

$B^0 \rightarrow \pi^0 \pi^0$  analysis

Sebastiano

# Overview

$BF$  and  $A_{CP}$  of  $B^0 \rightarrow \pi^0\pi^0$  decays: fundamental measurements at Belle II.

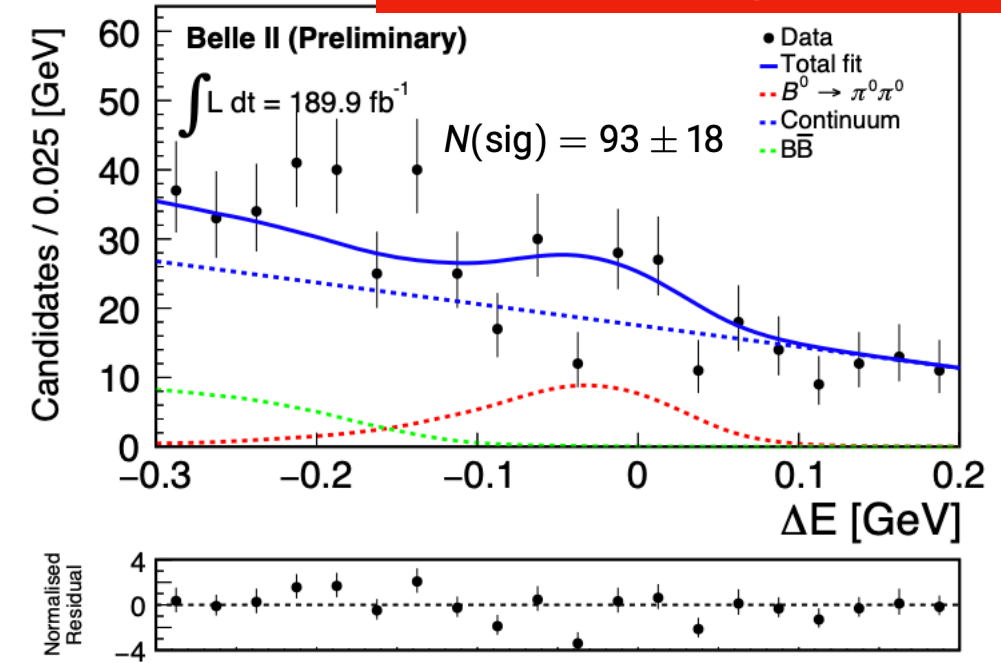
Results (@189.9fb<sup>-1</sup>) by Francis shown at ICHEP2022.

Now: prepare new analysis for pre-LS1 dataset.

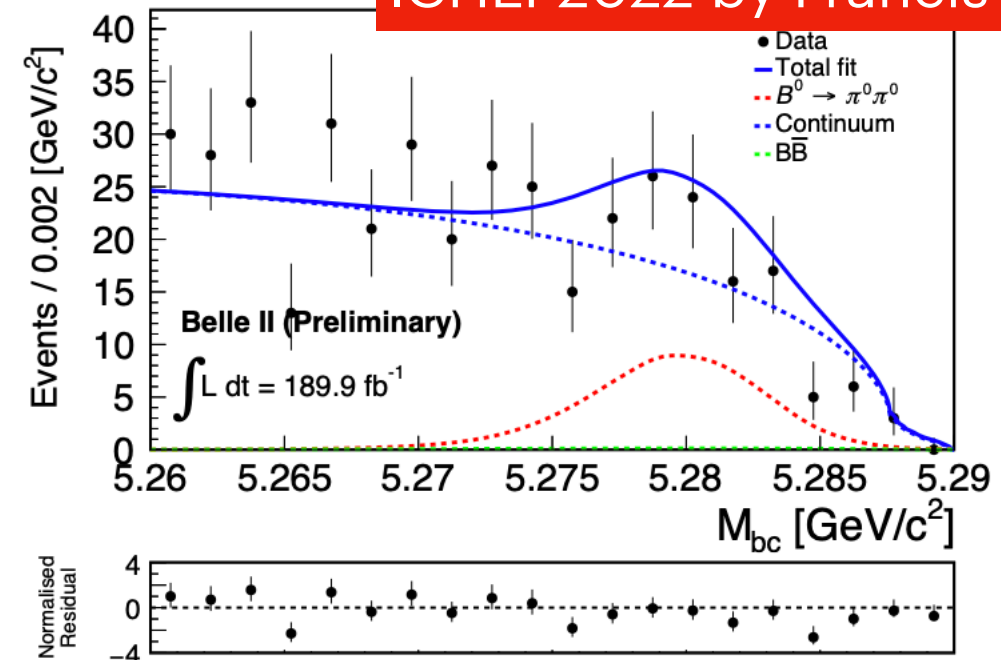
Plan:

- revisit photonMVA looking at variables with good data/MC agreement
- revisit CSBDT adding BTag variables to suppress even more  $e^+e^- \rightarrow q\bar{q}$
- Introduce specific BDT trained against continuum  $\rho$ 's

ICHEP2022 by Francis



ICHEP2022 by Francis



$$A^{CP} = -0.14 \pm 0.46 \text{ (stat.)} \pm 0.07 \text{ (syst.)}$$

$$B = (1.27 \pm 0.25 \text{ (stat.)} \pm 0.17 \text{ (syst.)}) \cdot 10^{-6}$$

# Photon MVA

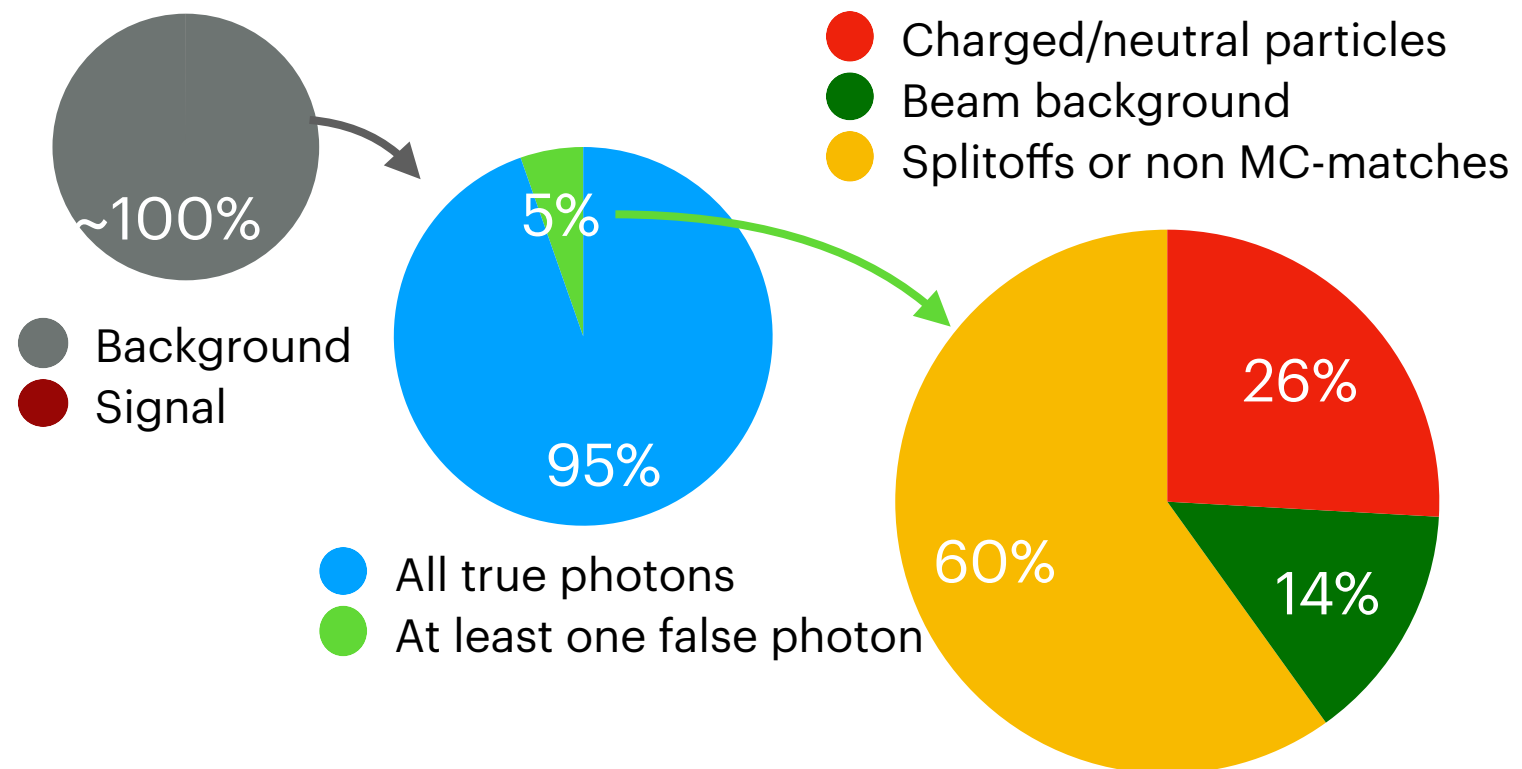
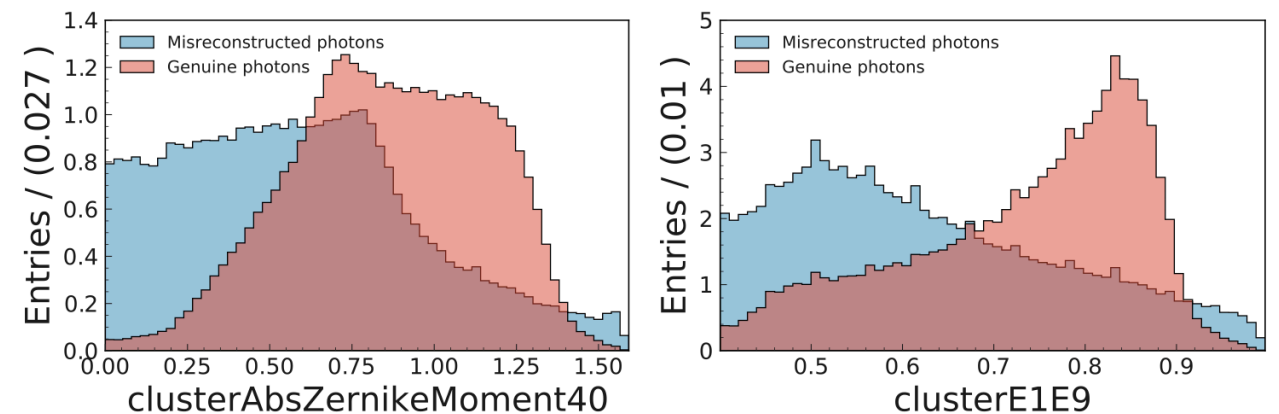
# Photon MVA

Distinguish between real photons and “false” photons: beam backgrounds, other particles, energy releases from other particles (split-offs)....

Combine highly-discriminant cluster- and photon-variables in a MVA.

False photons have usually low energies, while  $B^0 \rightarrow \pi^0\pi^0$  photons high-energy.

After the default selection on photons and  $\pi^0$ 's, the residual bkg is mainly composed by true combinatorial  $\pi^0$ 's.





# Photon MVA: inputs validation

Ideally we need a sample of true photons and a sample of false photons (difficult to obtain).

Use **inclusive sample of photons from  $D^* \rightarrow D^0(K\pi\pi^0)\pi$  decays**: apply same  $\pi^0$  selections of my analysis  $\rightarrow$  same  $\pi^0$  kinematic distributions.

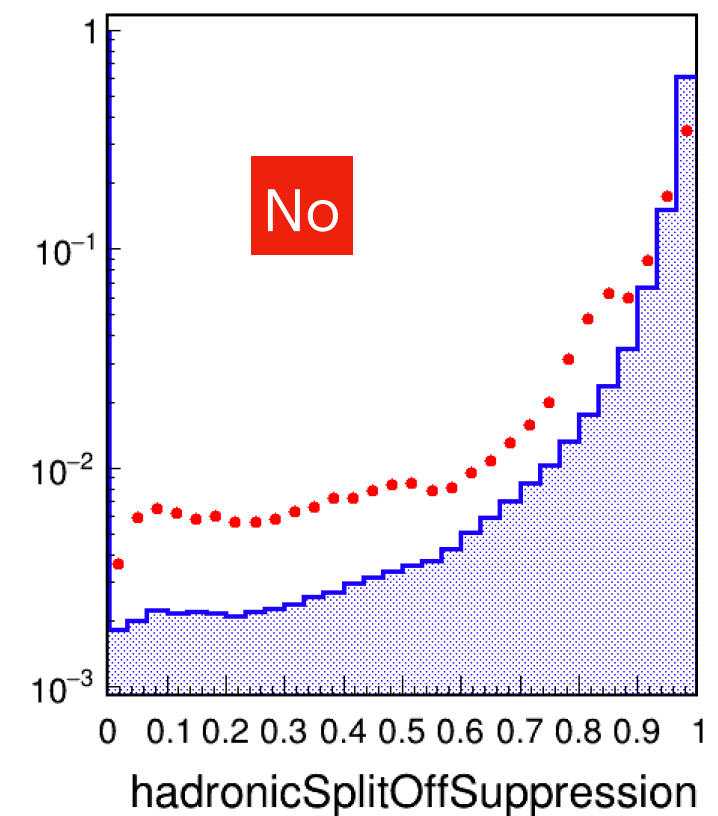
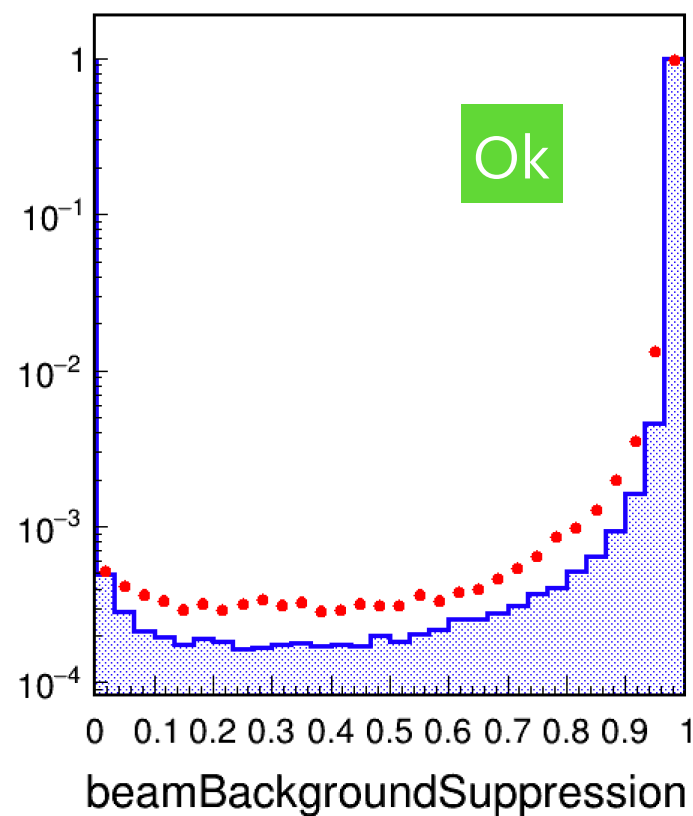
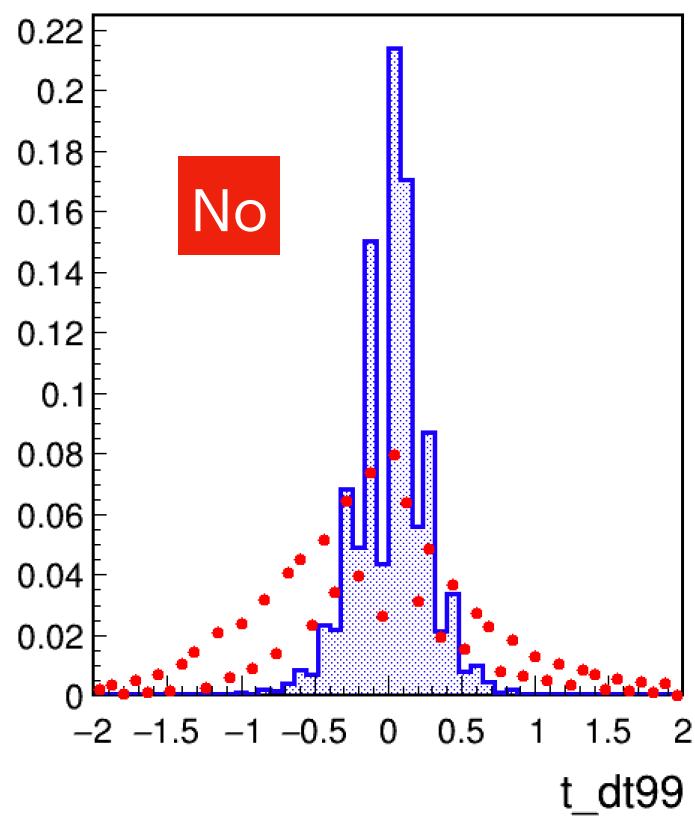
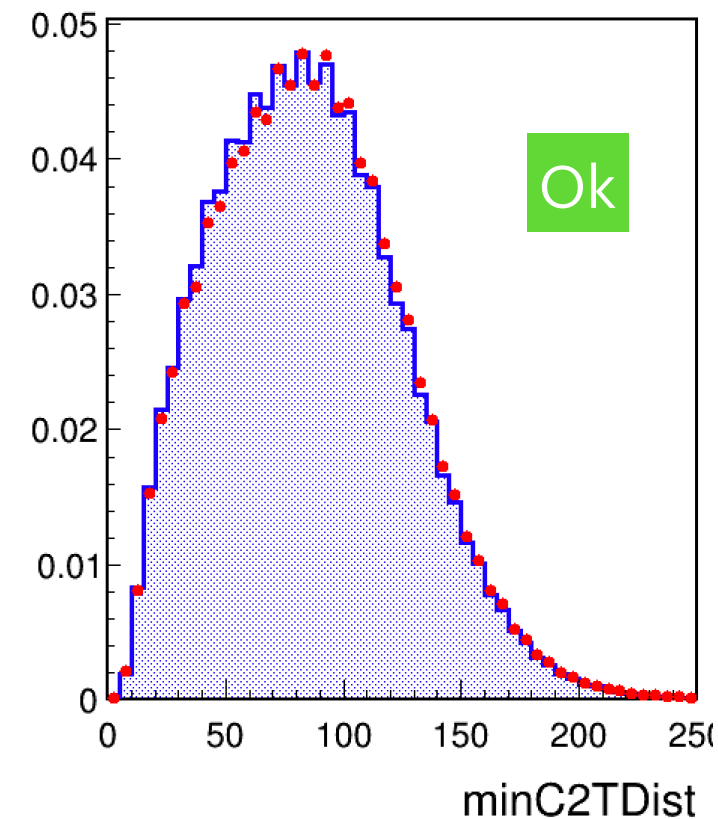
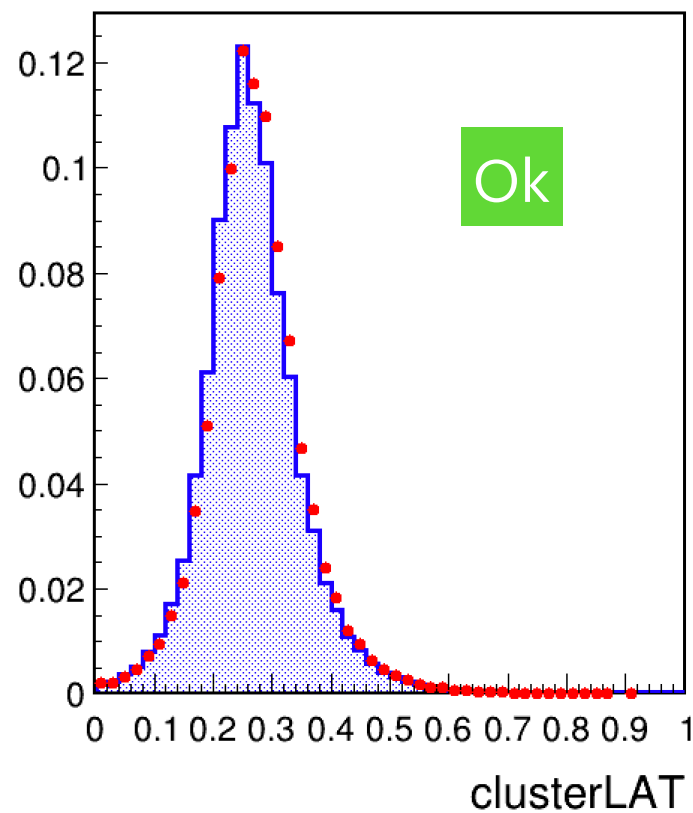
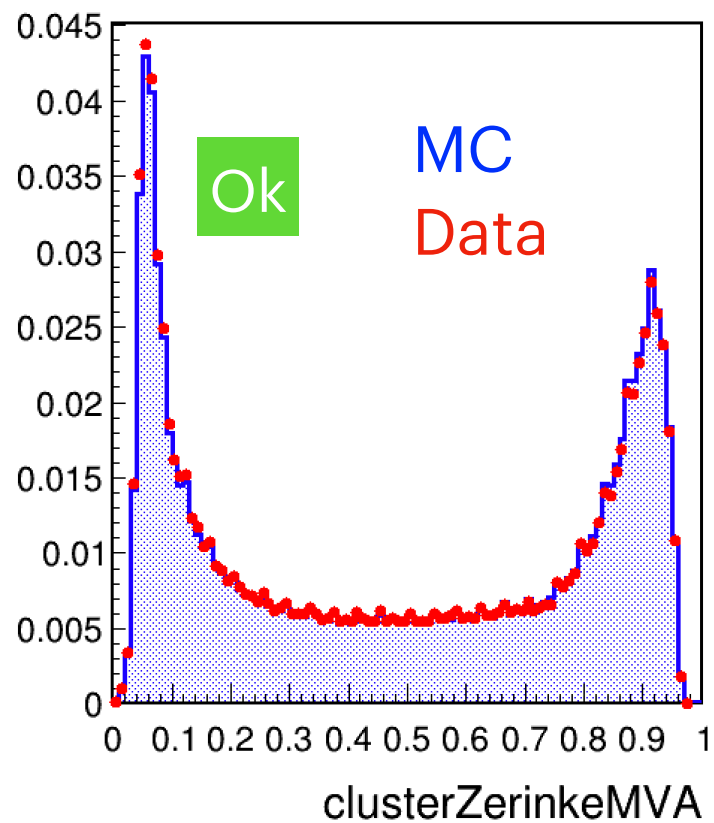
Sample is signal dominated  $\rightarrow$  ~all true photons (as in  $B^0 \rightarrow \pi^0\pi^0$ ).

Compare input distributions using MC14rd (1 ab<sup>-1</sup>)/Proc12+AllBuckets(189 fb<sup>-1</sup>) and MC15ri (200 fb<sup>-1</sup>)/Proc13c1(8 fb<sup>-1</sup>).

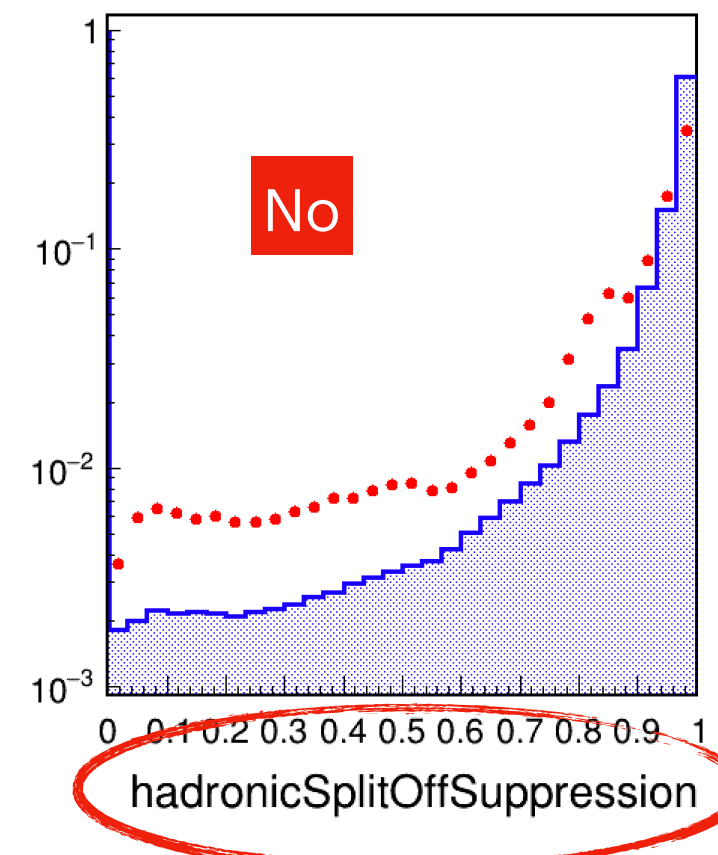
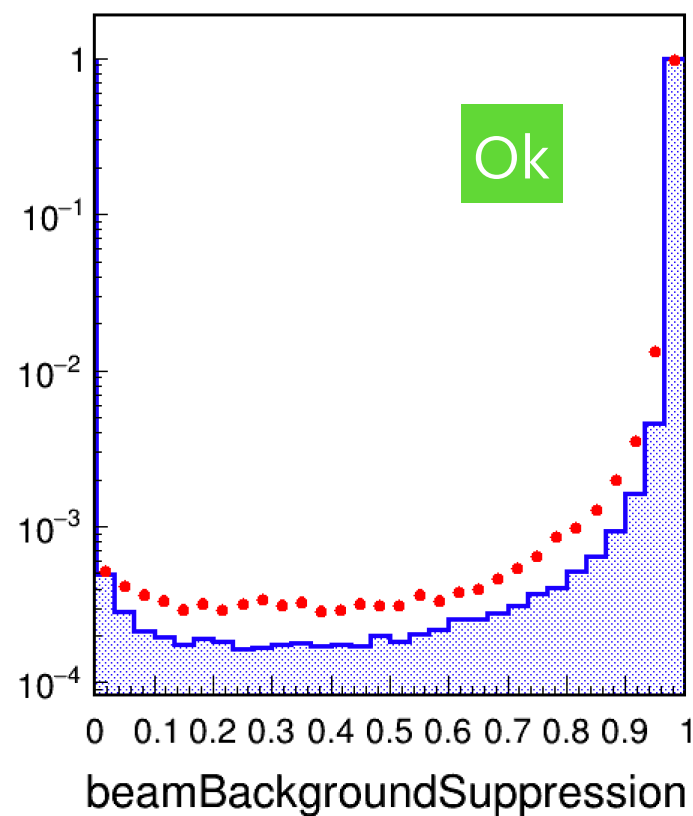
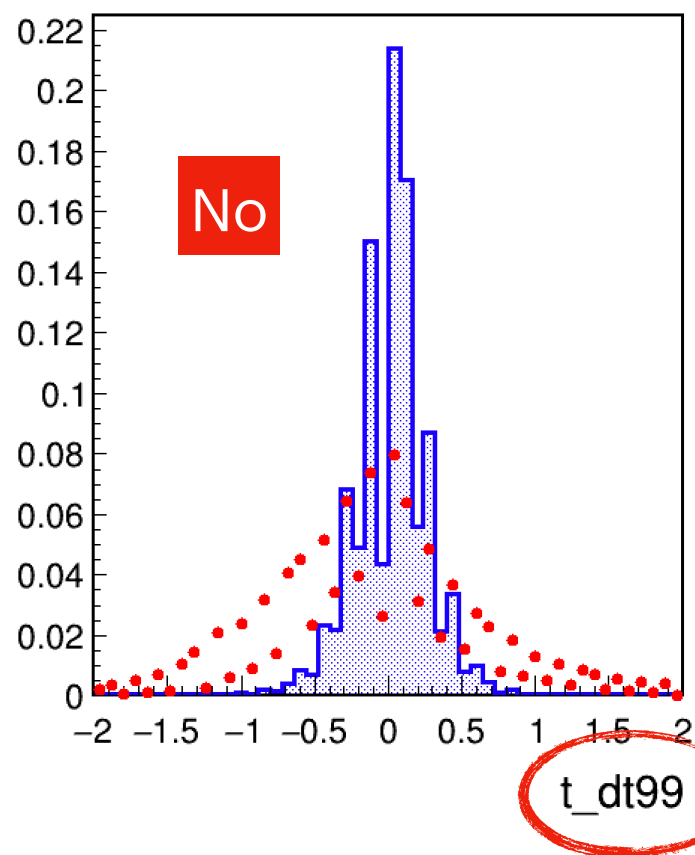
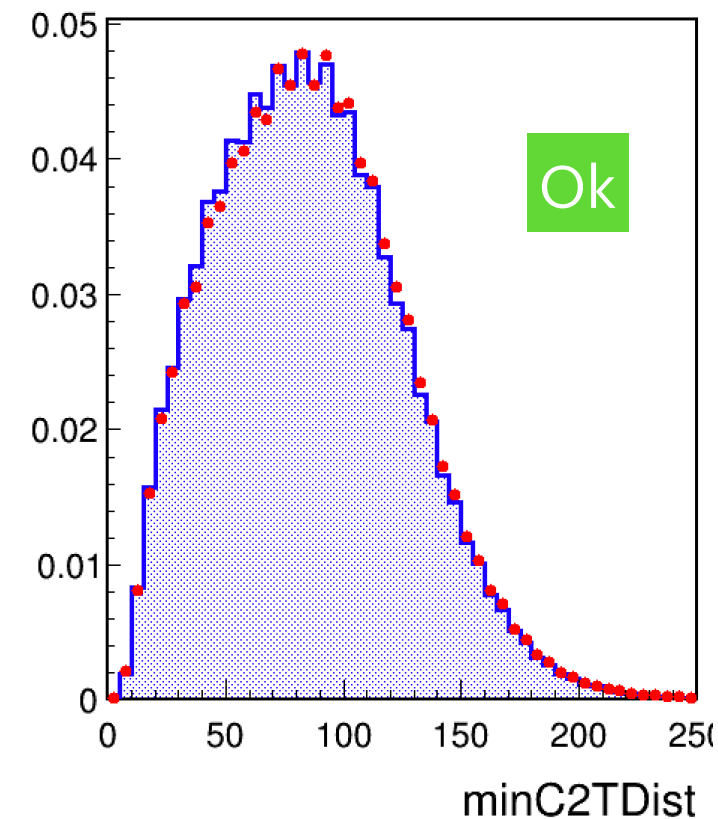
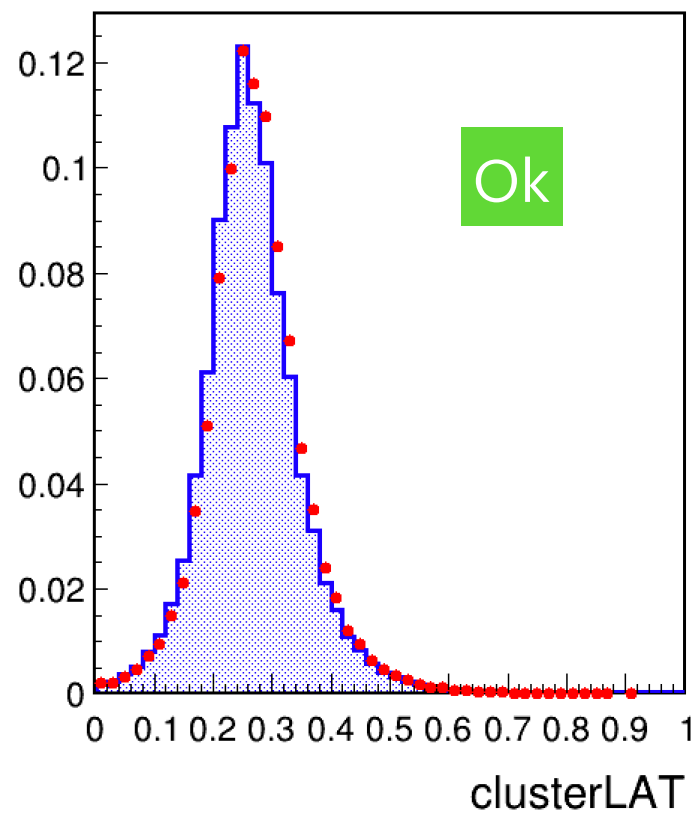
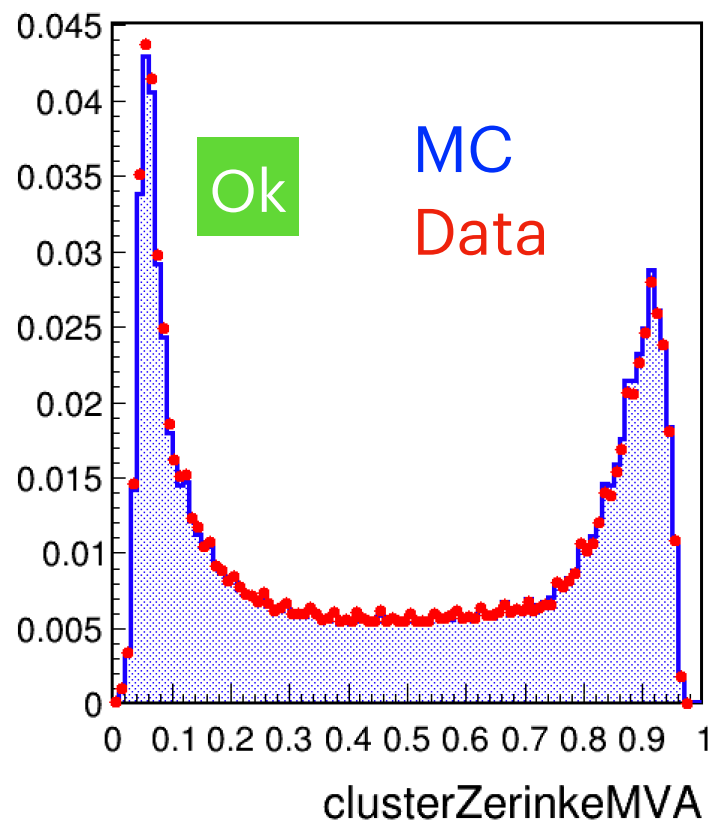
MC14 vs Proc12+AllBuckets

Release-05

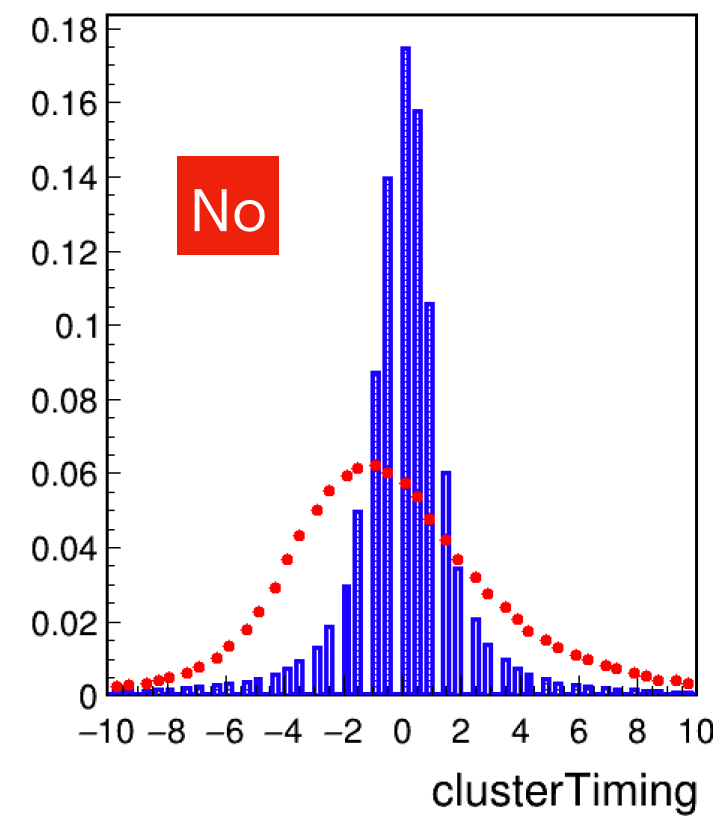
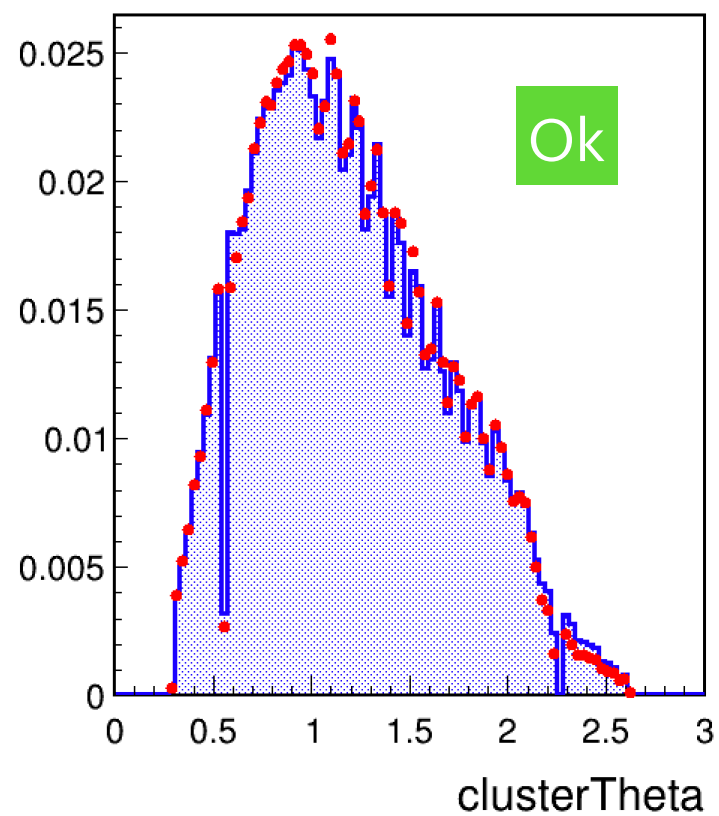
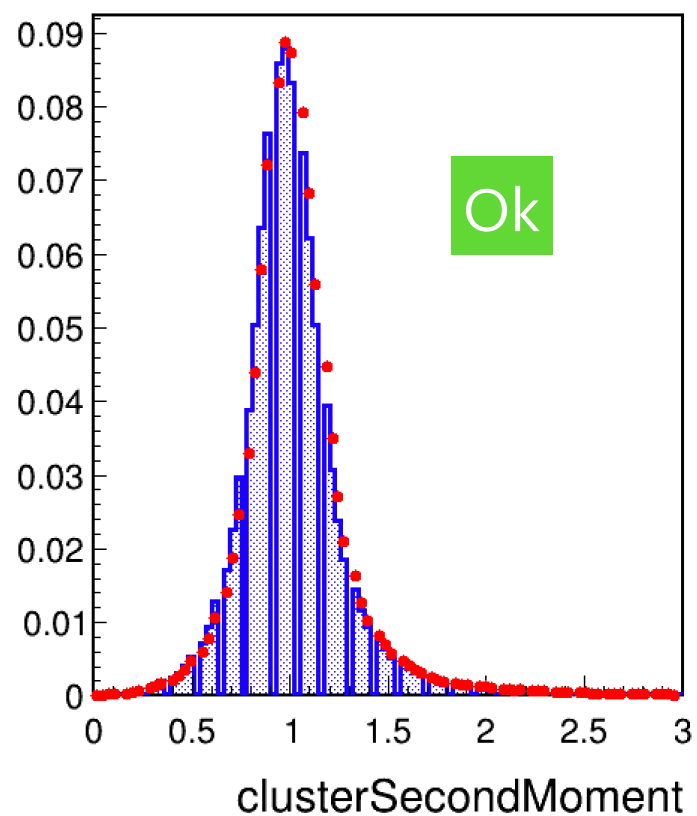
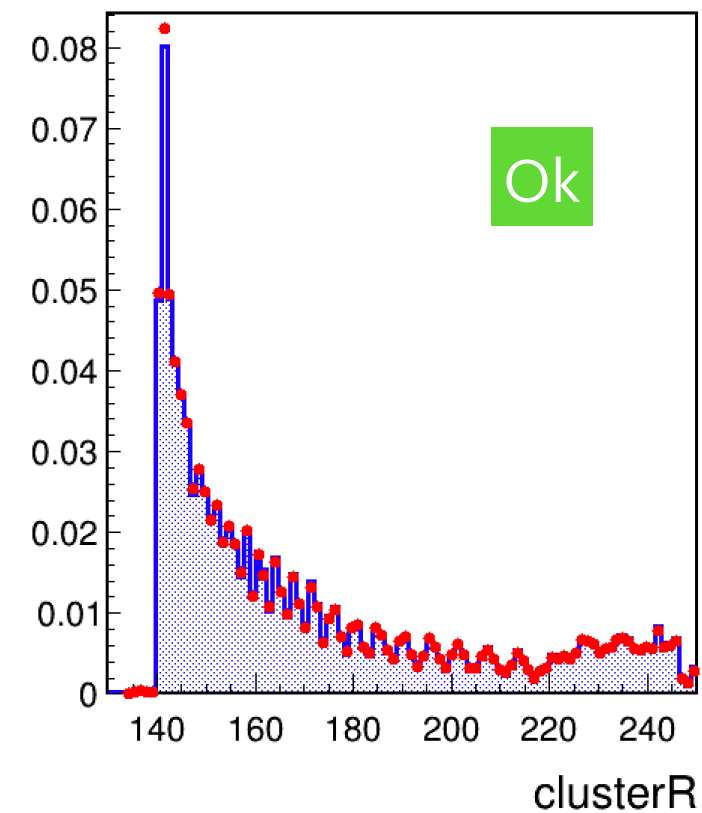
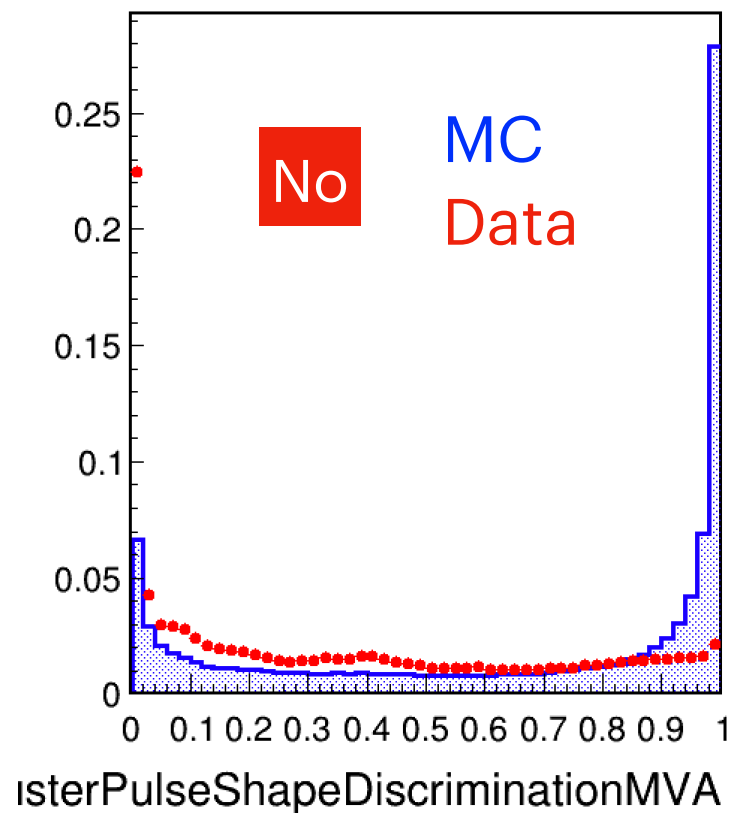
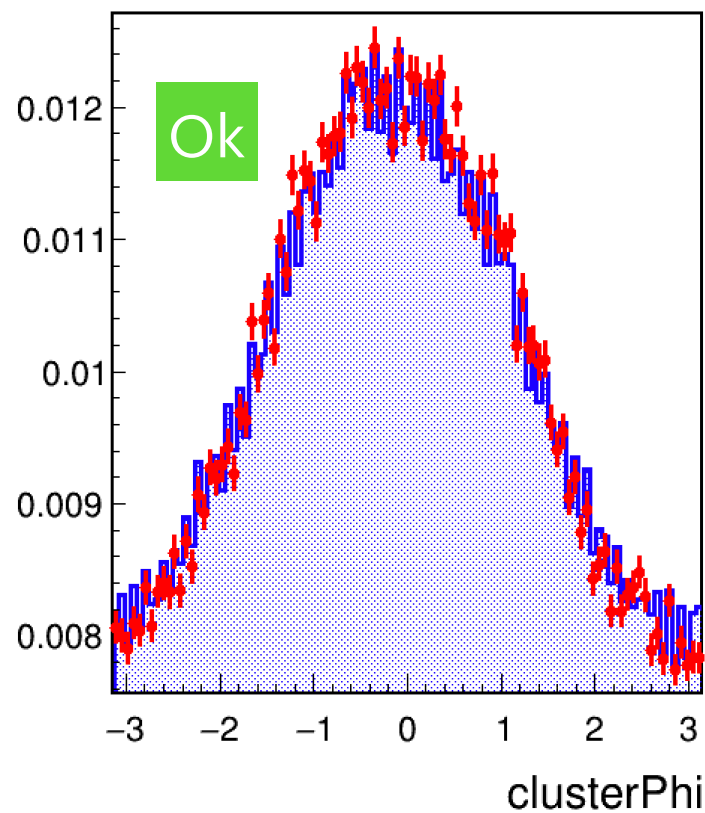
# Photon MVA: inputs validation (rel-05)



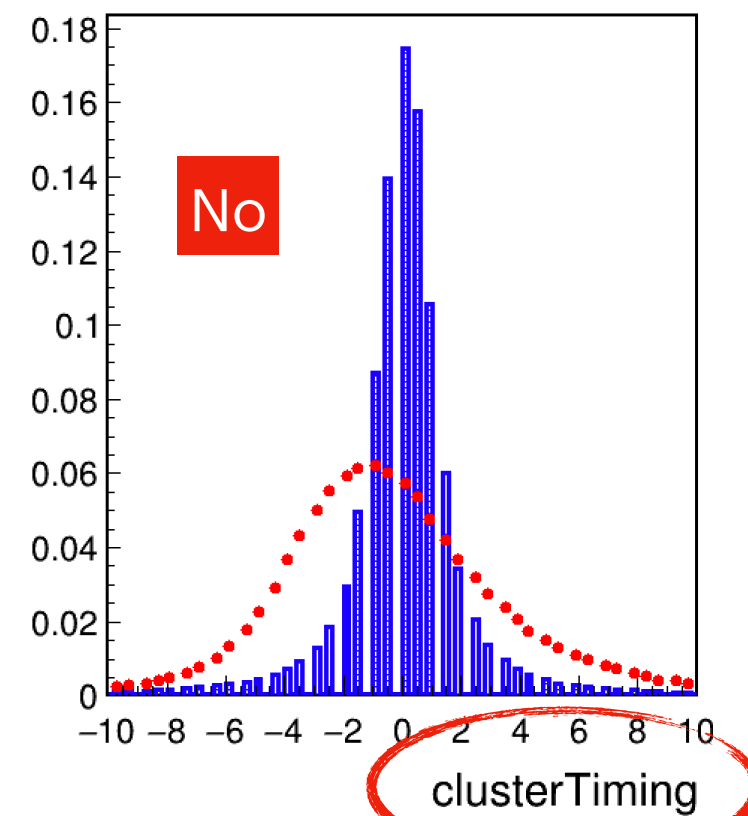
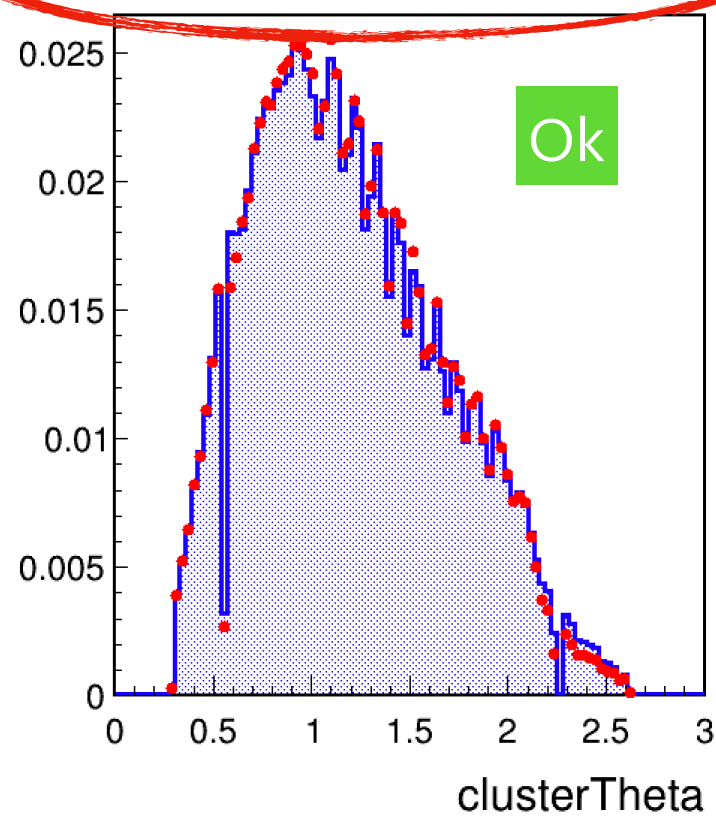
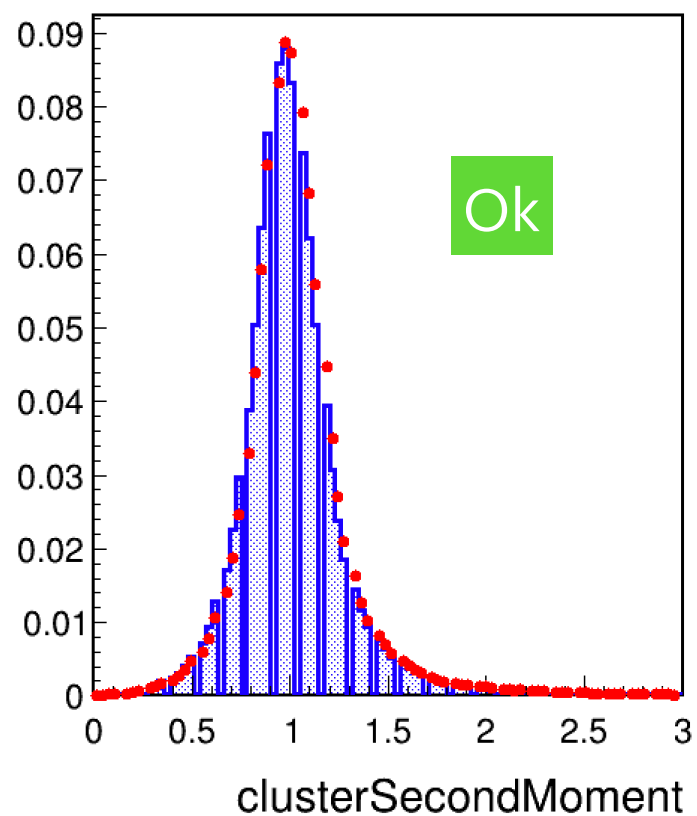
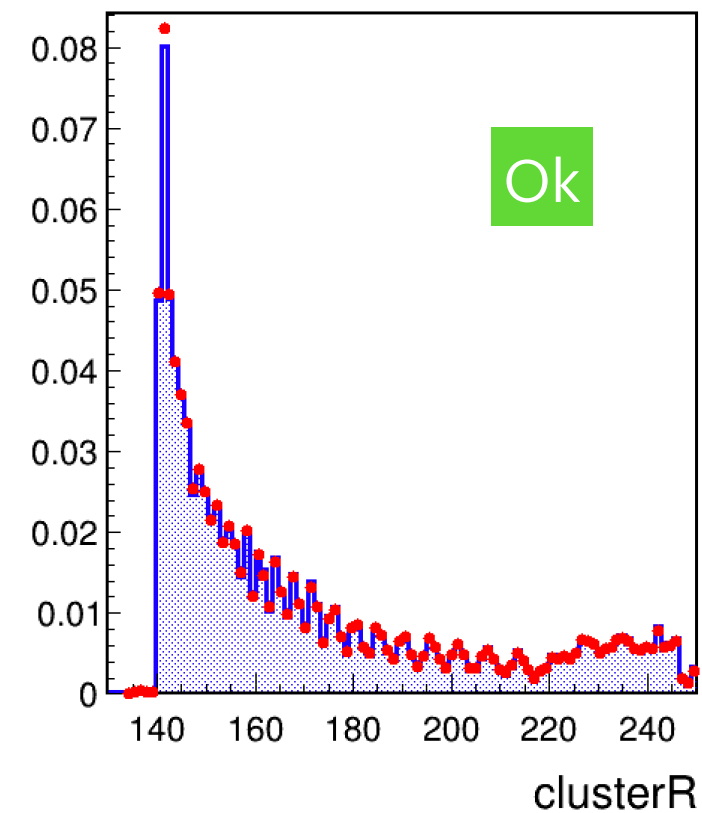
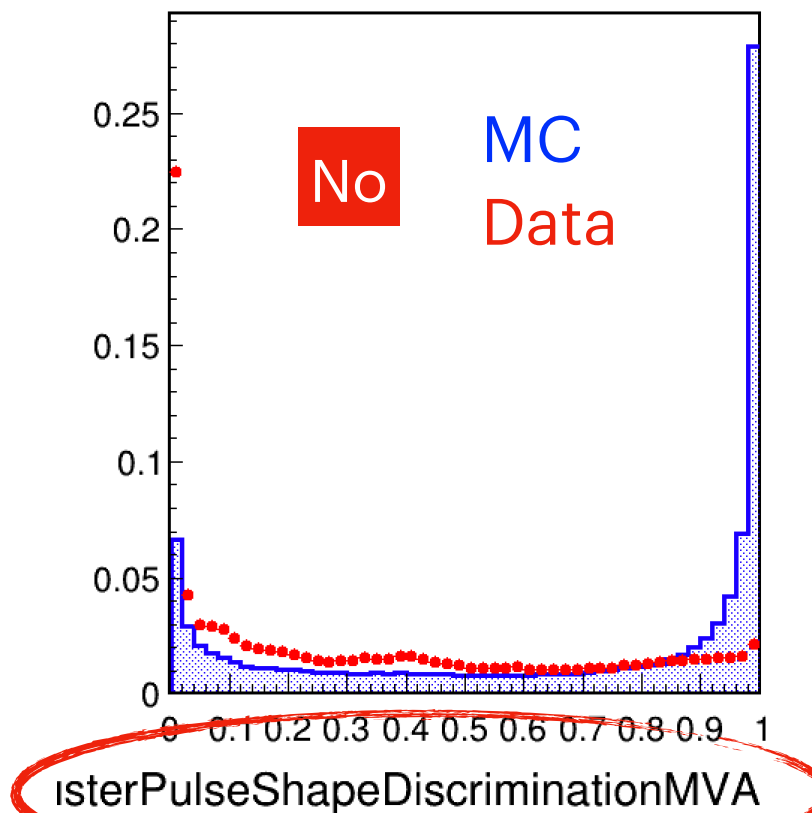
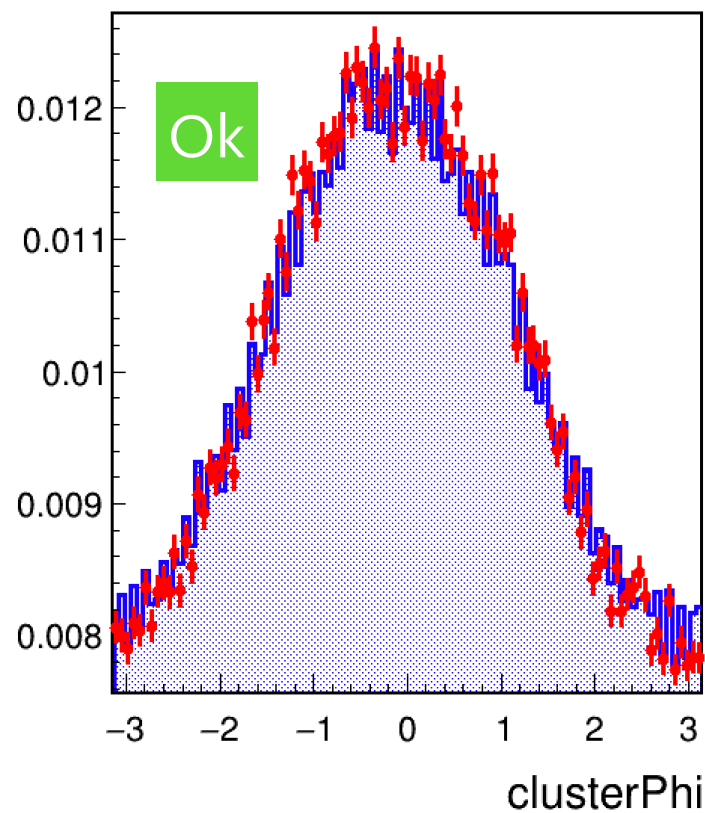
# Photon MVA: inputs validation (rel-05)



