
Search for electroweak production of dark matter particles in compressed mass spectra with the ATLAS detector at LHC

14/09/2021

Second Year Seminaire

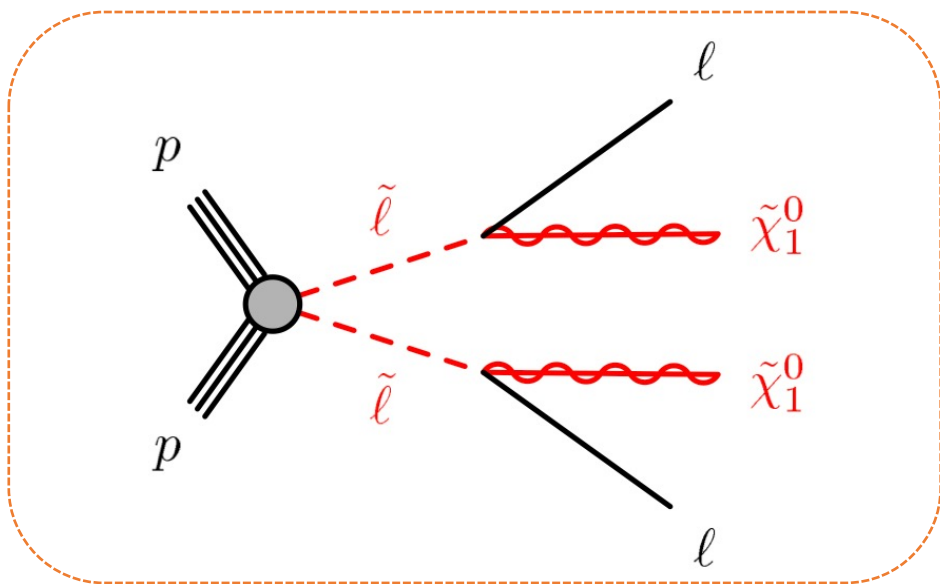
E. Ballabene

Introduction

- 2 analyses with 2 different analysis strategies
- Both targeting 2 leptons in the final state without associated hadronic radiation (“2L0J”)

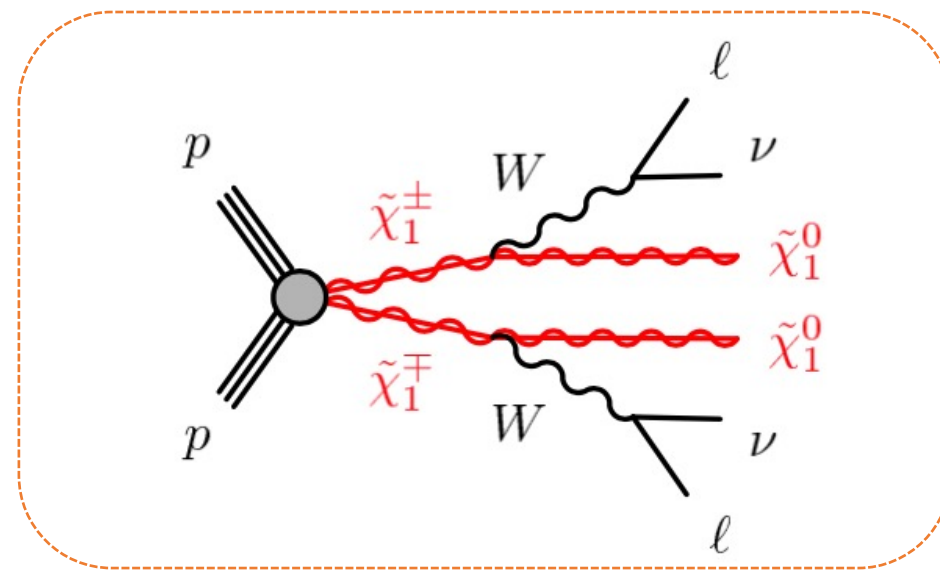
Slepton production

Unblinded on 19 February 2021 [\(link\)](#)



Charginos production

Unblinded on 20 August 2021 [\(link\)](#)



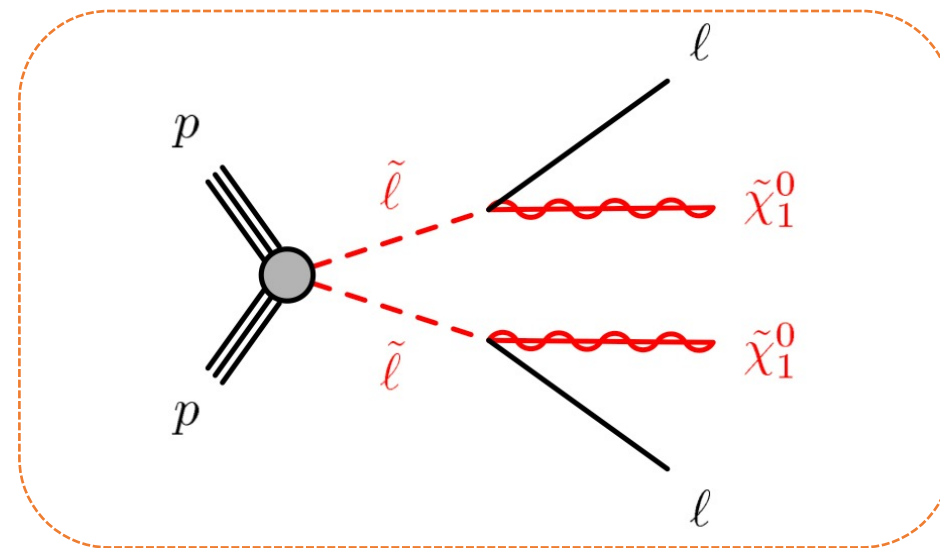
- Focusing into compressed mass spectra: $\Delta m(\tilde{\ell}, \chi_1^0), \Delta m(\chi_1^\pm, \chi_1^0) < 100$ GeV
- Unblinded very recently!

Preselection

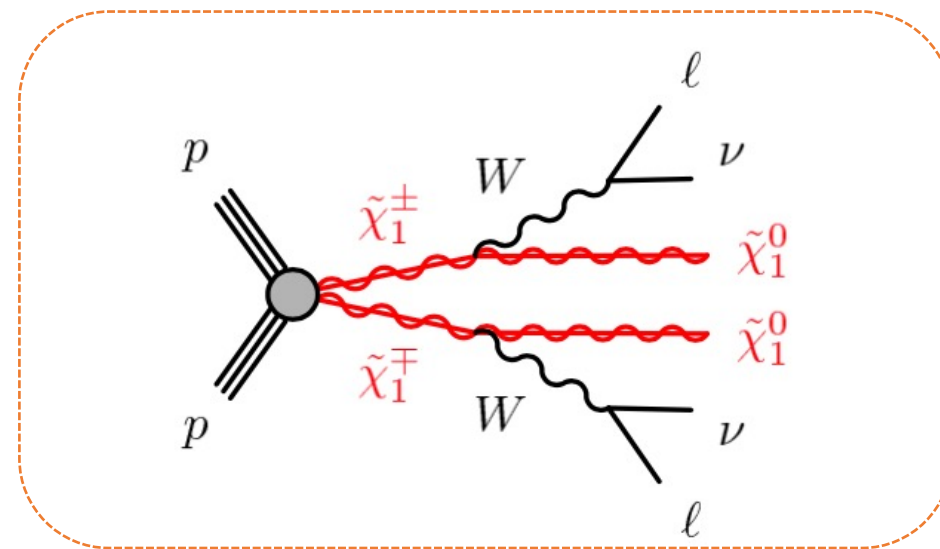
- Preselection applied to both analyses

Variable	Cut
$N_{\text{OS leptons}}$	$= 2$
$p_T^{\ell_1}$	$> 27 \text{ GeV}$
$p_T^{\ell_2}$	$> 9 \text{ GeV}$
$m_{\ell\ell}$	$> 11 \text{ GeV}$
$n_{\text{jet}-20}$	< 2
$n_{\text{bjet}-20}$	$= 0$
E_T^{miss} significance	> 3
$ m_{\ell\ell} - m_Z $	$> 15 \text{ GeV (for SF only)}$

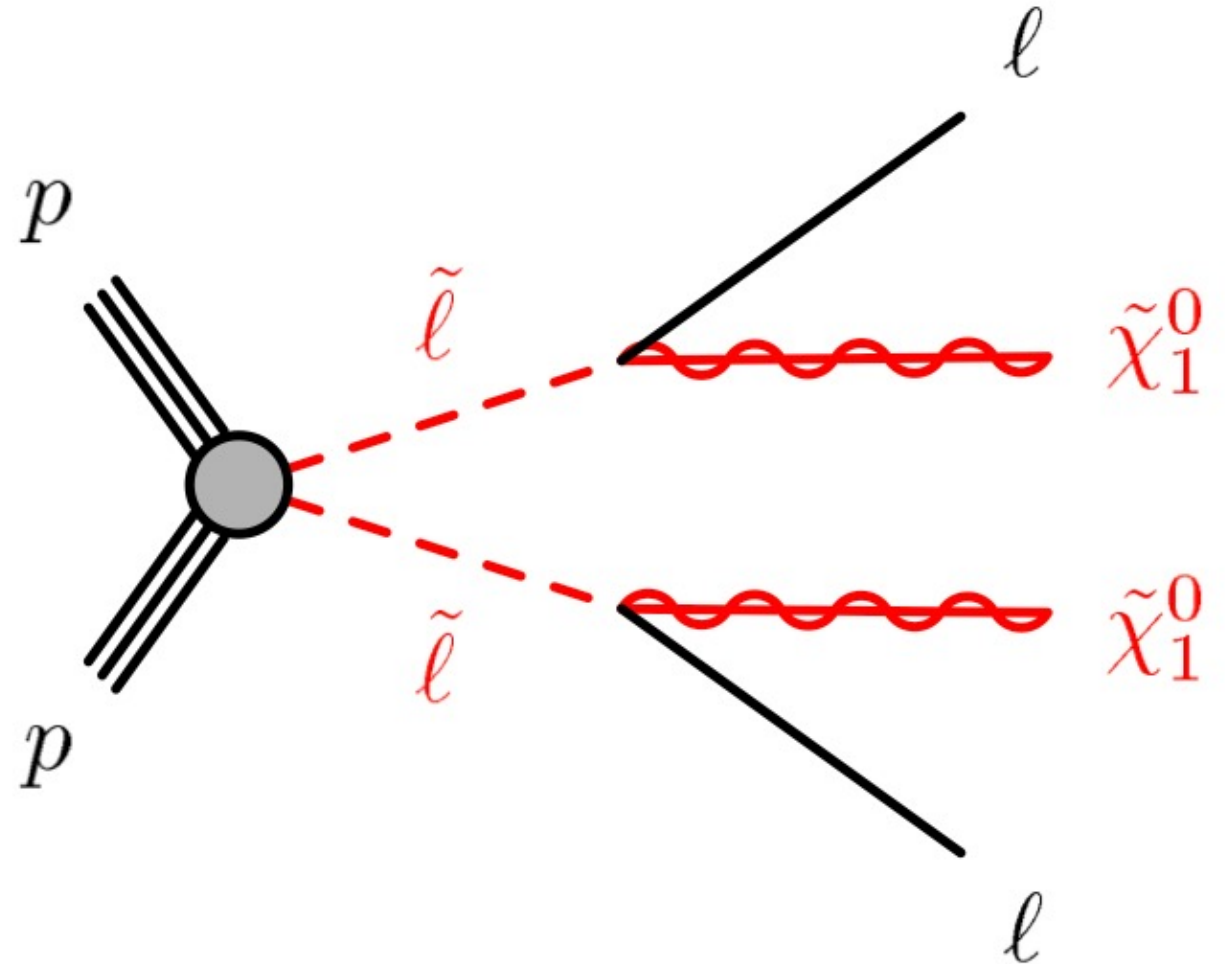
Slepton production



Charginos production



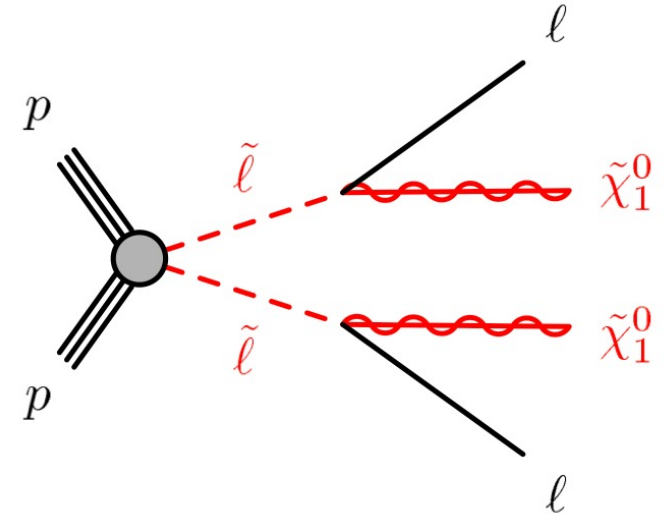
Slepton analysis



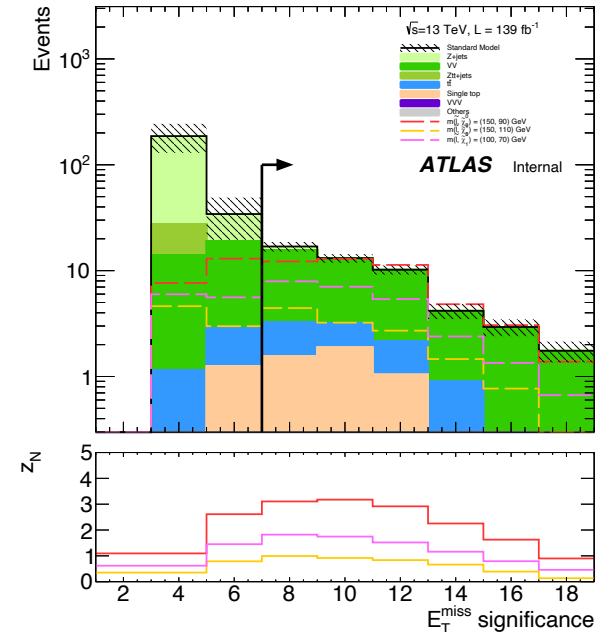
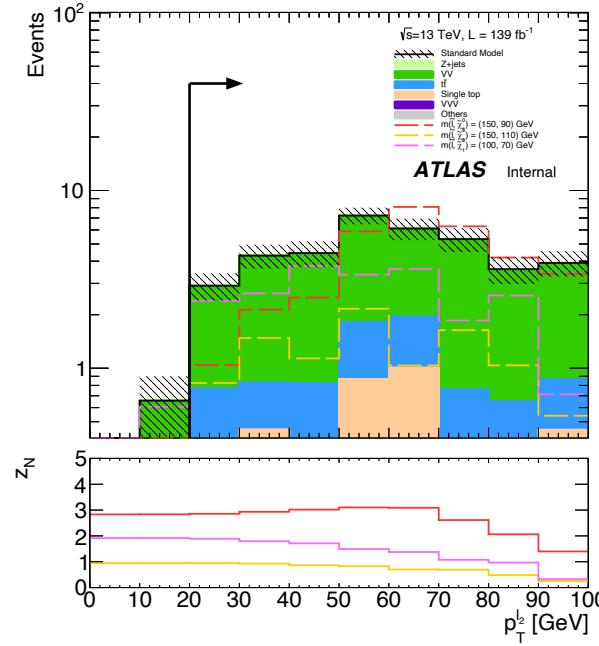
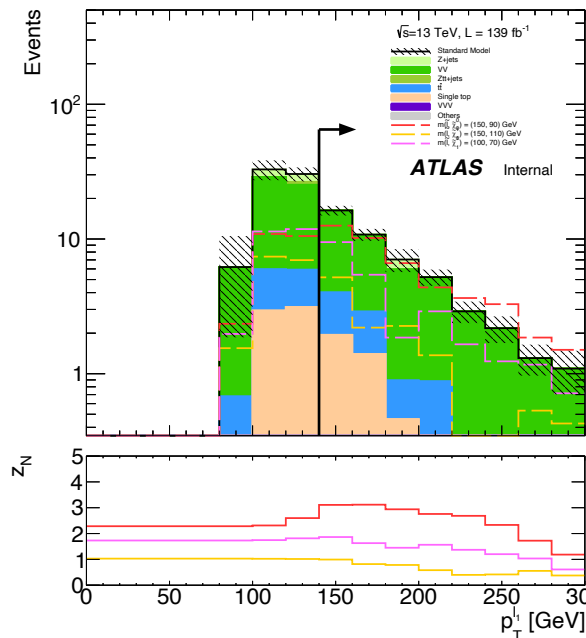
Slepton analysis

- Cut&count optimization of statistical significance

$$p_T^{\ell_1}, p_T^{\ell_2}, E_T^{\text{miss}} \text{ significance}, m_{\ell\ell}, p_{T,\text{boost}}^{\ell\ell}, \cos\theta_{\ell\ell}^*, \Delta\phi_{\ell_1, \ell_2}, \Delta\phi_{E_T^{\text{miss}}, \ell_1}$$



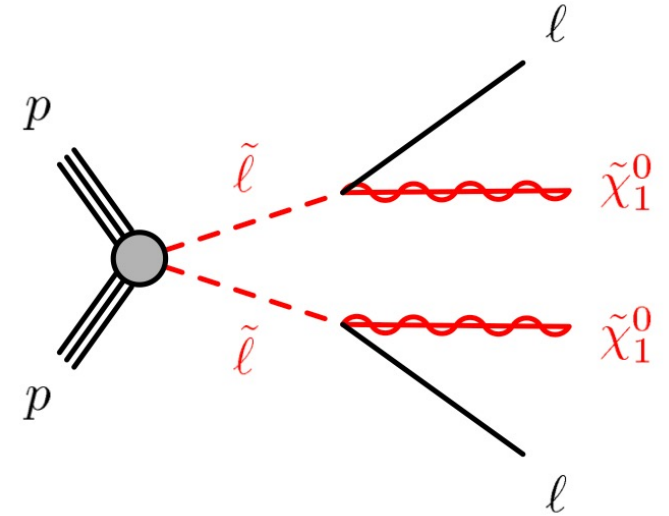
Variable	Cut
$n_{\text{jet}-20}$	$= 0$
$n_{b\text{jet}-20}$	$= 0$
$N_{\text{OS SF leptons}}$	$= 2$
$p_T^{\ell_1}$	$> 140 \text{ GeV}$
$p_T^{\ell_2}$	$> 20 \text{ GeV}$
E_T^{miss} significance	> 7
$m_{\ell\ell}$	$> 11 \text{ GeV}$
$ m_{\ell\ell} - m_Z $	$> 15 \text{ GeV}$
$p_{T,\text{boost}}^{\ell\ell}$	$< 5 \text{ GeV}$
$\cos\theta_{\ell\ell}^*$	< 0.2
$\Delta\phi_{\ell, \ell}$	> 2.2
$\Delta\phi_{E_T^{\text{miss}}, \ell_1}$	> 2.2



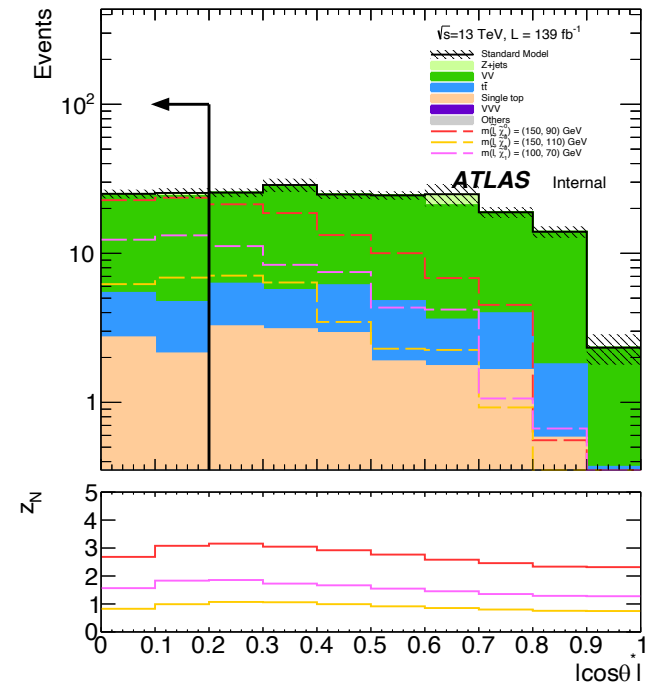
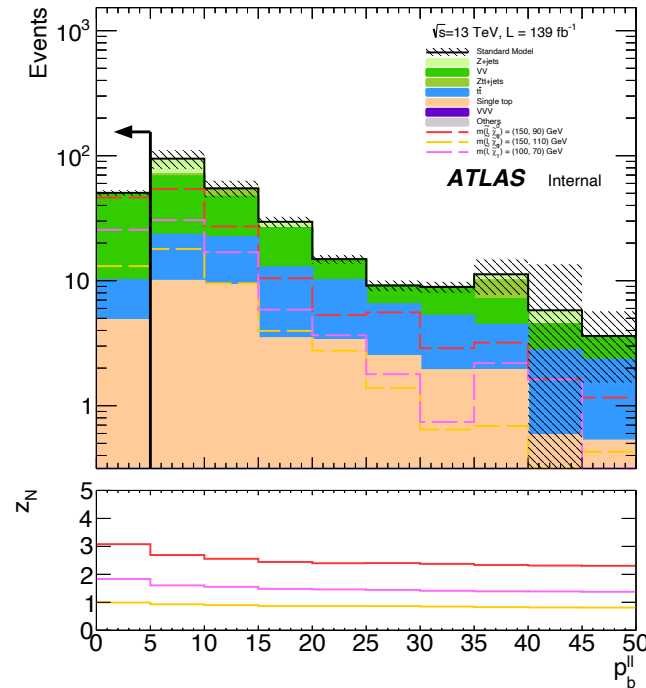
Slepton analysis

- Cut&count optimization of statistical significance

$p_T^{\ell_1}, p_T^{\ell_2}, E_T^{\text{miss}}$ significance, $m_{\ell\ell}, p_{T,\text{boost}}^{\ell\ell}, \cos\theta_{\ell\ell}^*, \Delta\phi_{\ell_1, \ell_2}, \Delta\phi_{E_T^{\text{miss}}, \ell_1}$



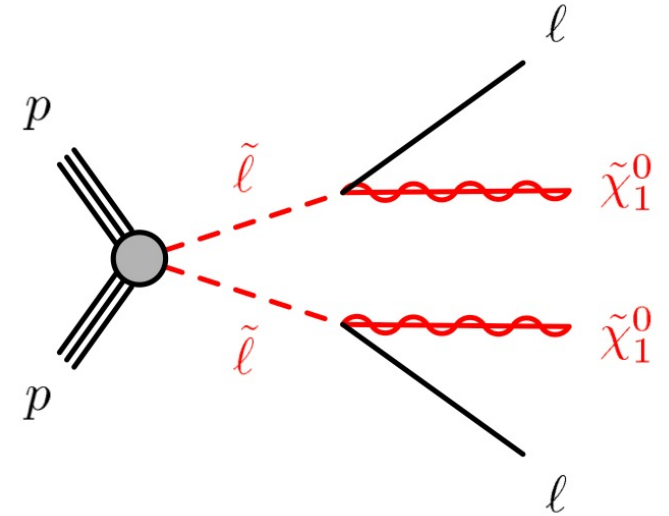
Variable	Cut
$n_{\text{jet}-20}$	= 0
$n_{\text{bjet}-20}$	= 0
NOS SF leptons	= 2
$p_T^{\ell_1}$	> 140 GeV
$p_T^{\ell_2}$	> 20 GeV
E_T^{miss} significance	> 7
$m_{\ell\ell}$	> 11 GeV
$ m_{\ell\ell} - m_Z $	> 15 GeV
$p_{T,\text{boost}}^{\ell\ell}$	< 5 GeV
$\cos\theta_{\ell\ell}^*$	< 0.2
$\Delta\phi_{\ell, \ell}$	> 2.2
$\Delta\phi_{E_T^{\text{miss}}, \ell_1}$	> 2.2



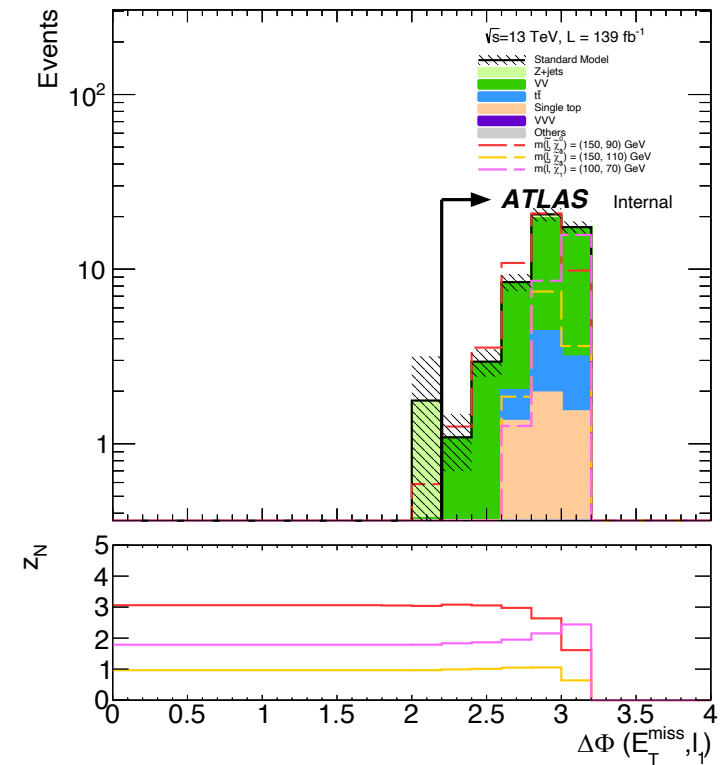
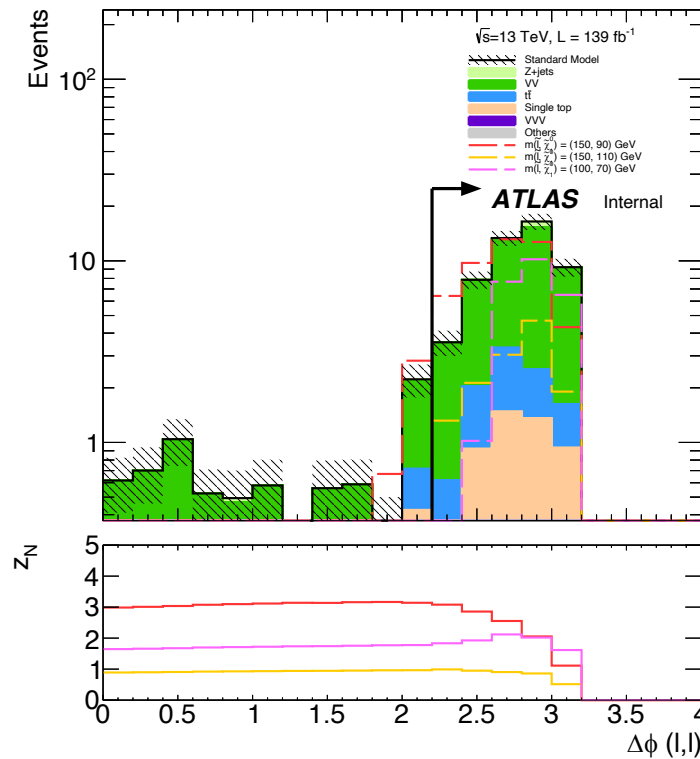
Slepton analysis

- Cut&count optimization of statistical significance

$p_T^{\ell_1}, p_T^{\ell_2}, E_T^{\text{miss}}$ significance, $m_{\ell\ell}, p_{T,\text{boost}}^{\ell\ell}, \cos\theta_{\ell\ell}^*, \Delta\phi_{\ell_1, \ell_2}, \Delta\phi_{E_T^{\text{miss}}, \ell_1}$



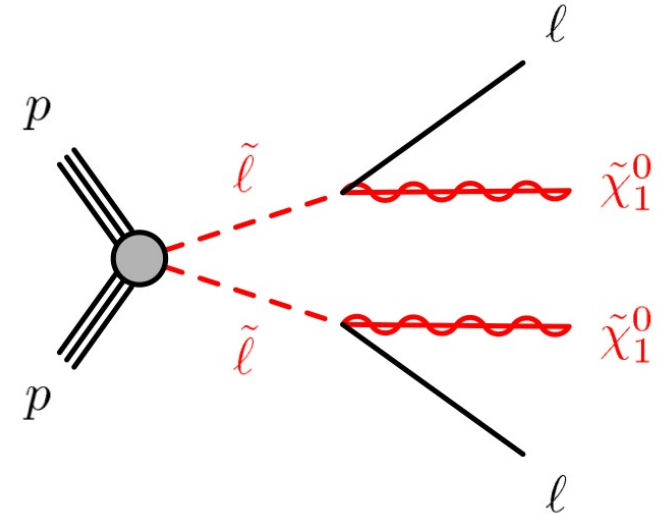
Variable	Cut
n_{jet-20}	= 0
$n_{bjet-20}$	= 0
$N_{OS\ SF\ leptons}$	= 2
$p_T^{\ell_1}$	> 140 GeV
$p_T^{\ell_2}$	> 20 GeV
E_T^{miss} significance	> 7
$m_{\ell\ell}$	> 11 GeV
$ m_{\ell\ell} - m_Z $	> 15 GeV
$p_{T,\text{boost}}^{\ell\ell}$	< 5 GeV
$\cos\theta_{\ell\ell}^*$	< 0.2
$\Delta\phi_{\ell, \ell}$	> 2.2
$\Delta\phi_{E_T^{\text{miss}}, \ell_1}$	> 2.2



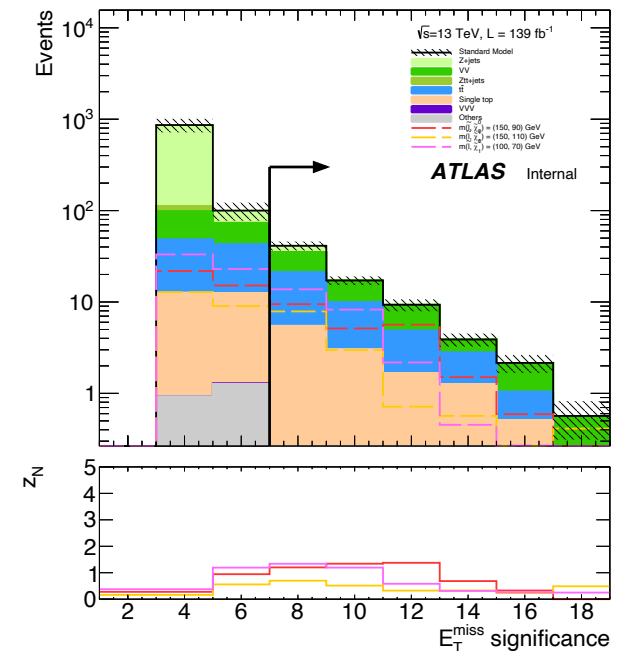
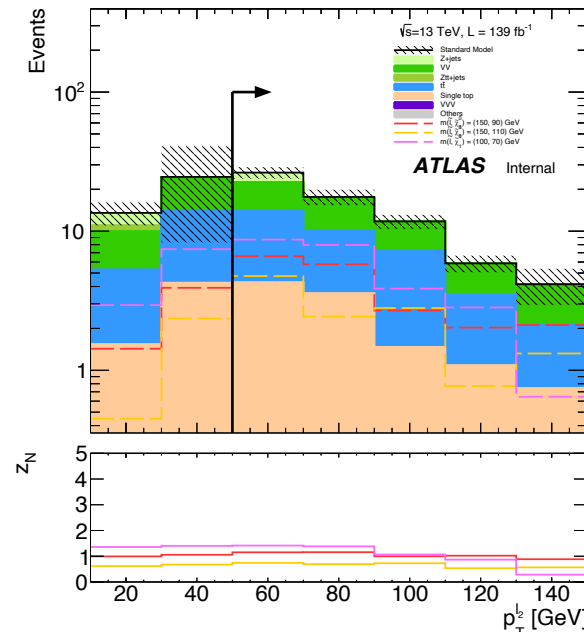
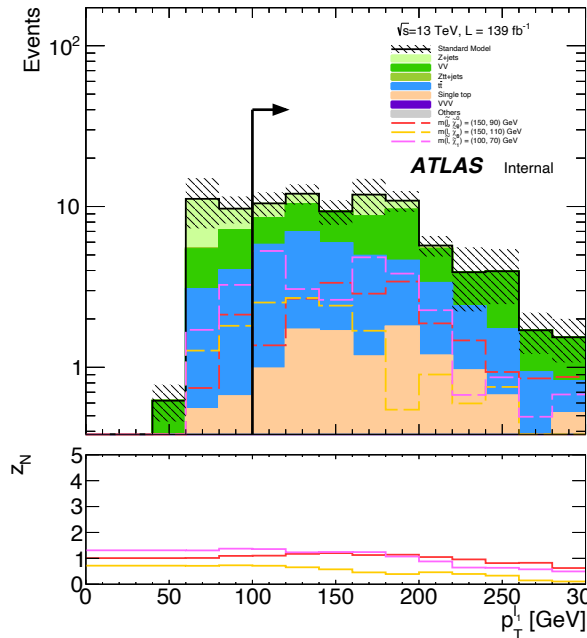
Slepton analysis

