Higgs CP measurement with EFT model in lepton collider

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Summary

Introduction

Properties of Higgs in Standard Model: $m_H = 125.10 GeV, J^{PC} = 0^{++}$

Related experiments in LHC:

◦ The hypothesis of spin-1 or spin-2 Higgs has been excluded by the ATLAS and CMS at >99% CL in $\sqrt{s} = 7\&8$ TeV, 25 fb^{-1} data. Eur. Phys. J. C75 (2015) 476

◦ The results of the study on the CP properties of the Higgs boson interactions with gauge bosons by the ATLAS and CMS show no deviations from the SM predictions.

Higgs-gauge vector boson interaction lacks precise measurement in all inclusive Higgs production mode(i.e. ggF dominant).

Any observation of CP violation in Higgs would be New Physics!

What we want to study is the Higgs CP mixing model aiming to find the CP-odd Higgs.

Introduction

Future e^+e^- collider experiment as Higgs factory :

◦ At a center of mass energy of $\sqrt{s} \sim 240 GeV$ which maximizes the Higgs boson production cross section through $e^+e^- \to ZH$ process.

◦ Cleaner environment and more events produced than (HL)-LHC.

◦ More precise Higgs-gauge boson coupling study.

**CEPC, 5.6 ab^{-1} @ 240GeV**

FCC-ee, 5 ab^{-1} @240GeV

ILC, 2 ab^{-1} @250GeV
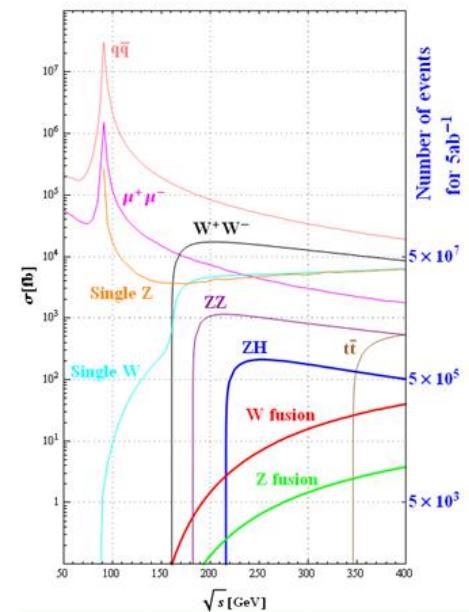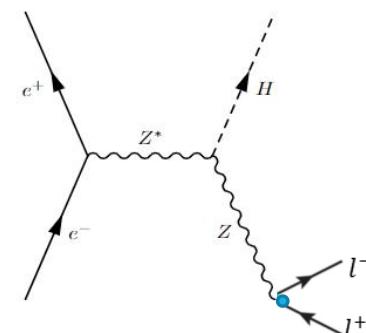
Theory model

Consider a 6-dimension EFT model: $\mathcal{L}_{eff} = \mathcal{L}_{SM}^{(4)} + \frac{1}{\Lambda^2} \sum_{k=1}^{59} \alpha_k \mathcal{O}_k \ (\mathcal{L}_{BSM})$

$$\mathcal{L}_{eff} \supset c_{ZZ}^{(1)} H Z_\mu Z^\mu + c_{ZZ}^{(2)} H Z_{\mu\nu} Z^{\mu\nu} + c_{Z\tilde{Z}} H Z_{\mu\nu} \tilde{Z}^{\mu\nu} + c_{AZ} H Z_{\mu\nu} A^{\mu\nu} + c_{A\tilde{Z}}^{HZ_{\mu\nu}} \tilde{A}^{\mu\nu}$$
$$+ H Z_\mu \bar{\ell} \gamma^\mu (c_V + c_A \gamma_5) \ell + Z_\mu \bar{\ell} \gamma^\mu (g_V - g_A \gamma_5) \ell - g_{em} Q_\ell A_\mu \bar{\ell} \gamma^\mu \ell$$

Where: $c_{ZZ}^{(1)} = m_Z^2 (\sqrt{2} G_F)^{1/2} \left(1 + \hat{\alpha}_{ZZ}^{(1)}\right)$, $c_{ZZ}^{(2)} \& = (\sqrt{2} G_F)^{1/2} \hat{\alpha}_{ZZ}$, $c_{Z\tilde{Z}} \& = (\sqrt{2} G_F)^{1/2} \hat{\alpha}_{Z\tilde{Z}}$,

$c_{AZ} = (\sqrt{2} G_F)^{1/2} \hat{\alpha}_{AZ}$, $c_{A\tilde{Z}} = (\sqrt{2} G_F)^{1/2} \hat{\alpha}_{A\tilde{Z}}$.

◦ In this base, the experimental observables G_F, m_z, α_{em} could be presented:

$m_z = m_{Z0}(1 + \delta_Z)$, $G_F = G_{F0}\left(1 + \delta_{G_F}\right)$, $\alpha_{em} = \alpha_{em0}(1 + \delta_A)$

where: $\delta_Z = \hat{\alpha}_{ZZ} + \frac{1}{4}\hat{\alpha}_{\Phi D}$, $\delta_{G_F} = -\hat{\alpha}_{4l} + 2\hat{\alpha}_{\Phi l}^{(3)}$, $\delta_A = 2\hat{\alpha}_{AA}$.

Theory model

The $H \to Zll$ matrix element:

$$\mathcal{M}^\mu_{HZ\ell\ell} = \frac{1}{m_H}\bar{u}(p_3,s_3)\left[\gamma^\mu(H_{1,V}+H_{1,A}\gamma_5)+\frac{q^\mu p\!\!\!/}{m_H^2}(H_{2,V}+H_{2,A}\gamma_5)+\frac{\epsilon^{\mu\nu\sigma\rho}p_\nu q_\sigma}{m_H^2}\gamma_\rho(H_{3,V}+H_{3,A}\gamma_5)\right]v(p_4,s_4)$$

◦ Where $\epsilon_{0123}=+1$ and $q=p_3+p_4$.

And the parameters in the function are following:

$$H_{1,V}=-\frac{2m_H\left(\sqrt{2}G_F\right)^{1/2}r}{r-s}g_V\left(1+\hat{\alpha}_1^{\text{eff}}-\frac{\kappa}{r}\hat{\alpha}_{ZZ}-\frac{\kappa}{2r}\frac{Q_\ell g_{em}(r-s)}{sg_V}\hat{\alpha}_{AZ}\right)$$

$$H_{1,A}=\frac{2m_H\left(\sqrt{2}G_F\right)^{1/2}r}{r-s}g_A\left(1+\hat{\alpha}_2^{\text{eff}}-\frac{\kappa}{r}\hat{\alpha}_{ZZ}\right),$$

$$H_{2,V}=-\frac{2m_H\left(\sqrt{2}G_F\right)^{1/2}}{r-s}g_V\left[2\hat{\alpha}_{ZZ}+\frac{Q_\ell g_{em}(r-s)}{sg_V}\hat{\alpha}_{AZ}\right]$$

$$H_{2,A}=\frac{4m_H\left(\sqrt{2}G_F\right)^{1/2}}{r-s}g_A\hat{\alpha}_{ZZ}$$

$$H_{3,V}=-\frac{2m_H\left(\sqrt{2}G_F\right)^{1/2}}{r-s}g_V\left[2\hat{\alpha}_{Z\tilde{Z}}+\frac{Q_\ell g_{em}(r-s)}{sg_V}\hat{\alpha}_{A\tilde{Z}}\right]$$

$$H_{3,A}=\frac{4m_H\left(\sqrt{2}G_F\right)^{1/2}}{r-s}g_A\hat{\alpha}_{Z\tilde{Z}}$$

$$\hat{\alpha}_1^{\text{eff}}\equiv\hat{\alpha}_{ZZ}^{(1)}-\frac{m_H\left(\sqrt{2}G_F\right)^{1/2}(r-s)}{2\sqrt{r}}\frac{\hat{\alpha}_{\Phi l}^V}{g_V}$$

$$\hat{\alpha}_2^{\text{eff}}\equiv\hat{\alpha}_{ZZ}^{(1)}+\frac{m_H\left(\sqrt{2}G_F\right)^{1/2}(r-s)}{2\sqrt{r}}\frac{\hat{\alpha}_{\Phi l}^A}{g_A}$$

