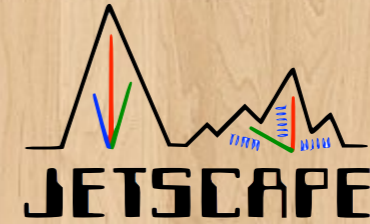


A multi-messenger Bayesian Inference analysis of QGP jet transport using inclusive hadron and reconstructed jet data by JETSCAPE

Yi Chen (MIT) for the JETSCAPE collaboration
Mar 28, 2023. Hard Probes 2023



A multi-messenger Bayesian
Inference analysis of QGP jet
transport using inclusive hadron and
reconstructed jet data by JETSCAPE

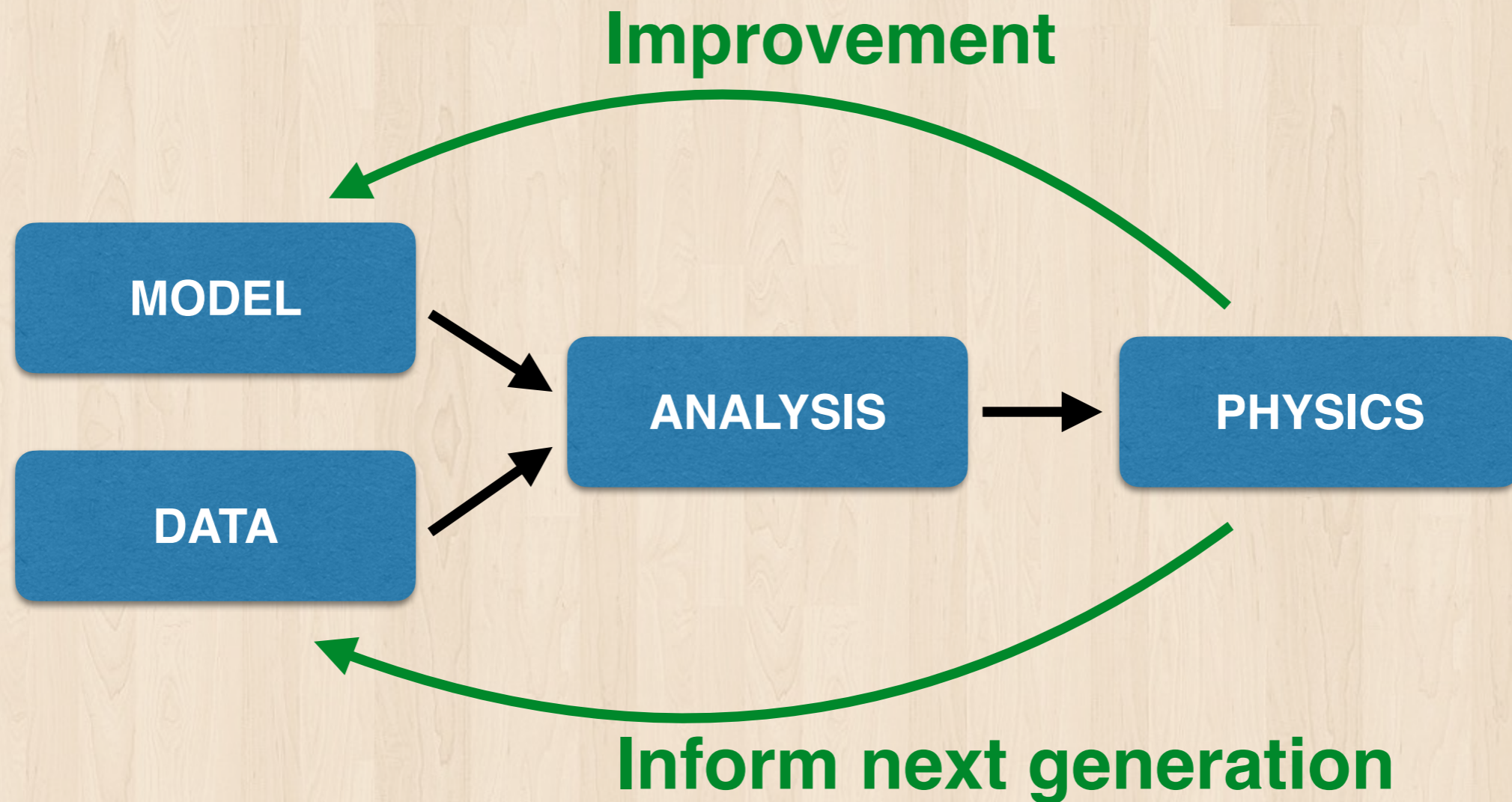
Yi Chen (MIT) for the JETSCAPE collaboration
Mar 28, 2023. Hard Probes 2023

Global Analysis



Gain physics insight by rigorous comparison

Global Analysis



...and also feedback to improve things!

Bayesian analysis

ANALYSIS

Bayes' theorem: $P(\vec{\theta} | \vec{x}) = \frac{P(\vec{x} | \vec{\theta})P(\vec{\theta})}{P(\vec{x})}$

Posterior encodes
all we want to learn

Allows a computationally tractable way to
extract parameters (though still CPU intensive)

Generally not dissimilar to previous analyses (backup)

First analysis (2021)

DATA

Hadron R_{AA}

3 energies
2 centralities each

Recreate experimental
uncertainty correlation
the best we can

MODEL

Extract $\hat{q}(T, E, Q)$

Goal: one step forward
from the JET result
unified \hat{q} across energy

Multistage:
MATTER+LBT

Current iteration

DATA

Hadron & **jet** R_{AA}

3 energies

ALL eligible data

Recreate experimental
uncertainty correlation
the best we can

MODEL

Extract $\hat{q}(T, E, Q)$

Re-parametrize \hat{q}

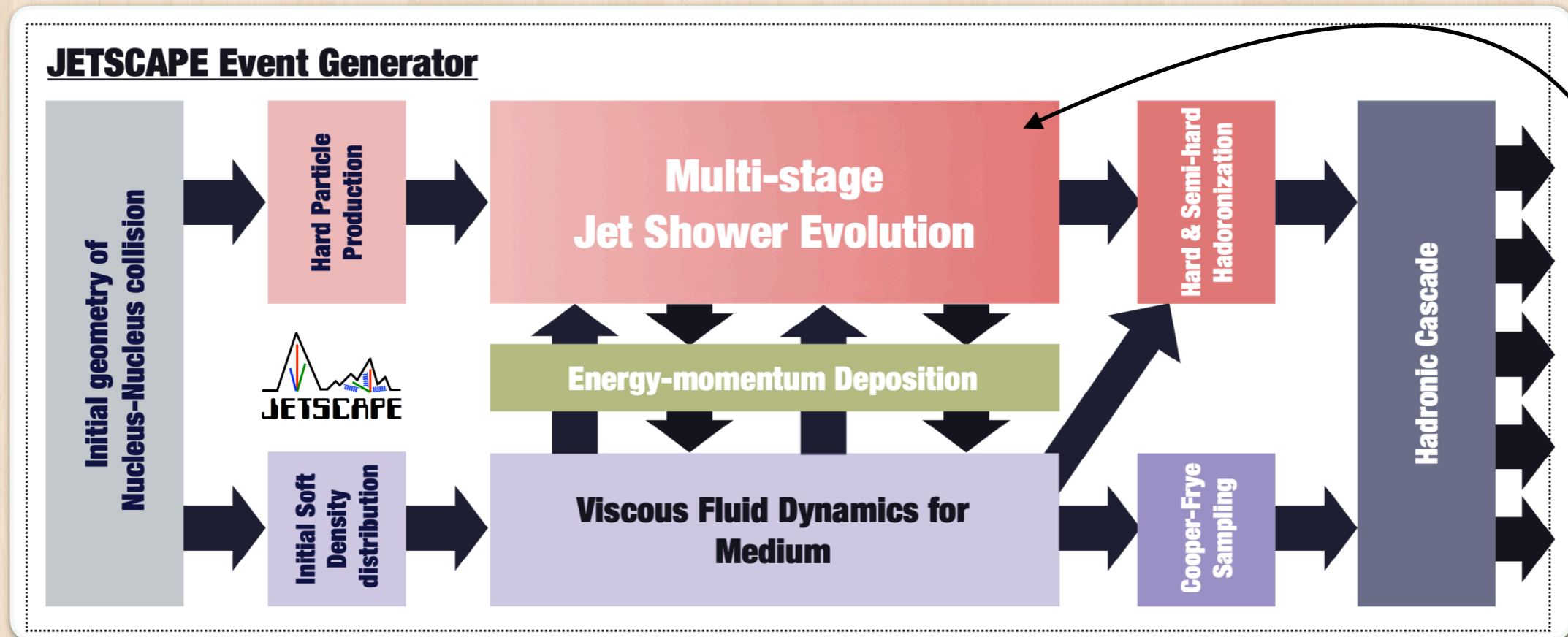
**Sample full posterior
from JETSCAPE soft
sector result**

MATTER+LBT

Goal: Explore what
jets bring to the table

JETSCAPE framework

Diagram courtesy Y. Tachibana



Modular framework:

- Easily extendible
- Testing out different modules while holding everything else identical
- Unified framework for complete heavy-ion events

We welcome new models!

Parametrization of \hat{q}

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

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

Inspired from exponential "PDF": $f_{QGP}(x) \sim e^{-c_3 x}$

$$\underline{f(Q^2)} \equiv N_0 \frac{\exp \left(c_3 \left(1 - \frac{Q^2}{2EM} \right) \right) - 1}{1 + c_1 \ln(Q^2/\Lambda_{QCD}^2) + c_2 \ln(Q^2/\Lambda_{QCD}^2)} \Big|_{Q^2 \geq Q_0^2}$$

Set by $f(Q_0^2) = 1$

Other parameters

Q_0 : virtuality switch to LBT

τ_0 : start time

Parametrization of \hat{q}

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

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

Inspired from exponential "PDF": $f_{QGP}(x) \sim e^{-c_3 x}$

$$f(Q^2) \equiv N_0 \frac{\exp \left(c_3 \left(1 - \frac{Q^2}{2EM} \right) \right) - 1}{1 + c_1 \ln(Q^2 / \Lambda_{QCD}^2) + c_2 \ln(Q^2 / \Lambda_{QCD}^2)} \Bigg|_{Q^2 \geq Q_0^2}$$

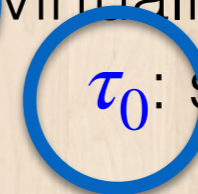
Set by $f(Q_0^2) = 1$



: parameters (6 in total)



Other parameters
 Q_0 : virtuality switch to LBT



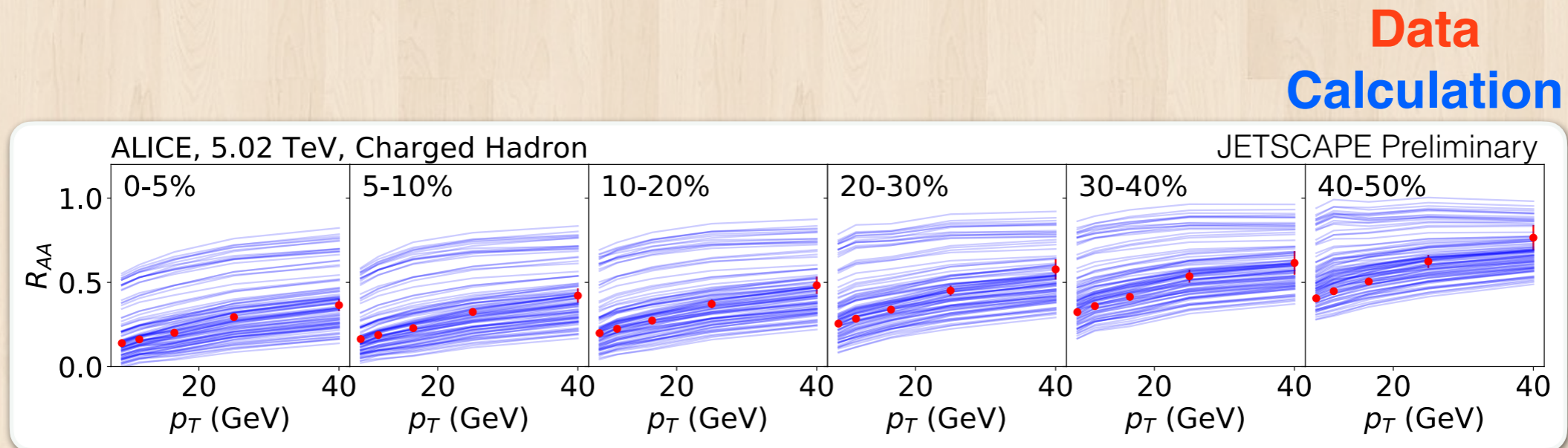
τ_0 : start time

Few words on the analysis

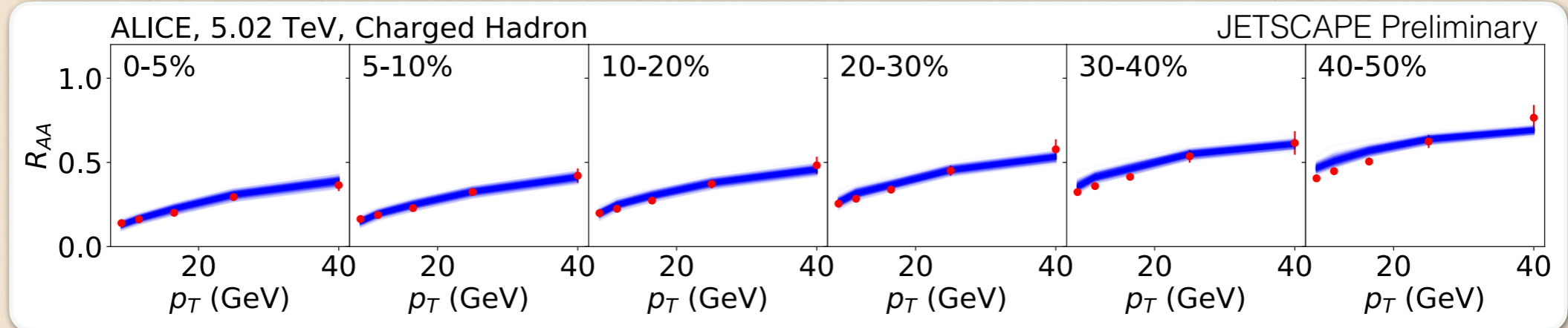
- Huge effort in computing during 2022
 - $O(10M)$ CPU hours, unified submission interface across multiple HPC systems, data curation including all systematic uncertainties, iteration on design points, etc
 - Calculated many more observables than are used in this iteration \rightarrow fast turnaround for next analyses
- Choose dimension of subspace based on statistical uncertainty on the computations

Nominal Results

Example: design vs posterior

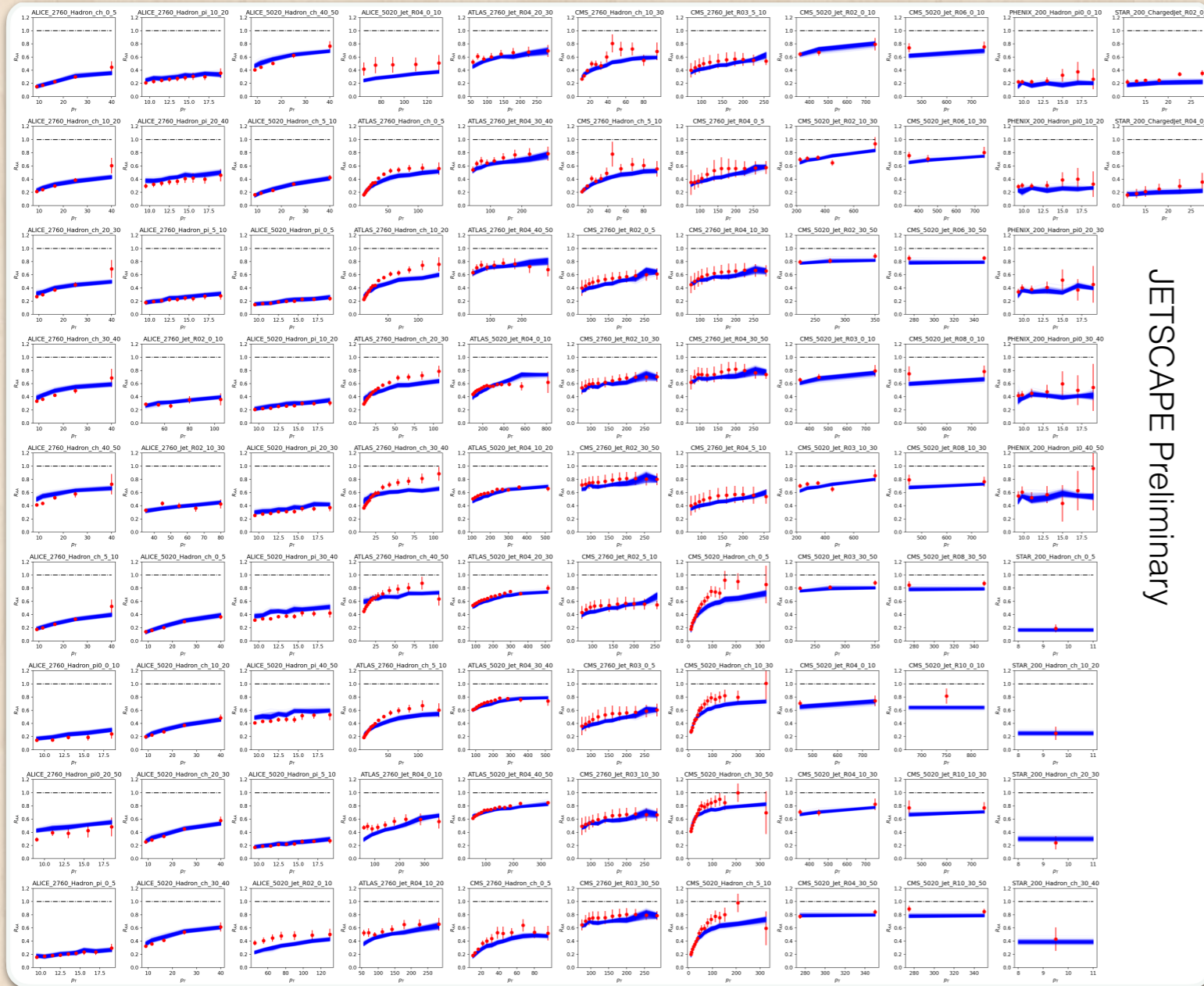


↓ Analysis



Posterior observables

(Don't stare too closely, we have zoomed in version in the next pages)



