

Analysis Methods & Techniques for Higgs analyses

Thomas Strebler
on behalf of the **ATLAS Collaboration**

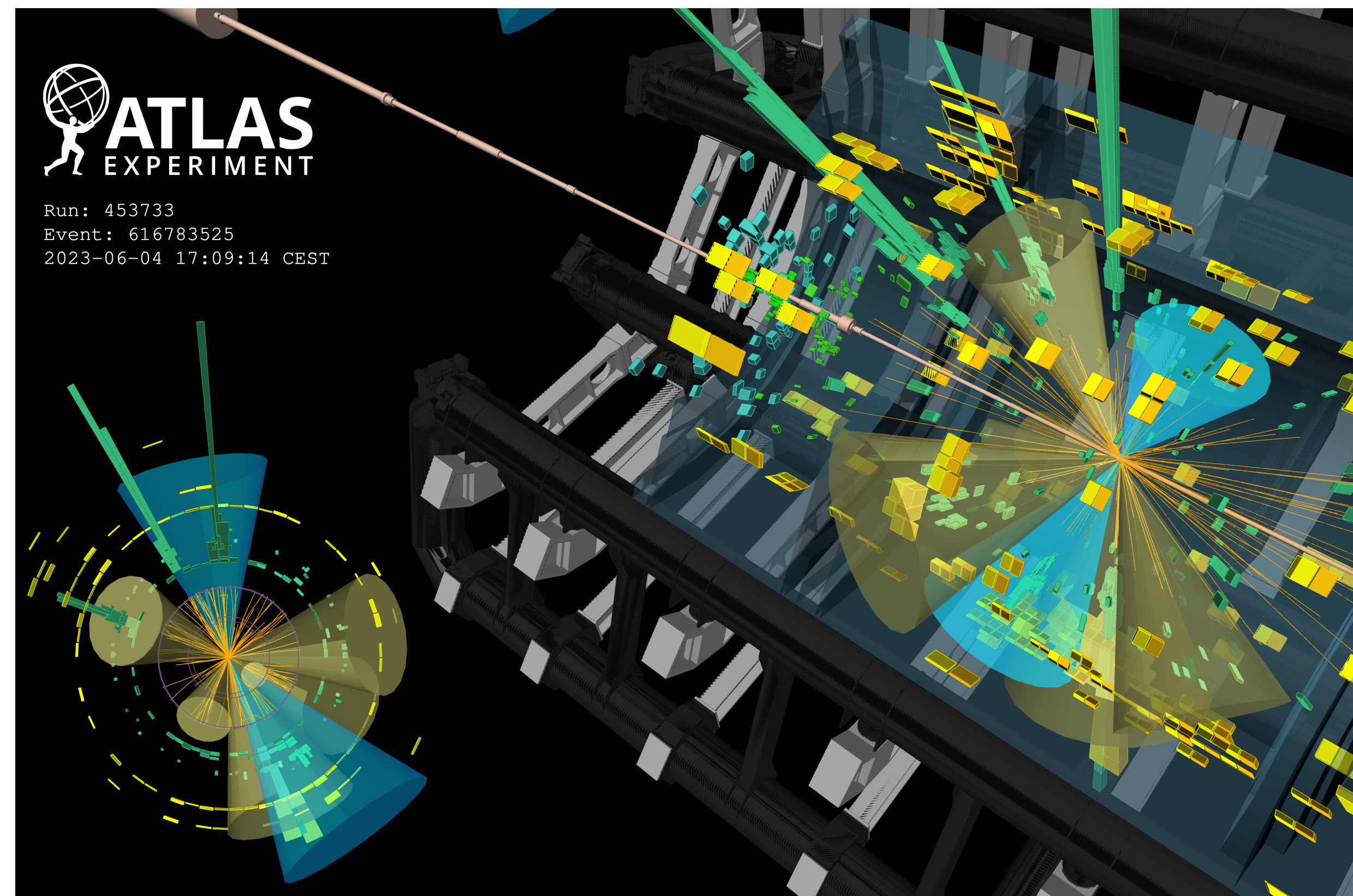
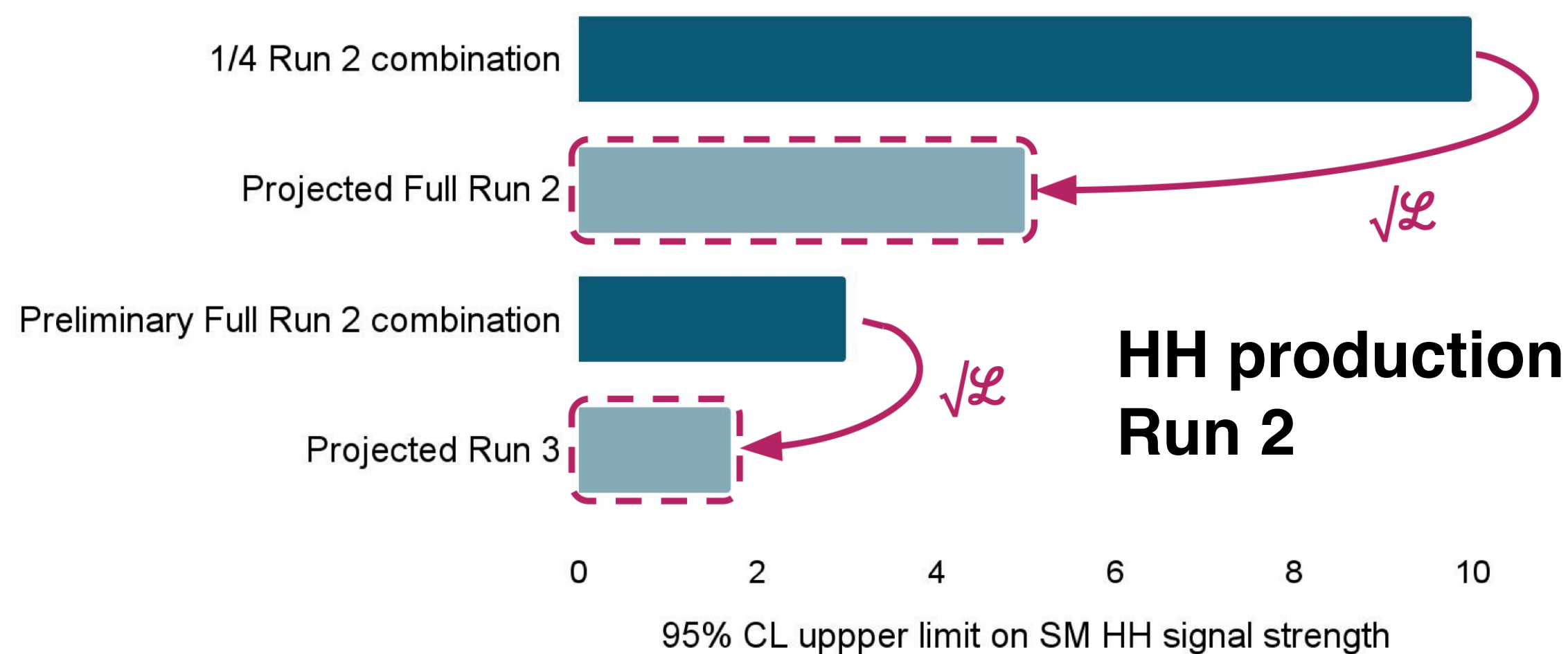
Centre de Physique
des Particules de Marseille
Aix-Marseille Université / CNRS-IN2P3

Higgs Hunting 2026
September 16th, 2026



Introduction

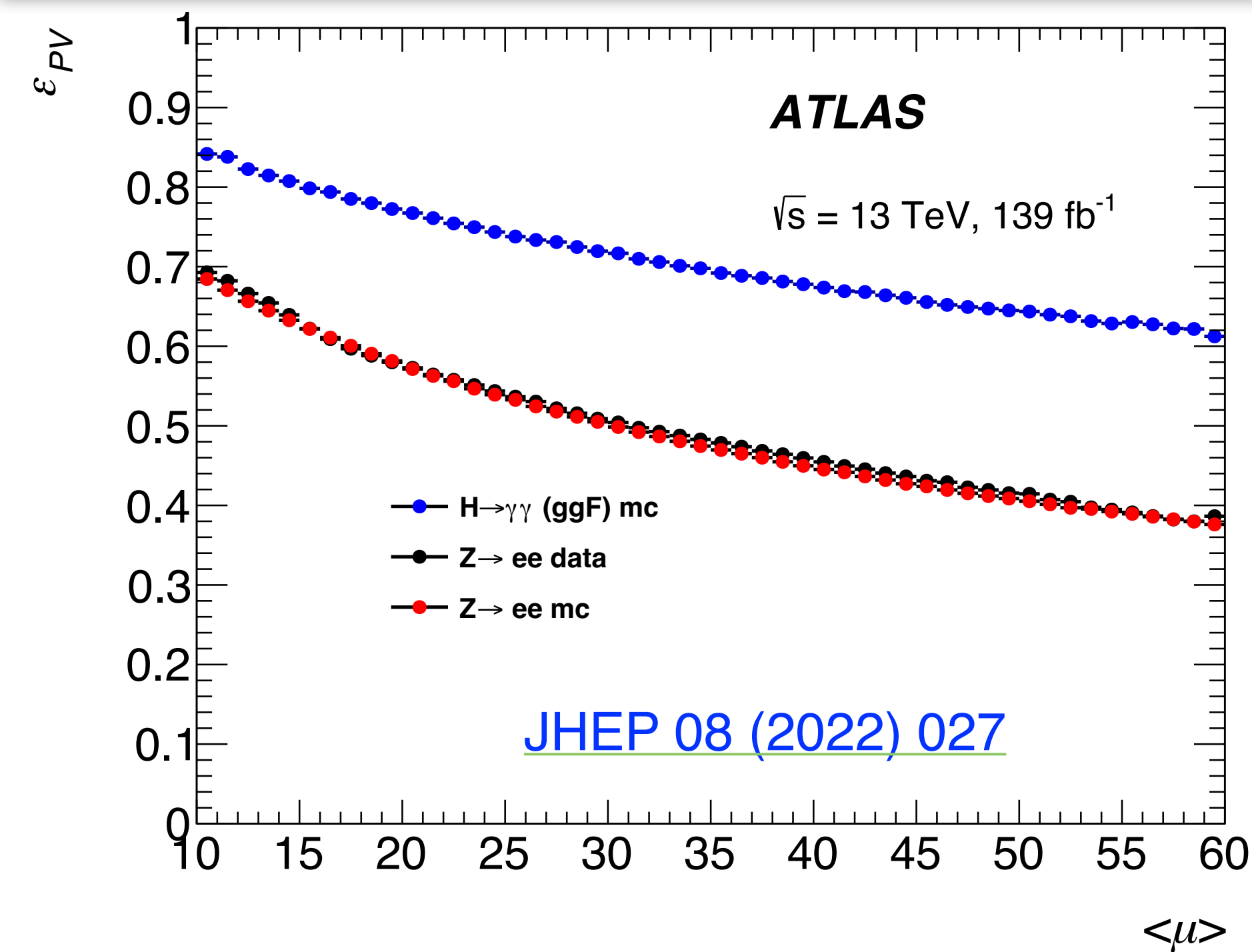
- Precision Higgs measurements and searches increasingly target **rare signals and complex final states**
- Improvements in sensitivity no longer come only from larger datasets in some channels



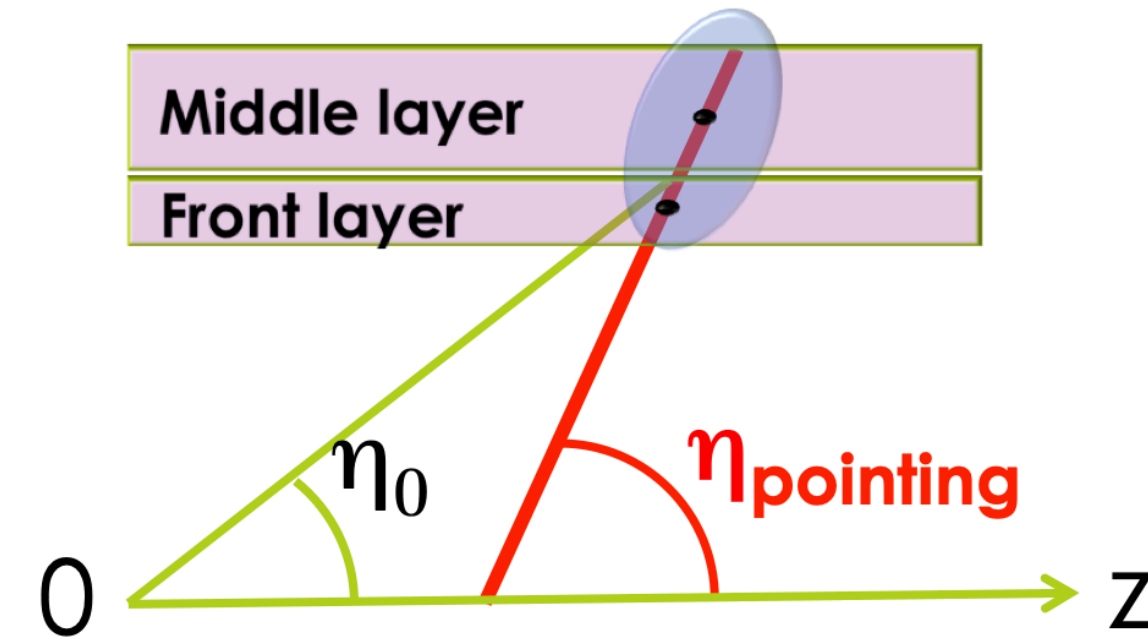
ttH H → γγ event

- **Analysis techniques are evolving at every level:**
reconstruction → identification → event categorisation → background estimation
=> expectations for analysis sensitivity often exceeded thanks to those
- **Recent ATLAS examples** illustrate how these developments translate into improved physics reach

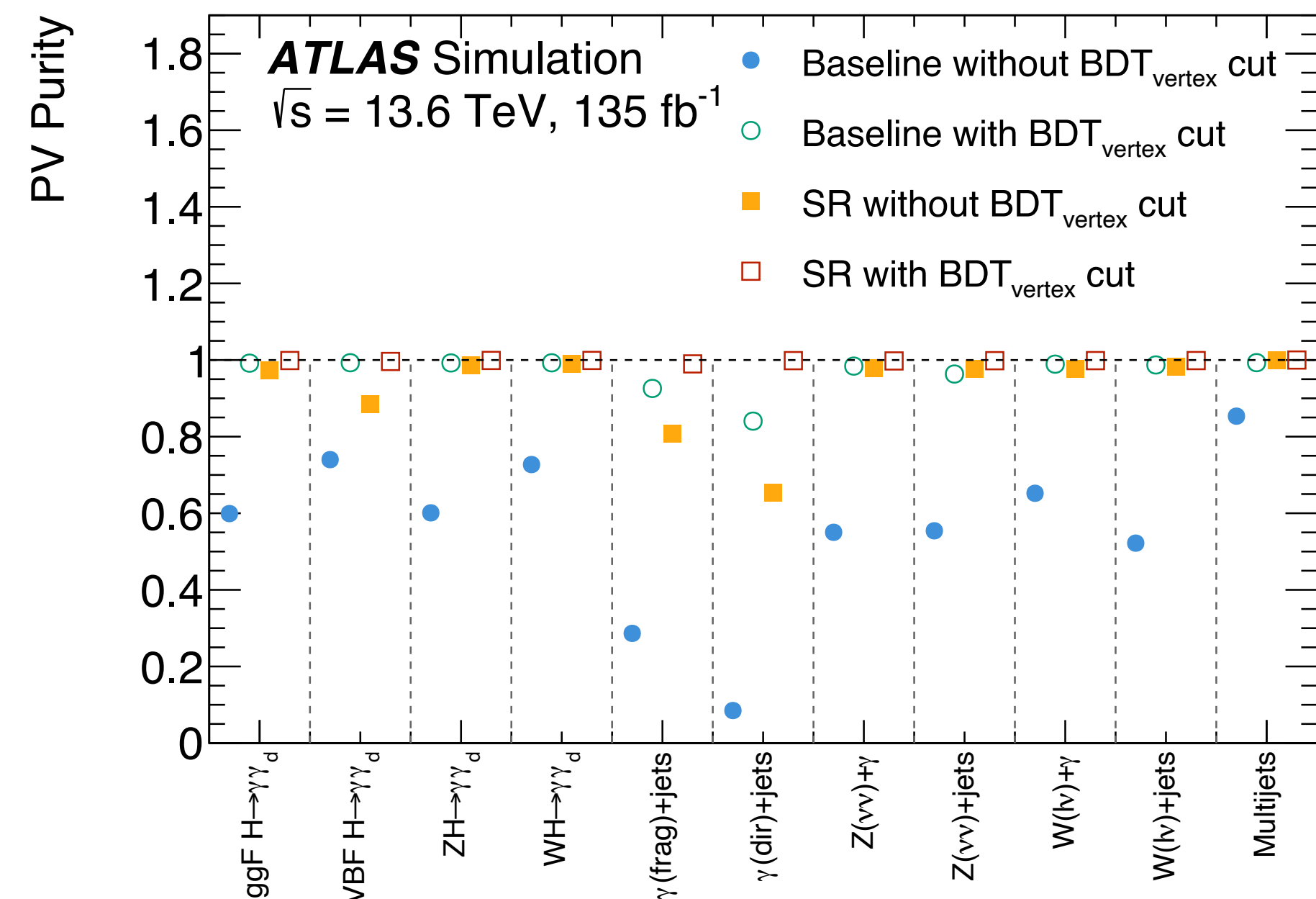
Objet reconstruction: primary vertex



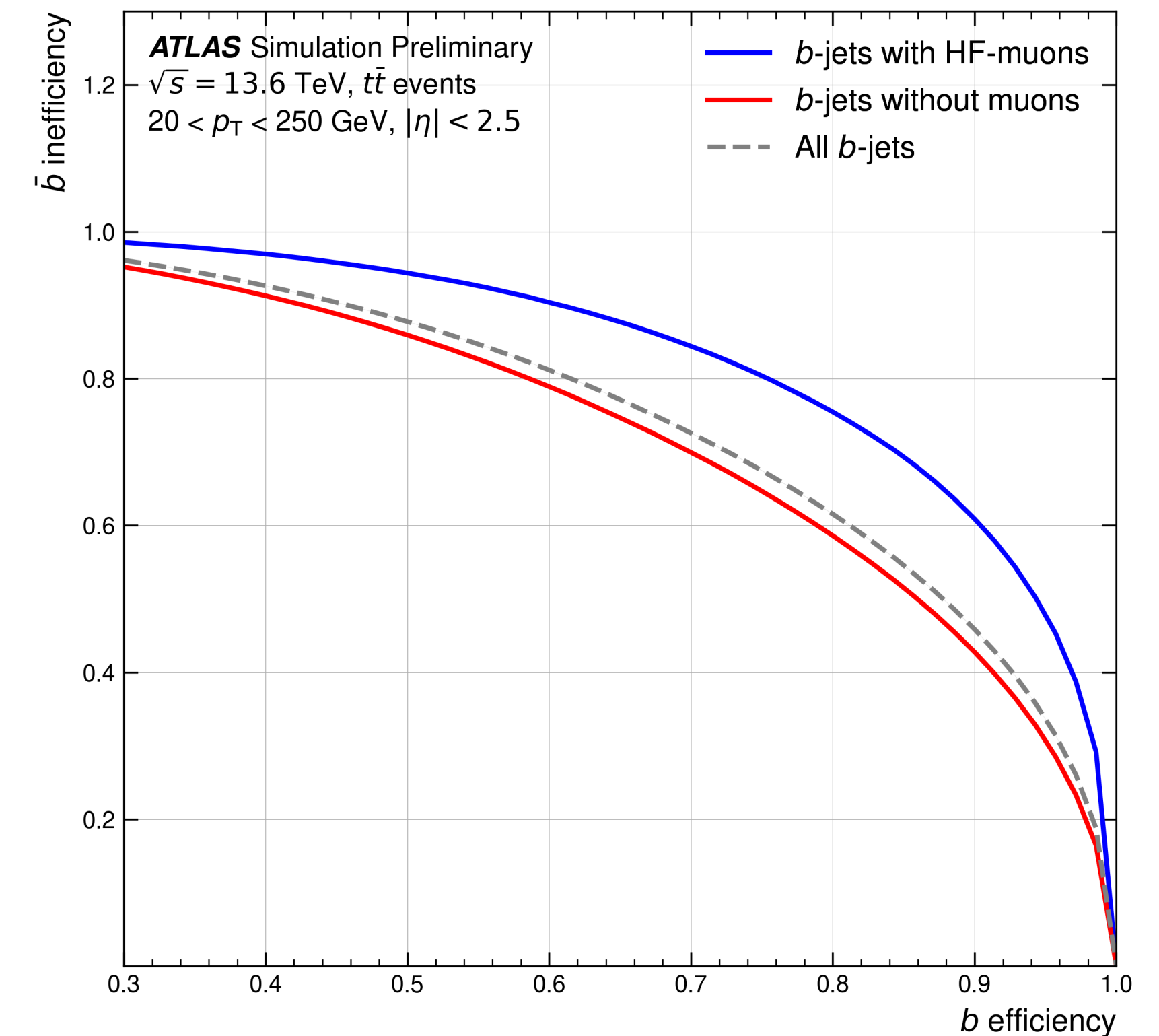
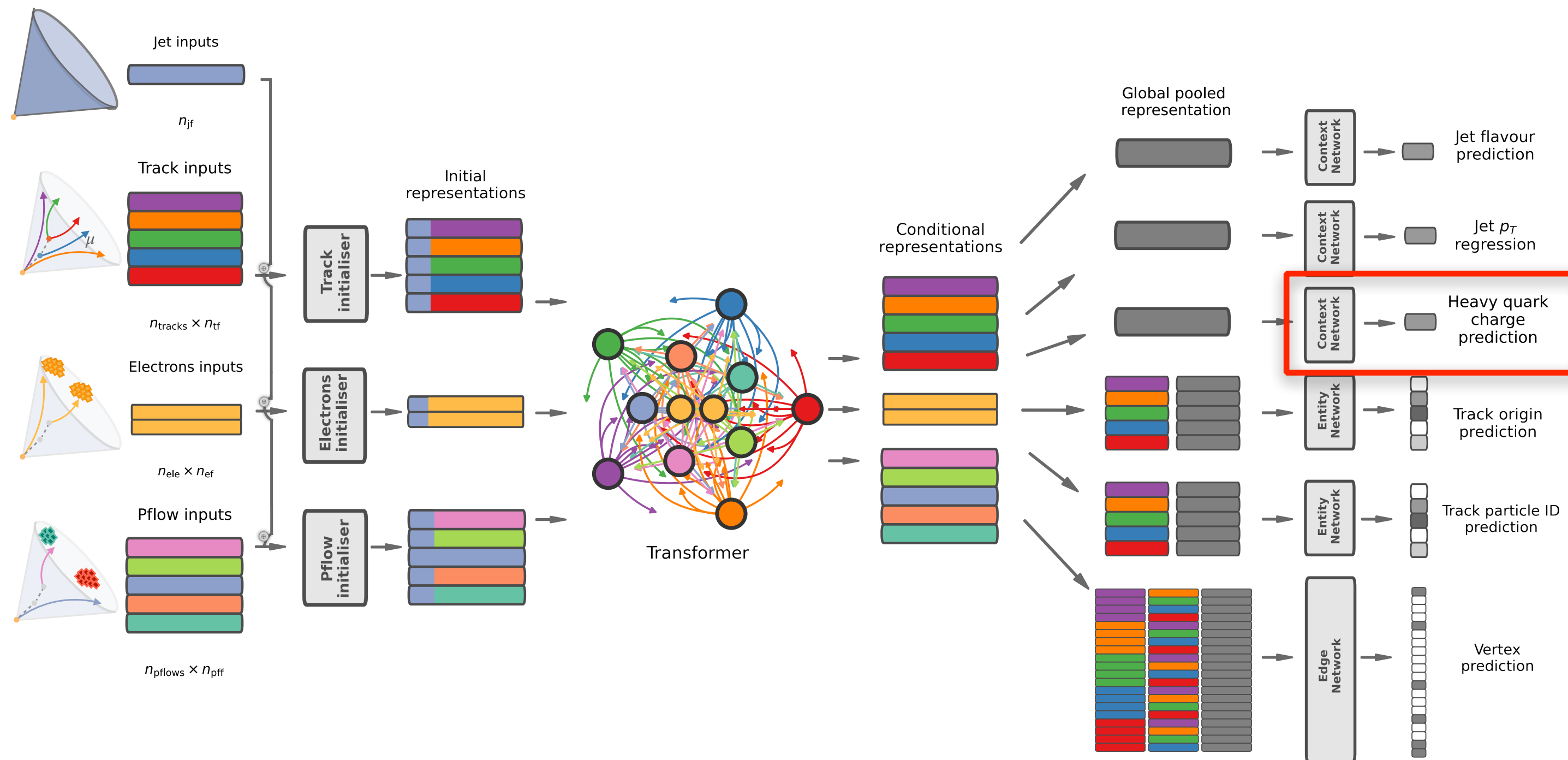
- PV selection essential for charged pile-up rejection, flavour-tagging...
- Default Σp_T^2 selection:
 - good performance for events with central tracks
 - reduced efficiency for $H \rightarrow \gamma\gamma$
- **Dedicated $H \rightarrow \gamma\gamma$ Neural Network:**
 - vertex tracks + photon pointing inputs
 - +8% in PV selection efficiency
 - improved $m(\gamma\gamma)$ resolution



- **$H \rightarrow \gamma\gamma_D$ in photon+MET analysis:**
 - BDT with photon + jet + MET inputs to reject events with wrong PV
 - reduces fake MET background
- **Analysis-specific PV choice challenging for reconstruction:**
 ongoing effort to provide universal PV selection algorithm



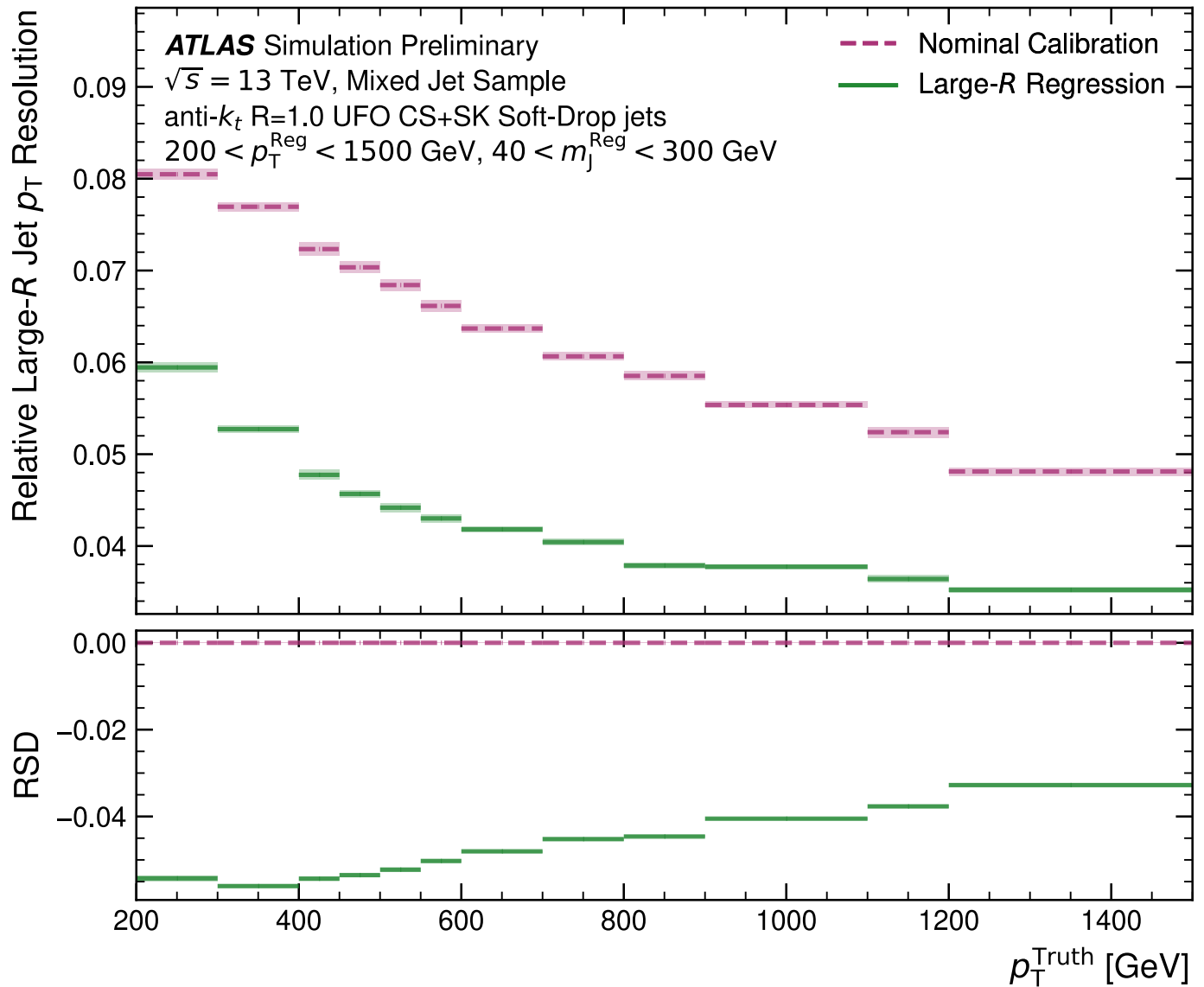
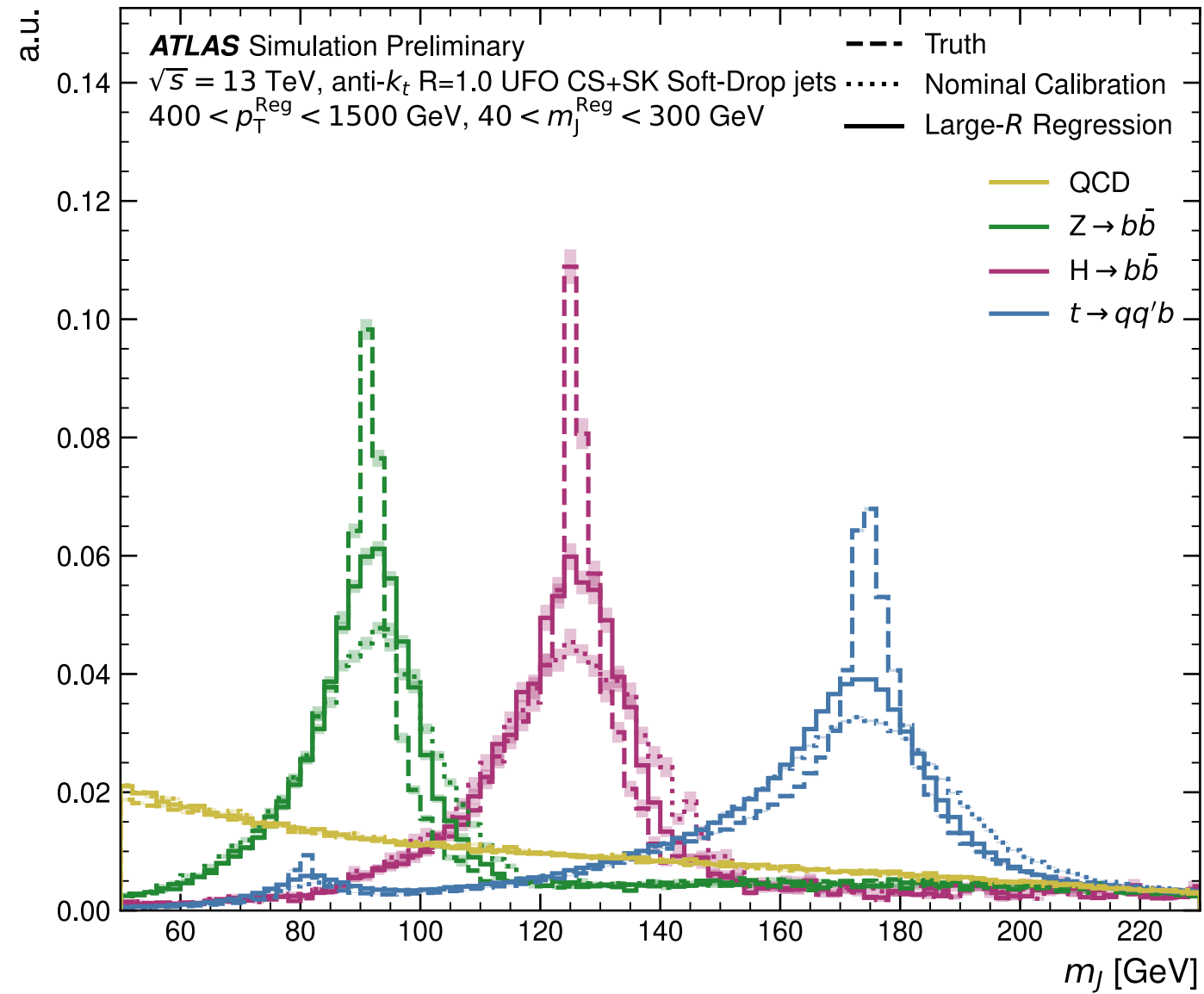
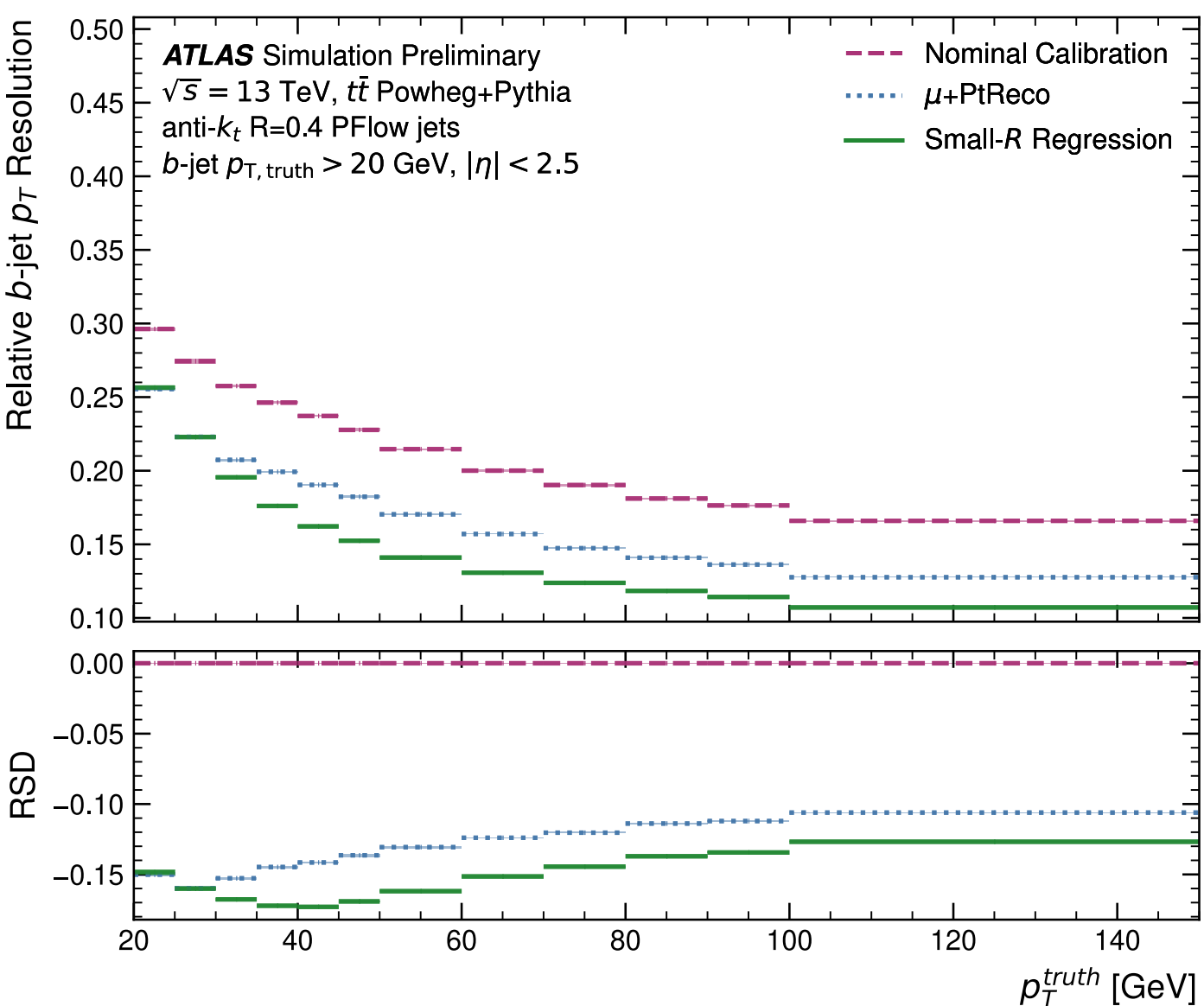
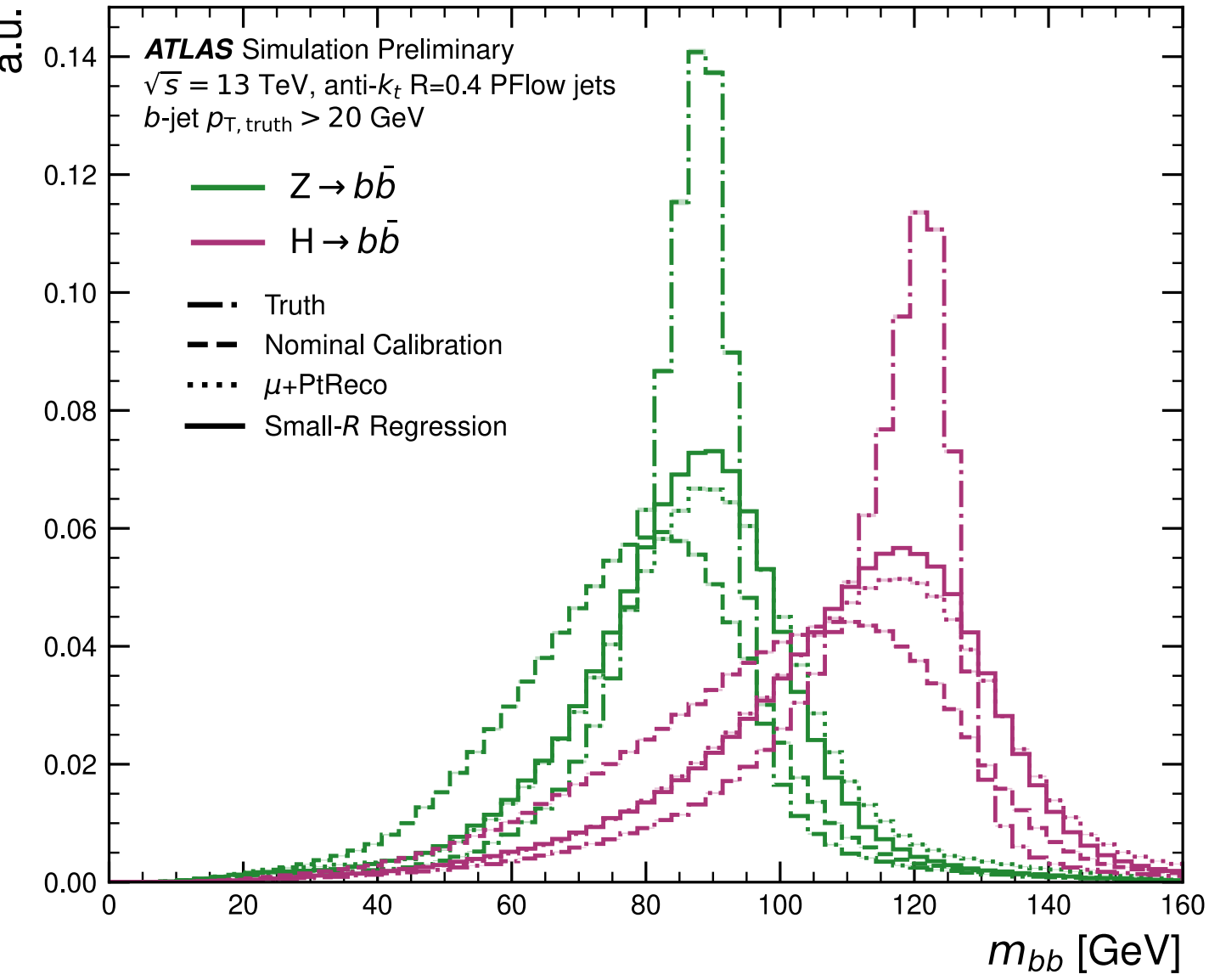
- **Steady developments for flavour-tagging ML-discriminants:**
Transformer architecture expanded with auxiliary tasks



- **New charge ID for heavy quarks:**
 - works even for jets without leptons
 - 50% eff. vs 13% mistag efficiency for b-quarks
- Studies of hadron-content dependence and interplay with tagging WP
- **Potential game changer for multi-b-jets final states, e.g. $HH \rightarrow 4b$**

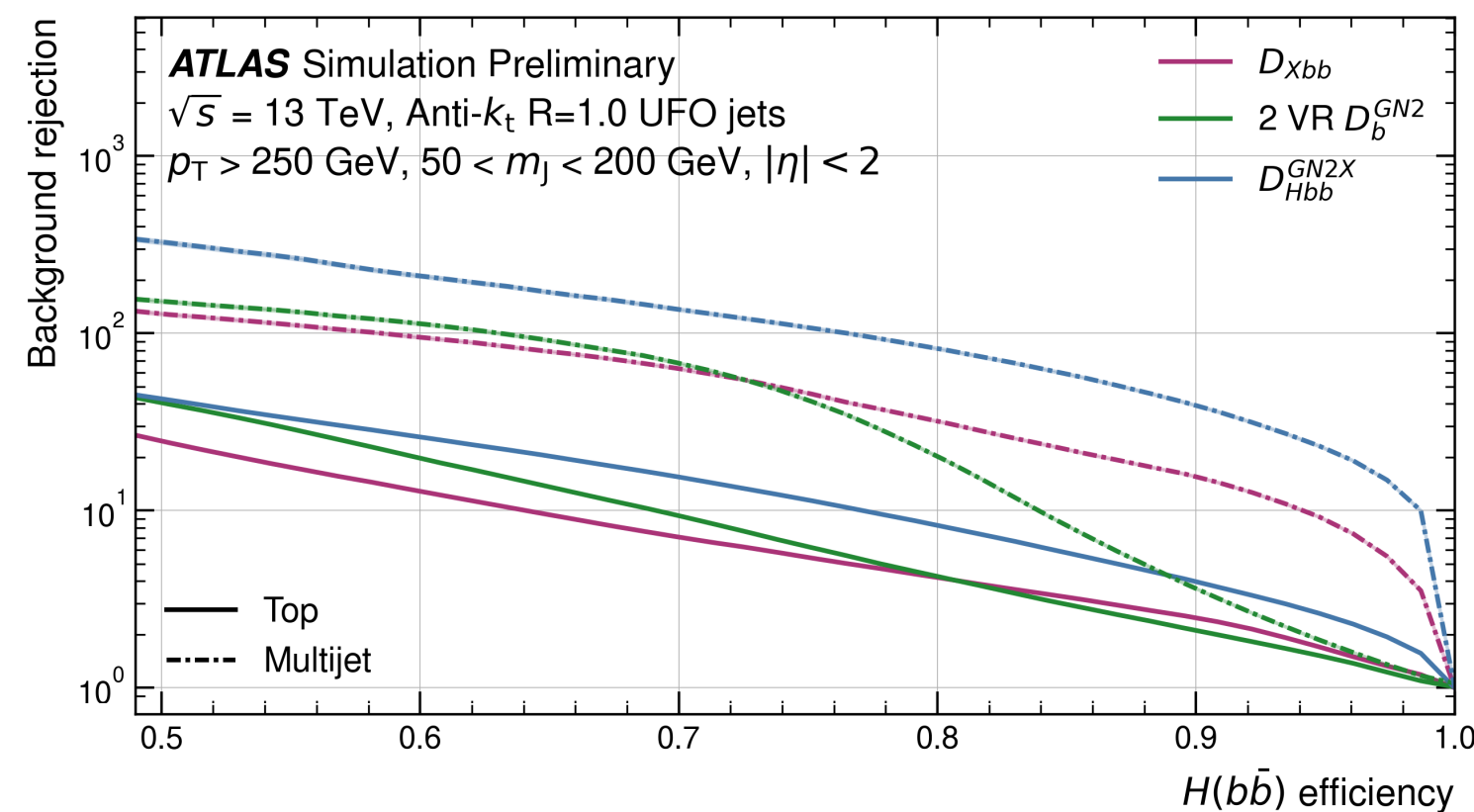
Objet reconstruction: b-jets and boosted $H \rightarrow b\bar{b}$

