

# VBS WH Inaugural Talk

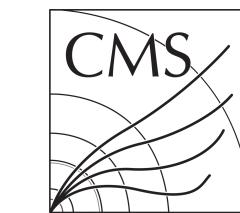
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<sup>2</sup>*University of California, San Diego*

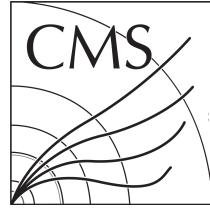
<sup>3</sup>*University of Florida*

CMS Weekly General Meeting

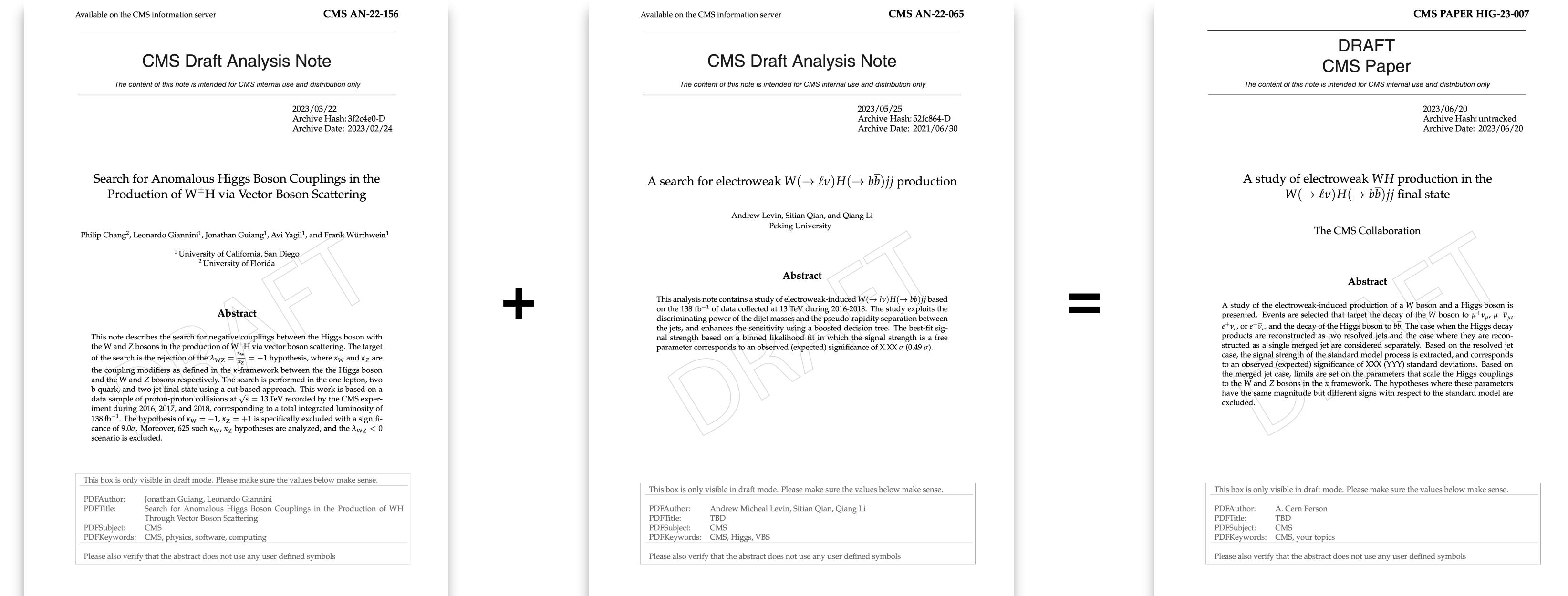


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# Documentation



AN-2022/156  
(boosted)

AN-2022/065  
(resolved)

HIG-23-007

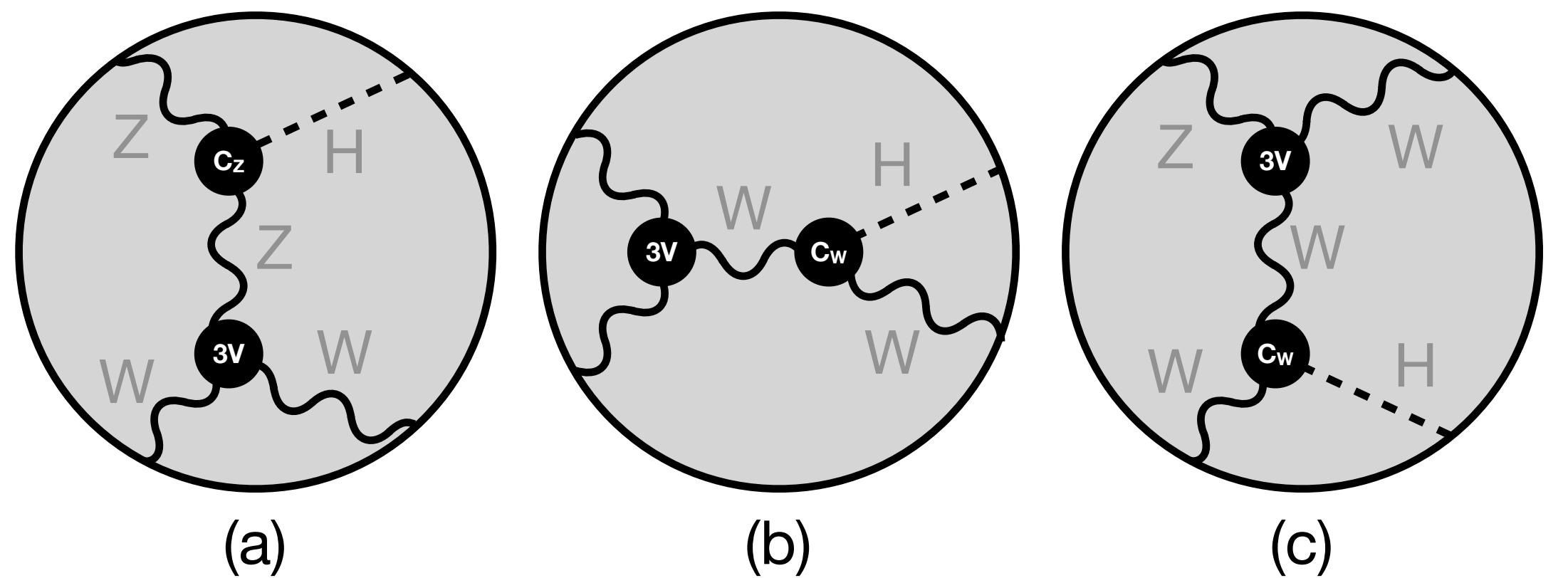
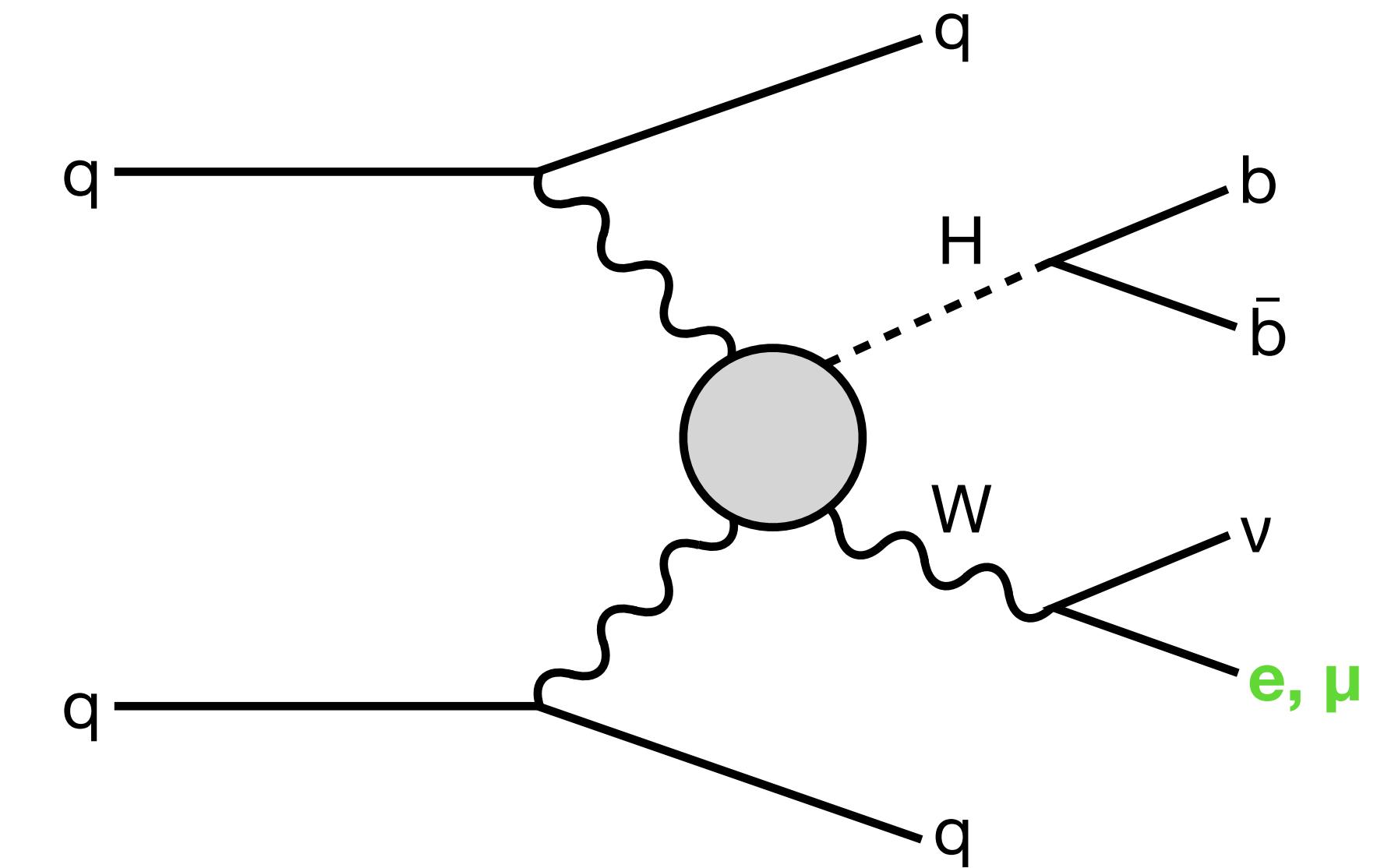
PubTalk: <https://cms-pub-talk.web.cern.ch/c/hig/hig-23-007>

CADI: <https://cms.cern.ch/iCMS/analysisadmin/cadilines?line=HIG-23-007>

Twiki: <https://twiki.cern.ch/twiki/bin/viewauth/CMS/ElectroweakWHjjQA>

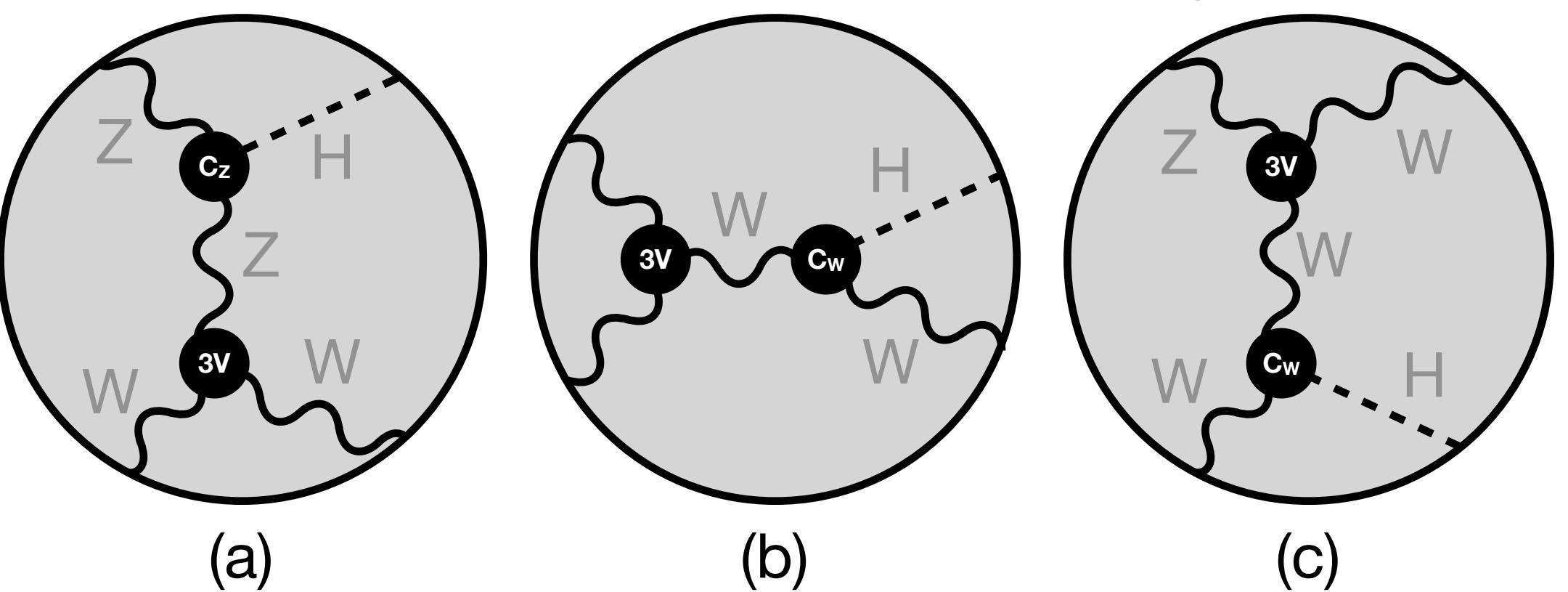
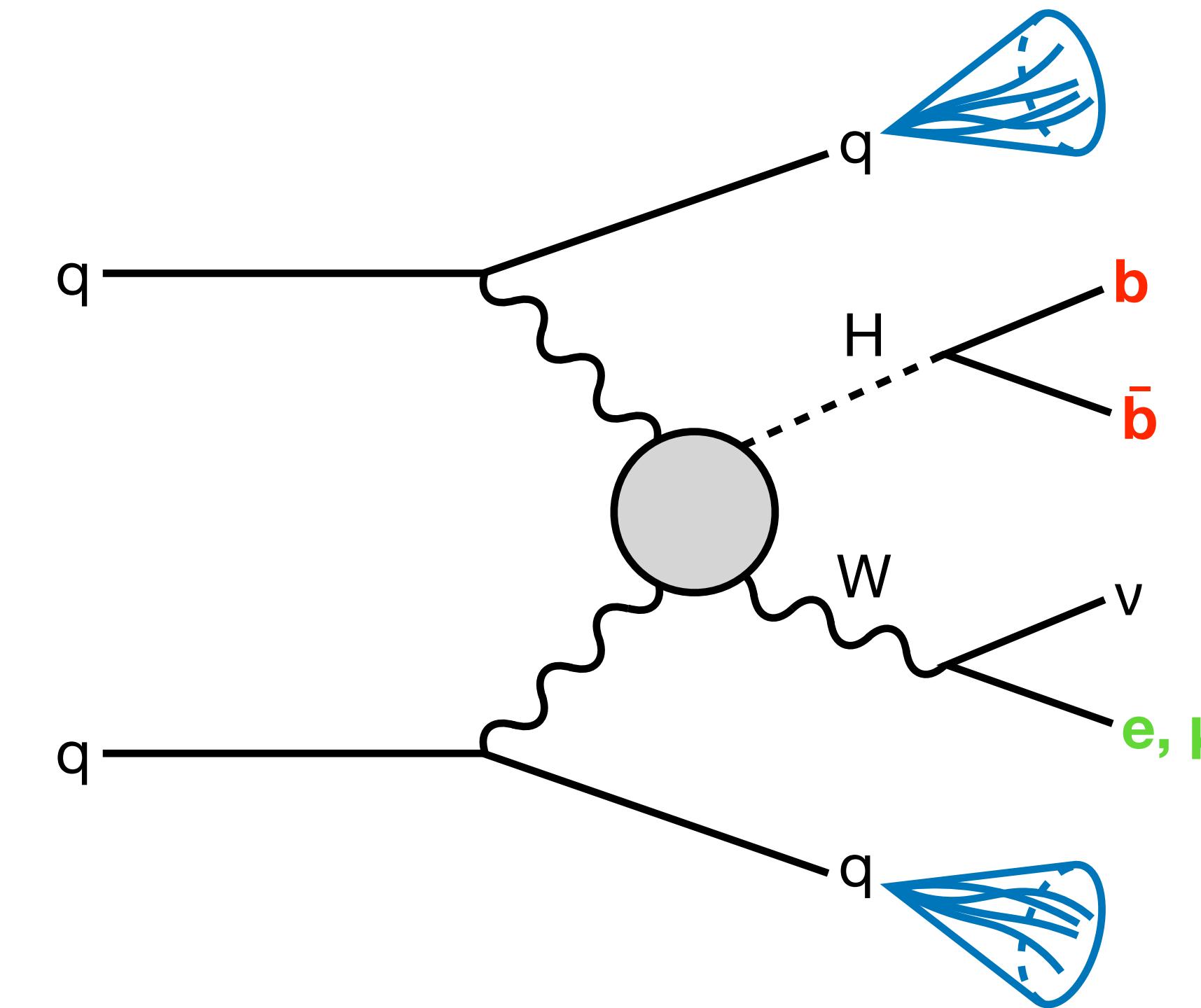
# Overview

- Targeting **VBS WH**
  - In particular:  $H \rightarrow b\bar{b}$  and  $W \rightarrow \ell\nu$
- **Boosted** analysis (UCSD + UFL)
  - $H \rightarrow b\bar{b}$  reconstructed as a single AK8 jet
  - Targeting an exclusion of BSM  $\kappa_W/\kappa_Z$  values
- **Resolved** analysis (PKU)
  - $H \rightarrow b\bar{b}$  reconstructed as two AK4 jets
  - Targeting an observation of SM VBS WH



# Signal Signature

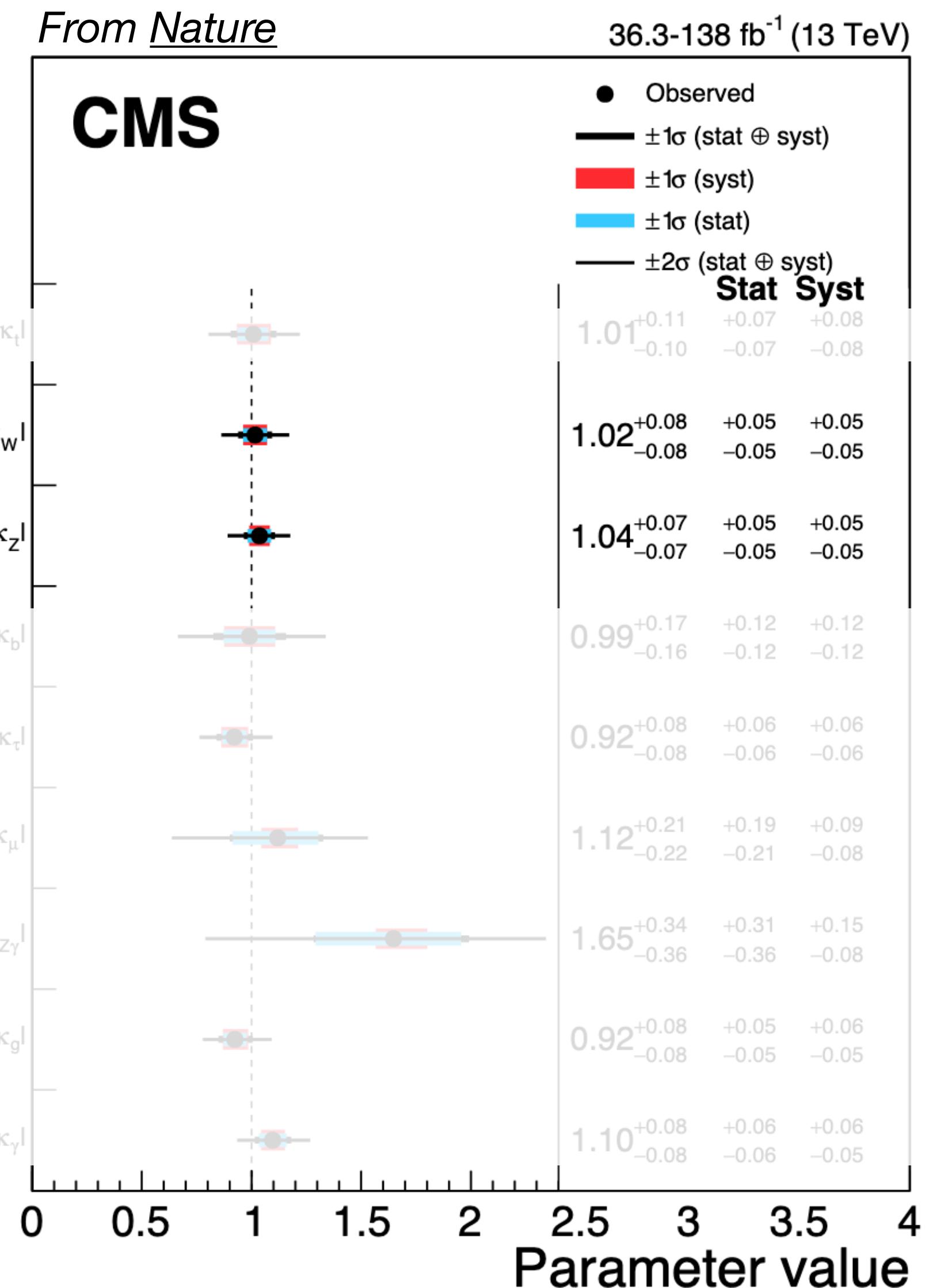
- **VBS**  $W H \rightarrow \ell v b \bar{b}$  signature:
  - **VBS quarks**  $\rightarrow$  2 jets w/ large  $\Delta\eta_{jj}$ ,  $M_{jj}$
  - **$H \rightarrow b\bar{b}$** 
    - Most favorable BR
    - **Boosted:** 1 fat jet tagged w/ **ParticleNet**
    - **Resolved:** 2 jets tagged w/ **DeepJet**
    - One and only **one lepton**
    - Used for trigger/cleaner signature



# Boosted Analysis

# Target Higgs Couplings

- CMS has already pinned  $|\kappa_w| = 1$  and  $|\kappa_z| = 1$ 
  - Within an **uncertainty of 10%**
  - Effectively restricted to  $\kappa_v^2$ , so only know **magnitude**
- SM predicts that they are the same sign
  - i.e. we **expect  $\lambda_{wz} = \kappa_w/\kappa_z = +1$**
- We have thus far not confirmed this prediction
  - Fun fact: best CMS limit\* slightly prefers  $\lambda_{wz} = -1$
  - **Need a process that is linear in  $\kappa_v$**