Data
Best fit

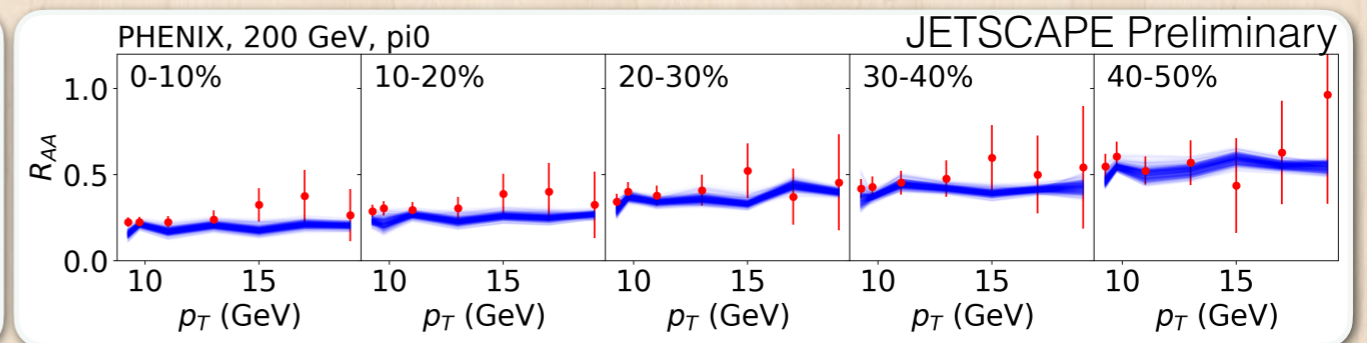
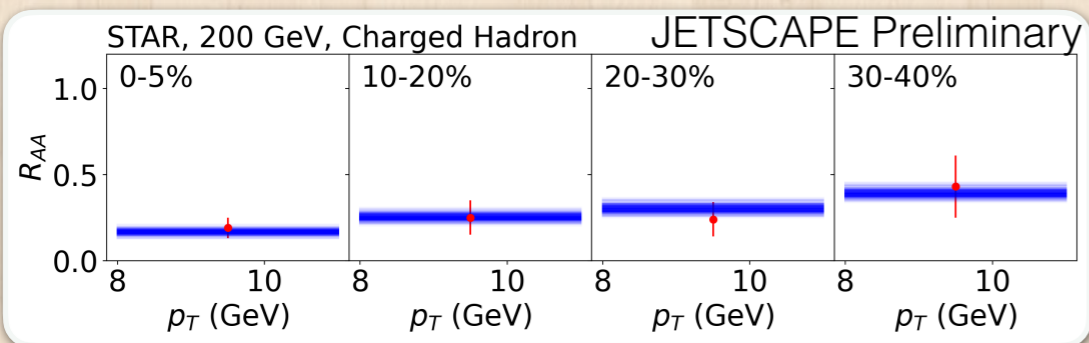
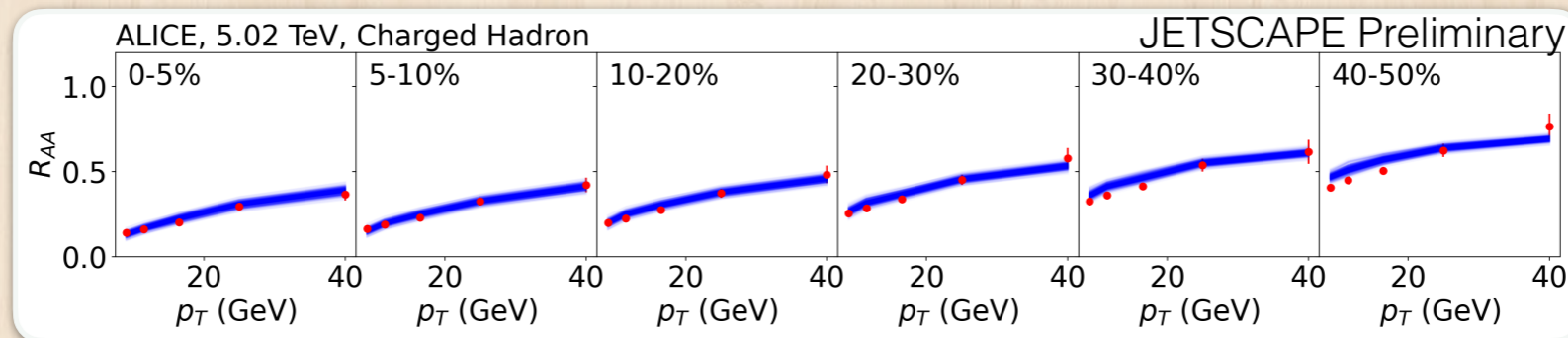
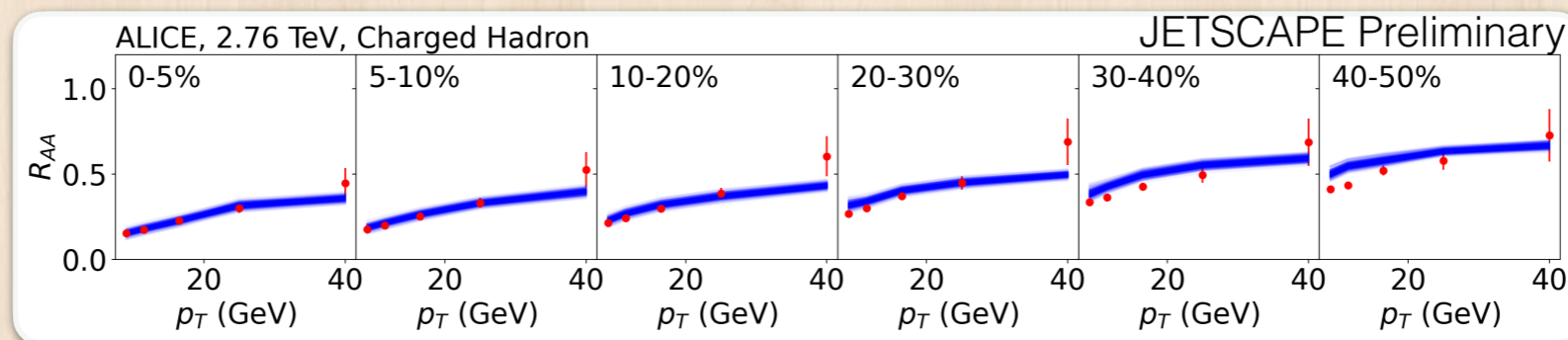
JETSCAPE Preliminary

Overall
reasonable
agreement is
observed

Tension for some
measurements

Looking closer — hadrons

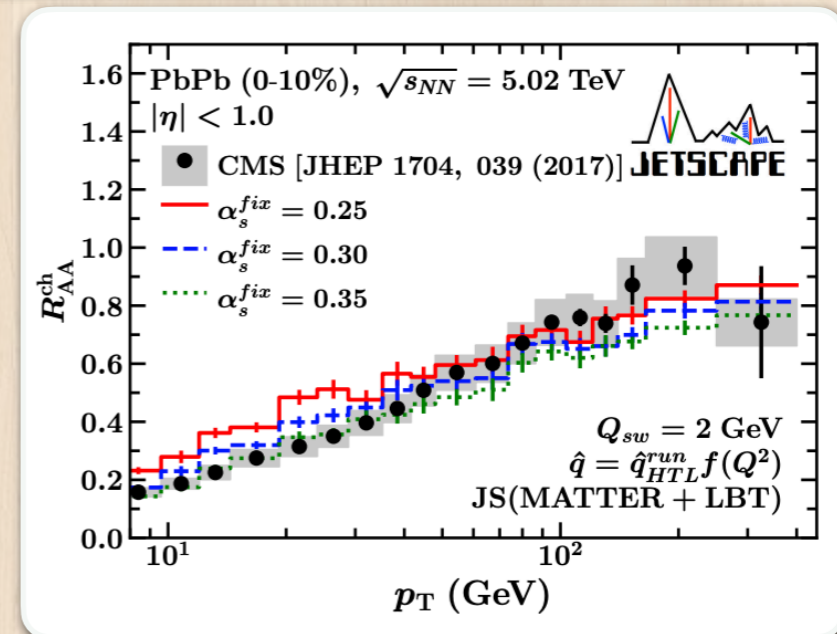
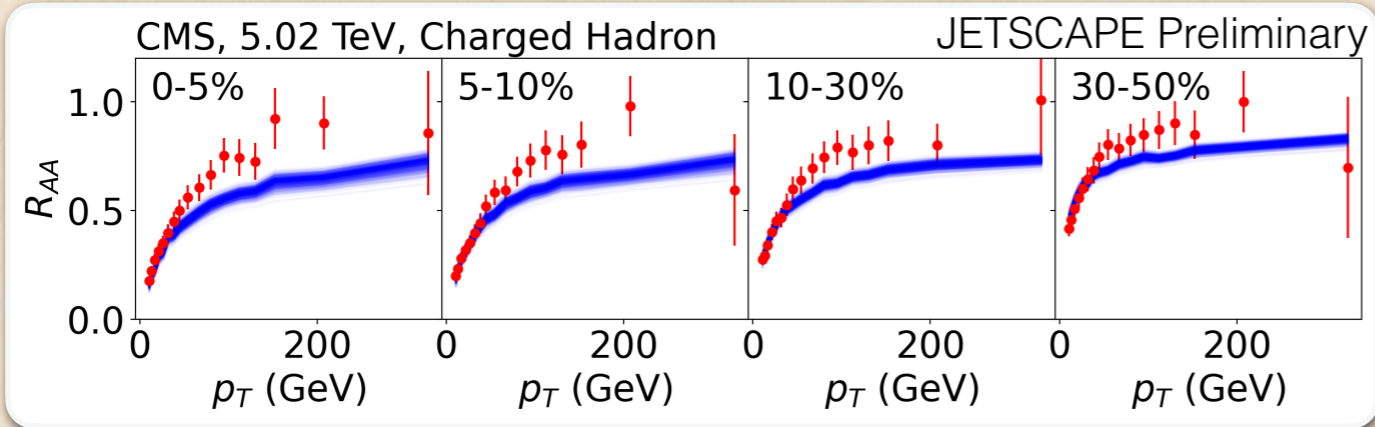
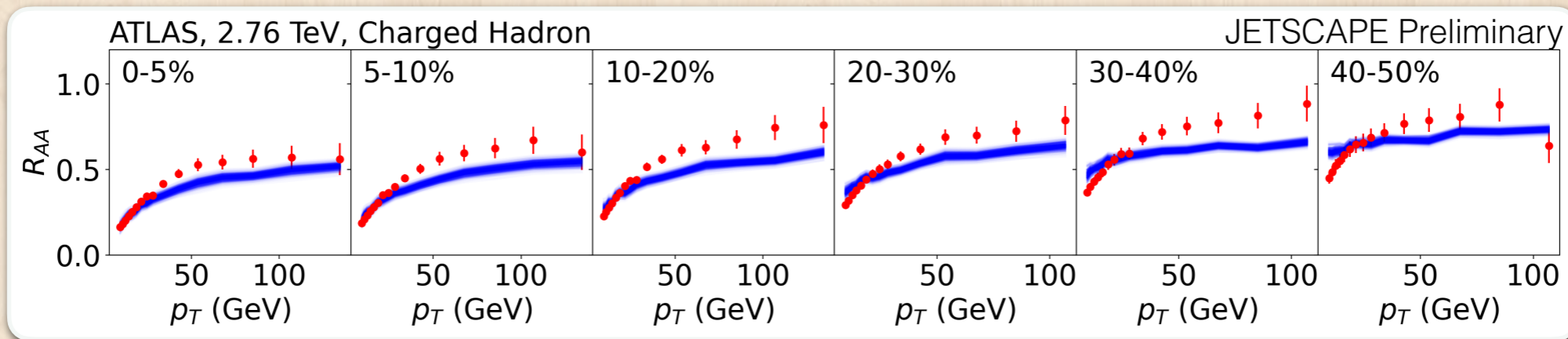
Generally great agreement at lower p_T
No large difference across experiments



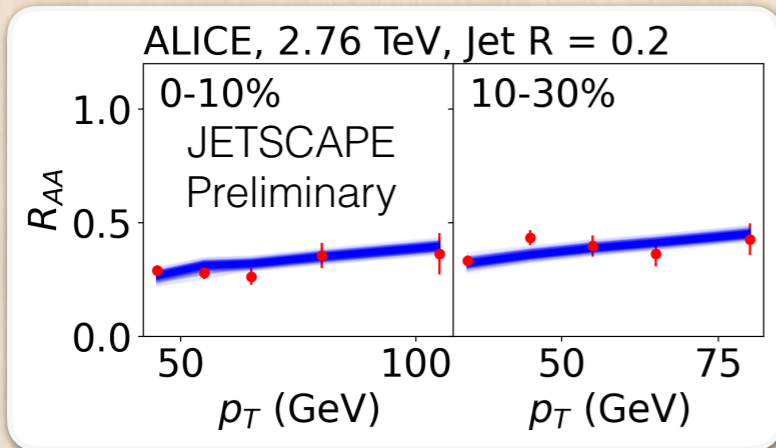
Looking closer — hadrons

Things deviate a bit going to higher p_T

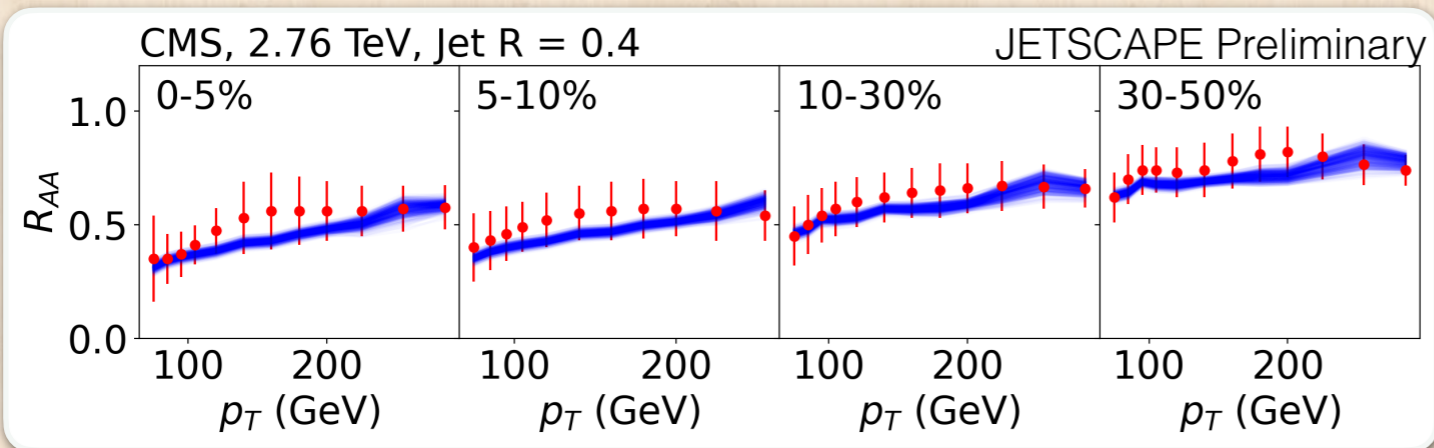
Uncertainty smallest at lower $p_T \rightarrow$ drives result