[ATL-PHYS-PUB-2024-015](#)



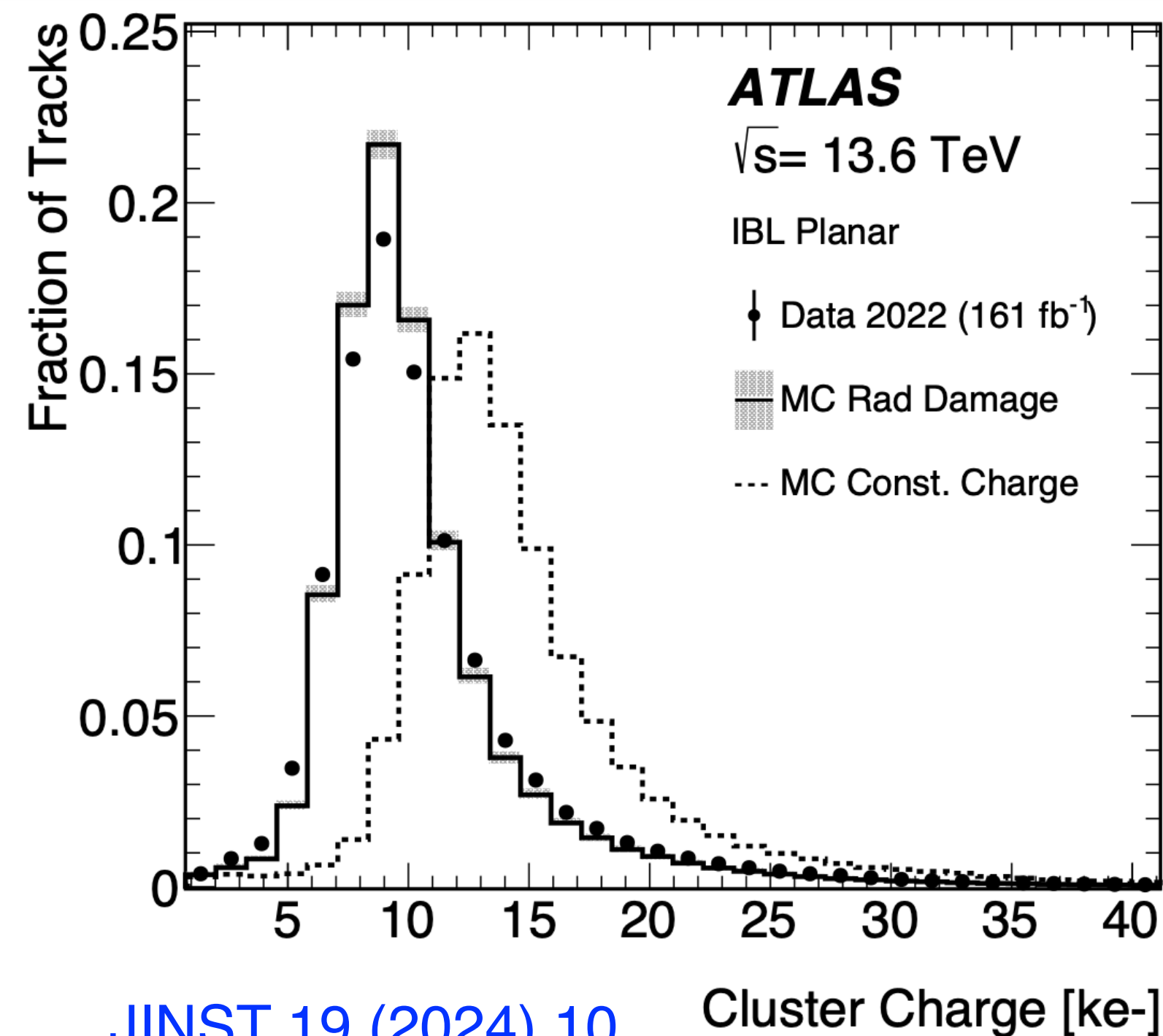
- Standard jet calibration not optimised for b-jets:
 - leptonic B hadron decays
 - different radiation patterns
- Previous improvement: **muon-in-jet + pT correction**
- **Transformer-based regression:**
 - 15-30% better small-R jet pT
 - 25-35% better large-R jet pT and mass
- Visible improvements expected for analyses with QCD backgrounds

Objet reconstruction: boosted $H \rightarrow b\bar{b}$

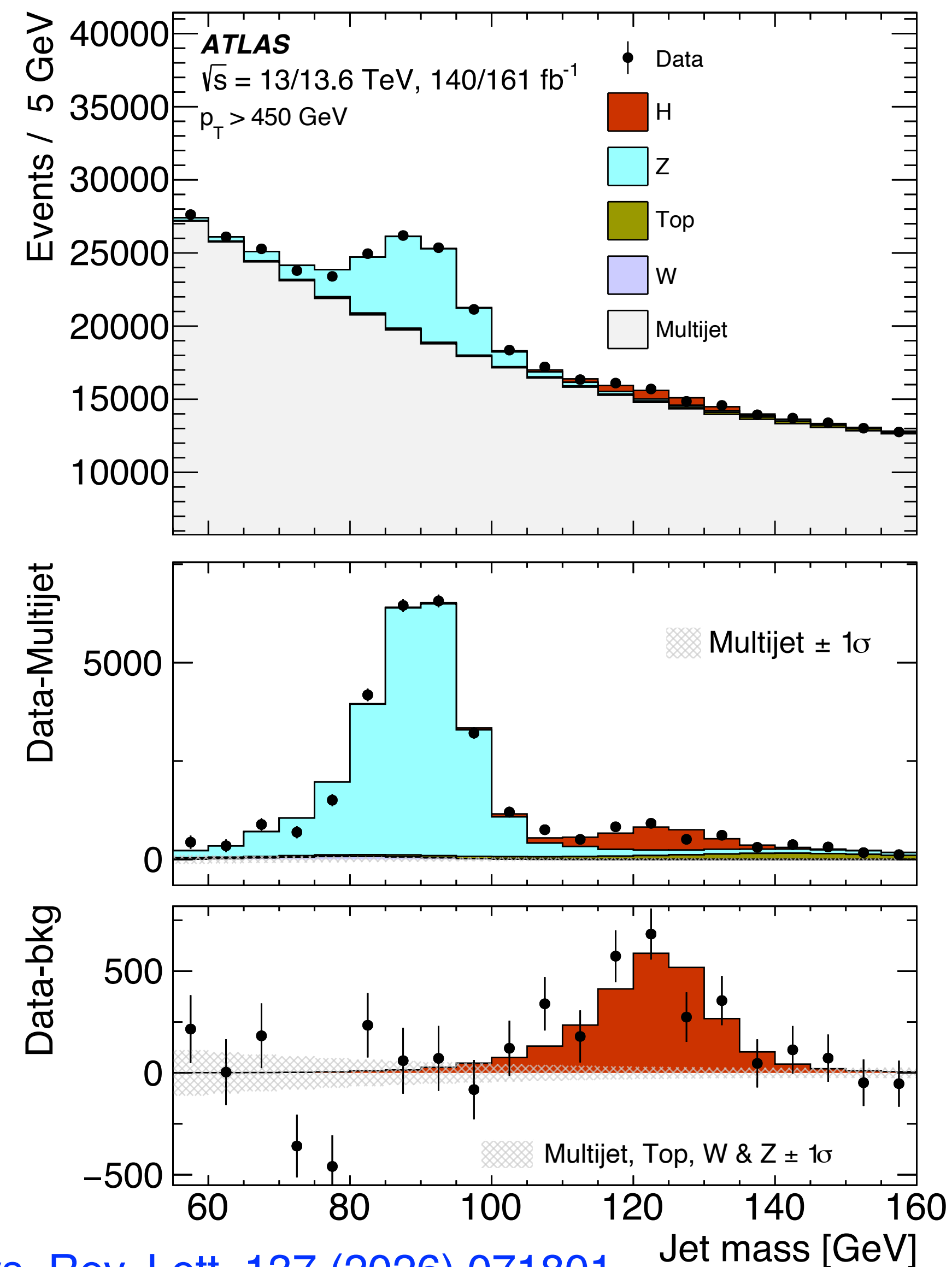


[ATL-PHYS-PUB-2023-021](#)

- **GN2X transformer tagger for large-R jets**
- Pixel detector conditions important: **radiation damage modelled in MC**
- Performance validated with boosted $Z \rightarrow b\bar{b}$
- Tagging + kin. regression applied to **inclusive high- p_T $H \rightarrow b\bar{b}$ analysis**:
 3.8σ observed (2.5σ expected) for $p_T(H) > 450$ GeV
Very large improvement wrt expectation from Run 2 analysis scaling

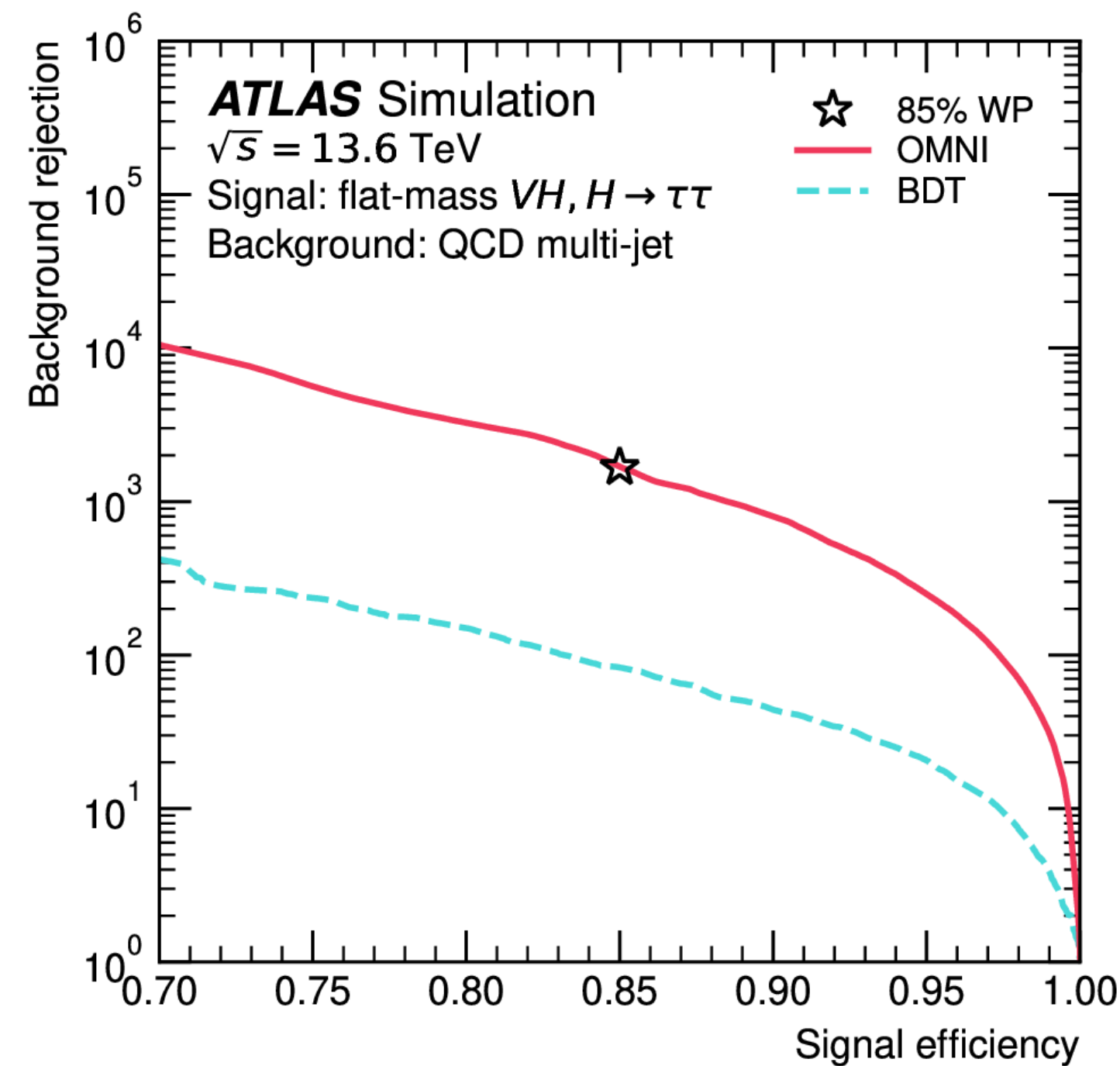
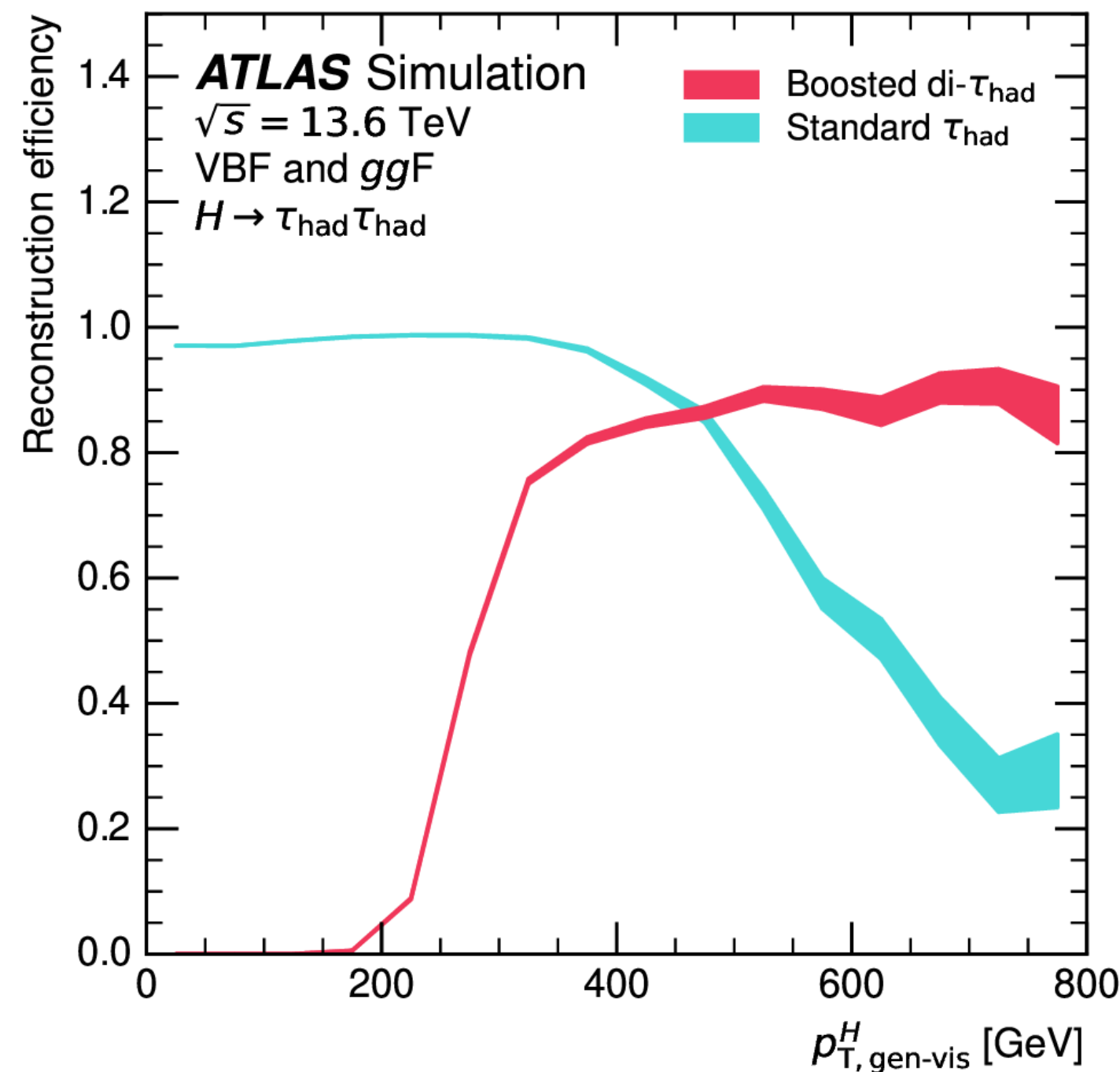
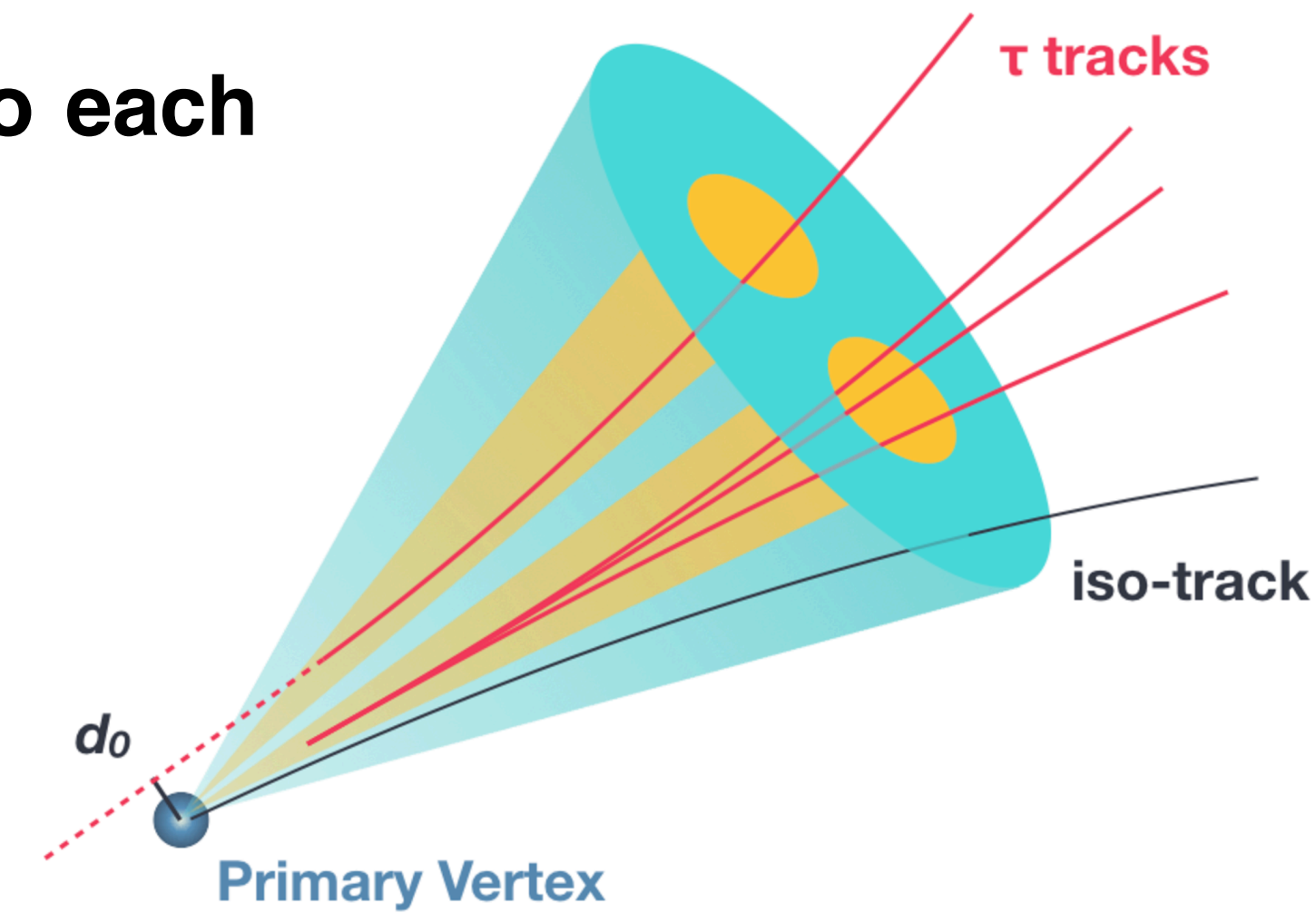


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[Phys. Rev. Lett. 137 \(2026\) 071801](#)

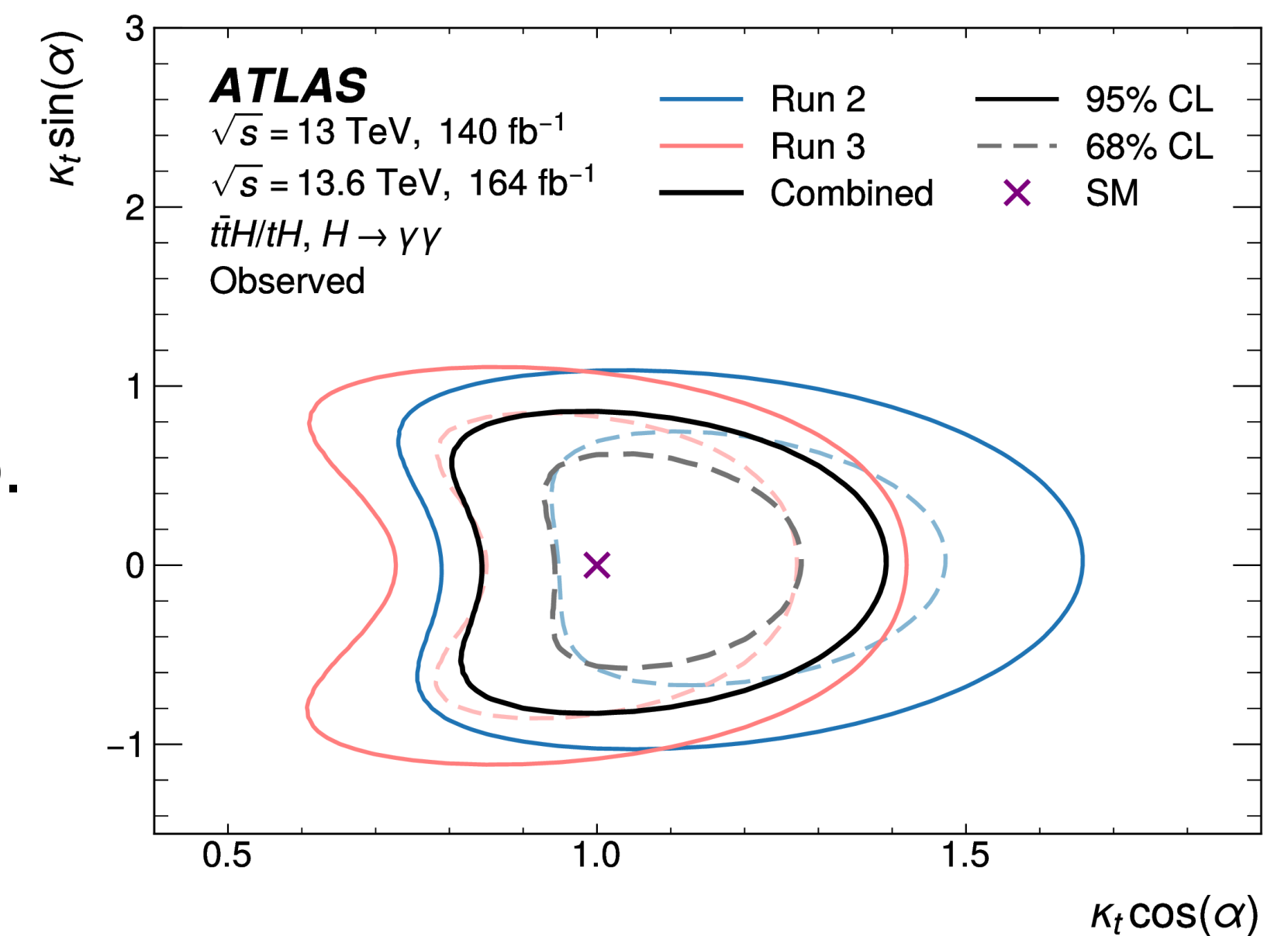
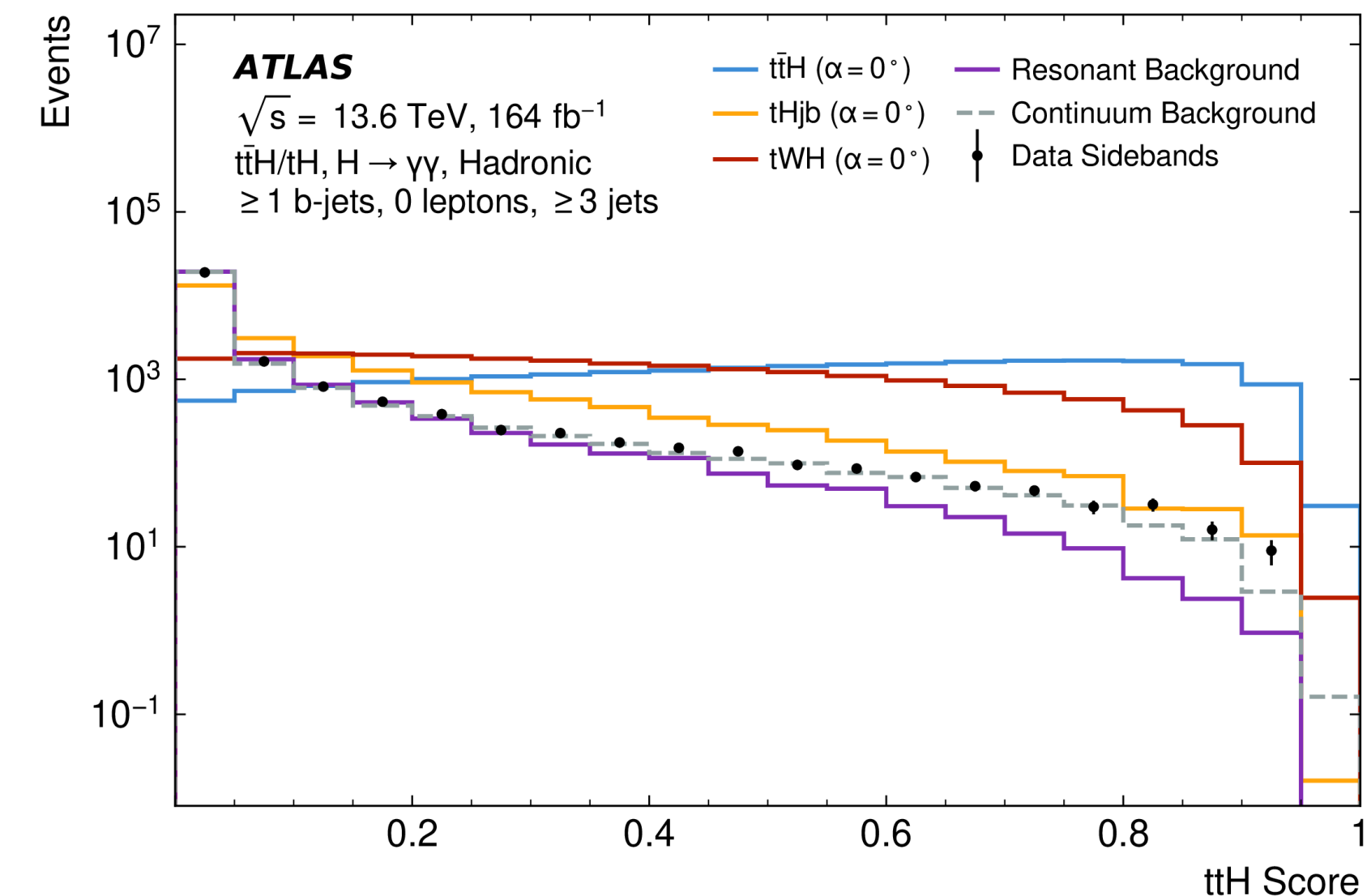
- Standard τ ID assumes low nearby hadronic activity: **close-by τ decays can veto each other**
- **Dedicated boosted di- τ reconstruction:**
 - $R=0.2$ τ subjects within $R=1.0$ large- R jets
 - dedicated energy calibration
 - Transformer-based OMNI tagger



- **Applied to boosted $H \rightarrow \tau\tau$ measurement:**
 3.8σ obs. (3.3 exp.) for $p_T(H) > 300$ GeV
 5% dedicated uncertainty from OMNI tagger modelling
- Alternative GN2X-based approach also studied [ATL-PHYS-PUB-2025-026](#)

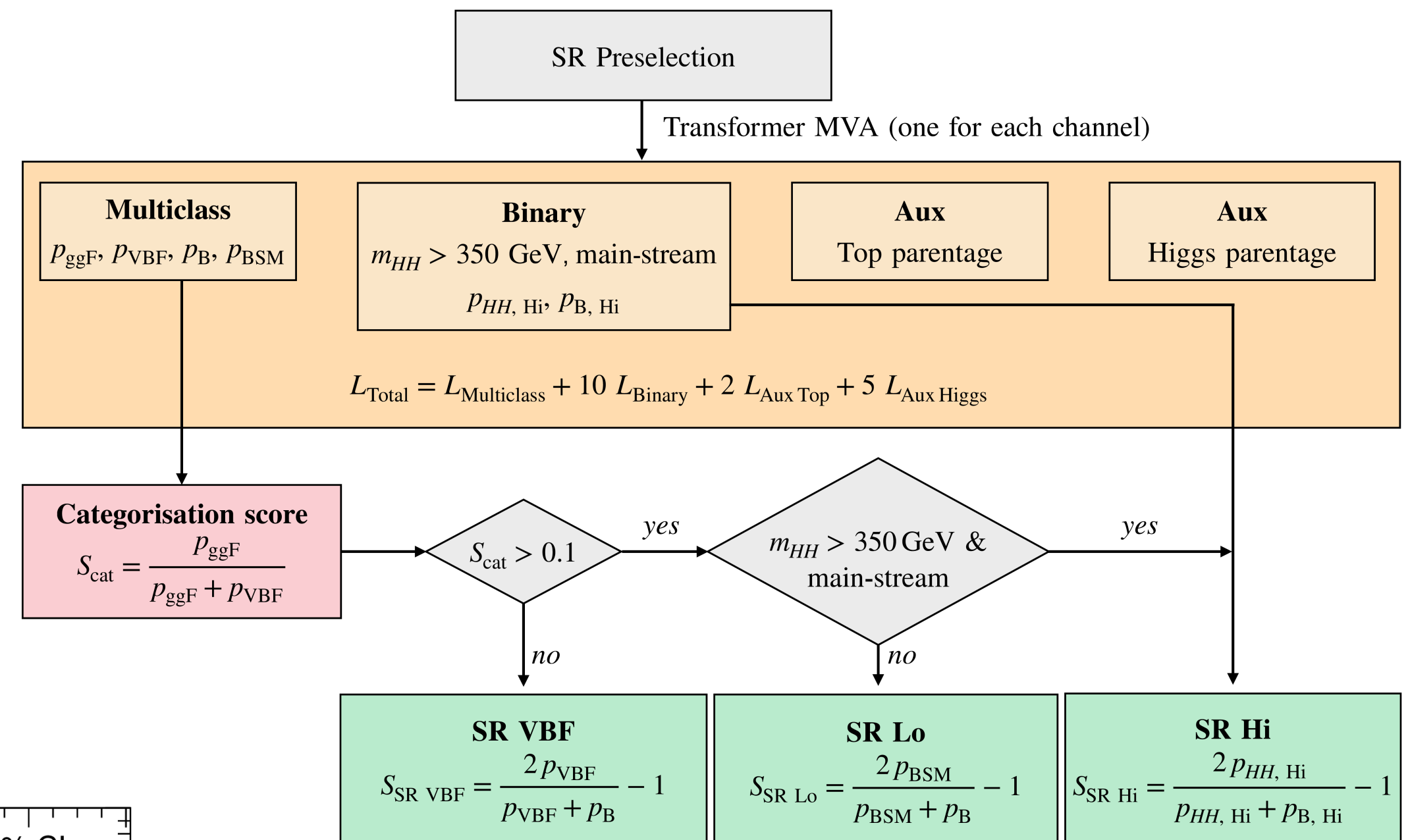
- Early Higgs analysis: **signal vs background MVA**
- **Multi-classifiers** enable:
 - better background constraints through dedicated CRs
 - improve STXS measurements
- **Example $t\bar{t}H$ $H \rightarrow \gamma\gamma$ CP measurement:**
 - GNN with 3 $H \rightarrow \gamma\gamma$ + top classes + other $H \rightarrow \gamma\gamma$ resonant background + continuum $\gamma\gamma$ background
 - **initialized from independent pre-training** with Delphes simulation <https://arxiv.org/abs/2412.10665>
=> 50% faster training
- **Categories built depending on:**
 - highest $t\bar{t}H$ / $tHj\bar{b}$ / tWH GNN prob.
 - binary CP GNN
 - subcat. based on background prob.
- **Results:**
 - 5.0σ obs. (4.7σ exp.) for $t\bar{t}H$
 - 0.87σ obs. (0.54σ exp.) for tH
 - $|\alpha| < 38^\circ$ at 95% CL

• Other example for $t\bar{t}H$ $H \rightarrow \tau\tau$ in [Morvan's talk](#)

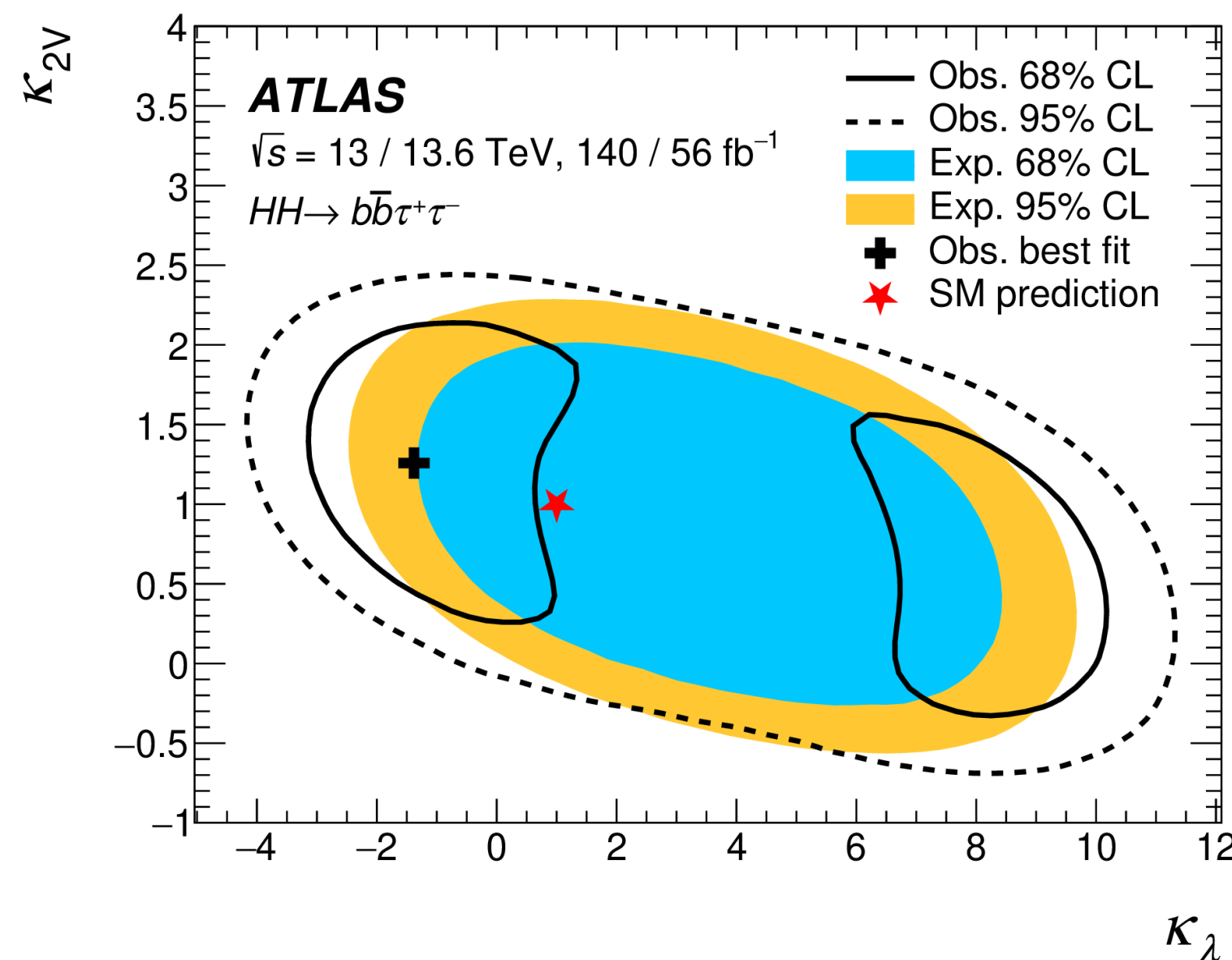


• Example $HH \rightarrow b\bar{b}\tau\tau$:

- transformer with SM ggF + VBF + BSM $\kappa\lambda=5$ + background nodes
- aux. tasks for object-parent associations
- staged event categorisation: optimal classifier in each category



- **Validation with ZH and ZZ:** first evidence for $ZH \rightarrow b\bar{b}\tau\tau$ 3.5σ obs. (2.4σ exp.)



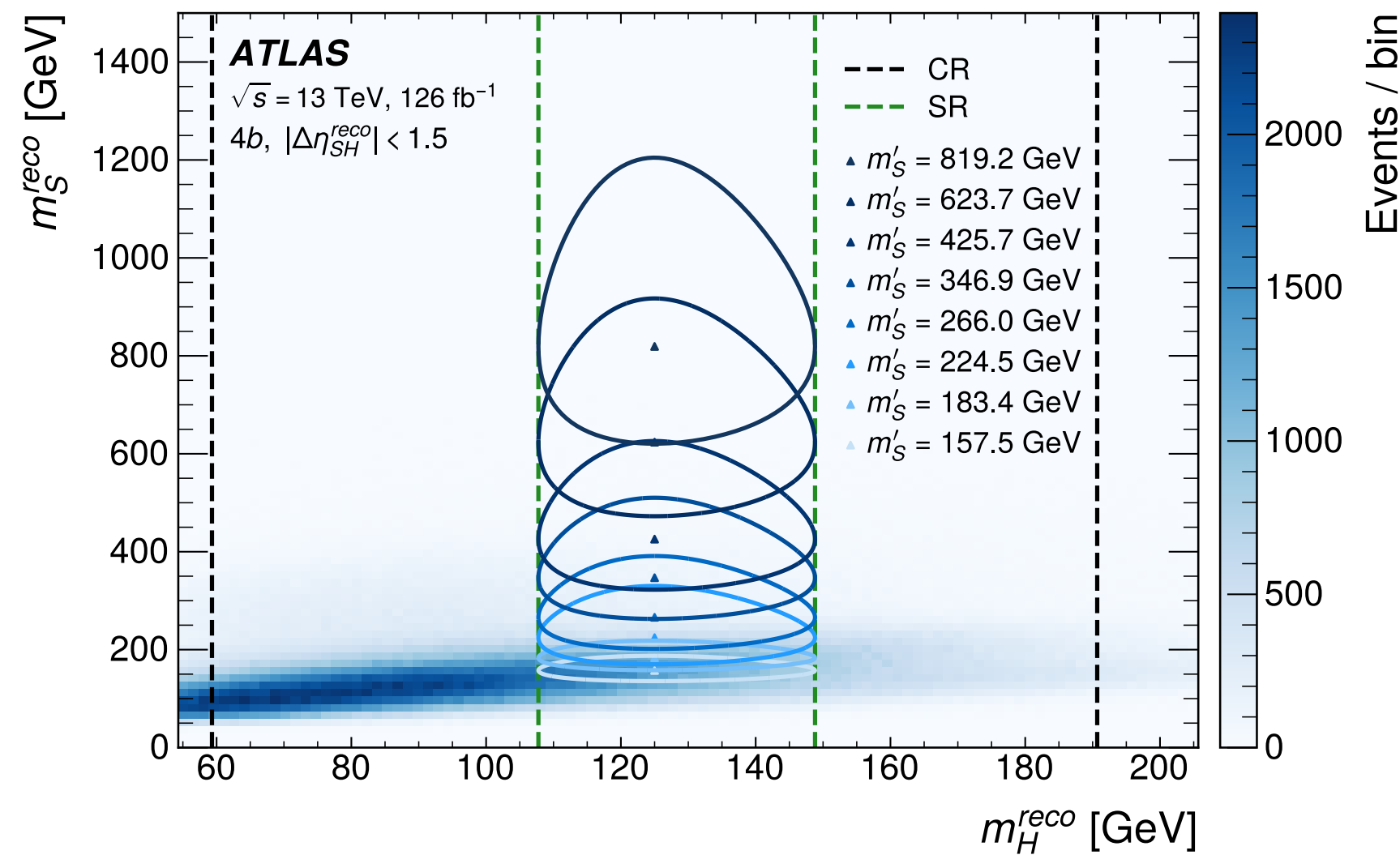
• Results:

- 2.6σ obs. (1.2σ exp.)
- $\mu(HH) = 2.6^{+1.4}_{-1.0}$
- $\kappa\lambda \in [-3.4, 1.5] \cup [5.5, 10.1] @ 95\% \text{ CL}$ ($[-1.7, 8.5]$ exp.)

