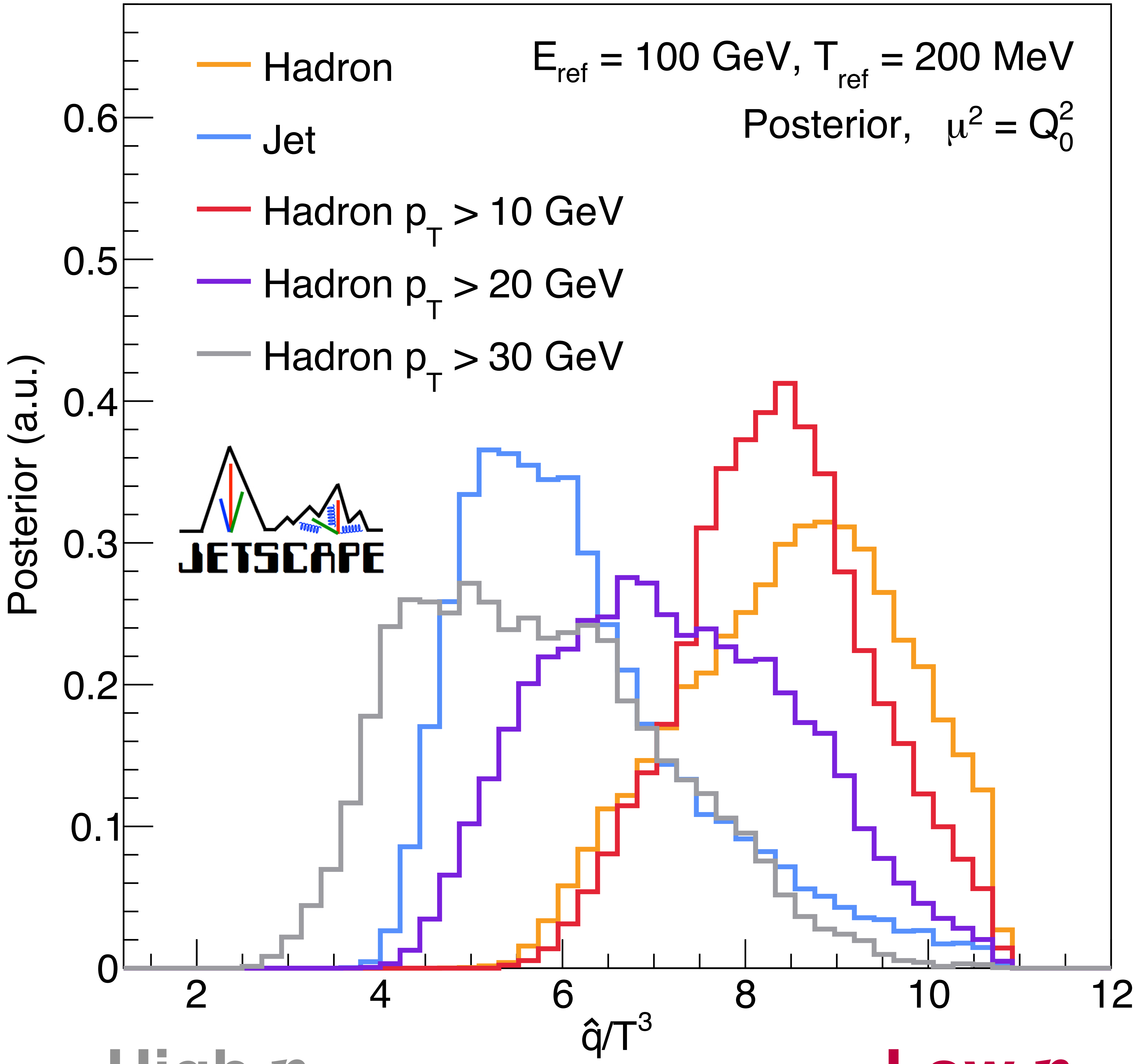
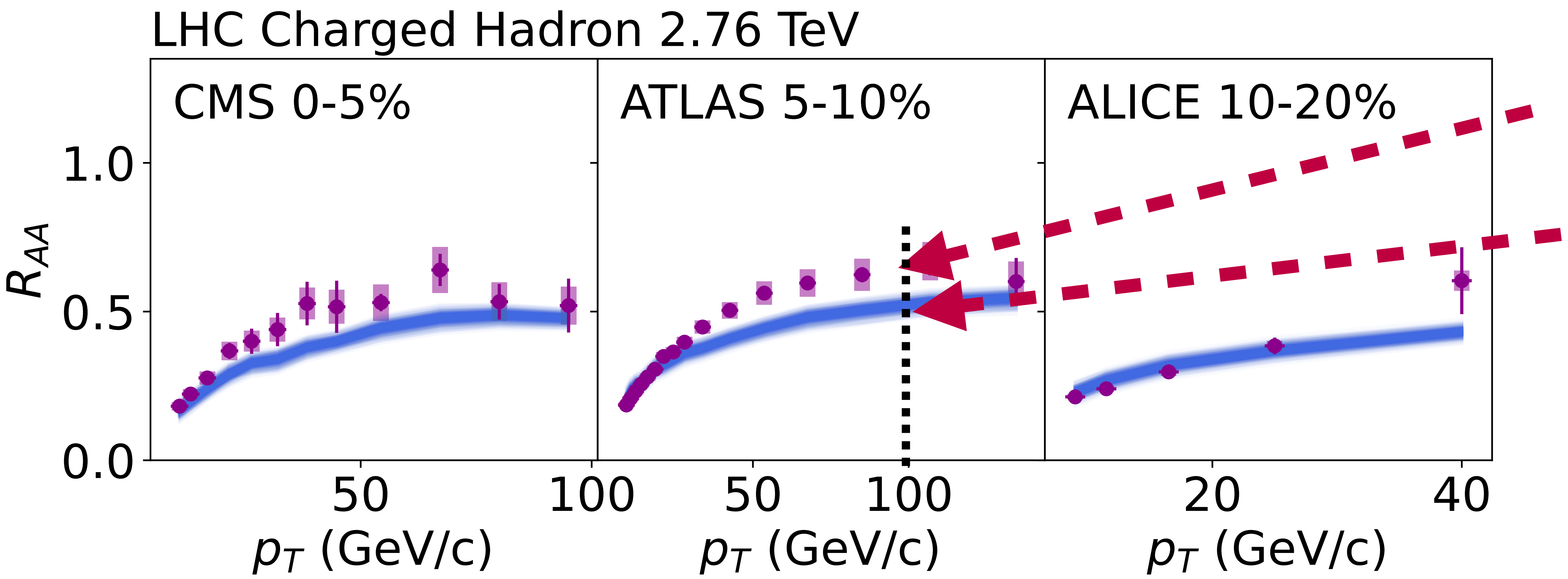


High p_T data ⟷ **Low p_T data**

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. LO $\hat{q}$, no shadowing included
- **Small exp. uncertainty where theory has largest uncertainty**

Peter Jacobs, Sep 23, 2024, 15:40 arXiv:2408.08247

Improving uncertainty treatment

Theory uncertainties

- **These analyses are inherently multi-scale and sensitive to many choices**
- **Theory uncertainties are an open question**

- Possible approaches:
- **Separating processes into multiple sectors**?
  - pQCD calculable w/ controllable uncertainty
  - Non-perturbative/strongly coupled, dominated by modeling
- **Move beyond LO $\hat{q}$**?
- **"Extra" source:** constant / parametrized?
- Start with **controllable vacuum parameters**? NLO production cross sections?
- New models, new approaches,...?

Experimental uncertainties

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Experimental uncertainties

Report signed uncertainties where possible!

- **Limited information reported** in uncertainties: often just statistical and systematic
  - Sometimes additional sources: scale, shape, etc...
- Systematic uncertainties are **often non-gaussian**
- Uncertainty correlations are non-trivial
- Estimated for Bayesian inference

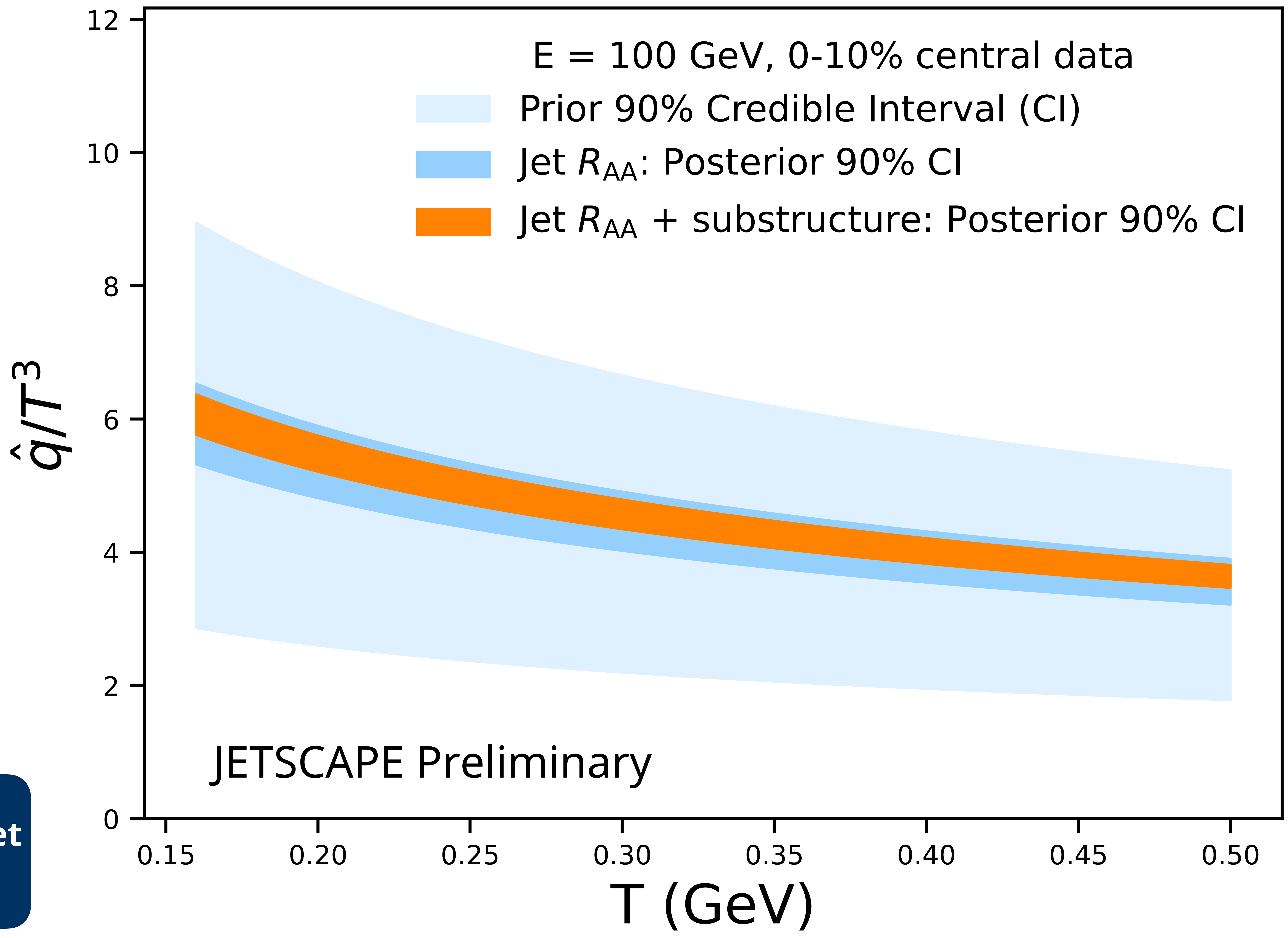
Significant opportunities!

Adding in jet substructure

- **What (additional) information do jet substructure observables contain**?
- **Consistent description of jet R_{AA} with substructure observables**
- Substructure yields **stronger relative constraint**[1]

Model: **JETSCAPE MATTER+LBT**

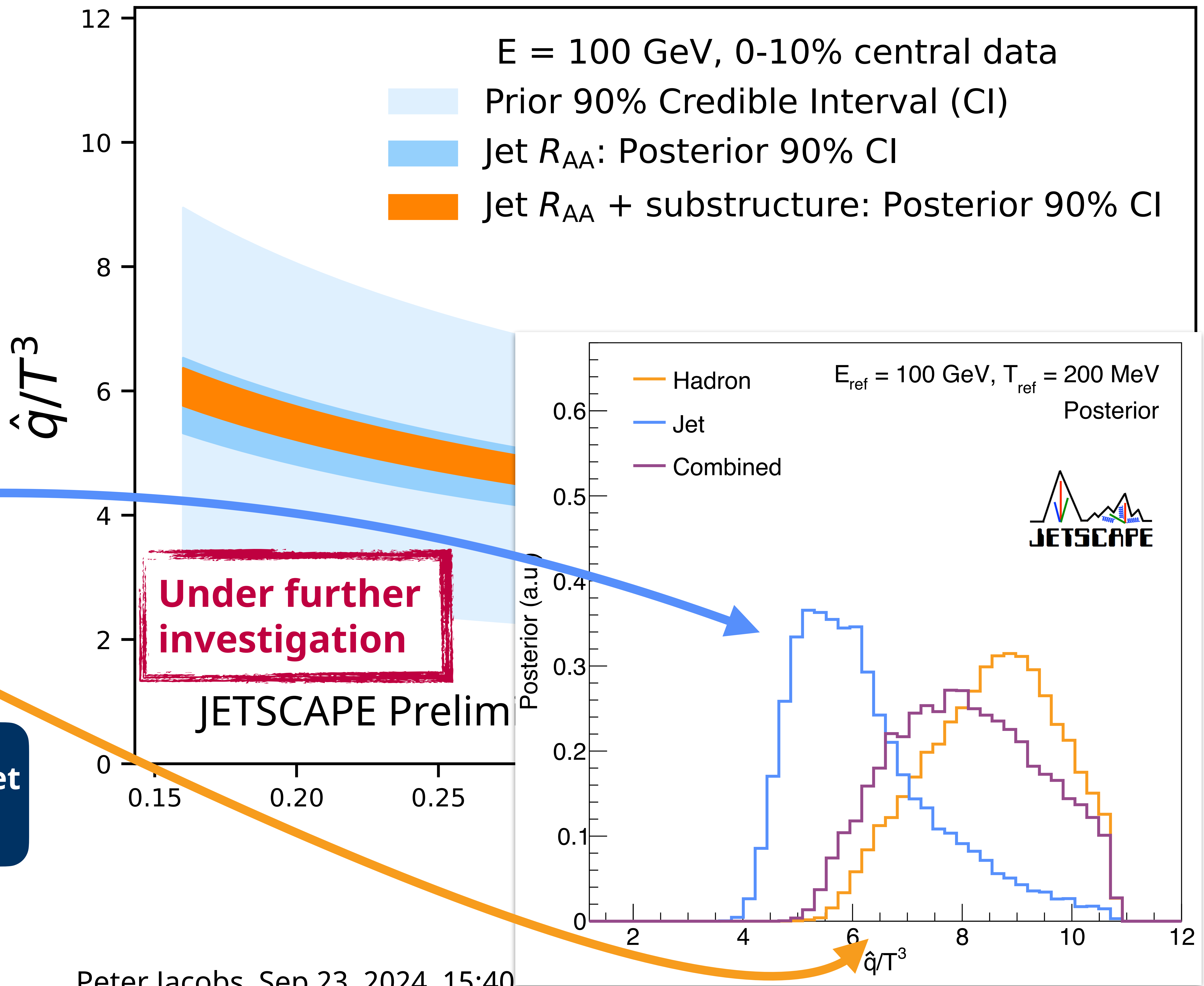
Data: **Selected incl. jet R_{AA}, substructure**



[1] Recent note: relative constraint holds, but y-scale may vary

Adding in jet substructure

- **What (additional) information do jet substructure observables contain**?
- **Consistent description of jet R_{AA} with substructure observables**
- Substructure yields **stronger relative constraint**[1]
- Tension between inclusive **jets** and (low p_T) **hadrons**, but low z jet fragmentation consistent…?



Model: JETSCAPE MATTER+LBT

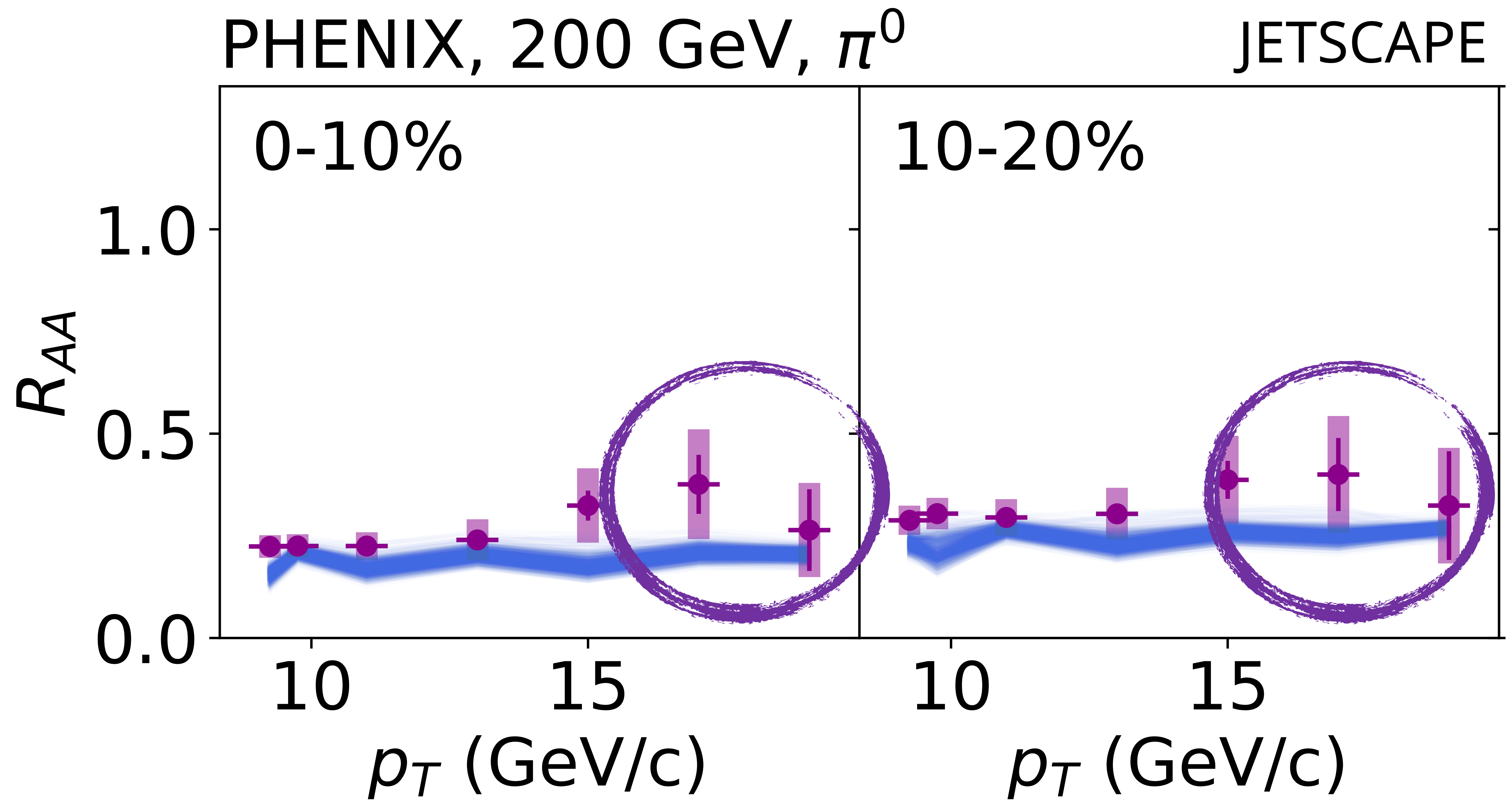
Data: Selected incl. jet R_{AA}, substructure

[1]Recent note: relative constraint holds, but y-scale may vary

What should we measure next?

