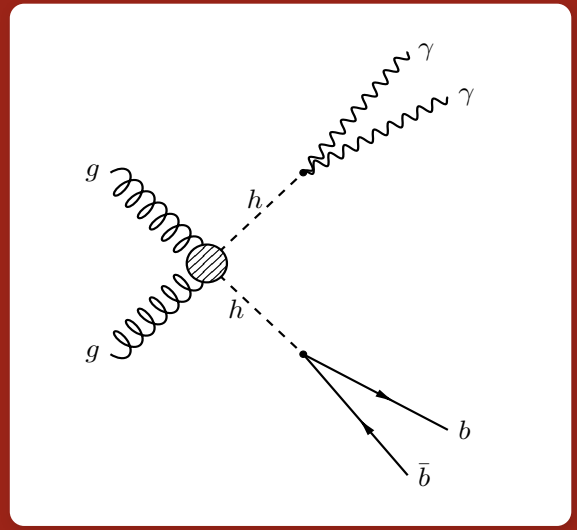
Search for HH → $b\bar{b}\gamma\gamma$ at CMS

Nonresonant Higgs boson pair production with the partial Run 3 dataset (61.9 fb^{-1}, 2022-2023) at $\sqrt{s}$ = 13.6 TeV

CMS-PAS-HIG-25-007



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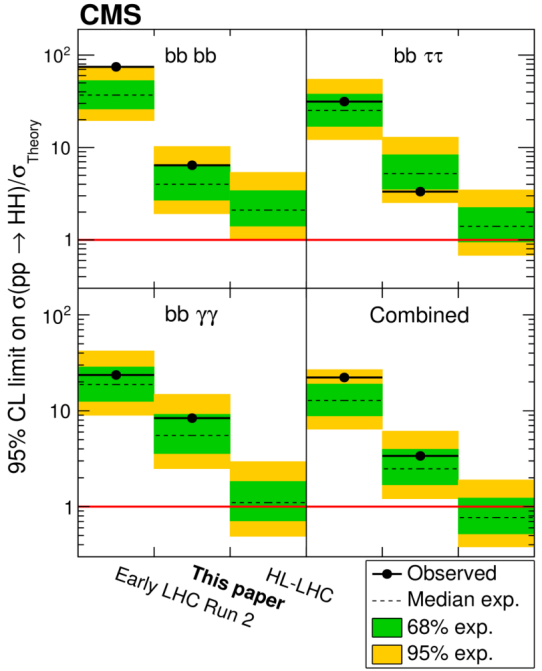
Why di-Higgs, and why $b\bar{b}\gamma\gamma$?

Physics motivation

- Tests the shape of the Higgs potential, still unprobed after Higgs discovery.
- Directly sensitive to the **Higgs self-coupling κ_λ**, a key SM prediction.
- Probes BSM effects in the Higgs sector.

The $b\bar{b}\gamma\gamma$ final state

- $H \to b\bar{b}$: **largest branching fraction** of the Higgs boson
- $H \to \gamma\gamma$: A clean final state with **excellent $m_{\gamma\gamma}$ resolution** and high trigger efficiency
- Best balance of **rate and resolution**, ideal for early Run 3 studies



