Enhancing Timing Information Reconstruction with LAr Calorimeter

Primary Vertex Timing

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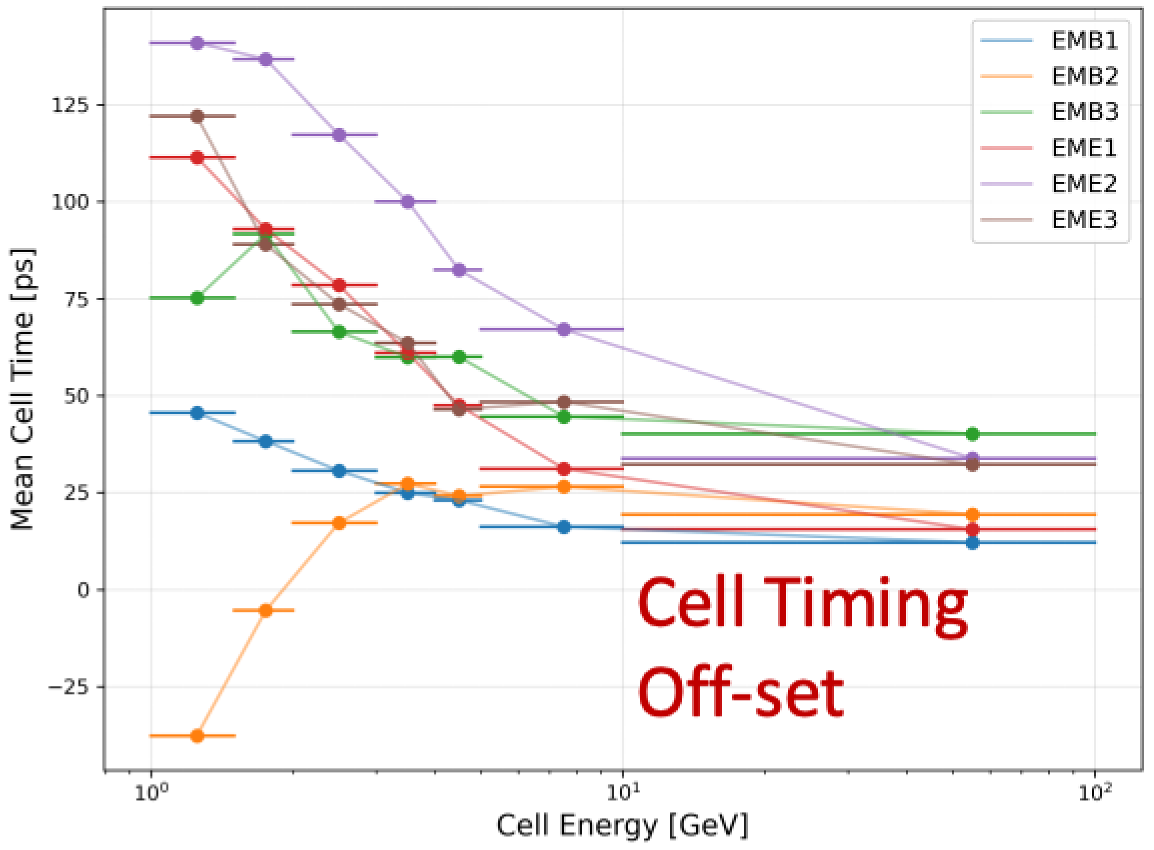
Part 1

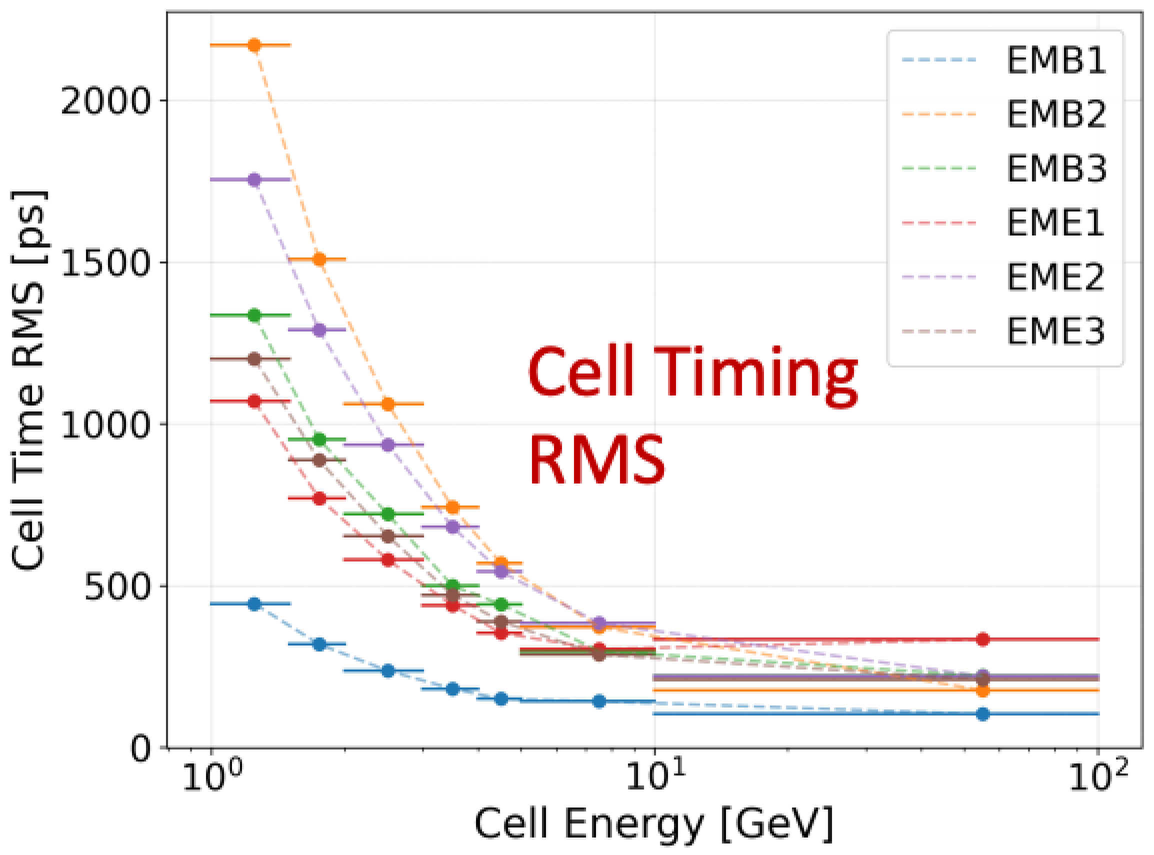
Review of Prior Progress

Inclusive PV t_0 Reconstruction with EM-layers

- Use All Cells in EM-layers (EMB&EMEC)
  - Cut for cells:
    E>=1.0GeV; Significance >= 4.0

Cells in EMB1 E_{cell} - bin 1	Cells in EMB1 E_{cell} - bin 2	… and so on
Cells in EMB2 E_{cell} - bin 1	Cells in EMB2 E_{cell} - bin 2	… and so on
… and so on	… and so on	… and so on



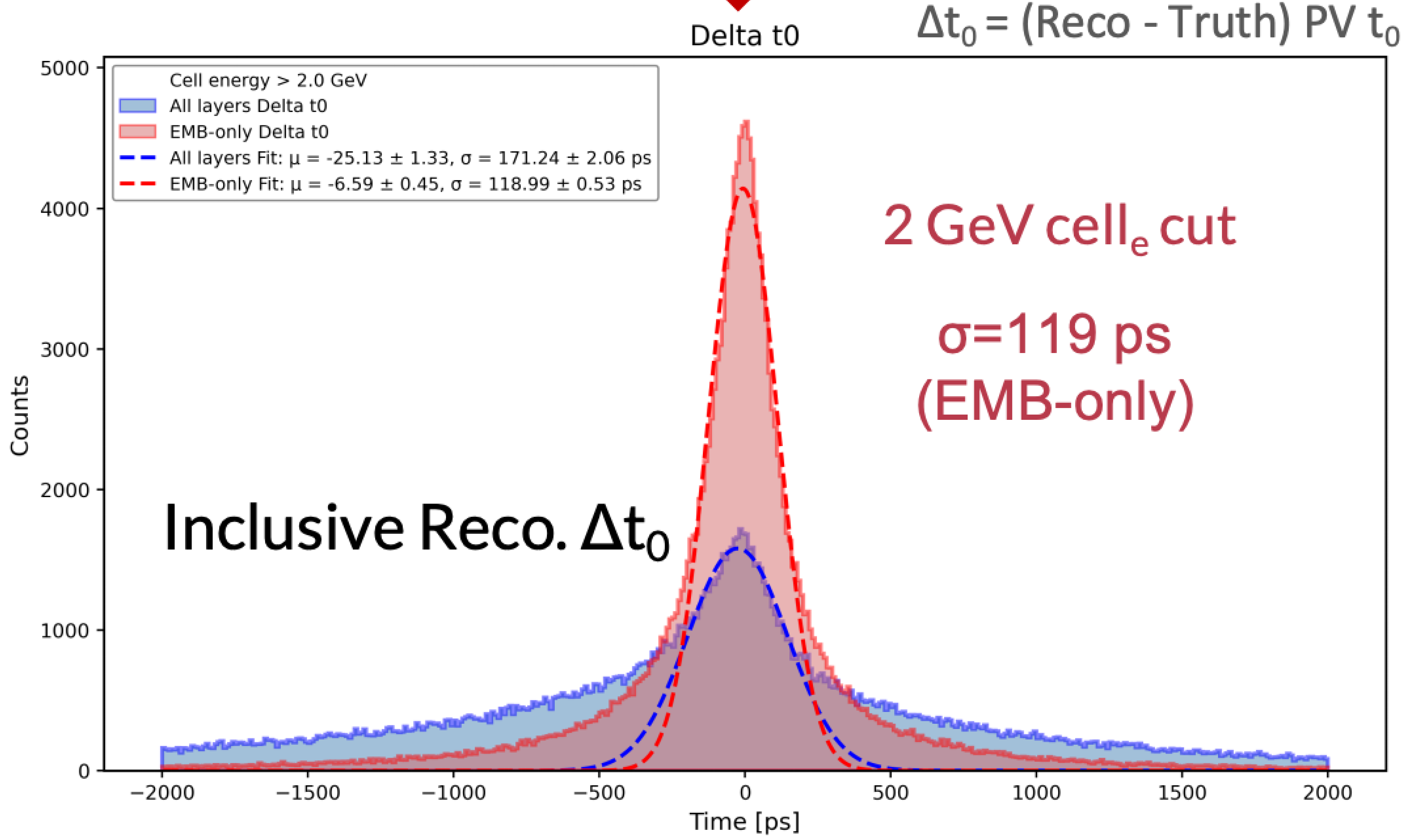


- Back to Reco. Level

$$t_0^{\rm PV} = \frac{\sum_{\rm cell} w^{\rm cell} t_0^{\rm cell}}{\sum_{\rm cell} w^{\rm cell}}$$ Weighted average

$$t_0^{\rm cell} = t_0^{\rm cell,\ AOD} + t_{\rm tof}\left(\vec{0}, \vec{r}^{\rm \,cell}\right) - t_{\rm tof}\left({\rm reco.\ PV}, \vec{r}^{\rm \,cell}\right) - t_{\rm offset}^{\rm cell}$$

$$w^{\rm cell} = \frac{1}{(\sigma_t^{\rm cell})^2}$$

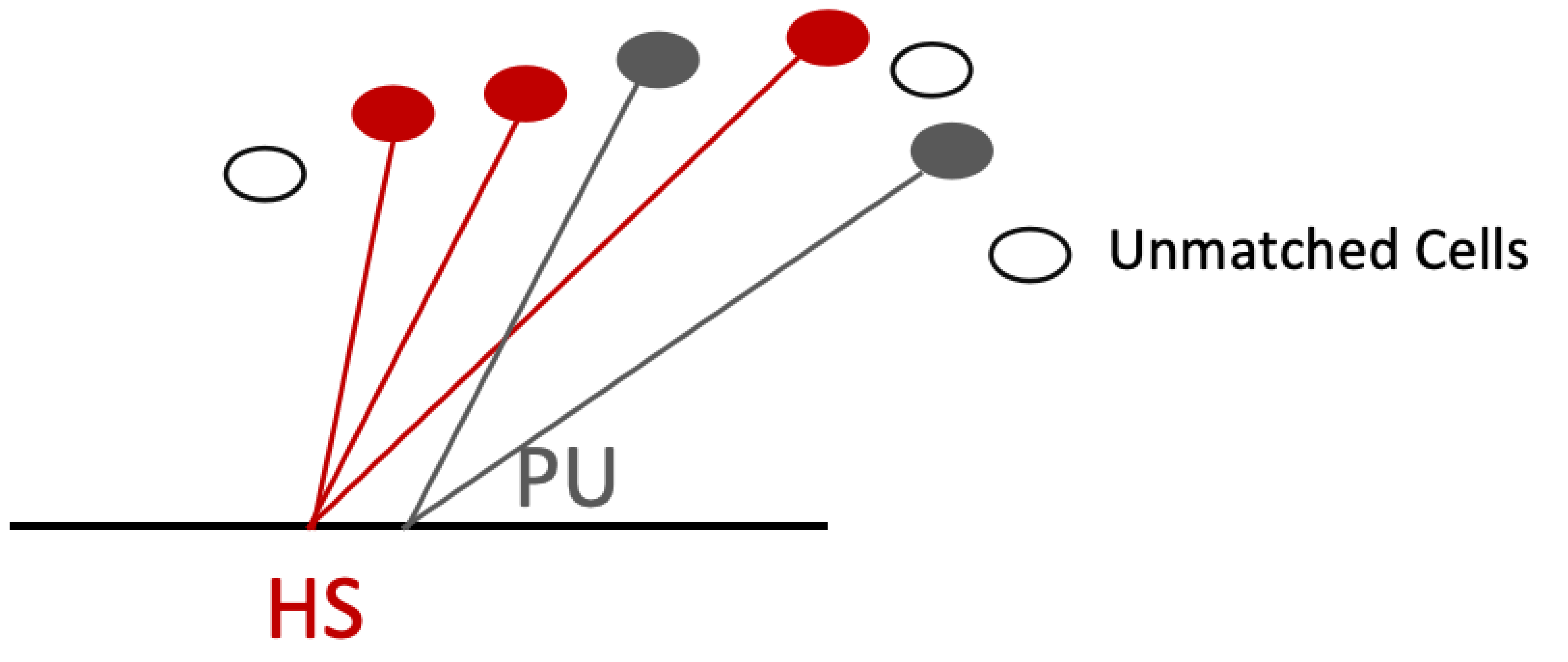


Incorporating Track/Jet Matching Information

Inclusive Reco. best: 119 ps

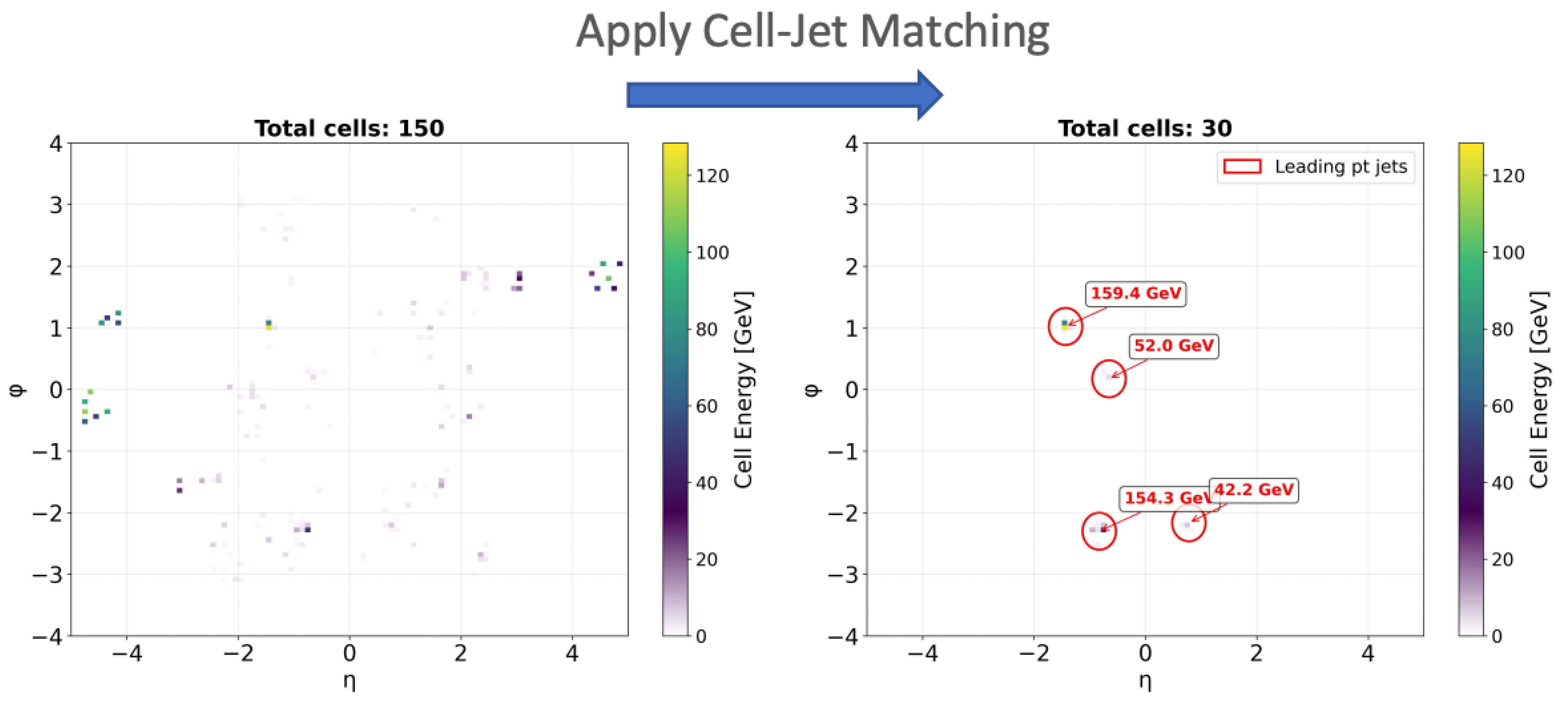
→ Cell-Track Matching

- ➢ ΔR(cell, track) ≤ 0.05, choosing highest p_T track
- ➢ Classification of cells:
  - Matched to a Hard-Scatter (HS) track
  - Matched to a Pile-Up (PU) track
  - Unmatched to any track

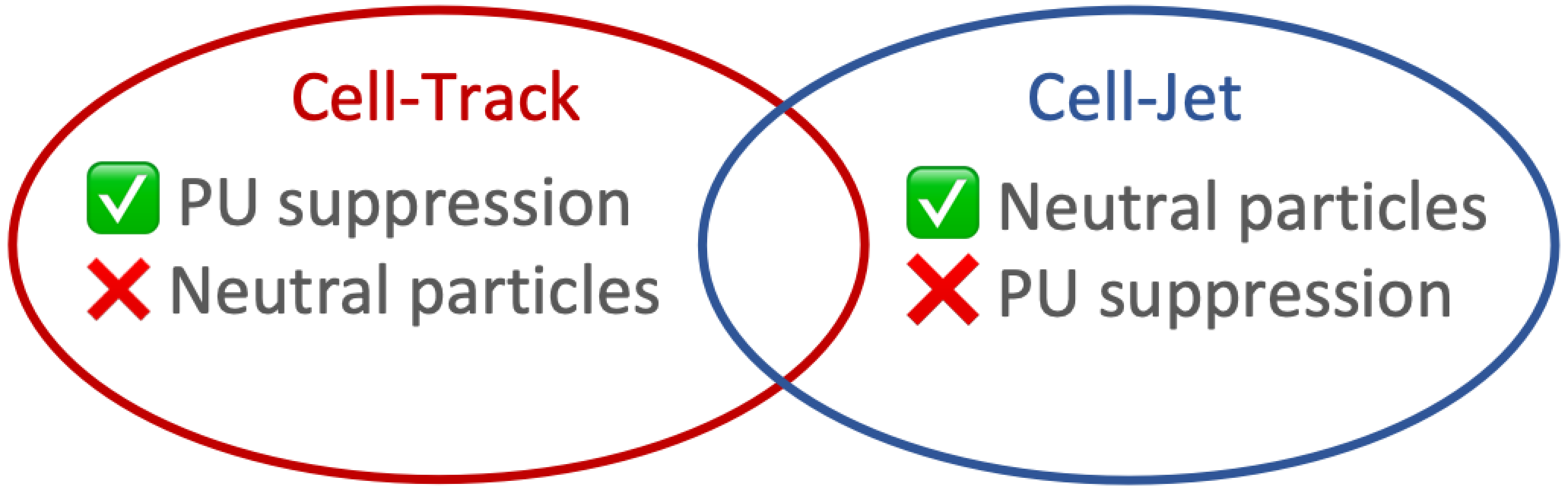


→ Cell-Jet Matching

- ➢ All reco. jets that satisfy:
  - $p_T \geq 30$ GeV
  - Matched to truth HS jets
- ➢ ΔR(cell, jet) ≤ 0.3 cells for t_0 reconstruction

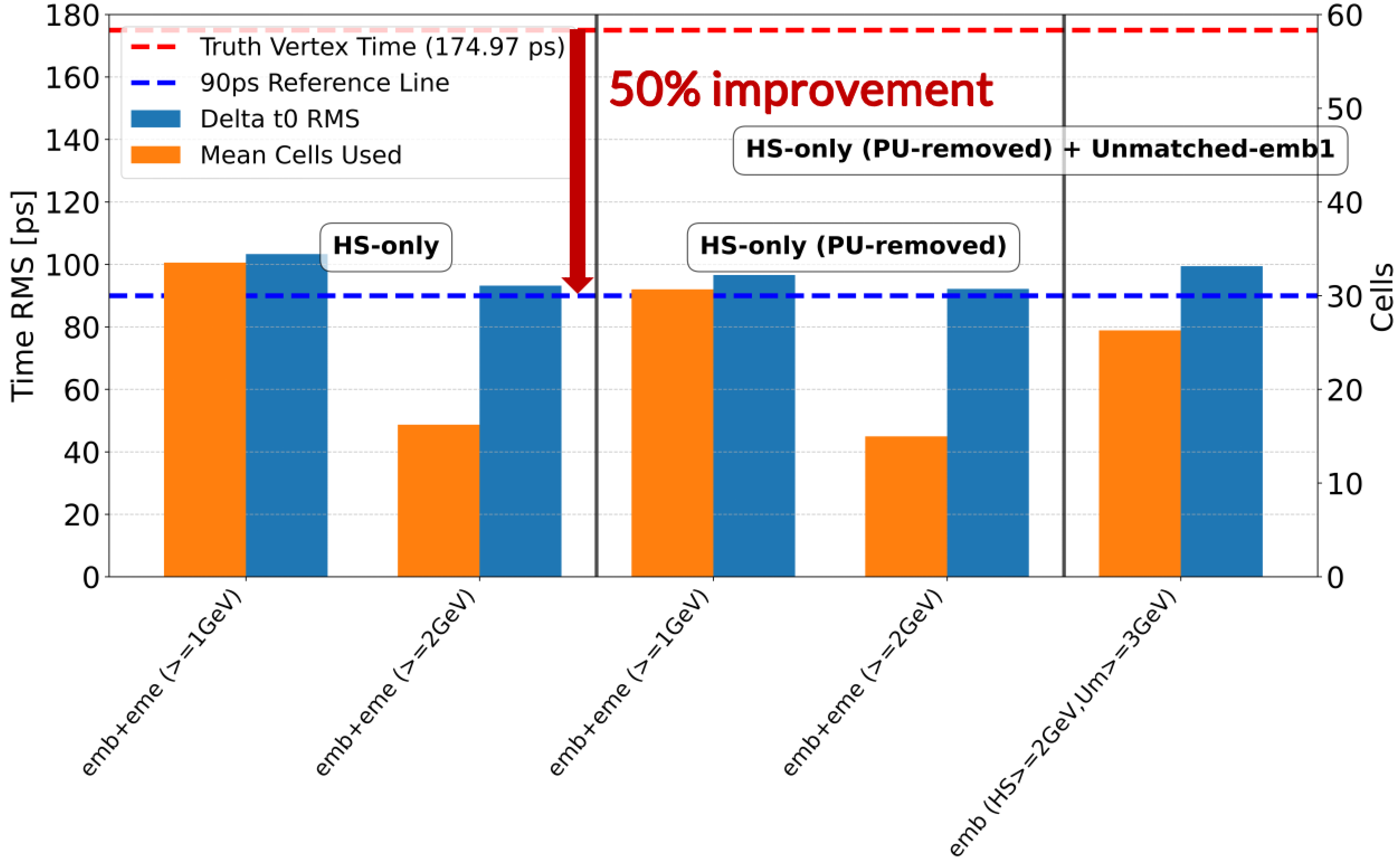


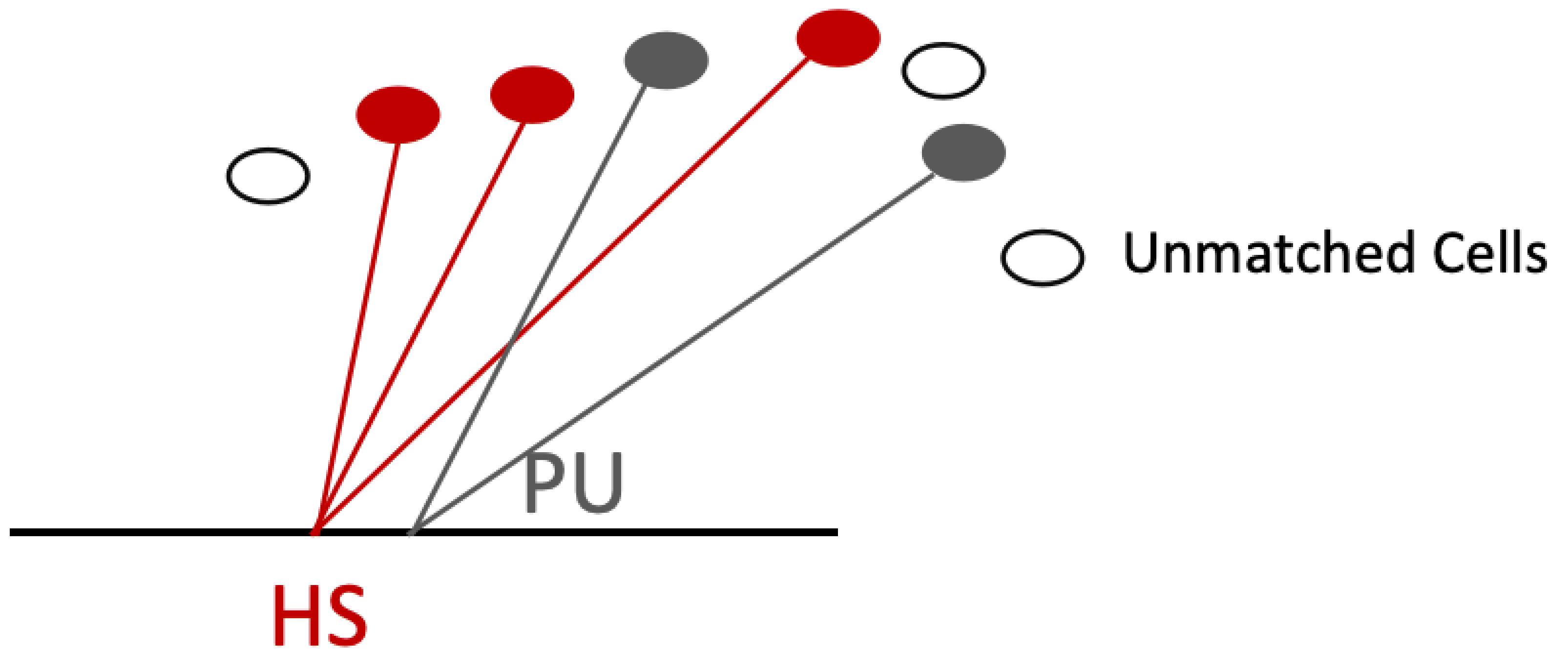
Event Display
(4 Leading Jets)

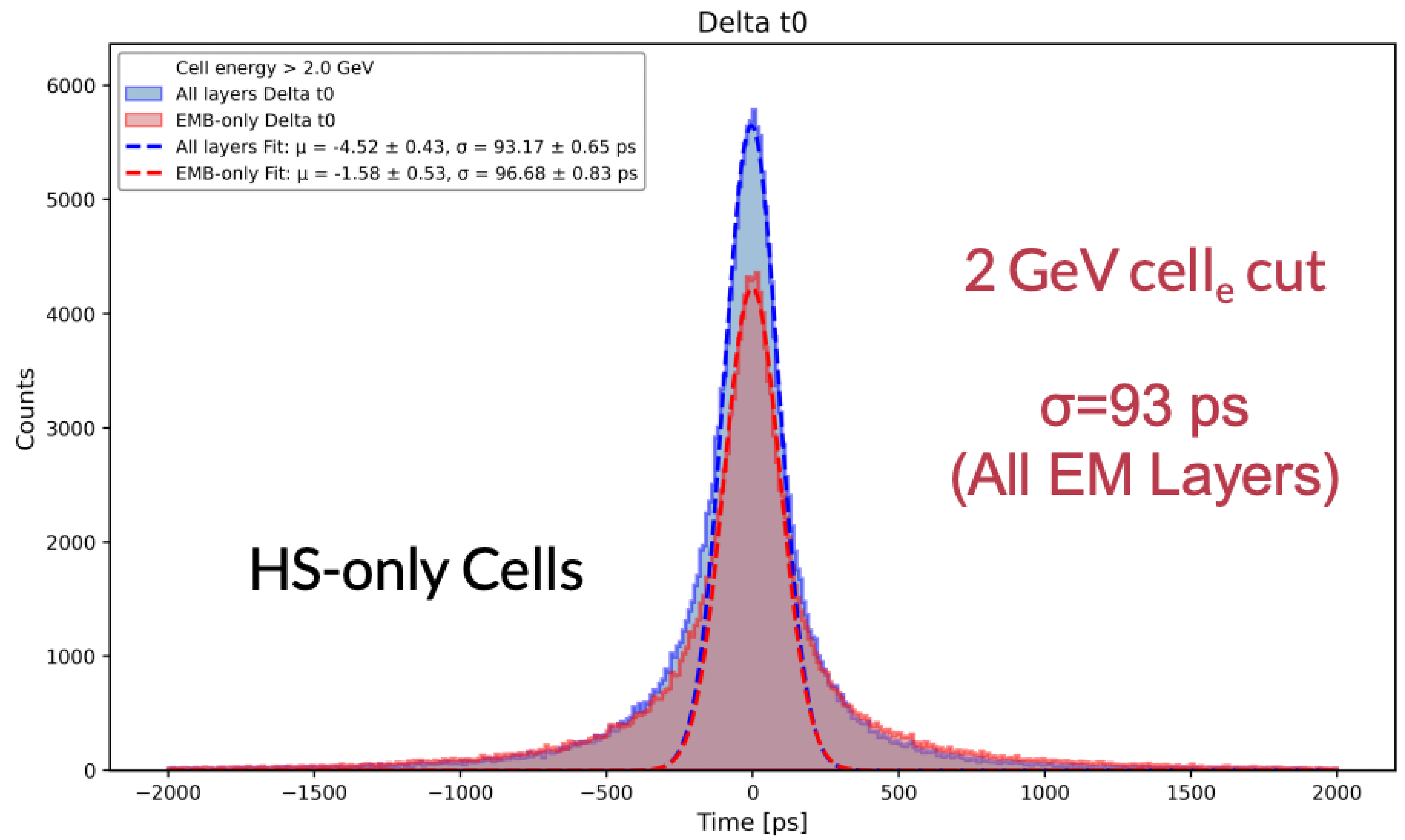


Summary of Cell-Track Matching

Selected Optimal Strategies





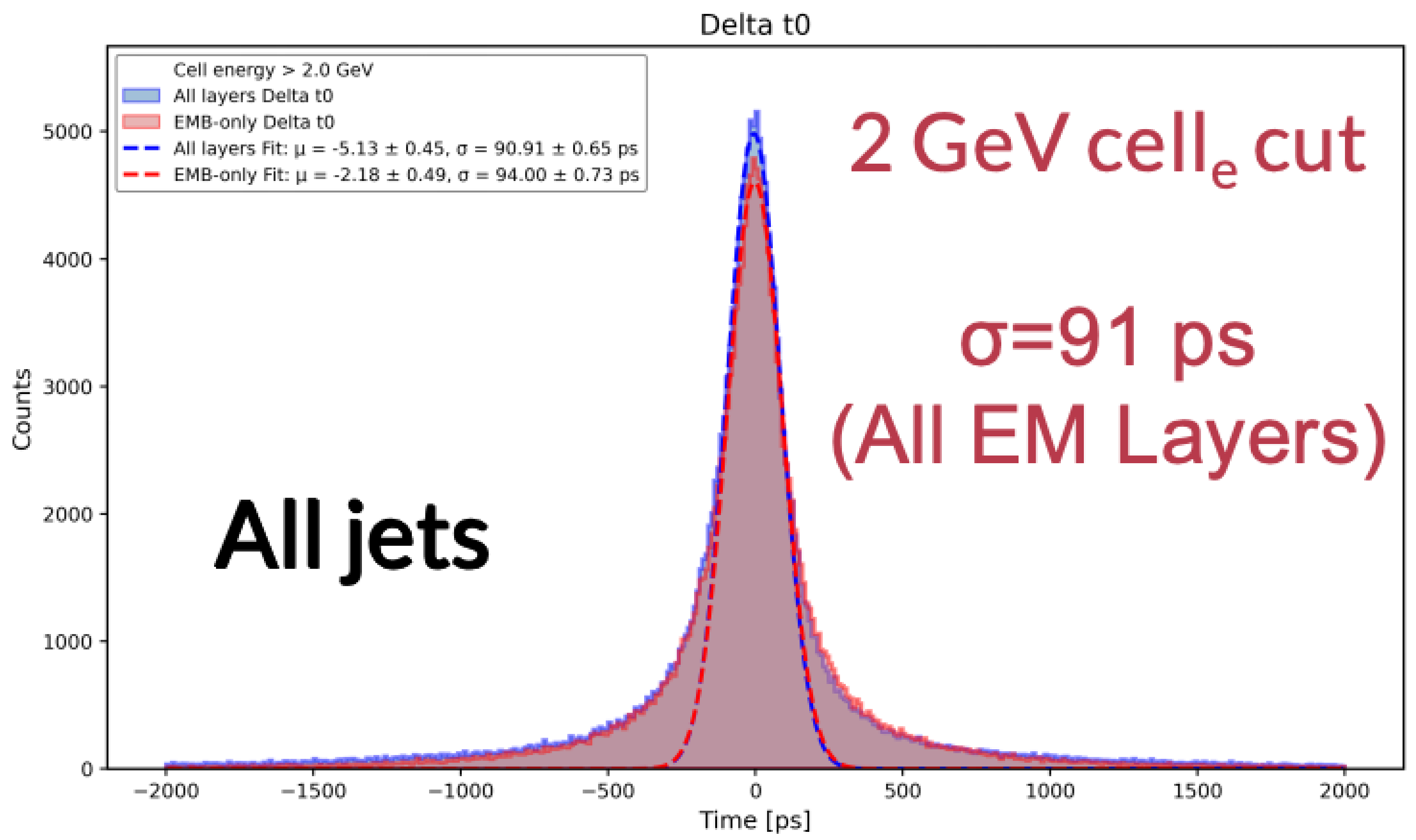


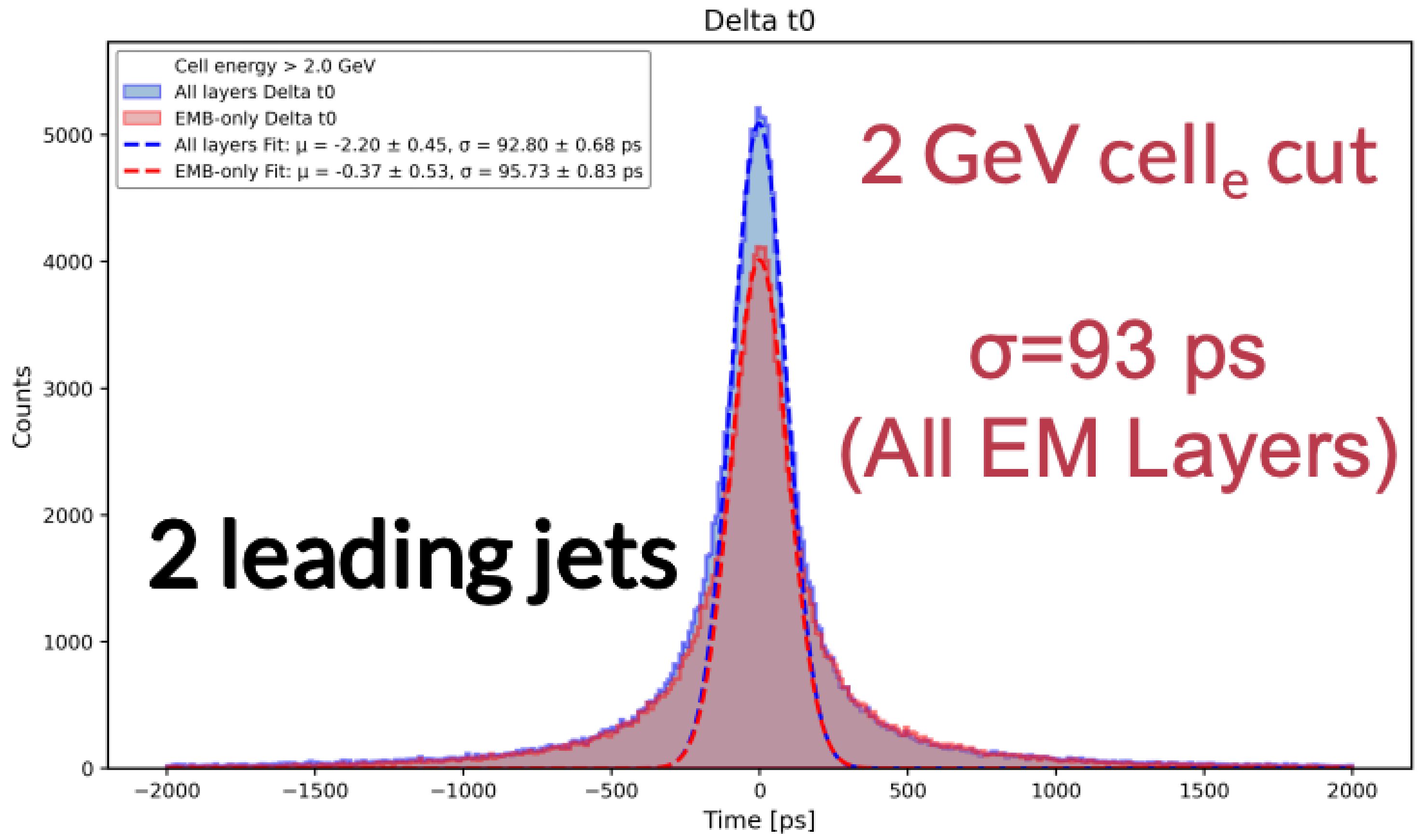
- The best timing resolution achieves ~93 ps with only 0.02% reconstruction failure rate.
- Increasing the cell energy cut improves resolution slightly.
- No significant improvement from lower cell significance or ΔR(cell, track) cut.

- **Sub-100 ps Δt_0 resolution** with HS-only cells
- Using all EM-layers did help!

Summary of Cell-Jet Matching

❑ All Jets vs 2 Leading Jets





- Reaching ~90 ps level
- Varying the ΔR doesn't help:
  0.15 --> 90.97 ps;
  0.30 --> 90.91 ps;
  0.40 --> 91.25 ps

PV t_0 Reconstruction Summary

	Inclusive	Track-matching	Jet-matching
Best Δt_0 Resolution [ps]	119.0	93.2	90.9
Layers	EMB-only	EMB & EMEC	EMB & EMEC
Cell Energy Cut [GeV]	2.0	2.0	2.0
Mean Cells Used	11.0	15.7	21.7

ML is coming in for the next step.

Part 2

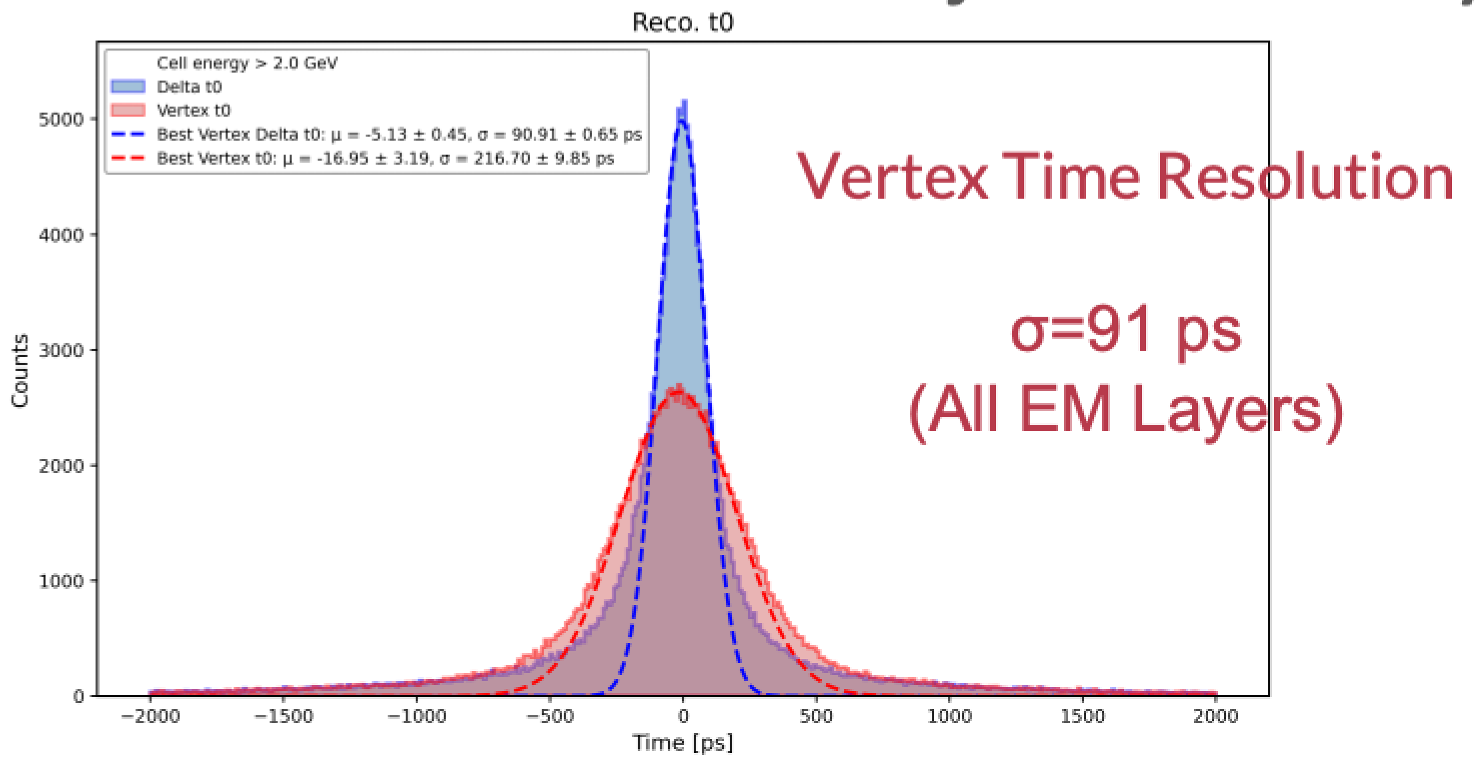
Impact of Shower Physics/Topology

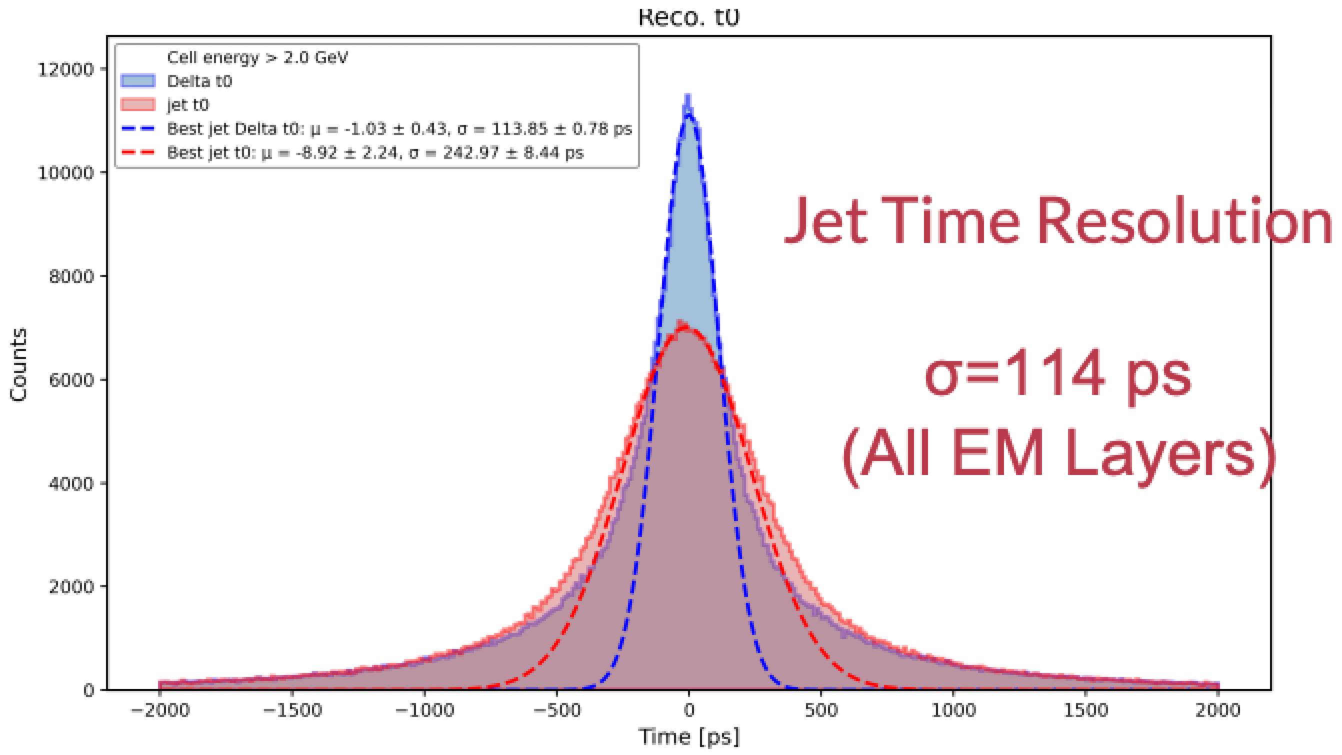
Shower Physics Impact on t_0 Resolution

❑ Motivation

- Do showers with different topologies exhibit different time resolution performance?