# Photon MVA: inputs validation (rel-05)

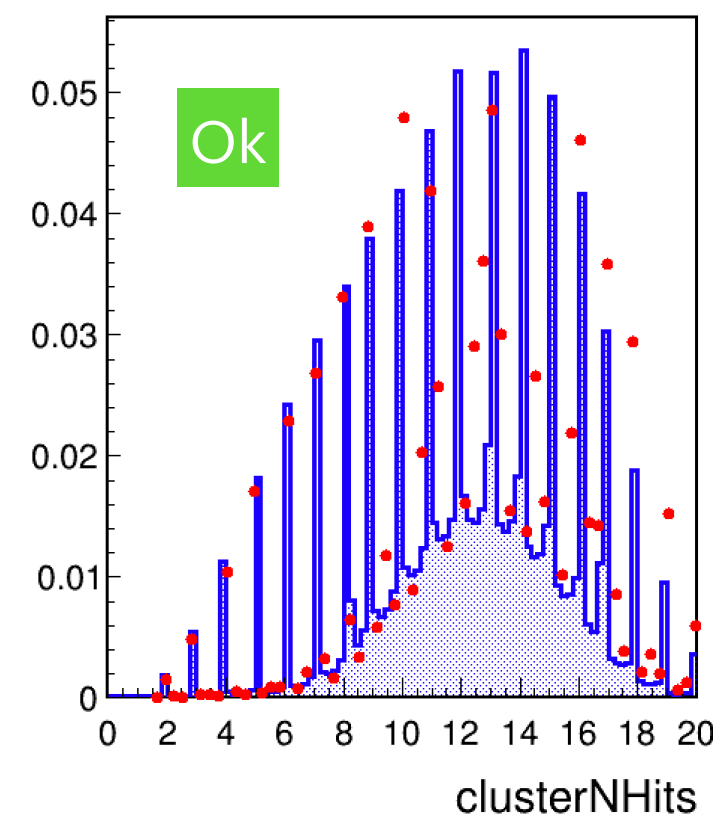
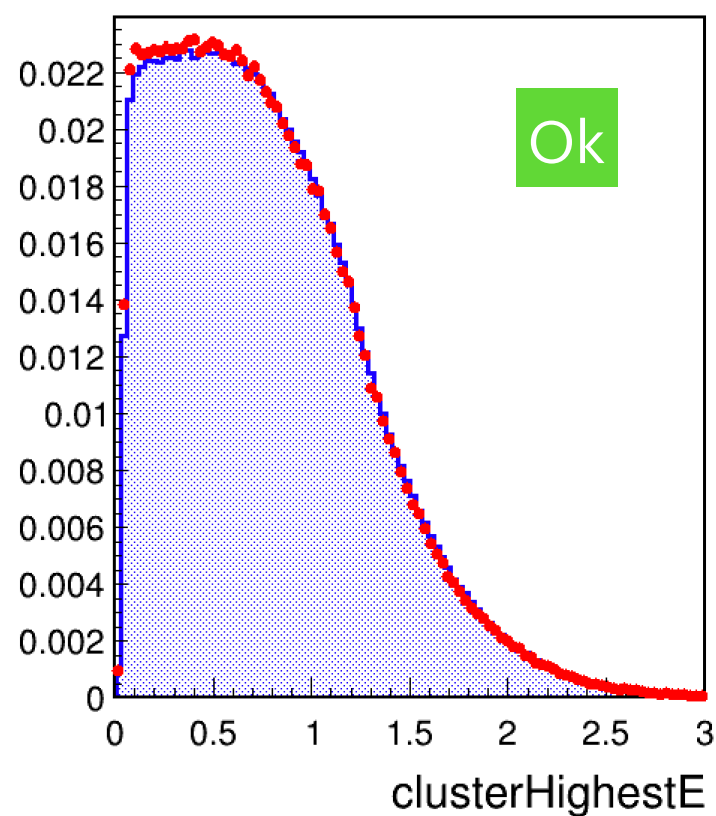
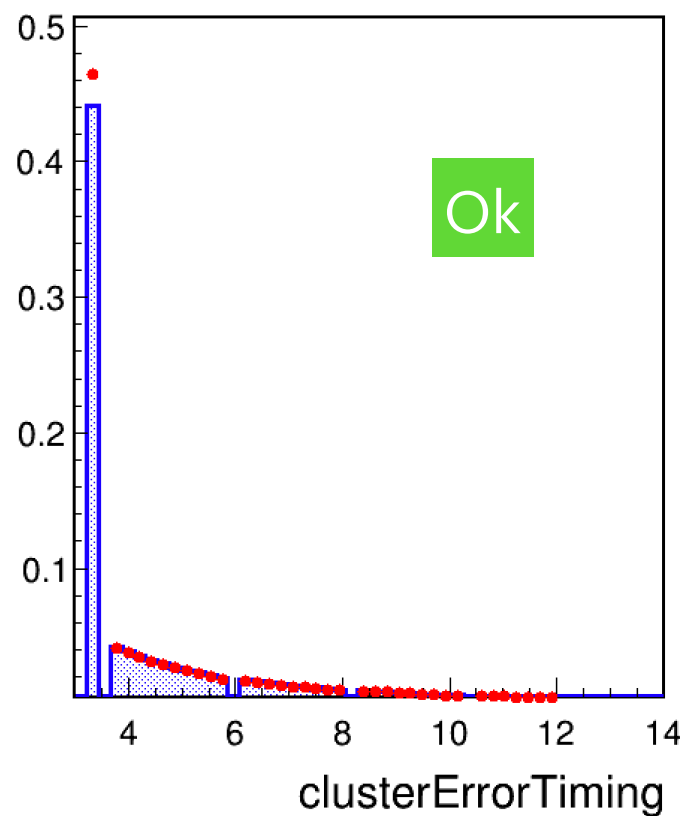
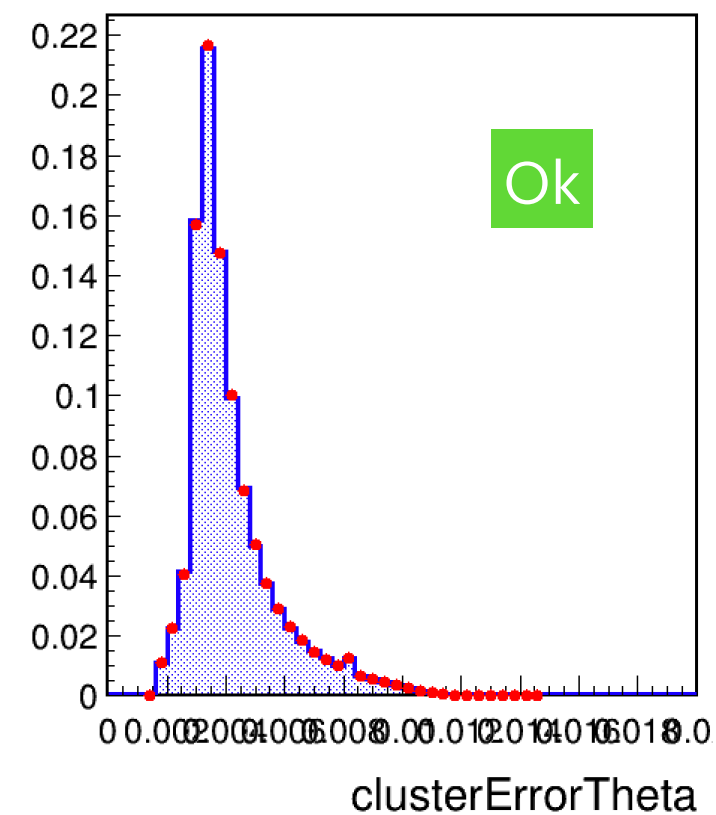
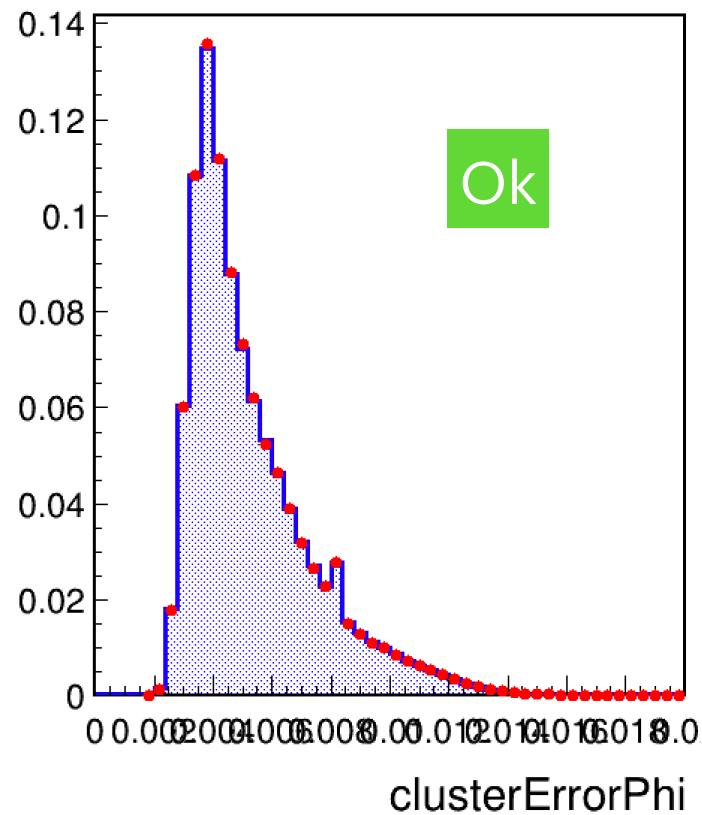
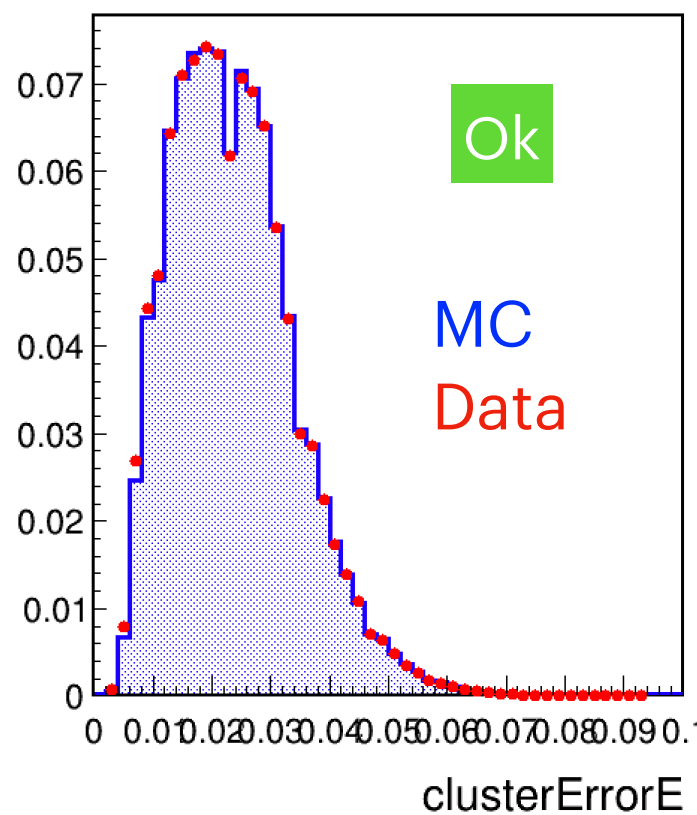


# Photon MVA: inputs validation (rel-05)

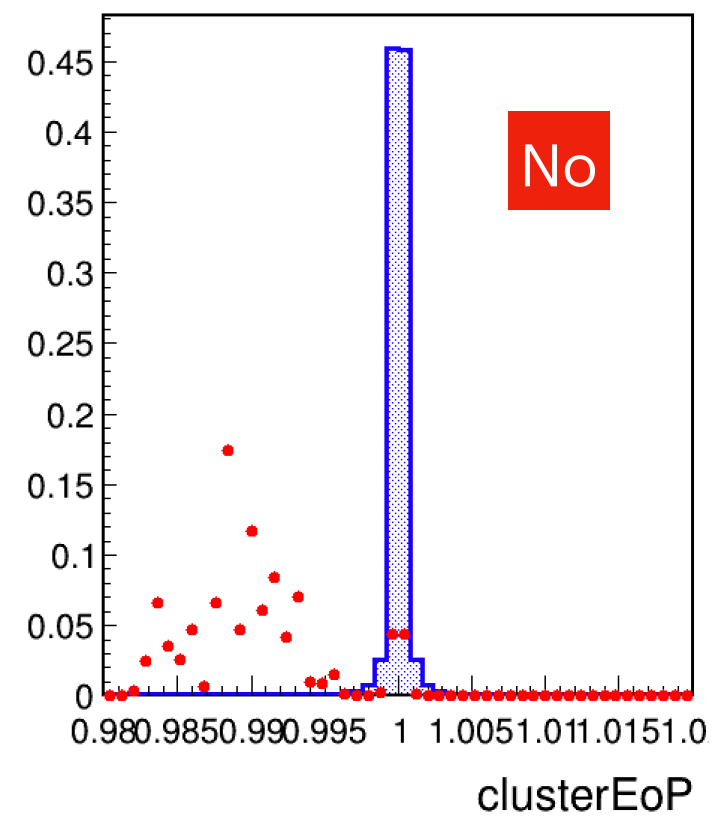
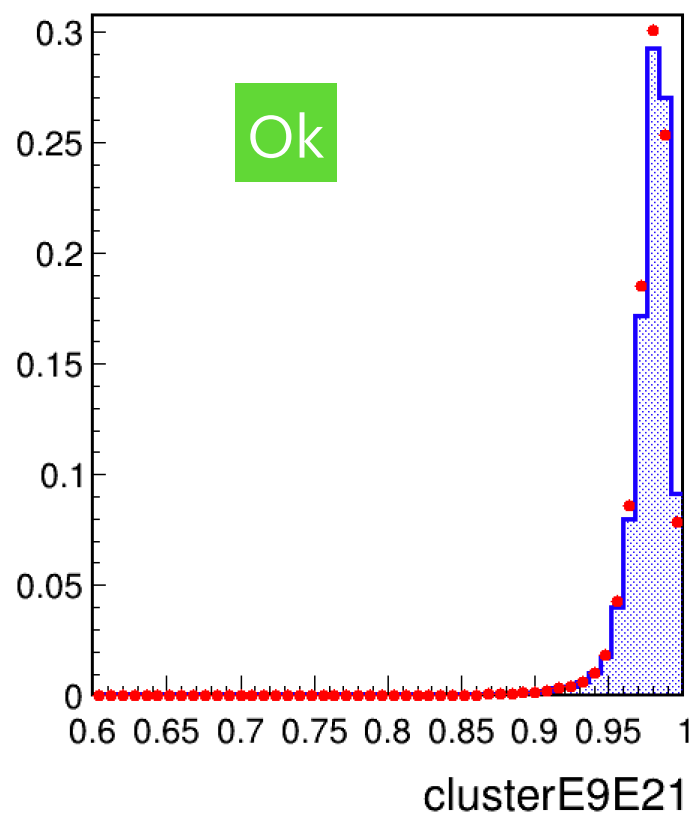
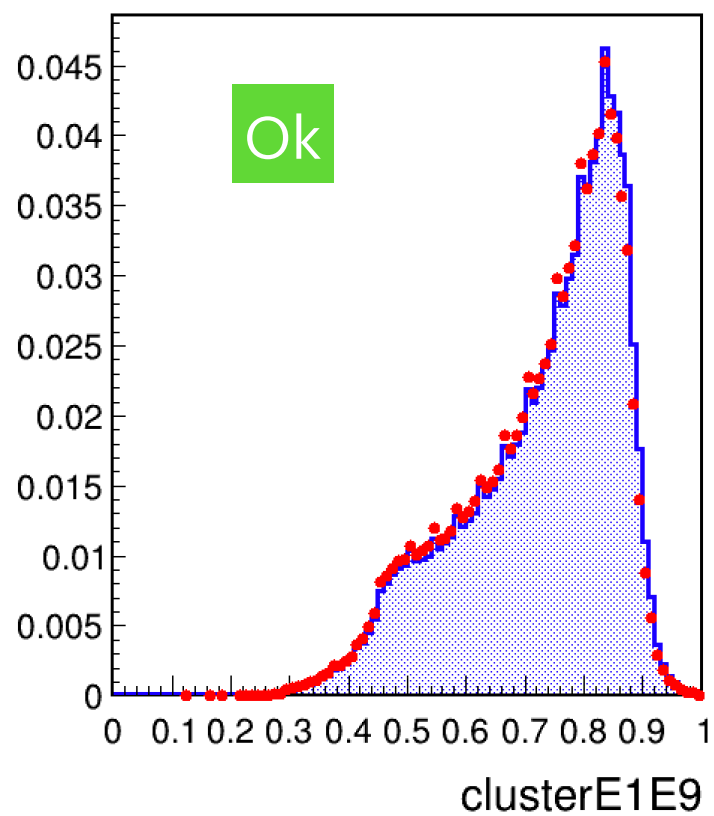
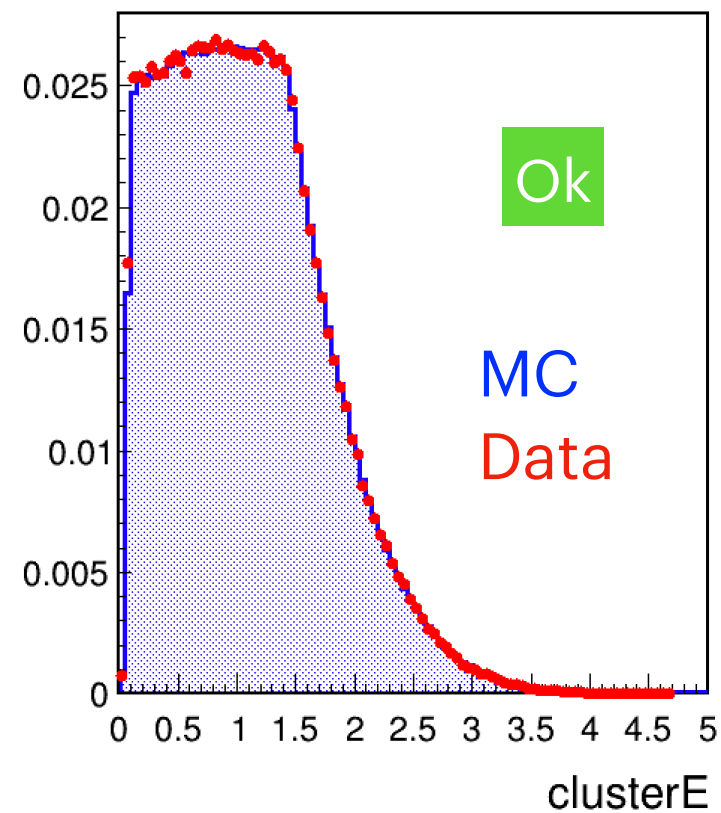
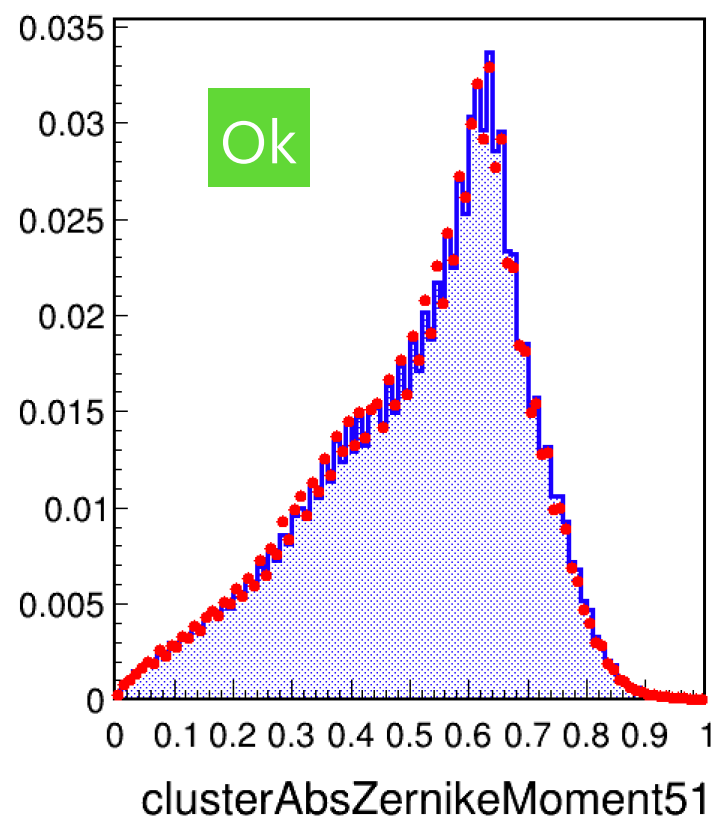
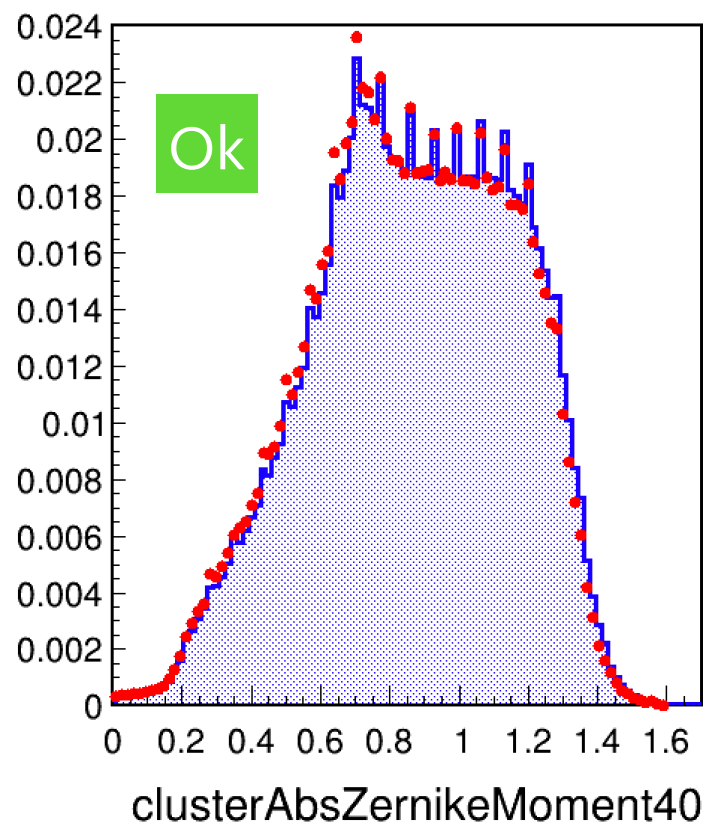




# Photon MVA: inputs validation (rel-05)

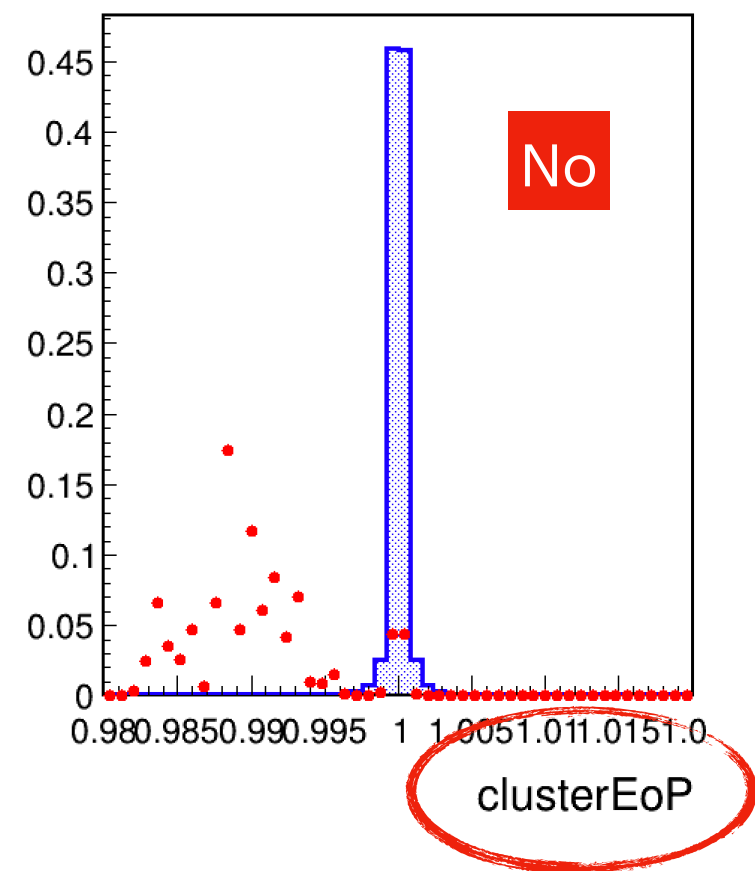
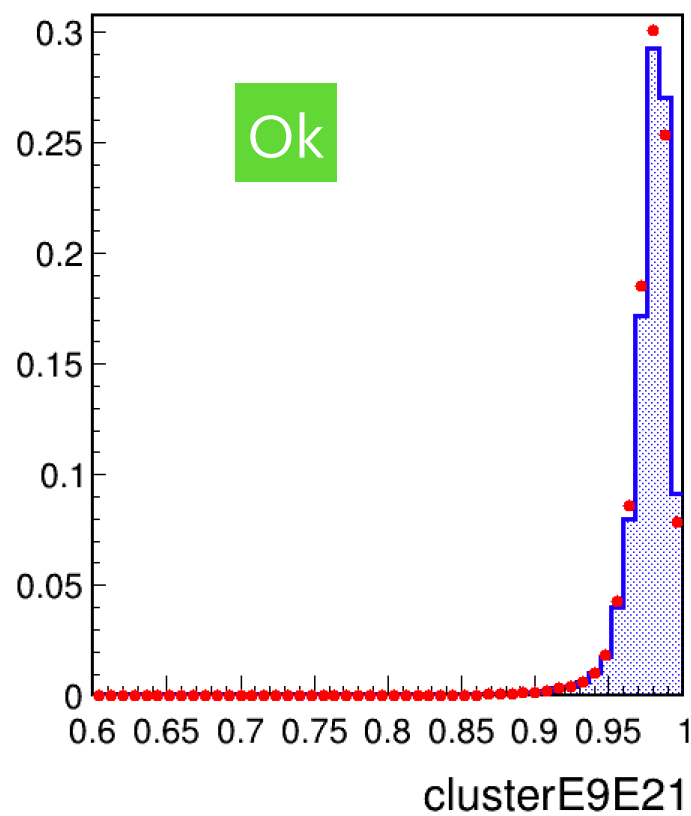
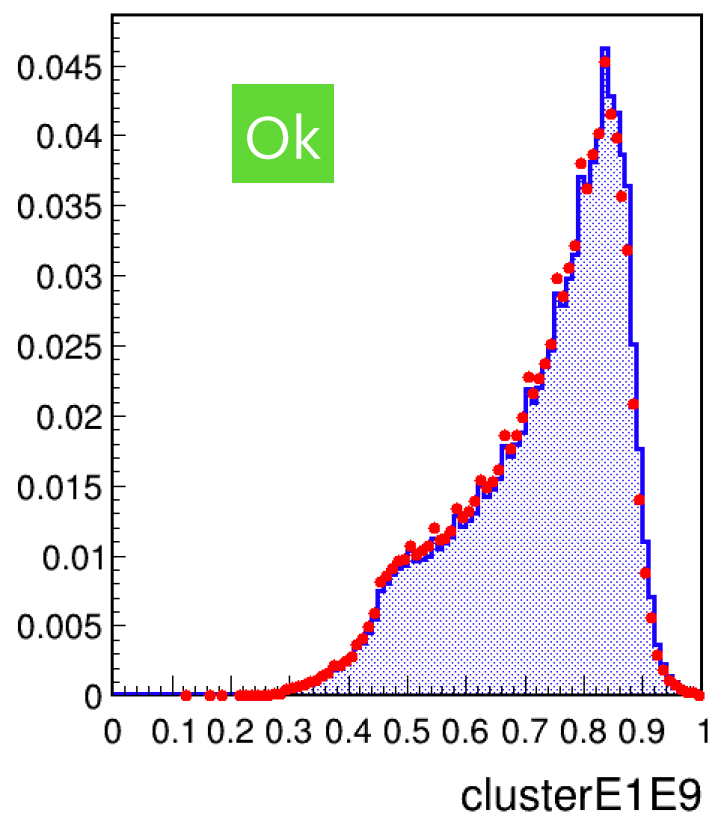
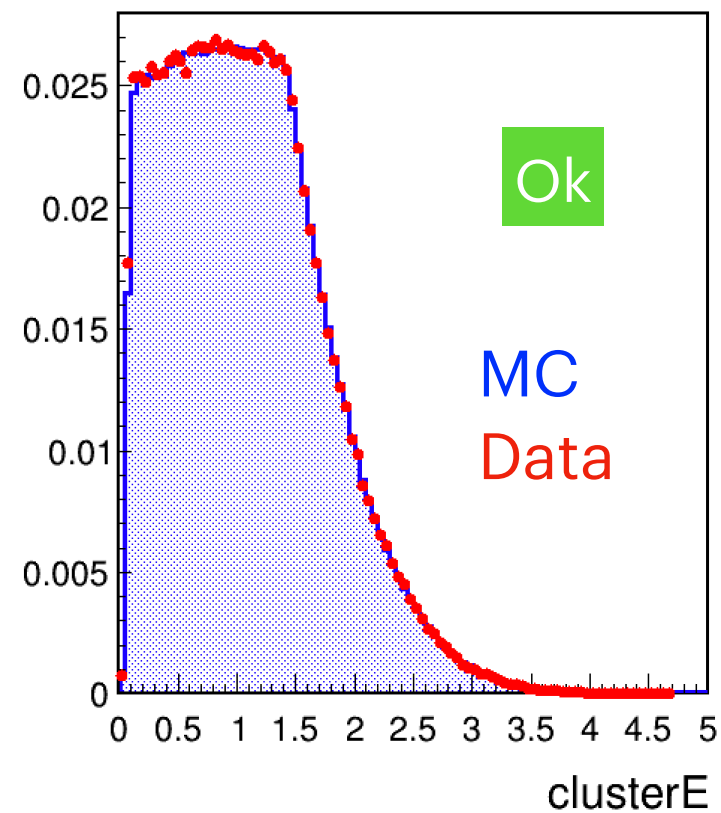
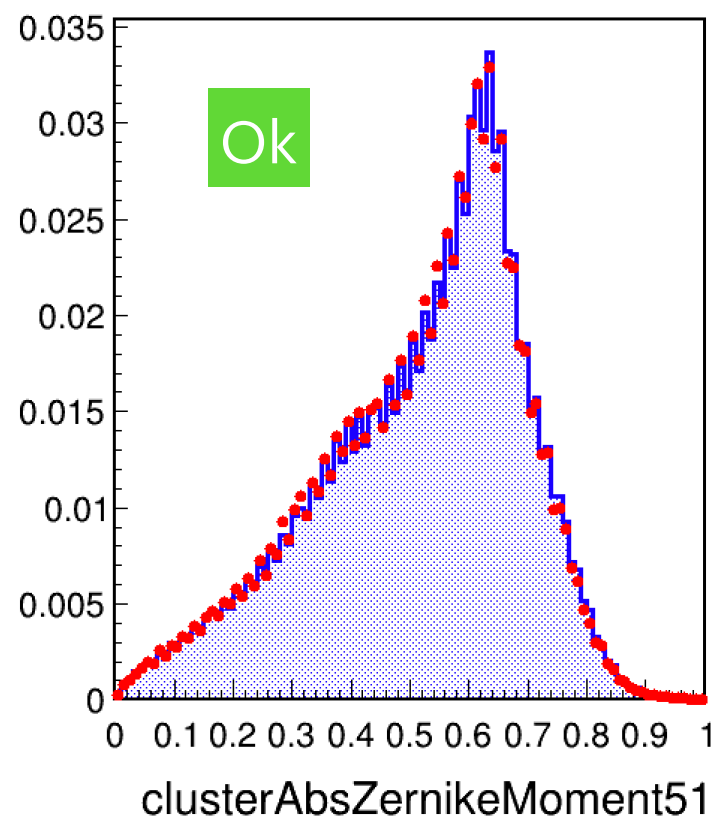
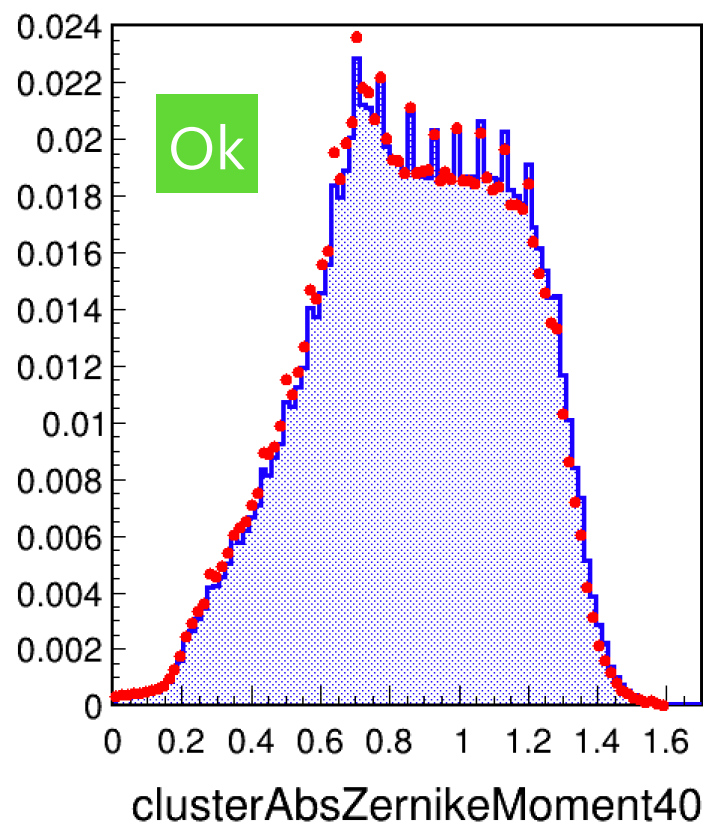


# Photon MVA: inputs validation (rel-05)





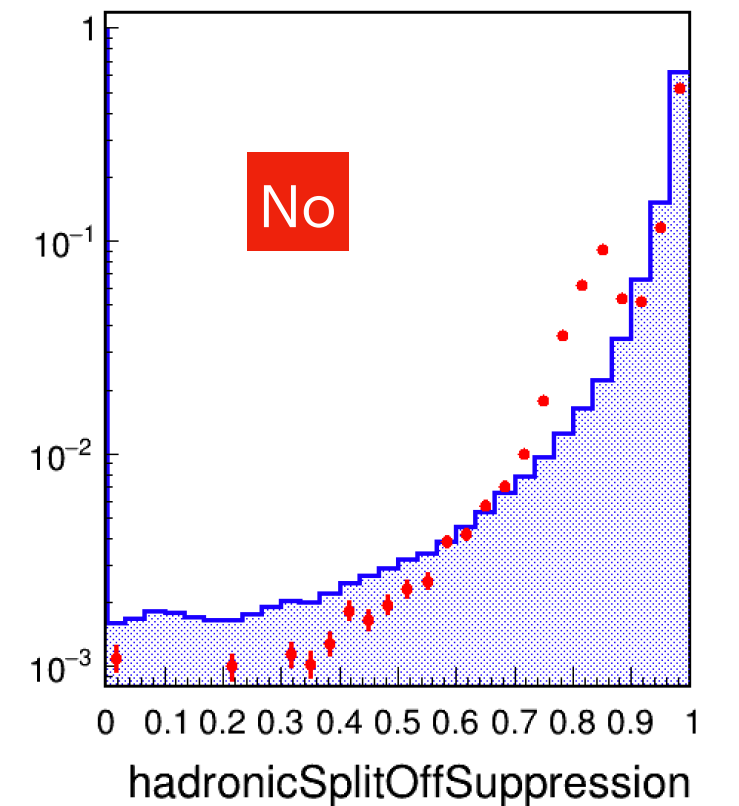
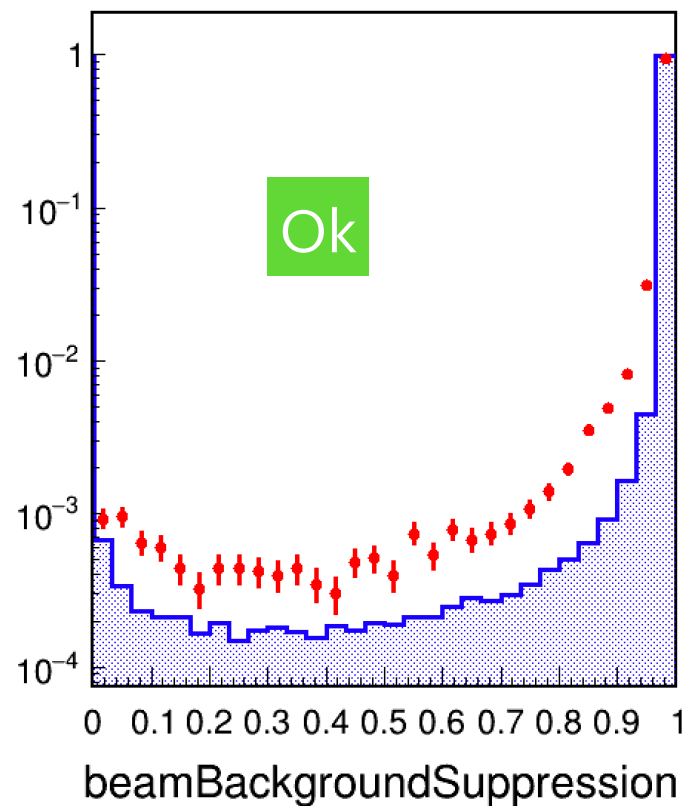
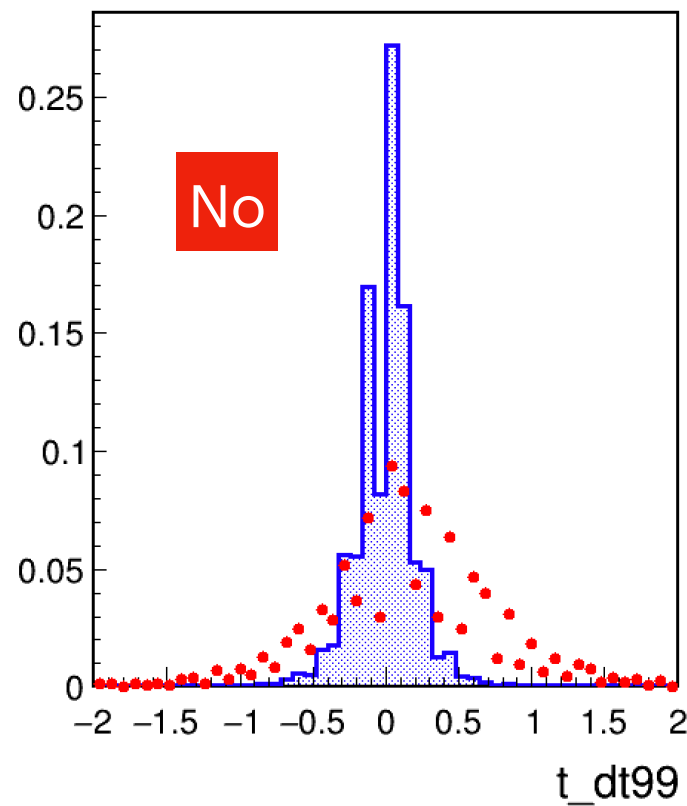
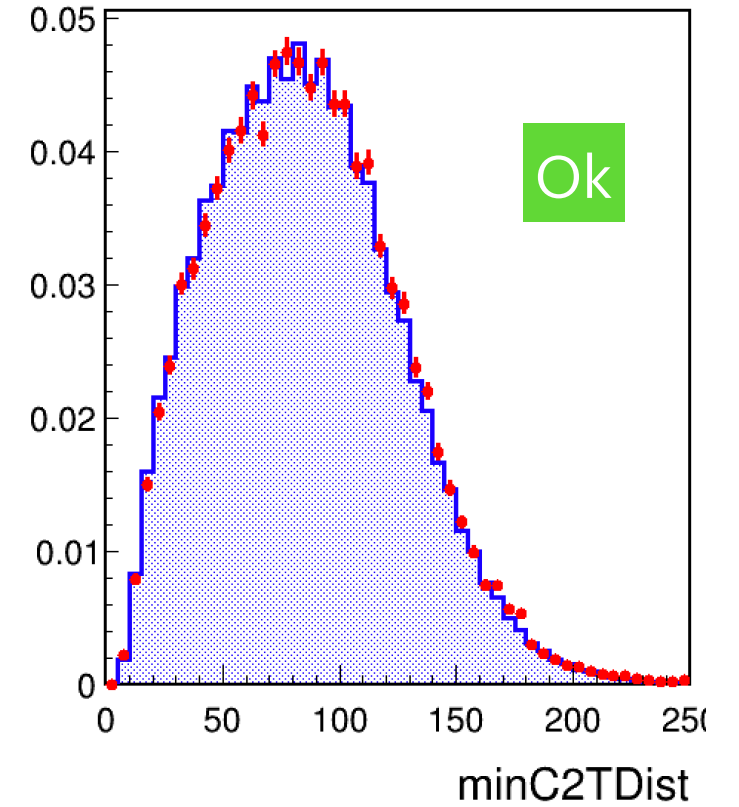
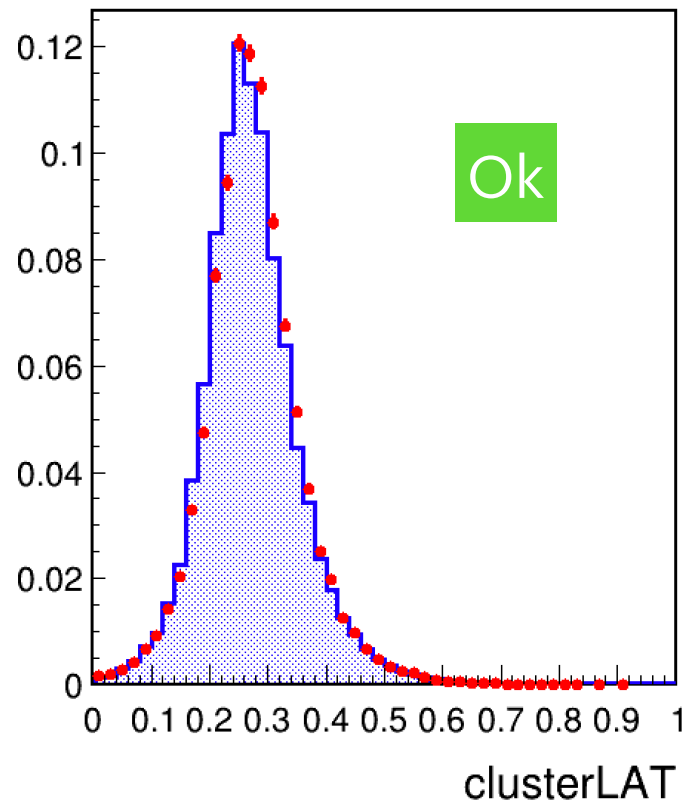
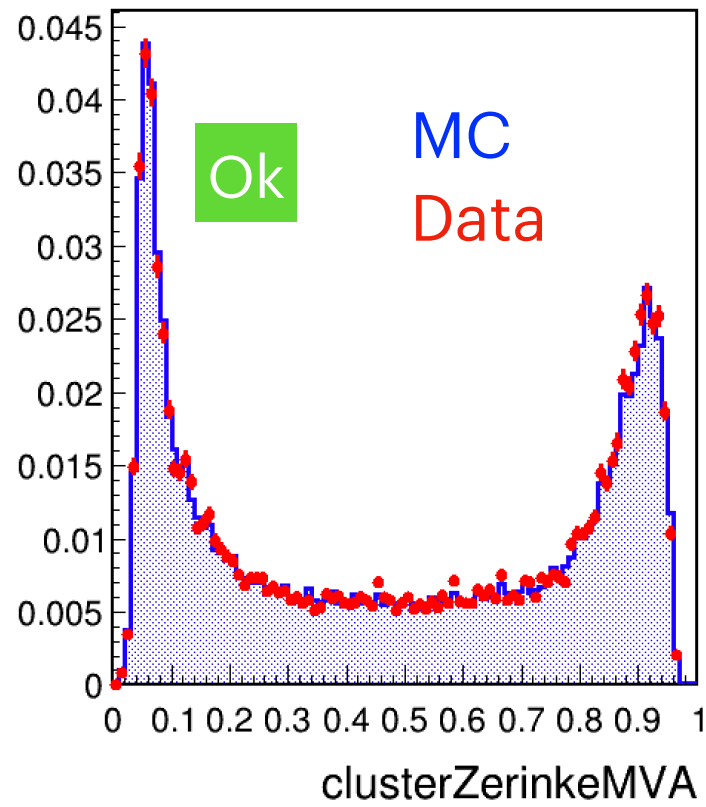
# Photon MVA: inputs validation (rel-05)



