

Thermalization of QGP through transverse momentum fluctuation in ultra-central Pb+Pb collision

Rupam Samanta

AGH University of Science and Technology, Krakow, Poland

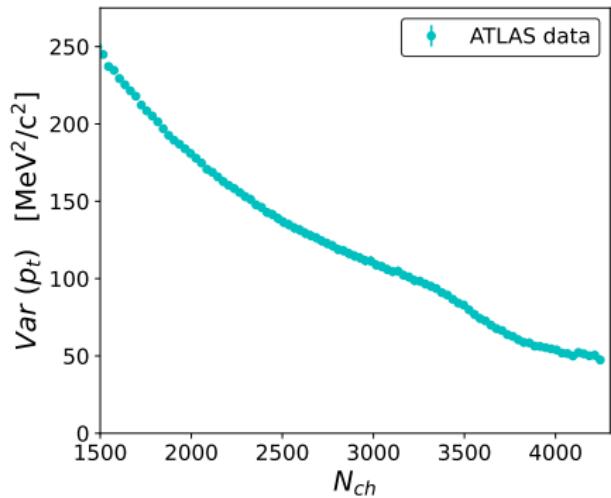
with Somadutta Bhatta, Jiangyong Jia, Matthew Luzum, Jean-Yves Ollitrault
...based on arXiv:2303.15323

Quark Matter 2023, Houston, Sept 5, 2023



ATLAS data for $[p_t]$ fluctuation

- Recent ATLAS data shows multiplicity (N_{ch}) dependence of the variance of transverse momentum per particle, $[p_t]$.



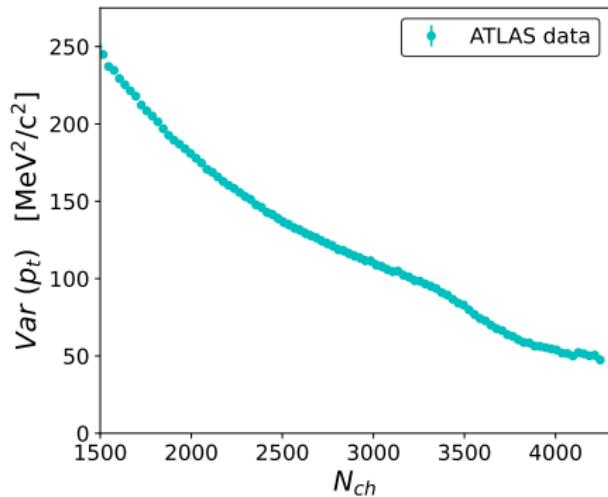
Variance of $[p_t]$ for Pb+Pb @ 5.02 TeV

PhysRevC.107.054910

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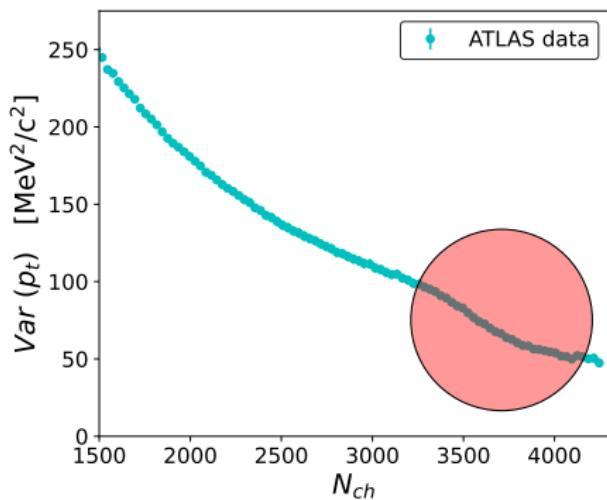
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- Puzzling behavior in ATLAS data : steep decrease over a narrow range of N_{ch}



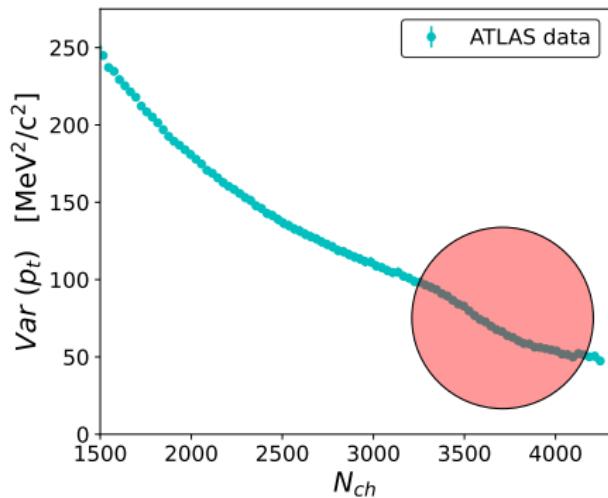
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- Puzzling behavior in ATLAS data : steep decrease over a narrow range of N_{ch}
- We will show that this is a consequence of thermalization !

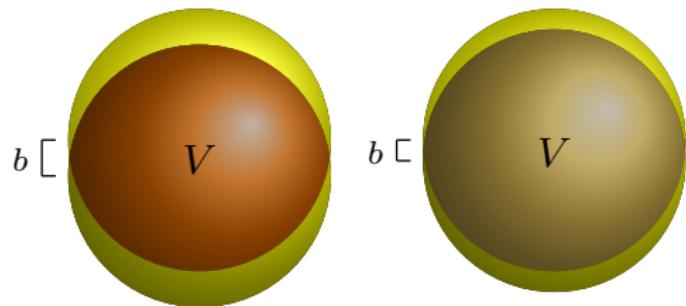


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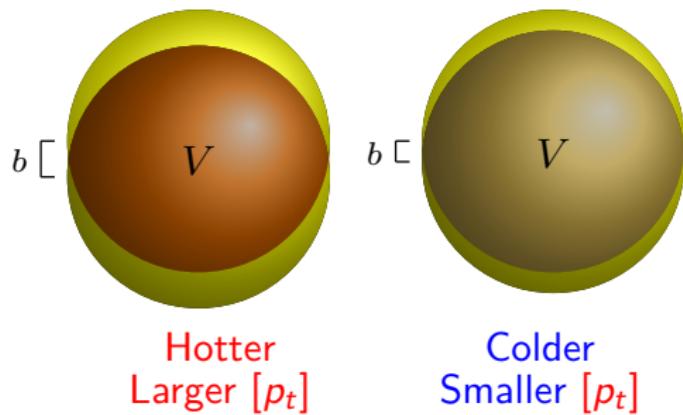
Impact parameter (b) is important !

- In experiment b is not known ! $\Rightarrow [p_t]$ fluctuation is measured for fixed N_{ch}



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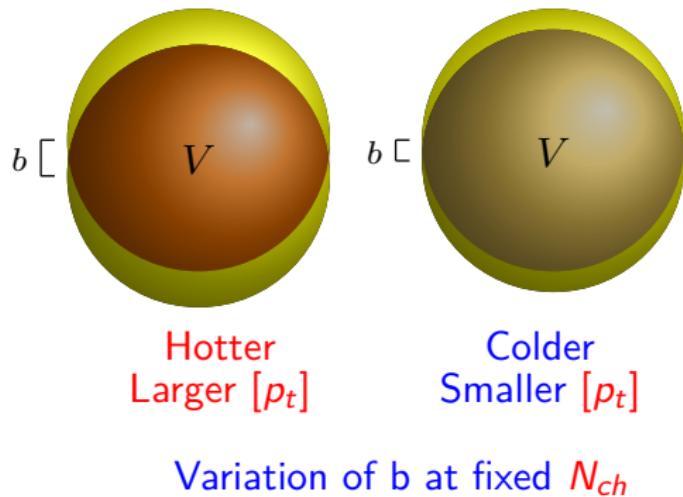
- In experiment b is not known ! $\Rightarrow [p_t]$ fluctuation is measured for fixed N_{ch}
- Fixed N_{ch} \Rightarrow finite range of b !