➢ From vertex-level to jet-level analysis

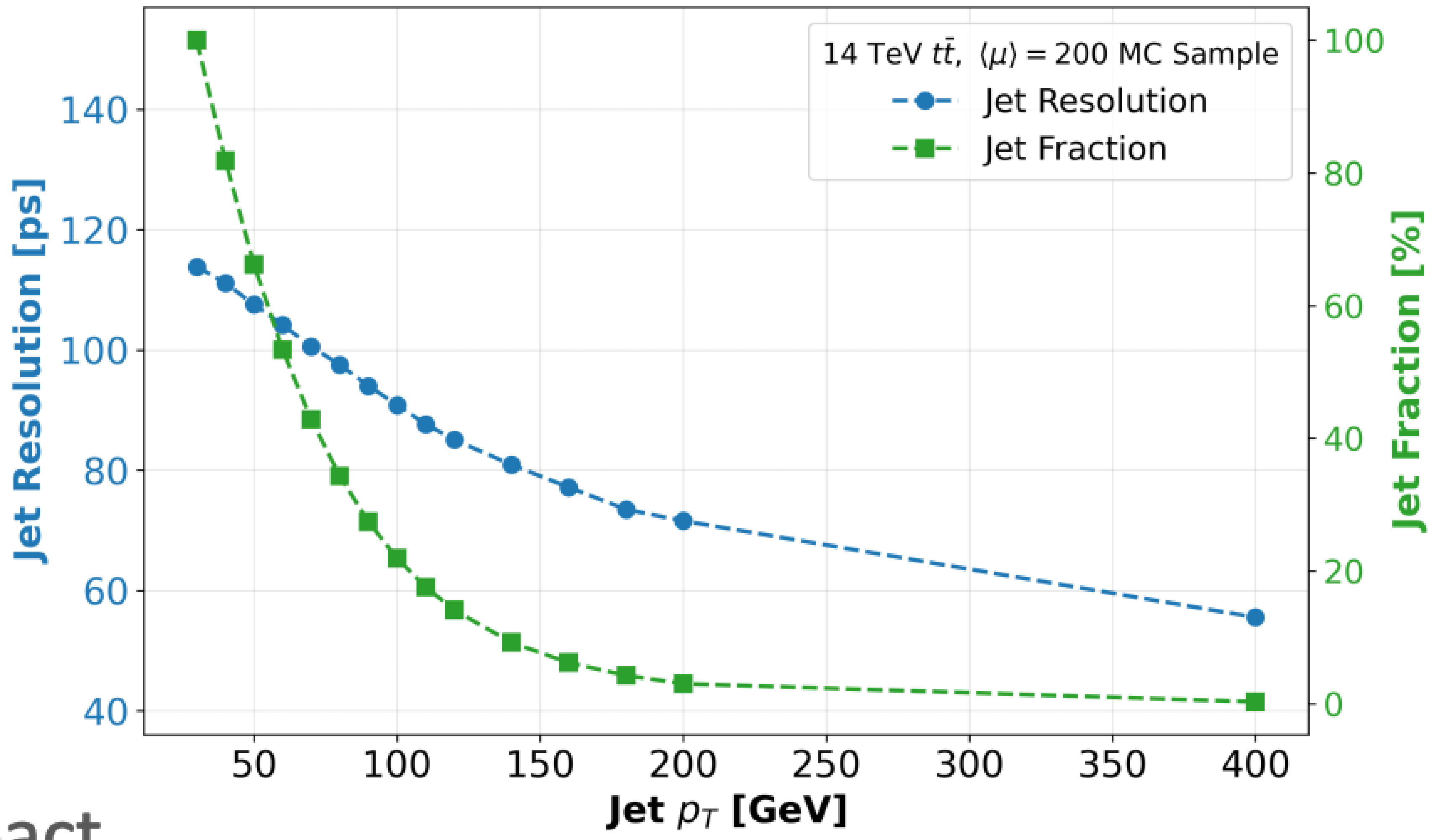




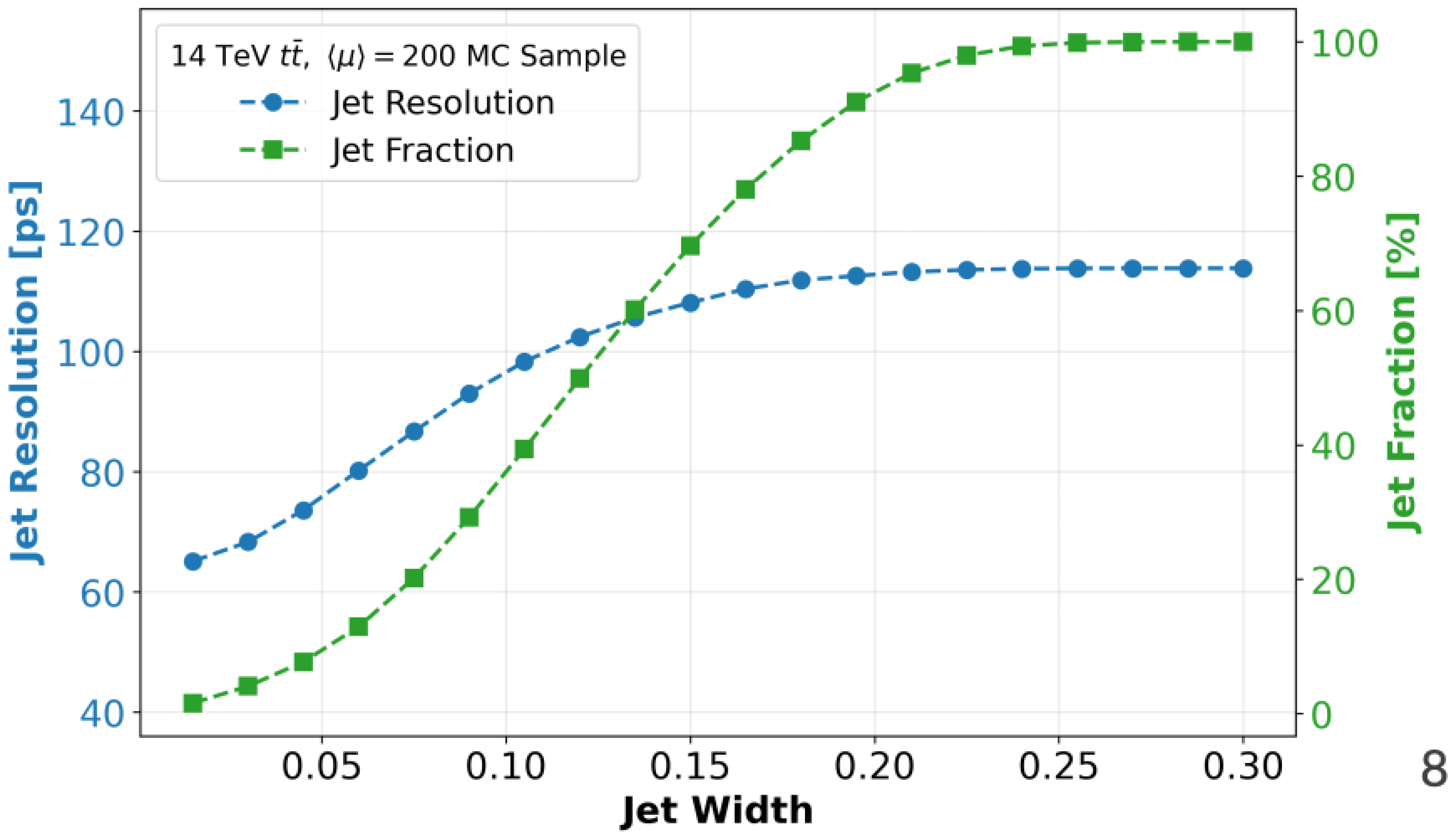
- **Jet Resolution:** resolution using only single-jet information.
- **Jet Fraction:** fraction of reco. jets passing specific cuts.

❑ Jet Physics Impact

➢ Jet-p_T Impact

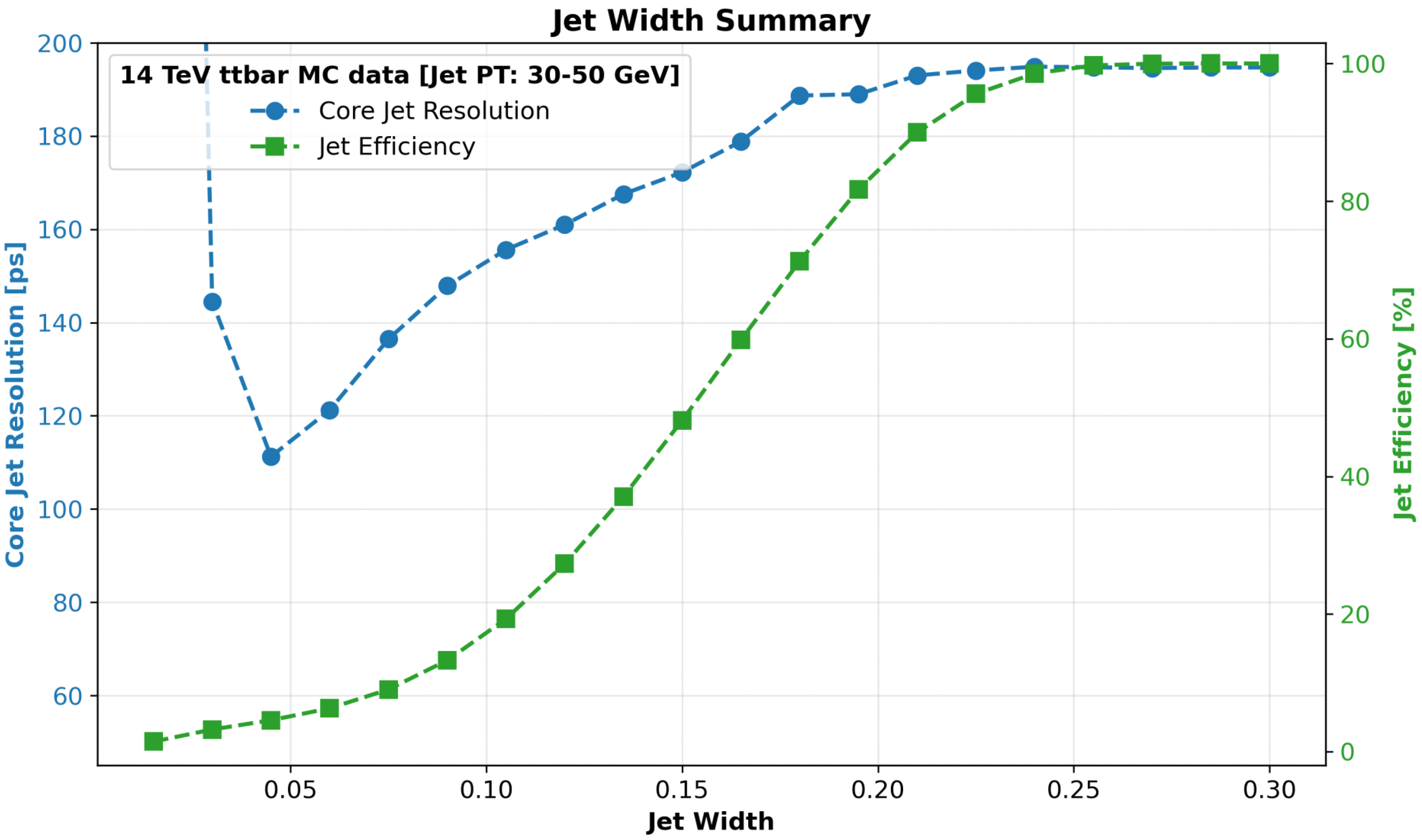


➢ Jet-width Impact

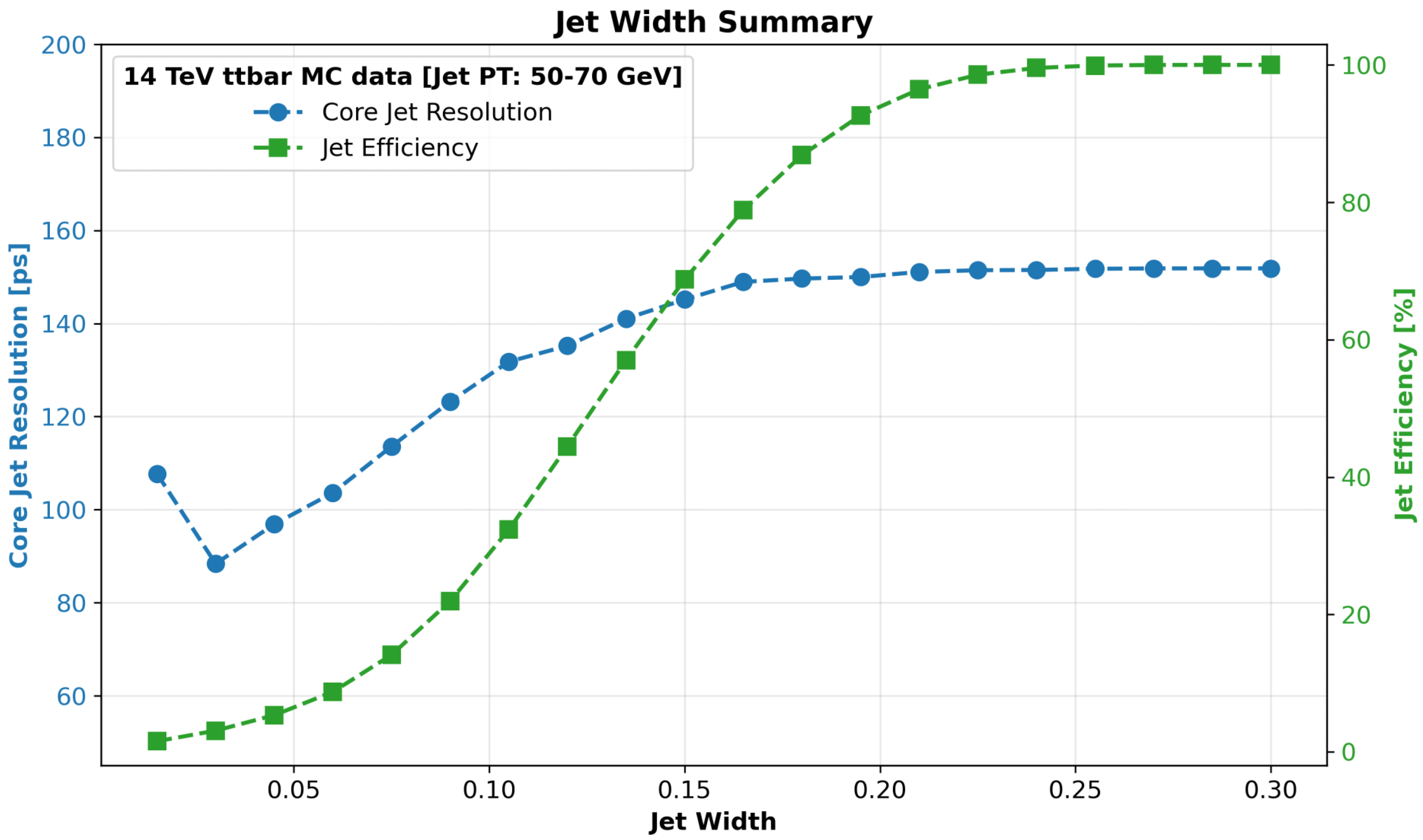


- Jets with higher p_T/narrower width exhibit better time resolution.

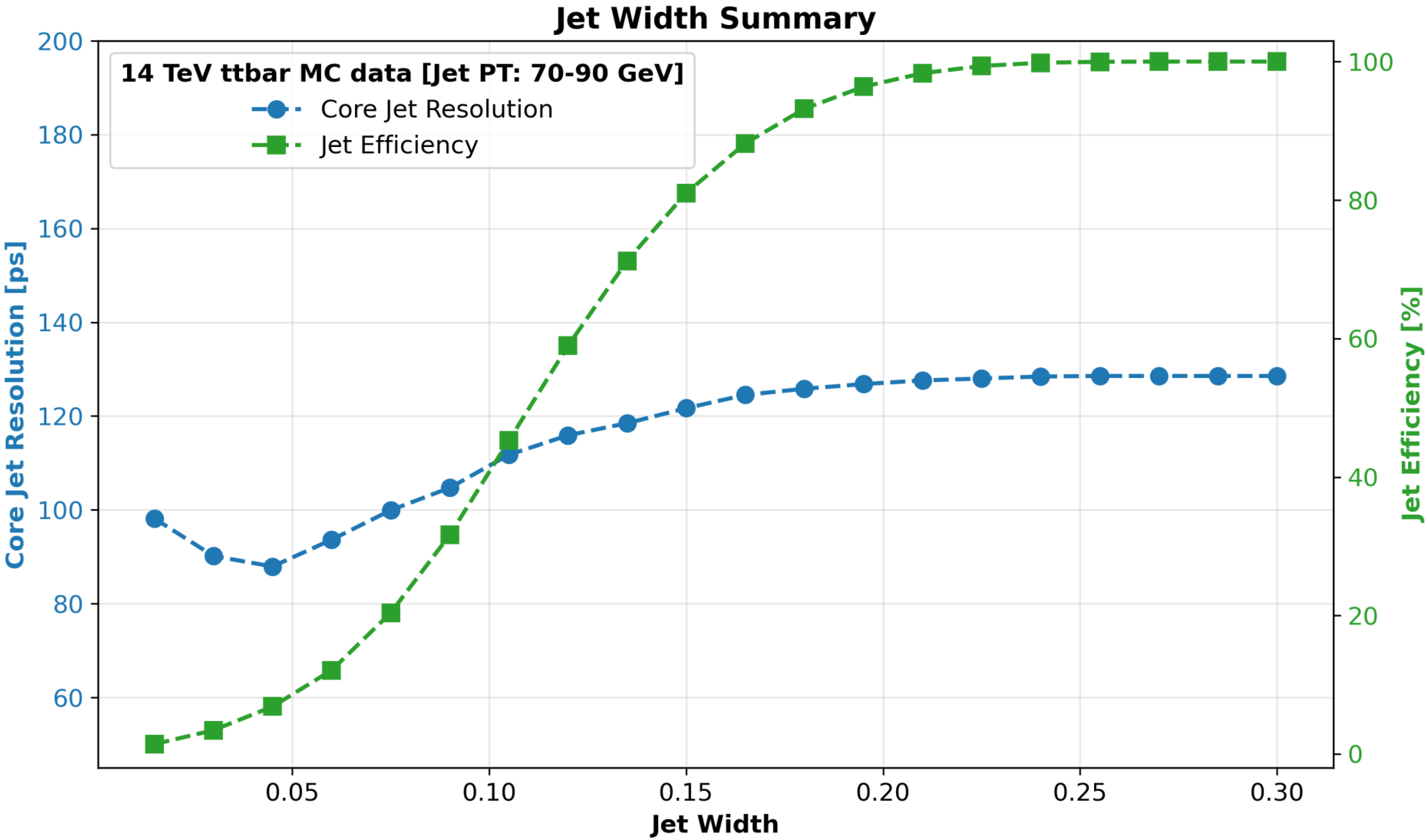
Jet-width Summary with Fixed Jet p_T Bins



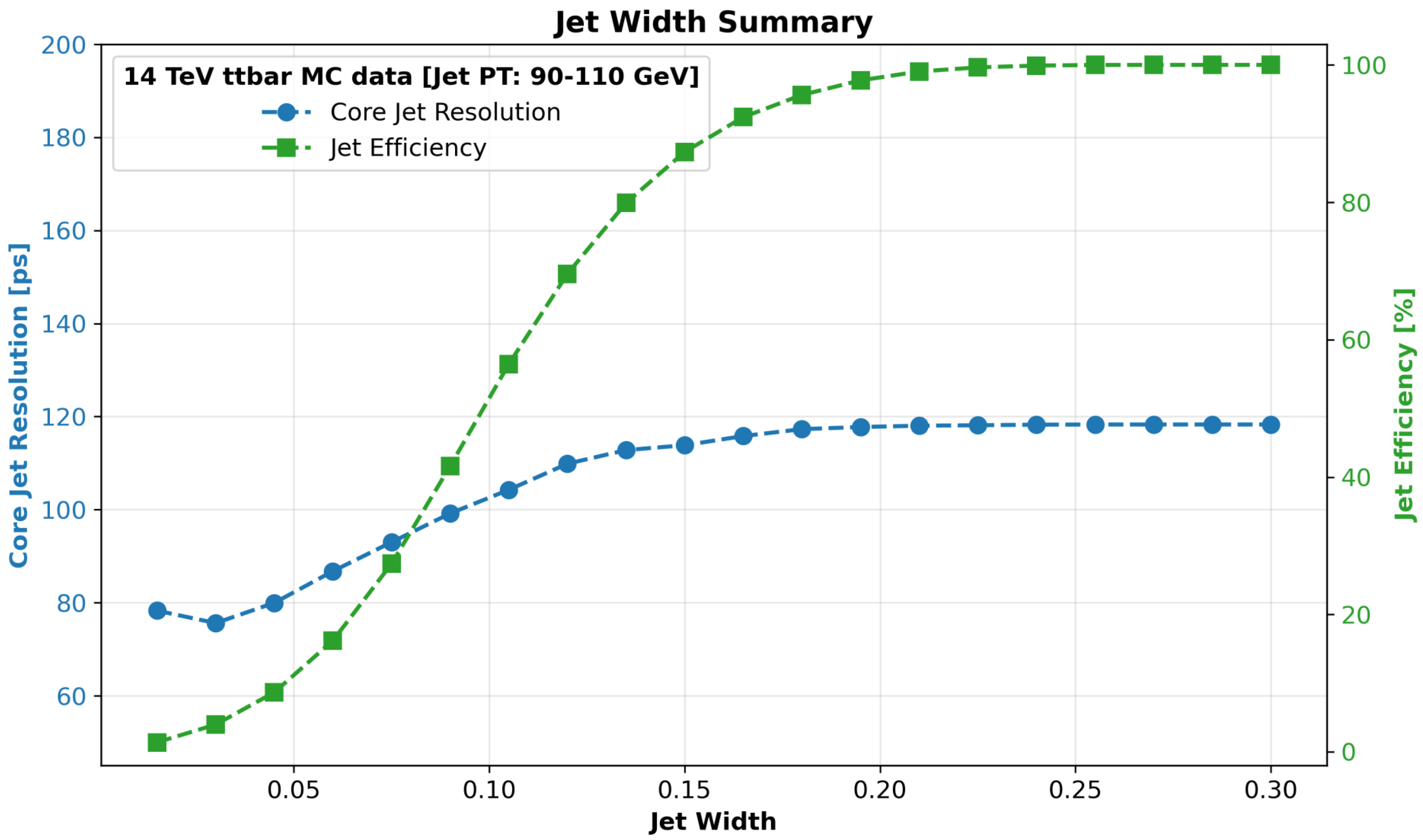
Jet-width Summary with Fixed Jet p_T Bins



Jet-width Summary with Fixed Jet p_T Bins



Jet-width Summary with Fixed Jet p_T Bins



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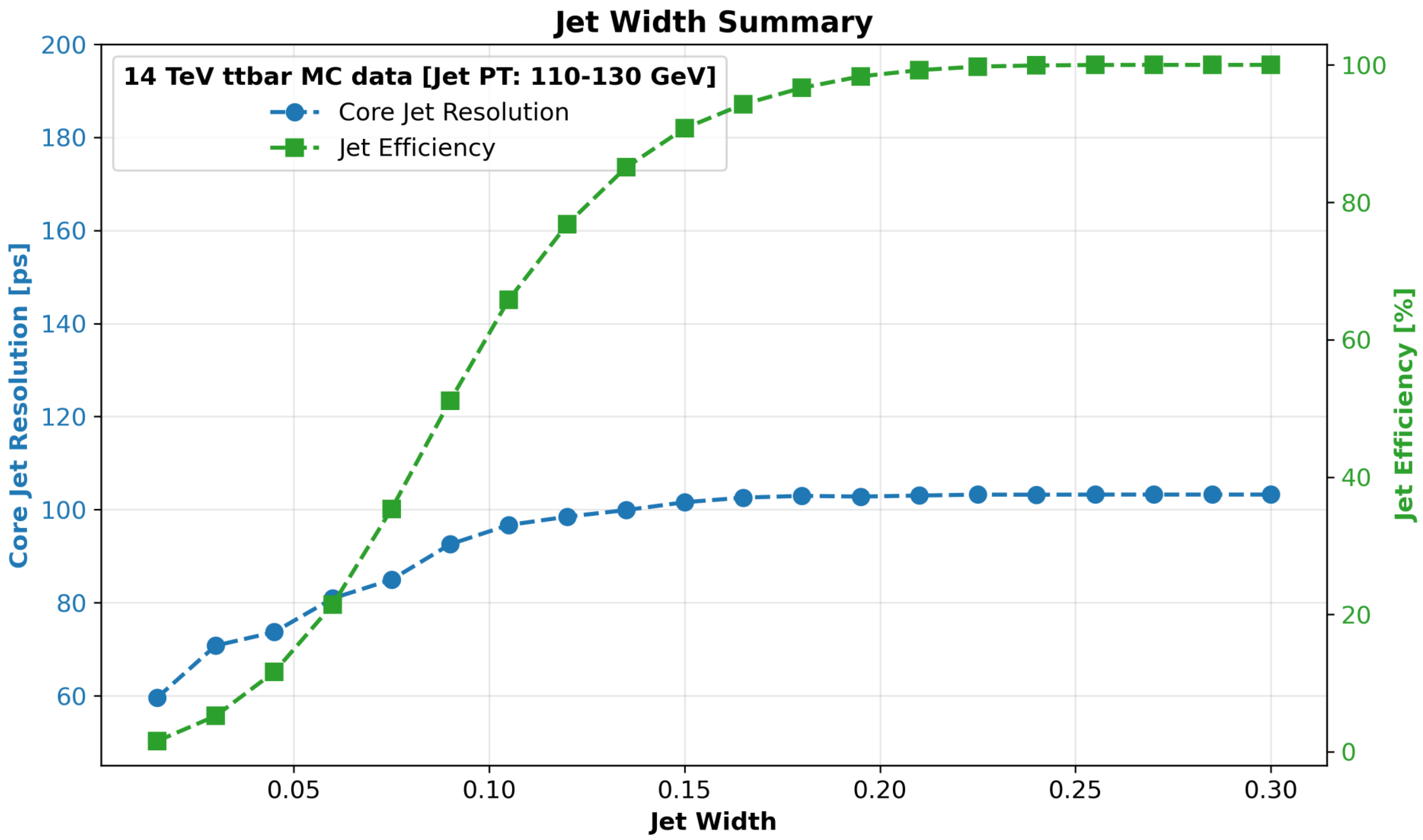

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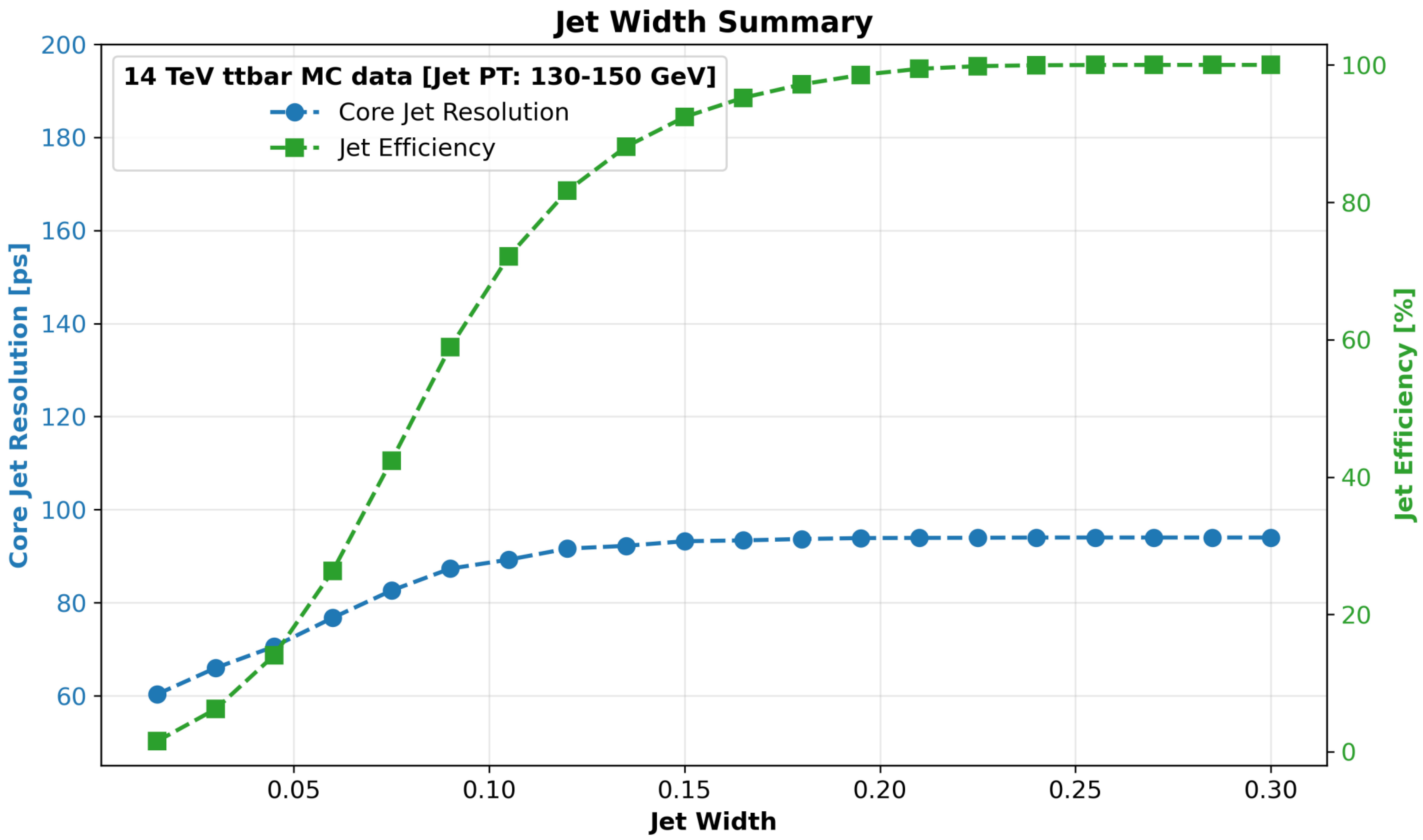
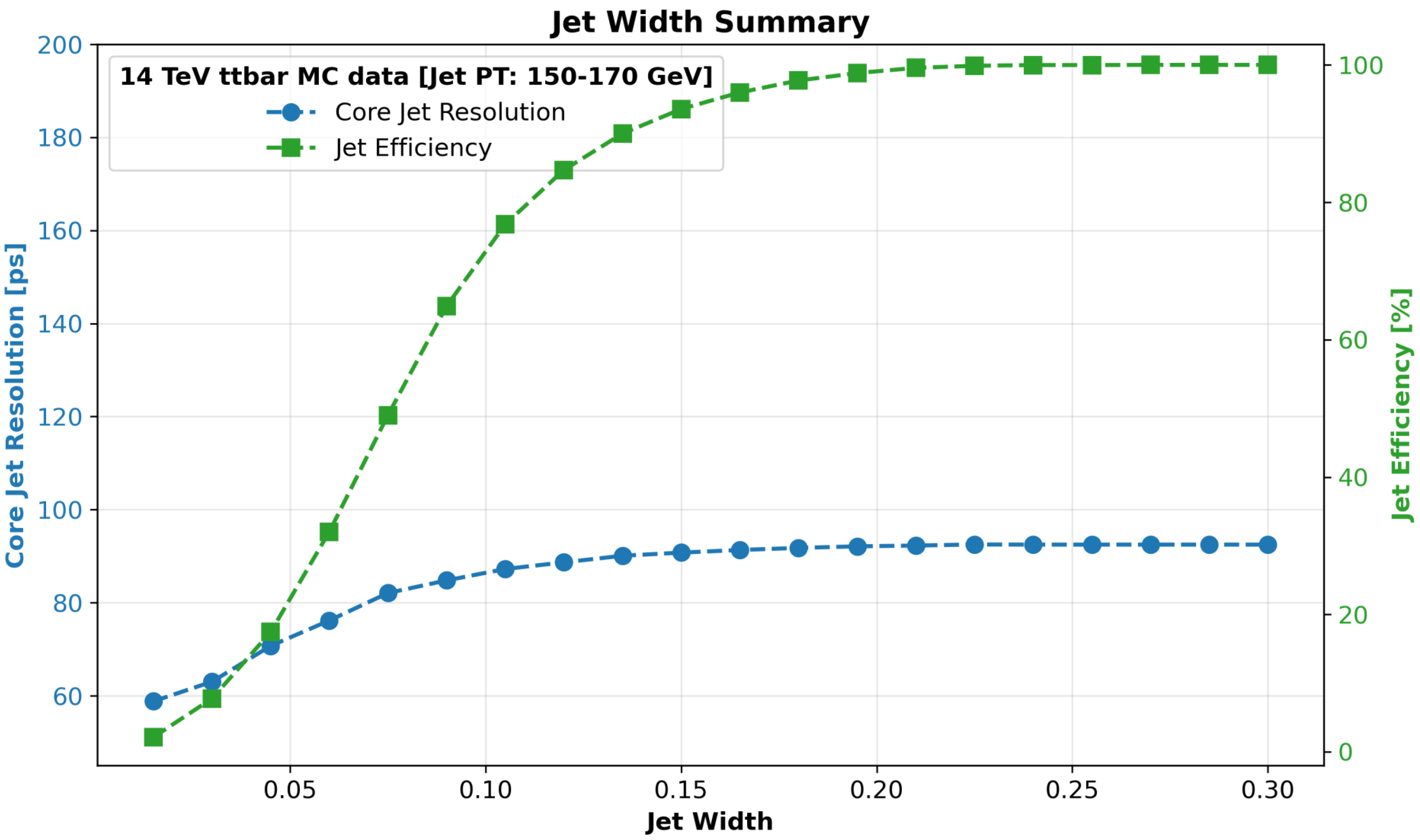
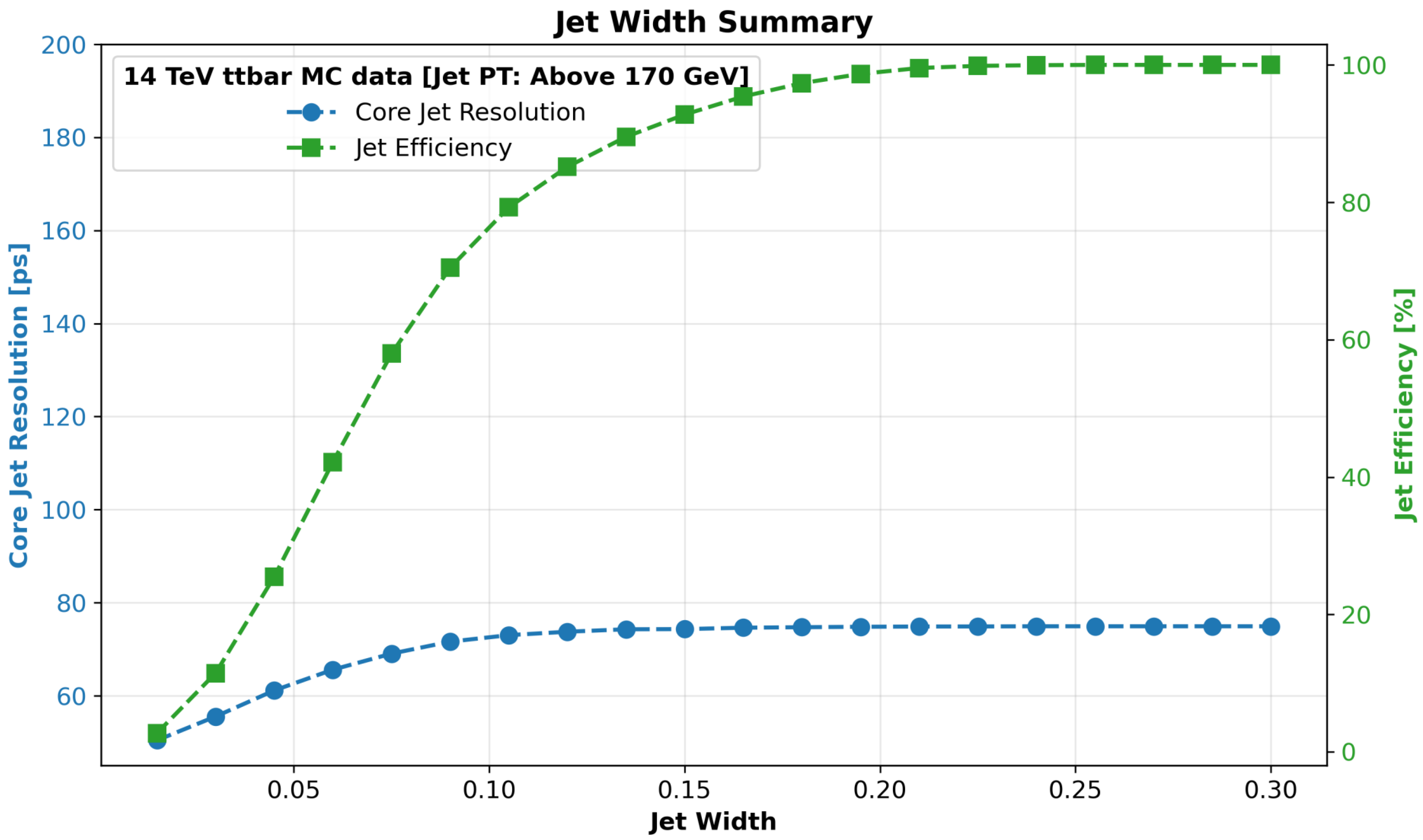


Jet-width Summary with Fixed Jet p_T Bins



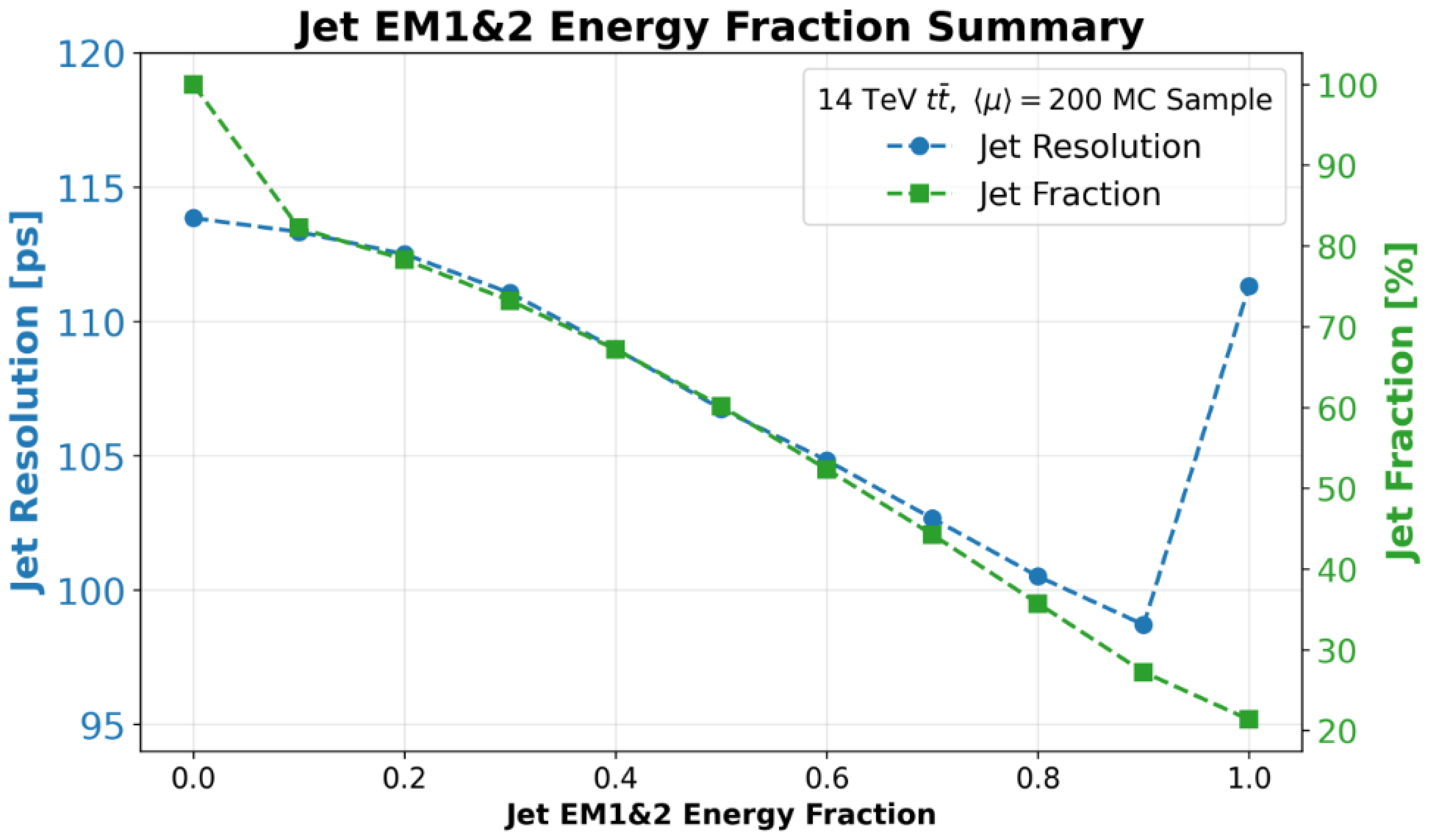
Jet-width Summary with Fixed Jet p_T Bins



Jet Longitudinal Impact

❑ Jet-EM Layer Fraction

➢ Evaluating Energy Deposition Ratios in Front-End EM Layers

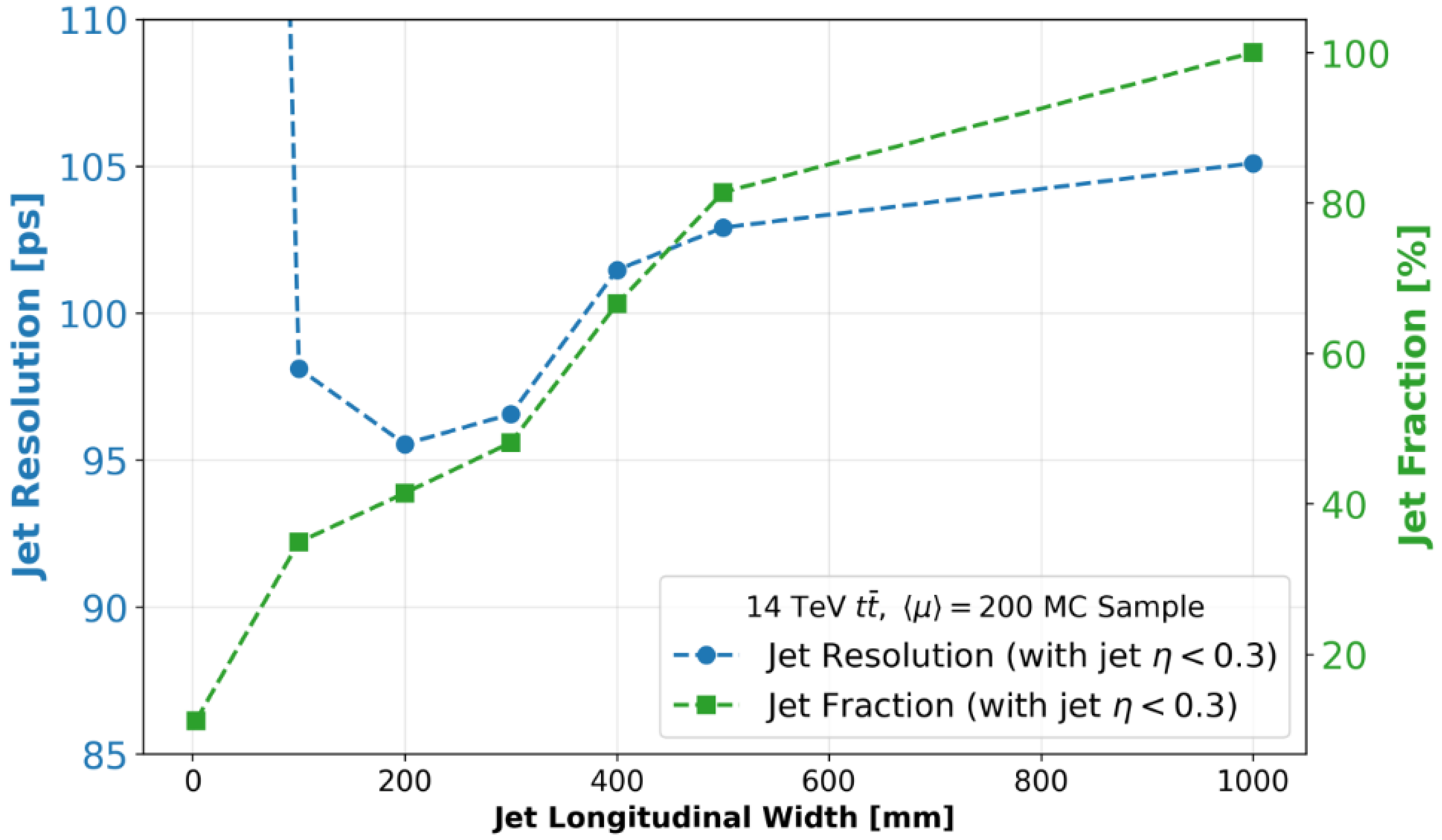


- Higher EM1&2 fraction indicates shallower showers, which provides better time resolution.

