
ESTIMATING AND CHECKING TRUNCATION ERRORS IN EFFECTIVE FIELD THEORY

Daniel Phillips
Ohio University

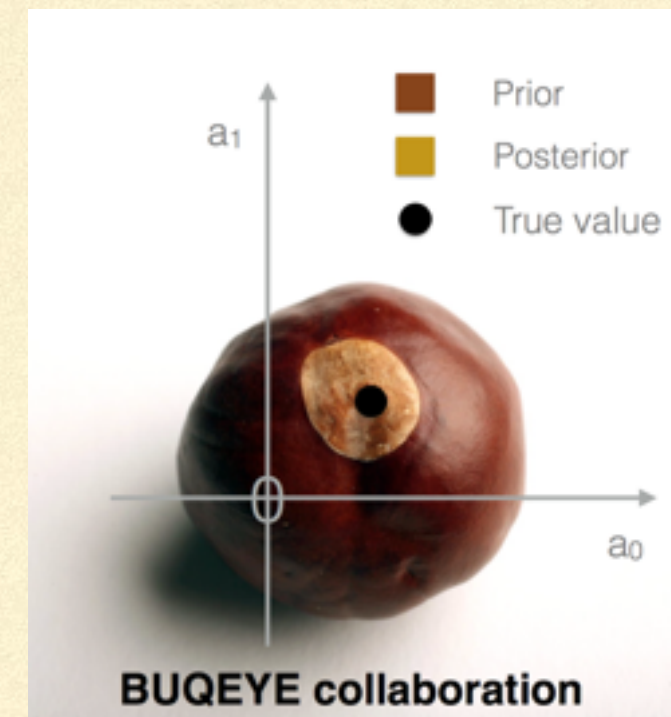
Natalie Klco
Ohio University & University of Washington

for the BUQEYE collaboration
(Bayesian Uncertainty Quantification: Errors for Your EFT)

R. J. Furnstahl, S. Wesolowski (Ohio State University)
NK (Ohio University & University of Washington)
DP, A. Thapaliya (Ohio University)



OHIO
UNIVERSITY



RESEARCH SUPPORTED BY THE US DOE AND NSF

EFFECTIVE FIELD THEORY

- Simpler theory that reproduces results of full theory at long distances
 - Short-distance details irrelevant for long-distance (low-momentum) physics, e.g. multipole expansion
 - Expansion in ratio of physical scales: p/Λ_b
 - Symmetries of underlying theory limit possibilities: all possible terms up to a given order present in EFT
 - Short distances: unknown coefficients at a given order in the expansion need to be determined. Symmetry relates their impact on different processes
 - Examples: standard model, chiral perturbation theory, Halo EFT
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Control over unknown short-distance dynamics

\Rightarrow error grows as first omitted term in expansion

A GENERIC EFT

$$g(x) = \sum_{i=0}^k \mathcal{A}_i(x) x^i$$

$$x = \frac{p}{\Lambda_b}$$

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- Suppose we are interested in a quantity as a function of a momentum, p , that is small compared to some high scale, Λ_b .

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- $f_i(x, \mu)$ is a calculable function, that encodes IR physics at order i
 - c_i is a low-energy constant (LEC): encodes UV physics at order i . Must be fit to data
 - Complications: multiple light scales, multiple functions at a given order, skipped orders,
-

TOY MODEL

$$y(x) = \sum_{i=0}^k c_i x^i + \delta(x) + \epsilon; \quad \delta(x) = \sum_{i=k+1}^{k_{\max}} c_i x^i$$

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- One light scale, non-analytic pieces absent

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 - Fit range: manage trade-off between more data (decreased statistical error) and importance of N^{k+1} LO (increased truncation error)
 - Overfitting (too many terms given data) and underfitting (too few terms to describe it)
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 - Help others who must deal with the same issues
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BAYESIAN TOOLS

Thomas Bayes (1701?-1761)



<http://www.bayesian-inference.com>

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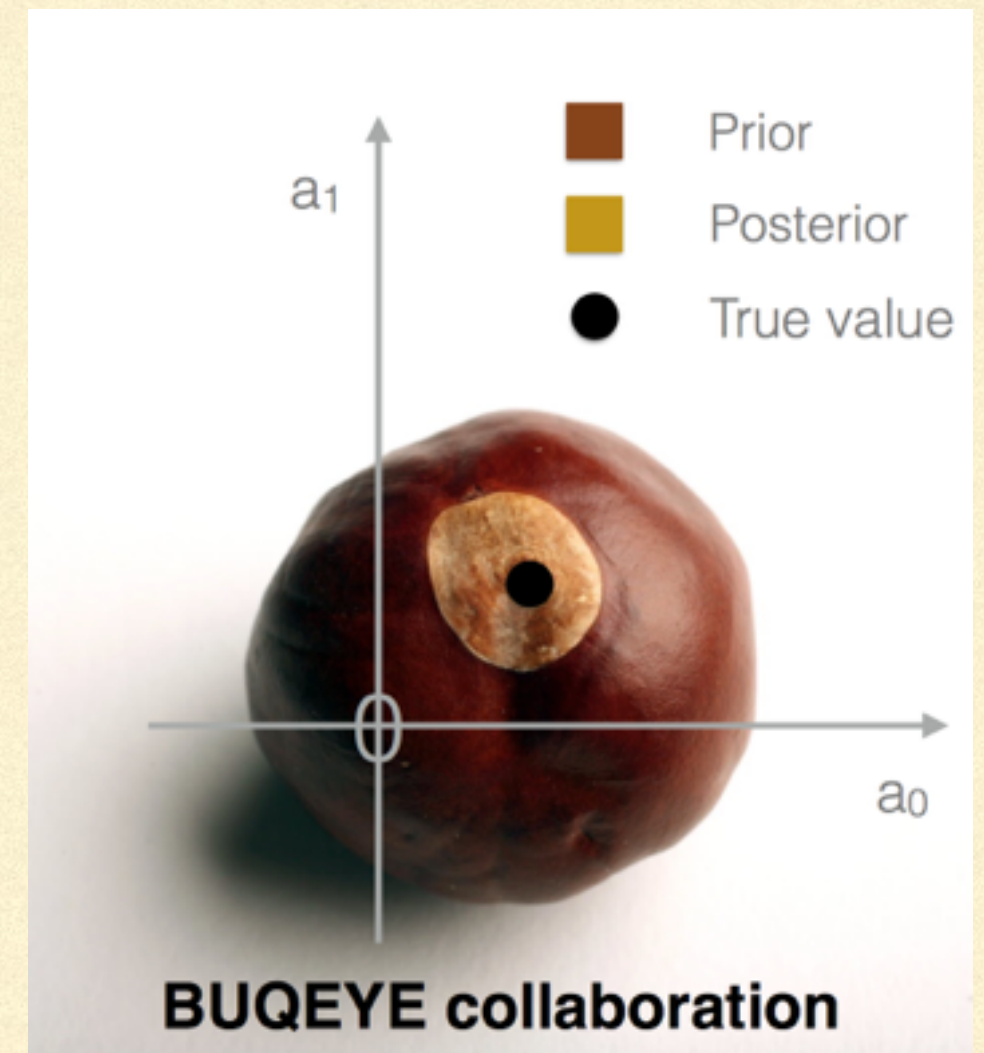


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Allows us to integrate out “nuisance” (e.g. higher-order) parameters

OUTLINE

- Introduction: EFT and Bayes
- Truncation errors in χ^{EFT}
- Checking the residuals: error plots
- Evidence ratio
- Summary



R. J. Furnstahl, D. R. Phillips and S. Wesolowski, *J. Phys. G* **42**, 034028 (2015)

R. J. Furnstahl, N. Klco, D. R. Phillips and S. Wesolowski, *Phys. Rev. C* **92**, 024005 (2015)

S. Wesolowski, N. Klco, R. J. Furnstahl, D. R. Phillips and A. Thapaliya, *J. Phys. G* **43**, 074001 (2016)

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 - In fact $\{c_n\} = \{1, -0.46, 0.75\}$. What then is expectation for c_3 ?
- One possibility: $c_3 = \max\{c_0, c_1, c_2\}$

Epelbaum, Krebs, Meissner (2014)

cf. McGovern, Griesshammer, Phillips (2013); many others.

