2016 SIMP L1L1 Unblinding Proposal

Alic Spellman

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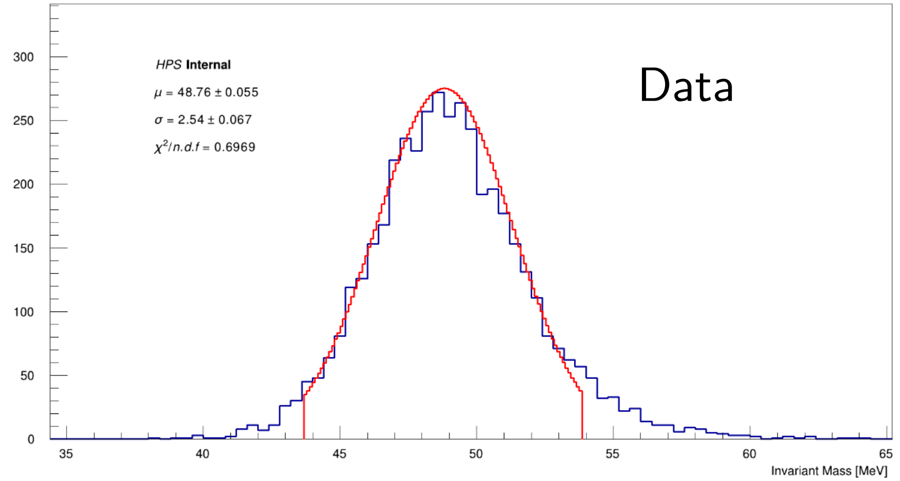
07/23/2024

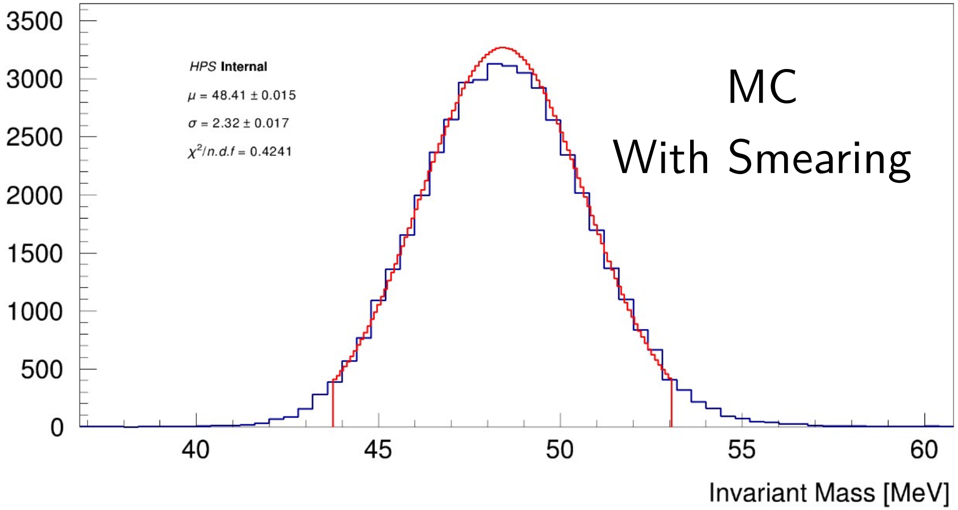
Introduction

- Request to unblind 100% SR data for 2016 L1L1 SIMPs
- Hit killing + momentum smearing applied to all MC samples
- MC background and Data agree well
- RadFrac + RadAcc + Mass resolution updated
- Full selection optimized using 10% Data in SR
- Background estimation and search window size studied using 10% Data in SR
  - Performance also tested on larger stats 100% **CR**
- *$z0_{min}$ cut shape was optimized using 10% data SR
  - Studied impact of further tightening cut to protect against statistical fluctuations in in the 100% data SR
  - Decided to tighten...**remaining events in 10% data now SR very low**
- OIM method sets upper limits on expected signal rate

Mass Resolution with MC Momentum Smearing

Moller Peaks with Momentum Smearing





Unconstrained Vtx KF Tracking

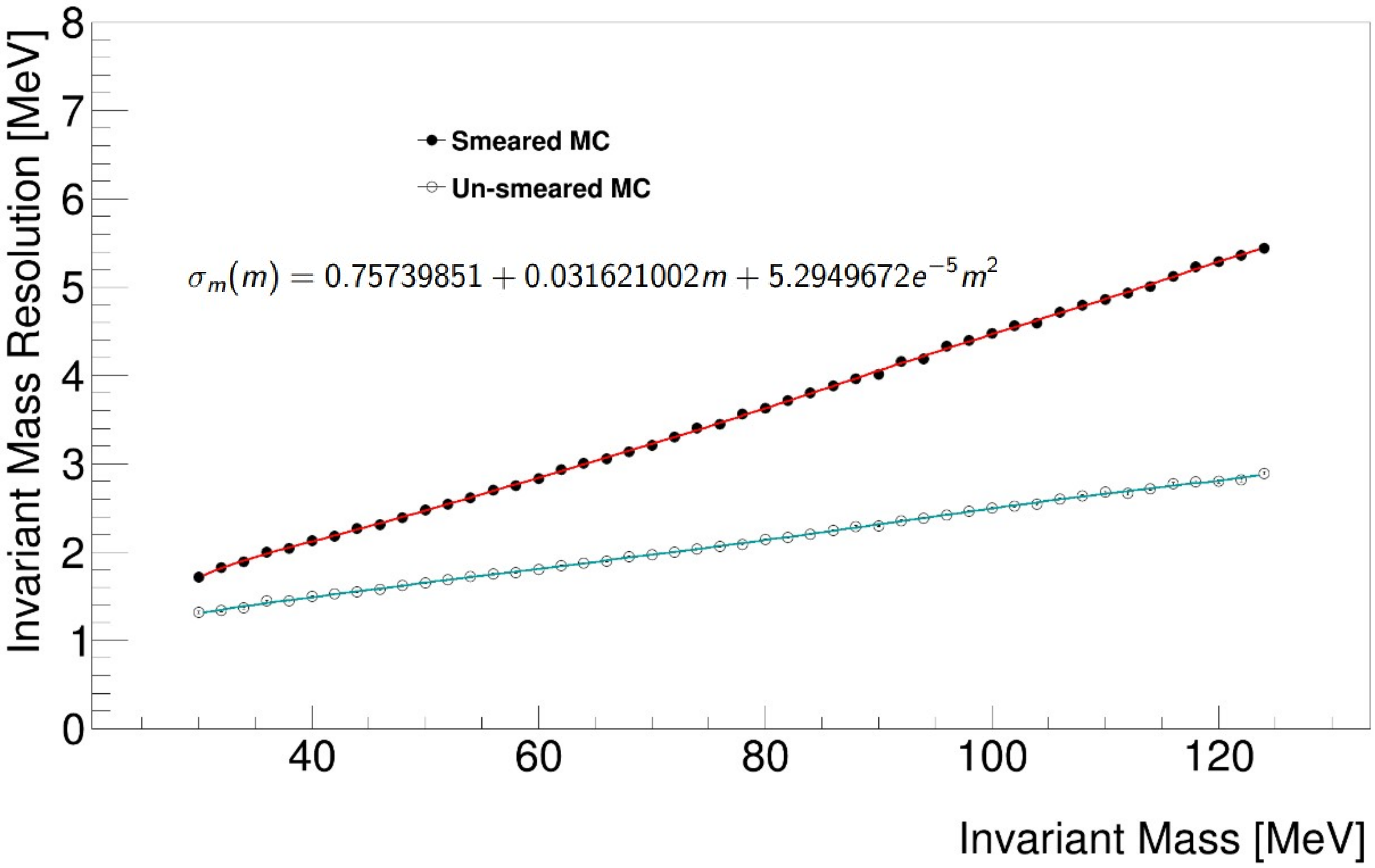
	μ [MeV]	σ [MeV]	σ_{err} [MeV]
Data	48.76	2.54	0.067
MC	48.52	1.87	0.016
$MC_{smeared}$	48.41	2.32	0.017

Constrained Vtx Seedtracker+GBL

	μ [MeV]	σ [MeV]	σ_{err} [MeV]
Data	48.93	2.06	0.012
MC unsmeared	48.43	1.	0.0033
MC smeared	48.35	1.93	0.0026

*MC Mollers skimmed from tritrig+beam MC, so difference in tails attributed to differences in MC beam and actual bkg in data

Smeared MC Mass Resolution



Selection

Preselection

Table 5: The Preselection cutflow efficiency after each cut is applied in order.

Cut Description	Requirement
Trigger	Pair1
Track Time	$\|Track_t\| < 6$ ns
Cluster Time Difference	$\Delta_t(Cluster_{e^-}, Cluster_{e^+} < 1.45$ ns
Track-Cluster Time Difference	$\Delta_t(Track, Cluster) < 4.0$ ns
Track Quality	$Track \chi^2/n.d.f. < 20.0$
Beam electron cut	$p_{e^-} < 1.75$ GeV
Minimum Hits on Track	$N_{2dhits}\, Track > 7.0$
Unconstrained Vertex Quality	$Vtx_{\chi^2} < 20.0$
Vertex Momentum	$p_{e^- + e^+} < 2.4$ GeV

Table 6: V_0 selection. The time offset for data is 56 ns and the time offset for MC is 43 ns.

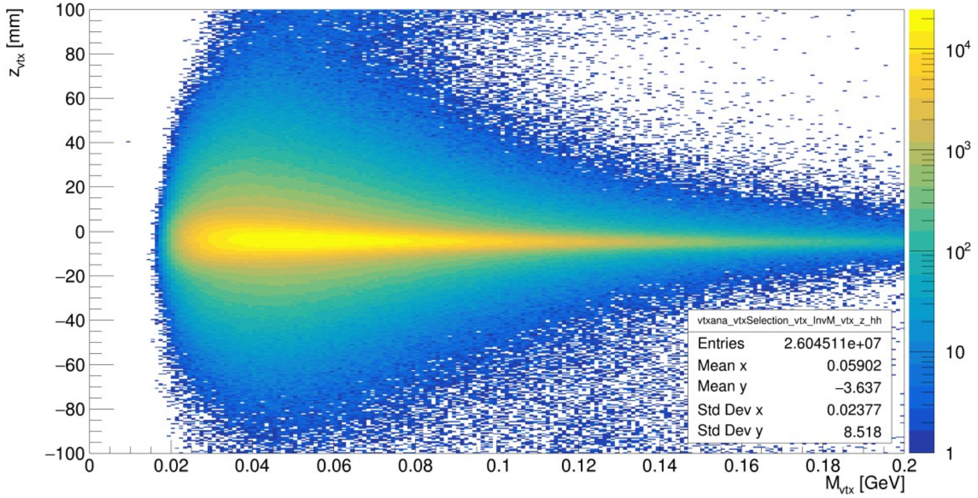
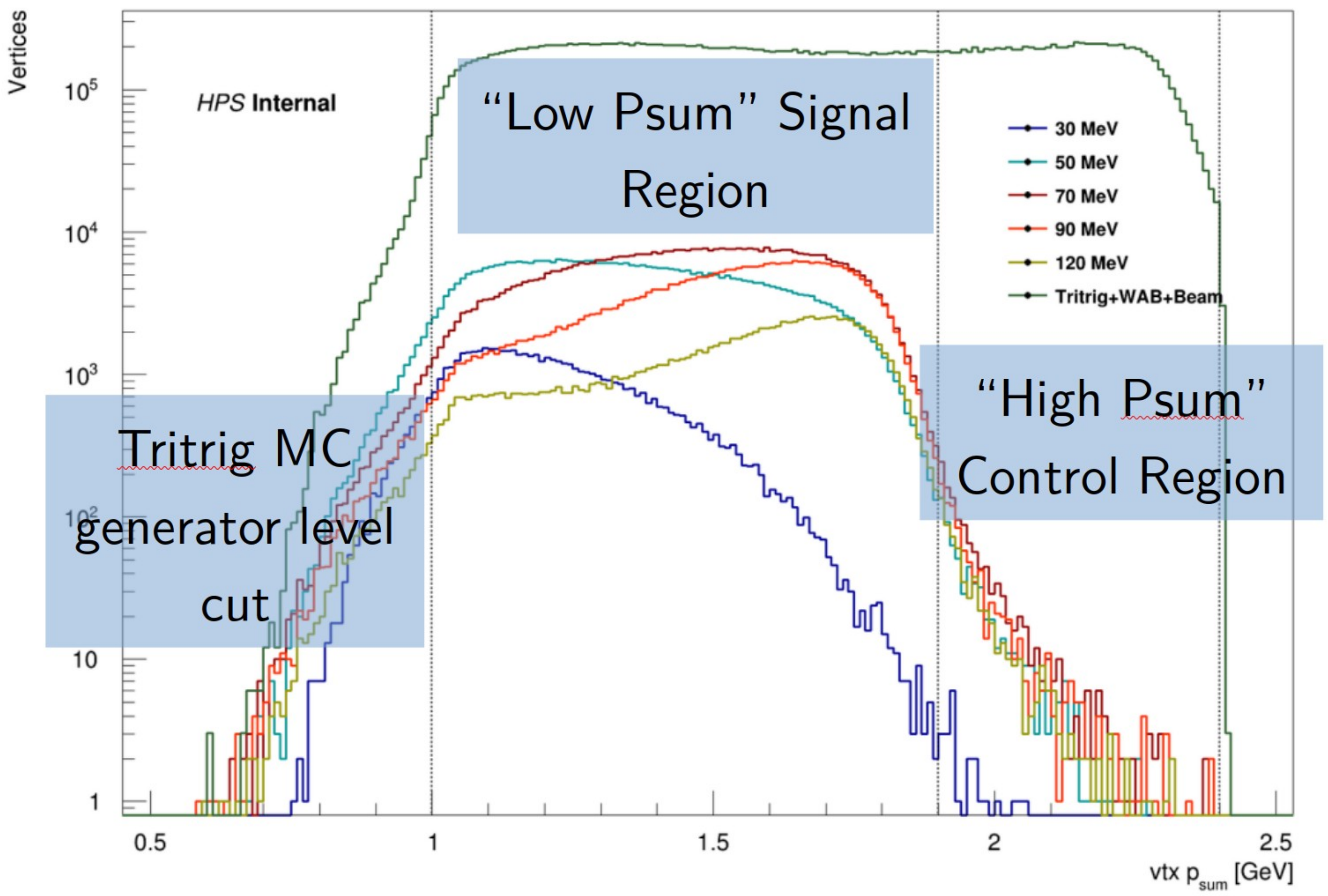


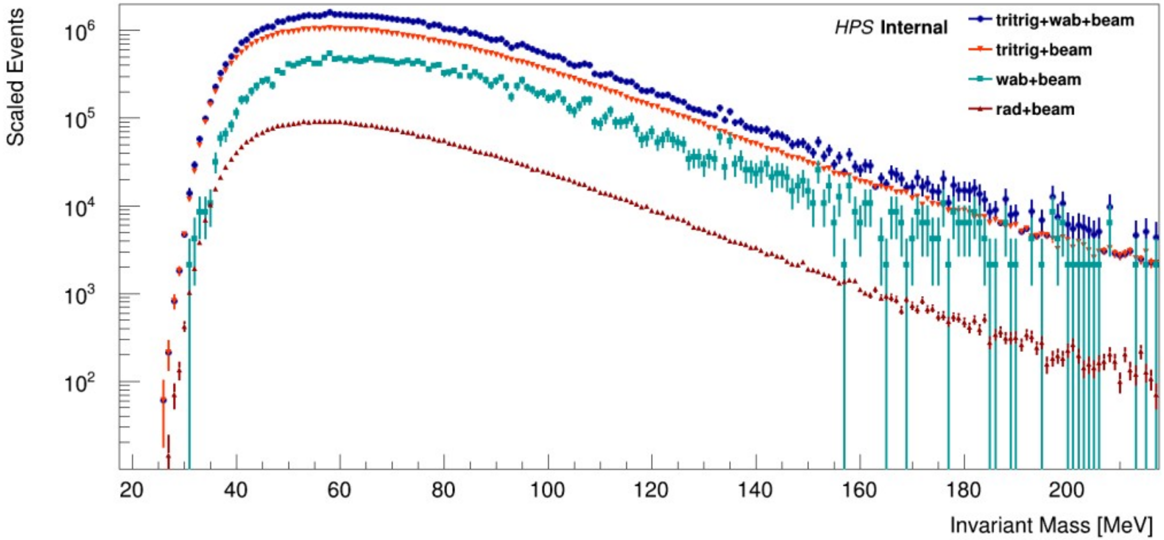
Figure 43: Reconstructed vertex z position versus Invariant Mass for the $\sim 10\,\%$ Data sample.

Signal and Control Regions



Expected Signal Calculation

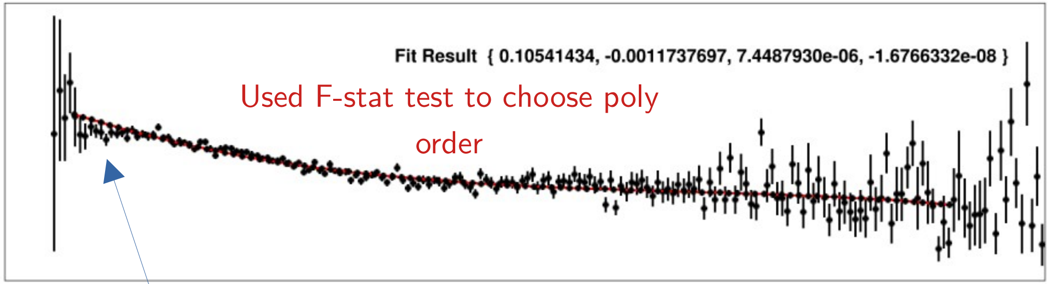
Radiative Fraction



$$f_{rad}(m_{A'}) = \frac{dN_{\gamma^* CR}}{dm_{A'}} / \frac{dN_{CR}}{dm_{reco}}$$

γ* truth-matched to eliminate false reconstructions

Not truth-matched

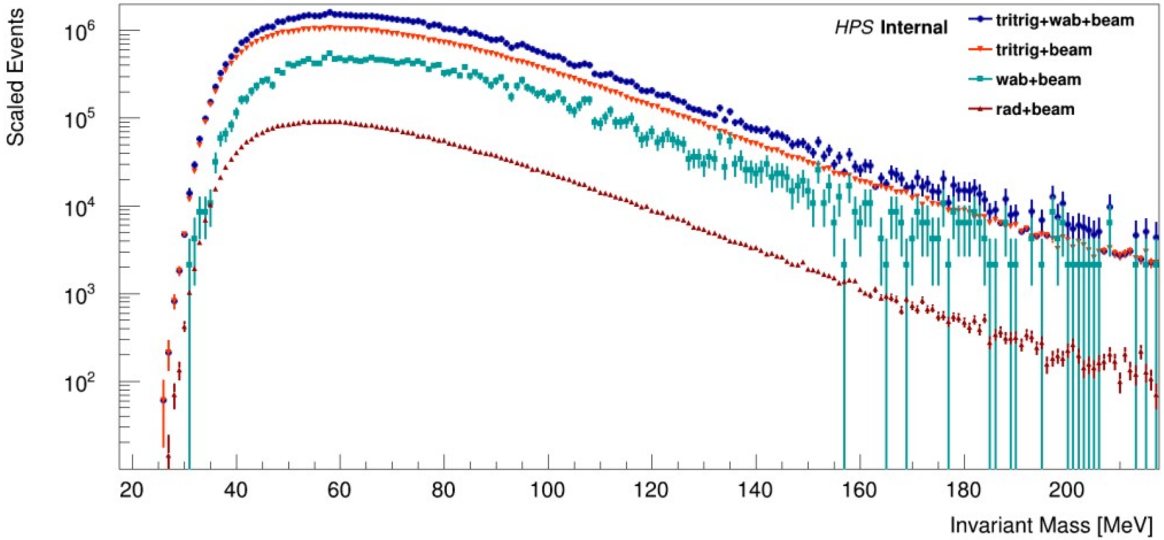


*Fit is kind of poor here

Systematic Uncertainty

- Driven by MC cross-section uncertainties
- Estimated as ~7% in 2016 A' analysis
- Same here

Radiative Fraction



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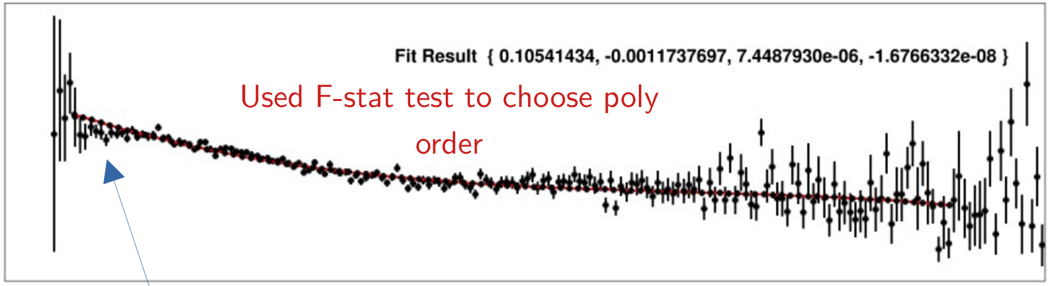


Used F-stat test to choose poly order

*Fit is kind of poor here

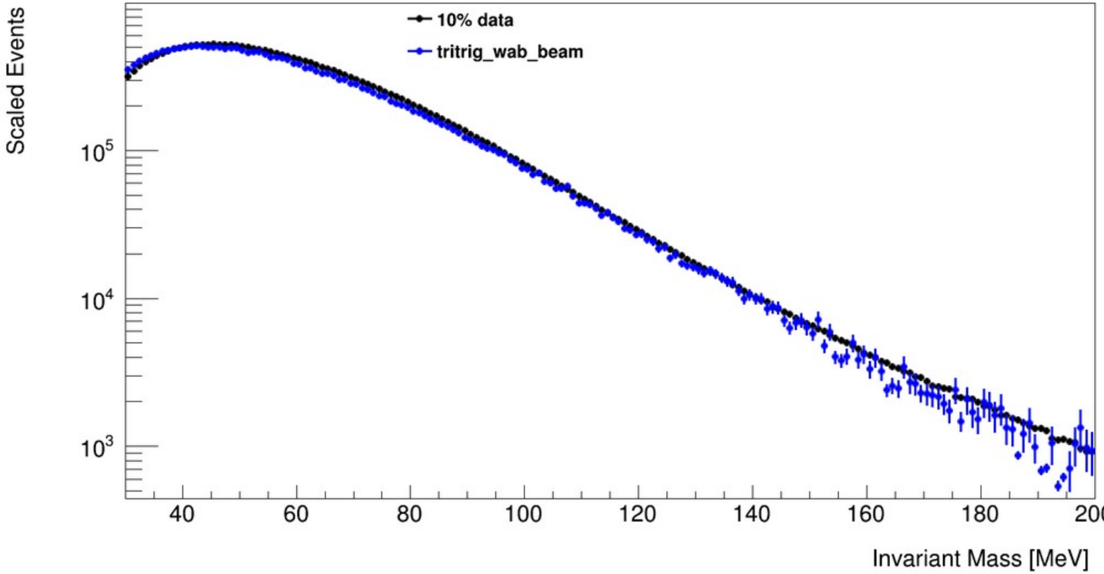
Is there a "fake" contribution to the reconstructed background rate in data?

