

GNN fit robustness II

06.09.24

“Mixing”

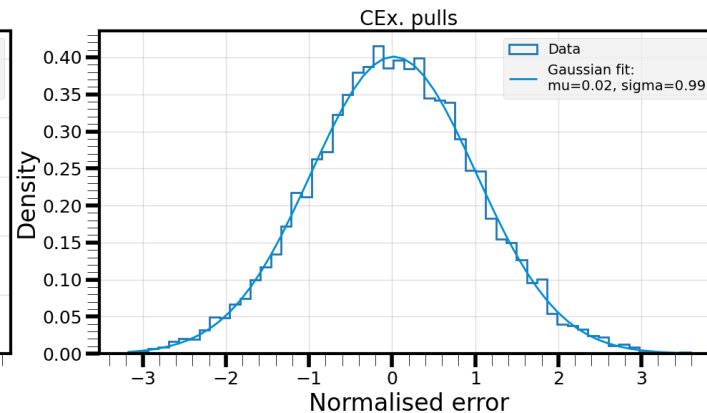
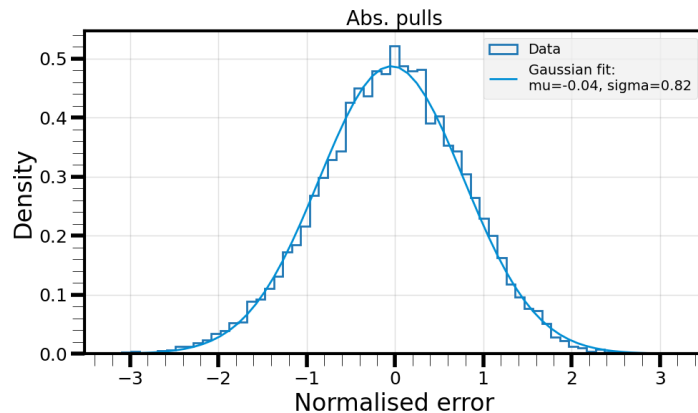
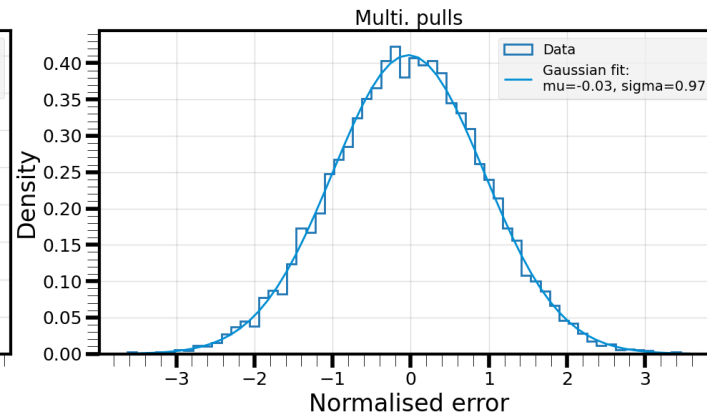
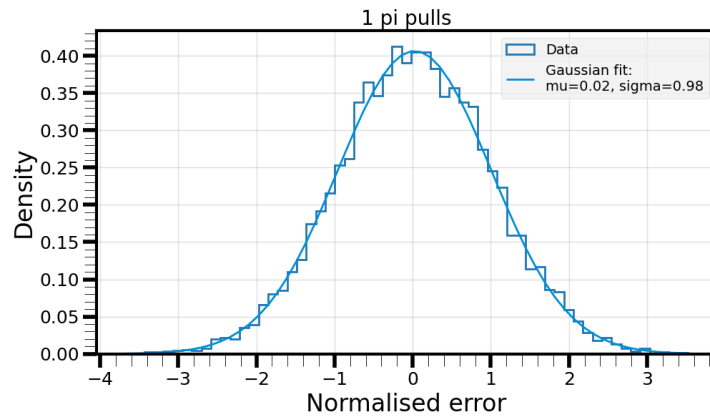
- Same source for all MC – draw from “true” distribution
- Previously, this was divided into two samples (files).
- From these, sub-samples were created.
- Treating the “true” distribution as a multinomially distributed set of bins.
- When sampling from the subsample, we sample with a probability $\frac{X}{N_{sub}} = p_{i,sub} \neq p_{i,true}$, where $X \sim \text{Multi}(N_{full}, p_{i,true})$ from the true multinomial.

“Mixing”

- Before showing any results:
- How large a pull is acceptable?
 - I’ve already looked at a bunch of results, so don’t trust myself to think about it sensibly

“Mixing” pulls

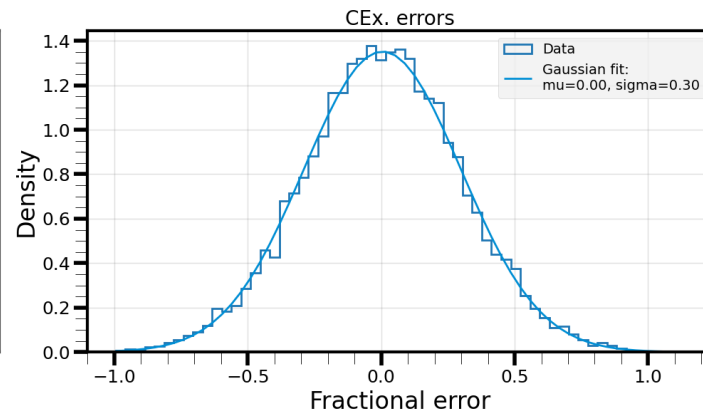
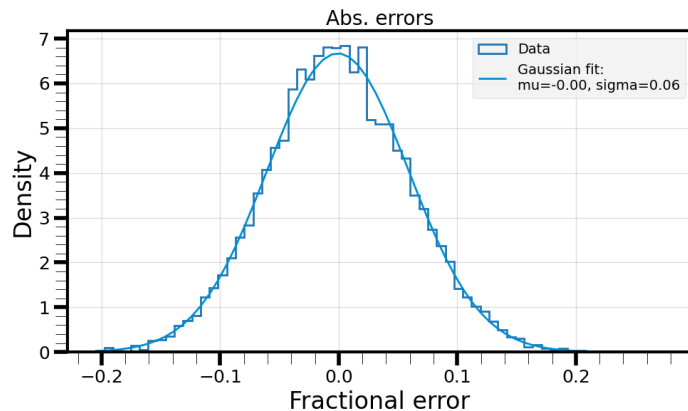
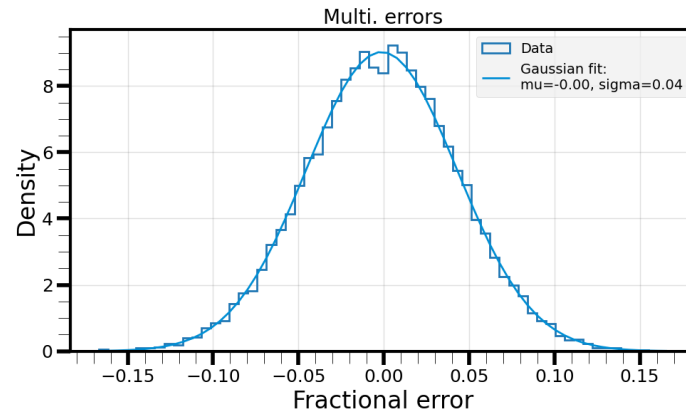
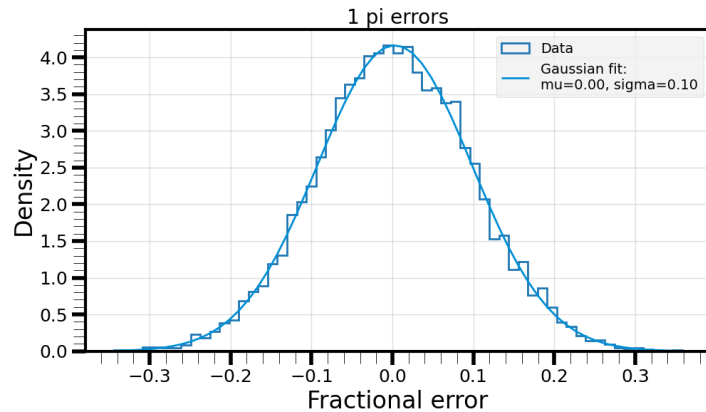
- Combining all MC events, and randomly splitting these removes pulls.