Variation of b at fixed N_{ch}

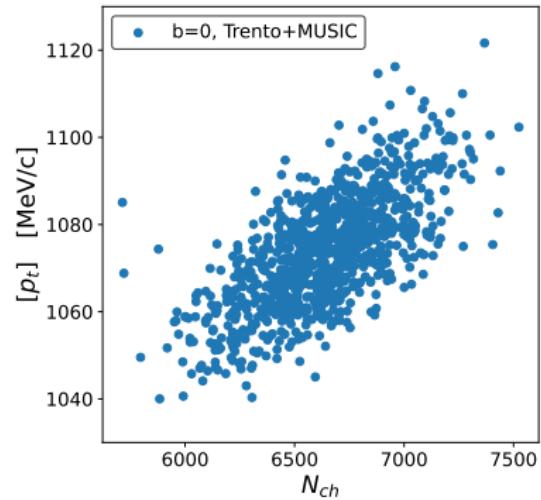
Impact parameter (b) is important !

- In experiment b is not known ! $\Rightarrow [p_t]$ fluctuation is measured for fixed N_{ch}
- Fixed $N_{ch} \Rightarrow$ finite range of b !
- Variation of b gives a contribution to the variation of $[p_t] \Rightarrow$ goes to 0 in ultracentral collisions !



Hydrodynamic simulation: b is known !

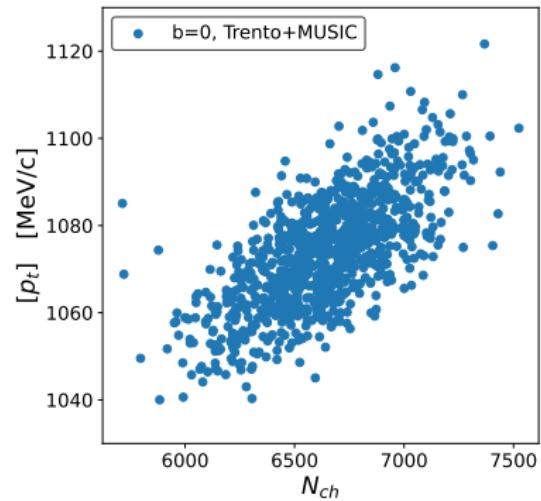
- Hydro : assumes thermalization !
⇒ We simulate Pb+Pb collisions at fixed b ($=0$) with TRENTO (initial condition) + MUSIC (hydro)



Pb+Pb @ 5.02 TeV

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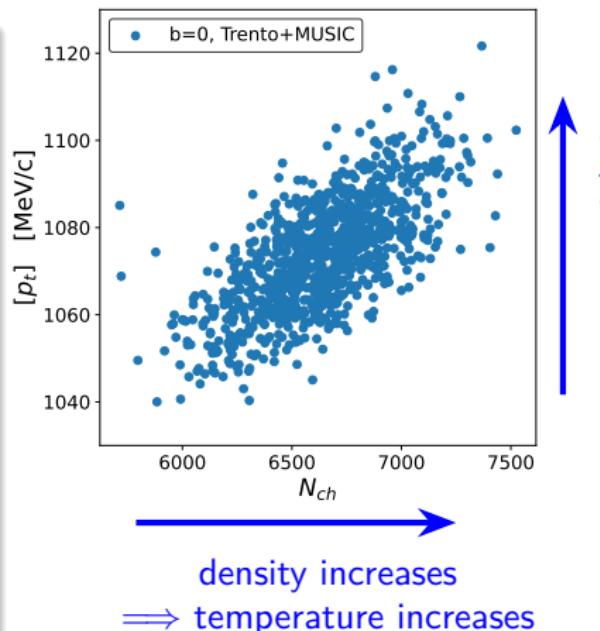
- ▶ Hydro : assumes thermalization !
⇒ We simulate Pb+Pb collisions at fixed b ($=0$) with TRENTO (initial condition) + MUSIC (hydro)
- ▶ Significant fluctuation of N_{ch} and modest fluctuation of $[p_t]$. Strong correlation between $[p_t]$ and N_{ch}



Pb+Pb @ 5.02 TeV

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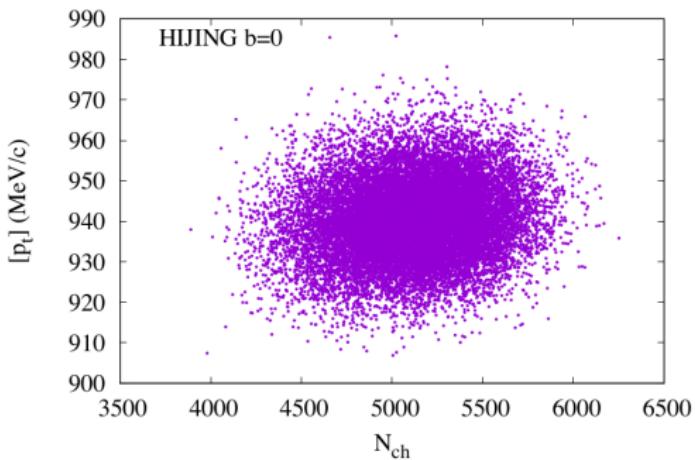
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- ▶ Fixed $b \Rightarrow$ fixed collision volume
Larger $N_{ch} \Rightarrow$ larger density
⇒ larger temperature
⇒ larger energy per particle
⇒ larger $[p_t]$



Comparing other models : HIJING simulation

Wang, Gyulassy, arXiv:nucl-th/9502021

- HIJING: microscopic model of HI collision \implies the system doesn't thermalize !

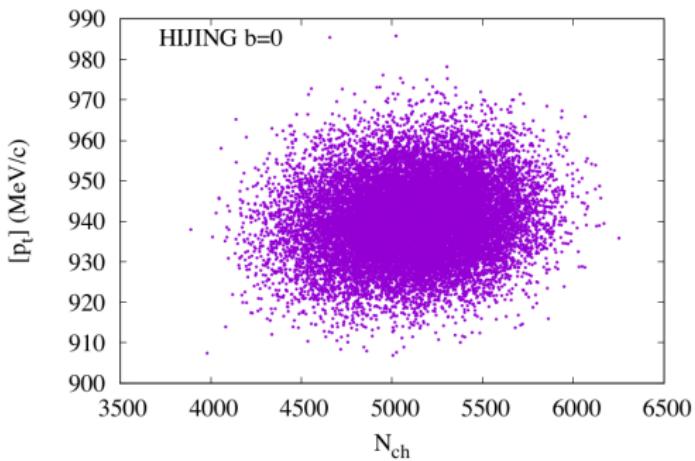


Pb+Pb @ 5.02 TeV

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- Very small correlation between N_{ch} and $[p_t] \sim 10 \times$ smaller !!



Pb+Pb @ 5.02 TeV

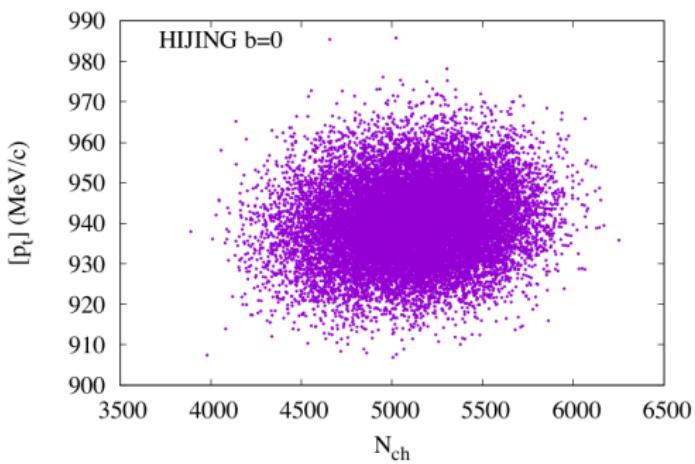
No thermalization

\Rightarrow Very little correlation !

