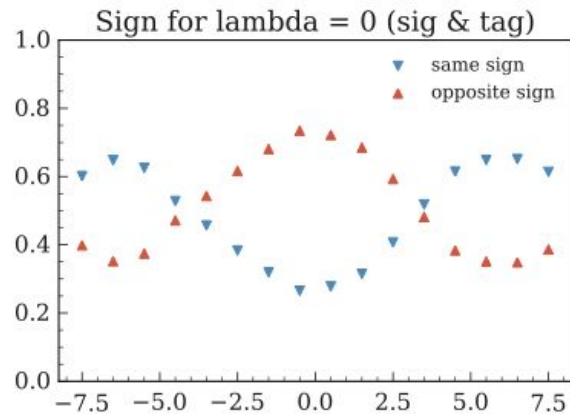
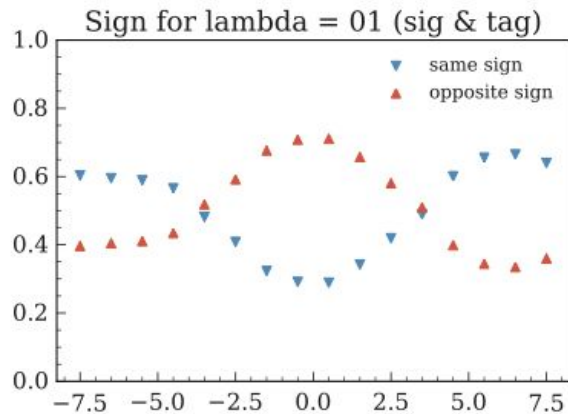


same/opposite sign plots using “sig/tagflav” and “mcsig/tagflav”:

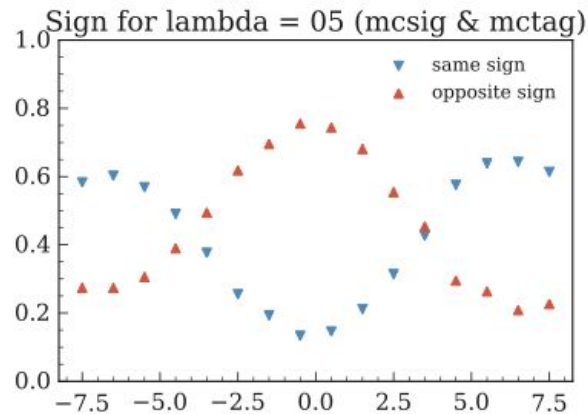
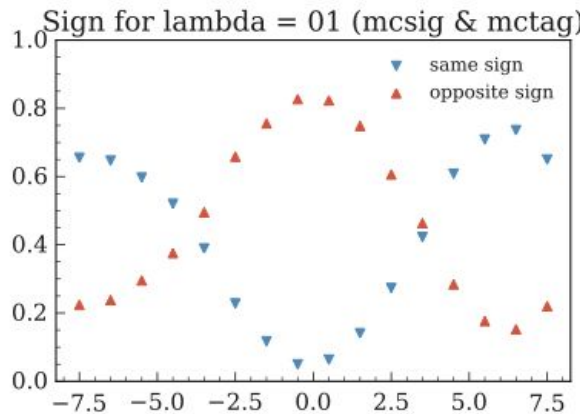
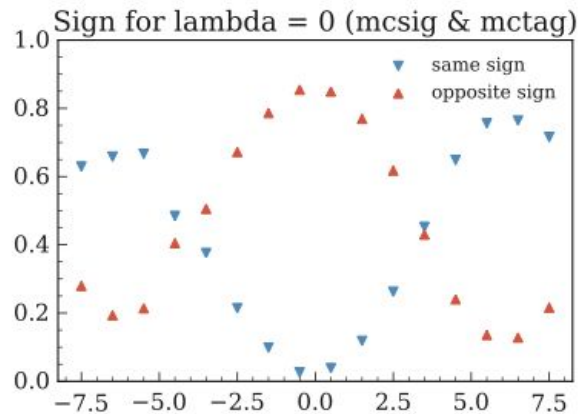
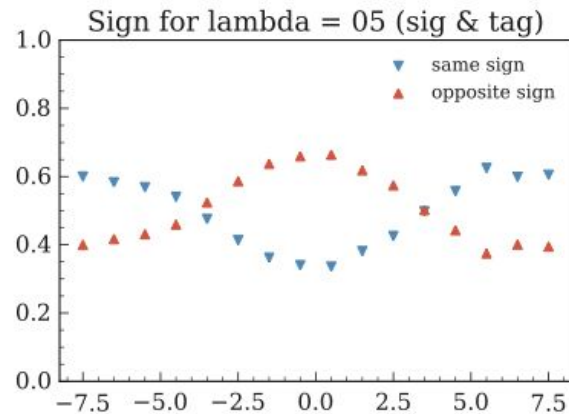
$\lambda=0$

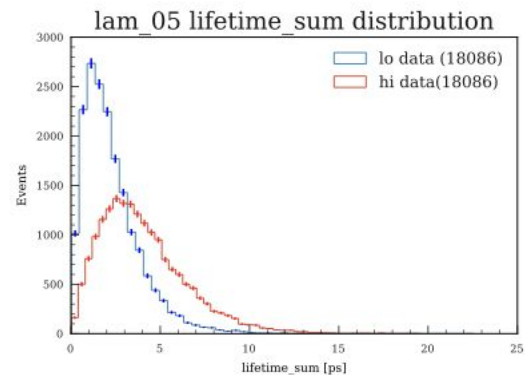
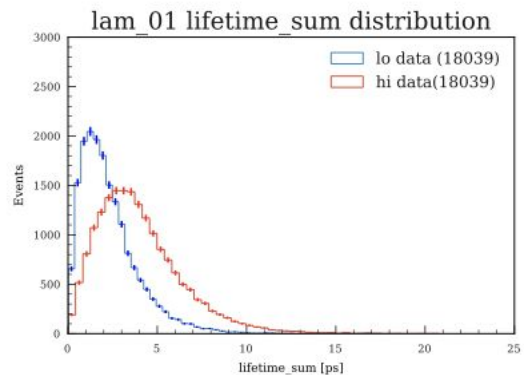
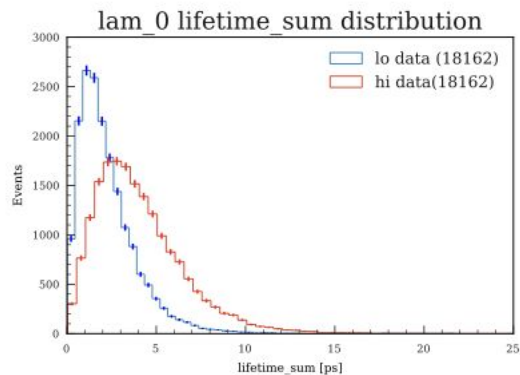


$\lambda=0.1$

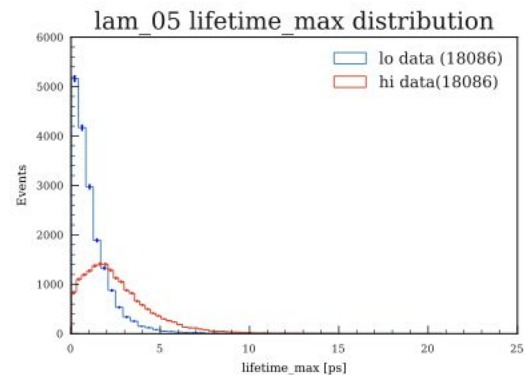
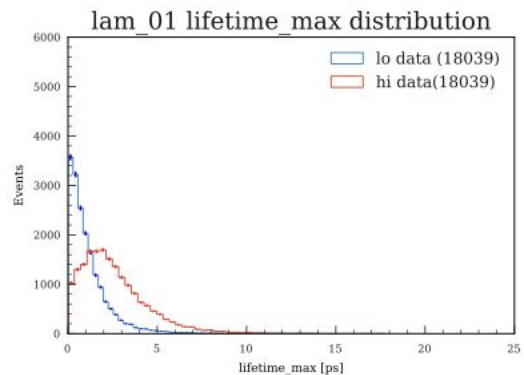
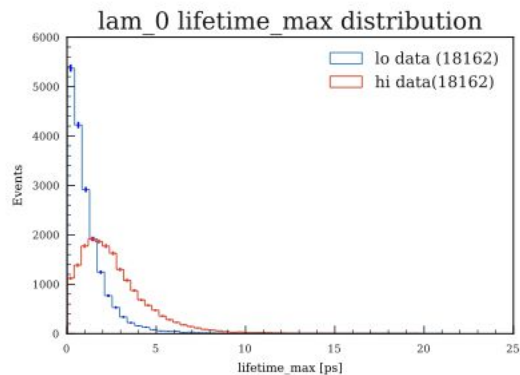


$\lambda=0.5$



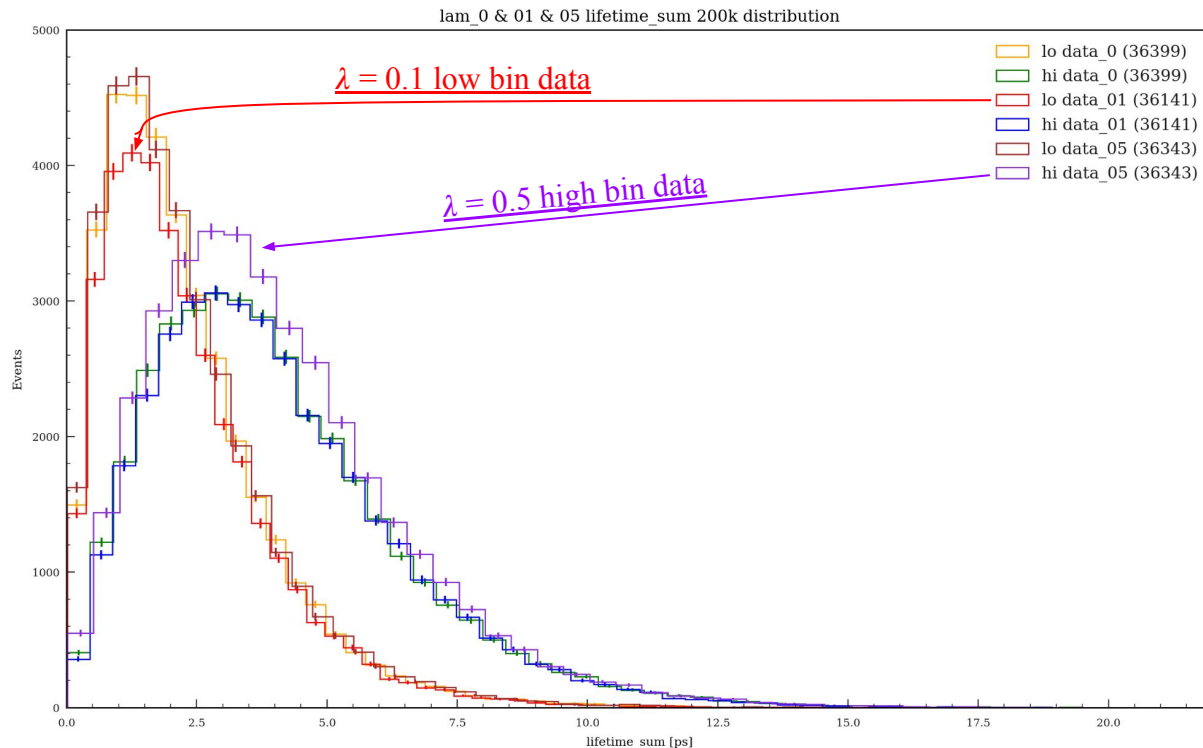


lifetime\_max = lifetime of B meson with larger x\_vertex from IP



From this distribution, we see significant deviations by the  $\lambda = 0.1$  low bin data, and the  $\lambda = 0.5$  high bin data. Either:

- These are bugs in the generation/analysis ( $\lambda = 0.5$  looks like it has too much data,  $\lambda = 0.1$  looks like it has too little)
- There is a non-trivial dependence on  $\lambda$  ( $\lambda = 0$  gives standard dist., turning on  $\lambda$  causes a discontinuity in dist., which then evolves continuously in  $\lambda$ )
  - want to test this by plotting different  $\lambda$  values ( $\lambda = 0.05$  &  $\lambda = 1$ )