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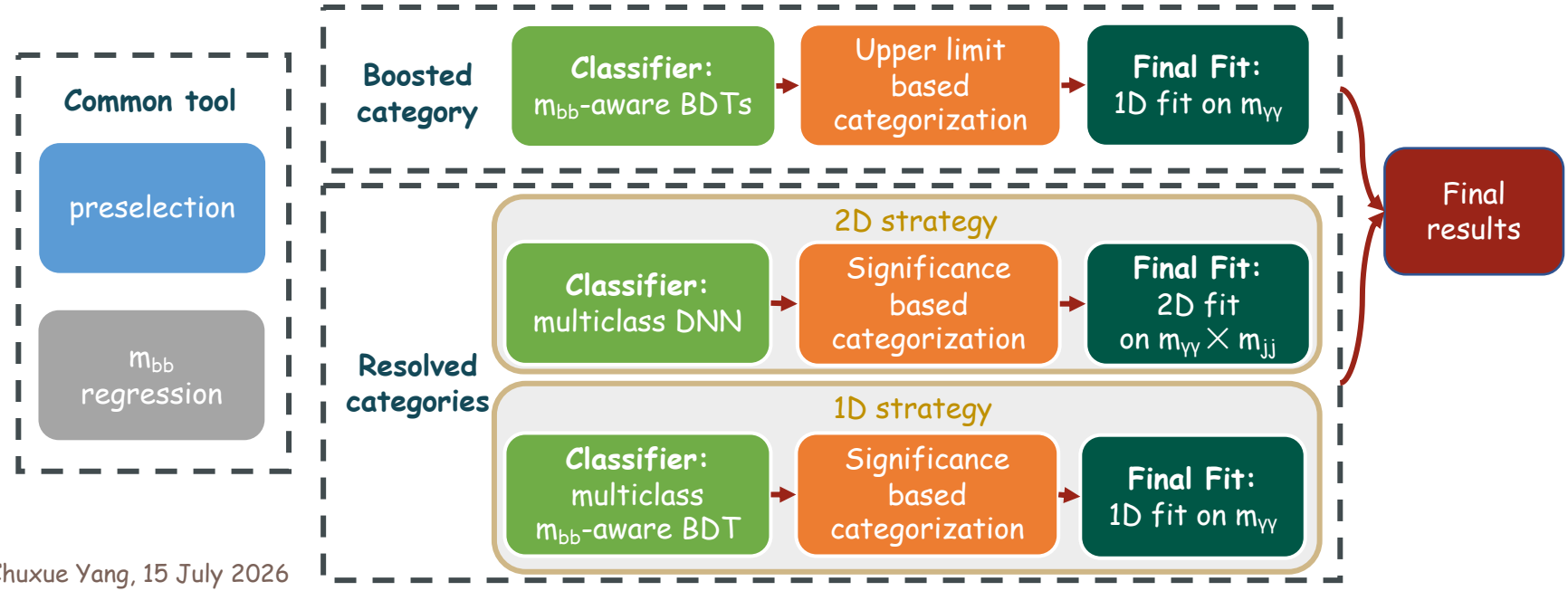
Analysis overview

- **Dataset: 61.9 fb^{-1}** of pp collisions at $\sqrt{s}$ = 13.6 TeV (2022–2023)
- Common objects & preselection
- A dedicated **boosted category** (AK8, high-p_T $H\to b\bar{b}$)
- **two complementary resolved strategies**: 1D fit on $m_{\gamma\gamma}$ and 2D fit on $m_{\gamma\gamma} \otimes m_{jj}$



Event selection & m_{bb} regression

Preselection

- Trigger:
  - Diphoton HLT: p_T > 30 / 22 GeV, loose shower-shape + isolation
- Photons follow the **H→γγ preselection**
- **Loose dijet preselection**
  - AK4, PUPPI, ParticleNet b tag
  - 70 < m_{jj} < 190 GeV
- **H candidates:**
  - Highest-p_T diphoton and highest-b-tag dijet
- Loose **lepton vetoes** against top-quark backgrounds

m_{bb} regression

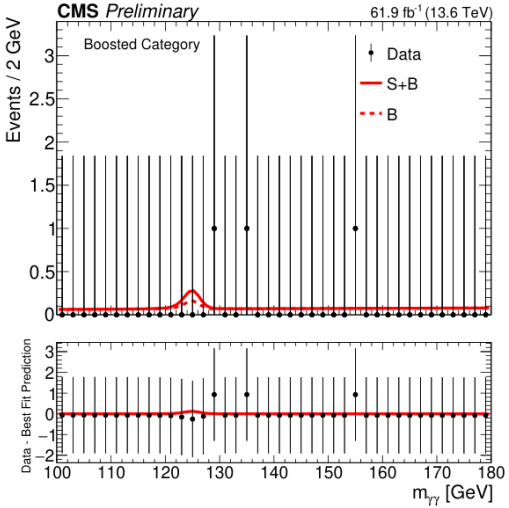
- Better m_{bb} resolution → sharper signal peak for selection **and** extraction
- Two methods on top of ParticleNet p_T regression:
  - central **PNet-based** regression
  - **custom DNN** trained on ggHH, predicts (gen – reco)/reco from jet- and event-level inputs