Comparing other models : HIJING simulation

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- HIJING: microscopic model of HI collision \Rightarrow the system doesn't thermalize !
- Very small correlation between N_{ch} and $[p_t] \sim 10 \times$ smaller !!
- Hence the correlation is a signature of thermalization !



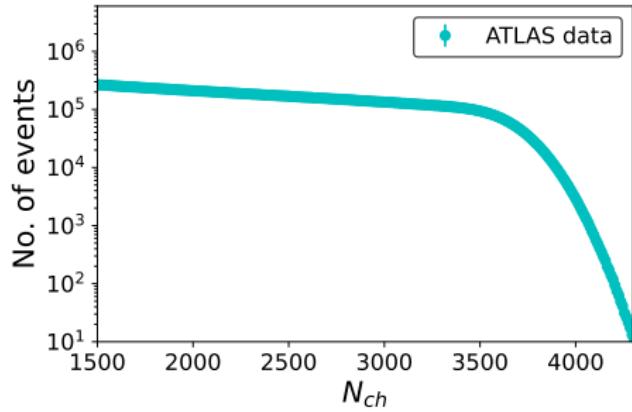
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Bayesian reconstruction of $P(\mathbf{b} | N_{ch})$

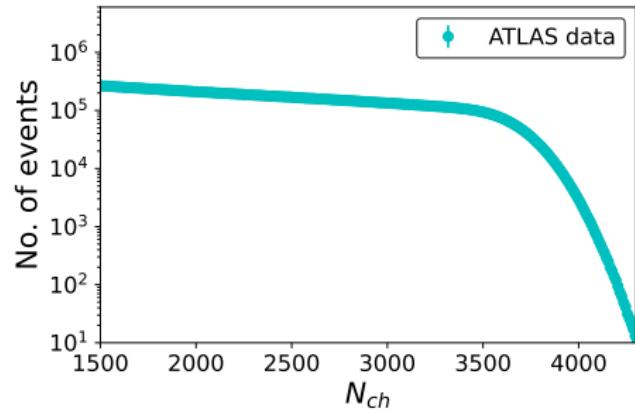
- First we solve the inverse problem:
what is the distribution of N_{ch} at fixed \mathbf{b} i.e. $P(N_{ch}|\mathbf{b})$?



N_{ch} distribution
for centrality classification !

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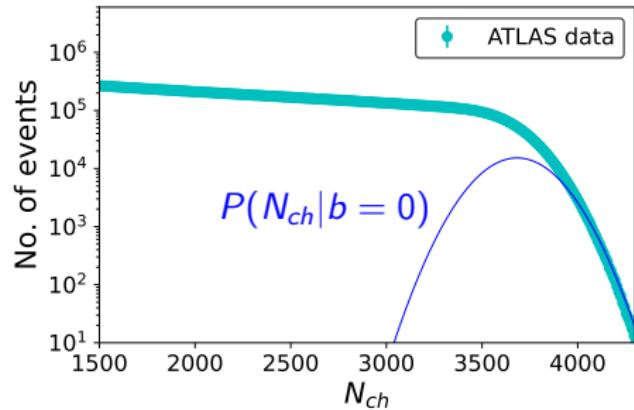
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$$P(\mathbf{b} | N_{ch}) P(N_{ch}) = P(N_{ch}|\mathbf{b}) P(\mathbf{b})$$



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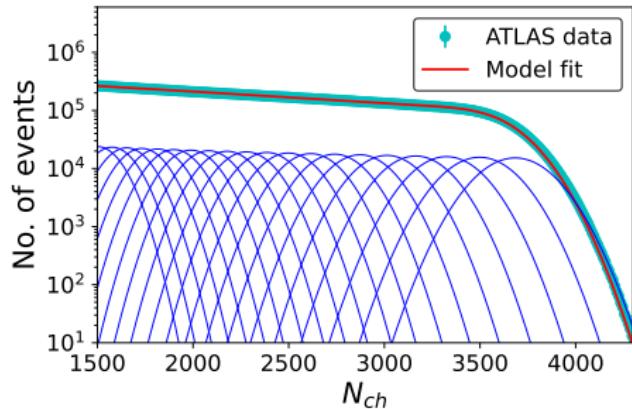
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$$P(\mathbf{b} | N_{ch}) P(N_{ch}) = P(N_{ch}|\mathbf{b}) P(\mathbf{b})$$
- We assume $P(N_{ch}|\mathbf{b})$ to be Gaussian !



N_{ch} distribution at fixed b
Gaussian assumption !

Bayesian reconstruction of $P(\mathbf{b} | N_{ch})$

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- Fit $P(N_{ch})$ as sum of Gaussians

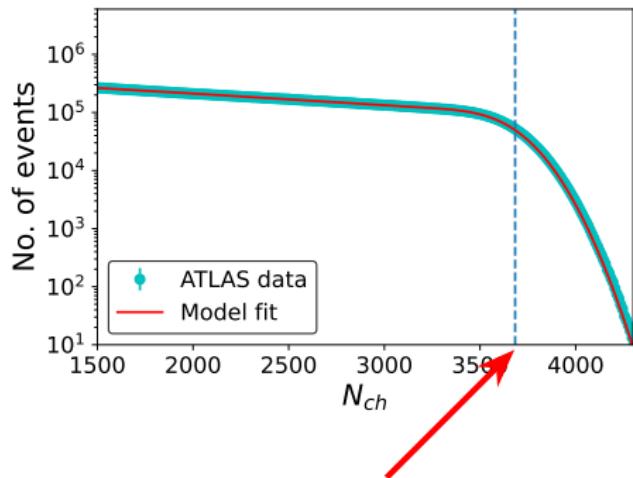


Sum of Gaussians at fixed \mathbf{b}

Das, Giacalone, Monard, Ollitrault
arXiv:1708.00081

Bayesian reconstruction of $P(\mathbf{b} | N_{ch})$

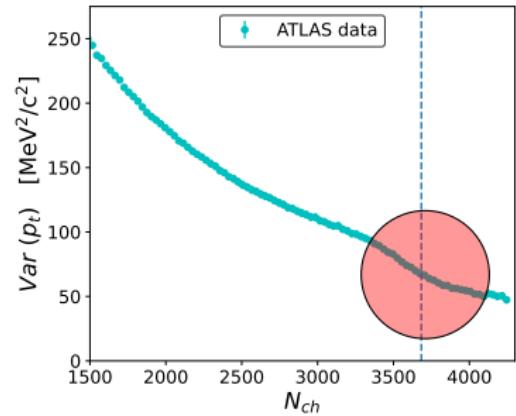
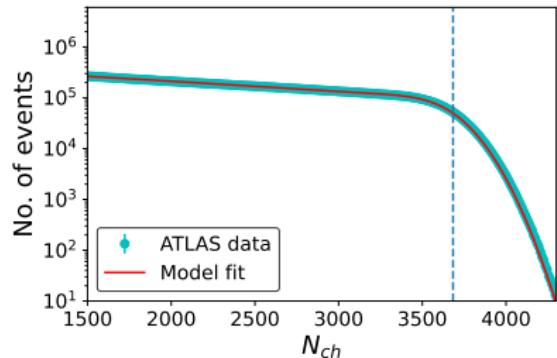
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- Fit $P(N_{ch})$ as sum of Gaussians
- We precisely reconstruct the knee (mean N_{ch} at $\mathbf{b}=0$)



Precise construction of knee
 $(N_{ch}|\mathbf{b} = 0)$

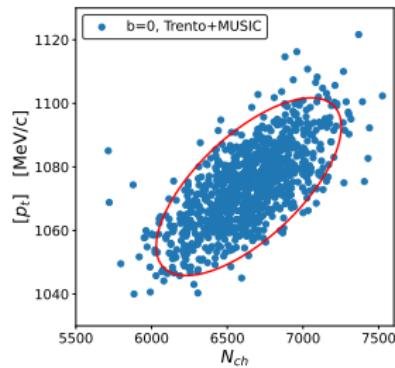
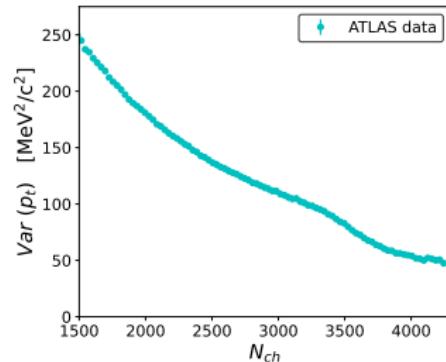
Bayesian reconstruction of $P(\mathbf{b} | N_{ch})$

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- Fit $P(N_{ch})$ as sum of Gaussians
- We precisely reconstruct the knee (mean N_{ch} at $\mathbf{b}=0$)
- The steep fall of the variance precisely occur at the knee !