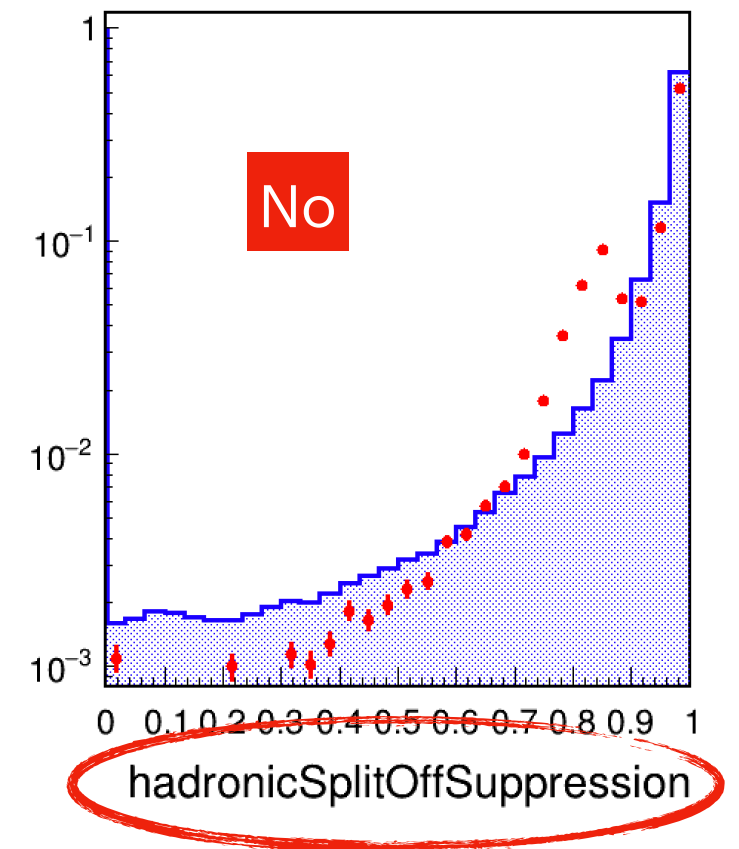
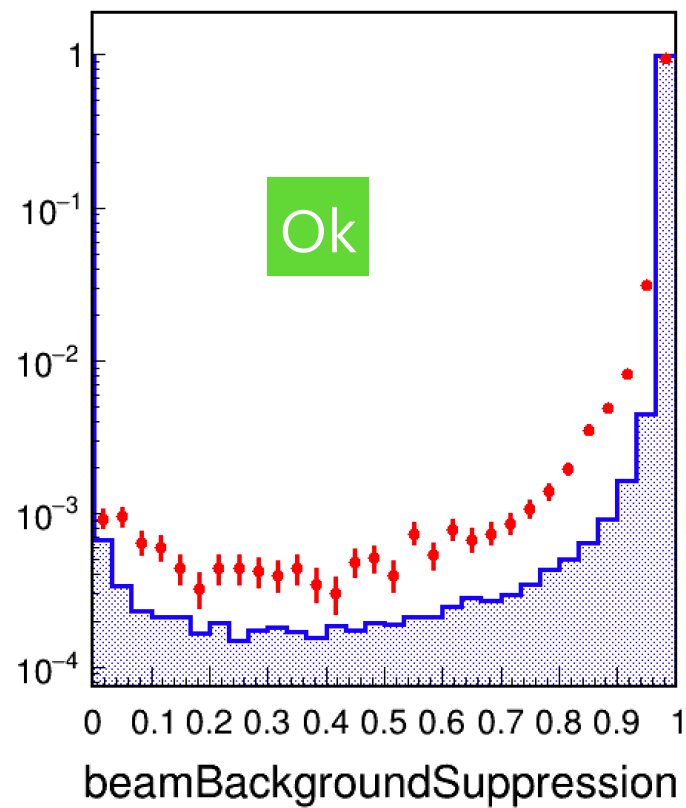
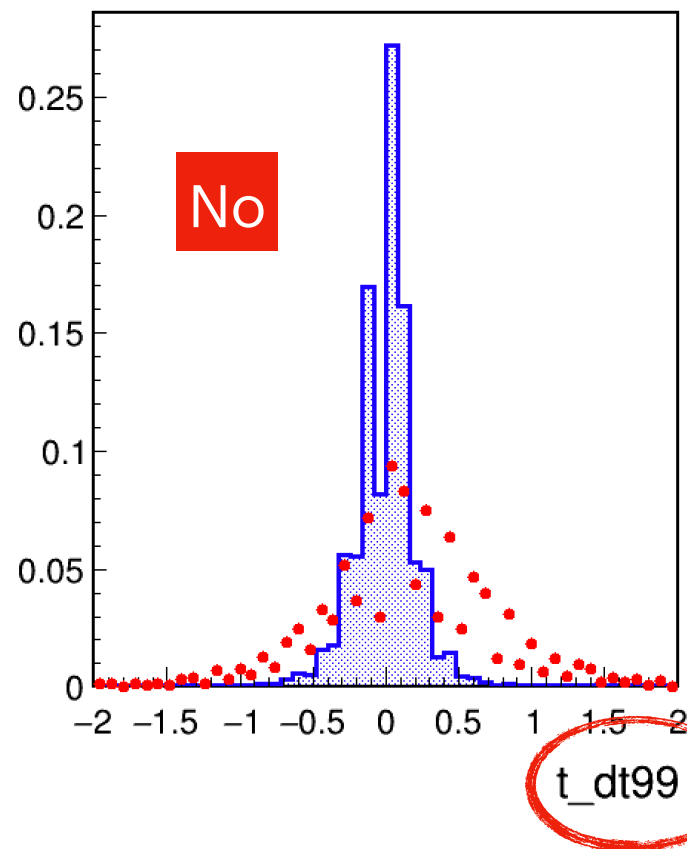
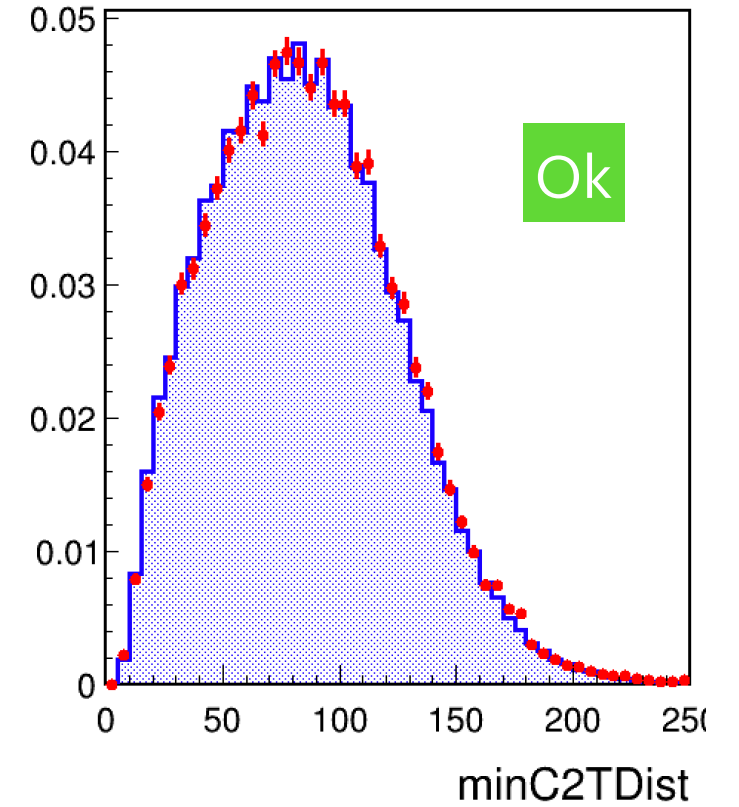
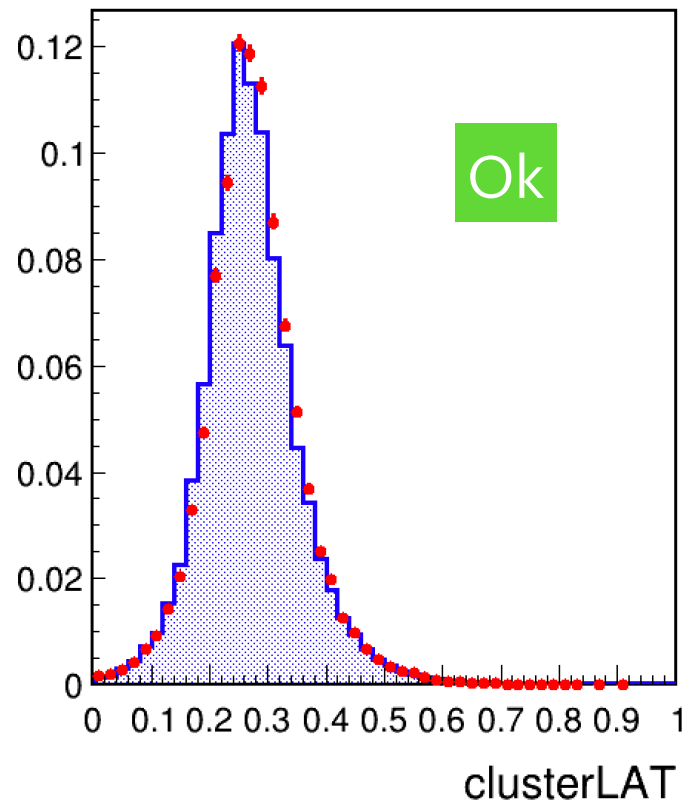
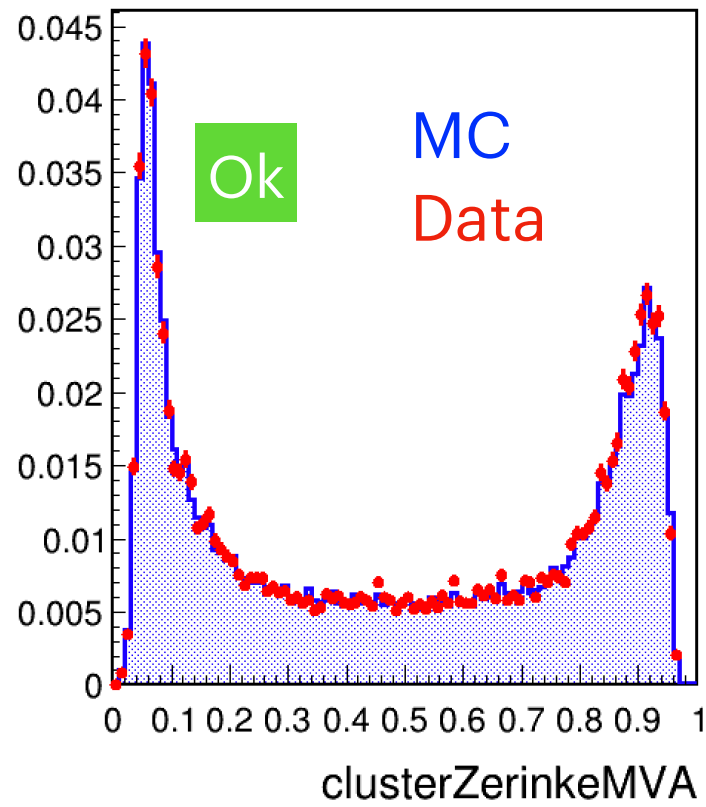
MC15 vs Proc13

Release-06

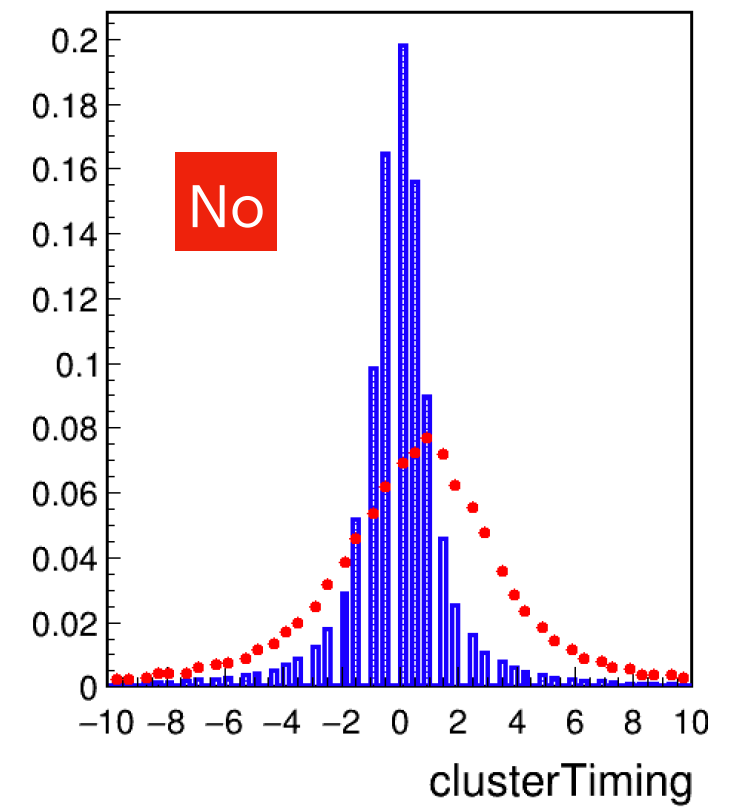
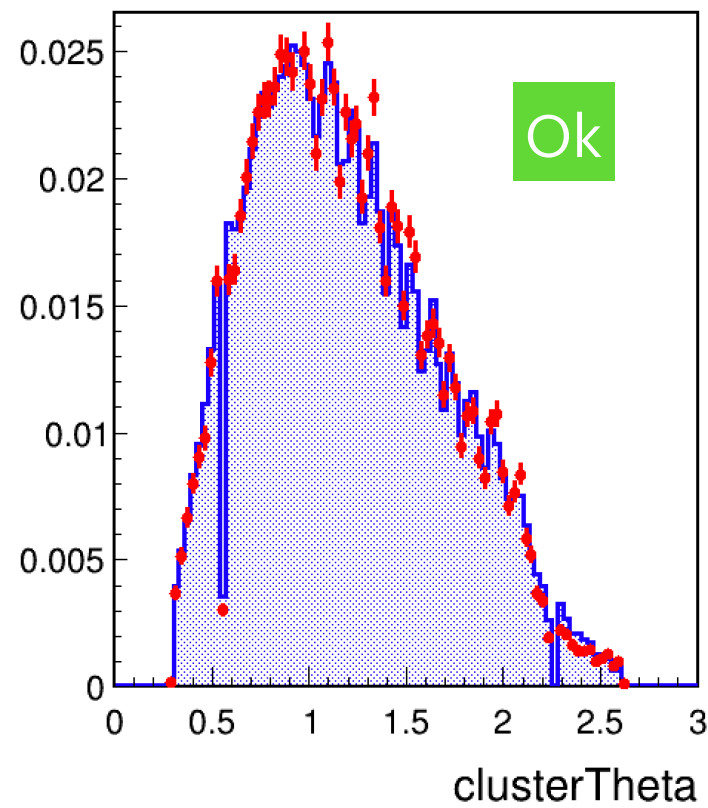
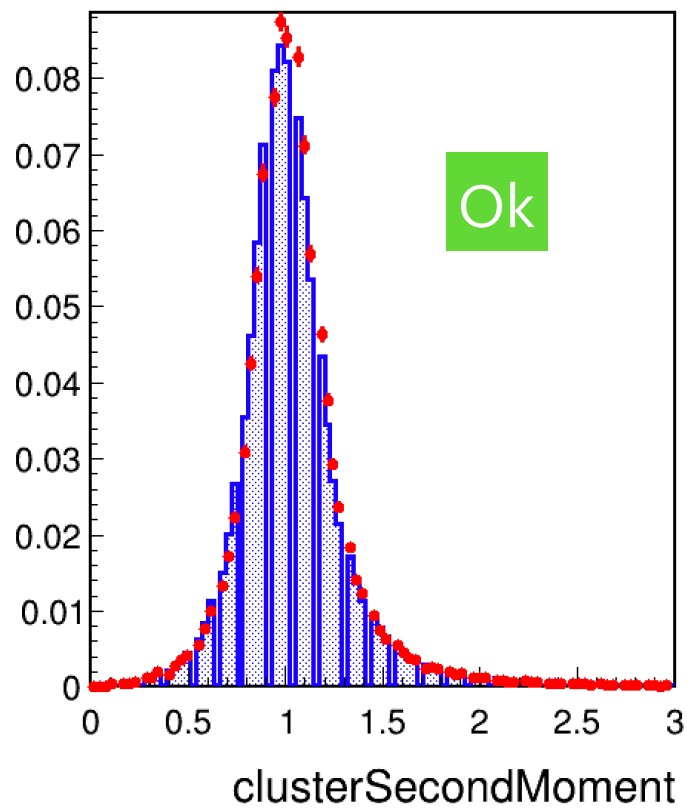
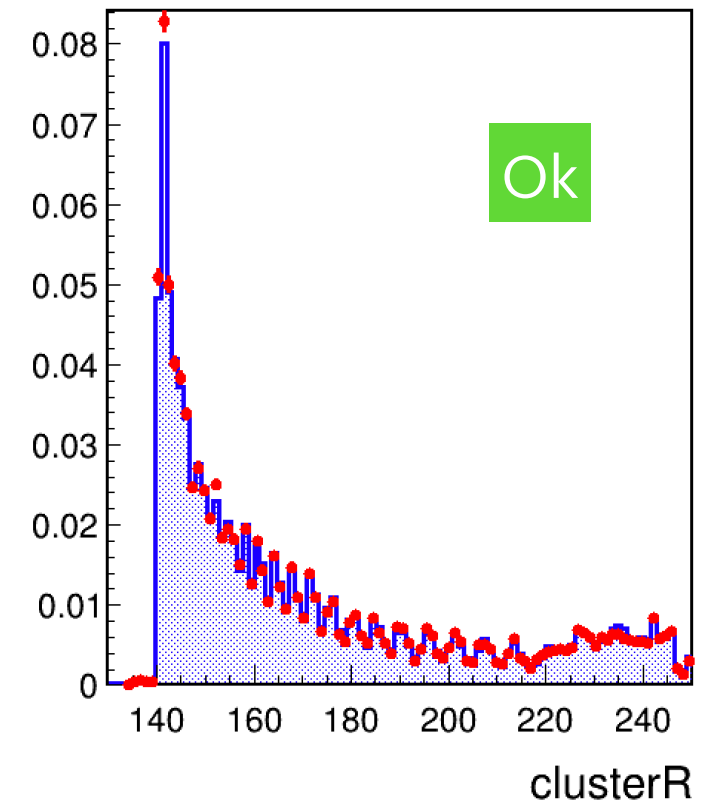
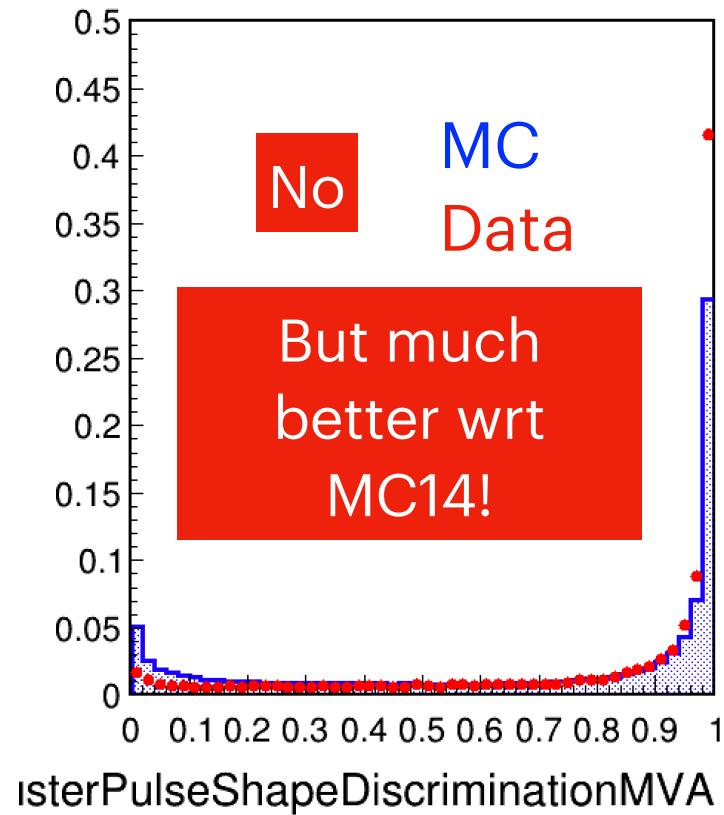
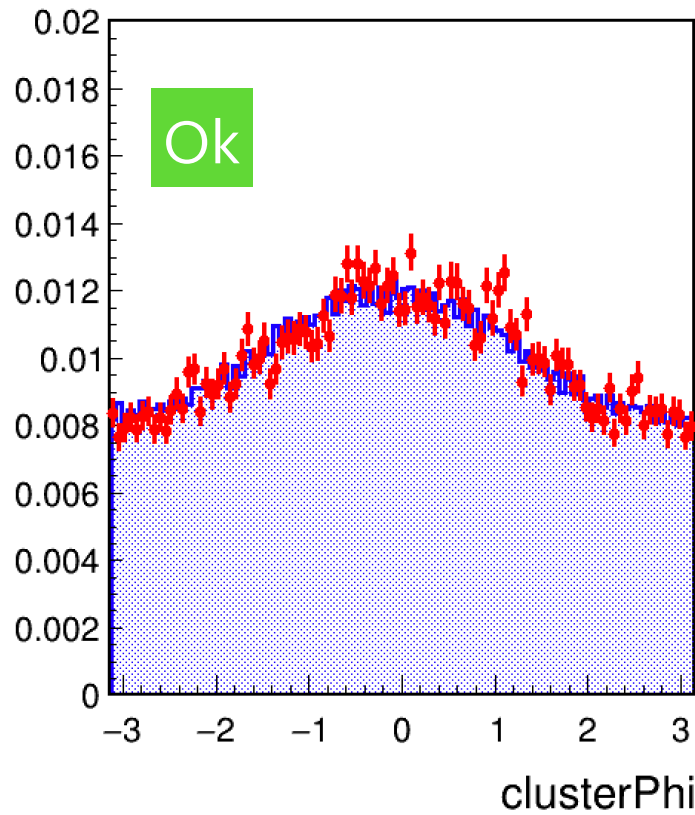
# Photon MVA: inputs validation (rel-06)



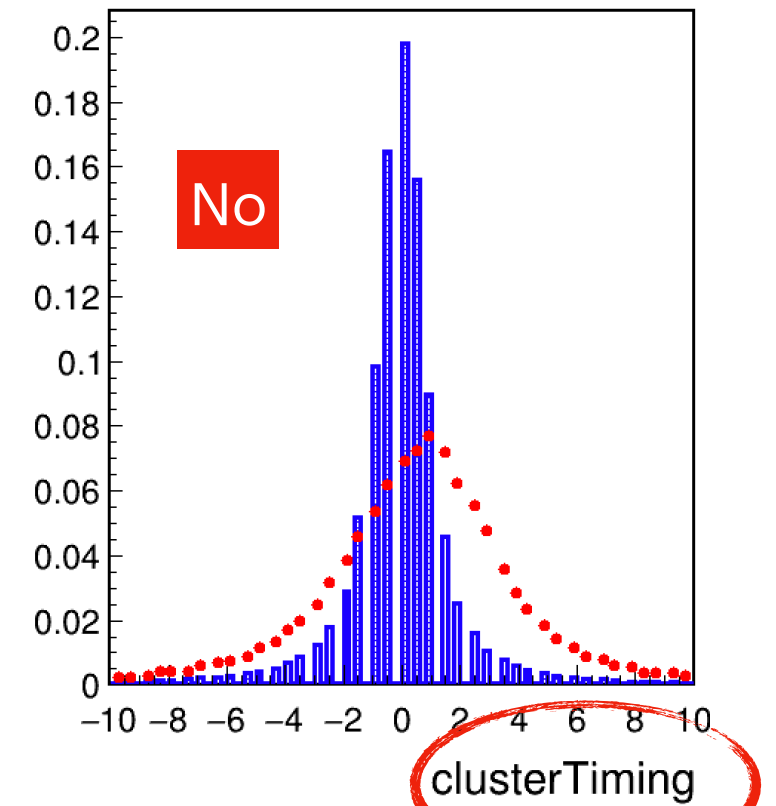
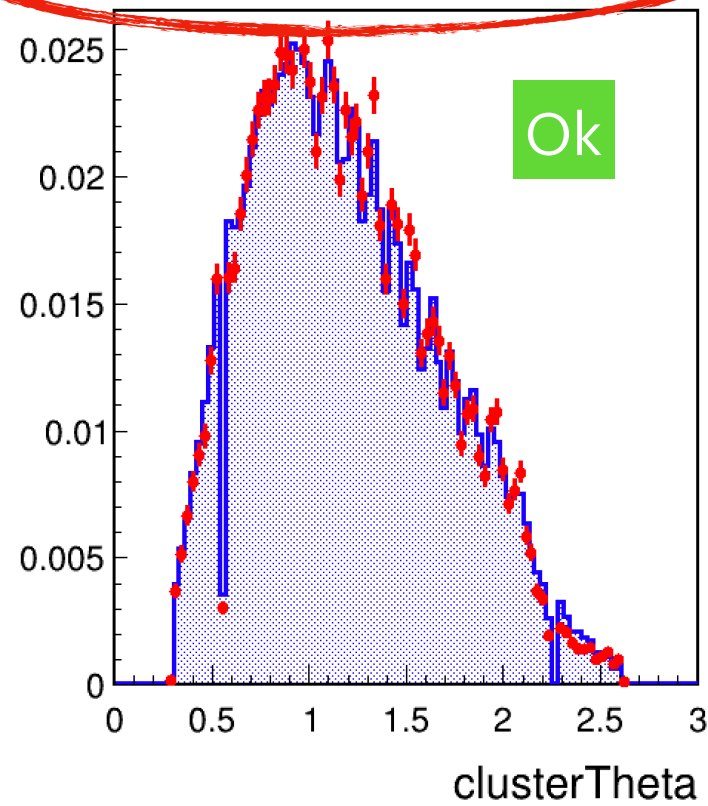
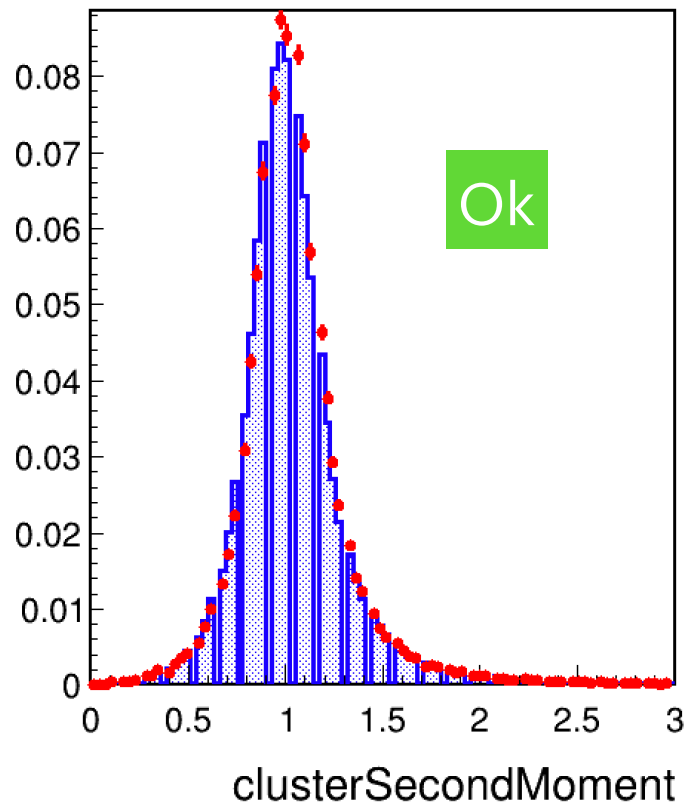
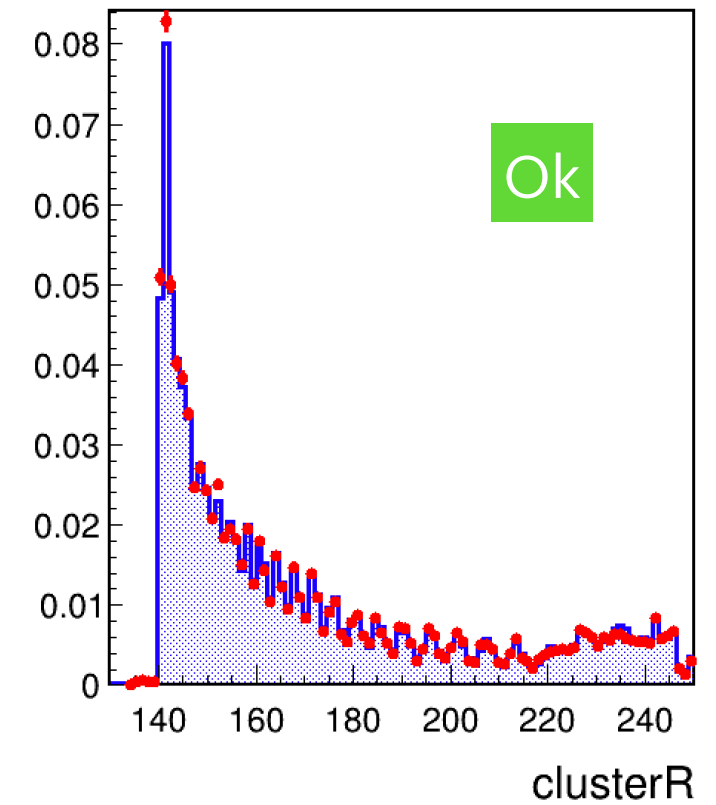
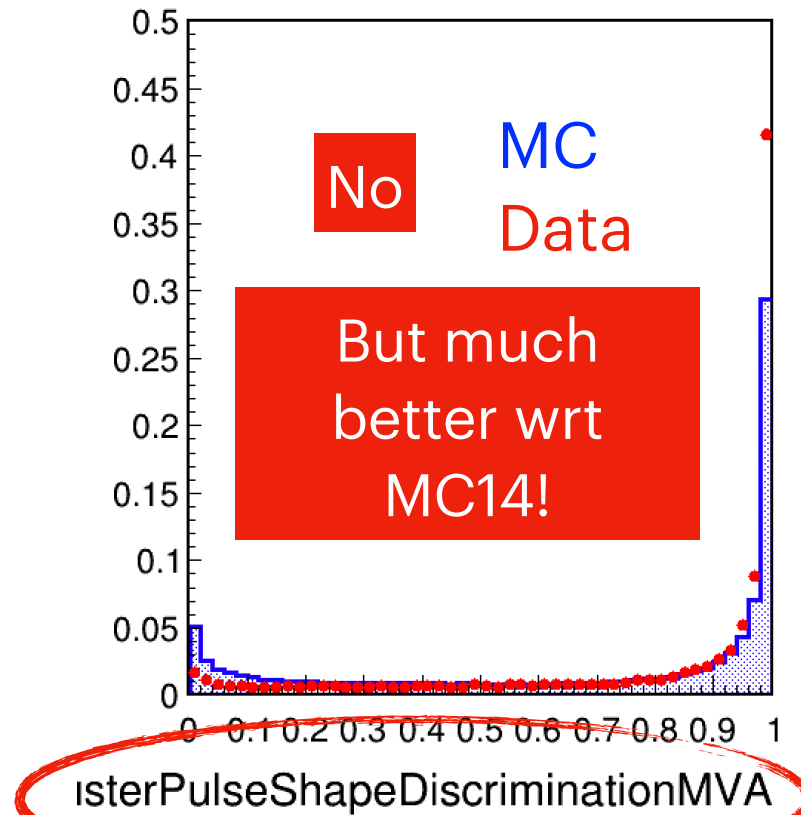
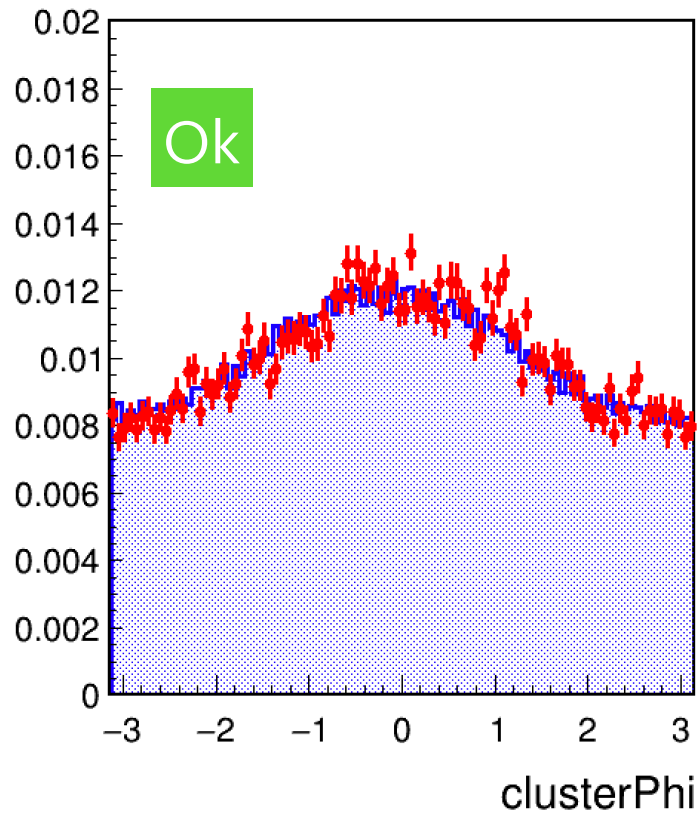
# Photon MVA: inputs validation (rel-06)



# Photon MVA: inputs validation (rel-06)

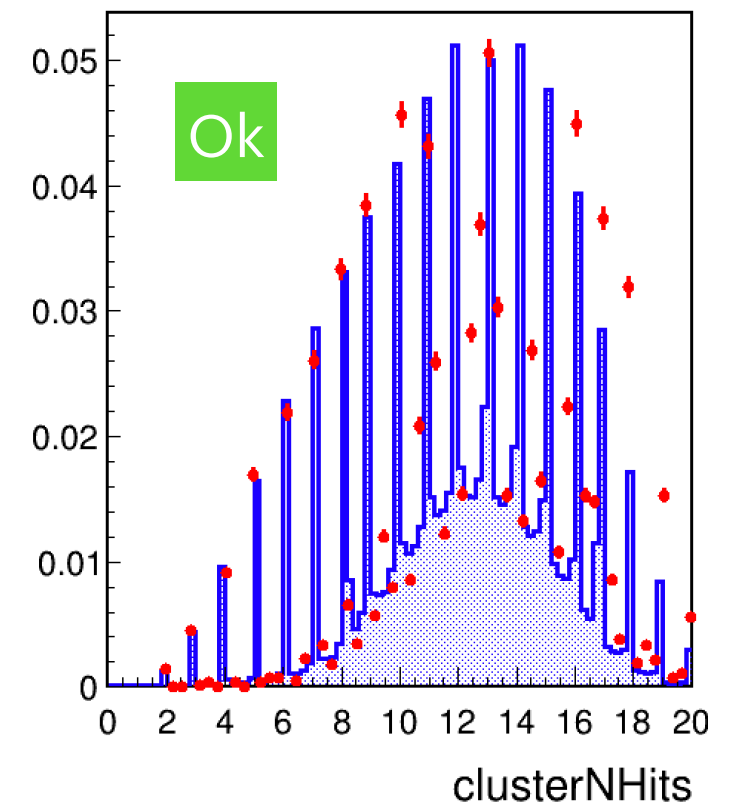
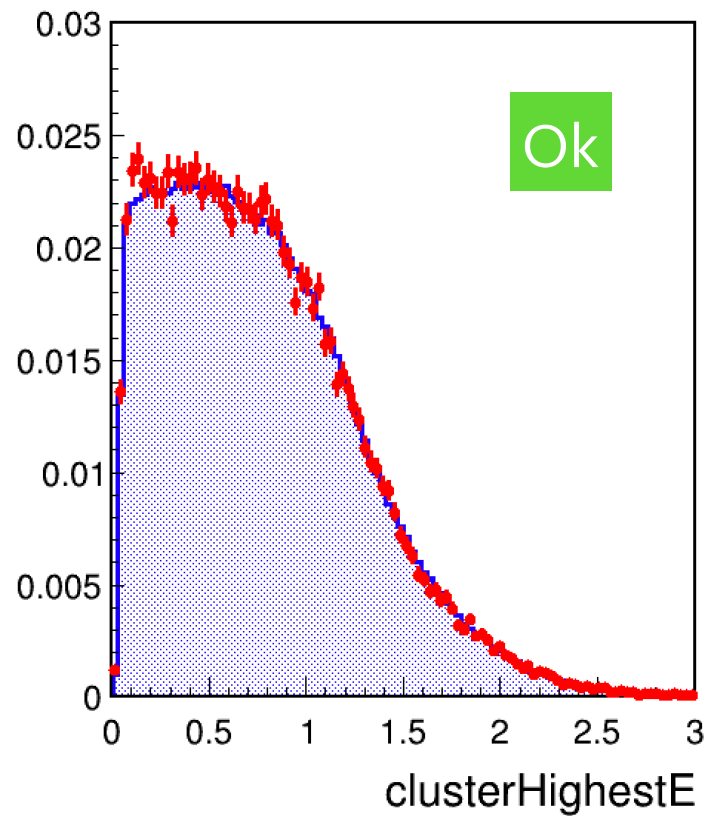
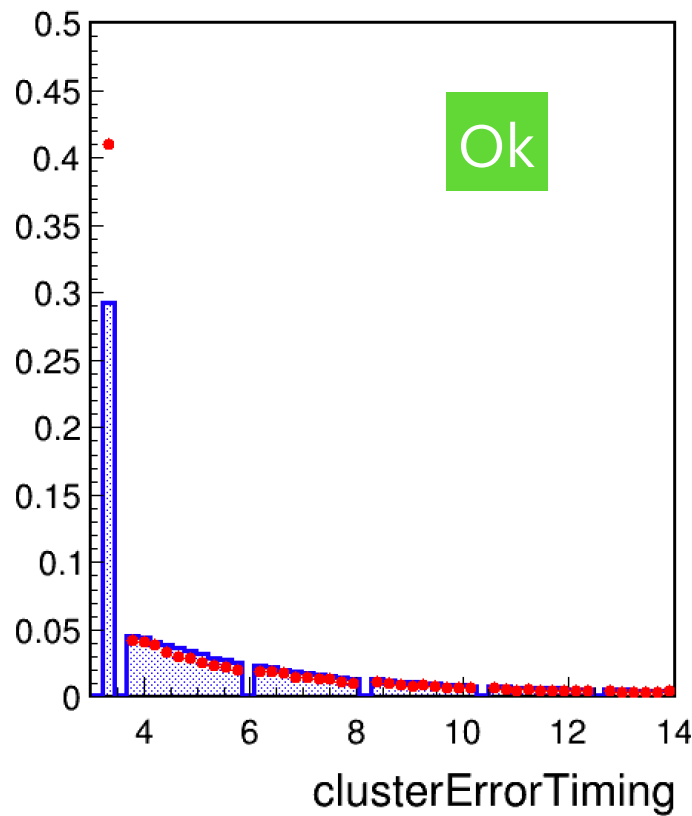
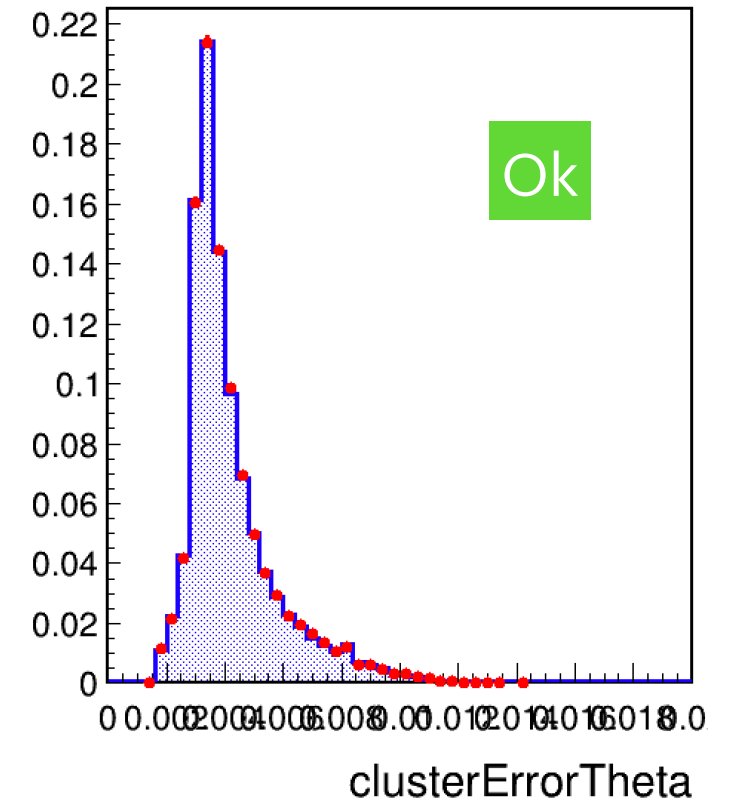
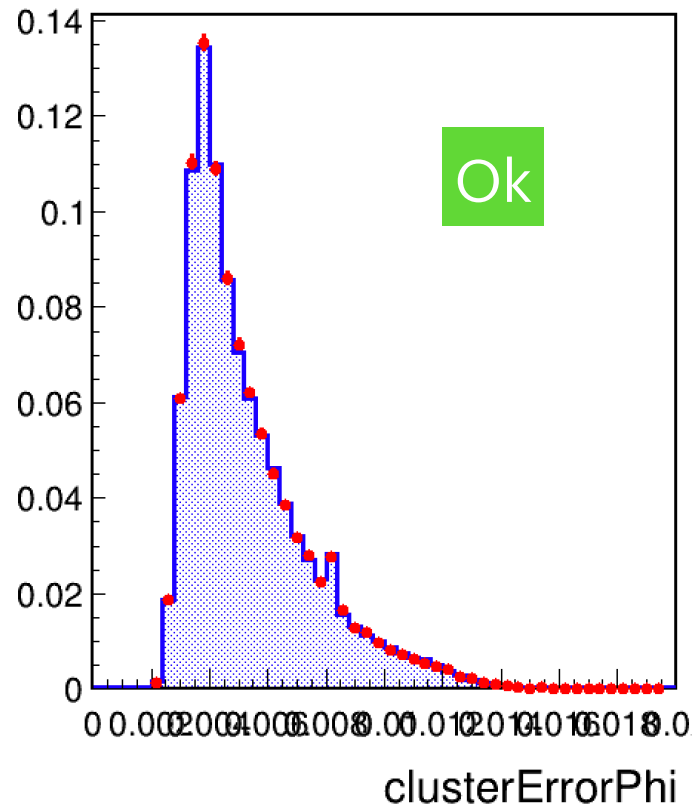
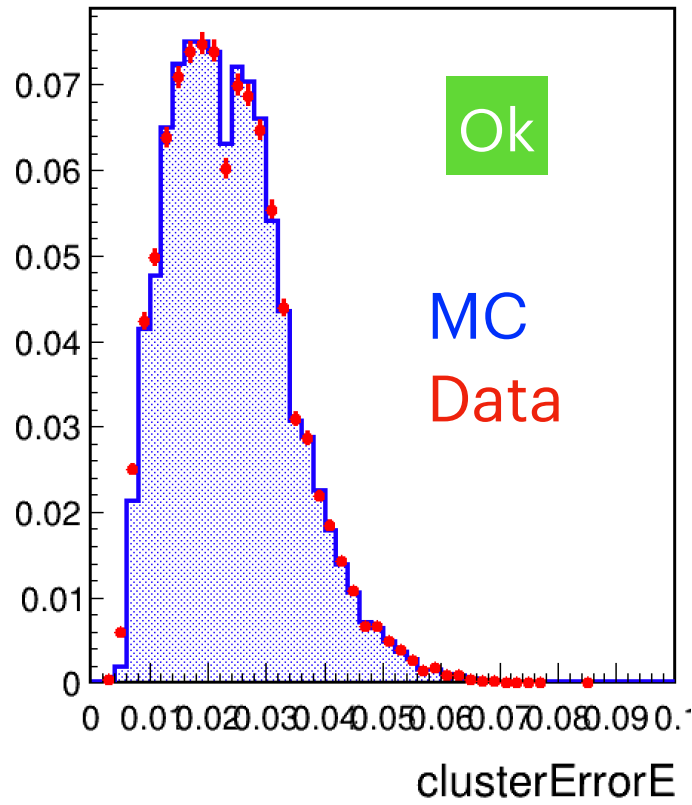


# Photon MVA: inputs validation (rel-06)

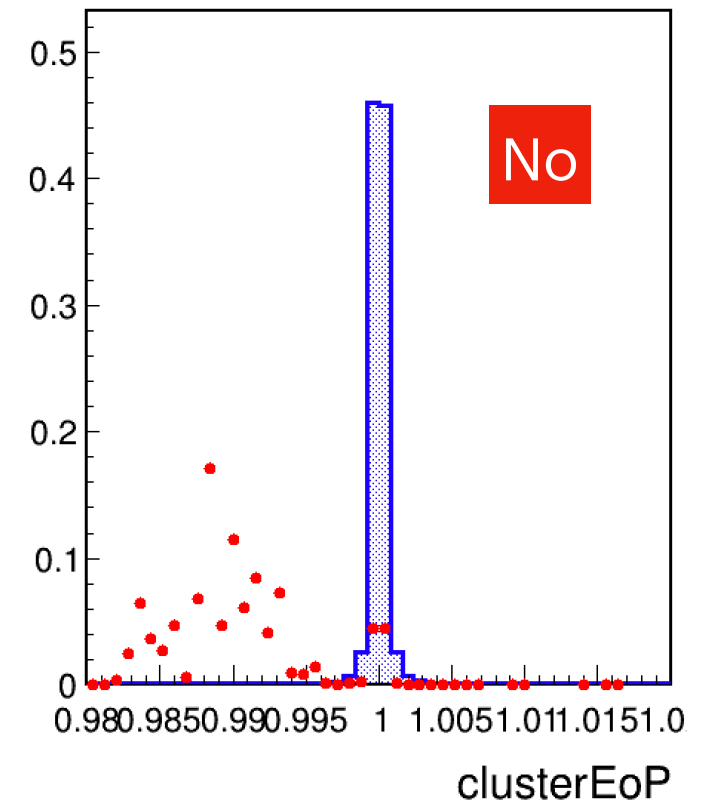
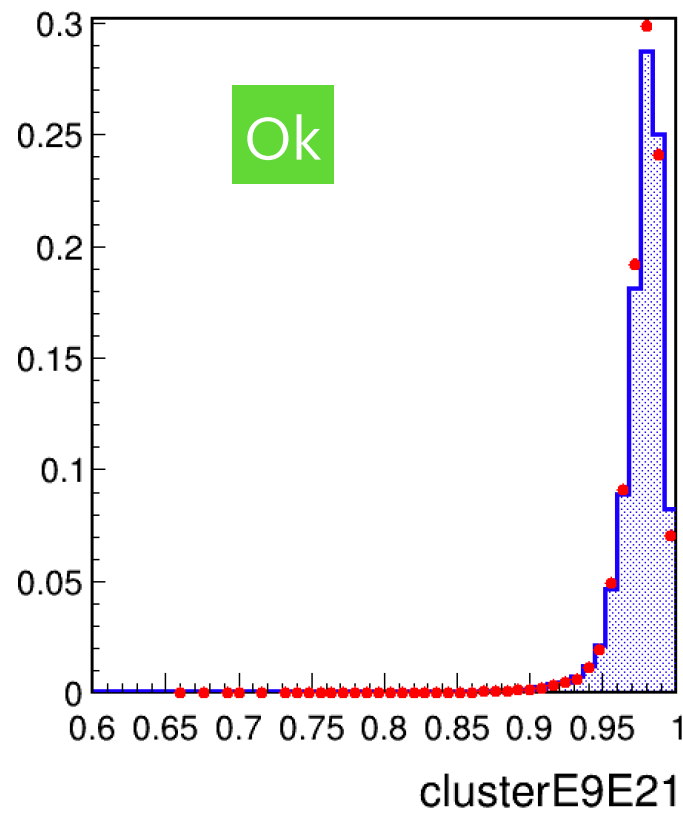
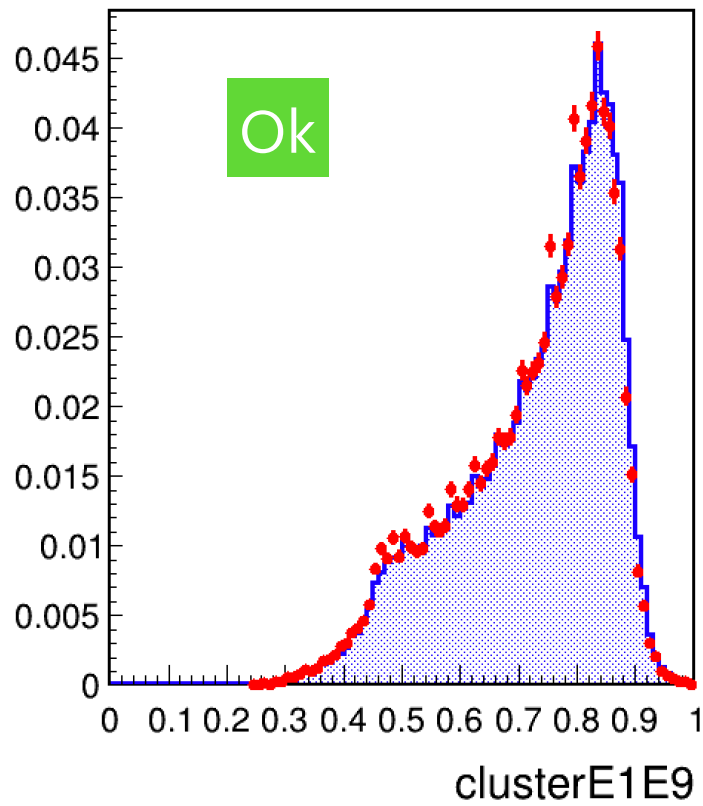
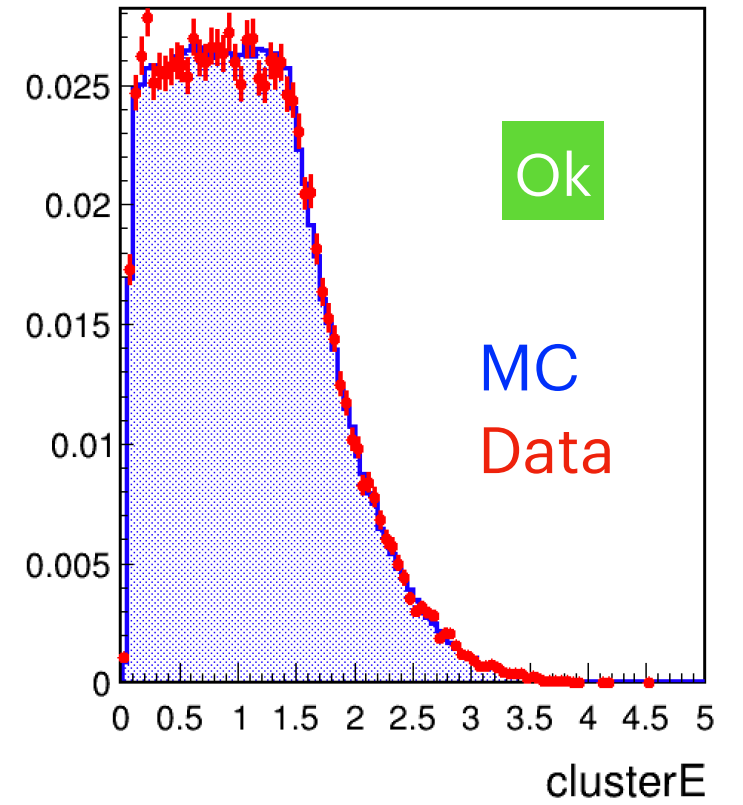
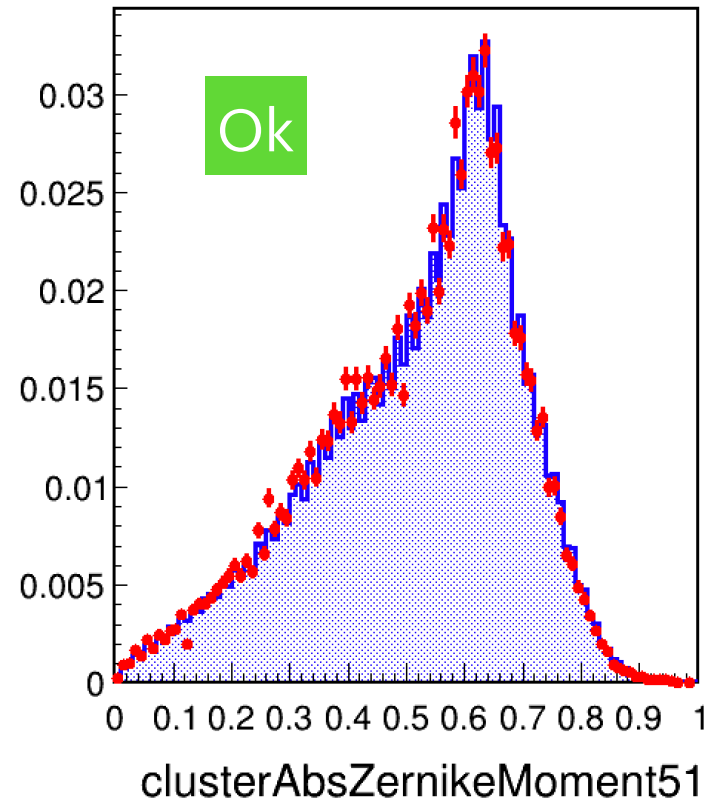
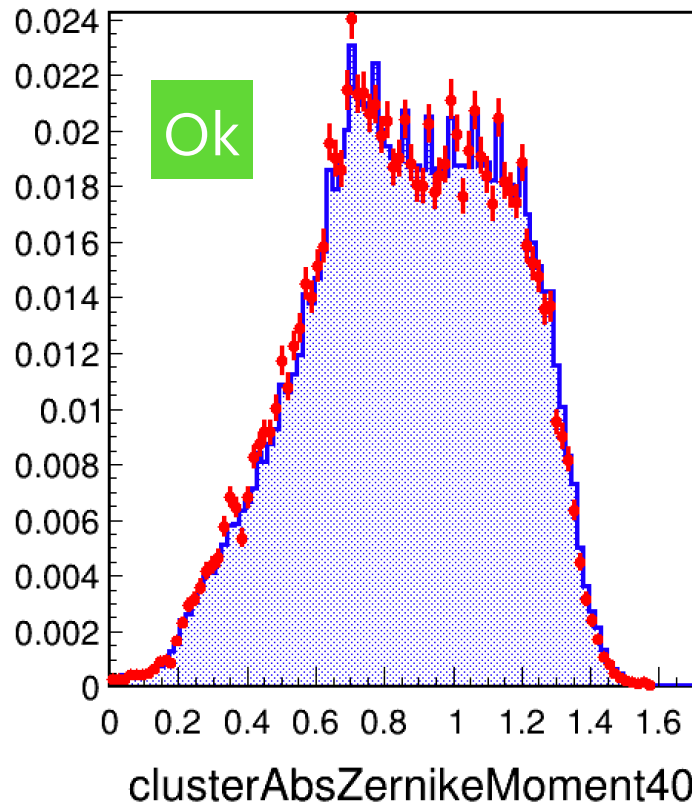