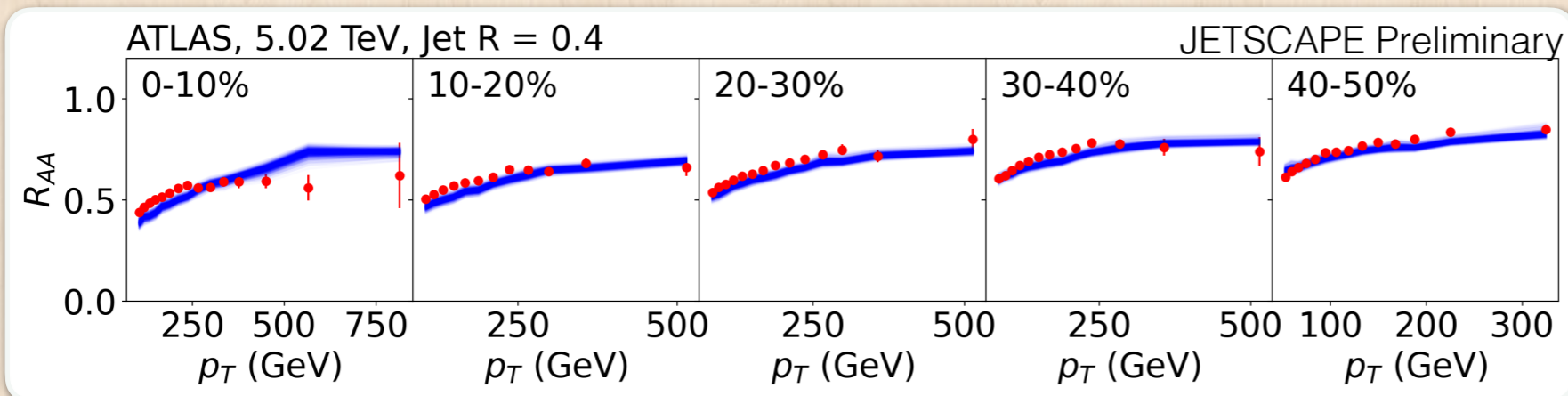
Looking closer — jets



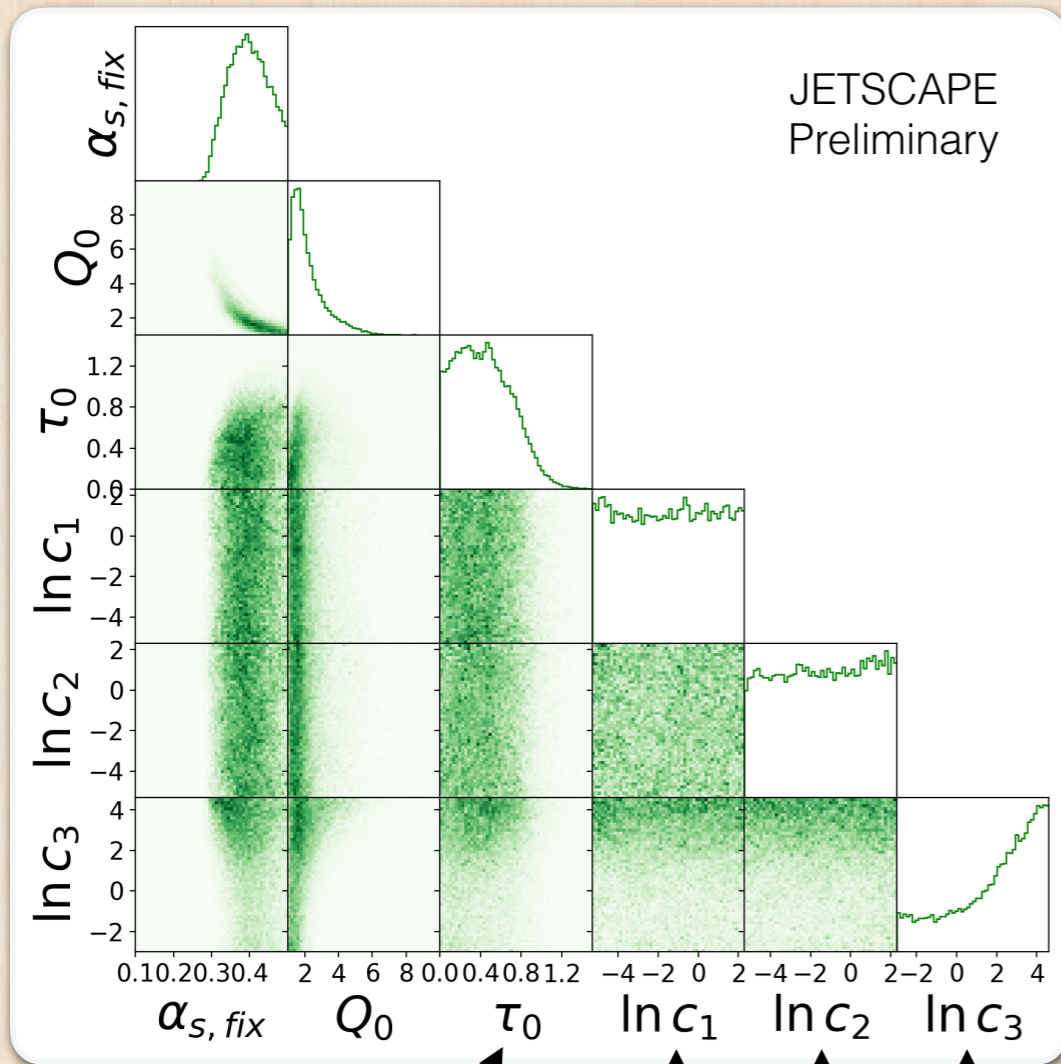
Also generally good agreement



Systematically slightly lower R_{AA}

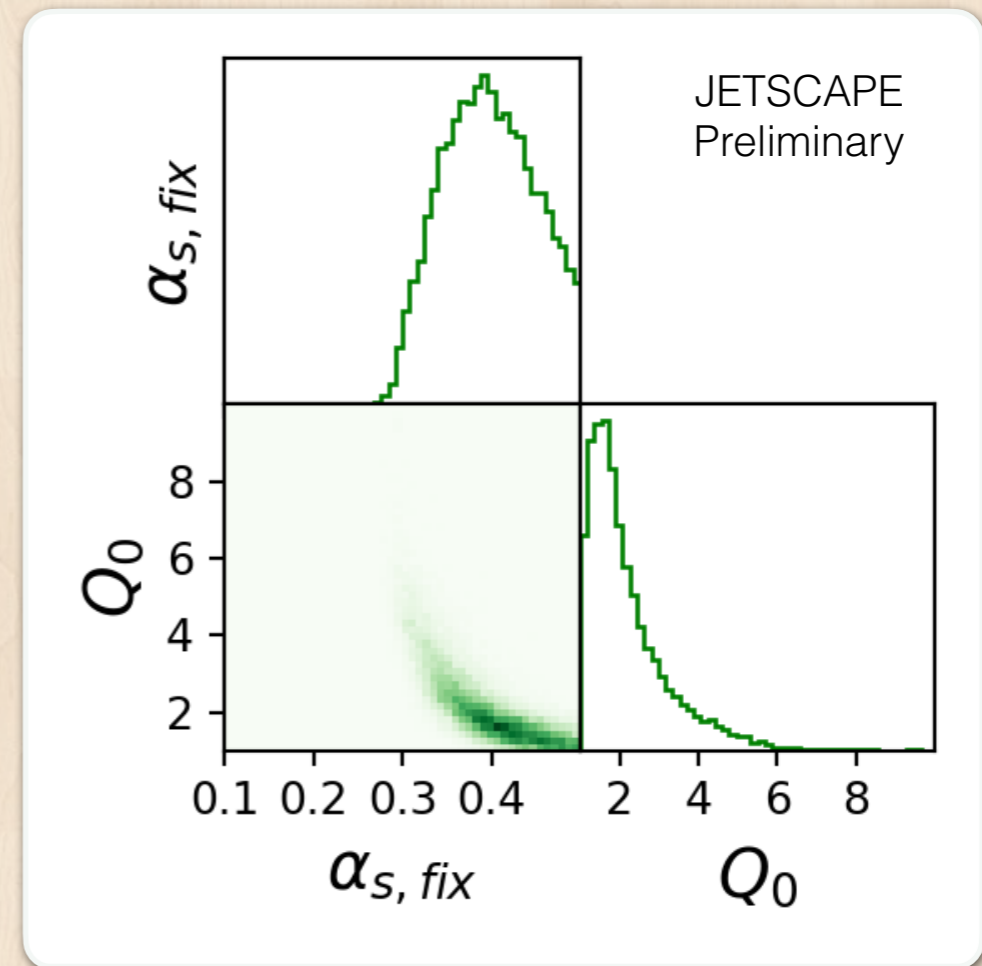


Posterior distribution



Start time

Virtuality dependent terms



Anti-correlation between $\alpha_{s,fix}$ and Q switch

$\propto \hat{q}$

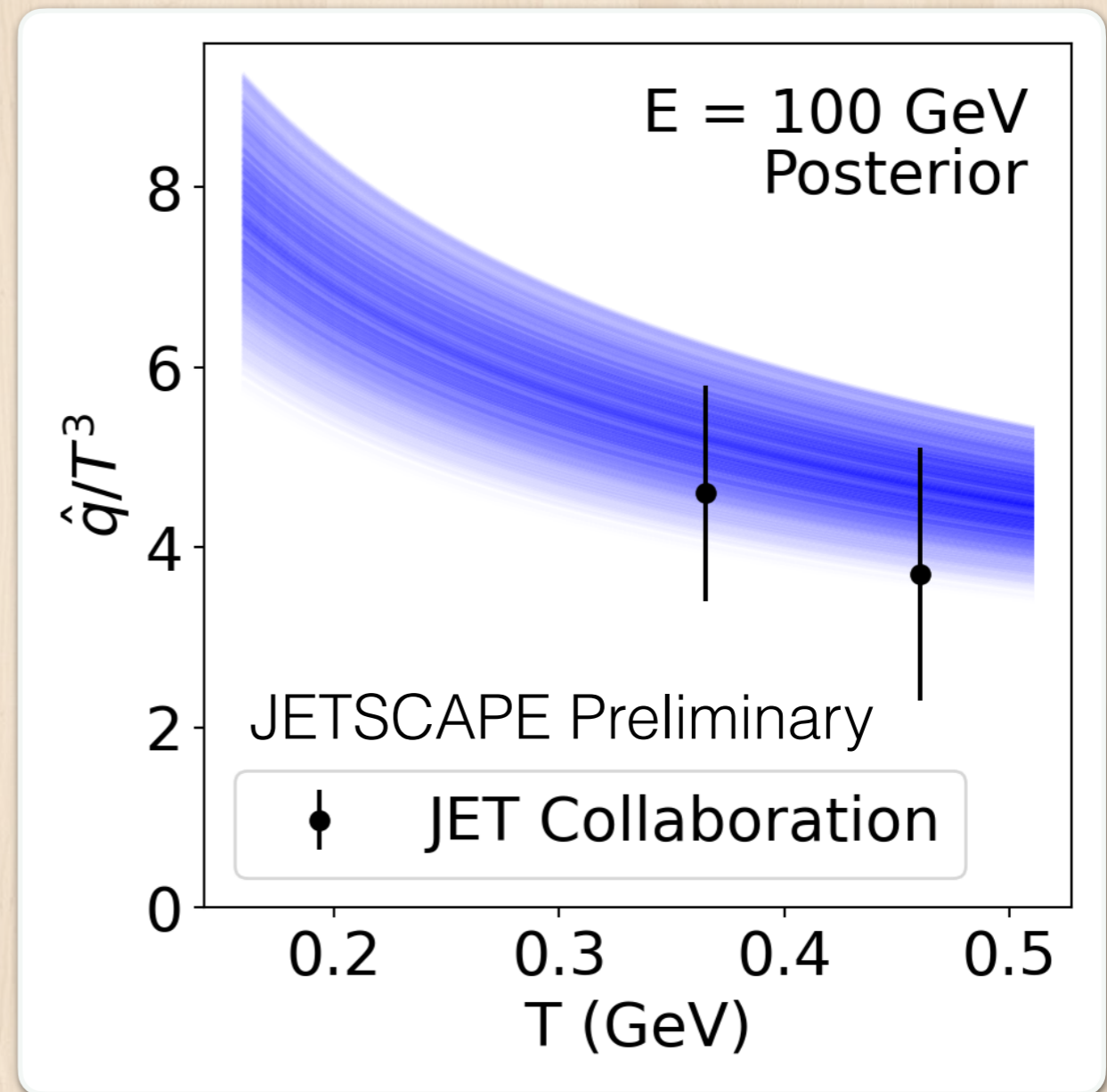
Between MATTER and LBT

Extracted \hat{q}

Compatible with previous extractions

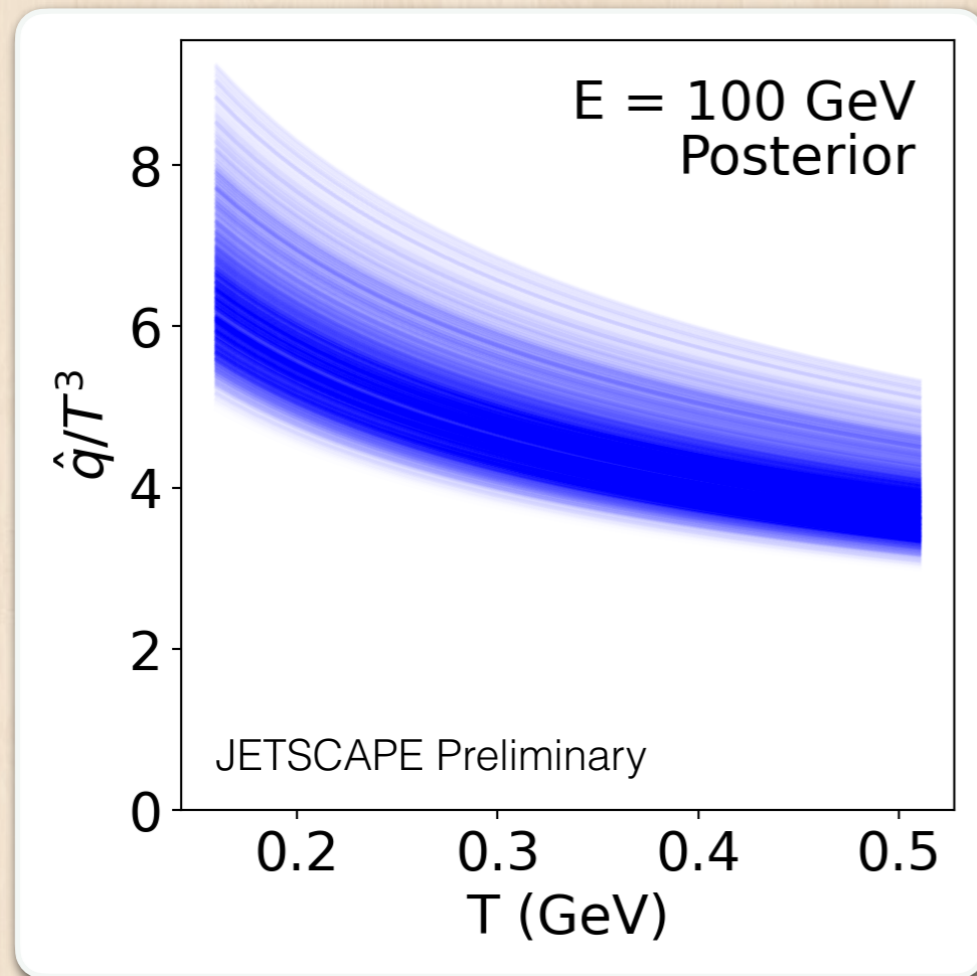
Here we plot the \hat{q} when virtuality is low i.e., $\hat{q} = \hat{q}_{HTL}^{run} \times f(Q^2)$

↑
this

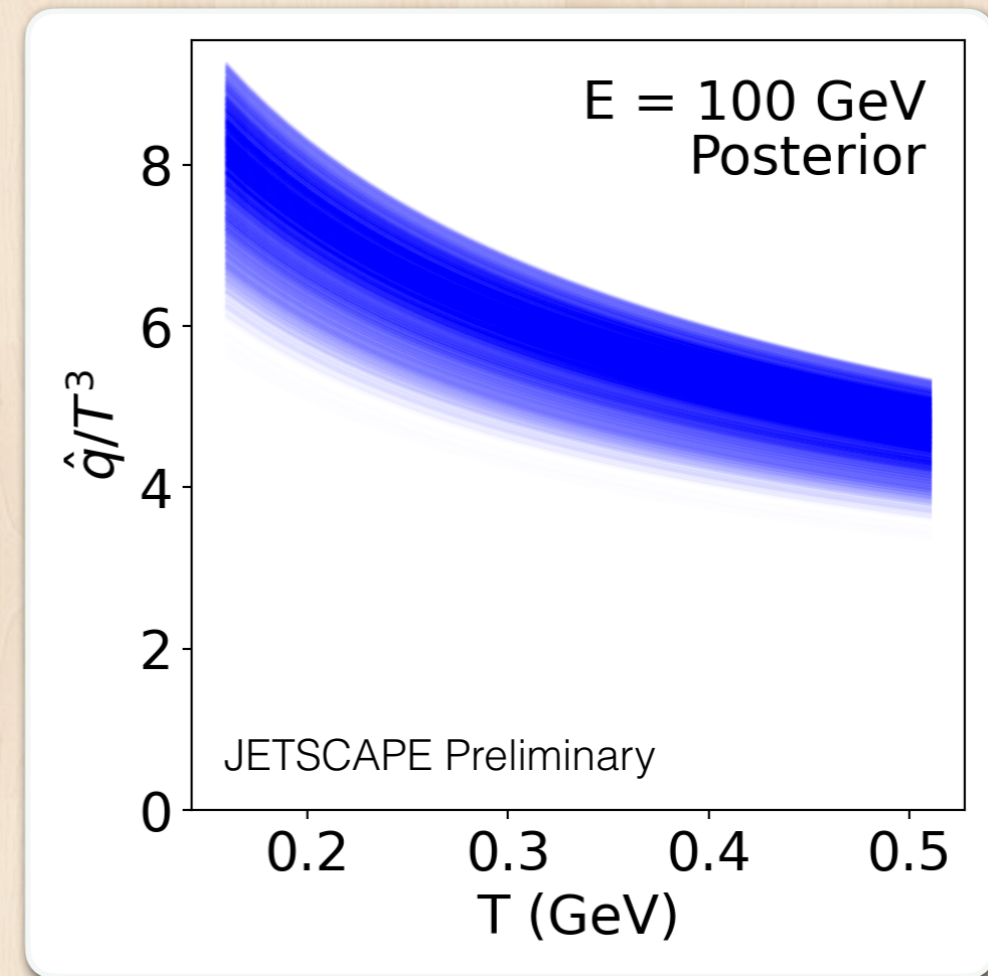


How can we gain
more insight?