• More details in [Salah-Eddine's talk](#)

Analysis strategy: normalising flow for bkg estimation

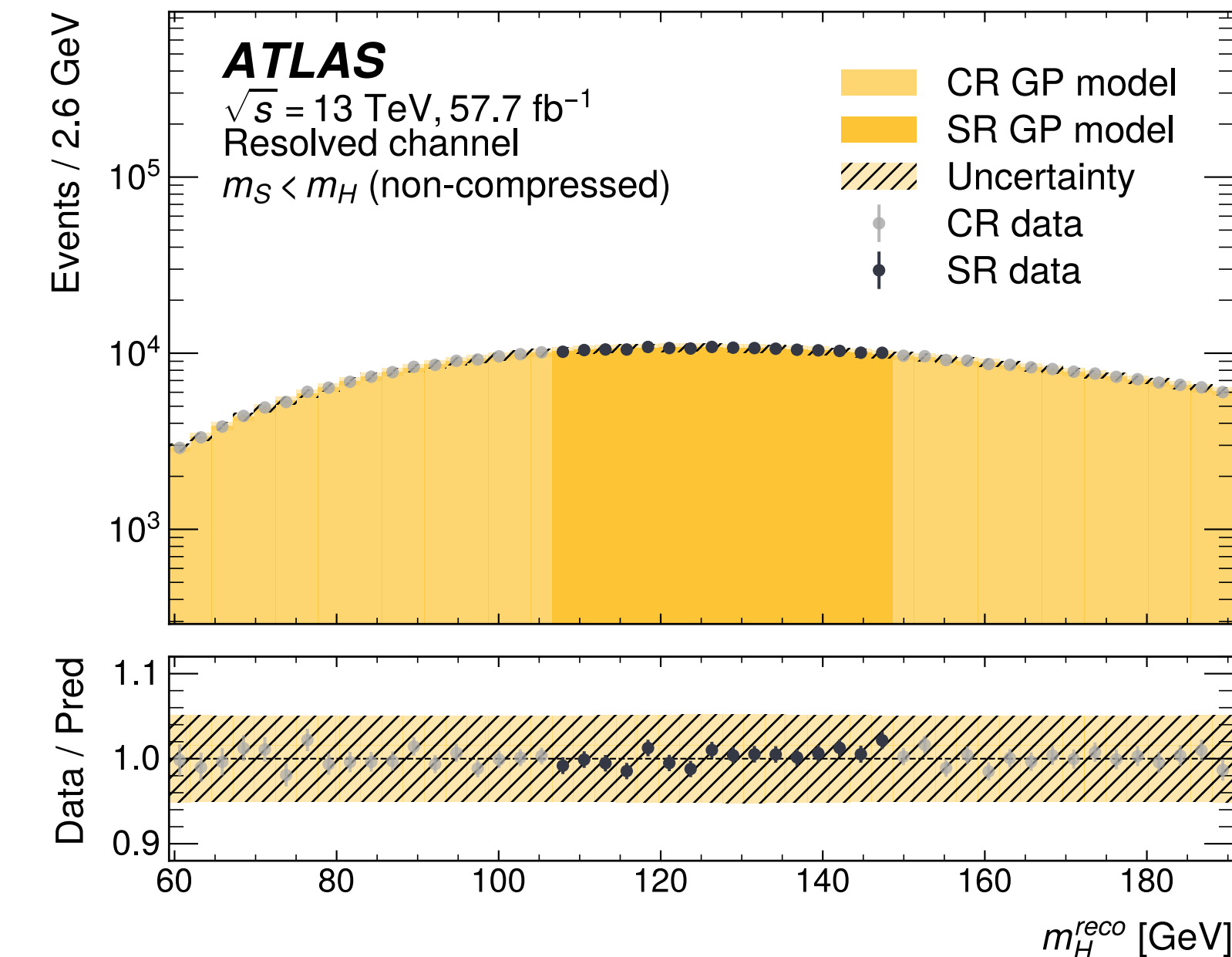
[HIGP-2024-31 \(subm. to PRD\)](#)



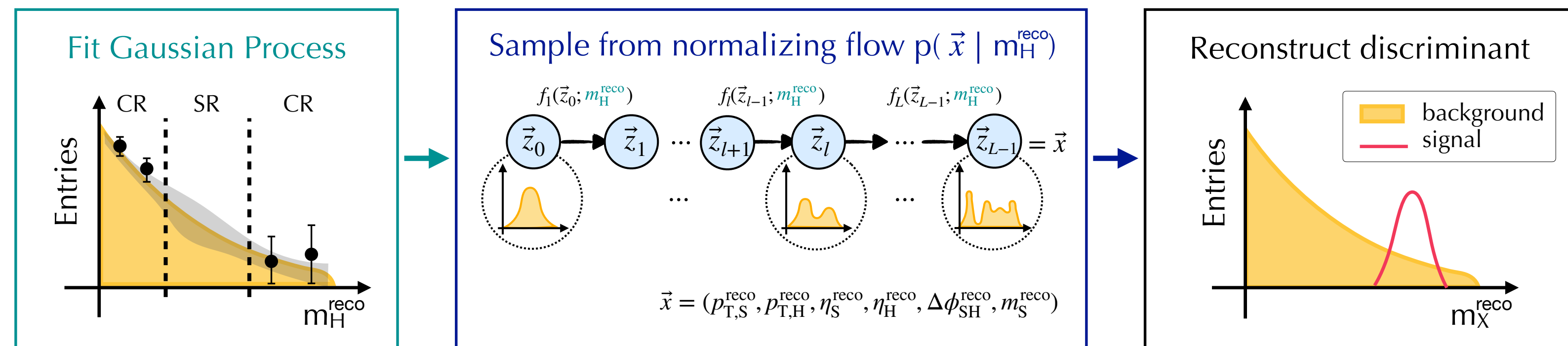
- New enhanced data-driven technique based on Normalising Flows for **BSM resonance $X \rightarrow SH \rightarrow 4b$ search with Run 2 data**

$$p(\vec{x}, m_H^{\text{reco}}) = p_{\text{GP}}(m_H^{\text{reco}}) \cdot p_{\text{flow}}(\vec{x} | m_H^{\text{reco}})$$

- **Gaussian Process (GP)** extrapolate from m_H sidebands



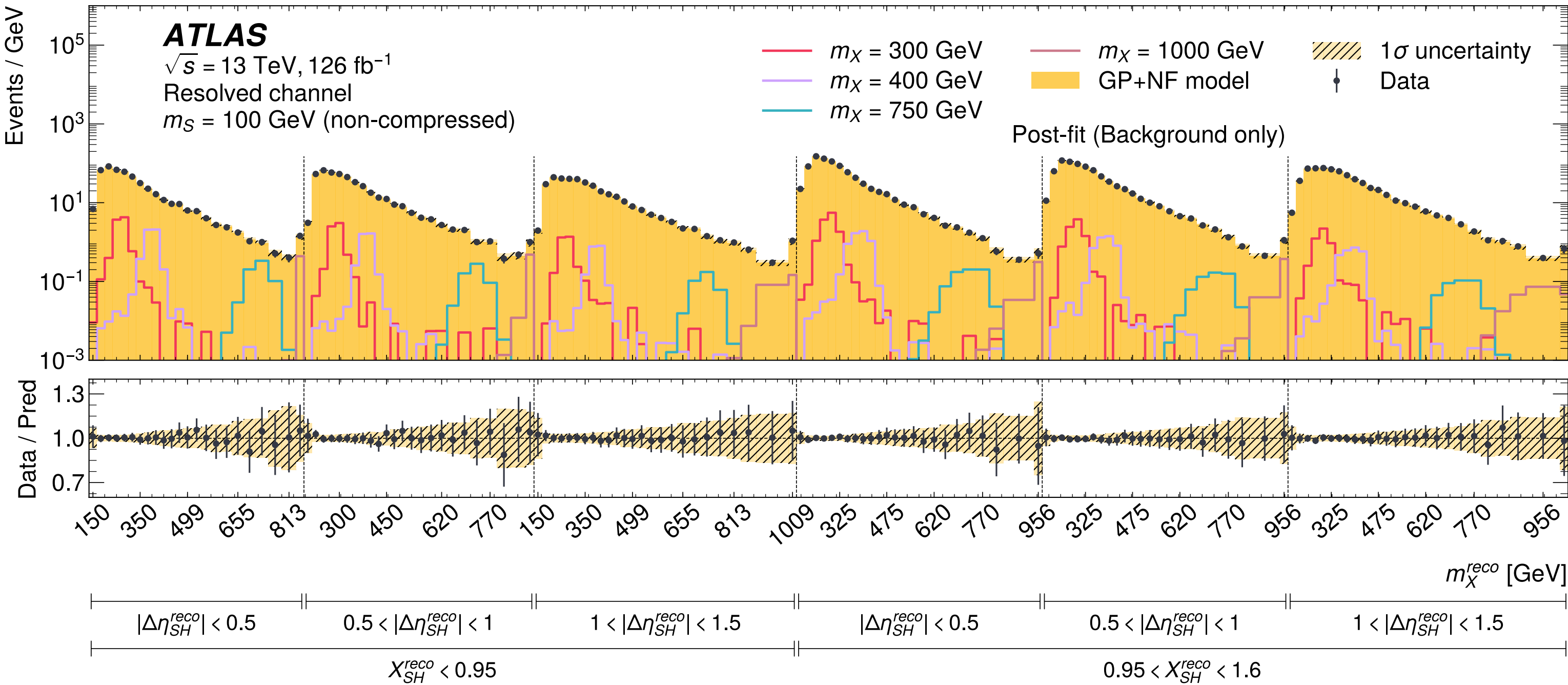
- **Normalizing Flow (NF):**
 - generates full S + H kinematics conditional on m_H
 - uses rational quadratic neural spline flows (RQ-NSF)



Analysis strategy: normalising flow for bkg estimation

HIGP-2024-31 (subm. to PRD)

- **Training uncertainty:**
 - 25 independent trainings
 - PCA-based uncertainty reduction
- **Non-closure uncertainty reduced by x2** wrt previous techniques



• Validation in regions with reduced b-tagging

m_X [GeV]	m_S [GeV]	Observed [fb]	Expected [fb]	Exp. $\pm 1\sigma$ [fb]	Exp. $\pm 2\sigma$ [fb]
650	350	96.7	122.0	(87.9, 181.4)	(65.5, 278.0)
700	400	62.1	96.5	(69.6, 142.7)	(51.8, 216.5)
1200	900	28.7	47.0	(33.8, 69.2)	(25.2, 104.6)

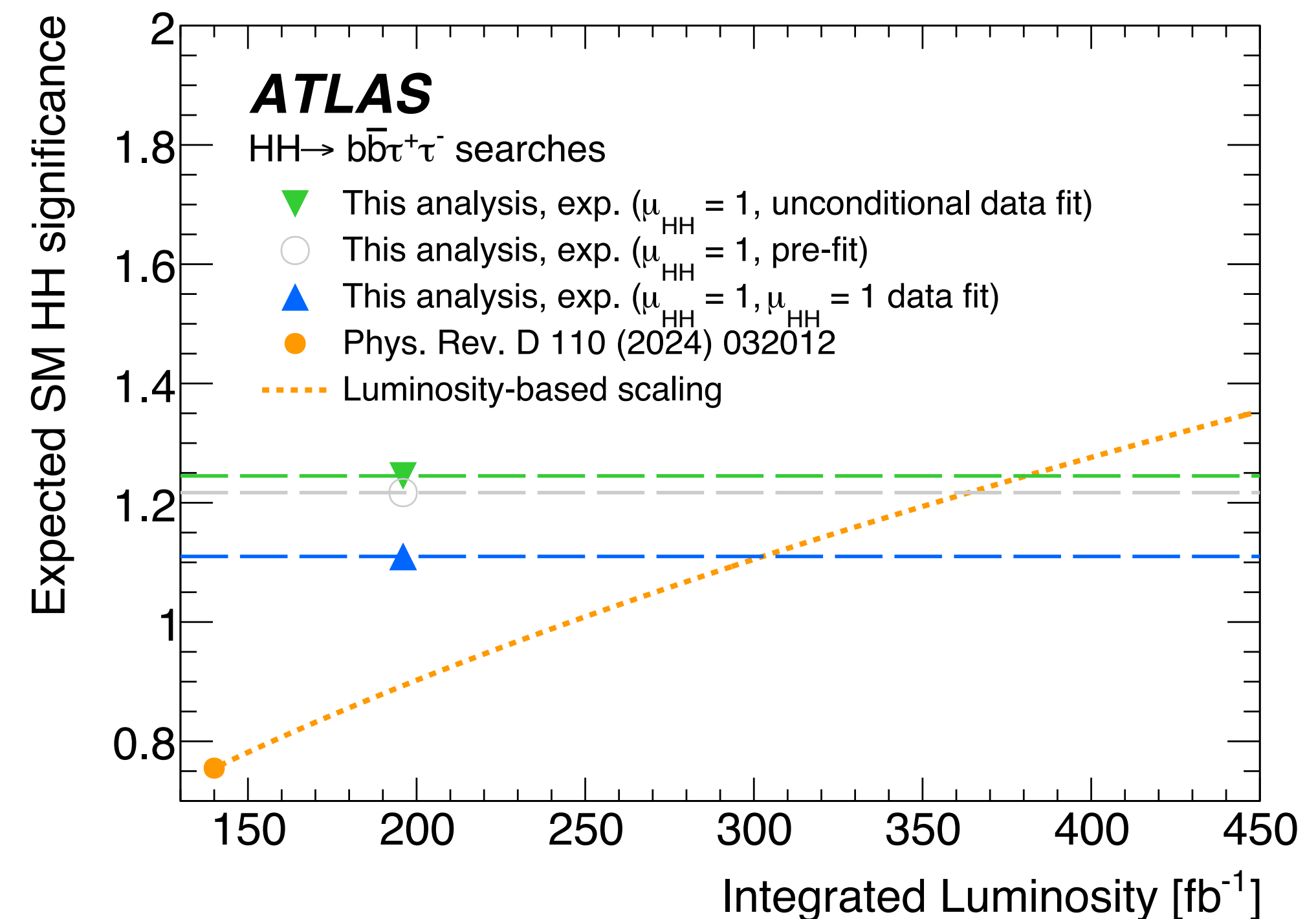
- Excess observed in CMS analysis [HIG-20-012 \(subm. to PRD\)](#) at $(m_X, m_S) = (600 \text{ GeV}, 400 \text{ GeV})$ disfavoured

Uncertainty source	Relative impact of uncertainties [%]	
	Resolved Channel	Mixed Channel
Data statistical uncertainty	24–51	55–74
All systematic uncertainties	49–76	26–45
Experimental	48–76	26–45
Detector response	9–15	24–33
Luminosity and pileup	<1	<1
Flavor tagging	0–5.4	22–32
Jet reconstruction	0.1–2.7	0.4–2.5
Trigger efficiency	8–9	<1
Background modeling	44–73	1–26
Network retraining and CR stats	36–63	0.1–23
Non-closure and normalization	0–25	0.4–7.2
Theoretical	<1	<1
MC statistical	<1	<1

Conclusion

- **Object reconstruction continues to evolve towards analysis-specific and ML-based approaches:**
 - improved vertex selection, flavour tagging and jet regression
 - dedicated reconstruction for challenging boosted topologies
- **More powerful event classifiers exploit the increasing complexity of Higgs final states:**
 - multi-class architectures and auxiliary tasks improve event categorisation and physics separation
 - dedicated training strategies can preserve information needed for the final measurement
- **Data-driven background modelling is increasingly benefiting from modern generative techniques:**

adversarial training and normalising flows provide new ways to control correlations and model complex backgrounds
- **Advances in analysis methodology are becoming a major driver of the sensitivity of ATLAS Higgs measurements and searches**

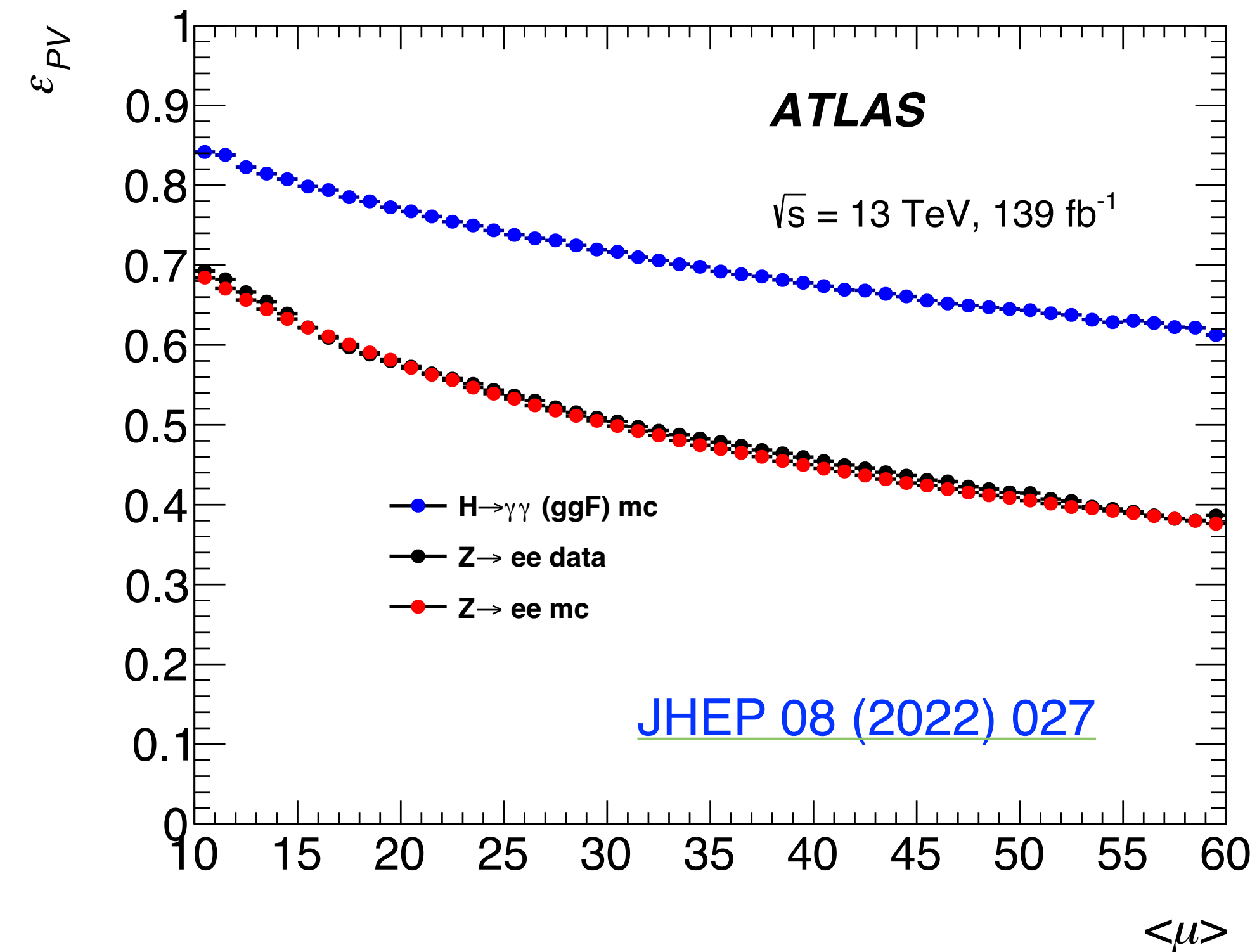


Back up

Objet reconstruction: primary vertex

- **Dedicated $H \rightarrow \gamma\gamma$ Neural Network for PV selection:**
 - vertex tracks + photon pointing inputs
 - 8% improvement in PV selection efficiency at analysis-level
 - improved $m(\gamma\gamma)$ resolution

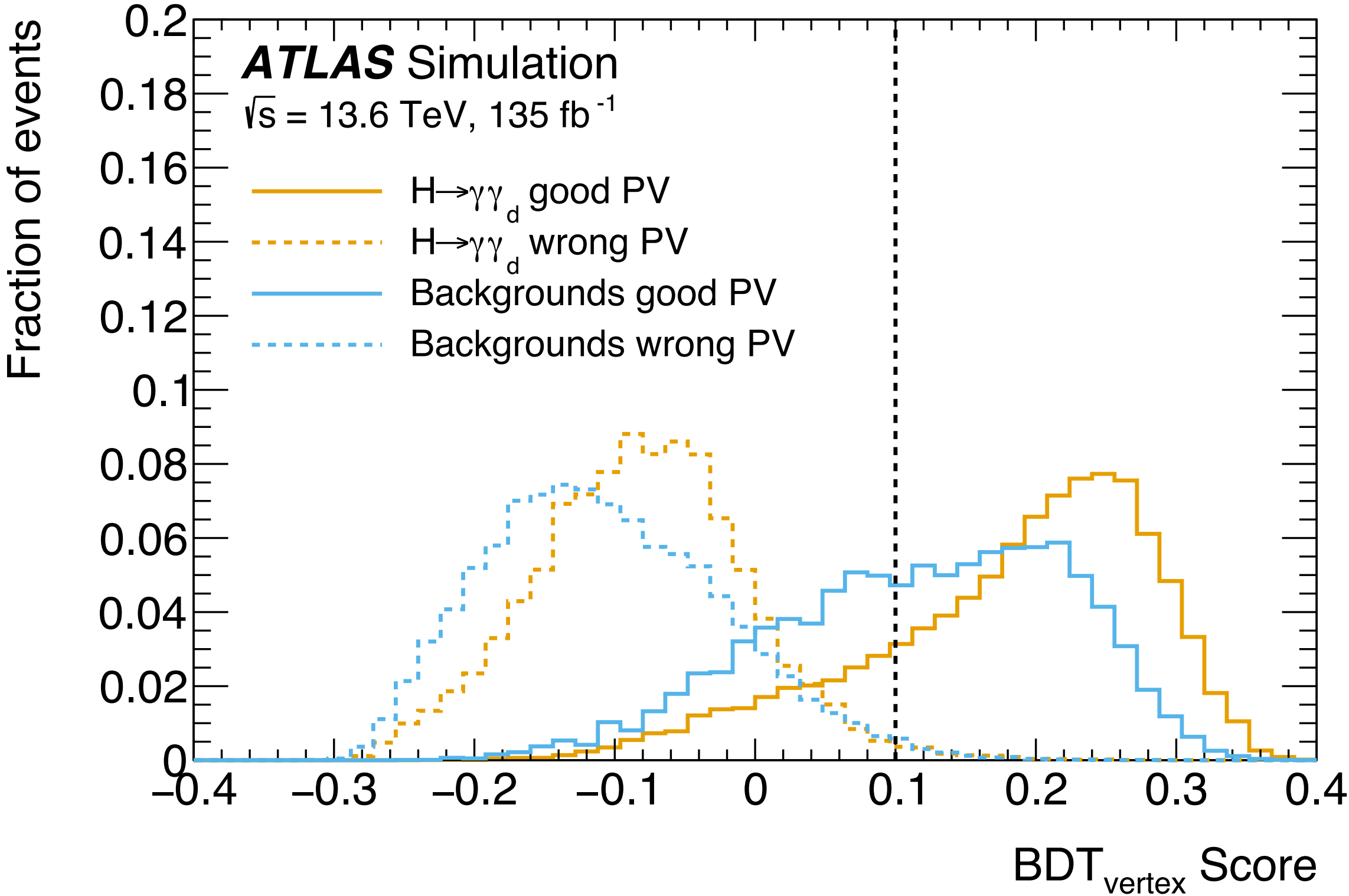
The diphoton production vertex is selected from the reconstructed collision vertices using a neural-network algorithm. For each vertex the algorithm takes the following as input: the combined z -position of the intersections of the extrapolated photon trajectories (reconstructed by exploiting the longitudinal segmentation of the calorimeter) with the beam axis; the sum of the squared transverse momenta $\sum p_T^2$ and the scalar sum of the transverse momenta $\sum p_T$ of the tracks associated with the vertex; the difference in azimuthal angle $\Delta\phi$ between the direction defined by the vector sum of the track momenta and that of the diphoton system. The trajectory of each photon is measured using the longitudinal segmentation of the calorimeter and a constraint from the average collision point of the proton beams. For converted photons, the position of the conversion vertex is also used if tracks from the conversion have hits in the silicon detectors.



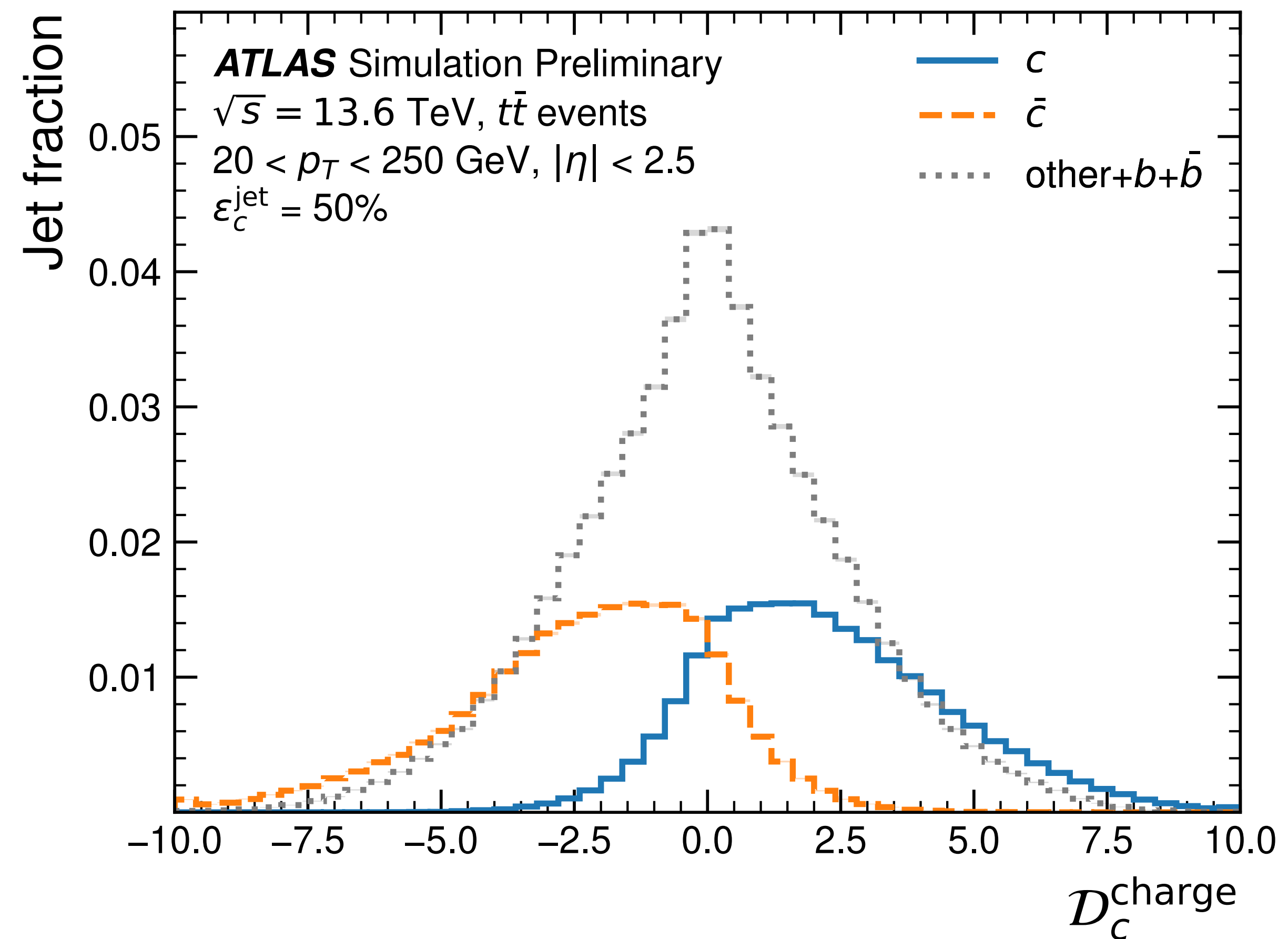
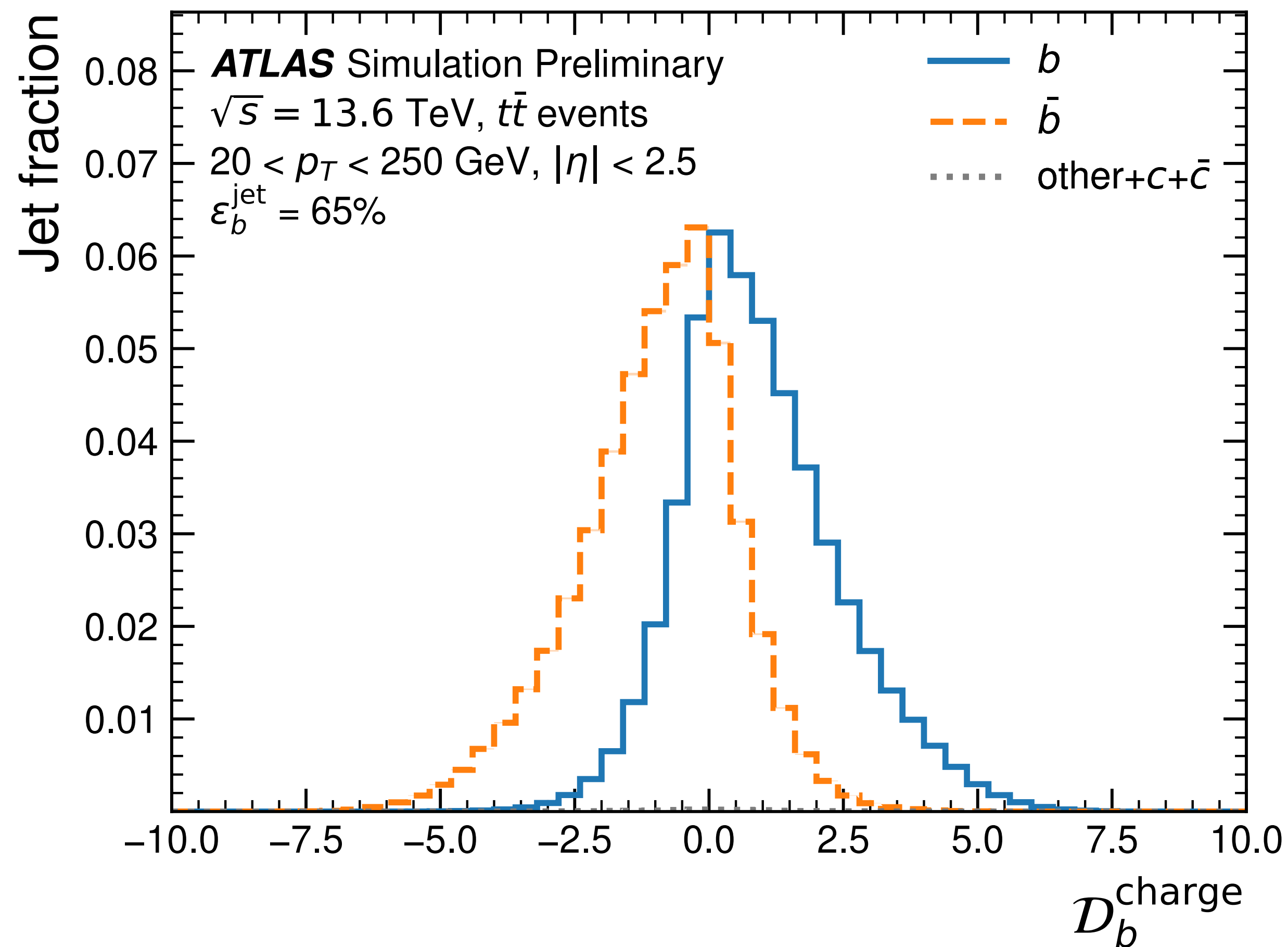
[Phys. Rev. D 90 \(2014\) 112015](#)

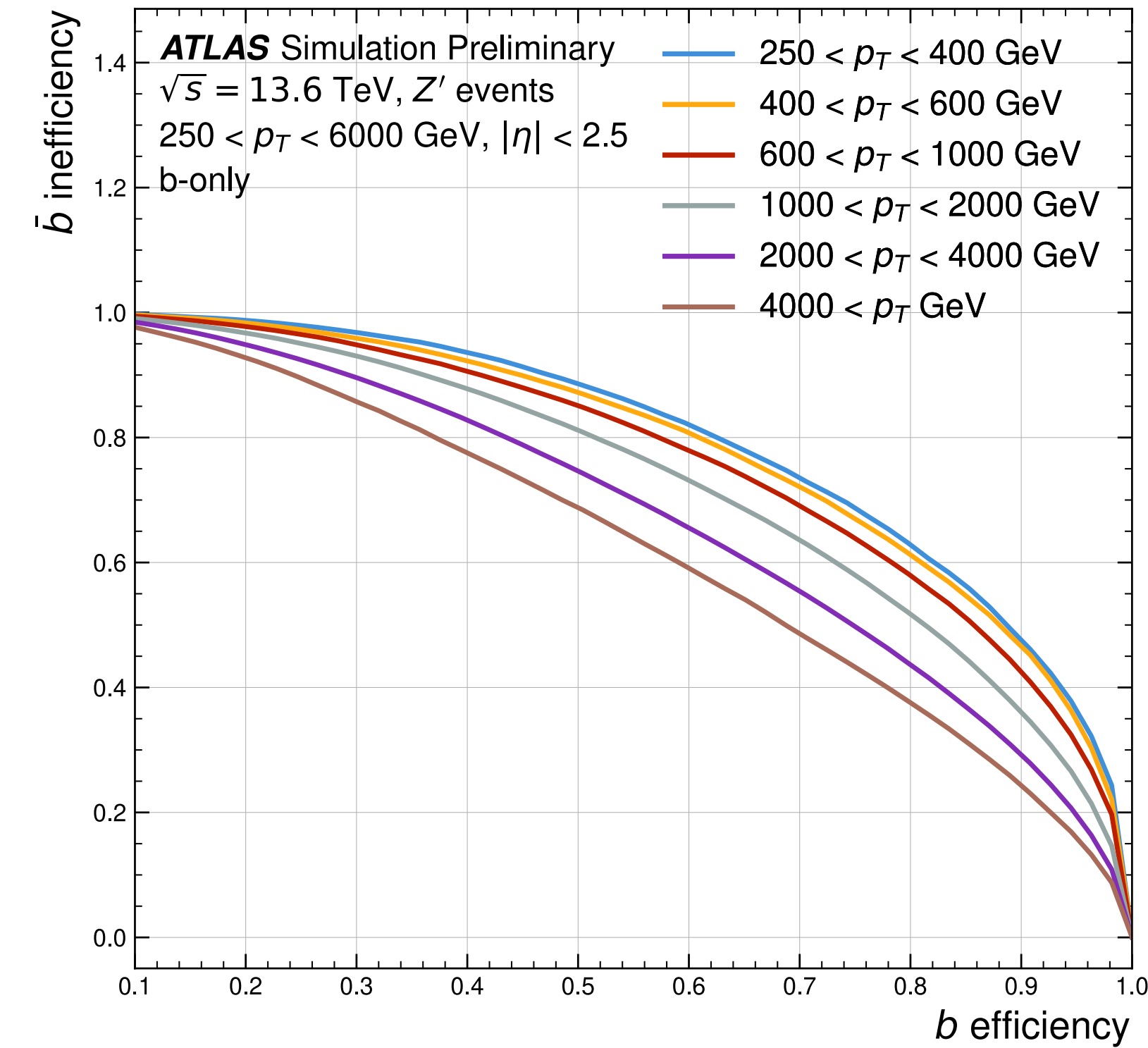
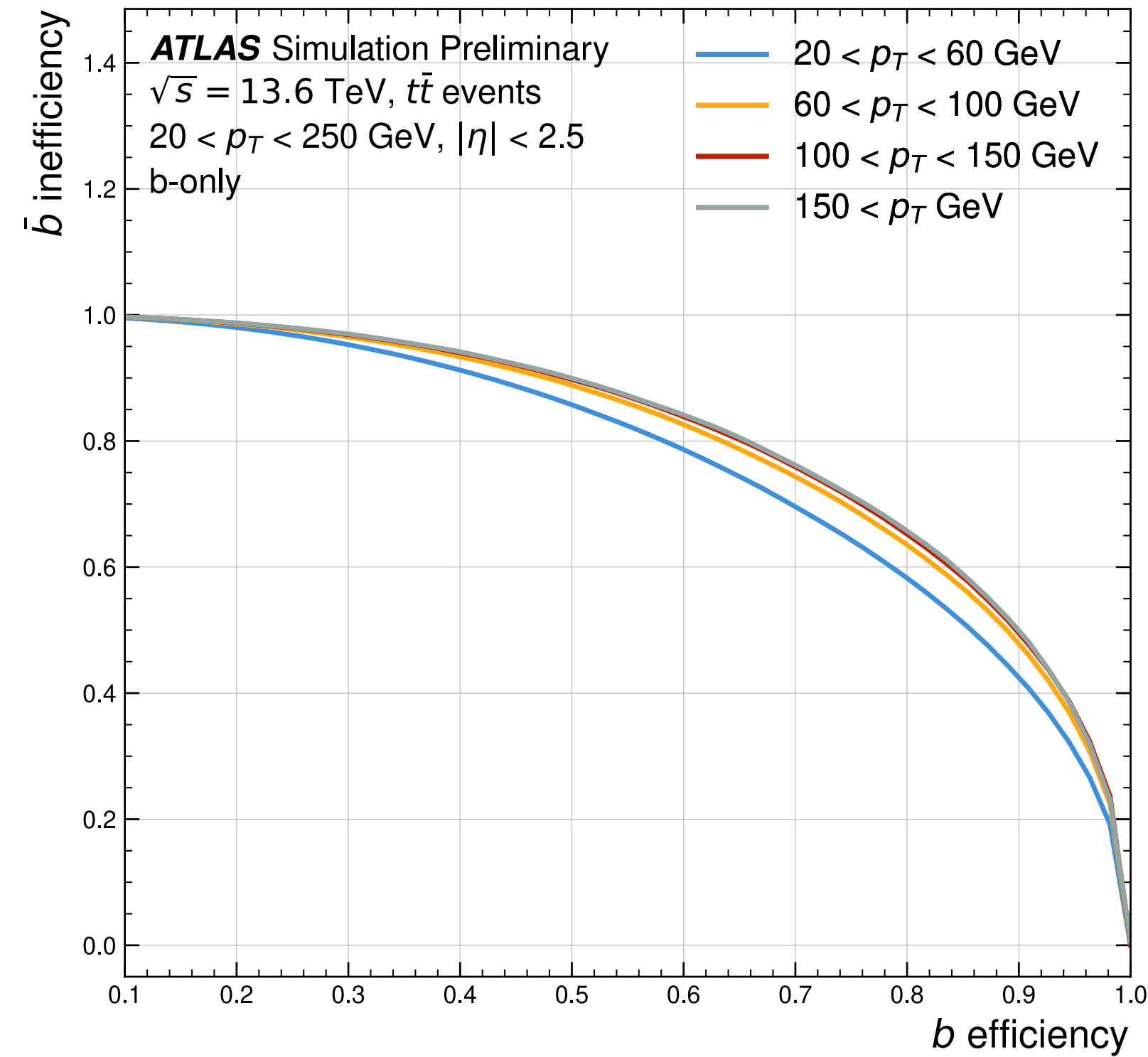
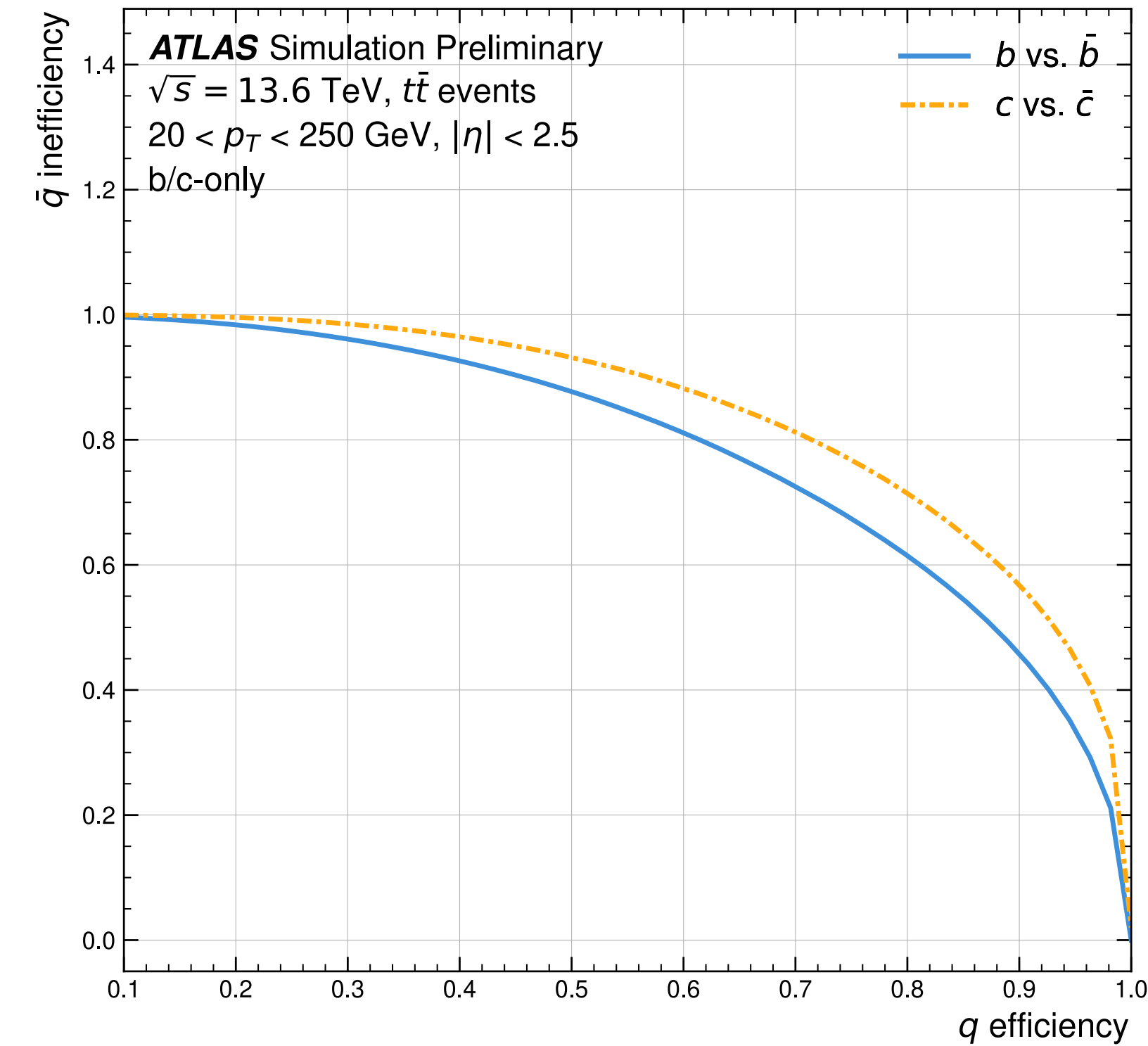
Variable	Description
$\log(\sum p_T^2(\text{tracks}))$	Logarithm of the sum of the squared transverse momenta of tracks associated with the vertex.
$ \Delta\phi(\vec{p}_{\text{vtx}}, \vec{p}_\gamma) $	Azimuthal separation between the momentum of the tracks associated with the vertex and the photon direction.
$ \Delta\phi(\vec{p}_T^{\text{miss}}, \vec{p}_T^j) $	Azimuthal separation between the missing transverse momentum and the leading jet.
$ \Delta\phi(j_1, j_2) $	Azimuthal separation between the two leading jets.
Δp_T^{miss}	Difference between the missing transverse momentum computed without JVT requirements and the nominal reconstruction.
$\mathcal{S}_{p_T^{\text{miss}}}$	Significance of the missing transverse momentum.
$(z_{\text{vtx}} - z_\gamma)/\sigma(z_\gamma)$	Distance along the longitudinal (z) axis between the reconstructed primary vertex and the vertex position inferred from the photon trajectory (photon pointing), normalised by the photon pointing resolution. The photon trajectory is reconstructed using its energy deposits in the first and second layer of the ECAL.
z_{skew}	Skewness of the z distribution of tracks associated with the vertex.
Number of central jets	Number of reconstructed jets in the central region ($ \eta < 2.5$).
$(p_T^{\text{miss}} + p_T^\gamma)/\sum p_T^{\text{jet}}$	Transverse momentum balance between the photon+ p_T^{miss} system and the reconstructed jets.
z_{kurt}	Kurtosis of the z distribution of tracks associated with the vertex.