# Photon MVA: inputs validation (rel-06)

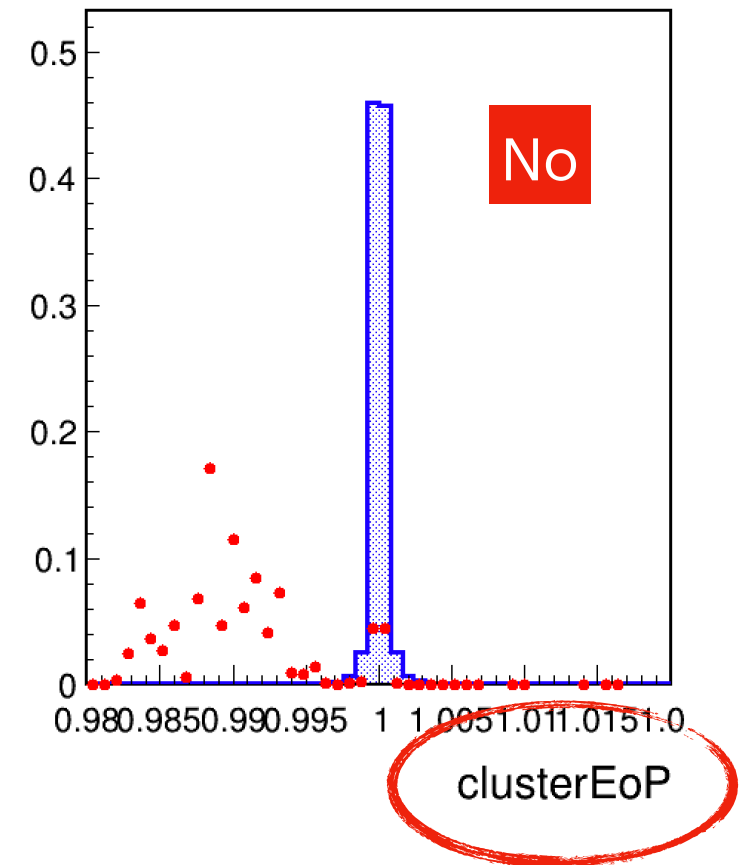
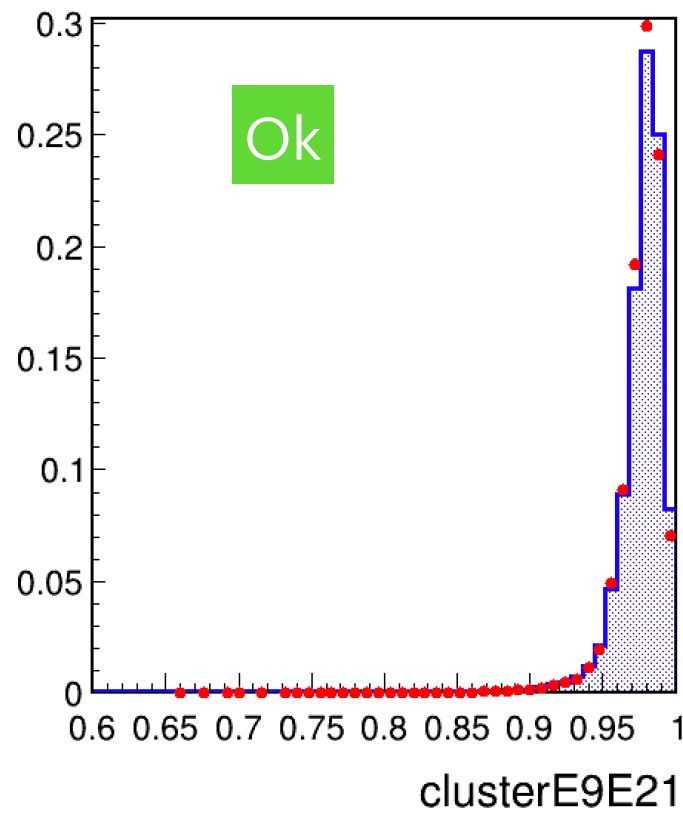
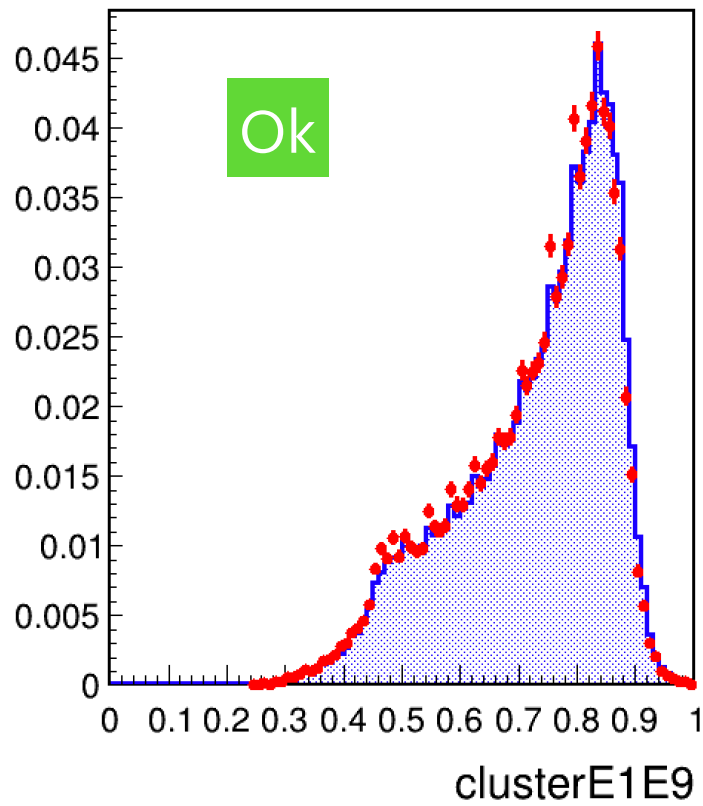
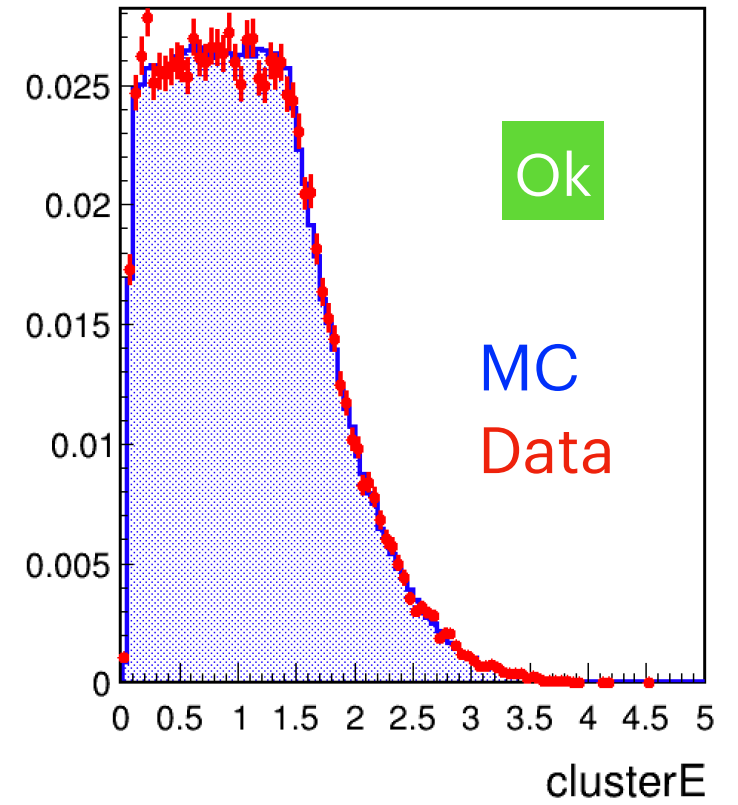
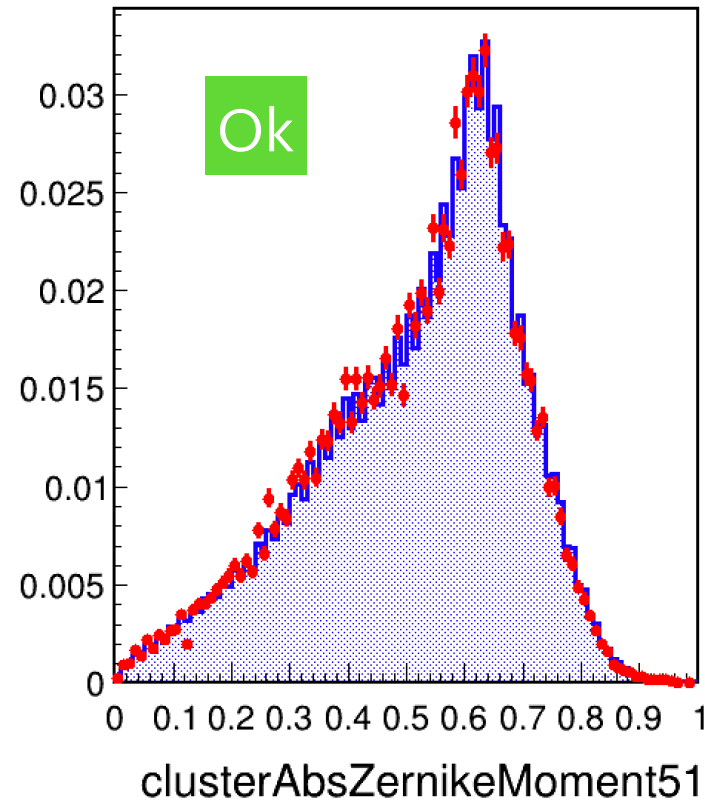
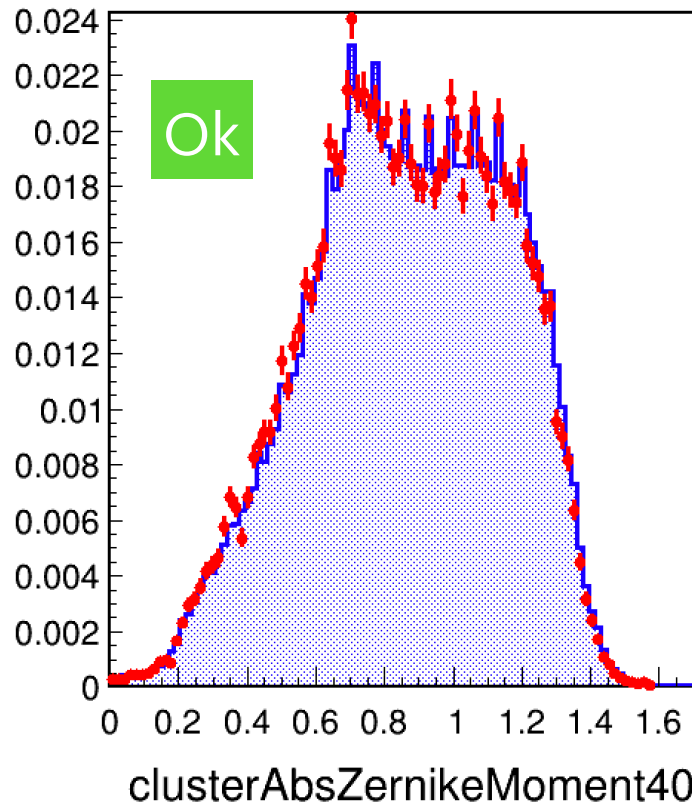


# Photon MVA: inputs validation (rel-06)

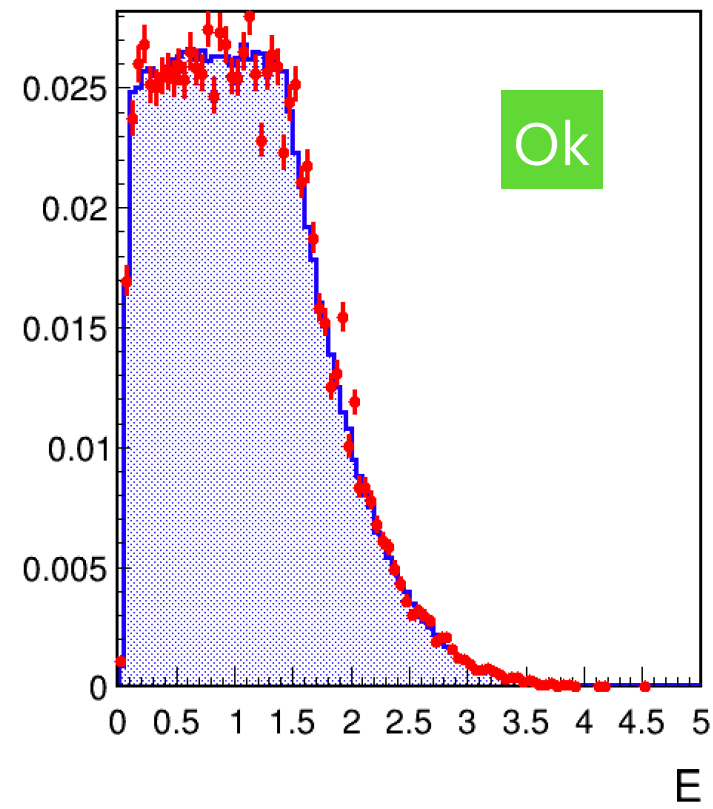
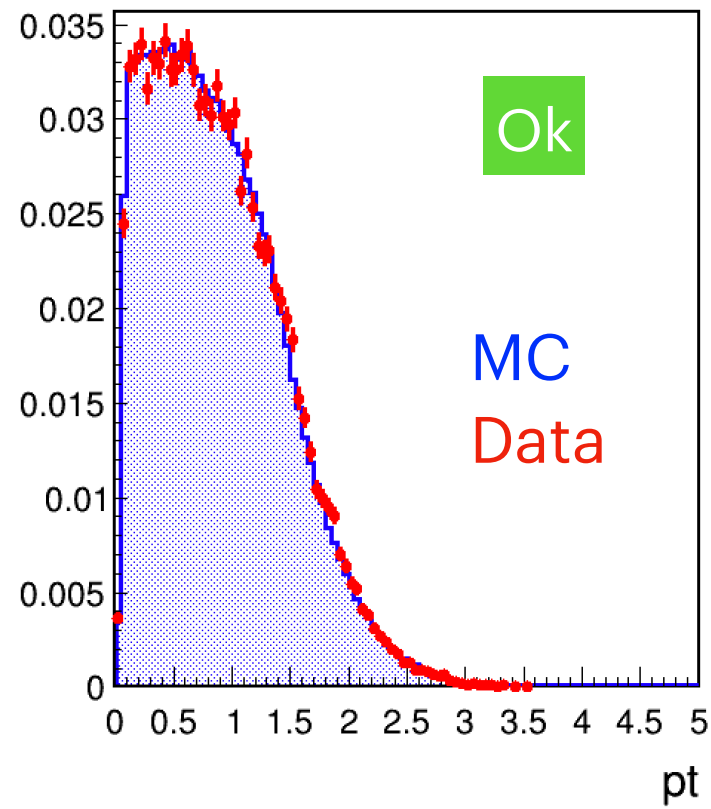




# Photon MVA: inputs validation (rel-06)



# Photon MVA: inputs validation (rel-06)



# Photon MVA results using release-06

Train on MC sample after applying all  $\pi^0$  selections.

## Inputs (after pruning)

pt

clusterE1E9

clusterErrorPhi

clusterHighestE

clusterSecondMoment

clusterZernikeMVA

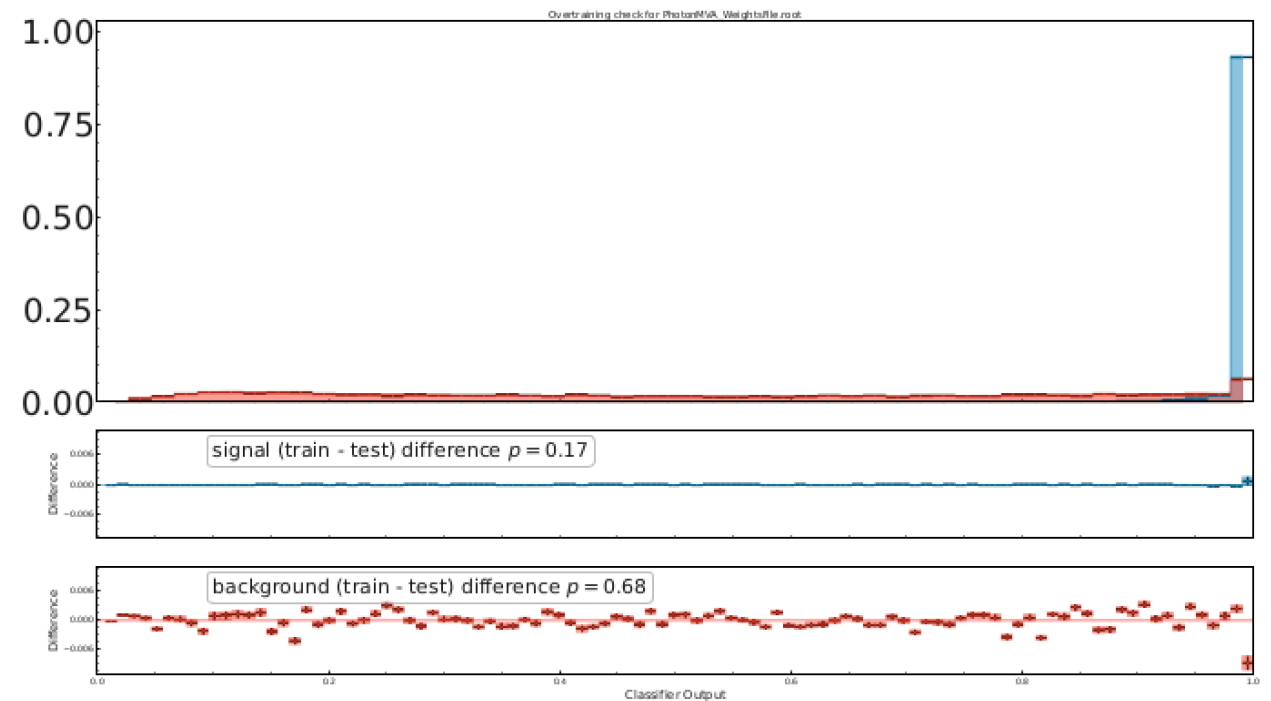
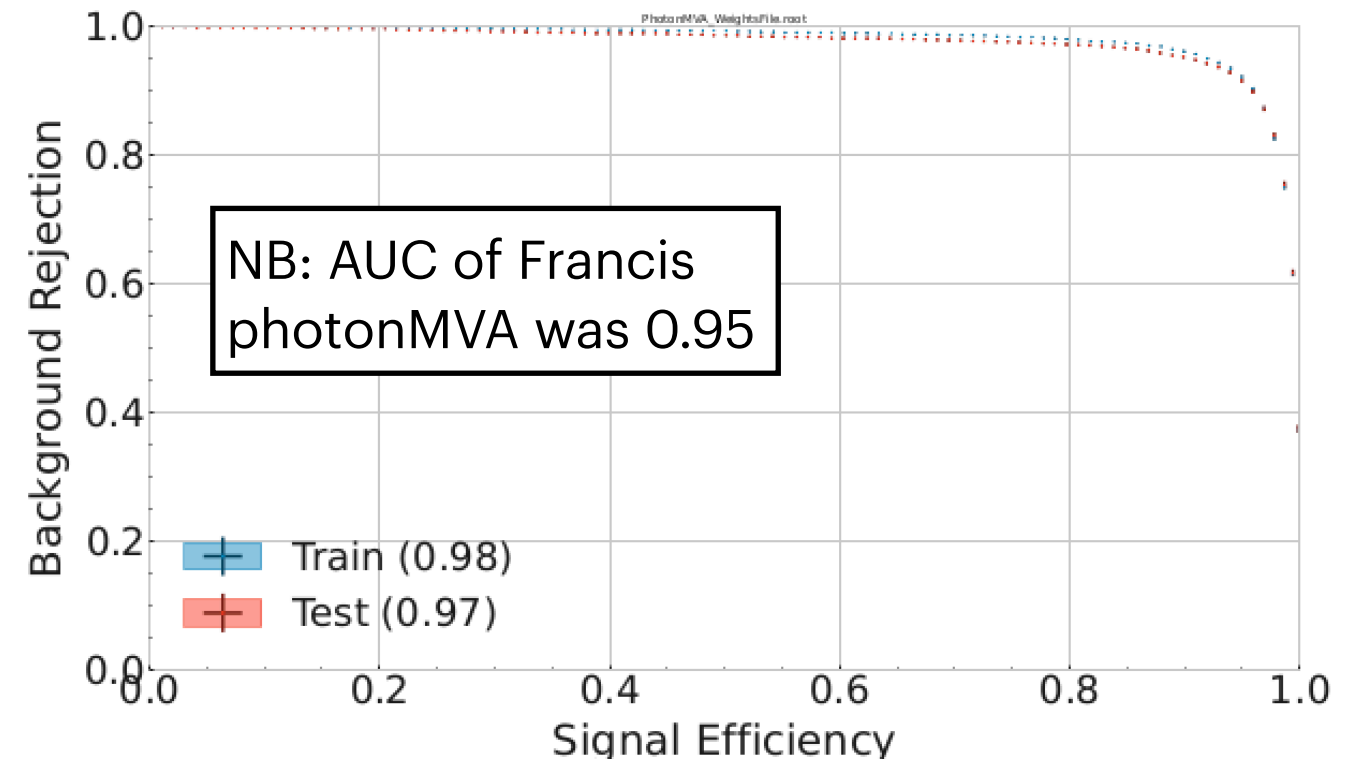
minC2TDist

clusterLAT

clusterNHits

clusterTheta

beamBackgroundSuppression

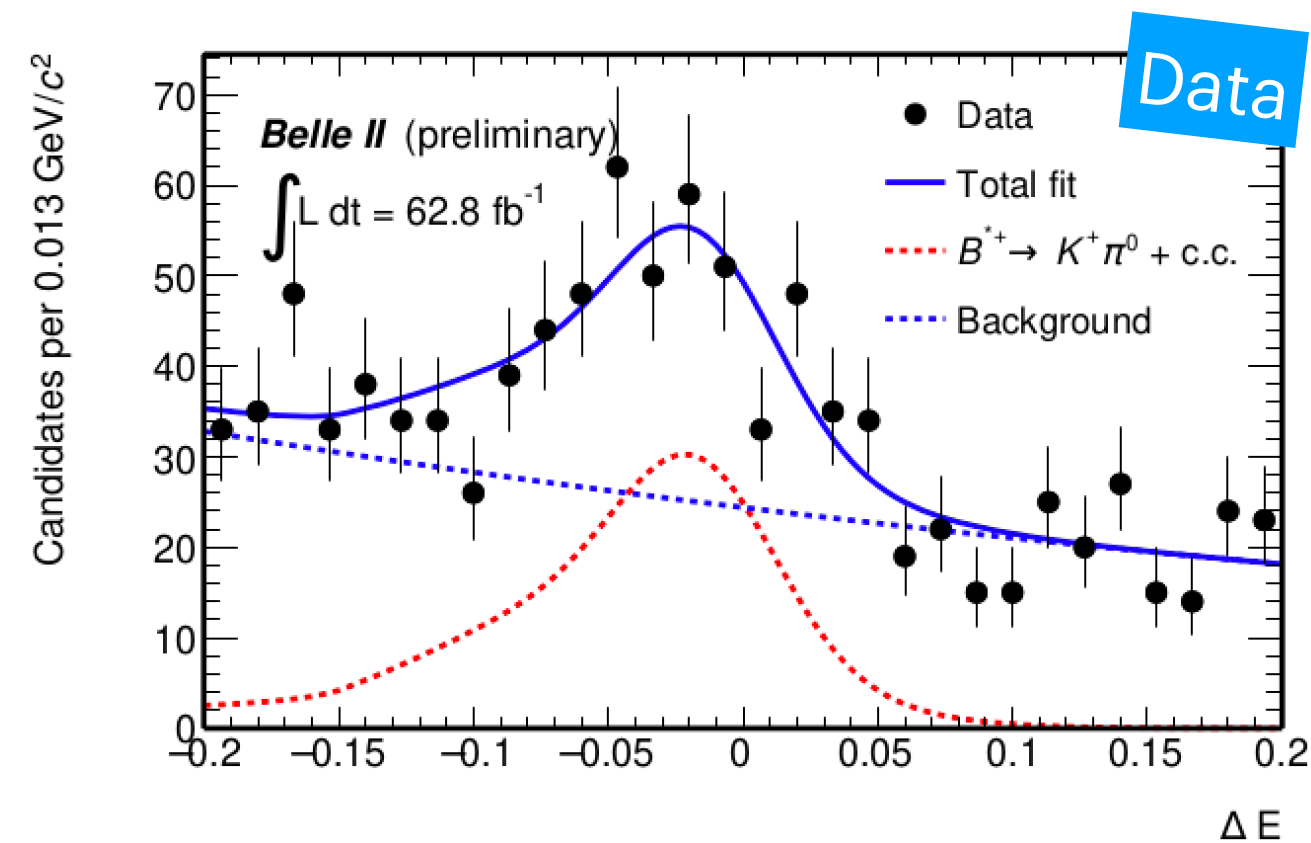


# Photon MVA validation

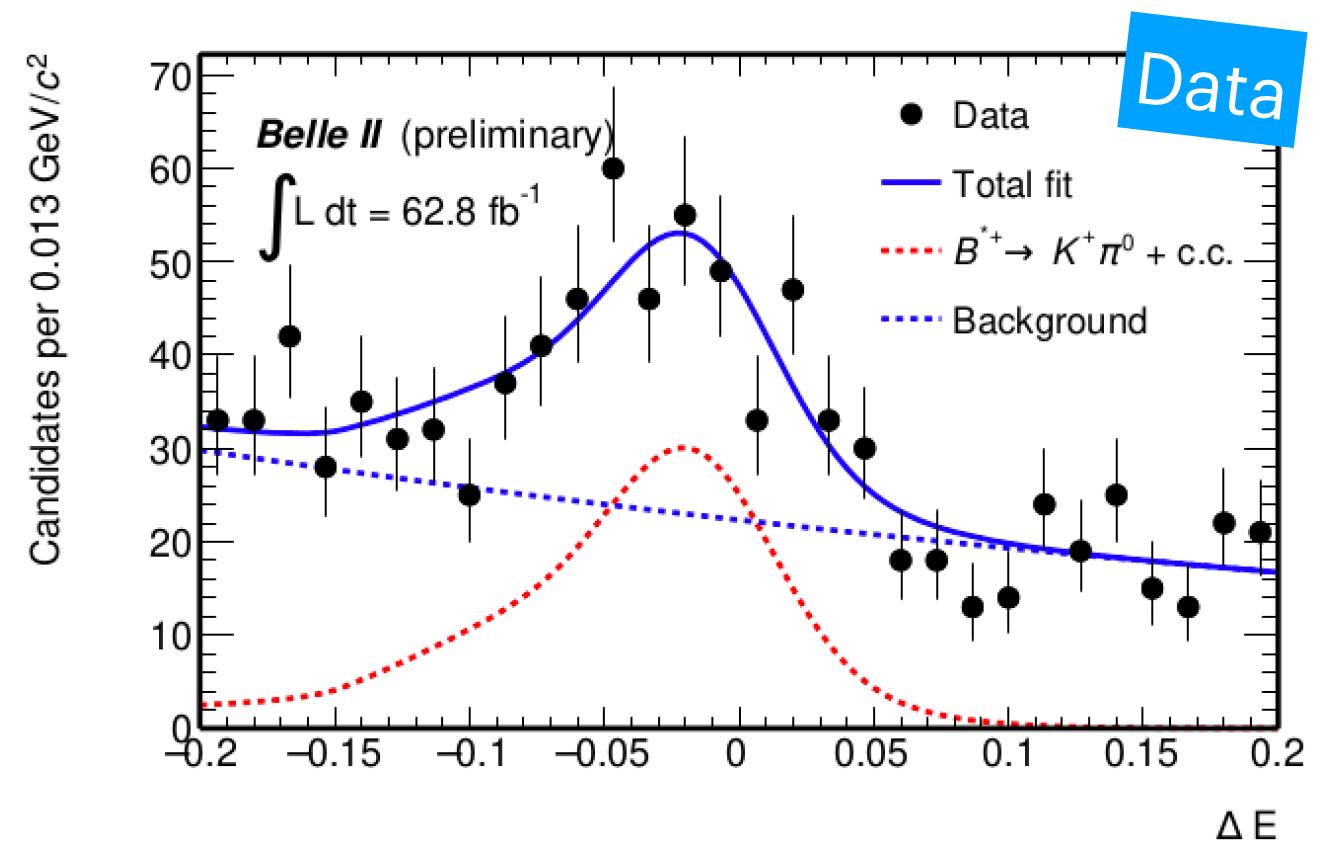
Apply photonMVA to  $B^+ \rightarrow K^+ \pi^0$  proc13 sample (chunk1+chunk2 — 62fb<sup>-1</sup>).

No photonMVA

PhotonMVA > 0.2



Background:  $742.64 \pm 40.1$   
 Signal:  $260.35 \pm 33.6$



Background:  $679.23 \pm 38.6$  (-8,5%)  
 Signal:  $258.76 \pm 32.6$  (-0.6%)

PhotonMVA works well. Modest impact, but still useful.

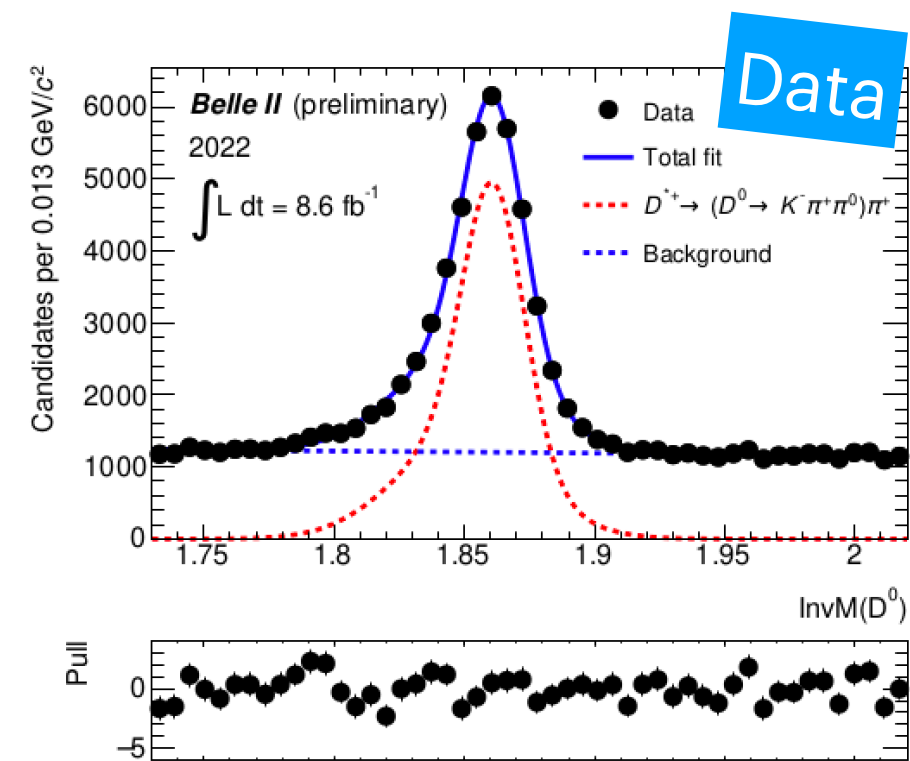
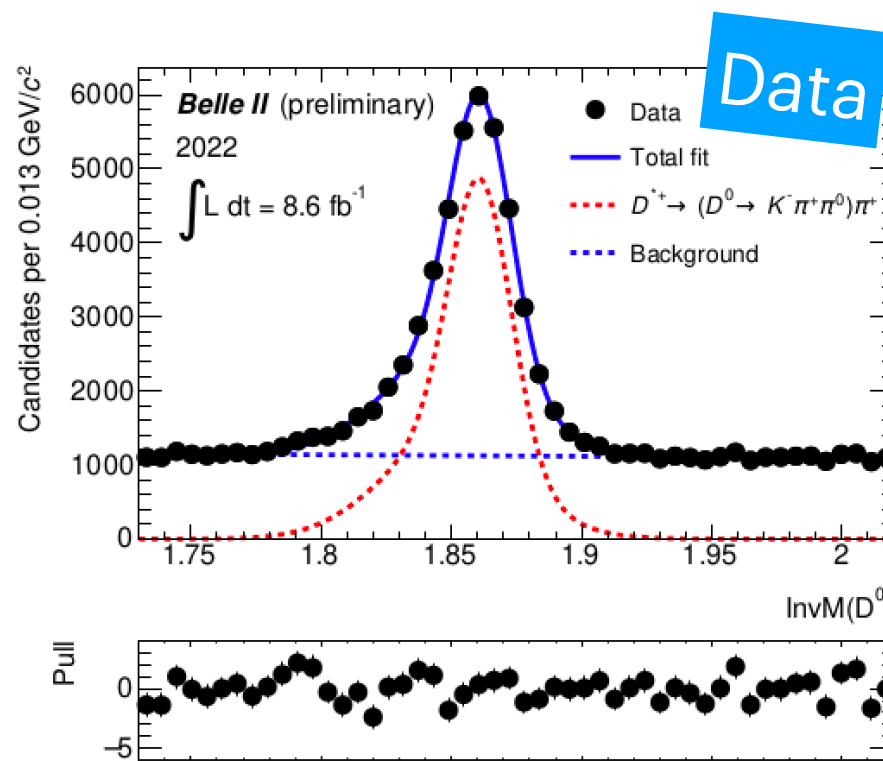
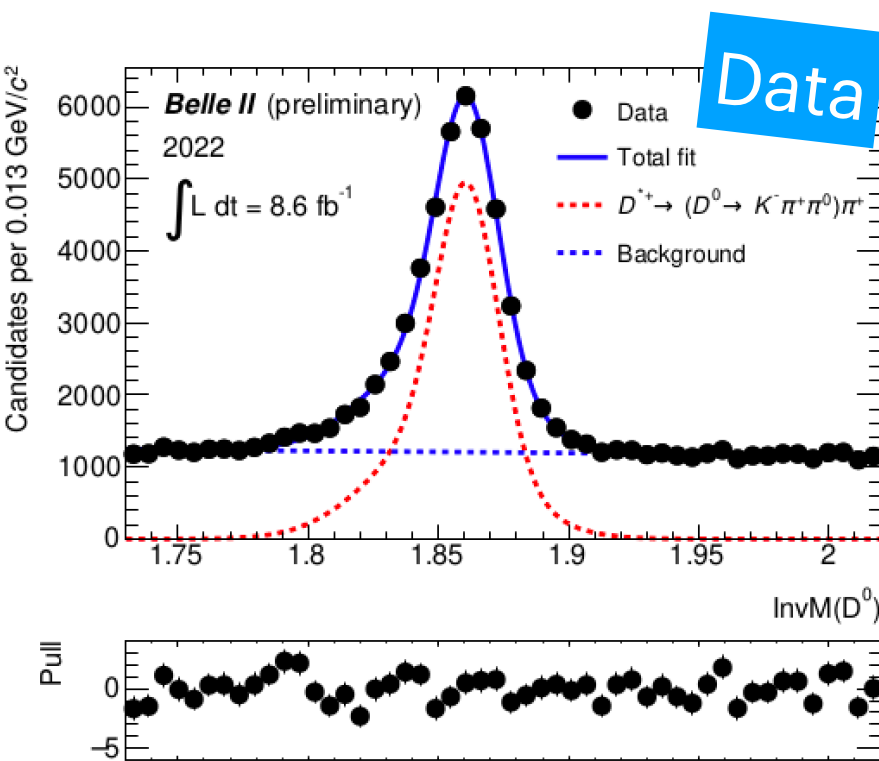
# Photon MVA validation

Apply photonMVA to  $D^* \rightarrow D^0(K\pi\pi^0)\pi$  proc13 sample (chunk1 — 8.6fb<sup>-1</sup>).

No photonMVA

My PhotonMVA > 0.05 (optimised)

Francis PhotonMVA > 0.05



Background:  $59902 \pm 74$   
 Signal:  $33944 \pm 69$   
 Significance: 110.804

Background:  $56066 \pm 490$  (-6.4%)  
 Signal:  $33422 \pm 528$  (-1.5%)  
 Significance: 111.724

Background:  $57410 \pm 70$  (-4.1%)  
 Signal:  $33519 \pm 61$  (-1.3%)  
 Significance: 111.158

PhotonMVA works well. Modest impact, but still useful.

CSBDT

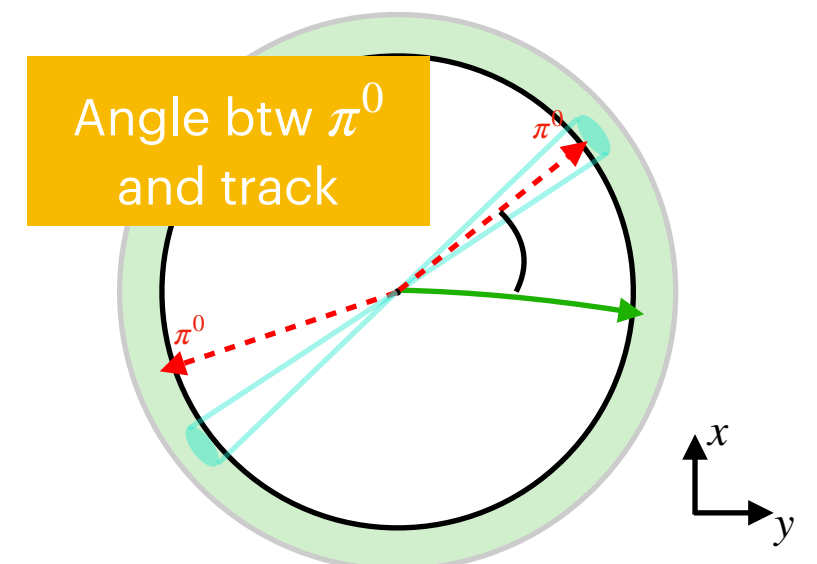
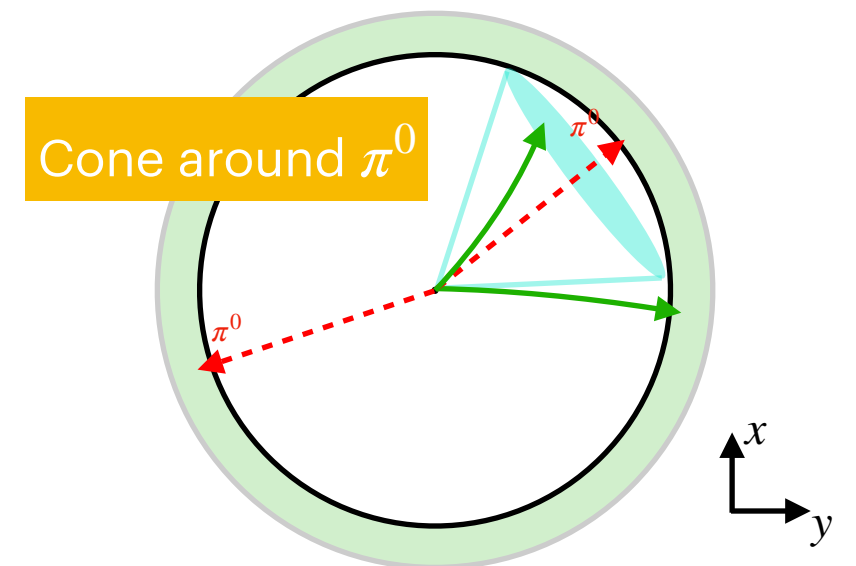
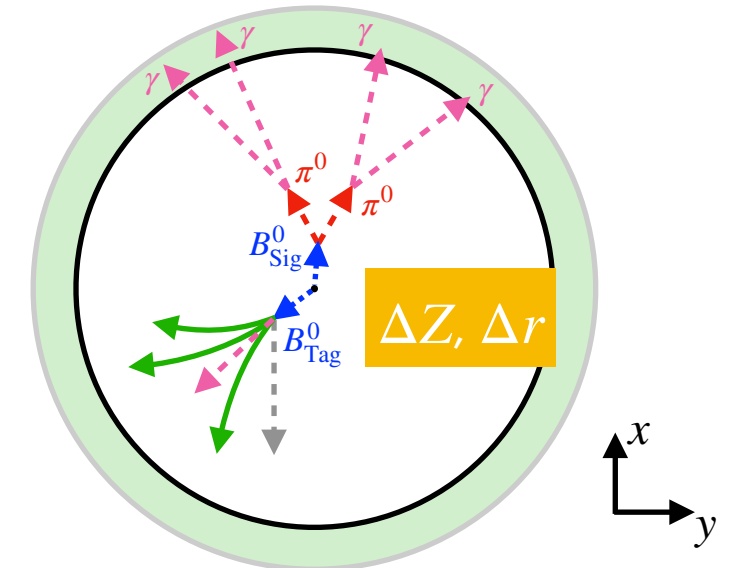
# CSBDT summary

New possible inputs:

Create continuum-suppression BDT using event-shape variables and  $B_{\text{Tag}}$  variables, avoiding large correlations (<10% — was 5% for Francis) and/or sculpting.

Must check if the use of  $B_{\text{Tag}}$  variables sculpts or introduces large correlations in the flavour tagger variables.

Note: 6.7% of the signal events doesn't have a  $B_{\text{Tag}}$  vertex  $\rightarrow$  remove these events (bkg: -9.4%).

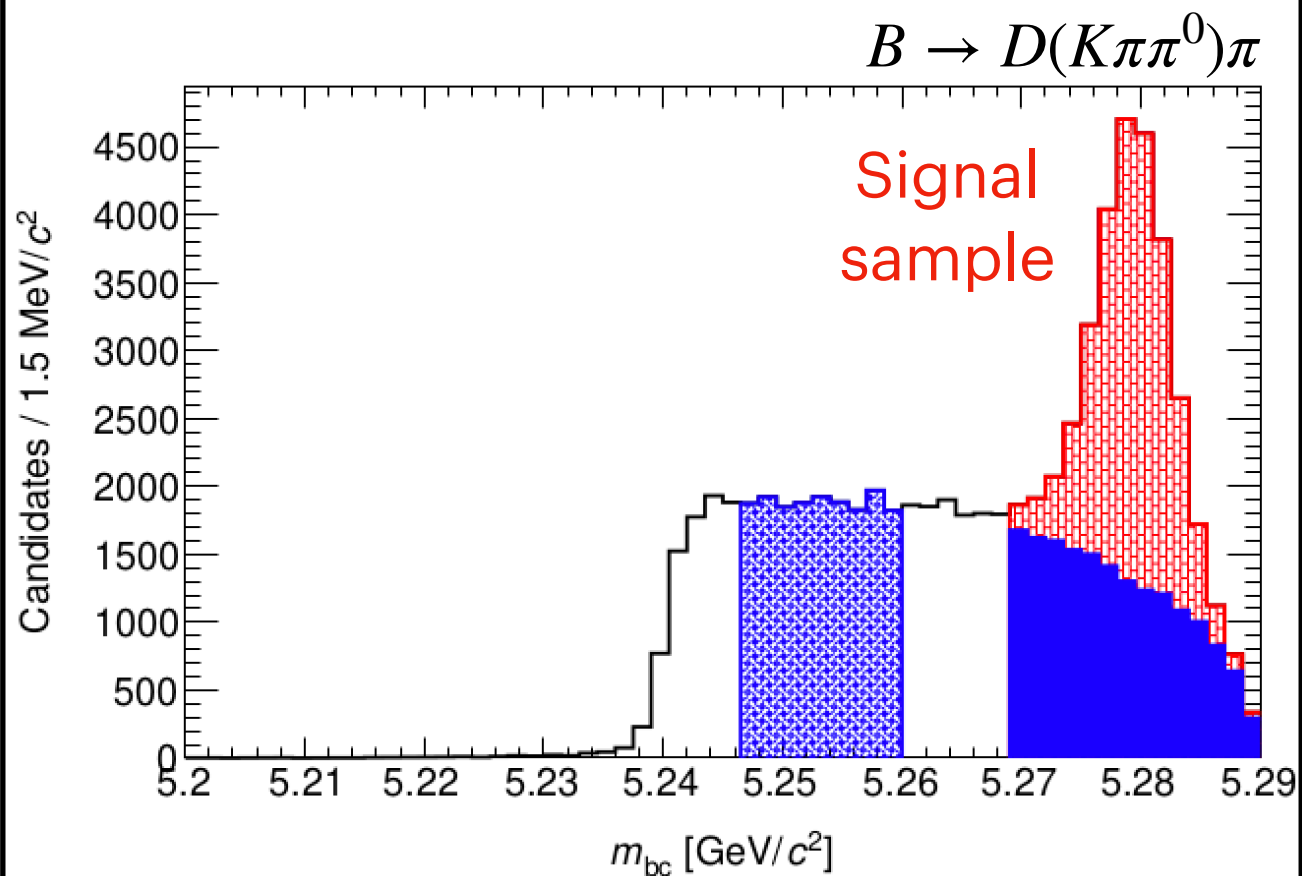




# CSBDT: inputs validation

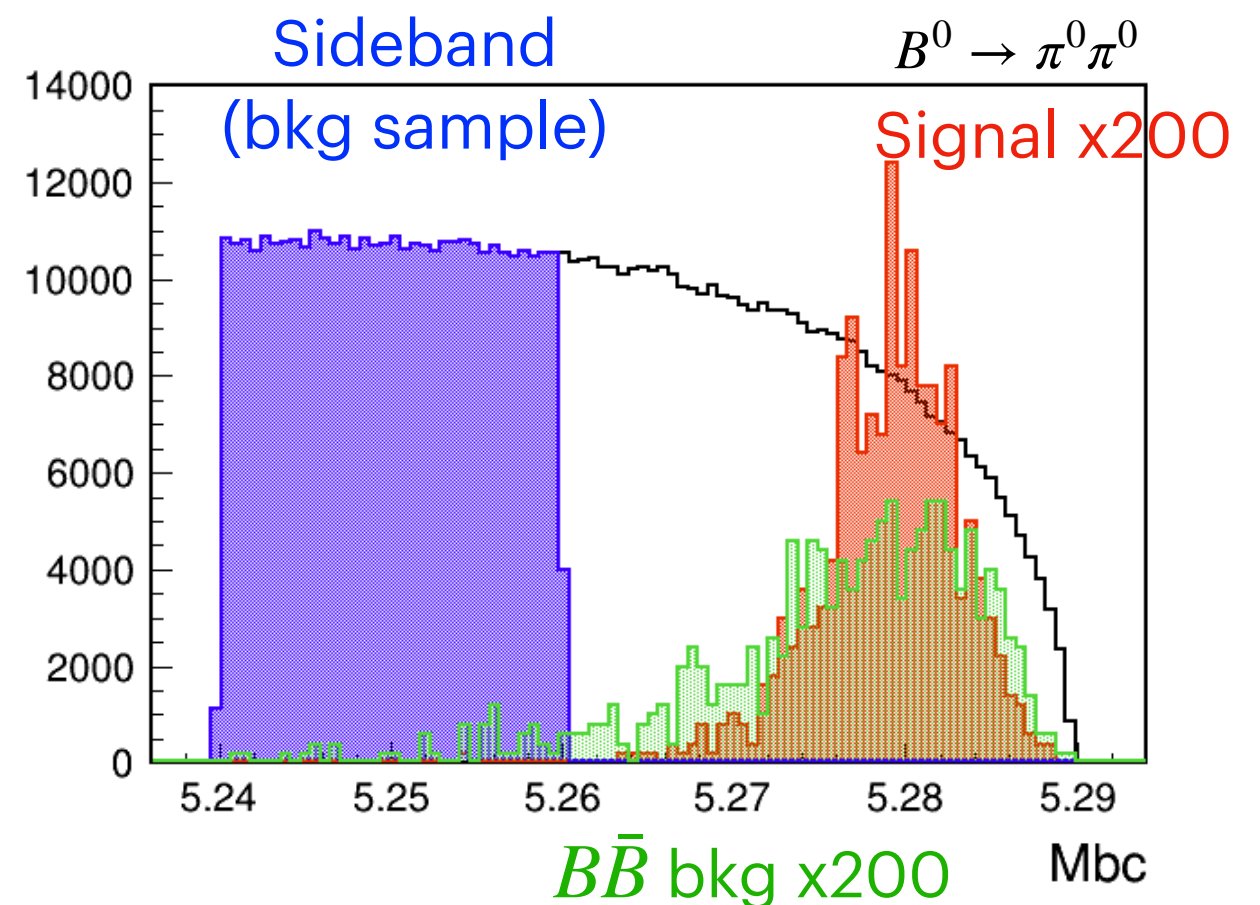
**Signal:** use  $B \rightarrow D(K\pi\pi^0)\pi$  sideband-subtracted data (proc13) and sideband-subtracted  $B \rightarrow D(K\pi\pi^0)\pi$  MC15

Do not use  $B \rightarrow D(K\pi\pi^0)\pi$  for bkg because of the different compositions



**Background:** use  $B^0 \rightarrow \pi^0\pi^0$  sideband data (proc13) and  $B^0 \rightarrow \pi^0\pi^0$  sideband MC15

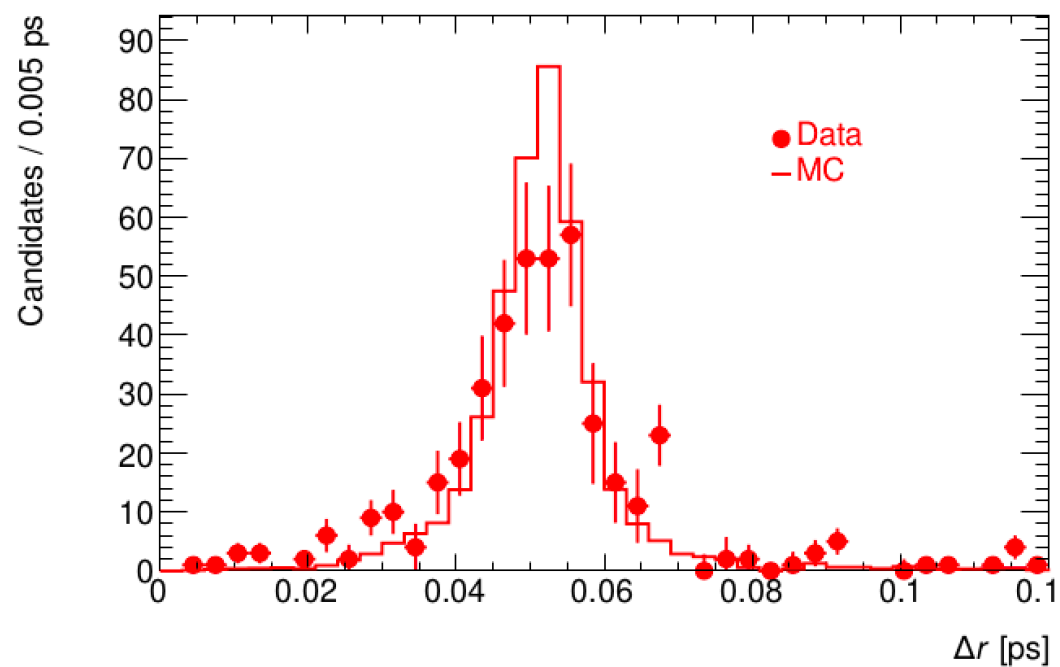
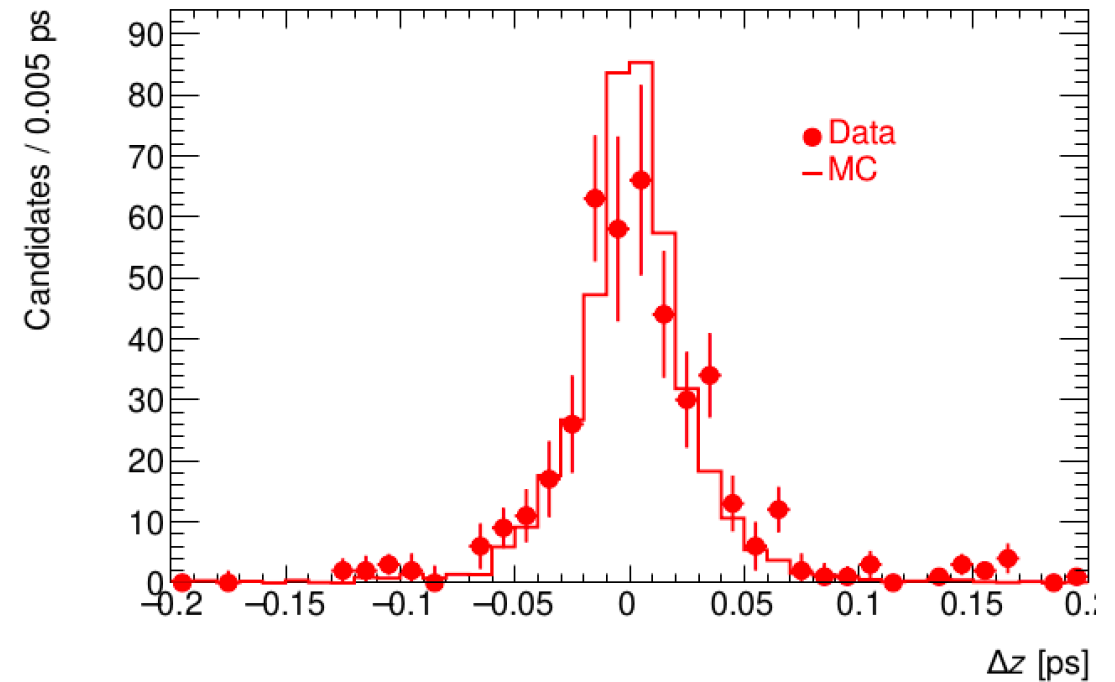
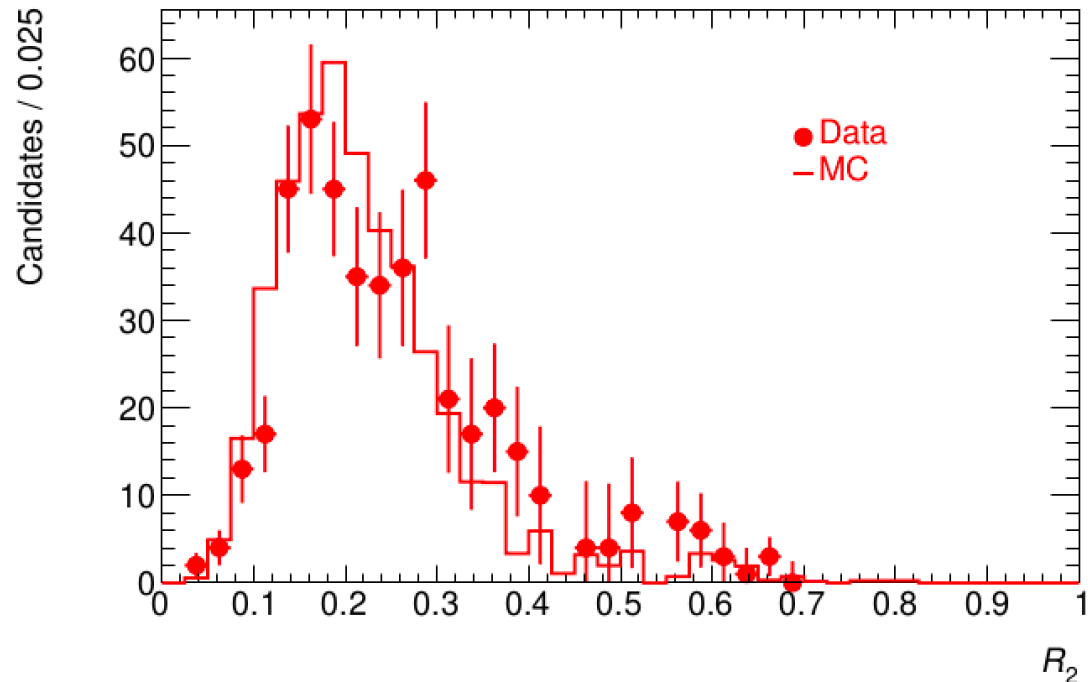
Need to check if bkg composition is the same in sideband and signal region