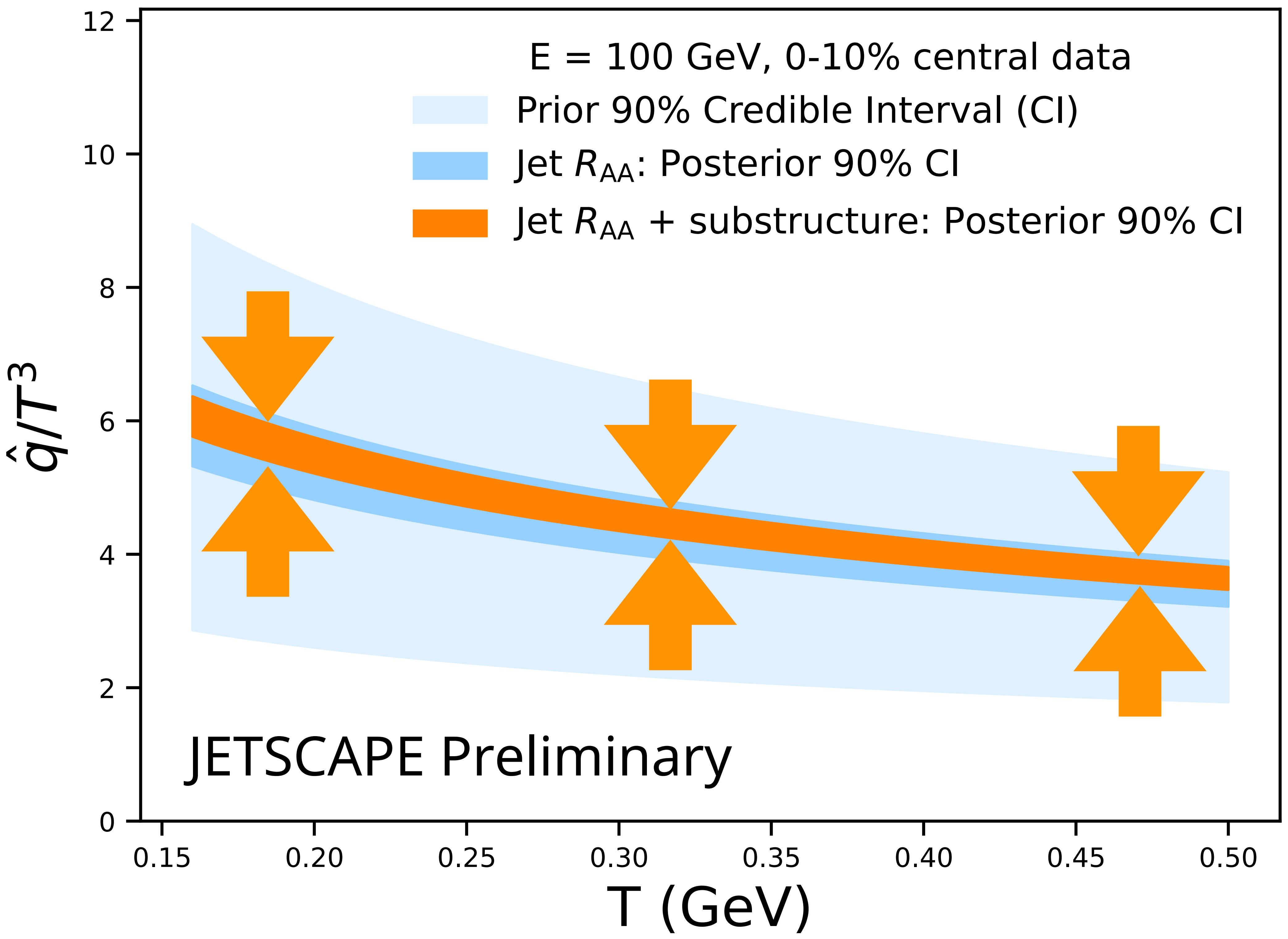
Need full sensitivity + experimental design studies. Until then…

High precision high p_T hadrons @ RHIC



Limited constraints from RHIC due to limited precision at high p_T

High precision jet substructure



Additional information + new observables: much to explore

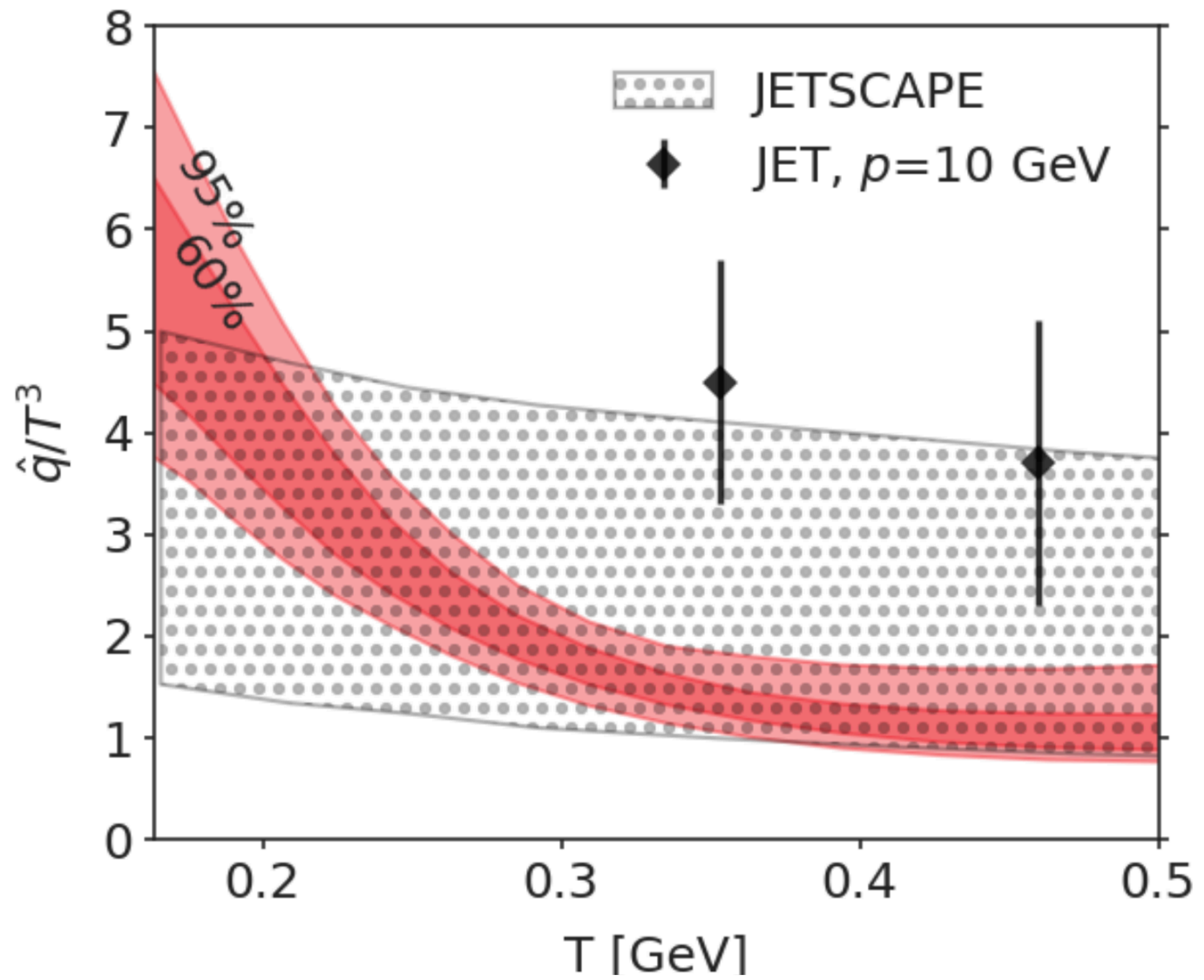
Summary

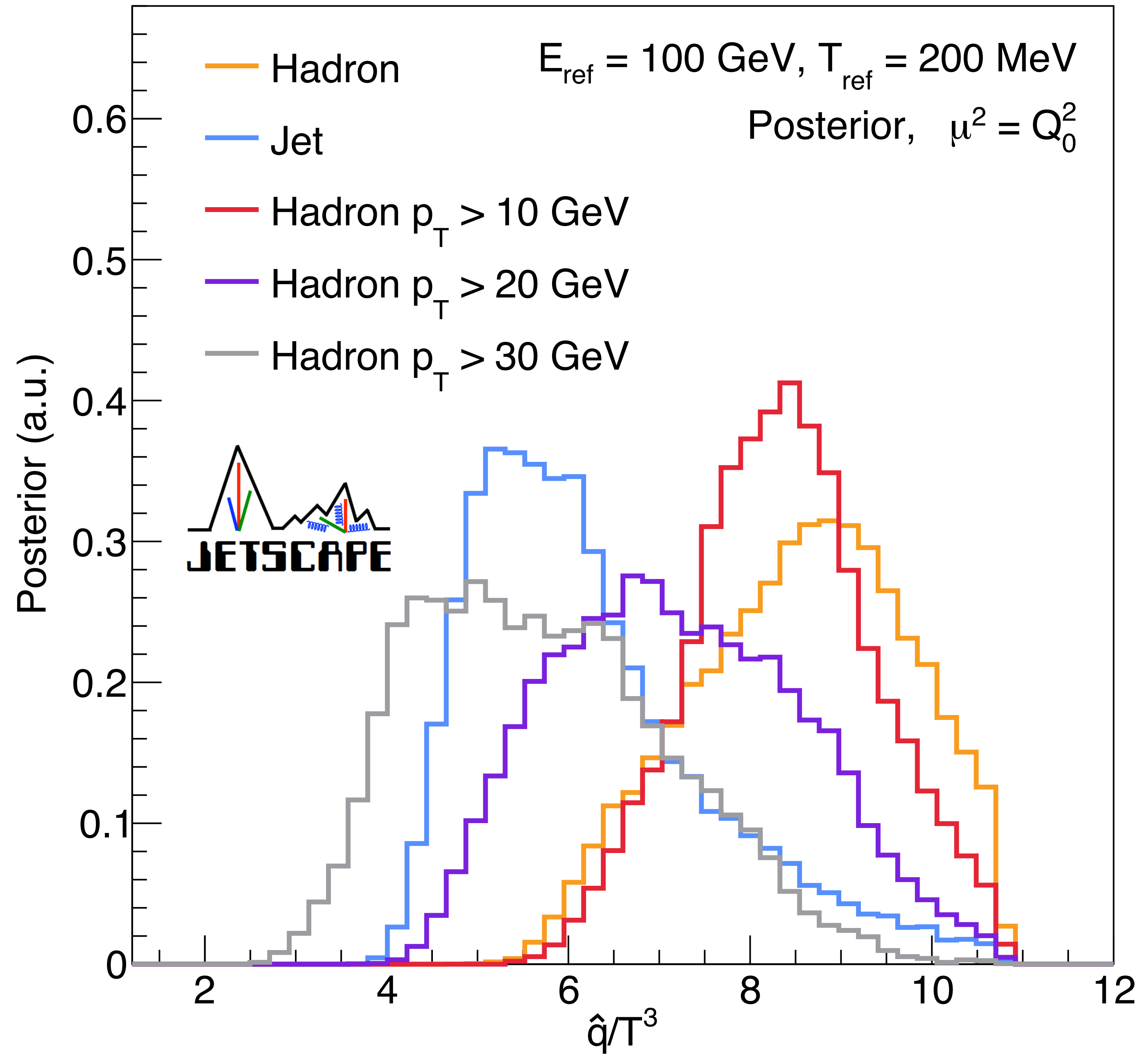
- **Bayesian inference: rigorous tool** to explore physics, **not just to extract model parameters!**

- Comprehensive studies using **all applicable hadron and jet suppression data**
- Differential studies of **RHIC vs LHC**, R_{AA} vs I_{AA}, **hadron vs jet**, **jet substructure** point to regions of **agreement, tension**
- **Observable sensitivity and exp. design,** pinpoint regions of interest, **provide important feedback for models**

- Requires **state-of-the-art cost-efficient computation**

  - Need **fully apples-to-apples comparisons**
    - Calibrate **different models under same conditions**
  - Essential: **significant theory and experimental uncertainties**





Bayesian inference @ Hard Probes 2024

Talks

Multi-Observable Analysis of Jet Quenching Using Bayesian Inference

Peter Jacobs, Sep 23, 2024, 15:40

Bayes-DREENA: Integrated QGP Parameter Inference from High-pt and Low-pt Data

Magdalena Djordjevic, Sep 24, 2024, 15:35

Flavor hierarchy of parton energy loss in quark-gluon plasma from a Bayesian analysis

Guang-You Qin, Sep 25, 2024, 10:00

Posters

Bayesian inference of the magnetic field and chemical potential on holographic jet quenching in heavy ion collisions

Liqiang Zhu

Exploring the universality of jet quenching via Bayesian inference

Alexandre Falcão

Nuclear shapes and spectator production

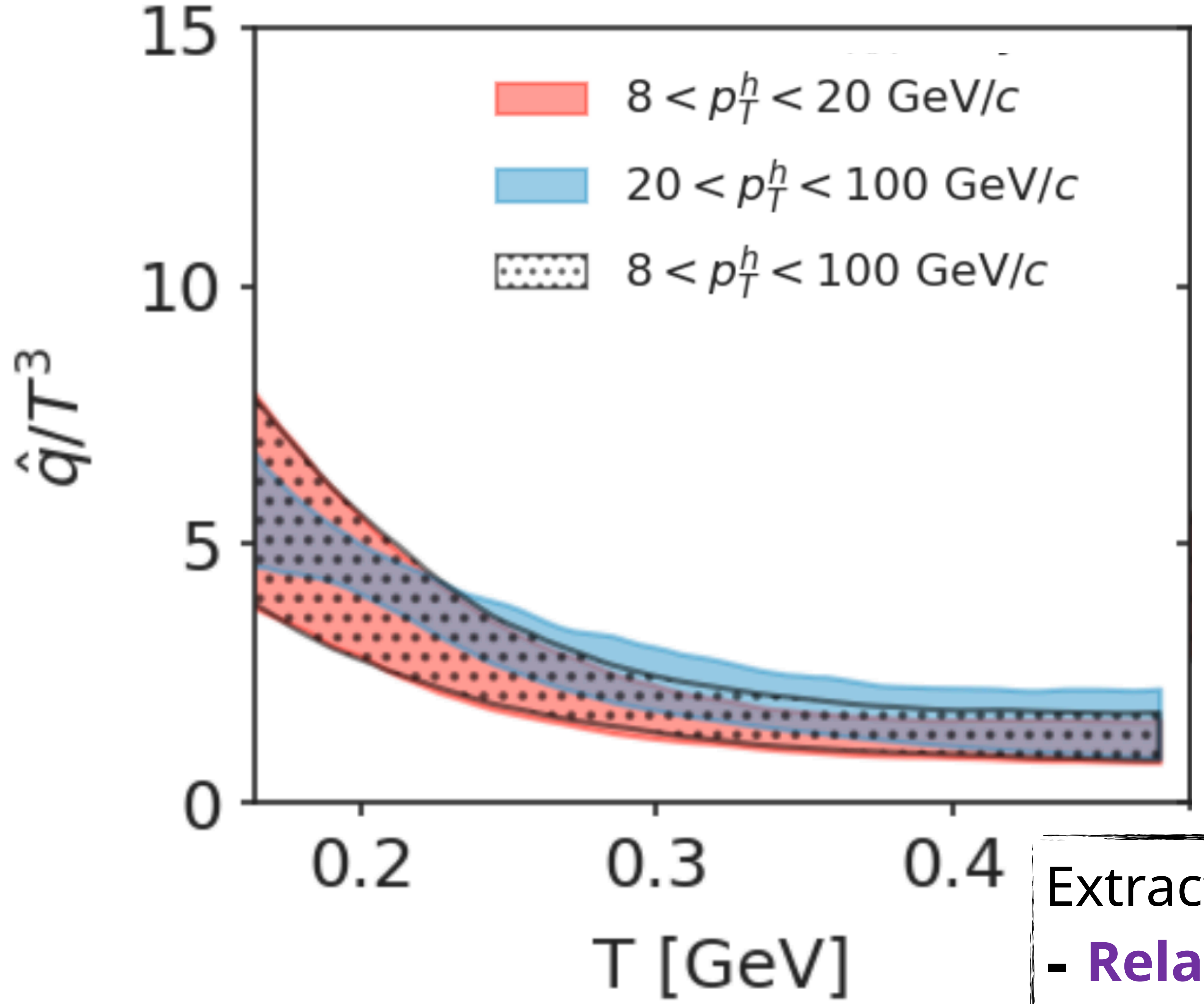
Wilke Van Der Schee

Thanks to Luna Chen, Peter Jacobs, Weiyao Ke, Leif Lonnblad, Abhijit Majumder, Yacine Mehtar-Tani, Govert Nijs, and Jean-Francois Paquet for useful input and discussions

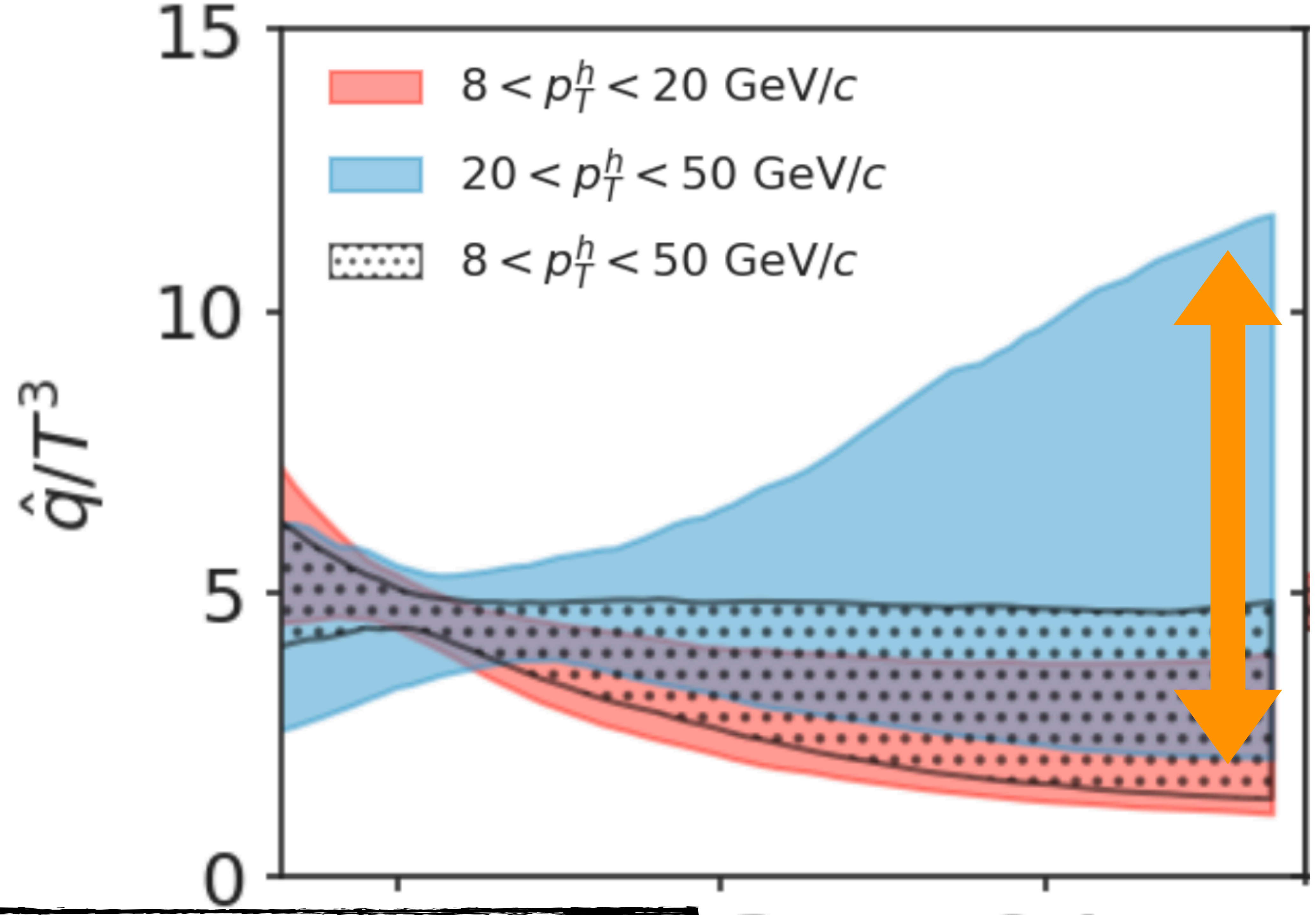
Backup

Differential studies: Observable dependence

R_{AA} only calibration



I_{AA} only calibration



Extraction limited by:
- Relatively large I_{AA} uncertainty
- Tension between model and data

Model: NLO Parton Model + Higher-twist

Data: Incl. hadron R_{AA}, di-hadron, γ-hadron corr.