PROBABILITY FOR EFT COEFFICIENTS

Furnstahl, Klco, DP, Wesolowski, PRC, 2015

after Cacciari and Houdeau, JHEP, 2011

- General EFT series for observable to order k : $X = X_0 \sum_{i=0}^k c_i x^i$
- Compute conditional probability distribution: $\text{pr}(c_{k+1} | c_0, \dots, c_k, l)$
- Information about χ_{EFT} , e.g. naturalness
- “Prior A”: $\text{pr}(c_n | \bar{c}) = \frac{1}{2\bar{c}} \theta(\bar{c} - |c_n|)$; $\text{pr}(\bar{c}) = -\frac{1}{2 \ln(\epsilon) \bar{c}} \theta\left(\frac{1}{\epsilon} - \bar{c}\right) \theta(\bar{c} - \epsilon)$
- Uniformly distributed coefficients up to maximum, maximum distributed uniformly in its logarithm. $\epsilon \rightarrow 0+$ at end
- Prior expectations will guide result, but they are not be all and end all
- Maximum of coefficients informed by known coefficients

BAYES → RESULT

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- Bayes theorem:
$$\begin{aligned}\text{pr}(\bar{c}|c_0, c_1, \dots, c_k) &= \frac{\text{pr}(c_0, c_1, \dots, c_k|\bar{c})\text{pr}(\bar{c})}{\text{pr}(c_0, c_1, \dots, c_k)} \\ &= \mathcal{N}\text{pr}(\bar{c})\prod_{n=0}^k\text{pr}(c_n|\bar{c})\end{aligned}$$

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- This is generic, but the integrals are simple in the case of “Prior A”

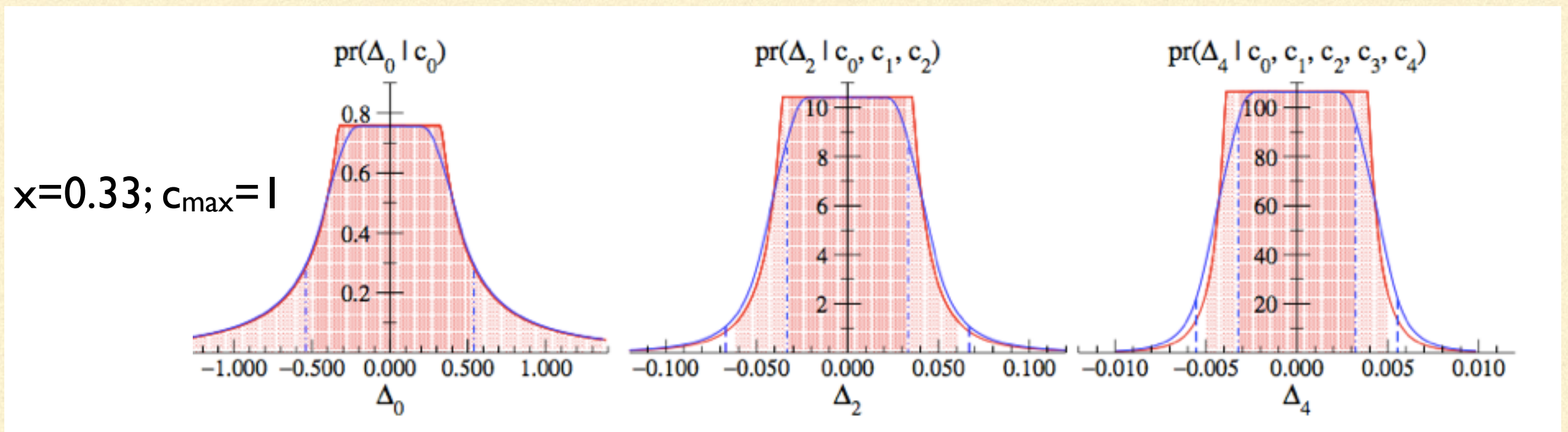
$$\text{pr}(\bar{c} | c_0, c_1, \dots, c_k) \propto \begin{cases} 0 & \text{if } \bar{c} < \max\{c_0, \dots, c_k\} \\ 1/\bar{c}^{k+2} & \text{if } \bar{c} > \max\{c_0, \dots, c_k\} \end{cases}$$

$$\text{pr}(c_{k+1} | c_0, c_1, \dots, c_k) \propto \begin{cases} 1 & \text{if } c_{k+1} < c_{\max} \\ \left(\frac{c_{\max}}{c_{k+1}}\right)^{k+2} & \text{if } c_{k+1} > c_{\max} \end{cases}$$

THE CANONICAL PROCEDURE

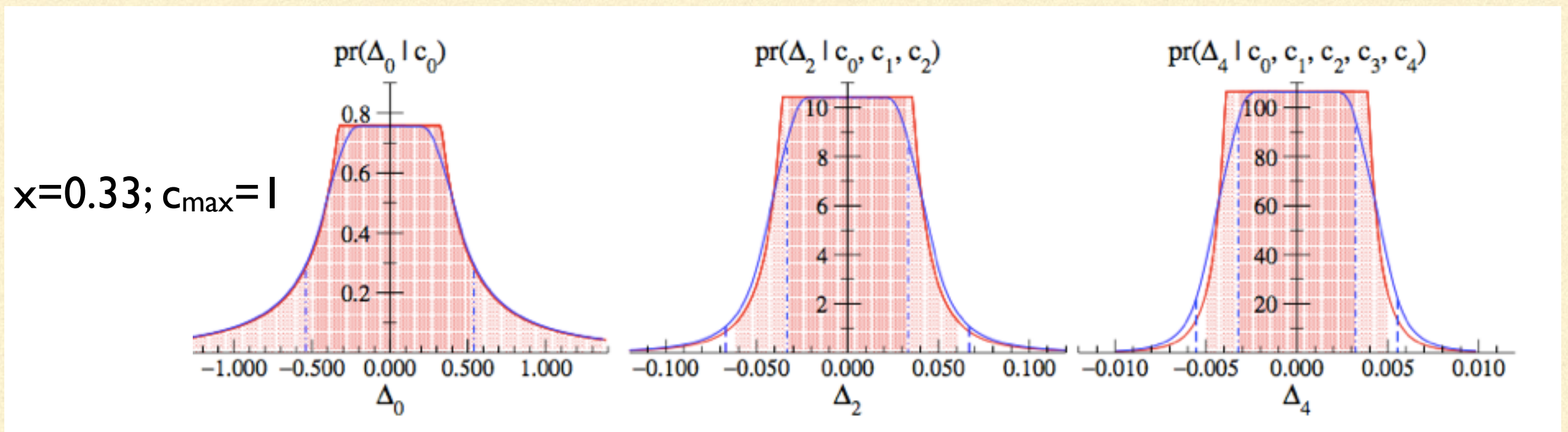
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- 68%, 95% DOB intervals from integration of probability distribution