\hat{q} : jets vs hadrons

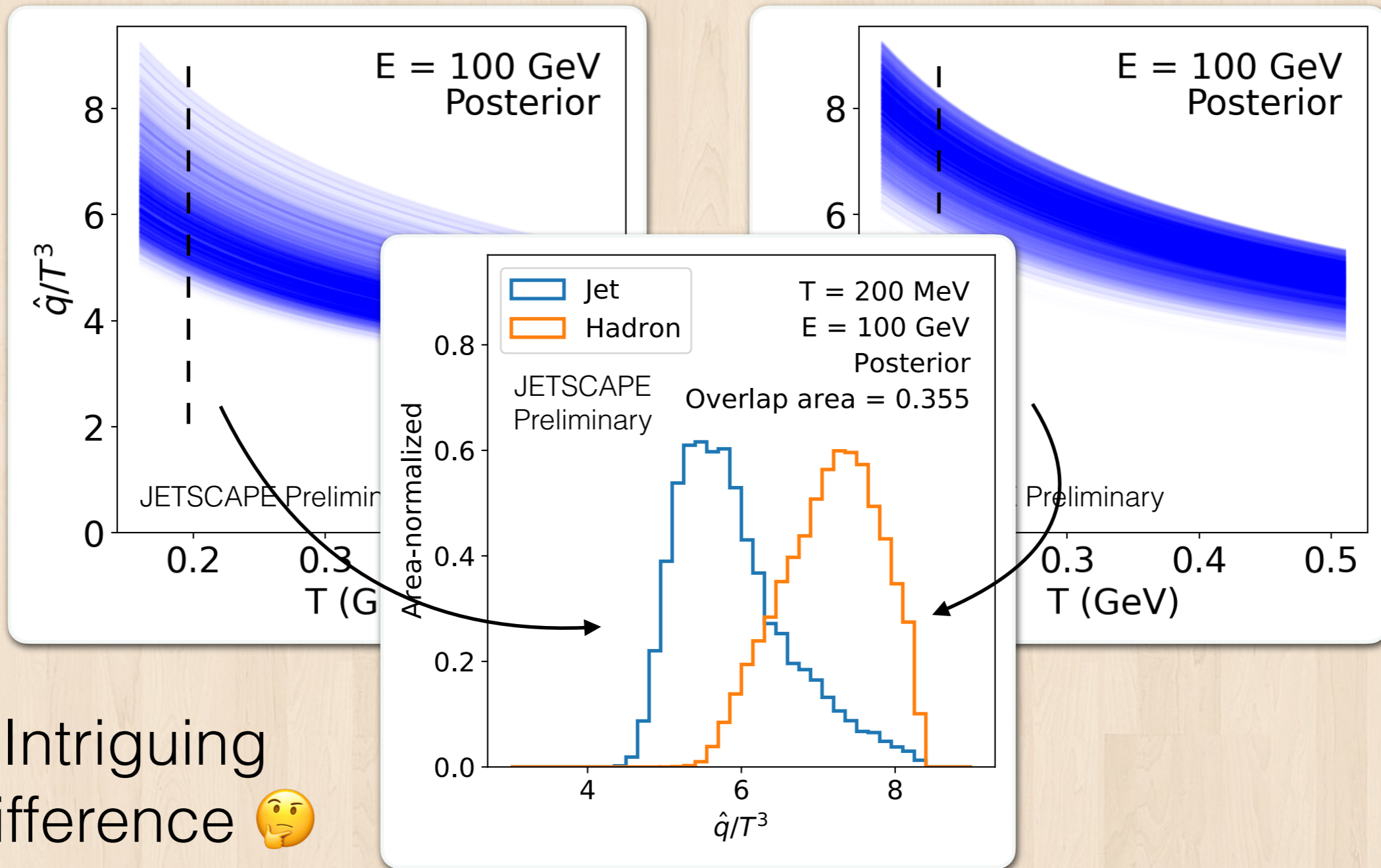


If we do analysis
with only jet data



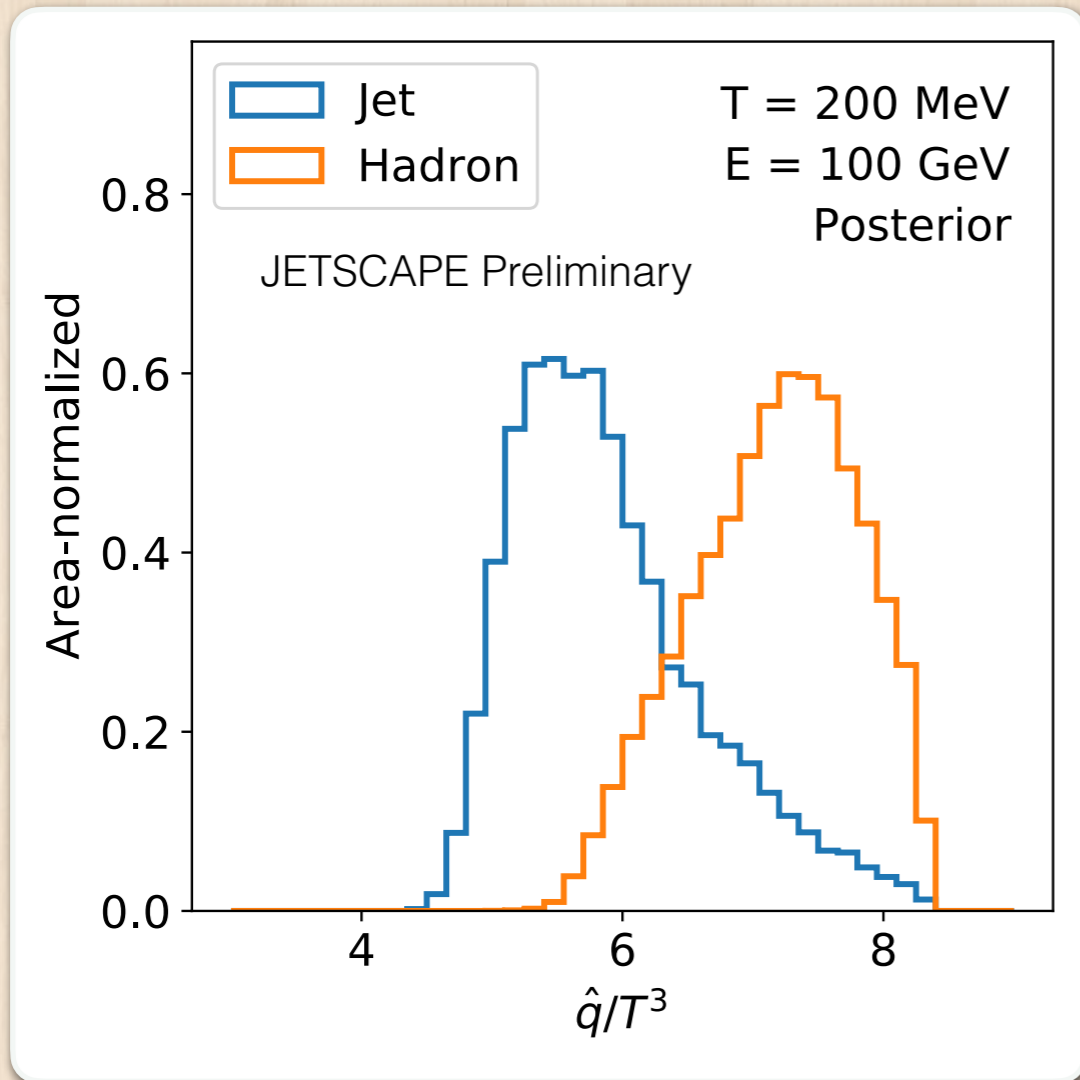
If we do analysis with
only hadron data

\hat{q} : jets vs hadrons

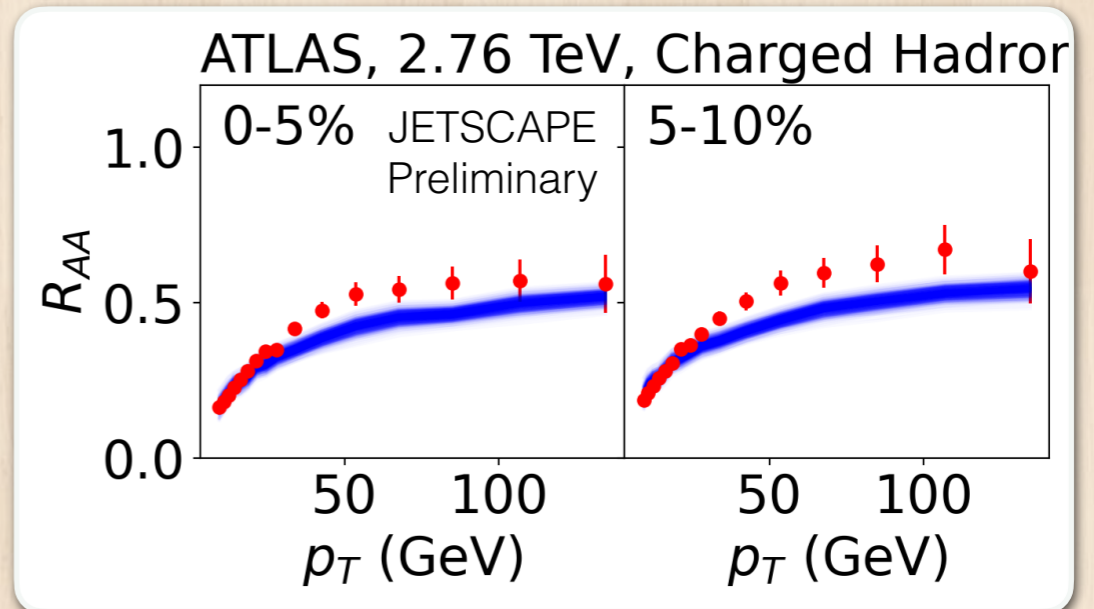


Intriguing
difference 🤔

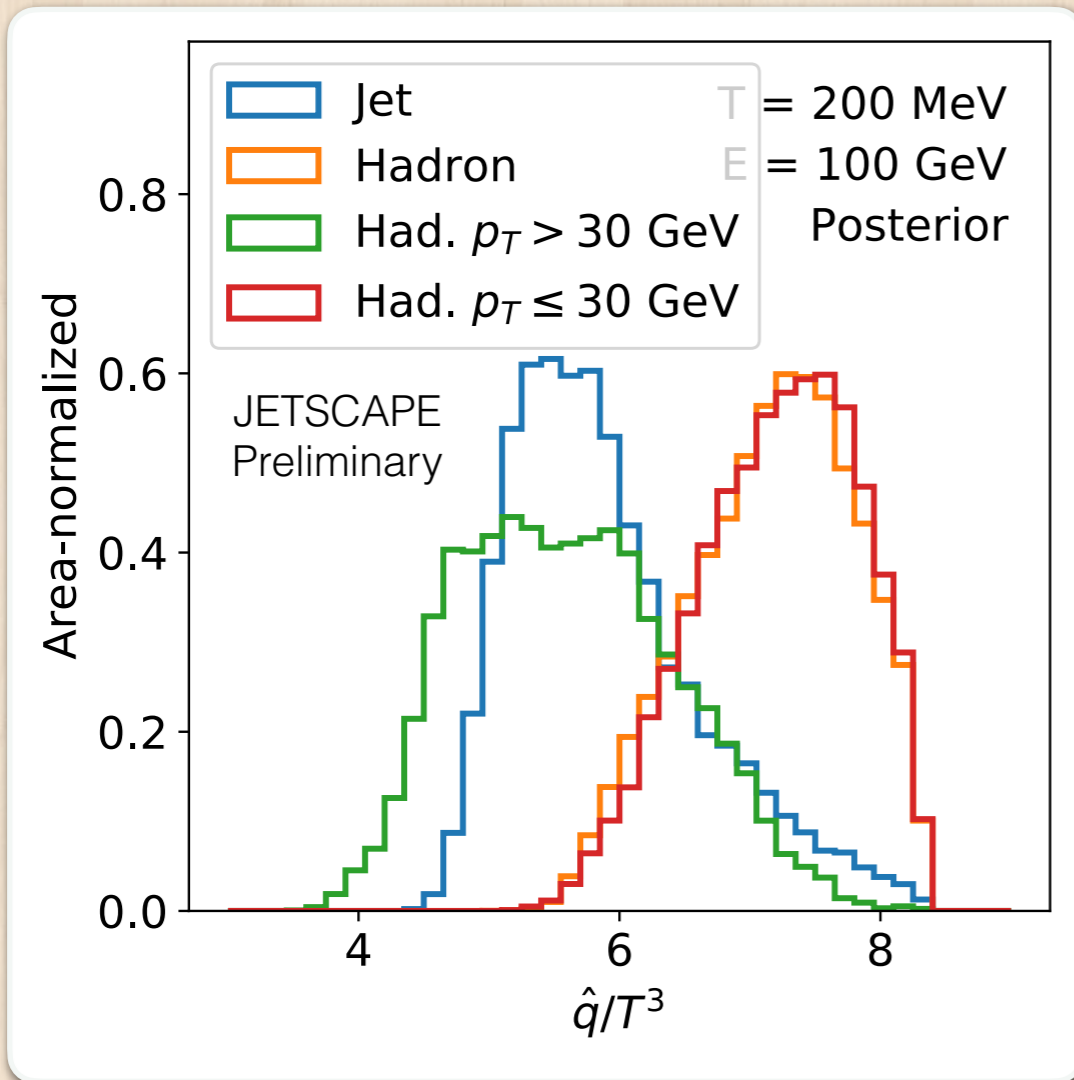
Hadrons, high vs low



Full p_T range

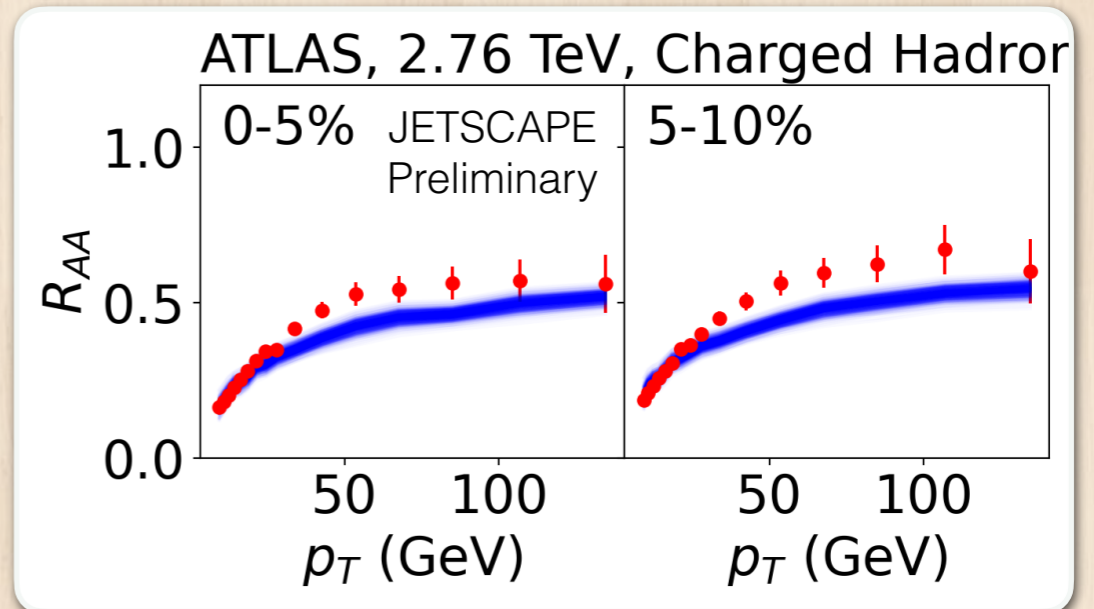


Hadrons, high vs low

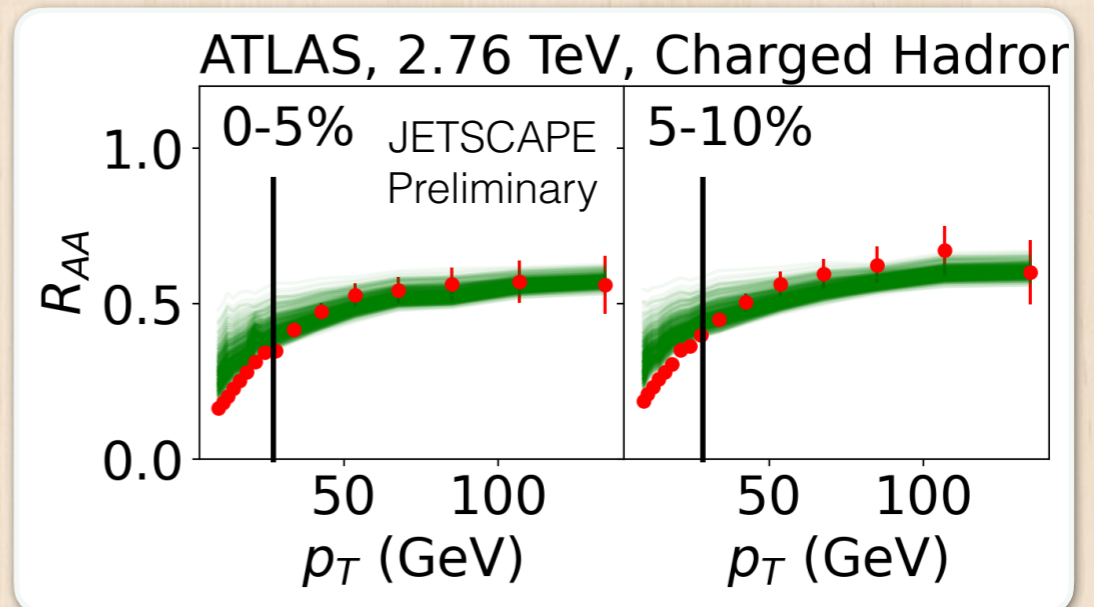


By eye green seems "better"!

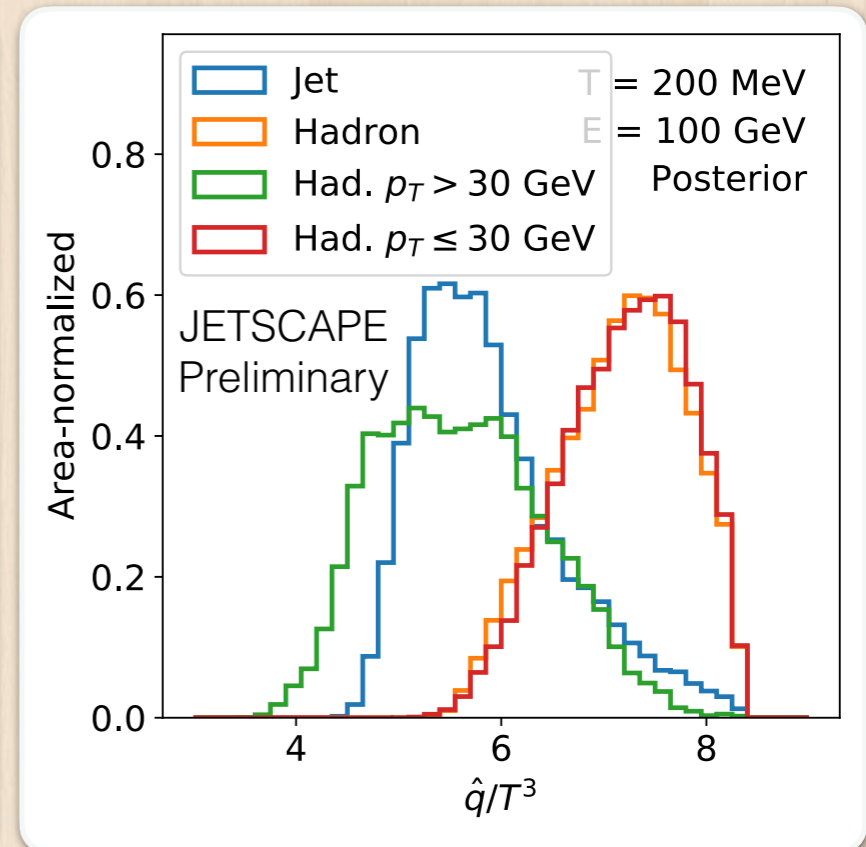
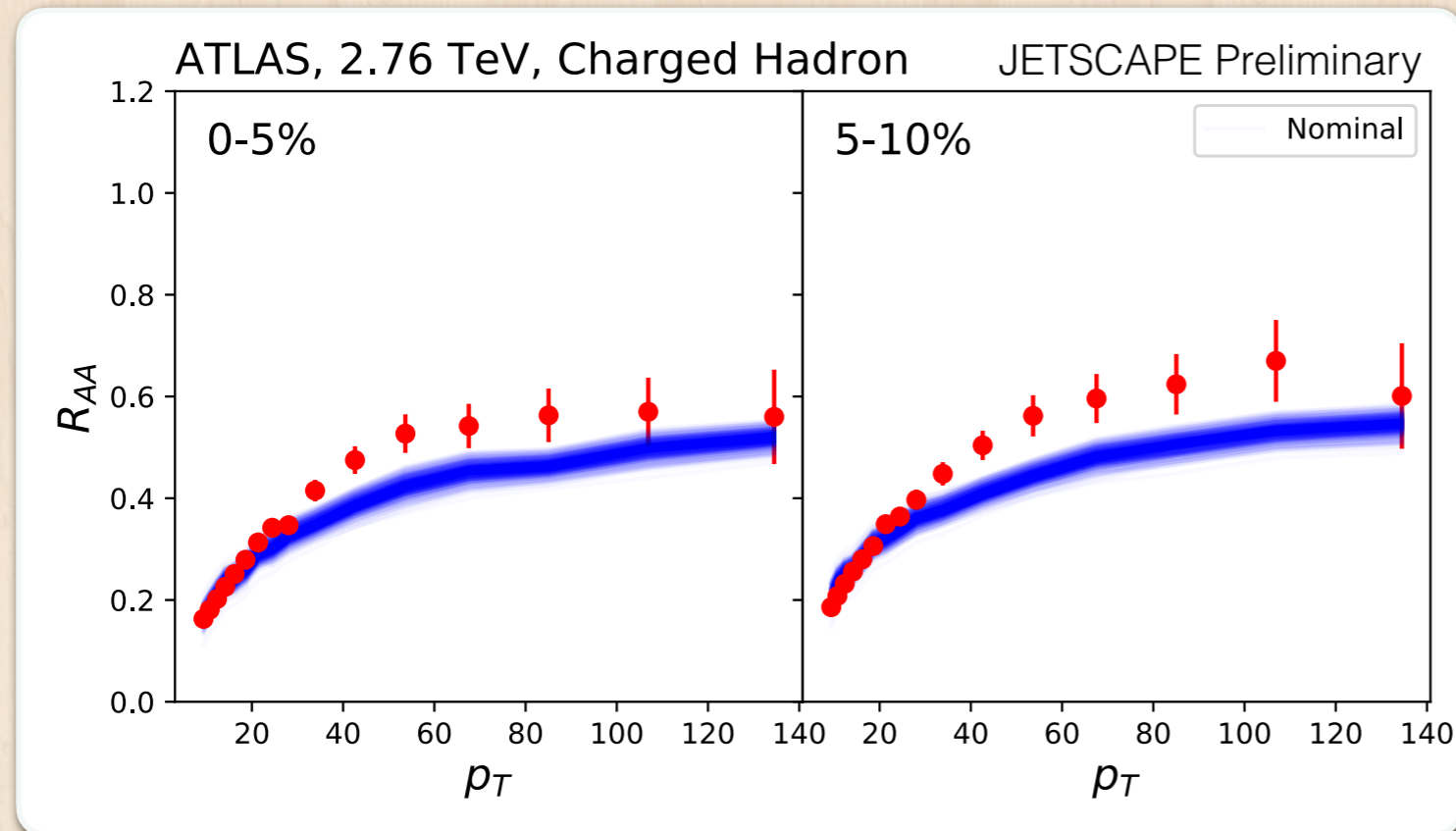
Full p_T range



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



What's happening?



Low p_T part dominates: small experimental uncertainty

High p_T part in line with jet data

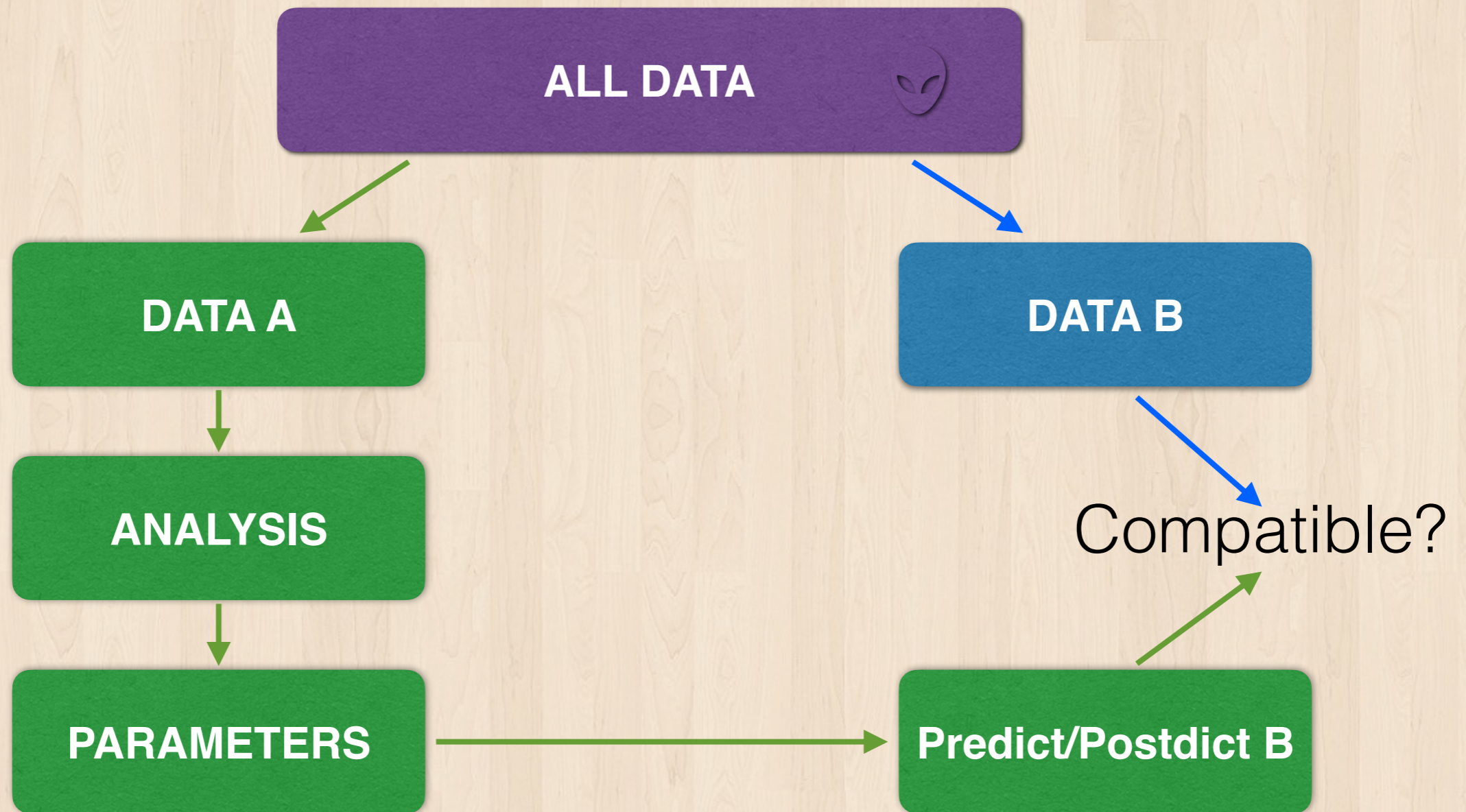
Points clearly to phase space for model improvement

Theory uncertainty is important

Implications

- We can **scrutinize** the specific **model** used in this round of simulations in great detail
 - Low vs high p_T , central vs peripheral, jet vs hadron, different radii jet, and so on
 - Future: **more models needed!**
- Isolate regions of interest
- Important feedback to models
- Points to interesting question: **theory uncertainties?**