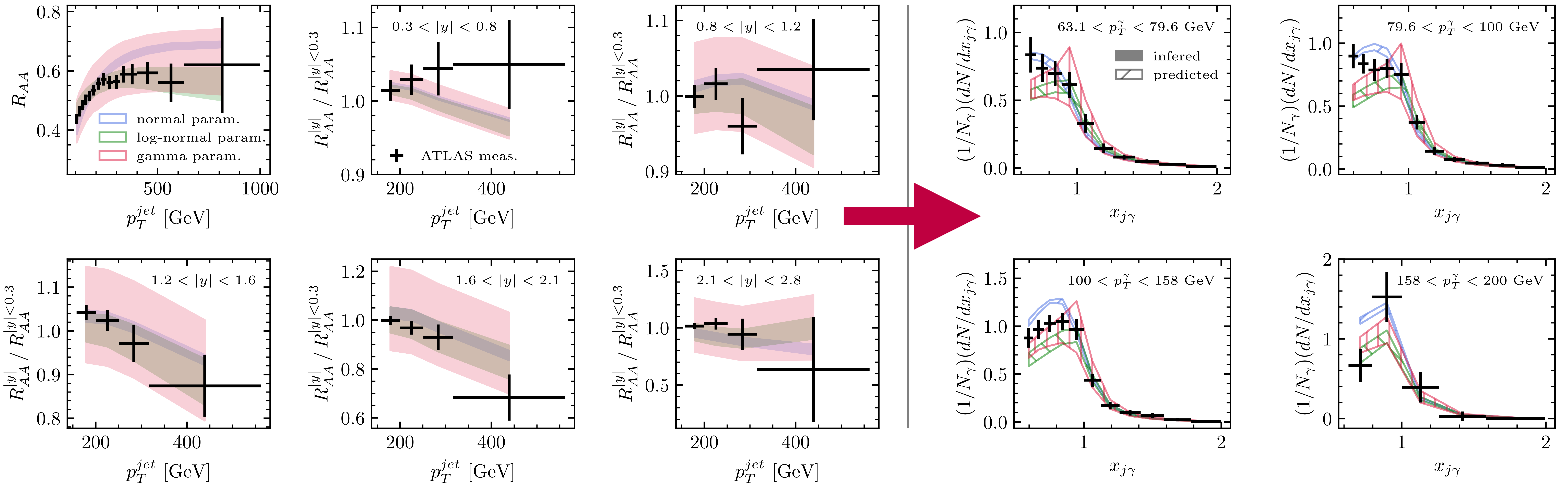
Opportunities for improvement in models + experiment

Xie, Ke, Zhang, Wang, PRC 108 (2023) 1, L011901
Xie, Ke, Zhang, Wang, PRC 109 (2024) 6, 064917

Functional dependence of energy-loss

Analysis A : Inclusive jet observables (used for inference)

γ-jet observables (predicted)



Model: **Parametrized energy-loss distribution**

Data: Inclusive, γ-tagged jet R_{AA}

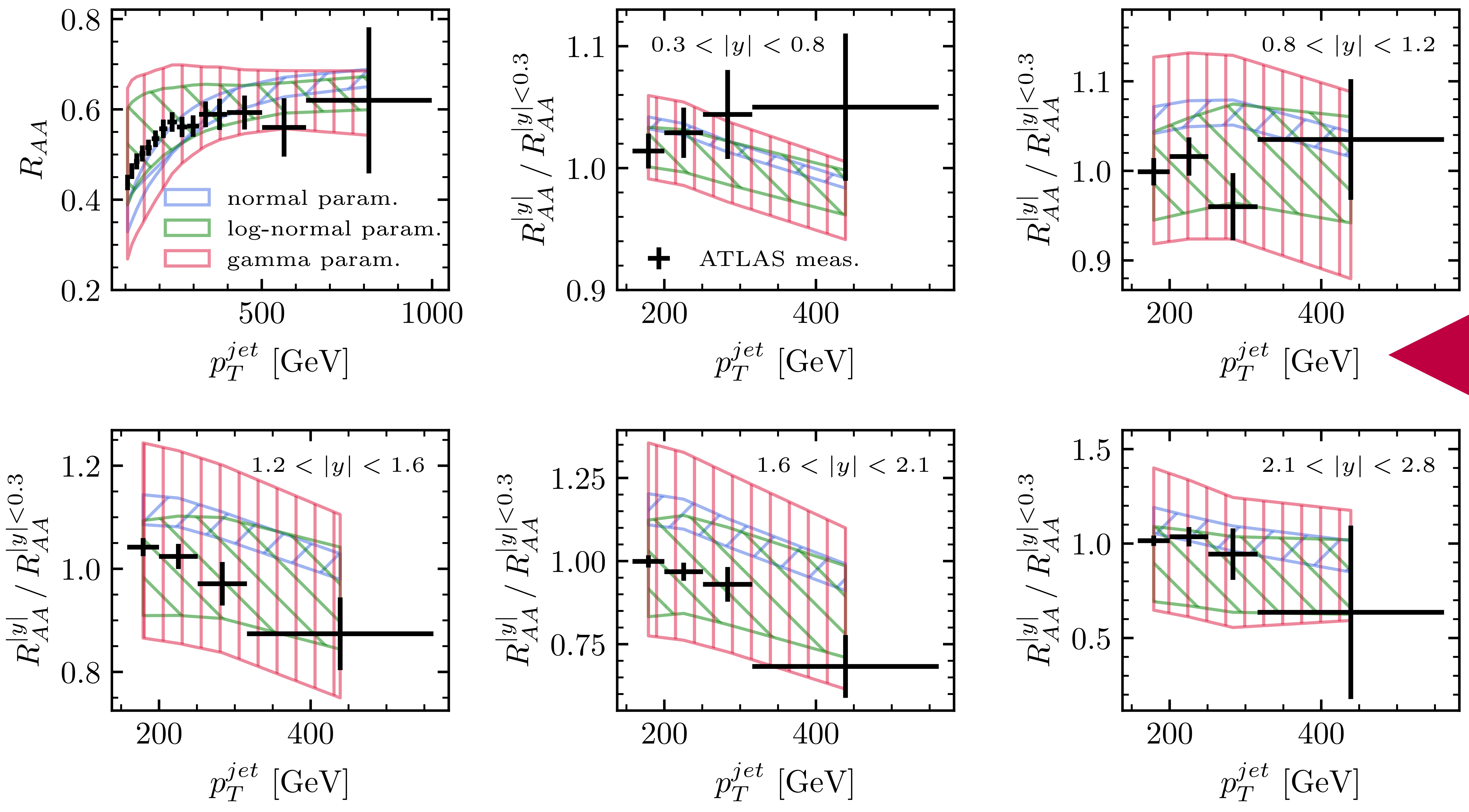
Calibration with different parametrizations
Sensitive to q/g fraction

- Calibrate on inclusive → γ-tagged well described
- Calibrate on quark dominated γ-tagged → **less well constrained for inclusive with gluon jet contribution**

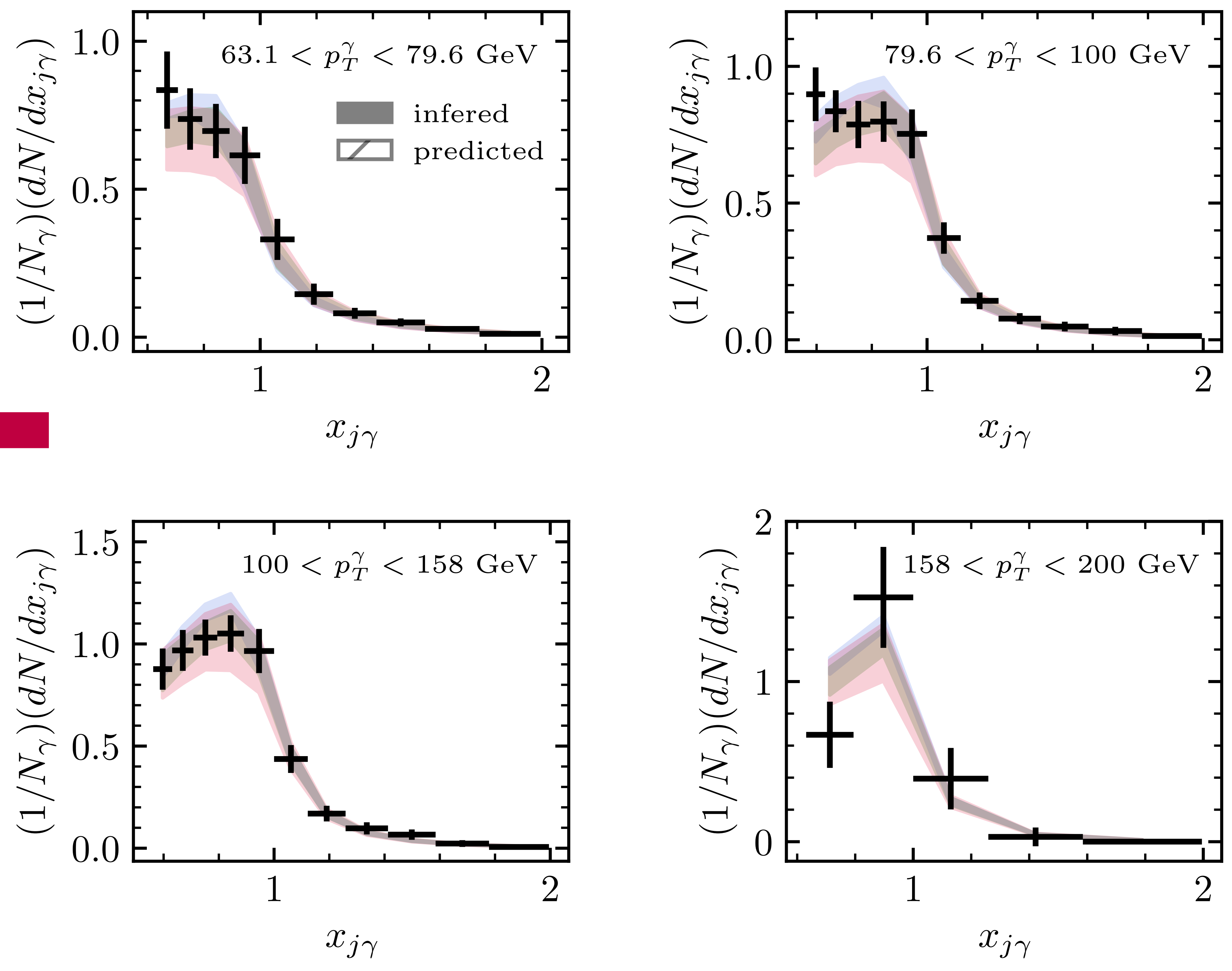
Poster: Alexandre Falcão

Functional dependence of energy-loss

Analysis B : Inclusive jet observables (predicted)



γ-jet observables (used for inference)



Calibration with different parametrizations
Sensitive to q/g fraction

- Calibrate on inclusive → γ-tagged well described
- Calibrate on quark dominated γ-tagged → **less well constrained for inclusive with gluon jet contribution**

Model: **Parametrized energy-loss distribution**

Data: Inclusive, γ-tagged jet R_{AA}

Bayesian analysis: Models for today

Analysis | **Model** | Data

JETSCAPE: MATTER + LBT

- Partonic energy loss: HTL multi-stage, virtuality-dependent
- 2+1D calibrated hydro

NLO Parton Model + Higher-Twist

- Partonic energy loss: Highter Twist
- Hydro: CLVisc 3+1D with Trento initial conditions

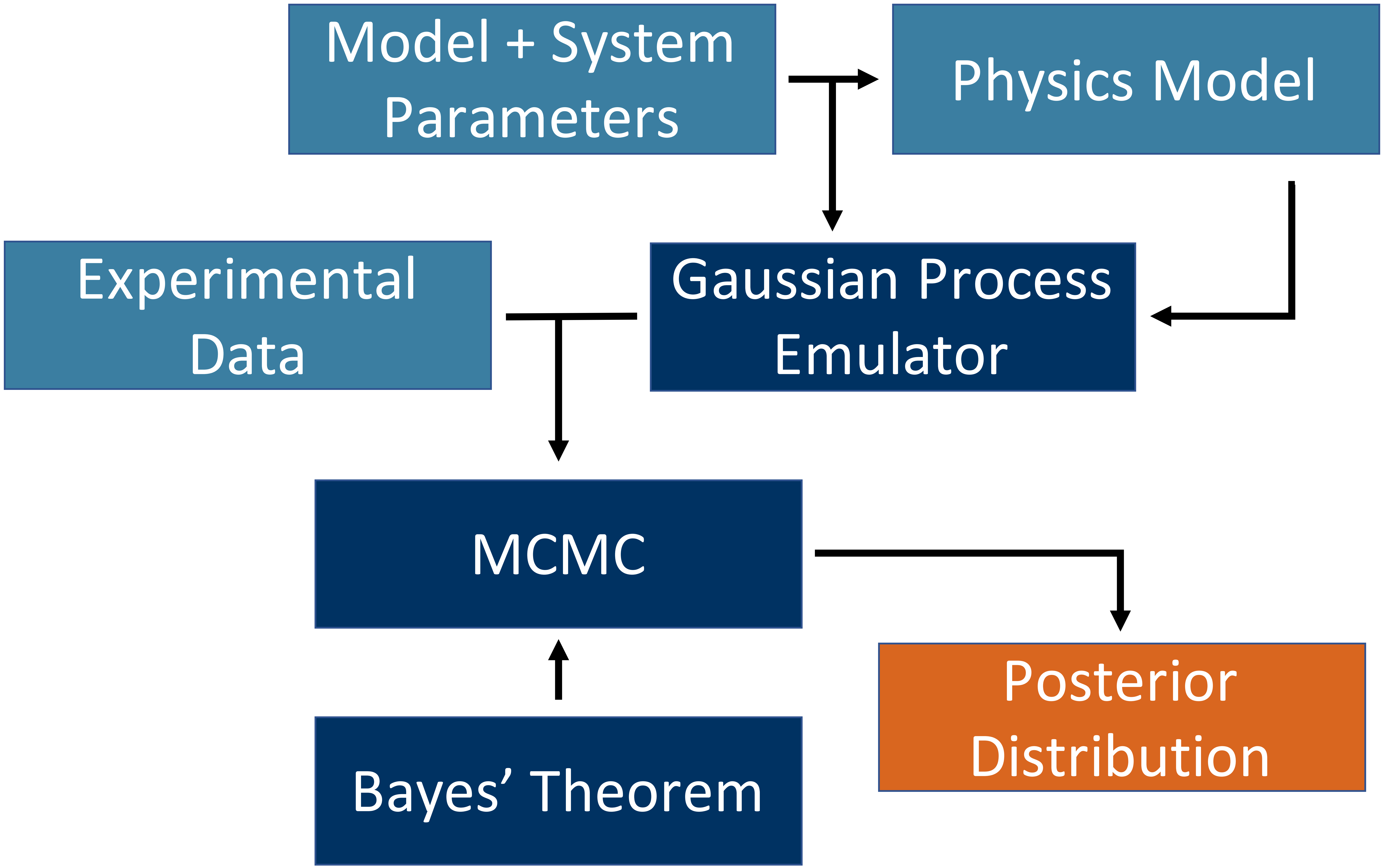
LIDO

- Partonic energy loss: pQCD matrix elements+Langevin transport
- 2+1D viscous hydro

DREENA-A

- Partonic energy loss: HTL with running coupling
- 3+1D viscous hydro
- MC-Glauber, Trento, IP-Glasma initial conditions