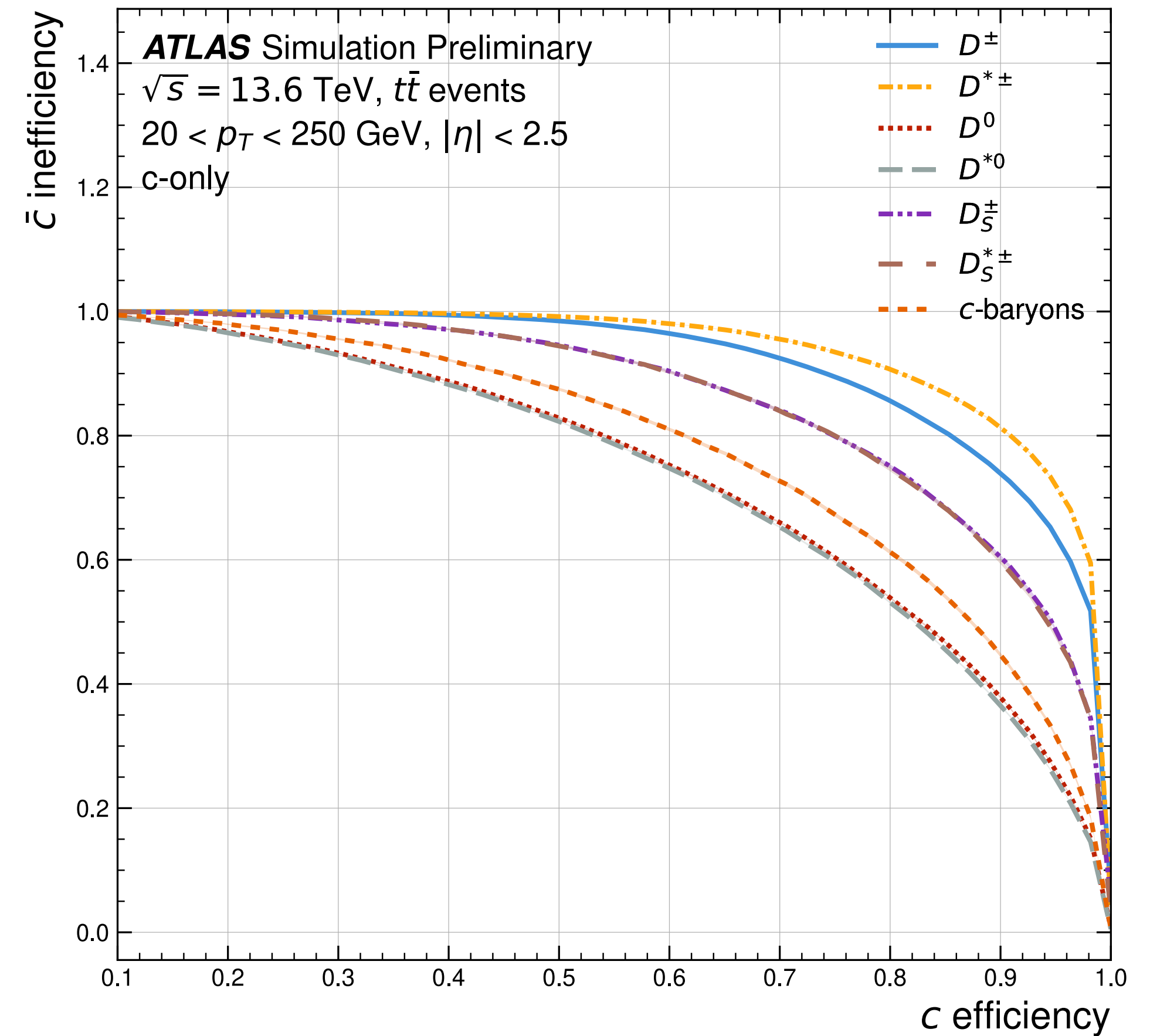
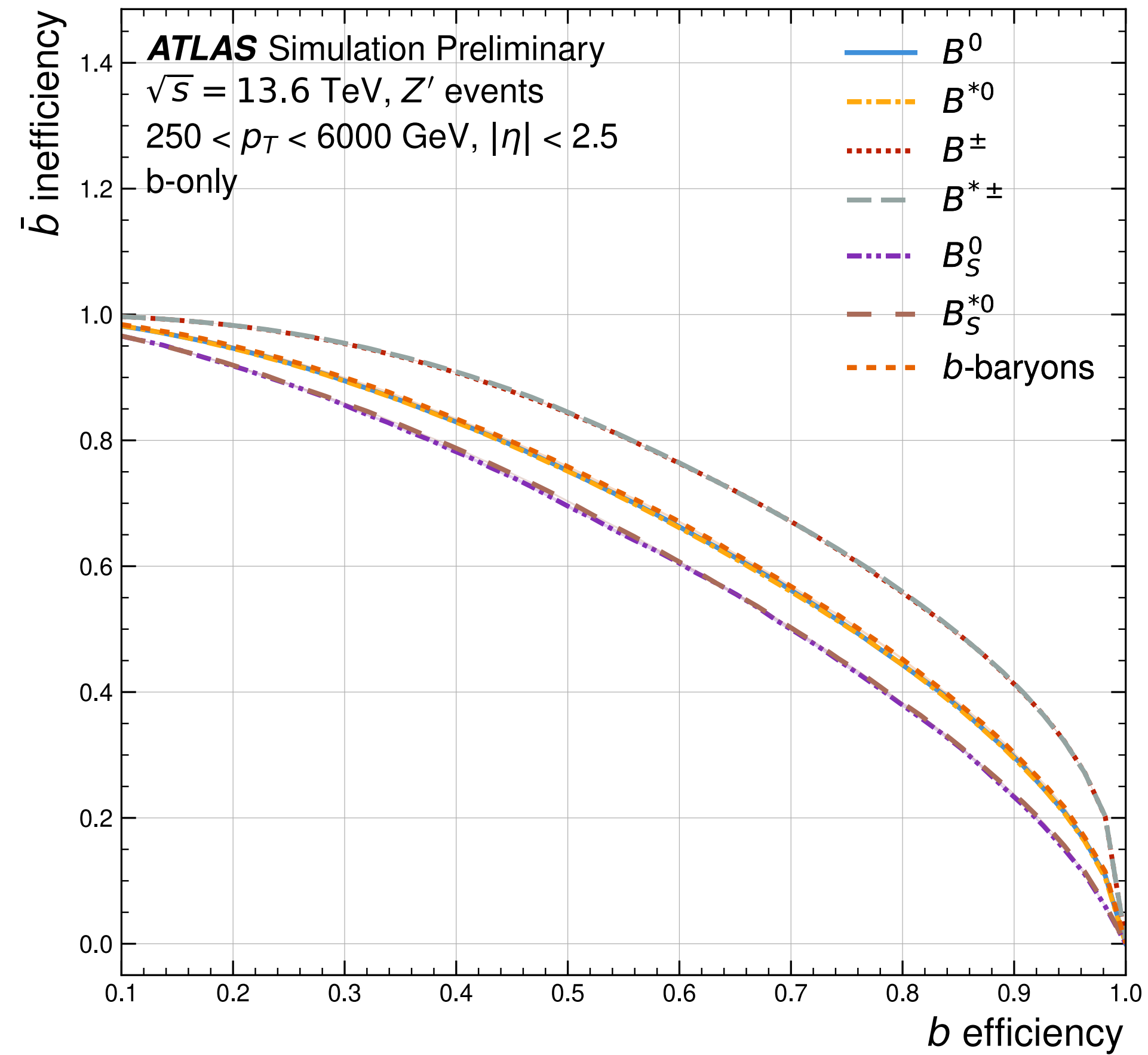
- **BDT to reject events with wrong PV** used in search for dark photon $H \rightarrow \gamma\gamma_D$ in photon+MET final state:
 - combines photon + jet + MET inputs
 - reduces background contamination from events with fake MET



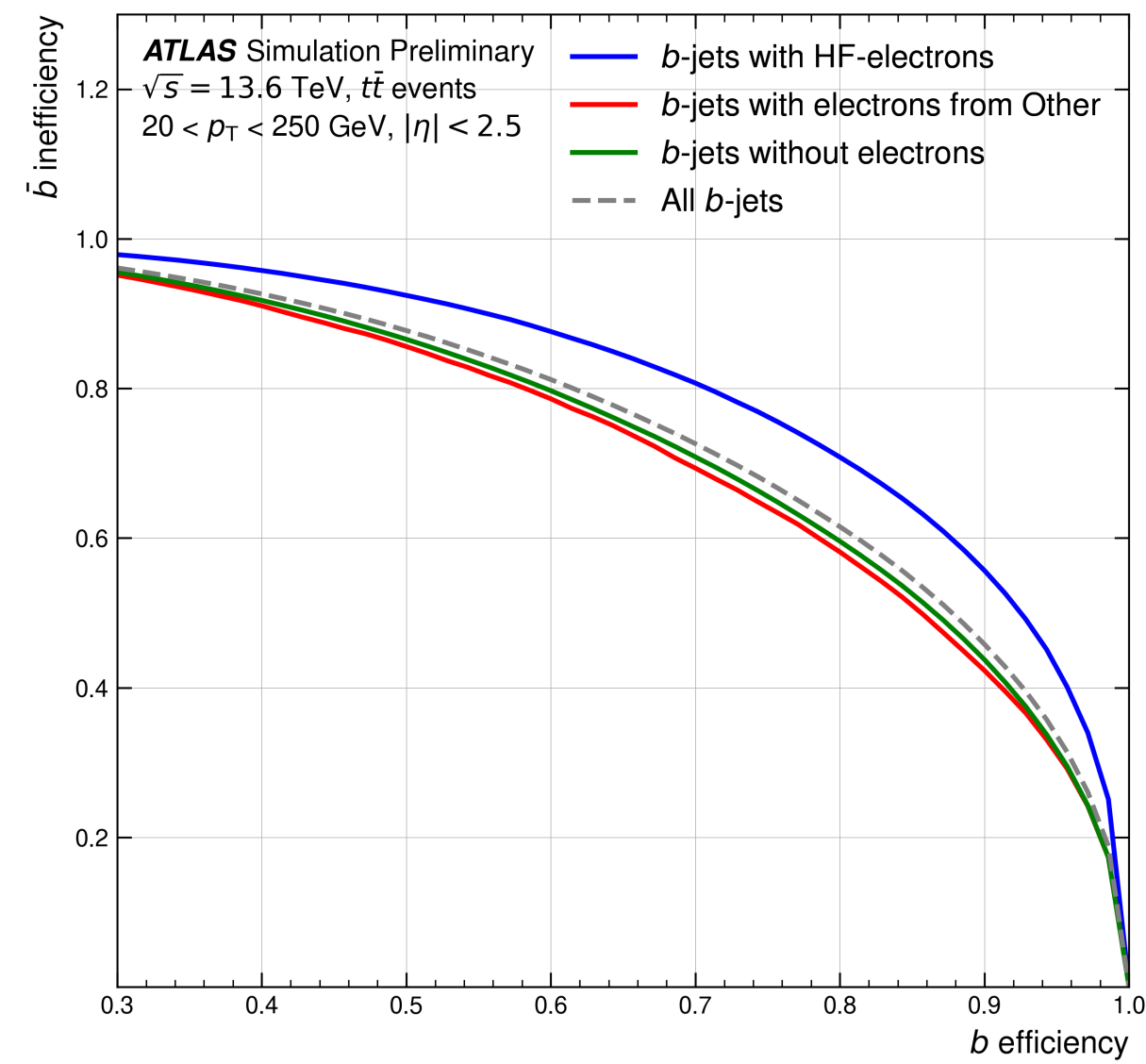
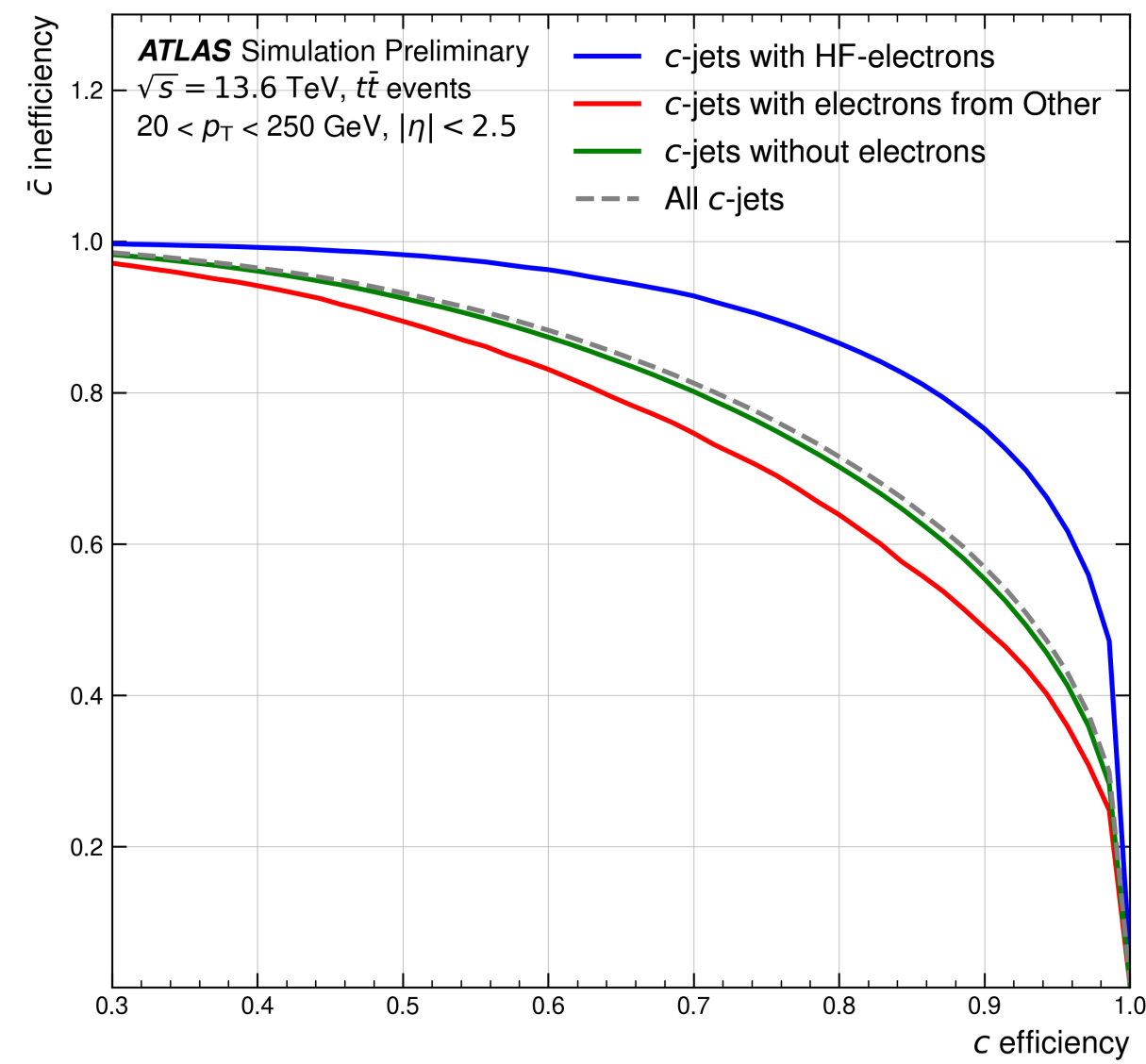
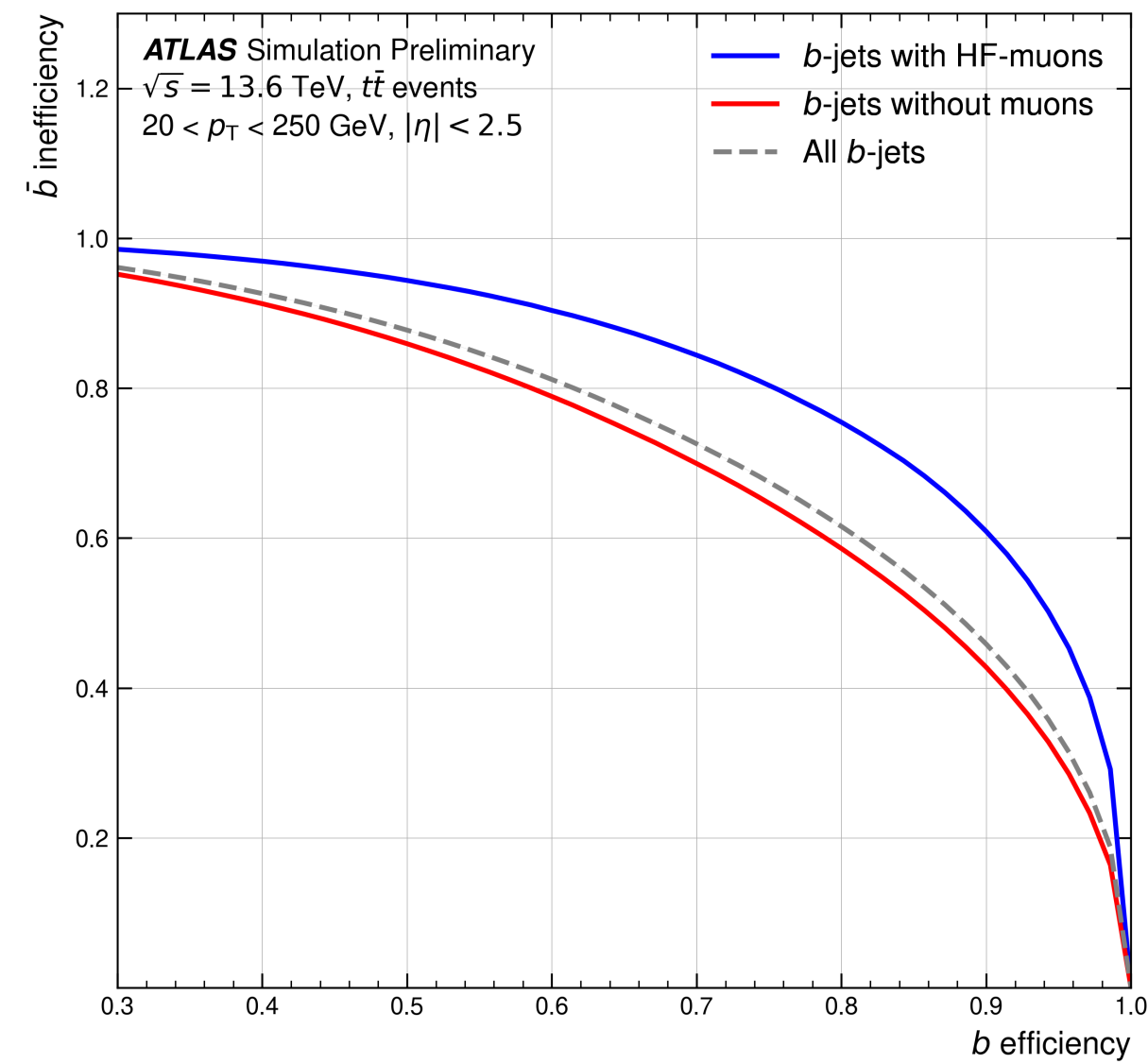
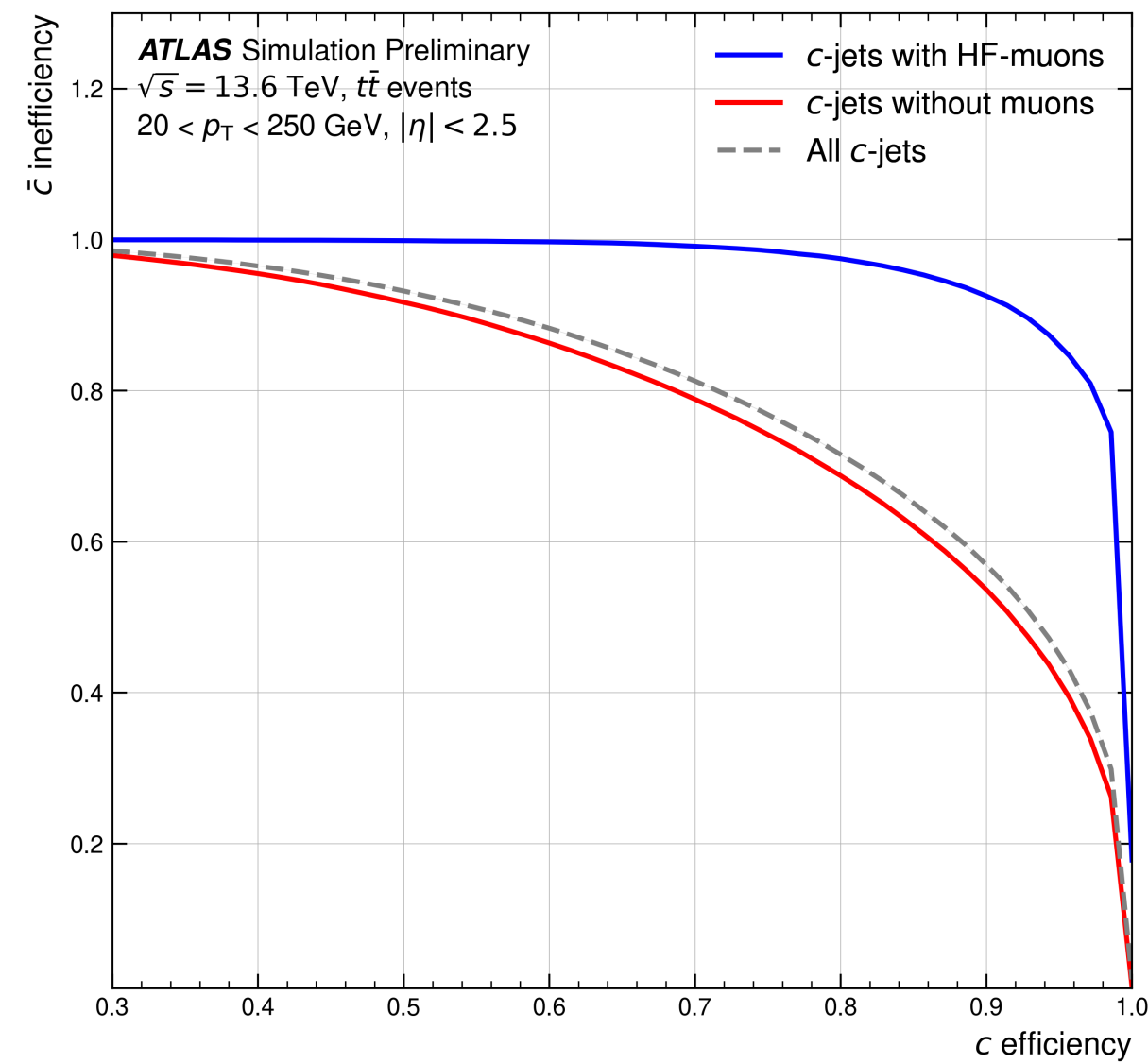
Category	Description	Name
Hadronic leakage	Ratio of E_T in the first layer of the hadronic calorimeter to E_T of the EM cluster (used over the ranges $ \eta < 0.8$ and $ \eta > 1.37$)	R_{had_1}
	Ratio of E_T in the hadronic calorimeter to E_T of the EM cluster (used over the range $0.8 < \eta < 1.37$)	R_{had}
EM third layer	Ratio of the energy in the third layer to the total energy in the EM calorimeter	f_3
EM second layer	Ratio of the sum of the energies of the cells contained in a 3×7 ($\eta \times \phi$) rectangle (measured in cell units) to the sum of the cell energies in a 7×7 rectangle, both centred around the most energetic cell	R_η
	Lateral shower width, $\sqrt{(\sum E_i \eta_i^2)/(\sum E_i) - ((\sum E_i \eta_i)/(\sum E_i))^2}$, where E_i is the energy and η_i is the pseudorapidity of cell i and the sum is calculated within a window of 3×5 cells	w_{η_2}
EM first layer	Ratio of the sum of the energies of the cells contained in a 3×3 $\eta \times \phi$ rectangle (measured in cell units) to the sum of the cell energies in a 3×7 rectangle, both centred around the most energetic cell	R_ϕ
	Total lateral shower width, $\sqrt{(\sum E_i (i - i_{\text{max}})^2)/(\sum E_i)}$, where i runs over all cells in a window of $\Delta\eta \approx 0.0625$ and i_{max} is the index of the highest-energy cell	$w_{s \text{ tot}}$
	Difference between the energy of the cell associated with the second maximum, and the energy reconstructed in the cell with the smallest value found between the first and second maxima	ΔE_s
	Ratio of the energy difference between the maximum energy deposit and the energy deposit in a secondary maximum in the cluster to the sum of these energies	E_{ratio}
Track conditions	Ratio of the energy measured in the first layer of the electromagnetic calorimeter to the total energy of the EM cluster	f_1
	Number of hits in the innermost pixel layer	$n_{\text{innermost}}$
	Number of hits in the pixel detector	n_{Pixel}
	Number of hits in the SCT detectors including expected in dead modules	n_{SCT}
	Transverse impact parameter relative to the beam-line	d_0
	Significance of transverse impact parameter defined as the ratio of d_0 to its uncertainty	$ d_0/\sigma(d_0) $
Track–cluster matching	Momentum lost by the track between the perigee and the last measurement point divided by the momentum at perigee	$\Delta p/p$
	Likelihood probability based on transition radiation in the TRT	eProbabilityHT
	$\Delta\eta$ between the cluster position in the first layer of the EM calorimeter and the extrapolated track	$\Delta\eta_1$
	$\Delta\phi$ between the cluster position in the second layer of the EM calorimeter and the momentum-rescaled track, extrapolated from the perigee, times the charge q	$\Delta\phi_{\text{res}}$
Electron isolation variables	Ratio of the cluster energy to the measured track momentum	E/p
	Scalar sum of the transverse momentum of tracks surrounding the electron within a radius defined as $\Delta R = \min(10/p_T, 0.3)$	$p_{\text{T}}^{\Delta R \leq 0.3}$





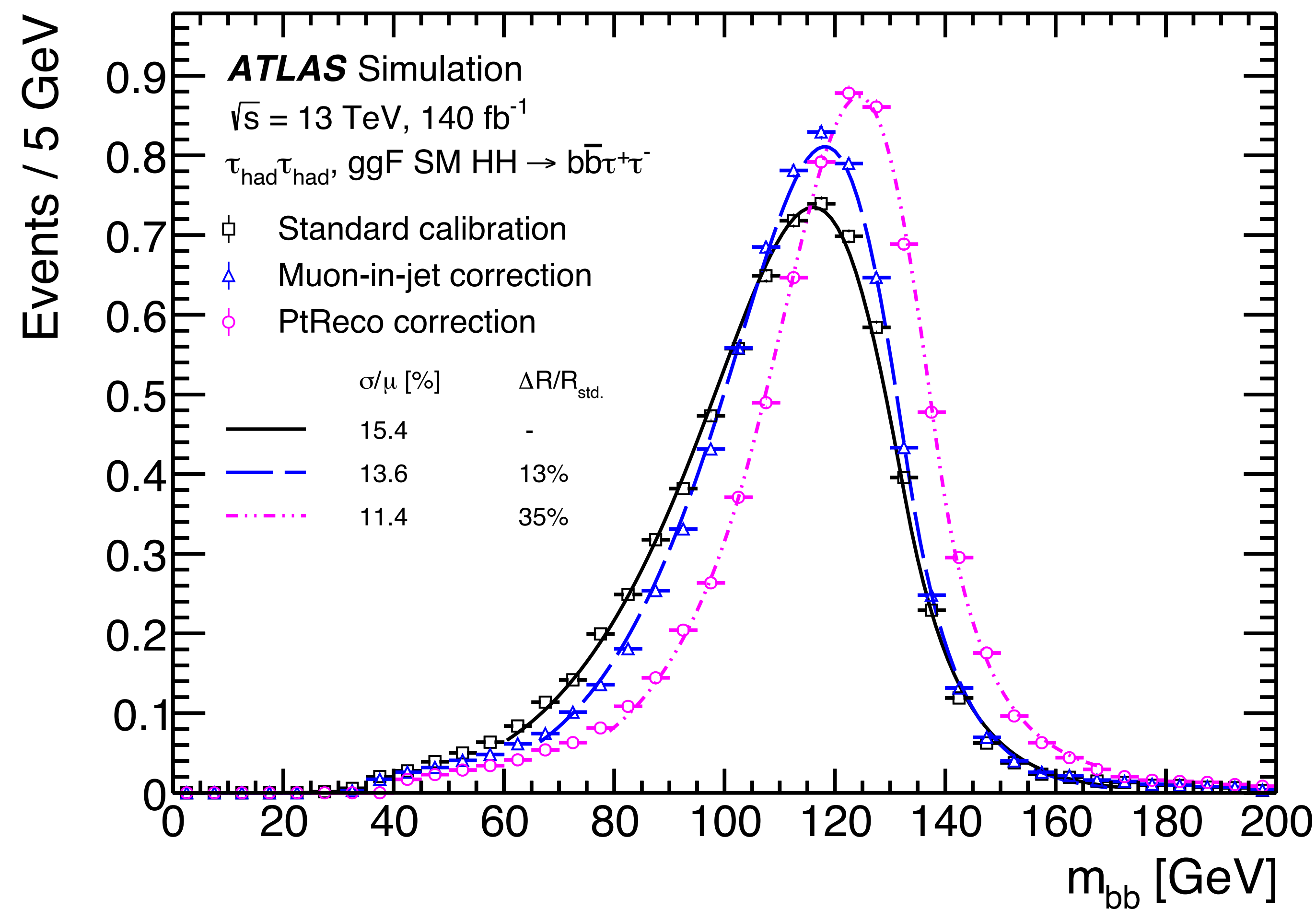


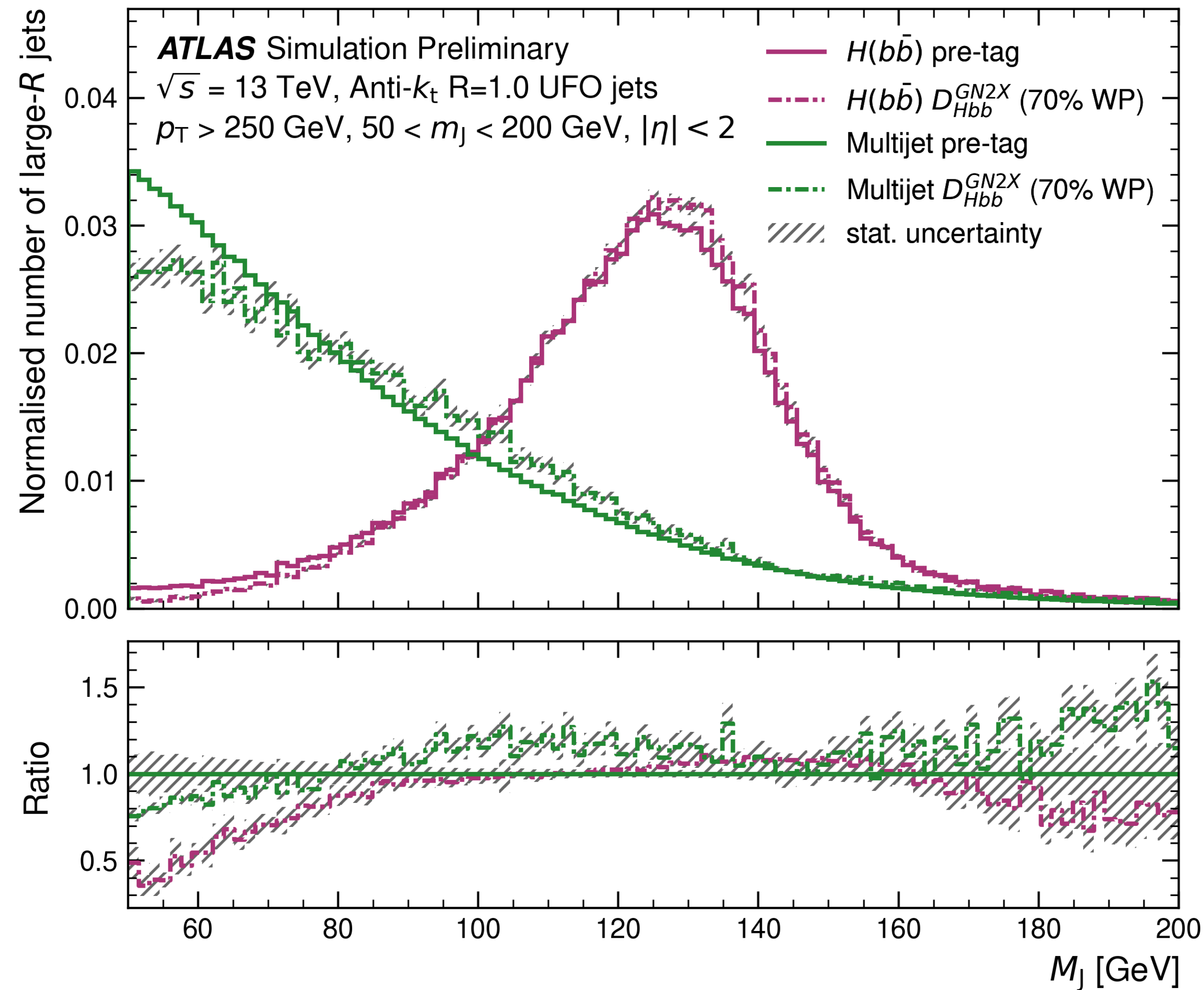
Objet reconstruction: jet charge tagging

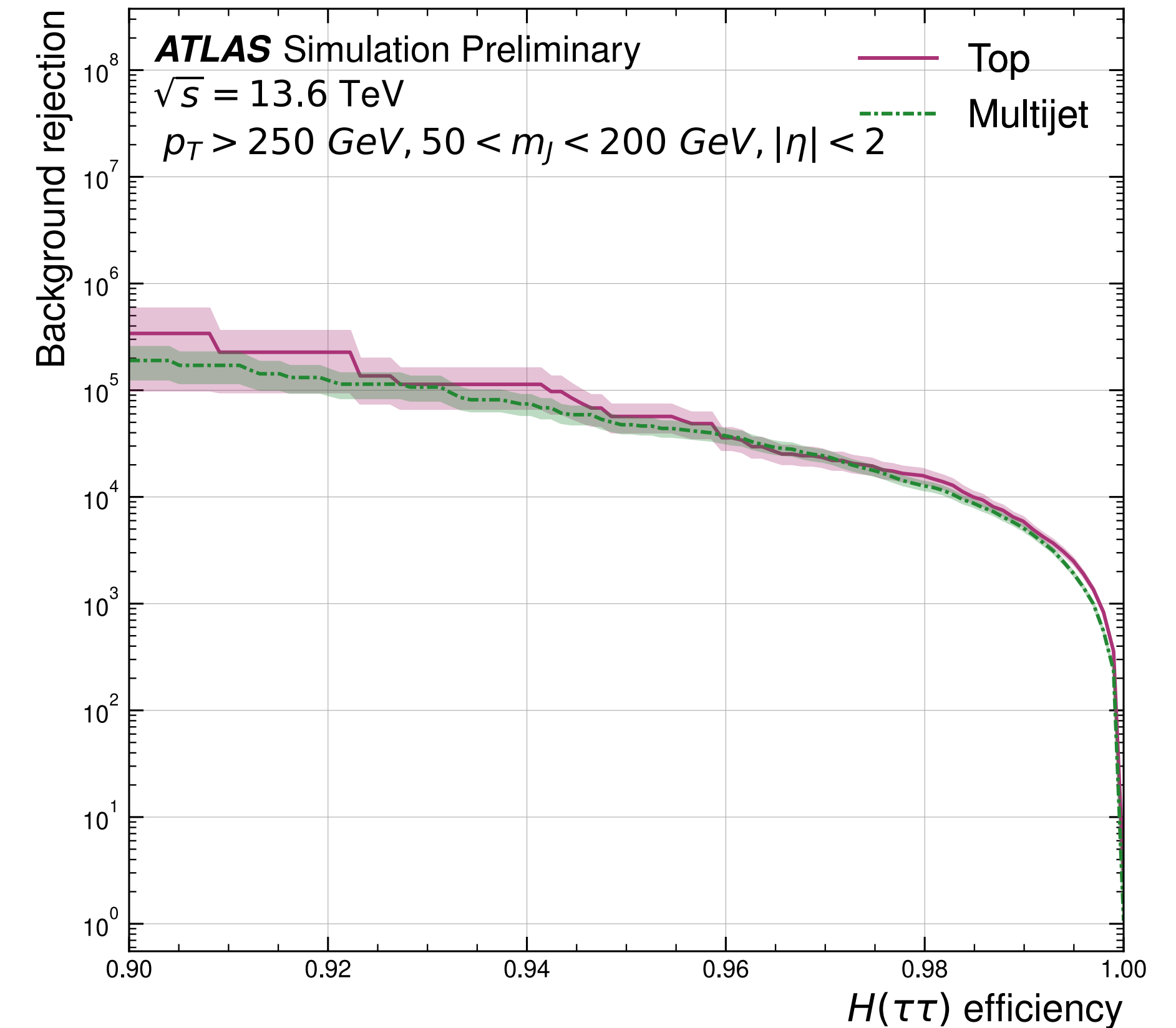
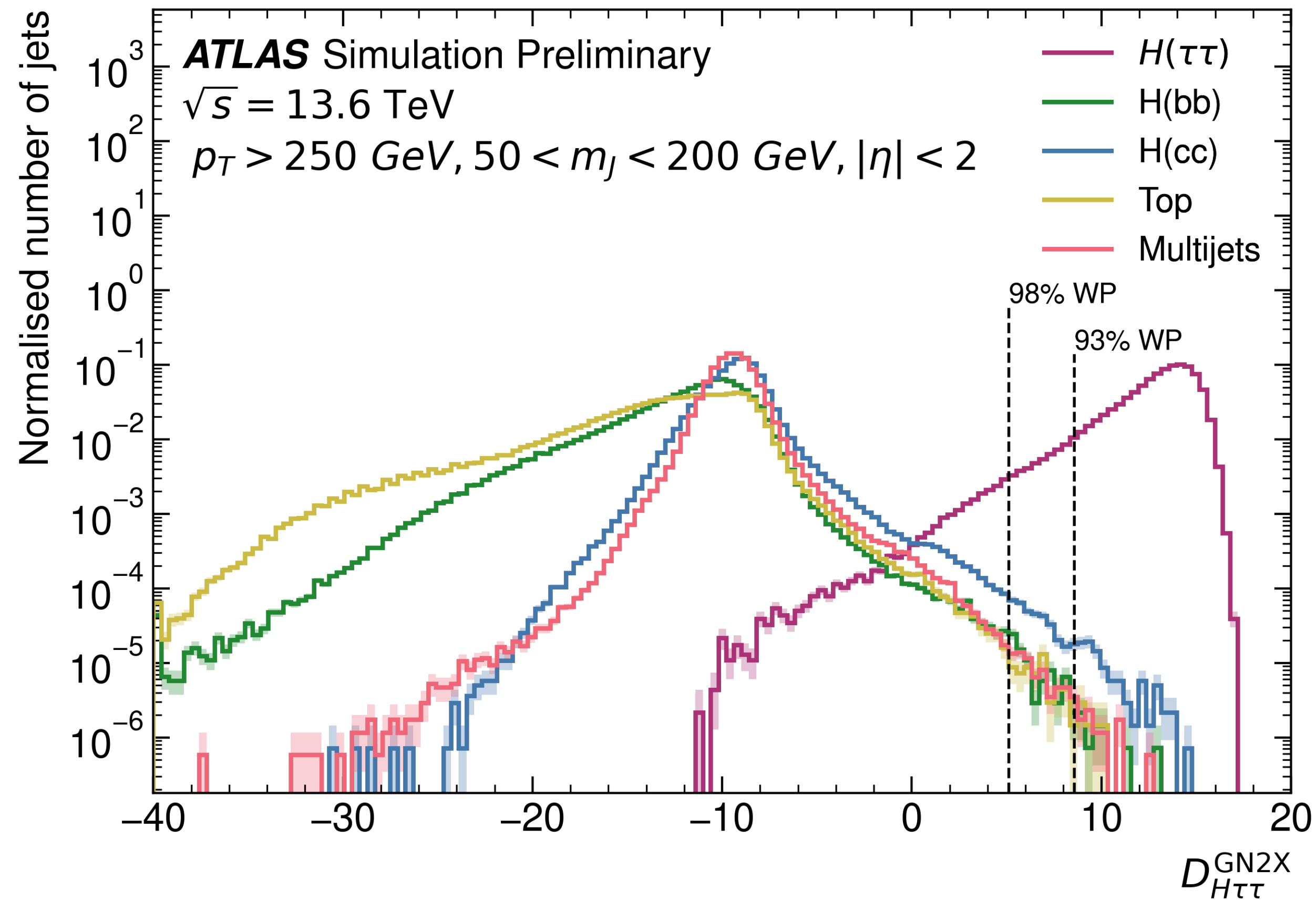


Objet reconstruction: b-jets and boosted $H \rightarrow b\bar{b}$

[HIGP-2024-37 \(subm. to EPJC\)](#)







Analysis strategy: multi-classifier boosted $H \rightarrow \tau\tau$

[HIGP-2024-49 \(subm. to JHEP\)](#)

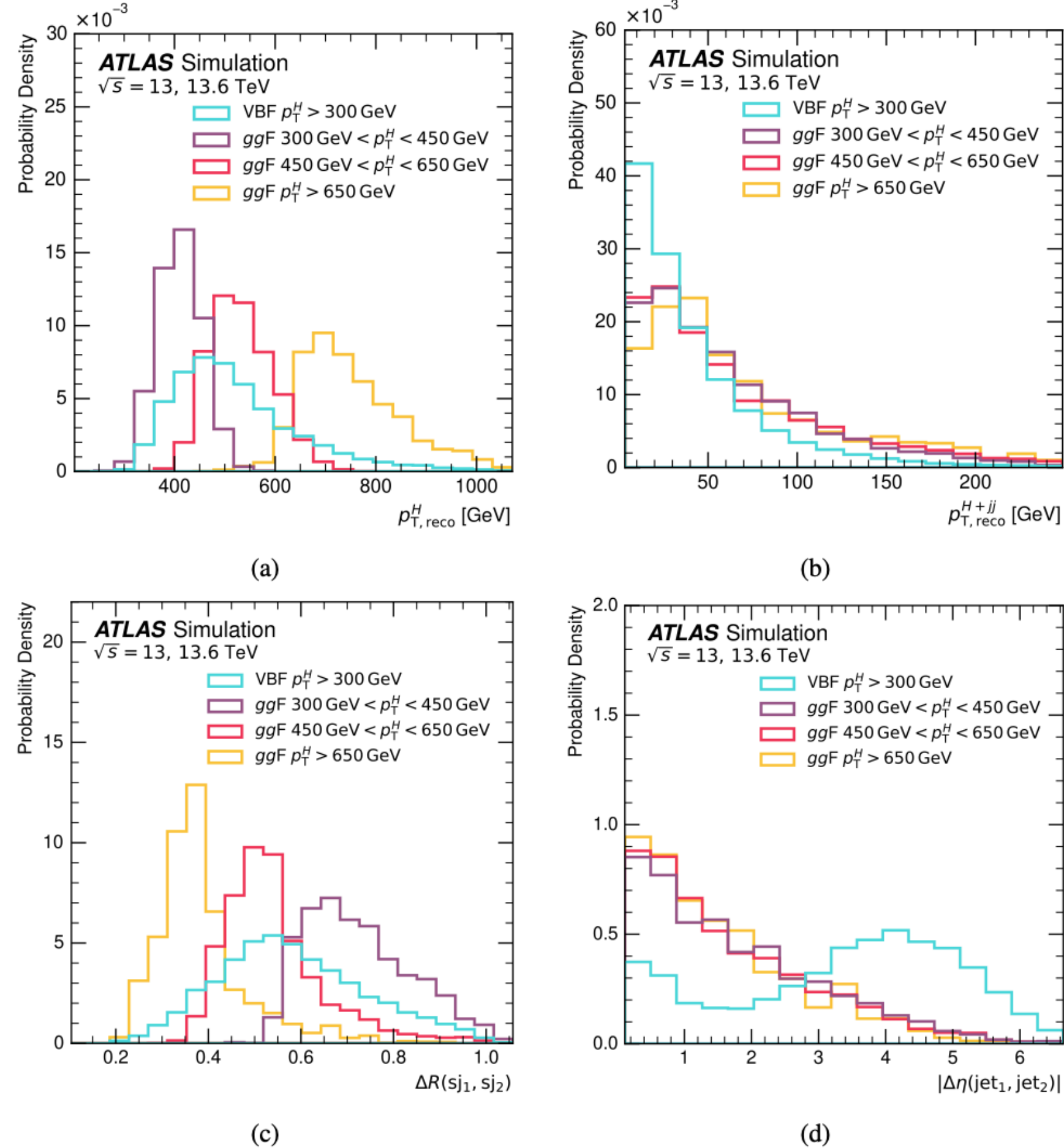


Figure 6: Probability density distribution of the dominant variables for the four classes of events (with the ggF p_T slices defined by the generated Higgs boson p_T): (a) the magnitude $p_{T, \text{reco}}^H$ of the vectorial sum of the two leading di- τ_{had} subjects and E_T^{miss} , (b) the magnitude $p_{T, \text{reco}}^{H+jj}$ of the vectorial sum of the two leading di- τ_{had} subjects, E_T^{miss} and the two additional small- R jets, (c) the angular separation $\Delta R(sj_1, sj_2)$ between the leading and subleading subjects of the di- τ_{had} candidate, and (d) the distance $|\Delta\eta(jet_1, jet_2)|$ between the two additional small- R jets.

