Logarithmic weighting

An Analysis on General Cut

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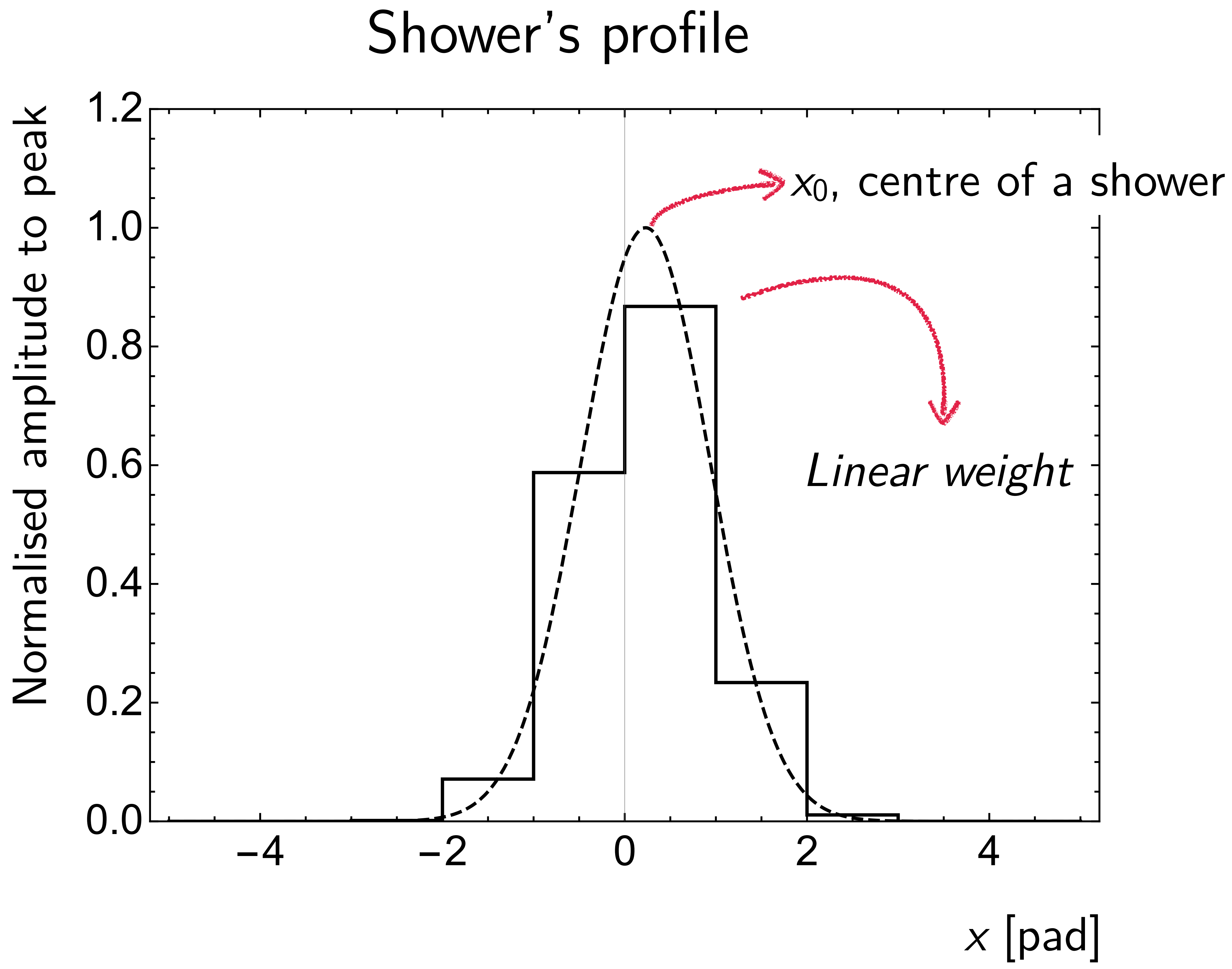
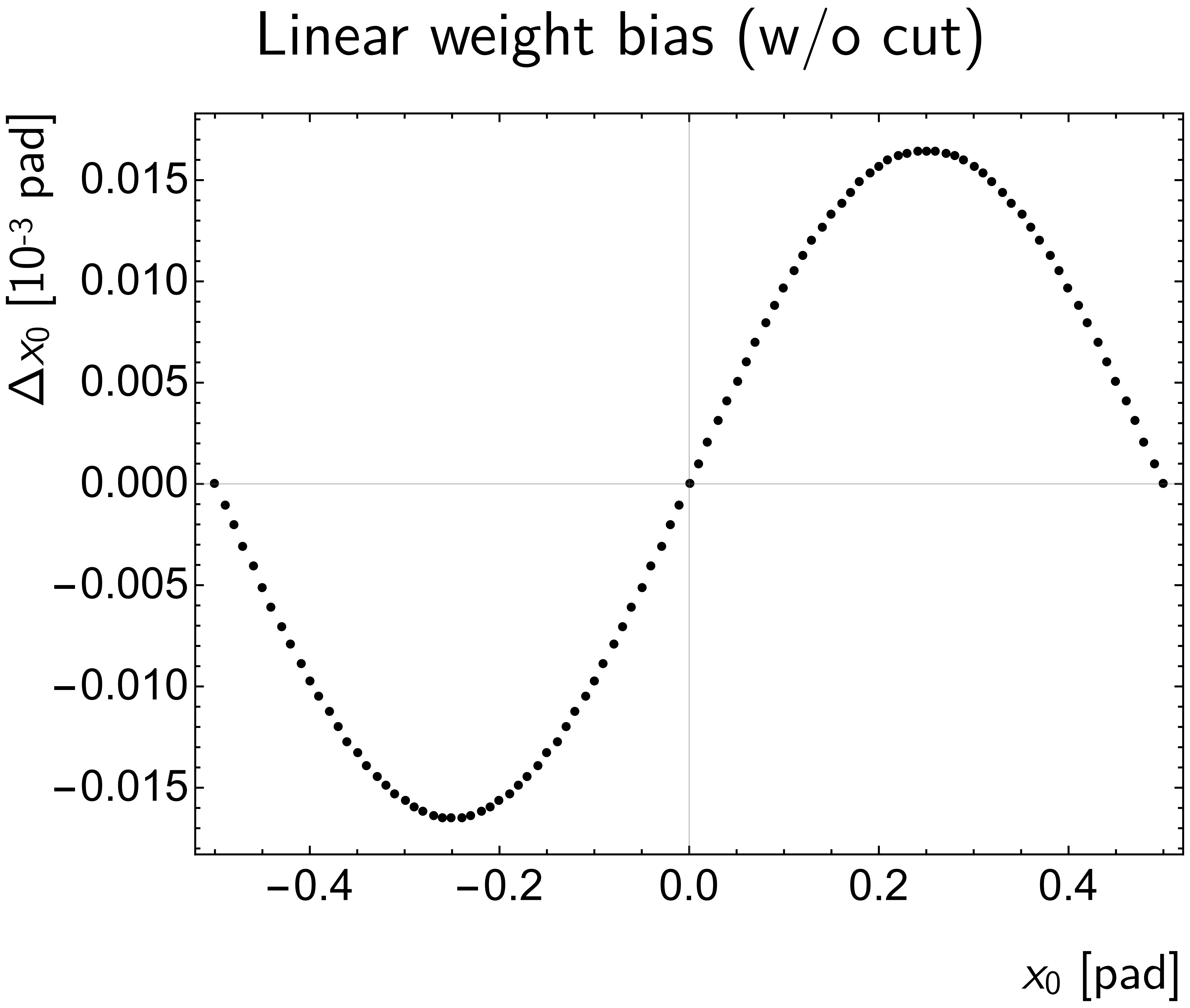
$\Delta x_0 = \mathrm{mean}(x) - x_0$