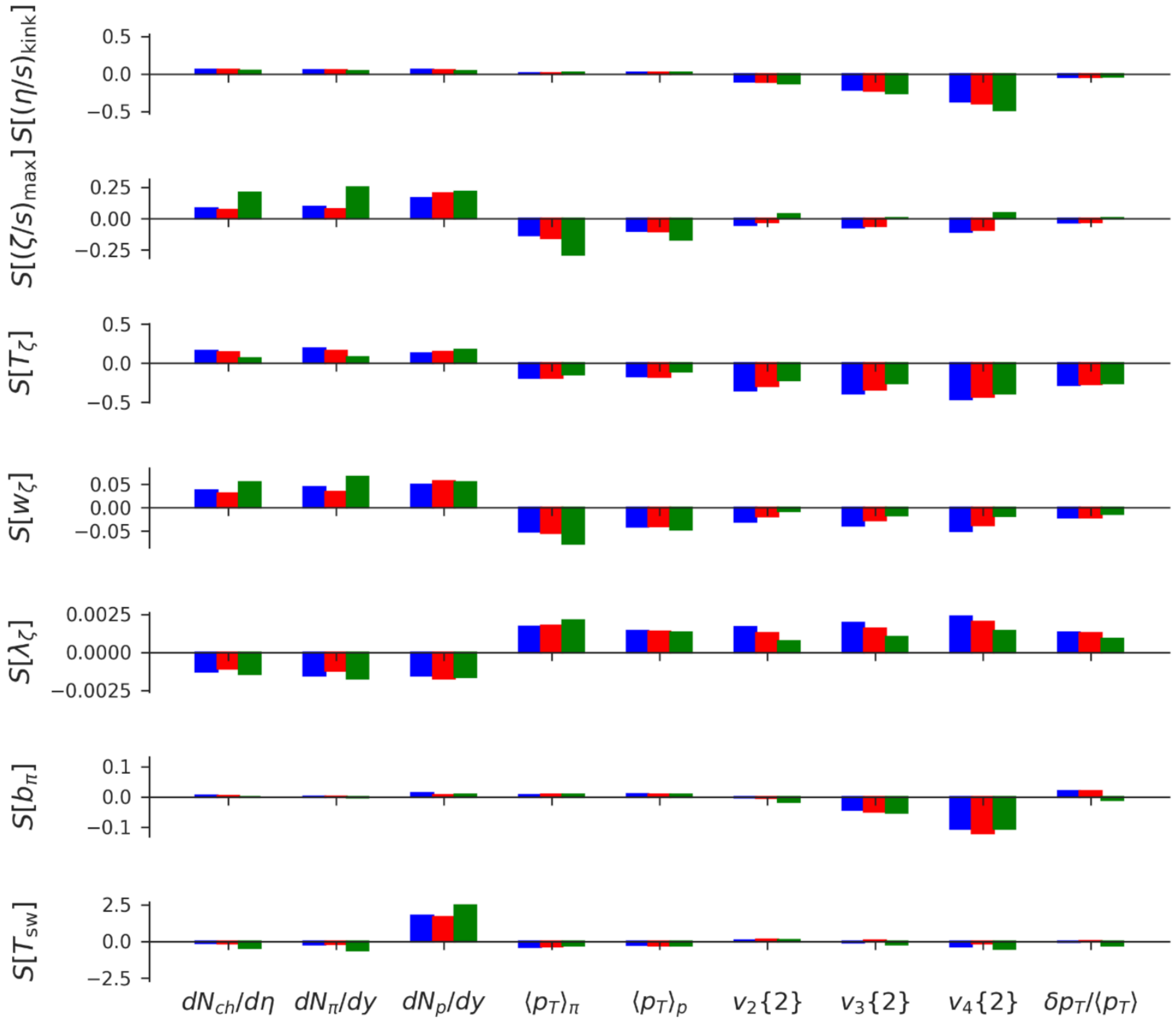
Bayesian inference workflow



Model sensitivity + experimental design

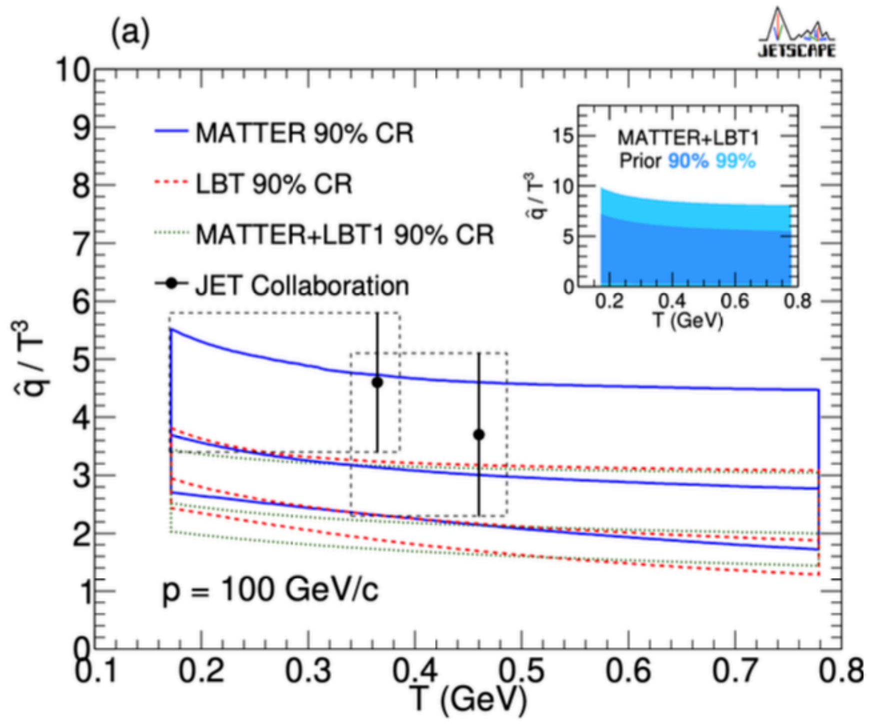
Observable sensitivity to posterior perturbation

JETSCAPE, PRC.103.054904

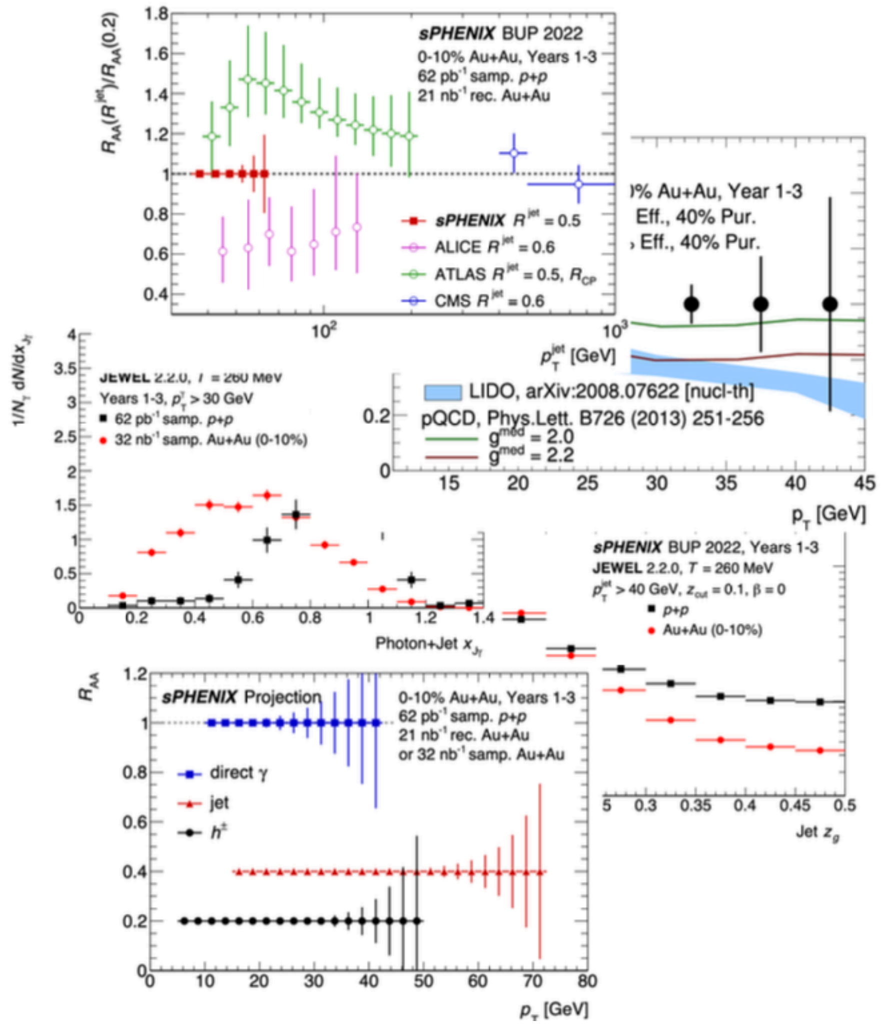


Identifying new + sensitive observables

e.g. "Bayesian experimental design"



New Bayesian analysis



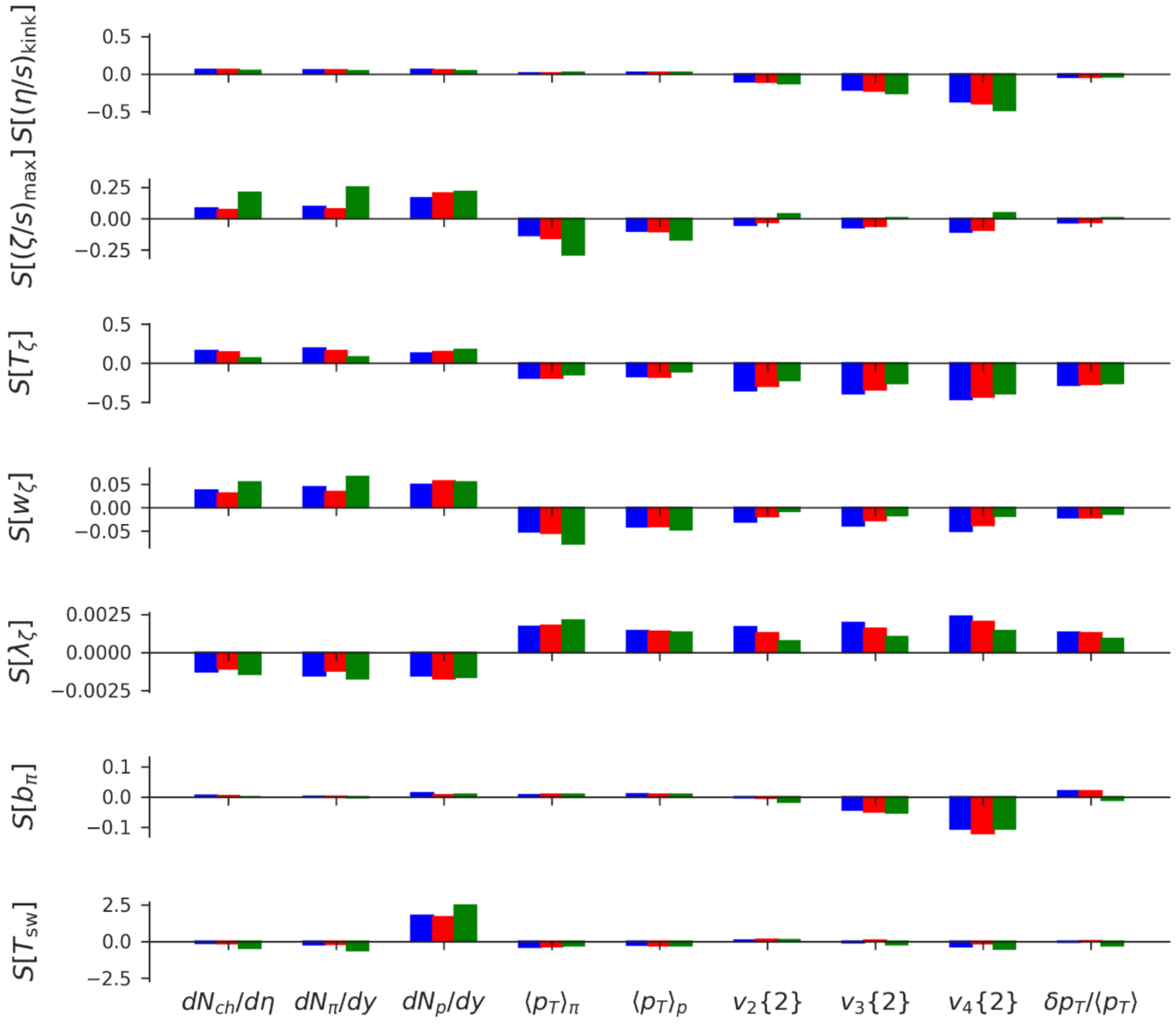
Further constraints

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

Model sensitivity + experimental design

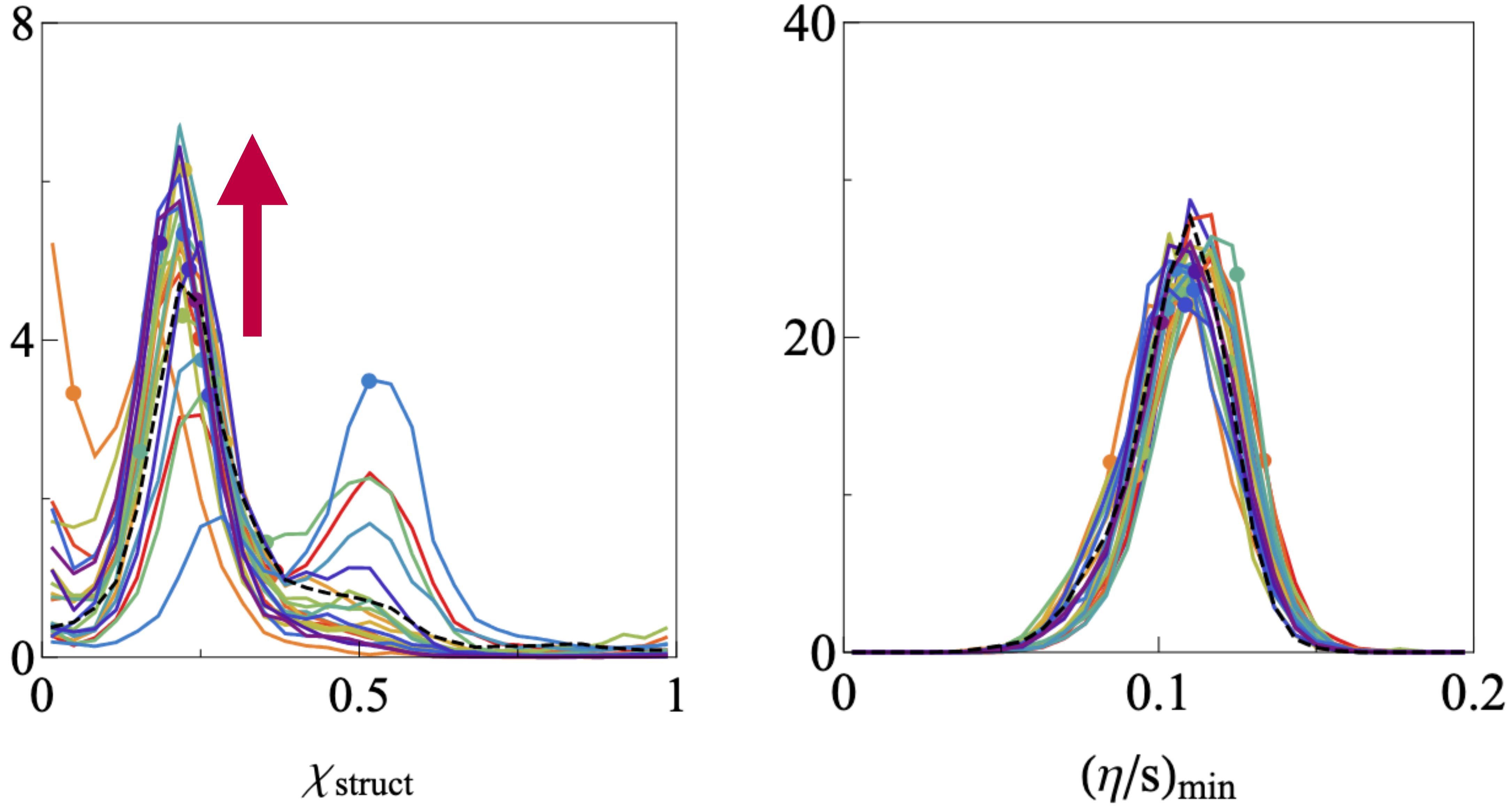
Observable sensitivity to posterior perturbation

JETSCAPE, PRC.103.054904



Identifying new + sensitive observables

e.g. “Bayesian experimental design”

