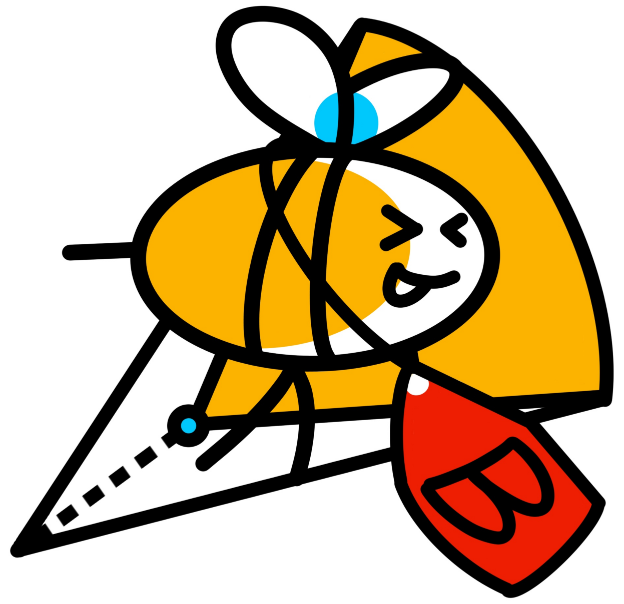
From jet flavour tagging to $H \to c\bar{c}$: probing Higgs couplings at CMS

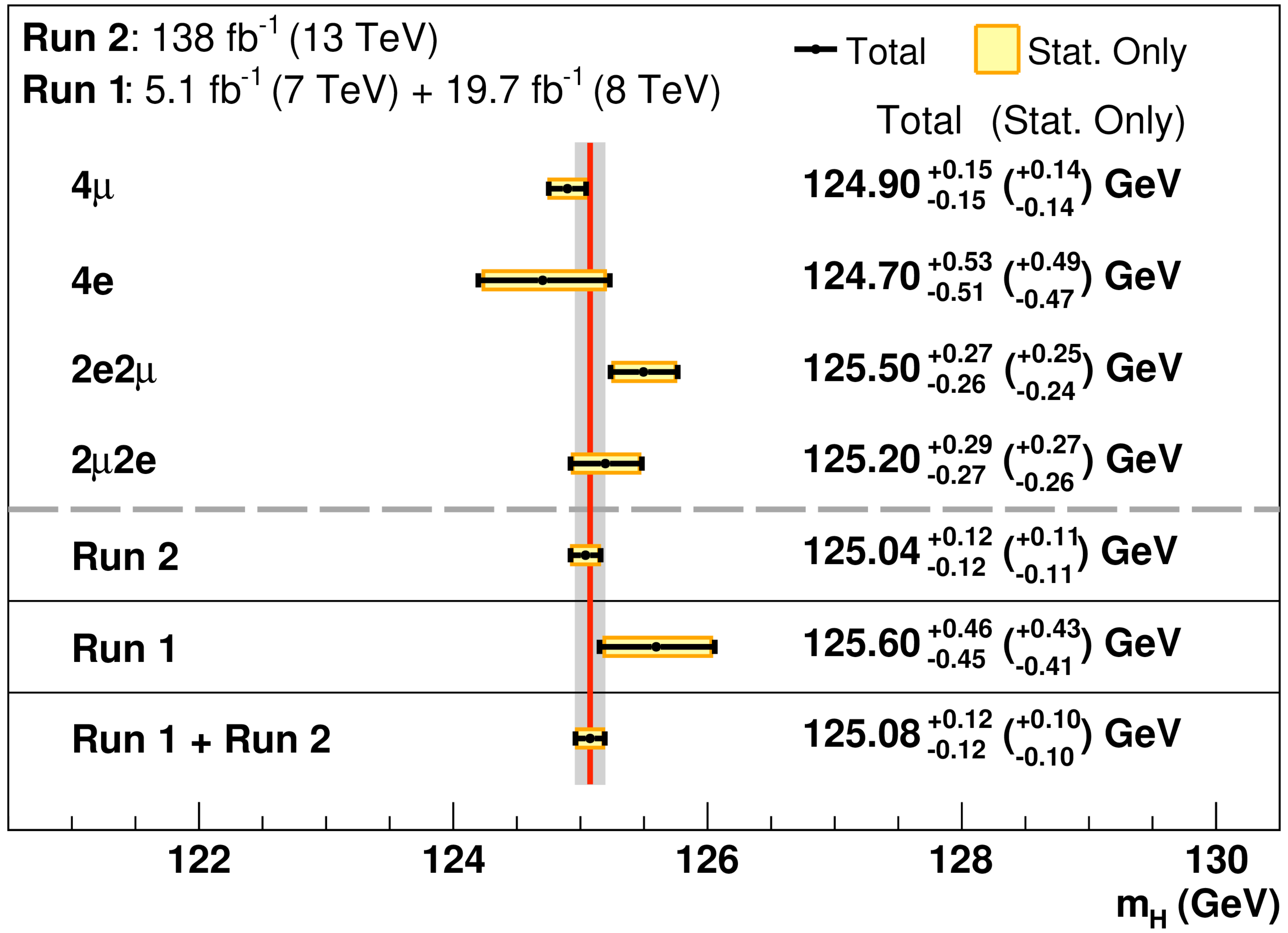


Sebastian Wuchterl (CERN)

Introduction and motivation

- 10+ years ago: A new era of particle physics
  - Confirmation of the Higgs-mechanism
  - Masses of W/Z bosons through EW symmetry breaking
  - Fermion masses added ad-hoc via Yukawa couplings

[CMS-HIG-21-019]



- Tremendous progress in understanding the Higgs boson
- Mass measured with per-mil precision
- From discovery to precision in one decade!

Introduction and motivation

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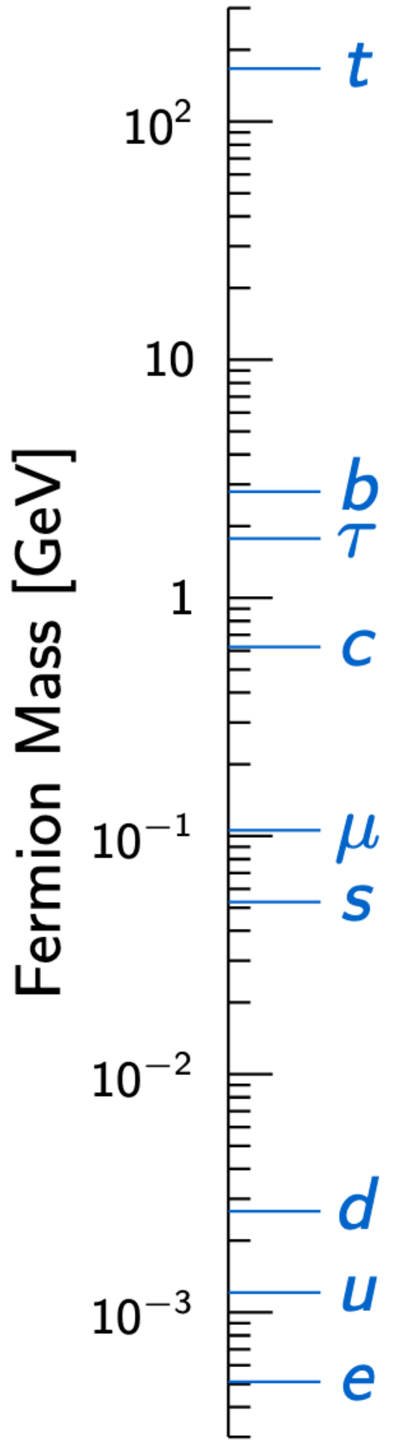


Mass hierarchy?

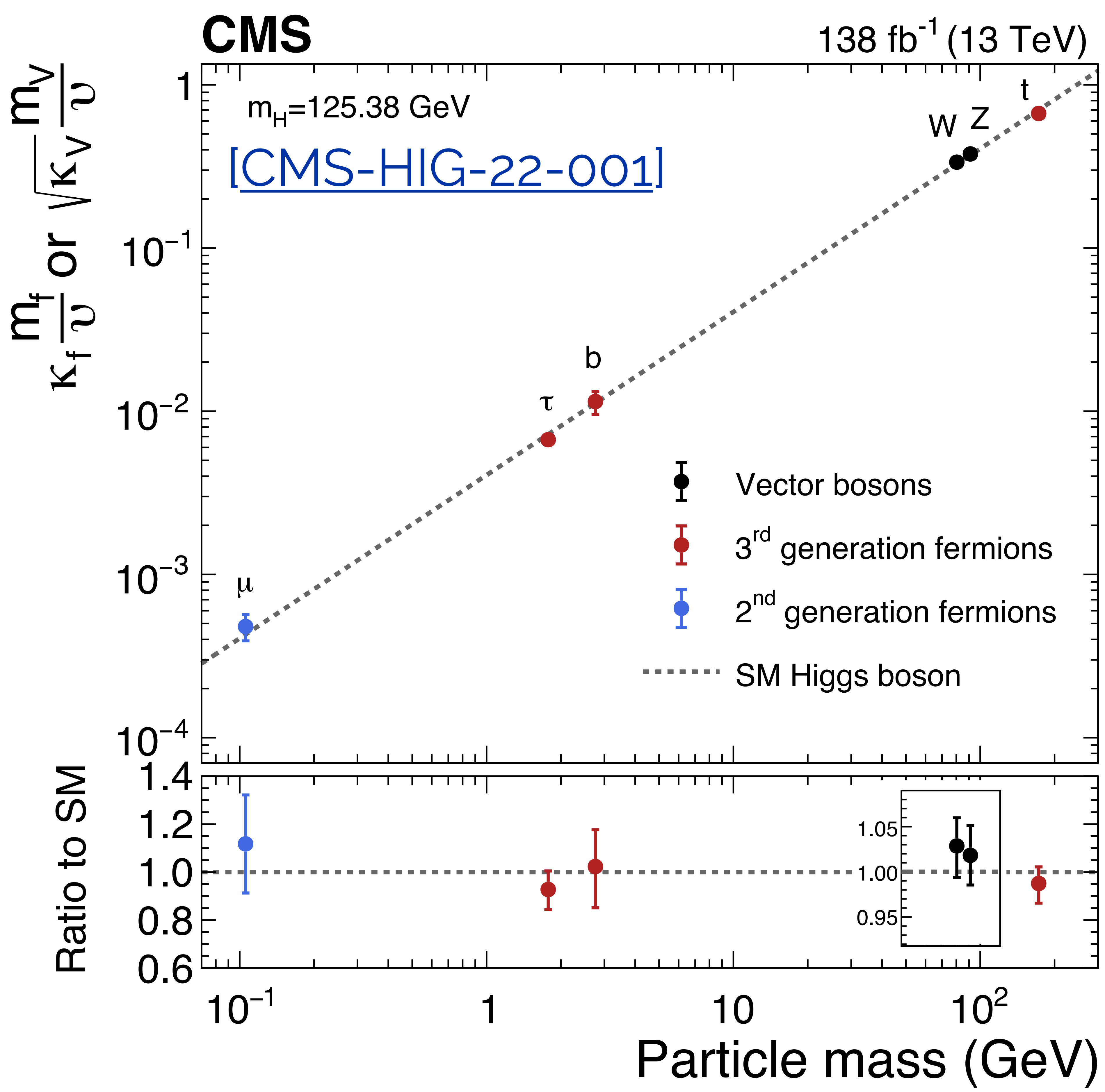
BSM modifications?

See e.g. arXiv:2410.05236
Phys. Rev. D 100, 115041
Phys. Rev. D 94, 115031

- But how much closer are we to fundamentally understanding fermion mass generation?
- With known m_H, fixed predictions for decay and production rates

Study of cross section and decay rates of utmost importance!

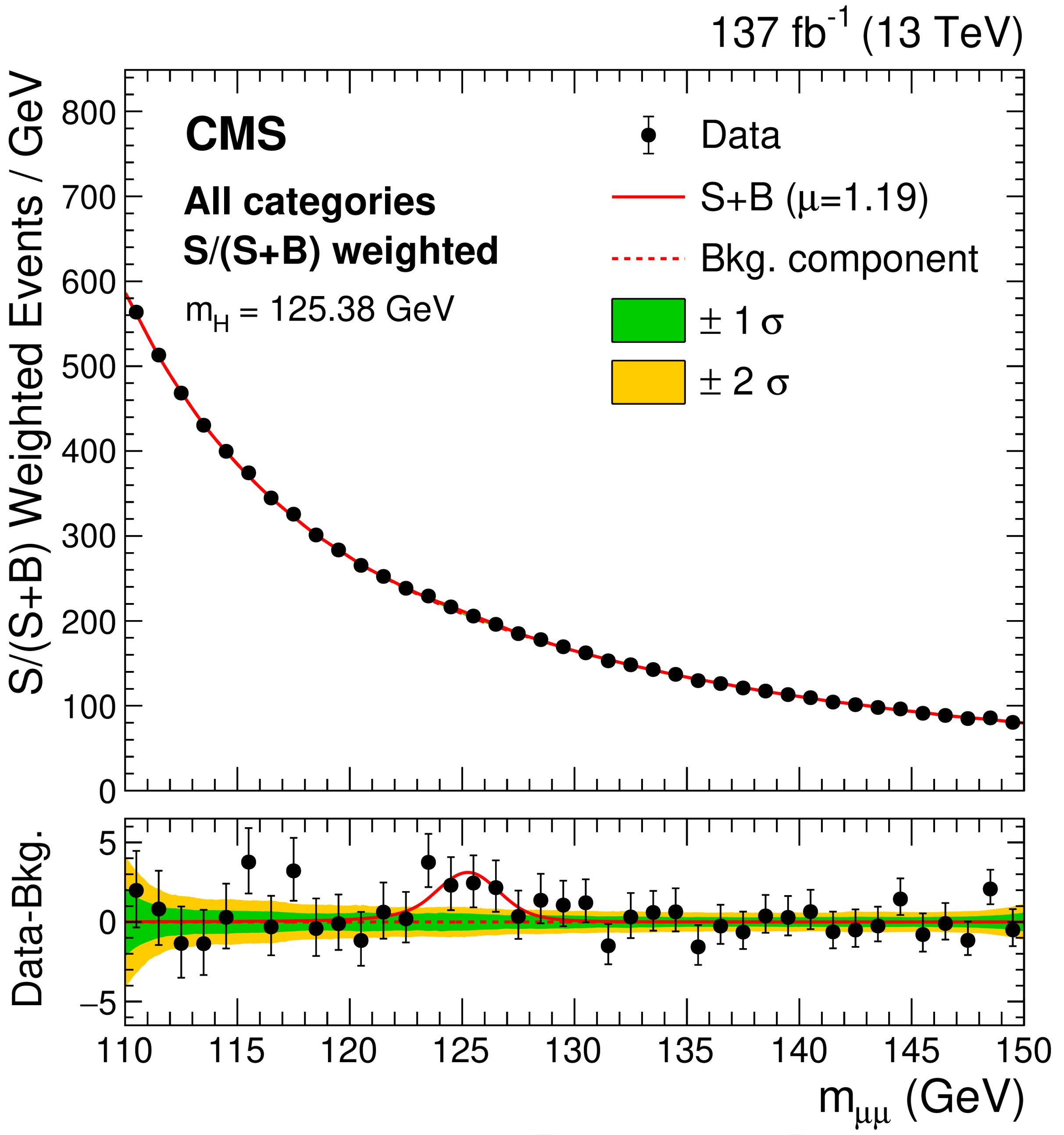
Confirmation of the Yukawa picture

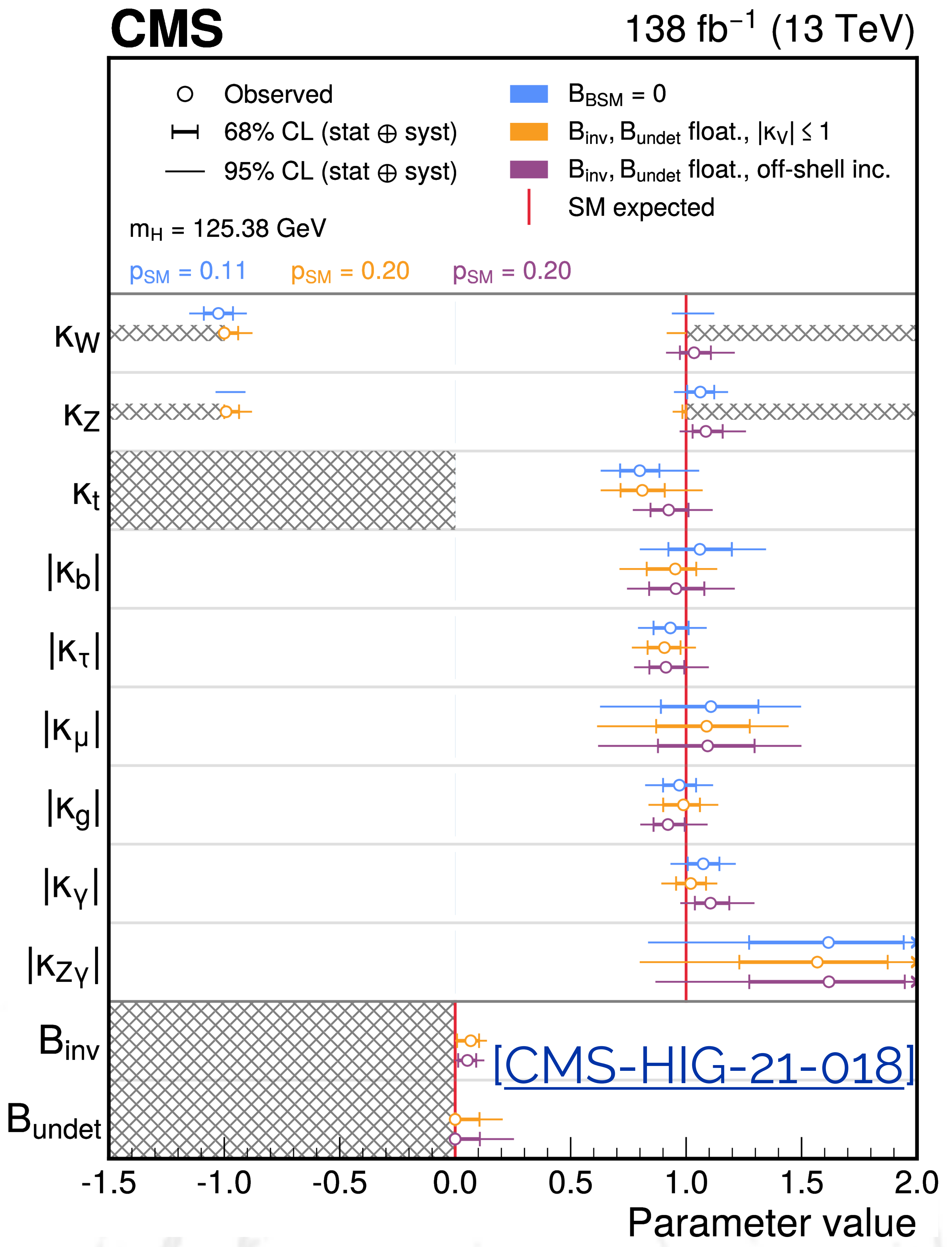


- Couplings to bosons and third generation fermions established (O(10%))
- Evidence for coupling to muons
- Any deviation could point to BSM physics

Evidence for H→μμ in 2020!
3.0σ obs. (2.5σ exp.)

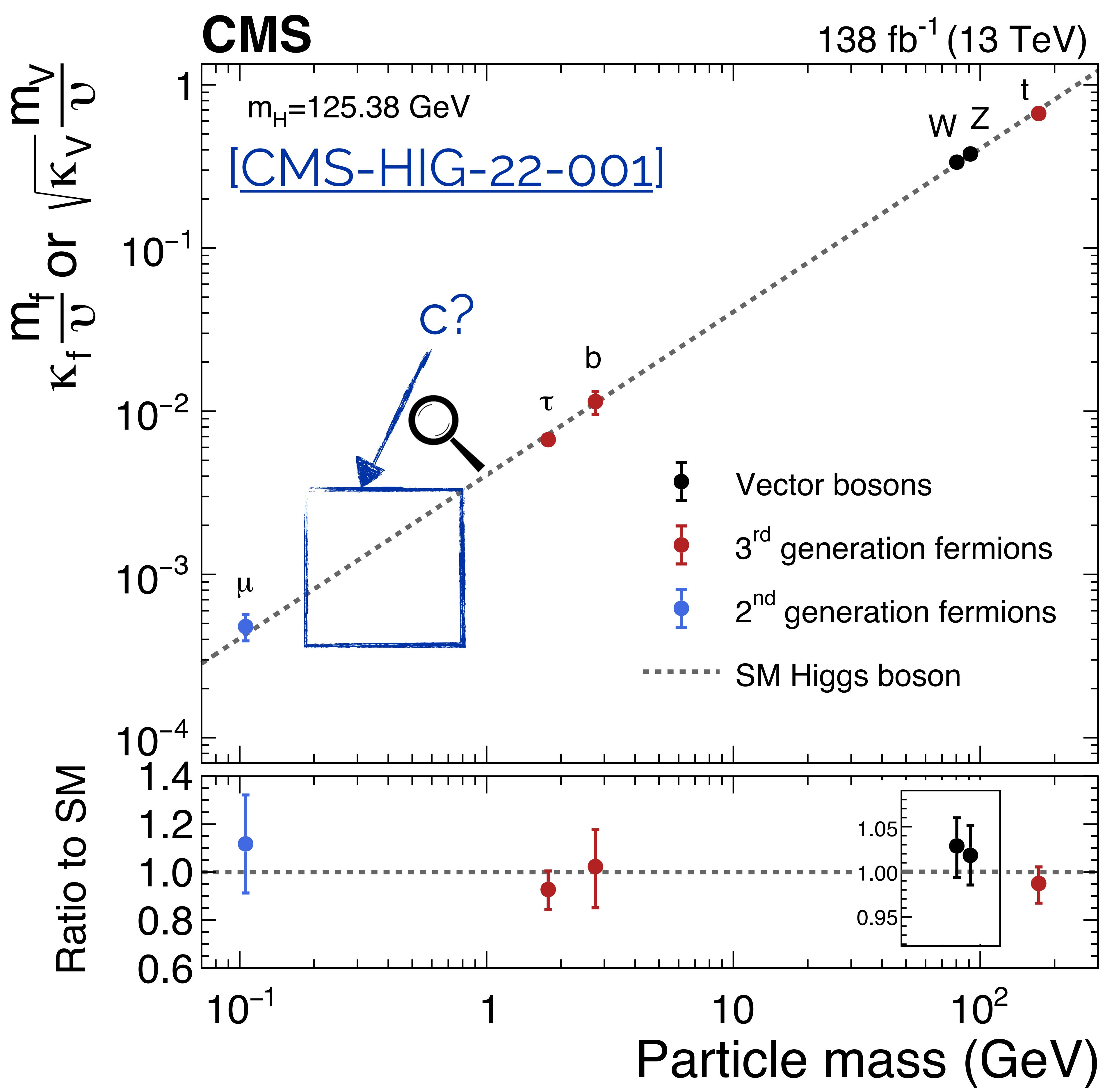
[CMS-HIG-19-006]





CMS combined coupling interpretation

Confirmation of the Yukawa picture



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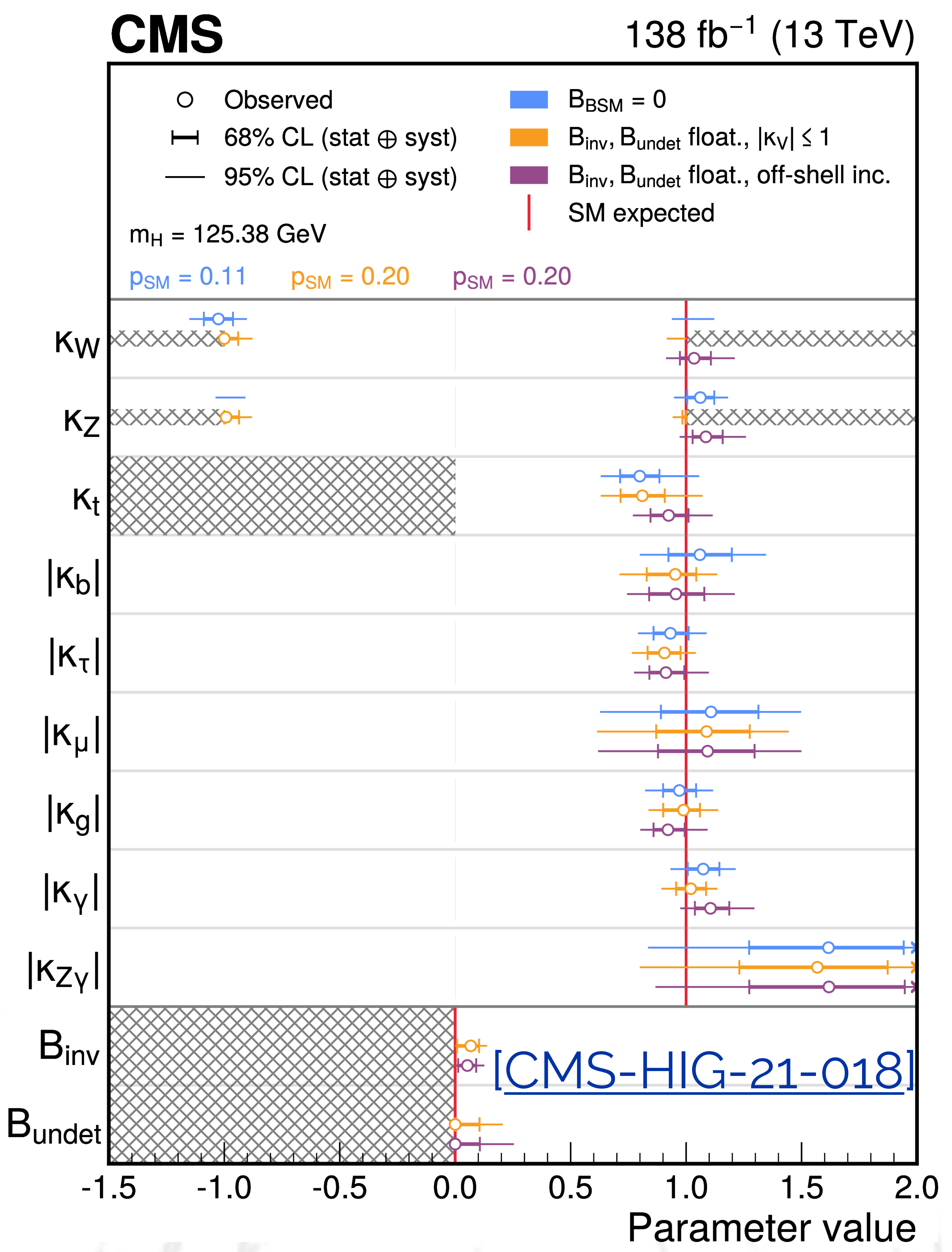
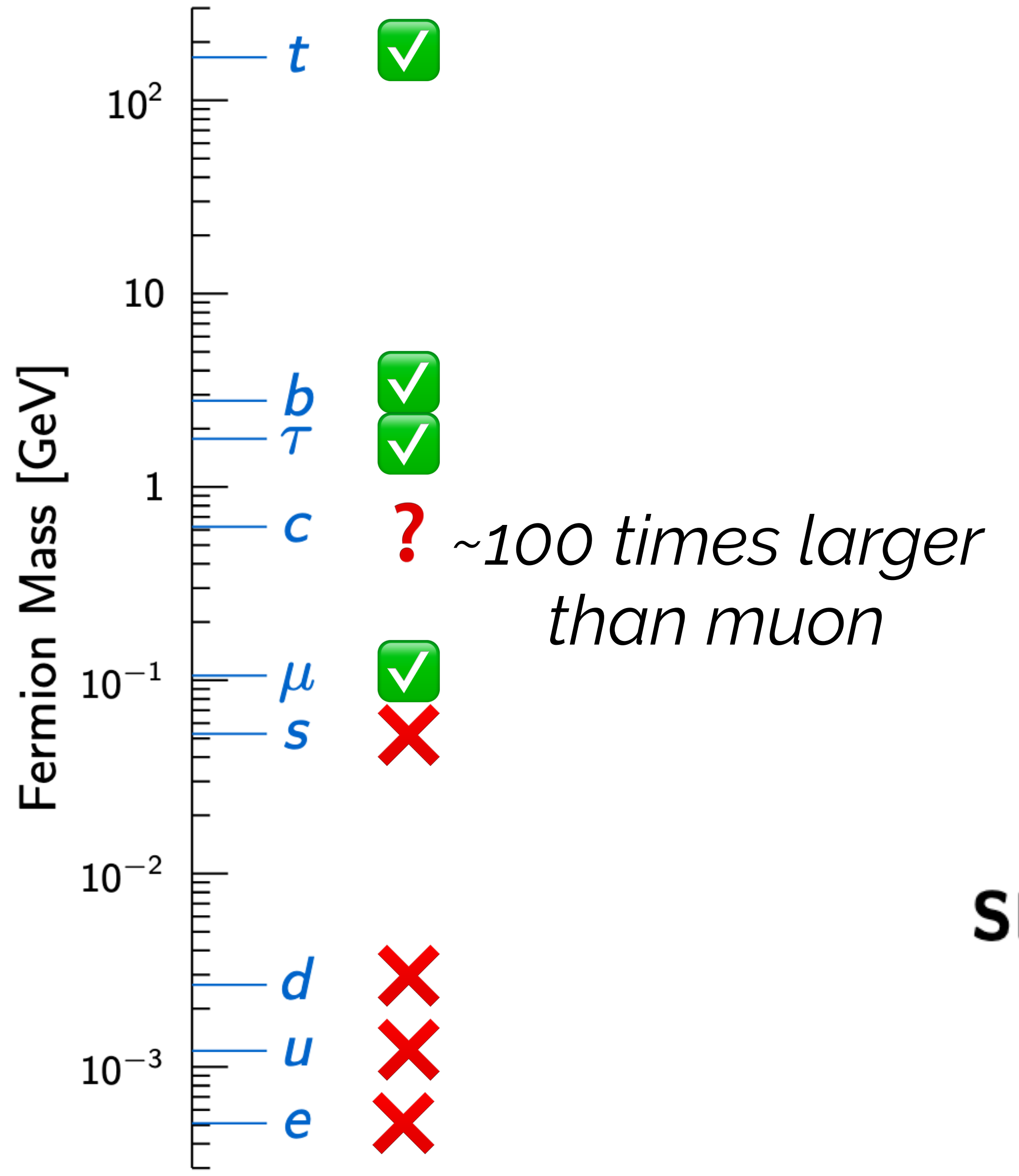


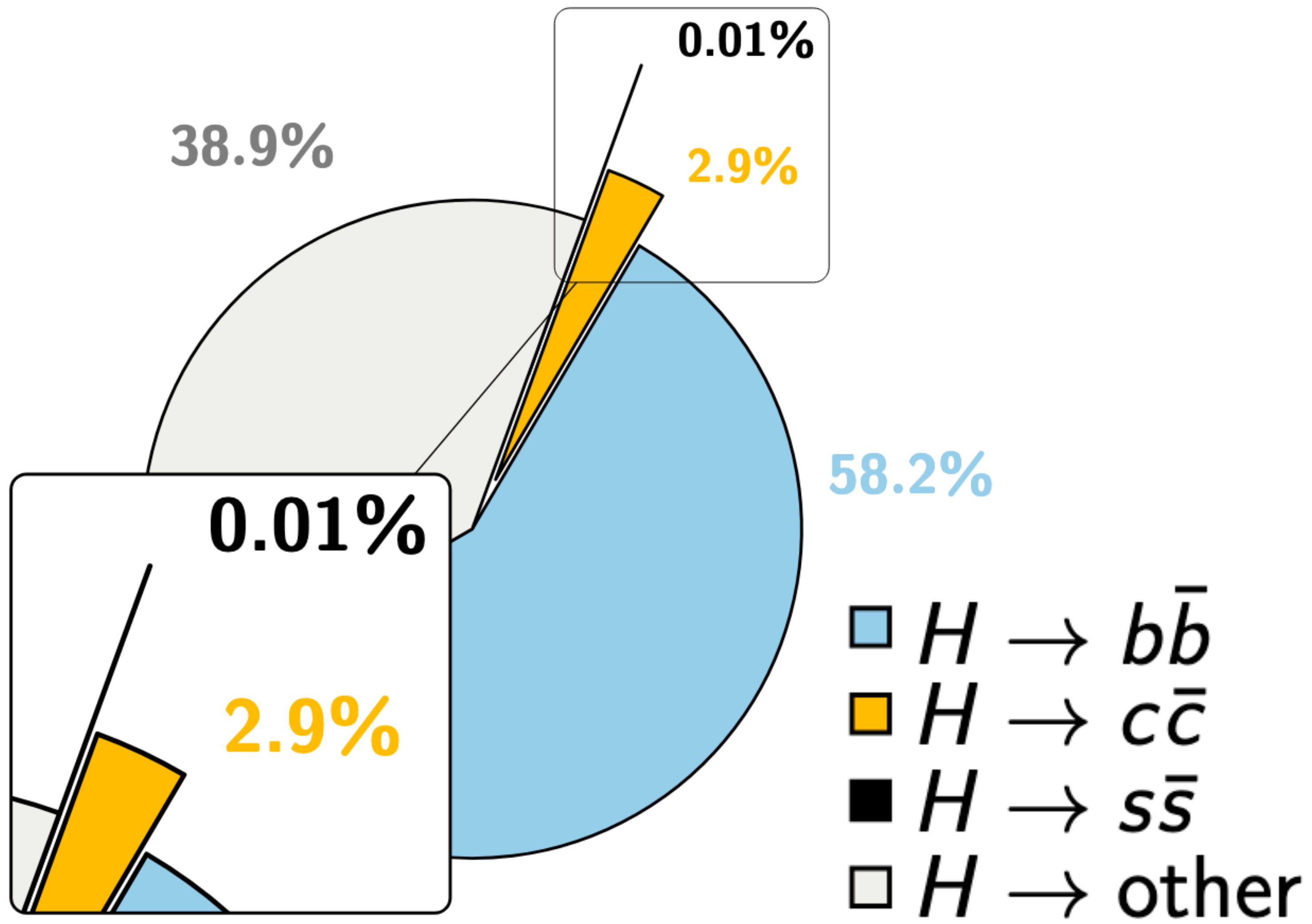
The measurement of the Higgs-charm coupling is at the frontier of Higgs physics!

CMS combined coupling interpretation

The Higgs-charm Yukawa coupling

- Smallness of the charm-quark Yukawa coupling
  - Any deviation could be interpreted as BSM physics
- Largest contribution to the undetected width
  - Remaining quarks and electron impossible at the LHC

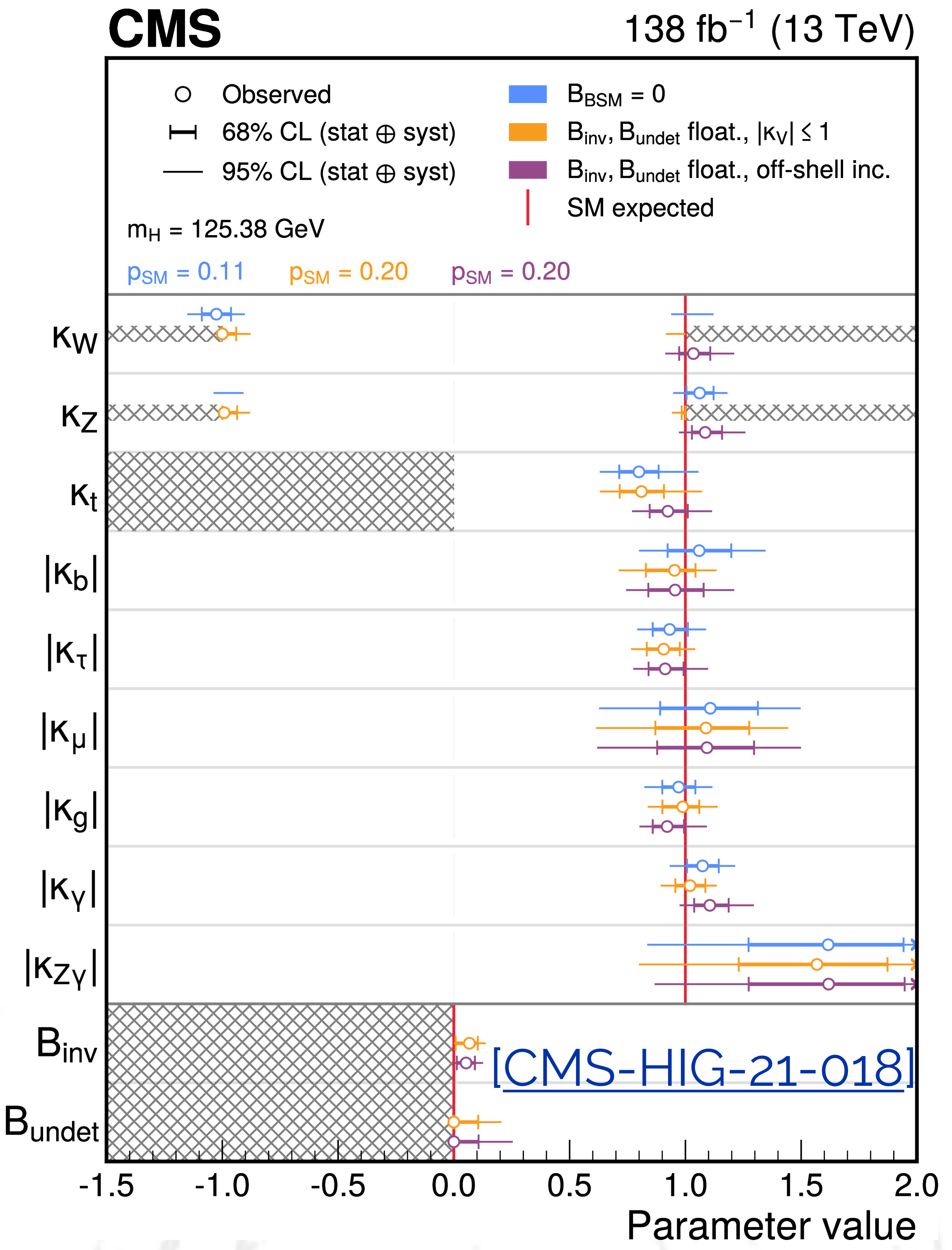




Credits to A. Chisholm

SM $m_H = 125$ GeV $H \to q\bar{q}$ branching fractions,

$H \to u\bar{u}/d\bar{d}$ too small to show!



Charm is ~what is left
(not considering first generation)

But… the quark sector is much harder!

So far: probing the Higgs-charm coupling

- Several methods explored by ATLAS and CMS to probe the Higgs-charm Yukawa coupling (y_c)

Indirect constraint from Higgs kinematics ← Model dependence? → Direct searches for $H \to c\bar{c}$

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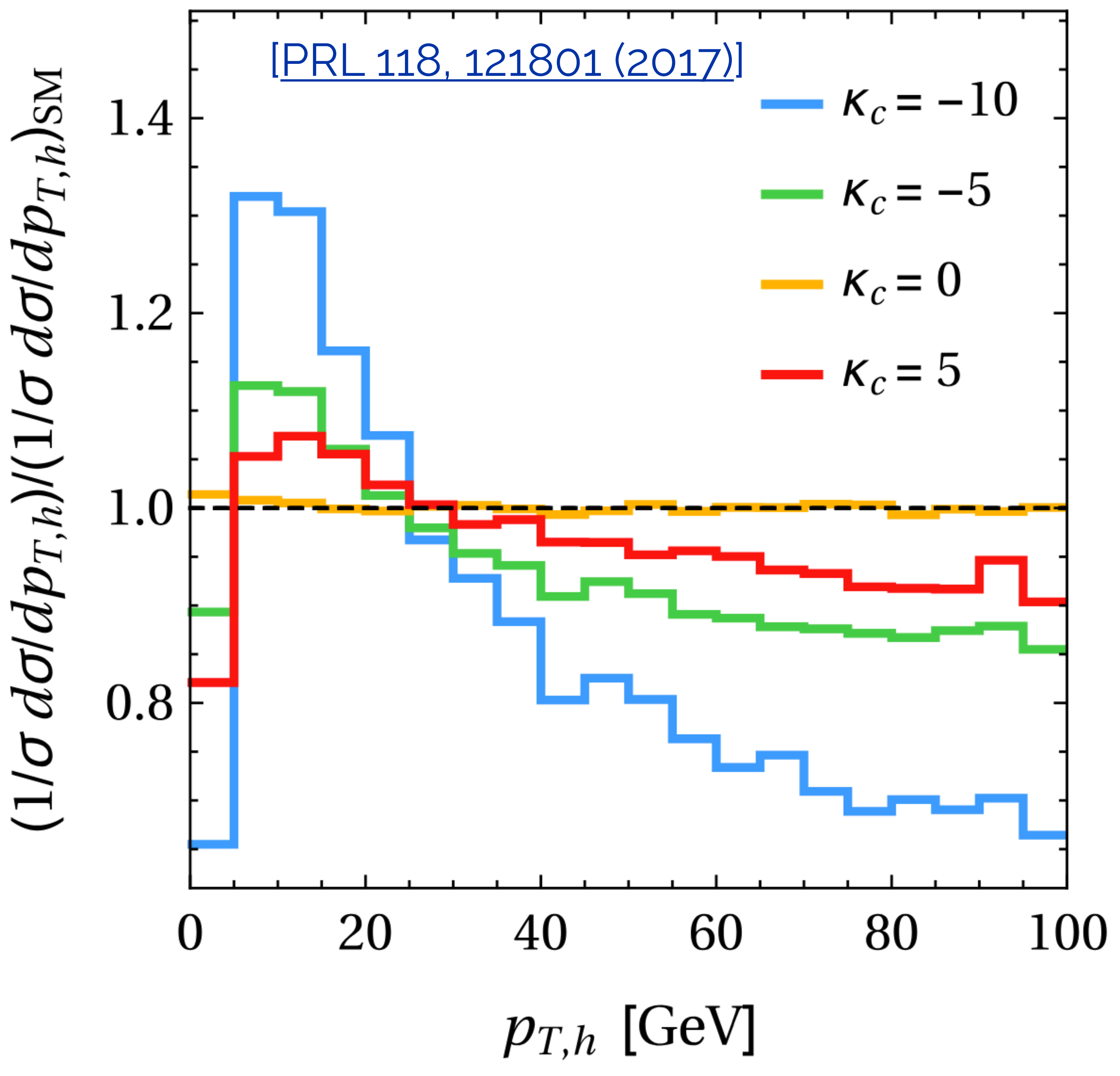
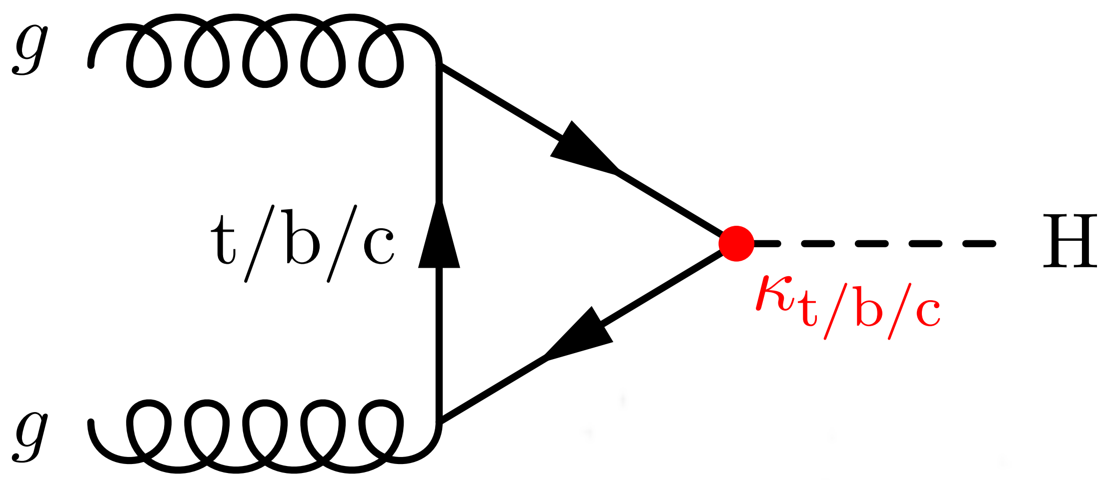


- Differential distributions are sensitive to y_c

Full Run 2 Higgs differential cross-section combination
[CMS-HIG-23-013]

$|\kappa_c| < 2$



Kappa framework

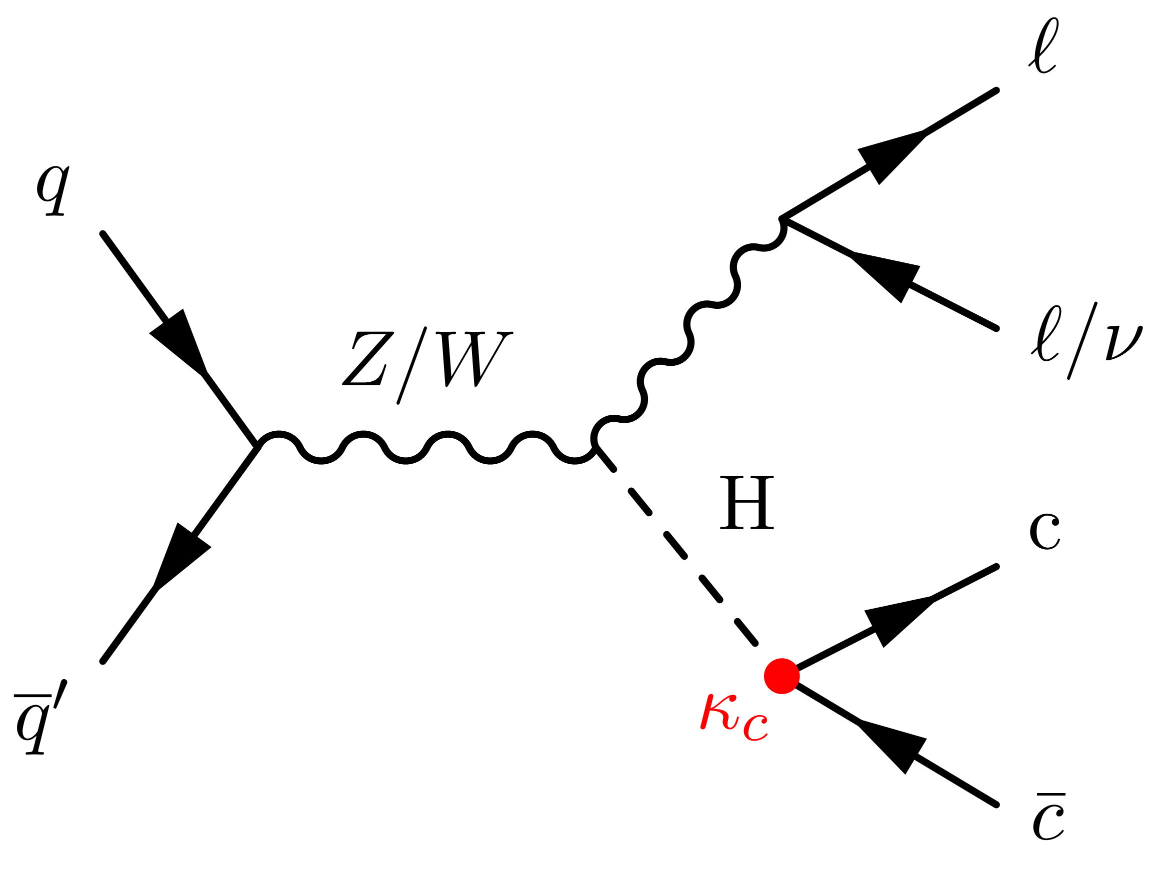
$$(\sigma \cdot \mathscr{B})(\mathrm{ii} \to \mathrm{H} \to \mathrm{ff}) = \frac{\sigma_{\mathrm{ii}} \cdot \Gamma_{\mathrm{ff}}}{\Gamma_{\mathrm{H}}} = \sigma_{\mathrm{ii}}^{SM} \cdot \mathscr{B}_{\mathrm{ff}}^{SM} \cdot \frac{\kappa_{\mathrm{i}}^2 \kappa_{\mathrm{f}}^2}{\kappa_{\mathrm{H}}^2}$$

κ_i: coupling wrt. SM expectation of 1

So far: probing the Higgs-charm coupling

- Several methods explored by ATLAS and CMS to probe the Higgs-charm Yukawa coupling (y_c)

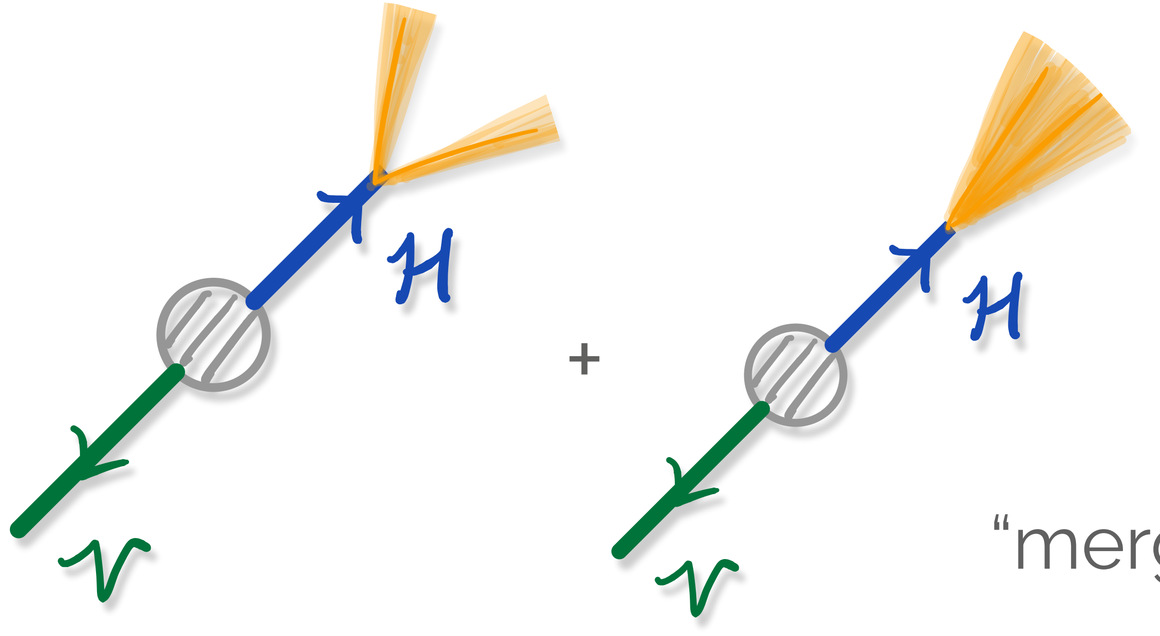
Indirect constraint from Higgs kinematics ⟷ Model dependence? ⟷ **Direct searches for $H \to c\bar{c}$**



VH as the "golden channel"

$1.1 < |\kappa_c| < 5.5$ (< 3.4) | **$\mu < 14$ (7.6)**

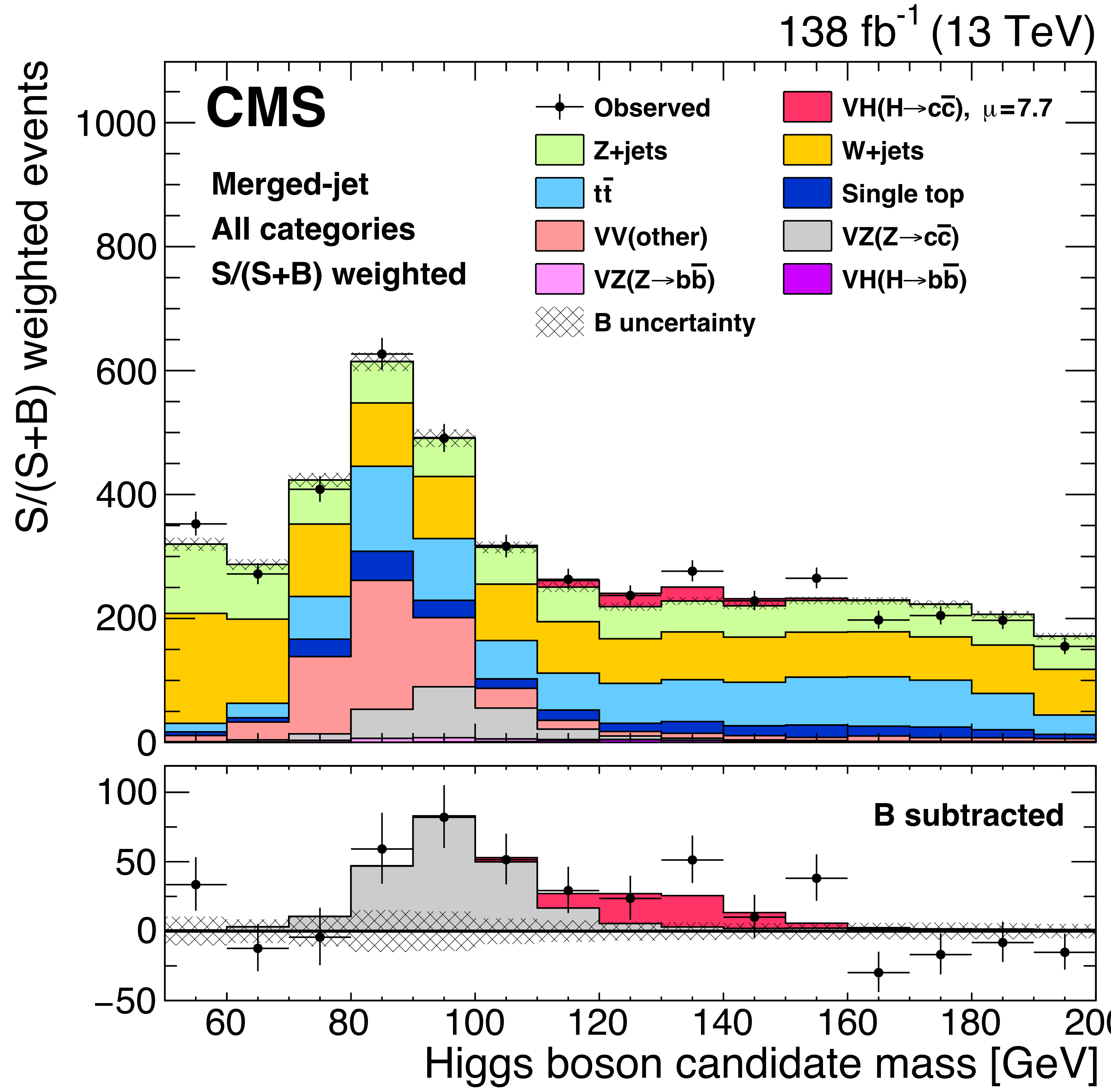
"resolved"



"merged"

From ATLAS:
$|\kappa_c| < 4.2$ (< 4.1)
$\mu < 12$ (11)
[JHEP 04(2025) 075]

We will come back to this..



[Phys. Rev. Lett. 131 (2023) 061801]

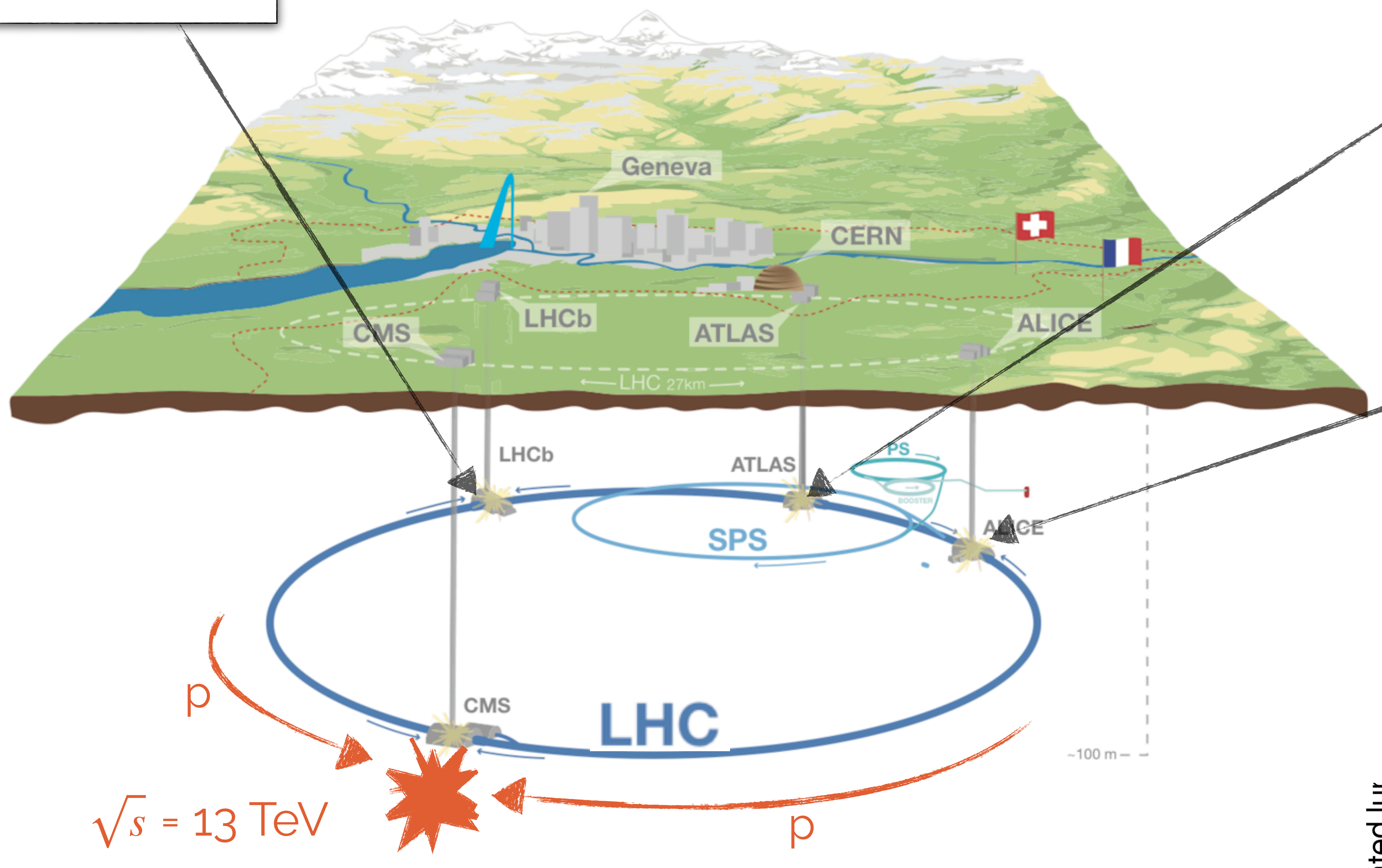
Which tools do we have?

The Large Hadron Collider (LHC)

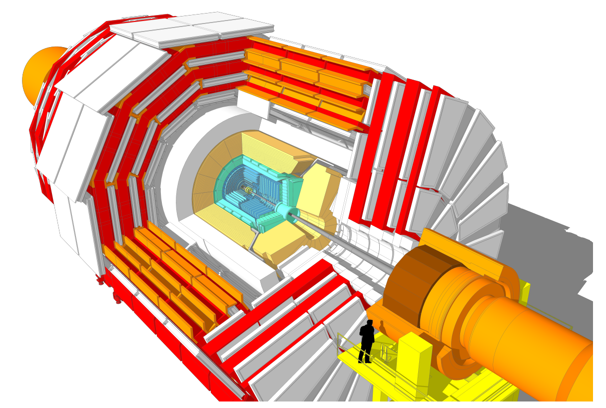
LHCb: b quark physics

ATLAS: general purpose experiment

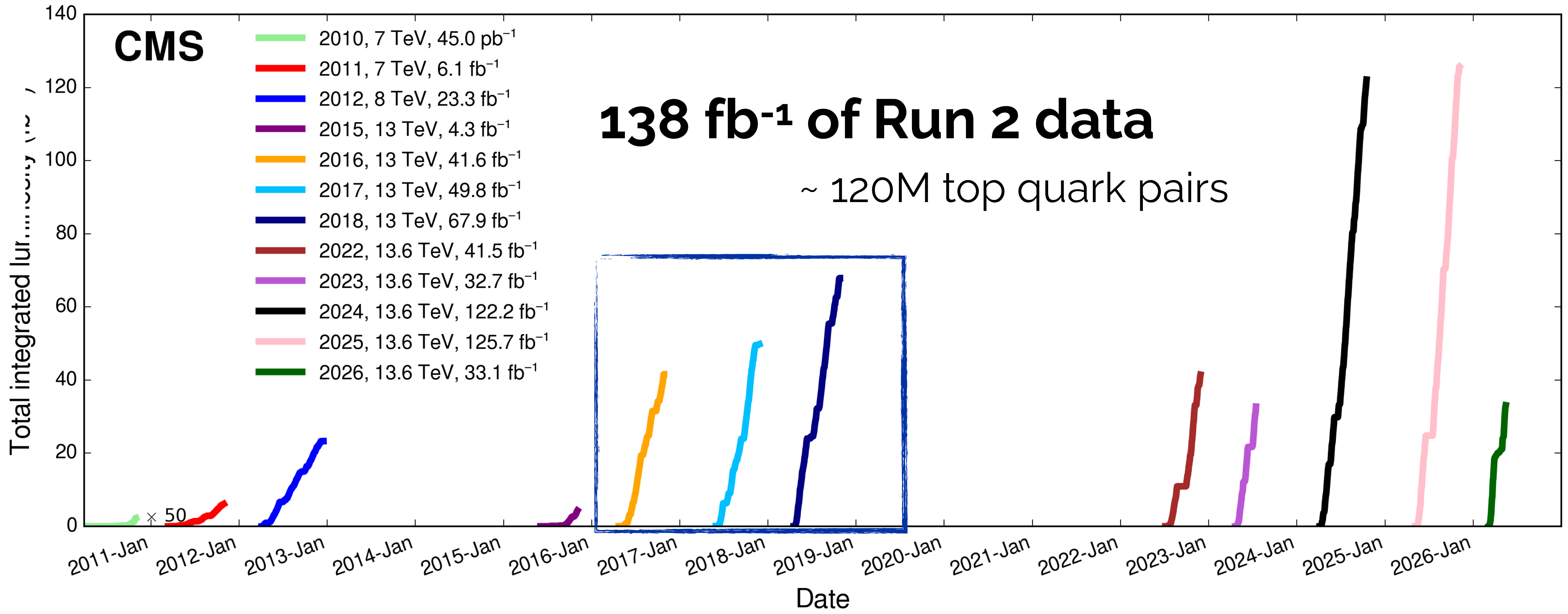
ALICE: heavy-ion physics



CMS: general purpose experiment



... just 1/3 of the Run 2 + 3 data



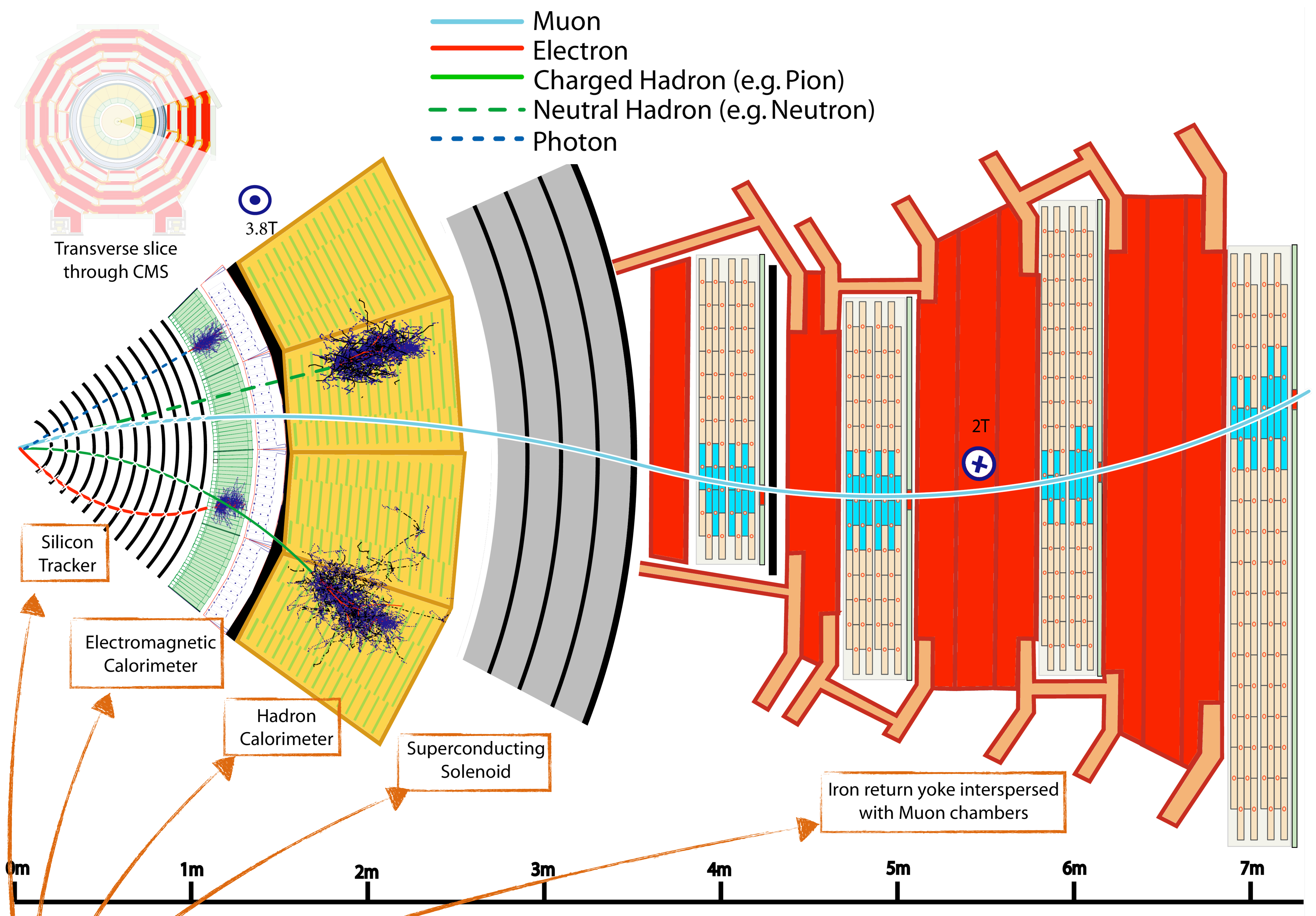
138 fb^{-1} of Run 2 data

~ 120M top quark pairs

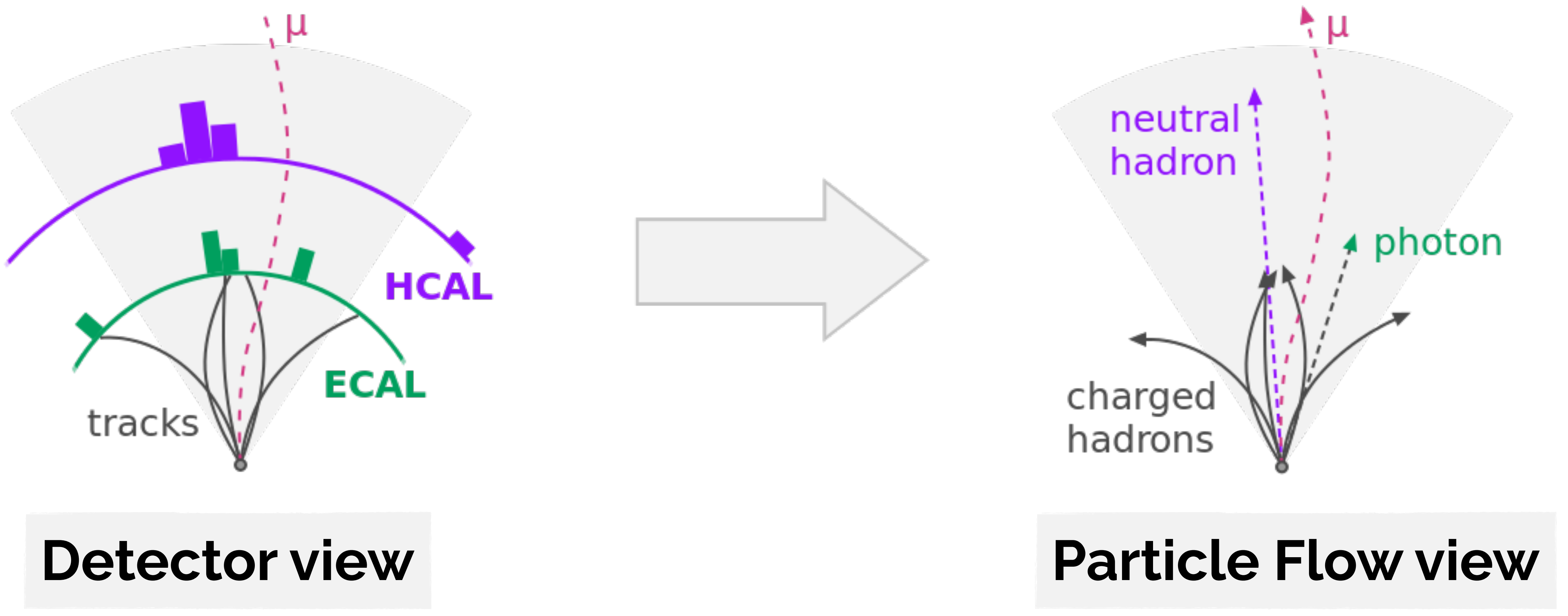
- Underground superconducting accelerator in Geneva at CERN
- Hadron-hadron collisions at the high-energy frontier, up to 14 TeV

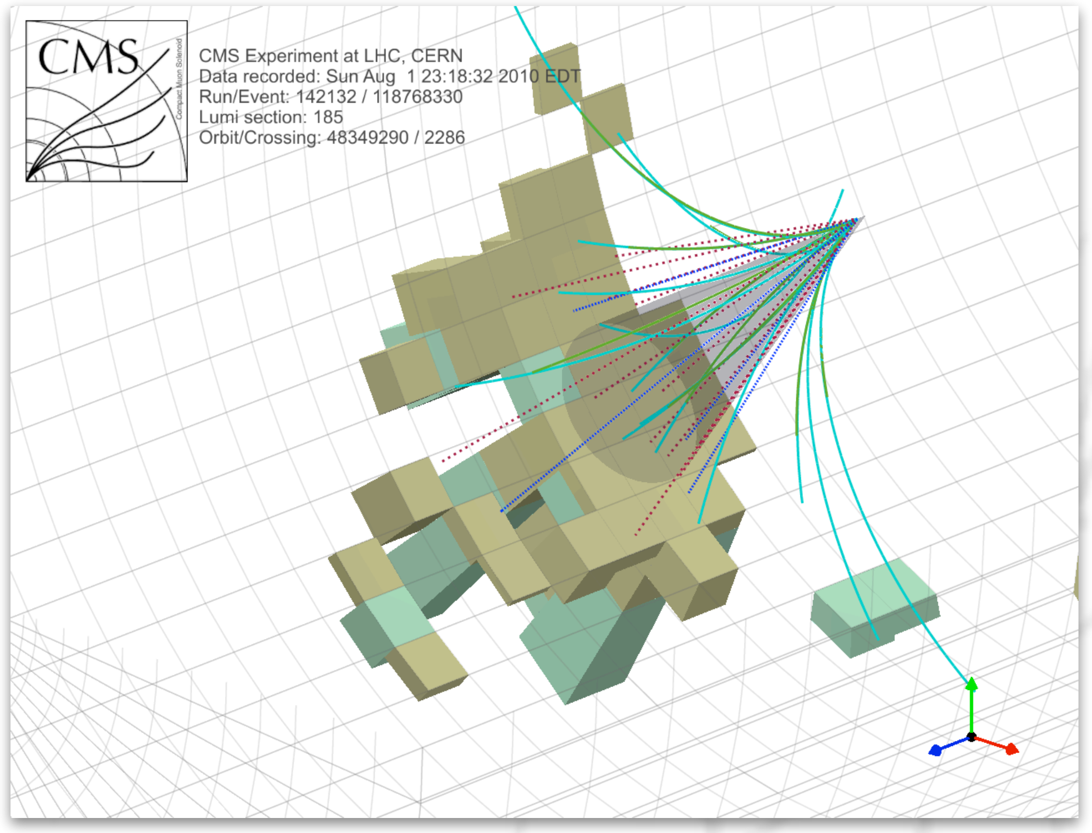
Which tools do we have?

The CMS experiment



[JINST 12 (2017) P10003]



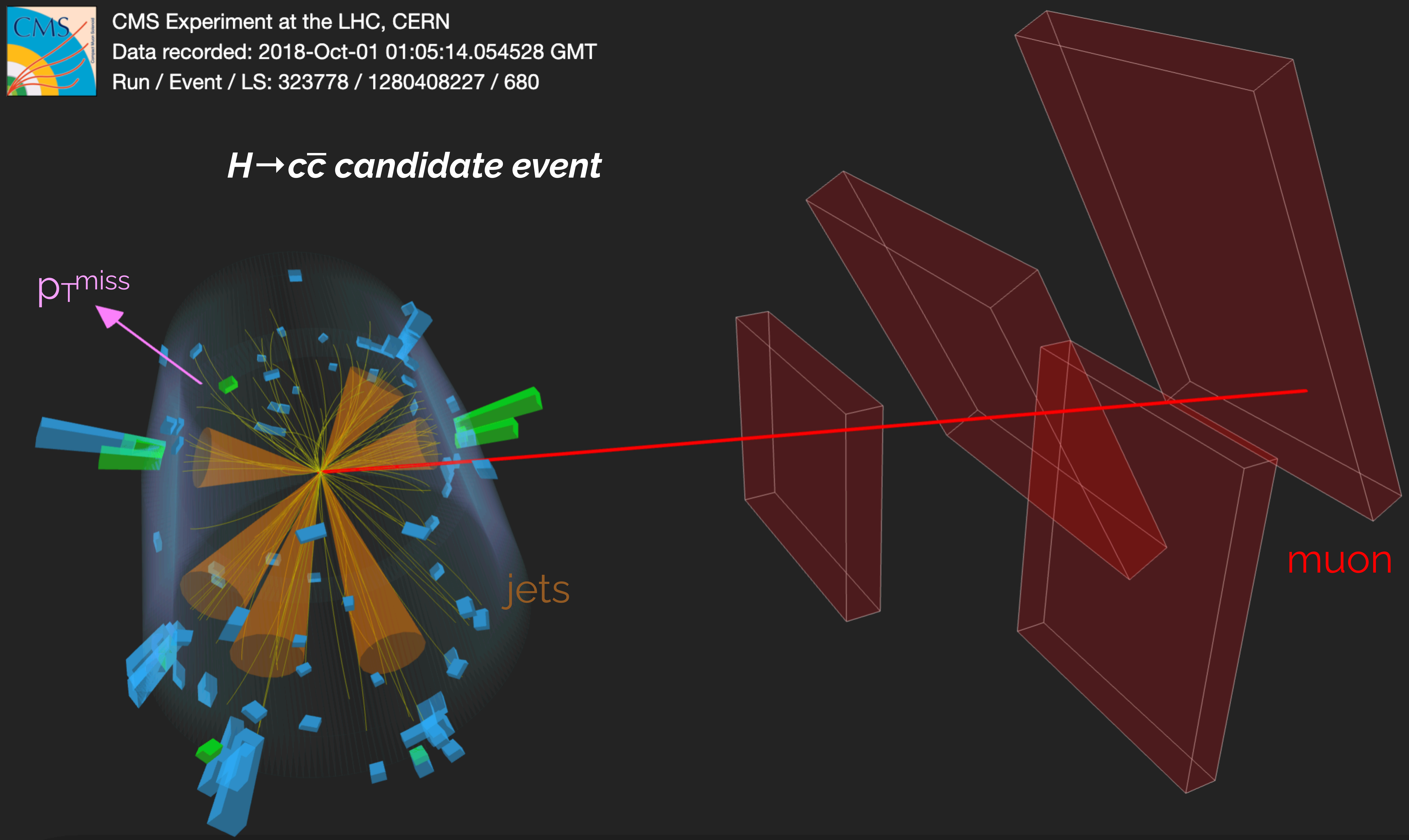


- **Particle flow reconstruction**:
  - Combined particle reconstruction with detailed properties
  - Excellent energy and momentum resolution

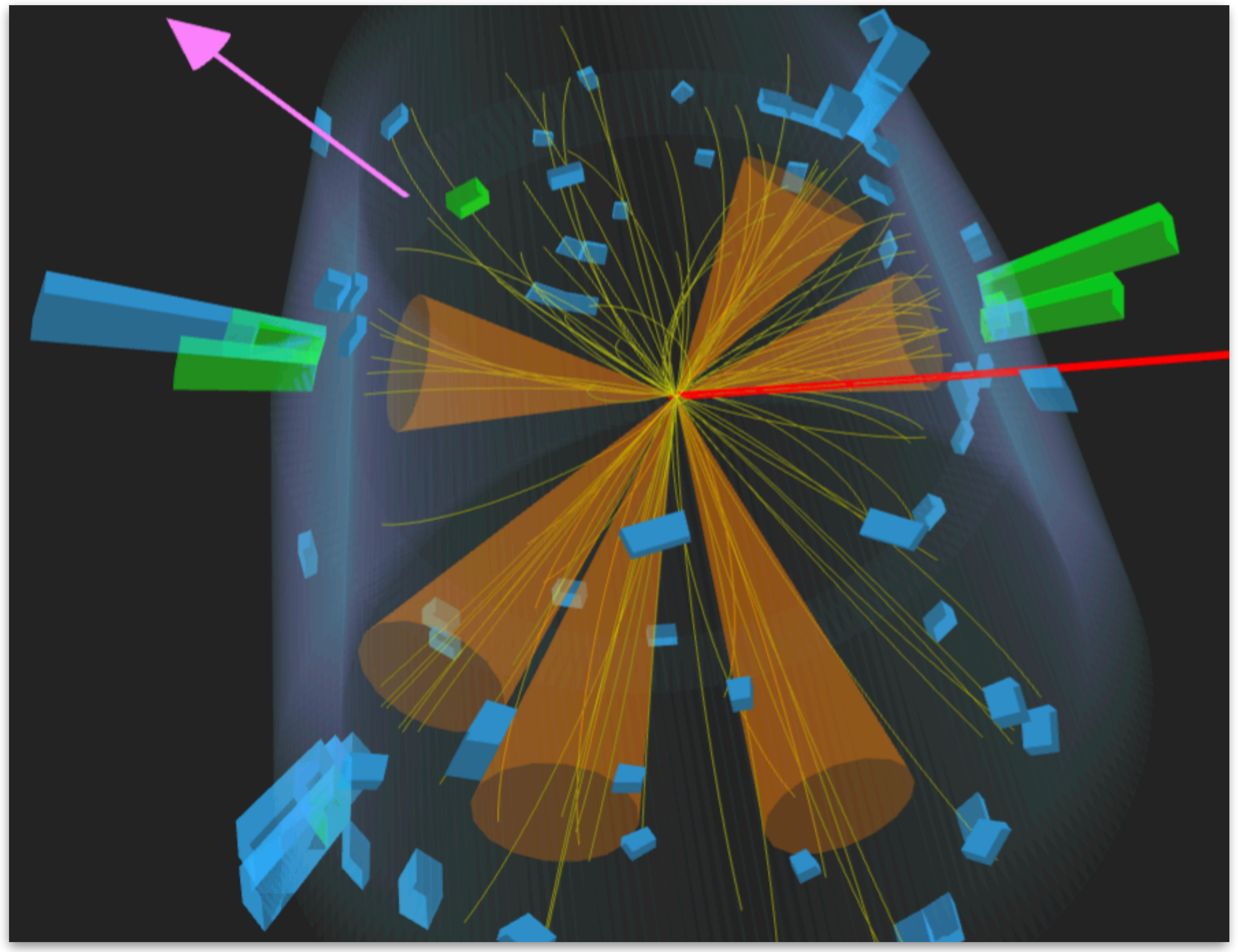
Jet reconstruction

- Clustering collimated sprays of particles as jets, initiated by partons
- Typical R=0.4, Anti k_T

Now let's do some analysis!

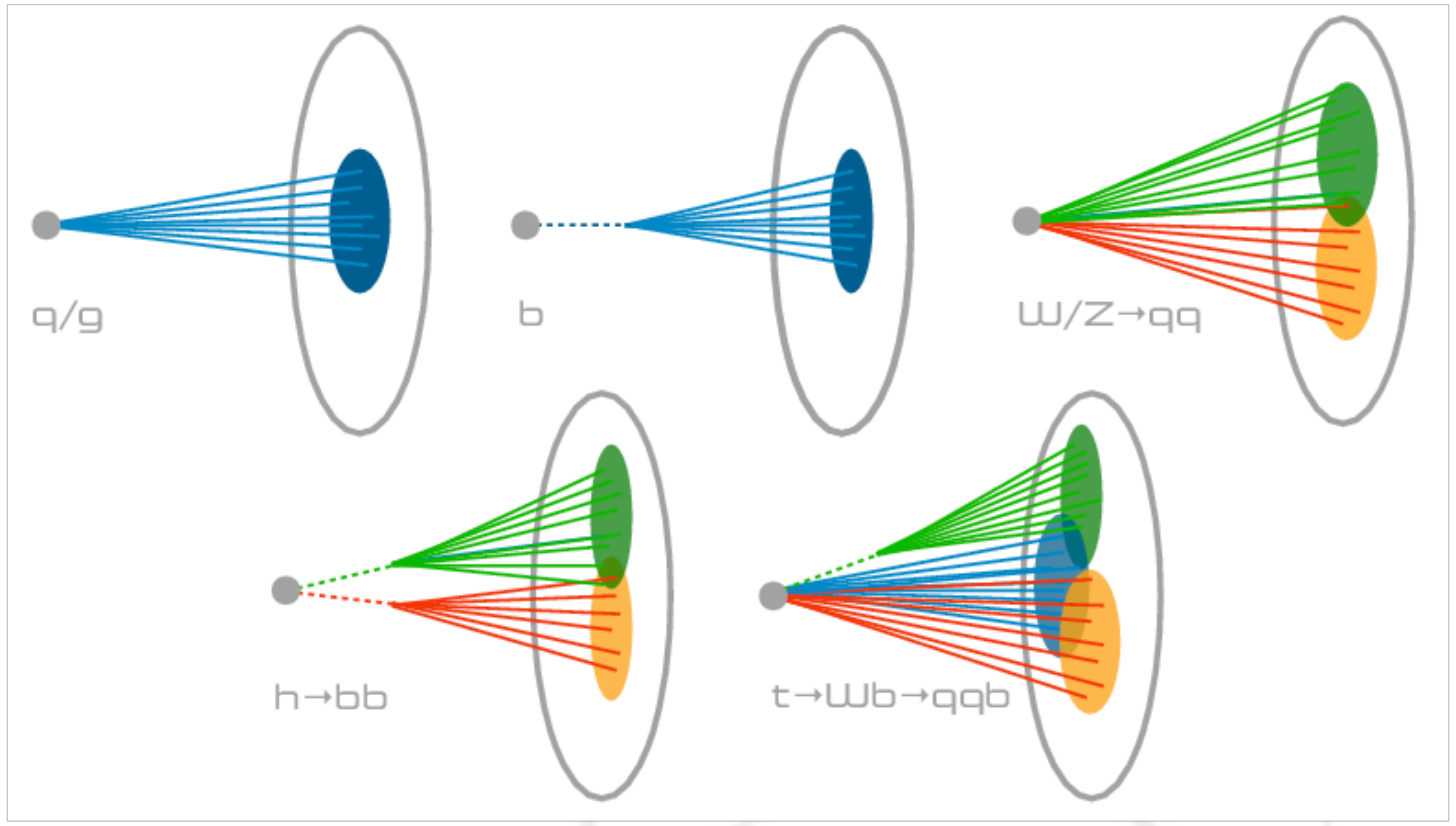


Not so fast!



What initiated the jets?

Resolved jet tagging



Boosted jet tagging

- Fragmentation structure depends on incoming parton type
- B/C hadrons have a larger lifetime: displaced tracks / secondary vertices (SV)
- Presence of non-isolated leptons in jets
- Jet-internal substructure: prongs

→ CMS Particle Flow provides perfect input for ML-based jet tasks!

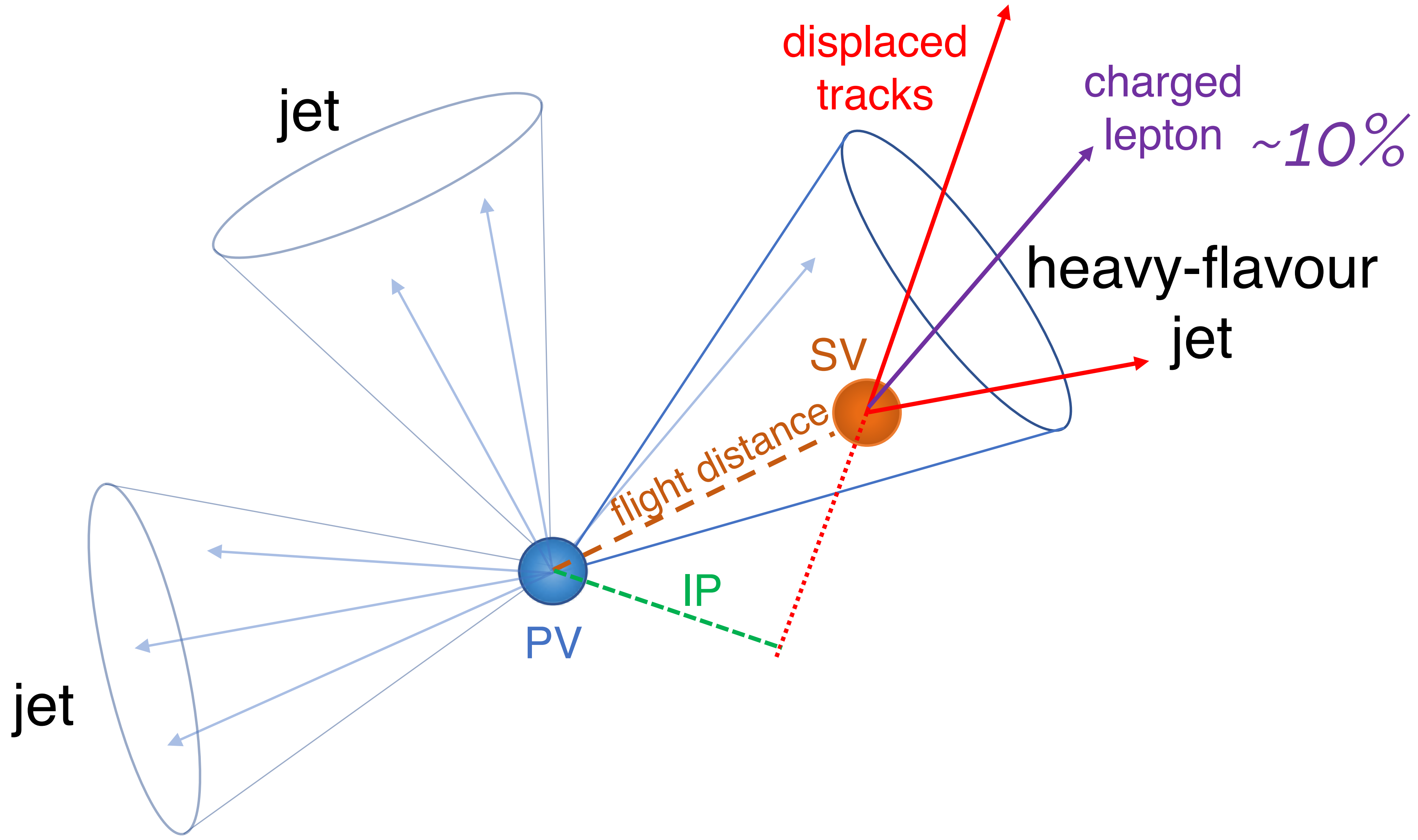
Jet flavour tagging

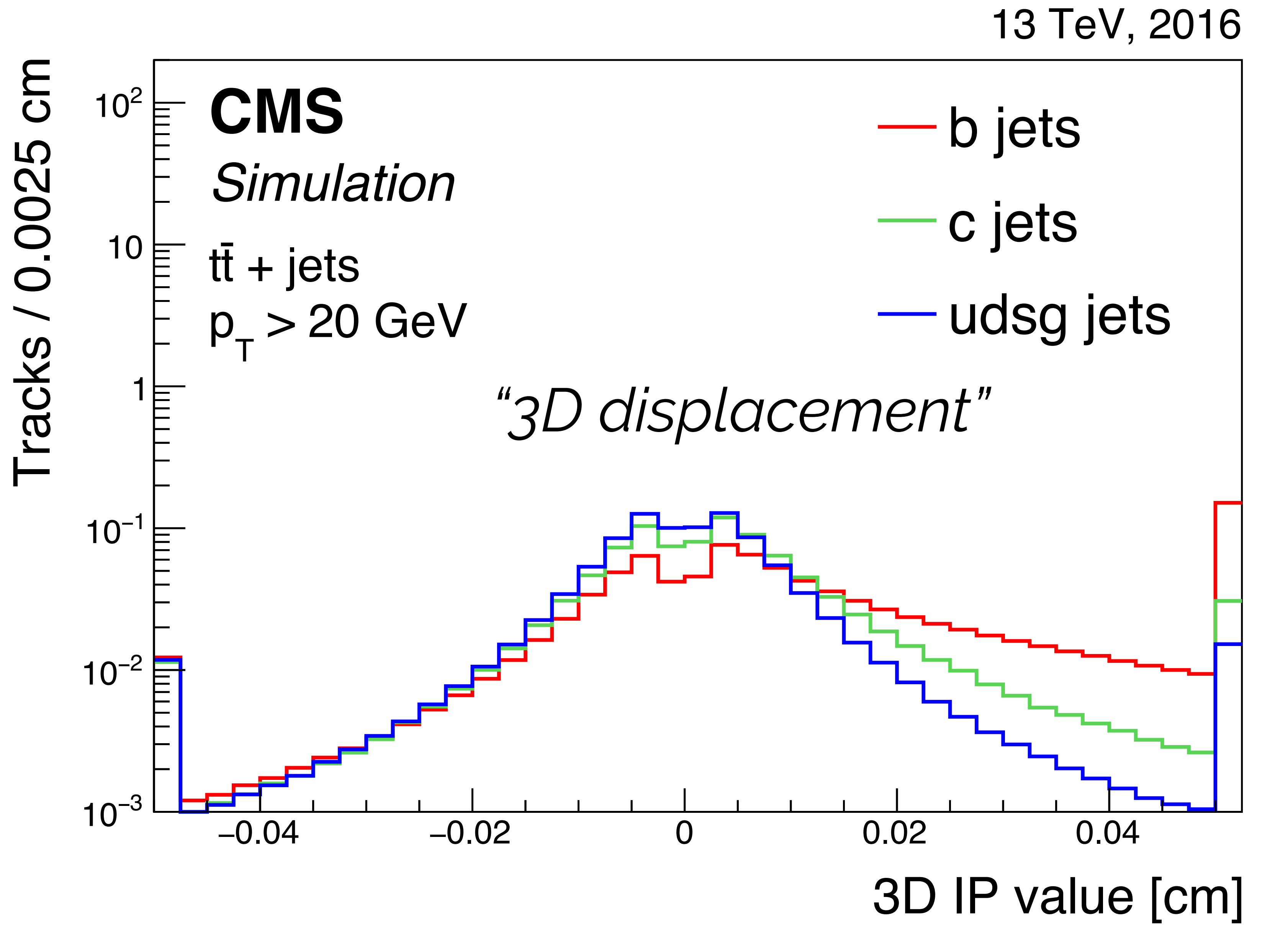
- Direct $H \to c\bar{c}$ searches only as good as the identification of real **c-jets**!