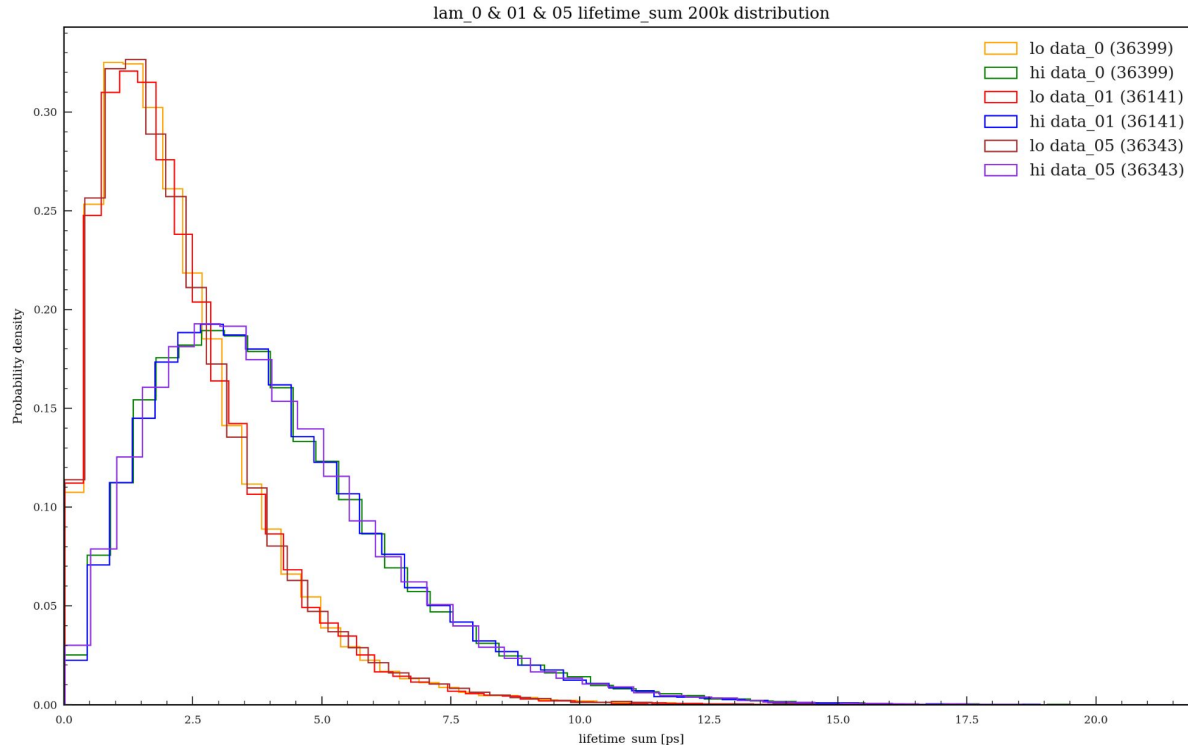


total events:  
`plt.hist(..., density=False, ...)`

A normalized plot of these distributions show a much more equal relationship for each  $\lambda$   
→ Implies issue with my analysis (analysis...) rather than decoherence dependence

## NOT SURE THAT THIS CAN BE TRUSTED!!

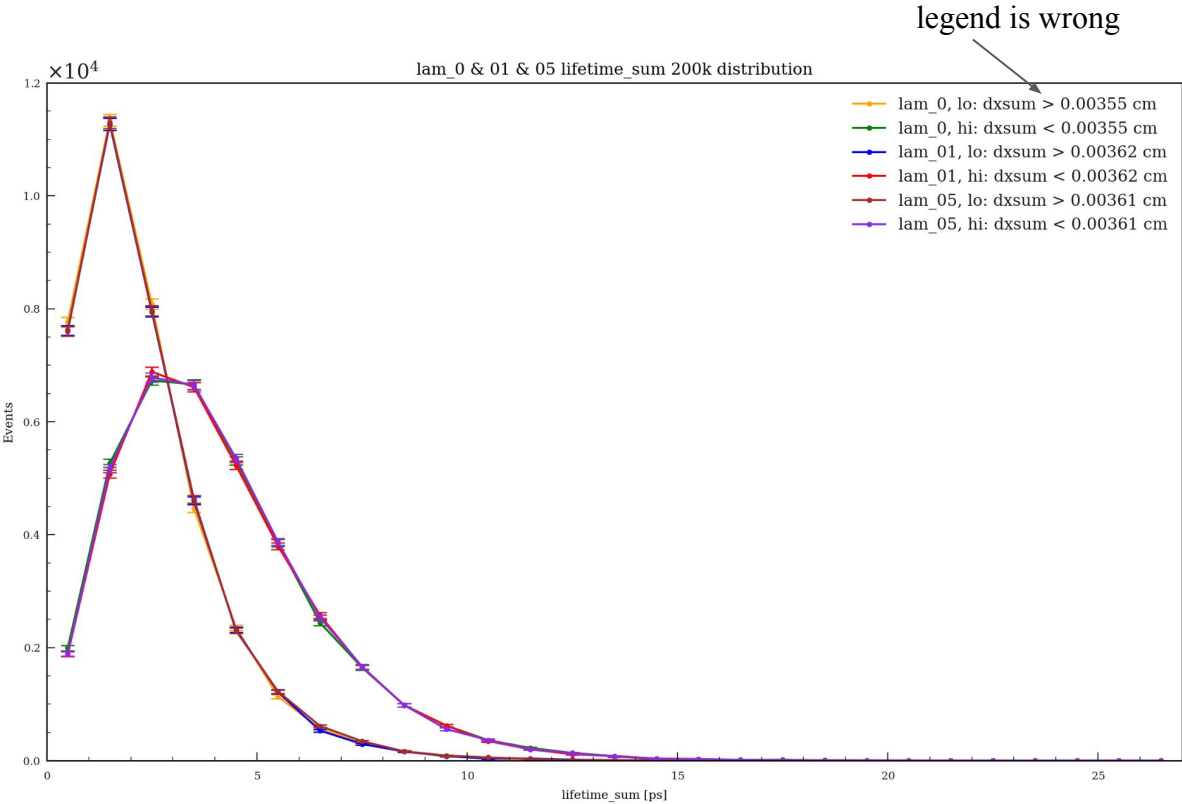
- normalizes each of the 6 curves individually → lo/hi bins know nothing about each other



relative:  
`plt.hist(..., density=True, ...)`

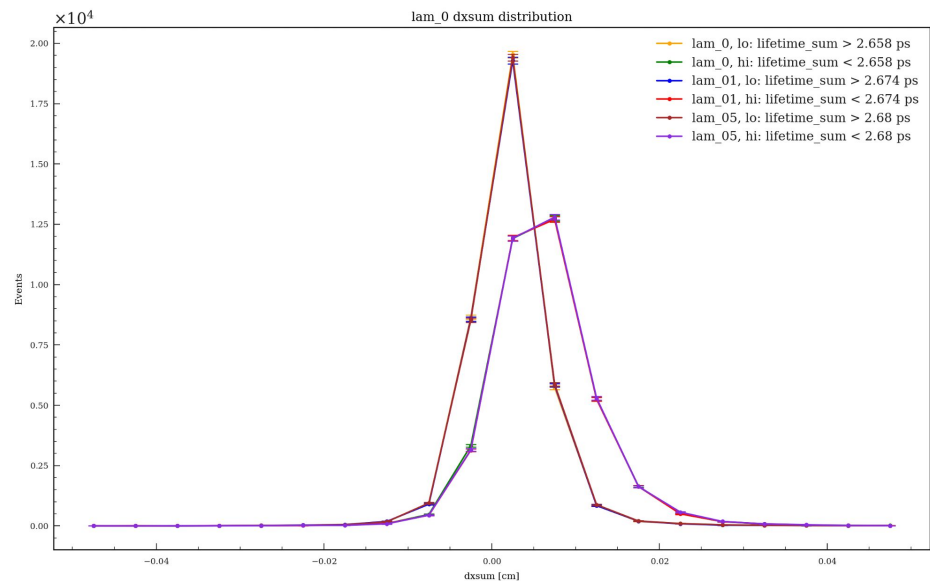
Standardize the  
binwidths/centers...

Making the binwidths the same for each dataset seems to fix things → no  $\lambda$  dependence

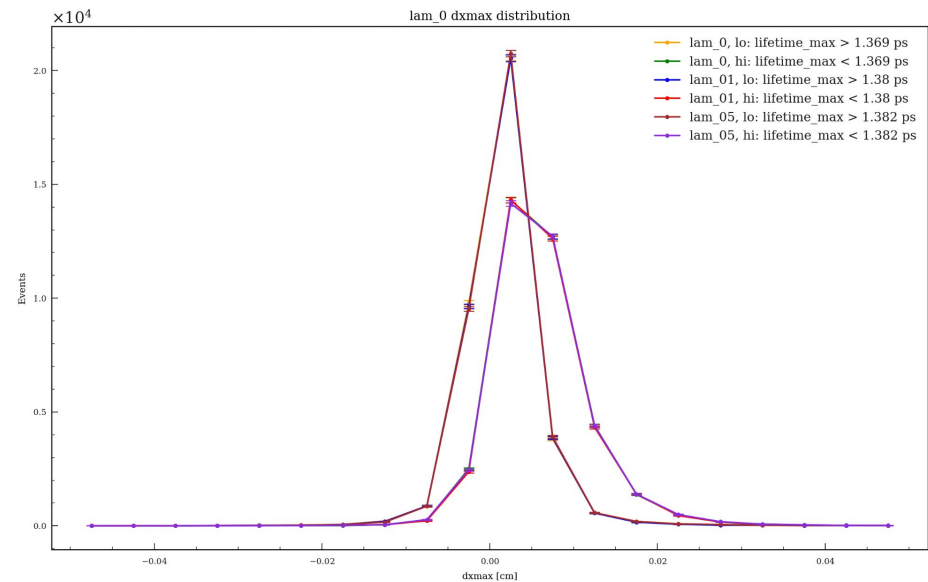


Looking at other relationships:

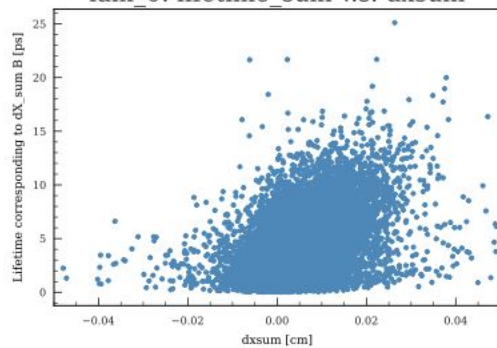
$\sum dx$  values for hi/lo  $\sum t$  bins



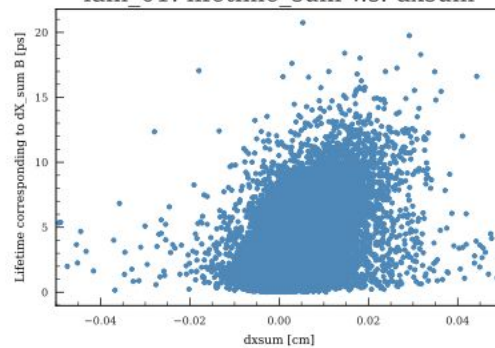
$dx_{\max}$  values for hi/lo  $t_{\max}$  bins