❑ Jet Longitudinal Width

$$Lw^{jet} = \sqrt{\frac{\sum_{cell} E^{jet}_{cell}(Z^{jet}_{cell} - c.o.e^{jet})^2}{\sum_{cell} E_{cell}{}^{jet}}}$$

$$c.o.e^{jet} = \frac{\sum_{cell} E_{cell}{}^{jet} Z^{jet}_{cell}}{\sum_{cell} E_{cell}{}^{jet}}$$



- Longitudinal width distribution seems to have correlation with jet timing.

Part 3

Machine Learning Attempts

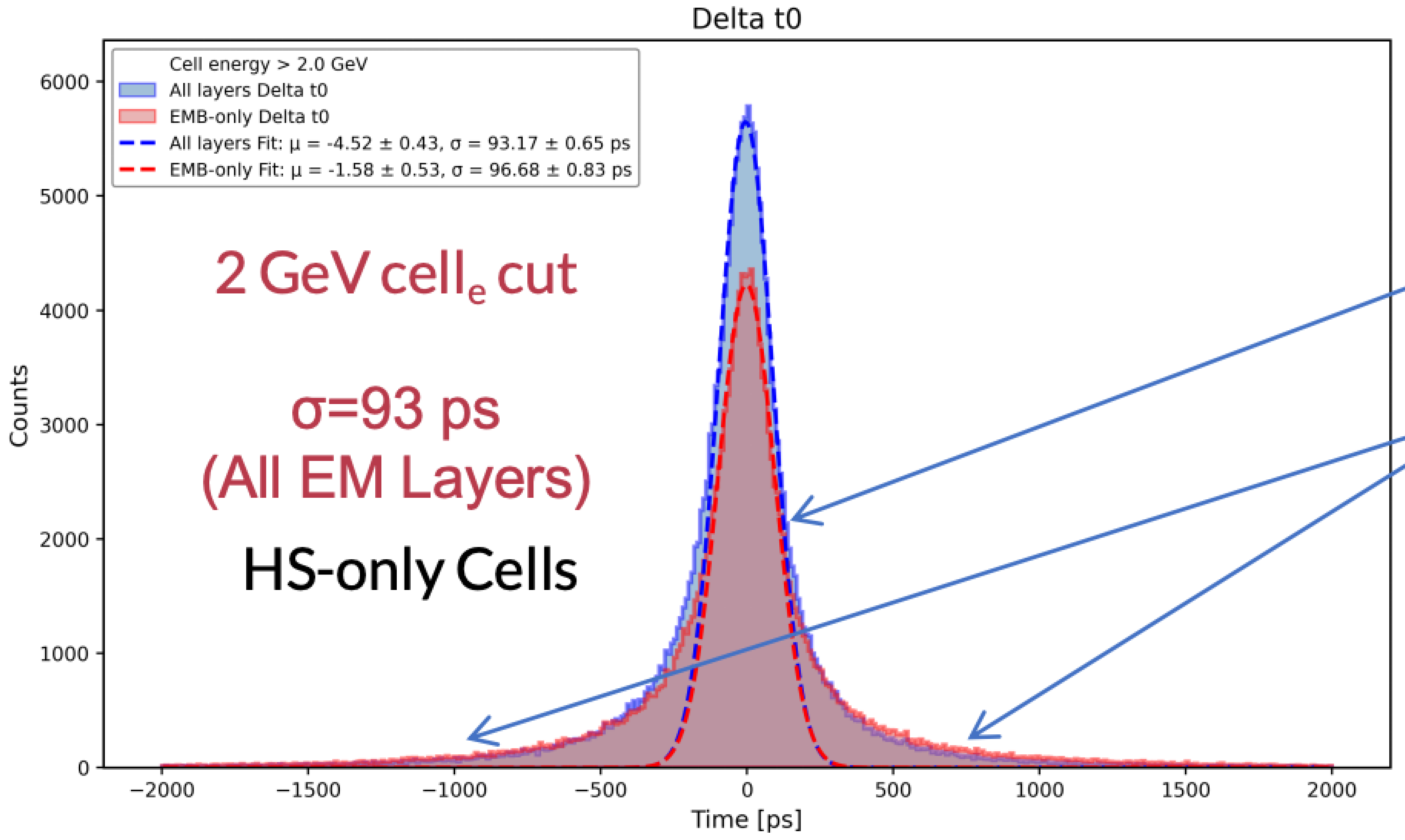
Machine Learning Approach for PV t_0

❑ Objective

- Leverage ML to predict primary vertex t_0 for each event
- Utilize cell-level data along with reco-track/jet info to further enhance time resolution

❑ Challenges with Conventional Methods

- e.g. Track-matching Result



Fittings exclusive to the core area

Long tails leads to non-Gaussian shapes

May not fully utilze all info to get the best resolution yet?

Starting Point: ML Regression Using Matched Cells

Input Features

```
all_cell_features:
– Cell_x
– Cell_y
– Cell_z
– Cell_eta
– Cell_phi
– Cell_Barrel
– Cell_layer
– Cell_time_TOF_corrected
– Cell_e
– Cell_significance
```

→ Calibrated before being provided to the ML model

→ Cell-Track Matching (if applicable)

```
track_features:
– matched_track_pt
– matched_track_deltaR
```

→ Cell-Jet Matching (if applicable)

```
jet_features:
– matched_jet_pt
– matched_jet_eta
– matched_jet_phi
– matched_jet_width
– matched_jet_deltaR
```

- Using leading energy cells (default: 40 cells)
- 3σ time significance cut for cell times ($175\text{ps} \oplus \sigma_{cell}$)
- Smart Padding:
  - Cell_time_TOF_corrected: 0.0
  - Cell_e: 0.0, Cell_significance: 0.0
  - Position features: All coordinates use 0.0
  - Classification features: Cell_Barrel: -1, Cell_layer: 0
  - Track matching: matched_track_pt: -1.0, matched_track_deltaR: -1.0
  - Jet matching: matched_jet_pt: -1.0, matched_jet_eta: -999.0, matched_jet_phi: -999.0

Two Architectures

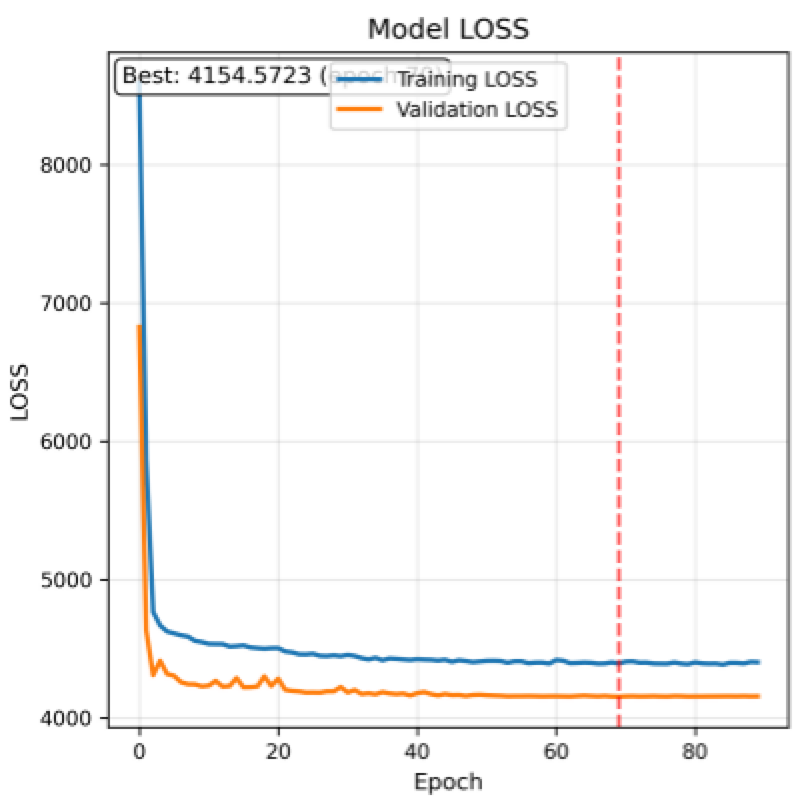
- Two-Stage DNN Model
  - Stage 1: Cell-level MLP → Cell representations
  - Stage 2: Masked Attention Pooling → Event representation
  - Stage 3: Event-level MLP → Vertex time
- Transformer Model
  - Stage 1: Cell features → Dense projection → Positional encoding
  - Stage 2: Embedded sequences → Transformer Blocks
  - Stage 3: Transformer outputs → Pooling → Event representation
  - Stage 4: Event-level MLP→ Vertex time

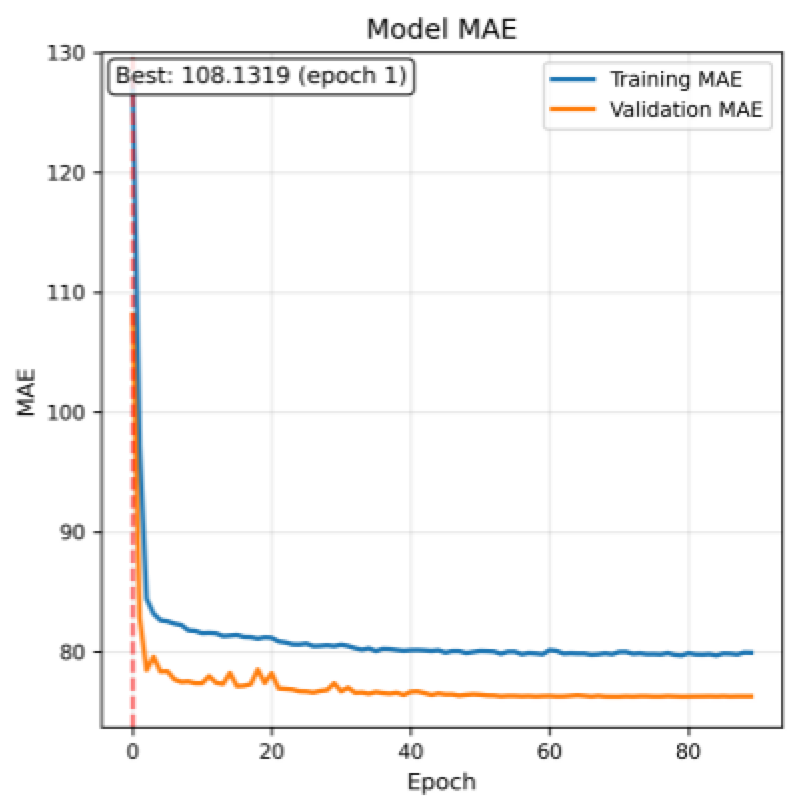
ML Regression Using Jet-Matched Cells

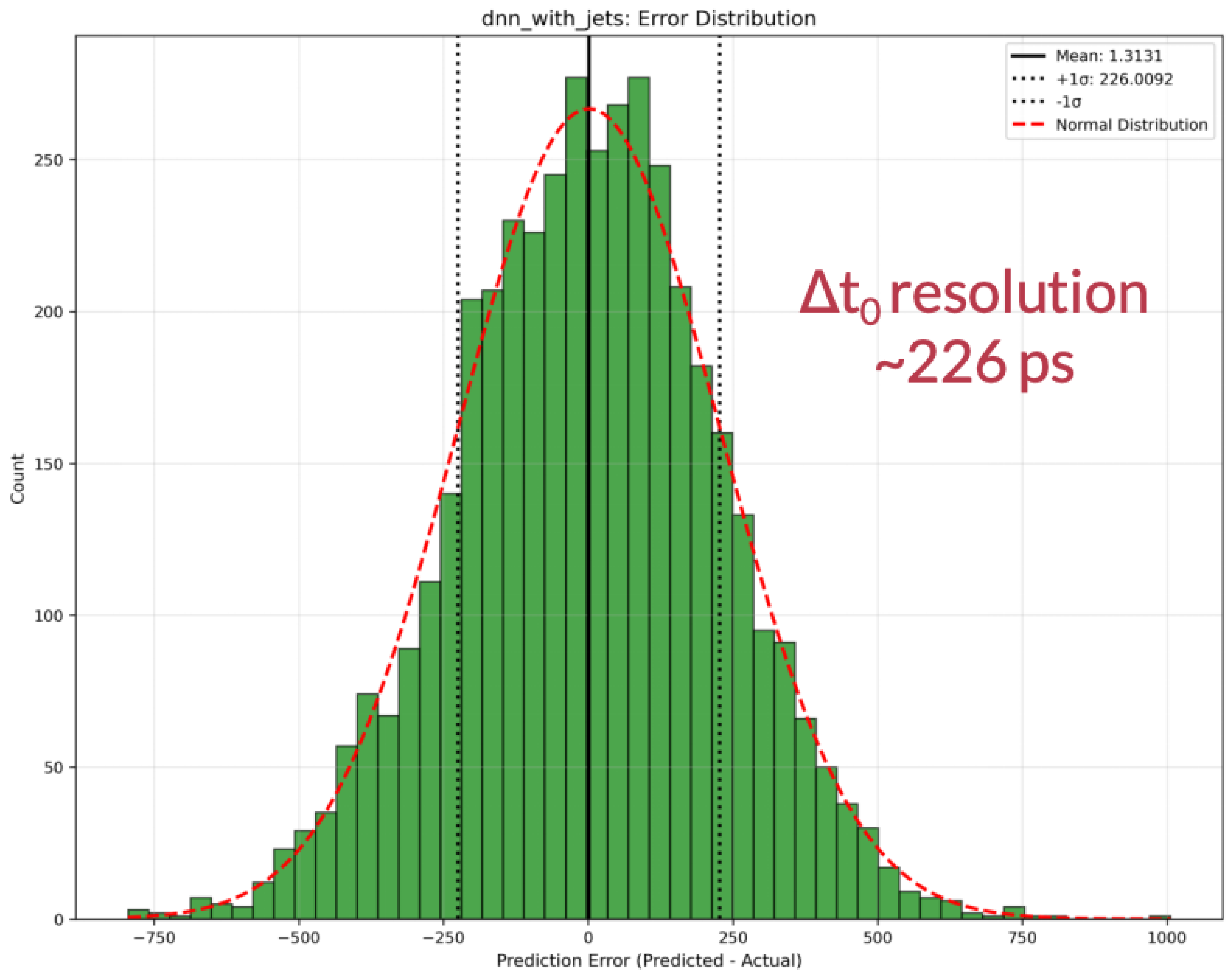
Model 1: Two Stage DNN

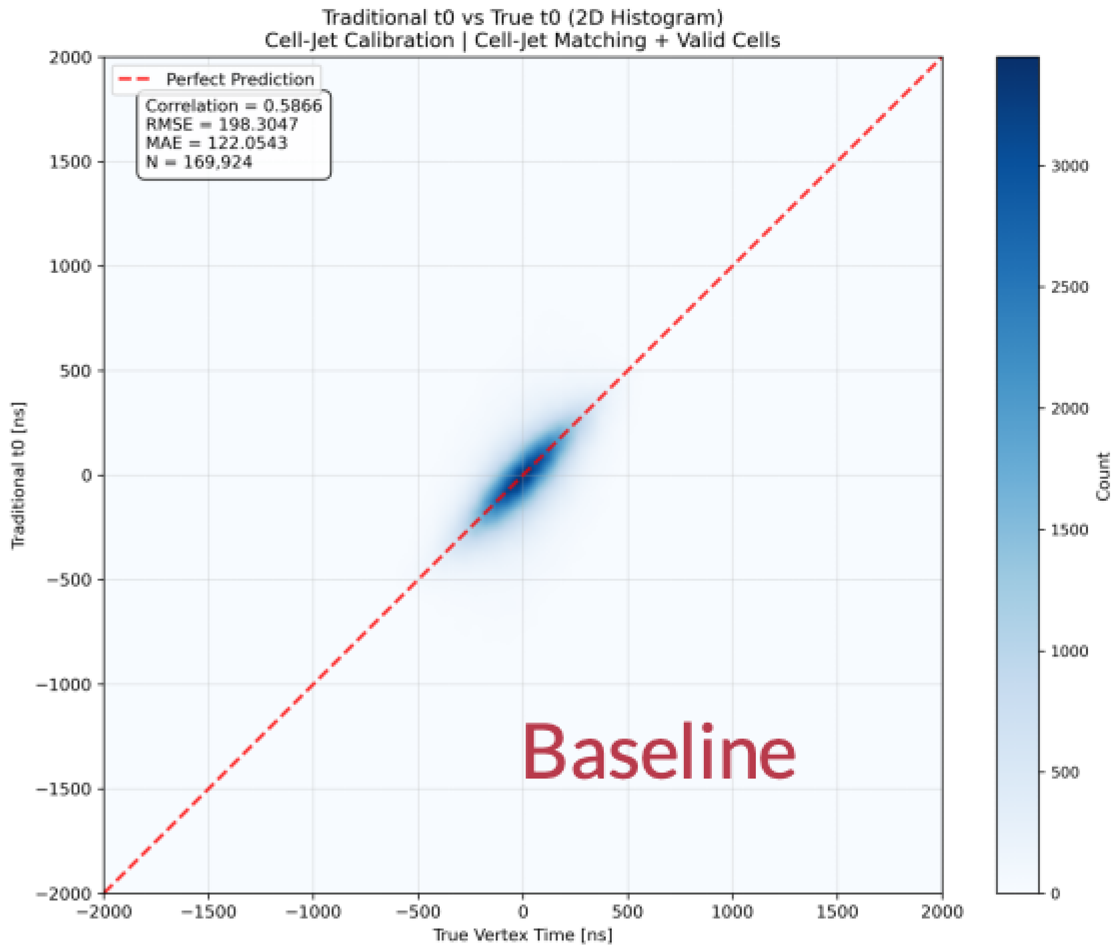
- Use cells following conventional cell-jet matching
- Calibrate cell times prior to inputting them into the model
- Loss function: huber (δ=100)

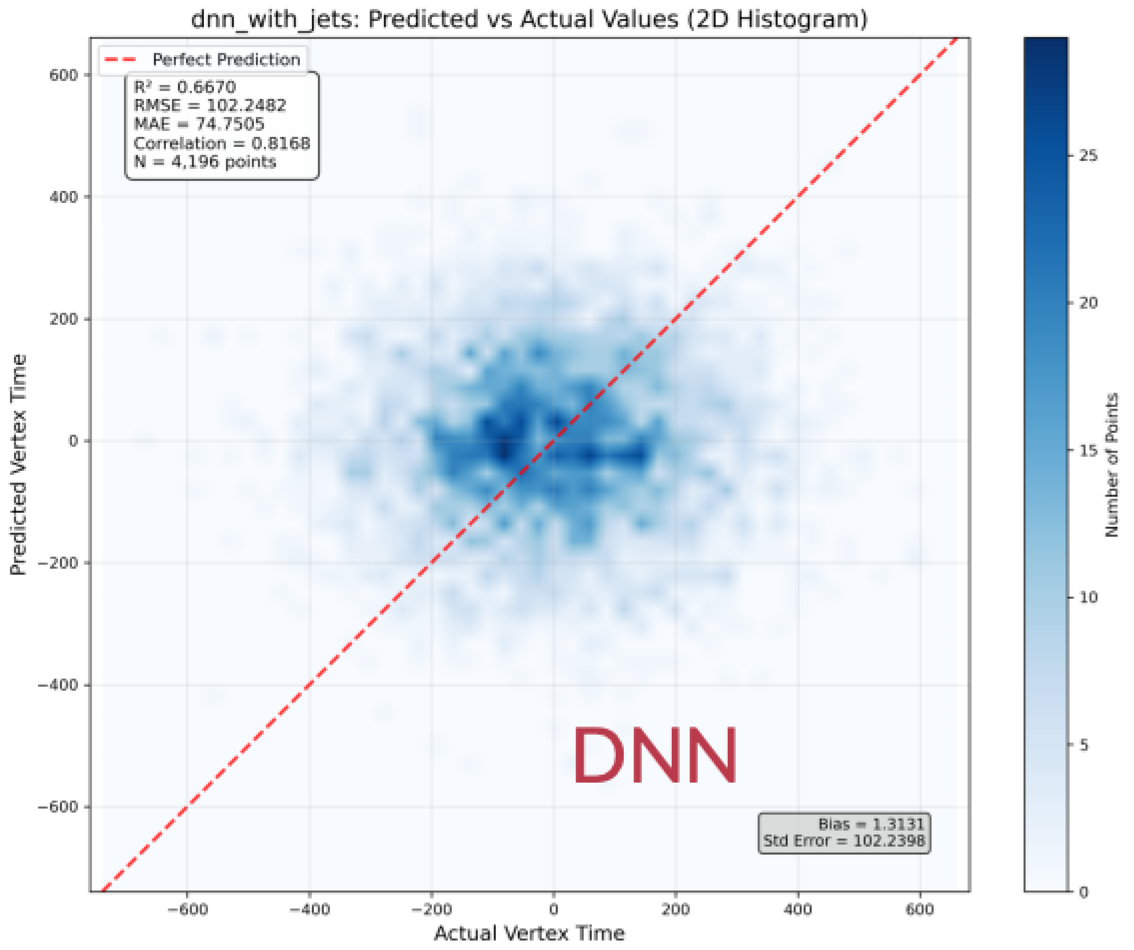
$$L_\delta(y, f(x)) = \begin{cases} \frac{1}{2}(y - f(x))^2 & \text{for } |y - f(x)| \le \delta, \\ \delta \cdot \left(|y - f(x)| - \frac{1}{2}\delta\right), & \text{otherwise.} \end{cases}$$











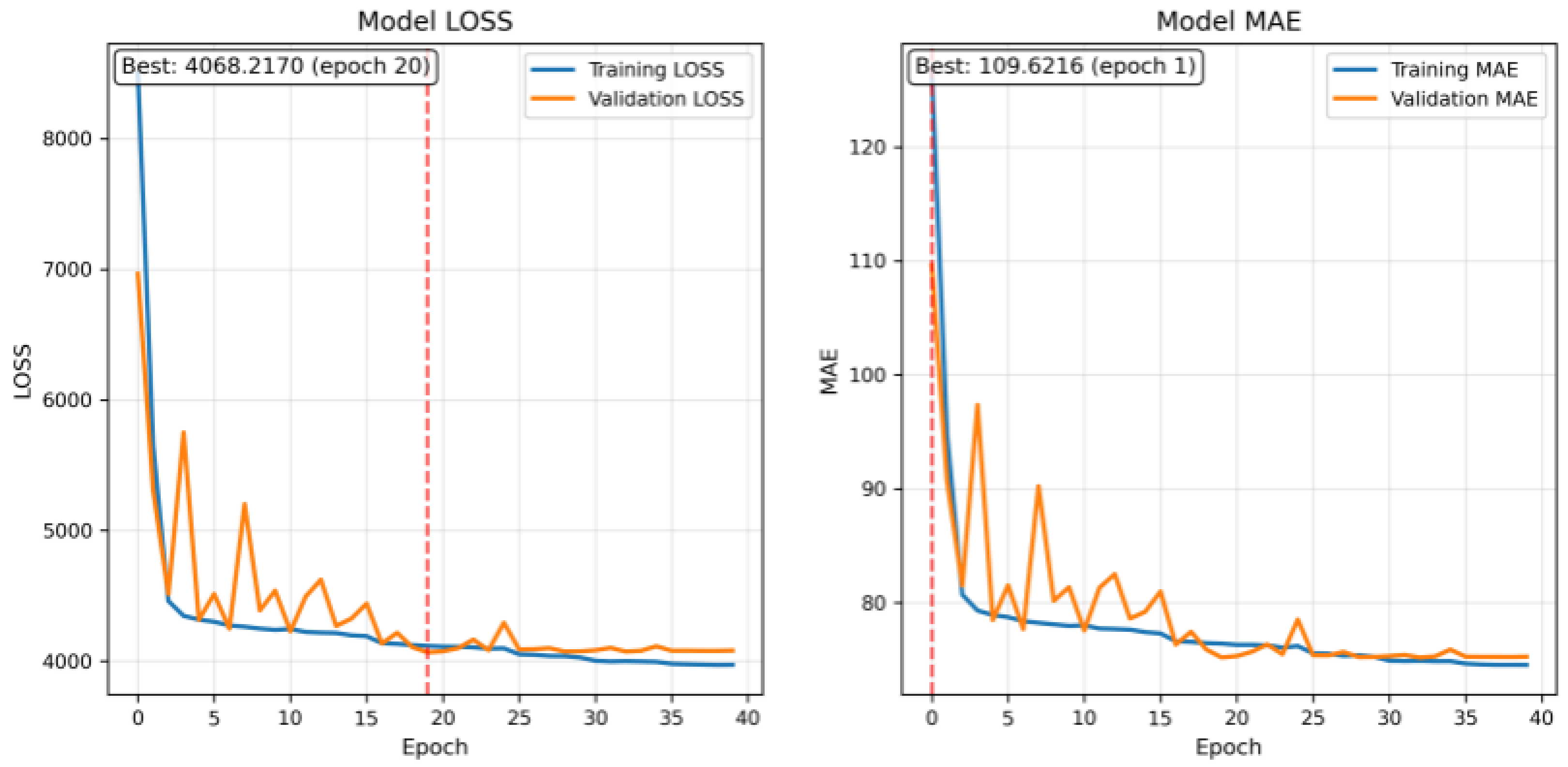
- Was the model just randomly guessing?

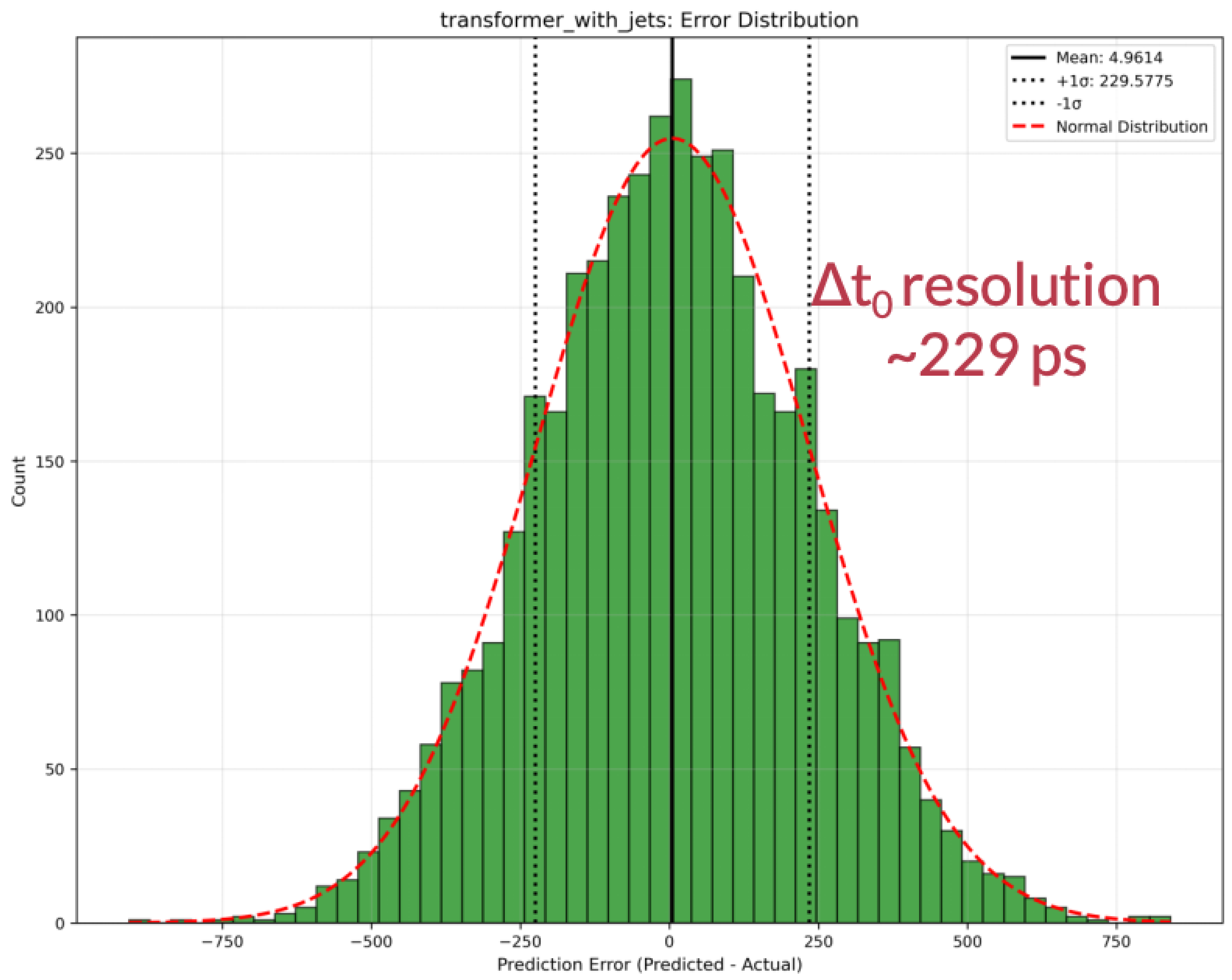
ML Regression Using Jet-Matched Cells

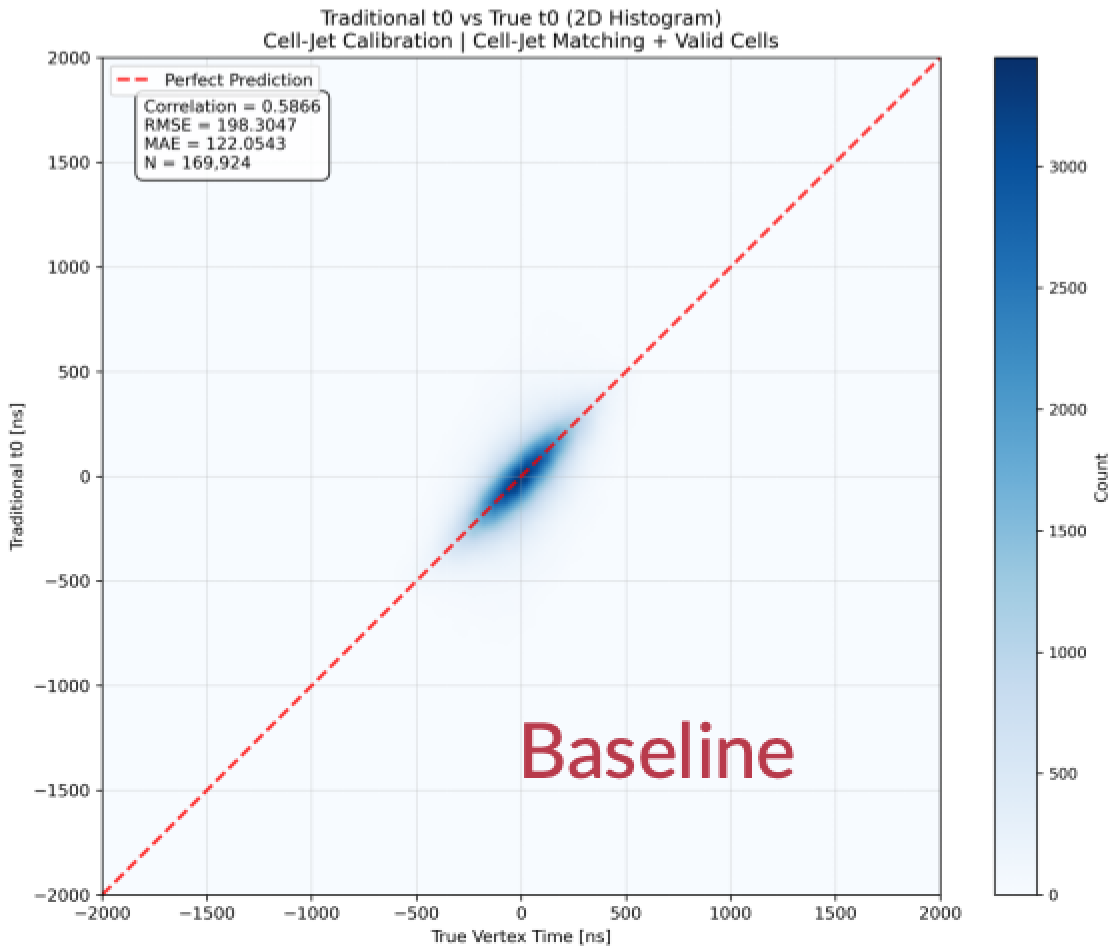
Model 2: Transformer

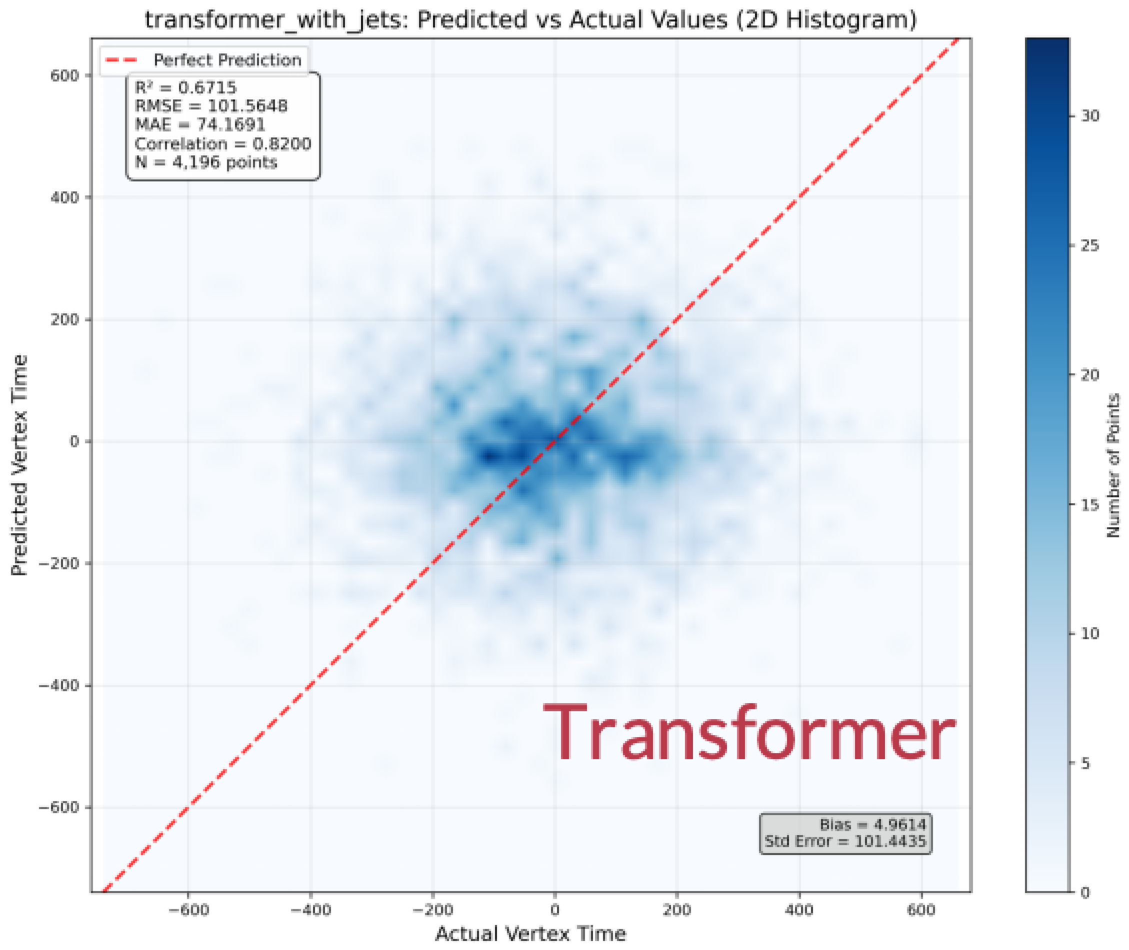
- Use cells following conventional cell-jet matching
- Calibrate cell times prior to inputting them into the model
- Loss function: huber (δ=100)

$$L_\delta(y, f(x)) = \begin{cases} \frac{1}{2}(y - f(x))^2 & \text{for } |y - f(x)| \le \delta, \\ \delta \cdot \left(|y - f(x)| - \frac{1}{2}\delta\right), & \text{otherwise.} \end{cases}$$









- Was the model just randomly guessing?
- Perhaps too many 'bad events' hindered the model from learning the correct reconstruction mode?