10-20%

improvement in m(bb) resolution, varying with the data-taking period

Boosted category: high-p_T $H \to b\bar{b}$

- At high $p_T(H) \gtrsim 350$ GeV the two b quarks merge
  - AK4 jets lose efficiency and **AK8 jets recover it**
- **Preselection:**
  - AK8 with ≥ 2 subjets,
  - $\tau_2/\tau_1 < 0.75$, PNet(X_{bb}) > 0.4, $30 < m_{SD} < 210$ GeV;
  - Candidate: highest PNet(X_{bb})
- **Two-step BDT:**
  - BDT1: ggHH vs VH
  - BDT2: ggHH vs all backgrounds (BDT1 score as input)
- One signal region from a **cut-and-count expected-limit optimization**
- Boosted events are removed from the resolved categories



$m_{\gamma\gamma}$ fit in the boosted category (1D)

Resolved category: multiclass MVA

- Multiclass discriminators separate HH signals from **nonresonant and single-H** backgrounds
- Two strategies, differing in how m_{jj} is used

1D strategy: m_{bb}-aware BDT

- m_{jj} is a **BDT input**; signal extracted from $m_{\gamma\gamma}$ alone
- Training optimized to suppress **single-H backgrounds resonant in $m_{\gamma\gamma}$**
- ~10^3 (10^2) rejection of QCD (top) at **60% (50%)** signal efficiency

2D strategy: m_{bb}-agnostic DNN

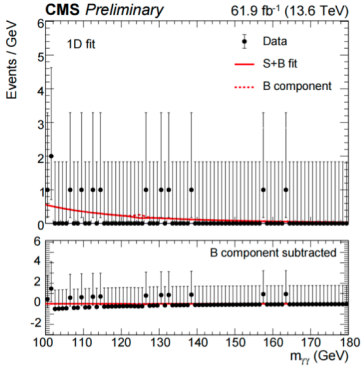
- DNN trained **agnostic to the m_{jj} scale** → m_{jj} used explicitly in the 2D fit $m_{\gamma\gamma} \otimes m_{jj}$
- Suppresses **all backgrounds**, incl. QCD and top
- ~10^3 (10^2) rejection of QCD (top) at **50% (55%)** signal efficiency

- Categories defined by cuts on the discriminants, optimized on the expected significance
  - 3 resolved categories per strategy

Signal extraction

1D fit: resolved & boosted

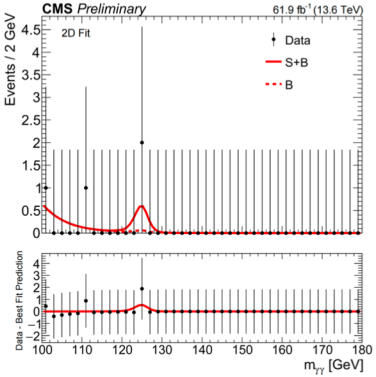
- Fit to $m_{\gamma\gamma}$ only
- Signal & resonant bkg:
  - sum of Gaussians / DCB
- Nonresonant bkg from data:
  - **discrete profiling** over smooth falling functions (F-tests)



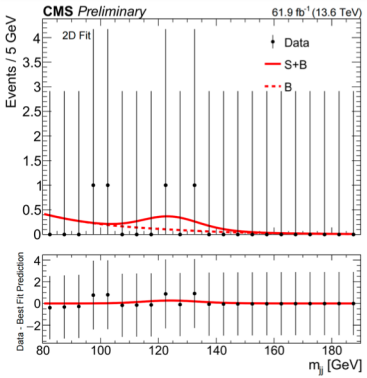
1D fit (cat. 1)

2D fit: resolved only

- Simultaneous fit to ($m_{\gamma\gamma}$, m_{jj}): role of m_{jj} explicit in the likelihood
- Single-H:
  - DCB in $m_{\gamma\gamma}$;
  - peaking (VH, ttH) or falling+peaking (ggH+VBFH) in m_{jj}
- Nonresonant bkg:
  - discrete profiling, as in 1D



2D fit, $m_{\gamma\gamma}$ (cat. 1)

