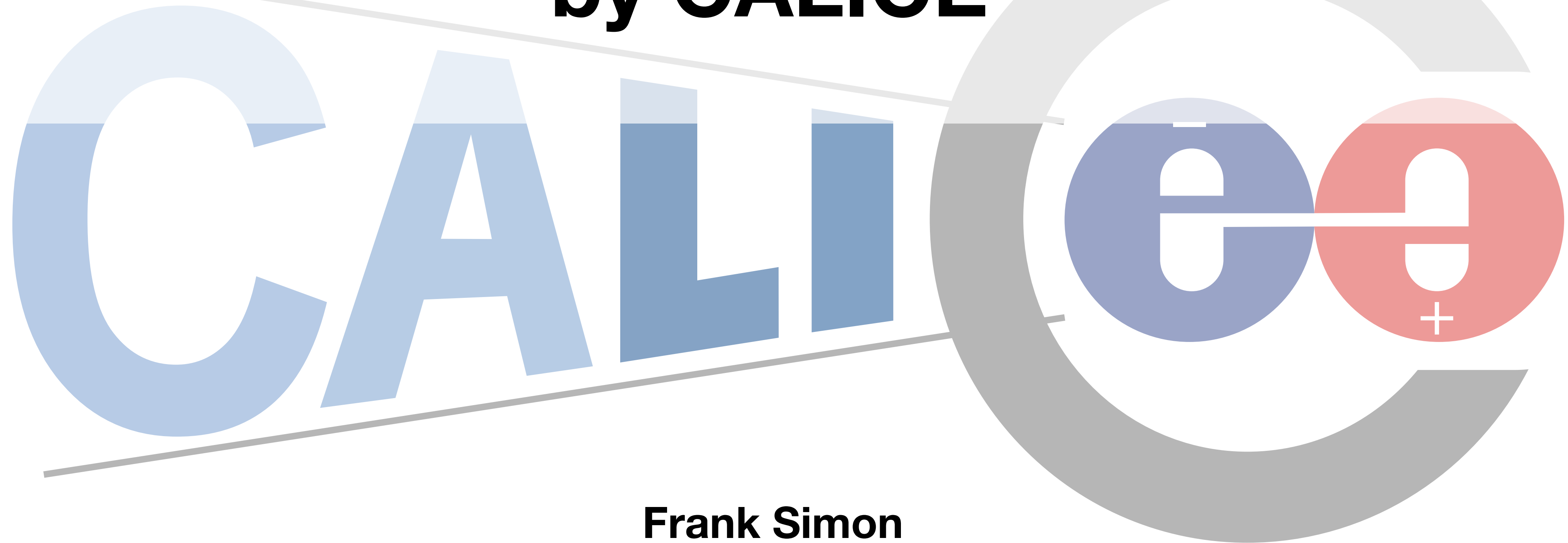


Development of Reconstruction Methods

by CALICE



Frank Simon

Max-Planck-Institute for Physics

CLIC Workshop

CERN, January 2019



Max-Planck-Institut für Physik
(Werner-Heisenberg-Institut)

Outline

- Introduction: Energy reconstruction in calorimeters
- Software compensation: Improving hadronic energy reconstruction
- Towards more complex techniques
- Outlook

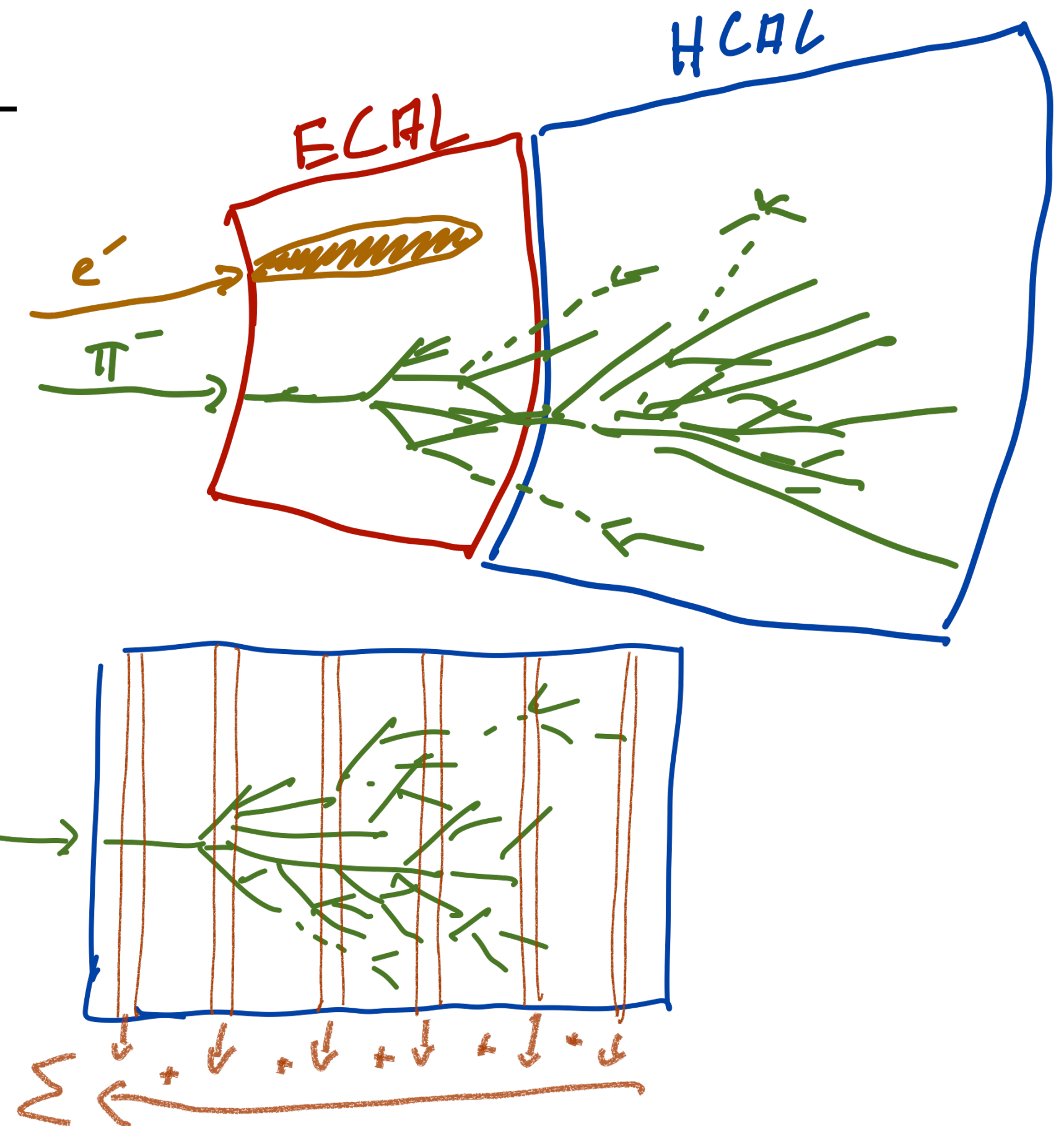
Introduction

Energy Reconstruction in Calorimeters

- Energy reconstruction is the key task of HEP calorimeter systems - for electromagnetic and hadronic particles

- The (somewhat naive) assumption: signals seen in active detector elements is a energy- and particle type - independent fraction of the particle energy:

$$E_{\text{reco}} \approx C_{\text{calib}} \times \sum E_{\text{cluster/tower/layer/hit}}$$



- In practice: Particle-type and possible energy dependent “calibration” of conversion of visible energy to particle energy a minimal requirement - *with more sophistication possible & useful*

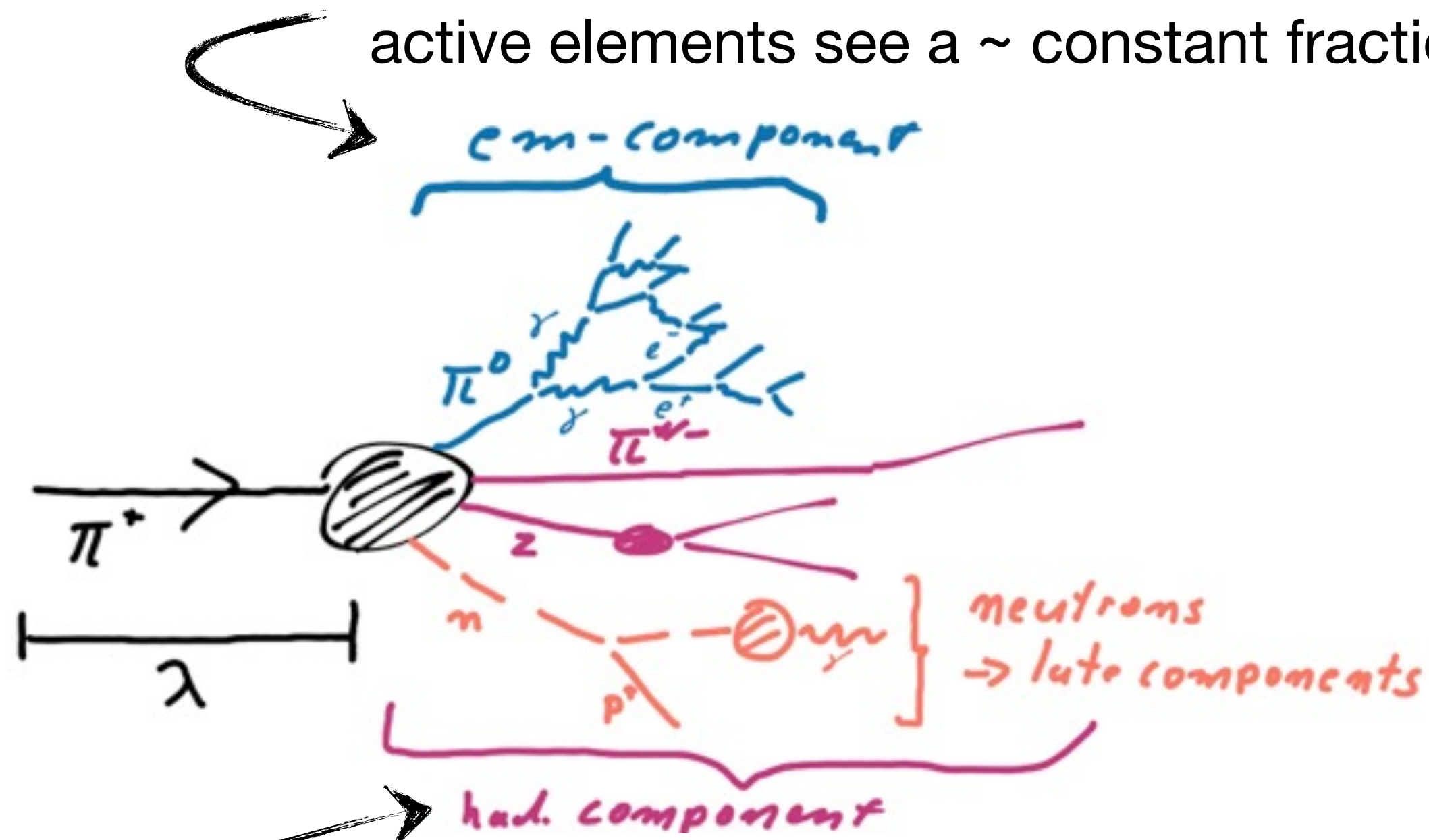
Limitations of Energy Resolution

... and Handles to improve it

- The energy resolution for hadronic showers typically is relatively poor:

prompt energy depositions only

active elements see a \sim constant fraction of shower energy



“invisible” energy due to binding energy losses
delayed & displaced energy depositions due to neutrons

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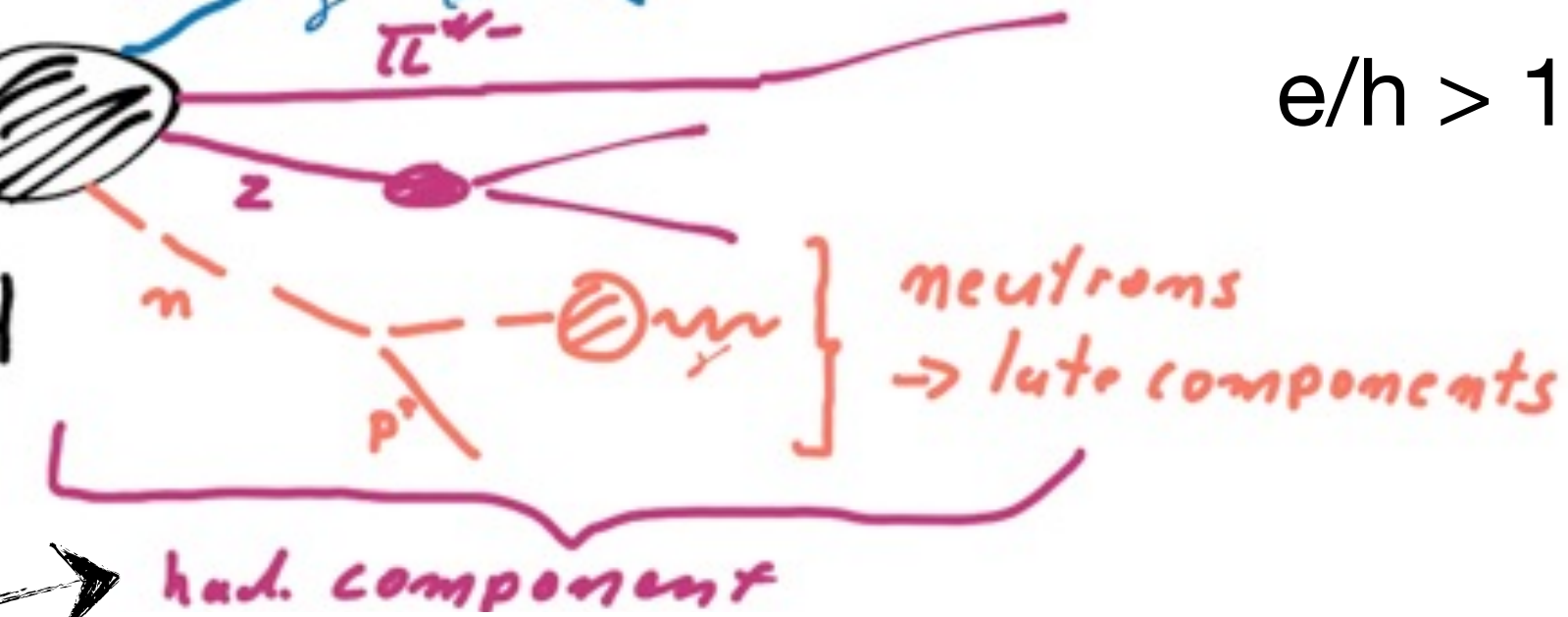
em-component



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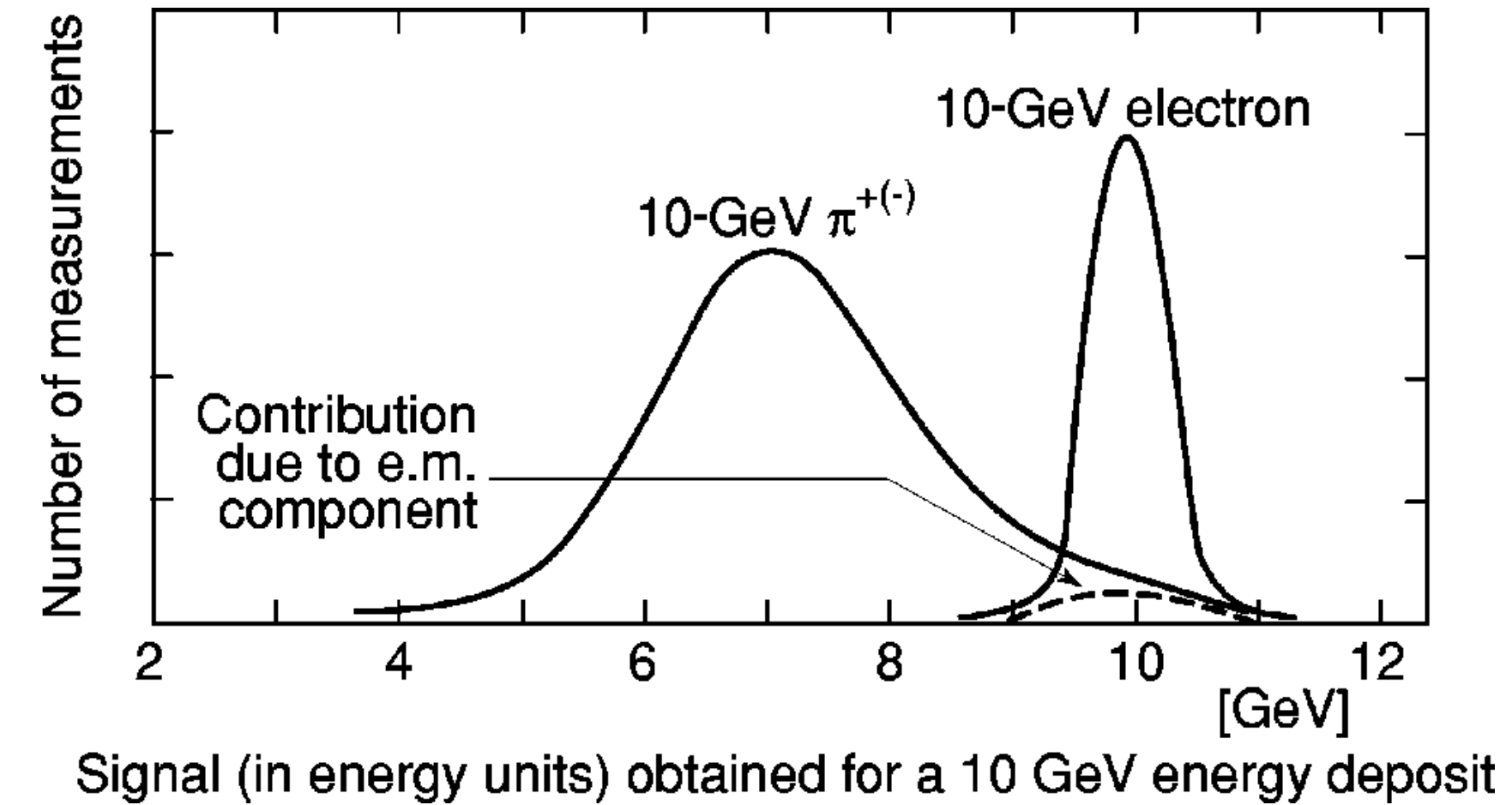
larger response for em showers than for hadronic showers:

$e/h > 1 \Rightarrow$ non-compensating



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Signal (in energy units) obtained for a 10 GeV energy deposit

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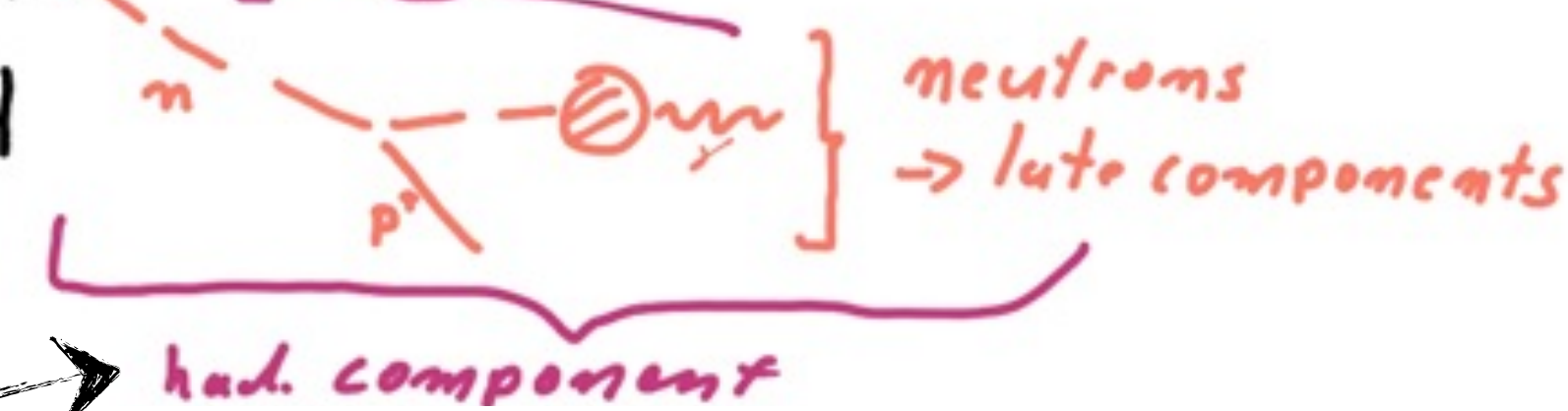
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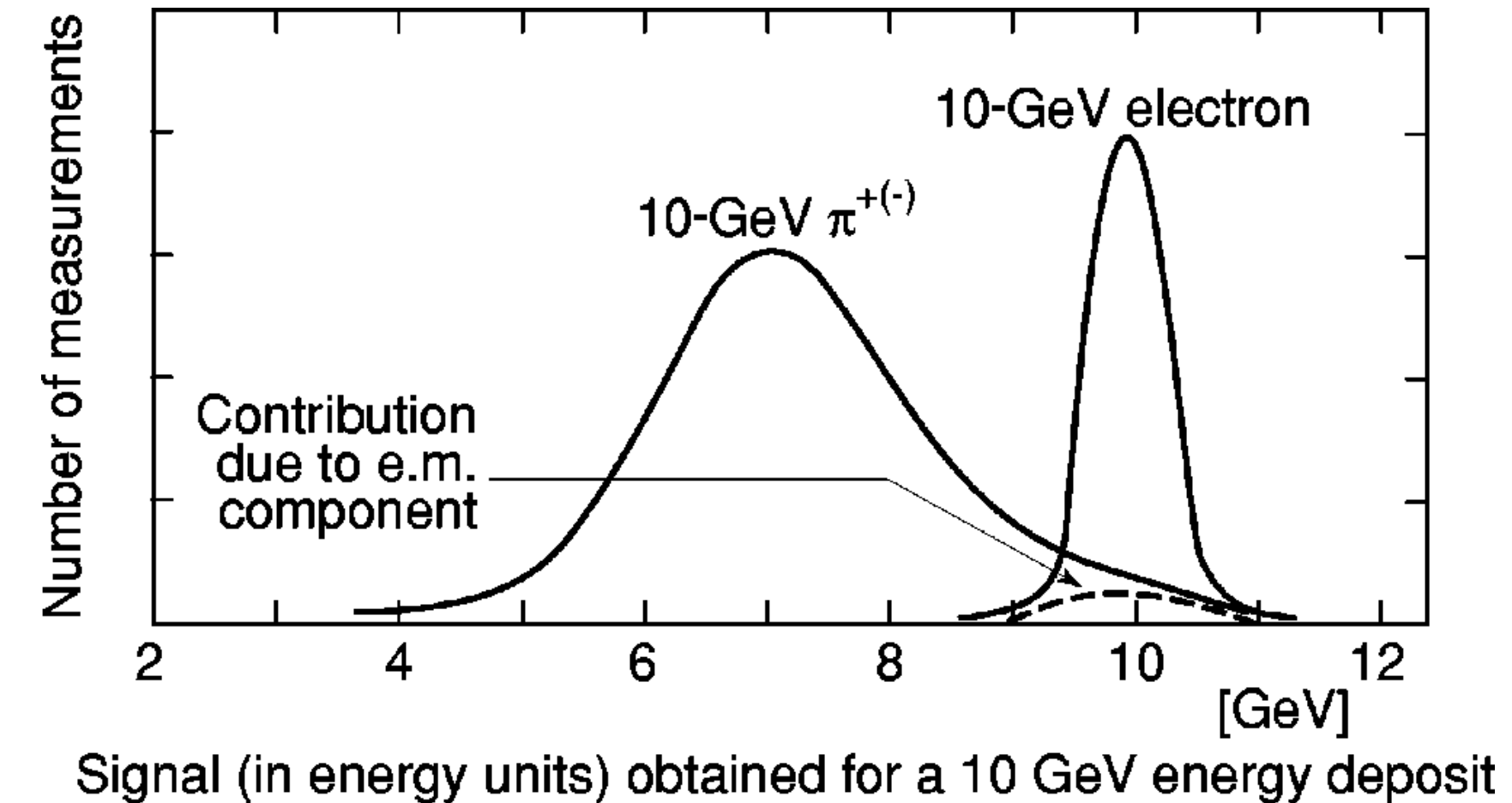
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The path to a better energy resolution:

- \Rightarrow Compensating calorimeters: Highest potential provided by *Dual Readout*
- \Rightarrow *Software compensation* / offline weighting: Shower-by-shower energy corrections, profits from high granularity

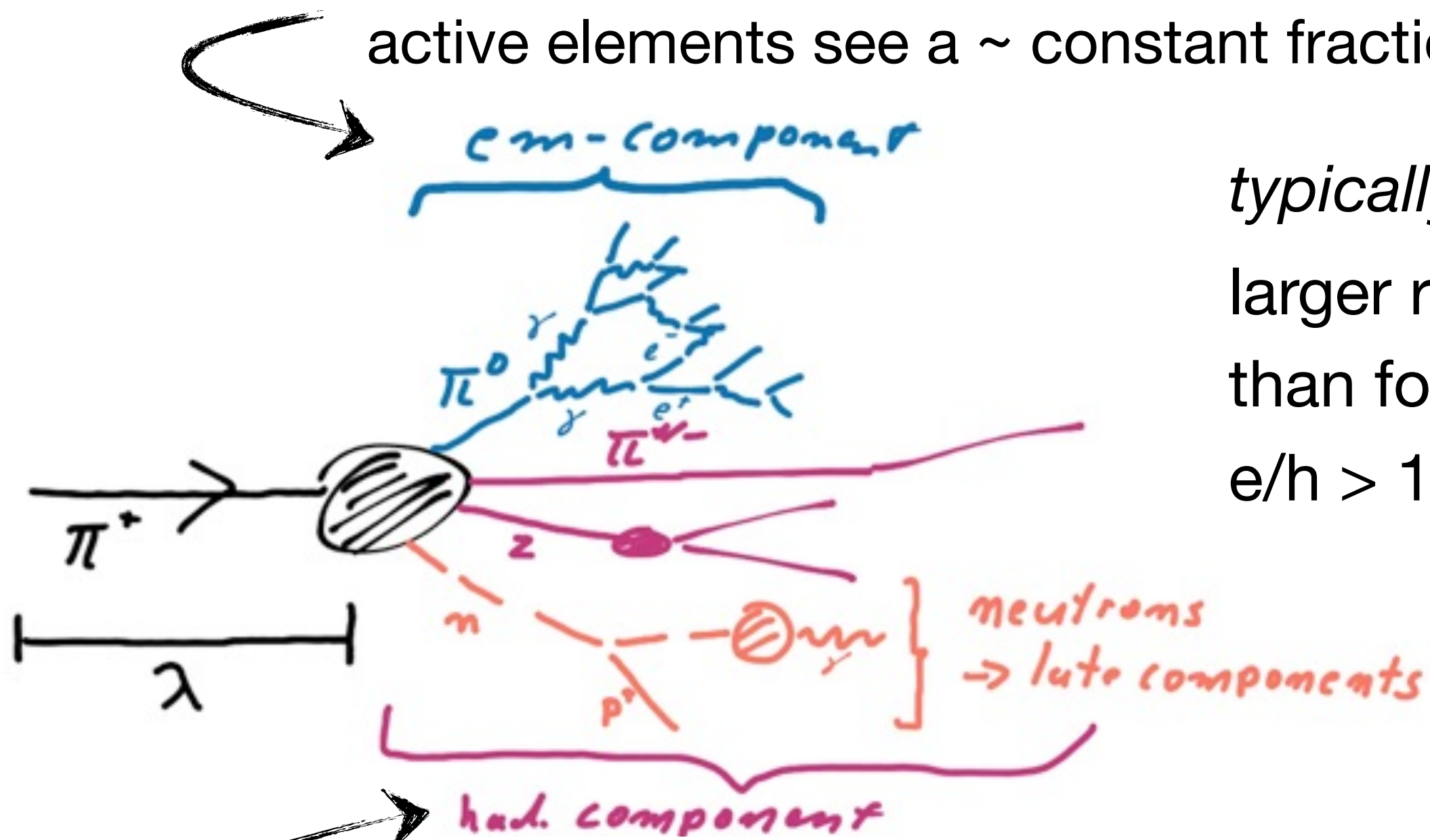
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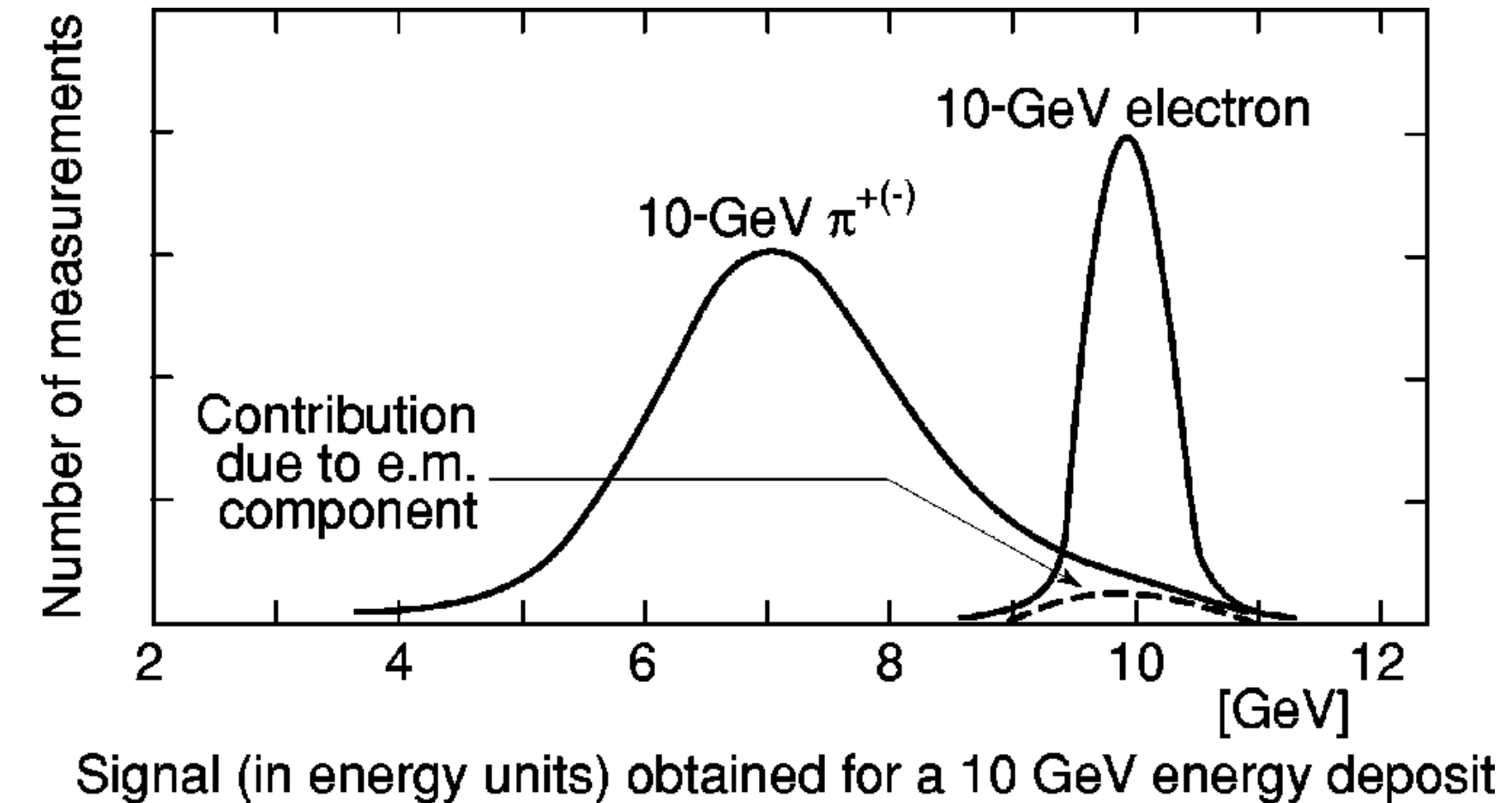
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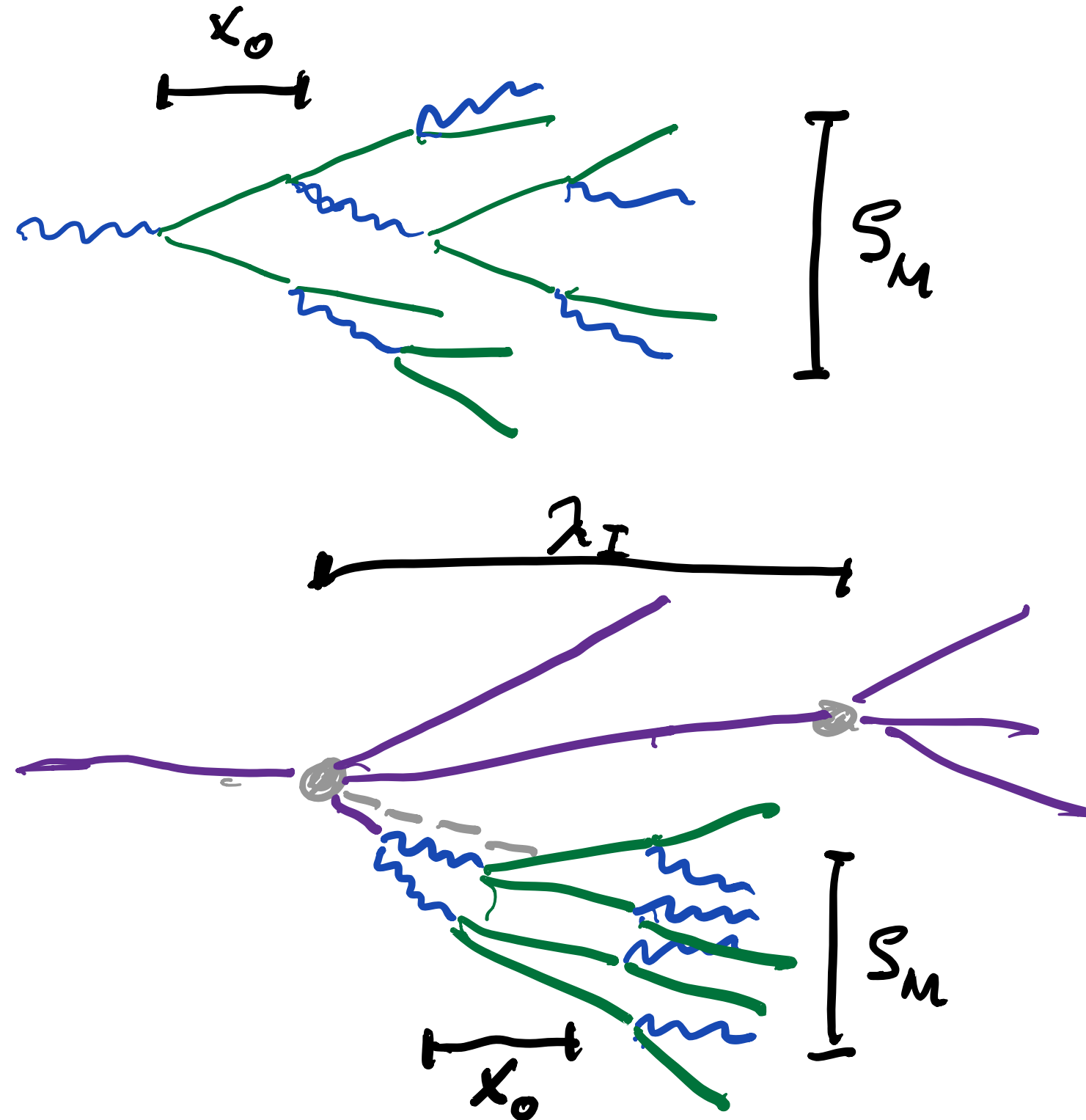
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The path to a better energy resolution:

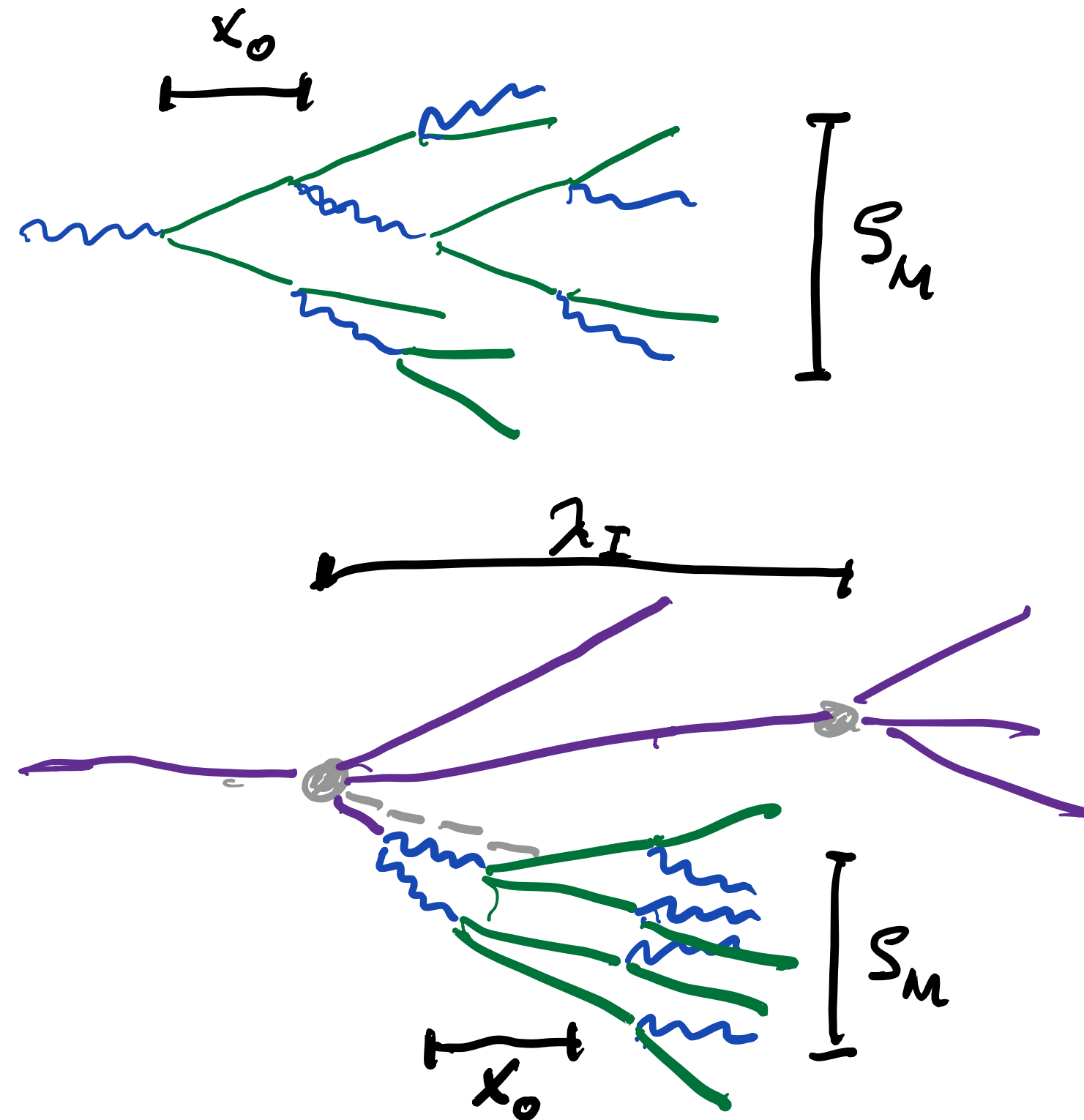
- ⇒ Compensating calorimeters: Highest potential provided by *Dual Readout*
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- Granularity motivated by shower physics:



Calorimeter voxel size given by
 $X_0, \rho_M \Rightarrow \sim (5 \text{ mm})^3 - (30 \text{ mm})^3$

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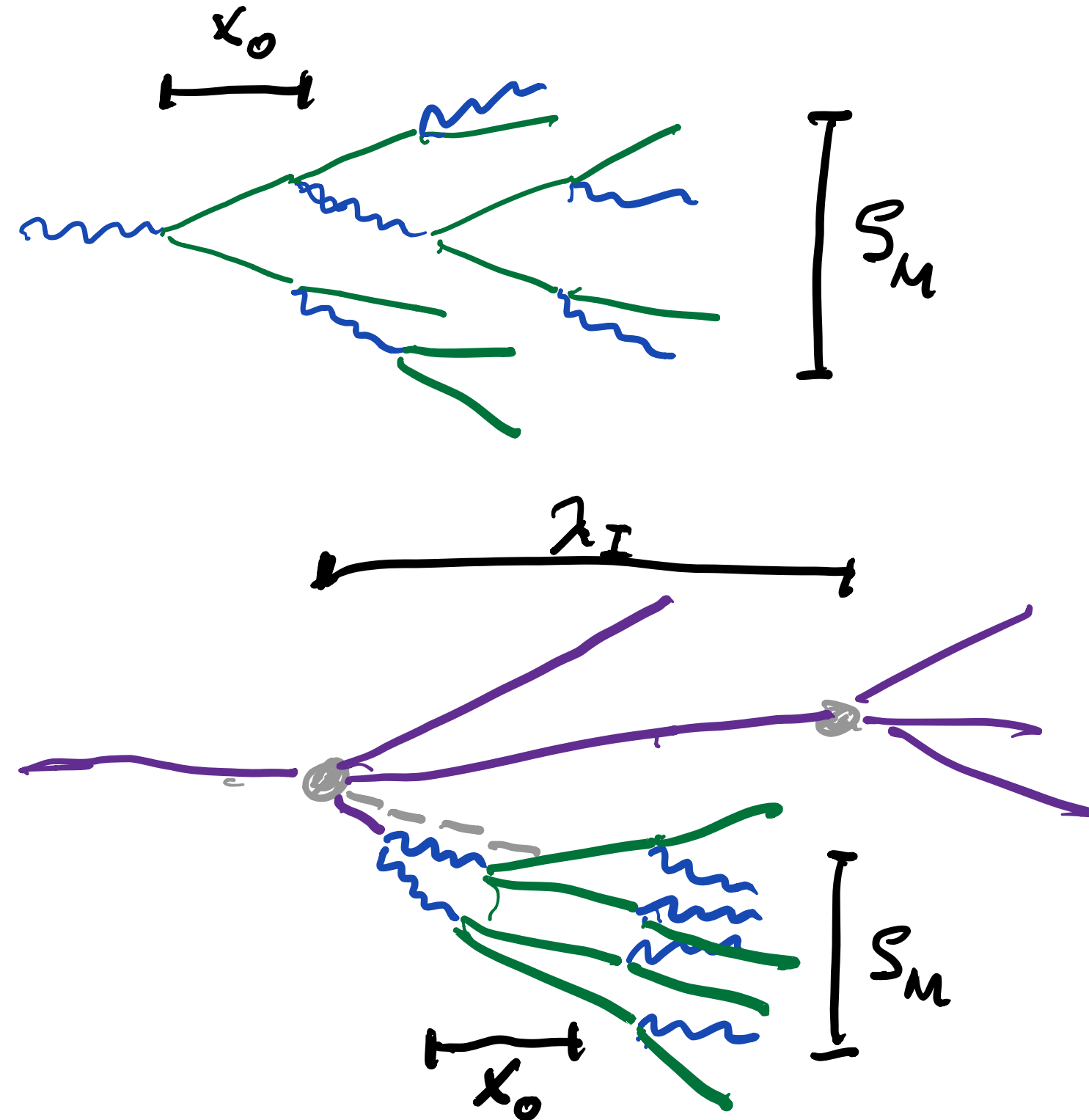


Consequences for the Calorimeter Systems:

- ⇒ $O 10^{7-8}$ cells in HCAL, 10^8 cells in ECAL for typical detector systems!
(compared to a few 10k - 100k for current LHC detectors)
- ⇒ fully integrated electronics needed
- ⇒ requires active elements that support high granularity and large channel counts
- ⇒ need technical solutions amenable to mass production & automatisisation

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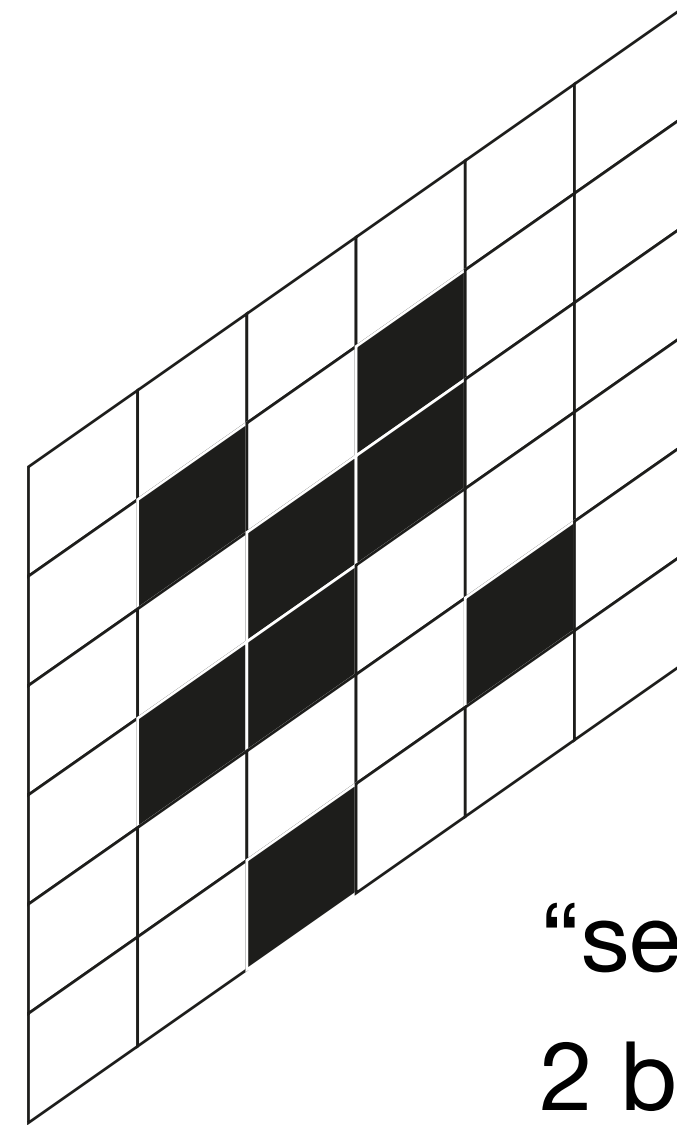
Developed and studied in CALICE

Principles, performance, technological feasibility and scalability demonstrated in the last 12 years

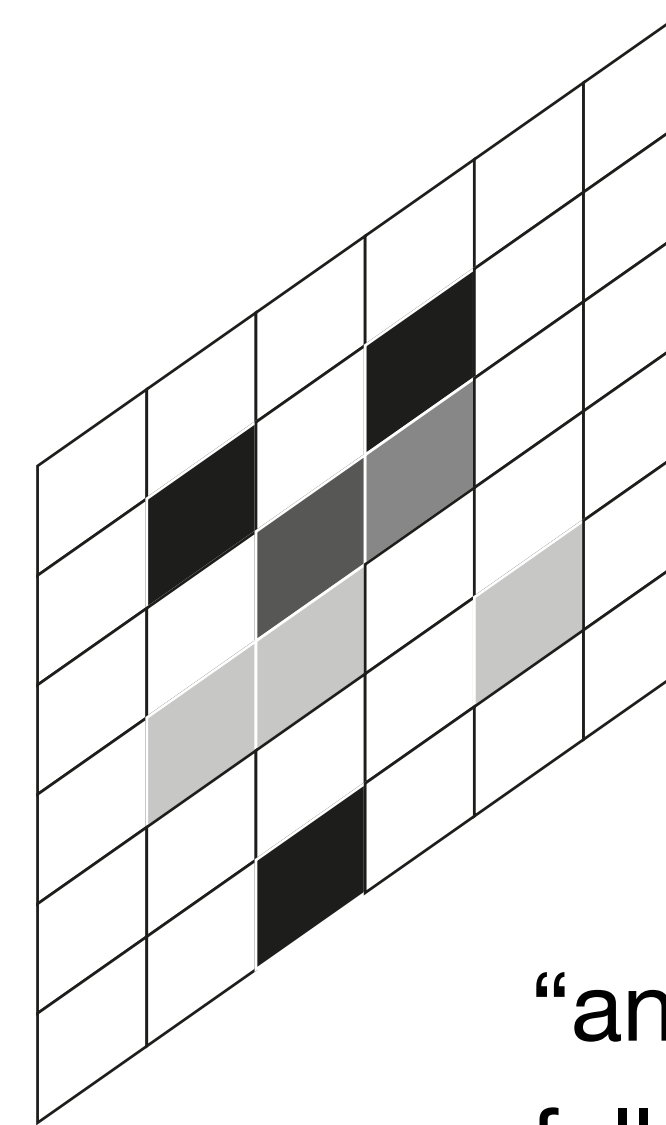
Calorimeter voxel size given by $X_0, \rho_M \Rightarrow \sim (5 \text{ mm})^3 - (30 \text{ mm})^3$

- Depending on active detector technology and granularity, different readout schemes are used:

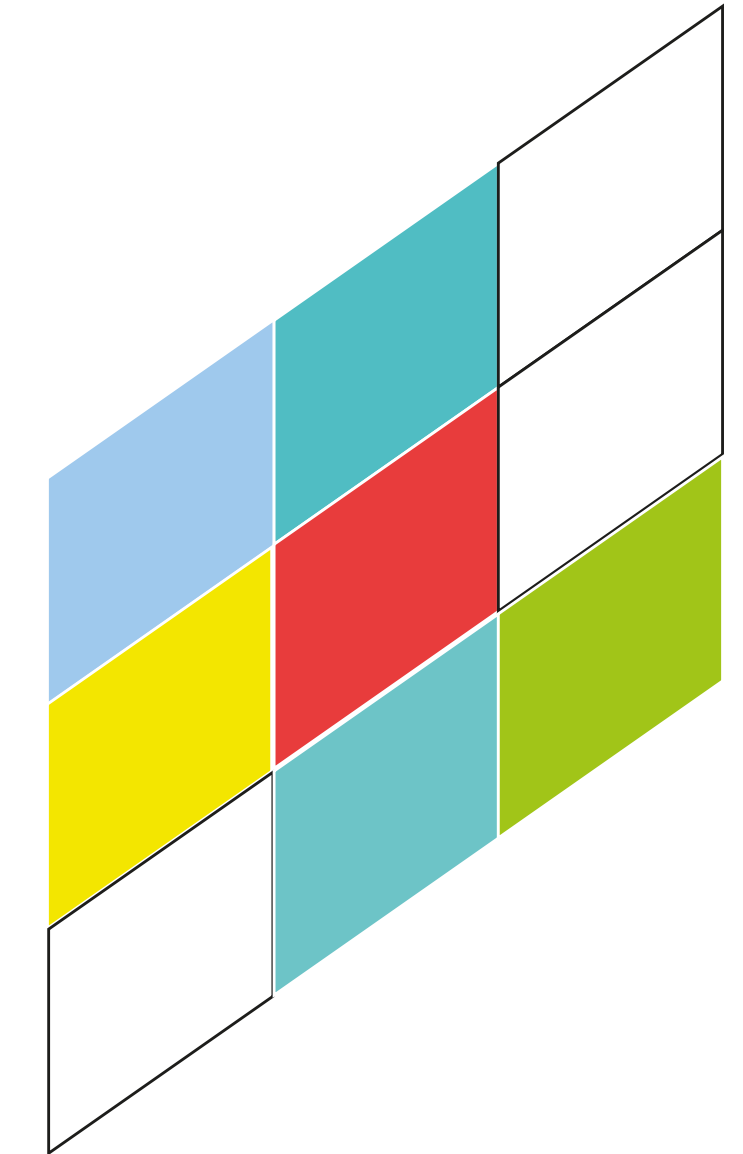
“digital”
counting hit cells



“semi-digital”
2 bits per cell:
one, a few, many particles



“analog”
full analog information
typically 14+ bits



Active elements:

gas detectors

gas detectors

Plastic scintillator elements

Silicon pixel detectors

Silicon pad detectors

Semi-Digital Energy Reconstruction in CALICE

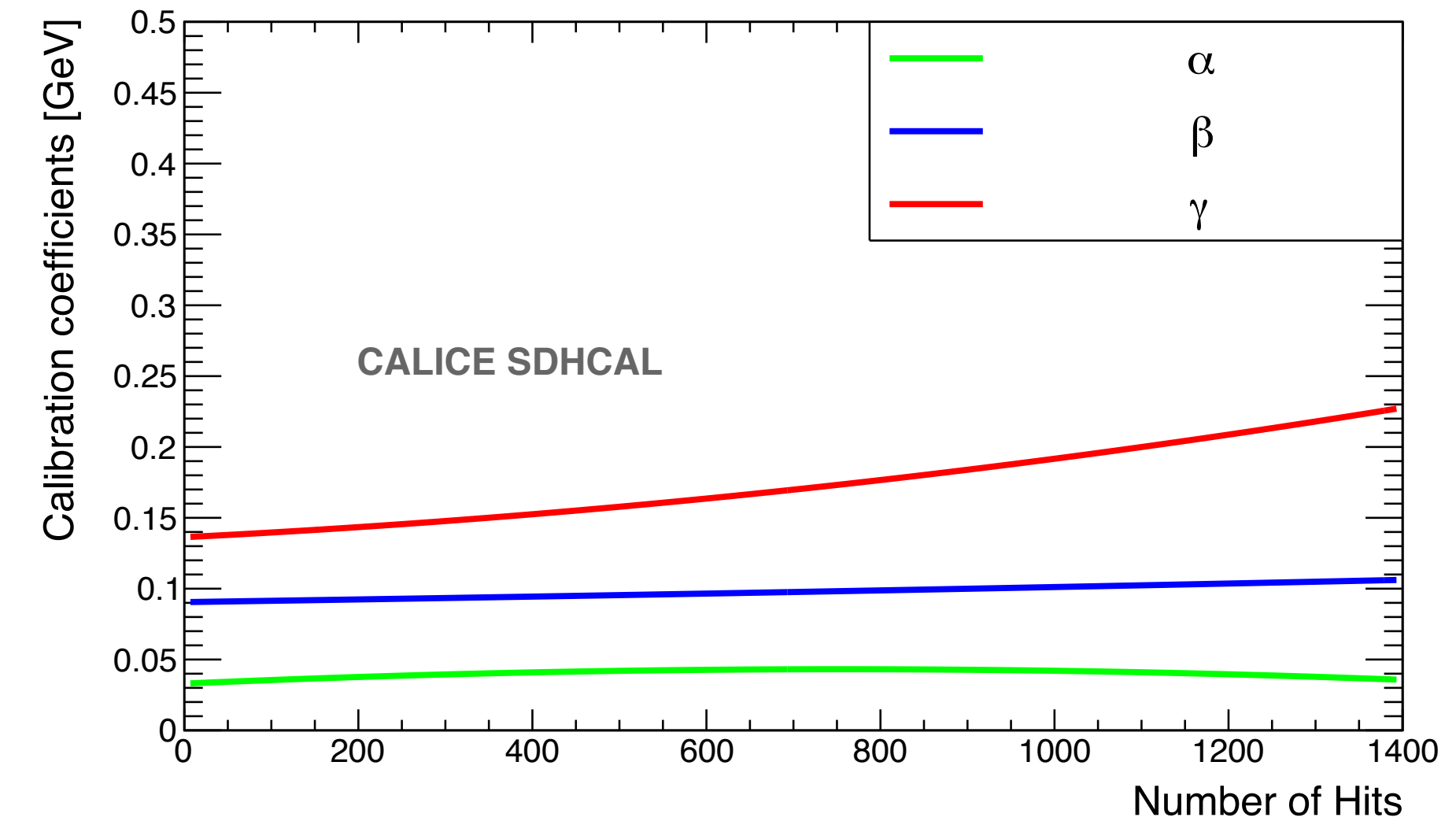
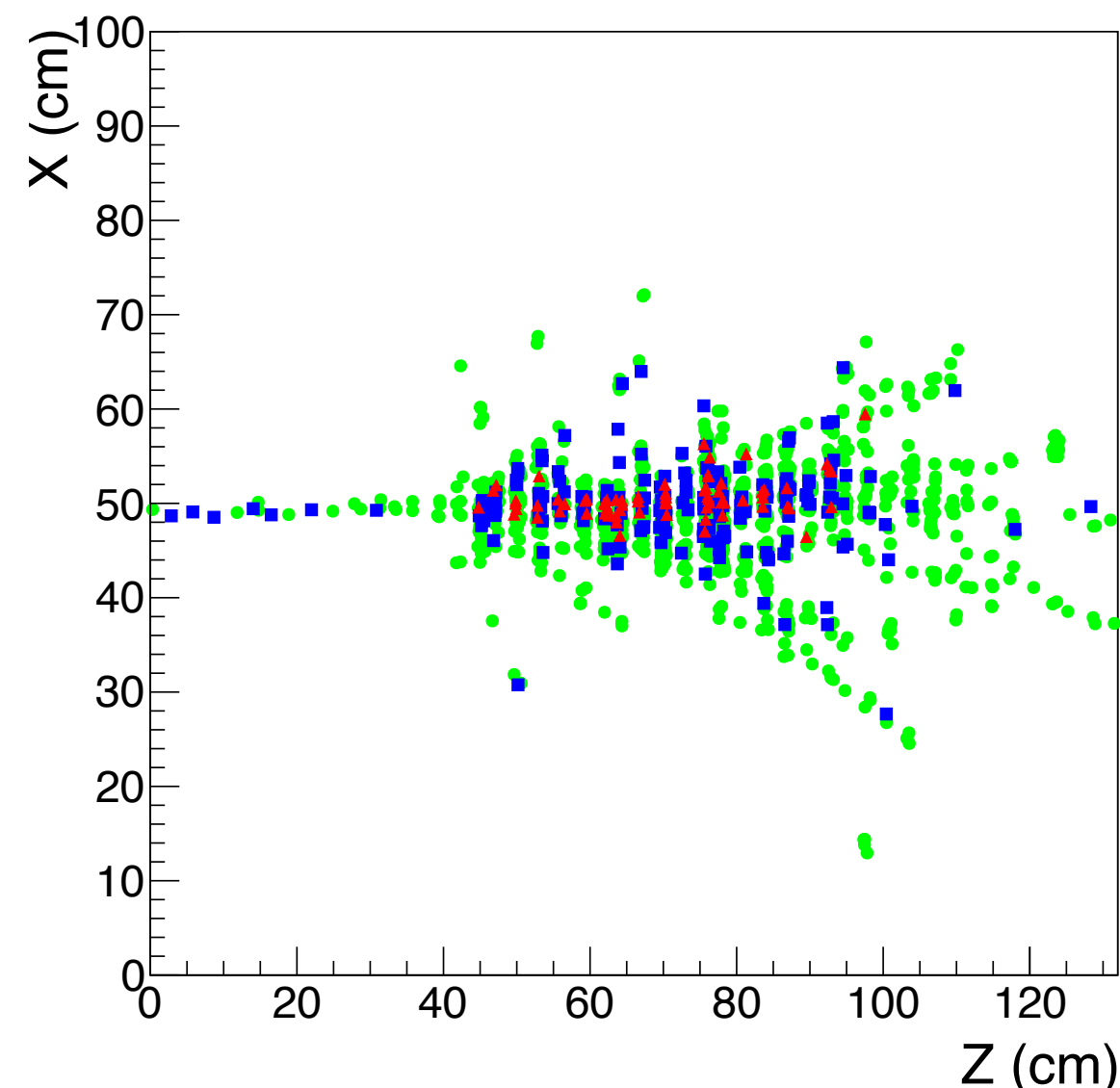
Performance of the RPC SDHCAL

- Exploitation of semi-digital readout requires energy (hit) - dependent calibration factors for each of the three thresholds

$$E_{\text{reco}} = \alpha N_1 + \beta N_2 + \gamma N_3$$

parameters determined by
optimising energy resolution

$$\chi^2 = \sum_{i=1}^N \frac{(E_{\text{beam}}^i - E_{\text{reco}}^i)^2}{\sigma_i^2}$$



Semi-Digital Energy Reconstruction in CALICE

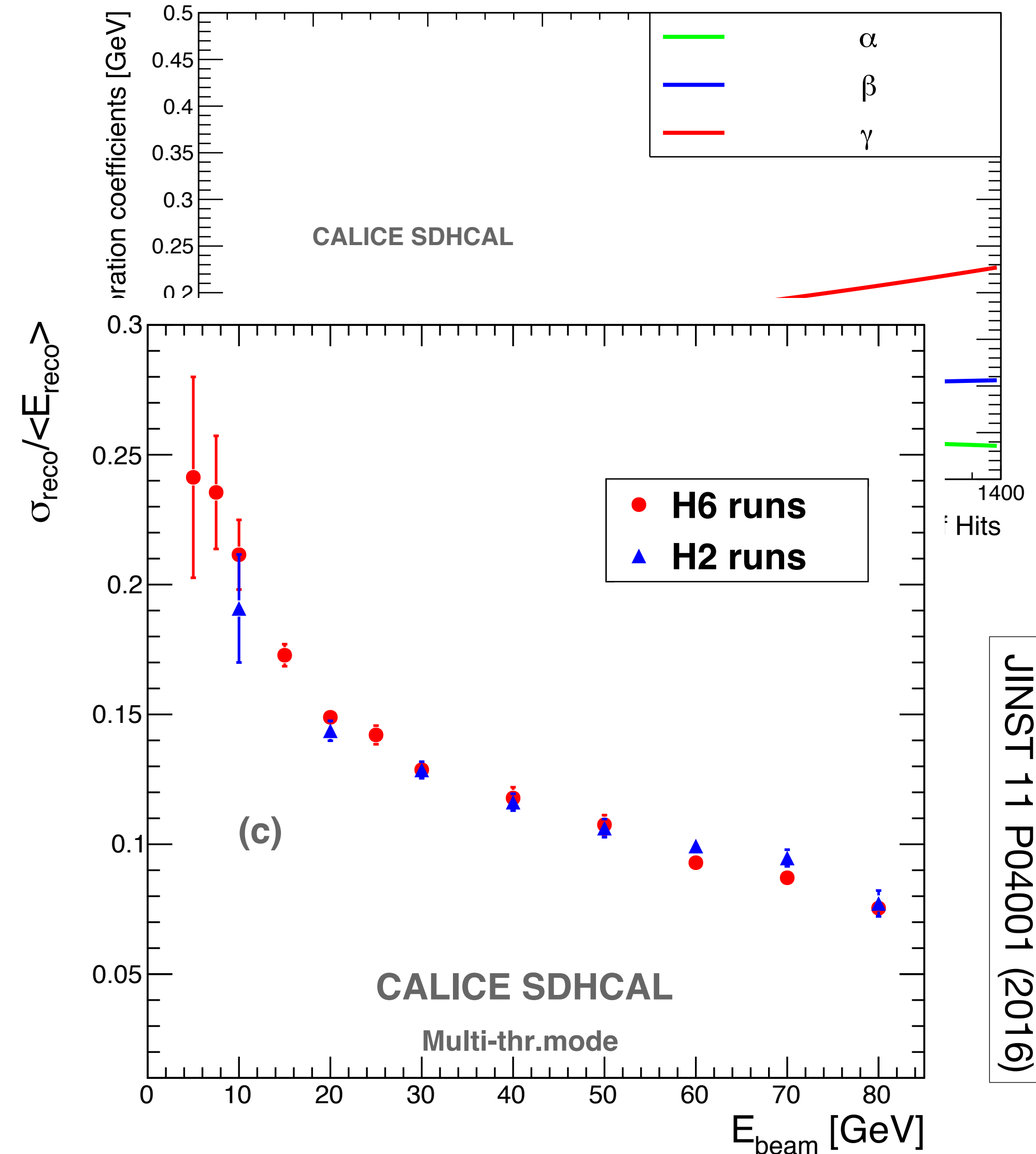
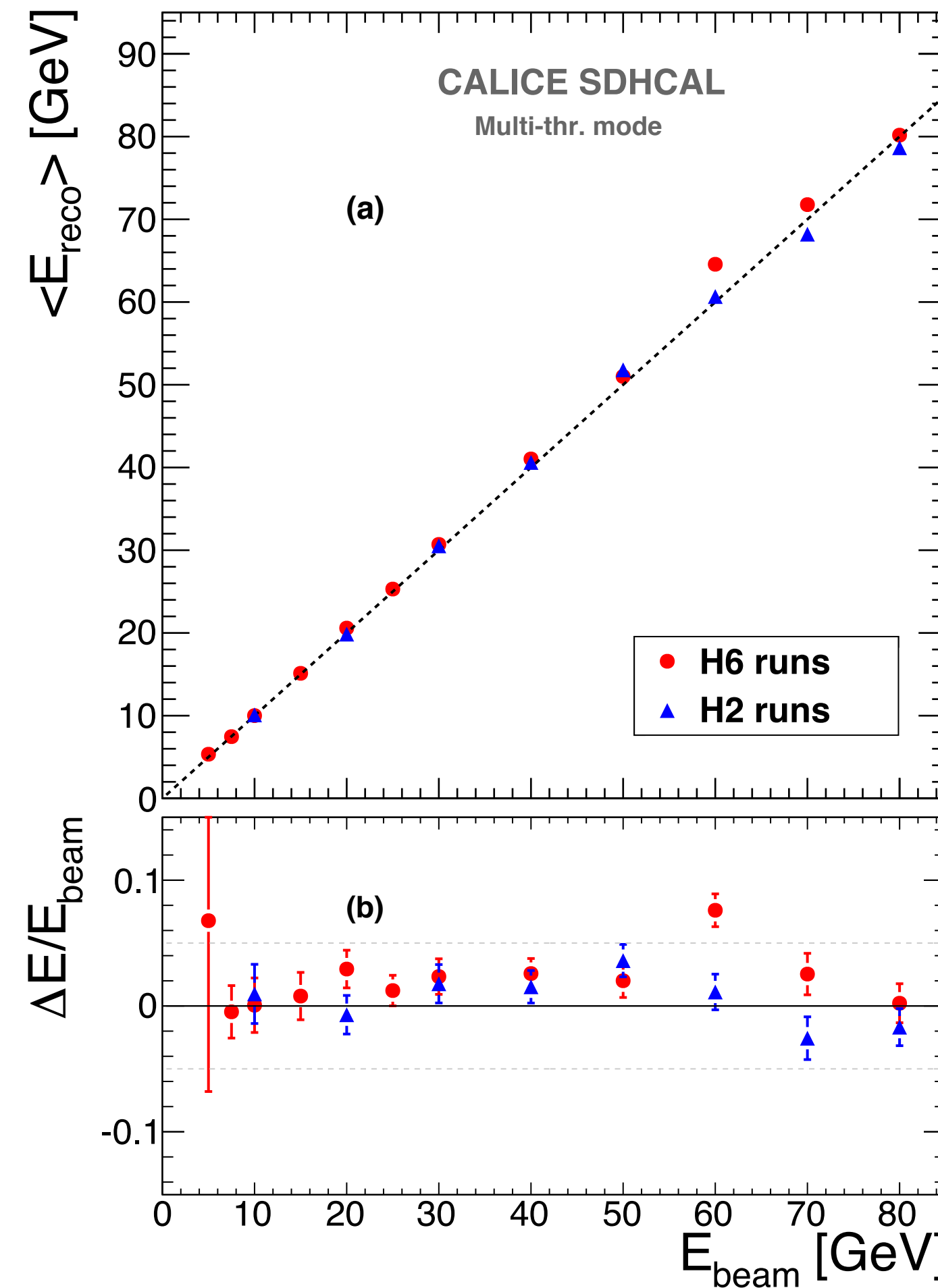
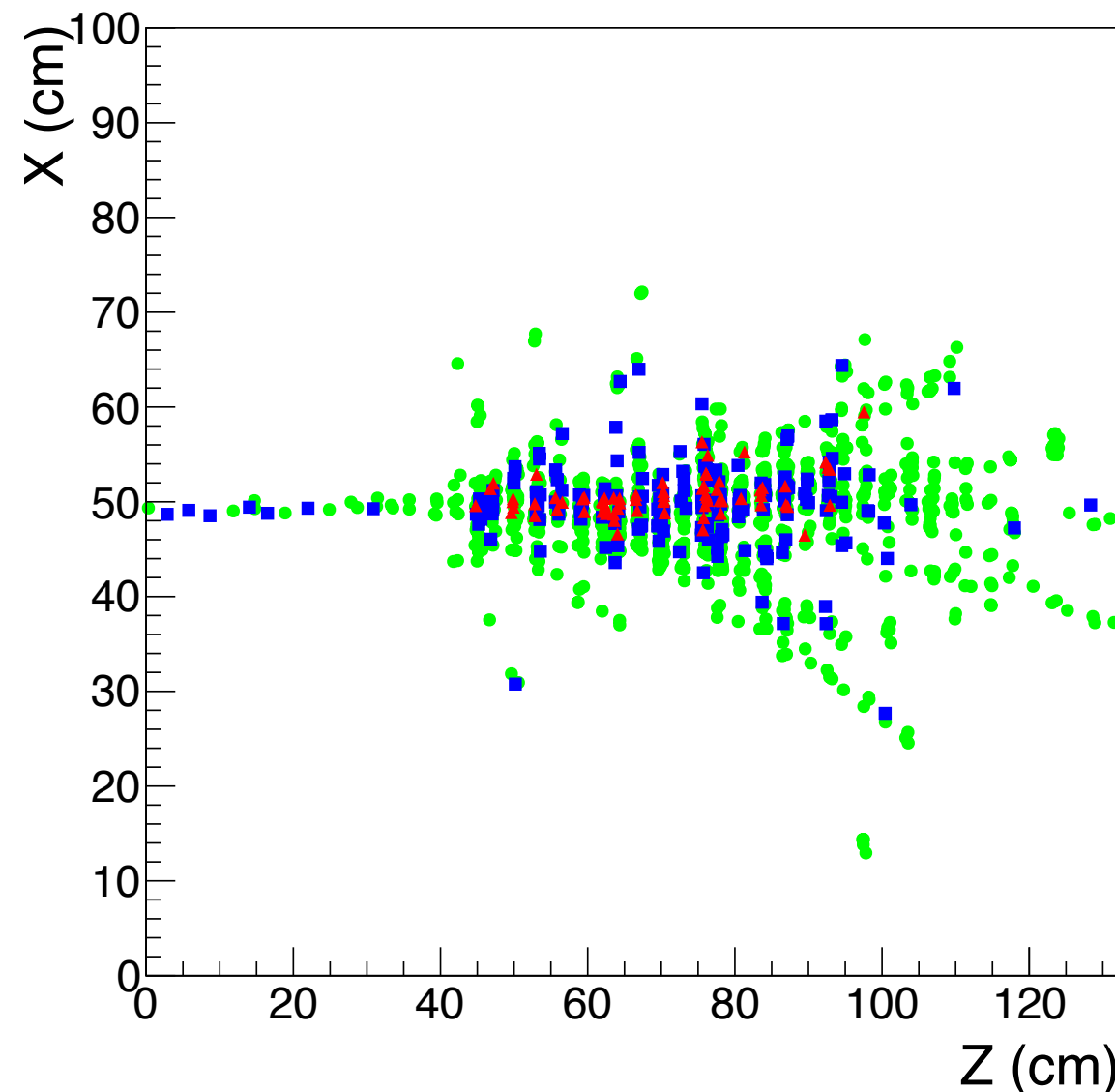
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Software Compensation in CALICE

Different Techniques to improve the Energy Resolution with Analog Readout



- Full analog energy information in each cell of the AHCAL provides different handles to implement energy reconstruction techniques. Two main strategies for software compensation studied:

JINST 7 P09017 (2012)

Software Compensation in CALICE

Different Techniques to improve the Energy Resolution with Analog Readout

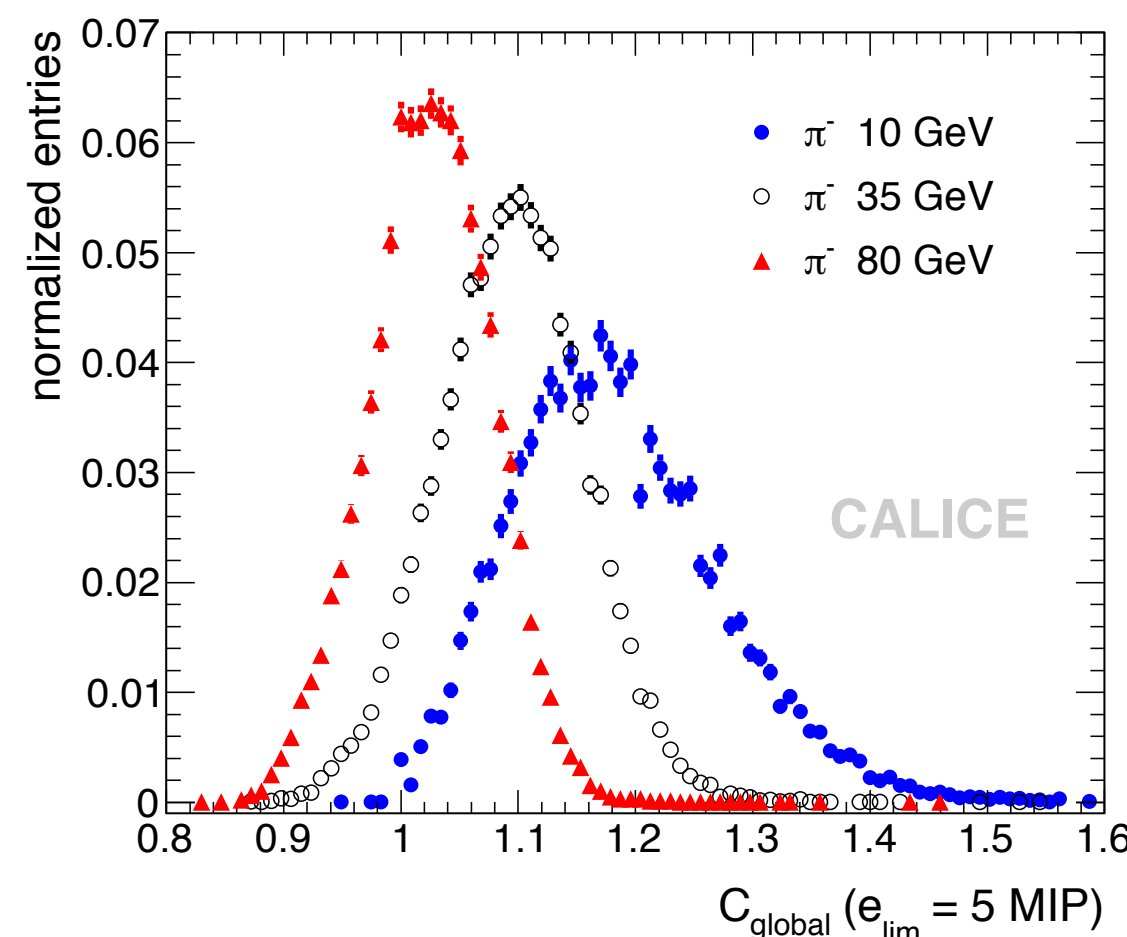
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Global