◯ : SM term
Others : EFT contribution

Theory model

Differential cross section for $e^+ e^- \to ZH \to llH$:

$$\frac{d\sigma}{d\cos\theta_1 \, d\cos\theta_2 \, d\phi} = \frac{\mathcal{N}_\sigma(q^2)}{m_H^2} \mathcal{J}(q^2, \theta_1, \theta_2, \phi),$$

$$\mathcal{N}_\sigma(q^2) = \frac{1}{2^{10}(2\pi)^3} \cdot \frac{1}{\sqrt{r}\gamma_Z} \cdot \frac{\sqrt{\lambda(1,s,r)}}{s^2}$$

$$\begin{aligned}
\mathcal{J}(q^2, \theta_1, \theta_2, \phi) = {}& J_1(1 + \cos^2\theta_1 \cos^2\theta_2 + \cos^2\theta_1 + \cos^2\theta_2) \\
& + J_2 \sin^2\theta_1 \sin^2\theta_2 + J_3 \cos\theta_1 \cos\theta_2 \\
& + (J_4 \sin\theta_1 \sin\theta_2 + J_5 \sin 2\theta_1 \sin 2\theta_2) \sin\phi \\
& + (J_6 \sin\theta_1 \sin\theta_2 + J_7 \sin 2\theta_1 \sin 2\theta_2) \cos\phi \\
& + J_8 \sin^2\theta_1 \sin^2\theta_2 \sin 2\phi + J_9 \sin^2\theta_1 \sin^2\theta_2 \cos 2\phi.
\end{aligned}$$

Variables for studying distribution: θ_1, θ_2, ϕ

Theory model

Differential cross section for $e^+ e^- \to ZH \to llH$:

$$\frac{d\sigma}{dcos\theta_1 \, dcos\theta_2 \, d\phi} = \frac{\mathcal{N}_\sigma(q^2)}{m_H^2} \mathcal{J}(q^2, \theta_1, \theta_2, \phi),$$

$$\mathcal{N}_\sigma(q^2) = \frac{1}{2^{10}(2\pi)^3} \cdot \frac{1}{\sqrt{r}\gamma_Z} \cdot \frac{\sqrt{\lambda(1,s,r)}}{s^2}$$
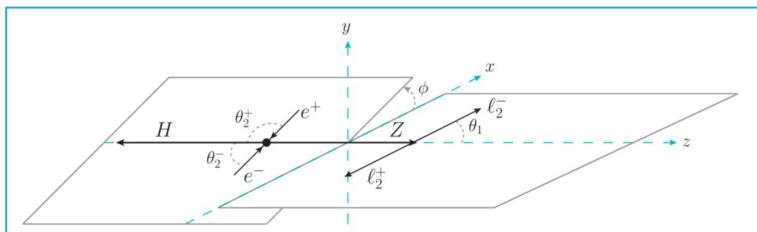
$$\begin{aligned}
\mathcal{J}(q^2, \theta_1, \theta_2, \phi) = {} & J_1(1 + \cos^2\theta_1 \cos^2\theta_2 + \cos^2\theta_1 + \cos^2\theta_2) \\
& + J_2 \sin^2\theta_1 \sin^2\theta_2 + J_3 \cos\theta_1 \cos\theta_2 \\
& + (J_4 \sin\theta_1 \sin\theta_2 + J_5 \sin 2\theta_1 \sin 2\theta_2)\sin\phi \\
& + (J_6 \sin\theta_1 \sin\theta_2 + J_7 \sin 2\theta_1 \sin 2\theta_2)\cos\phi \\
& + J_8 \sin^2\theta_1 \sin^2\theta_2 \sin 2\phi + J_9 \sin^2\theta_1 \sin^2\theta_2 \cos 2\phi.
\end{aligned}$$

Variables for studying distribution: θ_1, θ_2, ϕ

Assumption for simplification:

○ $\delta_{G_F} = \hat{\alpha}^V_{\phi l} = \hat{\alpha}^A_{\phi l} = \hat{\alpha}_{A\tilde{Z}} = \hat{\alpha}_{Z\tilde{Z}} = 10^{-3}$, others are set to 0, so $H_{2,V/A} = 0$.

○ $\hat{\alpha}_{A\tilde{Z}}$ and $\hat{\alpha}_{Z\tilde{Z}}$ have the most contribution for cp-odd.

$$J_1 = 2\, r\, s\, (g_A^2 + g_V^2)\,(|H_{1,V}|^2 + |H_{1,A}|^2),$$

$$J_2 = \kappa\,(g_A^2 + g_V^2)\,[\kappa\,(|H_{1,V}|^2 + |H_{1,A}|^2) + \lambda\,\mathrm{Re}\,(H_{1,V}H_{2,V}^* + H_{1,A}H_{2,A}^*)],$$

$$J_3 = 32\, r\, s\, g_A\, g_V\, \mathrm{Re}\,(H_{1,V}H_{1,A}^*),$$

$$J_4 = 4\kappa \sqrt{r\, s}\, \lambda\, g_A\, g_V\, \mathrm{Re}\,(H_{1,V}H_{3,A}^* + H_{1,A}H_{3,V}^*),$$

$$J_5 = \frac{1}{2}\kappa\sqrt{r\, s}\,\lambda\,(g_A^2 + g_V^2)\,\mathrm{Re}\,(H_{1,V}H_{3,V}^* + H_{1,A}H_{3,A}^*),$$

$$J_6 = 4\sqrt{r\, s}\, g_A\, g_V\,[4\kappa\,\mathrm{Re}\,(H_{1,V}H_{1,A}^*) + \lambda\,\mathrm{Re}\,(H_{1,V}H_{2,A}^* + H_{1,A}H_{2,V}^*)],$$

$$J_7 = \frac{1}{2}\sqrt{r\, s}\,(g_A^2 + g_V^2)\,[2\kappa\,(|H_{1,V}|^2 + |H_{1,A}|^2) + \lambda\,\mathrm{Re}\,(H_{1,V}H_{2,V}^* + H_{1,A}H_{2,A}^*)],$$

$$J_8 = 2\, r\, s\, \sqrt{\lambda}\,(g_A^2 + g_V^2)\,\mathrm{Re}\,(H_{1,V}H_{3,V}^* + H_{1,A}H_{3,A}^*),$$

$$J_9 = 2\, r\, s\,(g_A^2 + g_V^2)\,(|H_{1,V}|^2 + |H_{1,A}|^2).$$

6 of these 9 functions are independent

——	0 in assumption
☐	EFT CP-odd term
Others	CP-even contribution

Optimal variable approach

Differential cross section could be represent as:

$$\frac{d\sigma}{dcos\theta_1 dcos\theta_2 d\phi} = N \times (J_{CP-even}(\theta_1, \theta_2, \phi) + p \times J_{CP-odd}(\theta_1, \theta_2, \phi)).$$