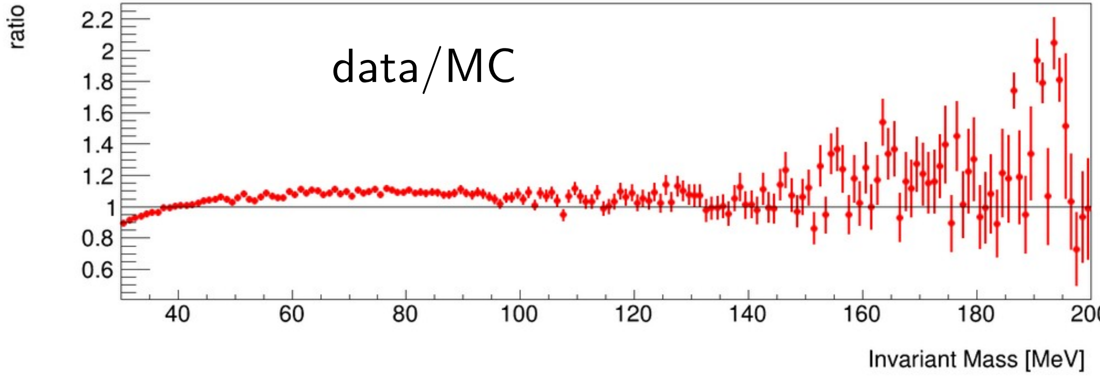
- D[...] uncertainties
- Estimated as ~7% in 2016 A' analysis
- Same here

Radiative Fraction – Fakes in Data?

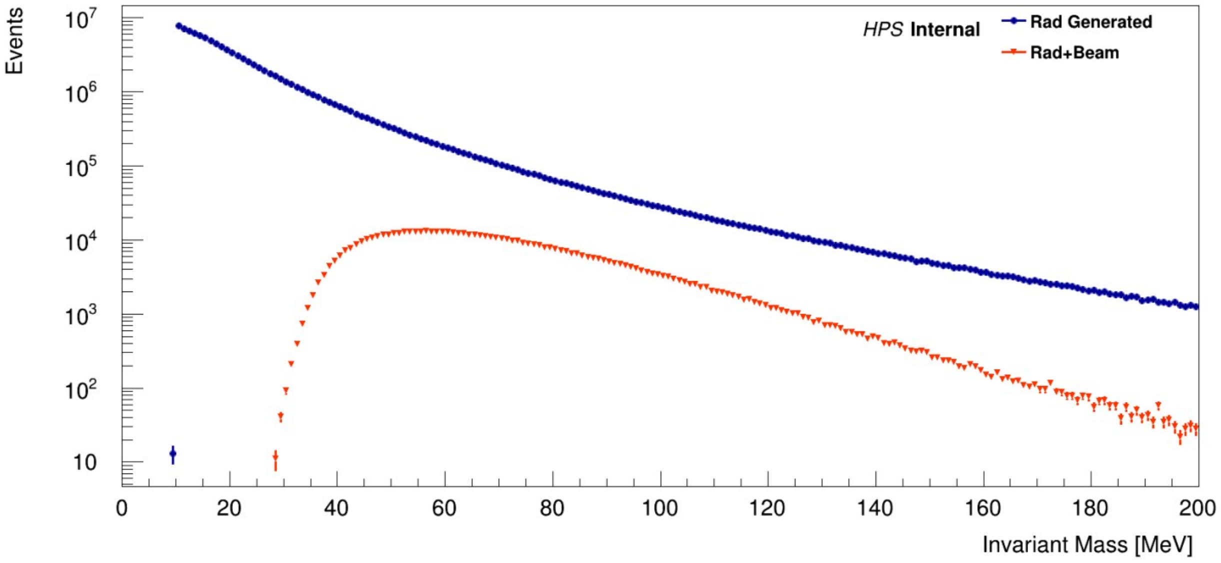
- Background primarily Bethe-Heitler+Radiative tridents and cWABs
- No processes expected to contribute to meaningful fake trident rate

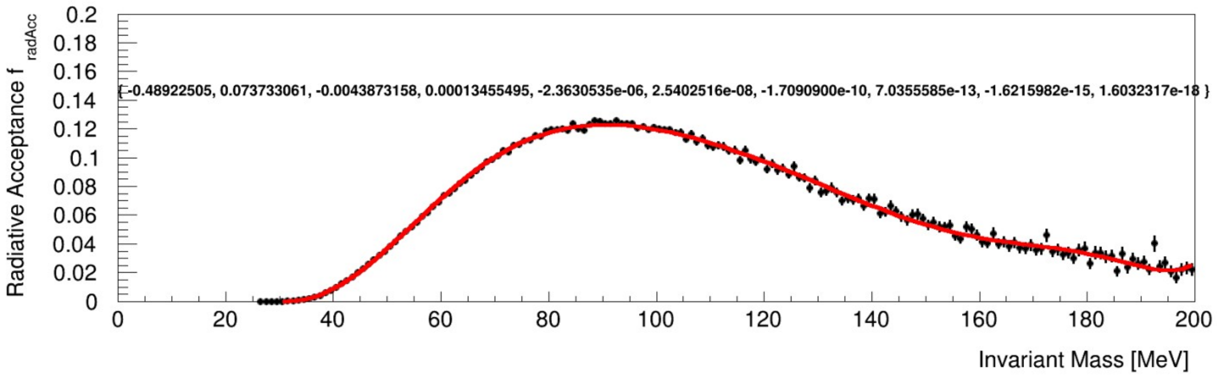
- Compare invariant mass in 10% data and tritrig+wab+beam (scaled to ∼10%)
- No evidence of significant fake trident process in data
- Scale and shape both look reasonable





Radiative Acceptance





Truth-matched

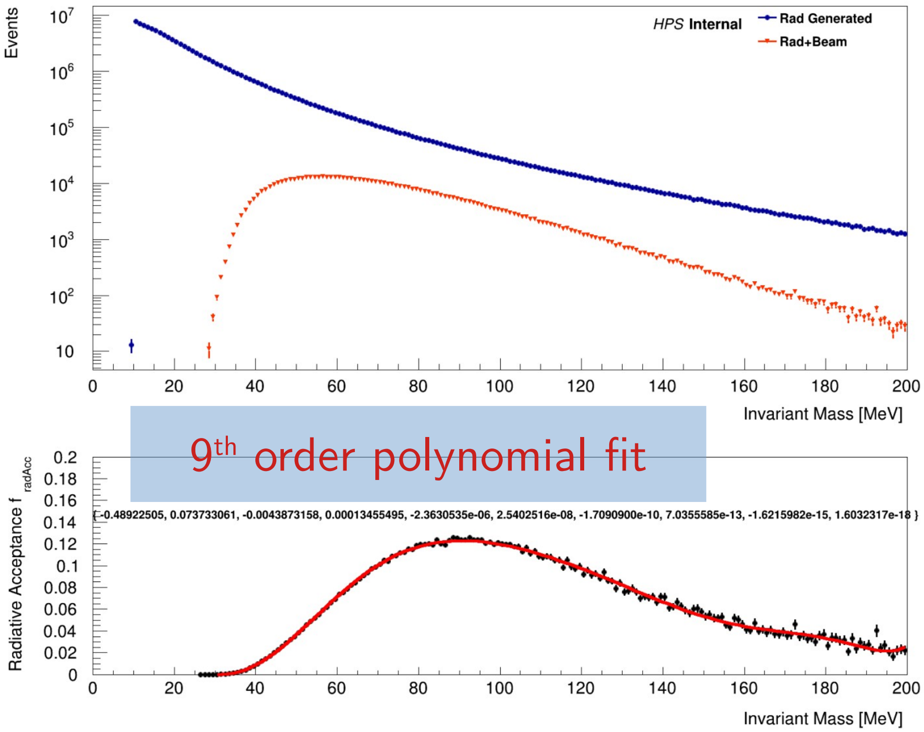
$$A_{rad}(m_{A'}) = \frac{dN_{\gamma^* CR}}{dm_{A'}} \Big/ \frac{dN_{\gamma^*}}{dm_{A'}}$$

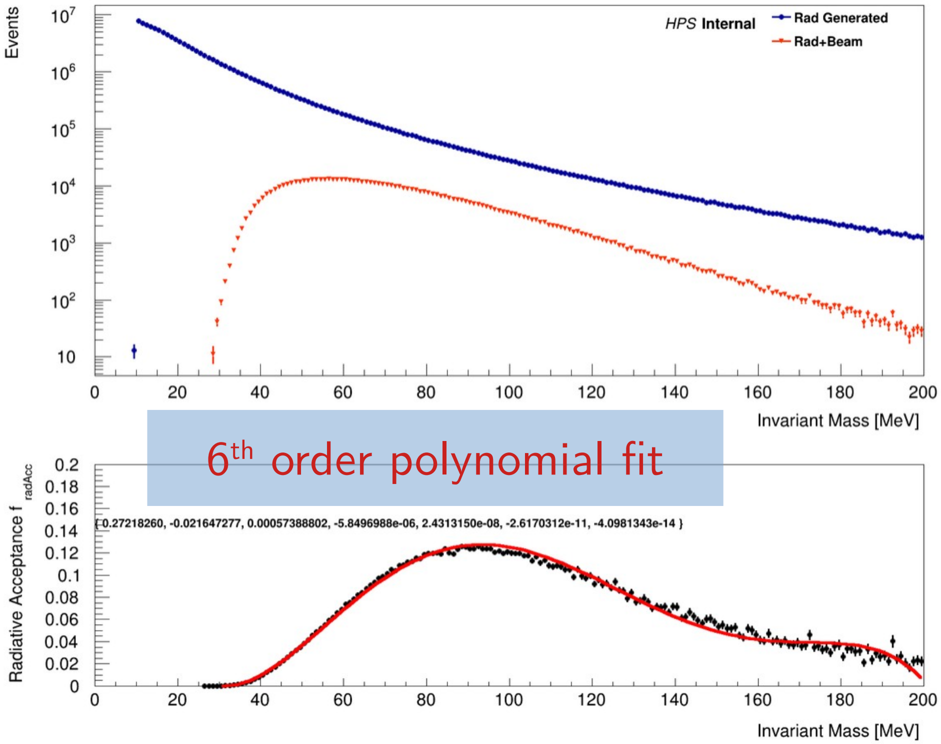
Generated

<u>Systematic Uncertainty</u>

- ~11% from Preselection cuts
- Need to study how acceptance changes with mis-alignments, and target position uncertainty *Sarah is producing these samples now!

Radiative Acceptance – Fit Polynomial






```
F-stat Test: [0.0, 445.8873264001735, 49.31428264707902, 222.16853689090675, 1705.0368133223403, 2287.5442058522844,
2.713528604174555, 239.05267186996403, 237.5954446109807, 121.49079724872668, 64.93822659490942]
```

6th **9th**

***can stop fit at 140MeV**

***also, might start at 40MeV instead**

Expected Signal Calculation

*systematic studies will involve mis-alignments and target uncertainty

$$N_{A'}(m_{A'},\epsilon) = \frac{3\pi m_{A'}\epsilon^2}{2N_{eff=1}\alpha}\frac{f_{rad}(m_{A'})}{A_{rad}(m_{A'})}\frac{dN_{CR}}{dm_{reco}}$$

Total number of A's

$$F(z) = \left(\left.\frac{dN^{\text{selected}}_{V_D}}{dz_{vtx_{\text{true}}}}\right|_{z_{vtx}=z}\right) \Big/ \left(\left.\frac{dN^{\text{generated}}_{V_D}}{dz_{vtx_{\text{true}}}}\right|_{z_{vtx}=z}\right)$$

Tight SELECTION acceptanceXefficiency for signal generated with constant lifetime out to 20cm in z

$$f_{V_D}(\epsilon,z) = \frac{\exp\left(\frac{z_{target}-z}{\gamma c\tau_{V_D}}\right)}{\gamma c\tau_{V_D}}F(z)$$

*F(z) uses truth z, so don't need to say z_{target}

Lifetime-weighted dark vector acceptanceXefficiency

$$N_{sig}(m_{A'},\epsilon) = N_{A'}\int_{z_{target}}^{\infty}\left(BR(\rho_D)f_{\rho_D}(\epsilon,z) + BR(\phi_D)f_{\phi_D}(\epsilon,z)\right)dz$$

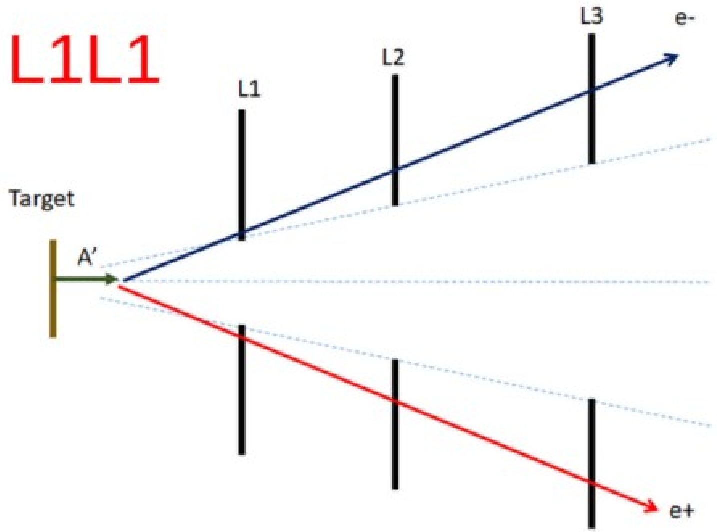
Full expected signal calculation

Tight Selection Variables

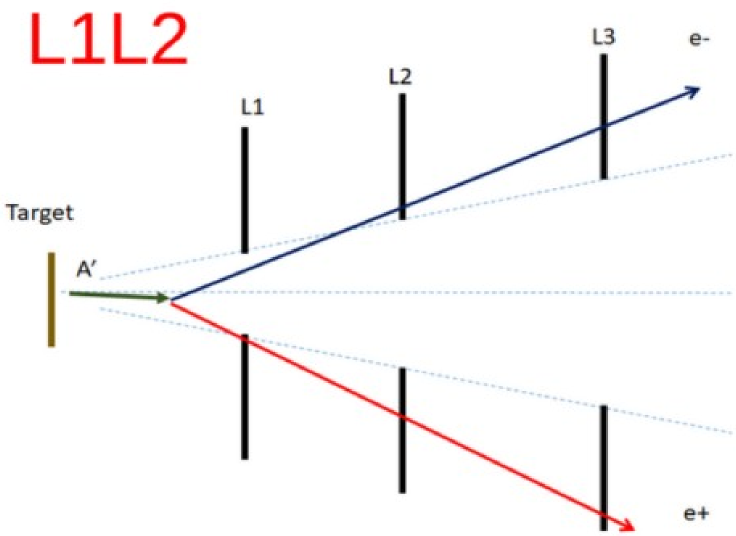
1. Target Projected Vertex Significance

L1L1 Hit Requirement

Alic



Tom

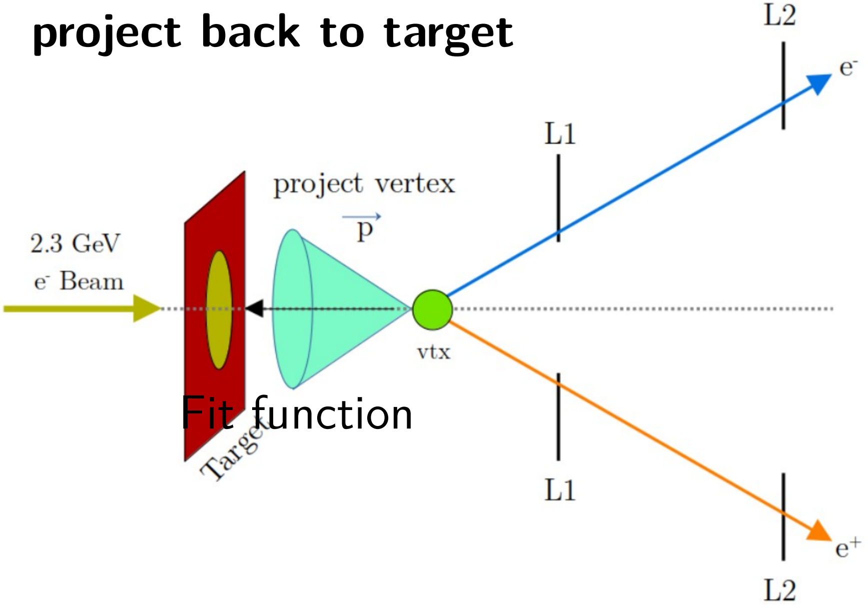


- Require axial+stereo hits in L1 and L2
- Gives best vertex resolution
- Restricted to shorter lifetimes than L1L2+L2L2

Target Projected Vertex Significance

*Use 1% of files ending in 0 from each run to fit run-dependent beamspot

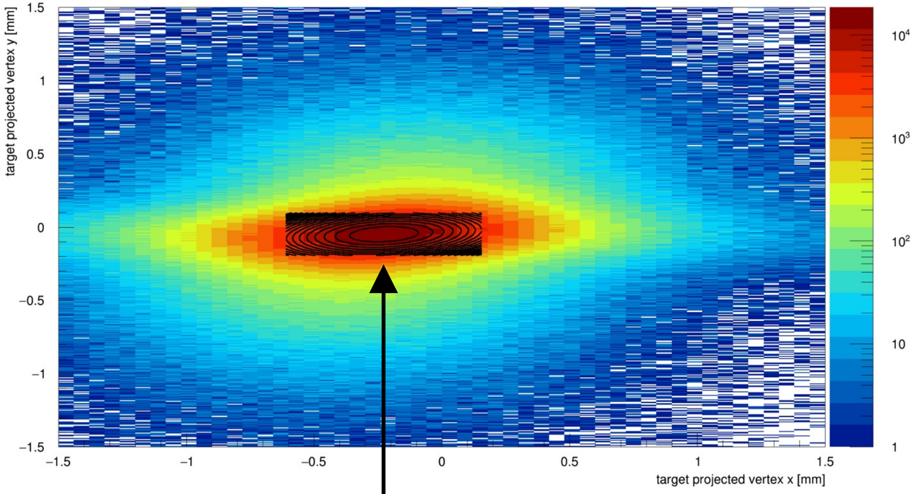
Displaced vertex should project back to target



Fit function

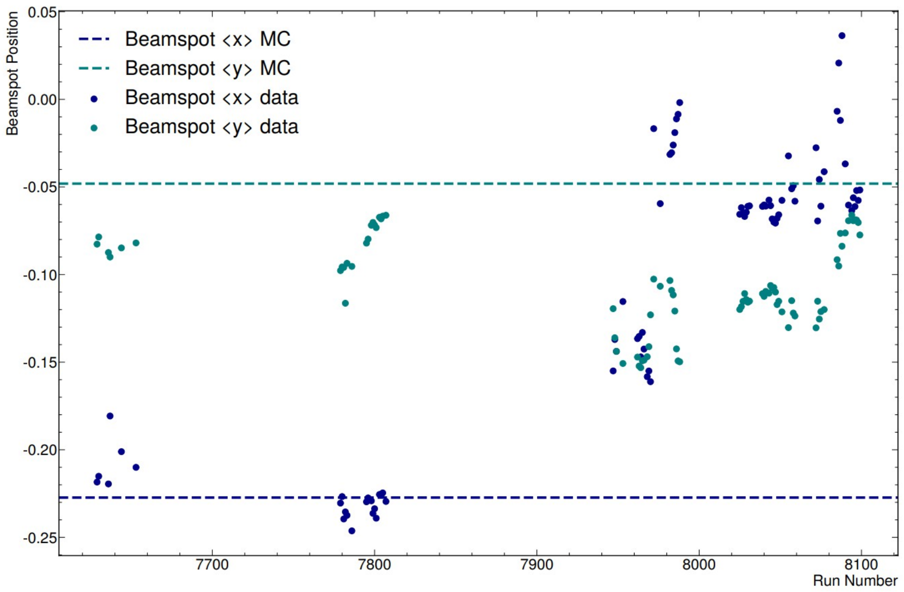
Preselection Unconstrained V0 Vertices

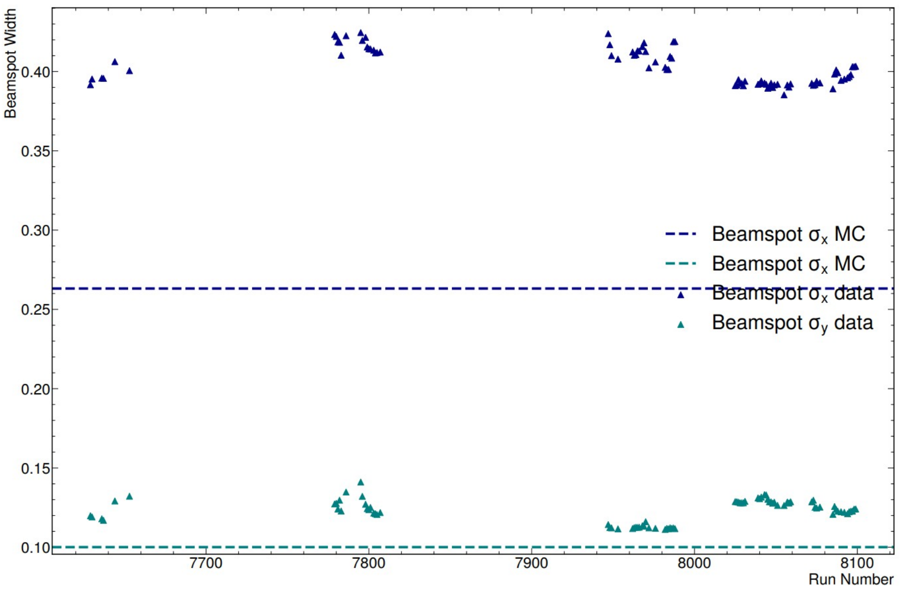
Projected to target z



$$f(x,y) = \exp\left(-\frac{(x_{rot}-\mu_{x_{rot}})^2}{2\sigma^2_{x_{rot}}} - \frac{(y_{rot}-\mu_{y_{rot}})^2}{2\sigma^2_{y_{rot}}}\right)$$