“Mixing” fractional errors

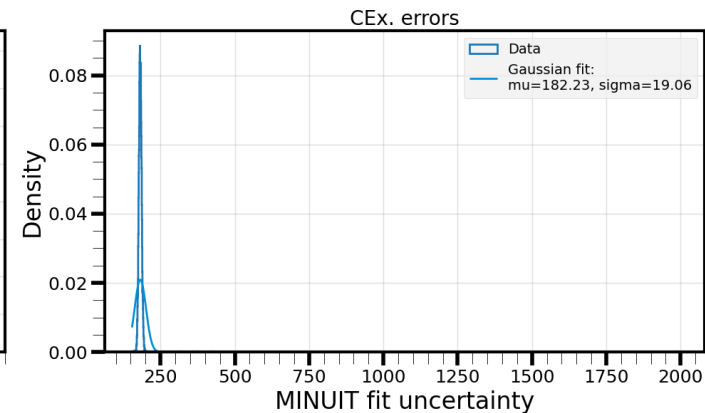
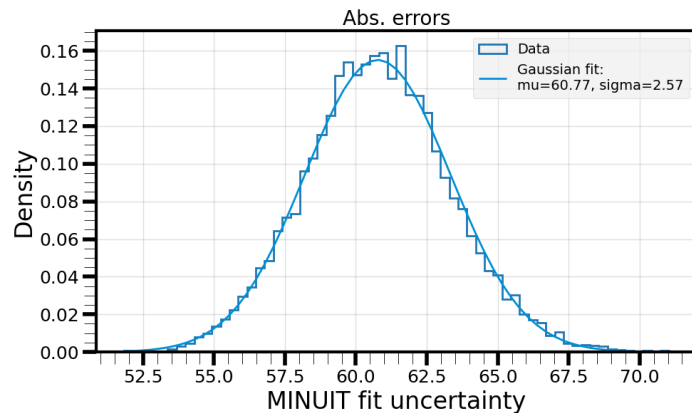
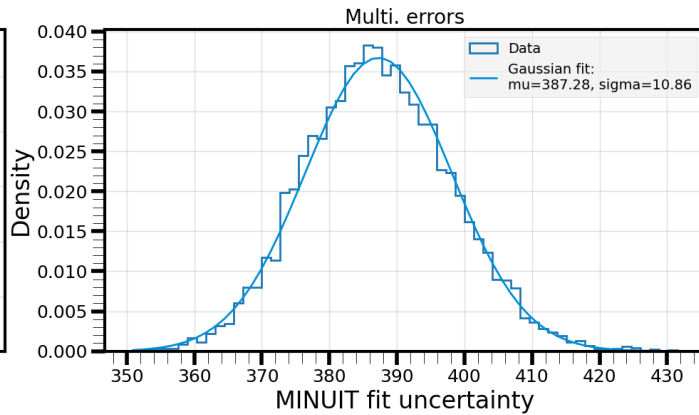
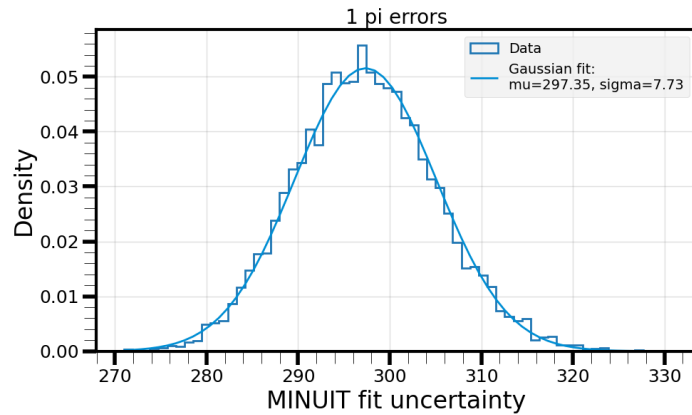
$$\frac{\text{Prediction}}{\text{True}} - 1$$

- Combining all MC events, and randomly splitting these removes pulls.



“Mixing” fit uncertainties

- Combining all MC events, and randomly splitting these removes pulls.