where p is an additional global CP-mixing parameter.
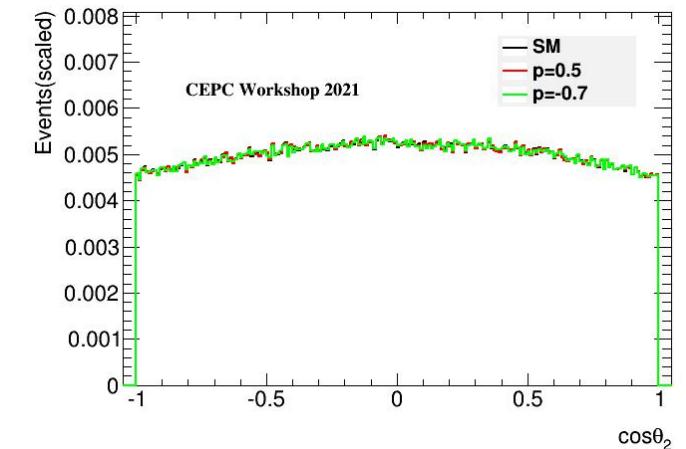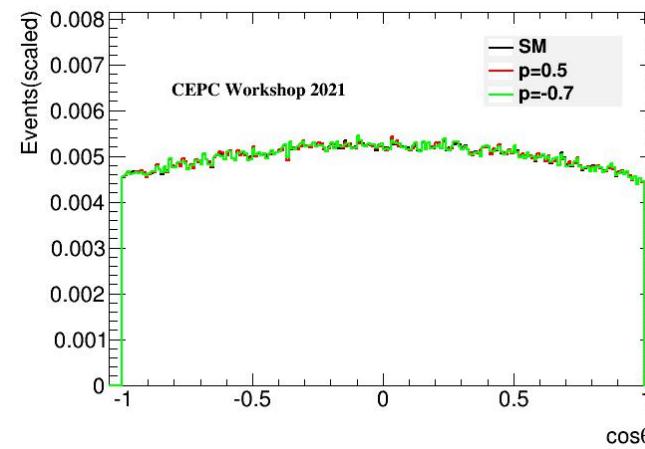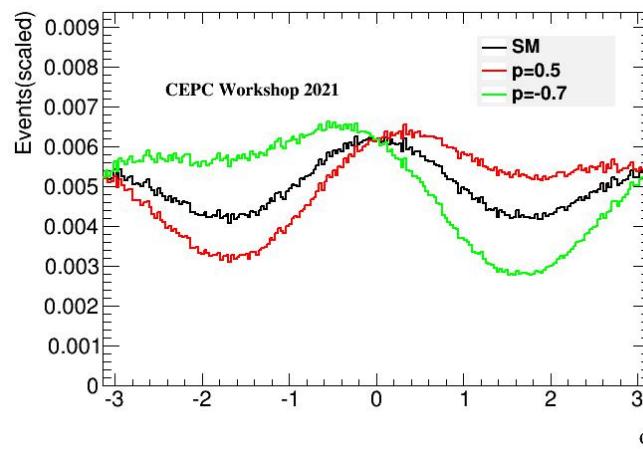
Optimal variable approach

$$\frac{d\sigma}{dcos\theta_1 dcos\theta_2 d\phi} = N \times (J_{CP-even}(\theta_1, \theta_2, \phi) + p \times J_{CP-odd}(\theta_1, \theta_2, \phi)).$$

In this formation, we could define an Optimal Variable ω which combines the information from $\{\theta_1, \theta_2, \phi\}$:

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$$\omega = \frac{J_{CP-odd}(\theta_1, \theta_2, \phi)}{J_{CP-even}(\theta_1, \theta_2, \phi)} \text{ to measure } p$$

Benefits:

◦ Combine the information from 3-dimension phase space

◦ Easier to study
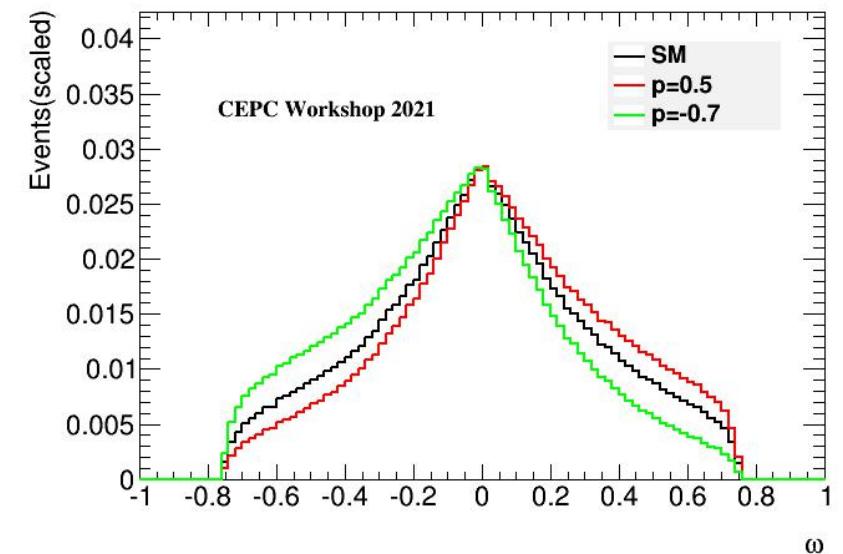
Monte Carlo samples

Two samples:

◦ MC Simulation: fast simulation based on CEPC-v4 detector design

◦ Truth level: simulate the physical process of $ee \rightarrow ZH$ directly in dynamics

MC simulation: Whizard 1.95 in CEPC, $e^+e^- \rightarrow ZH \rightarrow \mu^+\mu^- H$

◦ $\sqrt{s} = 240 GeV$

◦ The mass of Higgs boson is assumed to be 125GeV and the couplings are set to the SM predictions.

◦ All the MC datasets are normalized to the expected yields in data with an integrated luminosity of $5.6ab^{-1}$.

Event selection

(using Monte Carlo simulation sample)

- **Signal**: $e^+e^- \rightarrow ZH \rightarrow \mu^+\mu^- H(\rightarrow b\bar{b}/c\bar{c}/gg)$ channel
- **Background**: Irreducible background which contains the same final states as that in signal.

- Muon pair selection:

$$\left|cos\theta_{\mu^+\mu^-}\right| < 0.81 ; \qquad \text{Mass}_{\mu\mu} \epsilon (77.5GeV, 104.5GeV) ; \qquad M_{recoil\_\mu\mu} \epsilon (124GeV, 140GeV).$$

Where $M^2_{recoil\_\mu\mu} = \left(\sqrt{s} - E_{\mu\mu}\right)^2 - p^2_{\mu\mu} = s - 2E_{\mu\mu}\sqrt{s} + m^2_{\mu\mu}$

- Jets pair selection:

$$\left|cos\theta_{jet}\right| < 0.96 ; \qquad \text{Mass}_{jj} \epsilon (100GeV, 150GeV).$$