Variable	Definition
$p_T^{sj_1}$	p_T of the leading subjet
$p_T^{sj_2}$	p_T of the subleading subjet
m_{vis}	Visible mass, defined as the mass of the vectorial sum of the leading and subleading subjects
$m_{\text{collinear}}$	Invariant mass estimated under the collinear approximation hypothesis
$\Delta R(sj_1, sj_2)$	Angular separation between the leading and subleading subjects
$p_{T, \text{reco}}^H$	Magnitude of the vectorial sum of two leading di- τ_{had} subjects and E_T^{miss}
E_T^{miss}	Missing transverse energy
$E_T^{\text{miss}} \phi$ centrality	Quantification of where the E_T^{miss} lies between the two subjects of the di- τ_{had} system in the azimuthal plane
$\Delta R(sj_1, \text{di-}\tau_{\text{had}})$	Angular separation between the leading subjet and the di- τ_{had} system
$\eta_{\text{jet}_1} \times \eta_{\text{jet}_2}$	Product of the η of the two additional small- R jets
$p_T^{\text{jet}_1 + \text{jet}_2}$	Magnitude of the vectorial sum of the two additional small- R jets
$p_{T, \text{reco}}^{H+jj}$	Magnitude of the vectorial sum of the two leading di- τ_{had} subjects, E_T^{miss} and the two additional small- R jets
$m_{\text{jet}_1 + \text{jet}_2}$	Invariant mass of the two additional small- R jets
$\Delta R(\text{jet}_1, \text{di-}\tau_{\text{had}})$	Angular separation between jet_1 and the di- τ_{had} system
$\Delta\eta(\text{jet}_1, \text{jet}_2)$	Distance in η between the two additional small- R jets
$p_T^{\text{jet}_1}$	p_T of the highest- p_T additional small- R jet
$p_T^{\text{jet}_2}$	p_T of the second highest- p_T additional small- R jet
$\Delta R(E_T^{\text{miss}}, \text{jet}_1)$	Angular distance between E_T^{miss} and jet_1
$\Delta R(sj_1, \text{jet}_1)$	Angular distance between the leading subjet and jet_1
$\Delta R(sj_2, \text{jet}_1)$	Angular distance between the subleading subjet and jet_1
$\Delta\phi(E_T^{\text{miss}}, sj_1 + sj_2)$	Azimuthal angle between the missing transverse energy and the vectorial sum of the leading and subleading subjects

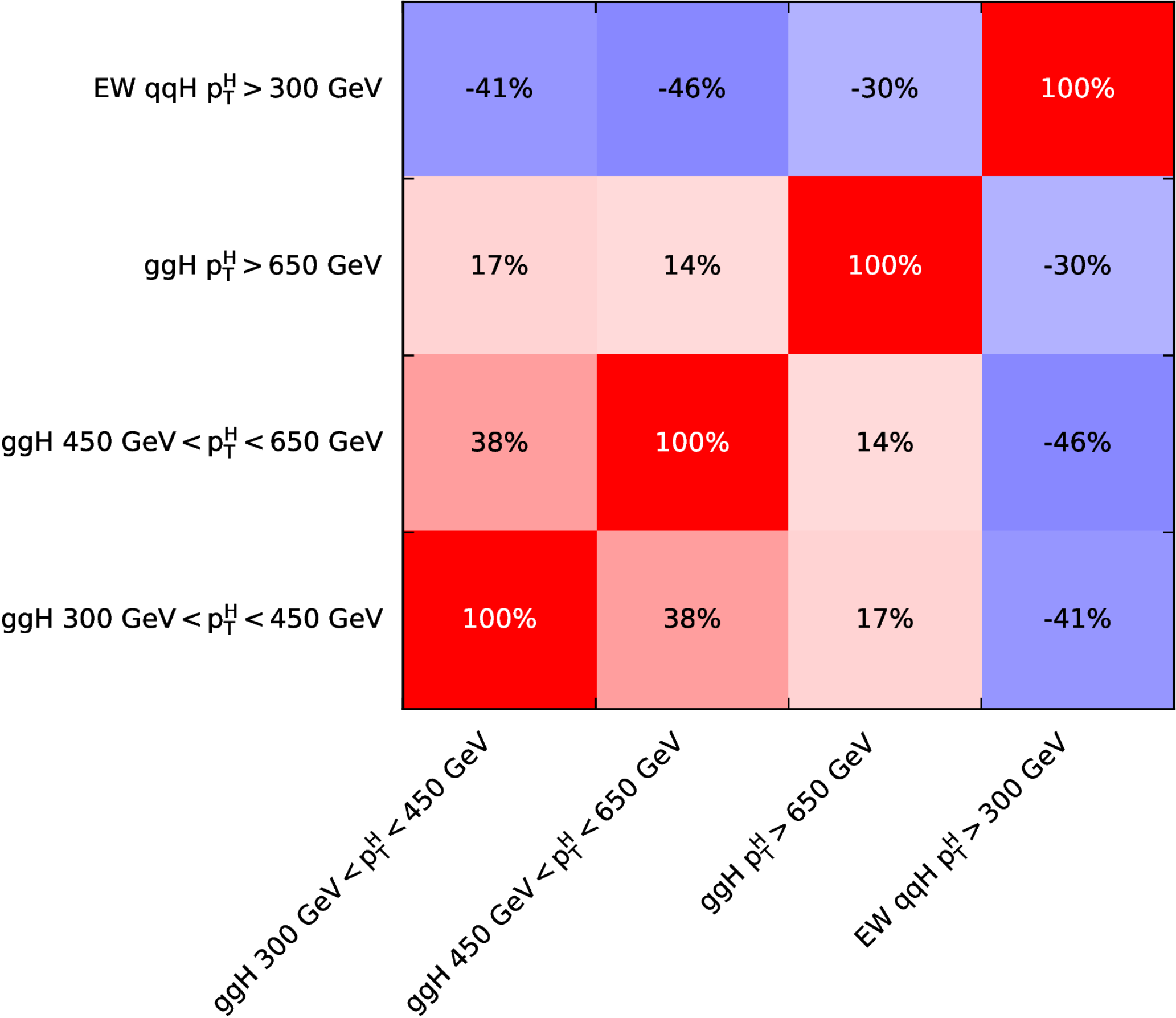
4-class BDT for boosted $H \rightarrow \tau\tau$
STXS measurement

Analysis strategy: multi-classifier boosted $H \rightarrow \tau\tau$

[HIGP-2024-49 \(subm. to JHEP\)](#)

ATLAS

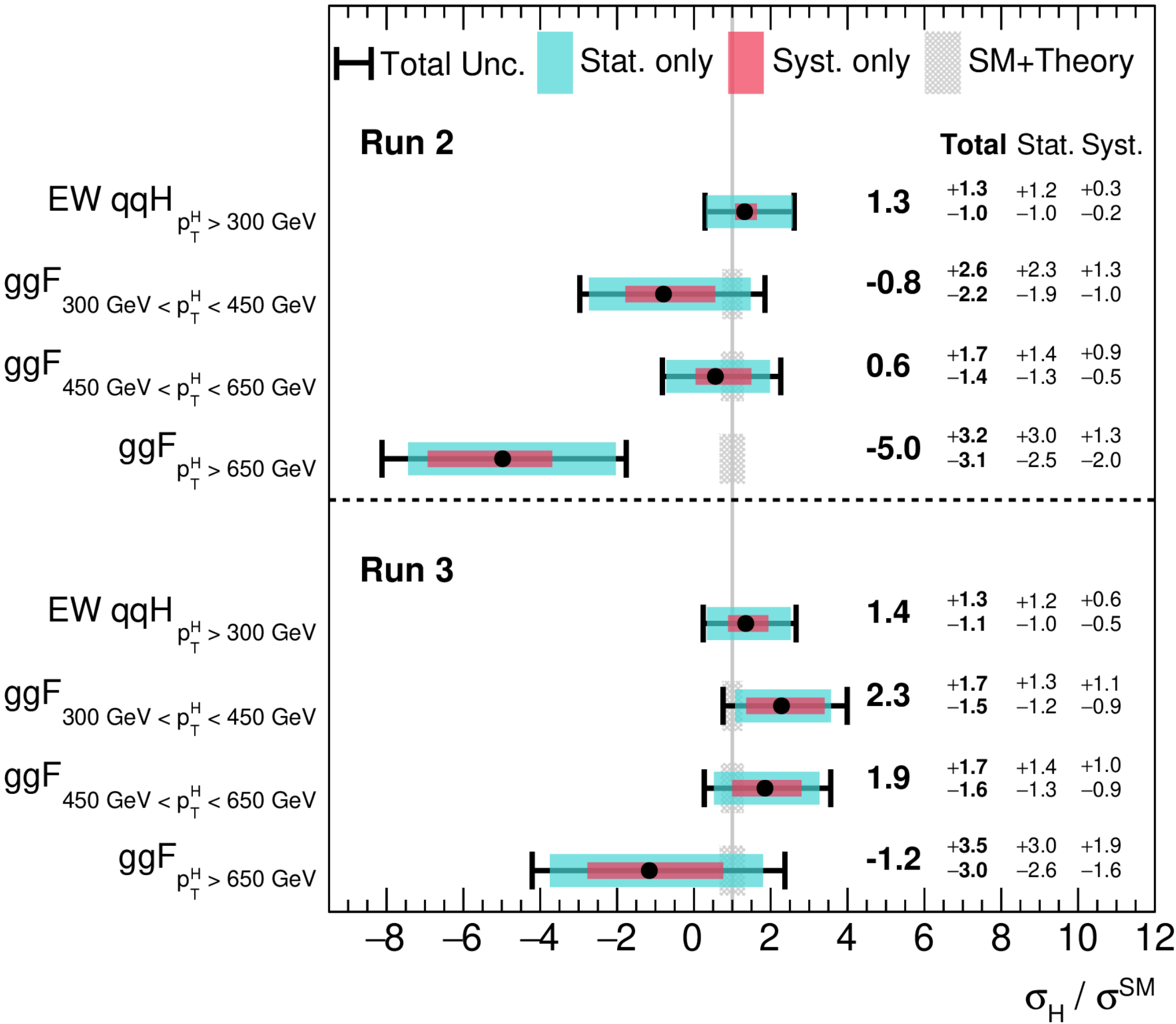
$\sqrt{s} = 13.6 \text{ TeV}, 162 \text{ fb}^{-1}$



4-class BDT for boosted $H \rightarrow \tau\tau$
STXS measurement

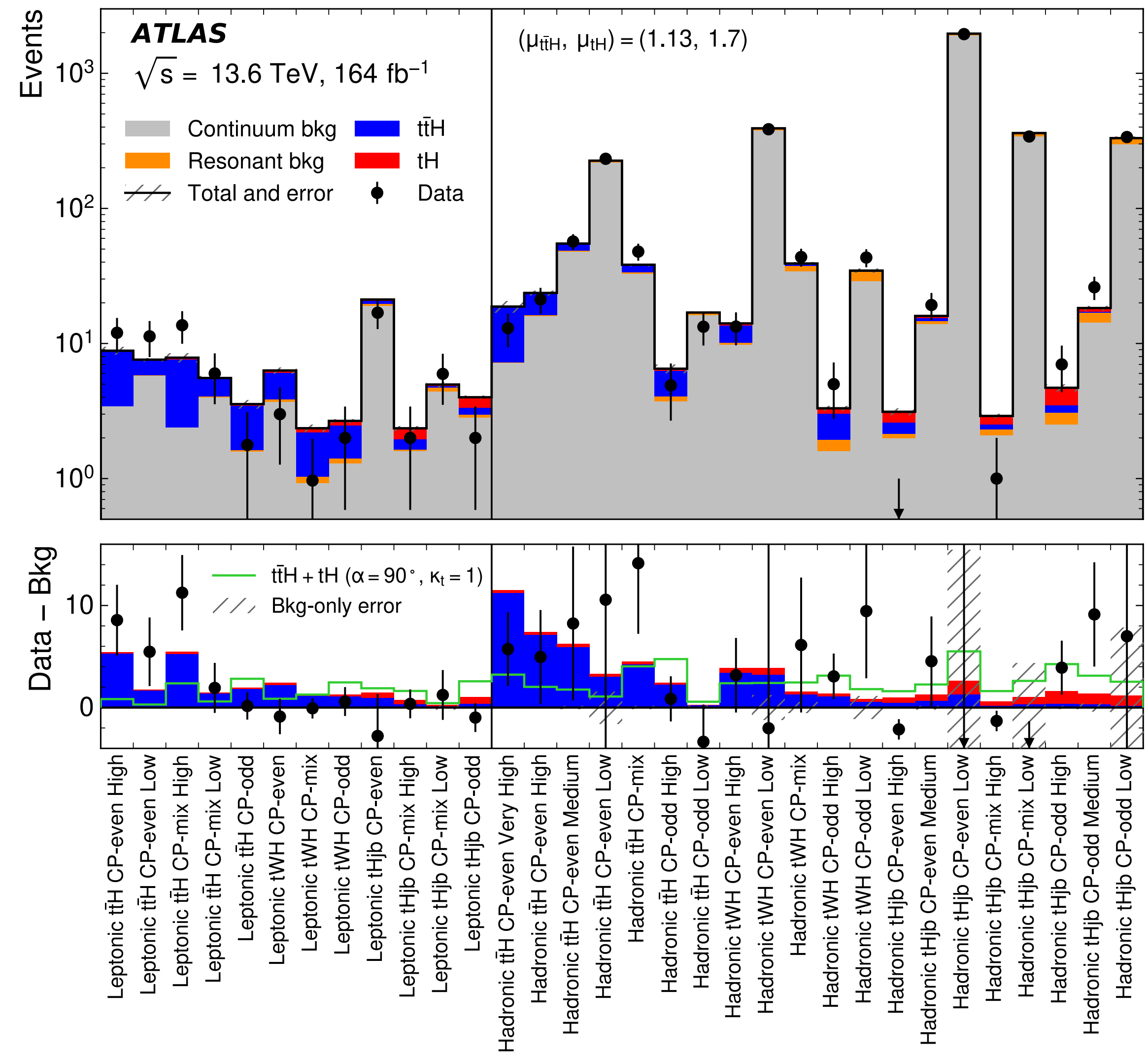
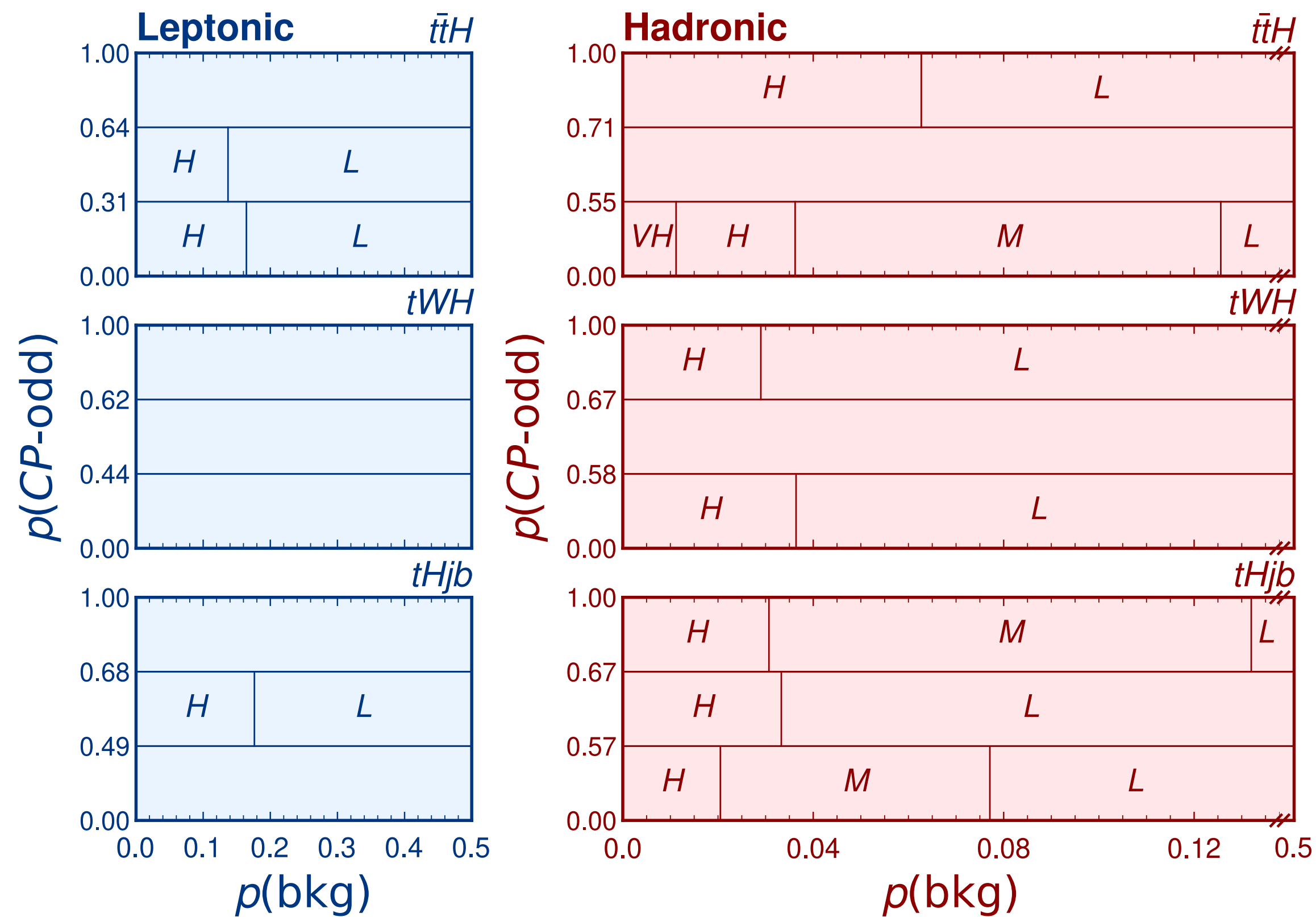
ATLAS

Run 2: $\sqrt{s} = 13 \text{ TeV}, 140 \text{ fb}^{-1}$
Run 3: $\sqrt{s} = 13.6 \text{ TeV}, 162 \text{ fb}^{-1}$



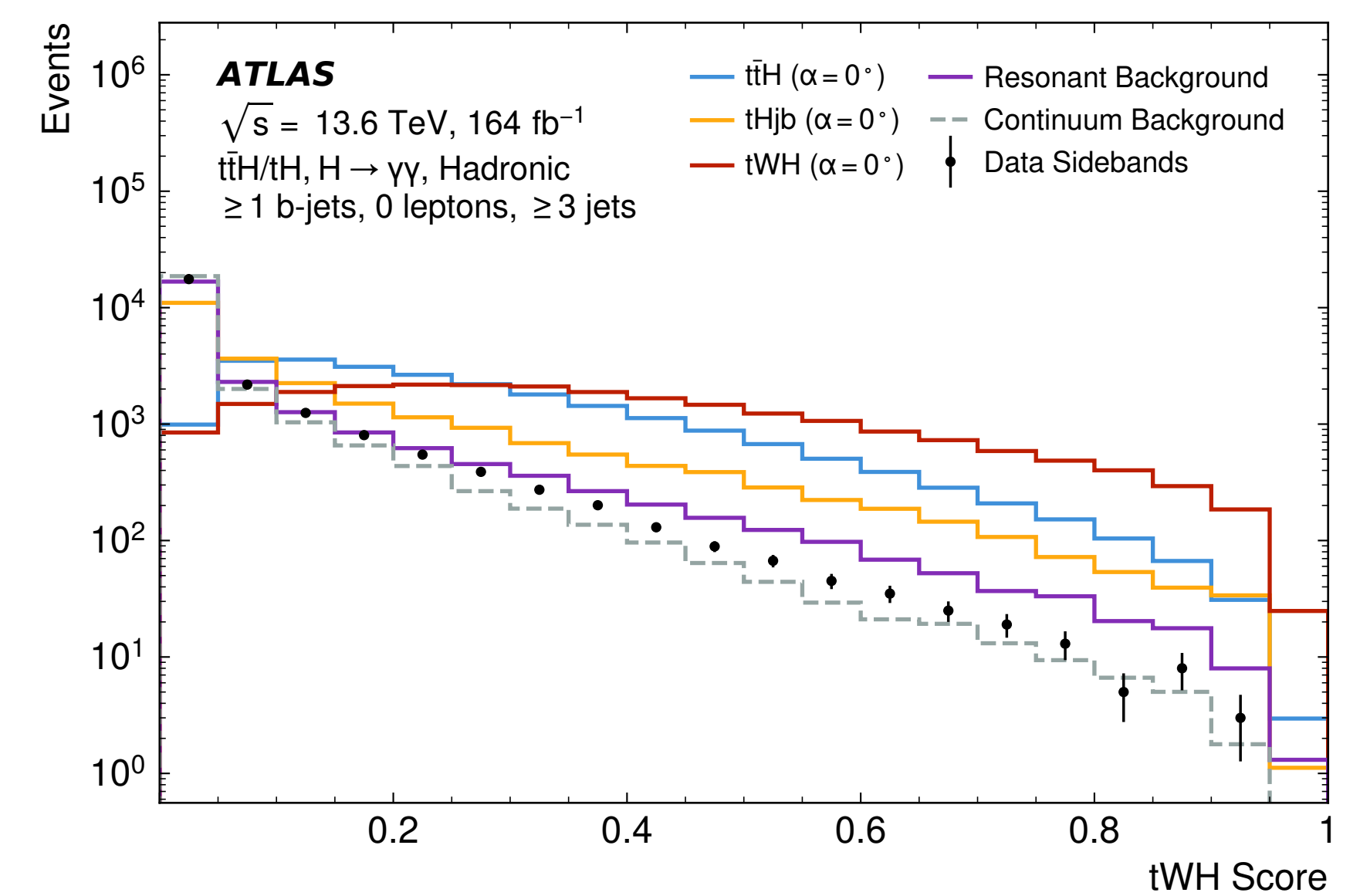
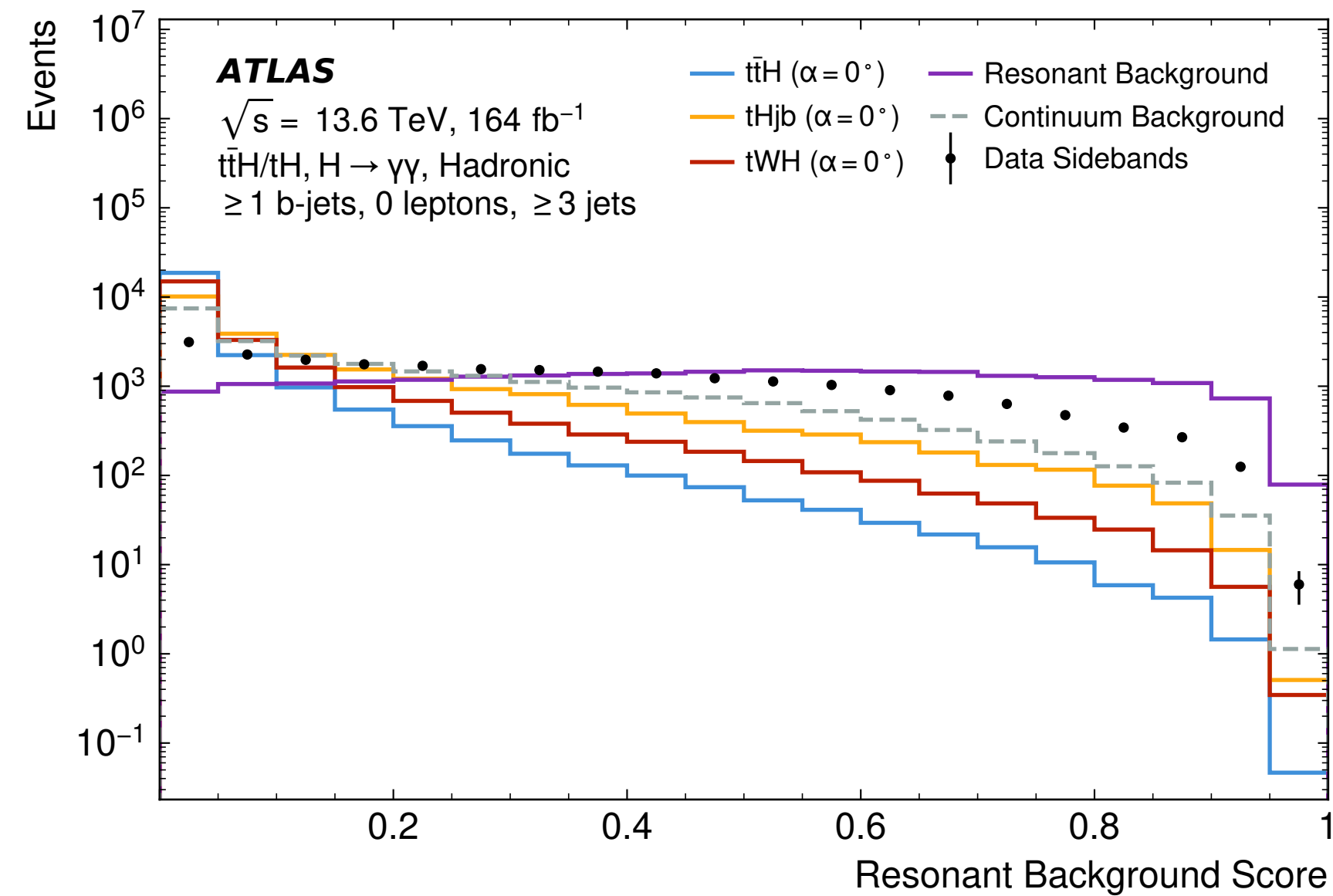
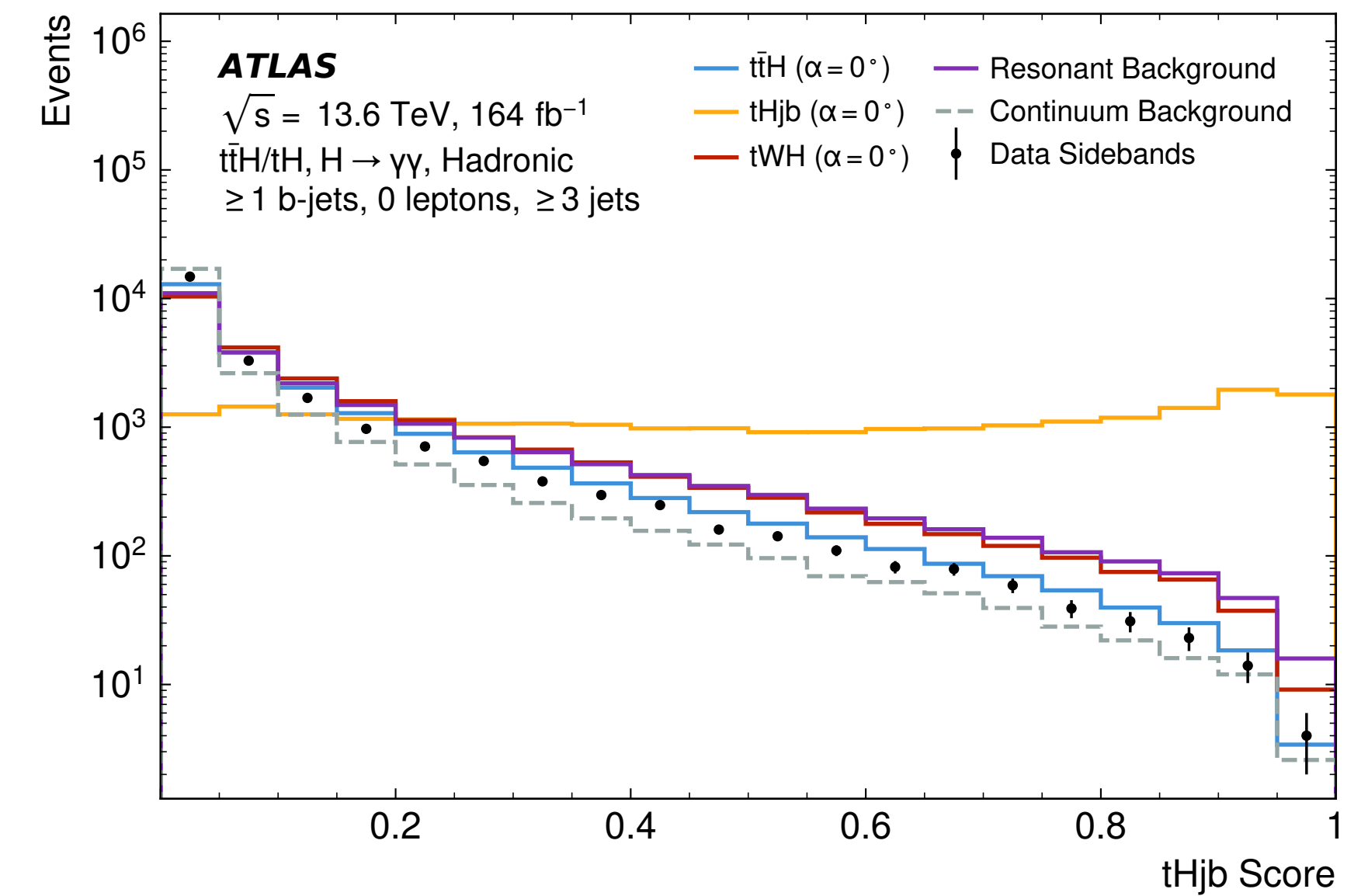
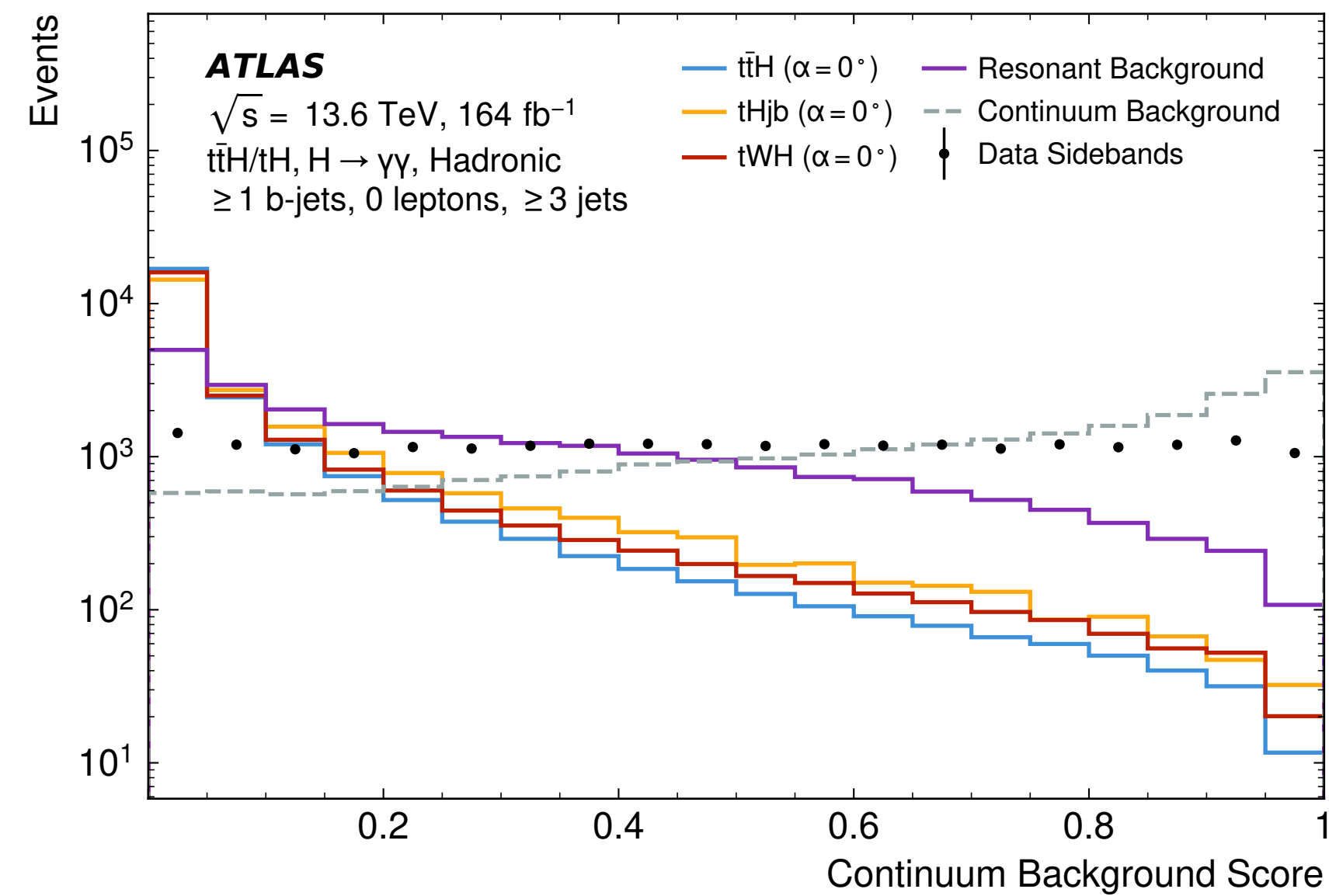
Analysis strategy: multi-classifier $t\bar{t}H$ $H \rightarrow \gamma\gamma$

HIGP-2024-24 (subm. to PRL)



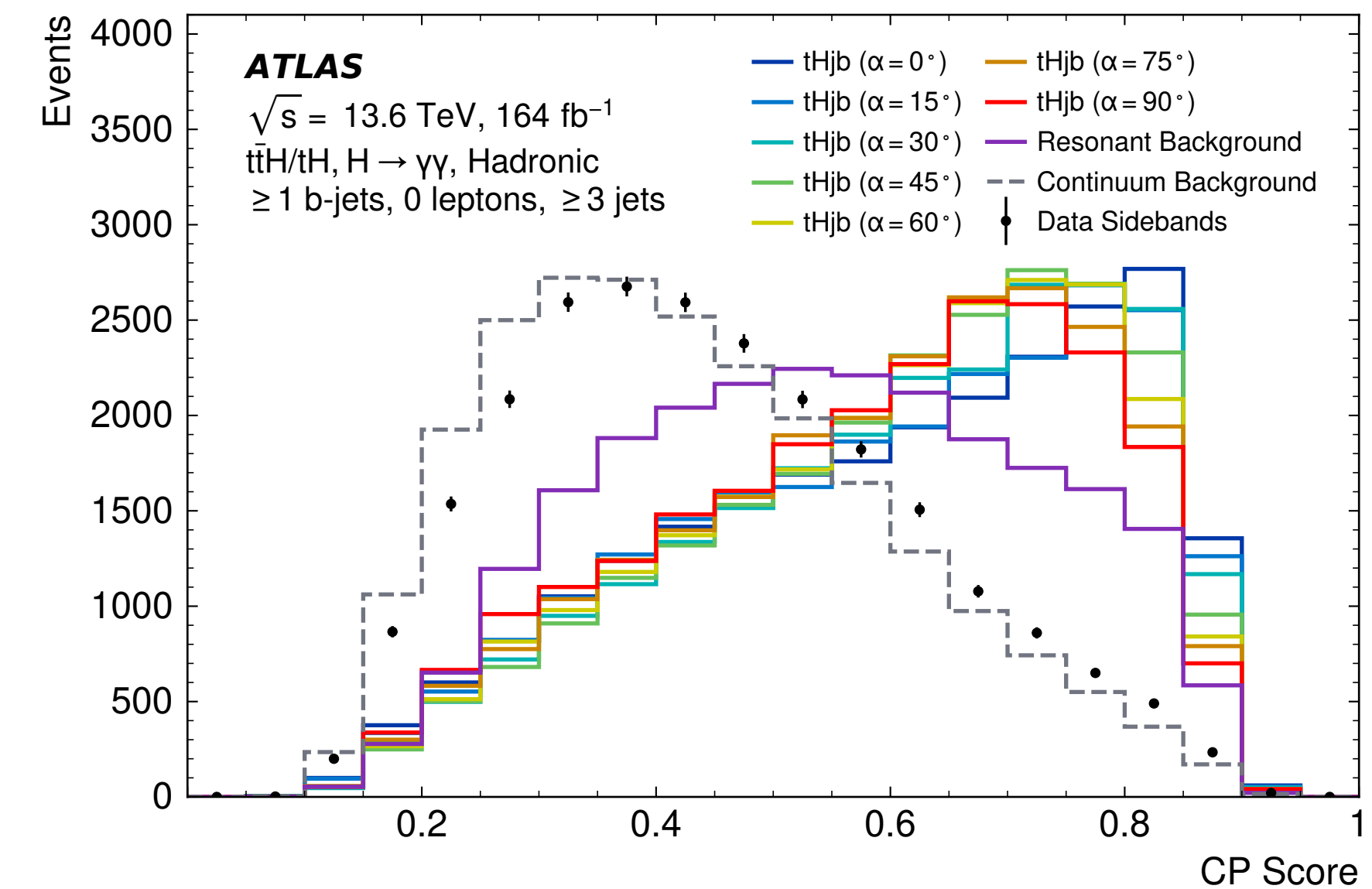
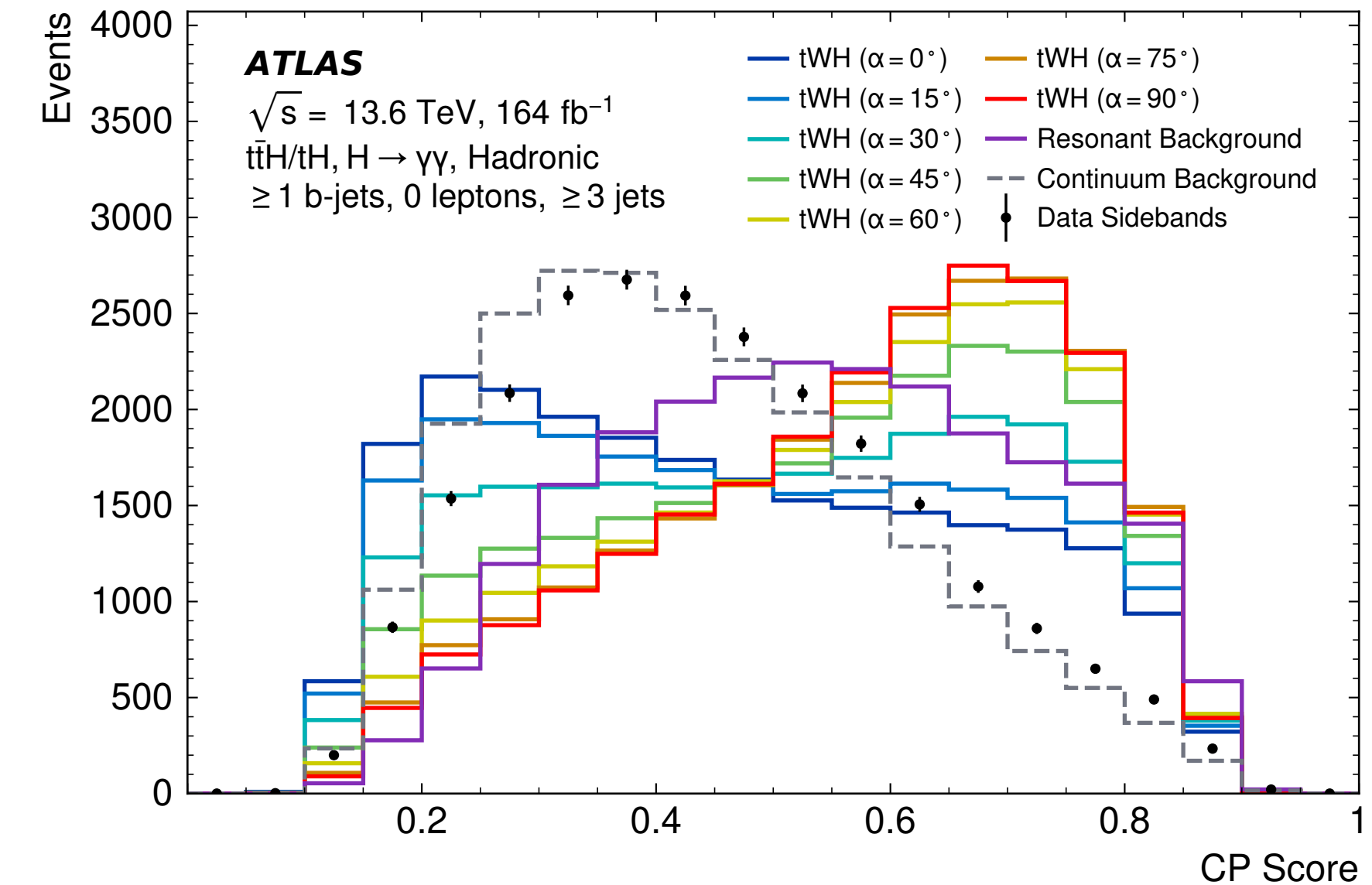
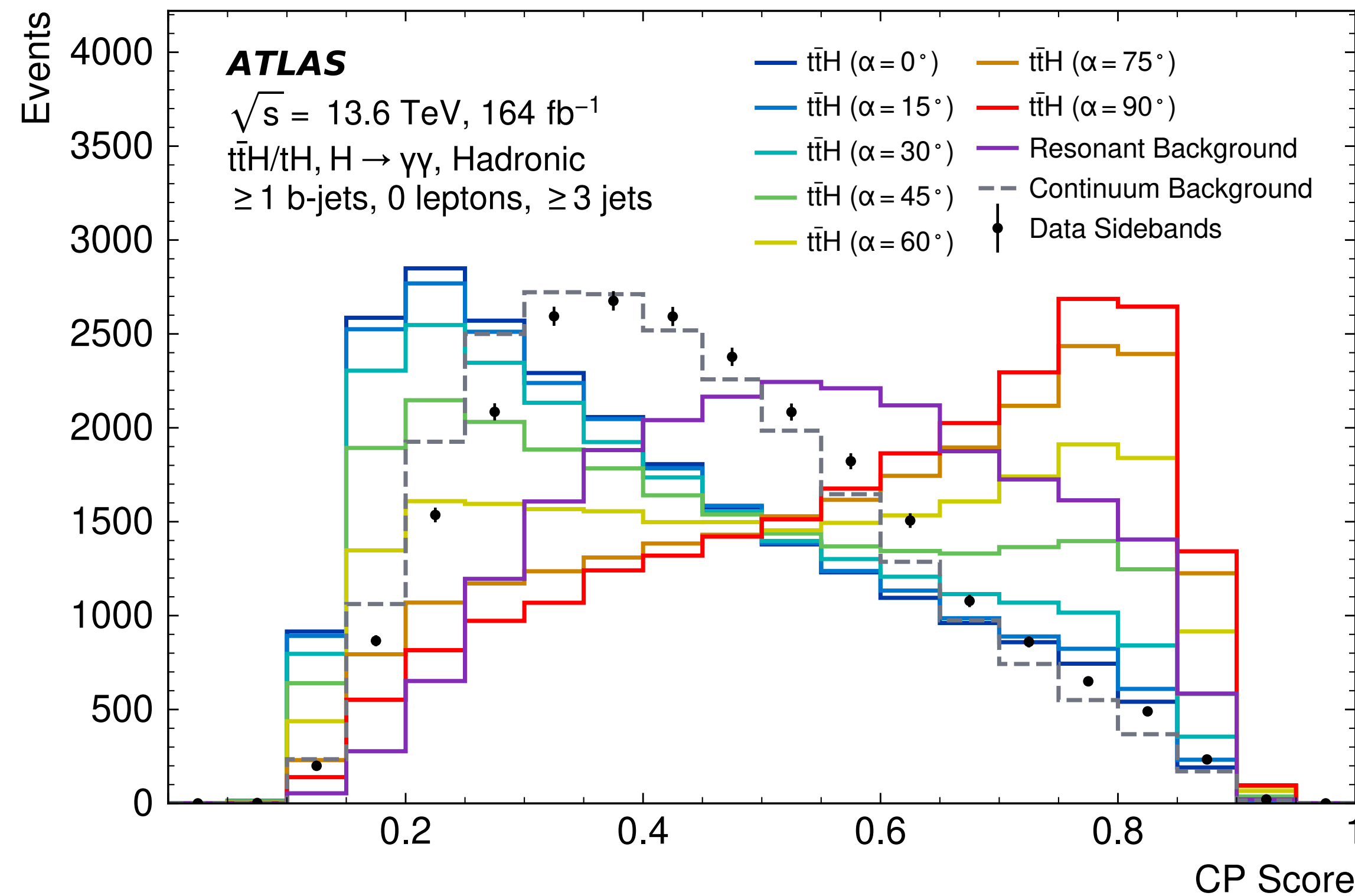
Analysis strategy: multi-classifier ttH $H \rightarrow \gamma\gamma$