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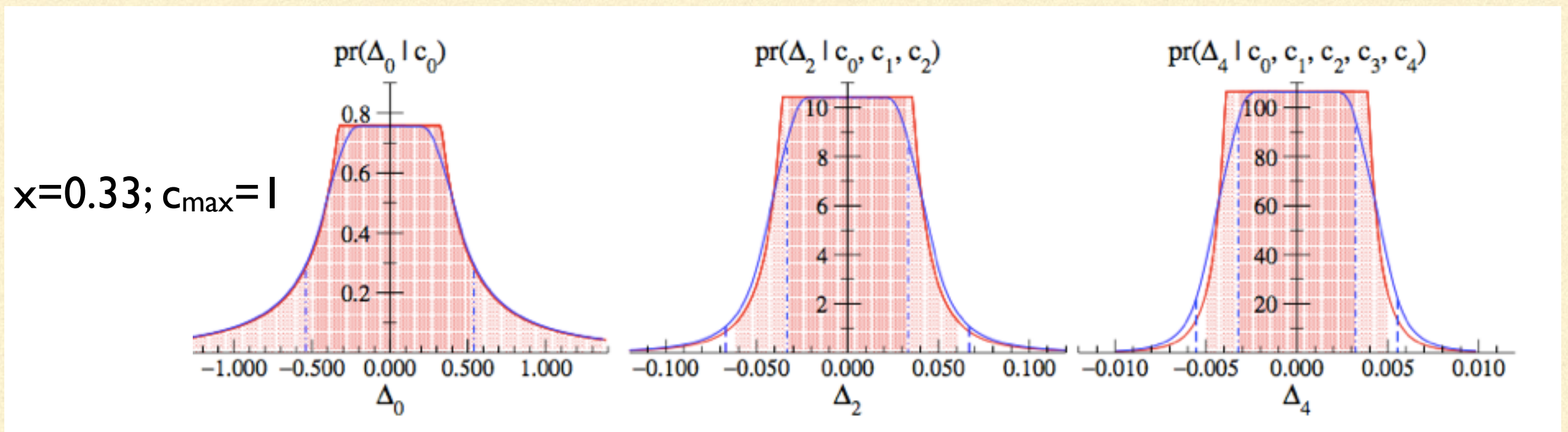
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- Not Gaussian!
- $[-c_{\max} X_0 x^{k+1}, c_{\max} X_0 x^{k+1}]$ is a $\frac{k+1}{k+2} * 100\%$ DoB interval

I DON'T LIKE THAT PRIOR!

- Modify Set A to restrict \bar{c} to a finite range, e.g. $A_{[0.25,4]}$
- Set B: give \bar{c} a log-normal prior: $\text{pr}(\bar{c}) = \frac{1}{\sqrt{2\pi\bar{c}\sigma}} e^{-(\log \bar{c})^2 / 2\sigma^2}$
- Set C: $\text{pr}(c_n | \bar{c}) = \frac{1}{\sqrt{2\pi\bar{c}}} e^{-c_n^2 / 2\bar{c}^2}$; $\text{pr}(\bar{c}) \propto \frac{1}{\bar{c}} \theta(\bar{c} - \bar{c}_<) \theta(\bar{c}_> - \bar{c})$
- Same formulas as before can be invoked. Now numerical.

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- You don't like these? Pick your own and follow the rules...
 - First omitted term approximation
-

EKM'S NN SCATTERING ANALYSIS

Epelbaum, Krebs, Meissner, PRC, 2015

$$\chi\text{EFT: } \mathcal{L}(N, \pi) \rightarrow V^{(k)} \rightarrow \delta$$

$$\sigma_{np}(E_{\text{lab}}) = \sigma_{\text{LO}} \sum_{n=0}^k c_n(p_{\text{rel}}) \left(\frac{p_{\text{rel}}}{\Lambda_b} \right)^n$$

$$x = \frac{p_{\text{rel}}}{\Lambda_b}$$

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Epelbaum, Krebs, Meissner, PRC, 2015

- NN cross section at $T_{\text{lab}}=50, 96, 143, 200$ MeV
- Potential regulated by local function, parameterized by R
- EKM identify $\Lambda_b=600$ MeV for smaller R values
- Here: R=0.9 fm data

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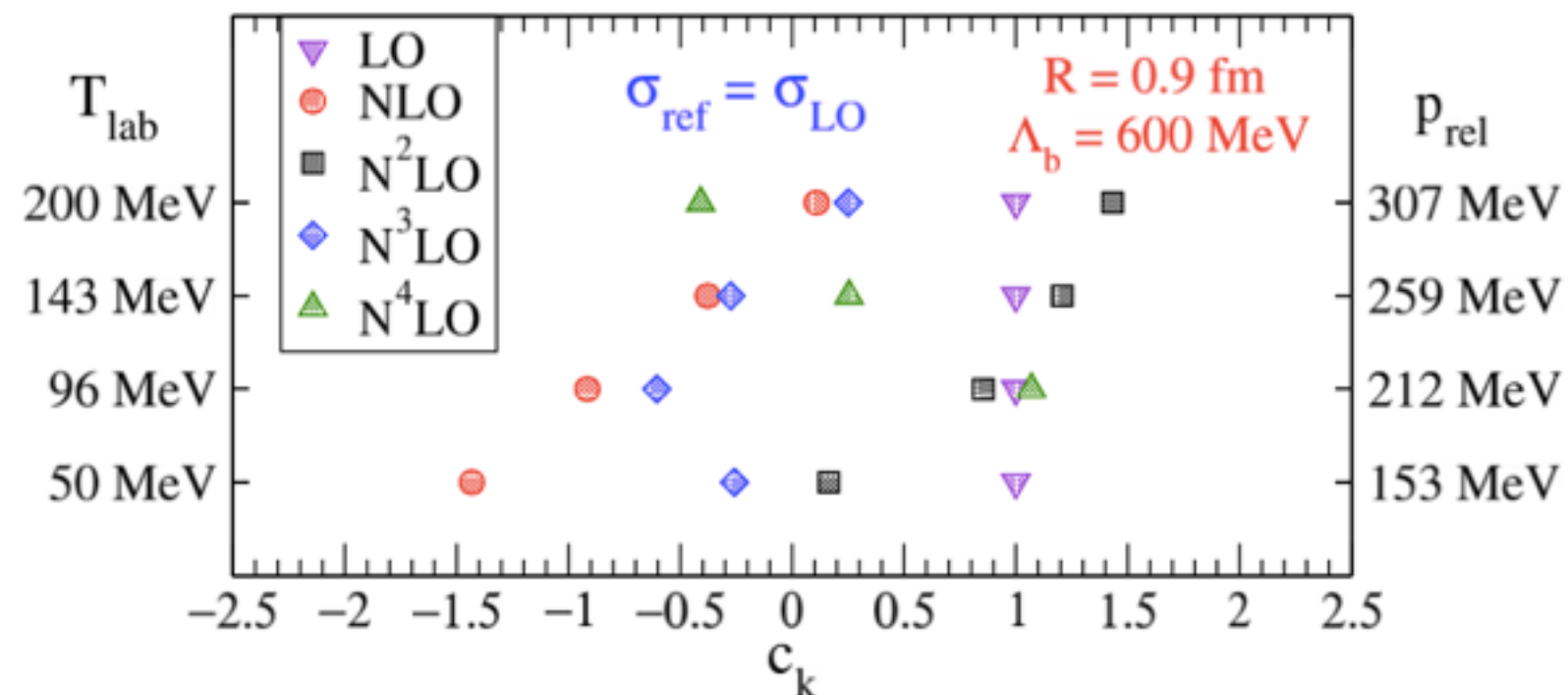
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$$\chi\text{EFT: } \mathcal{L}(N,\pi) \rightarrow V^{(k)} \rightarrow \delta$$

$$\sigma_{np}(E_{\text{lab}}) = \sigma_{\text{LO}} \sum_{n=0}^k c_n(p_{\text{rel}}) \left(\frac{p_{\text{rel}}}{\Lambda_b} \right)^n$$