Event selection

$|cos\theta_{\mu\mu}| < 0.81$

$\text{Mass}_{\mu\mu} \in (77.5GeV, 104.5GeV)$
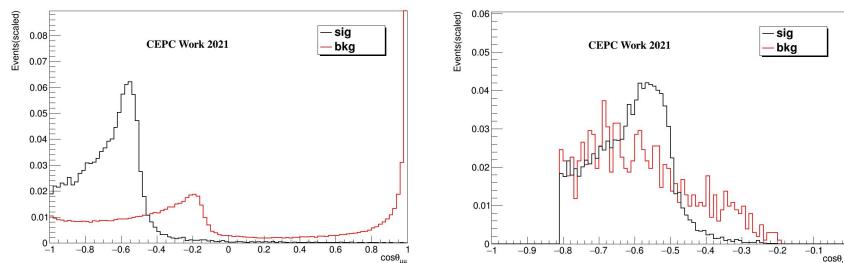
$M_{recoil\_\mu\mu} \in (124GeV, 140GeV)$
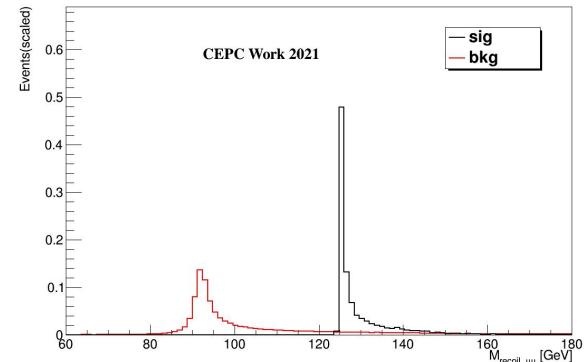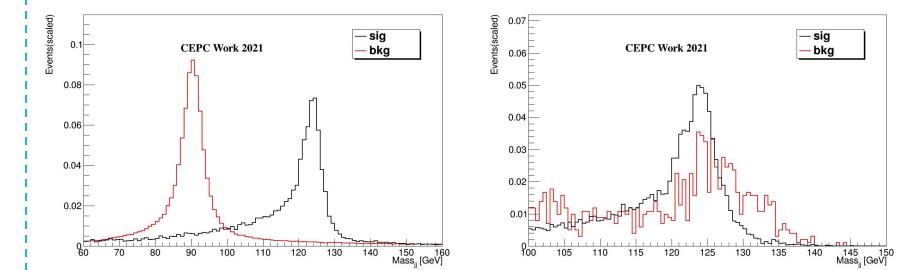
$\text{Mass}_{jj} \in (100GeV, 150GeV)$
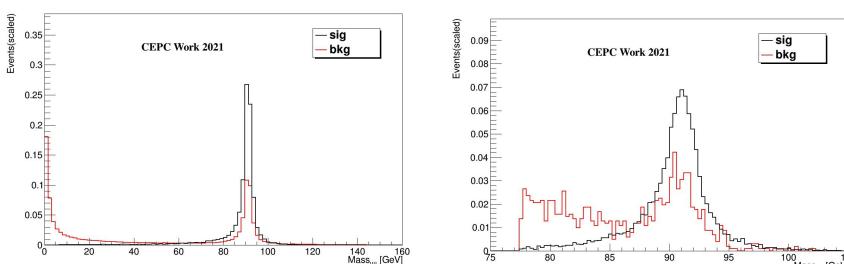
$|cos\theta_{jet}| < 0.96$
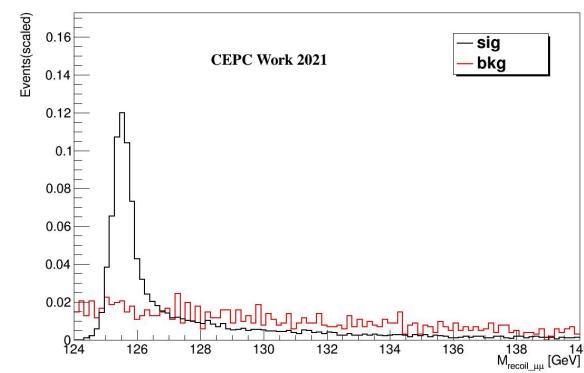
Event selection

Cut Flow:

$ZH \rightarrow \mu^+\mu^- + b\bar{b}/c\bar{c}/gg$ channel	Signal	Irreducible Background
Original	28627	1251768
Muon pair selection	18555 (efficiency:64.82%)	11198 (efficiency:0.89%)
All selection	13405 (efficiency:46.83%)	3610 (efficiency:0.29%)

Higgs CP-mixing measurement

Correlation:

- We can see that θ_1, θ_2, ϕ have little correlation with $cos\theta_{\mu^+\mu^-}$, $\text{Mass}_{\mu\mu}$, $M_{recoil\_\mu\mu}$, $cos\theta_{jet}$, Mass_{jj}.
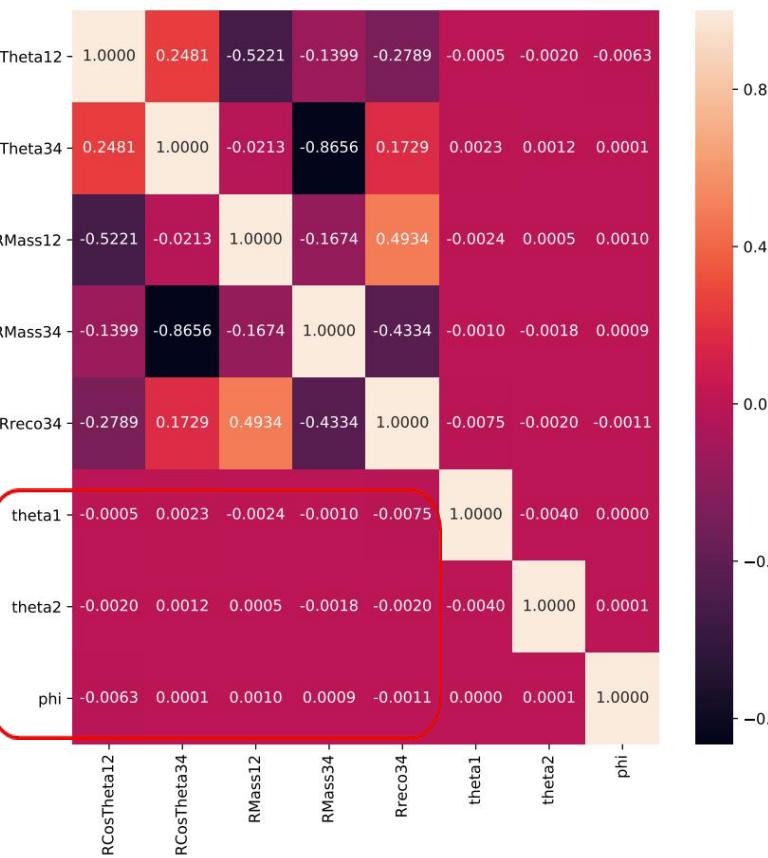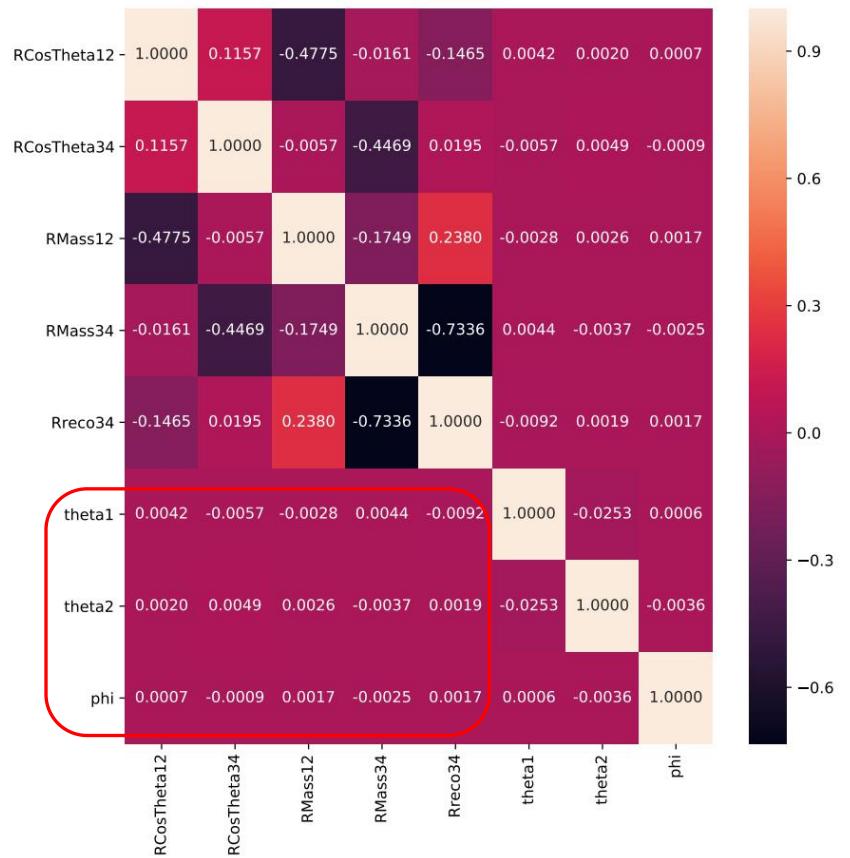

- So we can ignore the impact of event selections to θ_1, θ_2, and ϕ.