- Cut&count optimization of statistical significance

$p_T^{\ell_1}, p_T^{\ell_2}, E_T^{miss}$ significance, $m_{\ell\ell}, p_{T,boost}^{\ell\ell}, \cos\theta_{\ell\ell}^*, \Delta\phi_{\ell_1, \ell_2}, \Delta\phi_{E_T^{miss}, \ell_1}$



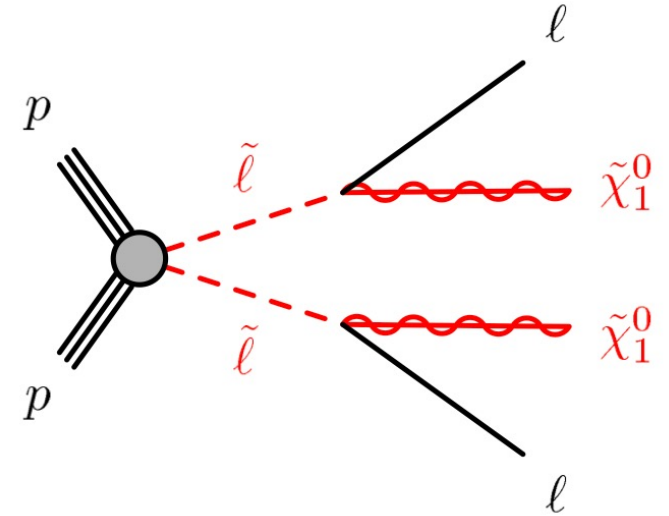
Variable	Cut
n_{jet-20}	= 1
$n_{bjets-20}$	= 0
NOS SF leptons	= 2
$p_T^{\ell_1}$	> 100 GeV
$p_T^{\ell_2}$	> 50 GeV
E_T^{miss} significance	> 7
$m_{\ell\ell}$	> 60 GeV
$ m_{\ell\ell} - m_Z $	> 15 GeV
$\cos\theta_{\ell\ell}^*$	< 0.1
$\Delta\phi_{\ell, \ell}$	> 2.8



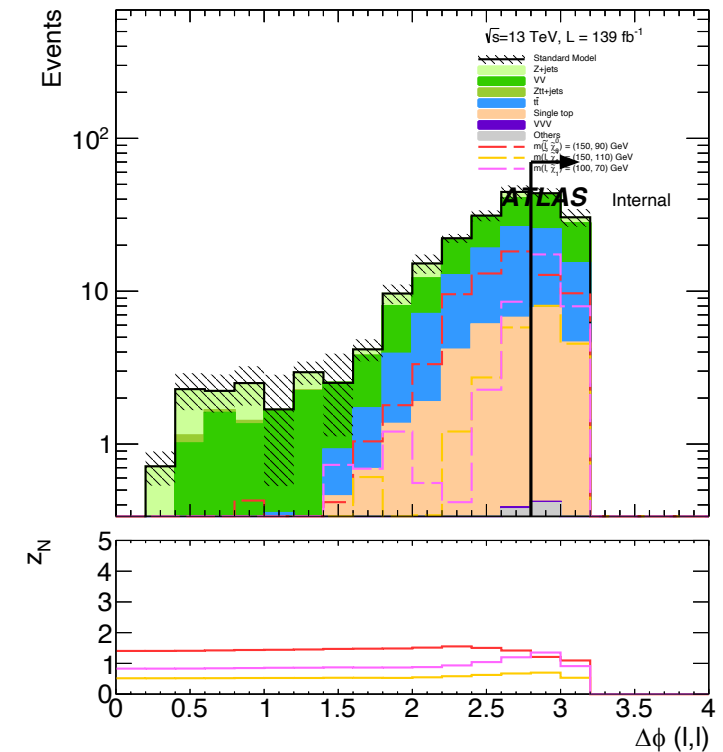
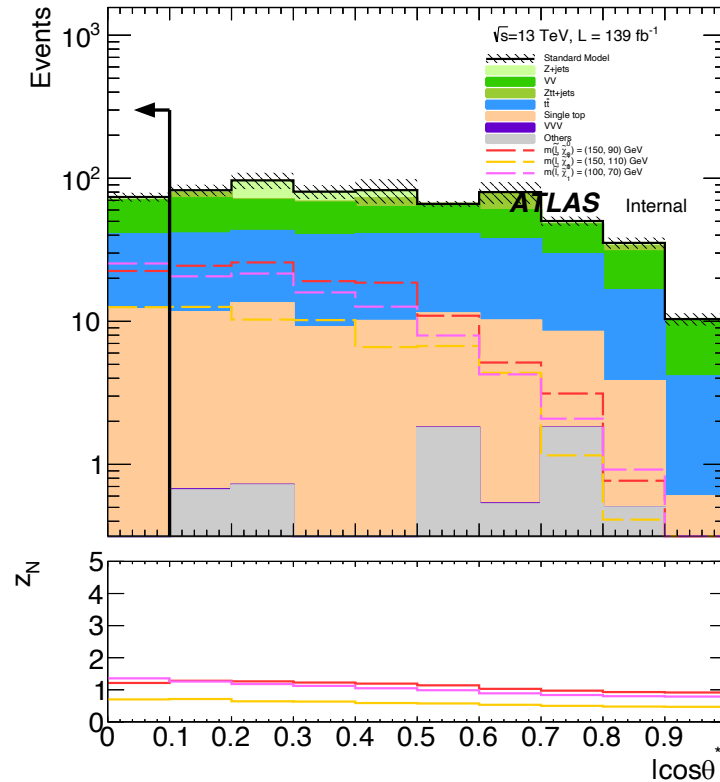
Slepton analysis

- Cut&count optimization of statistical significance

$p_T^{\ell_1}, p_T^{\ell_2}, E_T^{miss}$ significance, $m_{\ell\ell}, p_{T,boost}^{\ell\ell}, \cos\theta_{\ell\ell}^*, \Delta\phi_{\ell_1, \ell_2}, \Delta\phi_{E_T^{miss}, \ell_1}$



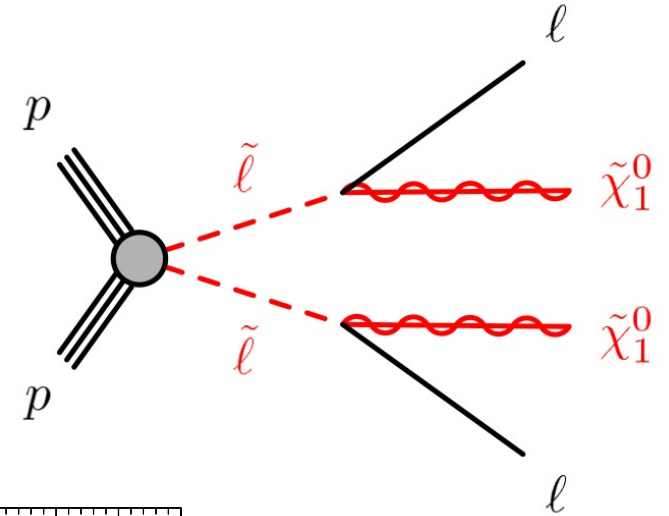
Variable	Cut
n_{jet-20}	= 1
$n_{bjet-20}$	= 0
N_{OS} SF leptons	= 2
$p_T^{\ell_1}$	> 100 GeV
$p_T^{\ell_2}$	> 50 GeV
E_T^{miss} significance	> 7
$m_{\ell\ell}$	> 60 GeV
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$\cos\theta_{\ell\ell}^*$	< 0.1
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Slepton analysis

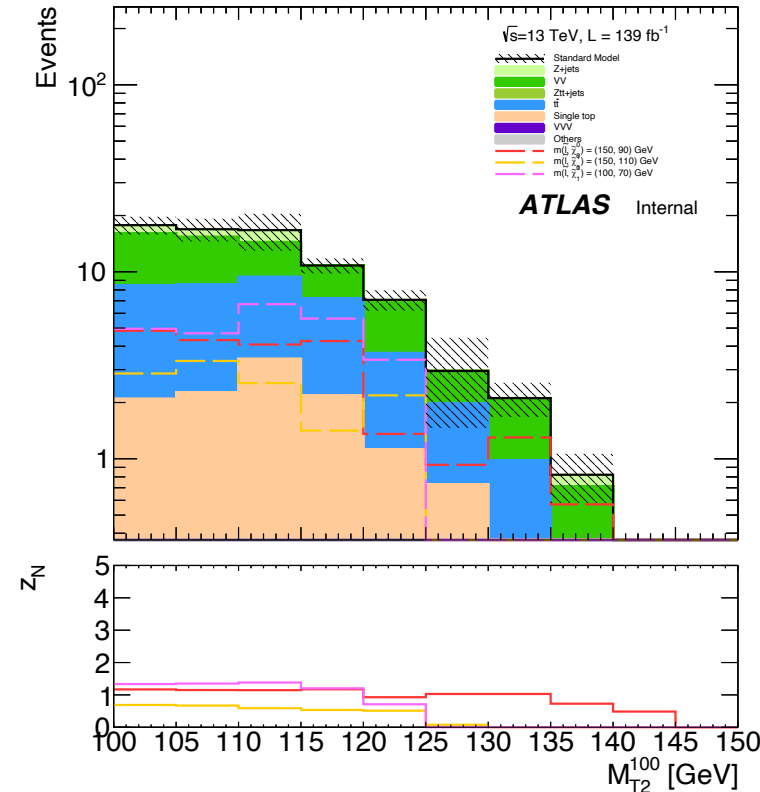
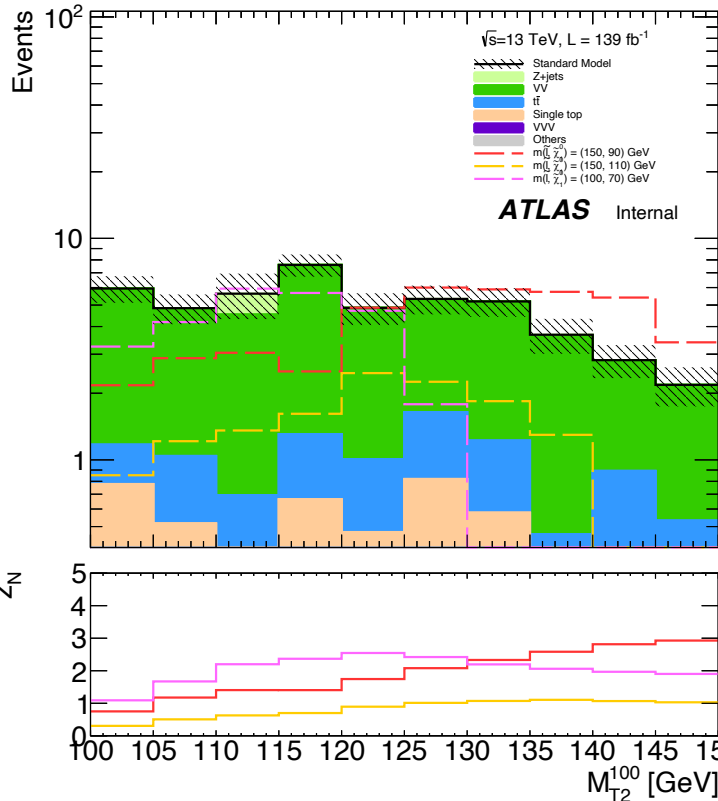
- Shape fit on m_T^{100}

Different binning choices have been studied, obtaining the best performance using 5 GeV for the first 6 bins:
 $m_{T2}^{100} = [100, 105, 110, 115, 120, 125, 130, 140, \infty)$.



SR-0jet

SR-1jet



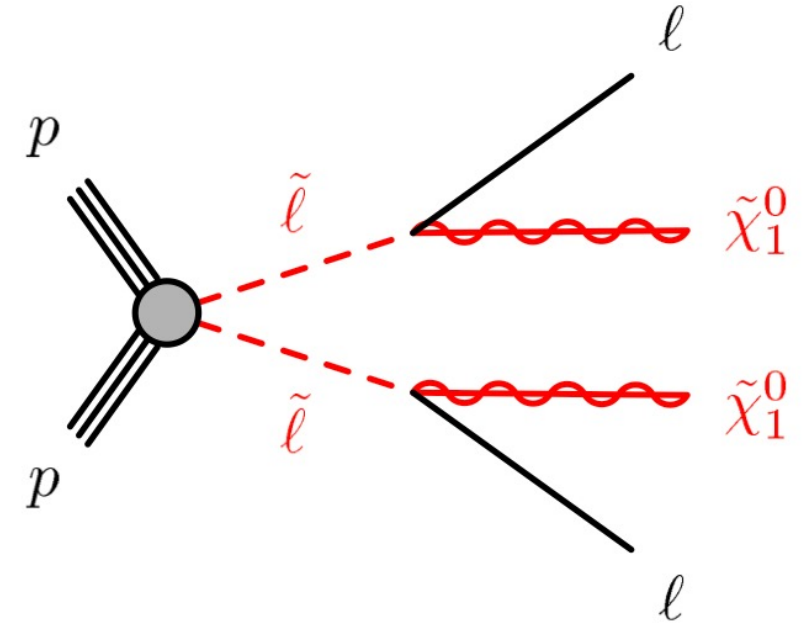
Variable	Cut
n_{jet-20}	= 0
$n_{bjjet-20}$	= 0
N_{OS} SF leptons	= 2
$p_T^{\ell_1}$	> 140 GeV
$p_T^{\ell_2}$	> 20 GeV
E_T^{miss} significance	> 7
$m_{\ell\ell}$	> 11 GeV
$ m_{\ell\ell} - m_Z $	> 15 GeV
$p_{T,boost}^{\ell\ell}$	< 5 GeV
$\cos\theta_{\ell\ell}^*$	< 0.2
$\Delta\phi_{\ell,\ell}$	> 2.2
$\Delta\phi_{E_T^{miss},\ell_1}$	> 2.2

Variable	Cut
n_{jet-20}	= 1
$n_{bjjet-20}$	= 0
N_{OS} SF leptons	= 2
$p_T^{\ell_1}$	> 100 GeV
$p_T^{\ell_2}$	> 50 GeV
E_T^{miss} significance	> 7
$m_{\ell\ell}$	> 60 GeV
$ m_{\ell\ell} - m_Z $	> 15 GeV
$\cos\theta_{\ell\ell}^*$	< 0.1
$\Delta\phi_{\ell,\ell}$	> 2.8

Slepton analysis

- Background estimation strategy based on a **data driven technique** to estimate “flavour symmetric” (FS) background processes (e.g. processes like WW , $t\bar{t}$, Wt and $Z(\rightarrow \tau\tau)+\text{jets}$ producing SF and DF lepton pairs with equal probabilities).

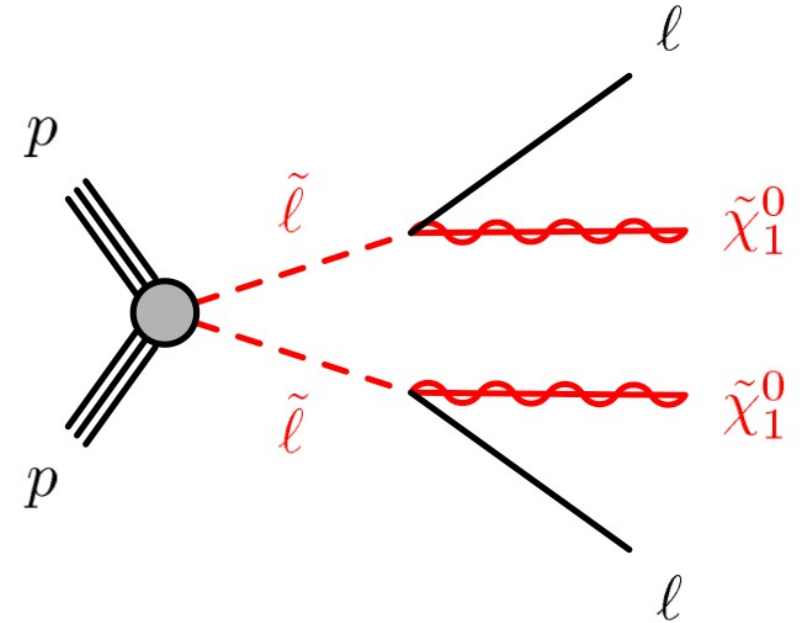
Background	Sleptons search
$t\bar{t}$	data driven
Wt	data driven
Diboson	WW/WZ - data driven ZZ - Monte Carlo
Triboson	Monte Carlo
$Z+\text{jets}$	$Z(ee, \mu\mu)$ - Monte Carlo $Z(\tau\tau)$ - data driven
Fake leptons	Matrix method
Minor backgrounds	Monte Carlo



- Slepton signal is only SF:** data driven background estimation technique exploits data in the DF channel to predict the FS backgrounds in the SF channel.

Slepton analysis

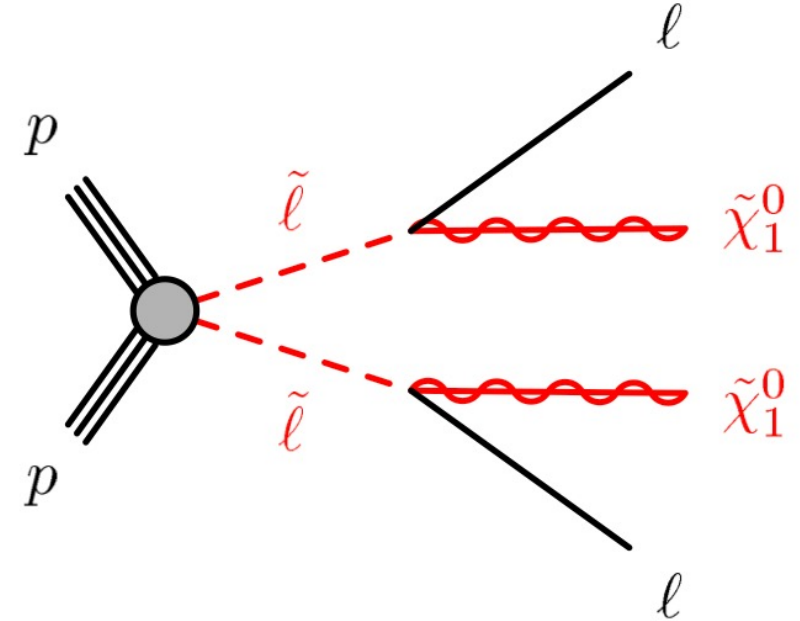
- In principle, one could simply count the number of DF events in the SR (without the SF selection) to obtain the flavour symmetric background events in the SF channel. This, however, is only true at generator level.
- The particles are identified by a detector, and since electrons and muons have different identification, isolation, reconstruction and trigger efficiencies, these differences have to be accounted for. Therefore, in order to extrapolate the count of DF events to the estimate of SF background events, these efficiency differences between electrons and muons must be taken into account and used to correct the DF count.
- Two different methods: the [efficiency correction method](#) (used as default) and the transfer factor method (used as crosscheck)
- Before applying these methods, all the non FS backgrounds are subtracted from the DF data events which are used to obtain the FS background in the SF channel.



Slepton analysis

Efficiency correction method

This technique consists in reweighting, on an event-by-event basis, for the reconstruction, isolation, identification and trigger efficiencies.



Expected dielectron events $N_{ee} = N \epsilon_e^{reco} \epsilon_e^{reco} \epsilon_{ee}^{trig}$,

Expected dimuon events $N_{\mu\mu} = N \epsilon_\mu^{reco} \epsilon_\mu^{reco} \epsilon_{\mu\mu}^{trig}$,

Expected emu events $N_{e\mu} = 2N \epsilon_e^{reco} \epsilon_\mu^{reco} \epsilon_{e\mu}^{trig}$, ← Assuming DF production is twice the SF one

$$\kappa = \sqrt{\frac{N_{\mu\mu}}{N_{ee}}} = \frac{\epsilon_\mu^{reco}}{\epsilon_e^{reco}} \sqrt{\frac{\epsilon_{\mu\mu}^{trig}}{\epsilon_{ee}^{trig}}}$$

$$\alpha = \frac{\sqrt{\epsilon_{ee}^{trig} \epsilon_{\mu\mu}^{trig}}}{\epsilon_{e\mu}^{trig}}$$

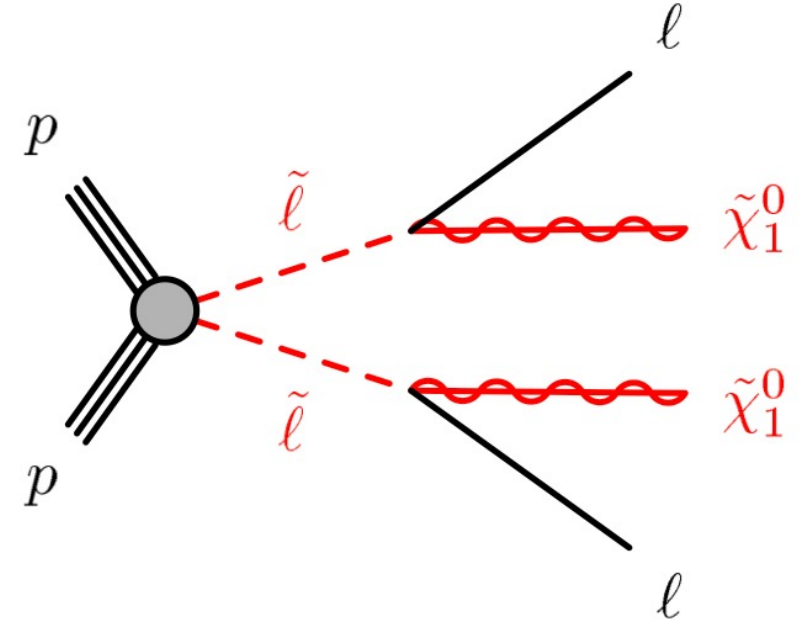
$$N_{ee} = \frac{1}{2} N_{e\mu} \frac{1}{\kappa} \alpha,$$

$$N_{\mu\mu} = \frac{1}{2} N_{e\mu} \kappa \alpha,$$

Slepton analysis

Efficiency correction method

This technique consists in reweighting, on an event-by-event basis, for the reconstruction, isolation, identification and trigger efficiencies.



Expected dielectron events $N_{ee}^{expected} = 0.5 \times \frac{1}{\kappa} \times \alpha \times N_{DF}$

Expected dimuon events $N_{\mu\mu}^{expected} = 0.5 \times \kappa \times \alpha \times N_{DF}$

Total expected events $N_{SF}^{expected} = 0.5 \times \left(\kappa + \frac{1}{\kappa} \right) \times \alpha \times N_{DF}$

Assuming DF production is twice the SF one

$$\kappa = \sqrt{\frac{N_{\mu^+\mu^-}}{N_{e^+e^-}}}$$

reconstruction, isolation, identification efficiency

$$\alpha = \frac{\sqrt{\epsilon_{ee}^{trig} \epsilon_{\mu\mu}^{trig}}}{\epsilon_{e\mu}^{trig}}$$

trigger efficiency

Slepton analysis

Efficiency correction method

This technique consists in reweighting, on an event-by-event basis, for the reconstruction, isolation, identification and trigger efficiencies.

$$\kappa = \sqrt{\frac{N_{\mu^+\mu^-}}{N_{e^+e^-}}} \quad \text{reconstruction, isolation, identification efficiency}$$

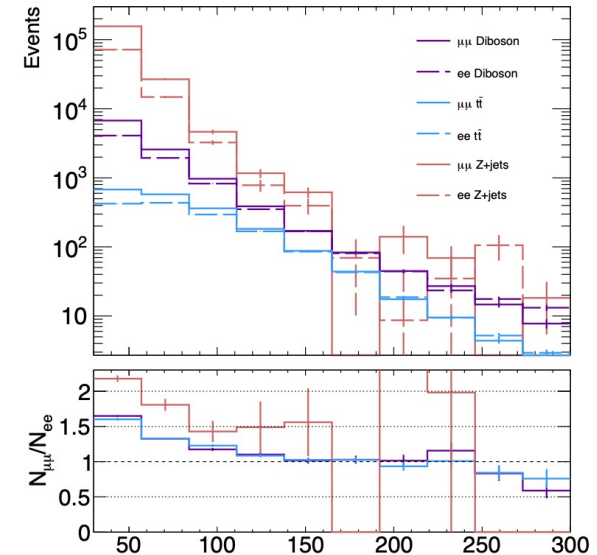
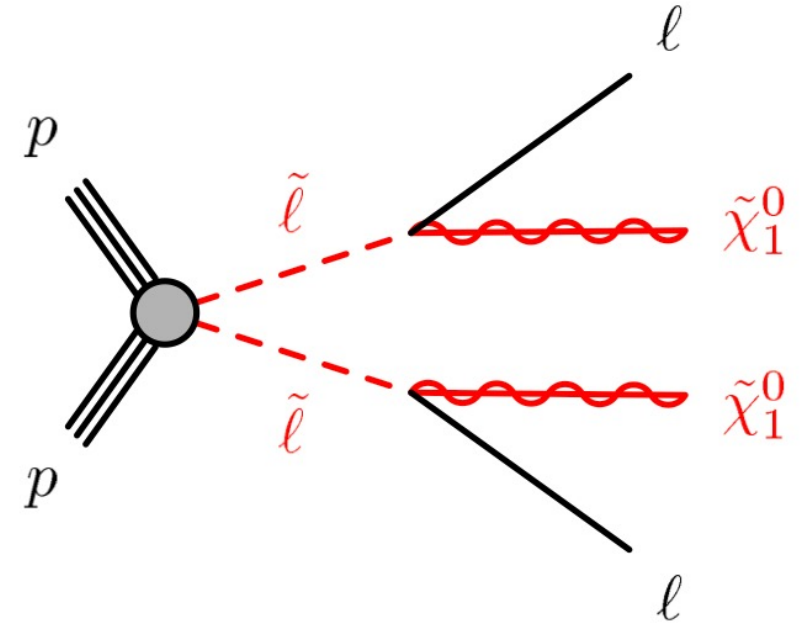
The correction factor κ is computed in a control region (CR_{eff})

Variable	Cut
n_{jet-20}	< 2
$N_{\text{OS leptons}}$	$= 2$
$p_T^{\ell_1}$	$> 30 \text{ GeV}$
$p_T^{\ell_2}$	$> 9 \text{ GeV}$
E_T^{miss} significance	> 6
$\cos\theta_{\ell\ell}^*$	> 0.2

Different reconstruction efficiencies observed for different backgrounds

Tighter cuts than preselection: purities more similar to SRs

Inverted to enrich VV events



Larger dimuon rec. eff for Zjets $lep1pT$ [GeV]

Slepton analysis

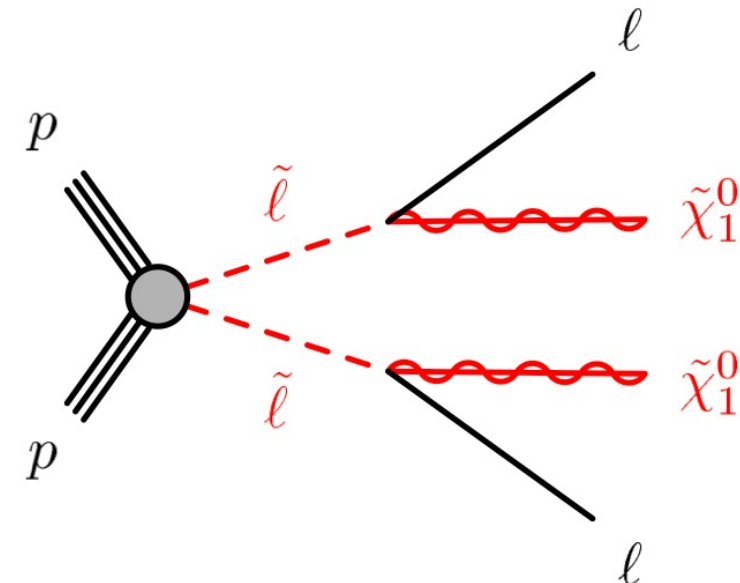
Efficiency correction method

This technique consists in reweighting, on an event-by-event basis, for the reconstruction, isolation, identification and trigger efficiencies.

$$\kappa = \sqrt{\frac{N_{\mu^+\mu^-}}{N_{e^+e^-}}} \quad \text{reconstruction, isolation, identification efficiency}$$

Reconstruction efficiencies can depend on the pseudo-rapidity region where the leptons reach the detector

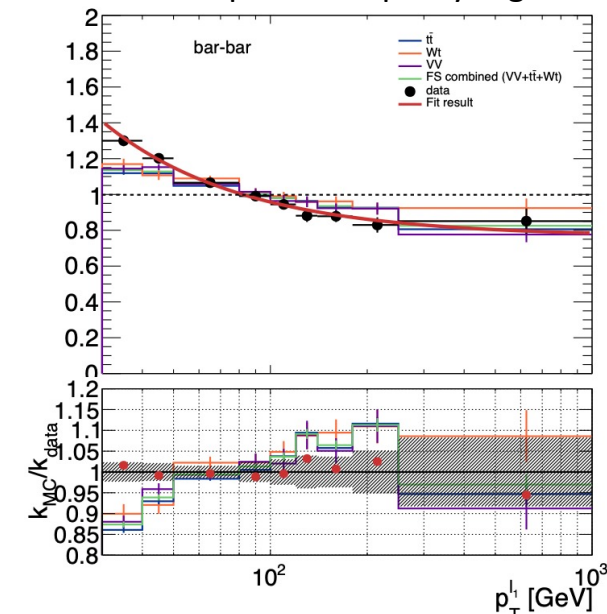
		MC (FS)	Data
Inclusive η	κ	1.1576 ± 0.0014	1.1942 ± 0.0043
$ \eta < 0.1$	$\kappa^{central}$	0.8509 ± 0.0042	0.852 ± 0.013
$ \eta < 1.05$	$\kappa^{bar-bar}$	1.0352 ± 0.0029	1.0655 ± 0.0089
$ \eta > 1.05$	$\kappa^{end-end}$	1.38526 ± 0.0042	1.440 ± 0.010
	$\kappa^{bar-end}$	1.1947 ± 0.0020	1.2198 ± 0.0061



Differences driven by the low $p_T^{\ell_1}$ region
At high $p_T^{\ell_1}$, the κ factors calculated agree in the different pseudo-rapidity regions

A fit performed in every $|\eta|$ region

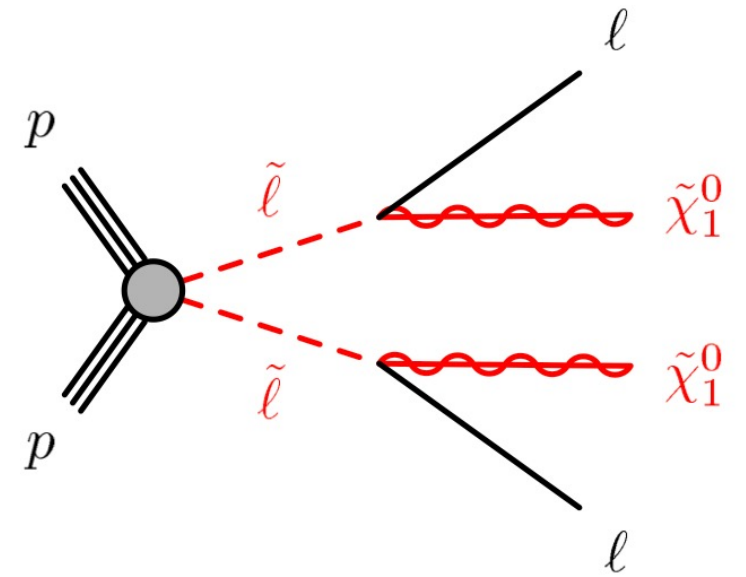
$$\kappa(p_T^{\ell_1}) = b + \frac{a}{p_T^{\ell_1}}$$



Slepton analysis

Efficiency correction method

This technique consists in reweighting, on an event-by-event basis, for the reconstruction, isolation, identification and trigger efficiencies.



$$\alpha = \frac{\sqrt{\epsilon_{ee}^{trig} \epsilon_{\mu\mu}^{trig}}}{\epsilon_{e\mu}^{trig}} \quad \text{Trigger efficiency}$$

Variable	Cut
n_{jet-20}	< 2
$N_{OS \text{ SF leptons}}$	$= 2$
$p_T^{\ell_1}$	$> 30 \text{ GeV}$
$p_T^{\ell_2}$	$> 20 \text{ GeV}$
E_T^{miss}	> 230
$m_{\ell\ell}$	$> 11 \text{ GeV}$
$ m_{\ell\ell} - m_Z $	$> 15 \text{ GeV}$

Tighter cuts to ensure the plateau of p_T /MET triggers

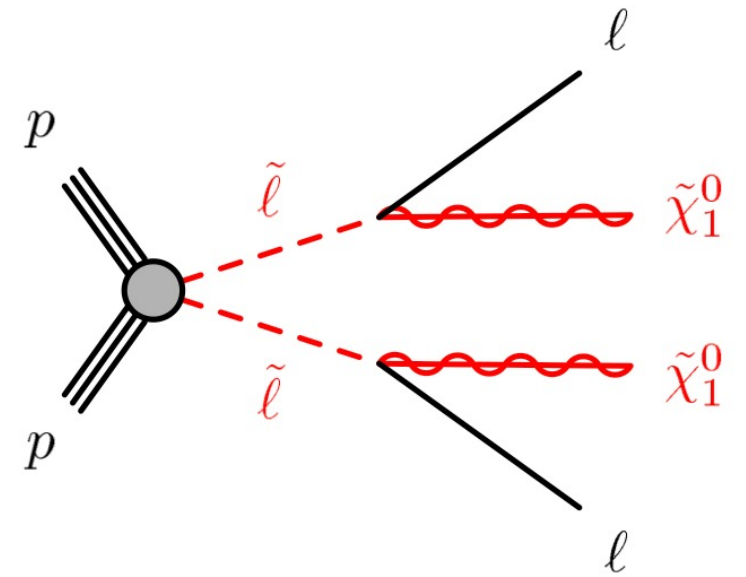
$$\epsilon^{trig} = \frac{N^{\text{METtrig and singlepTrig}}}{N^{\text{METtrig}}}$$