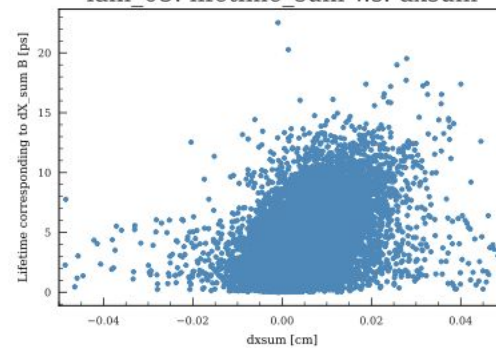
lam\_0: lifetime\_sum v.s. dxsum



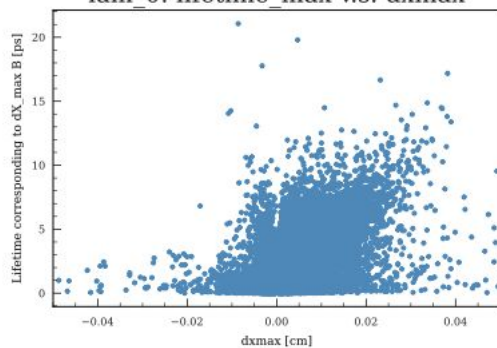
lam\_01: lifetime\_sum v.s. dxsum



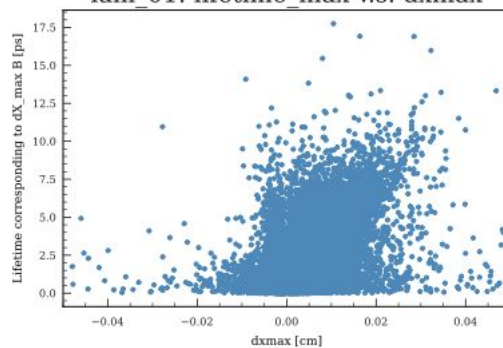
lam\_05: lifetime\_sum v.s. dxsum



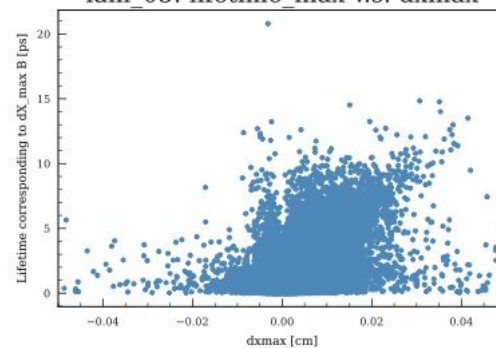
lam\_0: lifetime\_max v.s. dxmax



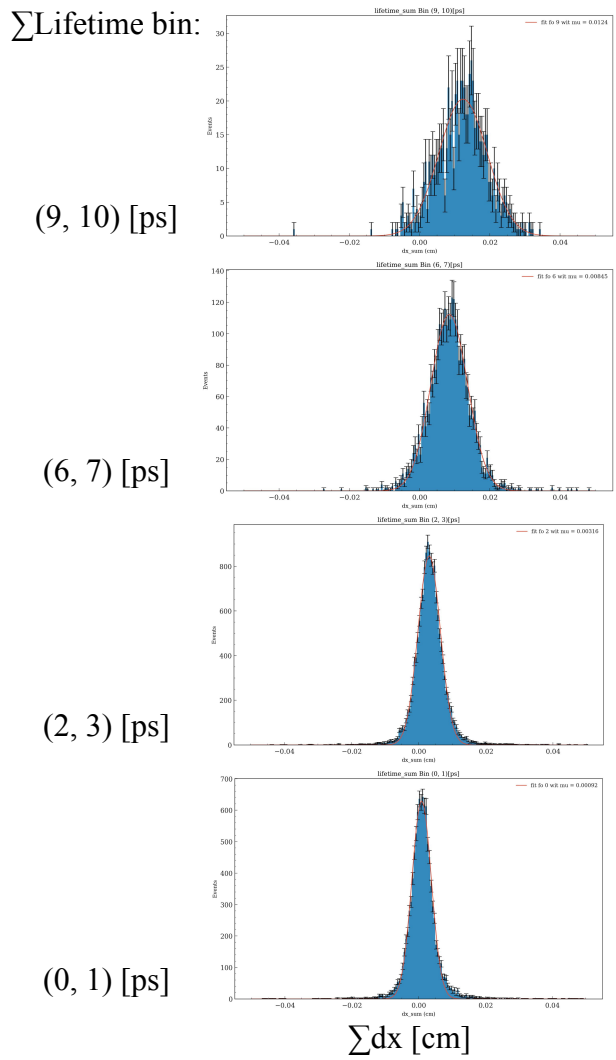
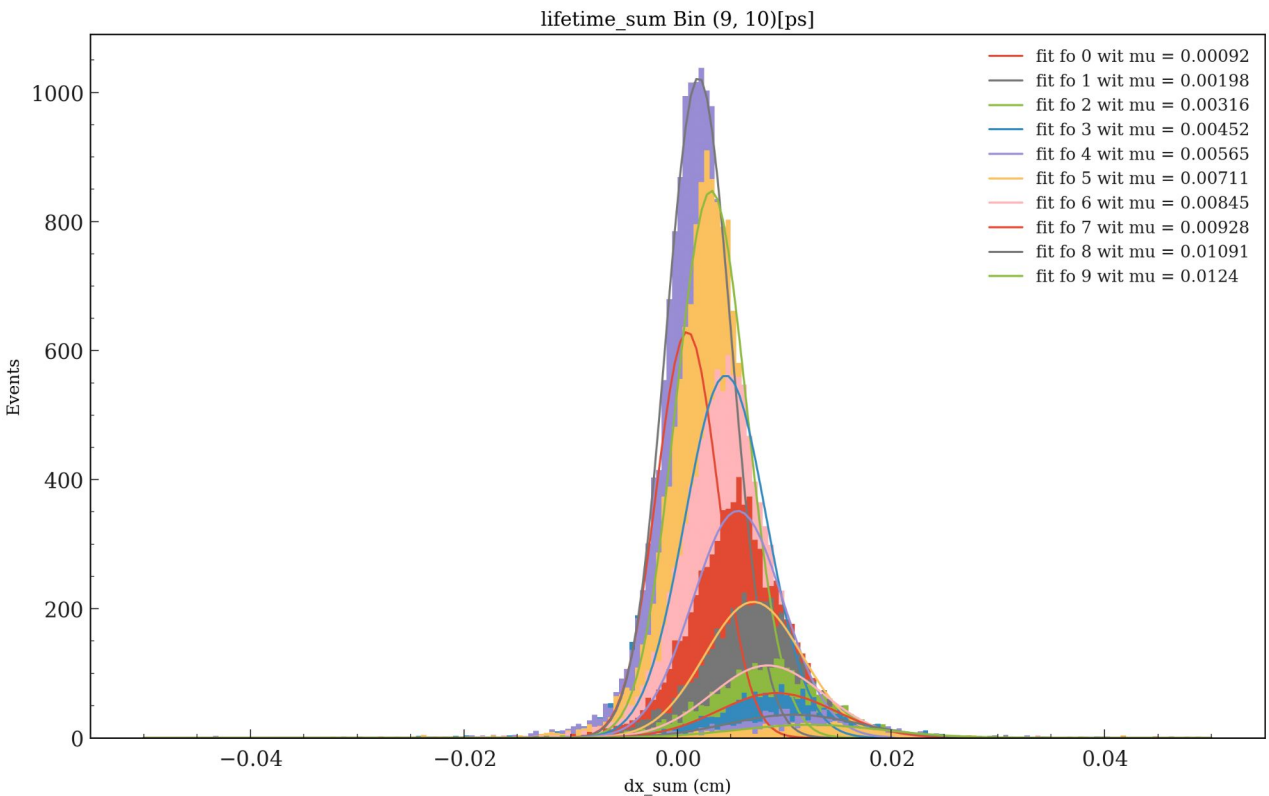
lam\_01: lifetime\_max v.s. dxmax