Fitting strategy and result

Fit strategy: Maximum-likelihood fit

- $f^p(\omega) = N_{sig} * f^p_{sig}(\omega) + N_{bkg} * f^p_{bkg}(\omega)$
- **Fit ω to get $f^p_{sig}(\omega)$ and $f^p_{bkg}(\omega)$**
- **Fit $M_{recoil\_\mu\mu}$ to get N_{sig} and N_{bkg}**
- Evaluate likelihood function for each p value hypothesis, and construct a ΔNLL as a function of p.
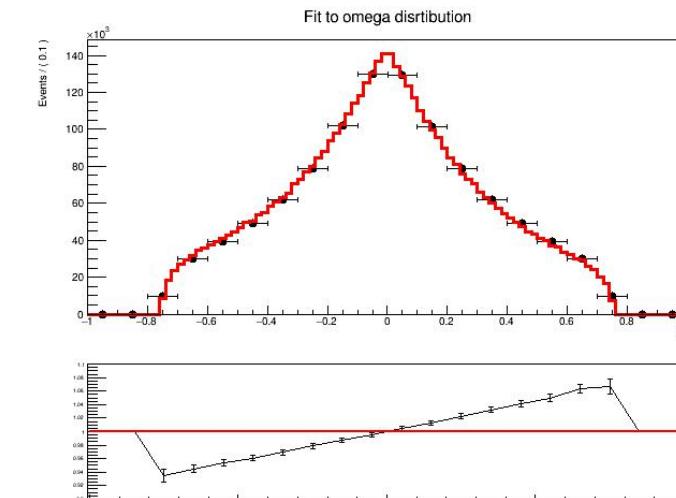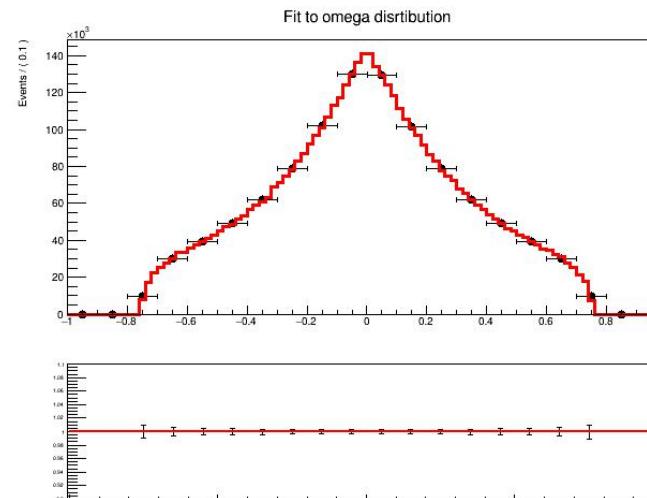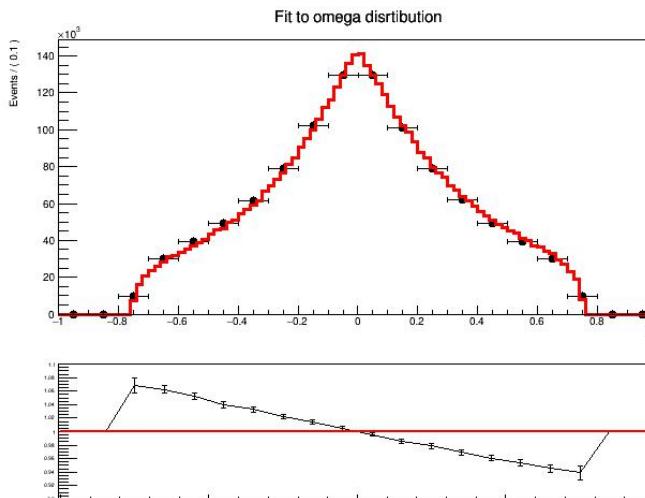
P= 0.09 compare p= 0   P= 0 compare p= 0   P= -0.09 compare p= 0

Fitting strategy and result

Fit ω :

◦ Use histogram pdf to fit **MC signal and background sample**.

◦ The red curve is global fit, the green curve is signal events, the blue curve is background events.
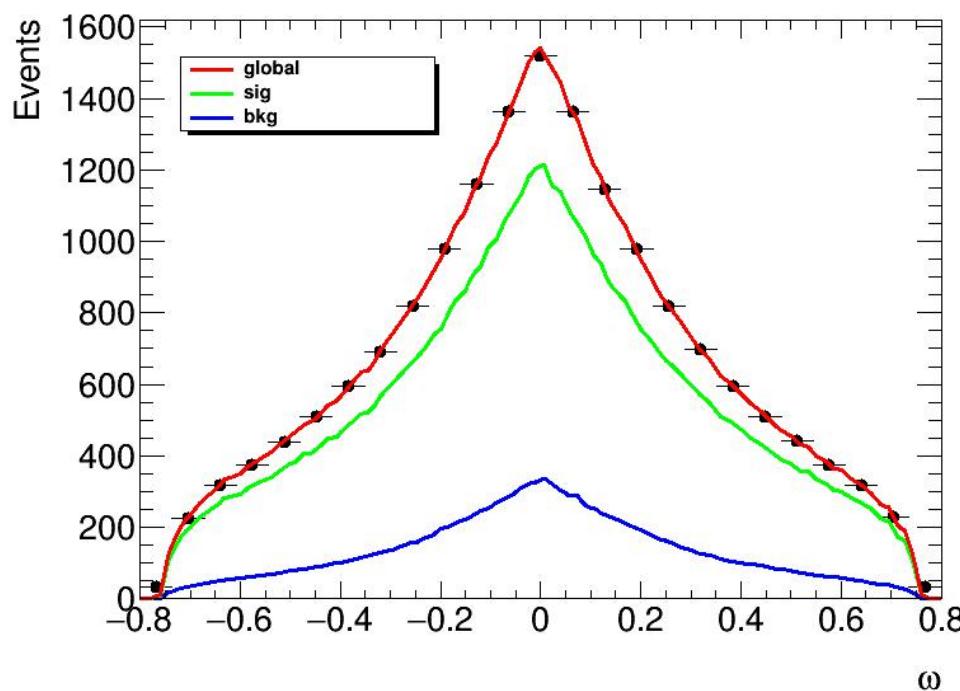
Fitting strategy and result

Fit $M_{recoil\_\mu\mu}$:

◦ Use histogram pdf to fit the $M_{recoil\_\mu\mu}$ of signal(the signal is **on truth level** after **doing the smear to simulate detector error**).

◦ The $M_{recoil\_\mu\mu}$ distribution of the combinatorial background (dominated by the $e^+e^- \rightarrow ZZ \rightarrow llq\bar{q}$) is modeled by a second order polynomial.

◦ Fit plots using truth level sample considering ISR(left) and not considering ISR(right).