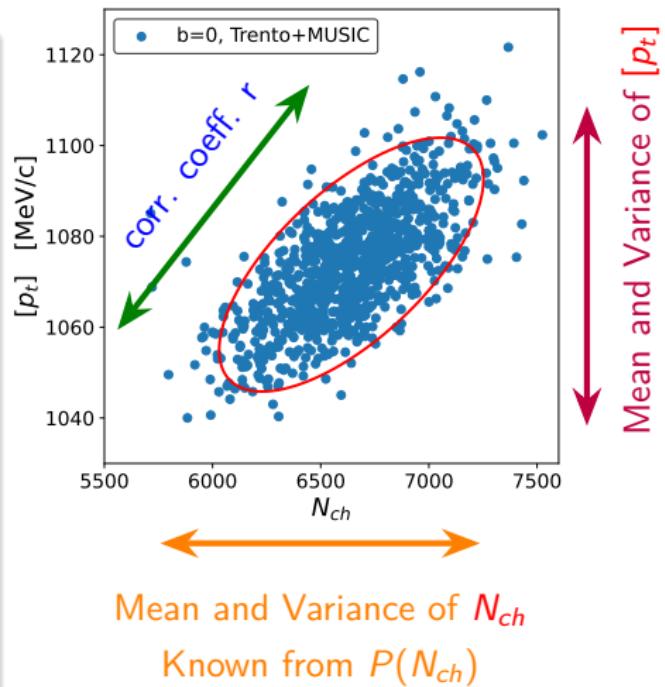
Understanding $[p_t]$ fluctuation data : Parametrizing $P(N_{ch}, [p_t] | b)$

- We assume a simple 2D correlated Gaussian between $[p_t]$ and N_{ch} at fixed impact parameter b : $P([p_t], N_{ch} | b)$.



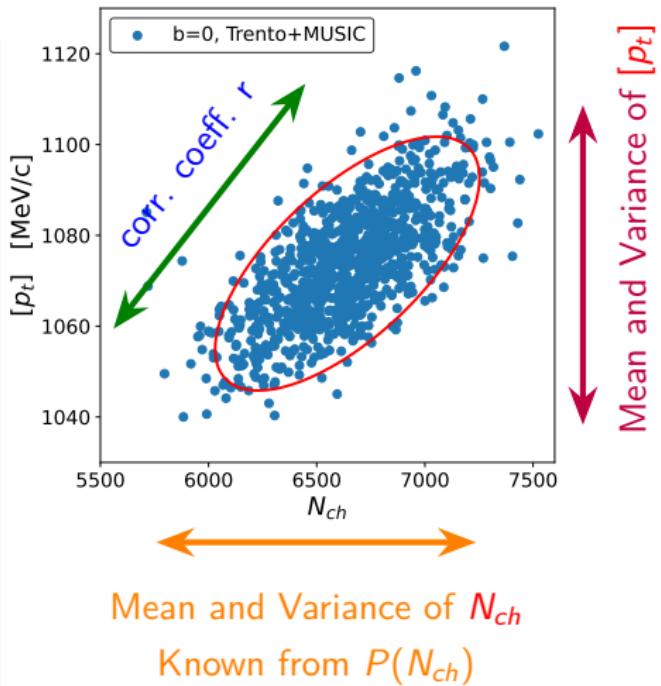
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- ▶ We assume a simple 2D correlated Gaussian between $[p_t]$ and N_{ch} at fixed impact parameter b : $P([p_t], N_{ch} | b)$.
- ▶ The distribution has 5 parameters : Mean and variance of N_{ch} , Mean and variance of $[p_t]$ and correlation coefficient r between N_{ch} and $[p_t]$.

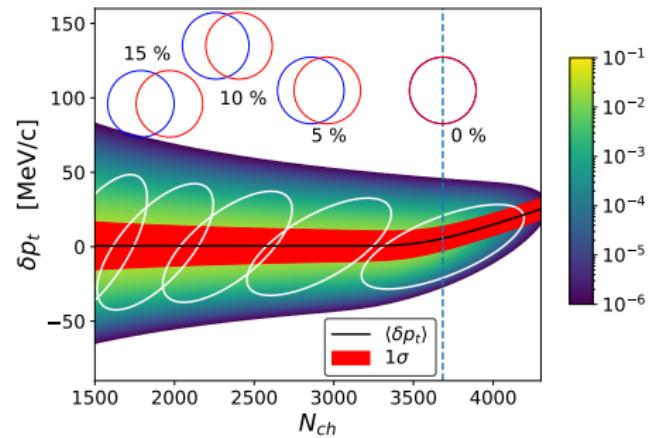


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- ▶ The distribution has 5 parameters : Mean and variance of N_{ch} , Mean and variance of $[p_t]$ and correlation coefficient r between N_{ch} and $[p_t]$.
- ▶ Mean value of $[p_t]$ is constant at fixed b and assuming it is independent of $b \implies$ we fit $P(\delta p_t, N_{ch} | b)$
 $\delta p_t = [p_t] - \langle [p_t] \rangle$



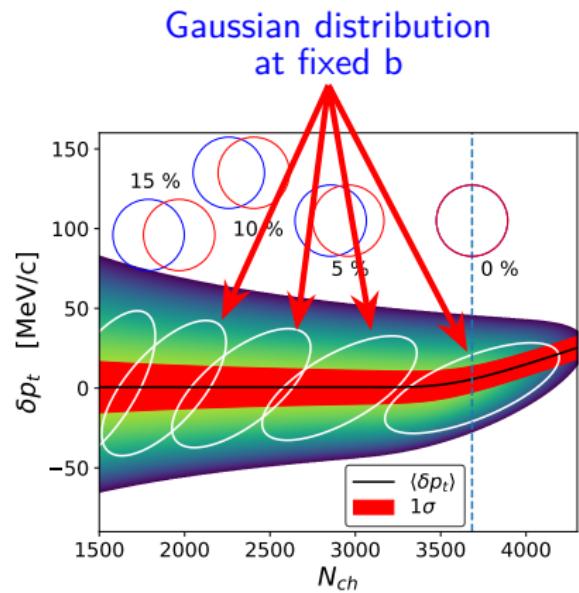
Fit result : $P(N_{ch}, \delta p_t)$



2D correlated gaussian
distribution of δp_t and N_{ch}

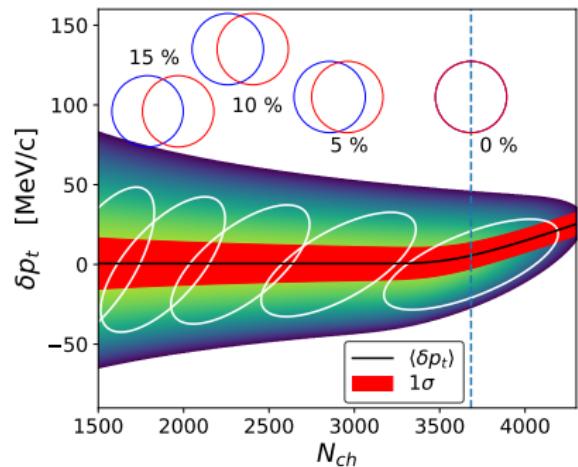
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- We get, $P(N_{ch}, \delta p_t) = \int P(N_{ch}, \delta p_t | b) P(b) db$