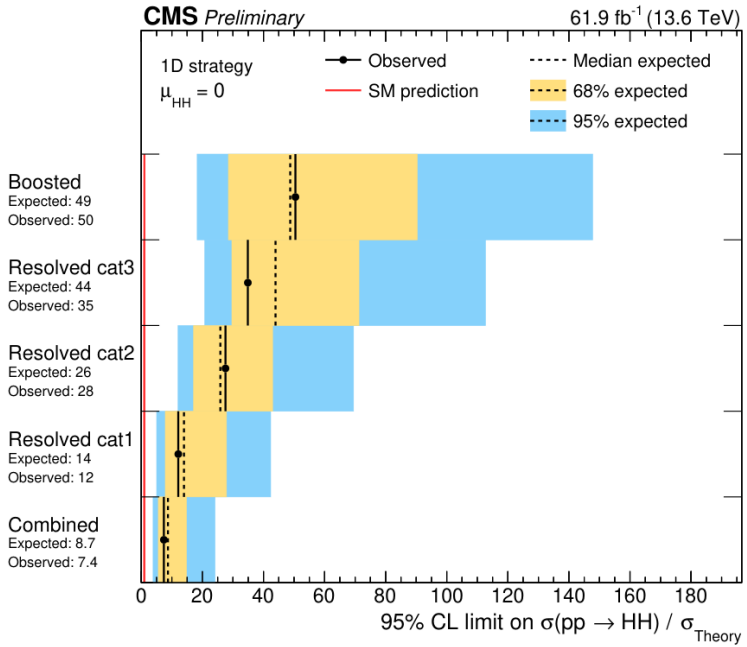


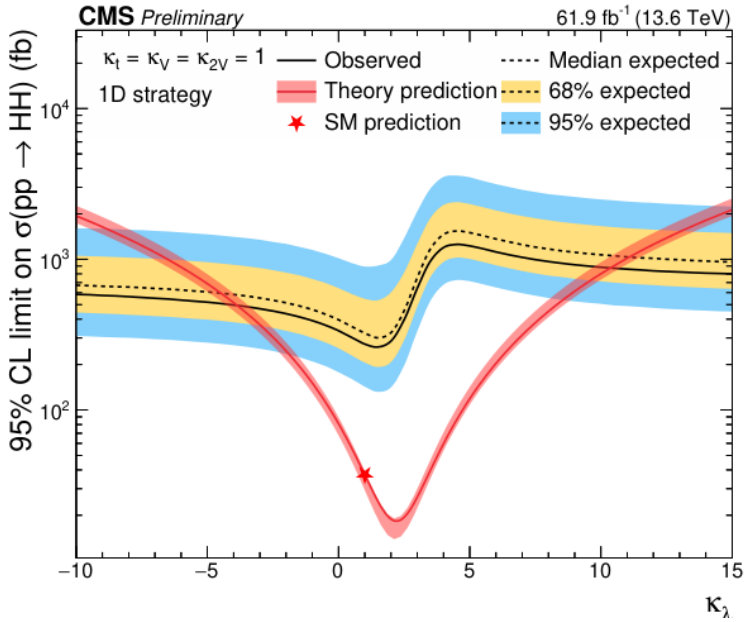
2D fit, m_{jj} (cat. 1)

Systematic uncertainties

- The analysis is **statistics-limited**
- Dominant systematics from **nonresonant background modeling**
  - Free-floating fit parameters
  - Function choice itself, via discrete profiling
- Experimental:
  - b tagging **6–9%**, JES **4–9%**, JER 1–4%
  - Photon energy scale & resolution (shape of $m_{\gamma\gamma}$)
  - Trigger / preselection / electron veto efficiency 1–2%, pileup 1–4%, luminosity 1.4%
- Theory:
  - Single-H cross sections (ttH **9%**, ggH / VBFH / VH 1-4%); bbH modelling in ggH **50%;**
  - Higgs BR 2%; PDF & αS 1–3%; MC statistics 1–20%;
  - HH cross section (23%)
- 2D fit: additional **bias uncertainty (3–30%)** on the mjj background function choice, from toys