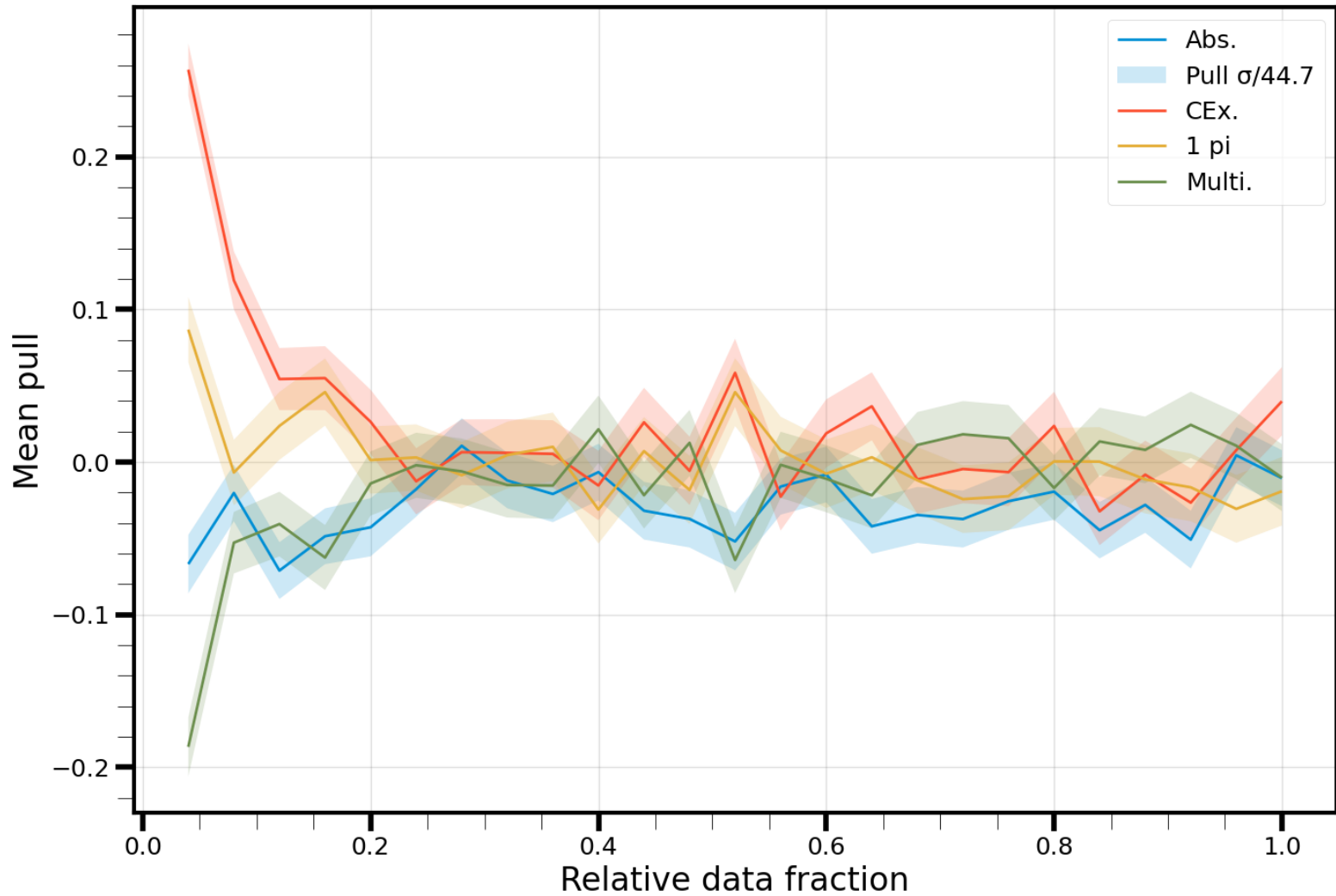


Tests

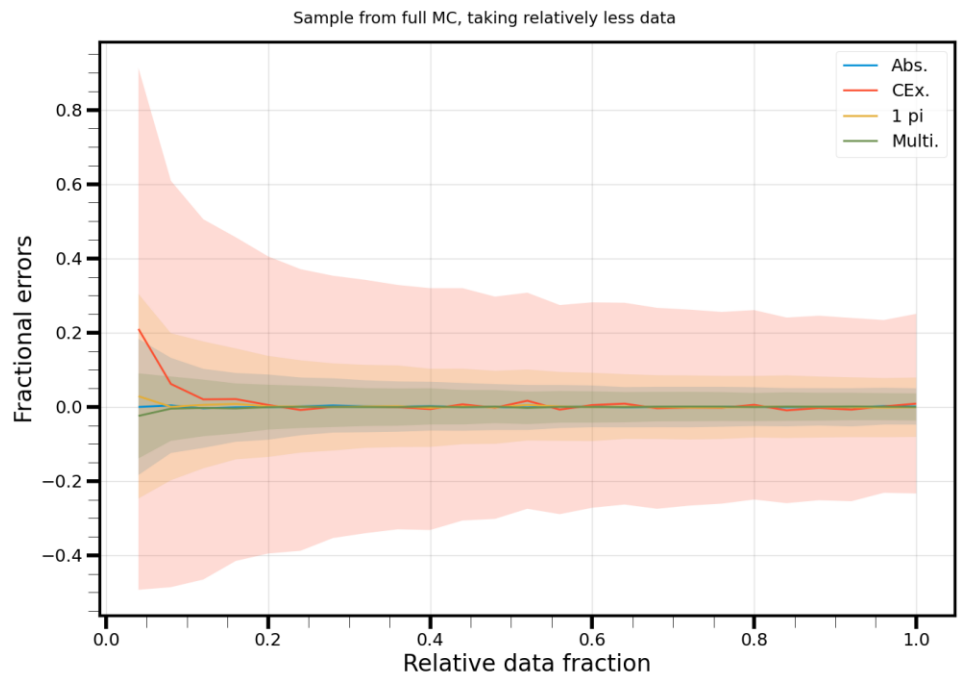
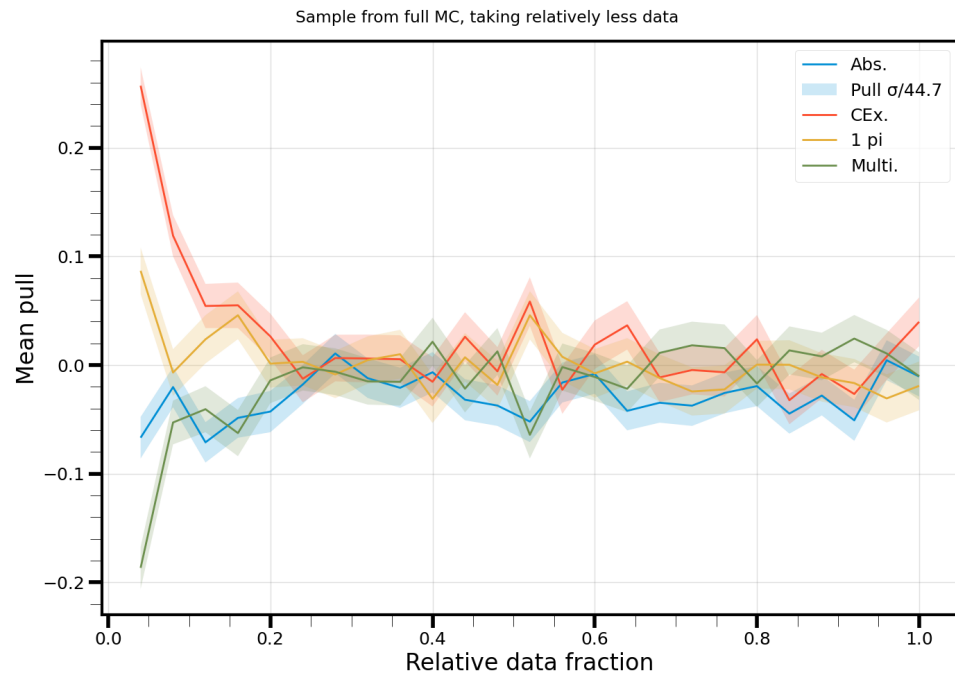
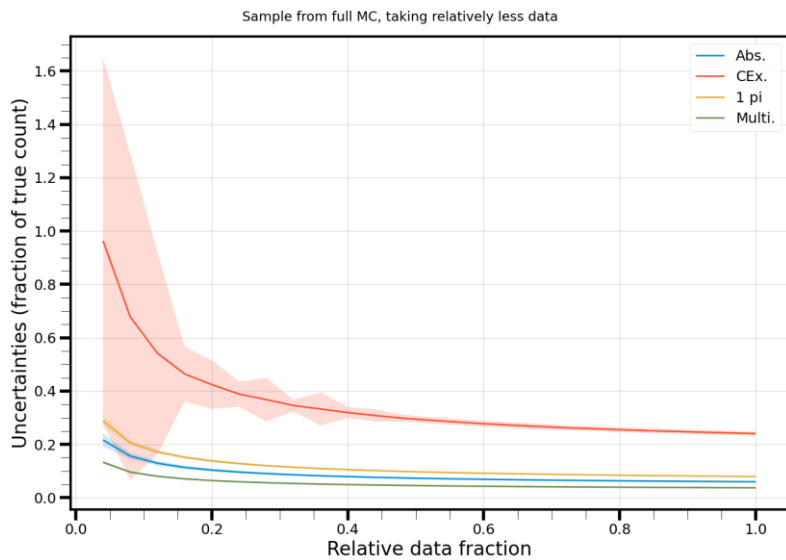
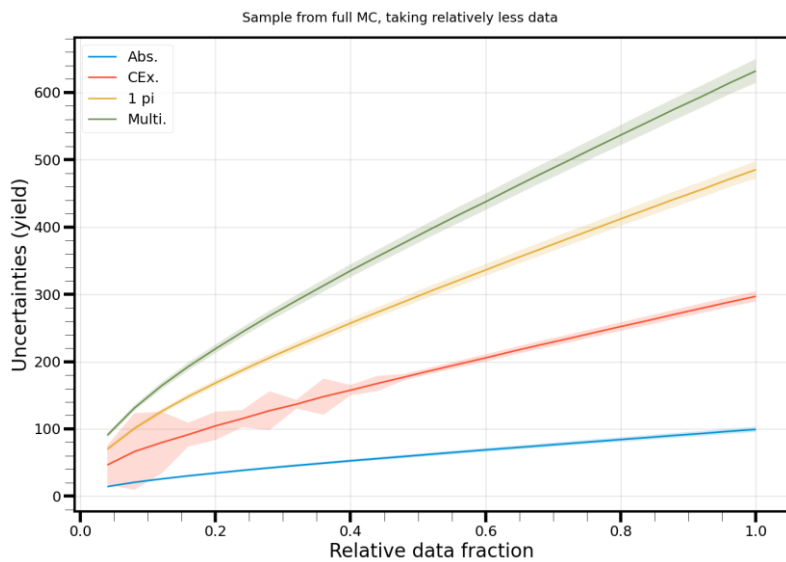
- Random fluctuation
- Data statistics
- Template statistics
- Re-weighted process fractions
- Initial fit predictions
- GNN score drift – some form of smearing the underlying distributions
 - Note: need to confirm Minuit works with non integer templates (nuisances **Poisson** distribute template bins)
- Outliers