	MC	Data	Data SUSY16
ϵ_{ee}^{trig}	0.9915 ± 0.0019	0.9945 ± 0.0039	0.9797 ± 0.0041
$\epsilon_{\mu\mu}^{trig}$	0.9791 ± 0.0027	0.9803 ± 0.0080	0.9119 ± 0.0086
$\epsilon_{e\mu}^{trig}$	0.9879 ± 0.0012	0.9865 ± 0.0045	0.9571 ± 0.0041
α	0.9973 ± 0.0021	$1.0008^{+0.0062}_{-0.0093}$	$0.9876^{+0.0066}_{-0.0074}$
$\alpha^{\text{bar-bar}}$	0.9968 ± 0.0035	$1.006^{+0.007}_{-0.016}$	$0.962^{+0.012}_{-0.013}$
$\alpha^{\text{end-end}}$	0.9902 ± 0.0048	$1.010^{+0.018}_{-0.037}$	$1.01088^{+0.015}_{-0.020}$
$\alpha^{\text{bar-end}}$	0.9996 ± 0.0031	$0.992^{+0.010}_{-0.018}$	$1.001^{+0.0096}_{-0.011}$

Slepton analysis

Efficiency correction method

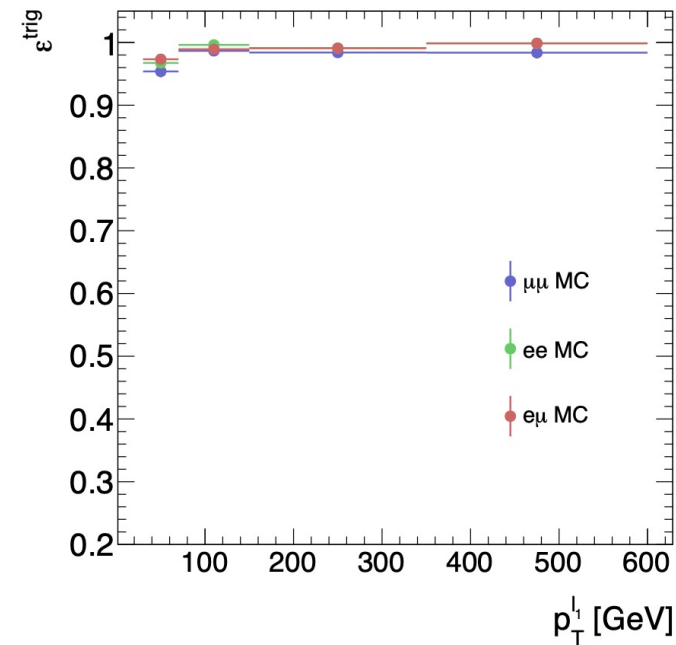
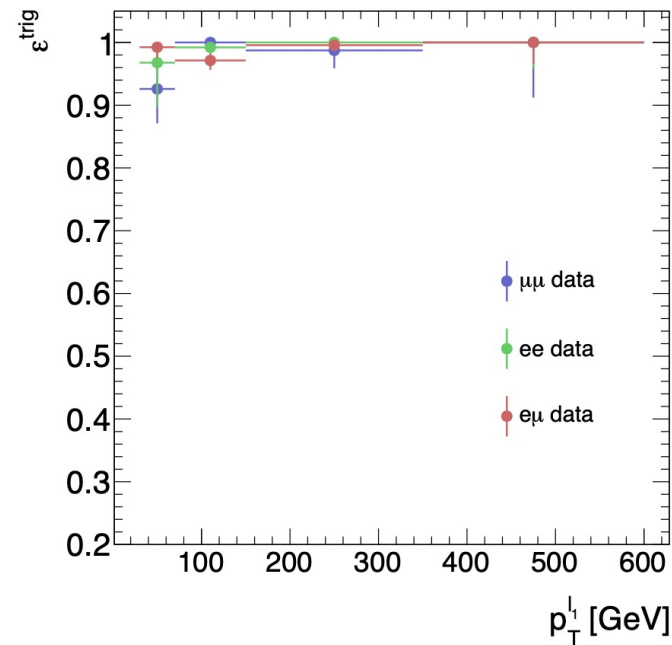
This technique consists in reweighting, on an event-by-event basis, for the reconstruction, isolation, identification and trigger efficiencies.



$$\alpha = \frac{\sqrt{\epsilon_{ee}^{trig} \epsilon_{\mu\mu}^{trig}}}{\epsilon_{e\mu}^{trig}} \quad \text{Trigger efficiency}$$

$$\epsilon^{trig} = \frac{N^{\text{METtrig and singlepTrig}}}{N^{\text{METtrig}}}$$

	MC	Data	Data SUSY16
ϵ_{ee}^{trig}	0.9915 ± 0.0019	0.9945 ± 0.0039	0.9797 ± 0.0041
$\epsilon_{\mu\mu}^{trig}$	0.9791 ± 0.0027	0.9803 ± 0.0080	0.9119 ± 0.0086
$\epsilon_{e\mu}^{trig}$	0.9879 ± 0.0012	0.9865 ± 0.0045	0.9571 ± 0.0041
α	0.9973 ± 0.0021	$1.0008^{+0.0062}_{-0.0093}$	$0.9876^{+0.0066}_{-0.0074}$
$\alpha^{\text{bar-bar}}$	0.9968 ± 0.0035	$1.006^{+0.007}_{-0.016}$	$0.962^{+0.012}_{-0.013}$
$\alpha^{\text{end-end}}$	0.9902 ± 0.0048	$1.010^{+0.018}_{-0.037}$	$1.01088^{+0.015}_{-0.020}$
$\alpha^{\text{bar-end}}$	0.9996 ± 0.0031	$0.992^{+0.010}_{-0.018}$	$1.001^{+0.0096}_{-0.011}$



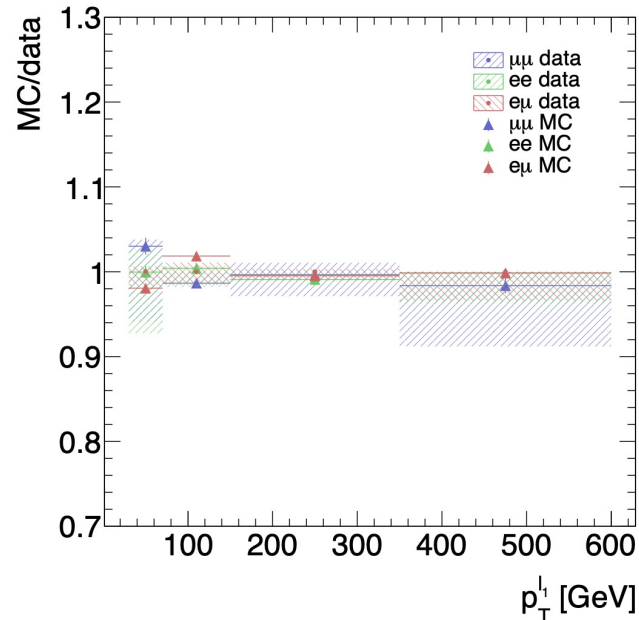
Slepton analysis

Efficiency correction method

This technique consists in reweighting, on an event-by-event basis, for the reconstruction, isolation, identification and trigger efficiencies.

$$\alpha = \frac{\sqrt{\varepsilon_{ee}^{trig} \varepsilon_{\mu\mu}^{trig}}}{\varepsilon_{e\mu}^{trig}} \quad \text{Trigger efficiency}$$

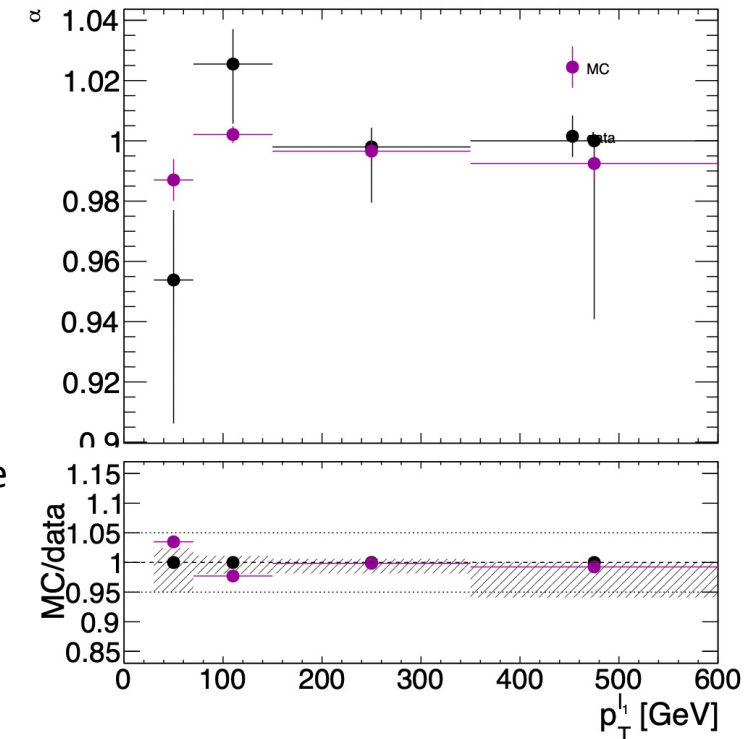
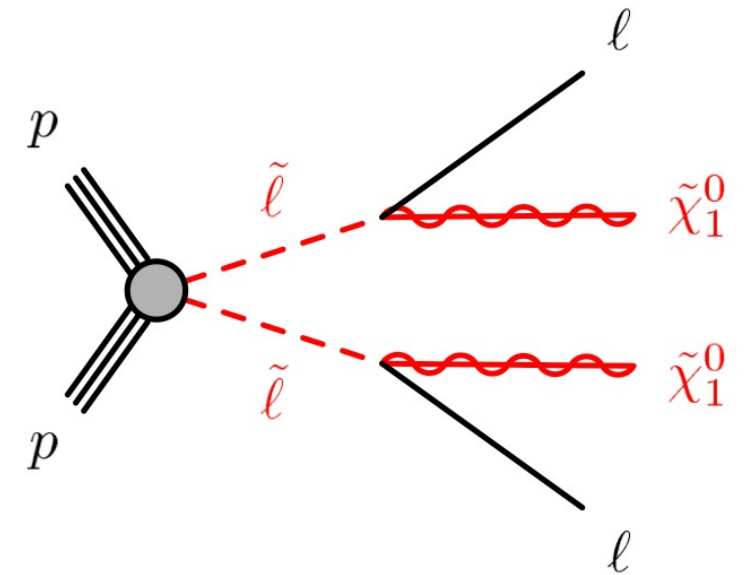
MC/data trigger efficiency ratio is also showing good agreement within statistical uncertainties in the whole $p_T^{\ell_1}$ range.



Trigger efficiency correction α calculated for data (black) and MC (purple).

MC includes: $t\bar{t}$, Wt , $Z(\rightarrow \tau\tau)$ + jets, VV , VVV and fakes.

The bottom frame shows the α values normalised to data. The uncertainties are statistical only.



Slepton analysis

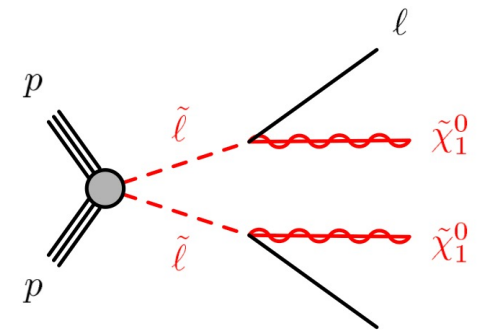
Systematic uncertainties

- **Uncertainty on α** : difference between data and MC global trigger efficiencies, combined with their statistical uncertainty, assuming they are uncorrelated among flavour channels.
- **Uncertainty on κ** . Difference between the global κ factors calculated in the different $|\eta|$ regions to cover small data-MC deviations.
- SF backgrounds yields using $p_T^{\ell_1}$ as the **fitting** variable gives differences below 1%. Therefore we consider an additional 1% uncertainty on the choice of $p_T^{\ell_1}$ as the fitting variable.
- **Uncertainty on the fit function $\kappa(p_T^{\ell_1})$** . The fit parameters (a, b) are varied by their uncertainty keeping the other parameter fixed. After the variations, the background yield changes by Δ_1, Δ_2 . The variance is then given by

$$\sigma = \mathbf{\Delta}^T \mathbf{C} \mathbf{\Delta} = (\Delta_1 \Delta_2) \begin{pmatrix} 1 & C_{12} \\ C_{12} & 1 \end{pmatrix} \begin{pmatrix} \Delta_1 \\ \Delta_2 \end{pmatrix}$$

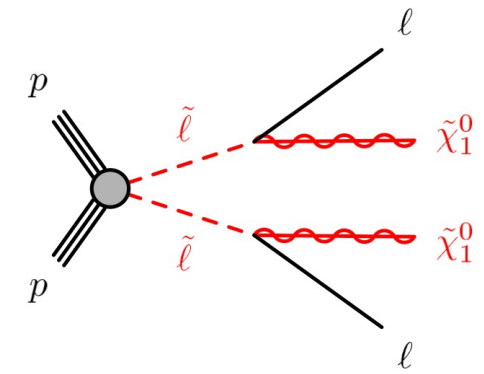
where C is the covariance matrix given by the fit, and C_{12} are the off-diagonal values of C . The uncertainty on the predicted yields is then the square root of the variance.

All these systematic uncertainties range from 1 to 2% in the final yield estimate, considering also data-MC agreement in the VRs, end up with a 10% overall uncertainty on the background estimate.

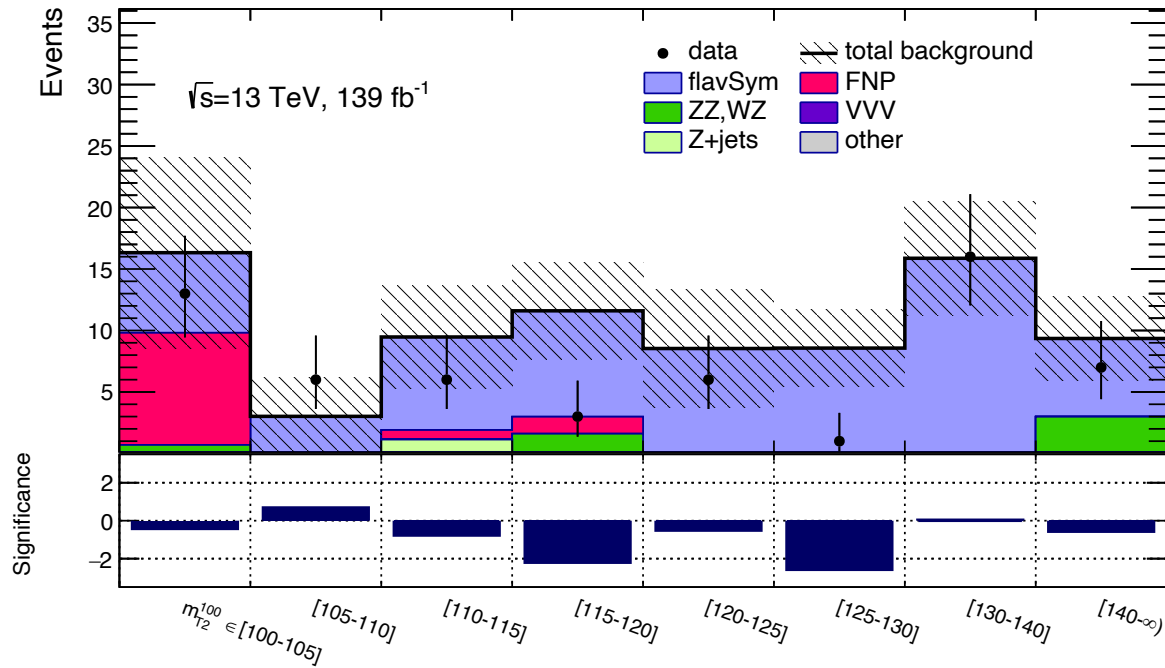


Slepton analysis

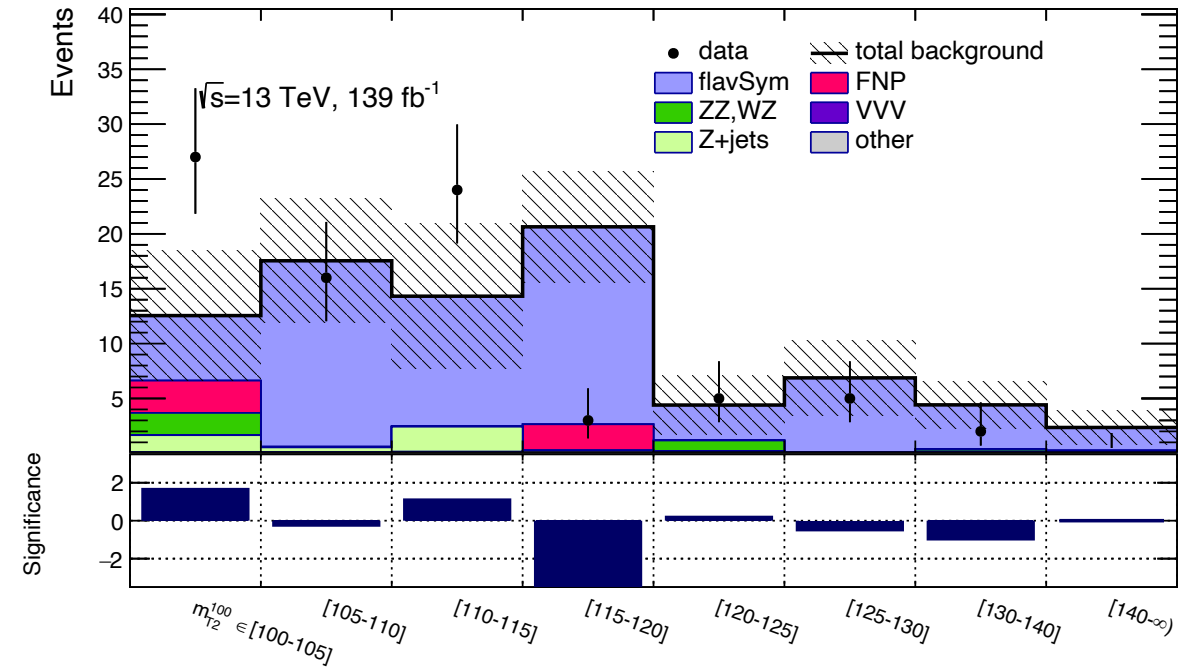
Pullplots



SR-0jet

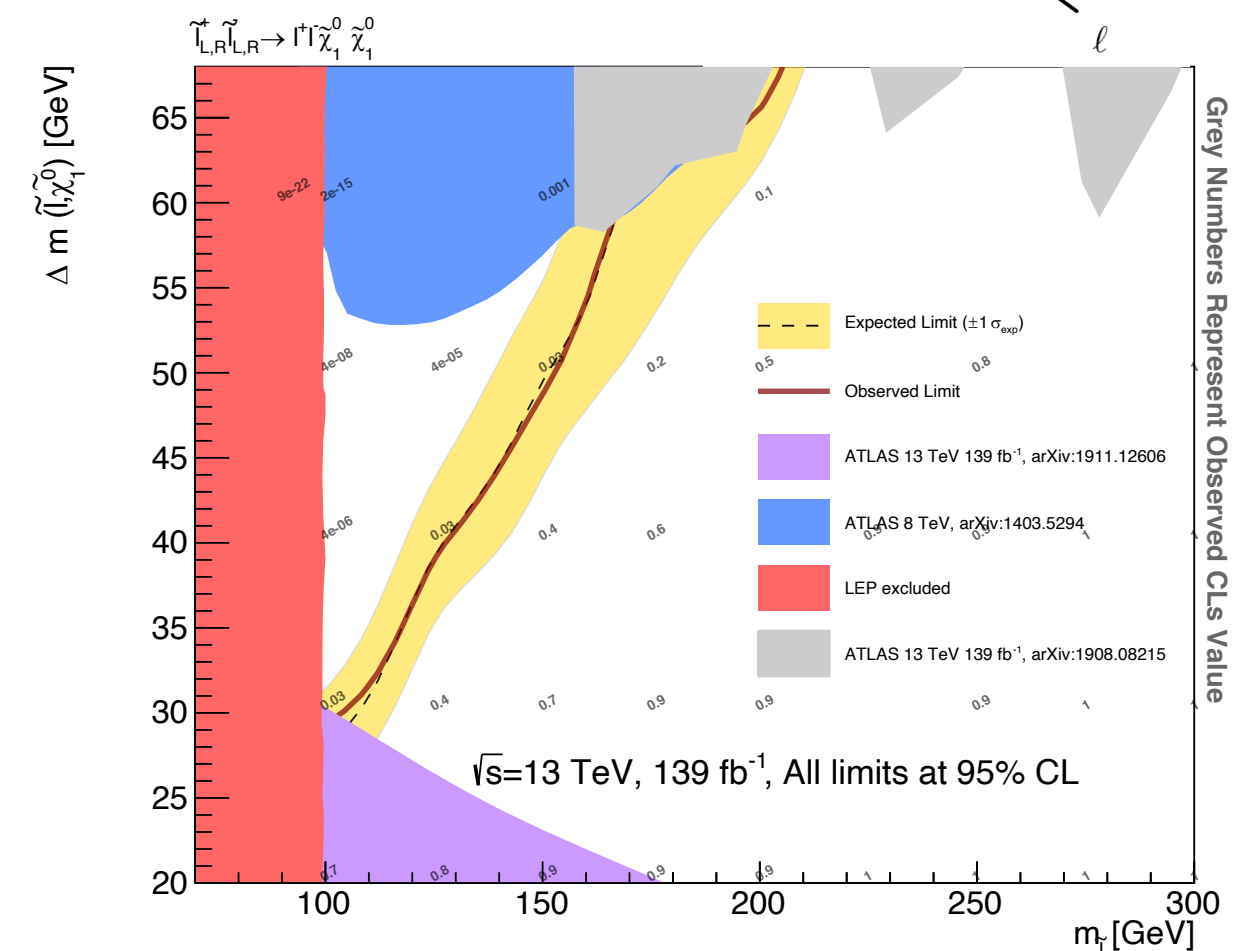
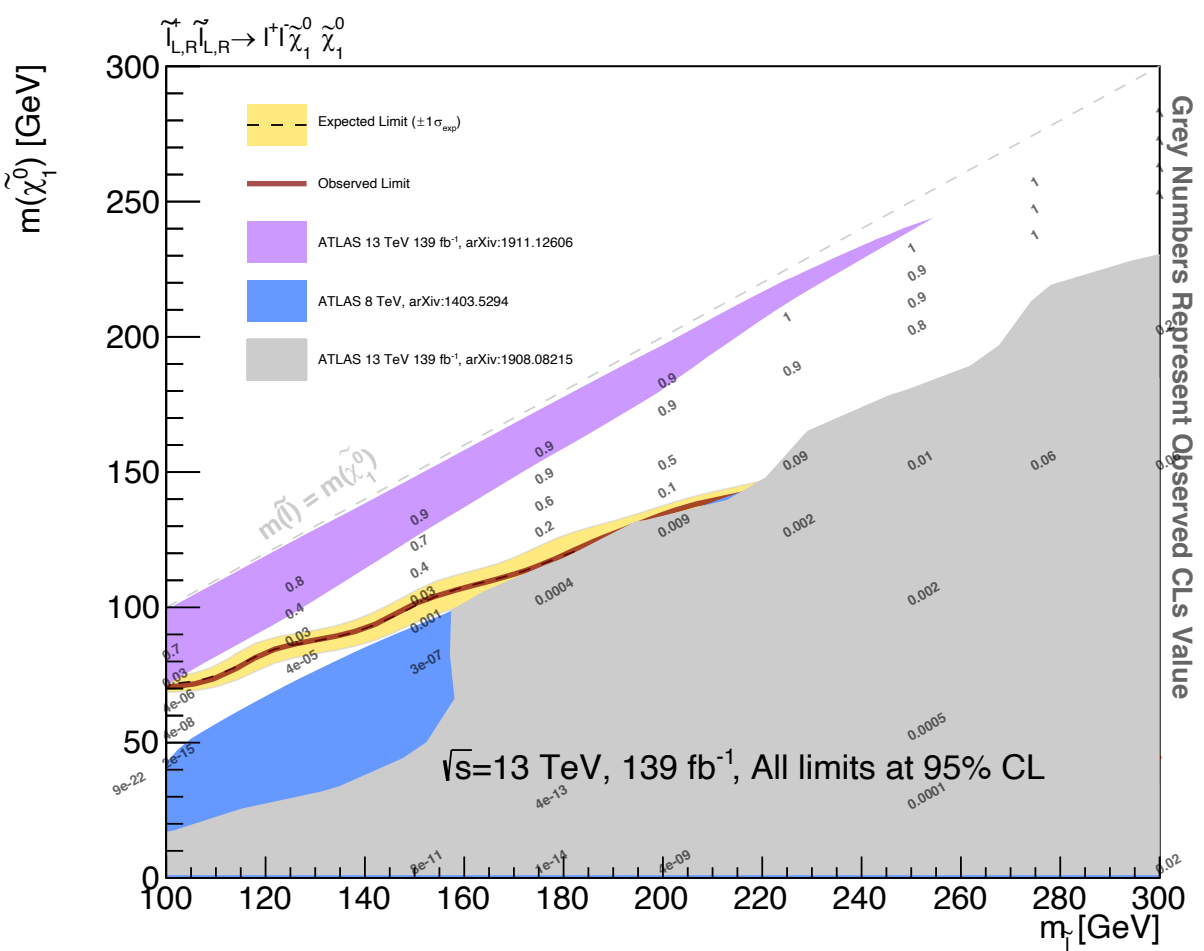
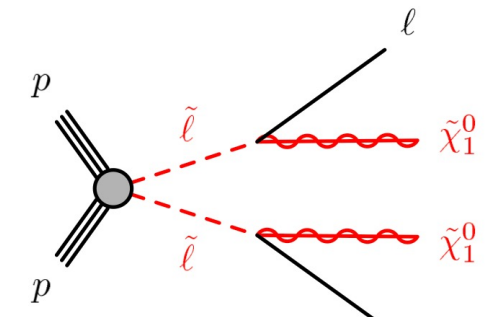


SR-1jet

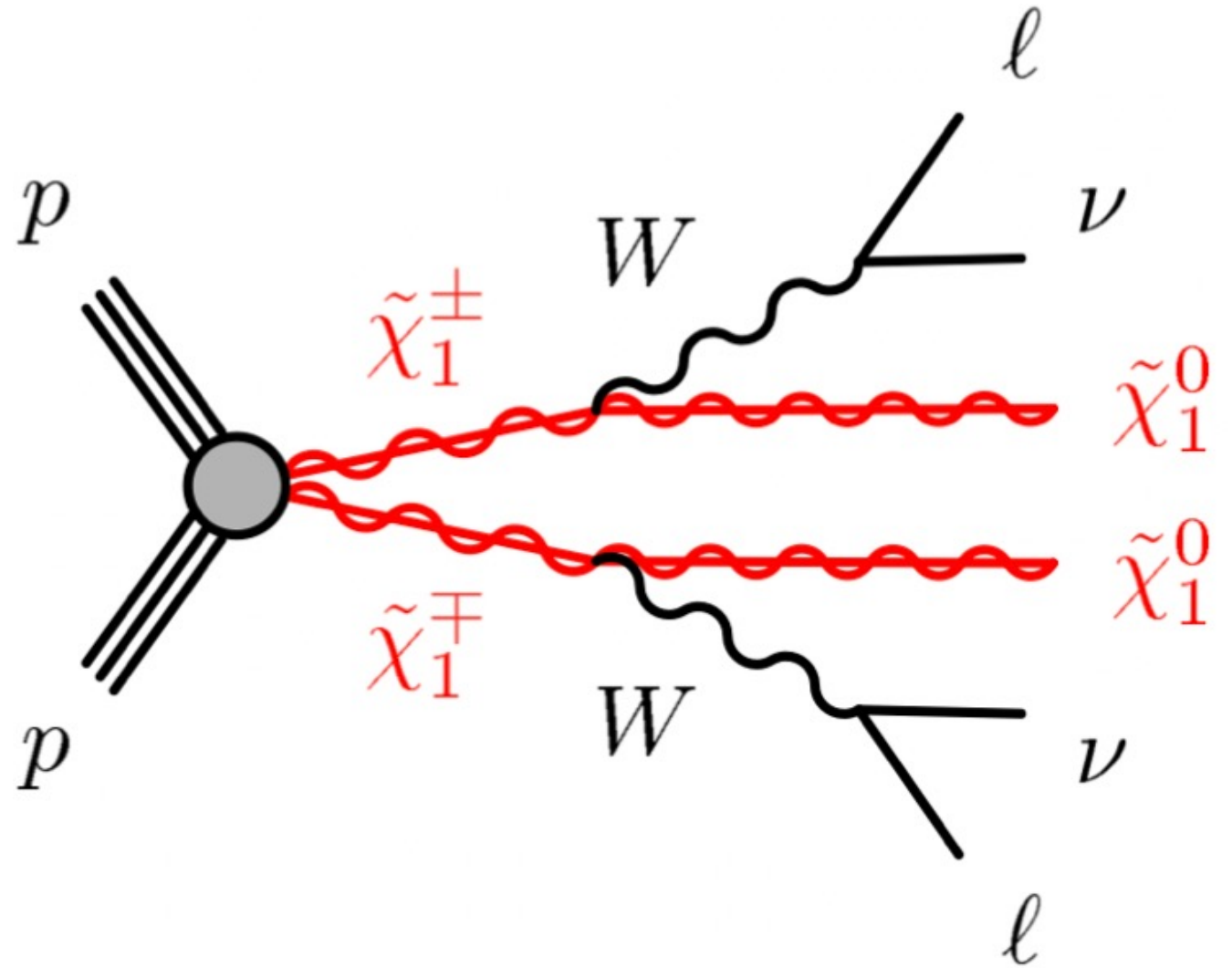


Slepton analysis

Exclusion contours

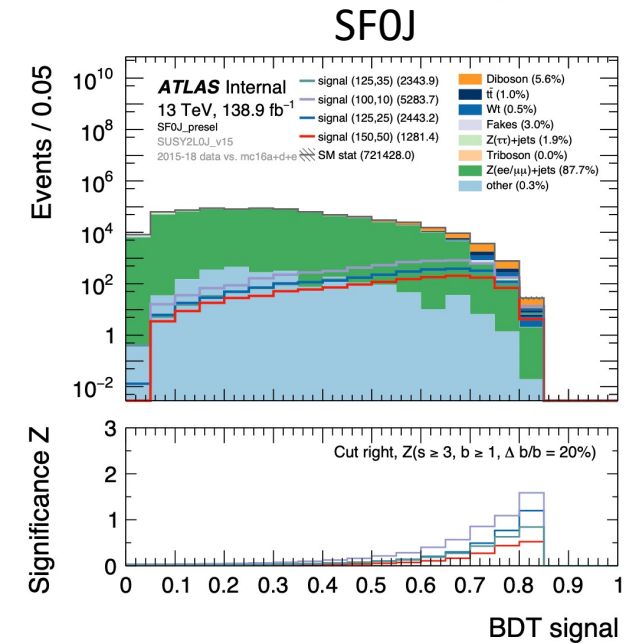
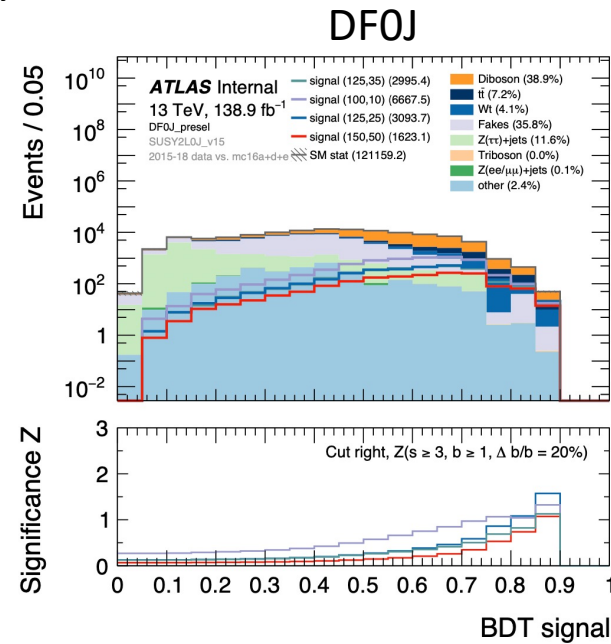
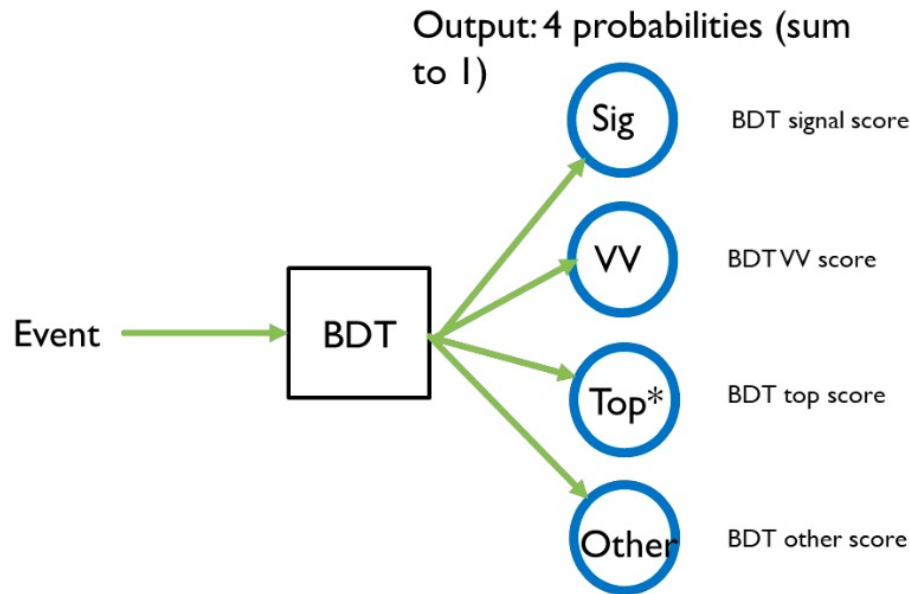
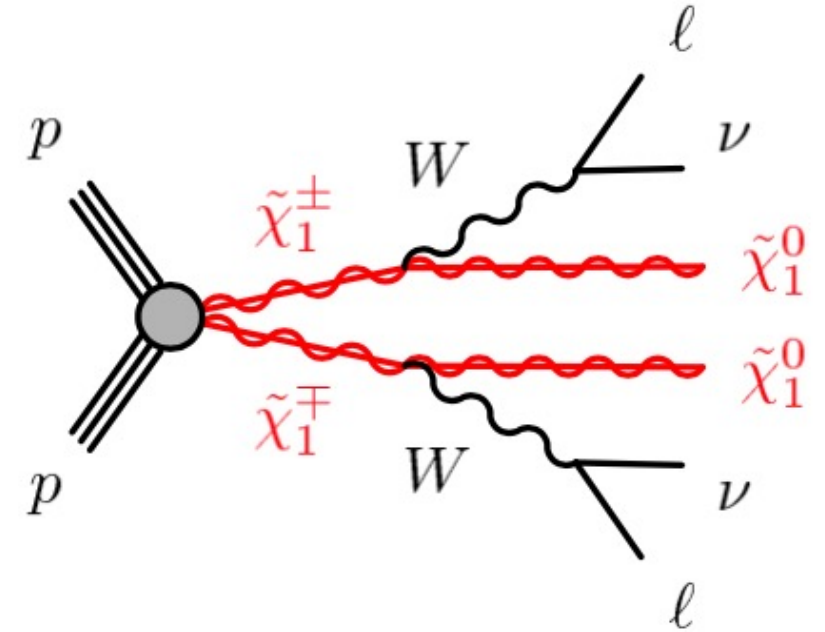