# Enter: VBS WH

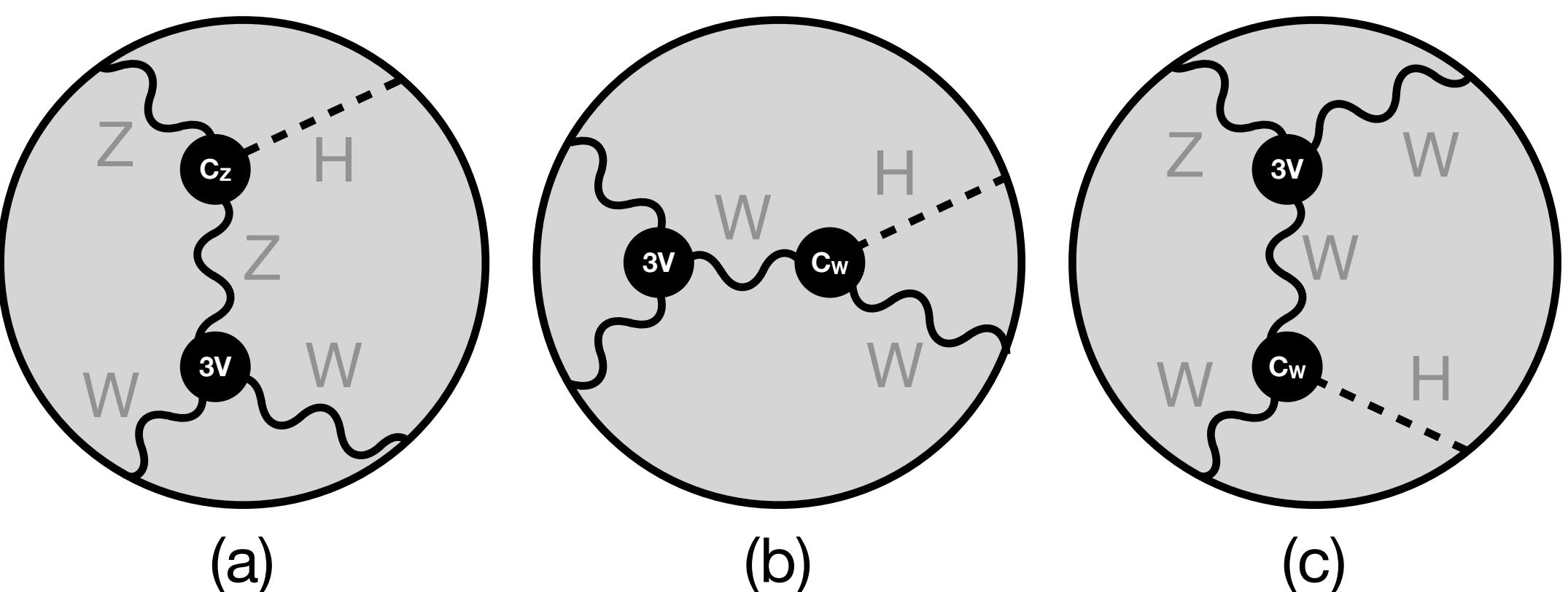
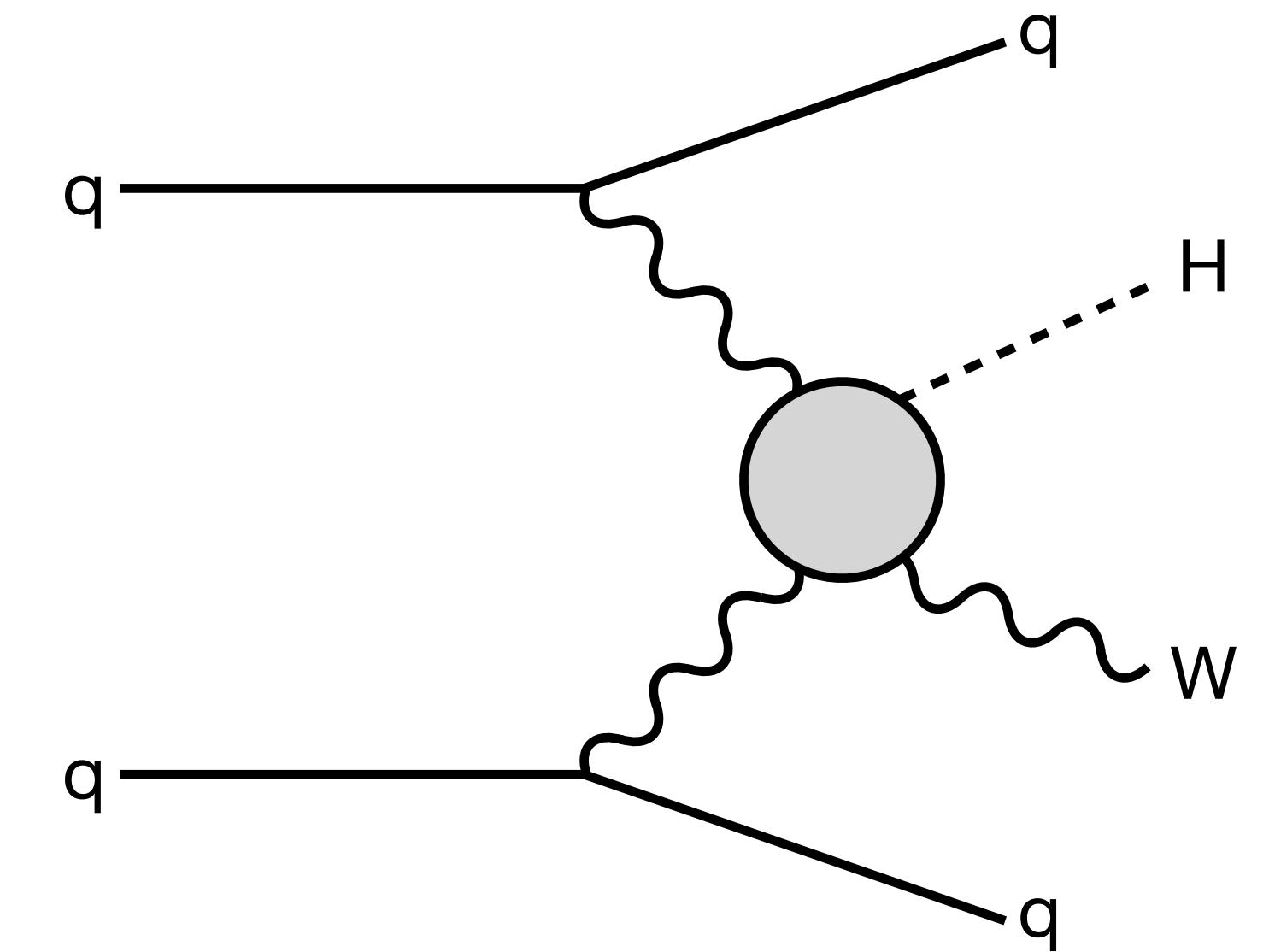
- Targeting **VBS WH**

- $\sigma = 0.075 \text{ pb } (\lambda_{WZ} = +1)$
- $\sigma = 0.433 \text{ pb } (\lambda_{WZ} = -1)$

- **Linear in  $\kappa_V$**

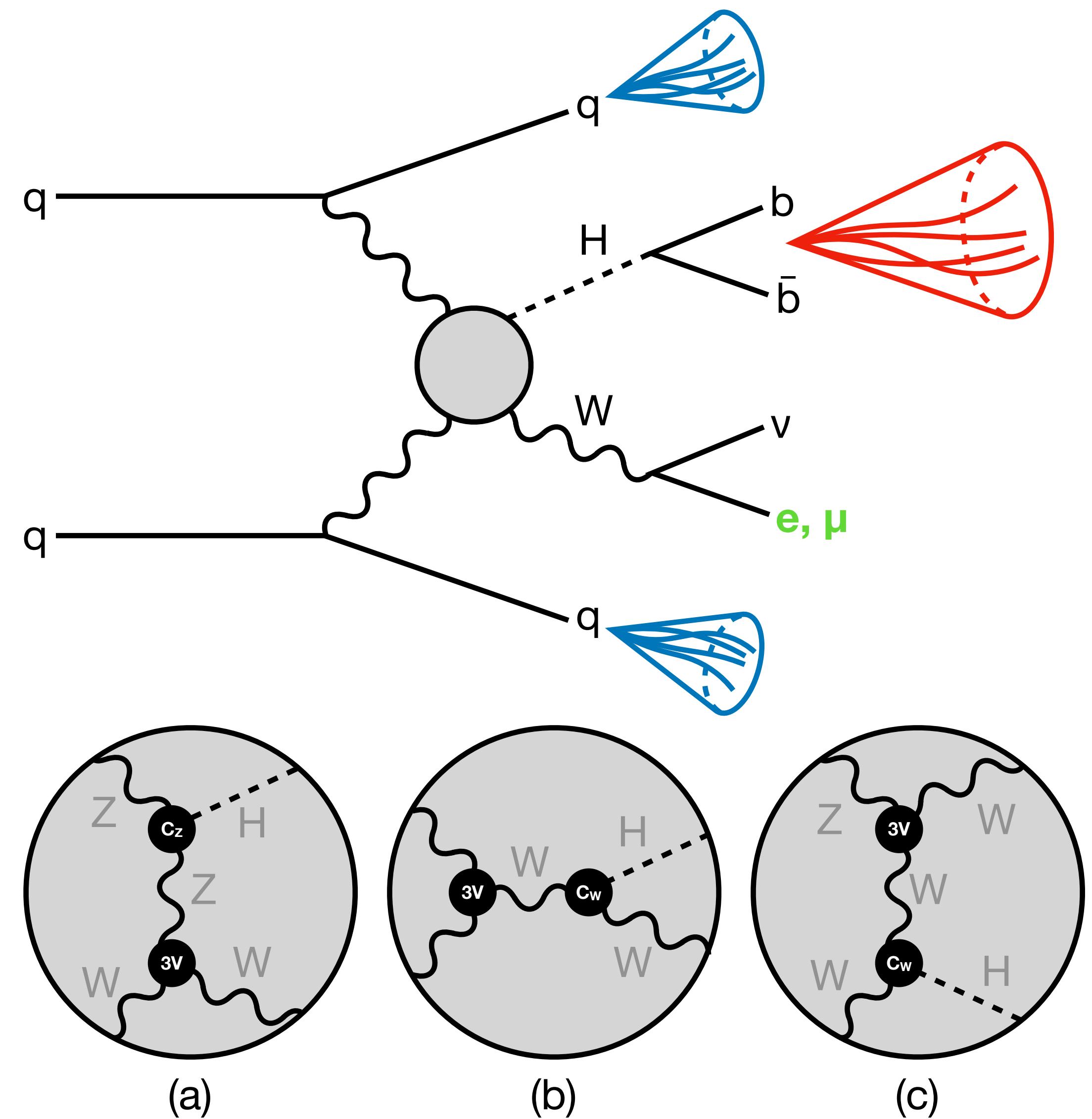
$$\sigma \propto |\mathcal{M}|^2 = \kappa_W^2 |\mathcal{M}_W|^2 + \kappa_W \kappa_Z \mathcal{M}_{WZ}^2 + \kappa_Z^2 |\mathcal{M}_Z|^2$$

- We present an analysis that can **strongly exclude** the  $\lambda_{WZ} < 0$  scenario
- Optimized for  $\lambda_{WZ} = -1$



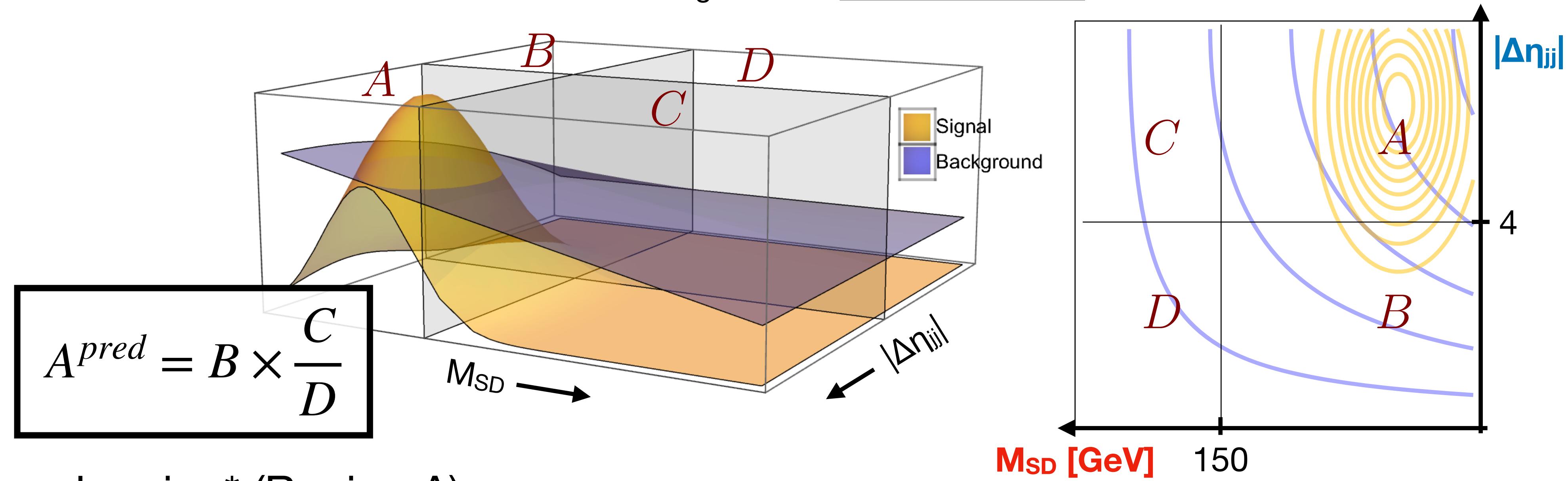
# Analysis Strategy

1. Leverage High Level Triggers (HLTs) for most basic selection
  - We use the **single lepton** triggers
2. Construct a Signal Region (SR) with a large signal-to-background ratio
  - Roughly 370 sig. vs. 120 bkg.
3. Implement a data-driven estimation of the background in the SR
4. Perform a **simple counting experiment**



# Data-Driven Background Extrapolation

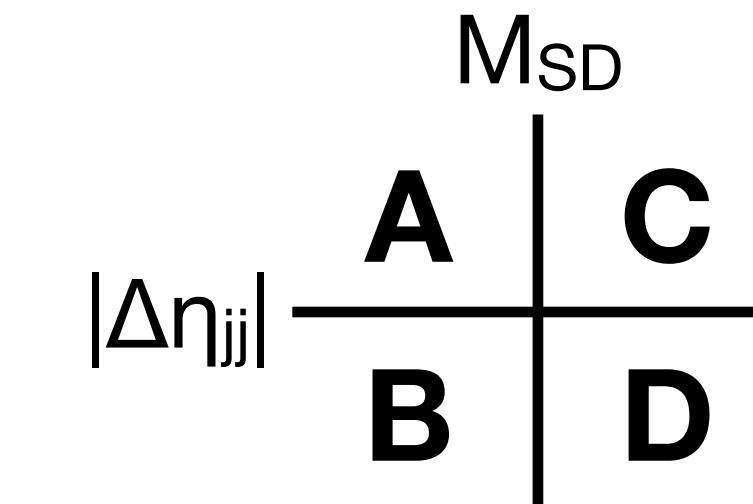
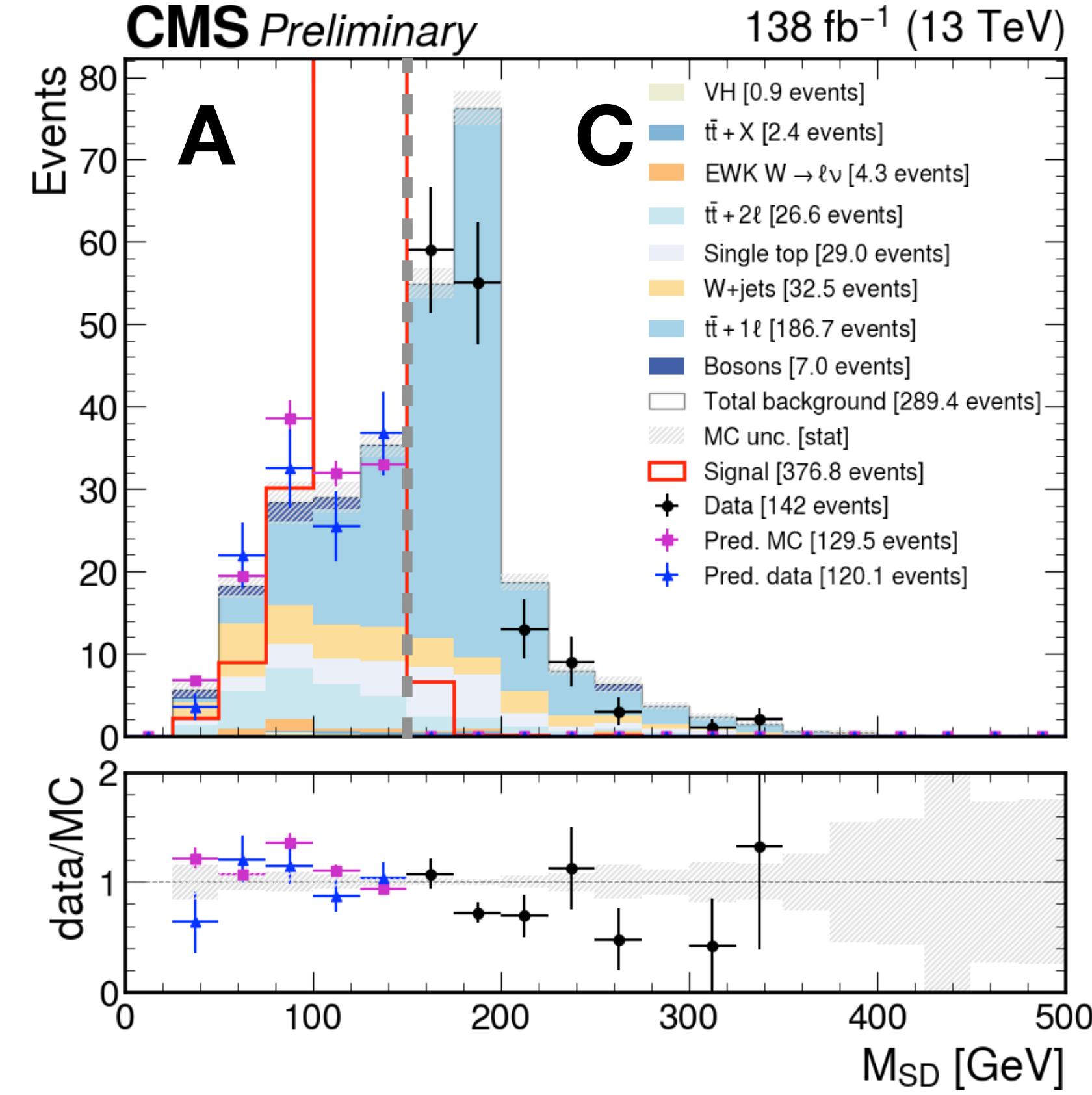
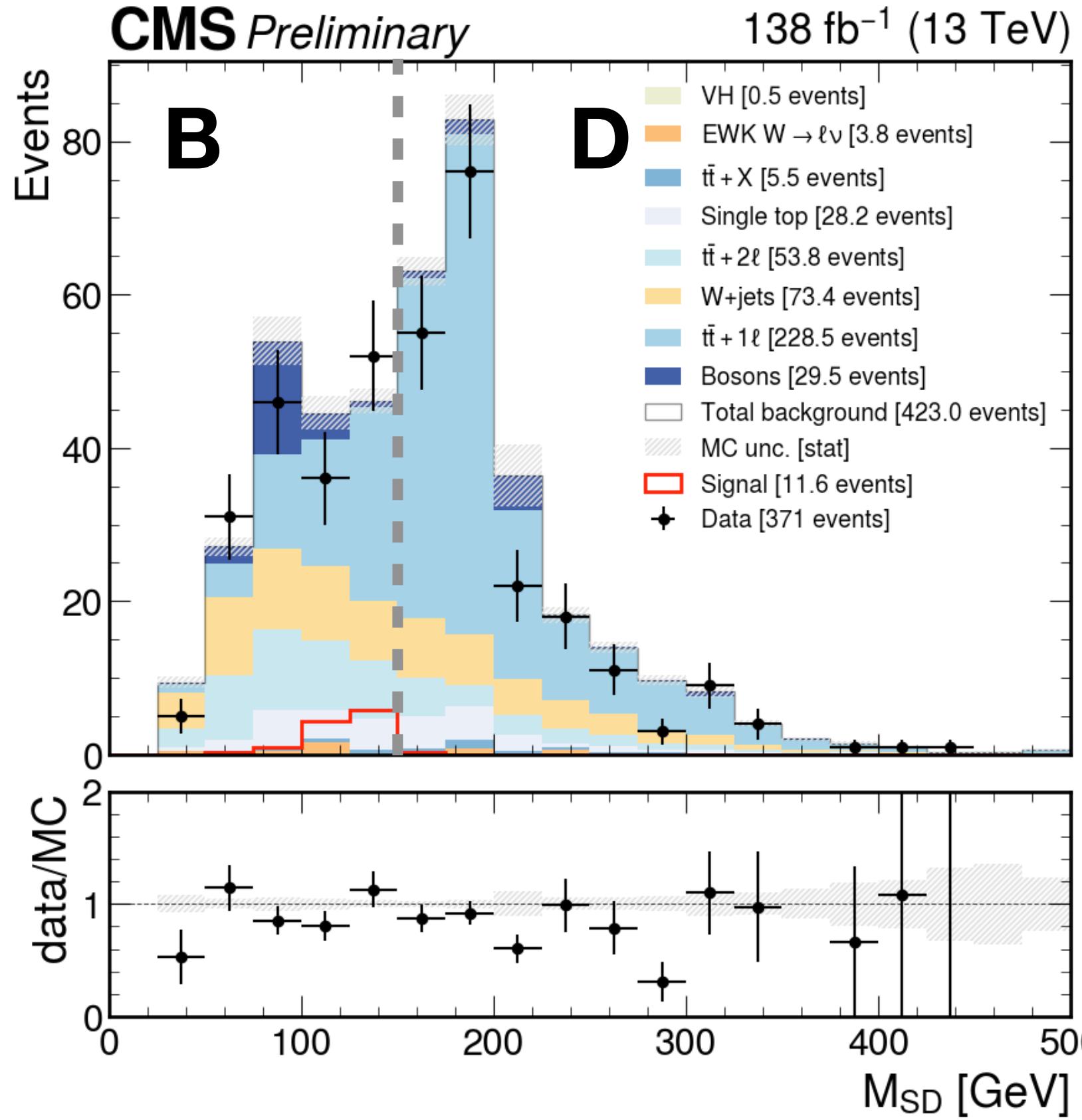
Diagram from [G. Kasieczka et al.](#)



- Signal region\* (Region A):
  - $M_{jj} > 600$  GeV &  $|\Delta n_{jj}| > 4$  &  $M_{SD} < 150$  GeV & ParticleNet Xbb > 0.9 &  $S_T > 900$  GeV
  - Background is predominantly from  $t\bar{t}+1\ell$  production
  - We use the ABCD ( $|\Delta n_{jj}|$  vs.  $M_{jj}$ ) method as above to estimate all bkg.

\*Defined within Preselection region (detailed in backup)

# Data-Driven Background Extrapolation



$$A_{MC}^{pred} = B \times \frac{C_{MC}}{D_{MC}} = 129 \text{ events}$$

Compared to actual MC  
yield  $\Rightarrow$  method closes well

$$A_{data}^{pred} = B \times \frac{C_{data}}{D_{data}} = 120 \text{ events}$$

Used for final prediction

**Region A**

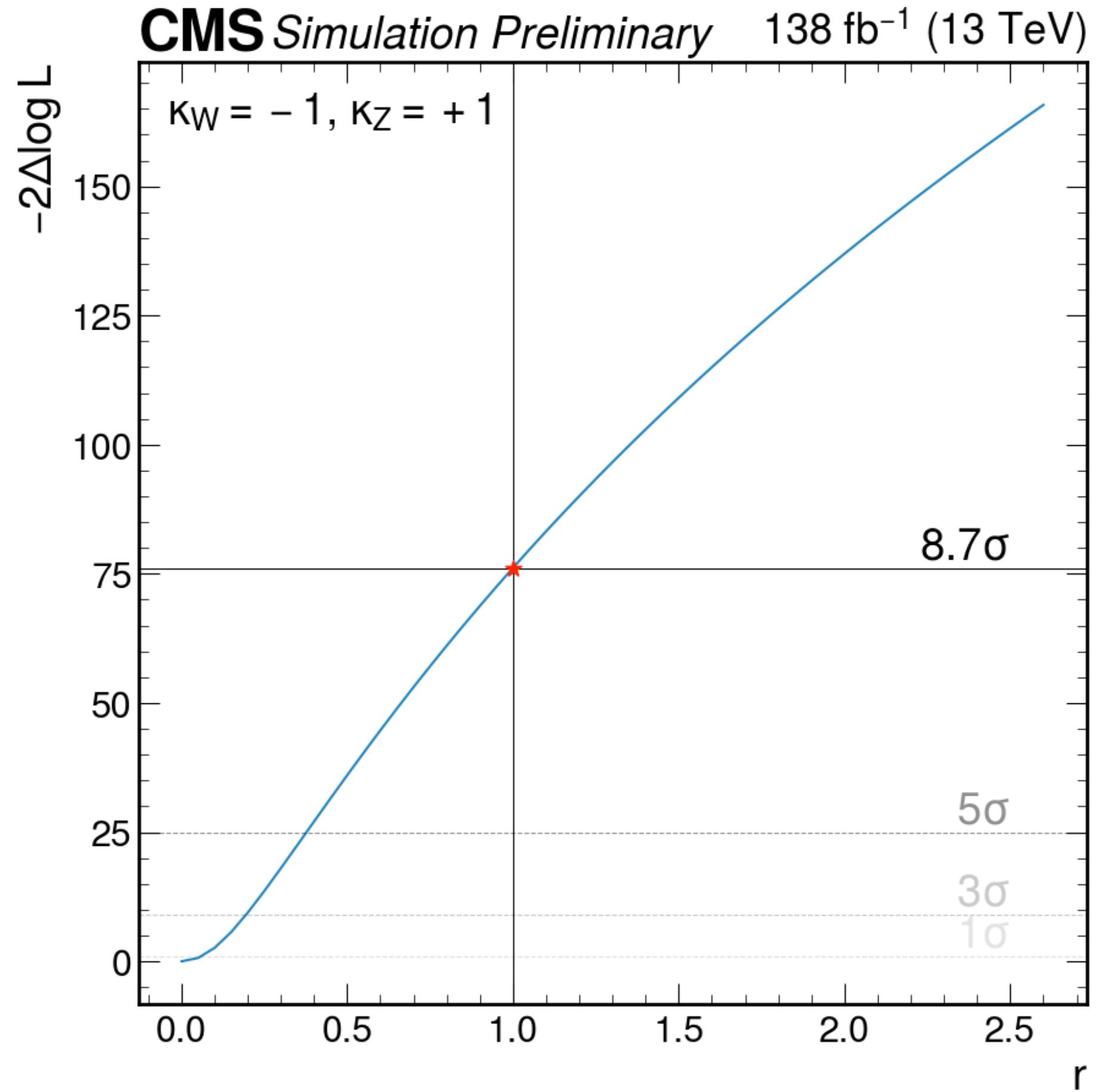
Expected signal ( $\lambda_{WZ} = -1$ ):  $366 \pm 2.9$   
Predicted background:  $120 \pm 16.1 \pm 15.3$

stat.

syst.

