Noise reduction strategies based on machine learning and their application to the muon $g-2$

Tom Blum, Alessandro Conigli, Lukas Geyer, Simon Kuberski, Alexander Segner, Hartmut Wittig

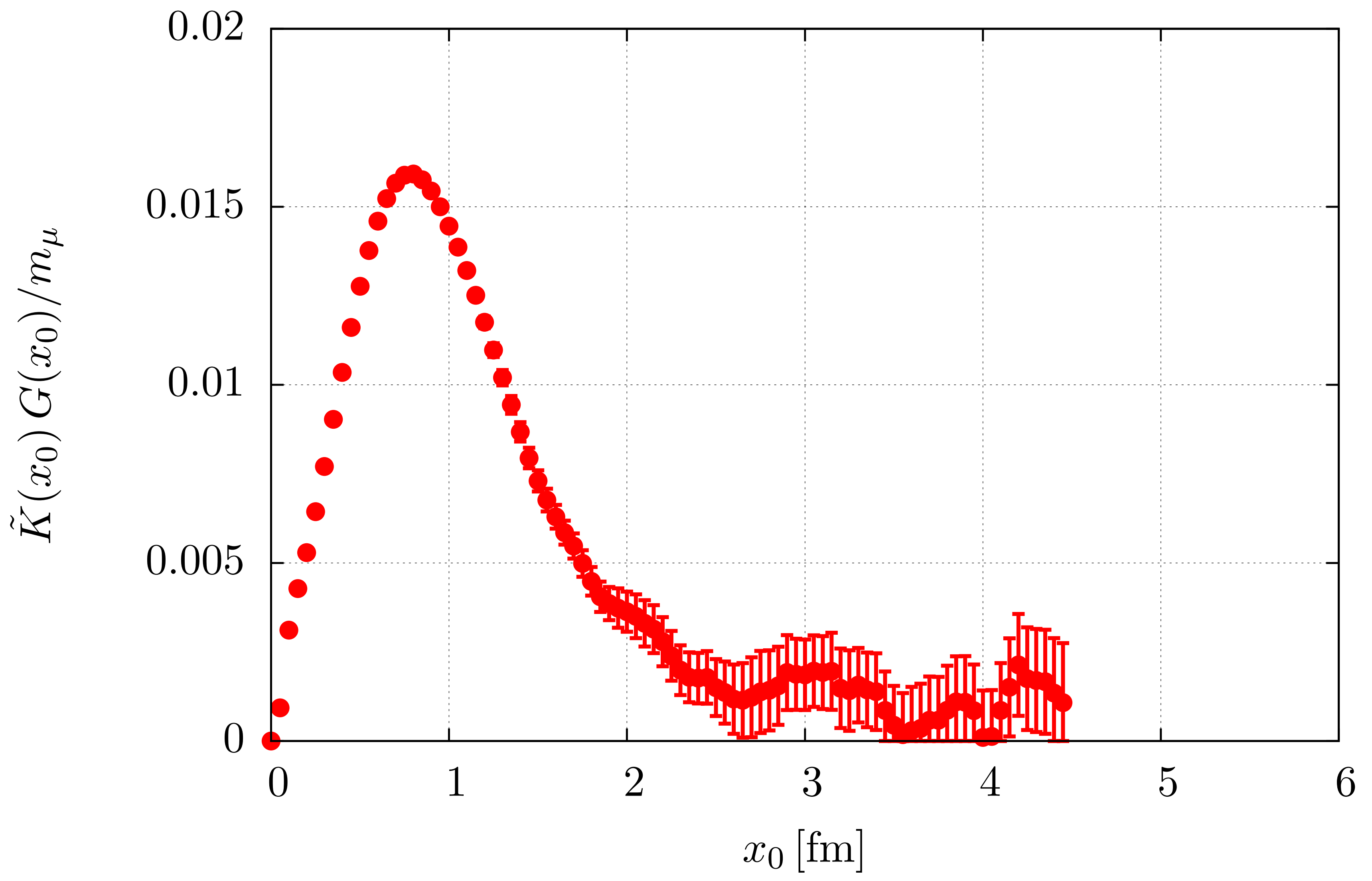
2024 German-Japanese Seminar
Johannes Gutenberg University Mainz
25–27 September 2024

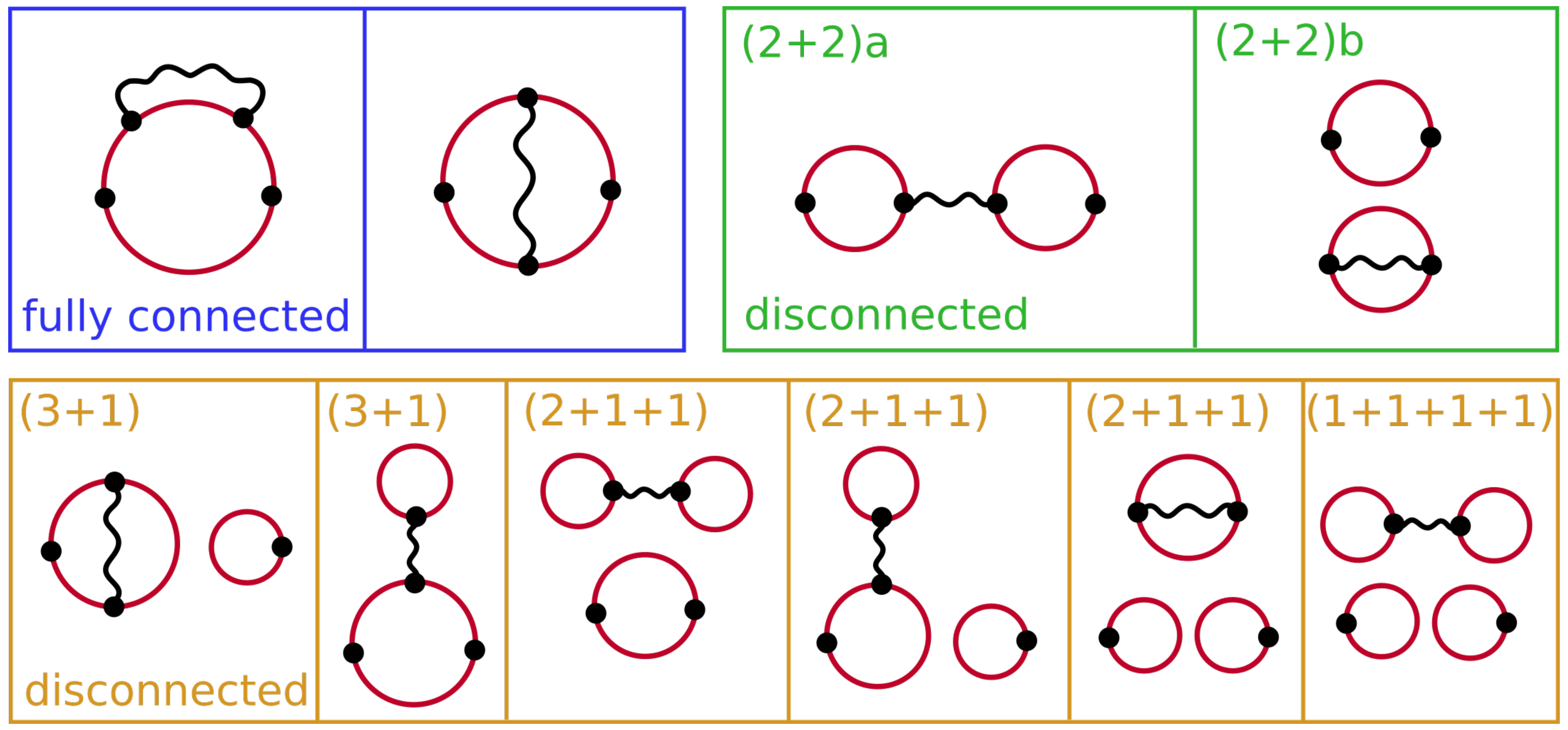
HIM
Helmholtz-Institut Mainz
PRISMA+
JOHANNES GUTENBERG UNIVERSITÄT MAINZ
JG|U

Motivation

Lattice QCD calculations of precision observables involve high numerical cost:

- Exponential rise of statistical noise at large distances
- Isospin-breaking corrections numerically small but expensive to compute





[©D. Erb, J. Parrino]

Idea: use trained neural net to

- Produce approximate estimates for correlation functions at low numerical cost
- Predict "expensive" contribution using a "cheap" observable

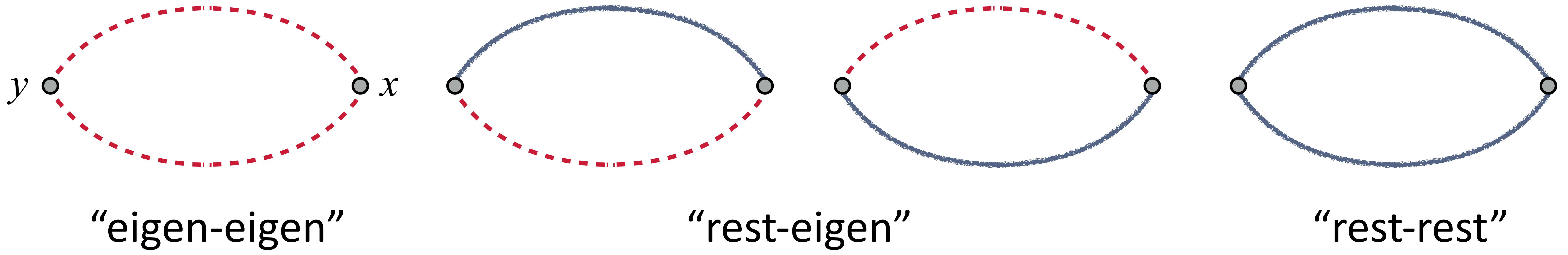
Low-mode averaging

[Giusti, Hernández, Weisz, H.W. 2004; DeGrand and Schaefer 2004]

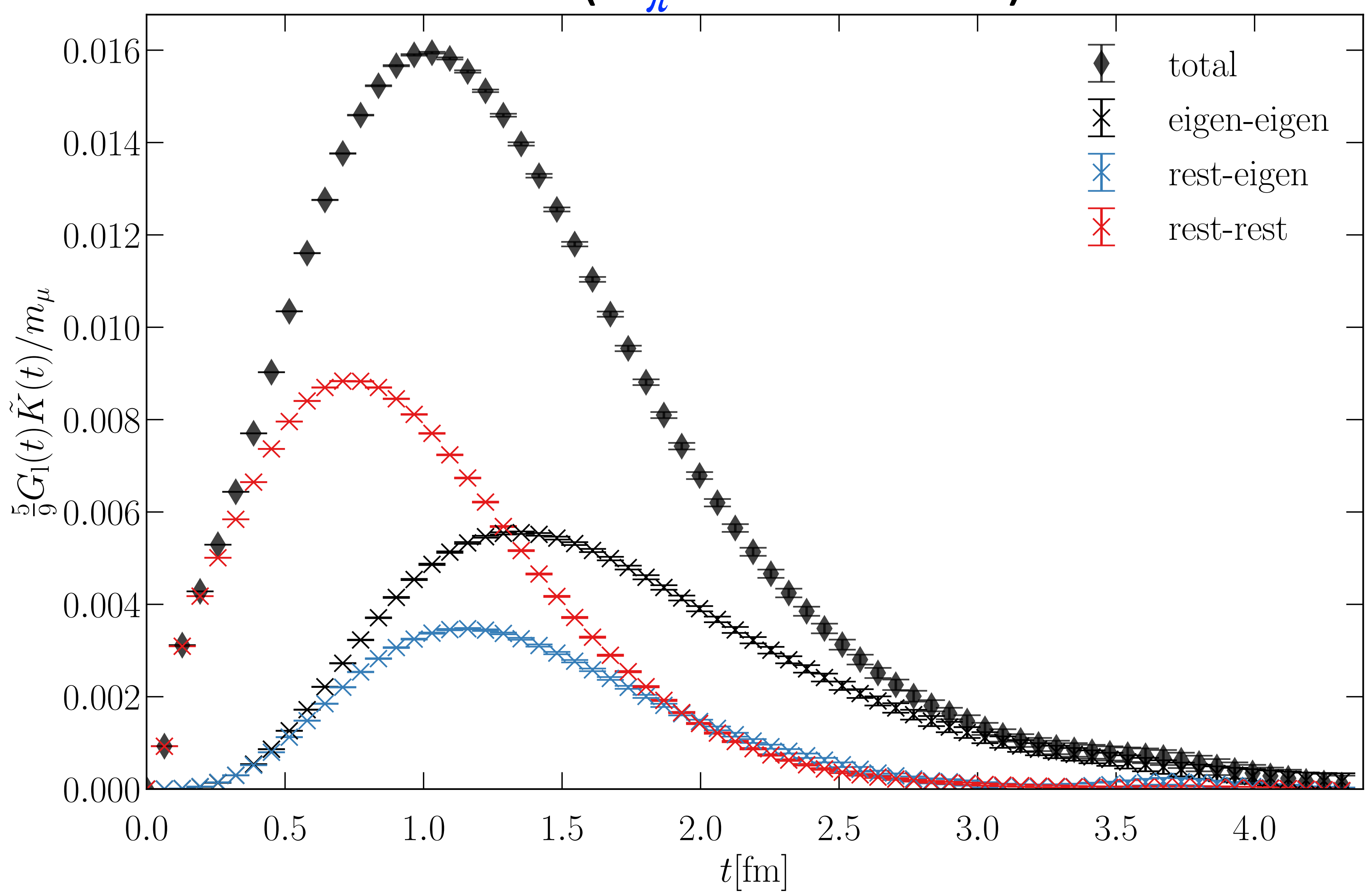
Split quark propagator into low-mode contribution and that from orthogonal complement

$$S(y,x) = S_{\rm eigen}(y,x) + S_{\rm rest}(y,x) \qquad S_{\rm eigen}(y,x) = \sum_{i=1}^{N_{\rm low}} \lambda_i^{-1}\, v_i(x) \otimes (\gamma_5 v_i(y))^\dagger\,, \qquad (\gamma_5 D_{\rm w})\, v_i(x) = \lambda_i\, v_i(x)$$