- Event-by-event correction of energy sum with a shower-dependent *global* factor

correction based on c_{global} , given by

$$c_{global} = \frac{N_{hits}(E_{hit} < e_{lim})}{N_{hits}(E_{hit} < \langle E_{hit} \rangle)}$$



with an additional energy dependence of the correction factor

$$e_{lim} = 5 \text{ MIP}$$

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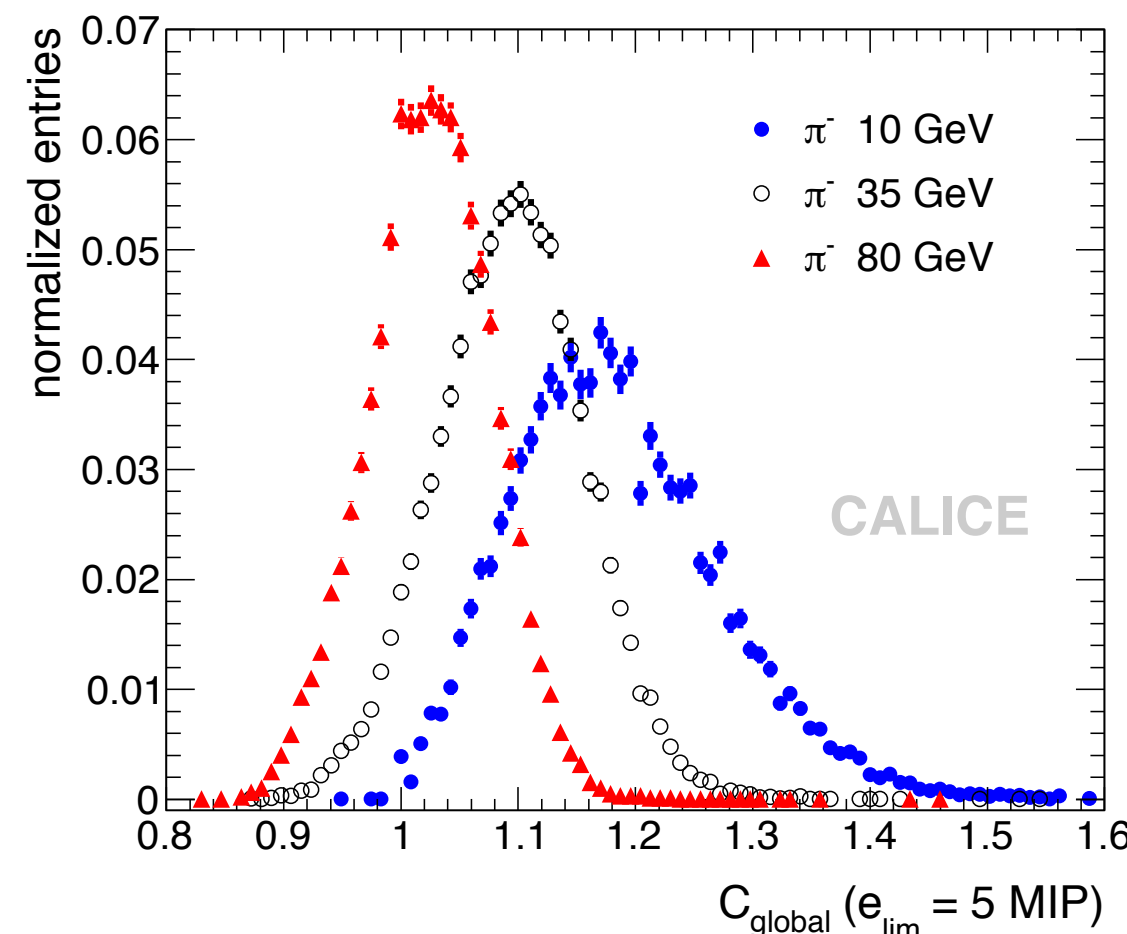
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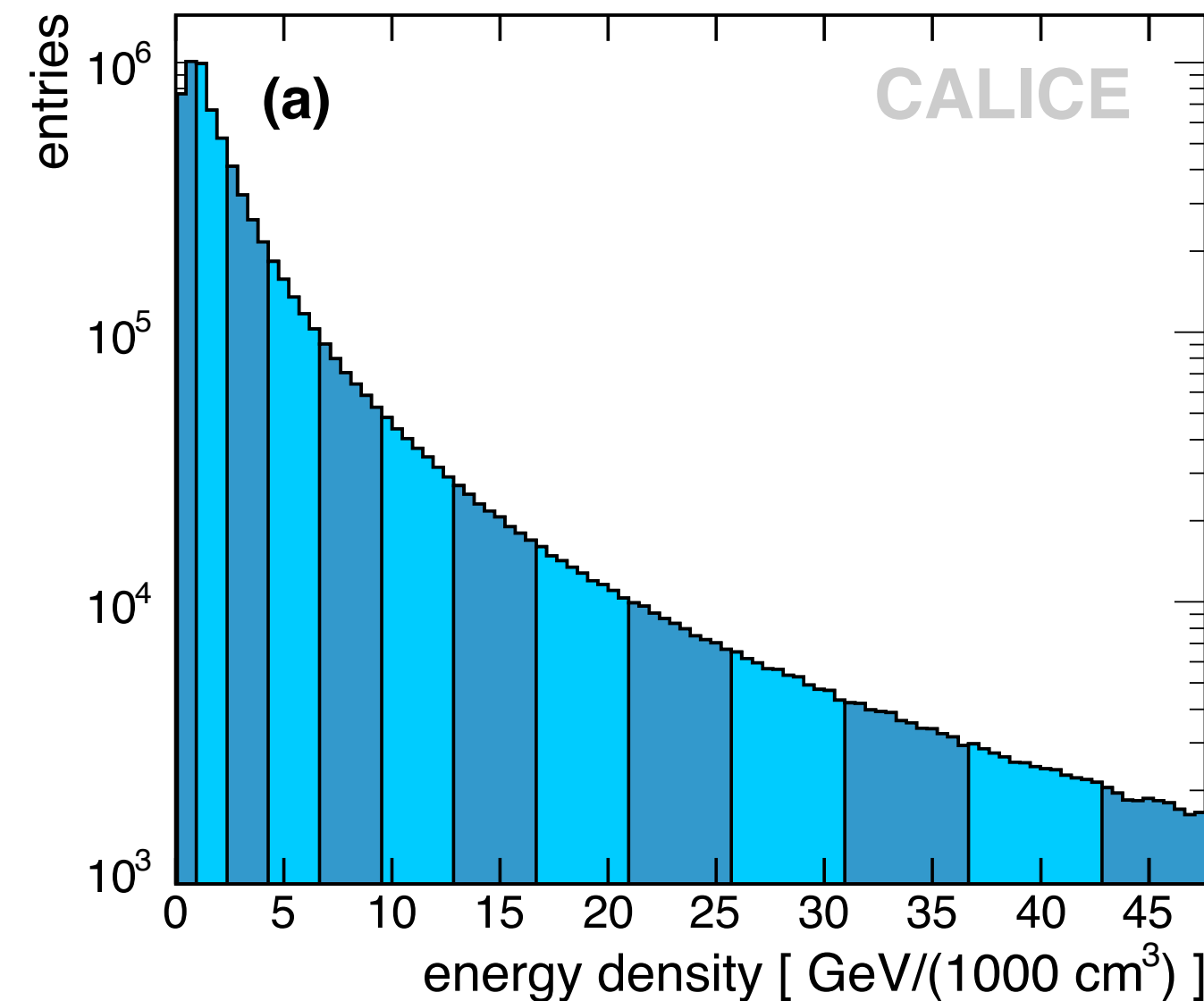
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Local

- Cell-by-cell correction of energy with energy-density dependent *weights*



additional parametrisation for energy dependence of the weights, separate weights for each energy-density bin

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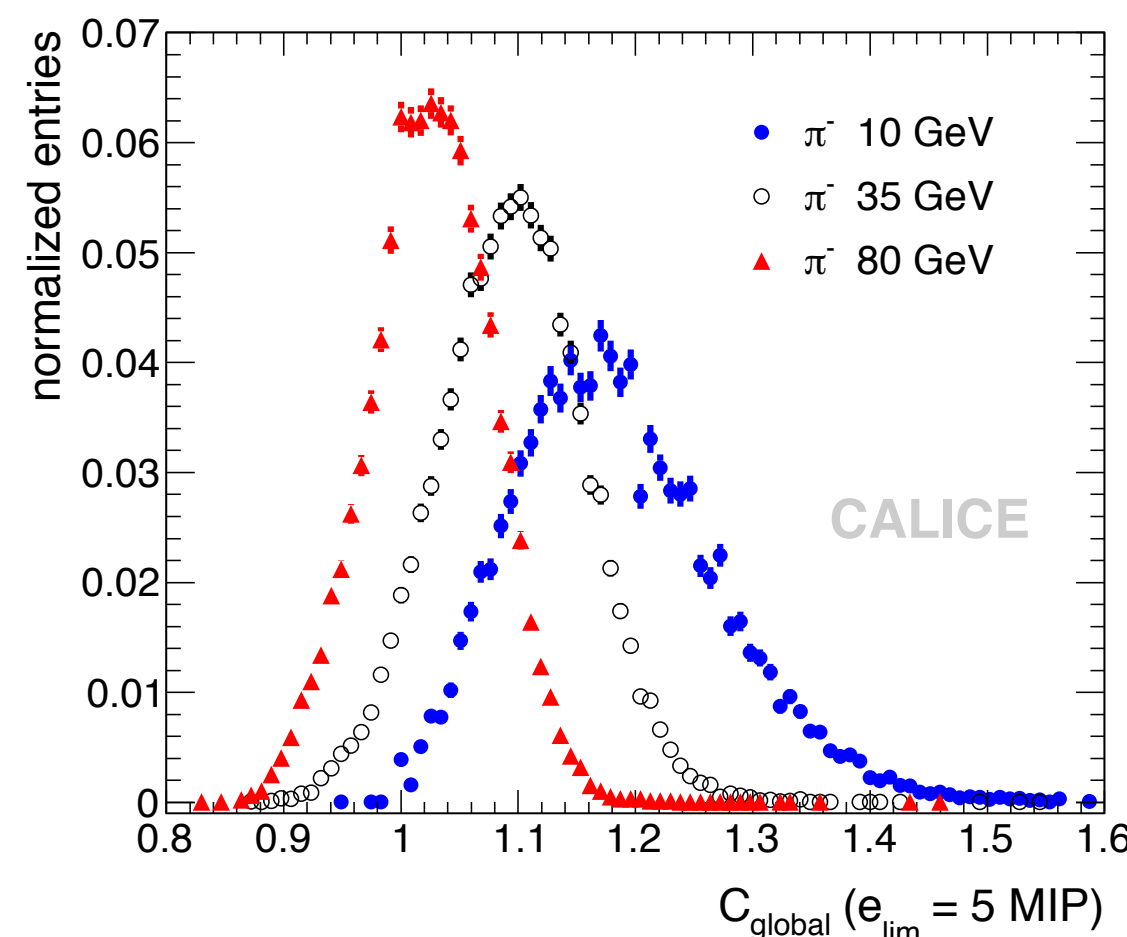
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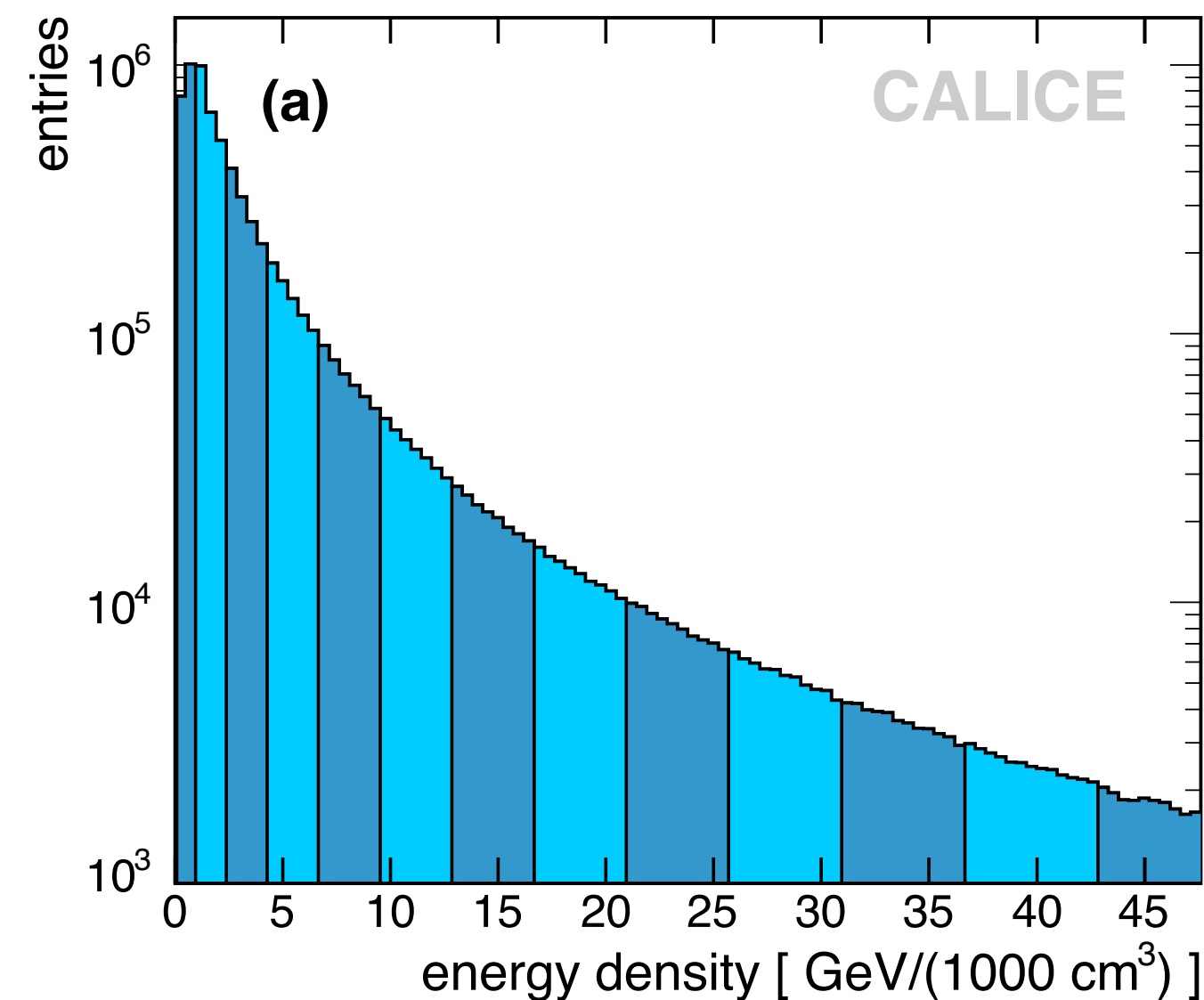
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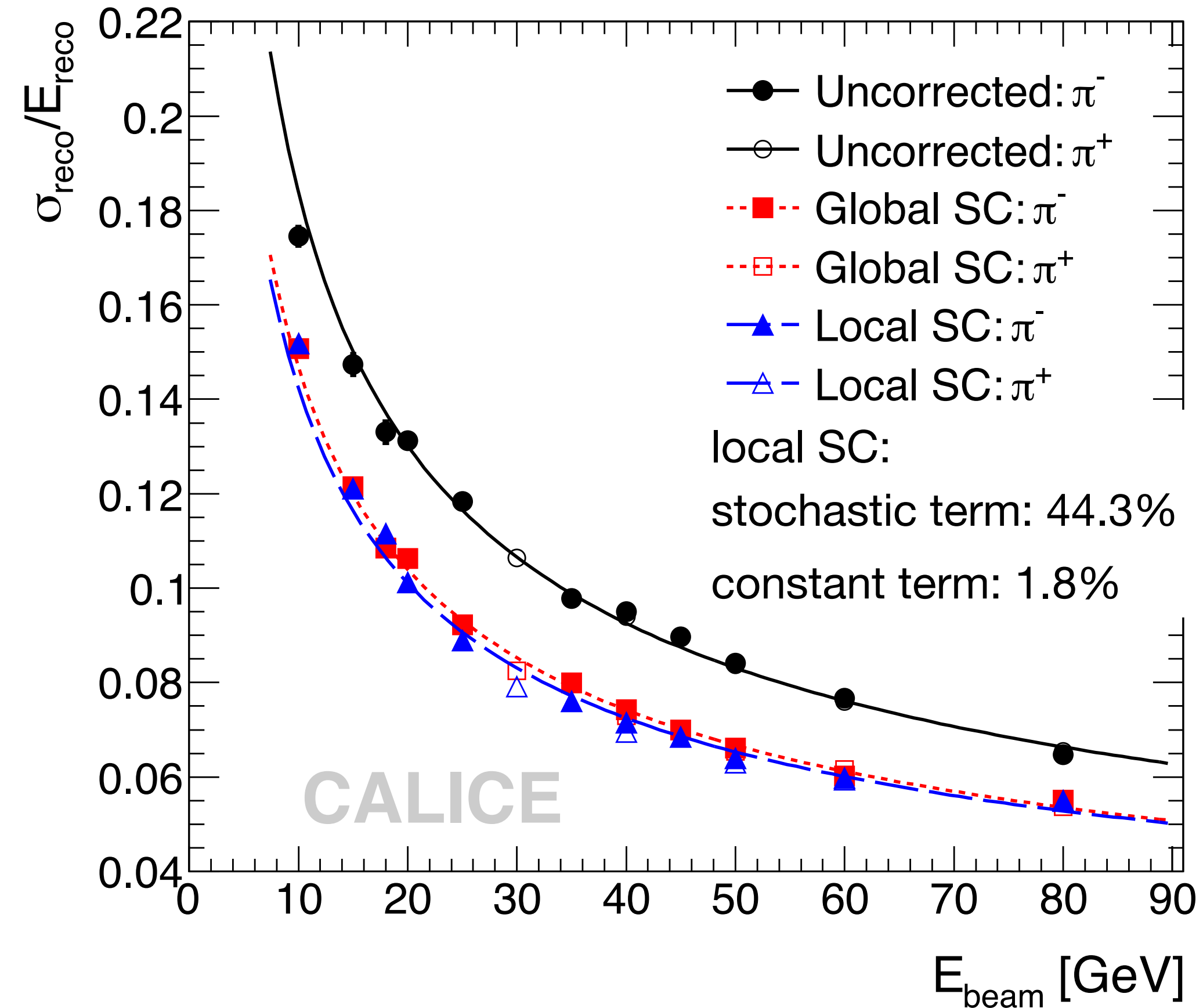
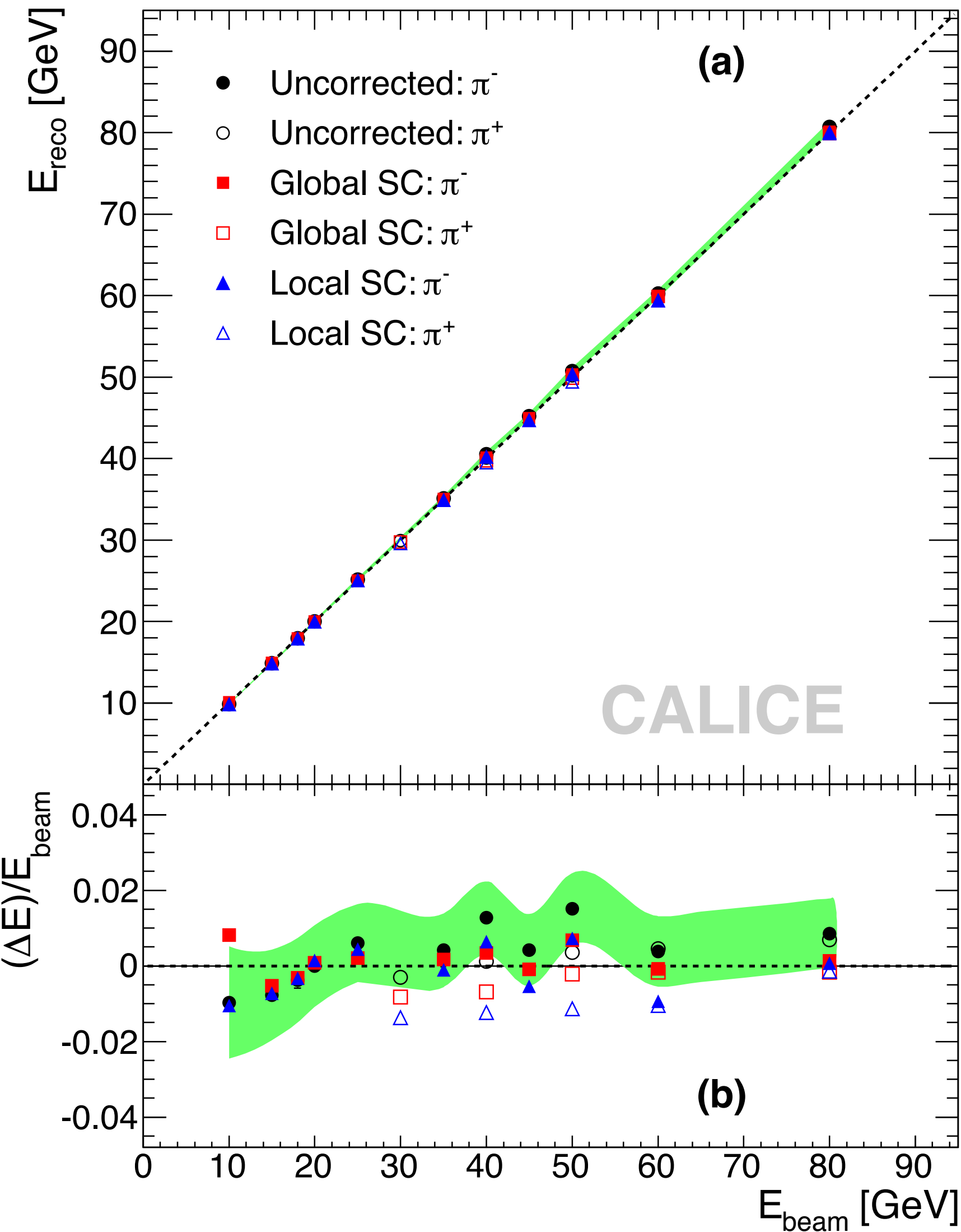
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For both: Parameters / weights determined by χ^2 minimisation of energy resolution

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Software Compensation in the AHCAL

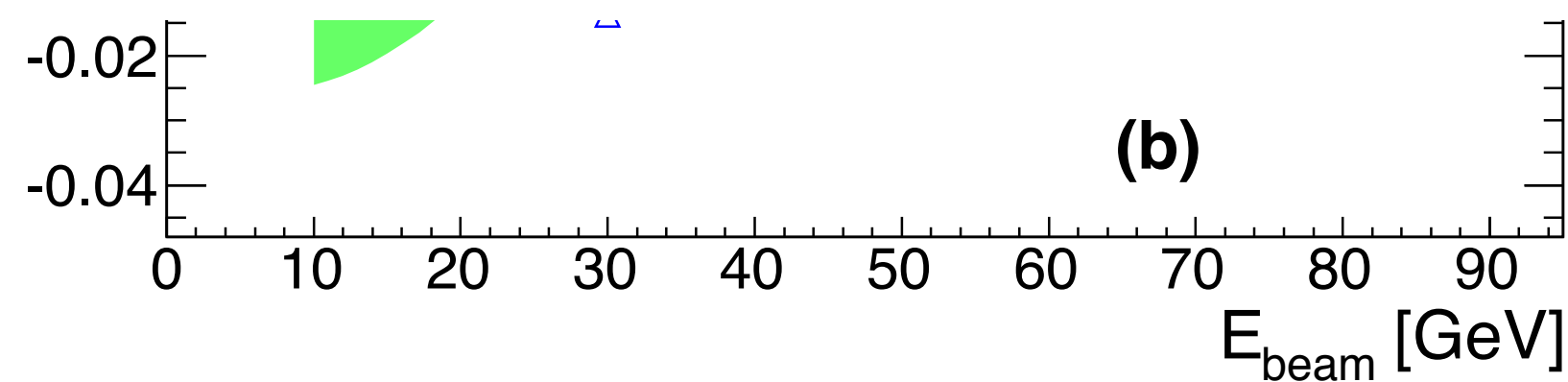
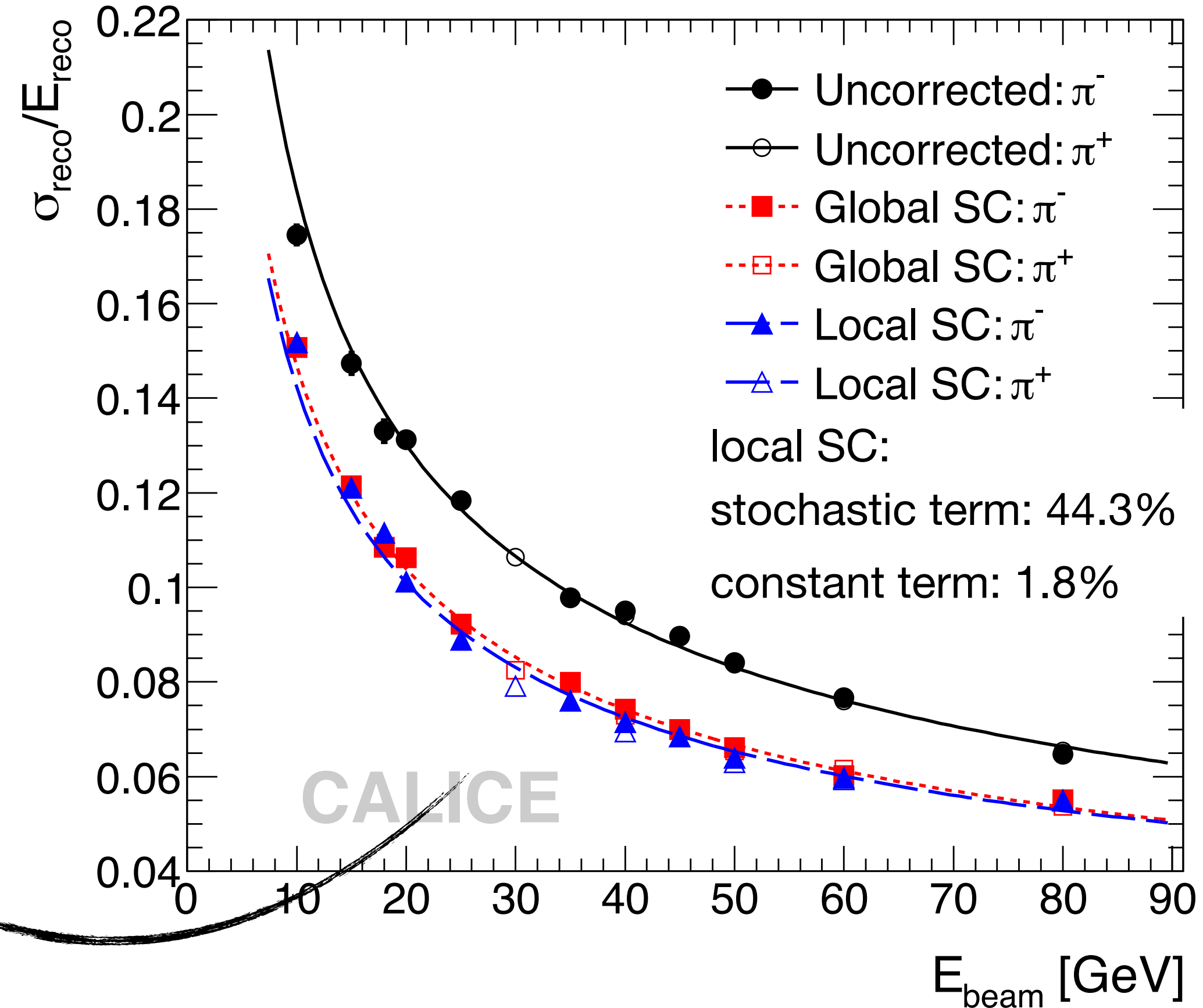
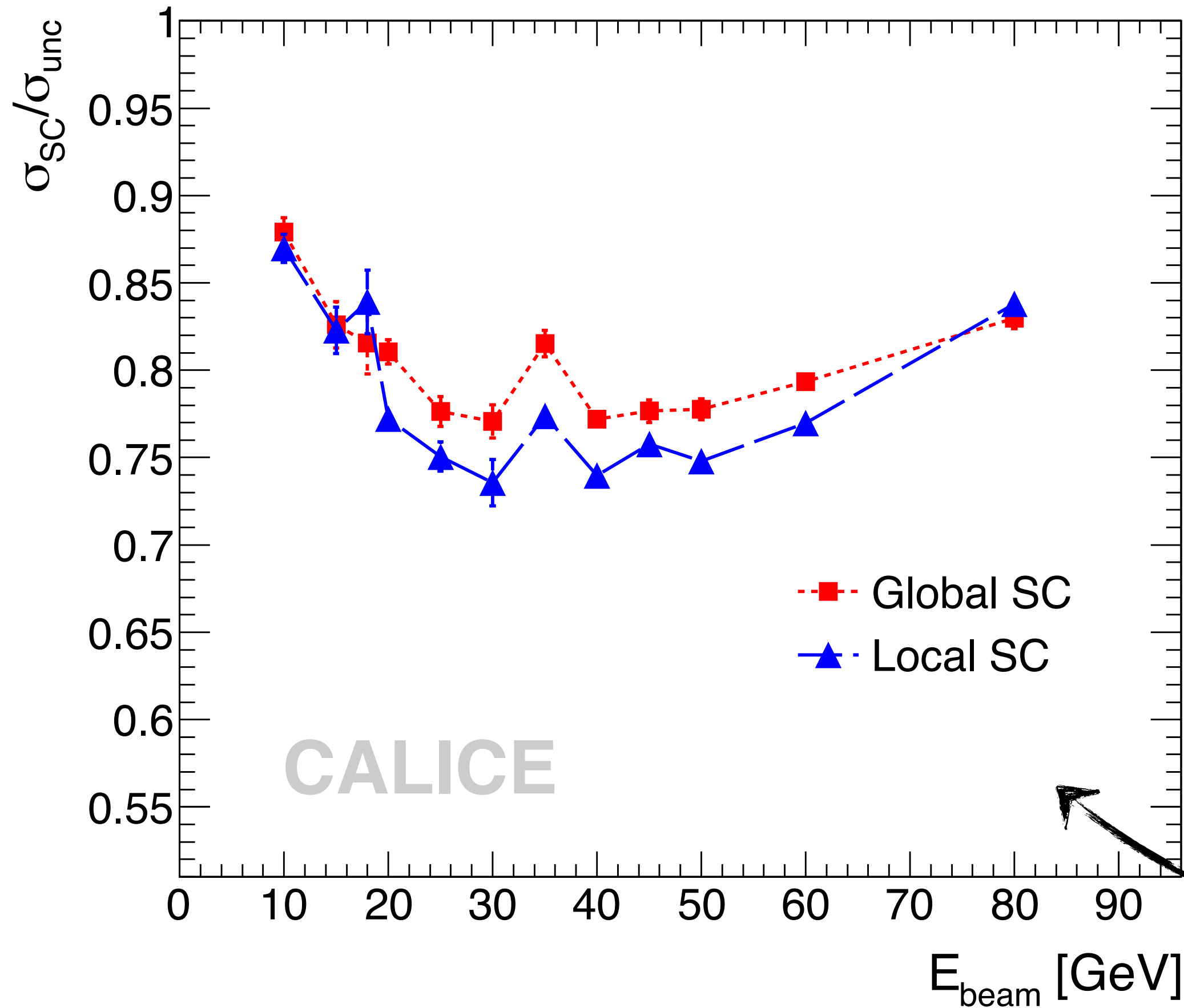
Comparing Local and Global SC



• Substantial improvement of energy resolution with SC

Software Compensation in the AHCAL

Comparing Local and Global SC



- Substantial improvement of energy resolution with SC
- Local SC slightly better improvement - in excess of 25% in intermediate energy range

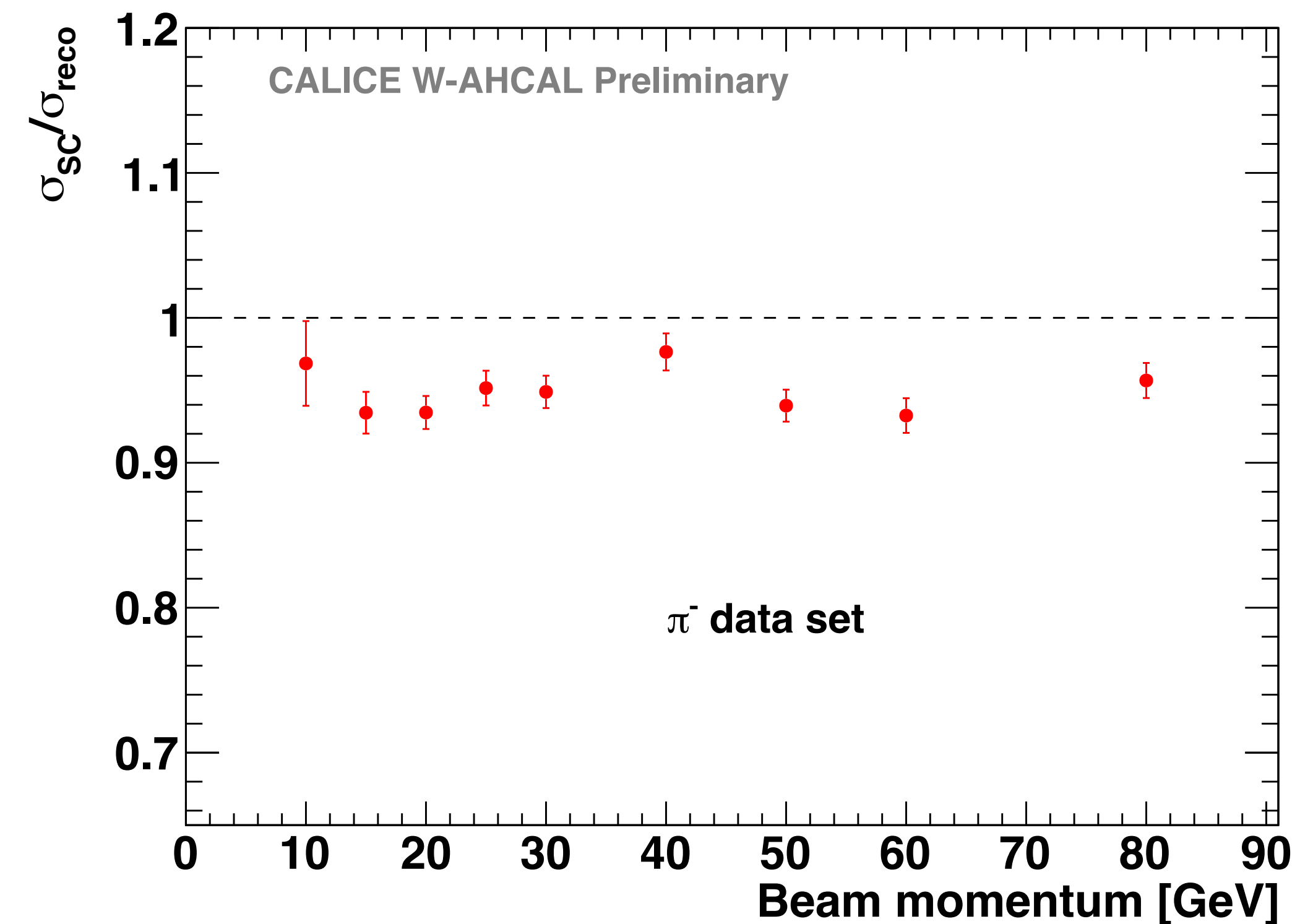
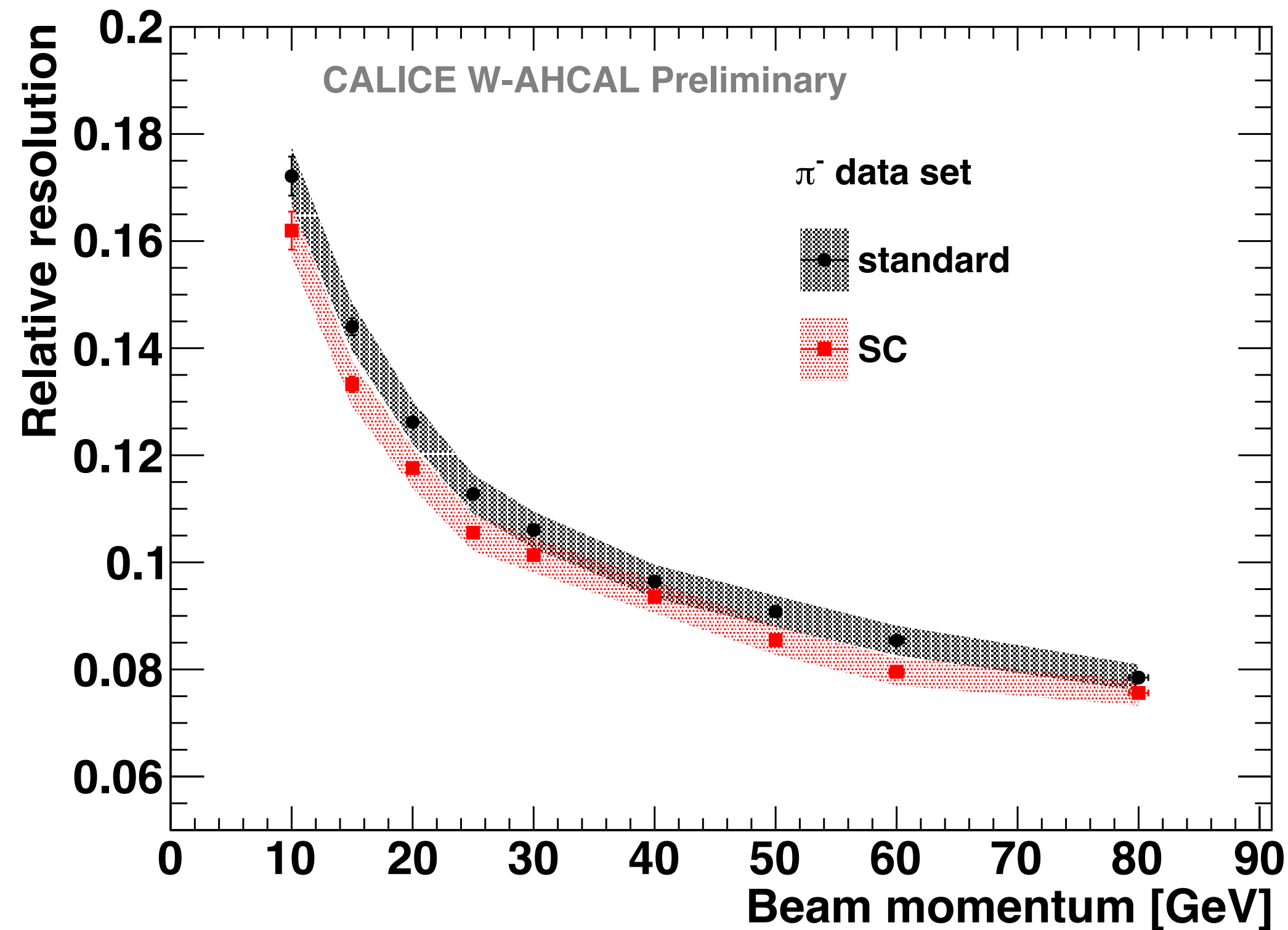
Software Compensation in the W-AHCAL

Global Software Compensation



- The CALICE W-AHCAL is close to compensating - leaves little handle for software compensation techniques
- ↳ Tested with global SC (local SC in progress)