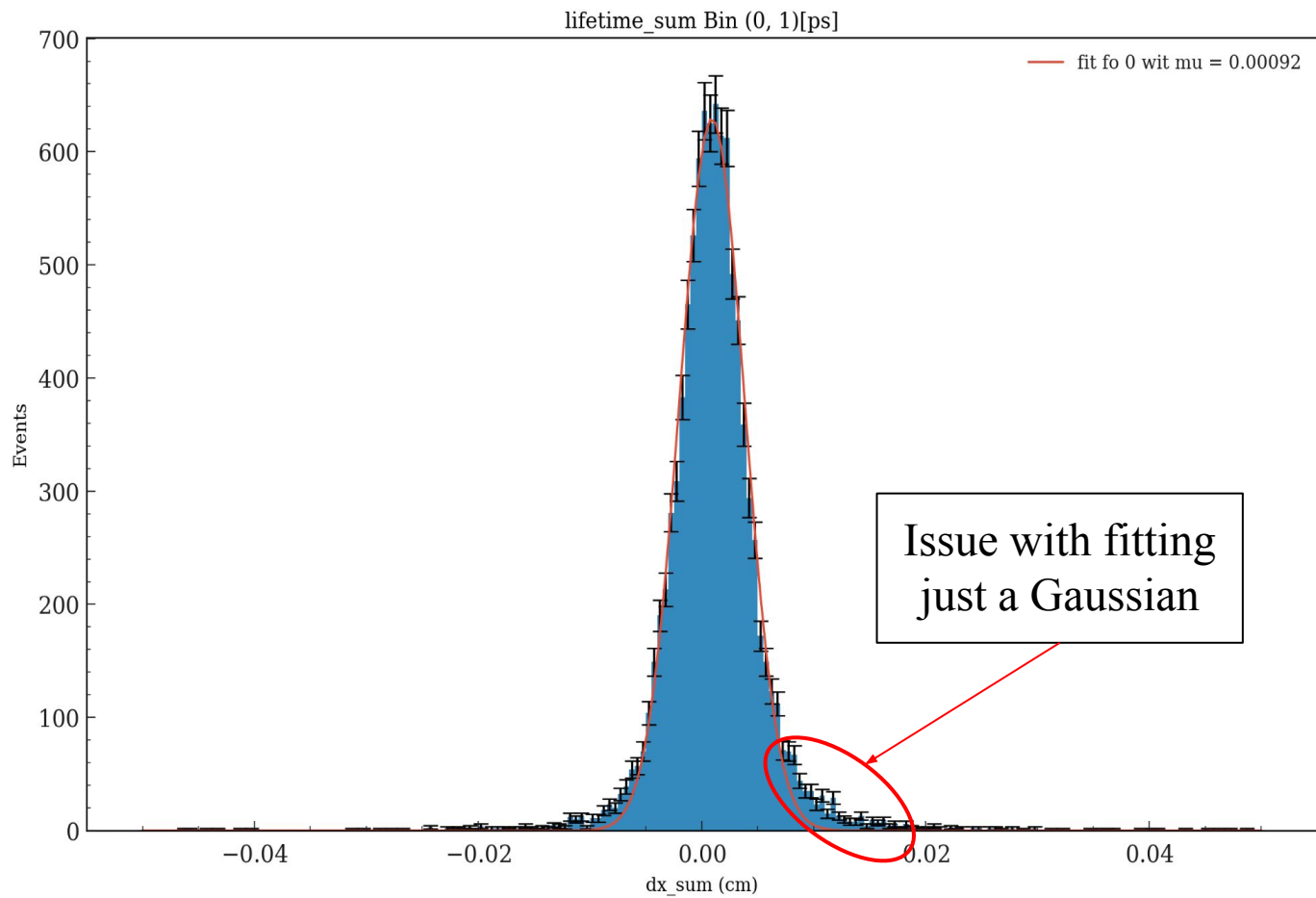
lam\_05: lifetime\_max v.s. dxmax



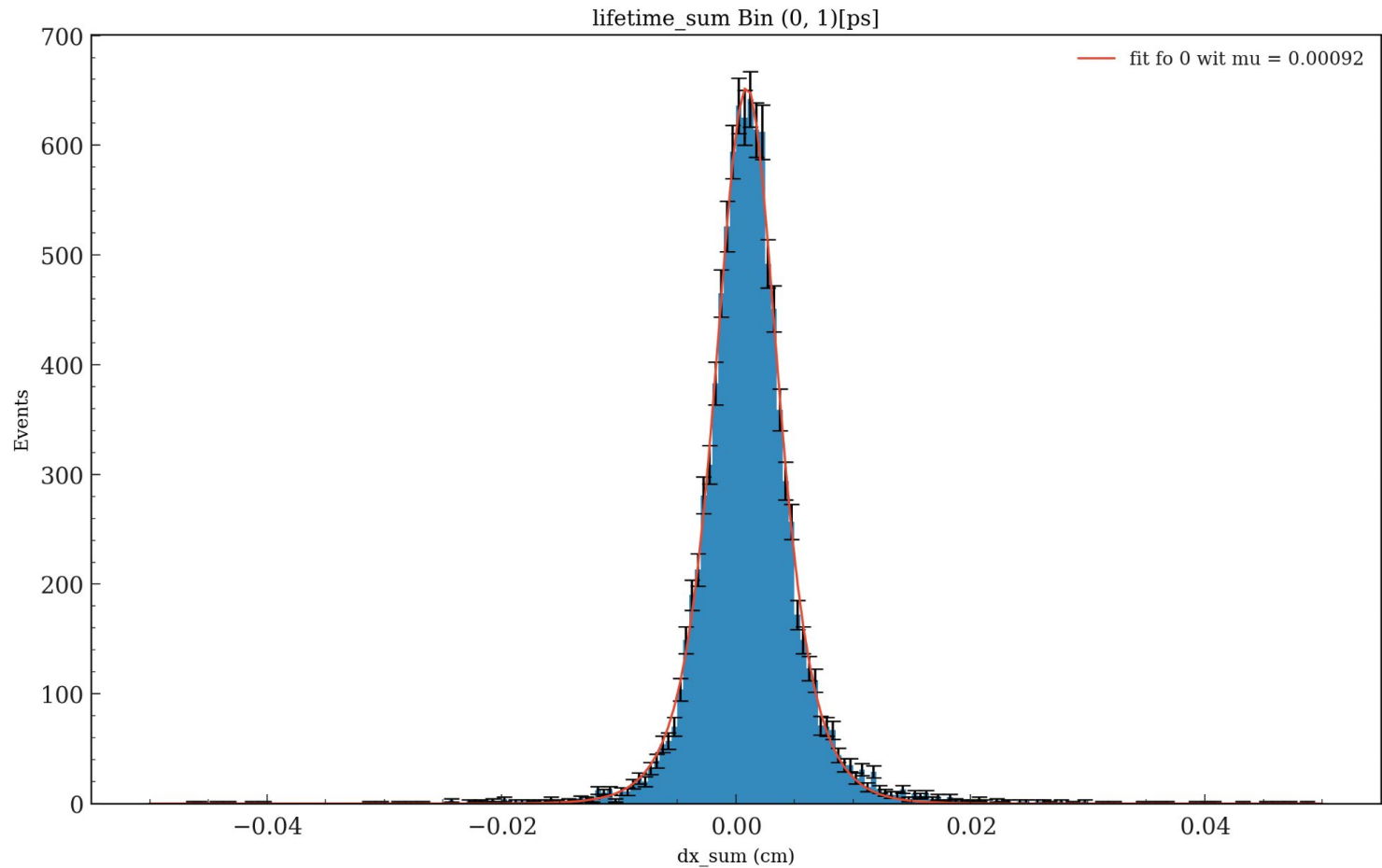
Linear binning of the  $\Sigma$ Lifetime variable. Fitting the corresponding  $\Sigma dx$  distribution with a Gaussian  $\rightarrow$  doesn't seem to describe tails well enough...



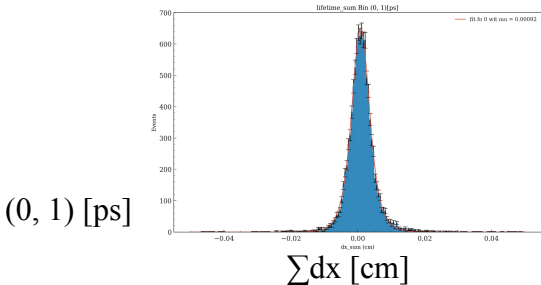
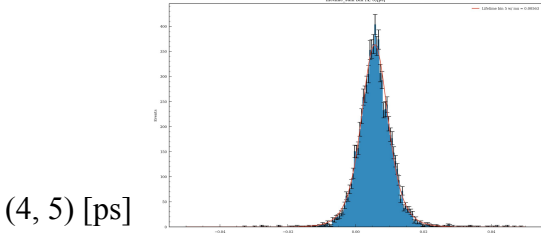
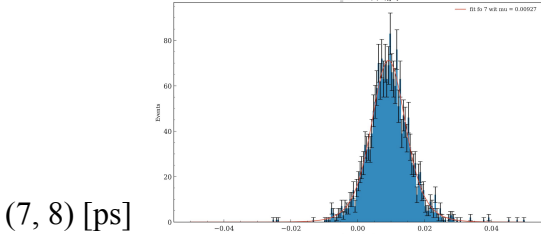
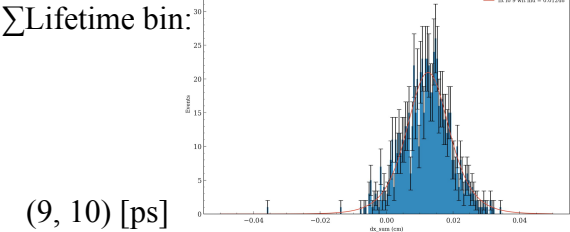
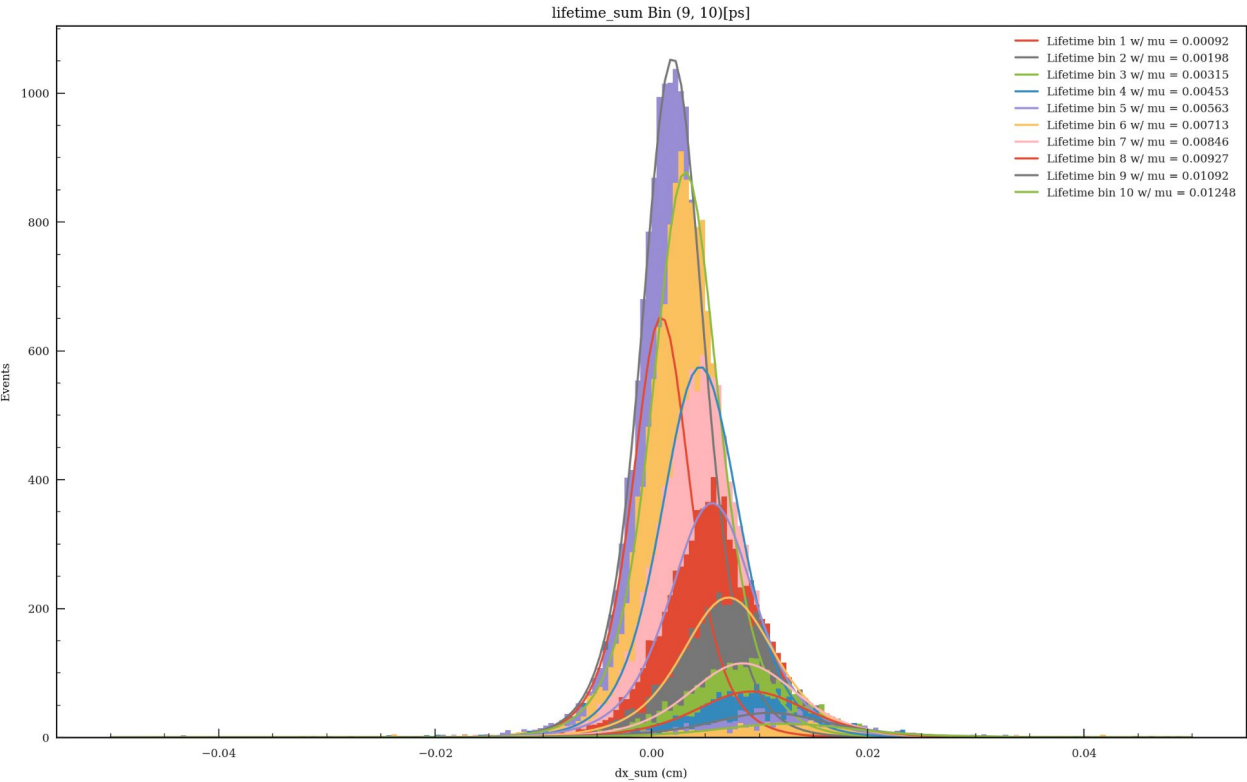




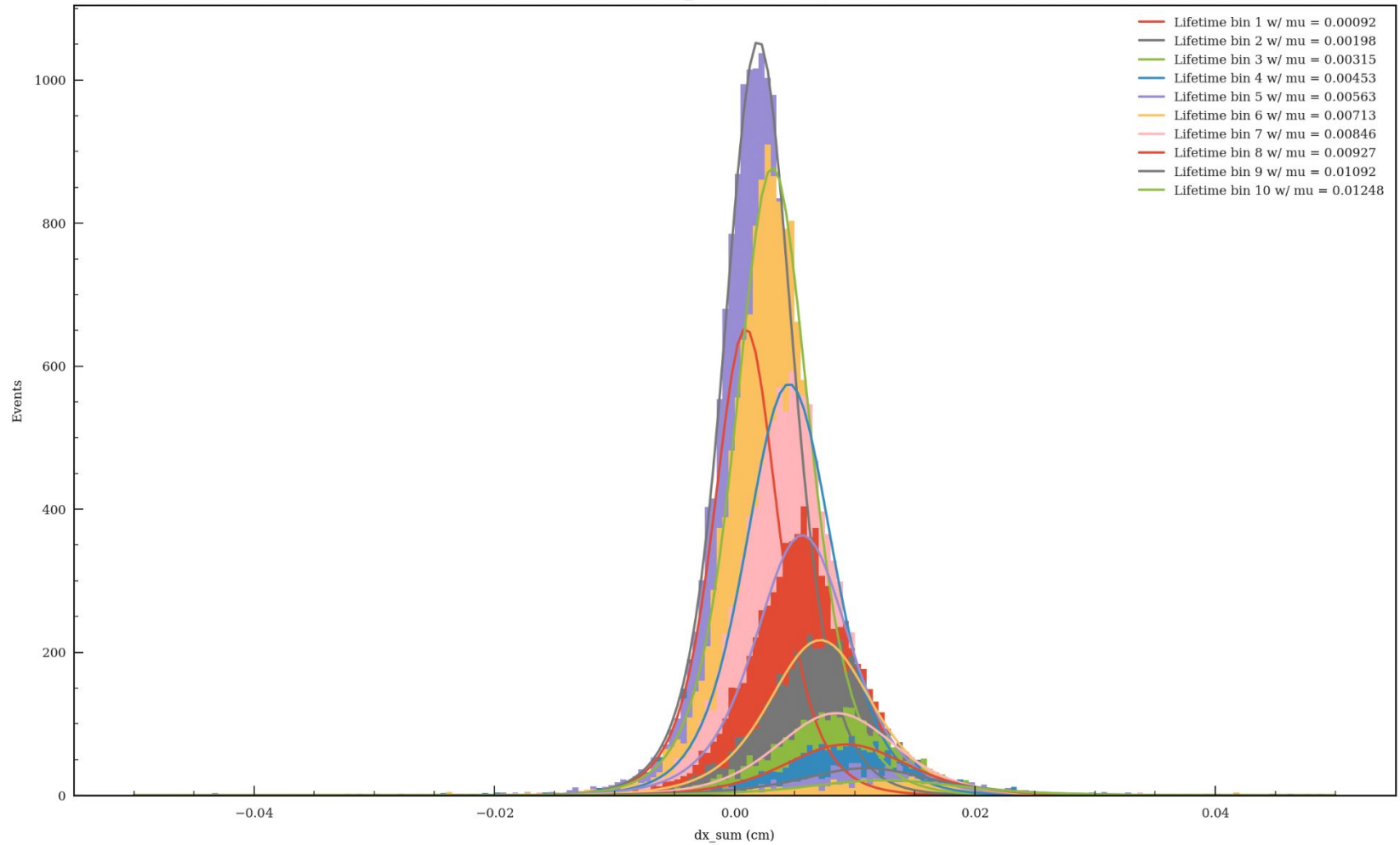
Initial results from a Gaussian convolved with Exponential tails to either side: (using curve\_fit,  $\chi^2/\text{NDF}$  needs to be calculated manually)