C1C1 WW analysis



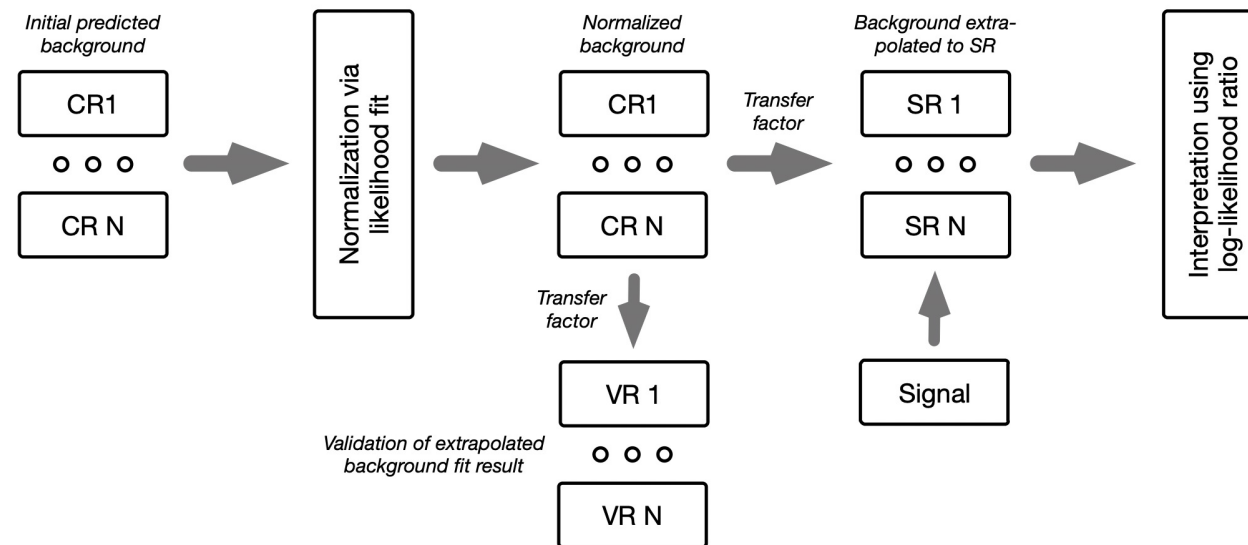
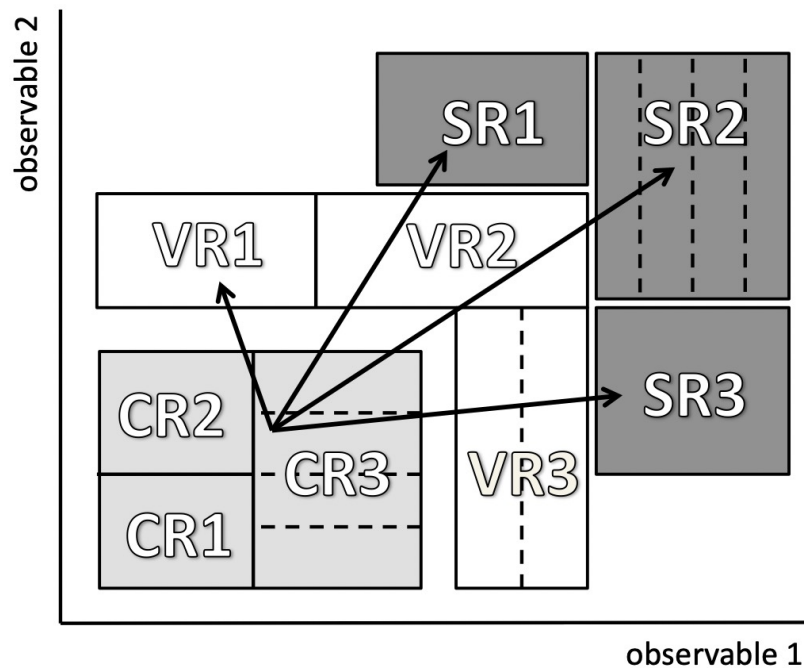
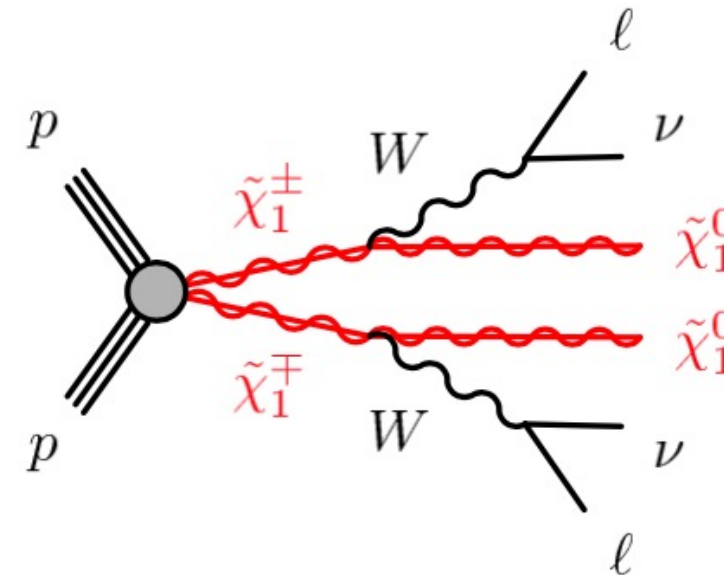
C1C1 WW analysis

- Analysis strategy based on **machine learning techniques**
 - BDT training with gradient boosting (LightGBM framework) based on full reconstructed background samples and AtlFast II signal samples with $\Delta m(\chi_1^\pm, \chi_1^0) = 90$ or 100 GeV.
 - Input features: $p_T^{\ell_1}, p_T^{\ell_2}, E_T^{miss}, E_T^{miss}$ significance, $m_{T2}, m_{\ell\ell}, \Delta\phi_{boost}, \Delta\phi_{E_T^{miss}, \ell_1}, \Delta\phi_{E_T^{miss}, \ell_2}, \cos\theta_{\ell\ell}^*$
 - Multiclass classification with 4 output categories: **BDT signal, BDT VV, BDT Top, BDT others**, for DF and SF separately.



C1C1 WW analysis

- Background normalization strategy based on CRs
- 2 CRs (CR_VV and CR_Top)
- 2 normalization factors μ_{VV} , μ_{top} estimated in CRs to control VV and Top (Top=ttbar+Wt) backgrounds
- Background estimation validated in VRs and propagated in the SRs through transfer factor approach.



C1C1 WW analysis

CRs

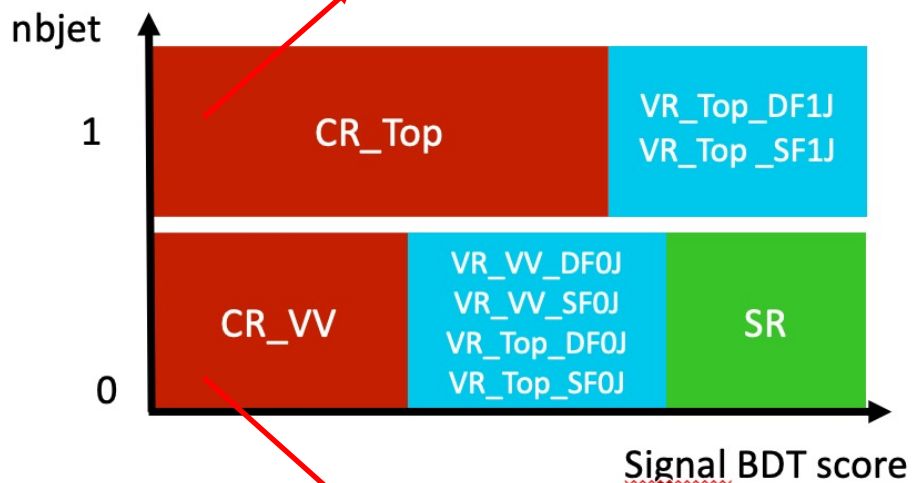
CR_Top

If DF, $0.5 < \text{Signal BDT score} < 0.7$

If SF, $0.7 < \text{Signal BDT score} < 0.75$, BDT others < 0.01

Purity: 98%

Signal contamination $< 0.6\%$



CR_VV

$0.2 < \text{Signal BDT score} < 0.65$

BDT top < 0.1 , BDT VV > 0.2

and if SF: BDT others < 0.01

Purity: 78%

Signal contamination $< 7\%$

Estimated scale factors:

$$\mu_{VV} = 1.387 \pm 0.083$$

$$\mu_{Top} = 1.058 \pm 0.026$$

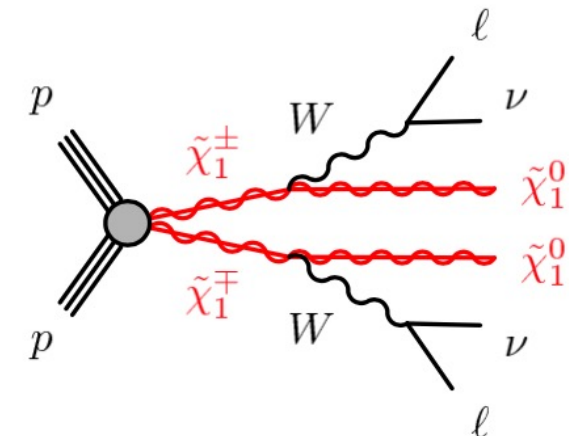
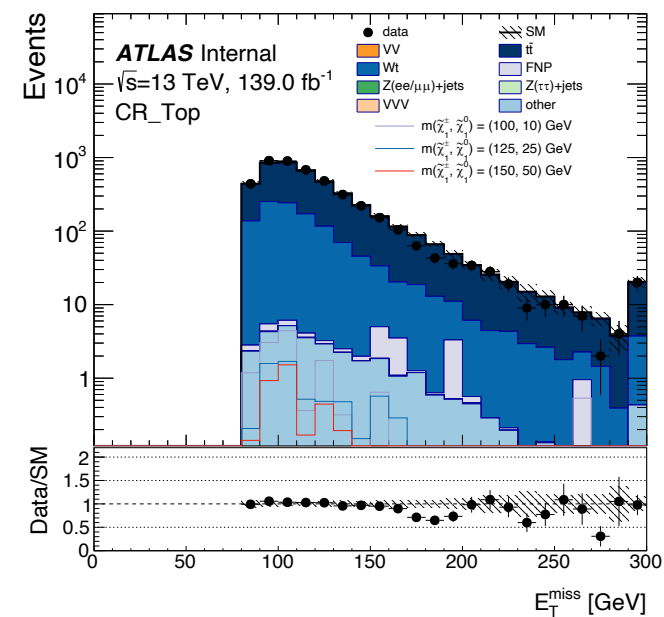
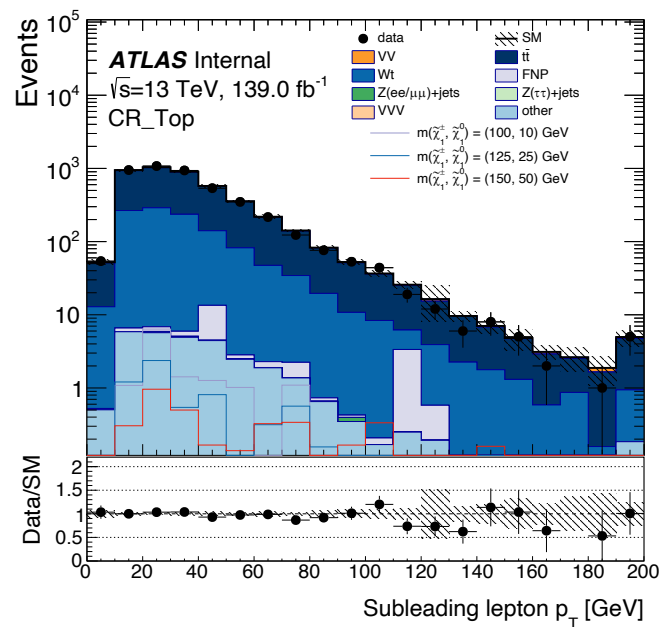
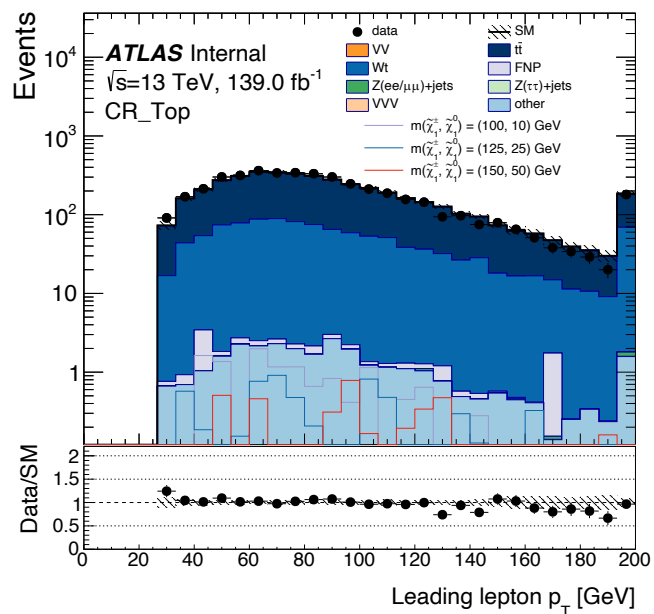
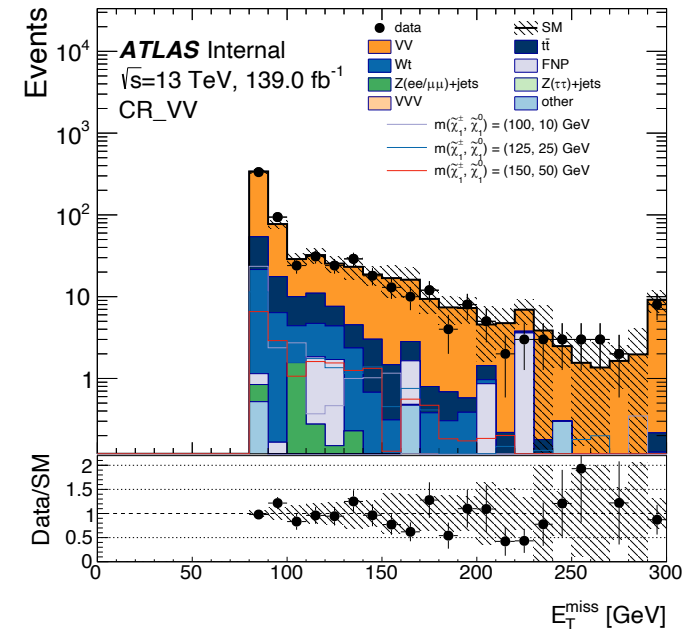
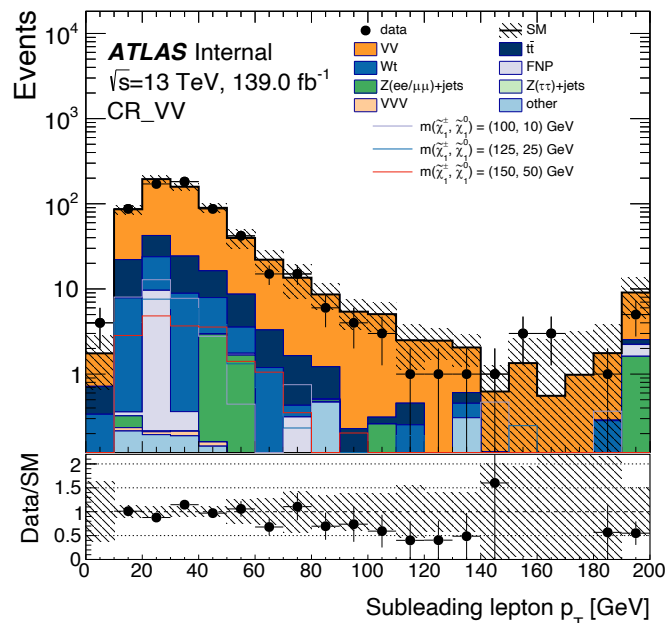
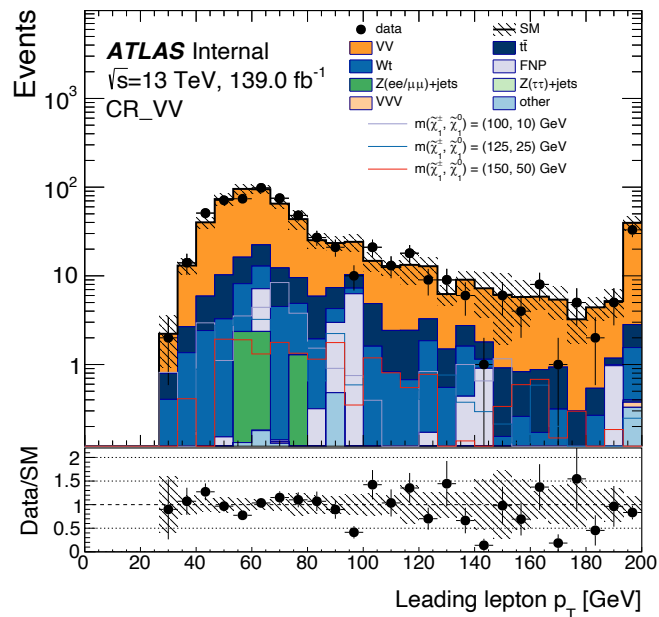


table.results.yields channel	CR_Dib	CR_Top
Observed events	632	4468
Fitted bkg events	632.00 ± 25.13	4468.18 ± 66.85
Fitted FNP events	$0.01^{+1.35}_{-0.01}$	$0.01^{+11.43}_{-0.01}$
Fitted Wt events	39.31 ± 4.99	1121.45 ± 62.41
Fitted Zjets events	$1.43^{+3.67}_{-1.43}$	0.00 ± 0.00
Fitted Zttjets events	0.00 ± 0.00	0.00 ± 0.00
Fitted VV events	521.69 ± 27.37	69.66 ± 12.28
Fitted other events	1.66 ± 0.36	29.22 ± 3.77
Fitted VVV events	0.14 ± 0.01	0.06 ± 0.01
Fitted ttbar events	67.77 ± 8.07	3247.78 ± 81.31
MC exp. SM events	480.61 ± 15.70	4210.16 ± 77.41
MC exp. FNP events	$0.01^{+1.41}_{-0.01}$	$0.01^{+11.93}_{-0.01}$
MC exp. Wt events	37.16 ± 5.23	1060.21 ± 75.92
MC exp. Zjets events	$1.43^{+3.69}_{-1.43}$	0.00 ± 0.00
MC exp. Zttjets events	0.00 ± 0.00	0.00 ± 0.00
MC exp. VV events	376.15 ± 9.28	50.23 ± 7.42
MC exp. other events	1.66 ± 0.36	29.22 ± 3.79
MC exp. VVV events	0.14 ± 0.01	0.06 ± 0.02
MC exp. ttbar events	64.07 ± 8.15	3070.44 ± 14.17

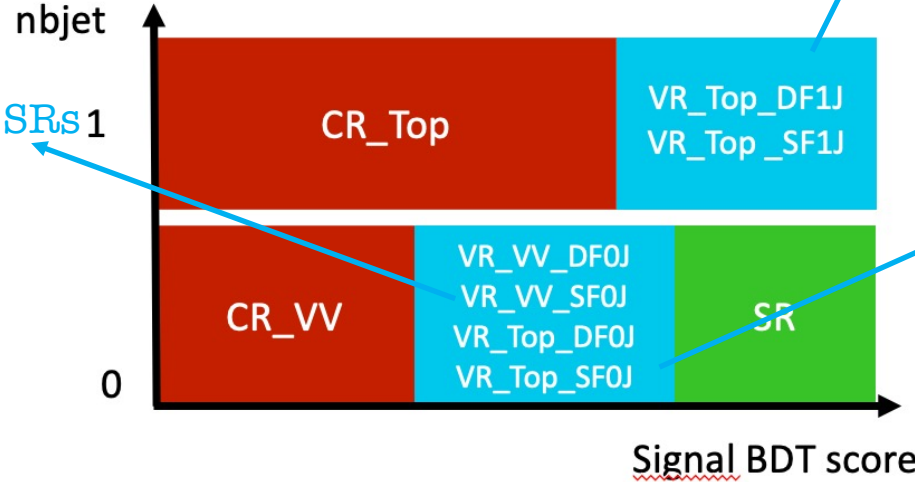


C1C1 WW analysis VRs

VV VRs defined between VV CR and SRs 1

VR_VV_DF0J:
 $0.65 < \text{Signal BDT score} < 0.81$,
 Top BDT score < 0.1 , VV BDT score > 0.2

VR_VV_SF0J:
 $0.65 < \text{Signal BDT score} < 0.77$,
 Top BDT score < 0.1 , VV BDT score > 0.2 ,
 BDT others < 0.01



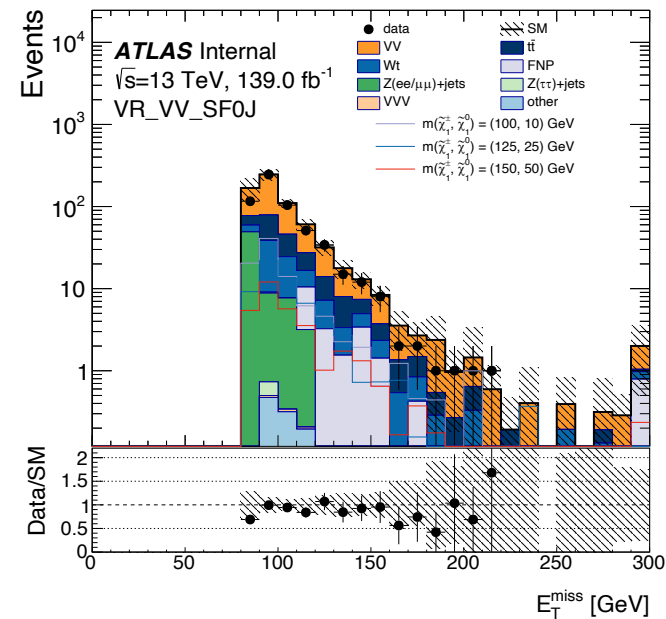
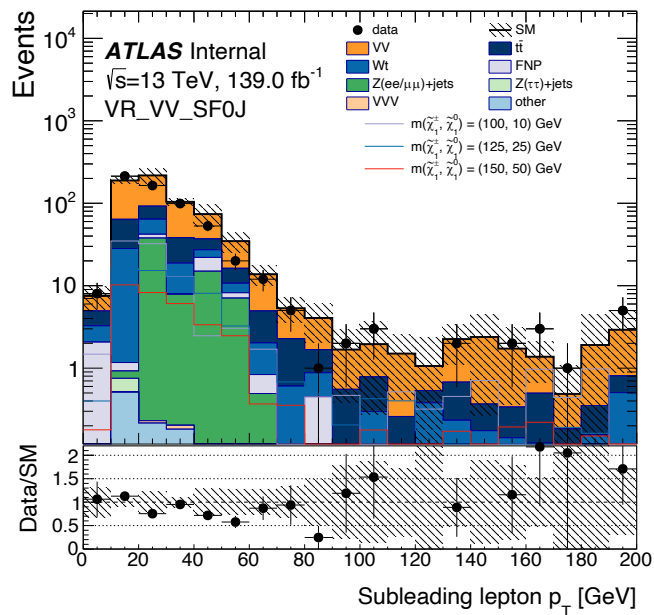
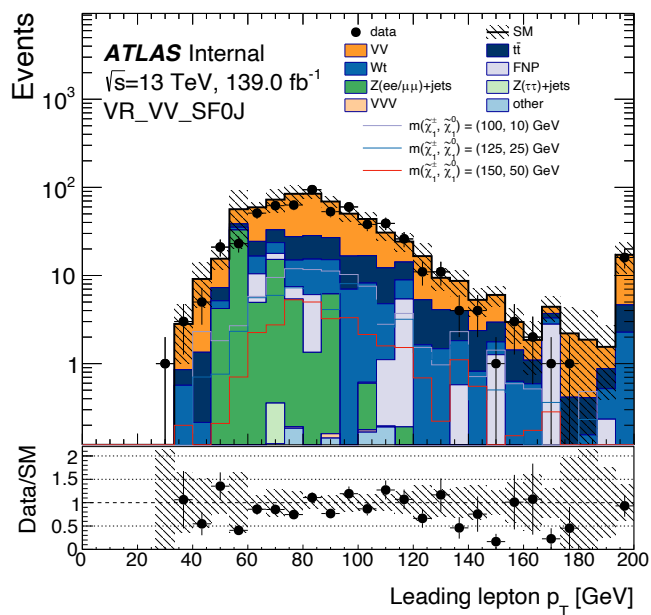
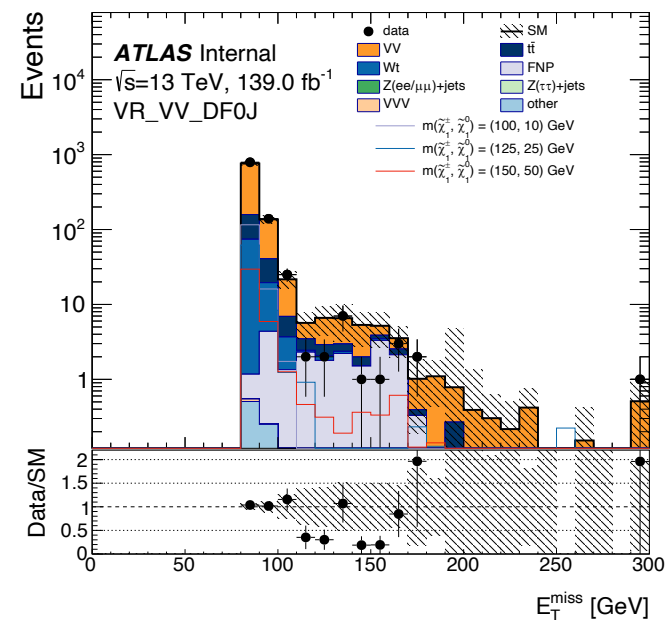
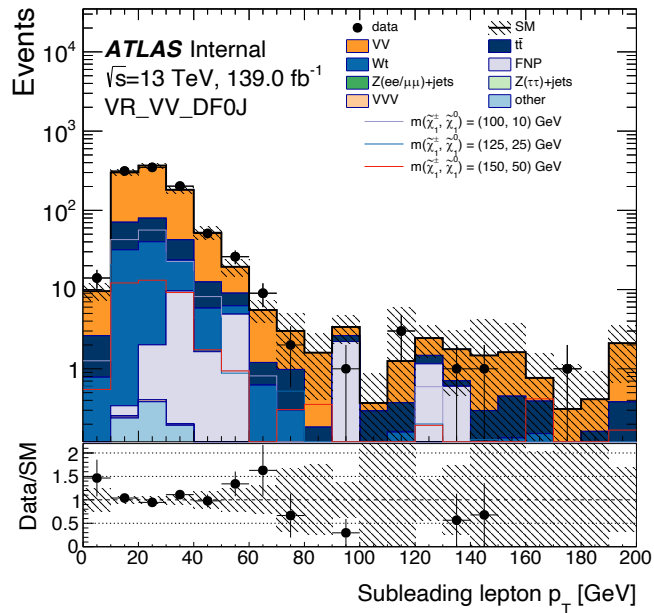
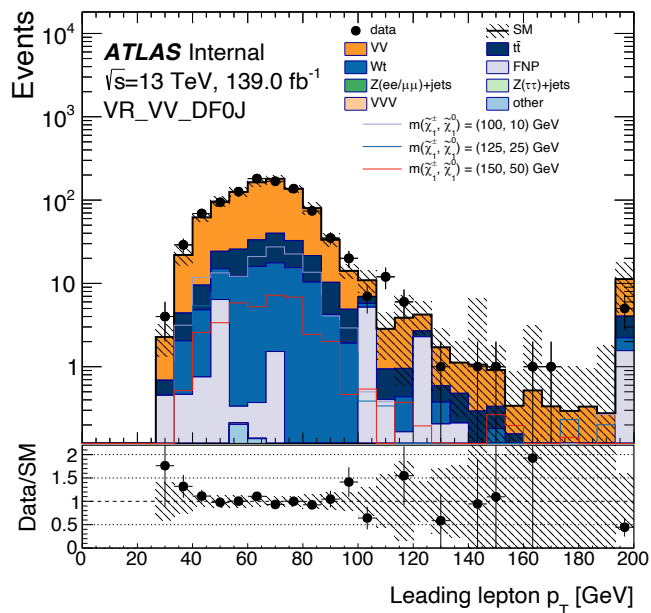
Top VRs defined in the 1J channel as the CR_Top