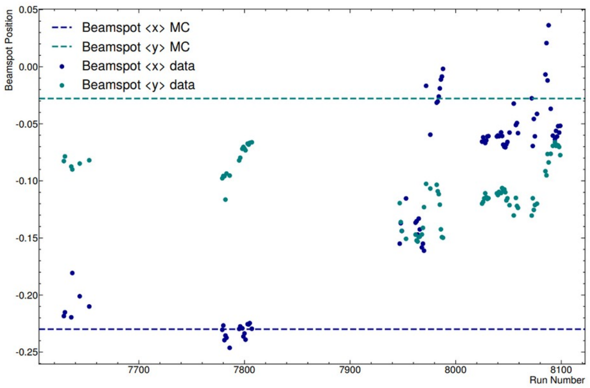
Run Dependent Beamspot – Unrotated Coordinates

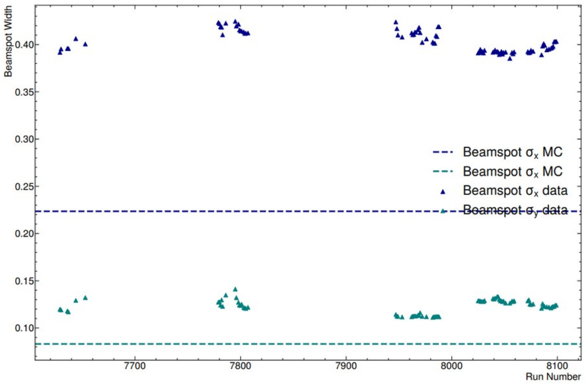


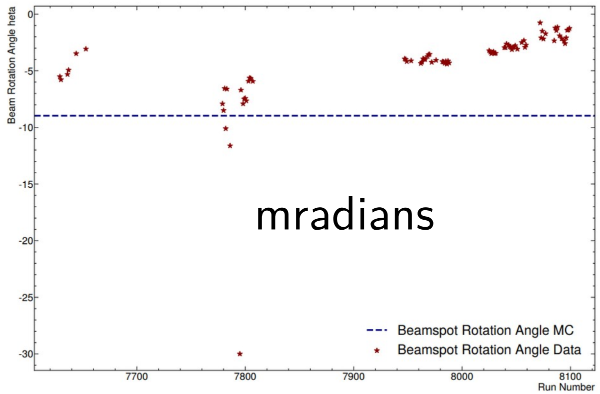


- *Why does the beamspot position change so much in data?
  - Machine control loves to mess with the beam
- Scale is mm, not crazy change
- Projection significance doesn't care, defined relative to beamspot parameters

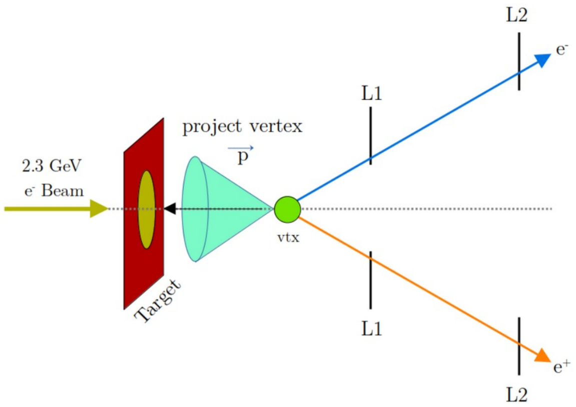
Run Dependent Beamspot – Rotated Coordinates

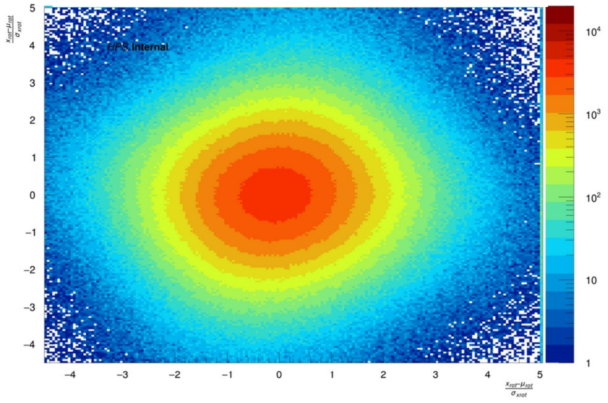






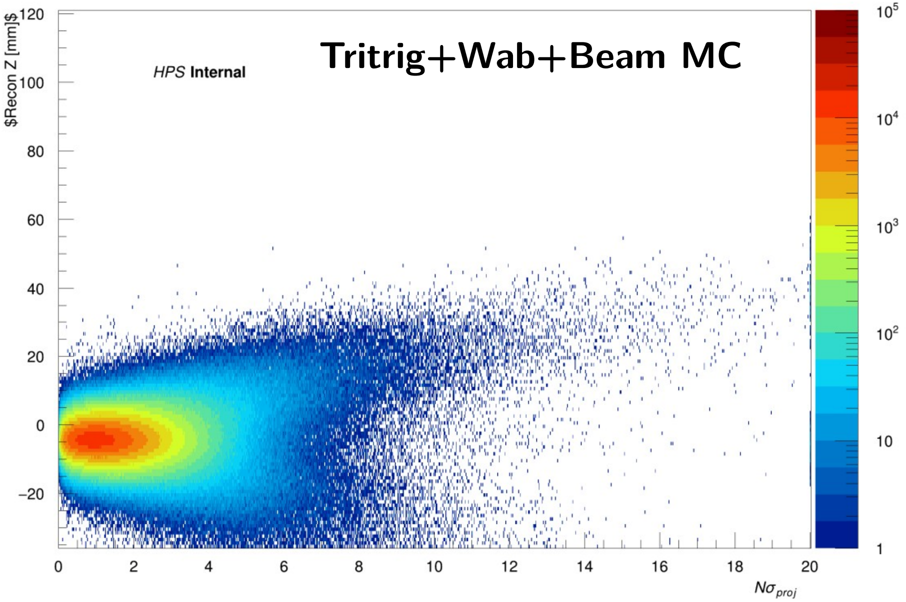
$$(N_{\sigma x_{rot}}, N_{\sigma y_{rot}}) = \left(\frac{x_{rot} - \mu_{x_{rot}}}{\sigma_{x_{rot}}}, \frac{y_{rot} - \mu_{y_{rot}}}{\sigma_{y_{rot}}}\right)$$

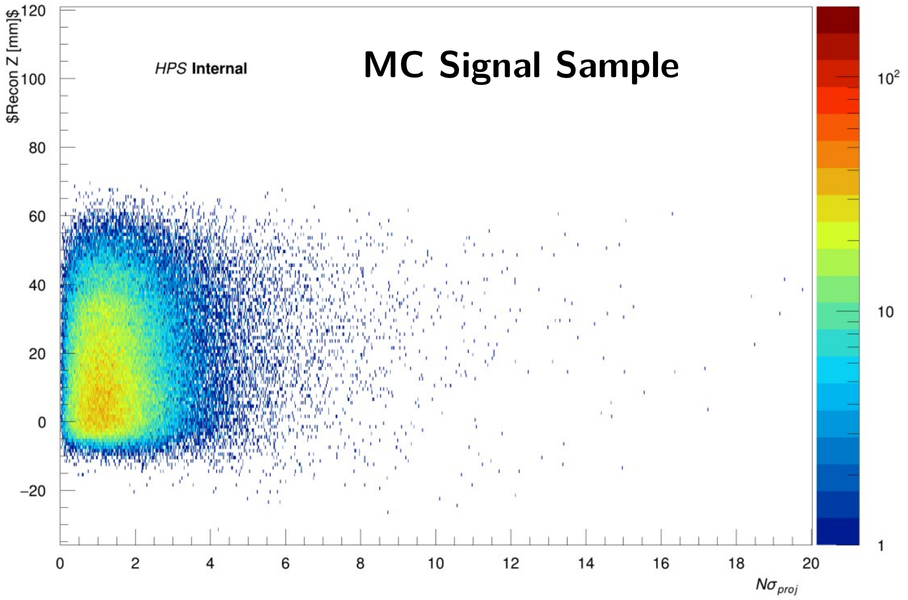




- Project vertex to target
- Rotate coordinates using fitted beamspot angle
- Use fitted beamspot to get significance

Target Projected Vertex Significance



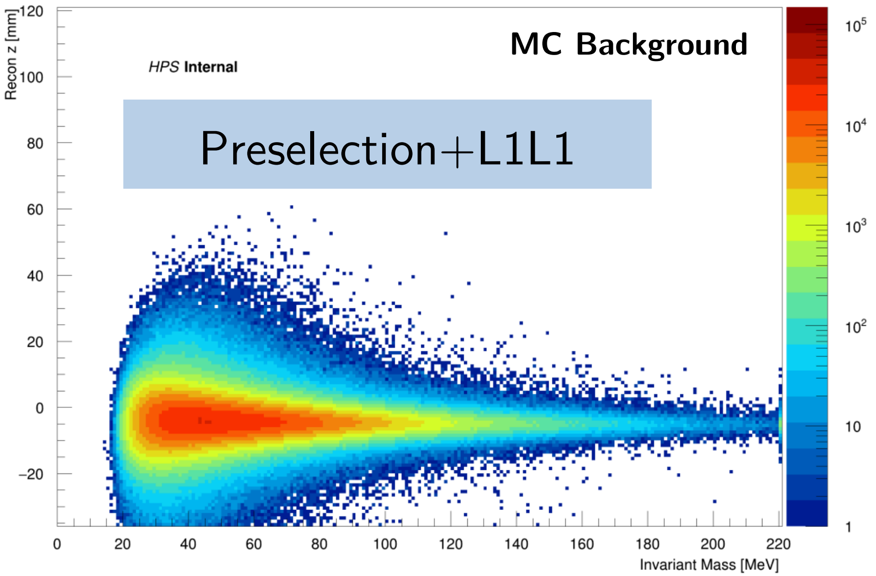


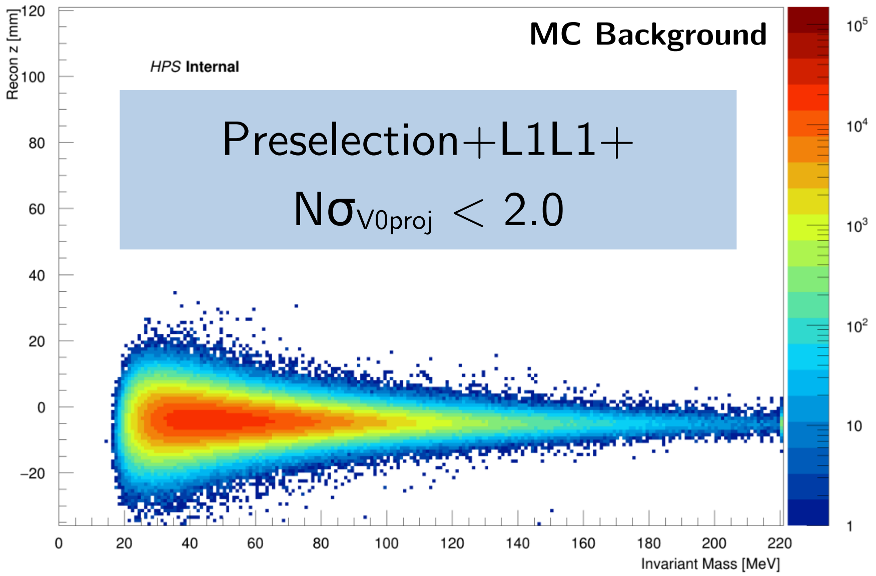
Combine x and y significance into single cut variable

"Target Projected Vertex Significance"

$$N\sigma_{V0_{proj}} = \sqrt{N^2_{\sigma x_{rot}} + N^2_{\sigma y_{rot}}}$$

Target Projected Vertex Significance

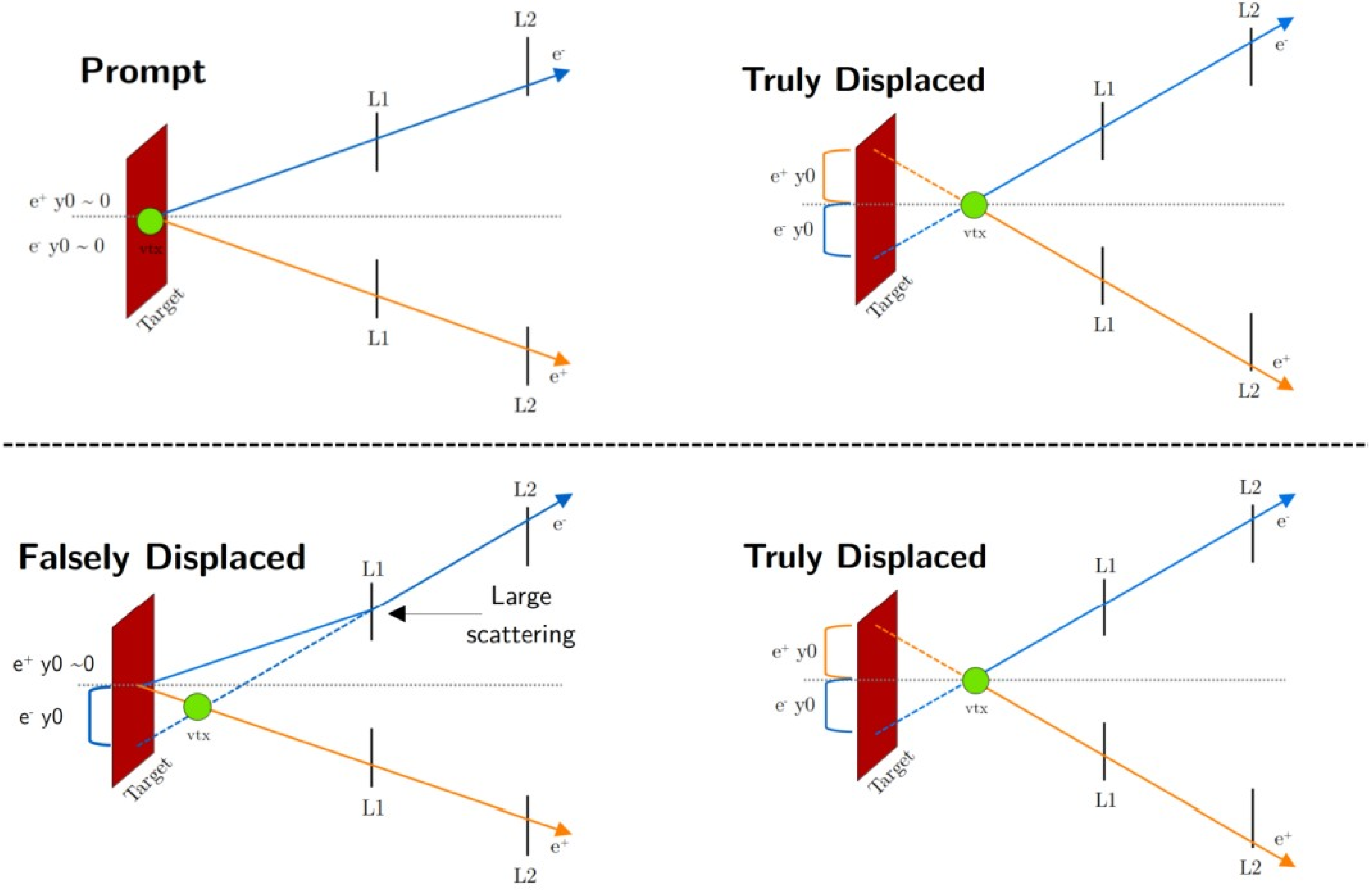




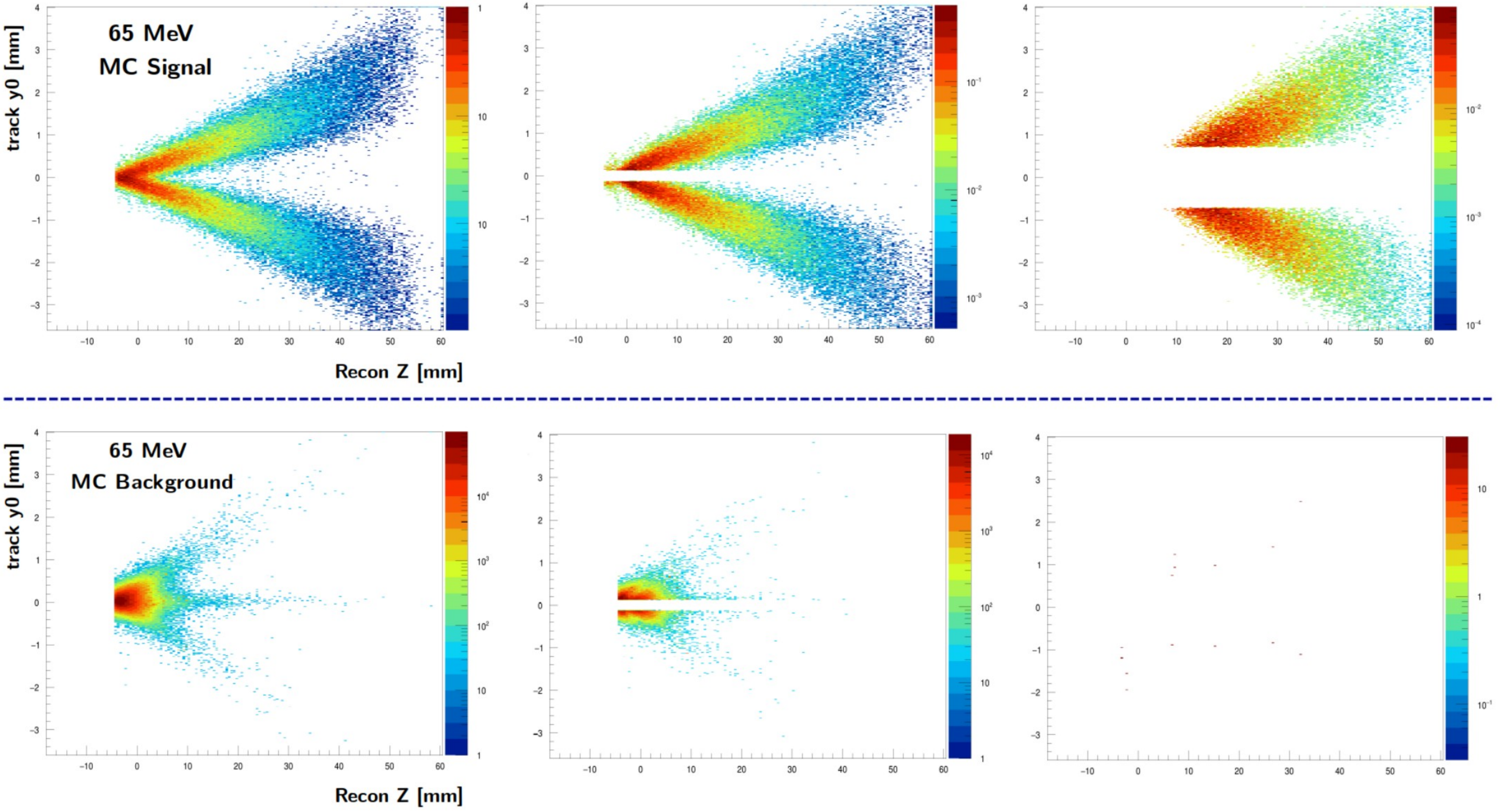
Tight Selection Variables
2. Vertical Impact Parameter