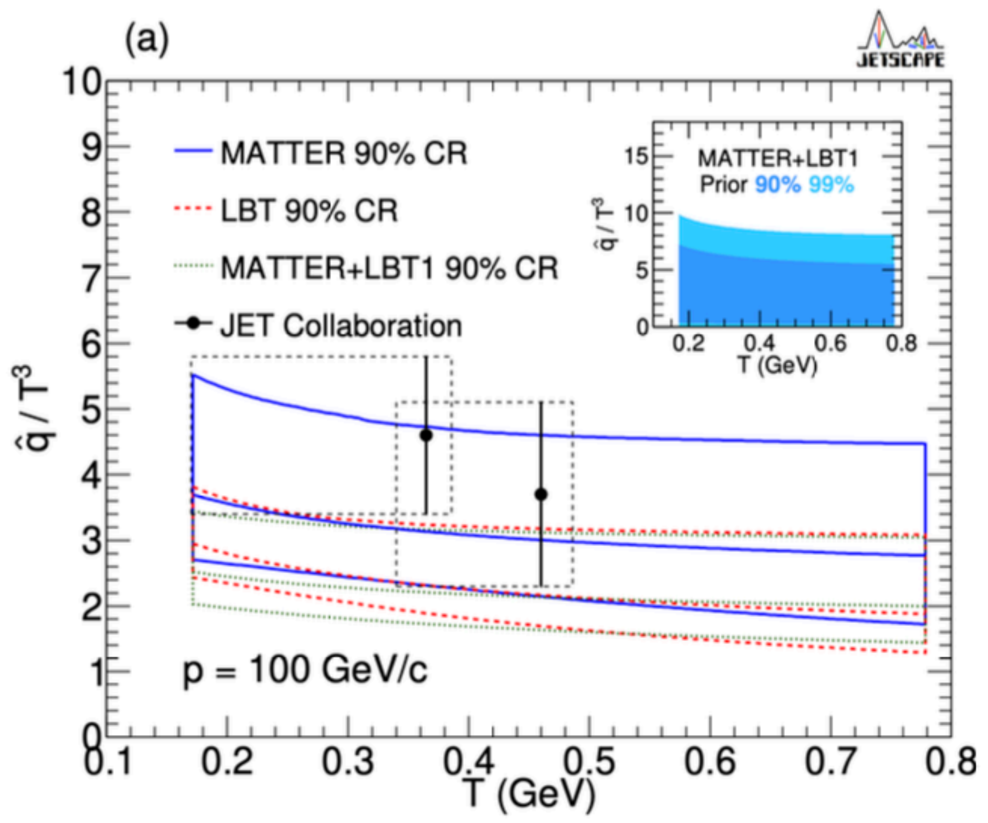


Nijs, van der Schee, PRC 106 (2022) 4, 044903

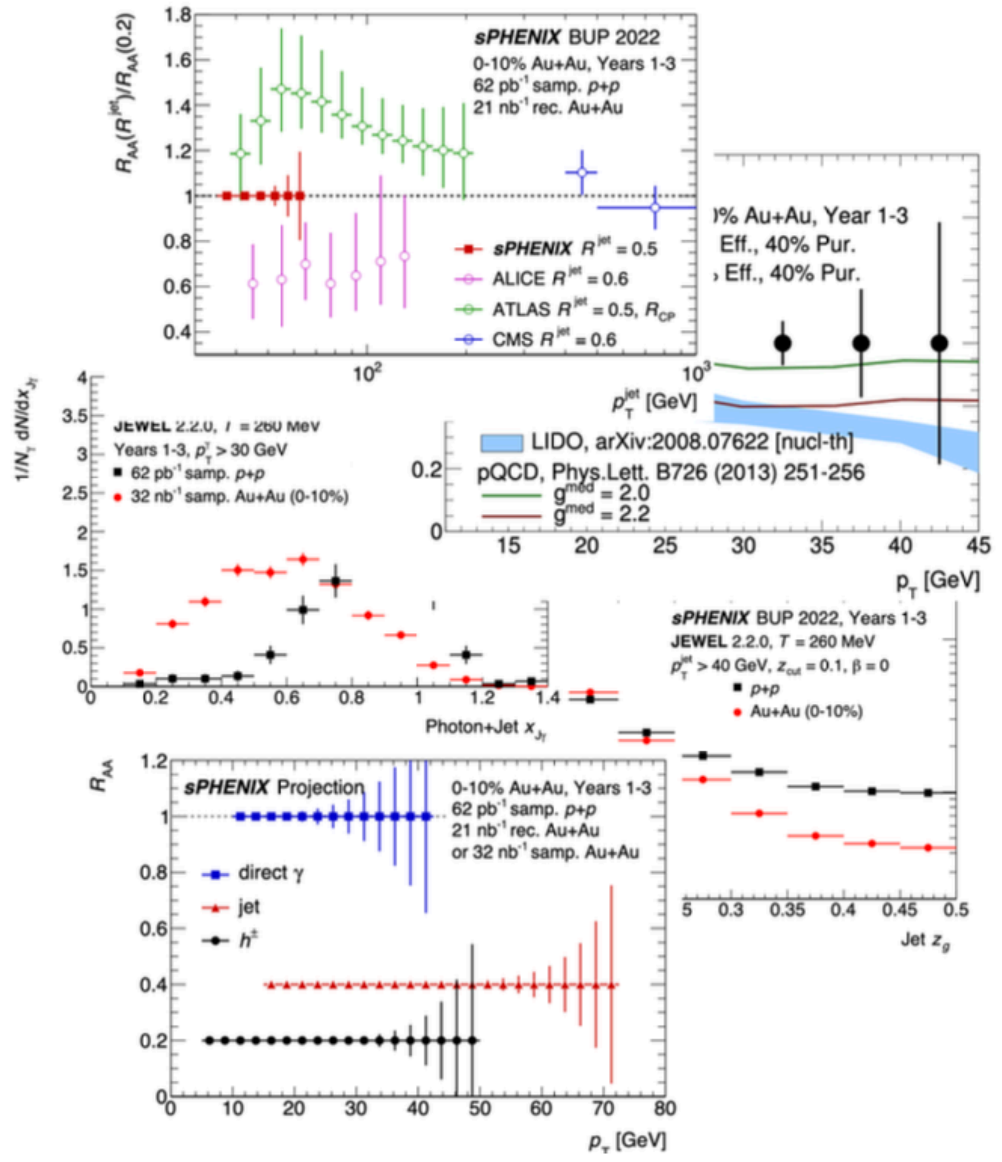
Example: Bayesian experimental design

- **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



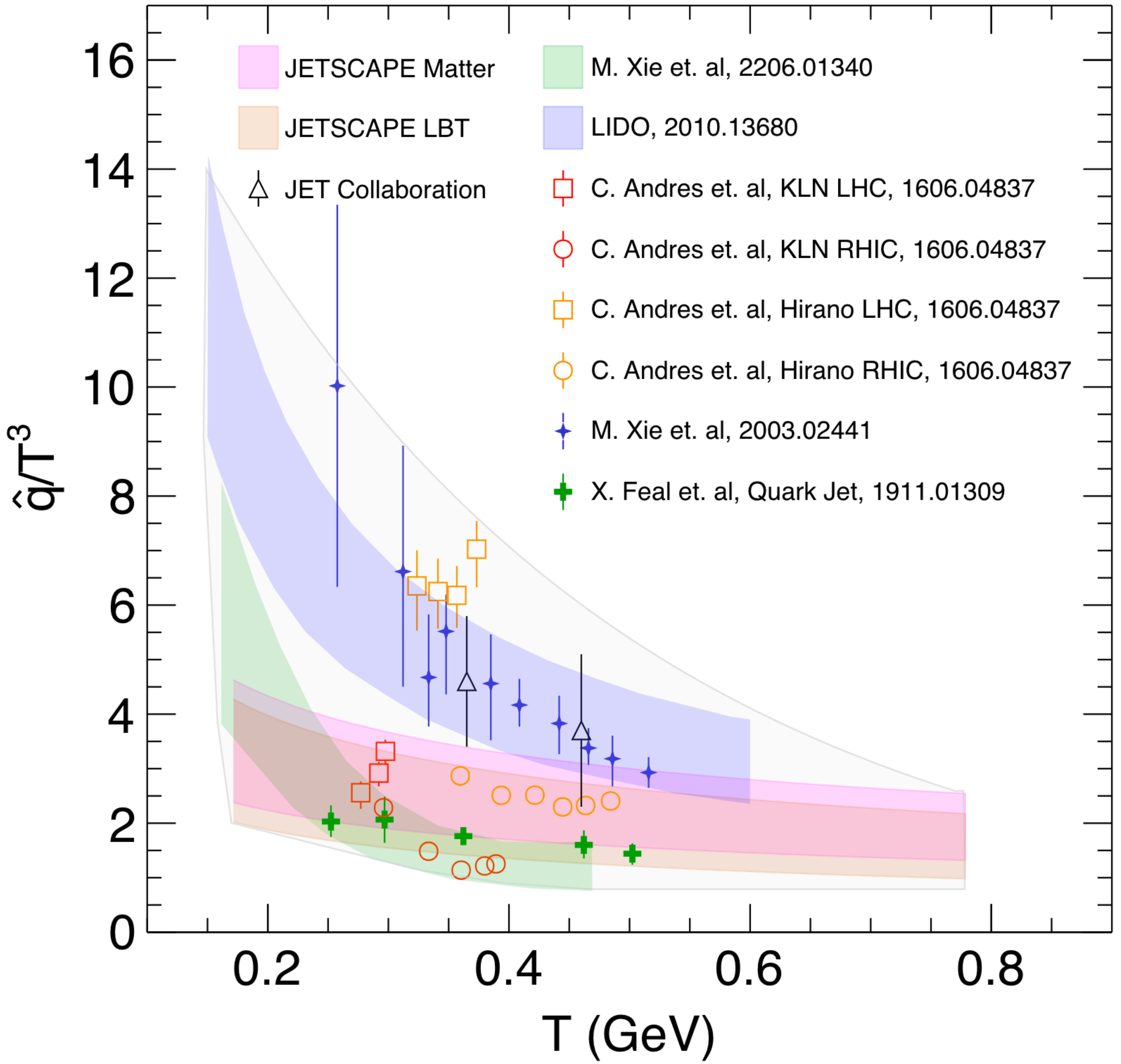
Further constraints

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

Not all $\hat{q}$ are equivalent

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

→ **Comparisons may not be equivalent**

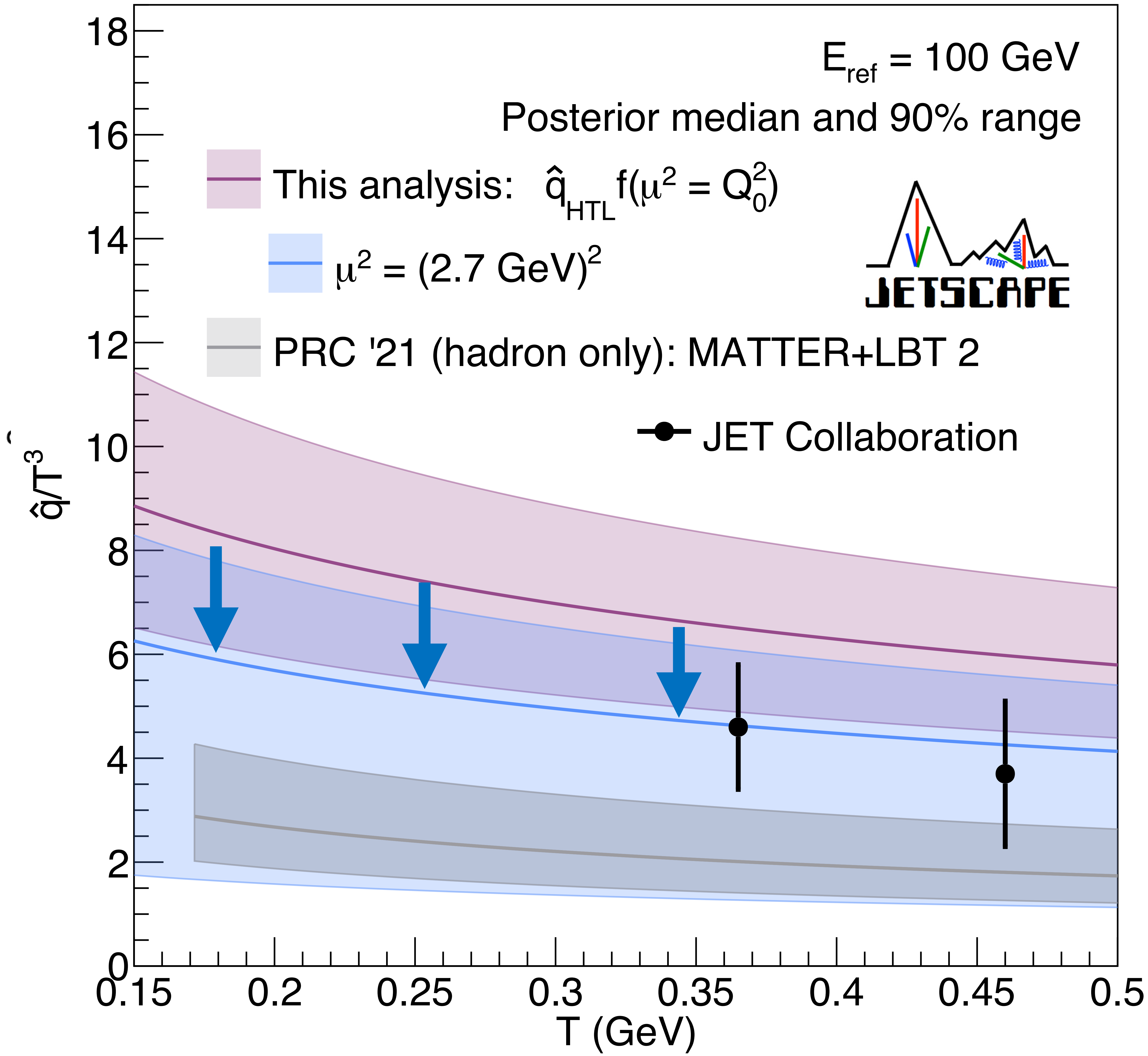


Apolinário, Lee, Winn: Prog.Part.Nucl.Phys. 127 (2022) 103990

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 μ^2**



arXiv:2408.08247

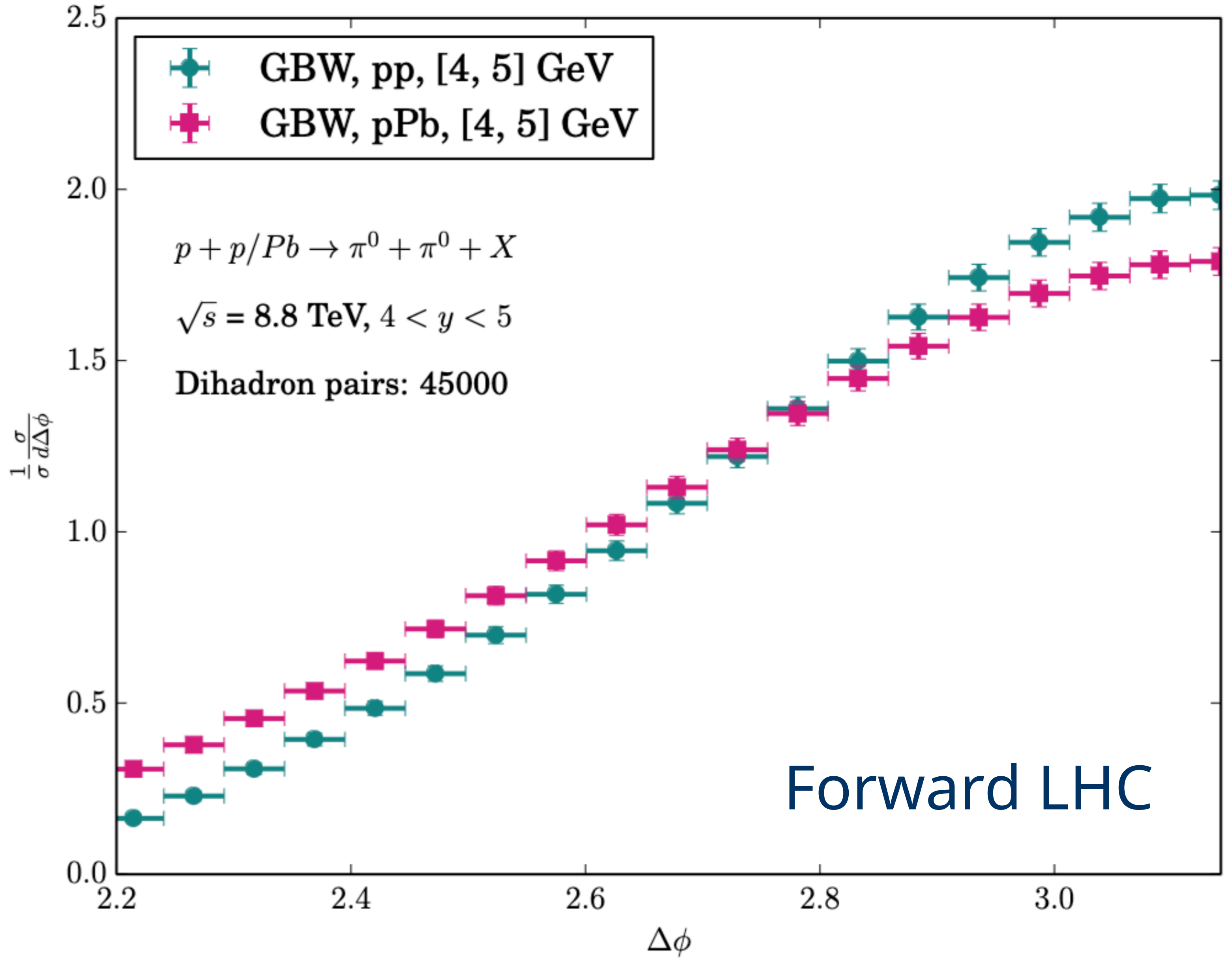
Connecting Forward LHC + EIC

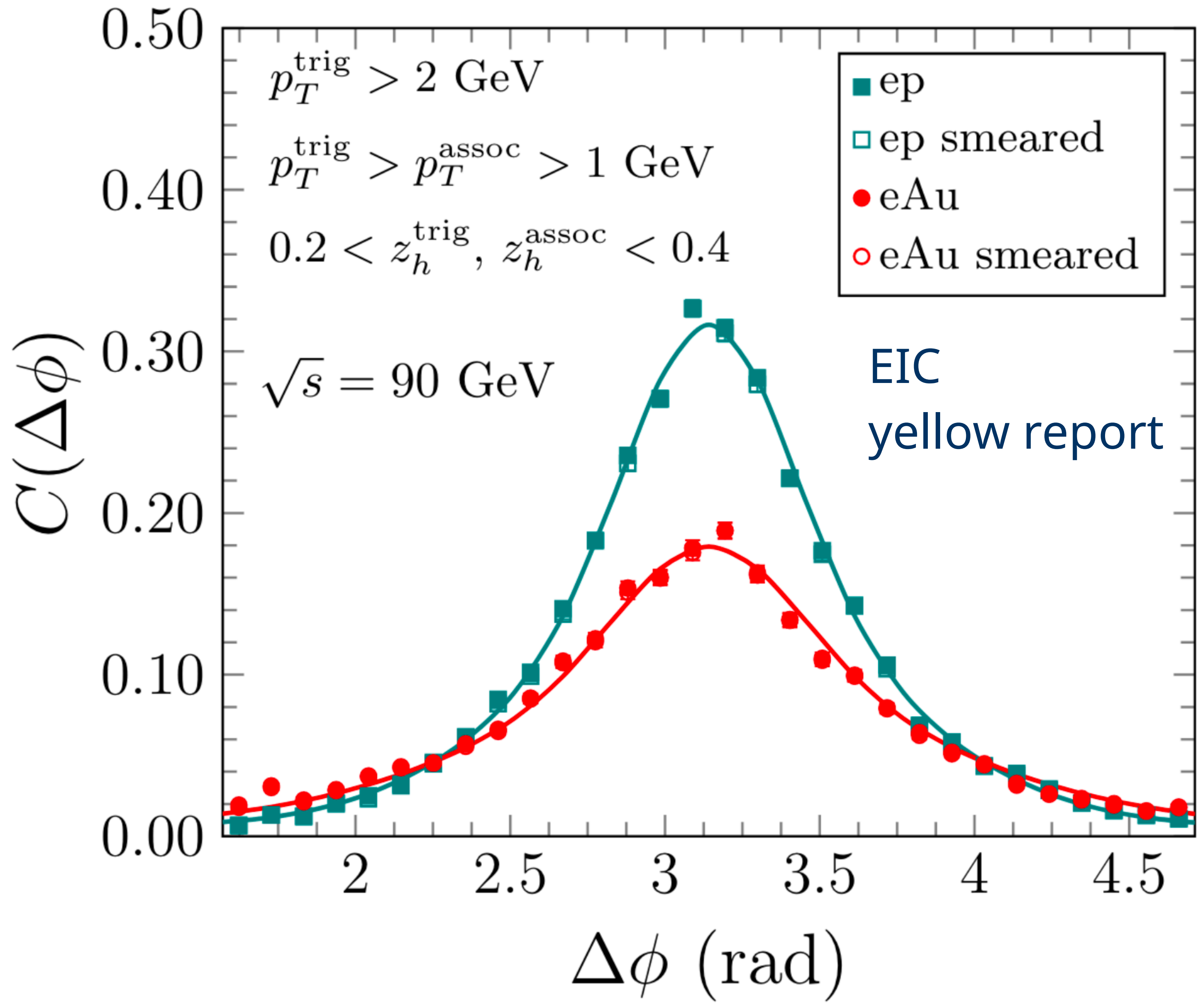
- **Complementarity between forward LHC/RHIC + EIC**
- Bayesian inference: **essential for comprehensive analysis of heterogeneous datasets (EIC, fLHC, fRHIC) with rigorous theory to explore linear/non-linear QCD evolution**

	Inclusive DIS	SIDIS	DIS dijet	Inclusive in p+A	γ+jet in p+A	dijet in p+A
xG_{WW}	−	−	+	−	−	+
xG_{DP}	+	+	−	+	+	+