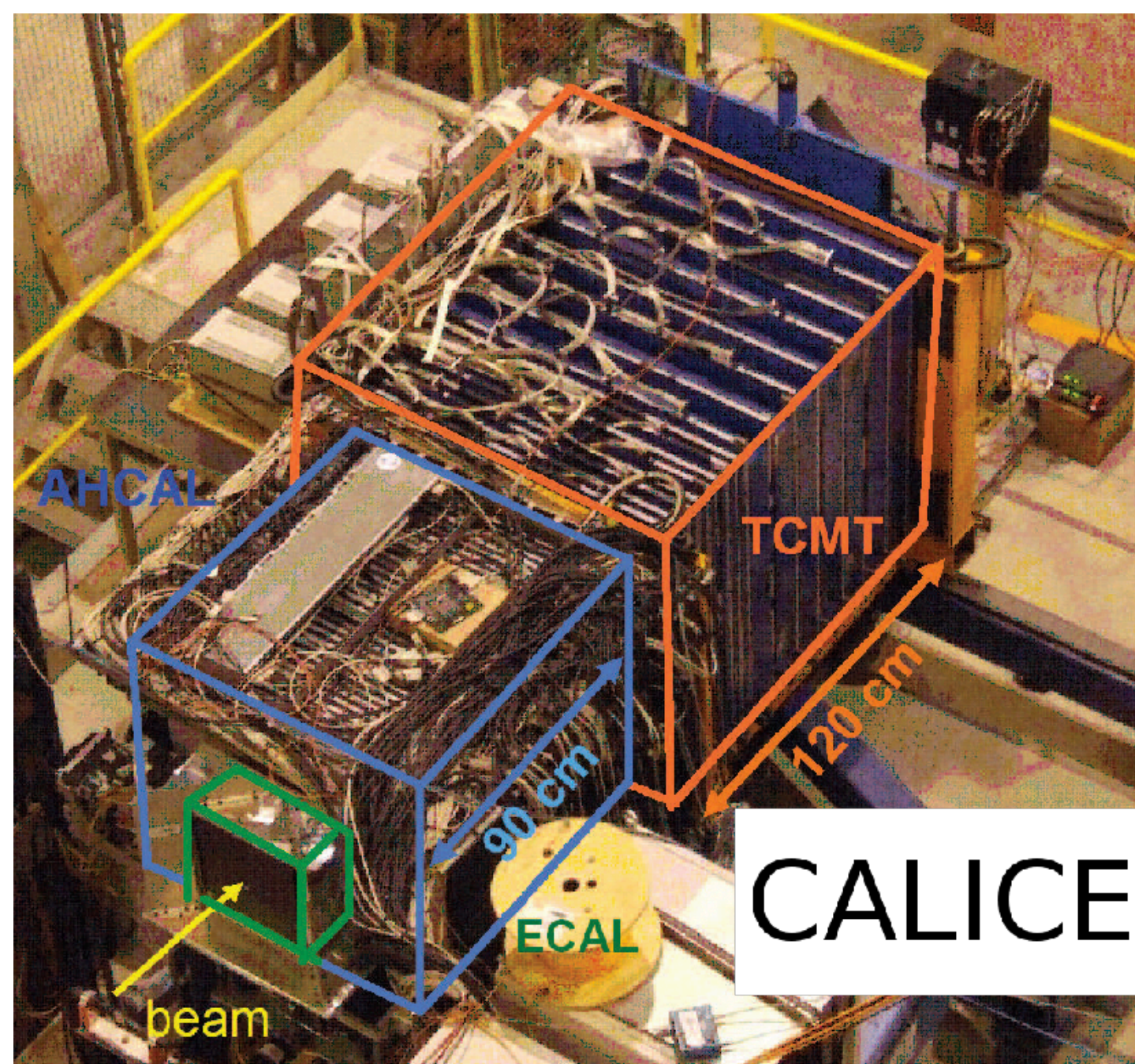
	Fe-AHCAL	W-AHCAL	ratio (Fe/W)
Number of layers	38	38*	1
Total depth [λ_I]	5.2	4.9	~ 1.06
Layer depth [mm]	31.73	24.73	~ 1.28
Layer depth [λ_I]	0.137	0.129	~ 1.06
Layer depth [X_0]	1.24	2.80	~ 0.44



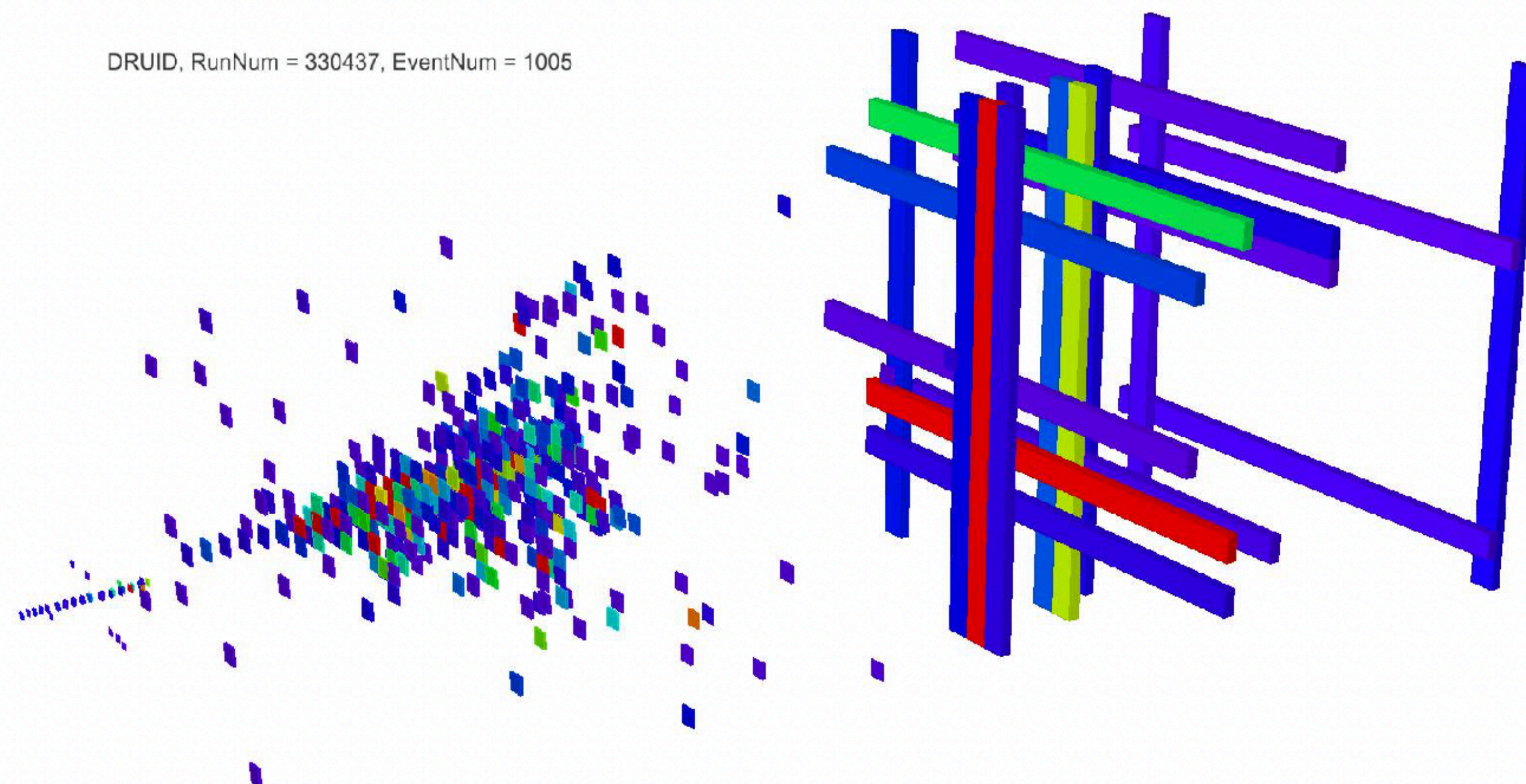
CAN-062

Extension to Combined ECAL/HCAL Systems

One Example: SiW ECAL + Scintillator / Fe HCAL



- Studying energy resolution in a “real-world” setting: A combined system of SiW ECAL, Scintillator/FE HCAL, Tail Catcher
- A combination of non-compensating systems with different active and absorber materials and varying longitudinal sampling
- Local software compensation extended by subsystem-dependent binning and weight parameter



ECAL (30 layers):

Absorber: W; 1.4 mm, 2.8 mm, 4.2 mm

Active: Si; 525 μm

HCAL (38 layers) / TCMT (8+8 layers):

Absorber: Steel; ~ 21 mm (including cassettes)

Active: Plastic scintillator; 5 mm

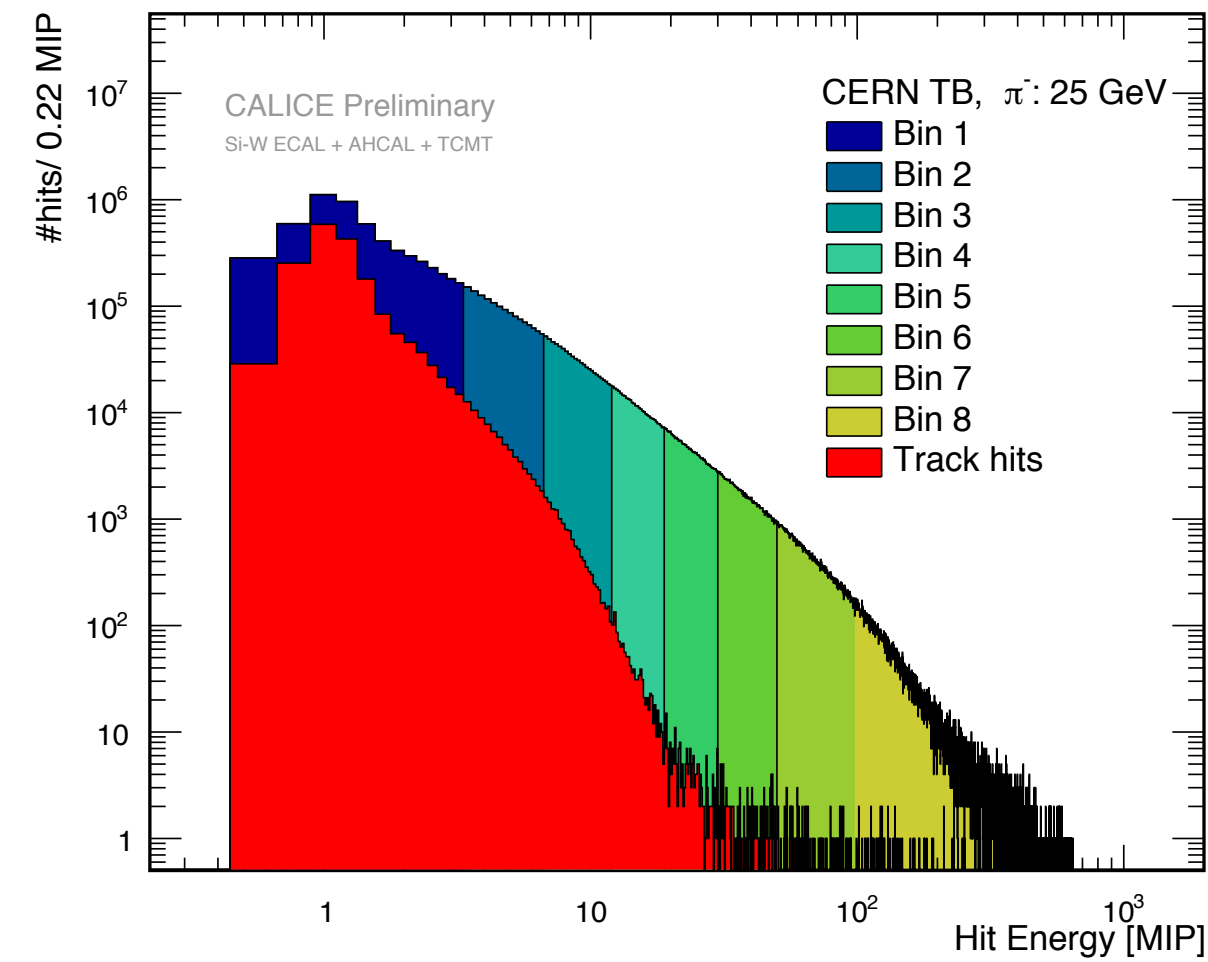
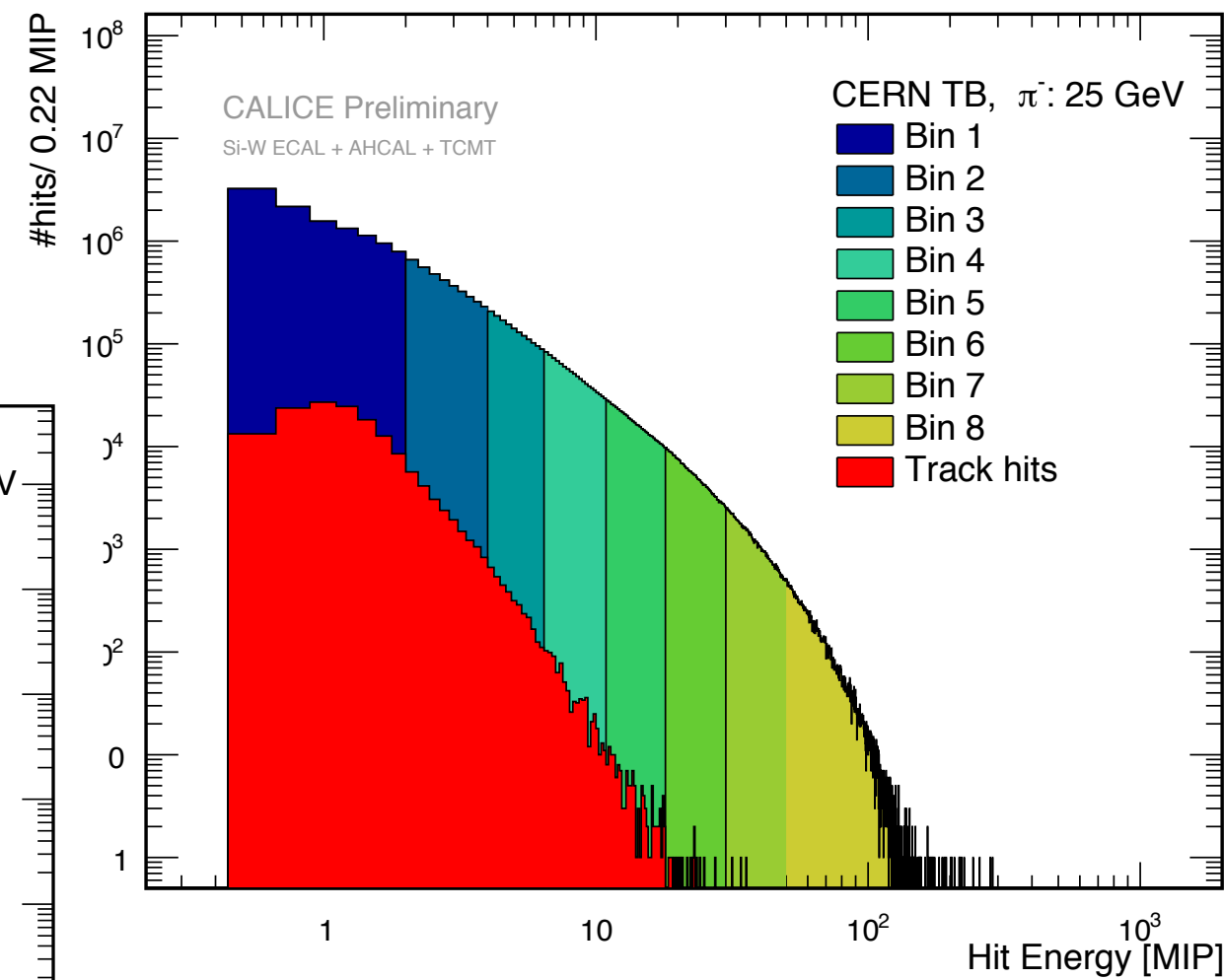
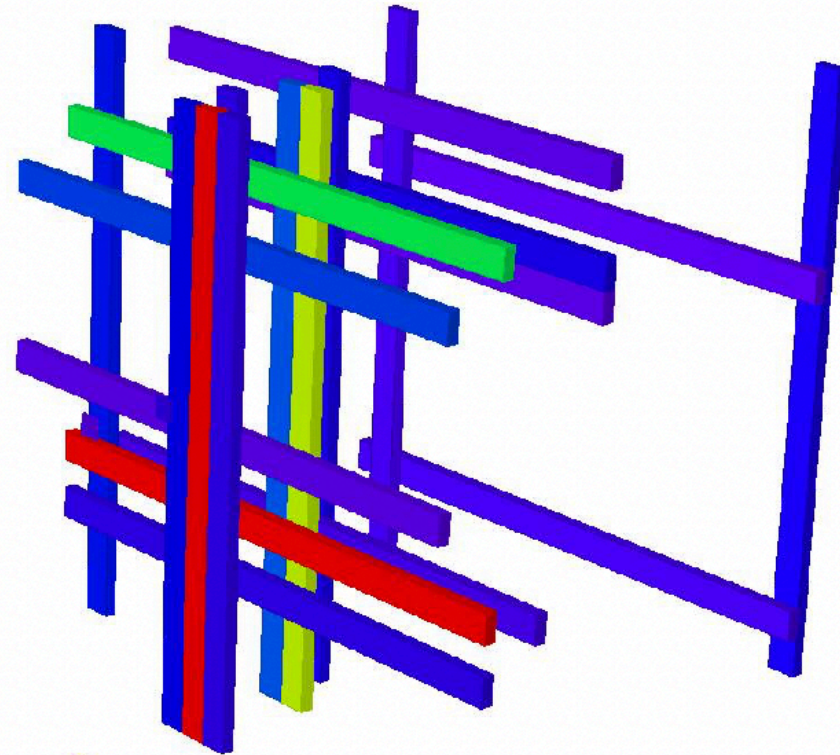
Local Software Compensation in Combined Systems

The Implementation

- Separate treatment of incoming track up to first interaction: calibration factor different than that for showers
- Digital weighting for first two bins: Slight advantage for energy resolution due to suppression of Landau fluctuations

CAN-058

DRUID, RunNum = 330437, EventNum = 1005

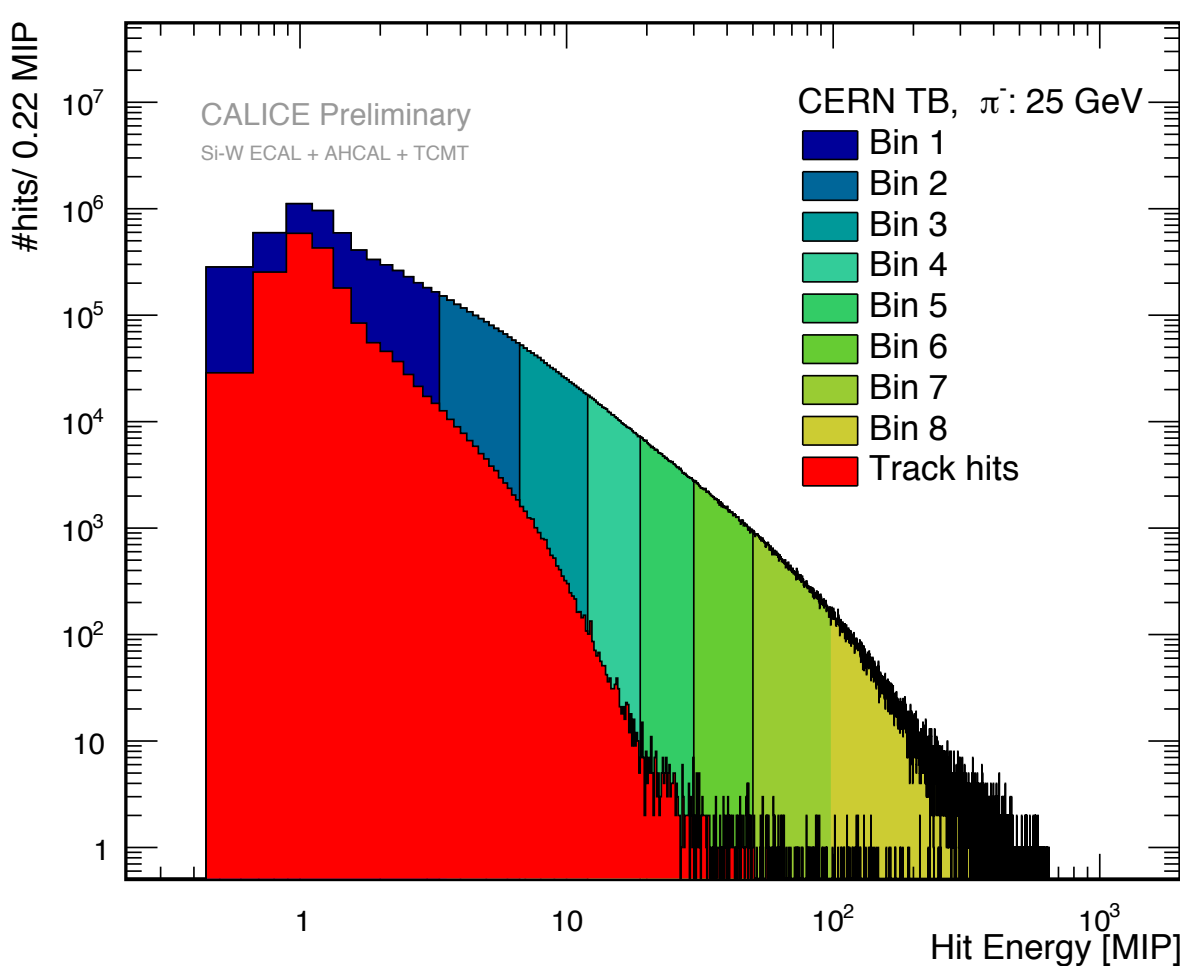
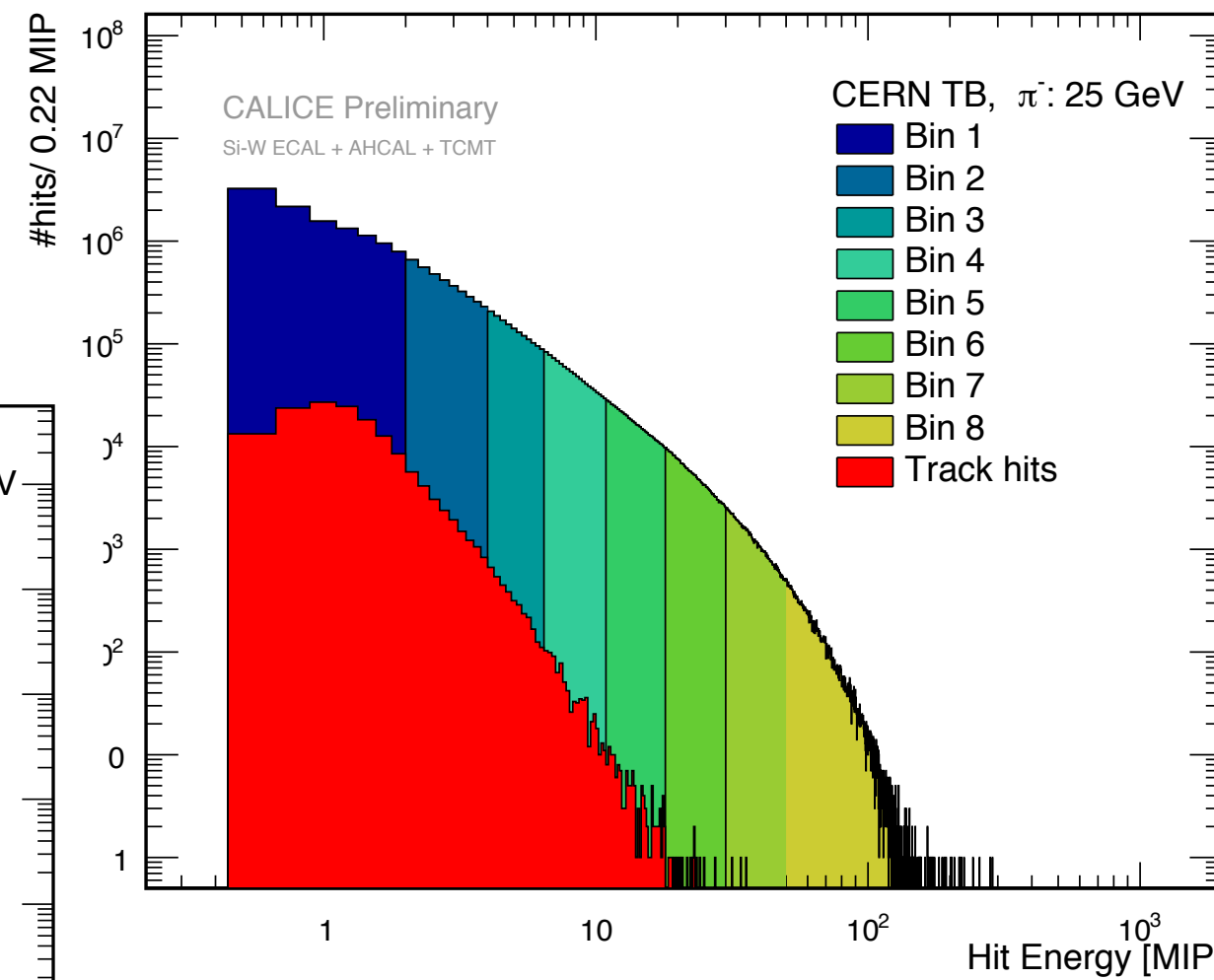
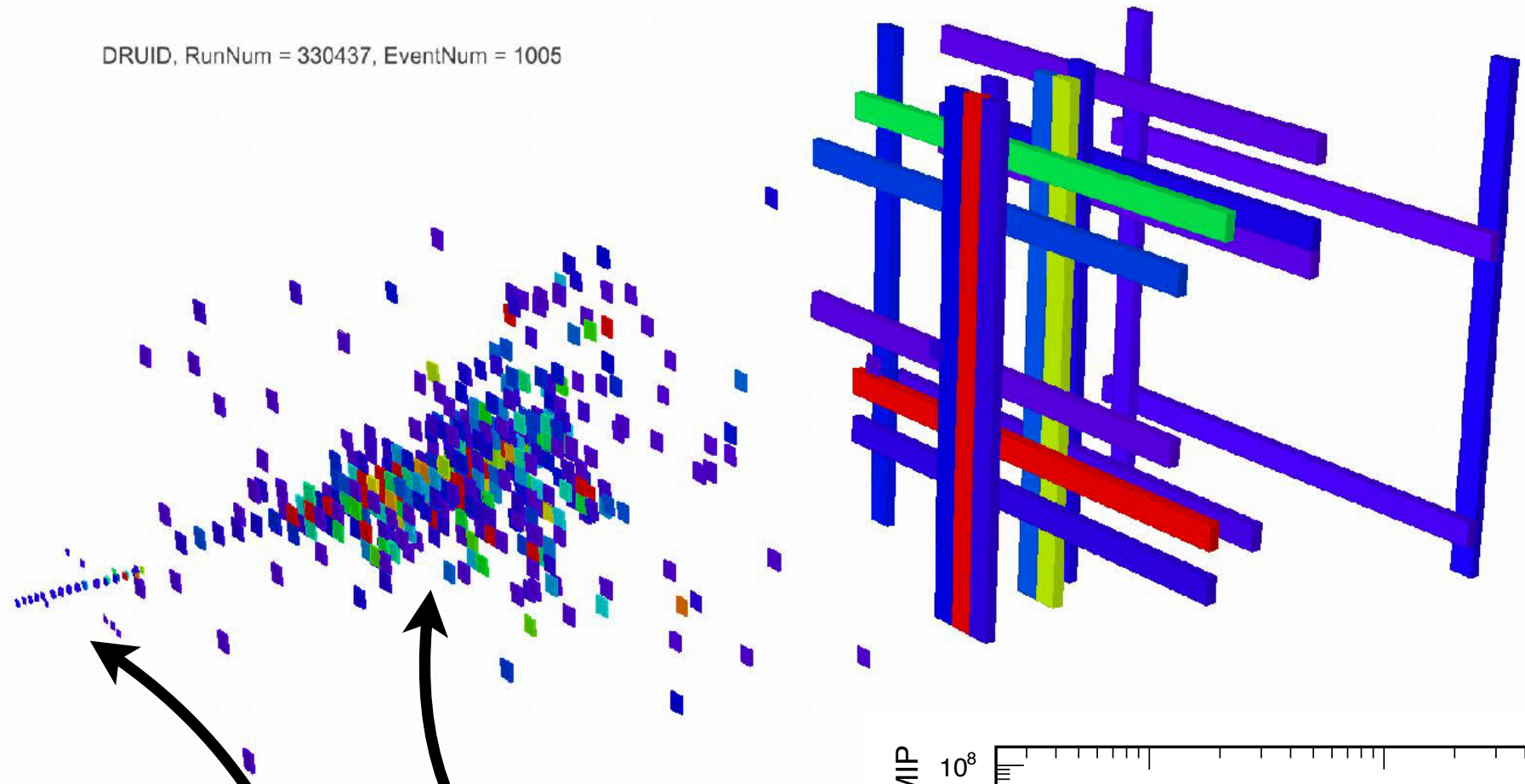


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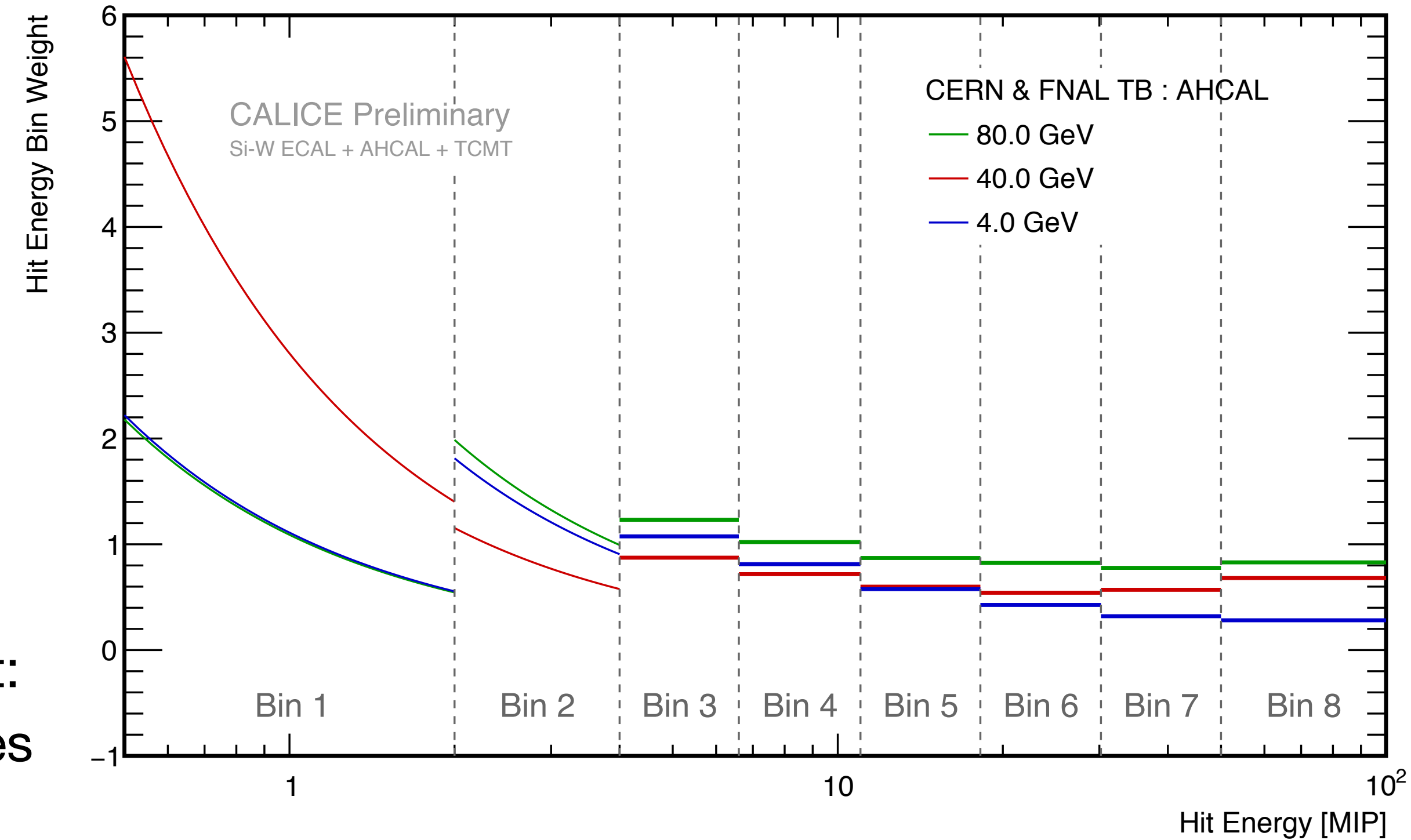
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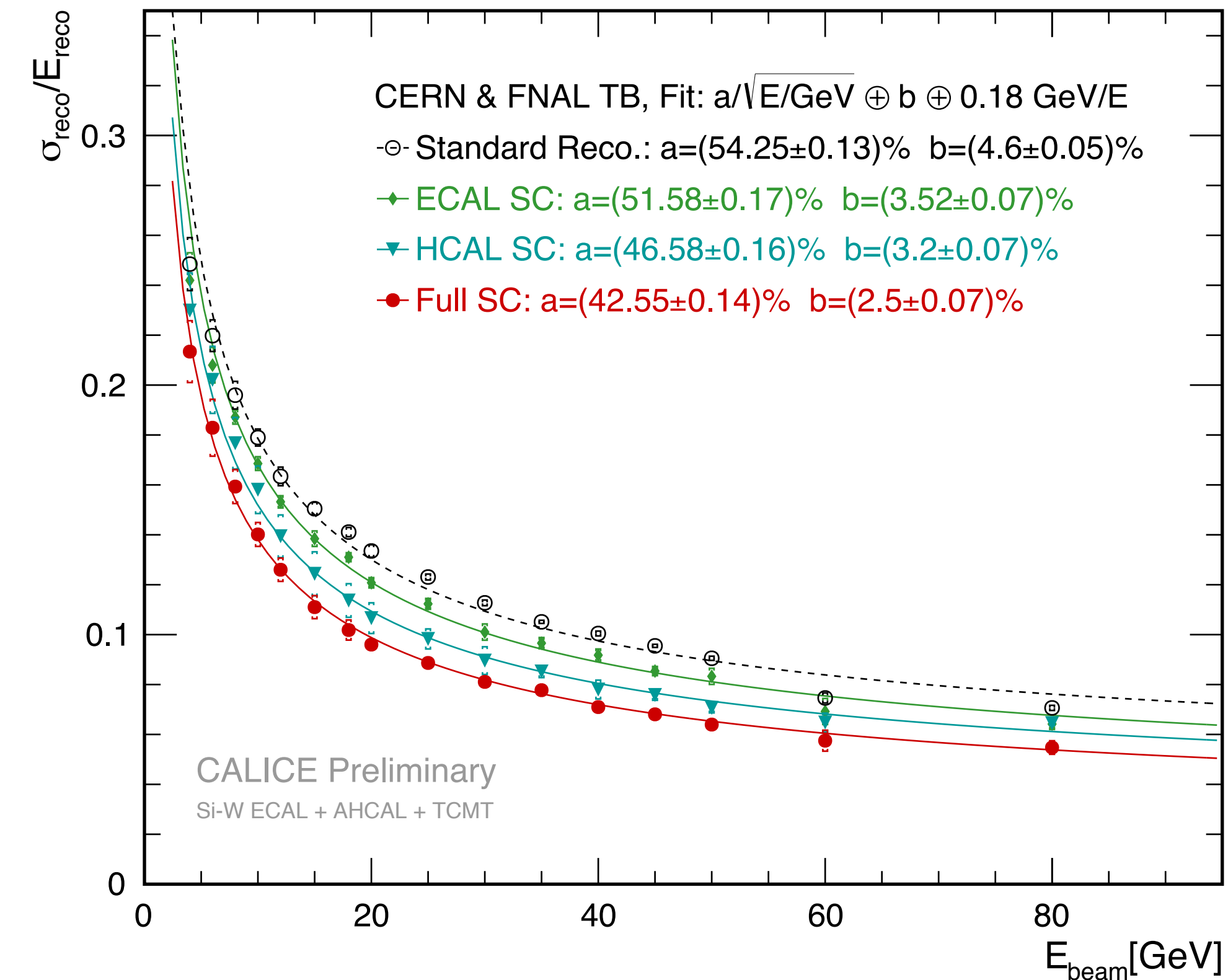
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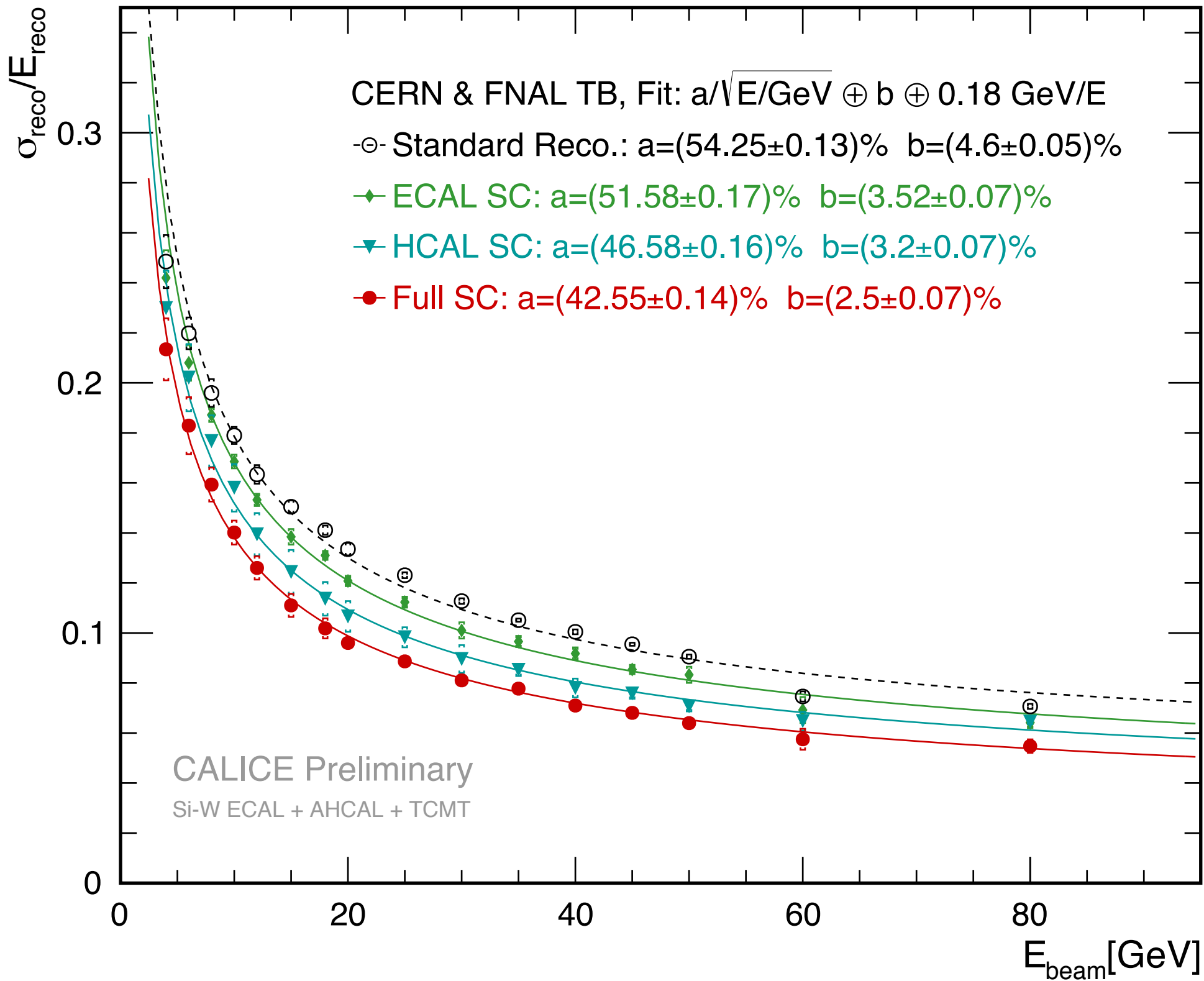
weights are energy dependent:
overall shower density changes
with energy!