A way to quantify compatibility



Explore how well model performs with new data

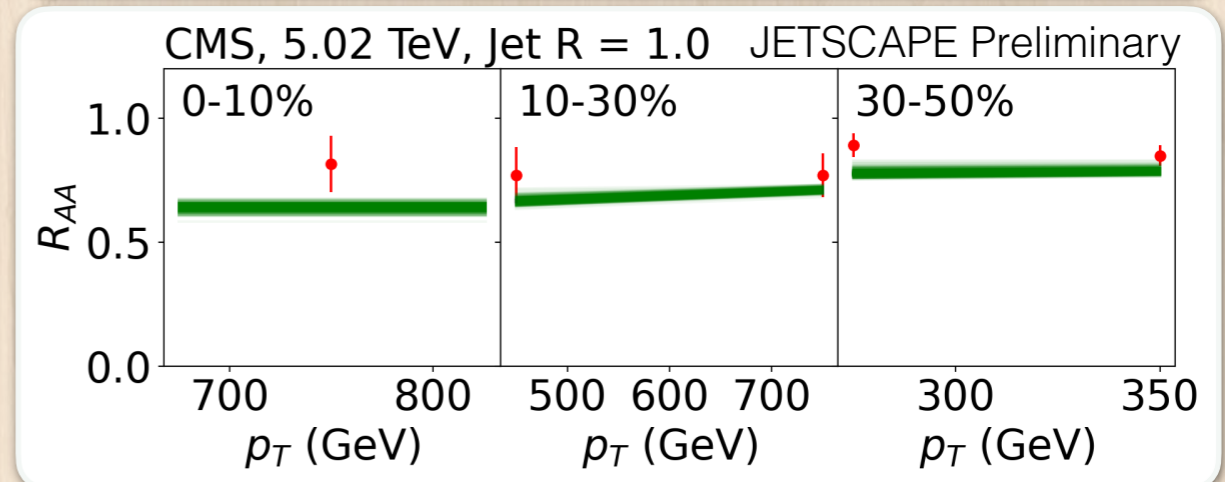
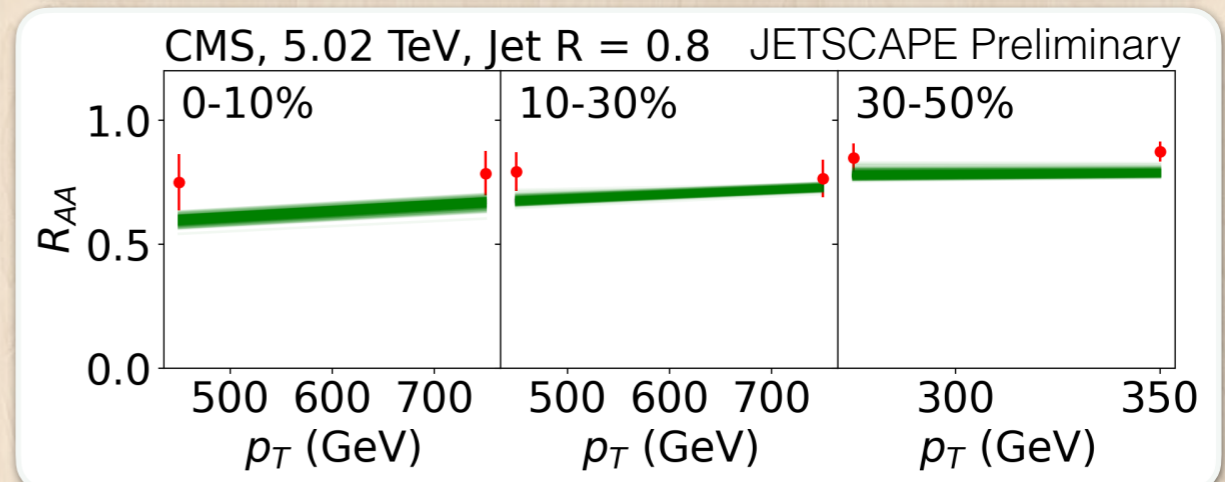
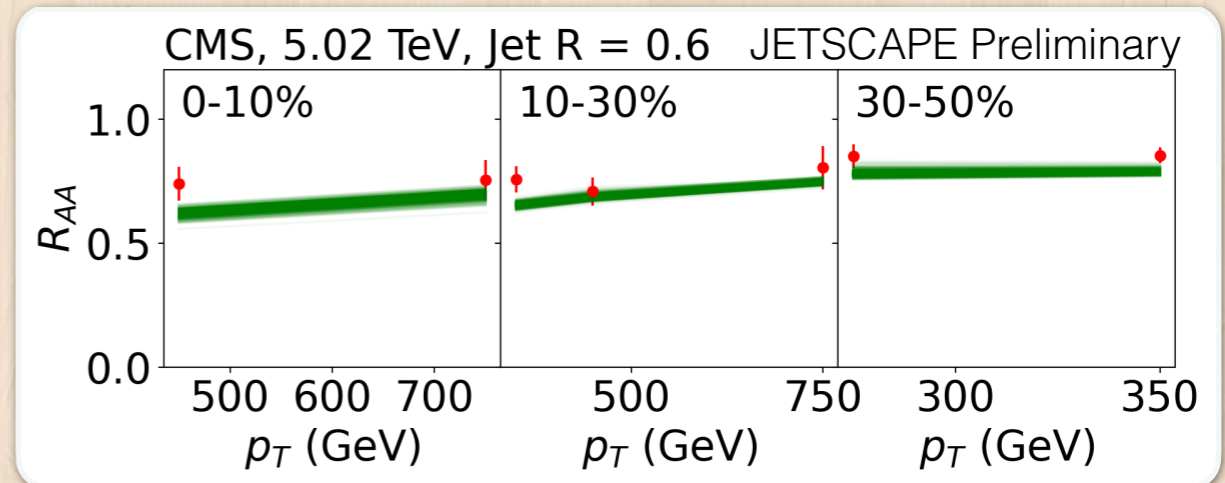
Example: small vs large radii

A: hadron & small jet data

B: large jet data

Reasonable agreement

Uncertainty correlation

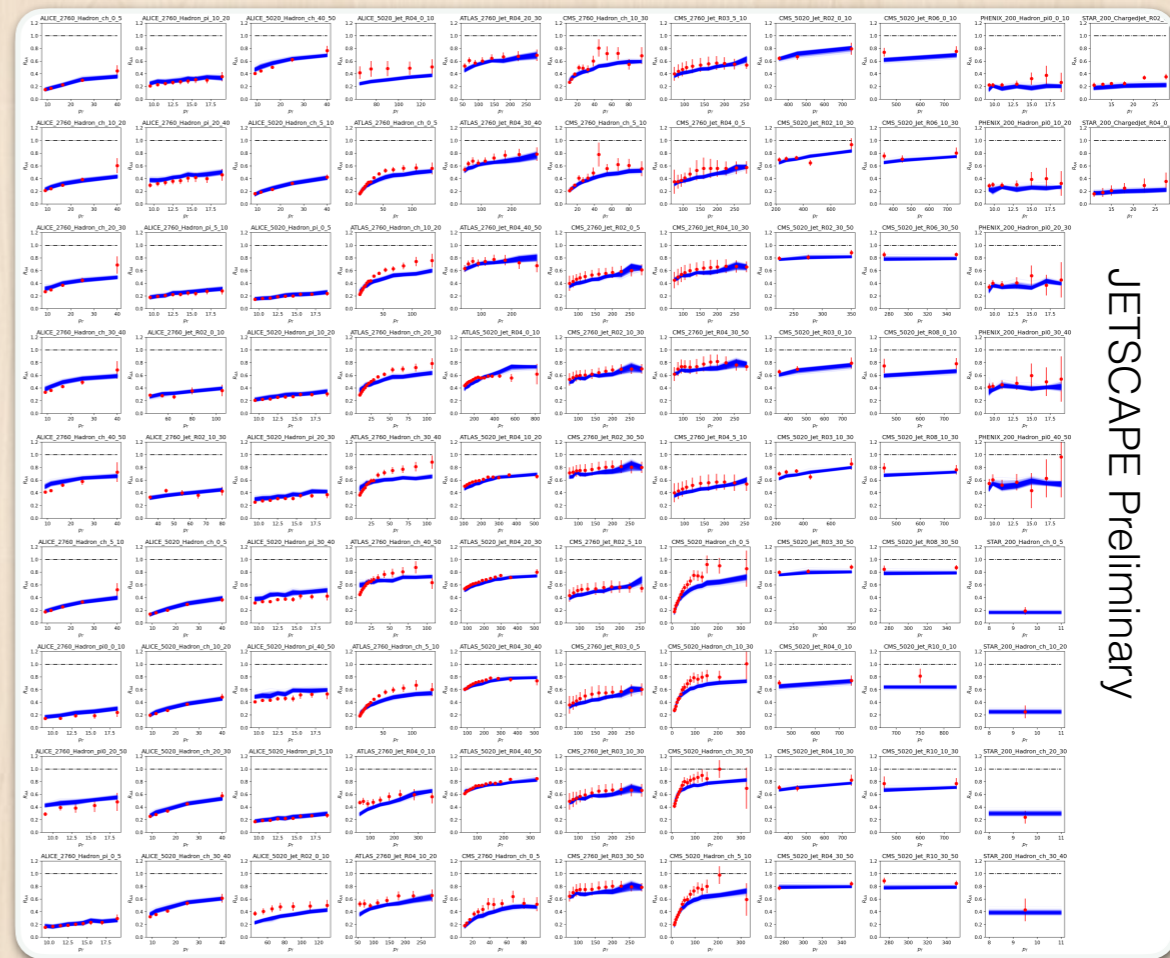
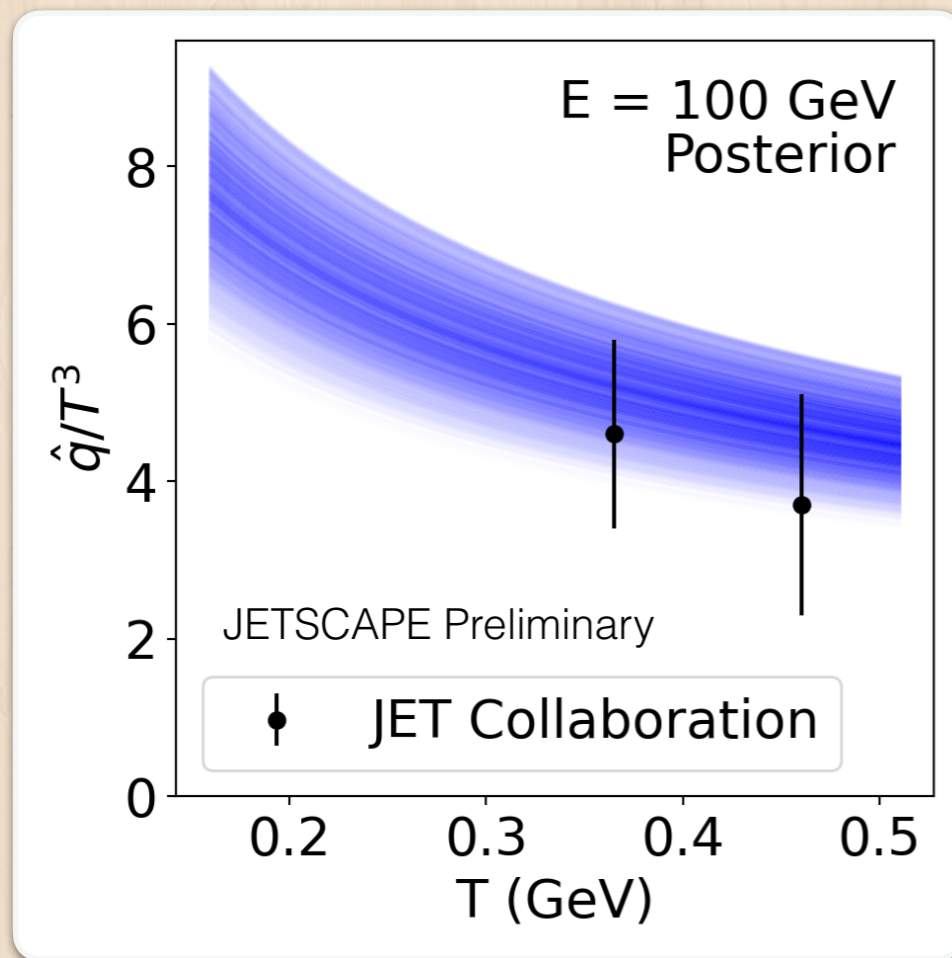


Concluding remarks

New analysis of \hat{q}

Included jet R_{AA} into the mix!

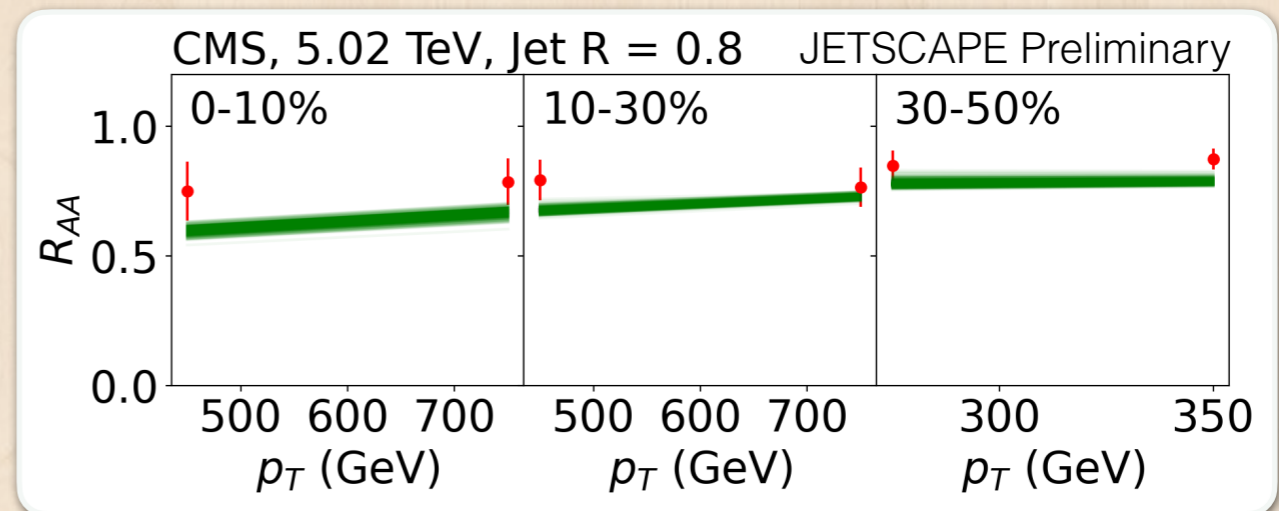
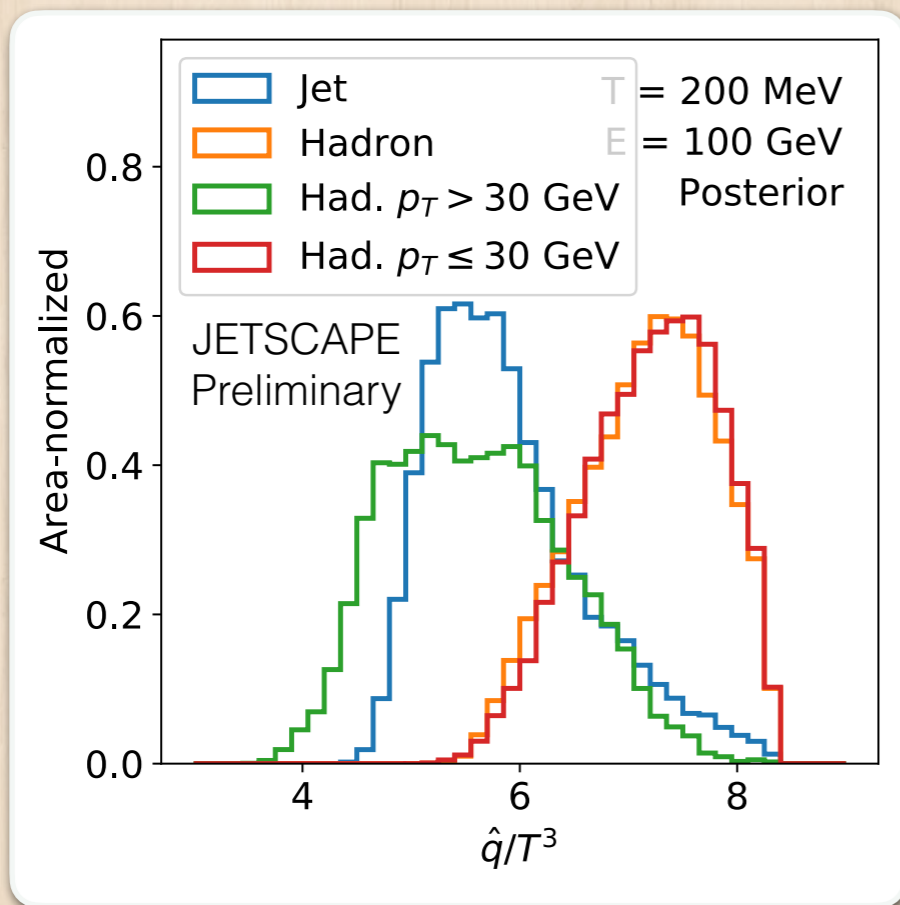
General reasonable description of data



All these impossible without a framework

Endless possibilities

Bayesian analysis: powerful tool for not only **parameter extraction** but also **model studies**



Pinpoint interesting phase space in model

Evaluate how well model does in new observables

Theory uncertainties?

(Near-) future prospects

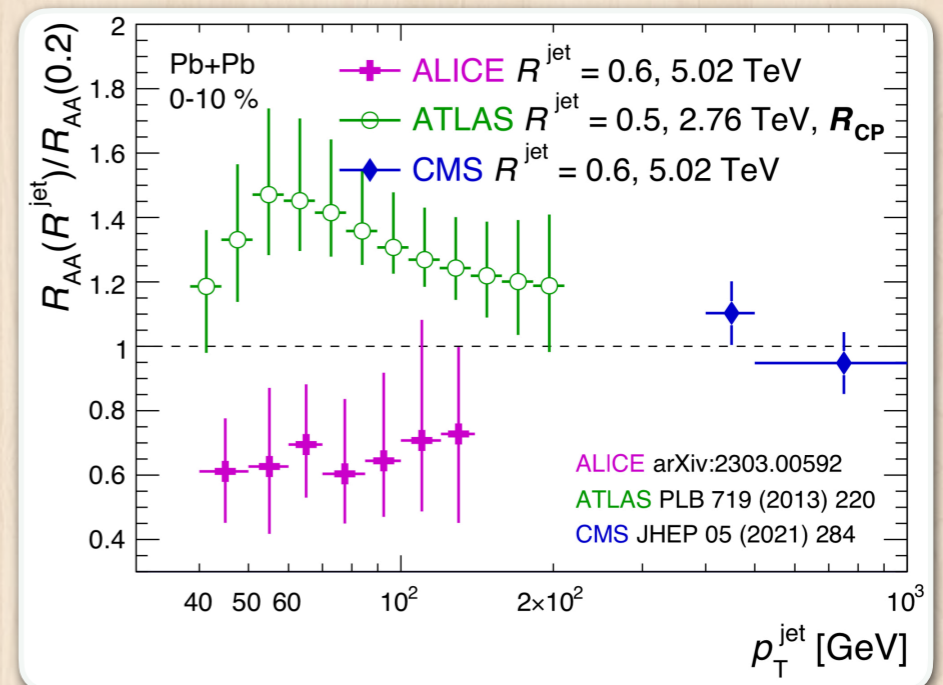
We also calculated huge number of **other jet-related observables**