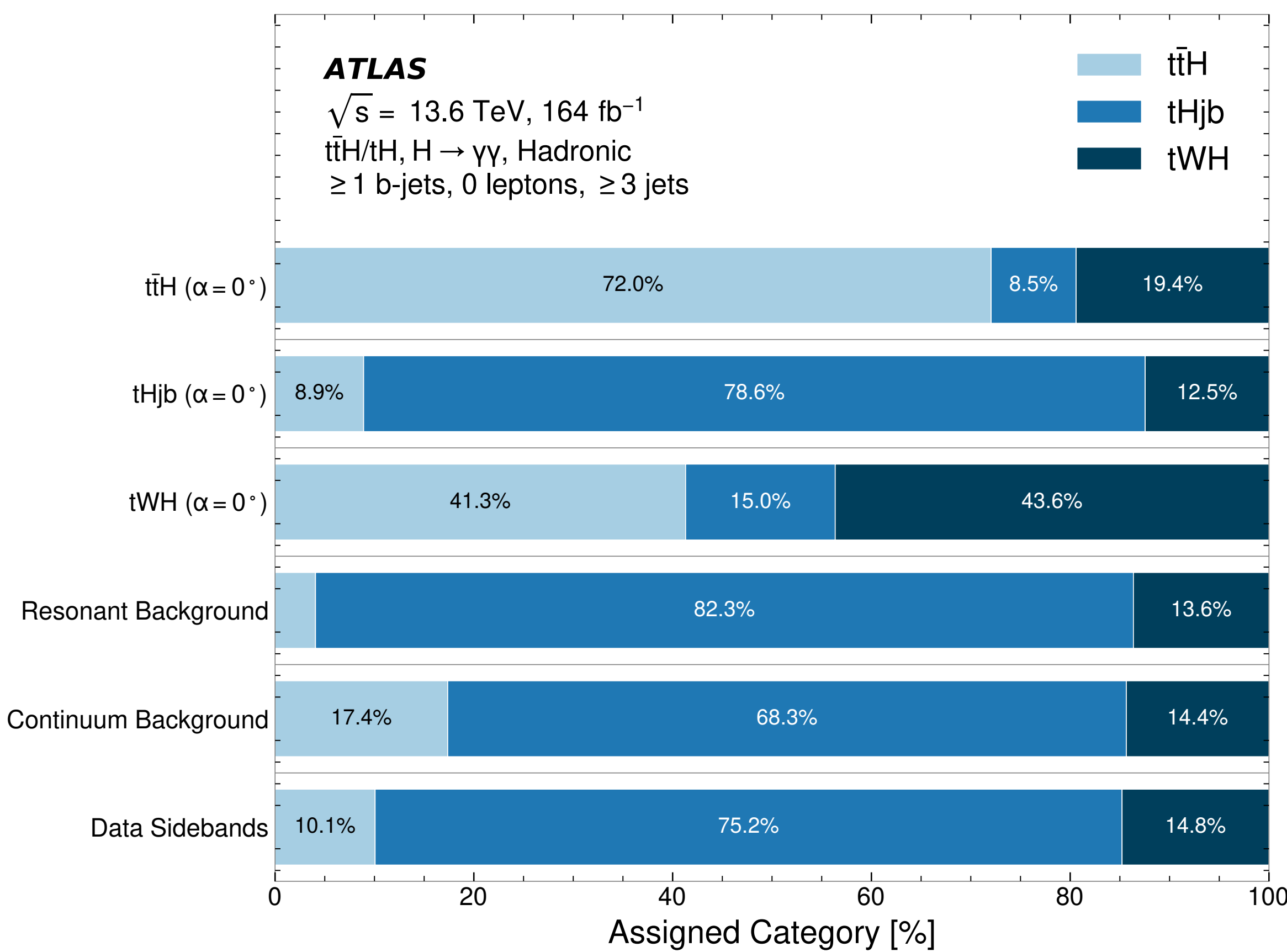
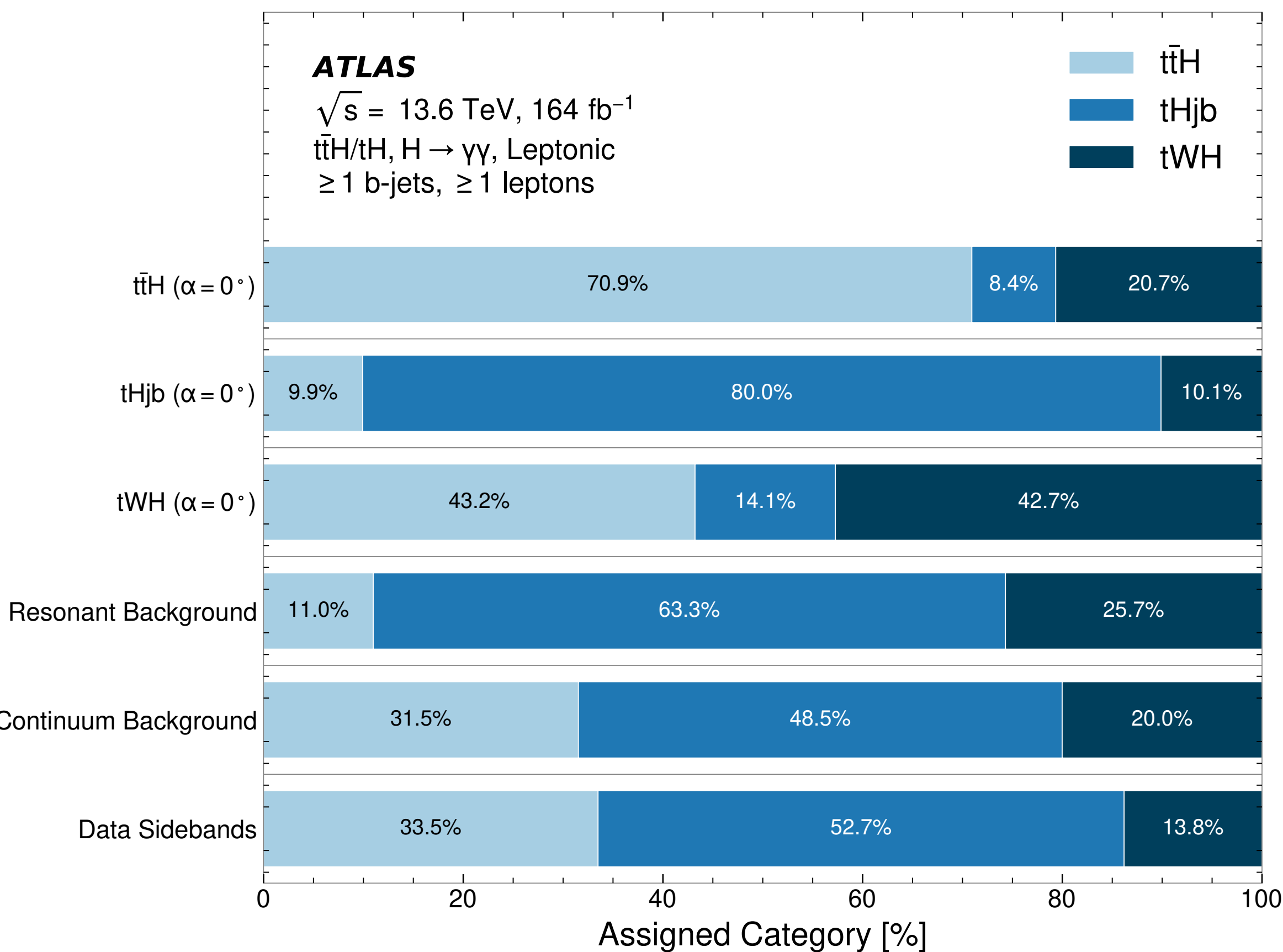
HIGP-2024-24 (subm. to PRL)



Analysis strategy: multi-classifier ttH $H \rightarrow \gamma\gamma$

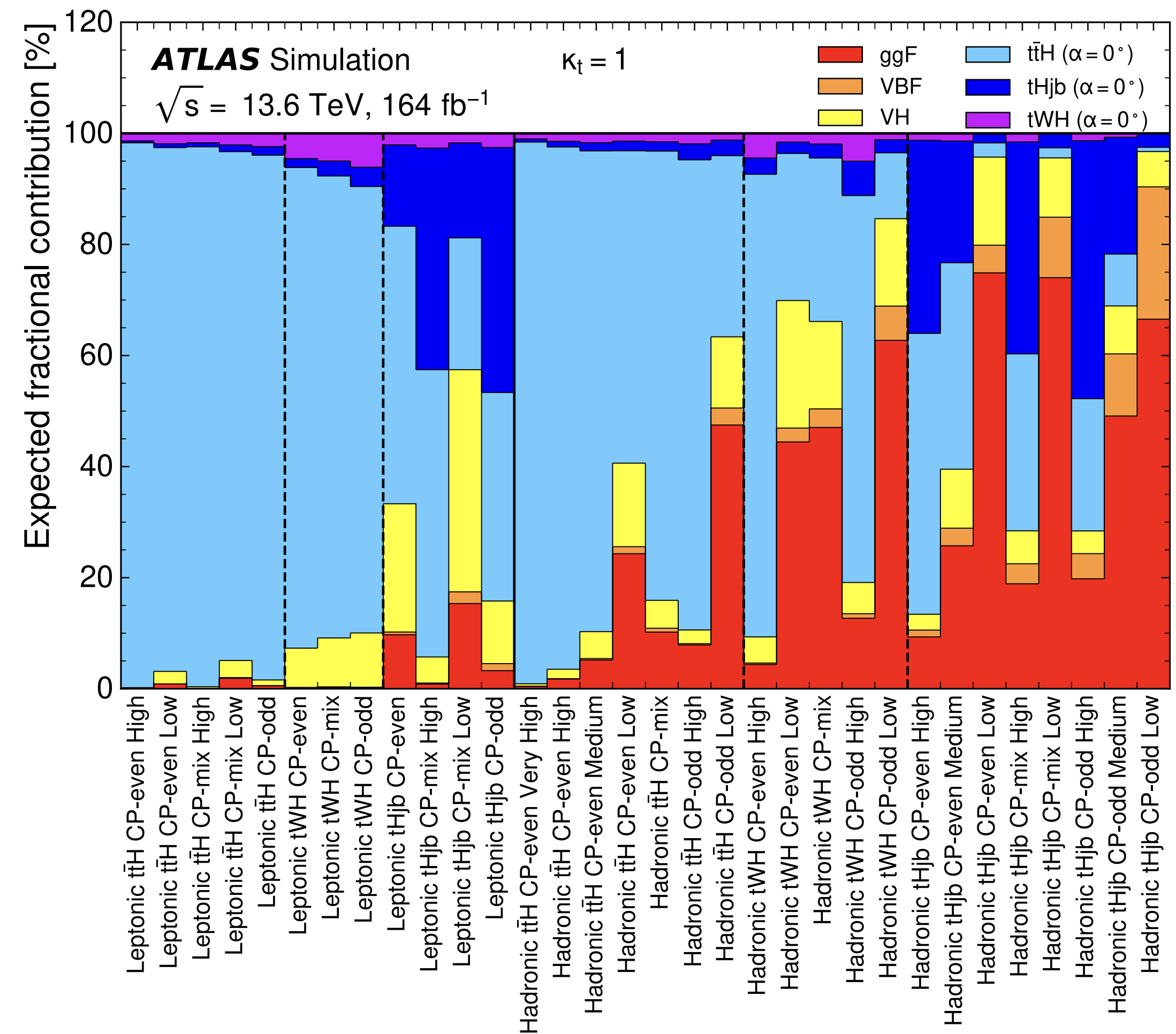
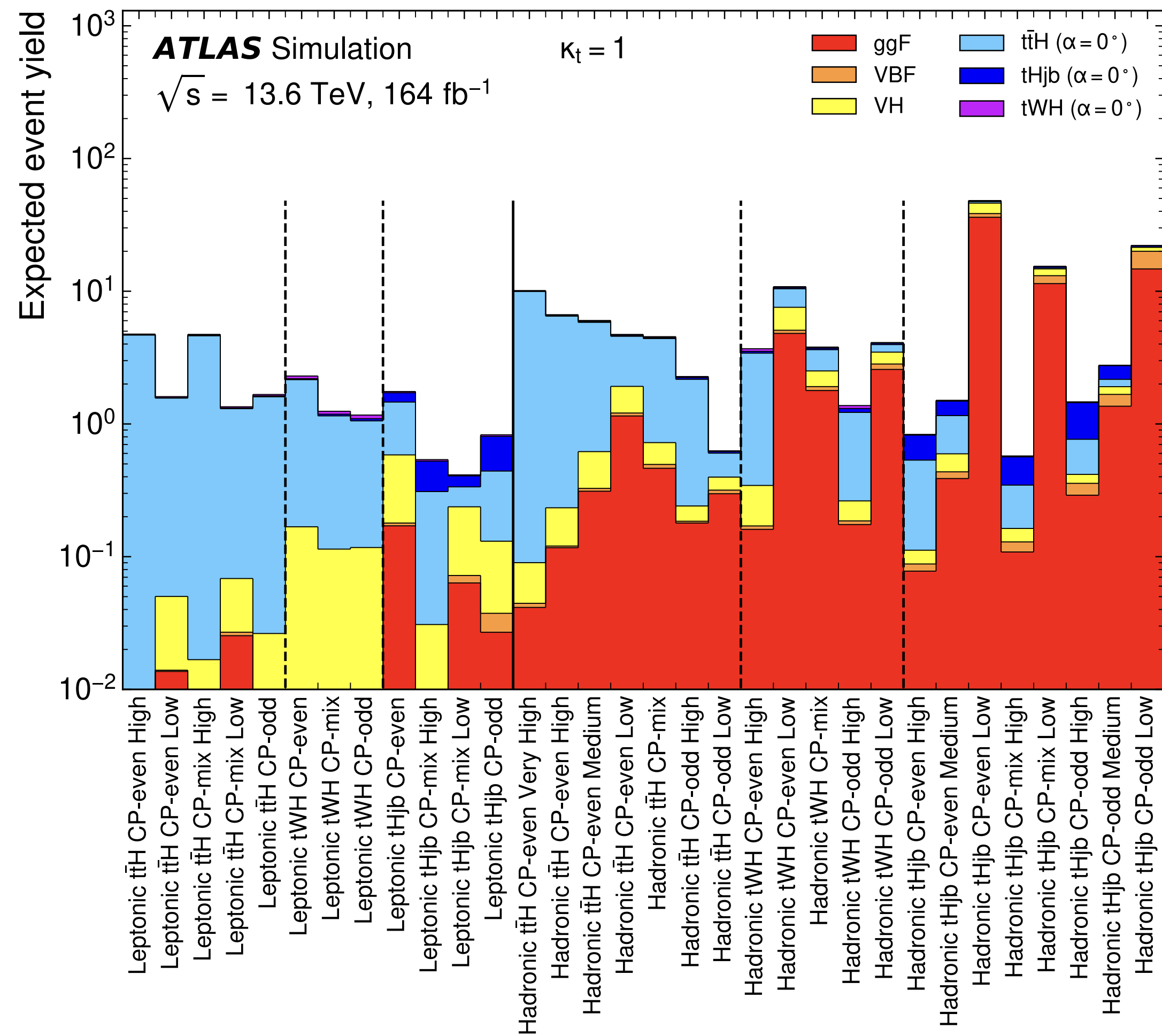
HIGP-2024-24 (subm. to PRL)





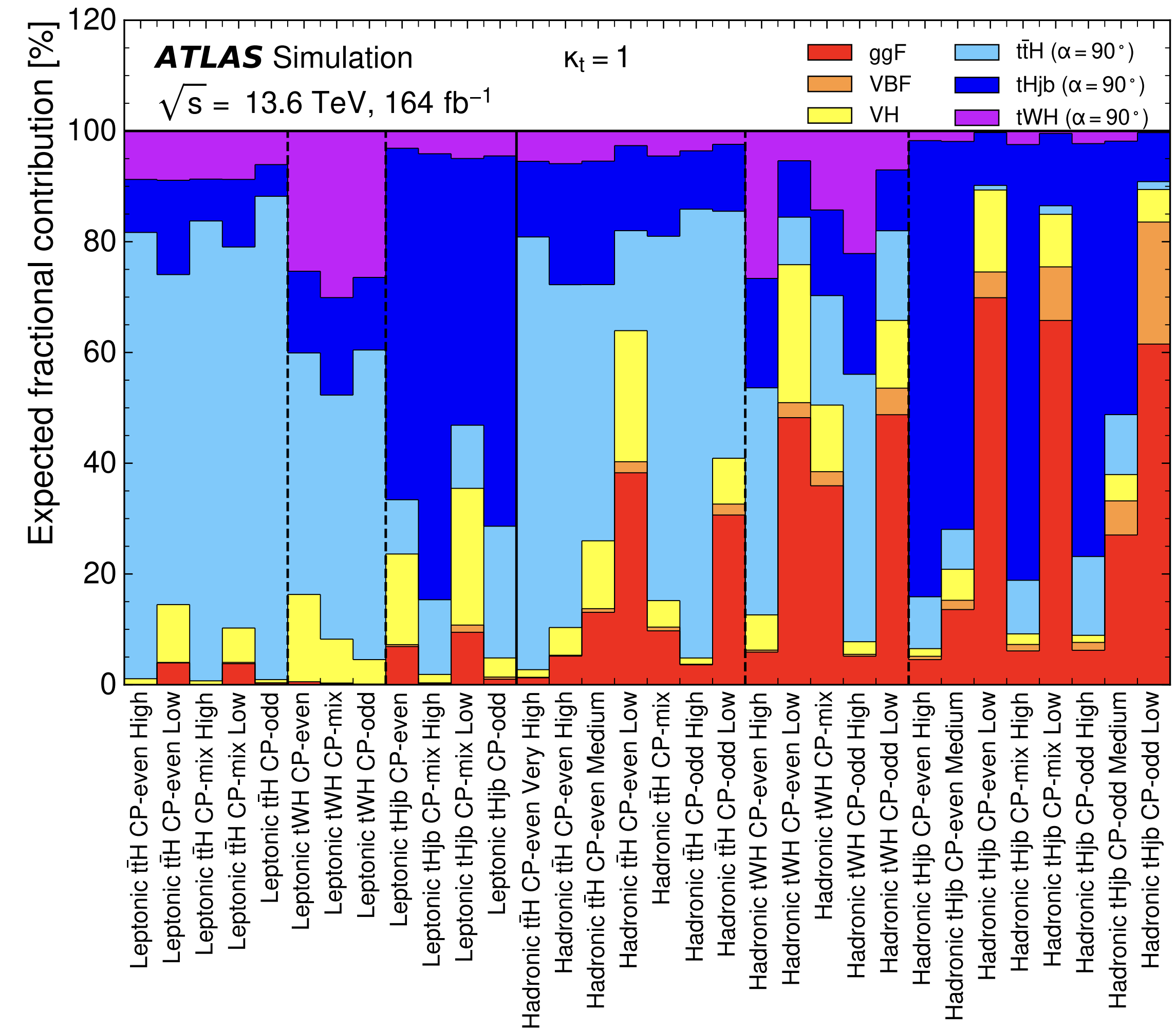
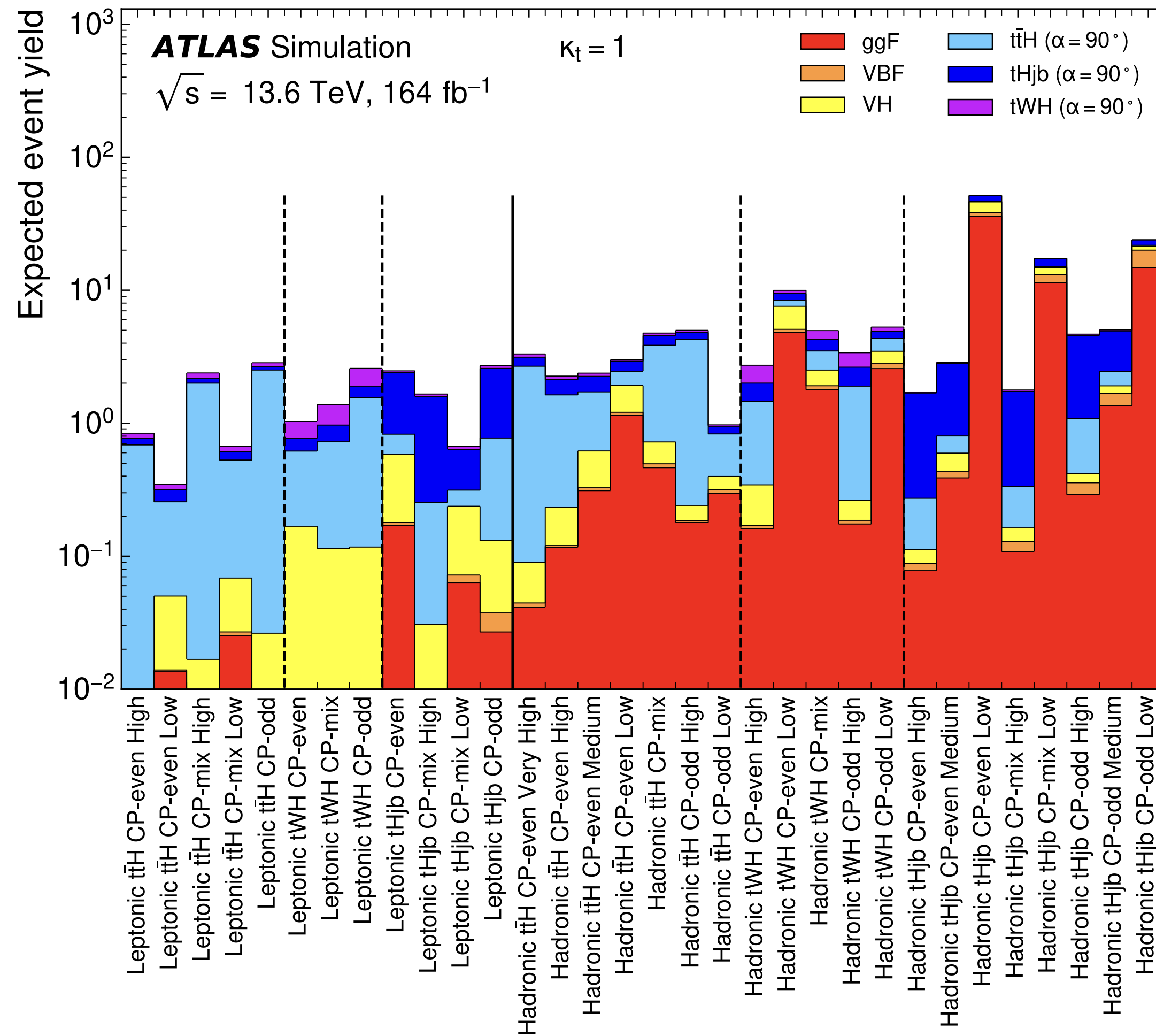
Analysis strategy: multi-classifier ttH $H \rightarrow \gamma\gamma$

HIGP-2024-24 (subm. to PRL)



Analysis strategy: multi-classifier ttH $H \rightarrow \gamma\gamma$

HIGP-2024-24 (subm. to PRL)

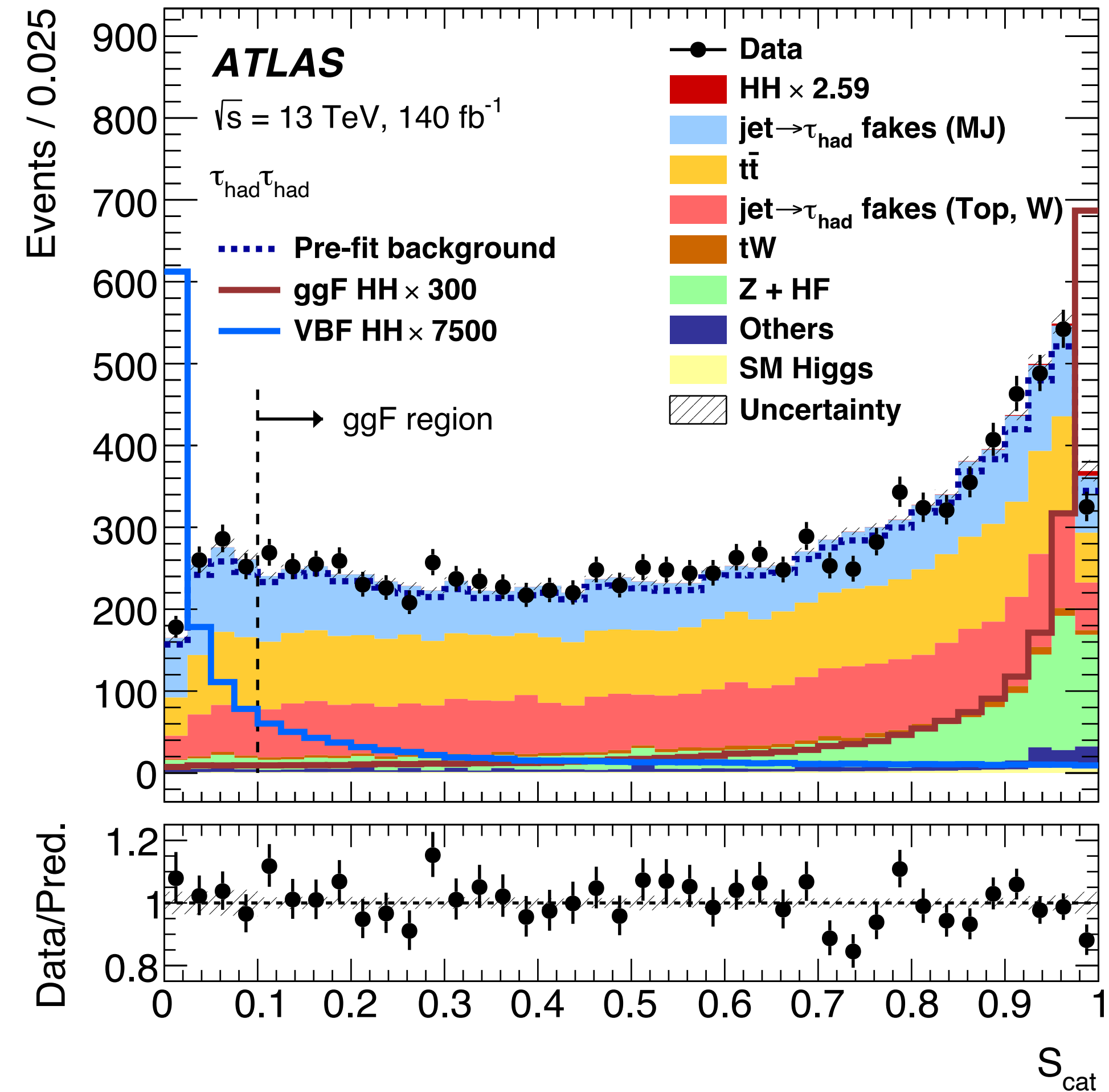
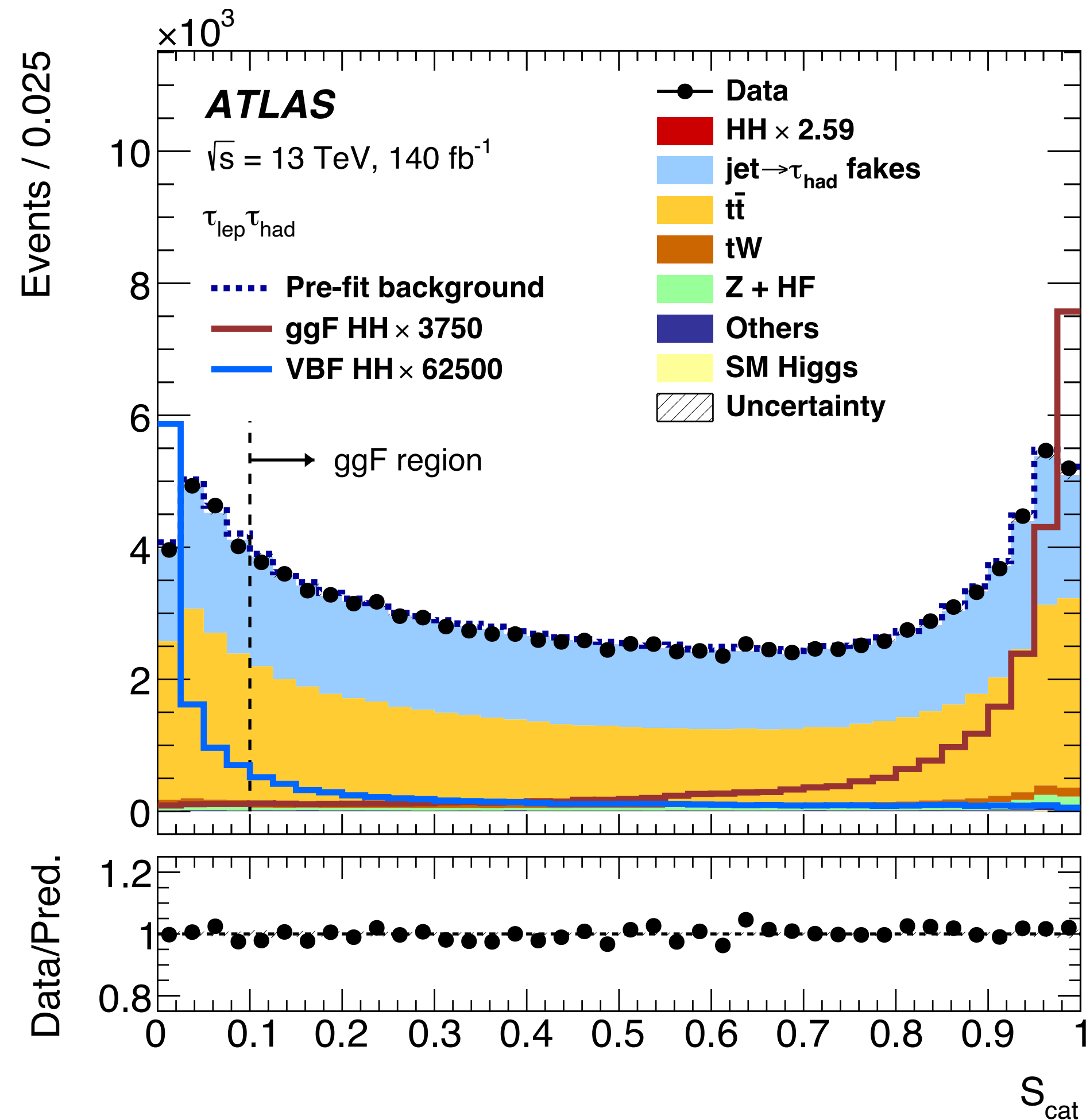


Analysis strategy: multi-classifier $HH \rightarrow bb\tau\tau$

HIGP-2024-37 (subm. to EPJC)

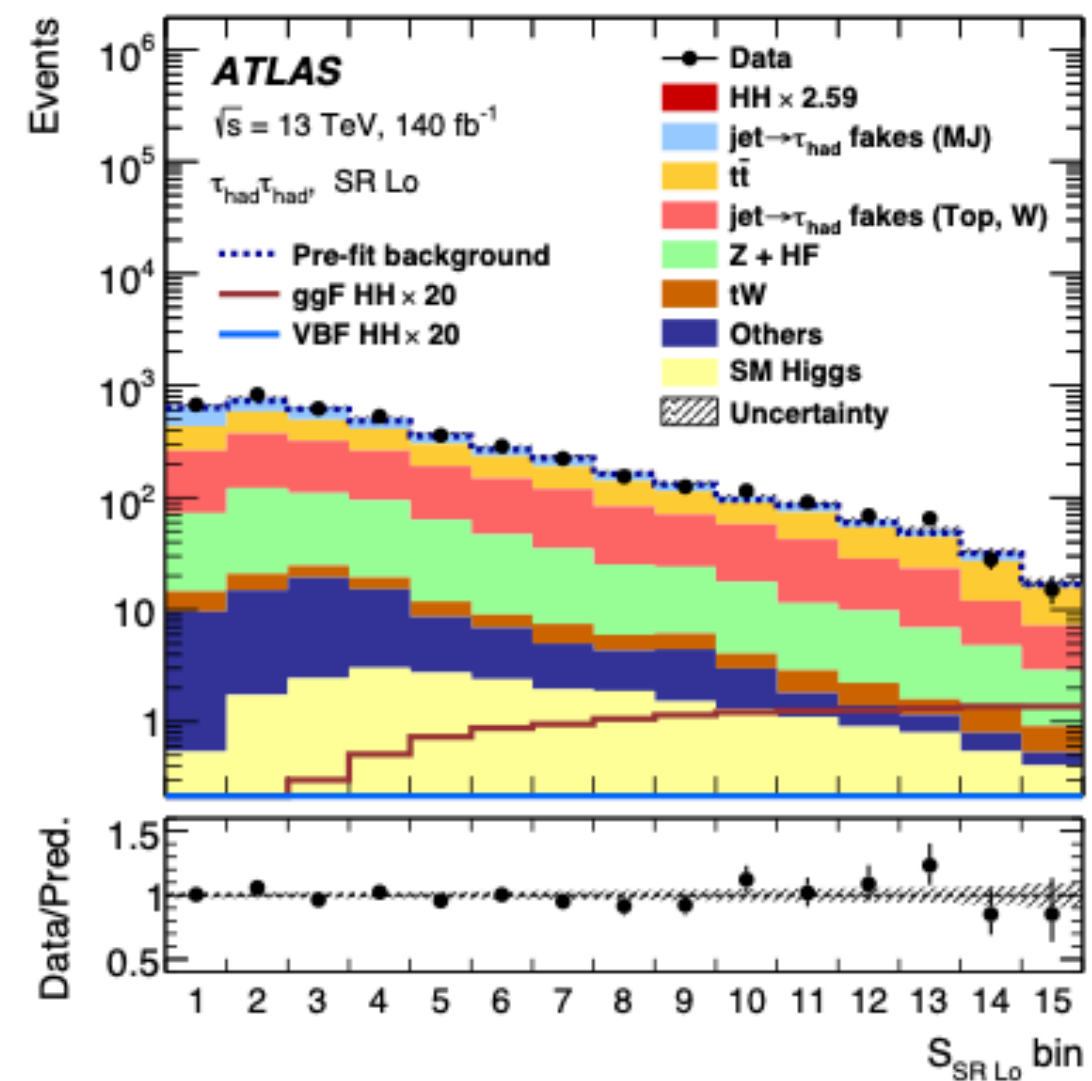
Categorisation score

$$S_{\text{cat}} = \frac{p_{\text{ggF}}}{p_{\text{ggF}} + p_{\text{VBF}}}$$

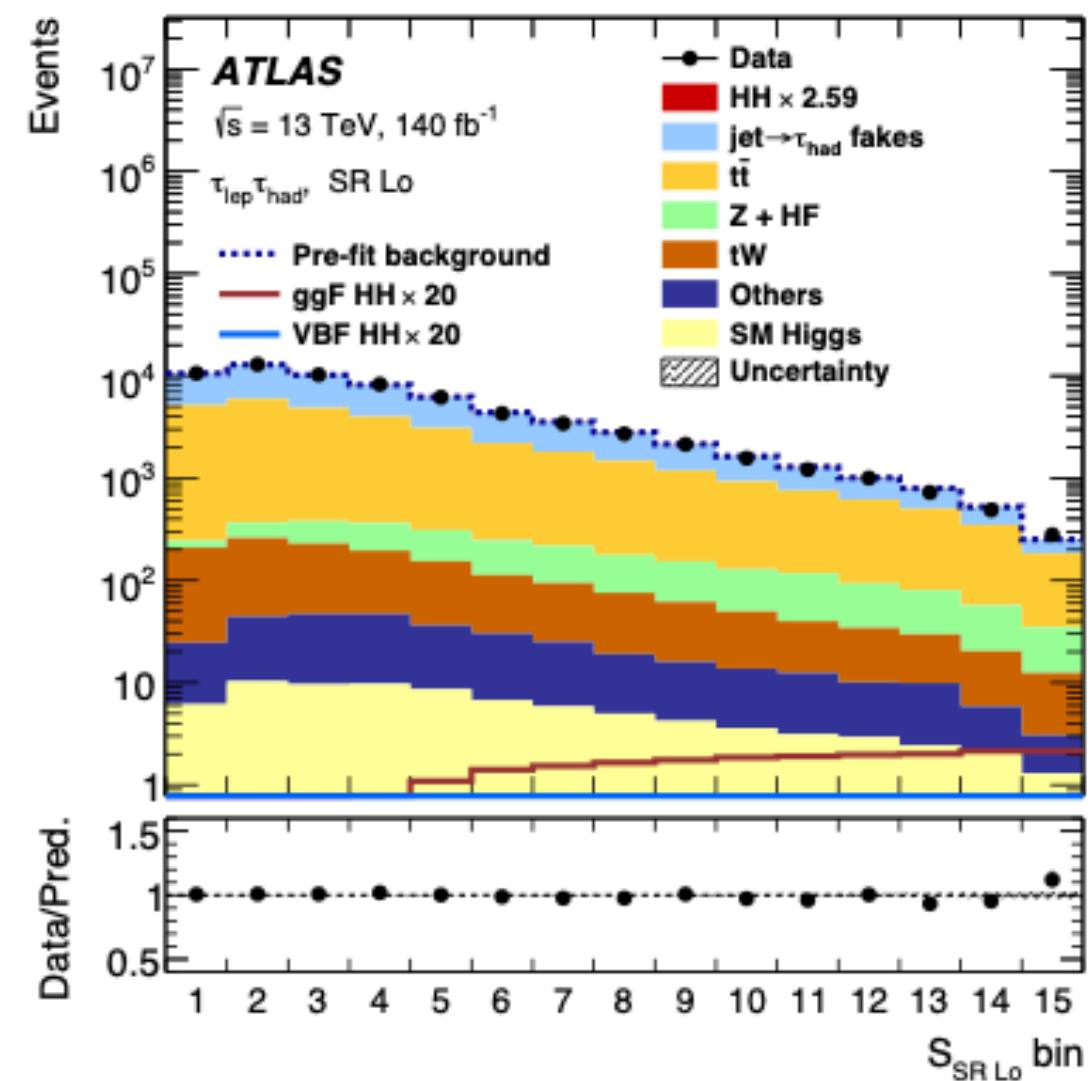


Analysis strategy: multi-classifier HH→bbττ

HIGP-2024-37 (subm. to EPJC)



(a)



(b)

↓

SR VBF

$$S_{\text{SR VBF}} = \frac{2p_{\text{VBF}}}{p_{\text{VBF}} + p_{\text{B}}} - 1$$

↓

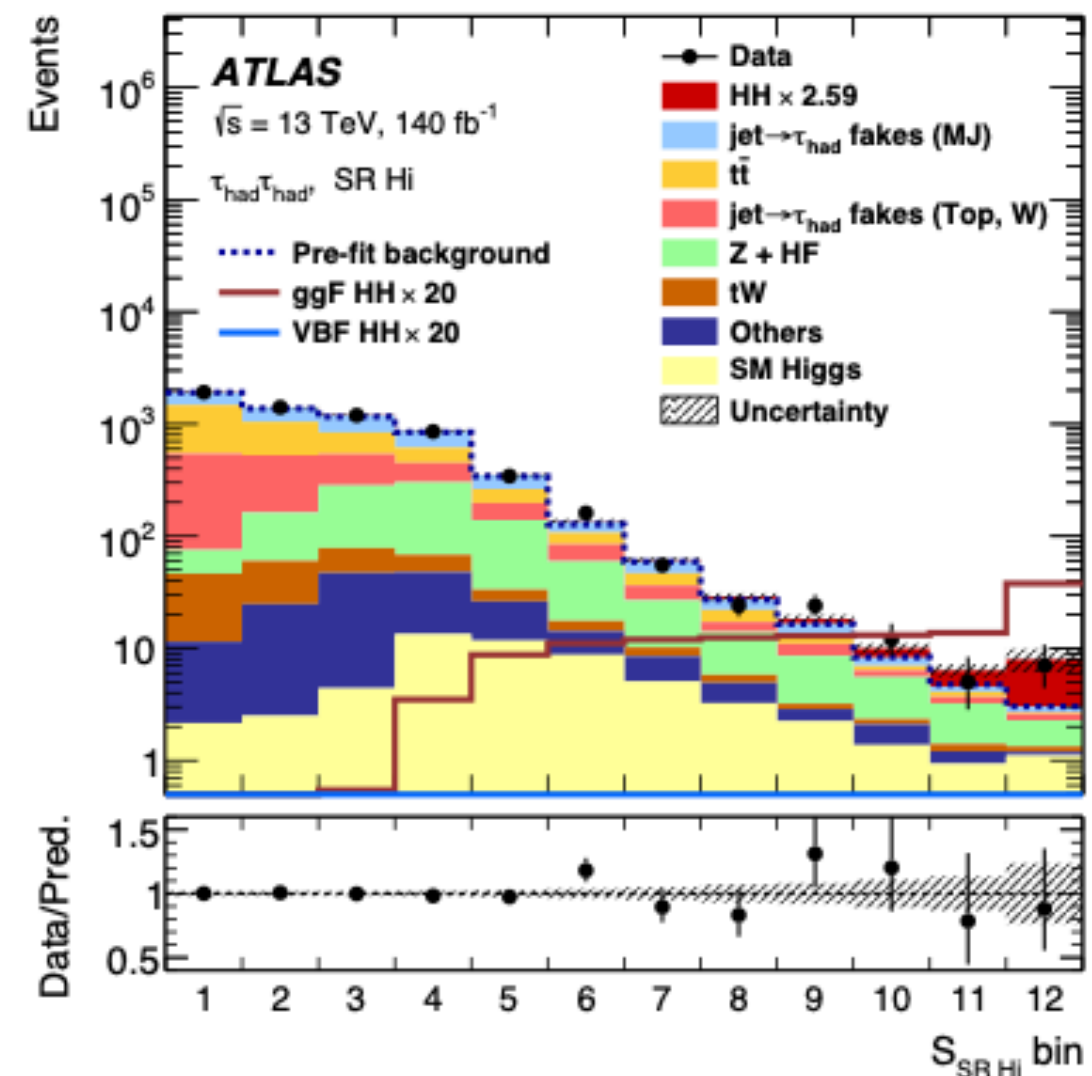
SR Lo

$$S_{\text{SR Lo}} = \frac{2p_{\text{BSM}}}{p_{\text{BSM}} + p_{\text{B}}} - 1$$

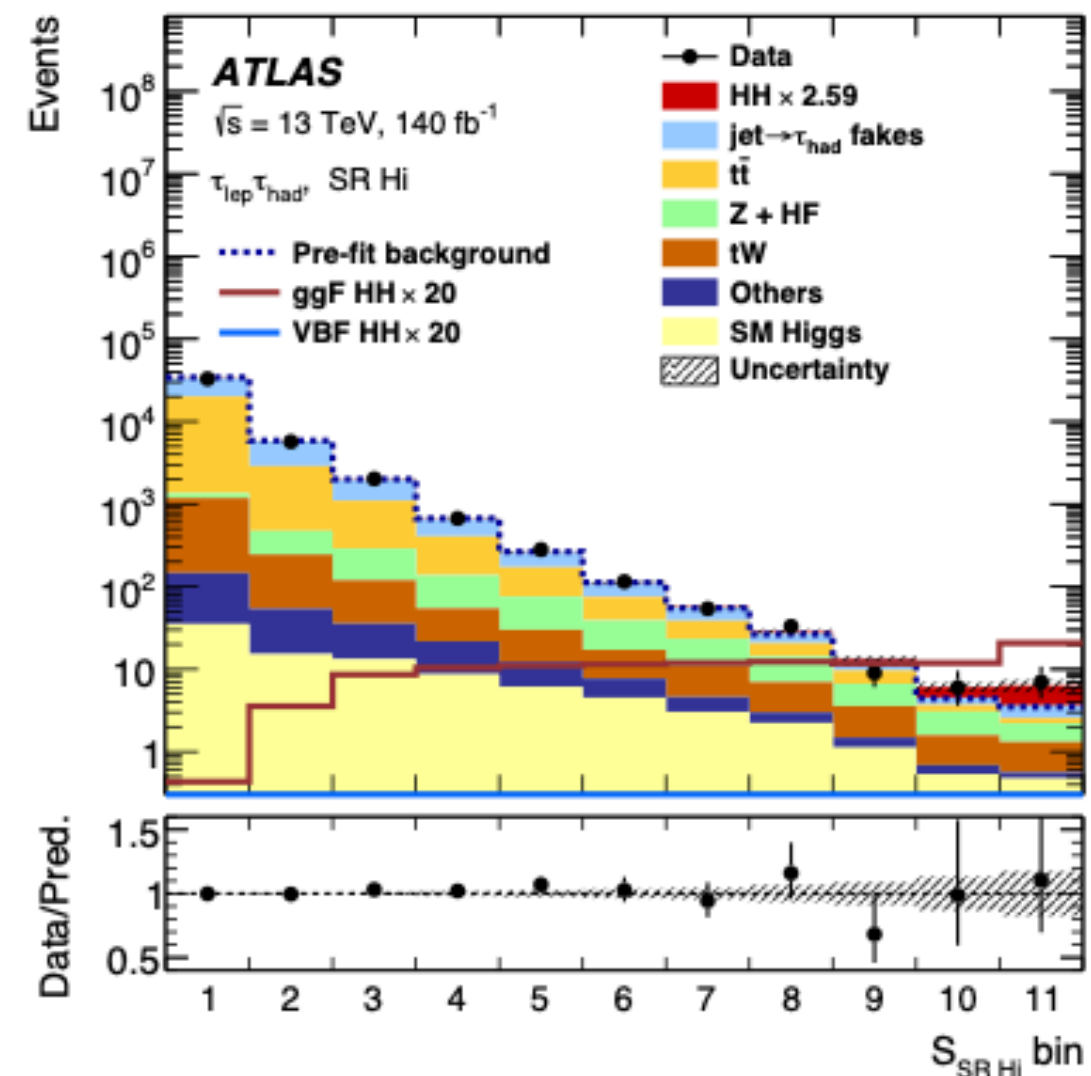
↓

SR Hi

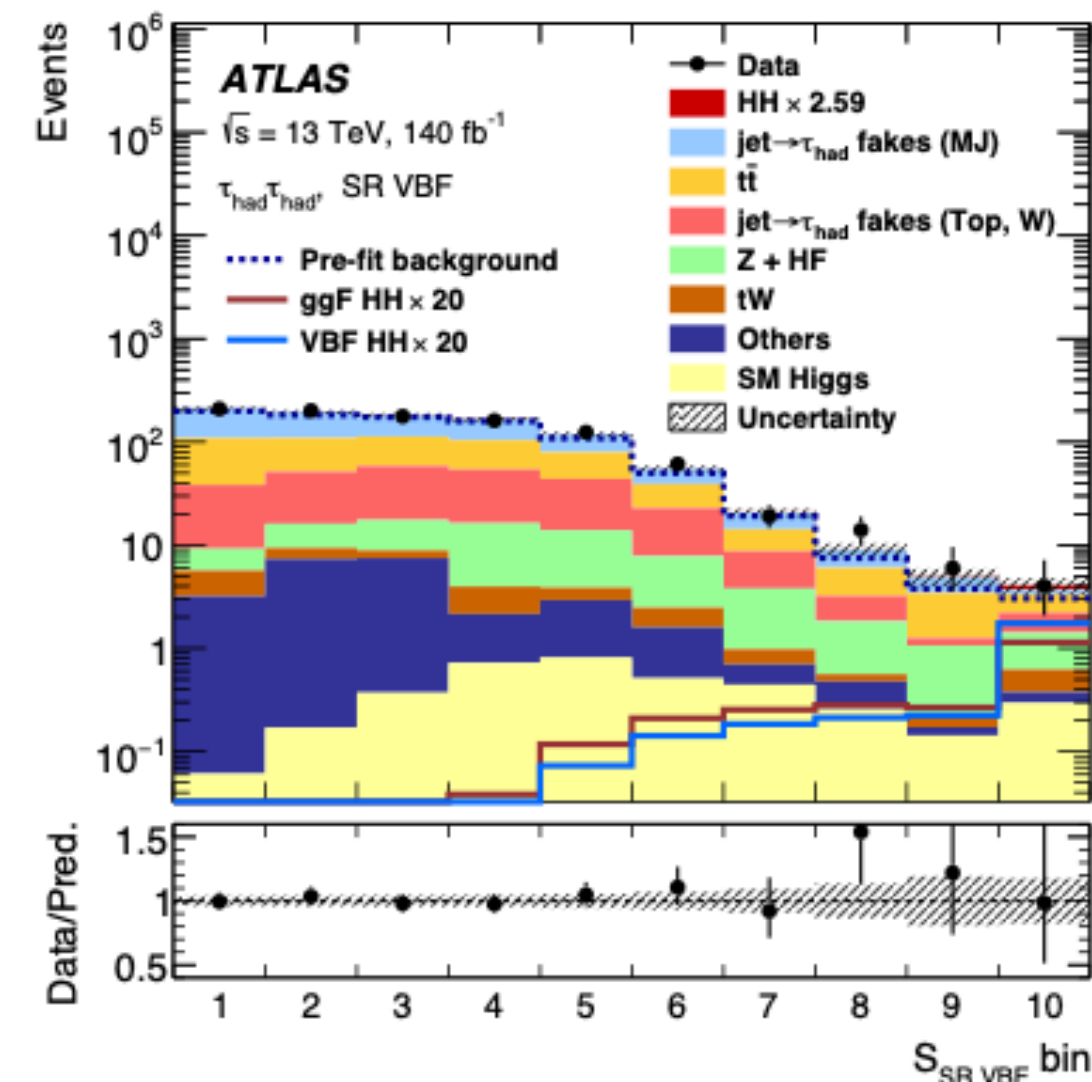
$$S_{\text{SR Hi}} = \frac{2p_{\text{HH, Hi}}}{p_{\text{HH, Hi}} + p_{\text{B, Hi}}} - 1$$