Vertical Impact Parameter Cut

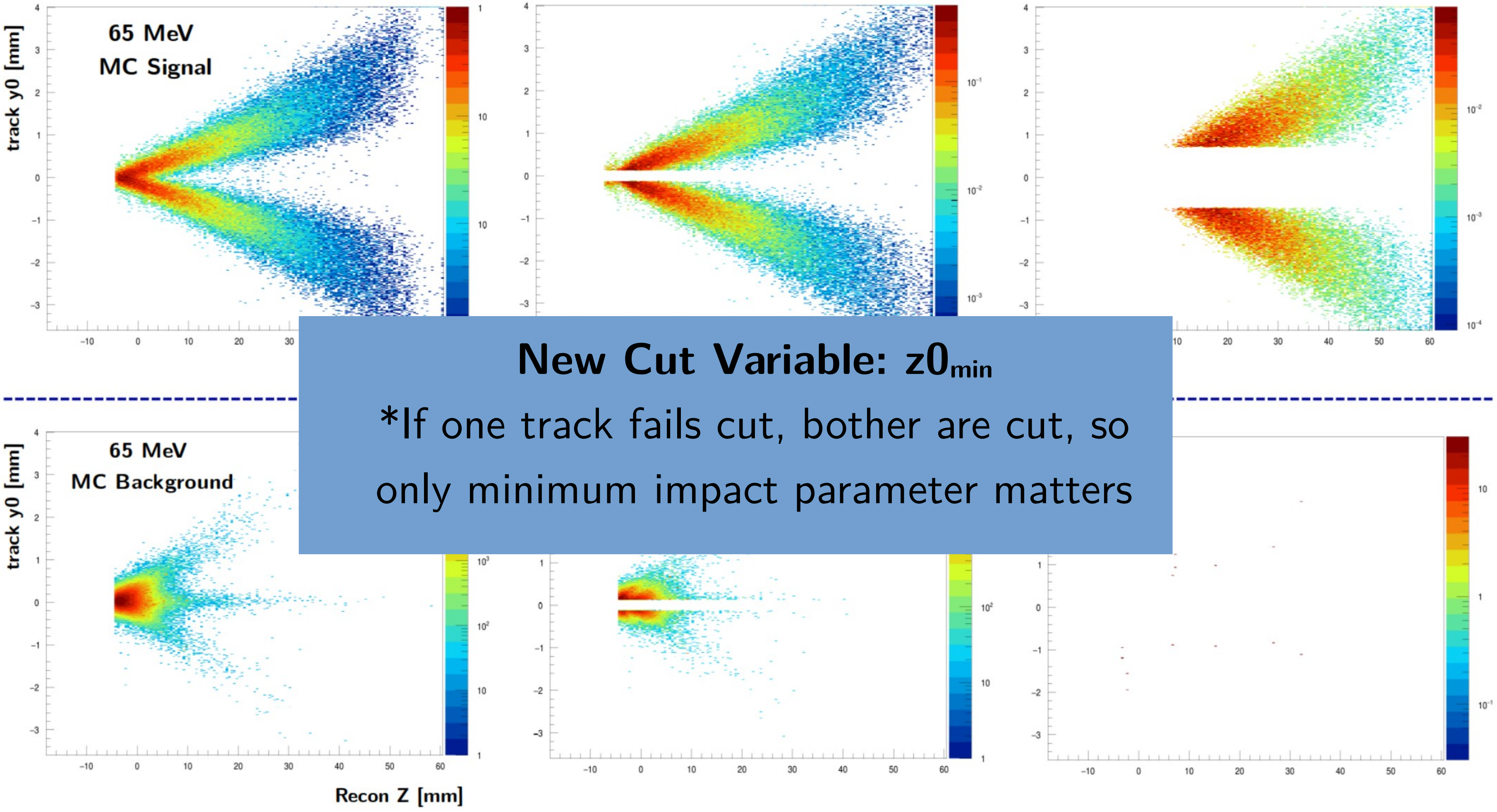
***y0 = z0**



Vertical Impact Parameter Cut



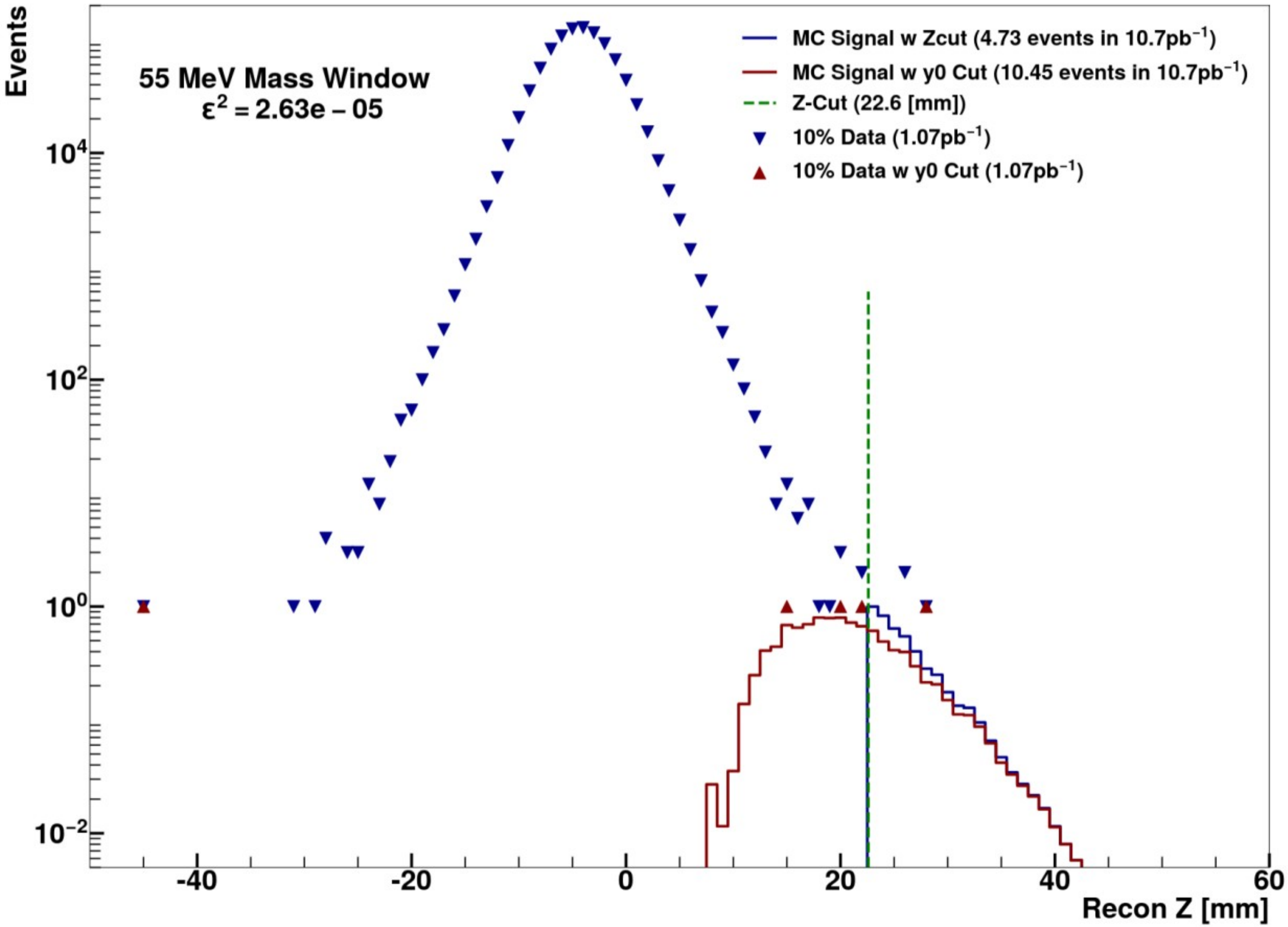
Vertical Impact Parameter Cut



New Cut Variable: $z0_{min}$

*If one track fails cut, bother are cut, so only minimum impact parameter matters

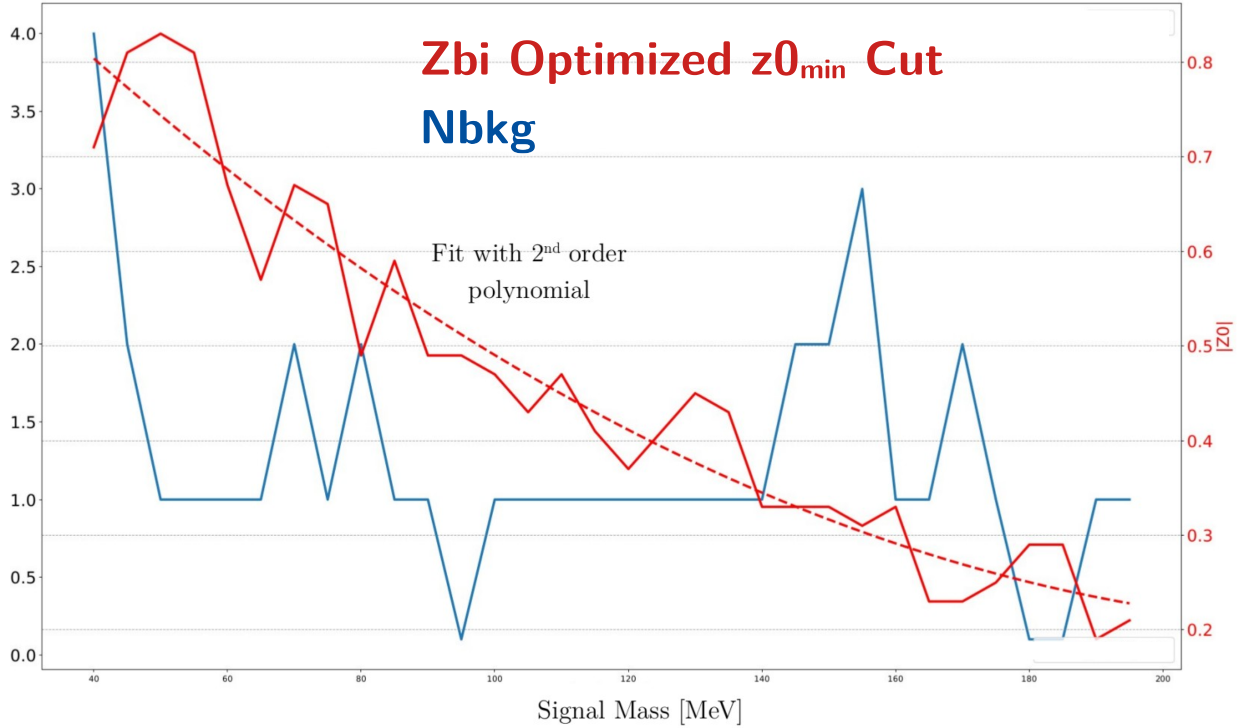
Vertical Impact Parameter Cut vs Zcut Analysis



*calculated using full expected signal calc.

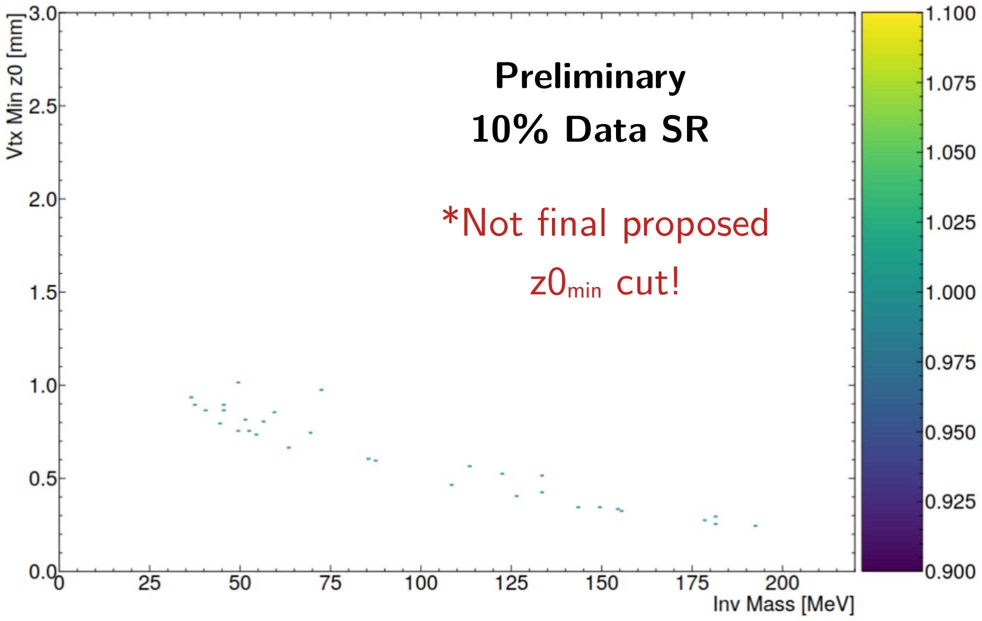
Vertical Impact Parameter Cut Optimization

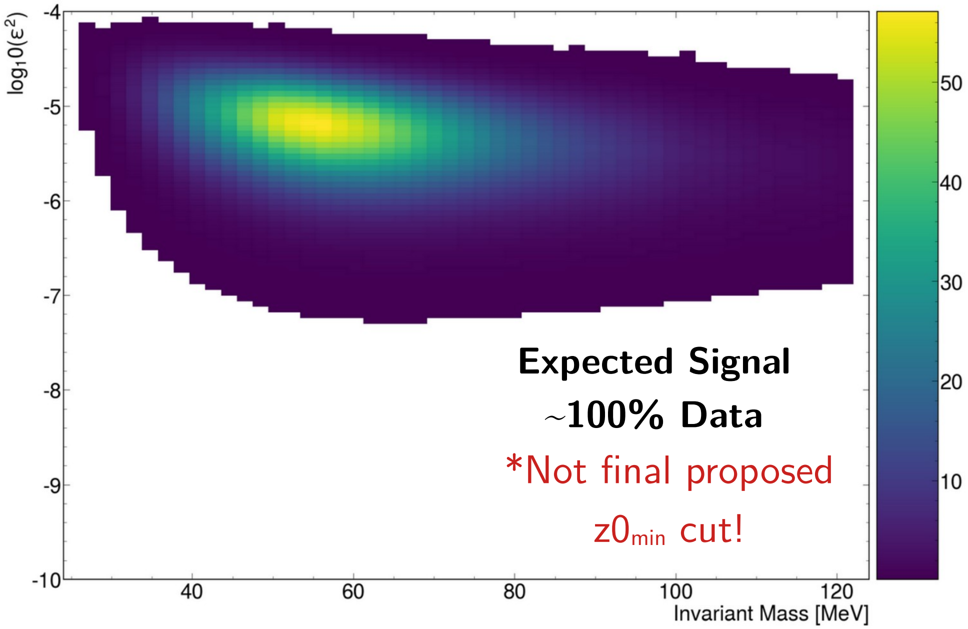
- $z0_{min}$ shape optimized **using 10% Data SR ONLY**
- Cut is function of invariant mass, fit with 2nd order polynomial
- ***This is not the final proposed cut**…tighten later (+0.1mm) to protect from large fluctuations in bkg in 100% data SR



$$z0_{min}(m) > 1.0762 - 7.44534\times10^{-3}m + 1.58746\times10^{-5}m2$$

Preliminary Tight Selection



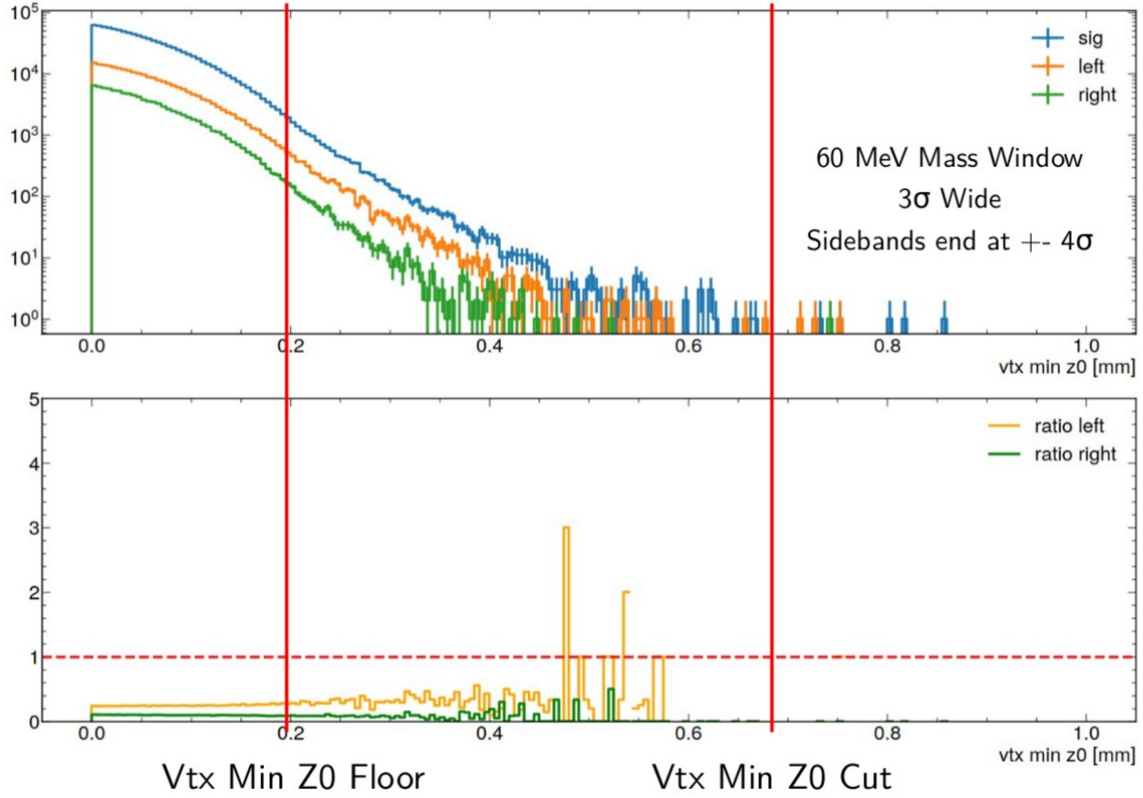


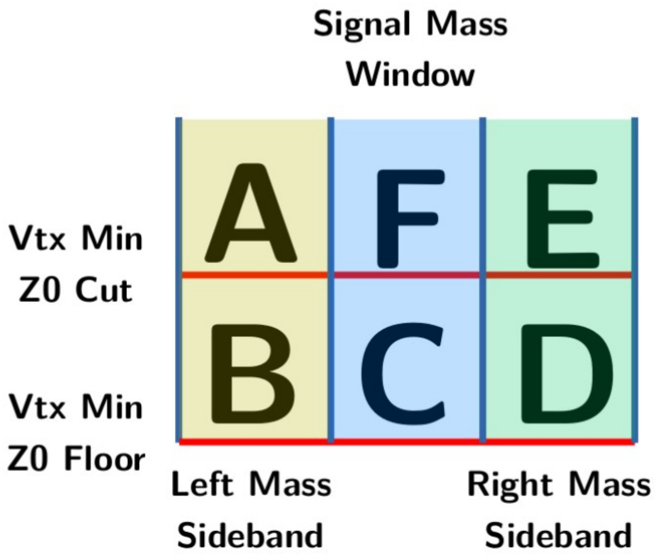
Cut	Condition
Layer 1 Requirement	e^- and e^+ have L1 axial+stereo hit
Layer 2 Requirement	e^- and e^+ have L2 axial+stereo hit
Target Projected Vertex Significance Cut ($V0_{proj}$)	$V0_{proj} < 2.0$
Target Z Cut	$z_{vtx} > -4.3$ [mm]
Impact Parameter Cut	$z0^{min}(m) > 1.0762 - 7.44534 \times 10^{-3} m + 1.58746 \times 10^{-5} m^2$

Signal Search:

Background Estimation

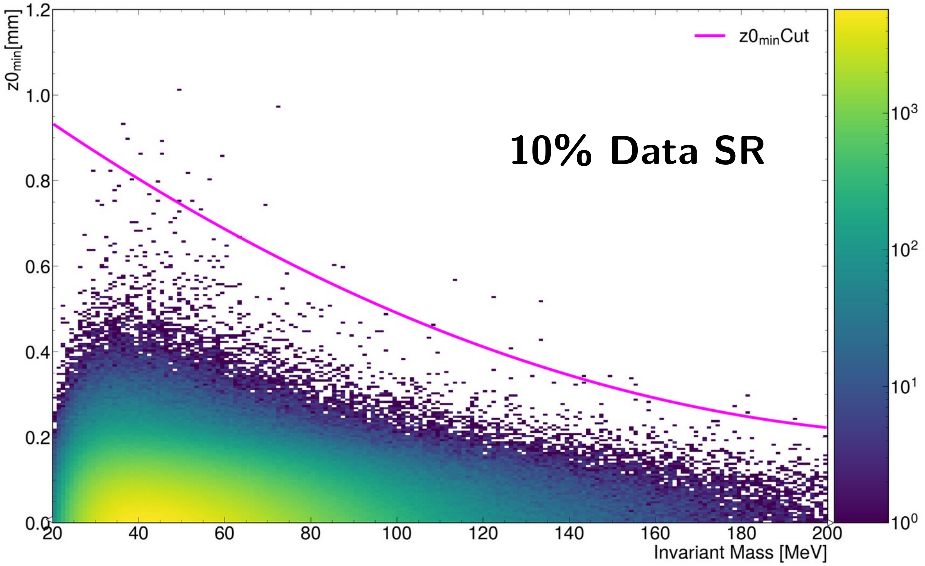
Background Estimation Method

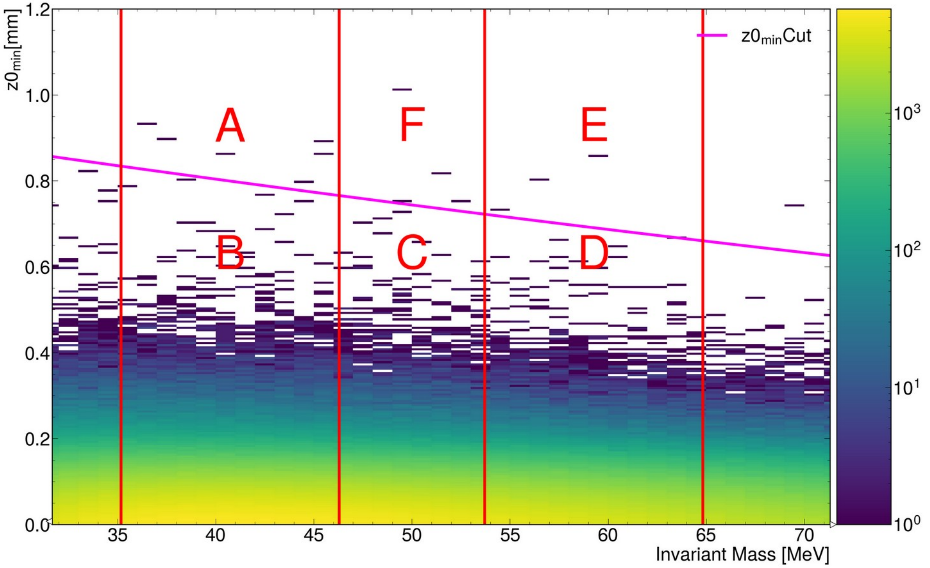




$$(A+E)/(B+D)*C = F$$

Background Estimation Method





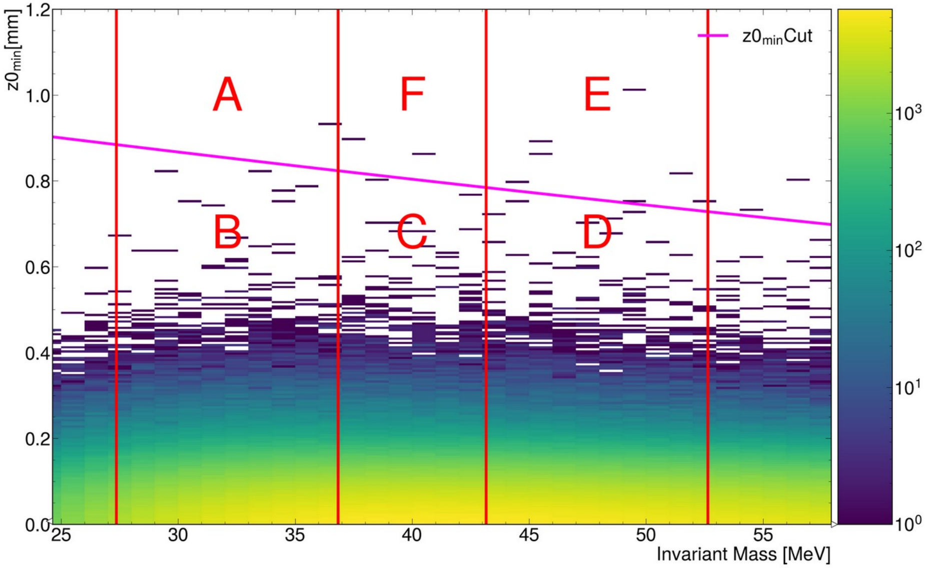
A bit of a correlation between $z0_{min}$ and Invariant Mass overall