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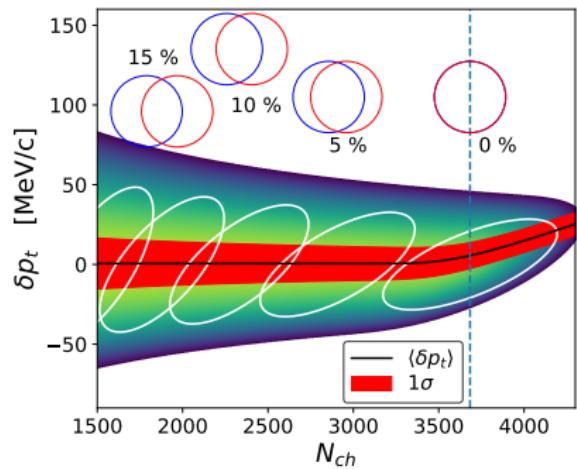
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 $P(\delta p_t | N_{ch}) = \frac{P(N_{ch}, \delta p_t)}{P(N_{ch})}$
 $\Rightarrow \text{Var}([\delta p_t] | N_{ch})$ is the squared width of $P(\delta p_t | N_{ch})$



2D correlated gaussian distribution of δp_t and N_{ch}

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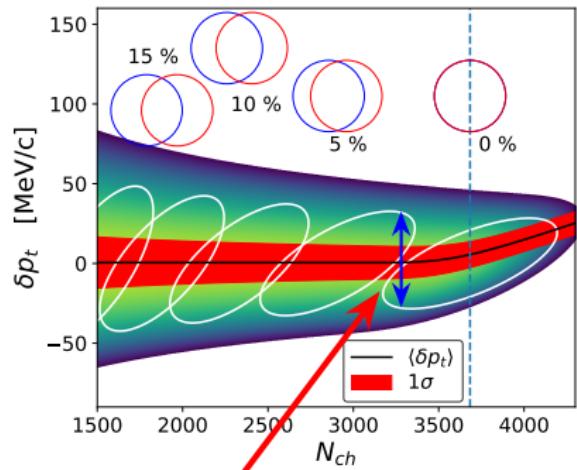
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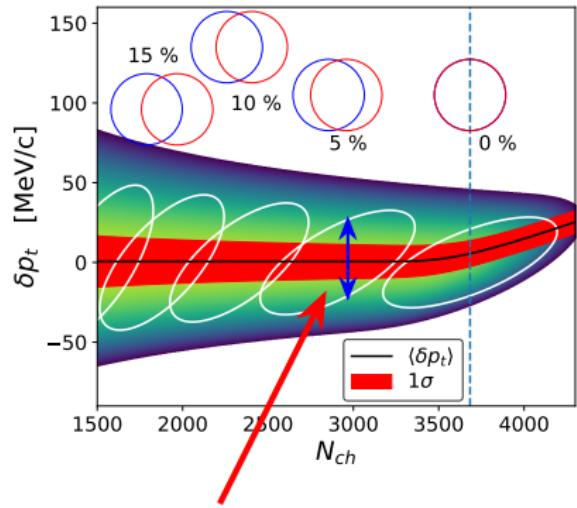
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⇒ Var($\delta p_t | N_{ch}$) is the squared width of $P(\delta p_t | N_{ch})$
 - The width of δp_t fluctuation has two contributions :
 - ① due to fluctuation of impact parameter b



fluctuation from the variation of b
(several ellipses contribute)

Fit result : $P(N_{ch}, \delta p_t)$

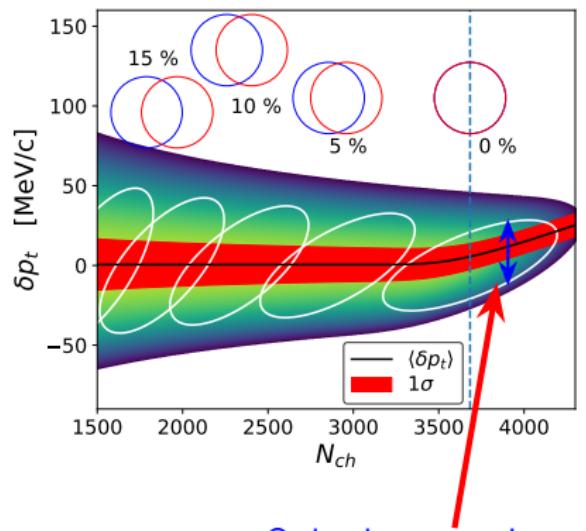
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- The width of $[\delta p_t]$ fluctuation has two contributions :
 - I due to fluctuation of impact parameter b
 - II the true intrinsic fluctuation



fluctuation of $[\delta p_t]$ at fixed b and fixed N_{ch}
 (height of a single ellipse)

Fit result : $P(N_{ch}, \delta p_t)$

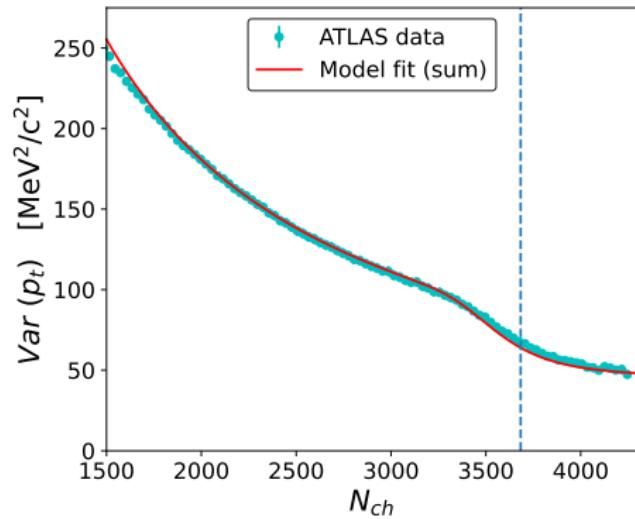
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- The width of $[\delta p_t]$ fluctuation has two contributions :
 - ① due to fluctuation of impact parameter b
 - ② the true intrinsic fluctuation
- Only the second term contributes above knee in the ultracentral regime.



Only the second term remains in ultracentral collisions

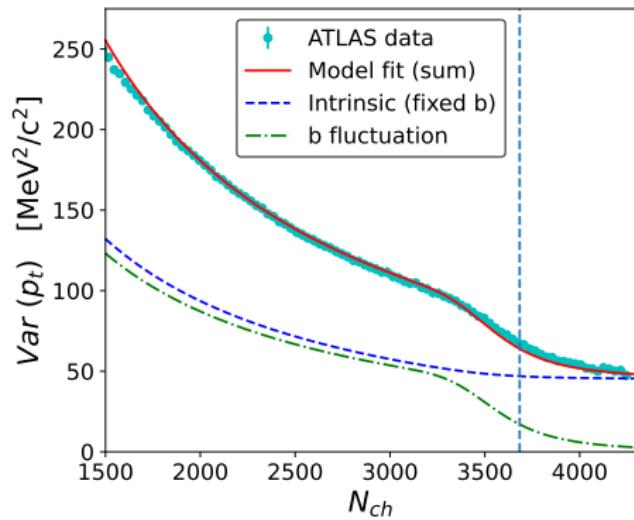
Fit result : $\text{Var}([p_t])$ vs N_{ch}

- Our simple model naturally reproduces the steep fall in the ATLAS data very well !