Two-point correlation function:



Ensemble D452 ($m_\pi = 155\,\mathrm{MeV}$)



- "eigen-eigen" part dominates long-distance regime
- "rest-eigen" part always sub-dominant, but numerical effort scales $\sim N_{\rm low} = \mathrm{O}(1000)$

Machine-learning strategy

All-Mode Averaging / Truncated Solver Method: *[Blum, Izubuchi, Shintani 2012]*

Compute many approximate solutions — obtain exact result after applying bias correction

Idea: Role of "sloppy solves" taken over by a machine-learning algorithm *[Yoon, Bhattacharya, Gupta 2018]*

$$\langle O\rangle = \left\langle O_{\rm appx}\right\rangle + \left\langle (O - O_{\rm appx})\right\rangle$$

exact "cheap" correction

Train model or network on the correlation between input and predicted quantities

Ideally $O_{\rm appx}$ should fluctuate closely with O

Machine-learning strategy

All-Mode Averaging / Truncated Solver Method: *[Blum, Izubuchi, Shintani 2012]*

Compute many approximate solutions — obtain exact result after applying bias correction

Idea: Role of "sloppy solves" taken over by a machine-learning algorithm *[Yoon, Bhattacharya, Gupta 2018]*

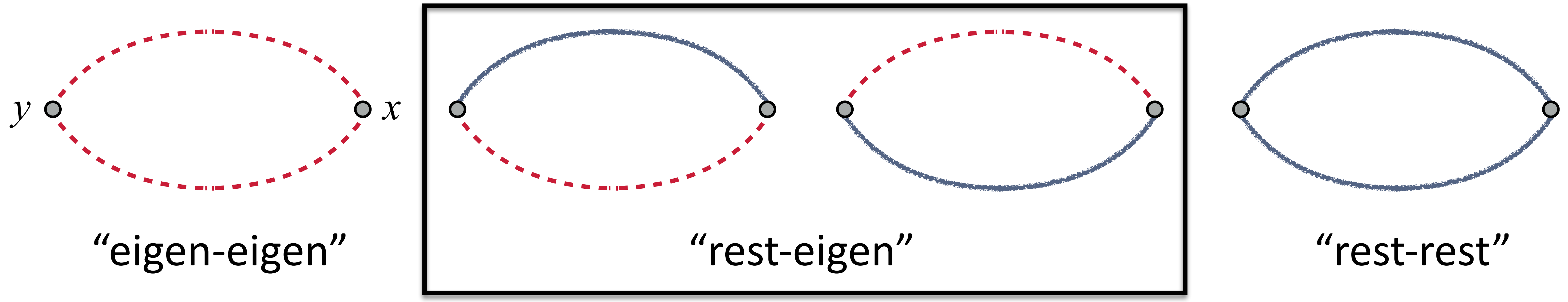
$$\langle O \rangle = \left\langle O_{\rm appx} \right\rangle + \left\langle (O - O_{\rm appx}) \right\rangle$$

exact — "cheap" — correction

Train model or network on the correlation between input and predicted quantities

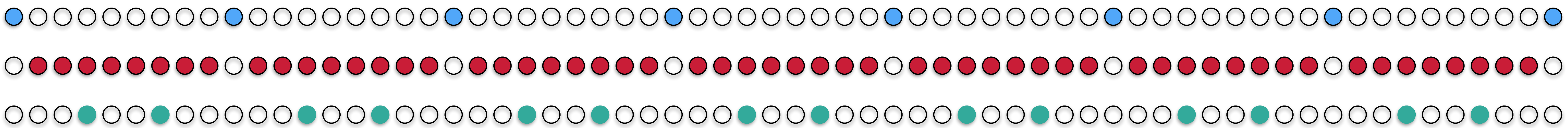
Ideally $O_{\rm appx}$ should fluctuate closely with O

Here: predict "rest-eigen" contribution given the "eigen-eigen" and "rest-rest" as input



Setup

Divide configurations within one ensemble into subsets for training, prediction and bias correction



Fully connected neural network with one hidden layer to predict all timeslices simultaneously:

- ReLU activation functions on hidden layer, linear activation function on output layers
- Dropout layers to help with overfitting

"rest-rest" and "eigen-eigen" contributions as input $\rightarrow$ Input layers of size $2 \cdot (T/a)$

"rest-eigen" contribution entering the loss function $\rightarrow$ Output layer of size (T/a)

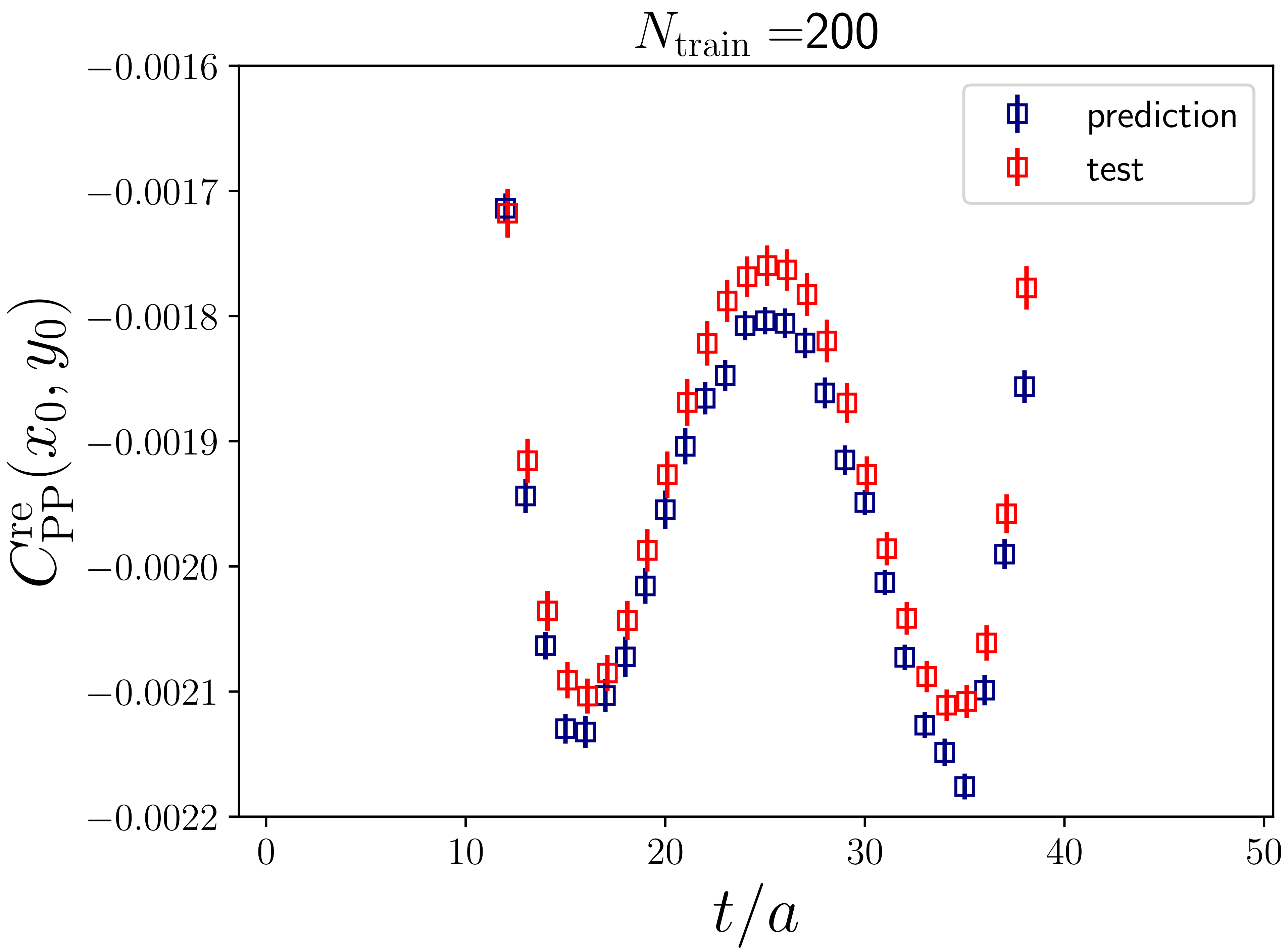
Ensembles:

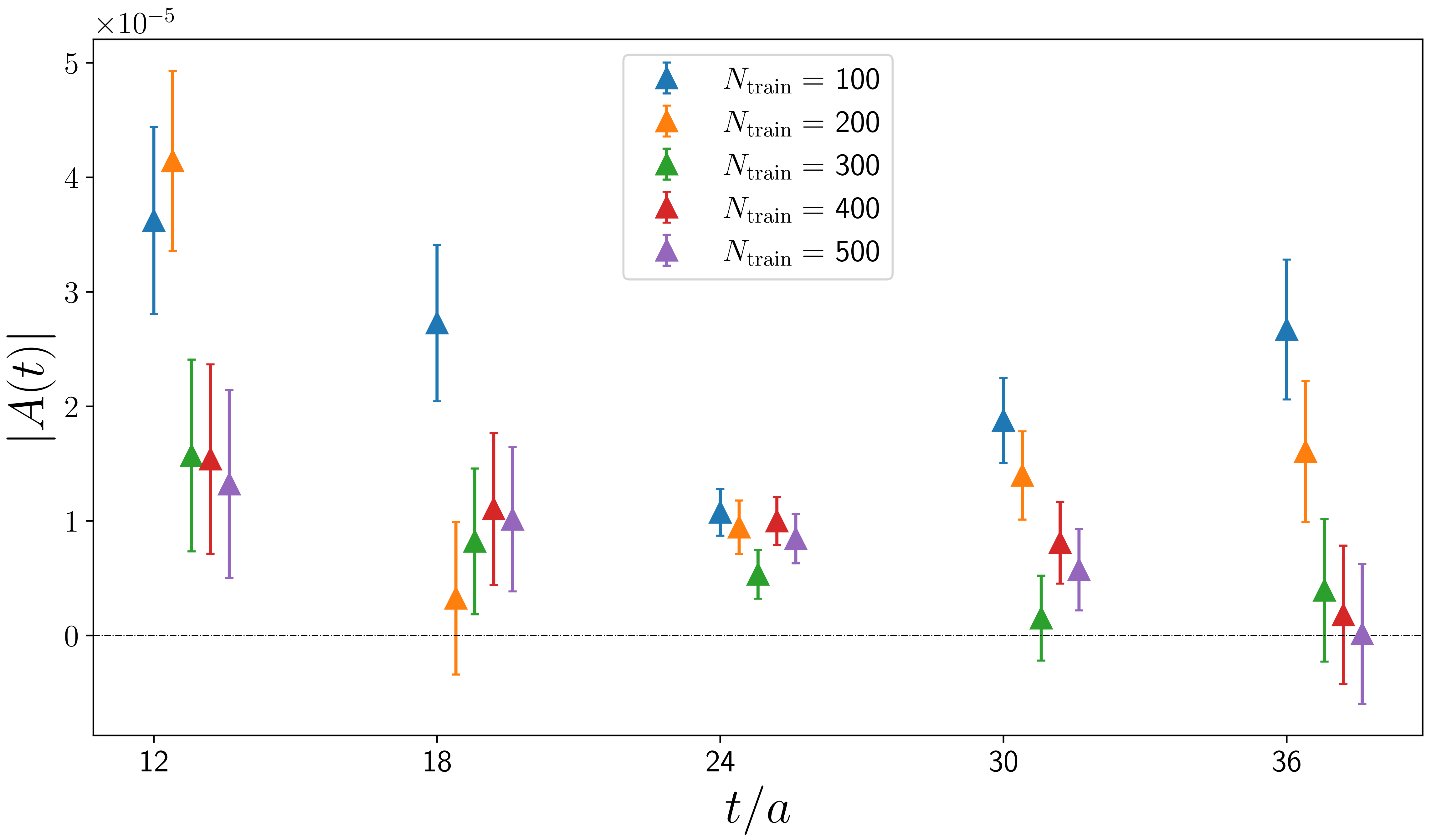
A654: $L/a = 24,\ T/a = 48,\quad m_\pi \simeq 420\,\mathrm{MeV},\quad N_{\mathrm{cfg}} = 2500$