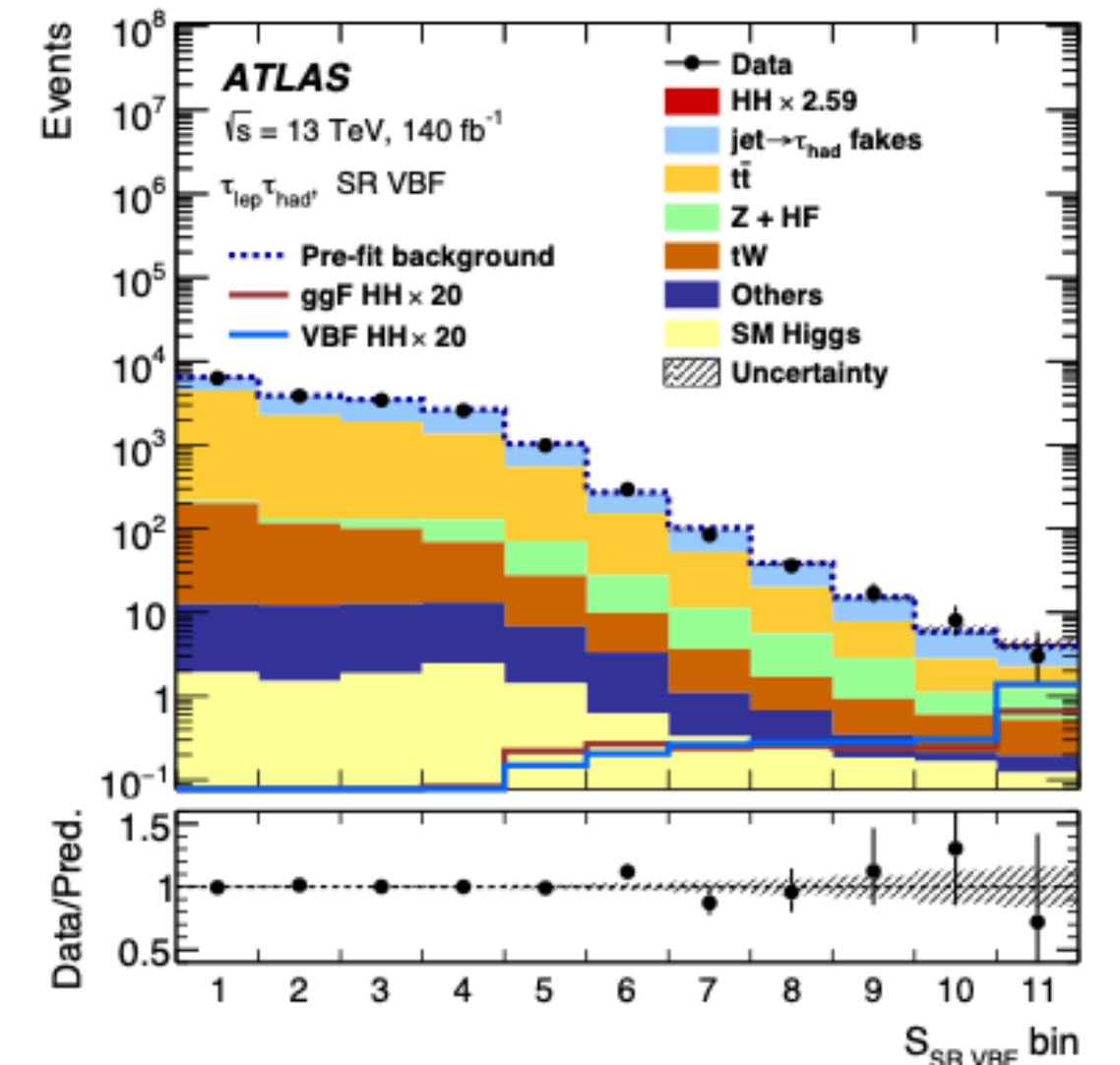
(c)



(d)



(e)

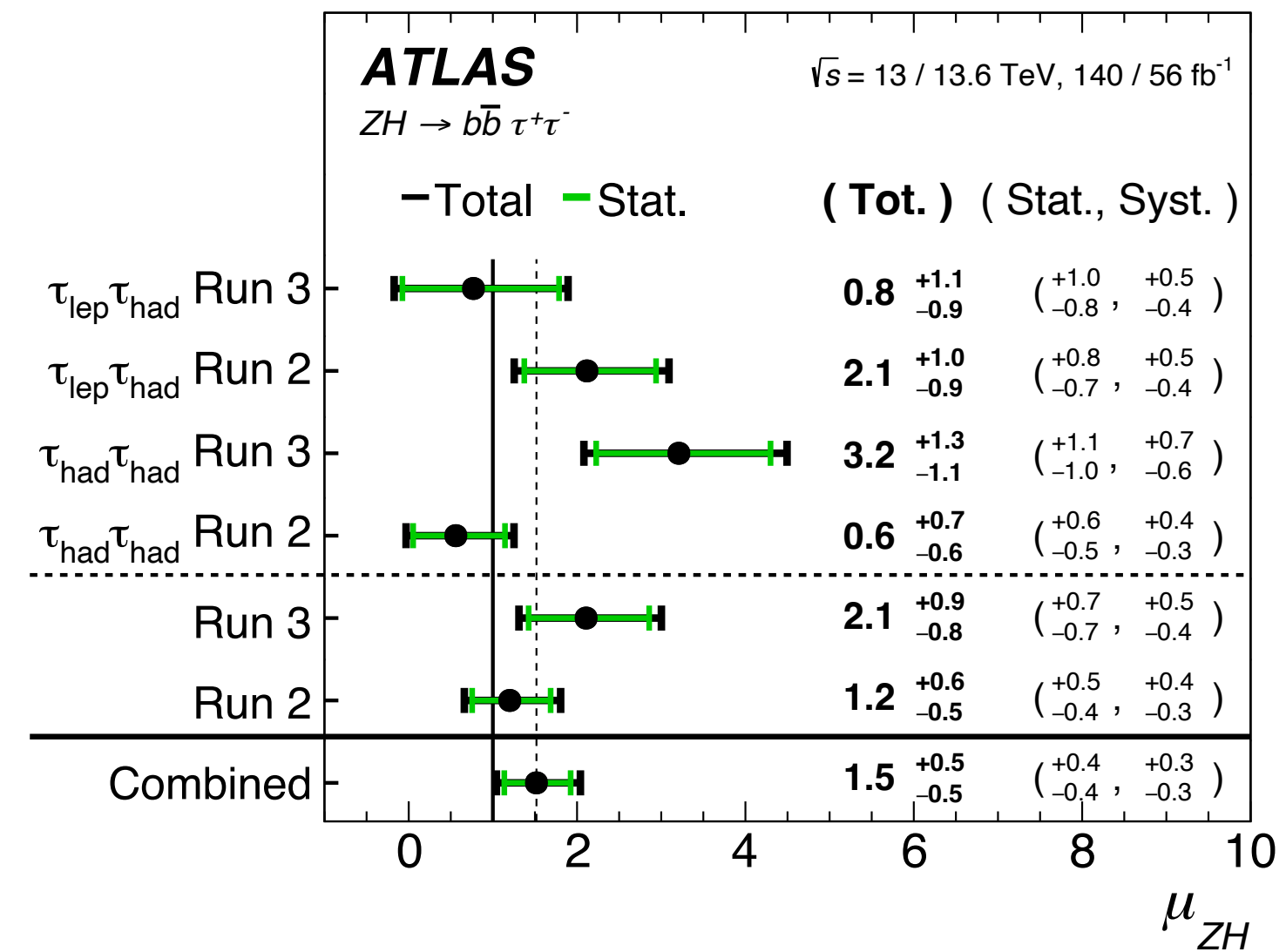
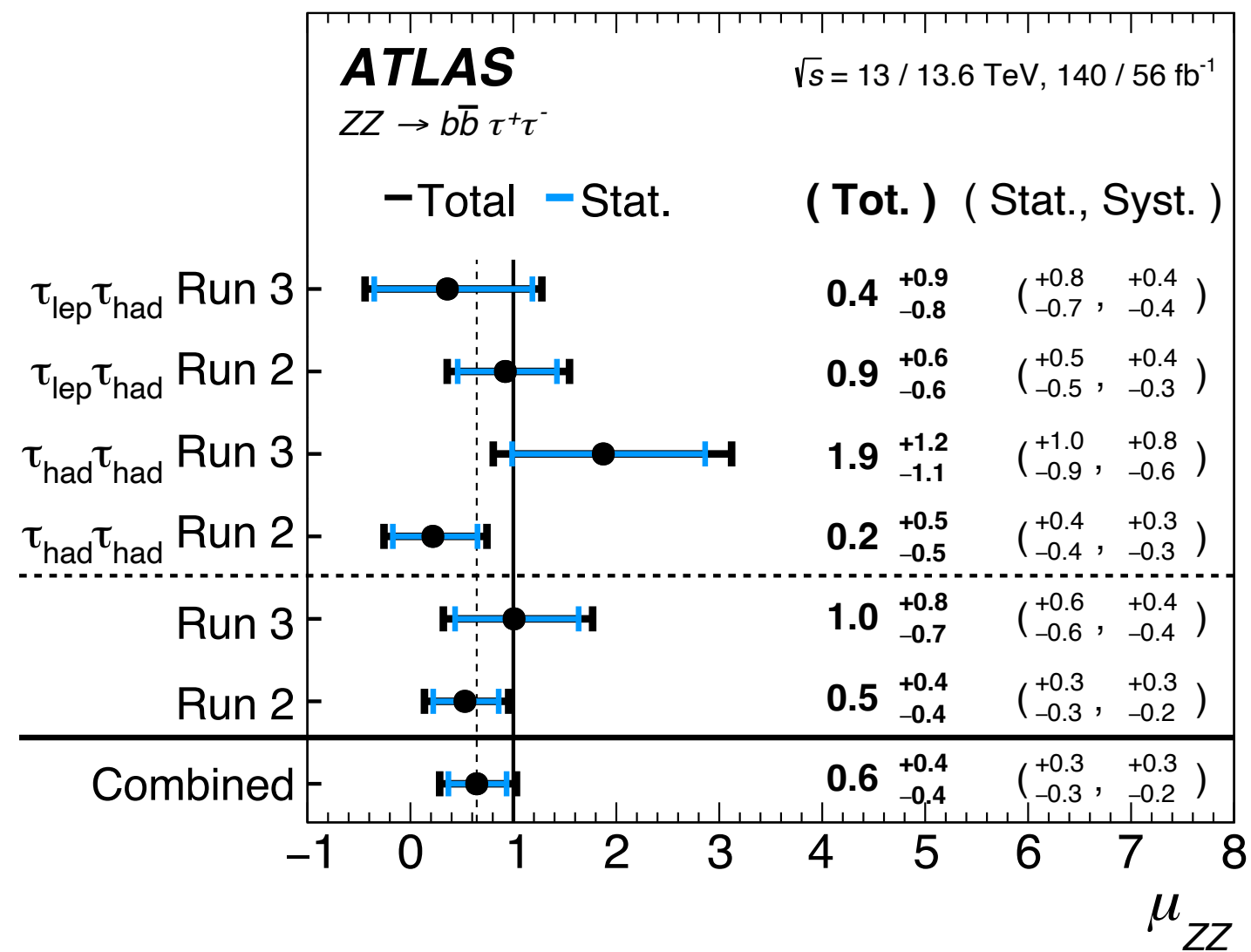
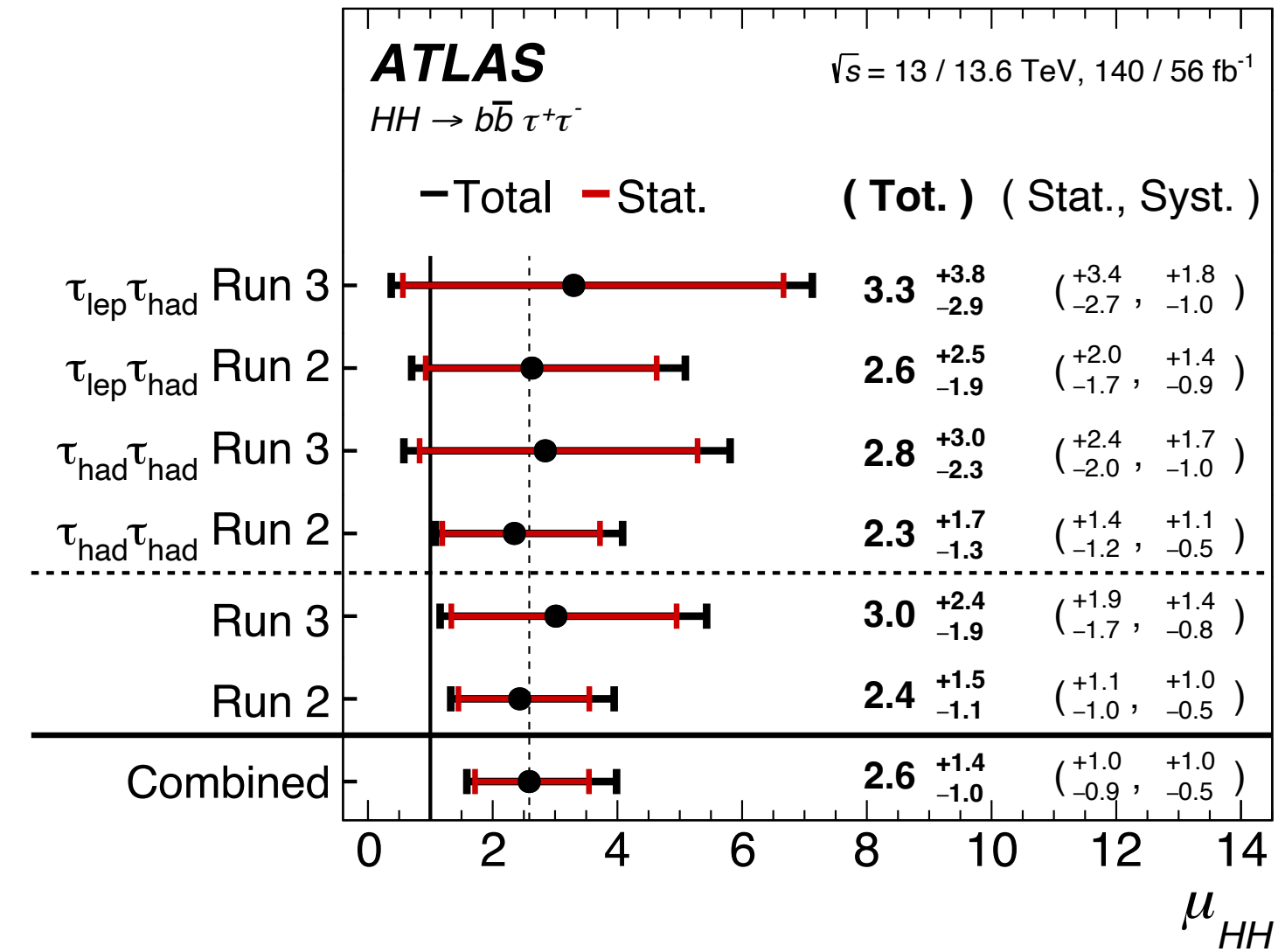
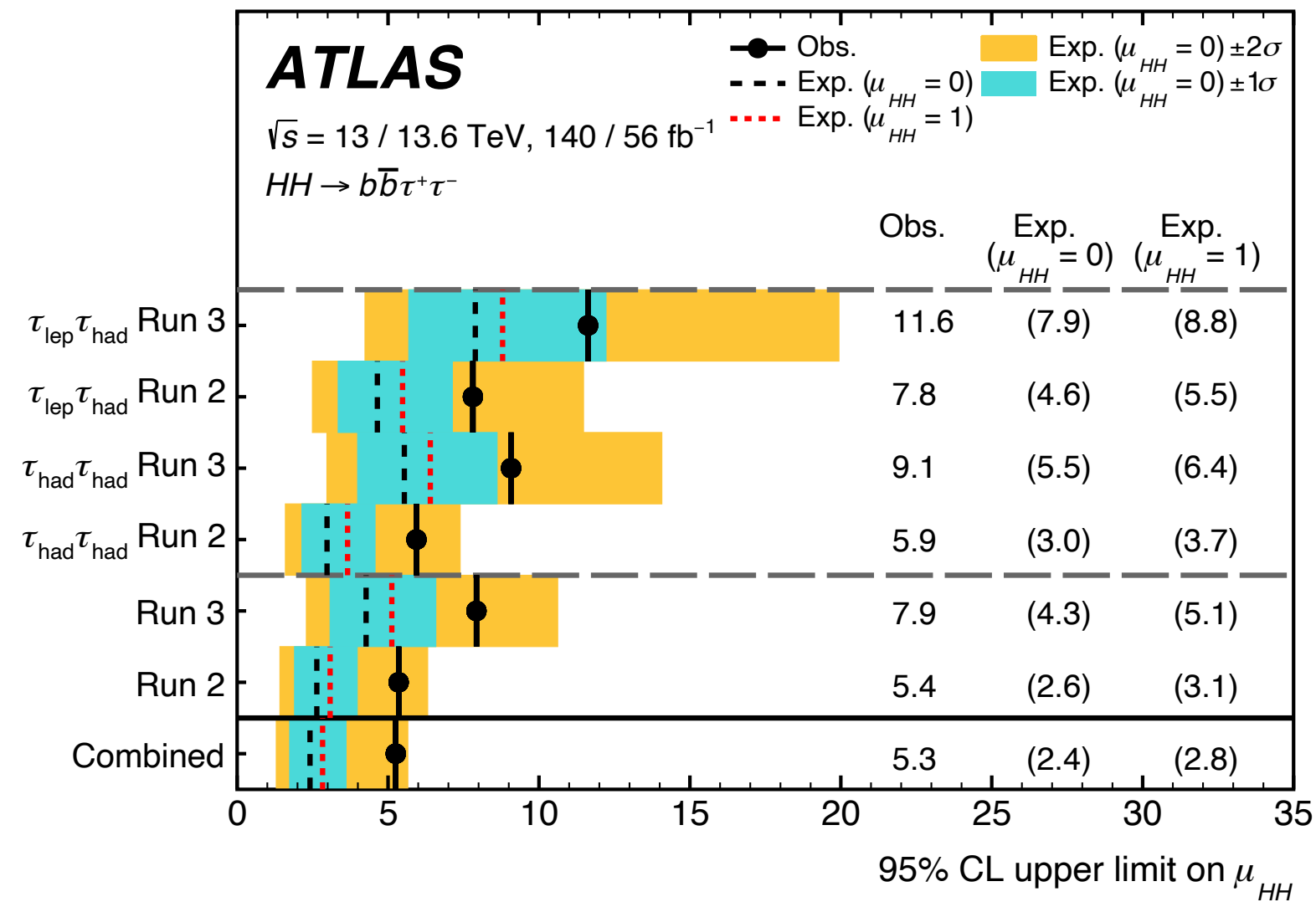


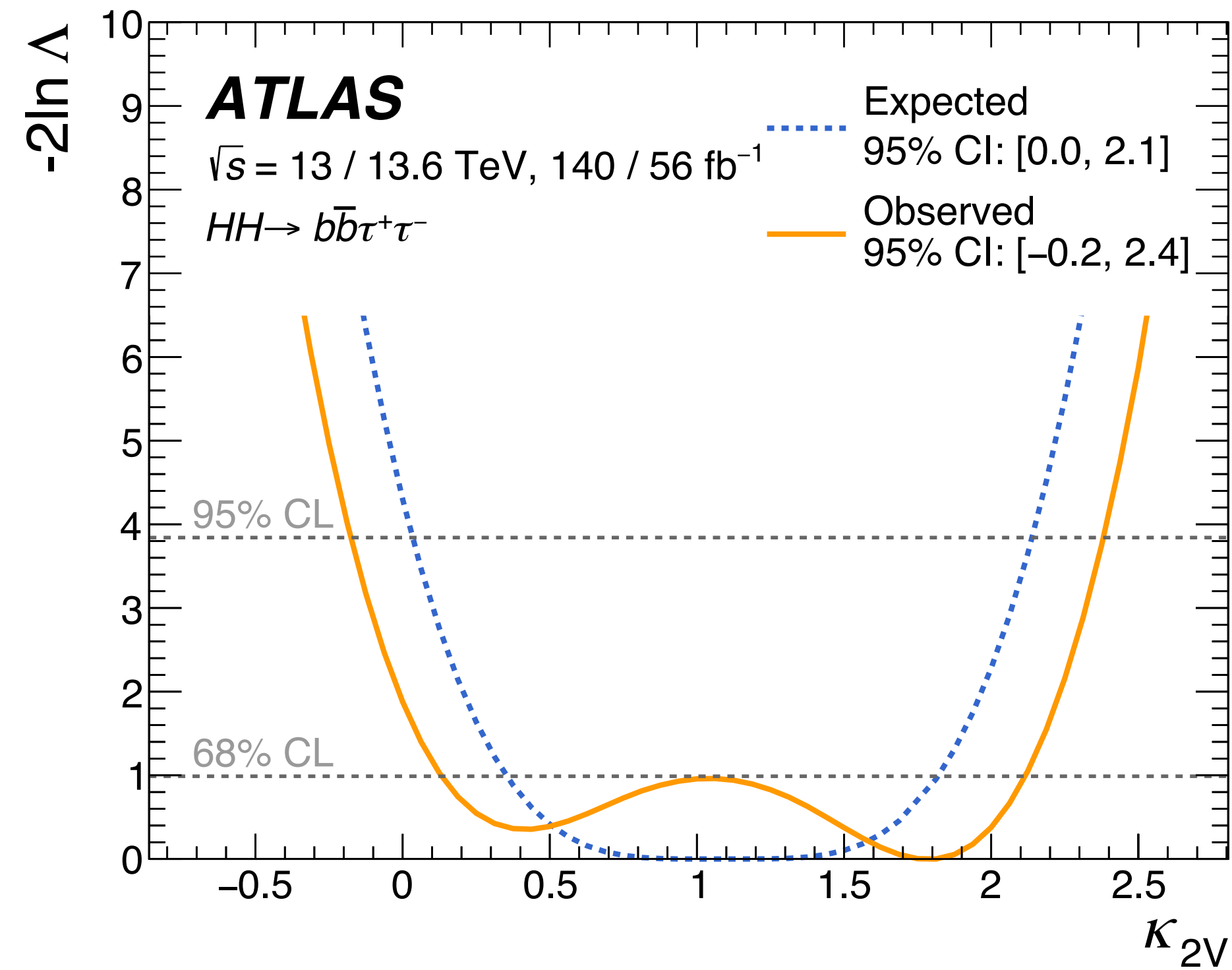
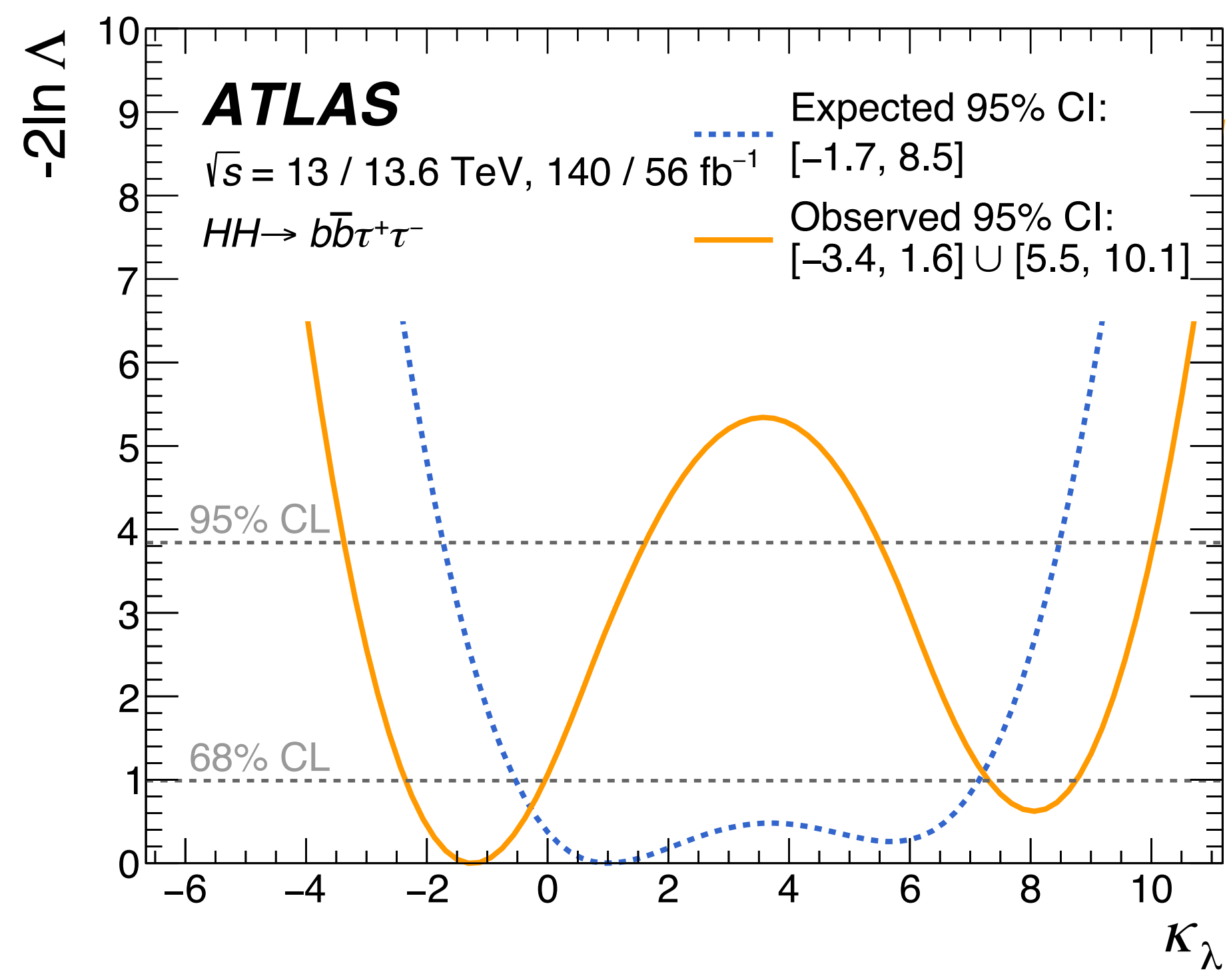
(f)

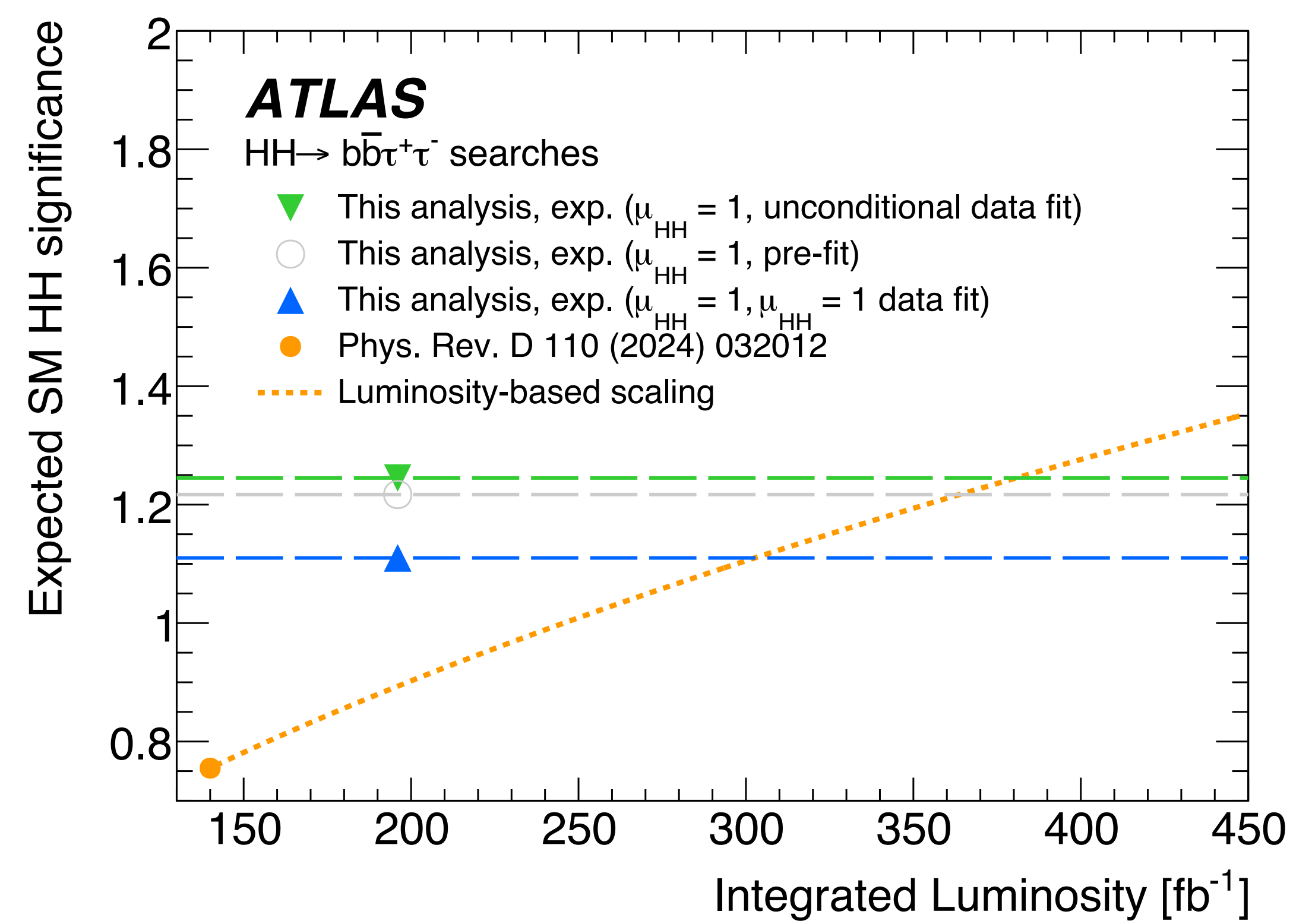
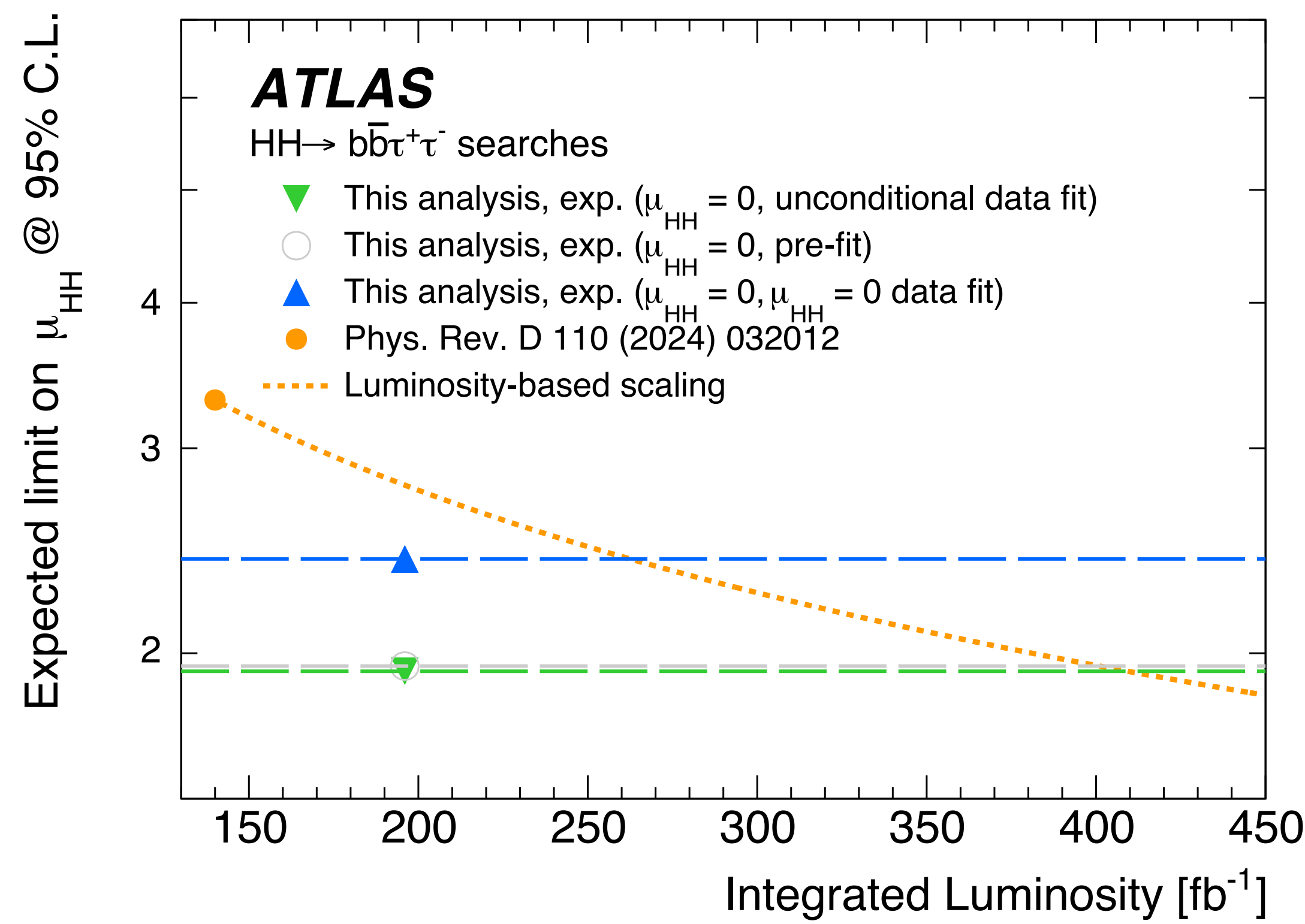
Variable	Description
Global event-level features: both channels	
m_{HH}	Invariant mass of the reconstructed HH system using the di- τ four-momentum after the MMC algorithm
m_{bb}	Invariant mass of the b -jet pair
ΔR_{bb}	ΔR between the two b -jets
m_{jj}	Invariant mass of the two leading VBF jets
ΔR_{jj}	ΔR between the two leading VBF jets
$\eta_{\text{VBF } j_0} \cdot \eta_{\text{VBF } j_1}$	Product of pseudorapidities of the two leading VBF jets
Global event-level features: $\tau_{\text{had}}\tau_{\text{had}}$ only	
$\Delta R_{\tau\tau}$	ΔR between the two τ_{had} candidates
Global event-level features: $\tau_{\text{lep}}\tau_{\text{had}}$ only	
$\Delta R(\tau_{\text{had}}, \ell)$	ΔR between the τ_{had} candidate and the electron or muon
$p_{\text{T}, HH}$	Transverse momentum of the reconstructed HH system
η_{HH}	Pseudorapidity of the reconstructed HH system
$E_{\text{T}}^{\text{miss}}$	Missing transverse energy
$\Delta R(b_0, \tau_{\text{had}})$	ΔR between the leading b -jet and the τ_{had} candidate
$\Delta R(b_1, \tau_{\text{had}})$	ΔR between the subleading b -jet and the τ_{had} candidate
$m_{b\ell}$	$\min(x, y)$, where $x = \max(m_{b_1, \tau_{\text{had}}}, m_{b_2, \ell})$ and $y = \max(m_{b_1, \ell}, m_{b_2, \tau_{\text{had}}})$
$m_{\tau\tau}^{\text{vis}}$	Invariant mass of the visible di- τ system
$p_{\text{T}, \tau\tau}^{\text{vis}}$	Transverse momentum of the visible di- τ system
T_1	Topness , with $\sigma_t = \sigma_W = 5$ GeV
H_{T}	Scalar sum of transverse momenta of all reconstructed objects
$\Delta\eta(bb, \tau\tau)$	$\Delta\eta$ between the b -jet pair and the MMC di- τ systems
$\Delta\phi(\tau\tau, E_{\text{T}}^{\text{miss}})$	$\Delta\phi$ between $\vec{p}_{\text{T}}^{\text{miss}}$ and the MMC di- τ system
$\Delta R(b_1, \ell)$	ΔR between the subleading b -jet and the lepton
$m_{\text{T}}(\tau_{\text{had}}, \vec{p}_{\text{T}}^{\text{miss}})$	Transverse mass of the τ_{had} candidate and $\vec{p}_{\text{T}}^{\text{miss}}$ system
Object-level features (per-object inputs to the transformer network)	
η	Pseudorapidity; set to 0 for $\vec{p}_{\text{T}}^{\text{miss}}$
ϕ	Azimuthal angle
m	Mass; set to 0 for $\vec{p}_{\text{T}}^{\text{miss}}$, leptons, and τ_{had} candidates
p_{T}	Transverse momentum
PCBT	GN2 pseudo-continuous b -tagging score (bins: 100%–90%–85%–77%–70%–65%) set to -2 for non-jet objects and -1 for forward jets
isTau	Boolean flag: object is a τ_{had} candidate
isJet	Boolean flag: object is a non- b -tagged jet
isBjet	Boolean flag: object is a b -tagged jet
isMET	Boolean flag: object is $\vec{p}_{\text{T}}^{\text{miss}}$
isMMC	Boolean flag: object is the MMC di- τ system
isLepton	Boolean flag: object is a lepton (only in $\tau_{\text{lep}}\tau_{\text{had}}$ channel)

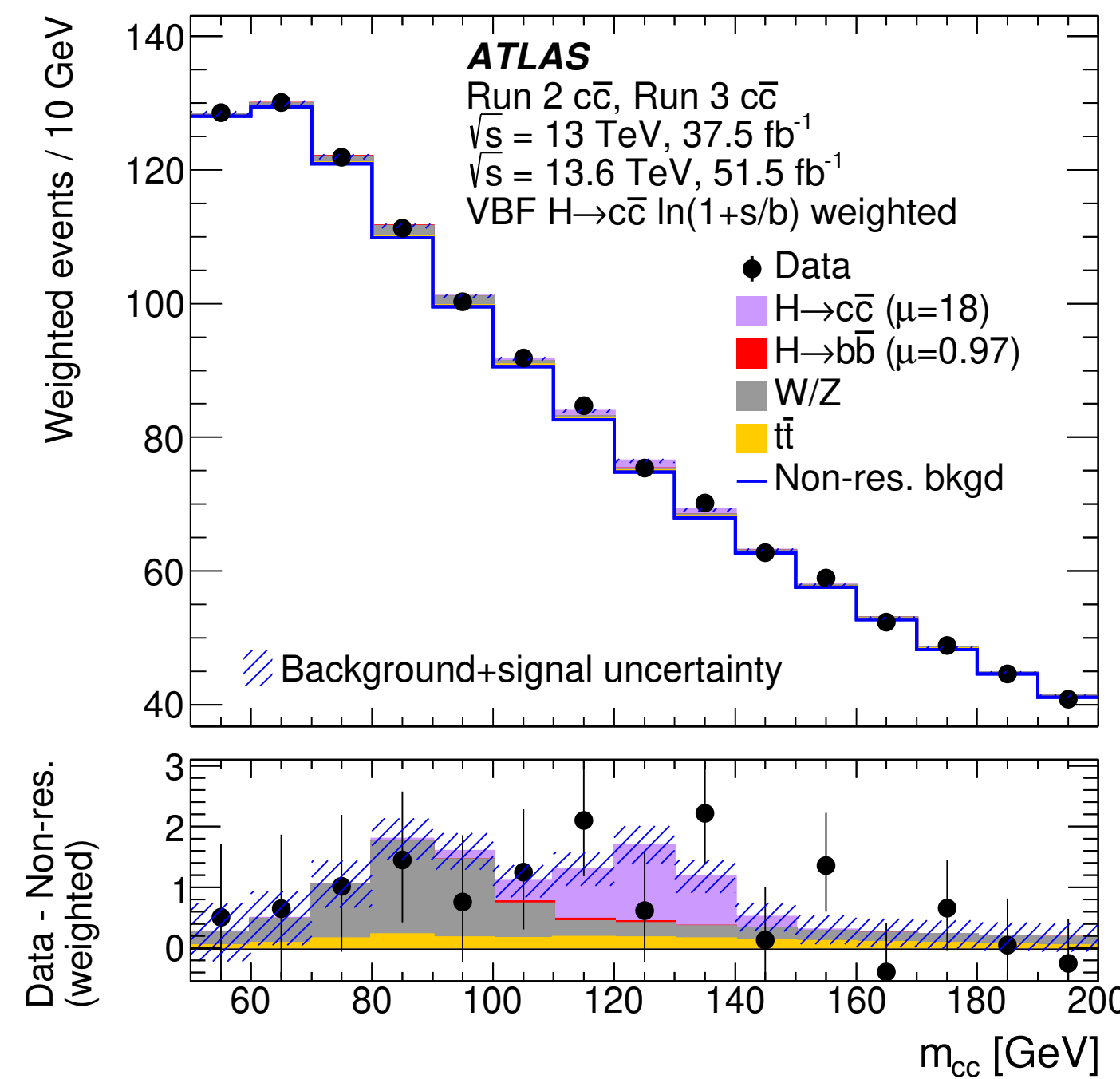
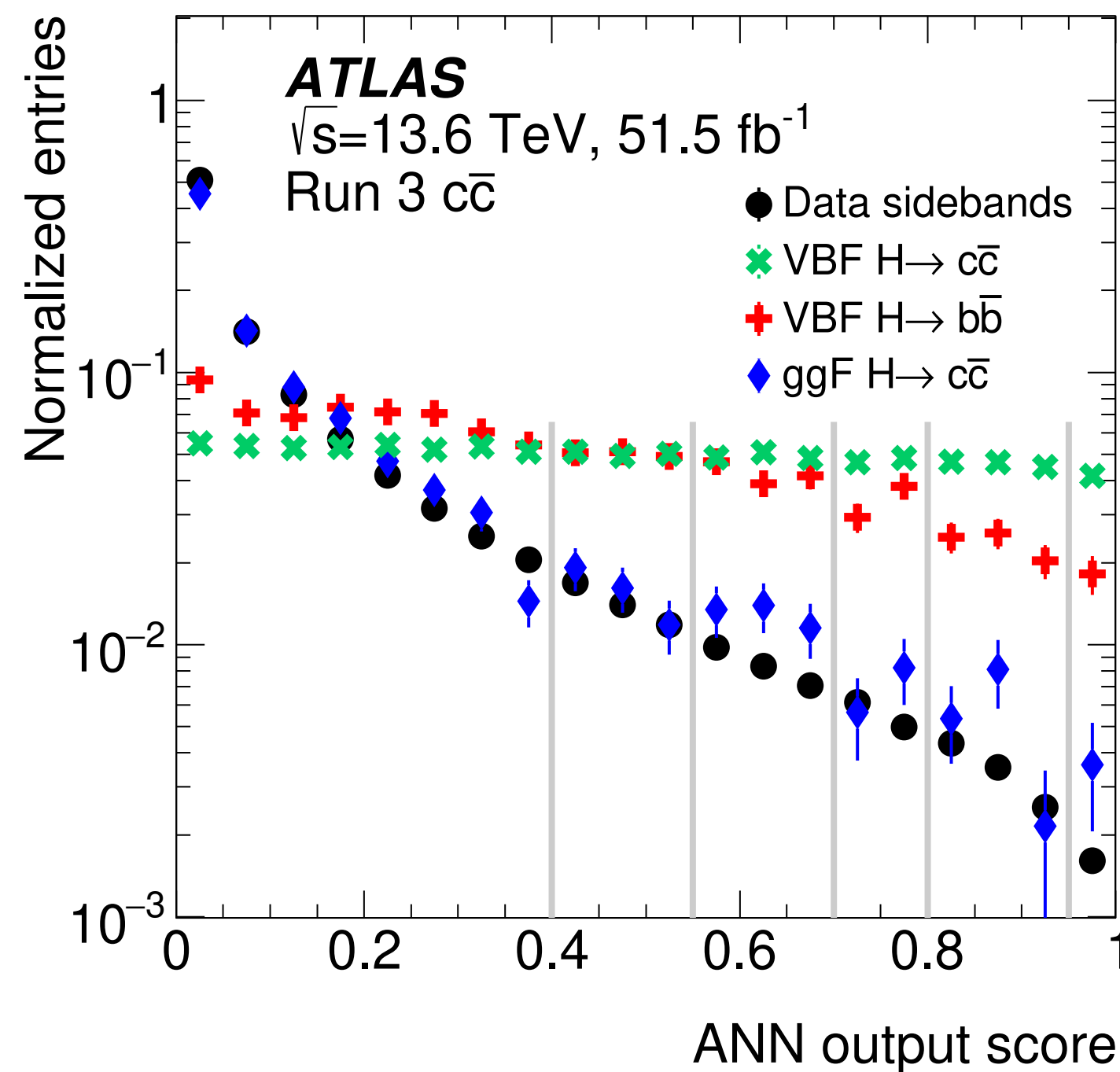
Analysis strategy: multi-classifier $HH \rightarrow b\bar{b}\tau\tau$