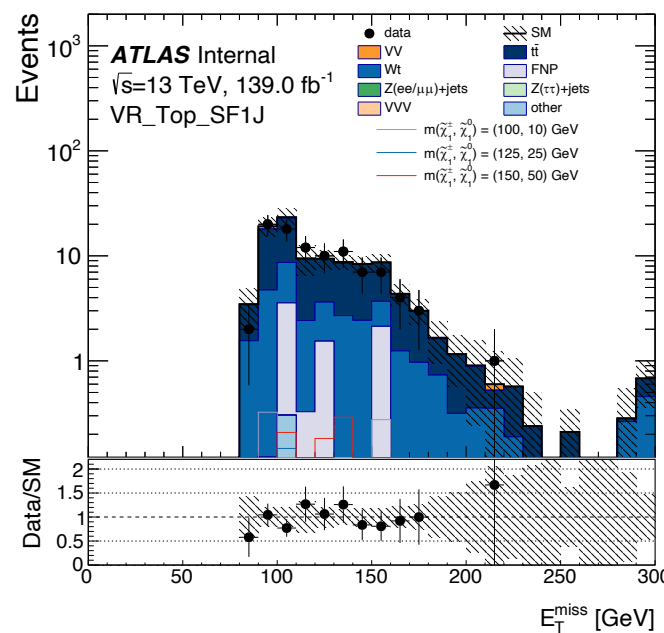
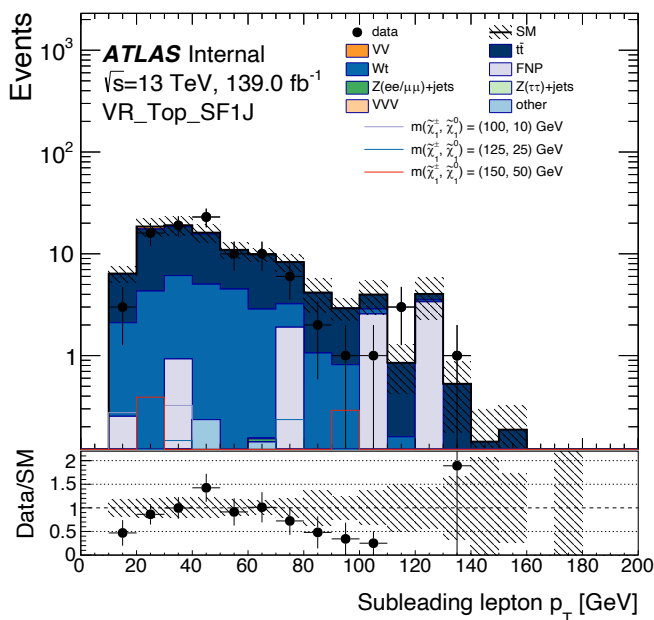
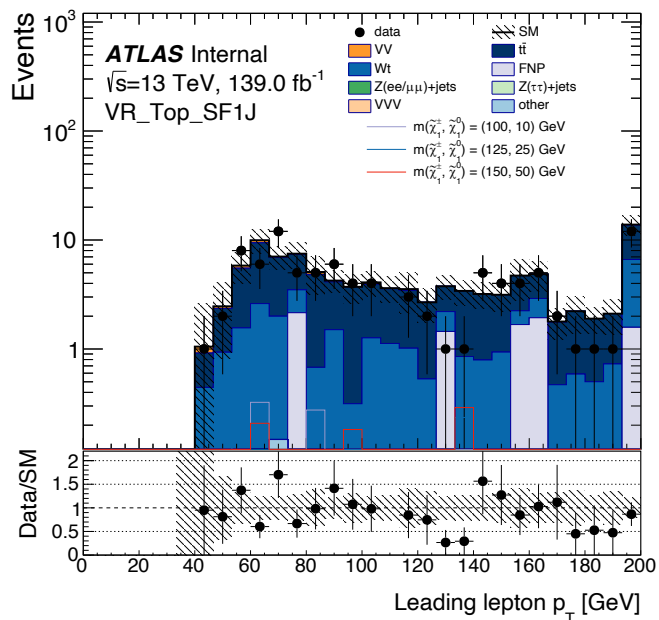
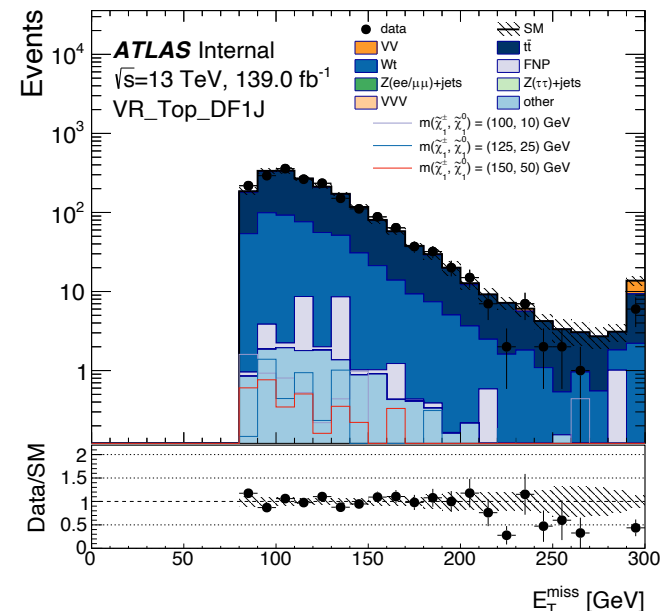
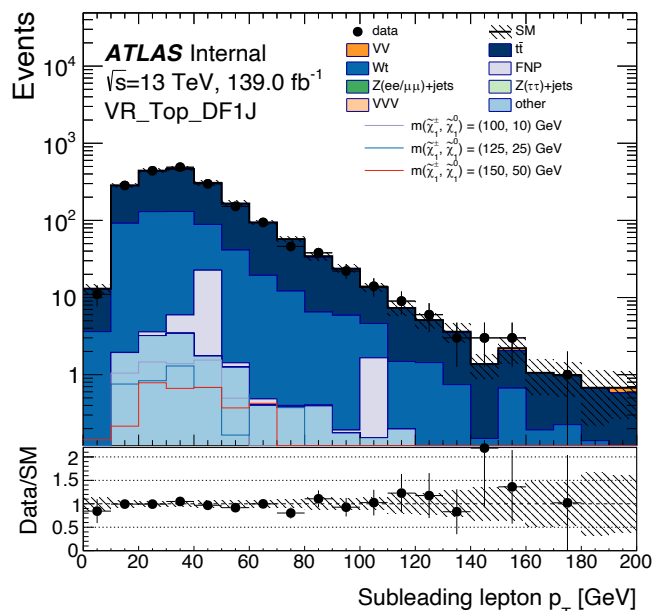
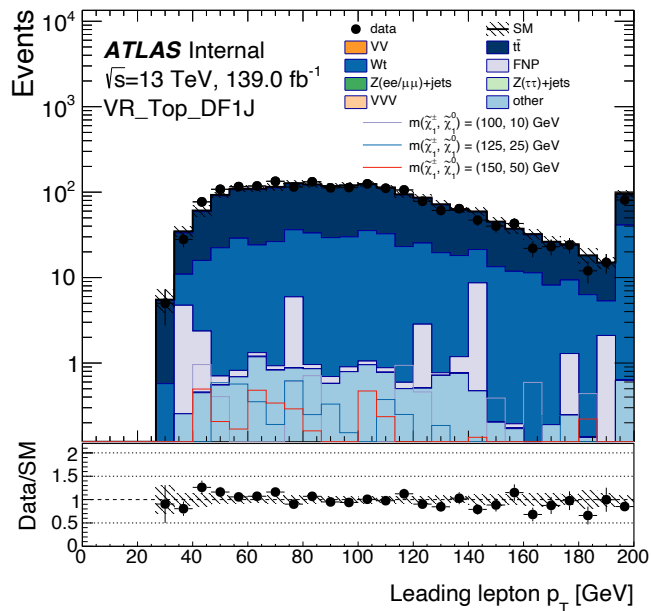
VR_Top_DF1J:
 $0.7 < \text{Signal BDT score} < 1$,
 VR_Top_SF1J:
 $0.75 < \text{Signal BDT score} < 1$, BDT others < 0.01

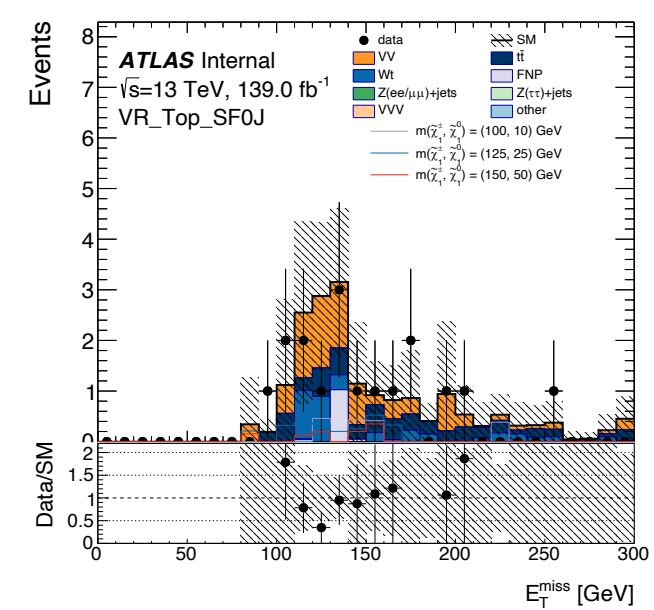
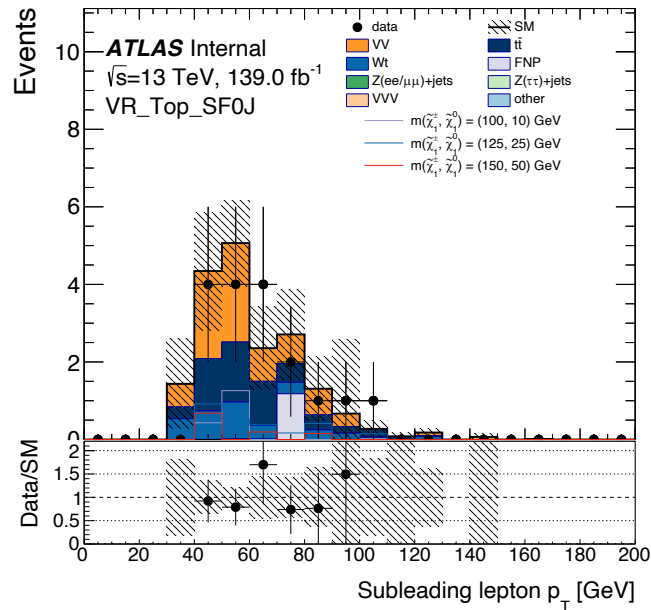
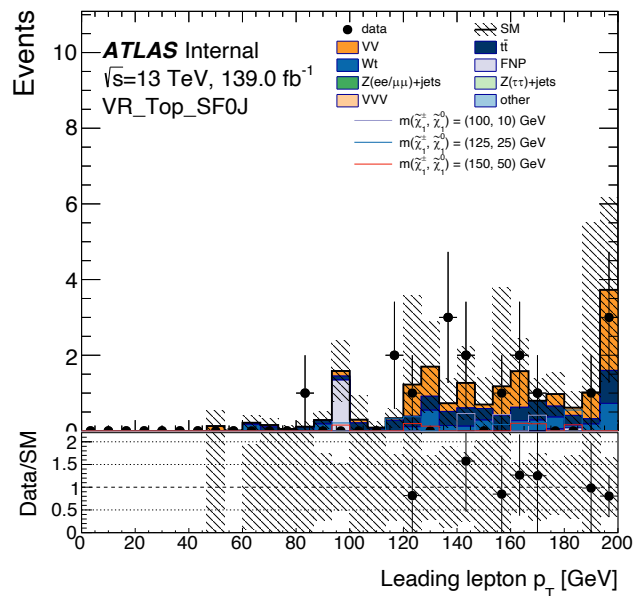
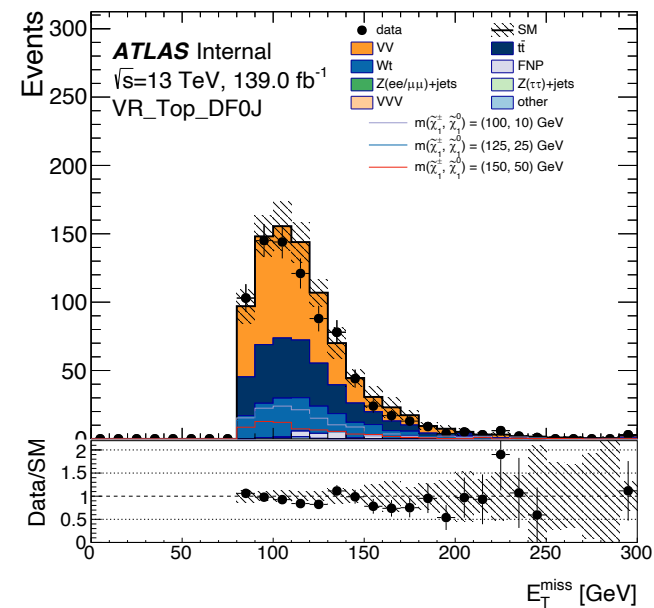
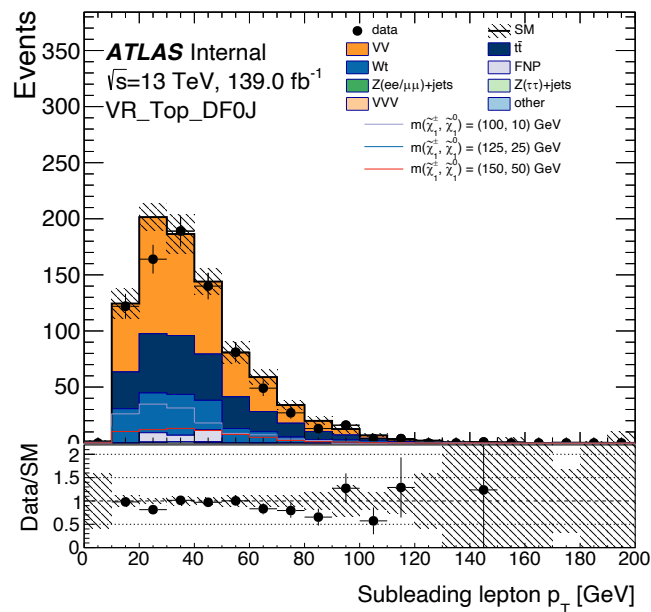
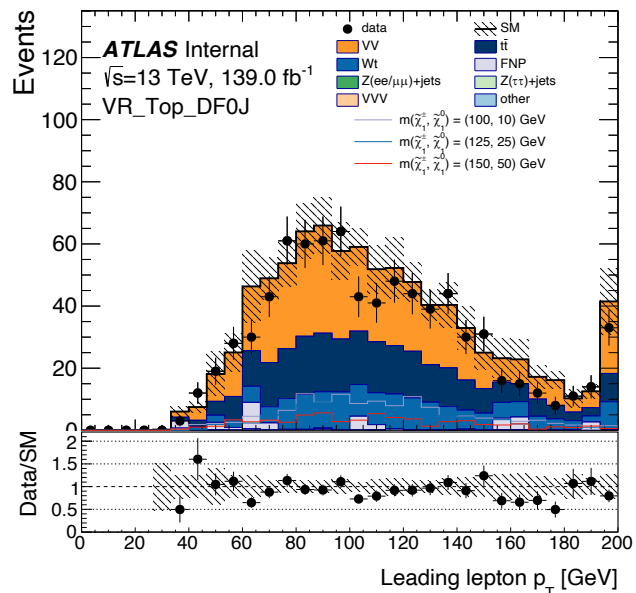
Top VRs defined in the 0J channel to allow the extrapolation of the top scale factor to the SRs, where $njet=0$

VR_Top_DF0J:
 $0.5 < \text{Signal BDT score} < 0.81$ BDT VV < 0.15
 VR_Top_SF0J:
 $0.5 < \text{Signal BDT score} < 0.77$,
 BDT VV < 0.15 and BDT others < 0.01

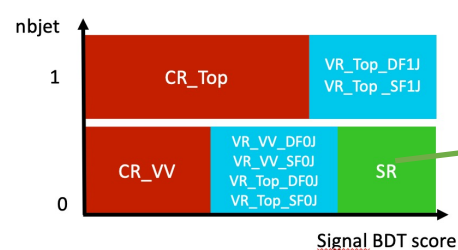
table.results.yields channel	VR_Dib_DF0J	VR_Dib_SF0J	VR_Top_DF1J	VR_Top_SF1J	VR_Top_DF0J	VR_Top_SF0J
Observed events	972	593	1910	95	810	17
Fitted bkg events	938.50 ± 59.54	662.15 ± 77.65	1900.47 ± 88.68	101.57 ± 8.88	874.88 ± 46.37	17.37 ± 3.71
Fitted FNP events	$0.01^{+2.18}_{-0.01}$	7.79 ± 3.95	$0.01^{+4.79}_{-0.01}$	4.23 ± 1.21	20.47 ± 8.19	$0.05^{+0.13}_{-0.05}$
Fitted Wt events	91.65 ± 13.56	73.34 ± 10.76	501.22 ± 45.95	27.02 ± 4.54	163.90 ± 16.26	3.40 ± 0.48
Fitted Zjets events	0.00 ± 0.00	67.53 ± 35.27	0.02 ± 0.00	$0.04^{+0.10}_{-0.04}$	0.00 ± 0.00	0.00 ± 0.00
Fitted Zttjets events	0.00 ± 0.00	0.24 ± 0.20	0.00 ± 0.00	0.00 ± 0.00	0.50 ± 0.35	0.00 ± 0.00
Fitted VV events	732.70 ± 51.65	403.10 ± 49.36	32.37 ± 12.87	2.23 ± 1.84	431.18 ± 32.22	8.18 ± 2.60
Fitted other events	0.99 ± 0.26	1.16 ± 0.32	13.56 ± 1.91	0.75 ± 0.22	3.53 ± 0.75	0.05 ± 0.01
Fitted VVV events	0.06 ± 0.01	0.09 ± 0.01	0.03 ± 0.01	0.00 ± 0.00	0.16 ± 0.01	0.01 ± 0.00
Fitted ttbar events	113.09 ± 14.23	108.90 ± 13.22	1353.26 ± 59.24	67.31 ± 7.66	255.15 ± 21.71	5.70 ± 1.47
MC exp. SM events	722.91 ± 46.71	539.74 ± 70.02	1790.17 ± 102.09	95.80 ± 9.35	731.70 ± 43.97	14.59 ± 2.92
MC exp. FNP events	$0.01^{+2.27}_{-0.01}$	7.79 ± 4.12	$0.01^{+5.01}_{-0.01}$	4.23 ± 1.27	20.47 ± 8.56	$0.05^{+0.14}_{-0.05}$
MC exp. Wt events	86.65 ± 14.05	69.34 ± 11.15	473.85 ± 50.90	25.54 ± 4.68	154.95 ± 17.65	3.21 ± 0.46
MC exp. Zjets events	0.00 ± 0.00	67.53 ± 35.49	0.02 ± 0.00	$0.04^{+0.10}_{-0.04}$	0.00 ± 0.00	0.00 ± 0.00
MC exp. Zttjets events	0.00 ± 0.00	0.24 ± 0.21	0.00 ± 0.00	0.00 ± 0.00	0.50 ± 0.36	0.00 ± 0.00
MC exp. VV events	528.29 ± 27.82	290.64 ± 30.31	23.34 ± 9.27	1.61 ± 1.31	310.88 ± 15.17	5.90 ± 1.81
MC exp. other events	0.99 ± 0.26	1.16 ± 0.32	13.56 ± 1.92	0.75 ± 0.22	3.53 ± 0.75	0.05 ± 0.01
MC exp. VVV events	0.06 ± 0.01	0.09 ± 0.01	0.03 ± 0.01	0.00 ± 0.00	0.16 ± 0.01	0.01 ± 0.00
MC exp. ttbar events	106.91 ± 14.14	102.95 ± 13.30	1279.36 ± 60.82	63.63 ± 7.29	241.21 ± 22.41	5.39 ± 1.42



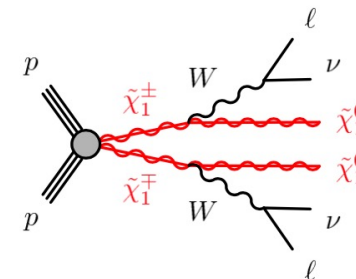




C1C1 WW analysis SRs



16 DFOJ SRs
starting from BDT signal > 0.81



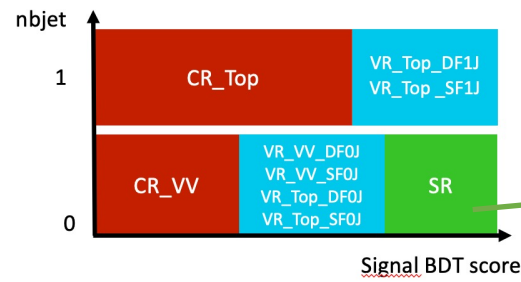
- Shape fit to enhance sensitivity. SRs binned in BDT signal score.

table.results.yields channel	SR_DF0J.81.8125	SR_DF0J.8125.815	SR_DF0J.815.8175	SR_DF0J.8175.82	SR_DF0J.82.8225	SR_DF0J.8225.825	SR_DF0J.825.8275	SR_DF0J.8275.83
Observed events	29	41	32	35	27	31	30	30
Fitted bkg events	31.55 ± 4.81	38.54 ± 12.49	27.50 ± 8.59	28.31 ± 7.60	36.40 ± 7.19	24.37 ± 6.01	29.20 ± 5.90	27.80 ± 5.94
Fitted FNP events	2.13 ± 0.30	3.50 ± 0.41	0.01 ^{+0.06} _{-0.01}	0.01 ^{+0.17} _{-0.01}	6.47 ± 0.76	1.35 ± 0.47	1.65 ± 0.57	0.01 ^{+0.18} _{-0.01}
Fitted Wt events	5.10 ± 1.23	7.06 ± 1.76	2.42 ^{+2.88} _{-2.42}	6.52 ± 1.18	4.36 ± 1.29	3.82 ± 1.97	4.53 ± 0.93	3.76 ± 1.15
Fitted Zjets events	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00
Fitted Zttjets events	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00
Fitted VV events	16.80 ± 4.16	20.51 ± 11.86	17.43 ± 4.62	14.15 ± 7.05	18.56 ± 6.21	13.75 ± 3.83	16.82 ± 4.66	15.79 ± 4.26
Fitted other events	0.04 ^{+0.05} _{-0.04}	0.05 ^{+0.05} _{-0.05}	0.05 ^{+0.09} _{-0.05}	0.16 ± 0.15	0.05 ^{+0.07} _{-0.05}	0.05 ^{+0.06} _{-0.05}	0.05 ± 0.01	1.70 ± 0.20
Fitted VVV events	0.01 ± 0.00	0.00 ± 0.00	0.01 ± 0.01	0.01 ^{+0.01} _{-0.01}	0.00 ^{+0.00} _{-0.00}	0.01 ± 0.01	0.01 ± 0.01	0.01 ± 0.01
Fitted ttbar events	7.48 ± 2.58	7.42 ± 2.29	7.58 ± 6.38	7.47 ± 1.95	6.96 ± 2.92	5.39 ± 2.49	6.14 ± 2.57	6.53 ± 2.34
MC exp. SM events	26.18 ± 3.96	32.02 ± 9.42	22.09 ± 7.67	23.60 ± 5.91	30.61 ± 5.70	20.03 ± 5.05	23.92 ± 4.76	22.84 ± 4.86
MC exp. FNP events	2.13 ± 0.31	3.50 ± 0.42	0.01 ^{+0.07} _{-0.01}	0.01 ^{+0.18} _{-0.01}	6.47 ± 0.79	1.35 ± 0.49	1.65 ± 0.60	0.01 ^{+0.19} _{-0.01}
MC exp. Wt events	4.82 ± 1.19	6.67 ± 1.74	2.29 ^{+2.75} _{-2.29}	6.17 ± 1.16	4.12 ± 1.28	3.61 ± 1.90	4.28 ± 0.92	3.55 ± 1.11
MC exp. Zjets events	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00
MC exp. Zttjets events	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00
MC exp. VV events	12.11 ± 2.87	14.79 ± 8.63	12.57 ± 3.22	10.20 ± 5.17	13.38 ± 4.39	9.91 ± 2.76	12.12 ± 3.29	11.39 ± 3.04
MC exp. other events	0.04 ^{+0.05} _{-0.04}	0.05 ^{+0.05} _{-0.05}	0.05 ^{+0.09} _{-0.05}	0.16 ± 0.16	0.05 ^{+0.07} _{-0.05}	0.05 ^{+0.06} _{-0.05}	0.05 ± 0.01	1.70 ± 0.20
MC exp. VVV events	0.01 ± 0.00	0.00 ± 0.00	0.01 ± 0.01	0.01 ^{+0.01} _{-0.01}	0.00 ^{+0.00} _{-0.00}	0.01 ± 0.01	0.01 ± 0.01	0.01 ± 0.01
MC exp. ttbar events	7.07 ± 2.48	7.01 ± 2.21	7.16 ± 6.07	7.06 ± 1.87	6.58 ± 2.79	5.10 ± 2.37	5.81 ± 2.46	6.17 ± 2.24

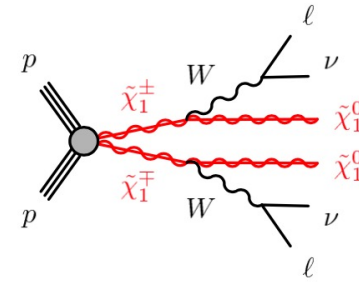
table.results.yields channel	SR_DF0J.83.8325	SR_DF0J.8325.835	SR_DF0J.835.8375	SR_DF0J.8375.84	SR_DF0J.84.845	SR_DF0J.845.85	SR_DF0J.85.86	SR_DF0J.86
Observed events	24	29	19	20	34	27	34	35
Fitted bkg events	29.66 ± 11.63	23.39 ± 9.14	25.96 ± 9.84	25.87 ± 6.08	30.42 ± 7.99	30.11 ± 9.26	36.89 ± 7.12	26.43 ± 8.51
Fitted FNP events	2.32 ± 1.21	0.43 ± 0.43	4.26 ± 1.19	6.05 ± 0.60	0.93 ± 0.72	4.59 ± 0.65	2.15 ± 0.56	0.09 ^{+0.31} _{-0.09}
Fitted Wt events	3.83 ± 2.40	2.46 ^{+2.84} _{-2.46}	3.36 ± 1.29	2.27 ± 0.65	4.55 ± 1.29	2.58 ± 1.10	5.27 ± 2.35	2.95 ± 2.37
Fitted Zjets events	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00
Fitted Zttjets events	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00
Fitted VV events	18.71 ± 10.93	15.72 ± 8.35	14.40 ± 8.98	13.98 ± 5.58	17.95 ± 7.40	17.99 ± 8.03	22.81 ± 6.77	19.23 ± 6.51
Fitted other events	0.06 ± 0.06	0.19 ± 0.10	0.03 ^{+0.05} _{-0.03}	0.01 ^{+0.02} _{-0.01}	0.12 ± 0.08	0.00 ± 0.00	0.11 ± 0.04	0.12 ± 0.02
Fitted VVV events	0.00 ± 0.00	0.01 ± 0.00	0.01 ± 0.00	0.00 ± 0.00	0.01 ± 0.00	0.00 ± 0.00	0.01 ± 0.00	0.01 ± 0.00
Fitted ttbar events	4.73 ± 2.10	4.58 ± 1.09	3.90 ± 1.16	3.56 ± 1.24	6.86 ± 2.13	4.94 ± 2.12	6.55 ± 2.17	4.02 ± 2.16
MC exp. SM events	23.98 ± 8.71	18.62 ± 6.96	21.54 ± 7.42	21.65 ± 4.57	24.79 ± 6.13	24.68 ± 7.20	29.89 ± 5.58	20.68 ± 6.90
MC exp. FNP events	2.32 ± 1.27	0.43 ^{+0.45} _{-0.43}	4.26 ± 1.24	6.05 ± 0.61	0.93 ± 0.75	4.59 ± 0.67	2.15 ± 0.58	0.09 ^{+0.32} _{-0.09}
MC exp. Wt events	3.62 ± 2.29	2.33 ^{+2.71} _{-2.33}	3.17 ± 1.27	2.15 ± 0.64	4.30 ± 1.28	2.44 ± 1.07	4.98 ± 2.27	2.79 ± 2.25
MC exp. Zjets events	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00
MC exp. Zttjets events	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00
MC exp. VV events	13.49 ± 7.84	11.33 ± 5.99	10.38 ± 6.46	10.08 ± 4.02	12.94 ± 5.29	12.97 ± 5.89	16.44 ± 4.80	13.87 ± 4.81
MC exp. other events	0.06 ± 0.06	0.19 ± 0.10	0.03 ^{+0.05} _{-0.03}	0.01 ^{+0.02} _{-0.01}	0.12 ± 0.08	0.00 ± 0.00	0.11 ± 0.04	0.12 ± 0.02
MC exp. VVV events	0.00 ± 0.00	0.01 ± 0.00	0.01 ± 0.00	0.00 ± 0.00	0.01 ± 0.00	0.00 ± 0.00	0.01 ± 0.00	0.01 ± 0.00
MC exp. ttbar events	4.48 ± 2.02	4.33 ± 1.04	3.69 ± 1.11	3.36 ± 1.18	6.49 ± 2.04	4.67 ± 2.02	6.19 ± 2.08	3.80 ± 2.06

C1C1 WW analysis

SRs



8 SFOJ SRs
starting from BDT signal > 0.77
requiring BDT others < 0.01

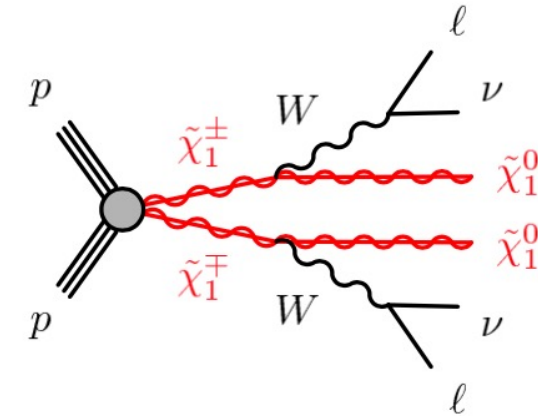
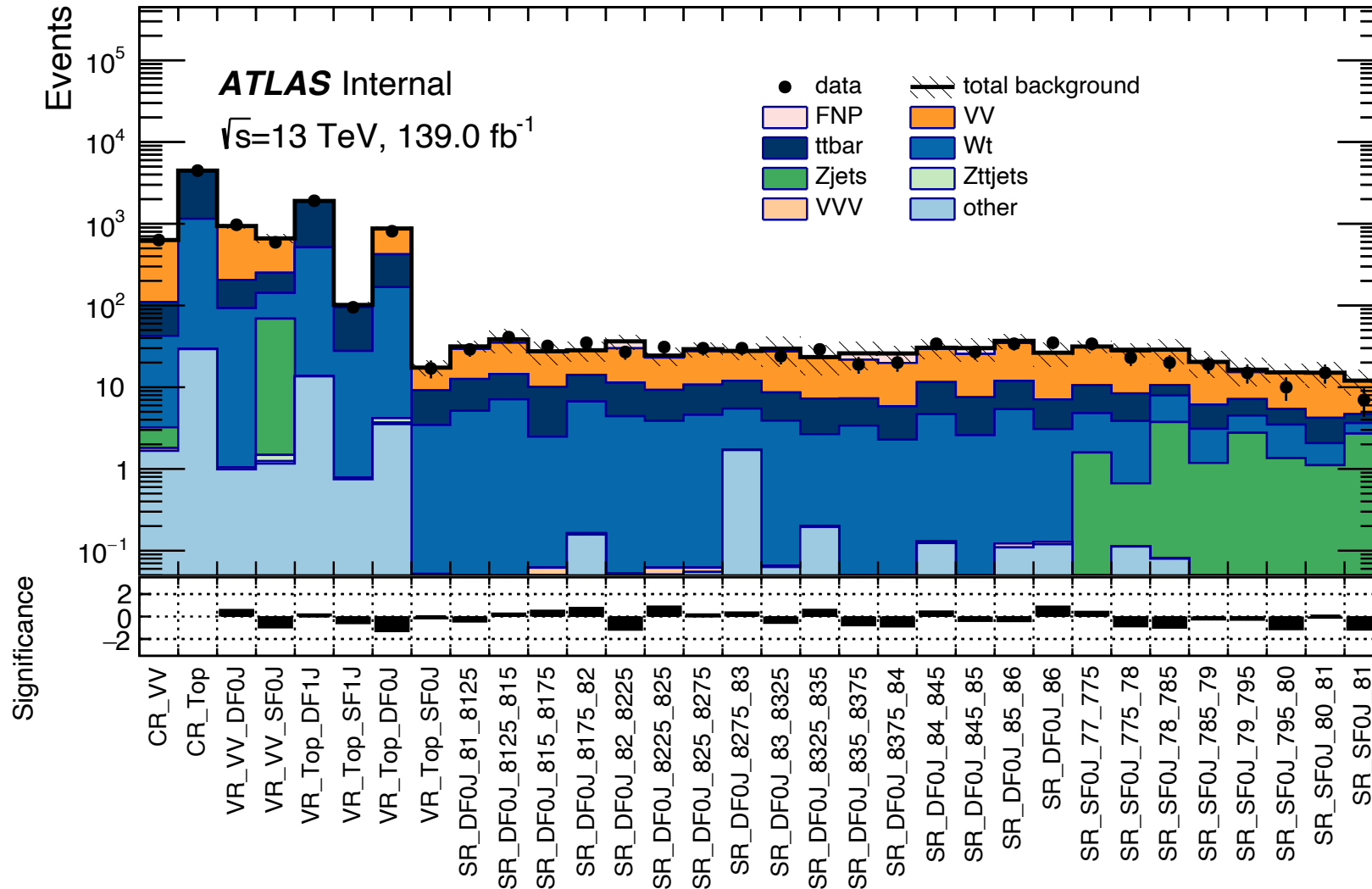


- Shape fit to enhance sensitivity. SRs binned in BDT signal score.