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# Expected Results

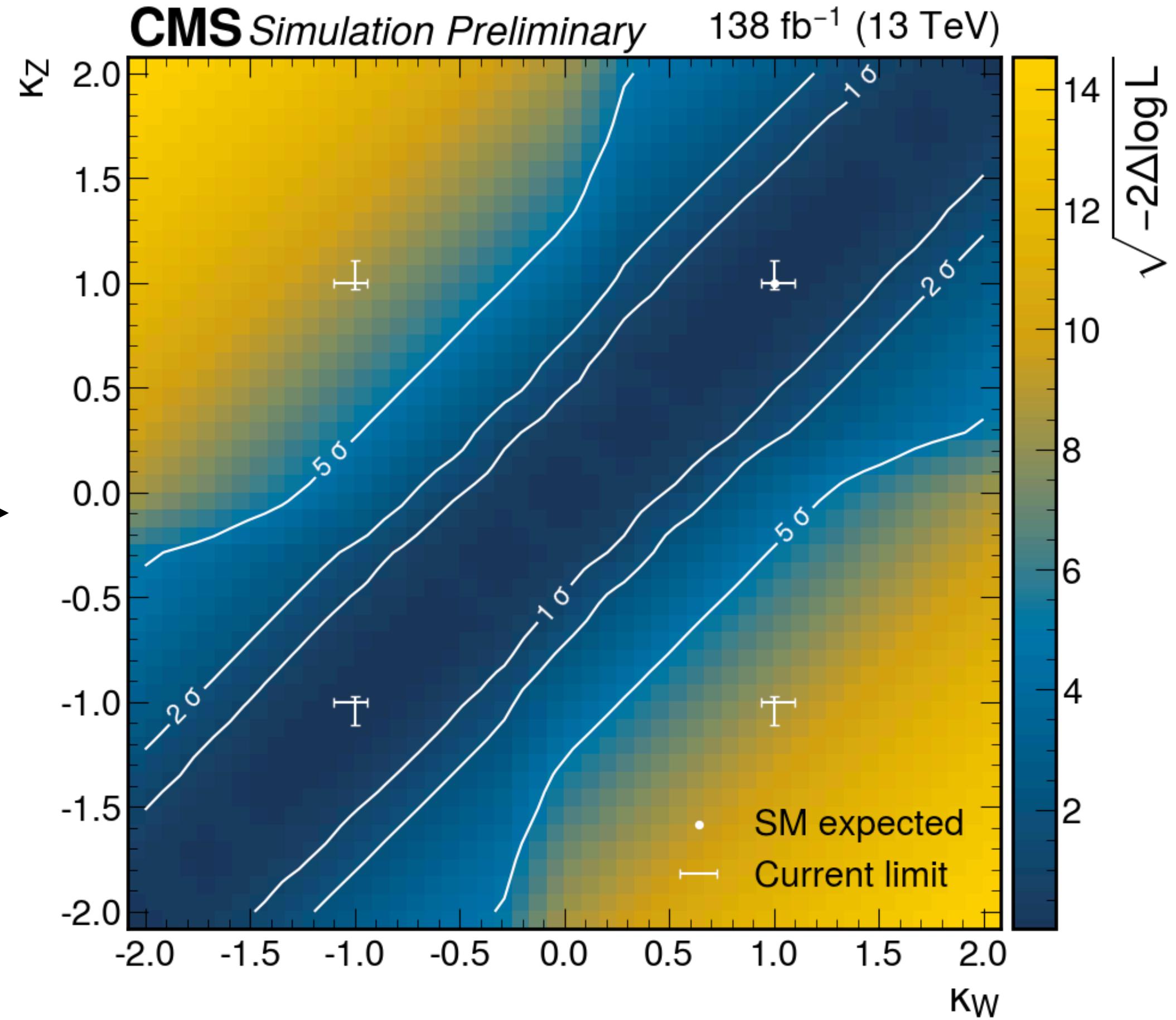


Expected signal ( $\lambda_{WZ} = -1$ ):  $366 \pm 2.9$   
 Predicted background:  $120 \pm 16.1 \pm 15.3$   
stat. syst.

Madgraph  
reweighting

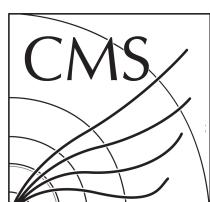
→

Interpolated  
exclusion  $\sigma$  for  
each  $\kappa_W, \kappa_Z$  point



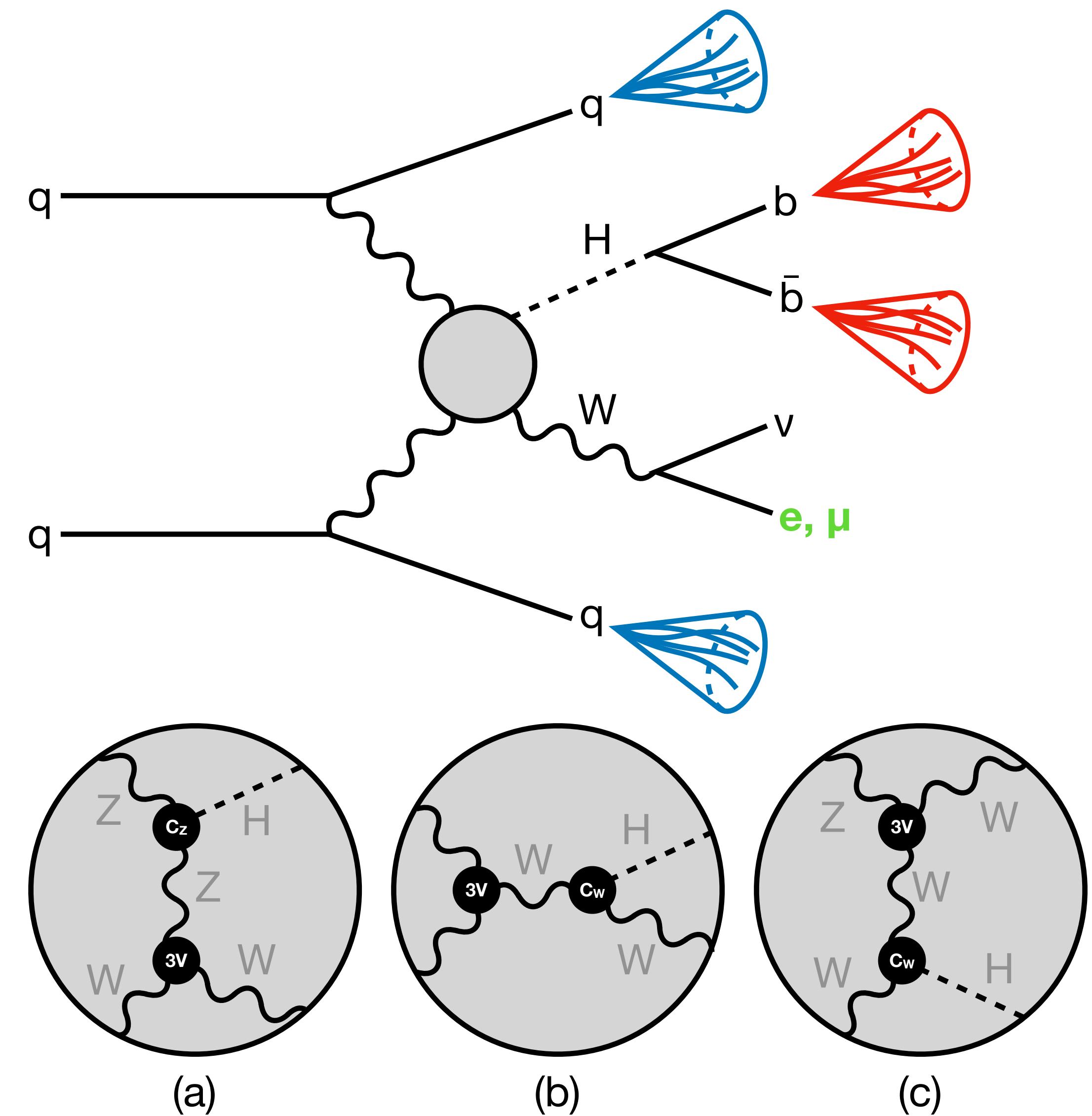
Strong exclusion of  $\lambda_{WZ} < 0$  scenarios  
allowed by current limits

# Resolved Analysis



# Analysis Strategy

1. Leverage High Level Triggers (HLTs) for most basic selection
  - We use the **single lepton** triggers
2. Construct a Signal Region (SR) for final fit
  - Train a BDT here to more efficiently select signal events
3. Construct a Control Region (CR) for MC validation and final fit
4. Perform two binned likelihood fits



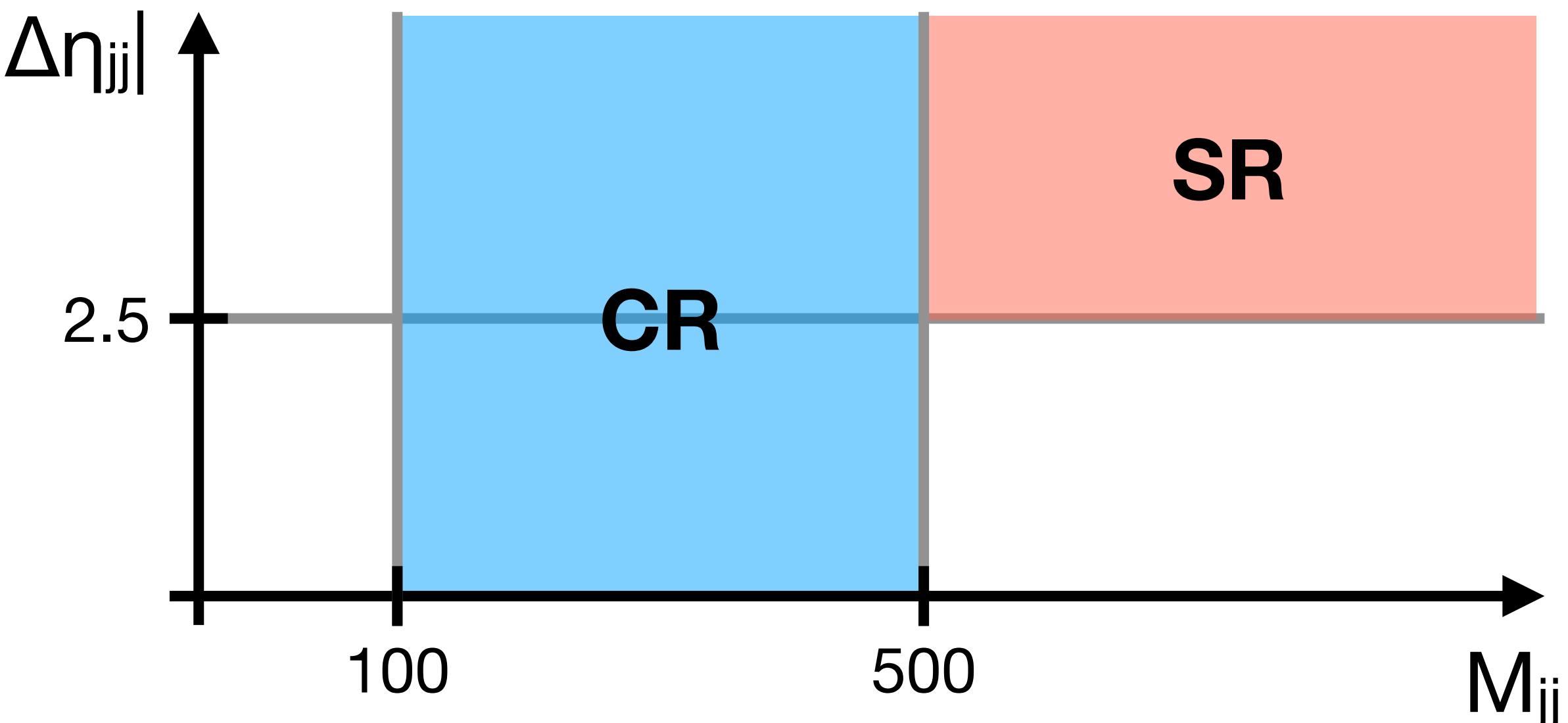
# Signal and Control Regions

- Preselection applied to both CR and SR
- SR defined in large  $M_{jj}$  and  $|\Delta n_{jj}|$  region
  - BDT trained here
- CR defined in low  $M_{jj}$  sideband
  - Data/MC agreement validated for bkg.
- **Both of these regions are used in the final fit**

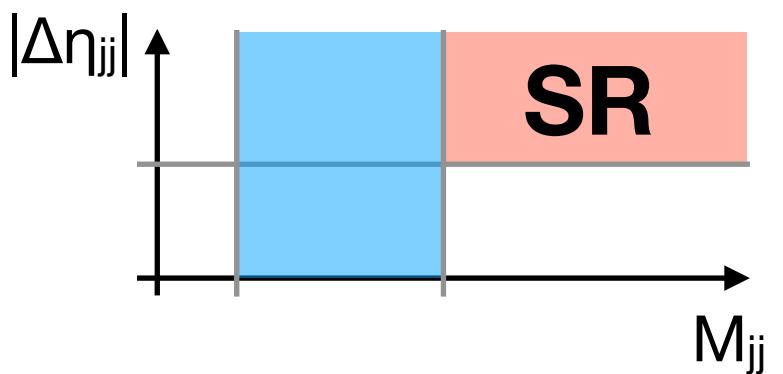
## Preselection:

- Single lepton HLTs
- Basic object selections (VBS,  $H \rightarrow b\bar{b}$  jets, 1 lepton)
- $p_T(W) = p_T(l) + \text{MET} > 35 \text{ GeV}$
- $M_{bb} \in [50, 150] \text{ GeV}$

## CR vs. SR topography:

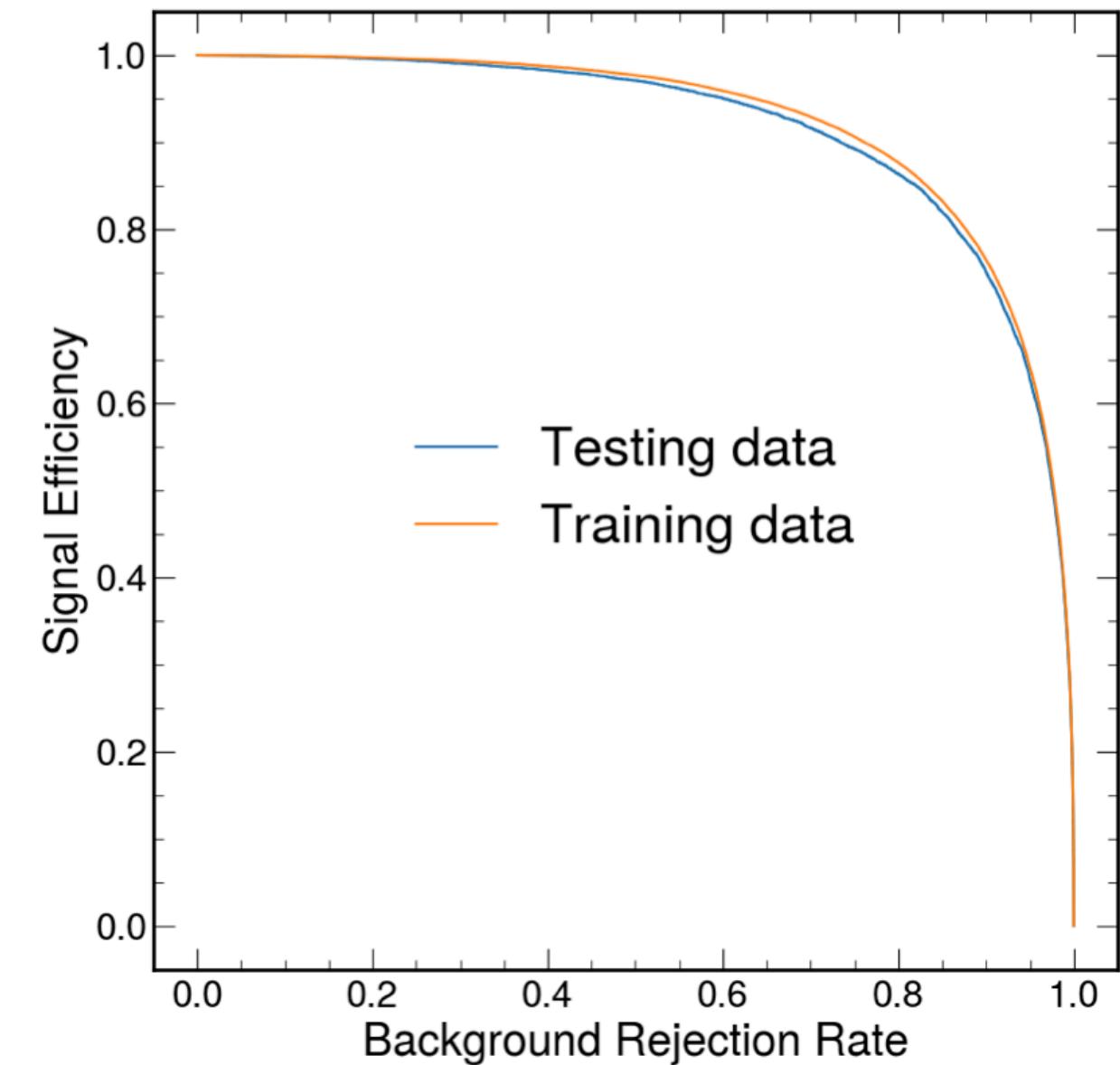
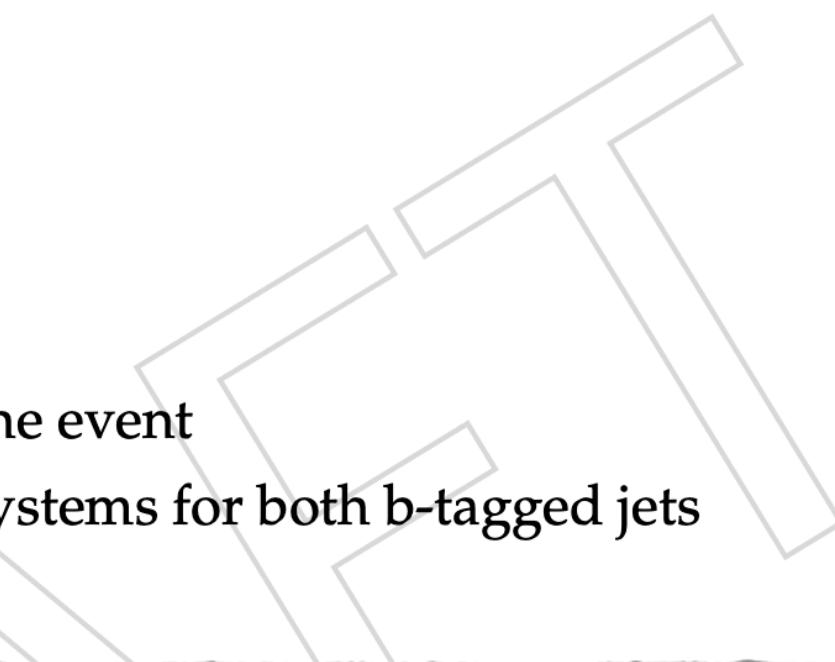


# SR: BDT Training



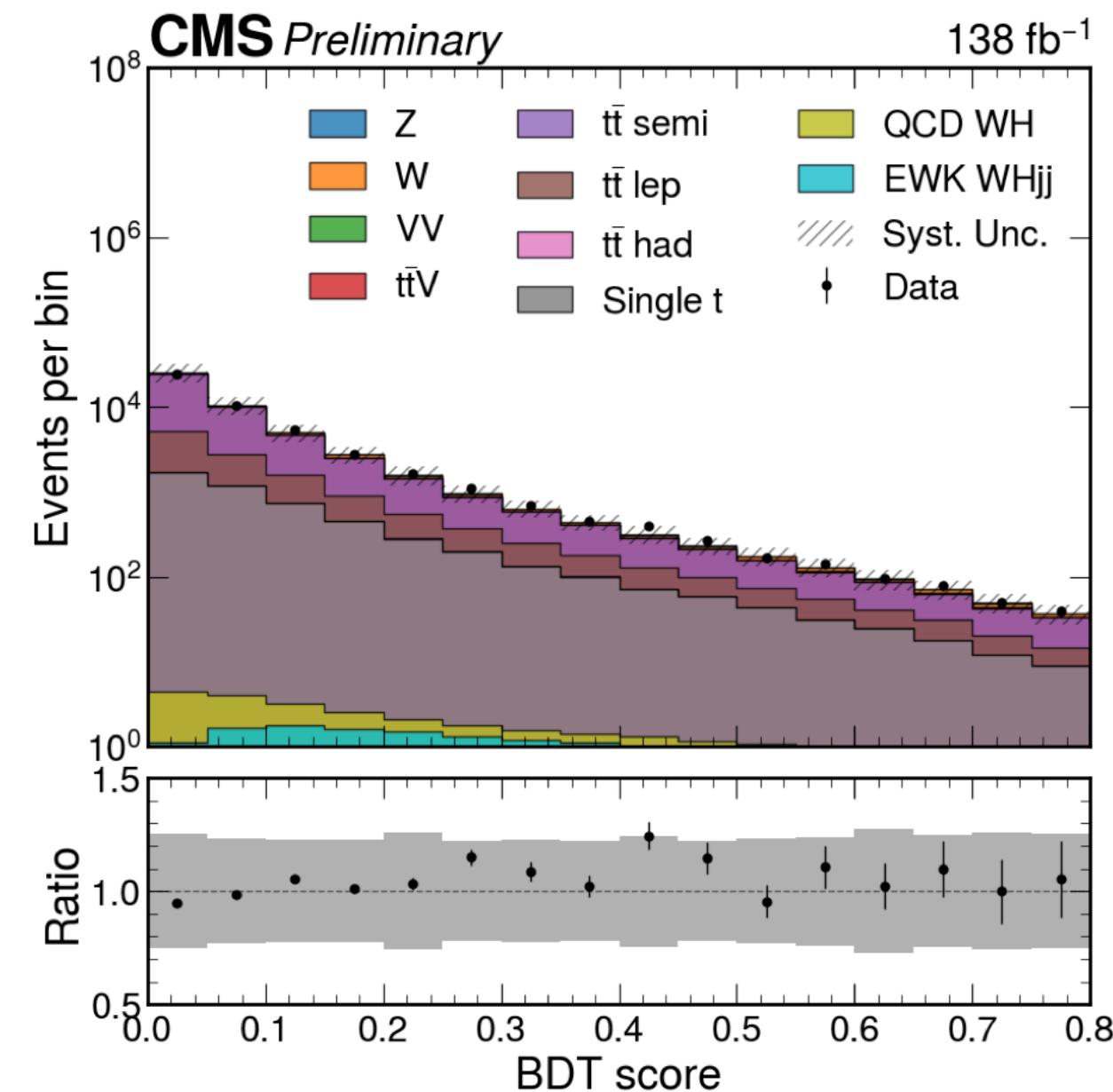
## Input features

- The  $p_T$ ,  $\eta$ , and  $\phi$  of all selected leptons and jets
- The lepton charge, converted to a 0 or 1, where 0 corresponds to negative charge and 1 corresponds to positive charge
- The lepton flavor, converted to a 0 or 1, where 0 corresponds to muons and 1 corresponds to electrons
- The DeepJet b-tagging discriminator of all selected jets
- The MET  $p_T$  and  $\phi$
- The Higgs dijet mass
- The Higgs dijet  $\Delta\eta$
- The VBF dijet mass
- The VBF dijet  $\Delta\eta$
- The number of additional jets in the event
- The number of additional b-tagged jets in the event
- The transverse mass of the lepton plus jet systems for both b-tagged jets
- The  $\Delta R$  between all pairs of jets