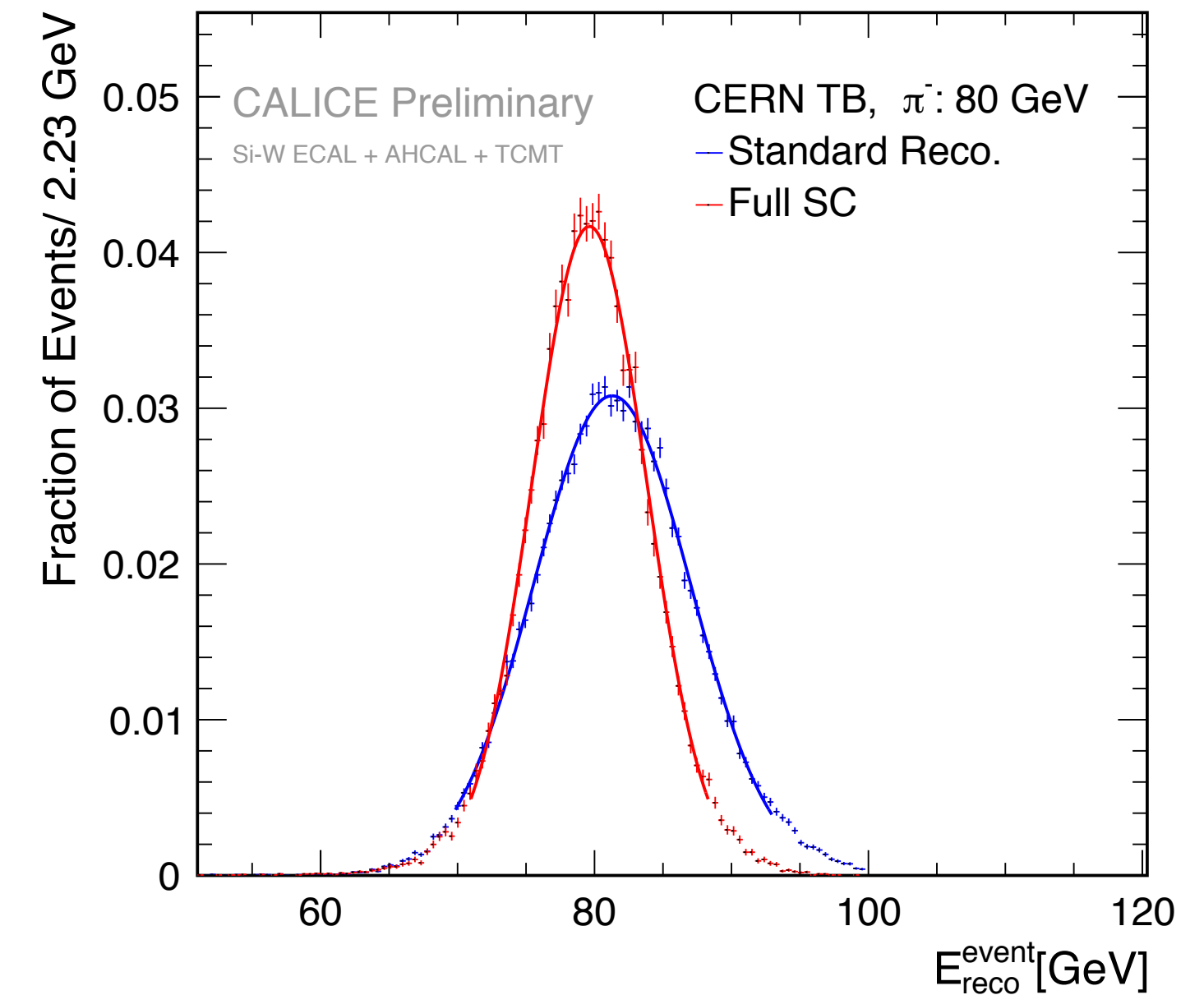
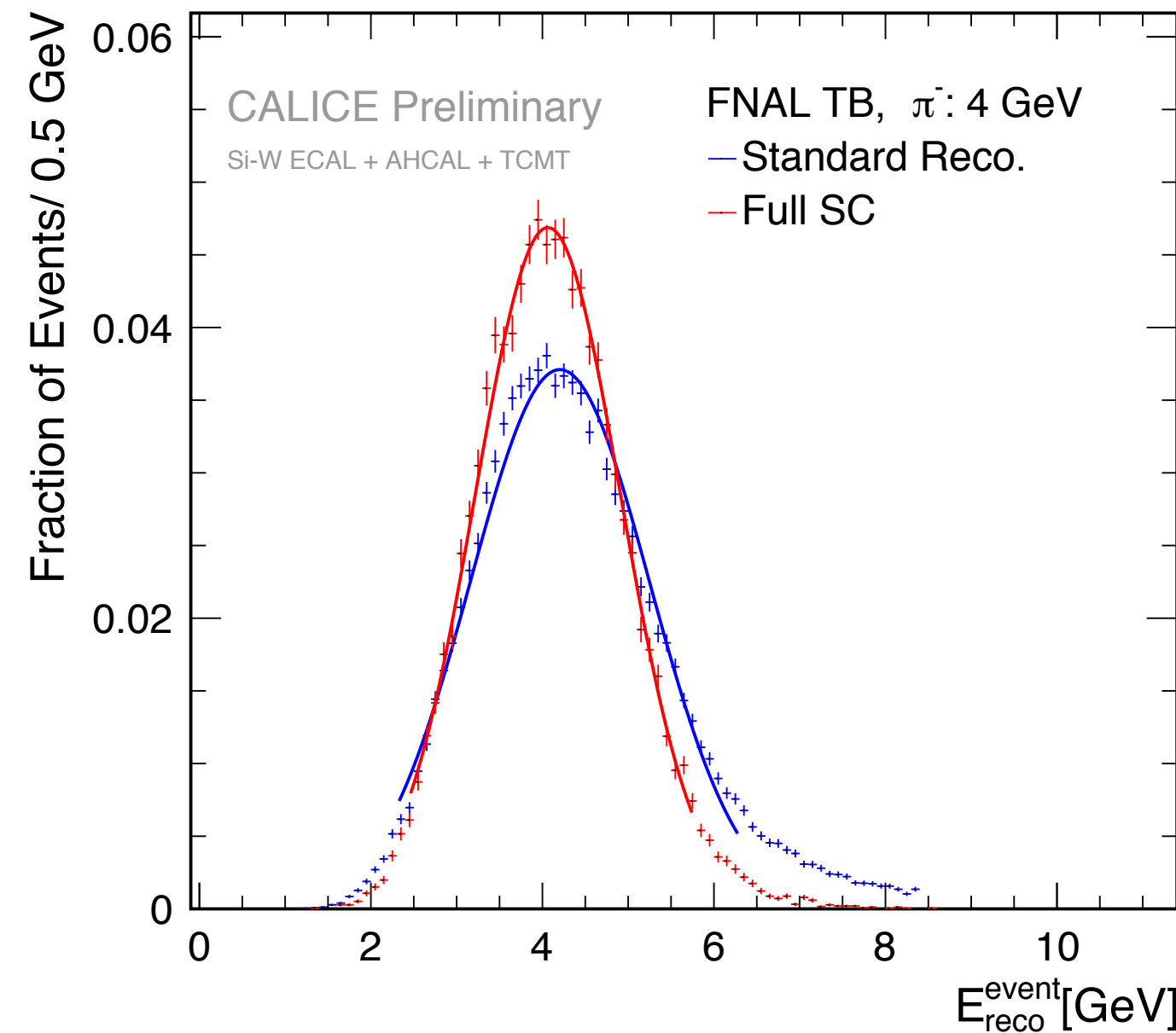


- Substantial improvement in energy resolution:
 - SC in ECAL alone up to 8% improvement
 - SC in HCAL alone up to 23% improvement
 - Full SC up to 30% improvement, for a stochastic term of 42.5% and a constant term of 2.5%
- ⇒ The bulk of the improvement is achieved in the AHCAL

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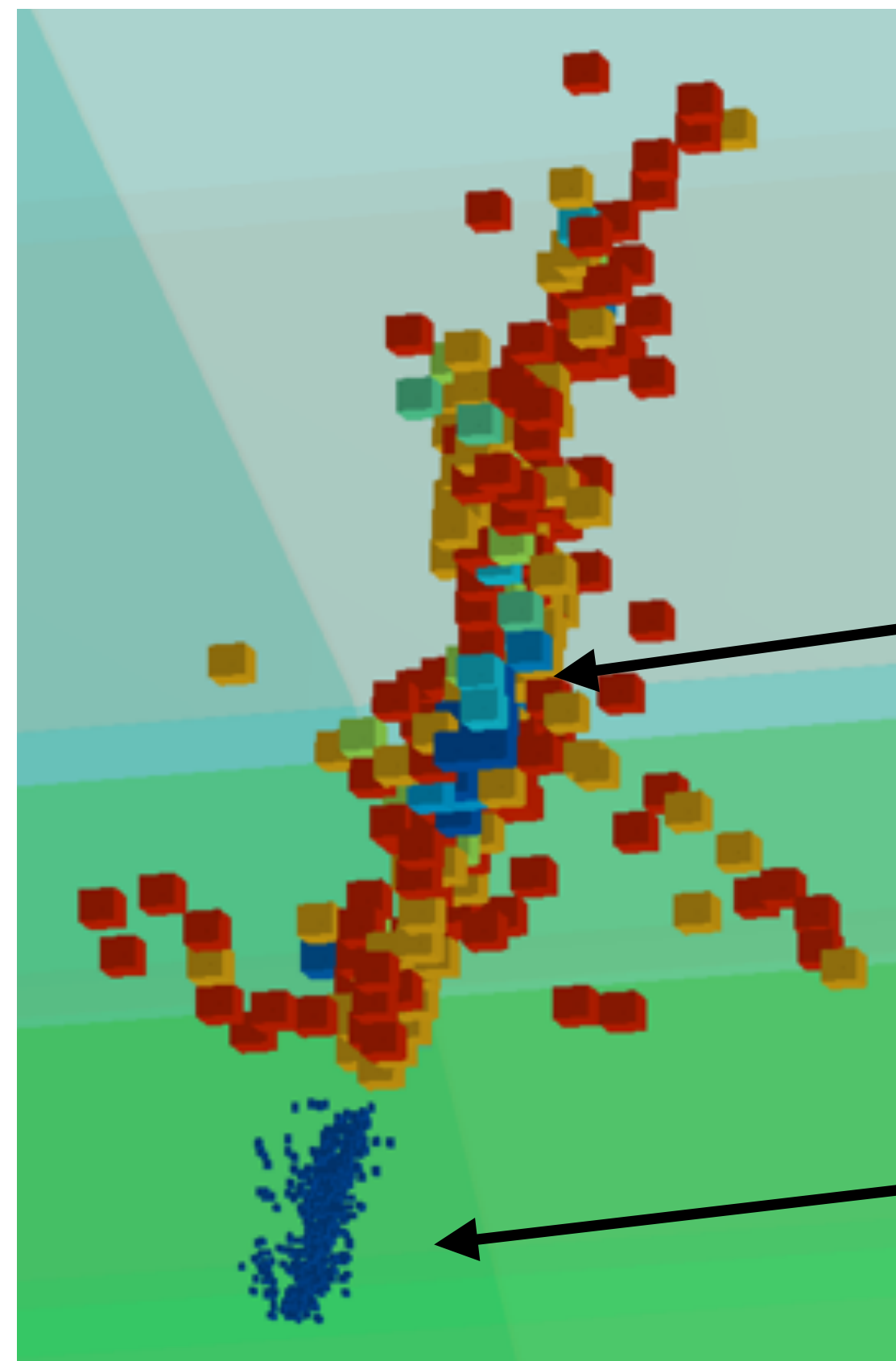
- Software compensation also reduces tails and asymmetries in the energy distribution, in particular at lower beam energies



Combining Software Compensation with Particle Flow

Local Software Compensation in PandoraPFA

- Particle flow algorithms make use of calorimeter energy at two main points
 - Track - calorimeter cluster matching, and iterative reclustering
 - Energy of neutral particles



transfer software compensation algorithm and training strategies from CALICE to full ILD detector simulations

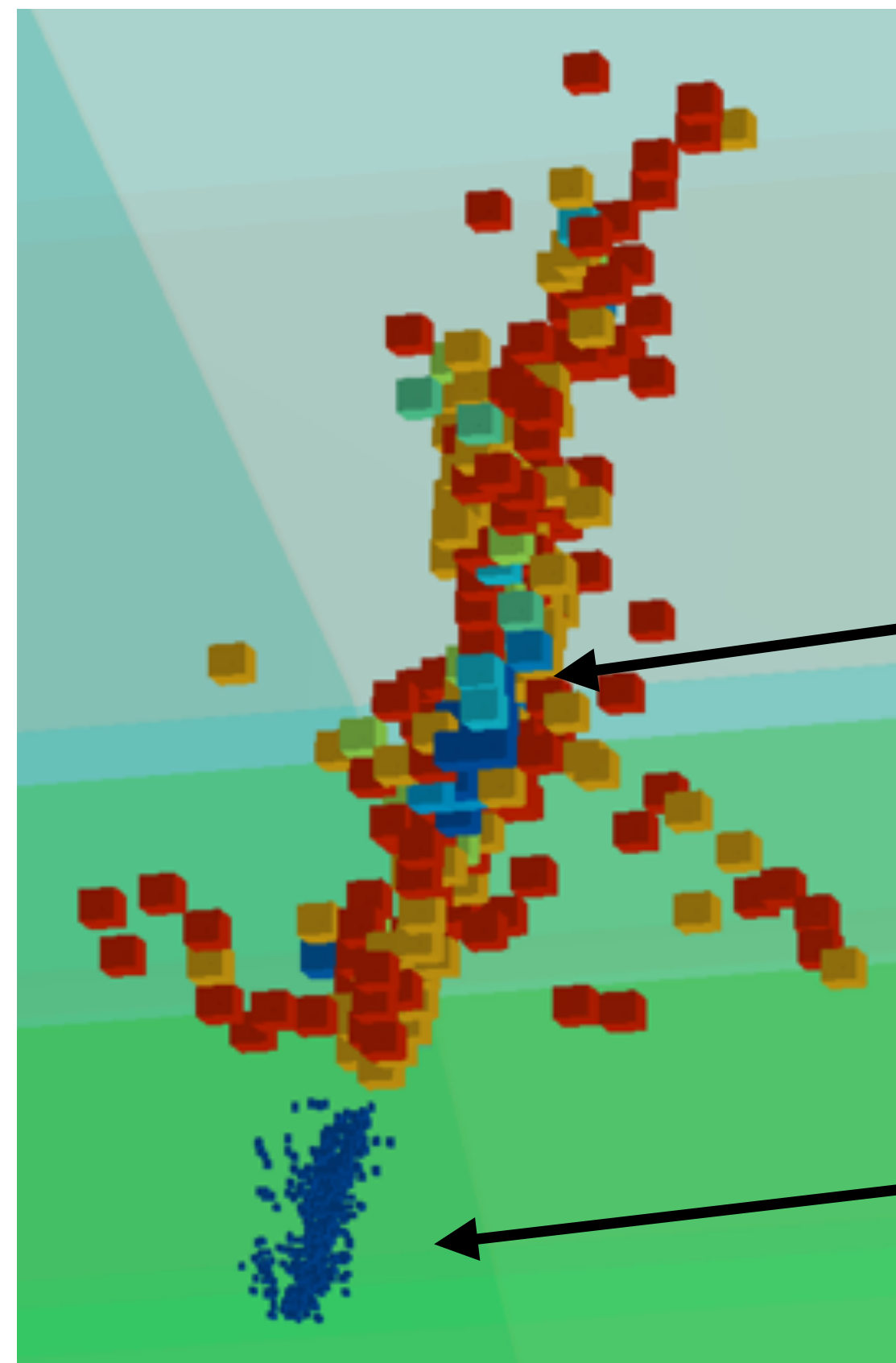
em sub showers (in shower core) weighted less than hadronic periphery

ECAL not yet included: standard reconstruction used

Combining Software Compensation with Particle Flow

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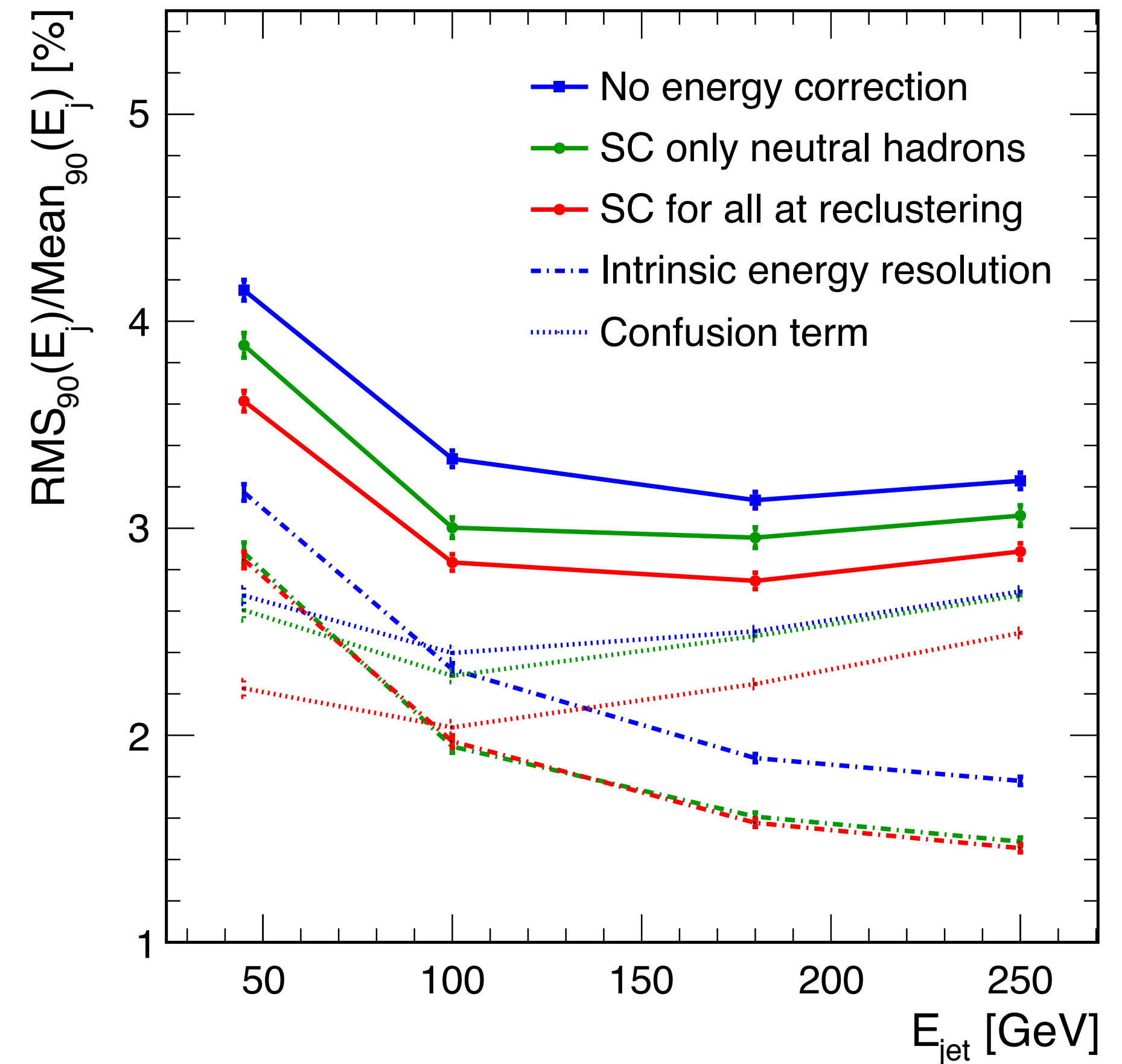
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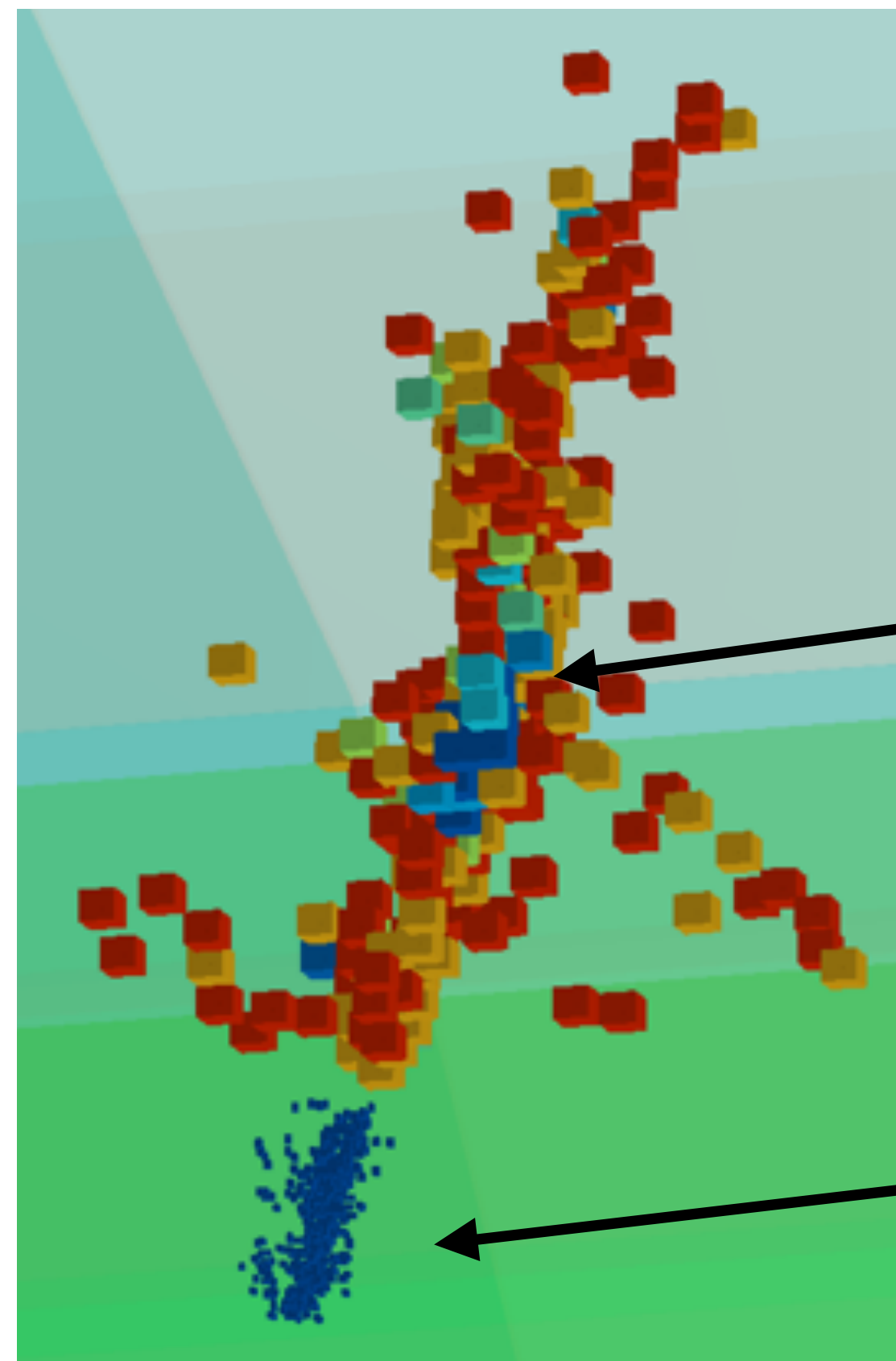


EPJ C77, 698 (2017)

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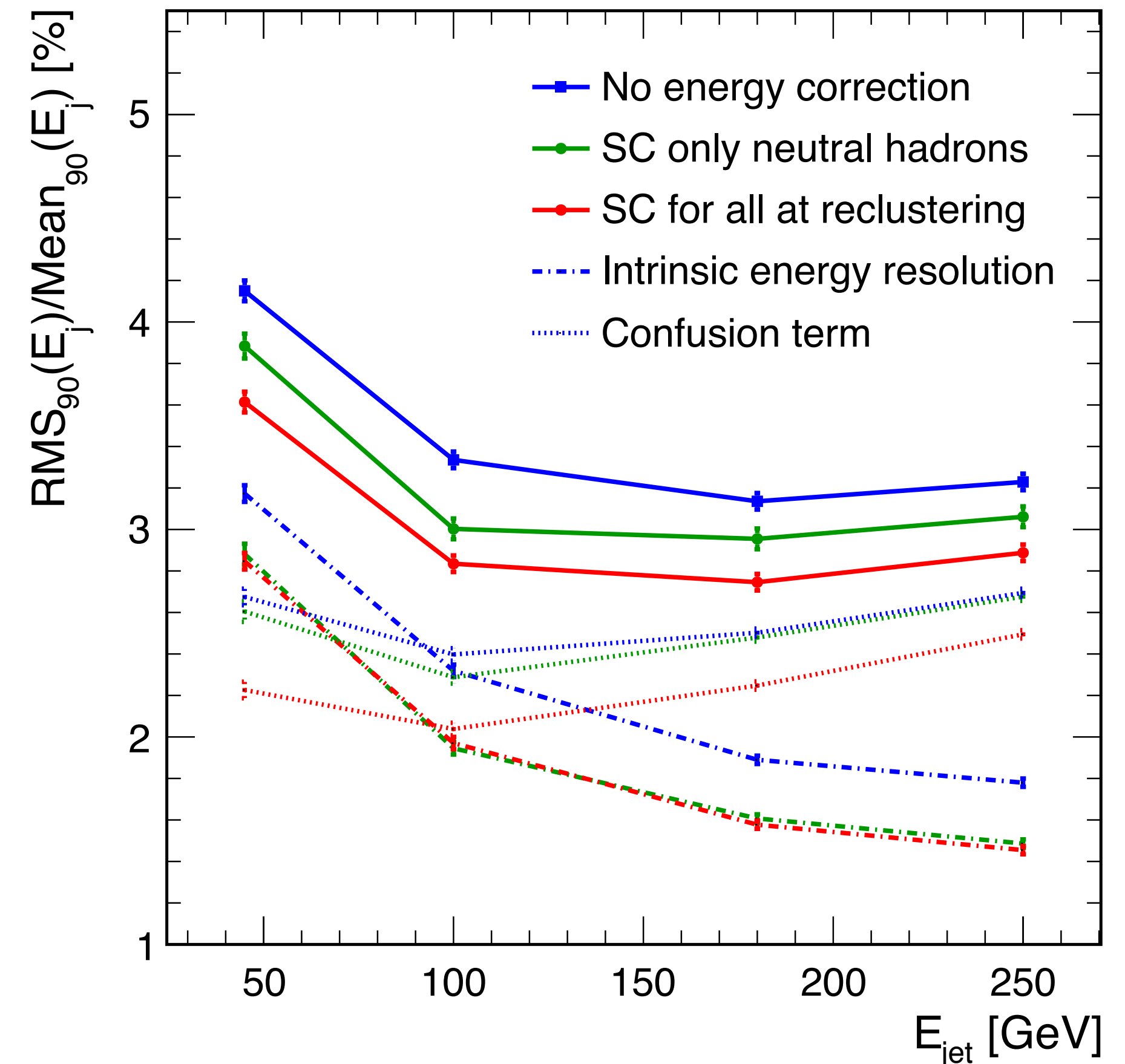
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Now the standard energy reconstruction method for CLIC and ILD physics and performance studies

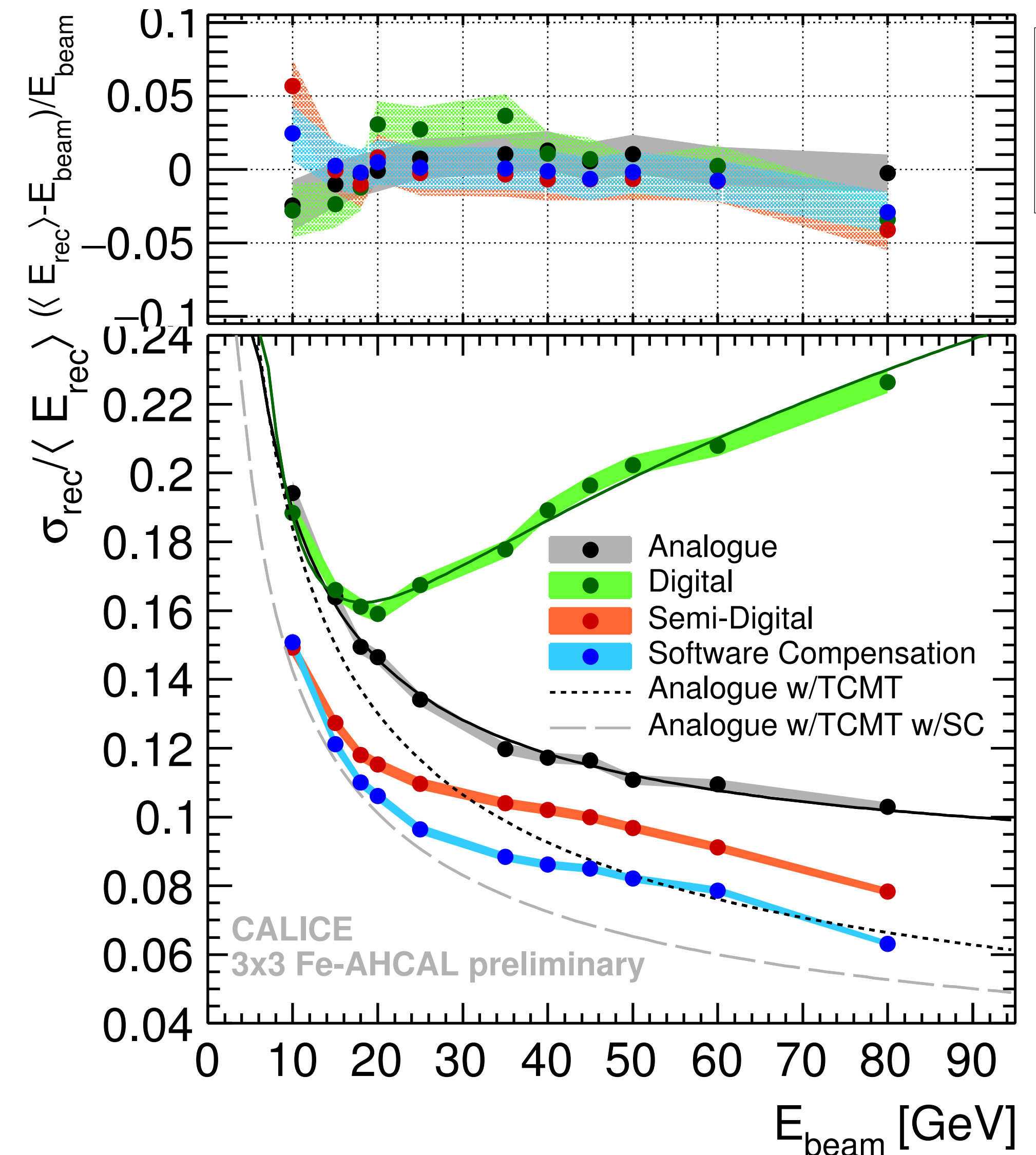
Energy Reconstruction & Readout Schemes

Understanding Resolution Impact of Granularity & Readout Technology

- CALICE hadron calorimeters use different schemes for energy reconstruction - depending on readout technology:
 - *scintillator*: analog & software compensation
 - *gas*: digital (1 bit), semi-digital (2 bit)

N.B.: Semi-digital reconstruction and software compensation are related: both use optimised hit or energy dependent weighting factors

- Different schemes tested on AHCAL data (3 x 3 cm² granularity)



CAN-049

Energy Reconstruction & Readout Schemes

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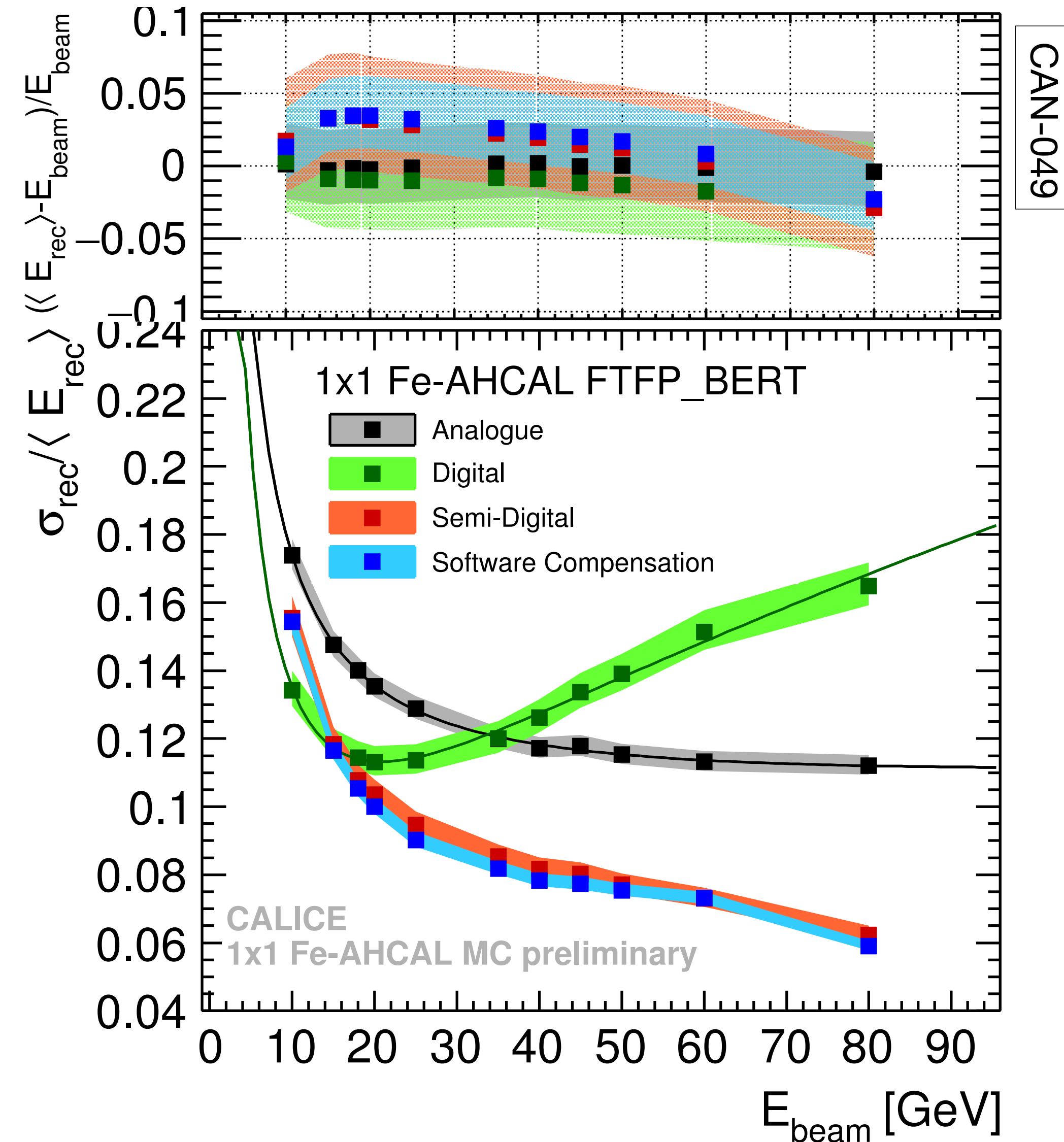


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- Different schemes tested on AHCAL data (3 x 3 cm² granularity)
- Simulations used to study 1 x 1 cm² granularity (scintillator)
 - Digital & fine granularity best at low energy: Suppression of fluctuations
 - SC & semi-digital comparable
- NB: Sampling fraction matters: Semi-digital reconstruction in RPCs does not reach the same resolution