- c-jets have intermediate properties to b- and light jets
  → A simultaneous 2D discrimination is needed

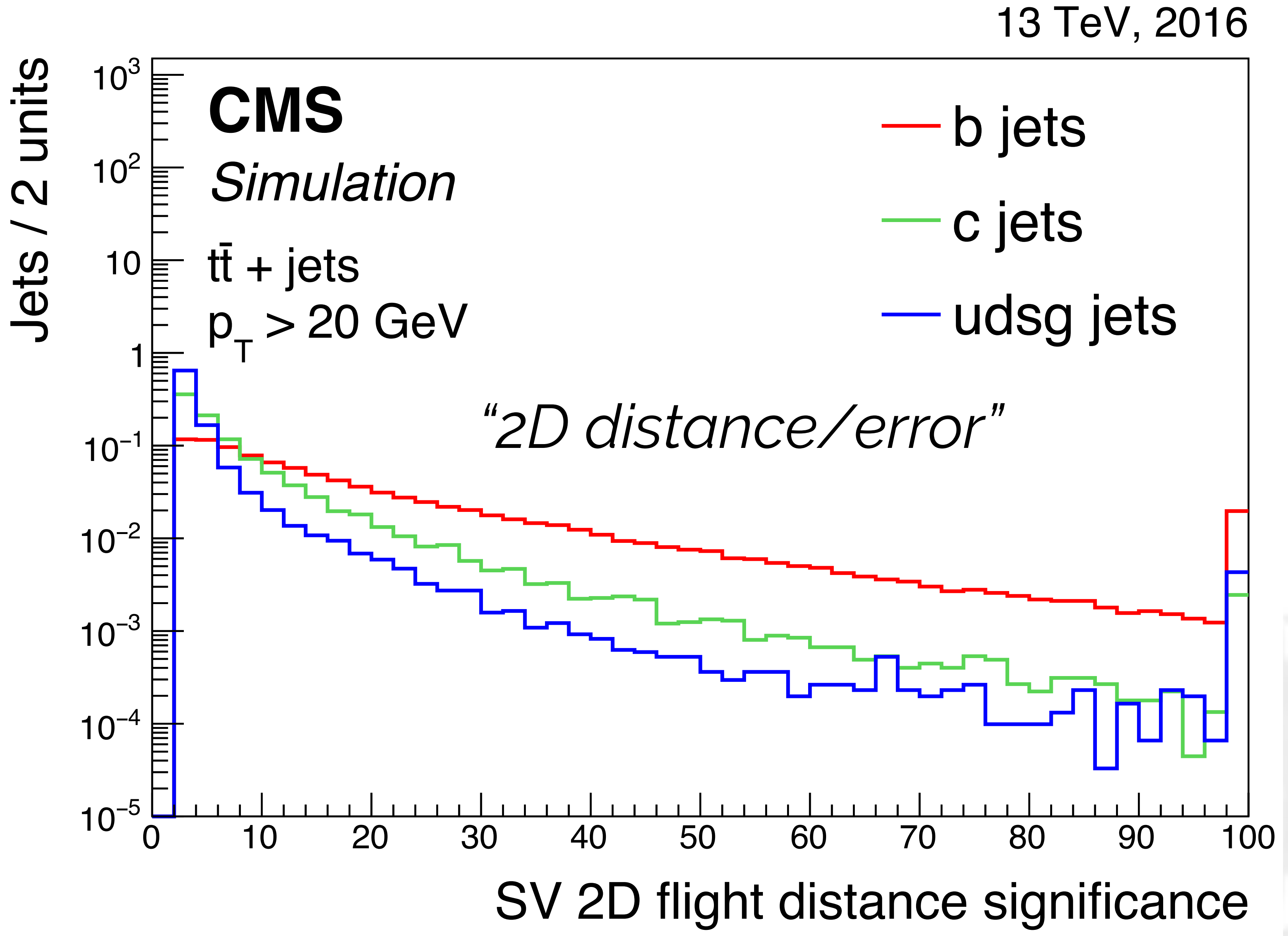
light ⟷ **c** ⟷ **b**

- Exploit low-level track and secondary vertex features in ML-algorithms
  - Significant improvement hand-in-hand with ML developments





[JINST 13 (2018) P05011]

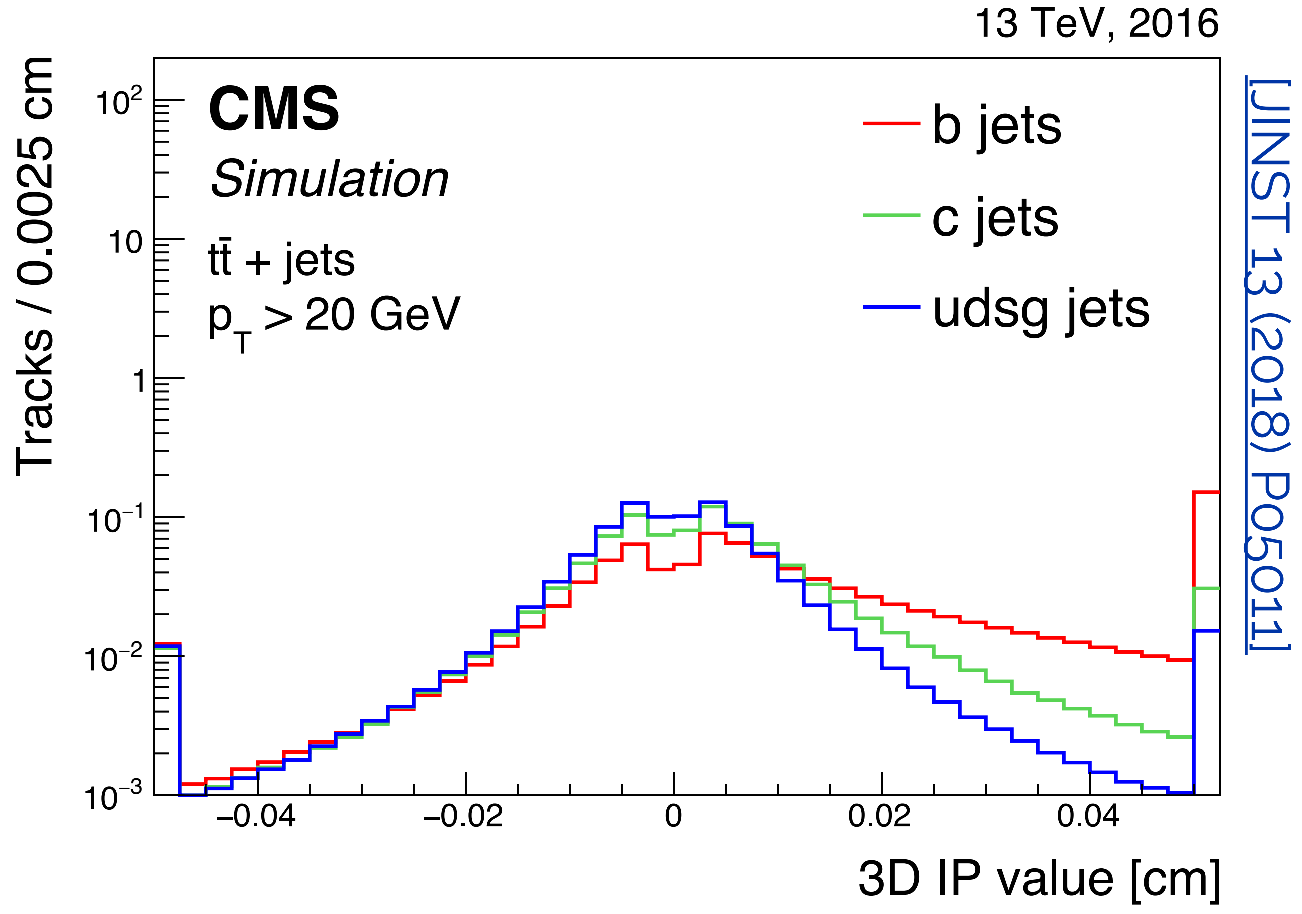


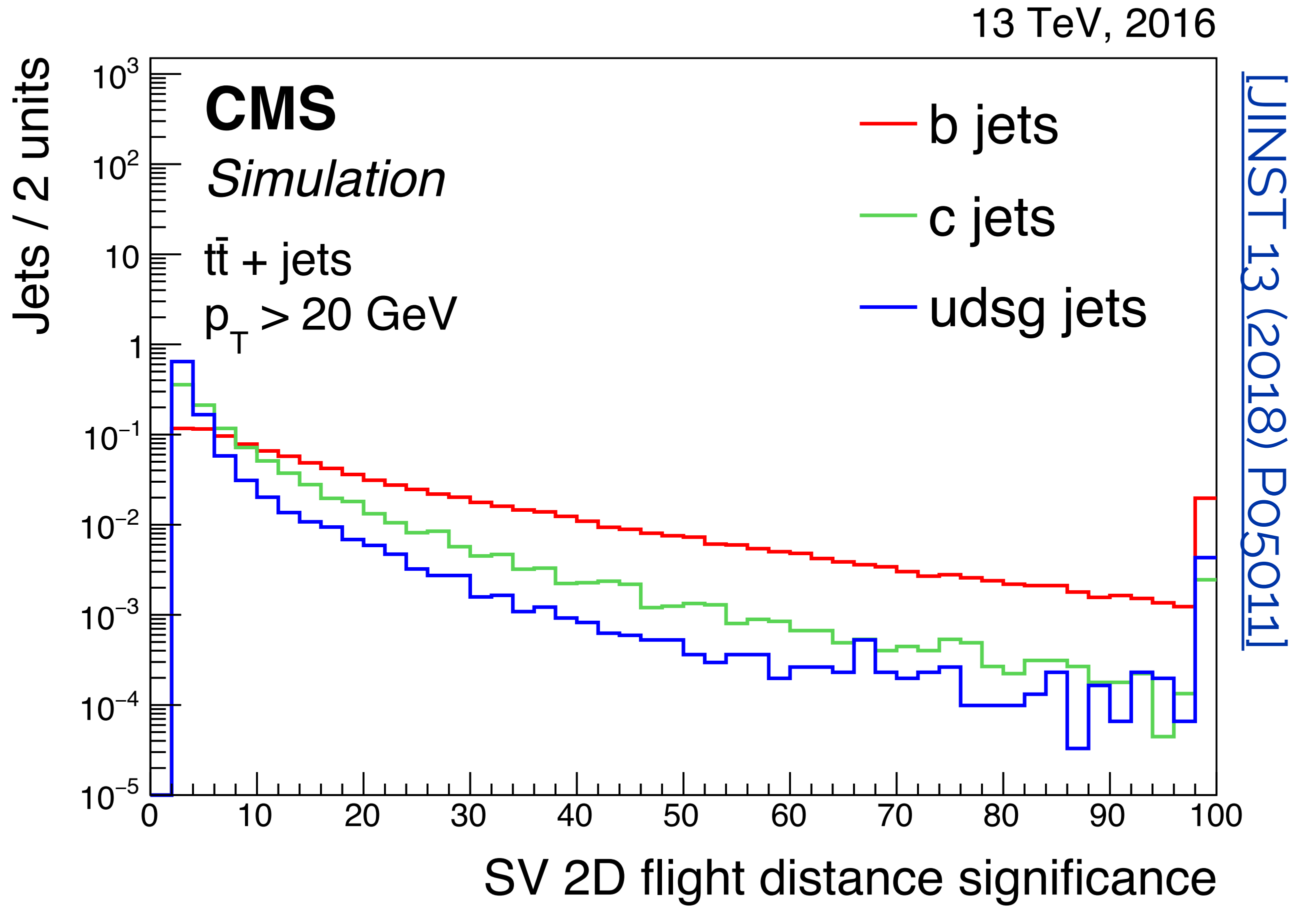
A bit of CMS history...

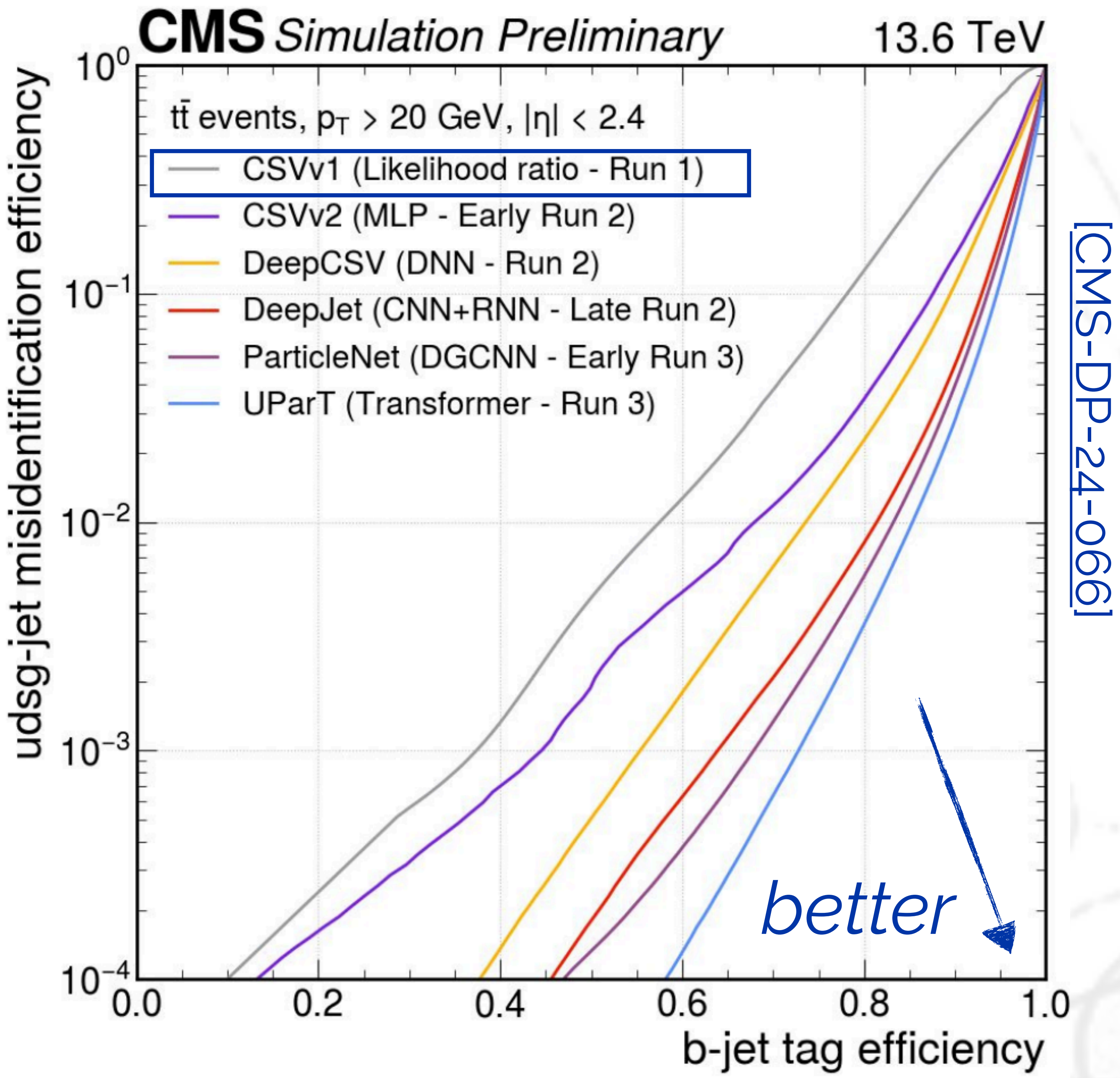
Run 1 (2011 - 2016)

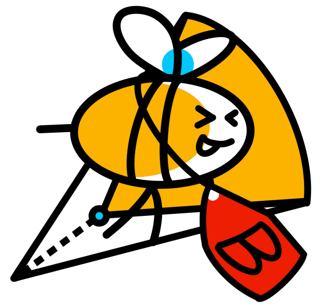
Jet probabilities

- Likelihood based sum over track-from-PV probabilities
- Combination of track/SV properties "by hand"









A bit of CMS history…

Run 2 (2016 - 2018)

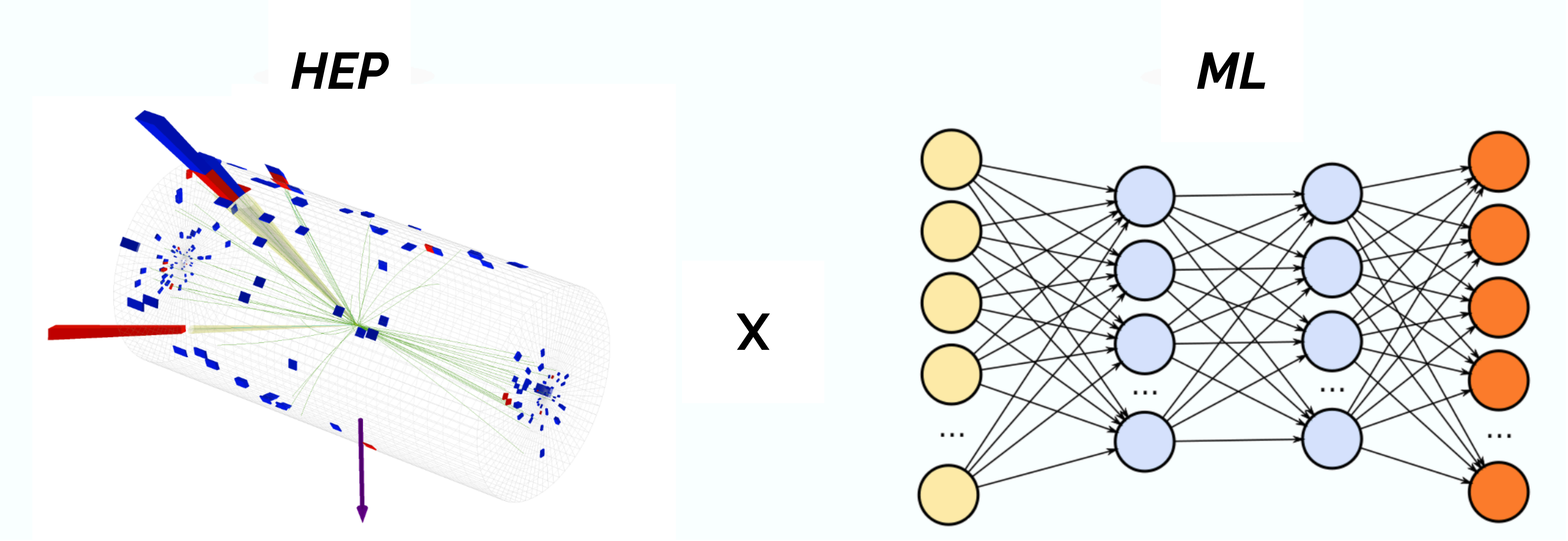
Run 1 (2011 - 2016)

Machine Learning

Jet probabilities

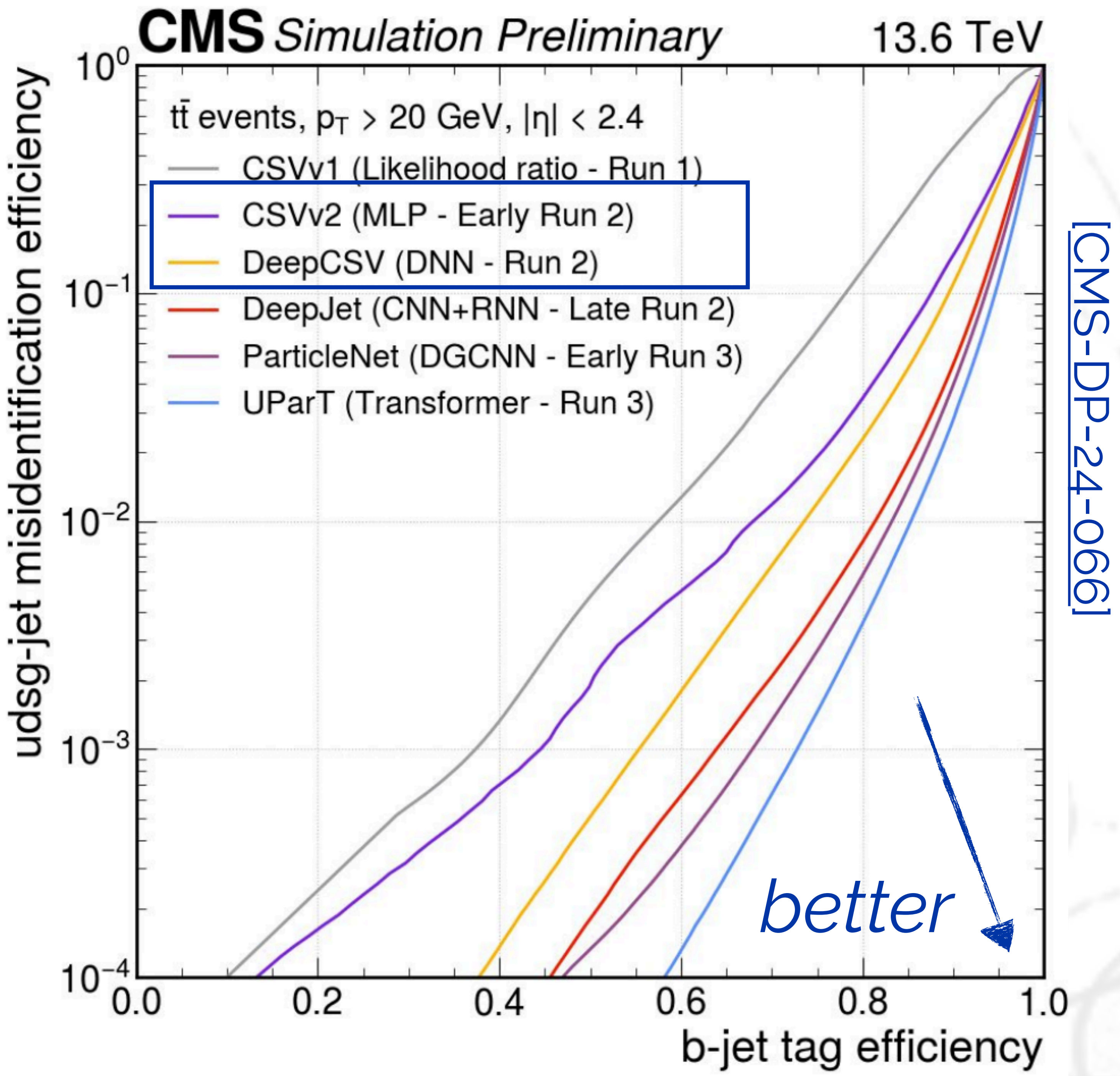
CSV/DeepCSV
Sub-jet tagging

- **How do we represent the data?**



Collisions, detector events, sensor arrays, …

- The traditional way: summarizing jets into a few high-level features
  - pT, η, ϕ, mass, …
- Then use boosted decision trees or fully-connected neural networks



A bit of CMS history…

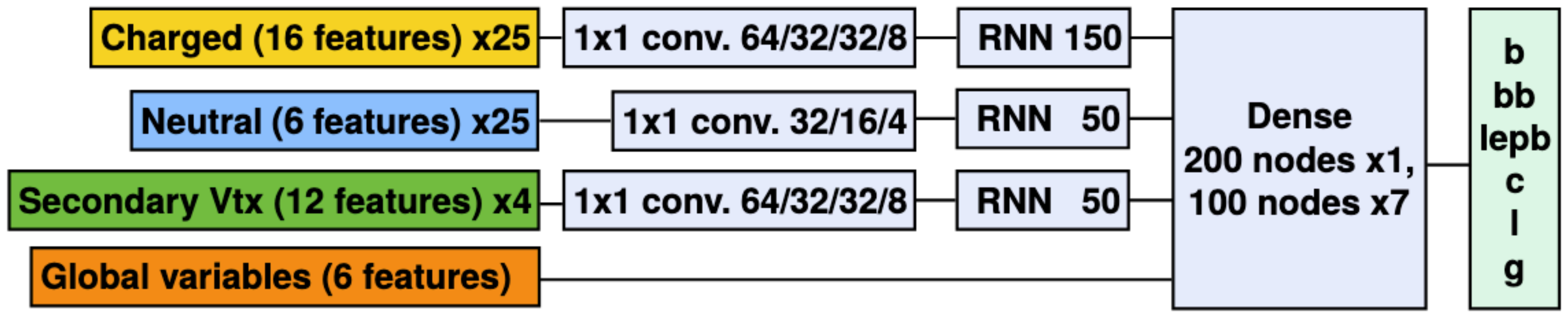
Run 1 (2011 - 2016) | Jet probabilities

Run 2 (2016 - 2018)

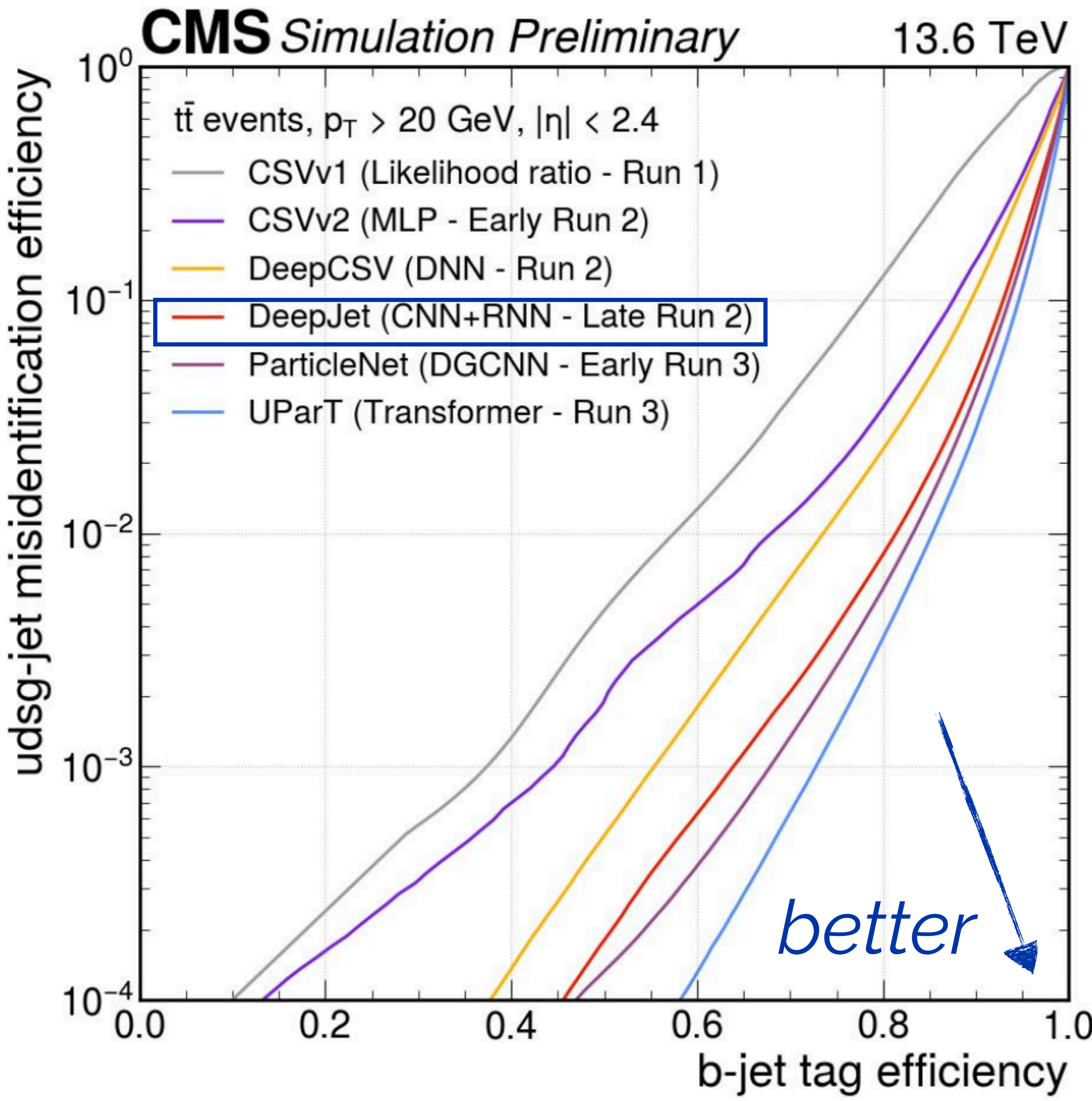
Machine Learning → CSV/DeepCSV Sub-jet tagging

Jets as a sequence → DeepJet/ DeepAK8

- A jet is a set of O(50-100) particles
  → Sequence as in language processing
- First models to focus on jet constituents: RNN+LSTM



[Bols et al (2020)]



[CMS-DP-24-066]

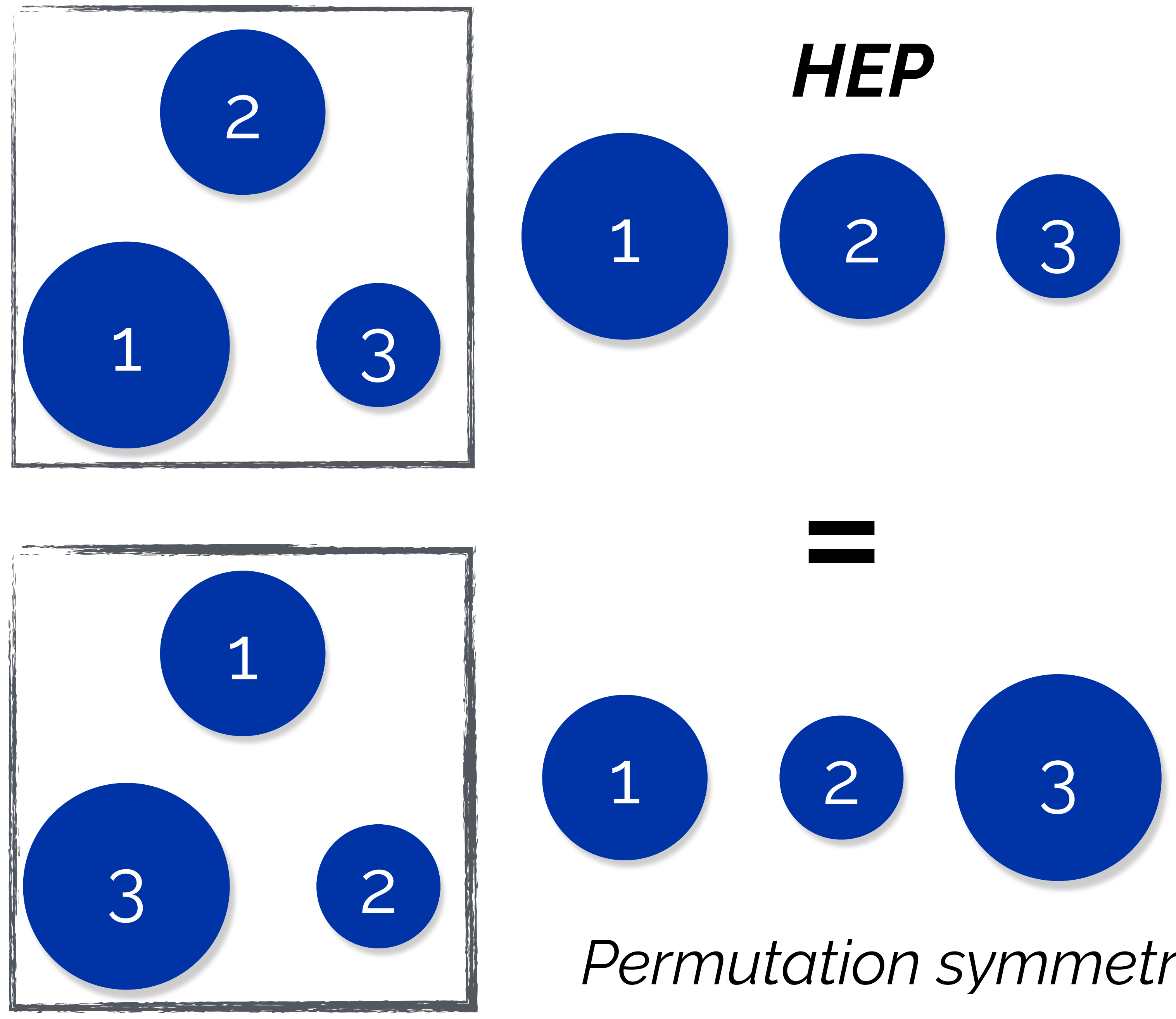
A bit of CMS history…

Run 1 (2011 - 2016) | *Run 2 (2016 - 2018)*

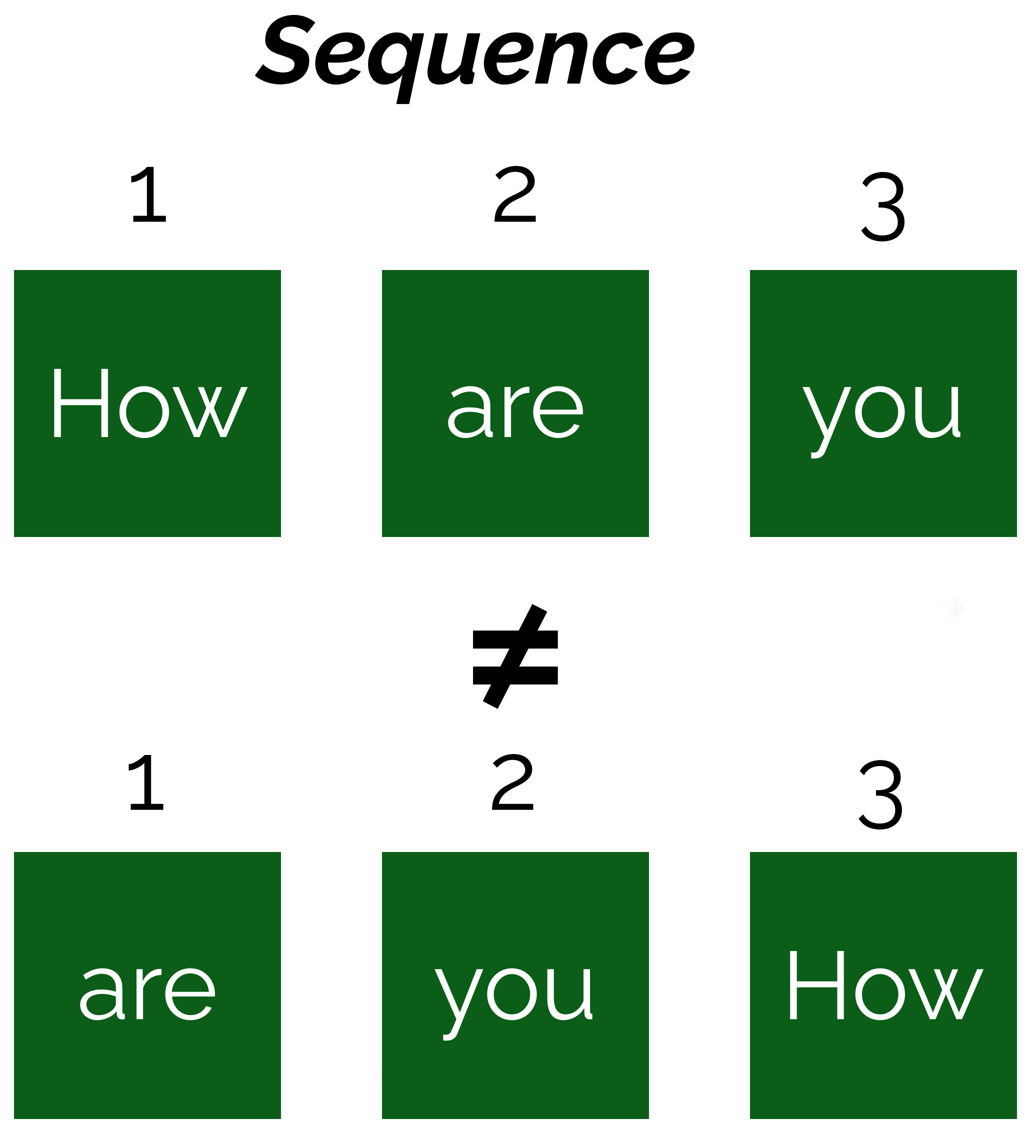
Machine Learning → *Jets as a sequence*

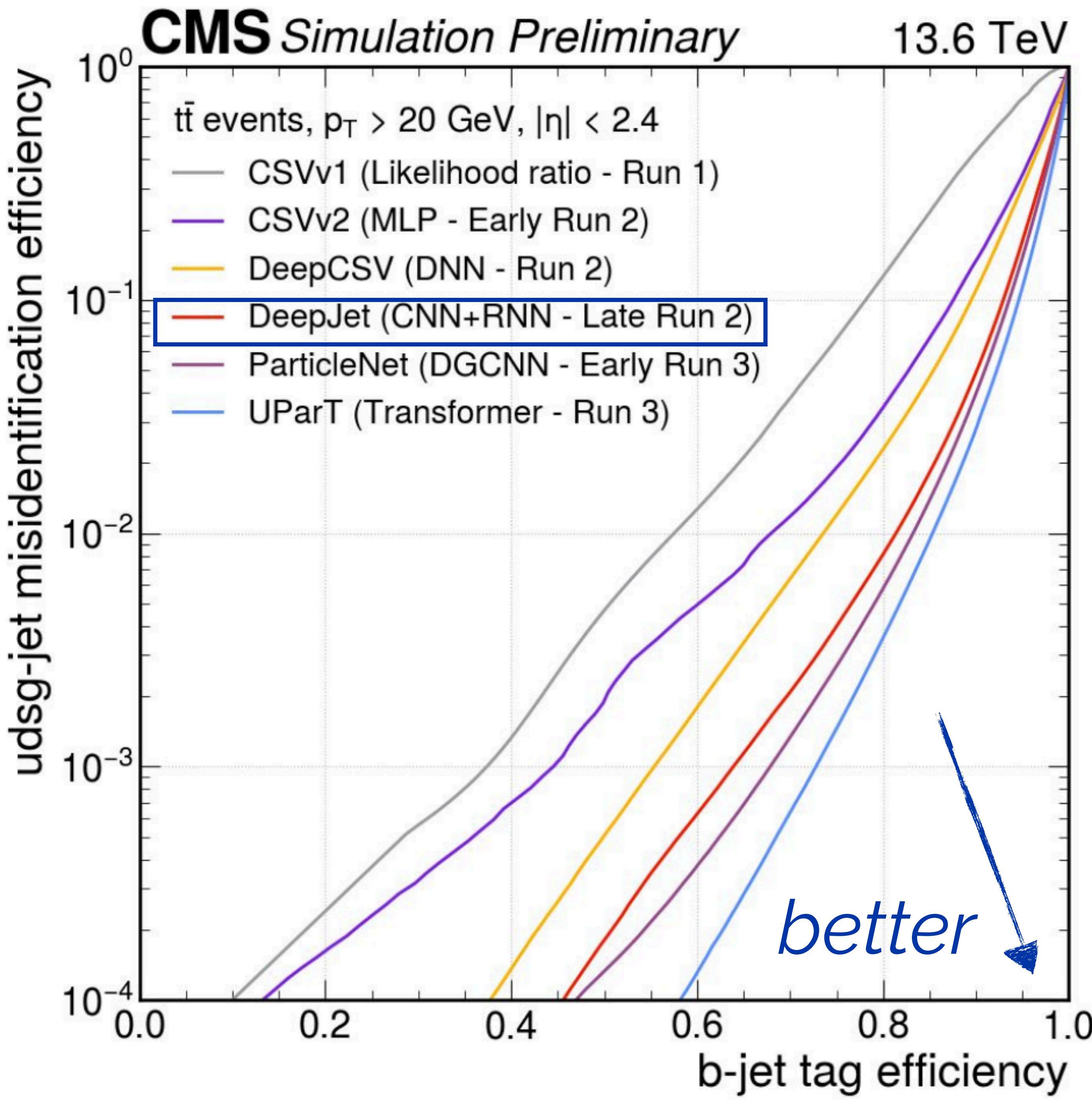
Jet probabilities → CSV/DeepCSV Sub-jet tagging → DeepJet/ DeepAK8

- Ordering of the sequence? We must impose a human inspired ordering (energy, displacement)…
- **Jet is intrinsically an un-ordered set of particles!**



Permutation symmetry





[CMS-DP-24-066]

A bit of CMS history...

Run 2 (2016 - 2018)

Run 1 (2011 - 2016)

Machine Learning → CSV/DeepCSV Sub-jet tagging

Jets as a sequence → DeepJet/ DeepAK8

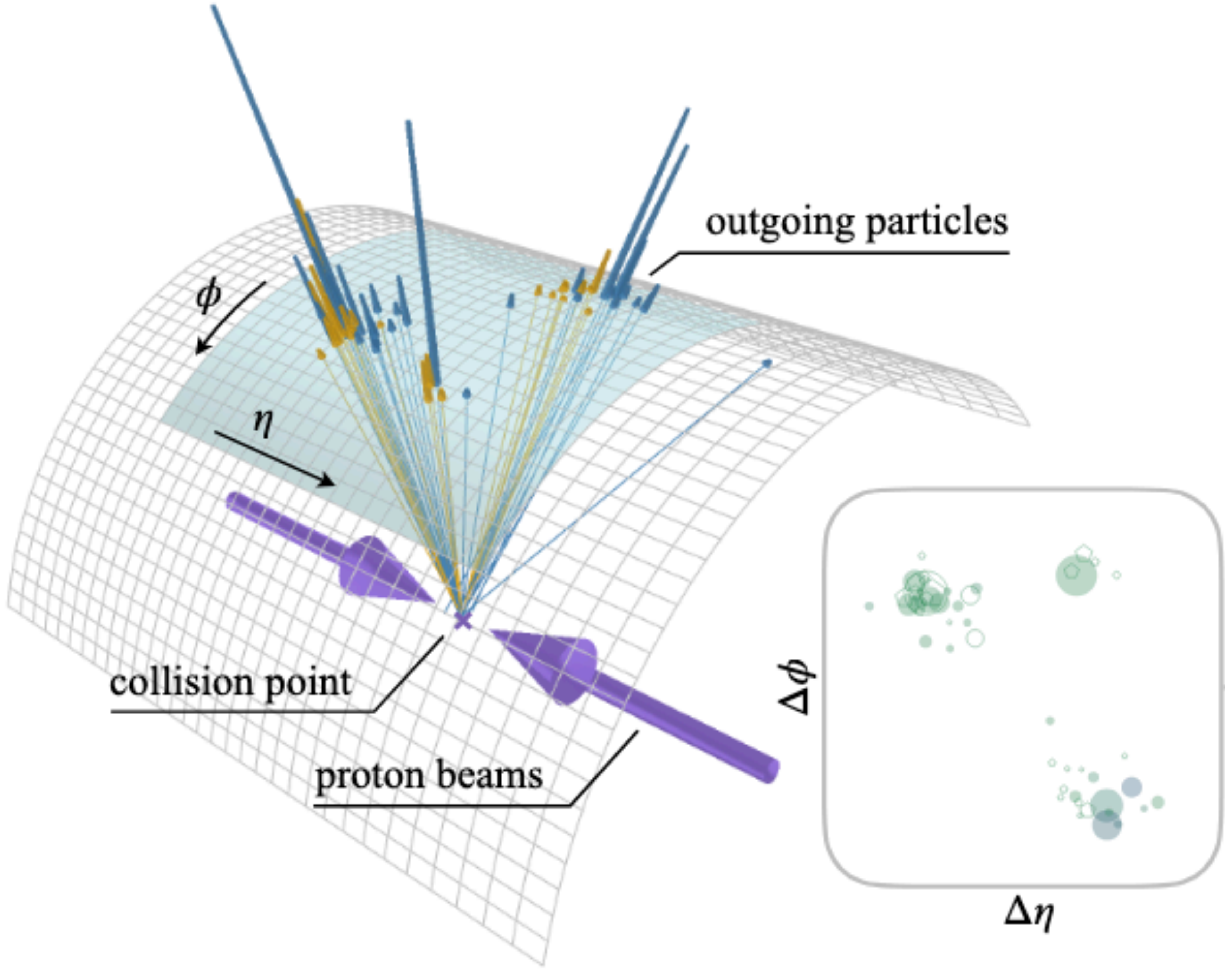
Jets as a ~~point~~ particle cloud → ParticleNet

Jet probabilities

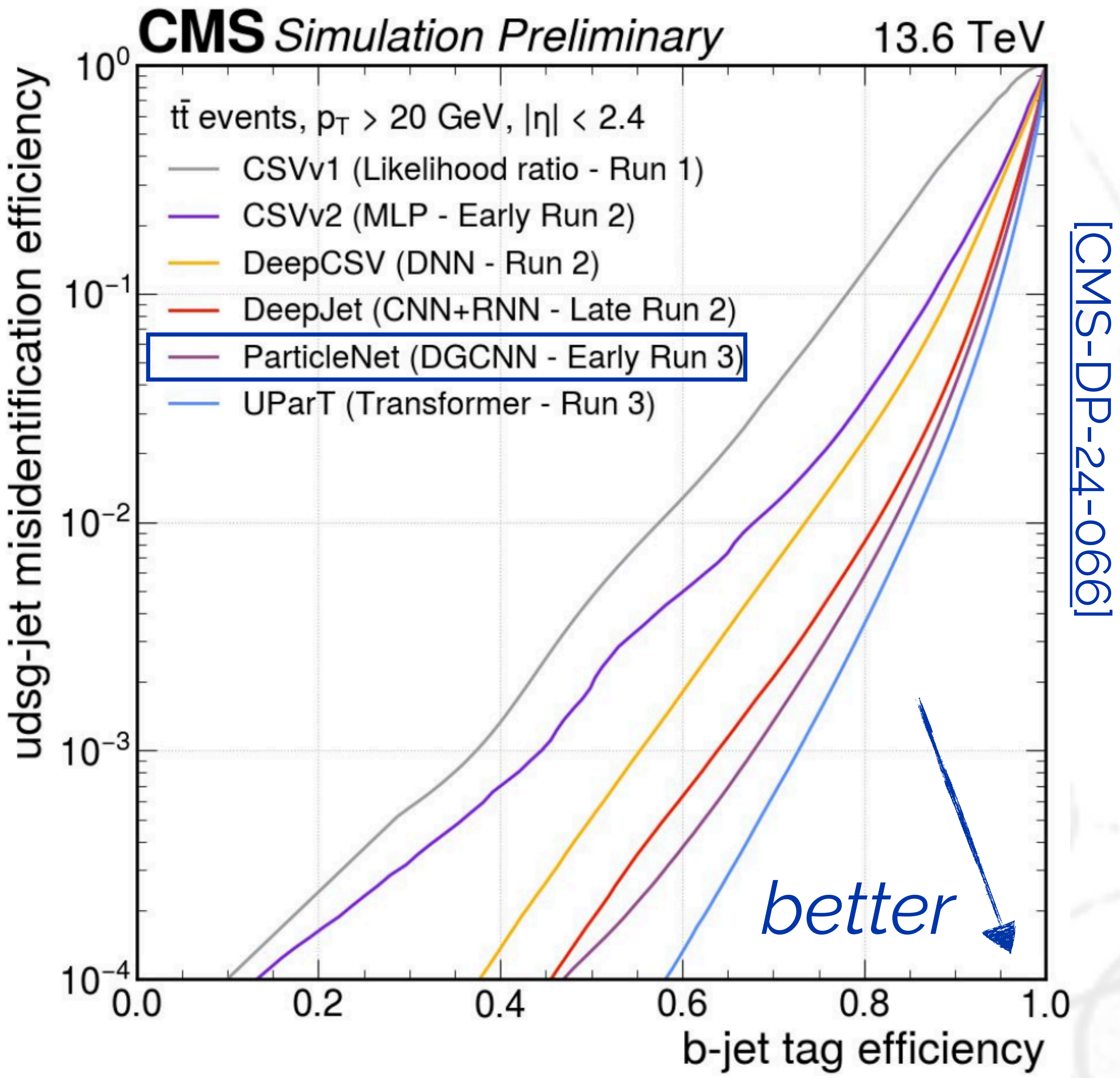
[Qu, H., Gouskos, L. (2019)]

- The revolution: unordered set of particles in graph / **point cloud**
- For each point: (spatial) coordinates + properties (energy/momentum, detector response, ...)
- Key feature: **permutation symmetry** via e.g. locally connected graph

Main tagger for CMS Run 2 H(cc) results!

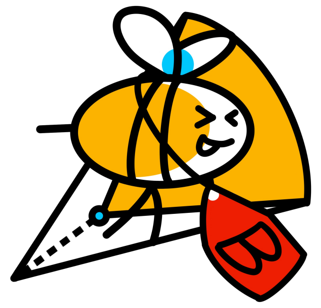


From [PMLR162:18281-18292,2022]



[CMS-DP-24-066]

A bit of CMS history...



Run 1 (2011 - 2016) — Jet probabilities

Run 2 (2016 - 2018)
- *Machine Learning* → CSV/DeepCSV Sub-jet tagging
- *Jets as a sequence* → DeepJet/ DeepAK8

Run 3 (2022 - 2026)
- *Jets as a ~~point~~ particle cloud* → ParticleNet, ParticleTransformer

- Transformers are taking on every task!
- Core concept: Self-attention mechanism

Attention Is All You Need

[Vasvani et al. (2017)]

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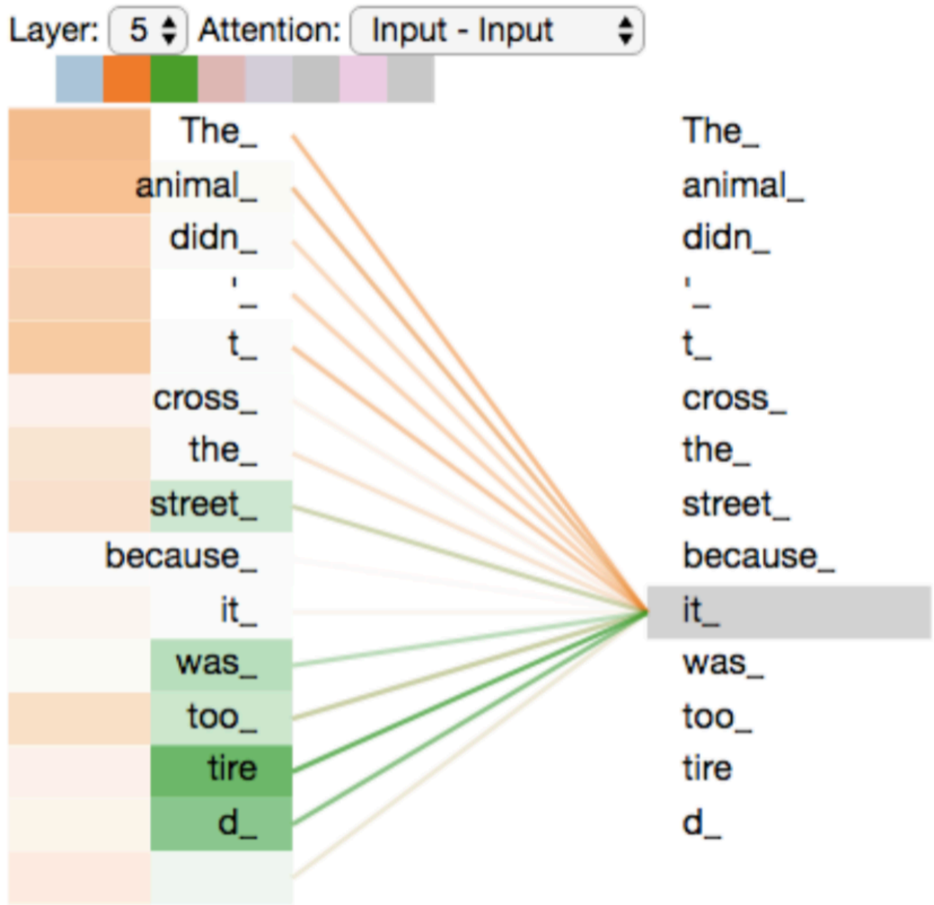
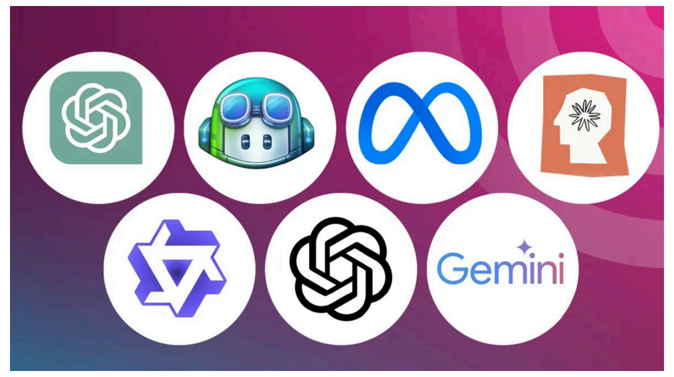
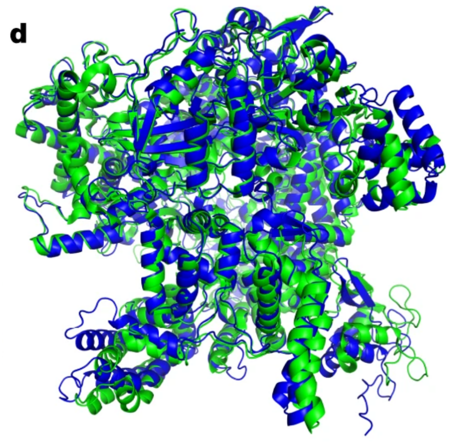


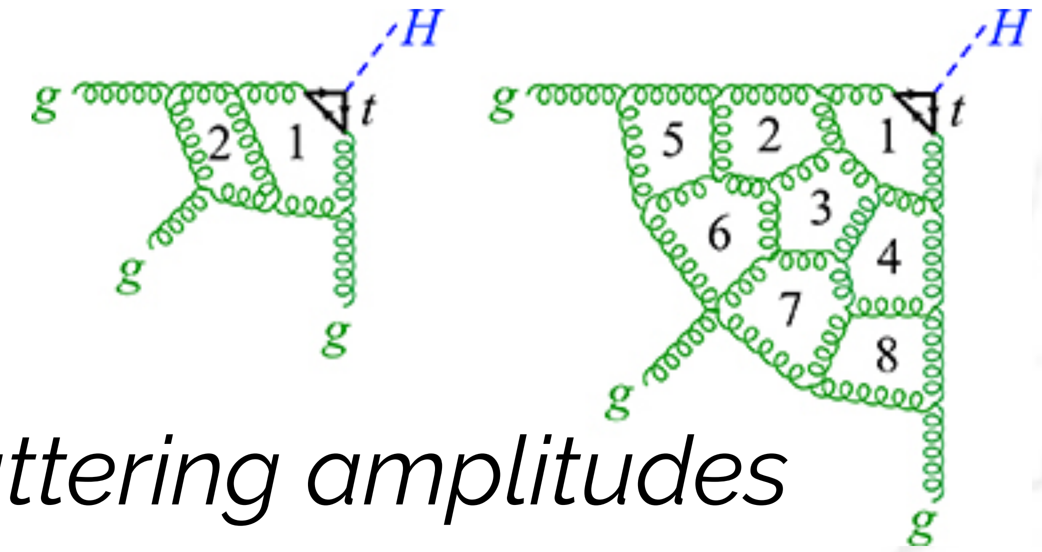
LLMs



Protein structure

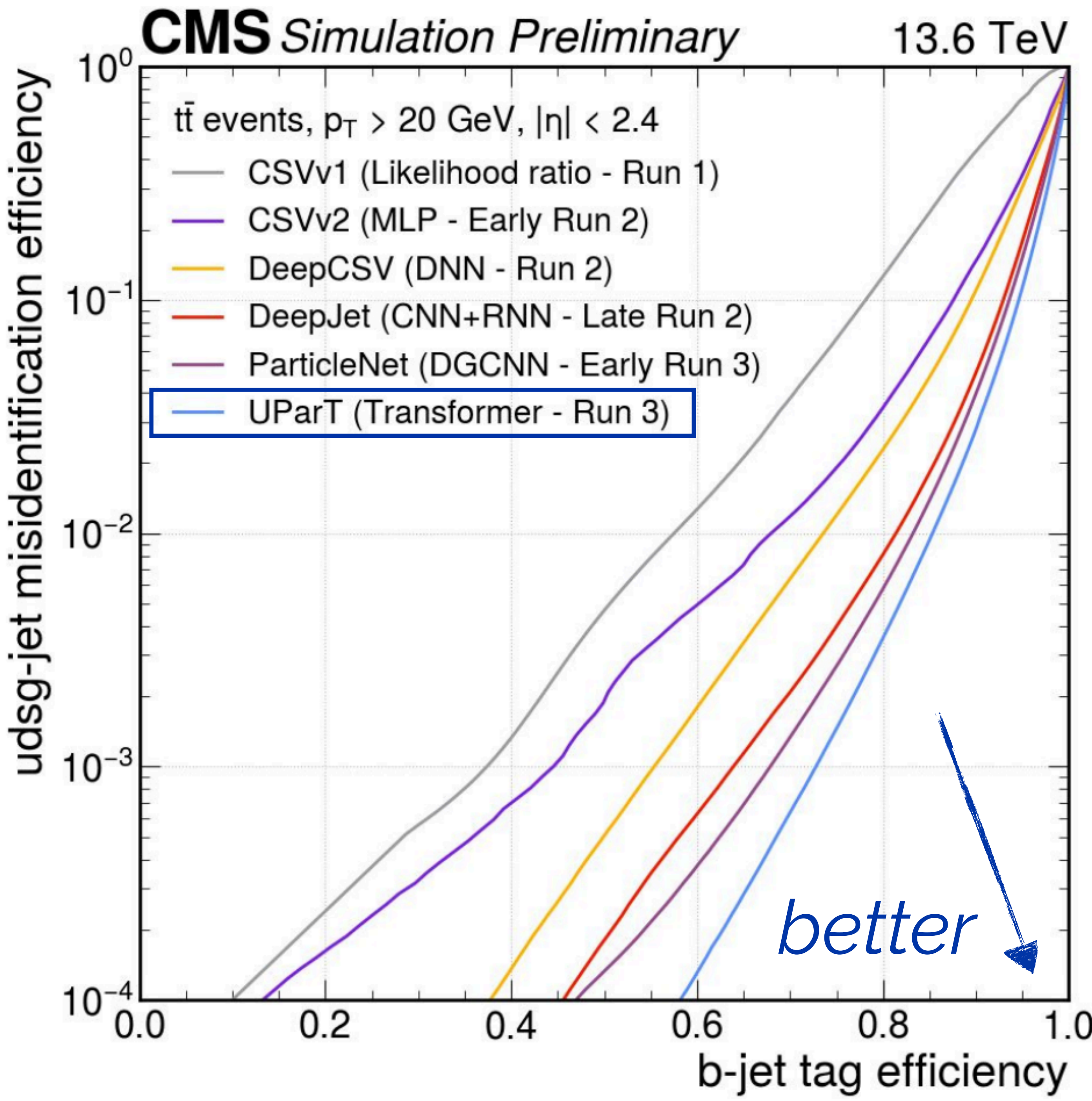


[Nature 596 (2021) 583]



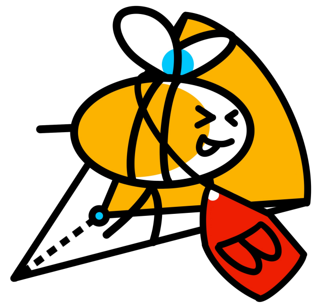
Scattering amplitudes

[MLST 5 (2024) 035073]



[CMS-DP-24-066]

A bit of CMS history…



Run 1 (2011 - 2016)

- Jet probabilities

Run 2 (2016 - 2018)

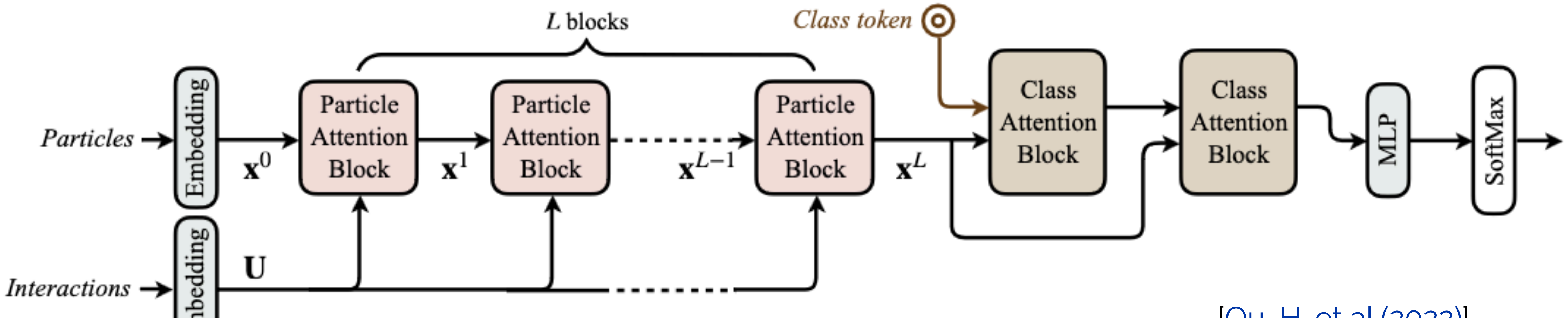
- Machine Learning → CSV/DeepCSV Sub-jet tagging
- Jets as a sequence → DeepJet/ DeepAK8

Run 3 (2022 - 2026)

- Jets as a ~~point~~ particle cloud → ParticleNet, ParticleTransformer

- Transformers are taking on every task!
- Core concept: Self-attention mechanism
- Physics-inspired pairwise features

Our tagger for CMS Run 3!



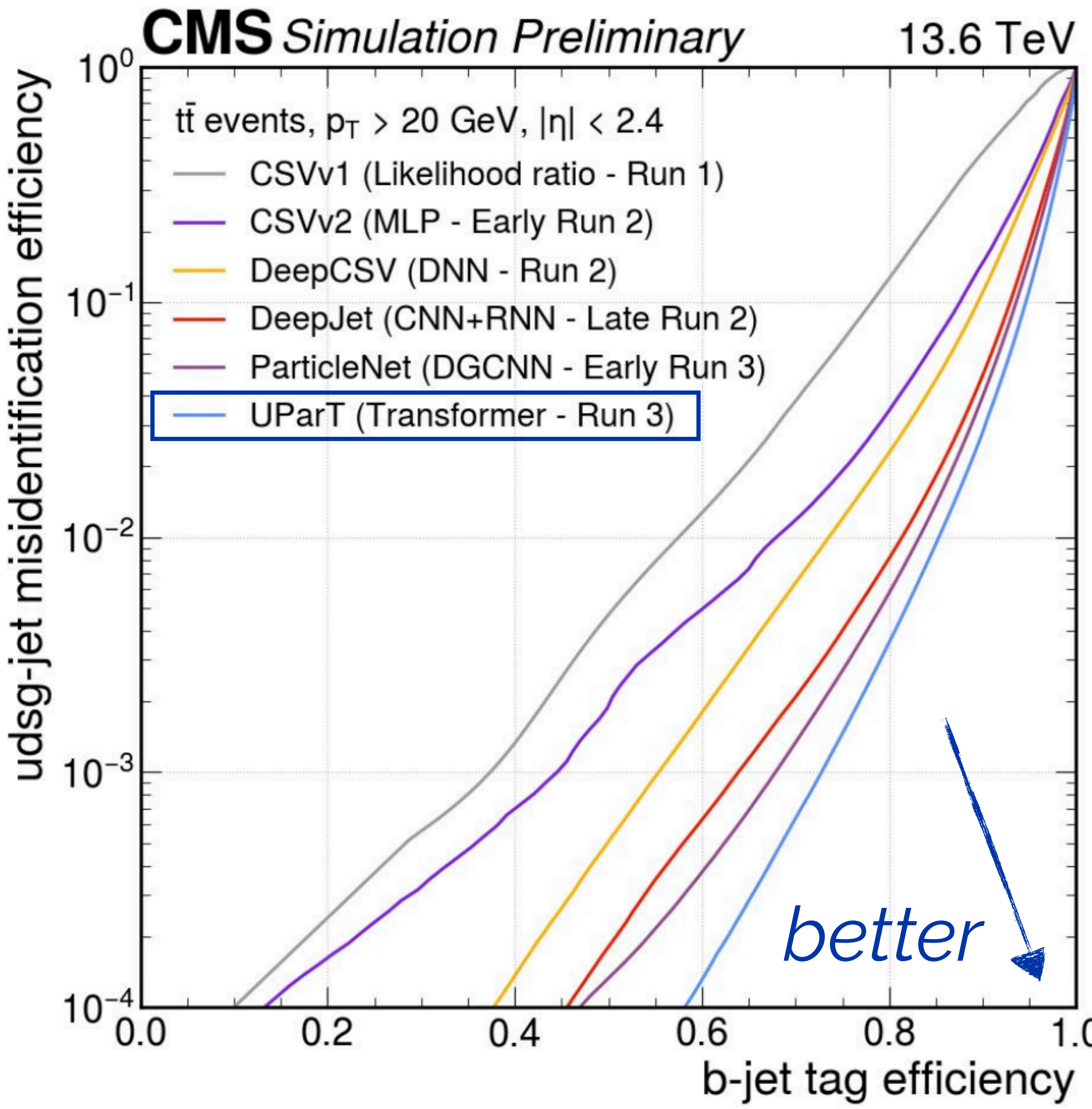
(a) Particle Transformer

[Qu, H. et al (2022)]

$$
\begin{aligned}
\Delta &= \sqrt{(y_a - y_b)^2 + (\phi_a - \phi_b)^2},\\
k_\mathrm{T} &= \min(p_{\mathrm{T},a}, p_{\mathrm{T},b})\Delta,\\
z &= \min(p_{\mathrm{T},a}, p_{\mathrm{T},b})/(p_{\mathrm{T},a} + p_{\mathrm{T},b}),\\
m^2 &= (E_a + E_b)^2 - \|\mathbf{p}_a + \mathbf{p}_b\|^2,
\end{aligned}
$$

Inject physics to "steer" model

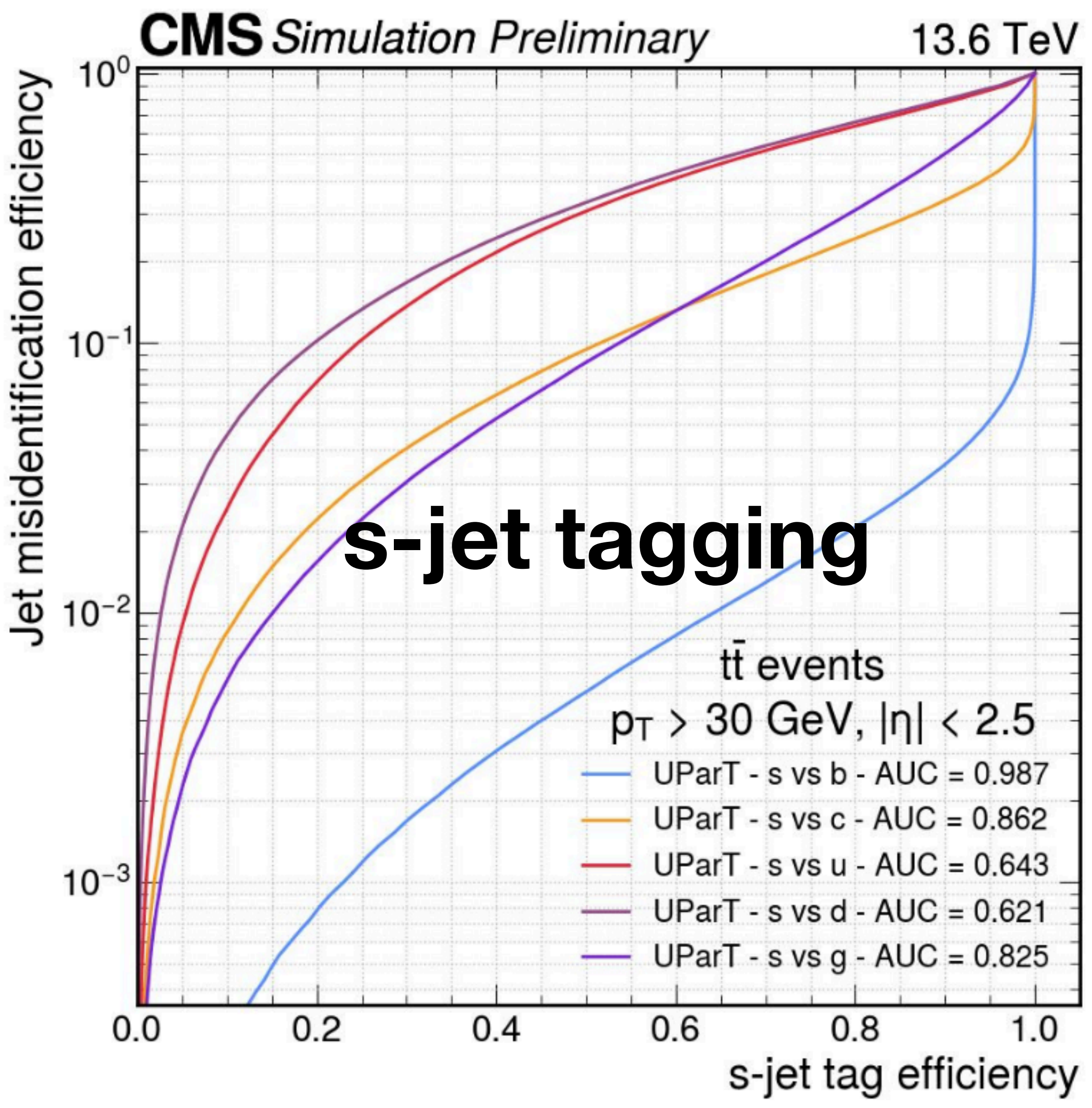
Output nodes

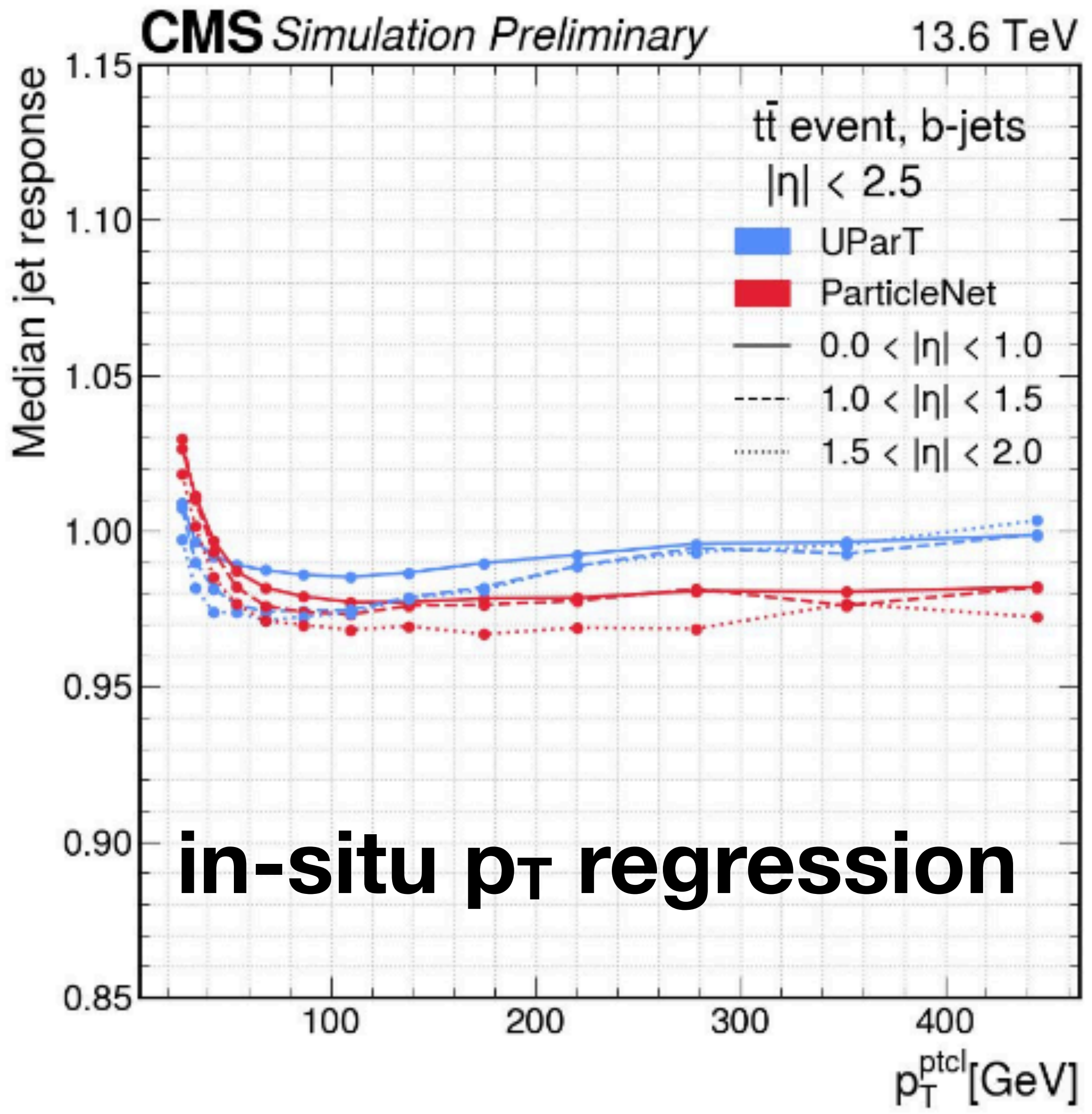


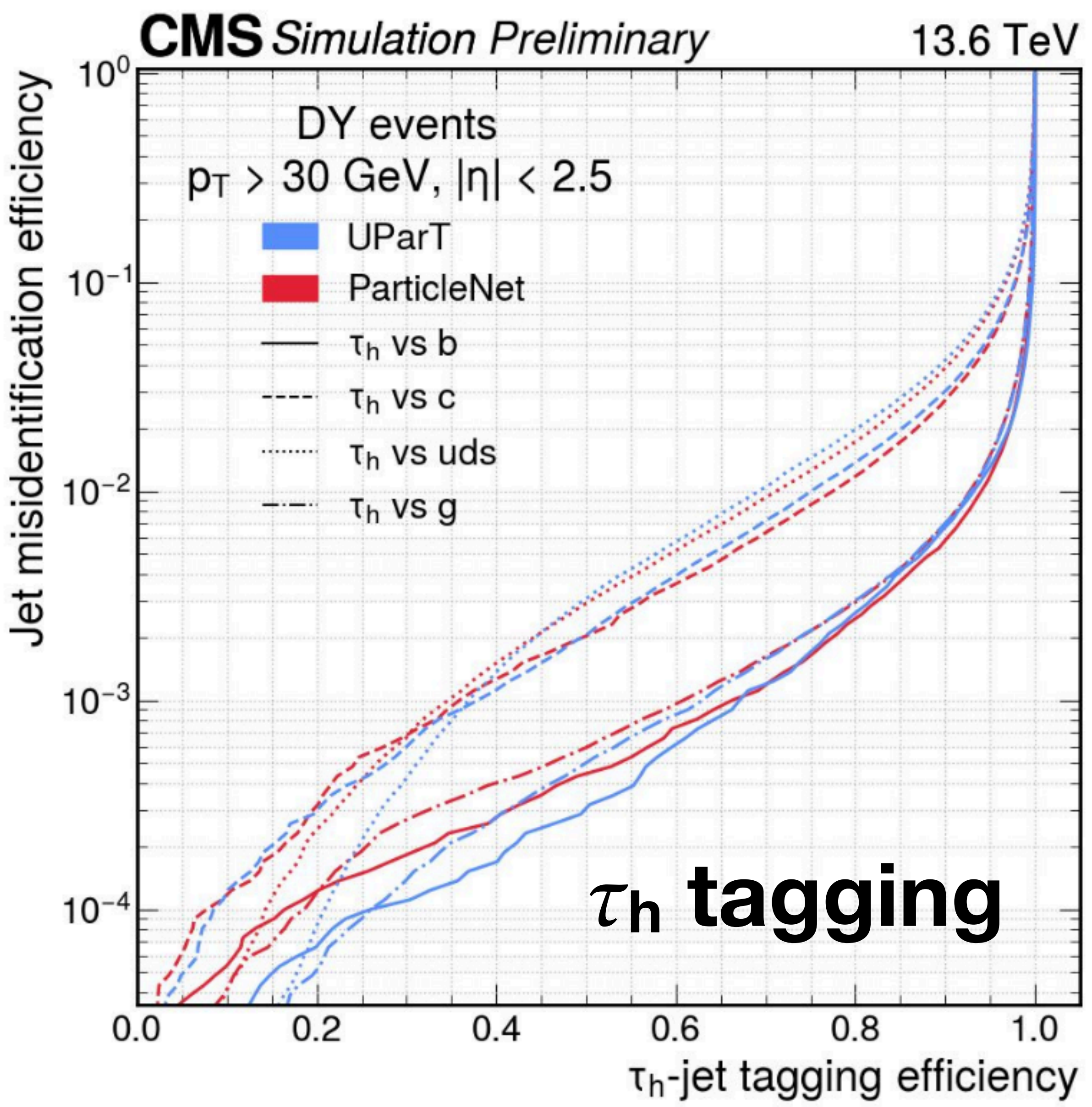
[CMS-DP-24-066]

The current SOTA: UParTAK4

[CMS-DP-24-066]

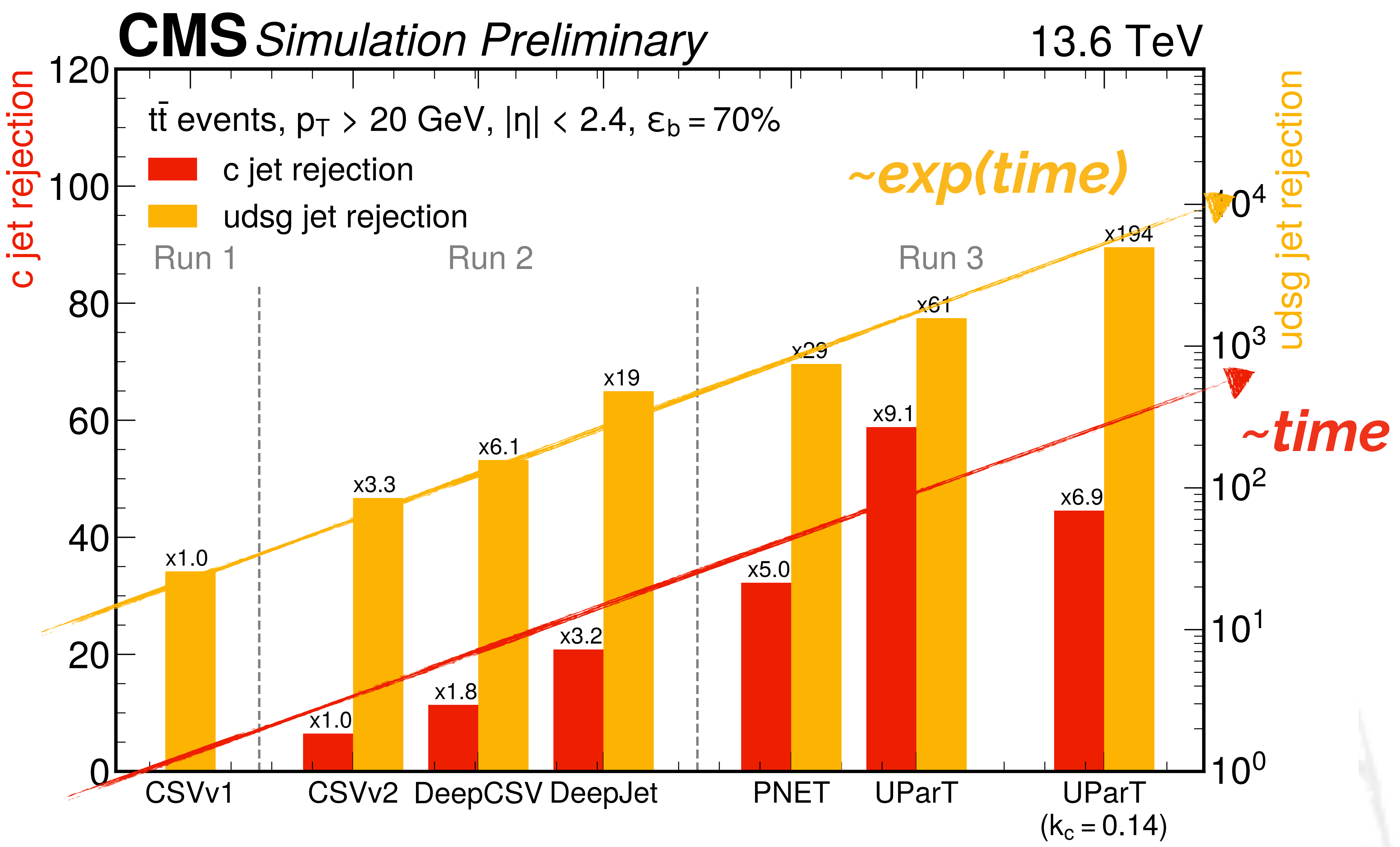






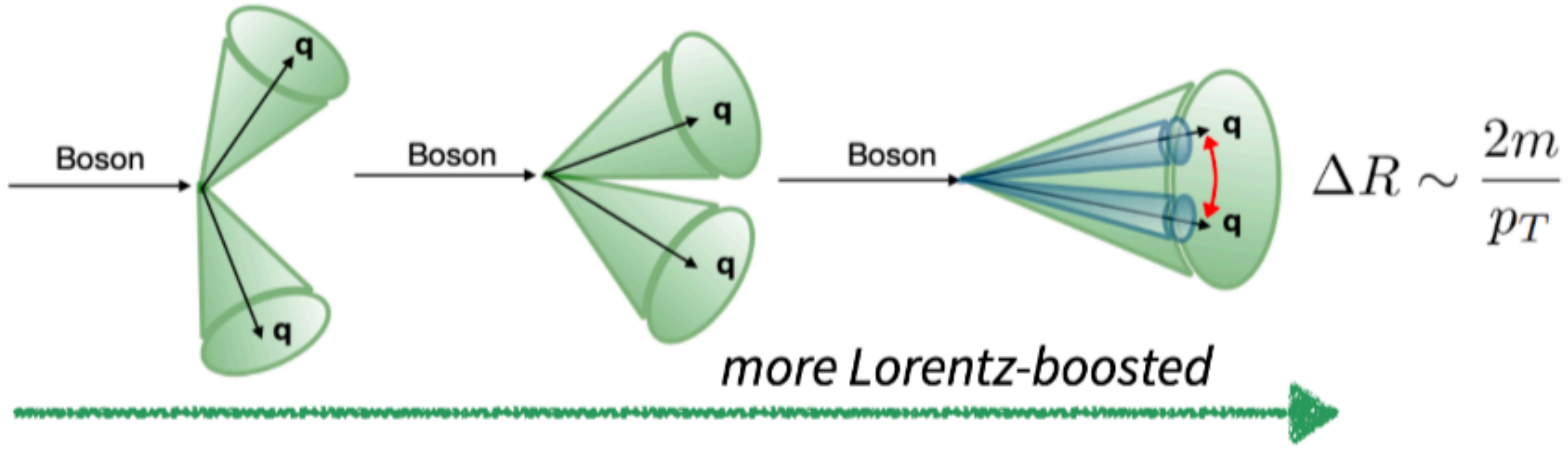
Towards a foundation model of jets?

N.B. ATLAS has similar results, although very different development over time..



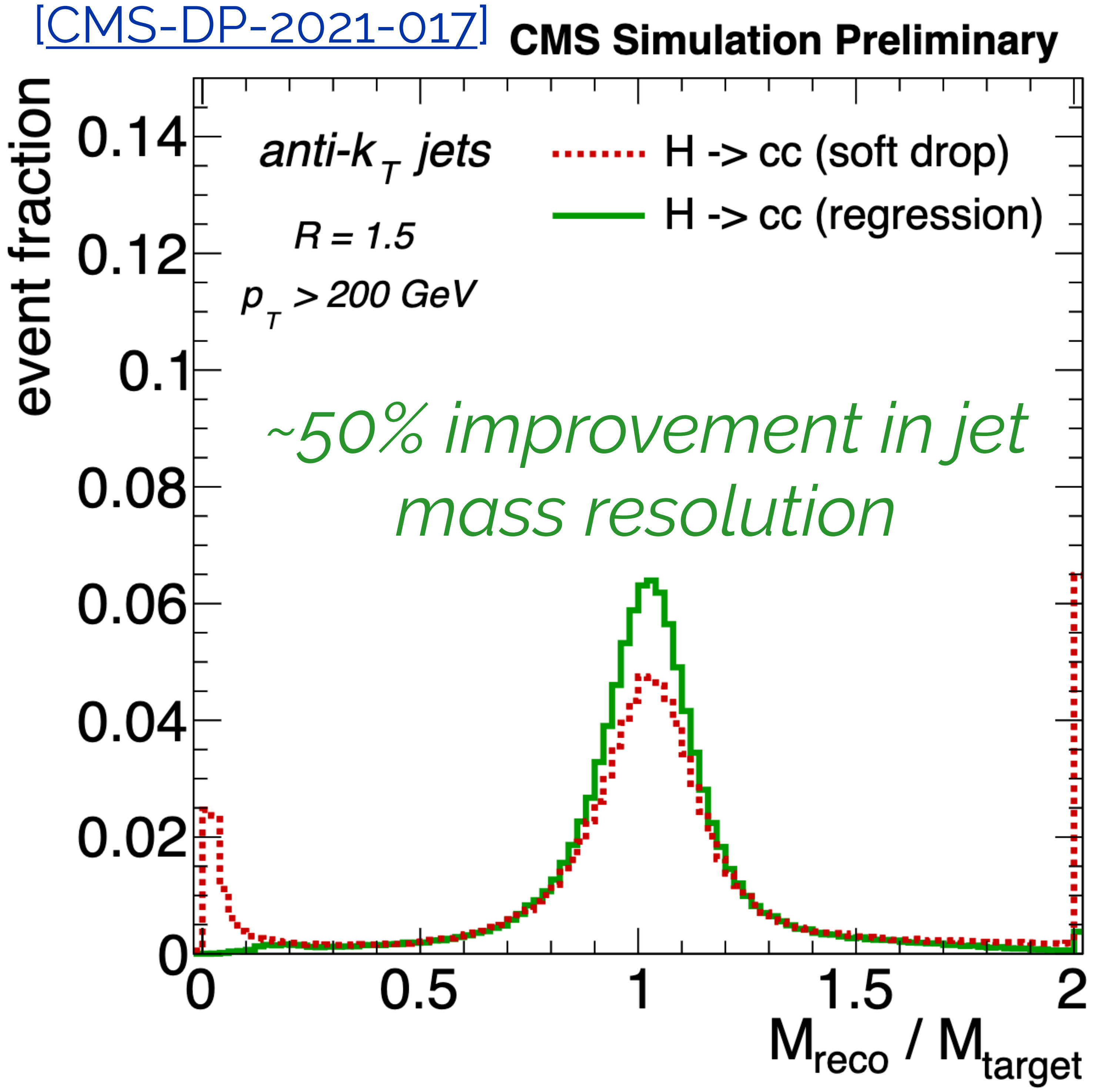
Impact of of ParticleNet on the example of VH(cc)

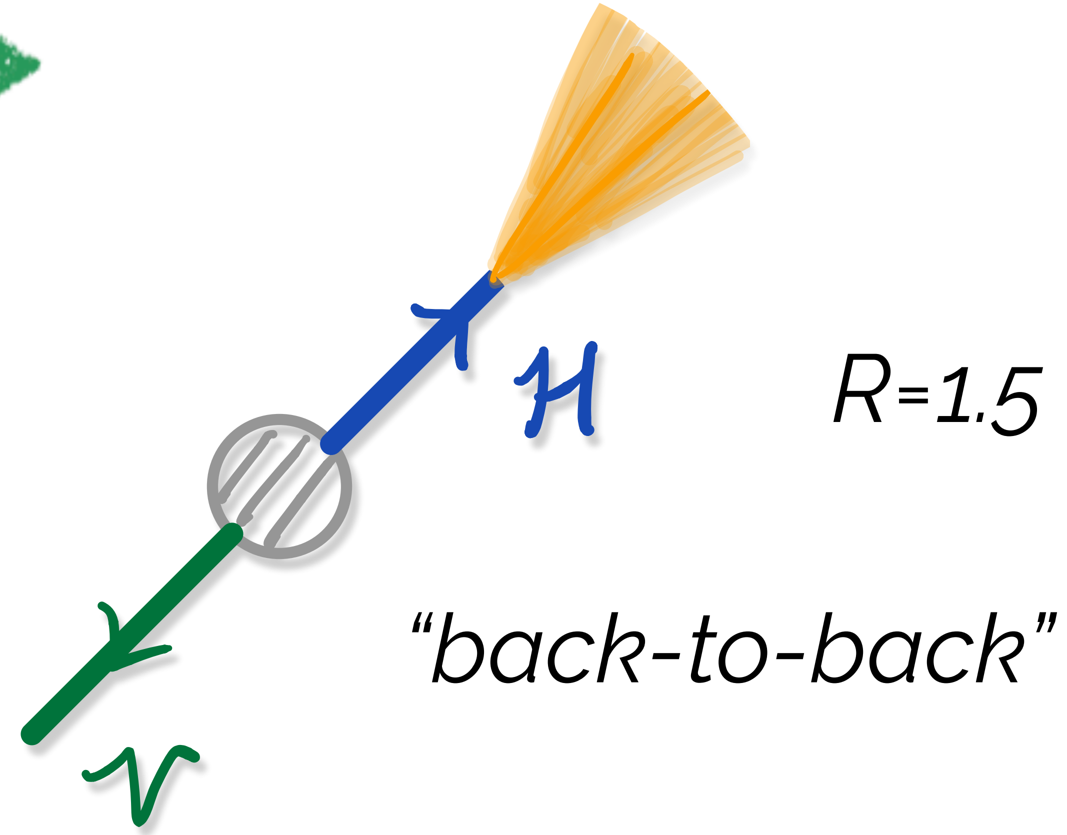
- Similar improvement in boosted jet tagging!



Merged regime

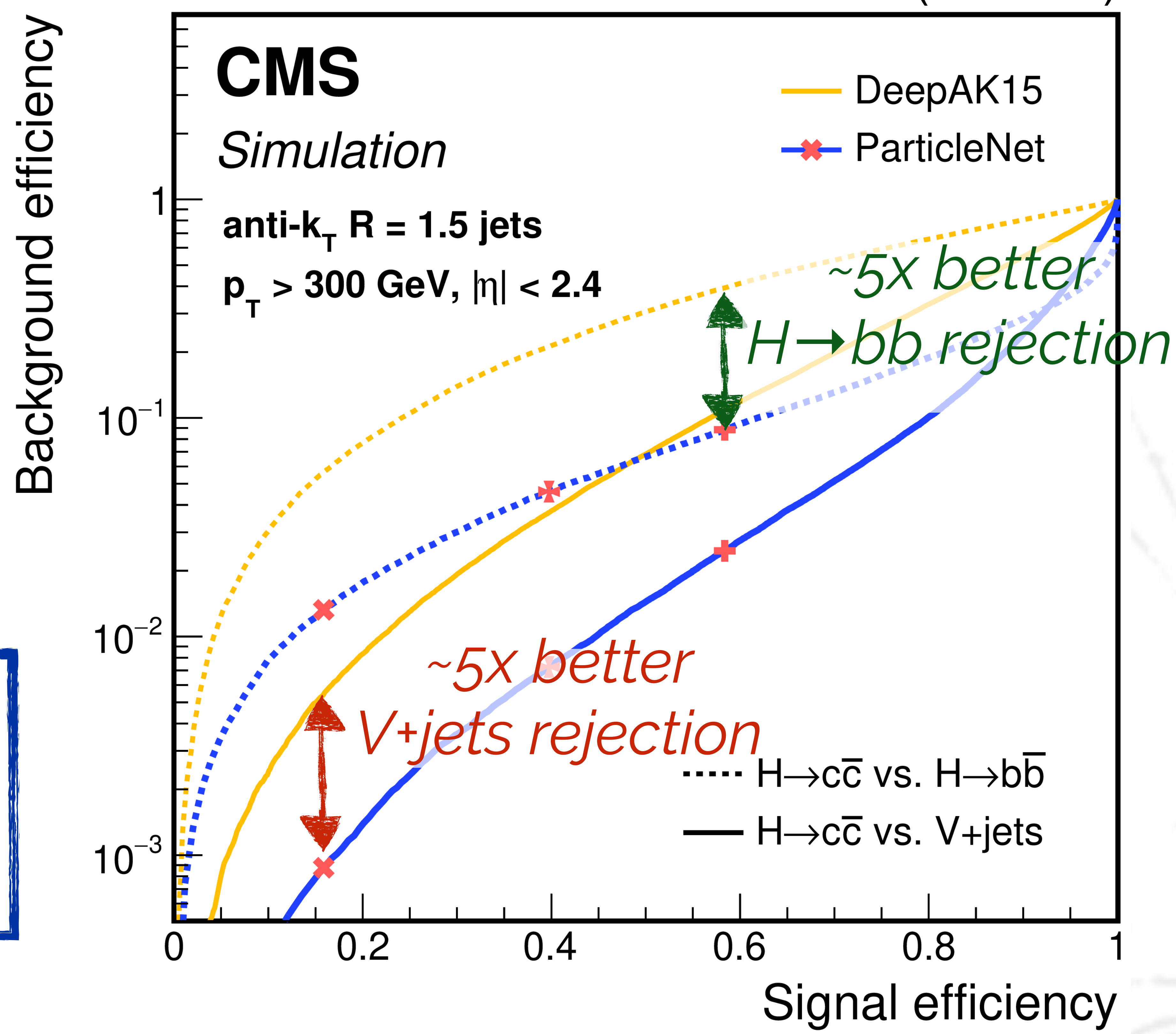
[CMS-DP-2021-017]





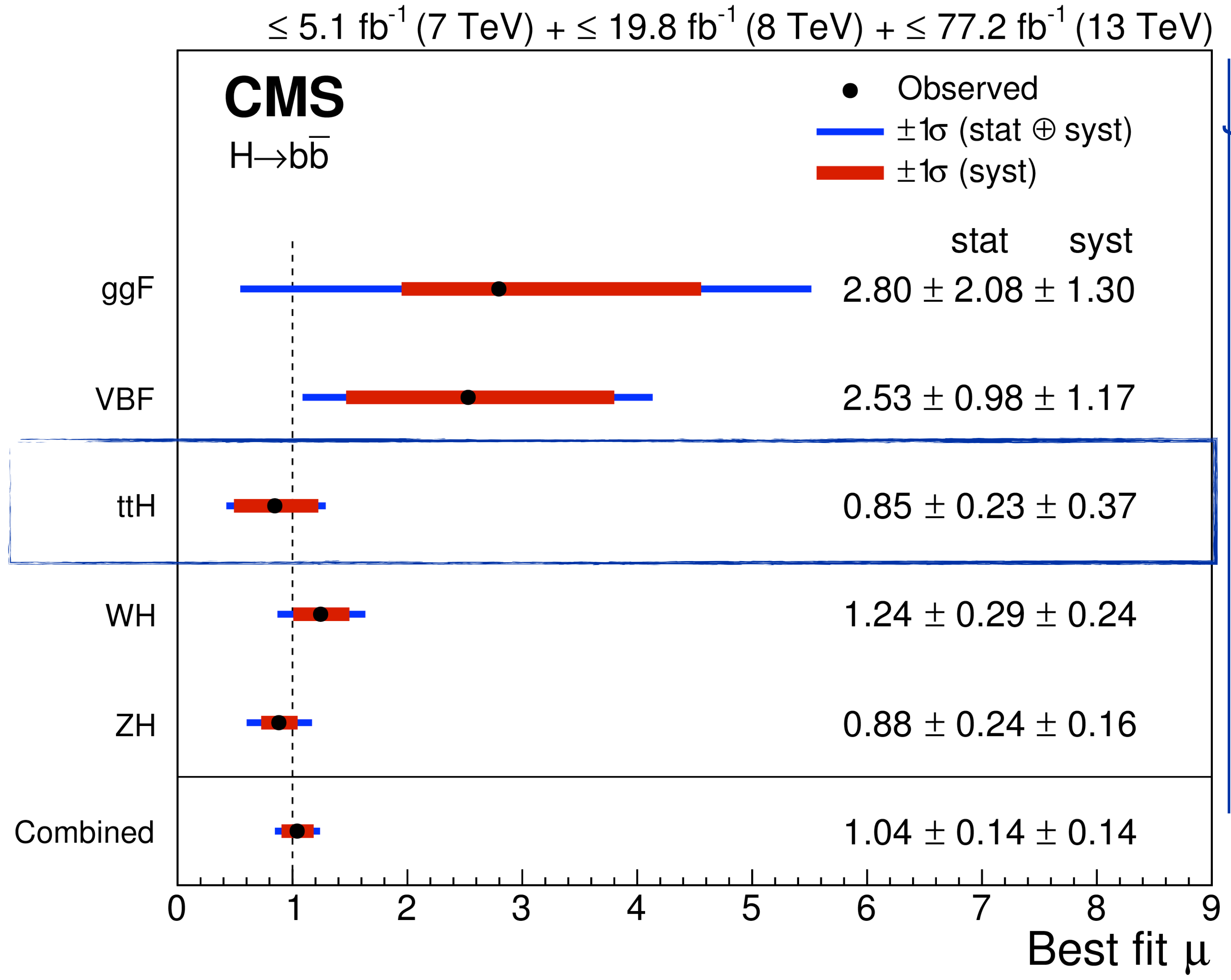
25% and 200% improvement in final sensitivity!

[PRL 131 (2023) 061801] (13 TeV)

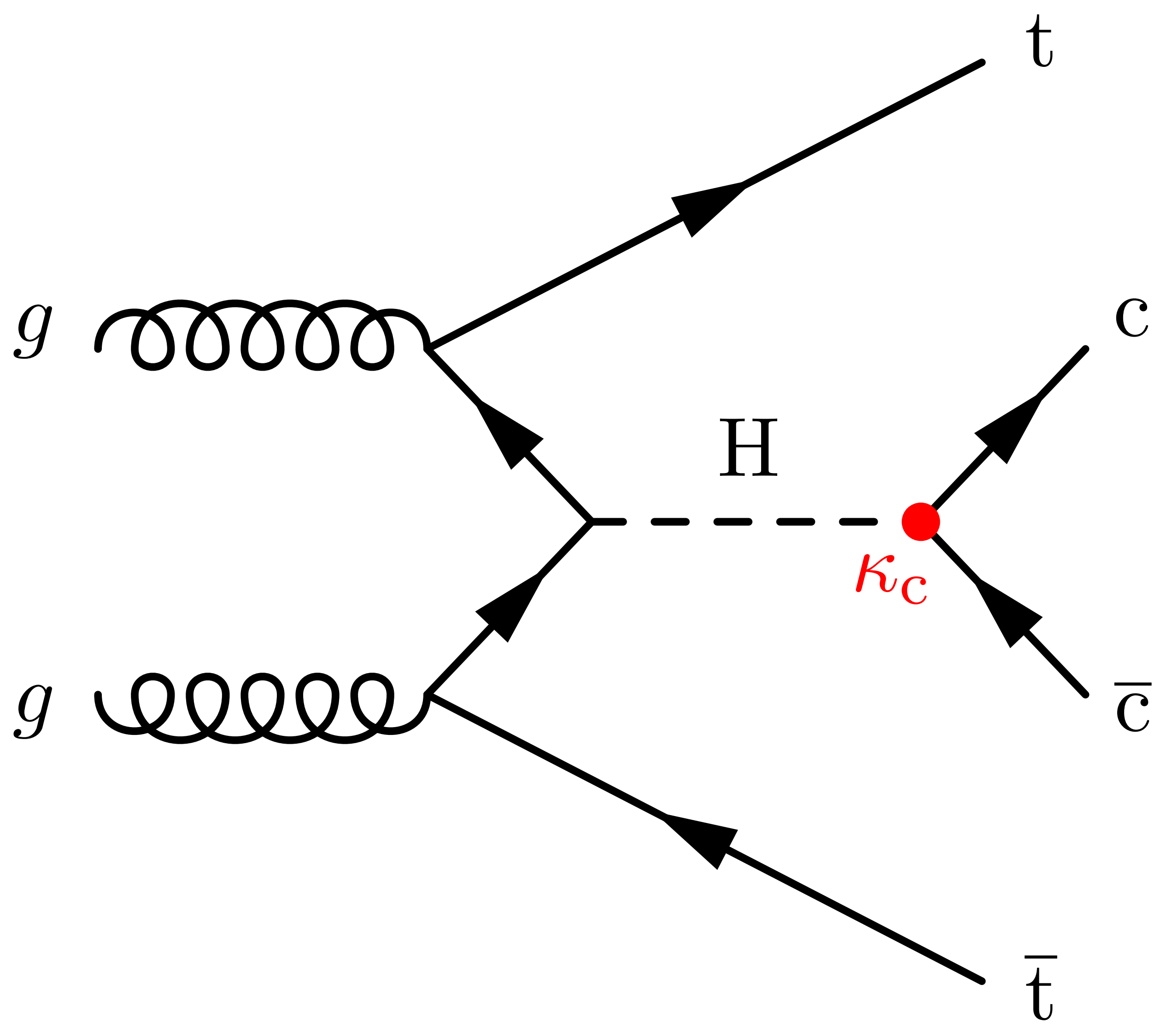


What can we add to VH?