Data statistics

Sample from full MC, taking relatively less data

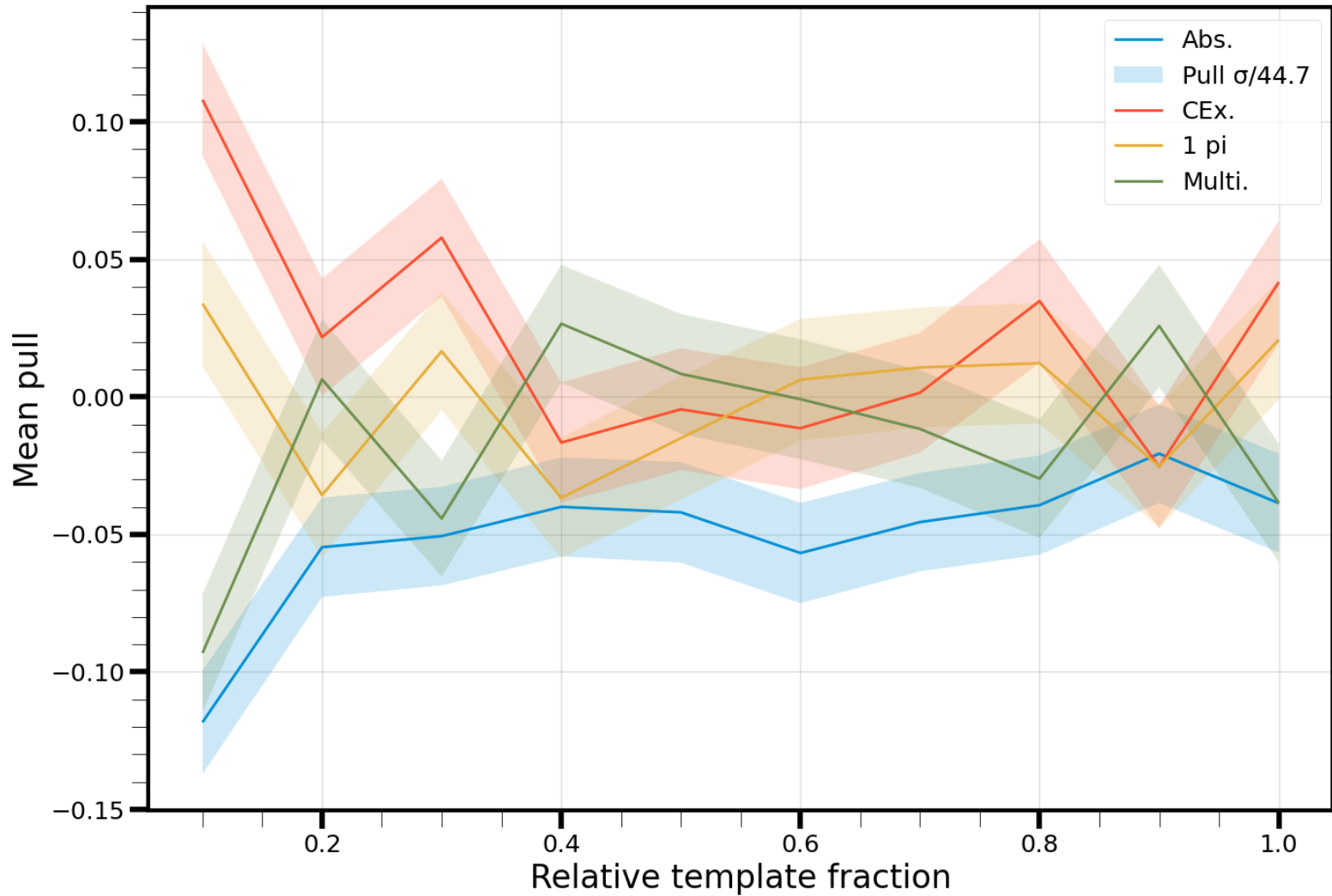


Data statistics

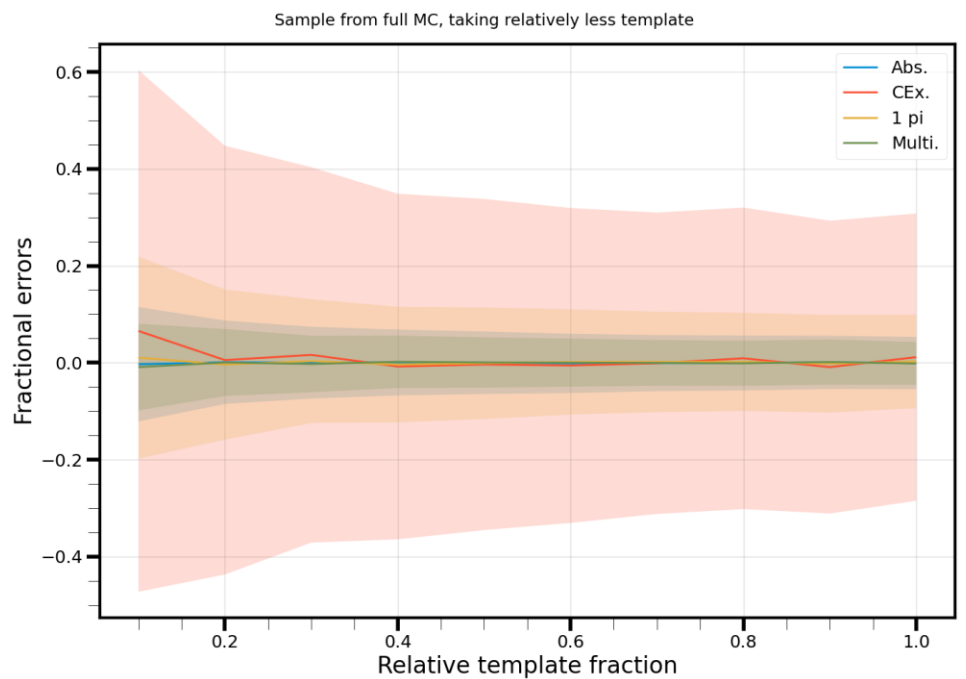
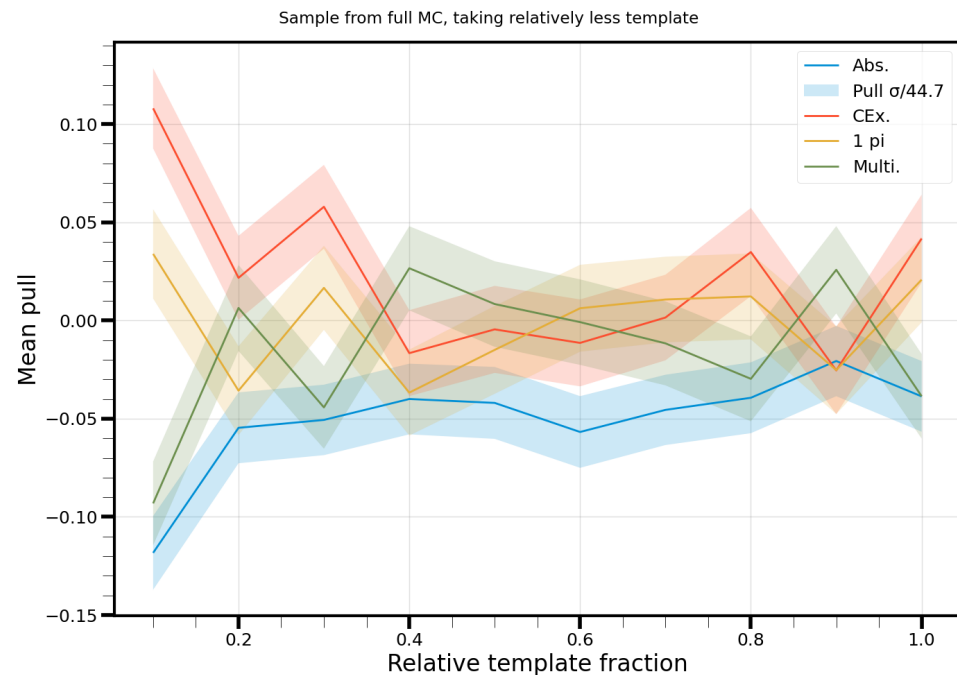
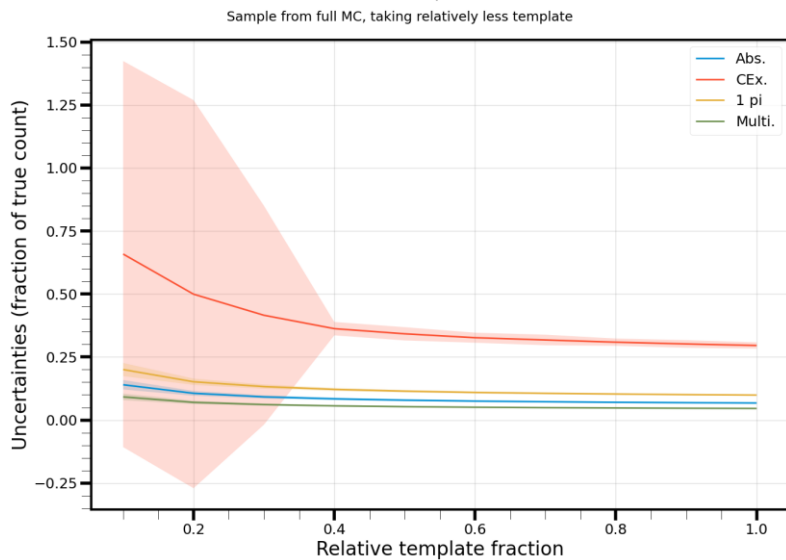
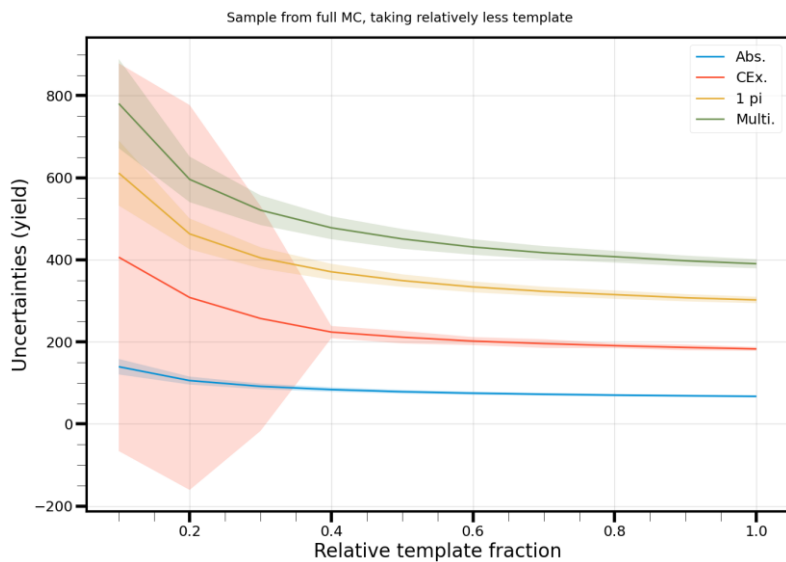