ML Regression Using Jet-Matched Cells

- Exhibition of some “bad events”

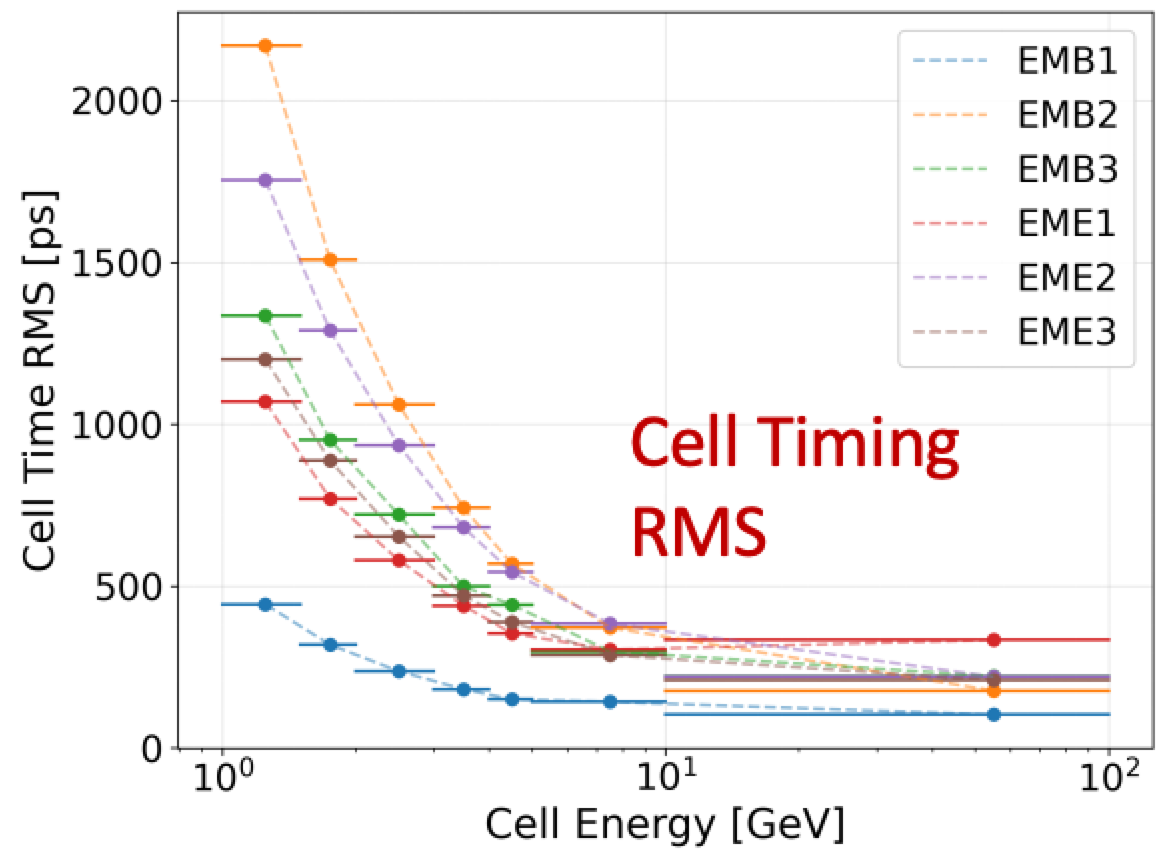
```
Truth time: -200.8873 ps
Reconstructed time: 5572.0681 ps
Error: 5772.9554 ps
Absolute error: 5772.9554 ps
Number of cells: 1
Cell energies: mean=1.00, std=0.00, min=1.00, max=1.00 GeV
Original cell times (before calibration): 5618.3 ps
Calibrated cell times (after calibration): 5572.1 ps
Cell time statistics - Original: mean=5618.29, std=0.00 ps
Cell time statistics - Calibrated: mean=5572.07, std=0.00 ps
Layer distribution: {np.int32(2): 1}
Detector region: {'Barrel': 1}
```

```
Truth time: -9.0438 ps
Reconstructed time: -5768.3108 ps
Error: -5759.2670 ps
Absolute error: 5759.2670 ps
Number of cells: 1
Cell energies: mean=1.28, std=0.00, min=1.28, max=1.28 GeV
Original cell times (before calibration): -5722.1 ps
Calibrated cell times (after calibration): -5768.3 ps
Cell time statistics - Original: mean=-5722.09, std=0.00 ps
Cell time statistics - Calibrated: mean=-5768.31, std=0.00 ps
Layer distribution: {np.int32(2): 1}
Detector region: {'Barrel': 1}
```

- Lots of them come from EMB1&EME2
- Excluding these bad timing cells leaves no usable cells
- May need either more events or additional information as input for the model to learn how to mitigate the effects of PU

```
Truth time: -70.1644 ps
Reconstructed time: -5334.2371 ps
Error: -5264.0727 ps
Absolute error: 5264.0727 ps
Number of cells: 1
Cell energies: mean=1.10, std=0.00, min=1.10, max=1.10 GeV
Original cell times (before calibration): -5288.0 ps
Calibrated cell times (after calibration): -5334.2 ps
Cell time statistics - Original: mean=-5288.01, std=0.00 ps
Cell time statistics - Calibrated: mean=-5334.24, std=0.00 ps
Layer distribution: {np.int32(2): 1}
Detector region: {'Barrel': 1}
```

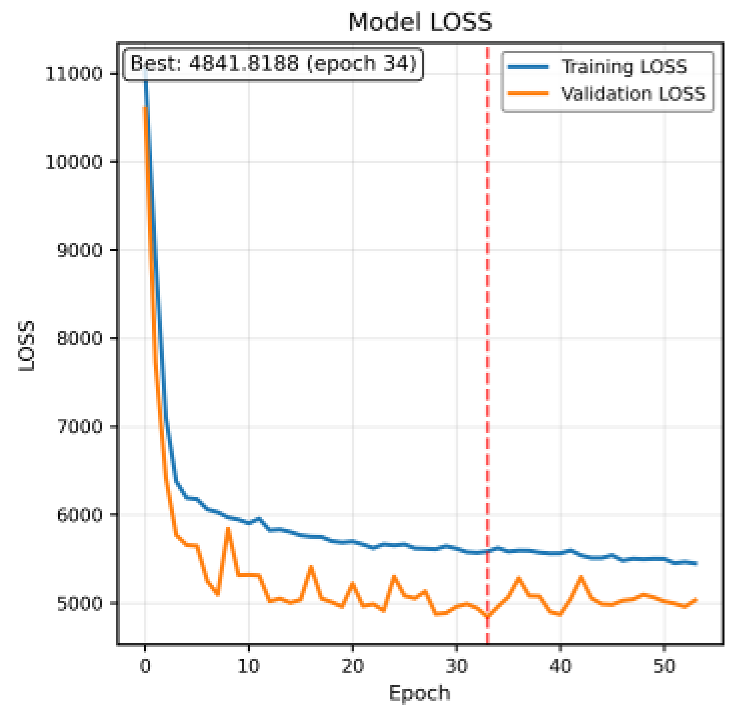
```
Truth time: 68.1768 ps
Reconstructed time: -4358.8383 ps
Error: -4427.0151 ps
Absolute error: 4427.0151 ps
Number of cells: 2
Cell energies: mean=1.38, std=0.05, min=1.32, max=1.43 GeV
Original cell times (before calibration): -2992.7, -5632.6 ps
Calibrated cell times (after calibration): -3038.9, -5678.8 ps
Cell time statistics - Original: mean=-4312.61, std=1319.96 ps
Cell time statistics - Calibrated: mean=-4358.84, std=1319.96 ps
Layer distribution: {np.int32(2): 2}
Detector region: {'Barrel': 2}
```

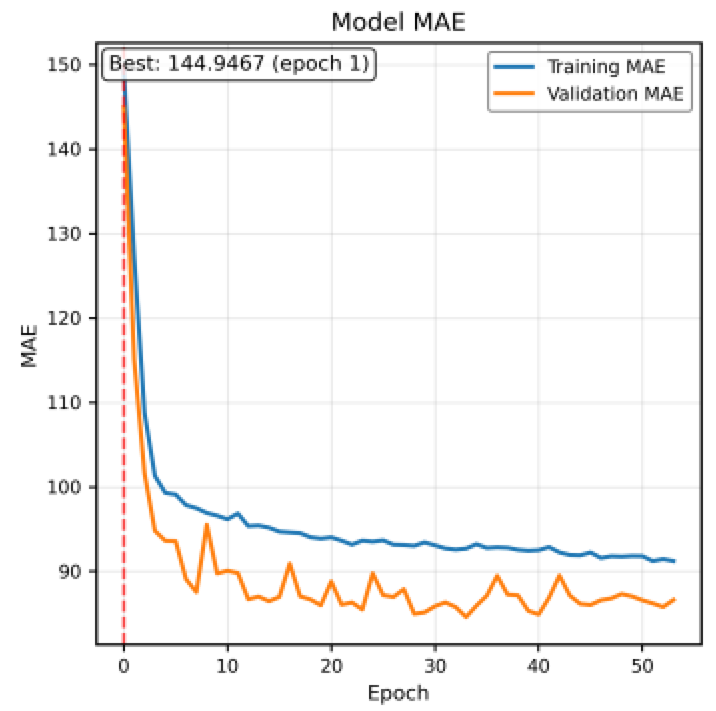


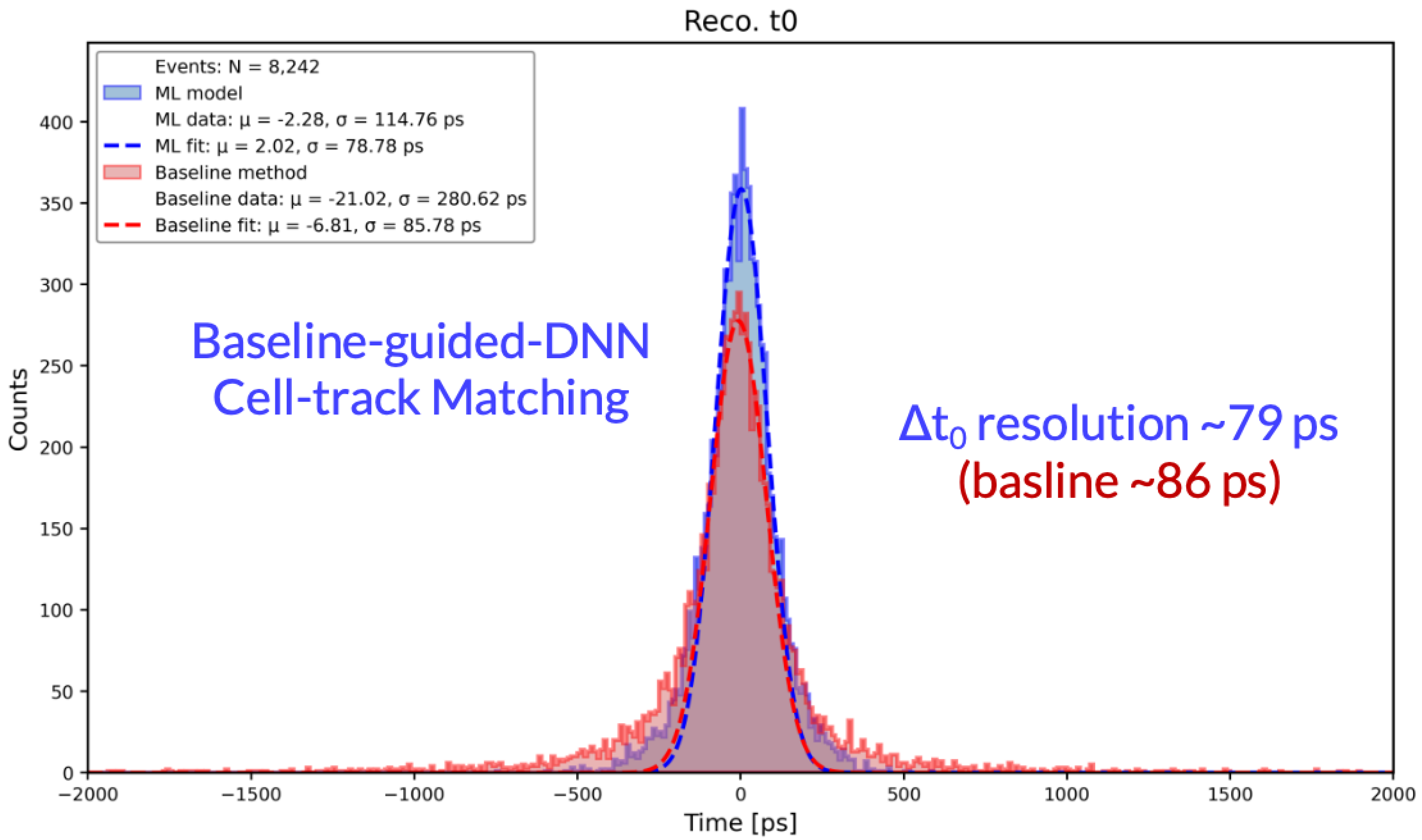
ML Regression Guided by Baseline Method

❑ Objective

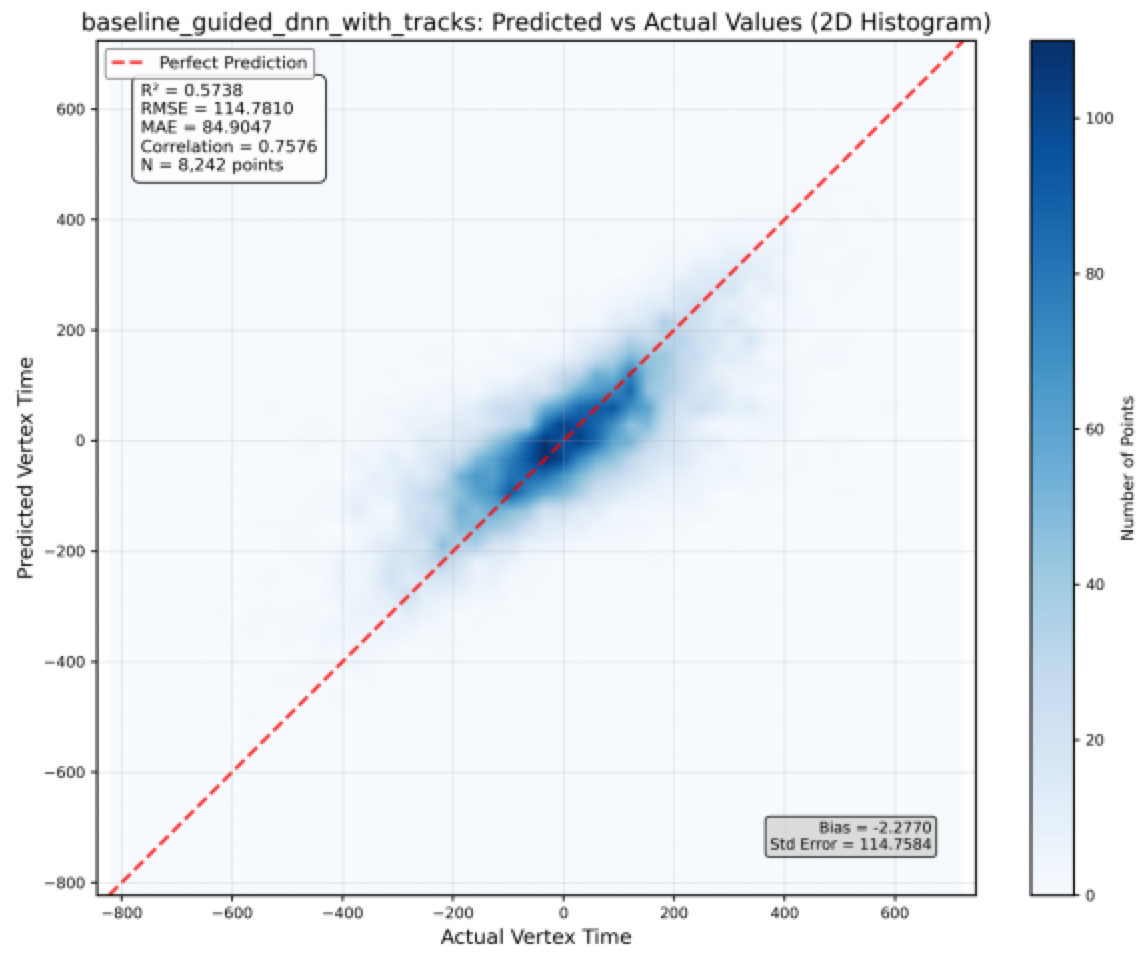
- ML model should perform at least as well as the baseline!
- Instead of predicting vertex t_0 directly, predicting <u>correction to the baseline result.</u>

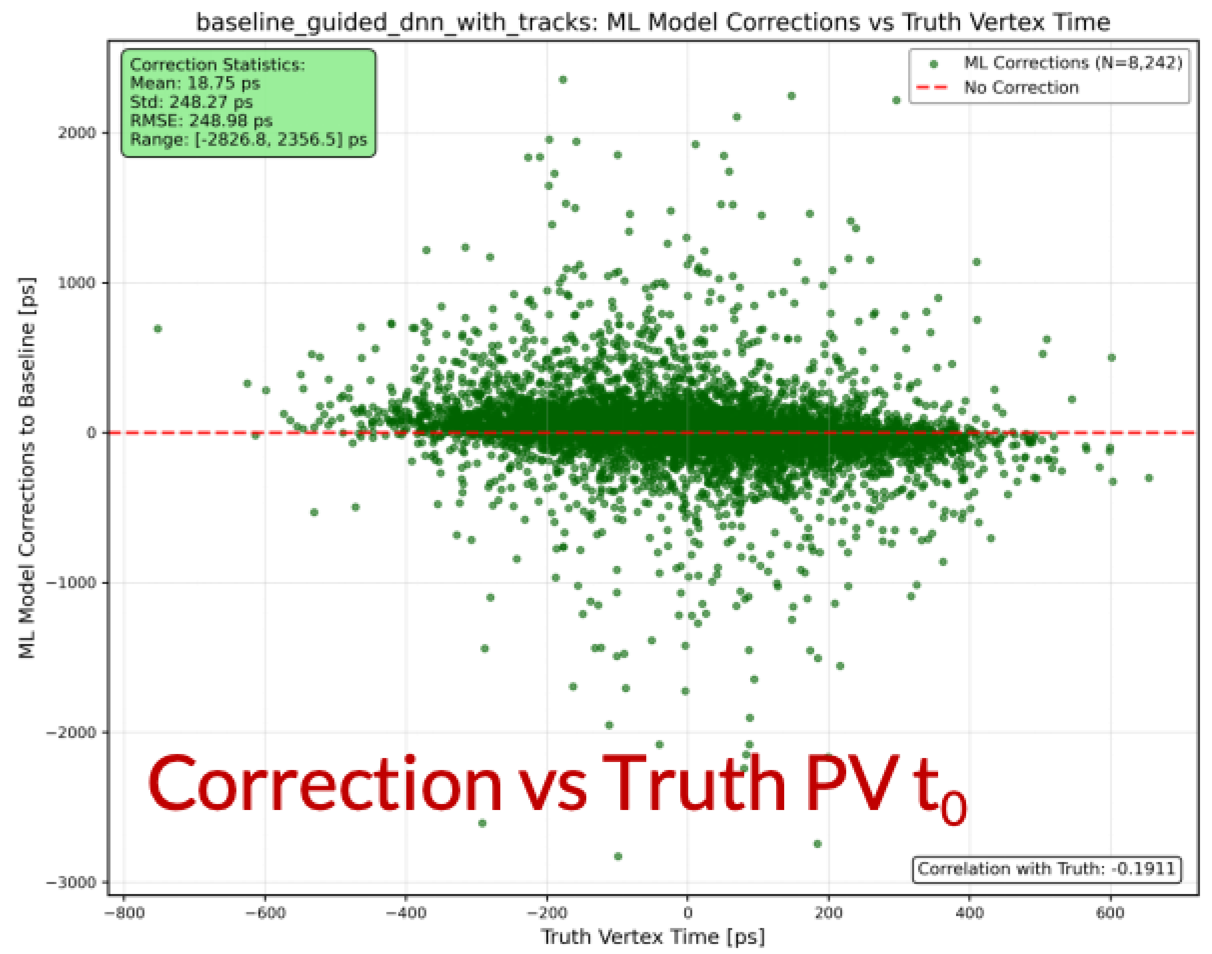






- Now improvement of ~7ps is observed with the ML
- The ML results exhibit a more Gaussian peak
- Cuts applied: $\text{Cell}_e \geq 2$ GeV, 3σ time significance cut



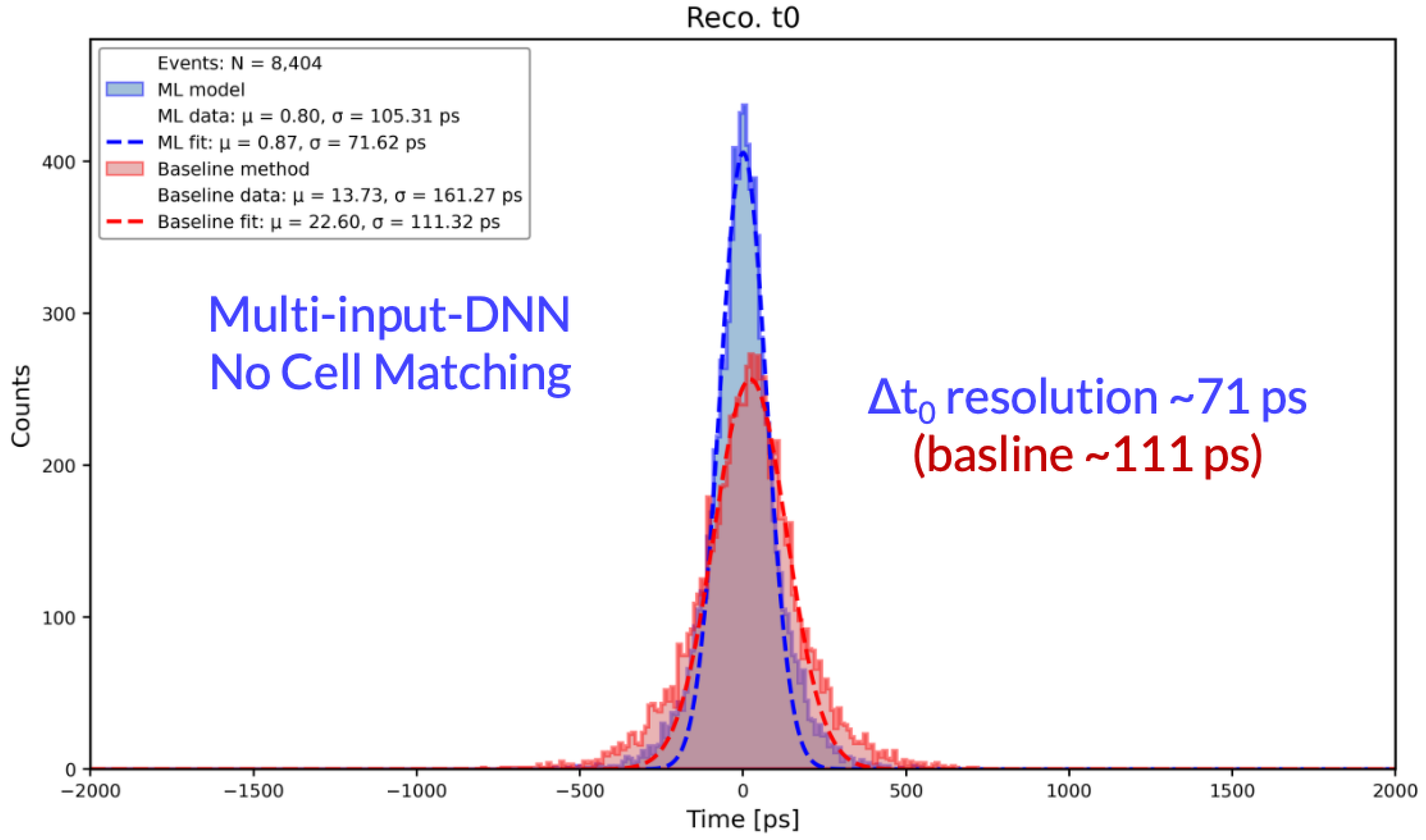


- The correlation between predicted&true values has markedly improved
- No distinct preference for corrections on specific vertex times; further investigation is needed

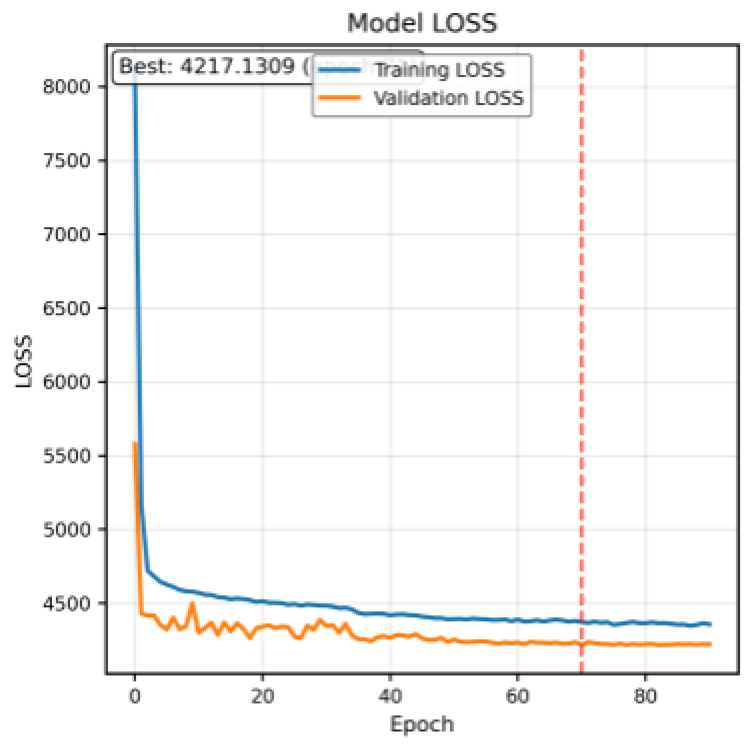
ML Regression w/o Matching Info

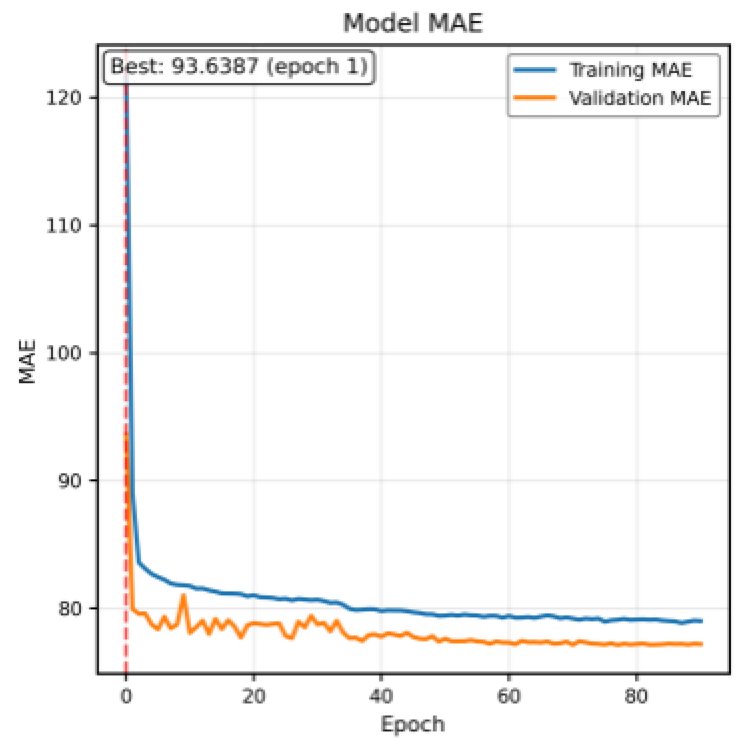
❑ Objective

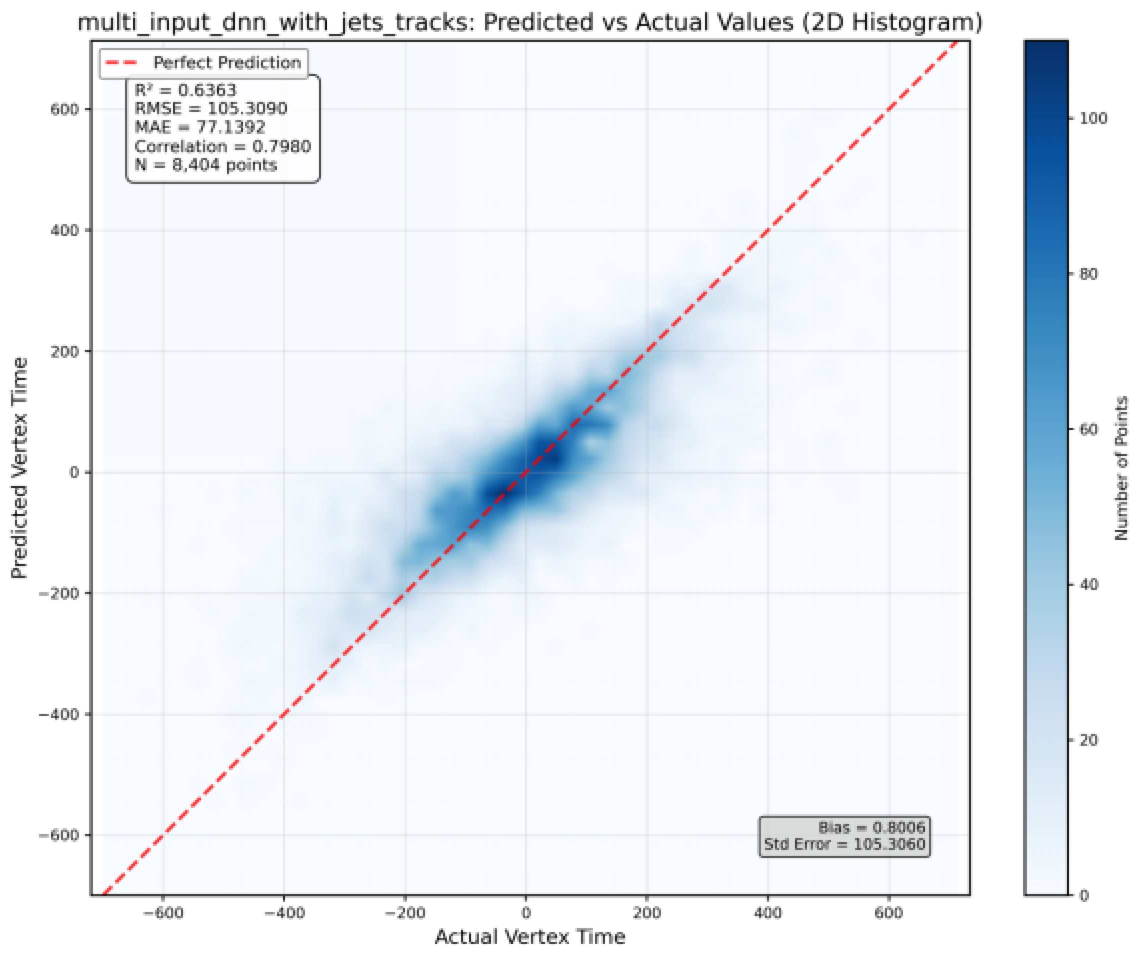
- Input more info (cell+HS jet+ HS track) to ML to enable it to learn how to mitigate PU (New features: HS jet p_T,η,ϕ,width; HS track p_T,η,ϕ,d0,z0)
- No pre-selection of track/jet matching, only inclusive calibration of cell times.

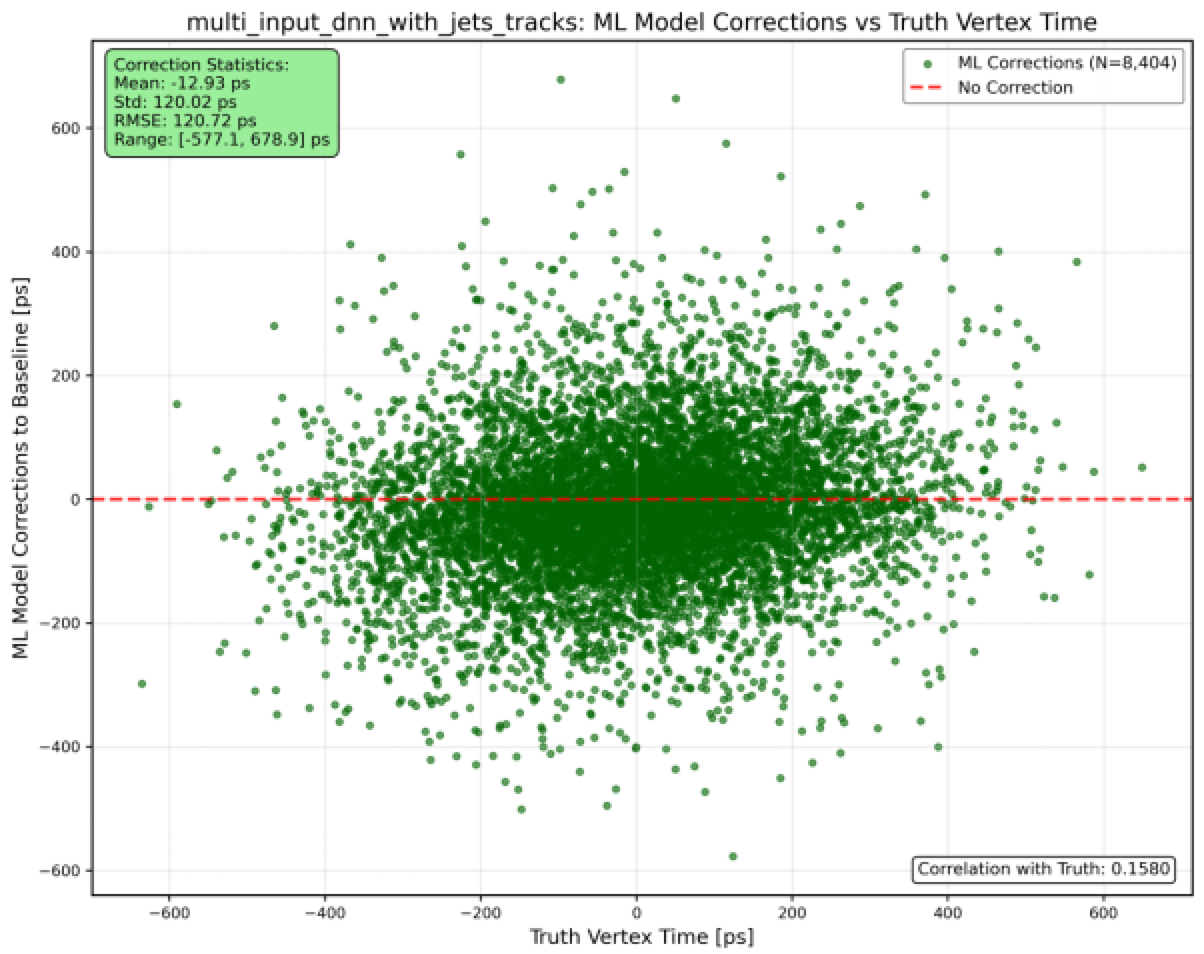


- Now improvement up to ~70ps seen from ML!
- More gaussian peak from ML
- Cuts applied: $\text{Cell}_e \geq 1$ GeV, 3σ time significance cut









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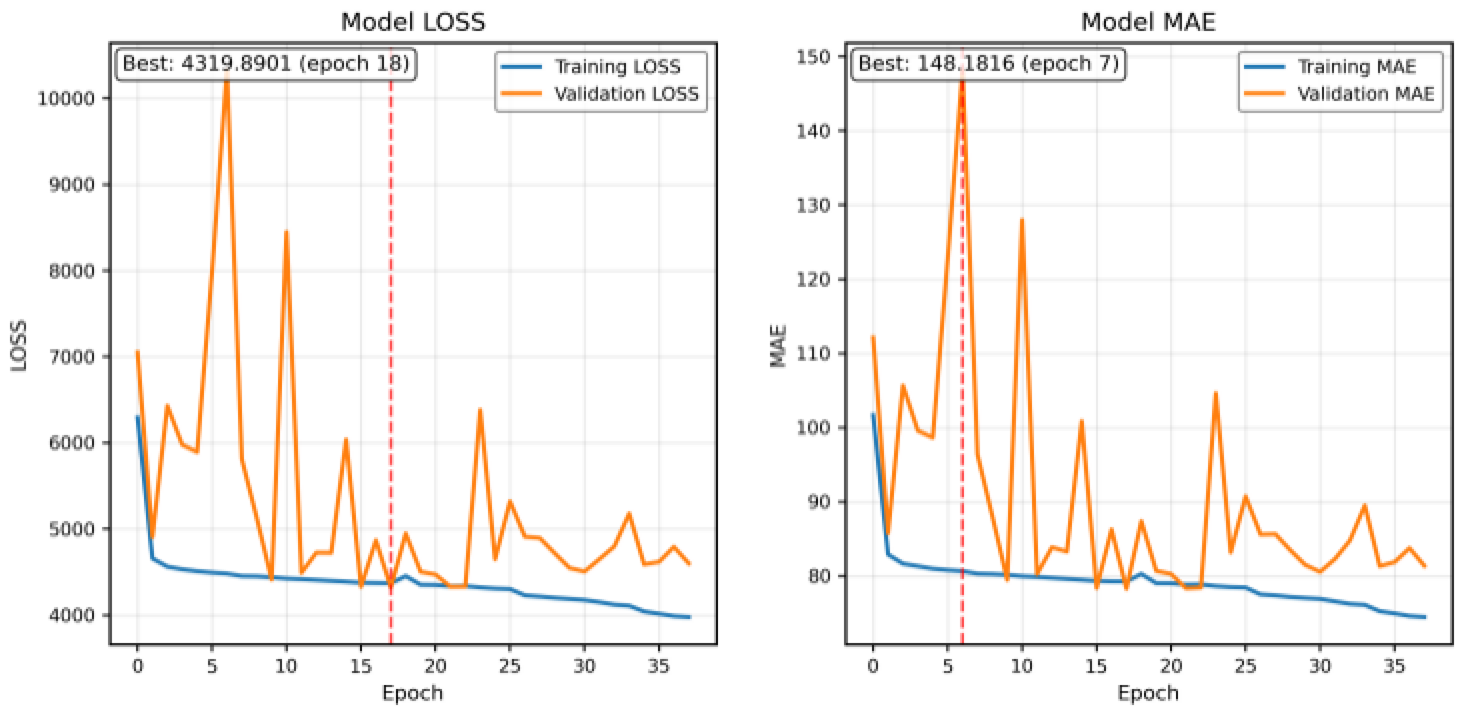
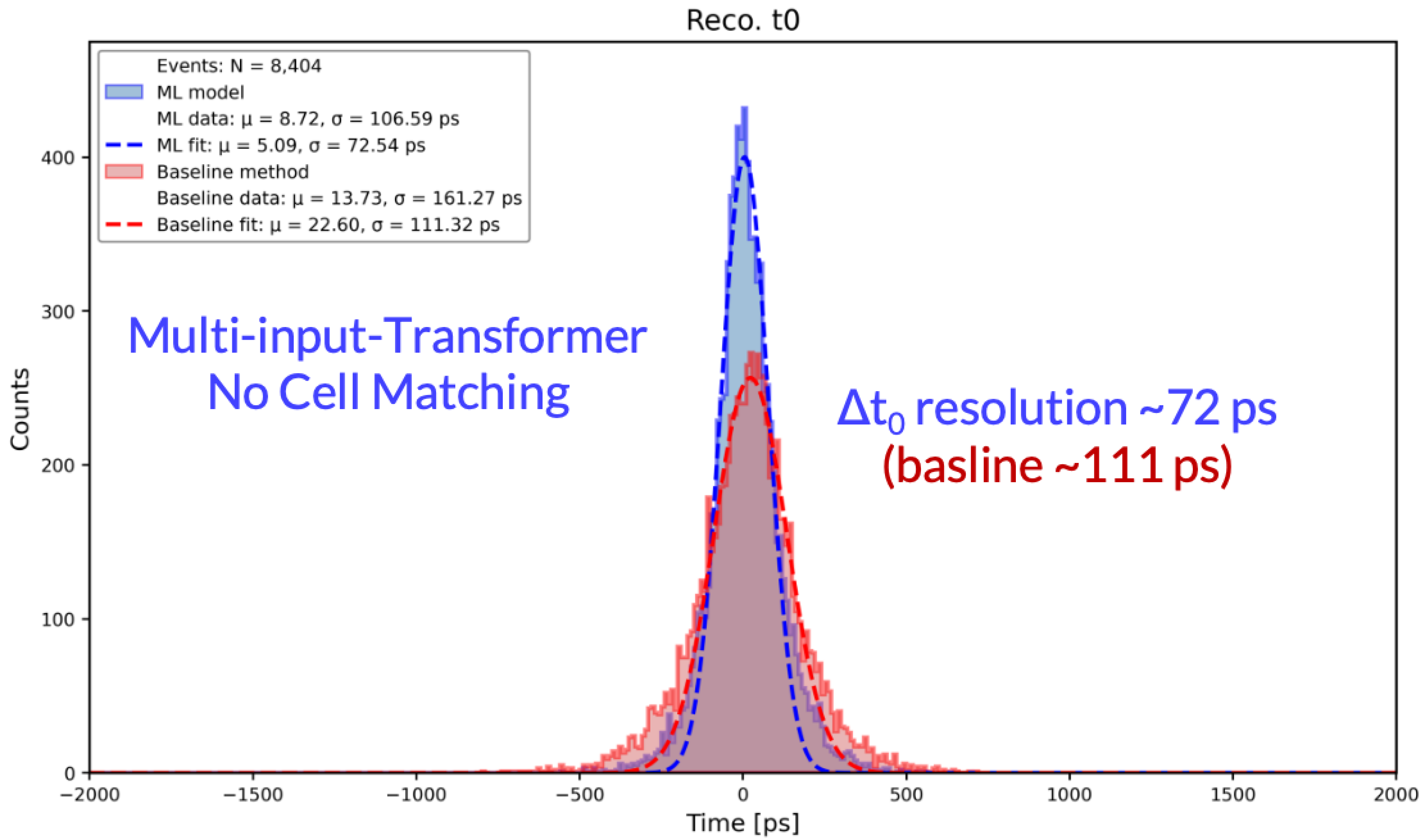
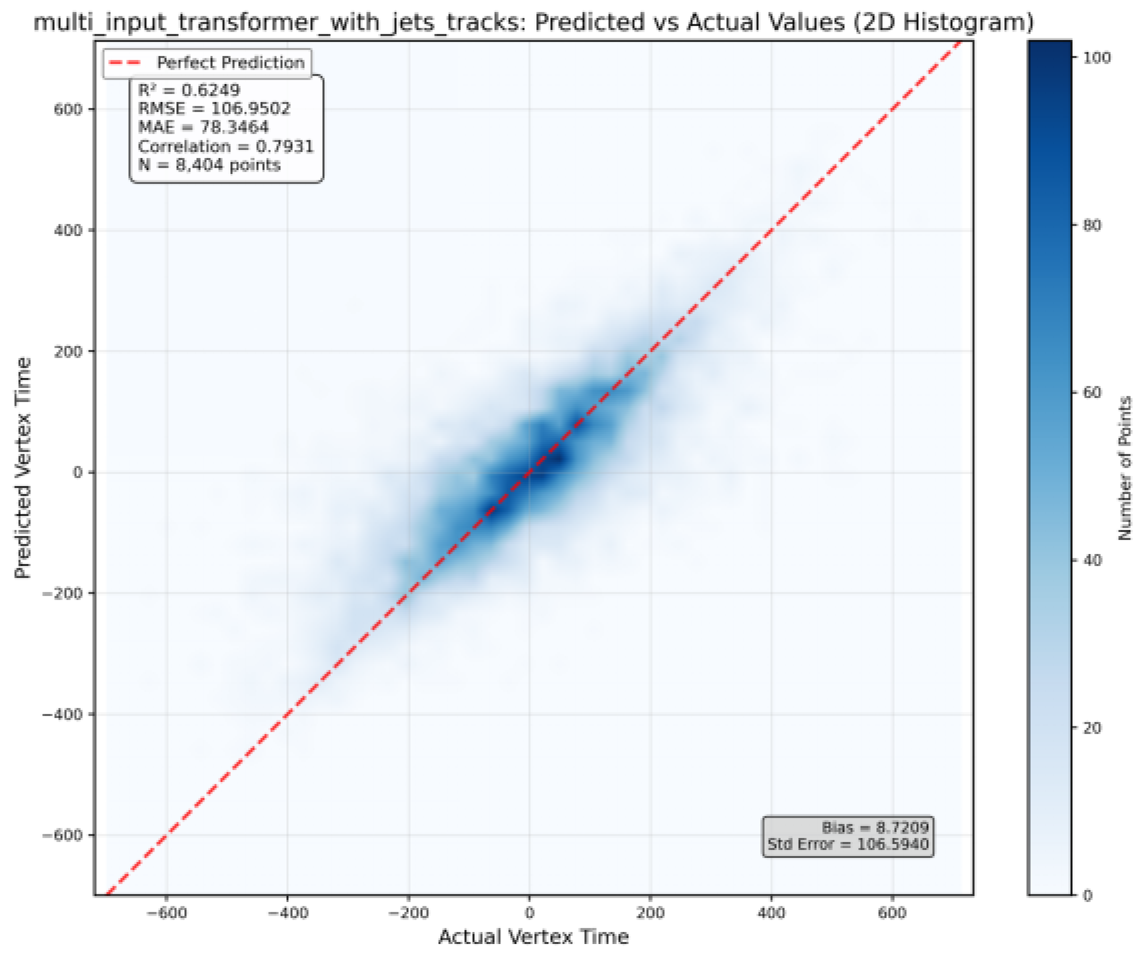
ML Regression w/o Matching Info

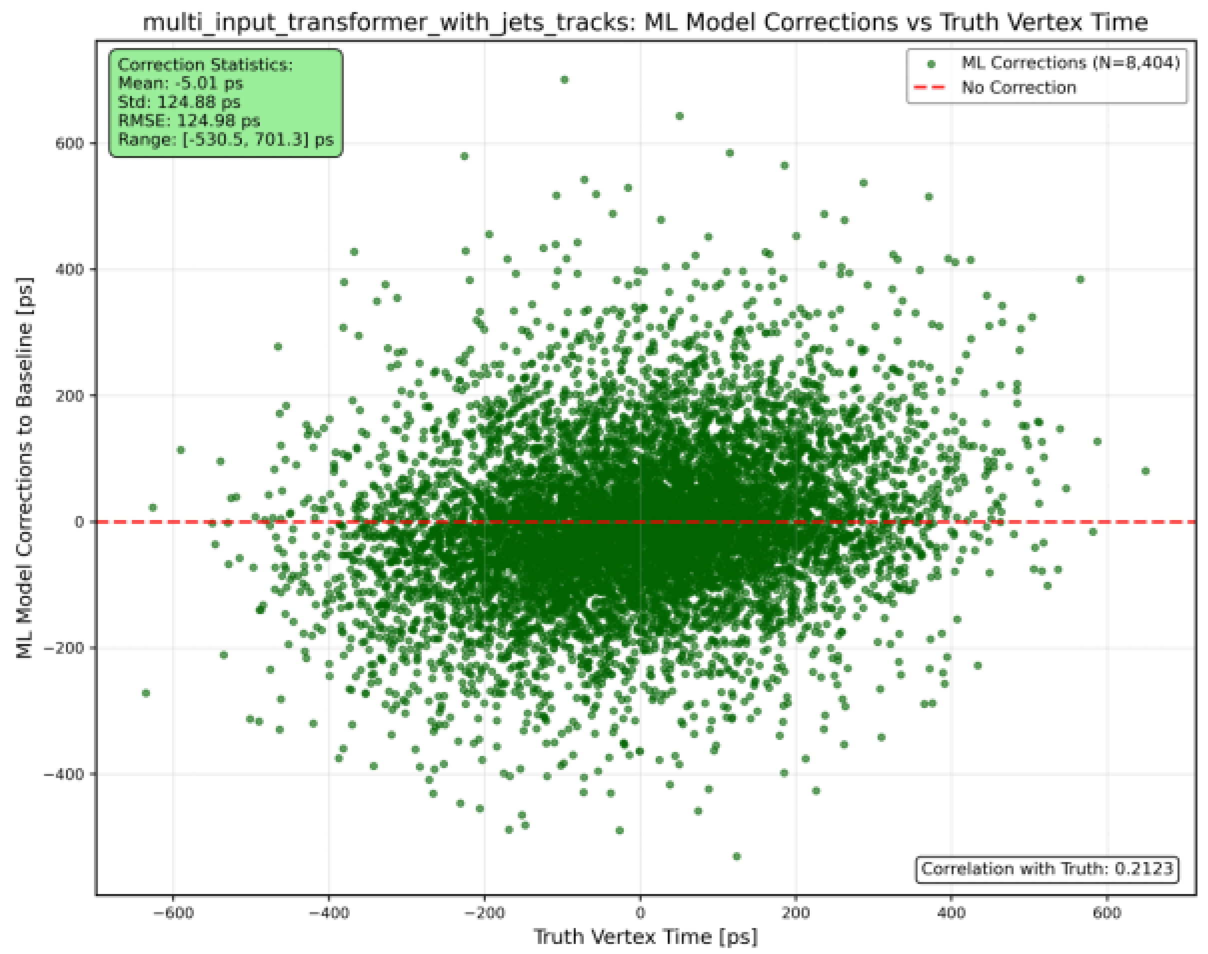
❑ Objective

- Input more info (cell+HS jet+ HS track) to ML to enable it to learn how to mitigate PU (New features: HS jet p_T,η,ϕ,width; HS track p_T,η,ϕ,d0,z0)
- No pre-selection of track/jet matching, only inclusive calibration of cell times.