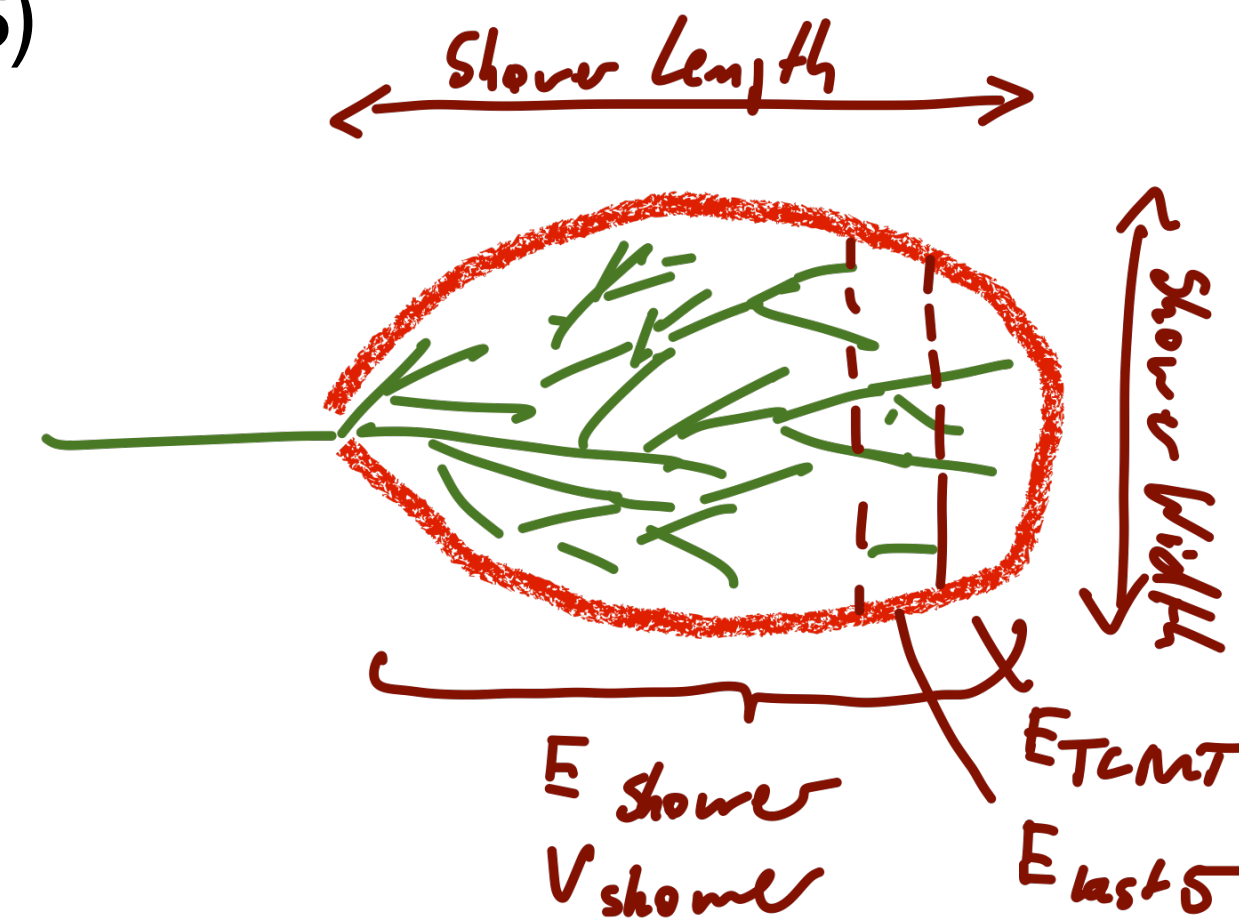
Towards Multivariate Techniques

Initial Studies with Neural Networks

- Performed with AHCAL physics prototype in 2010 (K. Seidel, FS)

The strategy:

- Use “simple” clustering to define a set of shower variables
- Train a neural network on MC data (NB: quasi-continuous energy distribution to avoid bias)
- Apply NN to data (requires additional energy correction to account for differences between data and MC)



Shower variables used in NN:
Global observables

Towards Multivariate Techniques

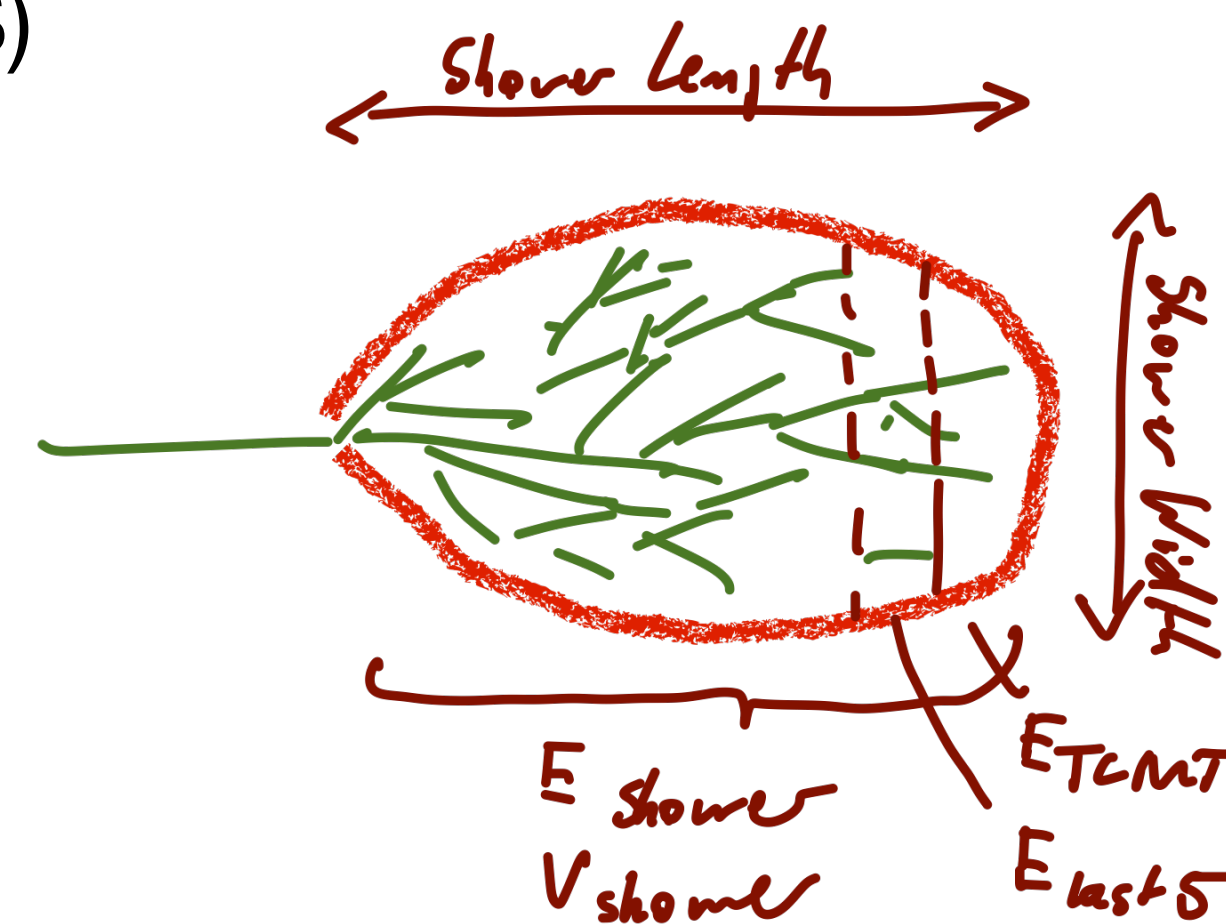
Initial Studies with Neural Networks

CAN-021

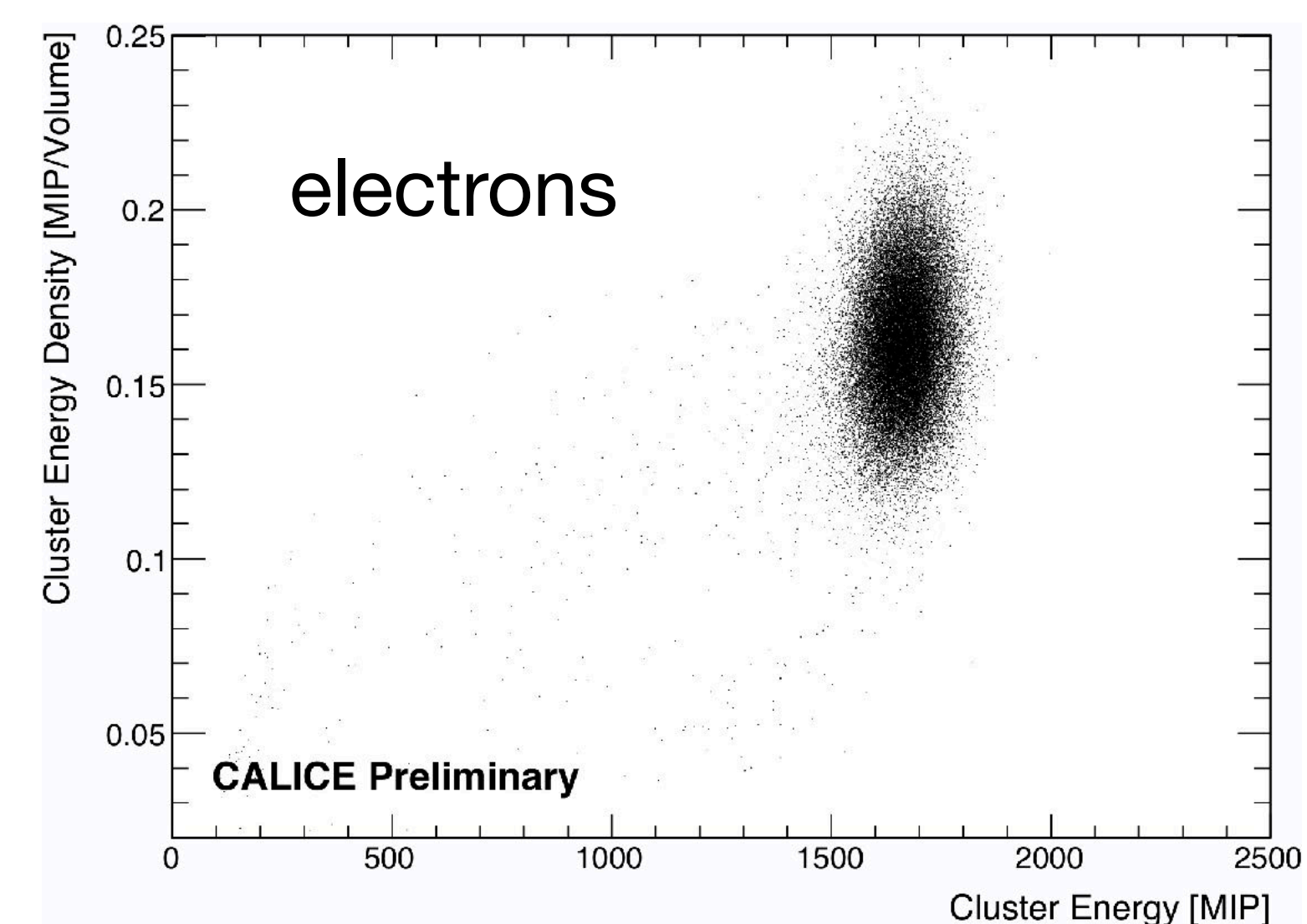
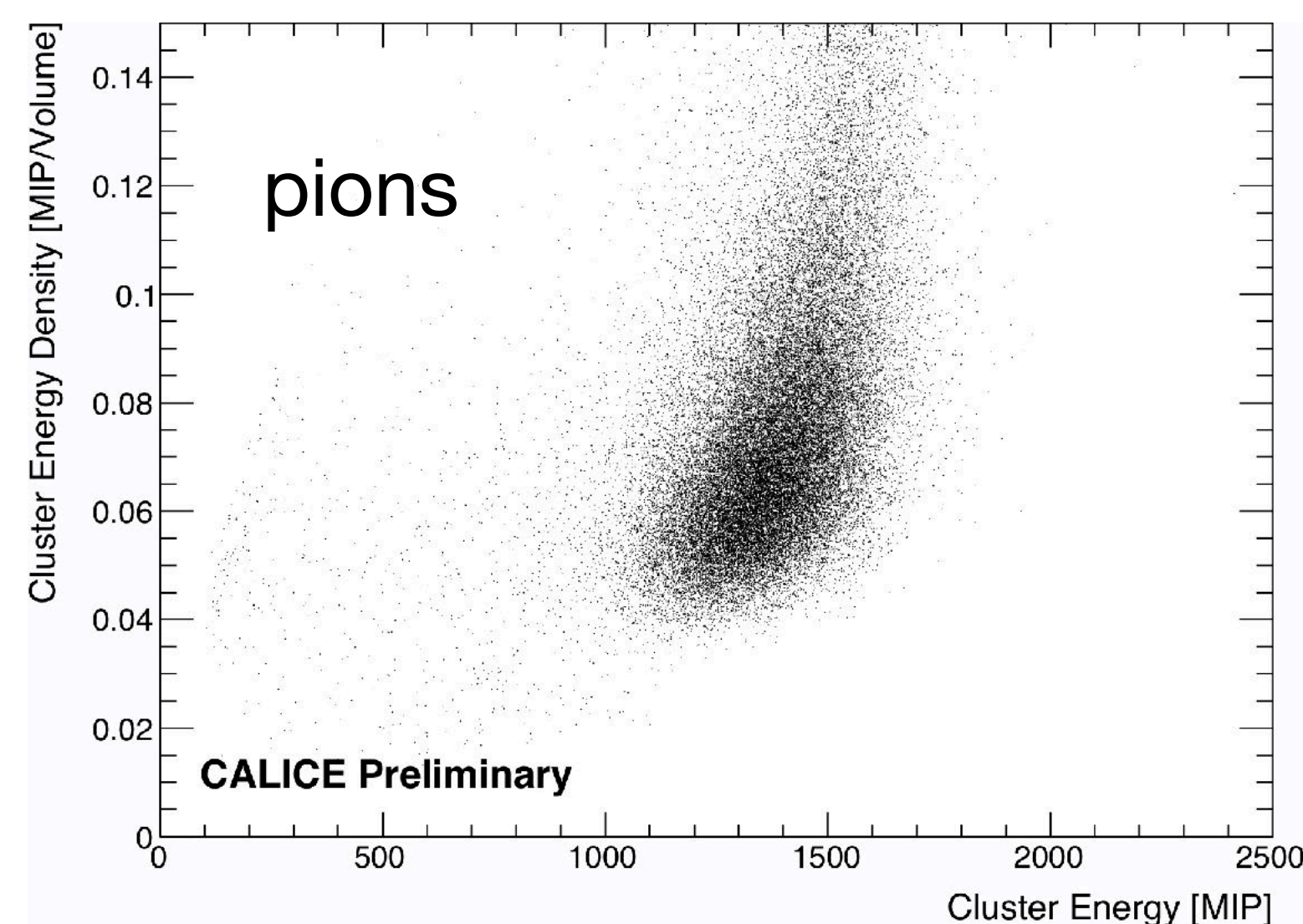
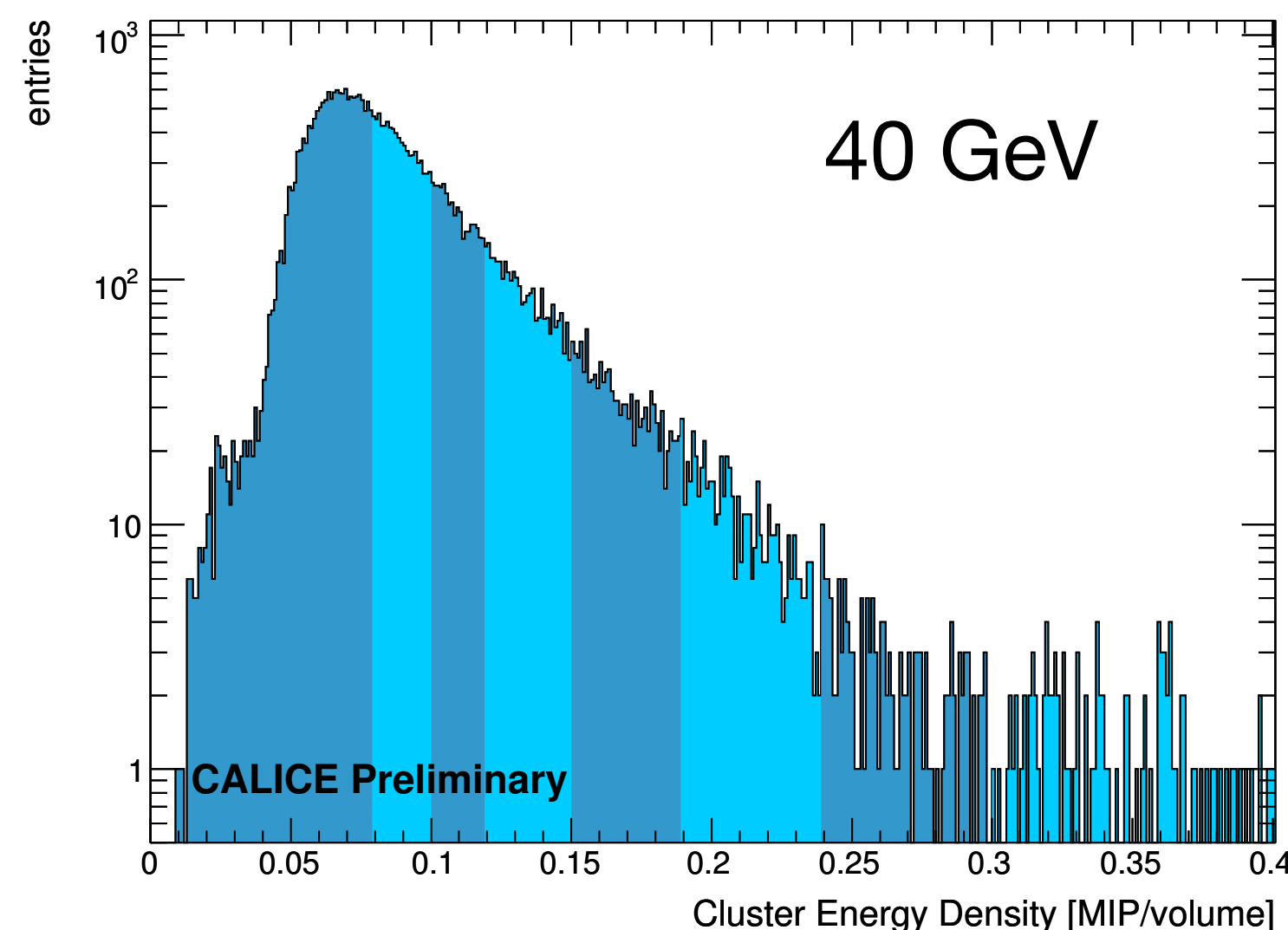
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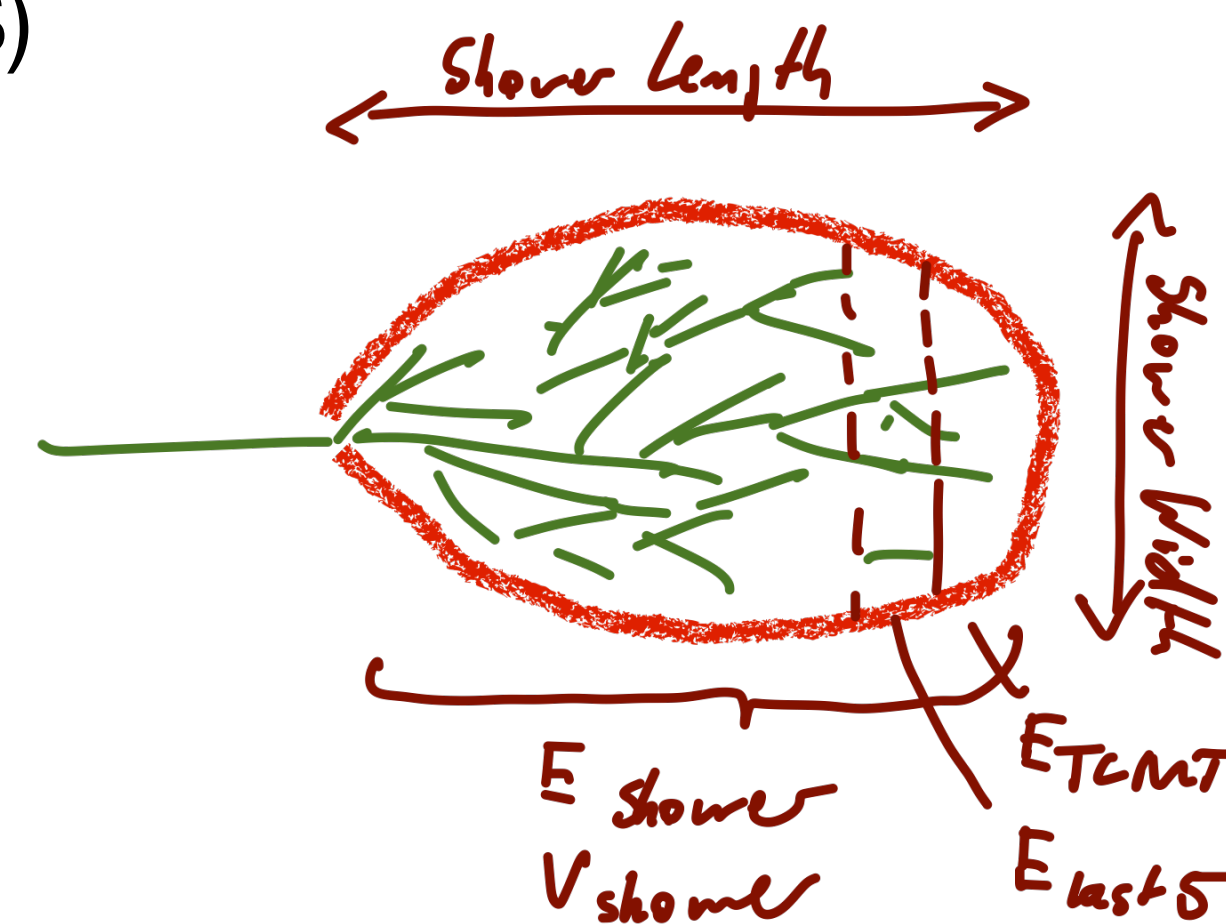
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CAN-021

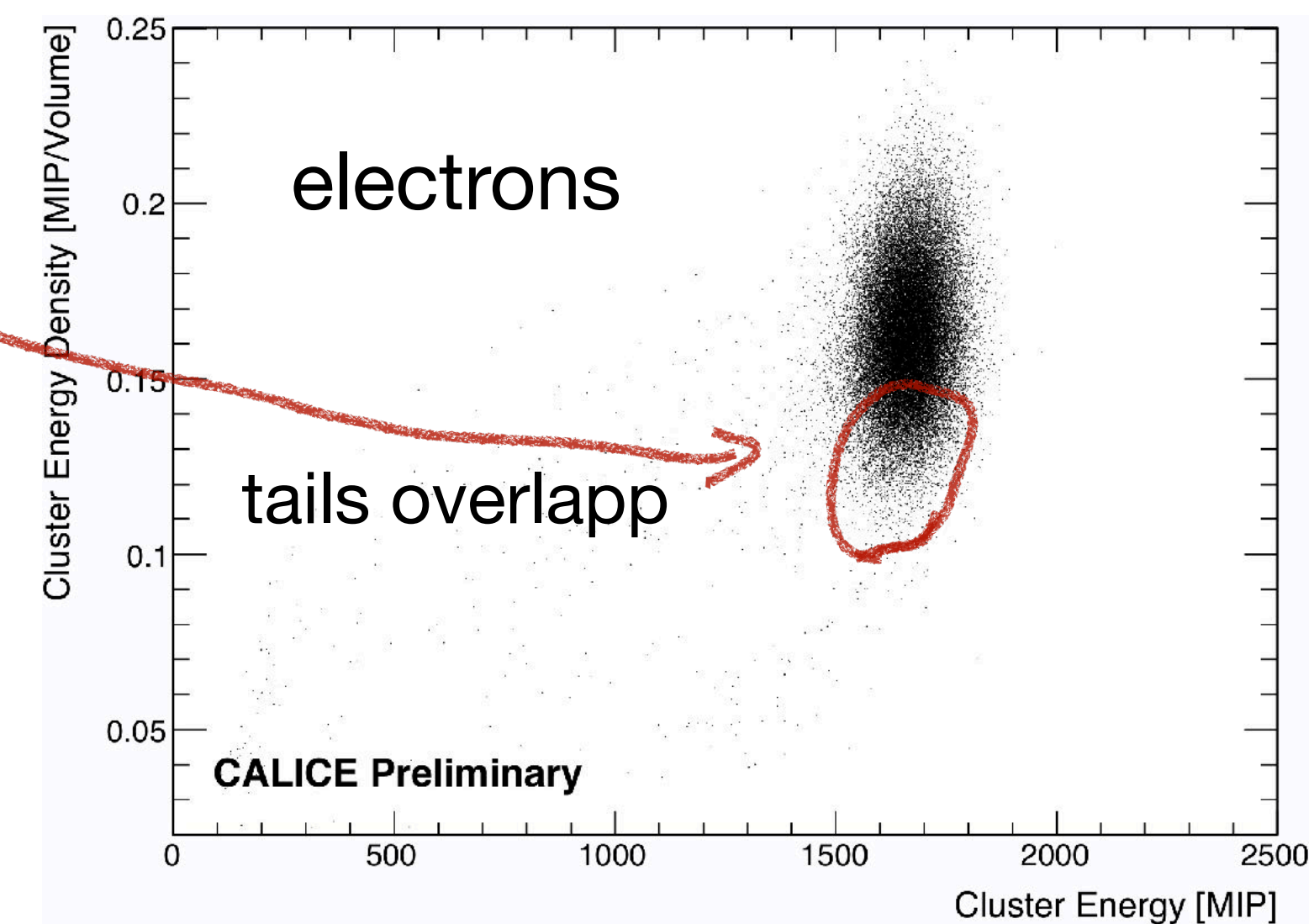
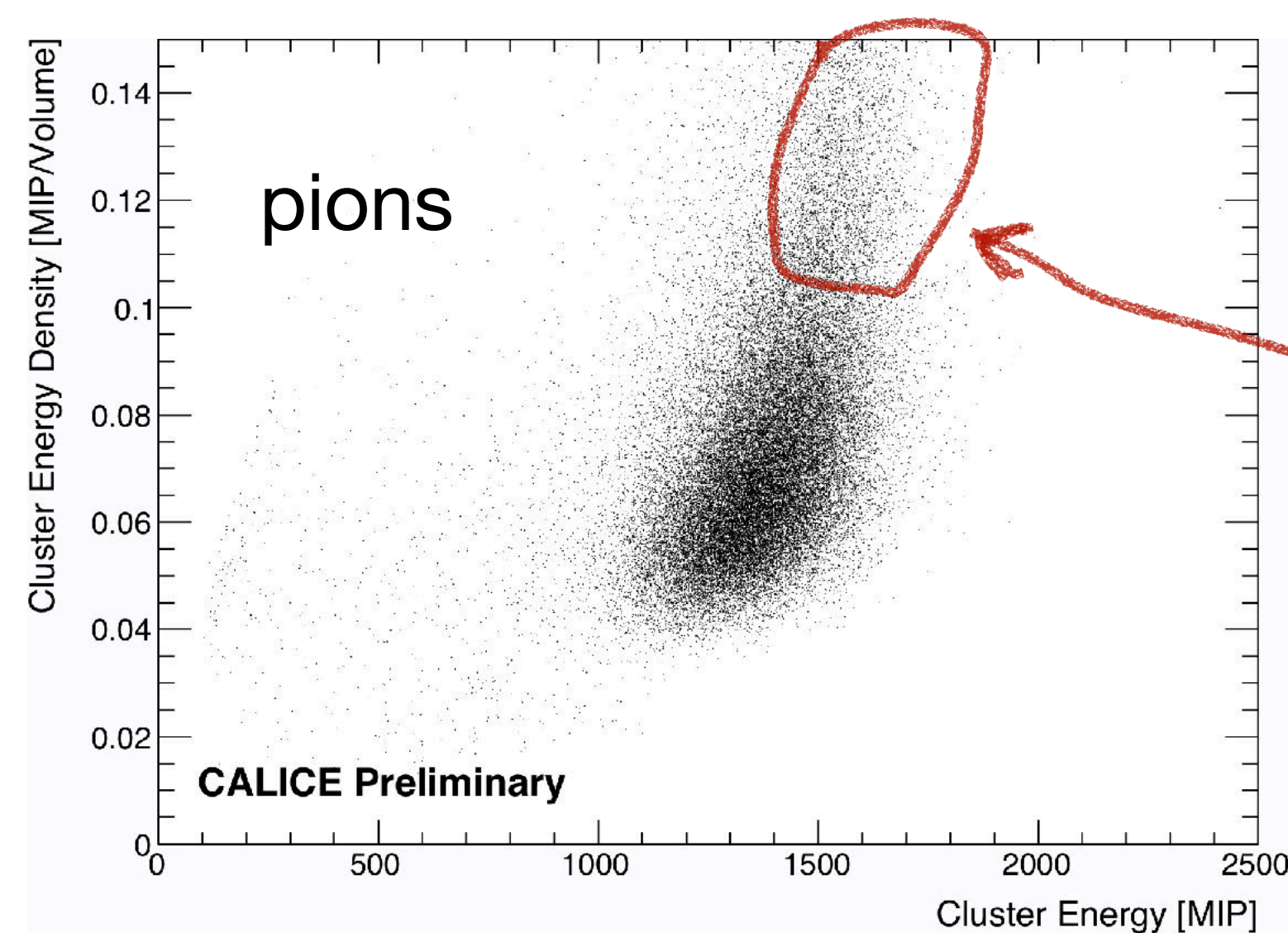
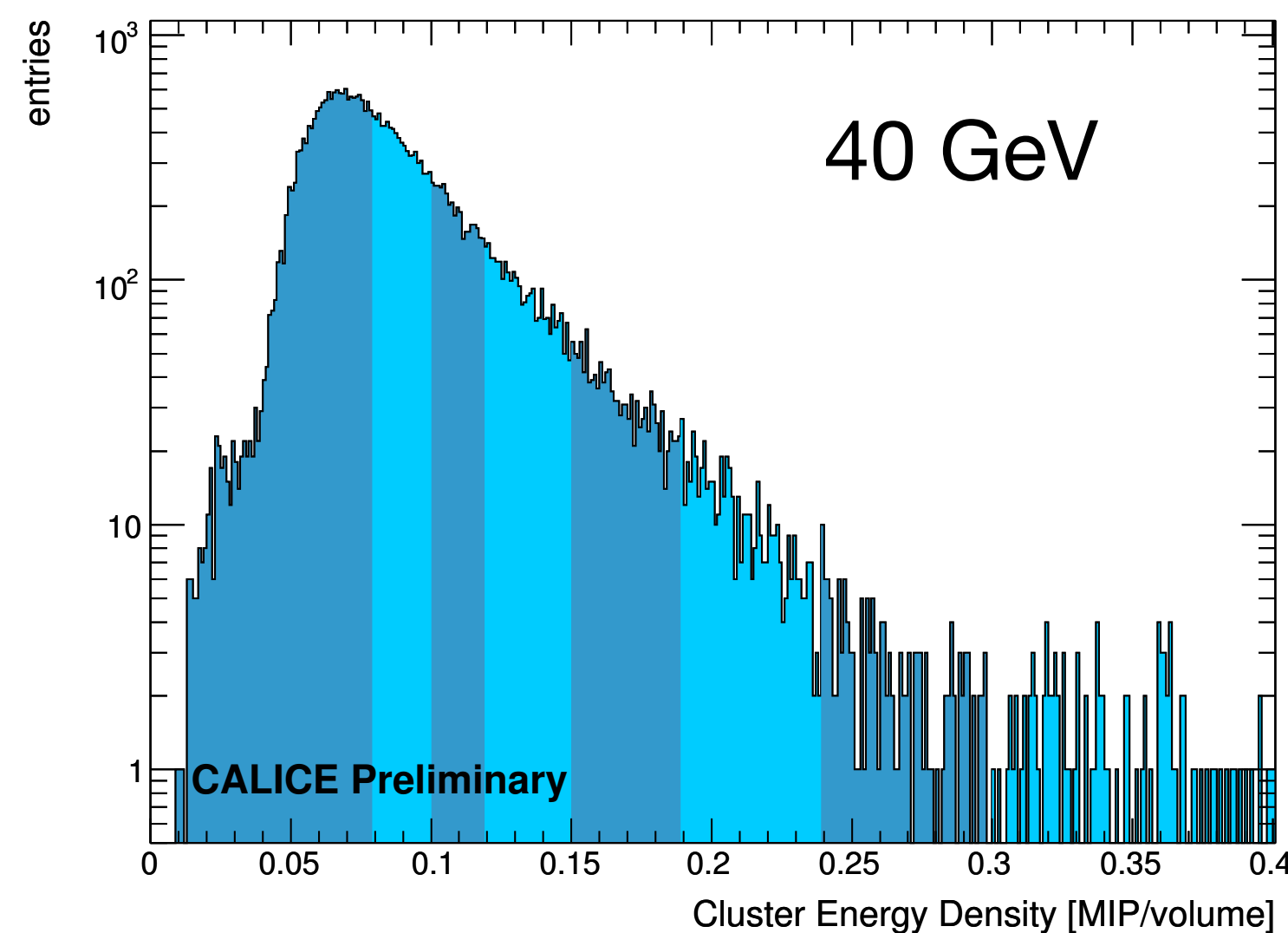
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Towards Multivariate Techniques

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Simple weighting using energy density only with parametrized weights from MC:
~ 15% improvement

Towards Multivariate Techniques

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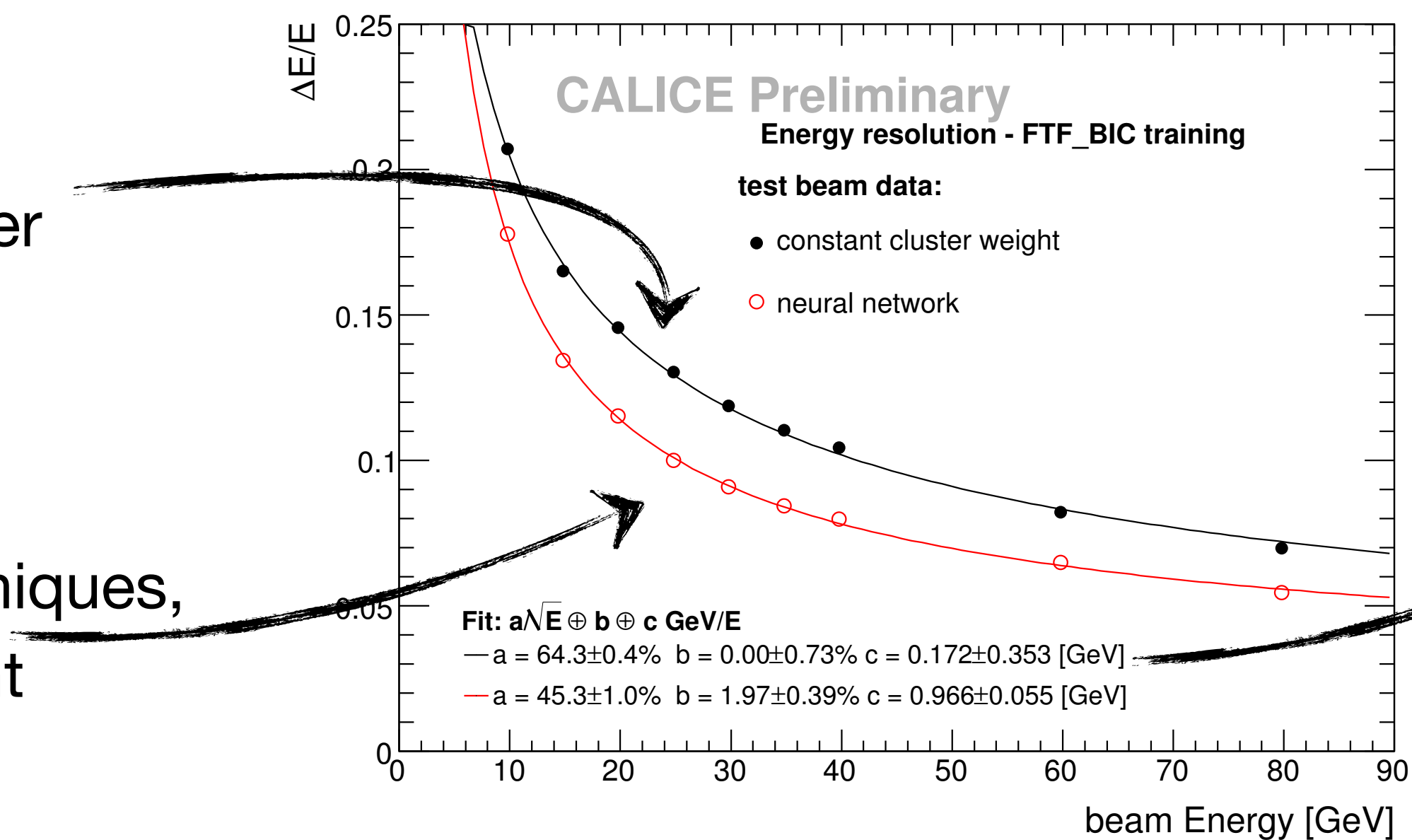
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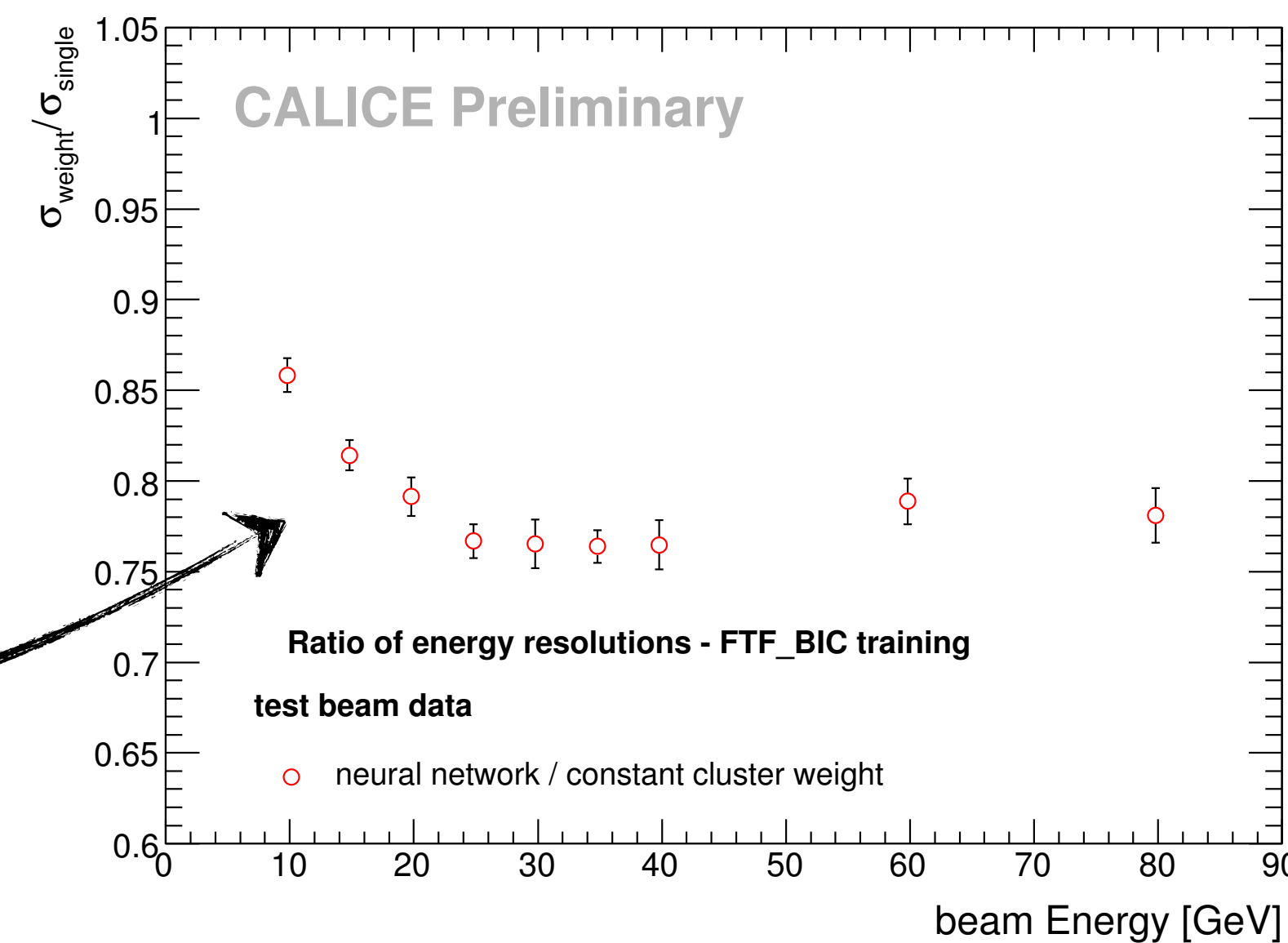
default resolution
~ 10-15% worse than other studies: clustering effects!