D450: $L/a = 64,\ T/a = 128,\quad m_\pi \simeq 280\,\mathrm{MeV},\quad N_{\mathrm{cfg}} = 500$

Pseudoscalar correlator: rest-eigen contribution

Test quality of prediction for "rest-eigen" contribution — no bias correction (A654 ensemble)

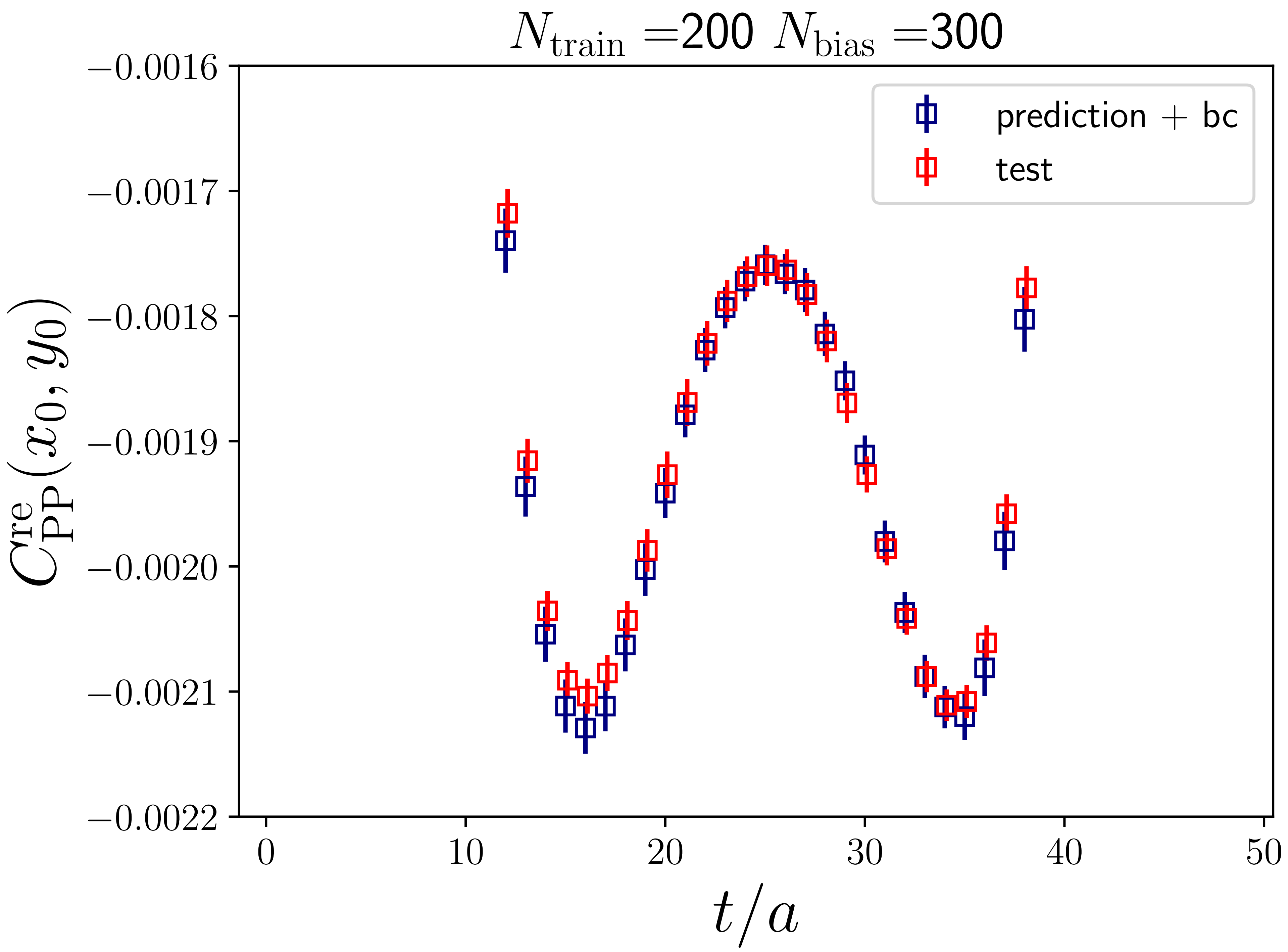


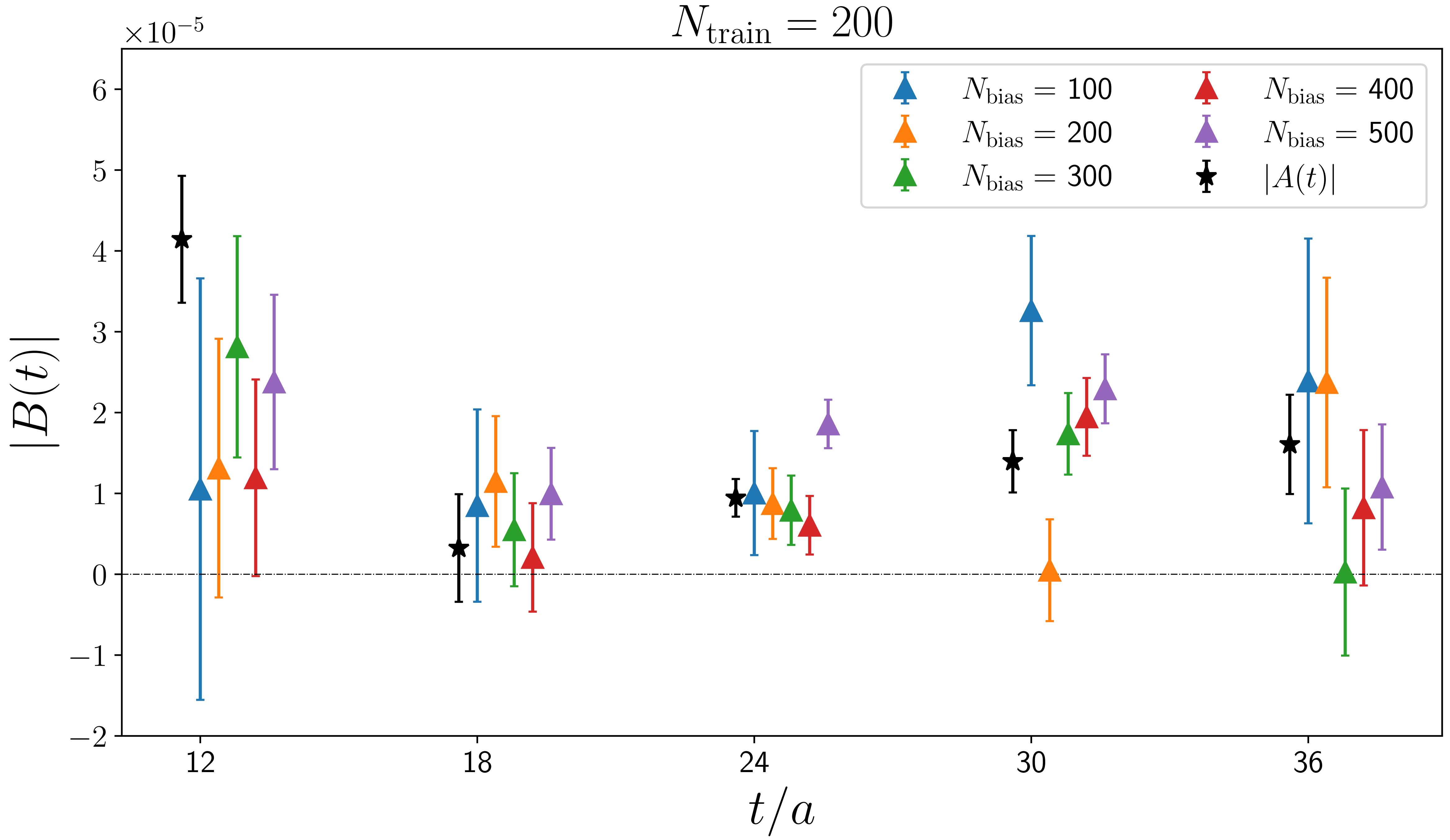


$$A(t) = \left\langle C^{\mathrm{exact}}(t) \right\rangle_{\mathrm{test}} - \left\langle C^{\mathrm{pred}}(t) \right\rangle_{\mathrm{test}}$$

Pseudoscalar correlator: rest-eigen contribution

Test quality of prediction for "rest-eigen" contribution — bias-corrected (A654 ensemble)



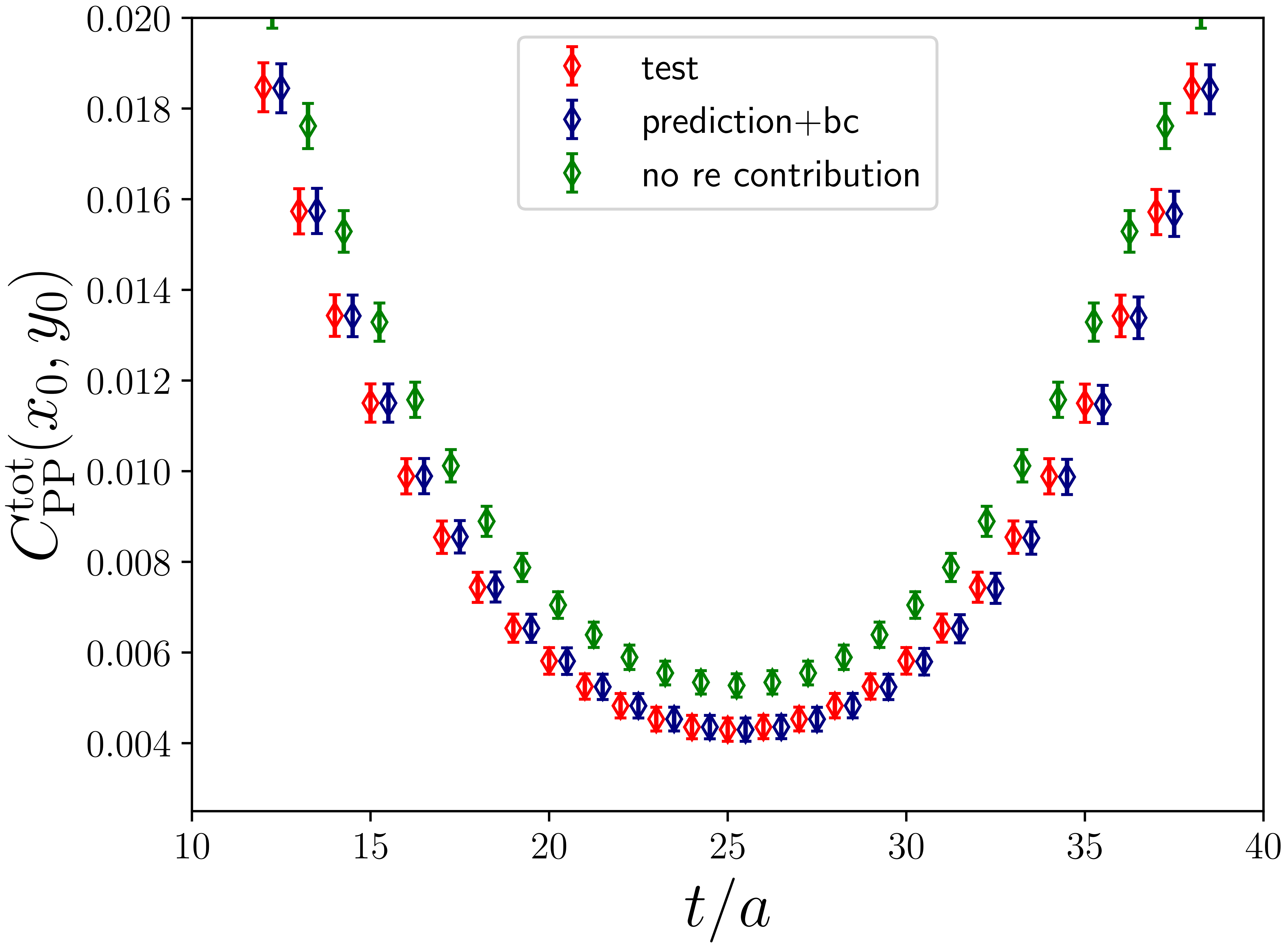


$$A(t) = \langle C^{\rm exact}(t) \rangle_{\rm test} - \langle C^{\rm pred}(t) \rangle_{\rm test}$$