- Now improvement up to ~72ps seen from ML!
- More gaussian peak from ML
- Cuts applied: $Cell_e \geq 1$ GeV, 3σ time significance cut

- The val-loss exhibits significant fluctuations, need further investigation
- Why does the transformer perform worse than the DNN?

Summary

- **The baseline method utilizing track/jet matching** achieves approximately 90 ps level PV t_0 resolution in MC data, and a better understanding of these results will aid in effectively mitigating pile-up effects.

- **The impact of jet topological features on timing** is observed clearly for the first time, requiring dedicated consideration.

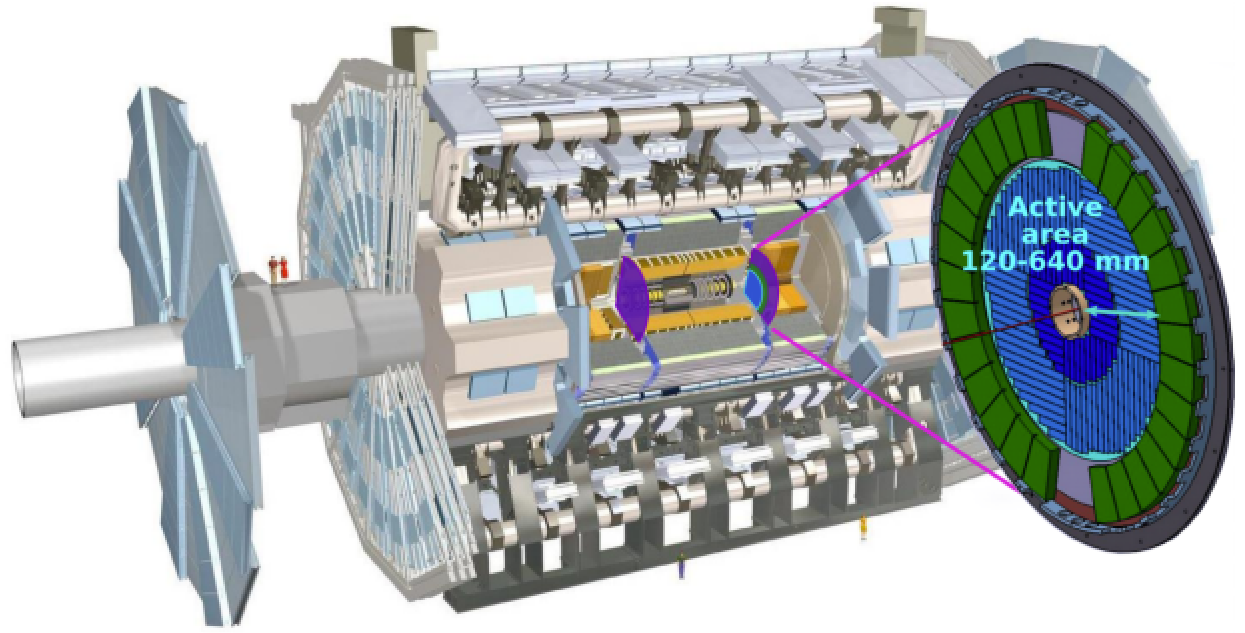
- **ML-based methods show promising performance** in PV t_0 reconstruction. The baseline-guided correction approach achieves ~80 ps resolution. The ML model utilizing cell, HS jet&track information for PU removal yields ~70 ps resolution, with the transformer model having potential for further improvement.

Back ups

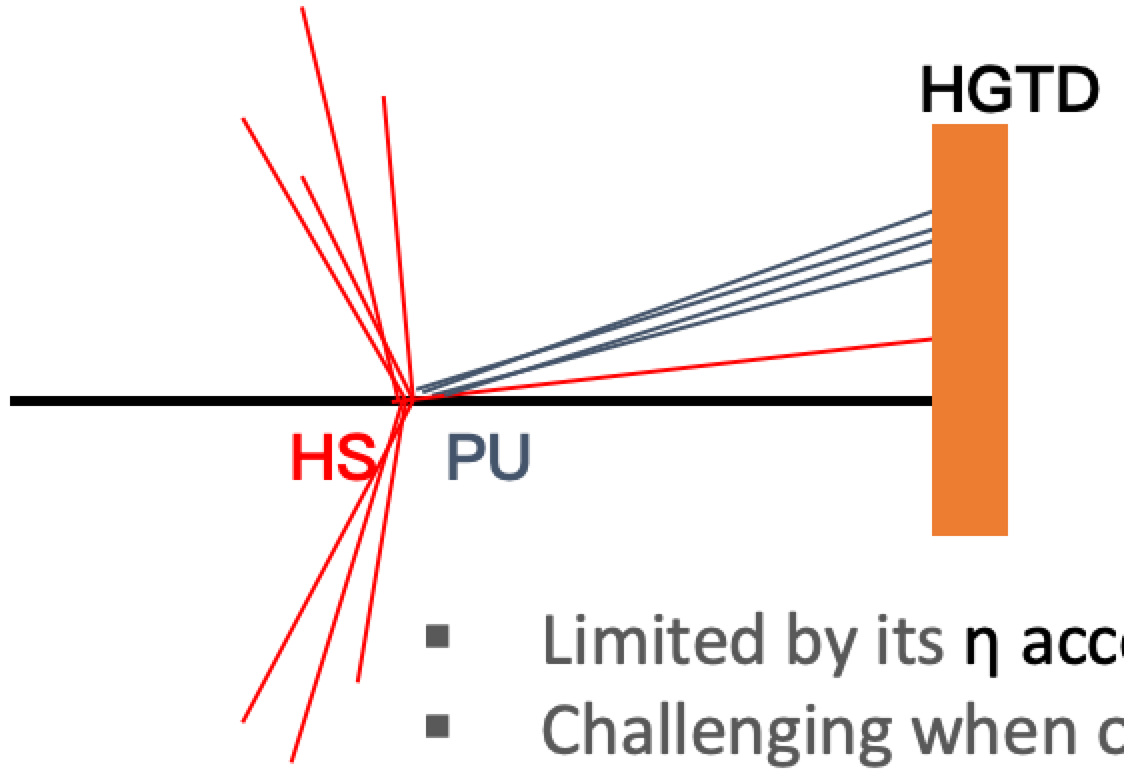
Pushing the Limits of LAr Timing

We'll have the HGTD in Run 4

- ~30 ps resolution for reconstructed tracks
- Require precise HS vertex time (t_0) knowledge



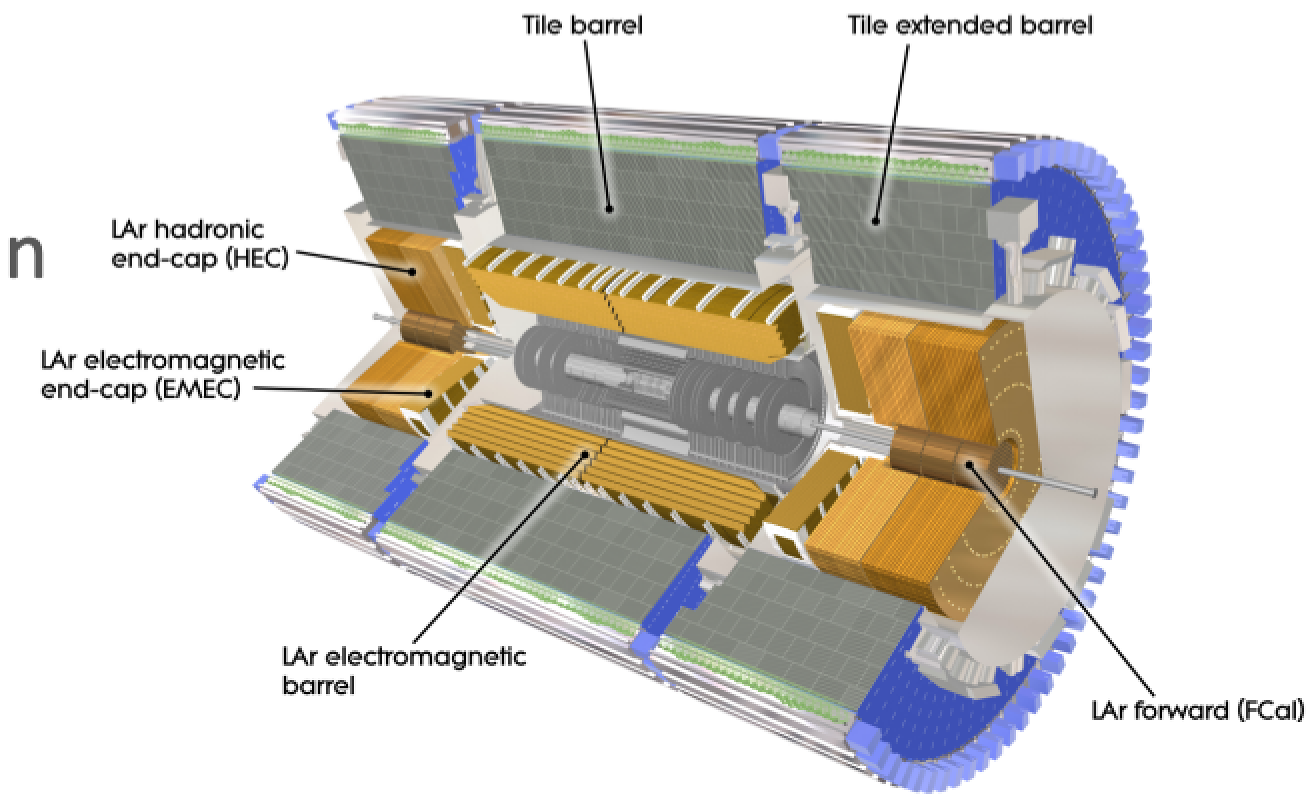
No central region coverage



- Limited by its η acceptance
- Challenging when only few forward HS tracks are available

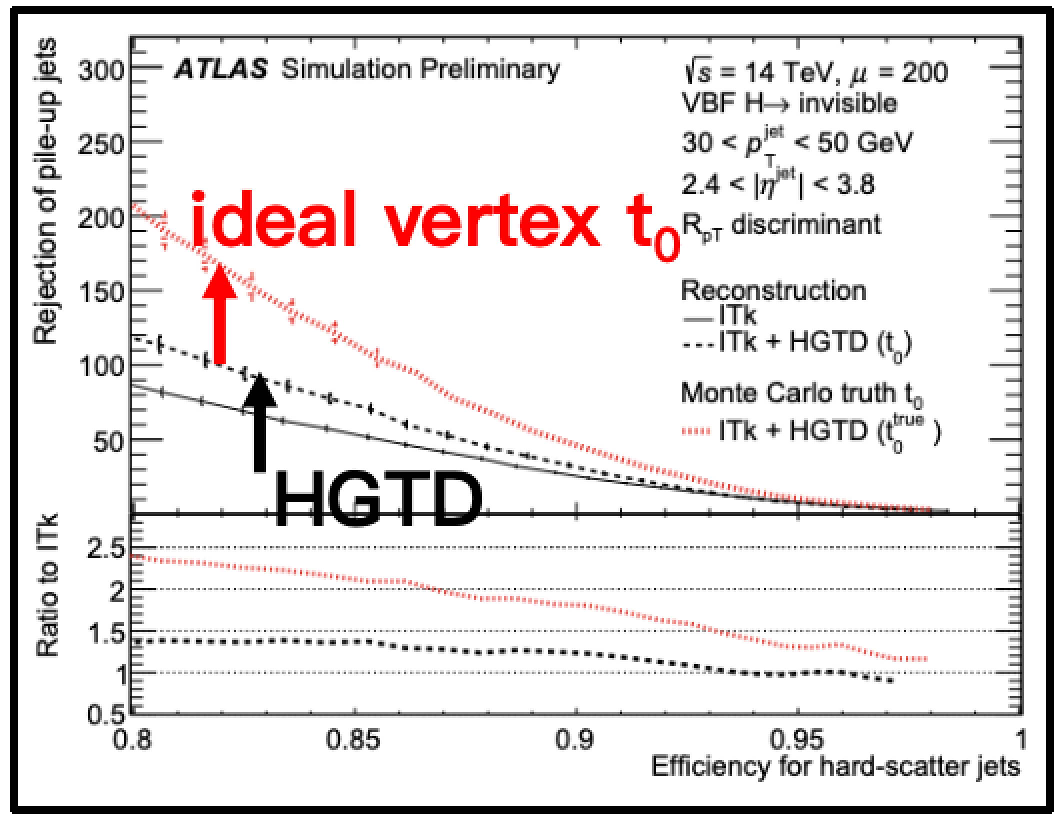
But, LAr is everywhere!

- Good intrinsic timing resolution O(100 ps)/better of best cells
- Include barrel timing for optimal t_0 determination



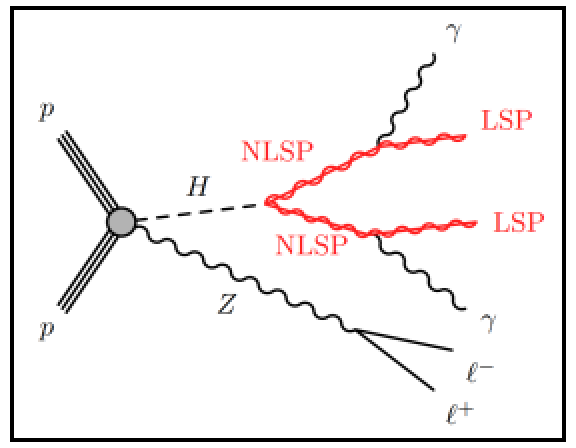
helps HGTD

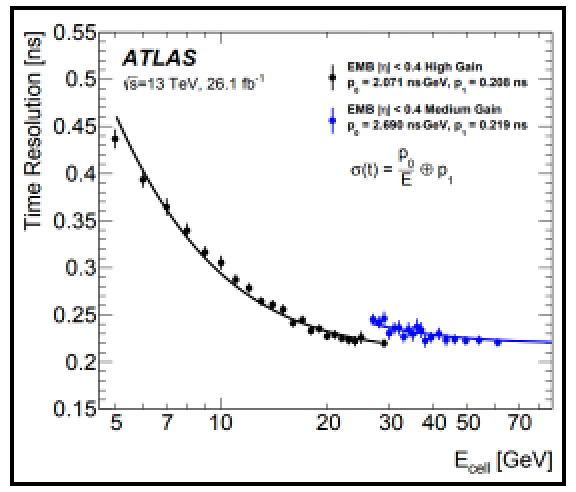
helps LLP searches



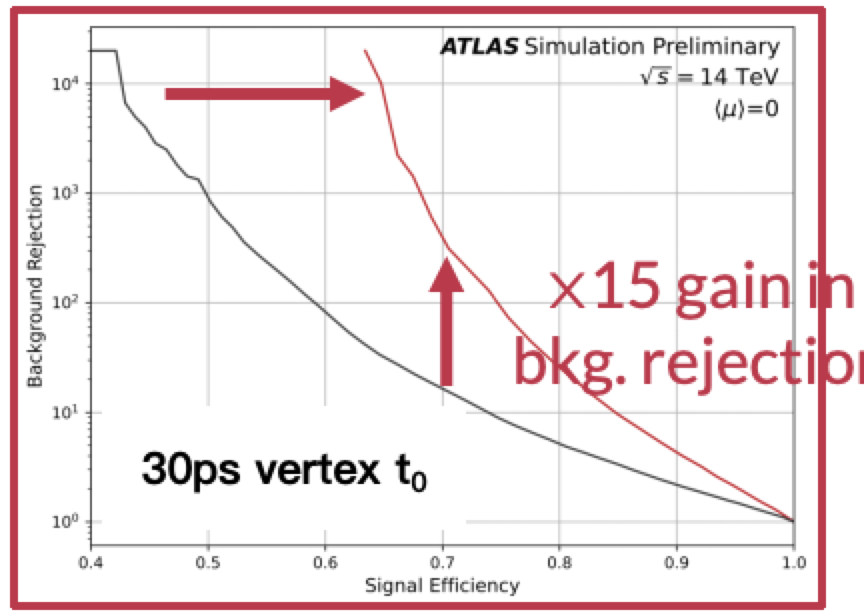
- Room for better PU jet suppression

[LLP searches using delayed photons]





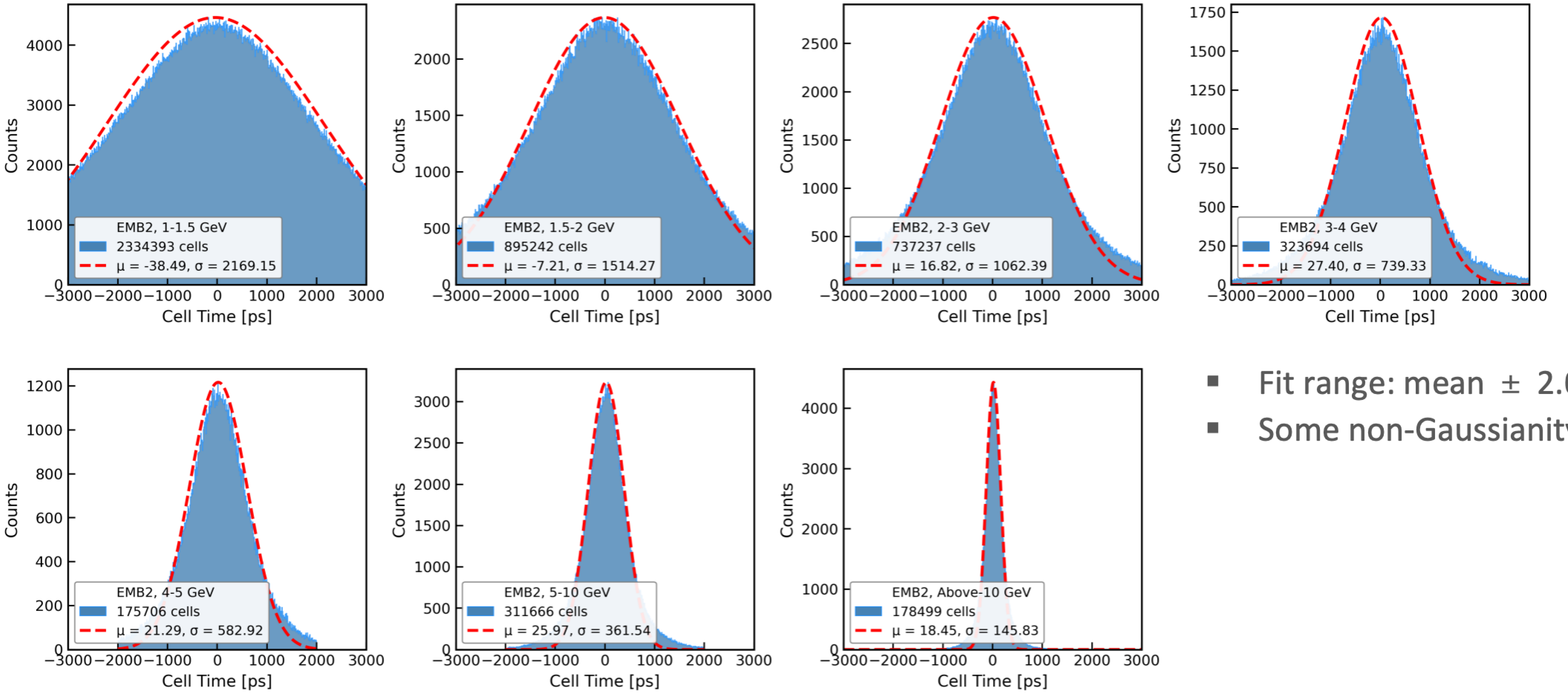
20% gain in sig. acceptance



- Could also help delayed jet searches

Inclusive Calibration for EM-layers

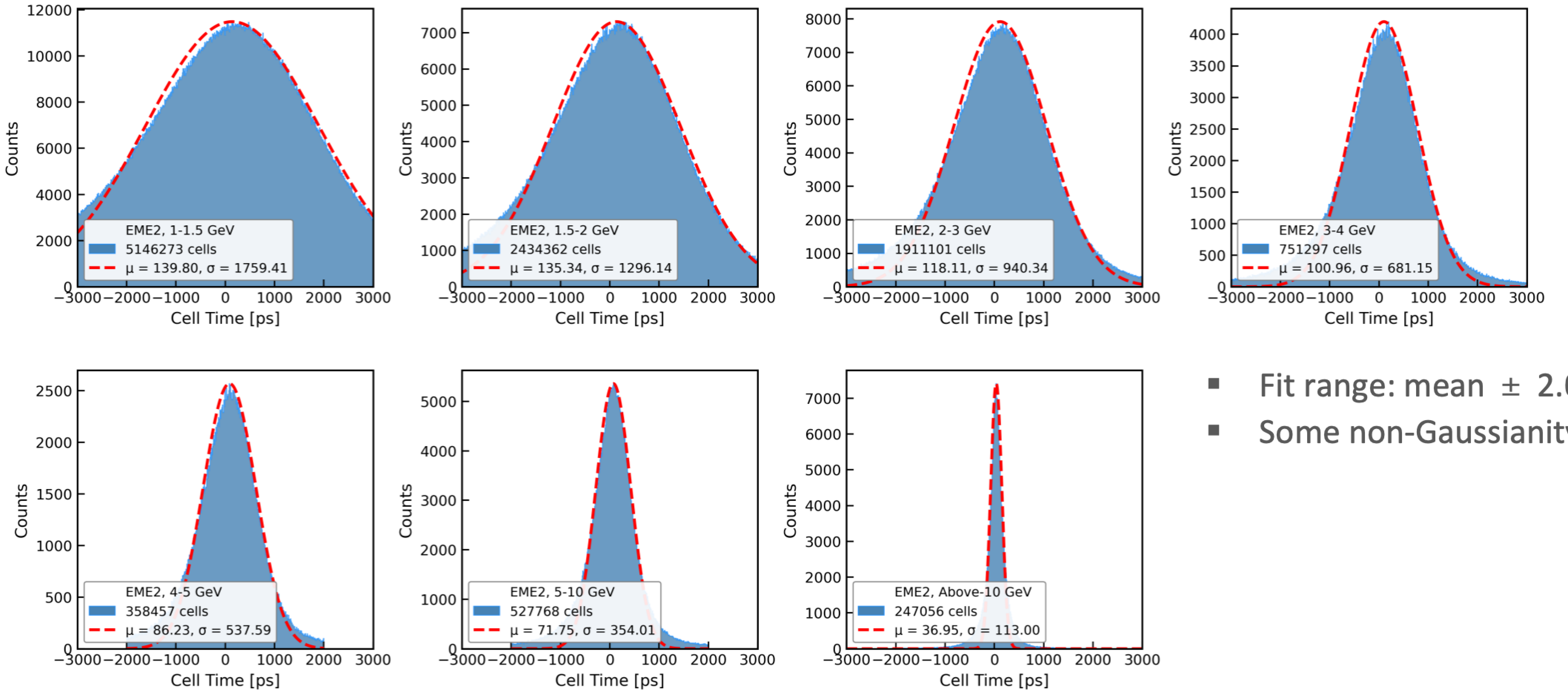
- Cell Timing Distribution (EM Barrel 2)



- Fit range: mean ± 2.0 std
- Some non-Gaussianity for low E

Inclusive Calibration for EM-layers

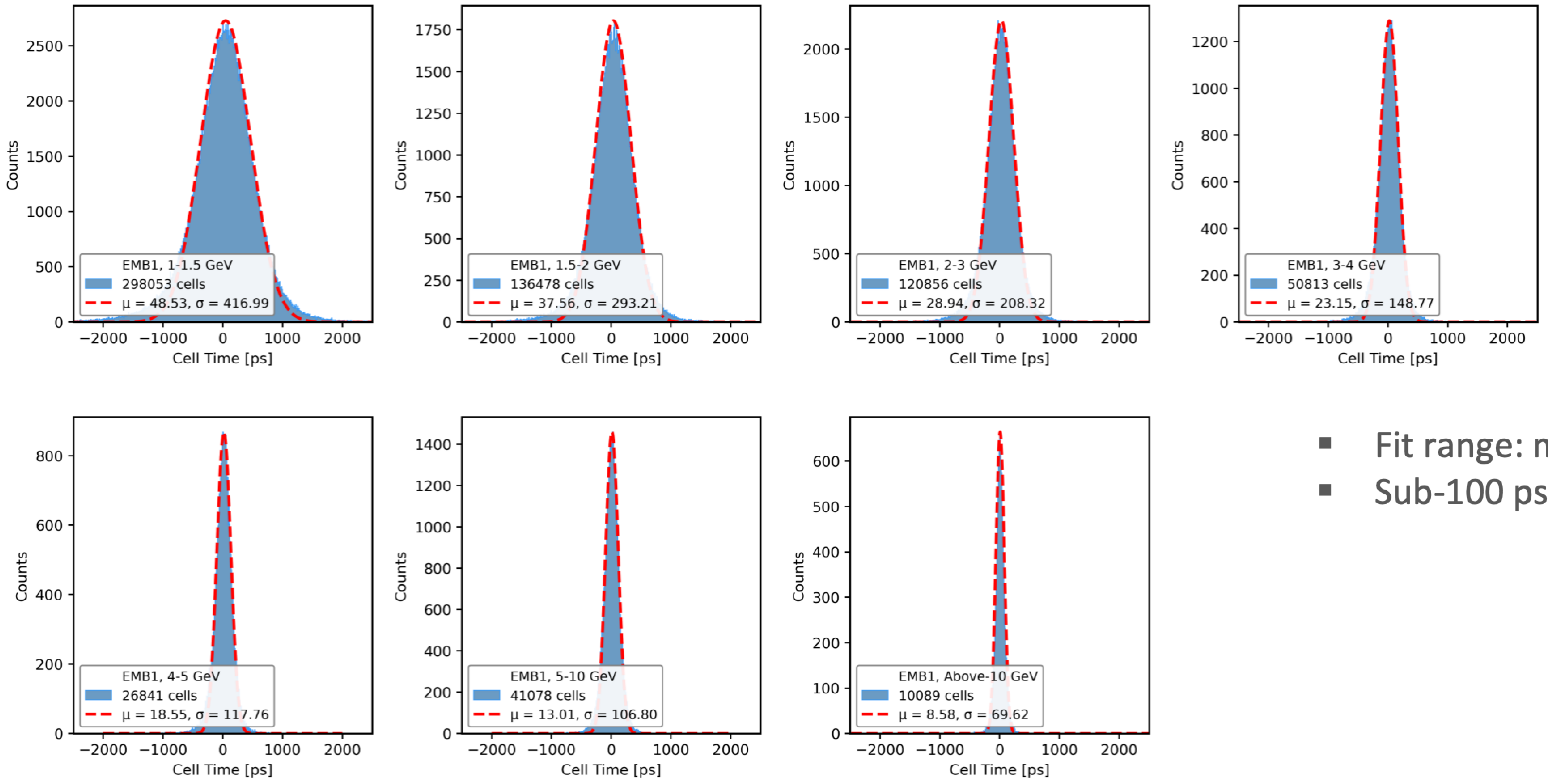
➢ Cell Timing Distribution (EM End-cap 2)



- Fit range: mean ± 2.0 std
- Some non-Gaussianity for low E

Calibration with Tracking Info

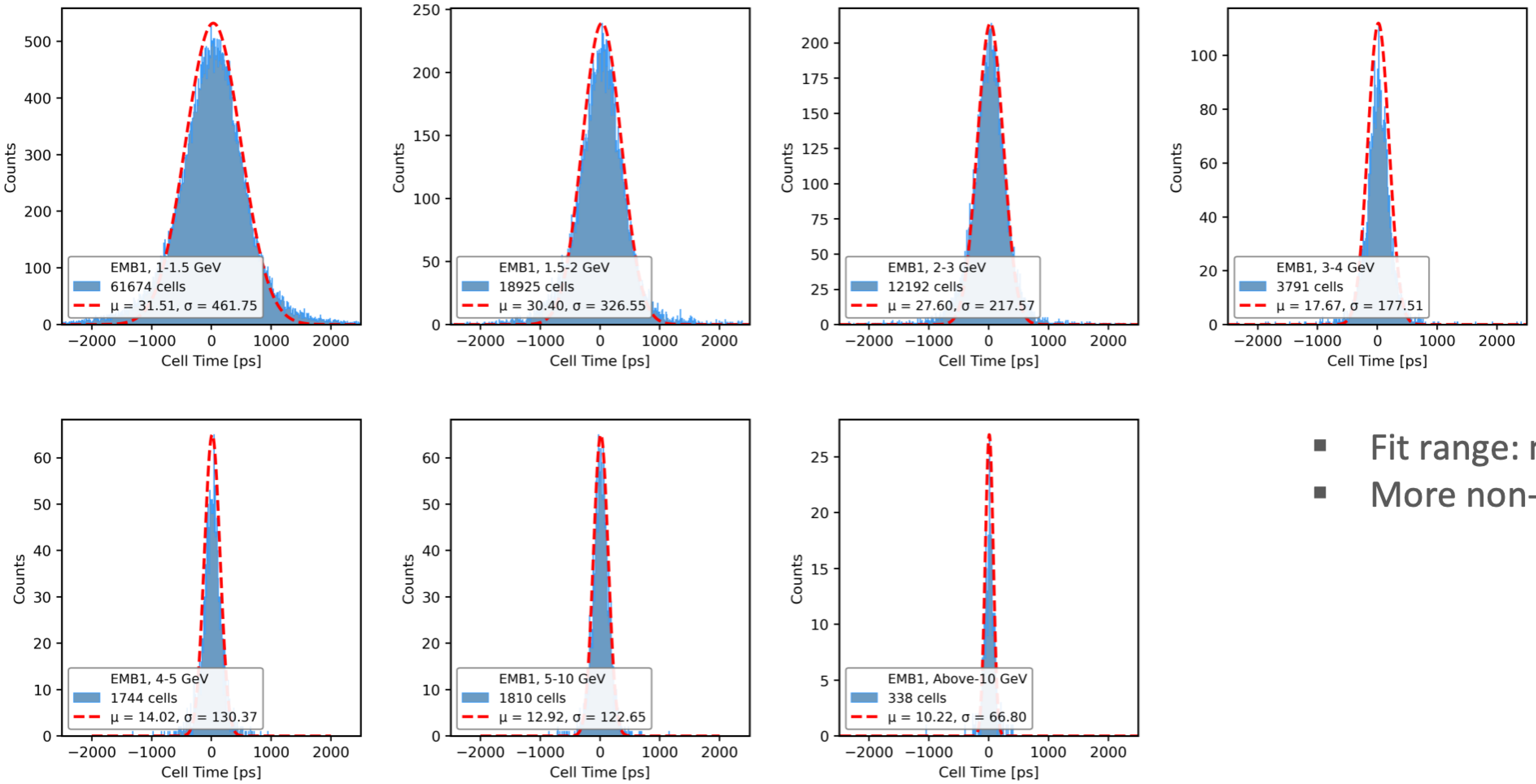
- Cell Timing Distribution (EM Barrel 1, HS)



- Fit range: mean ± 2.0 std
- Sub-100 ps at best cells

Calibration with Tracking Info

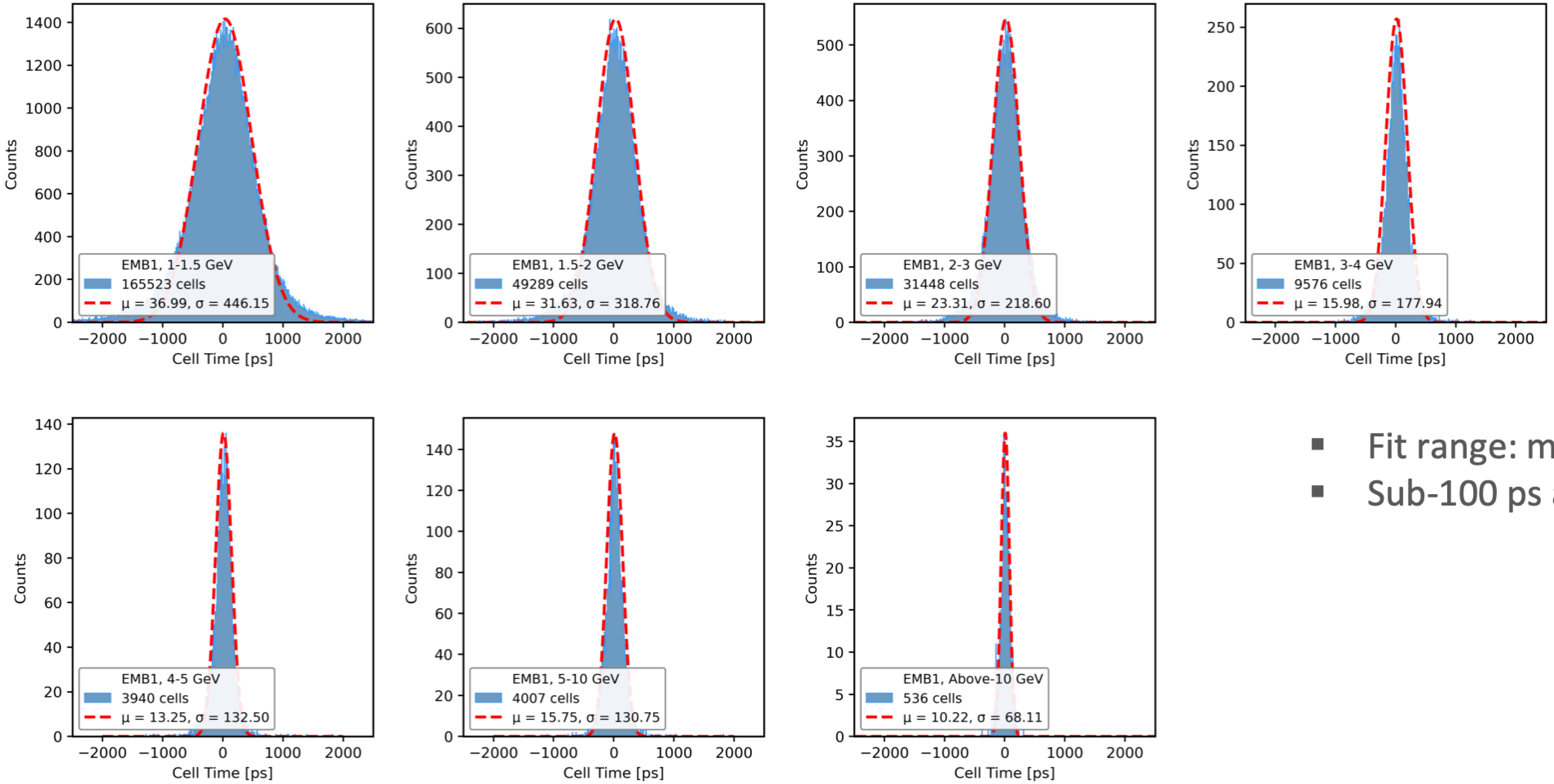
- Cell Timing Distribution (EM Barrel 1, PU)



- Fit range: mean $\pm$ 2.0 std
- More non-Gaussianity

Calibration with Tracking Info

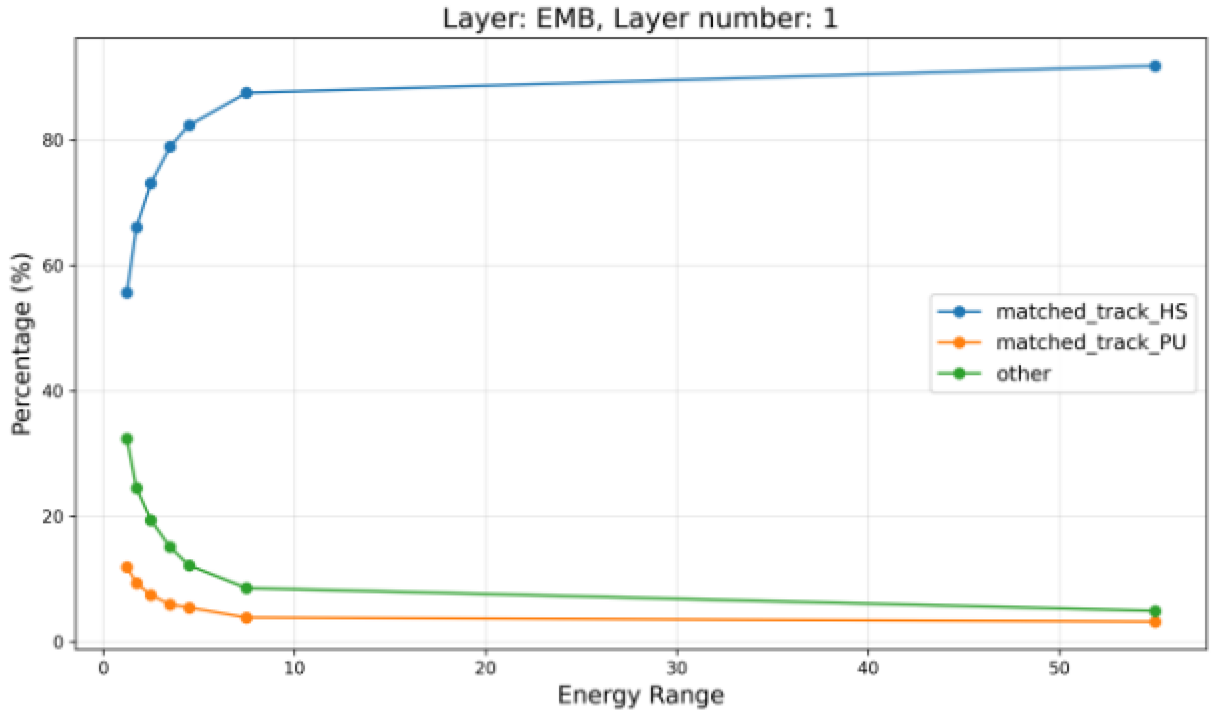
➢ Cell Timing Distribution (EM Barrel 1, Unmatched)

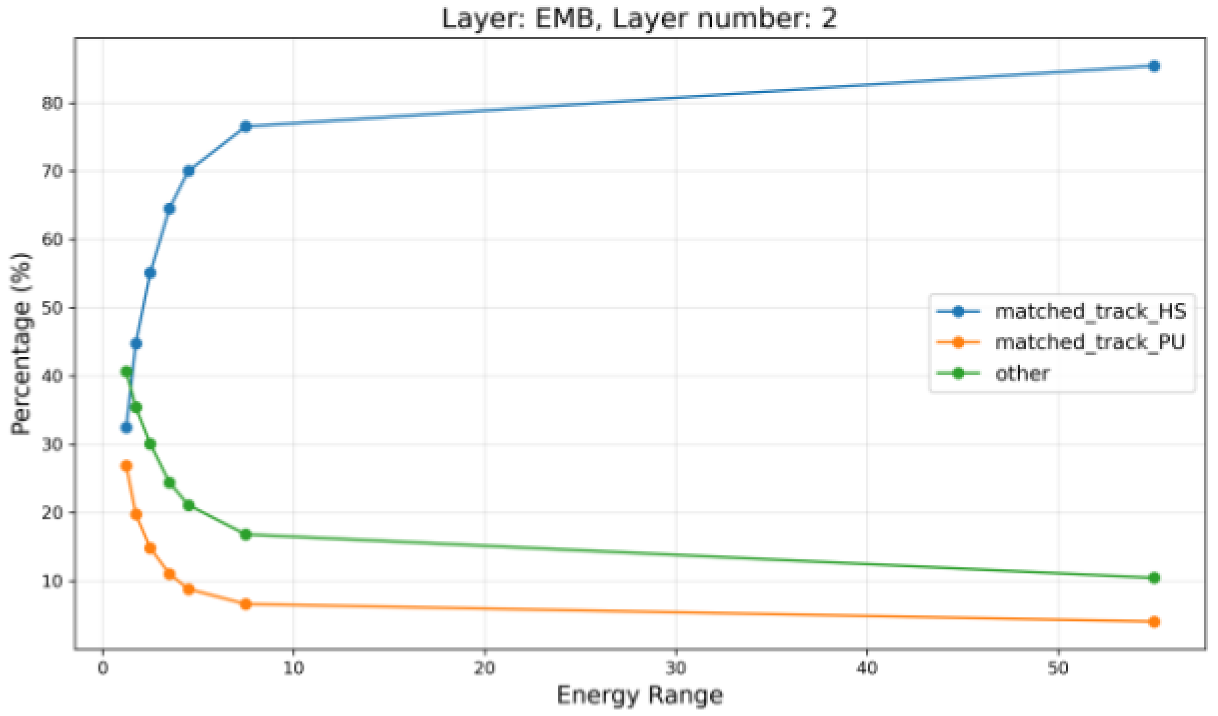


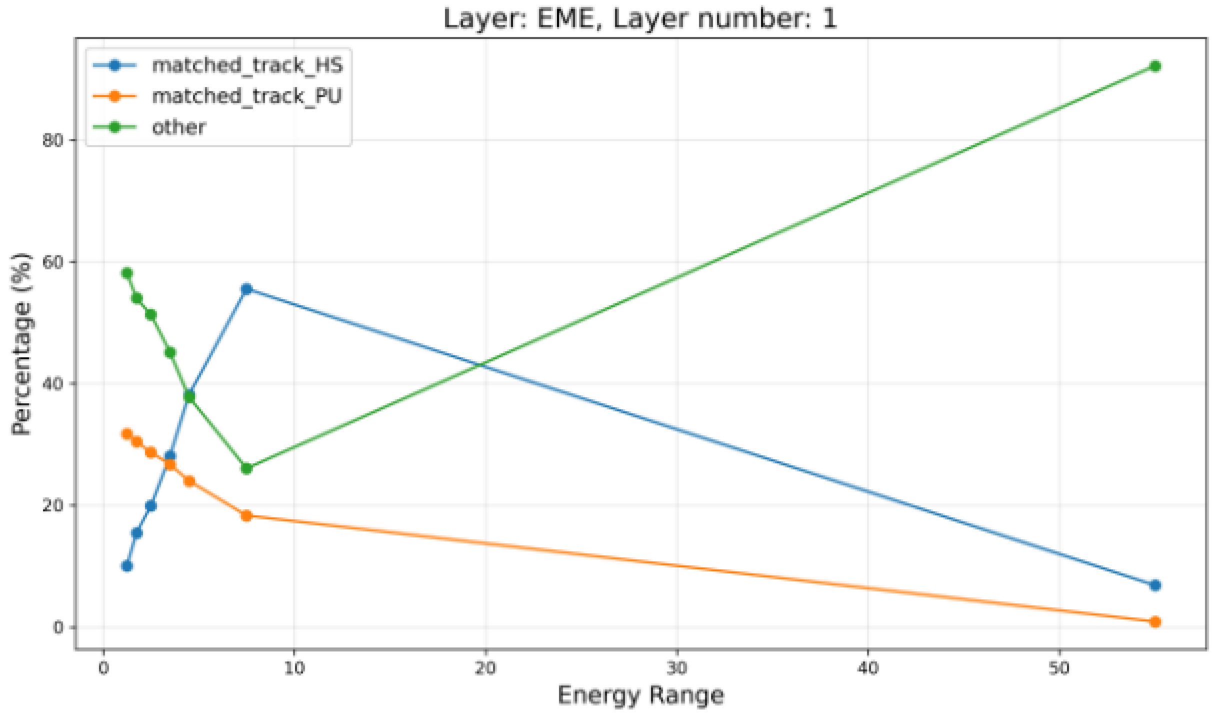
- Fit range: mean ± 2.0 std
- Sub-100 ps at best cells