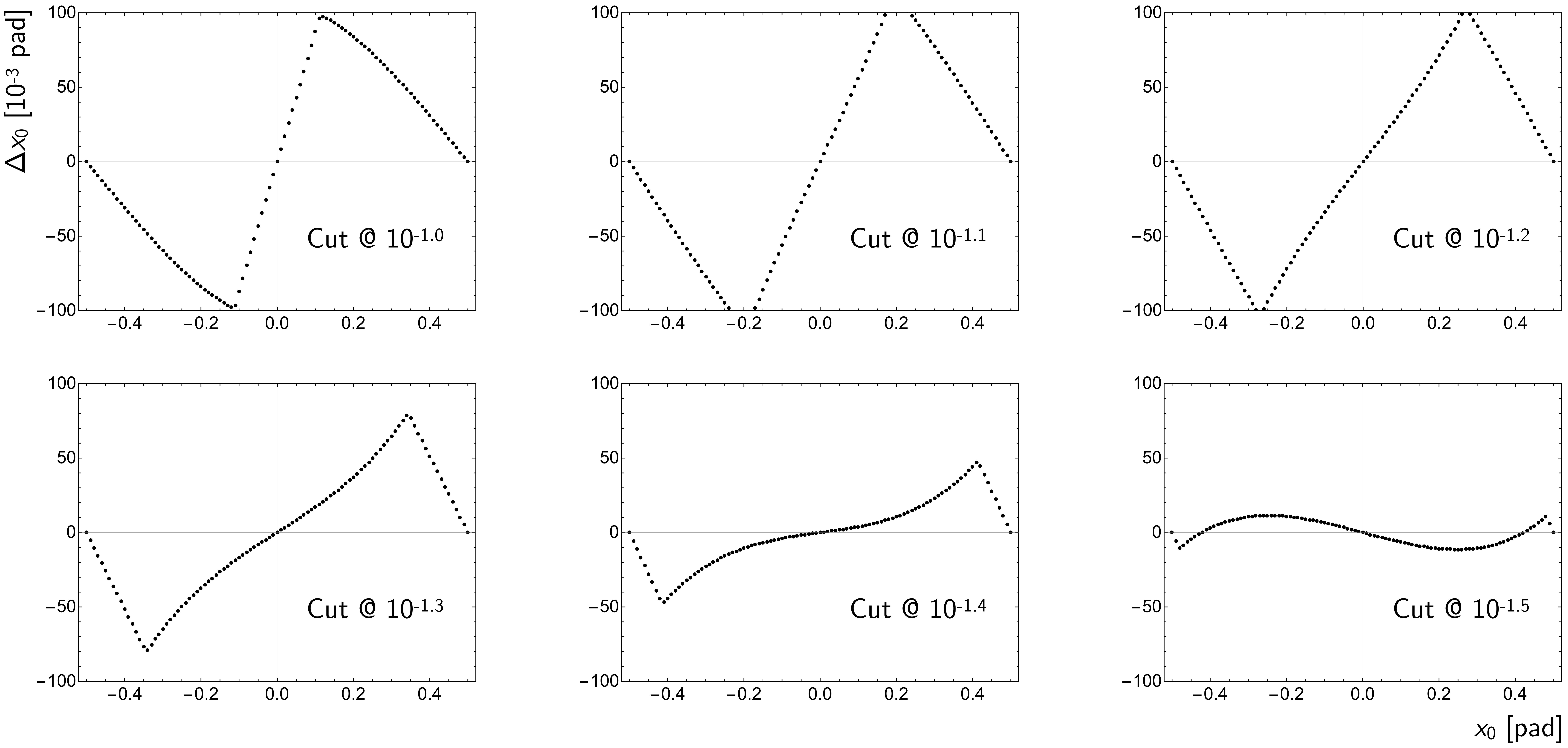


Linear weighting: Use the amplitude (E_{dep}) as the weight in bin coordinate's average:

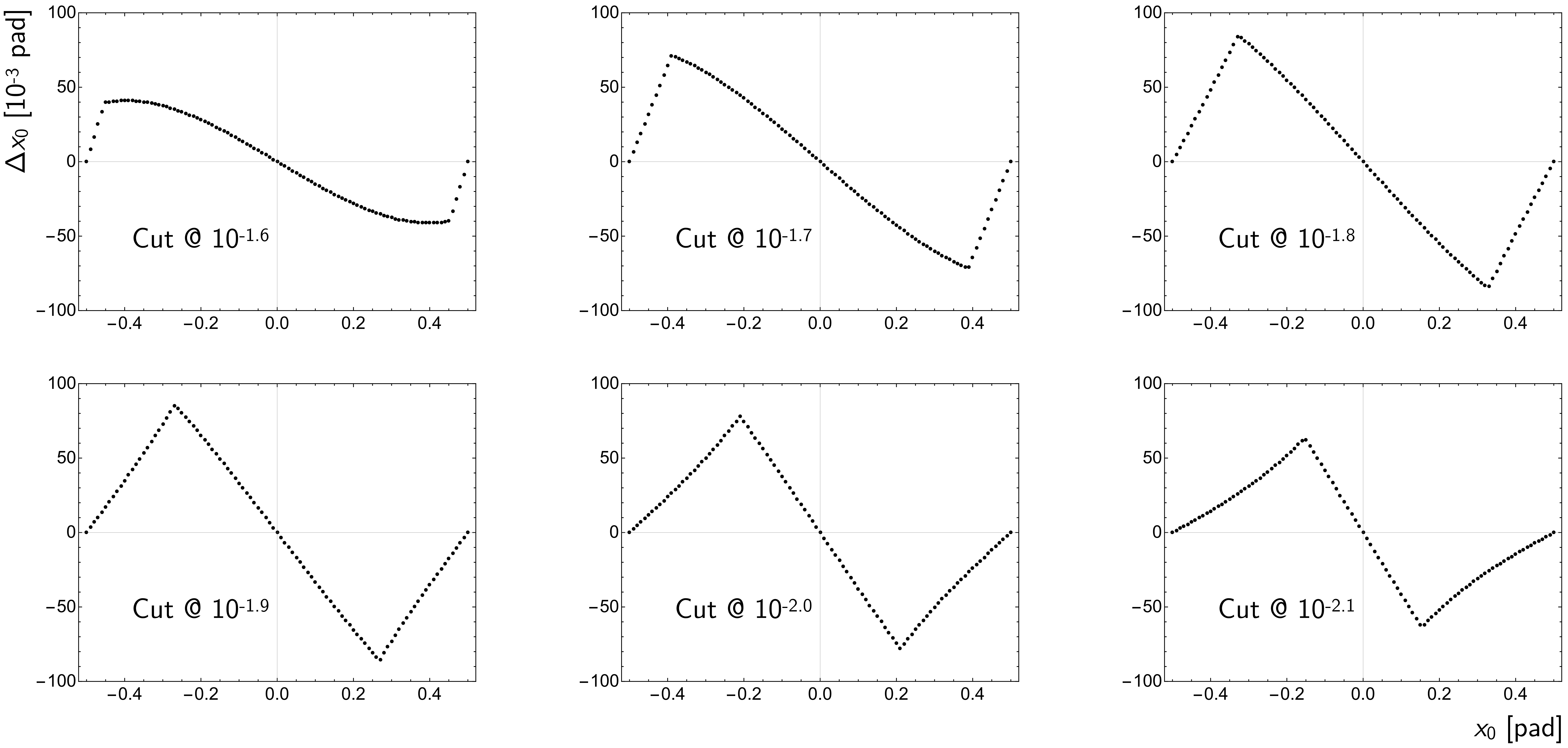
$$\mathrm{mean}(x) = \mathrm{sum}(x_i \times w_i)/\mathrm{sum}(w_i)$$

Just a repeat of the result

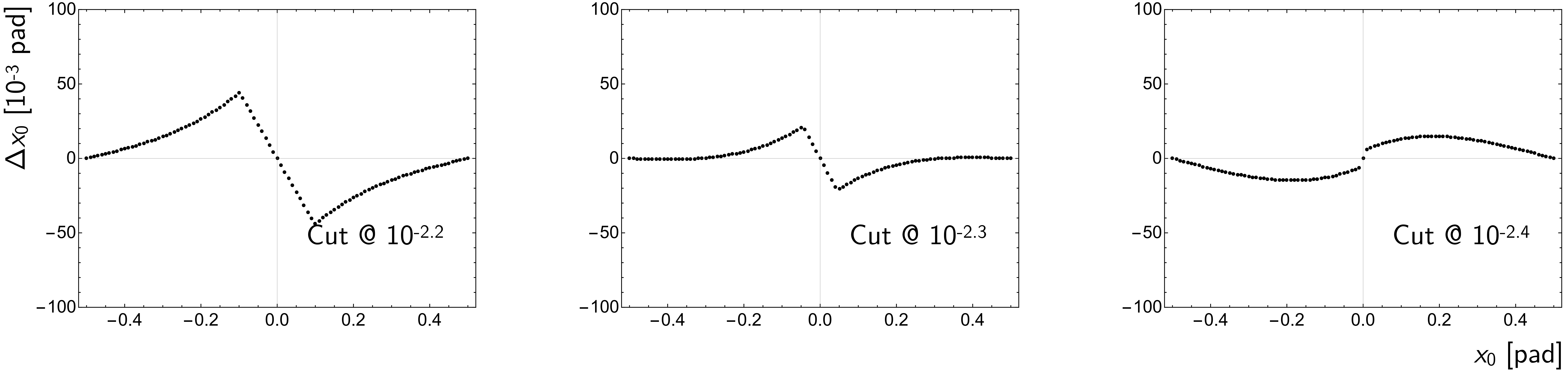
Without cut (i.e. ground tiny weights to 0), the weights are vulnerable to any kinds of noise.