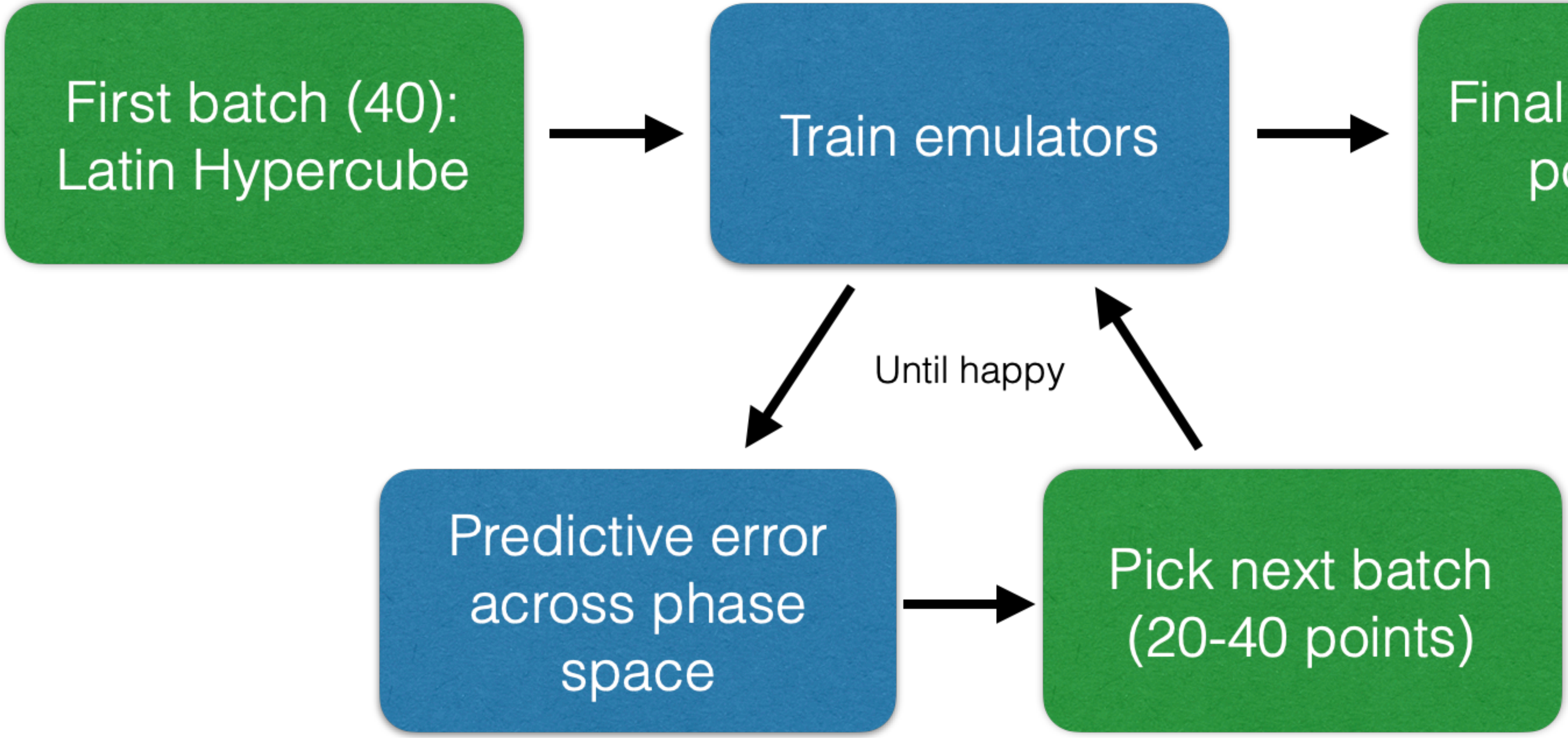
Table 7.2: The process dependence of two gluon distributions (i.e., the Weizsäcker-Williams (WW for short) and dipole (DP for short) distributions) in e+A(e+p) and p+Acollisions. Here the + and − signs indicate that the corresponding gluon distributions appear and do not appear in certain processes,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

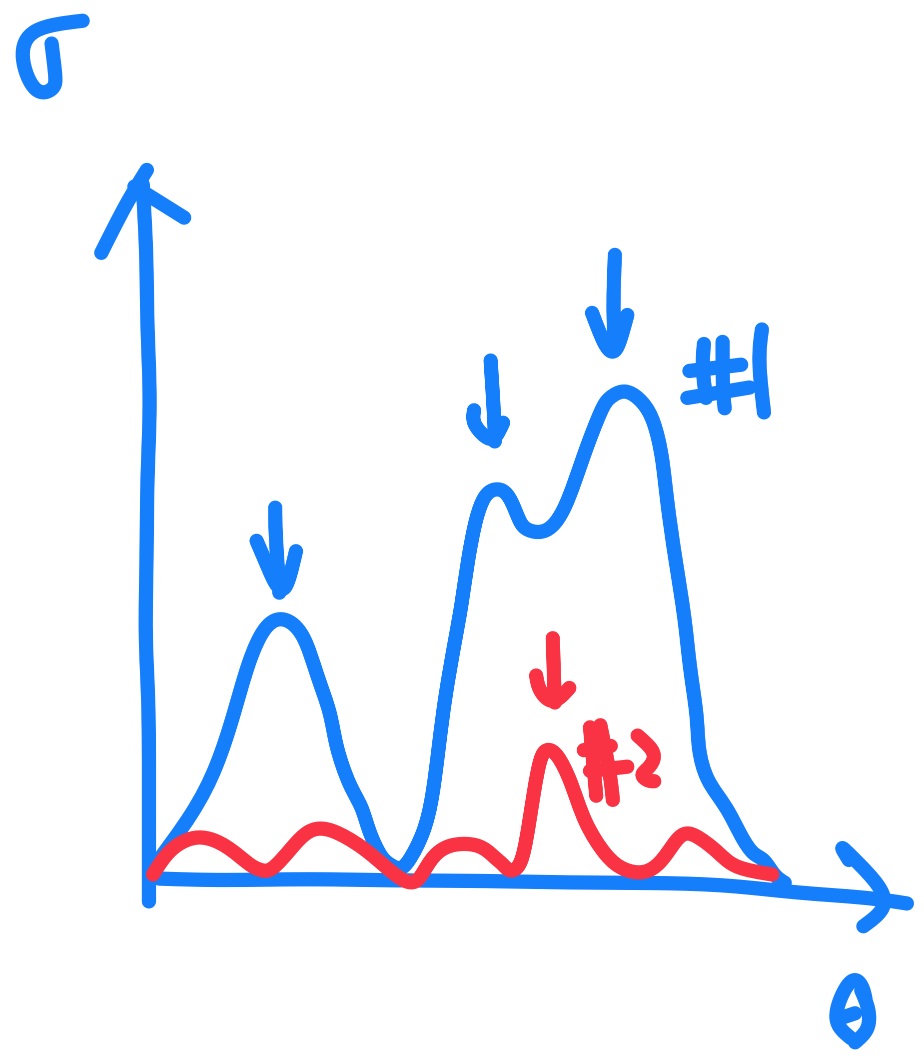
- Model **consistency with data**
- Models which **best describe data** (Bayes evidence)
- **Observable sensitivity** studies





Active learning design points





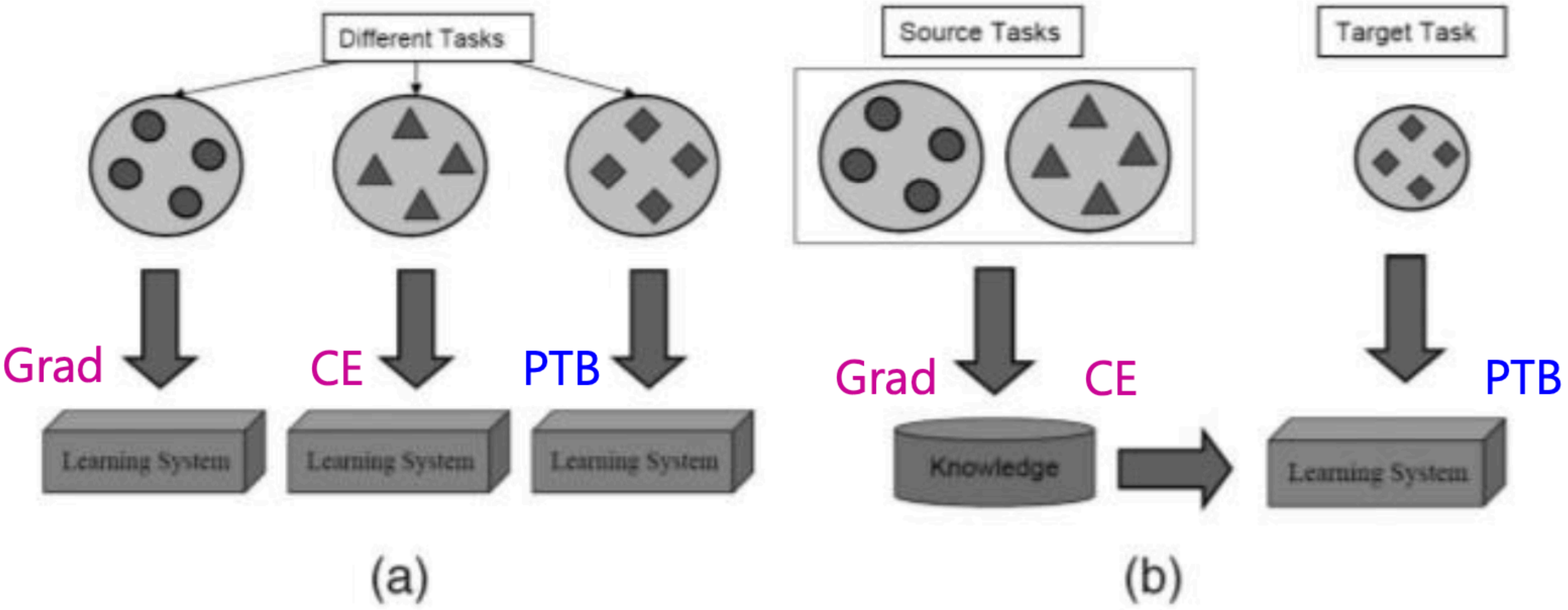
Prioritize r**educing predictive error across the full space**

Do not look at experimental data during this process

Journal of Artificial Intelligence Research (1996) 129–145

arXiv:2408.08247

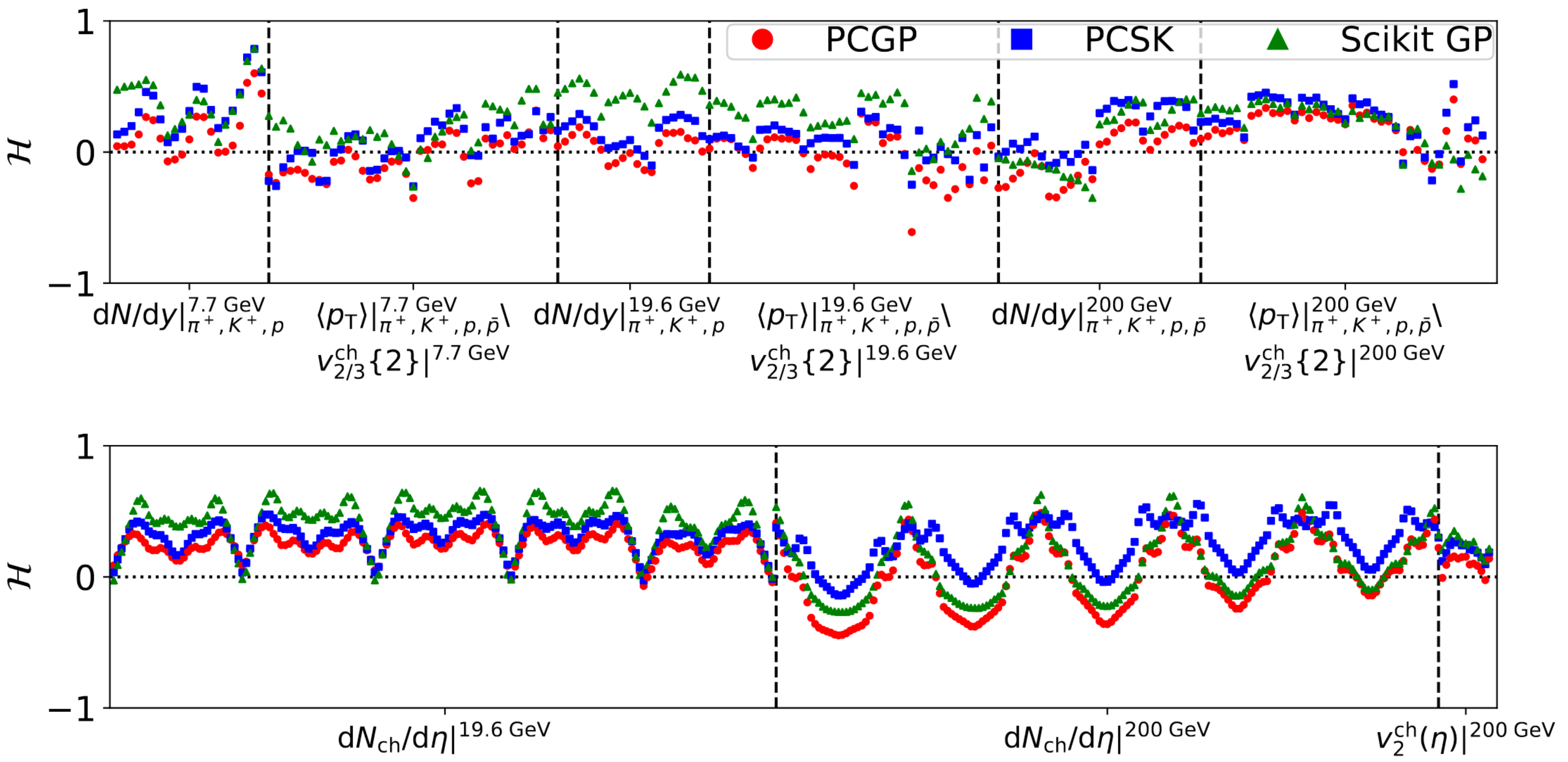
Transfer learning



Idea: Can we use data with **related collision (source) systems** for **cost-efficient** emulation of the desired **target** system?

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



Roch et al, arXiv:2405.12019

Improved uncertainty quantification + tools

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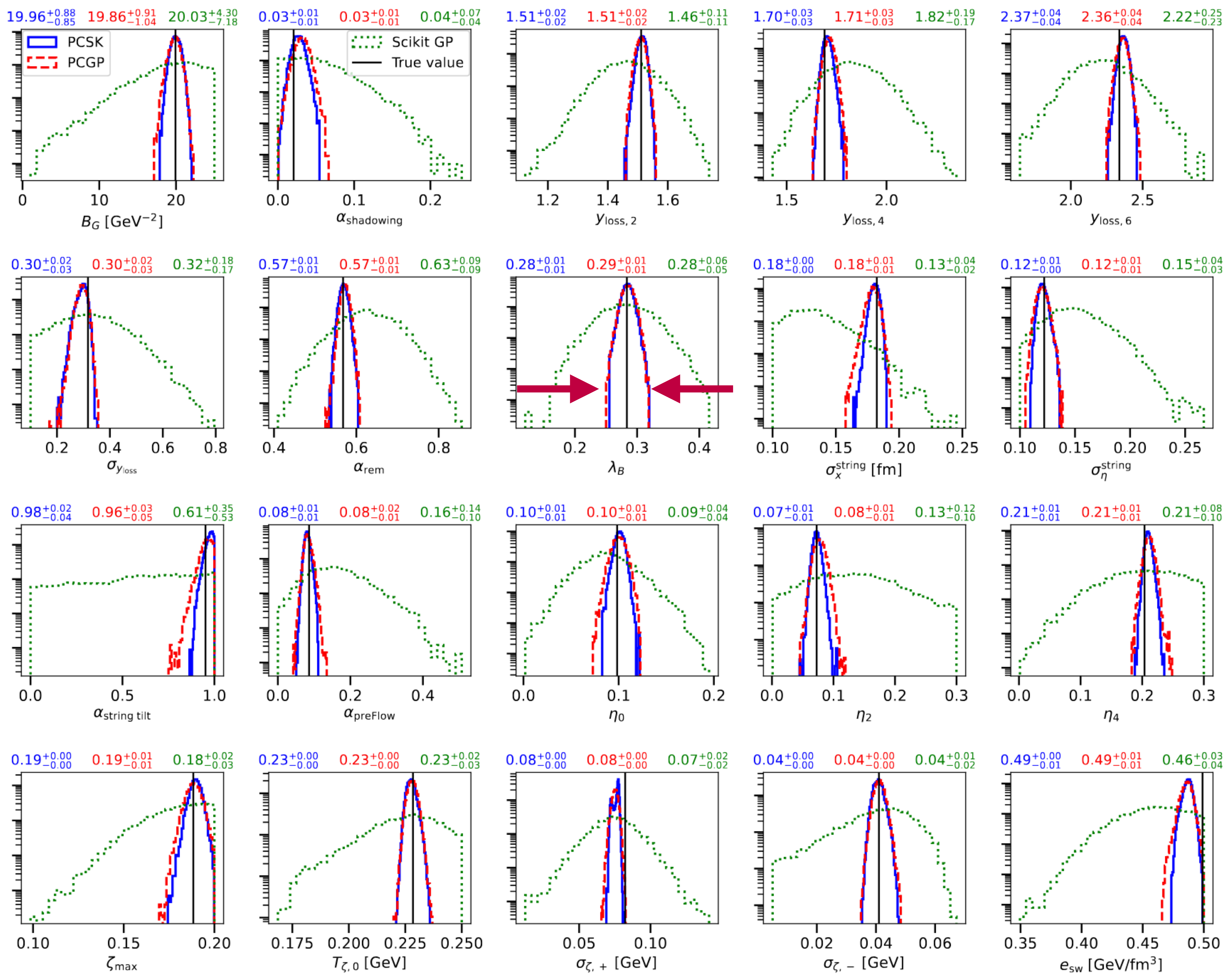
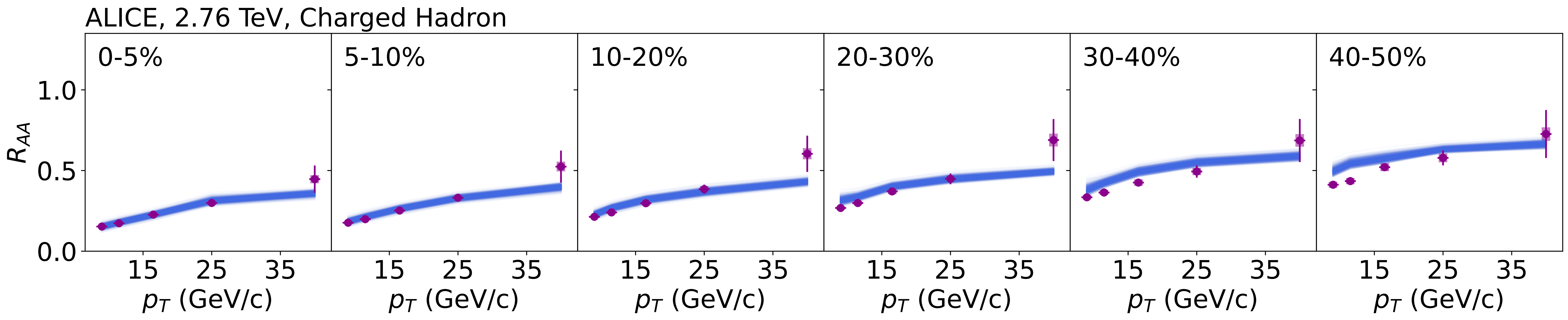