Move one step at a time and **sequentially include more observables** →

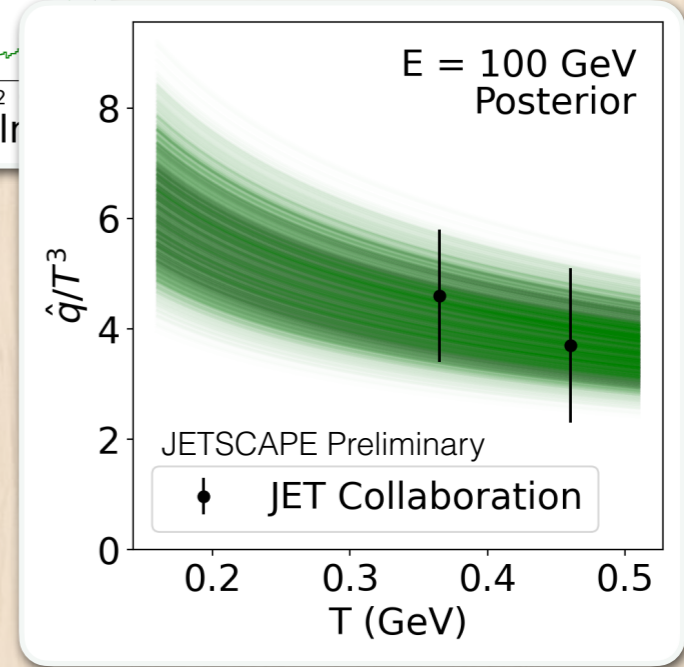
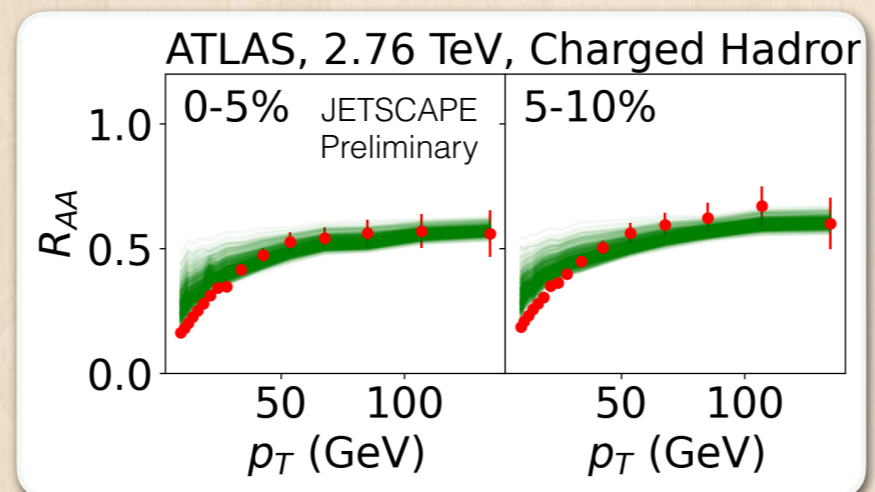
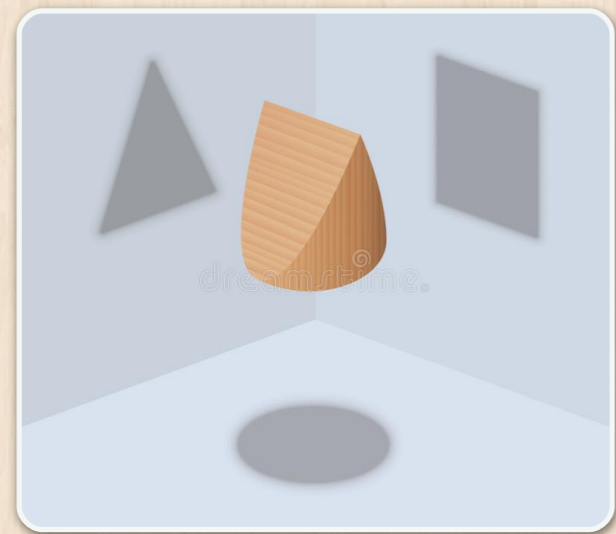
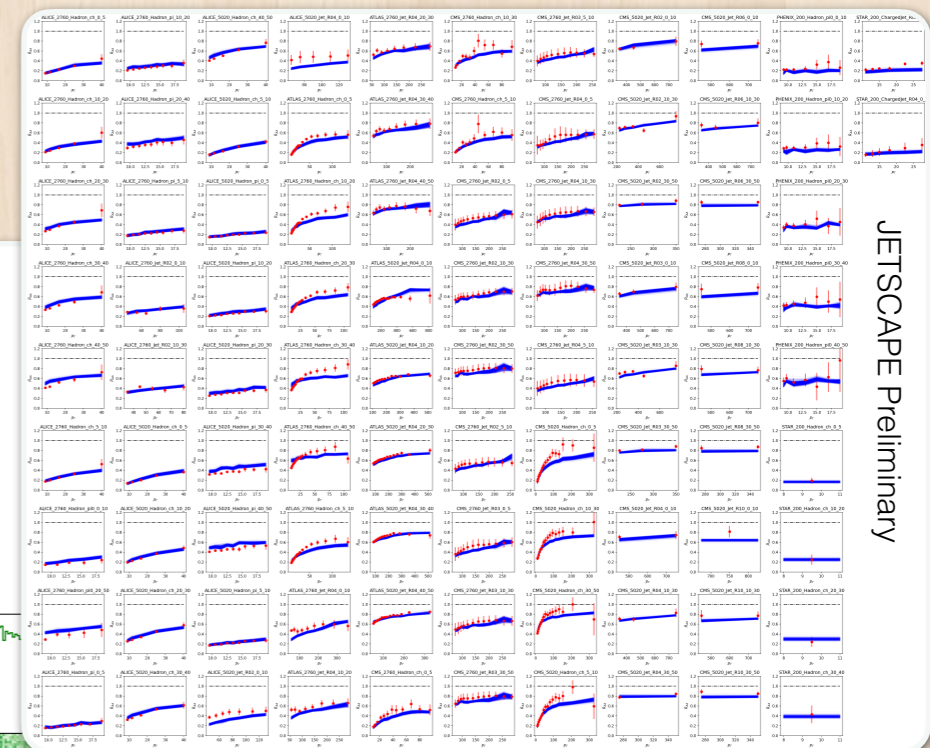
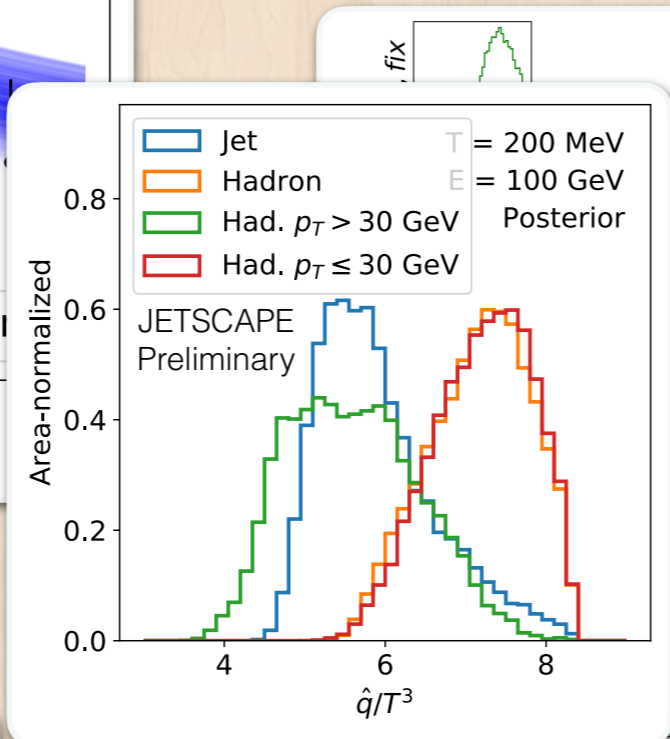
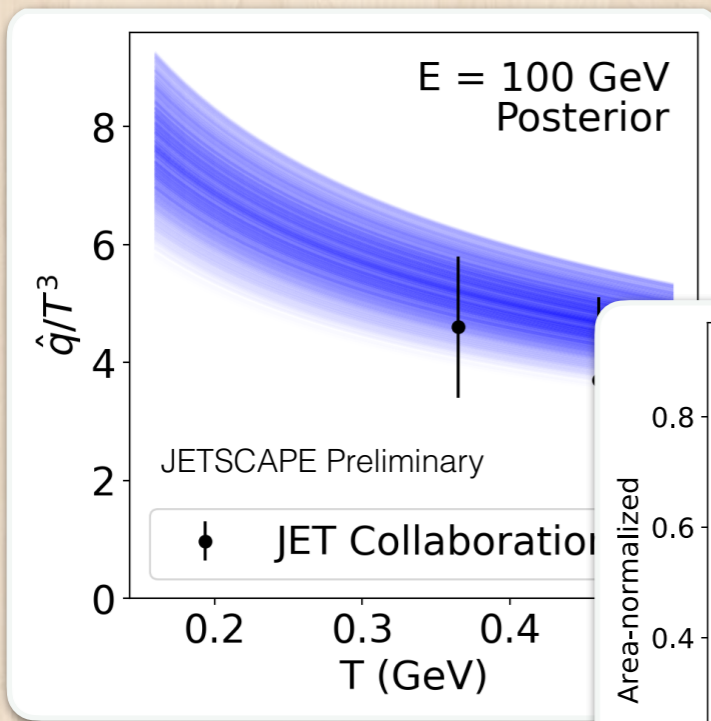
stay tuned for many new results in the near future!

Ready to explore the theory / experimental landscape

Plot taken from Y. Go, Mon Mar 27

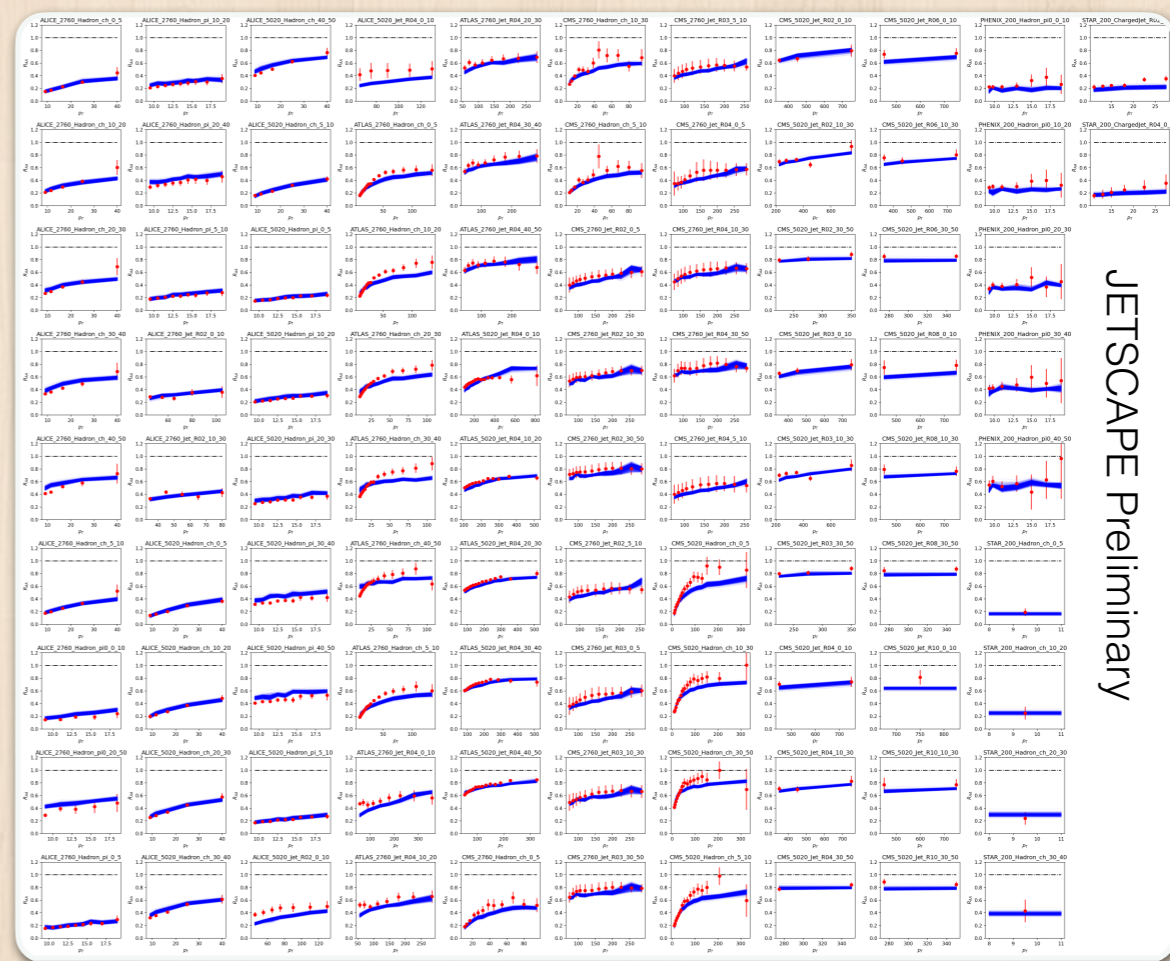
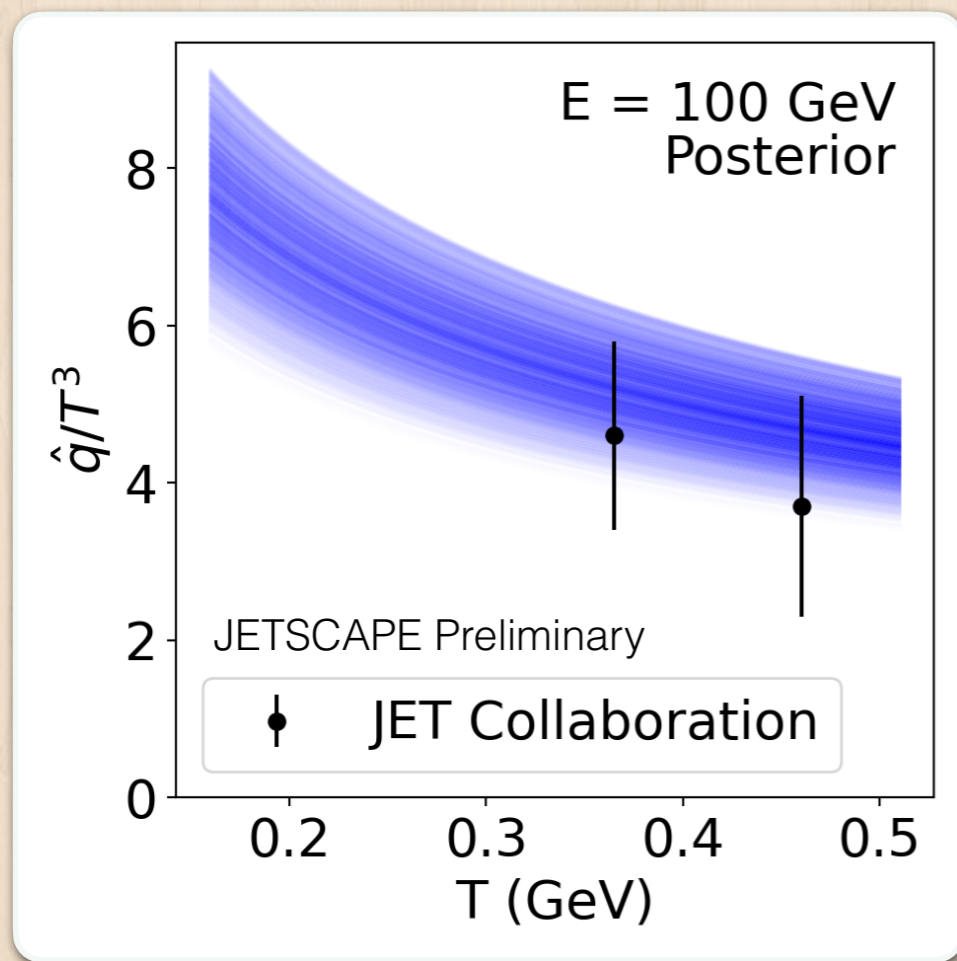


Important to include ALL eligible data

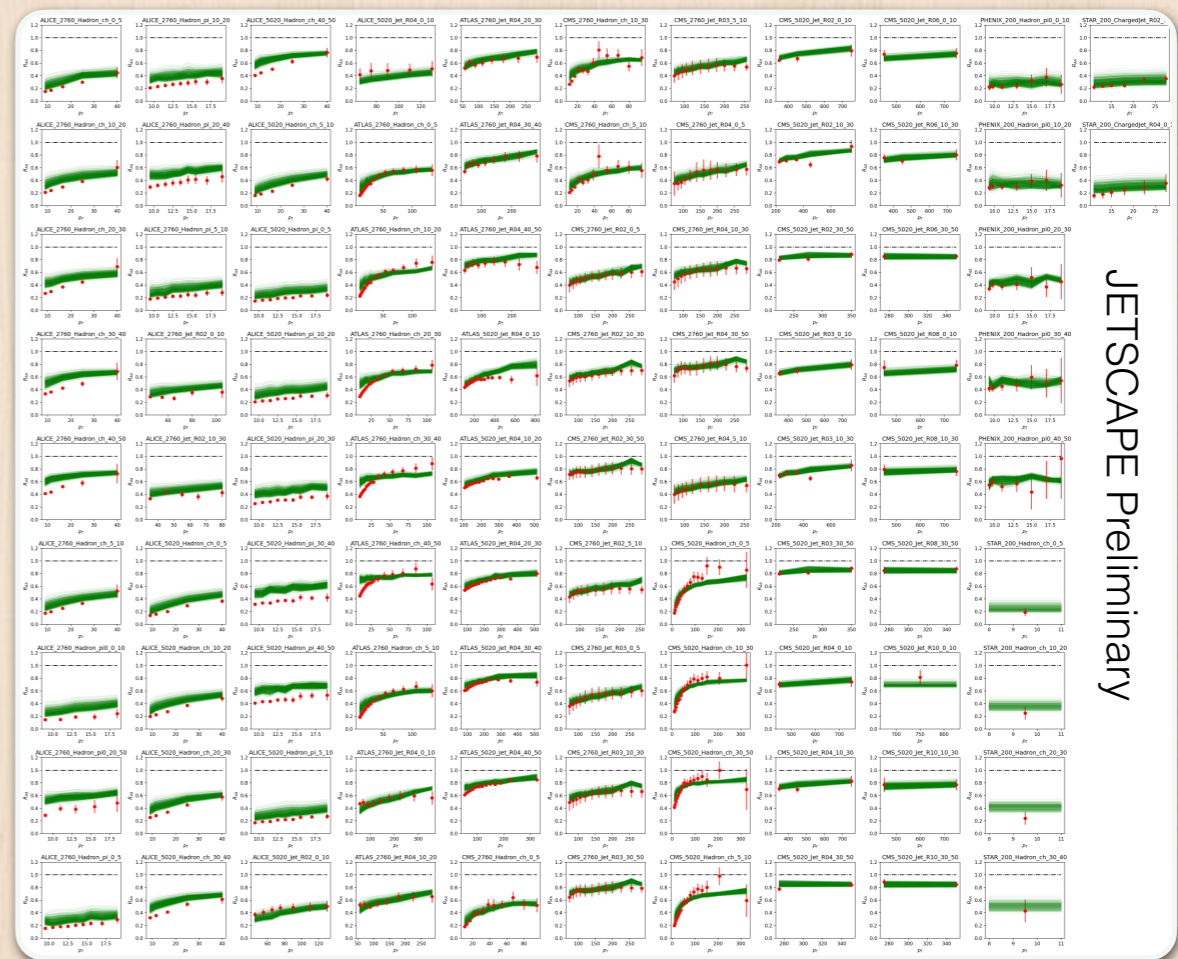
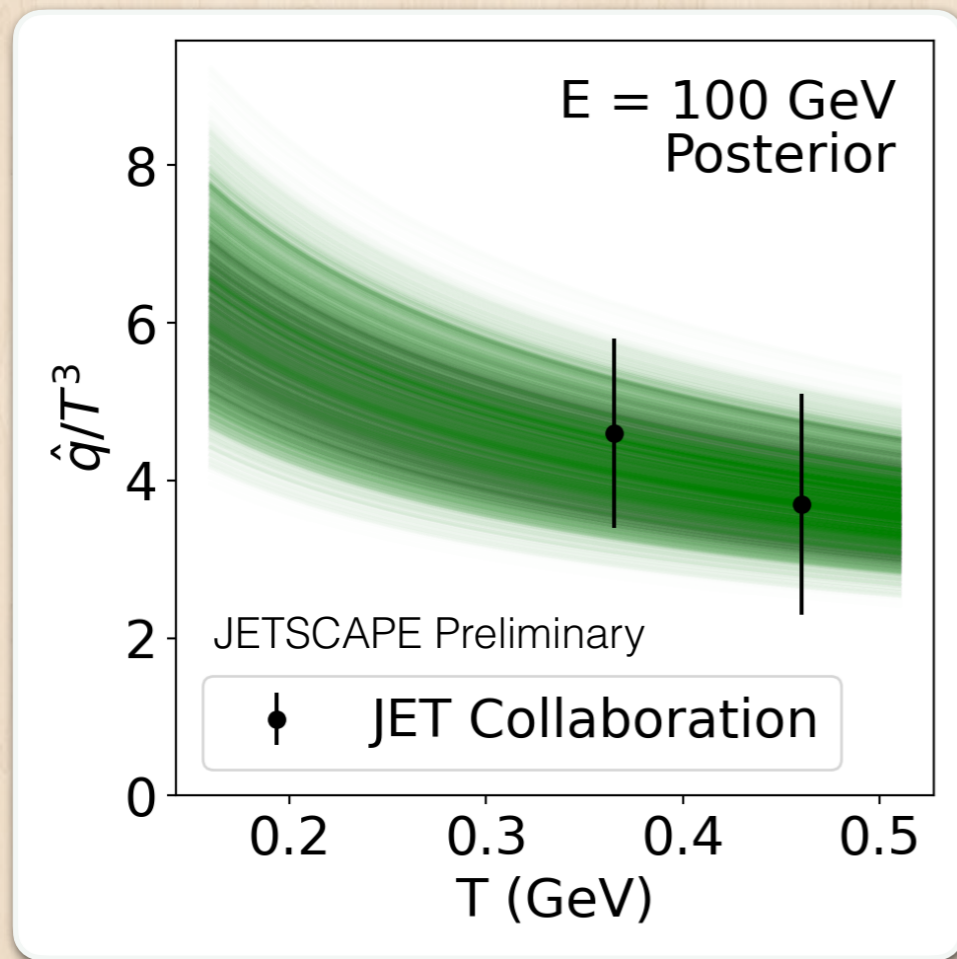