Template statistics

Sample from full MC, taking relatively less template



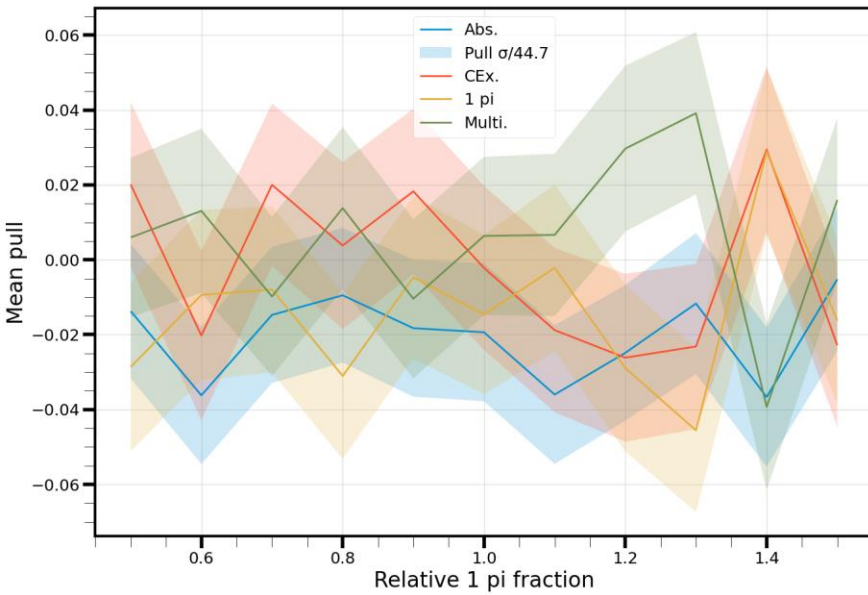
Temp. statistics



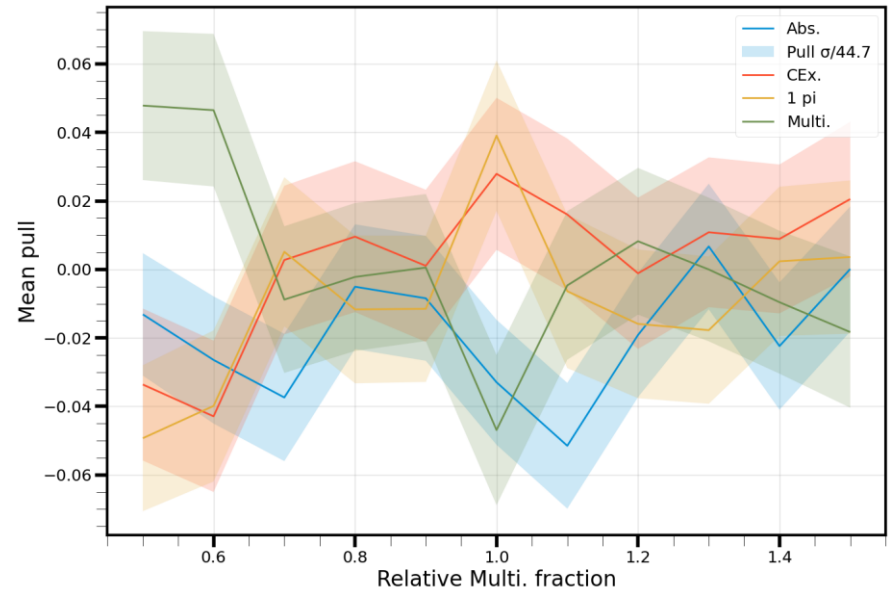
Weighting data

A bad method should show a negative gradient (over-estimate when data has a deficit)