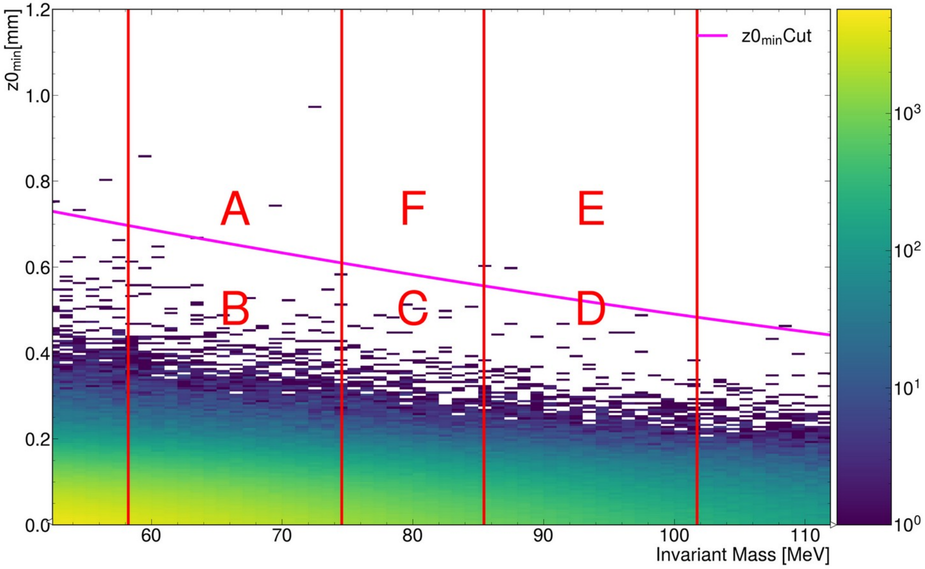
$z0_{min}$ versus mass is ~uncorrelated in narrow region centered on search window

Background Estimation Method

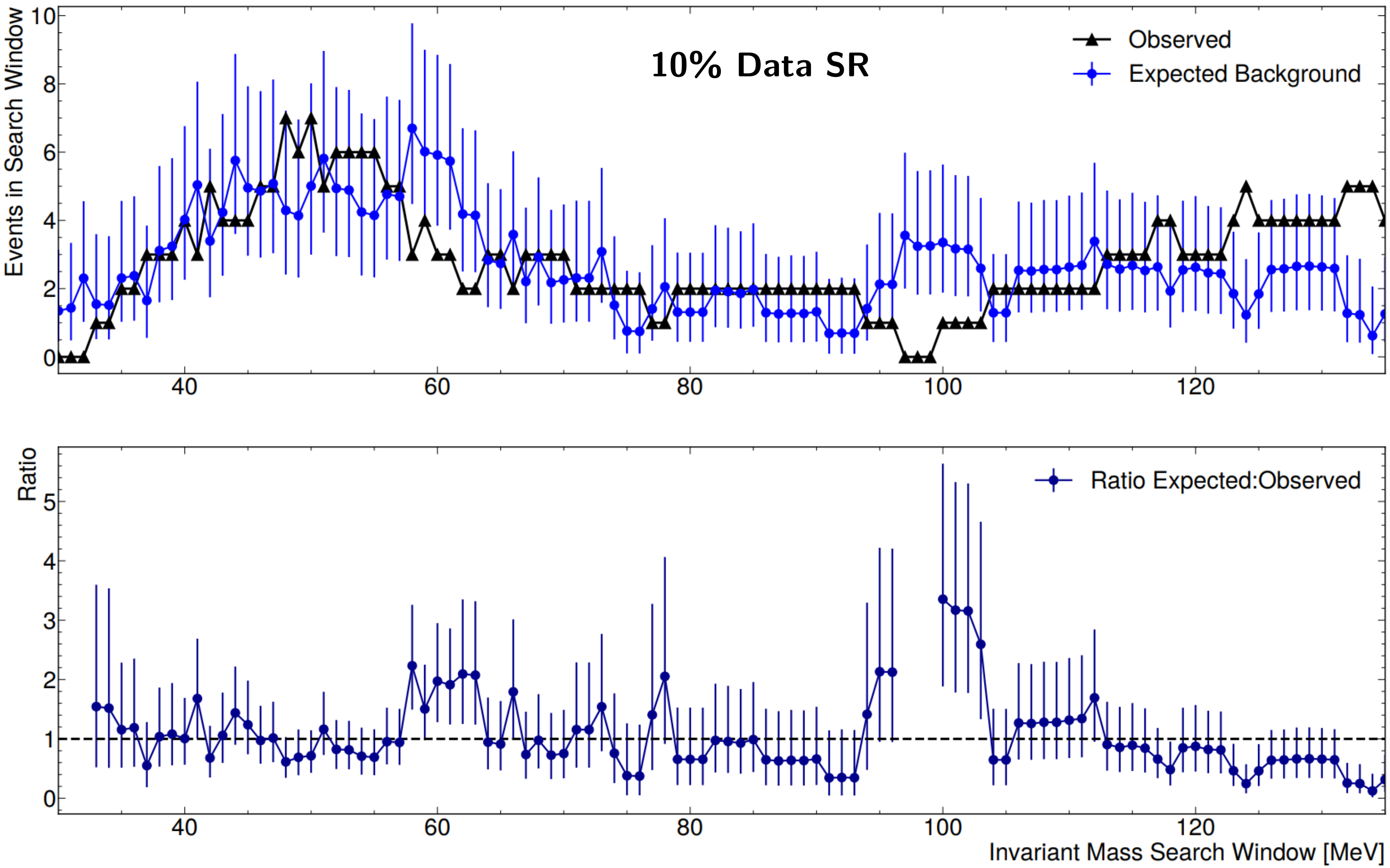
*Two different search windows

Using left and right mass sidebands tends to cancel the small linear correlation on either side





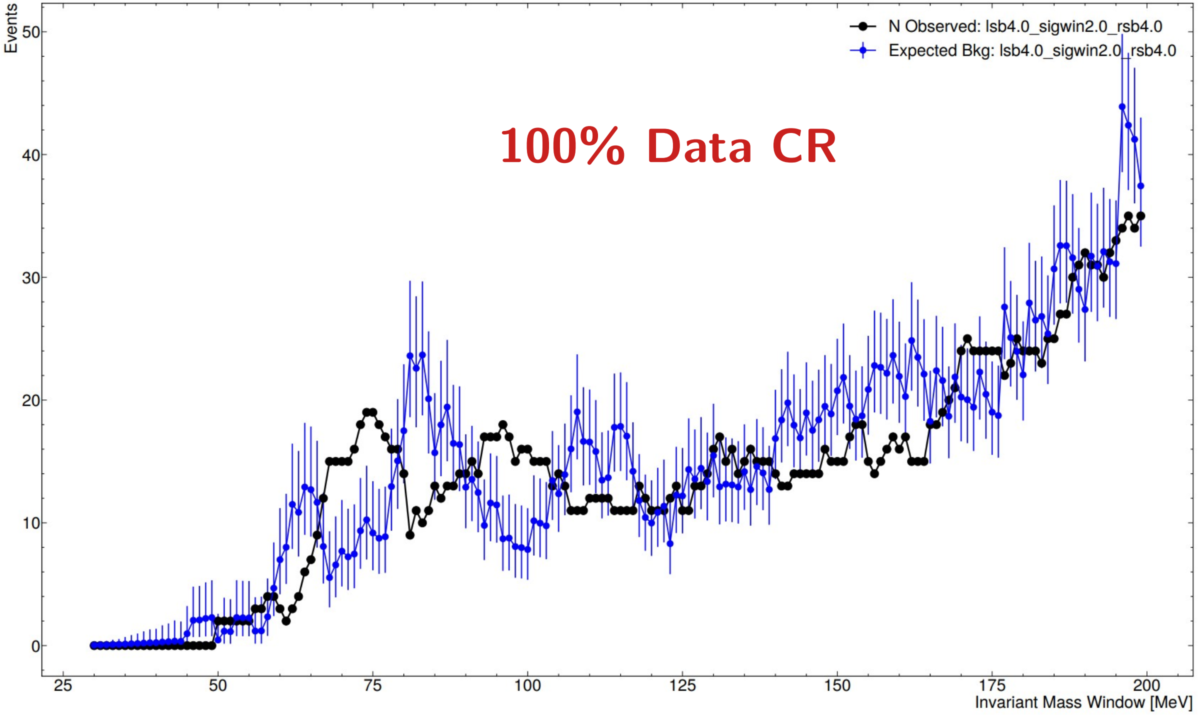
Background Estimation Method



Background Estimation Method

- **ONLY use 100% data CR** to evaluate how well background estimate reflects observed events
- Totally blind to 100% data SR
- **NO cuts are based on this study**

- *Larger statistics in this sample is convenient to test the ABCD mass sideband and search window size impact on background estimate quality
- *High psum vs low psum doesn't matter



Signal Search:
Data Significance

Calculating P-Value using MC Toys

- Bkg-only test statistic is random sample of Poisson with mean bkg b

$$f(x) = \frac{b^k}{x!} e^{-b} \qquad b = \left(\frac{A+E}{B+D}\right) C$$

- b calculated by sampling 3 parent distributions

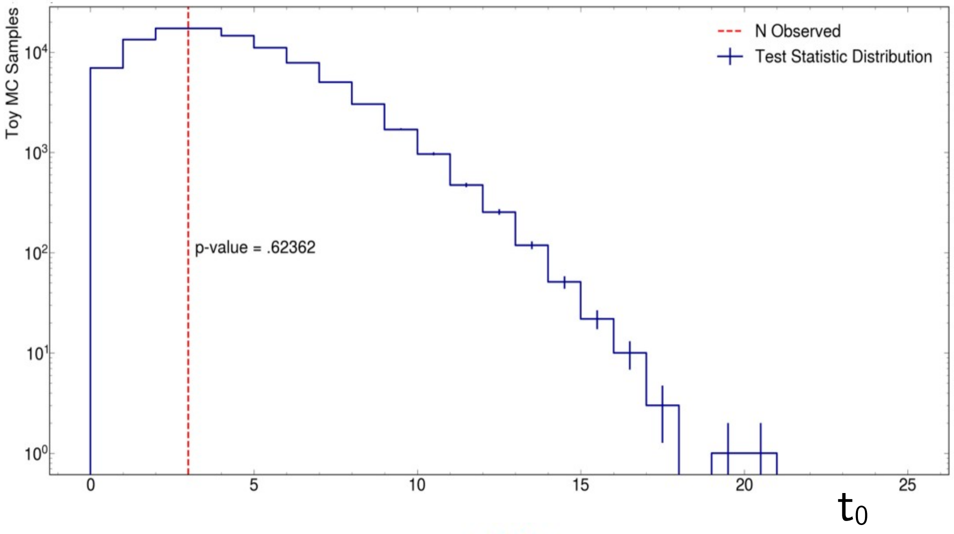
$$(B+D) \sim \mathcal{N}(B+D)$$

$$C \sim \mathcal{N}(C) \qquad {}^*\sigma_{Normal} = \text{sqrt}(N)$$

$$(A+E) \sim \text{Poisson}(A+E)$$

```
poisson_low_err = lambda n : np.sqrt(n - 0.25) if n >= 0.25 else 0.0
poisson_up_err = lambda n : np.sqrt(n+0.75) + 1
```

- Build t_0 distribution using MC Toys (~100 million +)



$$p_{local} = \int_{t_{obs}}^{\infty} f(t_0)\, dt_0$$

Calculating P-Value using MC Toys

- **Bkg-only test statistic** is random sample of Poisson with mean bkg b

$$f(x) = \frac{b^k}{x!} e^{-b} \qquad b = \left(\frac{A+E}{B+D} \right) C$$

- **Sample from 3 parent distributions**

$$(B+D) \sim \mathcal{N}(B+D)$$

$$C \sim \mathcal{N}(C) \qquad *\sigma_{Normal}=\text{sqrt}(N)$$

$$(A+E) \sim \text{Poisson}(A+E)$$

```
poisson_low_err = lambda n : np.sqrt(n - 0.25) if n >= 0.25 else 0.0
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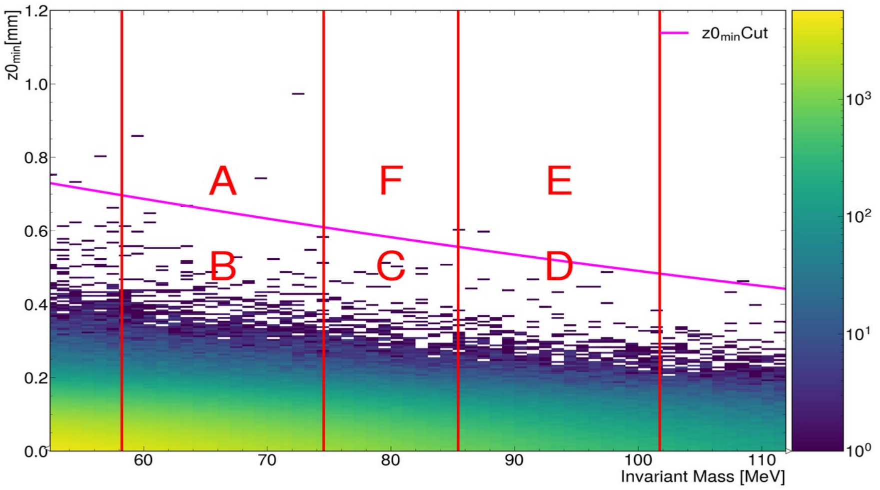
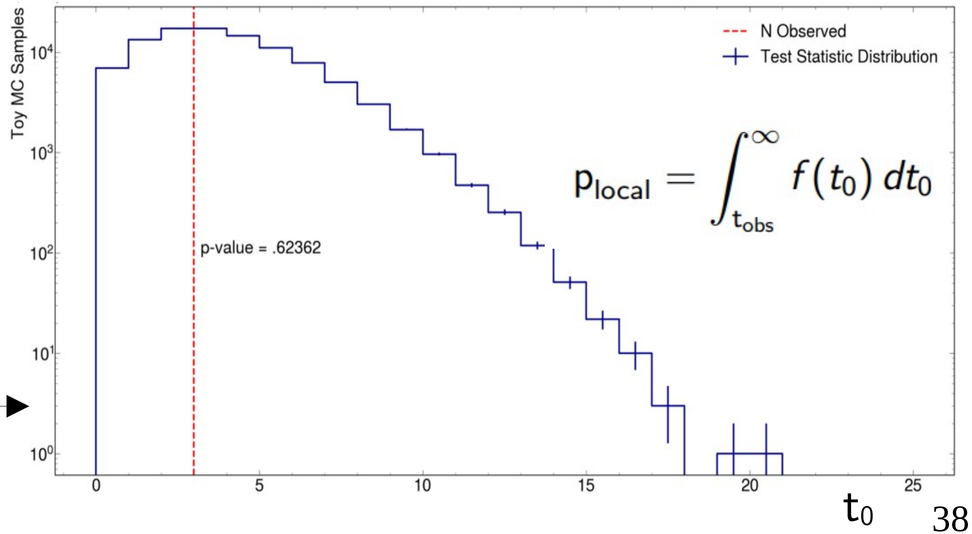
- **Build t_0 distribution using MC Toys** (~100 million +)





Calculating P-Value using MC Toys

- **Bkg-only test statistic** is random sample of Poisson with mean bkg b

$$f(x) = \frac{b^k}{x!}e^{-b} \qquad b = \left(\frac{A+E}{B+D}\right)C$$

- **Sample from 3 parent distributions**

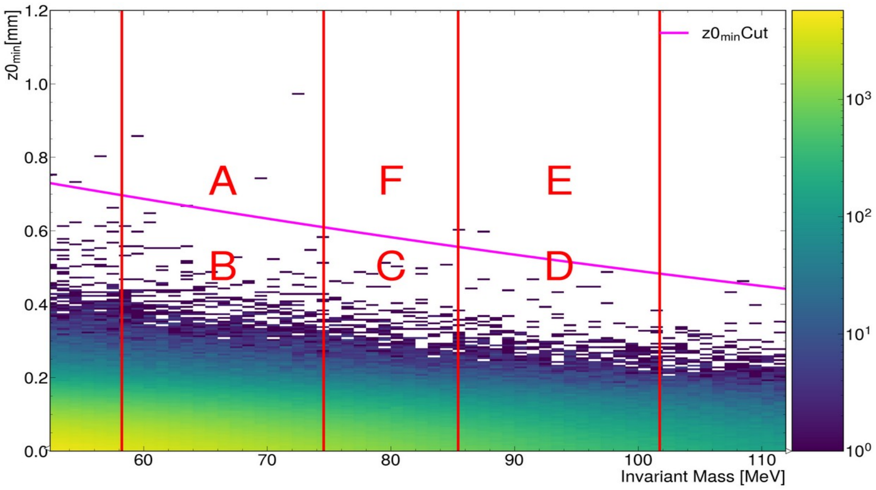
$$(B+D) \sim \mathcal{N}(B+D)$$

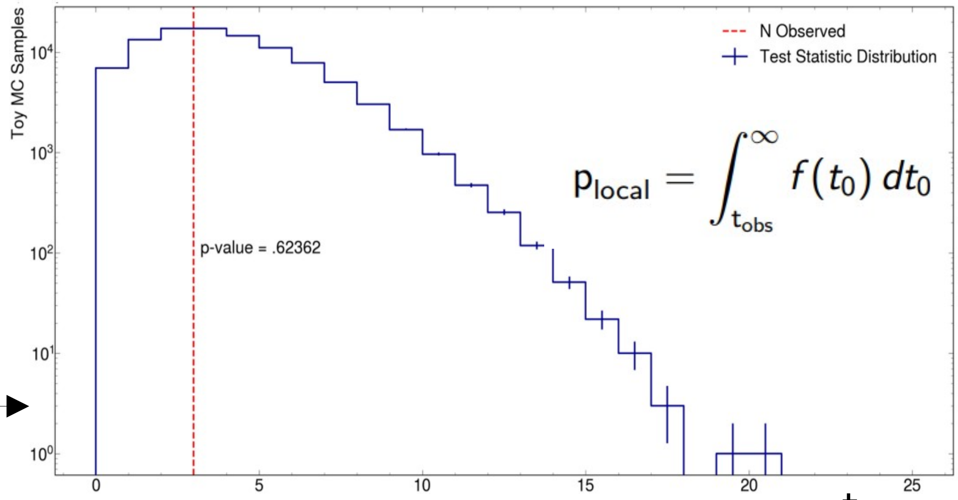
$$C \sim \mathcal{N}(C) \qquad *\sigma_{Normal}=\text{sqrt}(N)$$

$$(A+E) \sim \text{Poisson}(A+E)$$