$$x = \frac{p_{\text{rel}}}{\Lambda_b}$$



EKM'S NN SCATTERING ANALYSIS

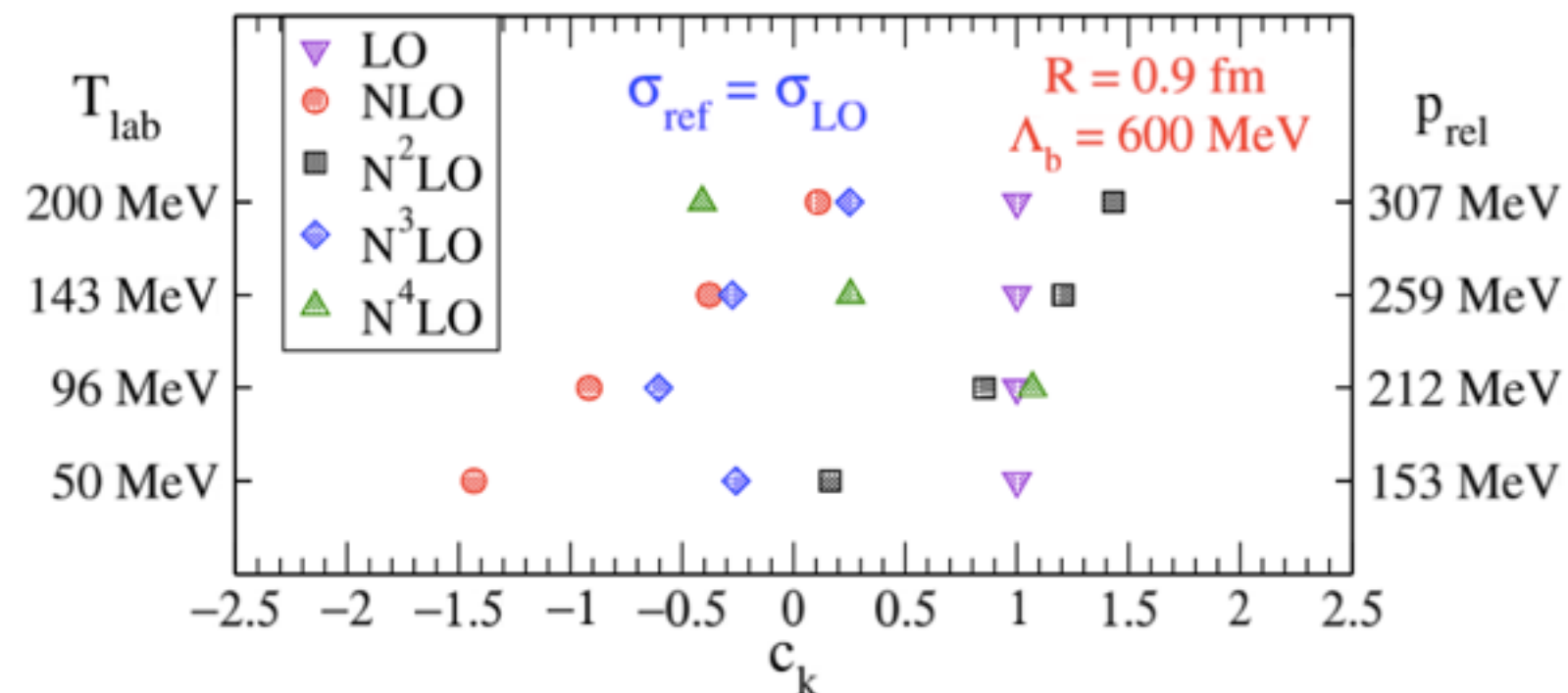
Epelbaum, Krebs, Meissner, PRC, 2015

- NN cross section at $T_{\text{lab}}=50, 96, 143, 200$ MeV
- Potential regulated by local function, parameterized by R
- EKM identify $\Lambda_b=600$ MeV for smaller R values
- Here: $R=0.9$ fm data
- Results at LO, NLO, $N^2\text{LO}$, $N^3\text{LO}$, $N^4\text{LO}$ ($k=0, 2, 3, 4, 5$)
- One outlier. Fitting procedure?