Logarithmic weighting: $w_i = \log(E_{\mathrm{dep}}/\mathrm{cut})$



Logarithmic weighting: $w_i = \log(E_{\text{dep}}/\text{cut})$



Logarithmic weighting: $w_i = \log(E_{\text{dep}}/\text{cut})$

Good results/small bias require a correct cut.

For the sake of simplicity, the results are evaluated by the largest bias: maximum of Δx_0

The correct cut is related to:

- shower's amplitude (here normalised to 1)
- shower's width (see the next slide)

It is almost impossible to satisfy everywhere with a general/universal cut.

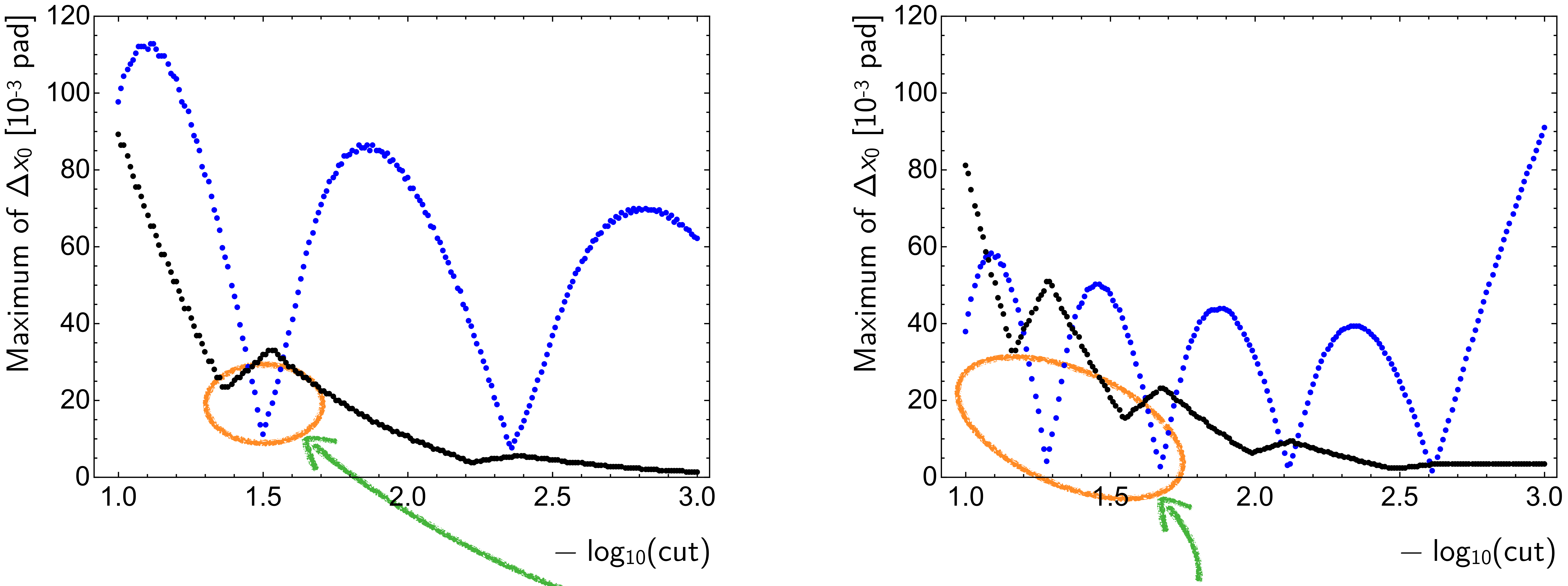
Some compromise needs to be made. (An item to be investigated, maybe with CNN?)

Blue: Logarithmic weighting

Black: Linear weighting with the same cut

Narrow shower

Wider shower



Logarithmic weighting has better performance when the shower is wider