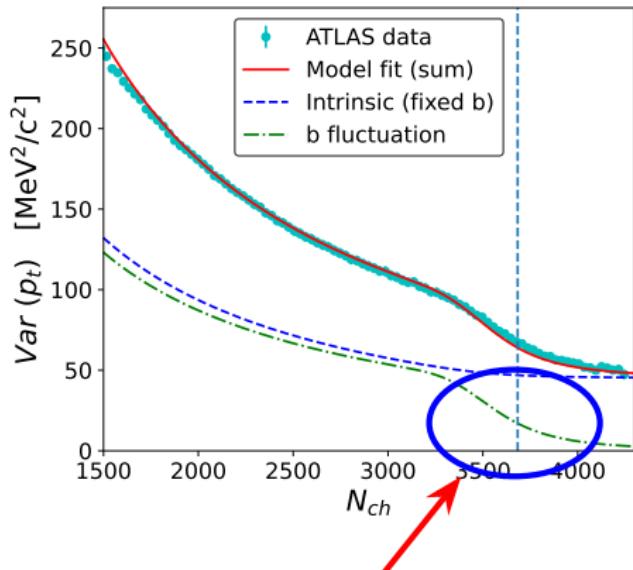
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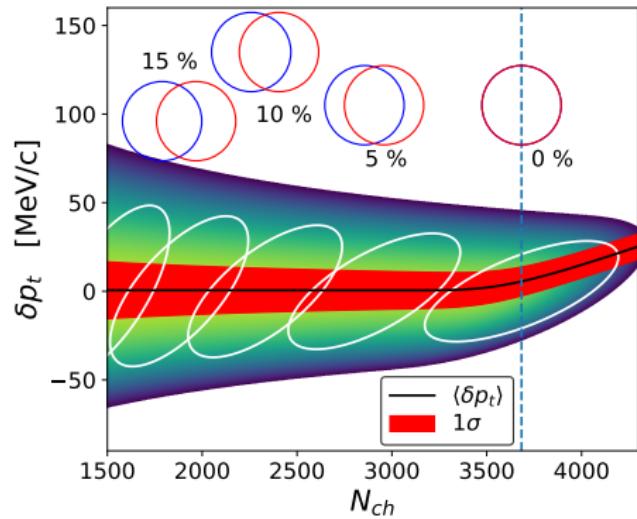
- Our simple model naturally reproduces the steep fall in the ATLAS data very well !
- Below the knee, half of the contribution is from impact parameter fluctuation
- The contribution gradually disappears around the knee !



Contribution of b-fluctuation disappears above knee

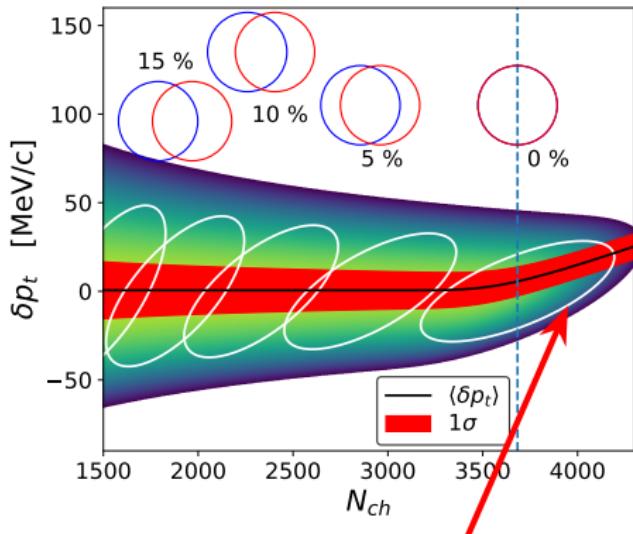
Thermalization observed !

- Our model fit returns $r = 0.676$!



Thermalization observed !

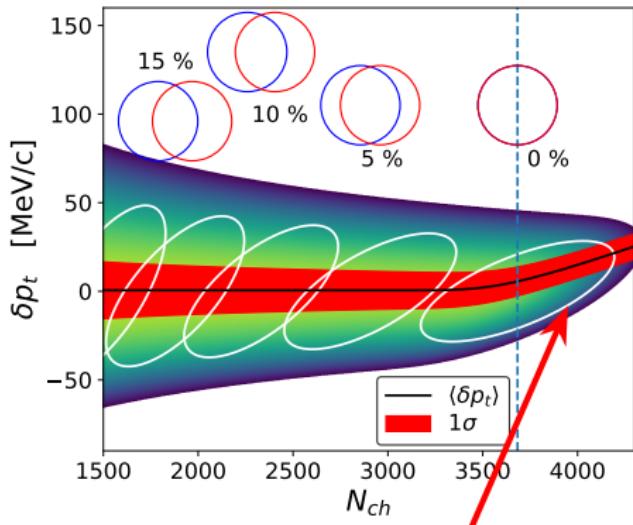
- Our model fit returns $r = 0.676$!
- It suggests strong correlation between $[p_t]$ and N_{ch} at fixed b



Strong correlation between
 $[p_t]$ and N_{ch} at fixed b
from our model fit

Thermalization observed !

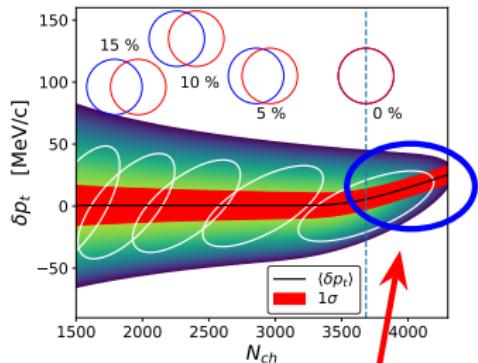
- Our model fit returns $r = 0.676$!
- It suggests **strong correlation** between $[p_t]$ and N_{ch} at fixed b
- Hence **thermalization is observed !**



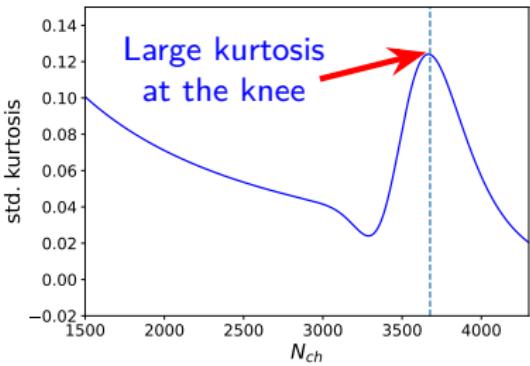
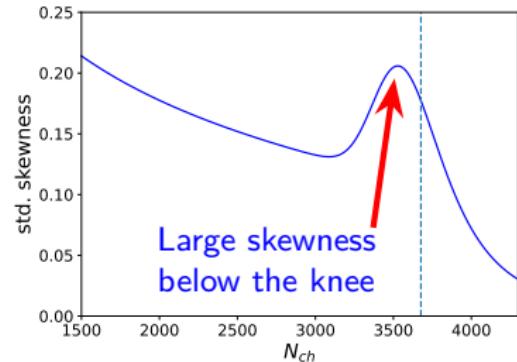
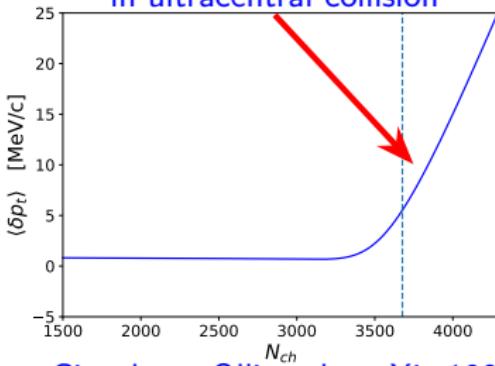
Strong correlation between
 $[p_t]$ and N_{ch} at fixed b
from our model fit

Further predictions !