Let's check out the previous generation!



Phys. Rev. Lett. 121 (2018) 121801



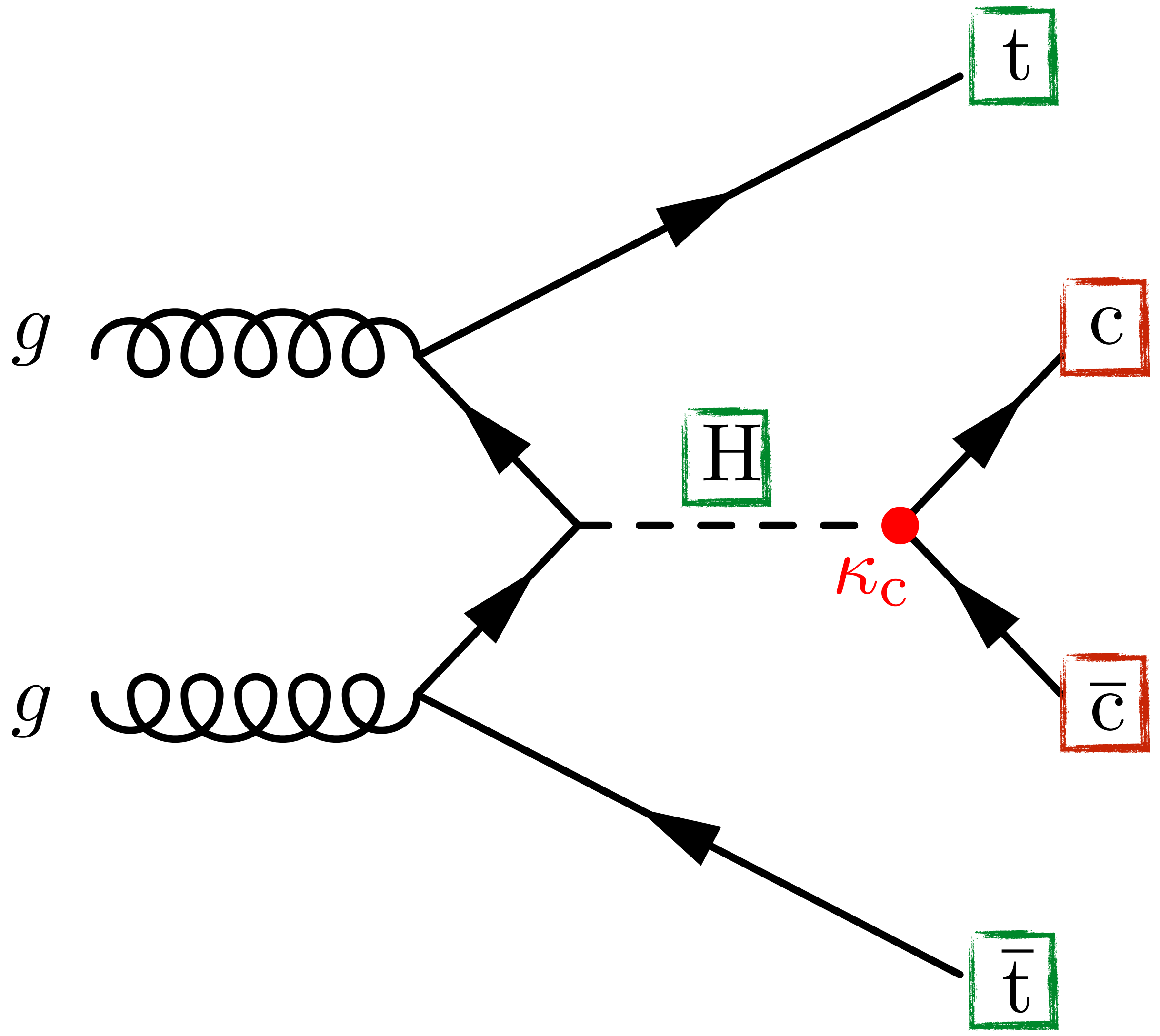
- **First search for $t\bar{t}$H(H → $c\bar{c}$)**
  - [PRL 36 (2026) 011801]
  - LHC Run 2 (138 fb^{-1})
  - Carried out as combination of 0L/1L/2L channels
  - Simultaneously measure **$t\bar{t}$H(H → $b\bar{b}$)**

- $t\bar{t}$H(H → $b\bar{b}$) important piece in the observation of H → $b\bar{b}$
- Adding $t\bar{t}$H(H → $c\bar{c}$) as a new puzzle piece
  - 0.5 pb vs. 2.5 pb of VH / large backgrounds
  - Challenging measurement, only **2000 $t\bar{t}$H(H → $c\bar{c}$)** events produced in CMS in Run 2

Why is $t\bar{t}H(H \rightarrow c\bar{c})$ challenging?

$t\bar{t}H(H \rightarrow c\bar{c})$ as an example of a modern LHC analysis

→ Smart usage of **physics-oriented machine learning**



Why is $t\bar{t}H(H \to c\bar{c})$ challenging?

- **1) Jet flavour identification (tagging):**
  - Multiple **heavy-flavour (HF) jets** in the final state
  - Crucial to identify HF jets efficiently

Exploit modern graph-based tagger (ParticleNet)

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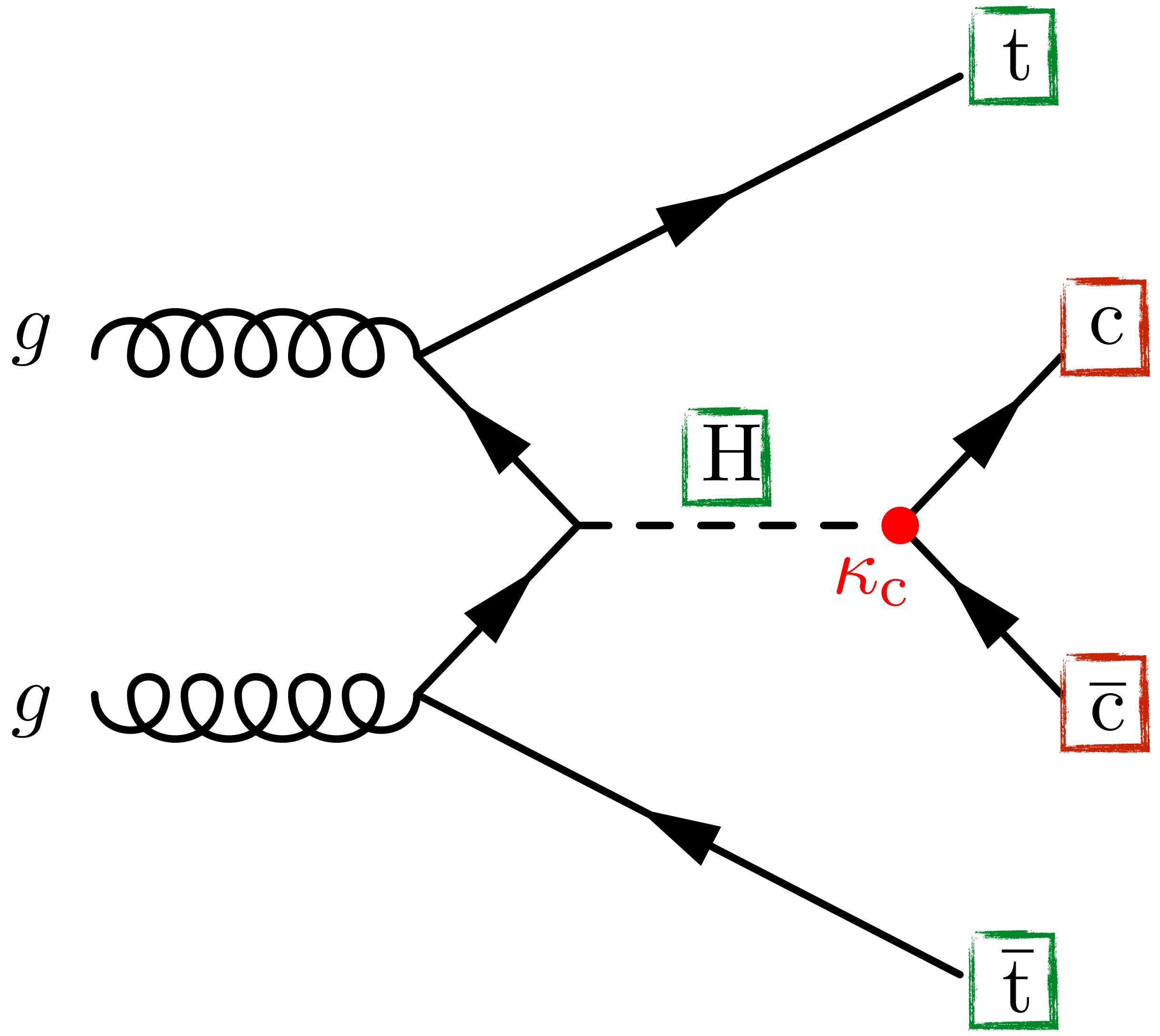

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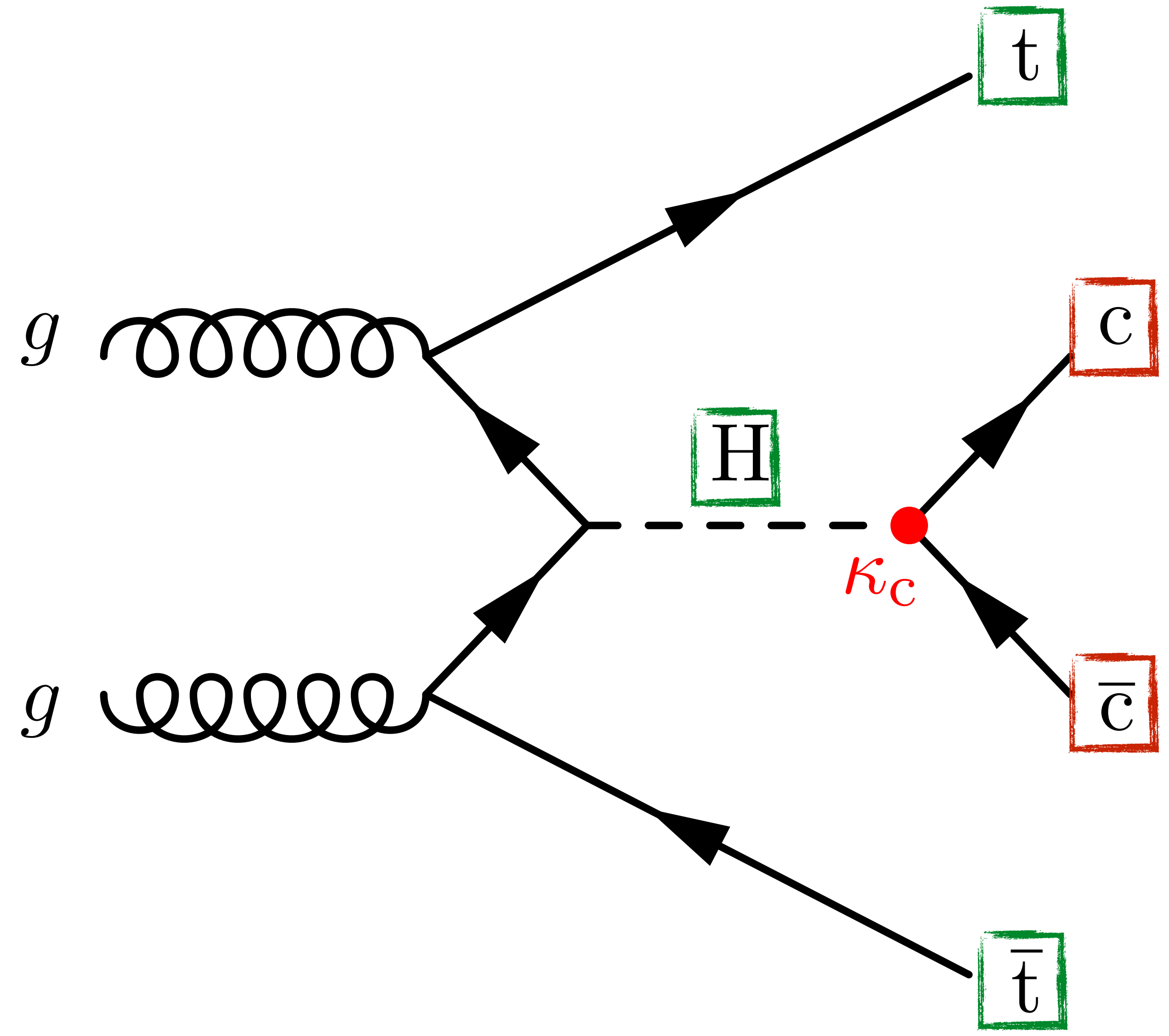

- **2) Event reconstruction:**
  - Complicated topology: High jet multiplicity & leptons (only e\μ)
    - e.g. 8 jets in 0L channel
  - Ambiguous combinatorics
    → **Higgs reconstruction challenge**

Neural network classifier learning correlations (ParticleTransformer)

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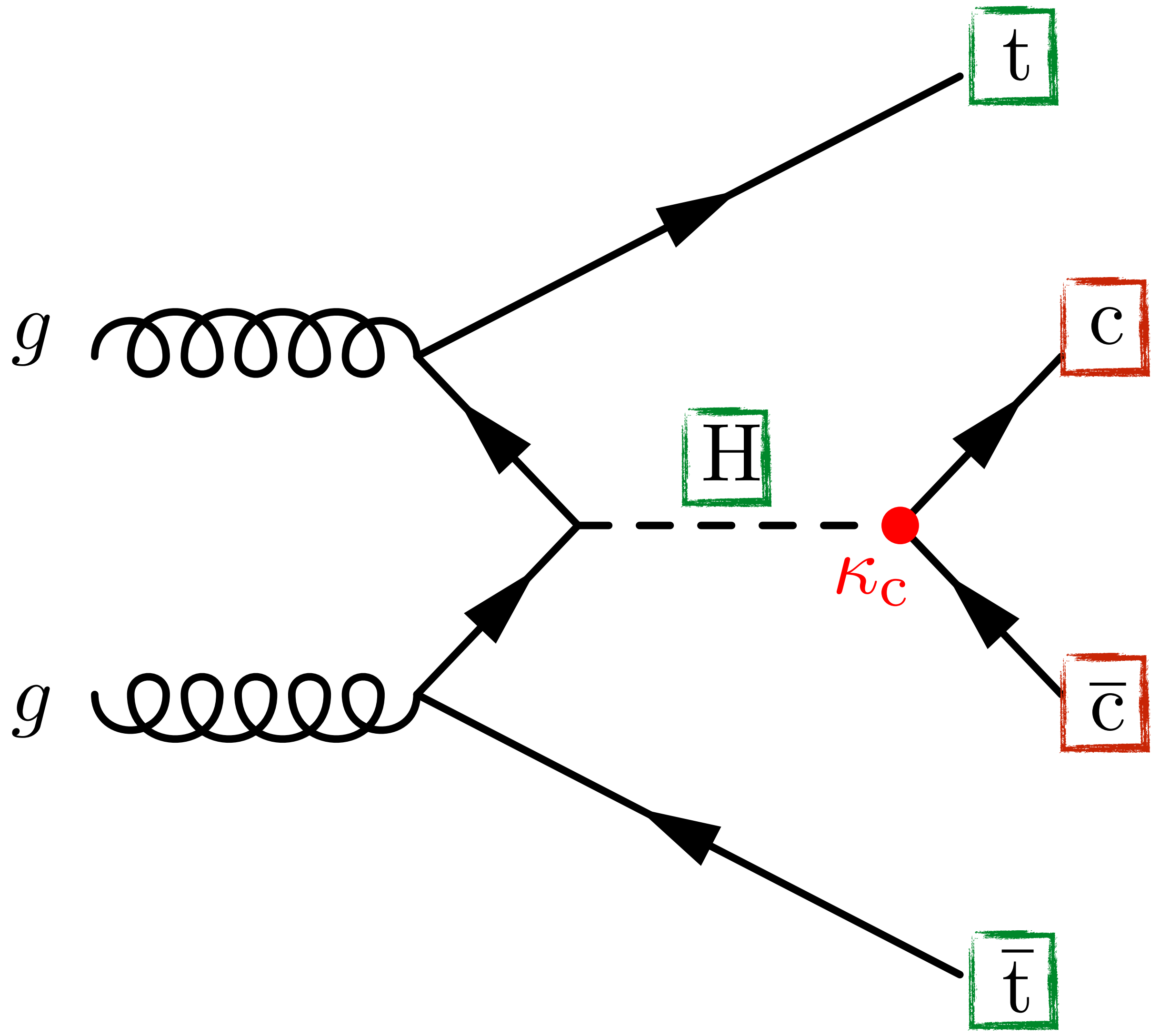

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    - e.g. 8 jets in 0L channel
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    → **Higgs reconstruction challenge**

Neural network classifier learning correlations (ParticleTransformer)

- **3) Background estimation:**
  - Dominant $t\bar{t}$+heavy-flavor (HF) jets (0L/1L/2L) and QCD multijet (0L)
  - Difficult to model in simulation

Data-driven background estimation

Heavy flavour jet identification for $t\bar{t}H(H \to c\bar{c})$

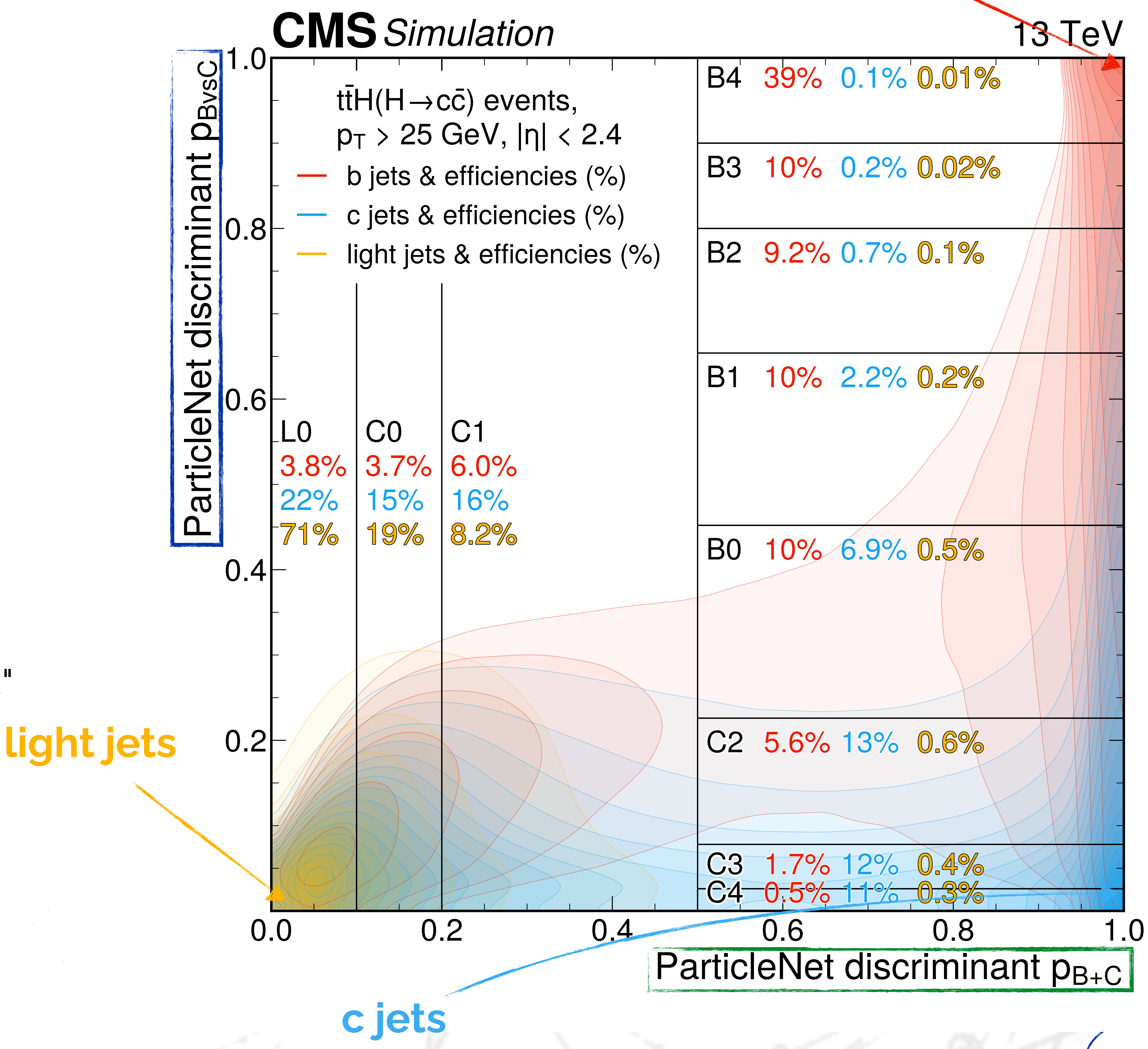
- This analysis exploits for the first time ParticleNet for small-radius jets in a Run 2 analysis in CMS

- For simultaneous b- and c-jet identification:

$$p_{\mathrm{B+C}} = \frac{p_{\mathrm{b}} + p_{\mathrm{bb}} + p_{\mathrm{c}} + p_{\mathrm{cc}}}{p_{\mathrm{b}} + p_{\mathrm{bb}} + p_{\mathrm{c}} + p_{\mathrm{cc}} + p_{\mathrm{uds}} + p_{\mathrm{g}}}$$

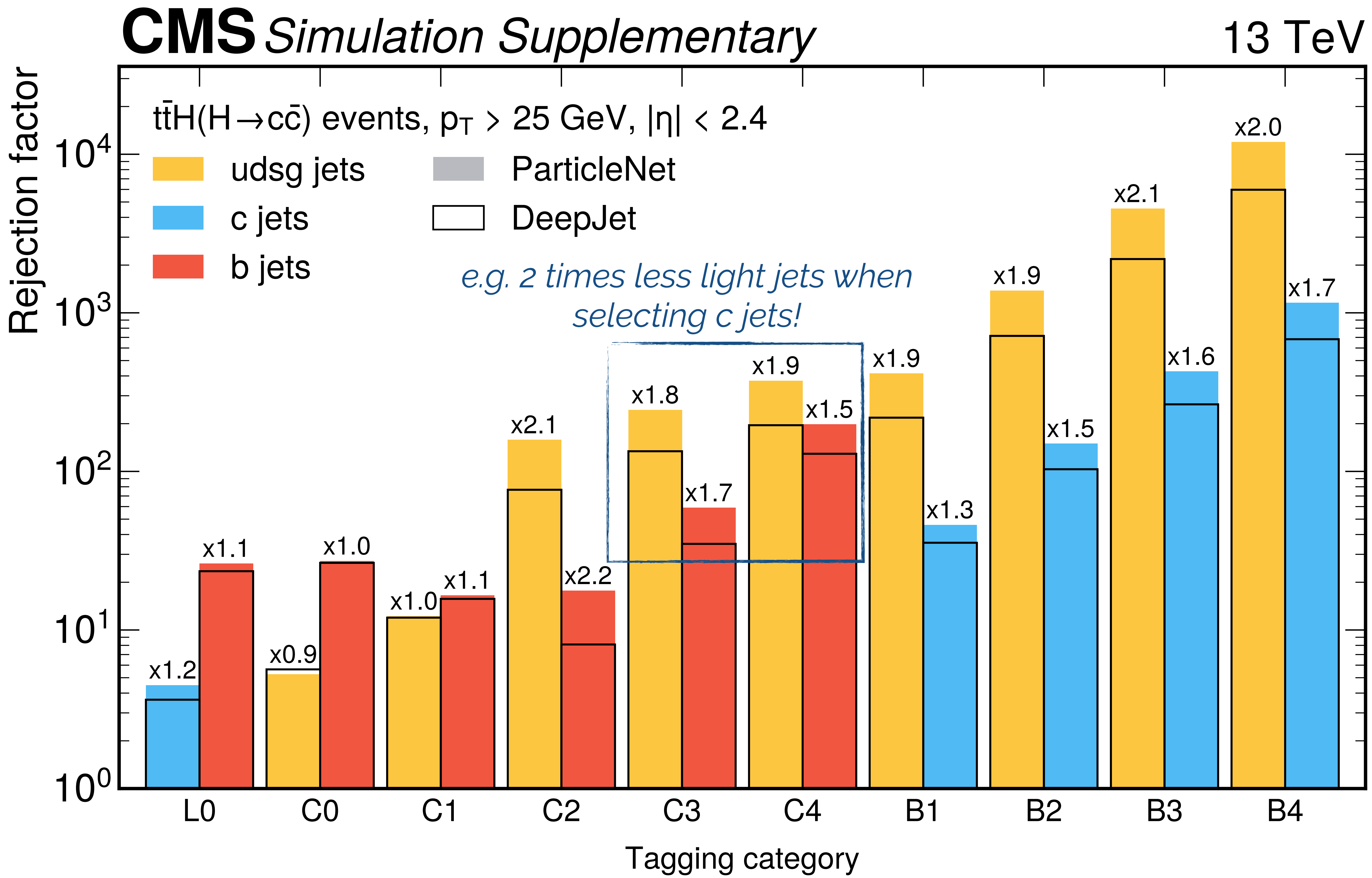
$$p_{\mathrm{BvsC}} = \frac{p_{\mathrm{b}} + p_{\mathrm{bb}}}{p_{\mathrm{b}} + p_{\mathrm{bb}} + p_{\mathrm{c}} + p_{\mathrm{cc}}}.$$

- Custom tagging categories:
  - Granular score information "pseudo continuous"
  - More robust calibration than full score
  - 5 b-jet enriched bins (B0 - B4)
  - 5 c-jet enriched bins (C0 - C4)
  - 1 light-jet (udsg) enriched bin (L0)



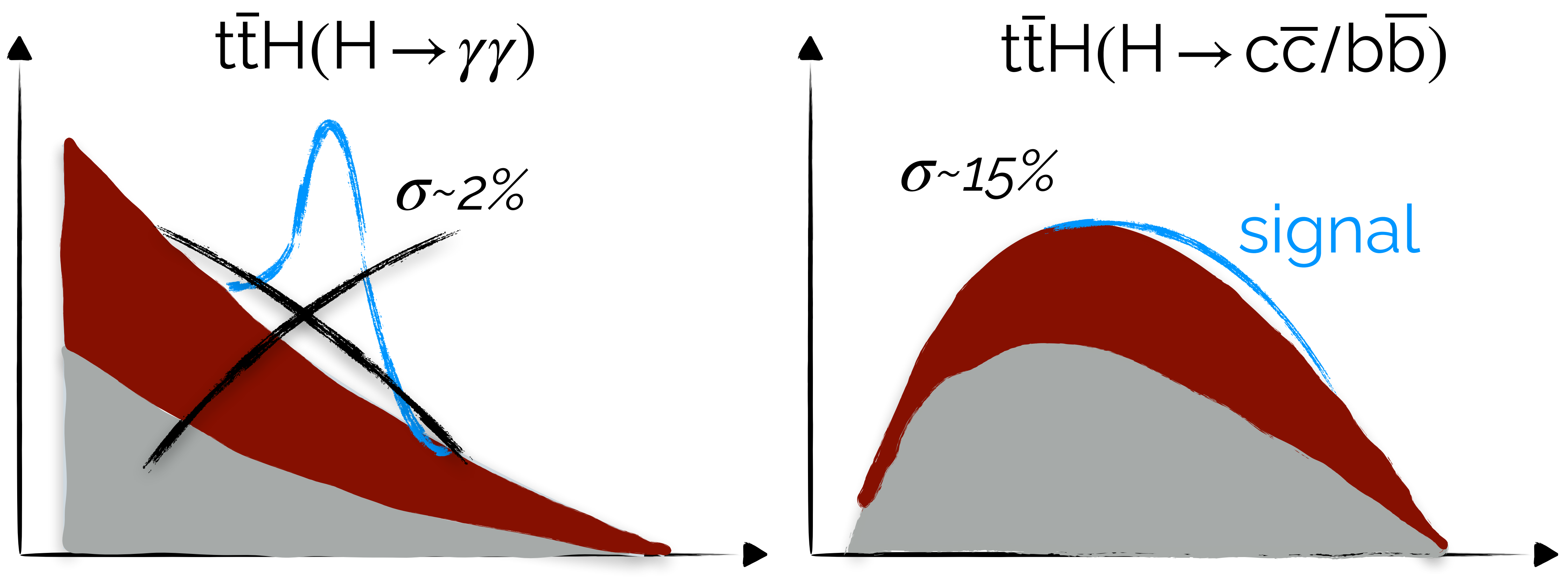
Heavy flavour jet identification for $t\bar{t}H(H \rightarrow c\bar{c})$

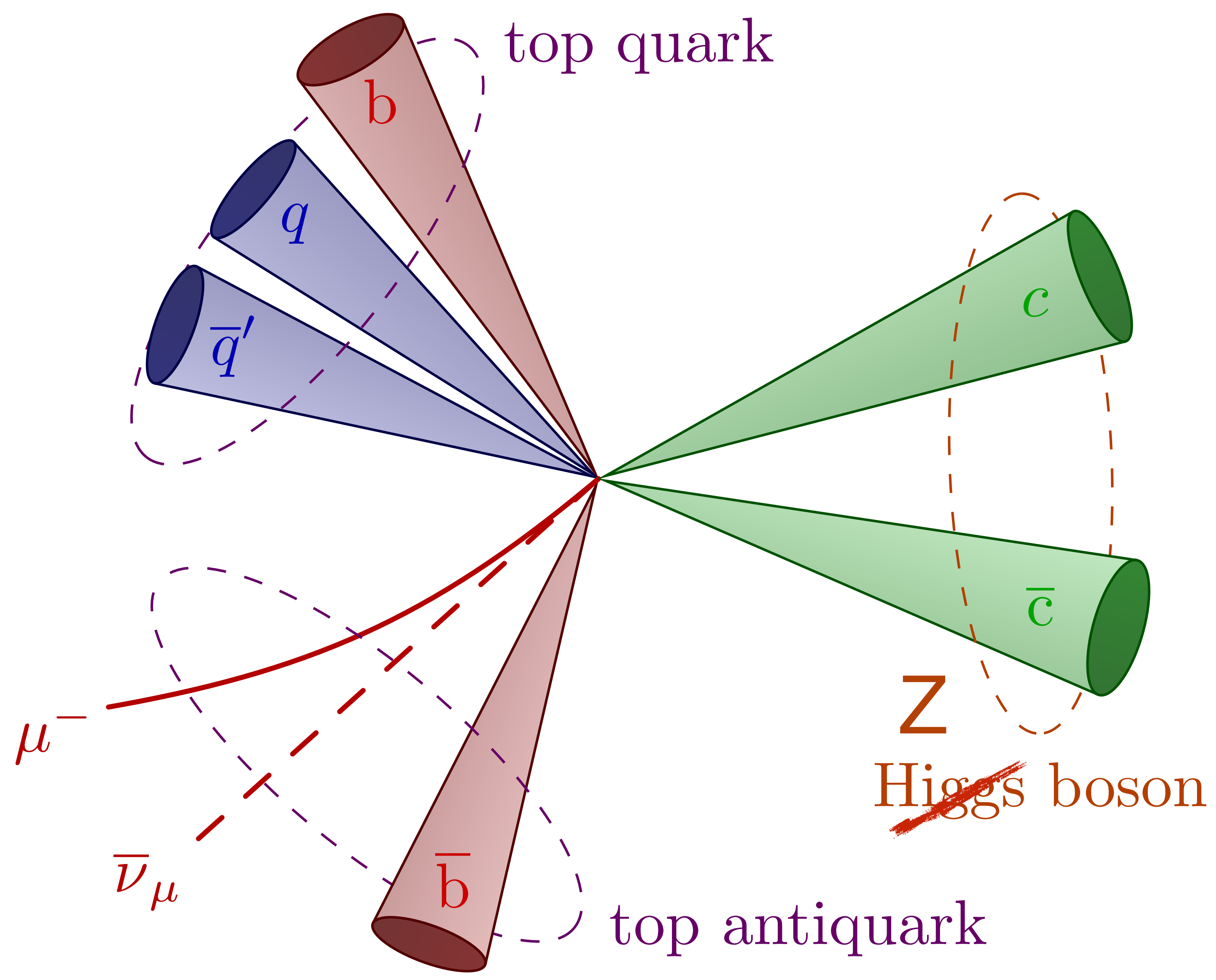
- How much do we gain by using ParticleNet in the $t\bar{t}H(H \rightarrow c\bar{c})$ analysis?
- Study **per-jet rejection for fixed signal-jet efficiencies** comparing DeepJet (CNN+RNN) vs. ParticleNet



Factor ~2 better than DeepJet (default for Run 2)!

Let's define the analysis strategy





- Combinatorics + jet resolution + complicated backgrounds
  → Mass fits not optimal
- Fitting neural network scores D_X
  - Need to validate background model, in e.g., CRs
  - But how well does it work for our signal?
- Find a good **proxy for validation**!

- Replace the Higgs boson with a Z boson
  - Very similar kinematic properties (except lower mass)
  - Known well enough from dedicated measurements
  - Large enough cross section (0.86 pb for $t\bar{t}Z$ vs. 0.51 pb for $t\bar{t}H$)

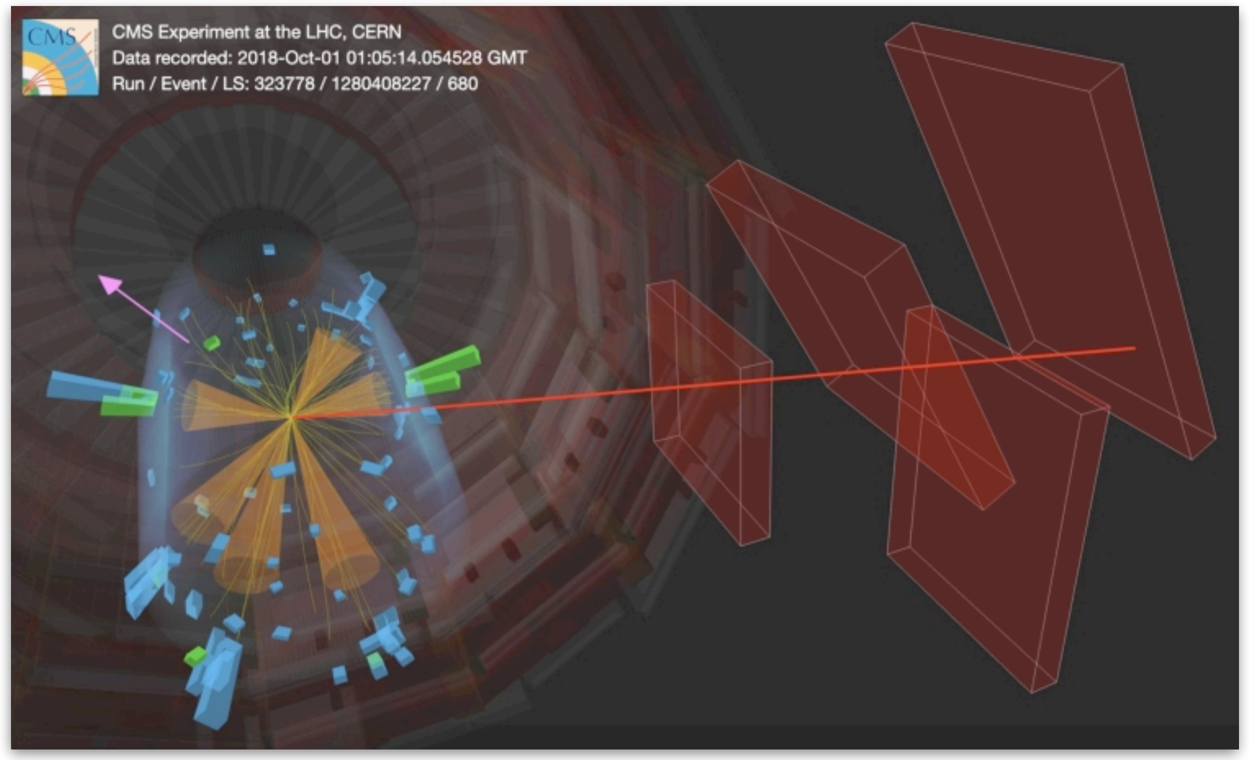
$b\bar{b}$: 12 % vs. 58 % BR
→ $t\bar{t}Z(Z\to b\bar{b})$ ~1/3 of $t\bar{t}H(H\to b\bar{b})$
$c\bar{c}$: 15 % vs. 3 % BR
→ $t\bar{t}Z(Z\to c\bar{c})$ ~**13 times $t\bar{t}H(H\to c\bar{c})$**

Analysis symmetric in $t\bar{t}Z$ and $t\bar{t}H$

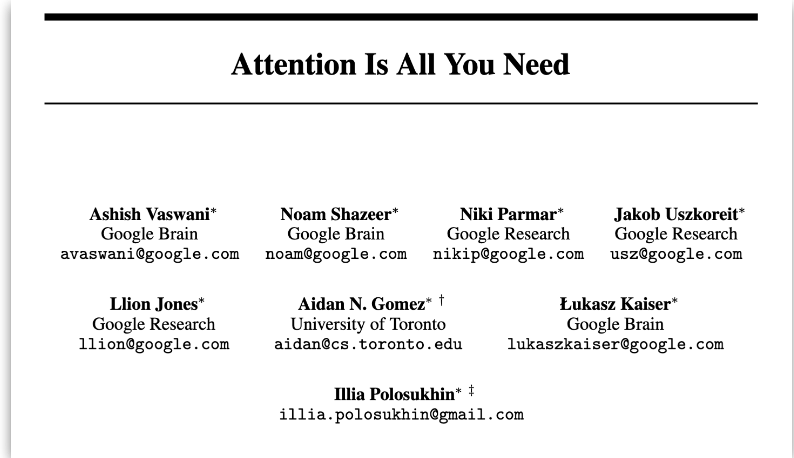
Multiclass event classification

- Complicated hadronic event topology can be a benefit:
  - 8 jets (0L), 1 lepton + 6 jets (1L), 2 leptons + 4 jets (2L)
  - 2 b jets, 2 c jets
  - Rich correlations and resonance structures (1 Higgs, 2 W's, 2 top quarks)

- Event classification using state-of-the-art transformer network
  - Let's bring the tagging improvements to the analysis level!



[Vasvani et al. 2017]



Attention Is All You Need

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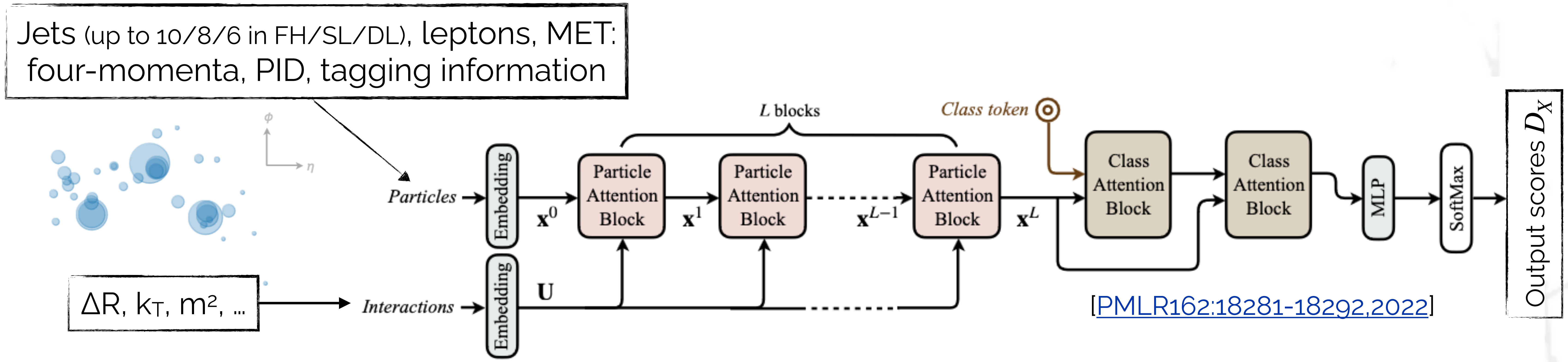
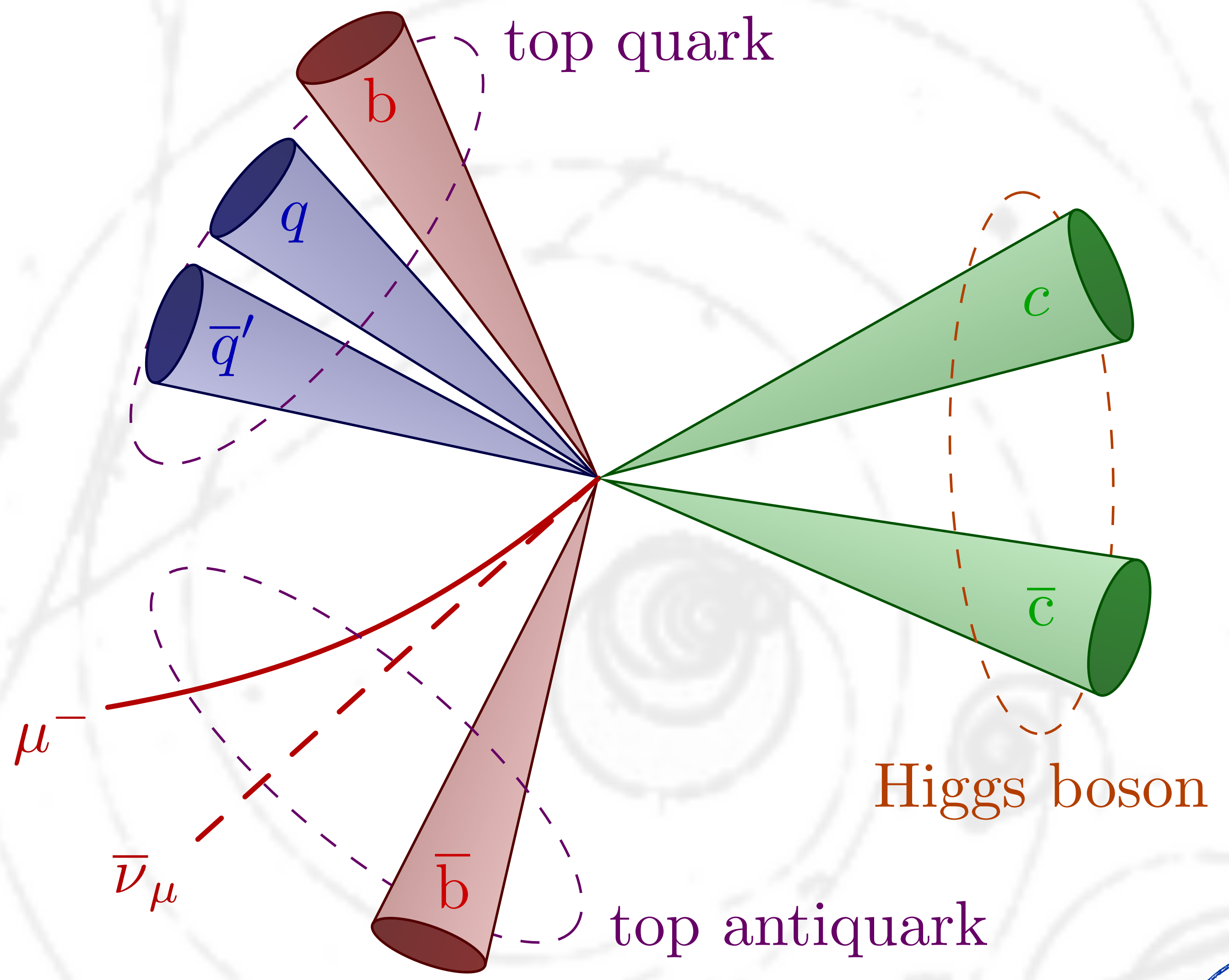
ML



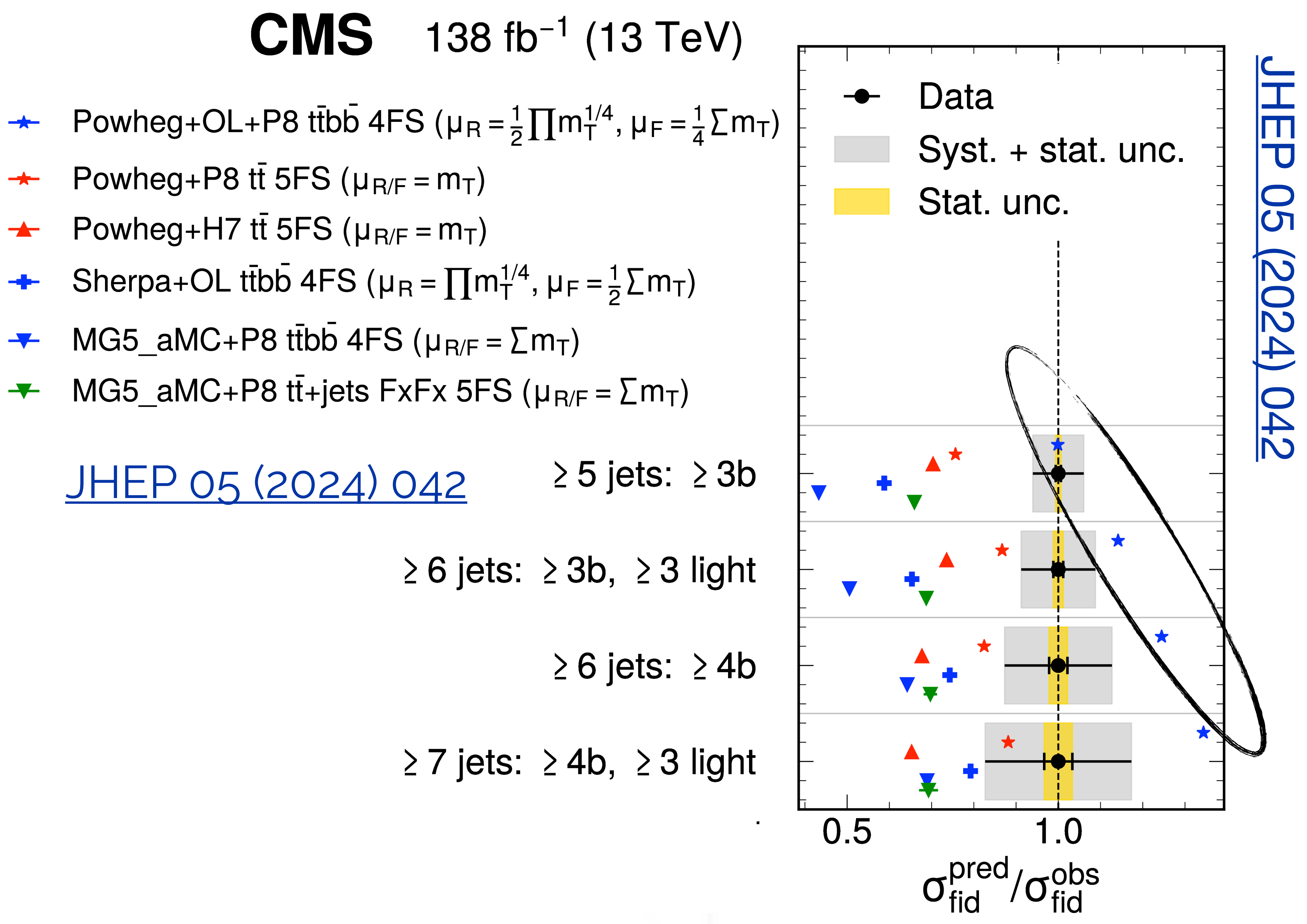
[PMLR162:18281-18292,2022]



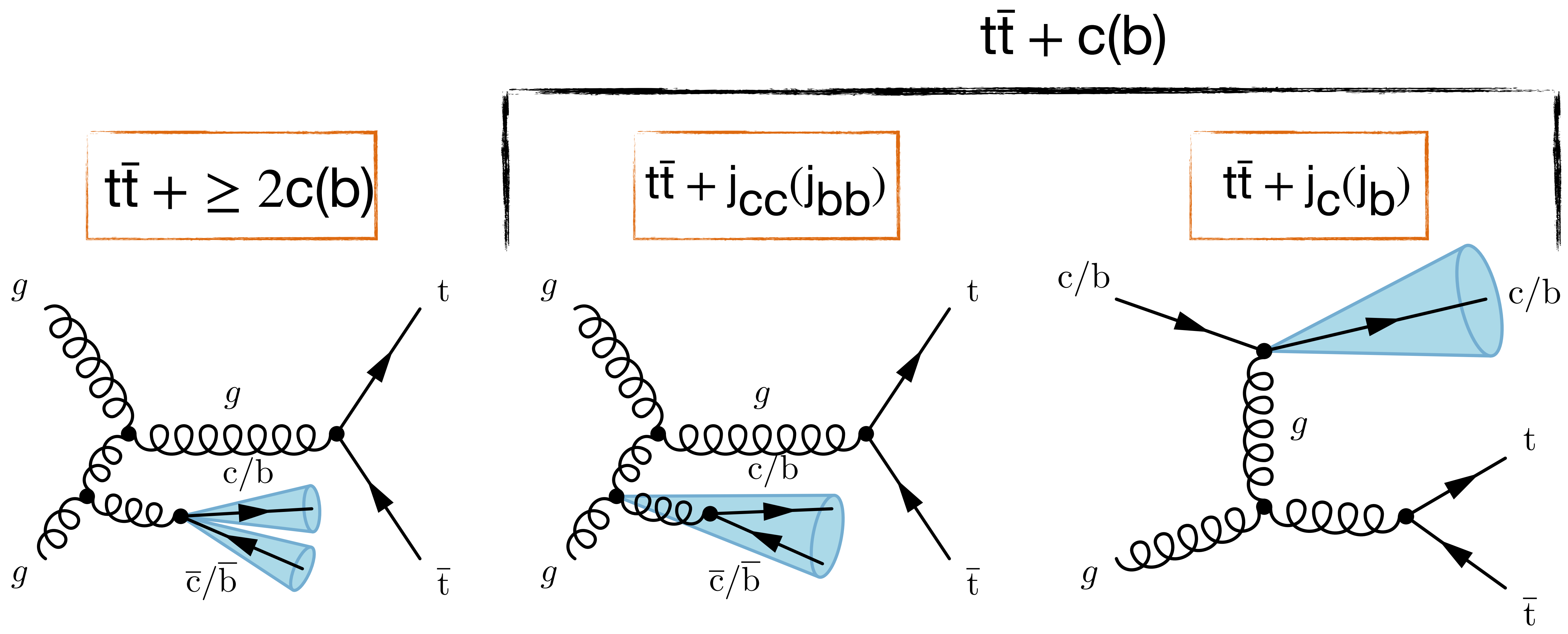
Background modeling & estimation

$t\bar{t}$+jets background model:

- **State-of-the-art merging of 5FS and 4FS predictions**
  - $t\bar{t}+\geq 2b$, $t\bar{t}+j_b$, $t\bar{t}+j_{bb}$ from 4FS $t\bar{t}b\bar{b}$
  - $t\bar{t}+\geq 2c$, $t\bar{t}+j_c$, $t\bar{t}+j_{cc}$, $t\bar{t}$+light from 5FS $t\bar{t}$+jets



JHEP 05 (2024) 042



Yielding a fit model with sufficient flexibility

Data-driven estimation:

- One control region (CR) for each contribution

$t\bar{t}+\geq 2c$	$t\bar{t}+c$	$t\bar{t}+\geq 2b$	$t\bar{t}+b$	$t\bar{t}$+light

For $t\bar{t}$+jets: 184 nuisance parameters in fit
+ 10 free-floating parameters

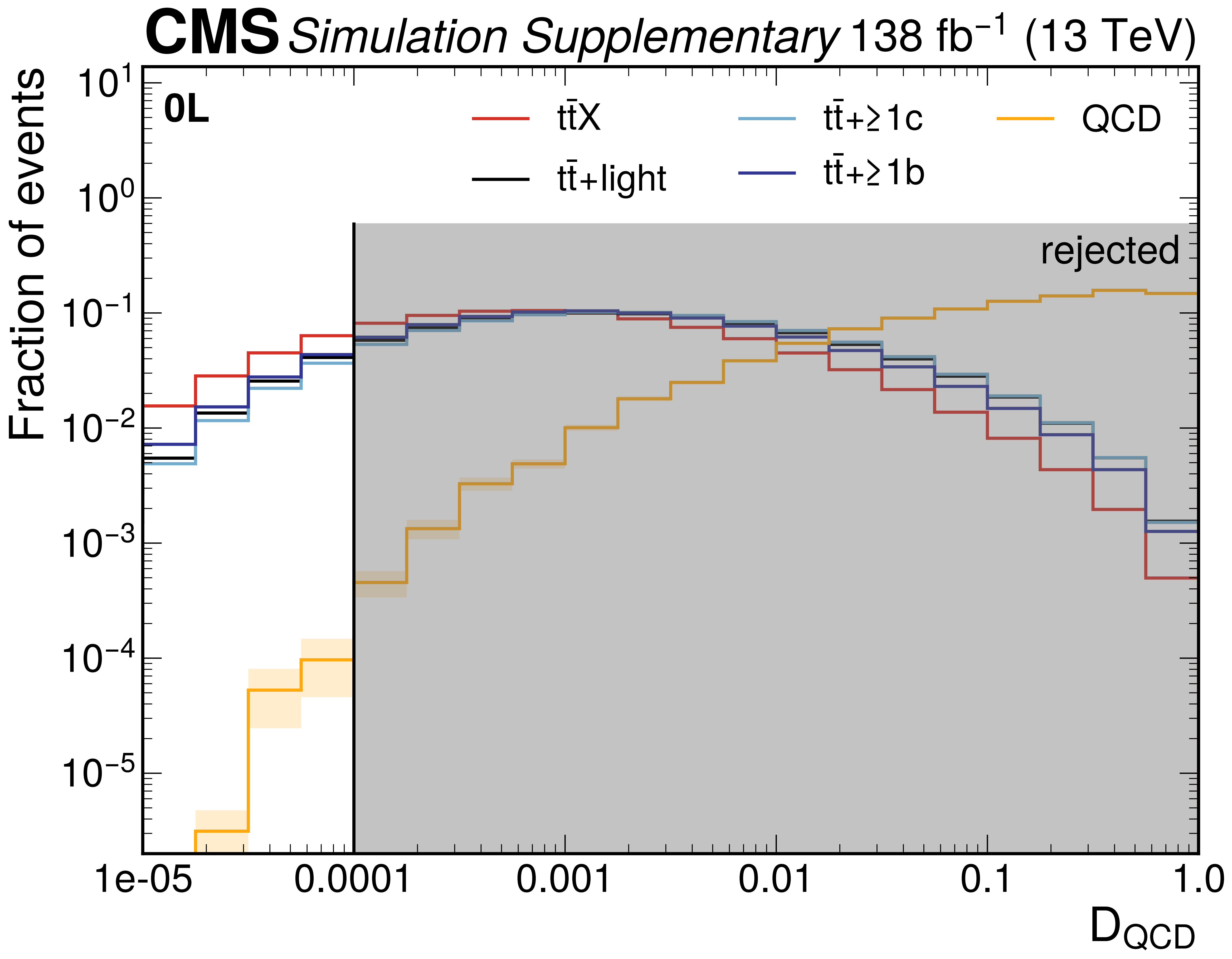
Event selection & categorisation

- Use scores (D_X) to select & categorise events

QCD suppression in FH channel:

- Event classifier very good at separating QCD ↔ $t\bar{t}$
- Only use events with QCD score < 10^{-4}
  - **QCD contribution becomes negligible (< 1%)**
  - At the cost of signal efficiency (~ 15%)

→ Same strategy & background estimation in 0L, 1L, 2L



Event selection & categorisation

- Use scores (D_X) to select & categorise events

Sideband for validation (VR)

- Independently test the background model

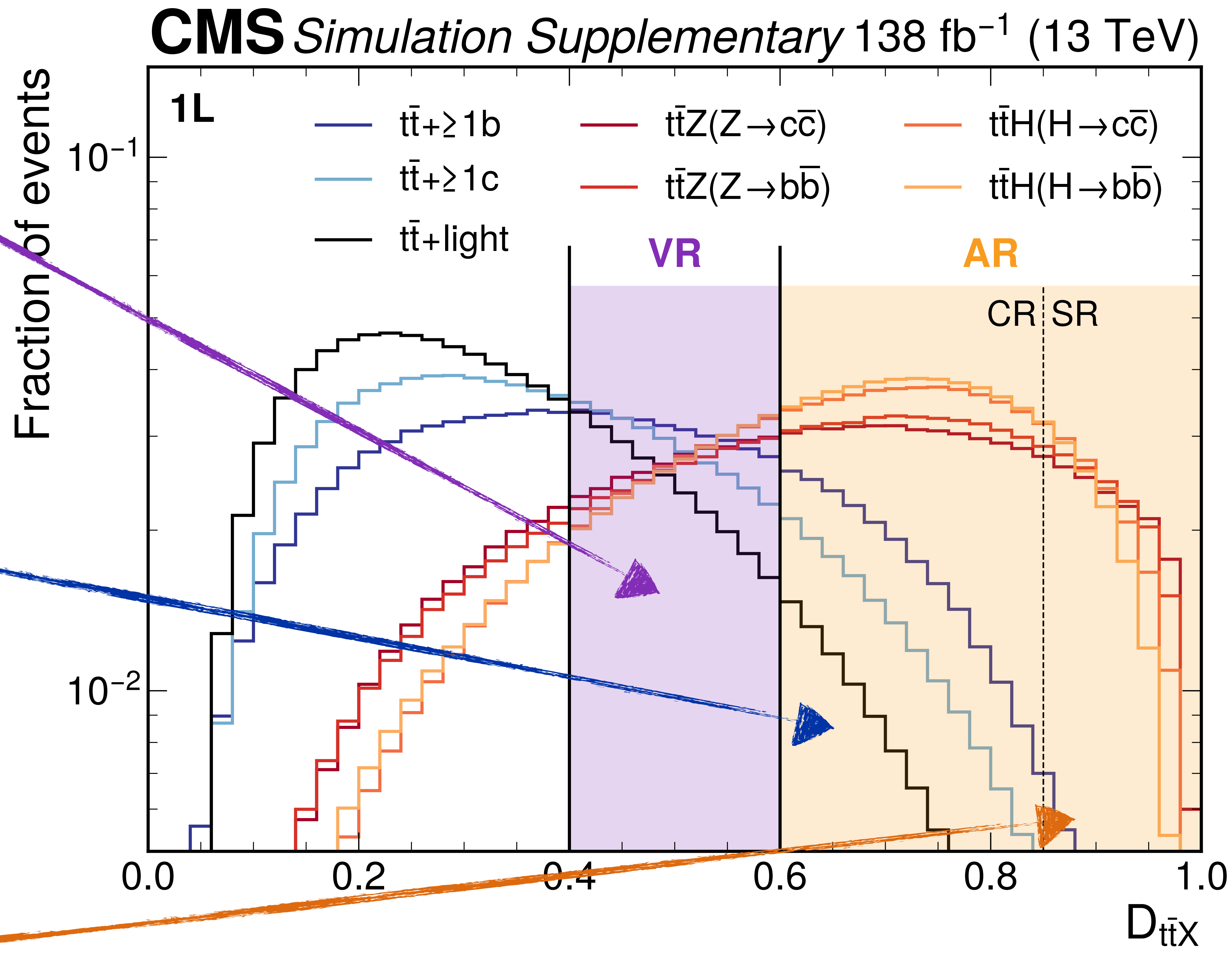
Sideband for background estimation (CR)

- **5 control regions**:
  - $t\bar{t}$+light, $t\bar{t}$+c, $t\bar{t}+\geq 2c$, $t\bar{t}$+b, $t\bar{t}+\geq 2b$

Signal sensitive region (SR)

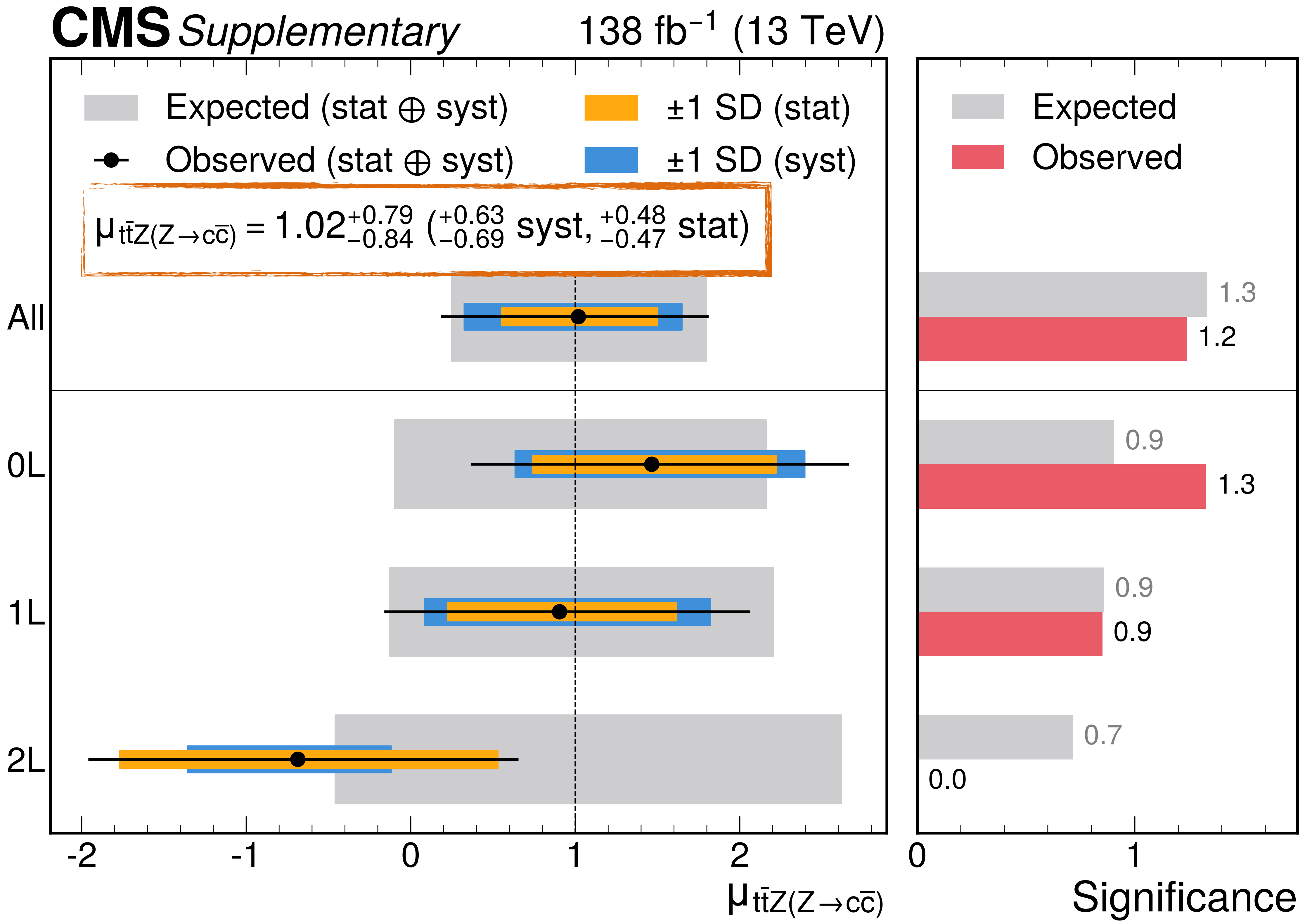
→ Reduced background extrapolation

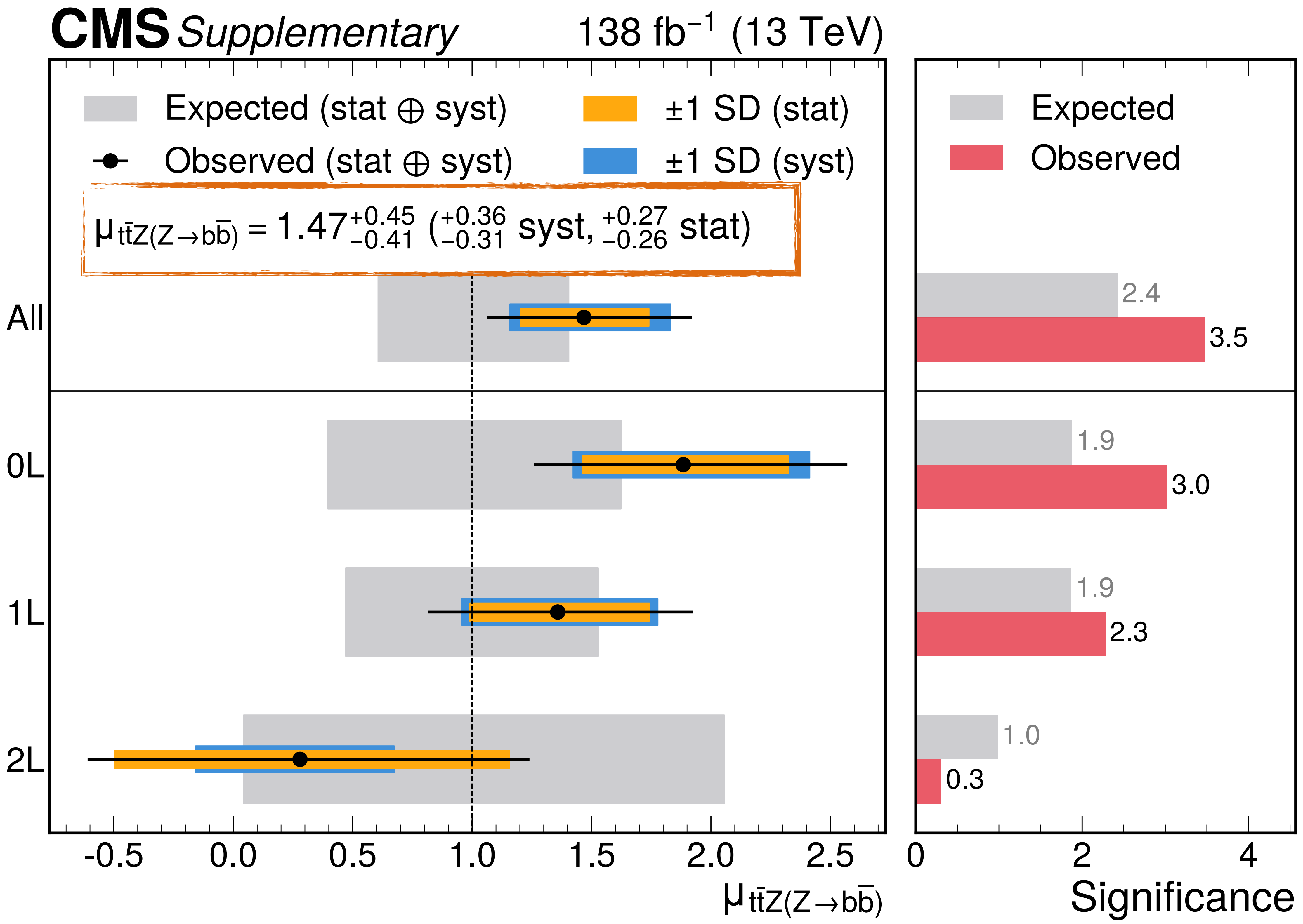
- **2+2** dedicated **signal regions**:
  - $t\bar{t}H(H\to c\bar{c})$, $t\bar{t}H(H\to b\bar{b})$, $t\bar{t}Z(Z\to c\bar{c})$, $t\bar{t}Z(Z\to b\bar{b})$



- Split **AR** into **signal region part (SR)** and **control region part (CR)**

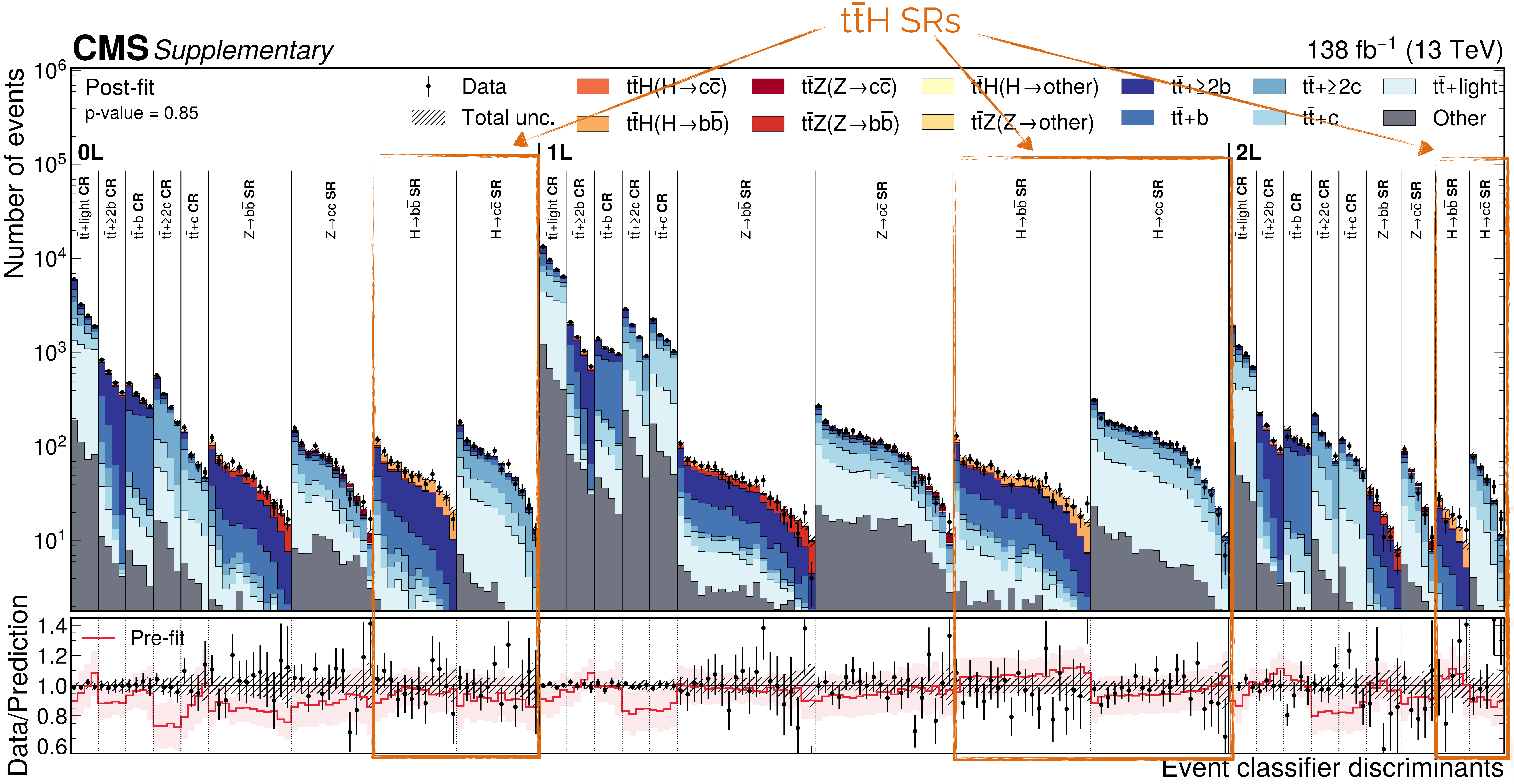
Validation with $t\bar{t}Z(Z \to c\bar{c}/b\bar{b})$ production





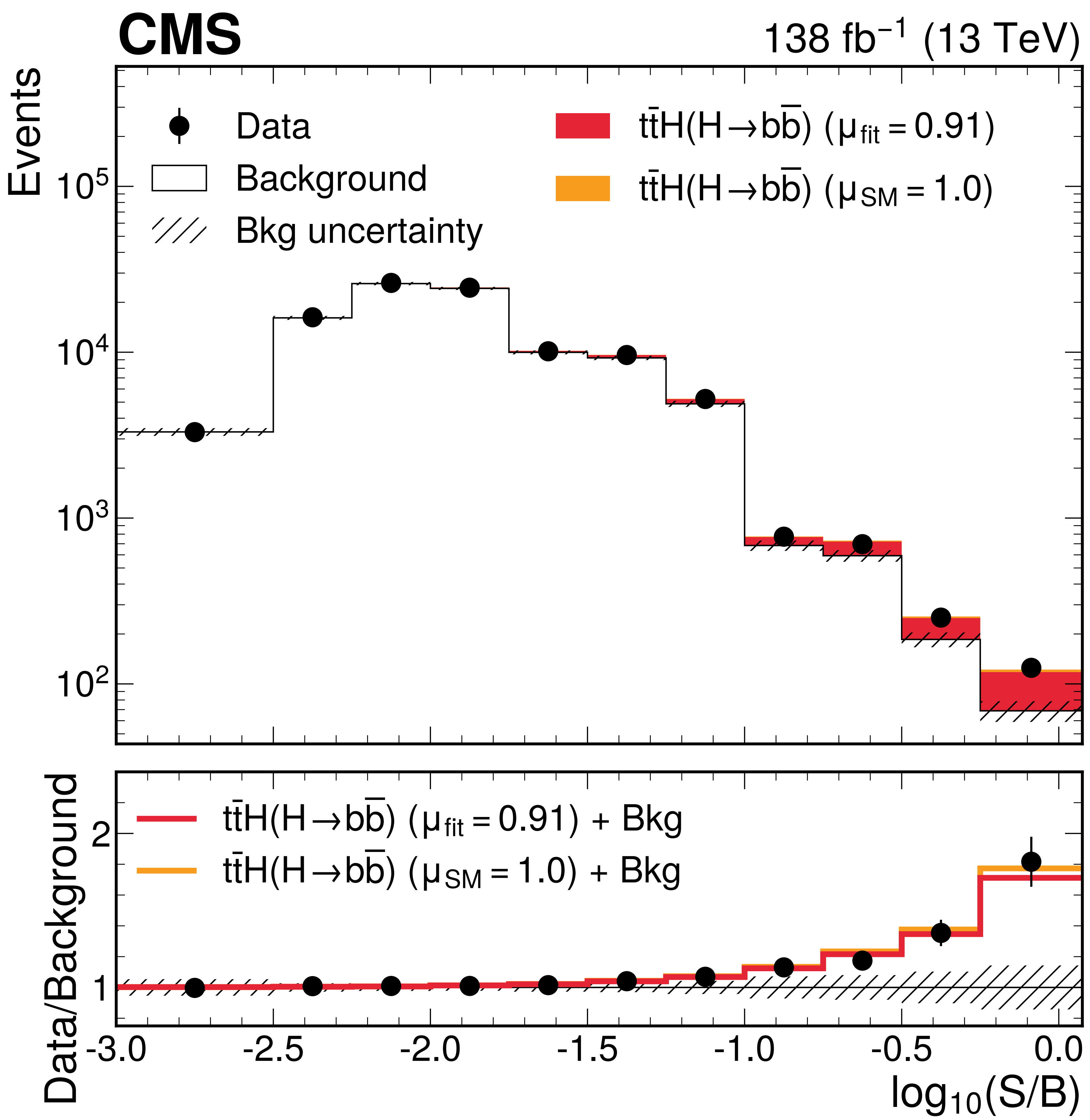
- $t\bar{t}Z$ signal strengths compatible with SM and LHC results
  - From leptonic channels: μ_{ttZ} ~ 1.1 with 8% precision
- **Good validation for $t\bar{t}H(H \to c\bar{c}/b\bar{b})$ analysis!**

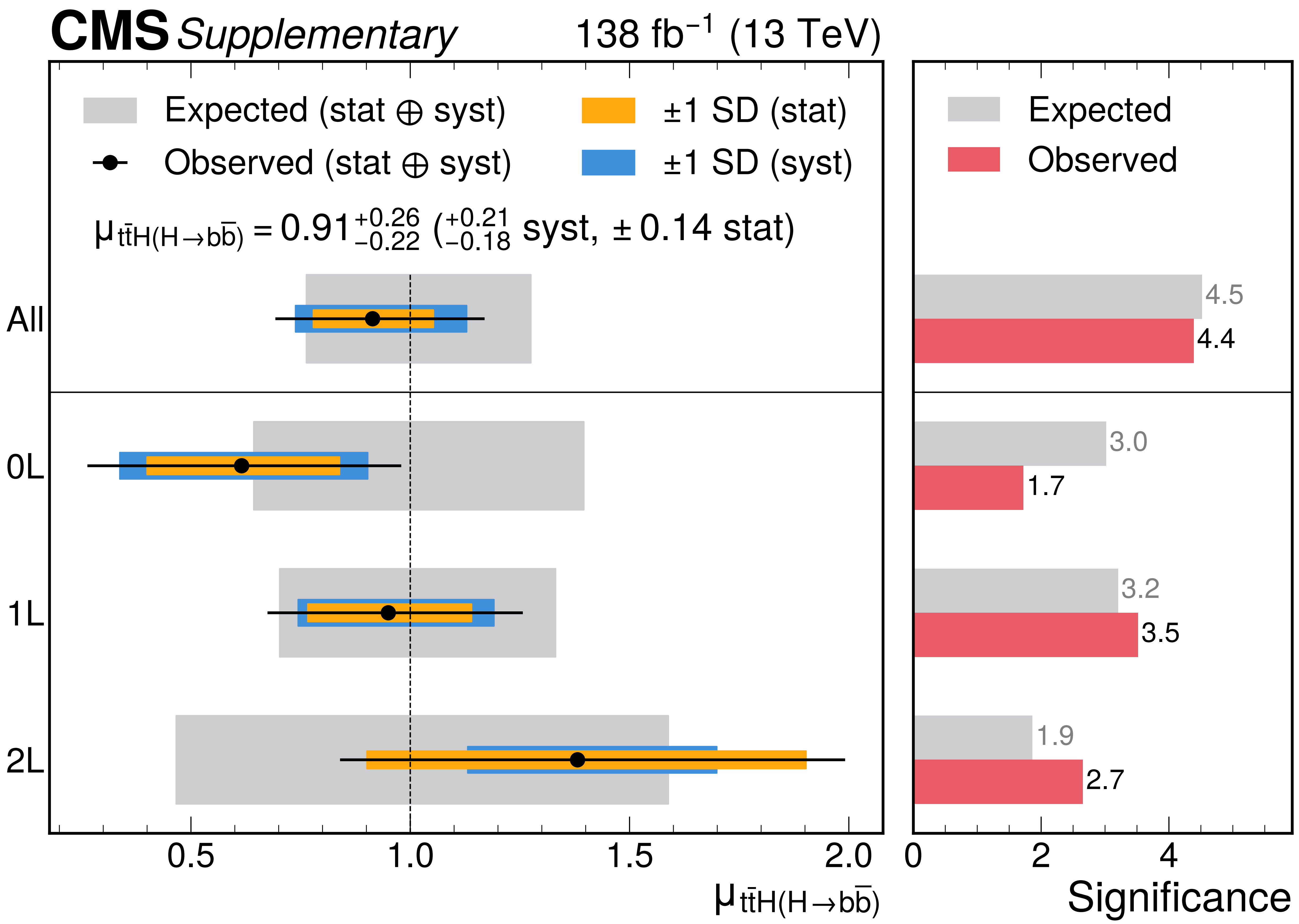
Comparing data to prediction in the full fit distribution



- Four POIs simultaneously extracted – $t\bar{t}H(H\rightarrow c\bar{c})$, $t\bar{t}H(H\rightarrow b\bar{b})$, $t\bar{t}Z(Z\rightarrow c\bar{c})$, $t\bar{t}Z(Z\rightarrow b\bar{b})$
  → Very good pre- and post-fit agreement!

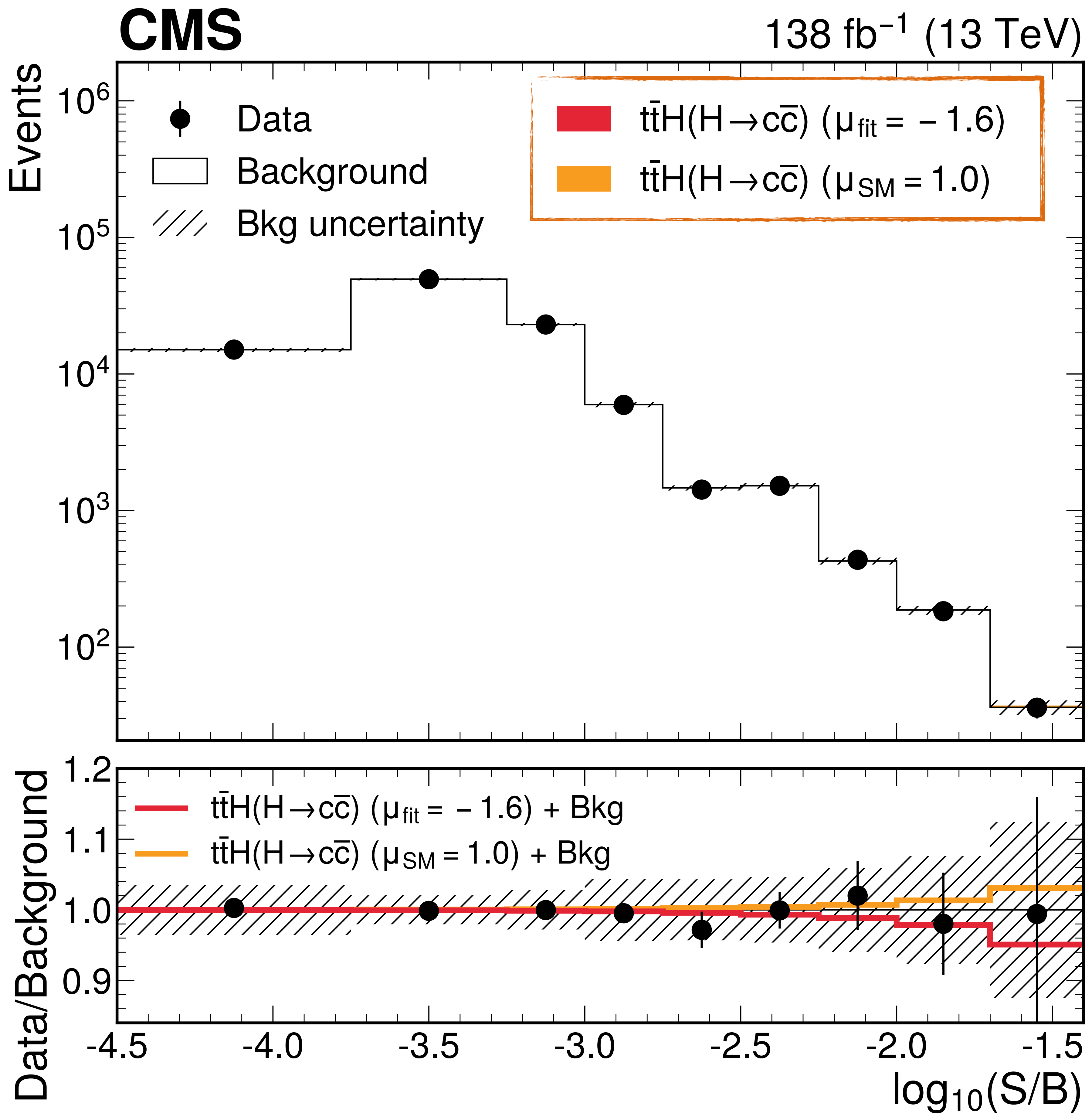
Results: $t\bar{t}H(H \to b\bar{b})$ production

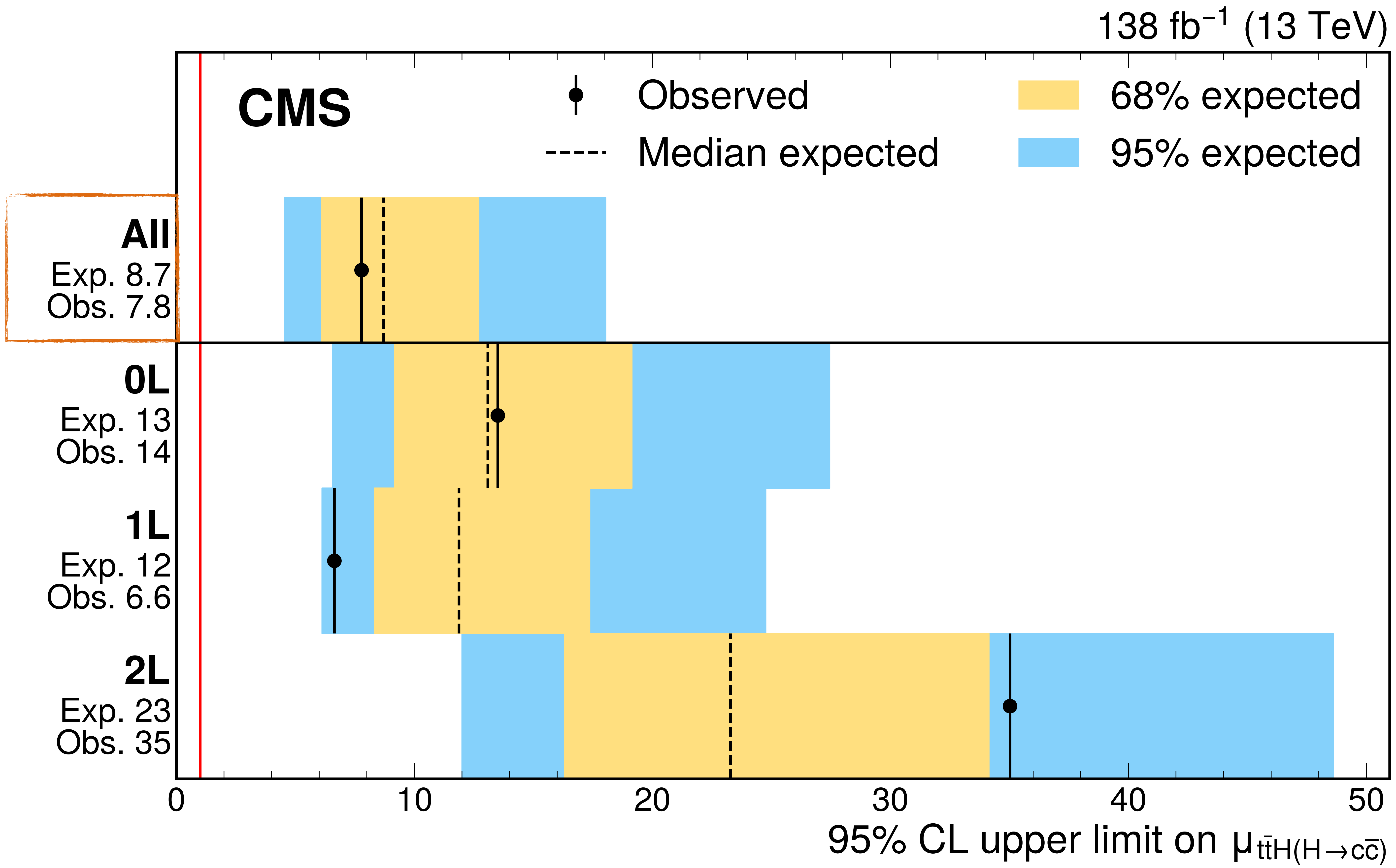




- **$\mu_{ttH(H\to bb)}$ = 0.91 +0.26/-0.22 — 4.4σ observed**
  - Good agreement with SM expectation

Results: $t\bar{t}H(H \to c\bar{c})$ production





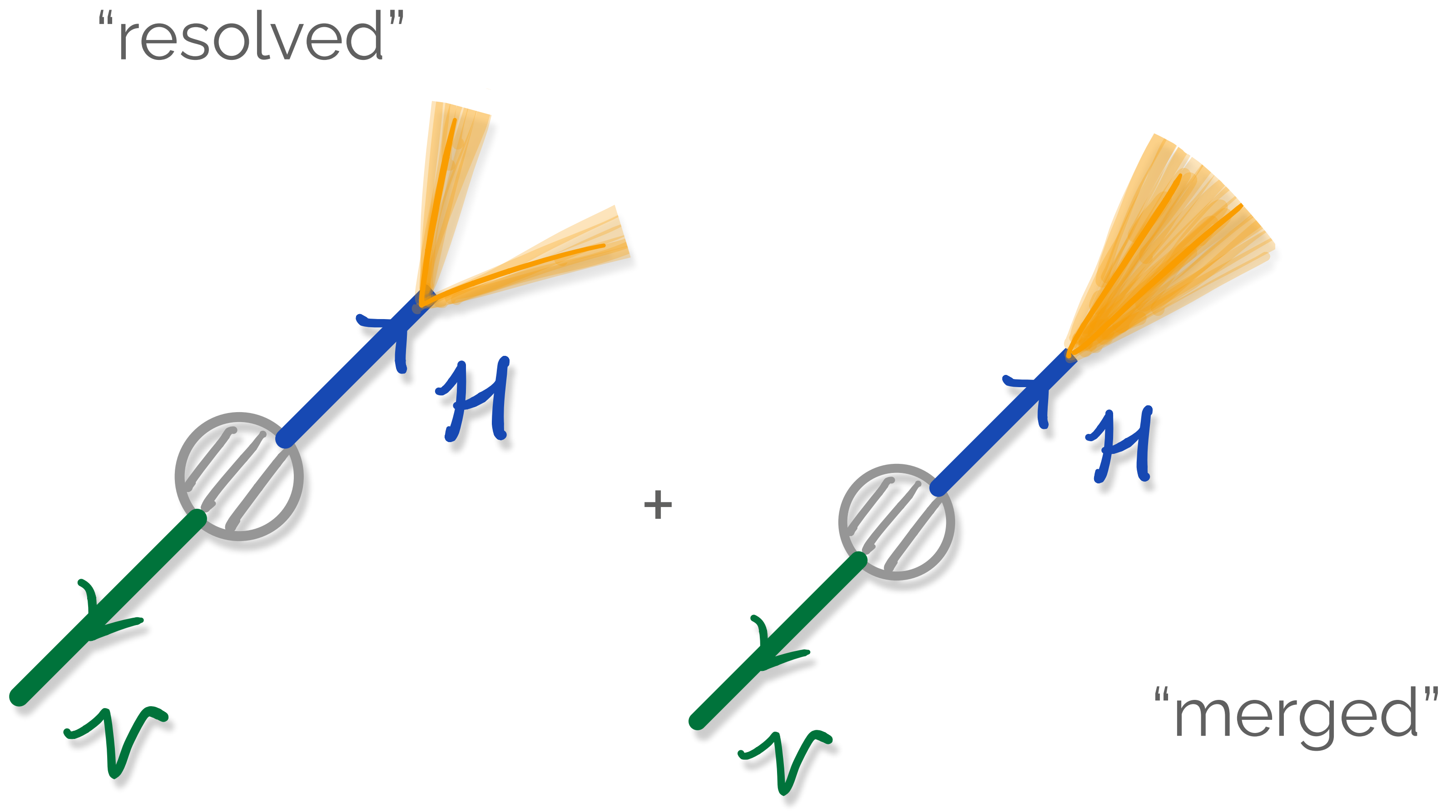
- **Limits on $\mu_{ttH(H\to cc)}$: ≲ 7.8 wrt. SM observed (≲ 8.7 expected)**
  - Similar sensitivity as compared to VH(cc) measurements!