$$B(t) = \langle C^{\rm exact}(t) - C^{\rm pred}(t) \rangle_{\rm bias}$$

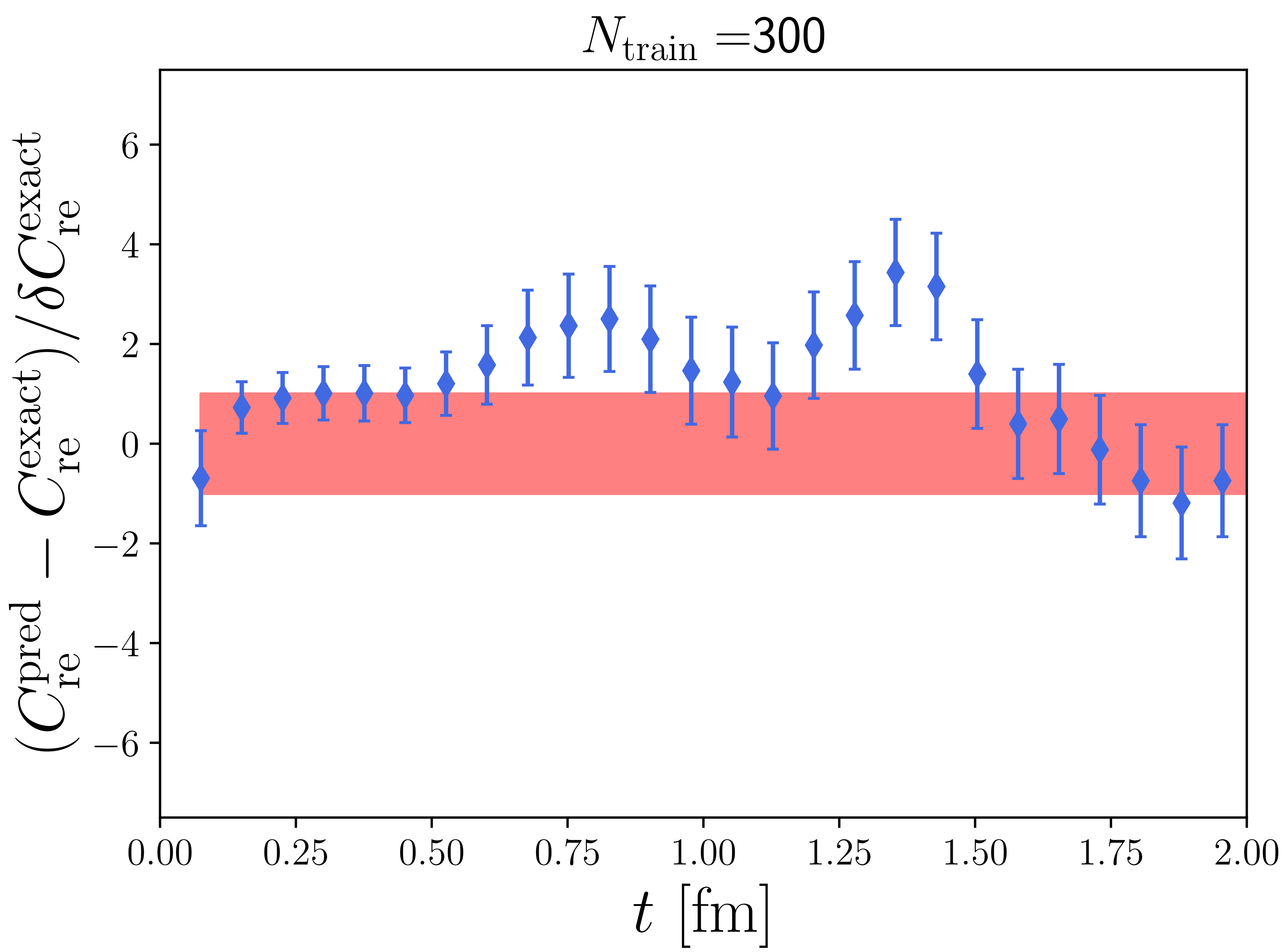
Pseudoscalar correlator: total contribution

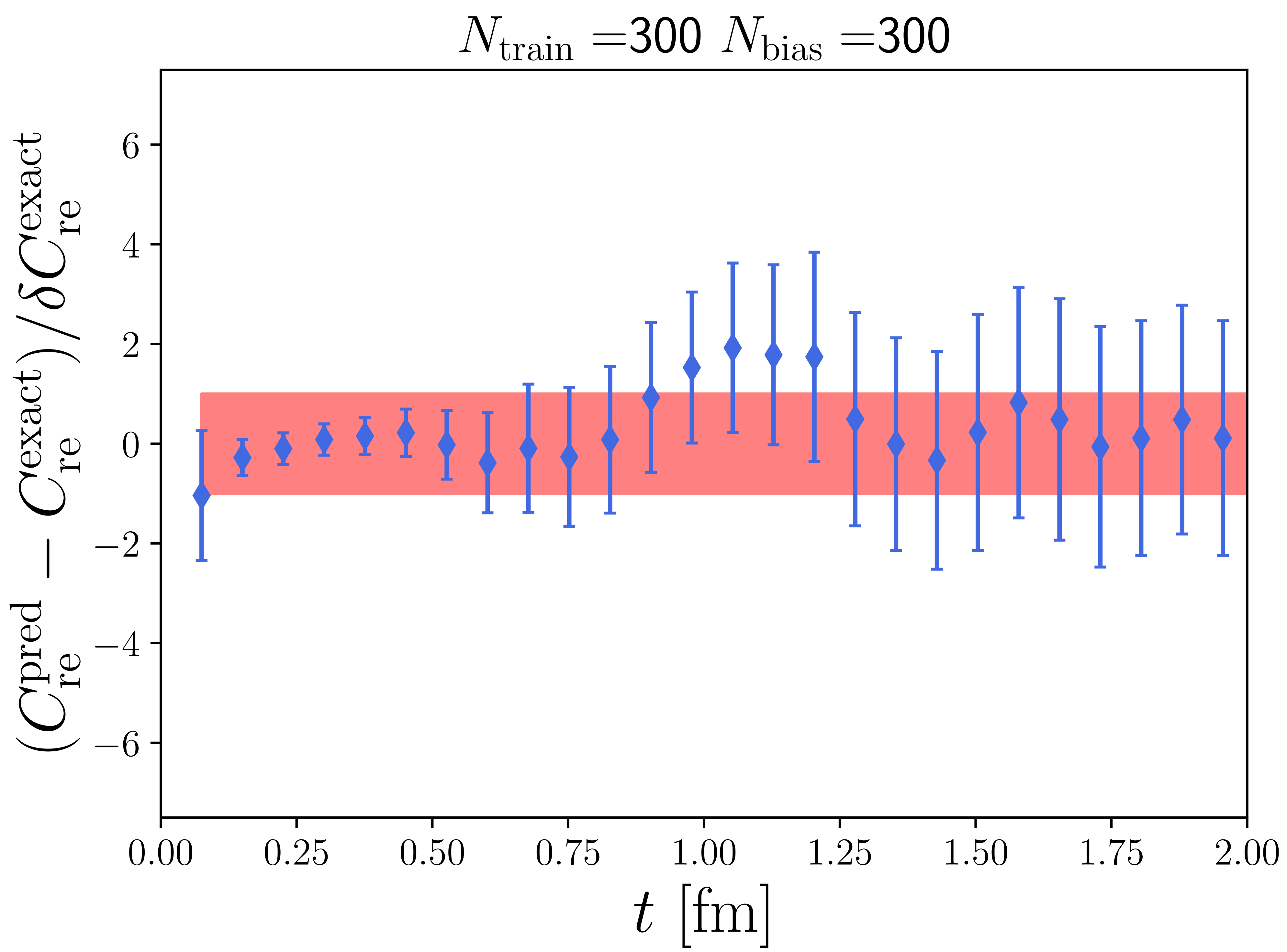
Total contribution (A654 ensemble)



Vector correlator

Test quality of prediction of rest-eigen part — with and without bias correction (A654 ensemble)