Backup Slides Ahead

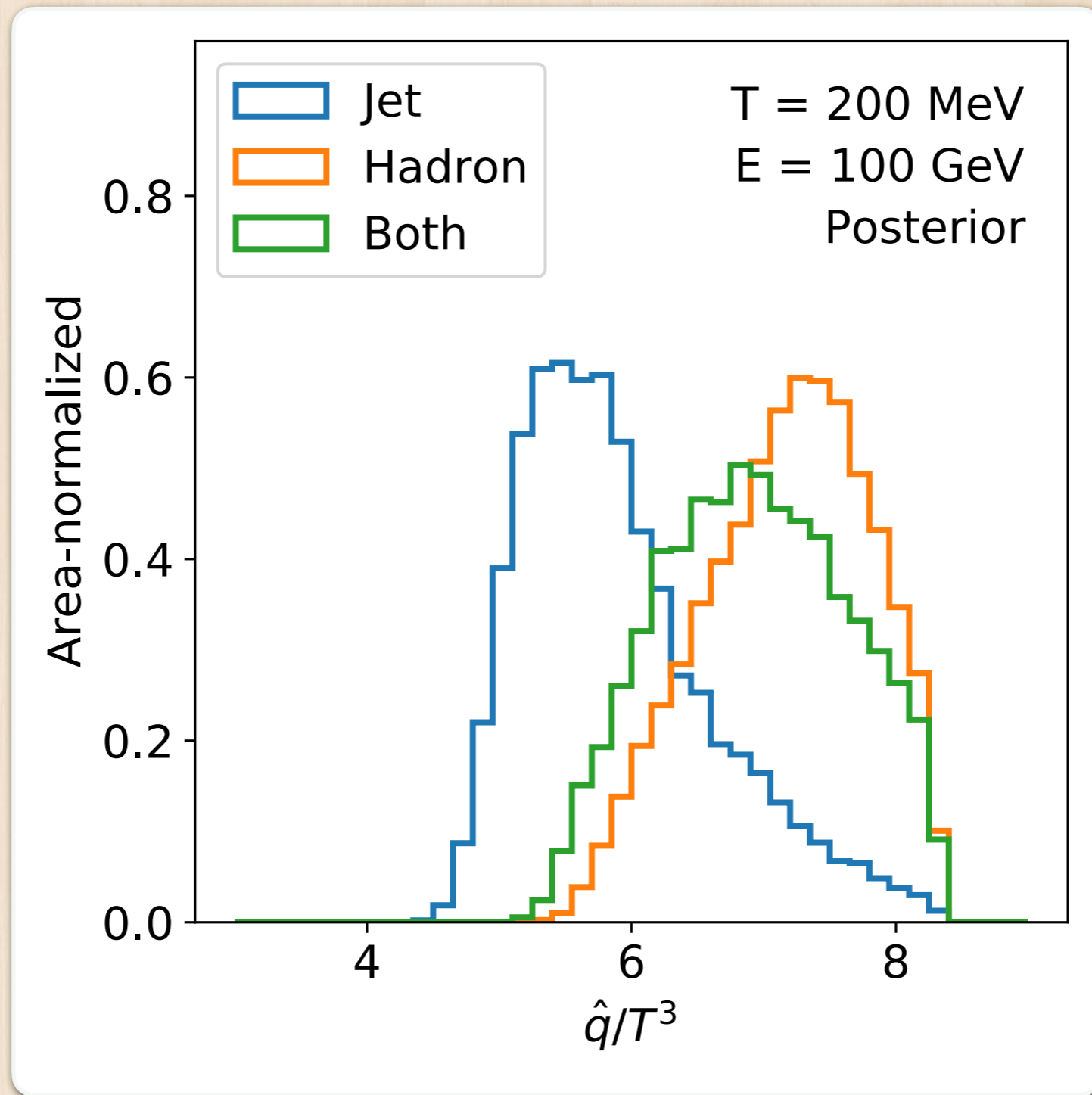
Nominal \hat{q}



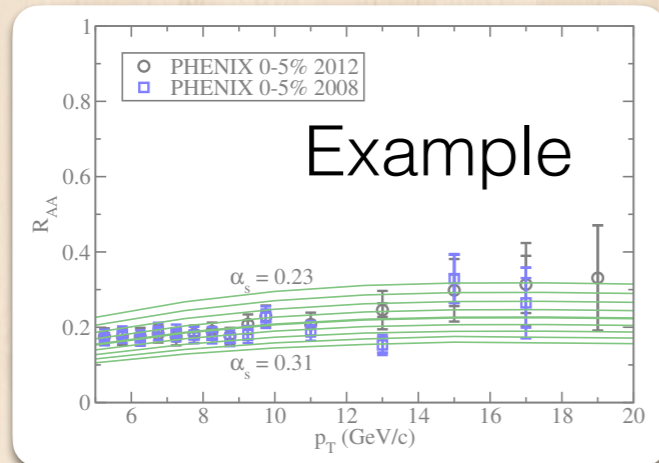
\hat{q} with hadron $p_T > 30$ GeV



Jet vs hadron vs both

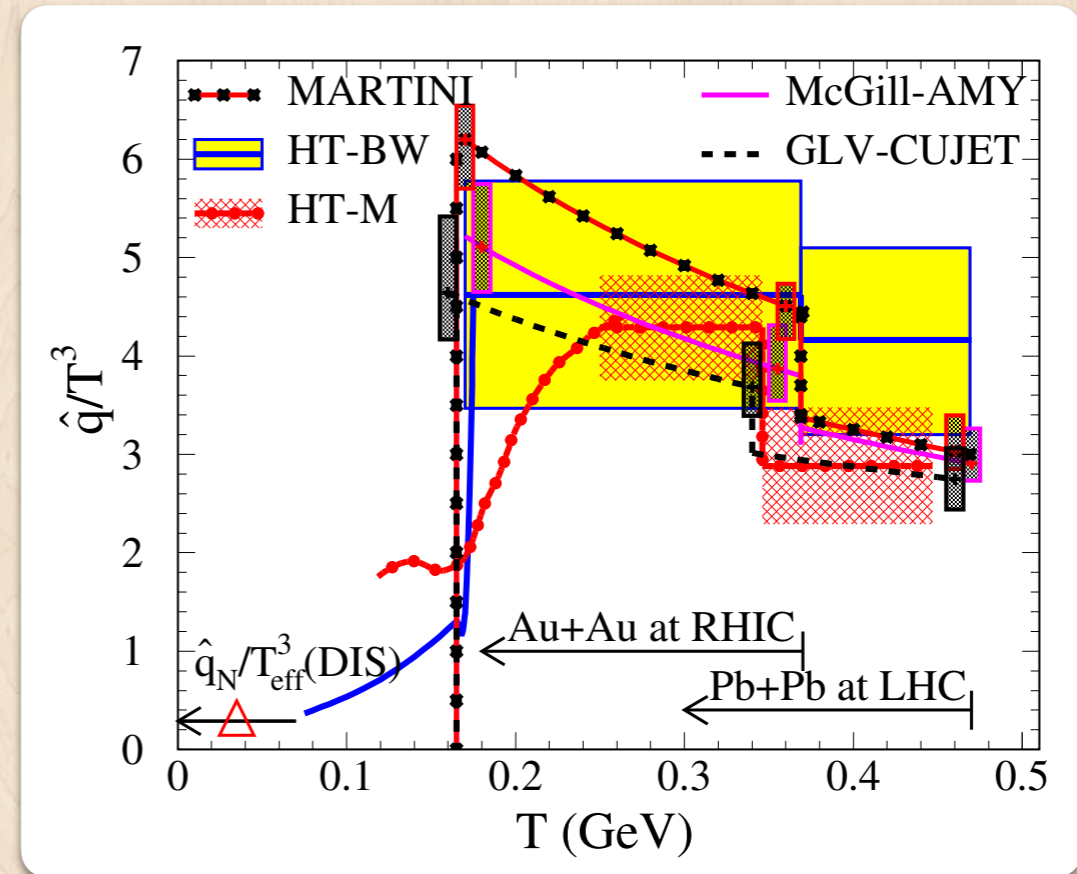


JET collaboration result



R_{AA} Data

Separate analyses
to RHIC and LHC
data from a variety
of models



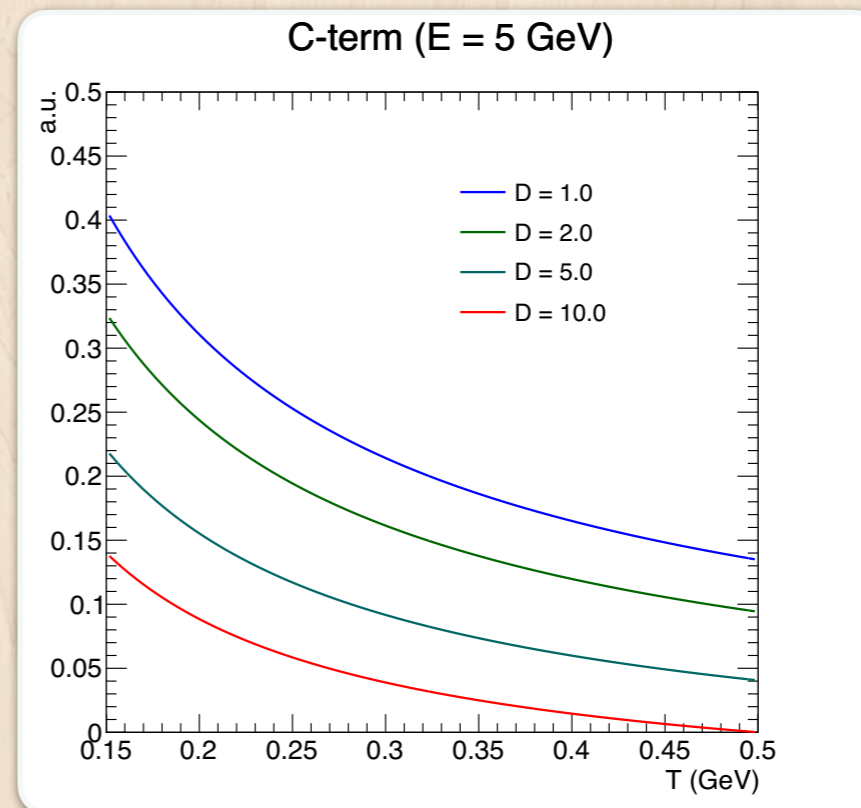
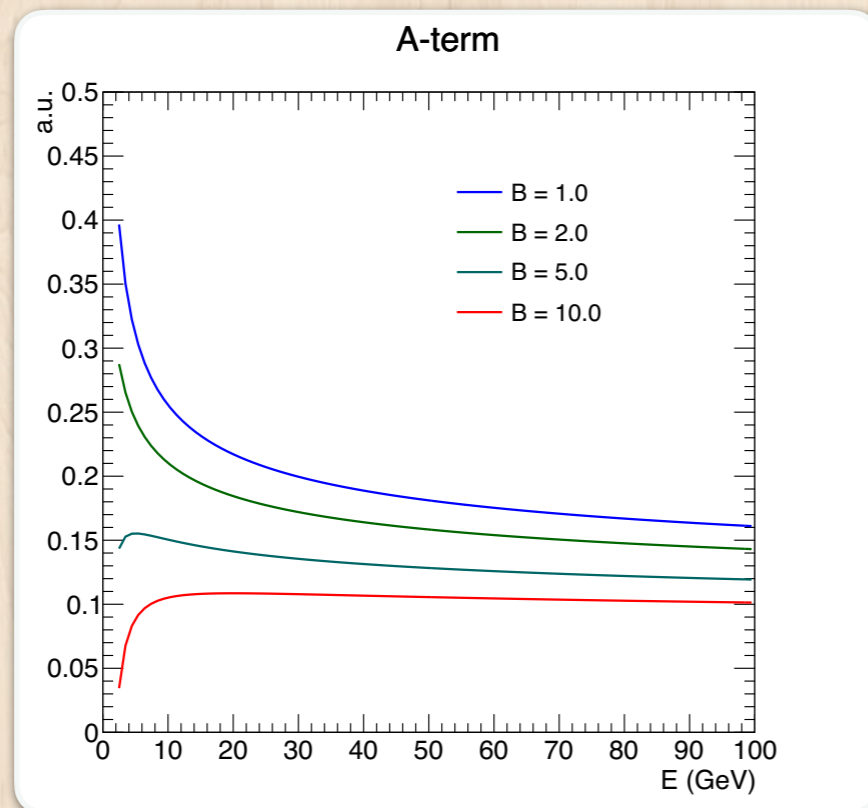
Taking it one step further

Previous iteration of \hat{q}

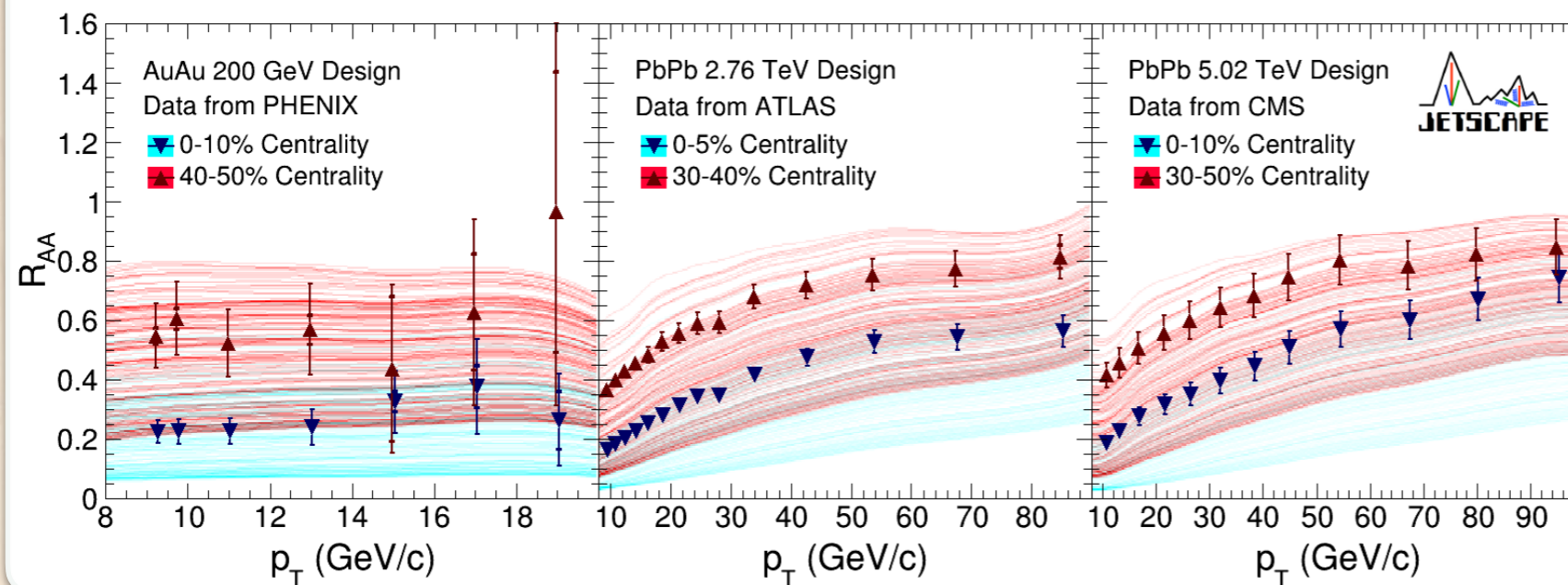
$$\frac{\hat{q}}{T^3} \propto A \frac{\ln(E/\Lambda) - \ln(B)}{\ln^2(E/\Lambda)} + C \frac{\ln(E/T) - \ln(D)}{\ln^2(ET/\Lambda^2)}$$