```
poisson_low_err = lambda n : np.sqrt(n - 0.25) if n >= 0.25 else 0.0
poisson_up_err = lambda n : np.sqrt(n+0.75) + 1
```

- **Build t_0 distribution using MC Toys** (~100 million +)





Calculating P-Value using MC Toys

- **Bkg-only test statistic** is random sample of Poisson with mean bkg b

$$f(x) = \frac{b^k}{x!}e^{-b} \qquad b = \left(\frac{A+E}{B+D}\right) C$$

- b calculated by **sampling 3 parent distributions**

$$(B+D) \sim \mathcal{N}(B+D)$$

$$C \sim \mathcal{N}(C) \qquad *\sigma_{Normal}=\text{sqrt}(N)$$

$$(A+E) \sim \text{Poisson}(A+E)$$

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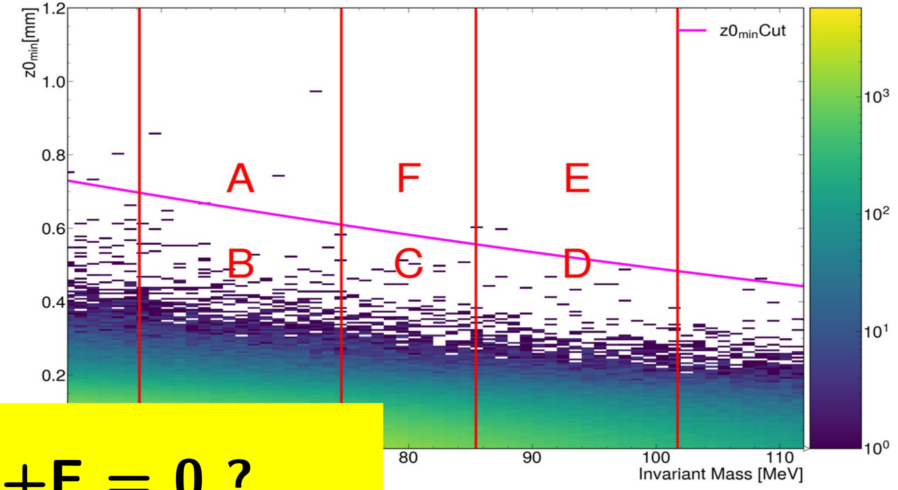
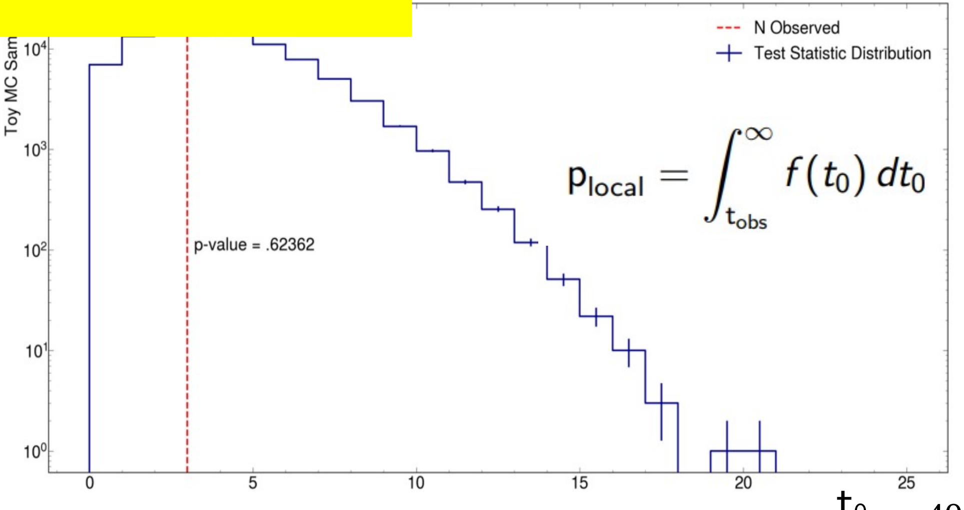
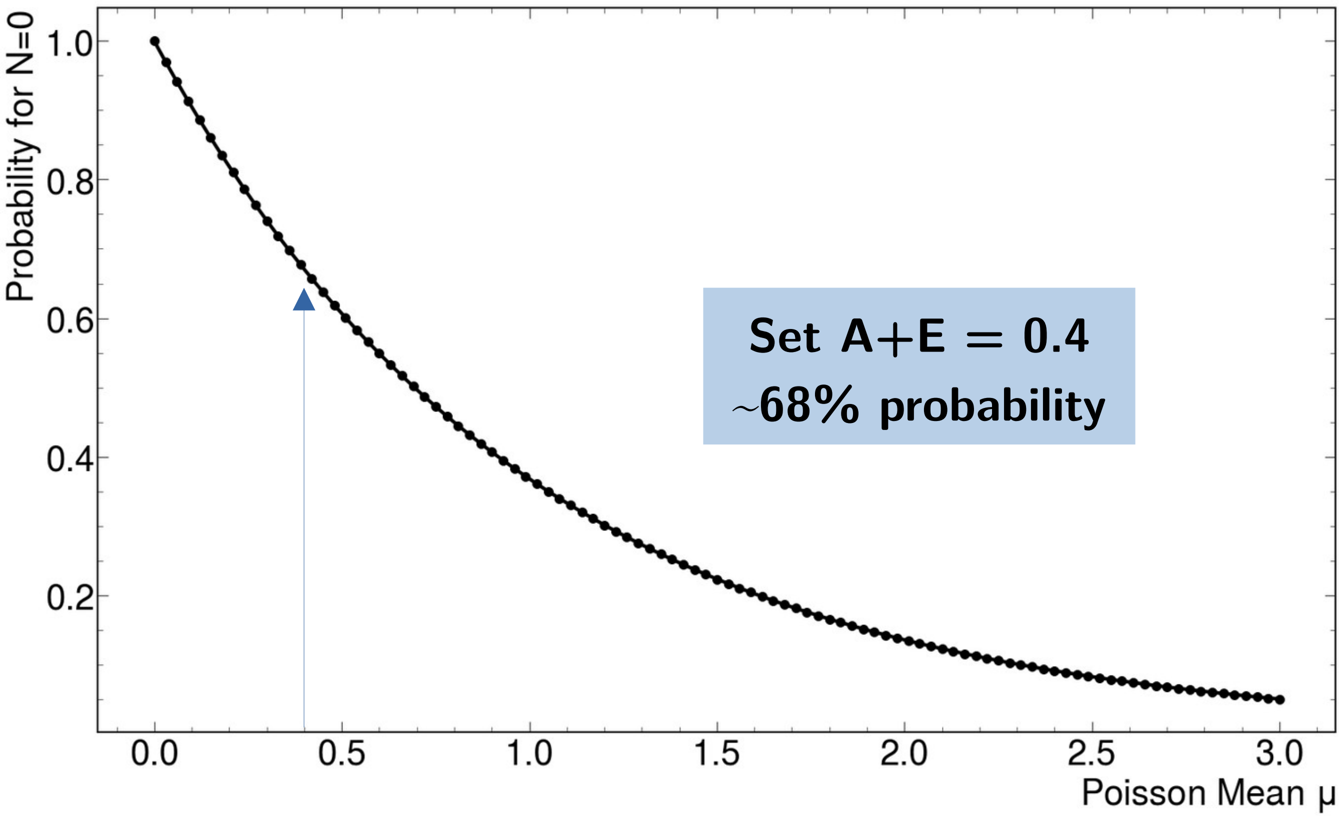


What if A+E = 0 ?



Error when A+E = 0?

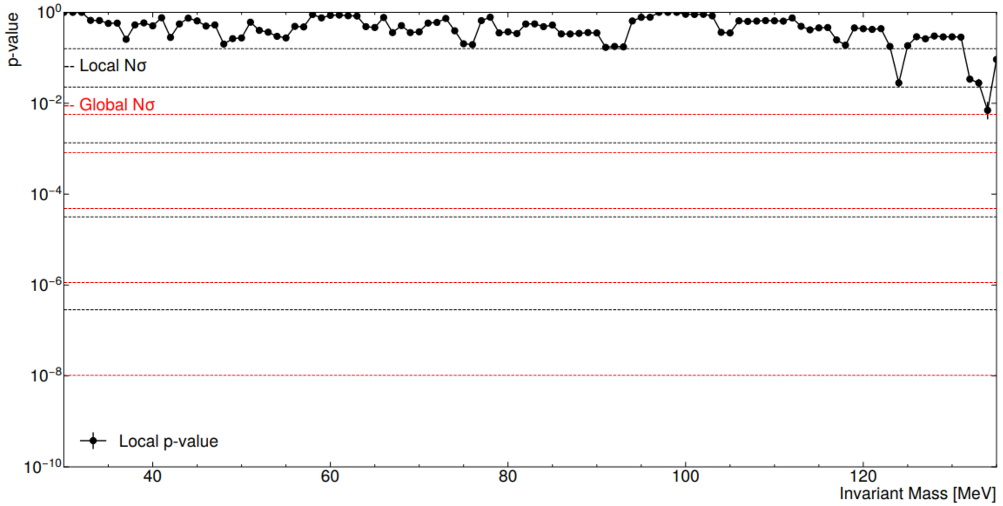
- If A+E = 0, we can't build a Poisson distribution for the toys
- We could just force A+E = 1, but that's very conservative

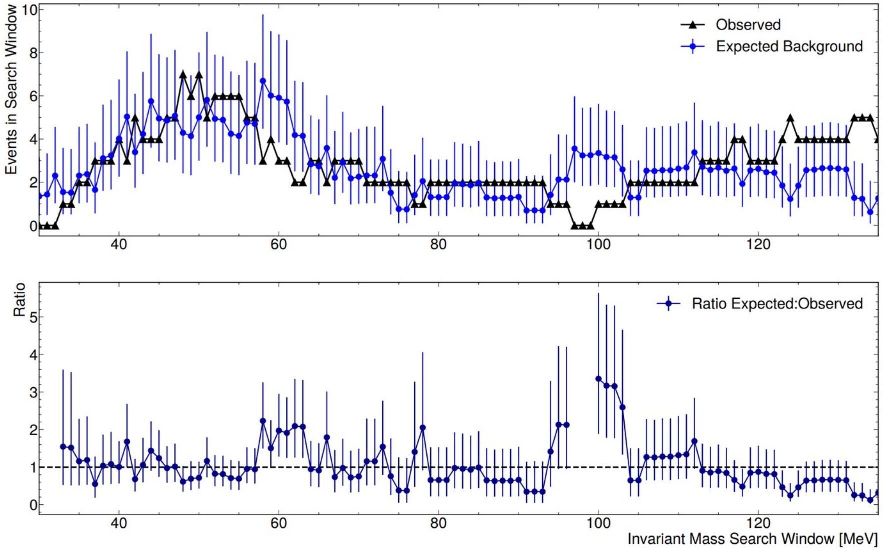


Calculating P-Value using MC Toys

Preliminary

10% Data SR



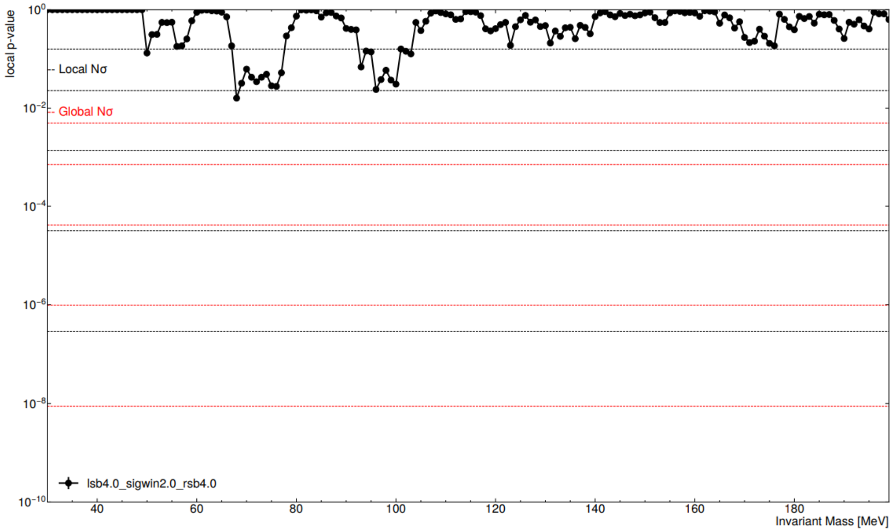


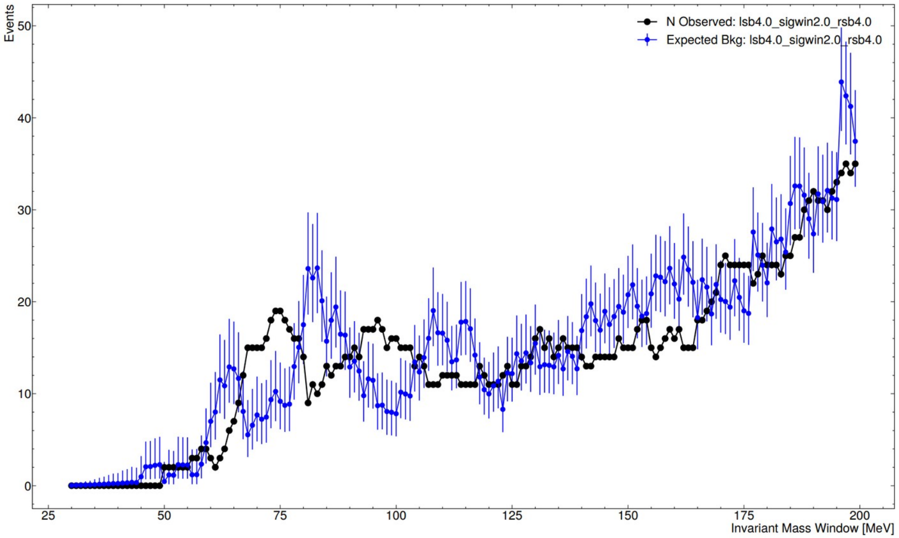
$$L_{corr} \approx \frac{m_{max} - m_{min}}{\sigma_{avg}}$$

Calculating P-Value using MC Toys

Preliminary
100% Data CR

*Just used as a sanity check for higher statistics





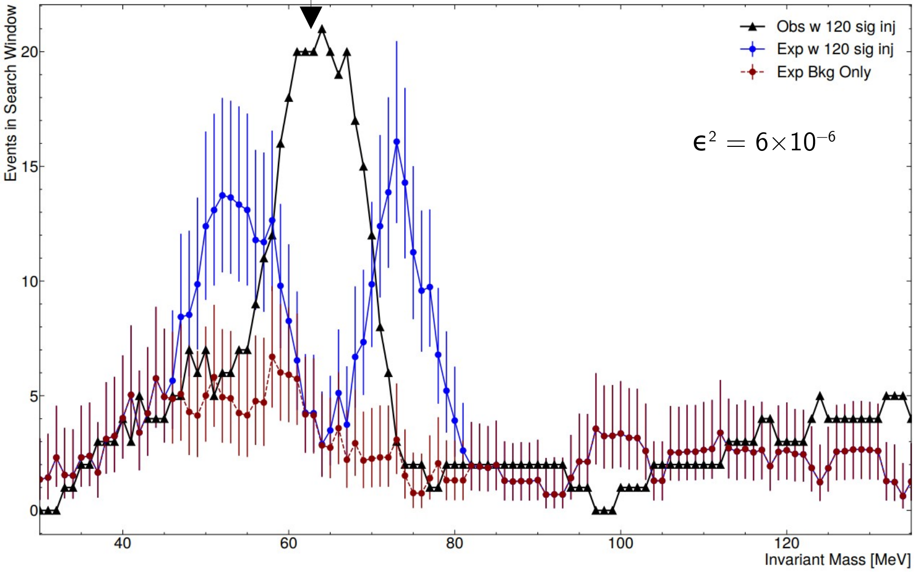
$$L_{corr} \approx \frac{m_{max} - m_{min}}{\sigma_{avg}}$$

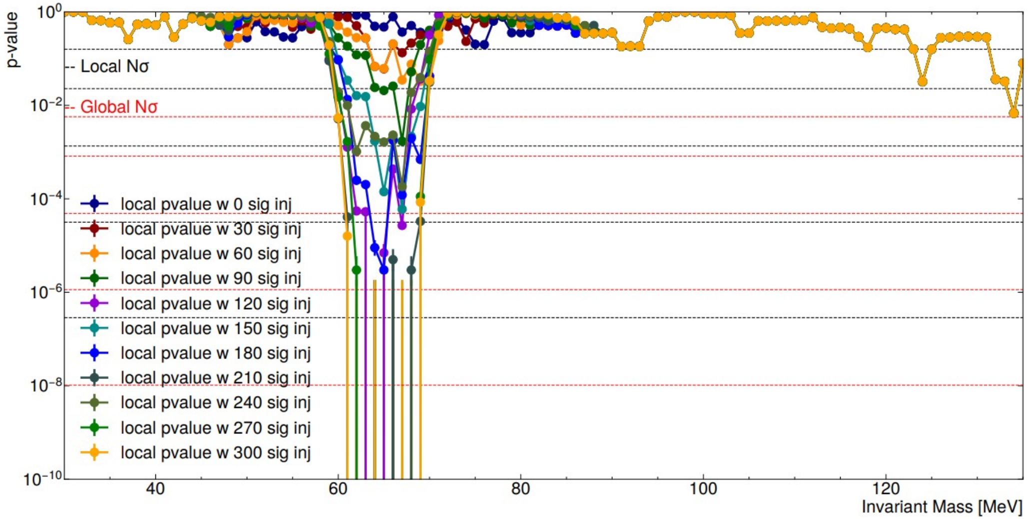
Signal Injected P-Values

Preliminary

10% Data SR

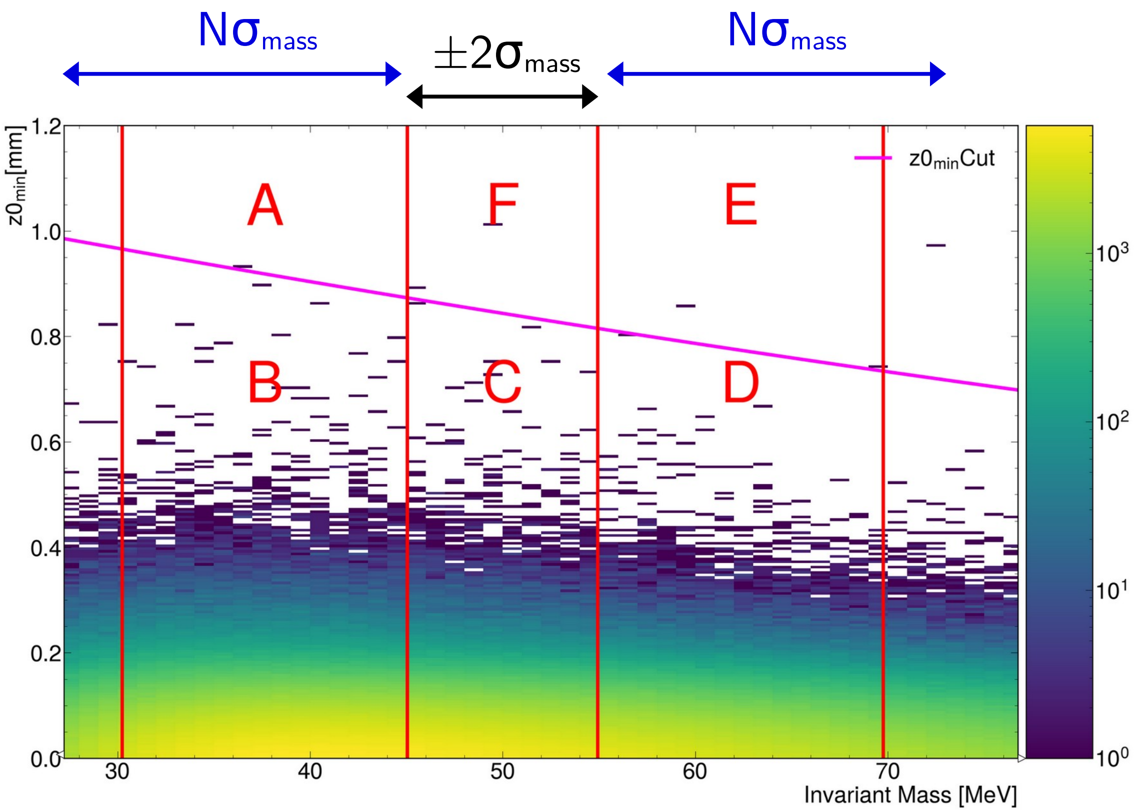
MC Signal injected at 64 MeV



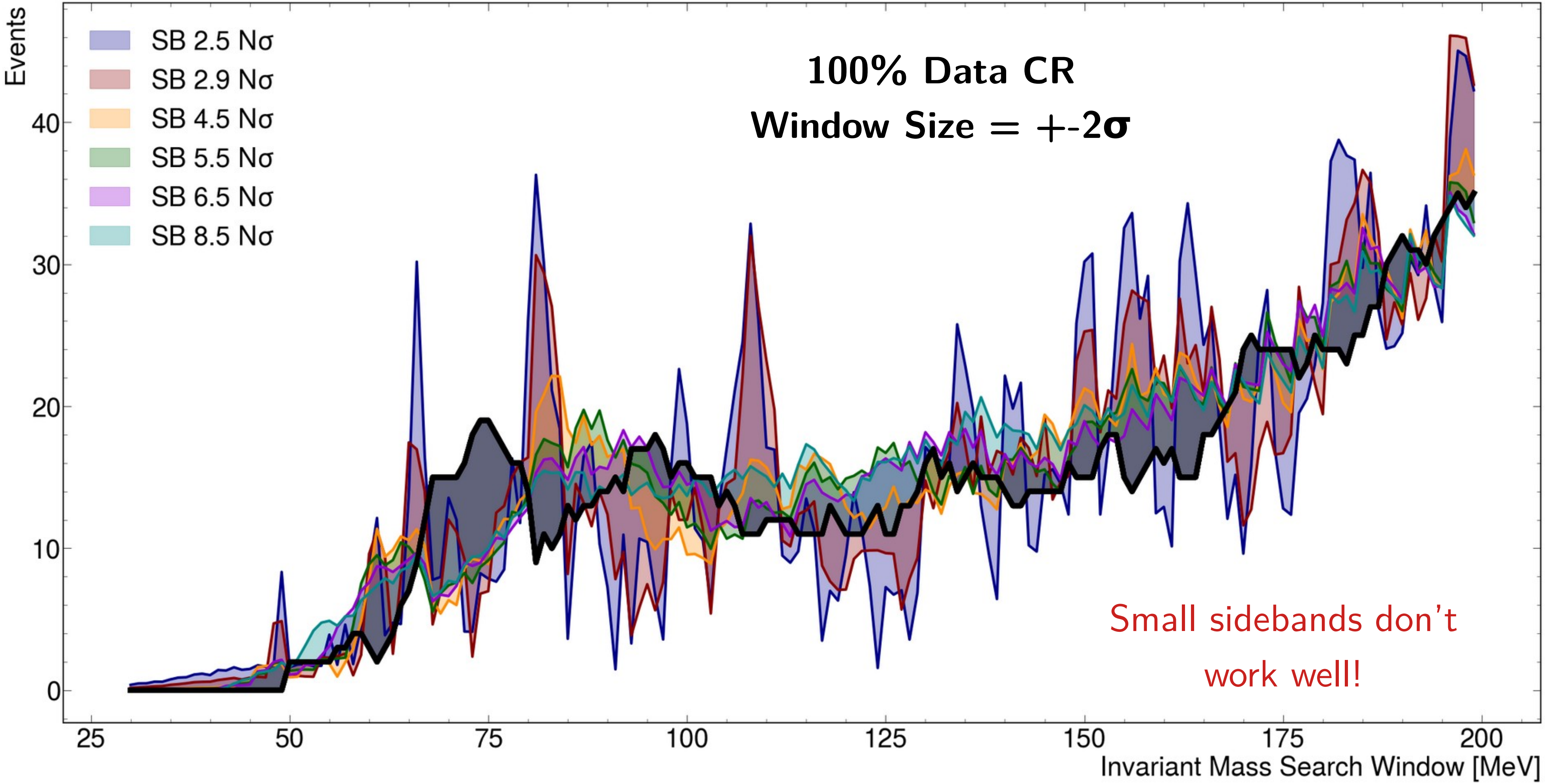