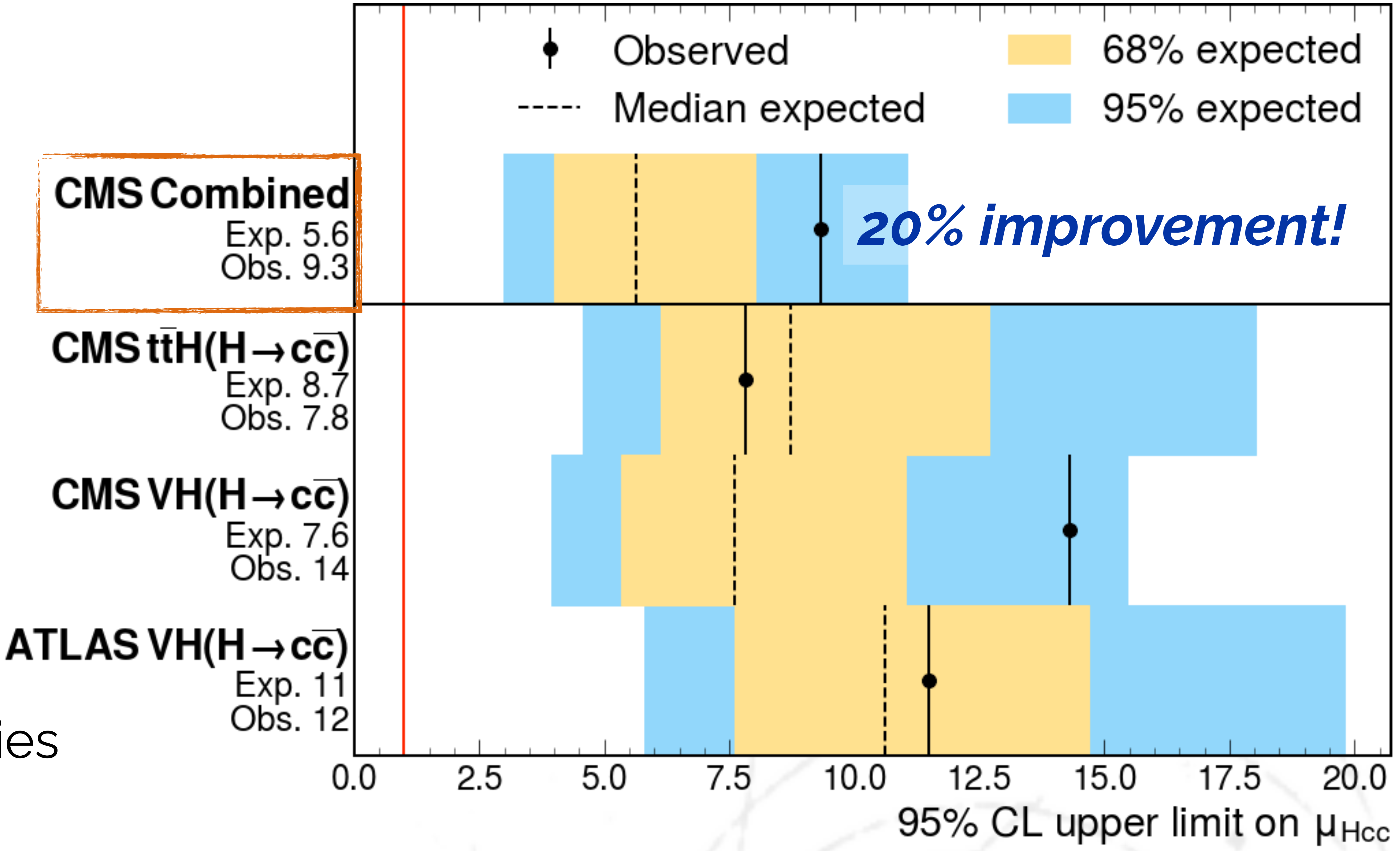
  From VH(cc): μ ≲ 12 (≲ 7.6 expected)

- **1D constraints: $|\kappa_c|$ ≲ 3.0 obs. (3.3 exp.)**

→ **Most stringent constraints to date!**

Combination with VH(H → $c\bar{c}$)



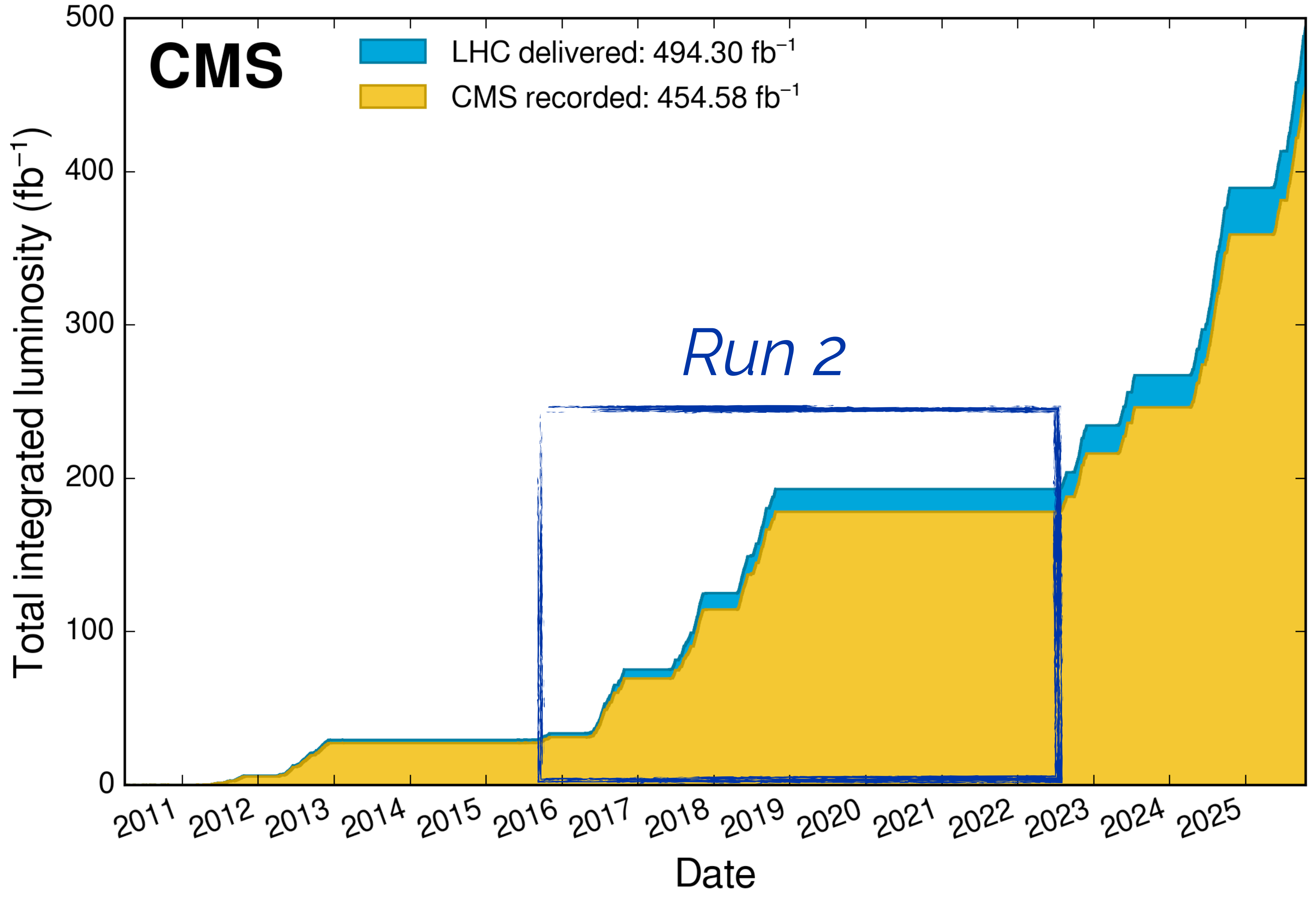


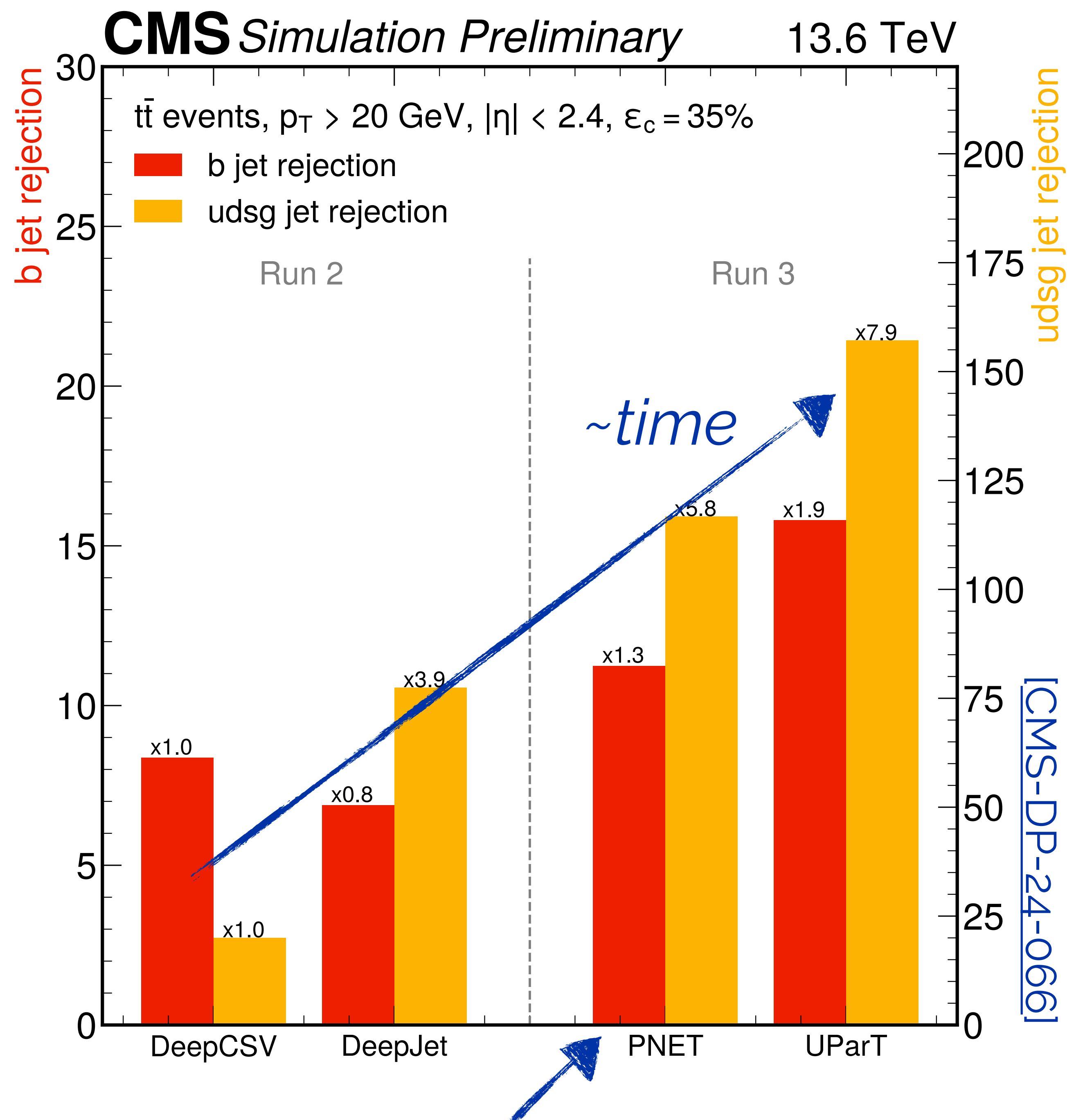
- Combine with VH(H → $c\bar{c}$):
  - Full Run 2 result from resolved+merged topologies
  - Correlated experimental uncertainties
  - Uncorrelated tagging uncertainties
  - Correlated theor. uncertainties (cross section / BR)

Combined signal strength interpretation:
$\mu_{(H\to cc)}$ **< 9.3 (5.6 expected)**

- VH(H → $c\bar{c}$): 1.1 < $|\kappa_c|$ < 5.5 (< 3.4 exp.)
- $t\bar{t}$H: $|\kappa_c|$ < 3.0 (< 3.3 exp.)
- Combined: **$|\kappa_c|$ < 3.5 (< 2.7 exp.)**

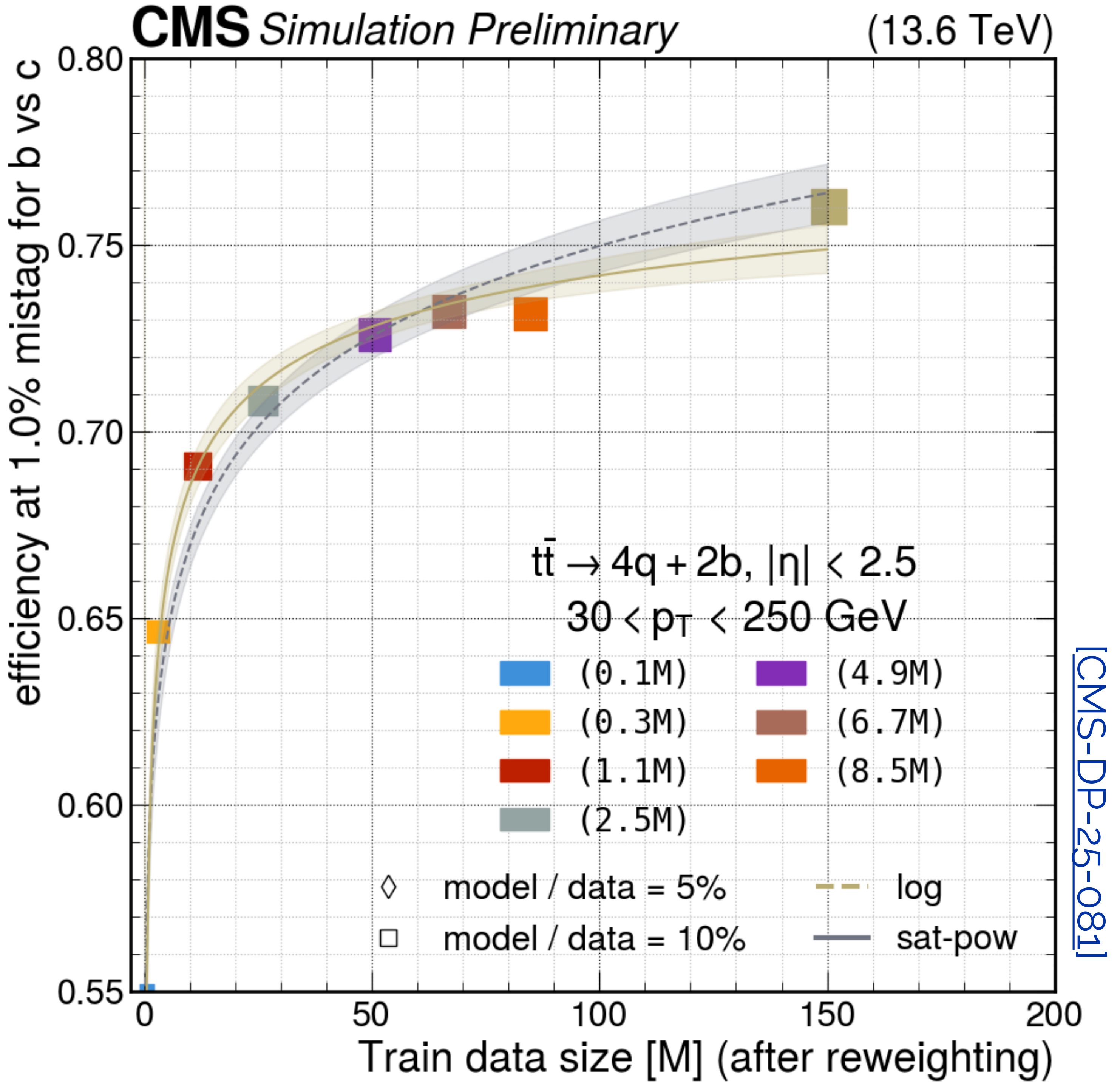
Outlook: What's next?





Used in results shown today

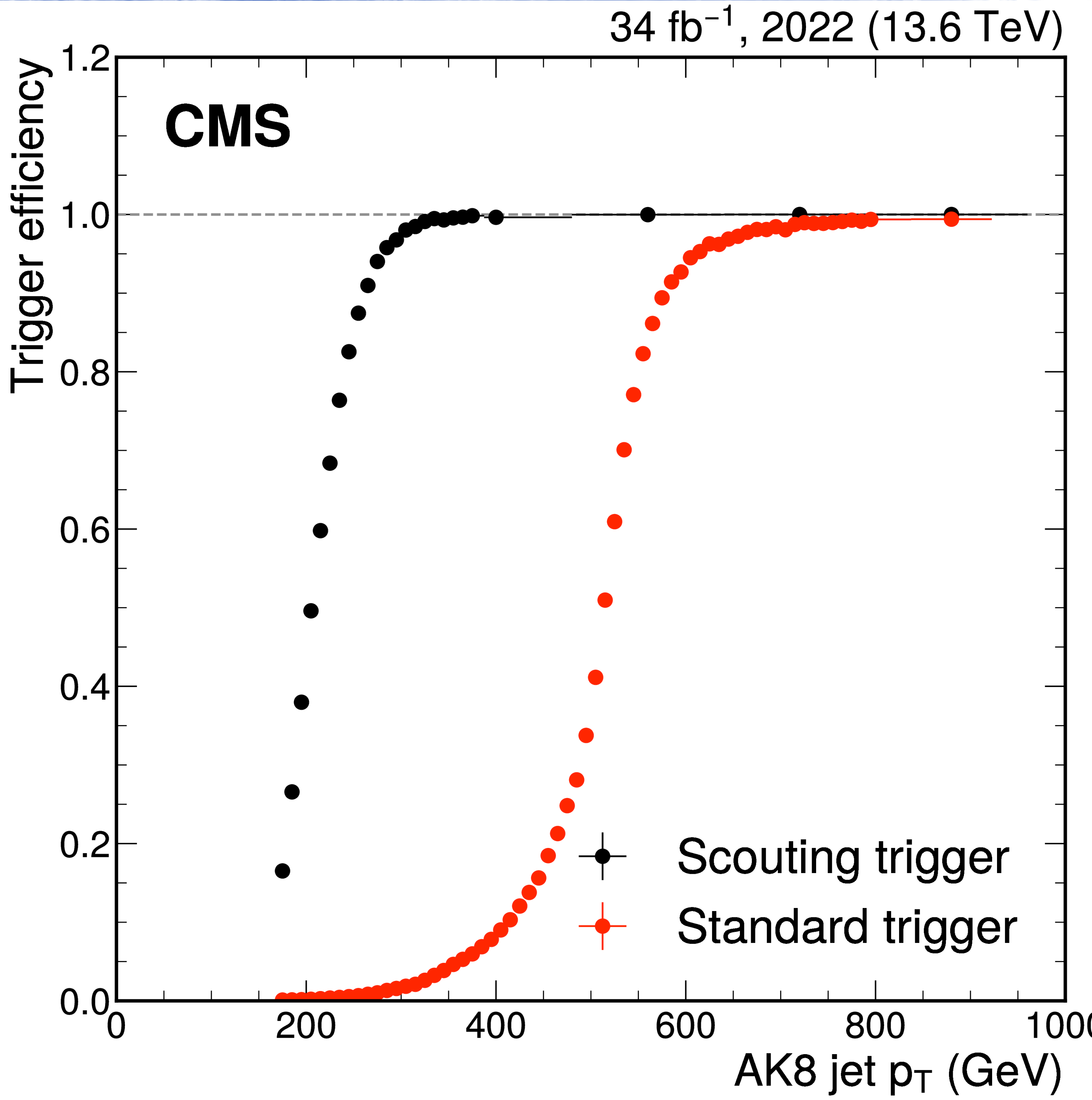
We are not saturating..



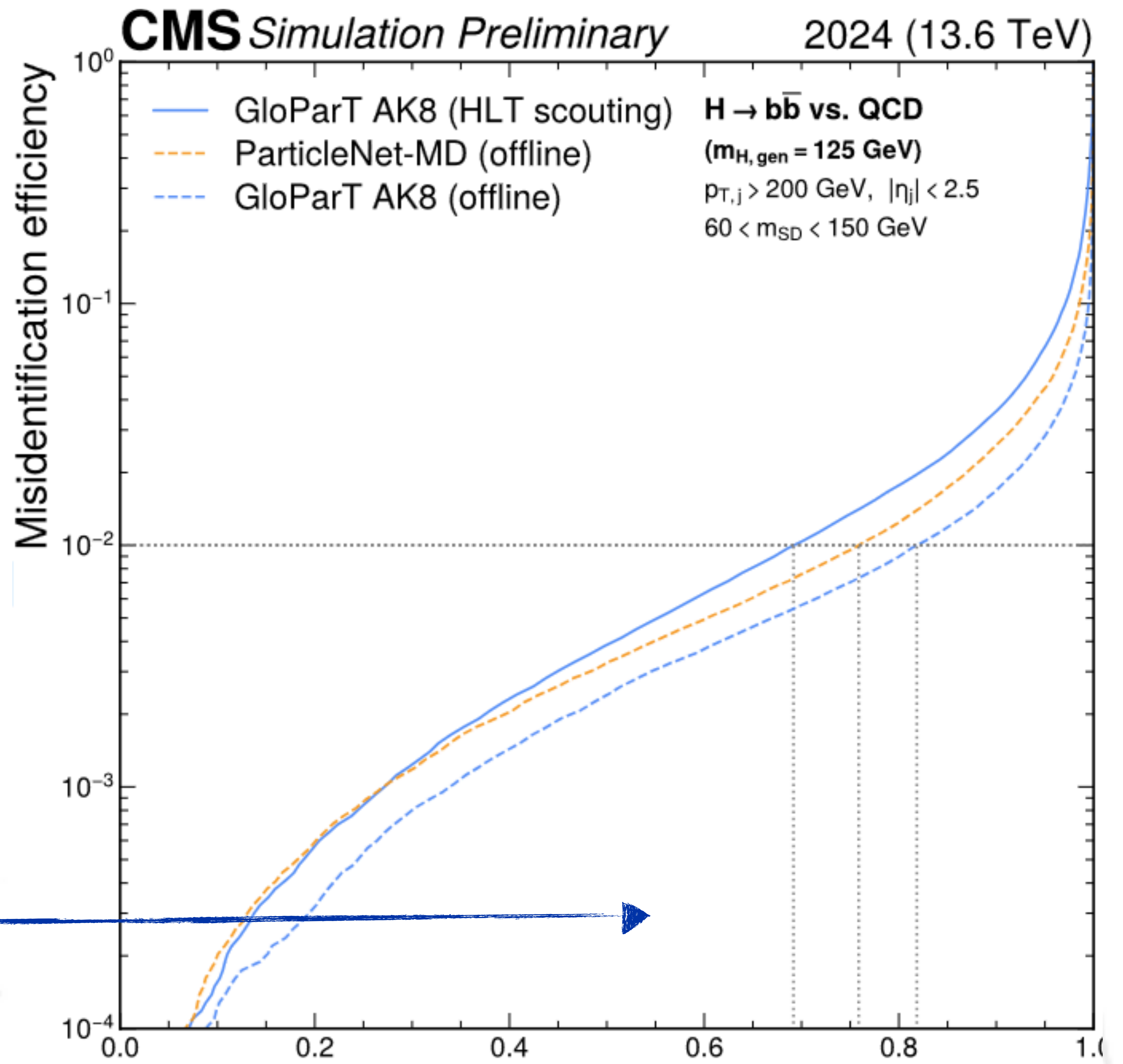
- Run 3 data taking:
  - With 2025+26 runs ~ 500/fb
- Will allow us to extend the analyses:
  - Explore merged regime in ttH?
  - Additional channels such as H+c & VBF

- Improvements in tagging are impressive, but can only help us that far…
  - Backgrounds are likely also real charm quarks
- Improvement in modeling & calibration needed to reduce uncertainties

Outlook: What's next?



[Physics Reports 1115 (2025) 678]

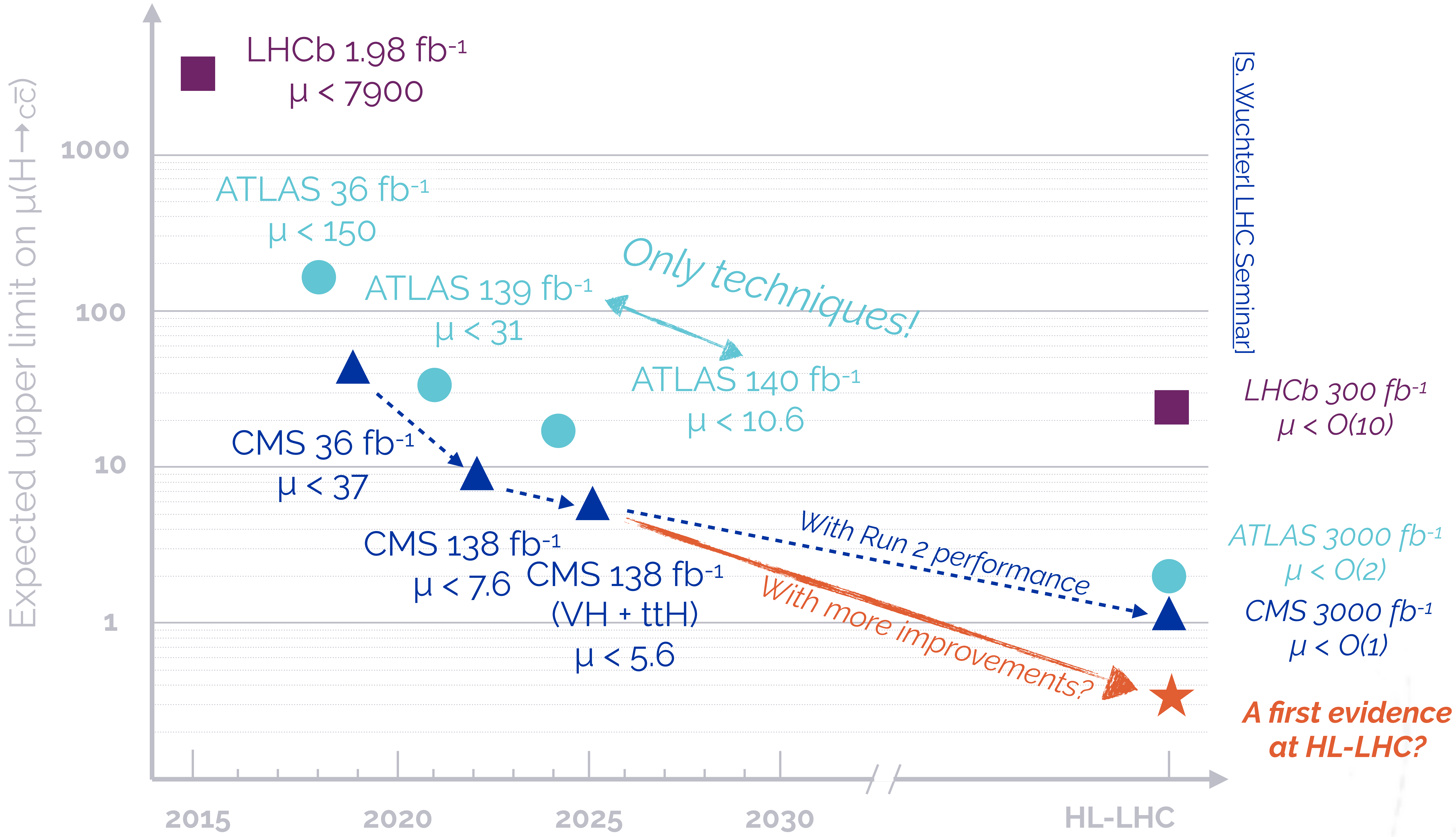


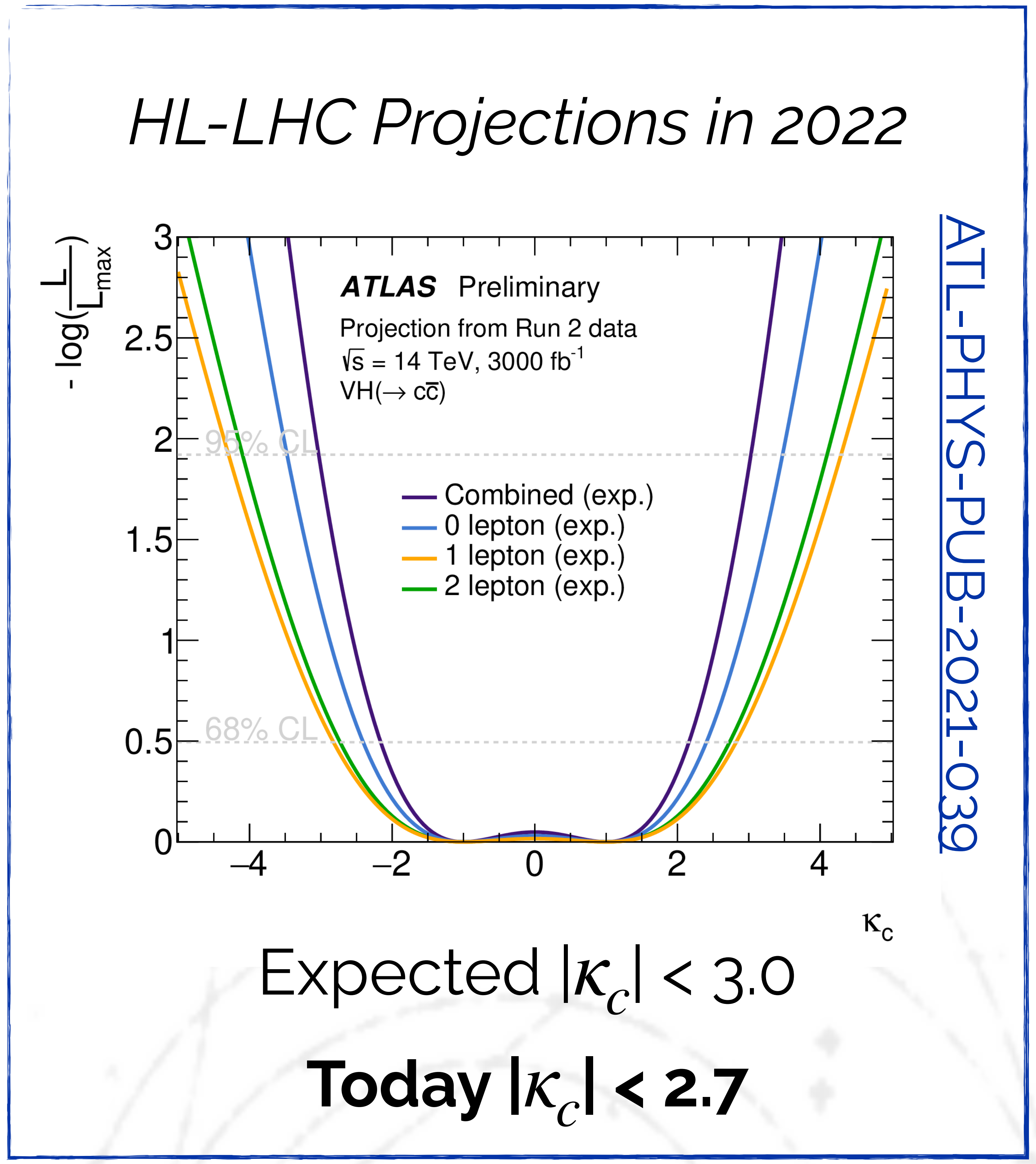
[E. Fontanesi LHC Seminar]

Usage of advanced taggers in software trigger and HLT scouting

- Run 3 data taking:
  - With 2025+26 runs ~ 500/fb
- Will allow us to extend the analyses:
  - Explore merged regime in ttH?
  - Additional channels such as H+c & VBF

Conclusions & some outlook…?

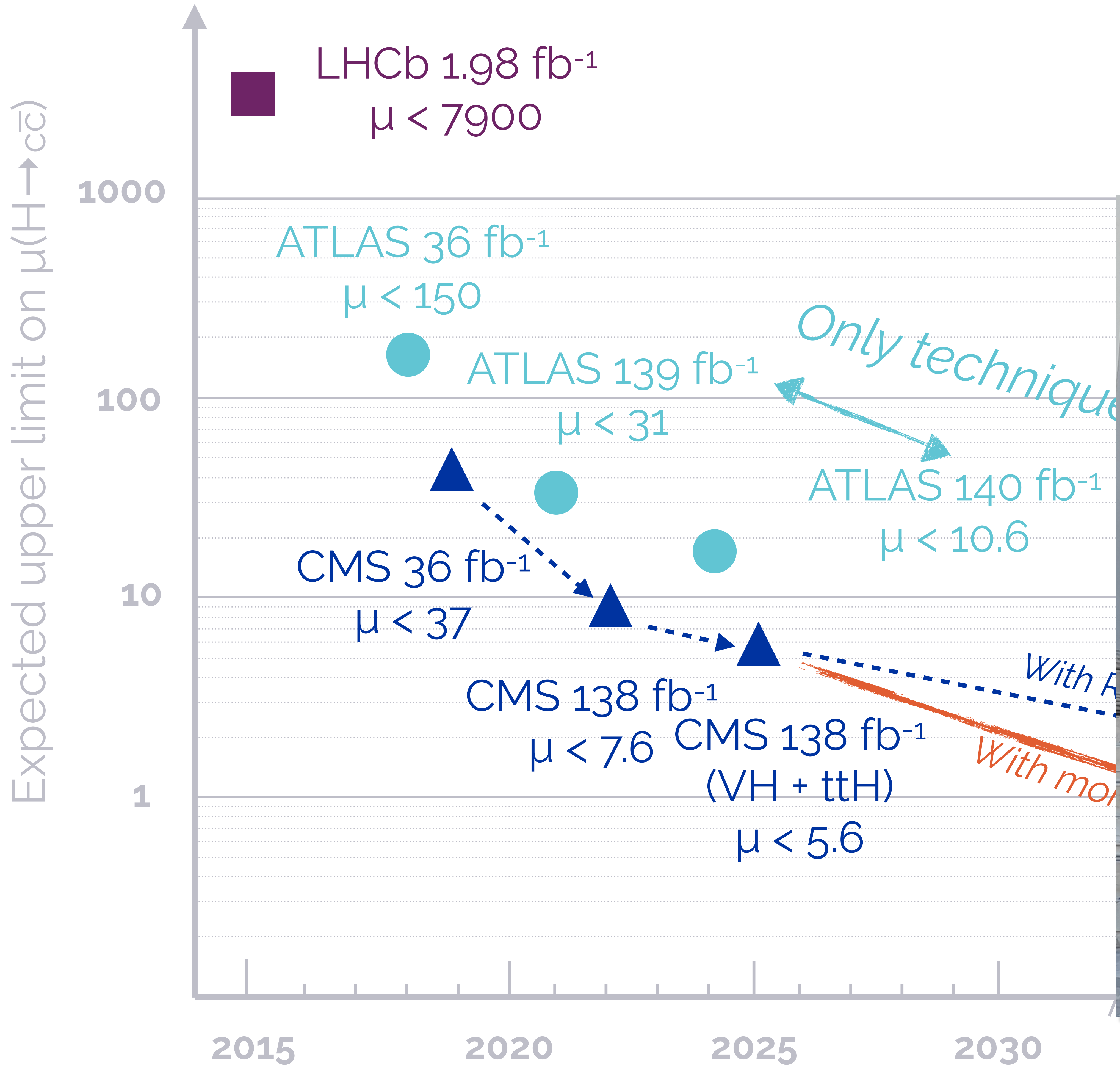




- Compared to old ATLAS VH(cc) projections
  - 18 years of progress in 3 years!

→ **We have a charming future ahead of us!**

Conclusions & some outlook...?



Thank you very much for your attention!

- Compared to old ATLAS VH(cc) projections
  - 18 years of progress in 3 years!

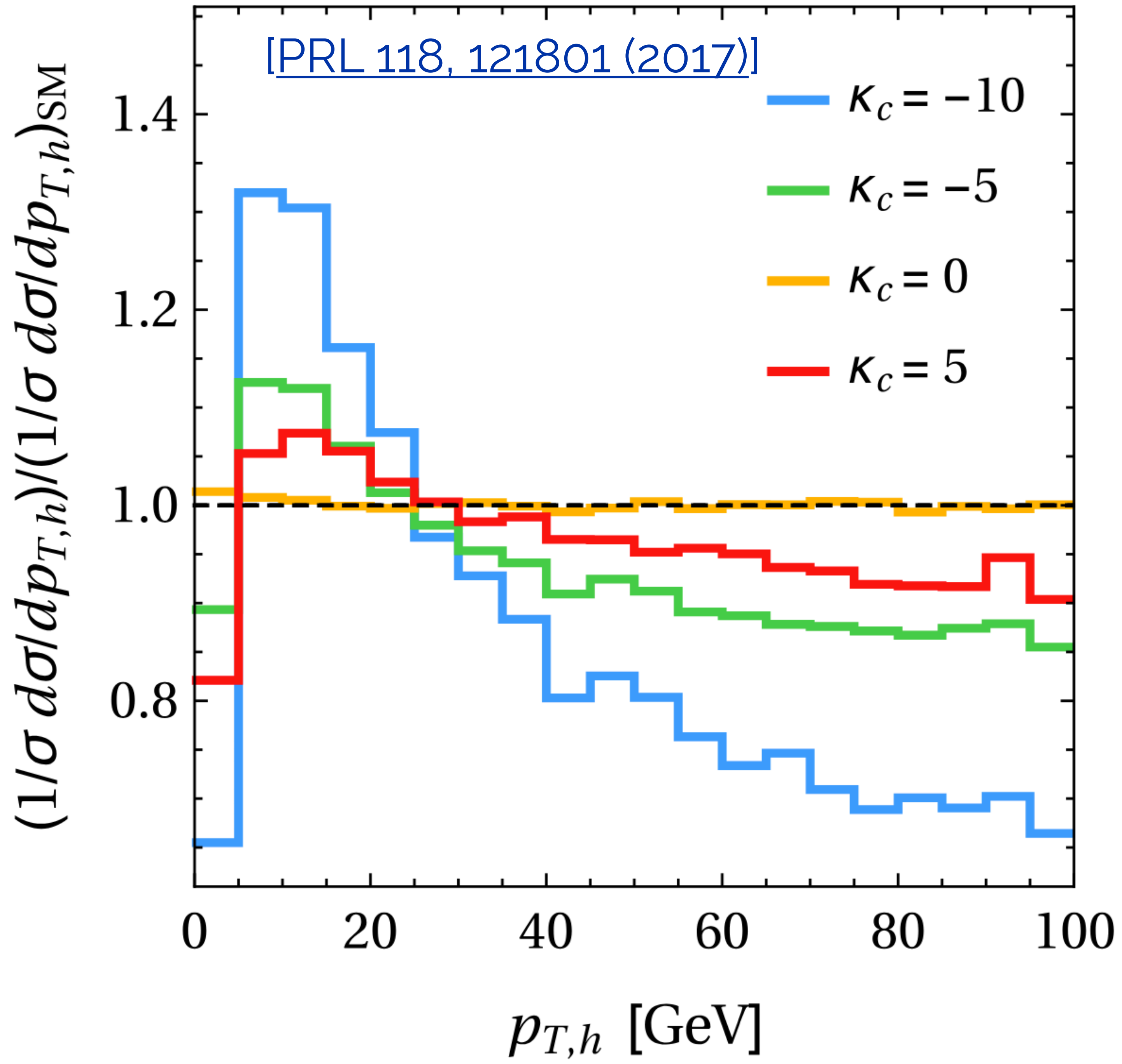
→ **We have a charming future ahead of us!**

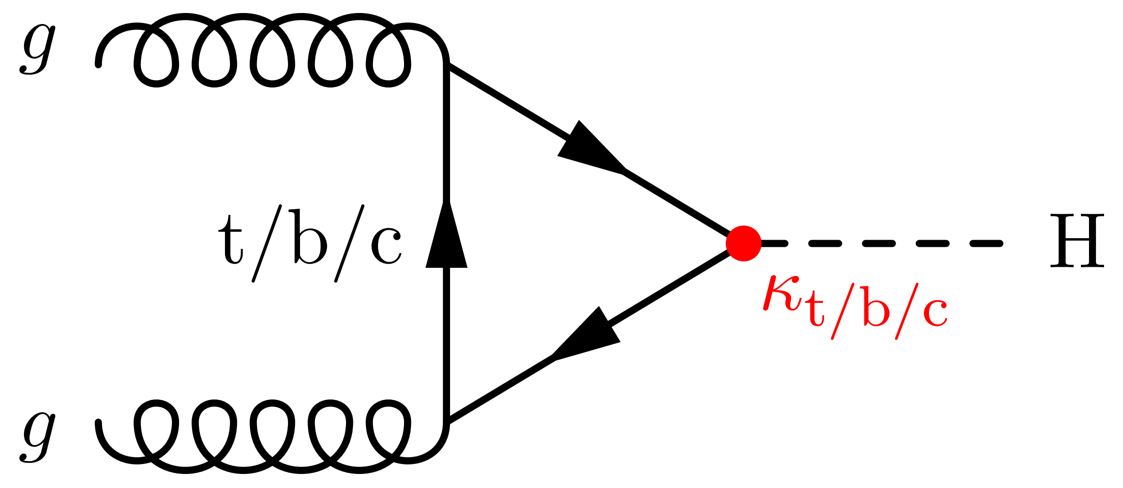
Additional slides

So far: probing the Higgs-charm coupling

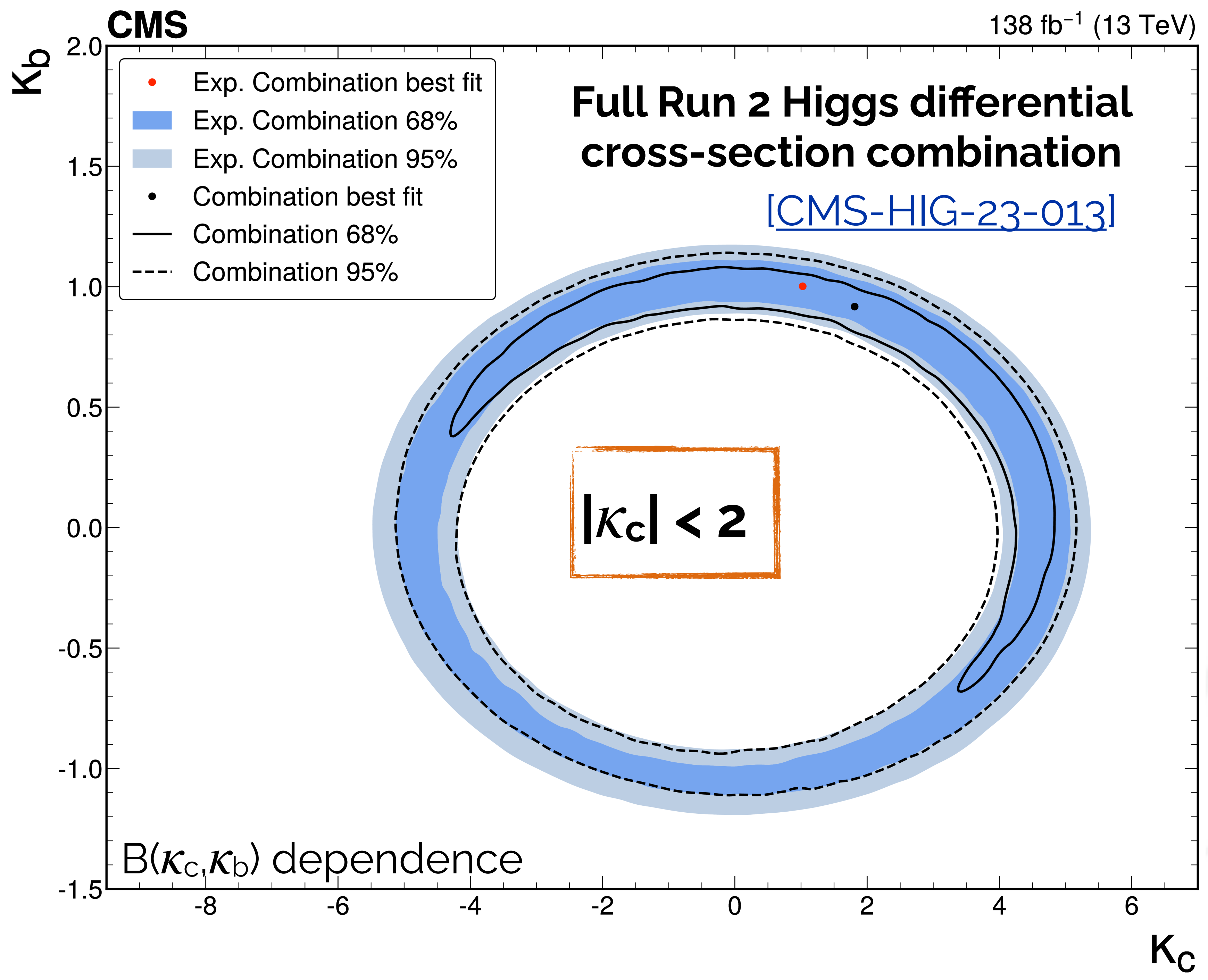
- Several methods explored by ATLAS and CMS to probe the Higgs-charm Yukawa coupling (y_c)

Indirect constraint from Higgs kinematics ← Model dependence? → **Direct searches for H→c$\bar{c}$**





- Differential distributions are sensitive to y_c



Kappa framework

$$(\sigma \cdot \mathscr{B})(\mathrm{ii} \to \mathrm{H} \to \mathrm{ff}) = \frac{\sigma_{\mathrm{ii}} \cdot \Gamma_{\mathrm{ff}}}{\Gamma_{\mathrm{H}}} = \sigma_{\mathrm{ii}}^{SM} \cdot \mathscr{B}_{\mathrm{ff}}^{SM} \cdot \frac{\kappa_{\mathrm{i}}^2 \kappa_{\mathrm{f}}^2}{\kappa_{\mathrm{H}}^2}$$

κ_i: coupling wrt. SM expectation of 1

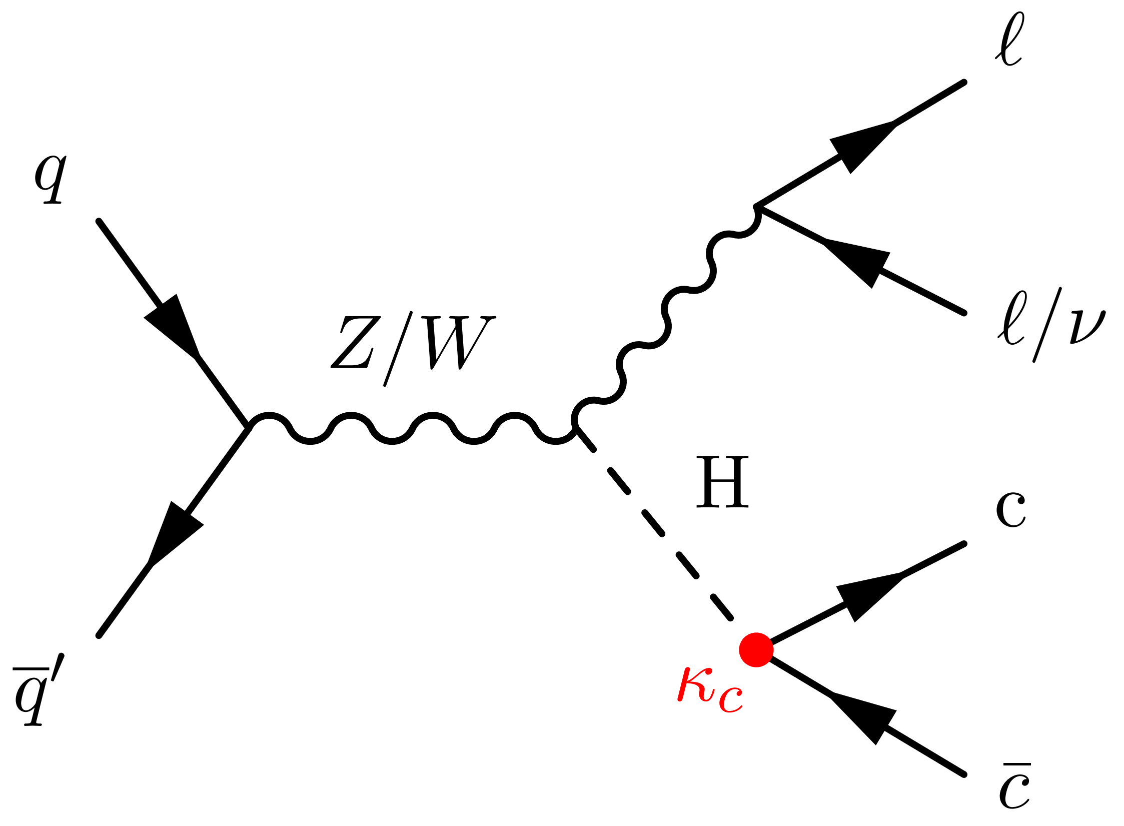
So far: probing the Higgs-charm coupling

- Several methods explored by ATLAS and CMS to probe the Higgs-charm Yukawa coupling (y_c)

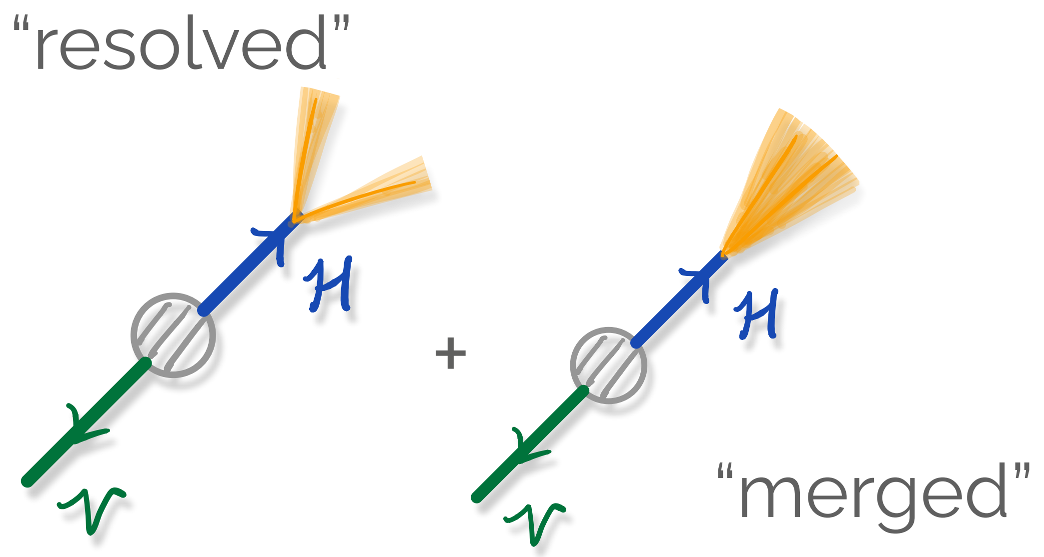
Indirect constraint from Higgs kinematics

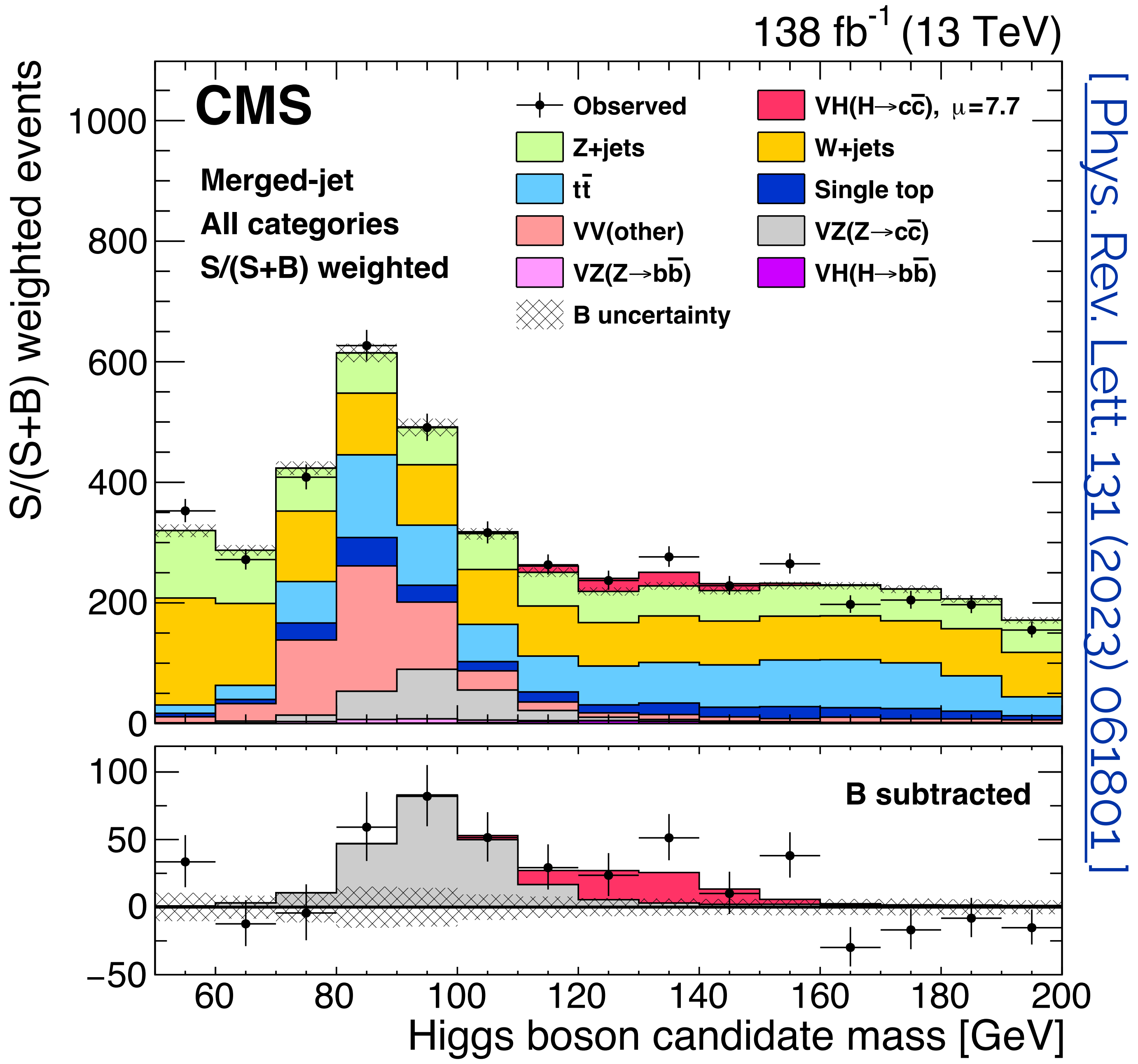
Model dependence?

Direct searches for $H \to c\bar{c}$



- VH as the "golden channel"





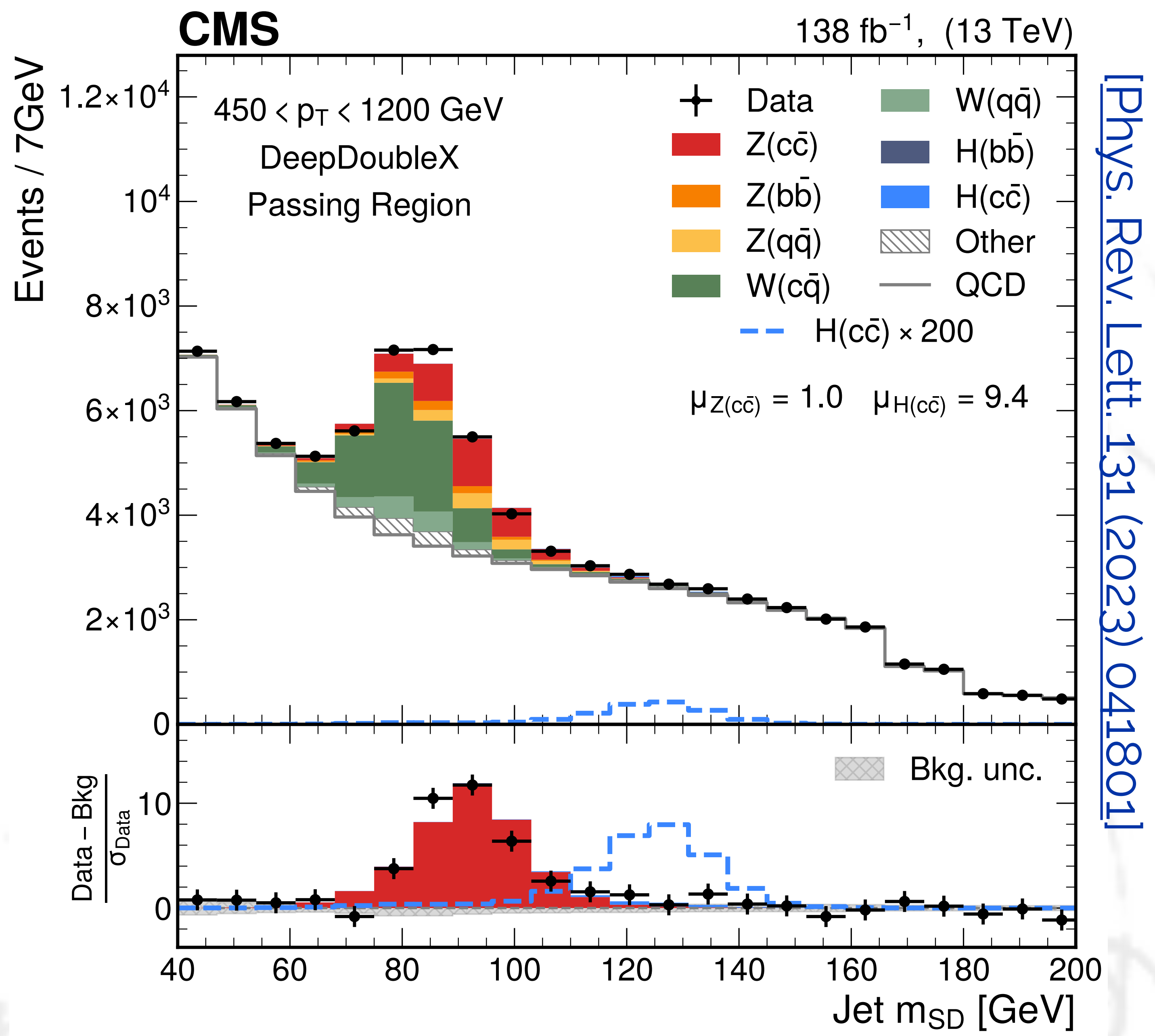
$1.1 < |\kappa_c| < 5.5$ (< 3.4)

$\mu < 14$ (7.6)

From ATLAS:
$|\kappa_c| < 4.2$ (< 4.1)
$\mu < 12$ (11)
[JHEP 04(2025) 075]

- Inclusive boosted $H \to c\bar{c}$

$\mu < 47$ (39)



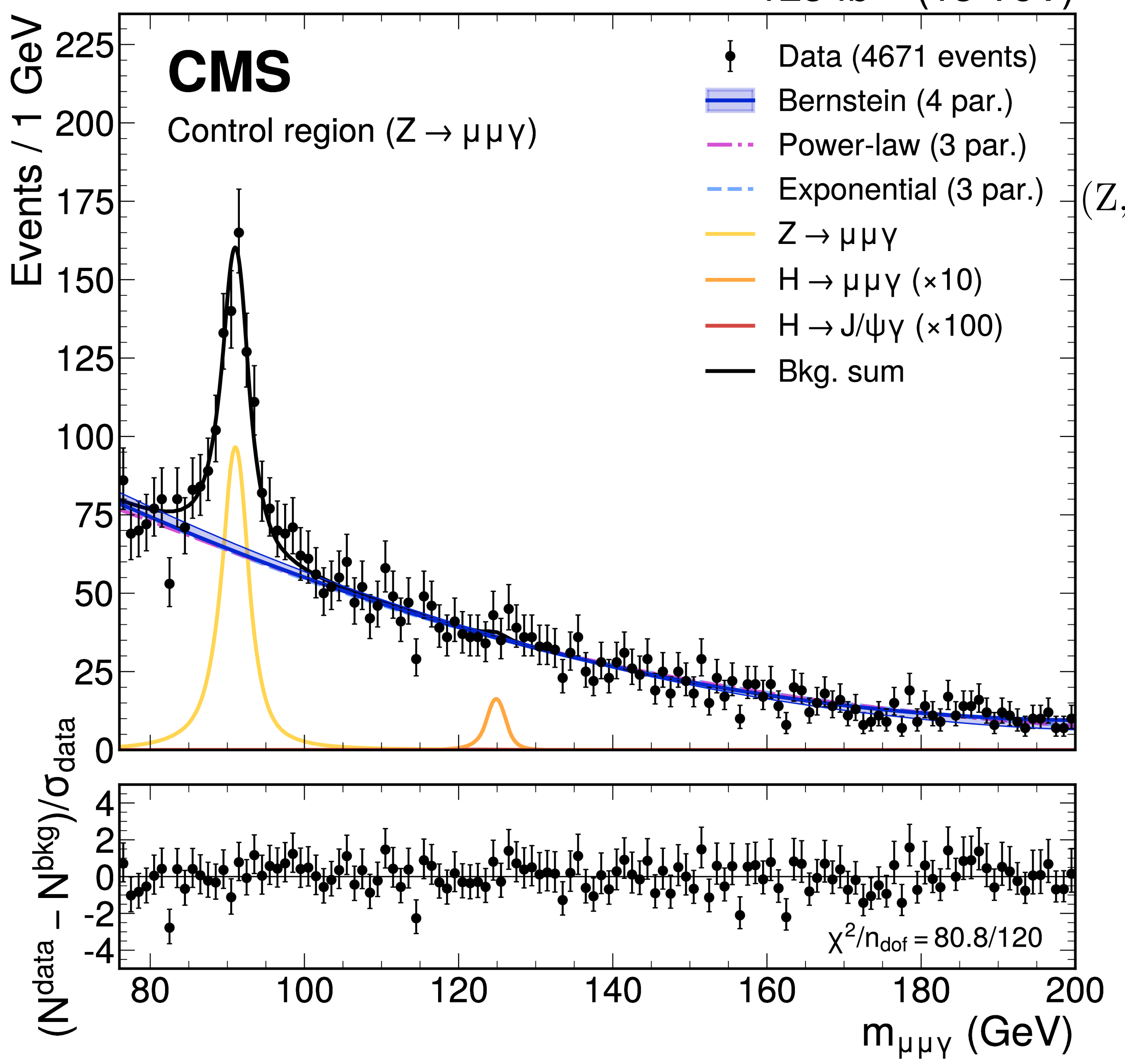
So far: probing the Higgs-charm coupling

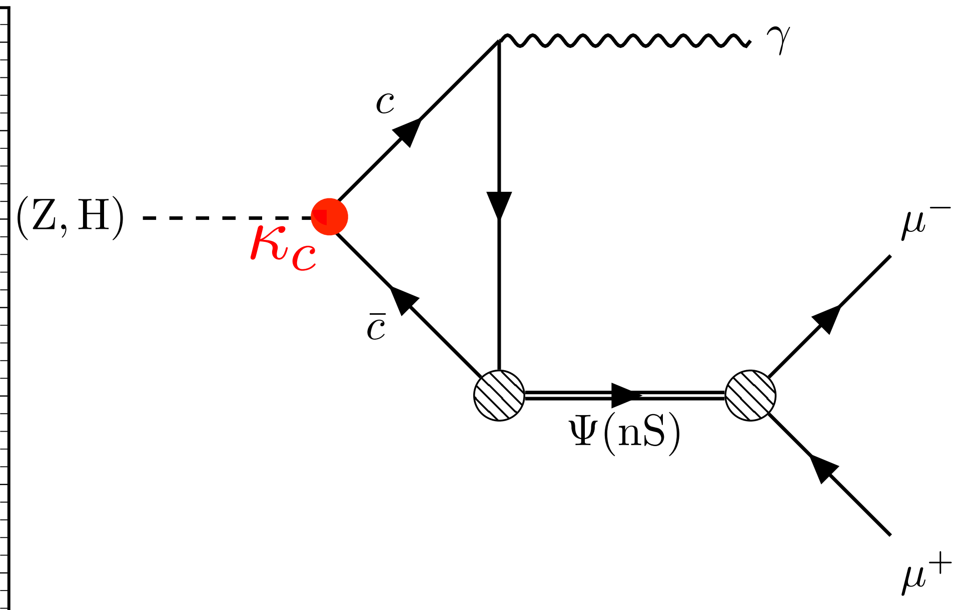
- Several methods explored by ATLAS and CMS to probe the Higgs-charm Yukawa coupling (y_c)

Indirect constraint from Higgs kinematics ⟵ Model dependence? ⟶ **Direct searches**

- Rare Higgs decays

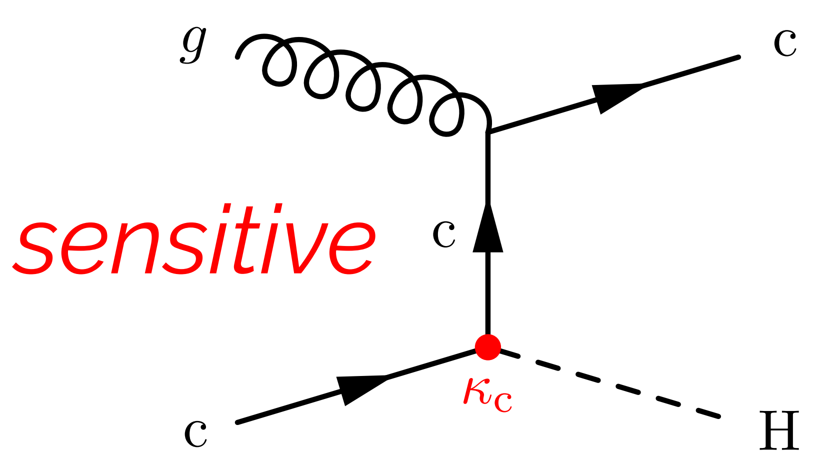
[Phys. Lett. B 865 (2025) 139462]

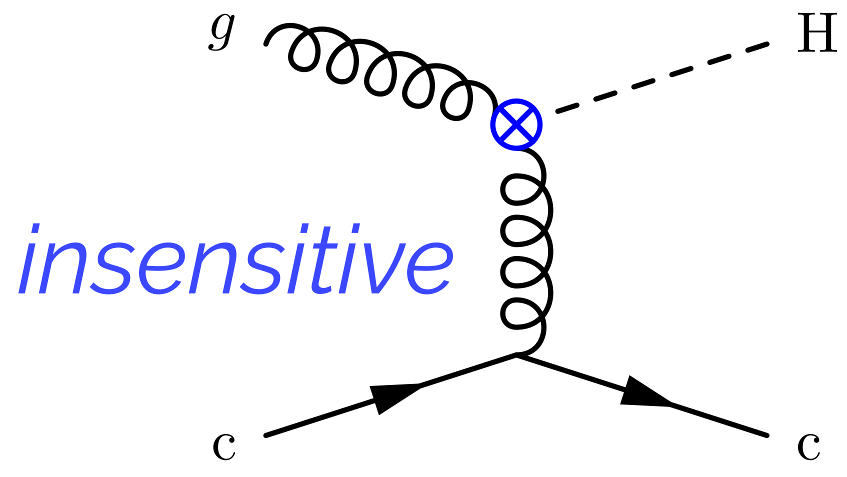


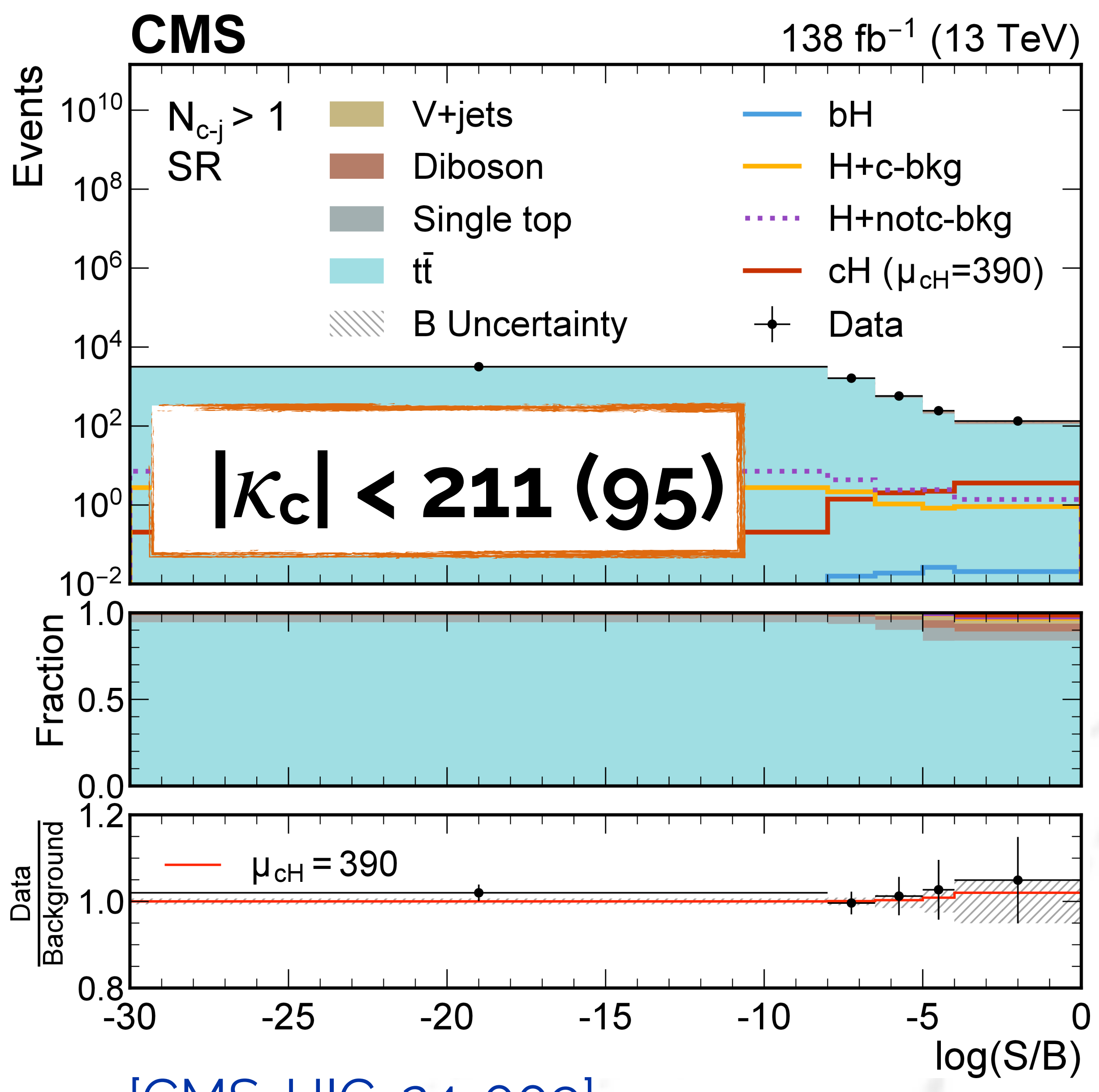


$|\kappa_c| < 200\ (170)$

- Associated production (H+c)

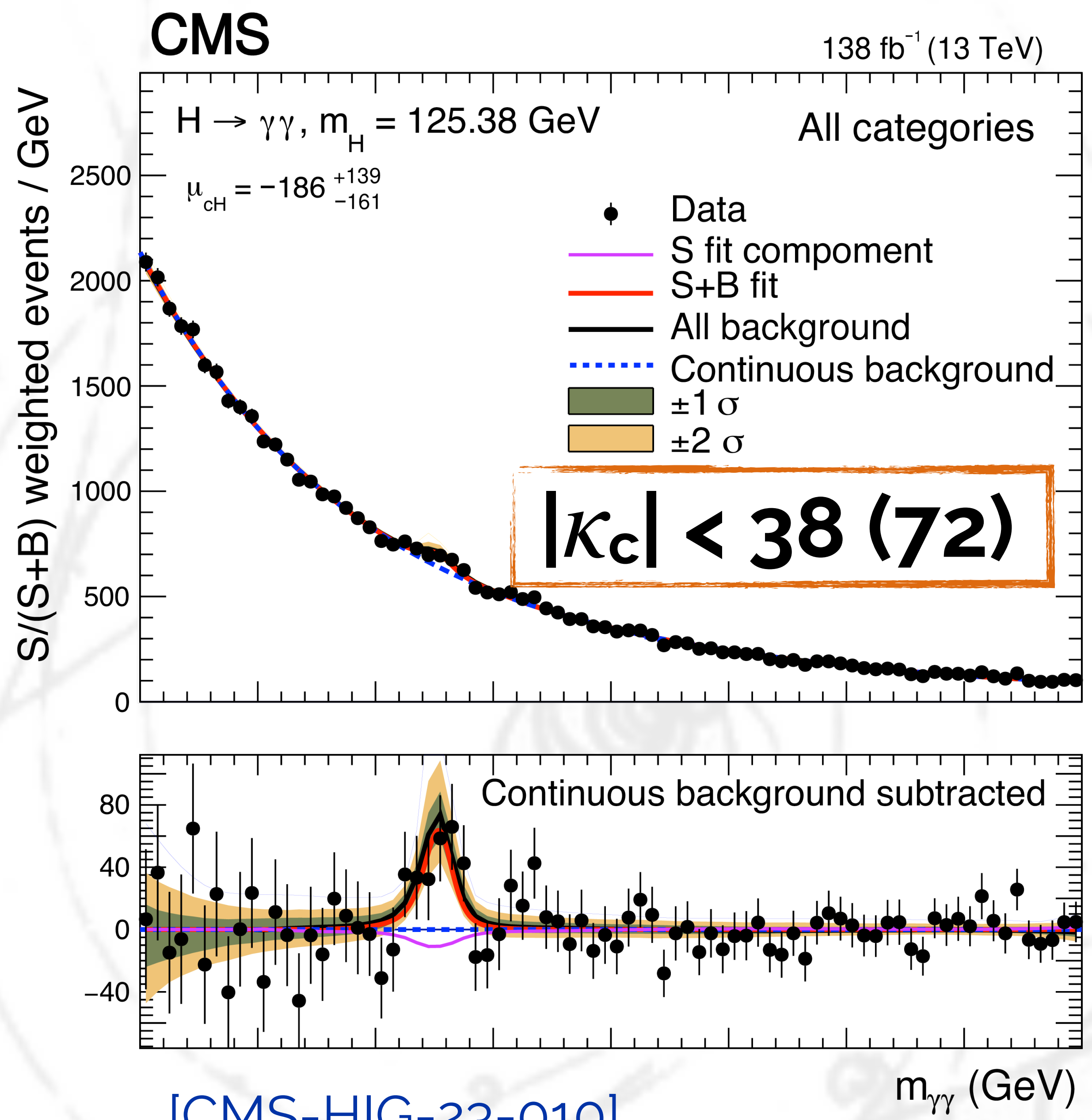






$|\kappa_c| < 211\ (95)$

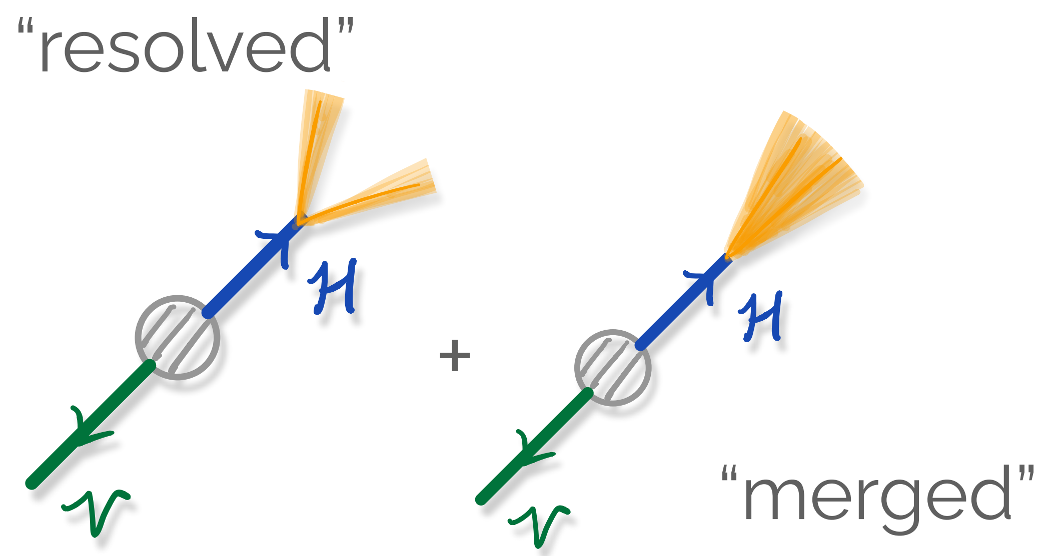
[CMS-HIG-24-009]

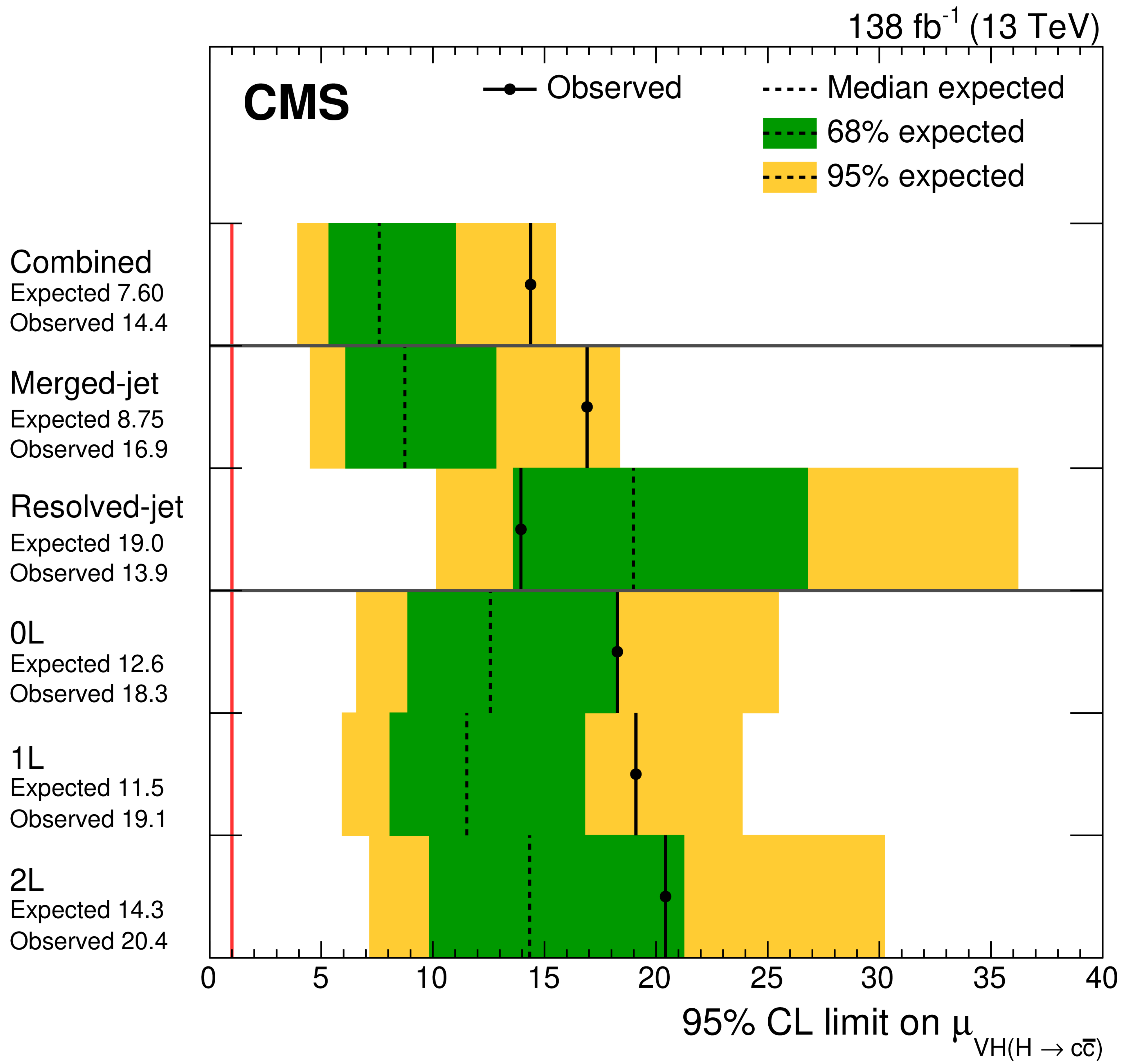


$|\kappa_c| < 38\ (72)$

[CMS-HIG-23-010]

So far: probing the Higgs-charm coupling





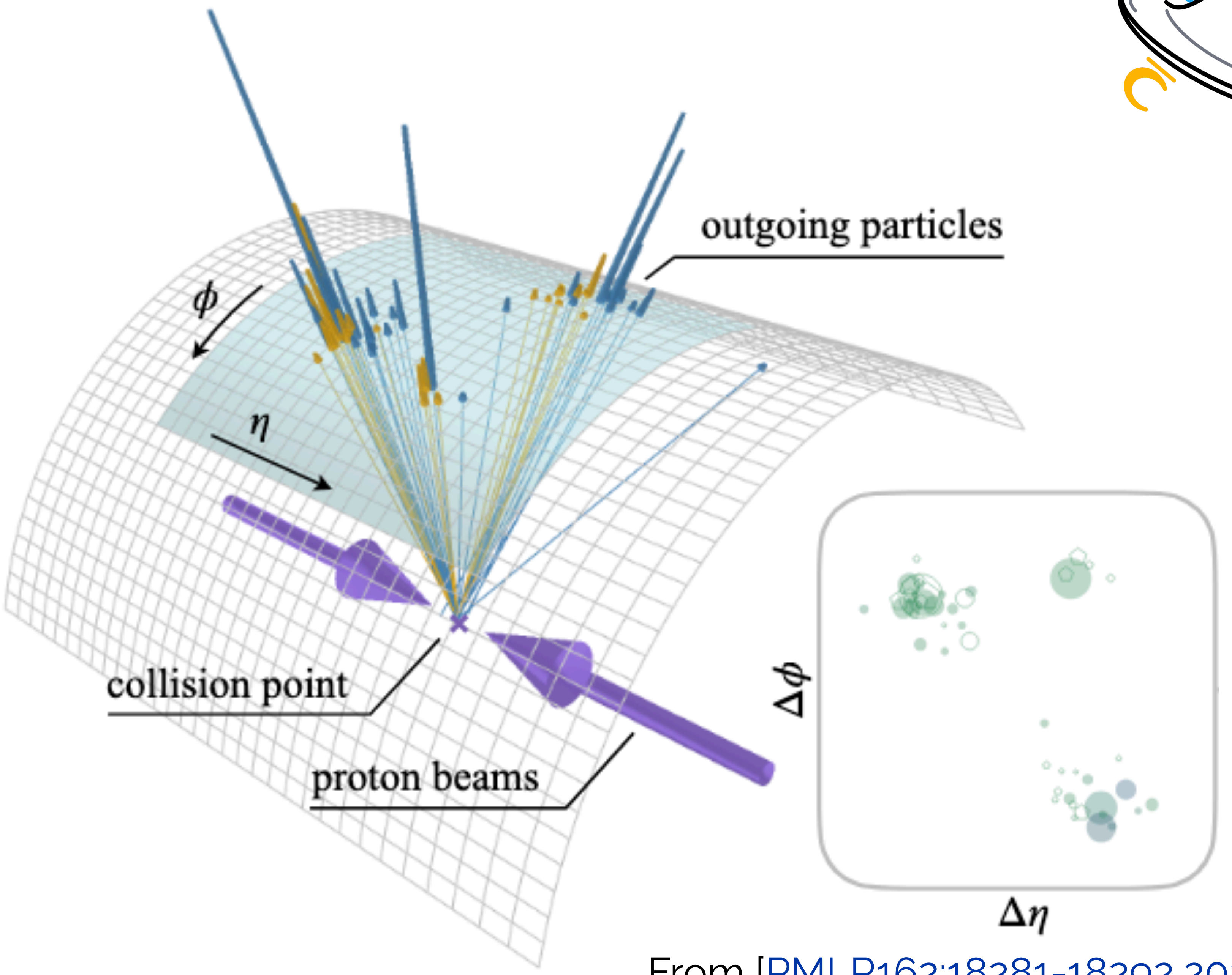
Uncertainty source	$\Delta\mu / (\Delta\mu)_{tot}$
Statistical	85%
Background normalizations	37%
Experimental	48%
Sizes of the simulated samples	37%
c jet identification efficiencies	23%
Jet energy scale and resolution	15%
Simulation modeling	11%
Integrated luminosity	6%
Lepton identification efficiencies	4%
Theory	22%
Backgrounds	17%
Signal	15%

[Phys. Rev. Lett. 131 (2023) 061801]

Jet flavour tagging

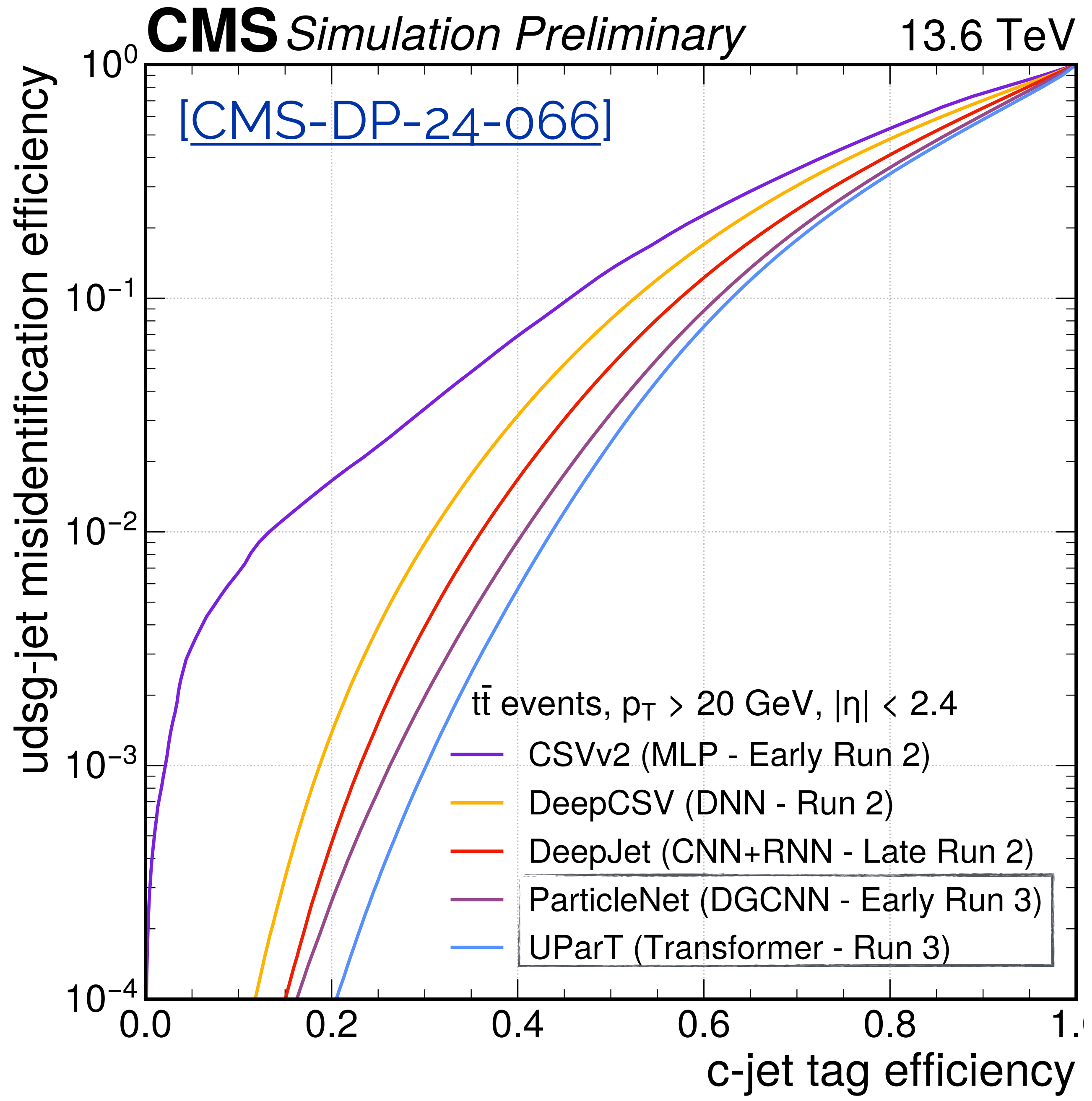
- c-jet identification much harder task than b vs. light separation

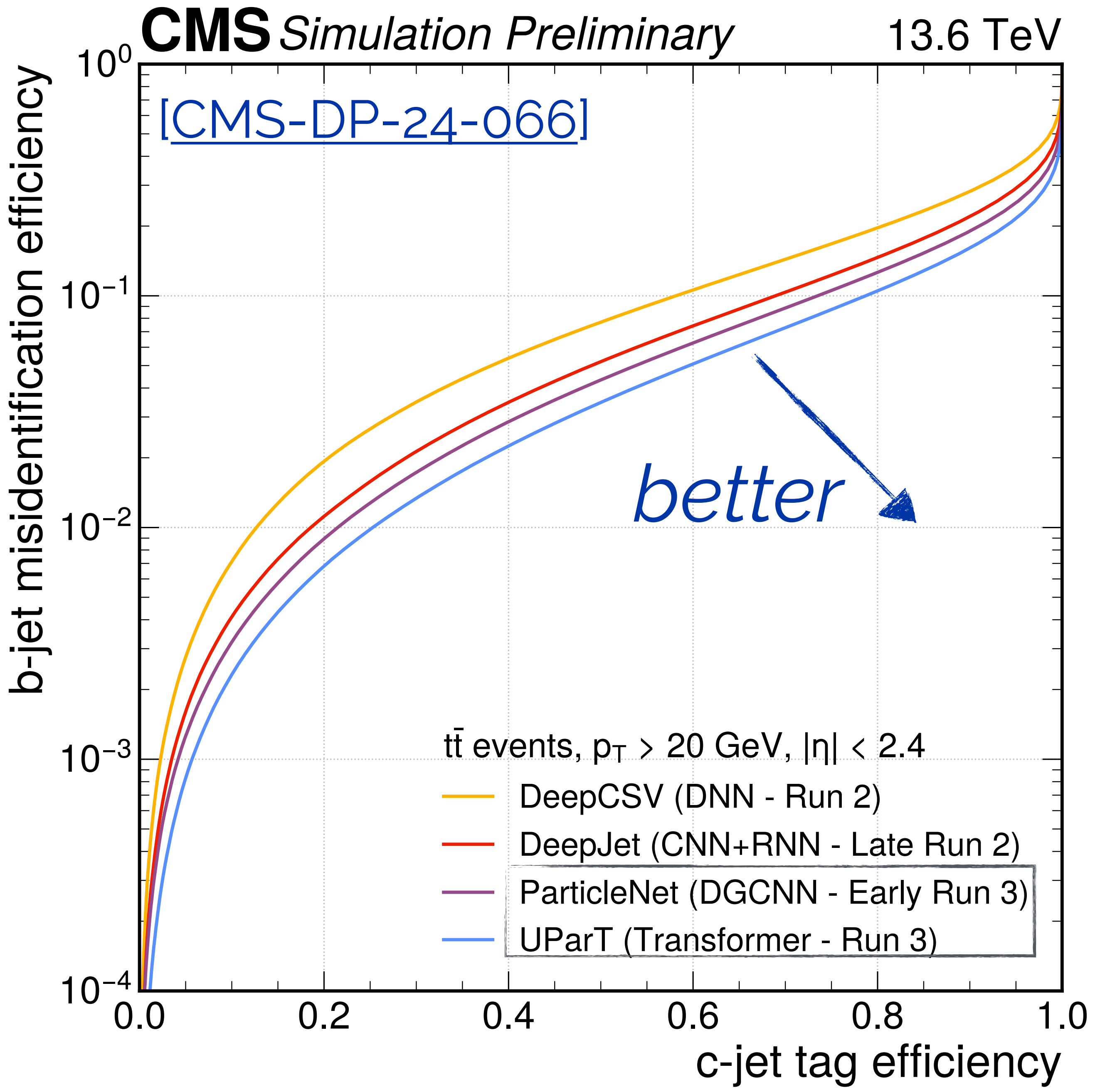
- We need modern algorithms that:
  - Represent the "physics picture"
  - Can learn particle-particle correlations
  - → Treat jet as unordered set of inputs ("particle cloud") in *graph-structure*



From [PMLR162:18281-18292,2022]

Order of magnitude improvement!