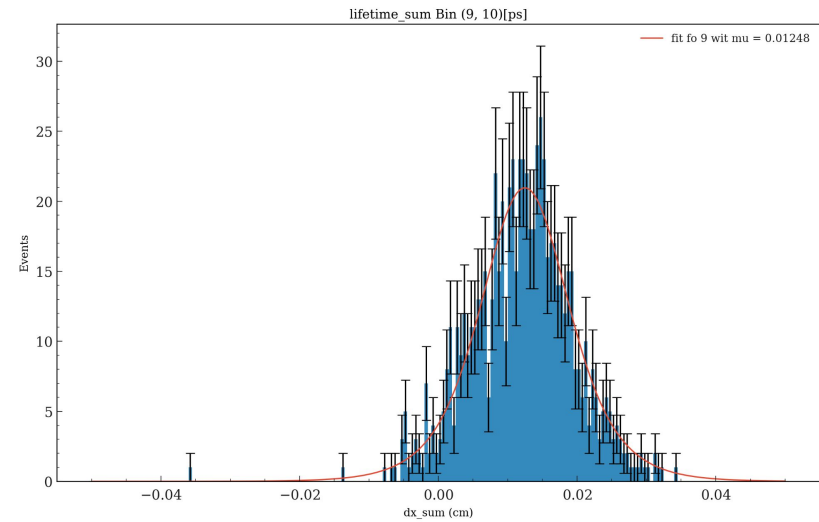
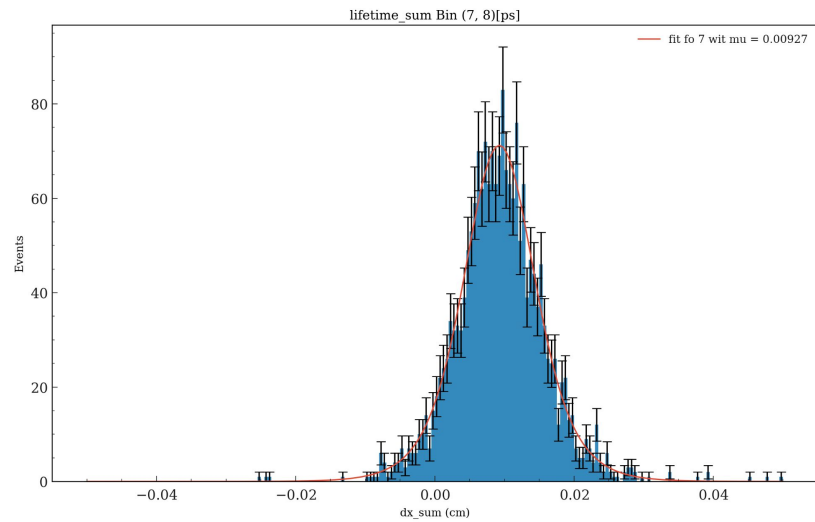
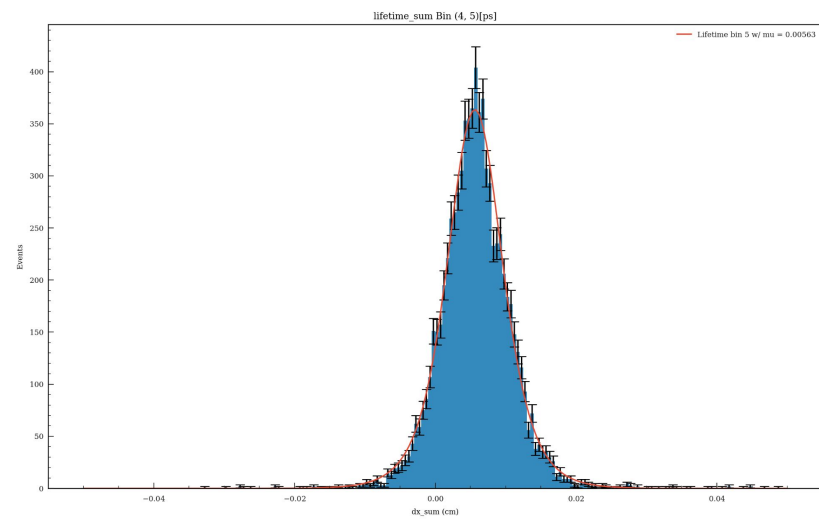
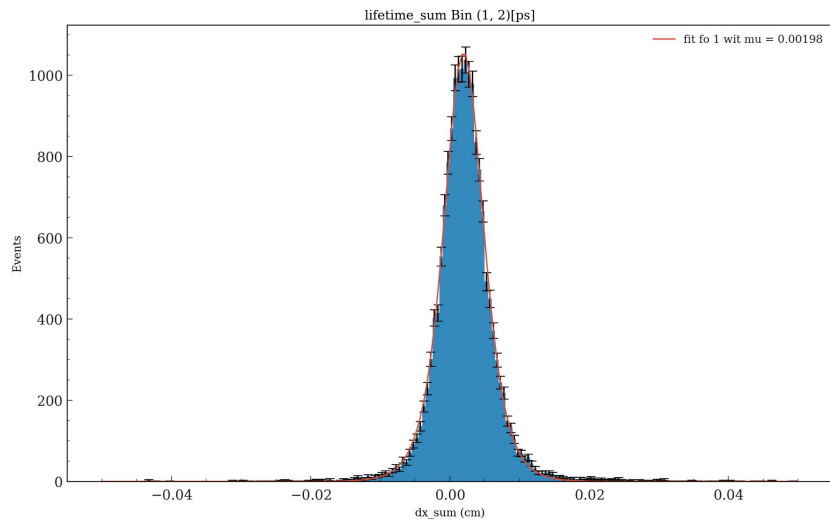


Updated using a Gaussian with exponential tails on either side. Rudimentary fitting using `curve_fit`,  $\chi^2/\text{NDF}$  needs to be calculated manually.

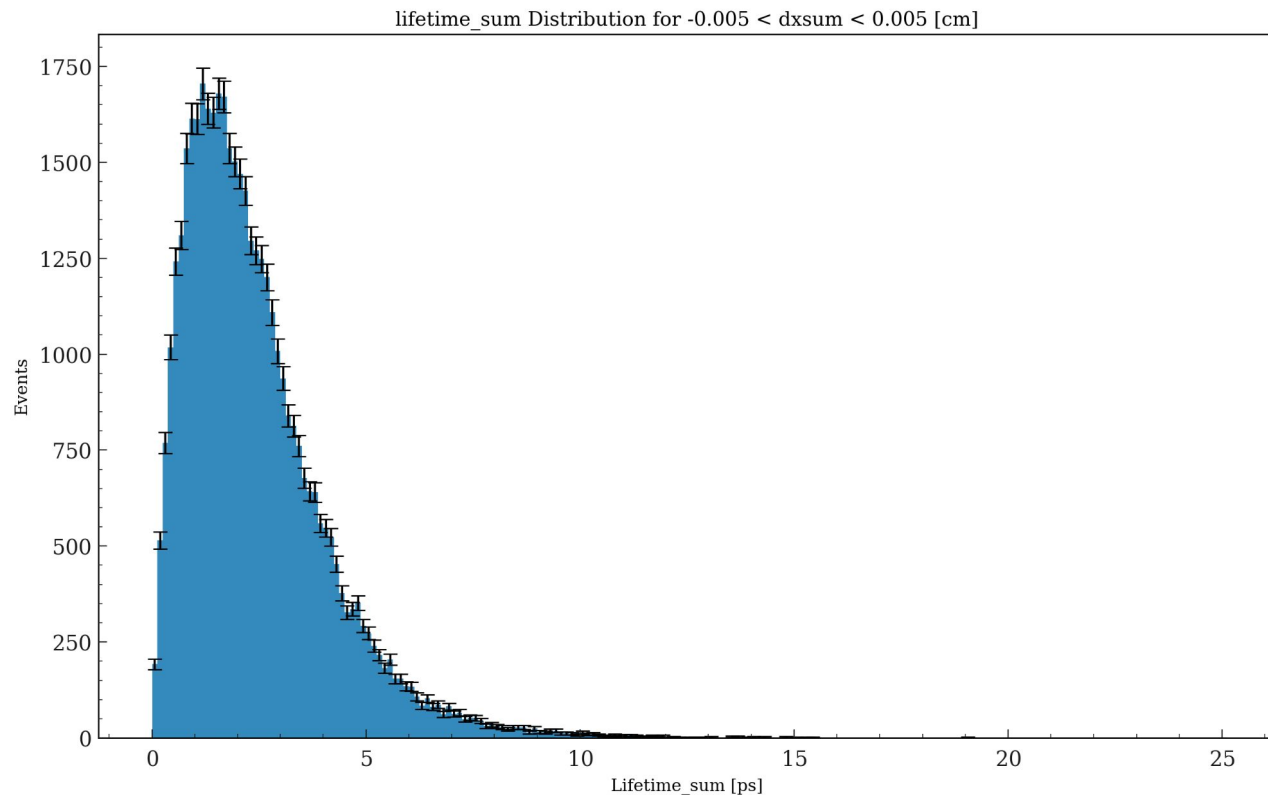


lifetime\_sum Bin (9, 10)[ps]



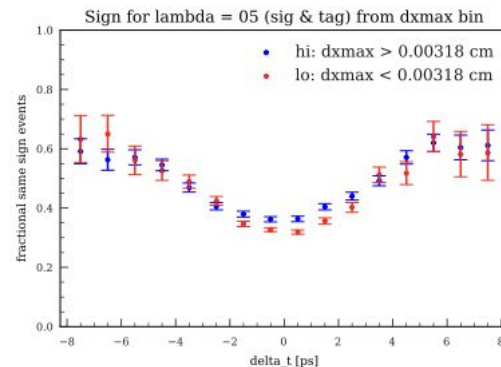
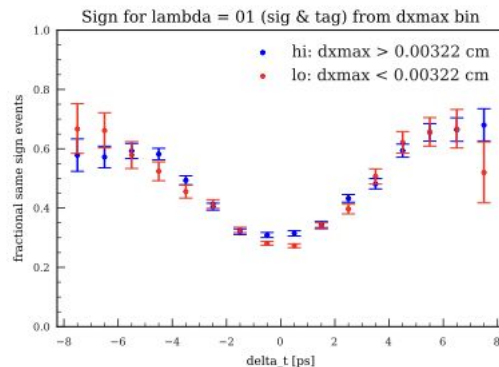
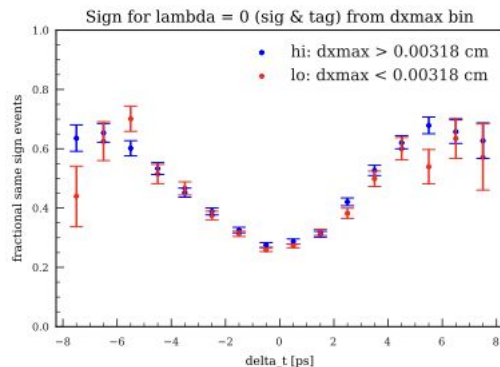
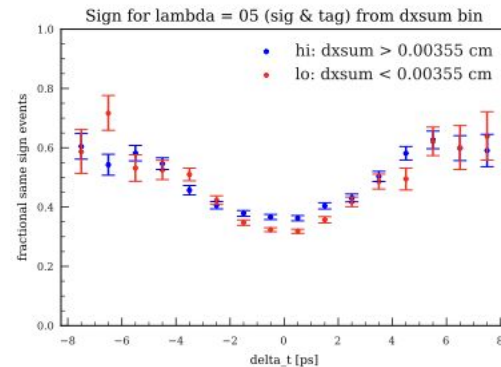
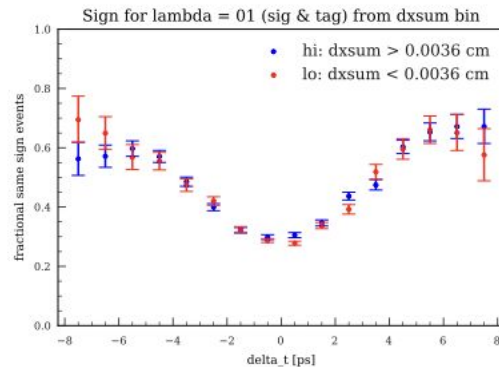
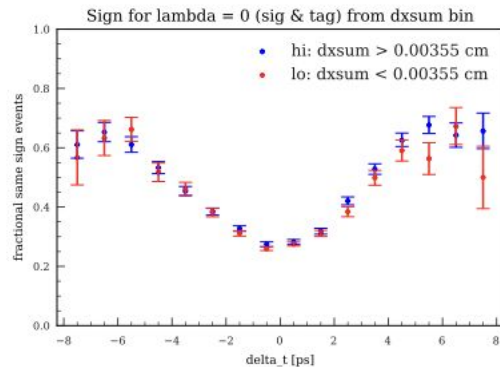