# Inputs validation — Signal only

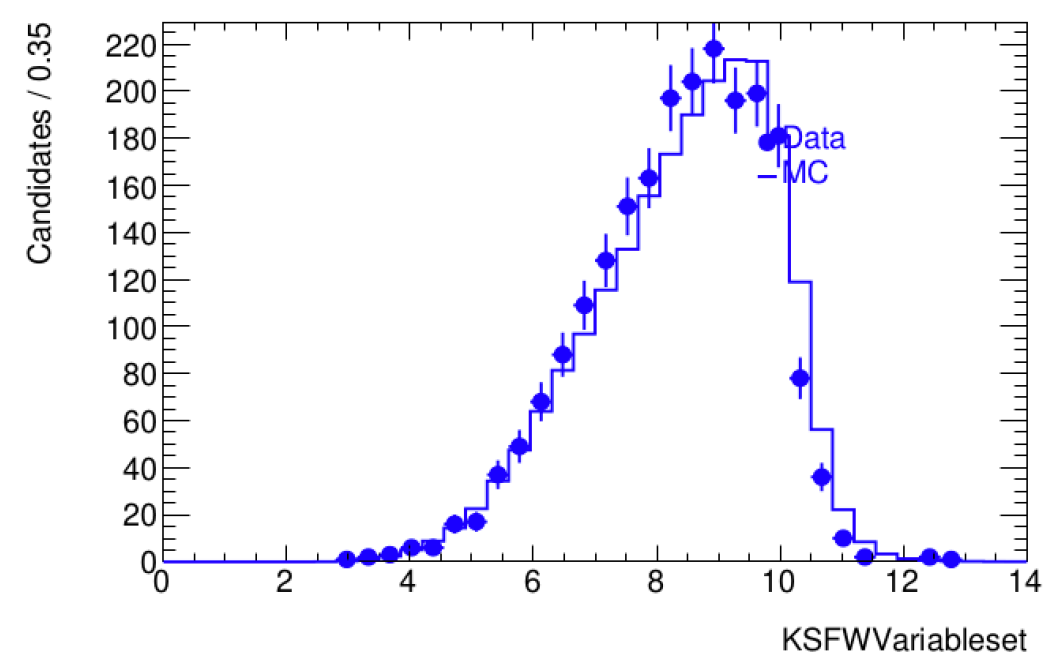
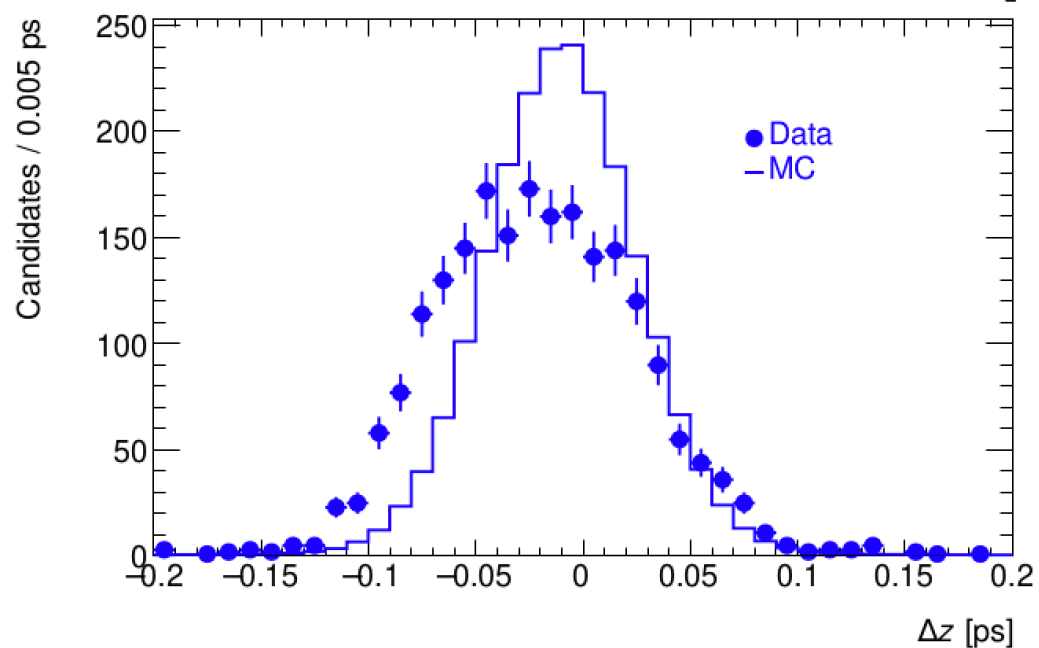
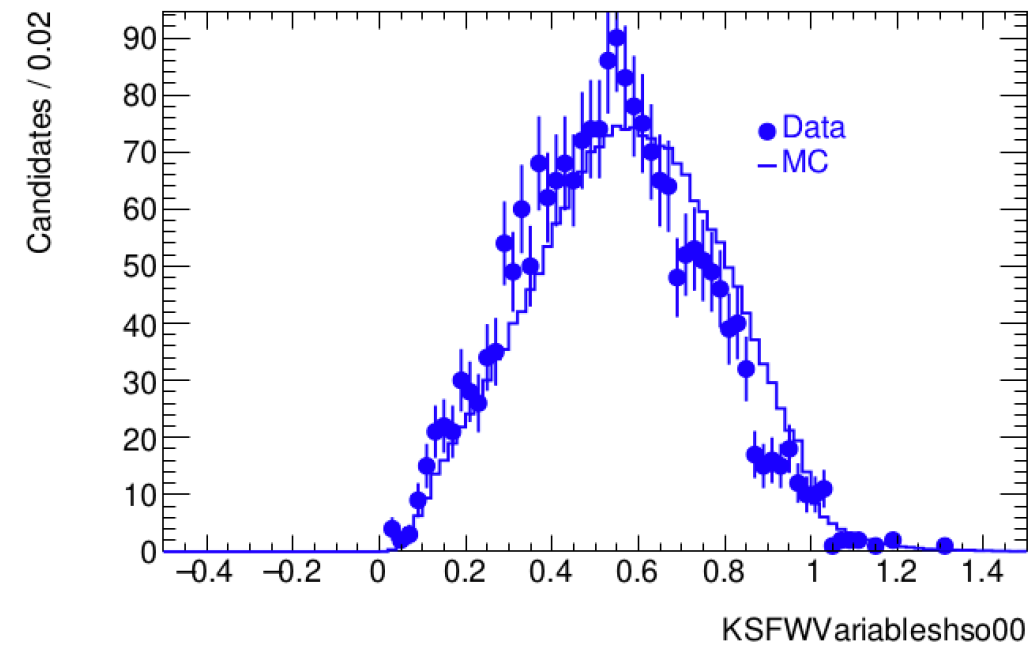
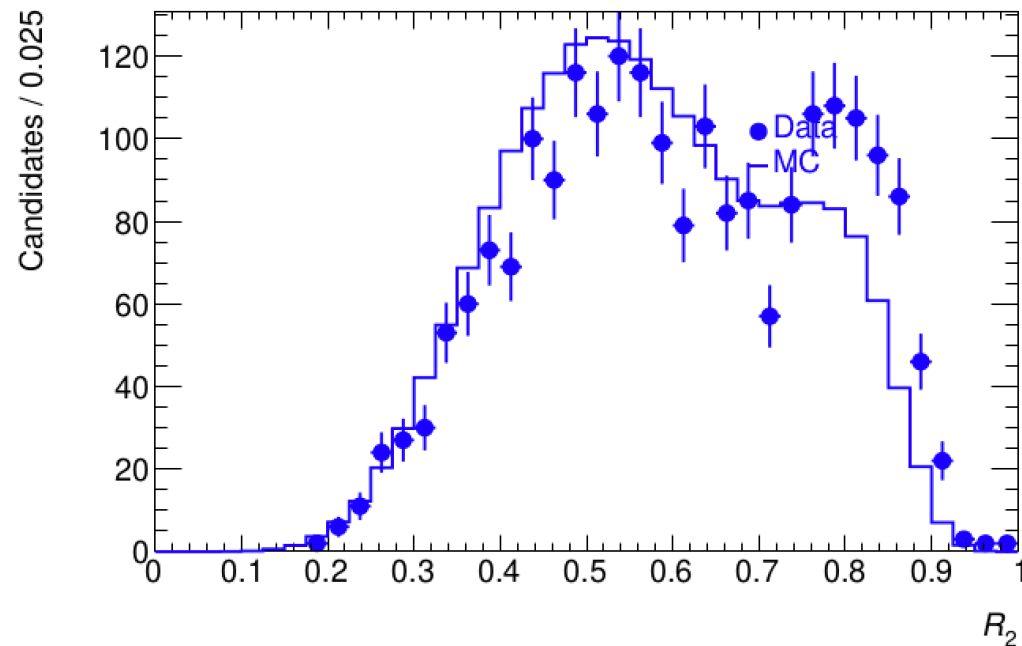
Use  $B \rightarrow D(K\pi\pi^0)\pi$  sideband-subtracted data (proc13) and sideband-subtracted  $B \rightarrow D(K\pi\pi^0)\pi$  MC15.



Sample has poor statistics, but do not observe any large discrepancy.

# Inputs validation — Background only

Use  $B^0 \rightarrow \pi^0\pi^0$  sideband data (proc13) and  $B^0 \rightarrow \pi^0\pi^0$  sideband MC15



Observe variables with some discrepancies.  
Better to use directly sideband data to train the CSBDT

# CSMVA (preliminary) result

Train on **MC sample** after applying all  $\pi^0$  selections.

## Inputs (after pruning)

7 Kakuno-Super-Fox-Wolfram moments

cosTBTO

1 CleoCone

cosTheta\*

R2

thrustOm

$\Delta Z$  (BTag)

$\Delta r$  (BTag)

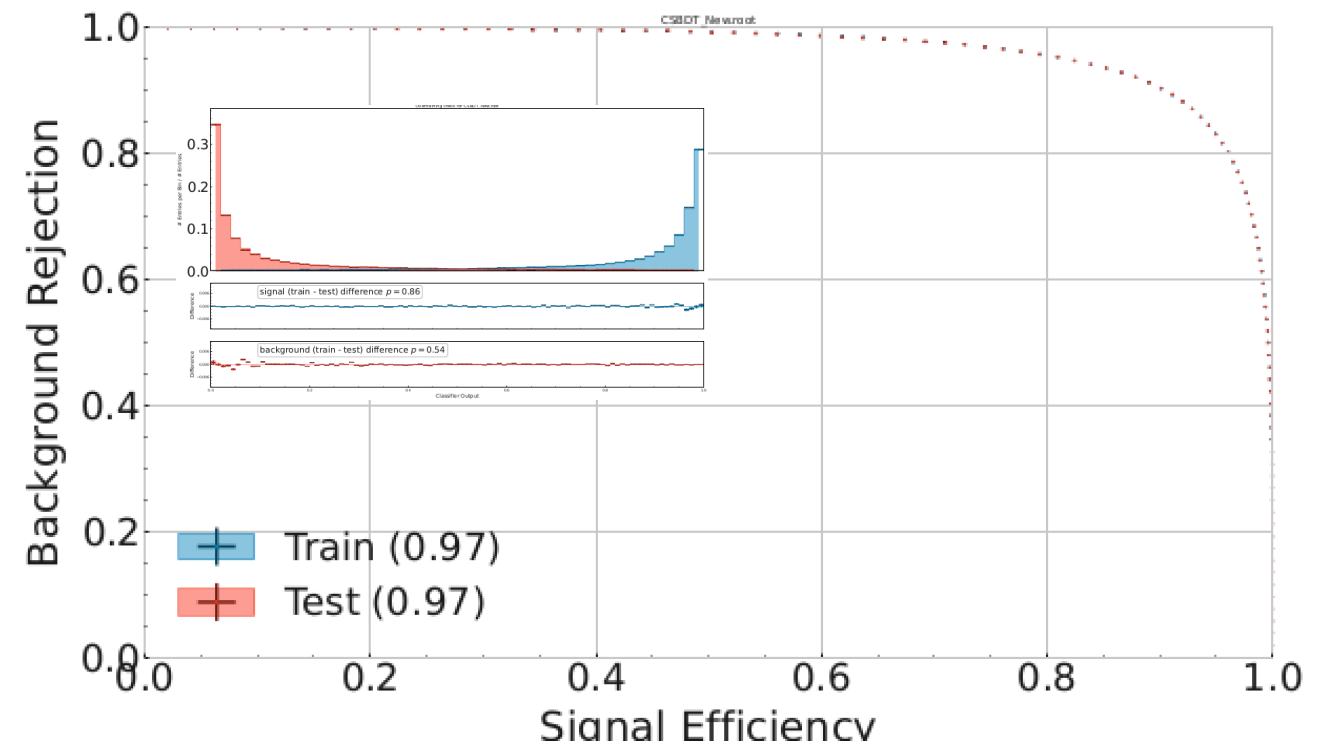
thrustAxisCosTheta

angle between  $\pi^0$ 's

cosHelicityAngle

KSFVVariableset

KSFVVariablesmm2



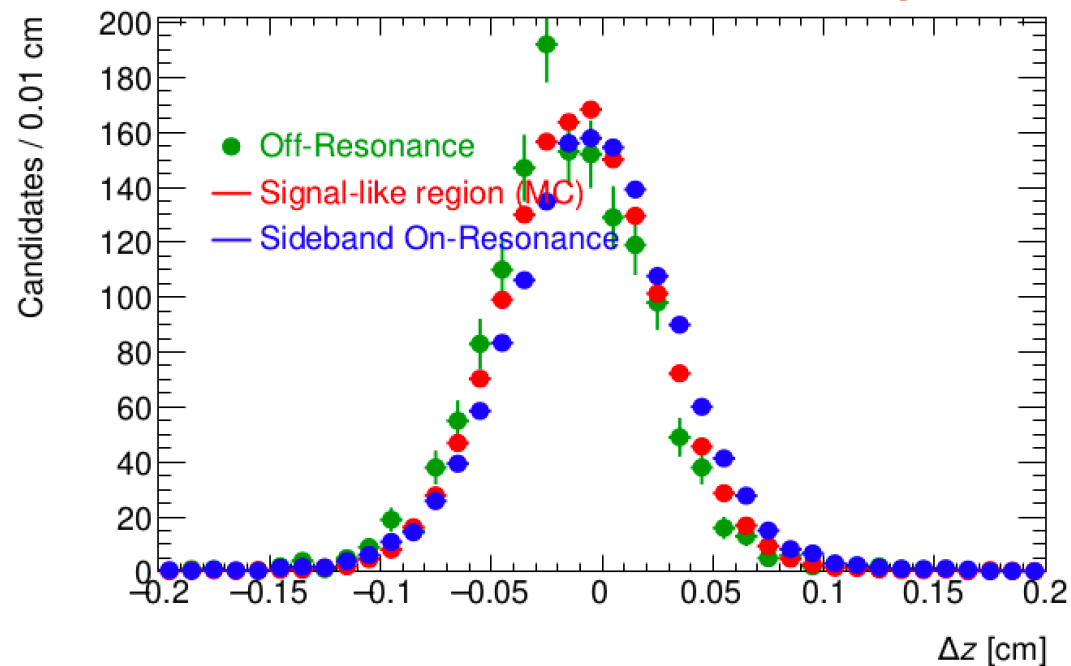
Better performance wrt old BDT  
(AUC=0.95).

Will repeat this using off-res data  
for the bkg training.

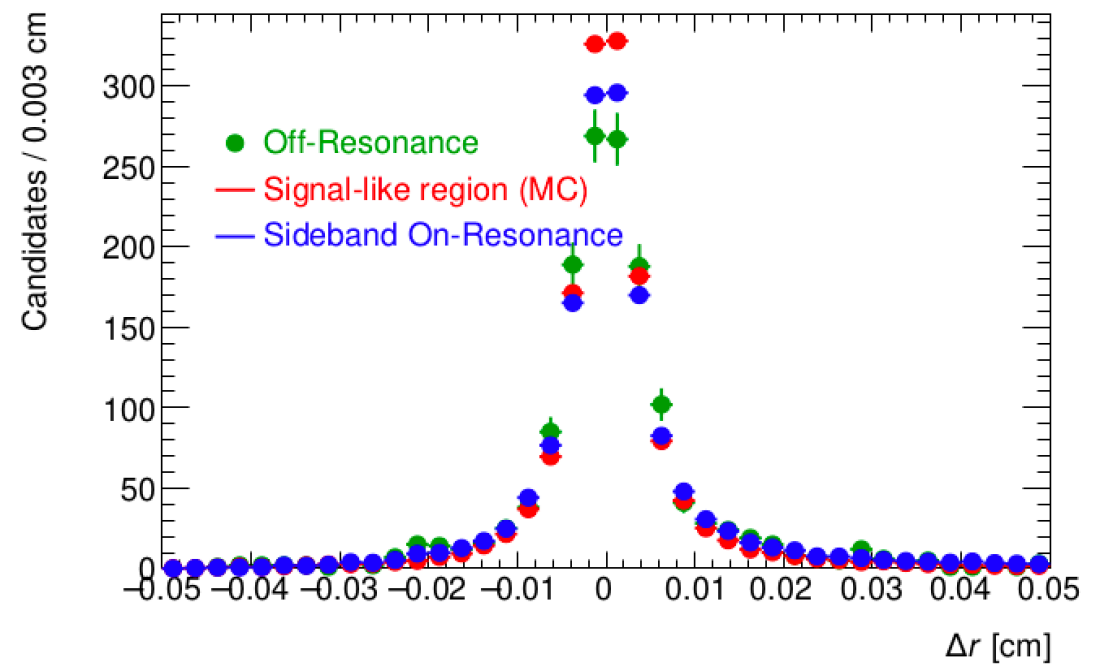
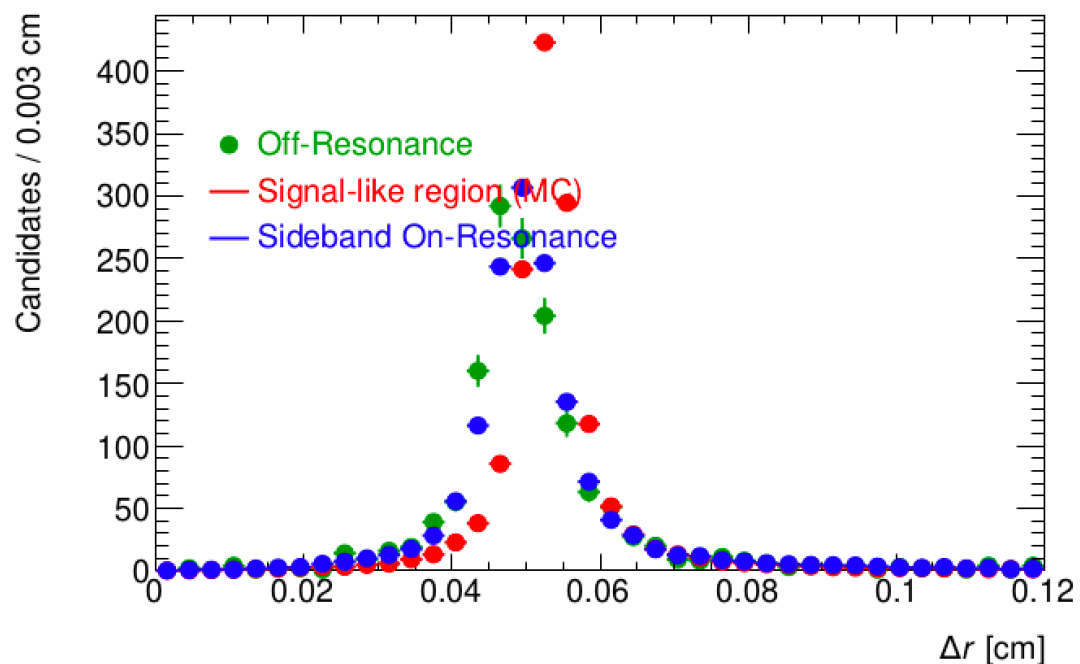
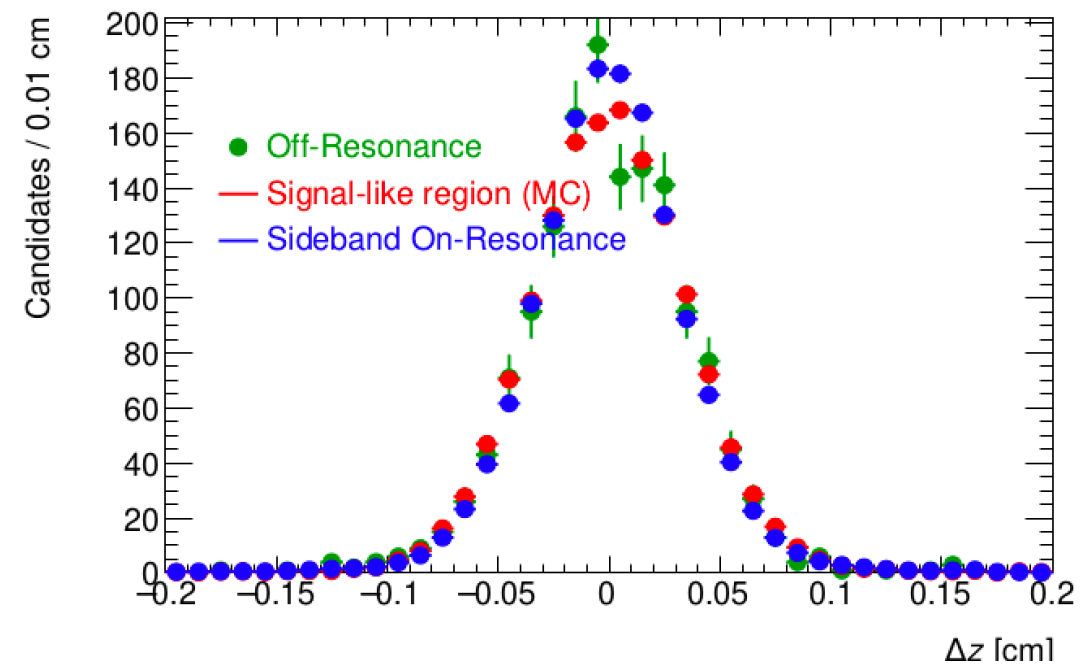
# Which are the correct $\Delta r$ and $\Delta Z$ distributions?

Sideband data and off-resonance data have different  $\Delta r$  and  $\Delta Z$  distributions. Use  $\Delta r$  and  $\Delta Z$  distributions with respect to the IP (not the lab origin).

with respect to the origin



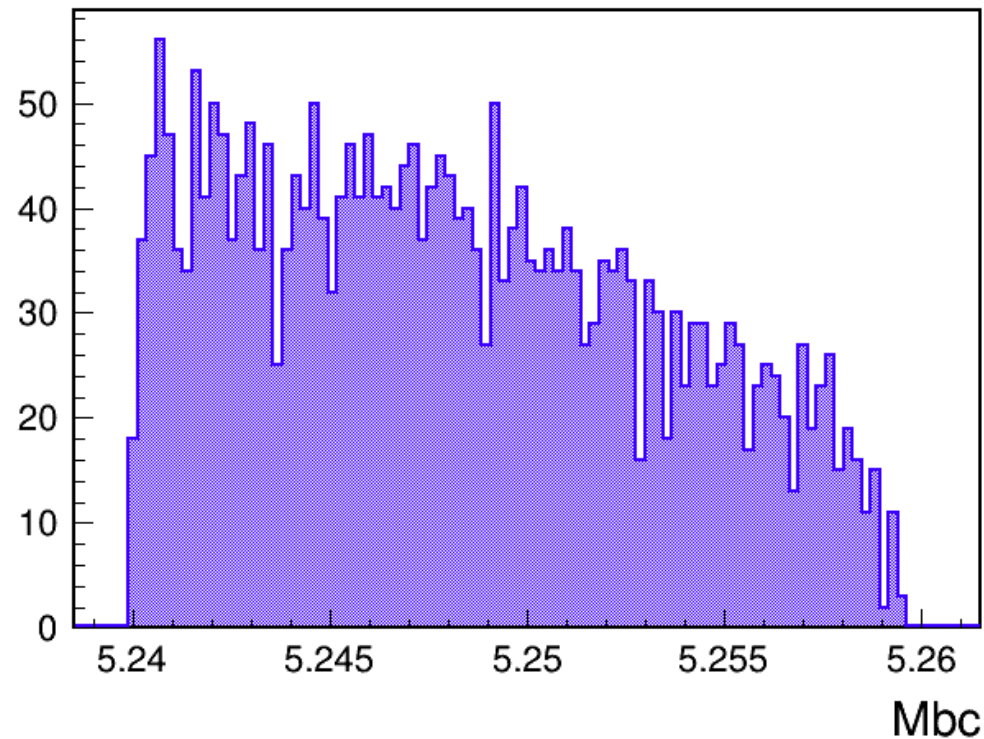
with respect to the IP



Improved situation

# CSMVA using data to train bkg

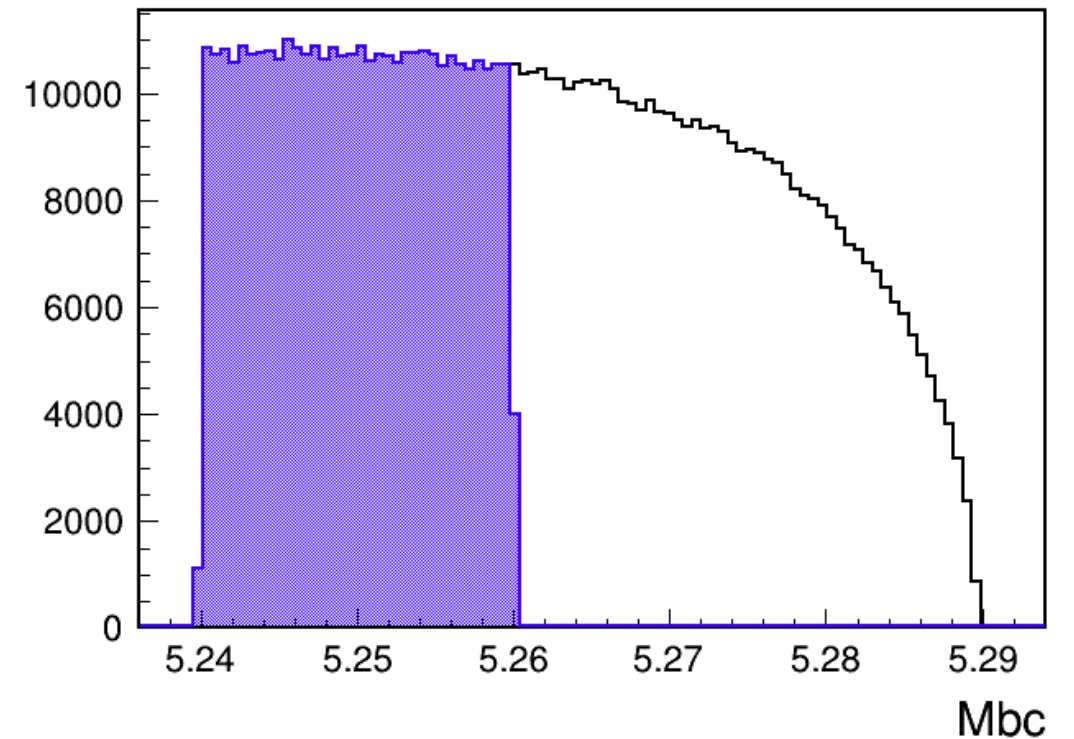
Off-resonance data



Pro: describes well the background in the signal-region in all the variables

Cons: very small amount of data

Sideband on-resonance data

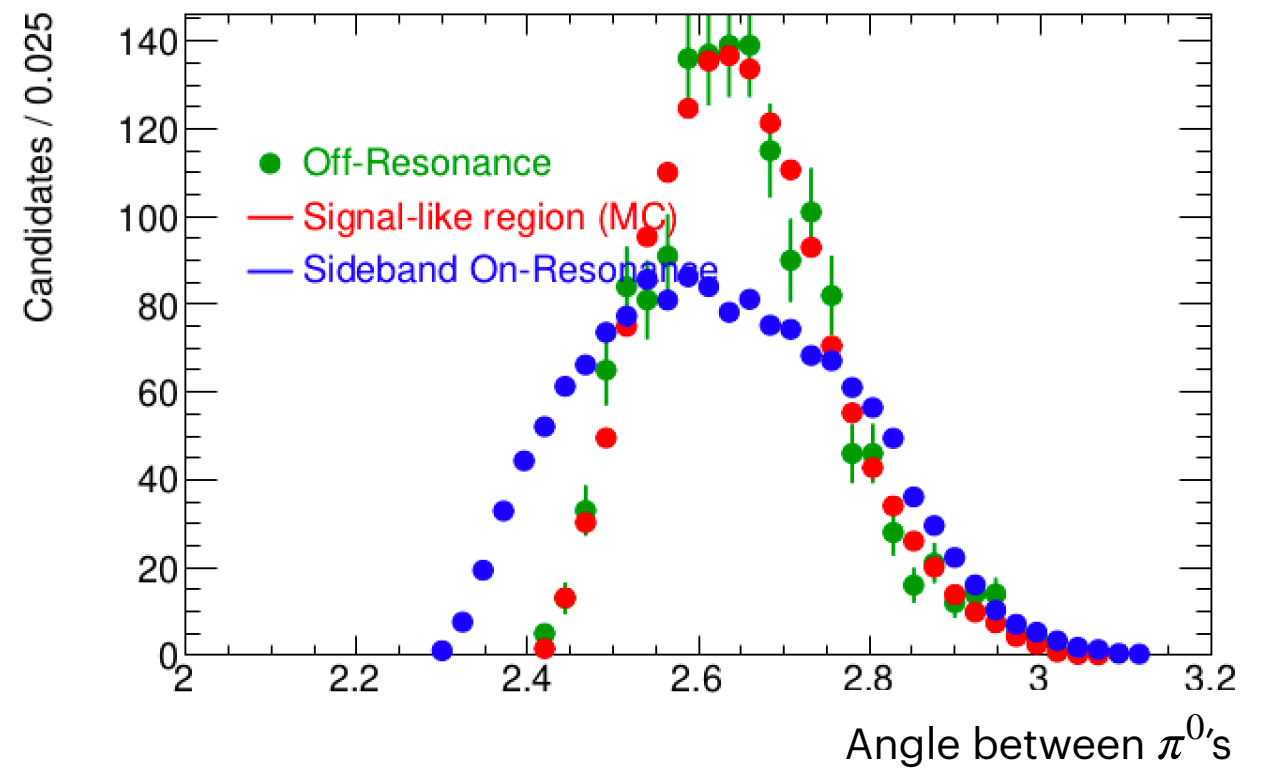
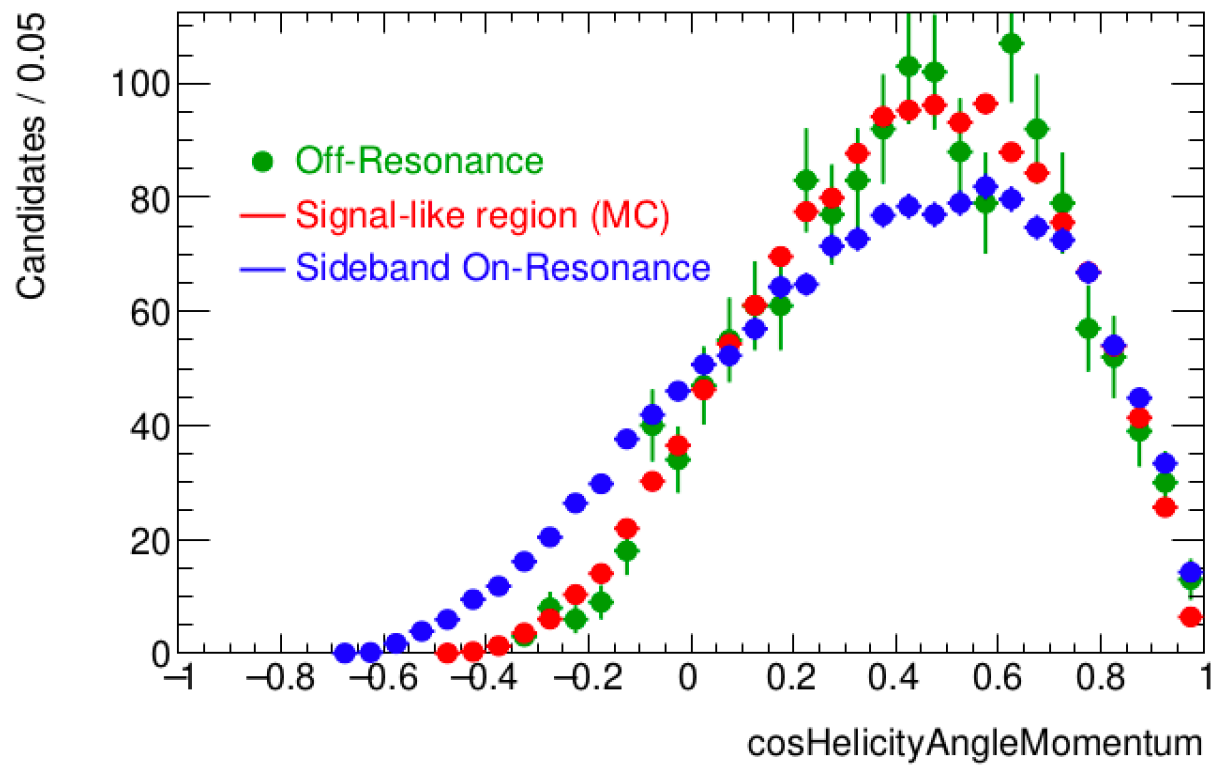


Pro: very large amount of data

Cons: doesn't describe well bkg in the signal region in two distributions (angles between pions)

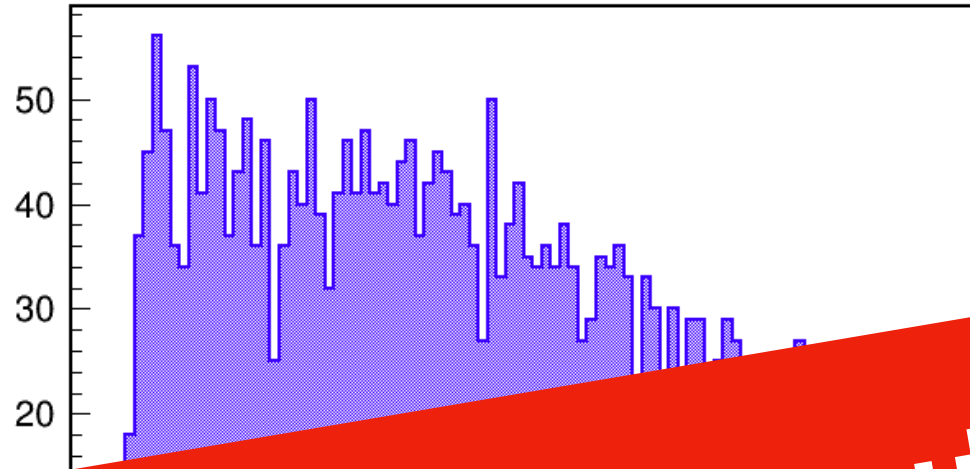
# Sideband on-resonance data

Only two distributions not describing well bkg in signal region:



# CSMVA using data to train bkg

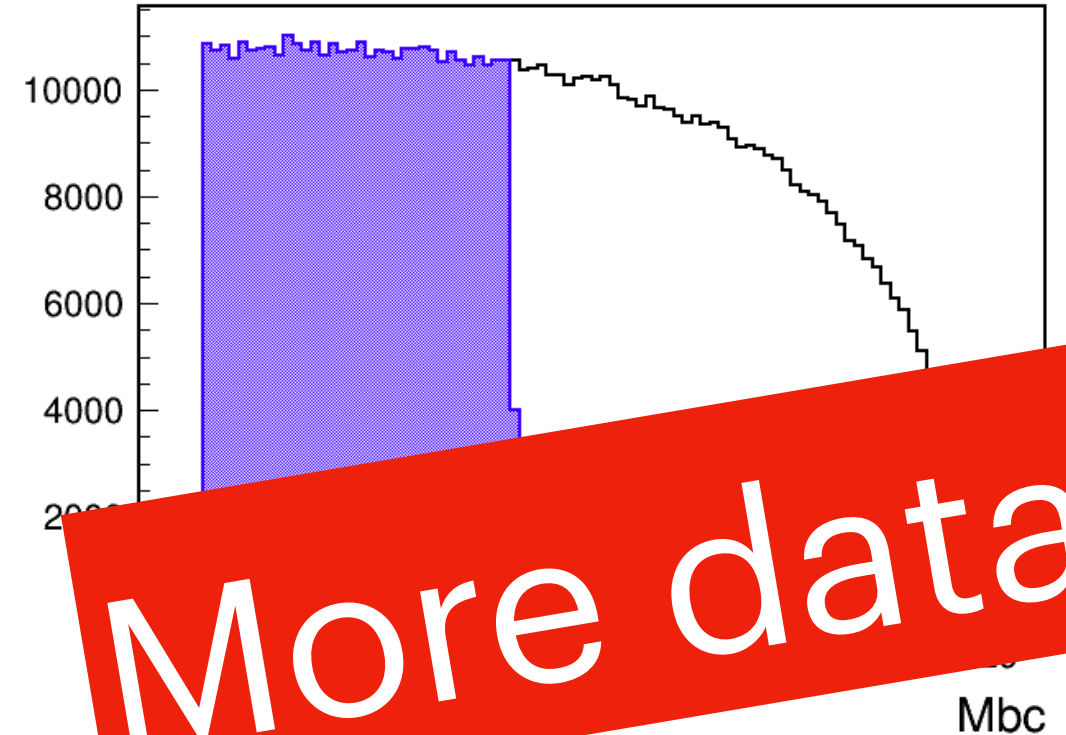
Off-resonance data



More input variables

Cons: very small amount of data

Sideband on-resonance data



More data

Pro: very large amount of data

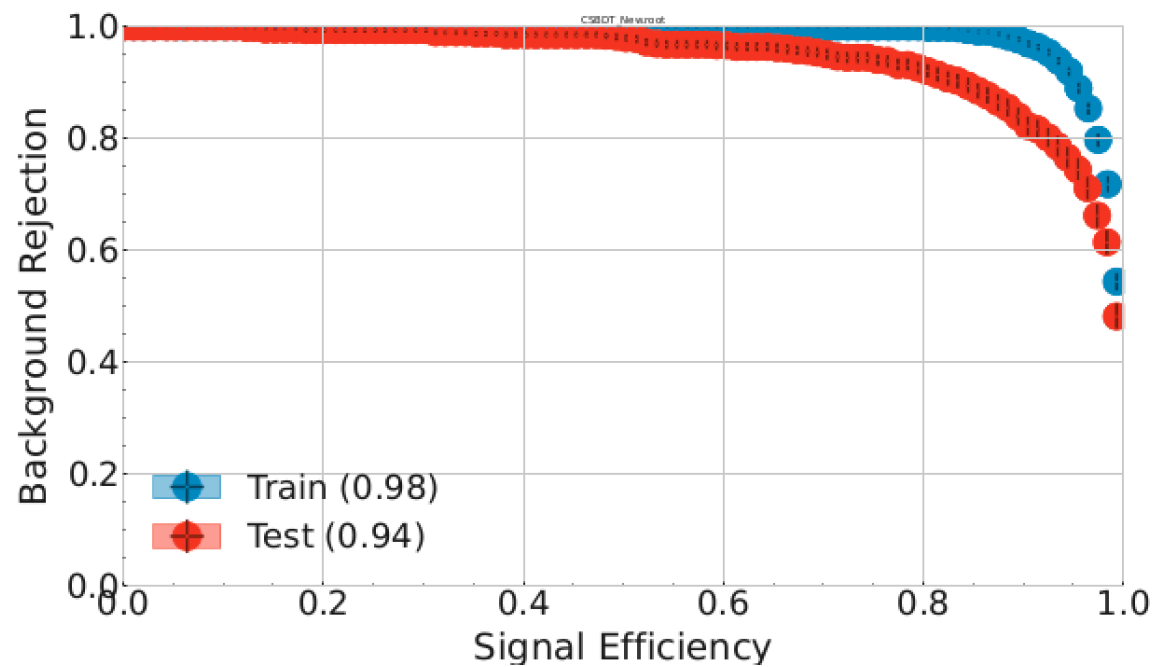
Cons: doesn't describe well bkg in the signal region in two distributions (angles between pions)



# CSMVA using data to train bkg

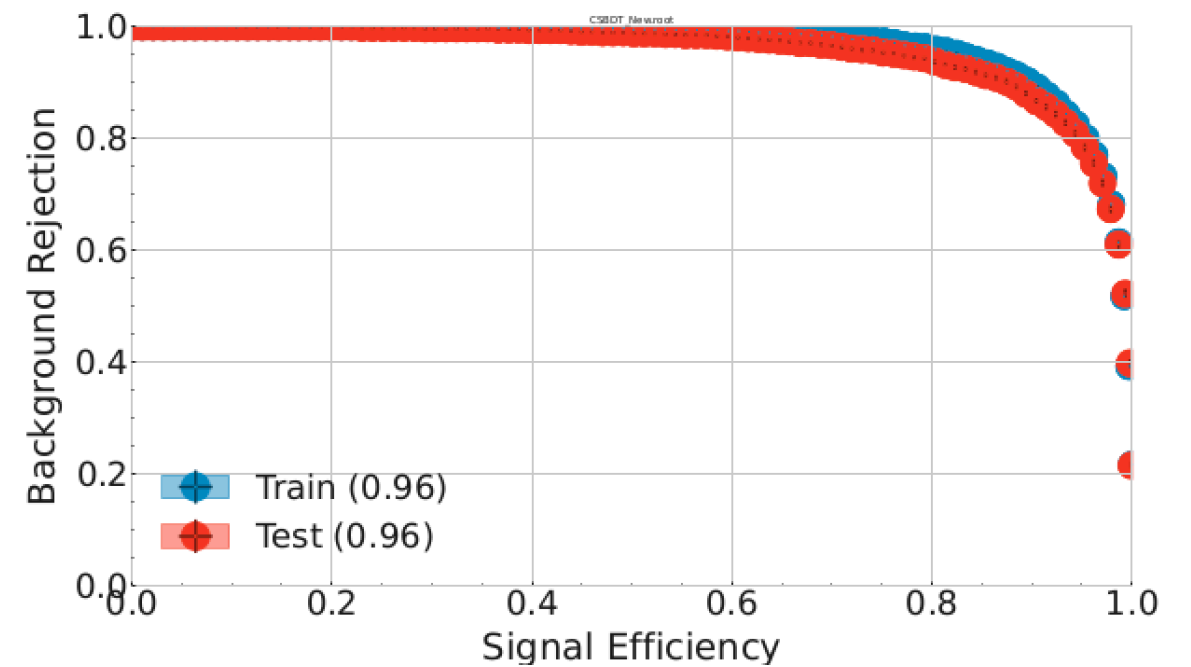
## Off-resonance data

Do not exclude the 2 variables from the BDT.



## Sideband on-resonance data

Exclude the 2 variables from the BDT.

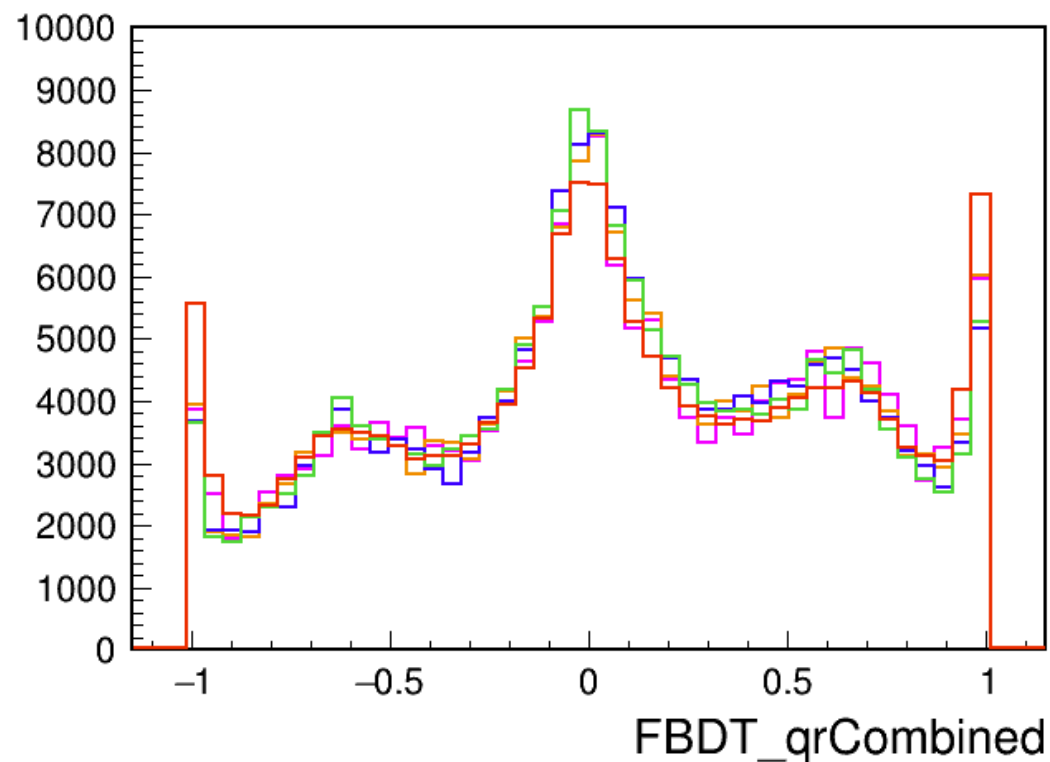
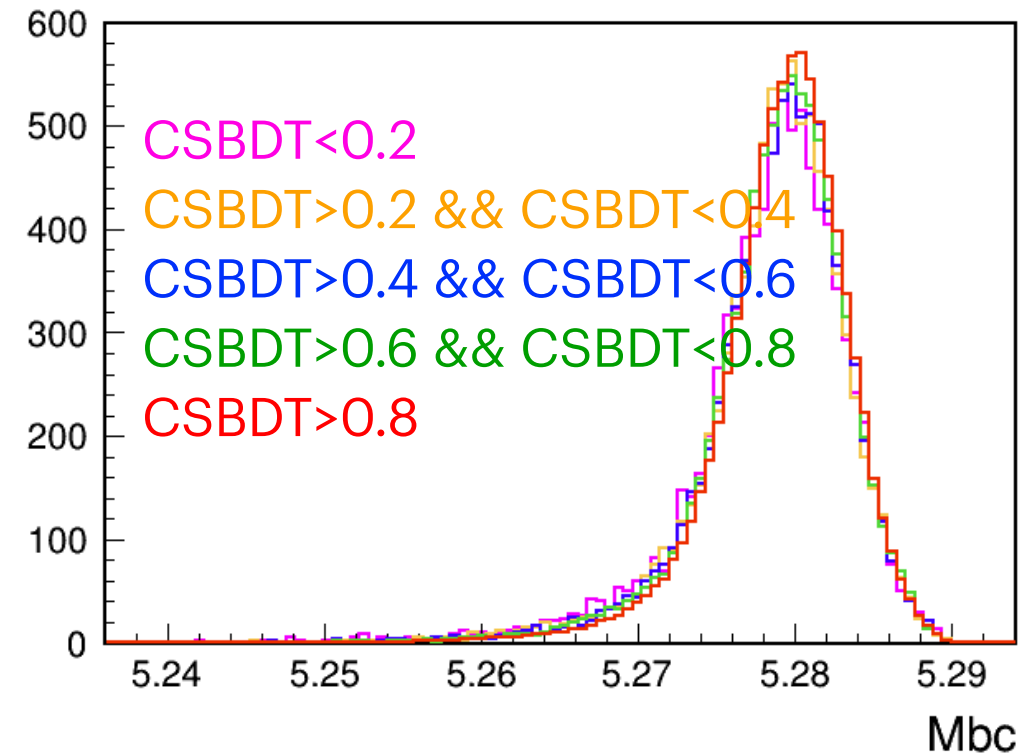
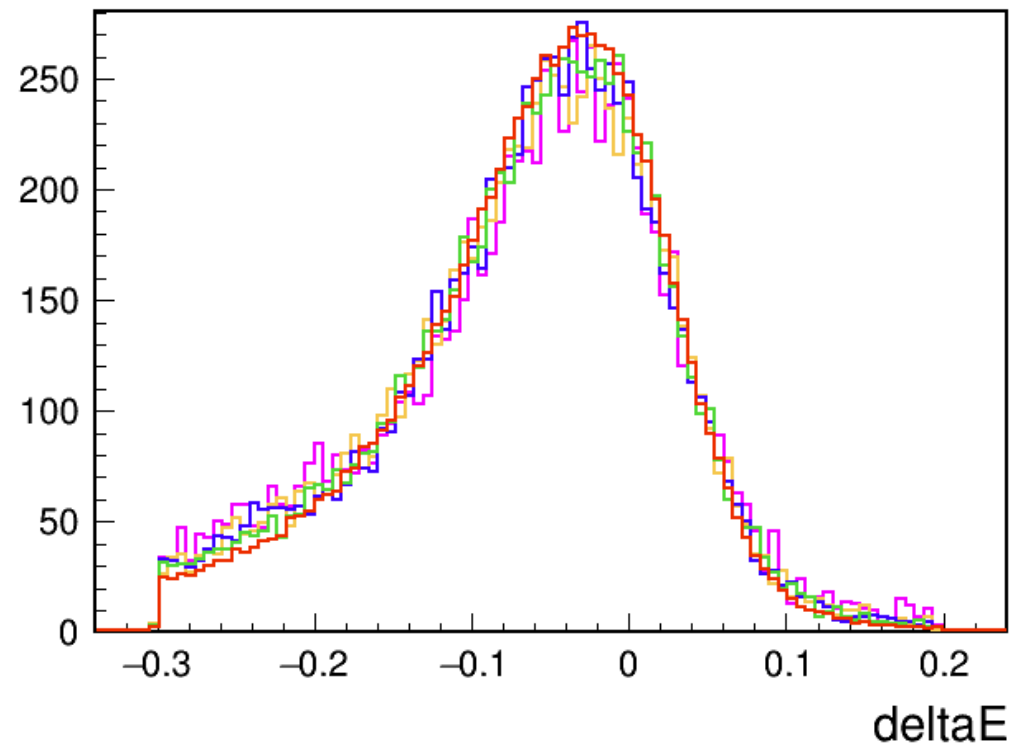


Small off-resonance data sample makes CSBDT not very reliable, while sideband data gives -2% in AUC.



# CSBDT dependences with fit variables

Draw fit variables in slices of CSBDT (signalMC only).