[HIGP-2024-37 \(subm. to EPJC\)](#)









- **Search for VBF H → cc production with Run 2 + 3 data:**
 - similar strategy as previous VBF H → bb analysis [Eur. Phys. J. C 81 \(2021\) 537](#)
 - benefits from **new inclusive VBF trigger** deployed in 2018
- **Analysis strategy:**
 - ANN defines regions of increasing signal purity
 - signal extraction from m(cc)
 - background shape from low-score region

- **ANN training:** $L = L_{\text{classifier}} - \lambda L_{\text{adversary}}$
 - categorical cross-entropy + adversary m(cc) bin prediction losses
 - background trained from m(cc) sidebands
 - residual decorrelation and sideband-extrapolation uncertainties

- **Results:**
 $\mu(\text{cc}) < 41$ obs. (25 exp.) @ 95%CL

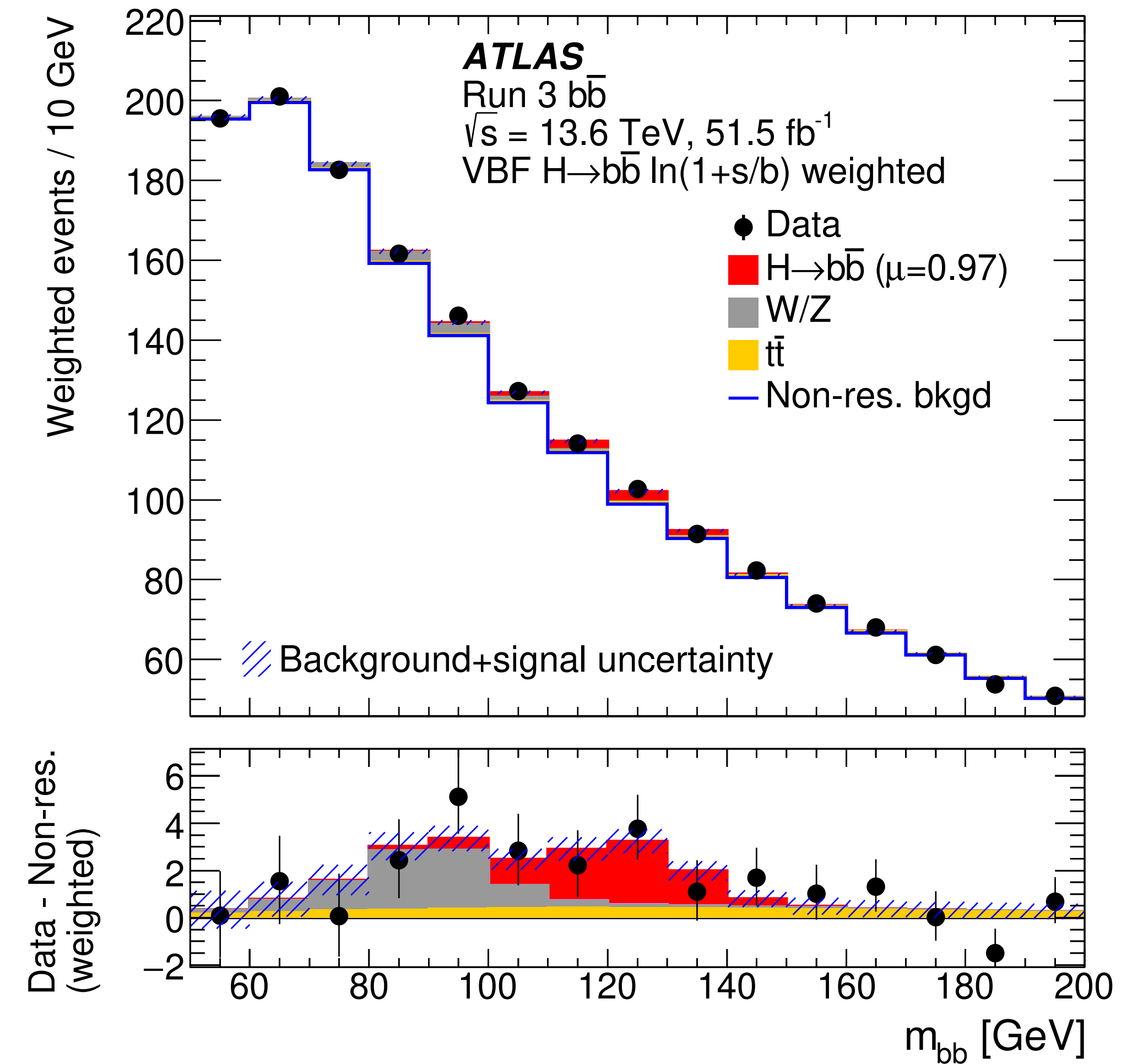
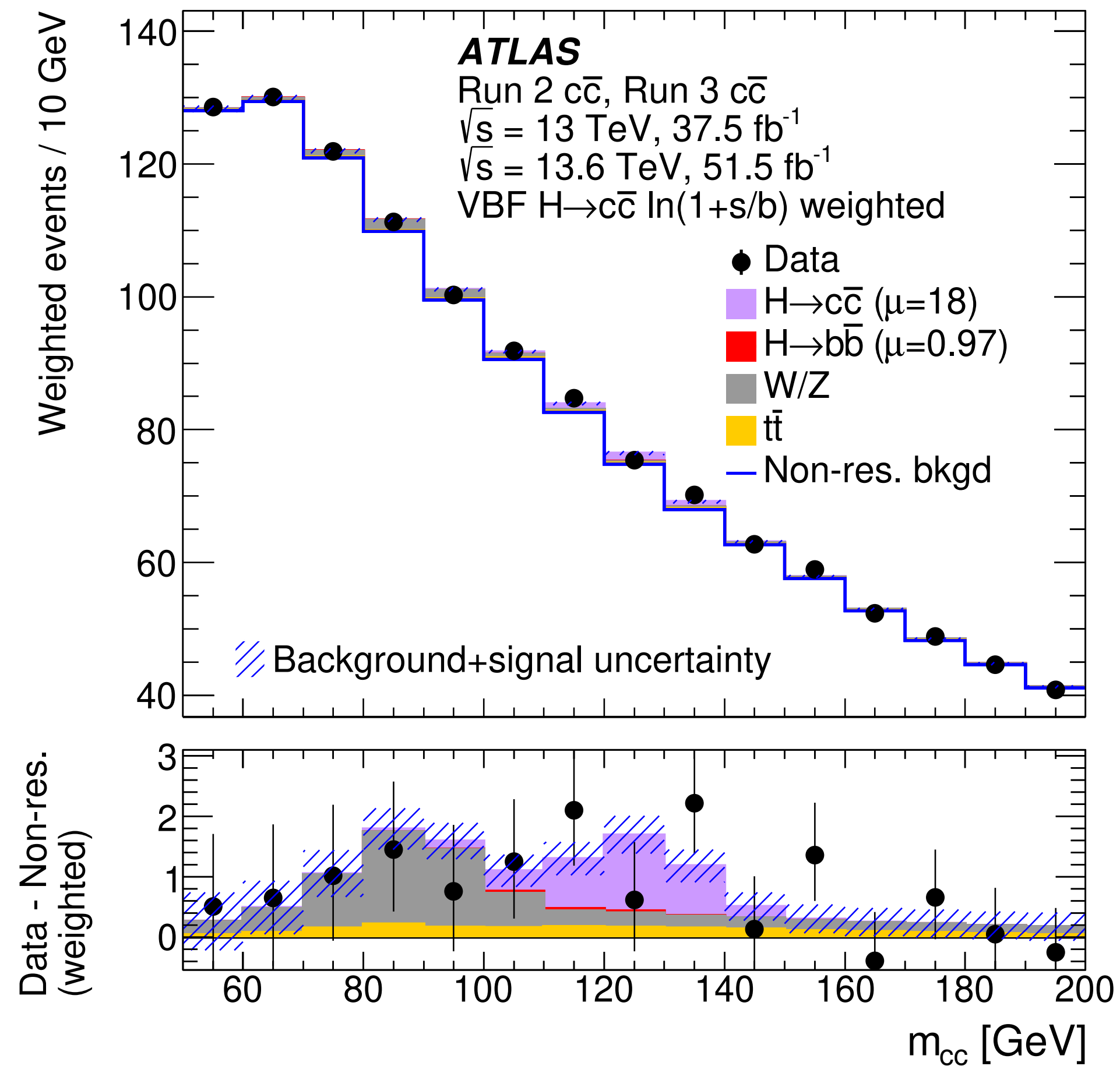
$$\mu^{b\bar{b}} = 0.97_{-0.50}^{+0.57} = 0.97 \pm 0.45 \text{ (stat.)}_{-0.22}^{+0.35} \text{ (syst.)}$$

$$\mu^{c\bar{c}} = 18 \pm 13 = 18 \pm 12 \text{ (stat.)} \pm 7 \text{ (syst.)}$$

Source of uncertainty	$\sigma(\mu^{c\bar{c}})$	$\sigma(\mu^{b\bar{b}})$
Total	13	0.53
Statistical	12	0.45
Data statistical	8.7	0.32
Non-res. bkgd normalization	4.9	0.19
Non-res. bkgd shape	4.6	0.20
Non-res. bkgd residual uncertainty	1.4	0.05
Other Higgs signal normalization	0.3	0.01
Systematic	6.5	0.28
Non-res. bkgd bias uncertainty	5.8	0.19

Analysis strategy: adversarial training VBF $H \rightarrow c\bar{c}$

[HIGP-2024-21 \(subm. to PRL\)](#)



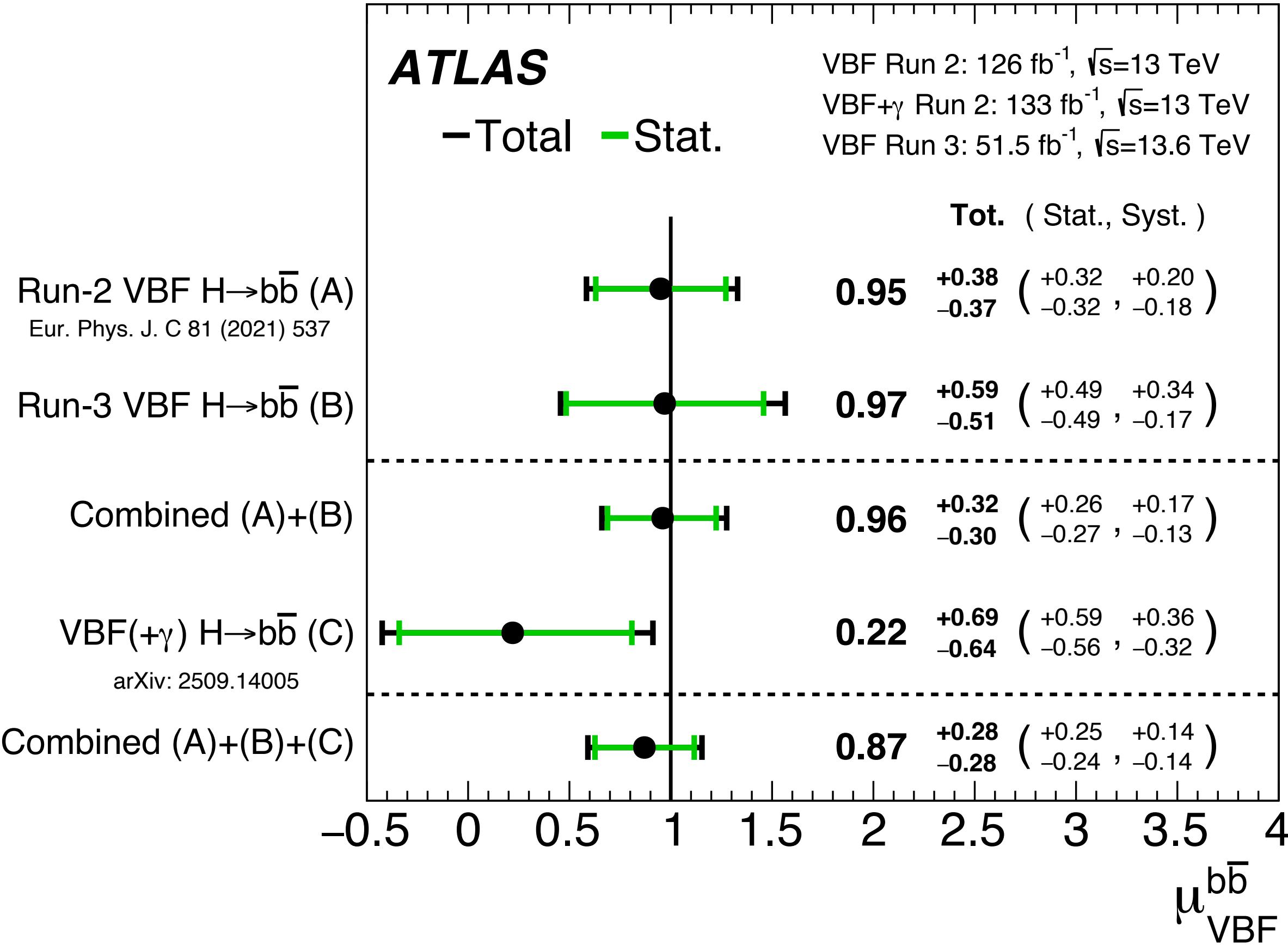
Analysis strategy: adversarial training VBF $H \rightarrow c\bar{c}$

[HIGP-2024-21 \(subm. to PRL\)](#)

Variable	$H \rightarrow c\bar{c}$ $H \rightarrow b\bar{b}$		Description
m_{jj}	✓	✓	Invariant mass of the VBF candidate jet pair.
$p_{T,jj}$	✓	✓	Transverse momentum of the VBF candidate jet pair.
$p_{T,j_h j_h}$	✓	✓	Transverse momentum of the Higgs jet pair.
p_T^{balance}	✓	✓	The ratio of the vectorial to scalar sums of the transverse momenta of j_{h1}, j_{h2}, j_1 and j_2 .
$\theta_{j_h j_h}$	✓	✓	Defined as $\tan^{-1} \left[\tan \left(\frac{\Delta\eta(j_h j_h)}{2} \right) / \tanh \left(\frac{\Delta\phi(j_h j_h)}{2} \right) \right]$, a measure of the relative angle of $\Delta\eta$ and $\Delta\phi$ between the two tagged jets.
$n_{\text{Jets}}^{\text{Rap}}$	✓	✓	The number of jets with $p_T > 20$ GeV and η between η_{j_1} and η_{j_2} .
$ \Delta\phi(j_h j_h, jj) $	✓	✓	The separation in ϕ between the Higgs jet pair and the VBF candidate jet pair.
$N_{\text{trk}}^{j_1}$	✓	✓	The number of tracks matched to the leading VBF candidate jet.
$N_{\text{trk}}^{j_2}$	✓	✓	The number of tracks matched to the sub-leading VBF candidate jet.
$D_{\text{GN2}}^{j_{h1}}$	✓		Binned output of the GN2 tagging algorithm for the leading c -tagged jet, with bin boundaries corresponding to 50%, 30%, and 10% c -tagging efficiencies.
$D_{\text{GN2}}^{j_{h2}}$	✓		Binned output of the GN2 tagging algorithm for the sub-leading c -tagged jet, with bin boundaries corresponding to 50%, 30%, and 10% c -tagging efficiencies.
p_T^{AddJet}		✓	Transverse momentum of the additional jet with the highest transverse momentum that does not belong to either the VBF candidate jets or the Higgs jets, and satisfies $ \eta < 2.5$. If no such jet exists, the value is set to 0 by default.

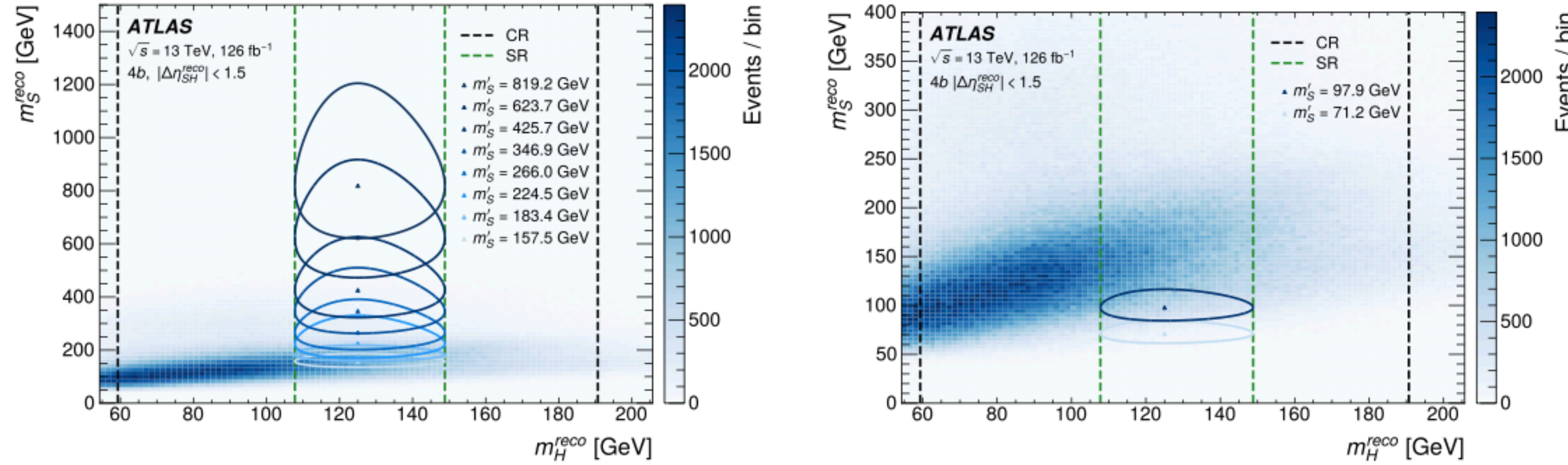
Analysis strategy: adversarial training VBF $H \rightarrow c\bar{c}$

[HIGP-2024-21 \(subm. to PRL\)](#)



Analysis strategy: normalising flow for bkg estimation

HIGP-2024-31 (subm. to PRD)



$$X_{SH}^{\text{reco}} = \sqrt{\left(\frac{m_H^{\text{reco}} - m'_H}{r_{f,H} \cdot m_H^{\text{reco}}}\right)^2 + \left(\frac{m_S^{\text{reco}} - m'_S}{r_{f,S} \cdot m_S^{\text{reco}}}\right)^2},$$

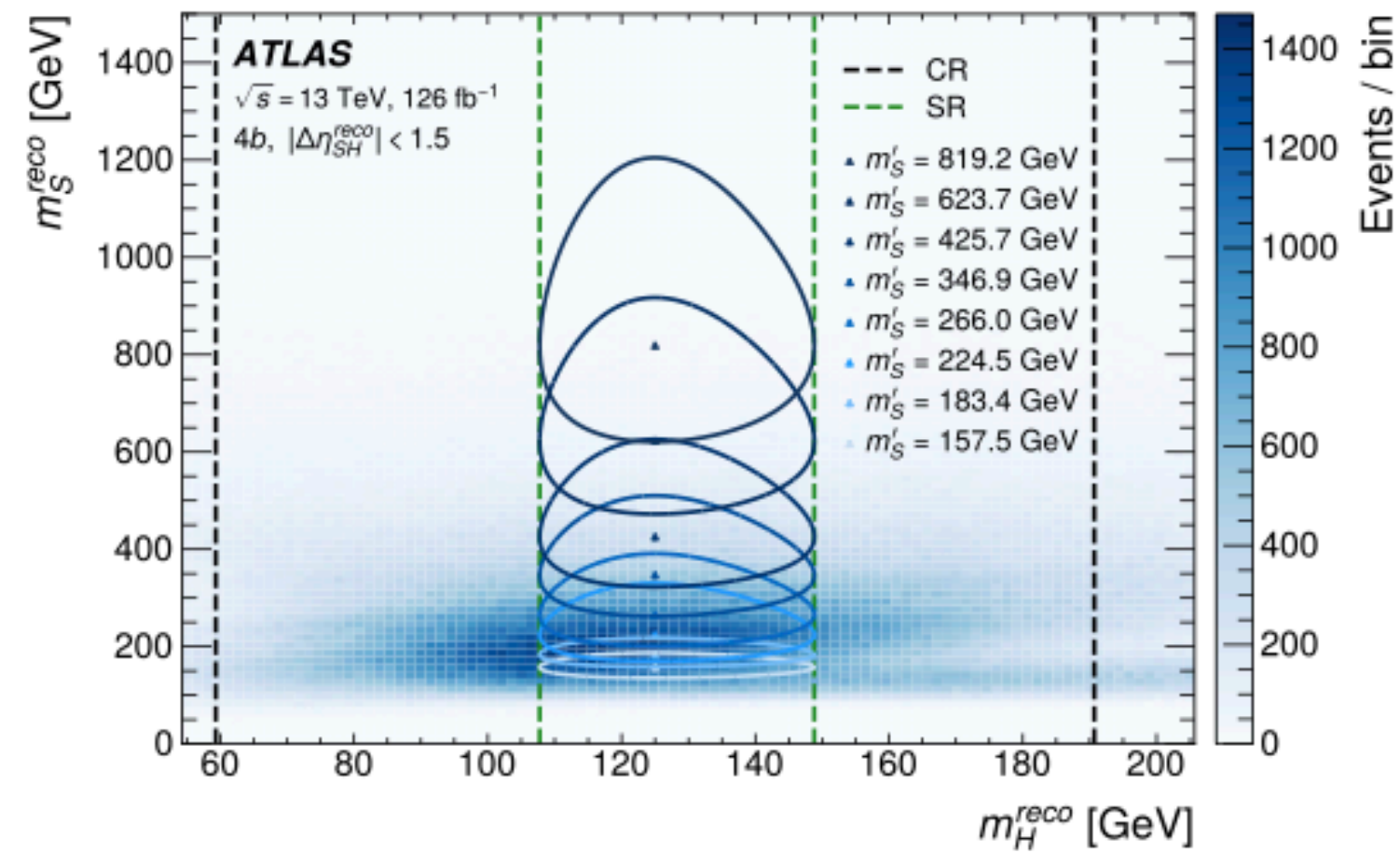
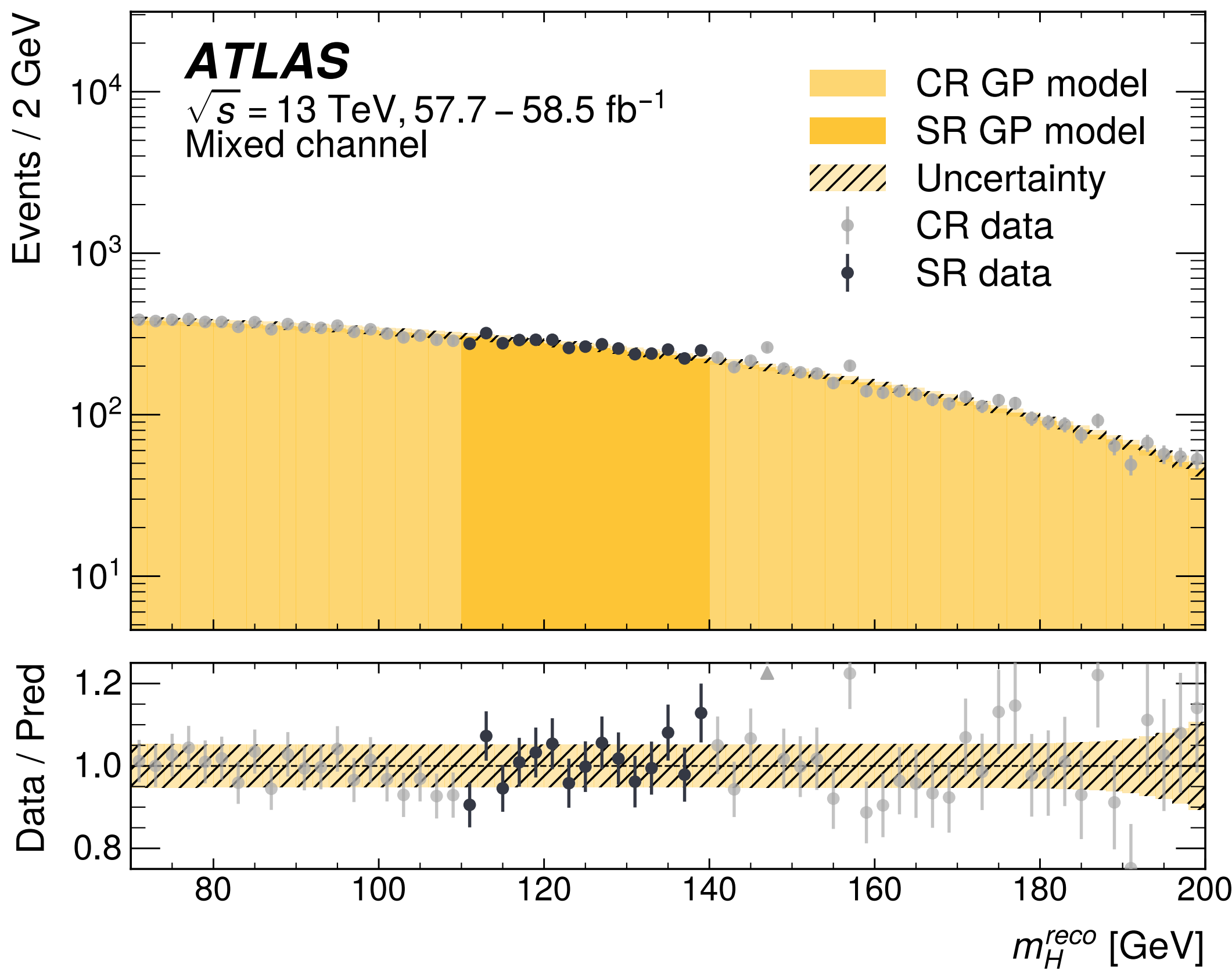
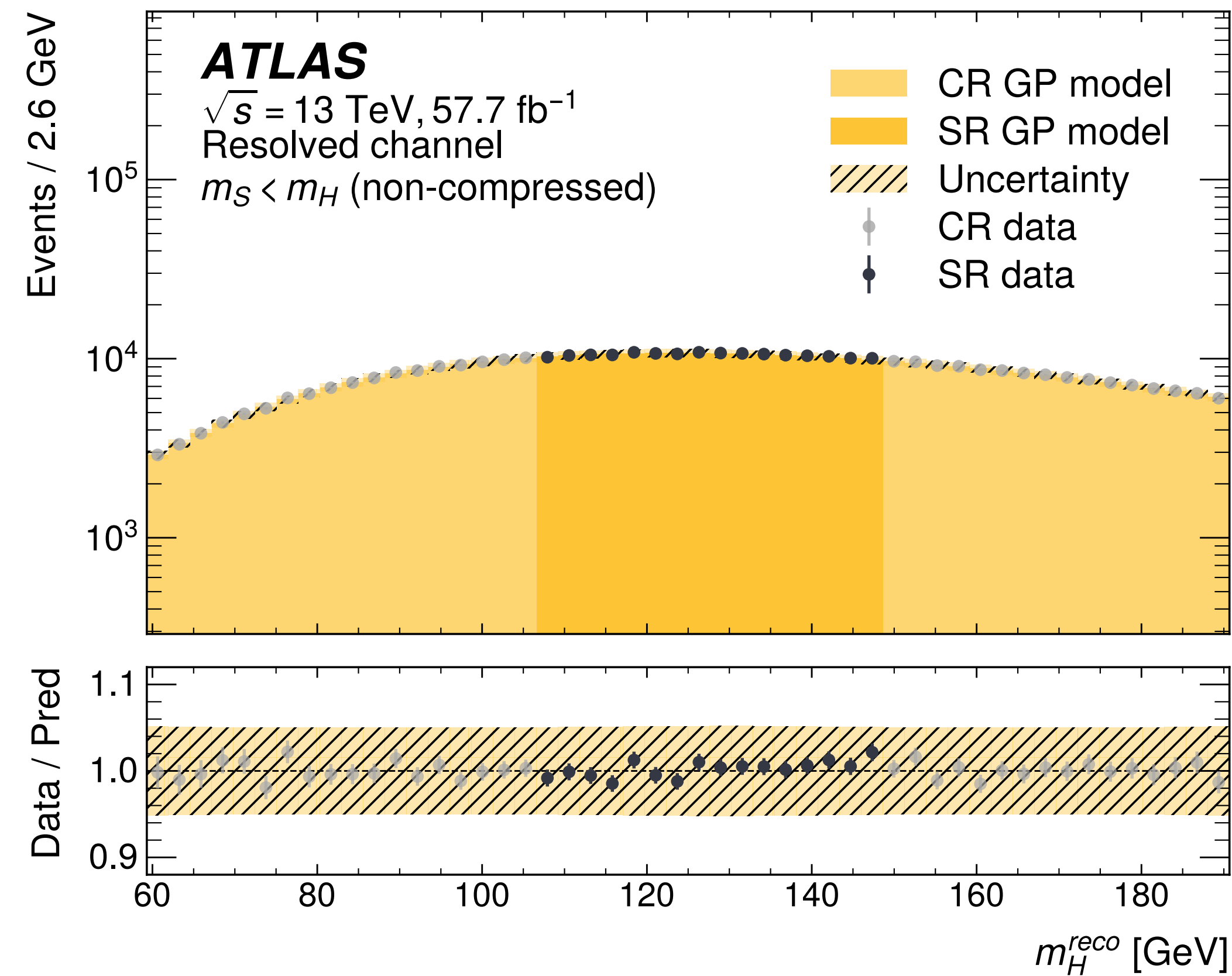


Figure 3: Data for the resolved analysis for different BDT training groups and different cases of scalar mass assignment, represented in the reconstructed $(m_H^{\text{reco}}, m_S^{\text{reco}})$ plane, for (a) the non-compressed regime with $m_S > m_H$, (b) the non-compressed regime with $m_S < m_H$, and (c) the compressed regime with $m_S > m_H$. The black dashed lines indicate the CR (the outer pair, used for training the background model), and the green dashed lines indicate the SR (the inner pair, blinded for the training). The rounded convex shapes indicate the final cut $X_{SH}^{\text{reco}} < 1.6$ applied after deriving the background model, with a different X_{SH}^{reco} definition for each m_S hypotheses. These regions are independent of m_X . Each resulting X_{SH}^{reco} SR is subsequently evaluated for several m_X signal hypotheses in the statistical fit.

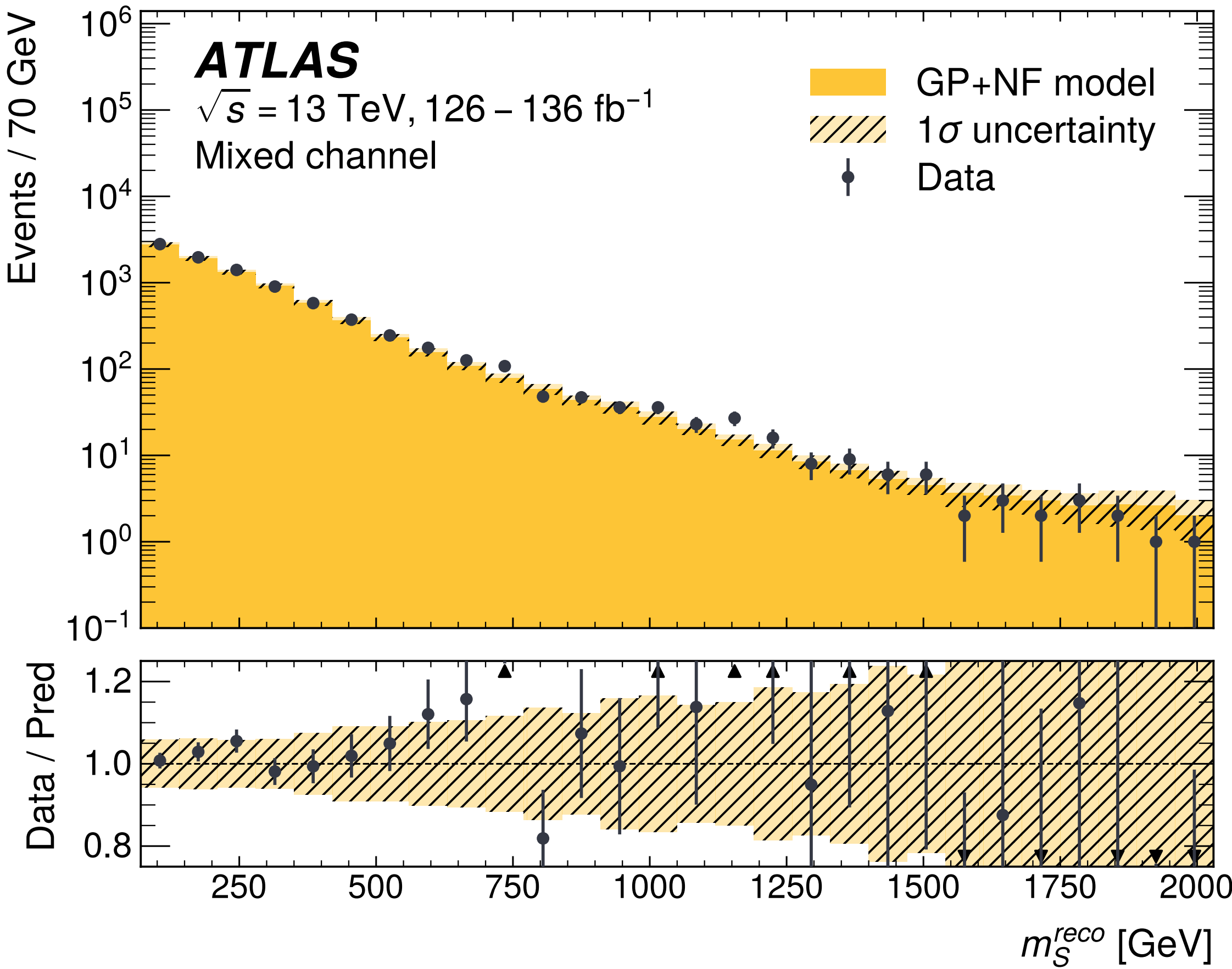
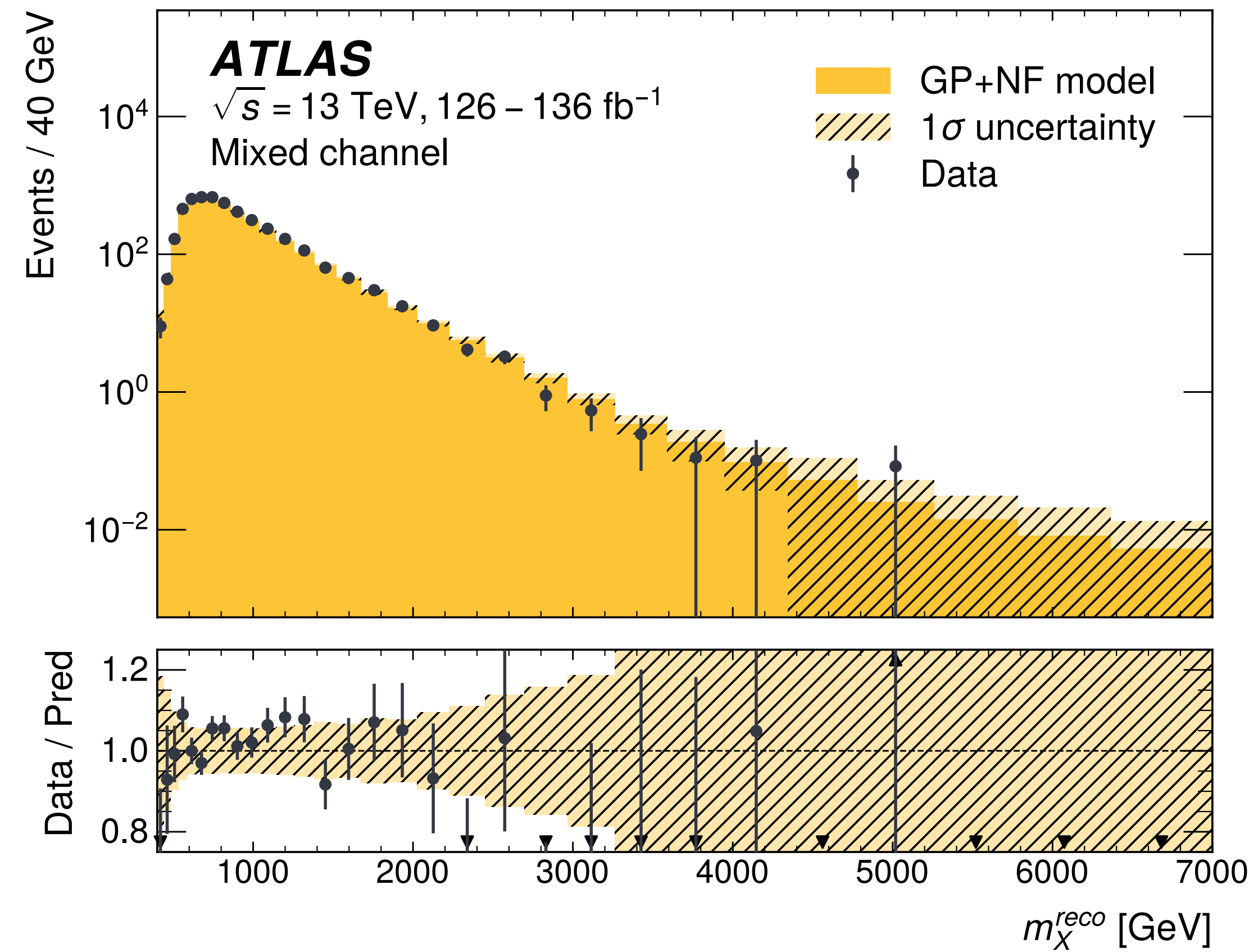
Analysis strategy: normalising flow for bkg estimation

[HIGP-2024-31 \(subm. to PRD\)](#)



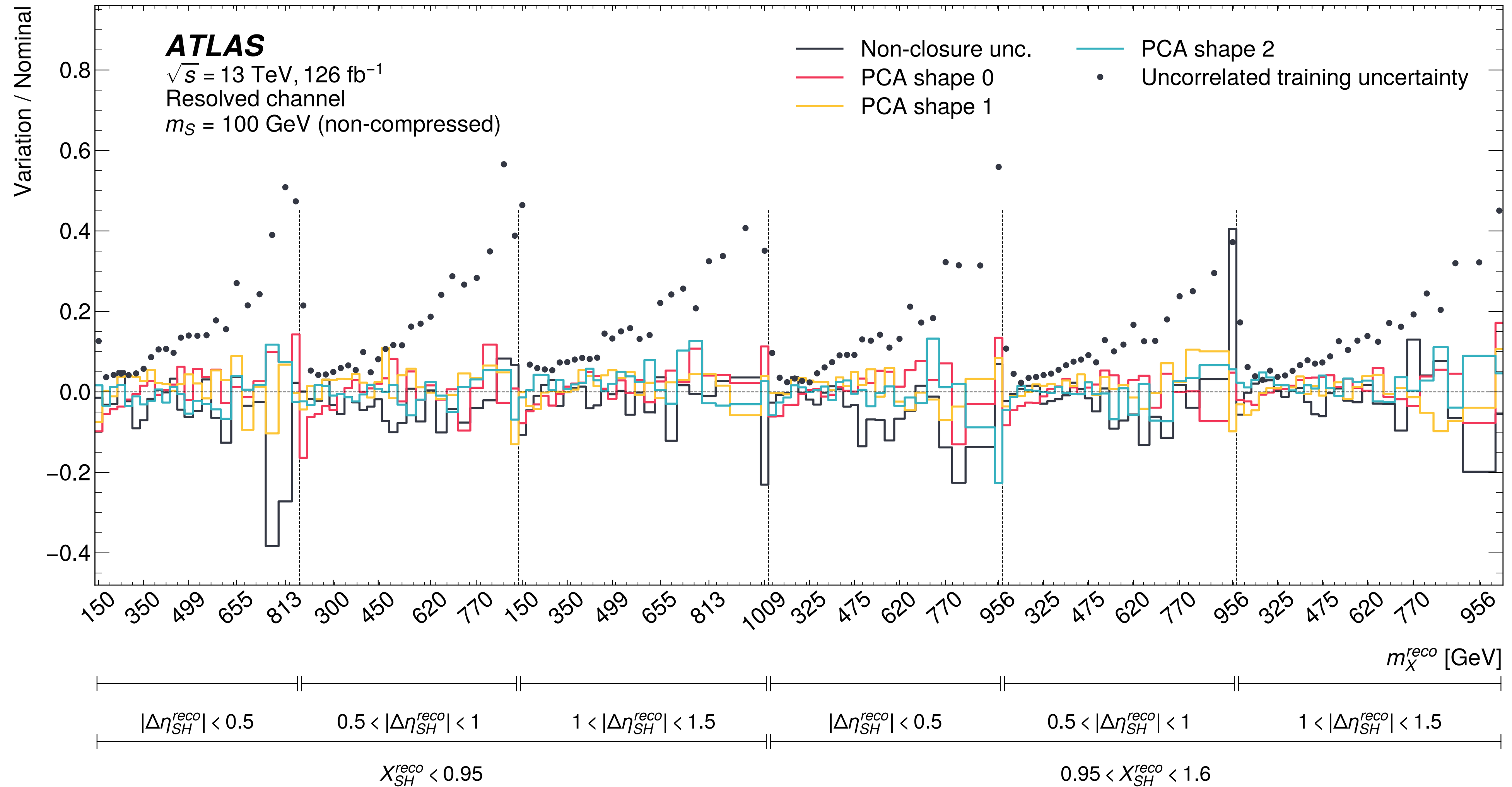
Analysis strategy: normalising flow for bkg estimation

[HIGP-2024-31 \(subm. to PRD\)](#)



Analysis strategy: normalising flow for bkg estimation

[HIGP-2024-31 \(subm. to PRD\)](#)



Analysis strategy: normalising flow for bkg estimation

[HIGP-2024-31 \(subm. to PRD\)](#)