Results: 1D strategy

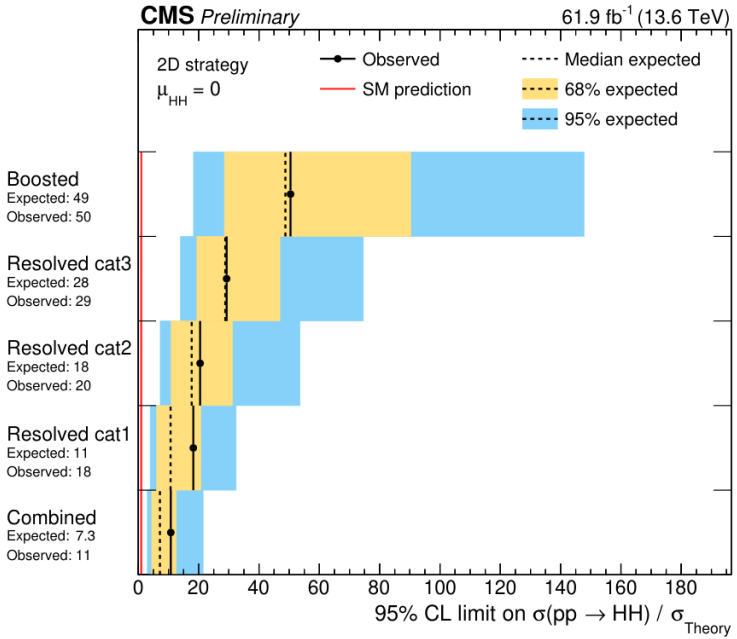


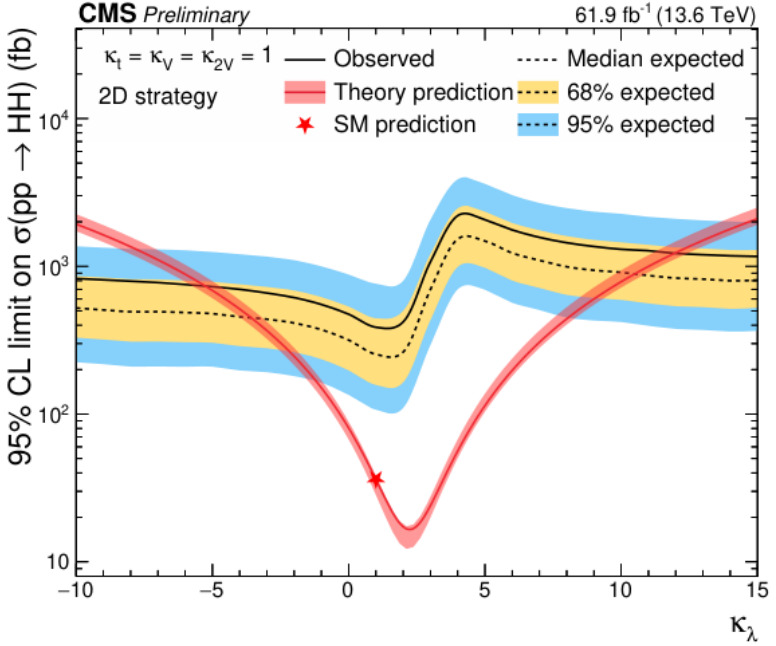


Observed (expected) limit: **7.4 (8.7) × σ_{SM}**

Observed (expected)
−3.9 (-4.5) < κ_λ < 10.1 (11.1) @ 95% CL

Results: 2D strategy





Observed (expected) limit: **11.0 (7.3) × σ_{SM}**

Observed (expected)
−6.1 (−3.6) < κ_λ < 12.8 (10.5) @ 95% CL

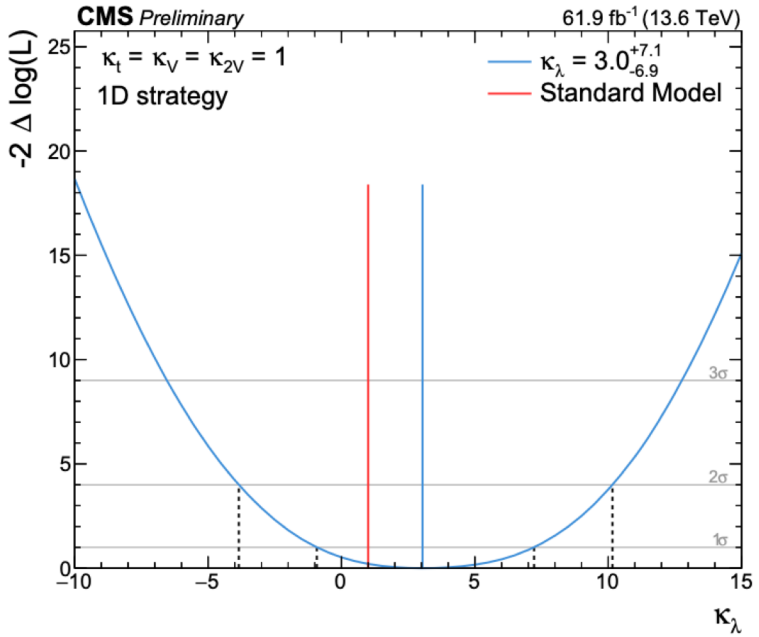
Summary & outlook

- **CMS HH → $b\bar{b}\gamma\gamma$ search at 13.6 TeV** using 61.9 fb^{-1} data (2022–2023)