*Sanity check to see if p-values show evidence for signal

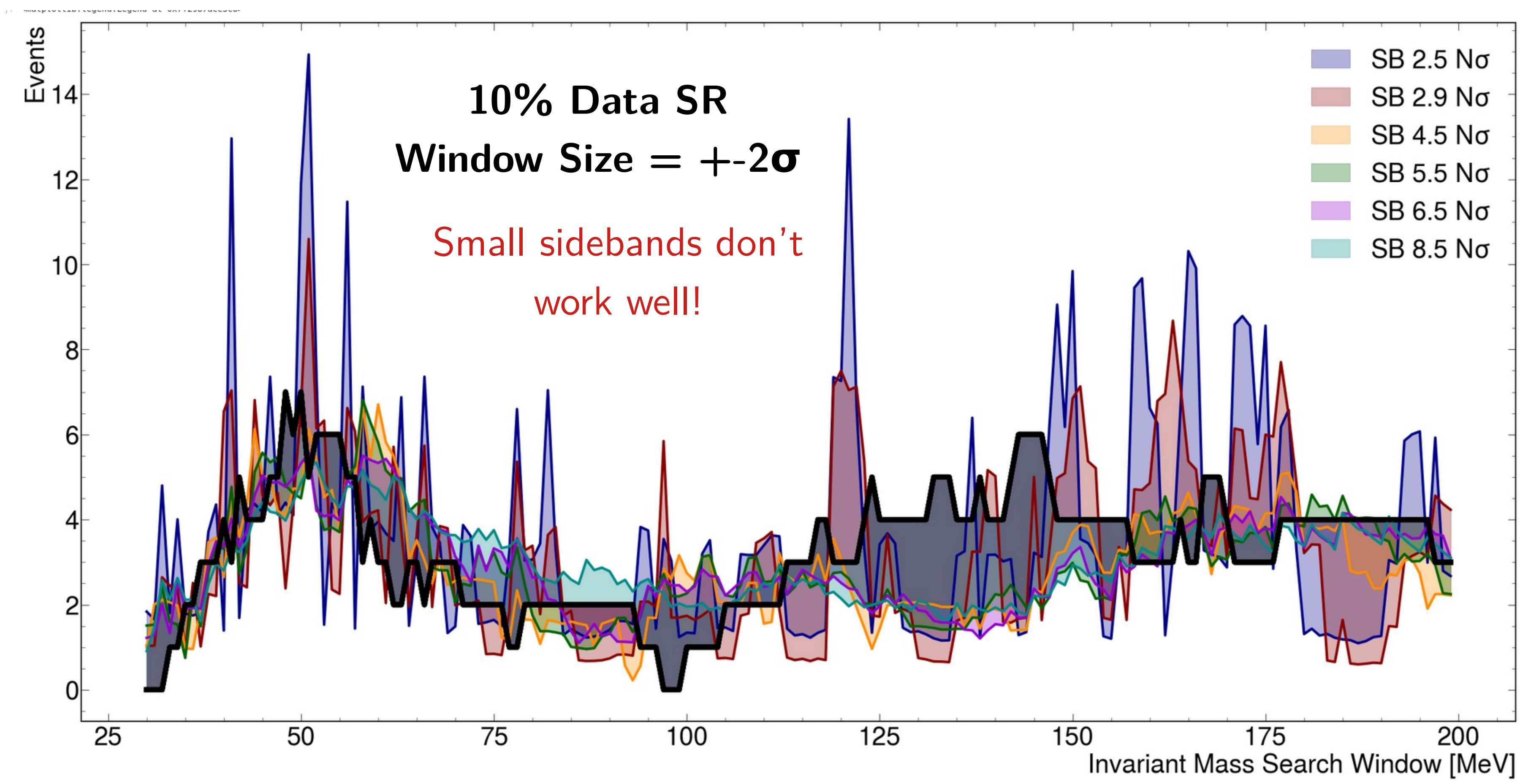
Optimize ABCD Mass Sidebands: ±2σ Search Window



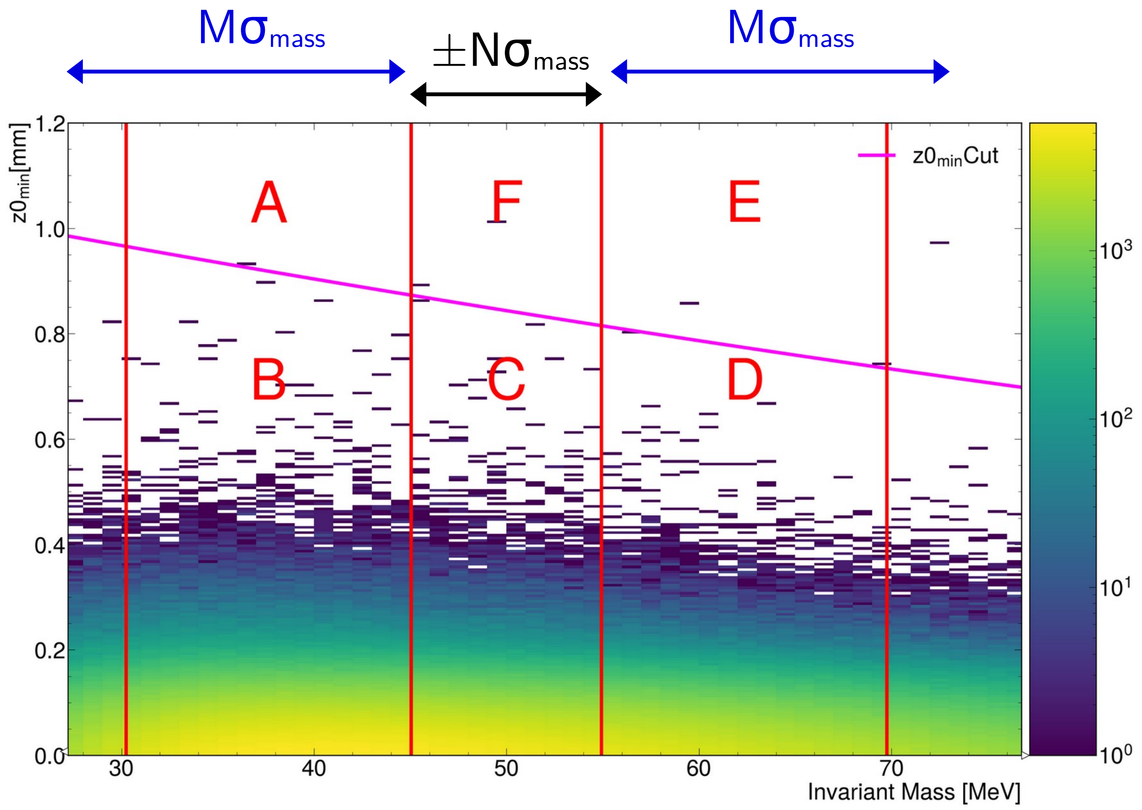
Optimize ABCD Mass Sidebands: ±2σ Search Window



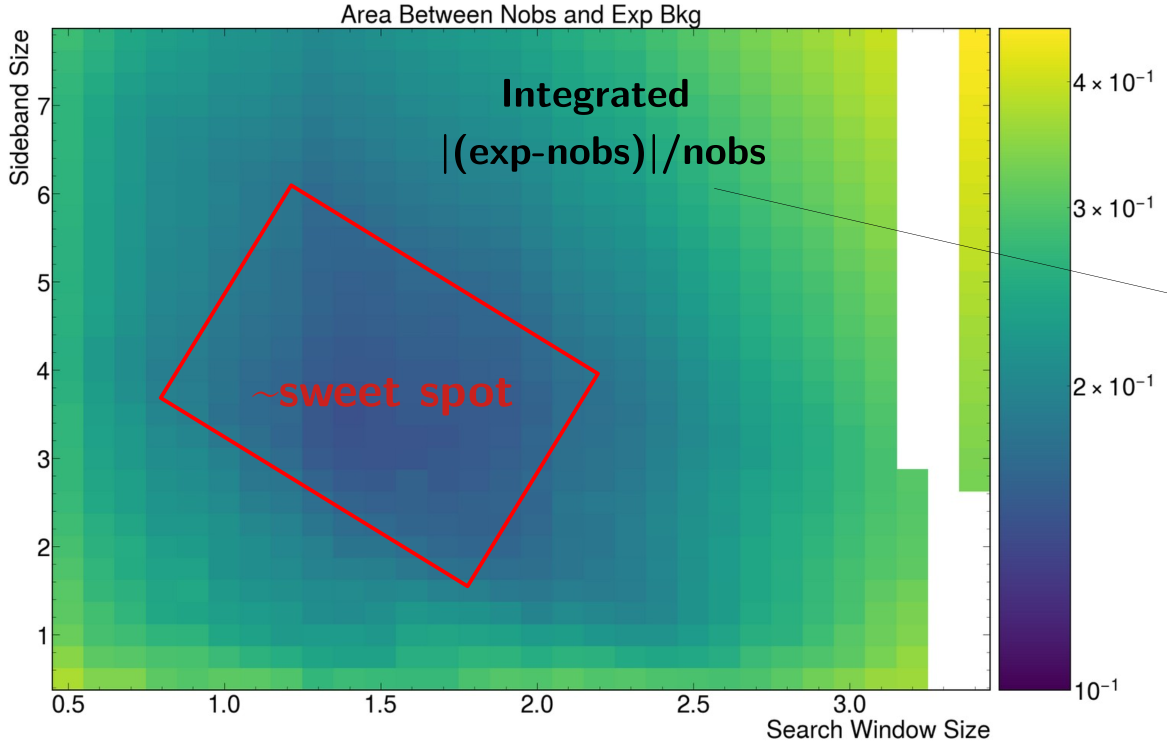
Optimize ABCD Mass Sidebands: ±2σ Search Window

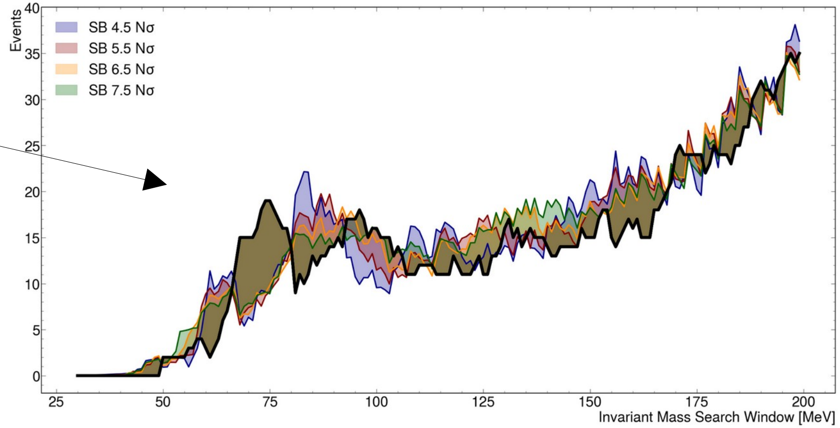


Optimize ABCD Mass Sidebands AND Search Window Size



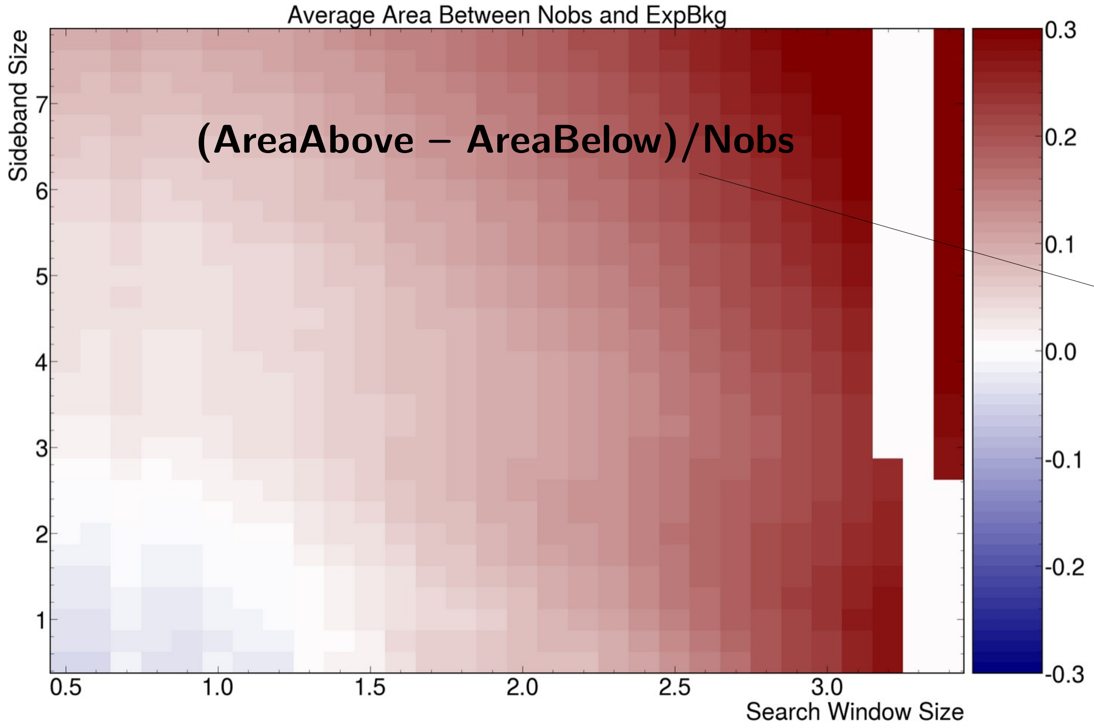
Scaled Area Between Observed and Expected

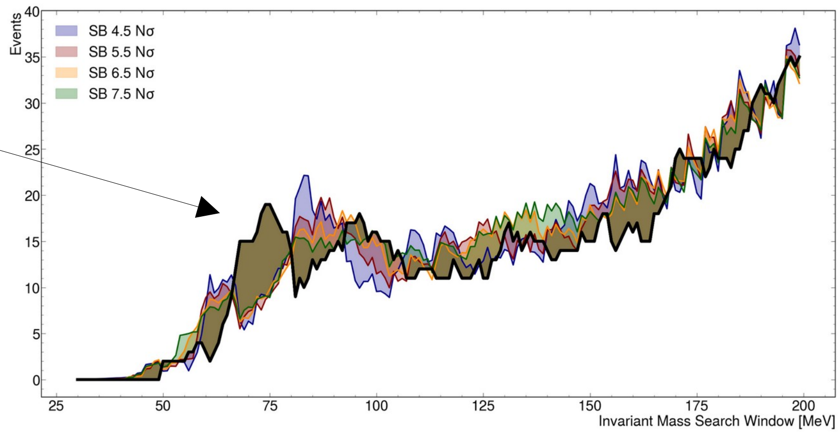




*Looks like Sideband width of 4σ works for search windows ±1-2.5σ

Scaled Averaged Area Above and Below

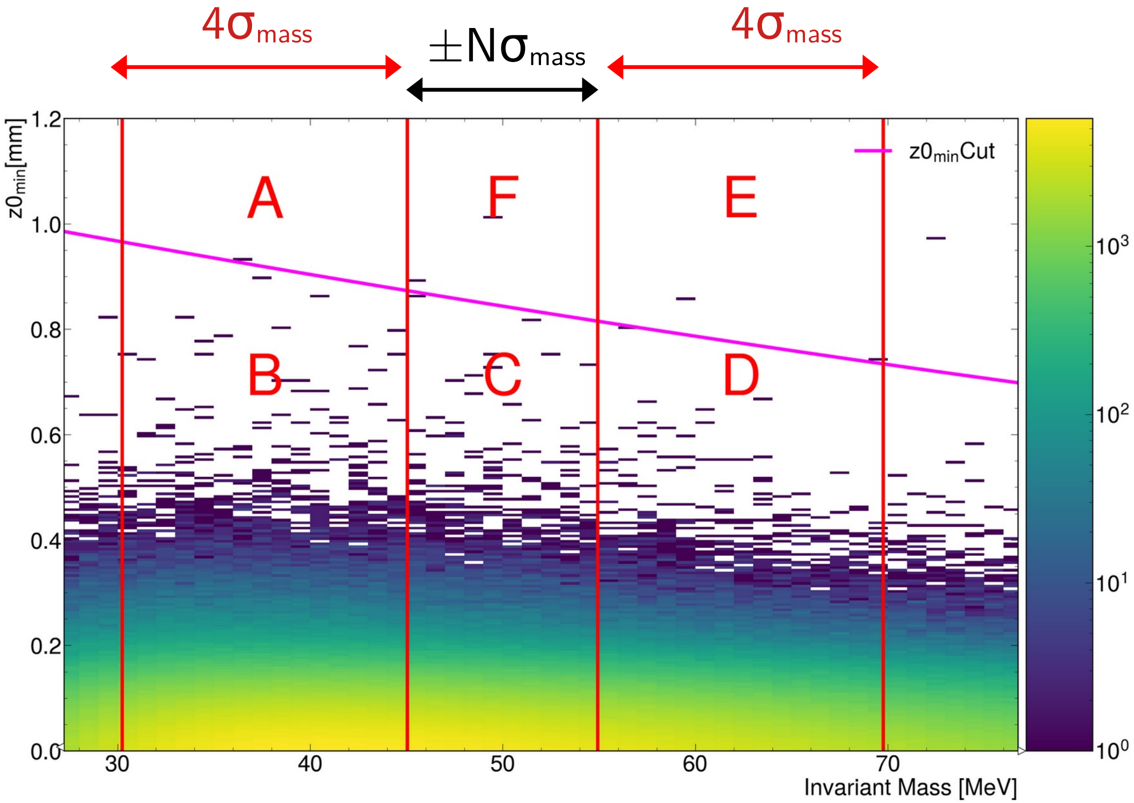




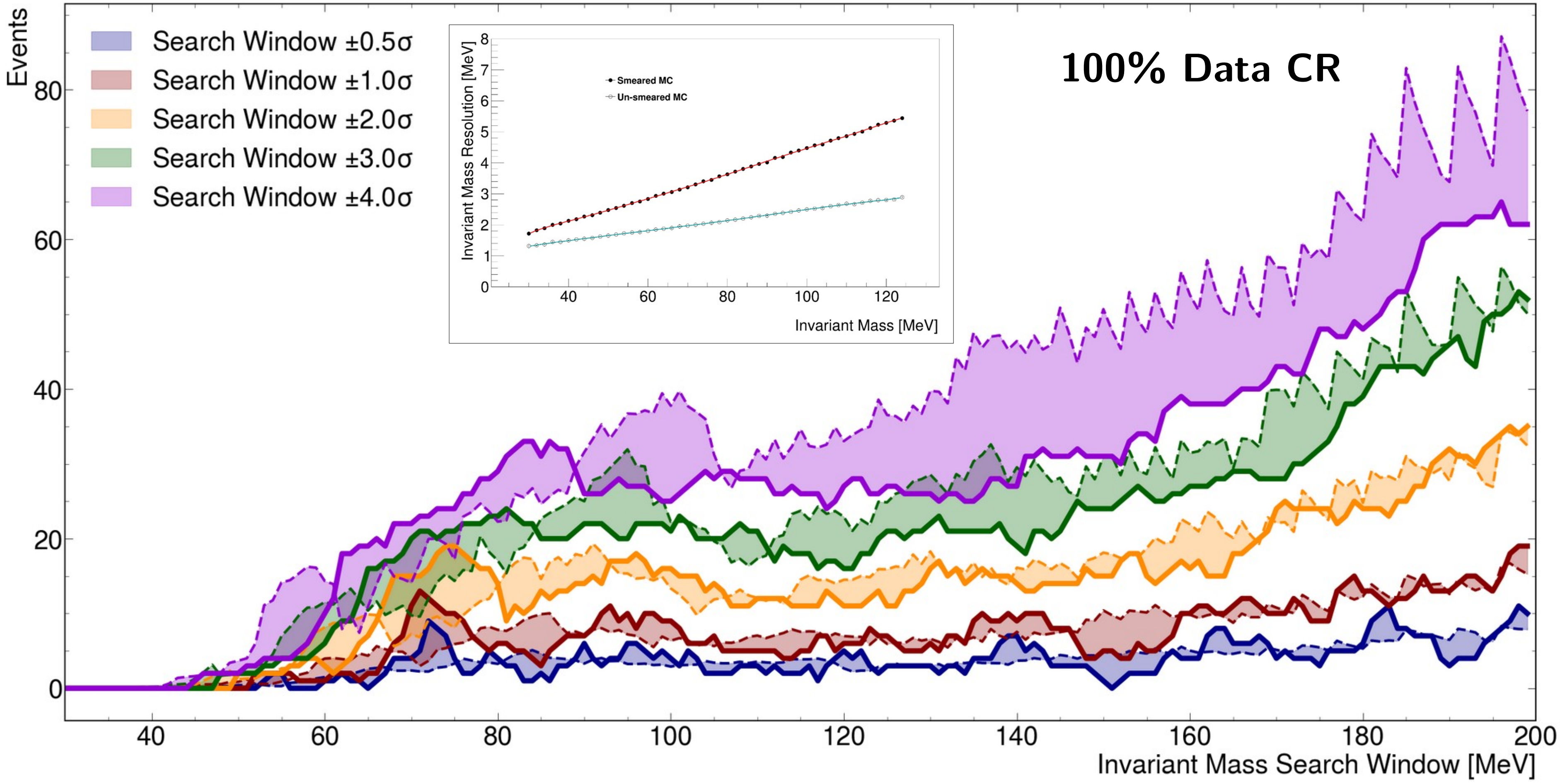
*Search window too large systematically overestimates bkg

*Looks like **Sideband width of 4σ** works for search windows ±1-2.5σ

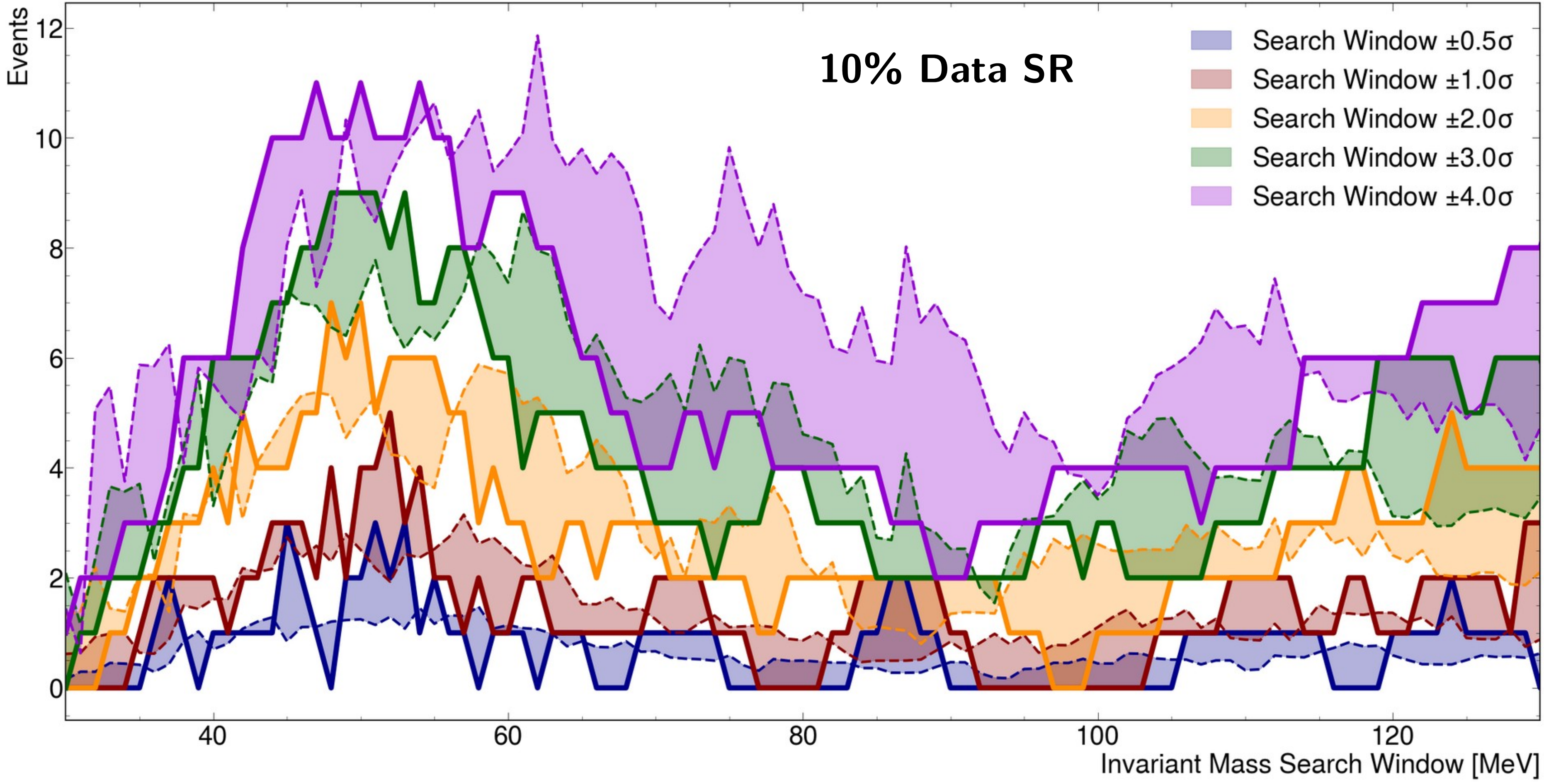
Optimize Search Window Size
ABCD Mass Sideband = 4σ



Scan Signal Window – 100% CR Data

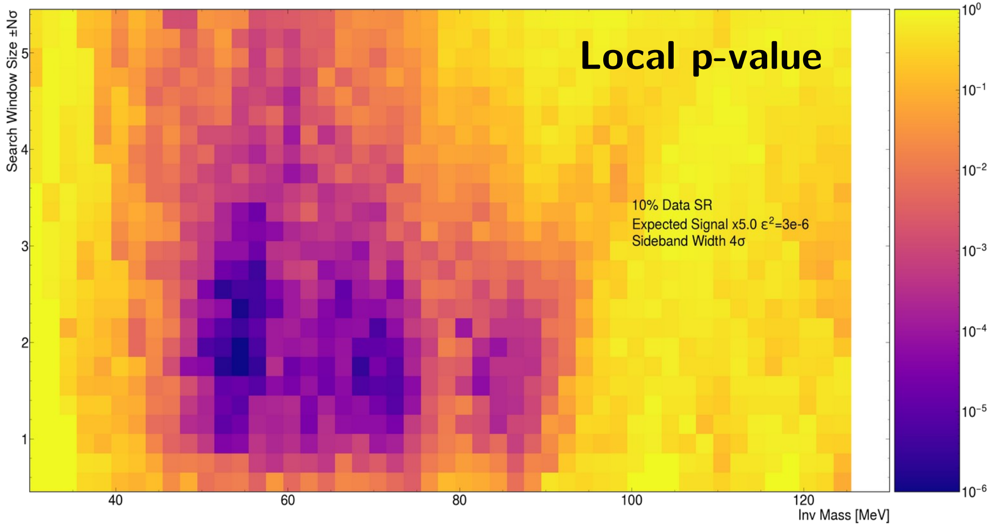


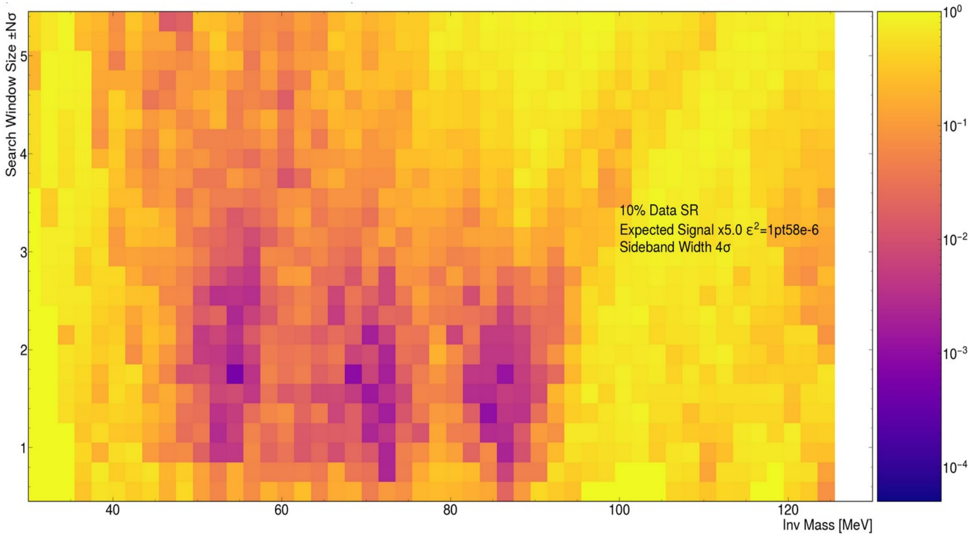
Scan Signal Window – 10% Data



MC Injected Signal – 10% Data

- Check impact of shrinking search window by measuring change in sensitivity
- Inject MC Signal at each mass
- Search window range 1.5-2.5σ results in similar sensitivity
- Confirmed for different values of ε^2
- Decide to use **Search Window = ±1.5σ**
- *Already shown the bkg estimate looks good for this search window size with **ABCD Mass Sideband Width = 4σ**



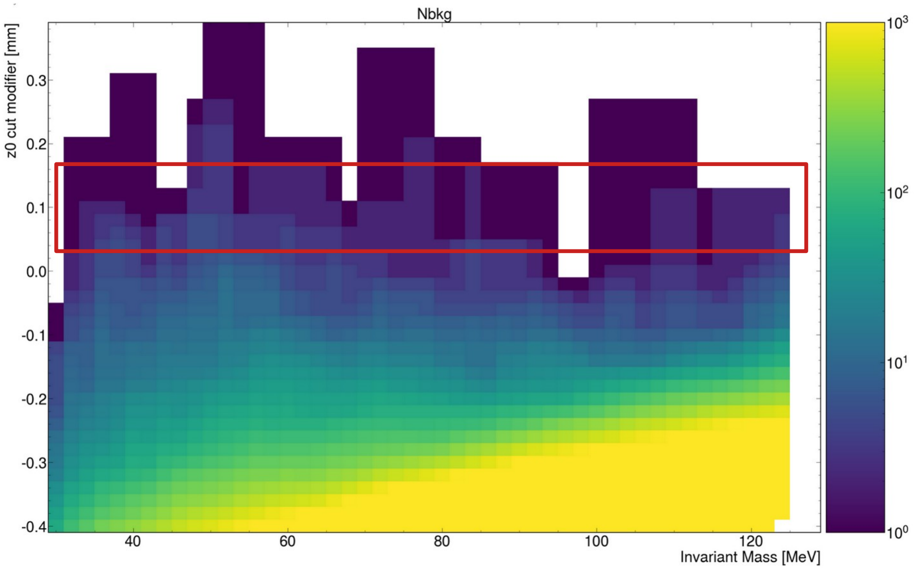


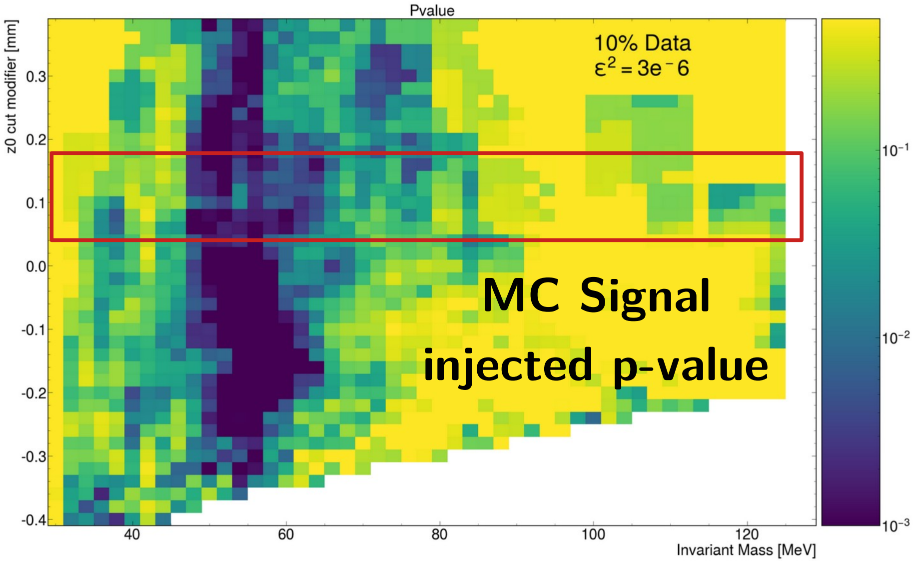
Further Tighten the $z0_{min}$ Cut?