RS, Picchetti, Luzum, Ollitrault, arXiv:2306.09294



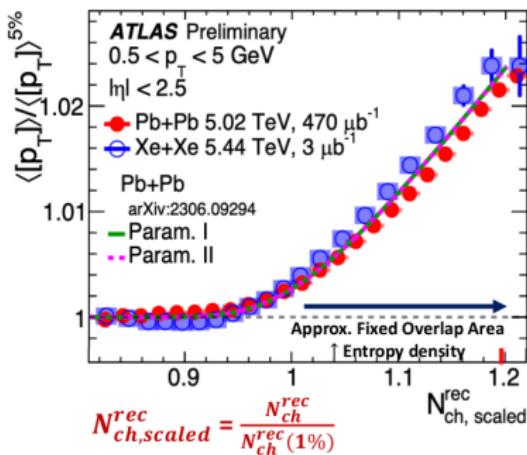
Slight increase of mean $\langle p_t \rangle$
in ultracentral collision



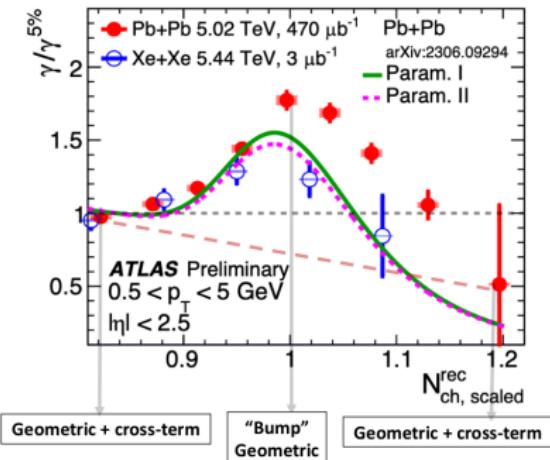
Gardim, Giacalone, Ollitrault, arXiv:1909.11609

ATLAS New Results !

See talk by T. Bold, Wed, 17:10, Ballroom C
Poster by S. Bhatta in the evening



mean $[p_t]$



$[p_t]$ - skewness

Using ATLAS data and our model we have new method to separate geometrical and intrinsic fluctuation !

Conclusions and Outlook

- Impact parameter fluctuation at fixed N_{ch} plays an important role in ultracentral collision !
- Two separate contributions to $[p_t]$ fluctuation :
 - i intrinsic fluctuation → originates from quantum fluctuation in the initial state
 - ii impact parameter fluctuation at fixed N_{ch} → disappears in ultracentral region → causes the steep fall at the knee
- Transverse momentum fluctuation in ultra central collision provides a new , direct probe of the thermalization !

... Thank you for your attention !

b-dependence of the fit parameters

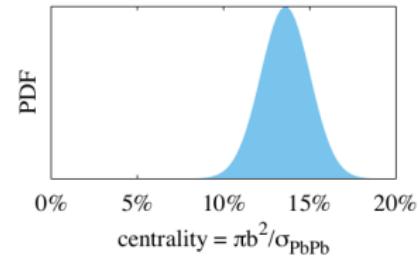
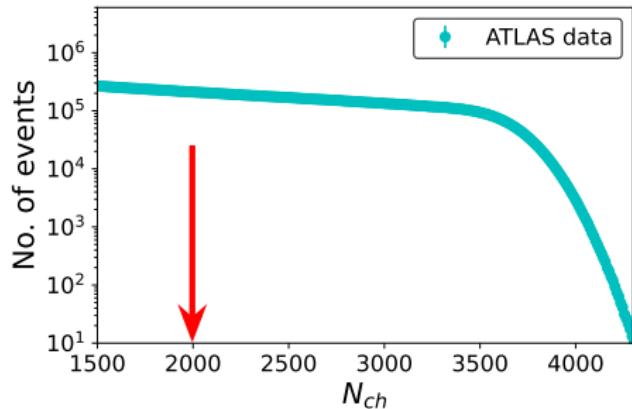
- We assume mean $[p_t]$ to be independent of b
- We assume $\text{Var}([p_t])$ is a smooth function of mean multiplicity :

$$\sigma p_t^2 \left(\frac{\langle N_{ch}(0) \rangle}{\langle N_{ch}(b) \rangle} \right)$$

- We also assume r to be independent of b for simplicity

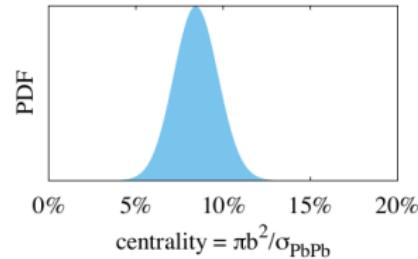
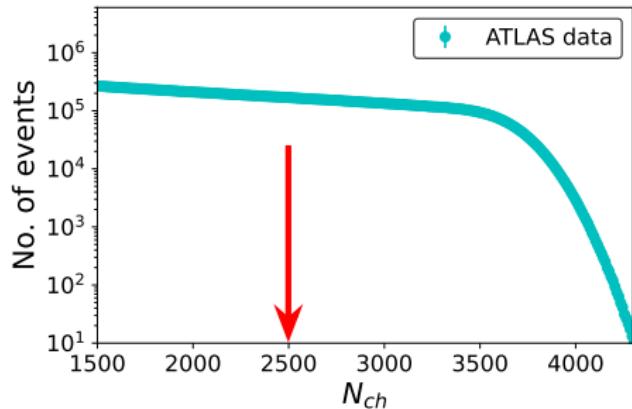
$P(b | N_{ch})$ from Bayesian reconstruction

- At smaller N_{ch} the distribution $P(b|N_{ch})$ is a full Gaussian



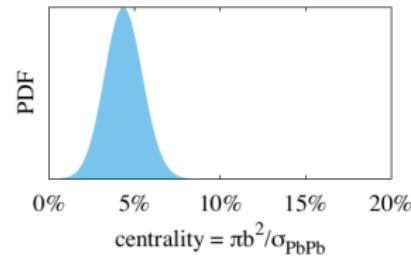
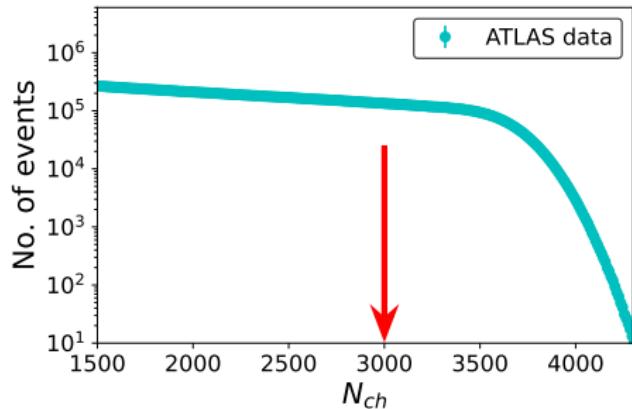
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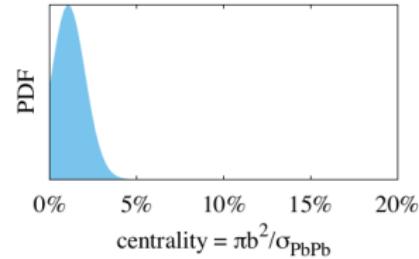
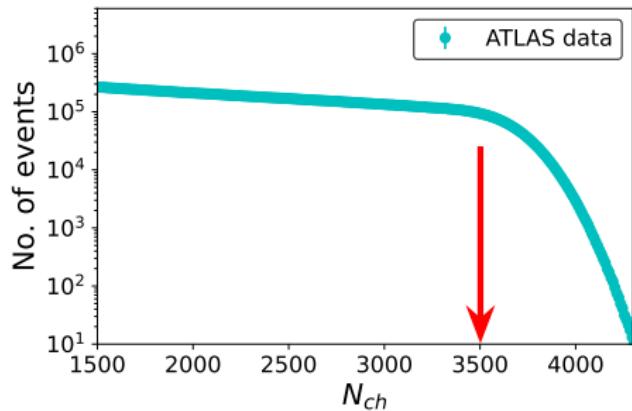
$P(\mathbf{b} | N_{ch})$ from Bayesian reconstruction