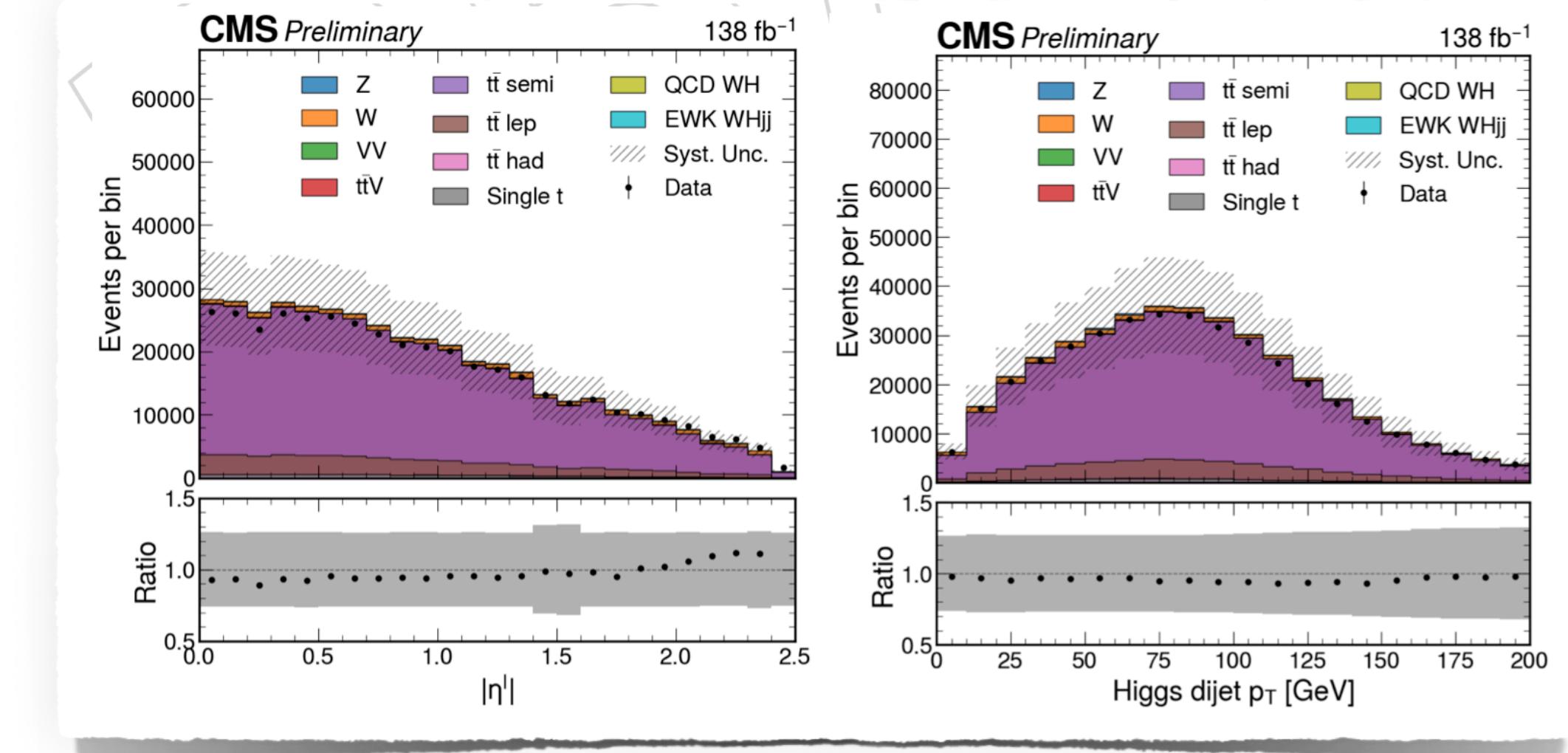
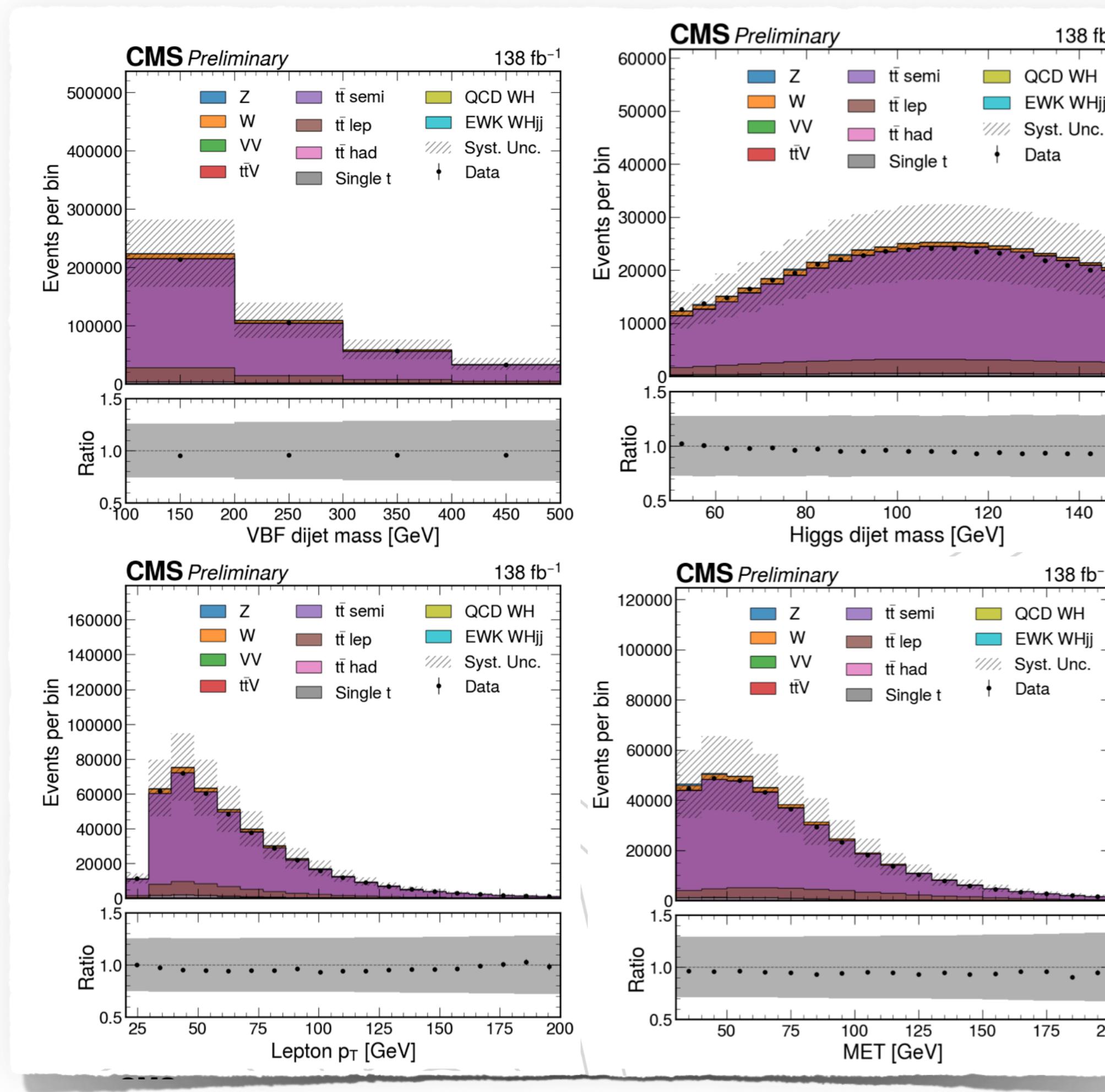
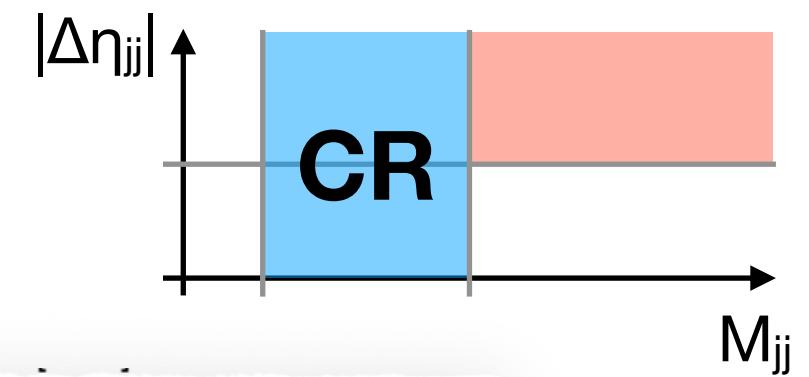
Good performance ✓

- Aforementioned signal features (plus a few more) used as input variables
  - Most important features:  $M_{bb}$ ,  $M_{jj}$ ,  $N_{\text{extra jets}}$ ,  $p_T, b$  (full feature ranking in backup)
- **Low BDT score (< 0.8) distribution validated against data**



Good agreement ✓

# CR: MC Validation

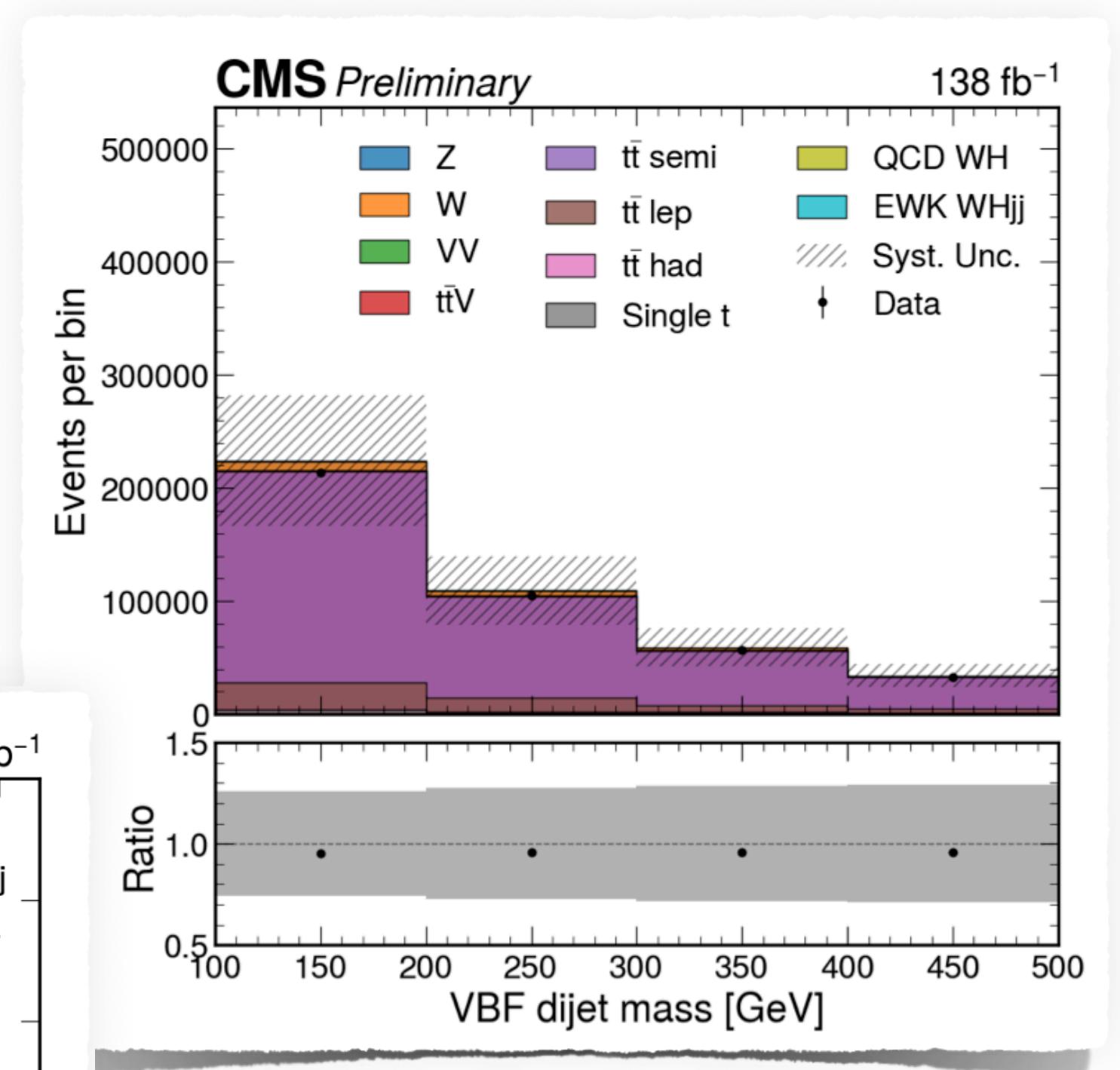
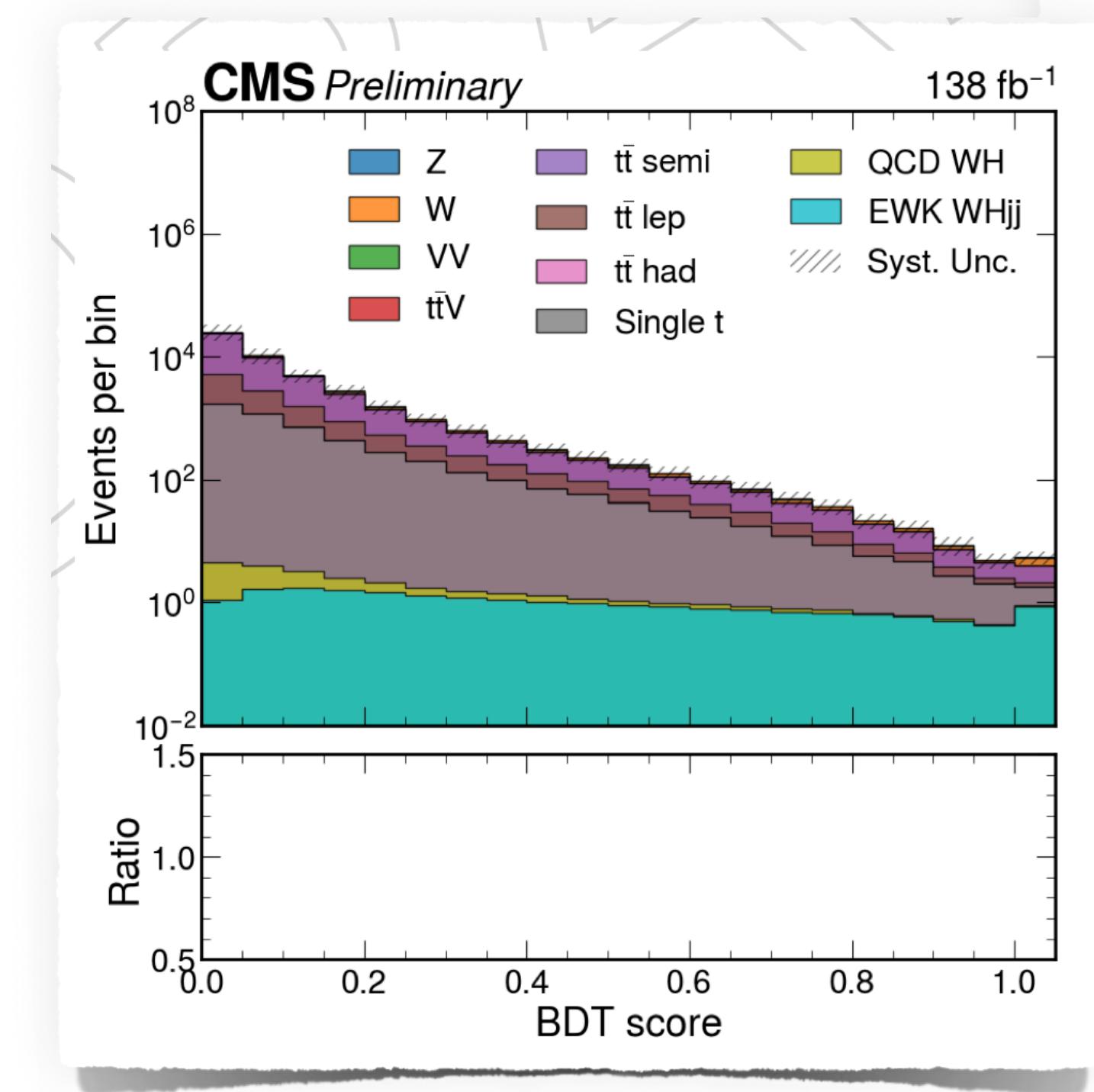


Good agreement ✓

Take expected background  
from MC

# Expected Results

- Perform a binned likelihood fit on two distributions:
  - CR divided into 4  $M_{jj}$  bins (100 GeV wide)
  - SR divided into 20 BDT score bins (0.05 wide)
- Expected significance: **0.49 $\sigma$**



# Backup (boosted)

# BSM Signal Models

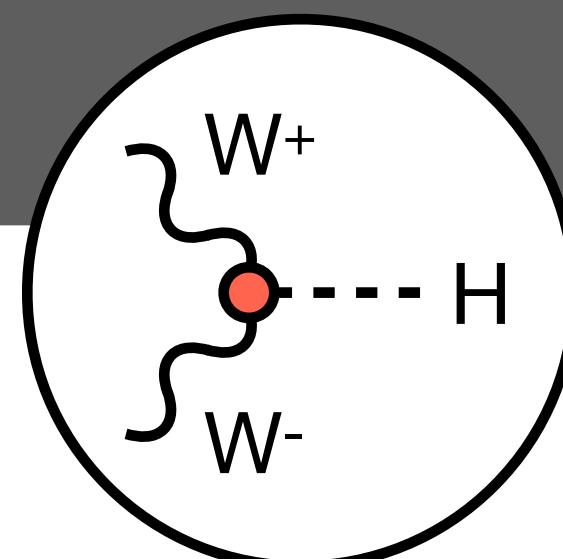
$K_W = -1$

models/sm/couplings.py

```
GC_72 = Coupling(name = 'GC_72',
                  value = '(ee**2*complex(0,1)*vev)/(2.*sw**2)',
                  value = '-((ee**2*complex(0,1)*vev)/(2.*sw**2))',
                  order = {'QED':1})
```

models/sm/vertices.py

```
V_52 = Vertex(name = 'V_52',
               particles = [ P.W_minus__, P.W_plus__, P.H ],
               color = [ '1' ],
               lorentz = [ L.VVS1 ],
               couplings = {(0,0):C.GC_72})
```



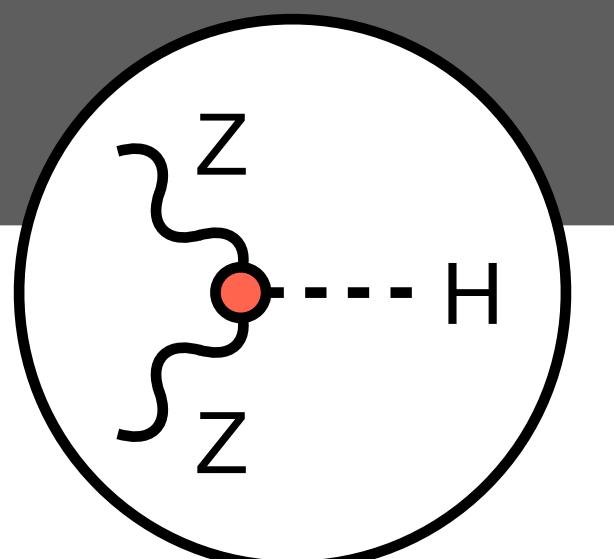
$K_Z = -1$

models/sm/couplings.py

```
GC_81 = Coupling(name = 'GC_81',
                  value = 'ee**2*complex(0,1)*vev + ...',
                  value = '-(ee**2*complex(0,1)*vev + ... )',
                  order = {'QED':1})
```

models/sm/vertices.py

```
V_69 = Vertex(name = 'V_69',
               particles = [ P.Z, P.Z, P.H ],
               color = [ '1' ],
               lorentz = [ L.VVS1 ],
               couplings = {(0,0):C.GC_81})
```



**Only changed one line in SM Madgraph model!**

# VBS WH Cross Sections

Model	$\sigma$ [pb]
$\kappa_W = \kappa_Z = +1$ (SM)	0.075
$\kappa_W = -1, \kappa_Z = +1$	0.433
$\kappa_W = +1, \kappa_Z = -1$	0.433

$\times 6$

- Setting  $\kappa_W = -1$  or  $\kappa_Z = -1$  equivalently enhances cross section by a factor of 6
- These numbers are taken from MadGraph: generate  $p\ p \rightarrow w\ h\ j\ j$  QCD=0
  - Includes gen-level filters (e.g. jet  $p_T > 10$  GeV)
  - Generated 10,000 events for each to obtain xsec value
- **Optimizing for  $\kappa_W = -1$**  (kinematics are equivalent to  $\kappa_Z = -1$ )
  - Generated 100k UL NanoAOD events for 2016 pre-VFP, 2016 post-VFP, 2017, and 2018

# 2016 CMS Result

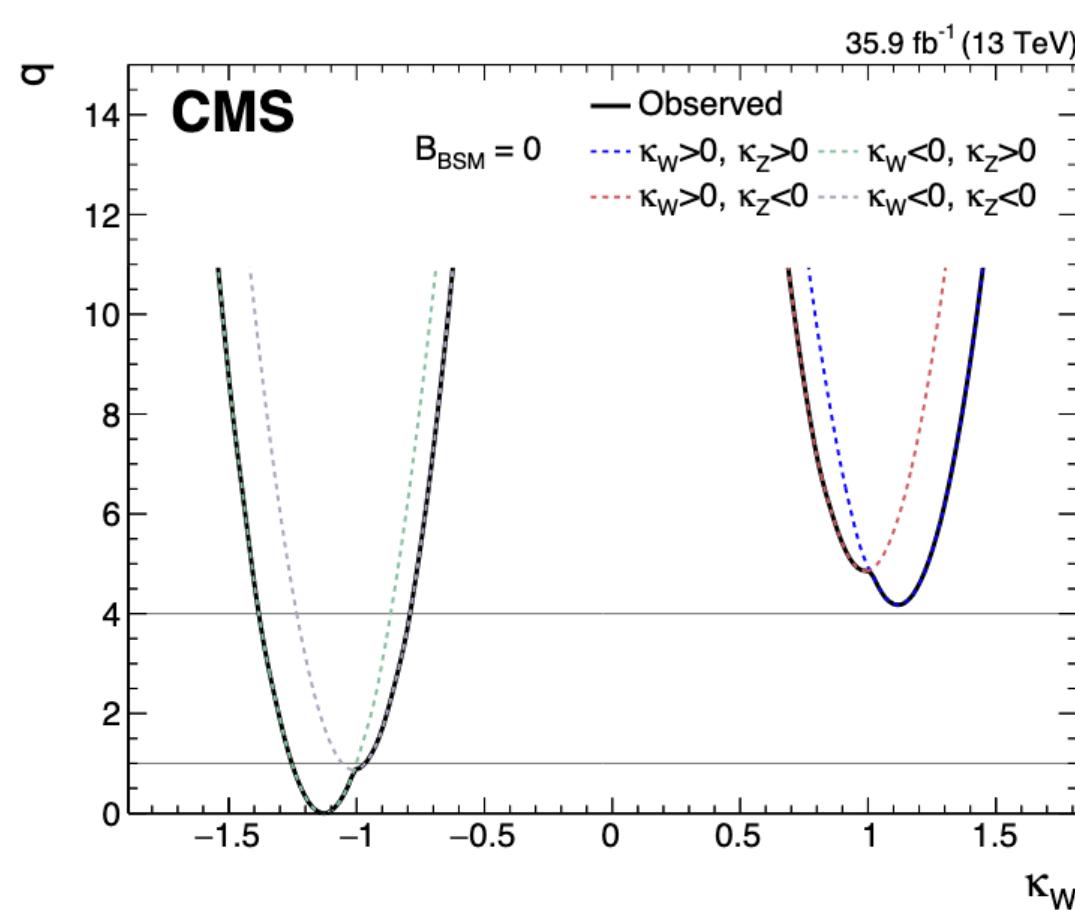


Figure 13: Scan of the test statistic  $q$  as a function of  $\kappa_W$  in the generic  $\kappa$  model assuming  $\mathcal{B}_{\text{BSM}} = 0$  (left) and allowing  $\mathcal{B}_{\text{inv}}$  and  $\mathcal{B}_{\text{undet}}$  to float (right). The different colored lines indicate the value of  $q$  for different combinations of signs for  $\kappa_W$  and  $\kappa_Z$ . The solid black line shows the minimum value of  $q(\kappa_W)$  in each case and is used to determine the best fit point and the  $1\sigma$  and  $2\sigma$  CL regions. The scan in the right figure is truncated because of the constraints of  $|\kappa_W| \leq 1$  and  $|\kappa_Z| \leq 1$ , which are imposed in this model.