table.results.yields channel	SR_SF0J_77-775	SR_SF0J_775-78	SR_SF0J_78-785	SR_SF0J_785-79	SR_SF0J_79-795	SR_SF0J_795-80	SR_SF0J_80-81	SR_SF0J_81
Observed events	34	23	20	19	15	10	15	7
Fitted bkg events	31.47 ± 5.04	28.73 ± 5.60	28.80 ± 9.41	20.42 ± 7.18	16.38 ± 6.13	15.19 ± 3.92	15.05 ± 5.16	12.05 ± 4.13
Fitted FNP events	$0.01^{+0.22}_{-0.01}$	1.41 ± 0.28	$0.01^{+0.10}_{-0.01}$	$0.01^{+0.02}_{-0.01}$	1.11 ± 0.31	$0.01^{+0.07}_{-0.01}$	$0.01^{+0.12}_{-0.01}$	$0.01^{+0.05}_{-0.01}$
Fitted Wt events	3.23 ± 1.17	3.20 ± 1.25	4.18 ± 1.54	1.91 ± 1.10	1.73 ± 0.78	2.13 ± 0.88	0.96 ± 0.63	0.93 ± 0.32
Fitted Zjets events	$1.57^{+1.88}_{-1.57}$	$0.56^{+1.02}_{-0.56}$	3.66 ± 2.47	$1.18^{+2.43}_{-1.18}$	2.77 ± 1.66	1.35 ± 0.30	$1.09^{+1.36}_{-1.09}$	2.70 ± 2.48
Fitted Zttjets events	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00
Fitted VV events	20.88 ± 3.54	18.91 ± 4.22	18.17 ± 8.24	14.27 ± 3.95	8.12 ± 4.47	9.78 ± 3.23	10.82 ± 4.51	7.35 ± 2.12
Fitted other events	$0.01^{+0.03}_{-0.01}$	0.11 ± 0.01	0.08 ± 0.04	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.02 ± 0.00	0.00 ± 0.00
Fitted VVV events	0.01 ± 0.00	$0.00^{+0.00}_{-0.00}$	0.00 ± 0.00	0.00 ± 0.00	$0.00^{+0.00}_{-0.00}$	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00
Fitted ttbar events	5.76 ± 2.05	4.54 ± 1.70	2.69 ± 1.72	$3.04^{+5.06}_{-3.04}$	2.65 ± 2.46	1.92 ± 1.11	2.15 ± 2.07	1.04 ± 0.54
MC exp. SM events	25.15 ± 4.43	23.03 ± 4.59	23.35 ± 7.43	16.17 ± 6.46	13.87 ± 5.14	12.24 ± 3.17	11.86 ± 4.02	9.89 ± 3.72
MC exp. FNP events	$0.01^{+0.23}_{-0.01}$	1.41 ± 0.29	$0.01^{+0.11}_{-0.01}$	$0.01^{+0.02}_{-0.01}$	1.11 ± 0.31	$0.01^{+0.07}_{-0.01}$	$0.01^{+0.13}_{-0.01}$	$0.01^{+0.05}_{-0.01}$
MC exp. Wt events	3.05 ± 1.14	3.02 ± 1.20	3.95 ± 1.50	1.81 ± 1.05	1.64 ± 0.75	2.01 ± 0.85	0.91 ± 0.60	0.88 ± 0.32
MC exp. Zjets events	$1.57^{+1.90}_{-1.57}$	$0.55^{+1.02}_{-0.55}$	3.66 ± 2.49	$1.18^{+2.45}_{-1.18}$	2.77 ± 1.67	1.35 ± 0.30	$1.09^{+1.37}_{-1.09}$	2.70 ± 2.50
MC exp. Zttjets events	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00
MC exp. VV events	15.05 ± 2.50	13.64 ± 3.15	13.10 ± 5.84	10.29 ± 2.87	5.85 ± 3.22	7.05 ± 2.42	7.80 ± 3.24	5.30 ± 1.50
MC exp. other events	$0.01^{+0.03}_{-0.01}$	0.11 ± 0.01	0.08 ± 0.04	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.02 ± 0.00	0.00 ± 0.00
MC exp. VVV events	0.01 ± 0.00	$0.00^{+0.00}_{-0.00}$	0.00 ± 0.00	0.00 ± 0.00	$0.00^{+0.00}_{-0.00}$	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00
MC exp. ttbar events	5.45 ± 1.95	4.30 ± 1.62	2.54 ± 1.64	$2.87^{+4.81}_{-2.87}$	2.50 ± 2.34	1.81 ± 1.05	2.03 ± 1.97	0.99 ± 0.51

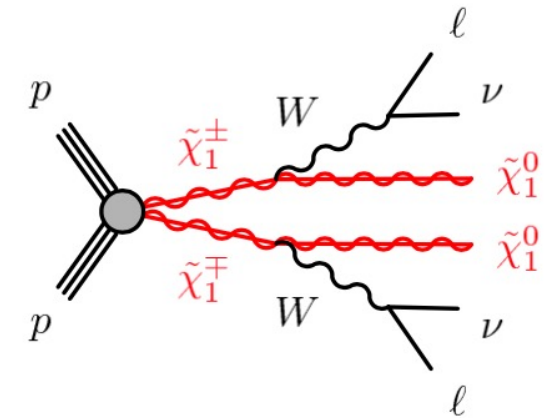
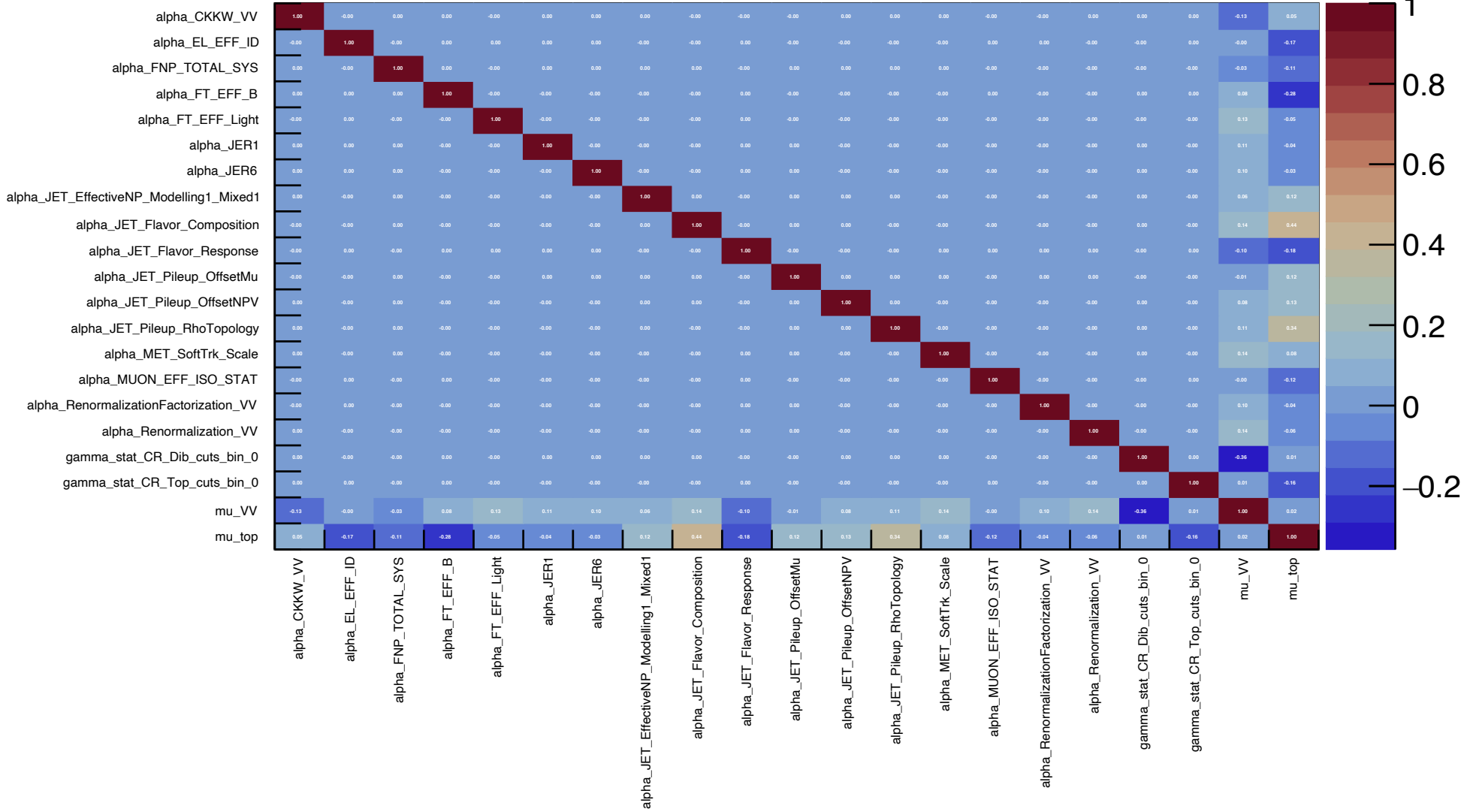
C1C1 WW analysis

- Bkg-only fit pullplot (using ATLAS recommended formula for the significance).
- All pulls ≈ 1 , the largest one occurs to be in a VR.



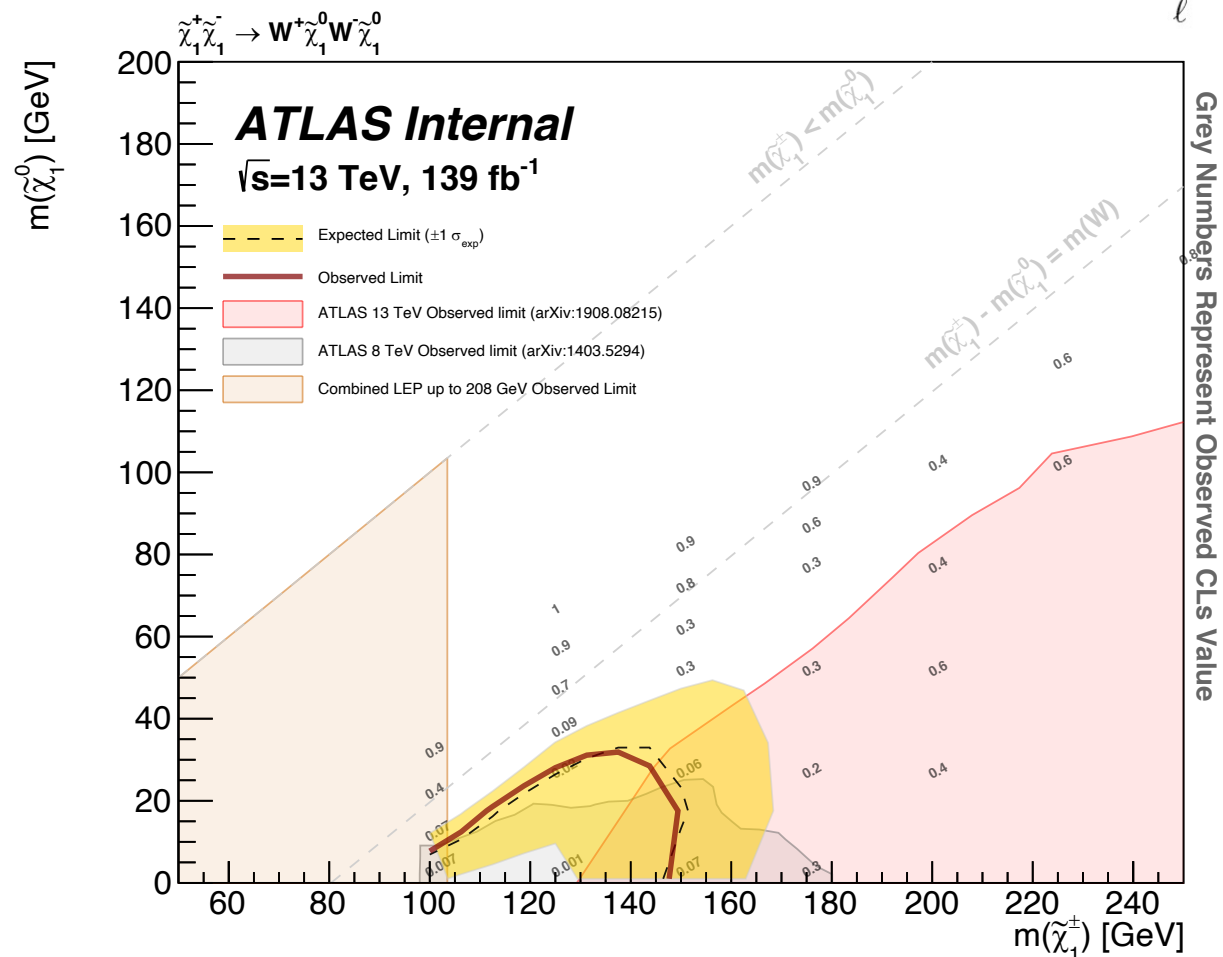
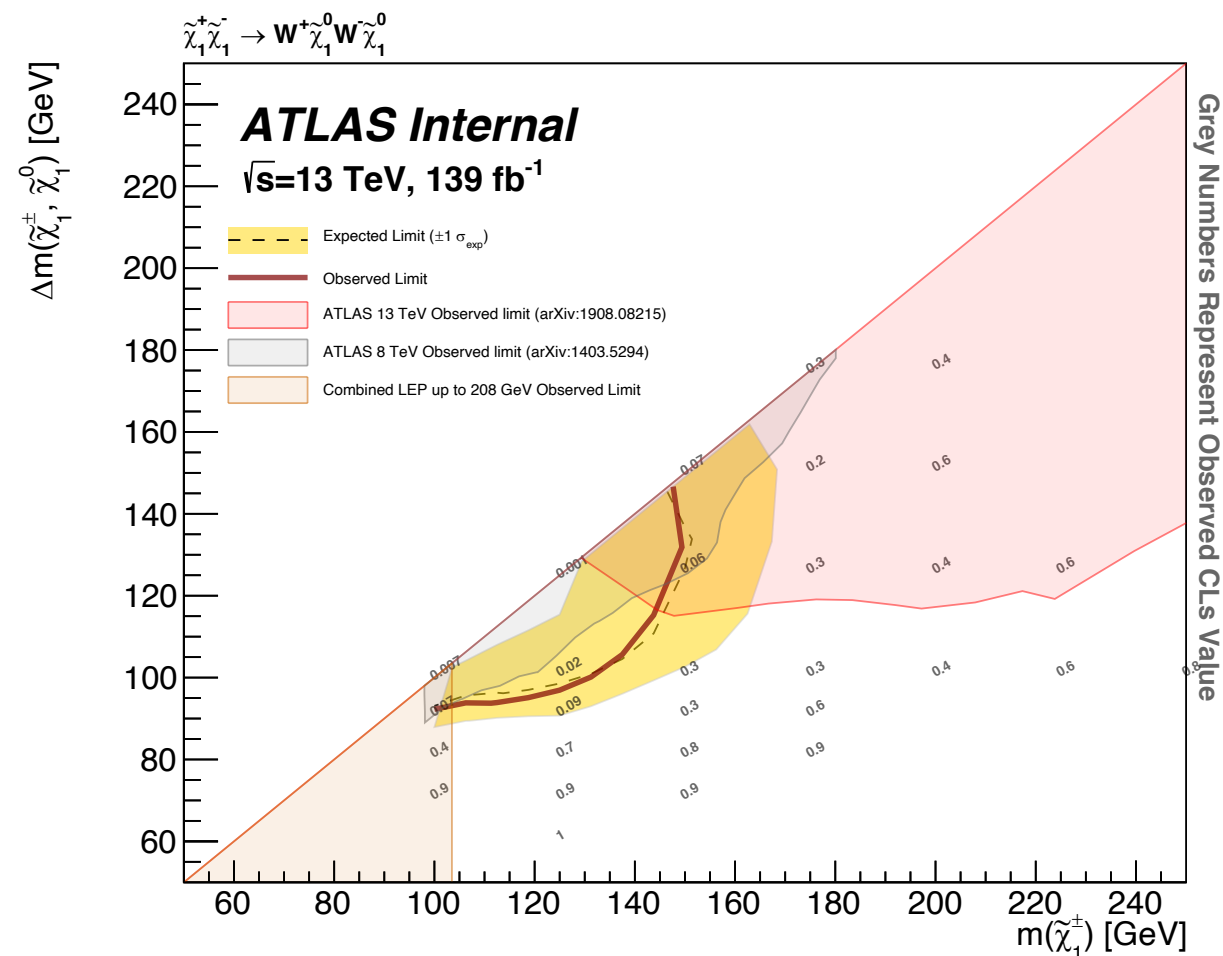
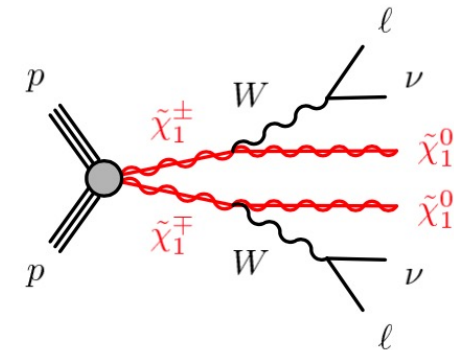
C1C1 WW analysis

Correlations



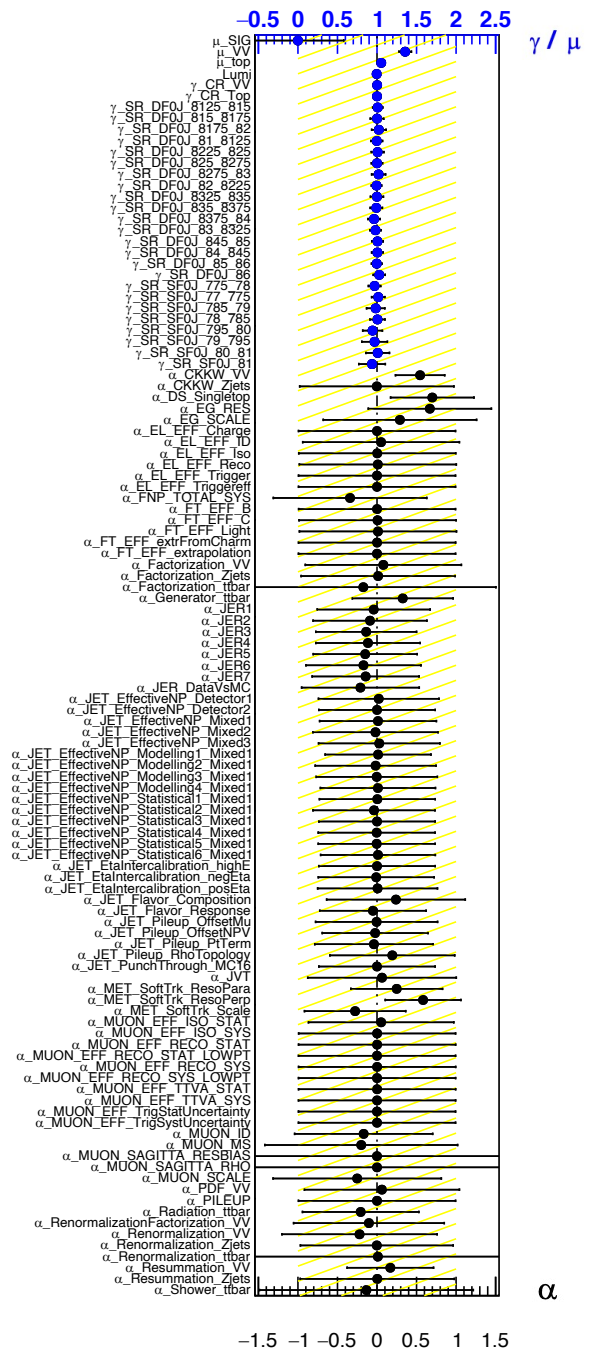
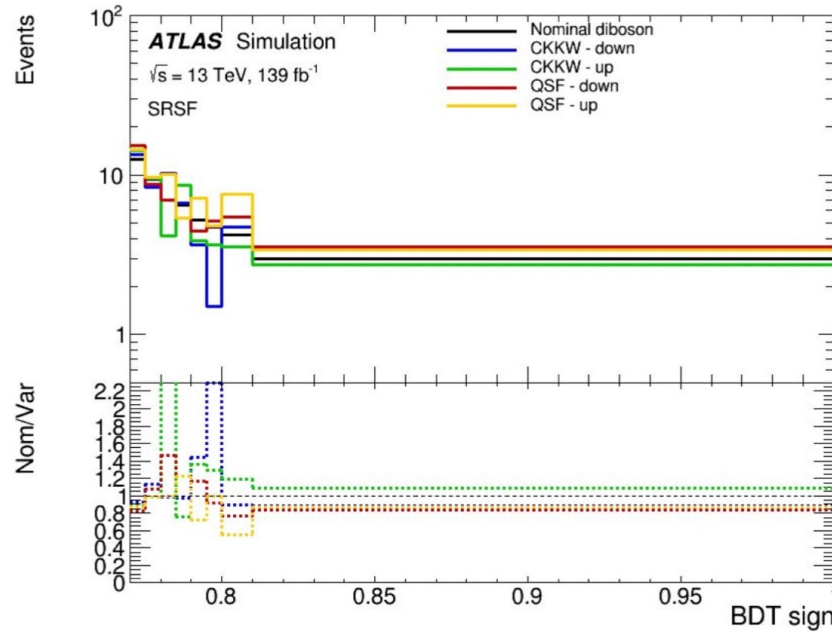
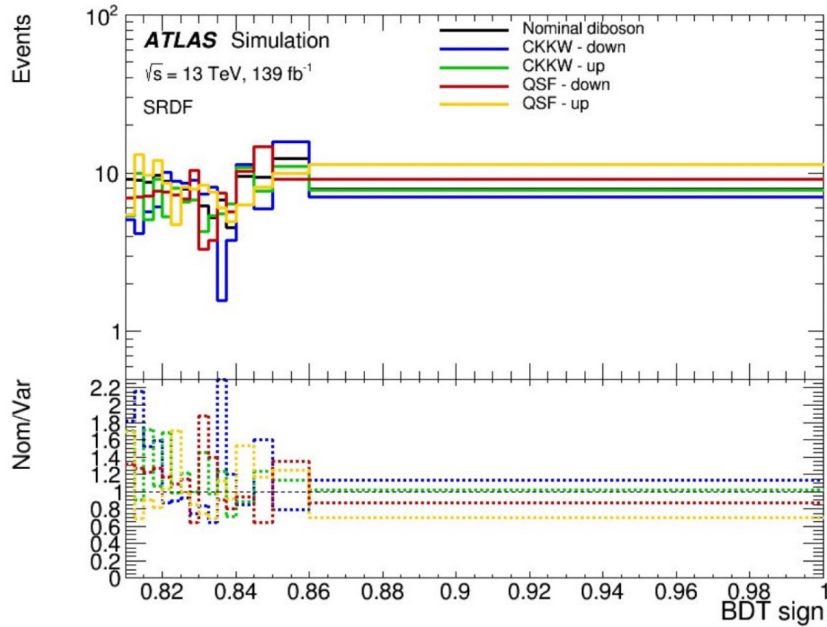
C1C1 WW analysis

Exclusion contours



C1C1 WW analysis

- Fit parameters for exclusion point 100_10.
- Found some pulling and profiling, especially for the theoretical uncertainties



Model independent signal fit

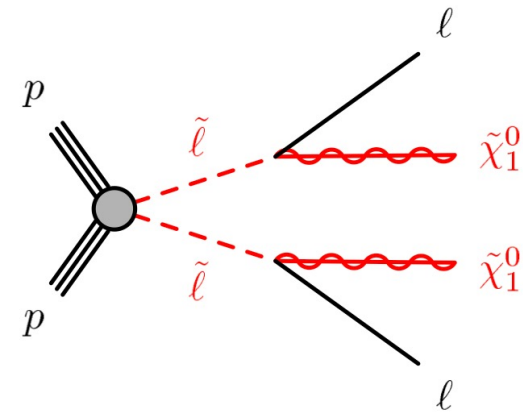
- An analysis searching for new physics phenomena typically sets model-independent upper limits on the number of events beyond the expected number of events in each SR. In this way, for any signal model of interest, anyone can estimate the number of signal events predicted in a particular signal region and check if the model has been excluded by current measurements or not.
- Setting the upper limit is accomplished by performing a model-independent signal fit. For this fit strategy, both the CRs and SRs are used, in the same manner as for the model-dependent signal fit. Signal contamination is not allowed in the CRs, but no other assumptions are made for the signal model, also called a “dummy signal” prediction. The SR in this fit configuration is constructed as a single-bin region, since having more bins requires assumptions on the signal spread over these bins. The number of signal events in the signal region is added as a parameter to the fit. Otherwise, the fit proceeds in the same way as the model-dependent signal fit.
- The model-independent signal fit strategy, fitting both the CRs and each SR, is also used to perform the background-only hypothesis test, which quantifies the significance of any observed excess of events in a SR, again in a manner that is independent of any particular signal model. The background-only hypothesis test quantifies the significance of an excess of events in the signal region by the probability that a background-only experiment is more signal-like than observed, also called the discovery p-value. The probability of the SM background to fluctuate to the observed number of events or higher in each SR has been capped at 0.5.

Slepton analysis

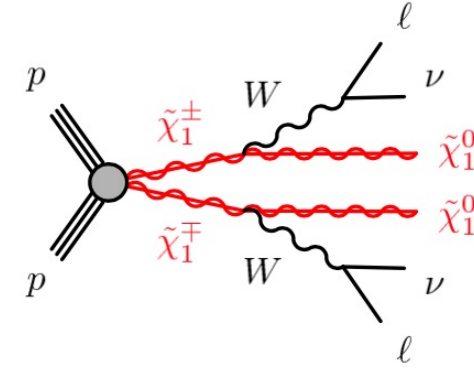
- For the model independent limits, 10 inclusive regions have been defined.
- Each fit will only include a single inclusive bin. The inclusive regions are defined, using the m_{T2}^{100} variable, asking for: $m_{T2}^{100} > 100$, $m_{T2}^{100} > 110$, $m_{T2}^{100} > 120$, $m_{T2}^{100} > 130$, $m_{T2}^{100} > 140$.

Signal region	Observed	Expected	$\langle \epsilon\sigma \rangle_{\text{obs}}^{95}$ [fb]	S_{obs}^{95}	S_{exp}^{95}	CL_B	$p(s = 0)$ (Z)
SR ^{0-jet} $m_{T2}^{100} \in [100, \infty)$	58	77.52 ± 13.31	0.12	17.0	25.7 ^{+10.0} _{-5.8}	0.12	0.93 (-1.51)
SR ^{0-jet} $m_{T2}^{100} \in [110, \infty)$	39	60.00 ± 10.77	0.09	13.0	20.9 ^{+7.8} _{-6.0}	0.05	0.98 (-2.07)
SR ^{0-jet} $m_{T2}^{100} \in [120, \infty)$	30	40.92 ± 8.74	0.10	13.3	18.6 ^{+6.4} _{-5.5}	0.17	0.94 (-1.53)
SR ^{0-jet} $m_{T2}^{100} \in [130, \infty)$	23	26.12 ± 6.32	0.10	13.9	15.3 ^{+6.0} _{-3.9}	0.38	0.80 (-0.84)
SR ^{0-jet} $m_{T2}^{100} \in [140, \infty)$	7	9.35 ± 3.39	0.06	7.7	8.6 ^{+3.3} _{-2.5}	0.36	0.82 (-0.92)
SR ^{1-jet} $m_{T2}^{100} \in [100, \infty)$	82	74.81 ± 13.44	0.27	37.0	31.0 ^{+12.0} _{-8.1}	0.69	0.28 (0.59)
SR ^{1-jet} $m_{T2}^{100} \in [110, \infty)$	39	49.35 ± 16.99	0.17	24.0	27.4 ^{+8.5} _{-6.4}	0.32	0.93 (-1.46)
SR ^{1-jet} $m_{T2}^{100} \in [120, \infty)$	12	17.45 ± 5.31	0.07	9.2	11.5 ^{+4.2} _{-3.1}	0.24	0.98 (-2.09)
SR ^{1-jet} $m_{T2}^{100} \in [130, \infty)$	2	6.83 ± 2.71	0.03	4.2	6.0 ^{+2.6} _{-1.7}	0.11	0.57 (-0.17)
SR ^{1-jet} $m_{T2}^{100} \in [140, \infty)$	0	2.36 ± 1.52	0.02	3.0	3.5 ^{+1.6} _{-0.6}	0.14	0.55 (-0.12)

Table 54: Left to right: observed yields, expected yields, 95% CL upper limits on the visible cross section ($\langle \epsilon\sigma \rangle_{\text{obs}}^{95}$) and on the number of signal events (S_{obs}^{95}). The third column (S_{exp}^{95}) shows the 95% CL upper limit on the number of signal events, given the expected number (and $\pm 1\sigma$ excursions on the expectation) of background events. The last column indicates the discovery p -value ($p(s = 0)$). The p -value is reported as 0.5 if the observed yield is smaller than the predicted.



C1C1 WW analysis



- A looser region discovery (SRD_DF0J_81_SF0J_77) with higher statistics including all the bins for the binned exclusion fit.
- Tighter regions are defined by taking BDT signal > 0.81 for DF0J and > 0.77 for SF0J which correspond to the significance peaks.

Signal channel	$\langle \epsilon\sigma \rangle_{obs}^{95}$ [fb]	S_{obs}^{95}	S_{exp}^{95}	CL_B	$p(s=0)$ (Z)
SRD_DF0J_81_SF0J_77	1.09	150.8	$154.7^{+59.3}_{-46.0}$	0.47	0.50 (0.00)
SRD_DF0J_81	0.82	114.3	$108.7^{+44.1}_{-31.7}$	0.55	0.44 (0.16)
SRD_DF0J_82	0.57	78.9	$82.3^{+33.3}_{-23.7}$	0.45	0.50 (0.00)
SRD_DF0J_83	0.40	55.1	$59.3^{+23.3}_{-16.5}$	0.41	0.50 (0.00)
SRD_DF0J_84	0.30	42.0	$38.5^{+14.5}_{-10.1}$	0.61	0.37 (0.32)
SRD_DF0J_85	0.23	32.0	$28.5^{+11.5}_{-7.8}$	0.65	0.33 (0.43)
SRD_SF0J_77	0.57	79.5	$106.2^{+13.1}_{-42.5}$	0.25	0.50 (0.00)
SRD_SF0J_78	0.45	62.6	$75.2^{+6.1}_{-16.5}$	0.22	0.50 (0.00)
SRD_SF0J_79	0.24	33.6	$36.7^{+8.6}_{-5.8}$	0.26	0.50 (0.00)
SRD_SF0J_80	0.14	19.9	$20.4^{+3.1}_{-0.9}$	0.30	0.50 (0.00)

Table 1: Left to right: 95% CL upper limits on the visible cross section ($\langle \epsilon\sigma \rangle_{obs}^{95}$) and on the number of signal events (S_{obs}^{95}). The third column (S_{exp}^{95}) shows the 95% CL upper limit on the number of signal events, given the expected number (and $\pm 1\sigma$ excursions on the expectation) of background events. The last two columns indicate the CL_B value, i.e. the confidence level observed for the background-only hypothesis, and the discovery p -value ($p(s=0)$).

Summary & outlook

- Slepton & C1C1 analyses
 - Both analyses unblinded and fit results presented to the SUSY WG
 - Data compatible with SM expectations
 - No significant data excess in the slepton analysis
 - No significant data excess in the C1C1 analysis (with all pulls $\lesssim 1$, the largest one occurs to be in a VR).
 - Observed exclusion limits slightly extending the previous ones.
- Both analyses are still wip and targeting SUSY WG Approval:
 - theory uncertainty for signal to be implemented
 - preparation of paper draft
 - recast workflow
 - provide material for combination
 - provide material for HEP-data

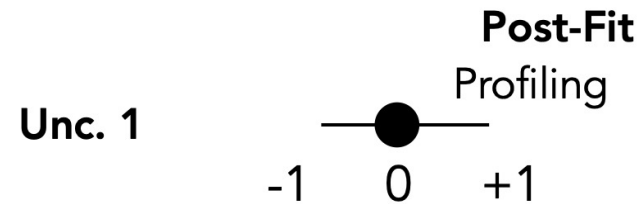
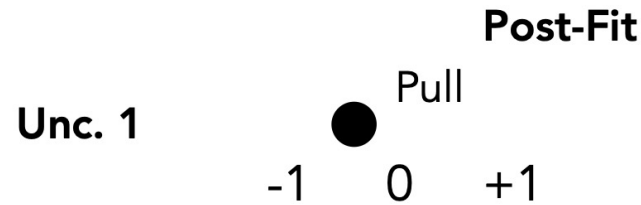
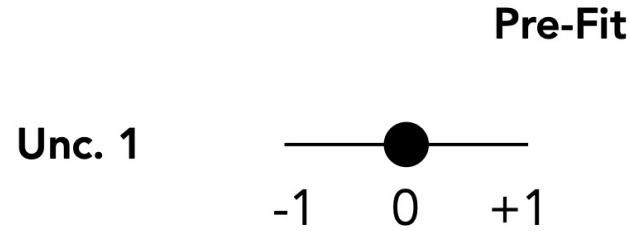
Backup

Definition of analysis variables

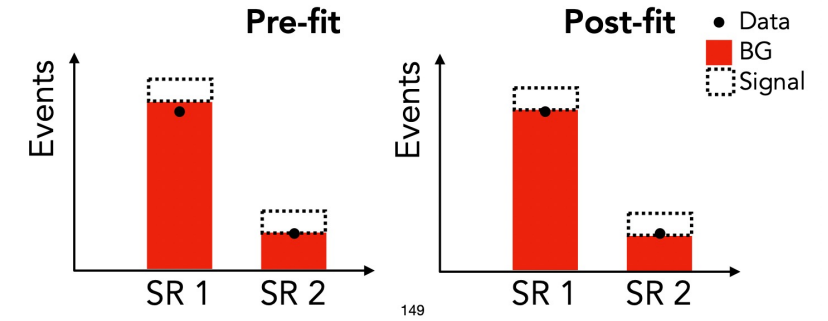
- $p_T^{\ell_1}$: the transverse momentum of the leading lepton
- $p_T^{\ell_2}$: the transverse momentum of the subleading lepton
- $m_{\ell\ell}$: the invariant mass of the two leptons
- $\Delta\phi_{\ell_1,\ell_2}$: the azimuthal angular separation between the two leptons
- $\Delta\phi_{E_T^{miss},\ell_1}$: the azimuthal angular separation between E_T^{miss} and the leading lepton
- $p_{T,boost}^{\ell\ell}$: the module of the vectorial sum of the p_T of the two leptons and the E_T^{miss}
- $m_{T2}^{m_\chi}$, the transverse mass as defined in [1, 2] with m_χ the mass of the invisible particles
- $\cos\theta_{\ell\ell}^* = \cos(2 \tan^{-1}(e^{\Delta\eta_{\ell\ell}/2})) = \tanh(e^{\Delta\eta_{\ell\ell}/2})$, sensitive to the spin of the particles [3]
- $\Delta\phi_{boost}$: the azimuthal angular separation between E_T^{miss} and the vectorial sum of the two leptons p_T and the E_T^{miss}

Systematic pulling and profiling

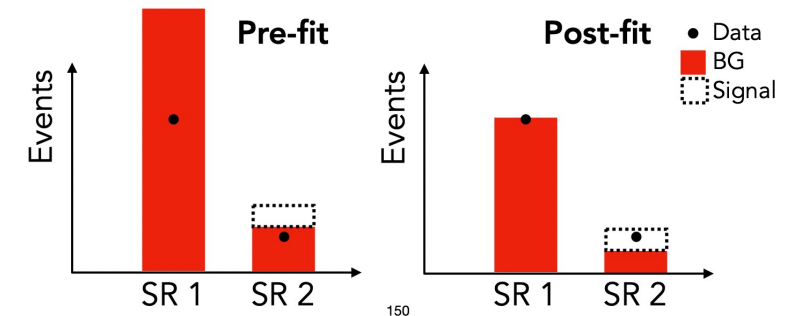
- The fits that we do don't *only* change normalizations
- They also "profile uncertainties"
 - They change the prediction within its uncertainties to better match the data (pulling)
 - They test the uncertainties for (in)consistency with the data and automatically reduce uncertainties that are demonstrably "too large" to be allowed (profiling)



- In simple cases, it's clear what happens



- But there are some cases where the outcome is the opposite of what one would expect. Particularly when the signal doesn't evenly populate bins and some signal region is constraining the background.