CSBDT > 0.5 && CSBDT < 0.6  
CSBDT > 0.6 && CSBDT < 0.7  
CSBDT > 0.7 && CSBDT < 0.8  
CSBDT > 0.8 && CSBDT < 0.9  
CSBDT > 0.9

Some sculpting in  $q_r$

# qr variables on SignalMC

$B^0 \rightarrow \pi^0 \pi^0$

$r$ - Interval	$\varepsilon_i$	$\Delta\varepsilon_i$	$w_i \pm \delta w_i$	$\Delta w_i \pm \delta \Delta w_i$	$\varepsilon_{eff,i} \pm \delta \varepsilon_{eff,i}$	$\Delta \varepsilon_{eff,i} \pm \delta \Delta \varepsilon_{eff,i}$	
0.000 – 0.100	16.9	0.17	$47.51 \pm 0.24$	$2.47 \pm 0.47$	$0.0420 \pm 0.0080$	$-0.0829 \pm 0.0193$	
0.100 – 0.250	16.6	0.12	$41.01 \pm 0.24$	$0.85 \pm 0.47$	$0.5356 \pm 0.0283$	$-0.0981 \pm 0.0571$	
0.250 – 0.500	21.1	0.75	$29.90 \pm 0.20$	$0.64 \pm 0.39$	$3.4112 \pm 0.0675$	$-0.0948 \pm 0.1350$	
0.500 – 0.625	11.7	-0.26	$20.87 \pm 0.23$	$1.87 \pm 0.46$	$3.9781 \pm 0.0667$	$-0.5973 \pm 0.1346$	
0.625 – 0.750	11.5	-0.03	$15.09 \pm 0.21$	$0.81 \pm 0.41$	$5.5976 \pm 0.0728$	$-0.2756 \pm 0.1460$	
0.750 – 0.875	8.7	0.06	$8.27 \pm 0.18$	$0.56 \pm 0.37$	$6.0356 \pm 0.0653$	$-0.1225 \pm 0.1307$	
0.875 – 1.000	13.5	-0.81	$1.74 \pm 0.07$	$0.21 \pm 0.14$	$12.5839 \pm 0.0721$	$-0.8637 \pm 0.1445$	
Total	$\varepsilon_{eff} = \sum_i \varepsilon_i \cdot \langle 1 - 2w_i \rangle^2 = 32.18 \pm 0.16$						$\Delta \varepsilon_{eff} = -2.13 \pm 0.32$

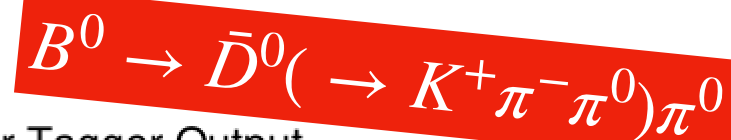
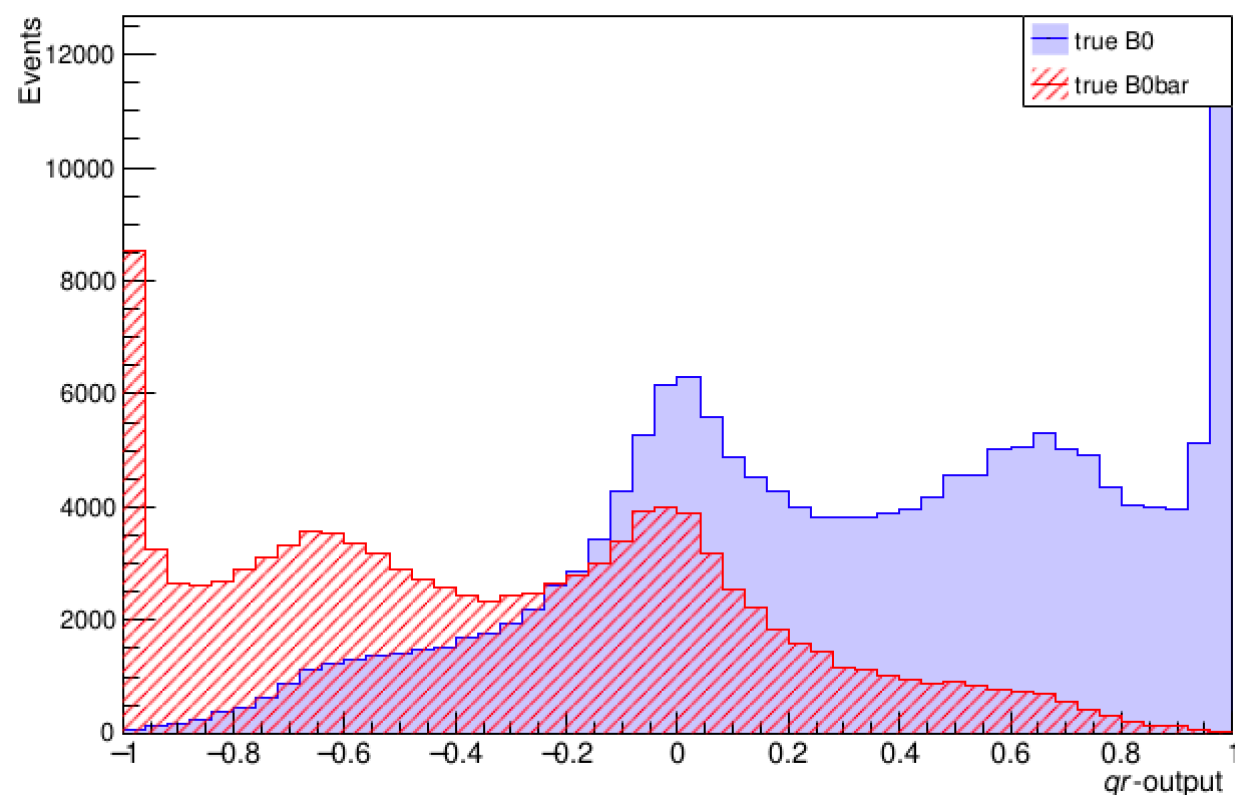
$B^0 \rightarrow \bar{D}^0 (\rightarrow K^+ \pi^- \pi^0) \pi^0$

$r$ - Interval	$\varepsilon_i$	$\Delta\varepsilon_i$	$w_i \pm \delta w_i$	$\Delta w_i \pm \delta \Delta w_i$	$\varepsilon_{eff,i} \pm \delta \varepsilon_{eff,i}$	$\Delta \varepsilon_{eff,i} \pm \delta \Delta \varepsilon_{eff,i}$	
0.000 – 0.100	17.7	0.27	$47.27 \pm 0.26$	$2.58 \pm 0.51$	$0.0526 \pm 0.0099$	$-0.0986 \pm 0.0217$	
0.100 – 0.250	16.8	0.26	$41.09 \pm 0.26$	$1.07 \pm 0.52$	$0.5322 \pm 0.0311$	$-0.1189 \pm 0.0623$	
0.250 – 0.500	21.1	0.60	$30.37 \pm 0.22$	$0.24 \pm 0.43$	$3.2461 \pm 0.0728$	$0.0138 \pm 0.1457$	
0.500 – 0.625	11.5	0.06	$21.40 \pm 0.26$	$1.66 \pm 0.52$	$3.7607 \pm 0.0723$	$-0.4175 \pm 0.1445$	
0.625 – 0.750	11.2	-0.13	$15.23 \pm 0.23$	$0.97 \pm 0.46$	$5.4192 \pm 0.0794$	$-0.3649 \pm 0.1588$	
0.750 – 0.875	8.6	-0.22	$8.46 \pm 0.20$	$0.46 \pm 0.41$	$5.9675 \pm 0.0721$	$-0.2828 \pm 0.1442$	
0.875 – 1.000	13.1	-0.85	$1.62 \pm 0.08$	$0.47 \pm 0.15$	$12.2983 \pm 0.0783$	$-1.0309 \pm 0.1565$	
Total	$\varepsilon_{eff} = \sum_i \varepsilon_i \cdot \langle 1 - 2w_i \rangle^2 = 31.28 \pm 0.17$						$\Delta \varepsilon_{eff} = -2.30 \pm 0.34$

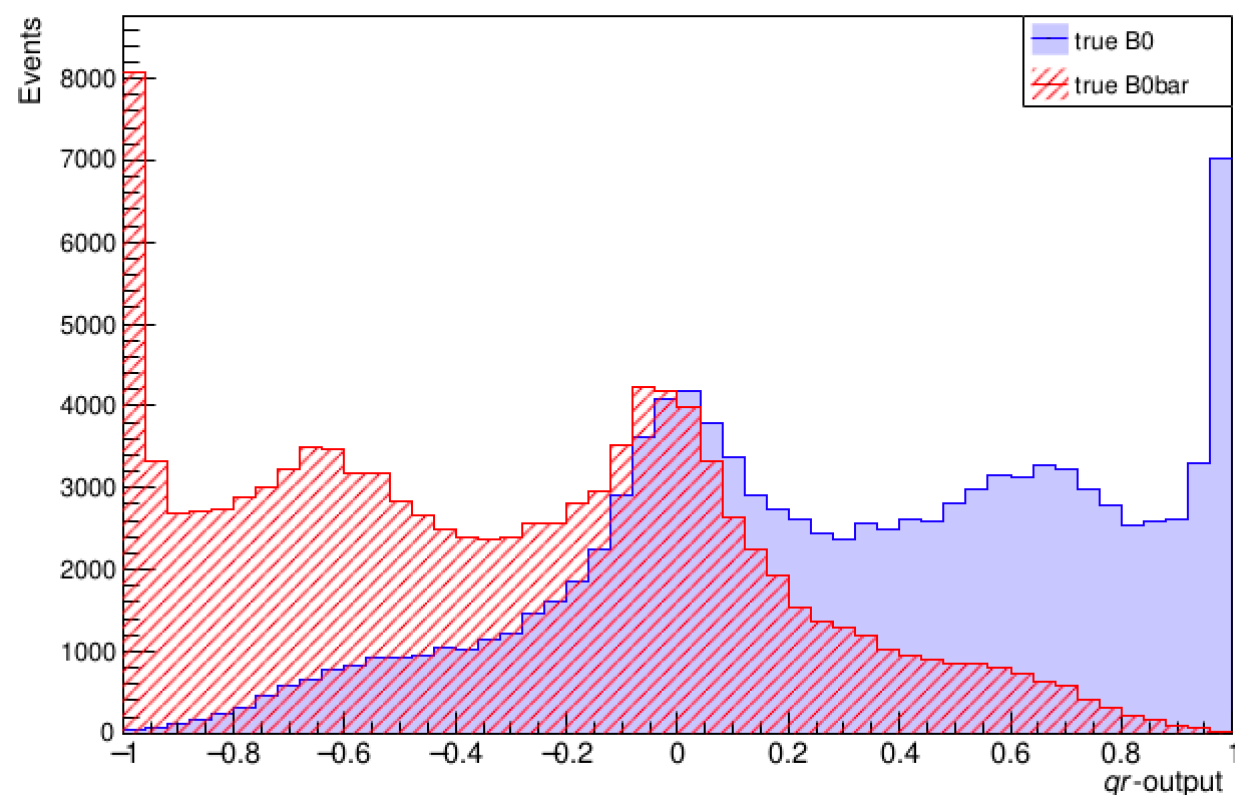
# qr variables on SignalMC



Final Flavor Tagger Output



Final Flavor Tagger Output



```

TOTAL NUMBER OF TAGGED EVENTS = 273256
TOTAL AVERAGE EFFICIENCY (q=+-1)= 100.00 +- 0.00 %
TOTAL AVERAGE EFFECTIVE EFFICIENCY (q=+-1)= 32.184039 +- 0.156912 %
TOTAL AVERAGE EFFECTIVE EFFICIENCY ASYMMETRY (q=+-1)= -2.134811 +- 0.315022 %
B0-TAGGER TOTAL EFFECTIVE EFFICIENCIES: 31.14 +- 0.20 % (q=+1) 33.27 +- 0.25 % (q=-1)
FLAVOR PERCENTAGE (MC): 60.52 % (q=+1) 39.48 % (q=-1) Diff=21.03 %
    
```

```

TOTAL NUMBER OF TAGGED EVENTS = 214462
TOTAL AVERAGE EFFICIENCY (q=+-1)= 100.00 +- 0.00 %
TOTAL AVERAGE EFFECTIVE EFFICIENCY (q=+-1)= 31.276453 +- 0.171015 %
TOTAL AVERAGE EFFECTIVE EFFICIENCY ASYMMETRY (q=+-1)= -2.299739 +- 0.341994 %
B0-TAGGER TOTAL EFFECTIVE EFFICIENCIES: 30.15 +- 0.24 % (q=+1) 32.45 +- 0.24 % (q=-1)
FLAVOR PERCENTAGE (MC): 49.59 % (q=+1) 50.41 % (q=-1) Diff=-0.82 %
    
```

# qr variables on SignalMC15

Check after CS selection (>0.7).

	Default CS	Default CS + $\Delta r$ and $\Delta Z$	Default CS + $\Delta r$ , $\Delta Z$ , and ROE tracks	Sato-san parameters
<b>Total effective efficiency (q=+-1)</b>	$33.48 \pm 0.20\%$	$33.16 \pm 0.19\%$	$34.81 \pm 0.19\%$	$33.73 \pm 0.03\%$
<b>Total effective efficiency asymmetry</b>	$-2.84 \pm 0.40\%$	$-2.58 \pm 0.39\%$	$-2.50 \pm 0.39\%$	$-0.09 \pm 0.06\%$
<b>B<sup>0</sup> effective efficiency</b>	$32.10 \pm 0.24\%$	$31.90 \pm 0.24\%$	$33.59 \pm 0.24\%$	$33,69 \pm ?\%$
<b>B<sup>0</sup>bar effective efficiency</b>	$34.93 \pm 0.31\%$	$34.48 \pm 0.30\%$	$36.09 \pm 0.30\%$	$33,78 \pm ?\%$

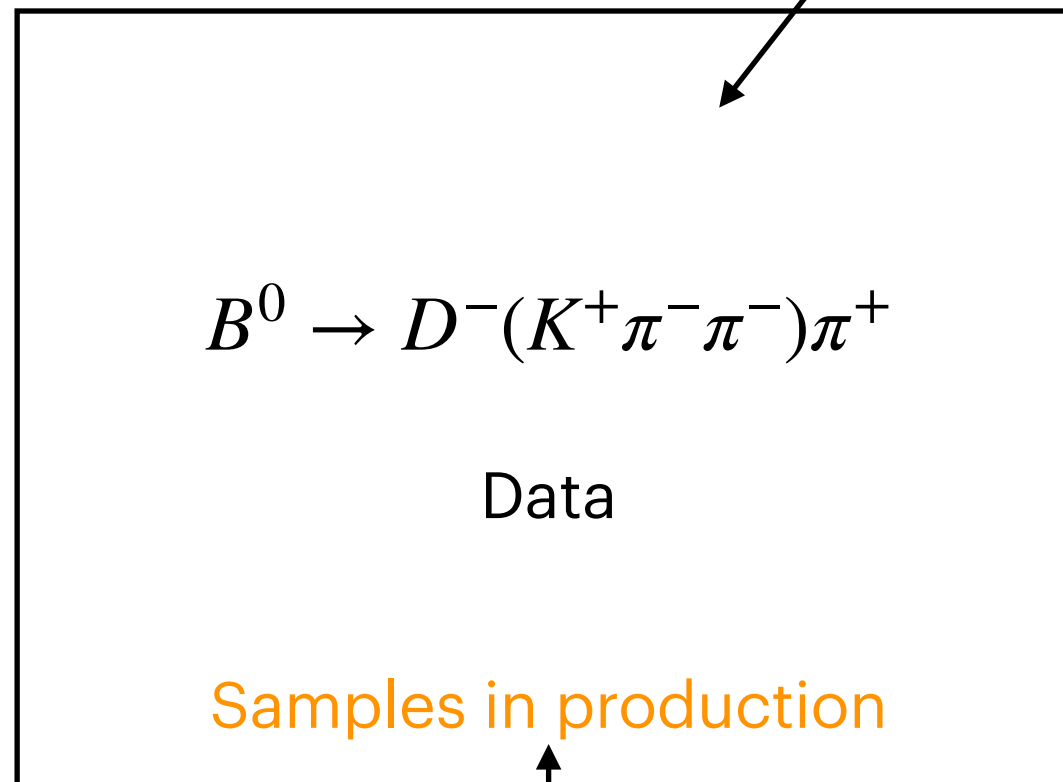
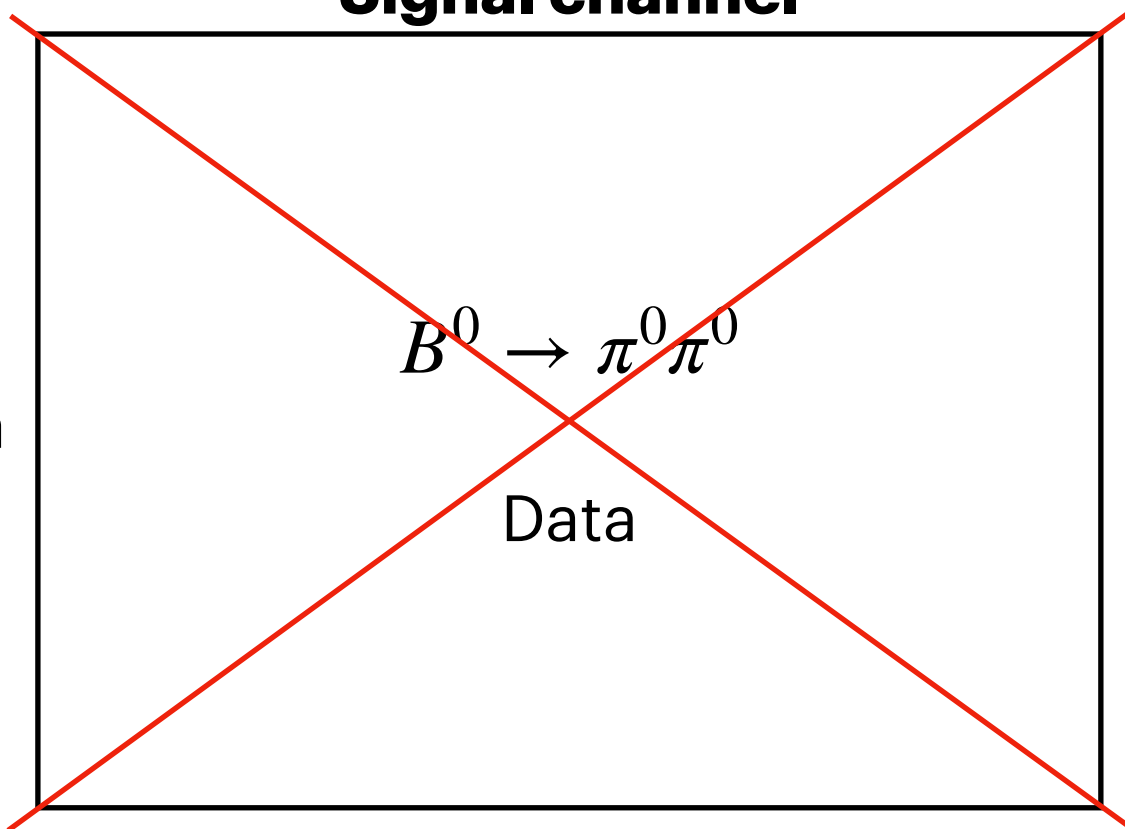
# Flavor tagging validation: to do

Sato-san  
parameters

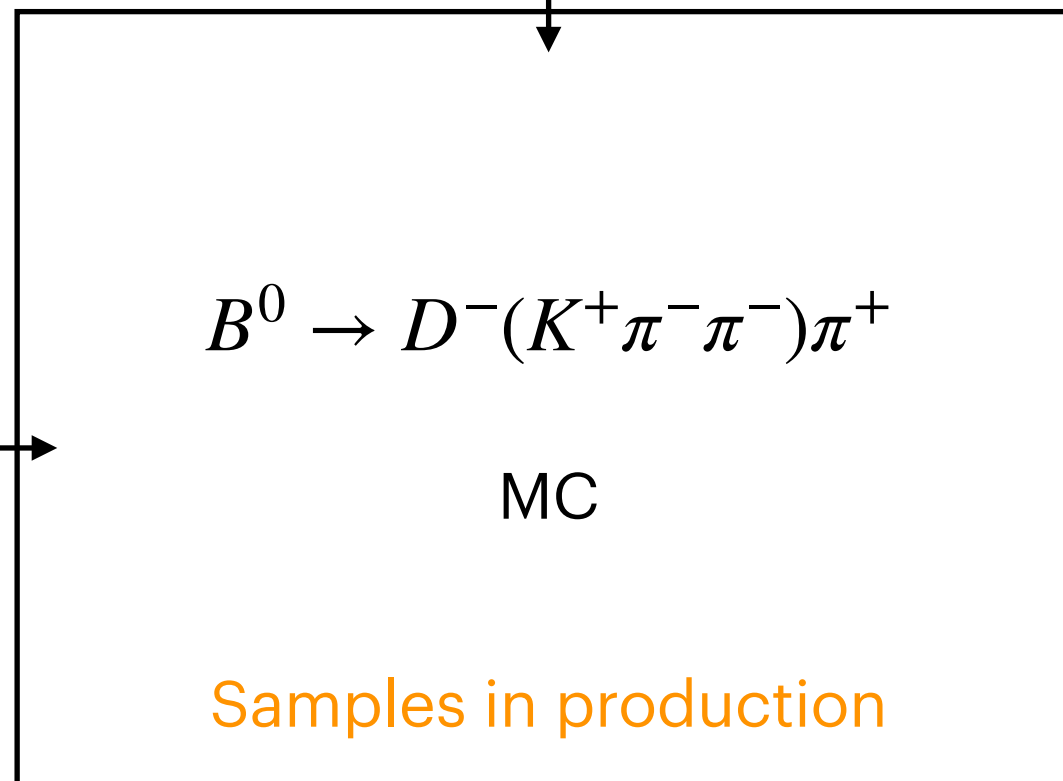
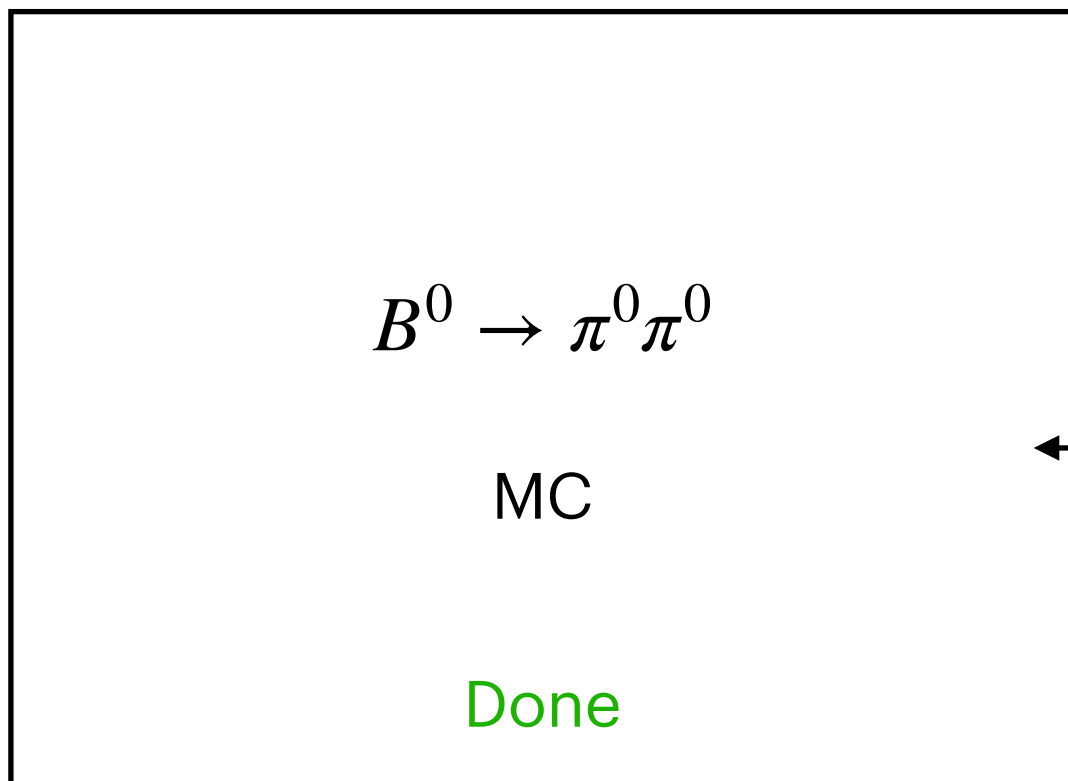
**Signal channel**

**Control channel**

**Data**



**MC**



Flavor tagging:  $B^0 \rightarrow D^-(K^+\pi^-\pi^-)\pi^+$  in MC

Using  $\sim 100\text{fb}^{-1}$  of MC with no selections at all, I obtain  $\Delta\varepsilon = -3 \pm 1.3\%$ .

Expect not very good precision with the current data.

$\rho$  MVA

# $\rho$ MVA

Beyond the CS: identify the principal bkg components.

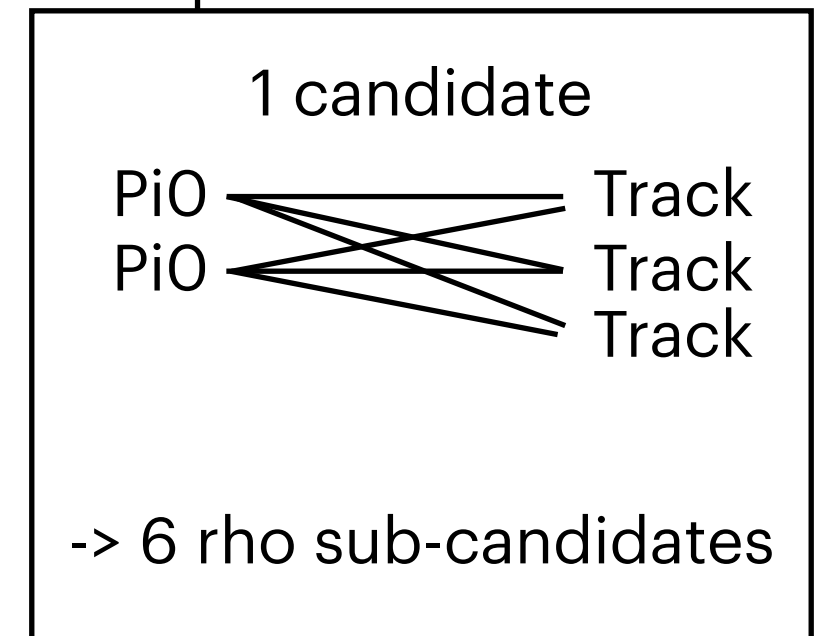
Events that have at least a $\pi^0$ from ...	
$\rho(770)^+$	47.1%
$Z^0$ (direct from $e^+e^-$ )	75.0%

Large number of continuum  $\pi^0$ 's come from a  $\rho \rightarrow$   
develop a specific BDT (in addition to the default CS BDT).

Combine each track in the event with each  $\pi^0$ .

Use kinematic and angular variables to distinguish  
between  $\rho$ 's and other particles.

Example:

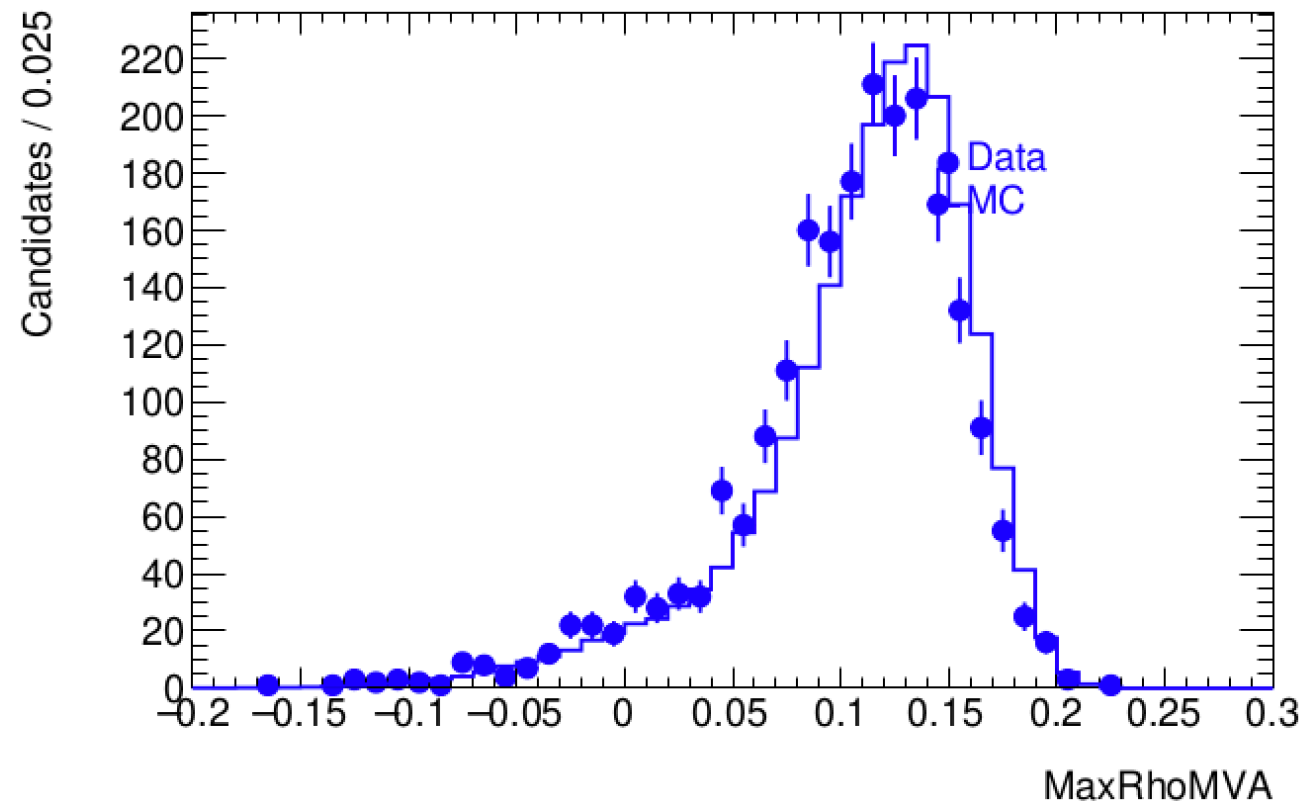
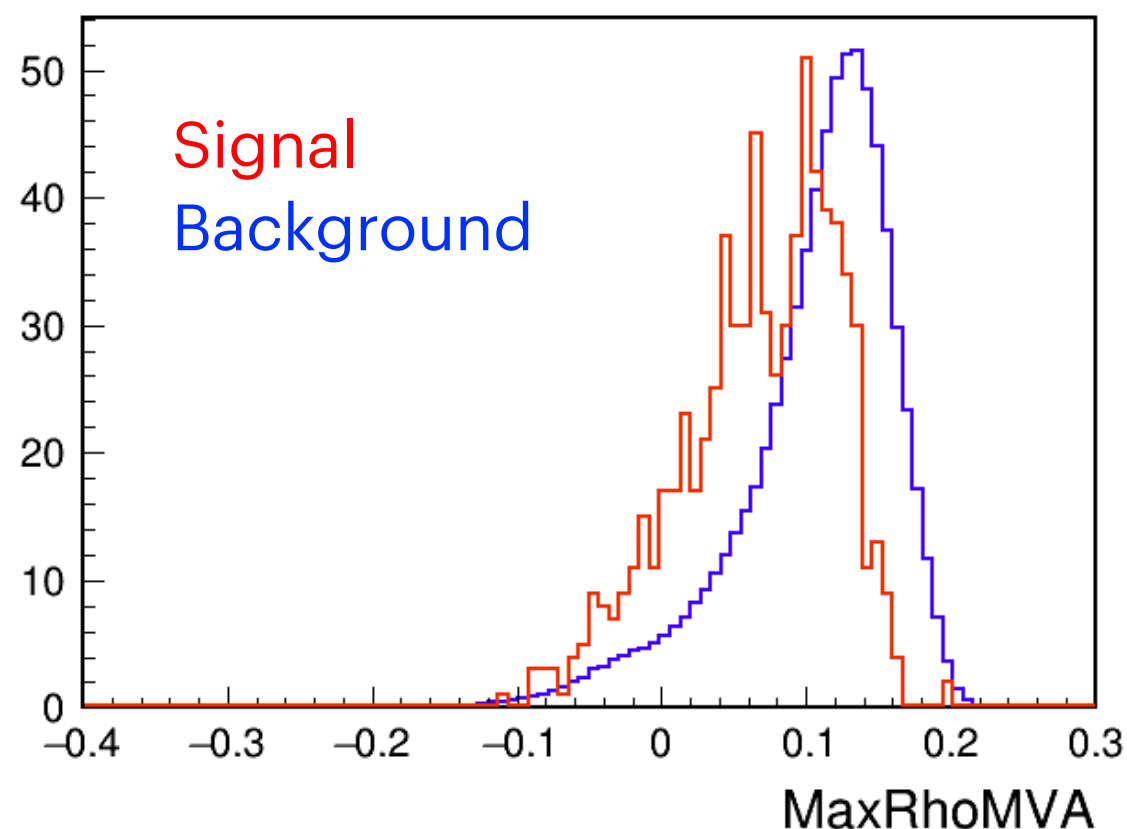




# Max $\rho$ MVA distribution

Each candidate has for example 20  $\rho$  sub-candidates. Take the one with largest rhoMVA (the one more similar to a  $\rho$ ).

Validation: use  $B^0 \rightarrow \pi^0\pi^0$  sideband (inclusive sample of true and false  $\rho$ ).



Variable gives separation, and discrepancy is acceptable

**Total candidates**

788473

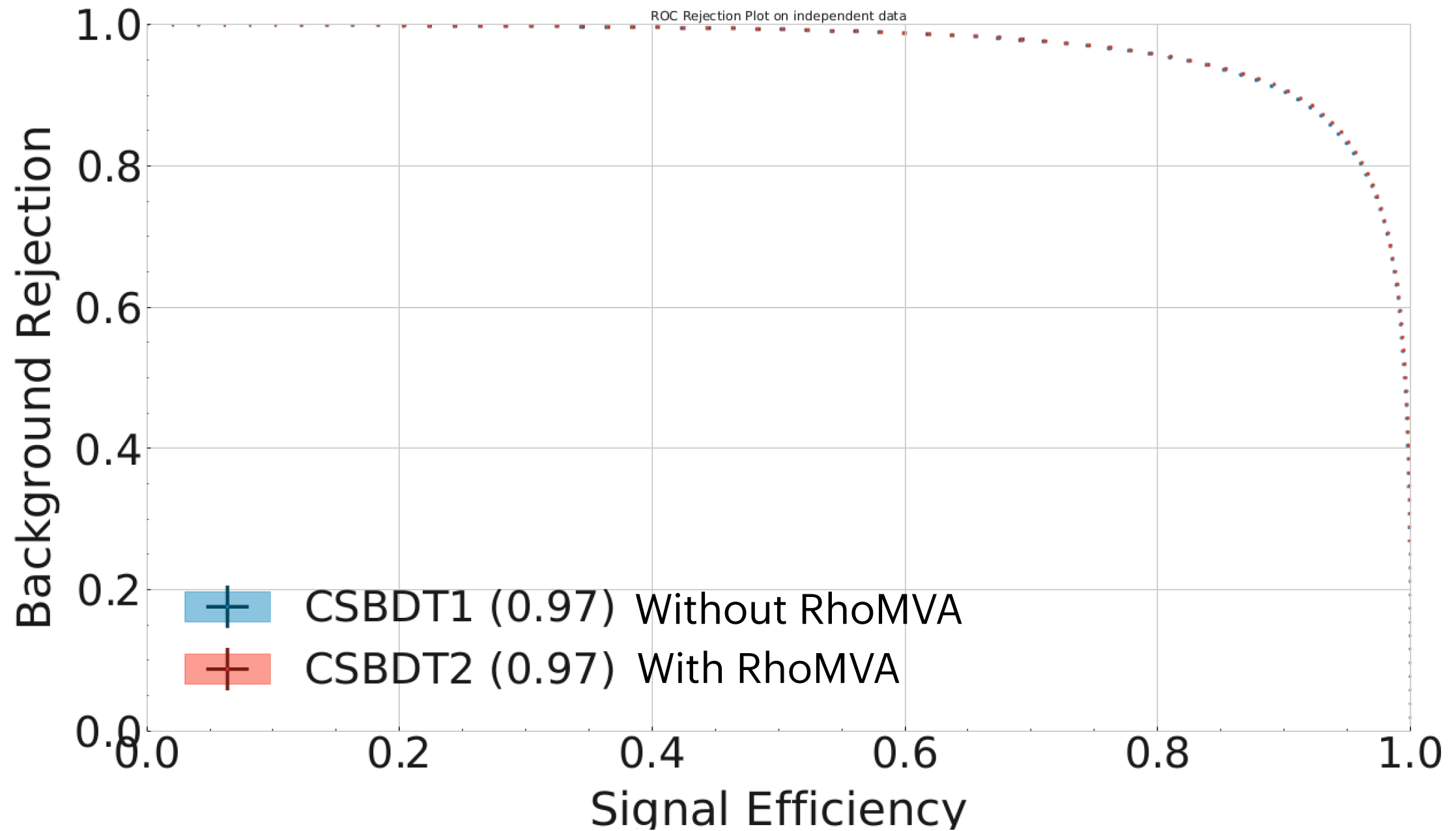
**Candidates with at least one rho**

285585

**Candidates where the rho has been correctly identified**

158393

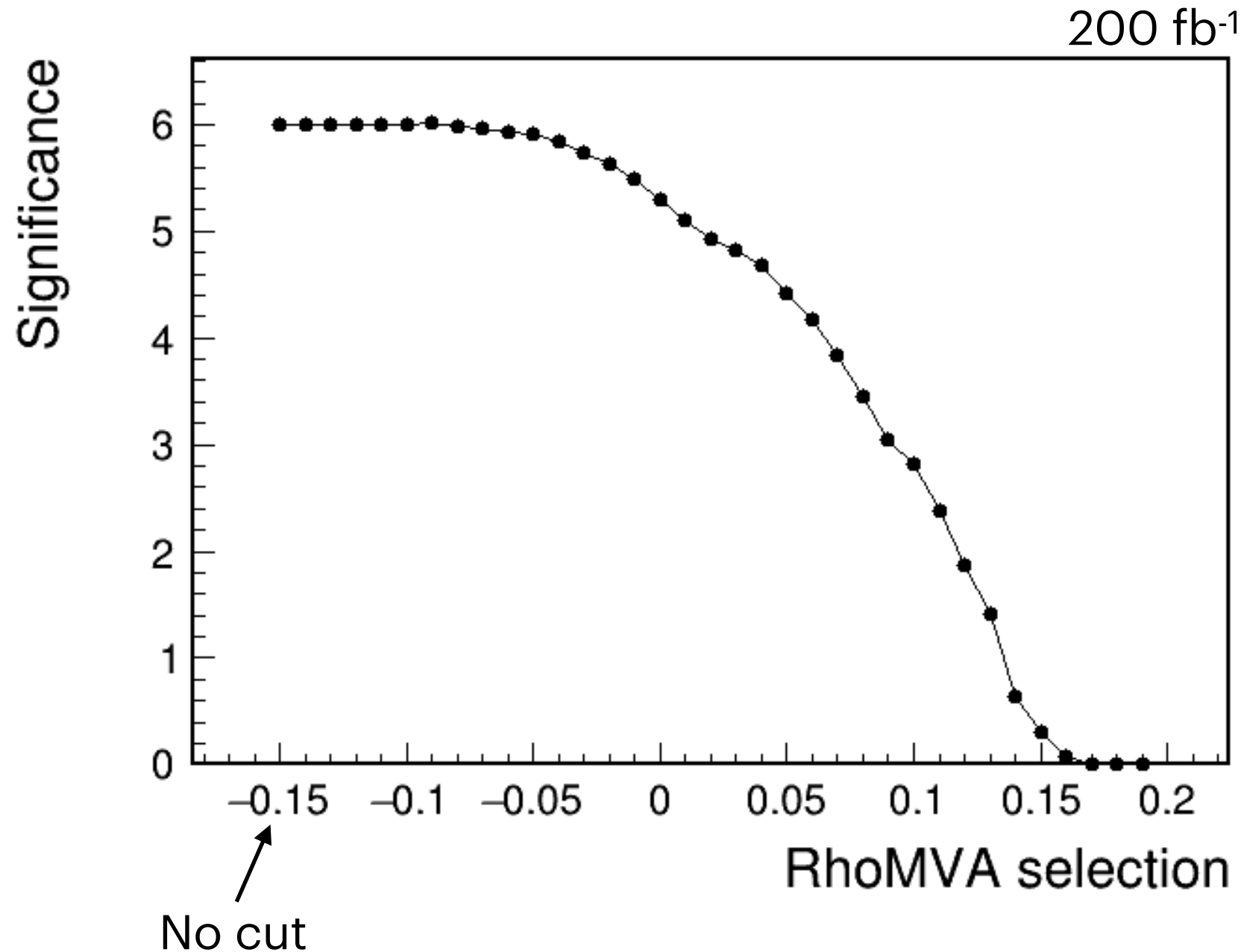
# Use $\rho$ MVA as input of the CSBDT



Inclusion of  $\rho$ MVA gives no improvement

# Other possibility: $\rho$ MVA after the CSBDT

Apply first the selection on the CSBDT ( $>0.8$ ),  $-0.2 < \Delta E < 0.1$  and  $M_{bc} > 5.27$ , then various selections on  $\rho$ MVA and calculate significance  $S/\sqrt{S+B}$ .



No gain in significance after selection on  $\rho$ MVA.

# Summary

Prepare  $B^0 \rightarrow \pi^0 \pi^0$  analysis for pre-LS1 dataset.

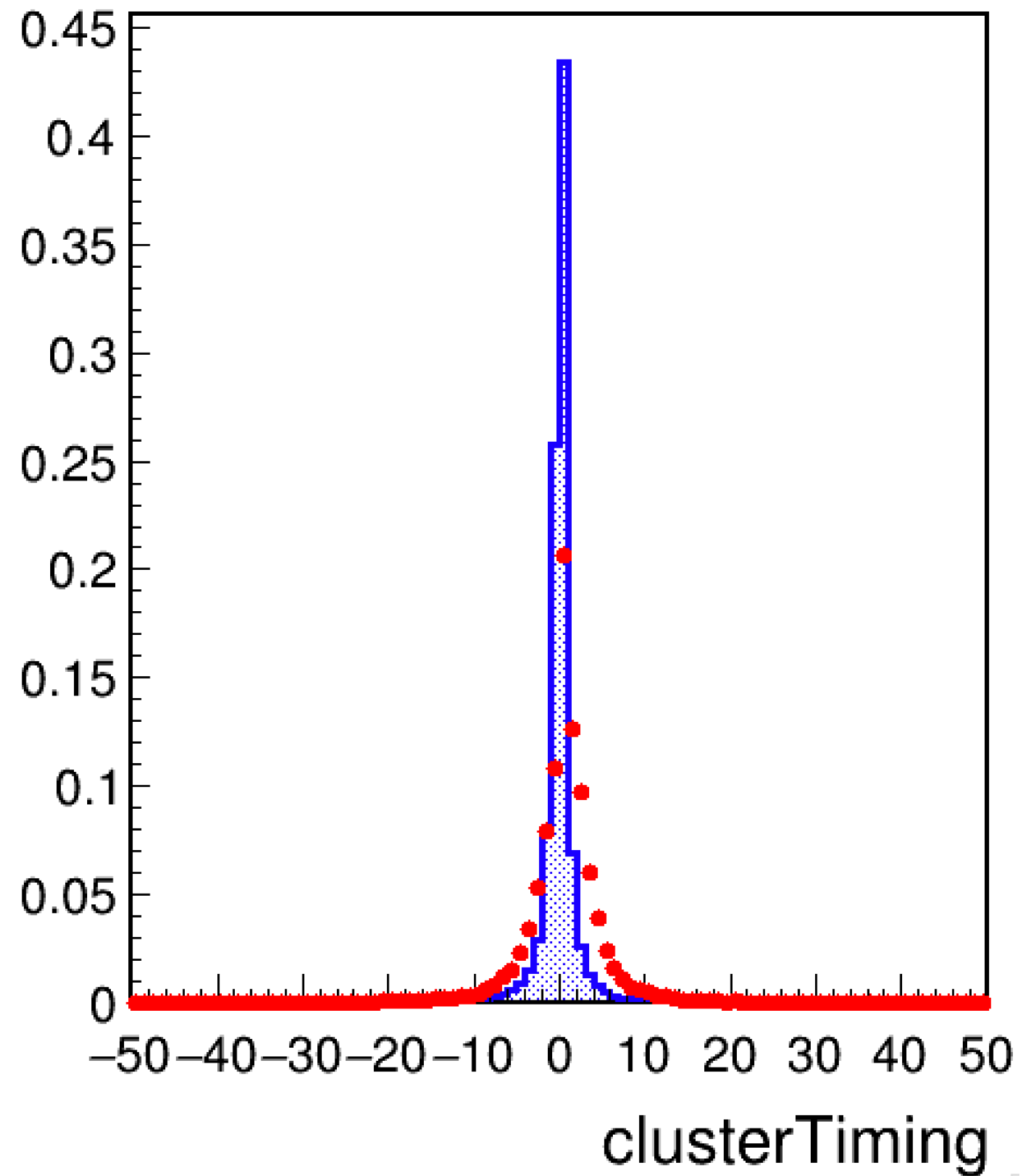
Revisited photonMVA: use new variables with good data/MC agreement.  
Already validated on data.

Revisited CSBDT: add  $B_{\text{Tag}}$  variables to suppress even more continuum.  
Variables are ready, but need to repeat training using off-res data (is it enough?). Check how the use of  $B_{\text{Tag}}$  variables impacts the flavour tagger.

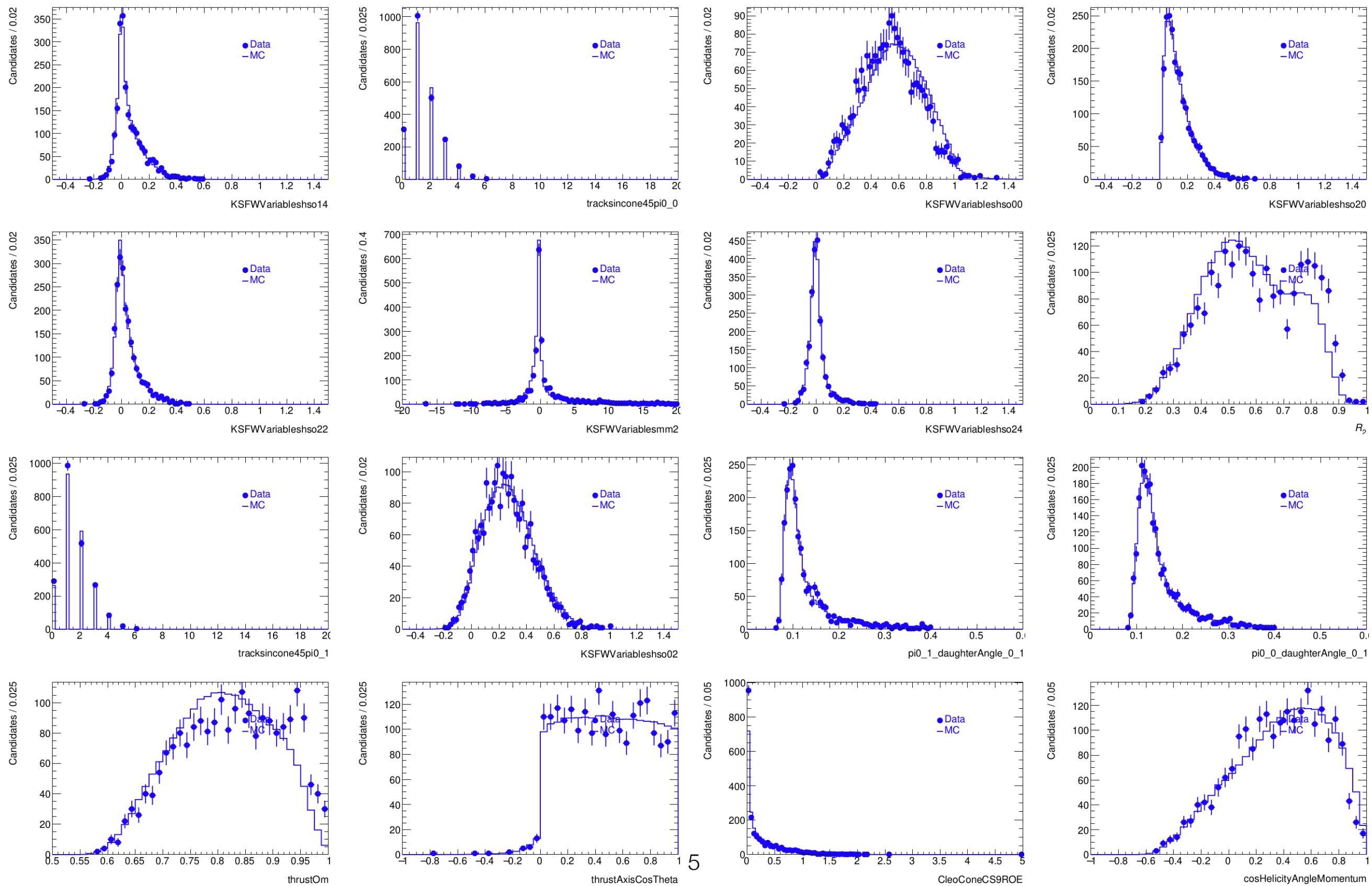
Introduced  $\rho$ BDT: improvement is negligible, maybe not useful to add it in the analysis.