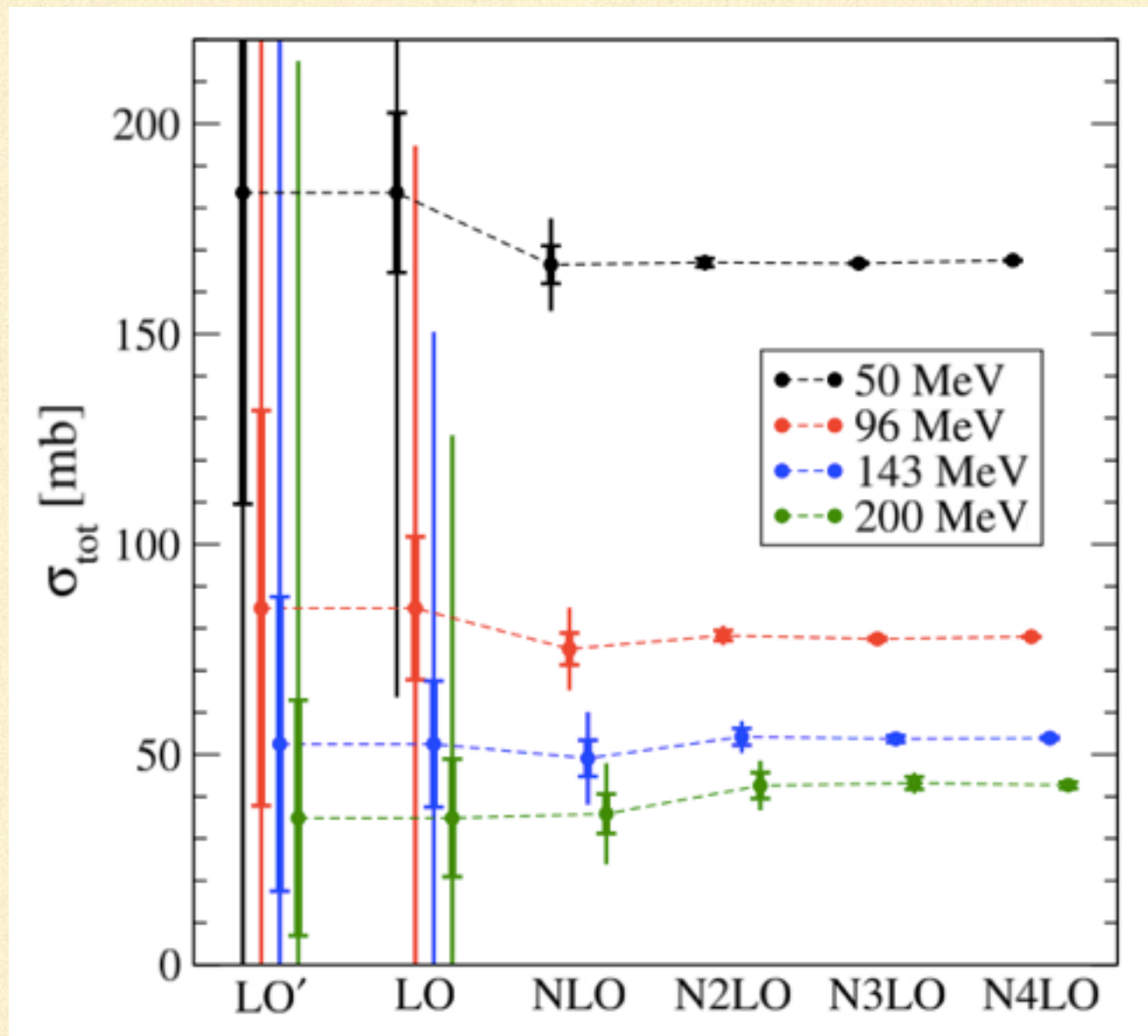
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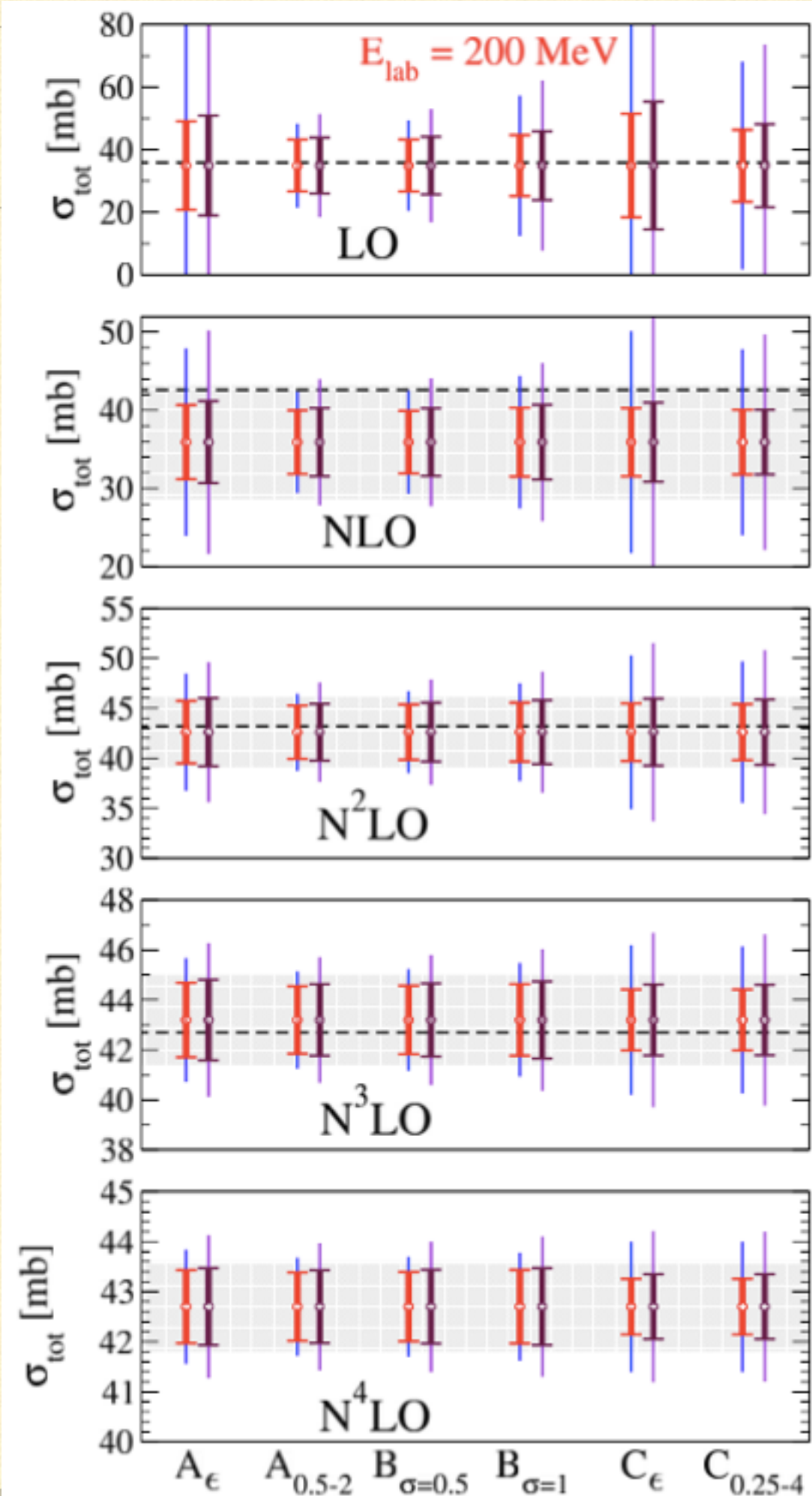
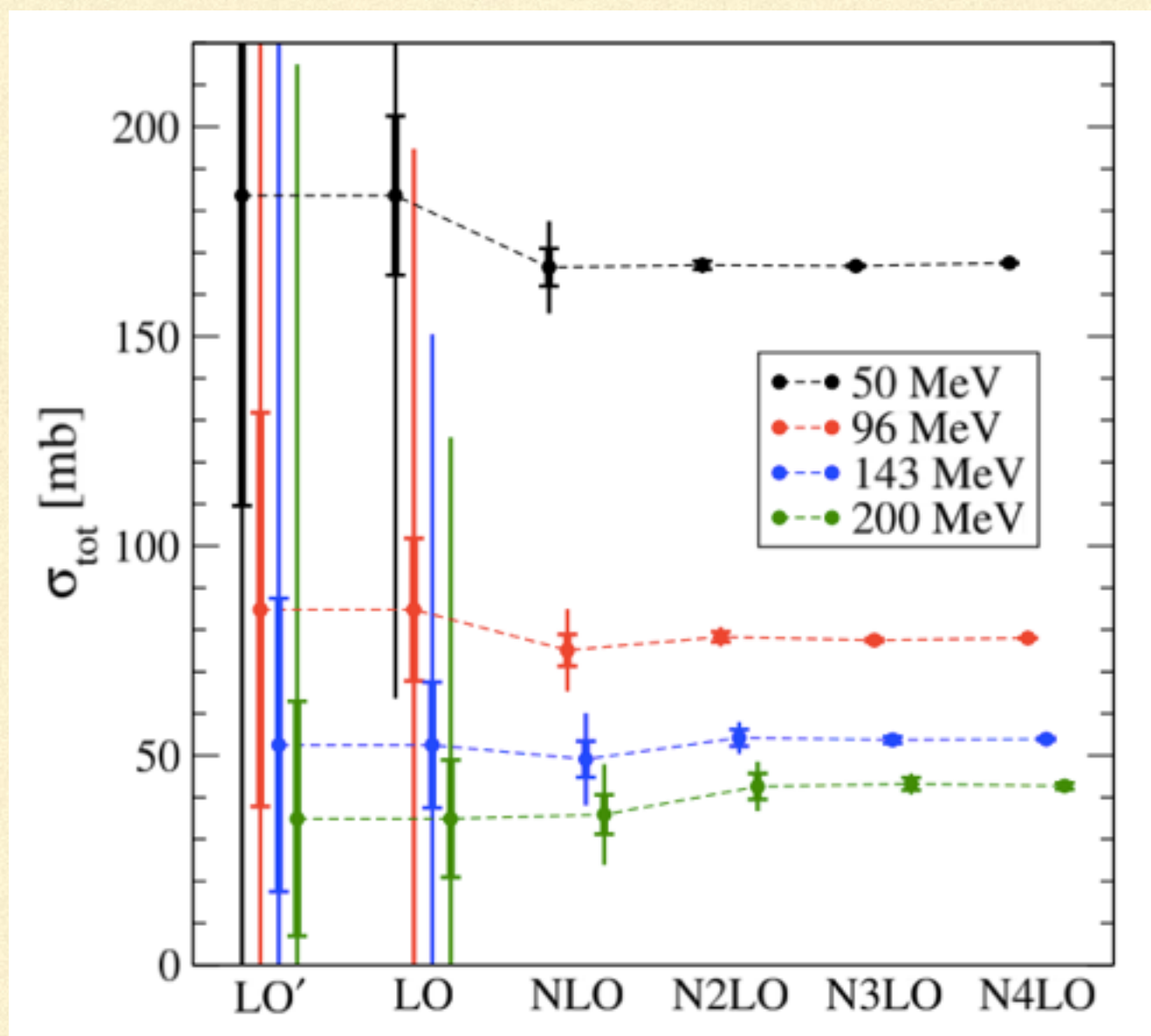
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RESULTS