NN achieves performance comparable to other techniques, slightly larger improvement

⇒ *Substantial potential!*



NN: up to 25% improvement



Towards Multivariate Techniques

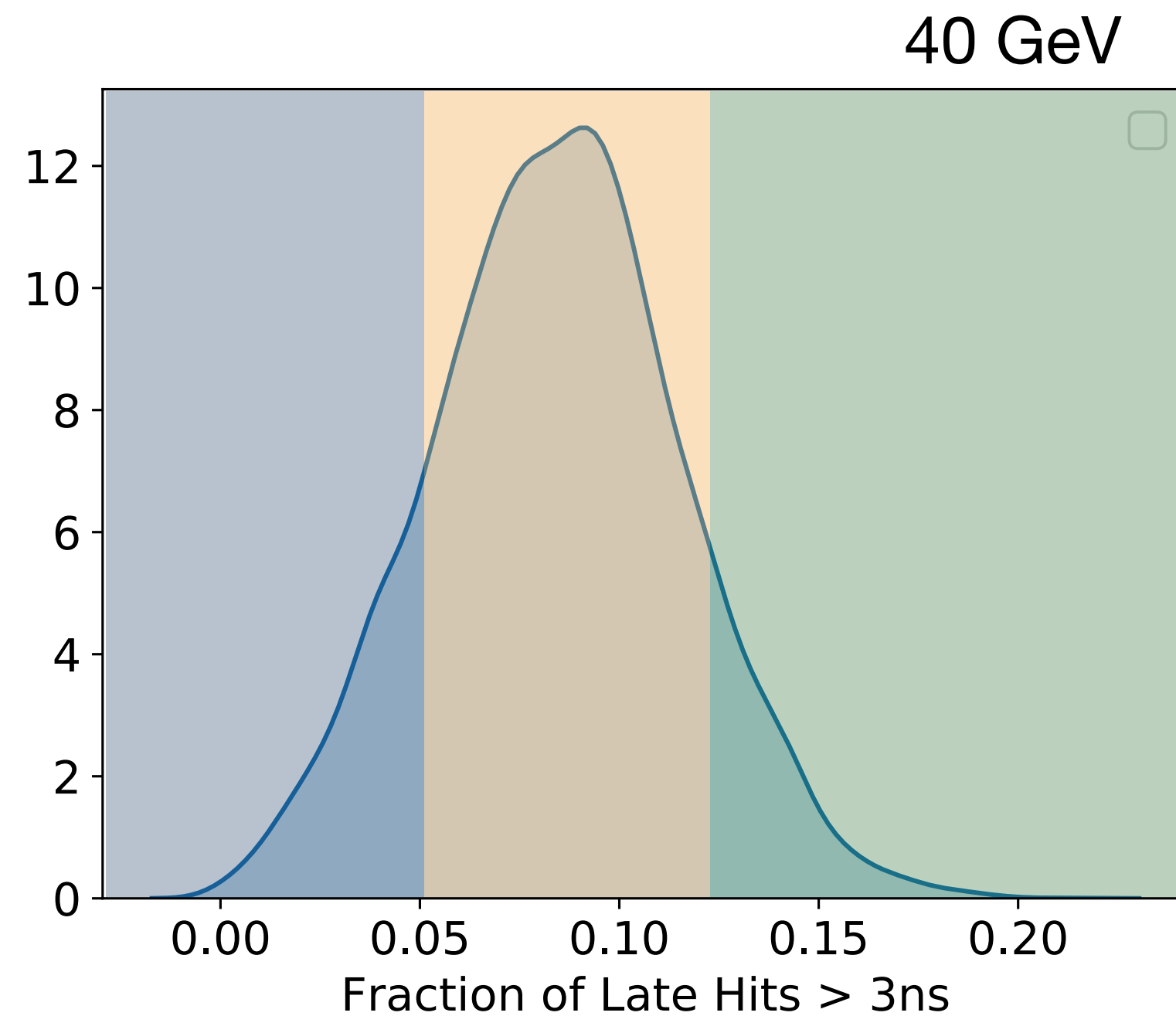
Machine Learning & Timing Information



C. Graf, work in progress

- New prototypes (and full detectors) will offer ns-level timing on the cell level
 - Obvious benefits for pattern recognition & background rejection
 - Benefits for energy resolution?

Simulation study for
AHCAL prototype



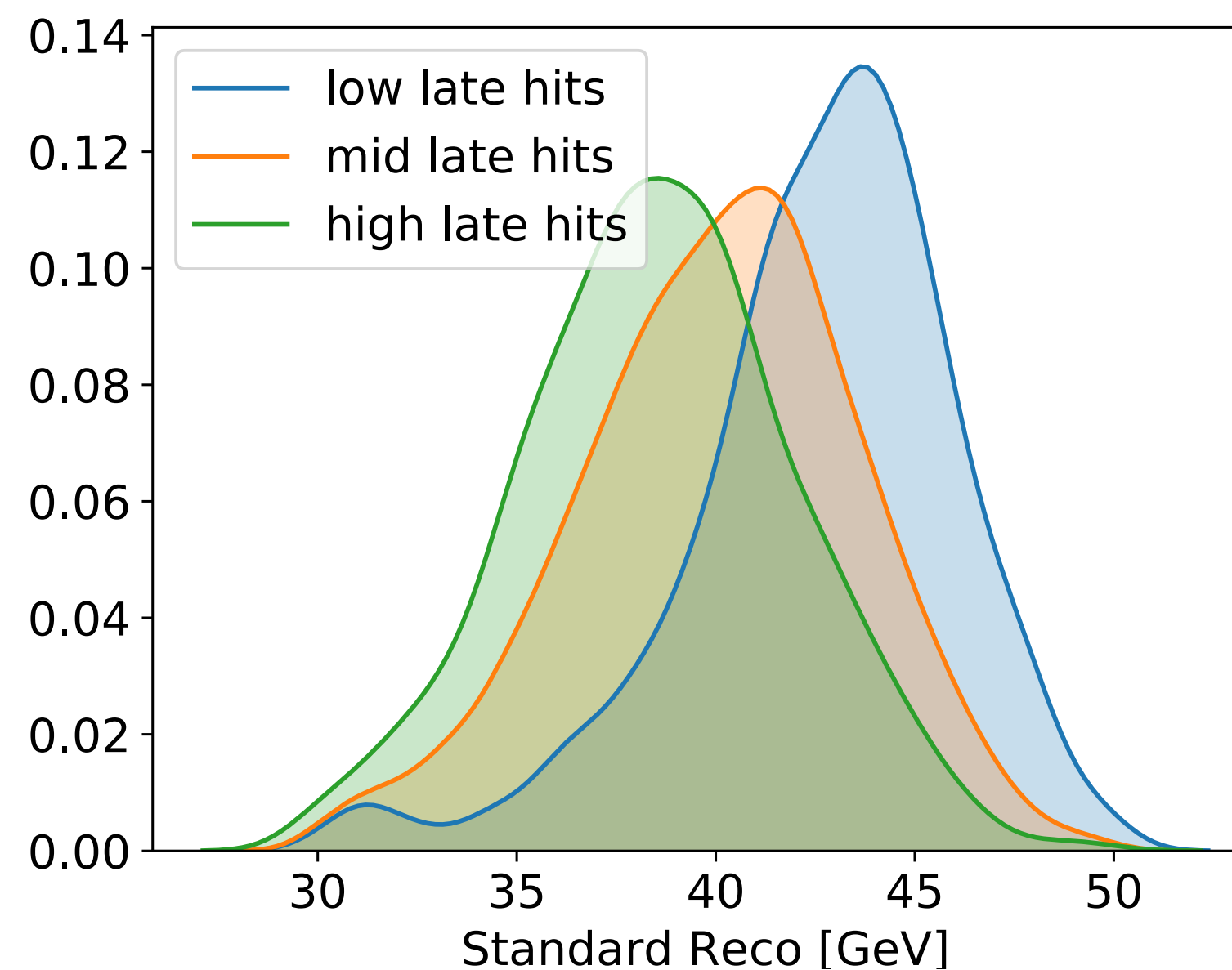
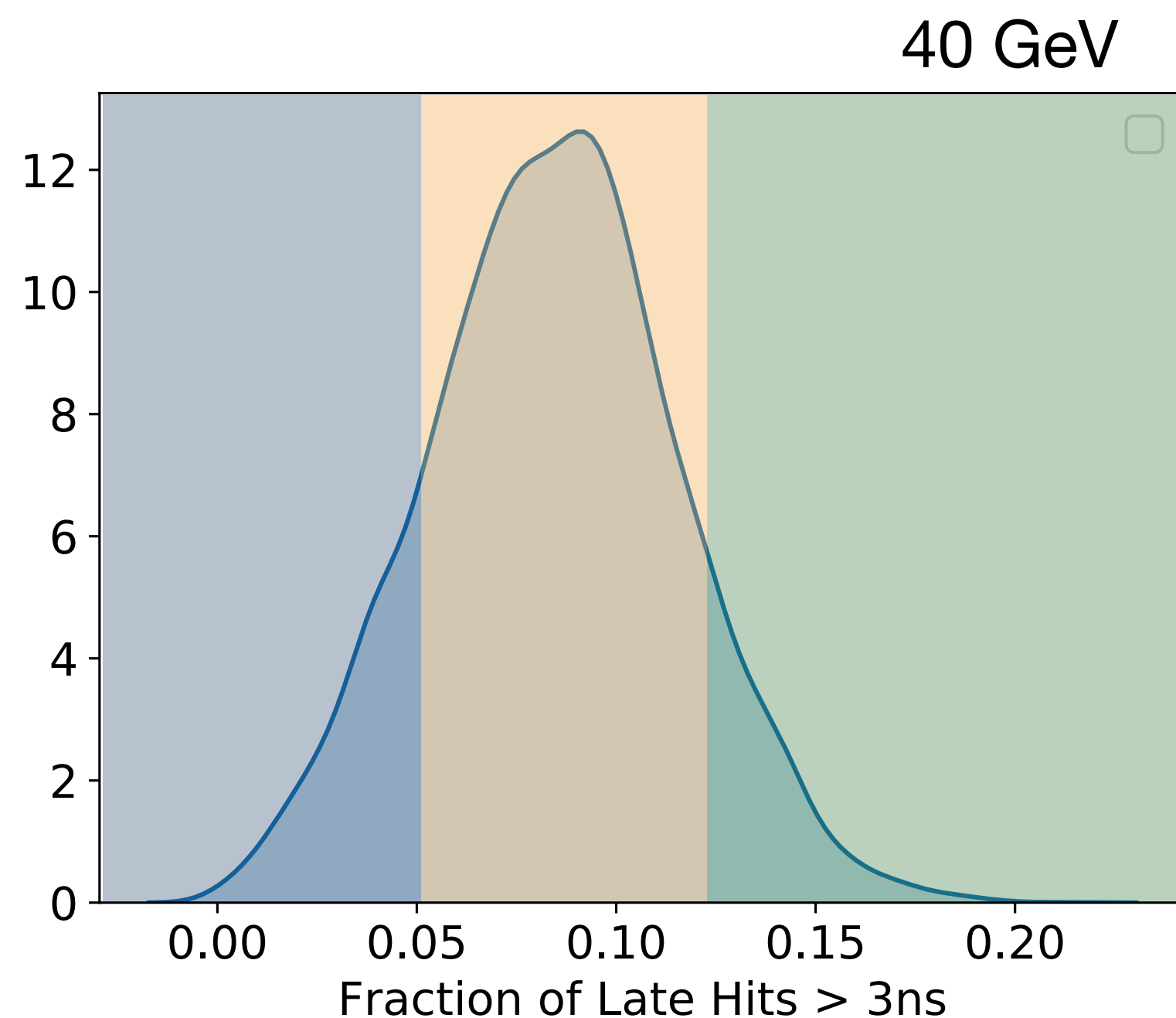
Towards Multivariate Techniques

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fraction of late hits in shower as
additional observable

Additional parameters, such as
layer-wise energy in neural network

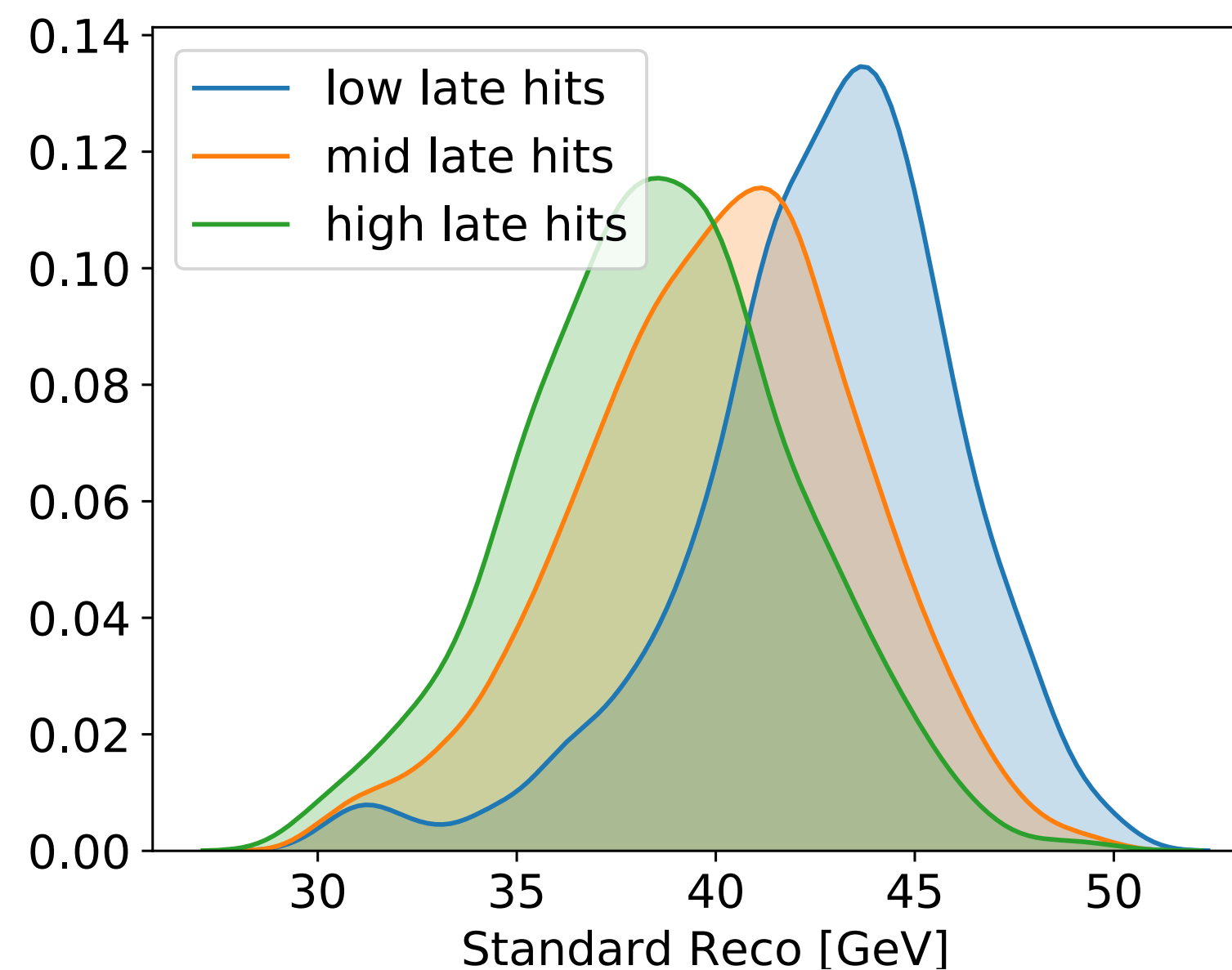
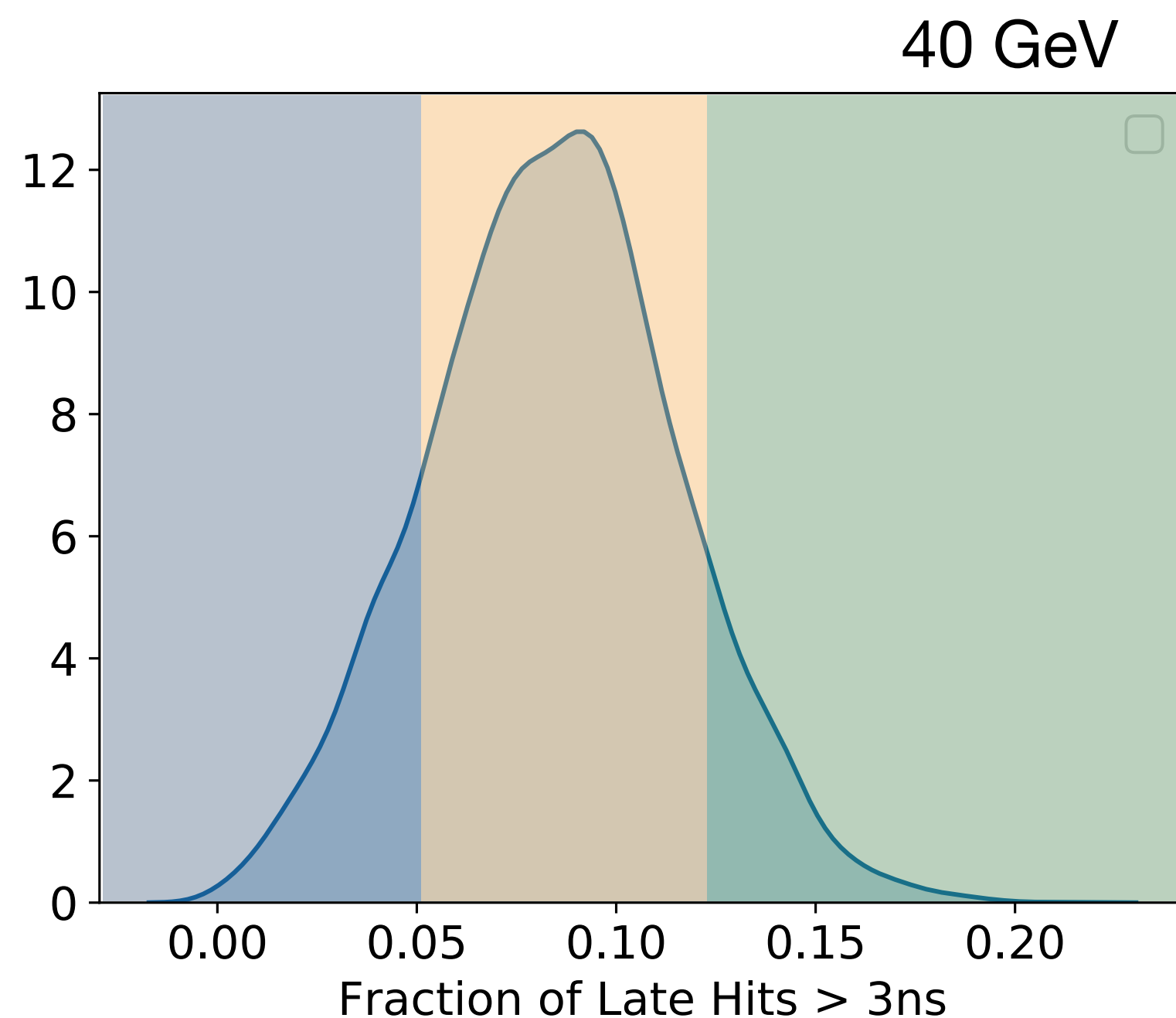
Towards Multivariate Techniques

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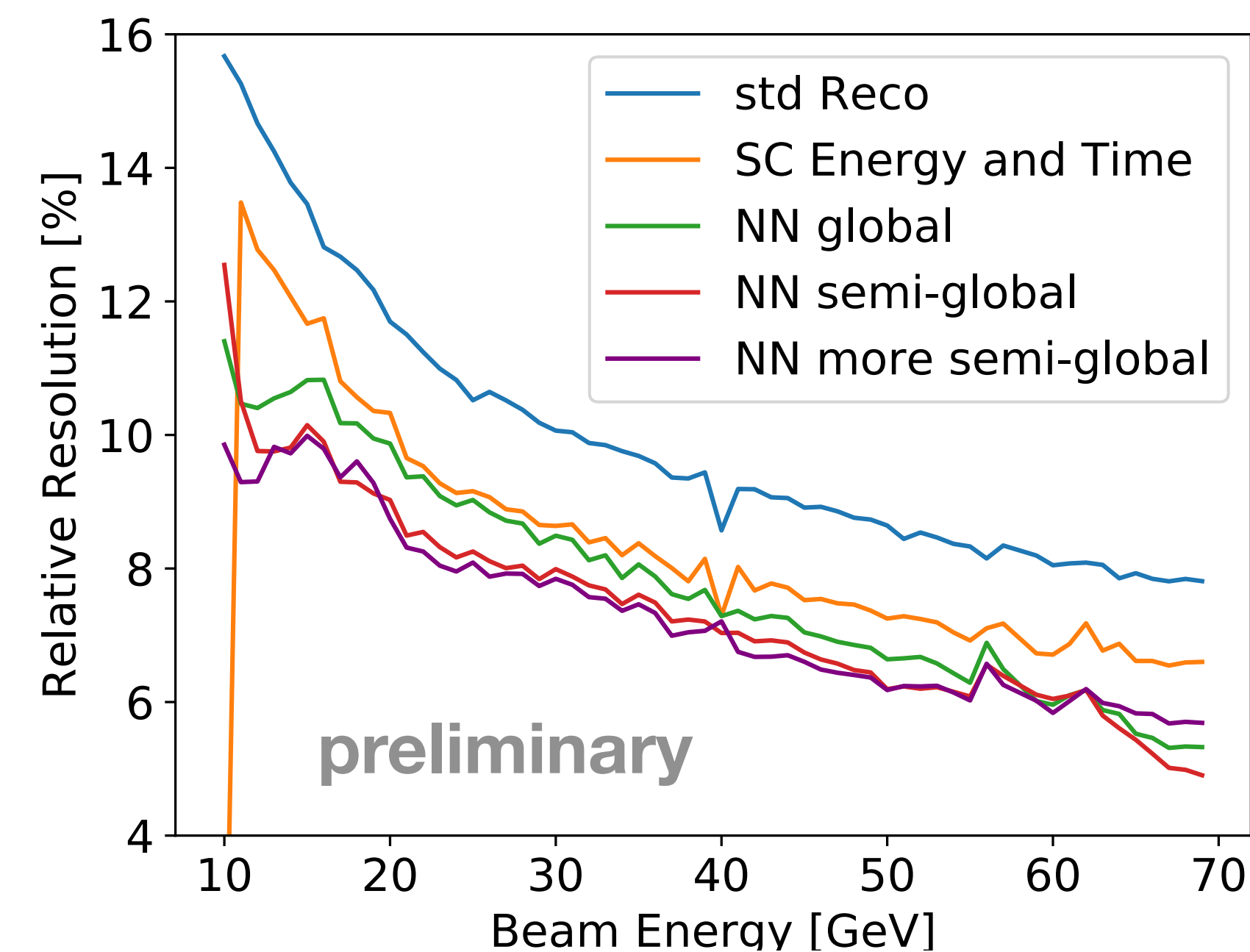
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fraction of late hits in shower as additional observable
Additional parameters, such as layer-wise energy in neural network



Study still in an early stage

- Timing adds some improvement to global SC (~ 10% in quadrature)
- Energy, in particular also local, more powerful

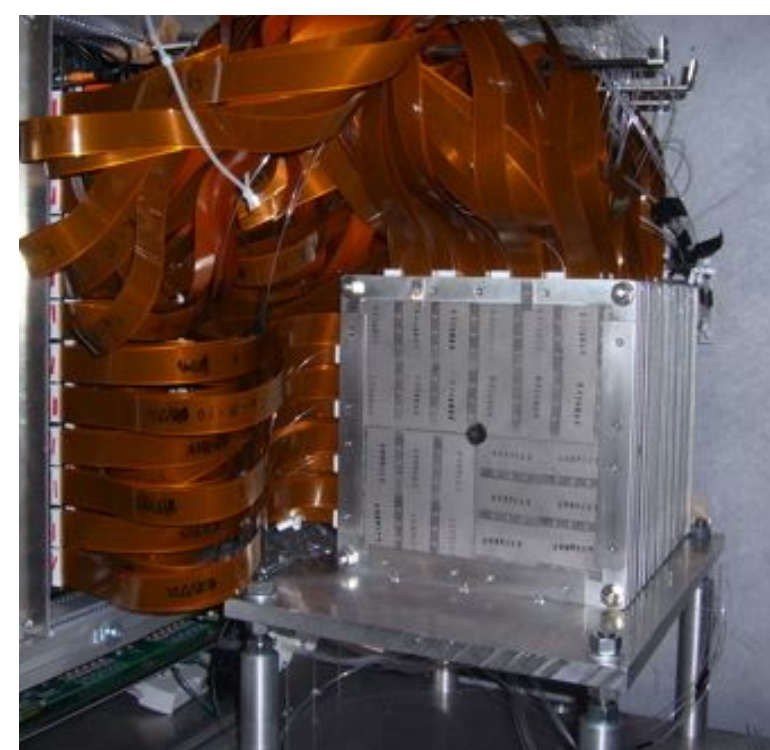
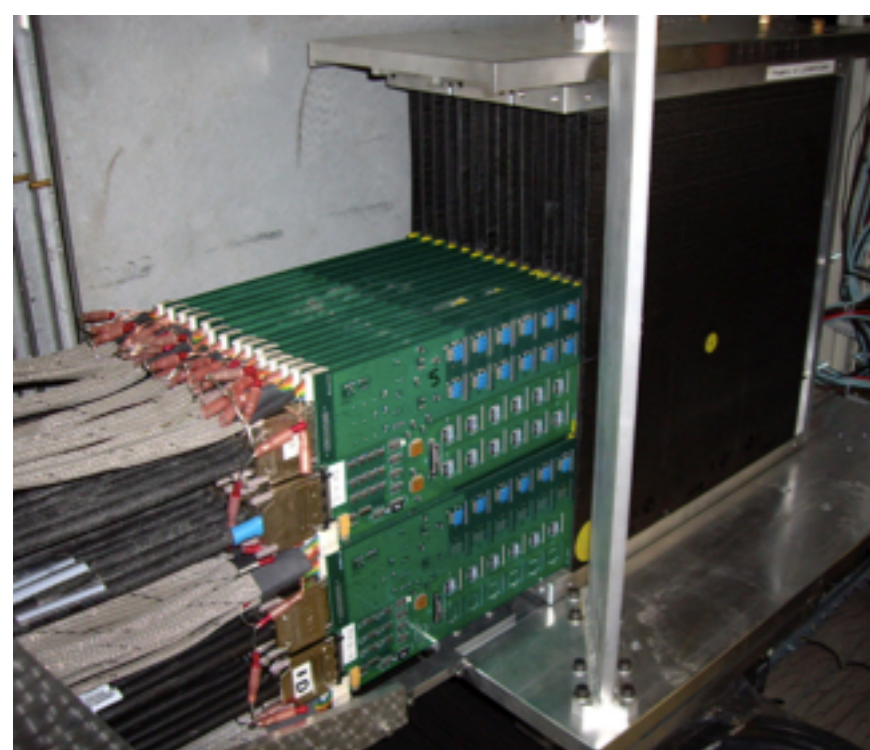
- Hadronic energy reconstruction in calorimeters is a challenge - and a limiting factor for overall detector performance
- Highly granular calorimeters provide detailed information on the shower substructure on an event-by-event level that can be used to improve the energy reconstruction & resolution: Used in **Software Compensation**
- Different techniques developed and studied in CALICE with test beam data:
Global and local software compensation, semi-digital reconstruction,
global software compensation with neural networks
 - Successfully applied to single detectors and combined ECAL and HCAL systems - with typical resolution improvement of 20% - 30% for pions with energies above ~ 15 GeV
 - Implemented in PandoraPFA for the AHCAL
- Substantial potential for further improvement: Addition of new variables (time), more sophisticated machine learning techniques, extension to electromagnetic showers, ...

Extras

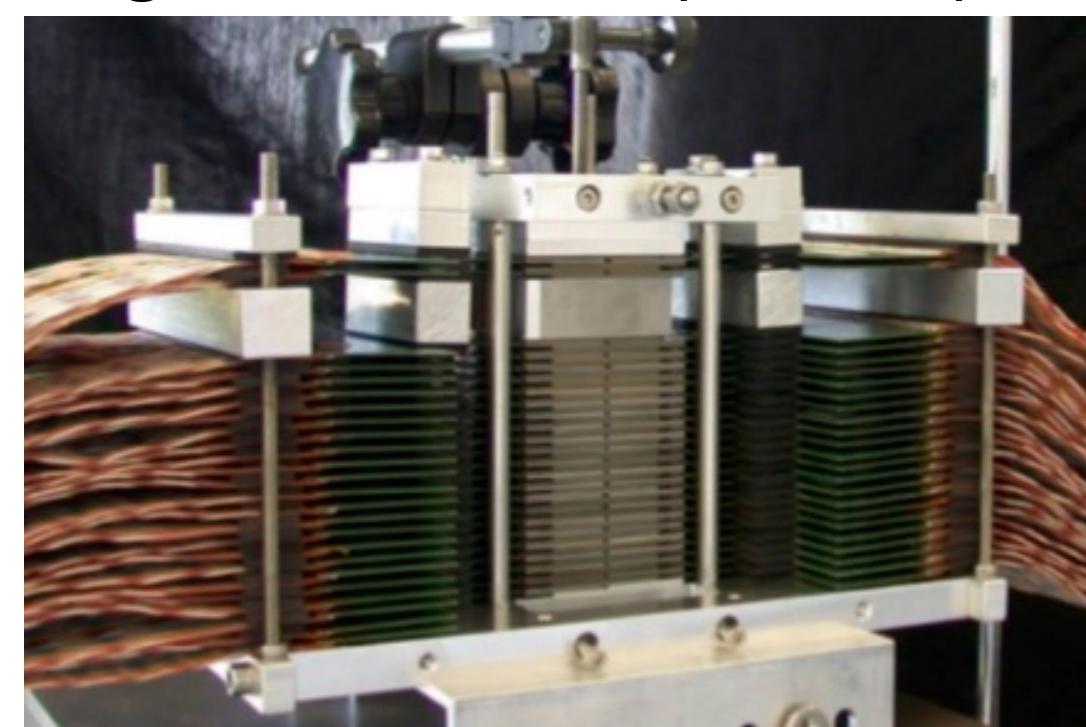
- A rich test beam program, with a variety of different prototypes

Electromagnetic - Tungsten absorbers

analog: Silicon and Scintillator/SiPM



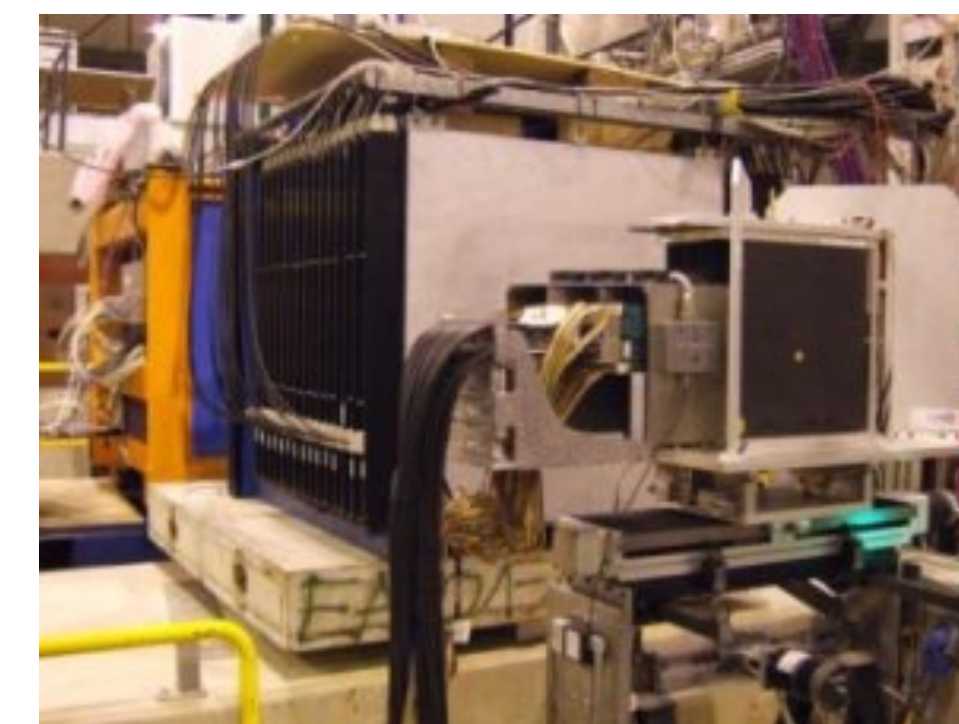
digital: Silicon (MAPS)



39 Mpixels in
160 cm²

Hadronic - Steel and Tungsten absorbers

analog:
Scintillator/SiPM
(Fe and W)



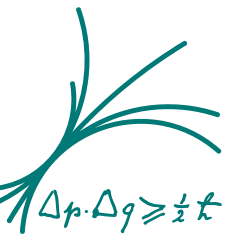
(Semi)digital: RPCs (Fe, W digital only)