Backup

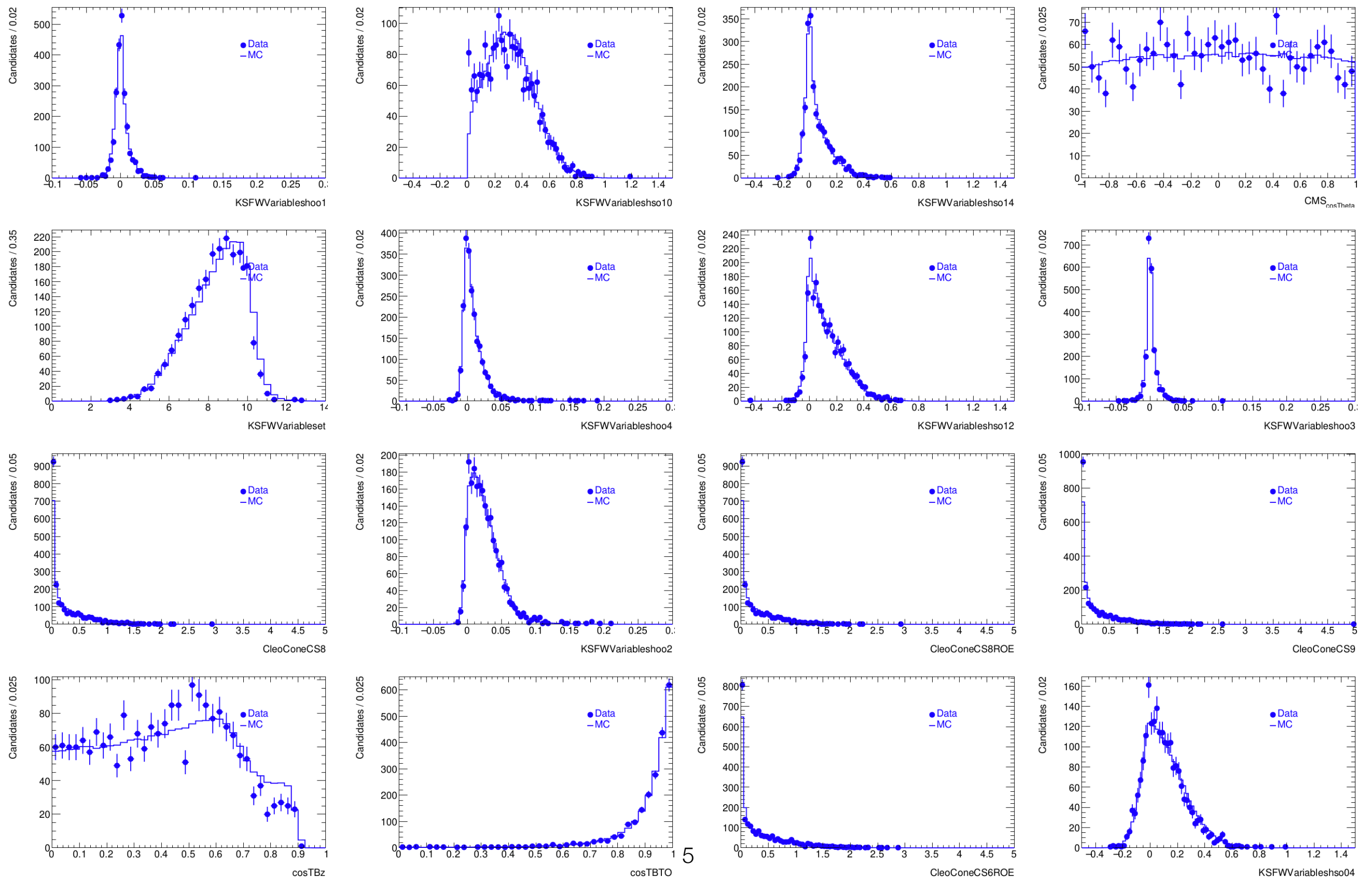
# ClusterTiming (rel-06)



# Inputs validation — Background only

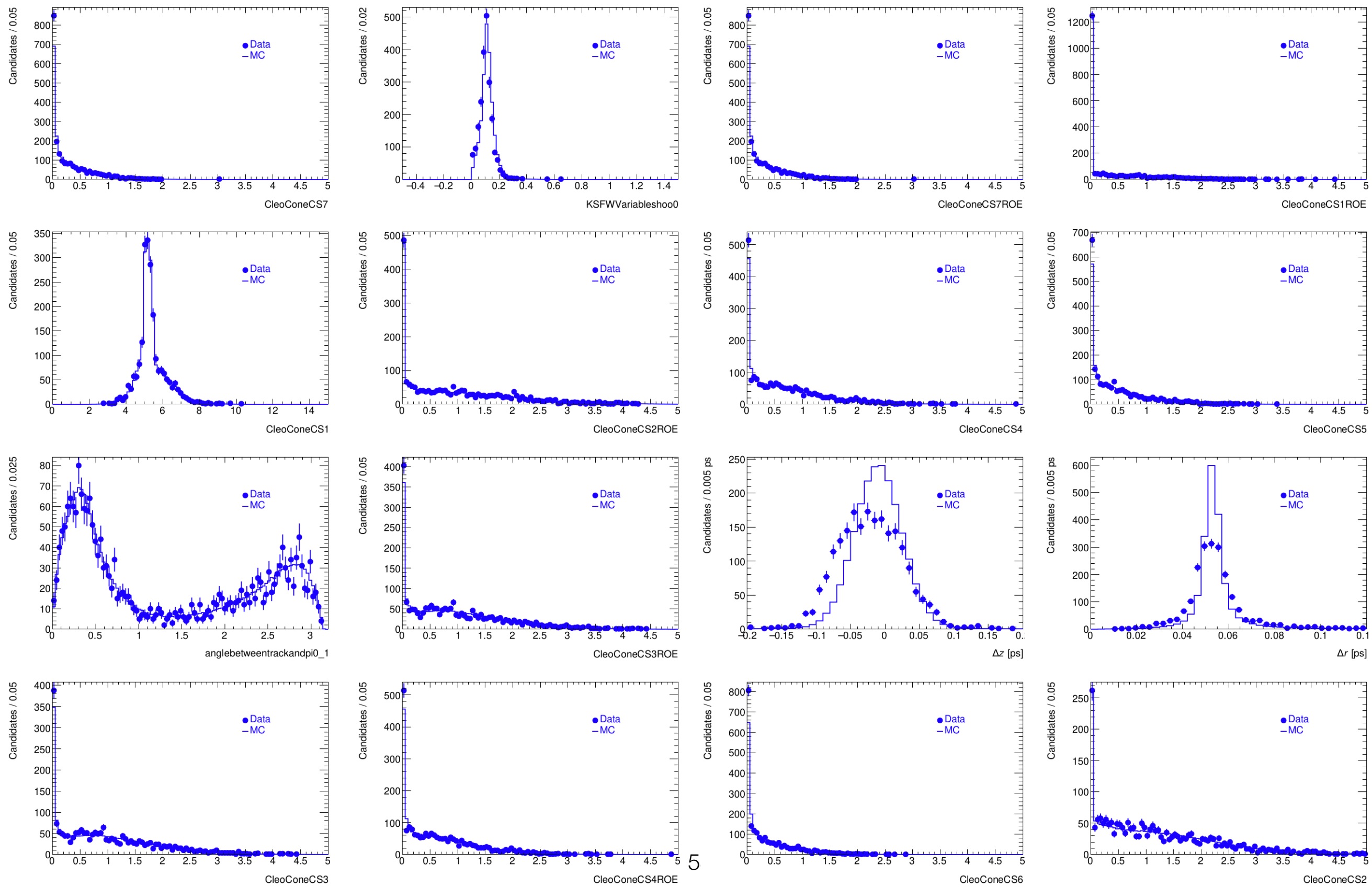


# Inputs validation — Background only

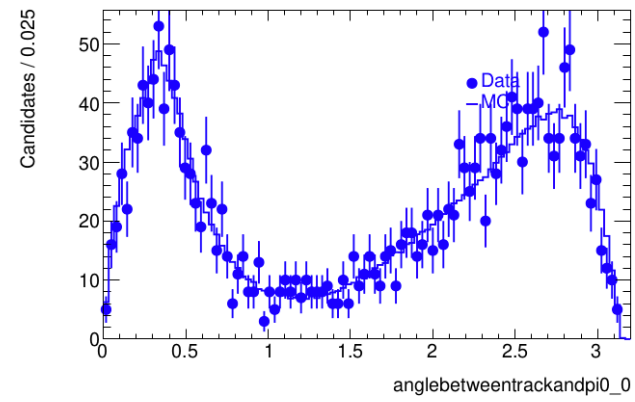




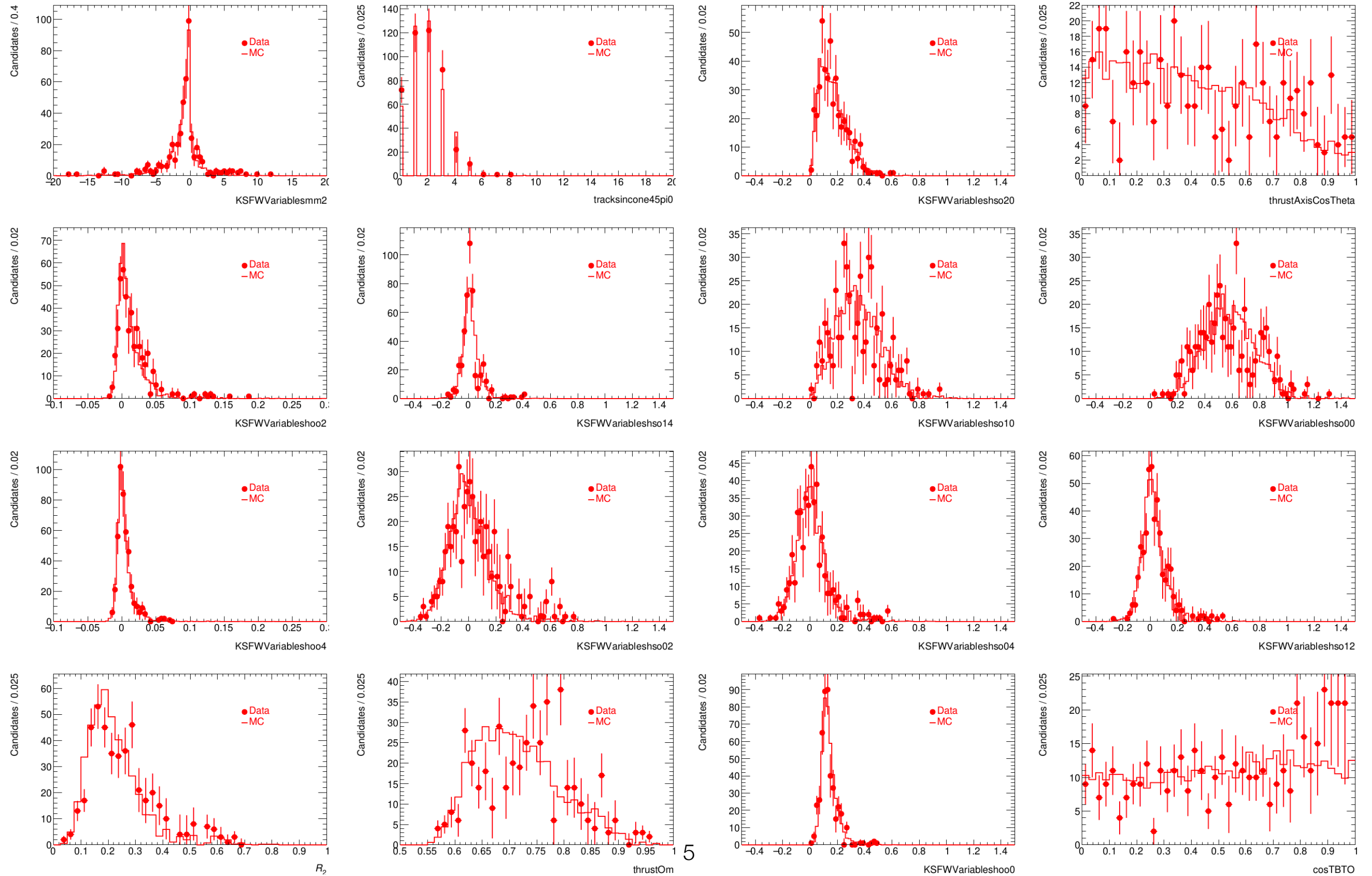
# Inputs validation — Background only



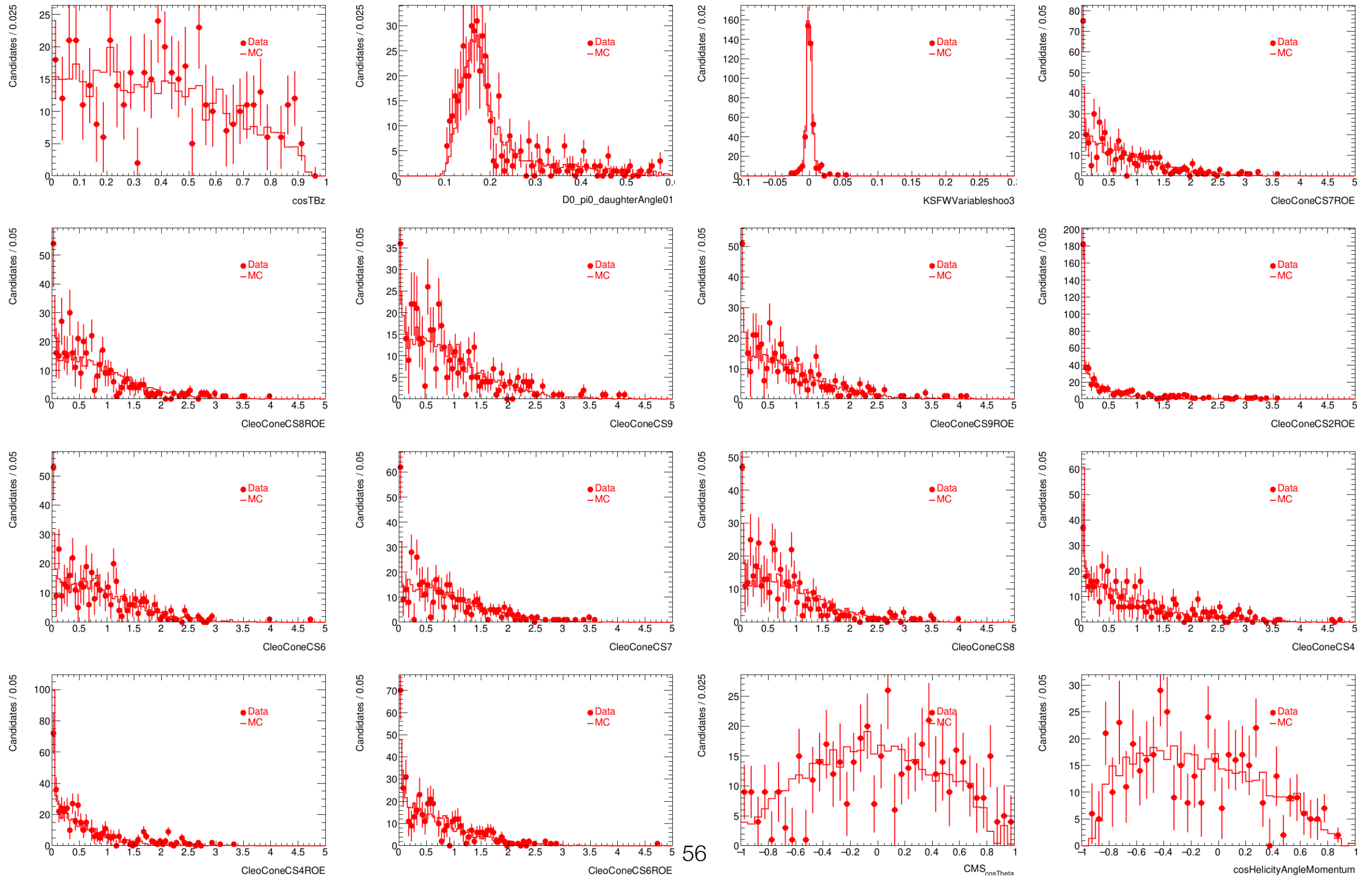
# Inputs validation — Background only



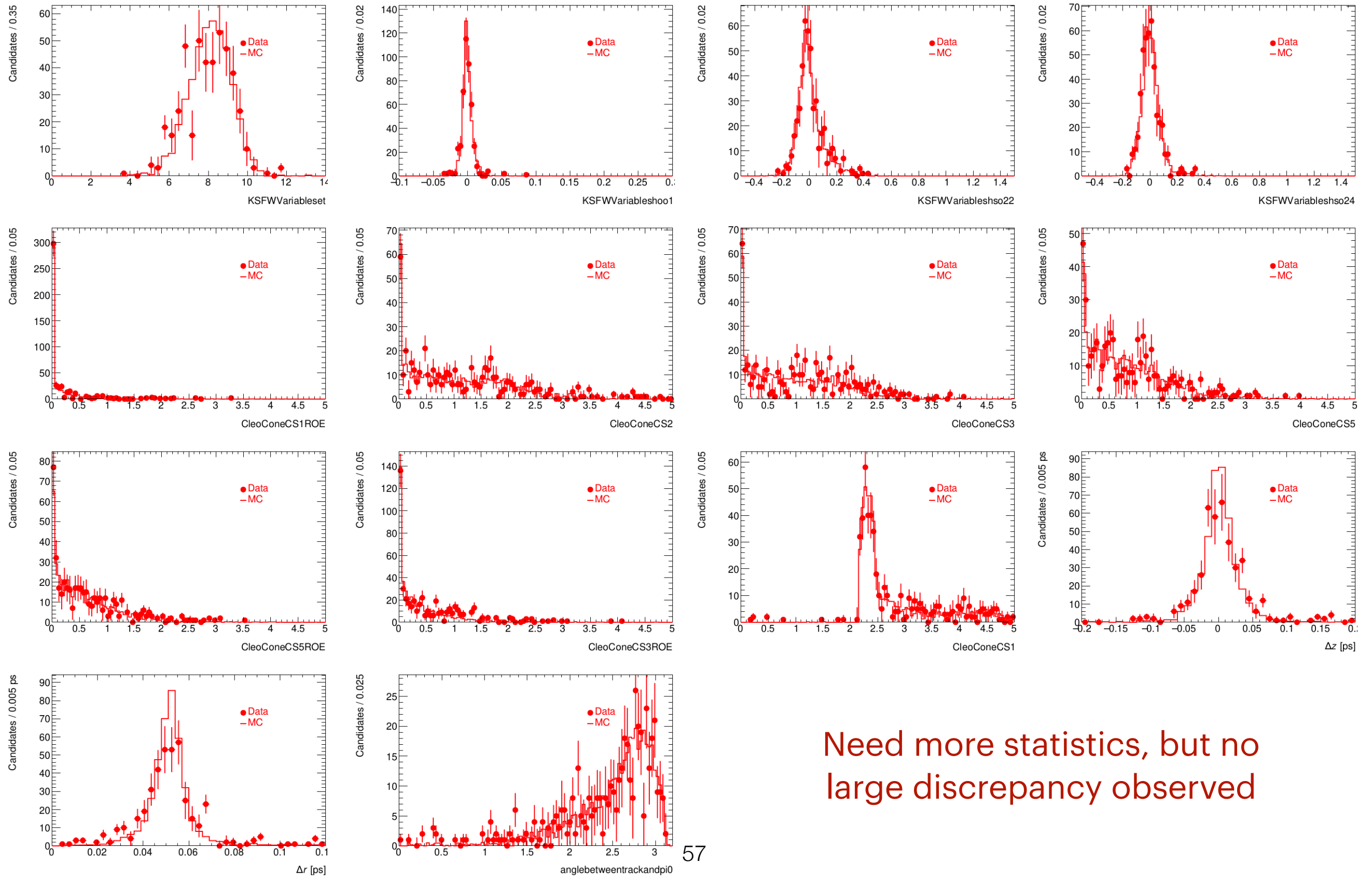
# Inputs validation — Signal only



# Inputs validation — Signal only



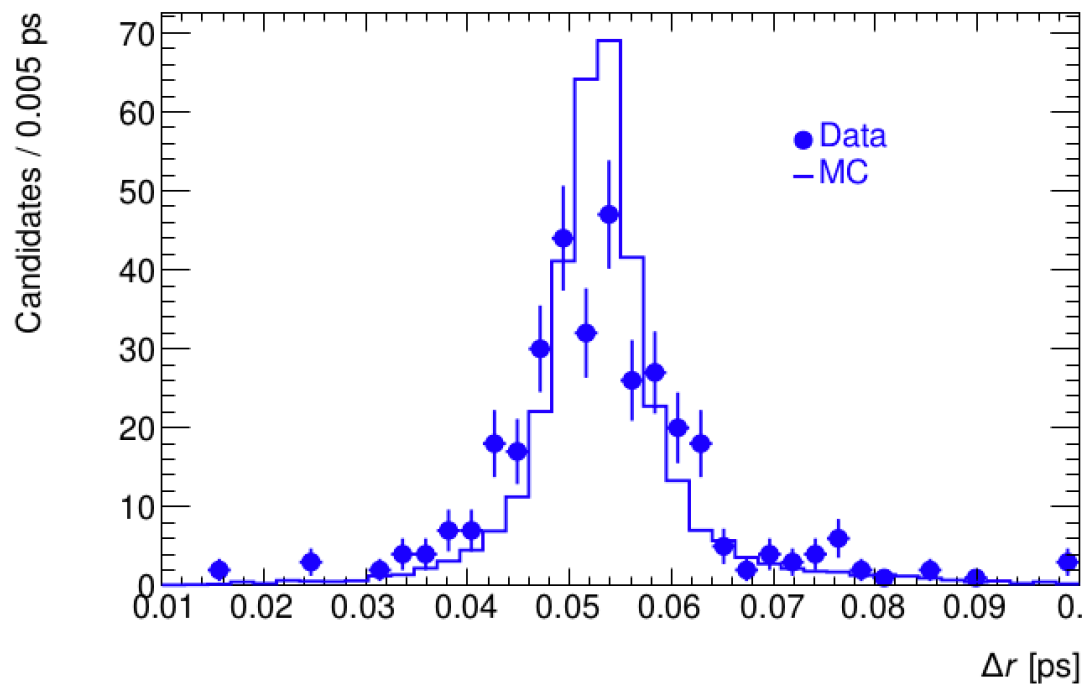
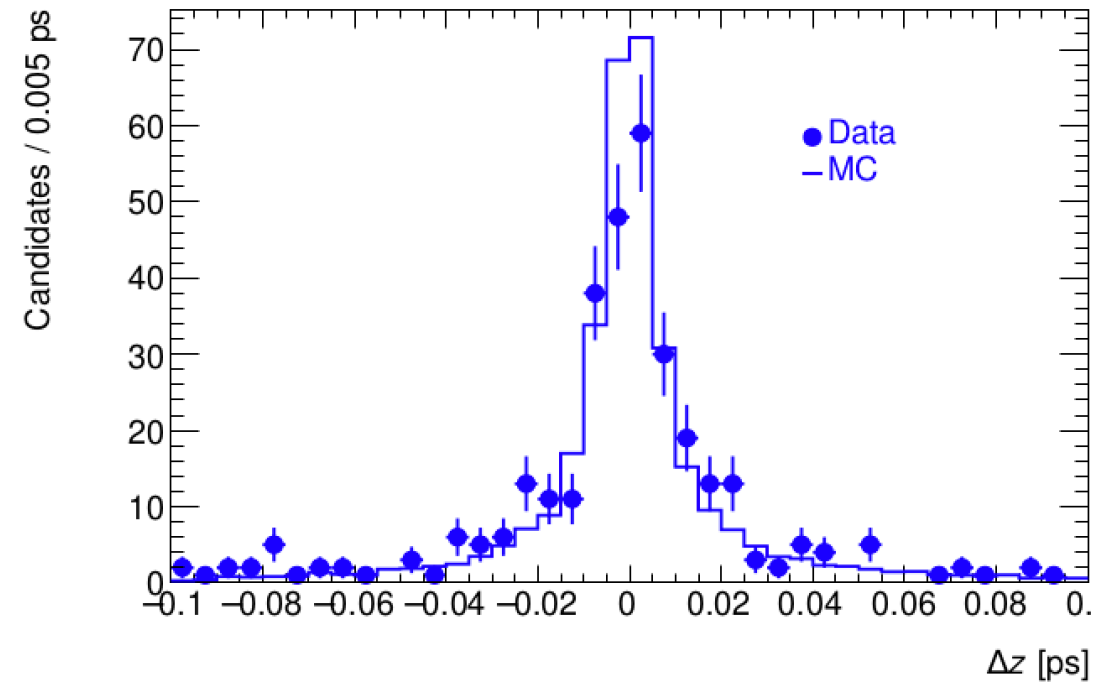
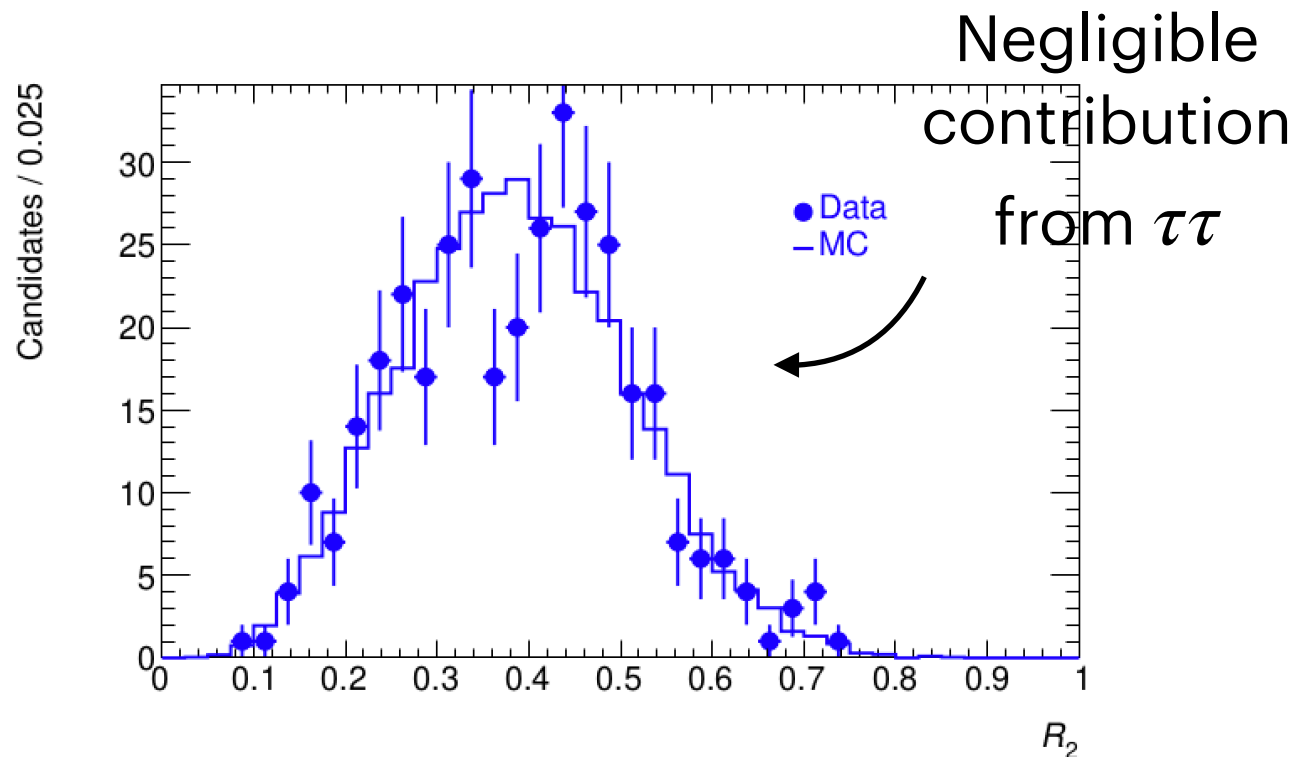
# Inputs validation — Signal only



Need more statistics, but no large discrepancy observed

# Check — Background only using

$$B \rightarrow D(K\pi\pi^0)\pi \text{ sideband}$$



Need more statistics — but observe smaller discrepancies in  $\Delta r$  and  $\Delta z$  wrt  $B^0 \rightarrow \pi^0\pi^0$ . Why?

# CSMVA using off-res data for the bkg

Train on **off-res data and signalMC** after applying all  $\pi^0$ ,  $\Delta E$ , and  $M_{bc}$  selections.

## Inputs (after pruning)

7 Kakuno-Super-Fox-Wolfram moments

cosTBTO

1 CleoCone

cosTheta\*

R2

thrustOm

$\Delta Z$  (BTag)

$\Delta r$  (BTag)

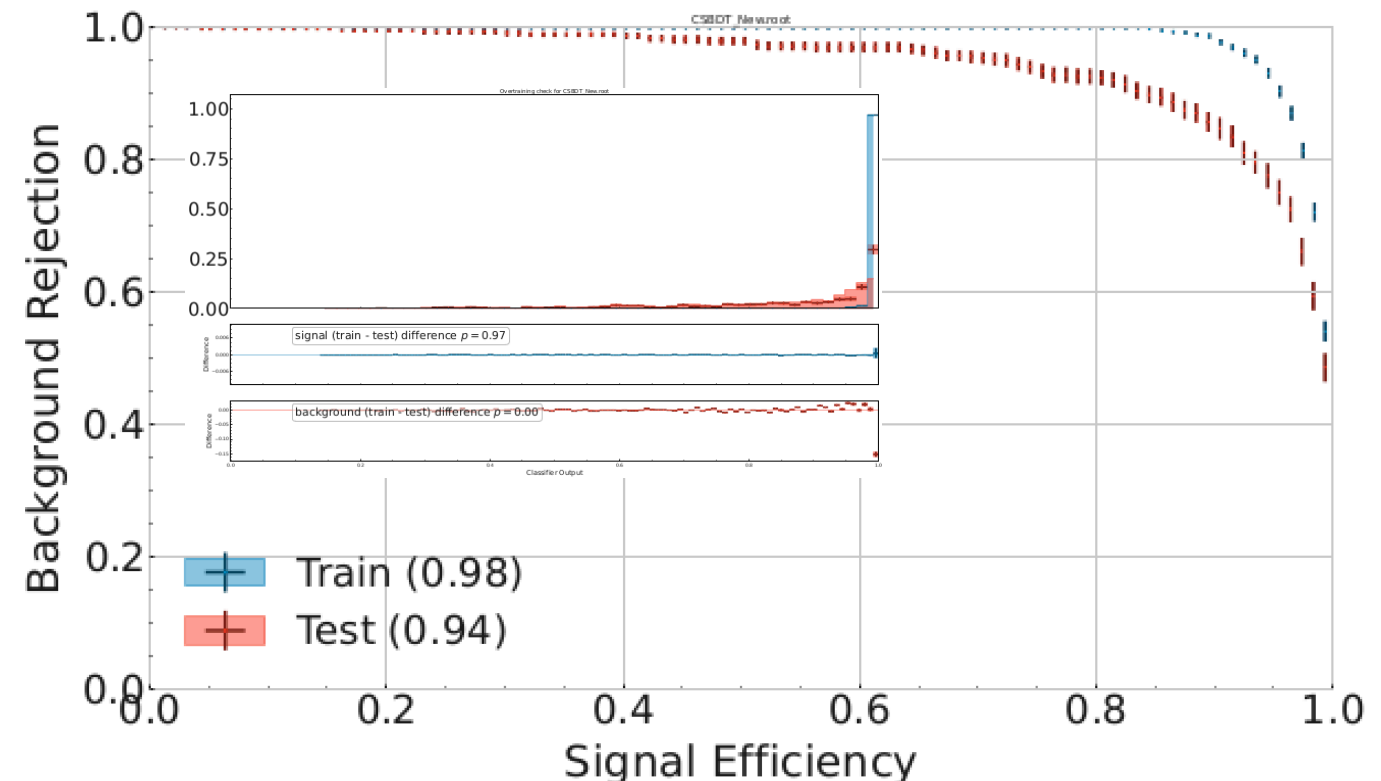
thrustAxisCosTheta

angle between  $\pi^0$ 's

cosHelicityAngle

KSFVVariableset

KSFVVariablesmm2



Train bkg sample (from offres): 1000 events  
Train sig sample (from MC): 180000 events  
Test bkg sample (from offres): 500 events  
Test sig sample (from MC): 90000 events

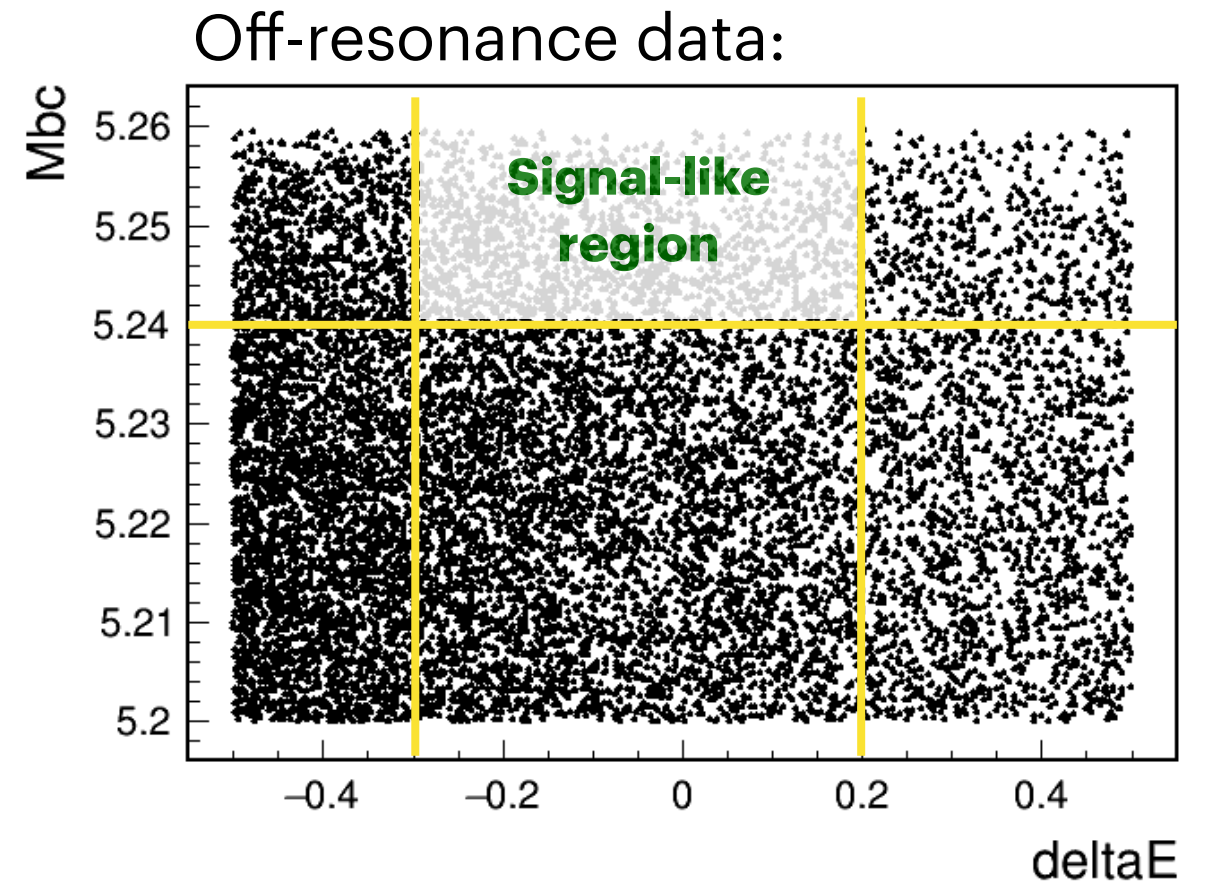
Very small off-res sample ( $9\text{fb}^{-1}$ )  
→ poor BDT (total off-res sample  
will be  $18\text{fb}^{-1}$ )



# CSMVA using off-res data for the bkg

But what off-resonance data can I use?

In previous result I was using only the **signal-like region**



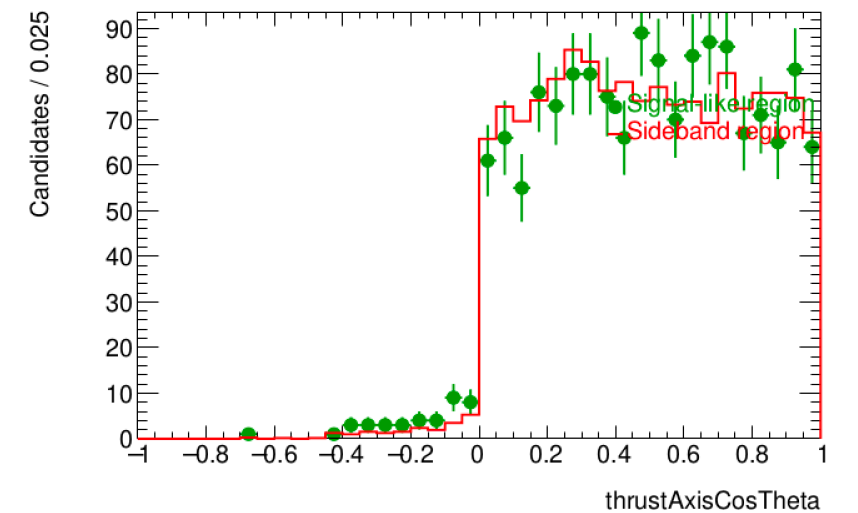
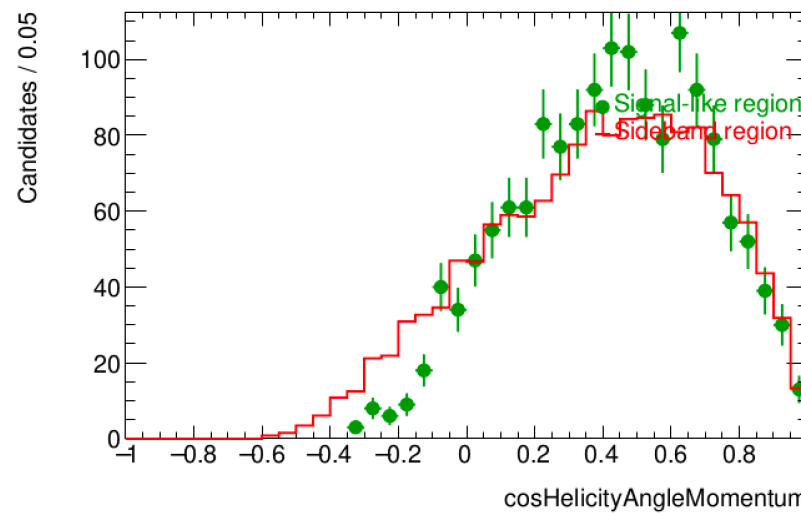
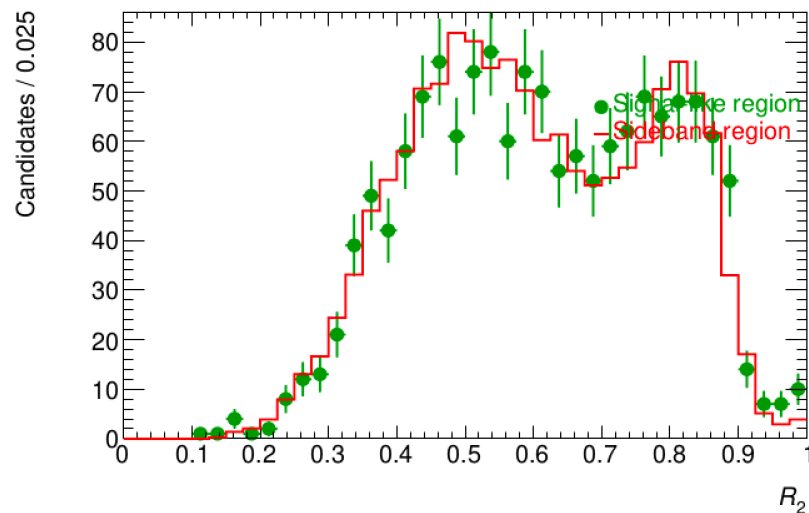
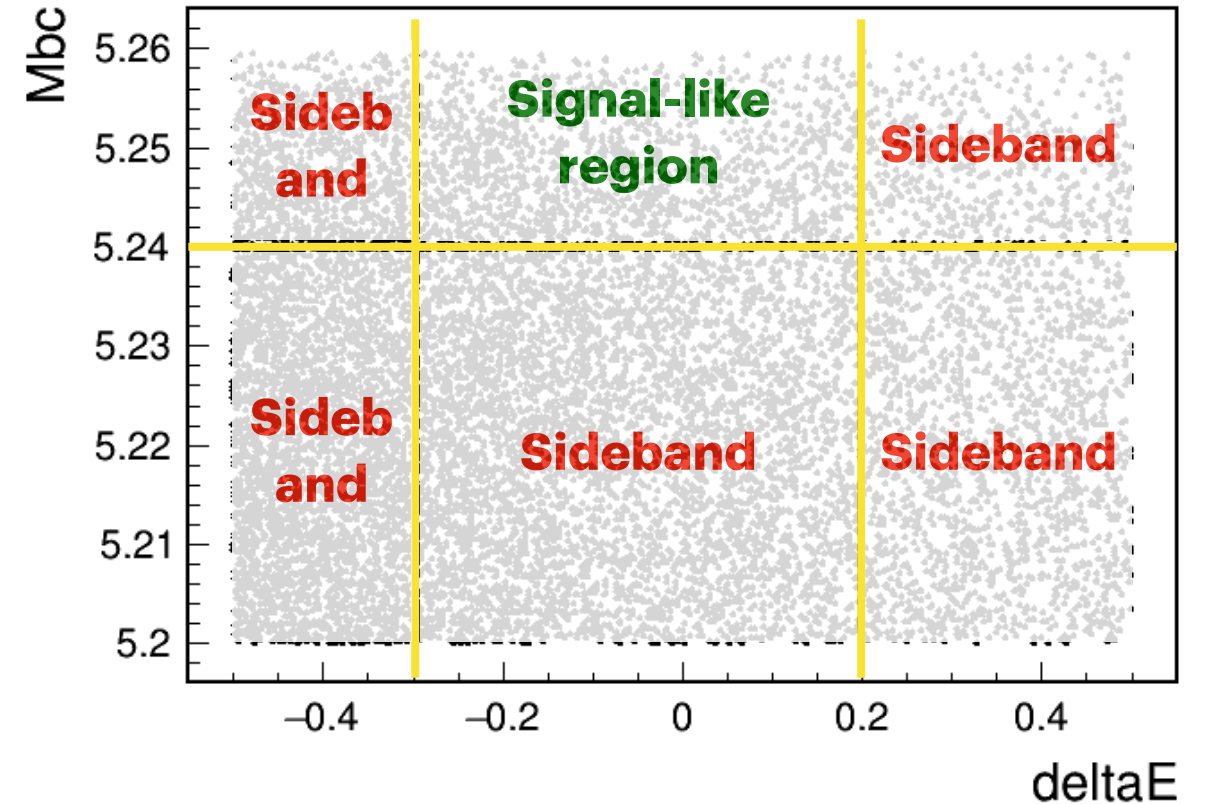
# CSMVA using off-res data for the bkg

But what off-resonance data can I use?

In previous result I was using only the **signal-like region**

Compare CS input distributions in **signal-like** and **sideband** regions (in off-resonance data):

Off-resonance data:



All variables that have discrepancies are not CS inputs anymore (after pruning), except cosHelAngleMomentum.

# CSMVA using off-res data for the bkg

Train on **off-res data and signalMC** after applying all  $\pi^0$  selections.  
Use all off-resonance data (including sidebands). Exclude cosHelicityAngle.

## Inputs (after pruning)

7 Kakuno-Super-Fox-Wolfram moments

cosTBTO

1 CleoCone

cosTheta\*

R2

thrustOm

$\Delta Z$  (BTag)

$\Delta r$  (BTag)

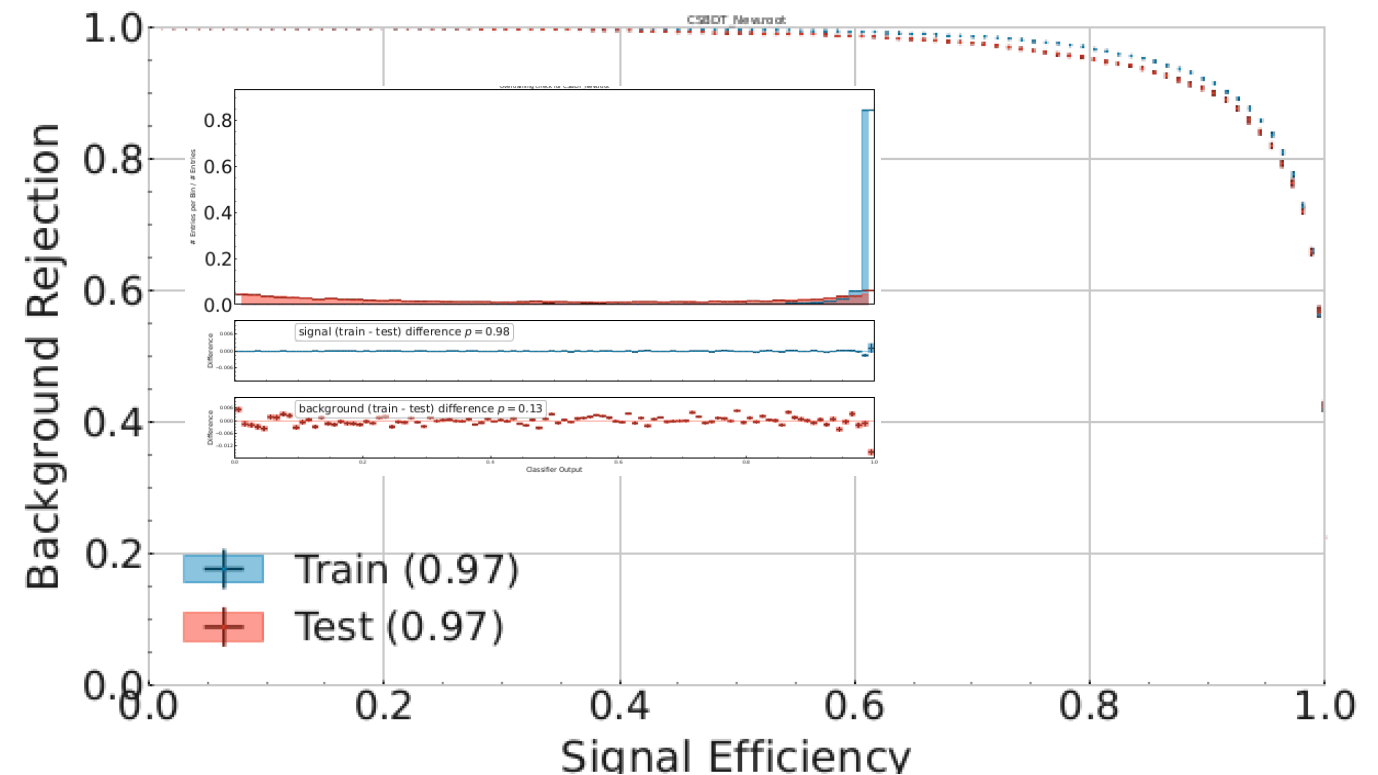
thrustAxisCosTheta

angle between  $\pi^0$ 's

~~cosHelicityAngle~~

KSFWVariableset

KSFWVariablesmm2

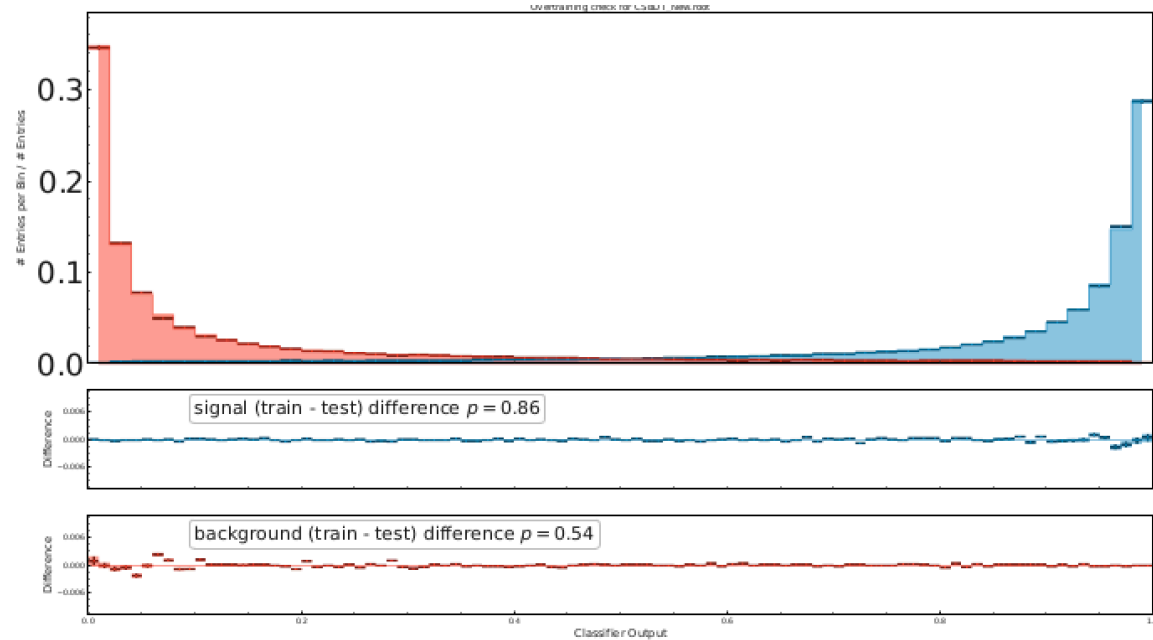
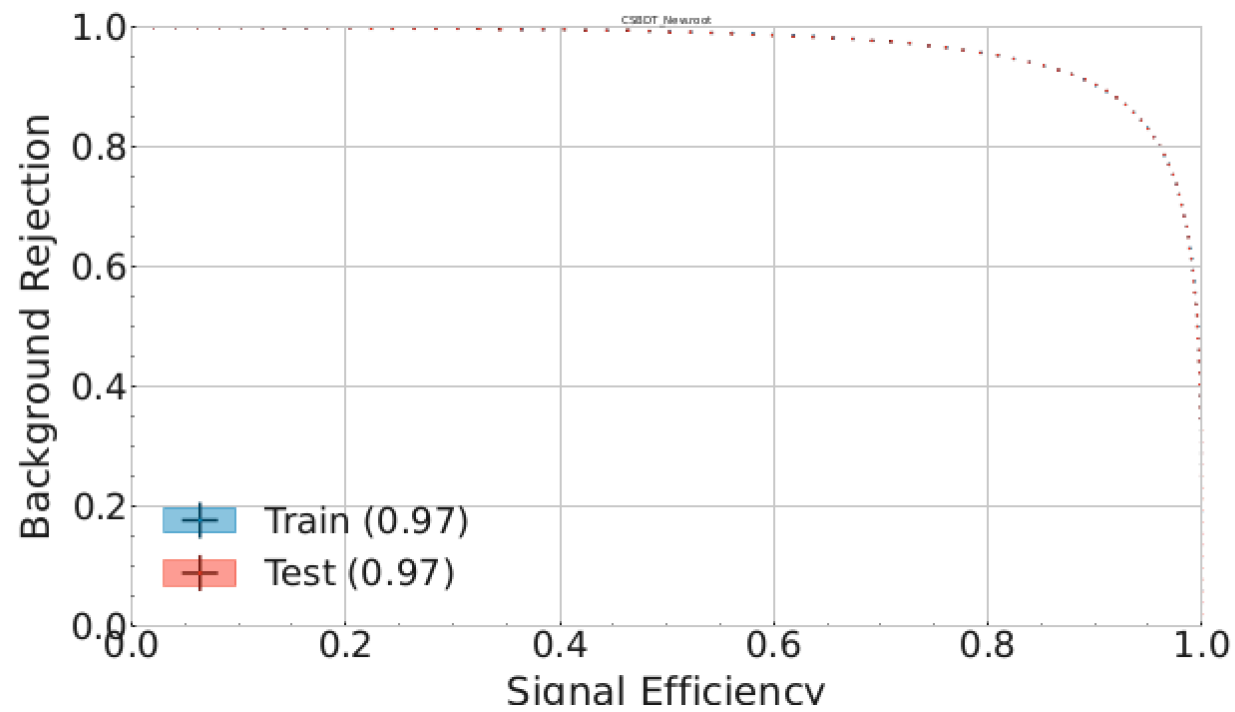


Train bkg sample (from offres): 8000 events  
Train sig sample (from MC): 180000 events  
Test bkg sample (from offres): 4000 events  
Test sig sample (from MC): 90000 events

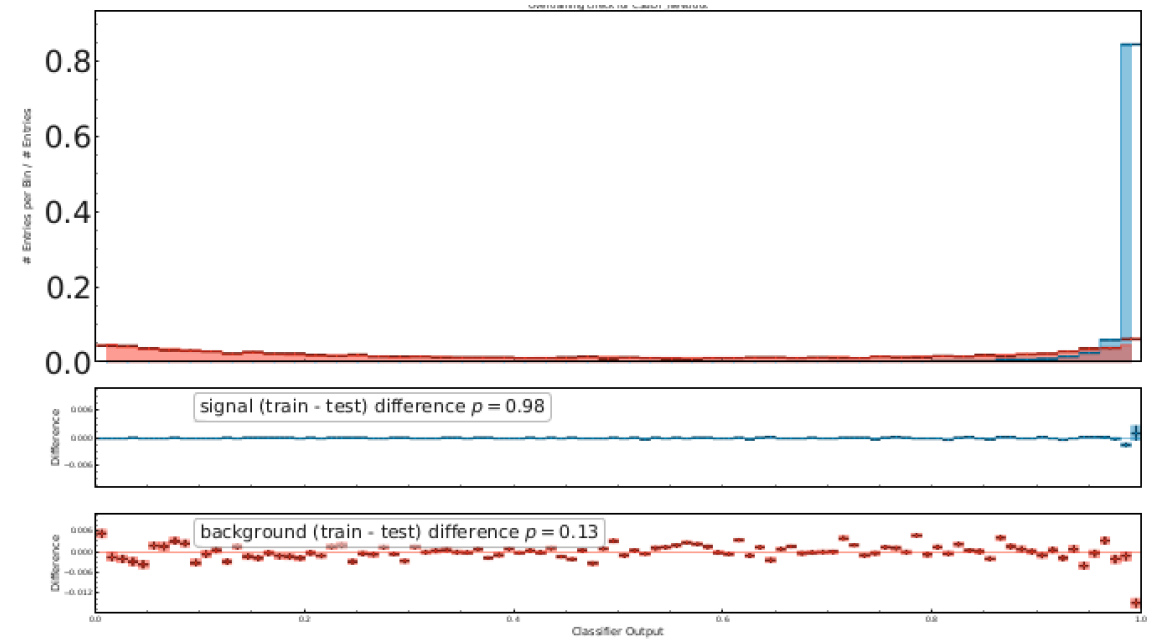
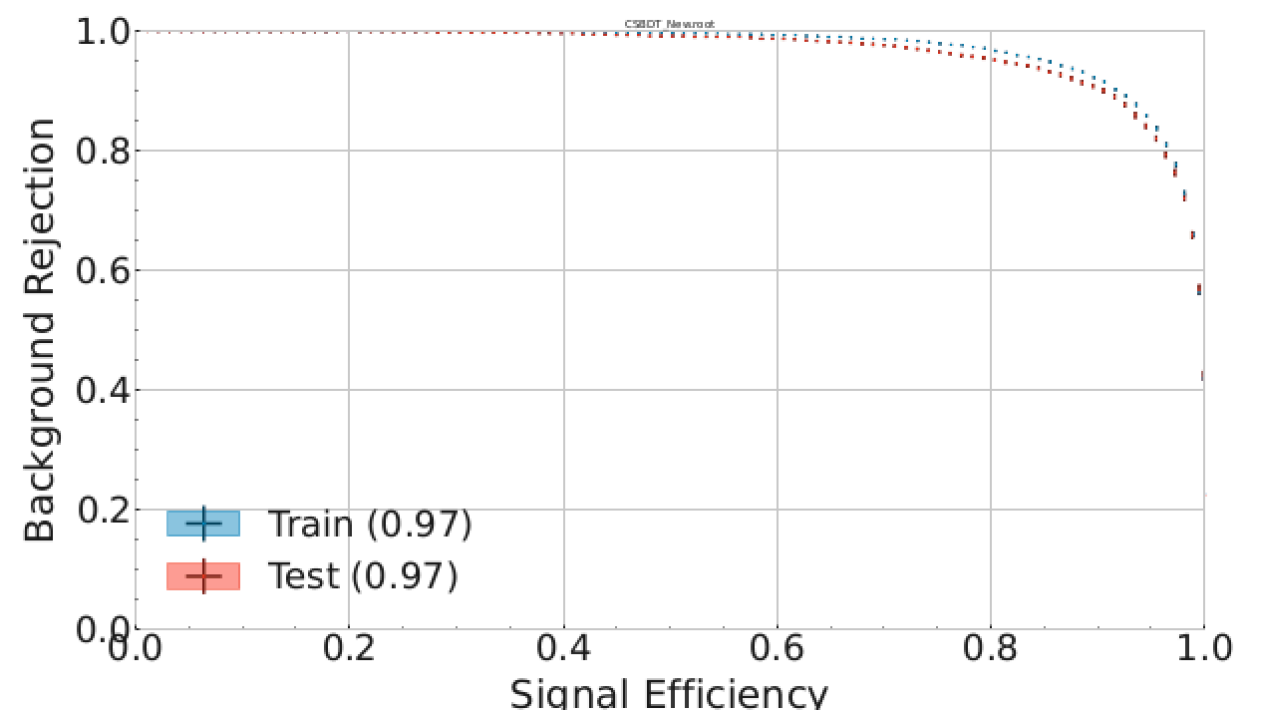
**Better result wrt previous one**