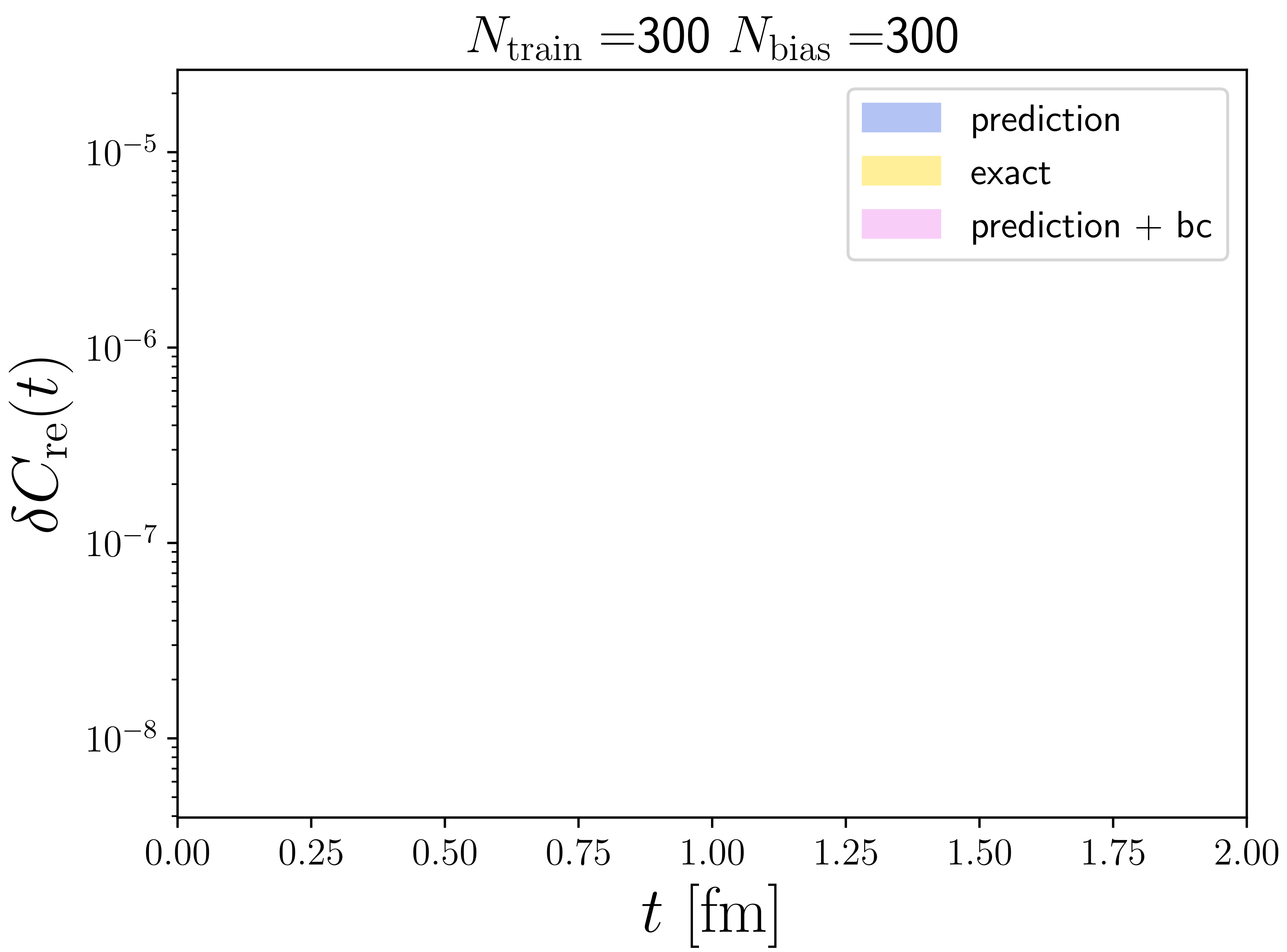


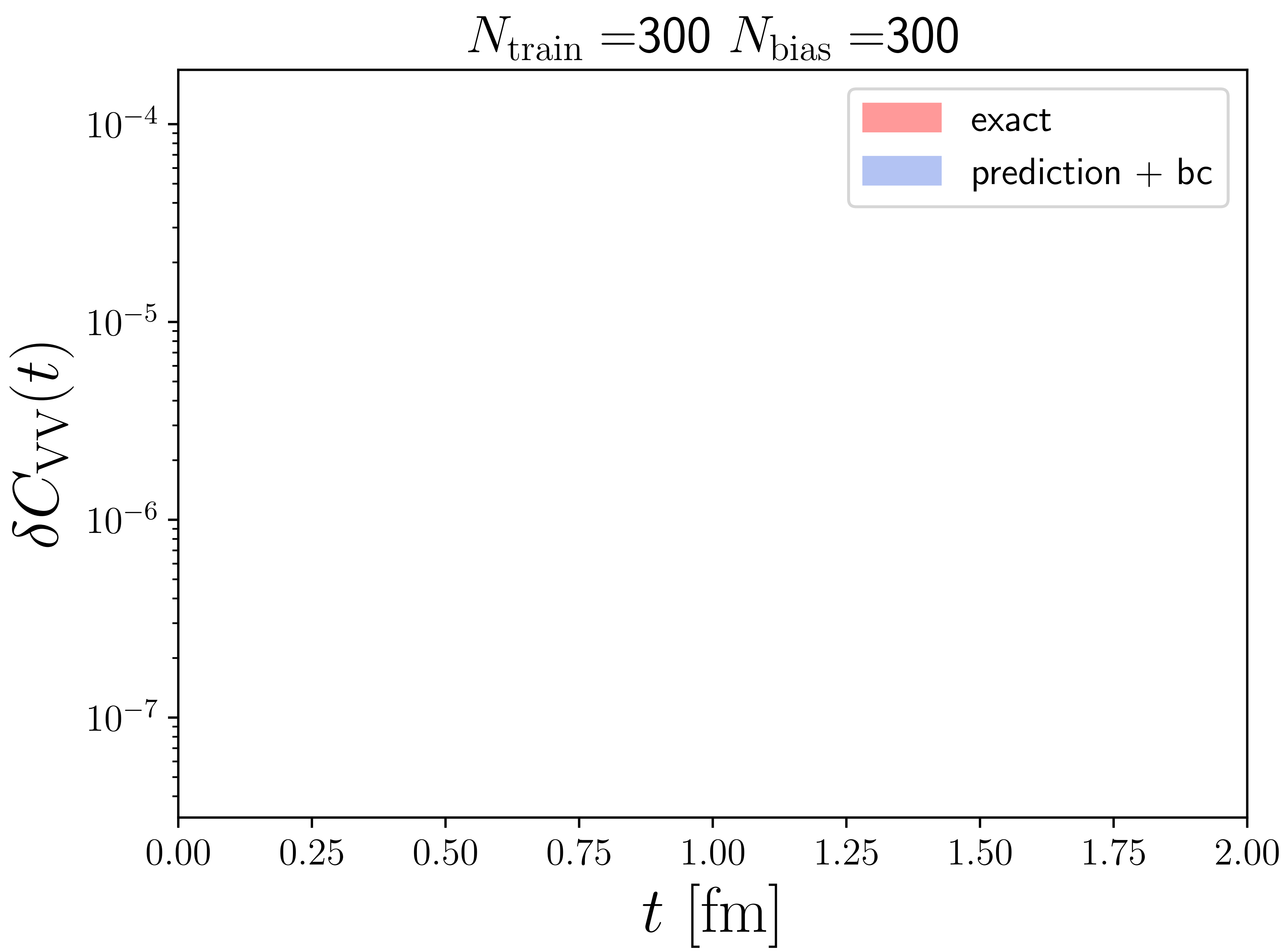


Bias-corrected "re"-correlator consistent with exact calculation, but errors increase at large t

Vector correlator

Absolute error of rest-eigen part and total contribution (A654 ensemble)



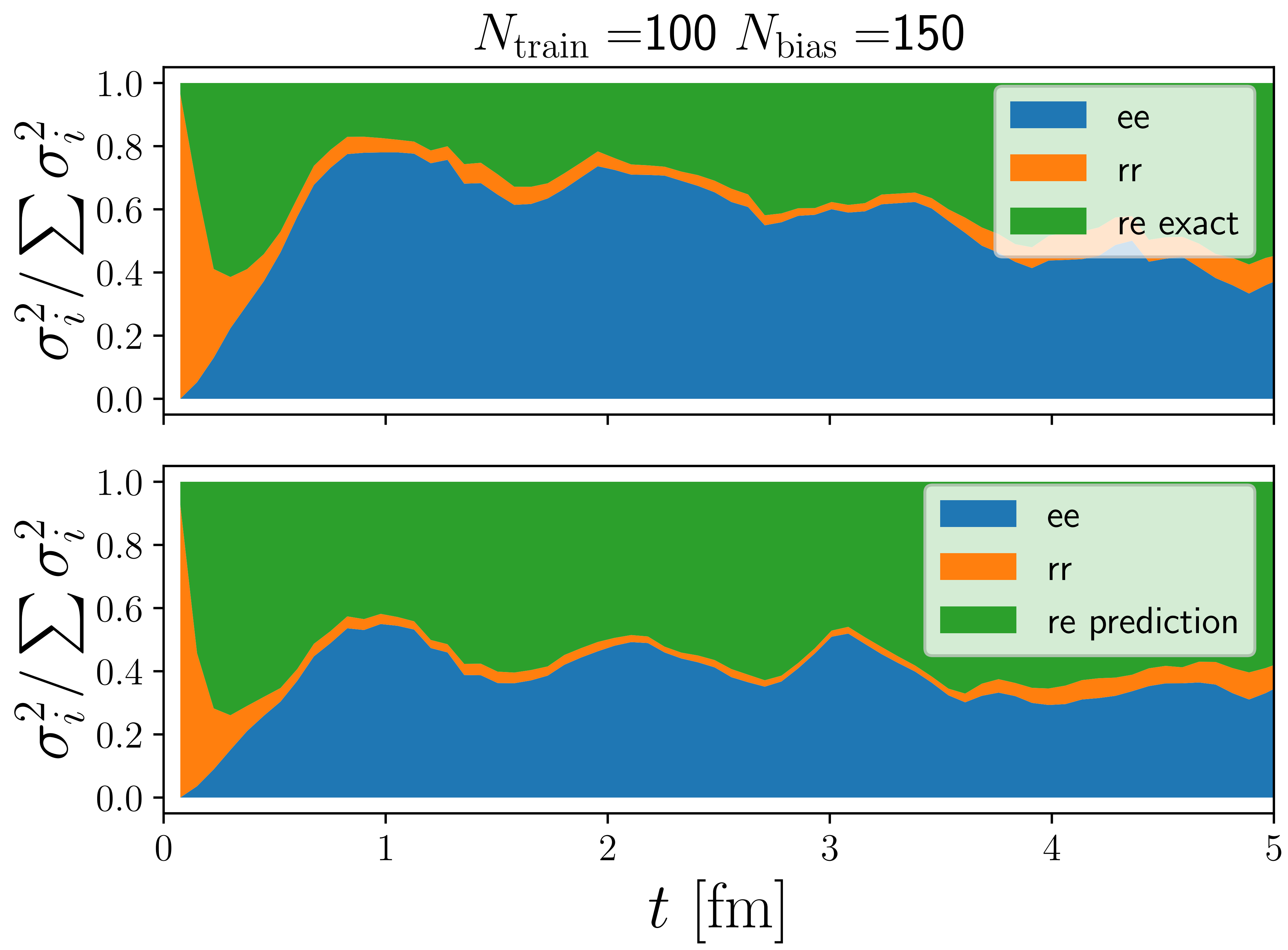


Bias-corrected "re"-correlator consistent with exact calculation, but errors increase at large t

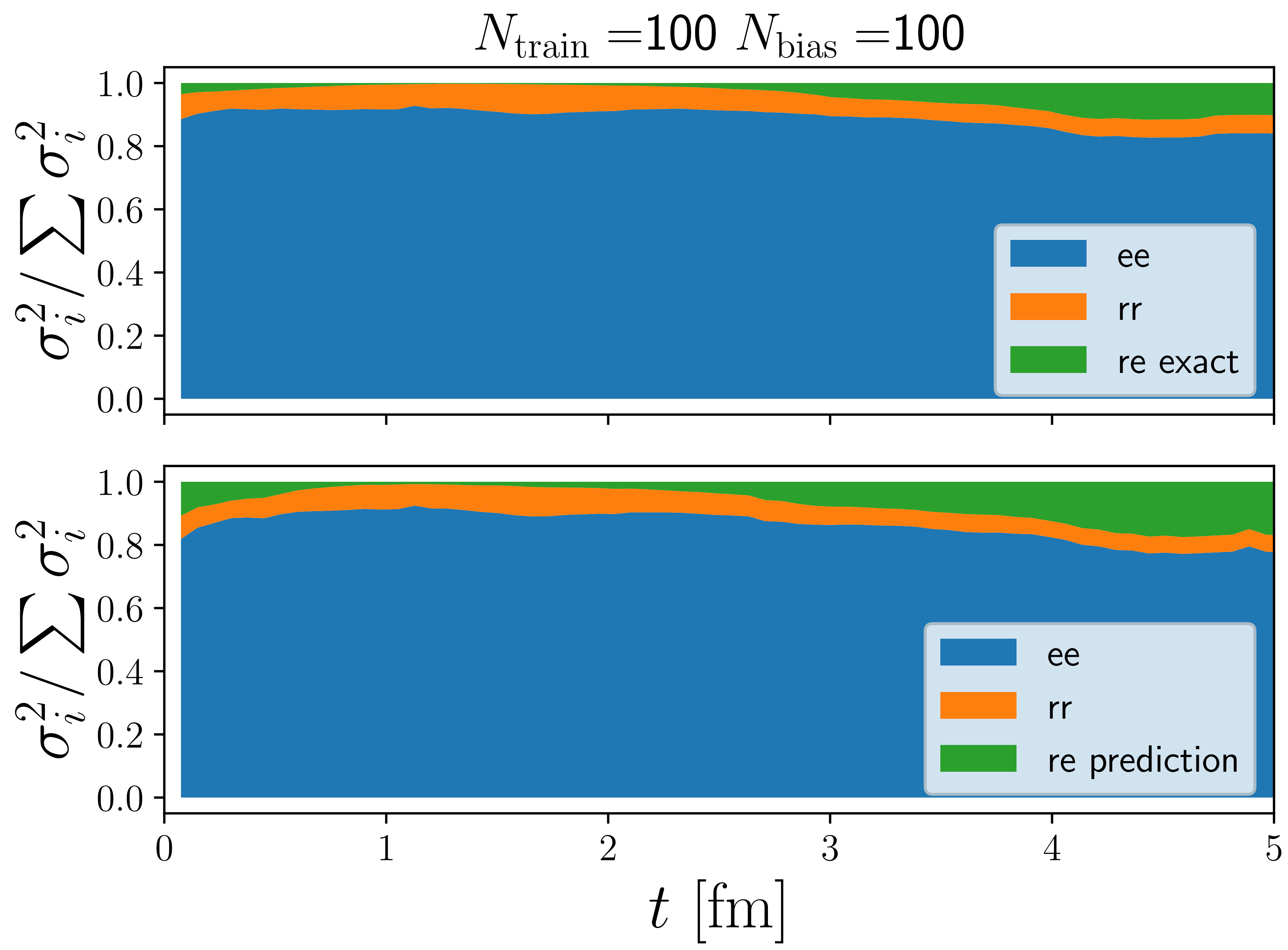
No gain in statistical precision after summing all contributions, unless N_{bias} is increased further

Vector vs. pseudoscalar correlator

Fraction of the total variance of "ee", "re" and "rr" contributions to (D450 ensemble)