## Binning in lifetime\_sum shape: not exponential

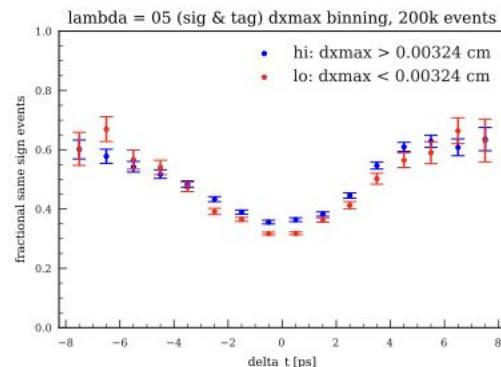
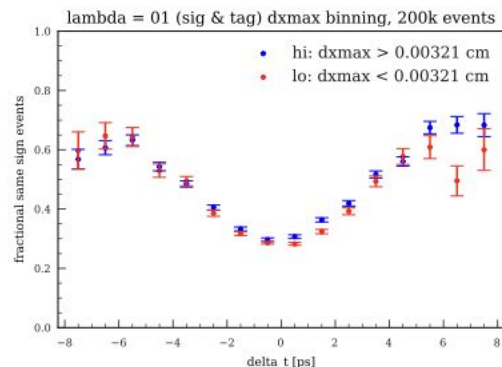
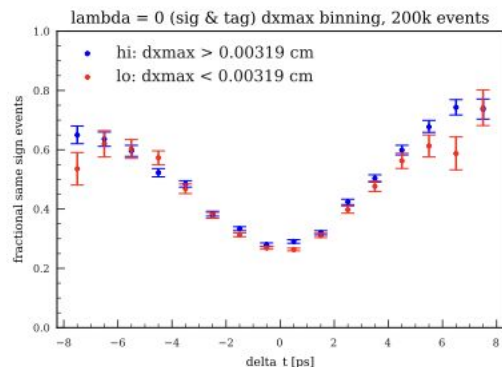
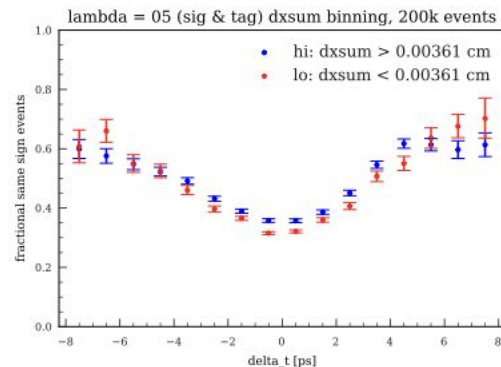
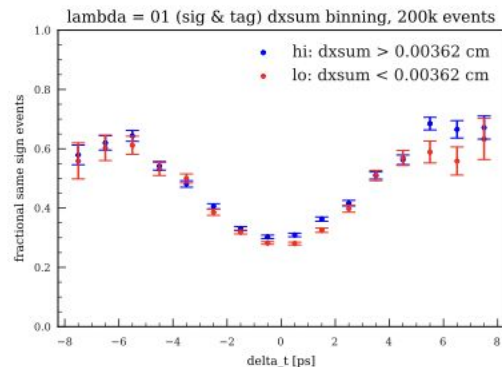
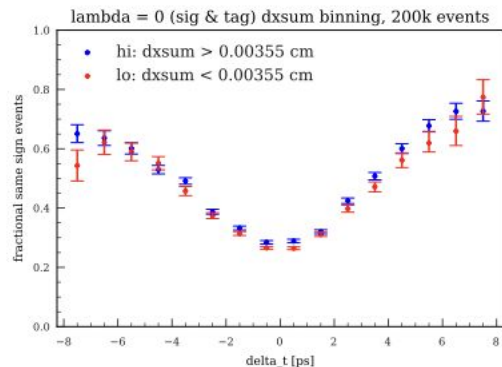


Can we do a binning that equalizes the events in each bin? How much does the  $dx$  distribution change within one of these high lifetime bins?

# reconstructed variables (100k events)

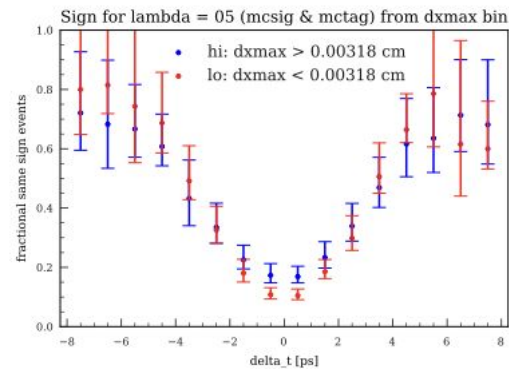
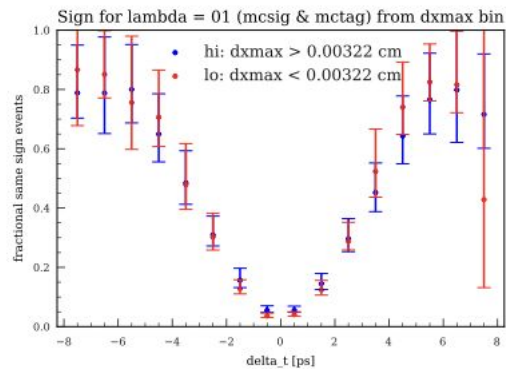
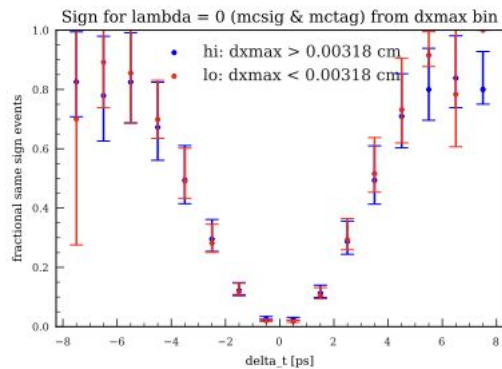
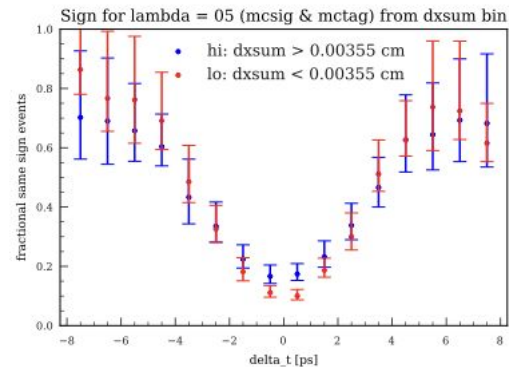
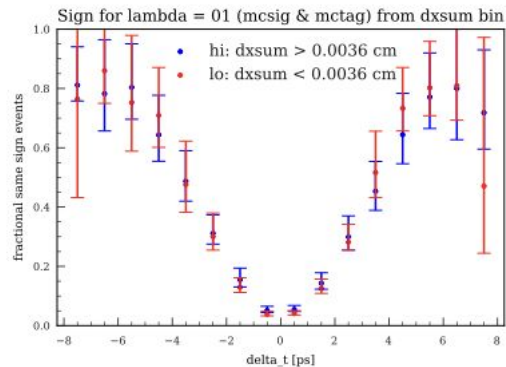
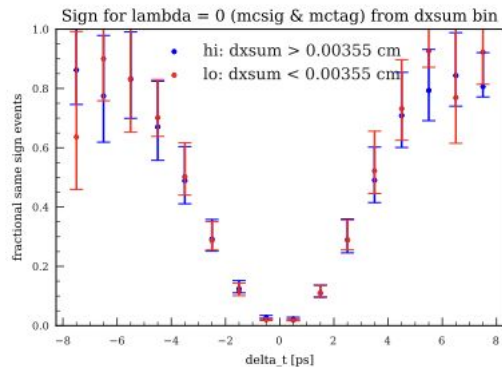


# reconstructed variables (200k events) $\rightarrow$ all r\_bins ( $\sim 72k$ events)

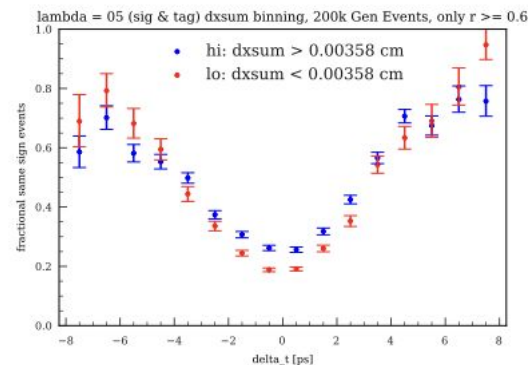
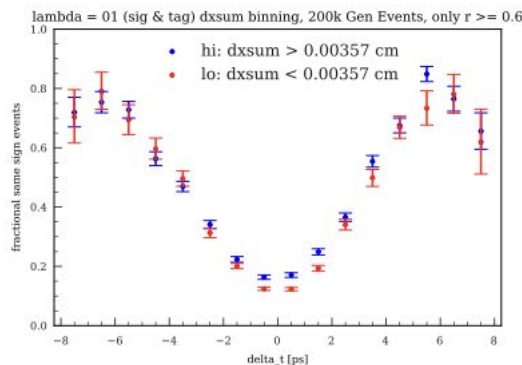
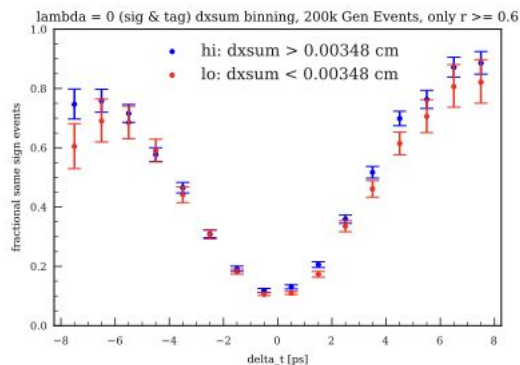




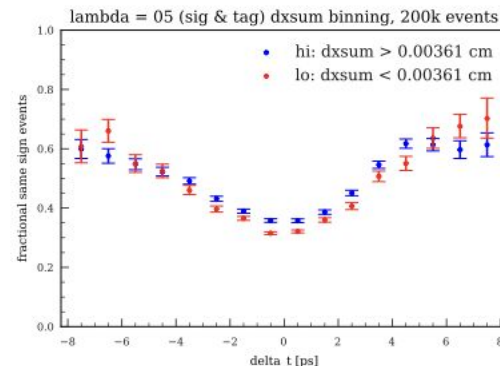
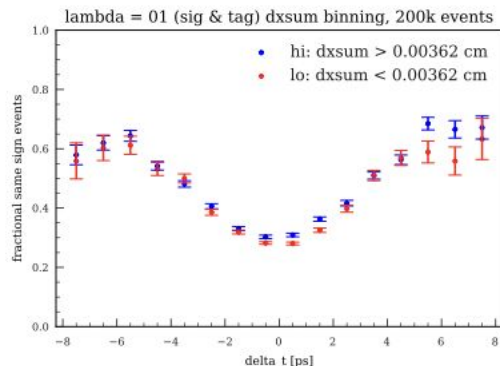
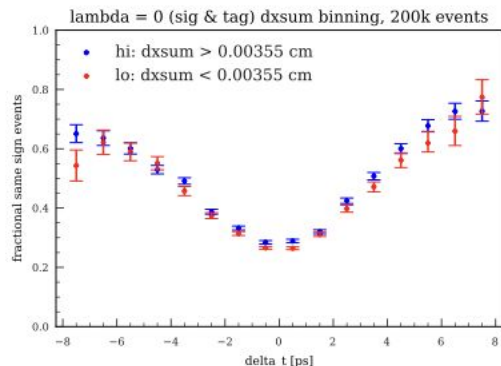
# MC variables (errorbars are unfinished) (100k events)