*This cut was optimized on 10% Data SR

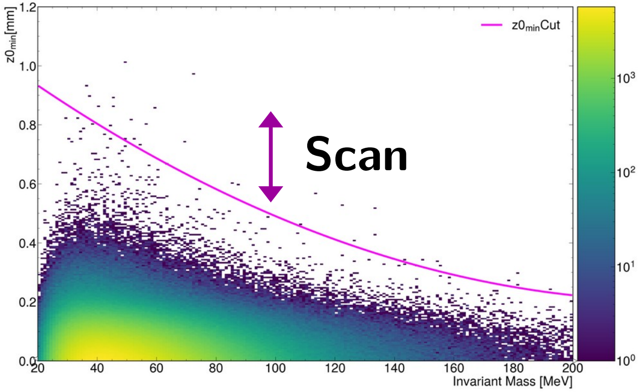
*Want to protect against large statistical fluctuations when unblinding 100% Data SR

Tightening $z0_{min}$ Cut

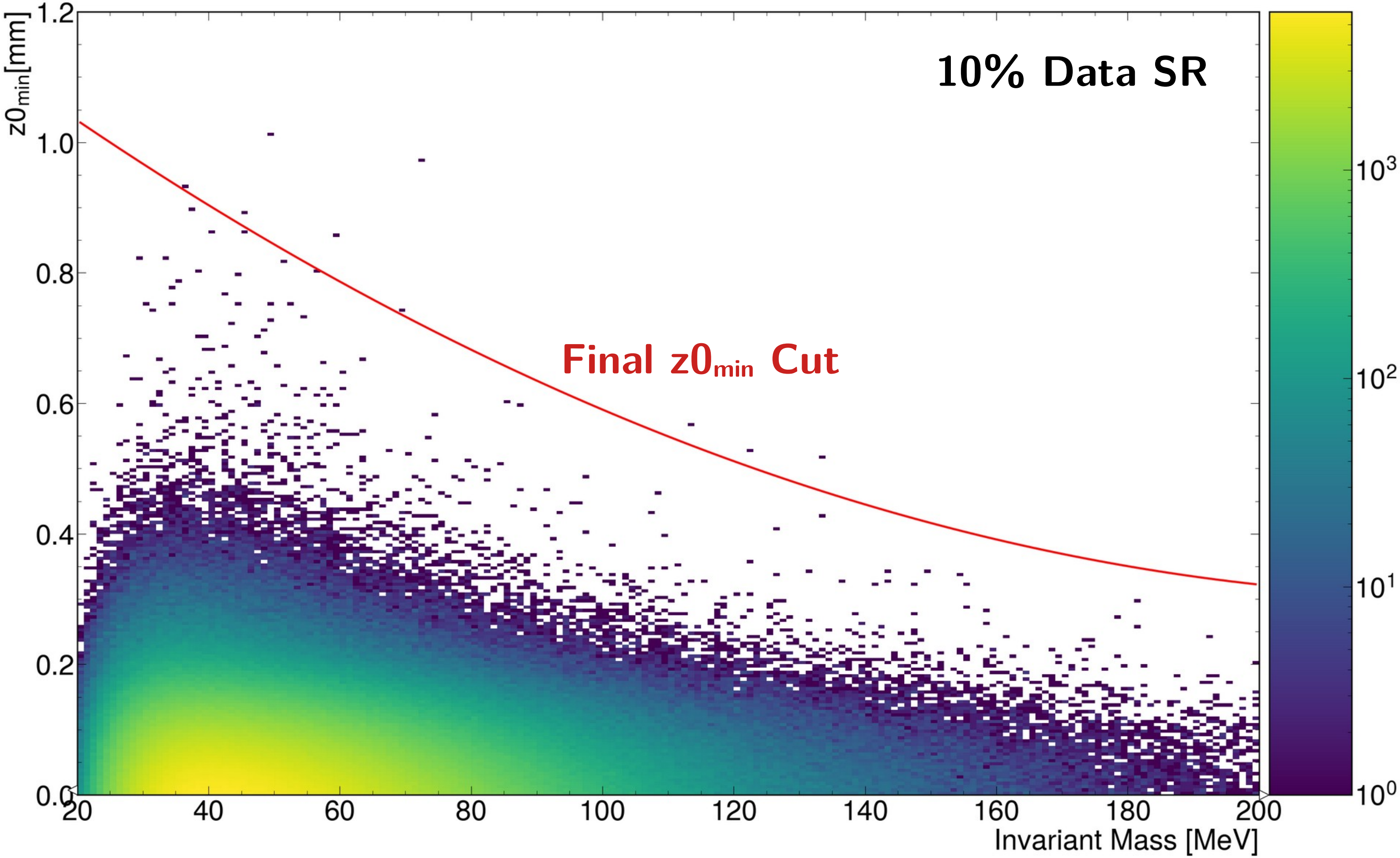




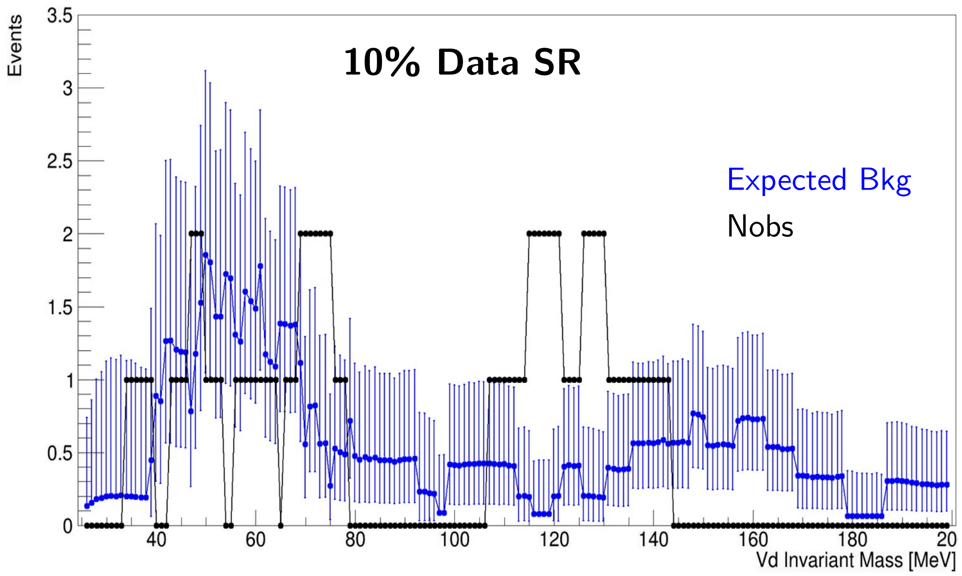
*Keep optimized shape, tighten cut by simply adding +N [mm] to cut polynomial

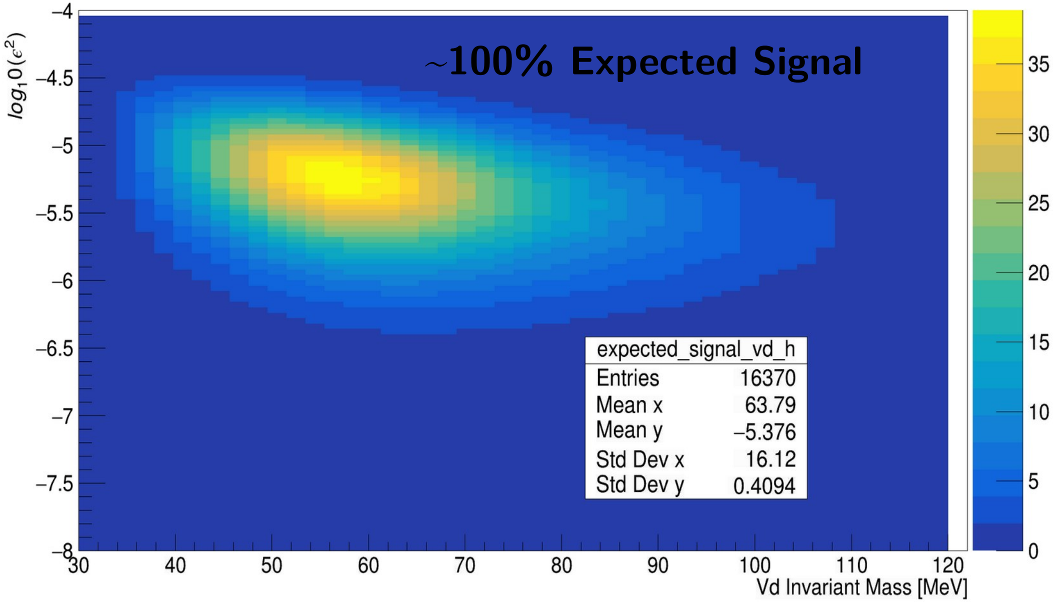


Tightening $z0_{min}$ Cut

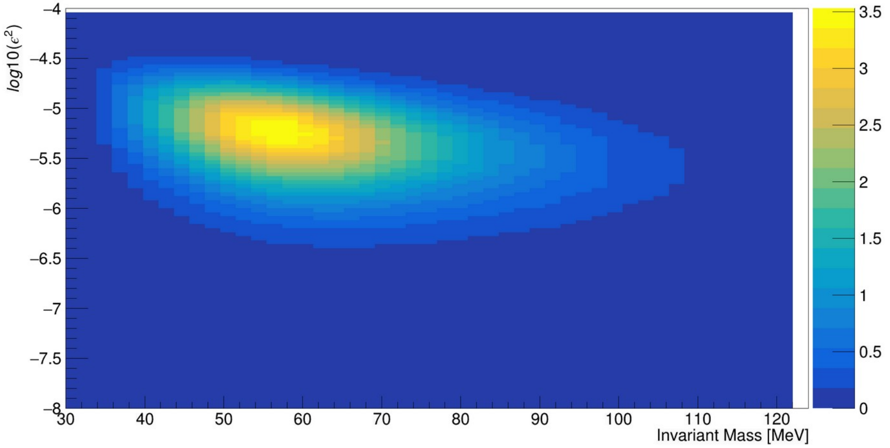


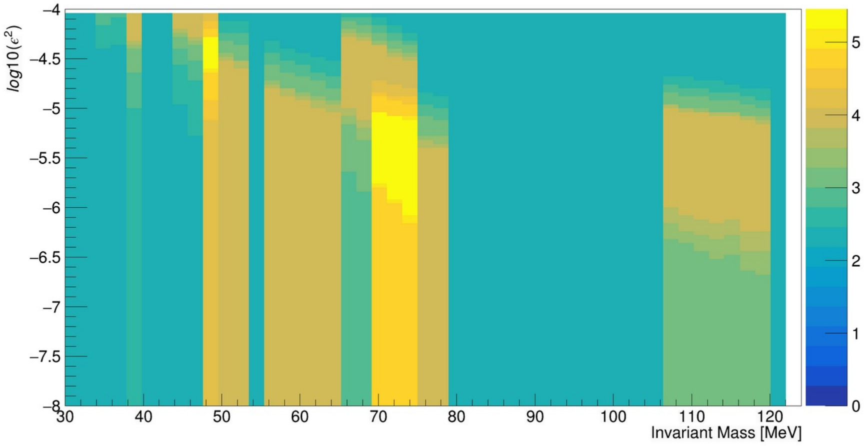
Final Selection - Background and Expected Signal

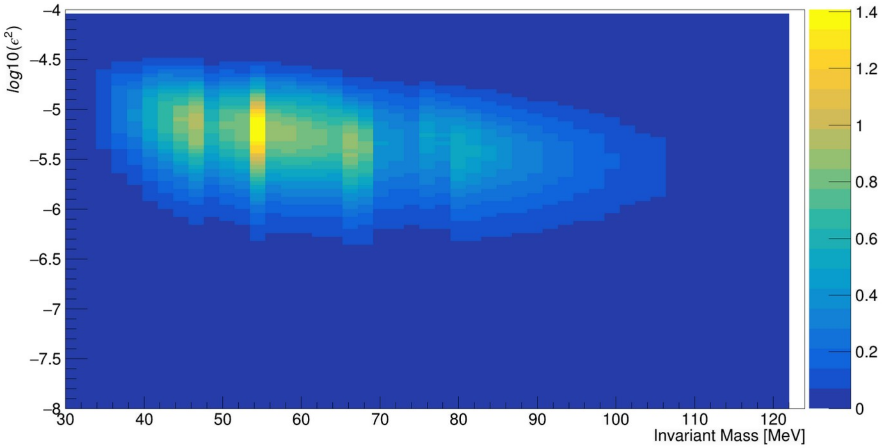




OIM Results for 10% Data







- Small region of exclusion in 10% data already

Backup

Preselection N-1 Cutflow Efficiency

	Data Eff	Tritrig-Beam Eff	WAB-Beam Eff	Tritrig-WAB-Beam Eff	40 MeV Signal Eff	100 MeV Signal Eff
$\|e^- Track_t\| < 6.0$ ns	1	1	1	1	1	1
$\|e^+ Track_t\| < 6.0$ ns	1	1	1	1	1	1
$\Delta_t(Cluster_{e^-}, Cluster_{e^+} < 1.45$ ns	0.96	0.99	0.99	0.99	0.98	0.98
$e^- \Delta_t(Track, Cluster) < 4.0$ ns	0.99	1	1	1	1	1
$e^+ \Delta_t(Track, Cluster) < 4.0$ ns	0.99	1	0.99	1	1	1
$e^- Track \chi^2/n.d.f. < 20.0$	0.99	1	1	1	0.99	0.99
$e^+ Track \chi^2/n.d.f. < 20.0$	0.98	1	0.98	0.99	0.99	0.99
$p_{e^-} < 1.75$ GeV	1	1	1	1	1	1
$N_{2dhits} e^-_{Track} > 7.0$	1	1	1	1	0.93	0.98
$N_{2dhits} e^+_{Track} > 7.0$	0.98	1	0.94	0.98	0.93	0.97
$Vtx_{\chi^2} < 20.0$	0.83	0.97	0.65	0.86	0.97	0.97
$p_{e^- + e^+} < 2.4$ GeV	0.99	1	0.99	1	1	1

Table 4: "n-1" cut efficiency. The efficiency of the cut under consideration is calculated assuming that all other cuts applied correspond to an efficiency of 1.