Vector correlator



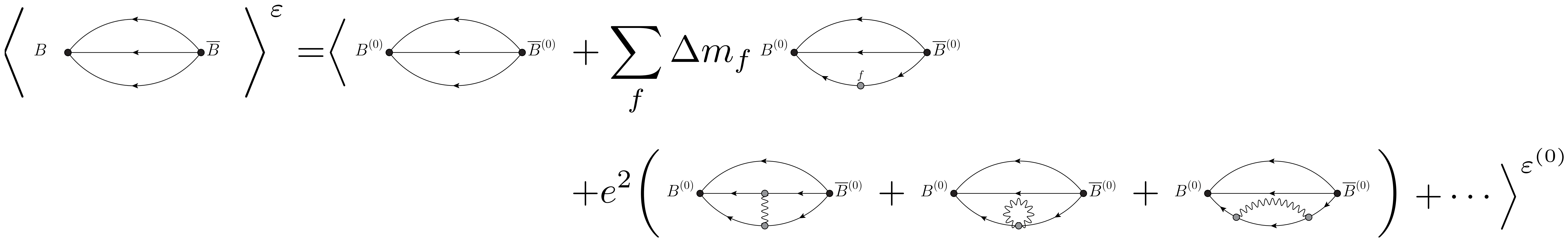
Pseudoscalar correlator

"Eigen-eigen" contribution dominates error in long-distance regime of the pseudoscalar correlator

Isospin-breaking corrections in baryon masses

Precision scale setting for $(g-2)_\mu$ HVP calculations

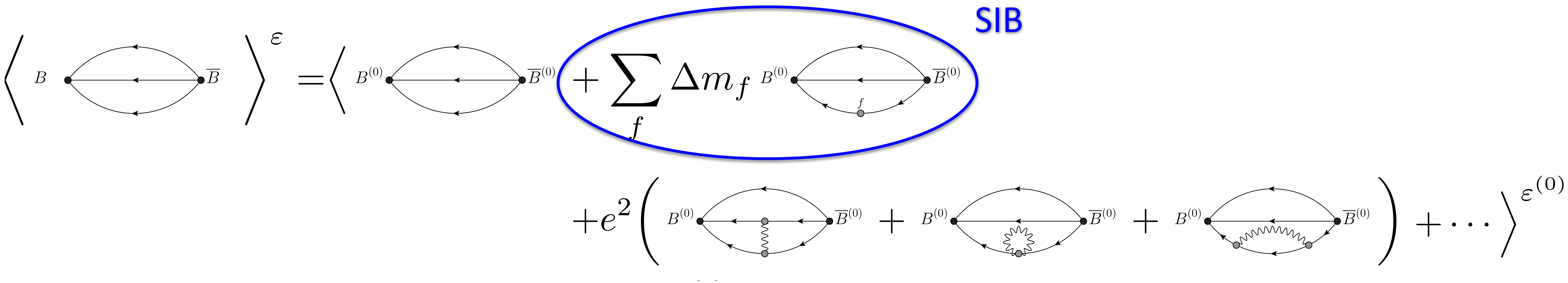
RM123 approach: expansion about iso-symmetric QCD



Isospin-breaking corrections in baryon masses

Precision scale setting for $(g-2)_\mu$ HVP calculations

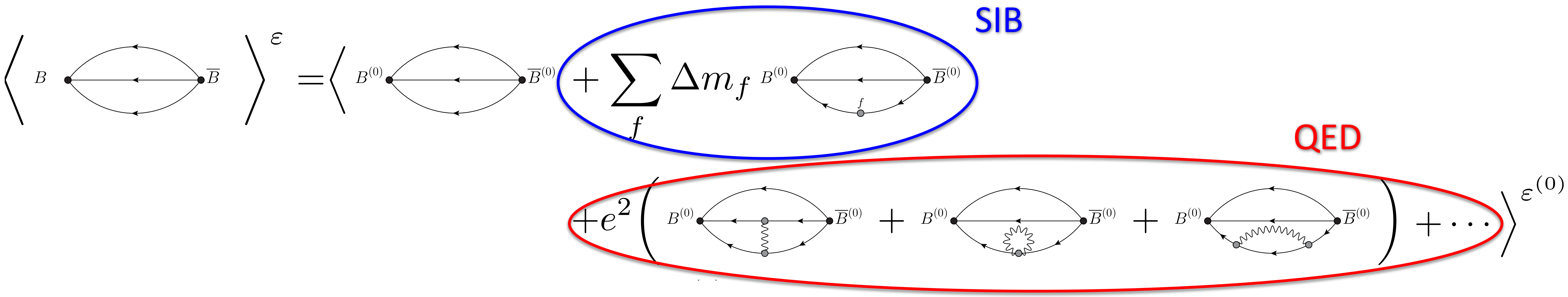
RM123 approach: expansion about iso-symmetric QCD



Isospin-breaking corrections in baryon masses

Precision scale setting for $(g-2)_\mu$ HVP calculations

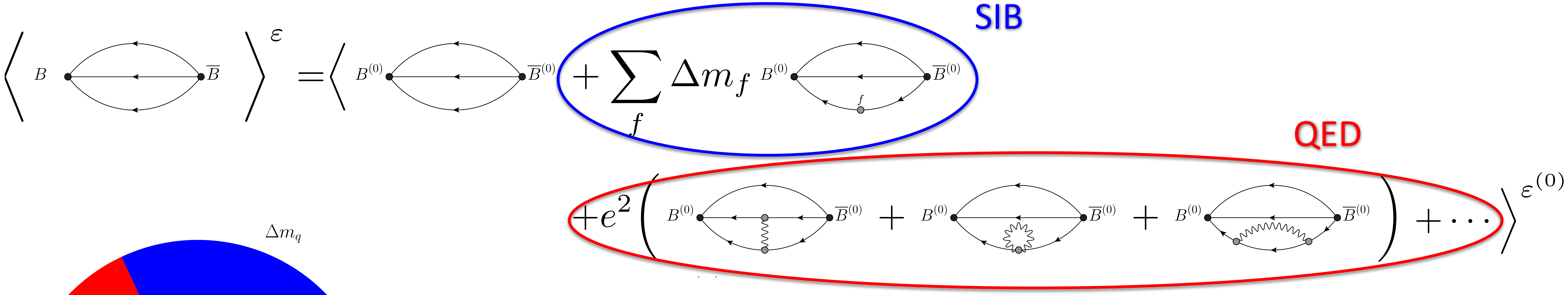
RM123 approach: expansion about iso-symmetric QCD

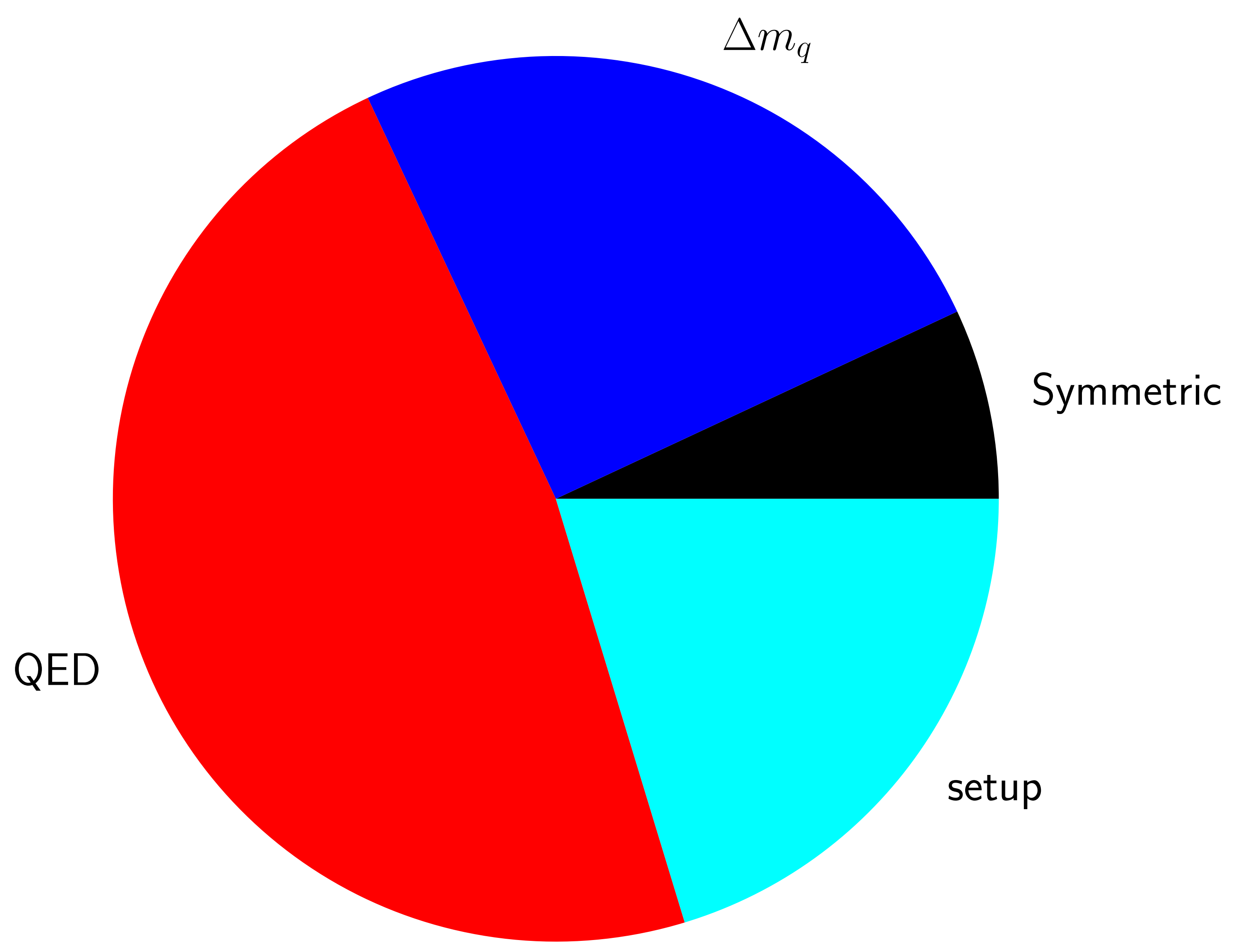


Isospin-breaking corrections in baryon masses

Precision scale setting for $(g-2)_\mu$ HVP calculations

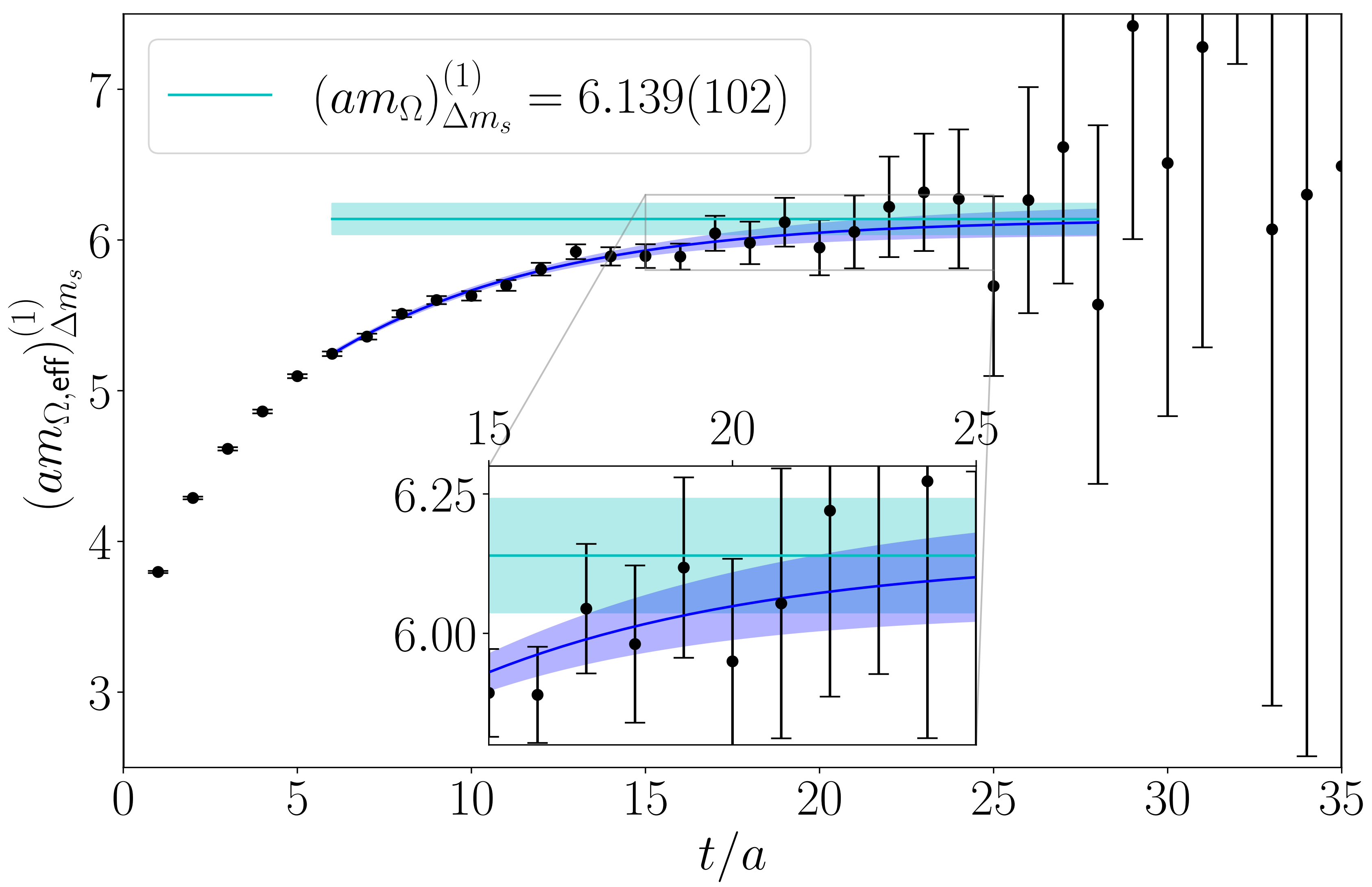
RM123 approach: expansion about iso-symmetric QCD