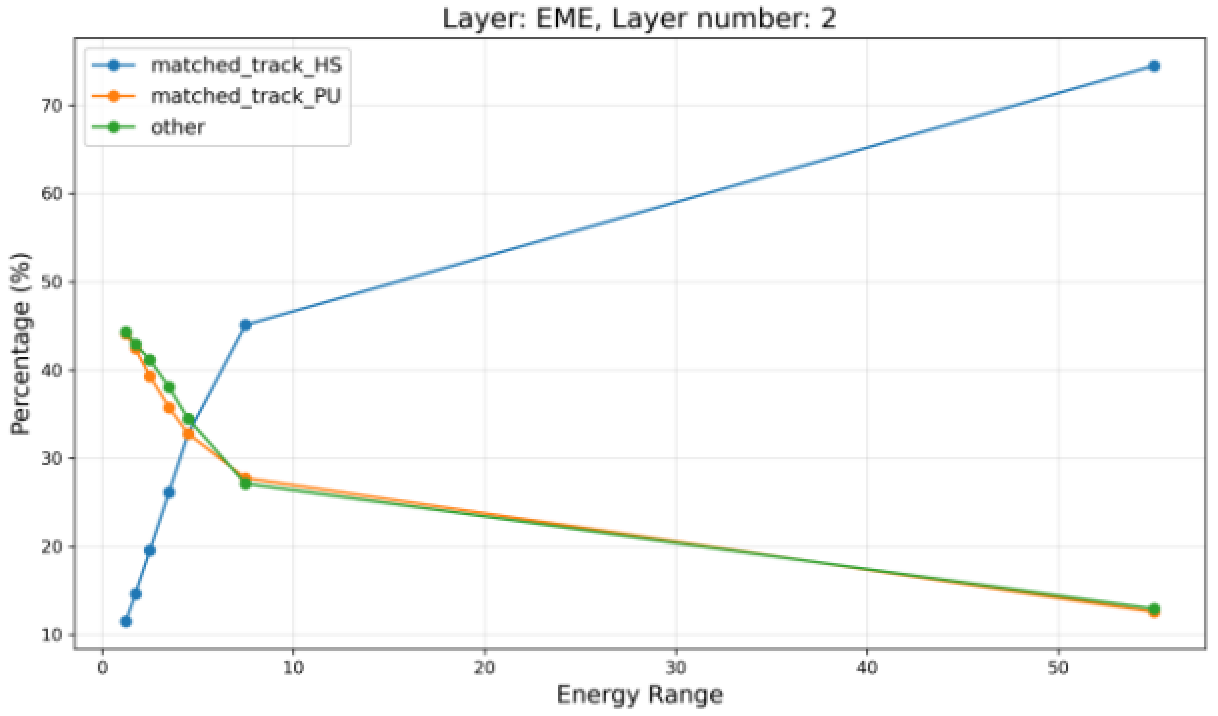
Calibration with Tracking Info

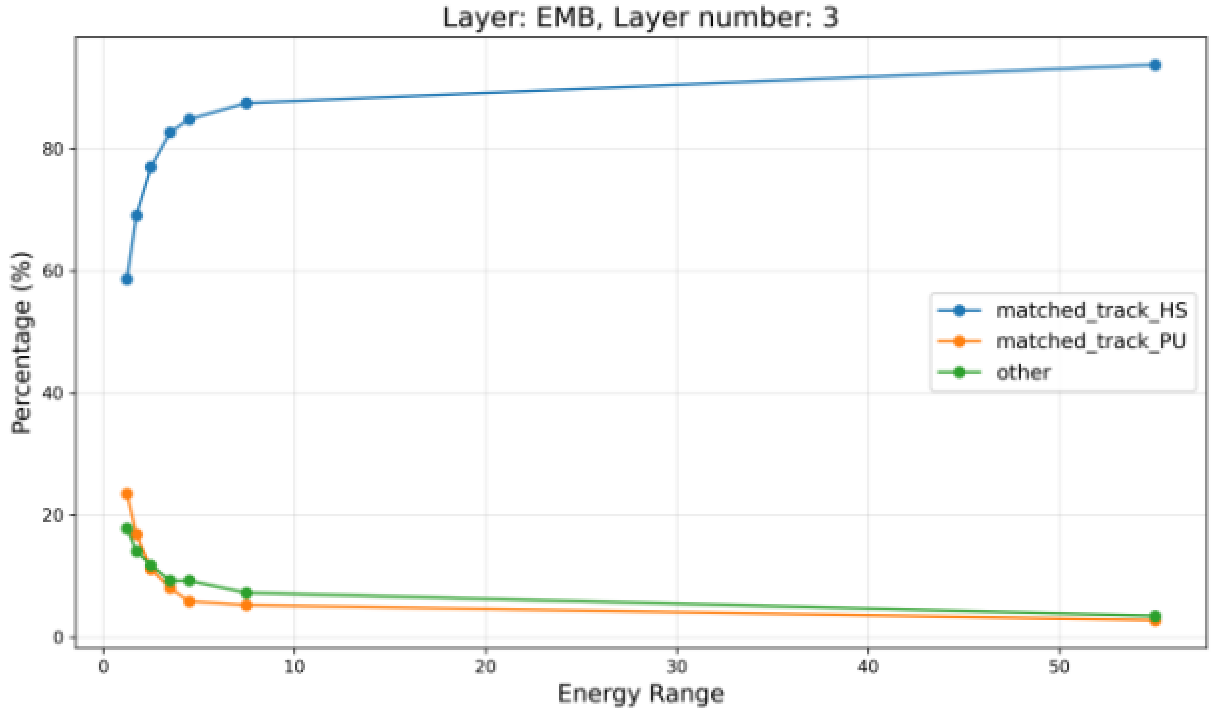
➢ Occupancy Statistics

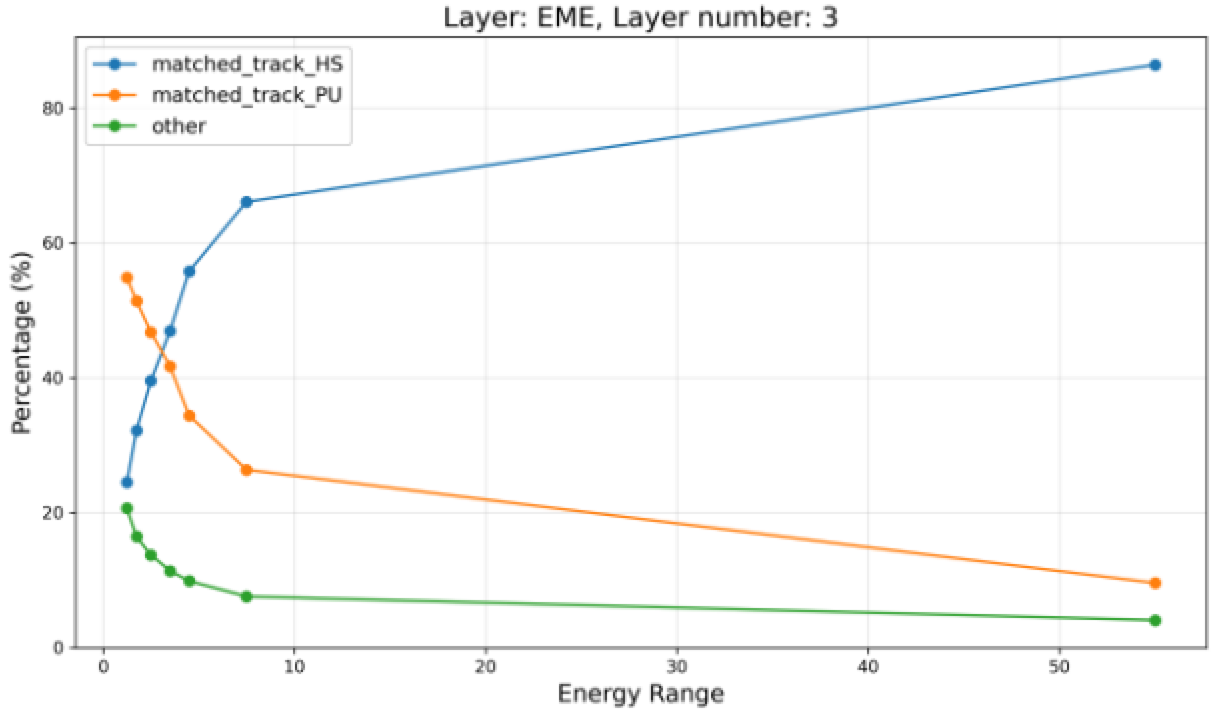








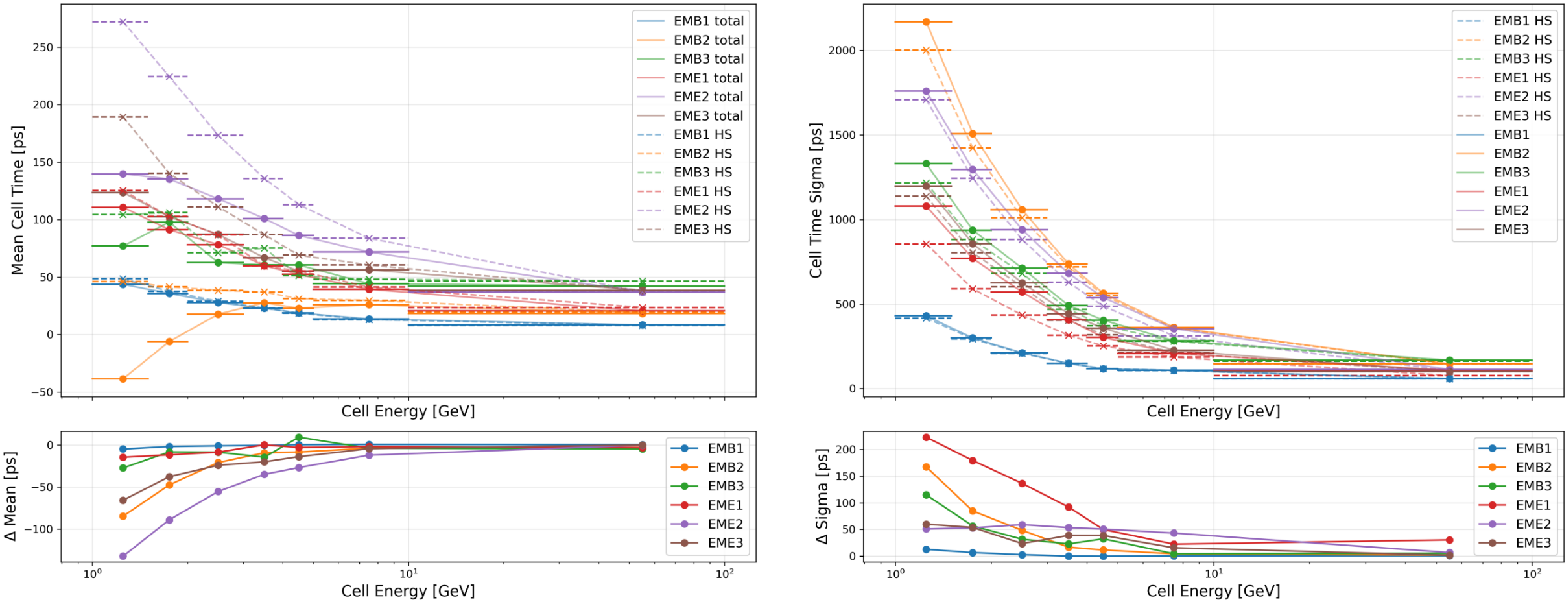




- Most cells with sufficient high energy are HS-matched.

Calibration with Tracking Info

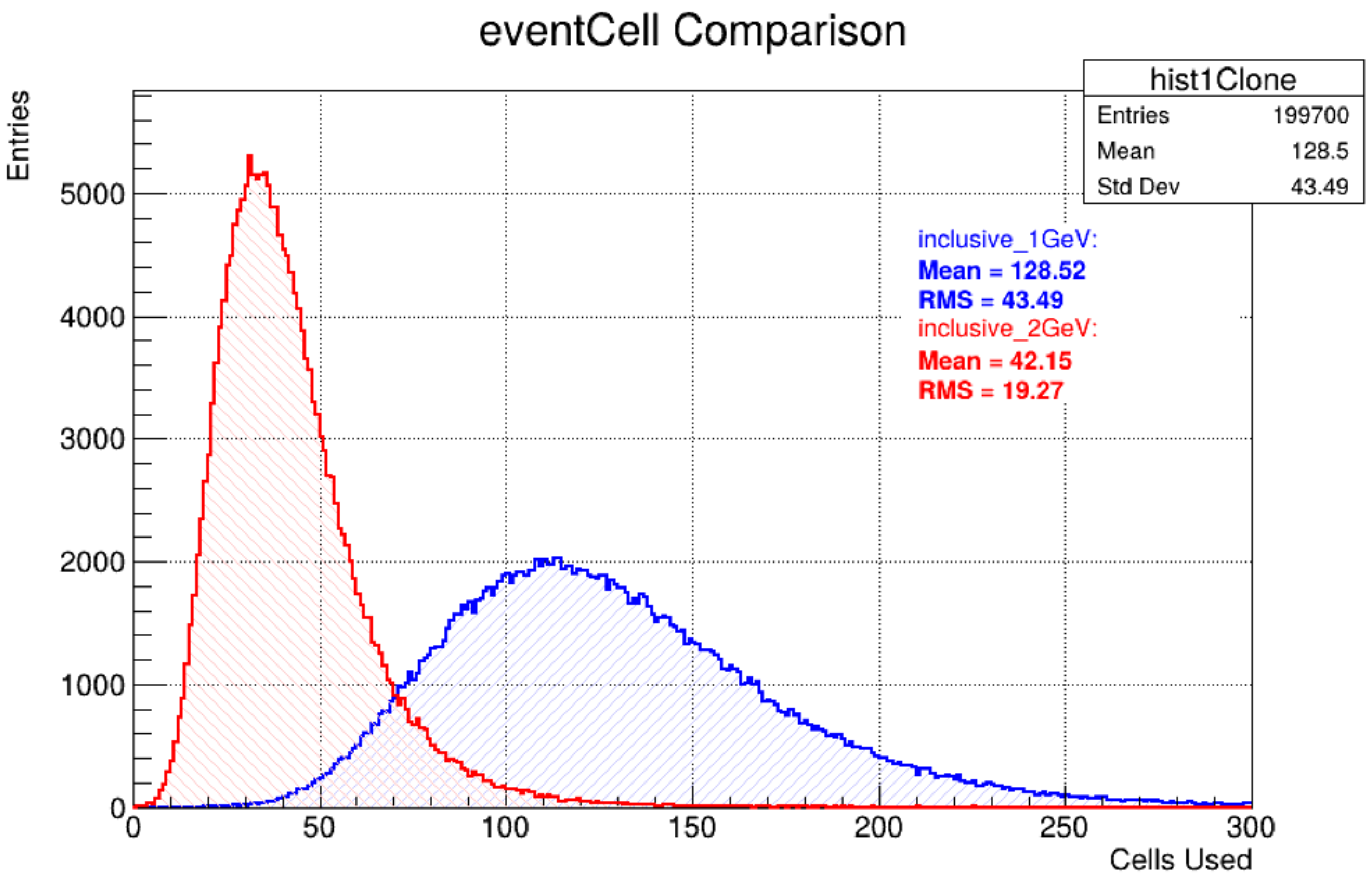
➢ Cell Timing Off-set & RMS

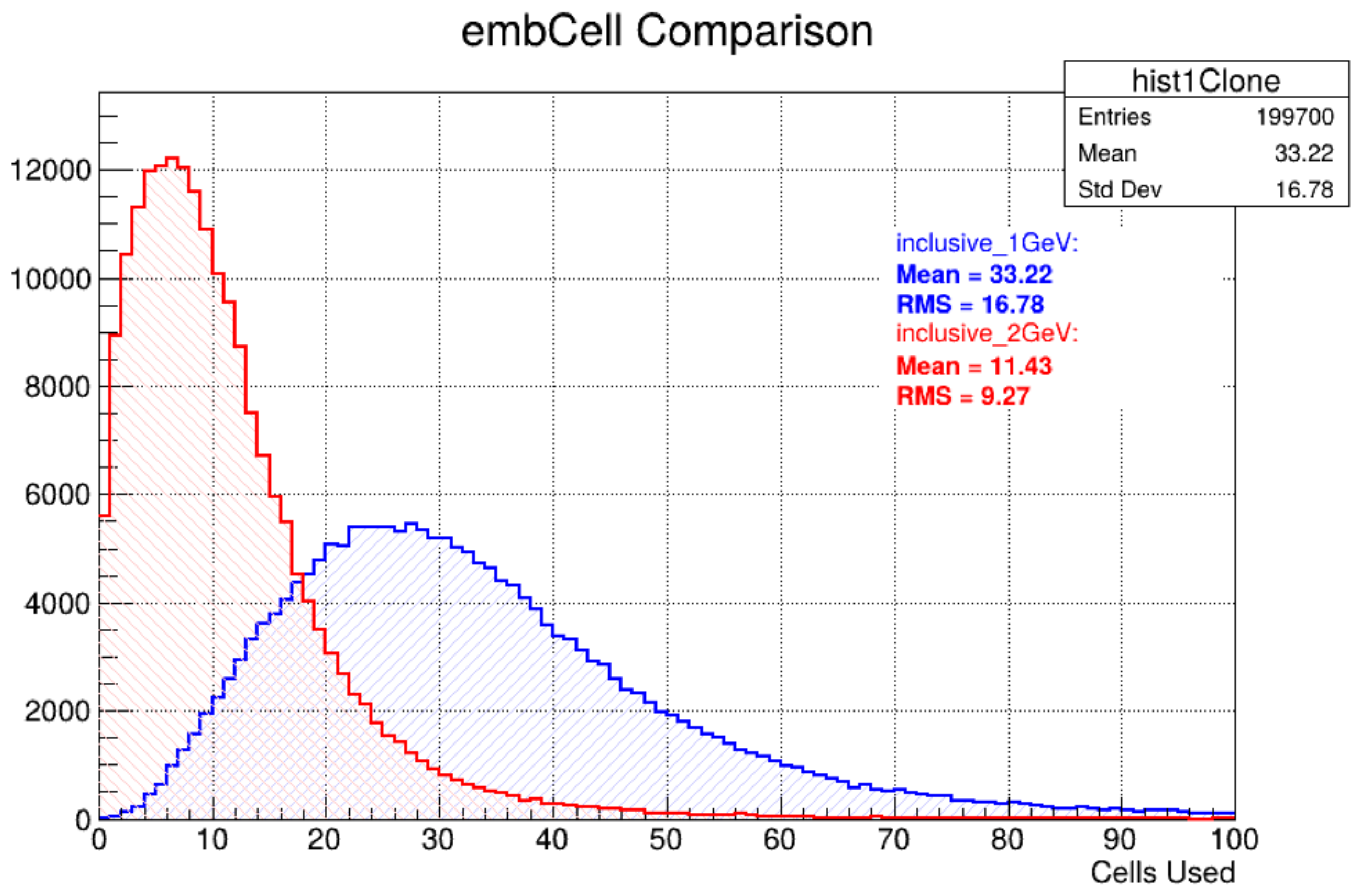


- Cells matched to a HS track result in a better resolution. (especially in lower-energy bins)

Inclusive Cells Count

- Cells Used Per Event

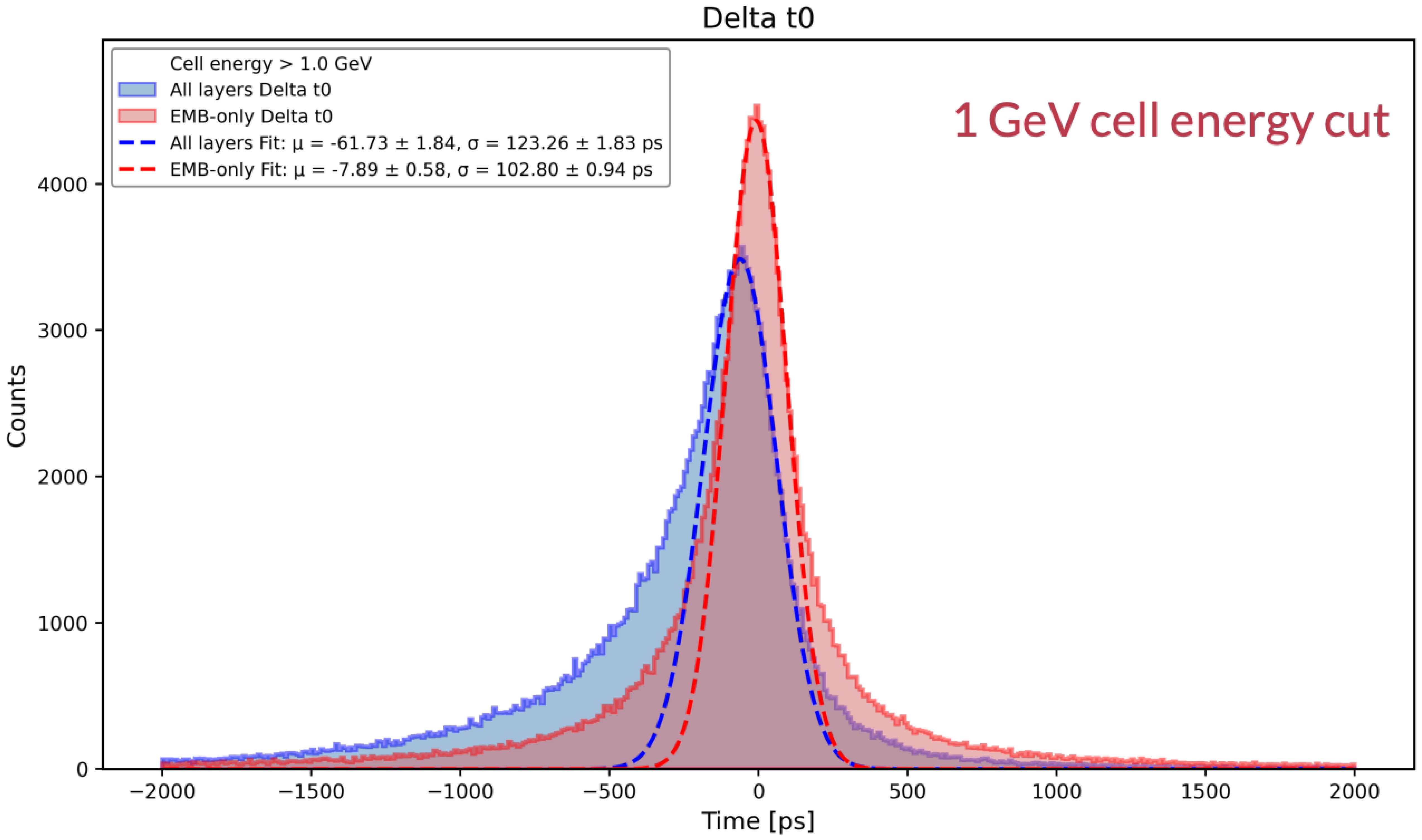


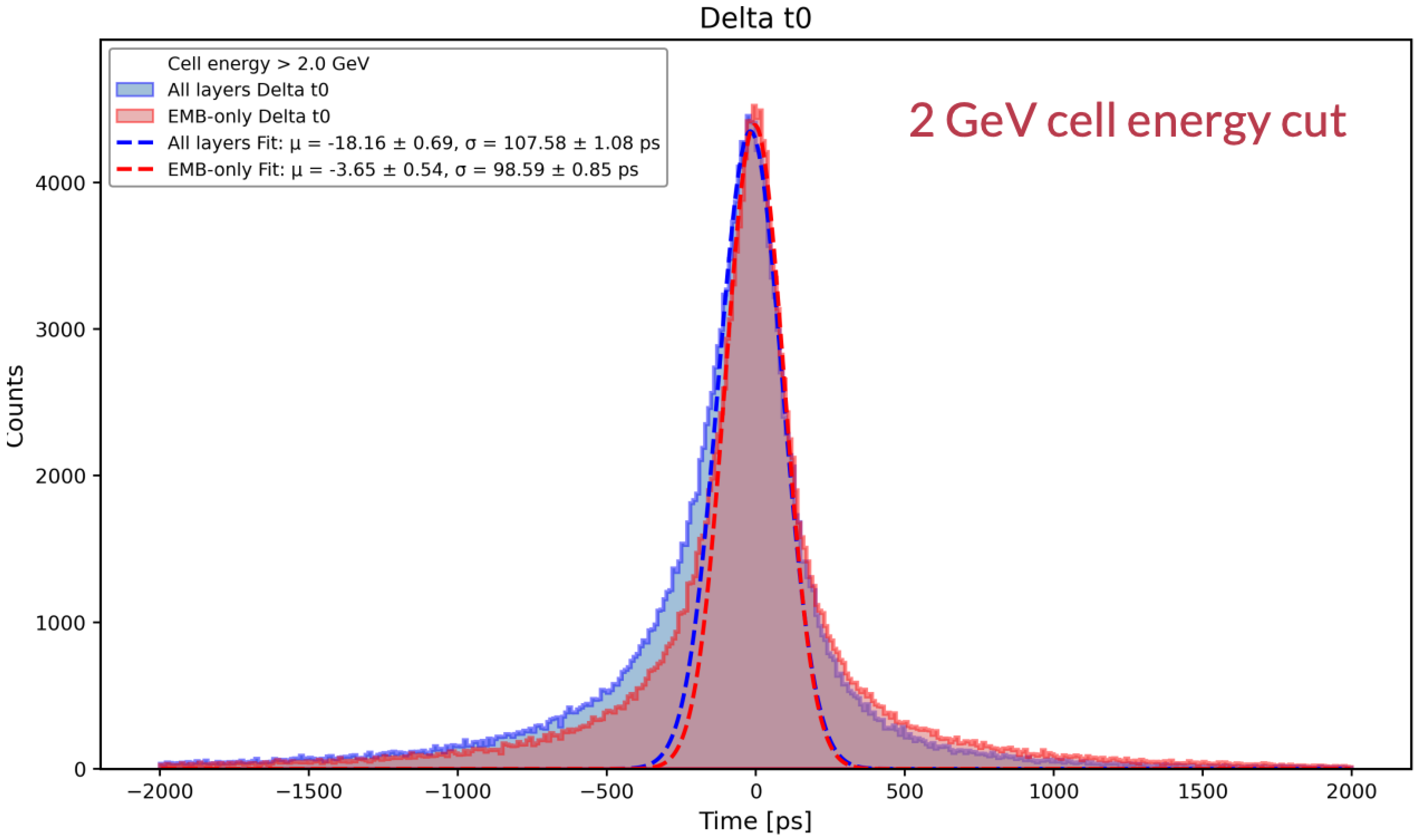


PV t_0 Reconstruction with Tracking Info

- Using PU-removed Cells:

  Once a cell is matched to PU-track during ΔR(cell, track) selection, remove it

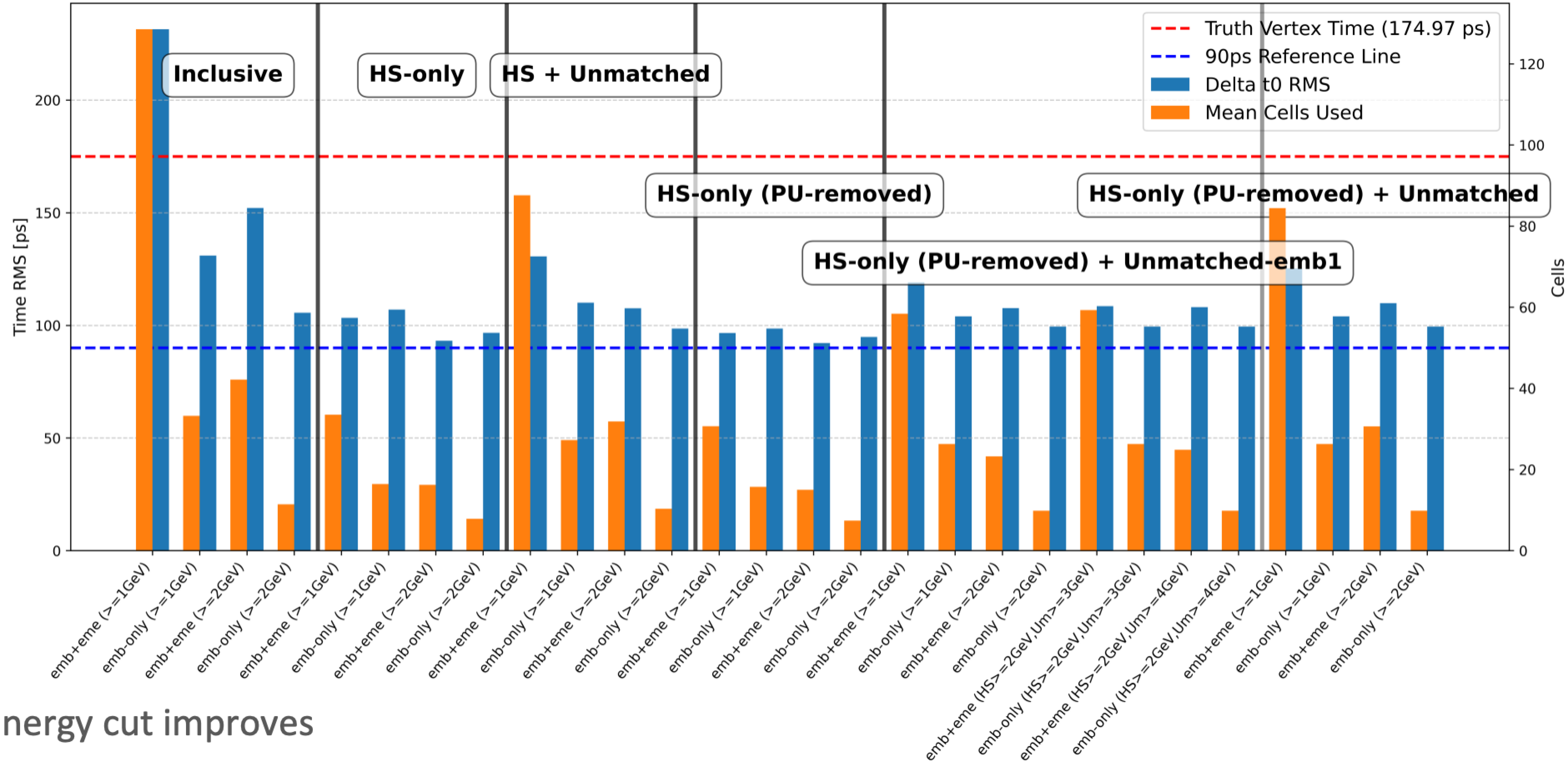




- No obvious improvement by combining the neutral events.

Summary of Tracking Info Combination

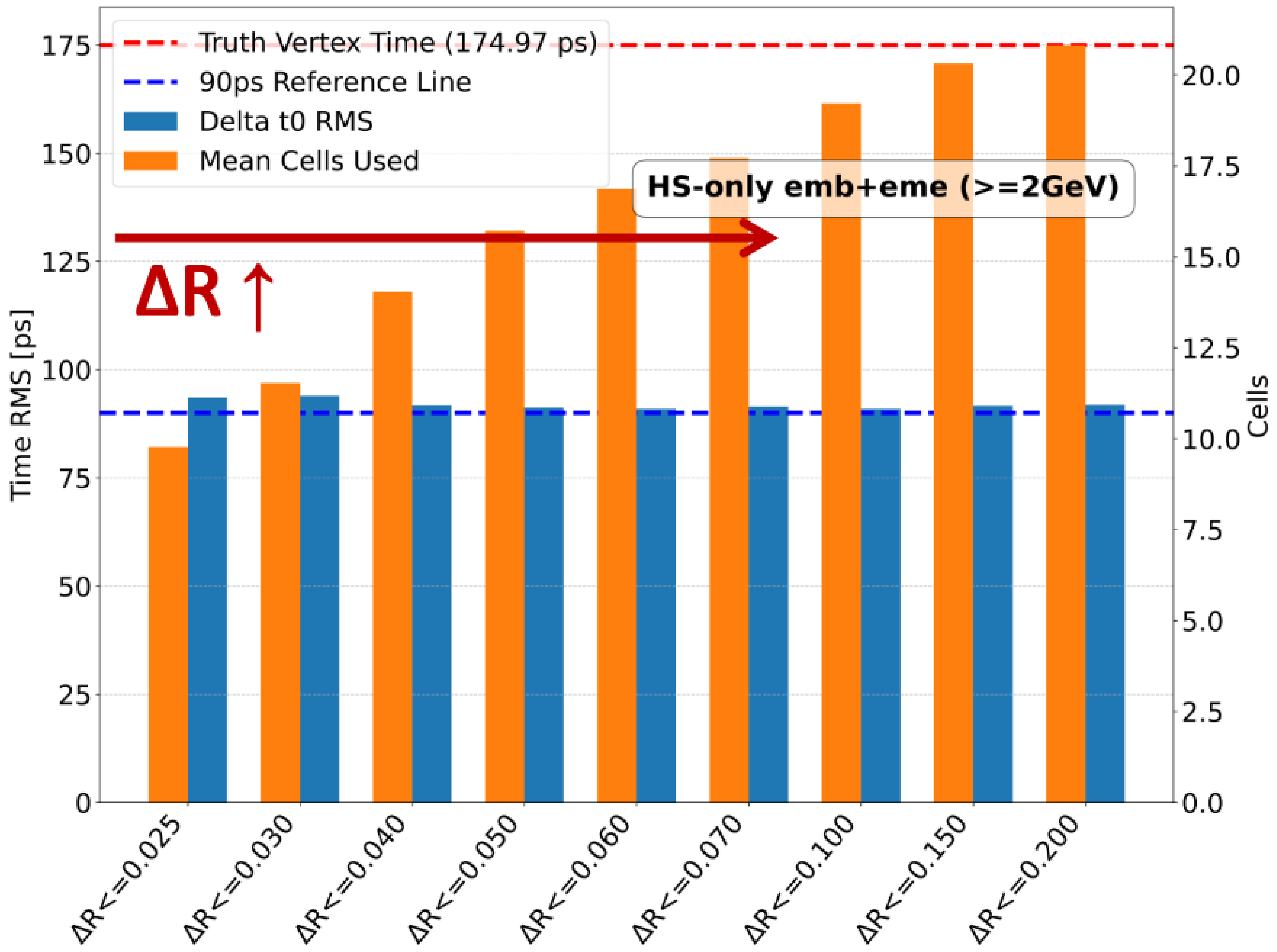
➢ A Lot Attempts



- Increasing the cell energy cut improves resolution slightly.

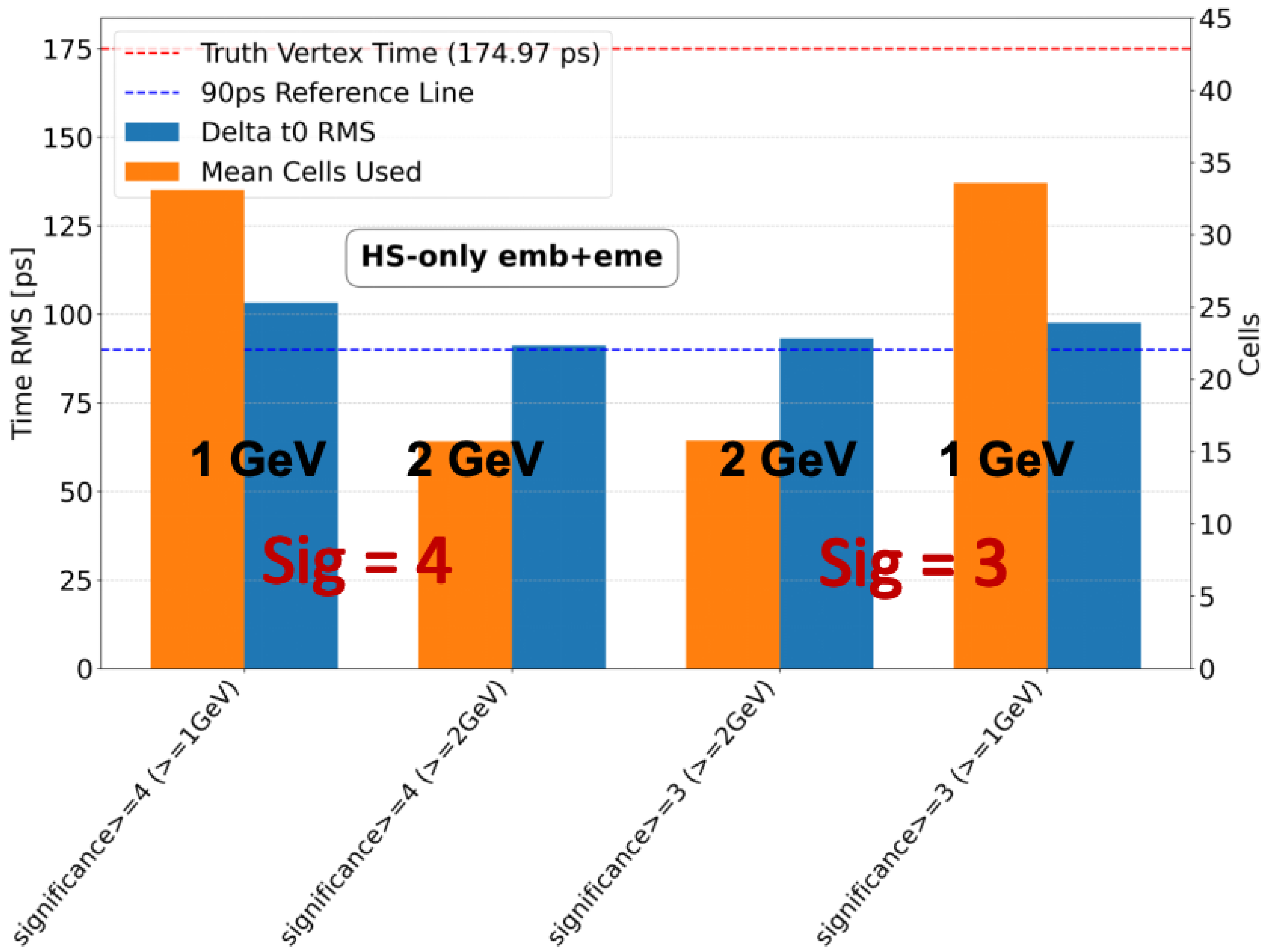
Summary of Cell-Track Matching

- Varying the ΔR(cell, track)



- Increasing ΔR threshold can slightly degrade the timing resolution, but relatively stable

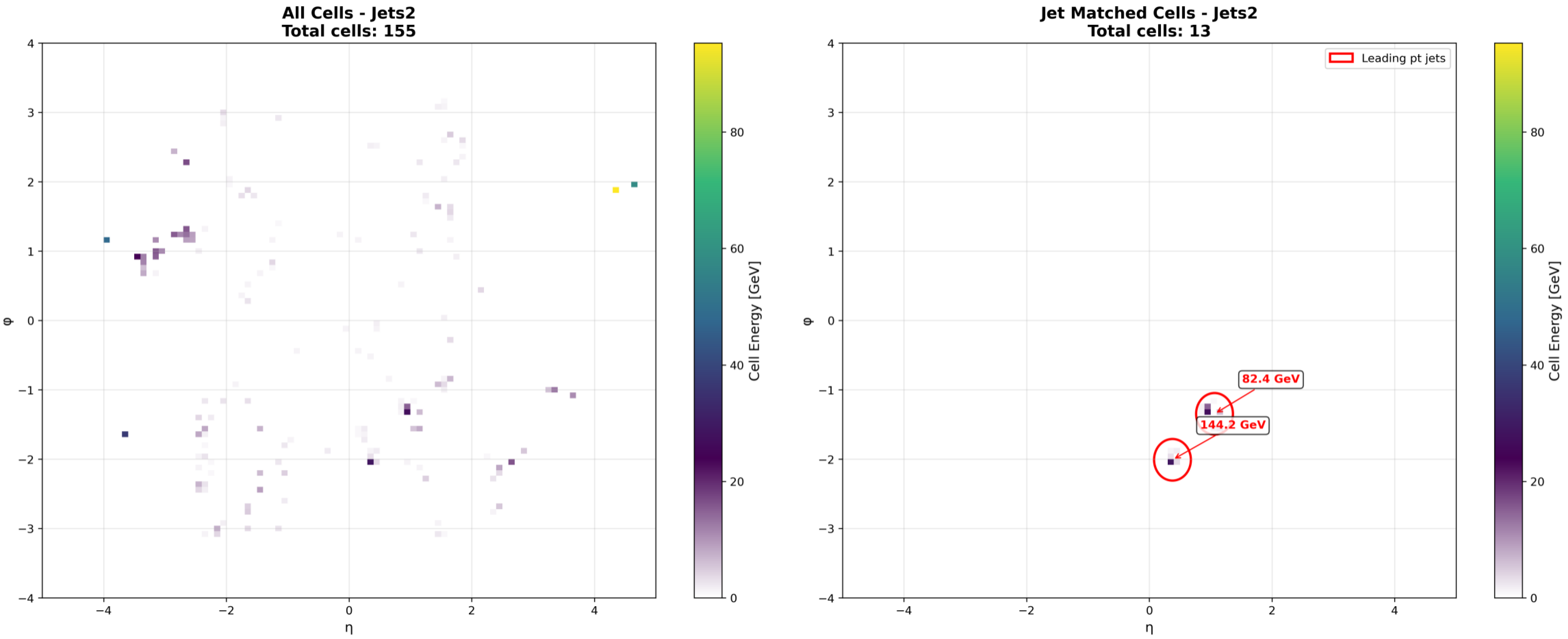
- Varying the Cell Significance



- No significant improvement from lower significance cut

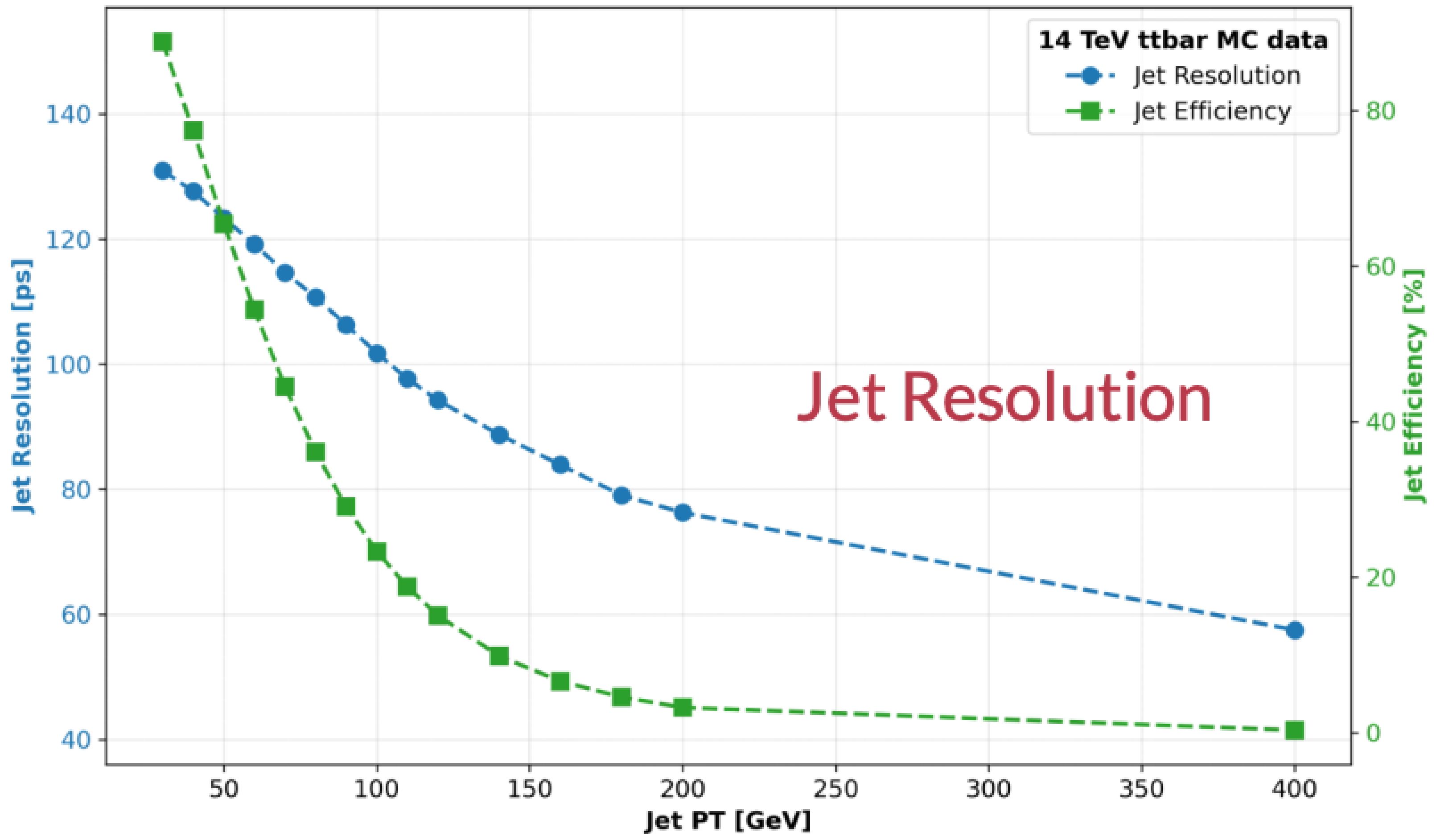
Incorporating Cell-Jet Matching Info

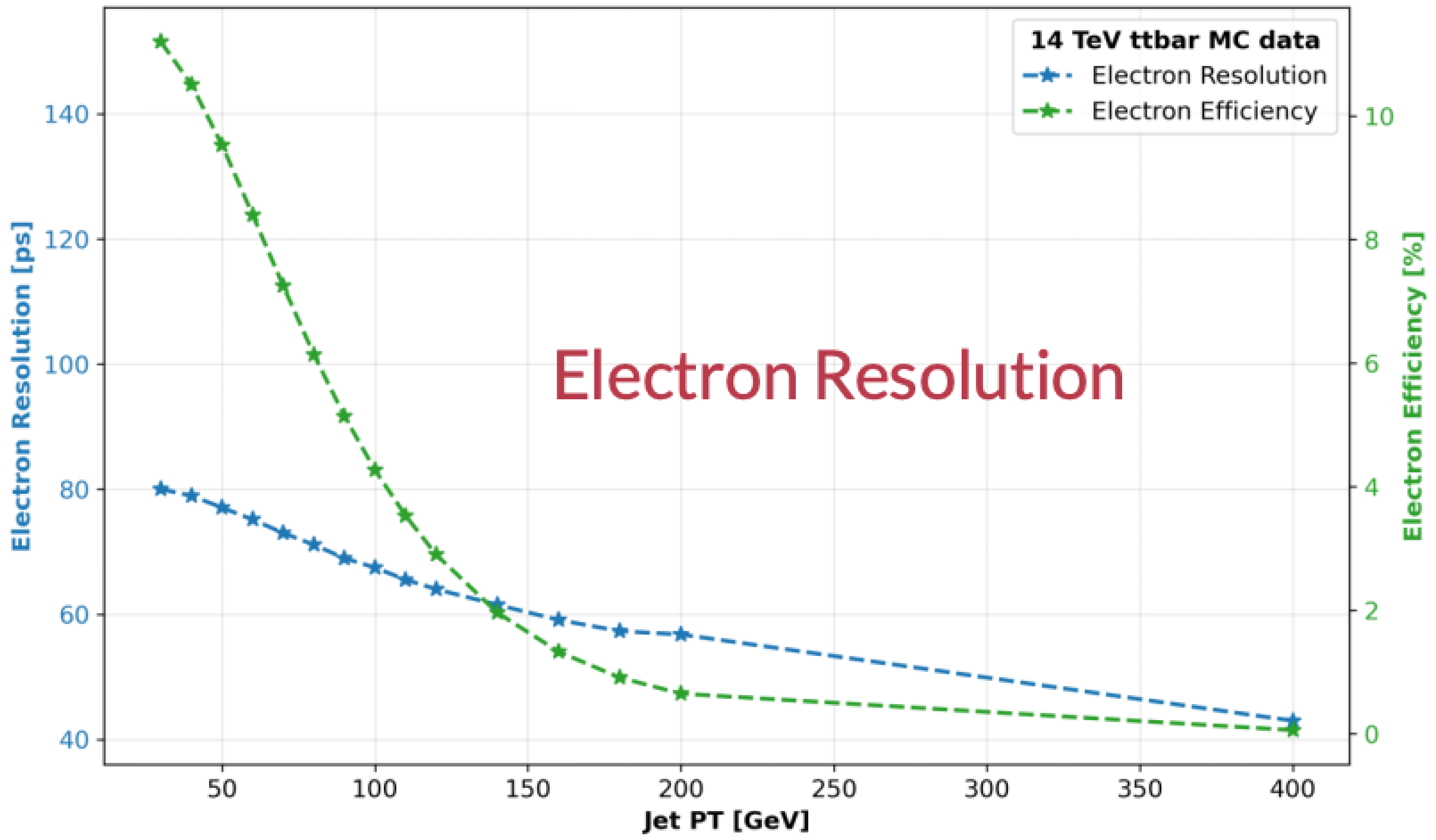
➢ Event Display (2 Leading Jets)