Slepton analysis

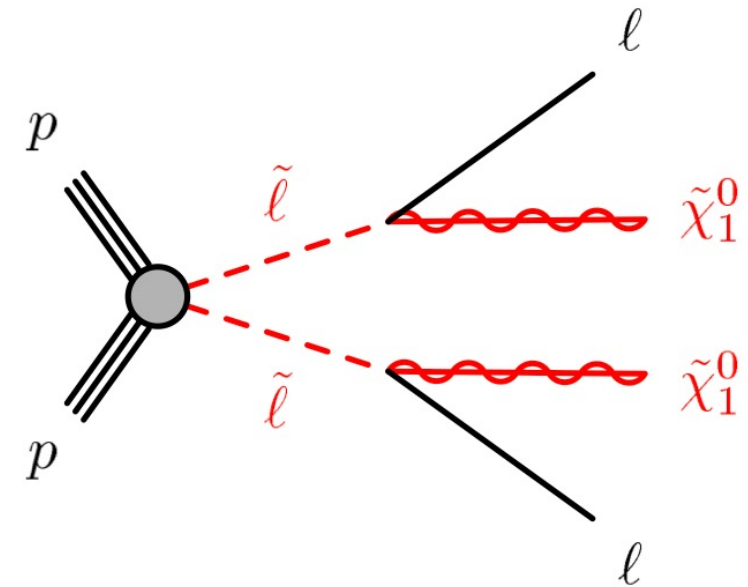
Efficiency correction method

This technique consists in reweighting, on an event-by-event basis, for the reconstruction, isolation, identification and trigger efficiencies.

$$\kappa = \sqrt{\frac{N_{\mu^+\mu^-}}{N_{e^+e^-}}} \quad \text{reconstruction, isolation, identification efficiency}$$

Reconstruction efficiencies can depend on the pseudo-rapidity region where the leptons reach the detector

		MC (FS)	Data
Inclusive η	κ	1.1576 ± 0.0014	1.1942 ± 0.0043
$ \eta < 0.1$ region	$\kappa^{central}$	0.8509 ± 0.0042	0.852 ± 0.013
$ \eta < 1.05$	$\kappa^{bar-bar}$	1.0352 ± 0.0029	1.0655 ± 0.0089
$ \eta > 1.05$	$\kappa^{end-end}$	1.38526 ± 0.0042	1.440 ± 0.010
	$\kappa^{bar-end}$	1.1947 ± 0.0020	1.2198 ± 0.0061



A fit performed in every $|\eta|$ region

$$\kappa(p_T^{\ell_1}) = b + \frac{a}{p_T^{\ell_1}}$$

a Central = 16.238

a BarEnd= 25.8058

b Central = 0.600167

b BarEnd= 0.819979

a BarBar= 19.2825

a EndEnd= 34.9074

b BarBar = 0.764995

a EndEnd= 0.871159

Sleptons: Yield Tables

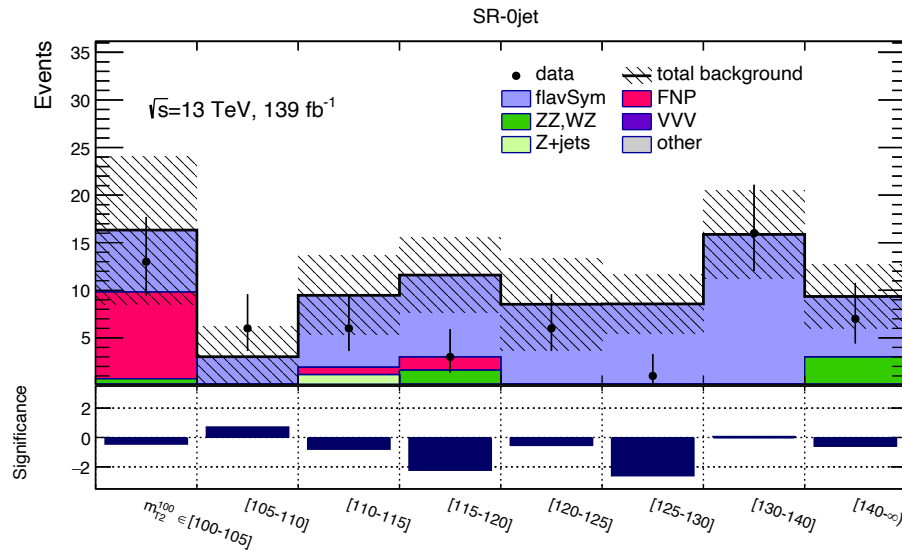
SR-Ojet

$m_{T2}^{100} \in$	[100, 105]	[105, 110]	[110, 115]	[115, 120]	[120, 125]	[125, 130]	[130, 140]	[140, ∞)
Observed events	13	6	6	3	6	1	16	7
MC exp. SM events	16.33 ± 7.77	$3.02^{+3.14}_{-3.02}$	9.47 ± 4.16	11.60 ± 3.93	8.53 ± 4.83	8.57 ± 3.11	15.87 ± 4.63	9.35 ± 3.39
MC exp. other events	$0.03^{+0.08}_{-0.03}$	0.00 ± 0.00	0.03 ± 0.01	0.00 ± 0.00	0.00 ± 0.00	$0.01^{+0.01}_{-0.01}$	0.05 ± 0.03	0.00 ± 0.00
MC exp. VVV events	0.01 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	$0.00^{+0.00}_{-0.00}$	0.00 ± 0.00	0.00 ± 0.00
MC exp. ZZ events	0.64 ± 0.32	$0.01^{+0.01}_{-0.01}$	0.01 ± 0.00	1.59 ± 0.73	0.01 ± 0.01	0.01 ± 0.00	0.01 ± 0.00	2.98 ± 1.39
MC exp. Zjets events	$0.01^{+0.03}_{-0.01}$	$0.01^{+0.03}_{-0.01}$	$1.10^{+1.80}_{-1.10}$	$0.01^{+0.03}_{-0.01}$	$0.01^{+0.03}_{-0.01}$	0.07 ± 0.04	$0.03^{+0.16}_{-0.03}$	$0.01^{+0.03}_{-0.01}$
MC exp. flavSym events	6.52 ± 2.75	$2.99^{+3.11}_{-2.99}$	7.56 ± 3.00	8.61 ± 2.95	8.50 ± 4.81	8.47 ± 3.07	15.78 ± 4.61	6.35 ± 2.26
MC exp. FNP events	9.12 ± 5.67	$0.01^{+0.02}_{-0.01}$	0.76 ± 0.75	1.38 ± 0.52	$0.01^{+0.01}_{-0.01}$	$0.01^{+0.02}_{-0.01}$	0.00 ± 0.00	0.01 ± 0.01

SR-1jet

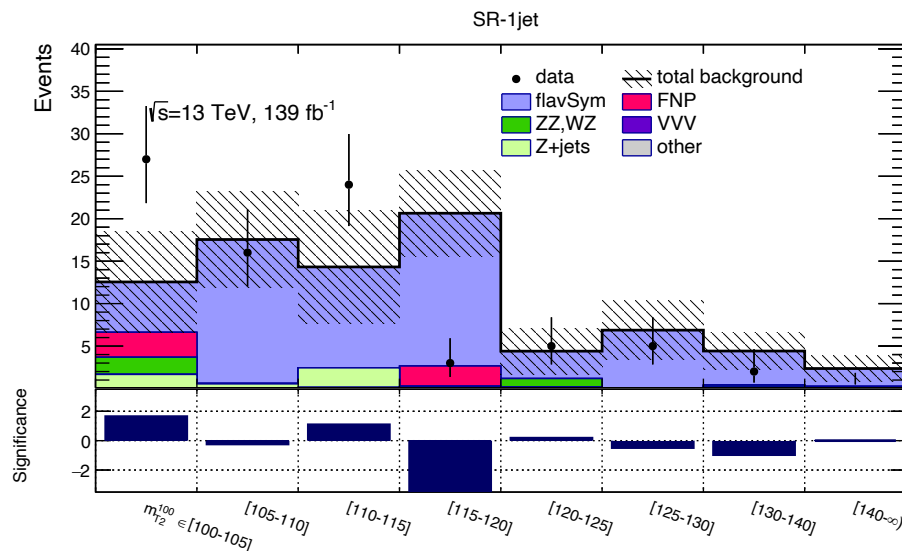
$m_{T2}^{100} \in$	[100, 105]	[105, 110]	[110, 115]	[115, 120]	[120, 125]	[125, 130]	[130, 140]	[140, ∞)
Observed events	27	16	24	3	5	5	2	0
MC exp. SM events	12.55 ± 5.94	17.55 ± 5.63	14.32 ± 6.62	20.64 ± 5.04	4.40 ± 2.69	6.88 ± 3.43	4.42 ± 2.17	2.36 ± 1.52
MC exp. other events	0.00 ± 0.00	$0.02^{+0.02}_{-0.02}$	0.14 ± 0.11	0.23 ± 0.13	$0.01^{+0.02}_{-0.01}$	$0.03^{+0.05}_{-0.03}$	0.05 ± 0.02	0.00 ± 0.00
MC exp. VVV events	0.01 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.01 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00
MC exp. ZZ events	2.02 ± 0.89	0.05 ± 0.02	0.01 ± 0.00	0.01 ± 0.00	0.98 ± 0.61	0.01 ± 0.01	0.24 ± 0.12	0.22 ± 0.14
MC exp. Zjets events	$1.65^{+2.33}_{-1.65}$	0.53 ± 0.26	$2.28^{+3.29}_{-2.28}$	$0.01^{+0.46}_{-0.01}$	0.18 ± 0.12	$0.01^{+0.03}_{-0.01}$	$0.09^{+0.50}_{-0.09}$	$0.02^{+0.32}_{-0.02}$
MC exp. flavSym events	5.93 ± 3.00	16.95 ± 5.46	11.87 ± 4.87	18.00 ± 4.46	3.22 ± 1.98	6.82 ± 3.40	4.02 ± 1.93	2.11 ± 1.33
MC exp. FNP events	2.94 ± 1.46	$0.01^{+0.27}_{-0.01}$	$0.01^{+0.09}_{-0.01}$	2.39 ± 0.60	$0.01^{+0.02}_{-0.01}$	0.01 ± 0.01	0.01 ± 0.01	0.01 ± 0.01

Pullplots



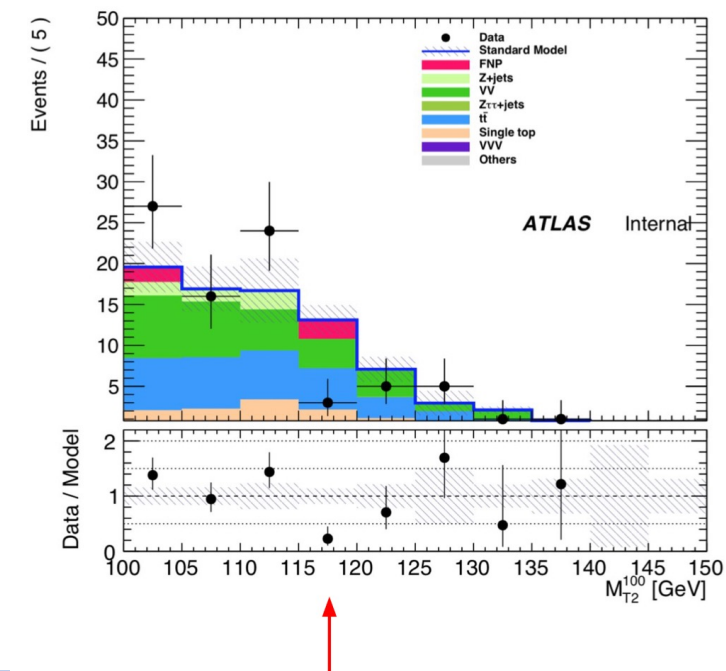
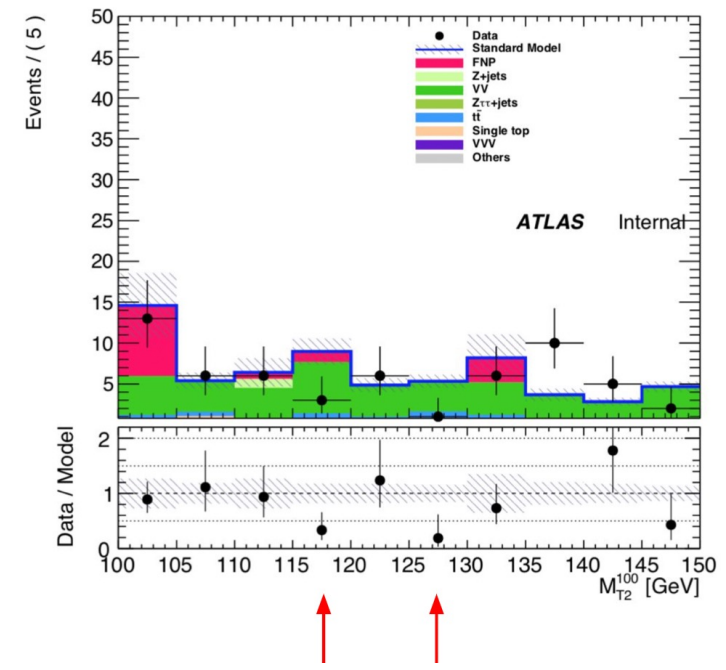
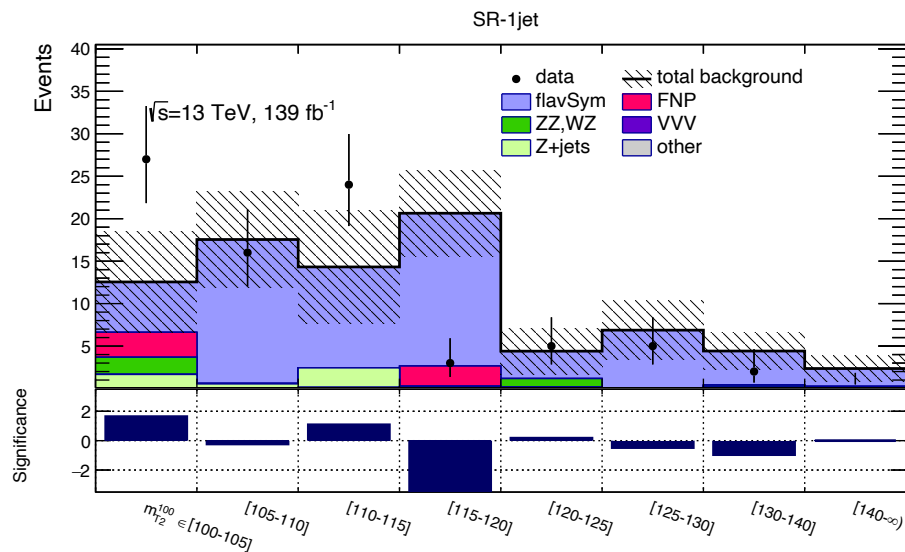
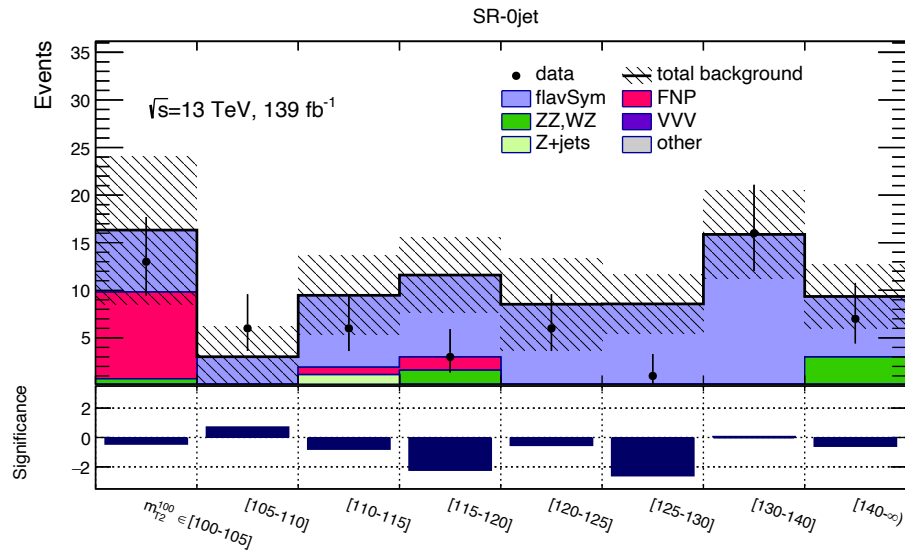
SR-0jet: the expected background overestimates the observed data in two m_{T2} bins, with a significance of about -2σ .

Fluctuations also observed when using pure MC for the FS estimate, suggesting that the observed disagreement is most likely arising from statistical under-fluctuations of the data.



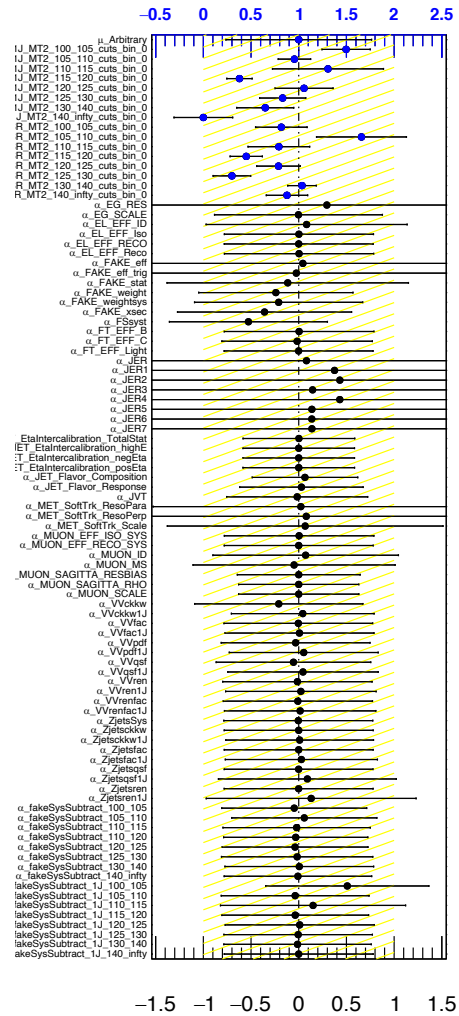
SR-1jet: two bins with excesses of about 1.5σ and one bin with a -3.5σ overestimation of the background are observed. Related to statistical fluctuations of data in SRDF-1jet (documented in Appendix D). Cross-checked with the 0-jet case where a similar behaviour with respect to the data-driven estimate was observed.

Pullplots



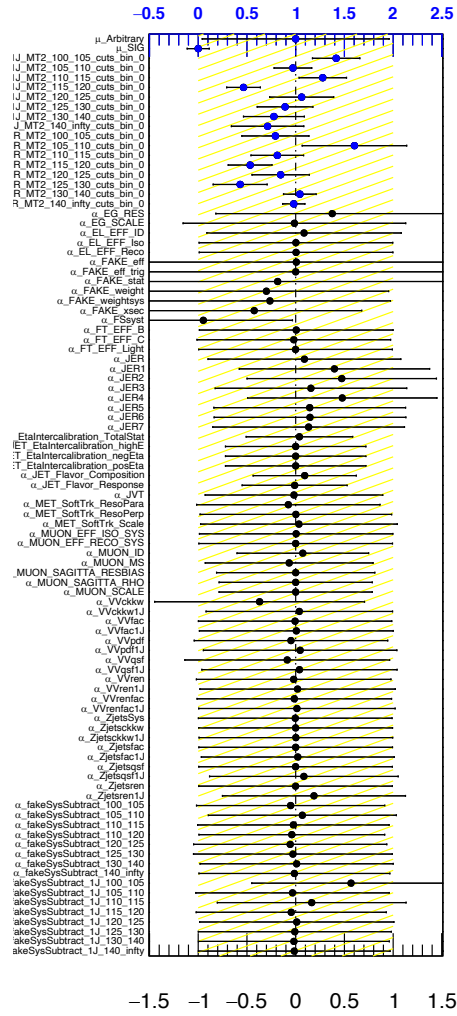
Fit parameters

Exclusion 200_10



α

SRs -> CRs



α

- No systematic pulling/profiling for blinded SRs as pre-fit yields = post-fit yields.
- Some pulling/profiling for unblinded SRs due to statistical fluctuations of data which constrain systematics in unblinded SRs.
- Cross-checked with a fit using all the SRs as CRs: similar systematic pulling/profiling.

C1C1WW – Normalization strategy

- Fitted_VV_in_CR_VV = μ_{VV} * expected_VV_events_in_CR_VV

$$\mu_{VV} = \frac{\text{Fitted_VV_in_CR_VV}}{\text{expected_VV_events_in_CR_VV}}$$

- Fitted_Top_in_CR_Top = μ_{top} * expected_Top_events_in_CR_Top

$$\mu_{top} = \frac{\text{Fitted_Top_in_CR_Top}}{\text{expected_Top_events_in_CR_Top}}$$

- Normalization strategy (fitted_events = observed_events)

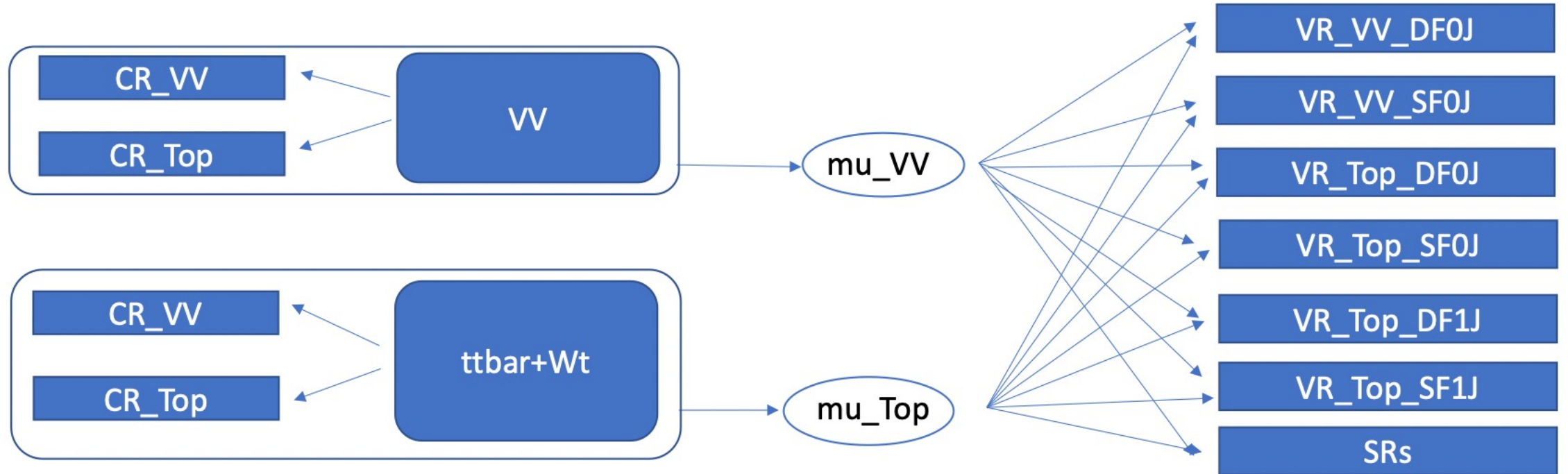
$$\begin{cases} \text{Obs_events_in_CR_VV} = (\mu_{VV} * \text{exp_VV_events_in_CR_VV}) + (\mu_{top} * \text{exp_Top_events_in_CR_VV}) + \text{exp_otherBkg_events_in_CR_VV} \\ \text{Obs_events_in_CR_Top} = (\mu_{VV} * \text{exp_VV_events_in_CR_Top}) + (\mu_{top} * \text{exp_Top_events_in_CR_Top}) + \text{exp_otherBkg_events_in_CR_Top} \end{cases}$$

$$\mu_{VV} = \frac{\text{exp_Top_events_in_CR_VV} (\text{exp_otherBkg_events_in_CR_Top} - \text{Obs_events_in_CR_Top}) + \text{exp_Top_events_in_CR_Top} (\text{Obs_events_in_CR_VV} - \text{exp_otherBkg_events_in_CR_VV})}{(\text{exp_Top_events_in_CR_Top} * \text{exp_VV_events_in_CR_VV}) - (\text{exp_Top_events_in_CR_VV} * \text{exp_VV_events_in_CR_Top})}$$

$$\mu_{top} = \frac{\text{exp_VV_events_in_CR_VV} (\text{Obs_events_in_CR_Top} - \text{exp_otherBkg_events_in_CR_Top}) + \text{exp_VV_events_in_CR_Top} (\text{exp_otherBkg_events_in_CR_VV} - \text{Obs_events_in_CR_VV})}{(\text{exp_Top_events_in_CR_Top} * \text{exp_VV_events_in_CR_VV}) - (\text{exp_Top_events_in_CR_VV} * \text{exp_VV_events_in_CR_Top})}$$

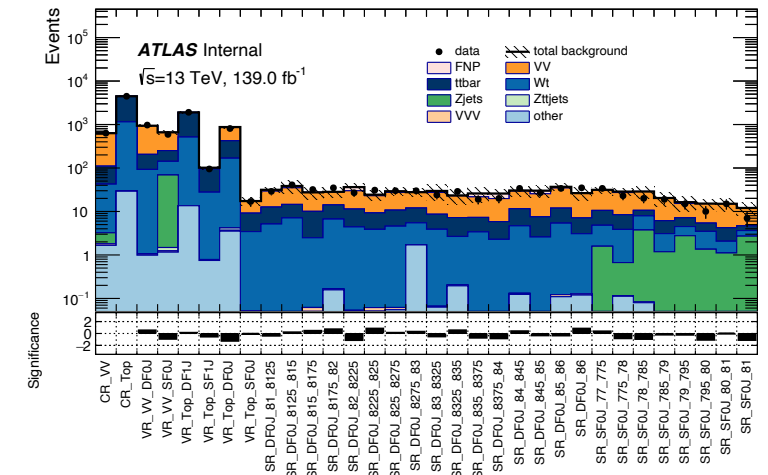


C1C1WW – Normalization strategy



C1C1WW - Pull values

- Bkg-only fit pulls using ATLAS recommended formula for the significance.
- All pulls $\lesssim 1$, the largest one occurs to be in a VR.



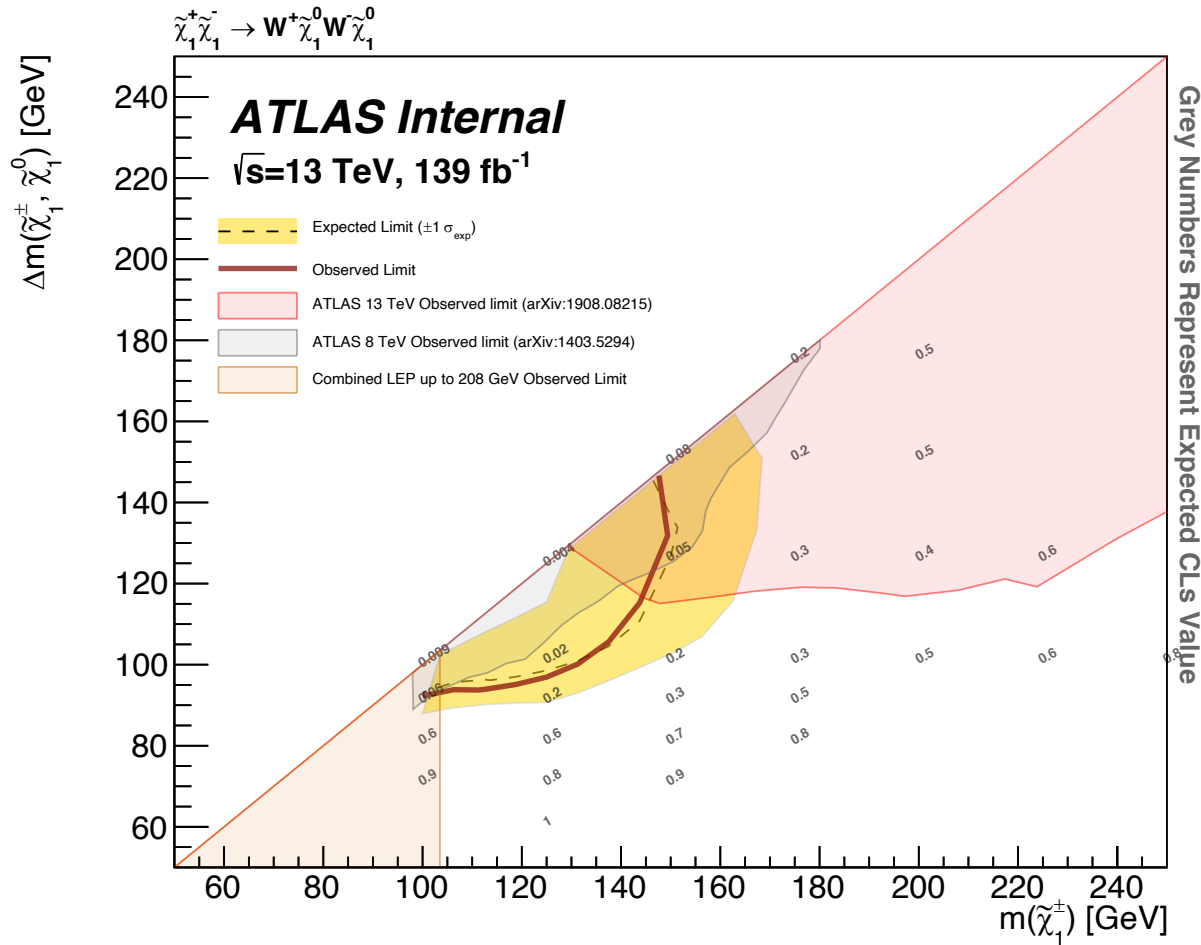
CR_Dib: 2.129606e-05
 CR_Top: -0.00189644
 VR_Dib_DFOJ: 0.4950505
 VR_Dib_SF0J: -0.875072
 VR_Top_DF1J: 0.096339
 VR_Top_SF1J: -0.497158
 VR_Top_DFOJ: -1.20554
 VR_Top_SF0J: -0.066893

SR_DFOJ_81_8125: -0.351801
 SR_DFOJ_8125_815: 0.173406
 SR_DFOJ_815_8175: 0.427902
 SR_DFOJ_8175_82: 0.678427
 SR_DFOJ_82_8225: -1.079950
 SR_DFOJ_8225_825: 0.797560
 SR_DFOJ_825_8275: 0.099505
 SR_DFOJ_8275_83: 0.2709230
 SR_DFOJ_83_8325: -0.469684
 SR_DFOJ_8325_835: 0.508156
 SR_DFOJ_835_8375: -0.68677
 SR_DFOJ_8375_84: -0.790854
 SR_DFOJ_84_845: 0.35726
 SR_DFOJ_845_85: -0.297985
 SR_DFOJ_85_86: -0.315978
 SR_DFOJ_86: 0.7928845