◦ Using ISR sample can simulate the small exponential tail (which corresponding to the expected distribution.)
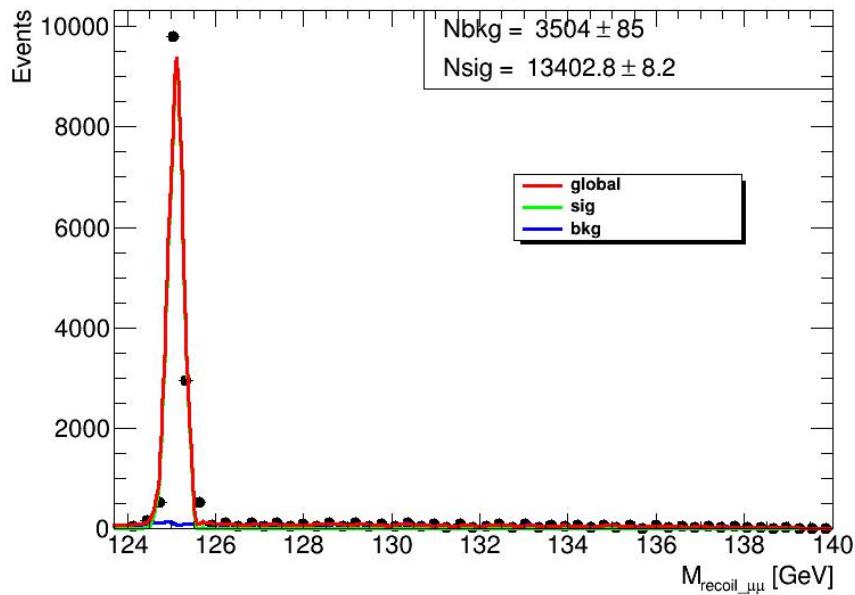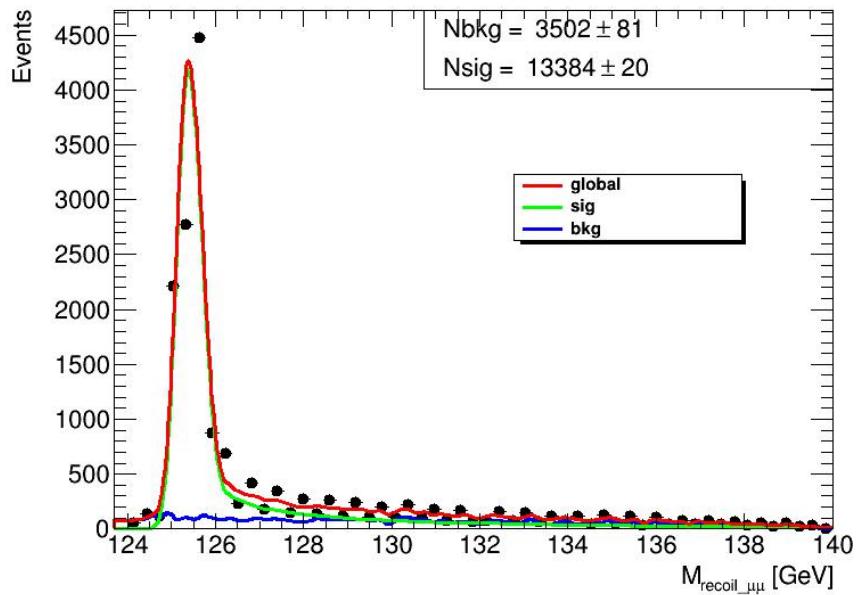
Fitting strategy and result

Fit ω :

◦ Use histogram pdf to fit **MC signal and background sample**.

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Fit $M_{recoil\_\mu\mu}$:

◦ Use histogram pdf to fit the $M_{recoil\_\mu\mu}$ of signal(the signal is **on truth level** after **doing the smear to simulate detector error** and **considering the ISR** to simulate the small exponential tail).

◦ The $M_{recoil\_\mu\mu}$ distribution of the combinatorial background (dominated by the $e^+e^- \to ZZ \to llq\bar{q}$) is modeled by a second order polynomial.
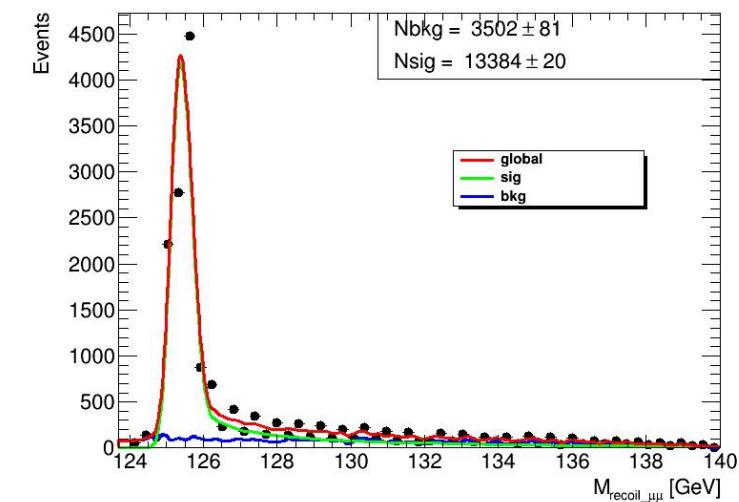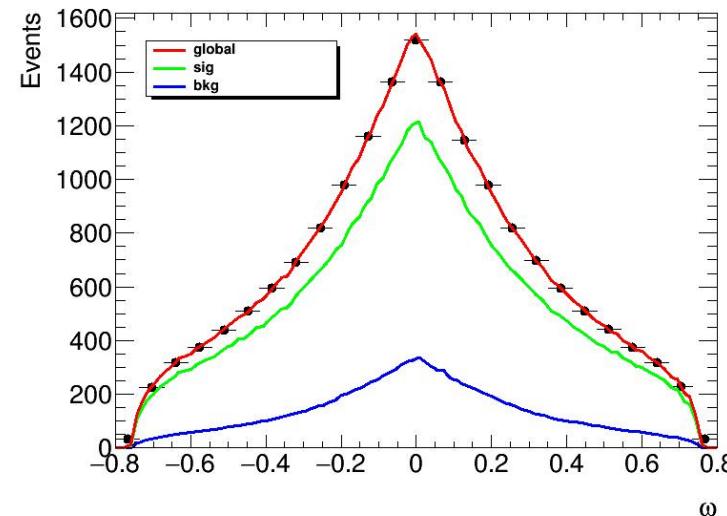
Fitting strategy and result

Extract maximum-likelihood fit p-value and interval

- ◦ Fit ΔNLL curve with a quadratic function $\Delta NLL(p) = a \cdot (p - p_0)^2$
- ◦ 68%(95%) CL interval corresponds to ΔNLL=0.5(1.96).
- ◦ Assumption: $\hat{\alpha}_{A\tilde{Z}} = \hat{\alpha}_{Z\tilde{Z}} = 10^{-3}$.
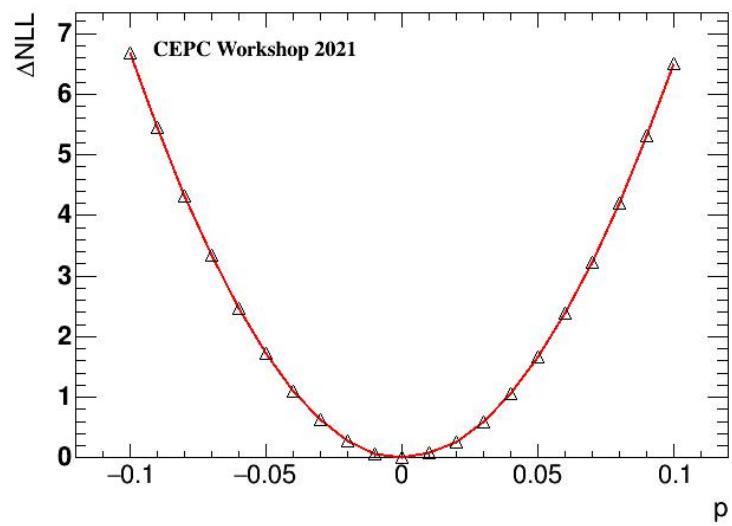
$$\Delta NLL(p|\omega) = 659.6(p - 5.6 \times 10^{-4})^2$$

For p:
68% CL: $[-2.79 \times 10^{-2}, 2.70 \times 10^{-2}]$
95% CL: $[-5.52 \times 10^{-2}, 5.40 \times 10^{-2}]$

$$\hat{\alpha}_{A\tilde{Z}} = \hat{\alpha}_{Z\tilde{Z}} = 10^{-3} \times \mathrm{p}$$

Fitting strategy and result

Extract maximum-likelihood fit p-value and interval
- Fit ΔNLL curve with a quadratic function $\Delta NLL(p) = a \cdot (p - p_0)^2$
- 68%(95%) CL interval corresponds to ΔNLL=0.5(1.96).
- Assumption: $\hat{\alpha}_{A\tilde{Z}} = 10^{-3}$, $\hat{\alpha}_{Z\tilde{Z}} = 0$.