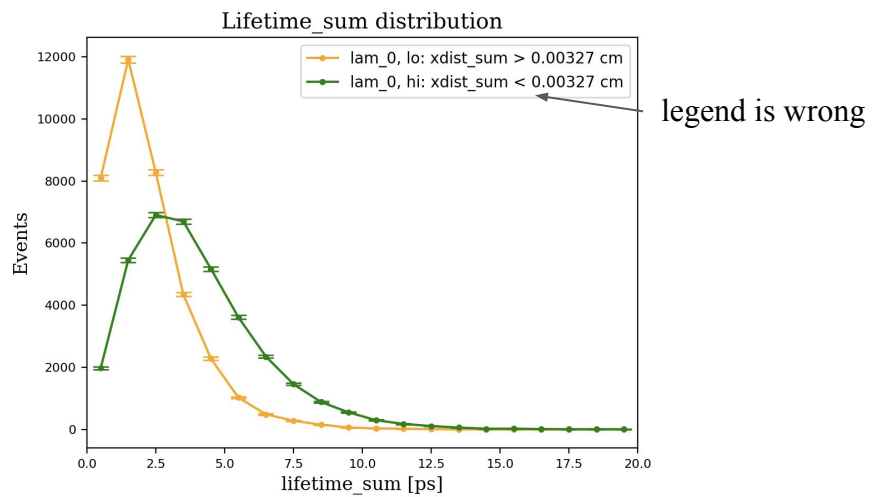
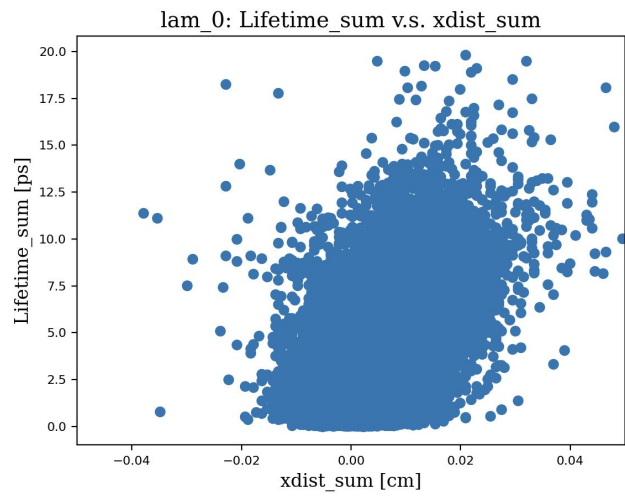
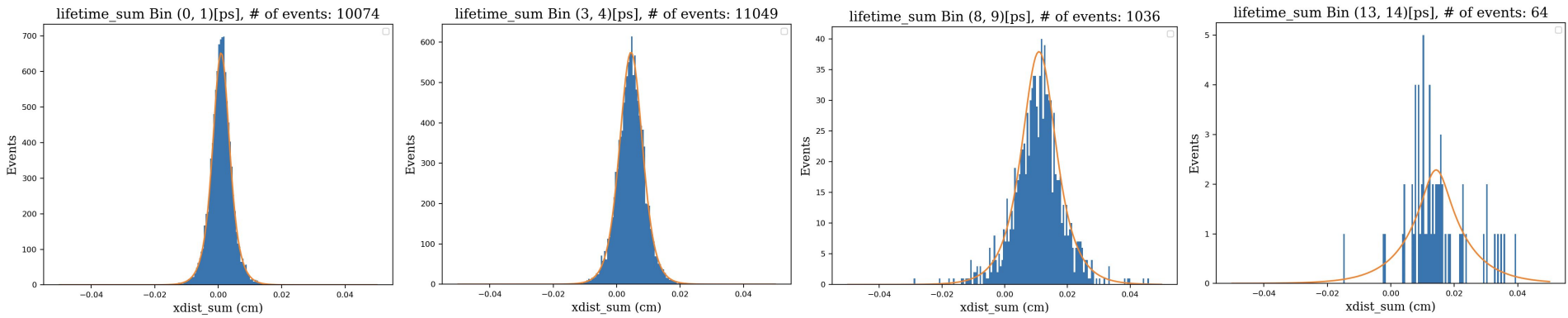
reconstructed variables (200k events)  $\rightarrow$  only  $r \geq 0.6$  (top 3 out of 7 bins) ( $\sim 28k$  events)



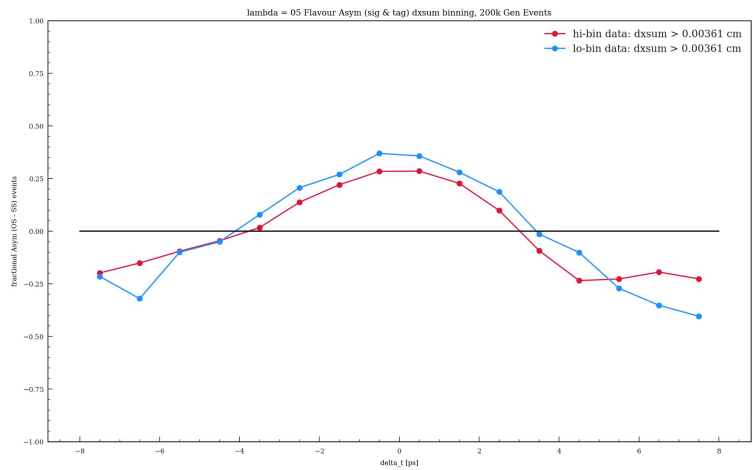
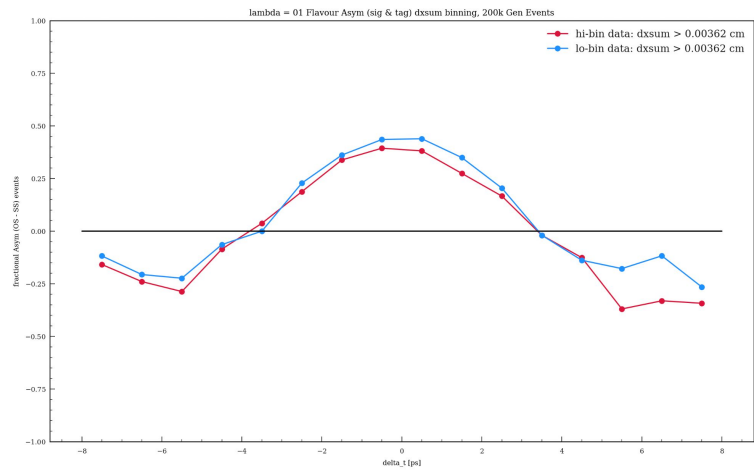
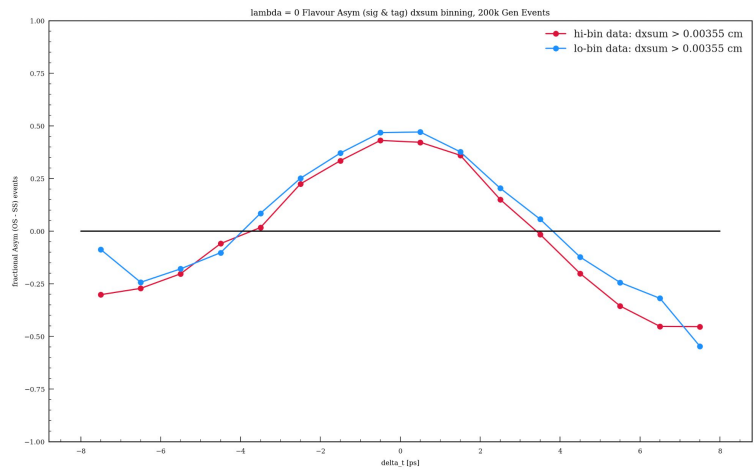
versus all r-bins ( $\sim 72k$  events)



Simulations: 72,798 B pairs simulated

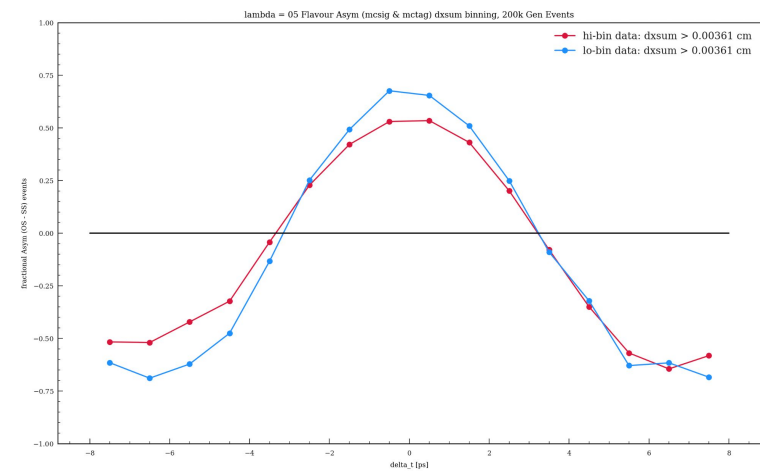
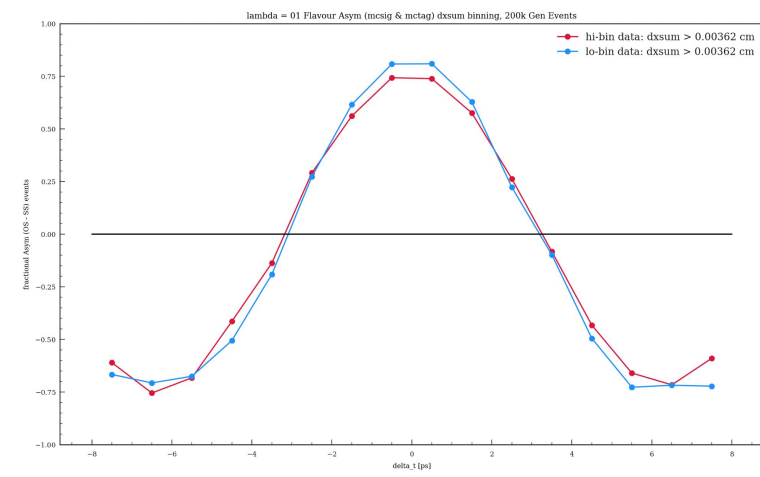
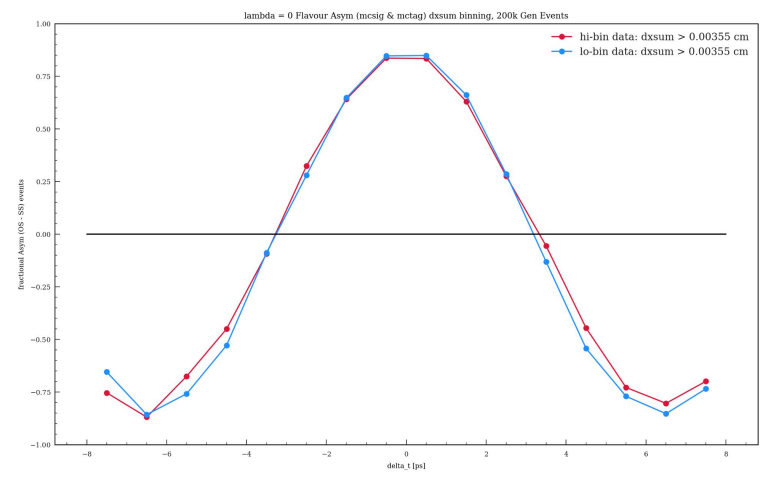


(Opp - Same) Asymmetry, full data (after recon & vertex cuts)