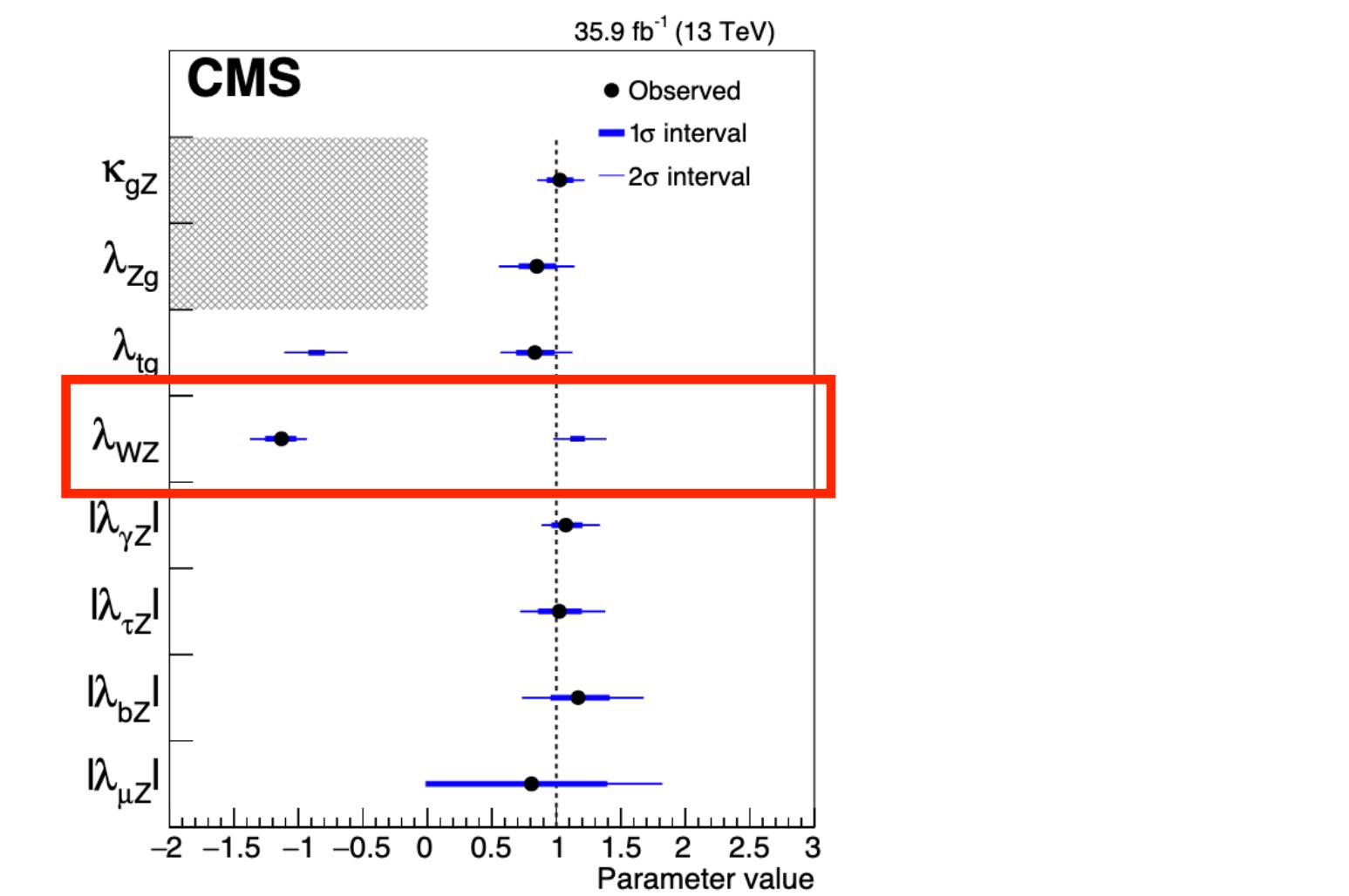
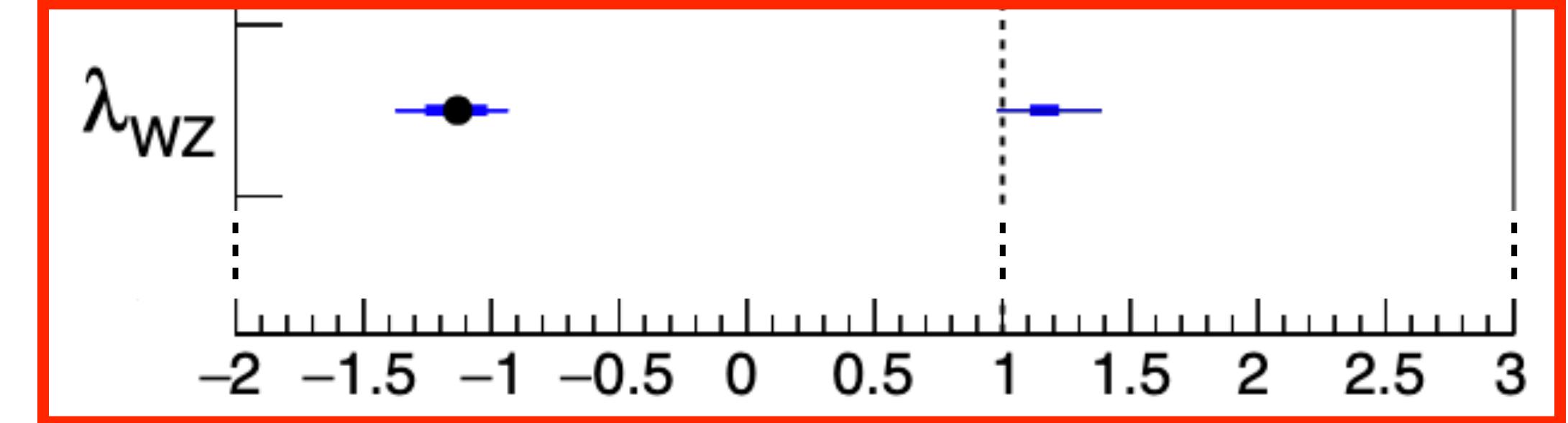
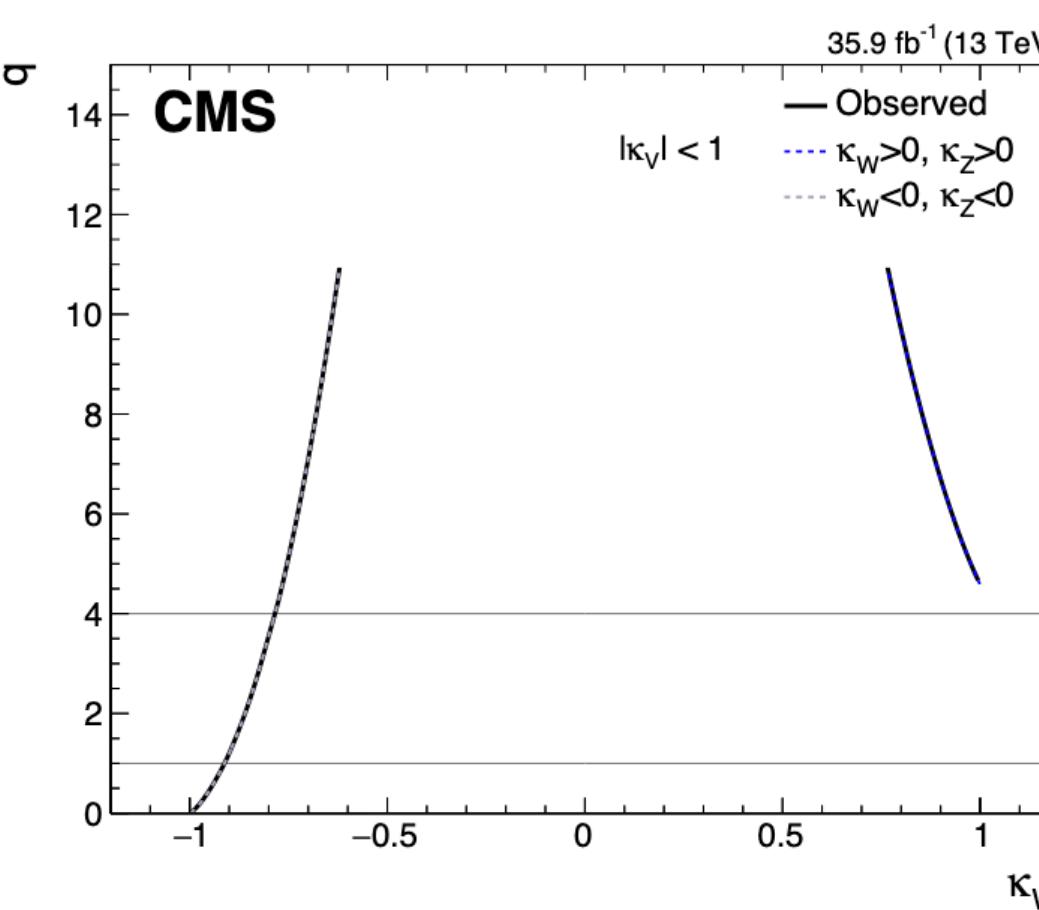
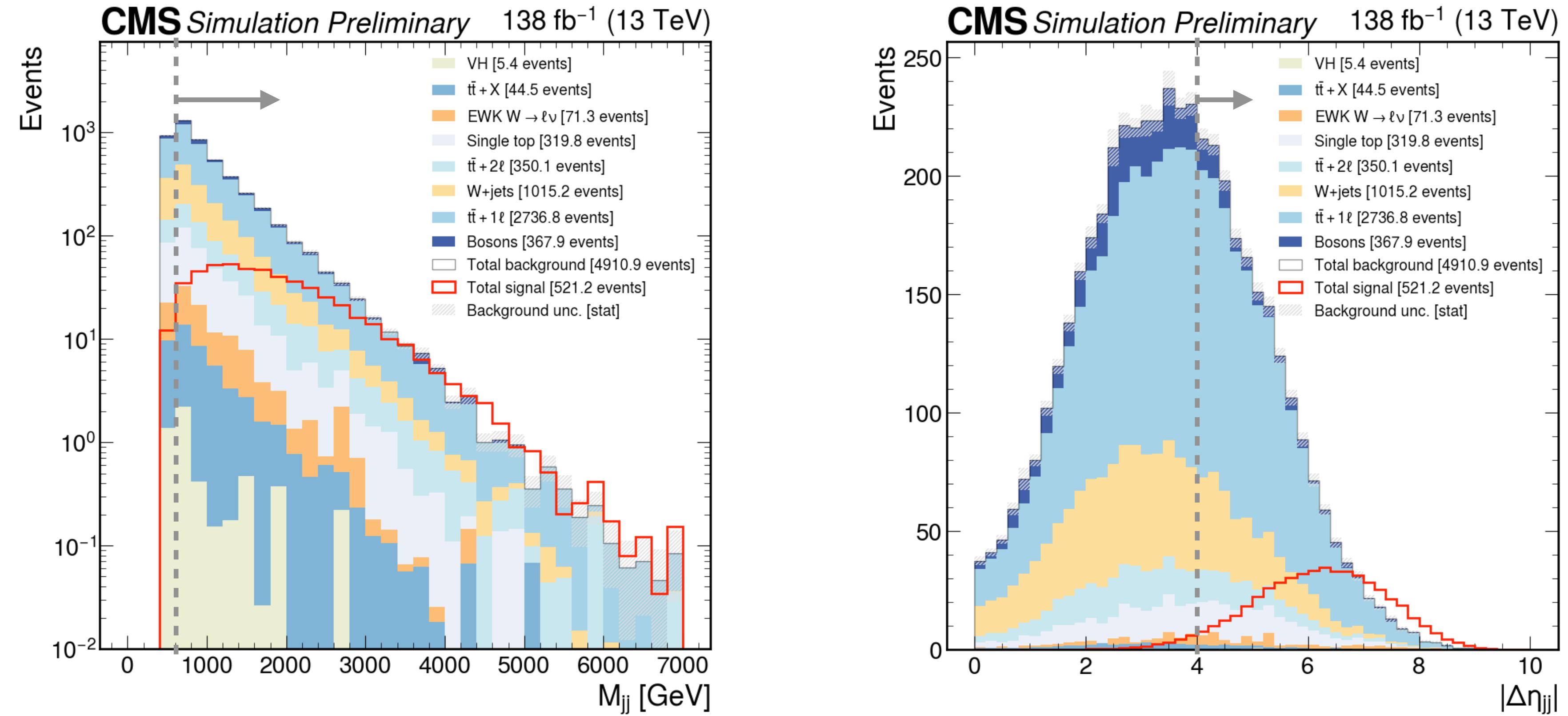


Figure 16: Summary of the model with coupling ratios and effective couplings for the  $ggH$  and  $H \rightarrow \gamma\gamma$  loops. The points indicate the best fit values while the thick and thin horizontal bars show the  $1\sigma$  and  $2\sigma$  CL intervals, respectively. For this model, both positive and negative values of  $\lambda_{WZ}$  and  $\lambda_{tg}$  are considered.

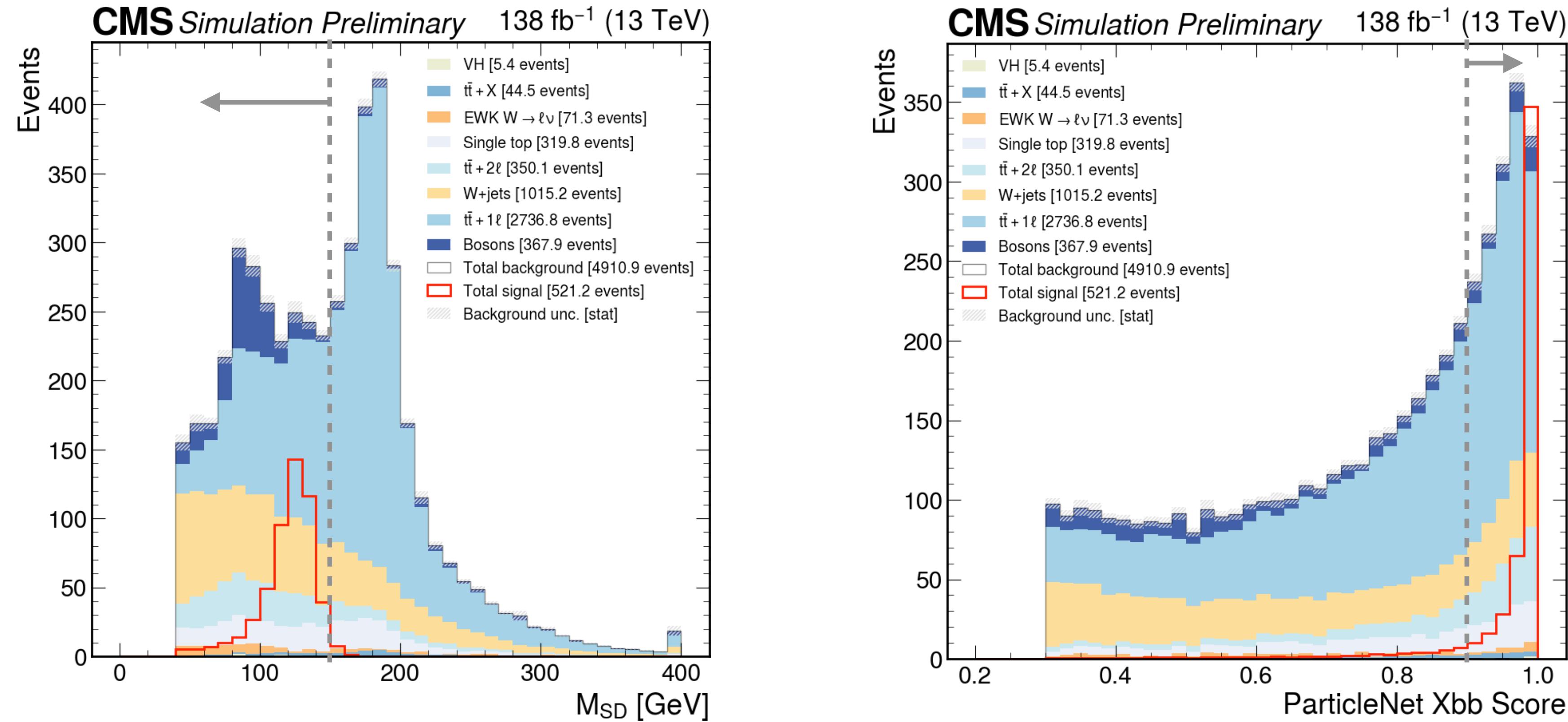
<https://arxiv.org/pdf/1809.10733.pdf>

# VBS Jets



- $M_{jj}$  = invariant mass of VBS system,  $|\Delta\eta_{jj}| = \eta_1 - \eta_2$
- **VBS signature for signal** is clear: large  $M_{jj}$  &  $|\Delta\eta_{jj}|$

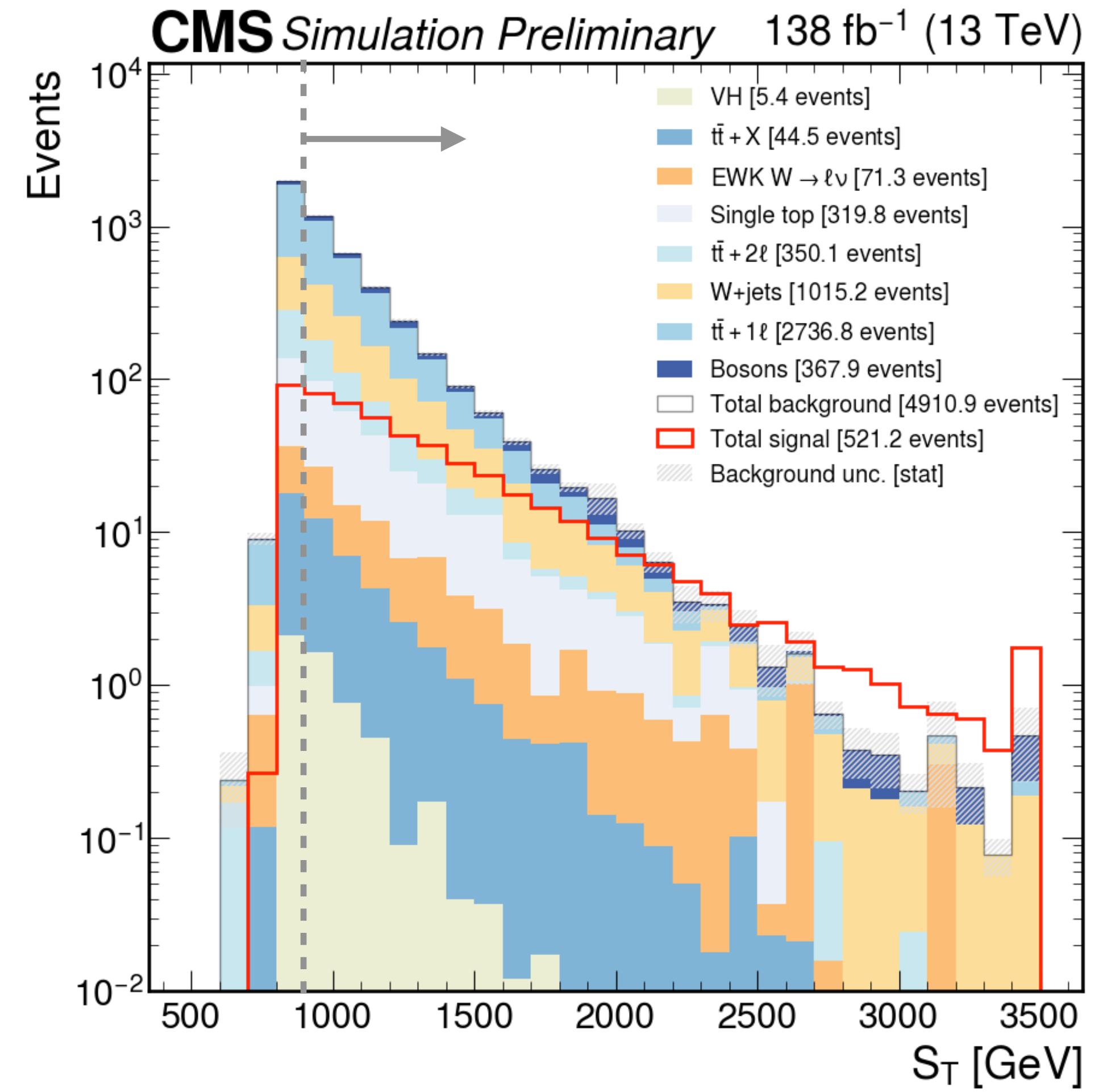
# H $\rightarrow$ bb Large-radius Jet



- $M_{SD}$  = “softdrop” mass of jet, ParticleNet Xbb = mass-decorrelated  $X \rightarrow bb$  jet tagger
- Higgs peak + performant tagger gives **strong signal separation**

# Boosted WH

- $S_T = p_T(\ell) + \text{MET} + p_T(H \rightarrow b\bar{b})$ 
  - i.e. transverse energy of  $W + H$
- Captures **boosted WH** from  $\lambda_{WZ} = -1$ 
  - Large number of signal events in  $S_T$  tail
  - Background falls exponentially
  - Signal is similarly boosted for most  $\kappa_W, \kappa_Z$  points where  $\lambda_{WZ} < 0$



# ABCD Systematic Error

Preselection AND  $M_{jj} > 600$  GeV AND  $S_T > 900$  GeV AND PNet Xbb > 0.9

Cut	Region	Bkg. (wgt)	Bkg. Err.*	Sig. (wgt)	Sig. Err.*	Data	Data Err.*
$ \Delta\eta_{jj}  > 4$ AND $M_{SD} \geq 150$ GeV	D	172.97	3.25	6.92	0.40	142	11.92
$ \Delta\eta_{jj}  \leq 4$ AND $M_{SD} \geq 150$ GeV	C	241.93	5.83	0.27	0.08	201	14.18
$ \Delta\eta_{jj}  \leq 4$ AND $M_{SD} < 150$ GeV	B	181.10	4.40	11.62	0.52	170	13.04
$ \Delta\eta_{jj}  > 4$ AND $M_{SD} < 150$ GeV (SR)	A	116.41	3.84	366.30	2.92	—	—

- Errors: 10% (syst.), 13% (stat.)

$$D_{MC}^{pred} = \frac{A_{MC}}{B_{MC}} \times C_{MC} = \mathbf{129.48}$$

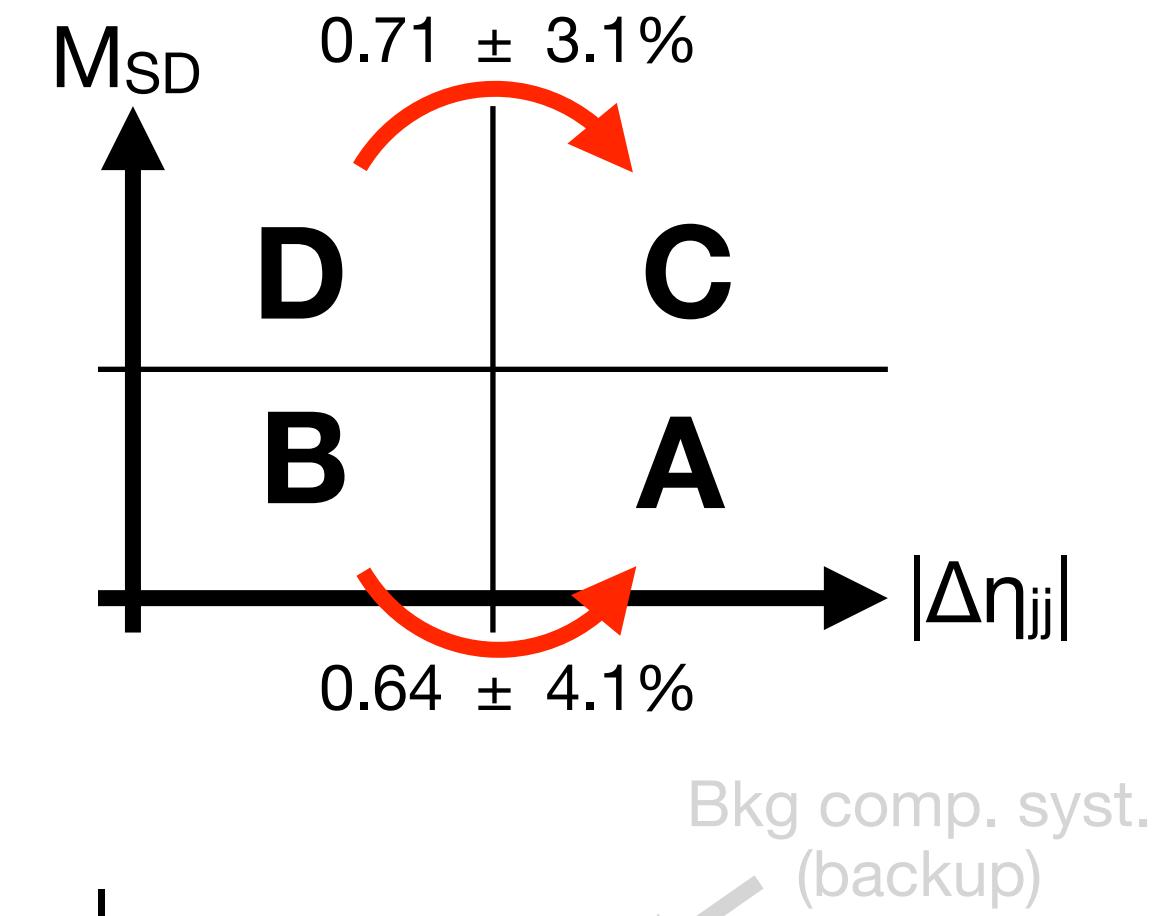
Over-predicted

$$\epsilon_{syst} = \left| 1 - \frac{D_{MC}^{pred}}{D_{MC}} \right| = \left| 1 - \frac{129.5}{116.4} \right| = 11\% \oplus 6\% = 13\%$$

$$D_{data}^{pred} = \frac{A_{data}}{B_{data}} \times C_{data} = 120.10$$

$$\begin{aligned} \epsilon_{stat} &= \sqrt{\left( \frac{\sqrt{A_{data}}}{A_{data}} \right)^2 + \left( \frac{\sqrt{B_{data}}}{B_{data}} \right)^2 + \left( \frac{\sqrt{C_{data}}}{C_{data}} \right)^2} \\ &= \sqrt{\frac{1}{A_{data}} + \frac{1}{B_{data}} + \frac{1}{C_{data}}} = 13\% \end{aligned}$$