- Two complementary strategies, **consistent and robust results** with different assumptions and statistical treatments
  - Obs. (exp.) 95% CL limit: **7.4 (8.7)** × σ_{SM} (1D), **11.0 (7.3)** × σ_{SM} (2D)
  - Obs. 95% CL constraint on κ_λ in [-3.9, 10.1] (1D), [-6.1, 12.8] (2D)
- **Statistics-limited:**
  - large gains expected with the full Run 3 dataset;
  - framework demonstrated and ready.
- Full Run 3 dataset already collected, analysis ongoing.
  - With a larger dataset and improved analysis techniques, substantial stronger constraints expected.
  - Stay tuned!

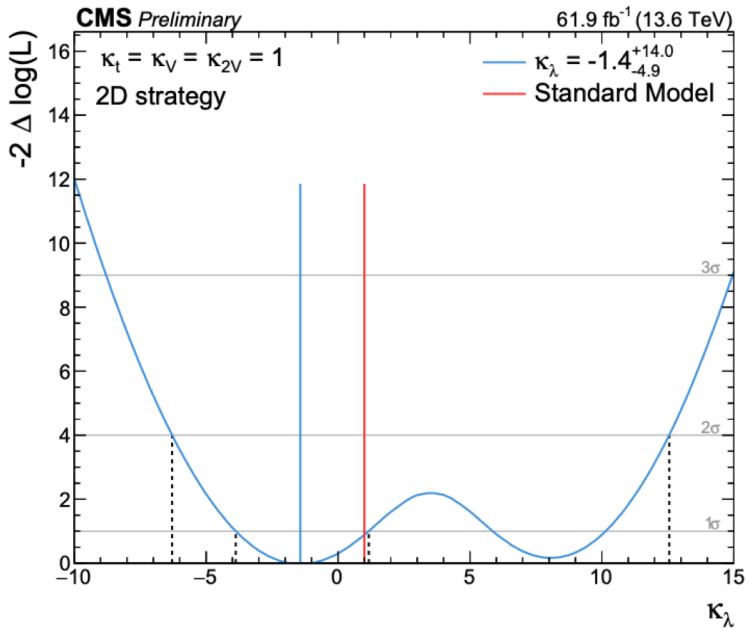
Thank you!