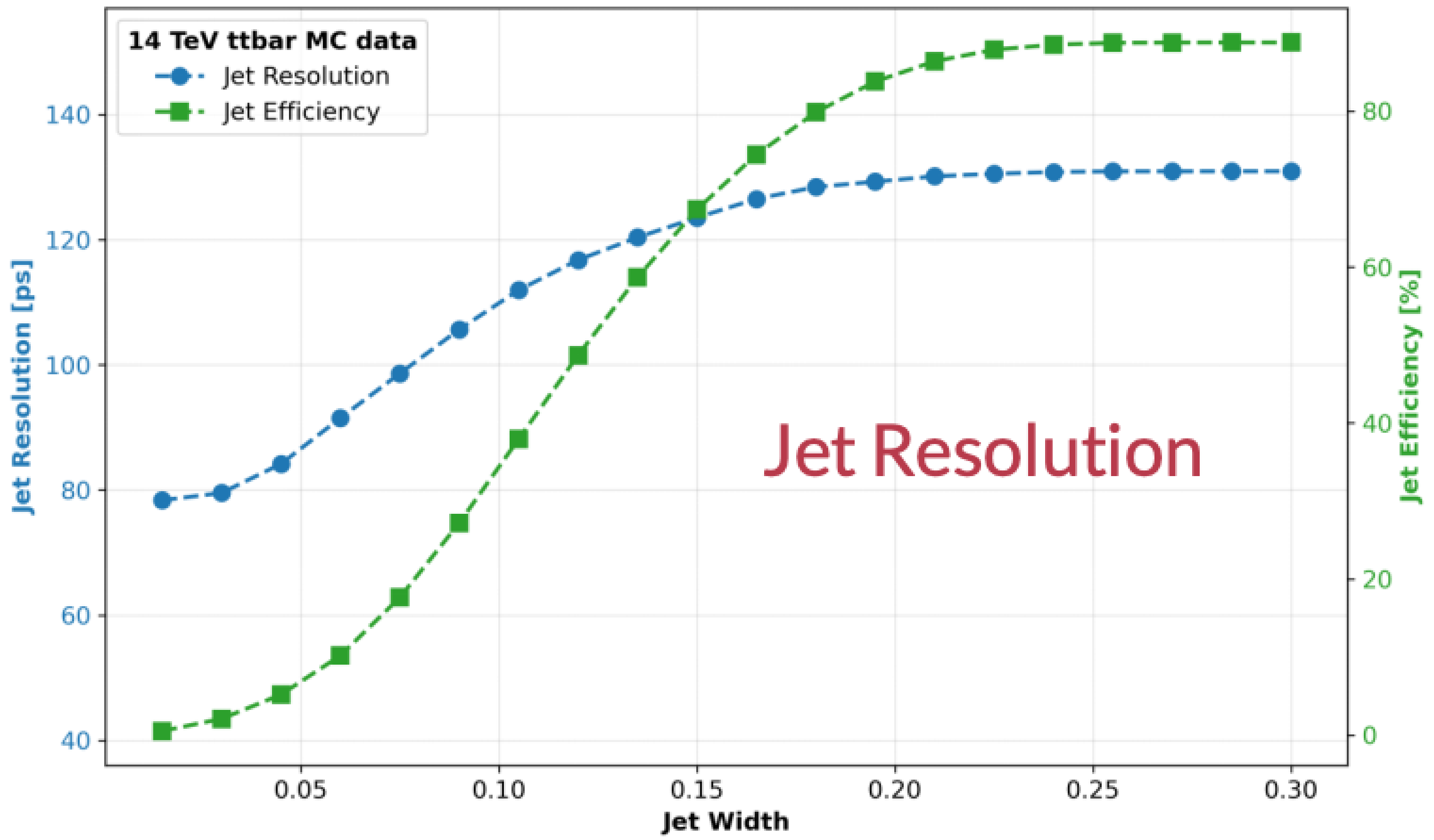
Separating Electrons from "Real" Jets

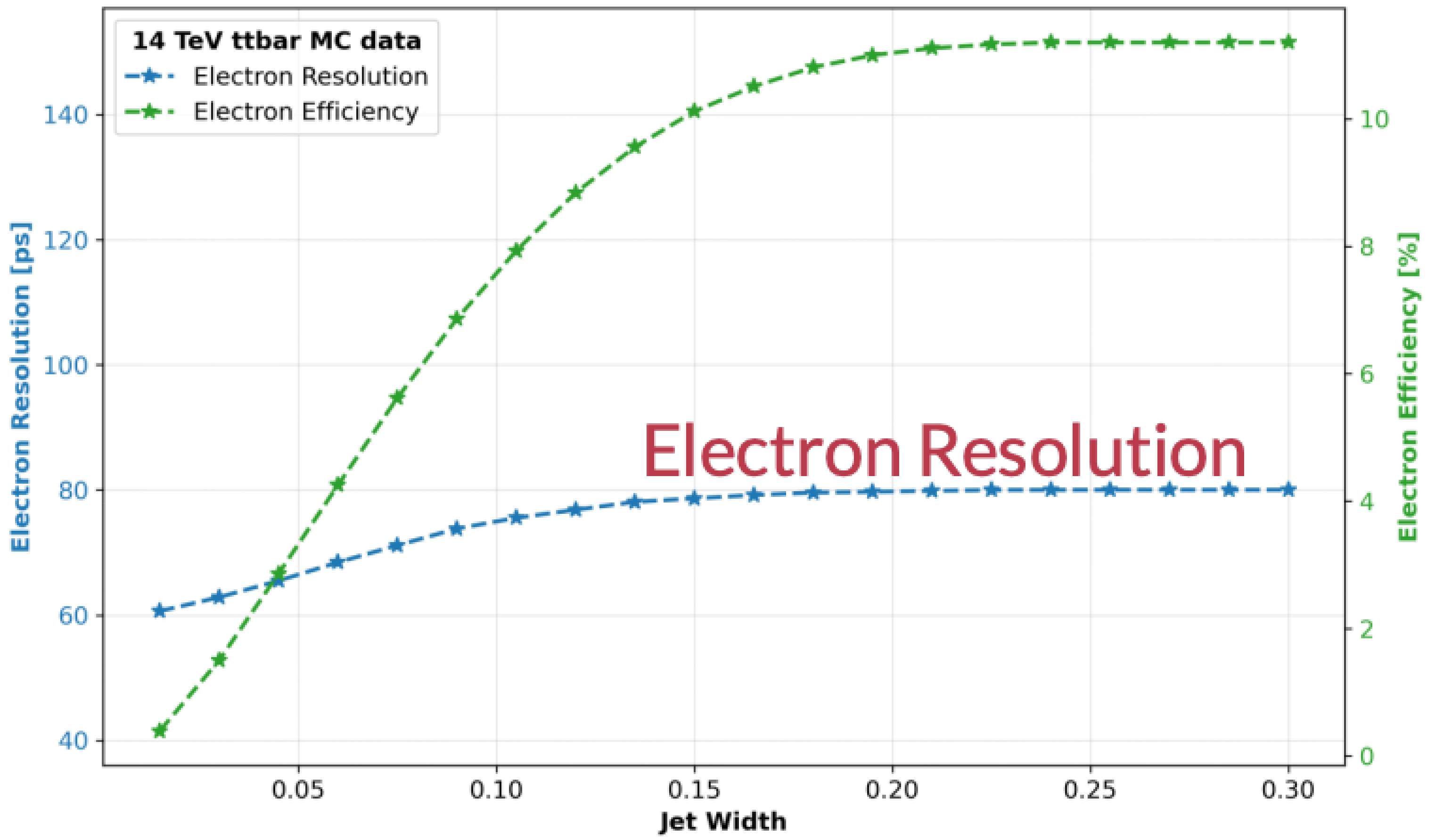
- Jet-p_T Impact





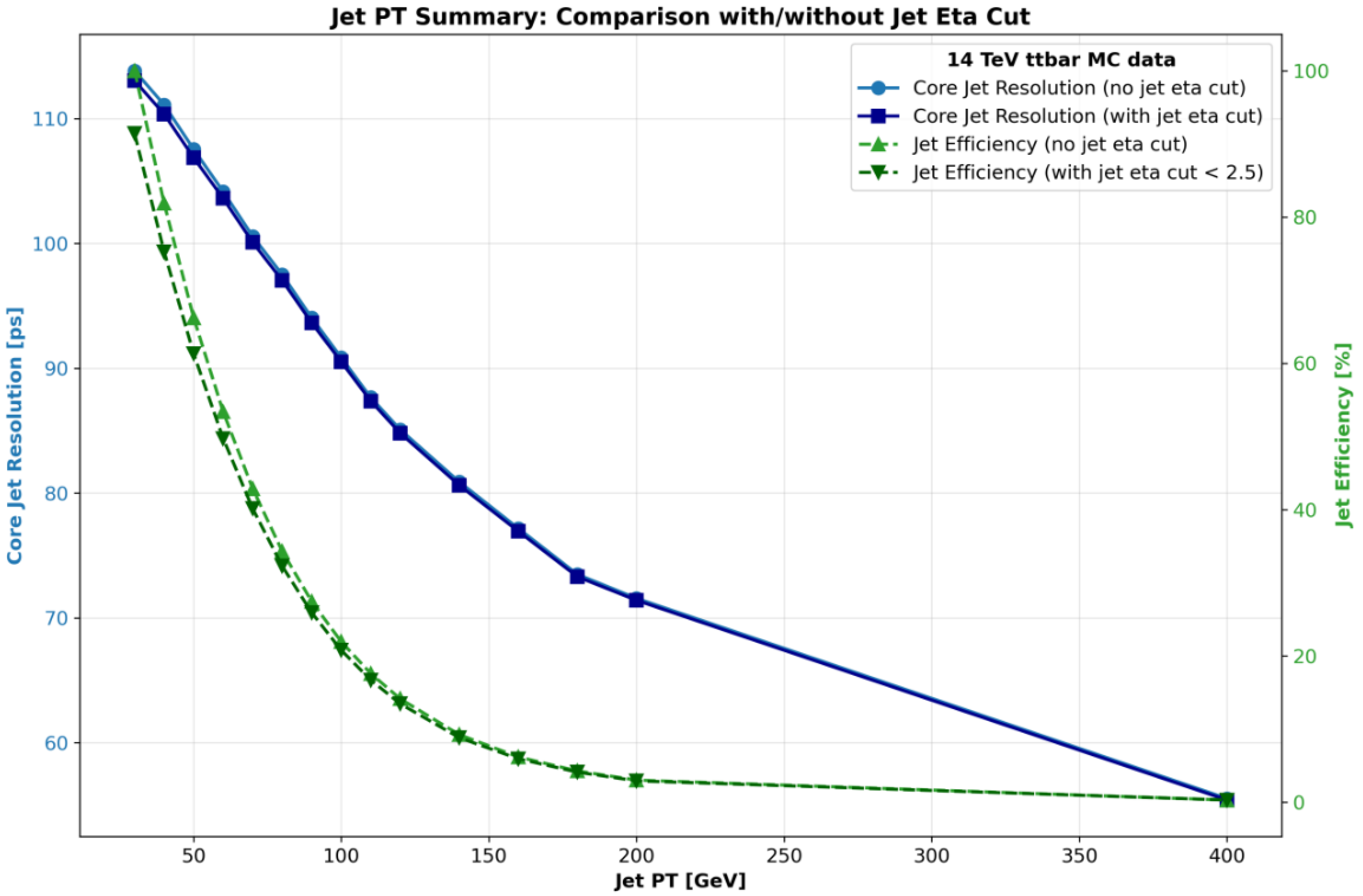
- Jet-width Impact

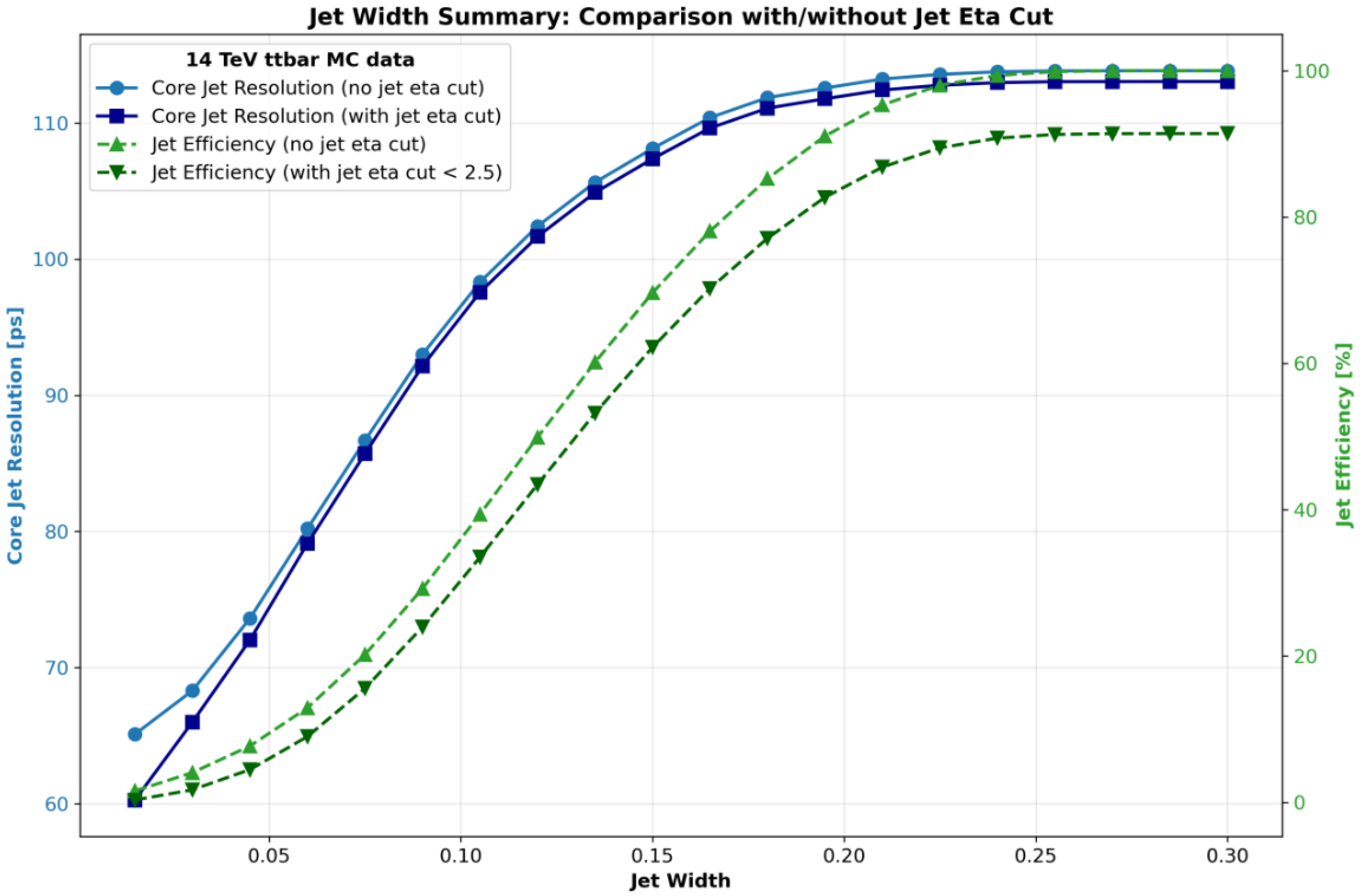




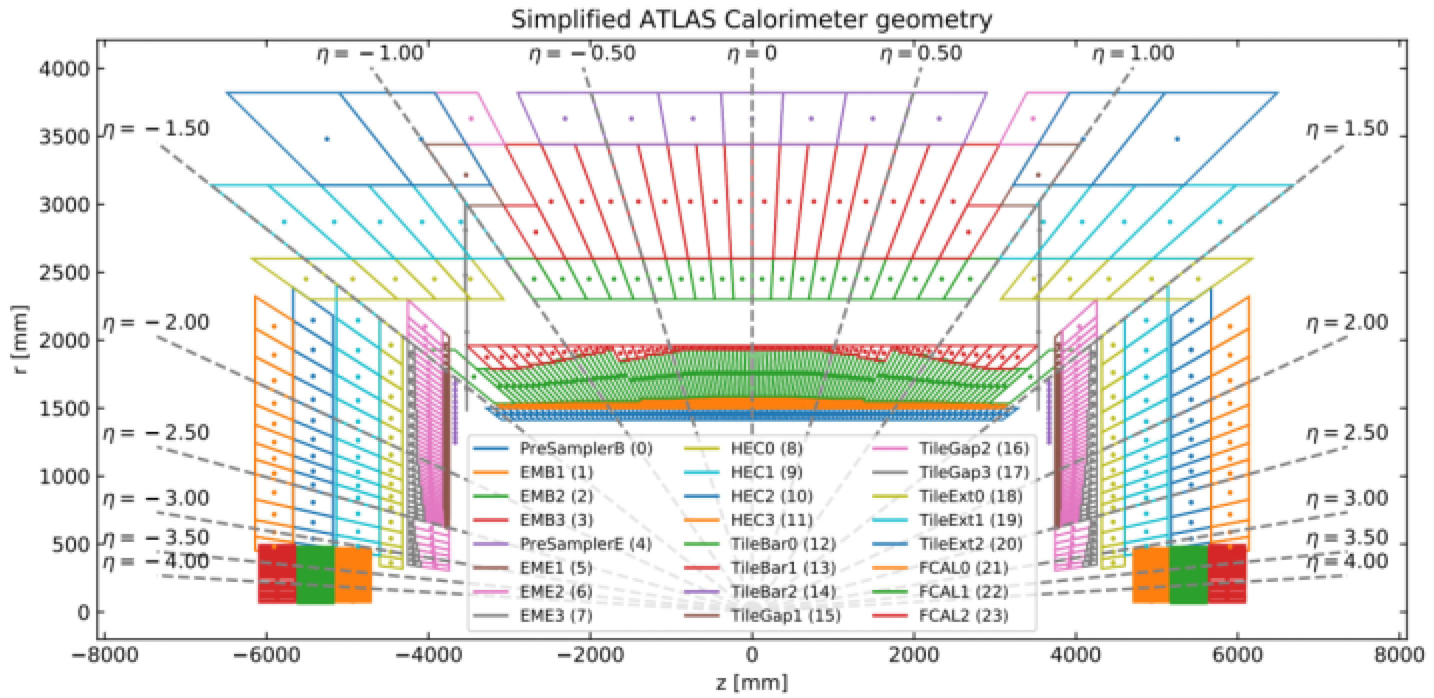
Jet-width Summary

➢ Excluding the Forward Jets



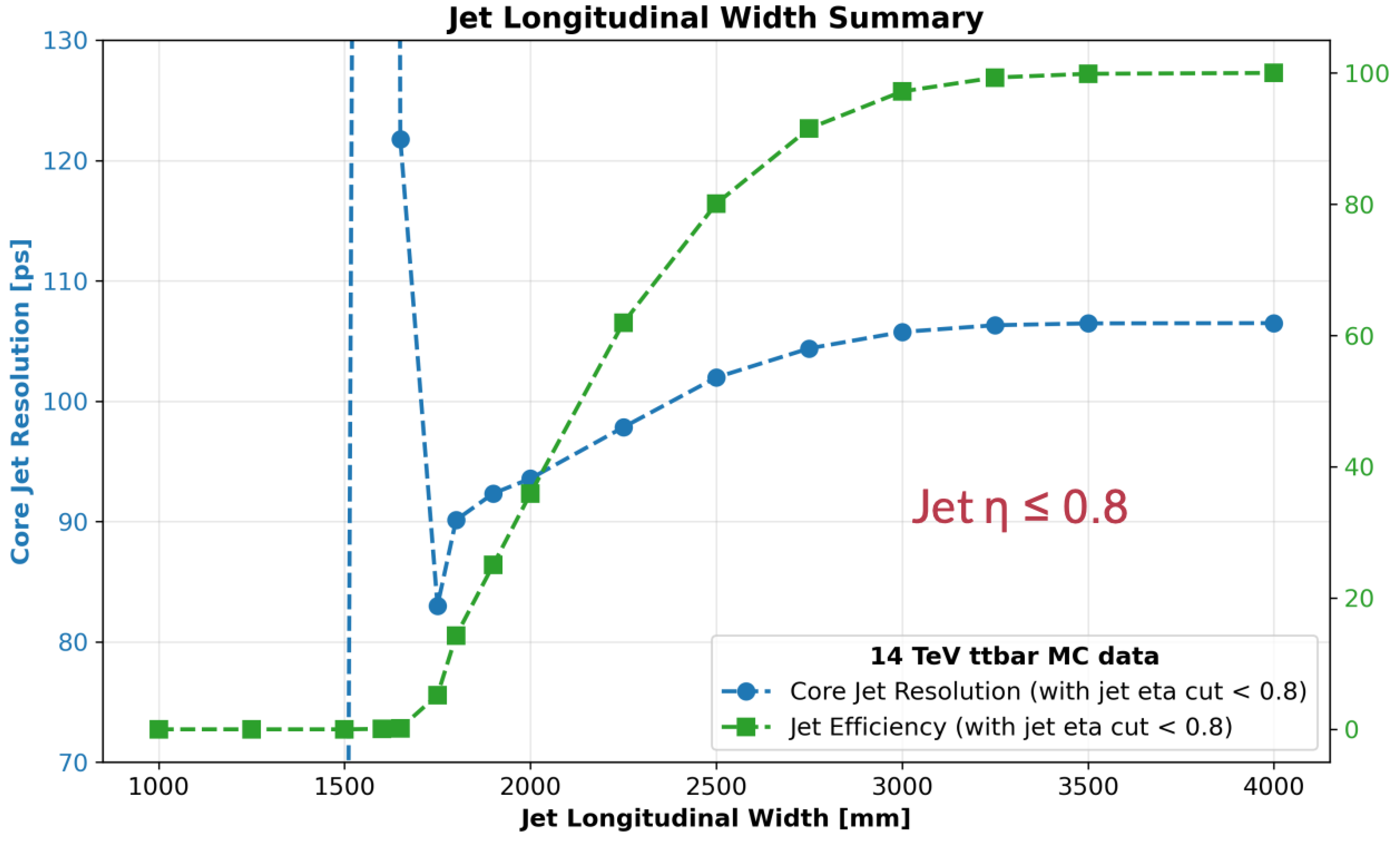


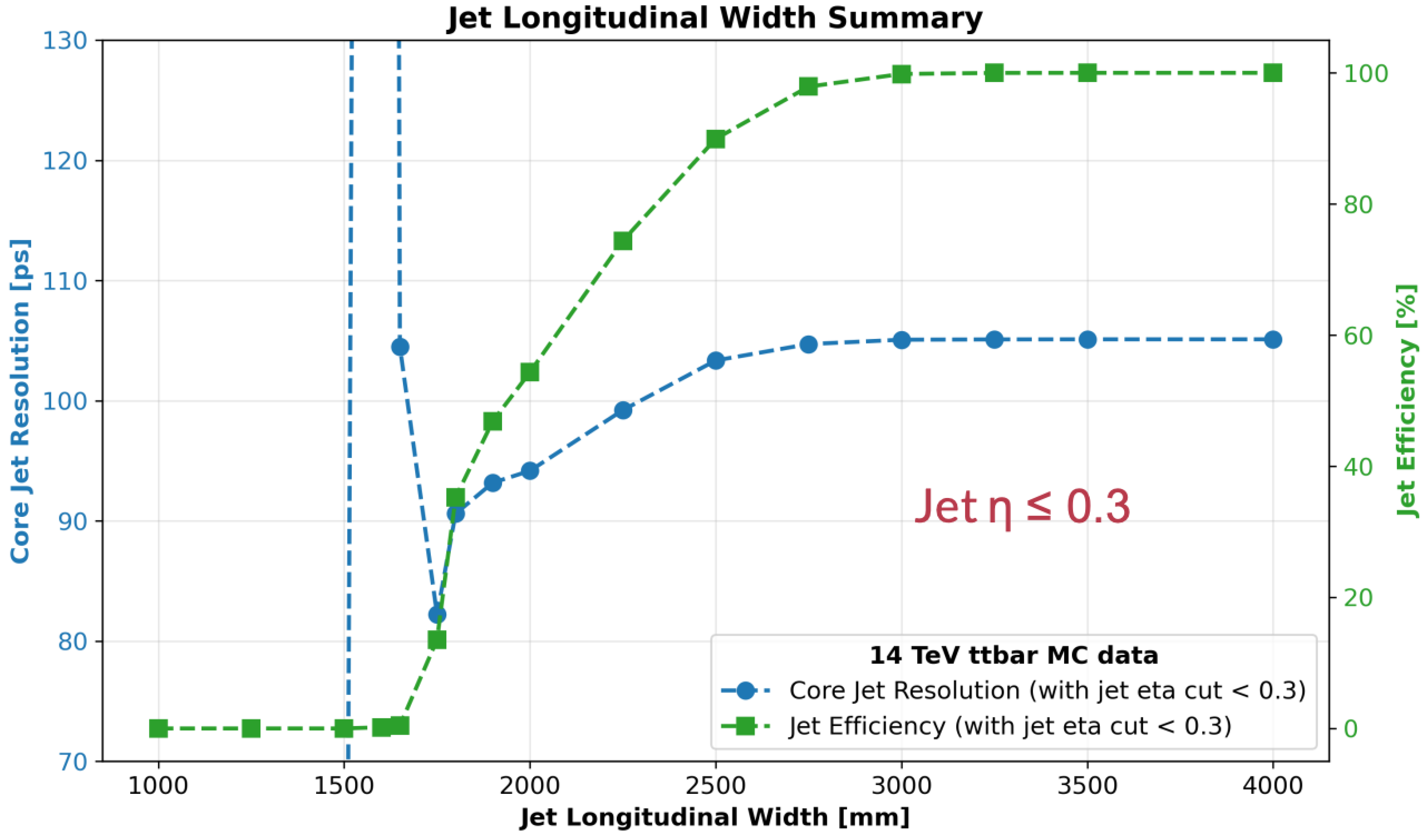
- Slightly Improvement but no significant difference.



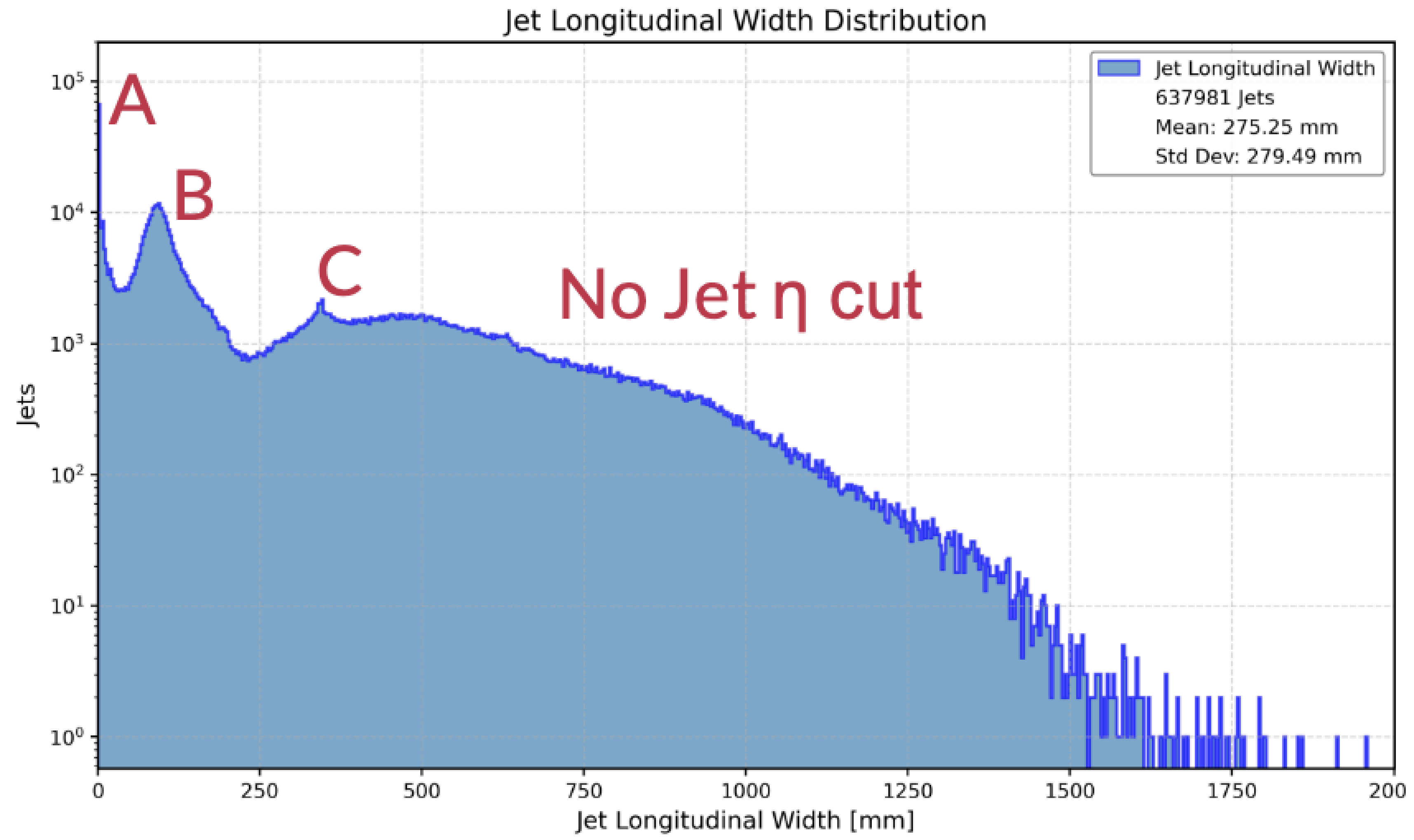
[ATLAS LAr Geometry]

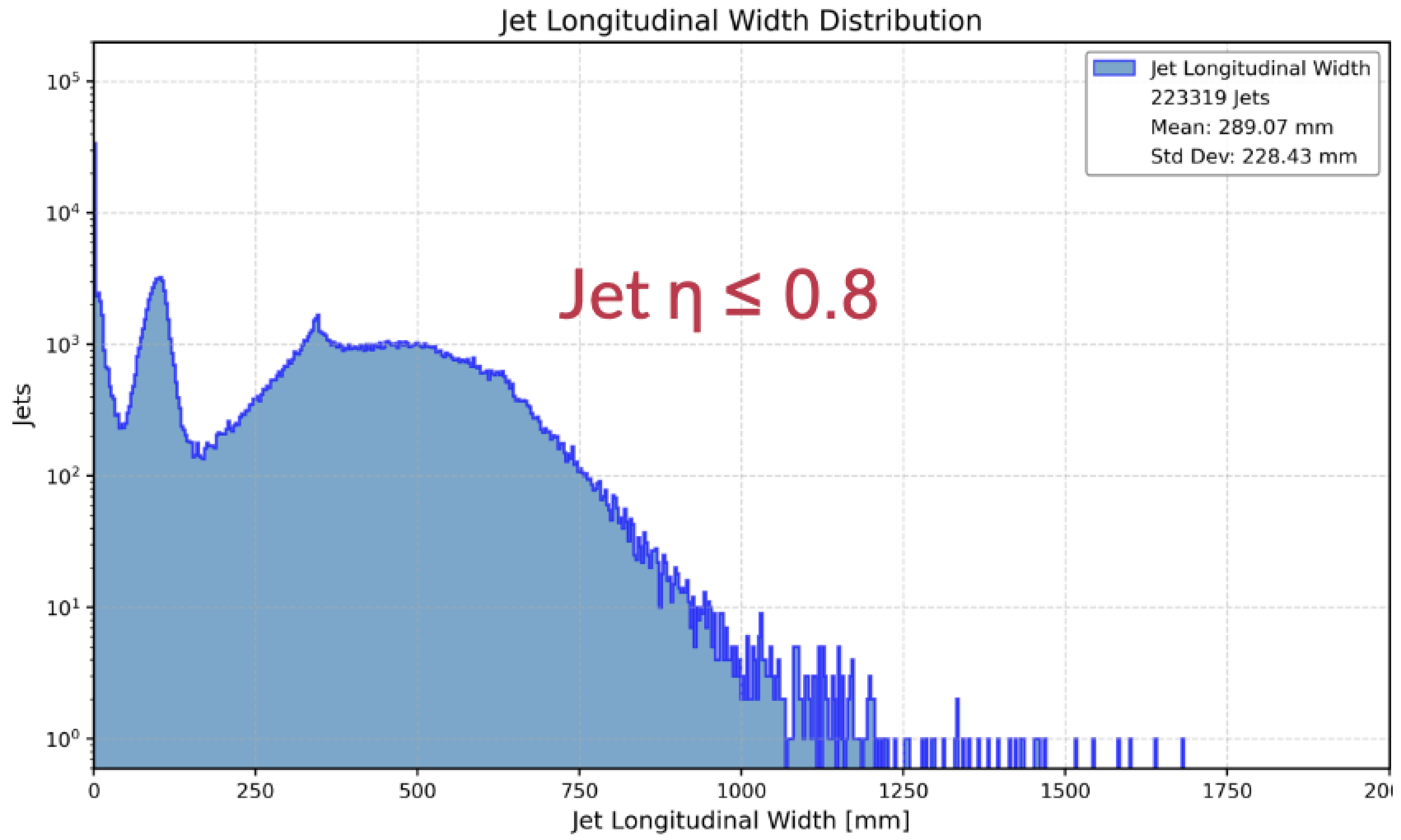
Jet Longitudinal Width (c.o.e) Summary

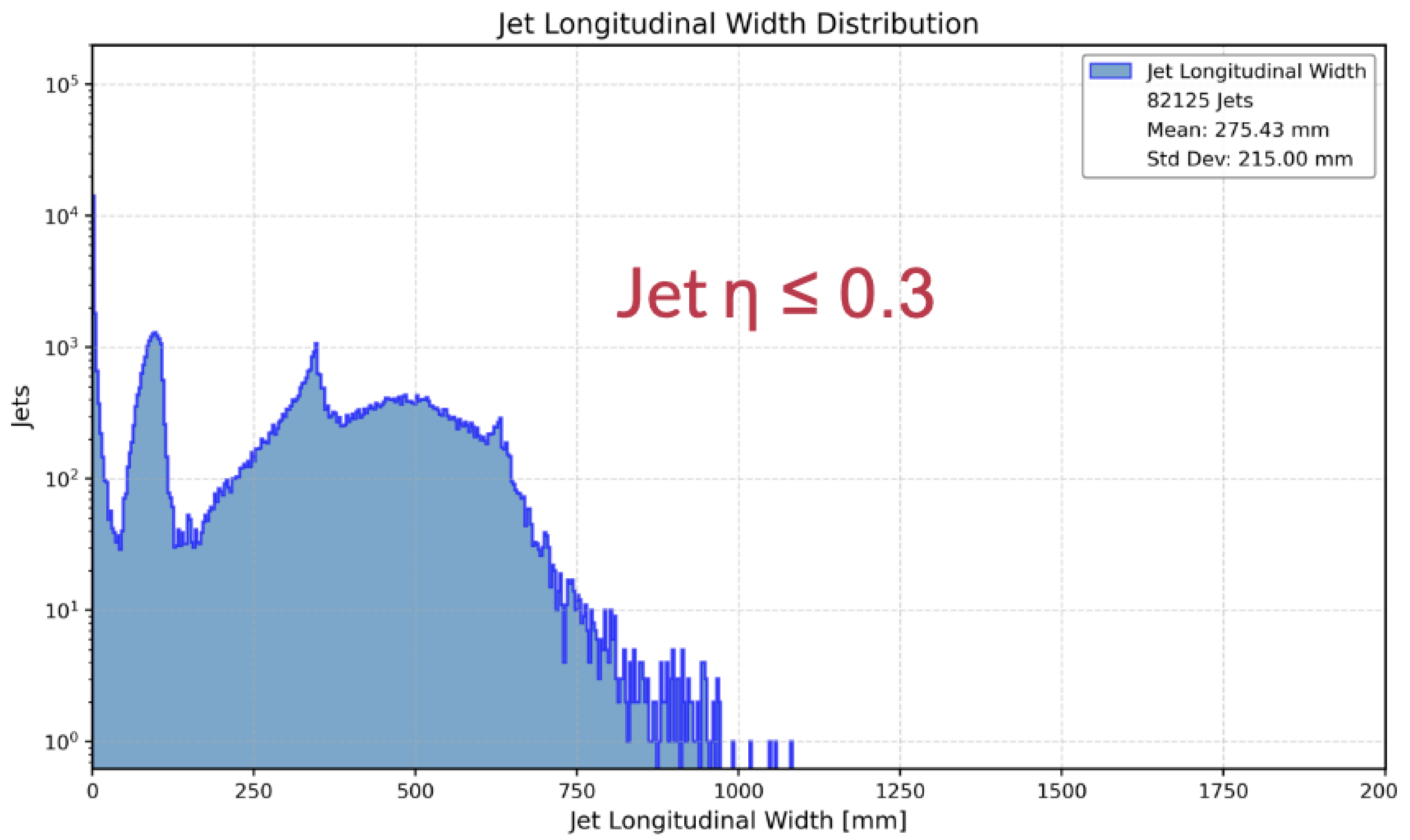




Jet Longitudinal Width Distribution

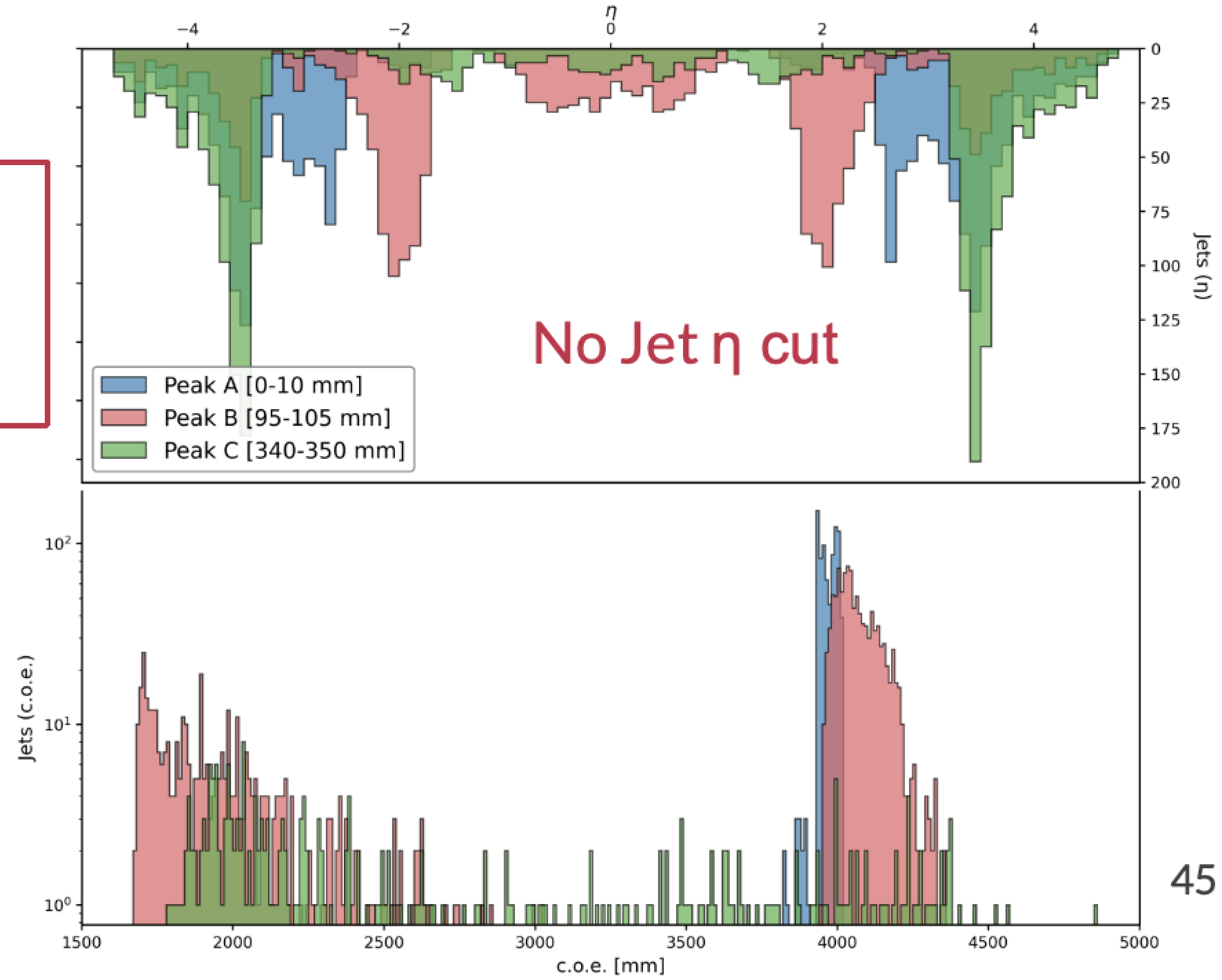






$$Lw^{jet} = \sqrt{\frac{\sum_{cell} E^{jet}_{cell}(Z^{jet}_{cell} - c.o.e^{jet})^2}{\sum_{cell} E_{cell}{}^{jet}}}$$