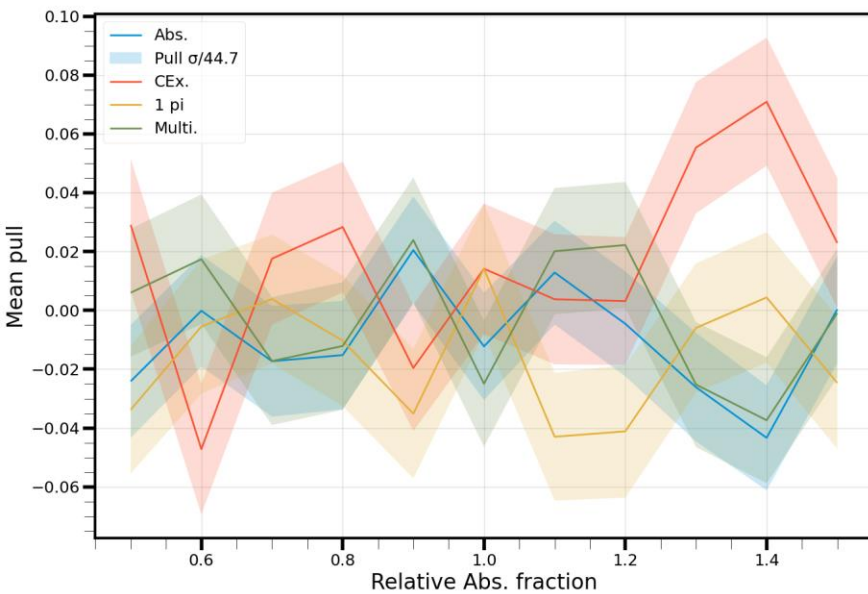
Sample from full MC, changing data 1 pi relative to baseline 25%



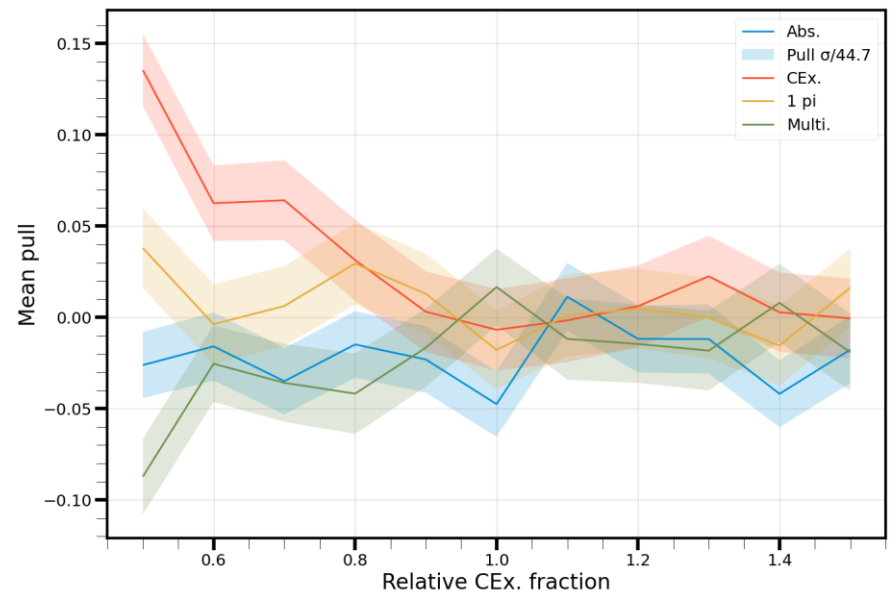
Sample from full MC, changing data Multi. relative to baseline 25%



Sample from full MC, changing data Abs. relative to baseline 25%



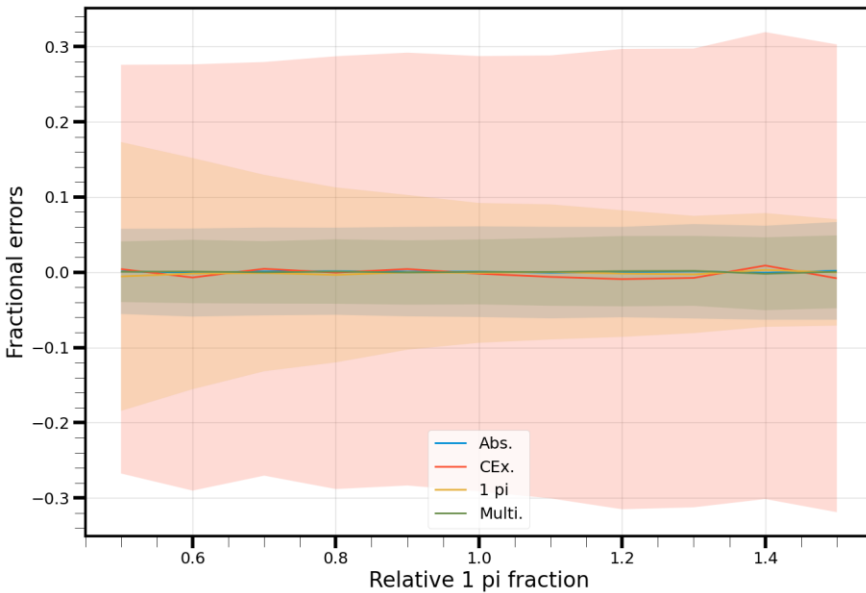
Sample from full MC, changing data CEX. relative to baseline 25%



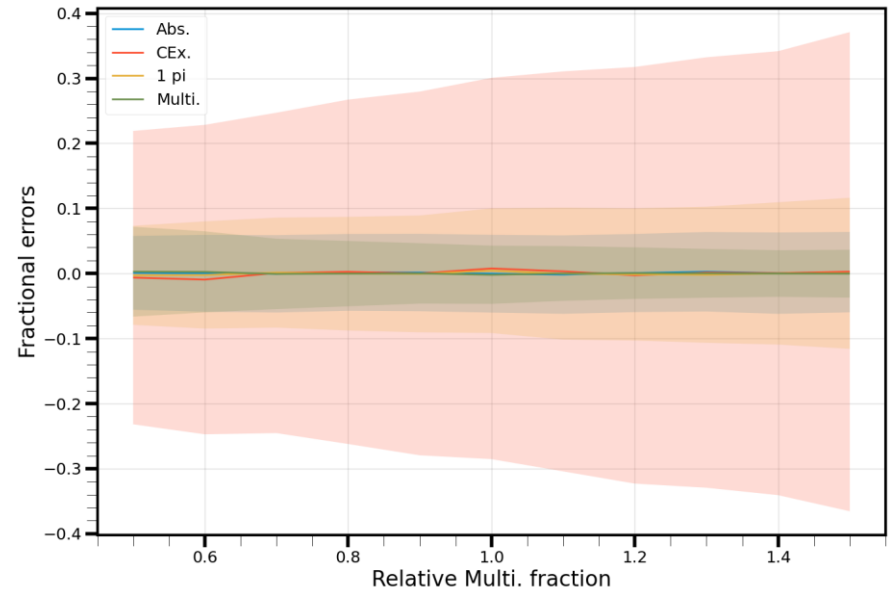
Weighting data

A bad method should show a negative gradient (over-estimate when data has a deficit)

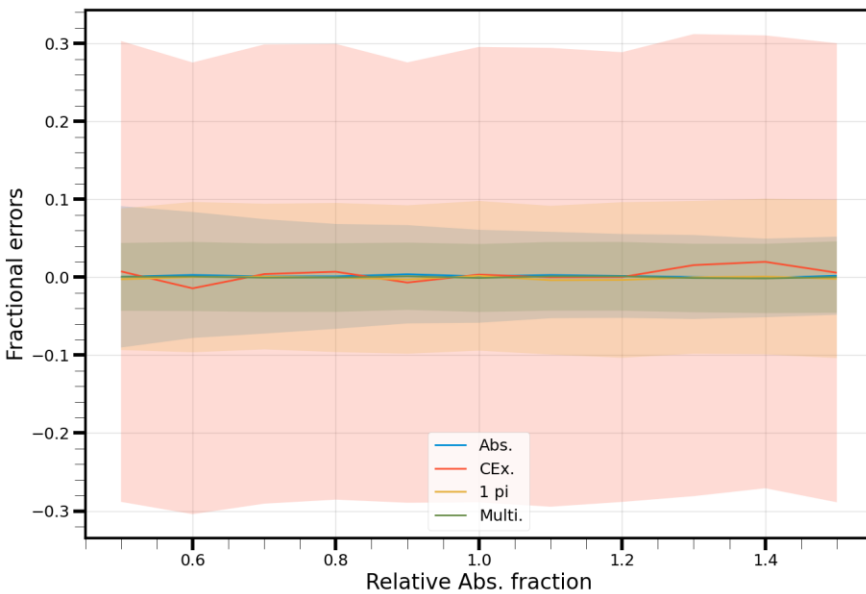
Sample from full MC, changing data 1 pi relative to baseline 25%