+ few-layer SD prototype with Micromegas

CALICE Prototypes

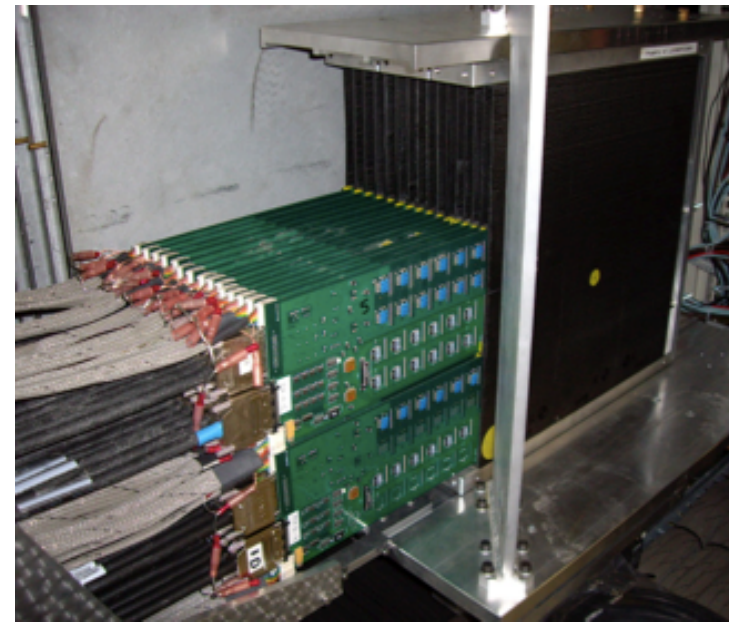
Evolution with Time



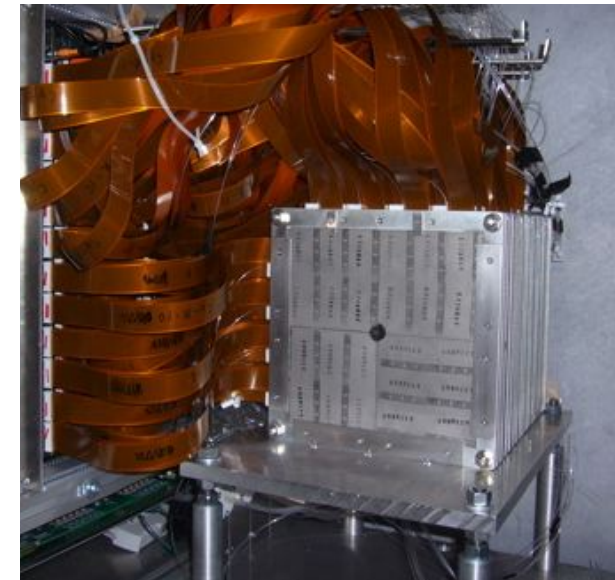
Physics Prototypes

Technological Prototypes

SiW ECAL



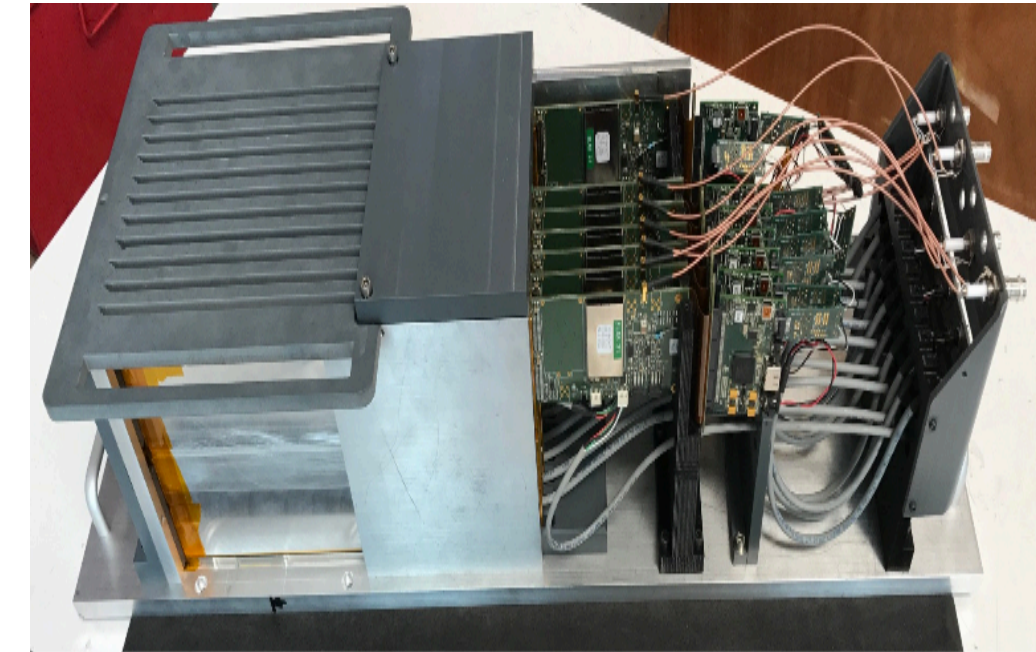
ScintW ECAL



SDHCAL



SiW ECAL



2006

2007

2008

2010

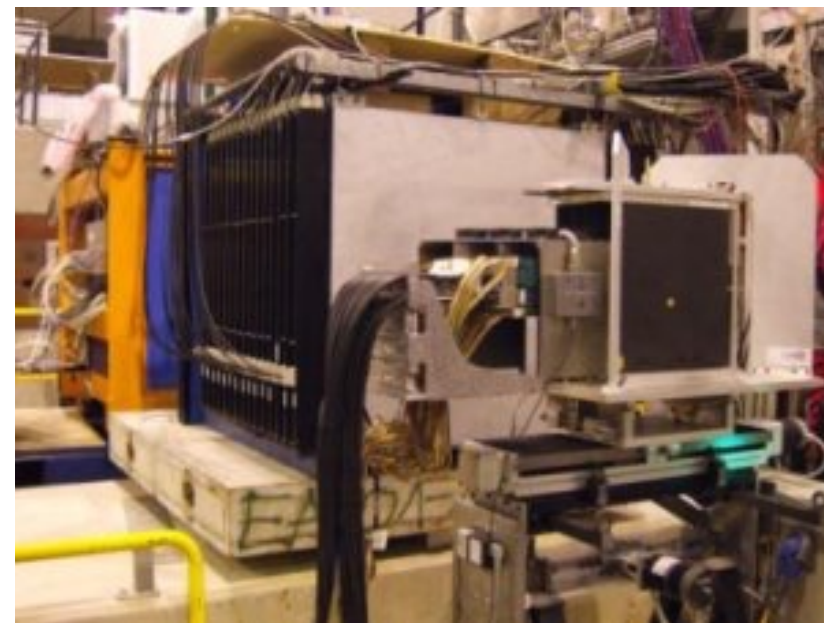
2012

2018

year of (first) TB

2005

AHCAL



DHCAL



AHCAL



also: W-AHCAL

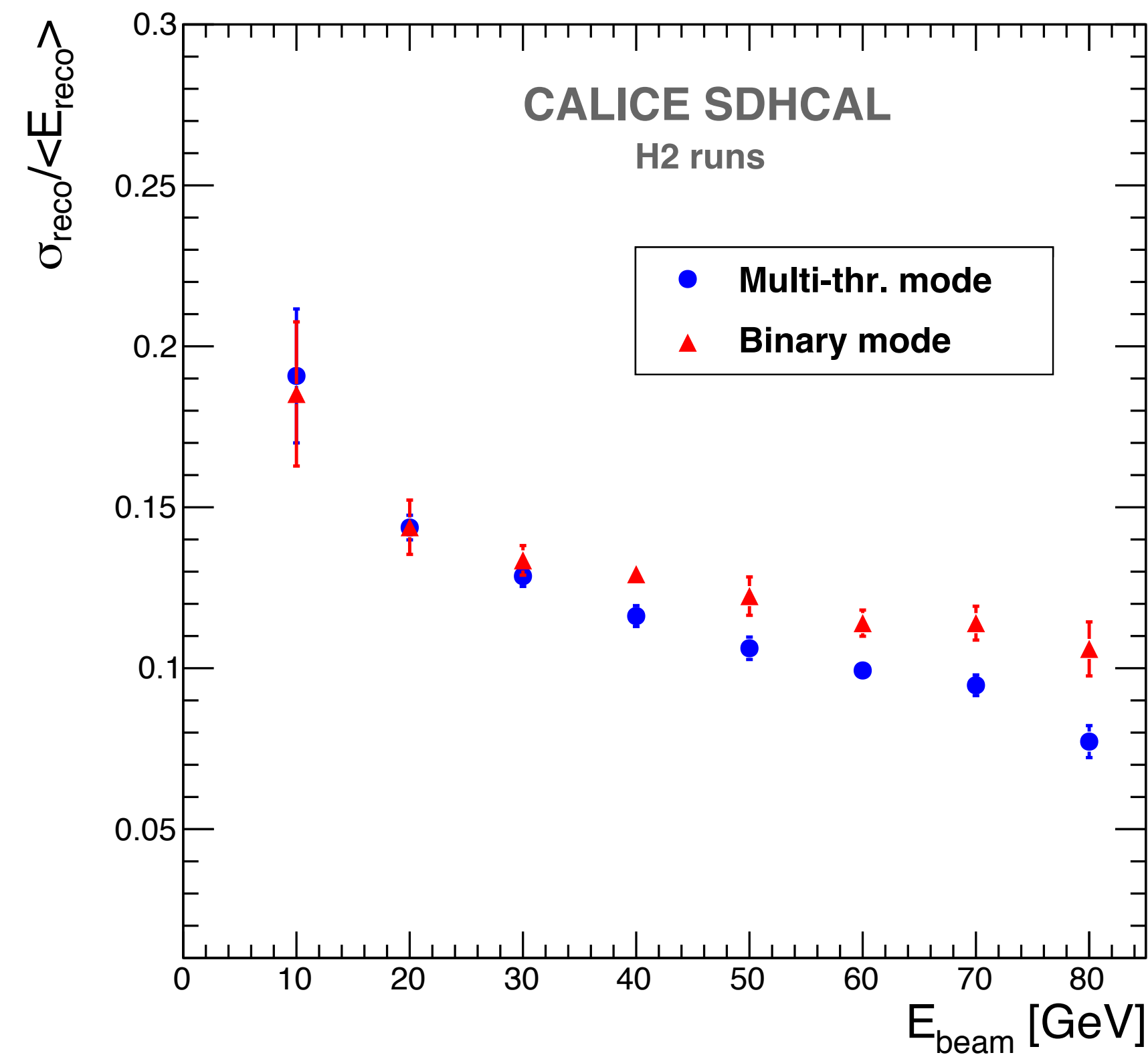
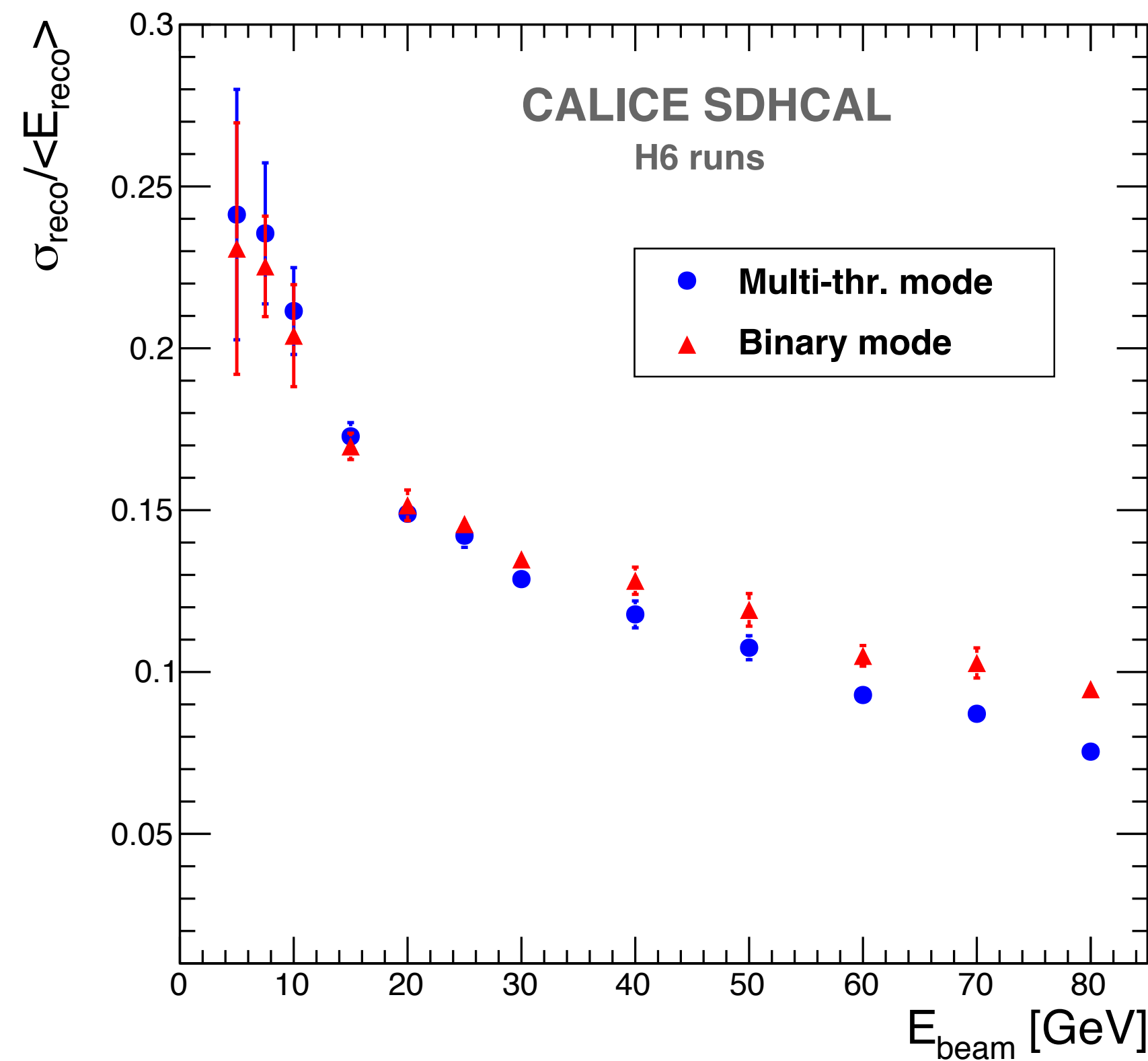
also: W-DHCAL

Digital vs Semi-Digital Reconstruction

In the RPC SDHCAL

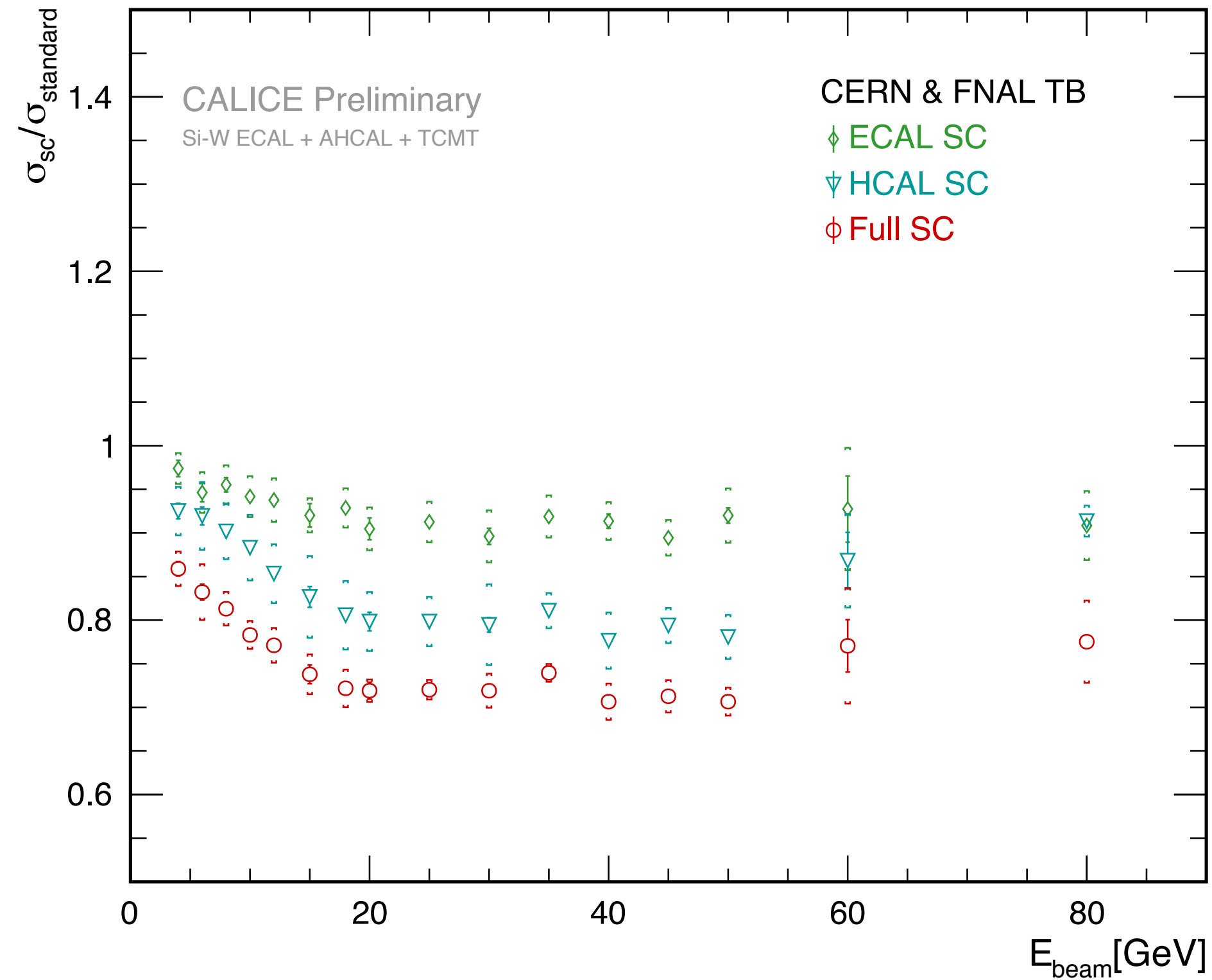
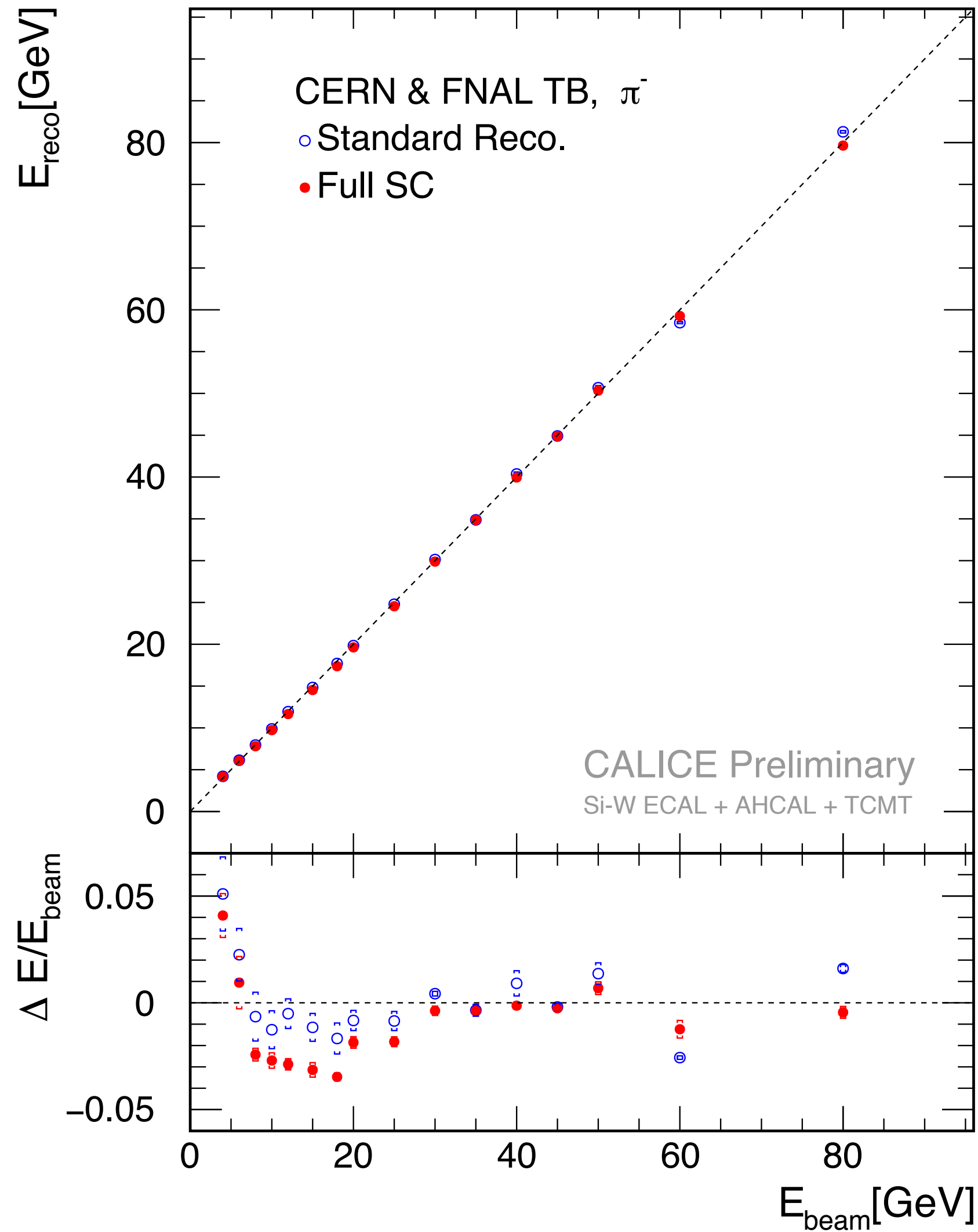


- At energies above 30 GeV semi-digital reconstruction provides a substantial performance advantage wrt digital reconstruction: Saturation effects become relevant



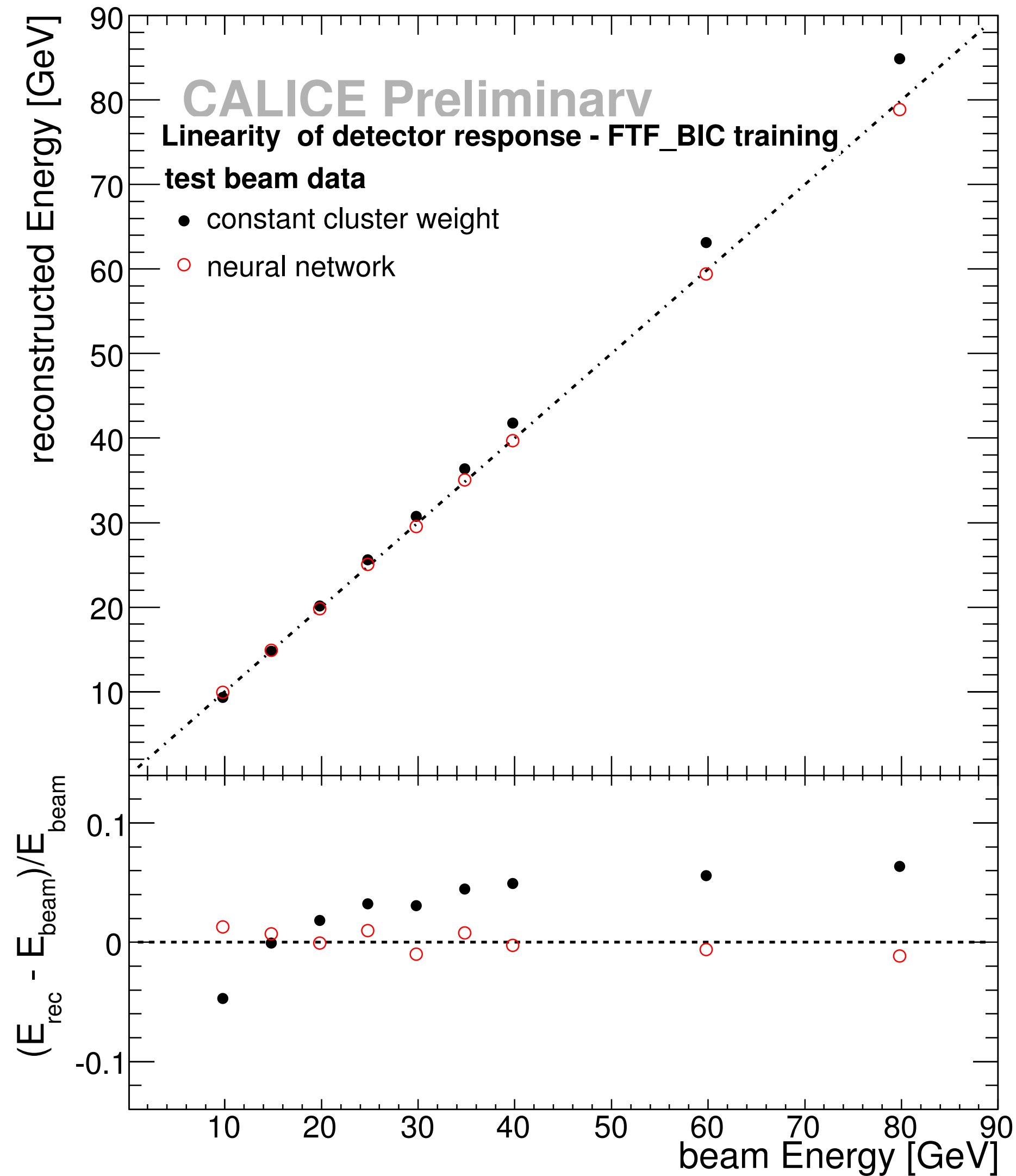
Comined ECAL/HCAL Software Compensation

Linearity & Resolution Improvement



Software Compensation with Neural Networks

CALICE AHCAL: Linearity



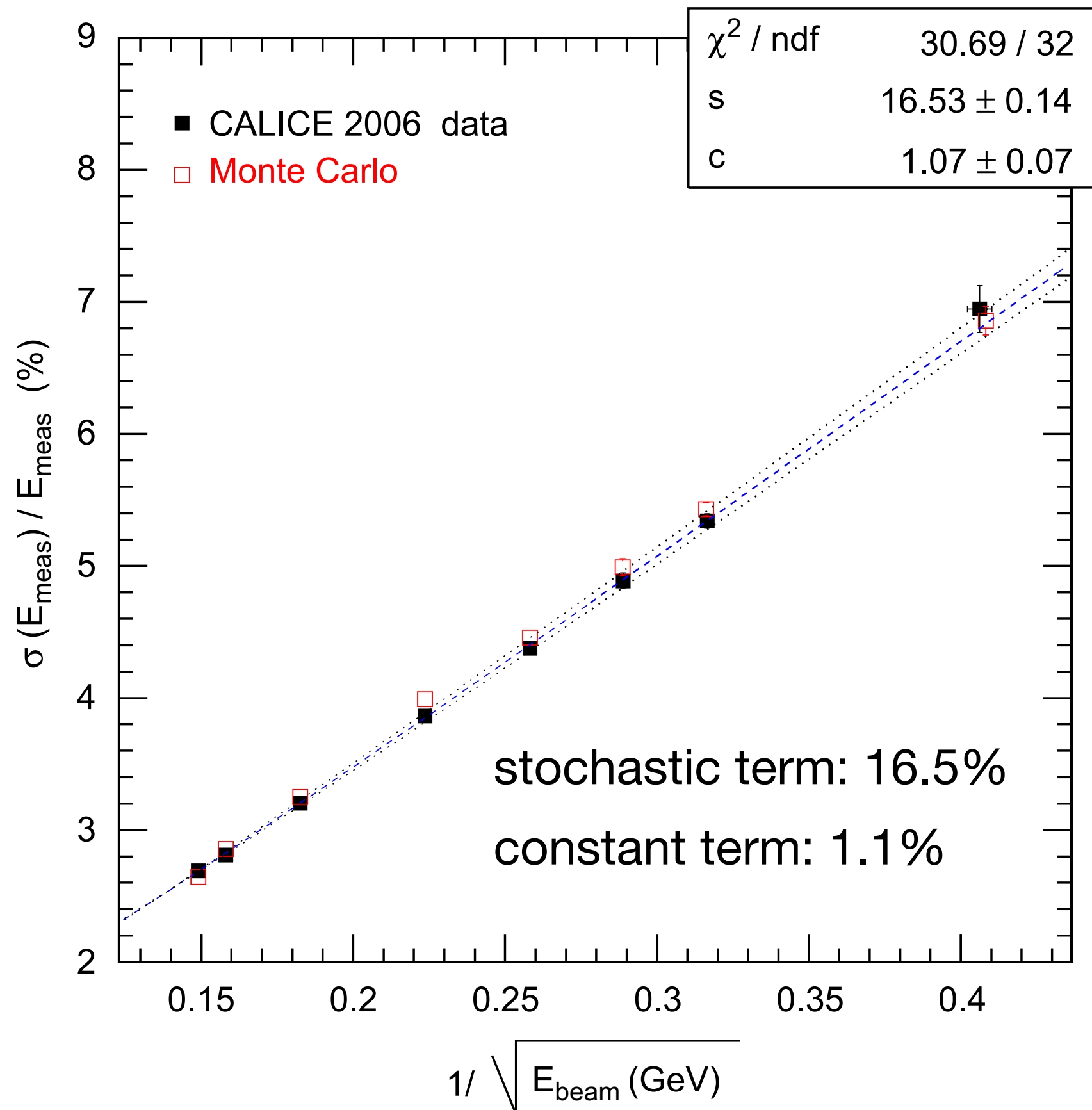
Performance of Highly Granular Calorimeters

Energy resolution - Electromagnetic

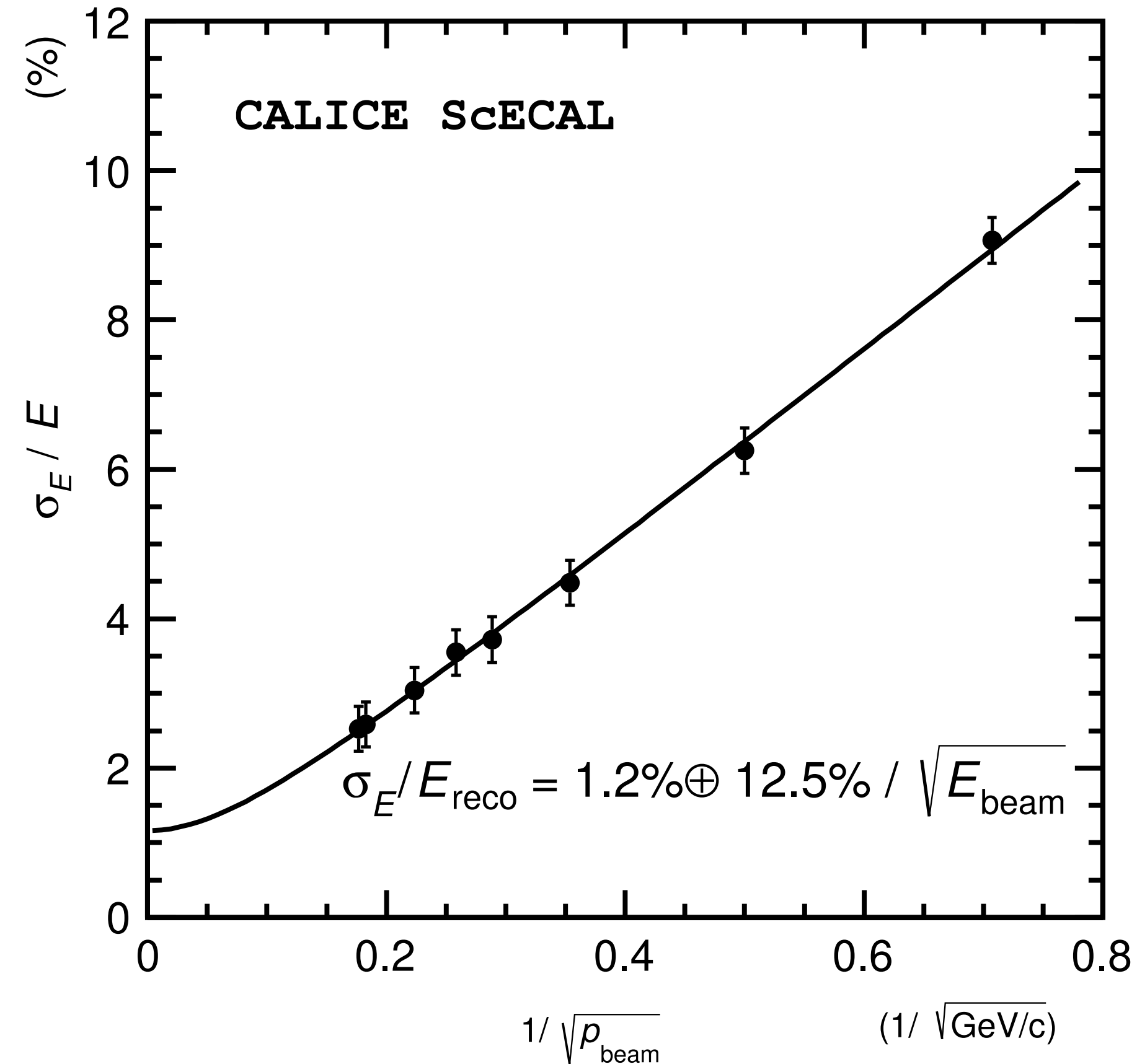


[N.B. Detector optimized for particle separation, not single particle resolution]

Silicon-Tungsten ECAL:



Scintillator-Tungsten ECAL:



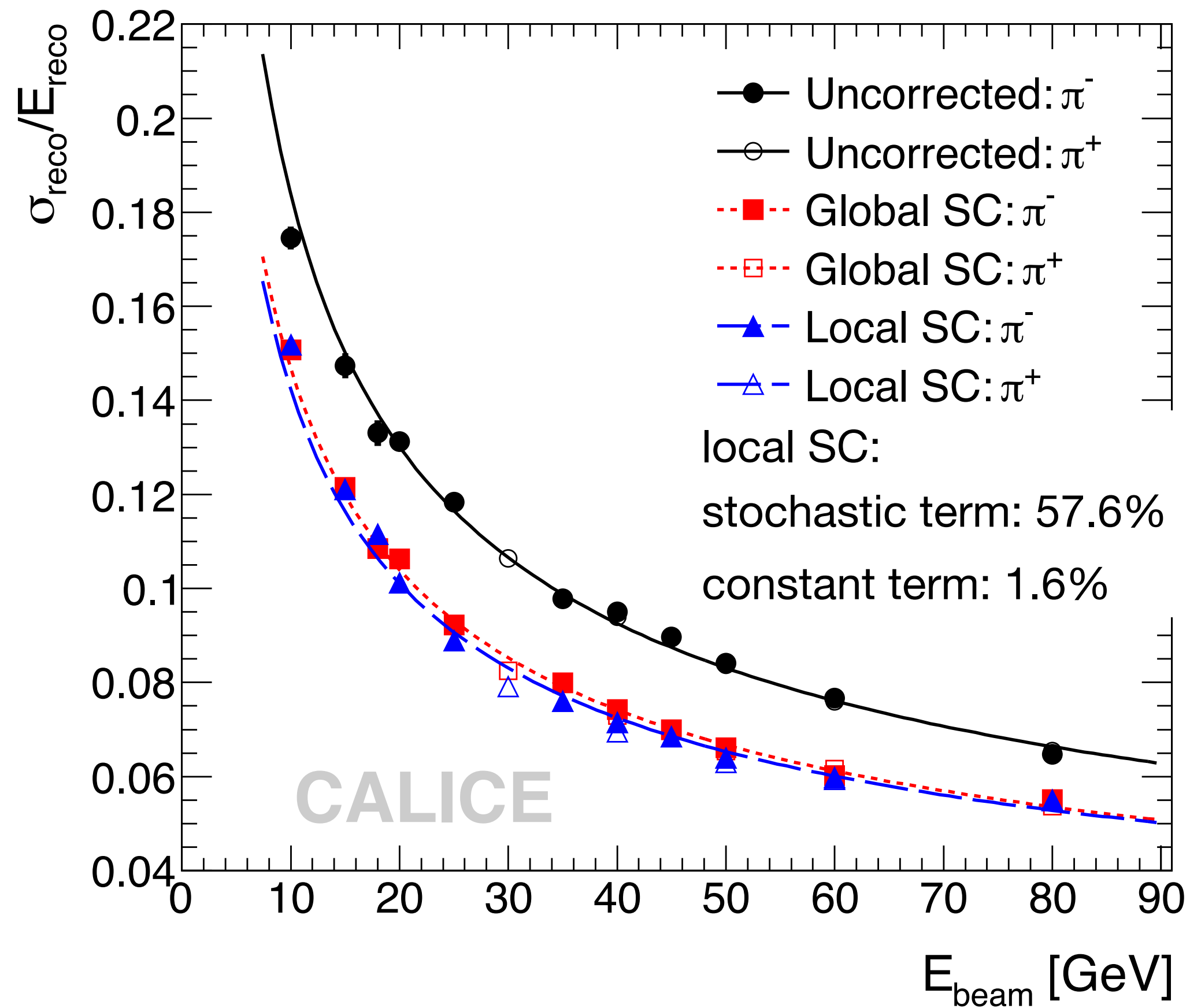
Scintillator provides better energy resolution due to larger sampling fraction, with a reduced compactness

Performance of Highly Granular Calorimeters

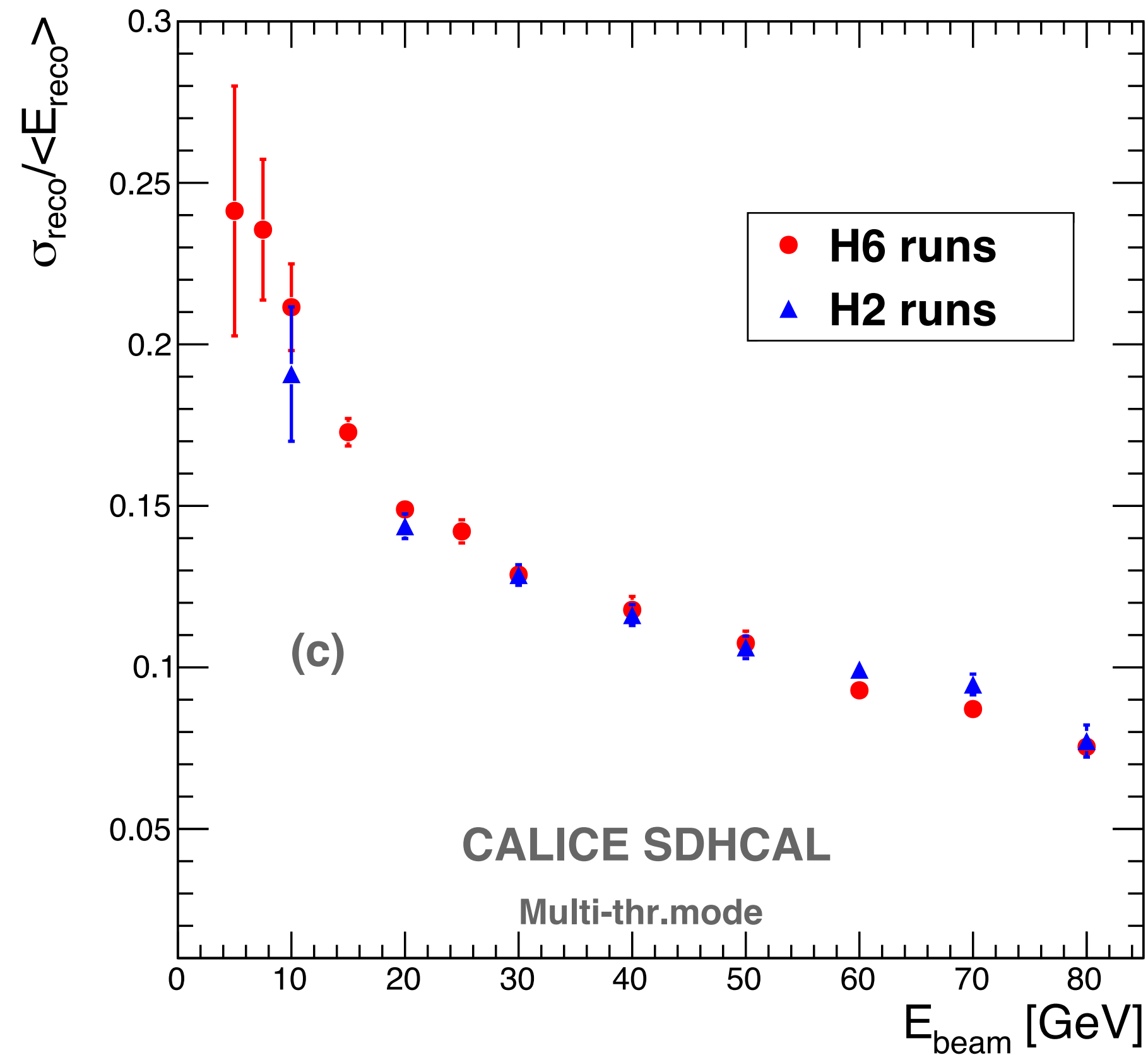
Energy resolution -Hadronic



Analog (Scintillator + SiPM)



semi-digital (RPCs)



Software compensation (SC) and semi-digital reconstruction use weighting factors to optimise energy resolution