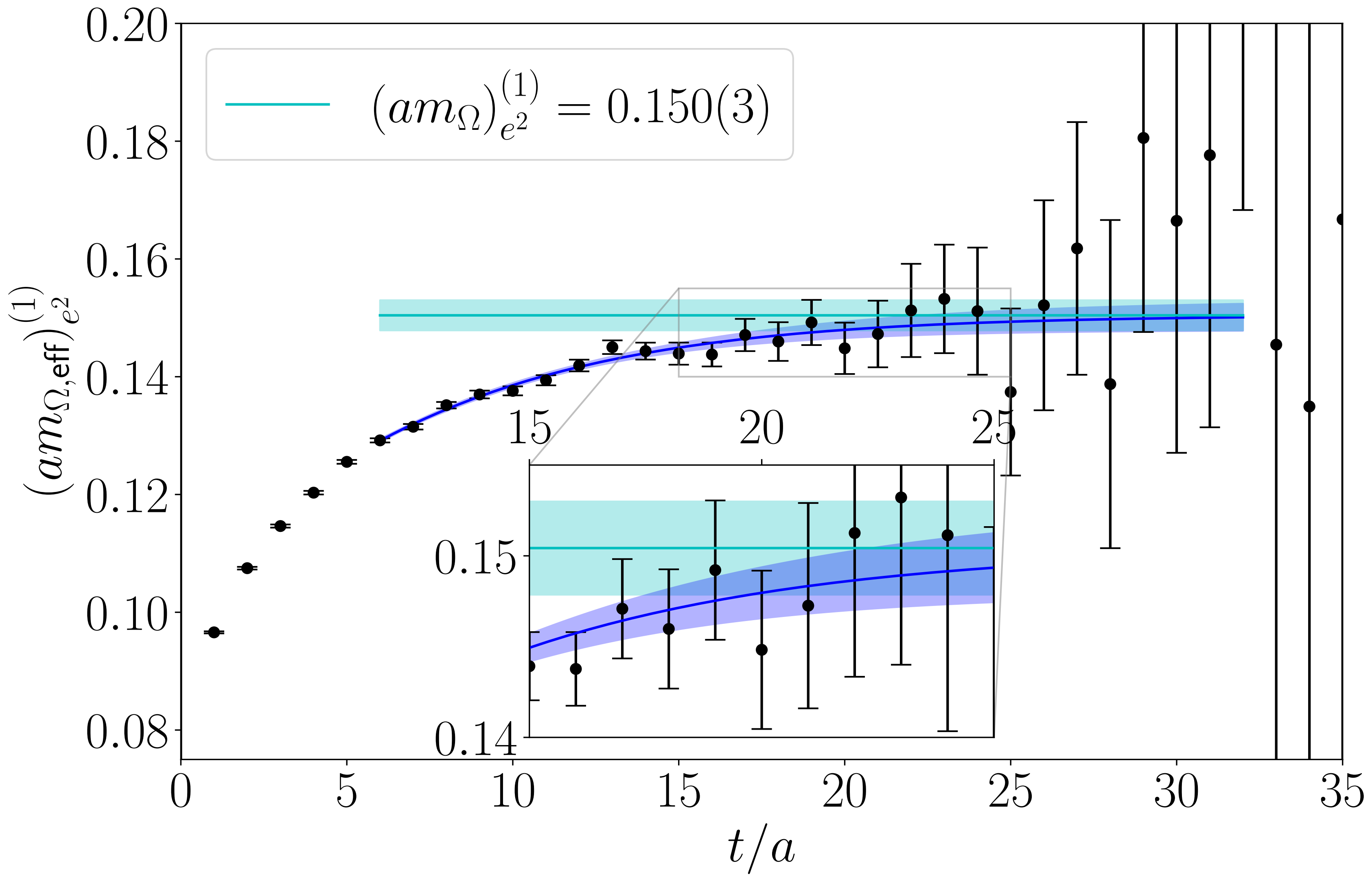




- QED contribution by far the most expensive part
- Observe strong correlation between the correlators describing QED and strong isospin-breaking contributions

Machine-learning model





- Train model $M(C^{(0)}, C^{(1)}_{\Delta m_u}, C^{(1)}_{\Delta m_d}, C^{(1)}_{\Delta m_s})$ to predict the QED contribution $C^{(1)}_{e^2}$

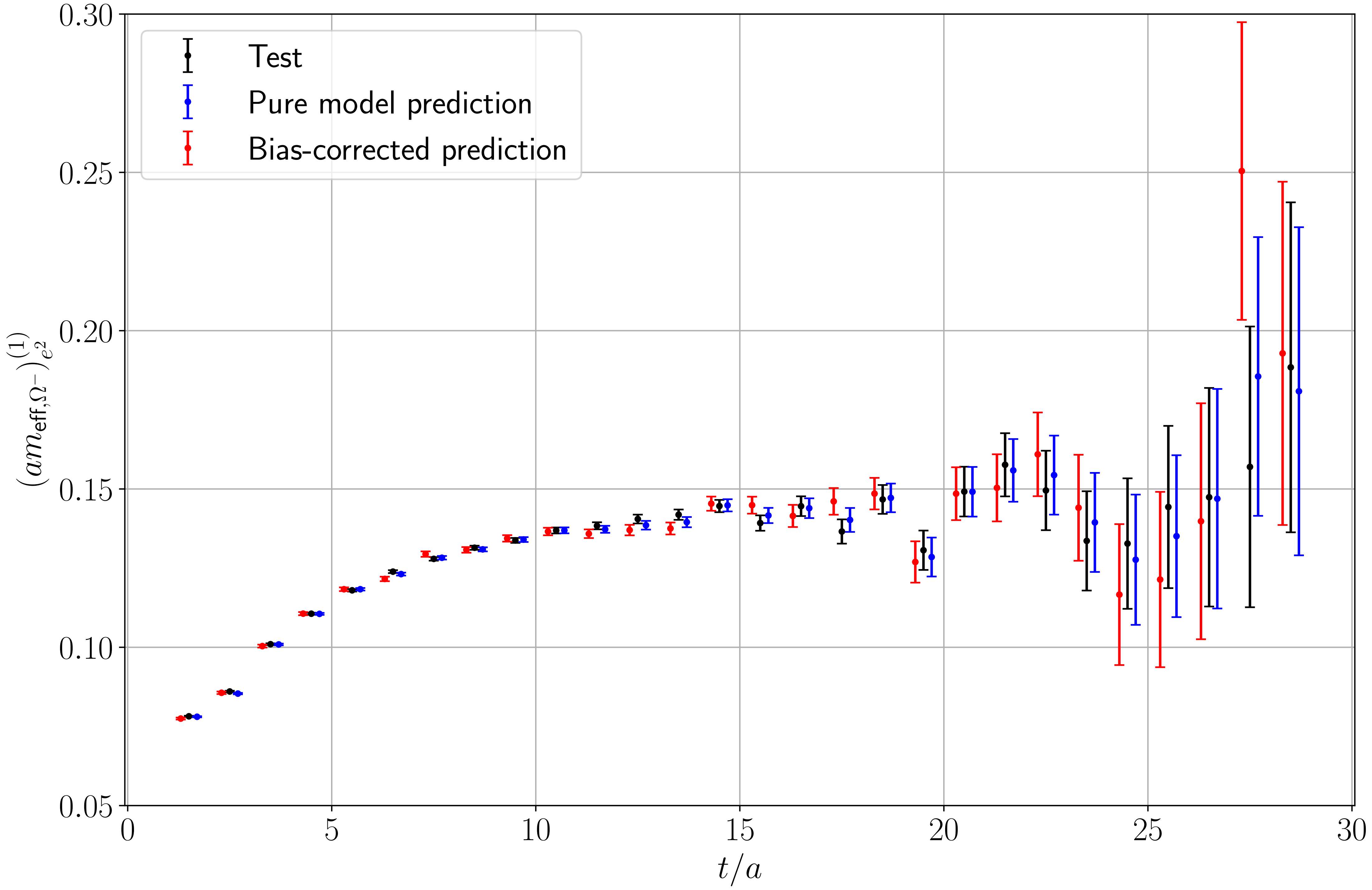
$$M(t) = \alpha\, C^{(0)}(t) + \beta\, C^{(1)}_{\Delta m_u}(t) + \gamma\, C^{(1)}_{\Delta m_d}(t) + \delta\, C^{(1)}_{\Delta m_s}(t) + \epsilon$$

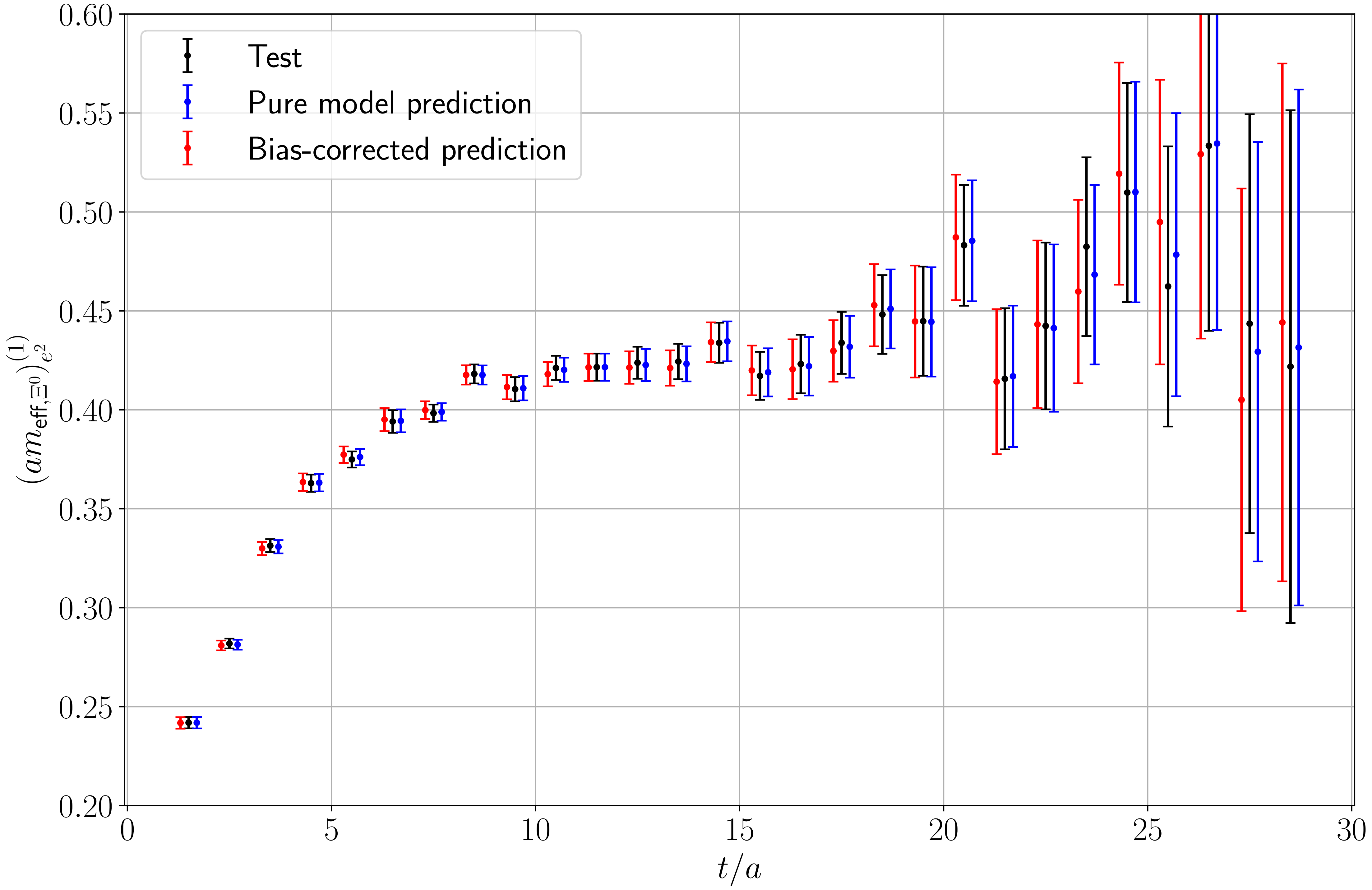
- Correct for bias by using a small number of sources on each configuration: $N_{\mathrm{src,\,bias}} \ll N_{\mathrm{src}}$