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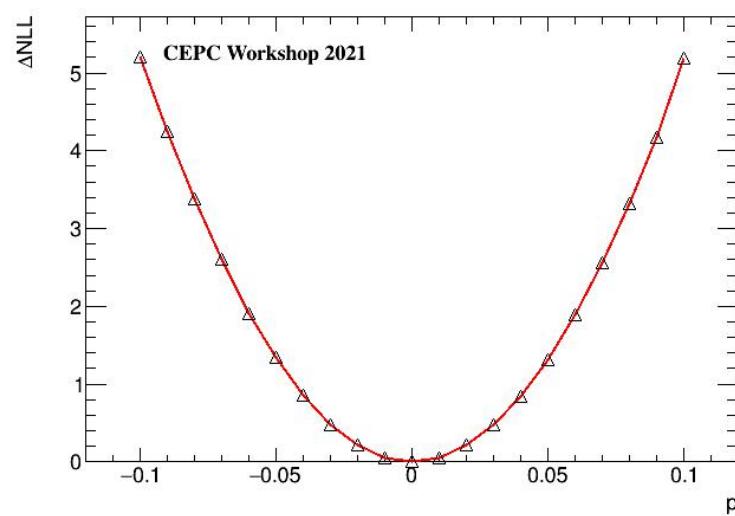
$$\Delta NLL(p|\omega) = 519.53(p - 2.32 \times 10^{-4})^2$$

For p:
68% CL: $[-3.13 \times 10^{-2}, 3.08 \times 10^{-2}]$
95% CL: $[-6.17 \times 10^{-2}, 6.12 \times 10^{-2}]$

$\hat{\alpha}_{A\tilde{Z}} = 10^{-3} \times \text{p}$

Fitting strategy and result

Extract maximum-likelihood fit p-value and interval

- Fit ΔNLL curve with a quadratic function $\Delta NLL(p) = a \cdot (p - p_0)^2$
- 68%(95%) CL interval corresponds to ΔNLL=0.5(1.96).
- Assumption: $\hat{\alpha}_{A\tilde{Z}} = 0, \ \hat{\alpha}_{Z\tilde{Z}} = 5 \cdot 10^{-3}$.
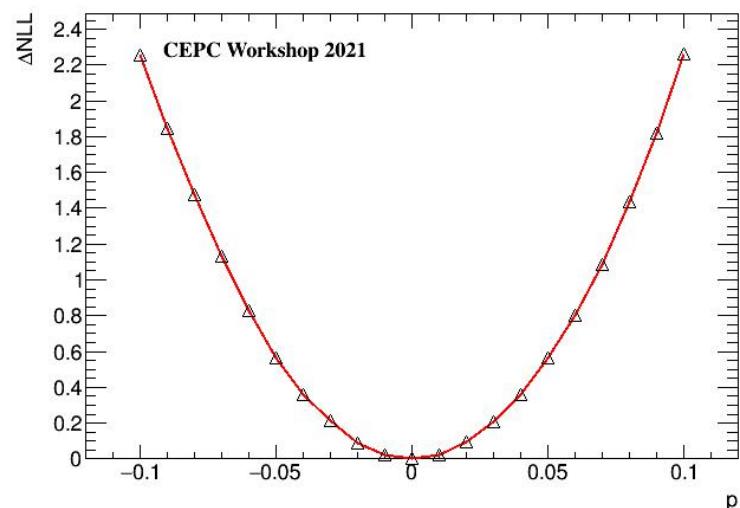
$$\Delta NLL(p|\omega) = 226.22(p - 2.73 \times 10^{-4})^2$$

For p:
68% CL: $[-4.73 \times 10^{-2}, 4.67 \times 10^{-2}]$
95% CL: $[-9.34 \times 10^{-2}, 9.28 \times 10^{-2}]$

$$\hat{\alpha}_{Z\tilde{Z}} = 5 \cdot 10^{-3} \times p$$

Result compare

In HL-LHC:

$$\mathcal{L}_{\text{CPV}} = \frac{H}{v}\left[\tilde{c}_{\gamma\gamma}\frac{e^2}{4}A_{\mu\nu}\tilde{A}^{\mu\nu} + \tilde{c}_{Z\gamma}\frac{e\sqrt{g_1^2+g_2^2}}{2}Z_{\mu\nu}\tilde{A}^{\mu\nu} + \tilde{c}_{ZZ}\frac{g_1^2+g_2^2}{4}Z_{\mu\nu}\tilde{Z}^{\mu\nu} + \tilde{c}_{WW}\frac{g_2^2}{2}W_{\mu\nu}^+\widetilde{W}^{\mu\nu}\right]$$

Compare theory model in P5, we can get that the value in red frame are same:

$(g1=0.358, g2=0.648, e=0.313, v = 1/\sqrt{\sqrt{2}G_F^0} = 2M_W/g \approx 246.22\text{GeV})$

$$\left(\sqrt{2}G_F\right)^{1/2}\hat{\alpha}_{Z\tilde{Z}}HZ_{\mu\nu}\tilde{Z}^{\mu\nu} = \frac{H}{v}\tilde{c}_{ZZ}\frac{g_1^2+g_2^2}{4}Z_{\mu\nu}\tilde{Z}^{\mu\nu}$$

$$\frac{g_1^2+g_2^2}{4} = 0.137$$

$$\left(\sqrt{2}G_F\right)^{1/2}\hat{\alpha}_{A\tilde{Z}}HZ_{\mu\nu}\tilde{A}^{\mu\nu} = \frac{H}{v}\tilde{c}_{Z\gamma}\frac{e\sqrt{g_1^2+g_2^2}}{2}Z_{\mu\nu}\tilde{A}^{\mu\nu}$$

$$\frac{e\sqrt{g_1^2+g_2^2}}{2} = 0.116$$

Result compare

In HL-LHC: (1sigma)

Parameter Analysis	$\tilde{c}_{Z\gamma}$	$\tilde{c}_{ZZ}$	Case
HL-LHC (4ℓ, incl.)	[-0.22,0.22]	[-0.33,0.33]	1P
	[-0.25,0.25]	[-0.27,0.27]	$1P_{marg.}$
HL-LHC (4ℓ, diff.)	[-0.10,0.10]	[-0.31,0.31]	1P
	[-0.13,0.13]	[-0.22,0.22]	$1P_{marg.}$
HE-LHC (4ℓ, incl.)	[-0.18,0.18]	[-0.17,0.17]	1P
	[-0.23,0.23]	[-0.20,0.20]	$1P_{marg.}$
HE-LHC (4ℓ, diff.)	[-0.05,0.05]	[-0.13,0.13]	1P
	[-0.06,0.06]	[-0.10,0.10]	$1P_{marg.}$

Result:

	$\tilde{c}_{Z\gamma}$	$\tilde{c}_{ZZ}$
68% CL(1σ)	$[-2.70 \times 10^{-4}, 2.66 \times 10^{-4}]$	$[-1.73 \times 10^{-4}, 1.70 \times 10^{-4}]$
95% CL(2σ)	$[-5.32 \times 10^{-4}, 5.28 \times 10^{-4}]$	$[-3.41 \times 10^{-4}, 3.39 \times 10^{-4}]$

Summary

An EFT based Higgs CP-mixing test is performed.

◦ Set up some basic assumptions to have a simplest CP-mixing model.

◦ Introduced optimal variable with better performance.

◦ Used ML-fit in ω distribution to extract p.

◦ Result: 95% CL $p \in [-5.5 \times 10^{-2}, 5.4 \times 10^{-2}]$, corresponding to $\delta G_F, \hat{\alpha}^V_{\phi l}, \hat{\alpha}^A_{\phi l}, \hat{\alpha}_{A\tilde{Z}}, \hat{\alpha}_{Z\tilde{Z}} < 10^{-4}$. Much better than HL-LHC

◦ Prepare to submit next mouth

Backup

Maximum likelihood fit

Construct a likelihood function

- $\mathcal{L}(\vec{x}|p,\vec{\theta}) = \prod_{data} f(x_i|p,\vec{\theta})$

 $\vec{\theta}$: nuisance parameter. p: POI, CP-mixing parameter. x_i: dataset (ω).