ParticleNet [2] algorithm originally designed for large-radius tagging successfully used here for c-jet identification

[2] [Phys.Rev. D 101, 056019 (2020)]

Tagging calibration

- Leverage established methods:
  - Simultaneous fit to determine all scale factors (SF)

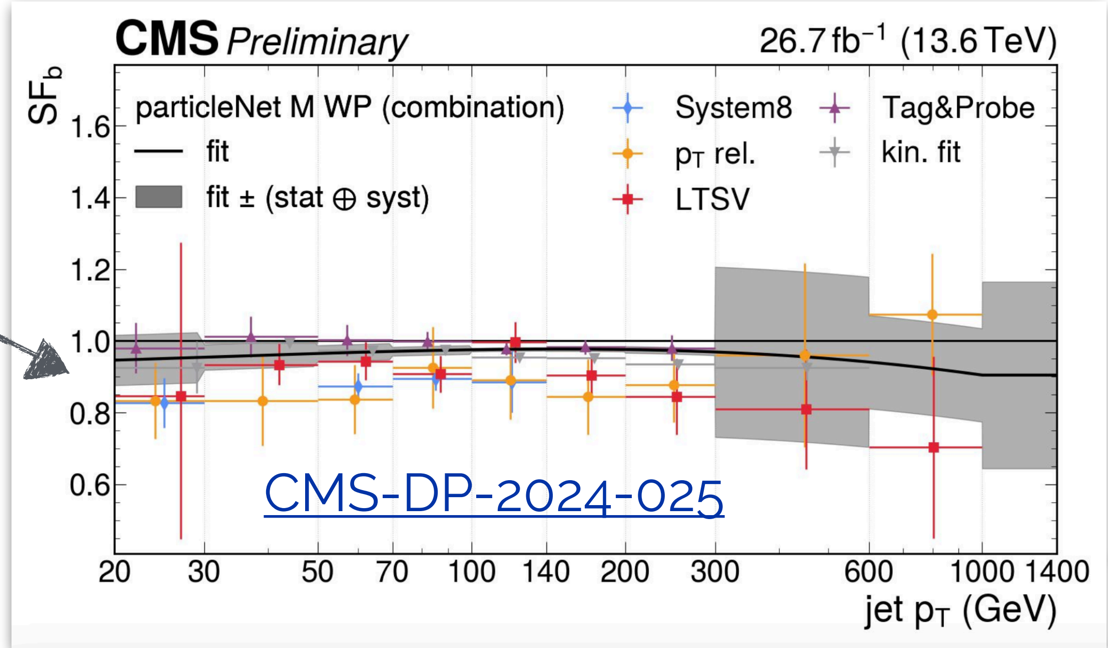
$$\sum_{\mathrm{WP}\in[\mathrm{L0,C0-C4,B0-B4}]} \epsilon_{\mathrm{MC}}(\mathrm{WP}|\mathrm{flav}) = \sum_{\mathrm{WP}} \epsilon_{\mathrm{Data}}(\mathrm{WP}|\mathrm{flav}) \equiv 1$$

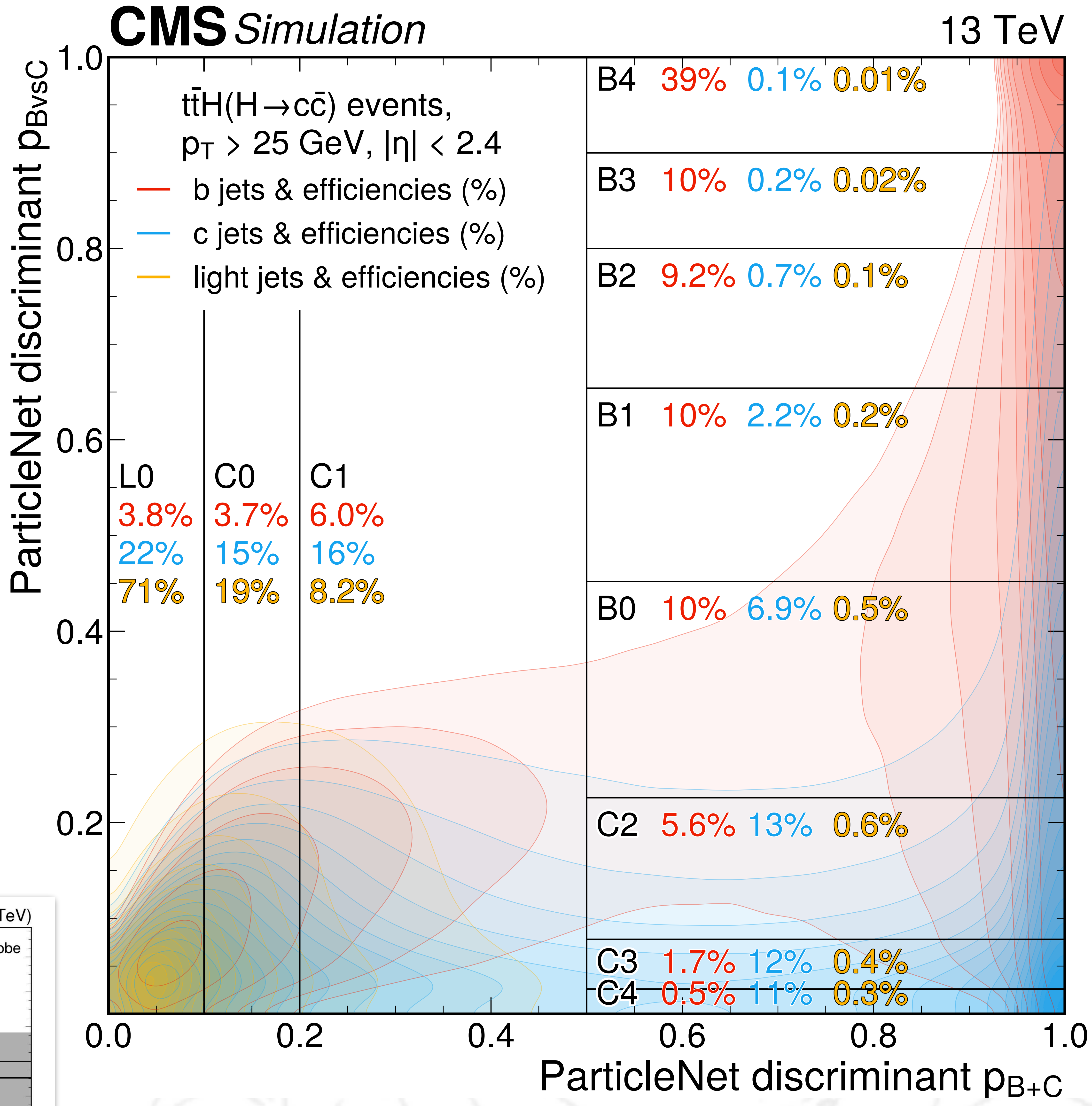
  - Fit 3 x 11 - 3 SFs in three selections:
    - W+jets: $\ell\nu$ + soft muon in jet → c jets
    - tt: dilepton eμ → b jets
    - Z+jets: dilepton ee/μμ → light jets

- Fit in different bins of jet pT:

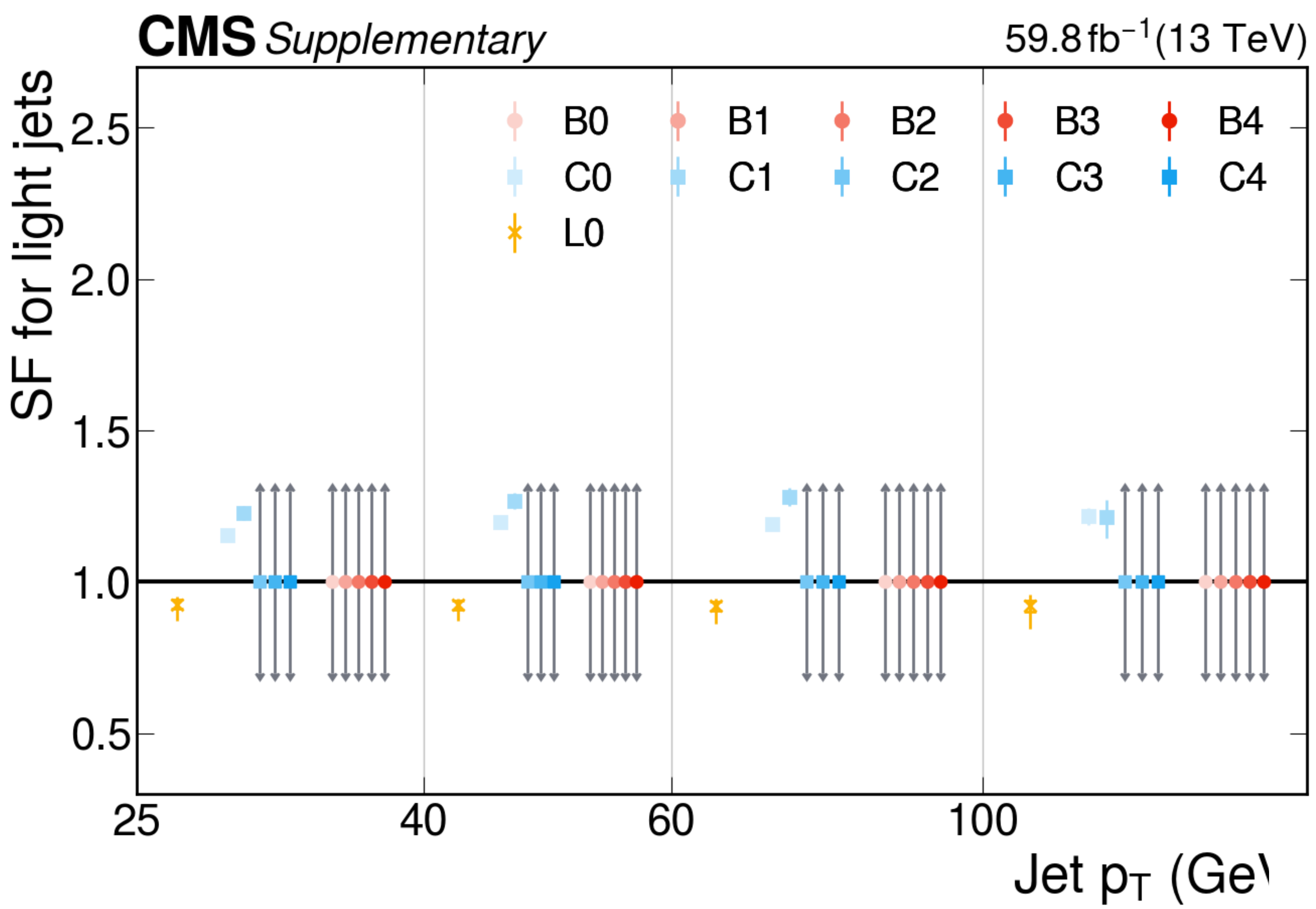
$$p_{\mathrm{T}}(\mathrm{jet}) \in [25, 35, 50, 70, 90, 120, \infty]\ \mathrm{GeV}$$

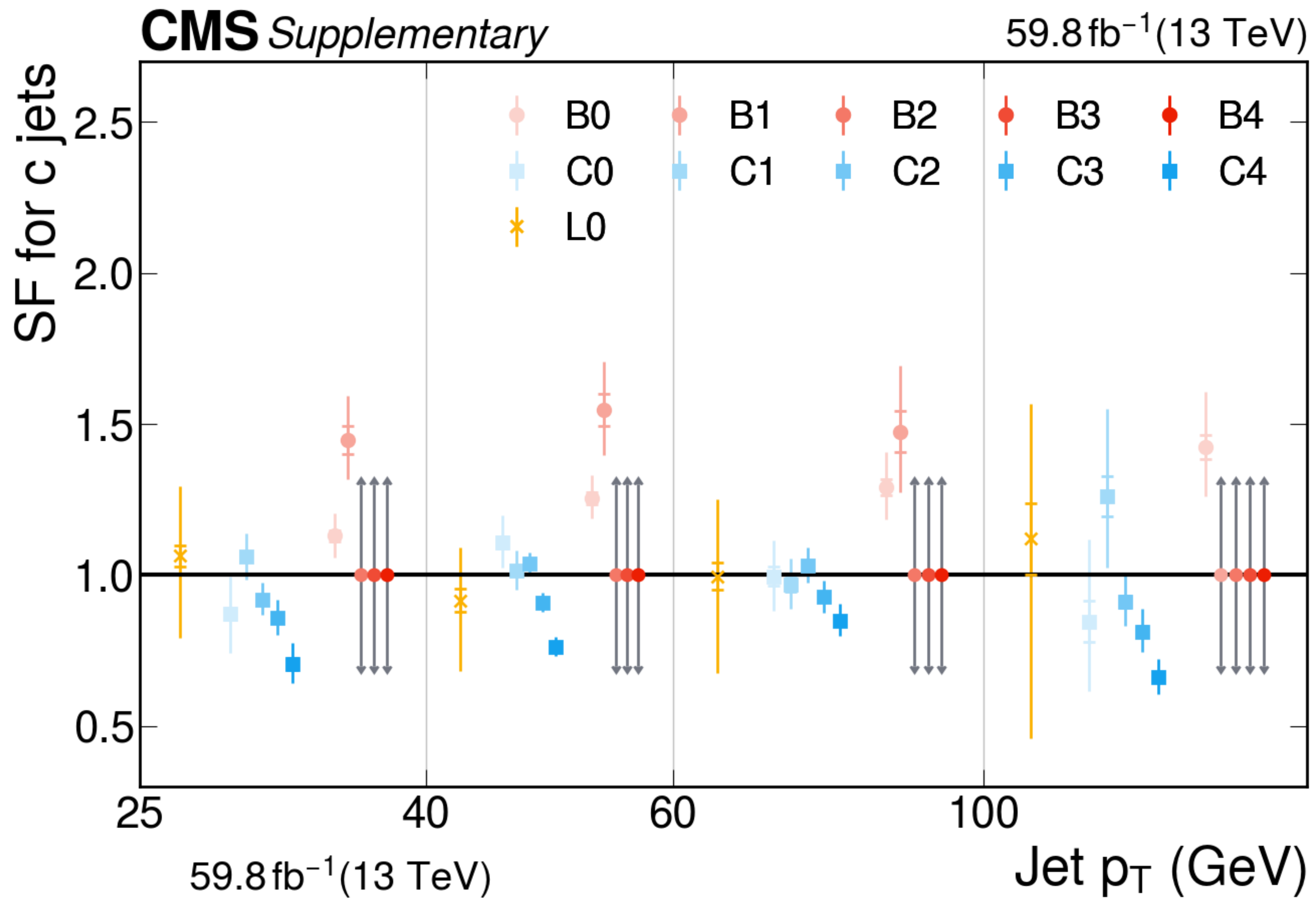
- SFs typically in range of [0.75, 1.5]
  - Also already calibrated in Run 3

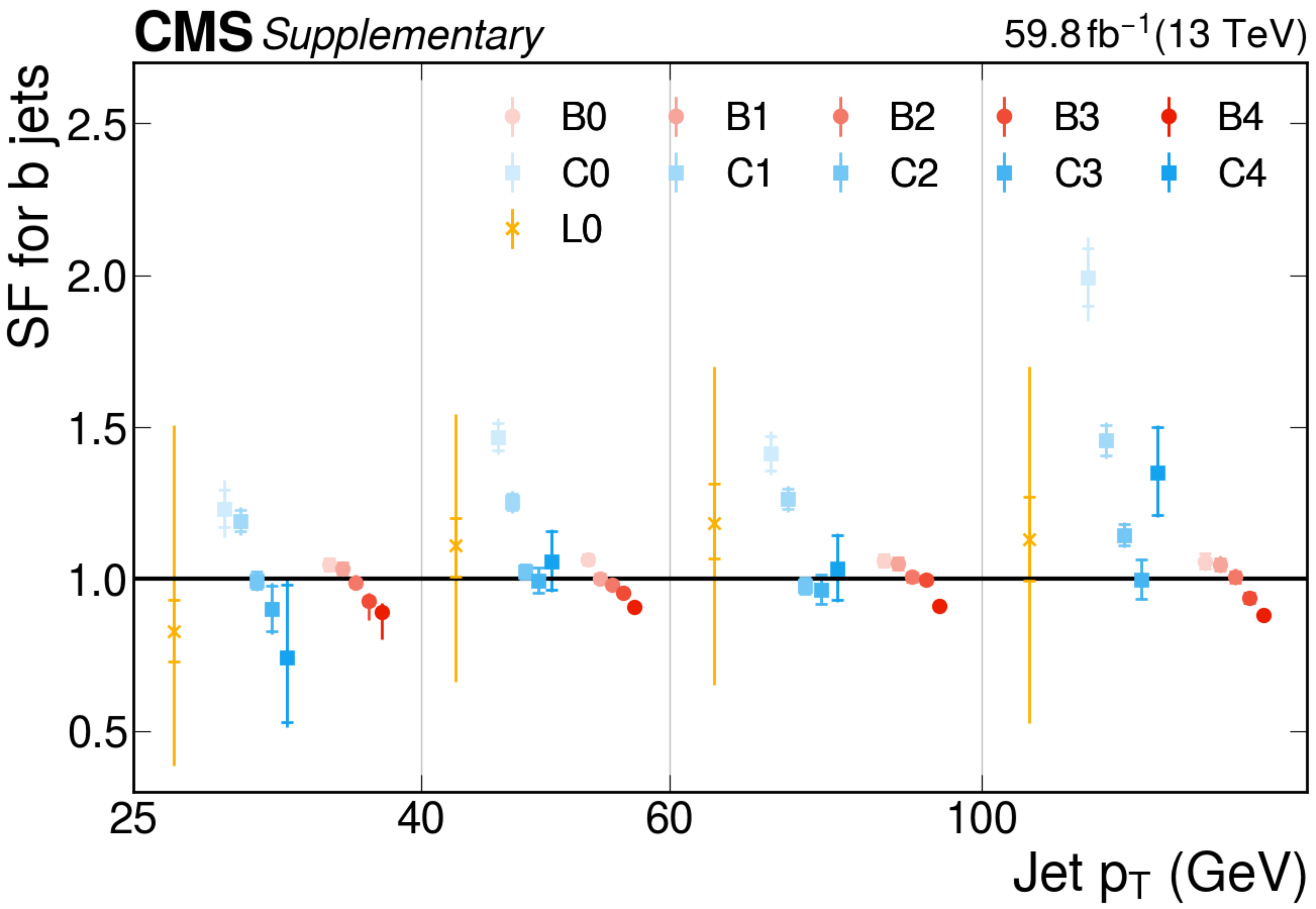




Tagging calibration

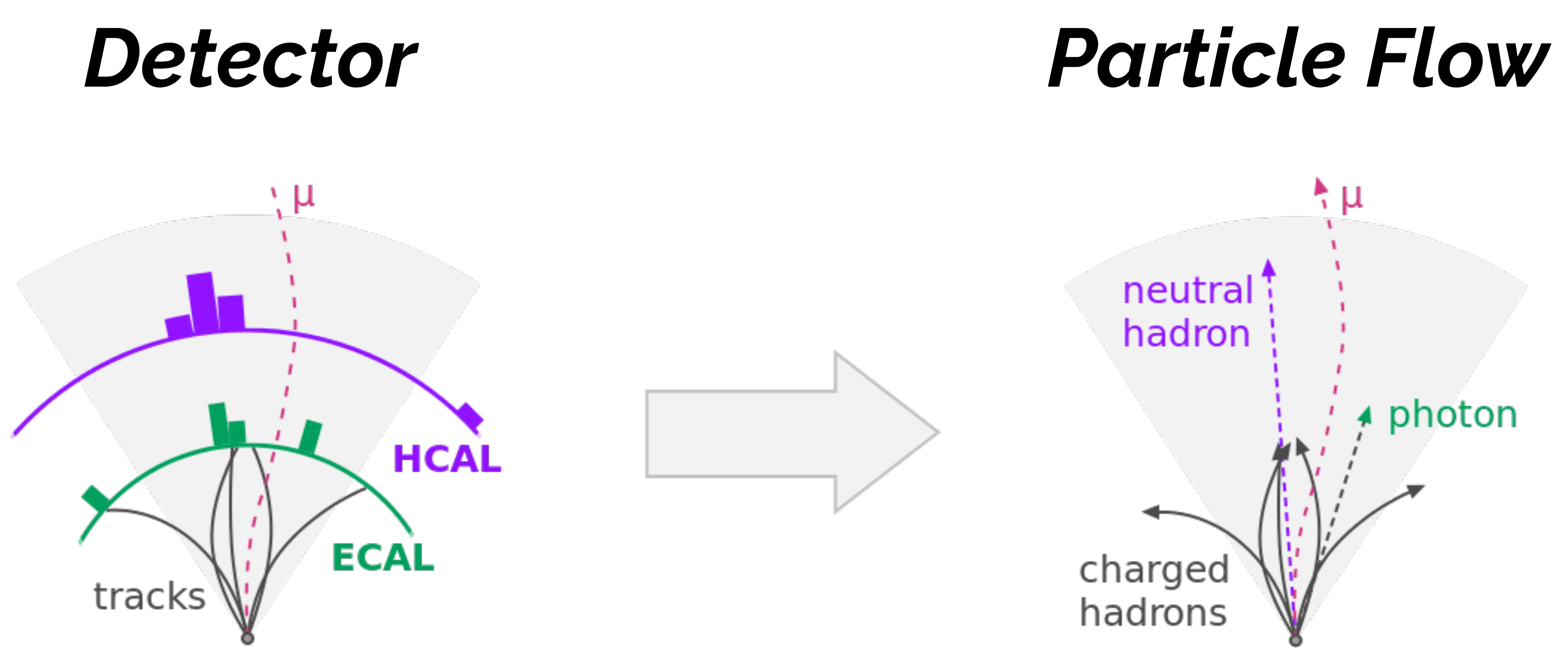






The basics: ingredients and CMS strategy

- Particle flow (PF) algorithm:
  - PF provides an improved event description by correlating sub-detector measurements
  - PF allows to reconstruct and identify each single particles
  - Outputs: energy/momentum, position, particle-type, track info and displacement, calorimeter deposit and cluster shape, etc.

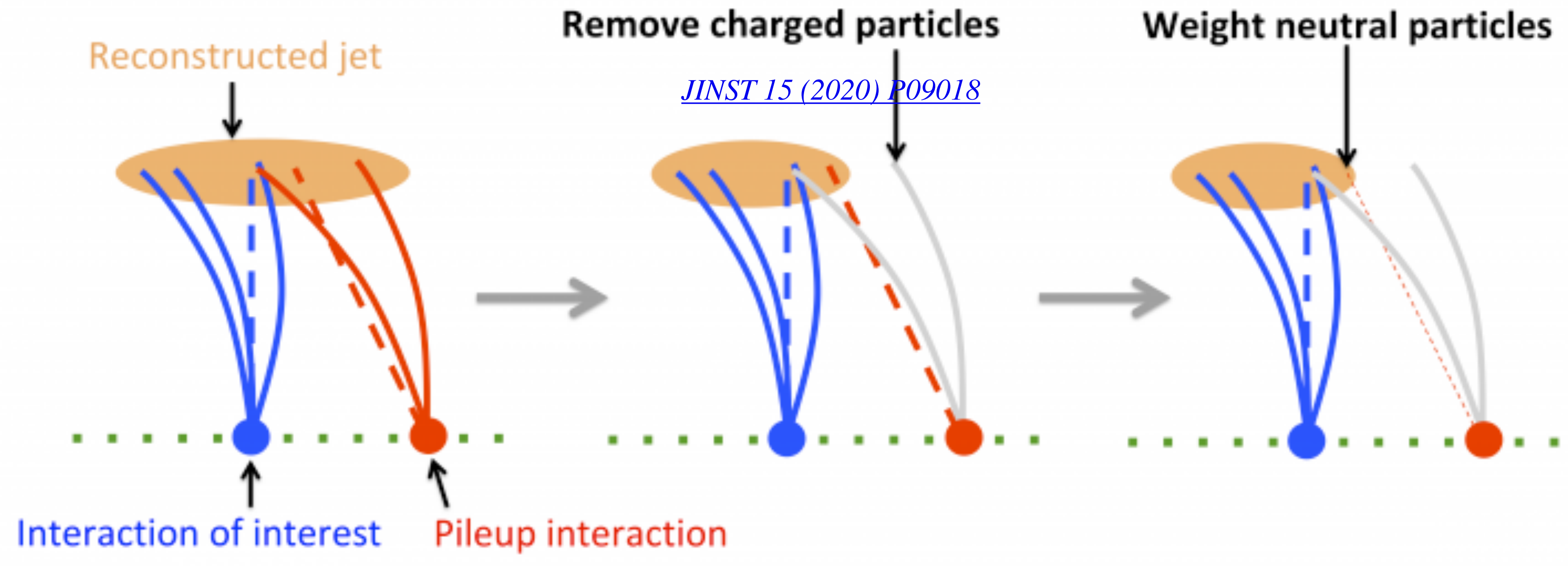


[JINST 12 (2017) P10003]

- Pileup mitigation via PileUp Per Particle Identification (PUPPI):
  - Remove particles that are produced by in-time pileup interactions and alter the jet radiation pattern
  - PUPPI assigns to each PF-candidate a probability (α_i) of coming from a pileup interaction
  - Charged particles have weight 1 or 0 depending on their association to PV, neutral particles have a weight assigned by

$$\alpha_i = \log \sum_{j \neq i, \Delta R_{ij} < R_0} \left(\frac{p_{T,j}}{\Delta R_{ij}} \right)^2$$

[JINST 15 (2020) P09018]



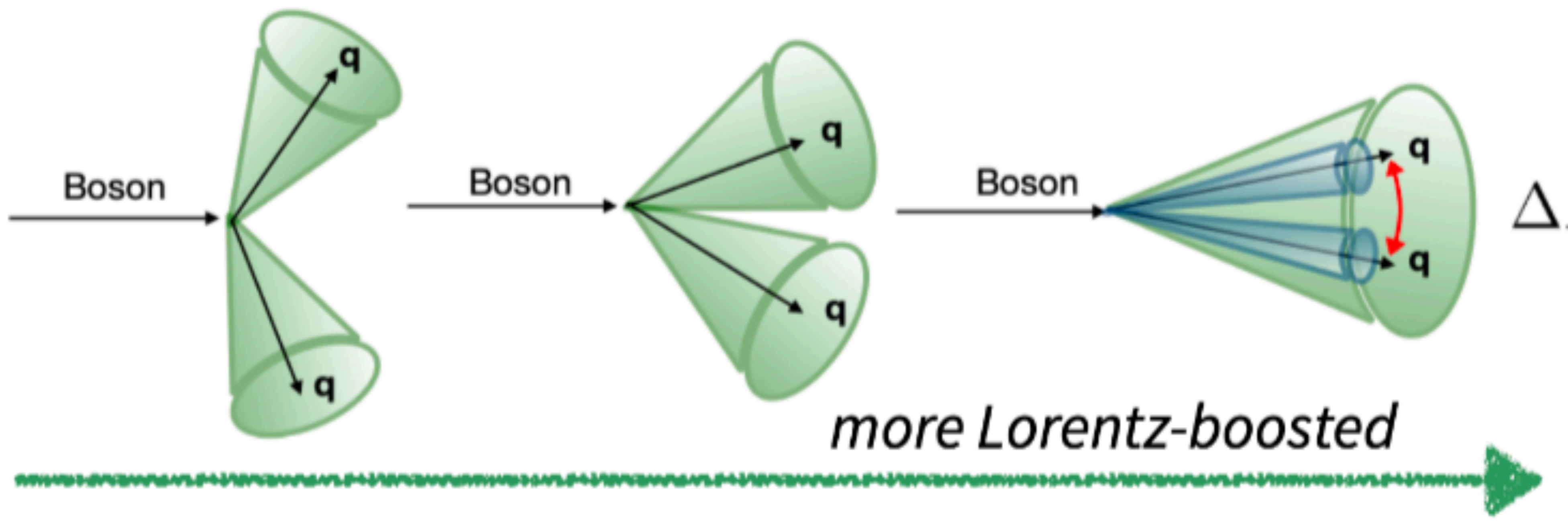
Recent important updates for tau-ID

[CMS-DP-2024-043]

→ **Perfect inputs for ML-based jet tasks! (Not only classification 🙂)**

Boosted jet tagging

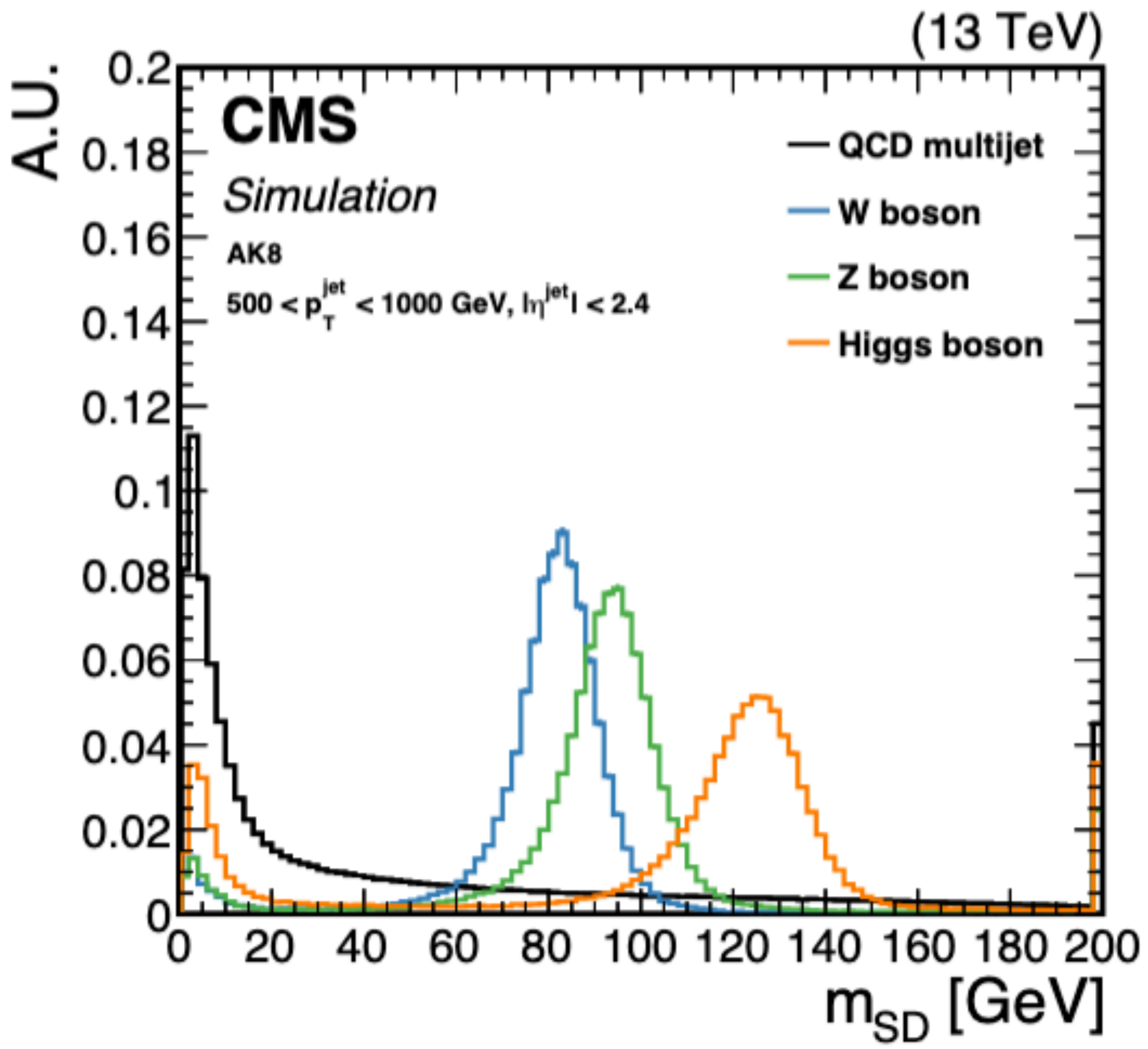
- Resonance decay with high Lorentz-boost:
  - Decay products clustered in single large-radius jet (AK8 or AK15)



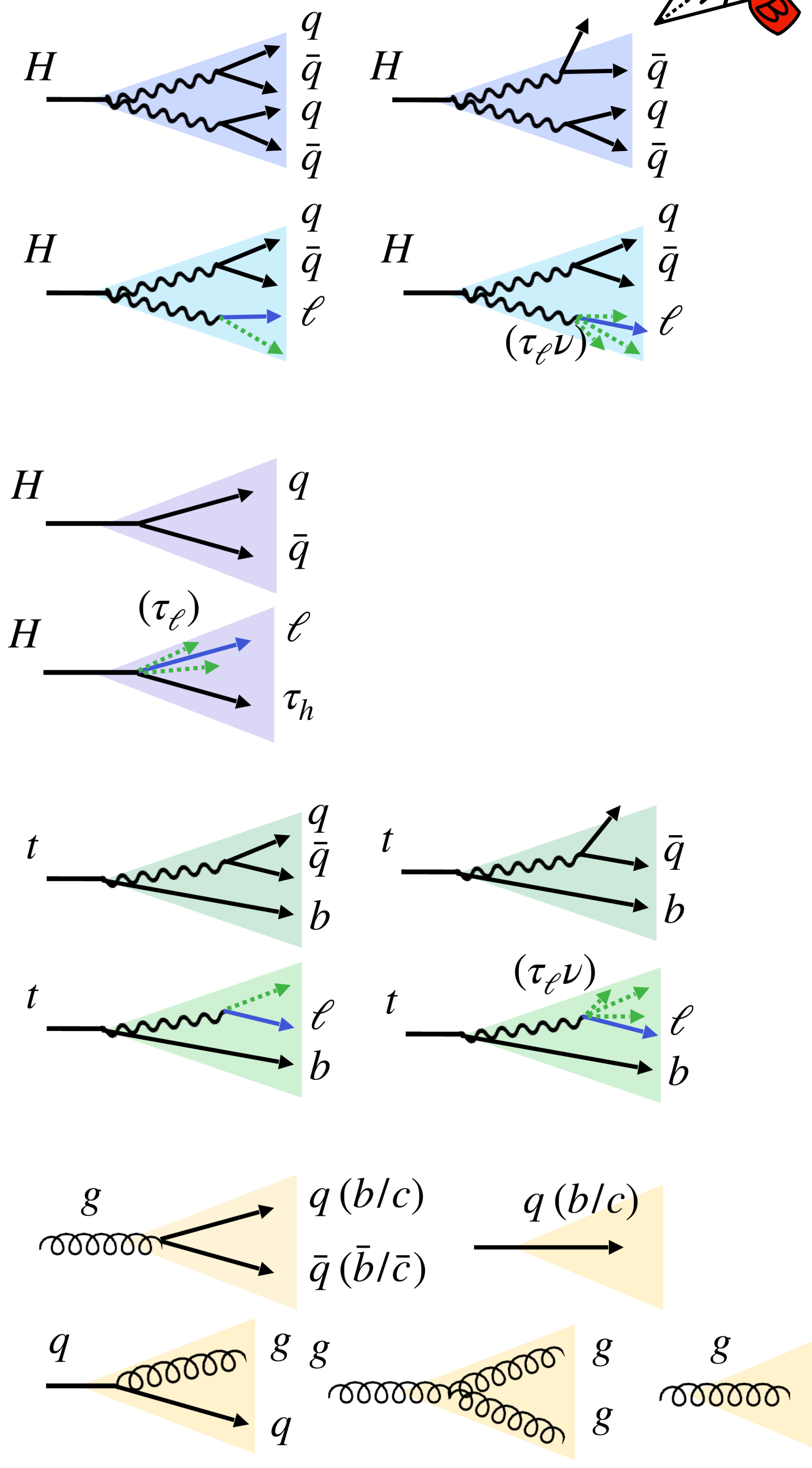
$$\Delta R \sim \frac{2m}{p_T}$$

- **ParticleNet** and **GloParT** established as strong baseline for multitude of developments in CMS

But what do we do with the jet mass?



Process	Final state/ prongness	heavy flavour	# of classes
H→VV (full-hadronic)	qqqq	0c/1c/2c	3
	qqq		3
H→WW (semi-leptonic)	eνqq	0c/1c	2
	μνqq		2
	τ_eνqq		2
	τ_μνqq		2
	τ_hνqq		2
H→qq		bb	1
		cc	1
		ss	1
		qq (q=u/d)	1
H→ττ	$\tau_e\tau_h$		1
	$\tau_\mu\tau_h$		1
	$\tau_h\tau_h$		1
t→bW (hadronic)	bqq	1b + 0c/1c	2
	bq		2
t→bW (leptonic)	beν	1b	1
	bμν		1
	bτ_eν		1
	bτ_μν		1
	bτ_hν		1
QCD		b	1
		bb	1
		c	1
		cc	1
		others (light)	1



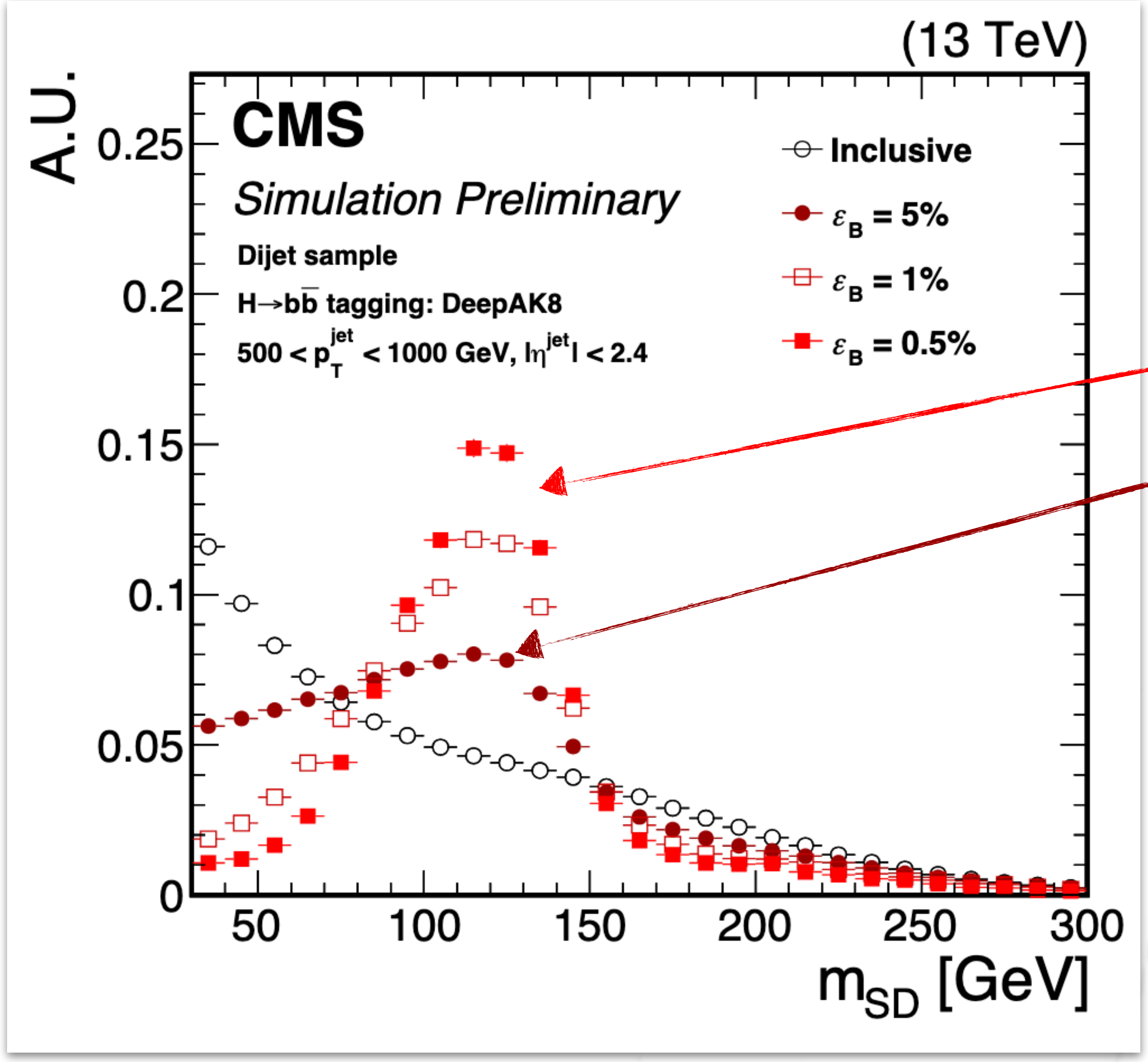
See, e.g., recent H→4b results for Run 3
[HIG-24-010]

Mass dependence

[CMS-DP-20-002]

- In several searches with boosted X(→YY) resonances → **signal is extracted from a fit to the jet mass**
- If the X(→YY) tagger is correlated with the jet mass → jet mass in background events becomes signal-like (**sculpting**) → extracting signal becomes more difficult

N.B.: It can also be desired to "learn" the mass and use it
→ both versions of the tagger exist!



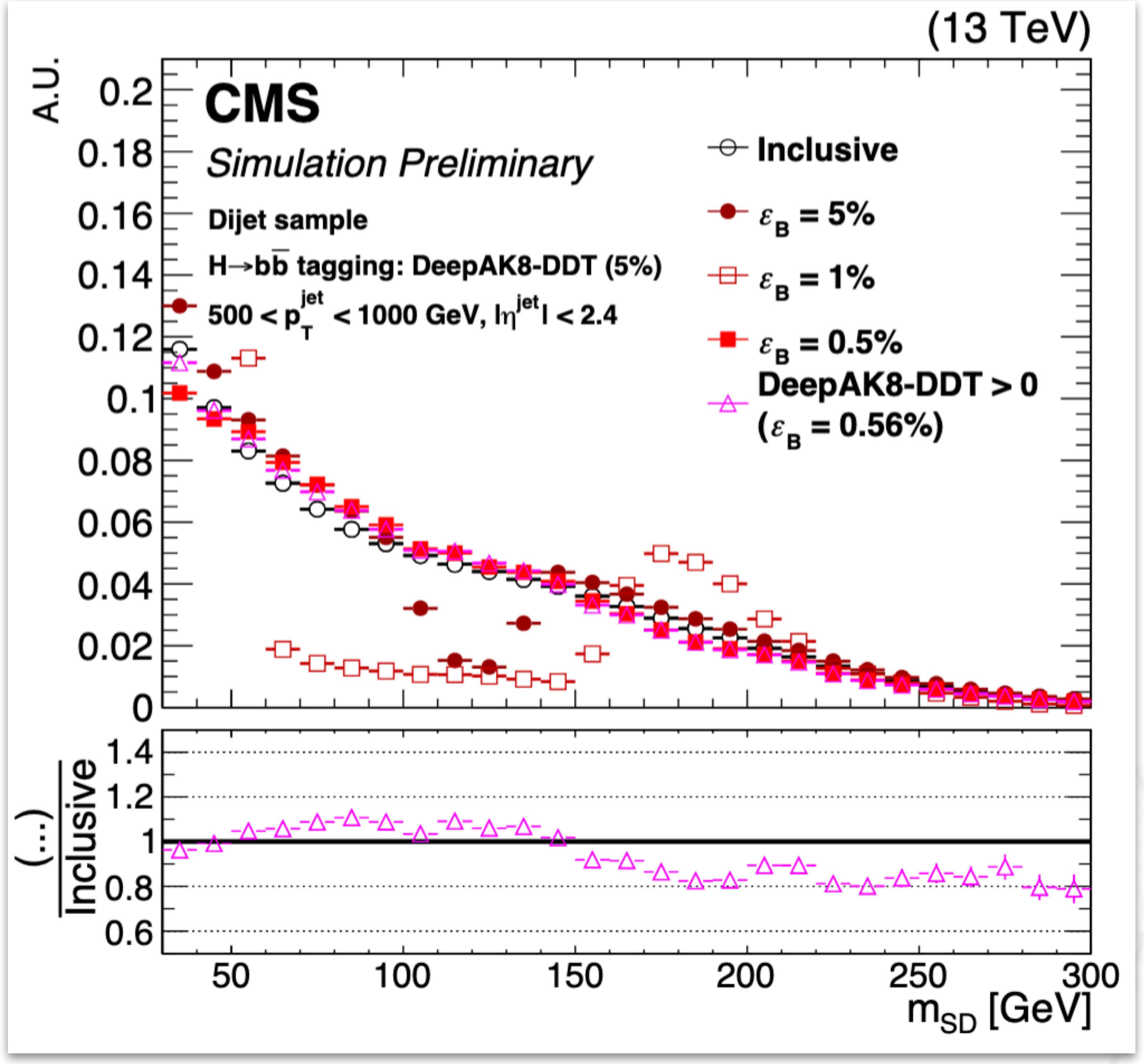
Gets worse with tighter selection!

Mass decorrelation techniques

- In several searches with boosted X(→YY) resonances → **signal is extracted from a fit to the jet mass**
- If the X(→YY) tagger is correlated with the jet mass → jet mass in background events becomes signal-like (**sculpting**) → extracting signal becomes more difficult

A-posteriori de-correlation (DDT)

- Define a metric that is sensitive to jet-mass through correlations: $\ln(m_{SD}^2/p_T^2)$ and p_T
- Transform tagger score to preserve constant background rejection vs. m_{jet} for a given efficiency



Mass decorrelation breaks down as soon as the selection is changed

[CMS-DP-20-002]

Mass decorrelation techniques

- In several searches with boosted X(→YY) resonances → **signal is extracted from a fit to the jet mass**
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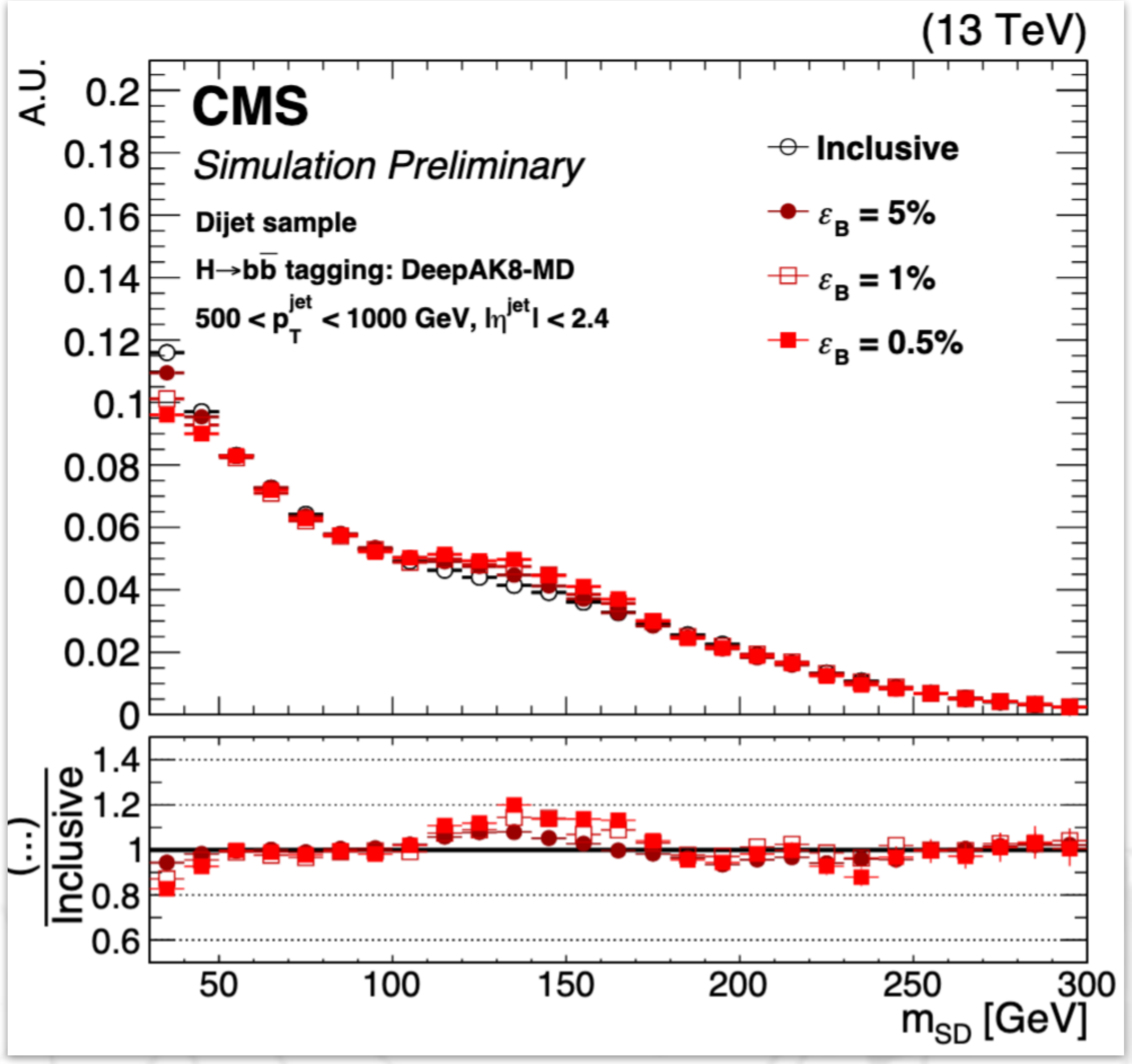
A-posteriori de-correlation (DDT)

- Define a metric that is sensitive to jet-mass through correlations: $\ln(m_{SD}^2/p_T^2)$
- Transform tagger score to preserve constant background rejection vs. m_{jet} for a given efficiency

Adversarial networks

- Add a NN that predicts m_{jet} from the feature embeddings of the nominal network
- Add penalty term in the loss function related to the prediction of the correct m_{jet}

Painful to train, significant loss in performance and not perfect mass de-correlation



Mass decorrelation techniques

[CMS-DP-20-002]

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A-posteriori de-co

- Define a metric th jet-mass through $\ln(m_{SD}^2/p_T^2)$
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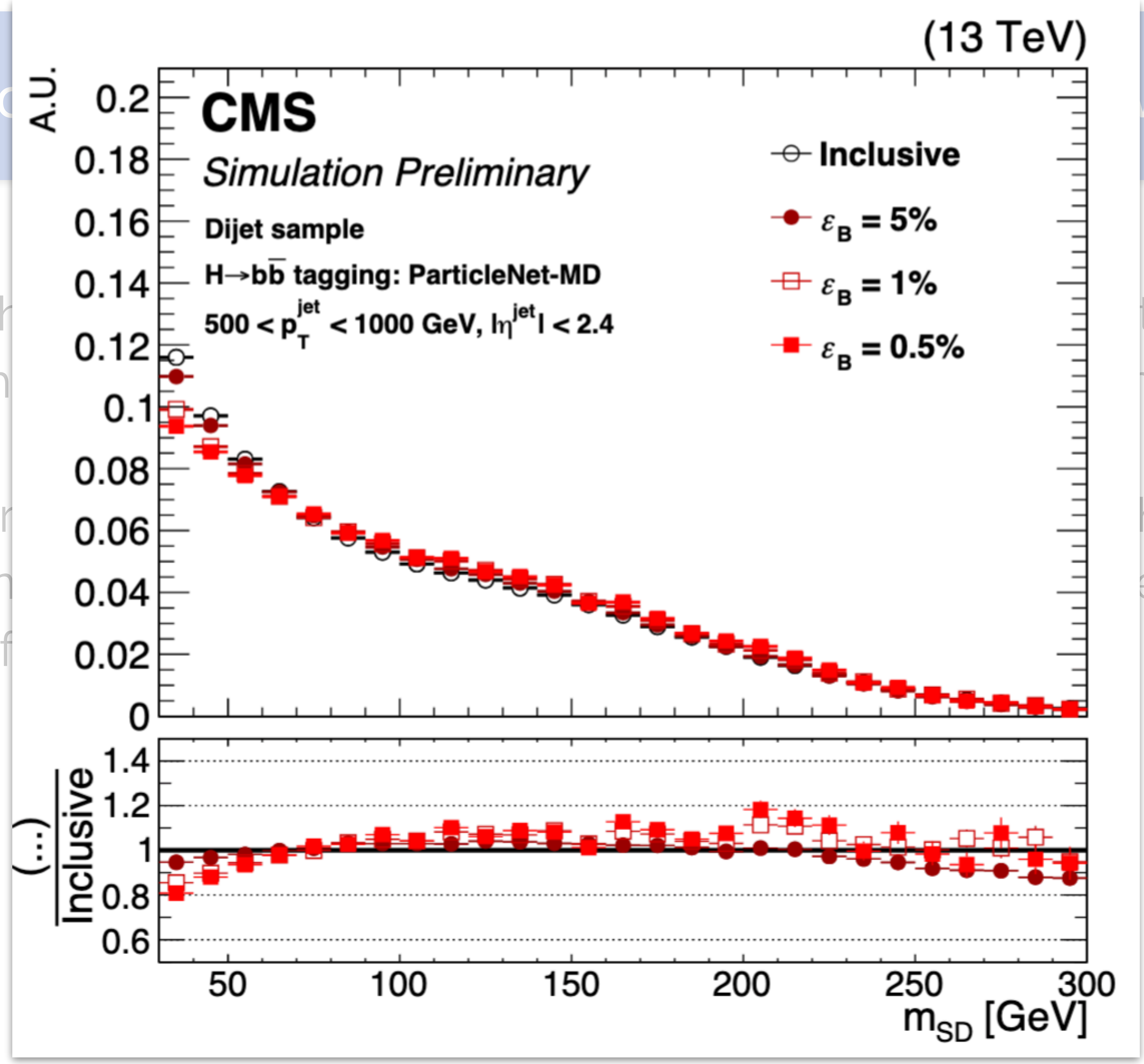


works

ts m_{jet} from ngs of the he loss e prediction

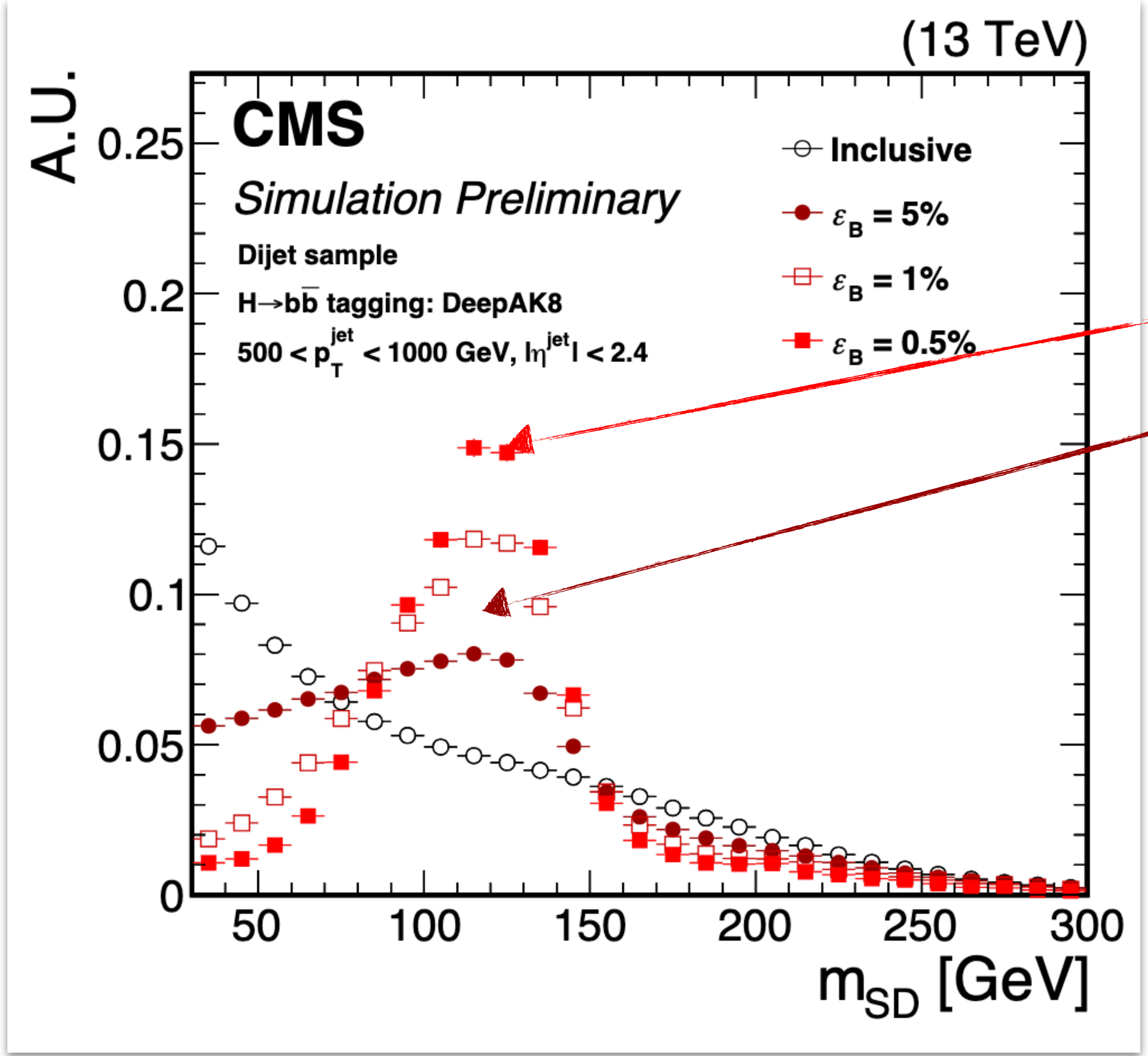
Mass uniform sampling in training

- Dedicated signal samples with flat resonance mass (m_X)
- All jet classes included in the training reweighted to a flat jet mass (m_{SD}) and p_T

Best method developed so far: minimal loss in performance and good mass decorrelation

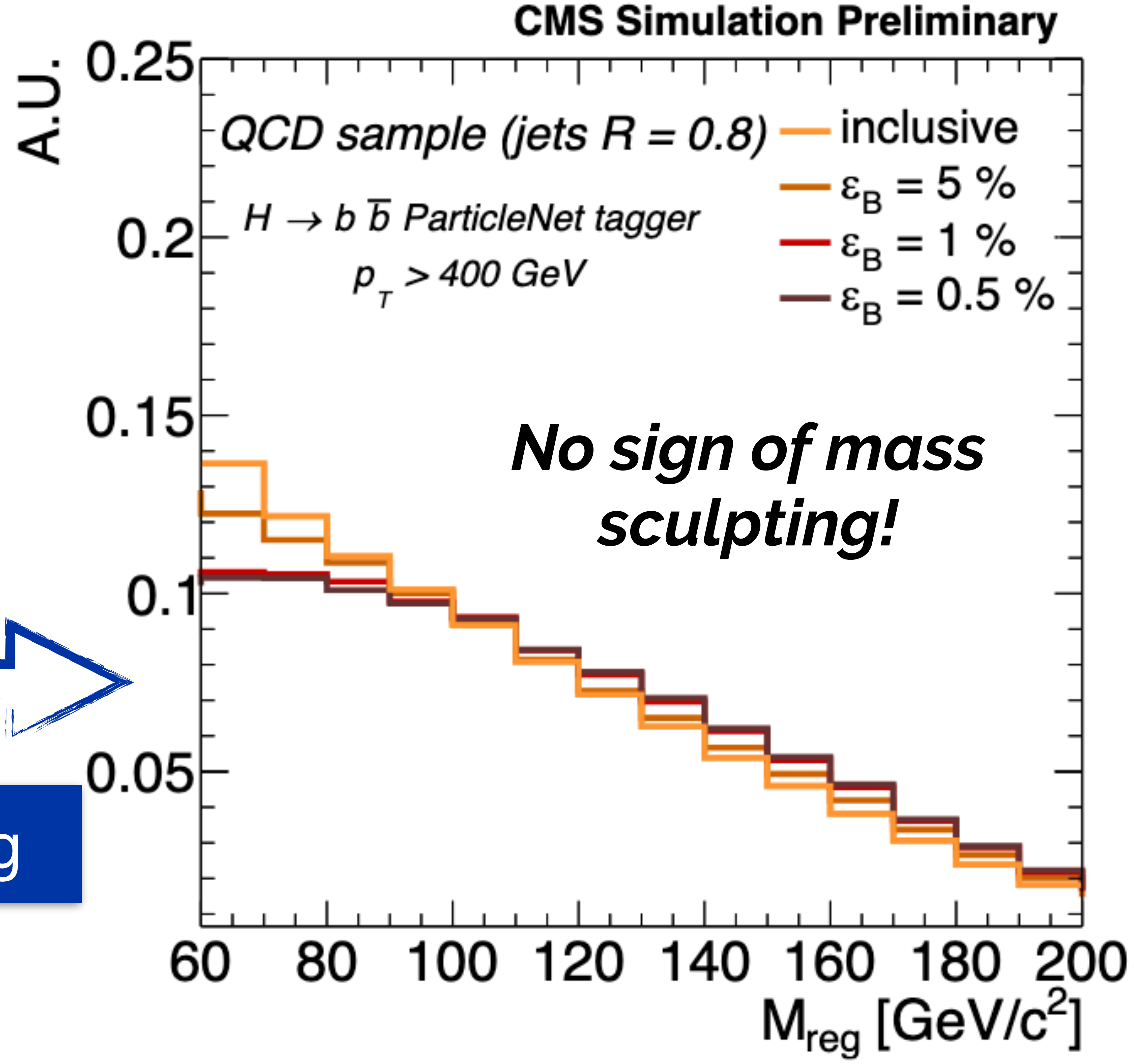
Mass decorrelation techniques

- In several searches with boosted X(→YY) resonances → **signal is extracted from a fit to the jet mass**
- If the X(→YY) tagger is correlated with the jet mass → jet mass in background events becomes signal-like (**sculpting**) → extracting signal becomes more difficult



Gets worse with tighter selection!

Mass uniform sampling in training



No sign of mass sculpting!

- Dedicated signal samples with flat mass (m_X)
- All jet classes included in the training reweighted to a flat jet mass (m_{SD}) and p_T

Minimal loss in performance and good mass decorrelation

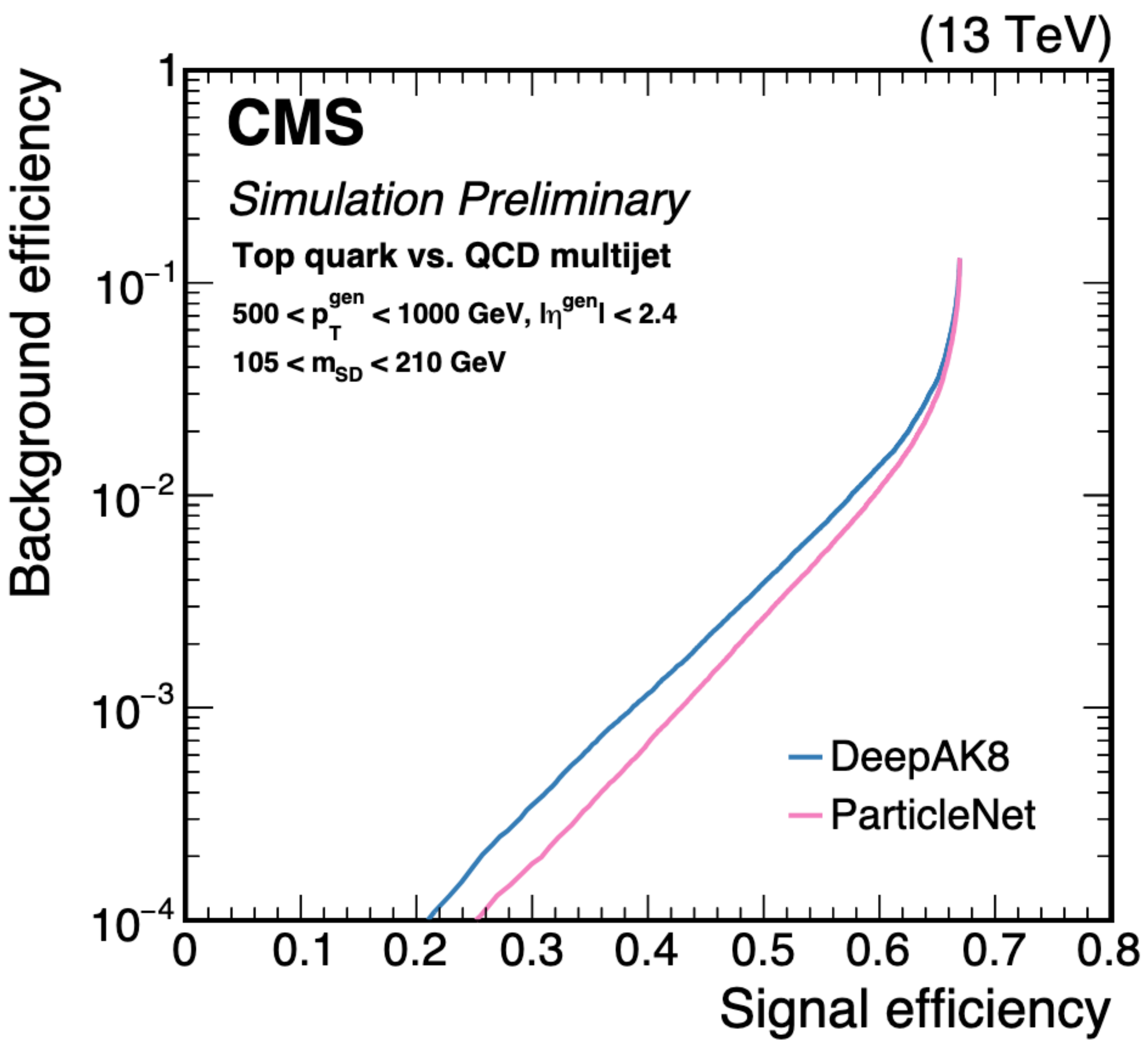
N.B.: It can also be desired to "learn" the mass → both versions of the tagger exist!

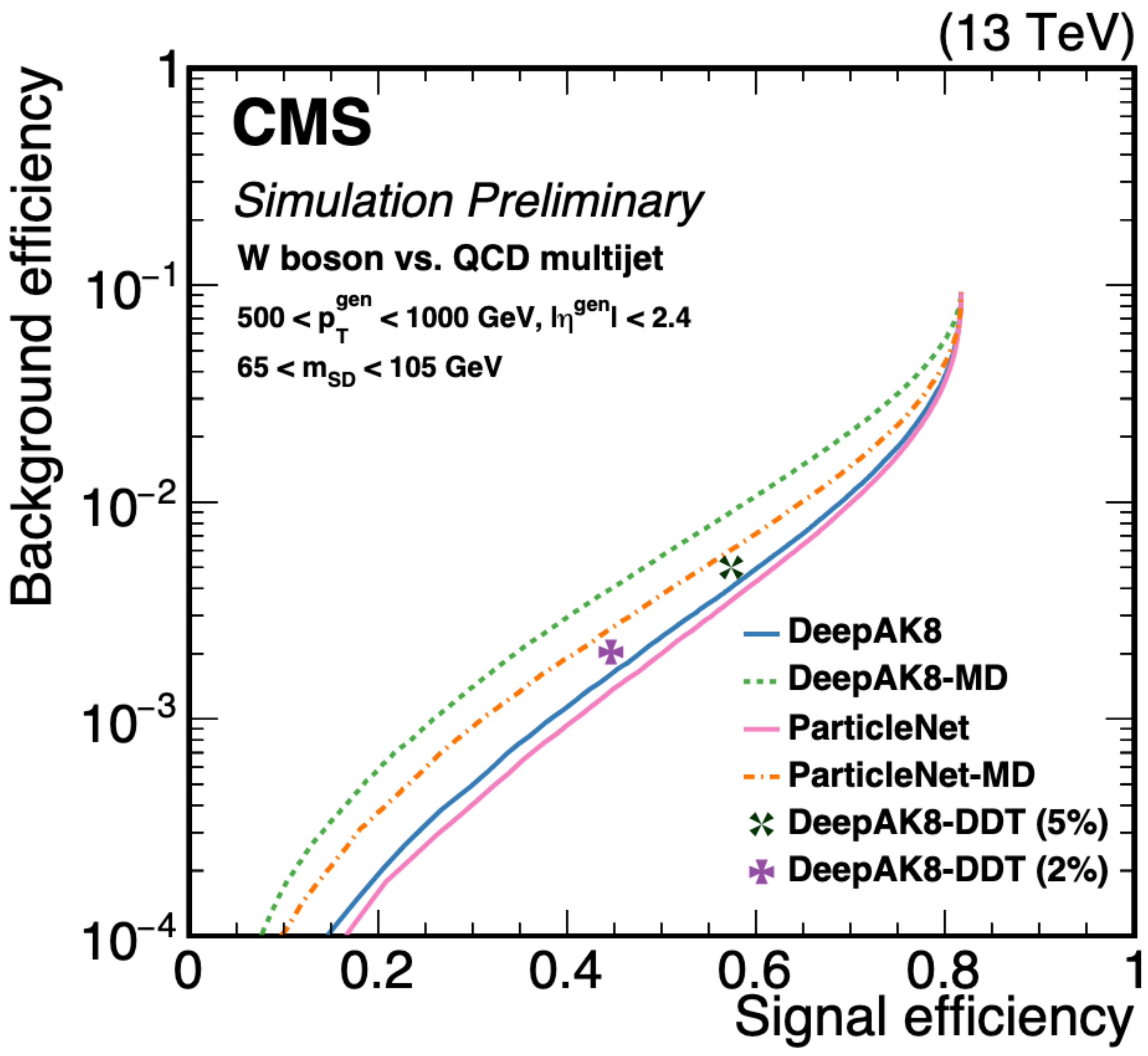
What about t and W?

[CMS-DP-2020-002]

See Fabio's talk

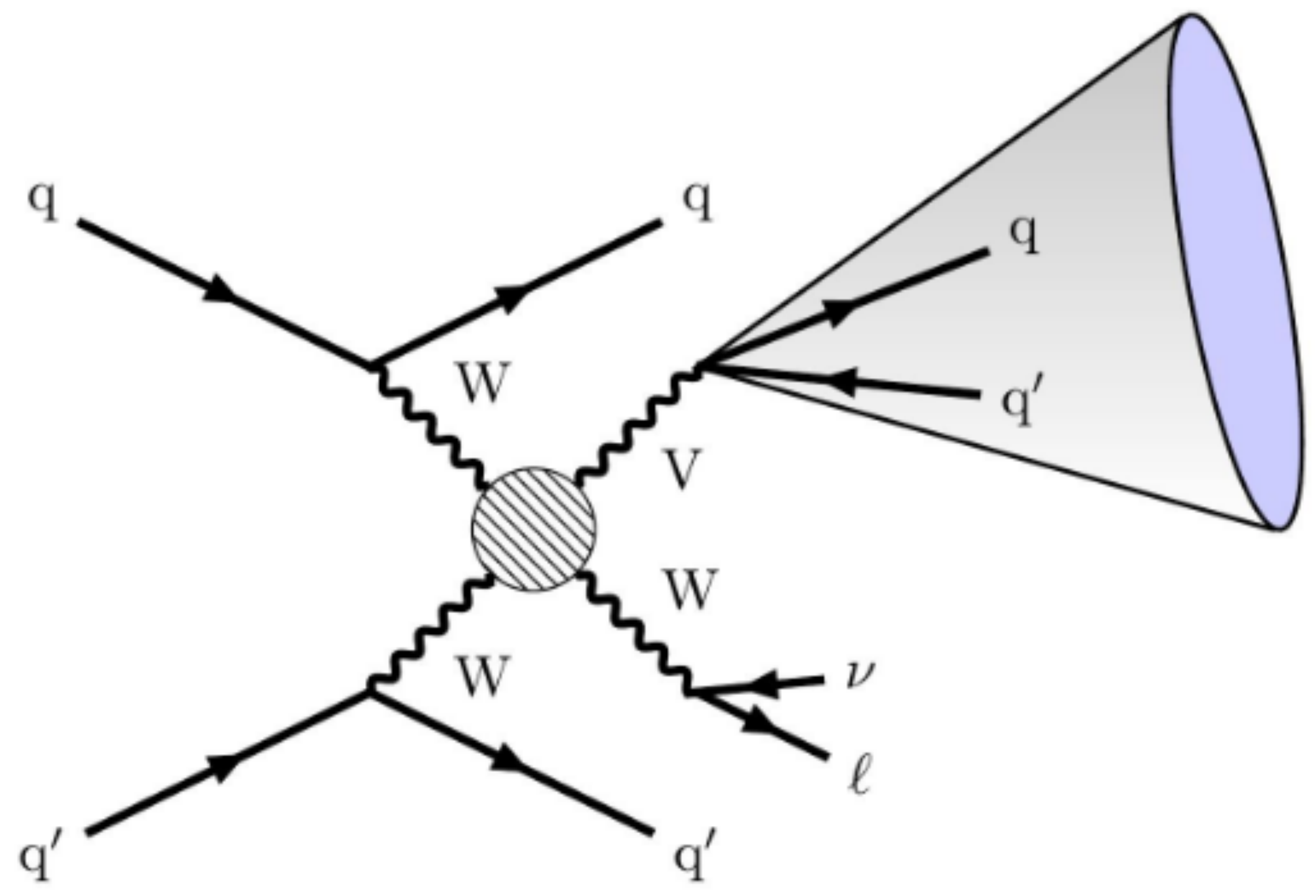
- Also here, ParticleNet is the state-of-the-art
  - Improvement with and without mass-decorrelation



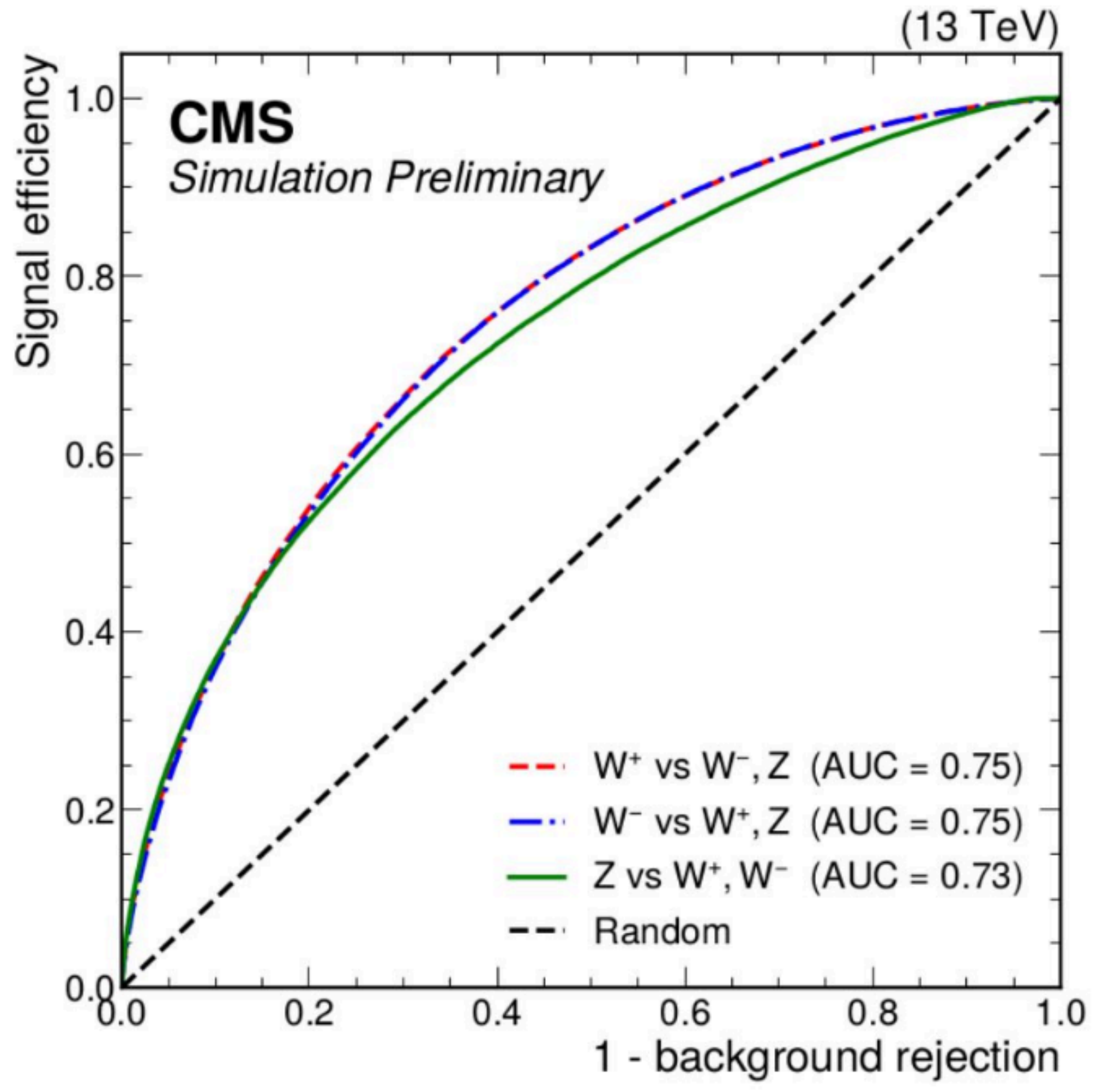


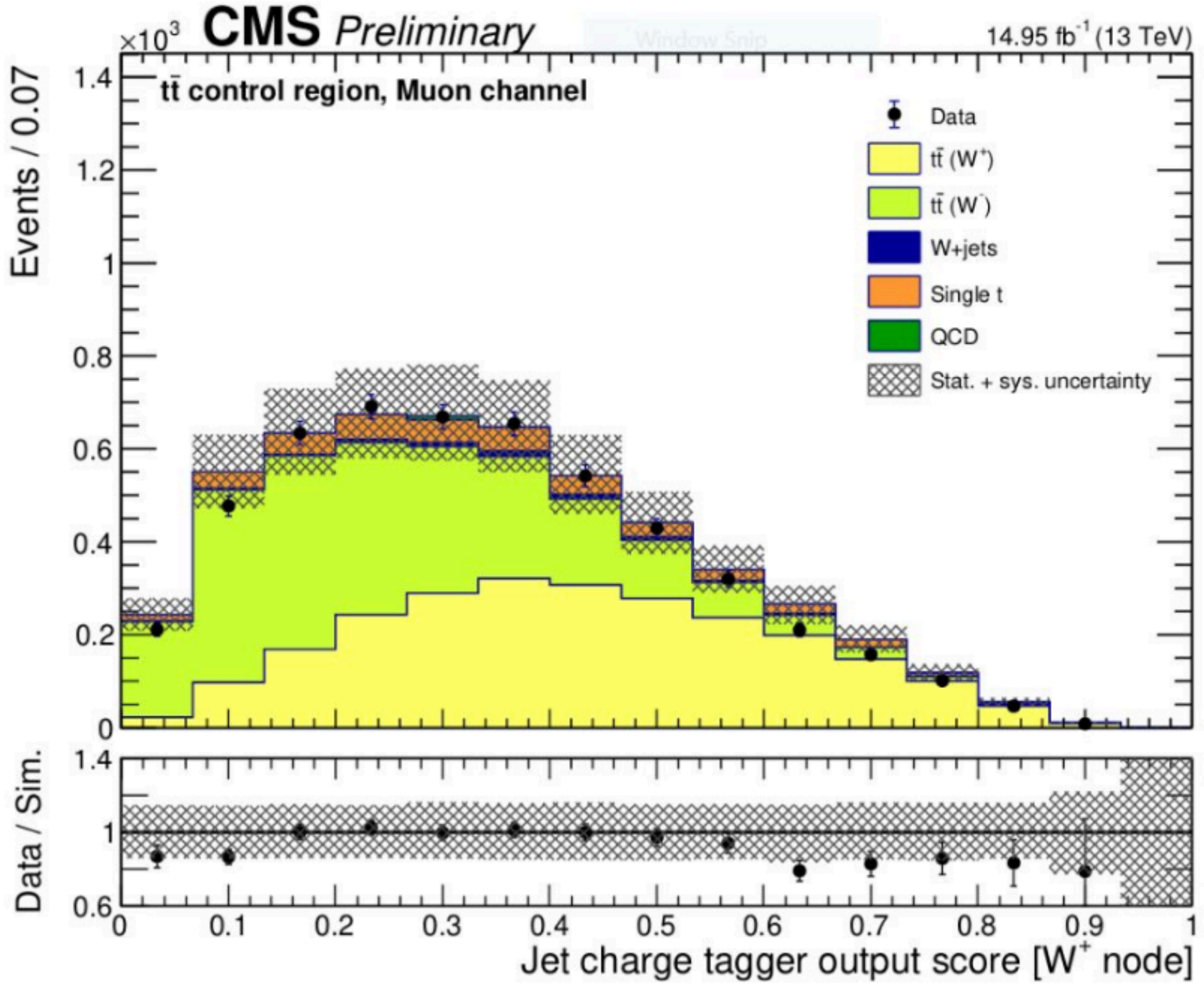
Extensions: Charge tagging

[CMS-DP-2024-044]



- When studying processes like same-sign VBS, signal can be isolated using jet charge
- Train ParticleNet to separate W+, W-, Z0





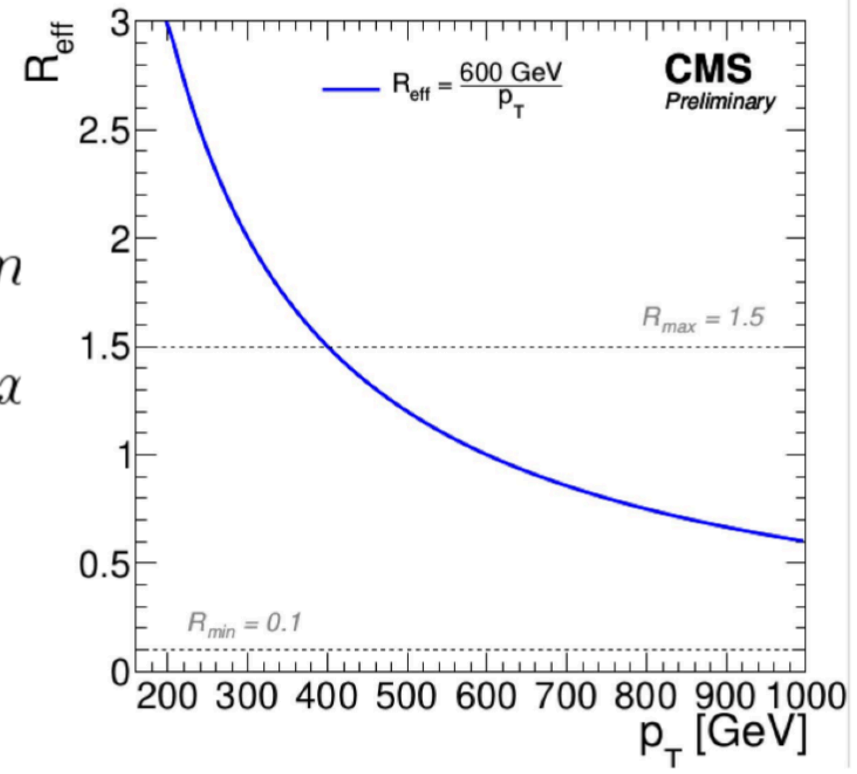
wrt. classical approach:

$$Q_k = \frac{\sum_i q_i (p_{\mathrm{T},i})^k}{(p_{\mathrm{T},jet})^k}$$

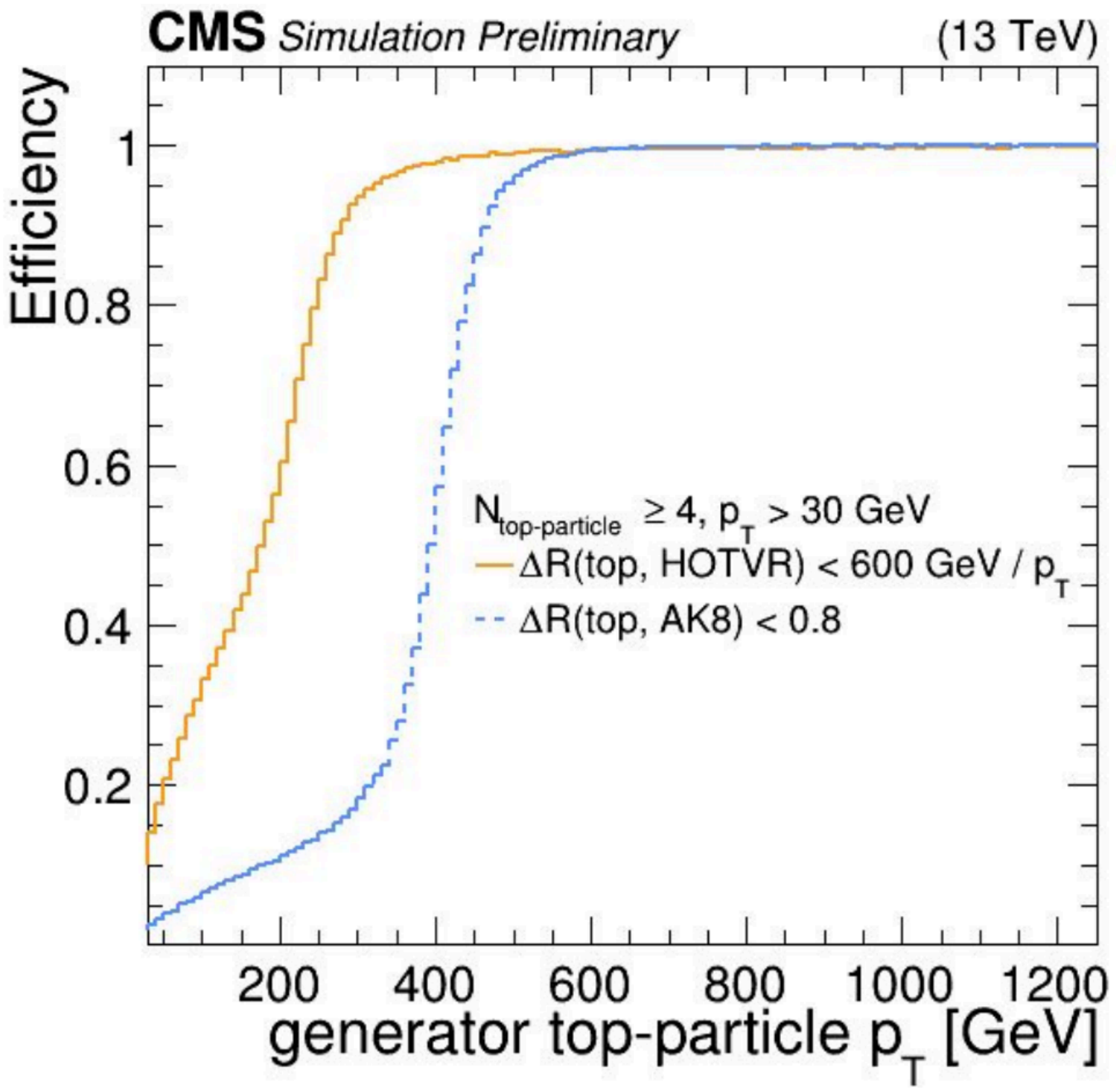
Extensions: HOTVR

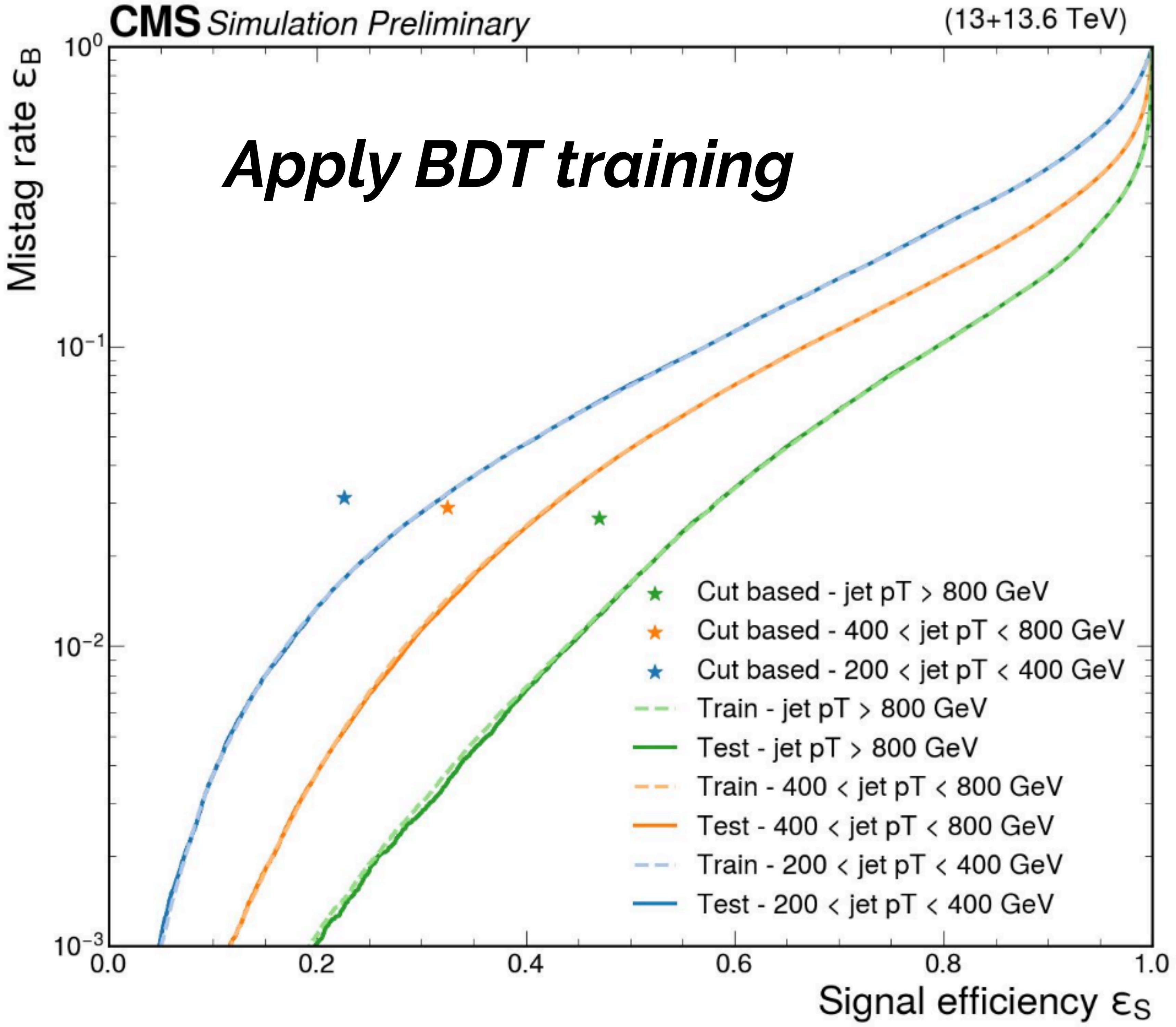
- Above methods work well for "standard" boosted regime
  - Suboptimal for highly boosted (> 800 GeV) and intermediate (~200 GeV)
  - Use HOTVR (Heavy Object Tagger with Variable Radius) to cluster jets
  - Apply PUPPI

$$R_{eff} = \begin{cases} R_{min} & \rho/p_{\mathrm{T}} < R_{min} \\ R_{max} & \rho/p_{\mathrm{T}} > R_{max} \\ \rho/p_{\mathrm{T}} & \text{else.} \end{cases}$$



Extend reach to lower top quark pT

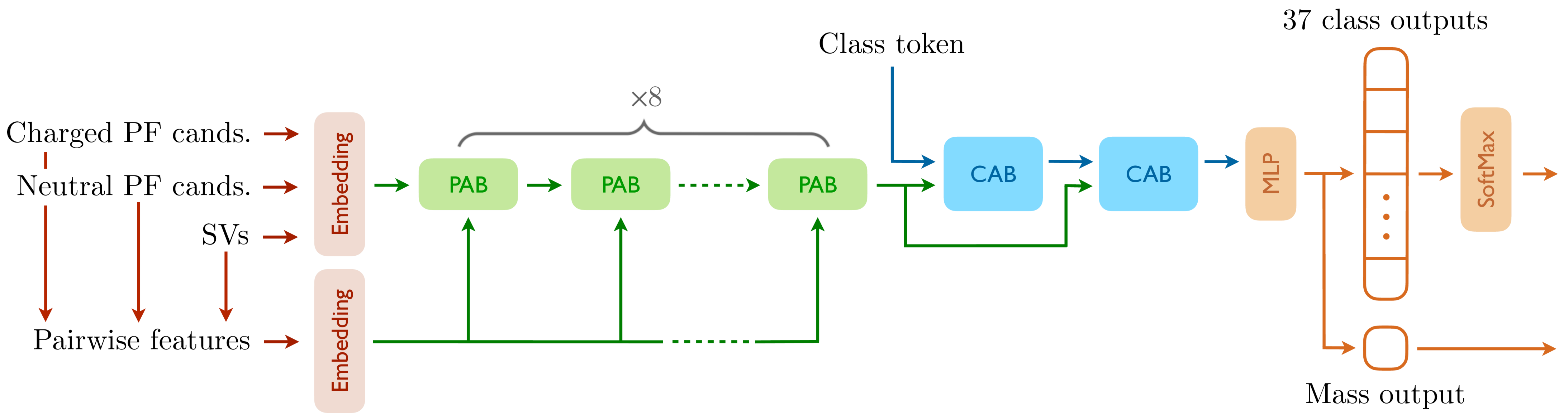




Towards a global tagger?

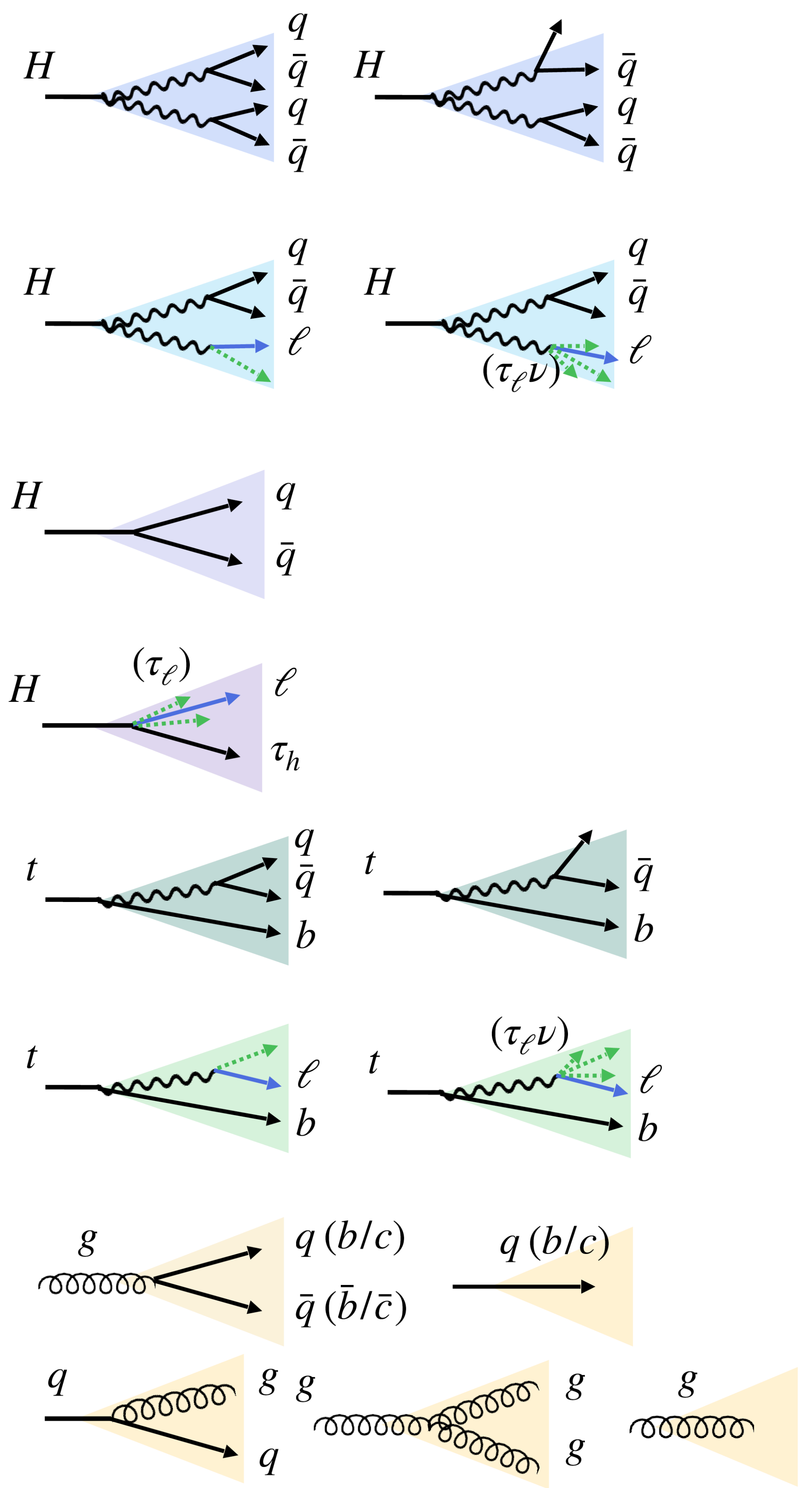
[JME-25-001]

- Leverage ParT architecture:



- Simultaneous classification + regression
- Extension to 37 (!) classes
  - Allowing H->WW tagging for the first time!

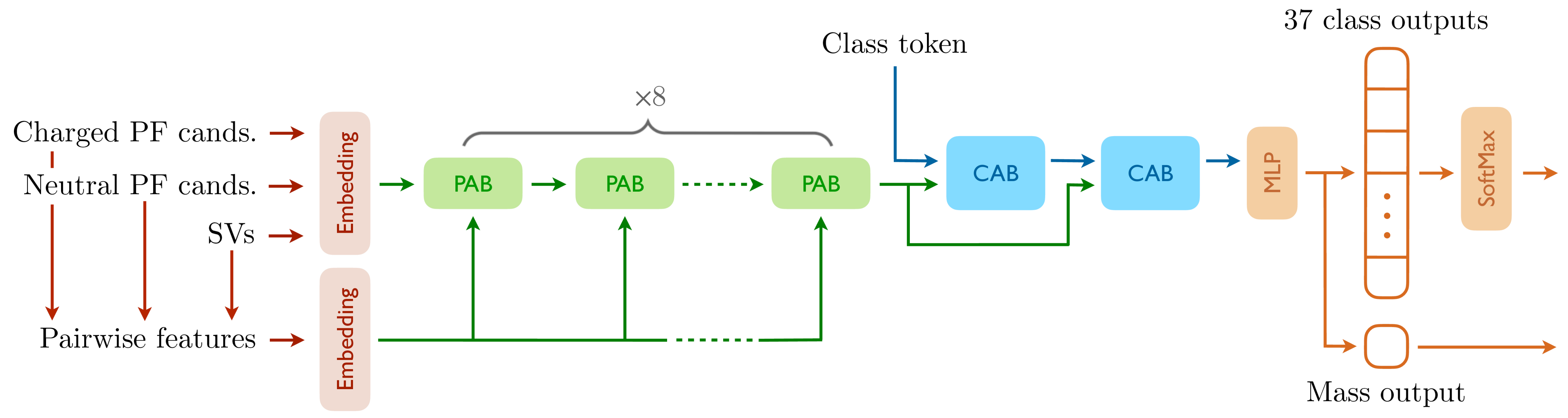
Process	Final state		Flavor	# of classes
H→WW (full-hadronic)	qqqq	⊗	0c / 1c / 2c	3
	qqq			3
H→WW (semi-leptonic)	eνqq	⊗	0c / 1c	2
	μνqq			2
	$\tau_e\nu qq$			2
	$\tau_\mu\nu qq$			2
	$\tau_h\nu qq$			2
H→qq		⊗	bb	1
			cc	1
			ss	1
			qq (q=u/d)	1
H→ττ	$\tau_e\tau_h$			1
	$\tau_\mu\tau_h$			1
	$\tau_h\tau_h$			1
t→bW (hadronic)	bqq	⊗	1b + 0c / 1c	2
	bq			2
t→bW (leptonic)	beν	⊗	1b	1
	bμν			1
	$b\tau_e\nu$			1
	$b\tau_\mu\nu$			1
	$b\tau_h\nu$			1
QCD			b	1
			bb	1
			c	1
			cc	1
			others (light)	1



Towards a global tagger?