# CSMVAs comparison

All MC



Off-res data + signalMC



ROC curves are the same, but distributions are quite different

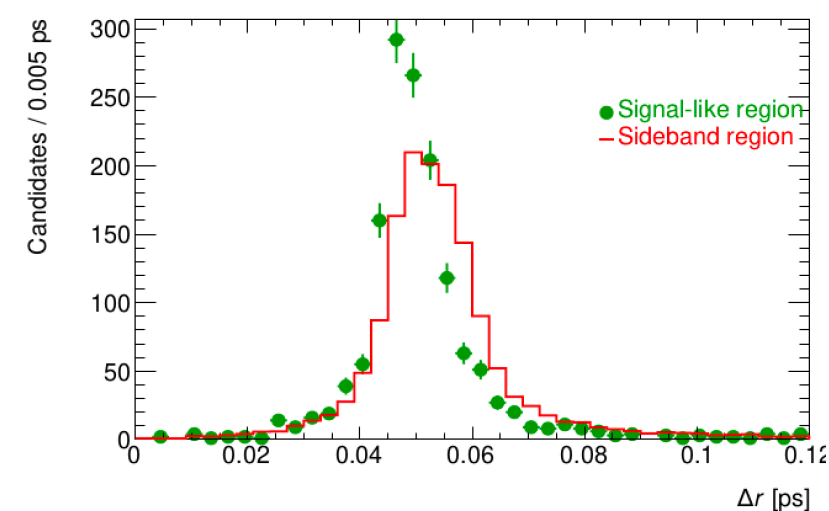
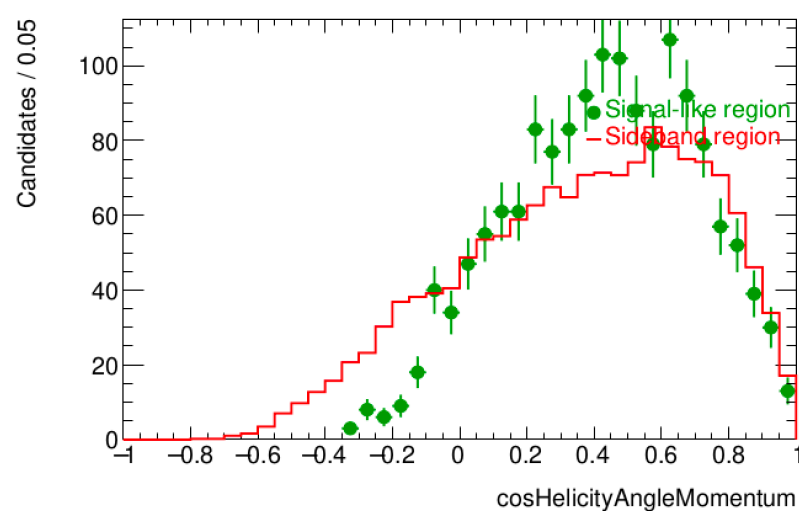
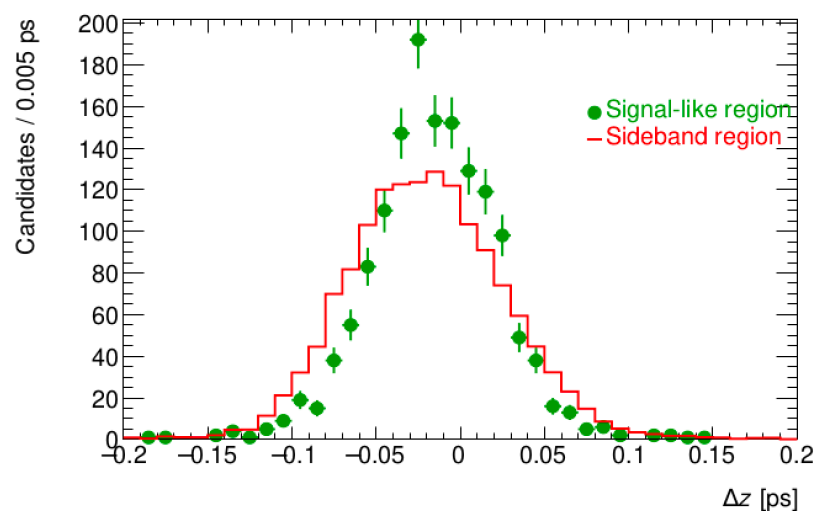
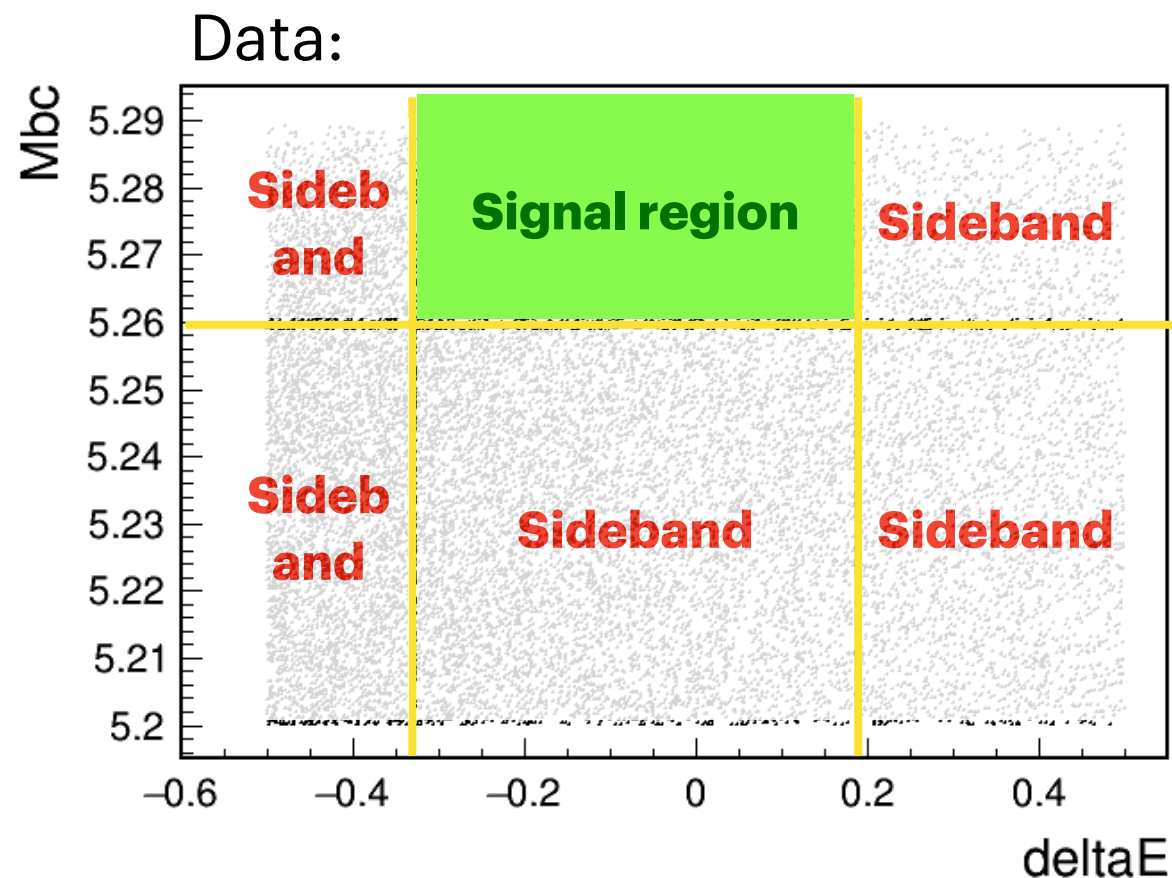
Sideband in off-res data is fine.

But then what about the  
on-resonance sideband data?

# Sideband data vs off-res data

Sideband distributions seem good in off-res.

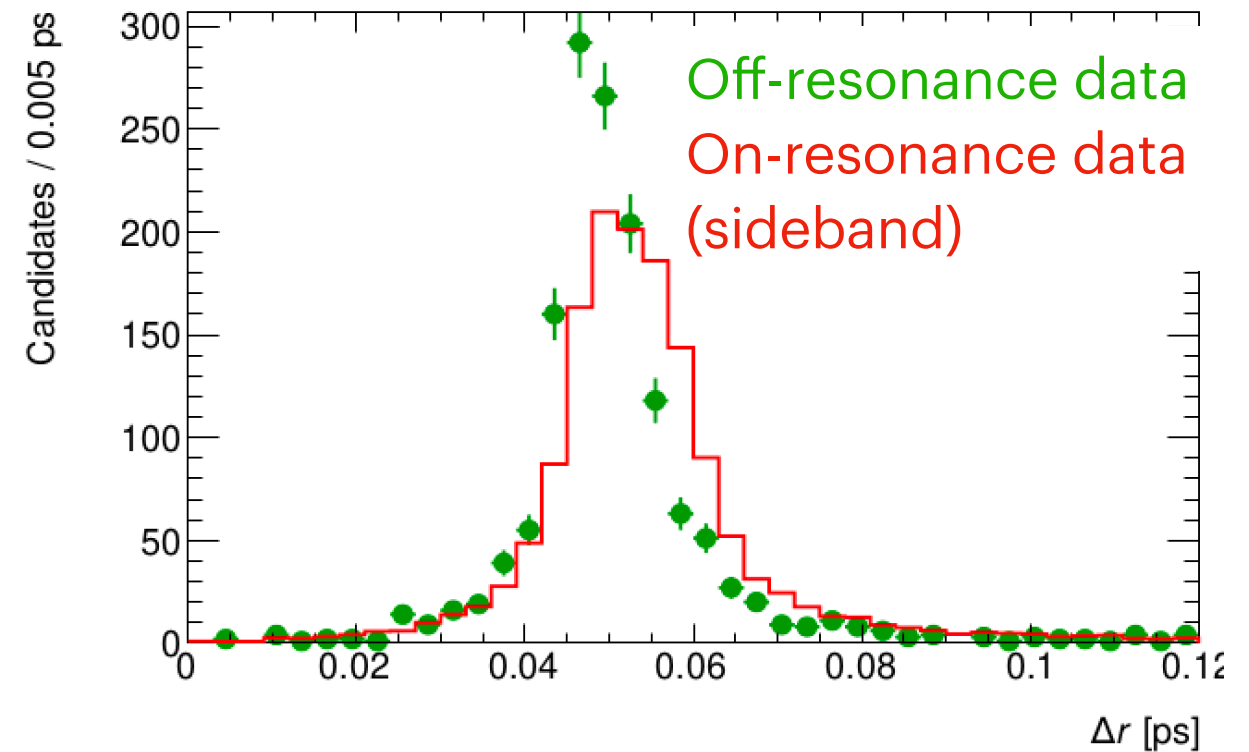
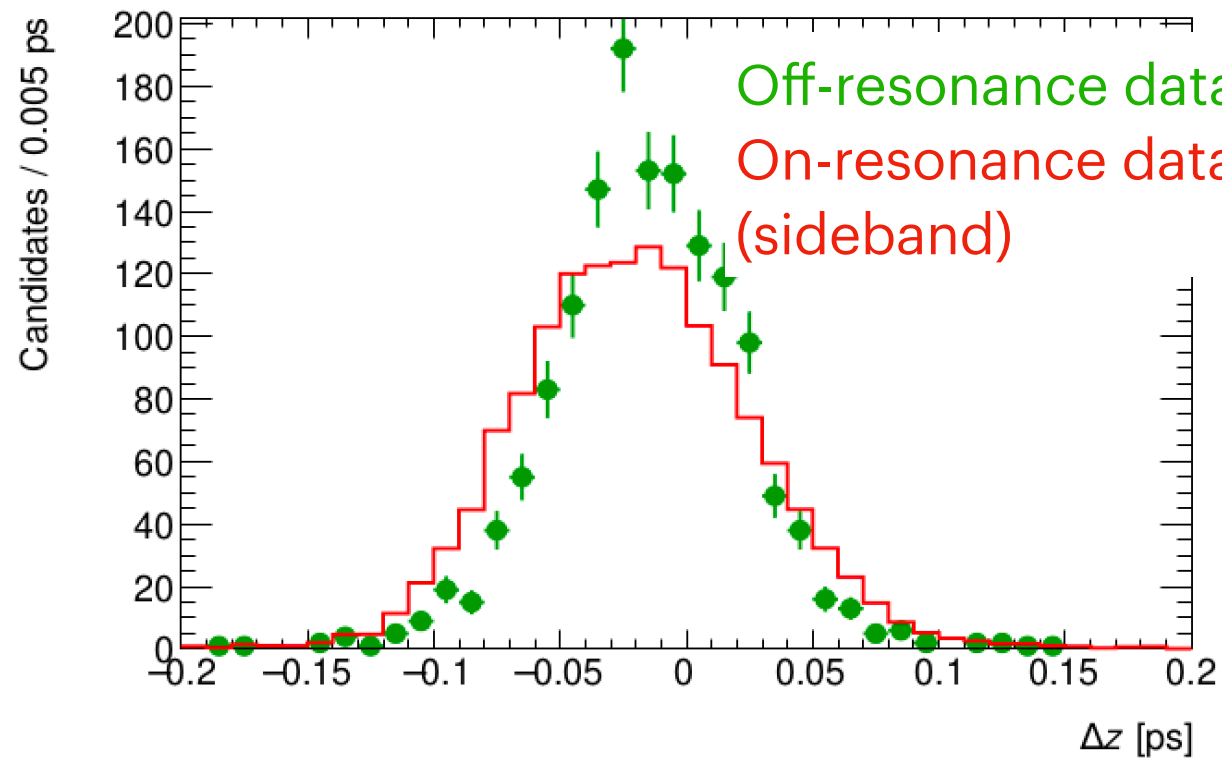
Compare CS inputs distributions in **signal-like region** (in off-resonance data) and **sideband regions** (in on-resonance data):



Observe large discrepancies also in  $\Delta r$  and  $\Delta Z$ .

# Which are the correct $\Delta r$ and $\Delta Z$ distributions?

Sideband data and off-resonance data have different  $r$  and  $\Delta Z$  distributions.



I need to understand which one reproduces correctly the signal region:

Red is correct → use sideband data (and exclude  $\cos\theta_{\text{HelAngle}}$  from the inputs)

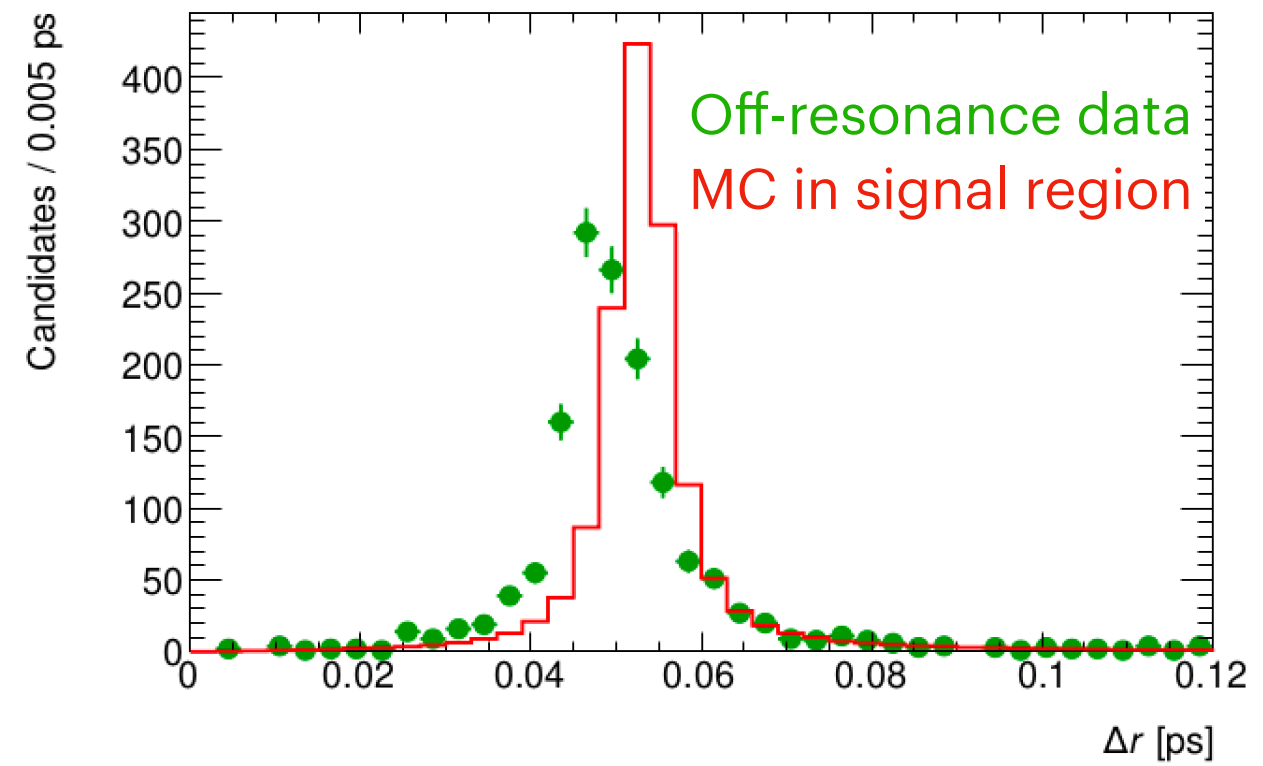
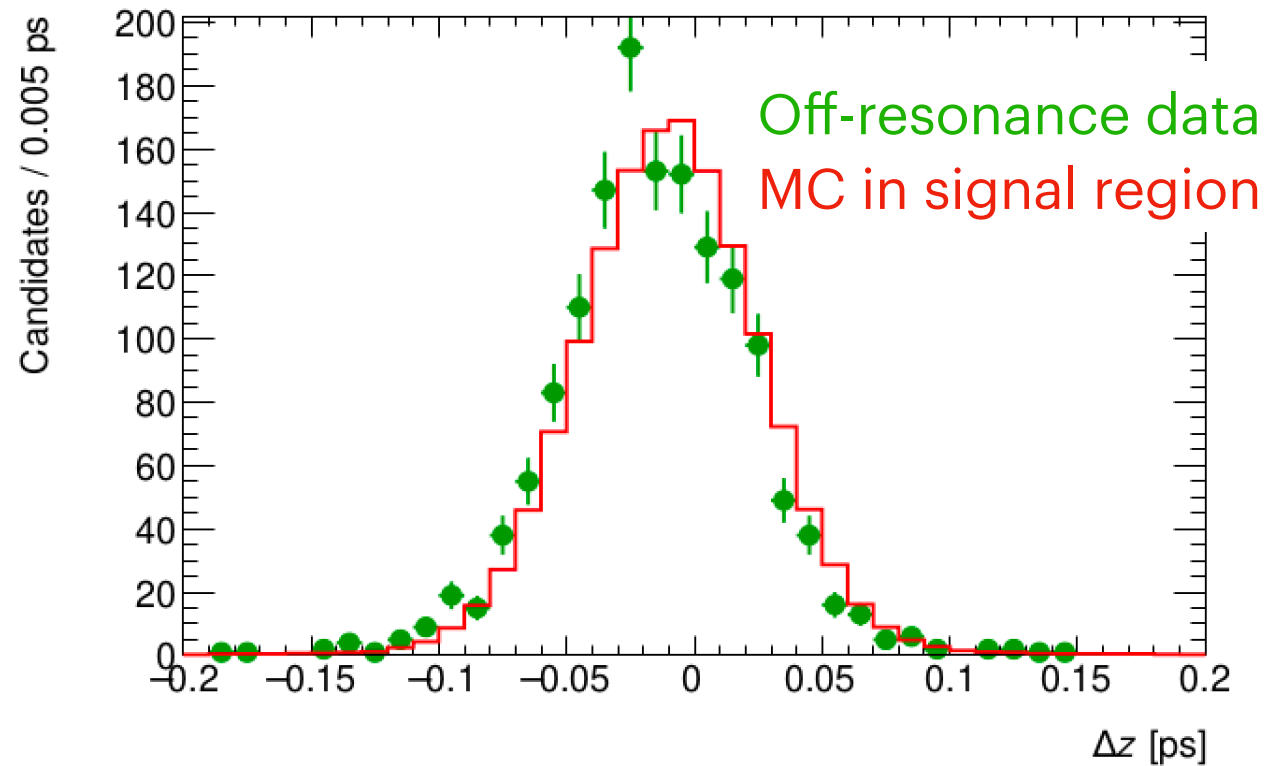
Green is correct → use off-res data (and exclude  $\cos\theta_{\text{HelAngle}}$  from the inputs)

Still thinking how to do this.



# Which are the correct $\Delta r$ and $\Delta Z$ distributions?

Sideband data and off-resonance data have different  $r$  and  $\Delta Z$  distributions.

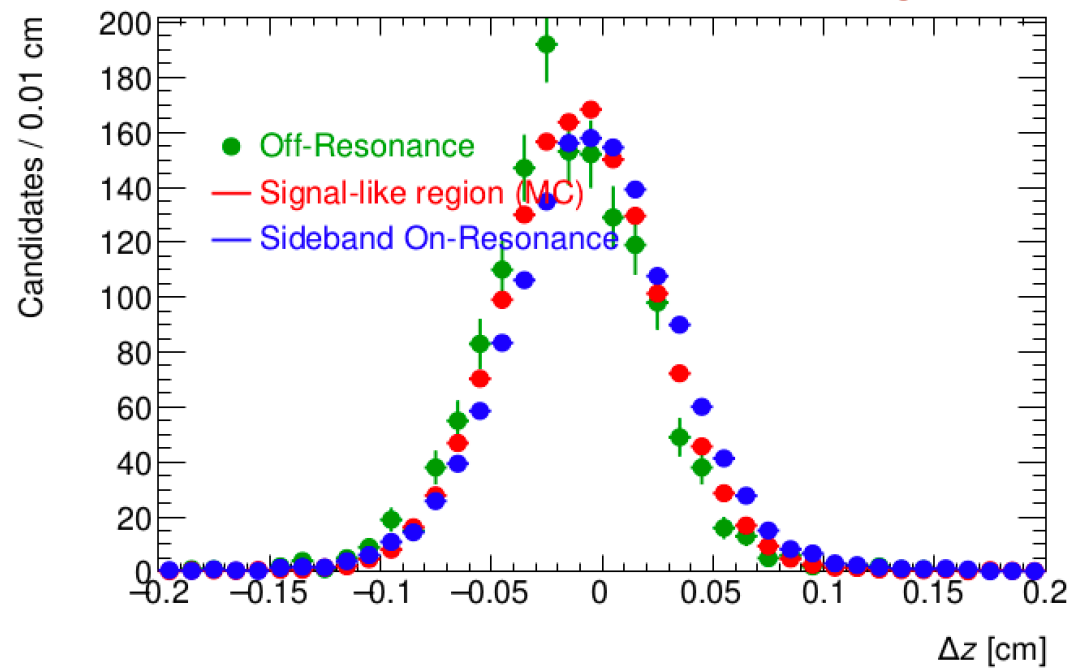


Metti tutti e tre insieme dai

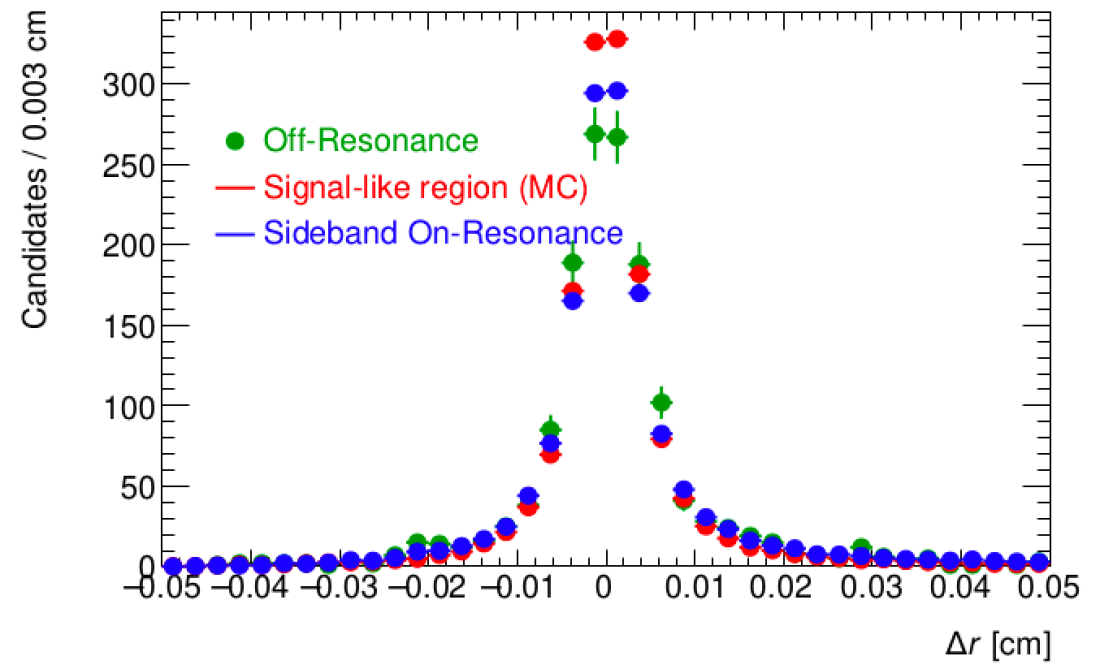
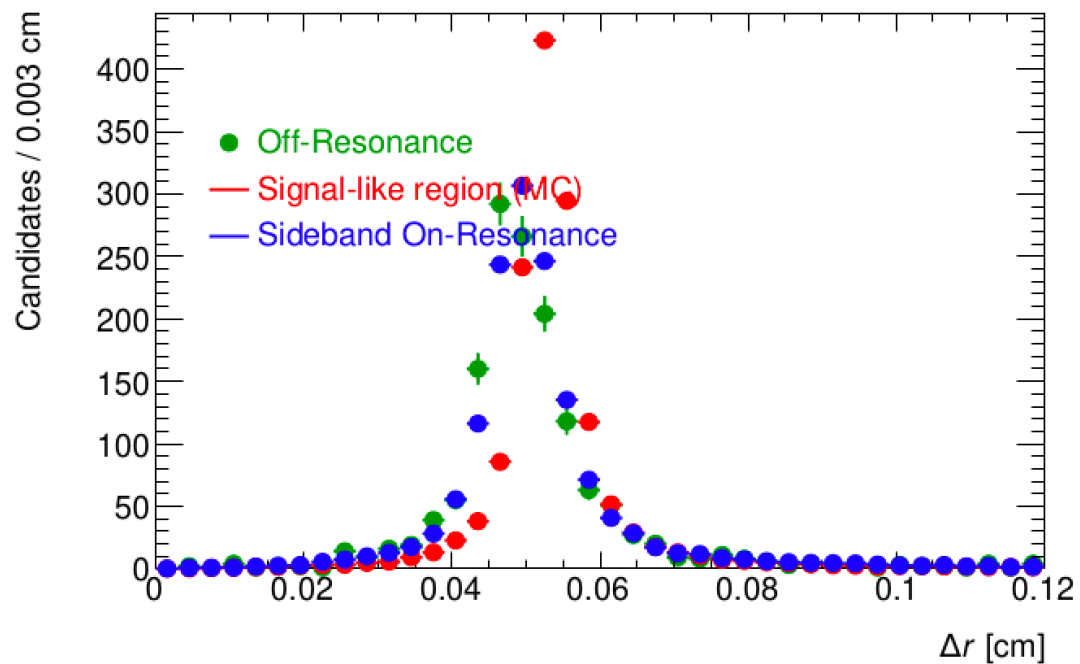
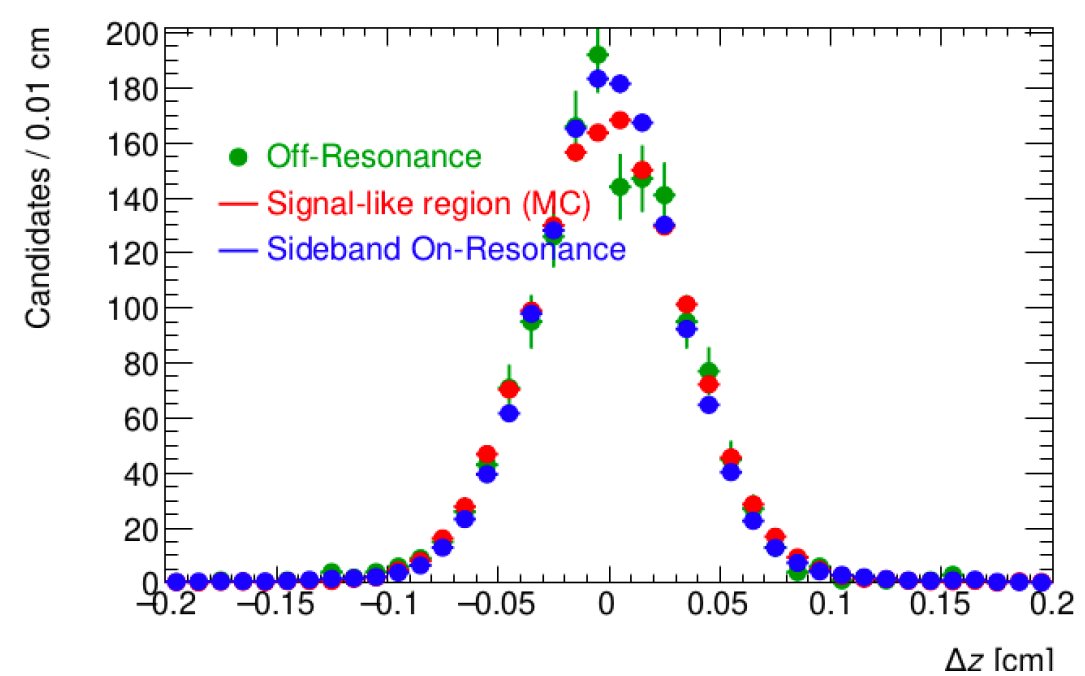
# Which are the correct $\Delta r$ and $\Delta Z$ distributions?

Sideband data and off-resonance data have different  $\Delta r$  and  $\Delta Z$  distributions. Use  $\Delta r$  and  $\Delta Z$  distributions with respect to the IP (not the lab origin).

with respect to the origin



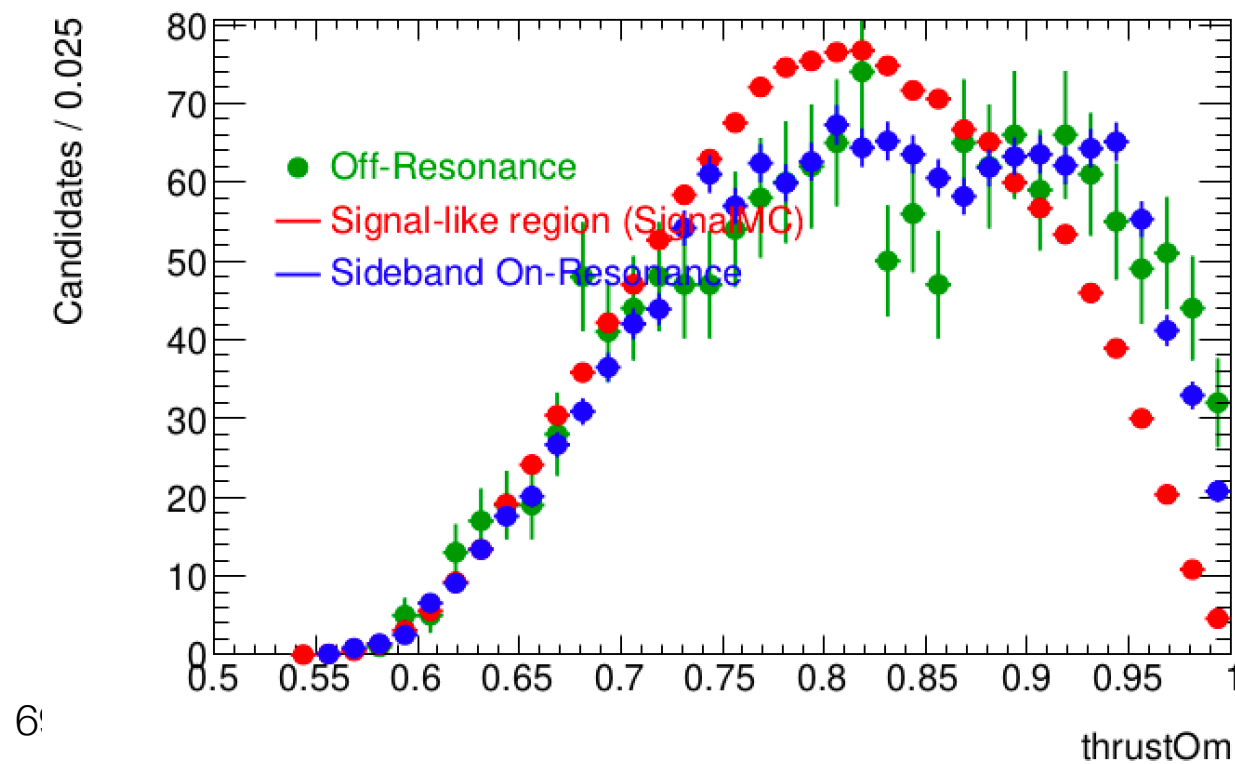
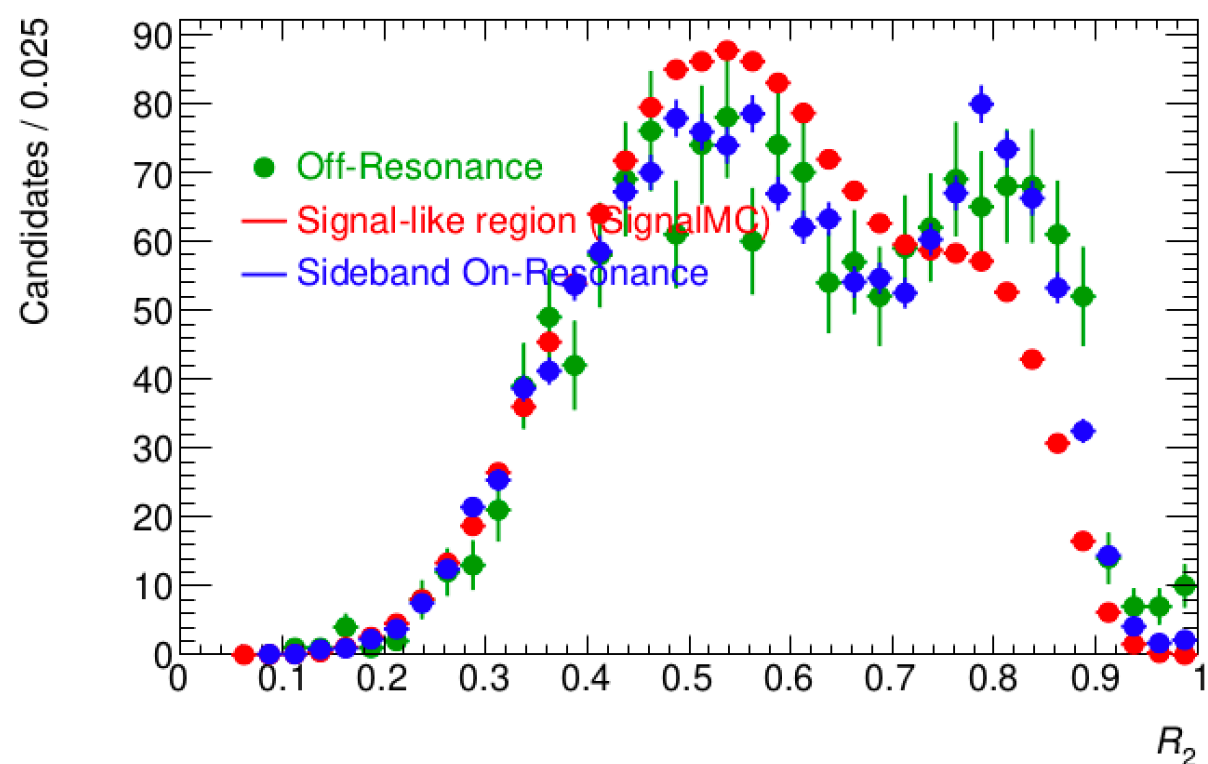
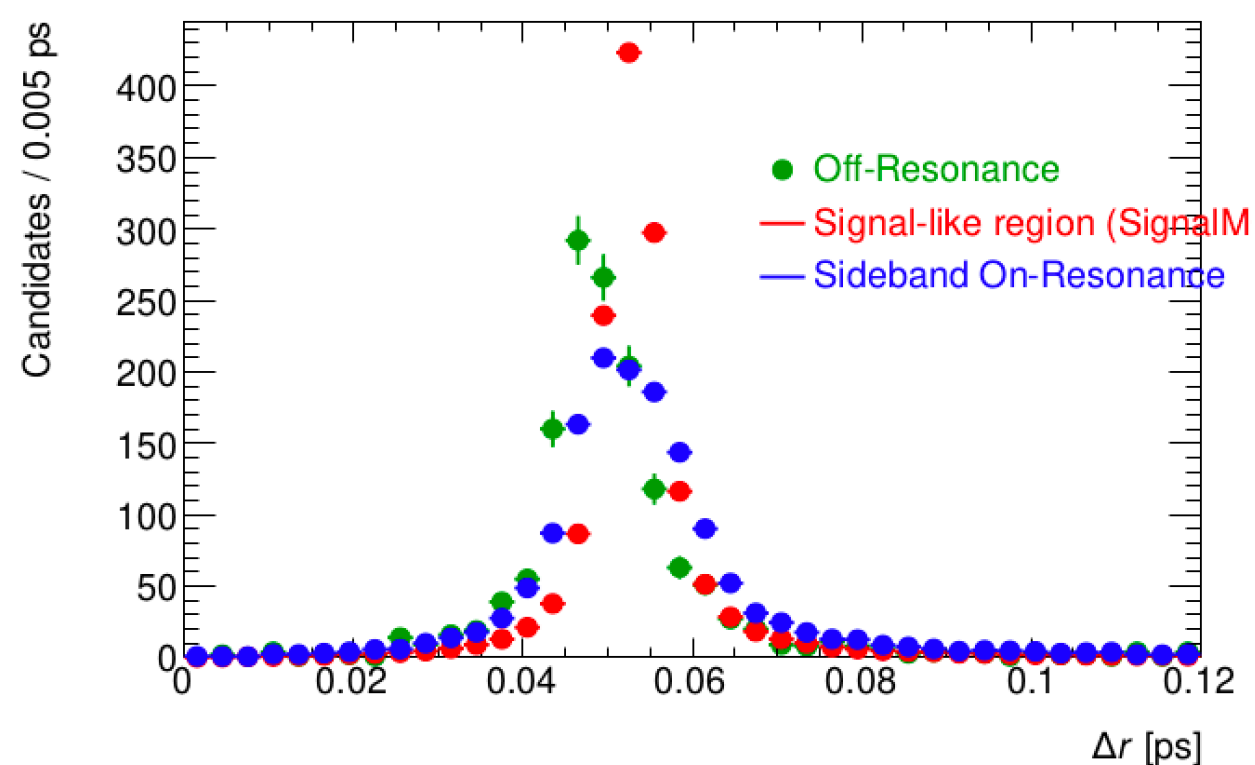
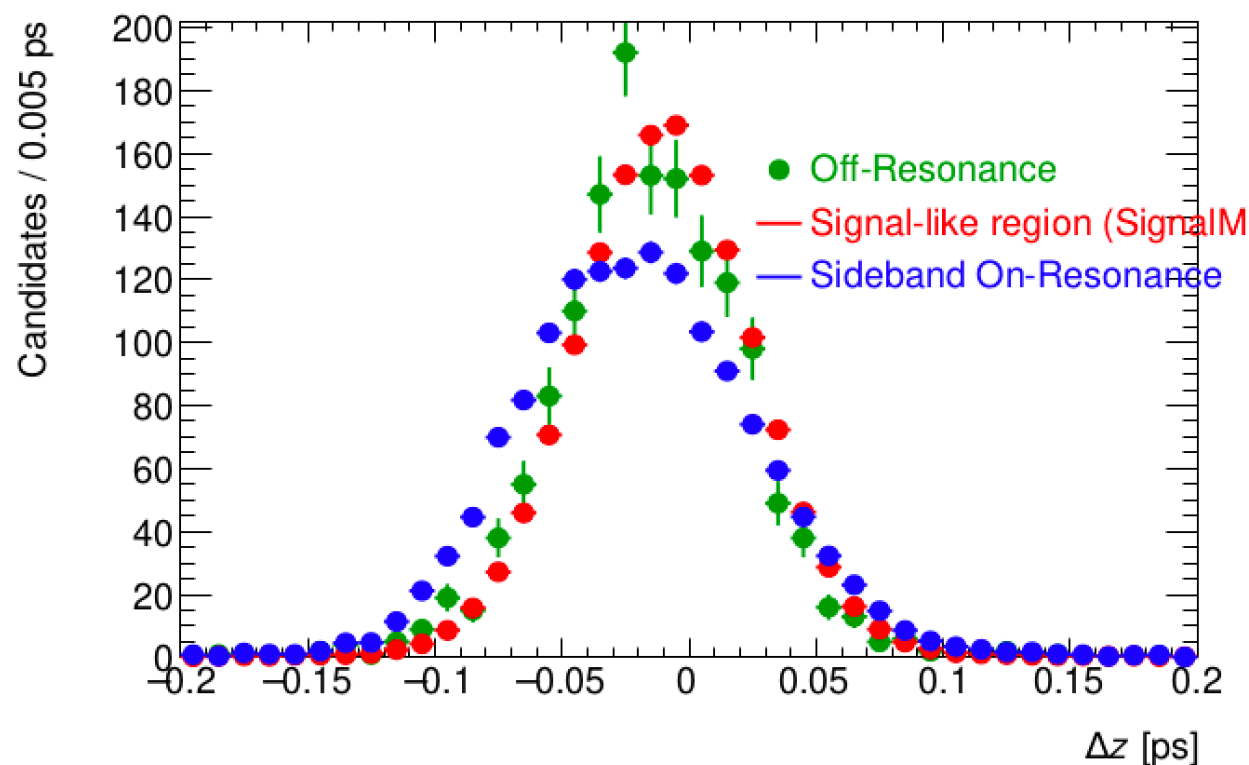
with respect to the IP



Improved situation

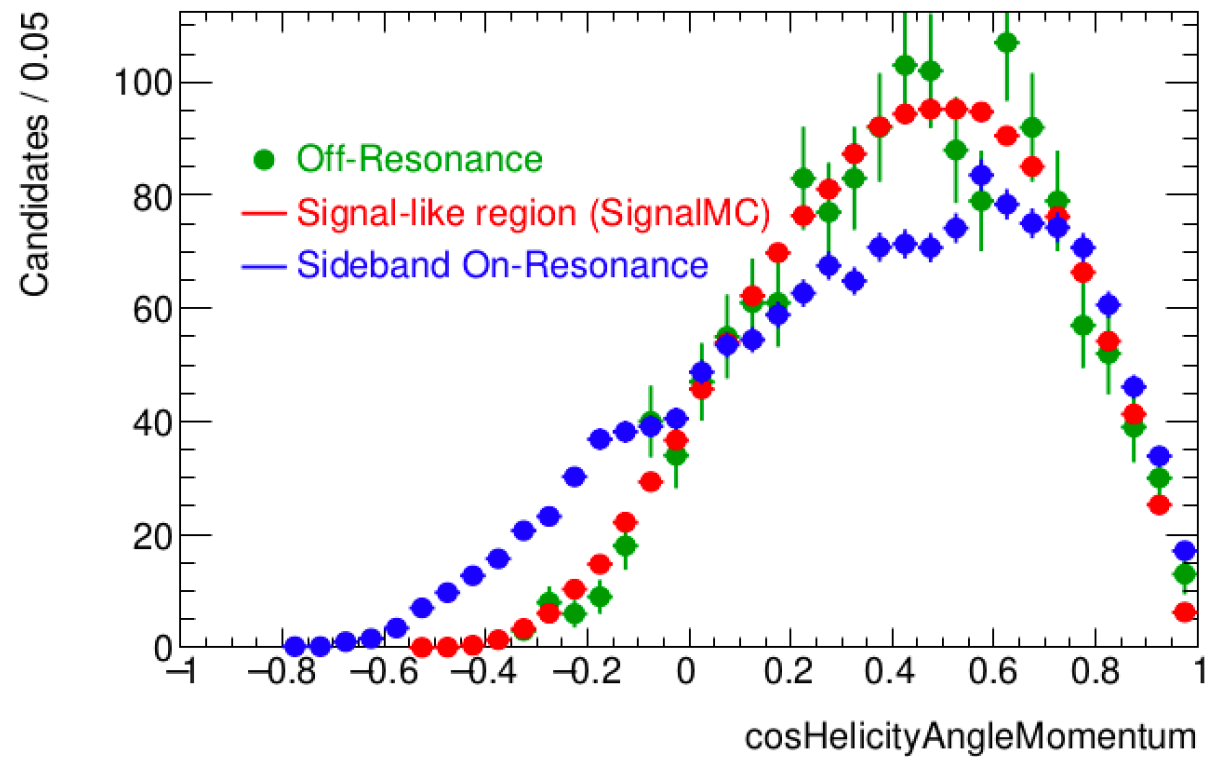
# Which are the correct $\Delta r$ and $\Delta Z$ distributions?

Sideband data and off-resonance data have different  $r$  and  $\Delta Z$  distributions.

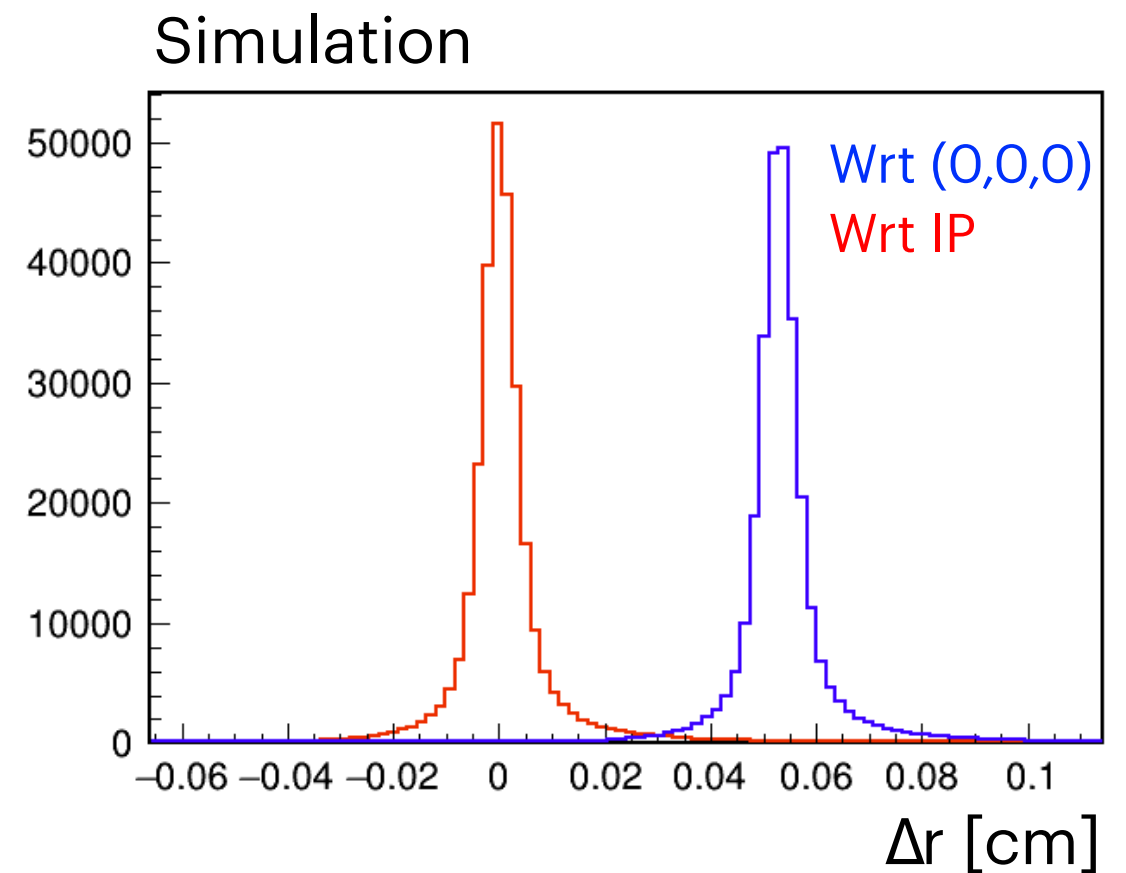
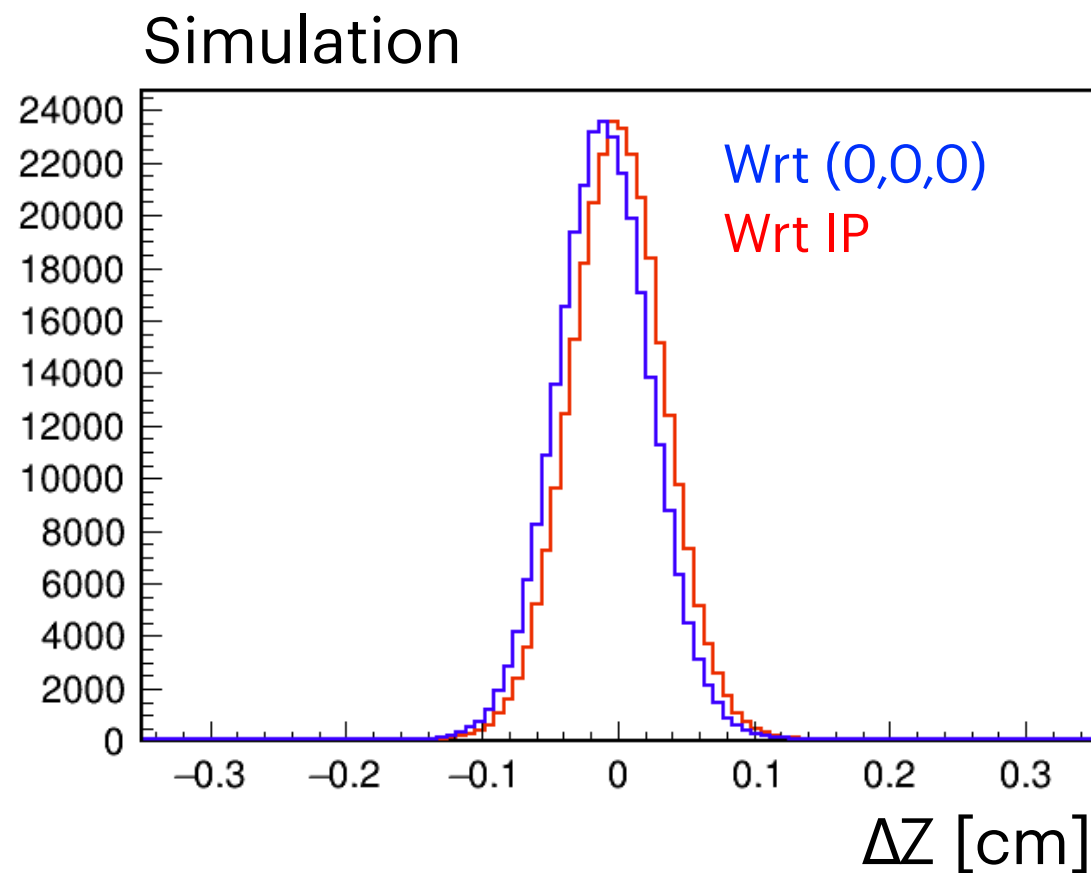


# Which are the correct $\Delta r$ and $\Delta Z$ distributions?

Sideband data and off-resonance data have different  $r$  and  $\Delta Z$  distributions.



# Which are the correct $\Delta r$ and $\Delta Z$ distributions?



Now we have the expected distributions!