Predicted SR Yield:  $120.1 \pm 16.07 \pm 15.30$   
*stat.*      *syst.*



\*err =  $\sqrt{(\sum_i w_i^2)}$  for MC,  $\sqrt{(\text{count})}$  for data

# ABCD W+jets Composition

Preselection AND  $M_{jj} > 600$  GeV AND  $S_T > 900$  GeV AND PNet Xbb > 0.9 (WJets x 2)

Cut	Region	Bkg. (wgt)	Bkg. Err.*	Sig. (wgt)	Sig. Err.*	Data	Data Err.*
$ \Delta\eta_{jj}  > 4$ AND $M_{SD} \geq 150$ GeV	D	184.26	3.48	6.92	0.40	142	11.92
$ \Delta\eta_{jj}  \leq 4$ AND $M_{SD} \geq 150$ GeV	C	272.50	5.98	0.27	0.08	201	14.18
$ \Delta\eta_{jj}  \leq 4$ AND $M_{SD} < 150$ GeV	B	223.95	4.72	11.62	0.52	170	13.04
$ \Delta\eta_{jj}  > 4$ AND $M_{SD} < 150$ GeV (SR)	A	137.64	4.42	366.30	2.92	—	—

Preselection AND  $M_{jj} > 600$  GeV AND  $S_T > 900$  GeV AND PNet Xbb > 0.9

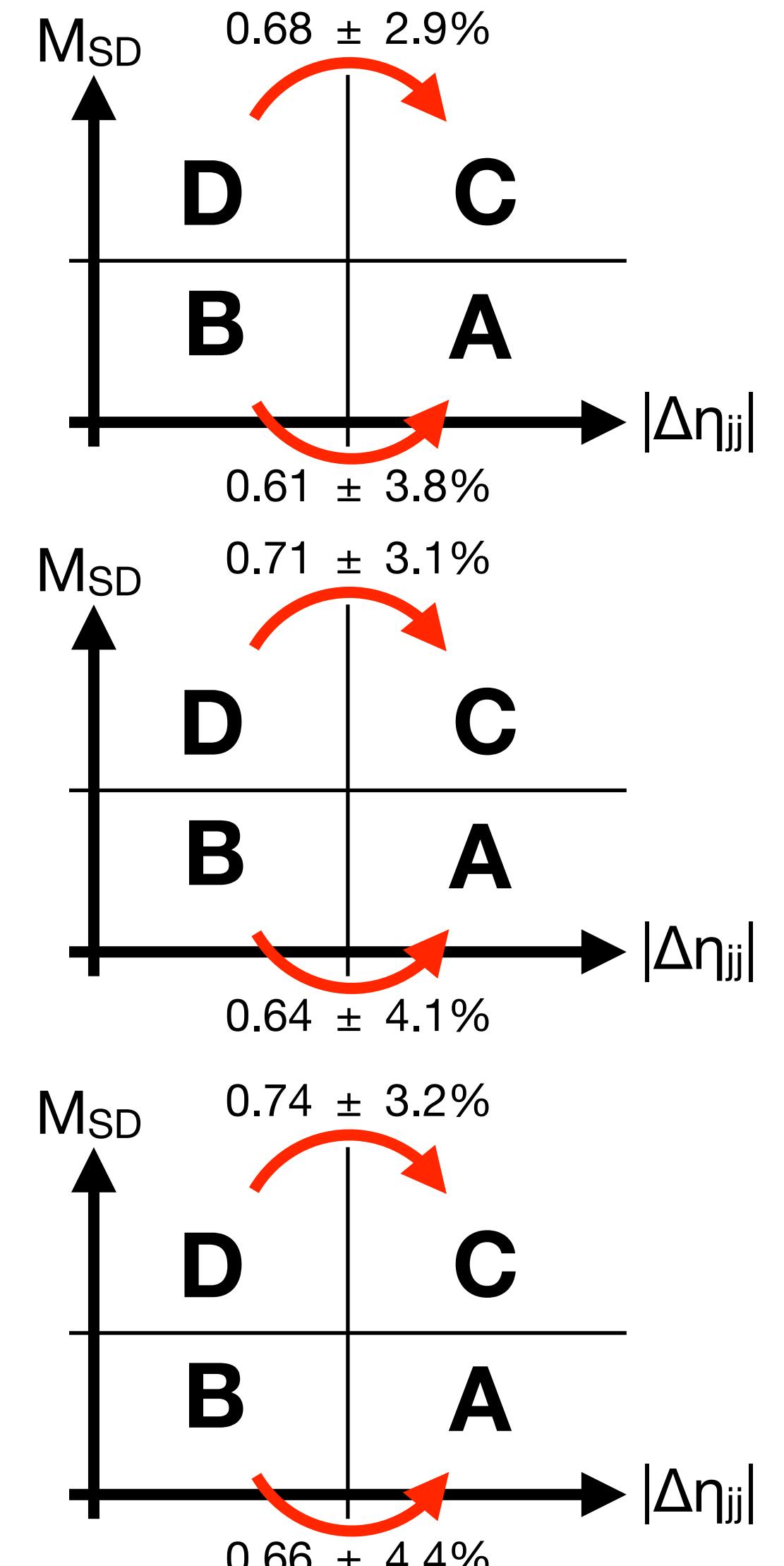
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Preselection AND  $M_{jj} > 600$  GeV AND  $S_T > 900$  GeV AND PNet Xbb > 0.9 (WJets x 0.5)

Cut	Region	Bkg. (wgt)	Bkg. Err.*	Sig. (wgt)	Sig. Err.*	Data	Data Err.*
$ \Delta\eta_{jj}  > 4$ AND $M_{SD} \geq 150$ GeV	D	167.32	3.19	6.92	0.40	142	11.92
$ \Delta\eta_{jj}  \leq 4$ AND $M_{SD} \geq 150$ GeV	C	226.65	5.79	0.27	0.08	201	14.18
$ \Delta\eta_{jj}  \leq 4$ AND $M_{SD} < 150$ GeV	B	159.67	4.32	11.62	0.52	170	13.04
$ \Delta\eta_{jj}  > 4$ AND $M_{SD} < 150$ GeV (SR)	A	105.79	3.68	366.30	2.92	—	—

\*err =  $\sqrt{(\sum_i w_i^2)}$  for MC,  $\sqrt{(\text{count})}$  for data

5.4% systematic



# ABCD Bosons Composition

Preselection AND  $M_{jj} > 600$  GeV AND  $S_T > 900$  GeV AND PNet Xbb > 0.9 (Bosons x 2)

Cut	Region	Bkg. (wgt)	Bkg. Err.*	Sig. (wgt)	Sig. Err.*	Data	Data Err.*
$ \Delta\eta_{jj}  > 4$ AND $M_{SD} \geq 150$ GeV	D	173.96	3.46	6.92	0.40	142	11.92
$ \Delta\eta_{jj}  \leq 4$ AND $M_{SD} \geq 150$ GeV	C	249.87	9.99	0.27	0.08	201	14.18
$ \Delta\eta_{jj}  \leq 4$ AND $M_{SD} < 150$ GeV	B	202.63	7.17	11.62	0.52	170	13.04
$ \Delta\eta_{jj}  > 4$ AND $M_{SD} < 150$ GeV (SR)	A	122.39	5.97	366.30	2.92	—	—

Preselection AND  $M_{jj} > 600$  GeV AND  $S_T > 900$  GeV AND PNet Xbb > 0.9

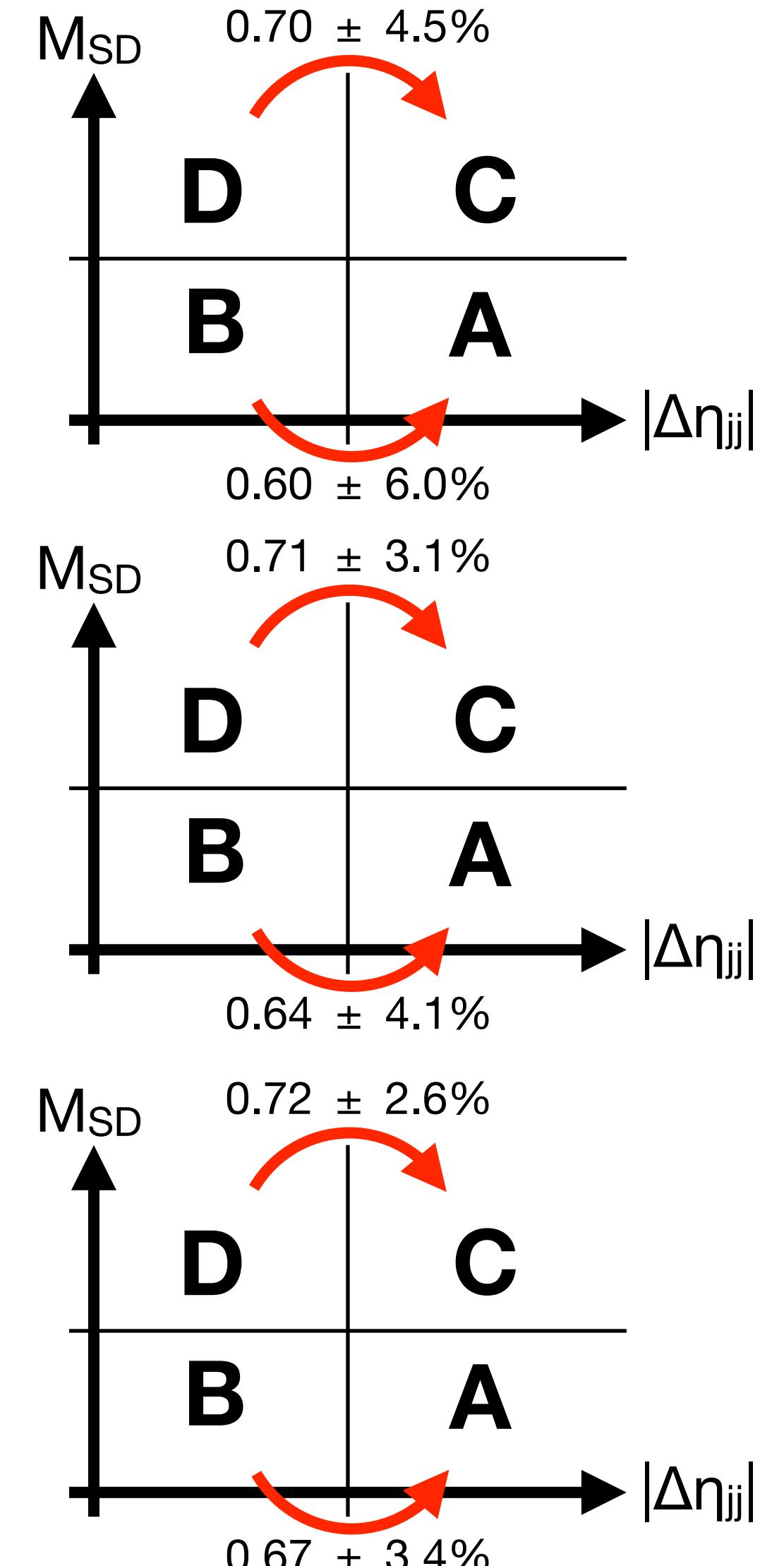
Cut	Region	Bkg. (wgt)	Bkg. Err.*	Sig. (wgt)	Sig. Err.*	Data	Data Err.*
$ \Delta\eta_{jj}  > 4$ AND $M_{SD} \geq 150$ GeV	D	172.97	3.25	6.92	0.40	142	11.92
$ \Delta\eta_{jj}  \leq 4$ AND $M_{SD} \geq 150$ GeV	C	241.93	5.83	0.27	0.08	201	14.18
$ \Delta\eta_{jj}  \leq 4$ AND $M_{SD} < 150$ GeV	B	181.10	4.40	11.62	0.52	170	13.04
$ \Delta\eta_{jj}  > 4$ AND $M_{SD} < 150$ GeV (SR)	A	116.41	3.84	366.30	2.92	—	—

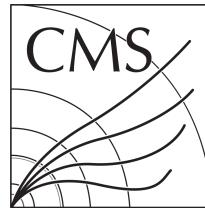
Preselection AND  $M_{jj} > 600$  GeV AND  $S_T > 900$  GeV AND PNet Xbb > 0.9 (Bosons x 0.5)

Cut	Region	Bkg. (wgt)	Bkg. Err.*	Sig. (wgt)	Sig. Err.*	Data	Data Err.*
$ \Delta\eta_{jj}  > 4$ AND $M_{SD} \geq 150$ GeV	D	172.47	3.20	6.92	0.40	142	11.92
$ \Delta\eta_{jj}  \leq 4$ AND $M_{SD} \geq 150$ GeV	C	237.97	4.18	0.27	0.08	201	14.18
$ \Delta\eta_{jj}  \leq 4$ AND $M_{SD} < 150$ GeV	B	170.33	3.38	11.62	0.52	170	13.04
$ \Delta\eta_{jj}  > 4$ AND $M_{SD} < 150$ GeV (SR)	A	113.42	3.08	366.30	2.92	—	—

\*err =  $\sqrt{(\sum_i w_i^2)}$  for MC,  $\sqrt{(\text{count})}$  for data

2.6% systematic





# Signal Systematics

- For most systematics:
  1. Get nominal yield in SR
  2. Get yield in SR after applying up/down variation
    - If scale factor: first divide each event weight by nominal value
  3. Systematic = largest % difference in yield

## Step 1

$$\text{yield} = y = \sum_{i=1}^N W_i$$

$$\text{where } W_i = \prod_j \omega_i$$

## Step 2

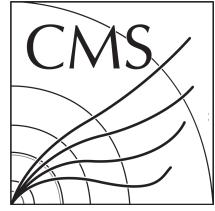
$$y_{var} = \sum_{i=1}^N W_i \times \frac{\omega_{var}}{\omega_{nom}}$$

## Step 3

$$\delta_{var} = \left| 1 - \frac{y_{var}}{y} \right|$$

$$\text{syst.} = \max(\delta_{up}, \delta_{down})$$

Systematic	Size
PDF variations	2.2%
$\mu_F$ scale	17.5%
Parton shower ISR weights	0.6%
Parton shower FSR weights	1.7%
Pileup reweighting	0.2%
Pileup jet ID	0.8%
L1 pre-fire corrections	0.9%
Single-electron HLT scale factors	0.7%
Single-muon HLT scale factors	0.1%
Simulation stat. unc.	0.8%
Electron ID scale factors	1.4%
Muon ID scale factors	0.1%
Electron reco. scale factors	0.3%
Muon iso. scale factors	0.0%
ParticleNet Xbb scale factors	1.3%
DeepJet b-tagging scale factors	0.2%
MET unc.	0.1%
Jet energy scale	7.0%
Jet energy resolution	0.4%
Luminosity	1.6%
H $\rightarrow$ b $\bar{b}$ BR	1.3%



# Signal Systematics: PDF Variations

- For (Hessian) PDF systematics:
  1. Get overall variation/inclusive ratio for each of the 100 PDF variations
  2. Get nominal yield in SR
  3. Get yield in SR after applying a given variation
  4. Systematic = % difference in yield for each variation added in quadrature

**Step 1**

$$R_{var} = \frac{\sum_{i=0}^N \omega_i^{var}}{\sum_{i=0}^N \omega_i^{gen}}$$

**Step 2**

$$\text{yield} = y = \sum_{i=1}^N W_i$$

where  $W_i = \prod_j \omega_j$

**Step 3**

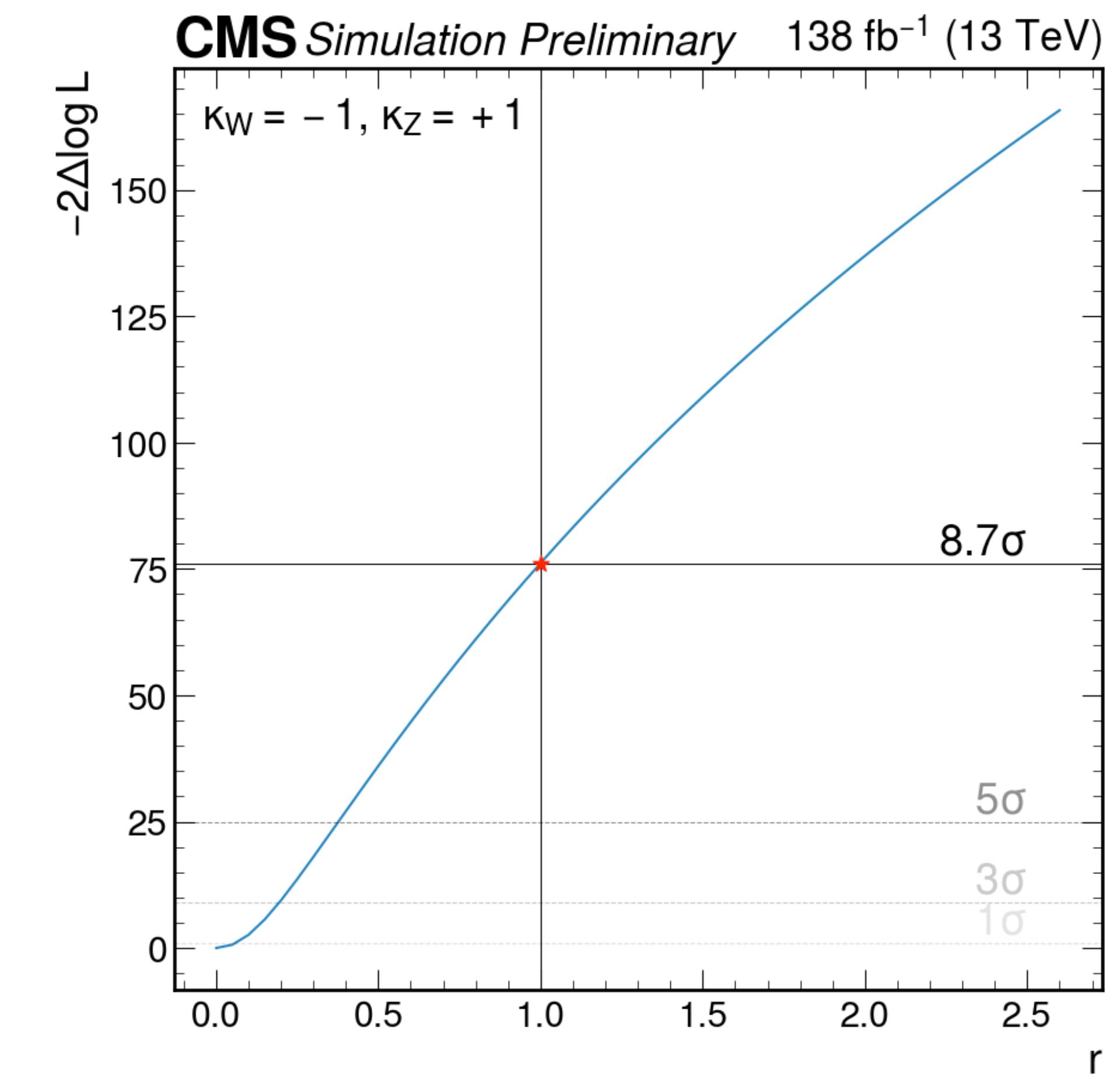
$$y_{var} = \sum_{i=1}^N W_i \times \frac{\omega_i^{var}}{R_{var}}$$

**Step 4**

$$\delta_{var} = \left| 1 - \frac{y_{var}}{y} \right|$$
$$\text{syst.} = \left[ \sum_{var} \delta_{var}^2 \right]^{1/2}$$

# Detailed Results

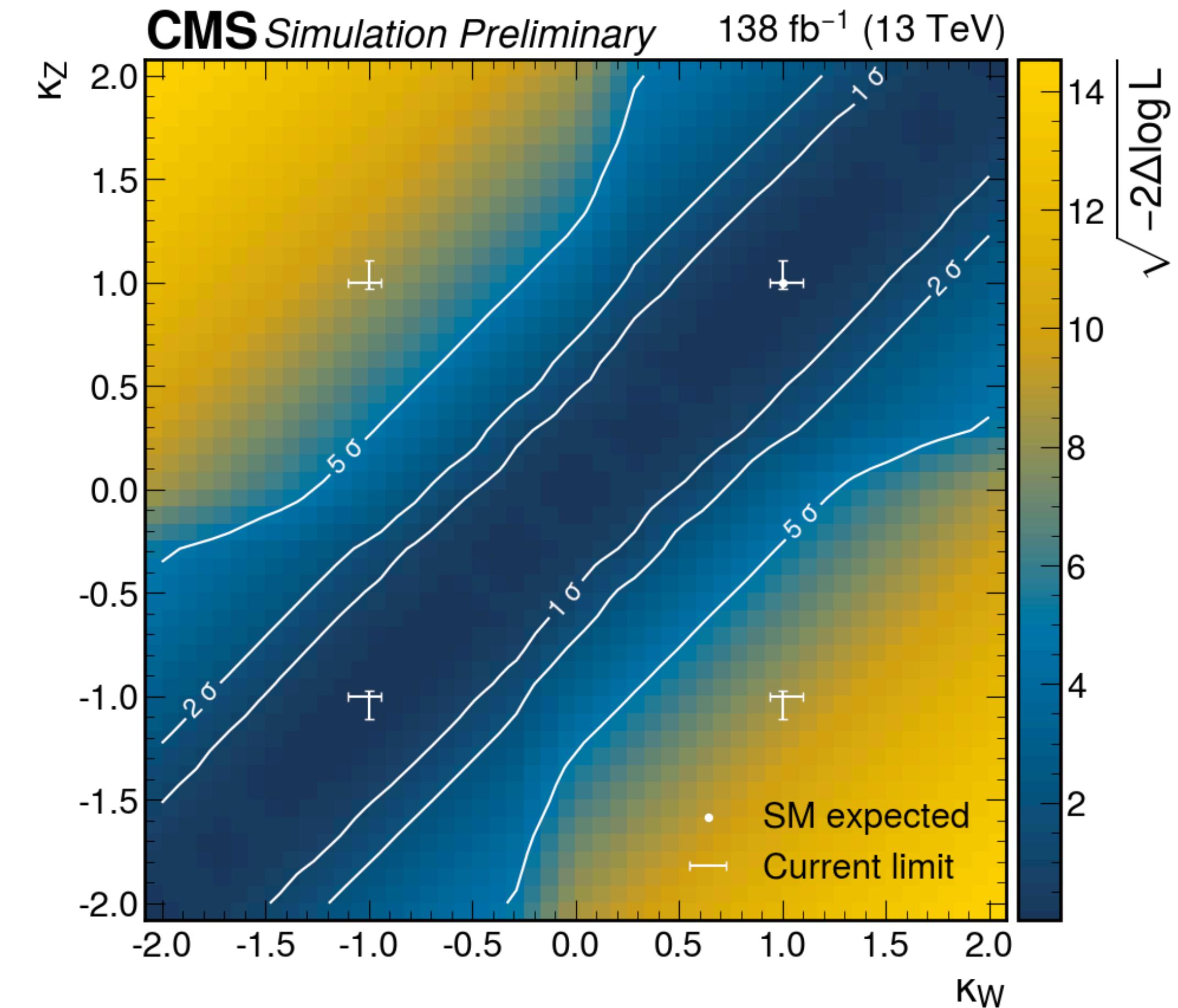
- Assessed rigorous set of systematics on signal simulation (backup)
- Maximum-likelihood fit for bkg-only hypothesis
  - “Observed” yield is artificially set to be equal to the predicted bkg. yield
  - Used CMS statistical tool\*
- **We expect to exclude  $\lambda_{WZ} = -1$  at  $9\sigma$**
- Waiting for internal approval to “unblind” analysis (i.e. look at the data in the SR)



**Expected signal ( $\lambda_{WZ} = -1$ ):  $366 \pm 2.9$**   
**Predicted background:  $120 \pm 16.1 \pm 15.3$**   
stat. syst.