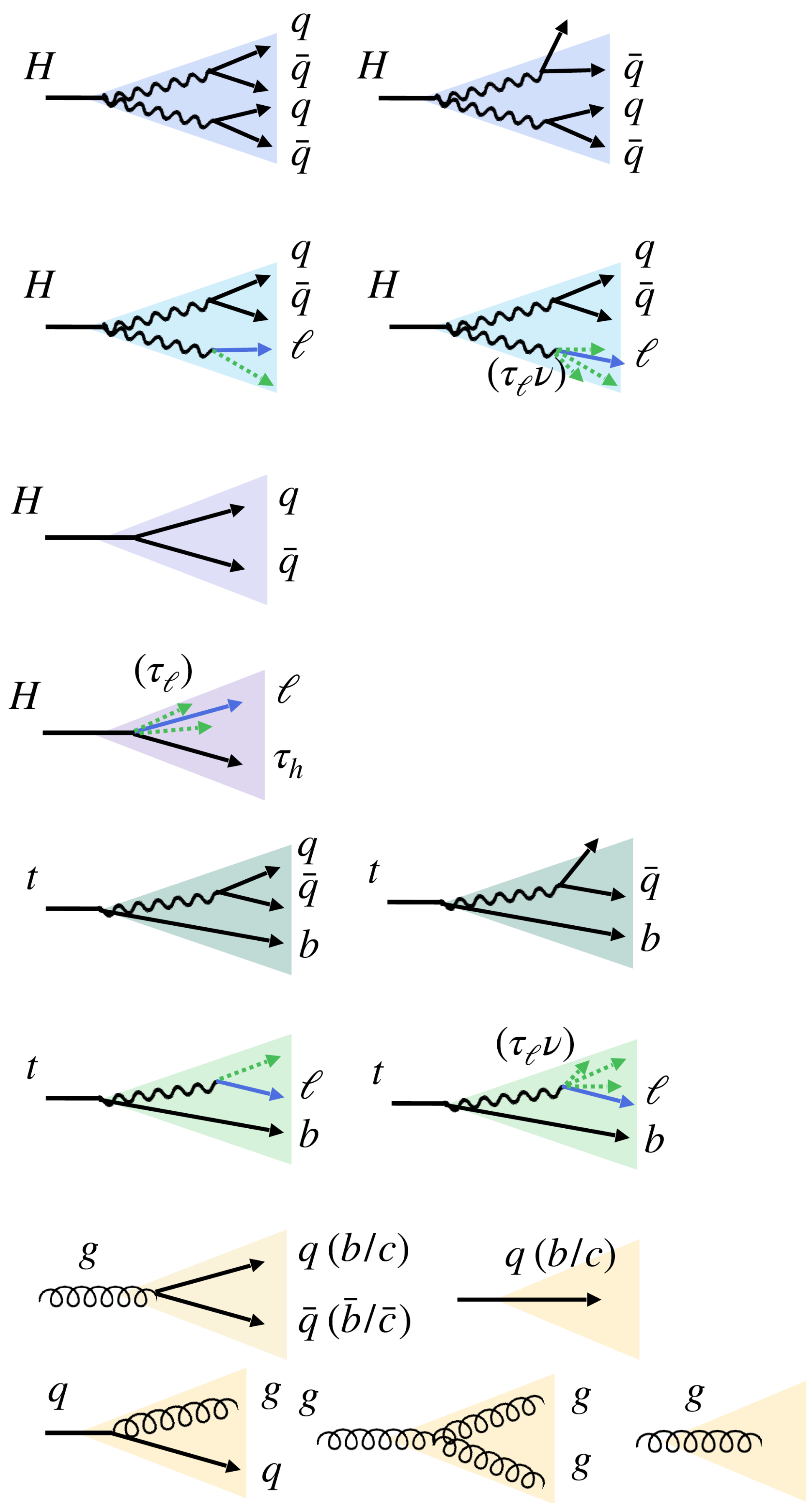
[JME-25-001]

- Leverage ParT architecture:



- Simultaneous classification + regression
- Extension to 37 (!) classes
  - Allowing H->WW tagging for the first time!

Process	Final state		Flavor	# of classes
H→WW (full-hadronic)	qqqq	⊗	0c / 1c / 2c	3
	qqq			3
H→WW (semi-leptonic)	eνqq	⊗	0c / 1c	2
	μνqq			2
	$\tau_e\nu$qq			2
	$\tau_\mu\nu$qq			2
	$\tau_h\nu$qq			2
H→qq		⊗	bb	1
			cc	1
			ss	1
			qq (q=u/d)	1
H→ττ	$\tau_e\tau_h$			1
	$\tau_\mu\tau_h$			1
	$\tau_h\tau_h$			1
t→bW (hadronic)	bqq	⊗	1b + 0c / 1c	2
	bq			2
t→bW (leptonic)	beν	⊗	1b	1
	bμν			1
	b$\tau_e\nu$			1
	b$\tau_\mu\nu$			1
	b$\tau_h\nu$			1
QCD			b	1
			bb	1
			c	1
			cc	1
			others (light)	1

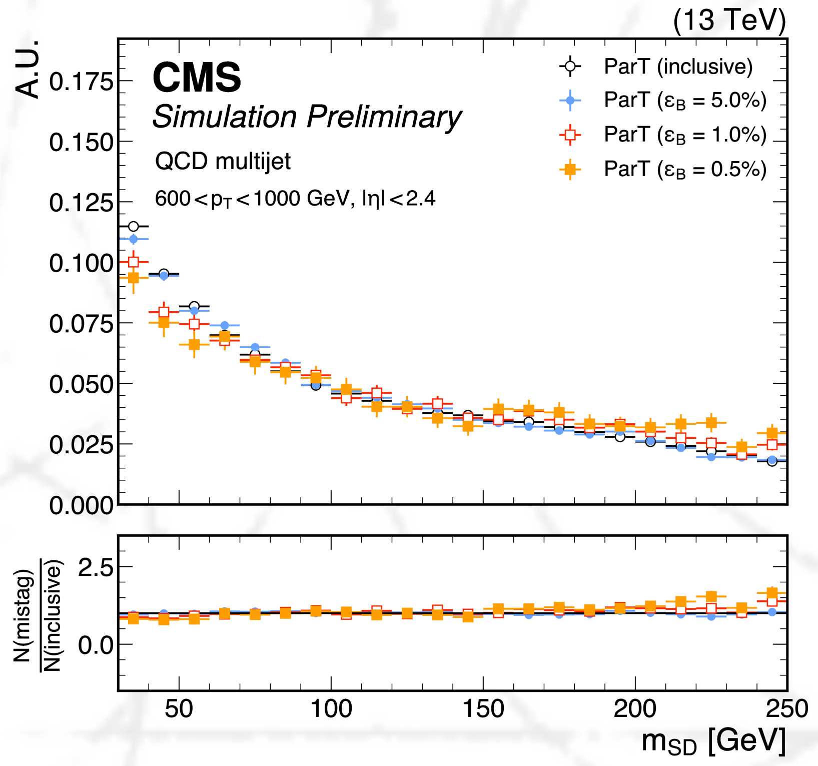


Mass decor relation via flat sampling

H-like ($G \to HH$)		t-like ($Z' \to t\bar{t}$)	
m_G	600–6000 GeV	$m_{Z'}$	600–6000 GeV
m_H	15–250 GeV	m_t	15–250 GeV
m_W	Fixed to SM ratio: $\frac{80.4}{125} m_H$	m_W	Fixed to SM ratio: $\frac{80.4}{172.5} m_t$

All other particles: SM values

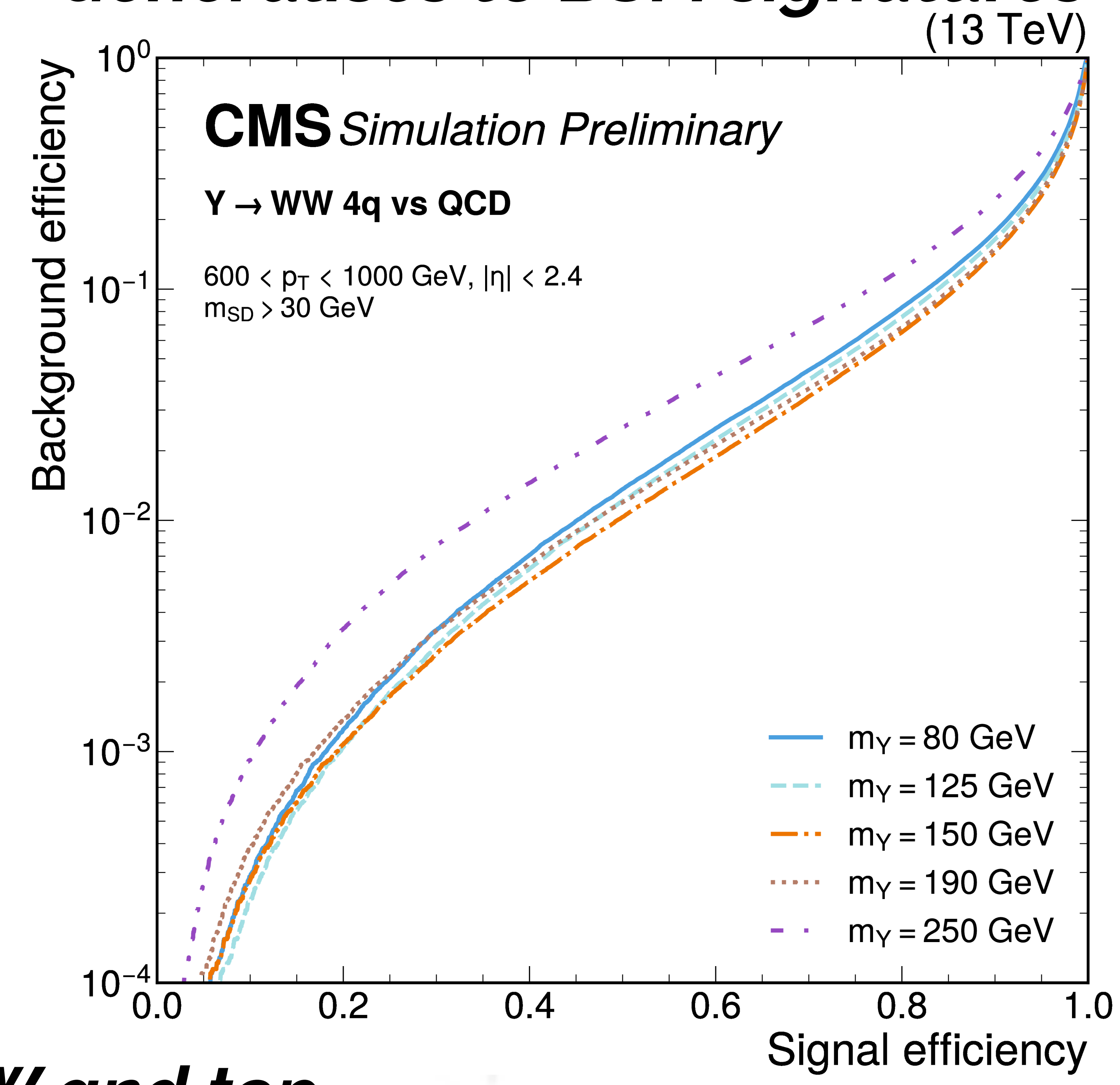
No sign of mass sculpting!

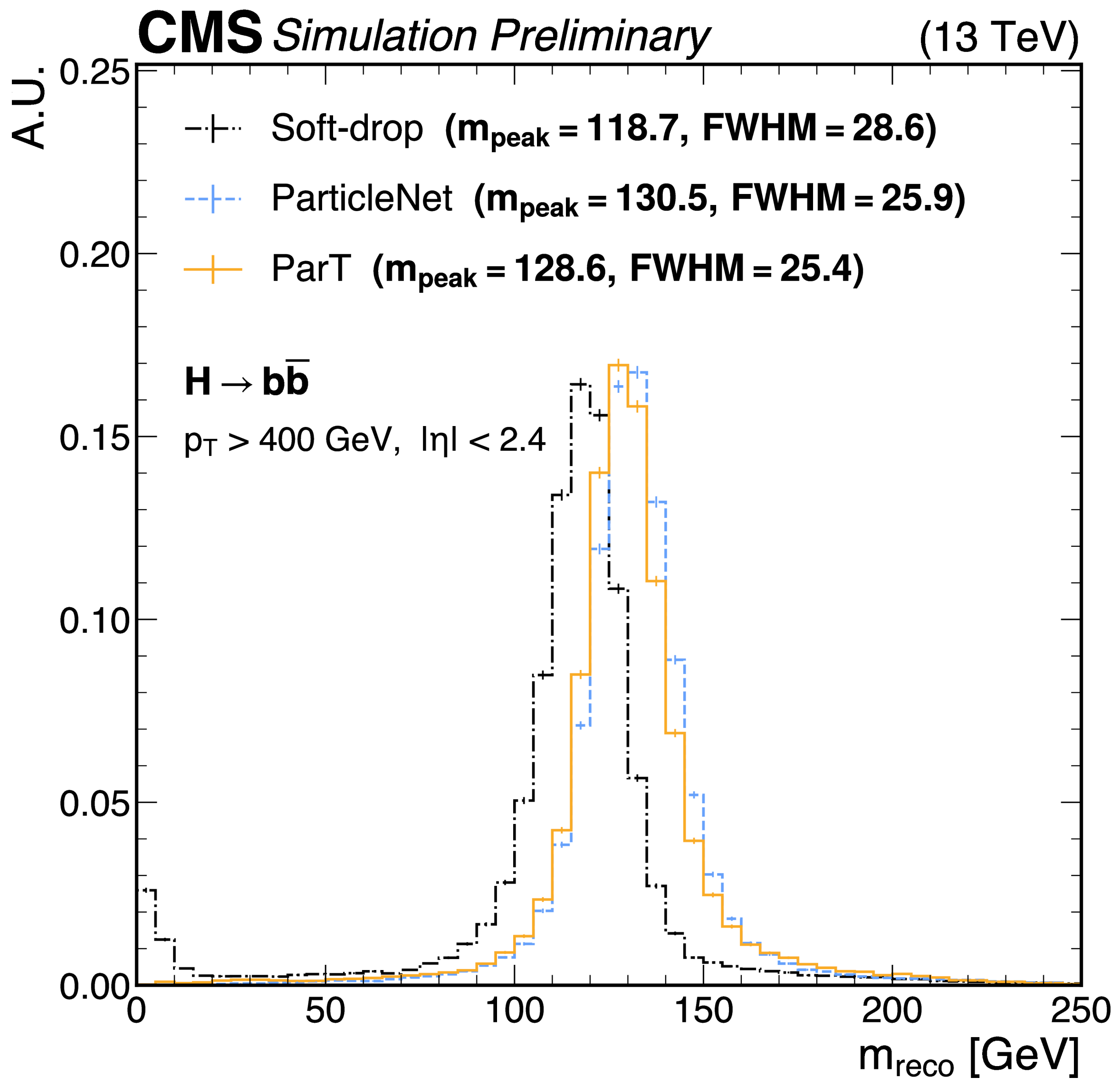


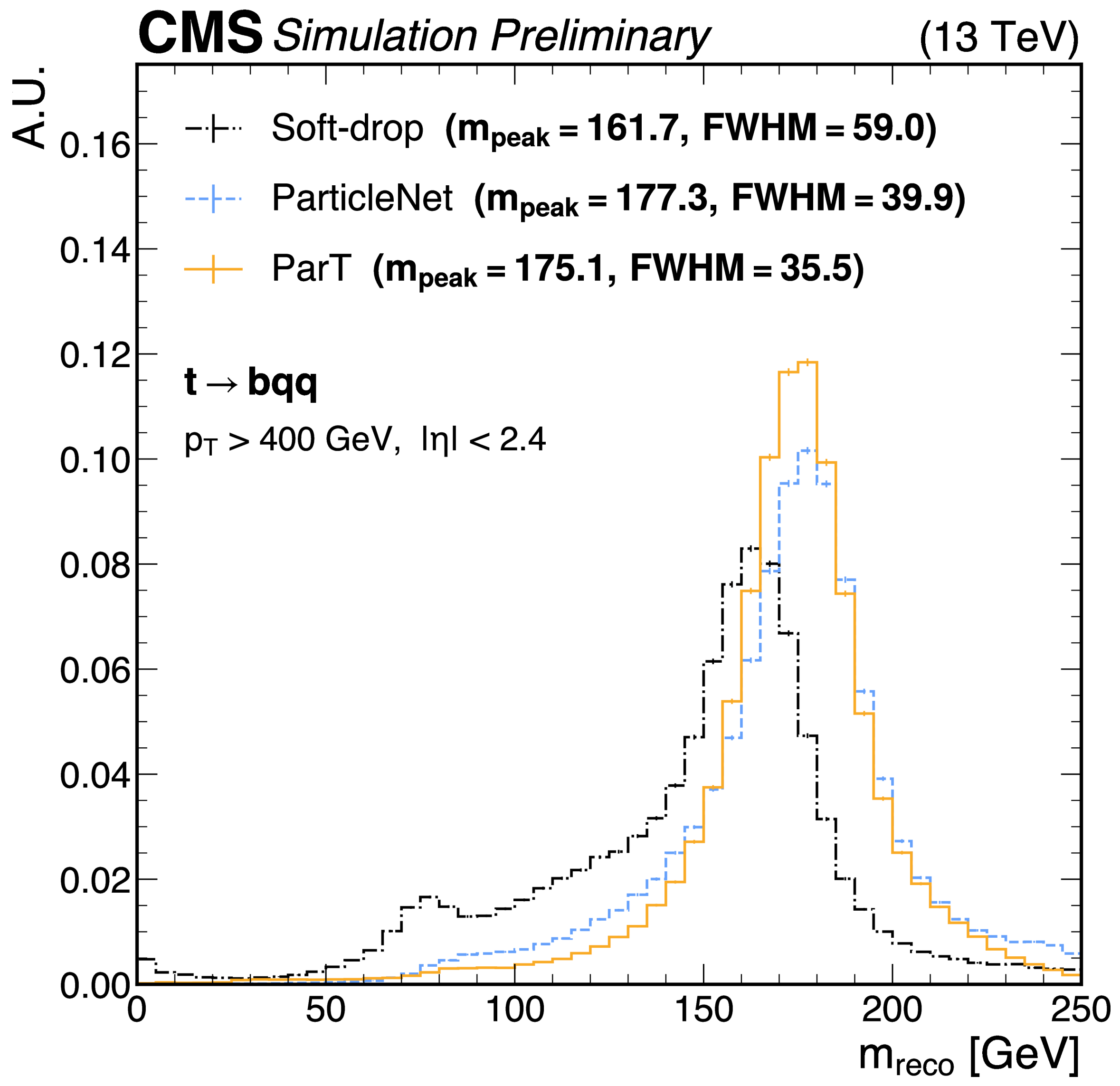
Towards a global tagger?

[JME-25-001]

Generalises to BSM signatures

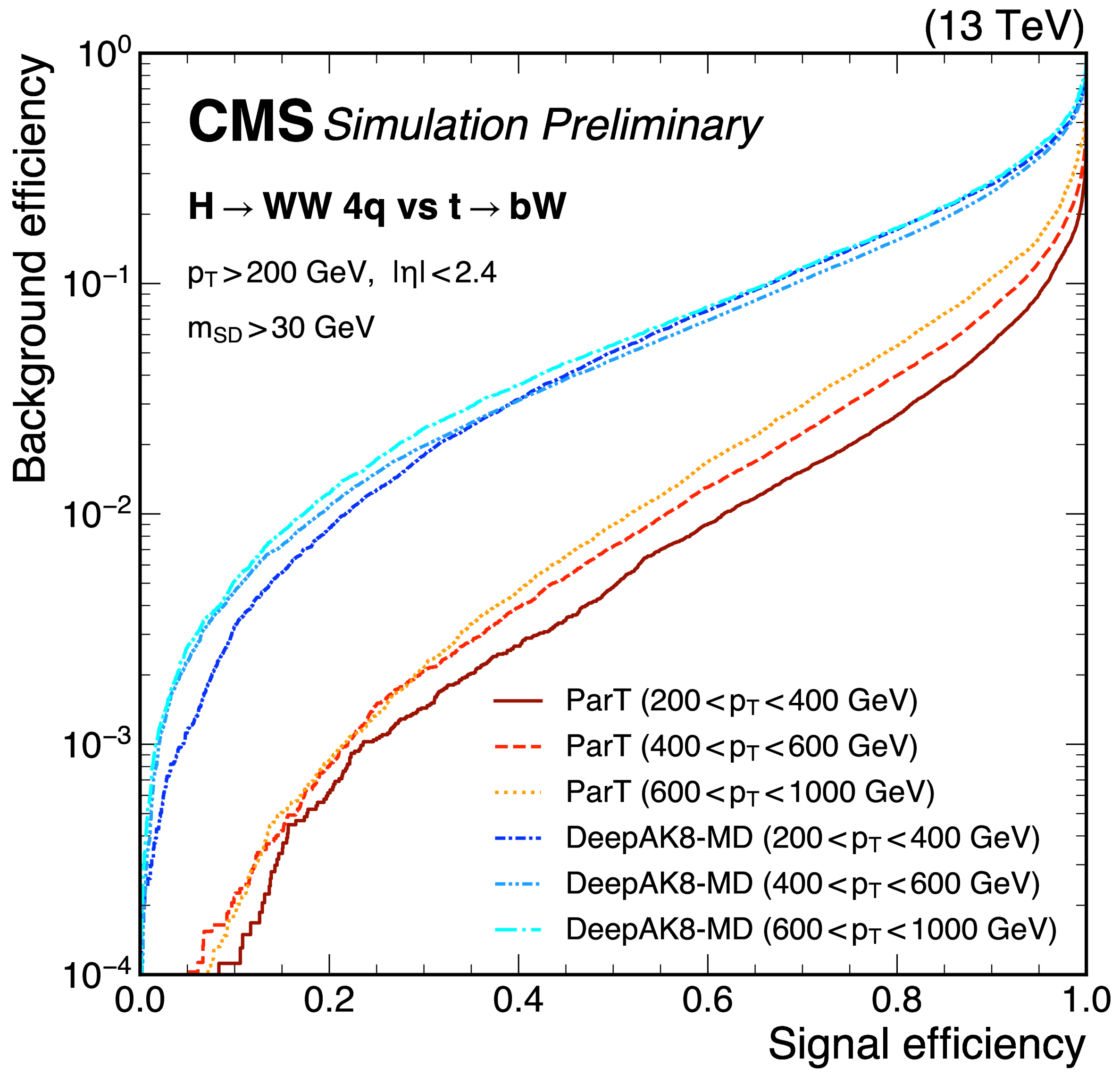


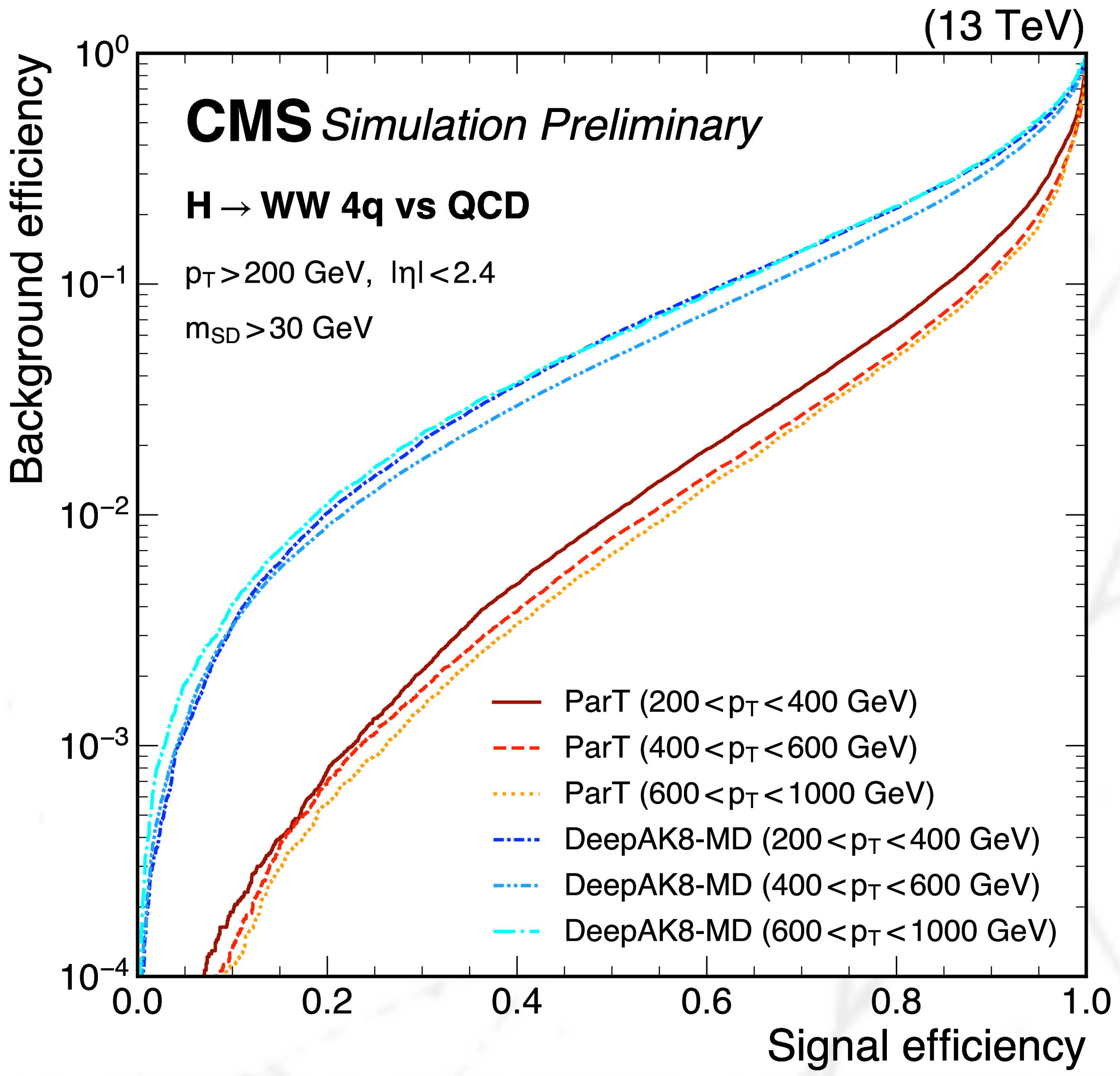




Powerful multi-prong mass regression

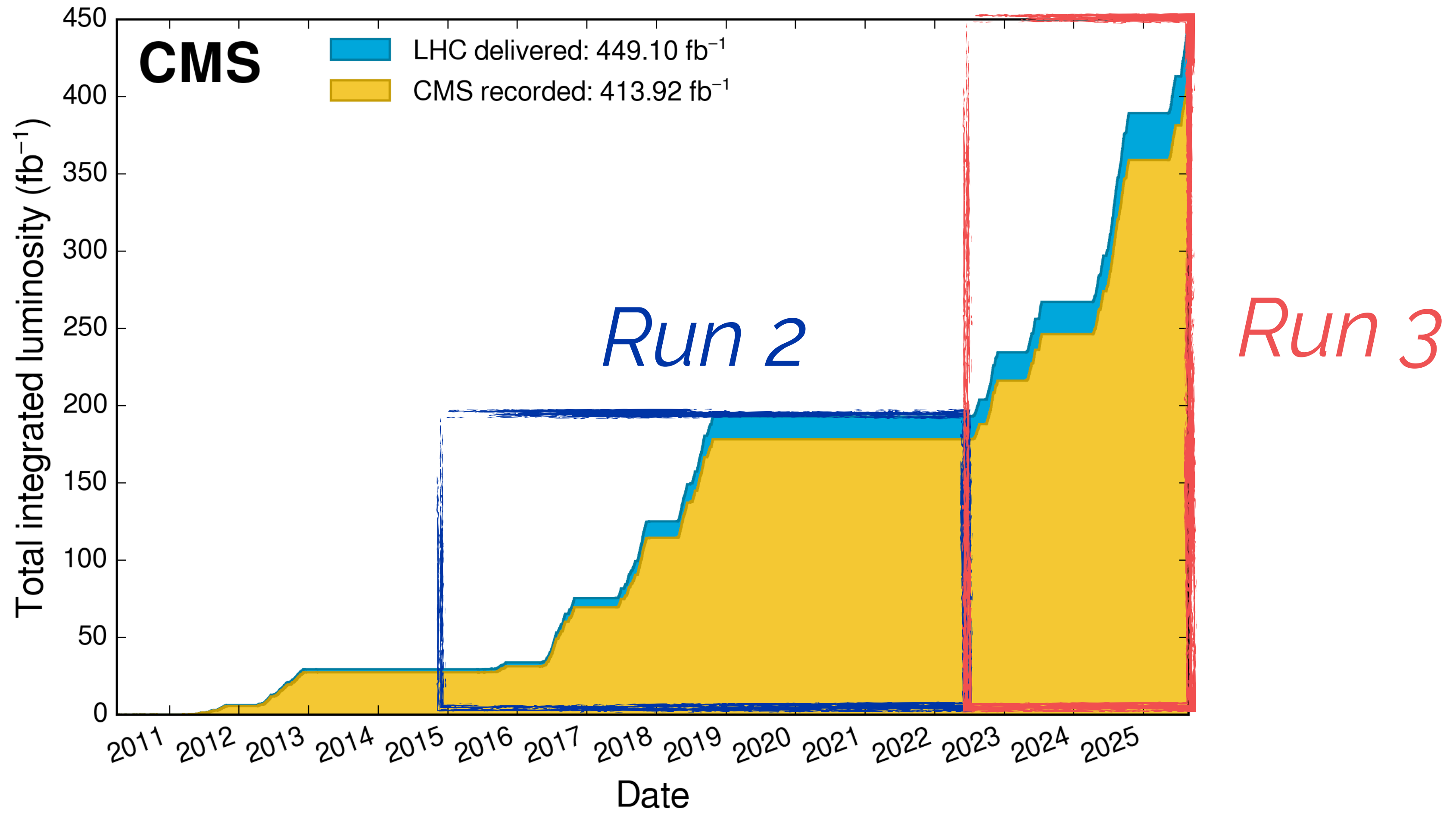
10x better background rejection for WW and top

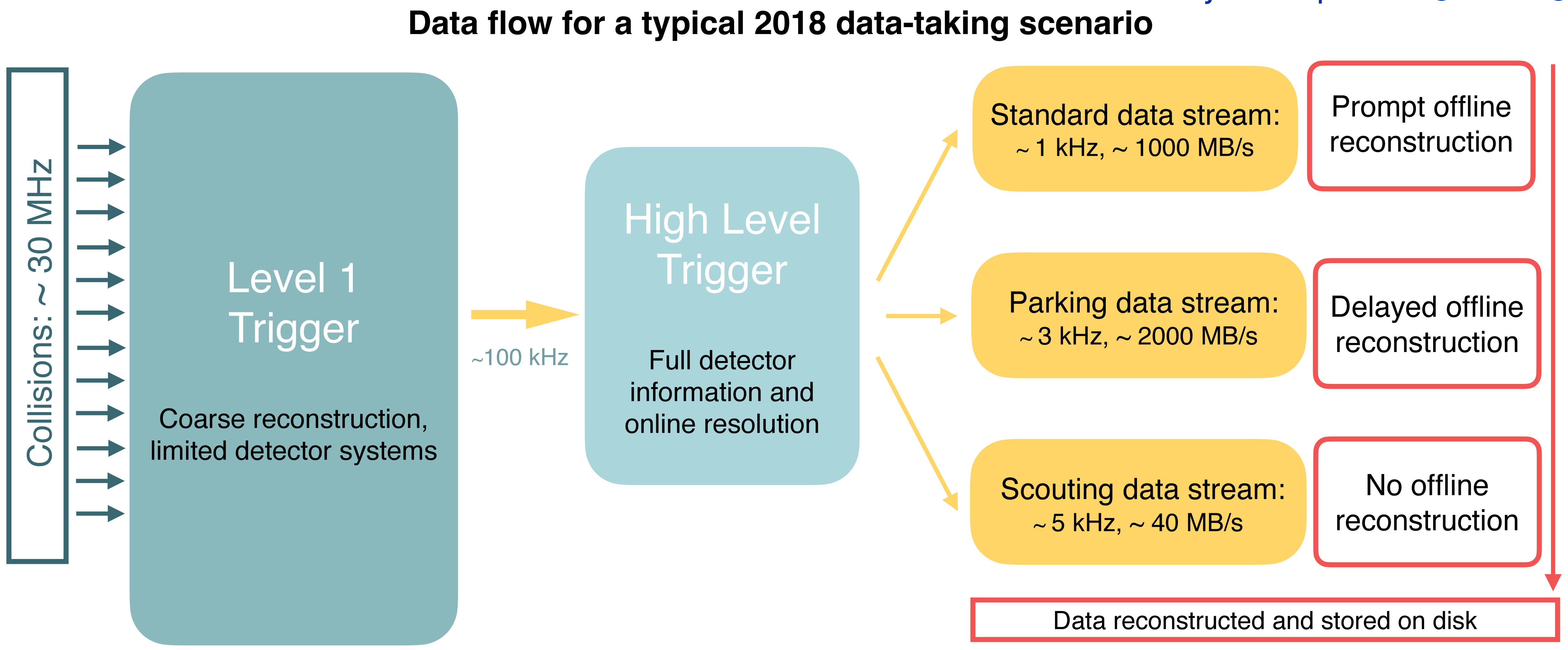




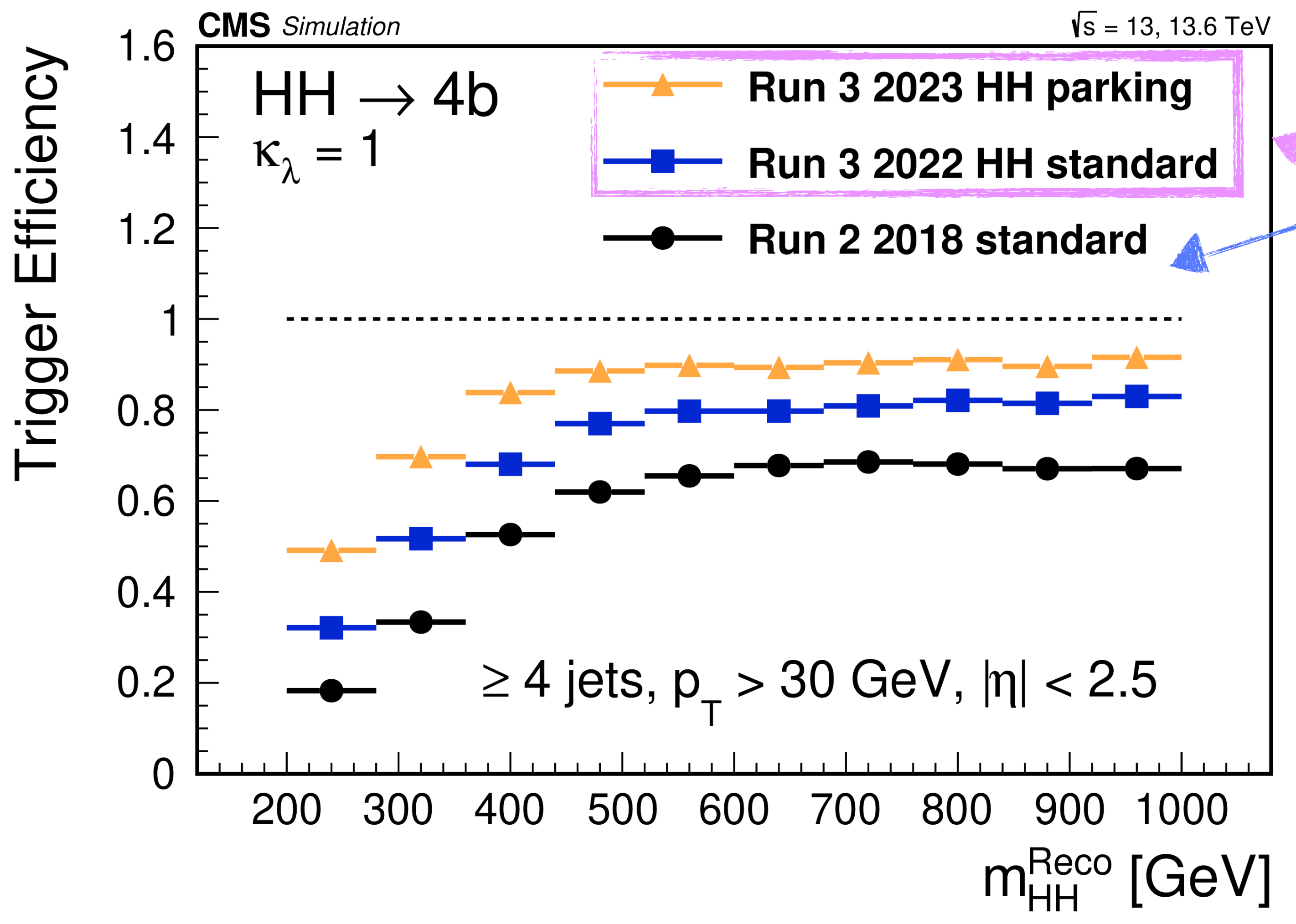
Tagging at the trigger level

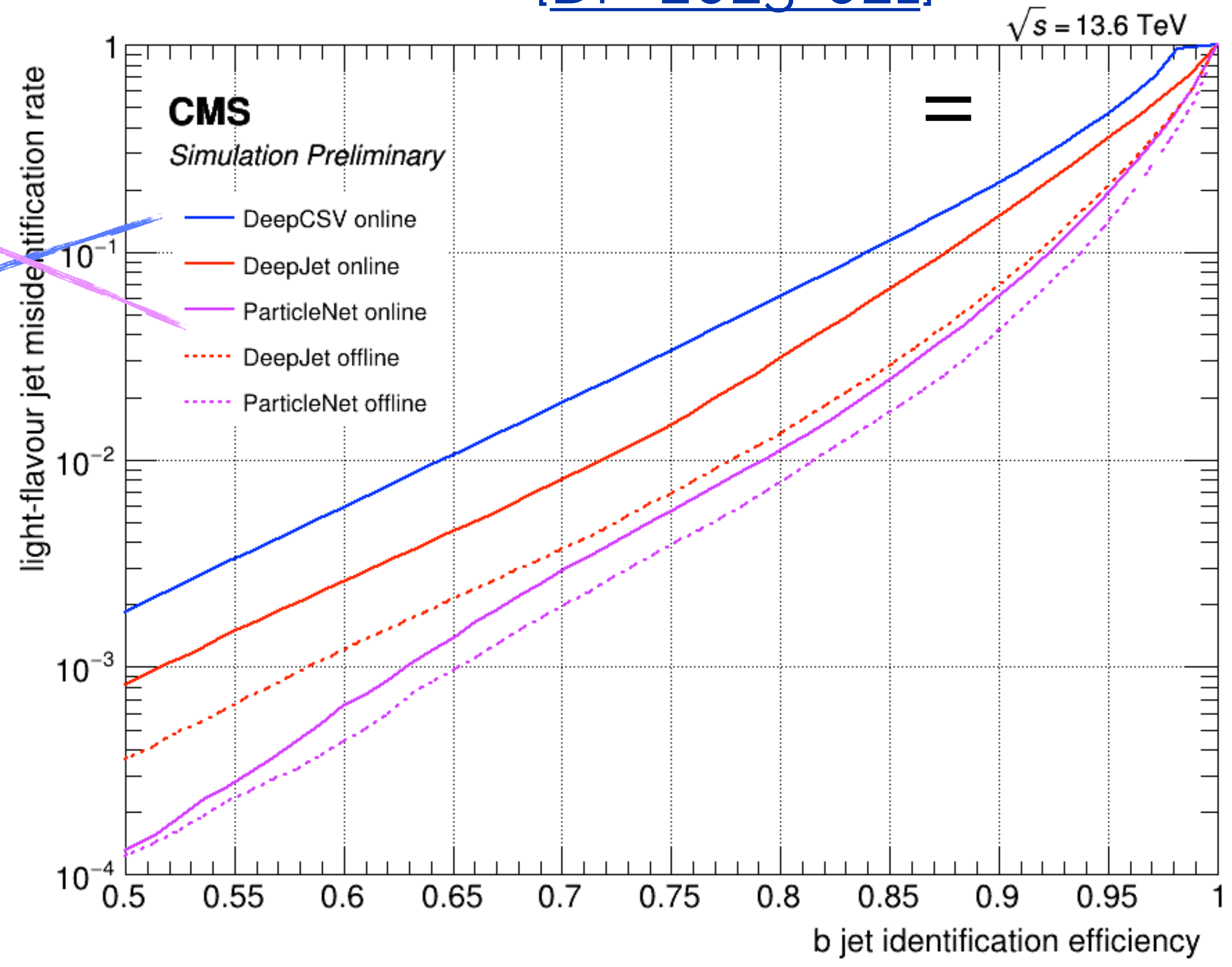
[Phys. Rept. 1115 (2025) 678]





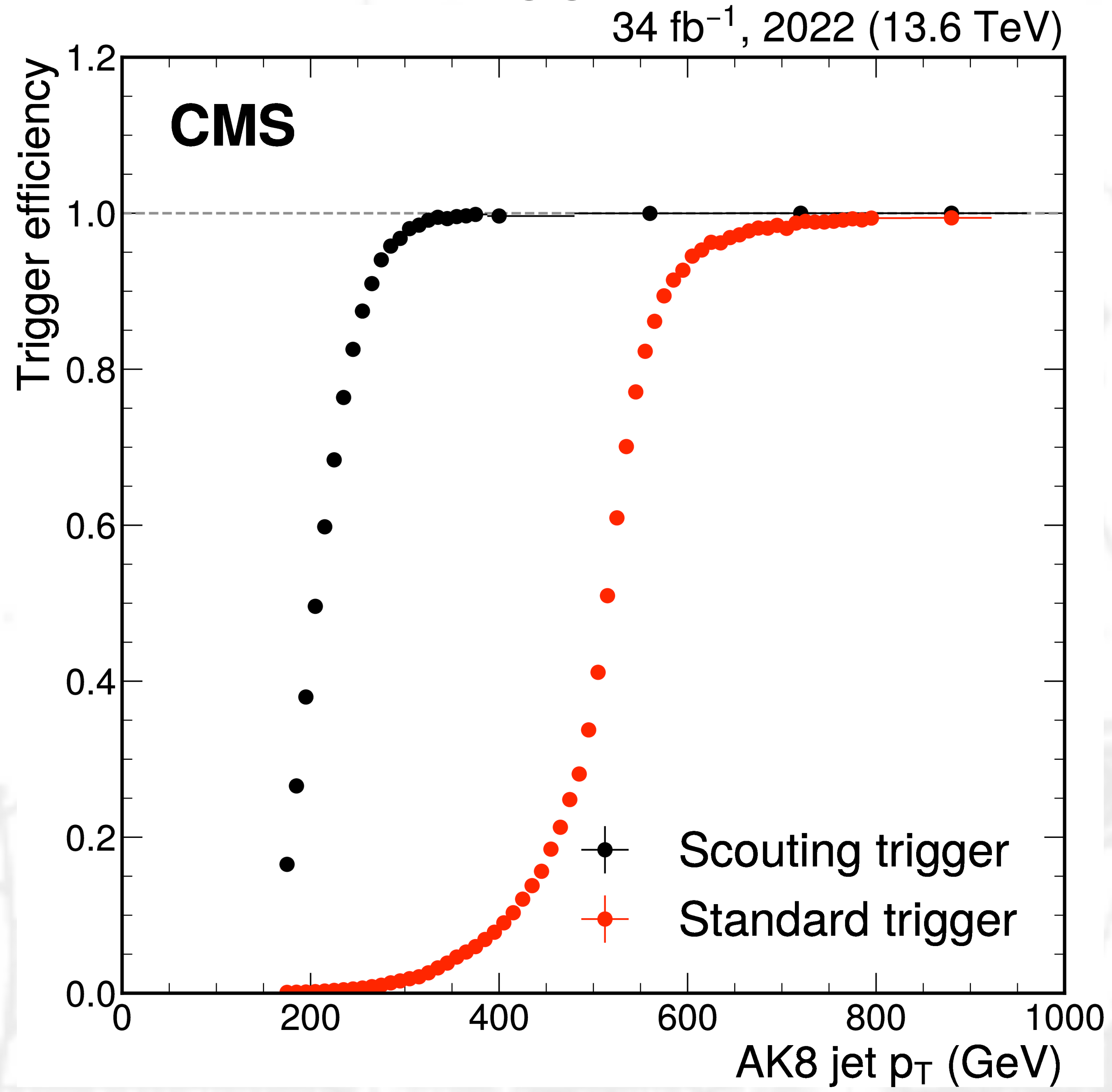
[DP-2023-021]





Usage of ParticleNetAK4 in software trigger and scouting, up to 60% improvement

Extended acceptance + ParticleNetAK8 in scouting and trigger



See Jieun' and Marko's talks

Multiclass event classification

- Simultaneous $\mathbf{t\bar{t}H(H \to c\bar{c})}$ and $\mathbf{t\bar{t}H(H \to b\bar{b})}$ measurement to handle $\mathbf{t\bar{t}H(H \to b\bar{b})}$ background
- **Introduced dedicated categories for** $\mathbf{t\bar{t}Z(Z \to c\bar{c})}$ and $\mathbf{t\bar{t}Z(Z \to b\bar{b})}$
  - Validation for $t\bar{t}H$ measurement, similar in the $VH(H \to c\bar{c})$ / $ggH(H \to c\bar{c})$ analyses
  - Employs a symmetric approach between $t\bar{t}H$ and $t\bar{t}Z$

- The target are four signal classes:

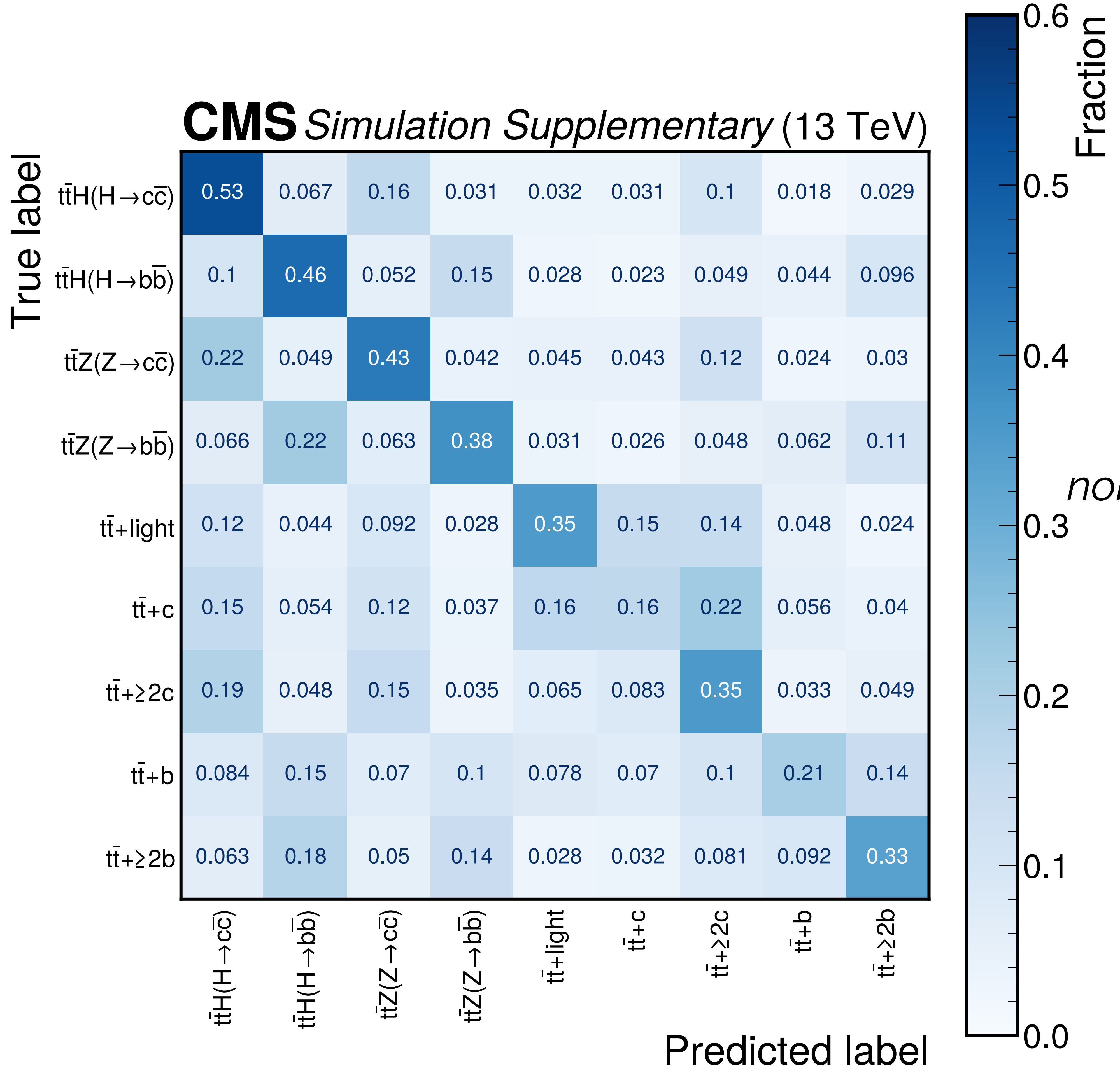
$t\bar{t}H(H \to c\bar{c})$ | $t\bar{t}H(H \to b\bar{b})$ | $t\bar{t}Z(Z \to c\bar{c})$ | $t\bar{t}Z(Z \to b\bar{b})$

- Five background classes:

$t\bar{t} + \geq 2c$ | $t\bar{t} + c$ | $t\bar{t} + \geq 2b$ | $t\bar{t} + b$ | $t\bar{t}$+light

- And in the 0L channel one additional background class:

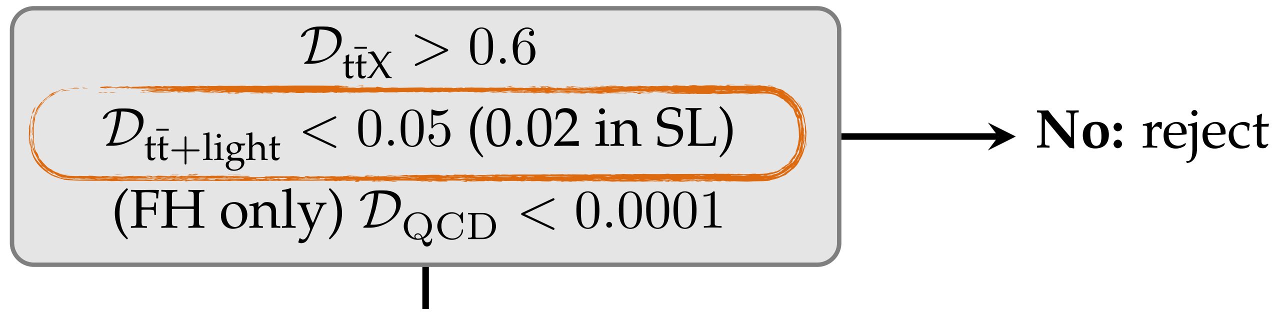
QCD

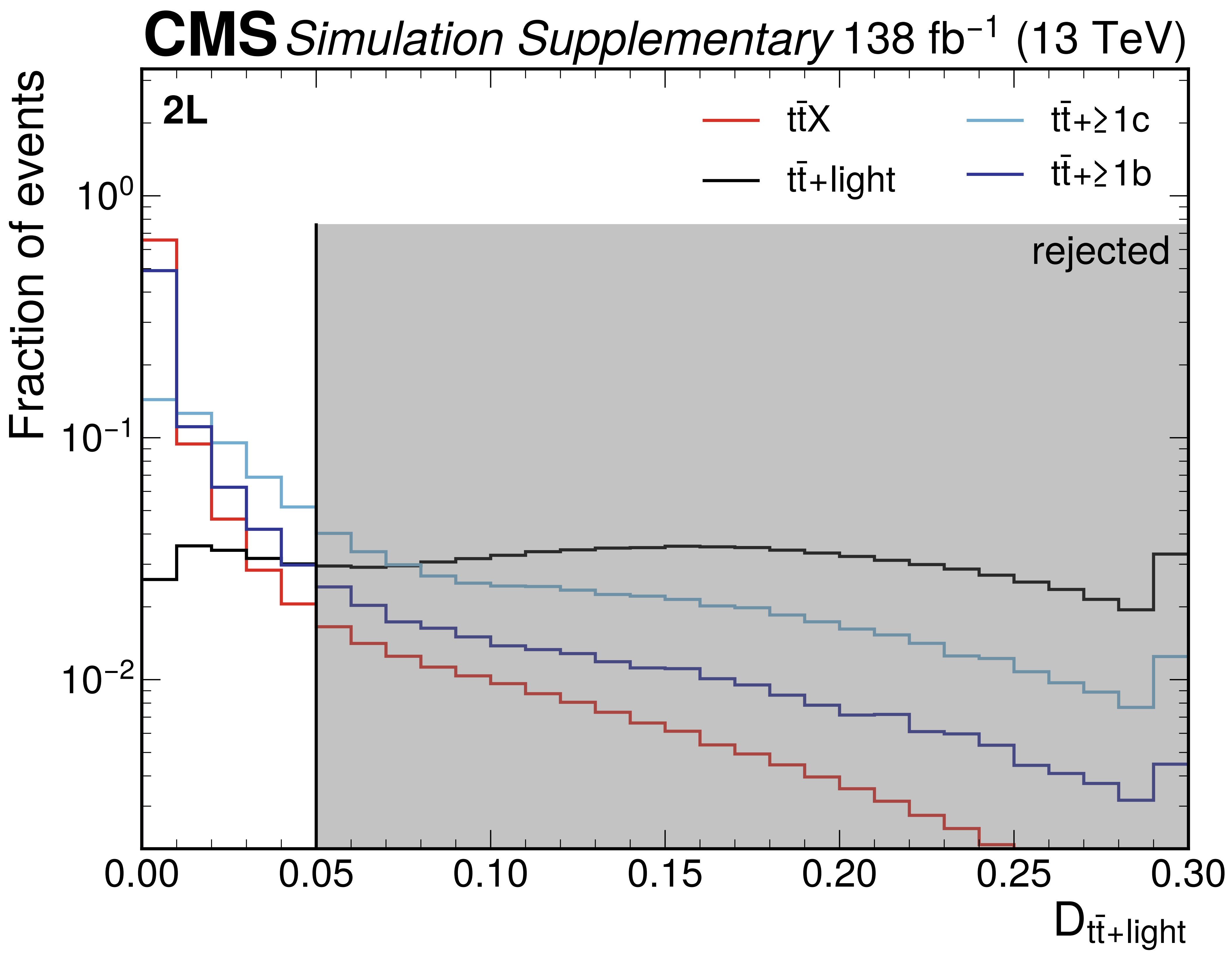


Truth normalised

Event selection & categorisation

- Use scores (D_X) to select & categorise events

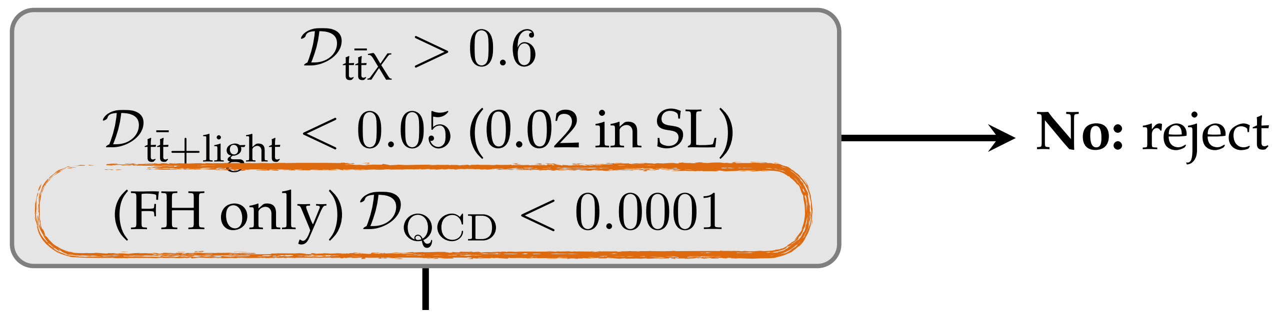


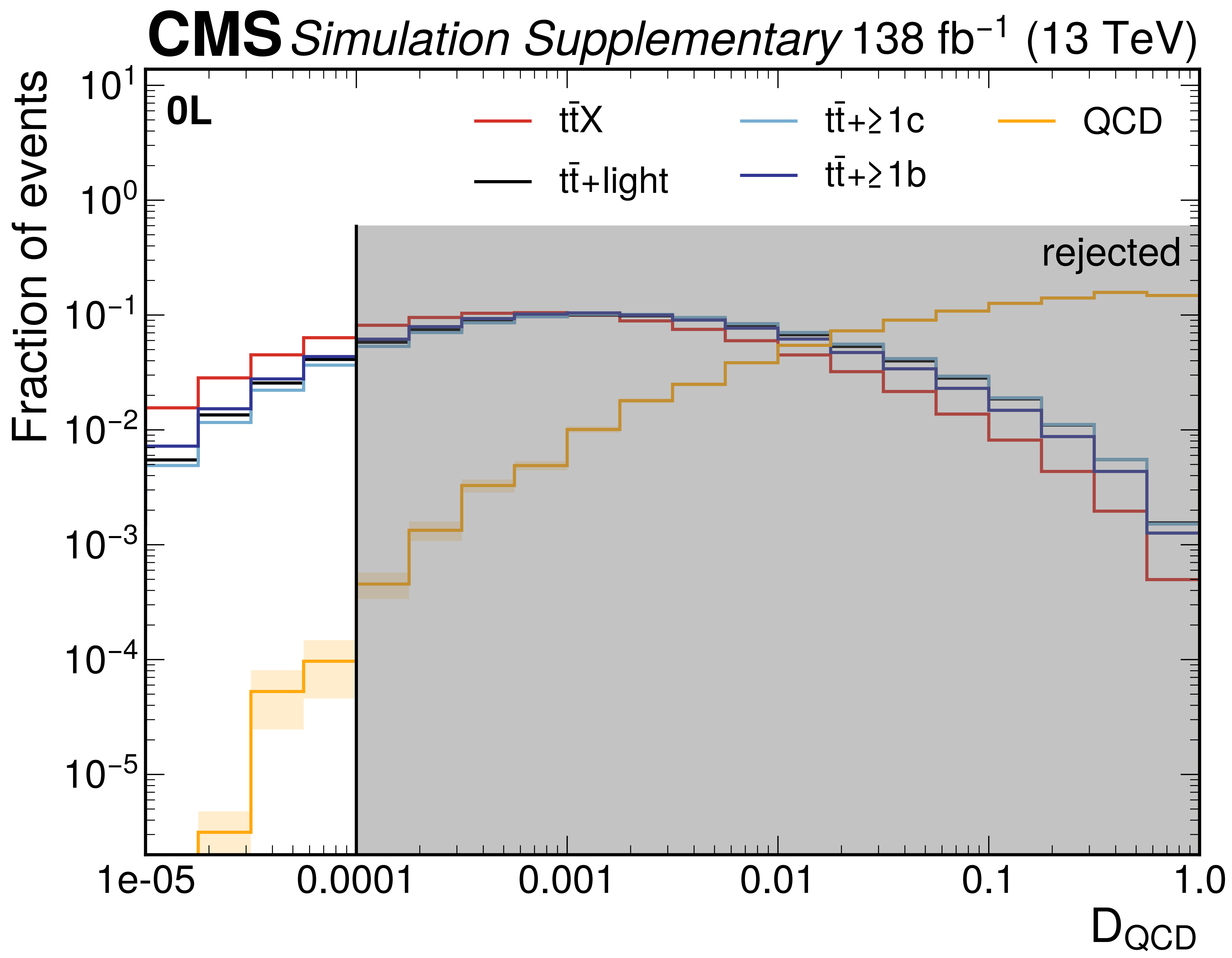


- Remove QCD and $t\bar{t}+$light contributions via selections on background scores

Event selection & categorisation

- Use scores (D_X) to select & categorise events





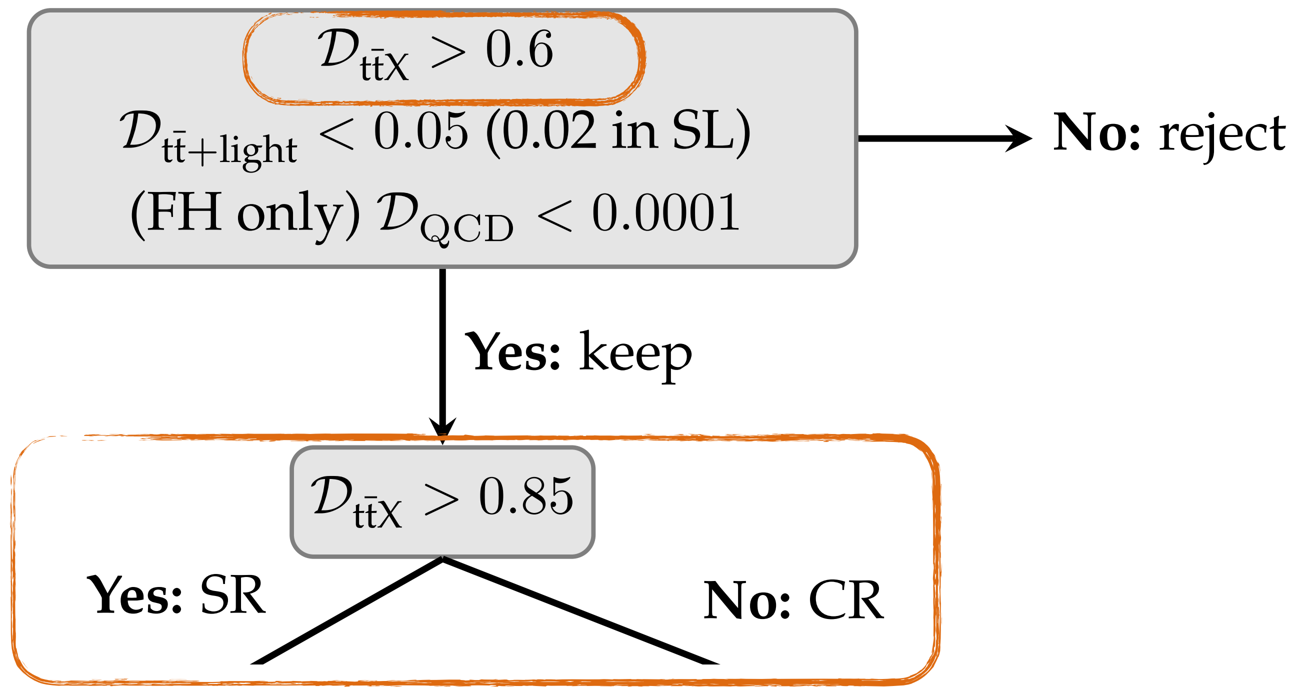
- Remove QCD and $t\bar{t}$+light contributions via selections on background scores

QCD suppression in FH channel:

- Event classifier very good at separating QCD ↔ $t\bar{t}$
- Only use events with QCD score < 10^{-4}
  - **QCD contribution becomes negligible (< 1%)**
  - At the cost of signal efficiency (~ 15%)

Event selection & categorisation

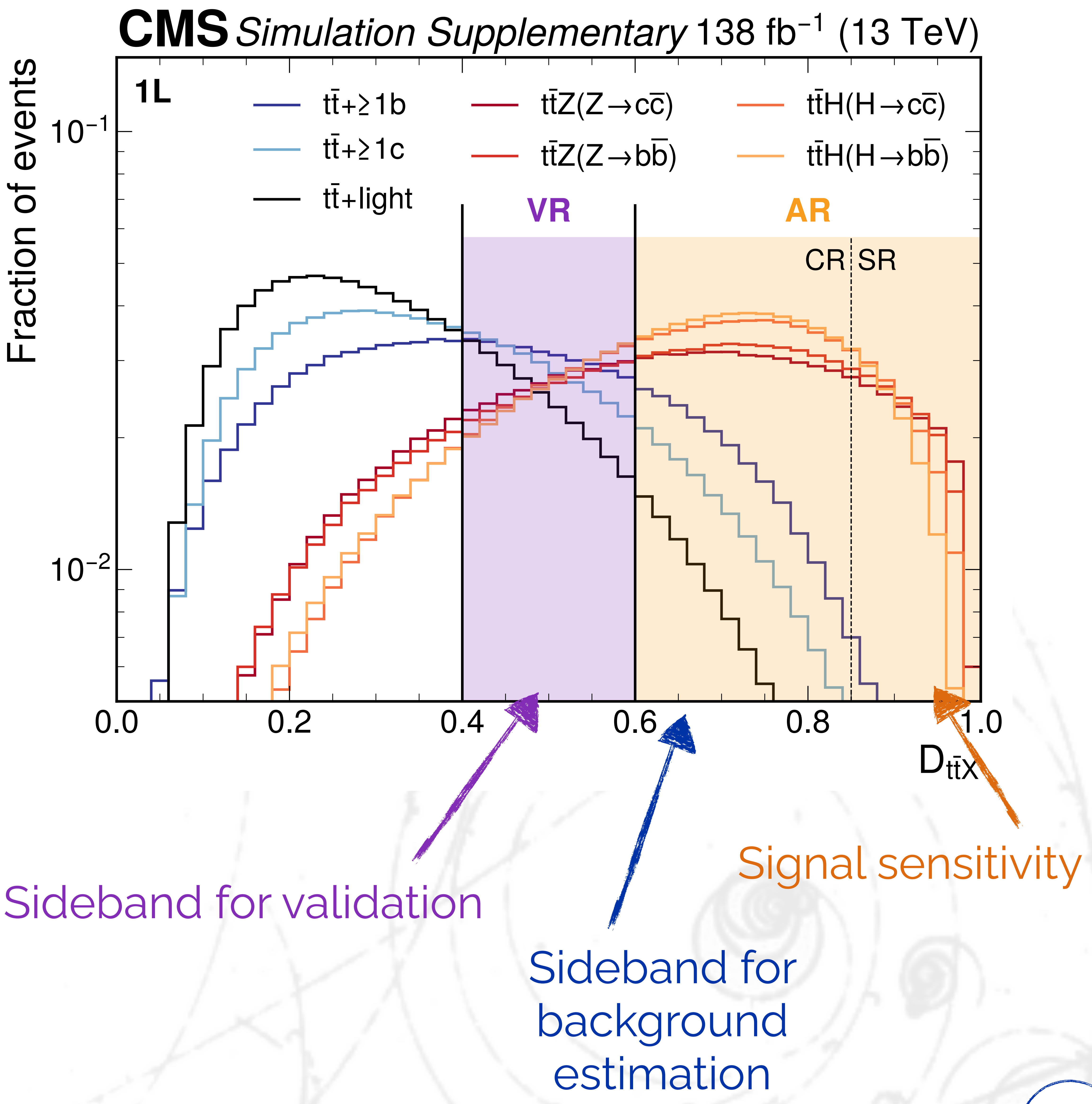
- Use scores (D_X) to select & categorise events



- Analysis region (**AR**) with signal-like events
  → Reduce background extrapolation

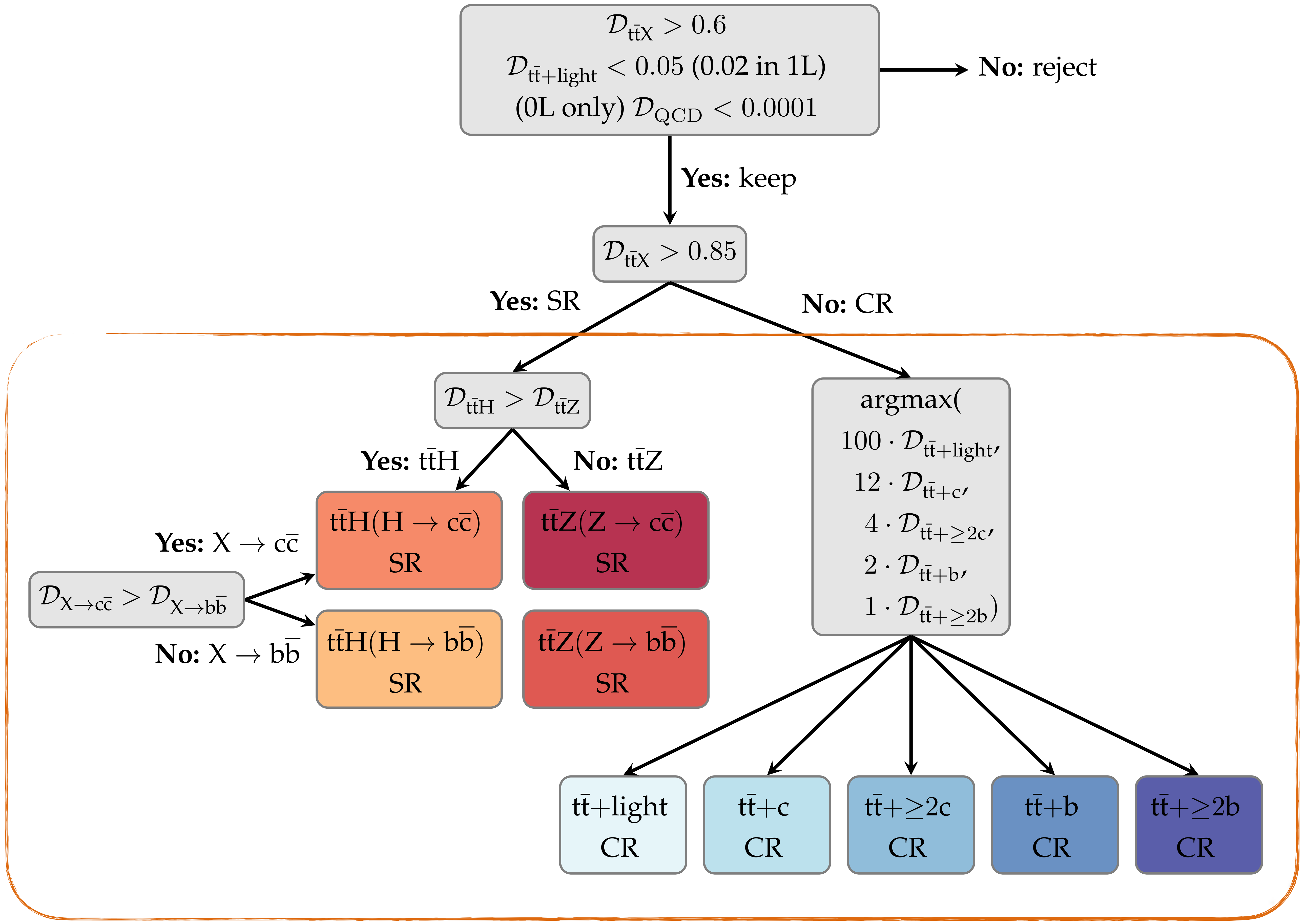
- Split **AR** into **signal region part** (**SR**) and **control region part (CR)**

- Introduce validation region (**VR**) to test the background model



Event selection & categorisation

- Use scores (D_X) to select & categorise events

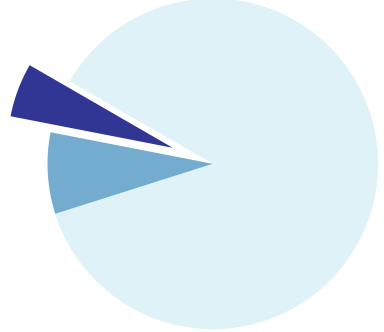


- Categorise signal-like events within **SR** into **2+2** dedicated **signal regions** (**SRs**):
  - $t\bar{t}H(H \to c\bar{c})$, $t\bar{t}H(H \to b\bar{b})$, $t\bar{t}Z(Z \to c\bar{c})$, $t\bar{t}Z(Z \to b\bar{b})$
- And **5 control regions (CRs)**:
  - $t\bar{t}$+light, $t\bar{t}$+c, $t\bar{t} + \geq 2c$, $t\bar{t}$+b, $t\bar{t} + \geq 2b$

- 9 regions in total for **AR**

- Employ importance weights to increase purities
- **VR**: ensure same background purities as **AR** to validate the final fit strategy

How well do we know the $t\bar{t}$+jets background?

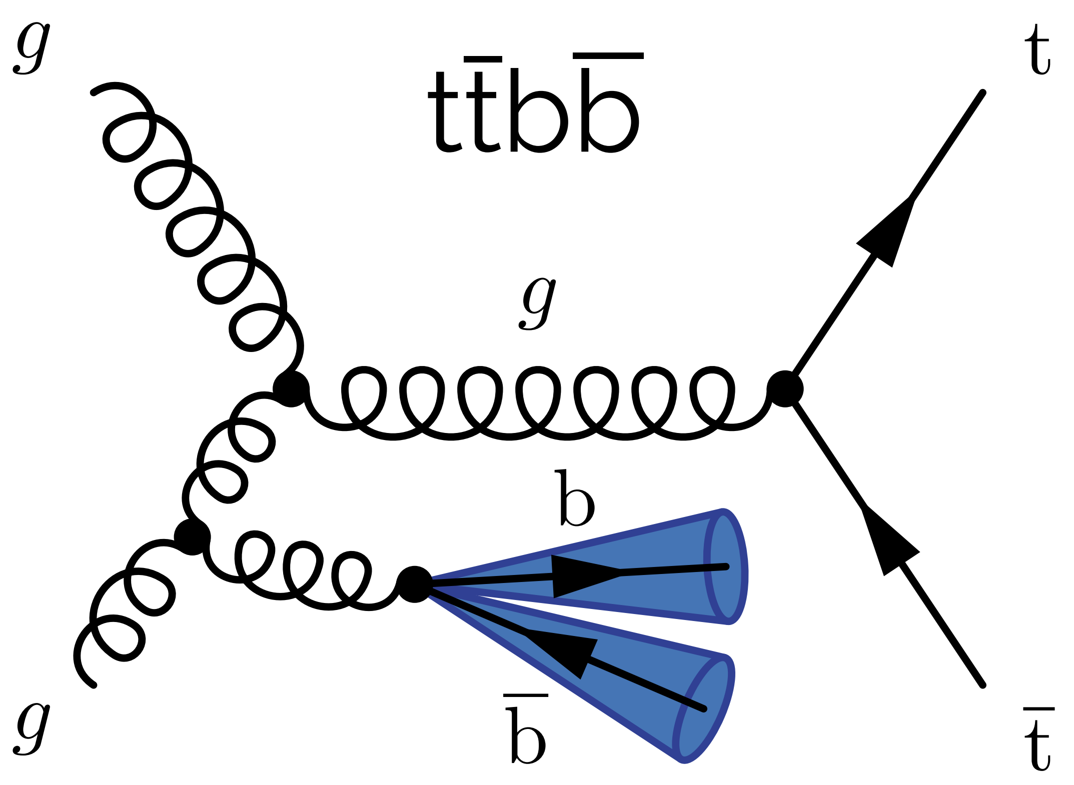


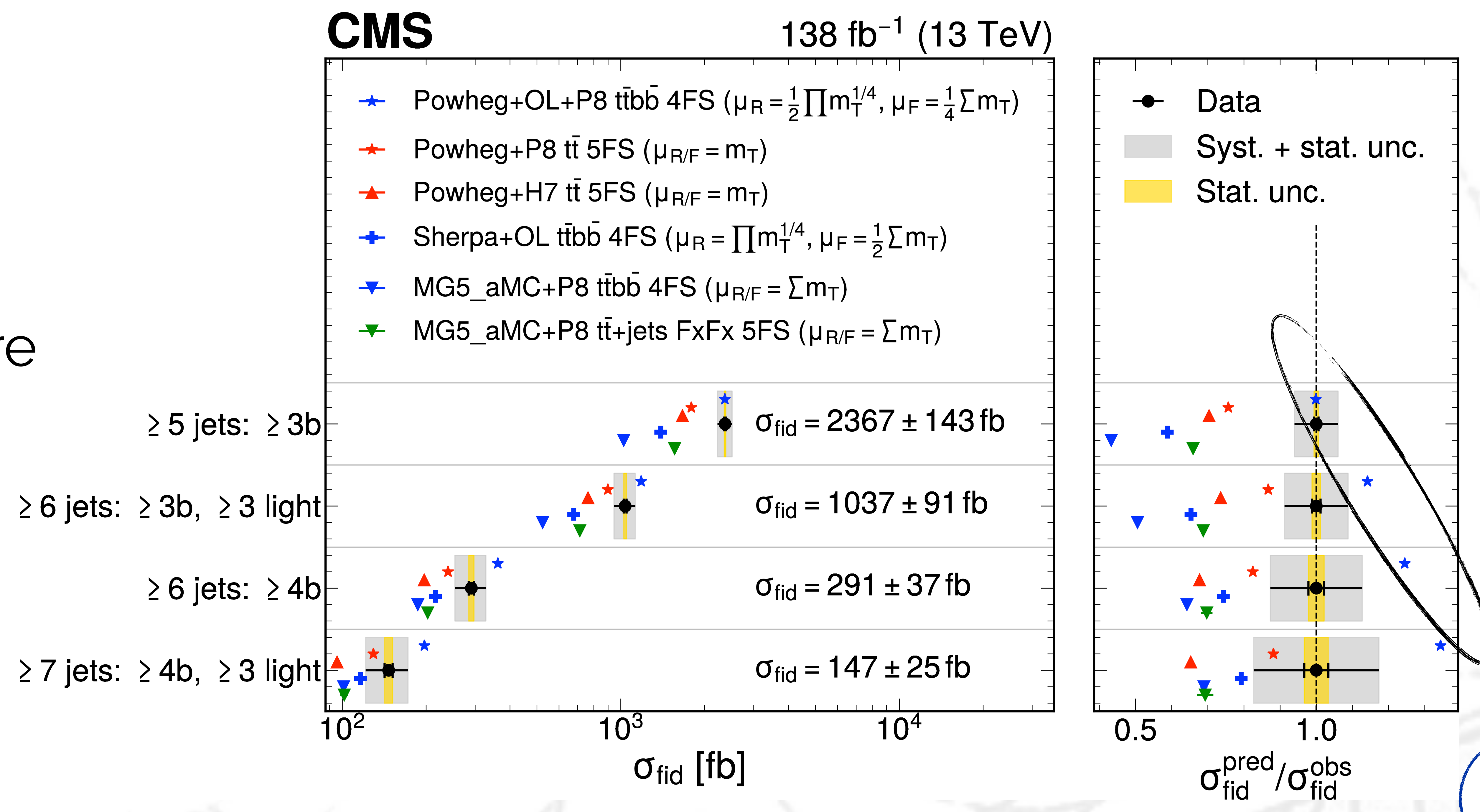
- Inclusive $t\bar{t}$ well described by NLO Powheg+Pythia8 5FS prediction
  - See e.g. multi-differential cross section measurements

- For $t\bar{t}b\bar{b}$:
  - Theoretical difficulties:
    - Massless or massive b-quarks?
      e.g. 5FS inclusive NLO prediction vs. 4FS dedicated $t\bar{t}b\bar{b}$ simulation
  - Experimental difficulties:
    - What do *we* consider a b-quark jet?

- Rich set of $t\bar{t}b\bar{b}$ measurements:
  - No generator has a good description everywhere
  - 4FS $t\bar{t}b\bar{b}$ simulation close to data inclusively
  - For differential distributions, agreement varies…

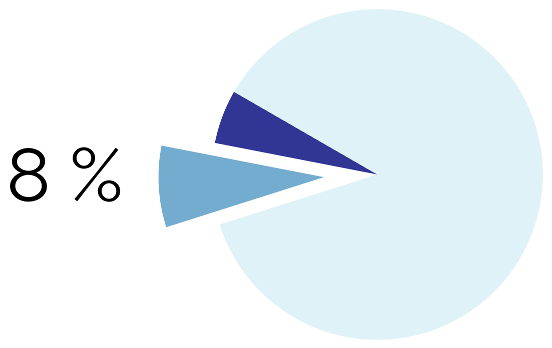
A background model with enough flexibility needed, based on 4FS $t\bar{t}b\bar{b}$



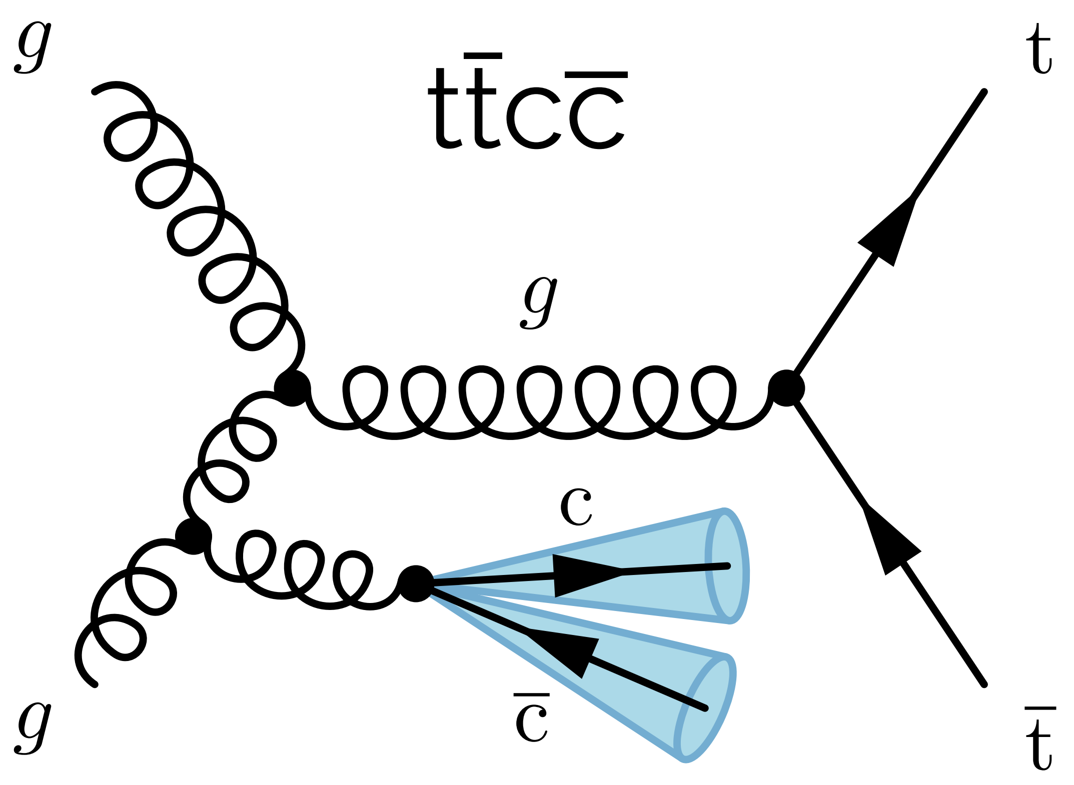


JHEP 05 (2024) 042

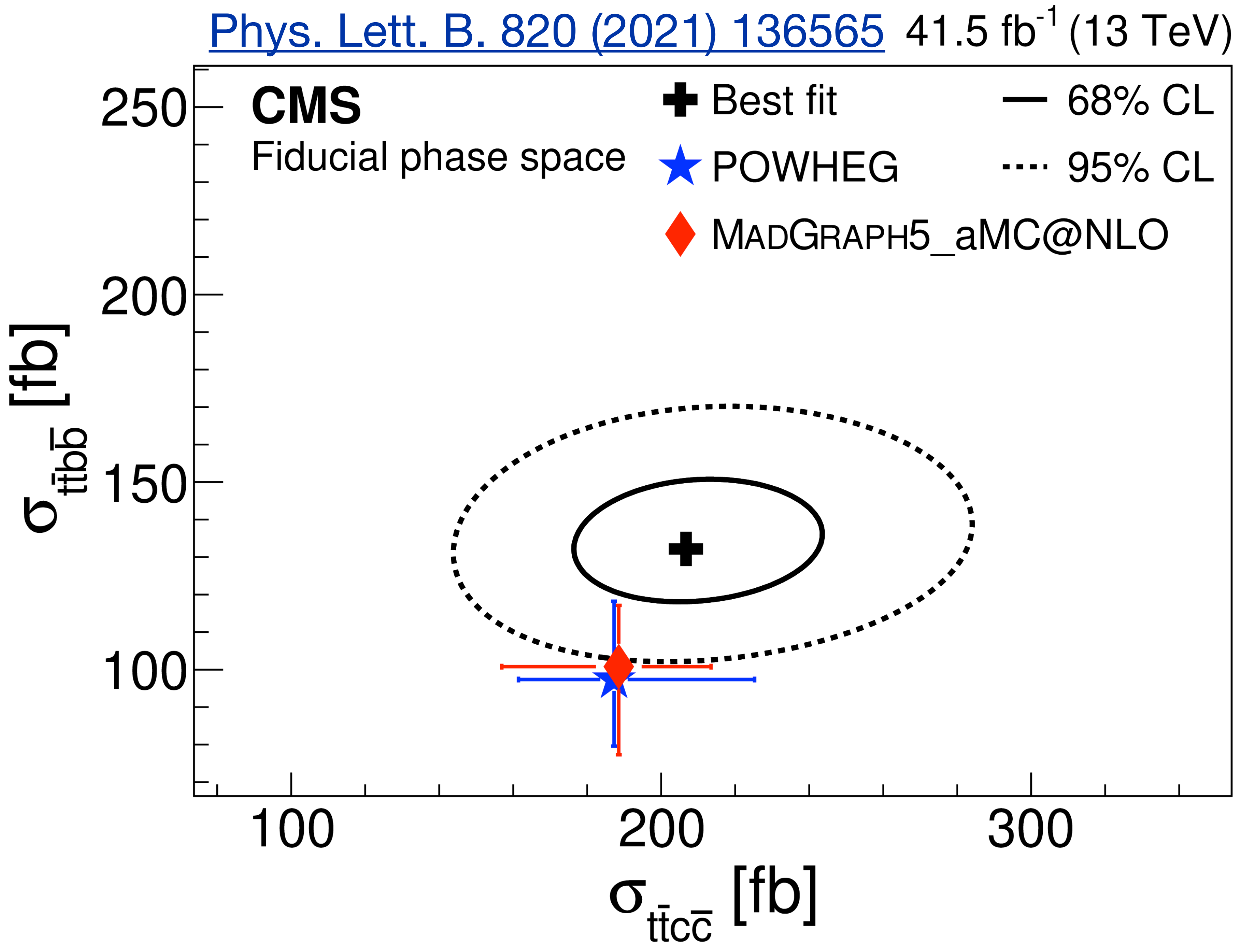
How well do we know the $t\bar{t}$+jets background?

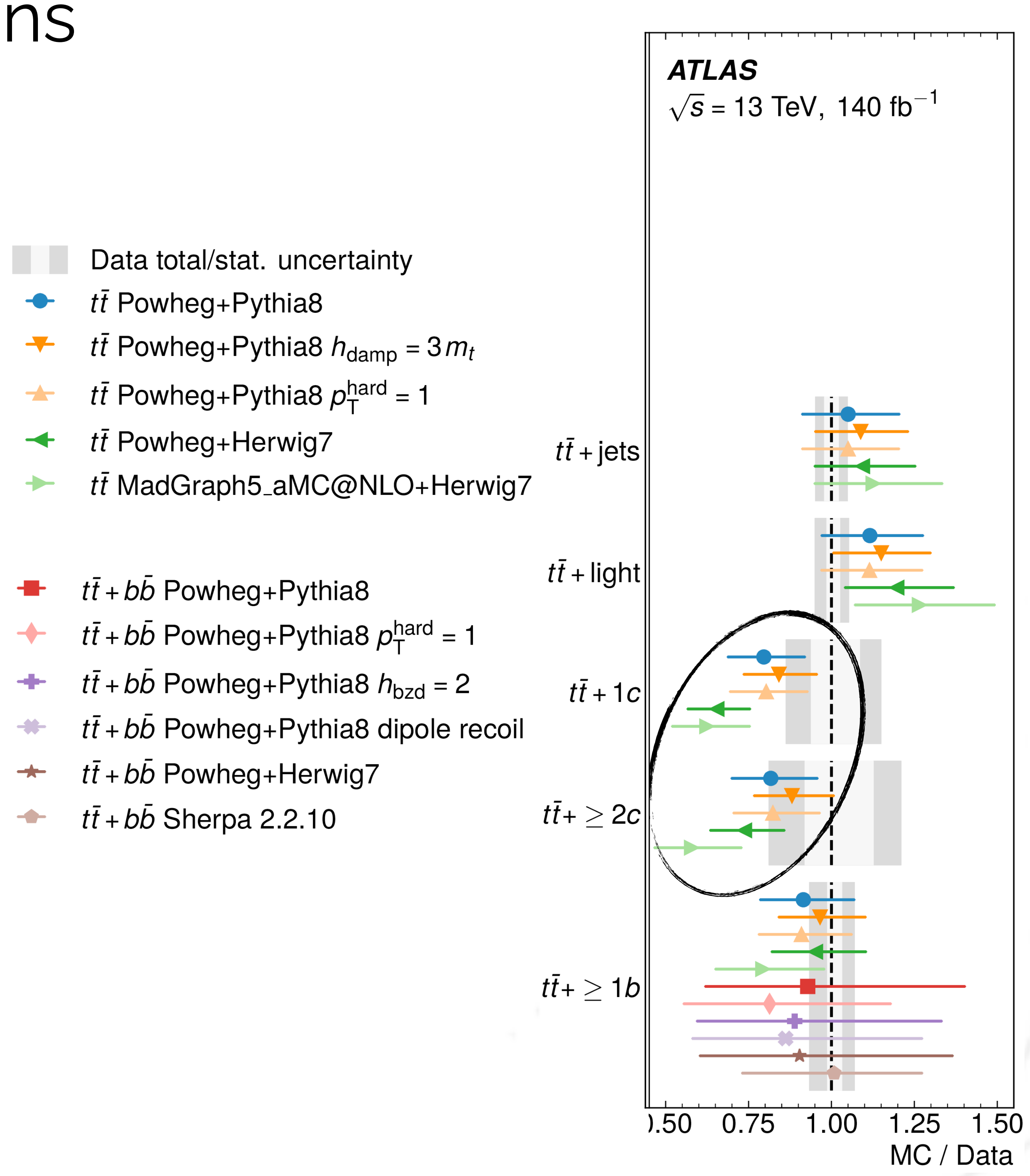


- For $t\bar{t}c\bar{c}$:
  - Only inclusive measurements available
  - General trend consistent
  - Also as seen in $t\bar{t}H(H \rightarrow b\bar{b})$ measurements
  - ~ μ = 1.1 - 1.5, varying with selections



Phys. Lett. B. 820 (2021) 136565





Phys. Lett. B 860 (2025) 139177

Eur. Phys. J. C 85 (2025) 210

Normalisation factor	$t\bar{t}$ + light	$t\bar{t}$ + ≥ 1c	$t\bar{t}$ + 1b	$t\bar{t}$ + 1B	$t\bar{t}$ + ≥ 2b
Single-lepton	$0.78^{+0.08}_{-0.08}$	$1.51^{+0.19}_{-0.18}$	$1.06^{+0.10}_{-0.10}$	$1.15^{+0.15}_{-0.14}$	$0.94^{+0.08}_{-0.08}$
Dilepton	$0.88^{+0.11}_{-0.10}$	$1.36^{+0.10}_{-0.10}$	$1.24^{+0.09}_{-0.09}$		

Beware the different nomenclature…

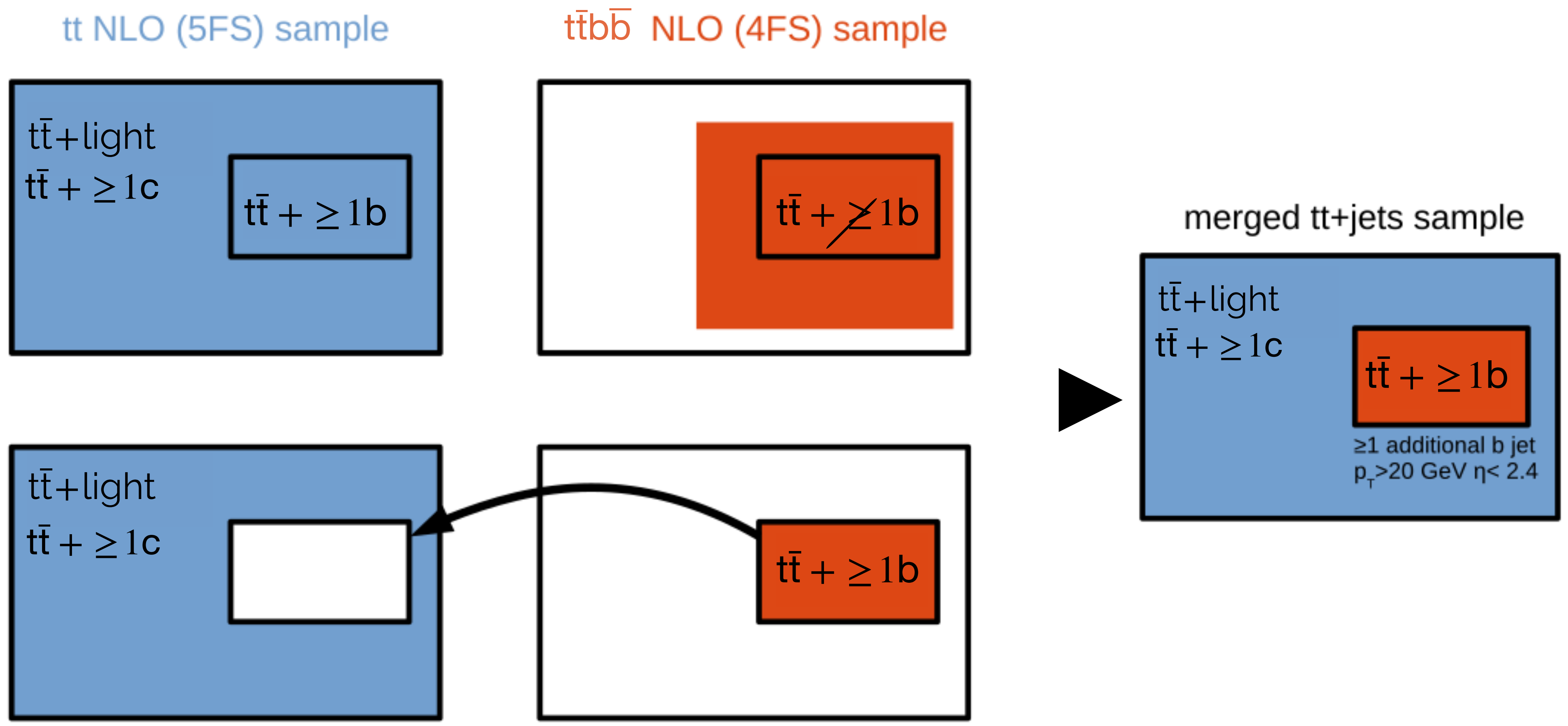
Future differential measurements particularly interesting!