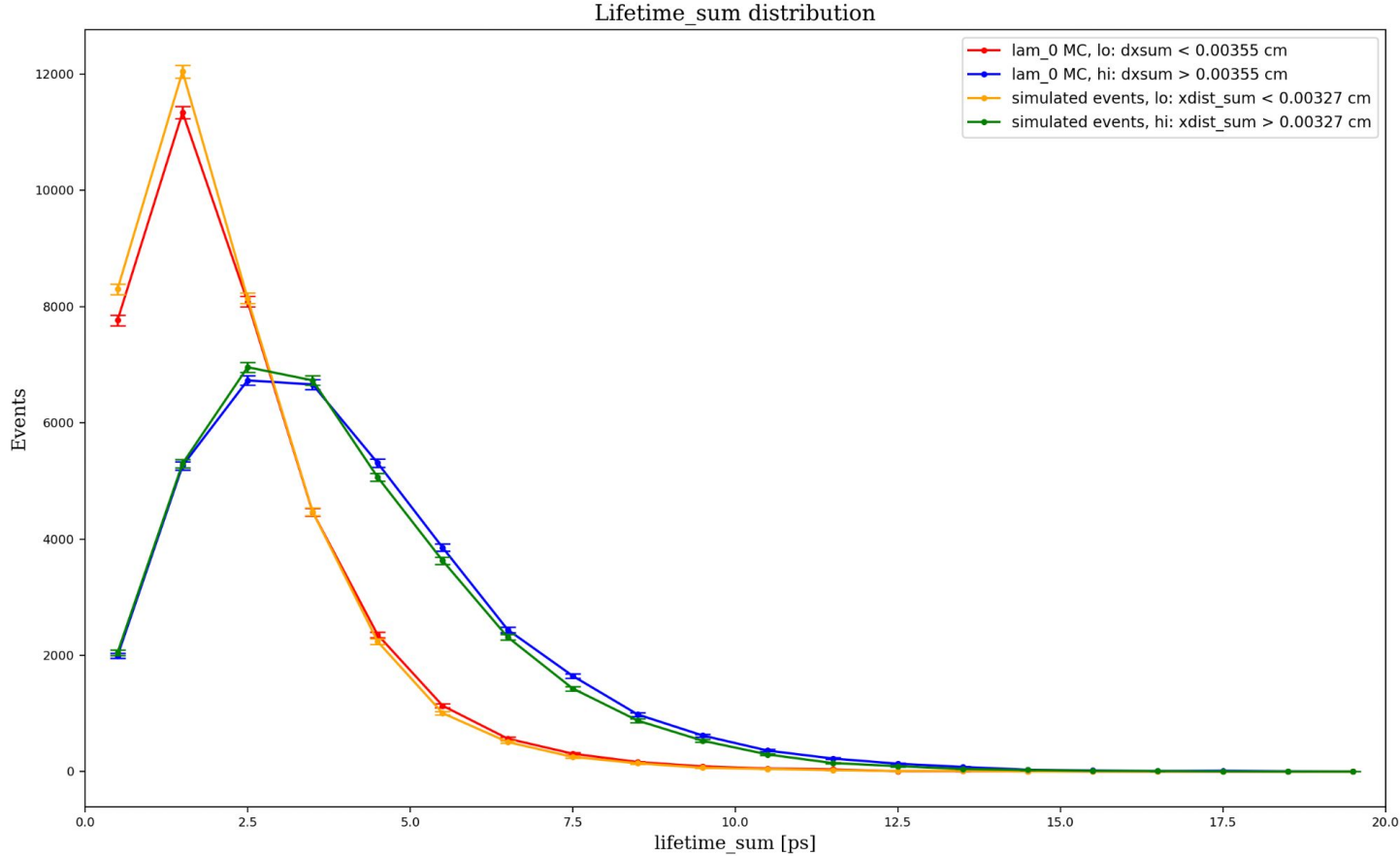


look into what  
may be causing  
this...

(Opp - Same) Asymmetry, full data (after recon & vertex cuts) using MC variables

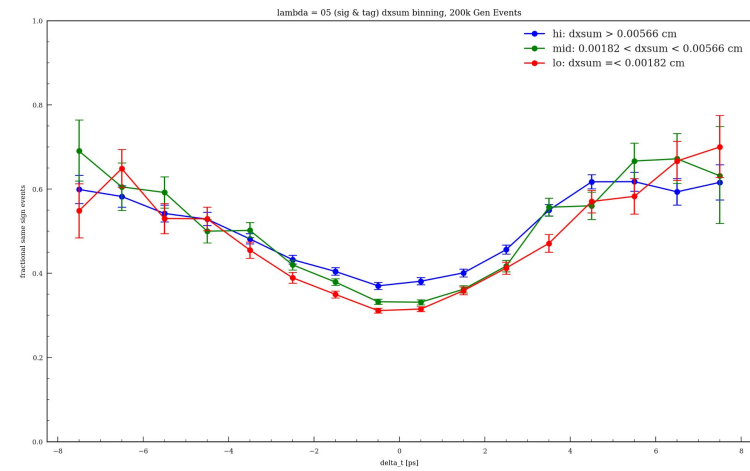
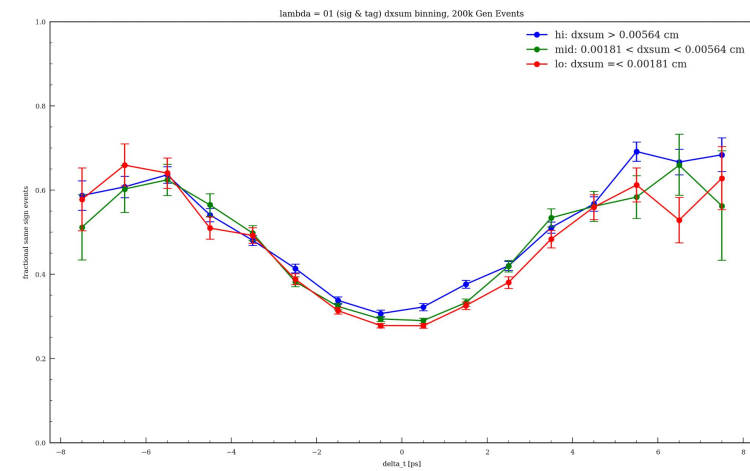
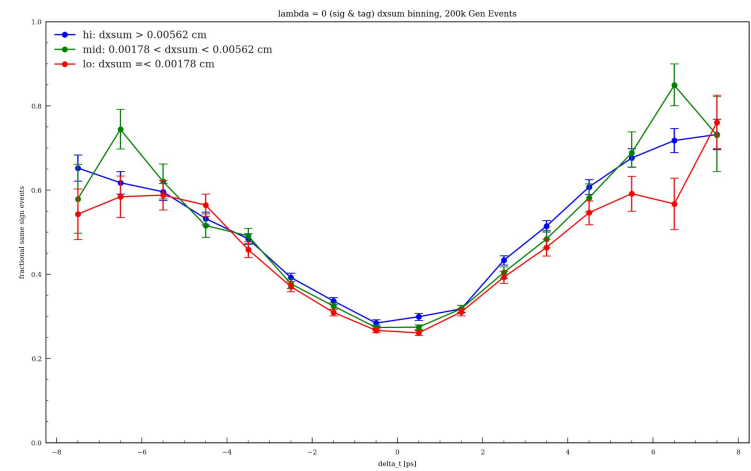


MC data versus simulated data:  $\lambda=0$

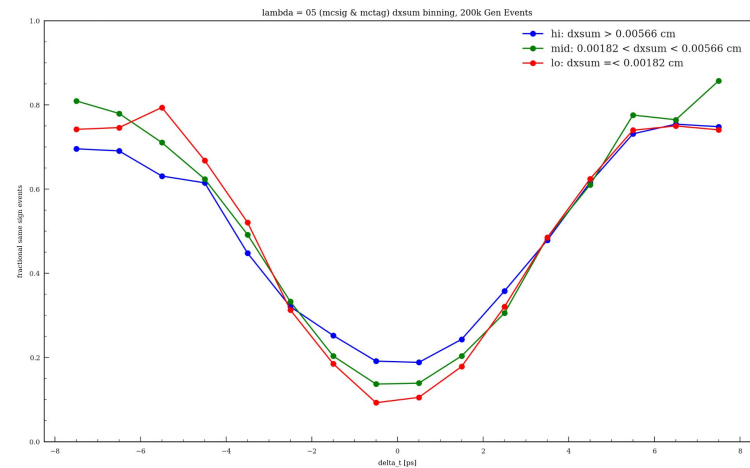
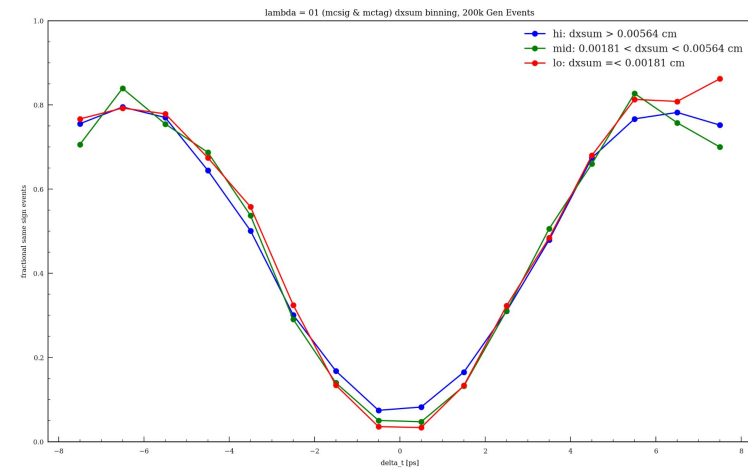
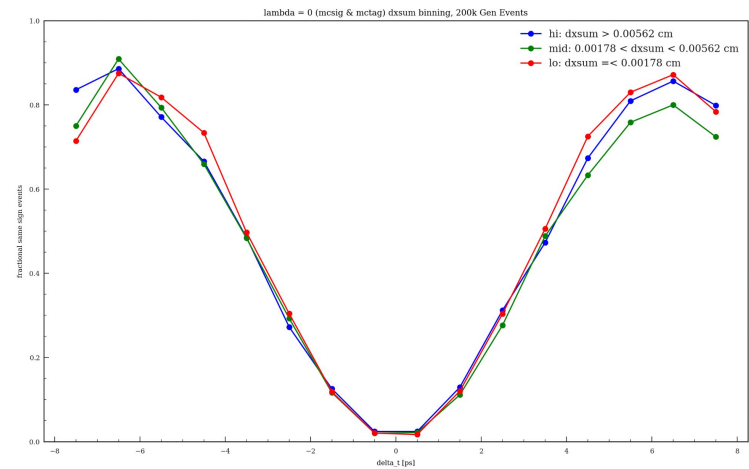


Distributions are similar, but not identical: shape and  $x_{\text{median}}$  values

Fractional same flavour (3 dx\_sum bins)



# Fractional same flavour (3 dx\_sum bins) MC variables





## Hand doing $\chi^2$ calculation for same flavour oscillation plots

full data/ $r \geq 0.6$  data      want to recheck the calculation??

lam\_0  
the total chi\_sq for deco data lam\_0 is: 41.74/27.71  
the number of degrees of freedom (# of bins) is: 16  
the reduced chi squared for deco data lam\_0 is: 2.61/1.73  
this is the result from scipy for lam\_0 and size 200k using flavour values: 0.644/0.647

lam\_01  
the total chi\_sq for deco data lam\_01 is: 52.02/72.58  
the number of degrees of freedom (# of bins) is: 16  
the reduced chi squared for deco data lam\_01 is: 3.25/4.54  
this is the result from scipy for lam\_01 and size 200k using flavour values: 0.562/0.78

lam\_05  
the total chi\_sq for deco data lam\_05 is: 98.98/145.89  
the number of degrees of freedom (# of bins) is: 16  
the reduced chi squared for deco data lam\_05 is: 6.19/9.12  
this is the result from scipy for lam\_05 and size 200k using flavour values: 0.931/0.95

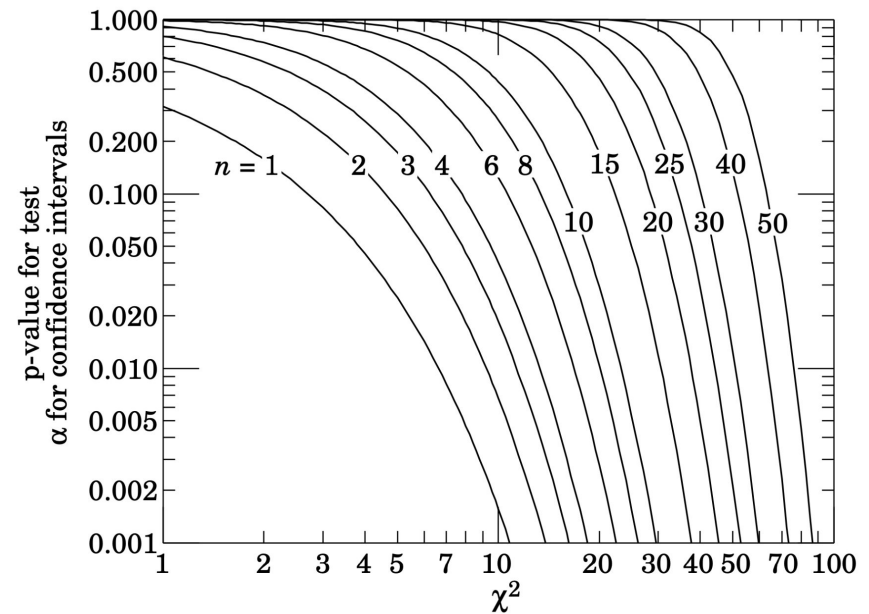


Figure 40.1: One minus the  $\chi^2$  cumulative distribution,  $1 - F(\chi^2; n)$ , for  $n$  degrees of freedom. This gives the  $p$ -value for the  $\chi^2$  goodness-of-fit test as well as one minus the coverage probability for confidence regions (see Sec. 40.4.2.2).