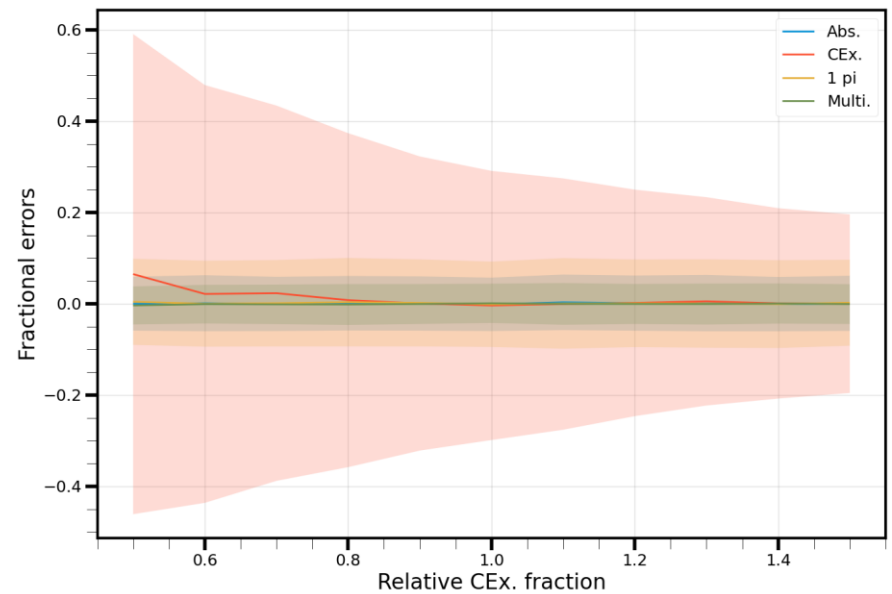
Sample from full MC, changing data Multi. relative to baseline 25%



Sample from full MC, changing data Abs. relative to baseline 25%



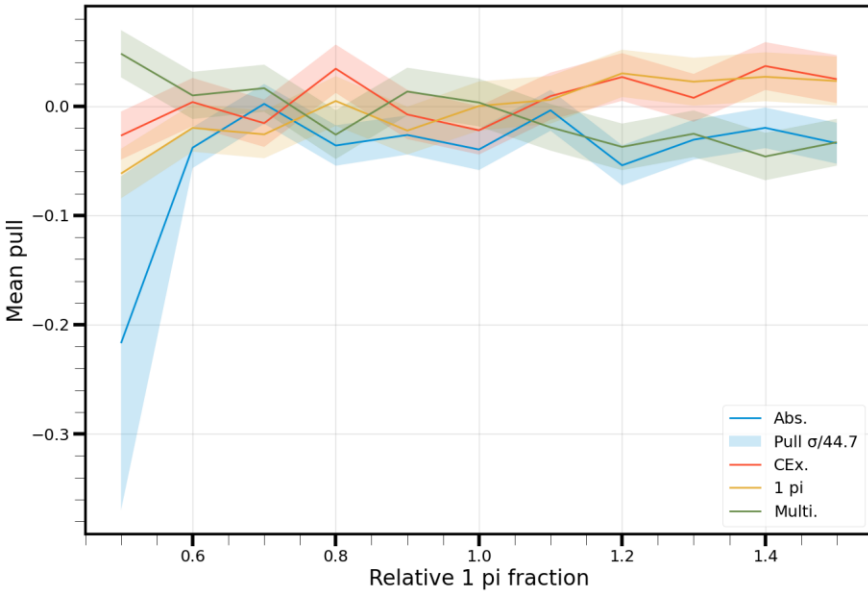
Sample from full MC, changing data CEx. relative to baseline 25%



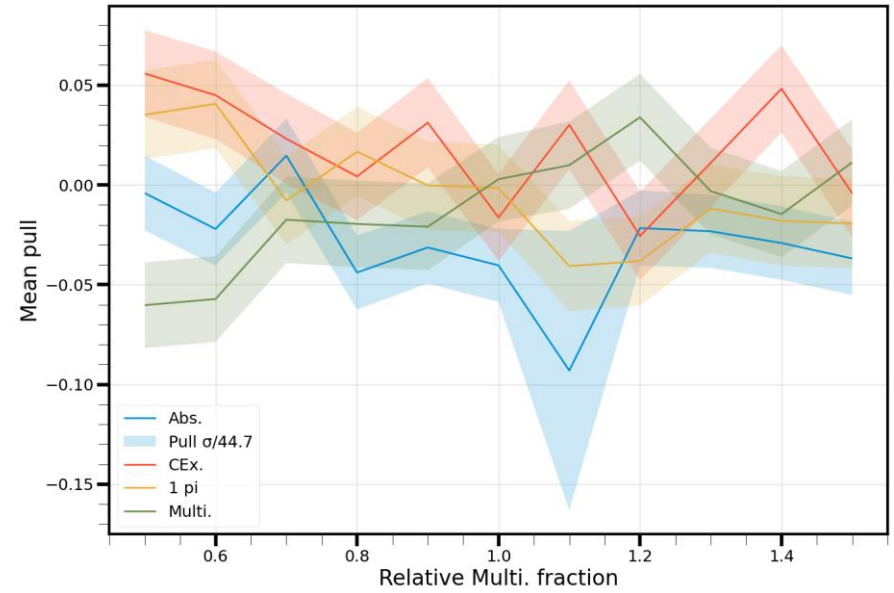
Weighting template

A bad method should show a positive gradient (under-estimate when template has a deficit)

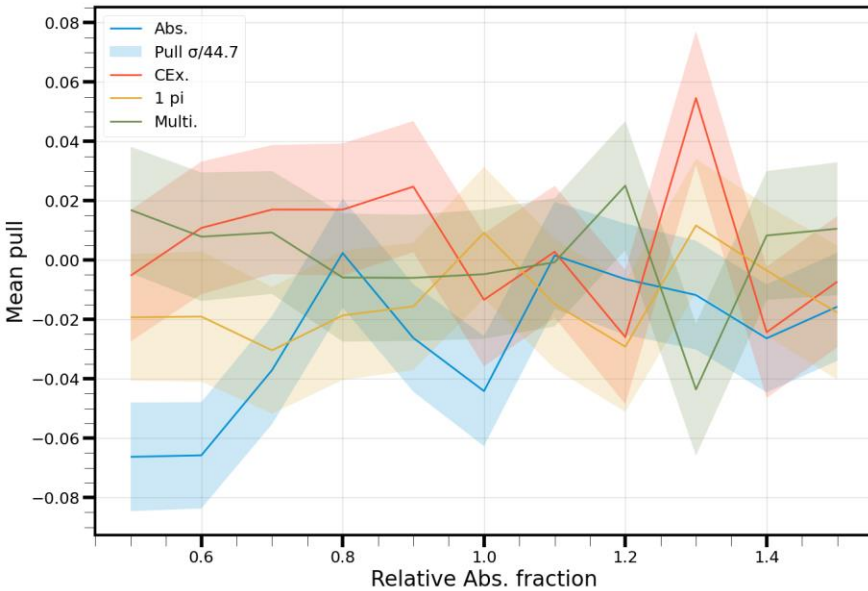
Sample from full MC, changing template 1 pi relative to baseline 30%, all data 25%