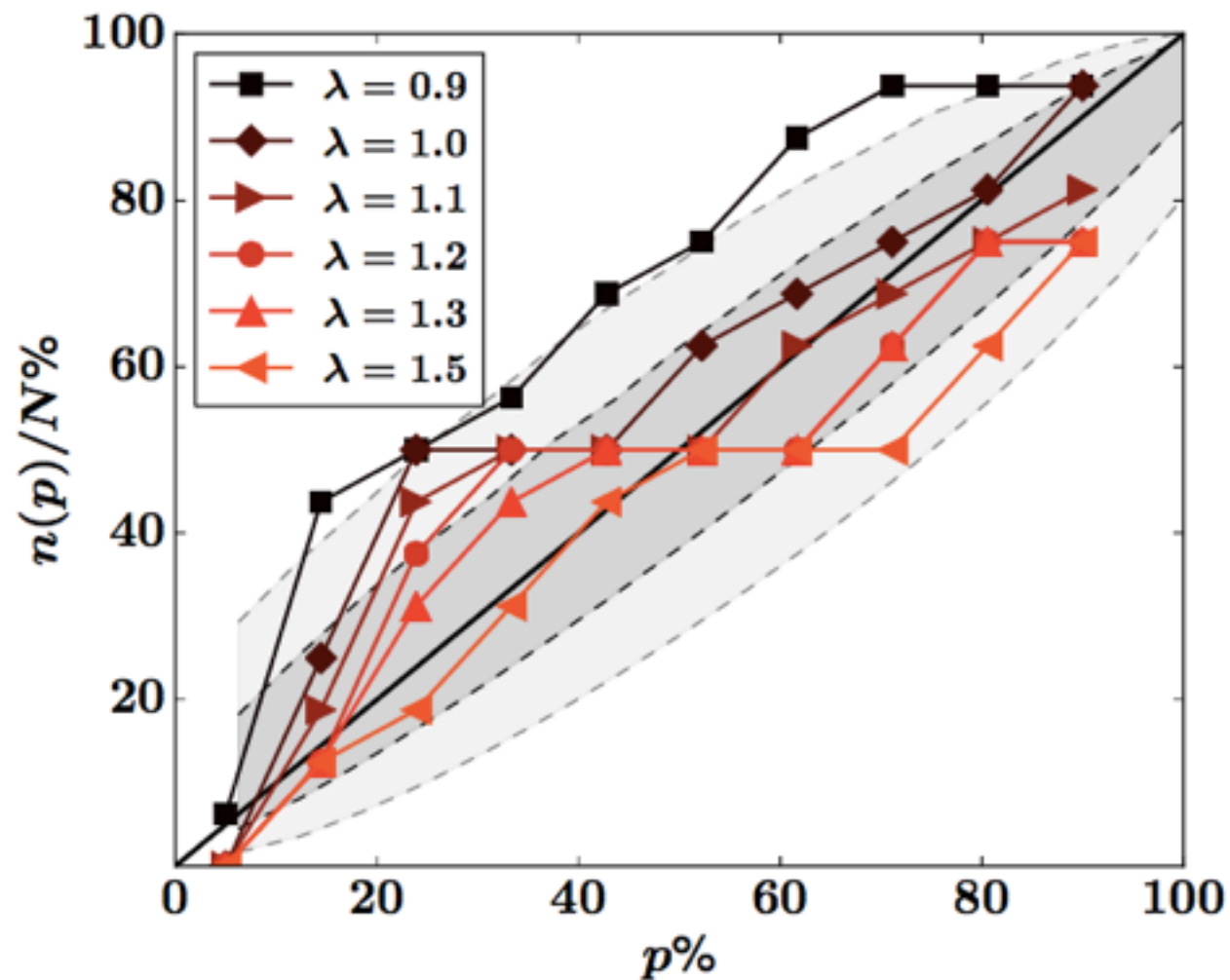
RESULTS



CONSISTENCY?

Furnstahl, Klco, DP, Wesolowski, PRC, 2015

after: Bagnaschi, Cacciari, Guffanti, Jenniches, 2015



- Now we consider predictions at each order, with their error bars, as data and test them to see if the procedure is consistent
- Fix a given DOB interval, compute actual success ratio and compare
- Look at this over EKM predictions at four different orders and four different energies
- Interpret in terms of rescaling of Λ_b by a factor λ

No evidence for significant rescaling of Λ_b

NORMAL NATURALNESS?

- Treat 19 coefficients as data and test for naturalness.
- Approach 1: coefficients should be normally distributed around a mean μ with a variance σ^2 .
- Approach 2: see if χ^2 has size expected, assuming $\mu=0$ and a particular σ .

Forte, Isgro, Vita, PLB, 2014

$$\chi^2 = \sum_{i=1}^{N_O} \sum_{n=0}^k \left(\frac{|c_n^{(i)}| \lambda^n - \mu}{\sigma} \right)^2$$

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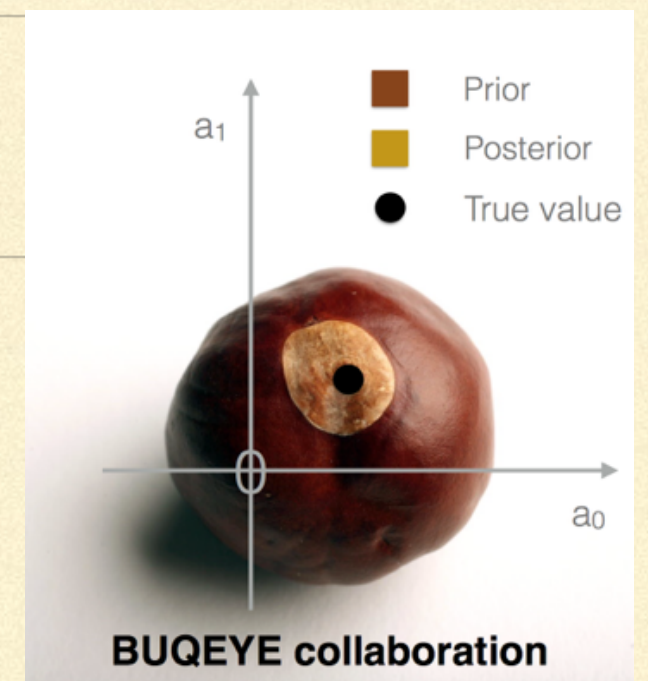
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- Approach 1 ($\sigma^2=1$): $\lambda = 1.01^{+0.18}_{-0.19}$
- Approach 2 ($\sigma^2=1$): $\lambda=1.09$ gives $\chi^2=19$. $\lambda=1.01 \rightarrow 1.15$ consistent.