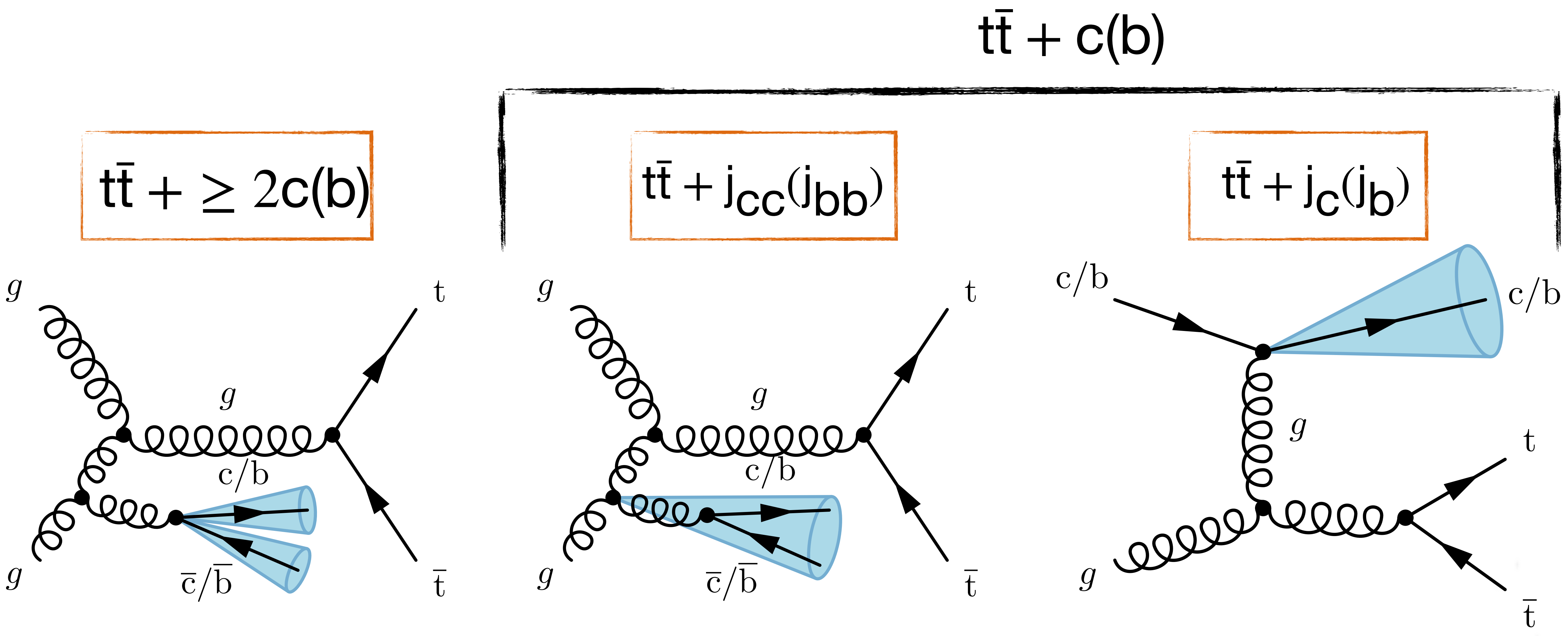
Background modeling & estimation

$t\bar{t}$+jets background model:

- **State-of-the-art merging of 5FS and 4FS predictions**
  - $t\bar{t} + \geq 2b$, $t\bar{t} + j_b$, $t\bar{t} + j_{bb}$ from 4FS $t\bar{t}b\bar{b}$

    – Additional double-parton-scattering $t\bar{t}b\bar{b}$ component, missing in merging, considered for the first time
  - $t\bar{t} + \geq 2c$, $t\bar{t} + j_c$, $t\bar{t} + j_{cc}$, $t\bar{t}$+light from 5FS $t\bar{t}$+jets





Data-driven estimation:

- One control region (CR) for each contribution

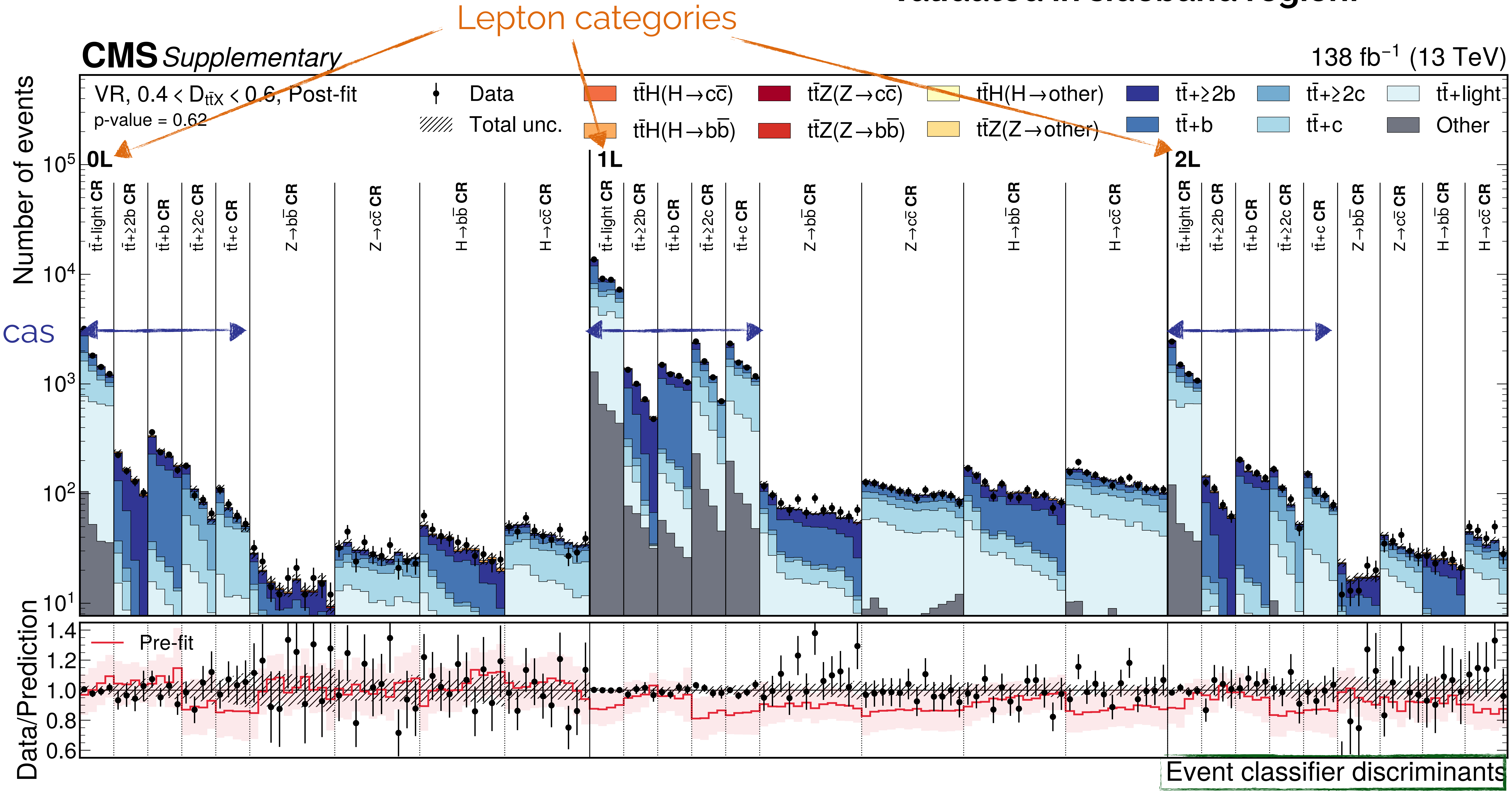
$t\bar{t} + \geq 2c$	$t\bar{t} + c$	$t\bar{t} + \geq 2b$	$t\bar{t} + b$	$t\bar{t}$+light

Yielding a fit model with sufficient flexibility

For $t\bar{t}$+jets: 184 nuisance parameters in fit
+ 10 free-floating parameters

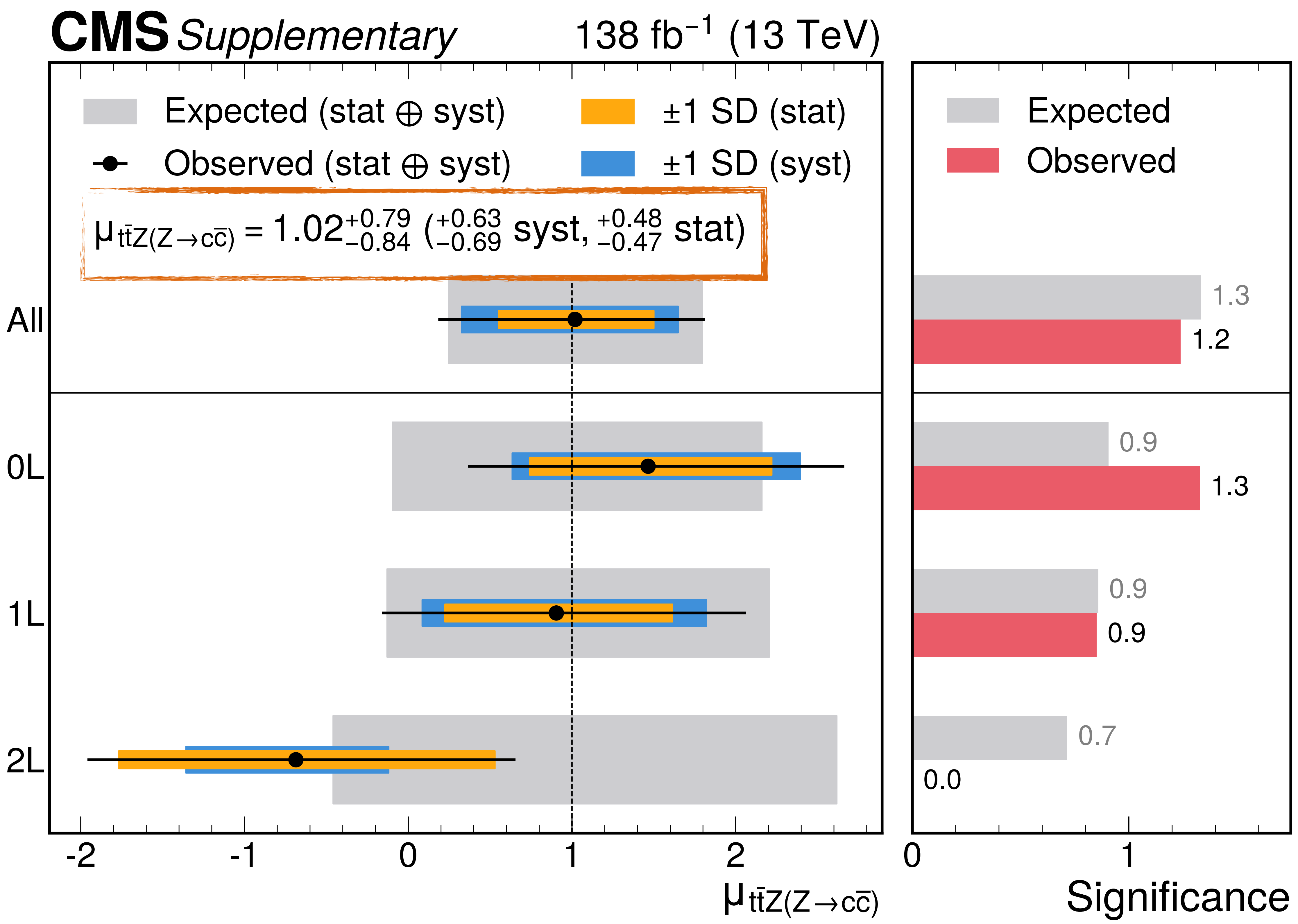
Validating the background model

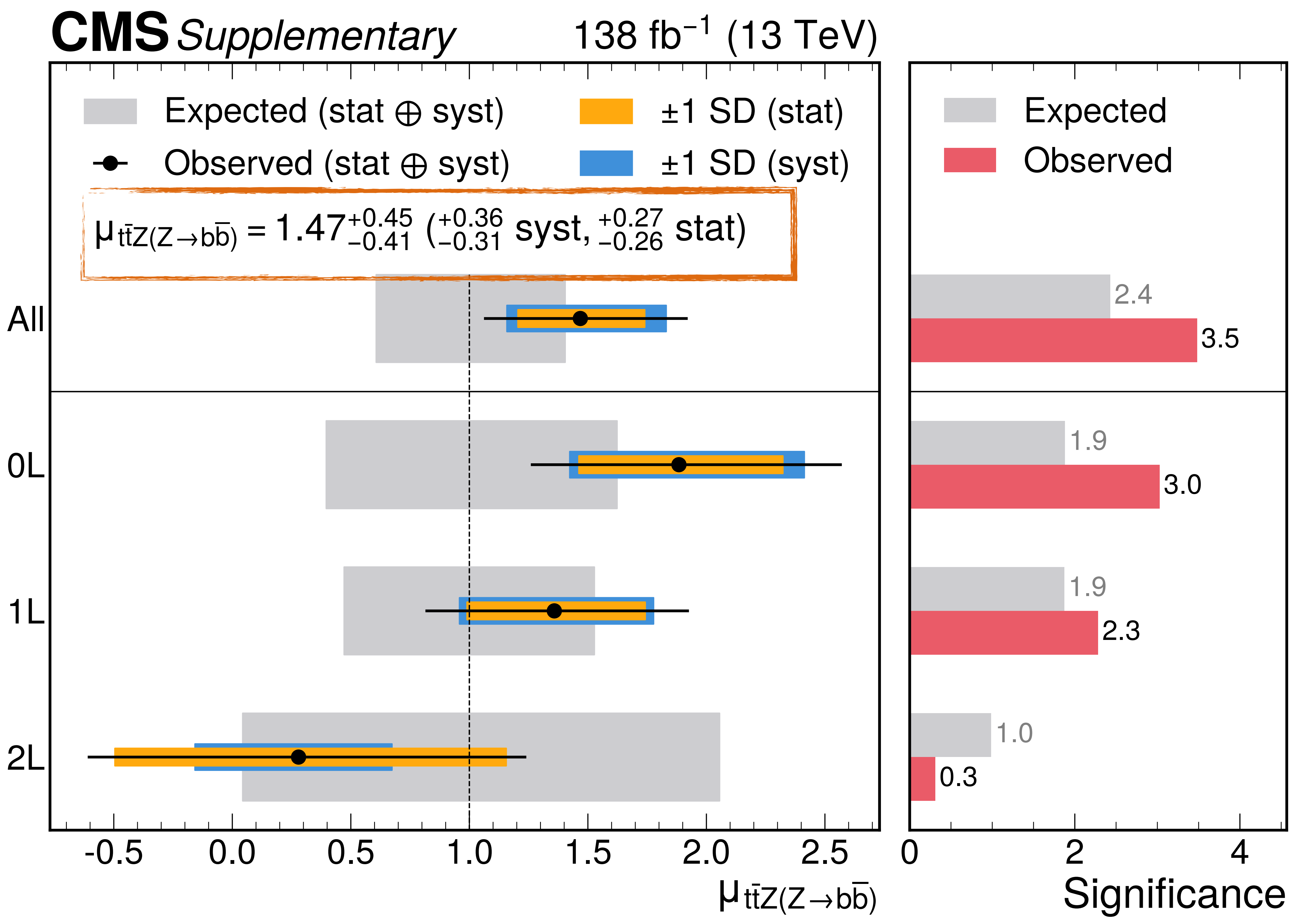
✅ → **Background model successfully validated in sideband region!**



- Note: For robustness and more granular binning: merge e/μ events in 1L/2L channels

Validation with $t\bar{t}Z(Z \to c\bar{c}/b\bar{b})$ production





- $t\bar{t}Z$ signal strengths SM & measurement compatible
- **Good validation for $t\bar{t}H(H \to c\bar{c}/b\bar{b})$ analysis!**

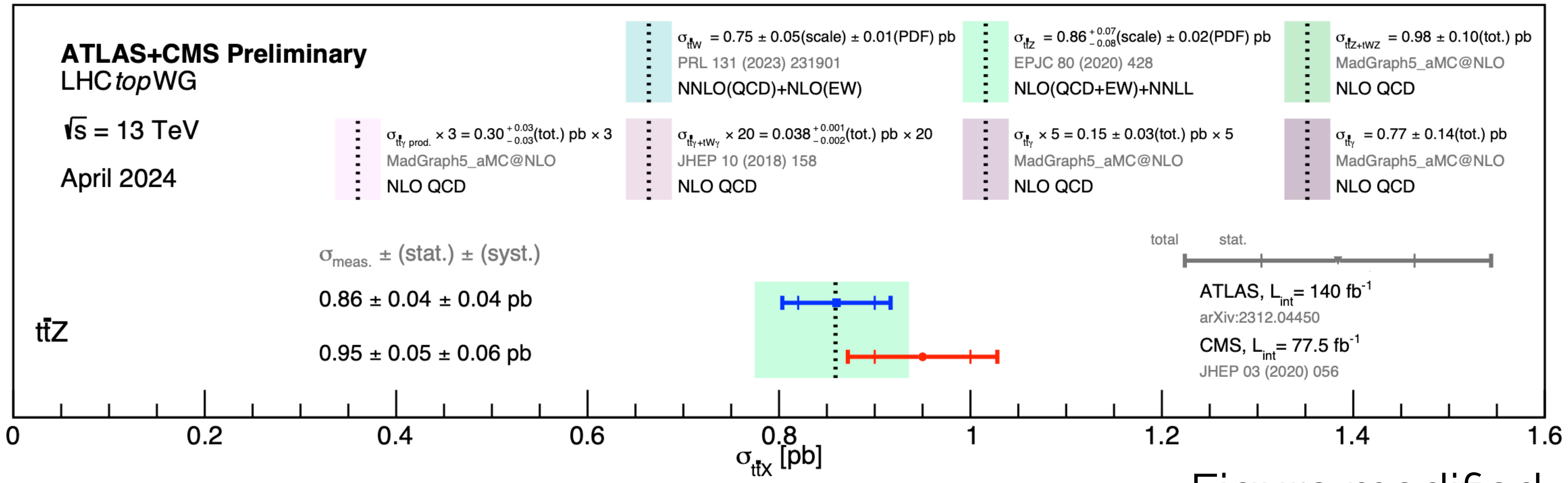
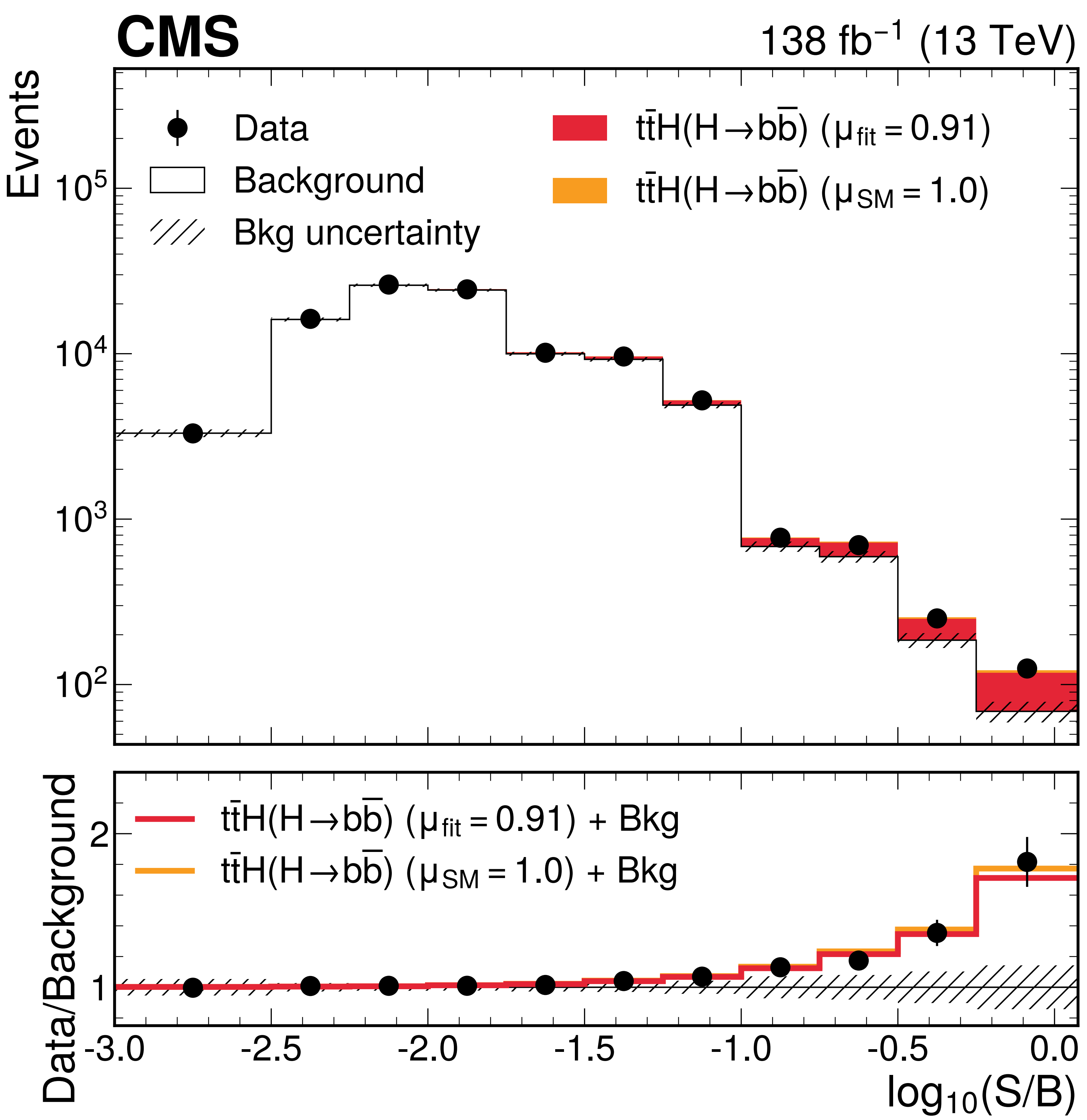
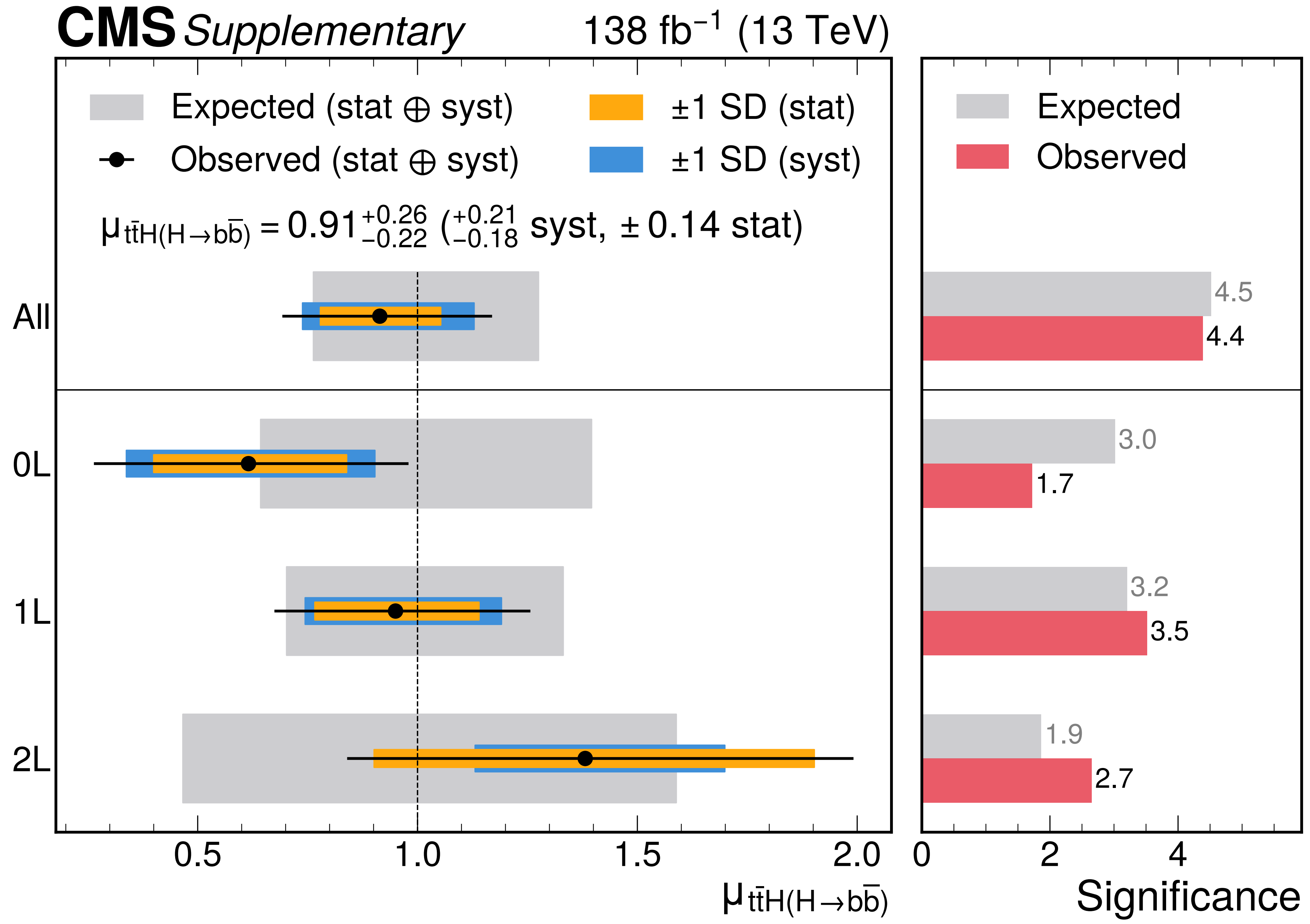
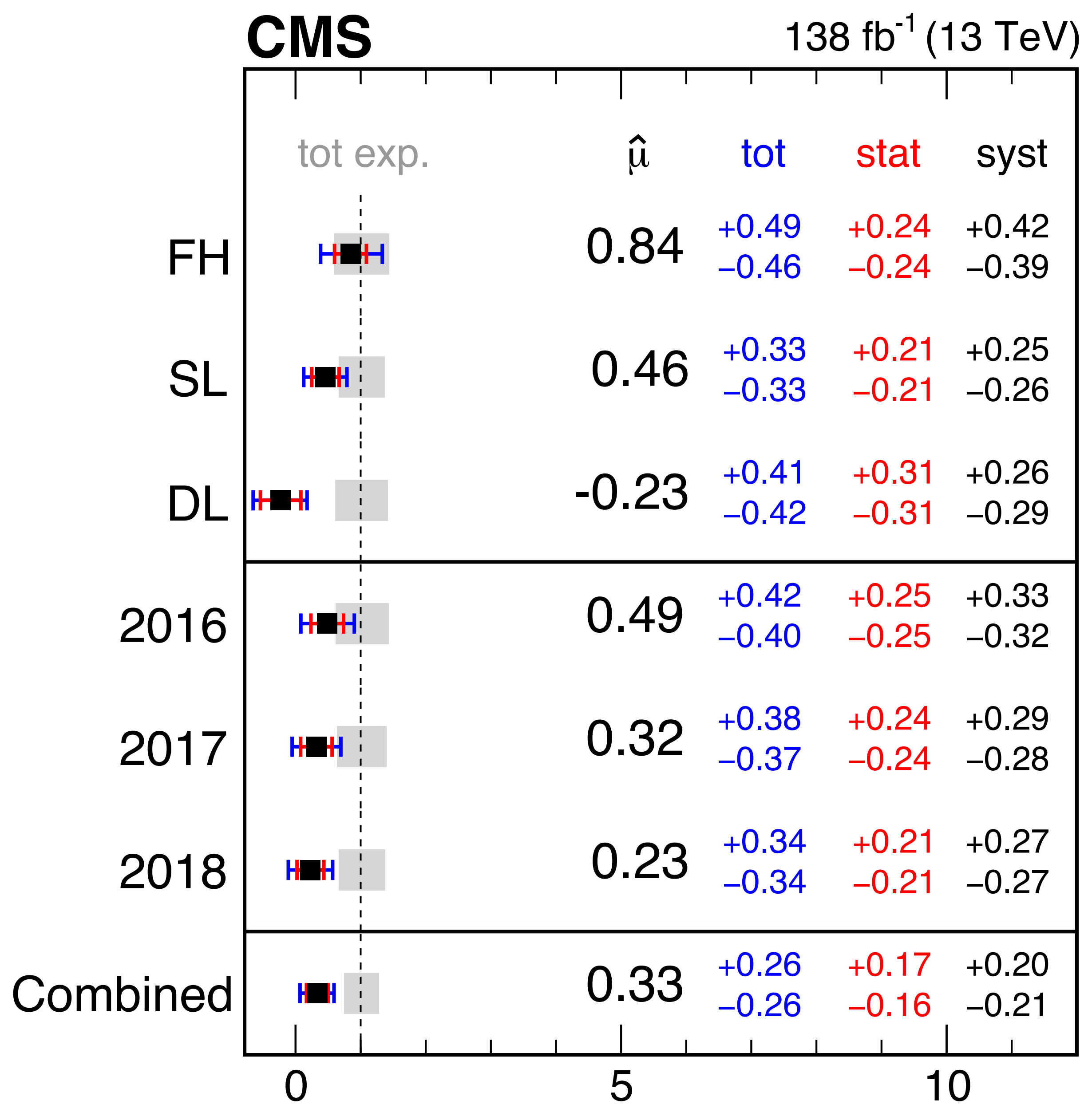


Figure modified

Results: $t\bar{t}H(H \to b\bar{b})$ production







[JHEP 02 (2025) 097] $\hat{\mu} = \hat{\sigma}/\sigma_{SM}$

- Compared to previous results:
  - More sophisticated & granular background model
  - More inclusive selection
  - Better MVA

- **$\mu_{ttH(H\to bb)}$ = 0.91 +0.26/-0.22 — 4.4σ observed**
  - Good agreement with SM expectation

Uncertainty breakdown

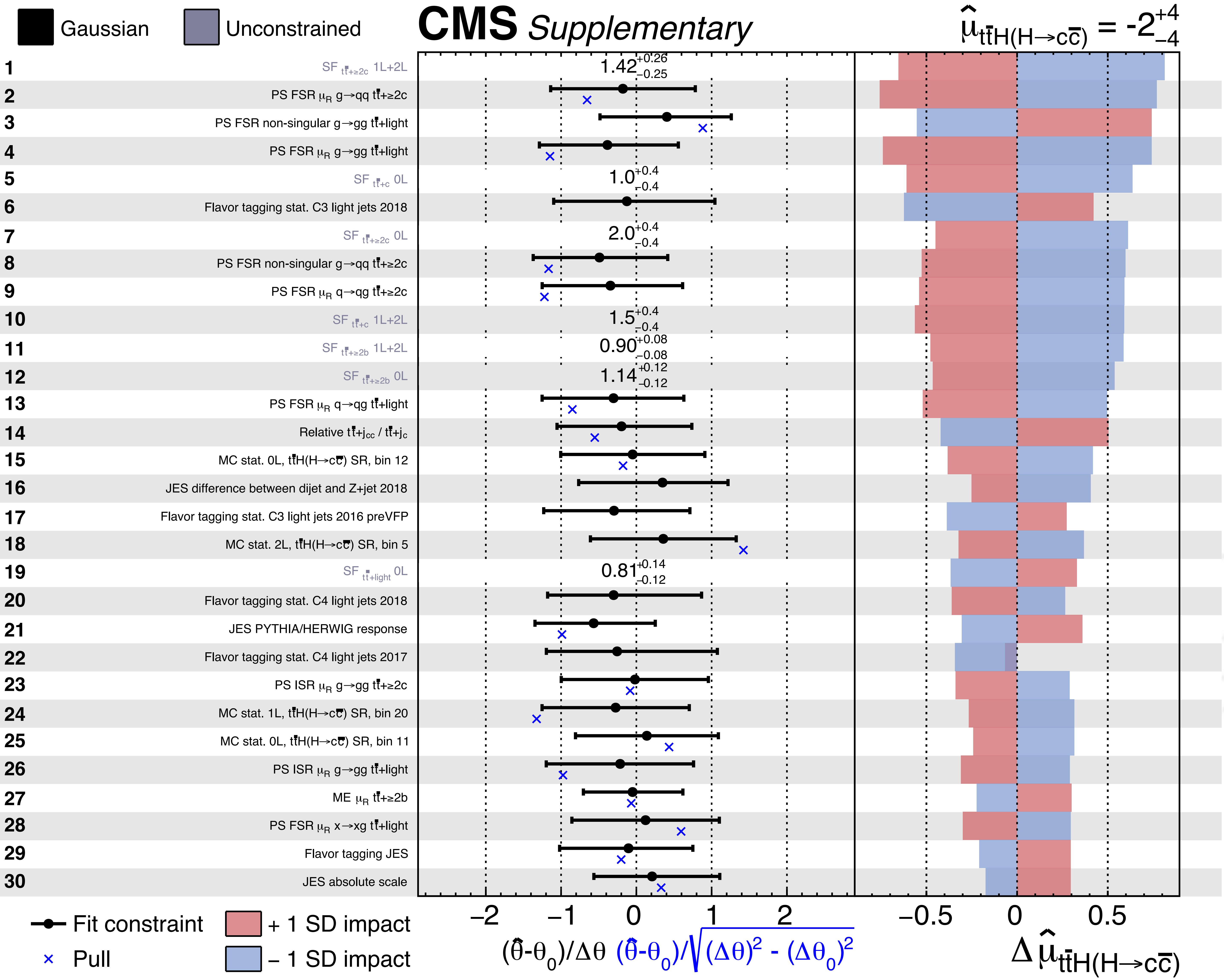
- Large statistical contribution:
  - Dominant for ttH(cc) and significant for ttH(bb)
- Tagging efficiency as main experimental uncertainty
  - Largest single contribution for ttH(cc)
- Modeling uncertainties:
  - Control over tt+jets backgrounds
    - tt+bb and tt+cc
  - Modeling of the ttH signal itself
- ttH(bb) and ttH(cc) correlation is only 1%

Uncertainty source	$\Delta\mu$ ($\Delta\mu/\Delta\mu_{tot}$) $\mu_{t\bar{t}H(H\to c\bar{c})}$		$\mu_{t\bar{t}H(H\to b\bar{b})}$	
Statistical	3.3	(74%)	0.14	(57%)
$t\bar{t}$+jets normalizations	1.4	(32%)	0.06	(26%)
$t\bar{t}Z$ normalizations	0.4	(8.4%)	0.06	(30%)
Theory	2.1	(47%)	0.18	(75%)
Signal	0.7	(15%)	0.11	(47%)
$t\bar{t}+\geq 1b$	0.7	(15%)	0.14	(60%)
$t\bar{t}+\geq 1c$	1.4	(32%)	0.01	(5.8%)
$t\bar{t}$+light	1.3	(29%)	0.01	(5.2%)
Minor backgrounds	0.2	(4.6%)	0.01	(4.6%)
Experimental	2.0	(47%)	0.07	(31%)
Jet flavor tagging	1.7	(39%)	0.07	(28%)
Size of the simulated samples	1.1	(24%)	0.05	(21%)
Jet energy scale and resolution	0.8	(18%)	0.02	(8.6%)
Lepton identification	0.3	(6.0%)	0.02	(6.3%)
Integrated luminosity	0.1	(2.0%)	0.02	(6.2%)
Total	4.5	(100%)	0.24	(100%)

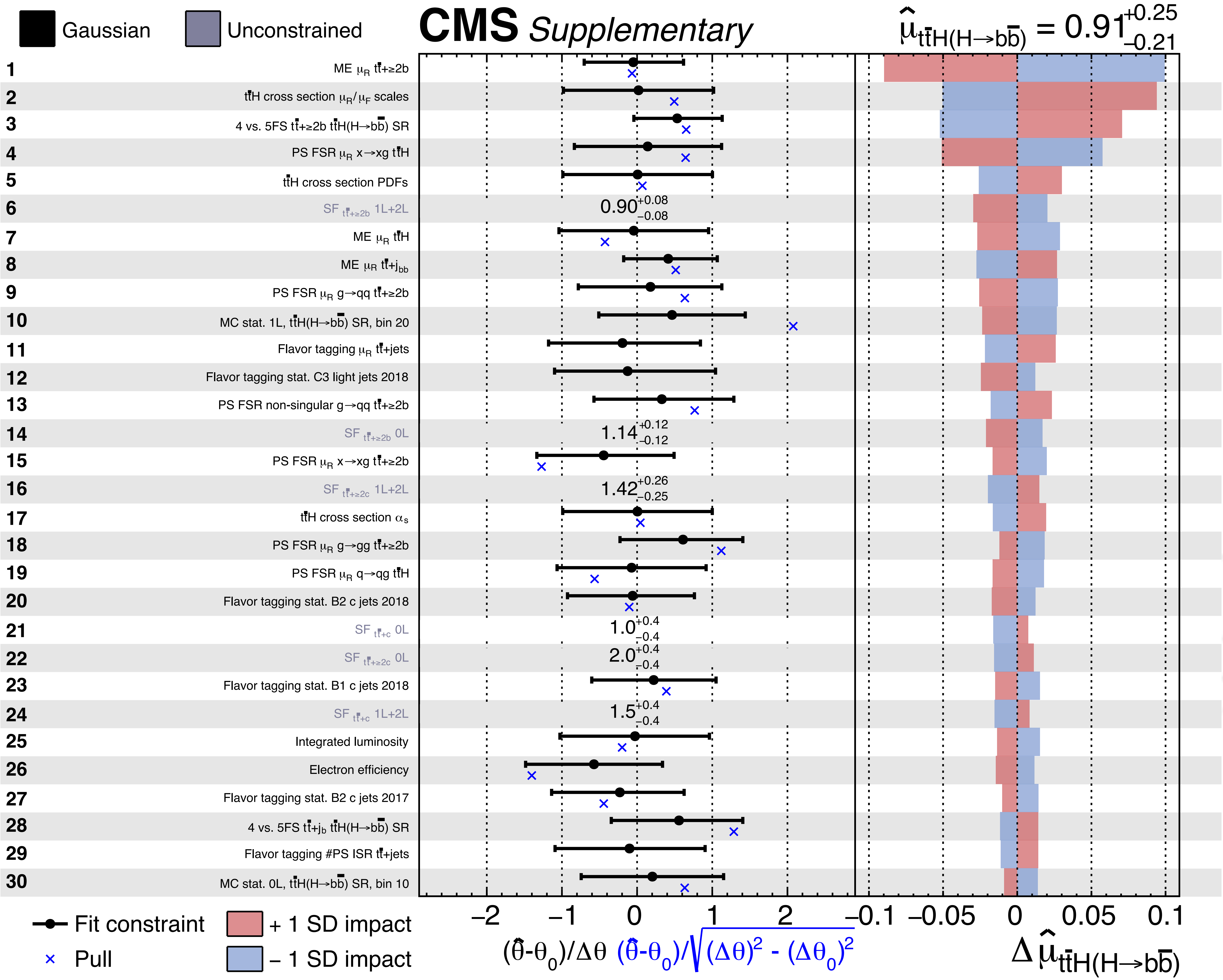
Considered uncertainties and correlations

	Source	Corr. (period)	Corr. (process)	Processes
Experimental	Integrated luminosity	$\sim$	✓	all
	Electron reconstruction and identification	✓	✓	all
	Muon reconstruction and identification	✓	✓	all
	Trigger efficiencies	$\times$	✓	all
	Pileup reweighting	✓	✓	all
	Jet energy scale (11 sources)	$\sim$	✓	all
	Jet energy resolution	$\times$	✓	all
	Unclustered $p_{\mathrm{T}}^{\mathrm{miss}}$	$\times$	✓	all
	Jet flavor tagging	$\sim$	✓	all
Modeling	Incl. cross sections & normalization	✓	$\sim$	all
	μ_{R} scale	✓	$\times$	$\mathrm{t\bar{t}}$+jets, $\mathrm{t\bar{t}X}$, single t
	μ_{F} scale	✓	$\times$	$\mathrm{t\bar{t}}$+jets, $\mathrm{t\bar{t}X}$, single t
	PDF shape	✓	$\times$	$\mathrm{t\bar{t}}$+jets, $\mathrm{t\bar{t}X}$
	PS scales: ISR	✓	$\times$	$\mathrm{t\bar{t}}$+jets, $\mathrm{t\bar{t}X}$, single t
	PS scales: FSR	✓	$\times$	$\mathrm{t\bar{t}}$+jets, $\mathrm{t\bar{t}X}$, single t
	ME-PS matching (h_{damp})	✓	$\times$	$\mathrm{t\bar{t}}$+jets
	ME (4 *vs.* 5 flavor scheme)	✓	$\times$	$\mathrm{t\bar{t}}+\geq 1\mathrm{b}$

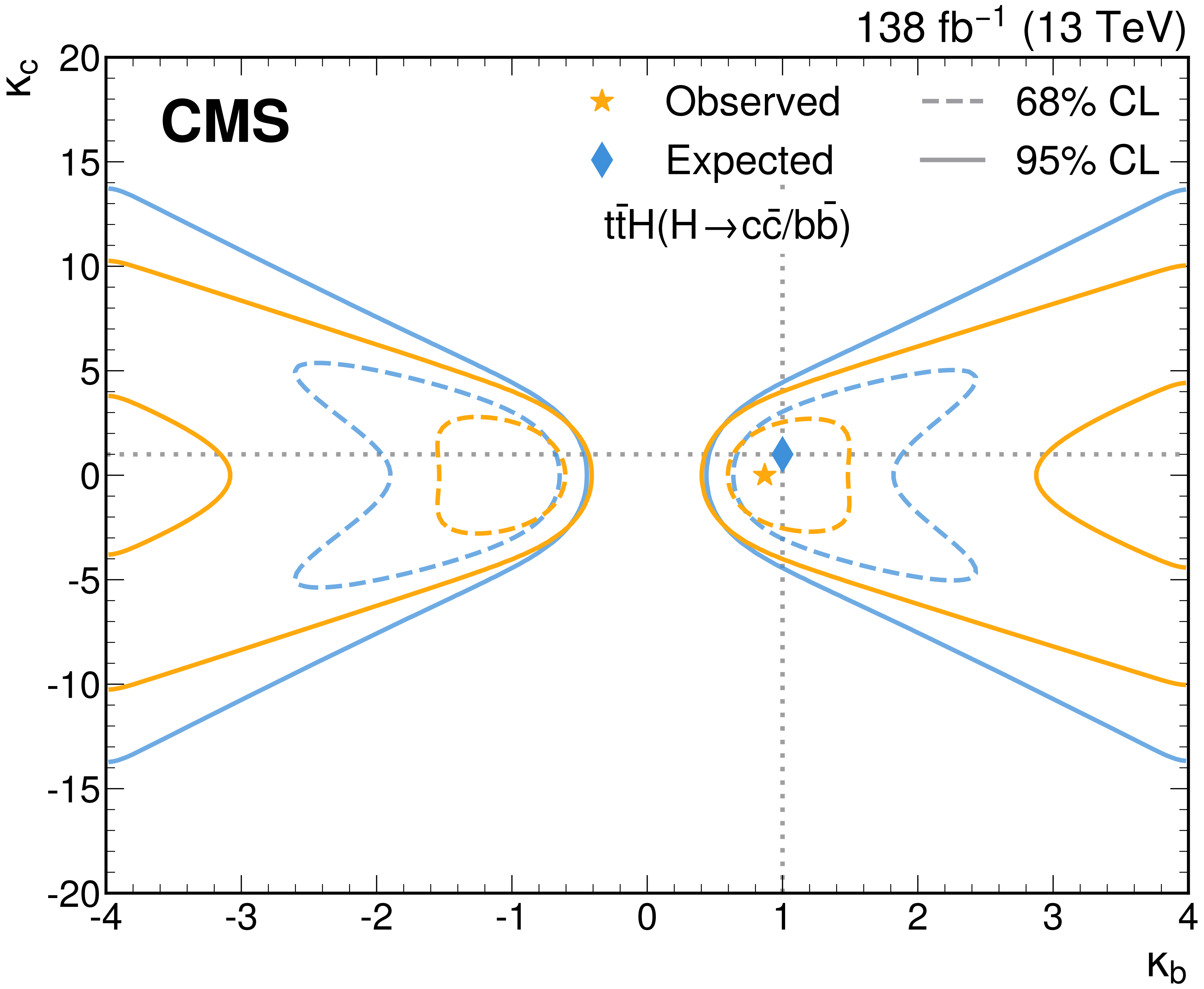
Nuisance parameter impacts



Nuisance parameter impacts



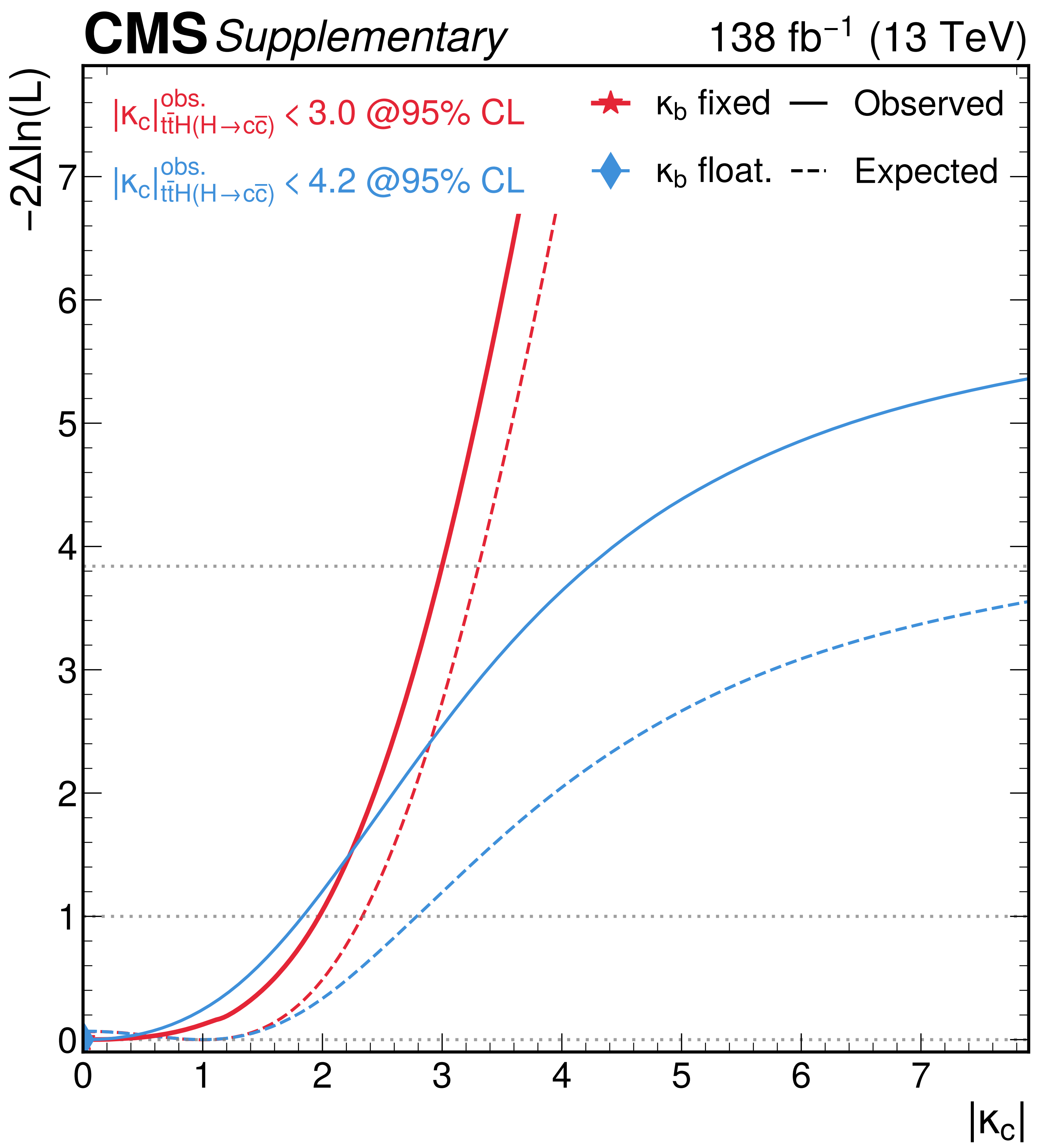
Results: coupling interpretation



All other kappas/couplings fixed to SM (k=1)

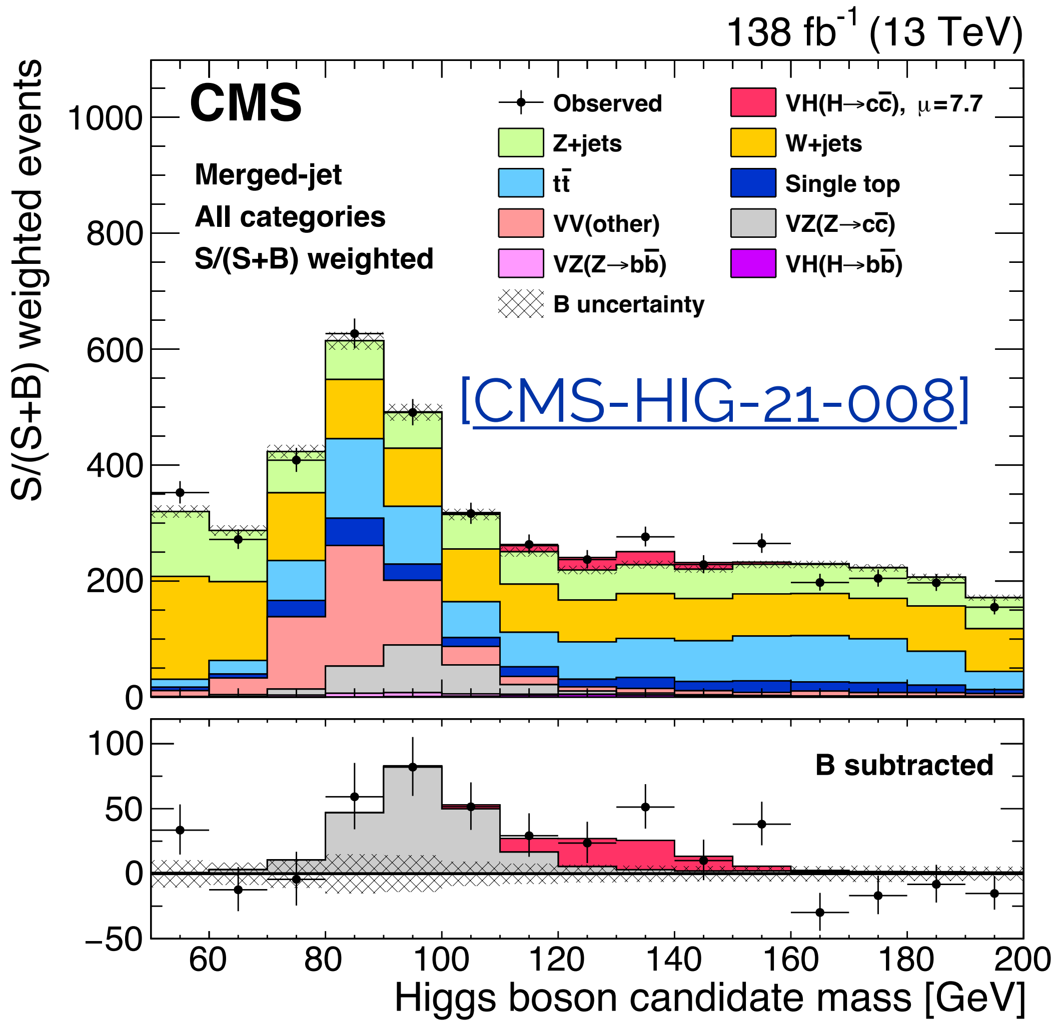
$$\mathcal{B}(H\rightarrow c\bar{c}) = \frac{\kappa_c^2 \cdot \mathcal{B}_{SM}^{H\rightarrow c\bar{c}}}{1 + (\kappa_c^2 - 1)\cdot \mathcal{B}_{SM}^{H\rightarrow c\bar{c}} + (\kappa_b^2 - 1)\cdot \mathcal{B}_{SM}^{H\rightarrow b\bar{b}}},$$

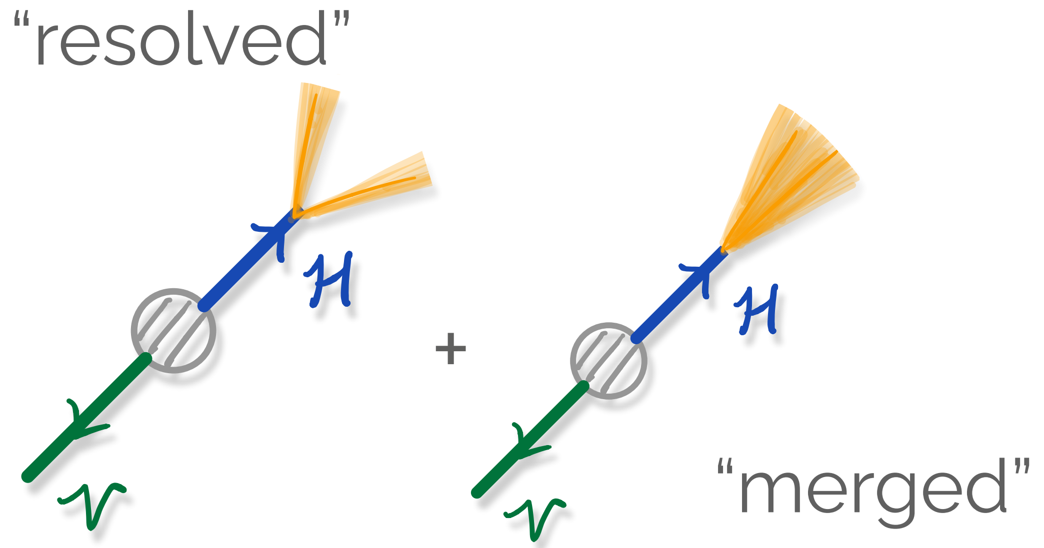
$$\mathcal{B}(H\rightarrow b\bar{b}) = \frac{\kappa_b^2 \cdot \mathcal{B}_{SM}^{H\rightarrow b\bar{b}}}{1 + (\kappa_c^2 - 1)\cdot \mathcal{B}_{SM}^{H\rightarrow c\bar{c}} + (\kappa_b^2 - 1)\cdot \mathcal{B}_{SM}^{H\rightarrow b\bar{b}}}.$$

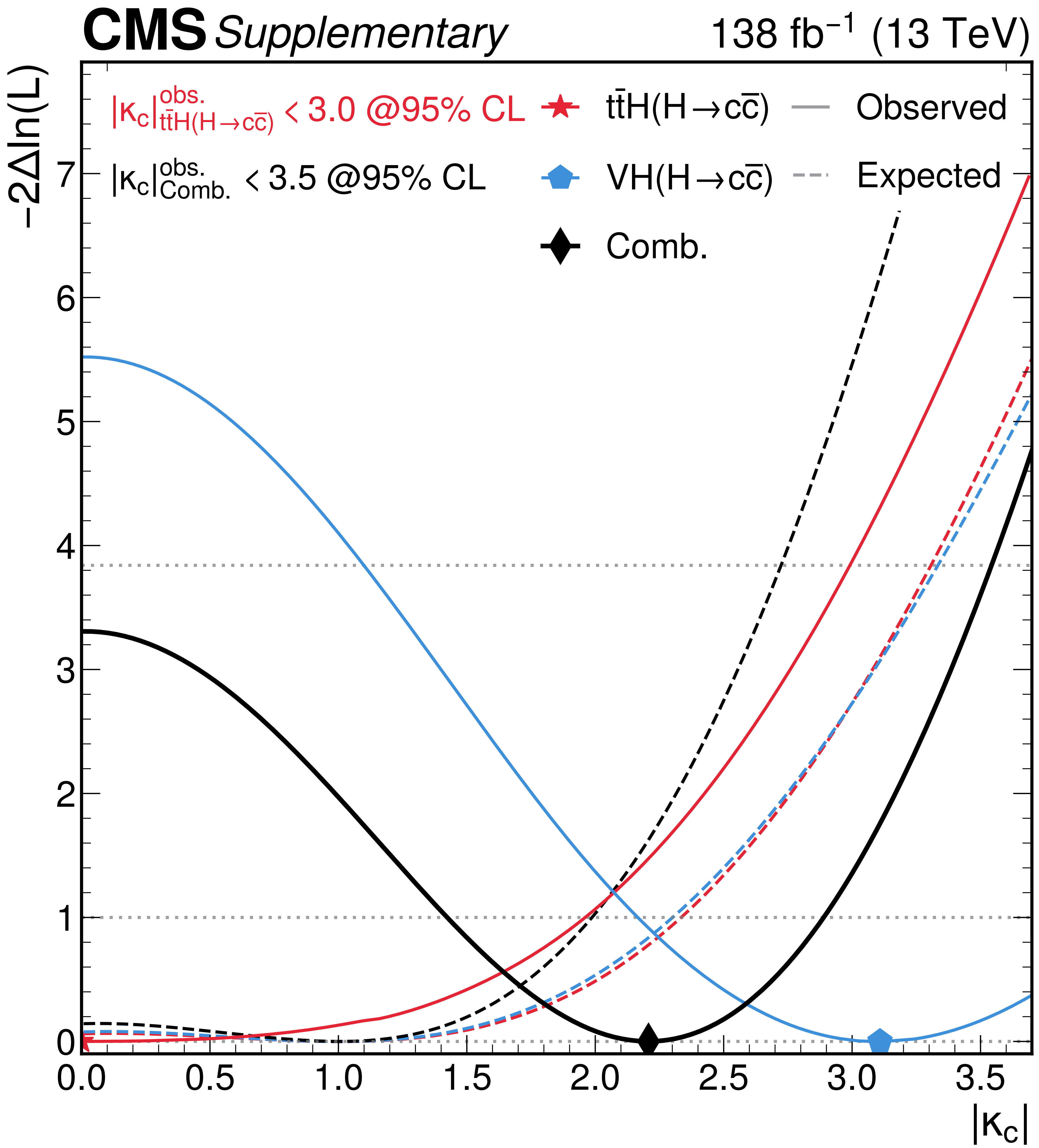


- **1D constraints on κ_c: $|\kappa_c| \lesssim$ 3.0 obs. (3.3 exp.)**
- **Most stringent constraints to date!** *κ_b fixed to 1*
  - Even better than VH(cc) results (4.1 (ATLAS) and 3.4 (CMS) exp.)

Combination with VH($H \to c\bar{c}$)







- Combine with VH($H \to c\bar{c}$):
  - Full Run 2 result from resolved+merged topologies
  - Correlated experimental uncertainties
  - Uncorrelated tagging uncertainties
  - Correlated theor. uncertainties (cross section / BR)

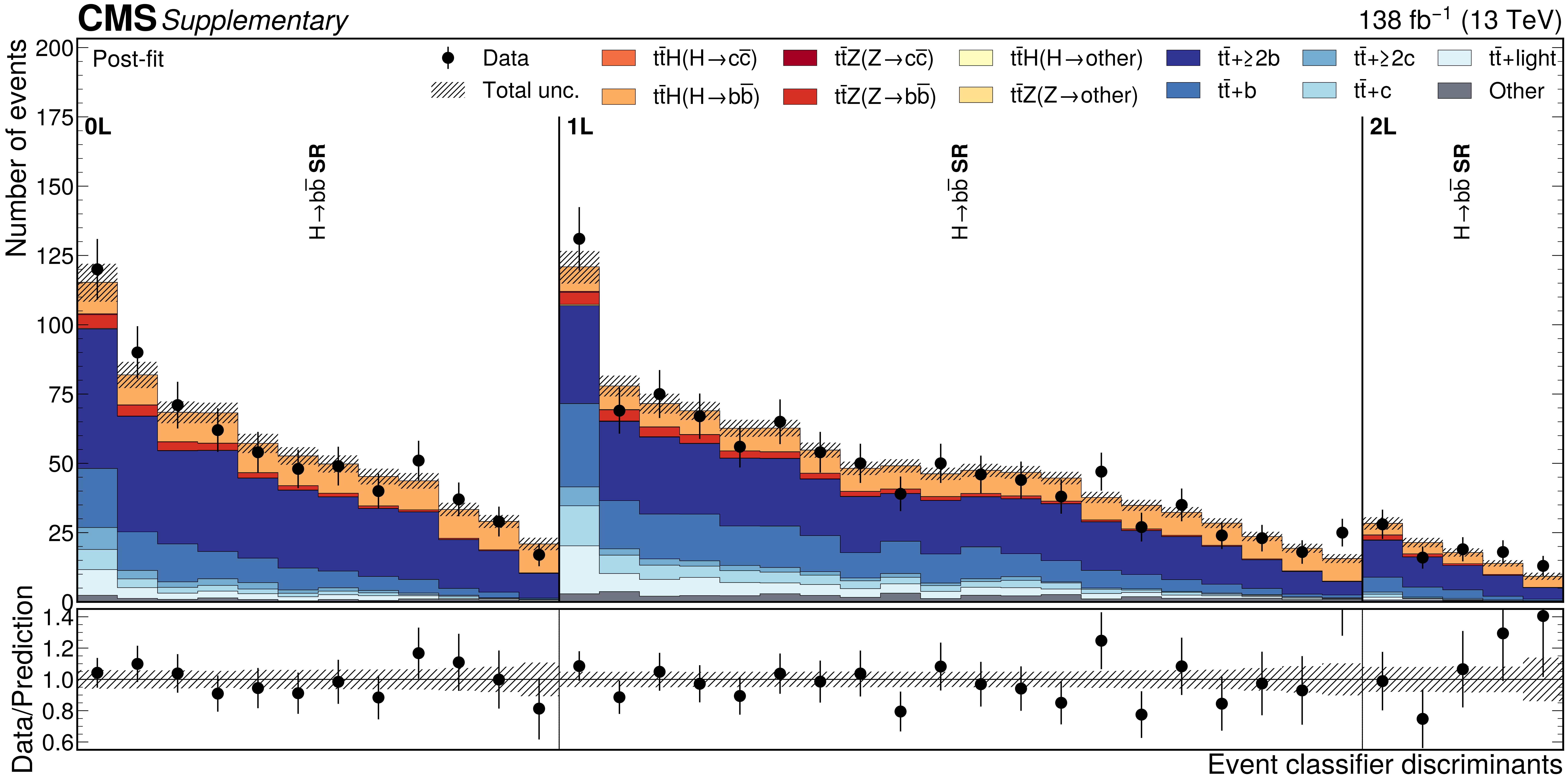
- VH($H \to c\bar{c}$) results: $1.1 < |\kappa_c| < 5.5$ (< 3.4 exp.)
- $t\bar{t}H$ results: $|\kappa_c| < 3.0$ (< 3.3 exp.)
- Combined: **$|\kappa_c| < 3.5$ (< 2.7 exp.)**

20% improvement!

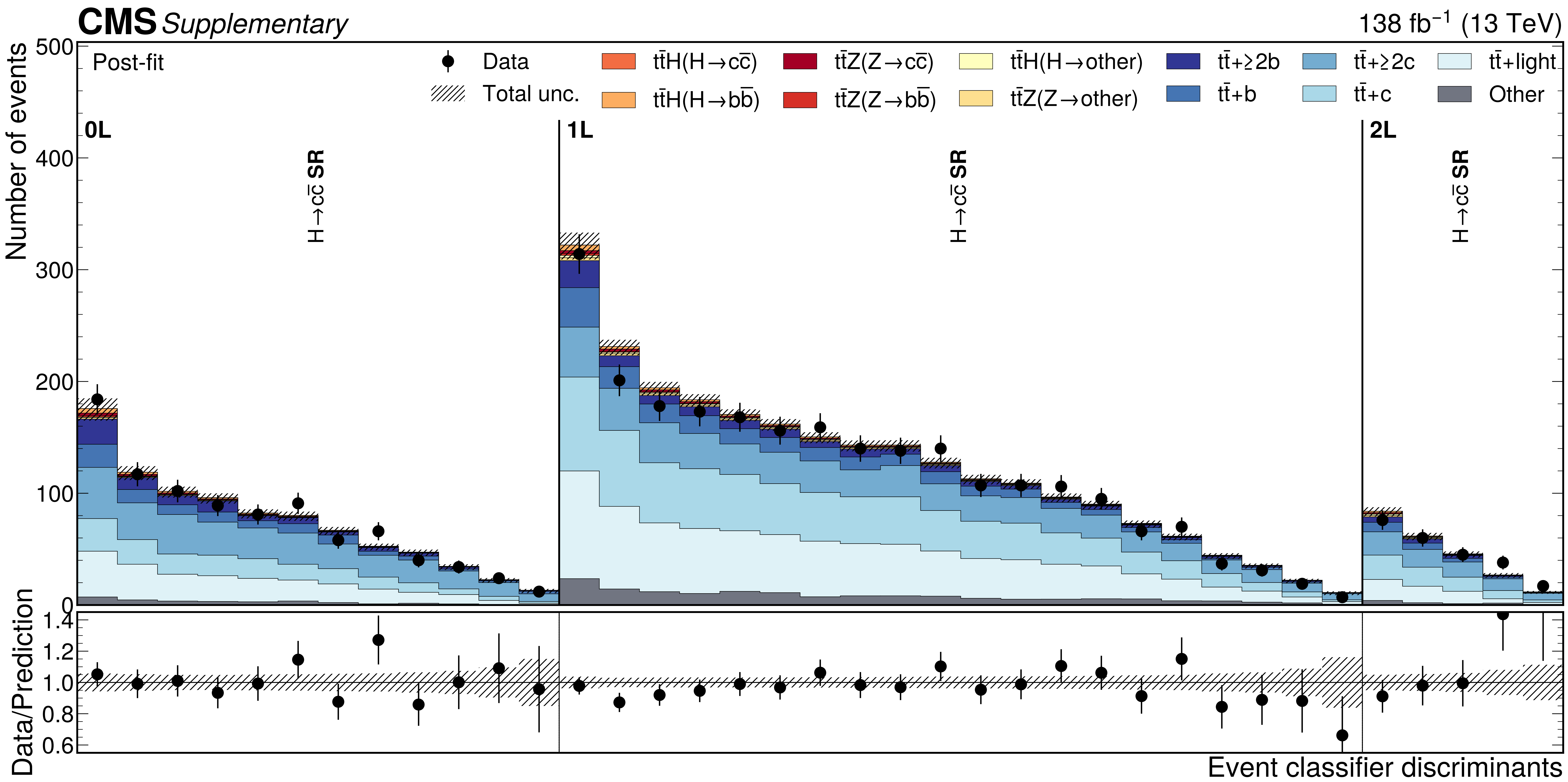
Objects and event selection

Selection criteria	0L channel	1L channel	2L channel
Number of leptons	0	1	2
Sign and flavor of leptons	—	$e^{\pm}$, $\mu^{\pm}$	$e^{+}e^{-}$, $\mu^{\pm}e^{\mp}$, $\mu^{+}\mu^{-}$
Min. p_T of p_T-leading electron [GeV]	—	29/30/30	25
Electron identification	—	Tight (80% efficiency)	Loose (90% efficiency)
Electron isolation	—	Tight (80% efficiency)	Loose (90% efficiency)
Min. p_T of p_T-leading muon [GeV]	—	26/29/26	25
Max. muon relative isolation	—	0.15	0.25
Min. $m_{ee/\mu\mu}$ [GeV]	—	—	20
Range of $m_{ee/\mu\mu}$ [GeV]	—	—	<76, >106
Min. p_T of jets [GeV]	25	25	25
Min. p_T of 6^{th} jet [GeV]	40	—	—
Max. $\|\eta\|$ of jets	2.4	2.4	2.4
Min. number of jets	7	5	4
Min. number of b-tagged jets	1	1	1
Min. number of HF (b- or c-tagged) jets	3	3	3
Min. H_T [GeV]	500	—	—
Min. p_T^{miss} [GeV]	—	20	20

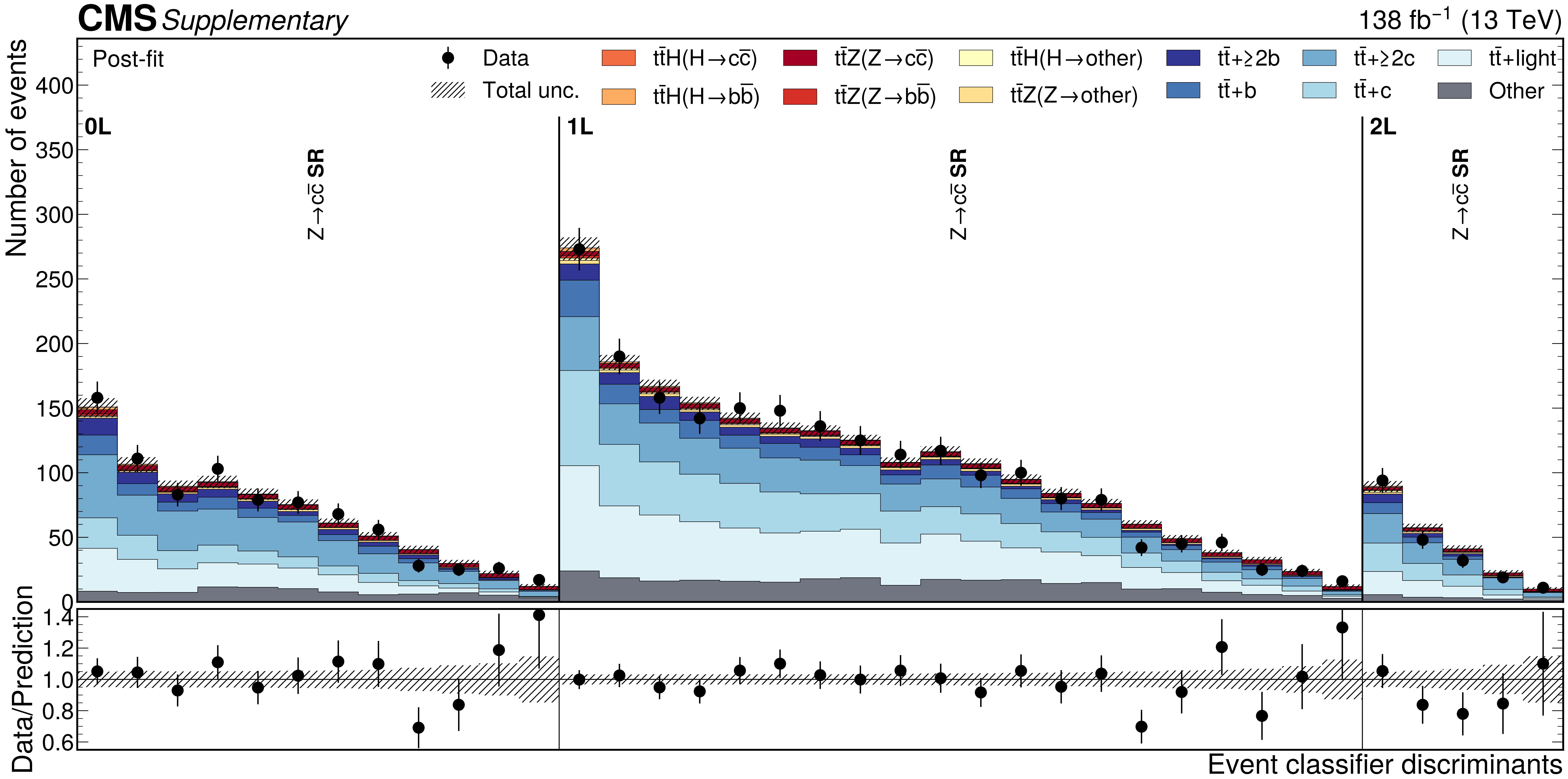
More post-fit plots



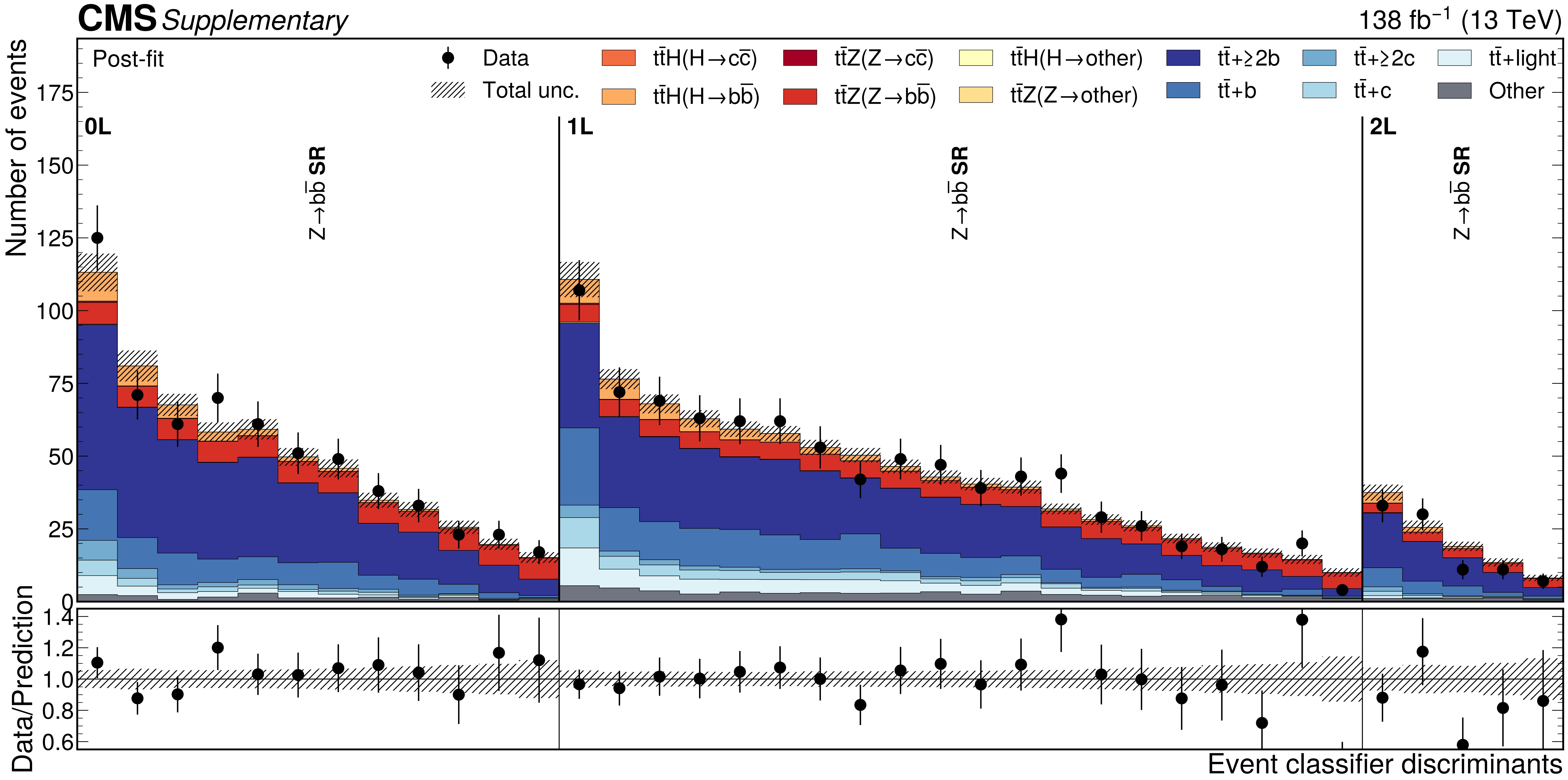
More post-fit plots



More post-fit plots



More post-fit plots



Additional robustness checks

- Background normalisation SFs compatible with:
  - Dedicated measurements
  - Previous CMS and ATLAs ttH analyses

Cat.	$t\bar{t}+\geq 2b$	$t\bar{t}+b$	$t\bar{t}+\geq 2c$	$t\bar{t}+c$	$t\bar{t}+\text{light}$
2L/1L	0.88 ± 0.07	0.92 ± 0.16	1.39 ± 0.23	1.41 ± 0.36	0.89 ± 0.11
0L	1.12 ± 0.11	0.89 ± 0.18	2.03 ± 0.41	0.95 ± 0.34	0.89 ± 0.17

$t\bar{t}+\geq 1b$ bkg. model	$\mu_{t\bar{t}H(H\to c\bar{c})}$	(95% CL)	$\mu_{t\bar{t}H(H\to b\bar{b})}$	(Sign. [s.d.])
Default	-1.6 ± 4.5	(<7.8)	$0.91^{+0.26}_{-0.22}$	(4.4)
Simple PS	-0.4 ± 4.4	(<8.8)	$0.91^{+0.27}_{-0.22}$	(4.4)
$\mu_F \times 2$	$-1.7^{+4.2}_{-4.3}$	(<8.0)	$0.94^{+0.26}_{-0.23}$	(4.4)
$\mu_F \times 2$ & Simple PS	-1.0 ± 4.4	(<8.5)	$0.97^{+0.28}_{-0.23}$	(4.5)
5FS	-1.8 ± 4.3	(<7.7)	$0.97^{+0.24}_{-0.20}$	(5.7)
5FS & Simple PS	-0.9 ± 4.5	(<7.6)	$1.02^{+0.26}_{-0.21}$	(6.0)

- Vary the background model and repeat the fit:
  - Default model: 8 independent variations per process:
    - Scale and splitting-kernel variations (x2) Phys. Rev. D 94, 074005 (2016)
    - Each for g→gg, g→qq, q→qg, x→xg (where x = t, b) splittings (x4)
  - Varied factorization scale for tt+bb 4FS (as used in recent ATLAS ttH(bb) measurement)
  - Using only the 5FS tt+jets simulation

→ **Results robust wrt. all variations!**

$t\bar{t}bb$ in $t\bar{t}H(H \rightarrow b\bar{b})$ over time

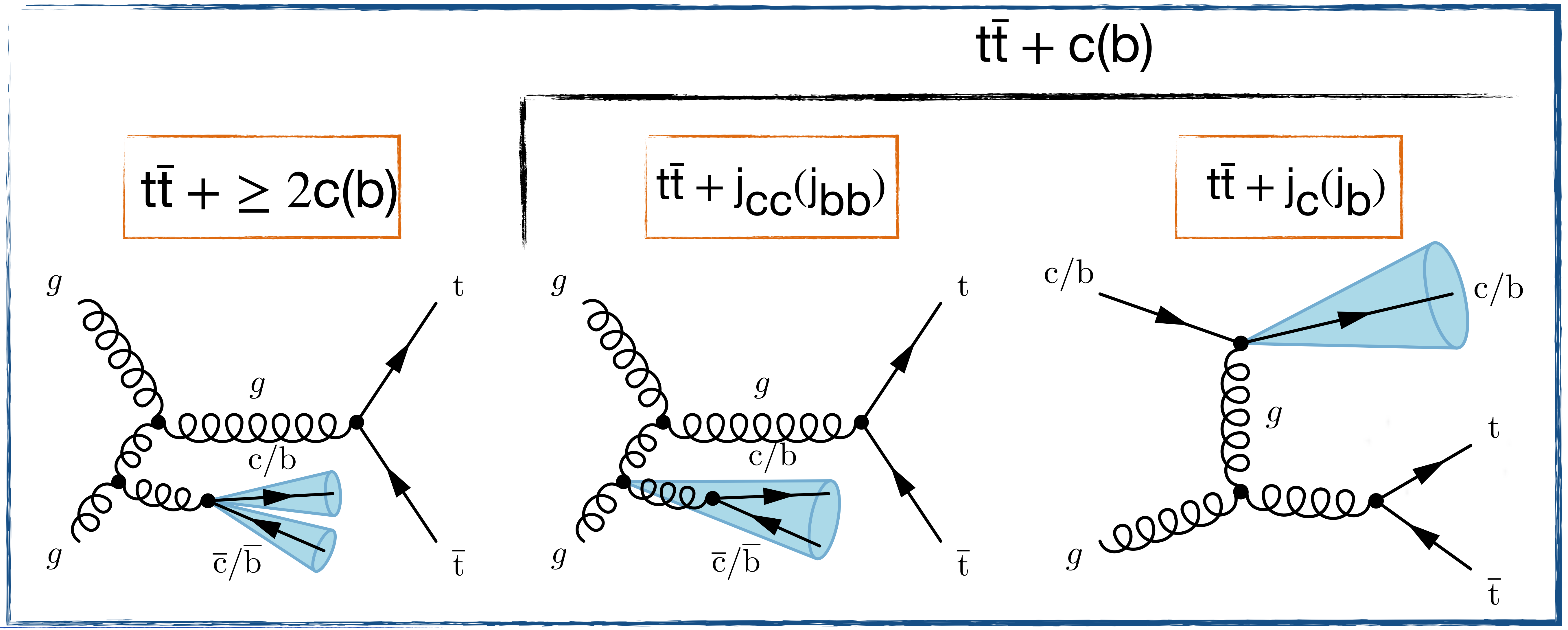
	ATLAS 36 fb^{-1}	ATLAS 139 fb^{-1}	ATLAS 140 fb^{-1}	CMS 36^{-1}+42^{-1}	CMS 138 fb^{-1}	This result
Generator	P+P8 tt 5FS scaled to Sherpa ttbb 4FS	P+P8 ttbb 4FS	P+P8 ttbb 4FS	P+P8 tt 5FS	P+P8 ttbb 4FS	P+P8 ttbb 4FS
μ_F	-	$\frac{1}{2} \cdot \sum m_T$	$\frac{1}{2} \cdot \sum m_T$	-	$\frac{1}{4} \cdot \sum m_T$	$\frac{1}{4} \cdot \sum m_T$
μ_R	-	$\prod m_T$	$\frac{1}{2} \cdot \prod m_T$	-	$\frac{1}{2} \cdot \prod m_T$	$\frac{1}{2} \cdot \prod m_T$
$\mu_{ttH(bb)}$	$0.84^{+0.64}_{-0.61}$	$0.35^{+0.36}_{-0.34}$	$0.81^{+0.22}_{-0.19}$	$1.15^{+0.44}_{-0.40}$	$0.33^{+0.26}_{-0.26}$	$0.91^{+0.26}_{-0.22}$

$$\sum m_T = \sum_{i=t,\bar{t},b\bar{b}} m_{T,i}$$

$$\prod m_T = \sqrt[4]{\prod_{i=t,\bar{t},b\bar{b}} m_{T,i}}$$

Comparison to CMS' 138 fb^{-1} $t\bar{t}H(H \to b\bar{b})$ analysis

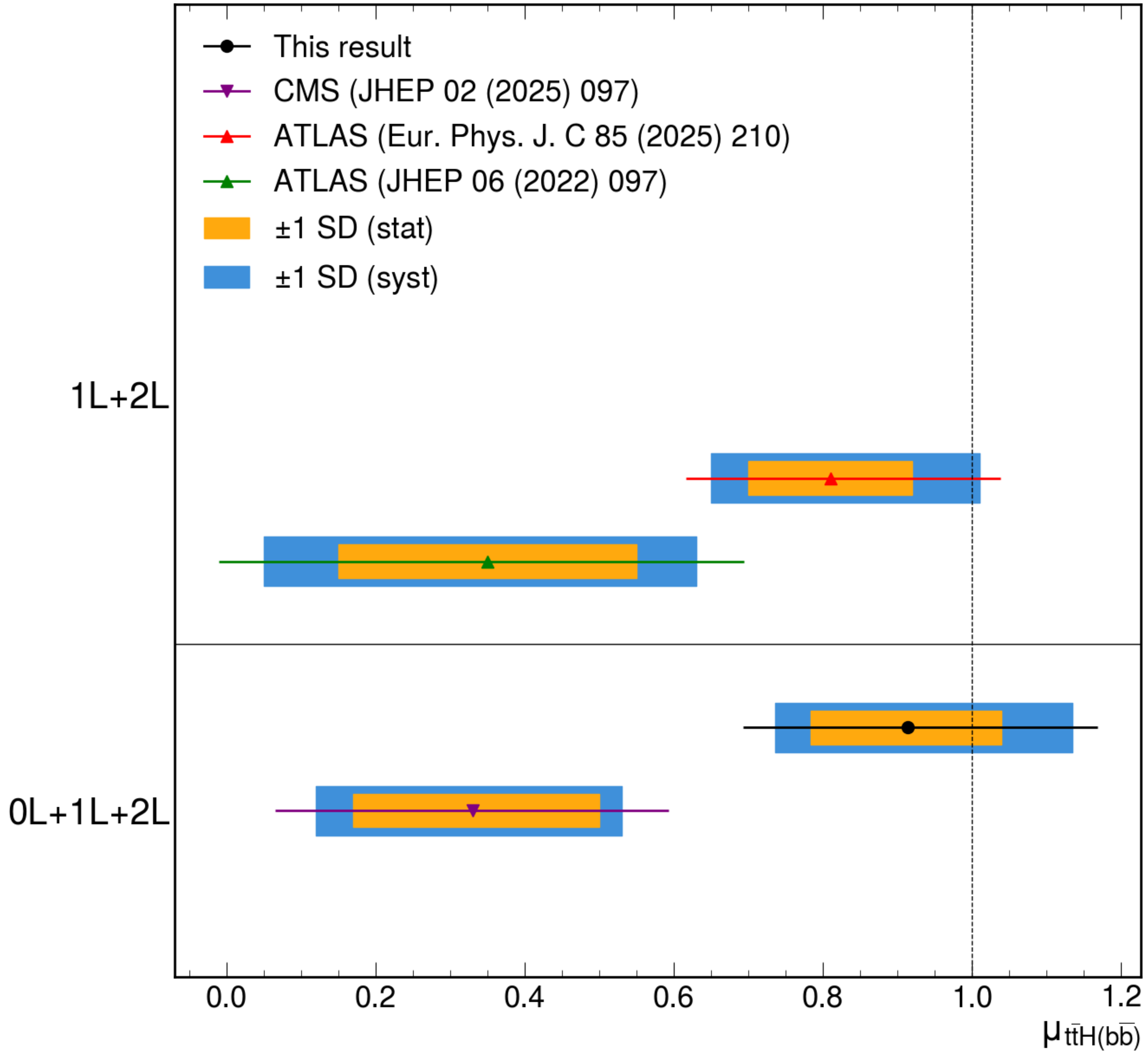
- CMS Full Run 2 ttH(bb) analysis: [JHEP 02 (2025) 097]
  - Split $t\bar{t}bb$ into:
    - $t\bar{t}+j_{bb}$ / $t\bar{t}+j_b$ + $t\bar{t}+\geq 2b$ / $t\bar{t}cc$ / $t\bar{t}$ + light
  - Categories / network scores for:
    - In 1L: $t\bar{t}+j_{bb}$ / $t\bar{t}+j_b$ + $t\bar{t}+\geq 2b$ / $t\bar{t}cc$ / $t\bar{t}$ + light
    - In 2L: $t\bar{t}bb$ / $t\bar{t}cc$ / $t\bar{t}$ + light
  - Free normalisation for:
    - $t\bar{t}cc$ / $t\bar{t}bb$



- This analysis:
  - Split $t\bar{t}bb$ into:
    - $t\bar{t}+j_{bb}$ + $t\bar{t}+j_b$ / $t\bar{t}+\geq 2b$ / $t\bar{t}+j_{cc}$ + $t\bar{t}+j_c$ / $t\bar{t}+\geq 2c$ / $t\bar{t}$ + light
  - Categories / network scores for:
    - $t\bar{t}+j_{bb}$ + $t\bar{t}+j_b$ / $t\bar{t}+\geq 2b$ / $t\bar{t}+j_{cc}$ + $t\bar{t}+j_c$ / $t\bar{t}+\geq 2c$ / $t\bar{t}$ + light
  - Free normalisation for:
    - $t\bar{t}+j_{bb}$ + $t\bar{t}+j_b$ / $t\bar{t}+\geq 2b$ / $t\bar{t}+j_{cc}$ + $t\bar{t}+j_c$ / $t\bar{t}+\geq 2c$ / $t\bar{t}$ + light
  - Granular Parton-Shower uncertainty treatment
  - 4FS vs. 5FS uncertainties
  - Better separation (48% vs. 10% correlation with ttbb)

Comparison to CMS' 138 fb^{-1} $t\bar{t}H(H \rightarrow b\bar{b})$ analysis

- Using *bootstrapping* method:
  resample data events and analyze simultaneously in both analyses to estimate their statistical correlation
  - Statistical correlation of the most sensitive channel is found to be 13%
    - Assuming independent systematic uncertainties, p- value that results are compatible is 10%
      - Very different background model
      - More inclusive event selection
      - Low correlation of the neural network scores
    - For an extreme systematic correlation of 50%, the p-value is found to be 3%

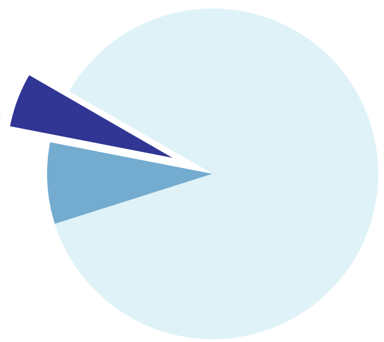


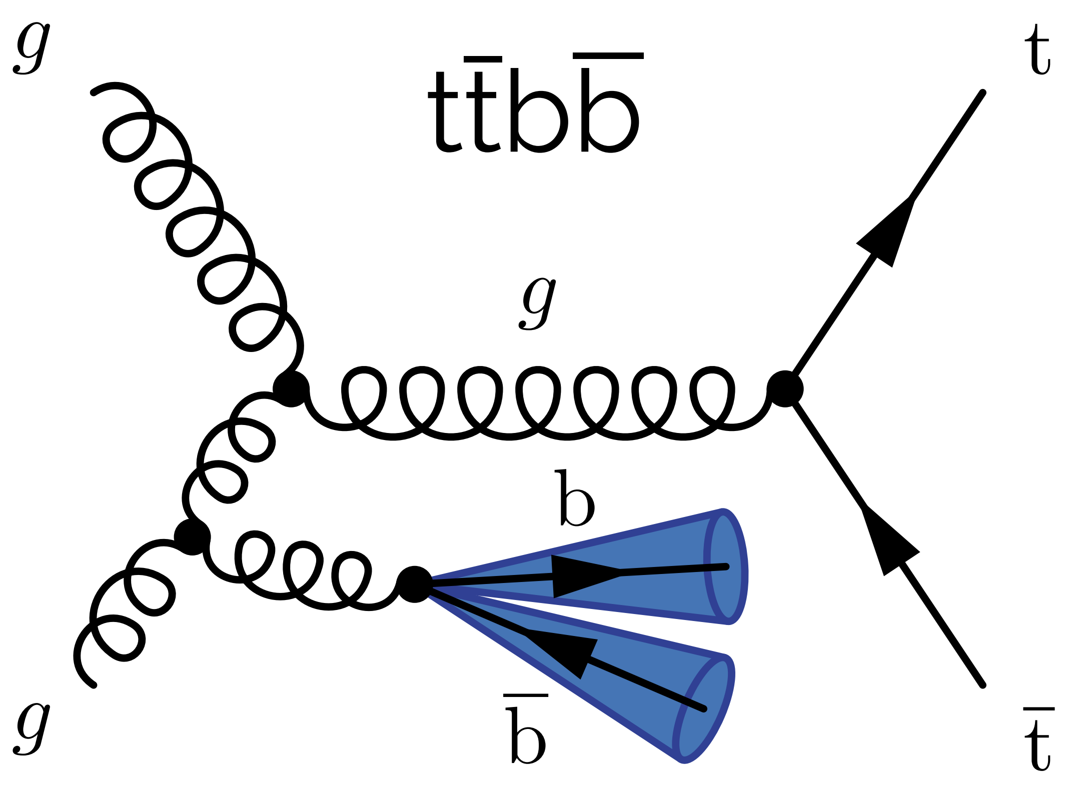
Generator choices for signal and background

Process	Groups	ME order	Generator	Notes
$t\bar{t}H$	$t\bar{t}H(H\to c\bar{c})$, $t\bar{t}H(H\to b\bar{b})$, $t\bar{t}H(H\to \text{Other})$	NLO	POWHEG v2	
$t\bar{t}Z$	$t\bar{t}Z(Z\to c\bar{c})$, $t\bar{t}Z(Z\to b\bar{b})$, $t\bar{t}Z(Z\to \text{Other})$	NLO	MADGRAPH5_aMC@NLO v2.6.1	MADSPIN for heavy particle decays
$t\bar{t}$	$t\bar{t}$+light, $t\bar{t}+\geq 2c$, $t\bar{t}+c$	NLO	POWHEG v2	
$t\bar{t}b\bar{b}$	$t\bar{t}+\geq 2b$, $t\bar{t}+b$	NLO	POWHEG-BOX-RES	
$t\bar{t}b\bar{b}$ DPS	$t\bar{t}+\geq 2b$, $t\bar{t}+b$	NLO / LO	POWHEG v2 / PYTHIA v8.240	$t\bar{t}$ NLO ME with POWHEG/ LO $b\bar{b}$ DPS with PYTHIA

Process	Group	ME order	Generator	Notes
tW			POWHEG v2	
t channel	single t	NLO	POWHEG v2	MADSPIN for heavy particle decays
s channel			MADGRAPH5_aMC@NLO v2.6.1	
$t\bar{t}W$	$t\bar{t}W$	NLO	MADGRAPH5_aMC@NLO v2.6.1	FxFx merging up to 1 additional jet MADSPIN for heavy particle decays
tWZ	tWZ	LO	MADGRAPH5_aMC@NLO v2.6.5	MADSPIN for heavy particle decays
QCD	QCD	LO	MADGRAPH5_aMC@NLO v2.5.1	MLM merging for ME-PS matching

How well do we know the $t\bar{t}$+jets background?

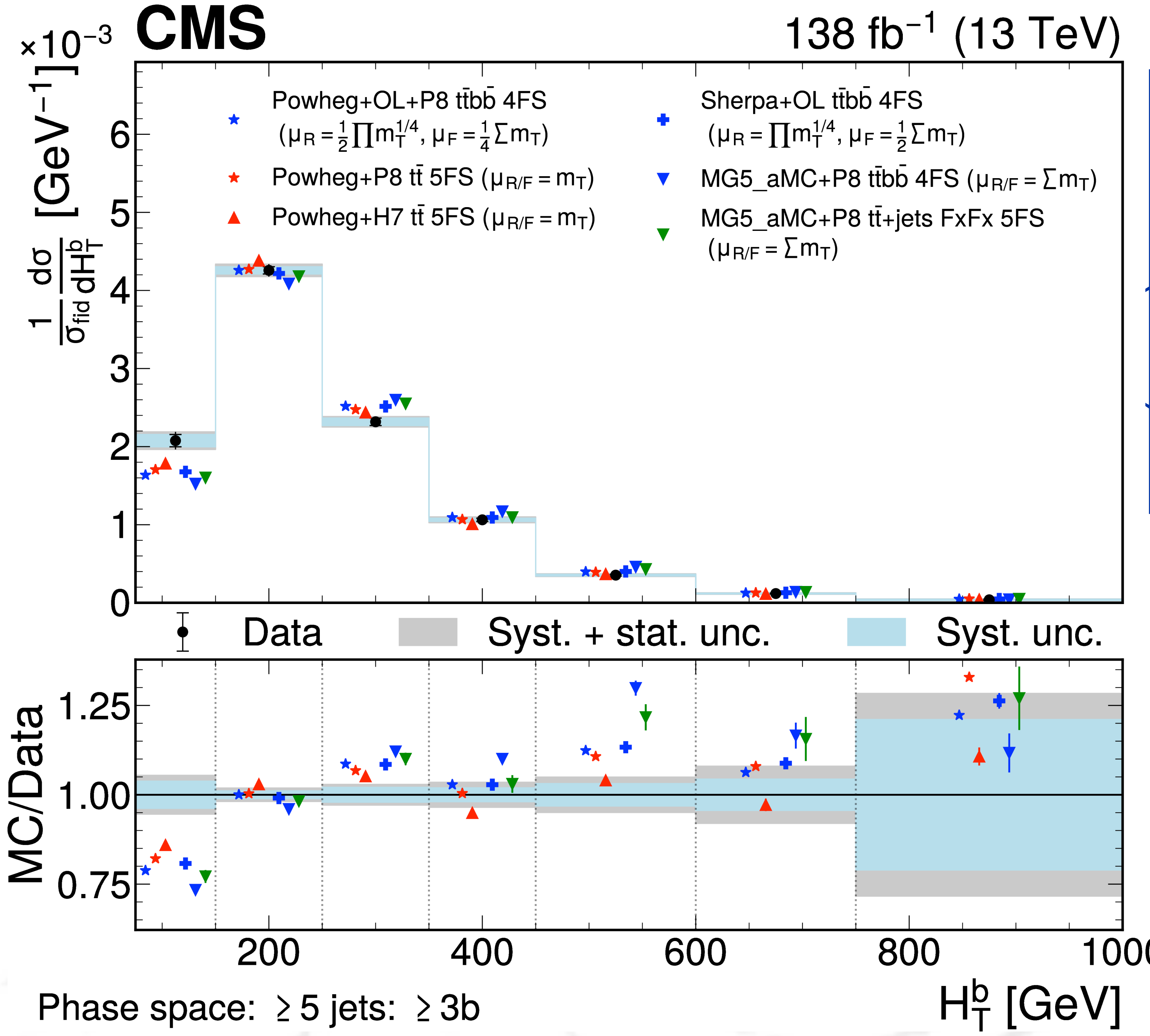




- Inclusive $t\bar{t}$ well described by NLO Powheg+Pythia8 prediction
  - See e.g. multi-differential cross section measurements
- Associated production with heavy-flavour quarks difficult:
  - Theoretical difficulties:
    - Massless or massive b-quarks?