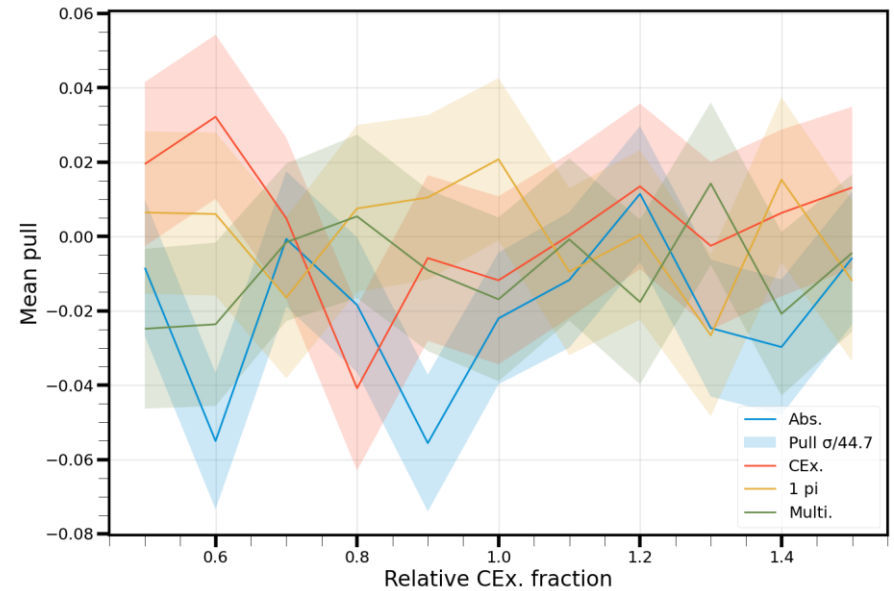
Sample from full MC, changing template Multi. relative to baseline 30%, all data 25%



Sample from full MC, changing template Abs. relative to baseline 30%, all data 25%



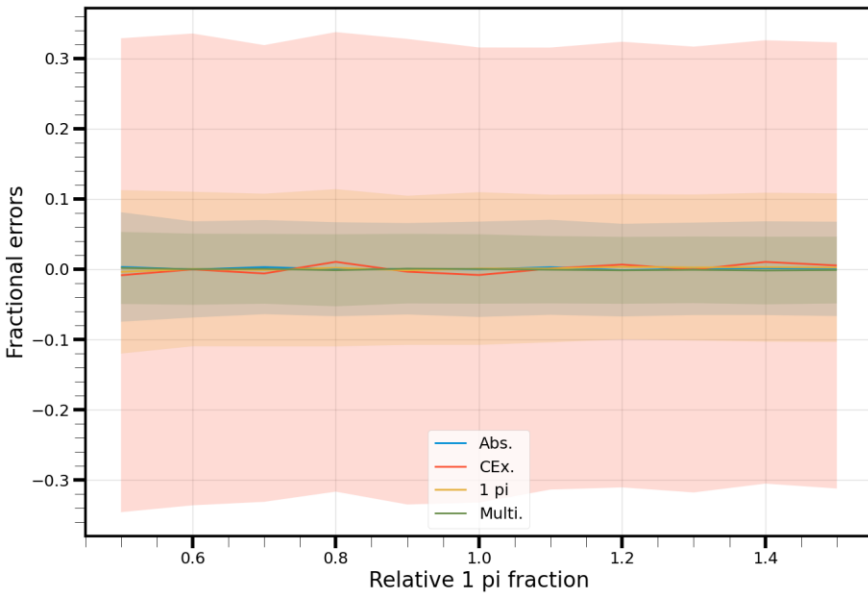
Sample from full MC, changing template CEX. relative to baseline 30%, all data 25%



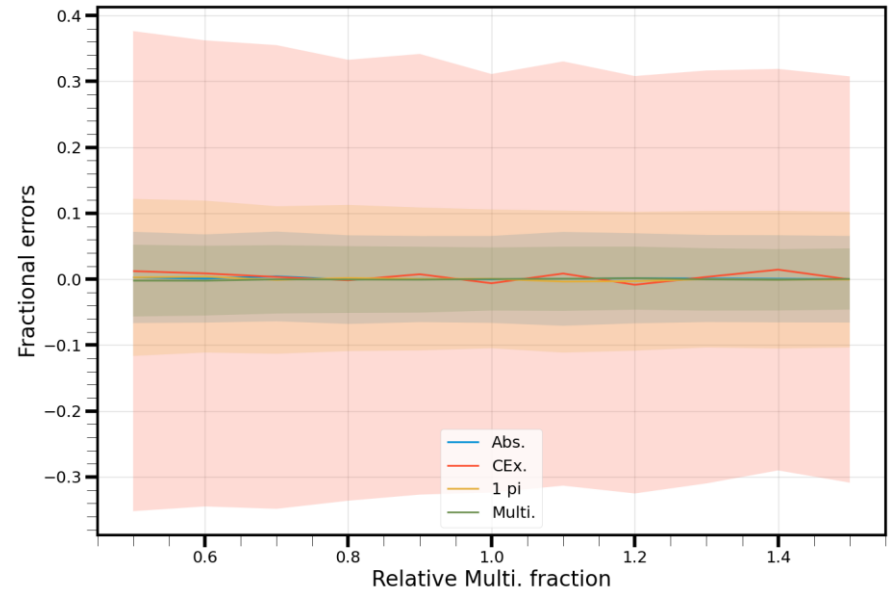
Weighting template

A bad method should show a positive gradient (under-estimate when template has a deficit)

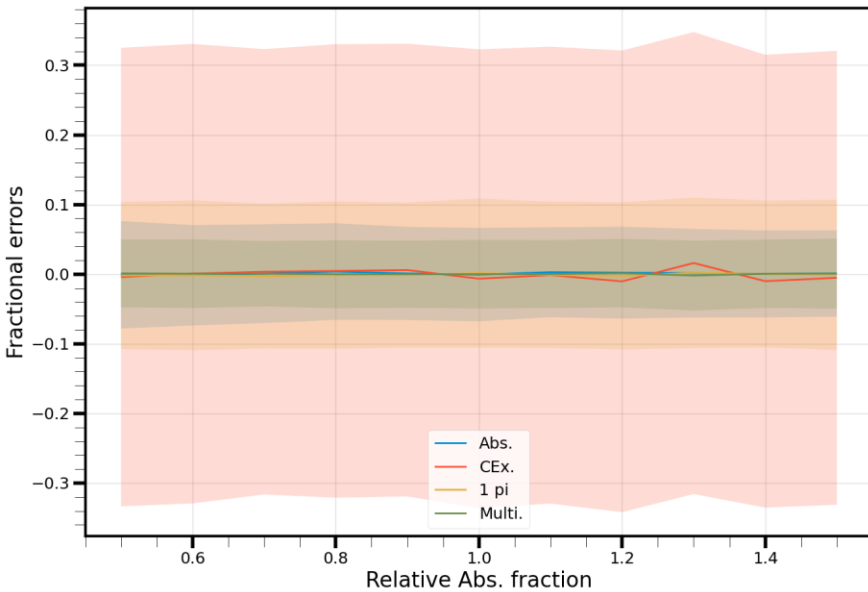
Sample from full MC, changing template 1 pi relative to baseline 30%, all data 25%



Sample from full MC, changing template Multi. relative to baseline 30%, all data 25%



Sample from full MC, changing template Abs. relative to baseline 30%, all data 25%



Sample from full MC, changing template CEx. relative to baseline 30%, all data 25%