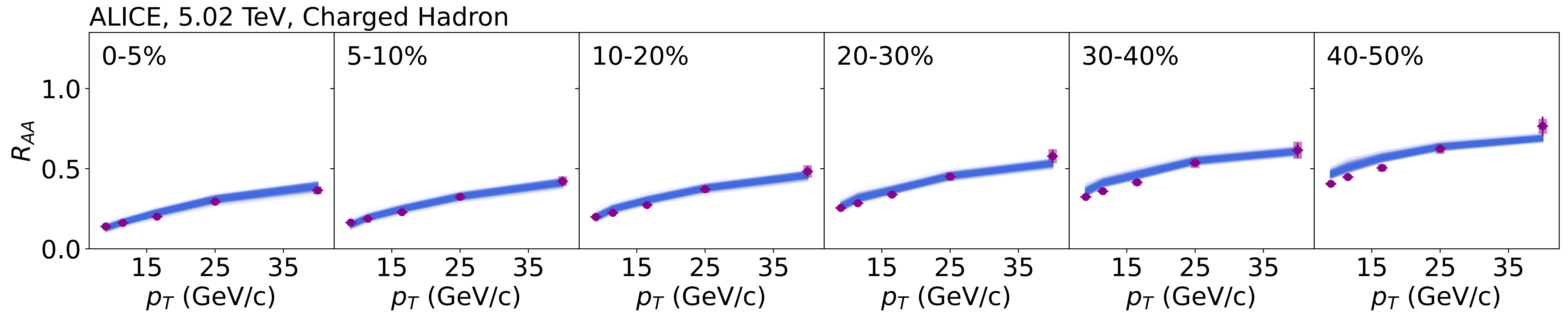
Roch et al, arXiv:2405.12019

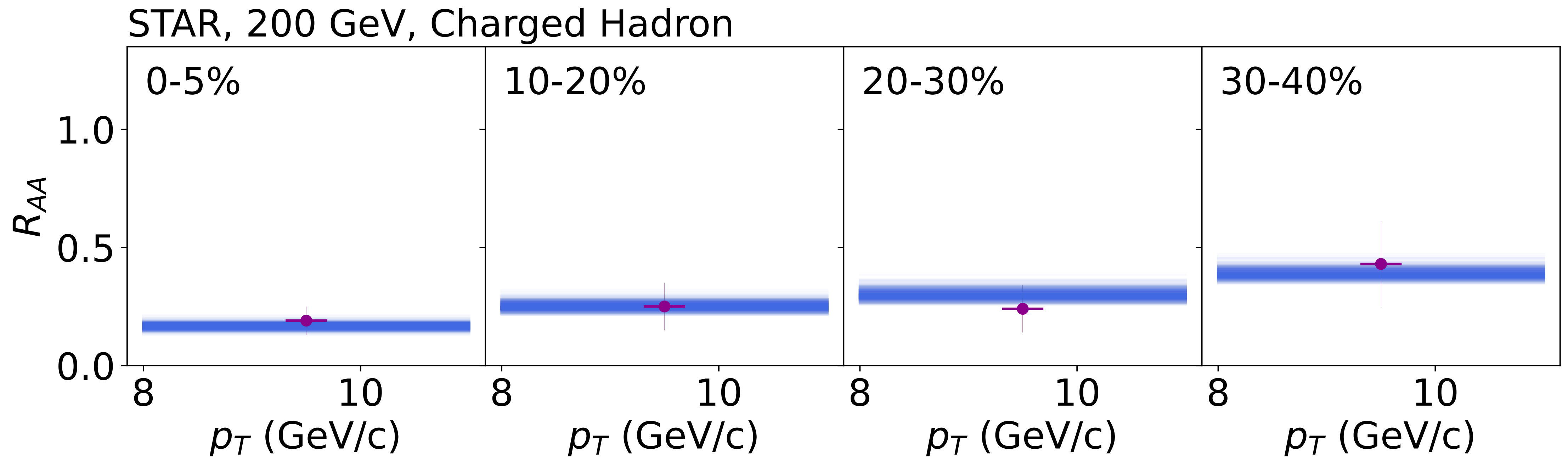
Posteriors: hadron R_{AA} at low p_{T}

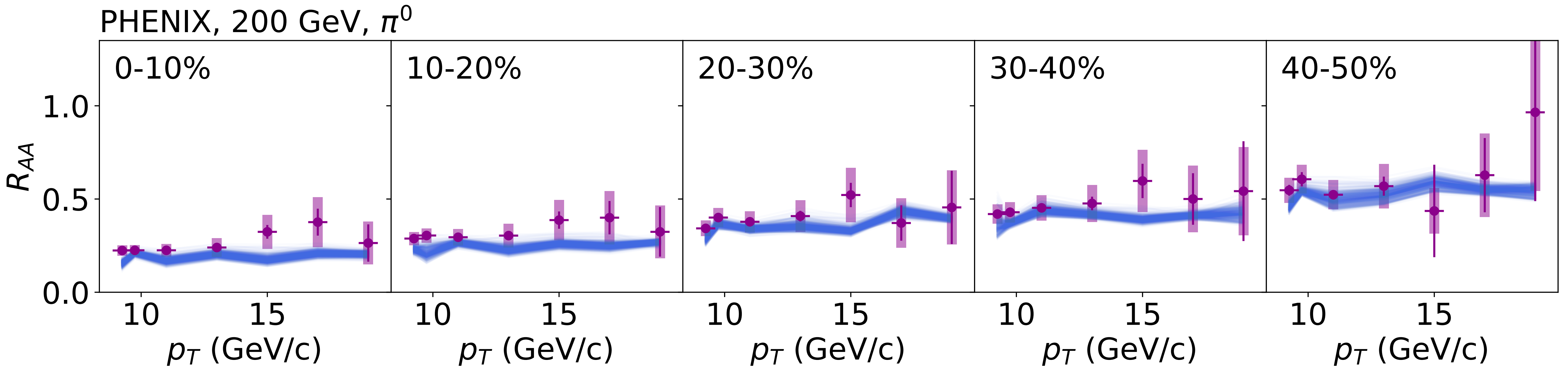
Good agreement at lower p_{T}

Fairly **consistent across experiments**









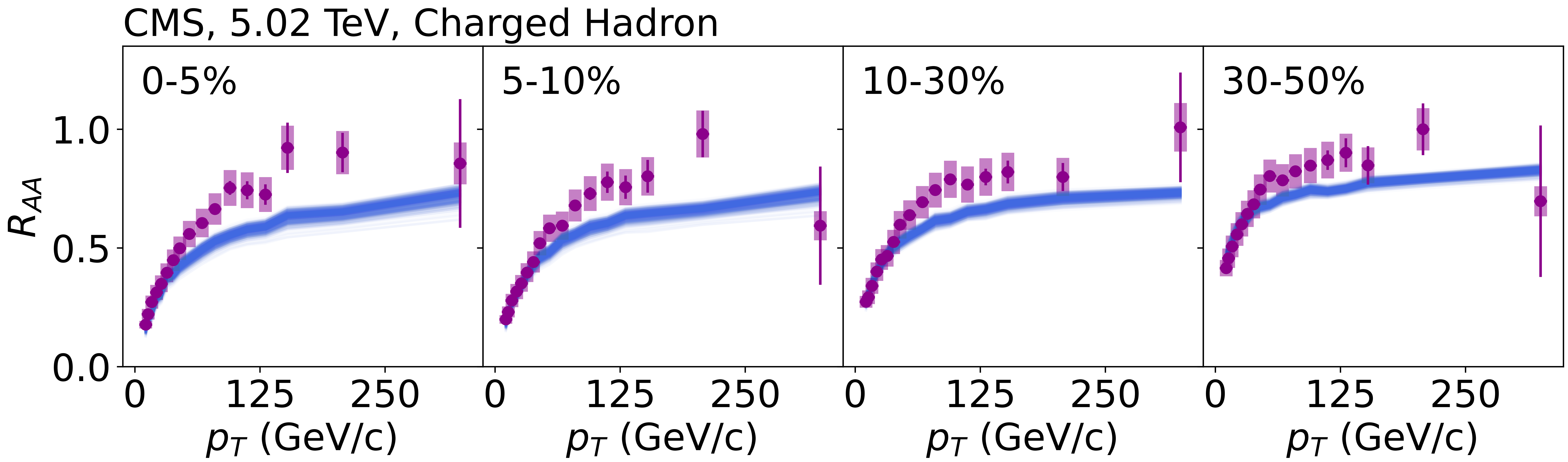
arXiv:2408.08247

Posteriors: hadron R_{AA} at high p_{T}

Some **tension at higher p_{T}**

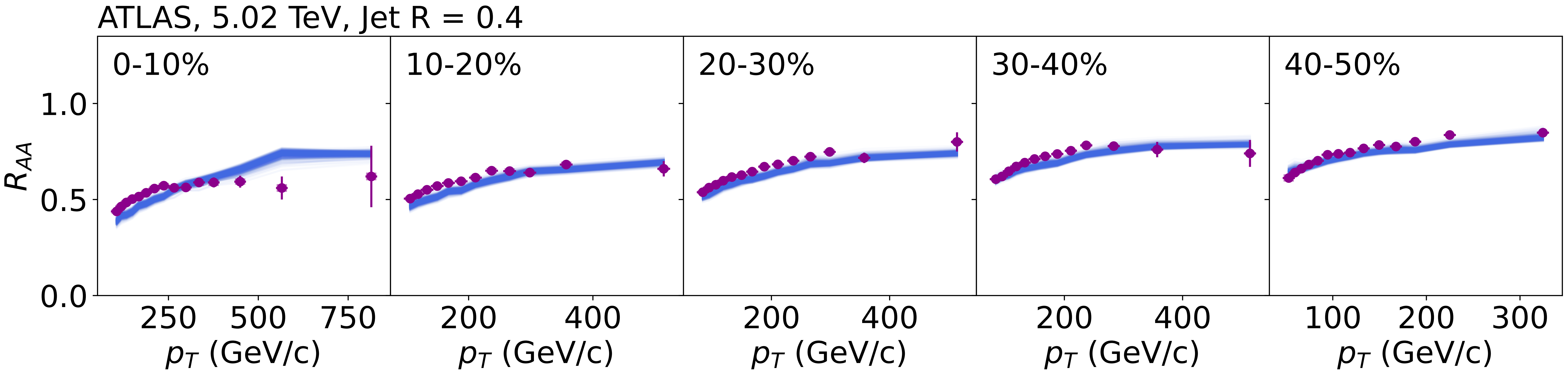
Uncertainty smallest at lower p_{T}

→ drives result

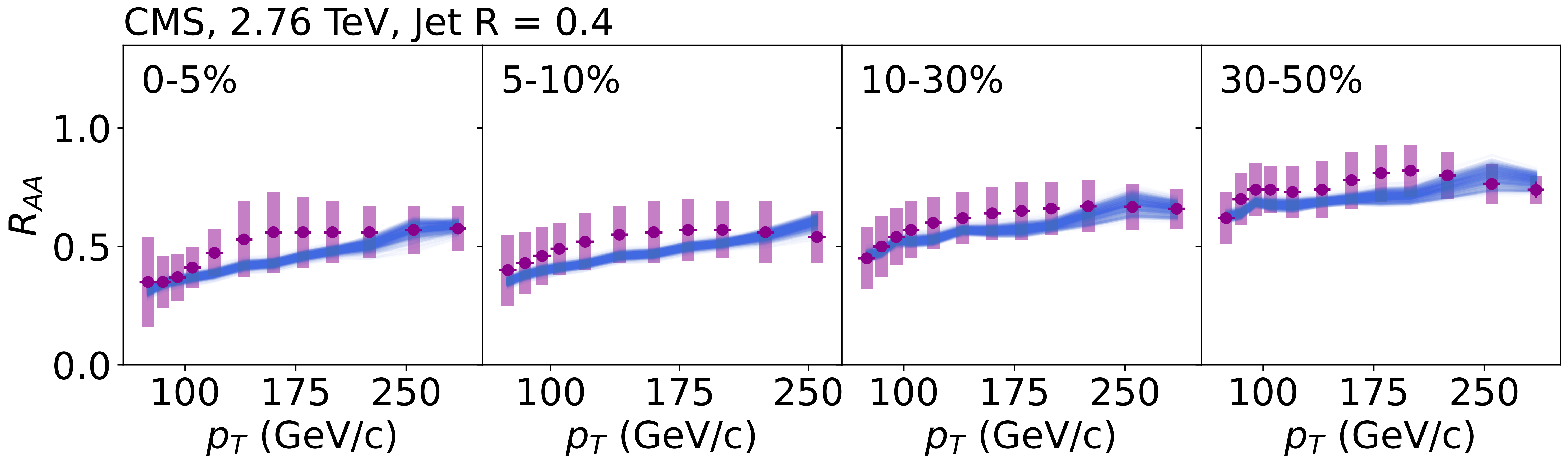


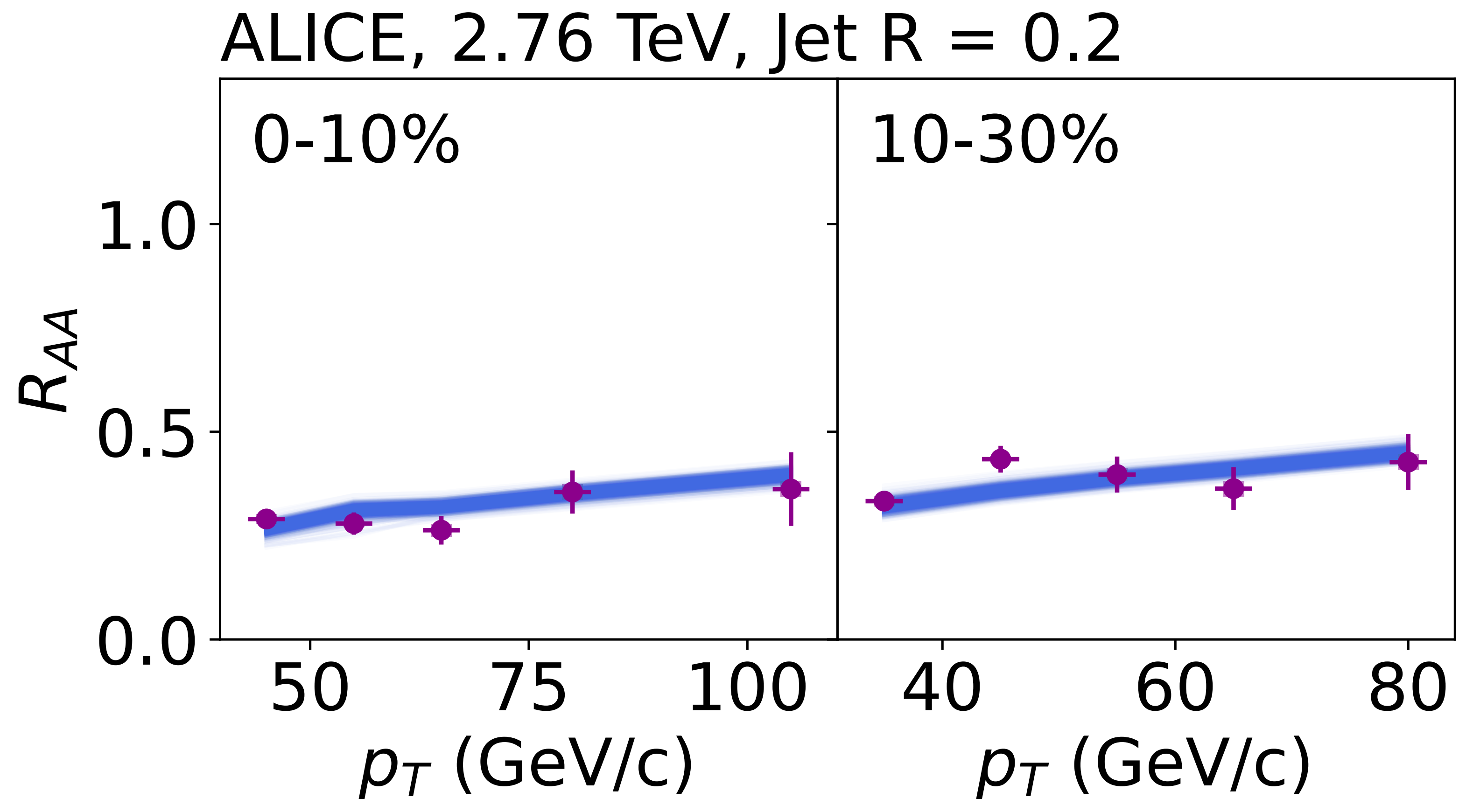
arXiv:2408.08247

Posteriors: jet R_{AA}



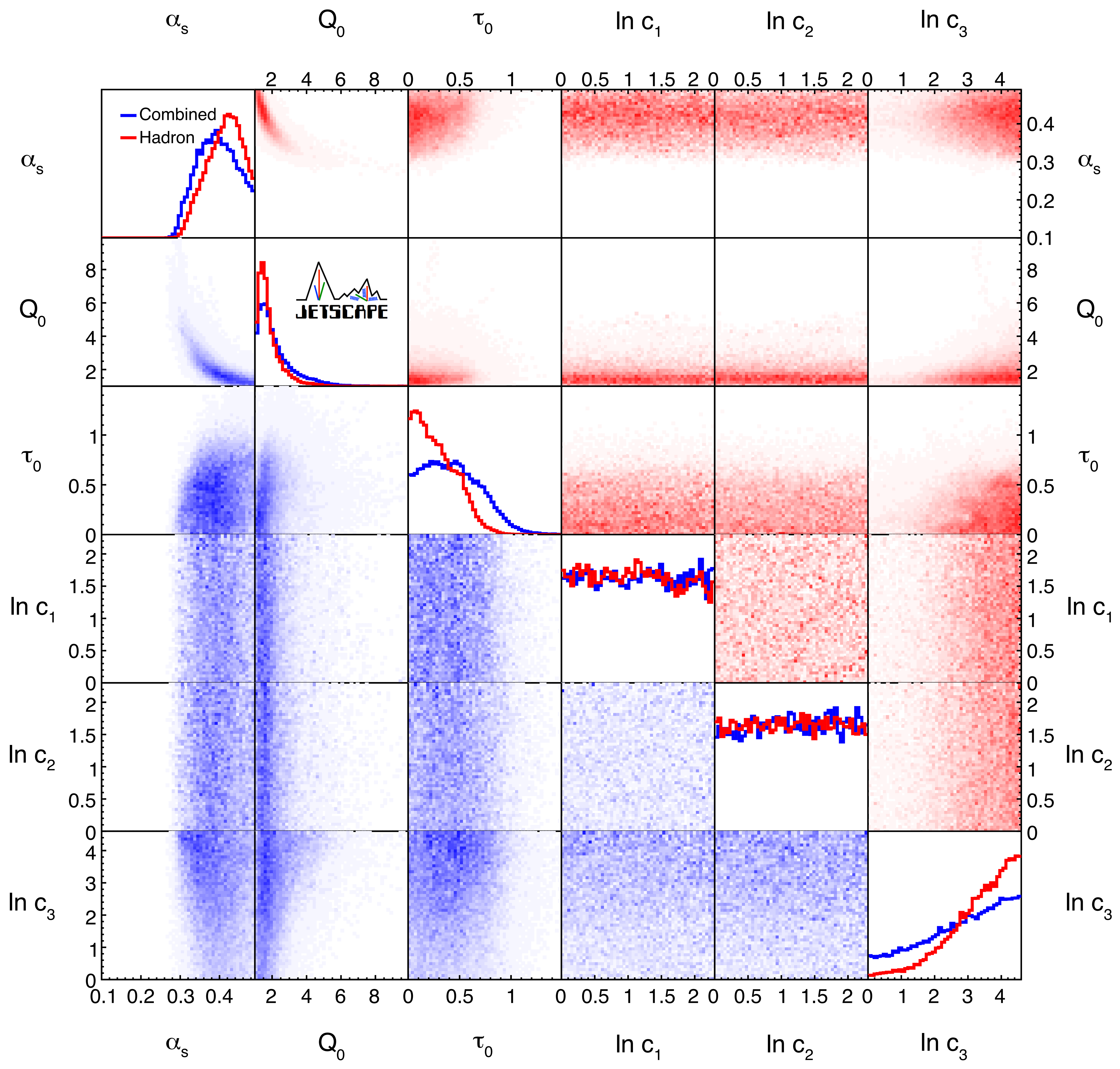
Generally **reasonable agreement**





arXiv:2408.08247

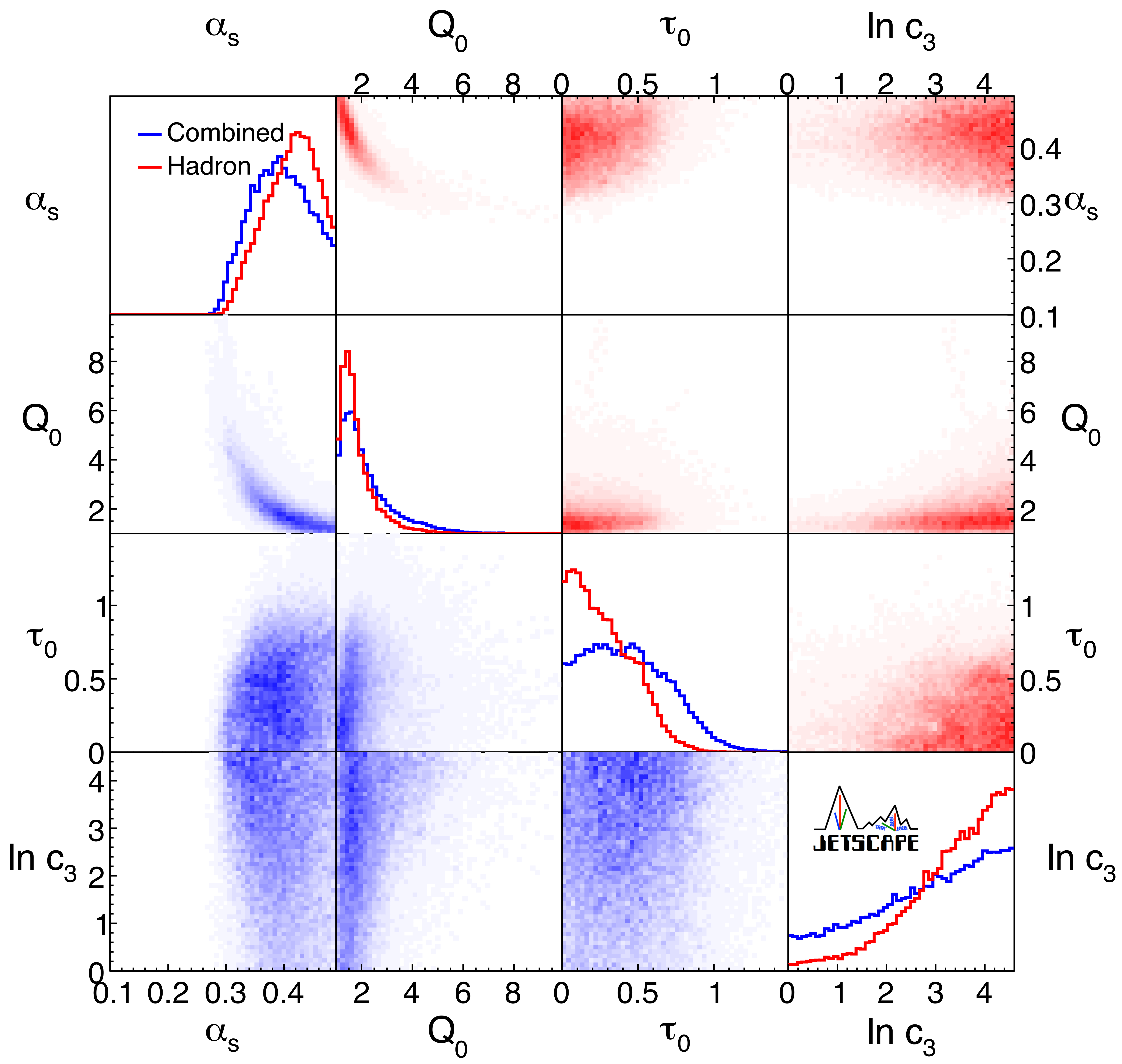
Parameter posterior distribution



Not much sensitivity to c1 and c2.
→ We'll skip them for now

arXiv:2408.08247

Parameter posterior distribution



α_S ~ 0.3-0.4