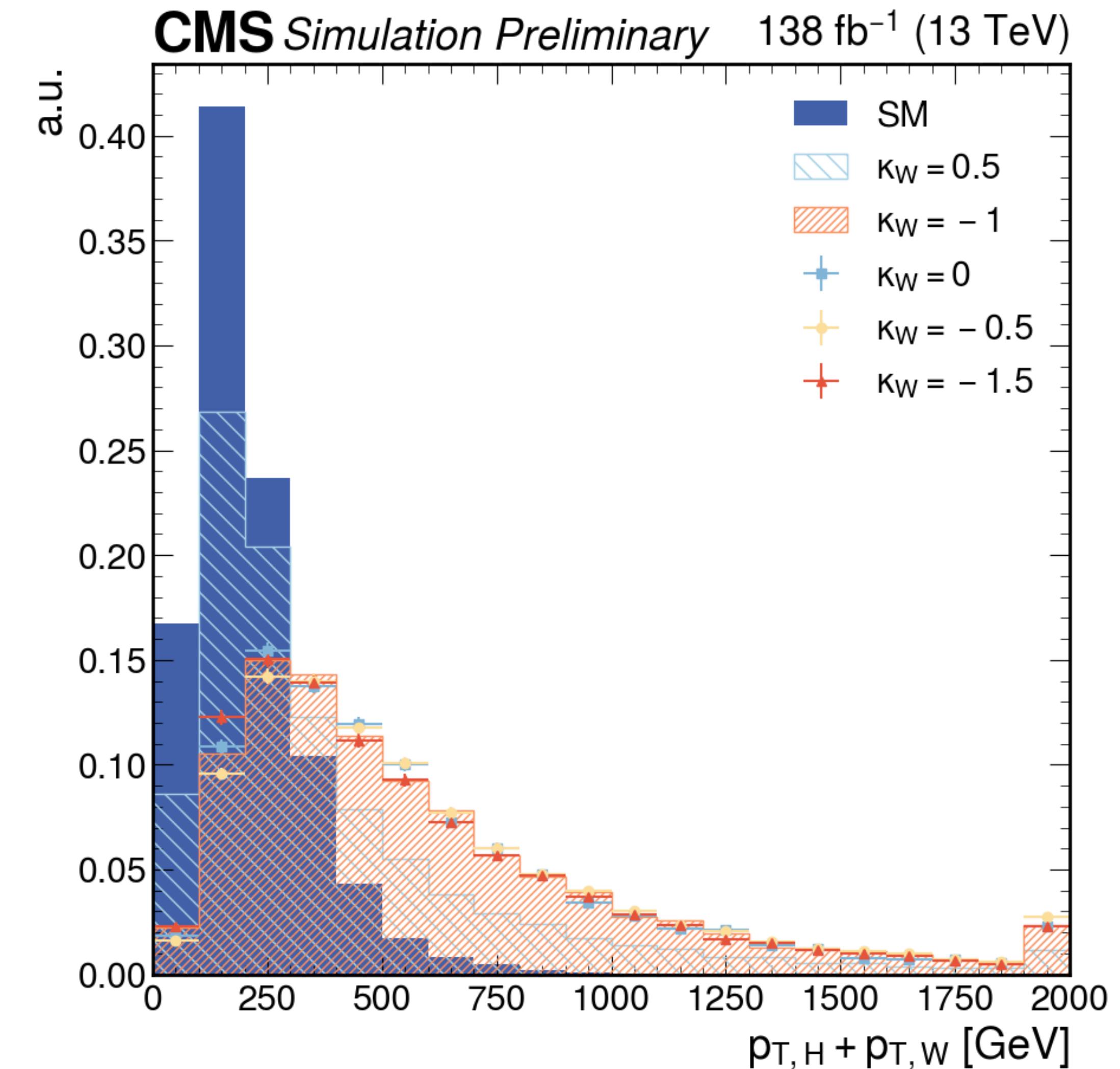
# Detailed Results (cont.)

- Used MadGraph reweighting to scan many  $\kappa_w$ ,  $\kappa_z$  values
- Interpolated exclusion limits plotted on z-axis
- Current best limits on  $|\kappa_v|$  are plotted as capped “error bars” (represent 1D limits, not 2D errors)
  - $|\kappa_w| = 1.02 \pm 0.08$ ,  $|\kappa_z| = 1.04 \pm 0.07$
- Contours show  $\sigma = 1, 2, 5$  exclusion boundaries
  - This shows we **can exclude**  $\lambda_{wz} < 0$  when considered alongside current best limits



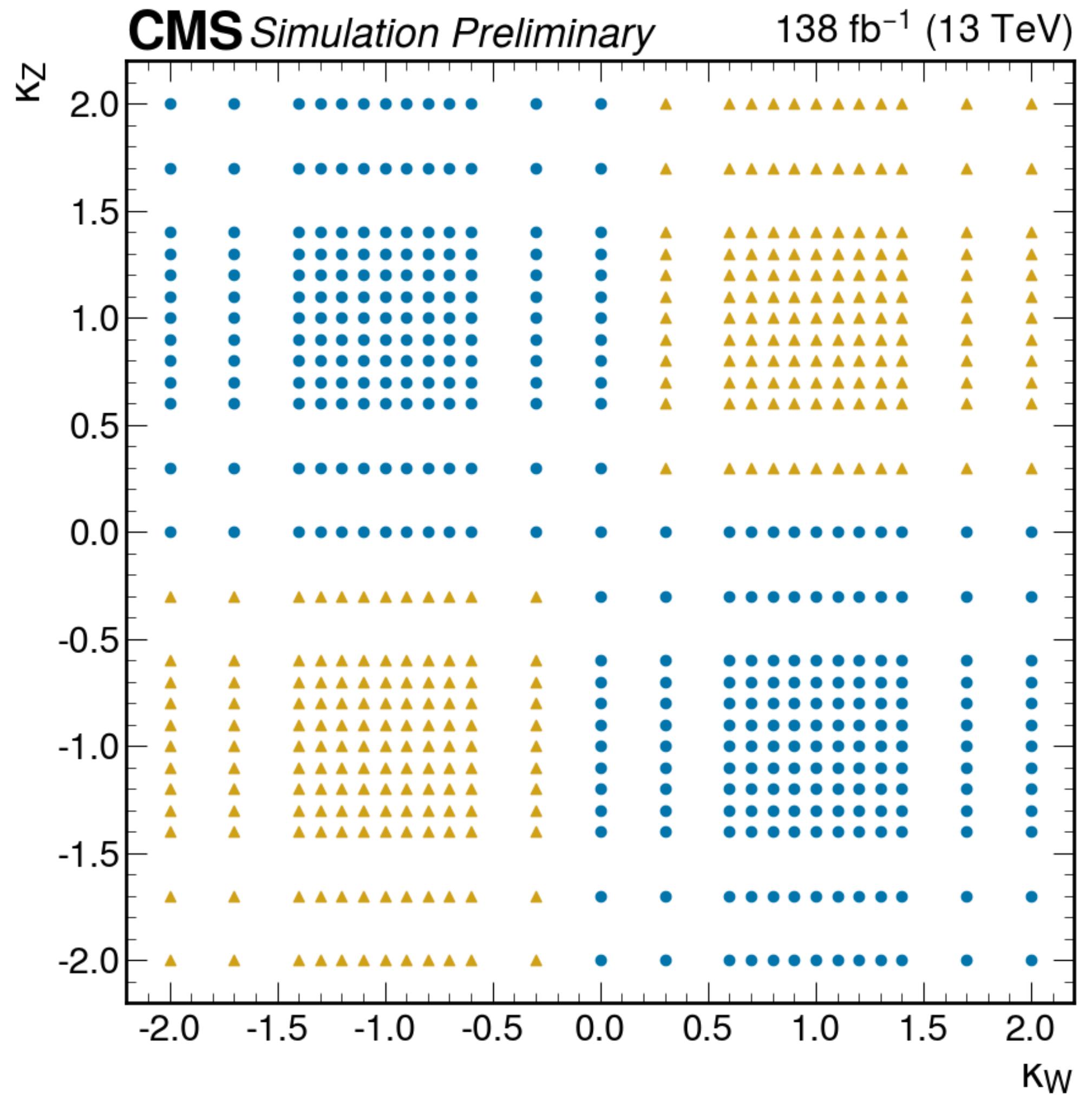
# Other $\lambda_{WZ}$ values

- Generated 10k events for various  $\kappa_W$  values
- Comparing kinematics at LHE level
  - Not much difference across a fairly large range of  $\kappa_W$  values
  - $\Rightarrow$  Acceptance  $\sim$ consistent for  $\kappa_W = -1 \pm \epsilon$

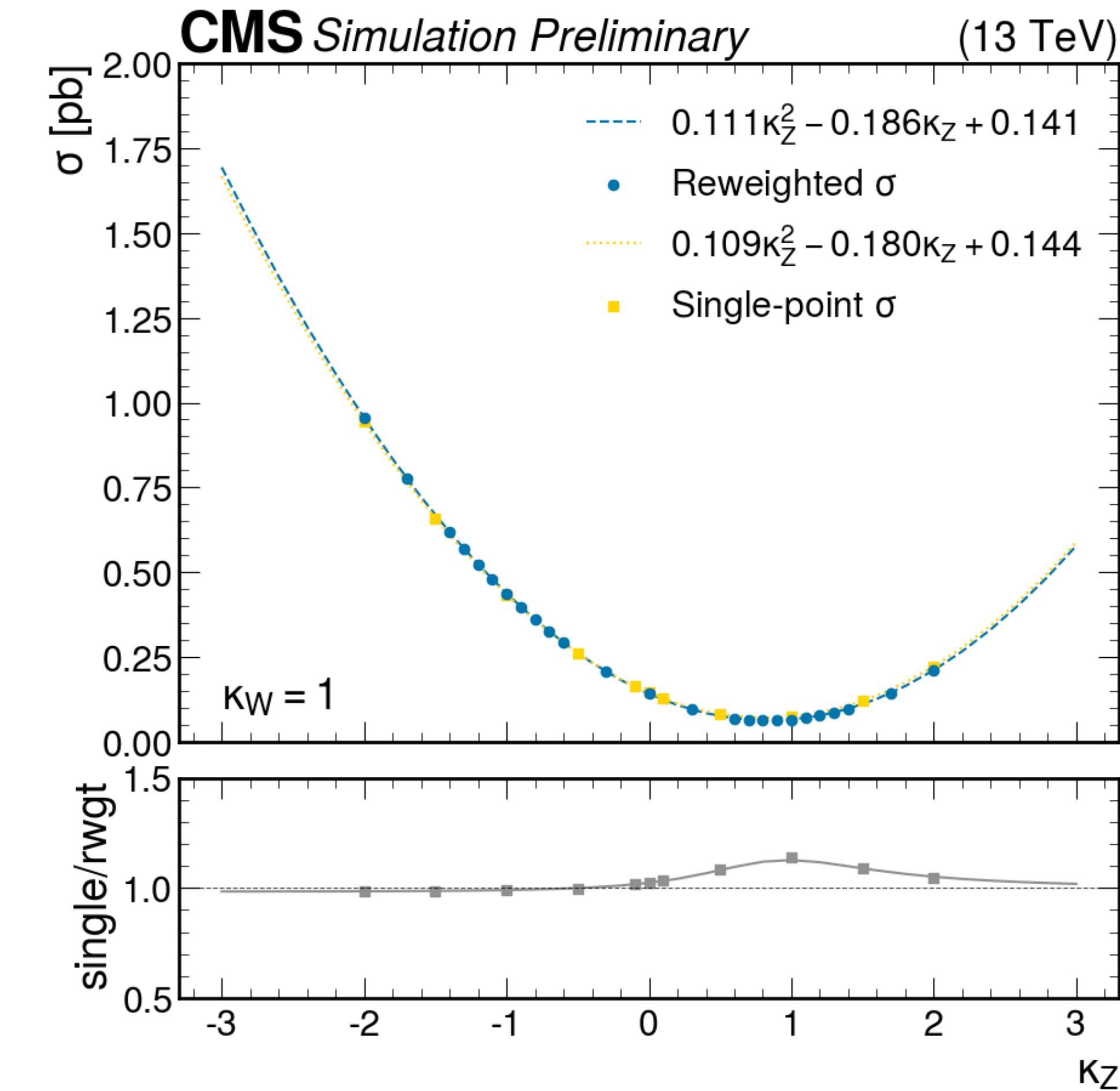
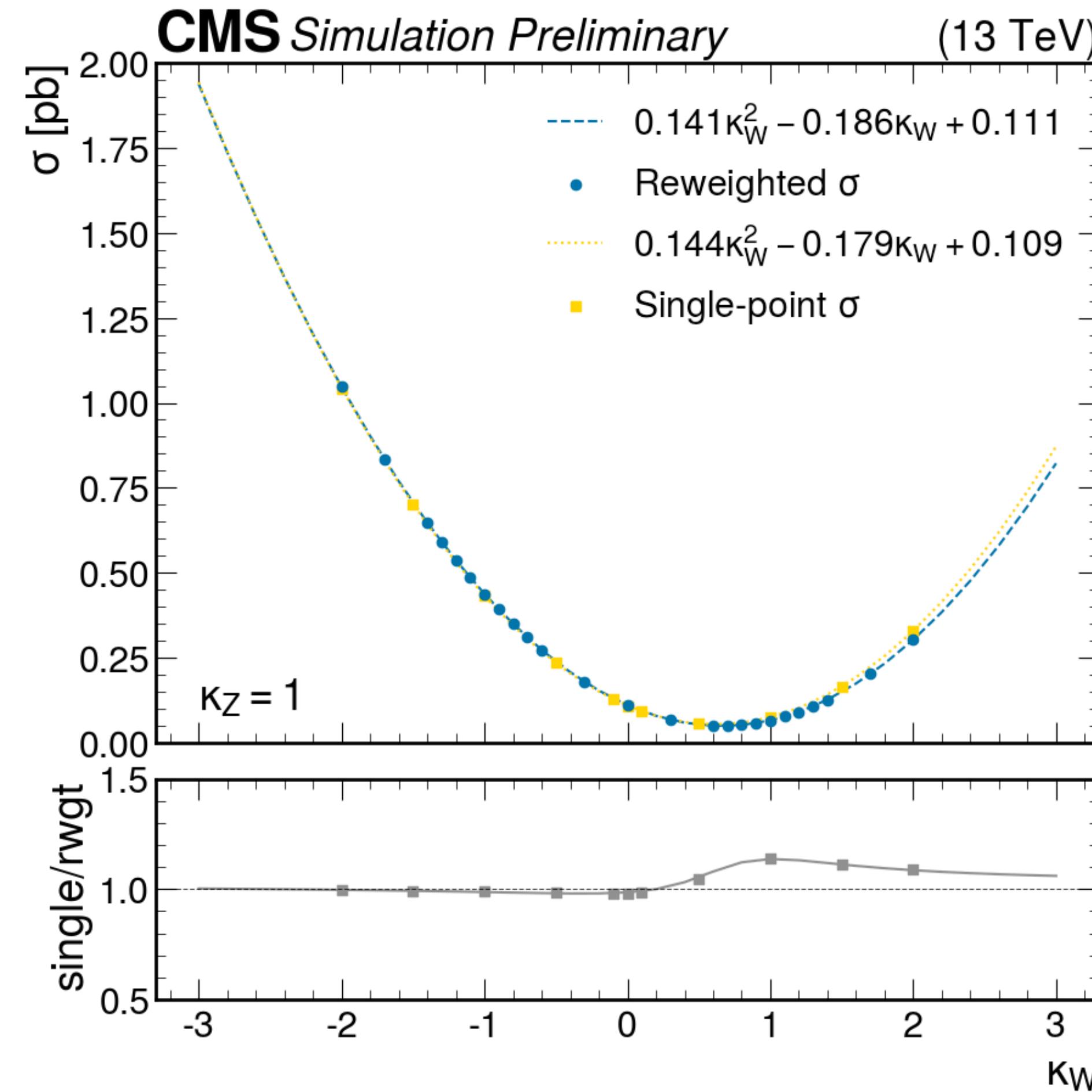


# $\lambda_{WZ}$ Scan

- Generated two signal samples:
  - $\lambda_{WZ} \leq 0$  sample
    - Reweighted around  $(\kappa_W = -1, \kappa_Z = +1)$
  - $\lambda_{WZ} > 0$  sample
    - Reweighted around  $(\kappa_W = +1, \kappa_Z = +1)$
- Used PKU reweighting model
- Full Run 2 samples
- 100k events per NanoAODv9 “year”



# New Signal Samples: Validation



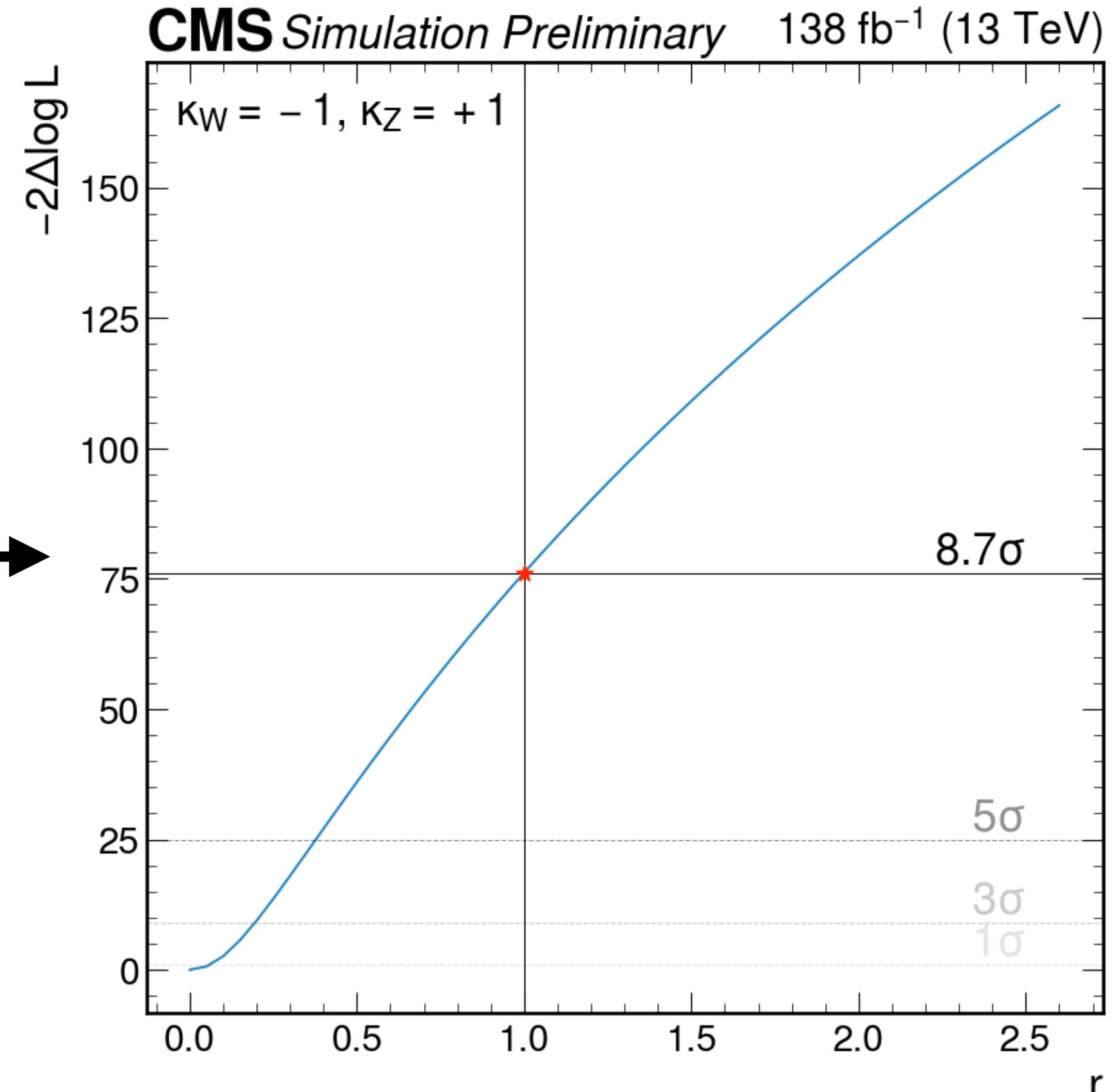
# HiggsCombine Settings

```
imax 1 number of channels
jmax 1 number of backgrounds
kmax 19 number of nuisance parameters
-----
bin observation bin1 128
bin process VBSWH_mKW bin1 0 TotalBkg 1
process rate 413.34 127.92
-----
abcd_syst lnN - 1.084
abcd_stat lnN - 1.133
pdf_vars lnN 1.022
muF_scale lnN 1.178
isr_weights lnN 1.001
fsr_weights lnN 1.015
pu_rwgt lnN 1.002
L1_prefire lnN 1.010
hlt_sfs lnN 1.008
mc_stat lnN 1.022
lep_id lnN 1.015
elec_reco lnN 1.003
muon_iso lnN 1.000
xbb_sfs lnN 1.057
btag_sfs lnN 1.003
met_unc lnN 1.003
jes lnN 1.066
jer lnN 1.008
lumi lnN 1.025
```

scan\_kW\_X\_kZ\_Y.dat

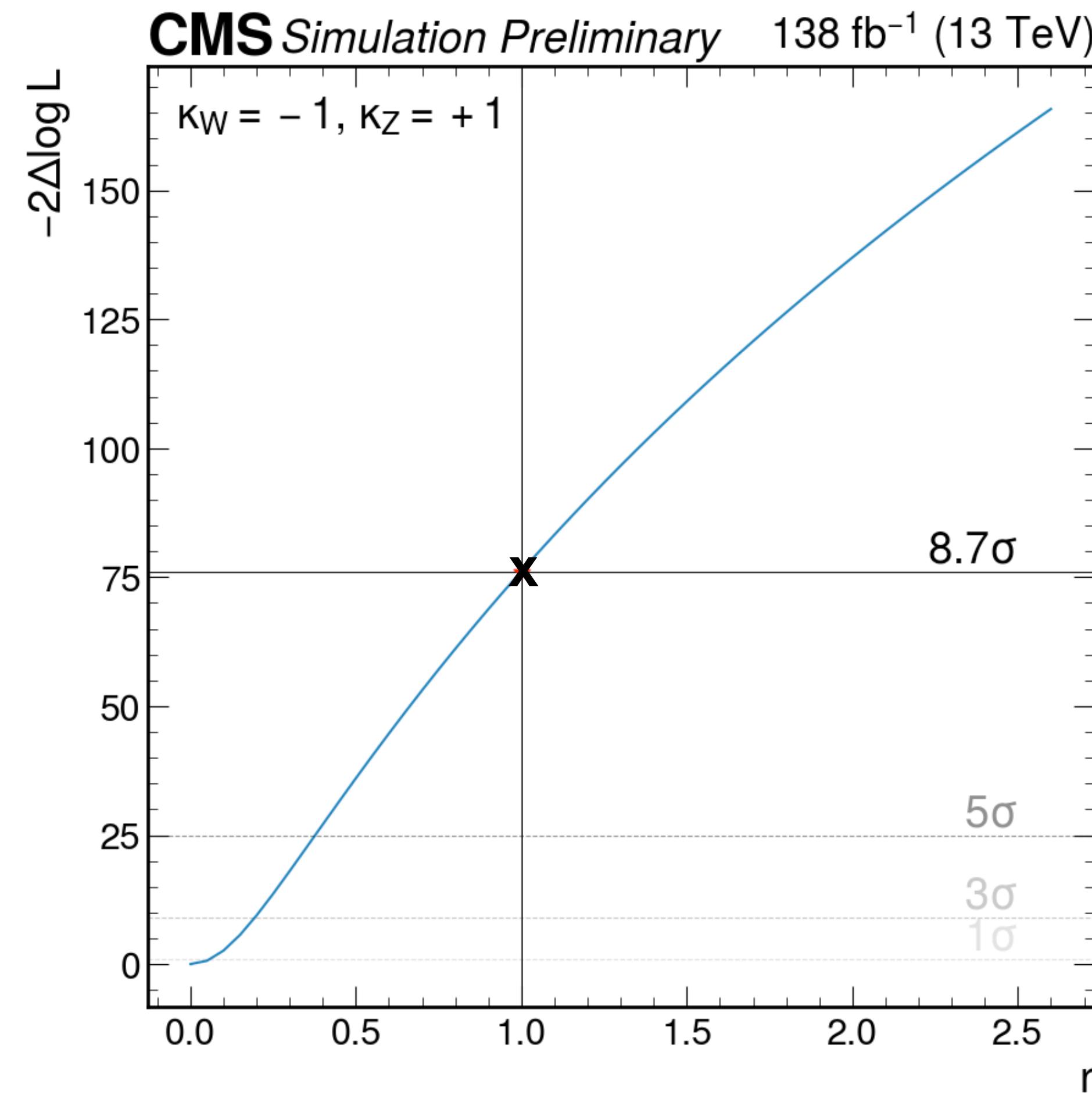


```
combine -M MultiDimFit -d scan_kW_X_kZ_Y.root
-m 125 -t -1
--expectSignal=0
--setParameterRanges r_VBSWH_mKW=0.0,2.0
--saveNLL
--algo grid
--points 101
--rMin 0 --rMax 5
--alignEdges 1
```