- At smaller N_{ch} the distribution $P(\mathbf{b}|N_{ch})$ is a full Gaussian
- But as we move closer and closer to the knee, $P(\mathbf{b}|N_{ch})$ becomes truncated due to the limit $\mathbf{b} \geq 0$



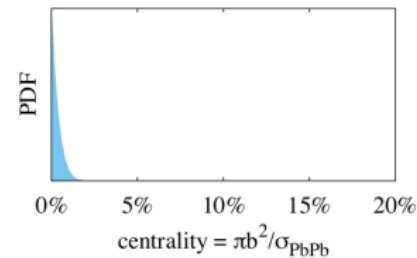
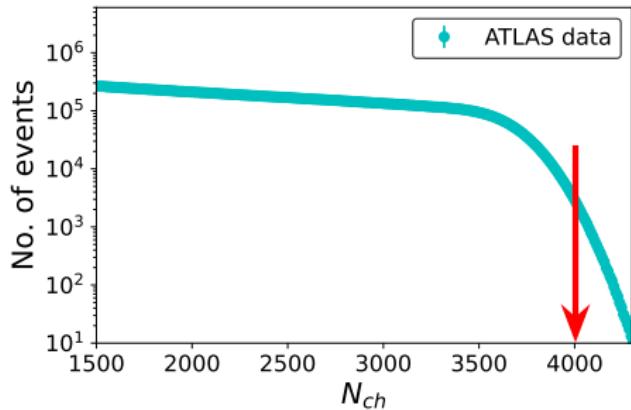
$P(\mathbf{b} | N_{ch})$ from Bayesian reconstruction

- At smaller N_{ch} the distribution $P(b|N_{ch})$ is a full Gaussian
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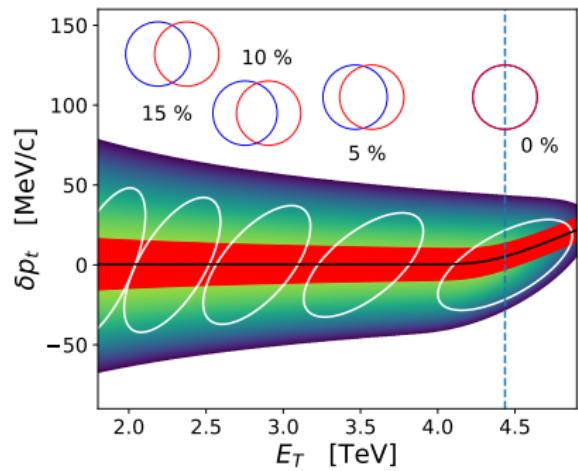
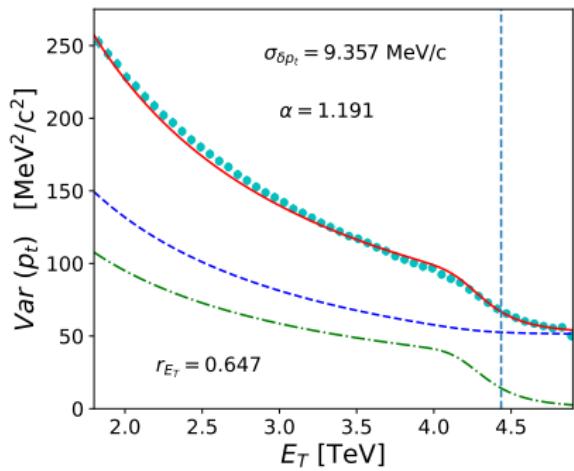


$P(\mathbf{b} | N_{ch})$ from Bayesian reconstruction

- At smaller N_{ch} the distribution $P(\mathbf{b}|N_{ch})$ is a full Gaussian
- But as we move closer and closer to the knee, $P(\mathbf{b}|N_{ch})$ becomes truncated due to the limit $\mathbf{b} \geq 0$
- Above the knee it gets extremely truncated \Rightarrow the impact parameter fluctuation gradually disappears !



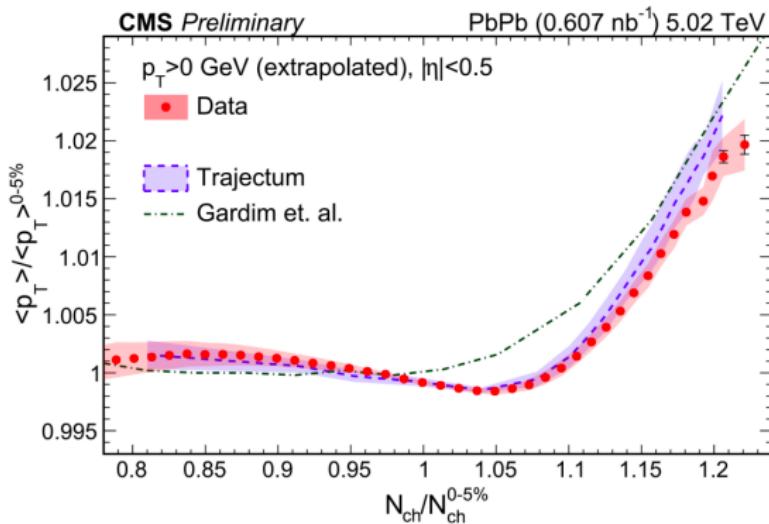
E_T -dependent [p_t]-fluctuation



Impact parameter fluctuation is small !

CMS Result on mean $[p_t]$!

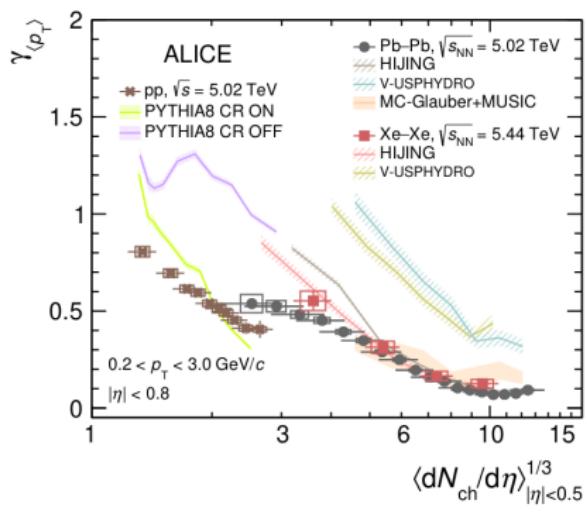
See CMS overview talk yesterday



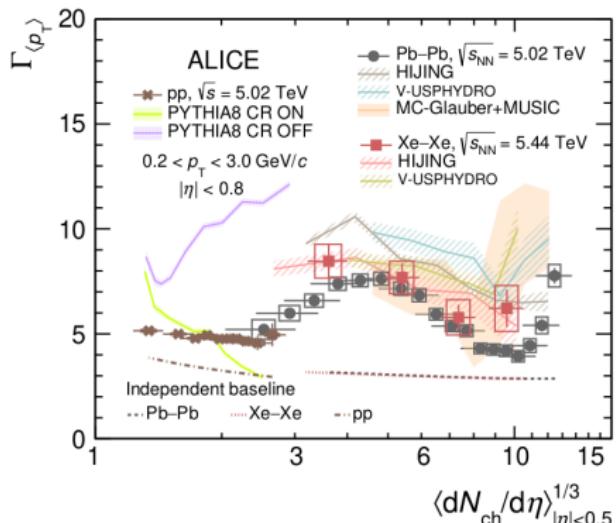
increase of mean $[p_t]$

ALICE Measurements of $[p_t]$ -skewness !

arXiv: 2308.16217



standardized $[p_t]$ -skewness



intensive $[p_t]$ -skewness