No evidence for significant rescaling of Λ_b

CAVEATS

- Naturalness of c_i 's in x -expansion for NN cross section assumed. Justified for perturbative process, but justification not so clear for NN
 - m_π not included in x (anticipate this is only a small effect)
 - We looked at results only for one R ; at larger R s the regulator effects dominate and:
 - The distribution $\{c_n\}$ is qualitatively different;
 - Λ_b is identified as lower by EKM. Cutoff artefact, not true EFT breakdown scale
 - We took EKM's LECs as given. LECs themselves have statistical errors, but we did not incorporate those in our analysis
 - LECs also have truncation errors, which should be included in their quoted errors
-

SUMMARY: PART I



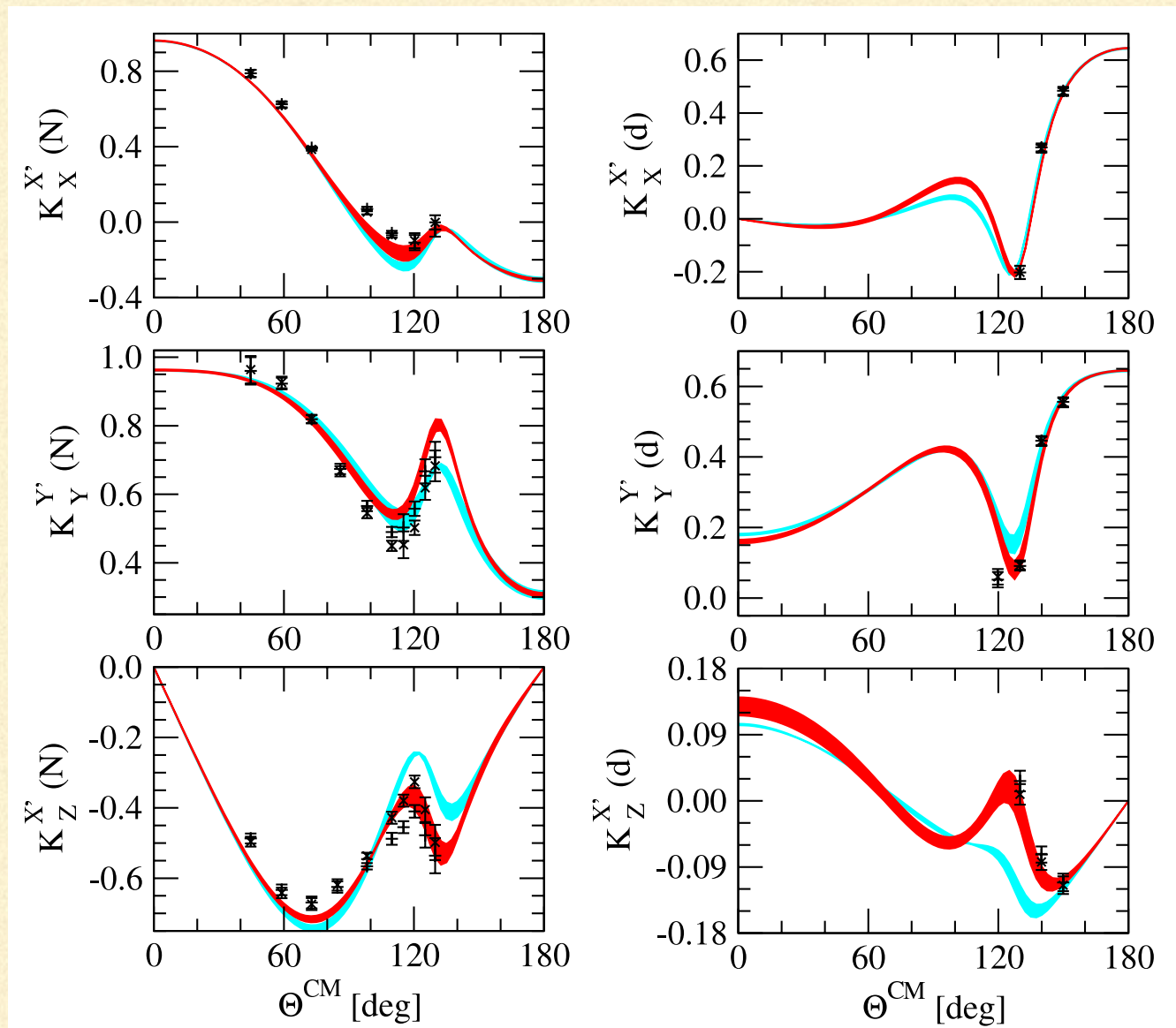
- EFTs are well set up for uncertainty quantification, since the parametric form of higher-order terms is, in principle, known.
- A Bayesian analysis of truncation error makes explicit assumptions about the pattern of EFT LECs, allowing rigorous consequences to be derived.
- “Set A_ϵ ” prior justifies the standard EFT error estimation procedure; truncation errors quite stable under choice of other (reasonable) priors.
- Analysis of residuals allows us to test if the EFT is working “as advertised”

UNCERTAINTY QUANTIFICATION IN χ EFT

*Chiral EFT predictions for p - d spin observables
with theory errors from cutoff variation*