- When statistics is large enough, we suppose $\mathcal{L}(\vec{x}|p,\vec{\theta}) \sim Gaus(\hat{p}, \sigma_p^2)$, so $ln\mathcal{L}(p) = ln\mathcal{L}_{max} - \frac{1}{2}\left(\frac{p-\hat{p}}{\sigma_p}\right)^2$

- From $\Delta NLL = NLL - NLL_{min}$ (negative log likelihood) we can extract maximum likelihood estimate $\hat{p}$ and its CL interval.
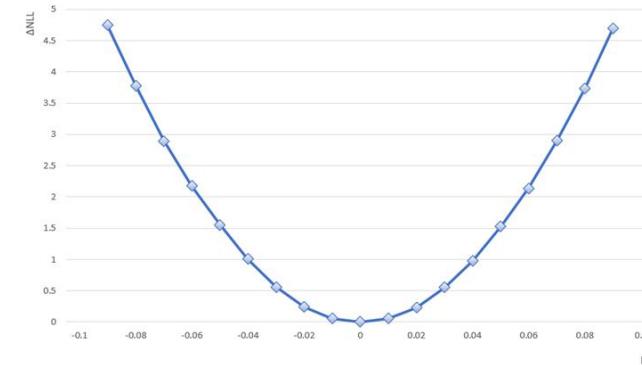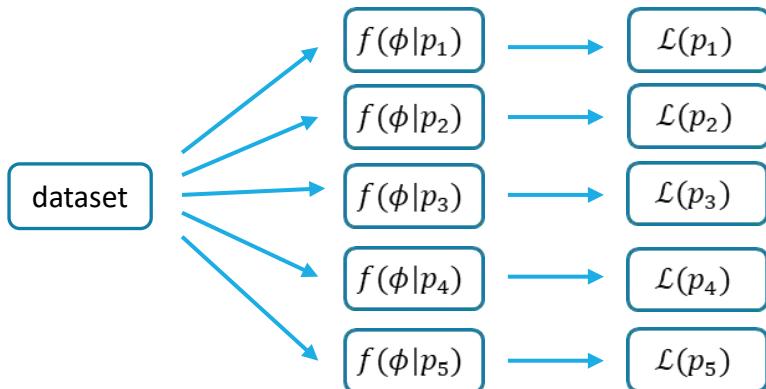
Maximum likelihood fit

Sample modelling

◦ ω modelling: Histogram pdf. Highly depends on the sample statistics used to build histogram and HistPdf.

P=0.09   P=0.08   P=0.07   P=0.06   P=0.05

P=0.04   P=0.03   P=0.02   P=0.01   P=0
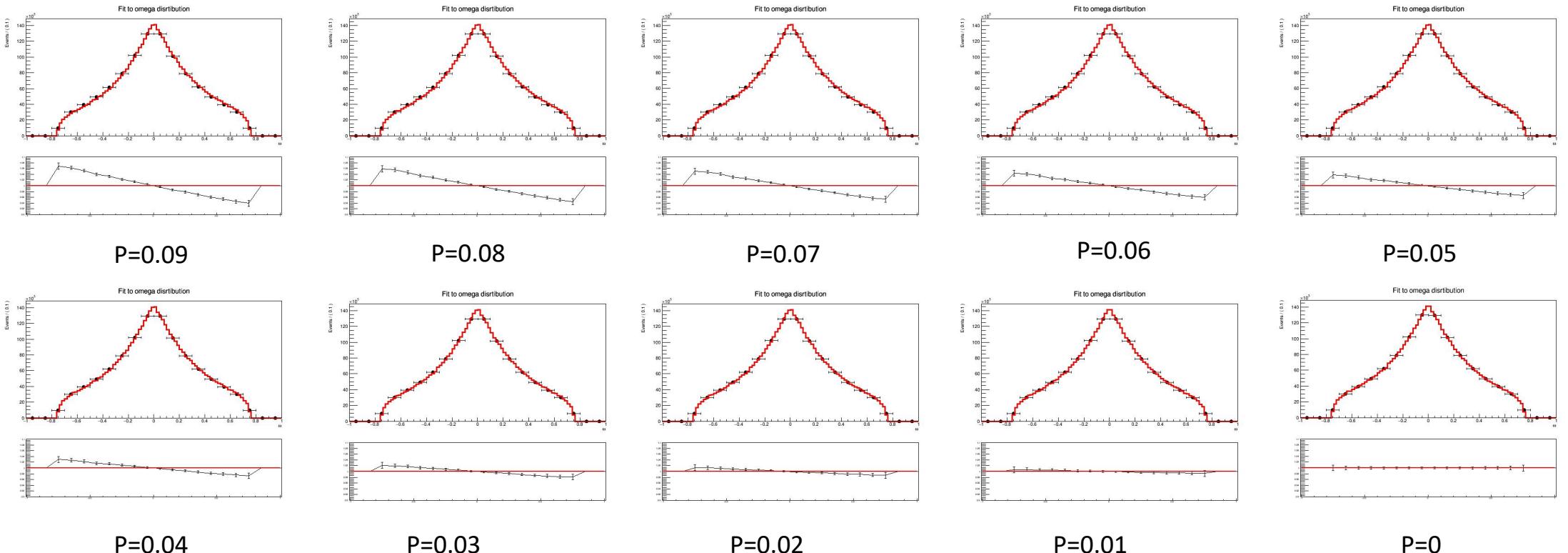
Maximum likelihood fit

Sample modelling

◦ ω modelling: Histogram pdf. Highly depends on the sample statistics used to build histogram and HistPdf.
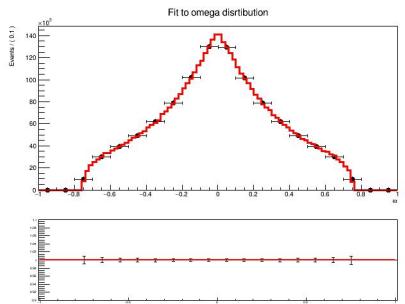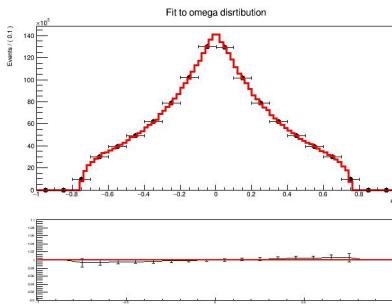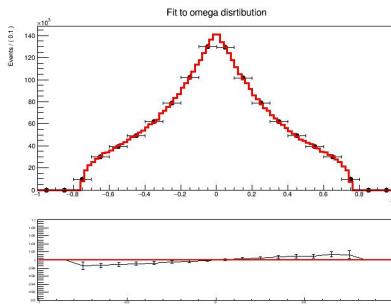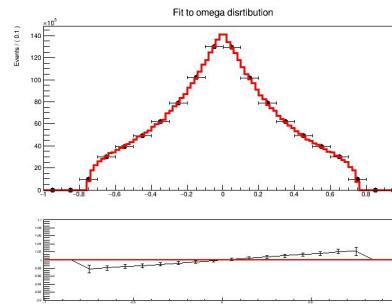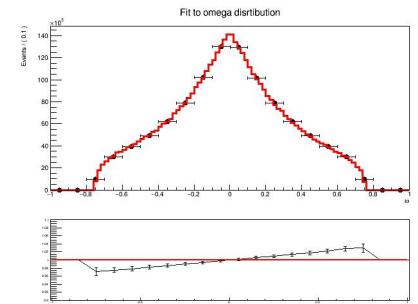
| P=0 | P= -0.01 | P= -0.02 | P= -0.03 | P= -0.04 |

| P= -0.05 | P= -0.06 | P= -0.07 | P= -0.08 | P= -0.09 |