      E.g. 5FS inclusive NLO prediction vs. 4FS dedicated $t\bar{t}b\bar{b}$ simulation
  - Experimental difficulties:
    - What do *we* consider a b-quark jet?
- Rich set of $t\bar{t}b\bar{b}$ measurements:
  - No generator has a good description everywhere
  - 4FS $t\bar{t}b\bar{b}$ simulation close to data inclusively
  - For differential distributions, agreement varies…

Model with enough flexibility needed

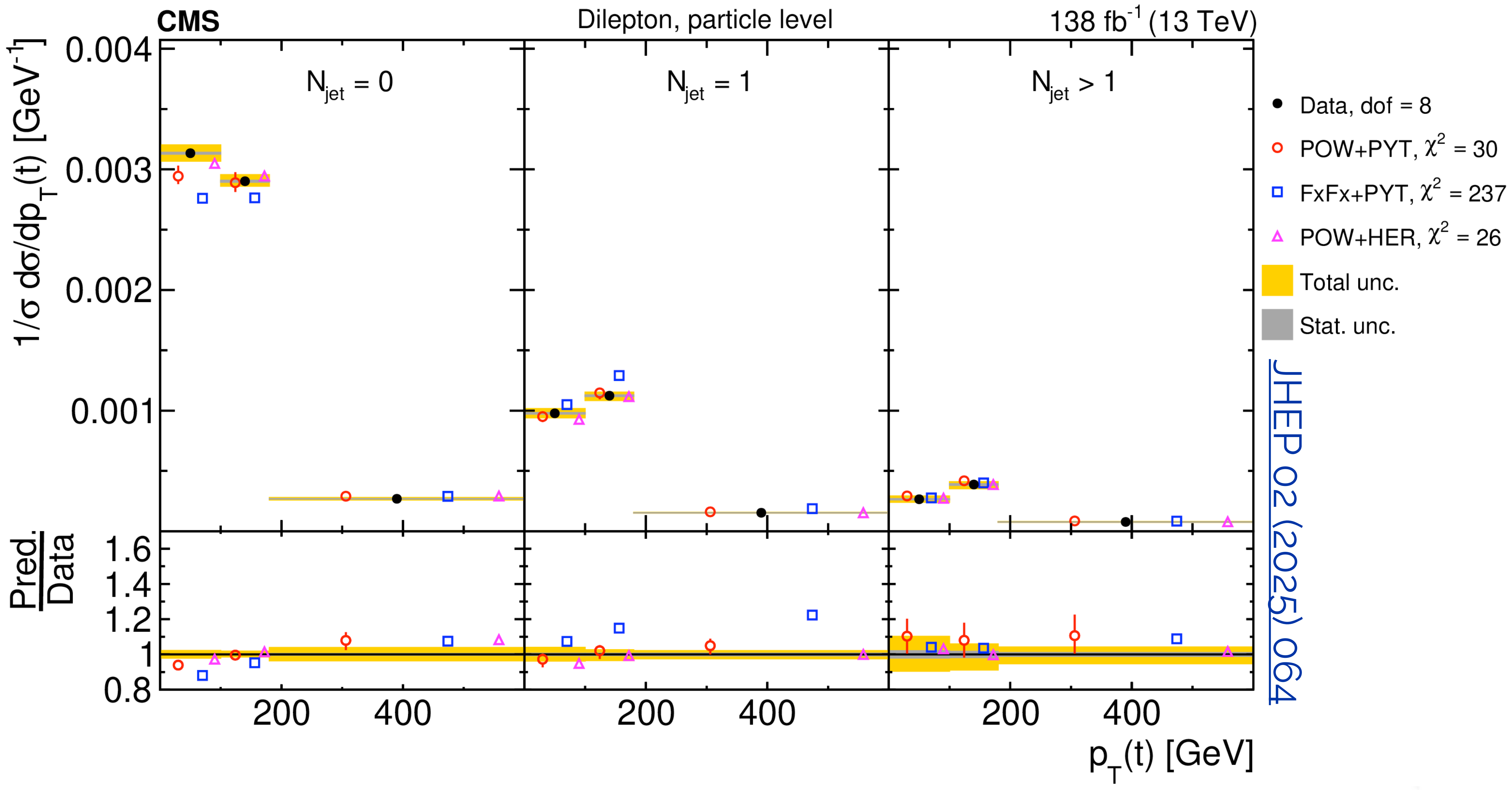


JHEP 05 (2024) 042

How well do we know the tt+jets background?

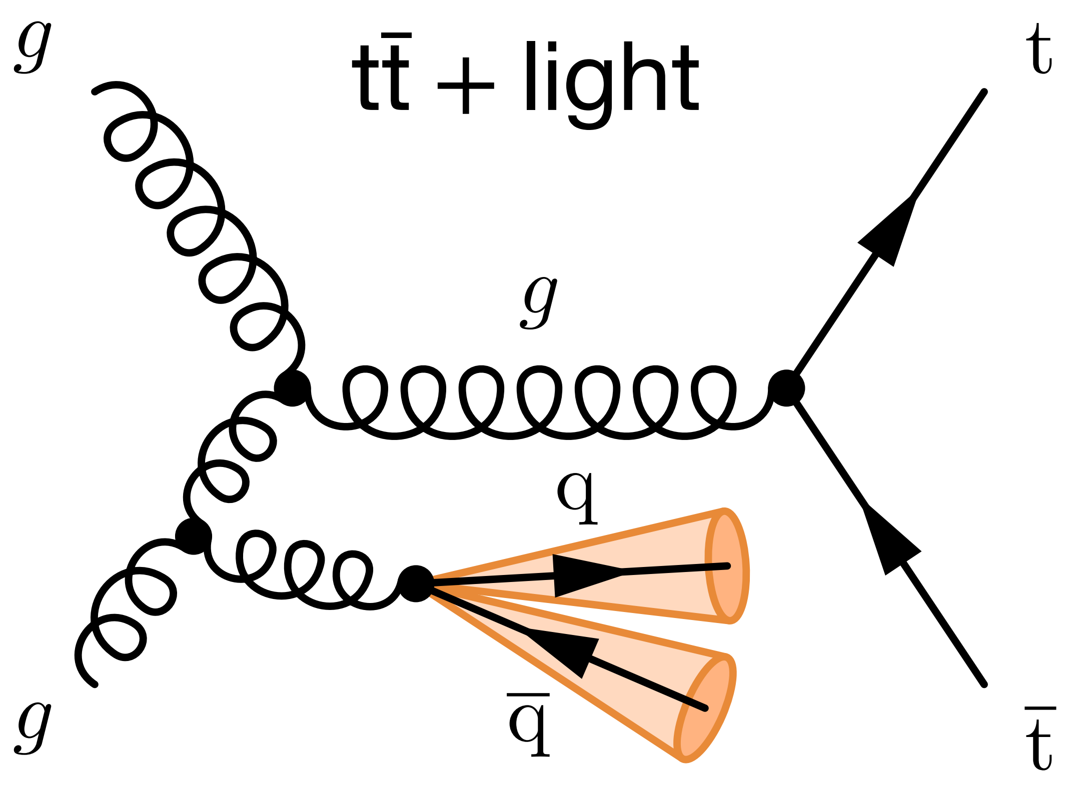
87 %

- For $t\bar{t}$ + light:
  - Extensive set of inclusive and differential measurements
  - Up to 3D in parton & particle level
  - Very good agreement by Powheg+Pythia simulation

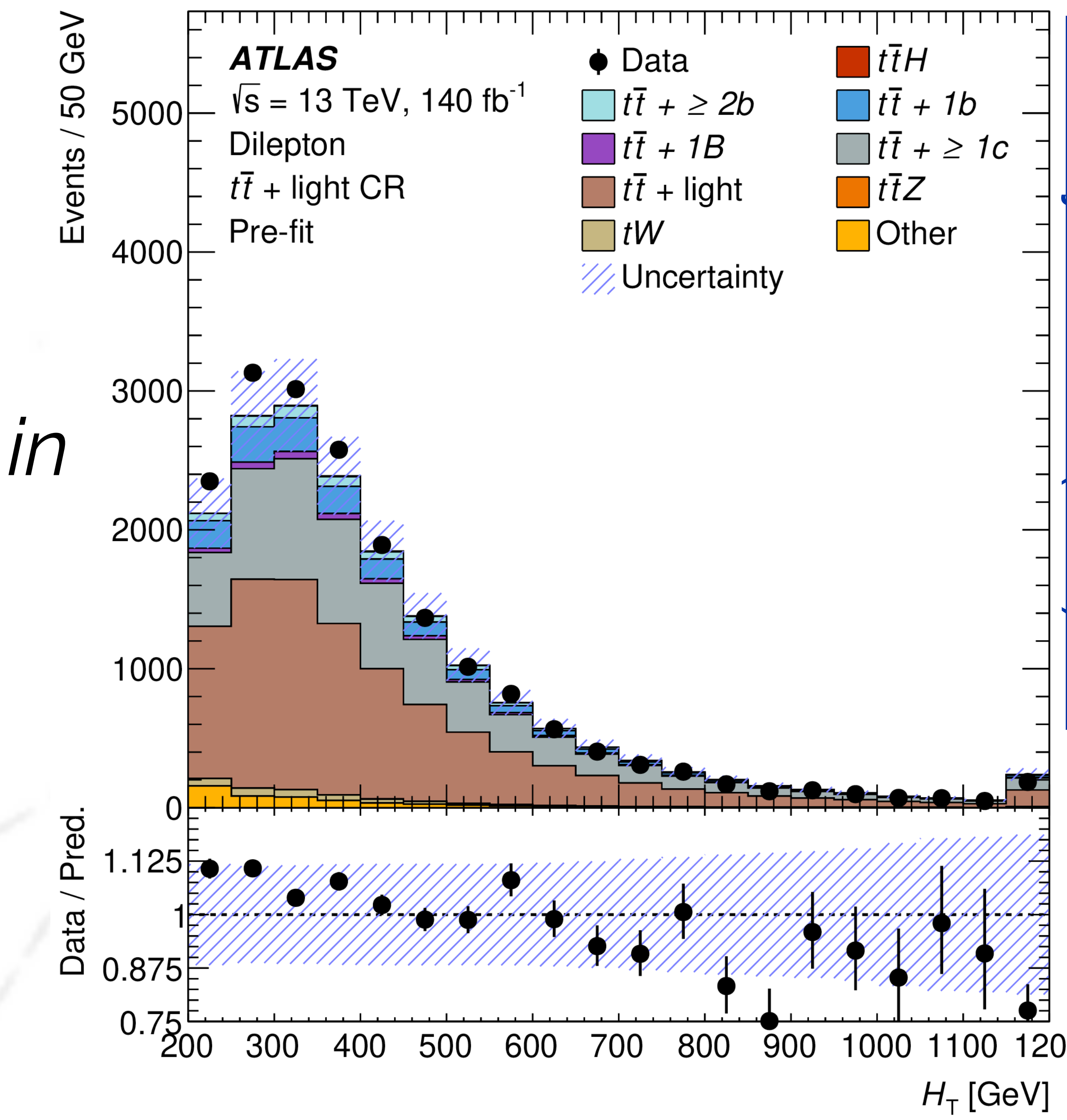


JHEP 02 (2025) 064

Dedicated $t\bar{t}$ measurements



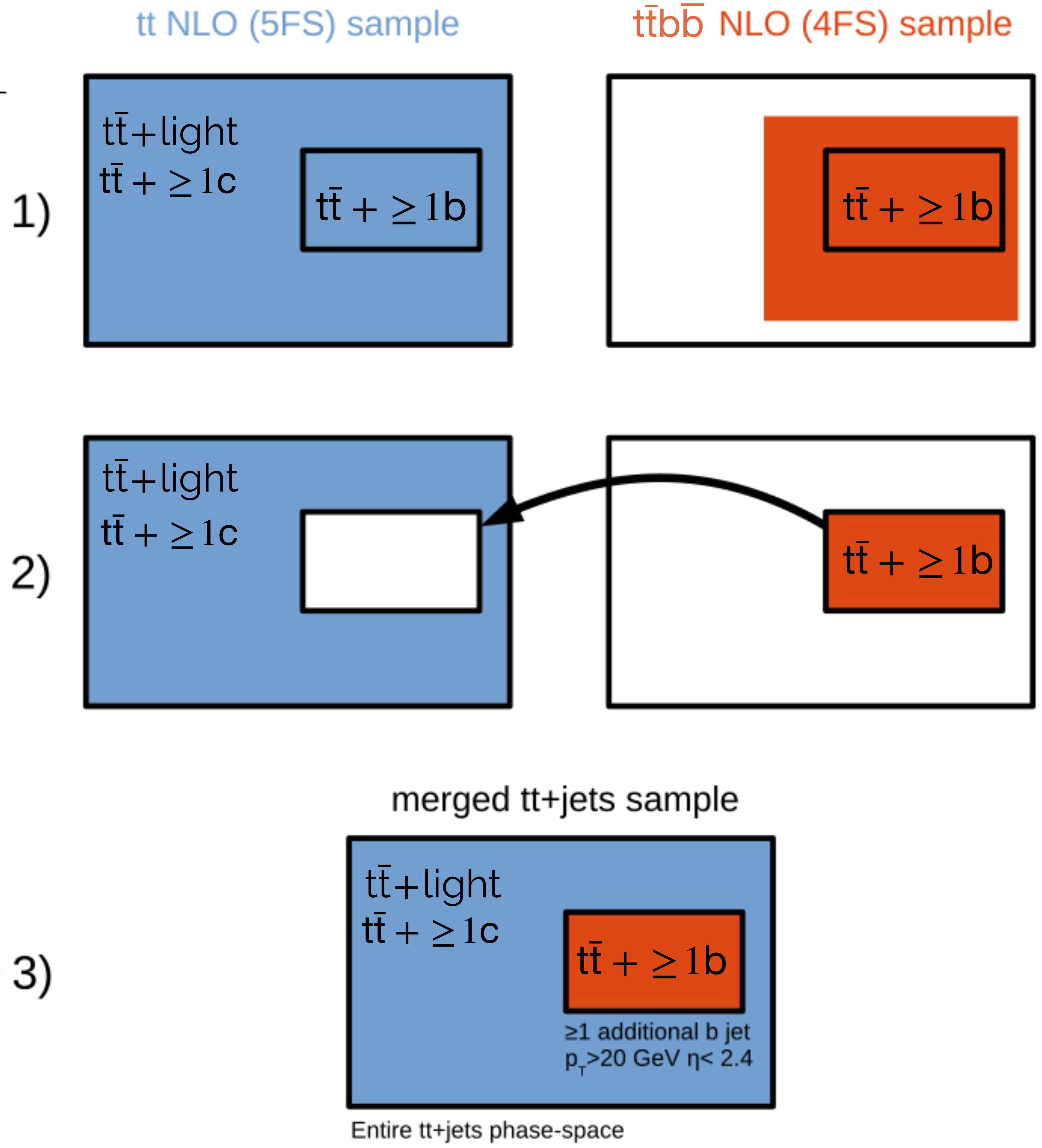
As background in $t\bar{t}H(H \to b\bar{b})$ searches



Eur. Phys. J. C 85 (2025) 210

tt+jets modeling

	$t\bar{t}$ NLO (5FS)	$t\bar{t}b\bar{b}$ NLO (4FS)
ME generator	POWHEG v2	POWHEG-BOX-RES
Parton shower	PYTHIA v8.230	PYTHIA v8.230
Flavor scheme	5FS	4FS
PDF set	NNPDF31_nnlo_hessian_pdfas	NNPDF31_nnlo_as_0118_nf_4
m_t	172.5 GeV	172.5 GeV
m_b	0	4.75 GeV
μ_R	$\sqrt{\frac{1}{2}\left(m^2_{rmT,t} + m^2_{T,\bar{t}}\right)}$	$\frac{1}{2}\sqrt[4]{m_{t,t}\, m_{t,\bar{t}}\, m_{t,b}\, m_{t,\bar{b}}}$
μ_F	μ_R	$\frac{1}{4}\left[m_{t,t} + m_{t,\bar{t}} + m_{t,b} + m_{t,\bar{b}} + m_{t,g}\right]$
h_{damp}	$1.379 m_t$	$1.379 m_t$
Tune	CP5	CP5

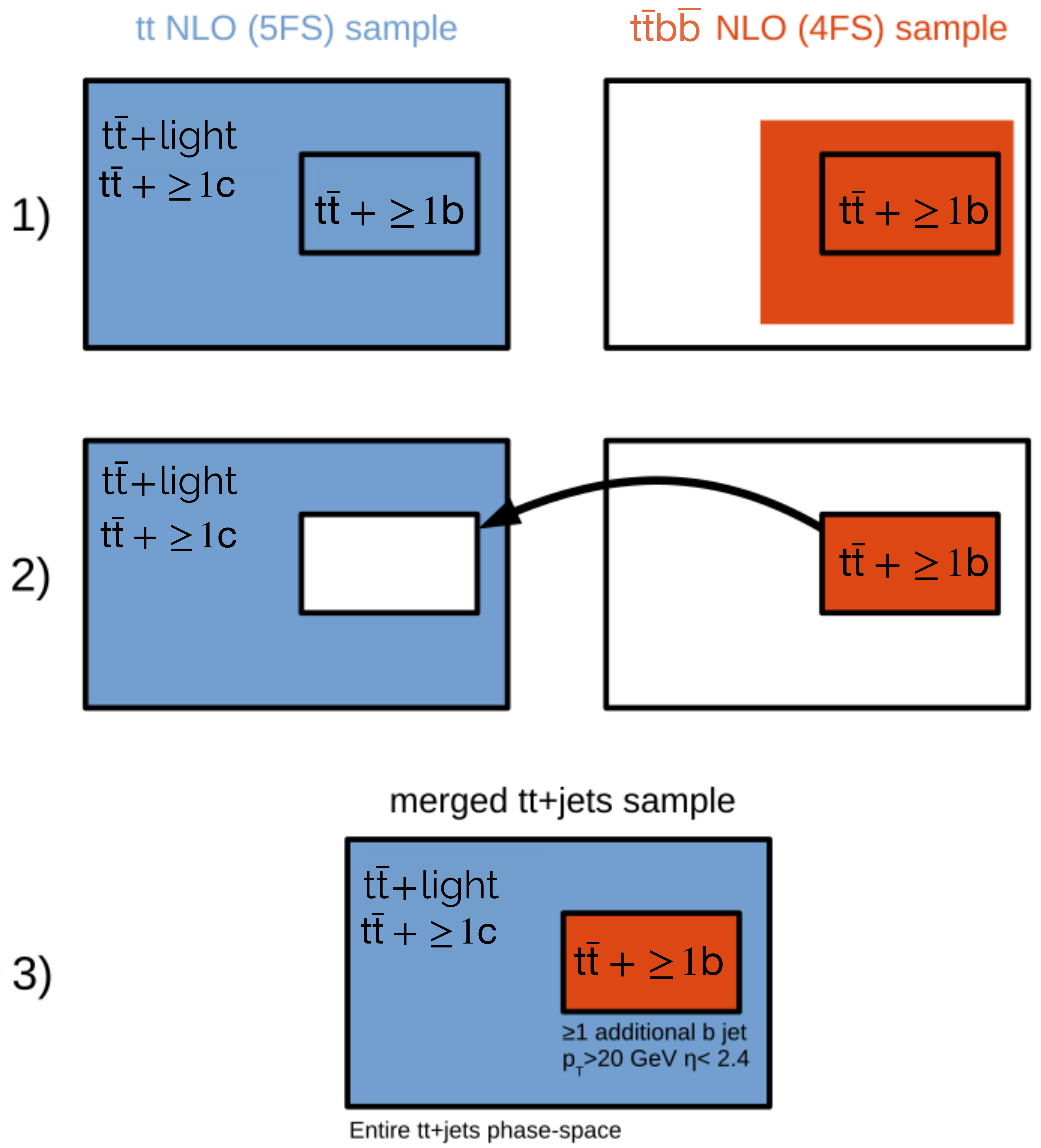


- State-of-the-art $t\bar{t}b\bar{b}$ background model:
  - Same procedure as in ATLAS measurement [1] (except for $\mu_F/2$)
- Replace PS-based emissions in inclusive 5FS $t\bar{t}$+jets with dedicated ME $t\bar{t}b\bar{b}$ 4FS simulation
- Consider 4FS cross section prediction (43.76 pb)

tt+jets modeling (DPS contribution)

- With stitching procedure, we remove also contributions from MPI
  - $t\bar{t}$ hard scatter + $b\bar{b}$ add. scatter removed from $t\bar{t}$ 5FS sample
  - $t\bar{t}b\bar{b}$ 4FS does not include such events
  - → Generate additional $t\bar{t}$ and $b\bar{b}$ DPS samples
    - At LO QCD using Powheg+Pythia
    - Estimated to be ~ 8 pb → ~15% of total $t\bar{t}b\bar{b}$
  - Small compared to ttH

- Discussed in CMS $t\bar{t}b\bar{b}$ measurement JHEP 05 (2024) 042



[1] [Eur.Phys.J.C85(2025)210]

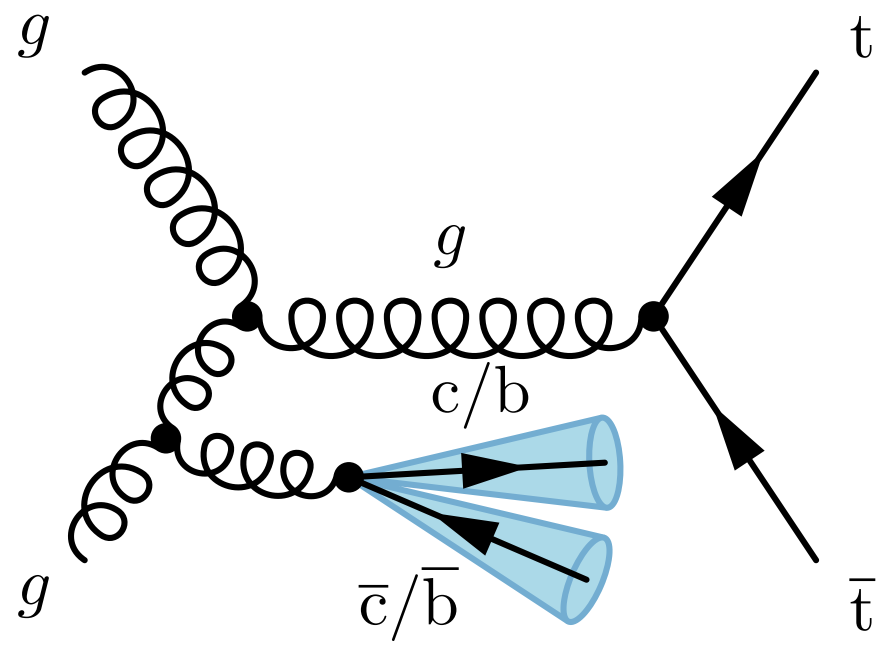
$t\bar{t}$+HF modeling

- Processes distinguished at generator level:
  - $t\bar{t}+\geq 2b$: at least **two** additional b jets, from **one or more b hadrons** each
  - $t\bar{t}+j_b$: exactly **one** additional b jet, from **one b hadron**
  - $t\bar{t}+j_{bb}$: exactly **one** additional b jet, from **two b hadrons**
  - $t\bar{t}+\geq 2c$: at least **two** additional c jets, from **one or more c hadrons** each
  - $t\bar{t}+j_c$: exactly **one** additional c jet, from **one c hadron**
  - $t\bar{t}+j_{cc}$: exactly **one** additional c jet, from **two c hadrons**
  - $t\bar{t}$+light: events **without** any additional c or b jet

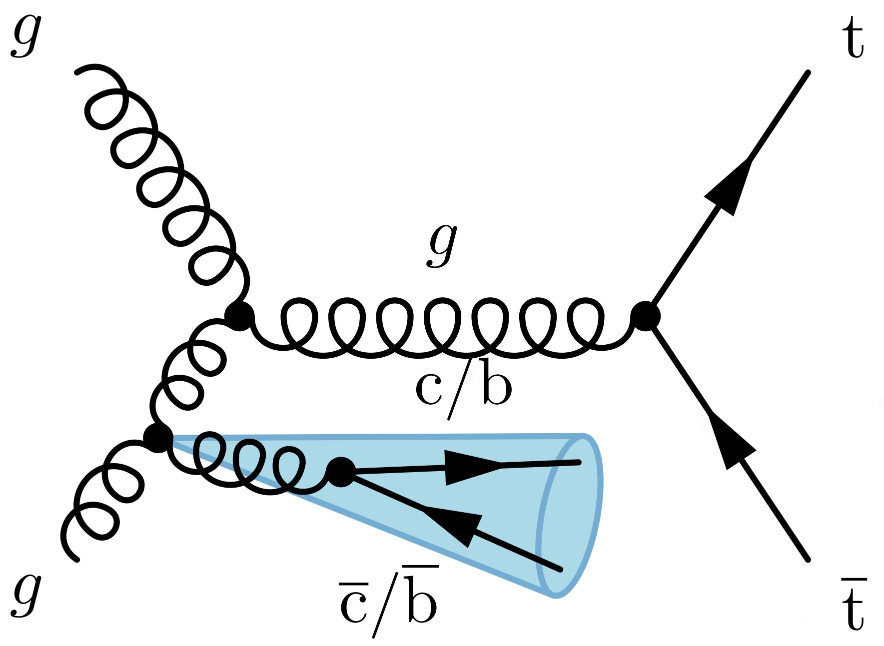
$t\bar{t}+b$ ($t\bar{t}+j_b$, $t\bar{t}+j_{bb}$); $t\bar{t}+\geq 1b$ ($t\bar{t}+\geq 2b$, $t\bar{t}+b$)

$t\bar{t}+c$ ($t\bar{t}+j_c$, $t\bar{t}+j_{cc}$); $t\bar{t}+\geq 1c$ ($t\bar{t}+\geq 2c$, $t\bar{t}+c$)

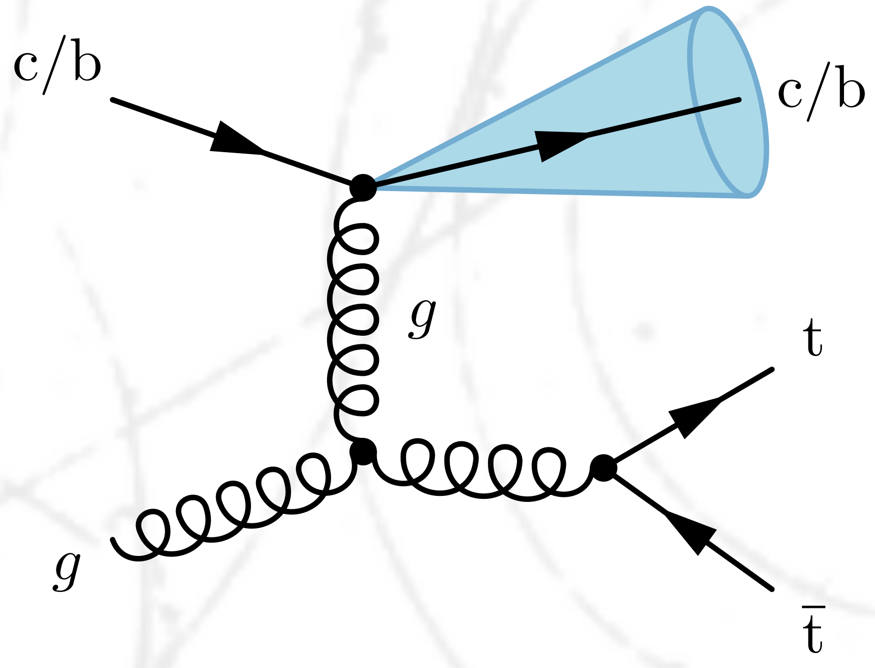
$t\bar{t}+\geq 2c$



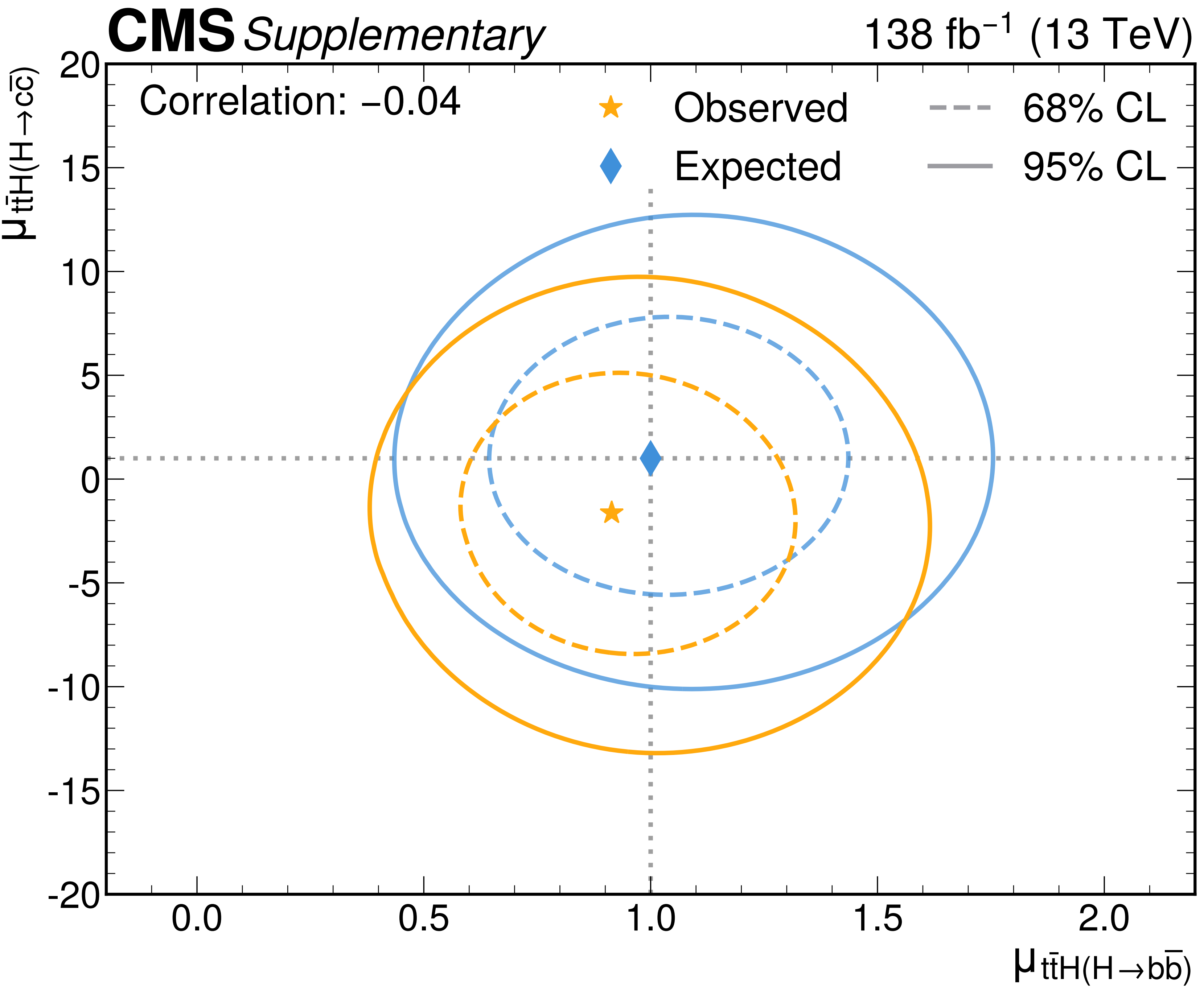
$t\bar{t}+j_{cc}$

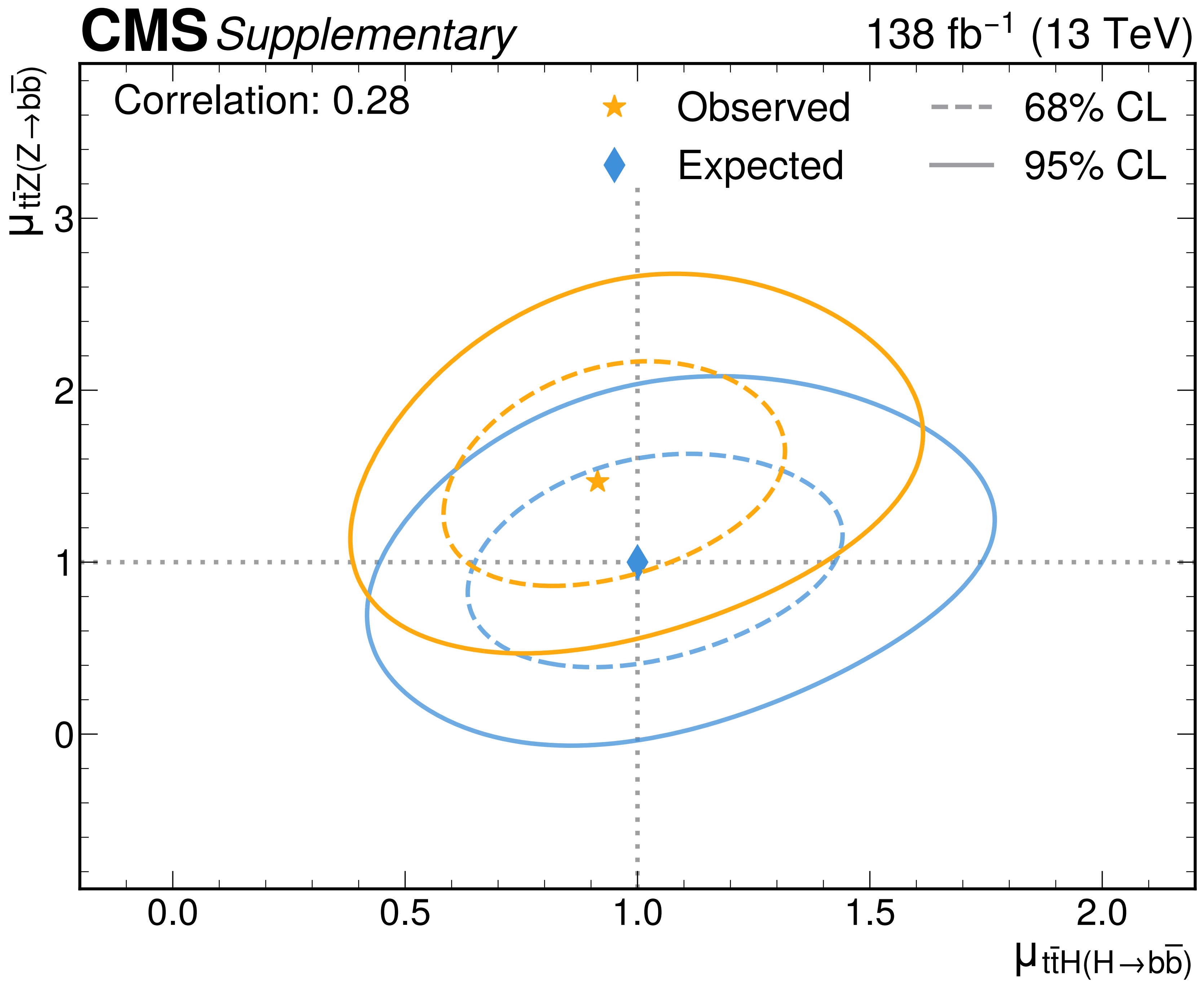


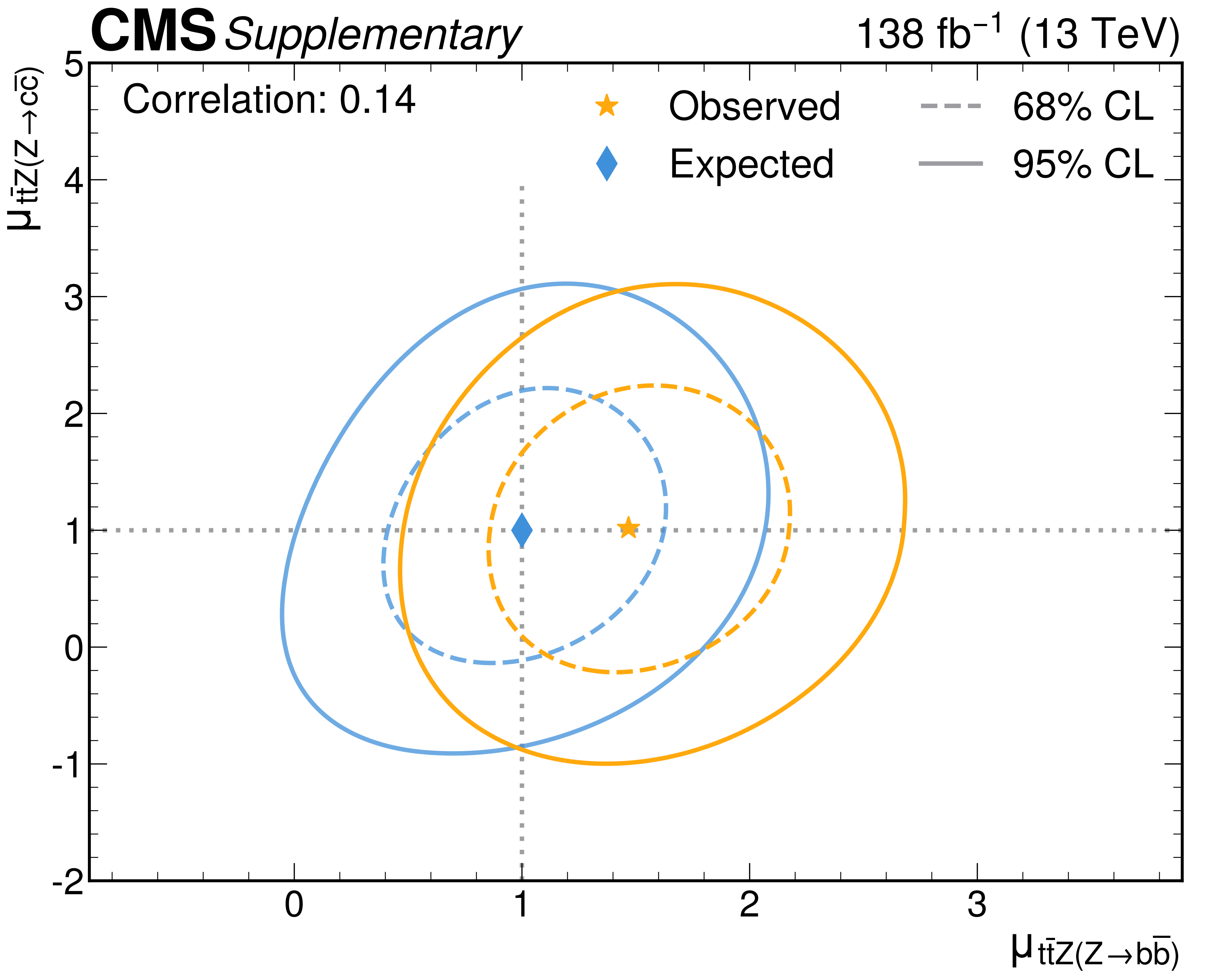
$t\bar{t}+j_c$

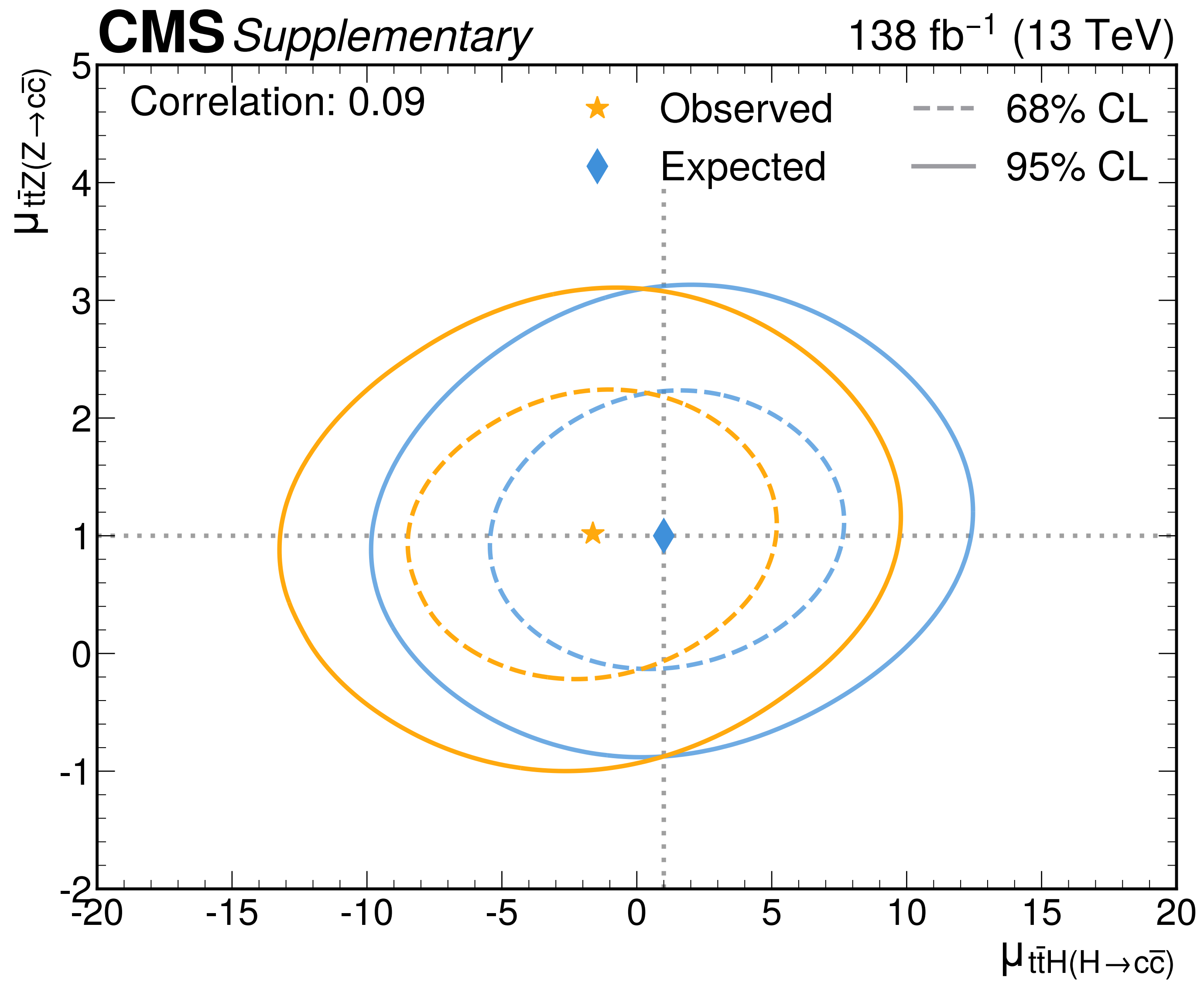


2D correlations - among signal strengths

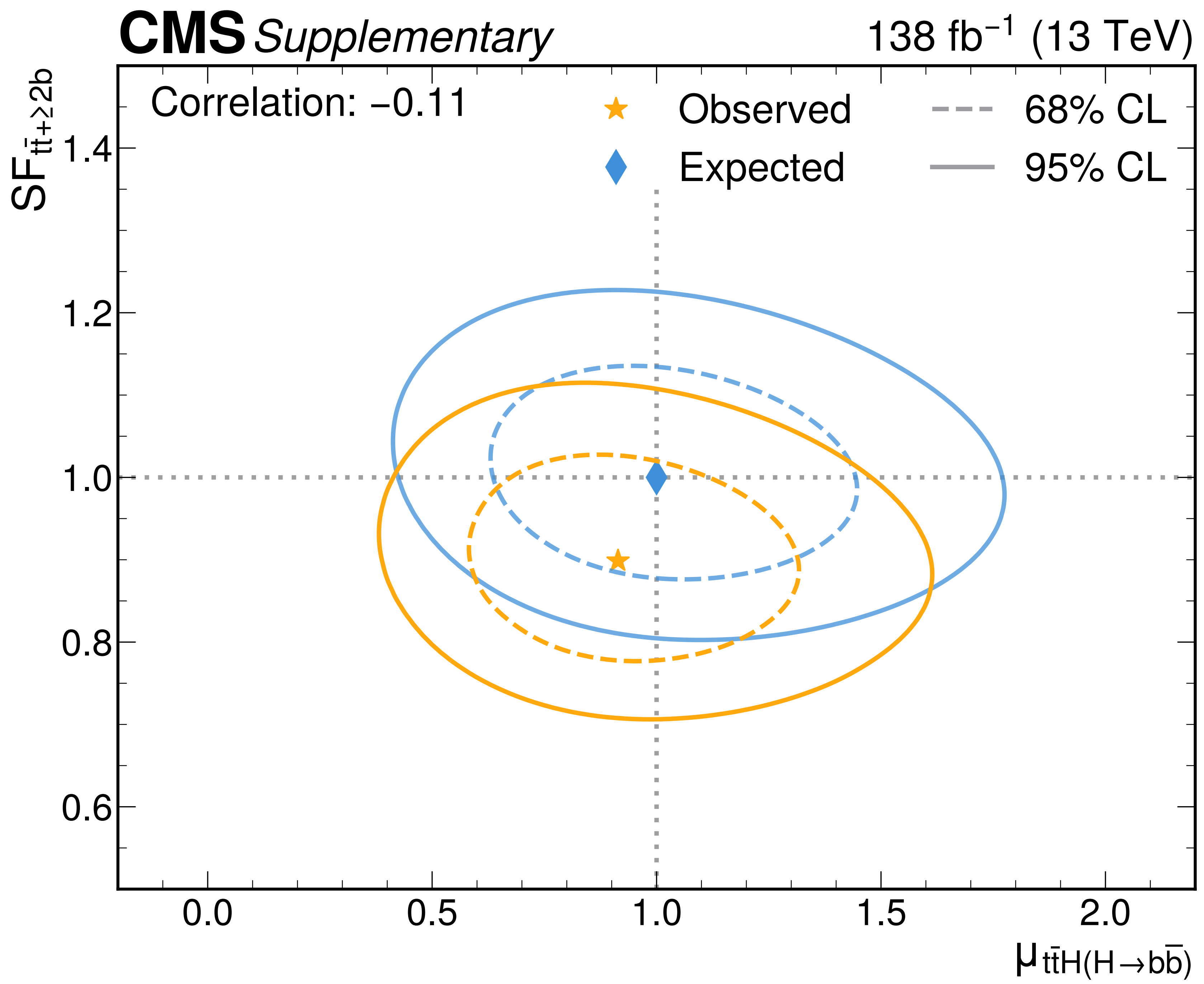


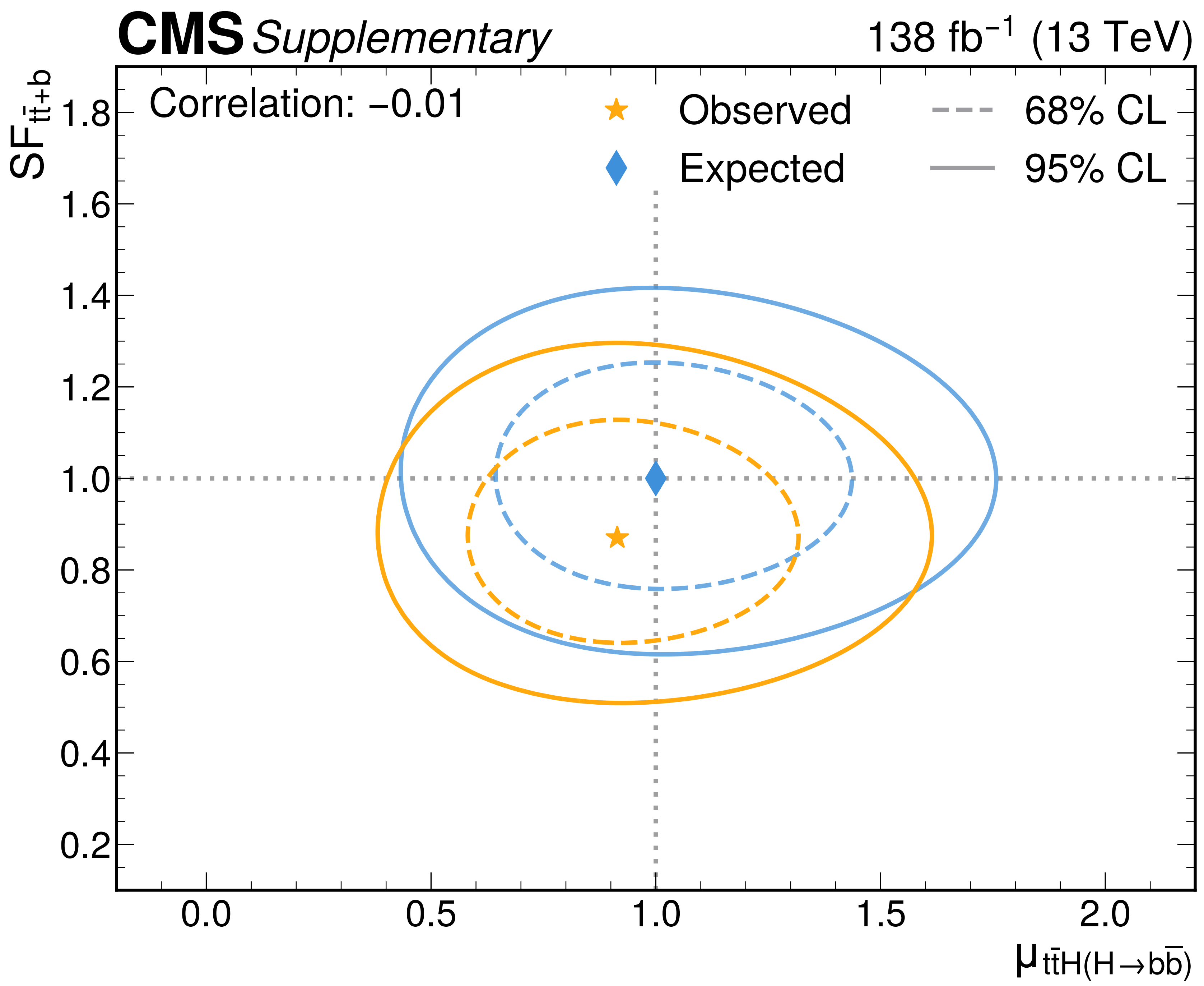




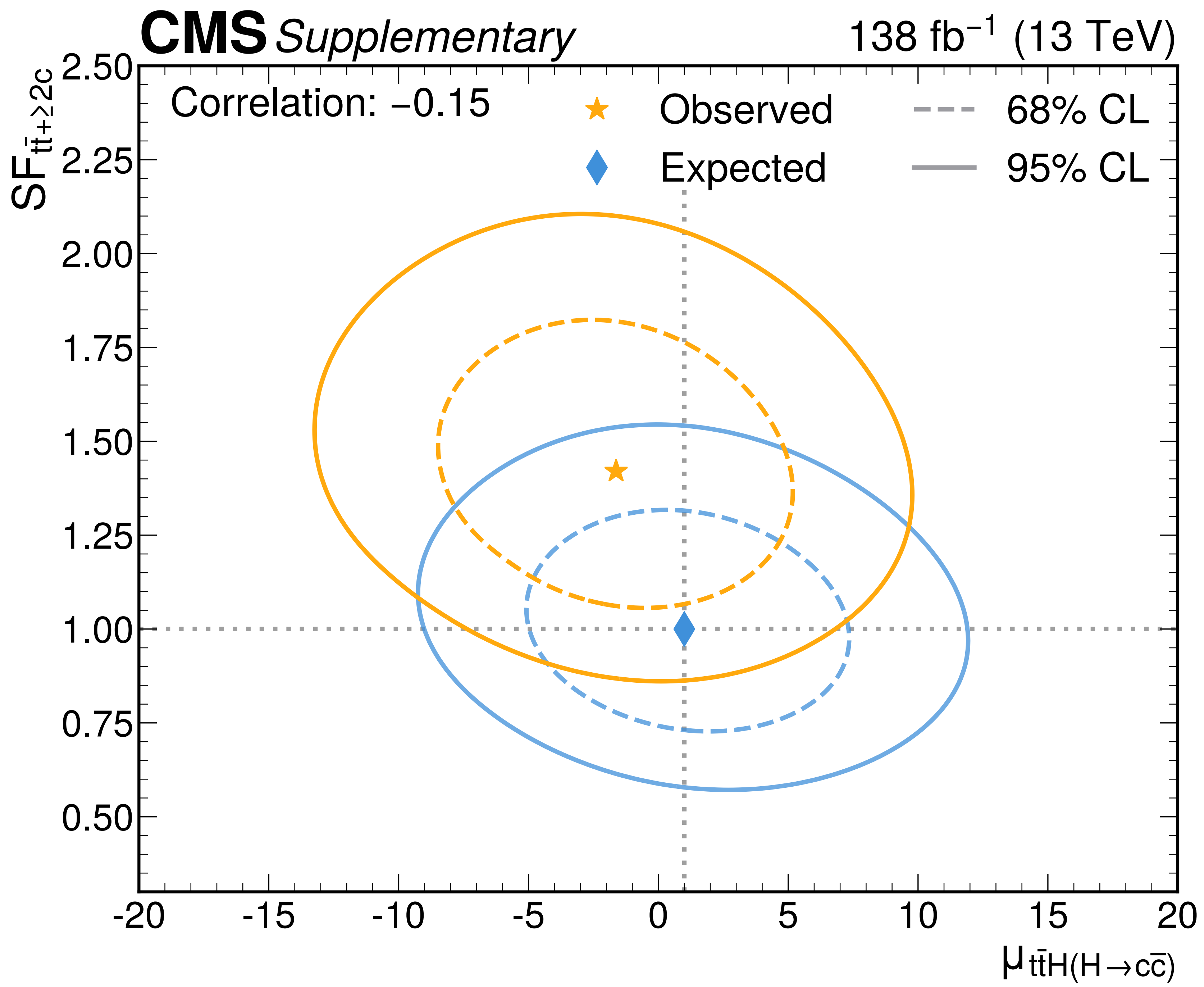


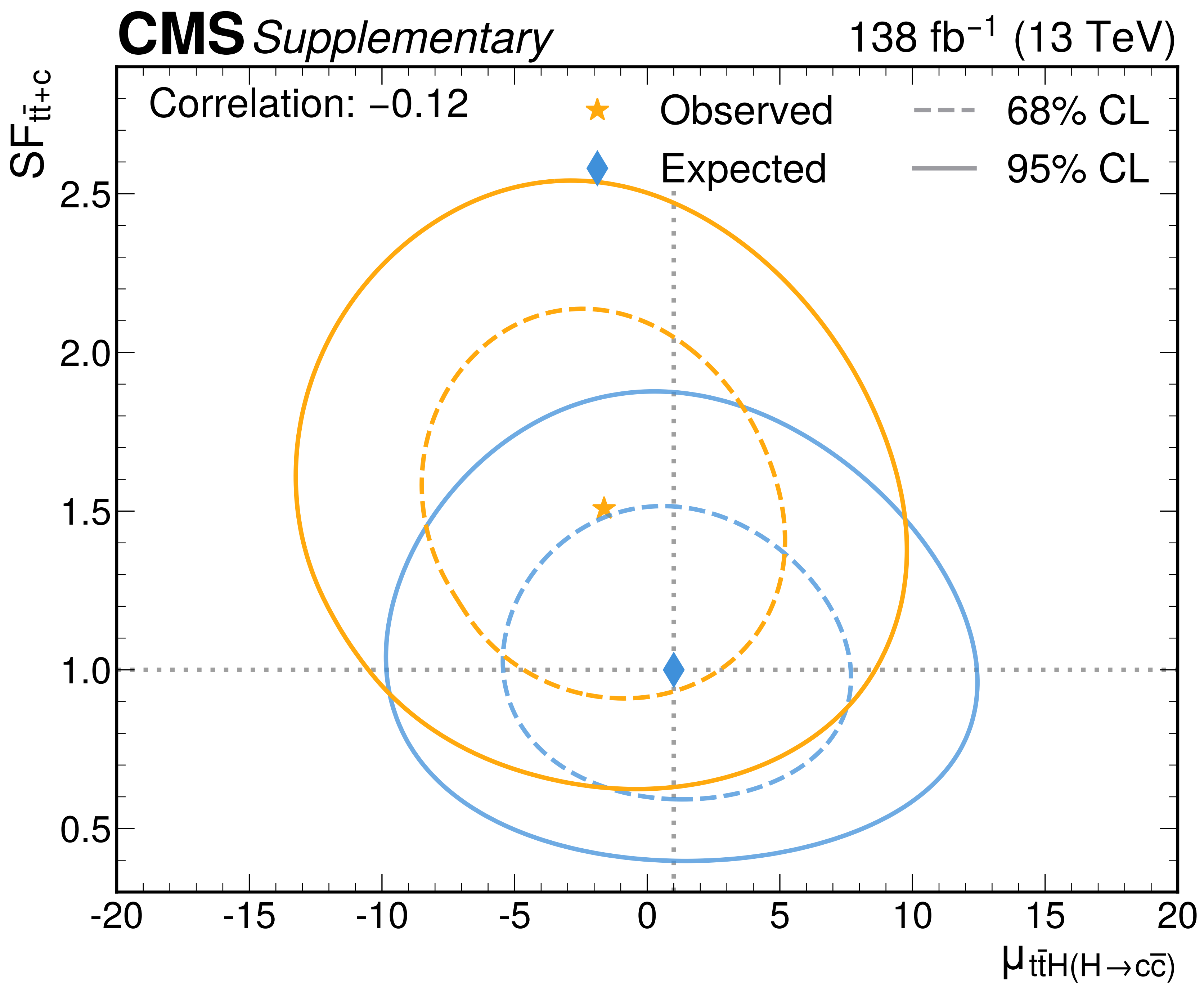
2D correlations - with background SFs



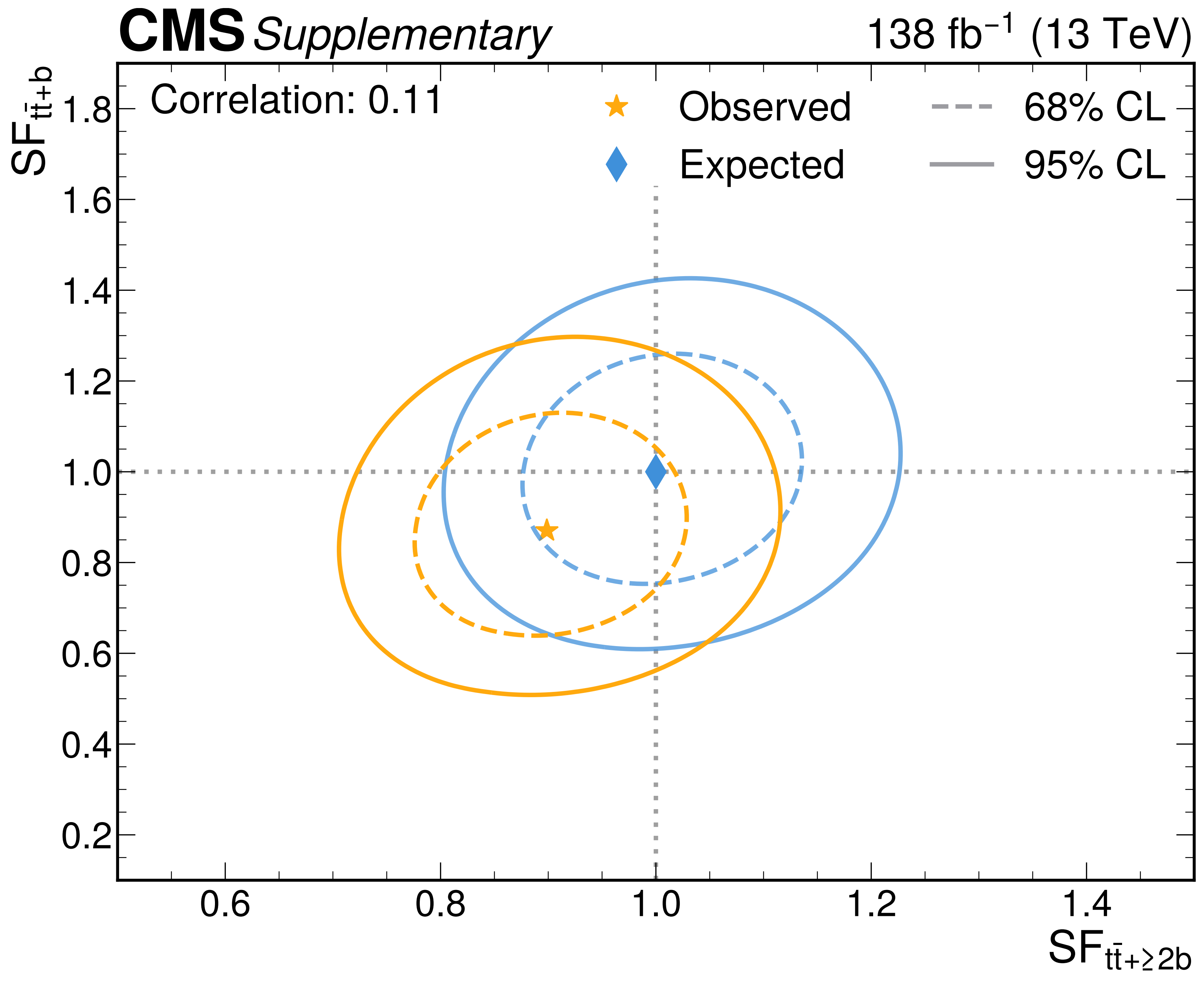


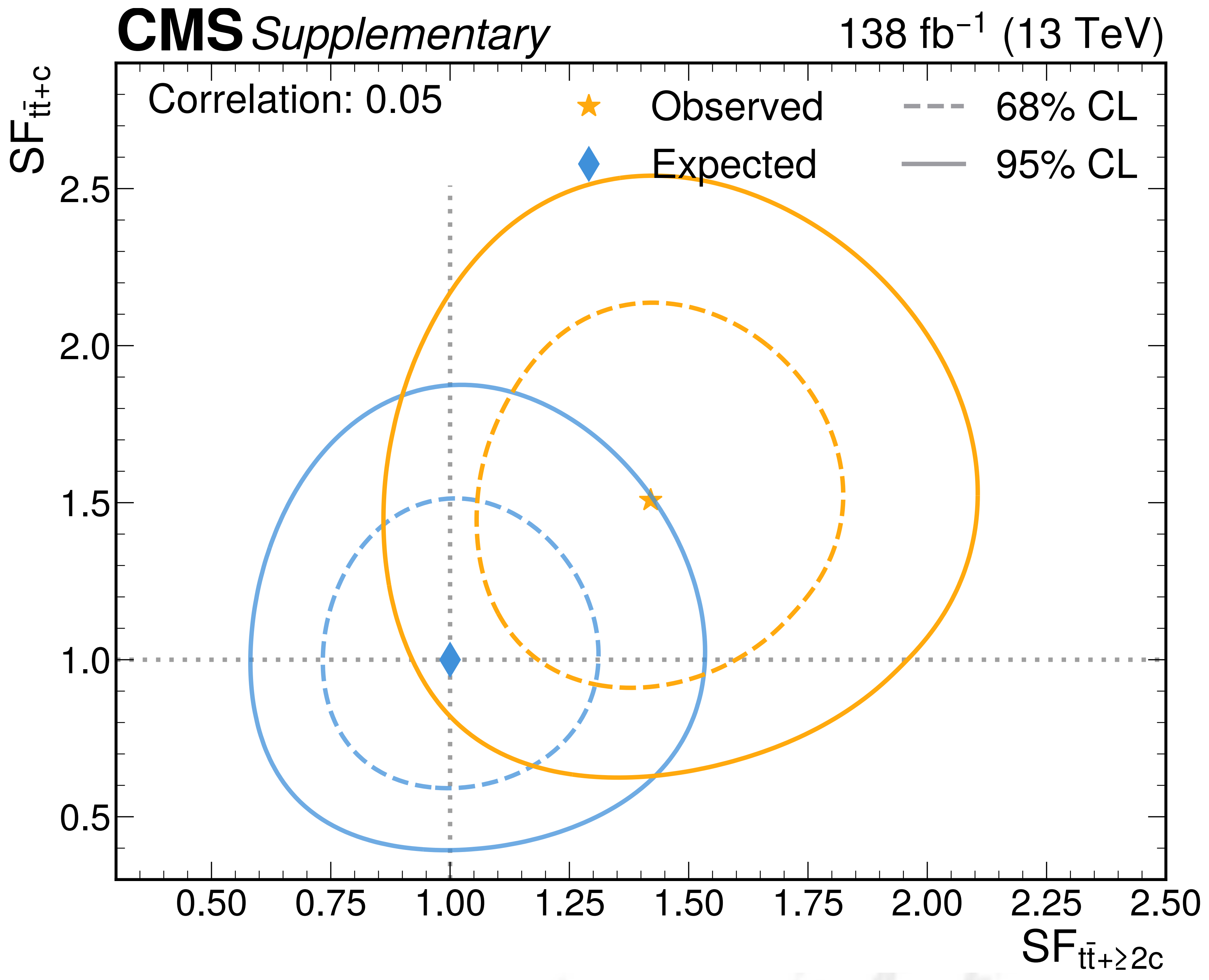
2D correlations - with background SFs



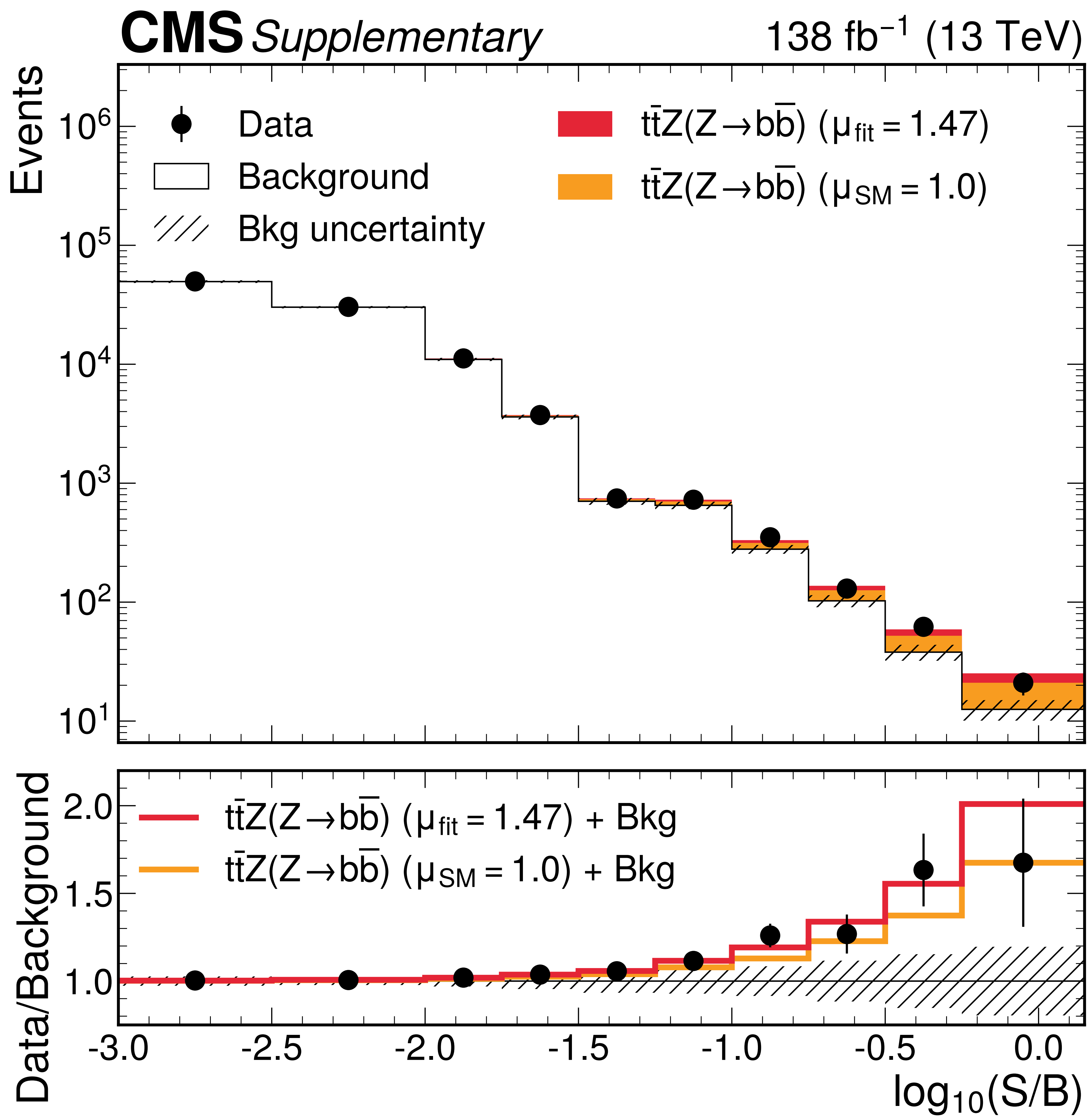


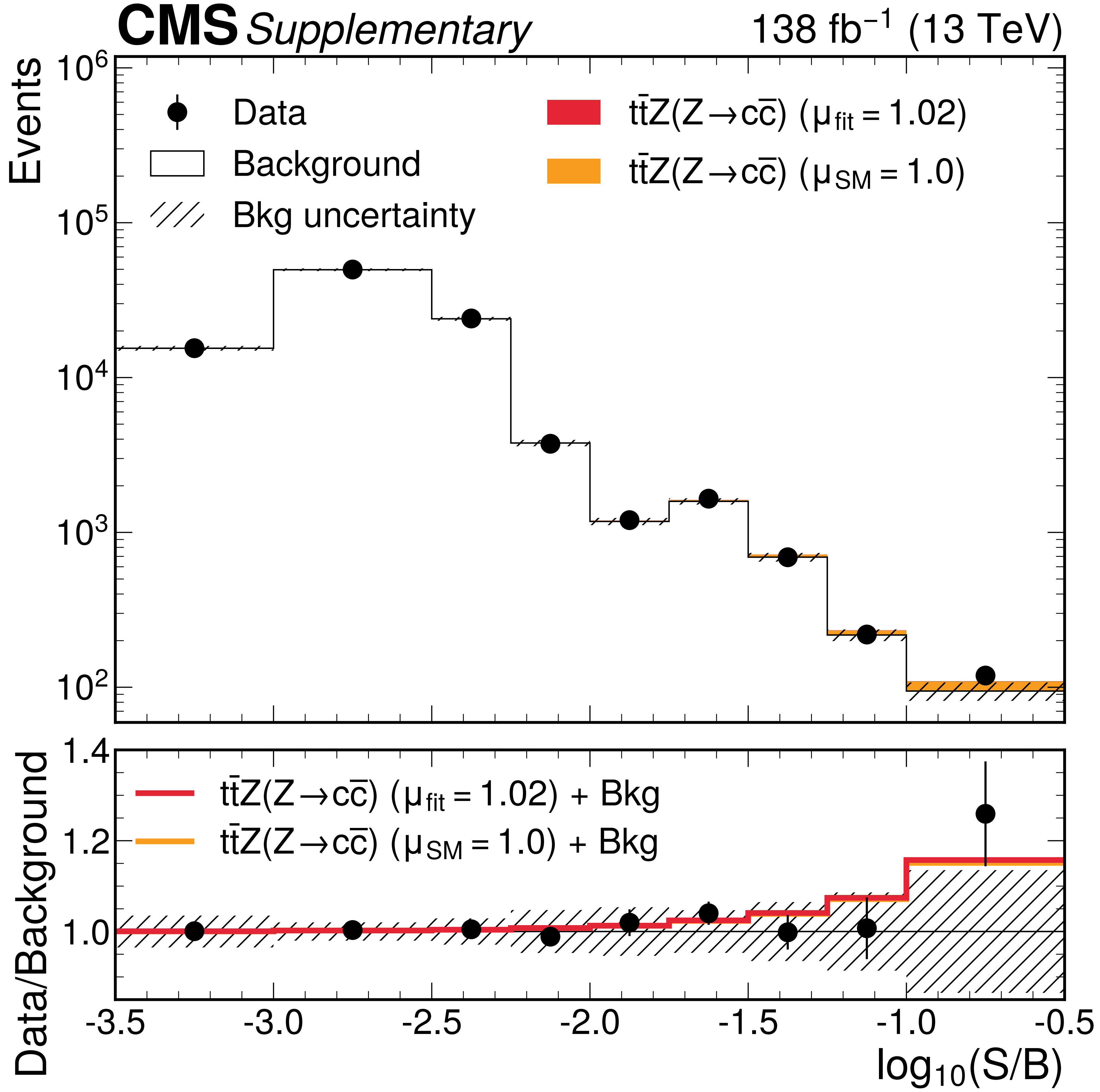
2D correlations - among background SFs





Accumulated plots for ttZ





Definition of scores and categories

Category	Discriminant
$\mathrm{H}\to c\bar{c}$ SR	$\mathcal{D}_{t\bar{t}H(H\to c\bar{c})}$
$\mathrm{H}\to b\bar{b}$ SR	$\mathcal{D}_{t\bar{t}H(H\to b\bar{b})}$
$\mathrm{Z}\to c\bar{c}$ SR	$\mathcal{D}_{t\bar{t}Z(Z\to c\bar{c})}$
$\mathrm{Z}\to b\bar{b}$ SR	$\mathcal{D}_{t\bar{t}Z(Z\to b\bar{b})}$
$t\bar{t}$+light CR	$\mathcal{D}_{t\bar{t}+\mathrm{light}}/\mathcal{D}_{t\bar{t}+\mathrm{jets}}$
$t\bar{t}$+c CR	$\mathcal{D}_{t\bar{t}+c}/\mathcal{D}_{t\bar{t}+\mathrm{jets}}$
$t\bar{t}+\geq 2c$ CR	$\mathcal{D}_{t\bar{t}+\geq 2c}/\mathcal{D}_{t\bar{t}+\mathrm{jets}}$
$t\bar{t}$+b CR	$\mathcal{D}_{t\bar{t}+b}/\mathcal{D}_{t\bar{t}+\mathrm{jets}}$
$t\bar{t}+\geq 2b$ CR	$\mathcal{D}_{t\bar{t}+\geq 2b}/\mathcal{D}_{t\bar{t}+\mathrm{jets}}$

Event yields - integrated

- Acceptance:
  - ttH(cc): ~ 3.2%
    - In SR: ~ 0.8%
  - ttH(bb): ~ 4.3%
    - In SR: ~0.8%

Process	2L	1L	0L	Total
$t\bar{t}H(H\to c\bar{c})$	-9 ± 18 (6 ± 11)	-62 ± 69 (38 ± 42)	-33 ± 42 (20 ± 25)	-100 ± 130 (64 ± 78)
$t\bar{t}H(H\to b\bar{b})$	137 ± 56 (151 ± 62)	1060 ± 220 (1150 ± 240)	580 ± 140 (630 ± 150)	1770 ± 410 (1930 ± 450)
$t\bar{t}Z(Z\to c\bar{c})$	32 ± 27	210 ± 110	112 ± 65	360 ± 200
$t\bar{t}Z(Z\to b\bar{b})$	75 ± 53	580 ± 210	290 ± 130	940 ± 400
$t\bar{t}+\geq2b$	1060 ± 180	8420 ± 650	4670 ± 480	14100 ± 1300
$t\bar{t}+b$	1310 ± 260	12100 ± 1000	3730 ± 530	17100 ± 1800
$t\bar{t}+\geq2c$	940 ± 160	7320 ± 610	3850 ± 460	12100 ± 1200
$t\bar{t}+c$	1730 ± 290	15600 ± 1200	3220 ± 390	20600 ± 1900
$t\bar{t}$+light	1700 ± 140	17080 ± 670	4990 ± 280	23800 ± 1100
Other	430 ± 200	5040 ± 810	870 ± 320	6300 ± 1300
Total	7410 ± 240	67300 ± 1400	22270 ± 720	97000 ± 2400
Data	7366	67370	22271	97007

Event yields - 2L channel

Process	SR $t\bar{t}H(H\to c\bar{c})$	SR $t\bar{t}H(H\to b\bar{b})$	SR $t\bar{t}Z(Z\to c\bar{c})$	SR $t\bar{t}Z(Z\to b\bar{b})$	CR $t\bar{t}+\geq 2b$	CR $t\bar{t}+b$	CR $t\bar{t}+\geq 2c$	CR $t\bar{t}+c$	CR $t\bar{t}$+light
$t\bar{t}H(H\to c\bar{c})$	-2.5 ± 4.4 (1.5 ± 2.8)	-0.06 ± 0.62 (0.03 ± 0.37)	-0.5 ± 1.8 (0.3 ± 1.1)	-0.02 ± 0.35 (0.01 ± 0.21)	-0.13 ± 0.83 (0.08 ± 0.50)	-0.04 ± 0.51 (0.02 ± 0.31)	-1.2 ± 2.8 (0.7 ± 1.7)	-0.4 ± 1.5 (0.24 ± 0.97)	-4.4 ± 5.2 (2.7 ± 3.2)
$t\bar{t}H(H\to b\bar{b})$	2.4 ± 3.1 (2.7 ± 3.4)	20.2 ± 9.6 (22 ± 11)	1.3 ± 2.1 (1.4 ± 2.2)	6.4 ± 4.7 (7.1 ± 5.2)	37 ± 12 (40 ± 13)	18.6 ± 8.1 (20.8 ± 9.0)	4.1 ± 3.4 (4.4 ± 3.6)	1.8 ± 2.4 (2.1 ± 2.6)	45 ± 11 (50 ± 13)
$t\bar{t}Z(Z\to c\bar{c})$	1.9 ± 2.7	0.11 ± 0.64	9.9 ± 7.1	0.21 ± 0.90	0.4 ± 1.1	0.12 ± 0.71	4.3 ± 4.2	1.2 ± 2.2	14.2 ± 7.4
$t\bar{t}Z(Z\to b\bar{b})$	0.7 ± 2.1	3.8 ± 4.7	1.1 ± 2.7	16 ± 11	19 ± 11	9.1 ± 7.2	2.1 ± 3.1	0.9 ± 2.2	23 ± 10
$t\bar{t}+\geq 2b$	12.7 ± 7.9	45 ± 16	11.8 ± 7.4	52 ± 17	370 ± 42	121 ± 24	52 ± 15	14.3 ± 8.0	385 ± 40
$t\bar{t}+b$	19 ± 14	14 ± 13	16 ± 12	17 ± 14	120 ± 32	303 ± 56	54 ± 22	37 ± 19	727 ± 81
$t\bar{t}+\geq 2c$	67 ± 21	1.9 ± 3.7	63 ± 20	2.4 ± 3.3	16.0 ± 7.7	5.5 ± 5.6	214 ± 35	44 ± 15	524 ± 52
$t\bar{t}+c$	61 ± 28	1.7 ± 4.0	49 ± 24	3.4 ± 6.8	16 ± 11	23 ± 16	121 ± 37	166 ± 43	1290 ± 120
$t\bar{t}$+light	50 ± 14	1.7 ± 2.7	44 ± 12	1.8 ± 2.7	8.1 ± 4.7	11.2 ± 6.1	60 ± 14	54 ± 13	1470 ± 74
Other	15 ± 18	2.8 ± 7.3	24 ± 24	5.4 ± 9.7	22 ± 17	8.5 ± 8.1	32 ± 25	13 ± 14	313 ± 75
Total	228 ± 14	90.7 ± 7.9	220 ± 14	103.6 ± 9.1	608 ± 22	499 ± 19	541 ± 27	332 ± 18	4790 ± 110
Data	236	93	204	92	605	463	546	343	4784

Event yields - 1L channel

Process	SR $t\bar{t}H(H\to c\bar{c})$	SR $t\bar{t}H(H\to b\bar{b})$	SR $t\bar{t}Z(Z\to c\bar{c})$	SR $t\bar{t}Z(Z\to b\bar{b})$	CR $t\bar{t}+\geq 2b$	CR $t\bar{t}+b$	CR $t\bar{t}+\geq 2c$	CR $t\bar{t}+c$	CR $t\bar{t}+$light
$t\bar{t}H(H\to c\bar{c})$	-16 ± 22 (10 ± 14)	-0.5 ± 3.6 (0.3 ± 2.1)	-3.1 ± 8.9 (1.9 ± 5.4)	-0.2 ± 1.9 (0.1 ± 1.1)	-1.2 ± 2.6 (0.7 ± 1.5)	-0.5 ± 1.8 (0.3 ± 1.0)	-11.7 ± 8.8 (7.0 ± 5.3)	-5.4 ± 5.9 (3.3 ± 3.6)	-24 ± 13 (14.8 ± 7.7)
$t\bar{t}H(H\to b\bar{b})$	21 ± 18 (23 ± 19)	166 ± 55 (181 ± 60)	9 ± 11 (10 ± 12)	43 ± 25 (47 ± 27)	264 ± 31 (284 ± 34)	139 ± 22 (153 ± 25)	52 ± 12 (55 ± 13)	35 ± 10 (38 ± 11)	327 ± 32 (356 ± 35)
$t\bar{t}Z(Z\to c\bar{c})$	16 ± 16	1.1 ± 4.1	59 ± 35	1.5 ± 4.9	3.5 ± 3.6	1.6 ± 2.5	37 ± 12	18.1 ± 8.6	78 ± 18
$t\bar{t}Z(Z\to b\bar{b})$	6 ± 12	32 ± 28	8 ± 14	114 ± 58	136 ± 28	70 ± 20	25 ± 11	19.2 ± 9.7	166 ± 29
$t\bar{t}+\geq 2b$	109 ± 48	387 ± 91	85 ± 41	360 ± 88	2760 ± 120	957 ± 67	633 ± 51	293 ± 34	2830 ± 110
$t\bar{t}+b$	198 ± 96	205 ± 97	168 ± 88	165 ± 87	1300 ± 110	2700 ± 170	841 ± 88	719 ± 81	5760 ± 240
$t\bar{t}+\geq 2c$	470 ± 110	26 ± 24	389 ± 99	19 ± 21	153 ± 26	60 ± 18	2080 ± 110	718 ± 63	3400 ± 140
$t\bar{t}+c$	700 ± 190	61 ± 54	470 ± 150	45 ± 46	256 ± 48	291 ± 59	1910 ± 150	2680 ± 180	9220 ± 330
$t\bar{t}+$light	780 ± 110	73 ± 33	605 ± 94	69 ± 33	205 ± 24	226 ± 29	1180 ± 65	1326 ± 70	12620 ± 220
Other	190 ± 120	43 ± 48	320 ± 160	58 ± 55	249 ± 50	136 ± 33	550 ± 86	423 ± 70	3080 ± 190
Total	2470 ± 92	993 ± 52	2115 ± 80	875 ± 48	5330 ± 110	4580 ± 110	7300 ± 200	6230 ± 190	37450 ± 530
Data	2411	983	2108	879	5372	4594	7317	6209	37497

Event yields - 0L channel

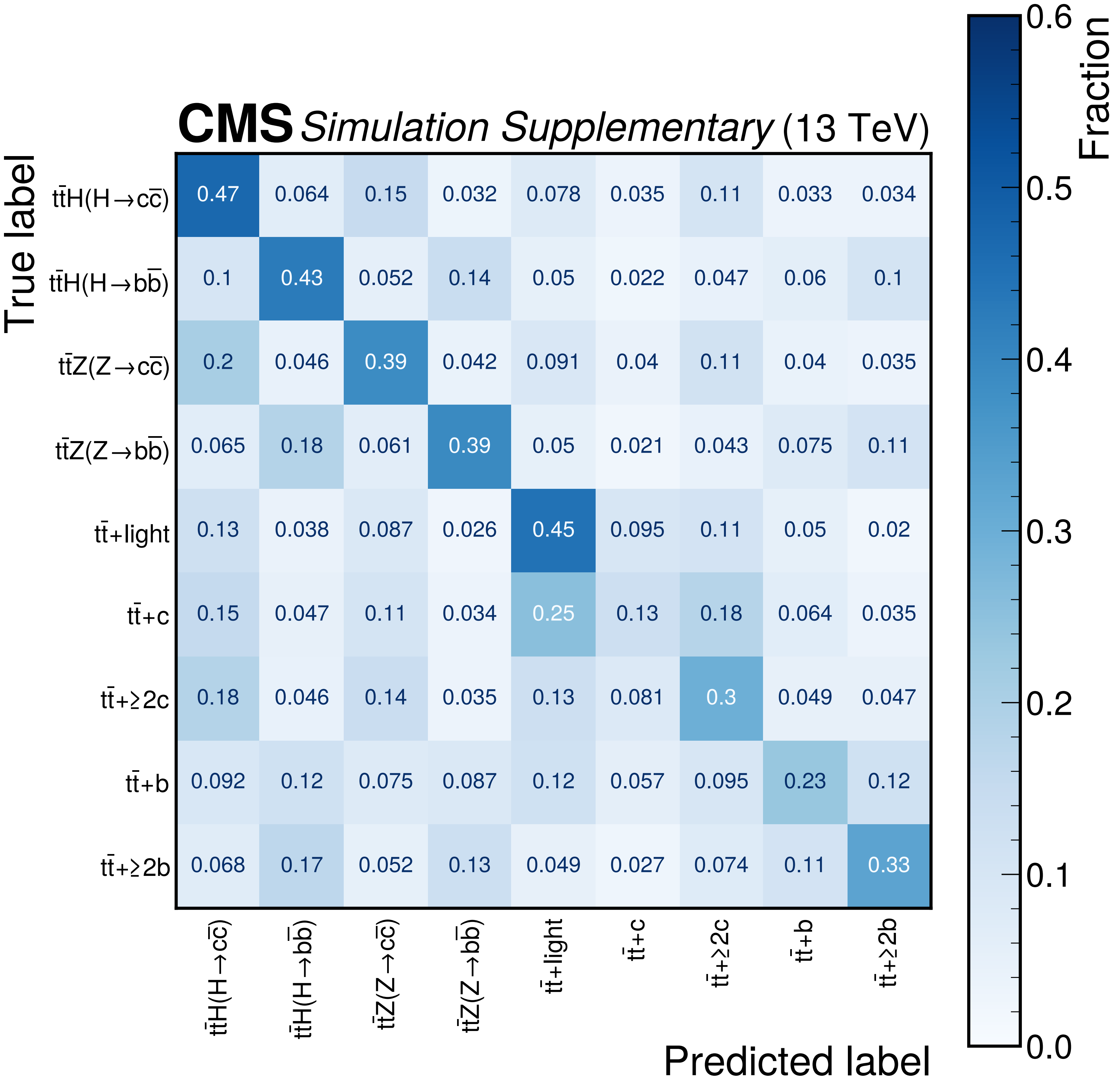
Process	SR $t\bar{t}H(H\to c\bar{c})$	SR $t\bar{t}H(H\to b\bar{b})$	SR $t\bar{t}Z(Z\to c\bar{c})$	SR $t\bar{t}Z(Z\to b\bar{b})$	CR $t\bar{t}+\geq 2b$	CR $t\bar{t}+b$	CR $t\bar{t}+\geq 2c$	CR $t\bar{t}+c$	CR $t\bar{t}+$light
$t\bar{t}H(H\to c\bar{c})$	-9 ± 13 (5.5 ± 8.1)	-0.4 ± 2.5 (0.2 ± 1.4)	-1.6 ± 5.0 (1.0 ± 3.0)	-0.1 ± 1.4 (0.08 ± 0.79)	-0.7 ± 1.9 (0.4 ± 1.1)	-0.3 ± 1.4 (0.17 ± 0.79)	-3.4 ± 4.7 (2.0 ± 2.8)	-0.5 ± 1.9 (0.3 ± 1.1)	-17 ± 10 (10.2 ± 6.2)
$t\bar{t}H(H\to b\bar{b})$	12 ± 10 (13 ± 11)	128 ± 38 (137 ± 41)	5.4 ± 6.5 (5.9 ± 7.1)	31 ± 16 (34 ± 17)	140 ± 23 (151 ± 24)	62 ± 15 (68 ± 16)	14.9 ± 6.5 (15.8 ± 6.9)	2.9 ± 2.8 (3.1 ± 3.0)	185 ± 23 (201 ± 25)
$t\bar{t}Z(Z\to c\bar{c})$	8.0 ± 9.0	0.8 ± 2.9	36 ± 21	1.3 ± 3.6	1.9 ± 2.6	1.0 ± 2.0	10.4 ± 6.7	2.0 ± 2.9	51 ± 14
$t\bar{t}Z(Z\to b\bar{b})$	3.1 ± 6.5	22 ± 18	4.7 ± 8.3	87 ± 40	62 ± 19	28 ± 13	6.2 ± 5.4	1.5 ± 2.7	75 ± 19
$t\bar{t}+\geq 2b$	73 ± 32	336 ± 73	55 ± 28	320 ± 70	1548 ± 97	452 ± 50	178 ± 30	28 ± 11	1677 ± 89
$t\bar{t}+b$	86 ± 47	96 ± 49	70 ± 43	88 ± 50	405 ± 60	742 ± 86	159 ± 37	45 ± 20	2040 ± 130
$t\bar{t}+\geq 2c$	296 ± 81	22 ± 21	260 ± 75	20 ± 19	74 ± 22	30 ± 15	653 ± 72	85 ± 25	2410 ± 130
$t\bar{t}+c$	163 ± 59	21 ± 20	113 ± 48	16 ± 17	49 ± 18	44 ± 19	180 ± 39	113 ± 30	2520 ± 140
$t\bar{t}+$light	213 ± 42	27 ± 15	165 ± 36	21 ± 13	44 ± 11	43 ± 12	122 ± 20	50 ± 13	4310 ± 120
Other	39 ± 40	13 ± 20	106 ± 67	18 ± 23	32 ± 19	24 ± 15	52 ± 29	17 ± 16	565 ± 88
Total	883 ± 50	665 ± 42	814 ± 47	602 ± 40	2357 ± 74	1426 ± 63	1372 ± 64	343 ± 26	13800 ± 310
Data	898	668	831	622	2345	1435	1382	357	13733

Event yields - split by categories

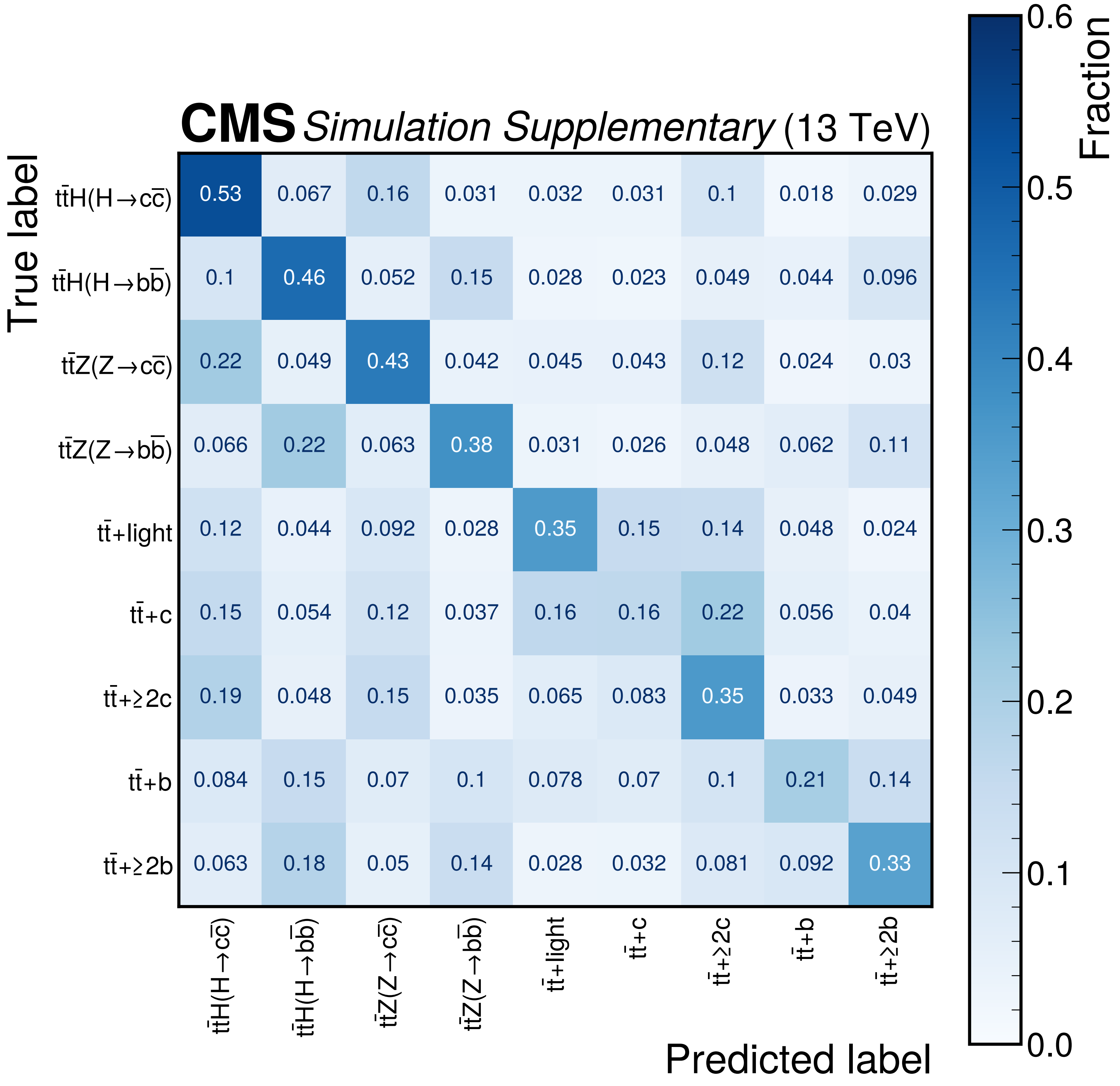
Process	SR $t\bar{t}H(H\to c\bar{c})$	SR $t\bar{t}H(H\to b\bar{b})$	SR $t\bar{t}Z(Z\to c\bar{c})$	SR $t\bar{t}Z(Z\to b\bar{b})$	CR $t\bar{t}+\geq 2b$	CR $t\bar{t}+b$	CR $t\bar{t}+\geq 2c$	CR $t\bar{t}+c$	CR $t\bar{t}+$light
$t\bar{t}H(H\to c\bar{c})$	-27 ± 40 (17 ± 25)	-0.9 ± 6.7 (0.5 ± 3.8)	-5 ± 16 (3.2 ± 9.5)	-0.3 ± 3.7 (0.2 ± 2.1)	-2.0 ± 5.4 (1.2 ± 3.1)	-0.8 ± 3.6 (0.5 ± 2.1)	-16 ± 16 (9.8 ± 9.8)	-6.3 ± 9.3 (3.9 ± 5.7)	-46 ± 28 (28 ± 17)
$t\bar{t}H(H\to b\bar{b})$	35 ± 31 (38 ± 34)	310 ± 100 (340 ± 110)	16 ± 20 (17 ± 21)	81 ± 45 (88 ± 49)	441 ± 65 (475 ± 71)	220 ± 45 (242 ± 50)	71 ± 22 (75 ± 24)	40 ± 15 (43 ± 17)	557 ± 67 (607 ± 73)
$t\bar{t}Z(Z\to c\bar{c})$	25 ± 28	2.0 ± 7.6	105 ± 63	2.9 ± 9.4	5.8 ± 7.3	2.7 ± 5.3	51 ± 23	21 ± 14	143 ± 40
$t\bar{t}Z(Z\to b\bar{b})$	10 ± 21	57 ± 51	14 ± 25	220 ± 110	218 ± 58	108 ± 40	34 ± 20	22 ± 15	263 ± 58
$t\bar{t}+\geq 2b$	194 ± 88	770 ± 180	152 ± 76	730 ± 170	4680 ± 260	1530 ± 140	862 ± 95	335 ± 53	4890 ± 240
$t\bar{t}+b$	300 ± 160	320 ± 160	250 ± 140	270 ± 150	1830 ± 200	3740 ± 310	1050 ± 150	800 ± 120	8520 ± 450
$t\bar{t}+\geq 2c$	830 ± 210	50 ± 49	710 ± 190	41 ± 43	244 ± 56	96 ± 39	2950 ± 220	850 ± 100	6330 ± 320
$t\bar{t}+c$	920 ± 270	84 ± 78	640 ± 230	64 ± 70	321 ± 77	358 ± 94	2210 ± 230	2960 ± 250	13030 ± 590
$t\bar{t}+$light	1050 ± 160	102 ± 51	810 ± 140	92 ± 49	257 ± 39	280 ± 47	1362 ± 99	1430 ± 96	18390 ± 410
Other	240 ± 180	58 ± 76	450 ± 250	82 ± 88	303 ± 87	169 ± 56	630 ± 140	453 ± 100	3950 ± 350
Total	3580 ± 160	1750 ± 100	3150 ± 140	1580 ± 97	8300 ± 210	6500 ± 200	9210 ± 290	6910 ± 240	56040 ± 950
Data	3545	1744	3143	1593	8322	6492	9245	6909	56014

Classifier performance

0L



1L



2L