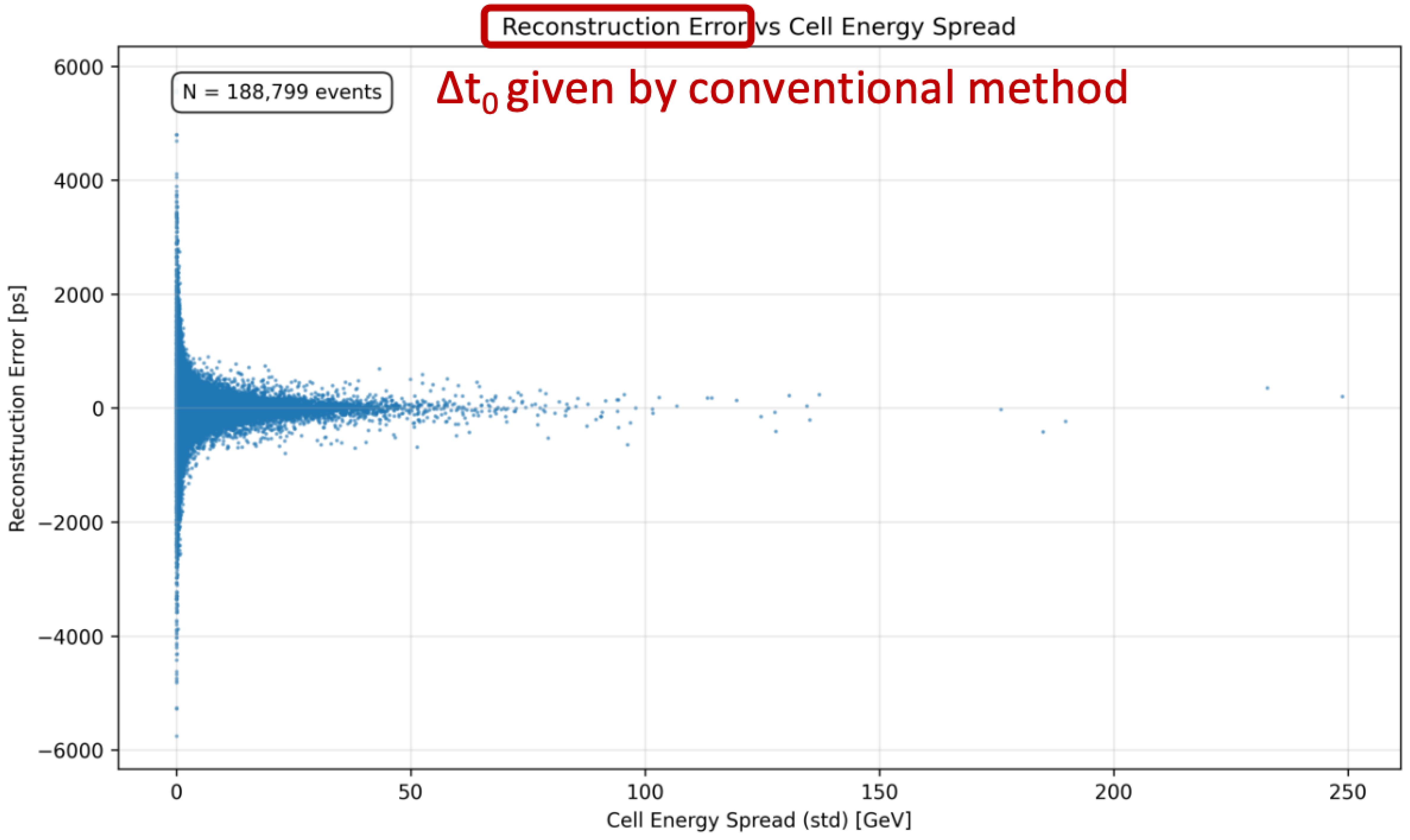
$$c.o.e^{jet} = \frac{\sum_{cell} E_{cell}{}^{jet} Z^{jet}_{cell}}{\sum_{cell} E_{cell}{}^{jet}}$$

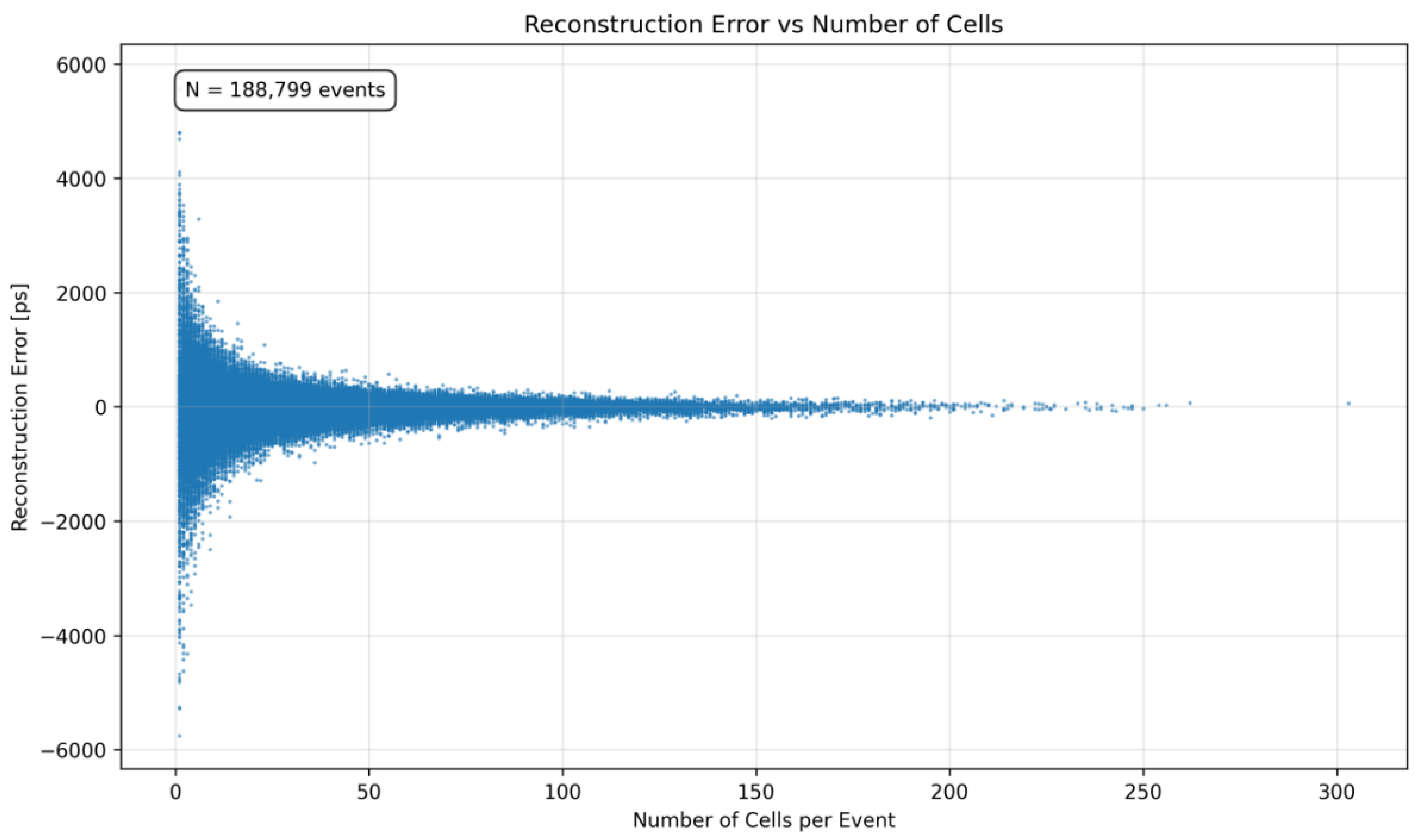


- The longitudinal width distribution is not strong-correlated with jet η.

ML Regression Using Jet-Matched Cells

- Exhibition of Δt_0 vs Cell Info

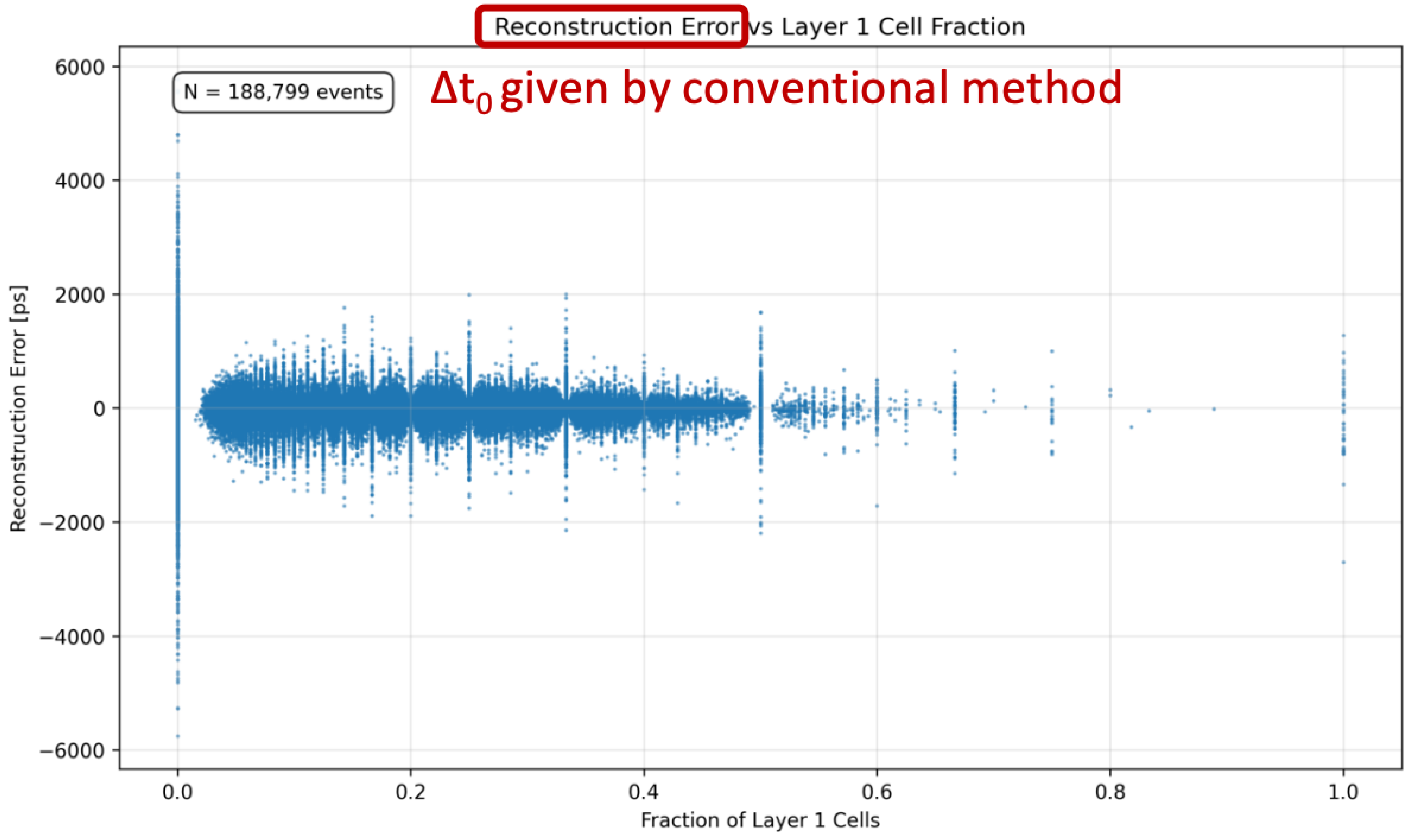


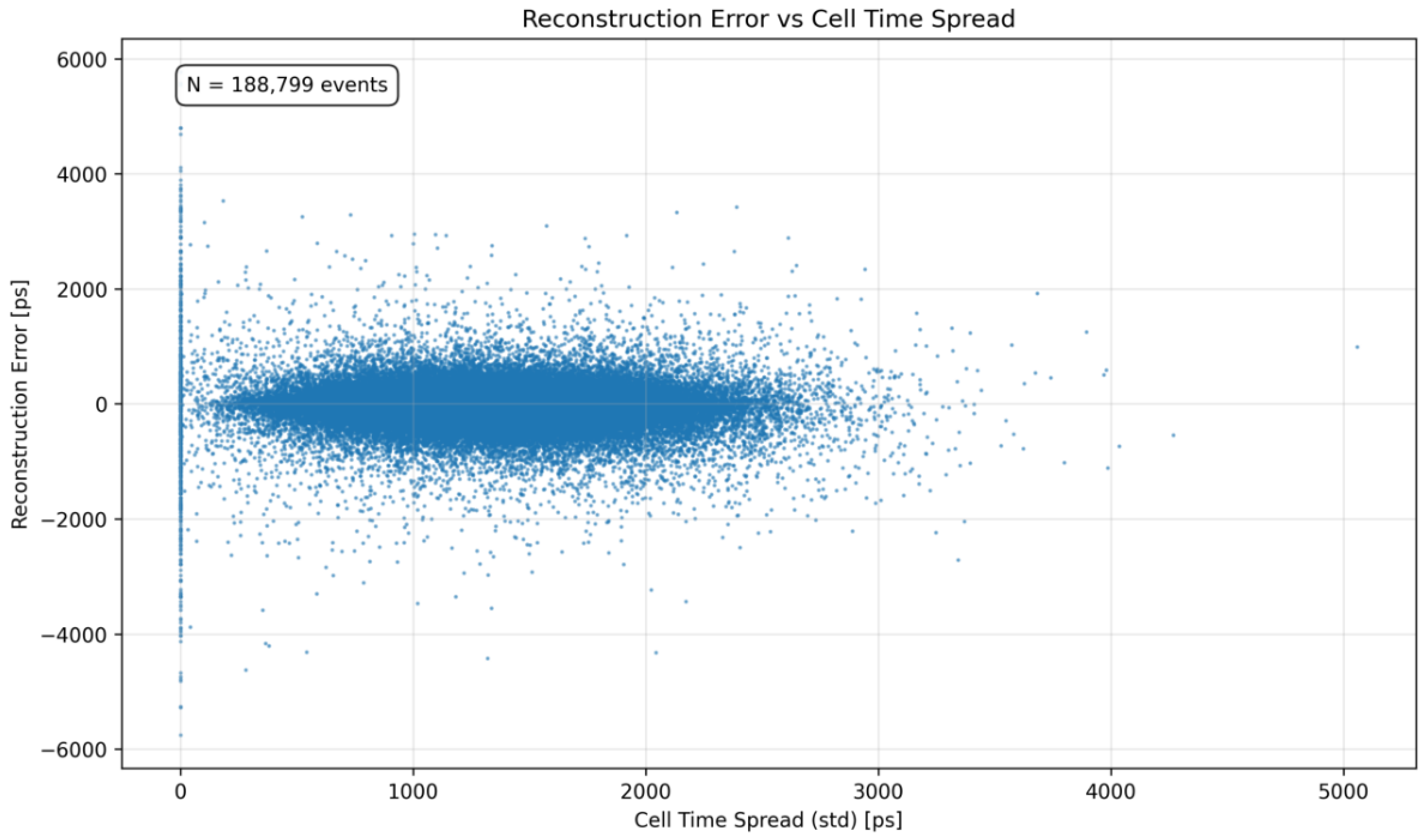


- More cut on the cell energy spread?
- Adjust Minimum cell number for each event?

ML Regression Using Jet-Matched Cells

- Exhibition of Δt_0 vs Cell Info

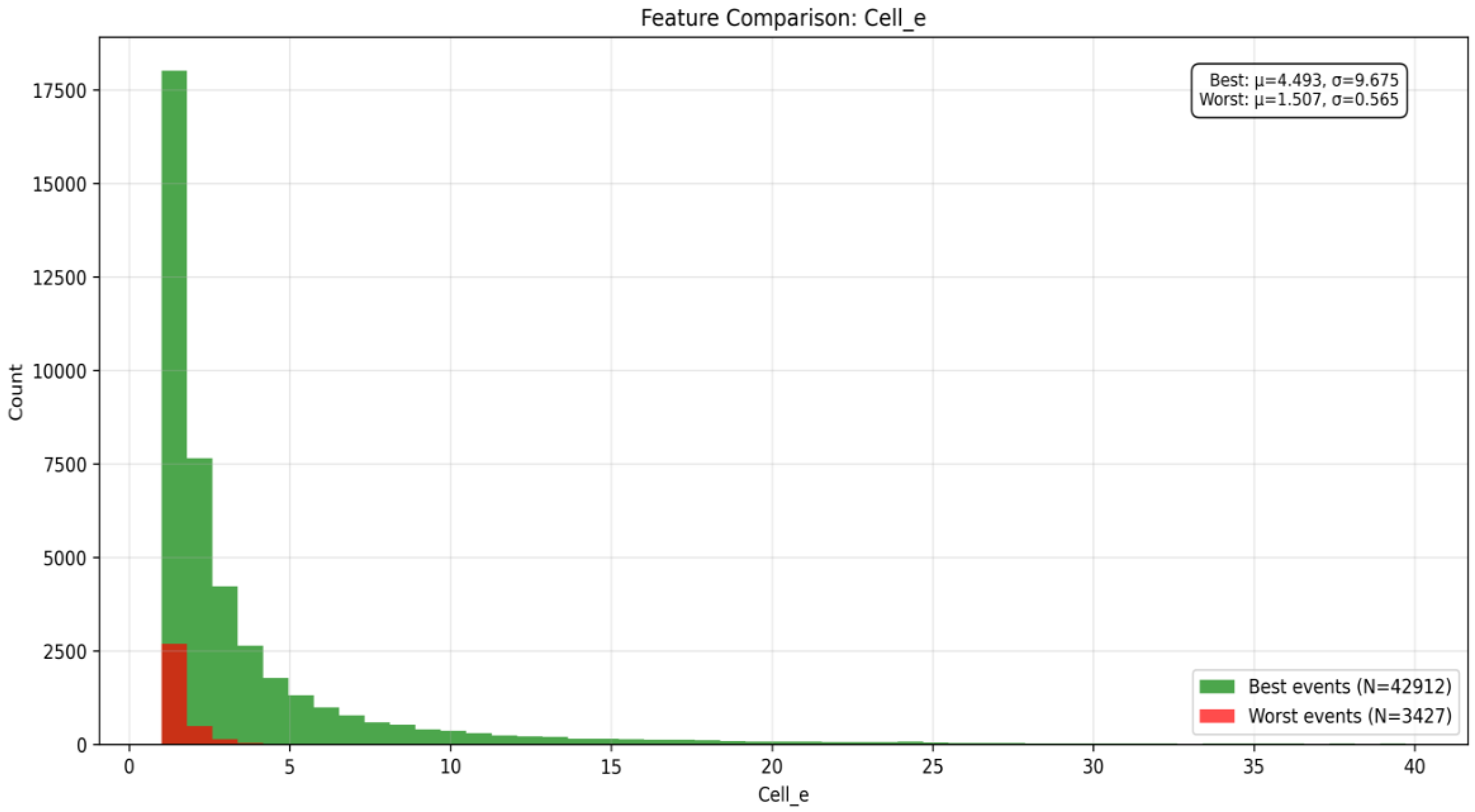


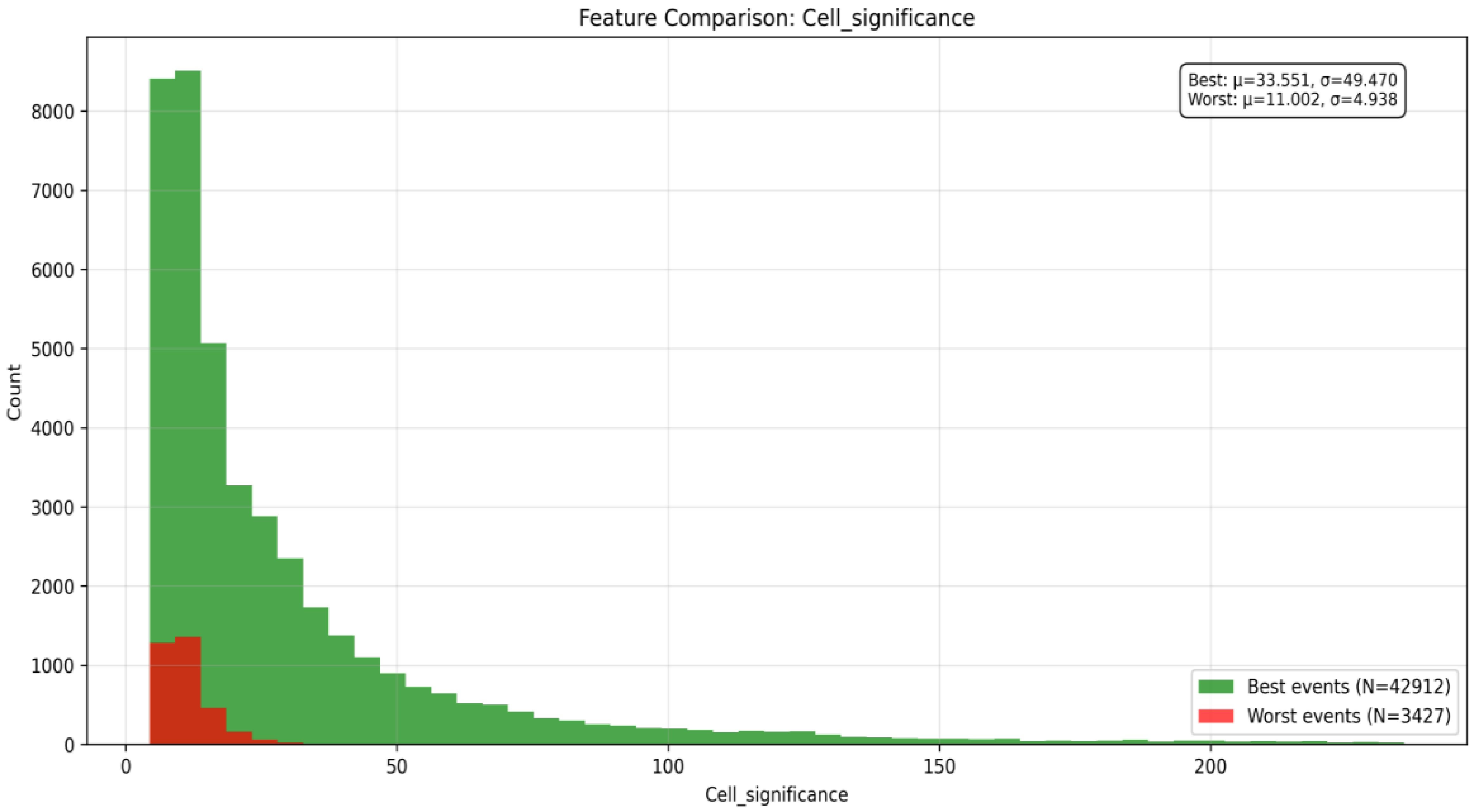


- Interesting pattern here in Fraction of Layer 1 Cells plot.
- Cell time std=0 usually means only 1 cell is available after cuts.

ML Regression Using Jet-Matched Cells

- Comparing 1,000 best and worst events (in terms of Δt_0)

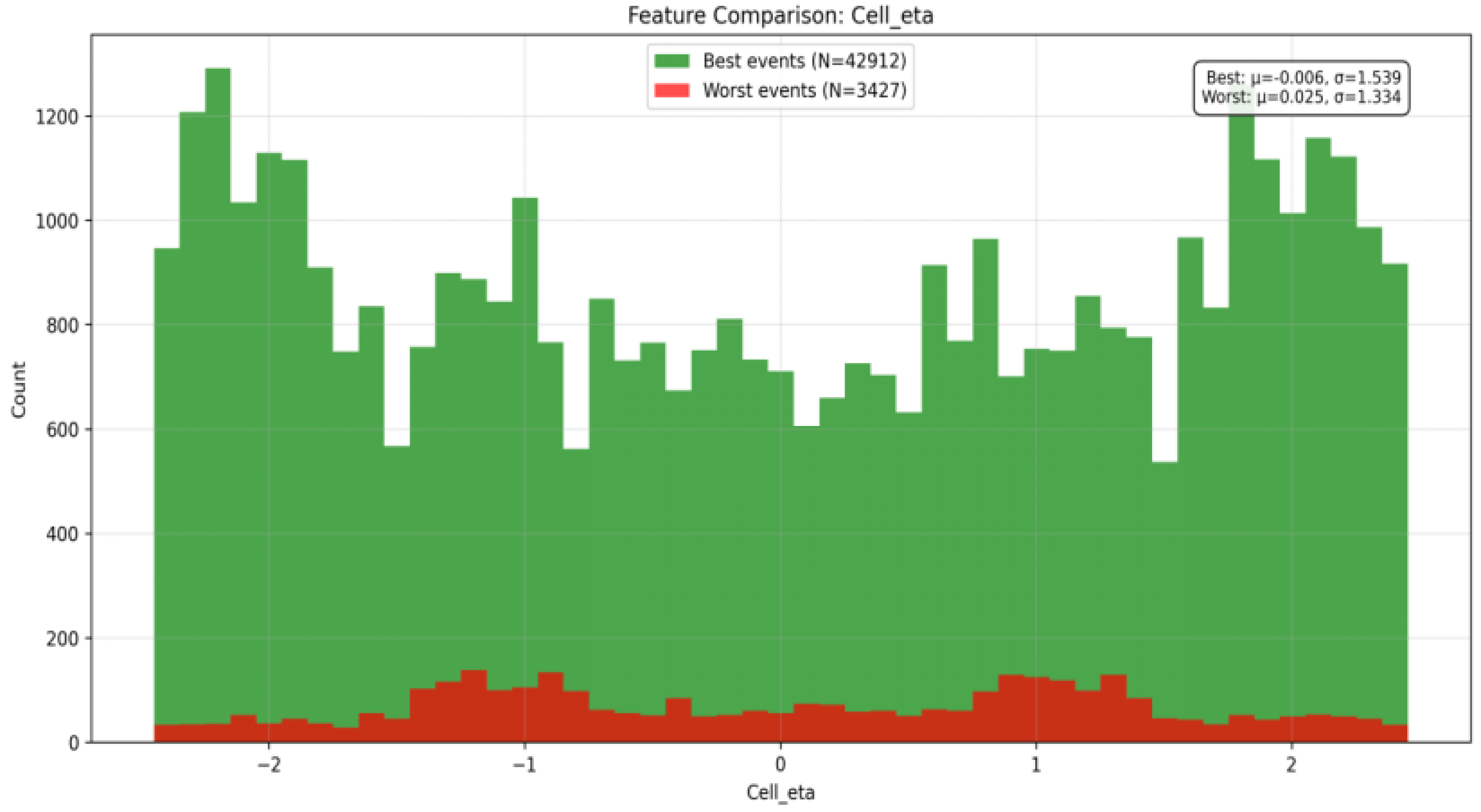


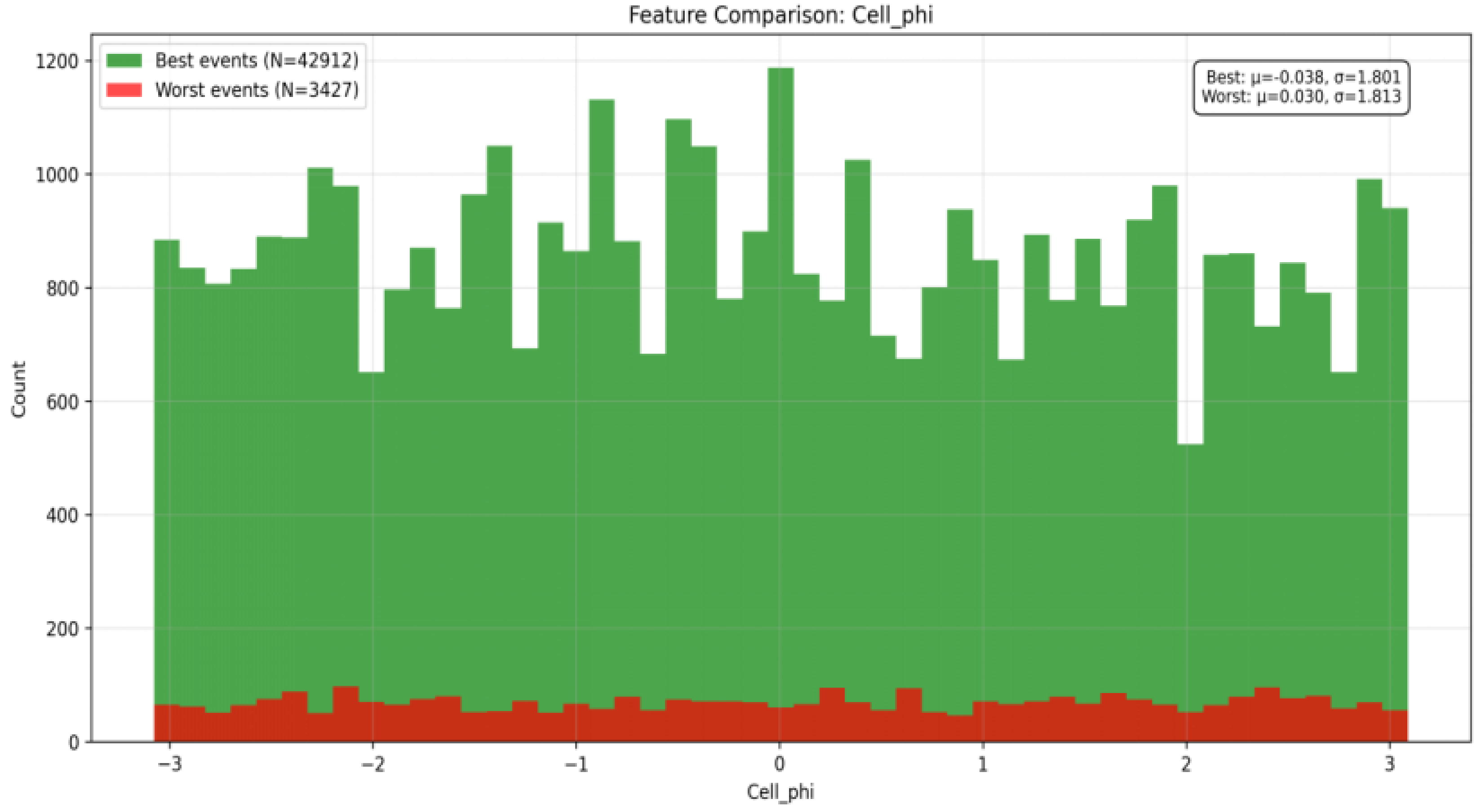


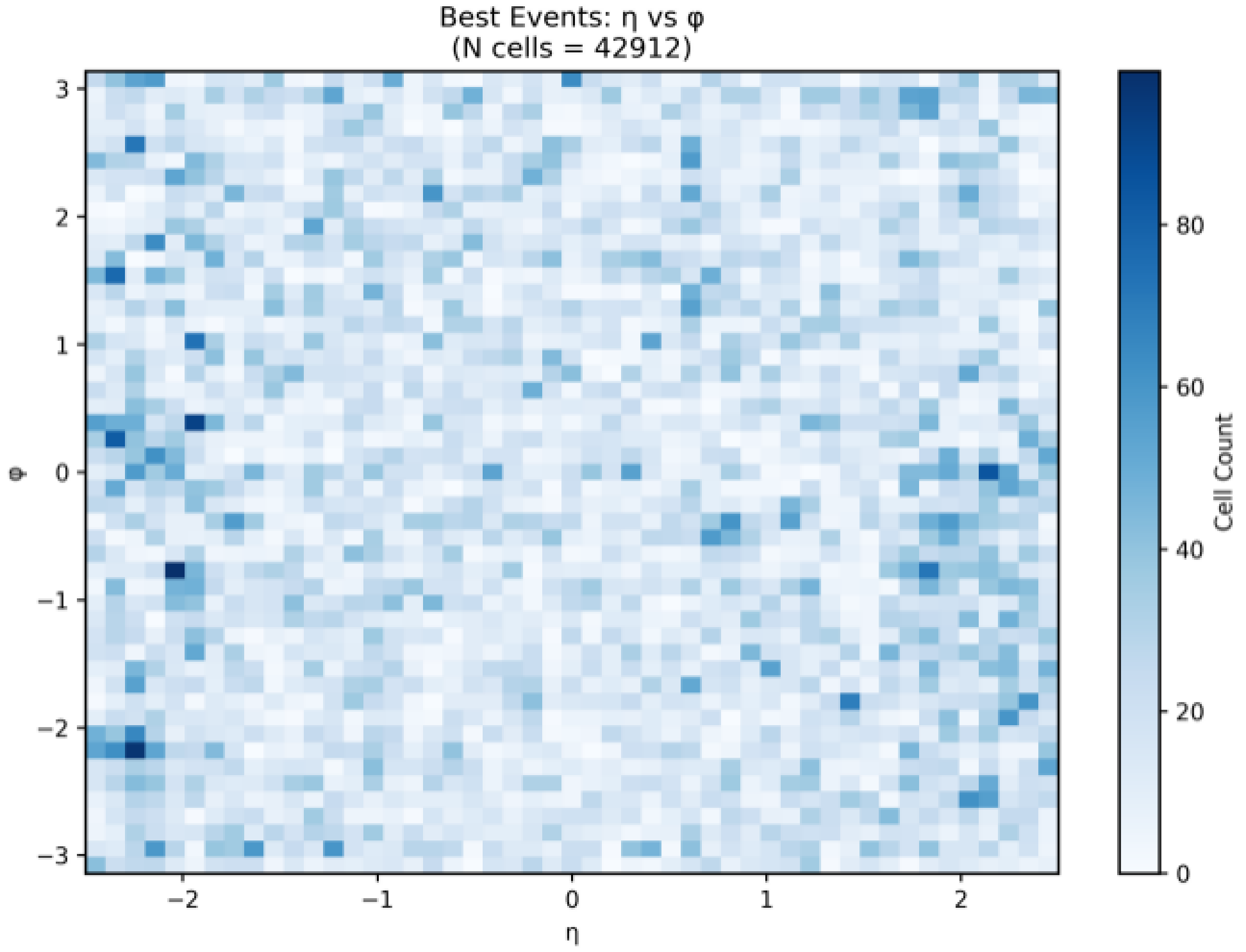
- Lower cell energy and significance and also much lower #cells to use in worst events.

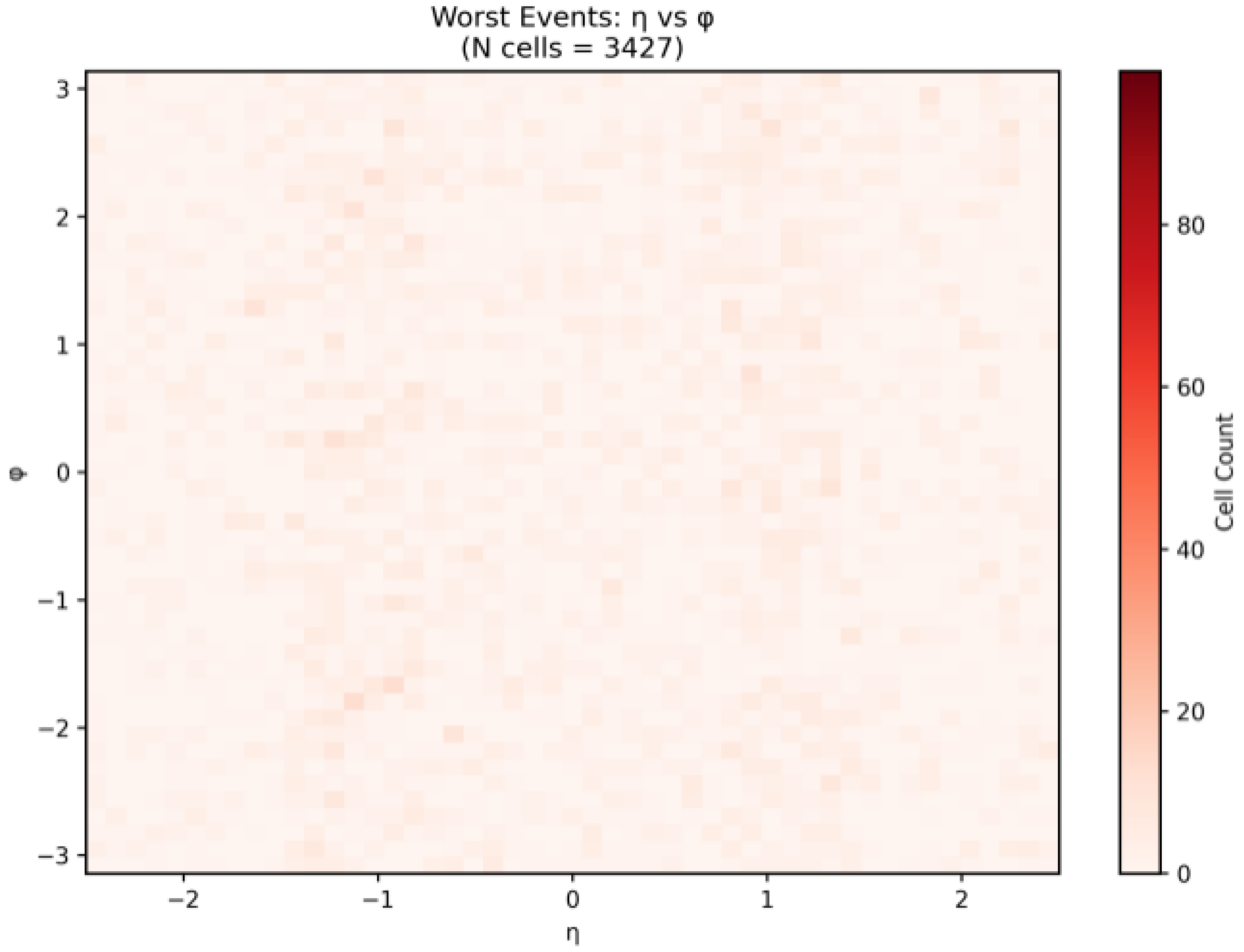
ML Regression Using Jet-Matched Cells

- Comparing 1,000 best and worst events





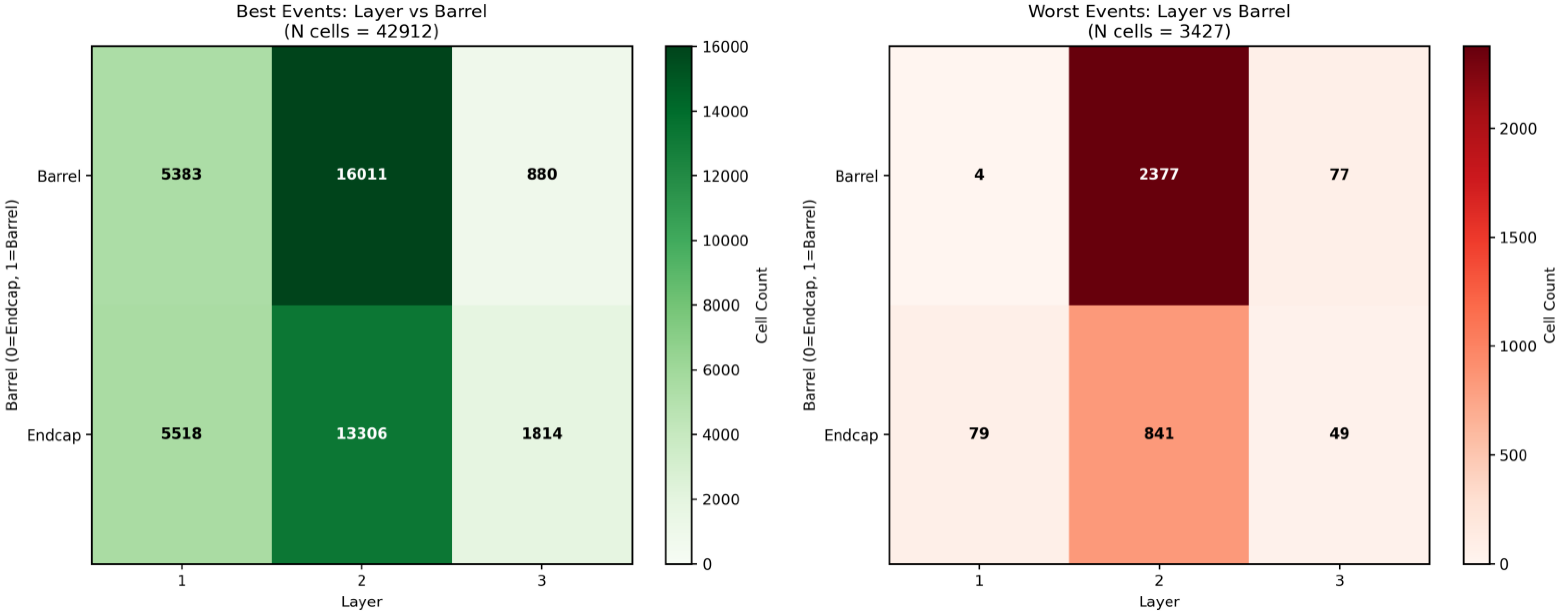




- No obvious conclusion here...

ML Regression Using Jet-Matched Cells

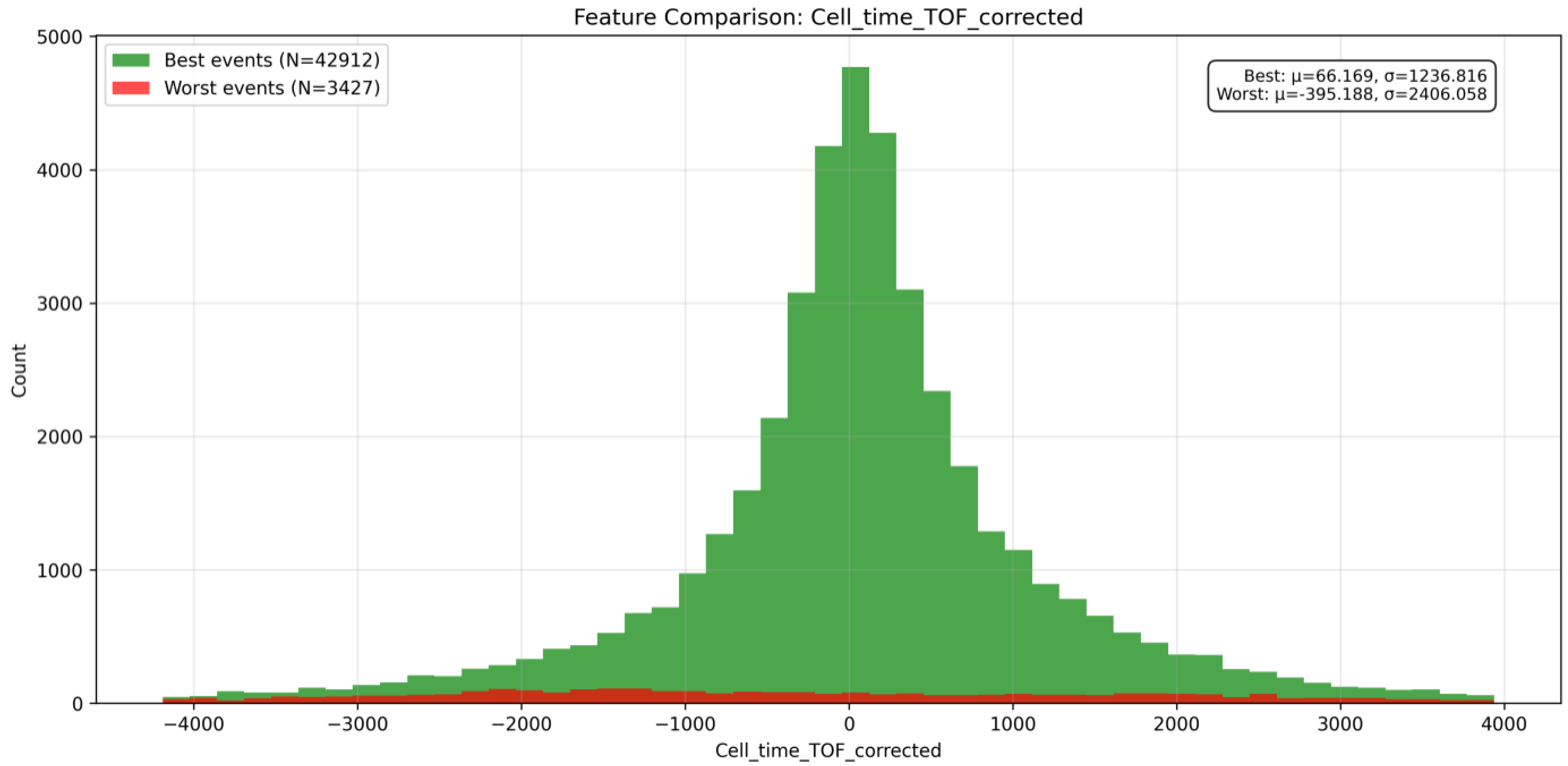
- Comparing 1,000 best and worst events



  - No obvious conclusion here...

ML Regression Using Jet-Matched Cells

- Comparing 1,000 best and worst events



  - More fraction of cells for worst events have time ~+-2000ps?