MATTER-inspired term

LBT-inspired term

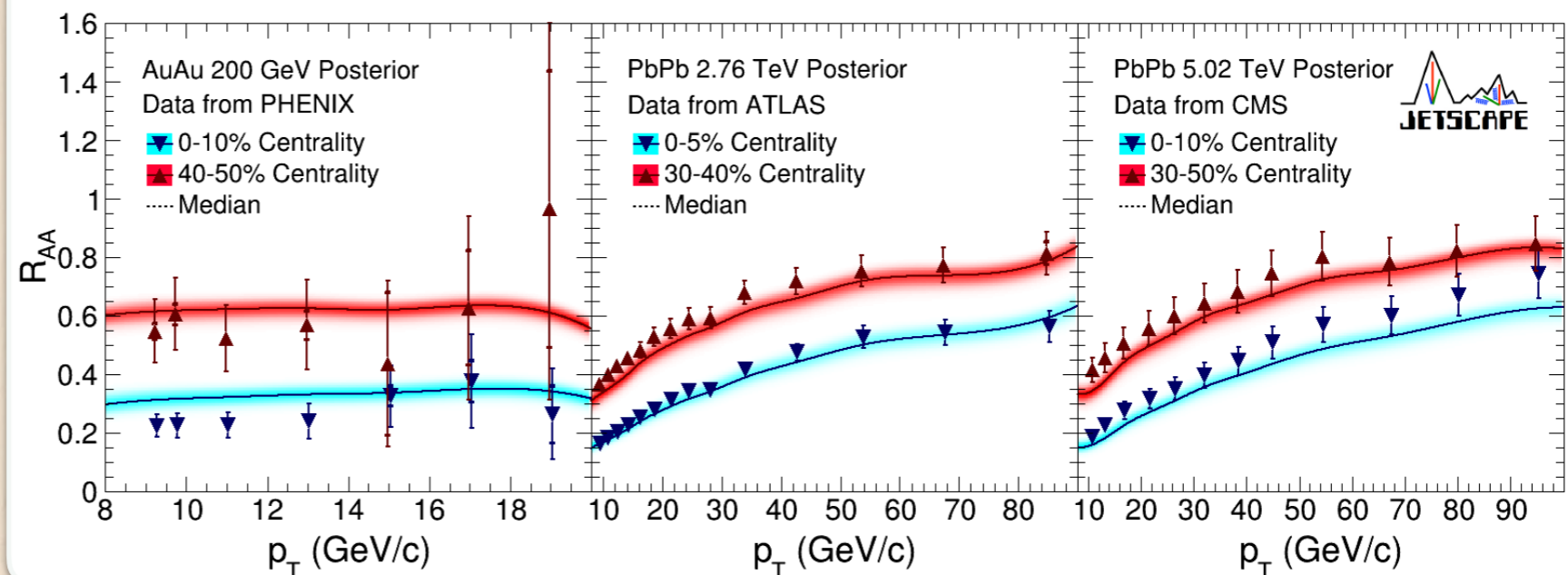


Previous iteration of \hat{q}

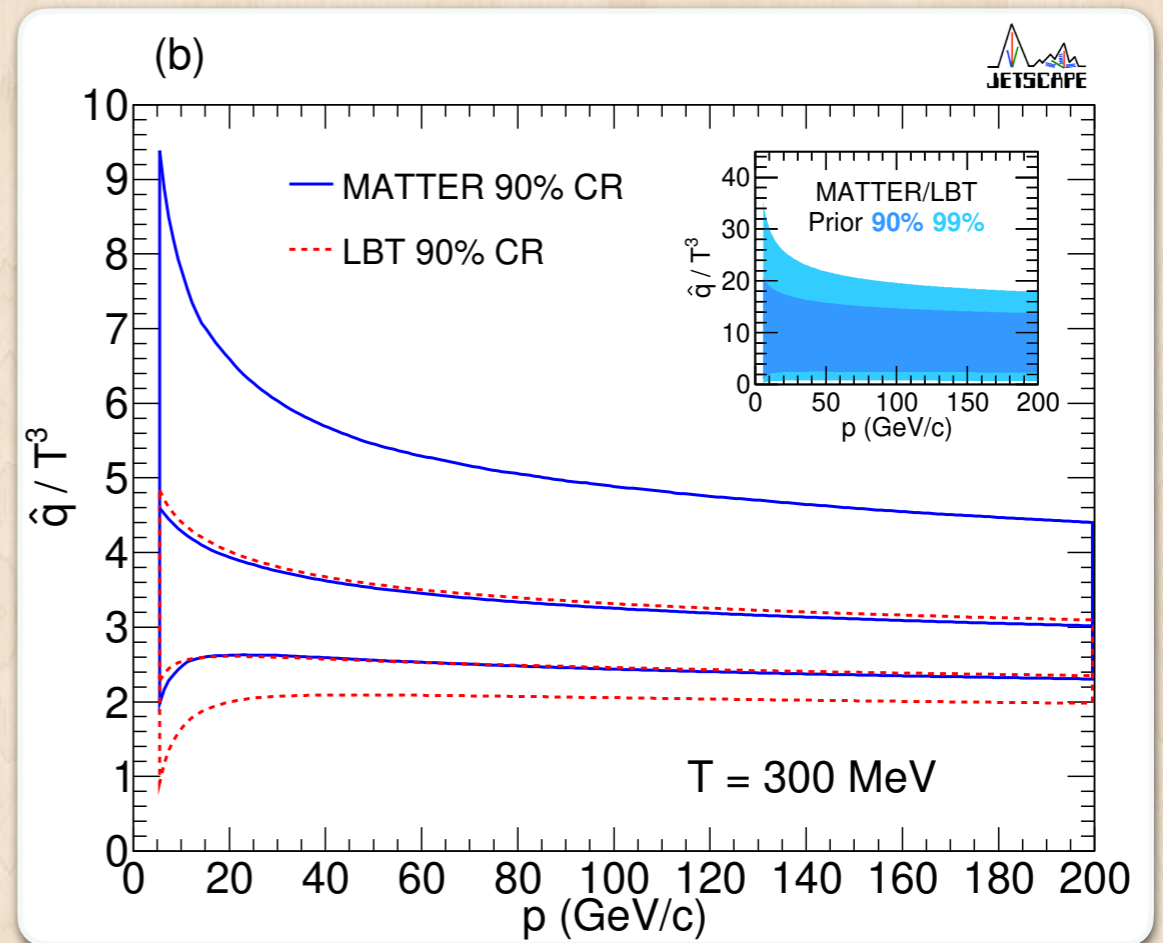
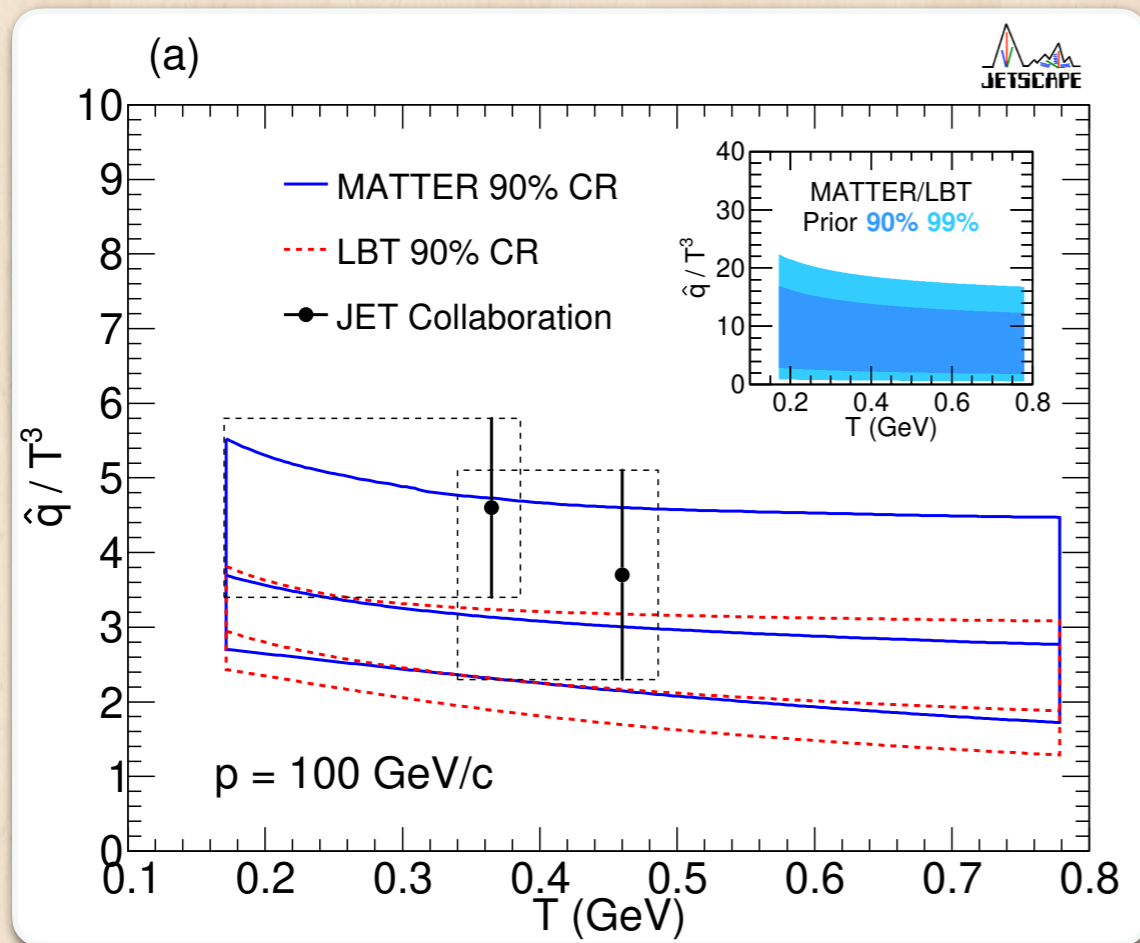


Before data
is used

After using
data



Previous iteration of \hat{q}



Compatible with JET collaboration results

Prior range \gg posterior range

Effect of $f(Q^2)$

- Type-1: HTL \hat{q} with fixed coupling (applies for any Q^2),

$$\hat{q} \equiv \hat{q}_{\text{HTL}}^{\text{fix}} = C_a \frac{50.484}{\pi} \alpha_s^{\text{fix}} \alpha_s^{\text{fix}} T^3 \ln \left[\frac{2ET}{m_D^2} \right], \quad (24)$$

where $m_D^2 = 6\pi T^2 \alpha_s^{\text{fix}}$ is the Debye mass for $N_f = 3$ flavors.

- Type-2: HTL \hat{q} with running coupling (applies for any Q^2),

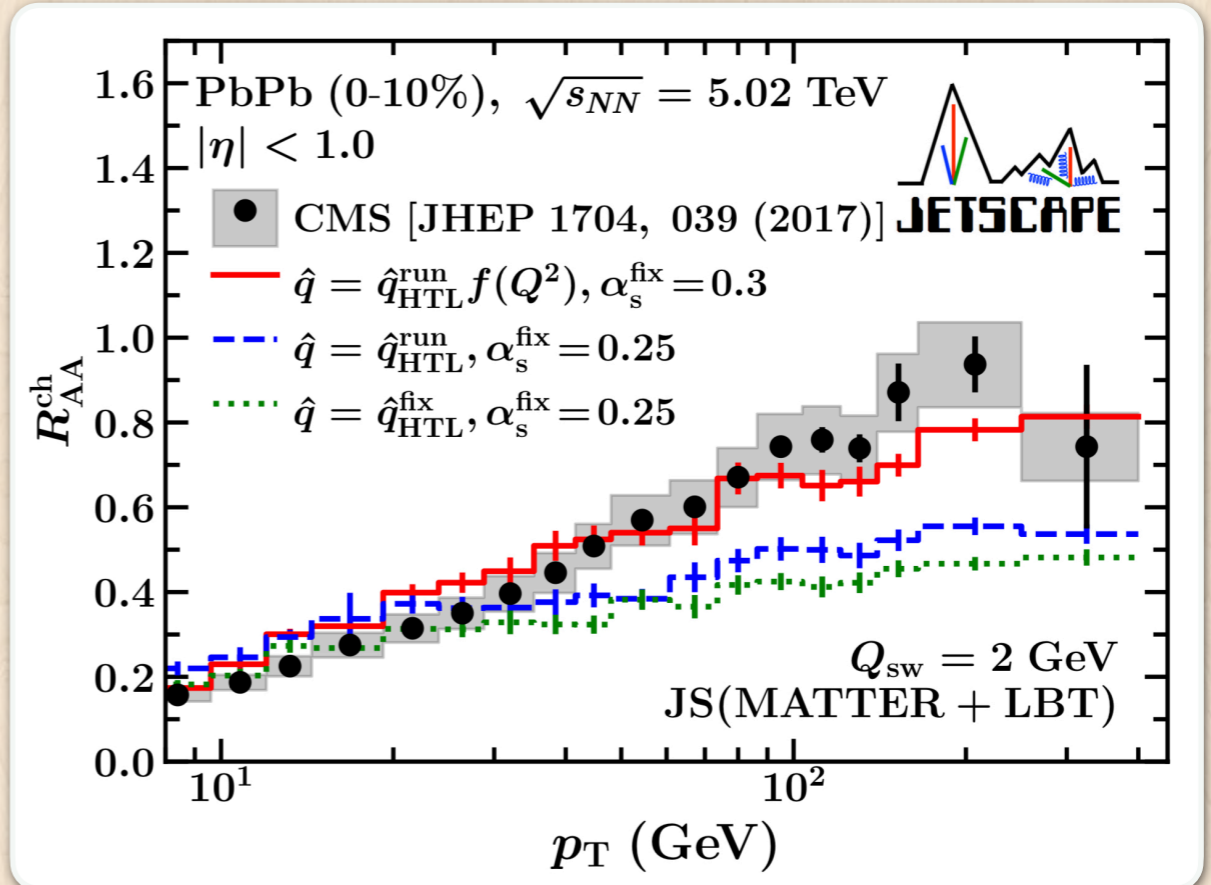
$$\hat{q} \equiv \hat{q}_{\text{HTL}}^{\text{run}} = C_a \frac{50.484}{\pi} \alpha_s^{\text{run}}(Q_{\text{max}}^2) \alpha_s^{\text{fix}} T^3 \ln \left[\frac{2ET}{m_D^2} \right], \quad (25)$$

where $Q_{\text{max}}^2 = 2ET$

- Type-3: HTL \hat{q} with a virtuality (Q^2) dependence factor

$$\hat{q} \cdot f \equiv \hat{q}_{\text{HTL}}^{\text{run}} f(Q^2) \quad (26)$$

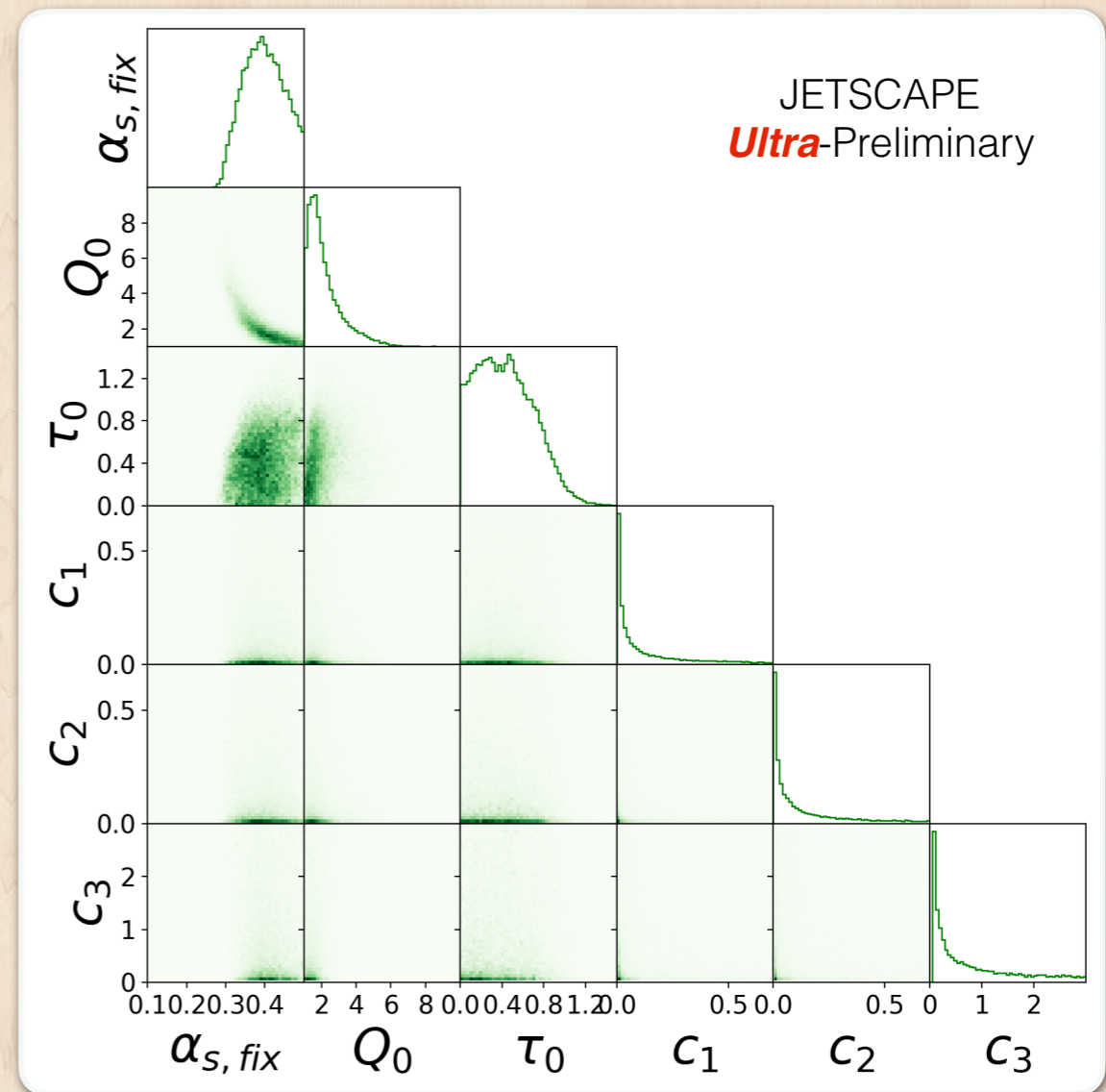
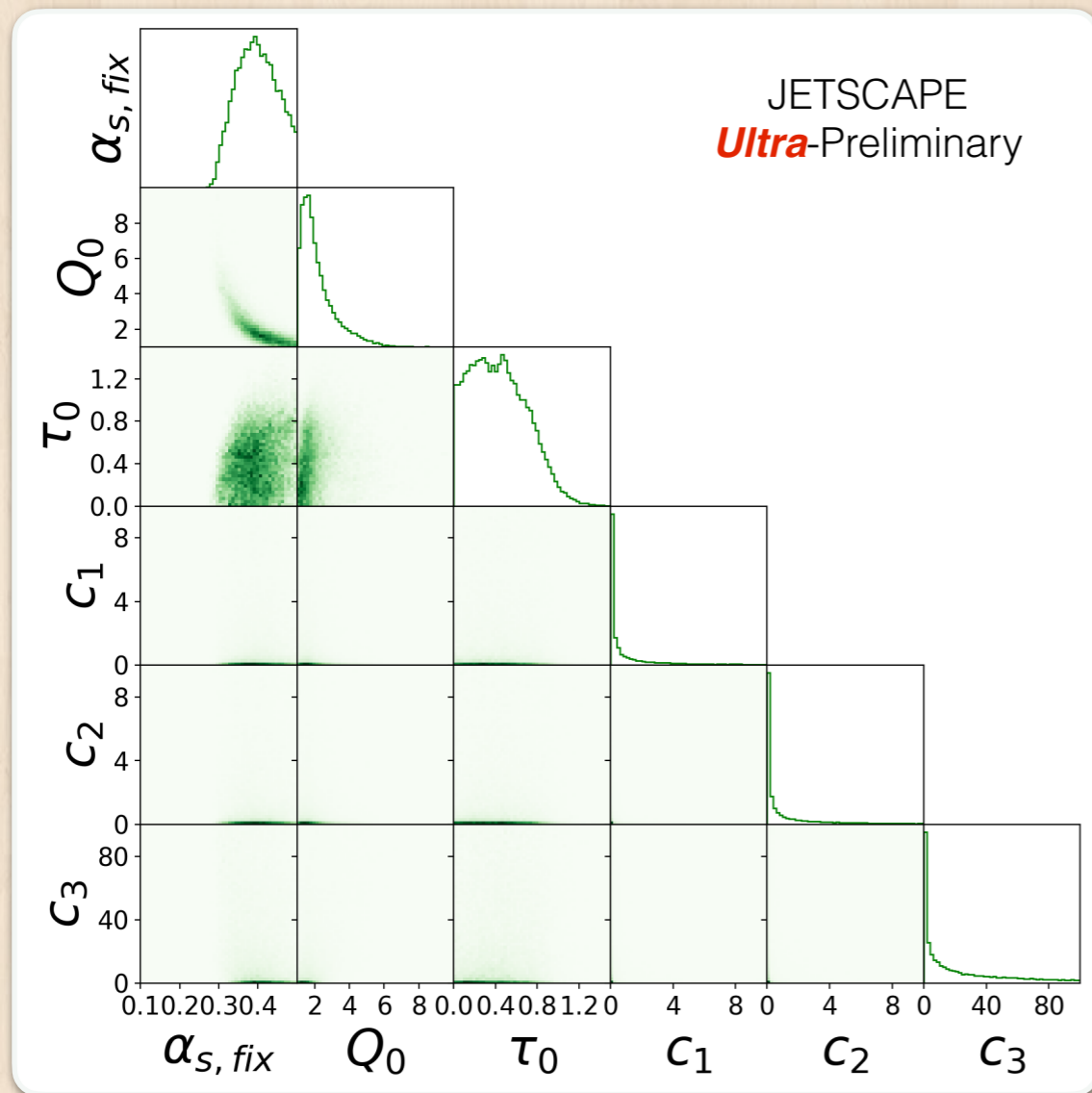
$$f(Q^2) = \begin{cases} \frac{1+10 \ln^2(Q_{\text{sw}}^2)+100 \ln^4(Q_{\text{sw}}^2)}{1+10 \ln^2(Q^2)+100 \ln^4(Q^2)} & Q^2 > Q_{\text{sw}}^2 \\ 1 & Q^2 \leq Q_{\text{sw}}^2 \end{cases}, \quad (27)$$



Type-2 → **Type-3**

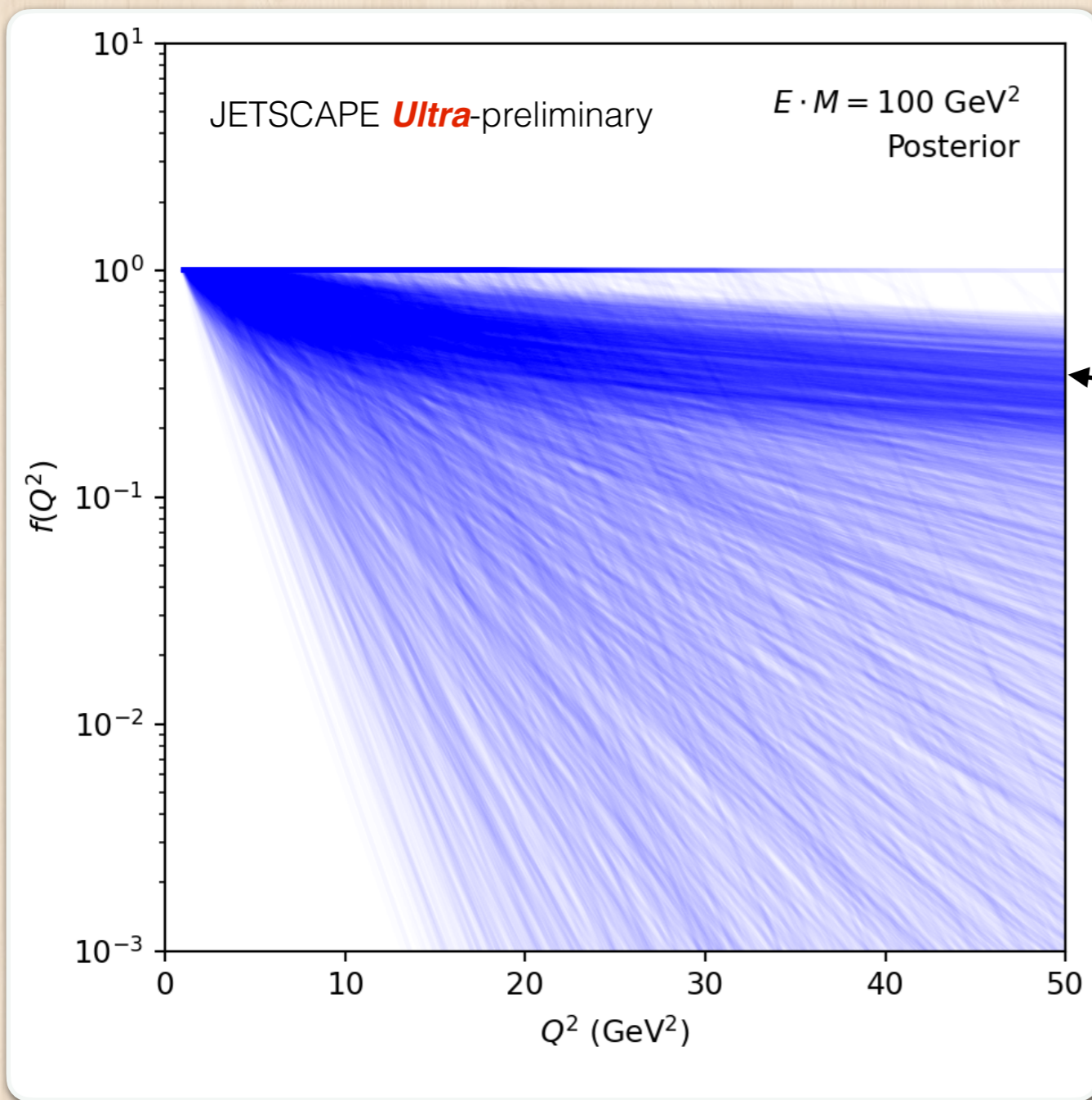
Reduction of \hat{q}_{eff} when Q^2 is large

Linear scale



Zoom in $c_{1,2,3}$

$$f(Q^2)$$



Relatively
shallow $f(Q^2)$

Under scrutiny!
still very preliminary