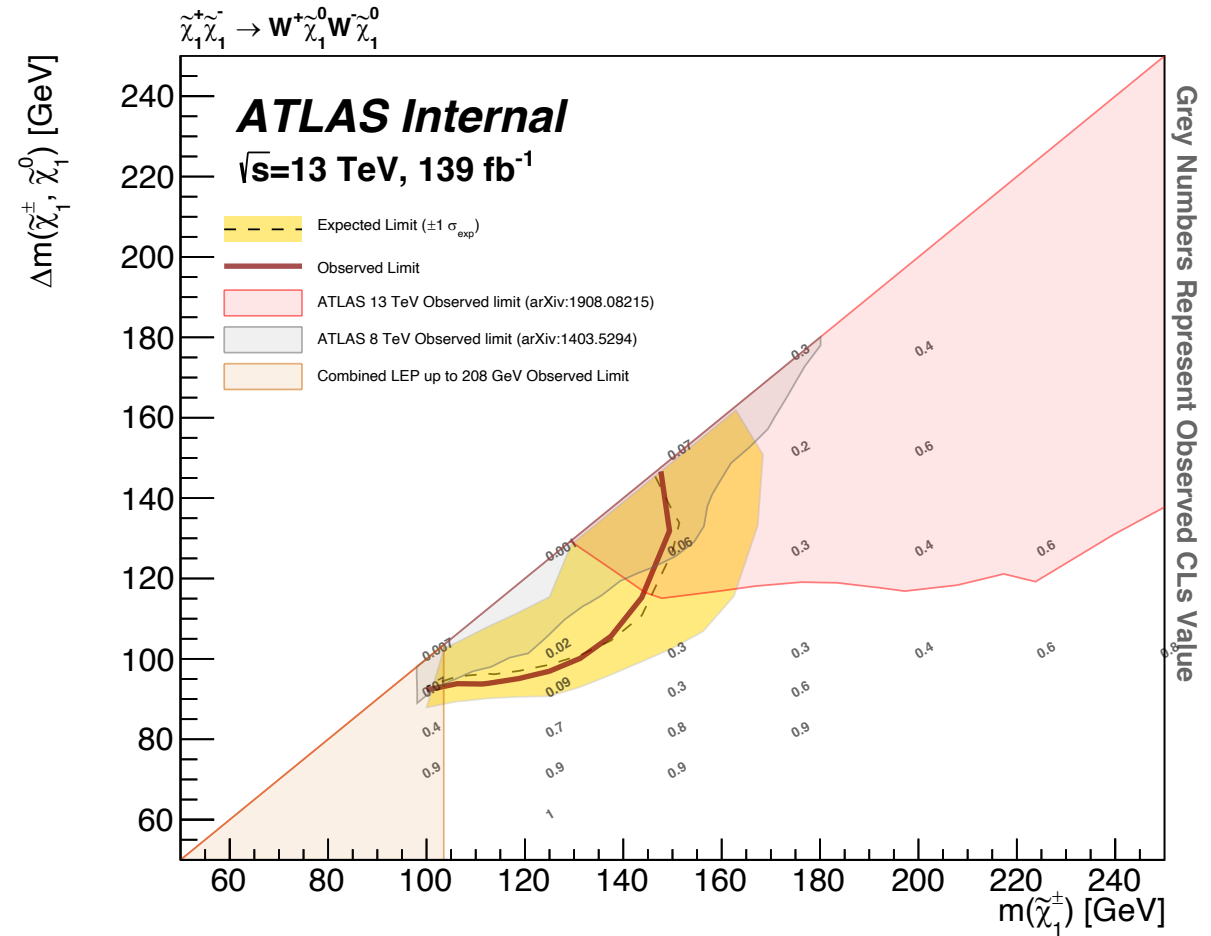
SR_SF0J_77_775: 0.329666965
 SR_SF0J_775_78: -0.77996
 SR_SF0J_78_785: -0.898968
 SR_SF0J_785_79: -0.170564
 SR_SF0J_79_795: -0.192424
 SR_SF0J_795_80: -1.035315
 SR_SF0J_80_81: -0.00838
 SR_SF0J_81: -1.066876

C1C1WW - Exclusion contours: CLs

Grid with expected CLs



Grid with observed CLs



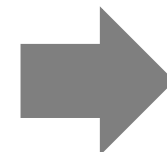
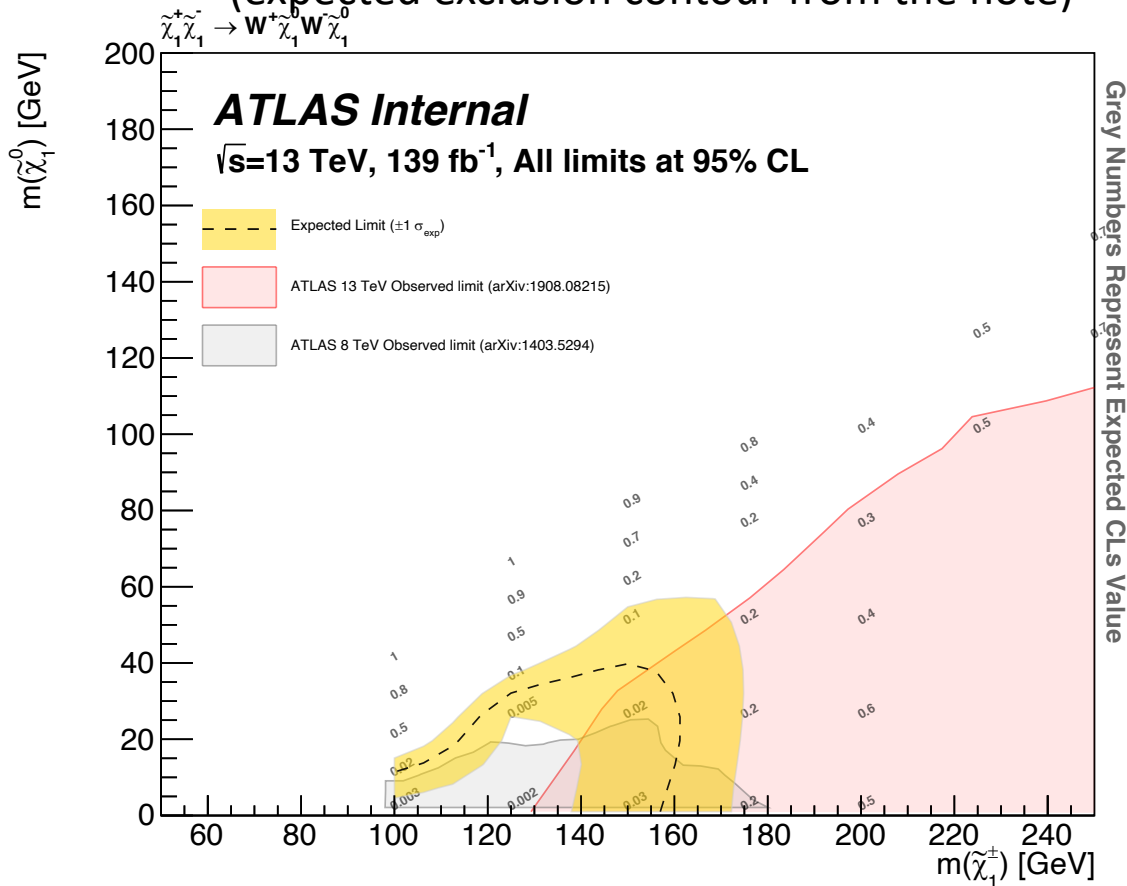
C1C1WW - Additional check

- The effect of unblinding the SRs with the old FNP estimates.

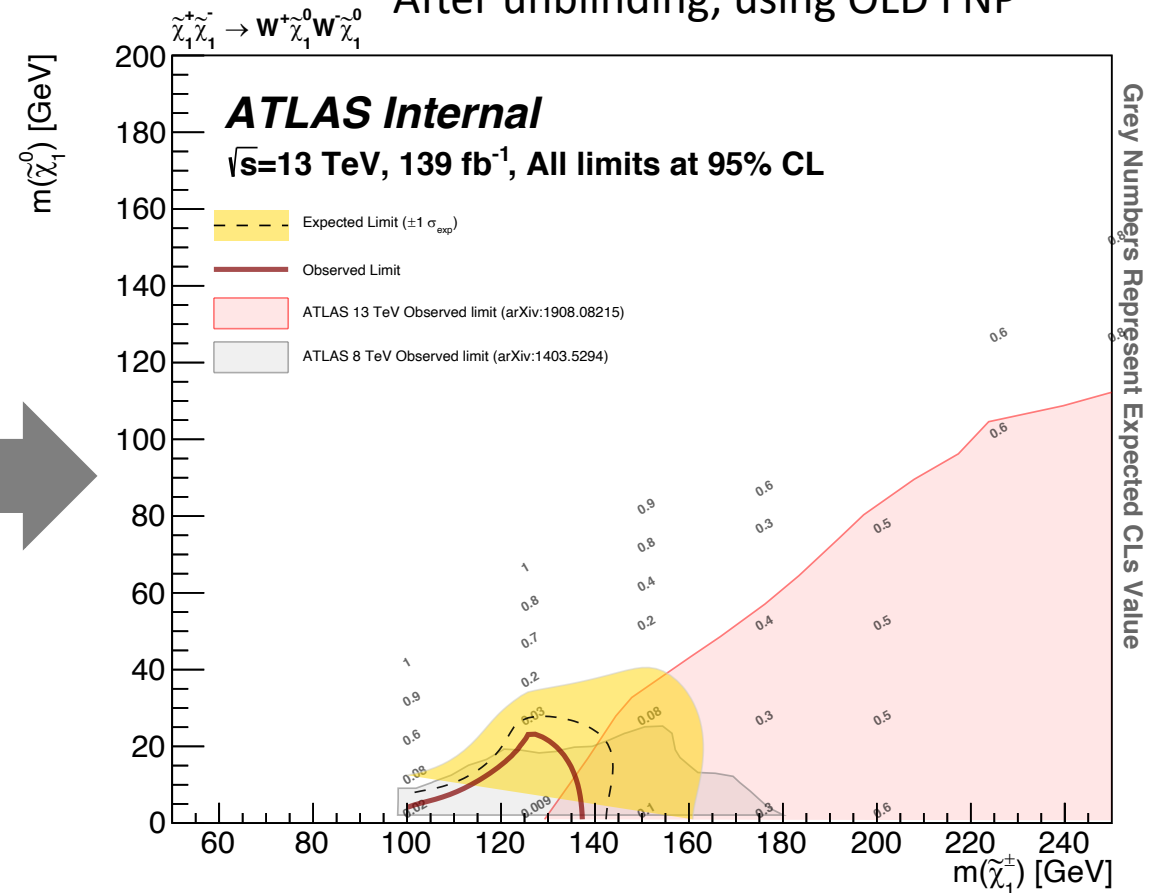
The profile-likelihood based hypothesis tests use the background-level estimates obtained from a background-only fit to both the CRs and SRs (the best estimates available). For consistency, both the observed and expected upper limit (or p-value) determination use the same background-level estimates, such that the expected limit is the most compatible and predictive assessment for the observed limit. As a consequence, the expected upper limit depends indirectly on the observed data.

Before unblinding

(expected exclusion contour from the note)



After unblinding, using OLD FNP

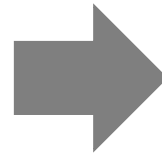
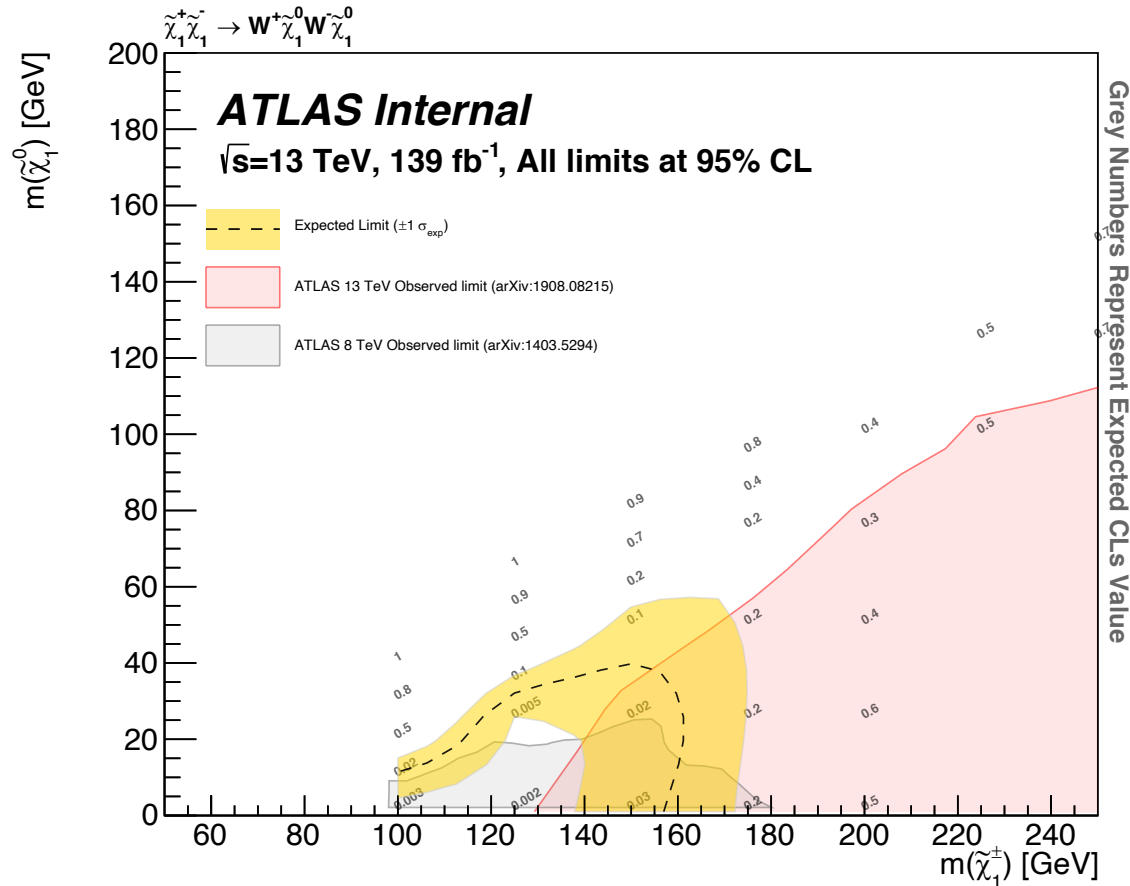


C1C1WW - Additional checks

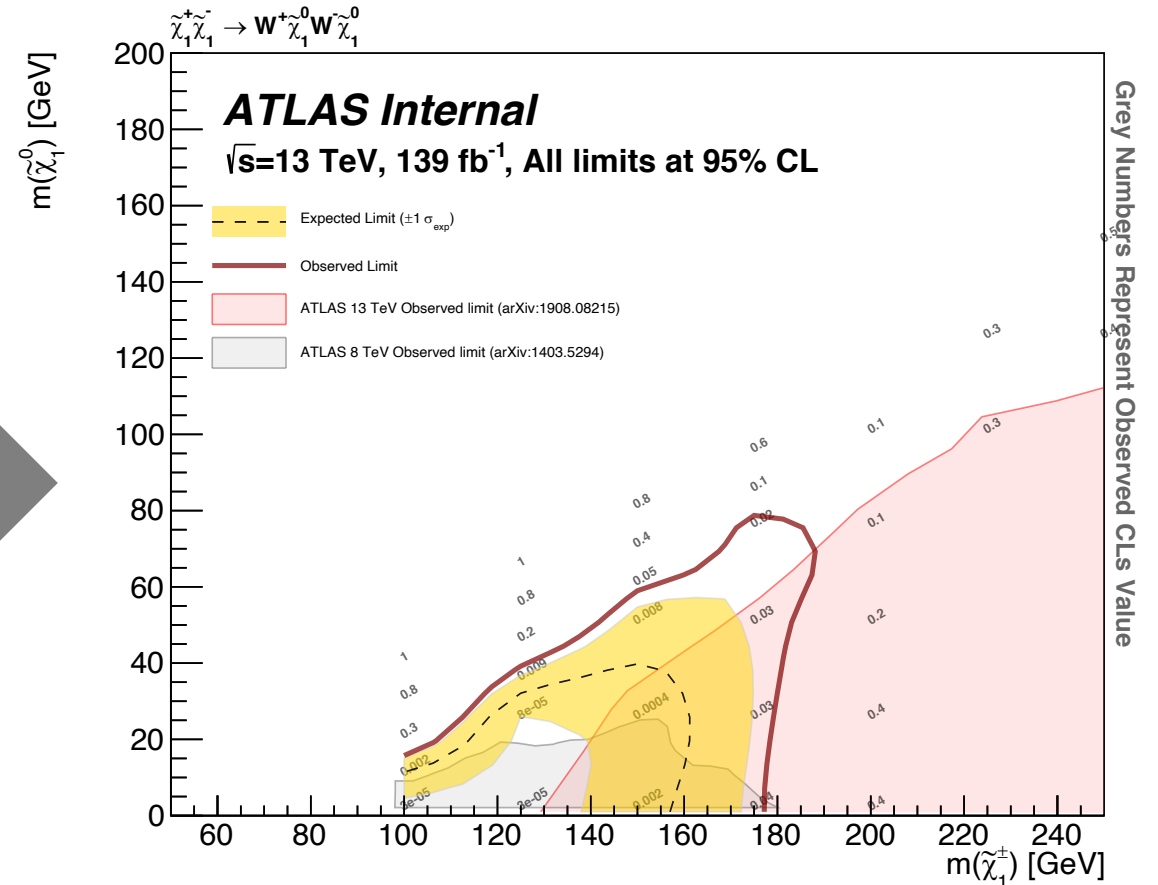
- Observed contour with Blinded SRs

Blinded SR: data = prefit bkg expectations
 2 sfs >1 → data undershooting post-fit MC bkg expectation
 → No space for SUSY to fill the the data-MC gap, observed limit extending higher to the expected one.

Before unblinding
 (expected exclusion contour from the note)



Before unblinding
 (dummy observed exclusion contour)



C1C1WW – Normalized type of systematics

$$\begin{aligned}\text{up_norm_variation_in_channel} &= \text{up_variation_in_channel} * (\text{nominal_in_CRs} / \text{up_variation_in_CRs}) \\ \text{down_norm_variation_in_channel} &= \text{down_variation_in_channel} * (\text{nominal_in_CRs} / \text{down_variation_in_CRs})\end{aligned}$$

Systematic scaling factor
(one systematic scaling factor for each
systematic, applied in every region)

Example

- Sample = VV, Systematic = JET_FLAVOR_COMPOSITION
 - Region = CR_Dib,
 - Nominal = 376.1466581406824, Up 358.0475063185111, Down = 386.76777661911495
 - Region = CR_Dib_CR_Top,
 - Nominal = 426.37399744088833, Up 406.3781023995014, Down = 439.5431148398273
 - JET_FLAVOR_COMPOSITION UP SCALING FACTOR = 426.37399744088833/406.3781023995014 = 1.04920514891
 - JET_FLAVOR_COMPOSITION DOWN SCALING FACTOR = 426.37399744088833/439.5431148398273 = 0.9700
 - Up_VV_Syst_NORM in CR = 358.0475063185111 * 1.04920514891=375.665287184 (lower than nominal yield)
 - Down_VV_Syst_NORM in CR = 386.76777661911495 * 0.9700=375.1647 (lower than nominal yield)
- Note: Being higher/lower than the nominal yield might change after systematic normalization!

C1C1WW - FNP systematics

- FNP estimates are negative in some of our analysis regions: set them to 0.01.
 - In particular, the statistics is high in CR_Top and so are the systematic variations relative to a 0.01 yield
- Now **considering the up/down variations relative to the nominal yields**: the nominal yield thus inherits the systematic shif. This fixes the large syst errors appended to zero/negative yields.
- In general, 2 ways to compute the systematic components:
 1. For every entry, compute the FNP_TOTAL_SYSTEMATIC from the FNP systematic components and finally read its value in a given channel
 2. For all the entries in a given channel, consider the FNP systematic components and compute the FNP_TOTAL_SYSTEMATICCurrently following **the second approach** which gives compatible results from the first approach but provides better systematic estimates for negative yields than the first approach (which overestimates them).
- FNP systematics computed by hand and careful implementation in the fit config as “userHistoSys” (with additional crosschecks of the produced up/down variation histograms from the HF data folder)

C1C1WW - FNP systematics

- FNP estimates are negative in our CRs: set to 0.01.
 - In particular, CR_Top statistics is large and so are the systematic variations relatively to a 0.01 yield
- Now considering the up/down variations relatively to the nominal yields: the nominal yield thus inherits the systematic shift. This fixes the large syst errors appended to zero/negative yields.
- In general, 2 ways to compute the systematic components:
 1. For every entry, compute the FNP_TOTAL_SYSTEMATIC from the FNP systematic components and finally read its value in a given channel
 2. For all the entries in a given channel, consider the FNP systematic components and compute the FNP_TOTAL_SYSTEMATIC
- Currently following the second approach which gives compatible results from the first approach but provides better systematic estimates for negative yields than the first approach (which overestimates them).

```
yield_down = get_quadrature_summed_weights_down(df_cut)
error_up = yield_up - region_yield
error_down = region_yield - yield_down
print("{0} FNP = {1:.2f}, +{2:.2f} - {3:.2f}".format(region, region_yield,
error_up, error_down))
```

```
def get_quadrature_summed_weights_up(df):
    """Combine difference in weights from the nominal in quadrature to get
    total uncertainty """
    nominal = sum(df['FNP_WEIGHTS'])
    df_differences_sq = (nominal - sum(df['FNP_STATUP']))**2 + \
        (nominal - sum(df['FNP_WEIGHTUP']))**2 + \
        (nominal - sum(df['FNP_XSECUP']))**2 + \
        (nominal - sum(df['FNP_EFF_TOTAL_1up']))**2 + \
        (nominal - sum(df['FNP_EFF_TRIG_TOTAL_1up']))**2 + \
        (nominal - sum(df['FNP_WEIGHTSYSTUP']))**2
    df_differences = df_differences_sq ** 0.5
    return nominal + df_differences
```

```
def get_quadrature_summed_weights_down(df):
    """Combine difference in weights from the nominal in quadrature to get
    total uncertainty"""
    nominal = sum(df['FNP_WEIGHTS'])
    df_differences_sq = (nominal - sum(df['FNP_STATDW']))**2 + \
        (nominal - sum(df['FNP_WEIGHTDW']))**2 + \
        (nominal - sum(df['FNP_XSECOW']))**2 + \
        (nominal - sum(df['FNP_EFF_TOTAL_1down']))**2 + \
        (nominal - sum(df['FNP_EFF_TRIG_TOTAL_1down']))**2 + \
        (nominal - sum(df['FNP_WEIGHTSYSTDW']))**2
    df_differences = df_differences_sq ** 0.5
    return nominal - df_differences
```


C1C1WW - FNP systematics

- FNP systematics computed by hand and careful implementation in the fit config as “userHistoSys” (with additional crosschecks of the produced up/down variation histograms from the HF data folder)

CR_Dib FNP = -10.59, +2.81 - 2.58
CR_Top FNP = -117.95, +23.86 - 23.42
VR_Dib_DFOJ FNP = -3.76, +4.54 - 4.21
VR_Dib_SF0J FNP = 7.79, +4.45 - 3.70
VR_Top_DF1J FNP = -25.01, +10.00 - 9.71
VR_Top_SF1J FNP = 4.23, +1.33 - 1.17
VR_Top_DFOJ FNP = 20.47, +8.63 - 8.40
VR_Top_SF0J FNP = 0.05, +0.22 - 0.22

SR_DFOJ_81_8125 FNP = 2.13, +0.30 - 0.24
SR_DFOJ_8125_815 FNP = 3.50, +0.37 - 0.34
SR_DFOJ_815_8175 FNP = -0.99, +0.12 - 0.12
SR_DFOJ_8175_82 FNP = -0.56, +0.34 - 0.35
SR_DFOJ_82_8225 FNP = 6.47, +0.67 - 0.67
SR_DFOJ_8225_825 FNP = 1.35, +0.48 - 0.47
SR_DFOJ_825_8275 FNP = 1.65, +0.57 - 0.60
SR_DFOJ_8275_83 FNP = -1.54, +0.37 - 0.36
SR_DFOJ_83_8325 FNP = 2.32, +1.26 - 1.25
SR_DFOJ_8325_835 FNP = 0.43, +0.46 - 0.44
SR_DFOJ_835_8375 FNP = 4.26, +1.20 - 1.19
SR_DFOJ_8375_84 FNP = 6.05, +0.47 - 0.46
SR_DFOJ_84_845 FNP = 0.93, +0.75 - 0.75
SR_DFOJ_845_85 FNP = 4.59, +0.61 - 0.57
SR_DFOJ_85_86 FNP = 2.15, +0.57 - 0.56
SR_DFOJ_86 FNP = 0.09, +0.55 - 0.53

SR_SF0J_77_775 FNP = -3.38, +0.45 - 0.42
SR_SF0J_775_78 FNP = 1.41, +0.33 - 0.20
SR_SF0J_78_785 FNP = -0.97, +0.20 - 0.18
SR_SF0J_785_79 FNP = -1.76, +0.23 - 0.23
SR_SF0J_79_795 FNP = 1.11, +0.19 - 0.20
SR_SF0J_795_80 FNP = -1.21, +0.13 - 0.11
SR_SF0J_80_81 FNP = -1.72, +0.24 - 0.23
SR_SF0J_81 FNP = -0.78, +0.09 - 0.08

C1C1WW - FNP systematics implementation

- Implementation in the fit of the FNP systematics

```
CR_VV=myTopLvl.addChannel("cuts", ['CR_Dib'], cutsNBins, cutsBinLow, cutsBinHigh)
CR_top=myTopLvl.addChannel("cuts", ['CR_Top'], cutsNBins, cutsBinLow, cutsBinHigh)
if doSyst == True:
    CR_VV.getSample("FNP").addSystematic( Systematic("FNP_TOTAL_SYS", "", (0.01+2.81)/0.01, 0., "user", "userHistoSys") )
    CR_top.getSample("FNP").addSystematic( Systematic("FNP_TOTAL_SYS", "", (0.01+23.86)/0.01, 0., "user", "userHistoSys") )

myTopLvl.addBkgConstrainChannels([CR_VV, CR_top])

if CRonlyFit == False:
    VR_VV_DF0J=myTopLvl.addChannel("cuts", ['VR_Dib_DF0J'], cutsNBins, cutsBinLow, cutsBinHigh)
    VR_VV_SF0J=myTopLvl.addChannel("cuts", ['VR_Dib_SF0J'], cutsNBins, cutsBinLow, cutsBinHigh)
    VR_top_DF1J=myTopLvl.addChannel("cuts", ['VR_Top_DF1J'], cutsNBins, cutsBinLow, cutsBinHigh)
    VR_top_SF1J=myTopLvl.addChannel("cuts", ['VR_Top_SF1J'], cutsNBins, cutsBinLow, cutsBinHigh)
    VR_top_DF0J=myTopLvl.addChannel("cuts", ['VR_Top_DF0J'], cutsNBins, cutsBinLow, cutsBinHigh)
    VR_top_SF0J=myTopLvl.addChannel("cuts", ['VR_Top_SF0J'], cutsNBins, cutsBinLow, cutsBinHigh)

    VR_VV_DF0J.getSample("FNP").addSystematic( Systematic("FNP_TOTAL_SYS", "", (0.01+4.54)/0.01, 0., "user", "userHistoSys") )
    VR_VV_SF0J.getSample("FNP").addSystematic( Systematic("FNP_TOTAL_SYS", "", (7.79+4.45)/7.79, (7.79-3.70)/7.79, "user", "userHistoSys") )
    VR_top_DF1J.getSample("FNP").addSystematic( Systematic("FNP_TOTAL_SYS", "", (0.01+10)/0.01, 0., "user", "userHistoSys") )
    VR_top_SF1J.getSample("FNP").addSystematic( Systematic("FNP_TOTAL_SYS", "", (4.23+1.33)/4.23, (4.23-1.17)/4.23, "user", "userHistoSys") )
    VR_top_DF0J.getSample("FNP").addSystematic( Systematic("FNP_TOTAL_SYS", "", (20.47+8.63)/20.47, (20.47-8.40)/20.47, "user", "userHistoSys") )
    VR_top_SF0J.getSample("FNP").addSystematic( Systematic("FNP_TOTAL_SYS", "", (0.05+0.22)/0.05, 0., "user", "userHistoSys") )

myTopLvl.addValidationChannels([VR_VV_DF0J, VR_VV_SF0J, VR_top_DF1J, VR_top_SF1J, VR_top_DF0J, VR_top_SF0J])
```

```
if ch == 'SR_DF0J_81_8125' and doSyst == True:
    SR_channel.getSample("FNP").addSystematic(Systematic("FNP_TOTAL_SYS", "", (2.13+0.30)/2.13, (2.13-0.24)/2.13, "user", "histoSys"))
elif ch == 'SR_DF0J_8125_815' and doSyst == True:
    SR_channel.getSample("FNP").addSystematic(Systematic("FNP_TOTAL_SYS", "", (3.50+0.37)/3.50, (3.50-0.34)/3.50, "user", "histoSys"))
elif ch == 'SR_DF0J_815_8175' and doSyst == True:
    SR_channel.getSample("FNP").addSystematic(Systematic("FNP_TOTAL_SYS", "", (0.01+0.12)/0.01, 0., "user", "histoSys"))
elif ch == 'SR_DF0J_8175_82' and doSyst == True:
    SR_channel.getSample("FNP").addSystematic(Systematic("FNP_TOTAL_SYS", "", (0.01+0.34)/0.01, 0., "user", "histoSys"))
elif ch == 'SR_DF0J_82_8225' and doSyst == True:
    SR_channel.getSample("FNP").addSystematic(Systematic("FNP_TOTAL_SYS", "", (6.47+0.67)/6.47, (6.47-0.67)/6.47, "user", "histoSys"))
elif ch == 'SR_DF0J_8225_825' and doSyst == True:
    SR_channel.getSample("FNP").addSystematic(Systematic("FNP_TOTAL_SYS", "", (1.35+0.48)/1.35, (1.35-0.47)/1.35, "user", "histoSys"))
elif ch == 'SR_DF0J_825_8275' and doSyst == True:
    SR_channel.getSample("FNP").addSystematic(Systematic("FNP_TOTAL_SYS", "", (1.65+0.57)/1.65, (1.65-0.60)/1.65, "user", "histoSys"))
elif ch == 'SR_DF0J_8275_83' and doSyst == True:
    SR_channel.getSample("FNP").addSystematic(Systematic("FNP_TOTAL_SYS", "", (0.01+0.37)/0.01, 0., "user", "histoSys"))
elif ch == 'SR_DF0J_83_8325' and doSyst == True:
    SR_channel.getSample("FNP").addSystematic(Systematic("FNP_TOTAL_SYS", "", (2.32+1.26)/2.32, (2.32-1.25)/2.32, "user", "histoSys"))
elif ch == 'SR_DF0J_8325_835' and doSyst == True:
    SR_channel.getSample("FNP").addSystematic(Systematic("FNP_TOTAL_SYS", "", (0.43+0.46)/0.43, 0., "user", "histoSys"))
elif ch == 'SR_DF0J_835_8375' and doSyst == True:
    SR_channel.getSample("FNP").addSystematic(Systematic("FNP_TOTAL_SYS", "", (4.26+1.20)/4.26, (4.26-1.19)/4.26, "user", "histoSys"))
elif ch == 'SR_DF0J_8375_84' and doSyst == True:
    SR_channel.getSample("FNP").addSystematic(Systematic("FNP_TOTAL_SYS", "", (6.05+0.47)/6.05, (6.05-0.46)/6.05, "user", "histoSys"))
elif ch == 'SR_DF0J_84_845' and doSyst == True:
    SR_channel.getSample("FNP").addSystematic(Systematic("FNP_TOTAL_SYS", "", (0.93+0.75)/0.93, (0.93-0.75)/0.93, "user", "histoSys"))
elif ch == 'SR_DF0J_845_85' and doSyst == True:
    SR_channel.getSample("FNP").addSystematic(Systematic("FNP_TOTAL_SYS", "", (4.59+0.61)/4.59, (4.59-0.57)/4.59, "user", "histoSys"))
elif ch == 'SR_DF0J_85_86' and doSyst == True:
    SR_channel.getSample("FNP").addSystematic(Systematic("FNP_TOTAL_SYS", "", (2.15+0.57)/2.15, (2.15-0.56)/2.15, "user", "histoSys"))
elif ch == 'SR_DF0J_86' and doSyst == True:
    SR_channel.getSample("FNP").addSystematic(Systematic("FNP_TOTAL_SYS", "", (0.09+0.55)/0.09, 0., "user", "histoSys"))

elif ch == 'SR_SF0J_77_775' and doSyst == True:
    SR_channel.getSample("FNP").addSystematic(Systematic("FNP_TOTAL_SYS", "", (0.01+0.45)/0.01, 0., "user", "histoSys"))
elif ch == 'SR_SF0J_775_78' and doSyst == True:
    SR_channel.getSample("FNP").addSystematic(Systematic("FNP_TOTAL_SYS", "", (1.41+0.33)/1.41, (1.41-0.20)/1.41, "user", "histoSys"))
elif ch == 'SR_SF0J_78_785' and doSyst == True:
    SR_channel.getSample("FNP").addSystematic(Systematic("FNP_TOTAL_SYS", "", (0.01+0.20)/0.01, 0., "user", "histoSys"))
elif ch == 'SR_SF0J_785_79' and doSyst == True:
    SR_channel.getSample("FNP").addSystematic(Systematic("FNP_TOTAL_SYS", "", (0.01+0.23)/0.05, 0., "user", "histoSys"))
elif ch == 'SR_SF0J_79_795' and doSyst == True:
    SR_channel.getSample("FNP").addSystematic(Systematic("FNP_TOTAL_SYS", "", (1.11+0.19)/1.11, (1.11-0.20)/1.11, "user", "histoSys"))
elif ch == 'SR_SF0J_795_80' and doSyst == True:
    SR_channel.getSample("FNP").addSystematic(Systematic("FNP_TOTAL_SYS", "", (0.01+0.13)/0.01, 0., "user", "histoSys"))
elif ch == 'SR_SF0J_80_81' and doSyst == True:
    SR_channel.getSample("FNP").addSystematic(Systematic("FNP_TOTAL_SYS", "", (0.01+0.24)/0.01, 0., "user", "histoSys"))
elif ch == 'SR_SF0J_81' and doSyst == True:
    SR_channel.getSample("FNP").addSystematic(Systematic("FNP_TOTAL_SYS", "", (0.01+0.09)/0.01, 0., "user", "histoSys"))

myTopLvl.addSignalChannels(SR_channel)
```