Backup

Backup — likelihood scan

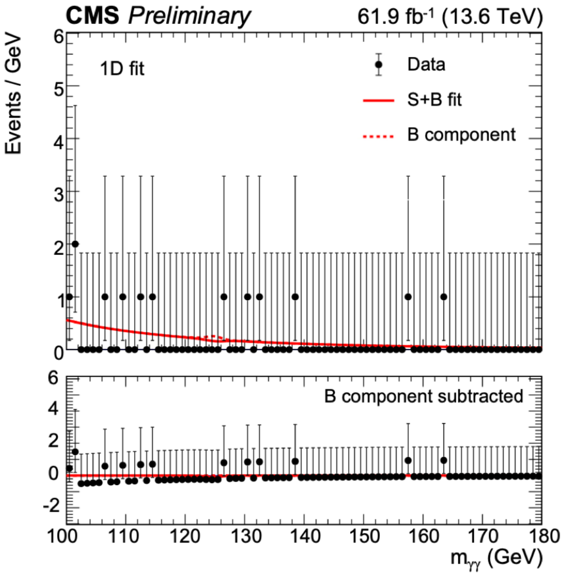


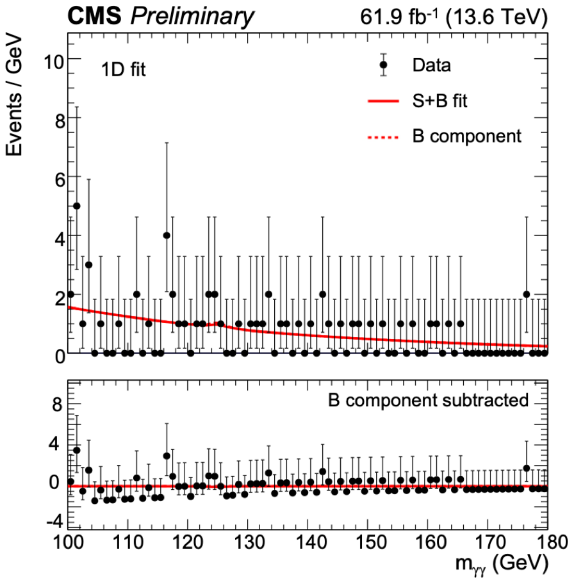
1D strategy

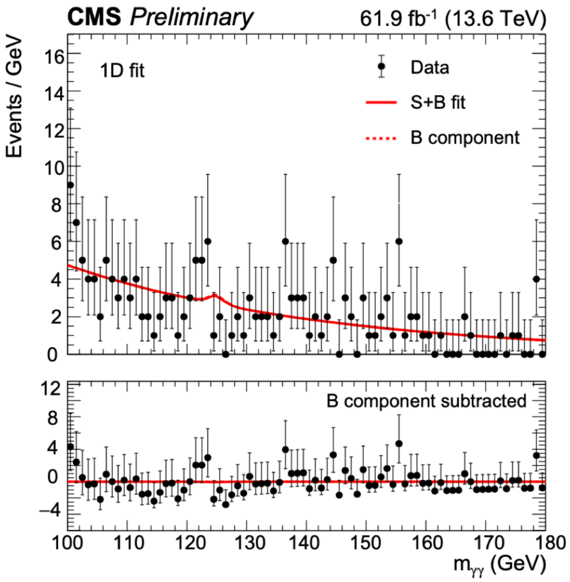


2D strategy

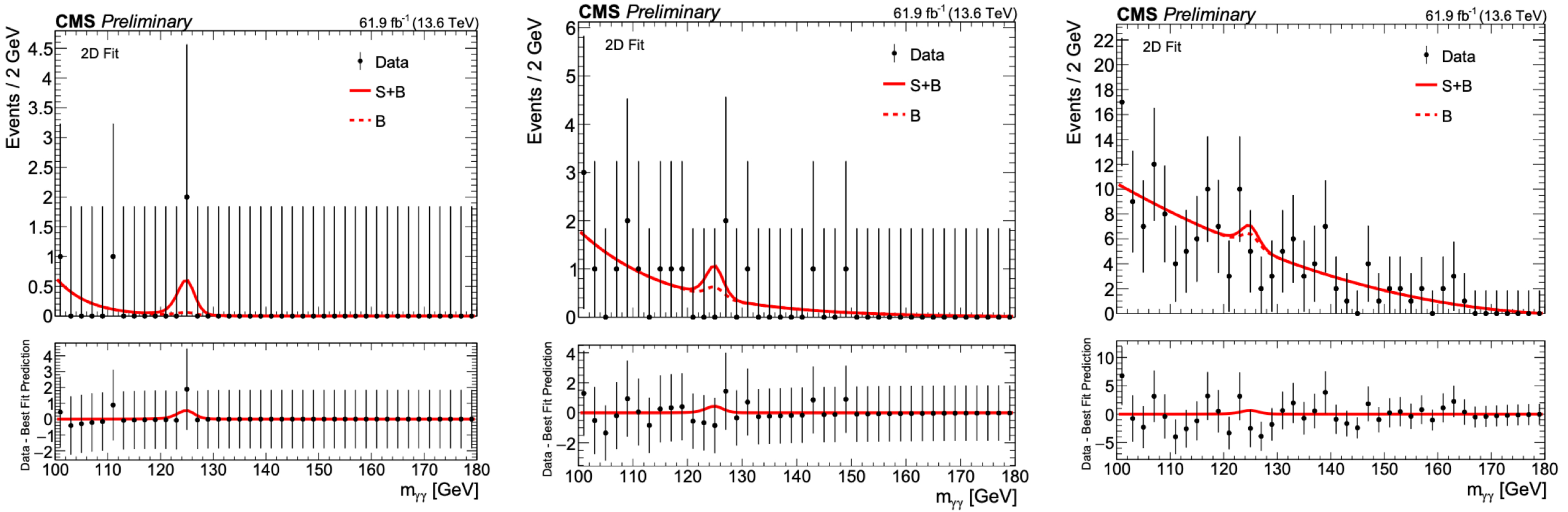
Backup — fit distributions (1D)







Backup — fit distributions (2D)



Backup — fit distributions (2D)