Epelbaum, Hammer, Meissner, RMP, 2009

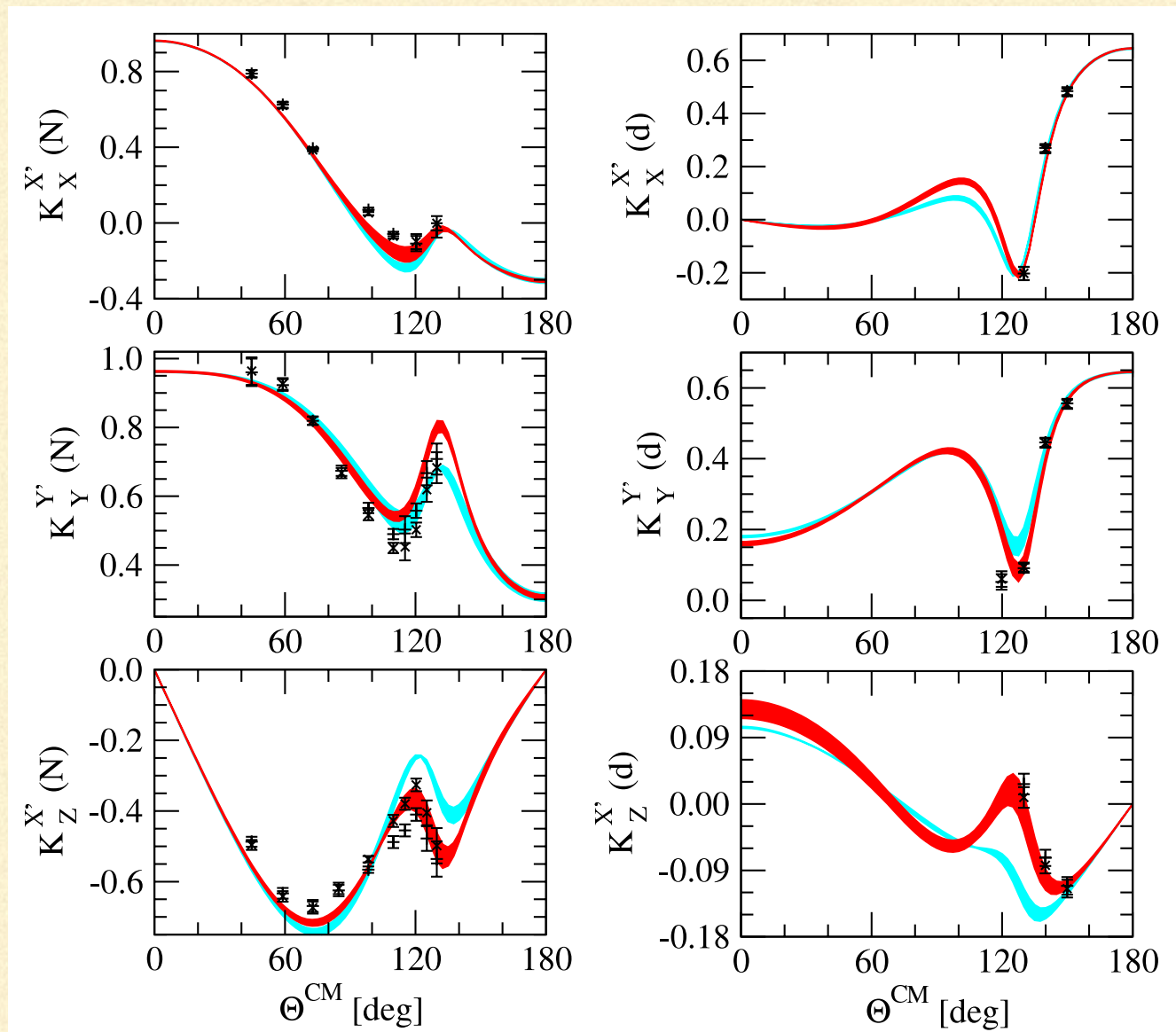
This talk: truncation errors
Standard technique in few-nucleon
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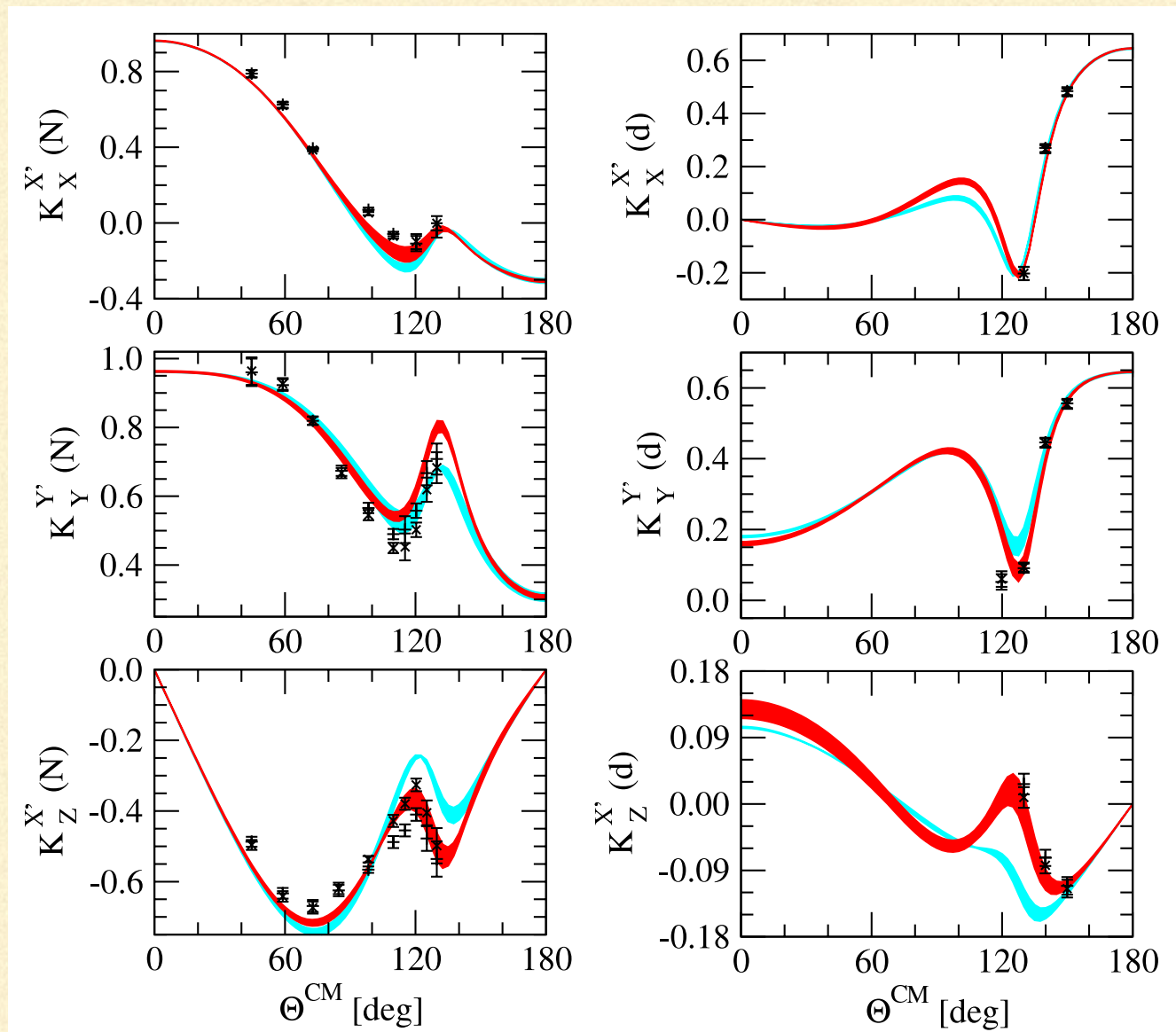
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- Size of error depends on how smart you are choosing regulator function;
- Depends on range of cutoffs chosen;
- Error does not necessarily decrease order-by-order;
- Only captures errors from even orders in the EFT;
- Statistical interpretation is not clear.

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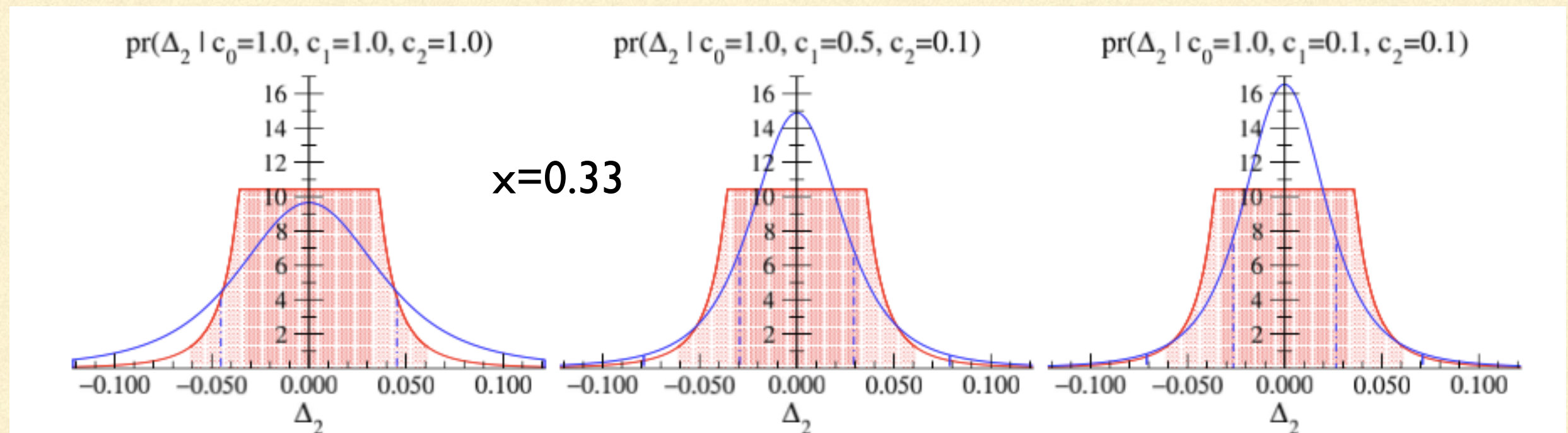
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Cutoff variation is a regulator artefact which may or may not reflect full size of theory uncertainty

REPRESENTATIVE EXAMPLES



- Set C differs from Set A in that entire distribution of $\{c_n\}$ matters
- Set A_ϵ and Set C_ϵ DOB intervals closest for most uniform $\{c_n\}$
- Choice of prior matters less and less at higher orders. At and beyond $k=2$ different choice of priors affect 68% DOB interval by at most 10-15%
- Updating refines knowledge of coefficients: Bayesian convergence
- Bigger effect on 95% DOB interval