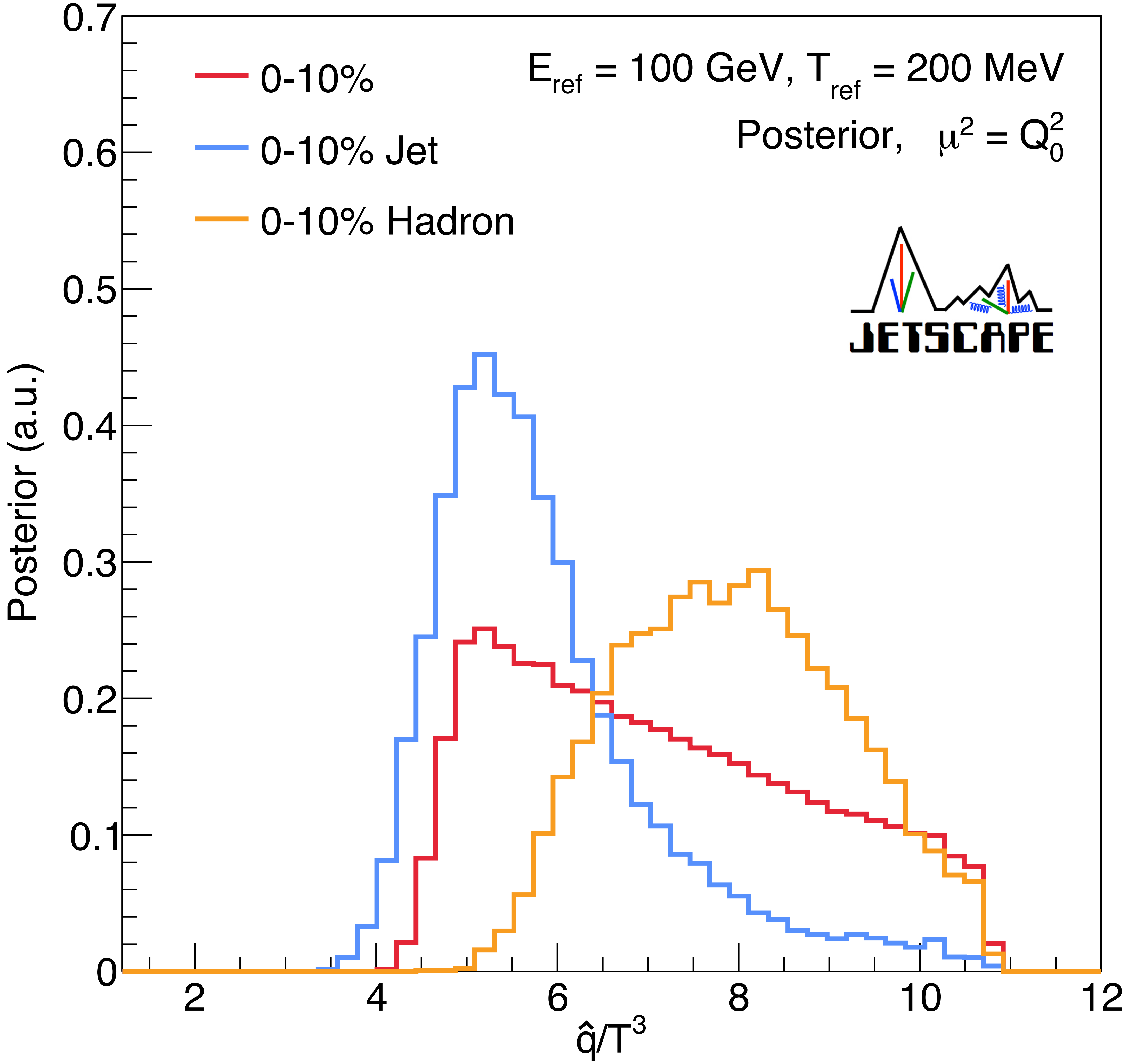
Low Q_0 (as expected)

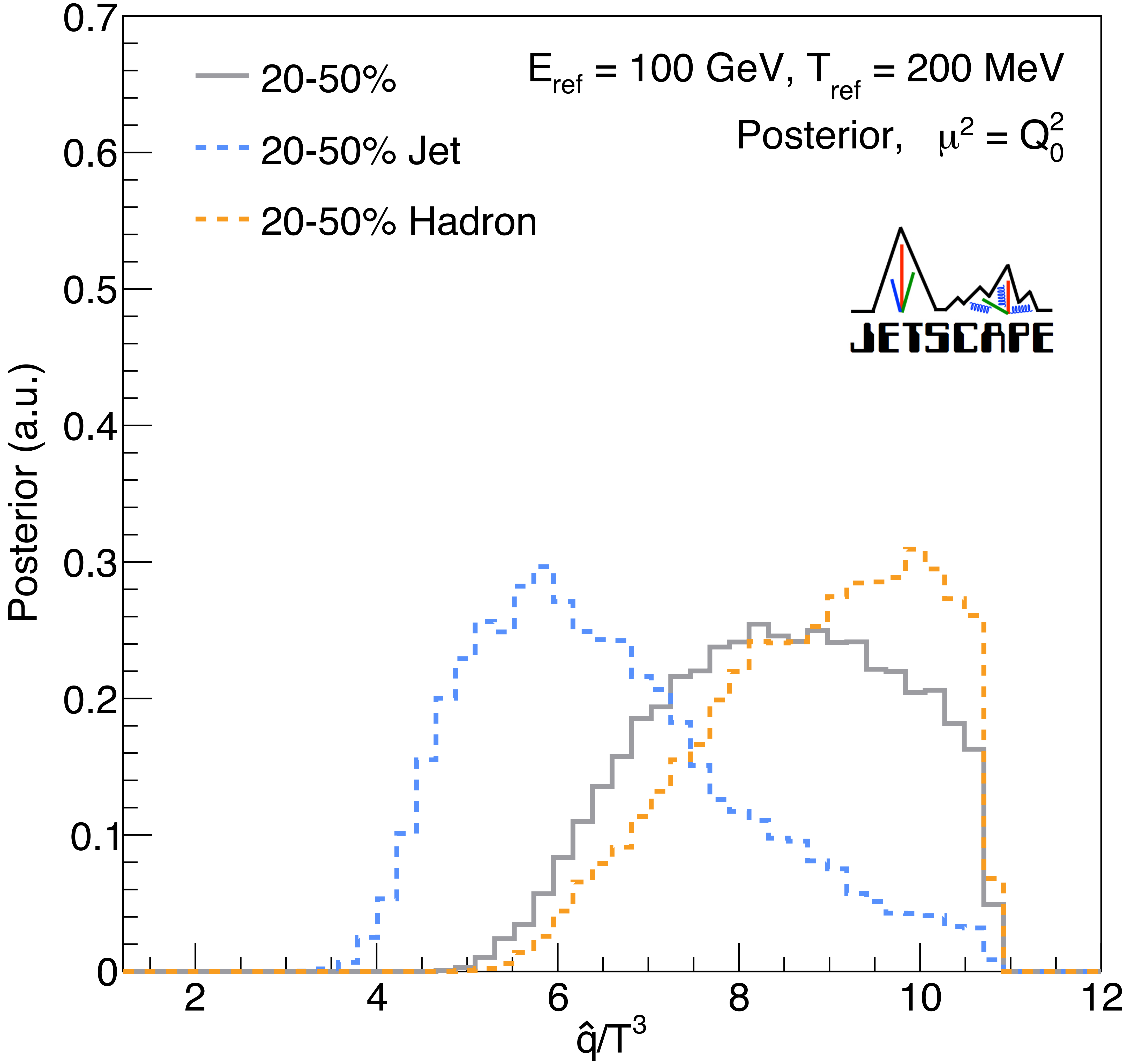
Wide τ_0 up to ~1 fm/c

Some preference for larger c3

arXiv:2408.08247

Centrality dependence





Doesn't change the jet vs hadron picture

Further investigations in the future

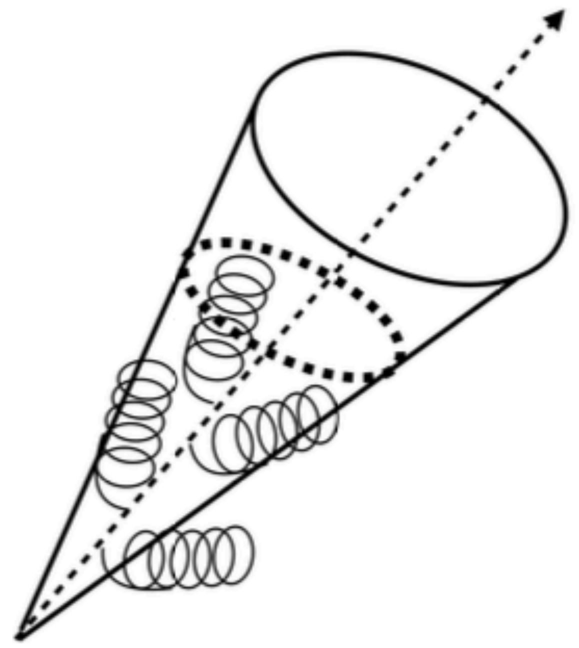
arXiv:2408.08247

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**

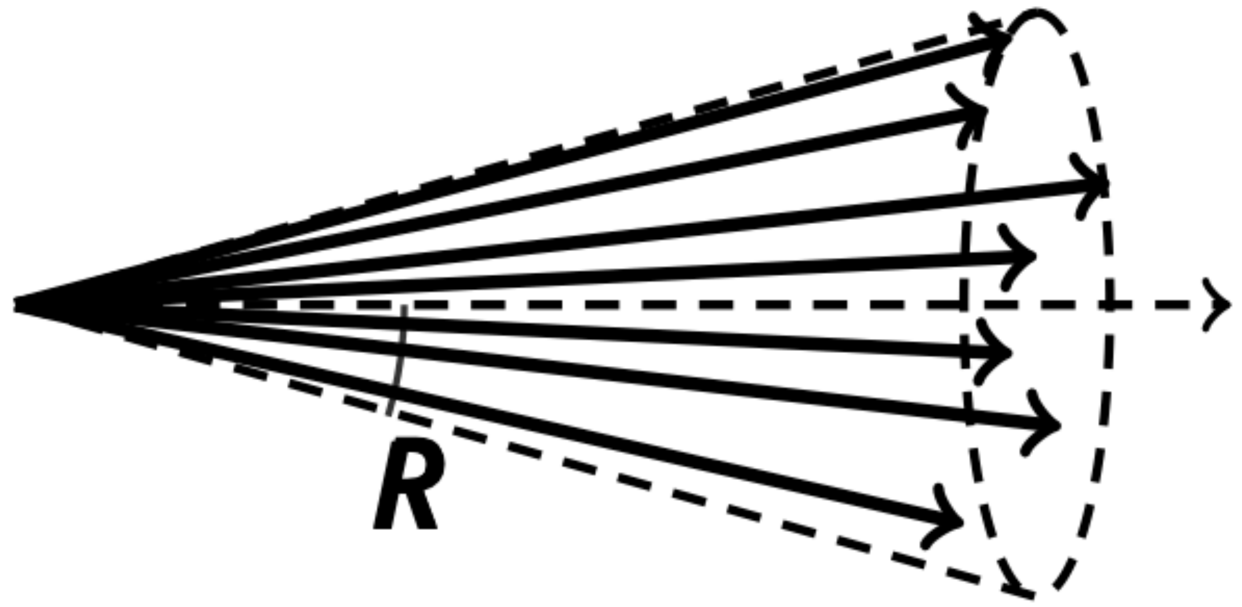
Jet R_{AA}

- ALICE, ATLAS, CMS, STAR



Fragmentation: $D(z)$

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



Groomed jet substructure

- ALICE: R_g, z_g

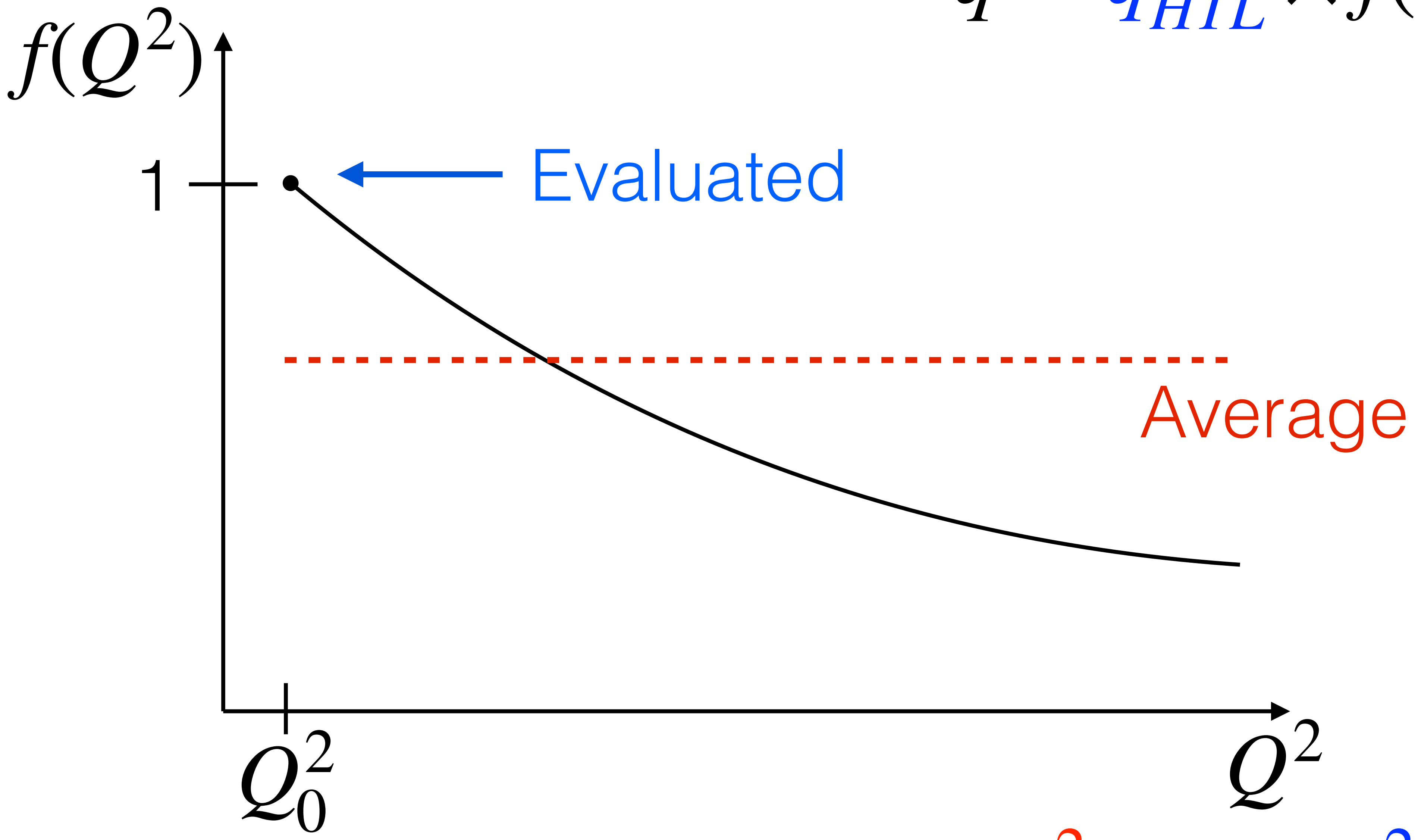
Model: JETSCAPE MATTER+LBT

Data: Selected inclusive jet R_{AA}, jet substructure

Evaluating virtuality dependence for $\hat{q}$

Imagine for now we stay with latest analysis

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



Average over the whole thing $\langle f(Q^2) \rangle < f(Q_0^2)$

Virtuality dependence: f(Q^2)