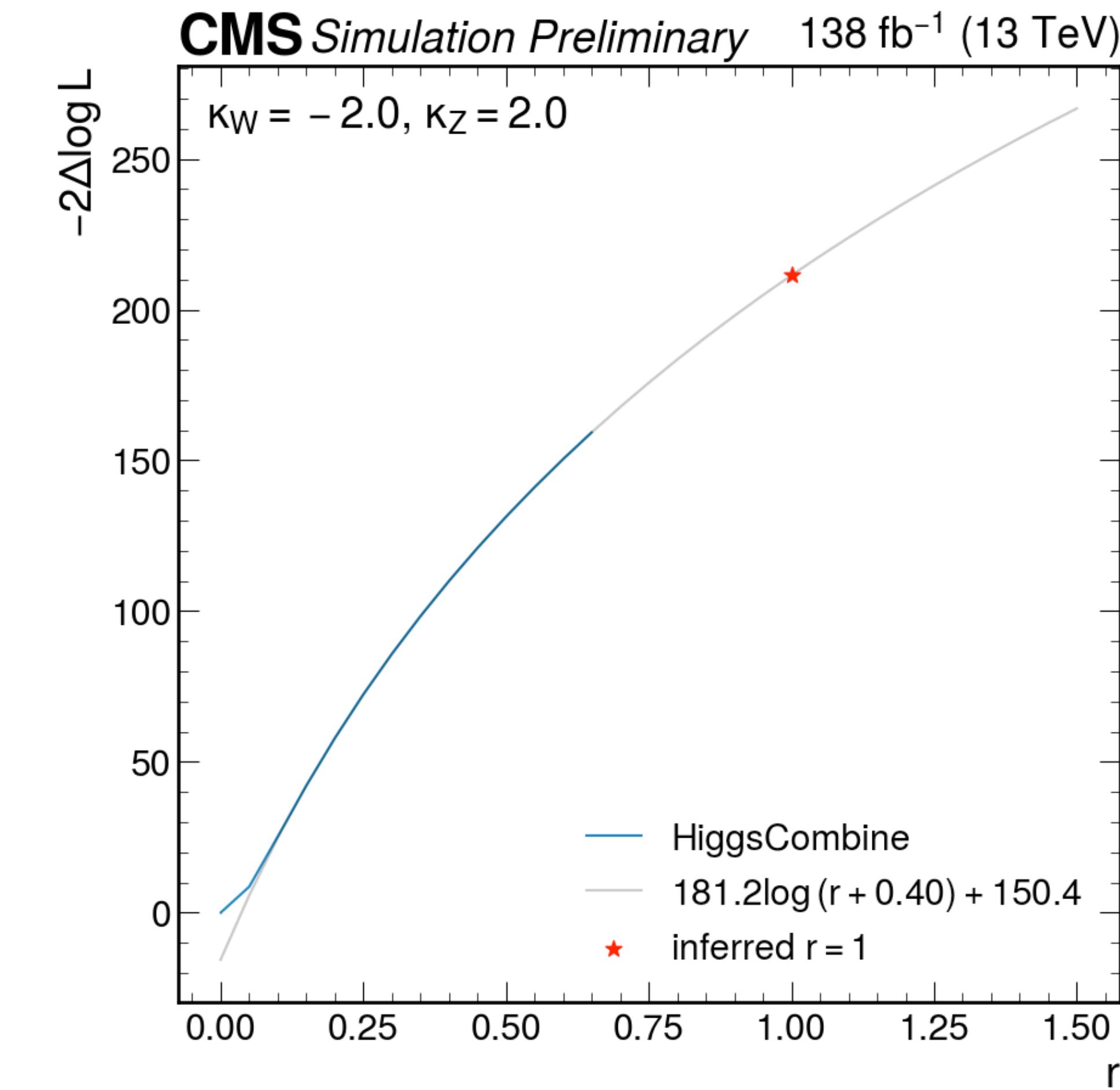


Repeat for each point  $K_W = X, K_Z = Y$

# Extrapolated Points



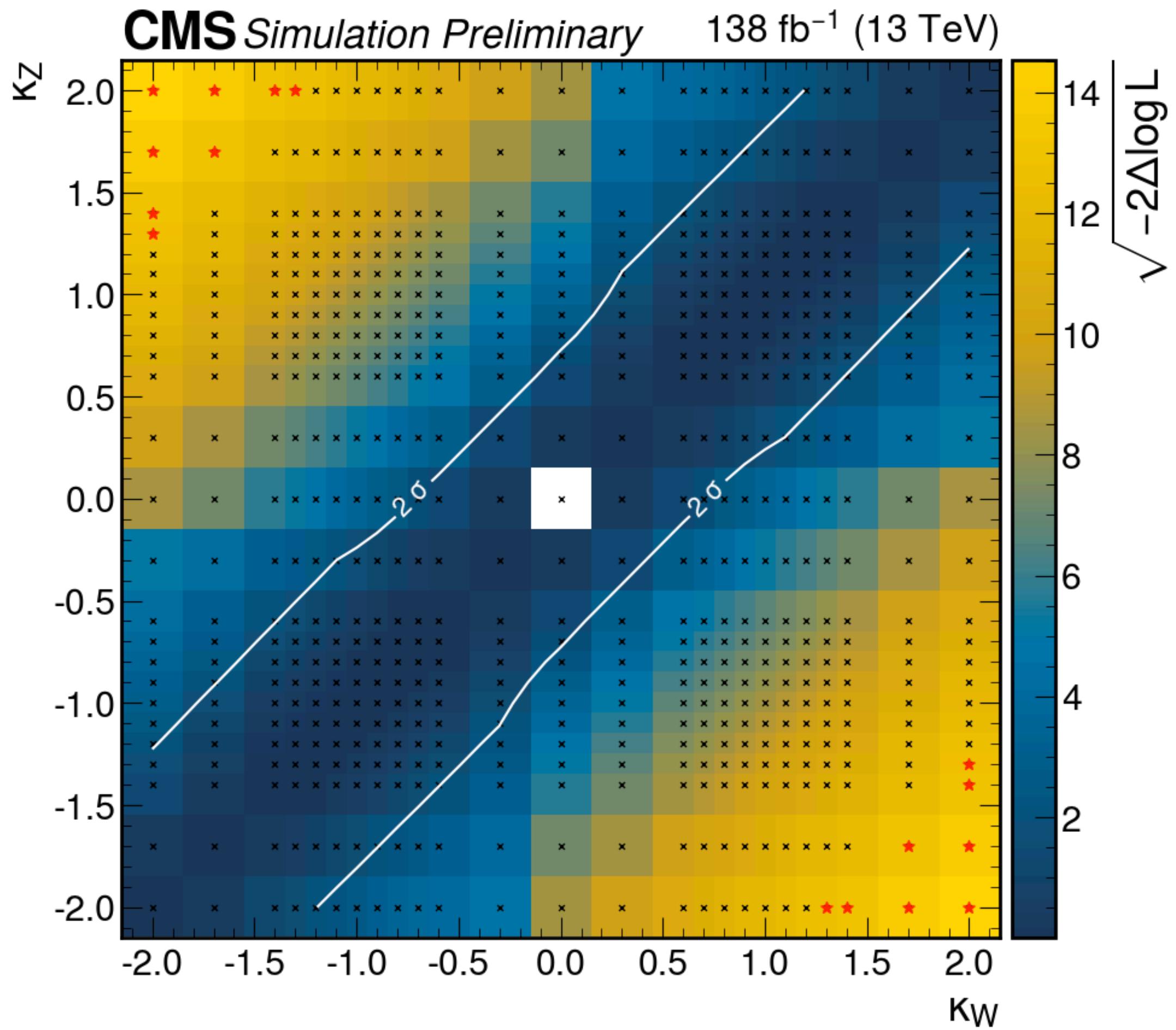
Take  $\sigma$  exclusion of  $r = 1$



Infer  $\sigma$  exclusion of  $r = 1$

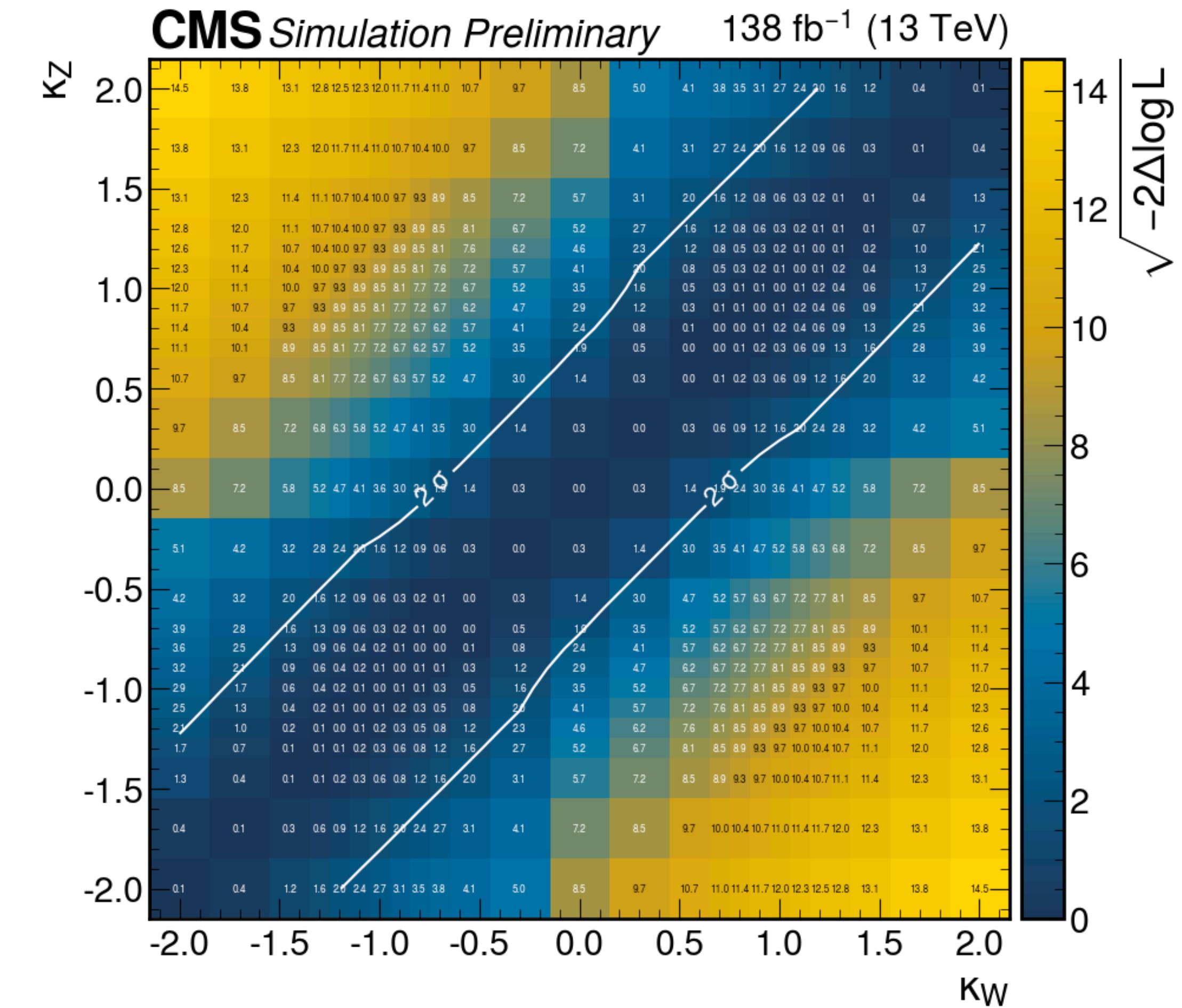
# Collected Results

- Bins centered on scanned  $\kappa_W$ ,  $\kappa_Z$  points
- Exclusion limit plotted on z-axis
- Contour roughly shows  $\sigma = 2$  boundary
  - Simplistically derived by Matplotlib
- Black x's taken directly from HiggsCombine plot
- Red  $\star$ 's inferred from plot



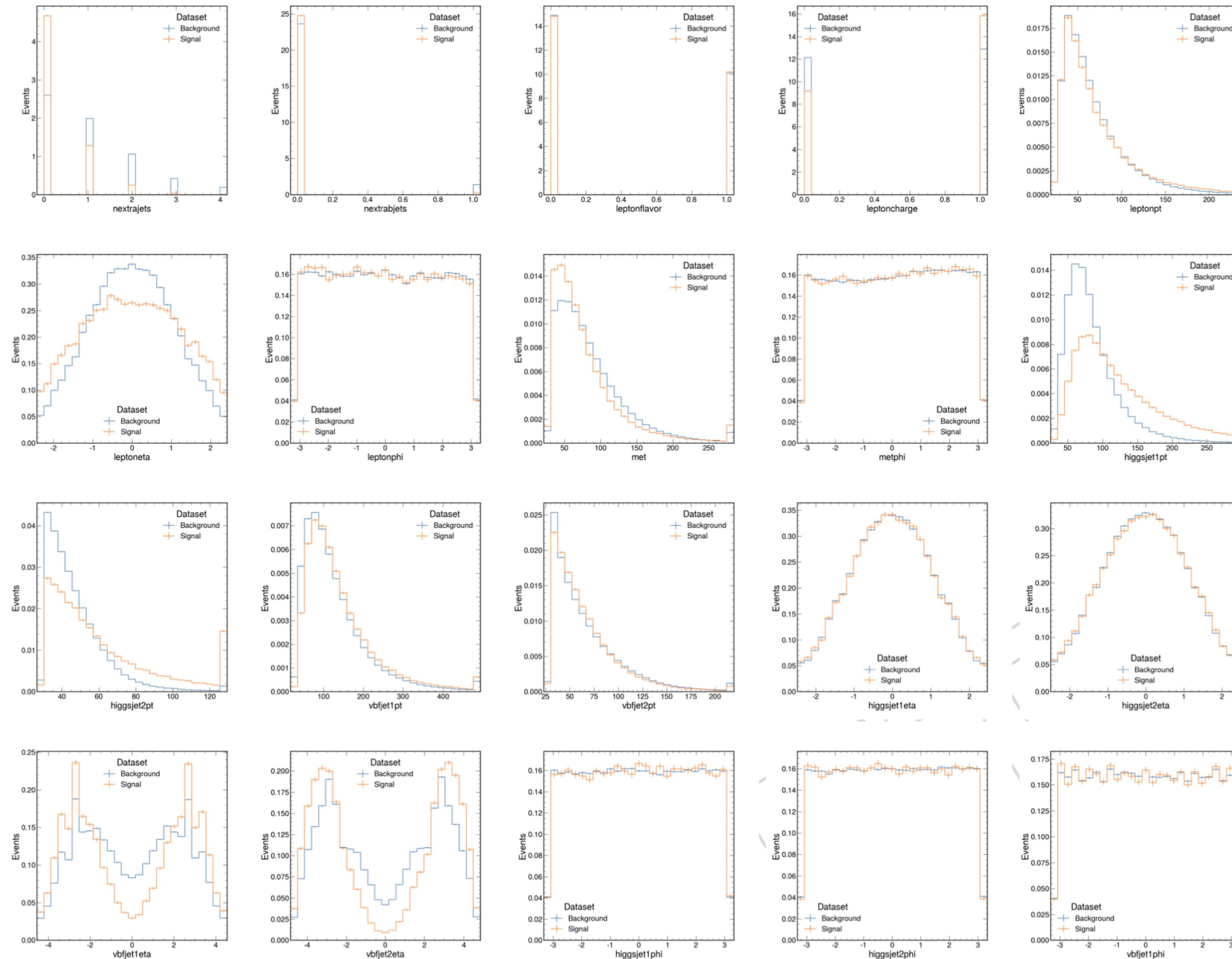
# Collected Results

- Bins centered on scanned  $\kappa_W$ ,  $\kappa_Z$  points
- Exclusion limit plotted on z-axis
- Contour roughly shows  $\sigma = 2$  boundary
  - Simplistically derived by Matplotlib
- Discontinuities do not affect contours
  - Caused by some failure in the reweighting
  - Cross sections are reweighted properly, acceptance is not
  - Smoothed out via interpolation

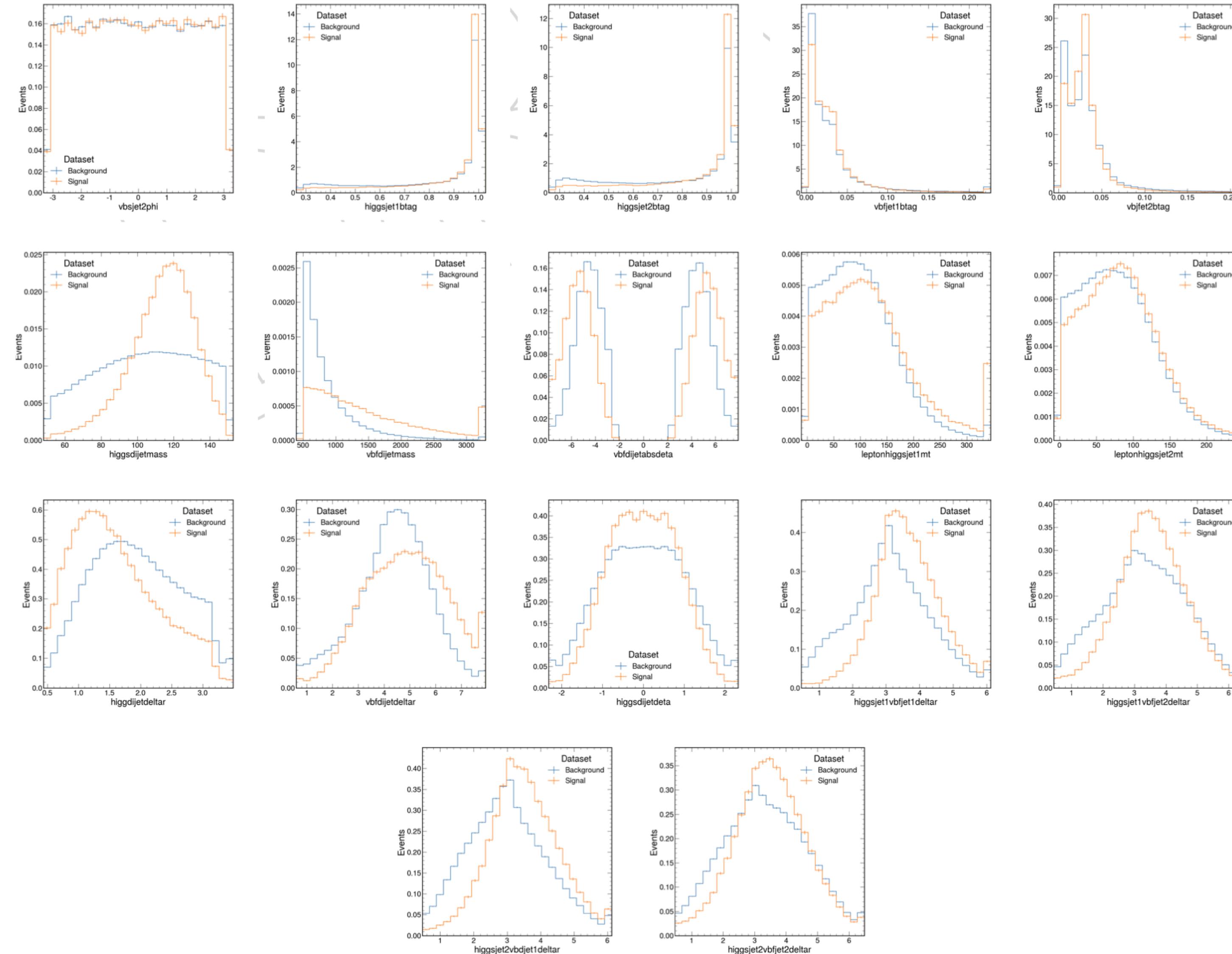


# Backup (resolved)

# BDT Input Variables



# BDT Input Variables (cont.)



# BDT Training

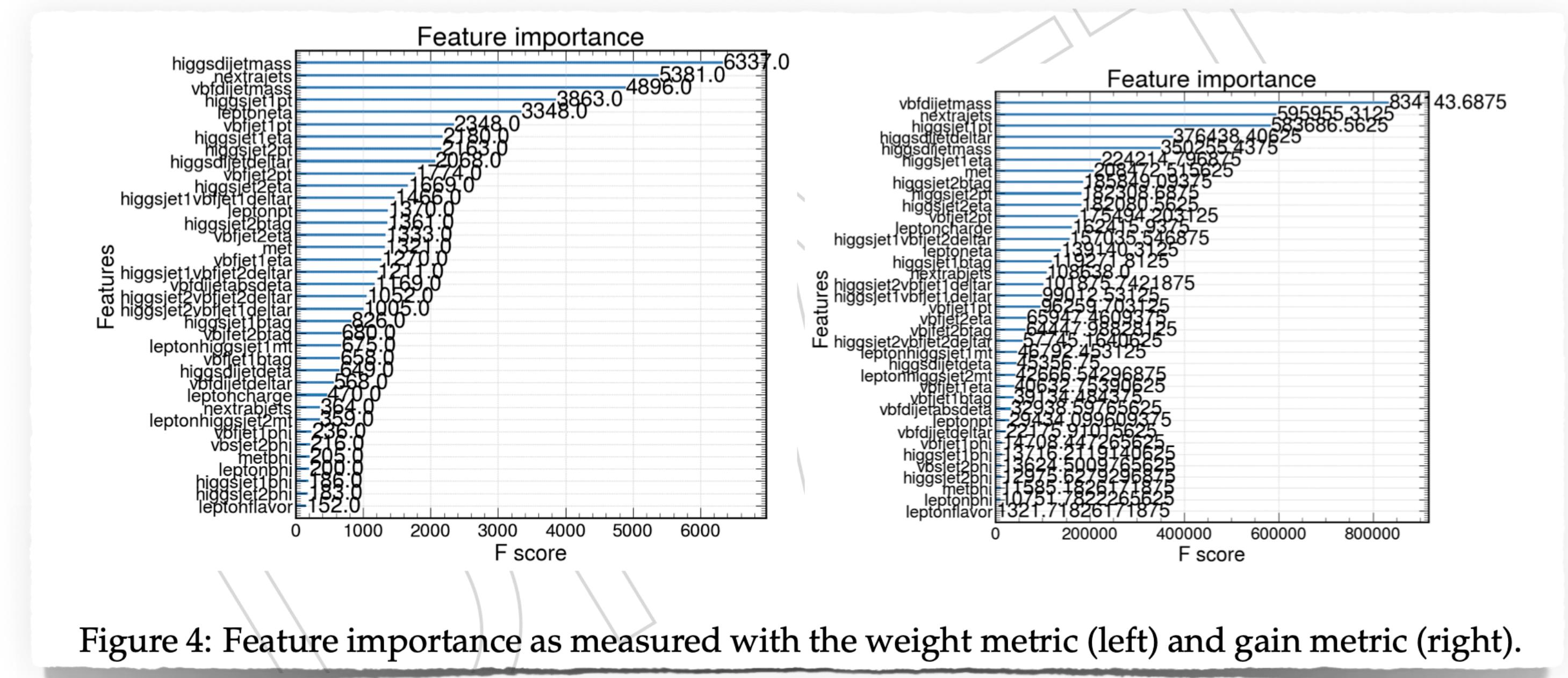


Figure 4: Feature importance as measured with the weight metric (left) and gain metric (right).

**Weight metric:** the number of times that feature is used to split the data

**Gain metric:** the average increase in the objective function for all splits based on that feature

- Used 90/10 train/test split
- Set weights =  $\text{abs}(\text{weights})$ , but affects < 1% of events

## BDT settings

Learning Rate	0.01
Max Depth	6
Early stopping rounds	1