- Ensemble N451: $48^3 \cdot 96, \quad m_\pi \simeq 280\,\mathrm{MeV}, \quad N_{\mathrm{cfg}} = 1011, \; N_{\mathrm{train}} = 20, \quad N_{\mathrm{src}} = 32, \quad N_{\mathrm{src,\,bias}} = 1$

Results

QED correction to Ω^- and Ξ^- masses on N451 ensemble

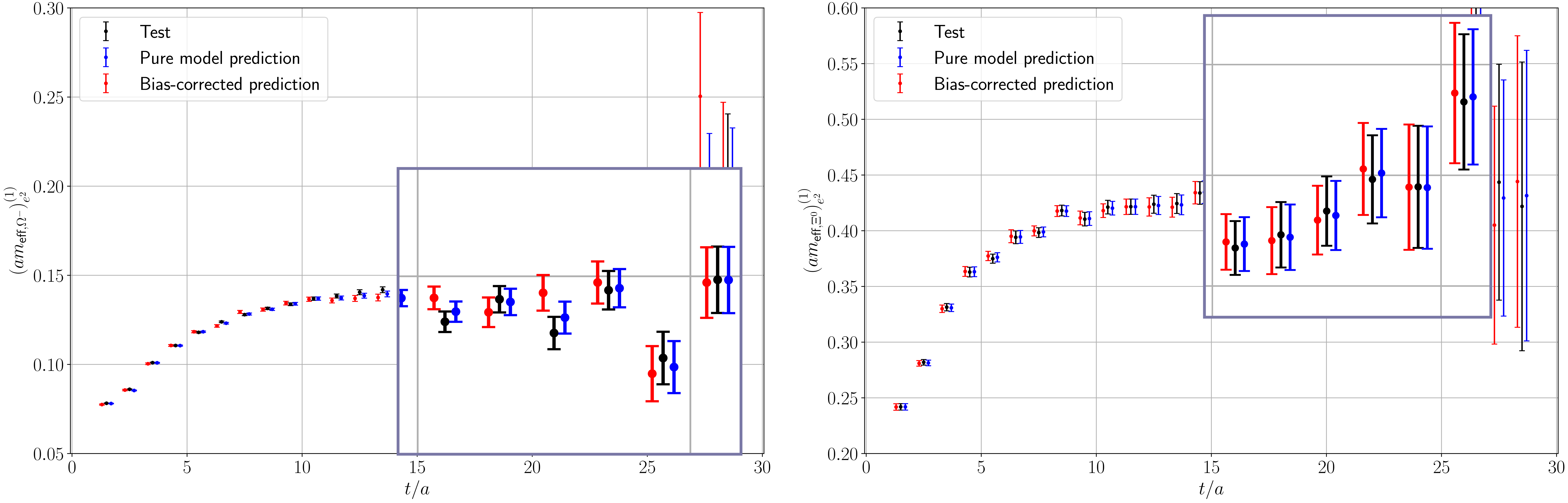




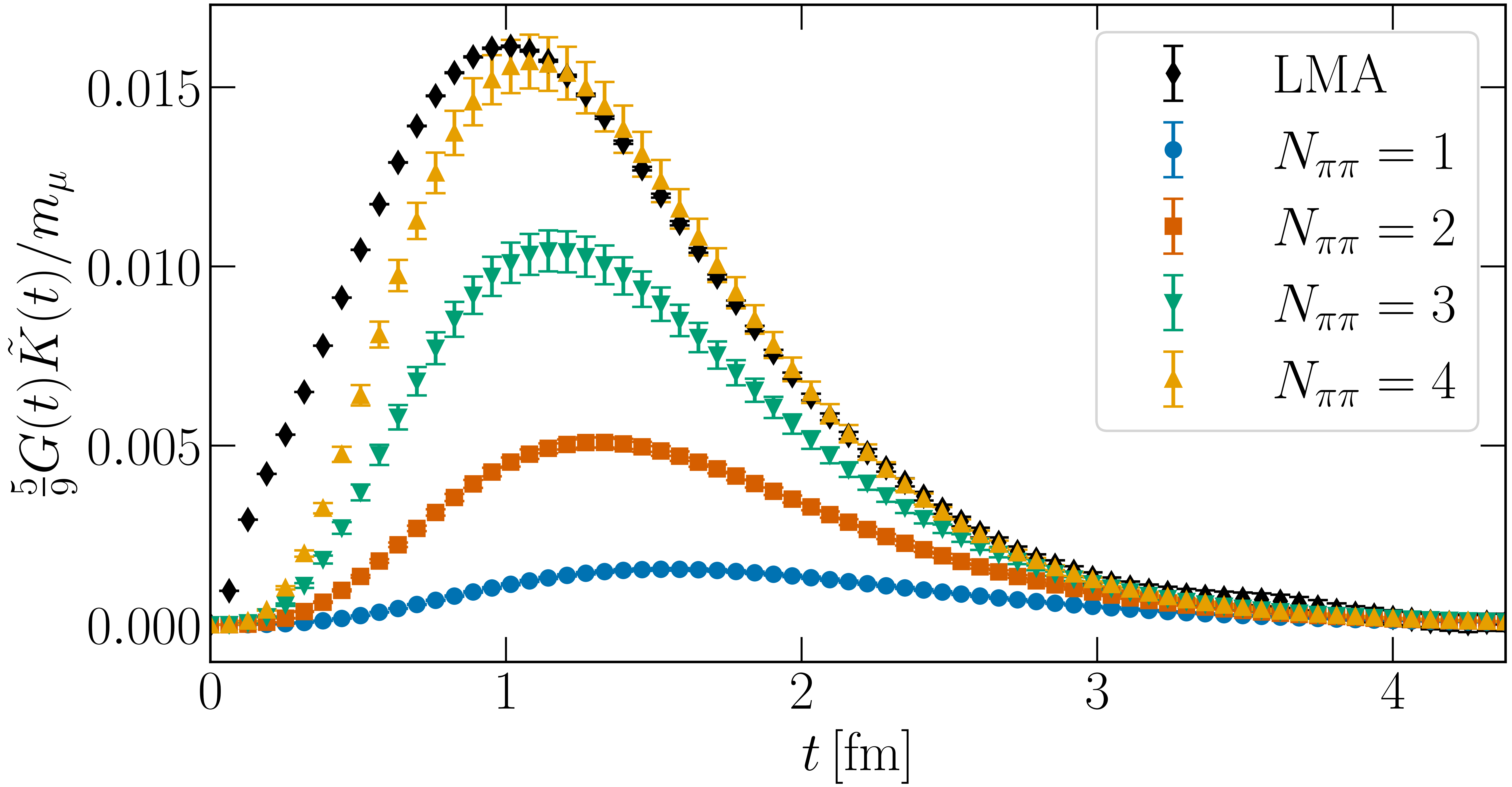
- Increasing $N_{\text{src, bias}}$ has no effect on the uncertainty in the bias-corrected result
- Training time negligible; reduction of numerical cost by 50%

Results

QED correction to Ω^- and Ξ^- masses on N451 ensemble



- Increasing $N_{\text{src, bias}}$ has no effect on the uncertainty in the bias-corrected result
- Training time negligible; reduction of numerical cost by 50%



[Nolan Miller @ Lattice24]:

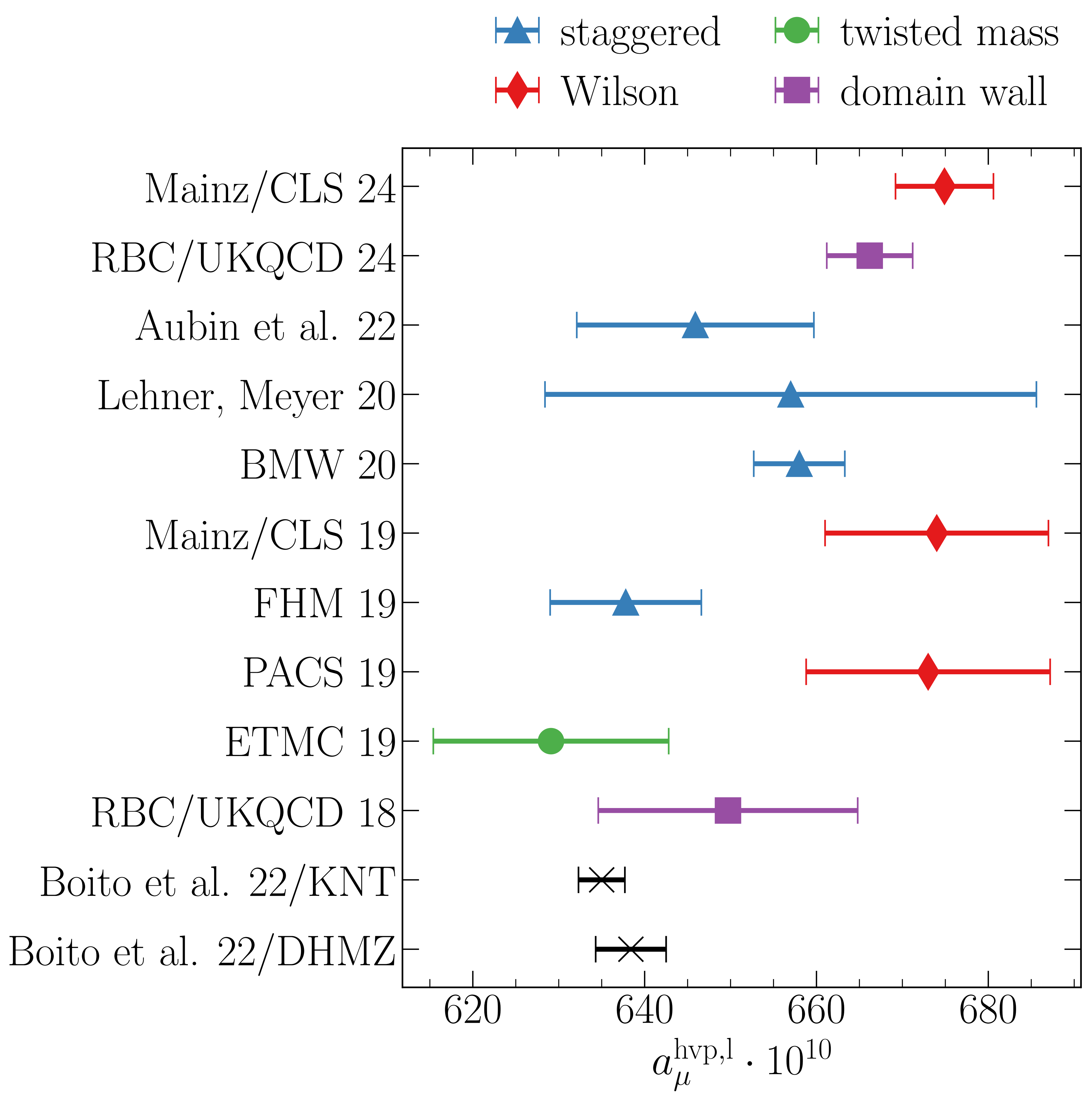
- Careful extraction of energies and overlaps.
- Work towards computing the timelike pion form factor.

- Spectral reconstruction of the isovector correlation function on E250 at $m_\pi^{\rm phys}$.
- Solves the signal-to-noise problem, but LMA is more precise for $t < 2.5\,\mathrm{fm}$.
- Reduces the uncertainty on this ensemble by another factor of 2: 0.4% for $a_\mu^{\rm hvp}$.

Slide by Simon Kuberski, 7th Plenary Workshop on $(g-2)_\mu$ KEK Sep 2024

New Mainz/CLS result

CONTRIBUTIONS TO $a_\mu^{\rm hvp}$ IN ISOQCD

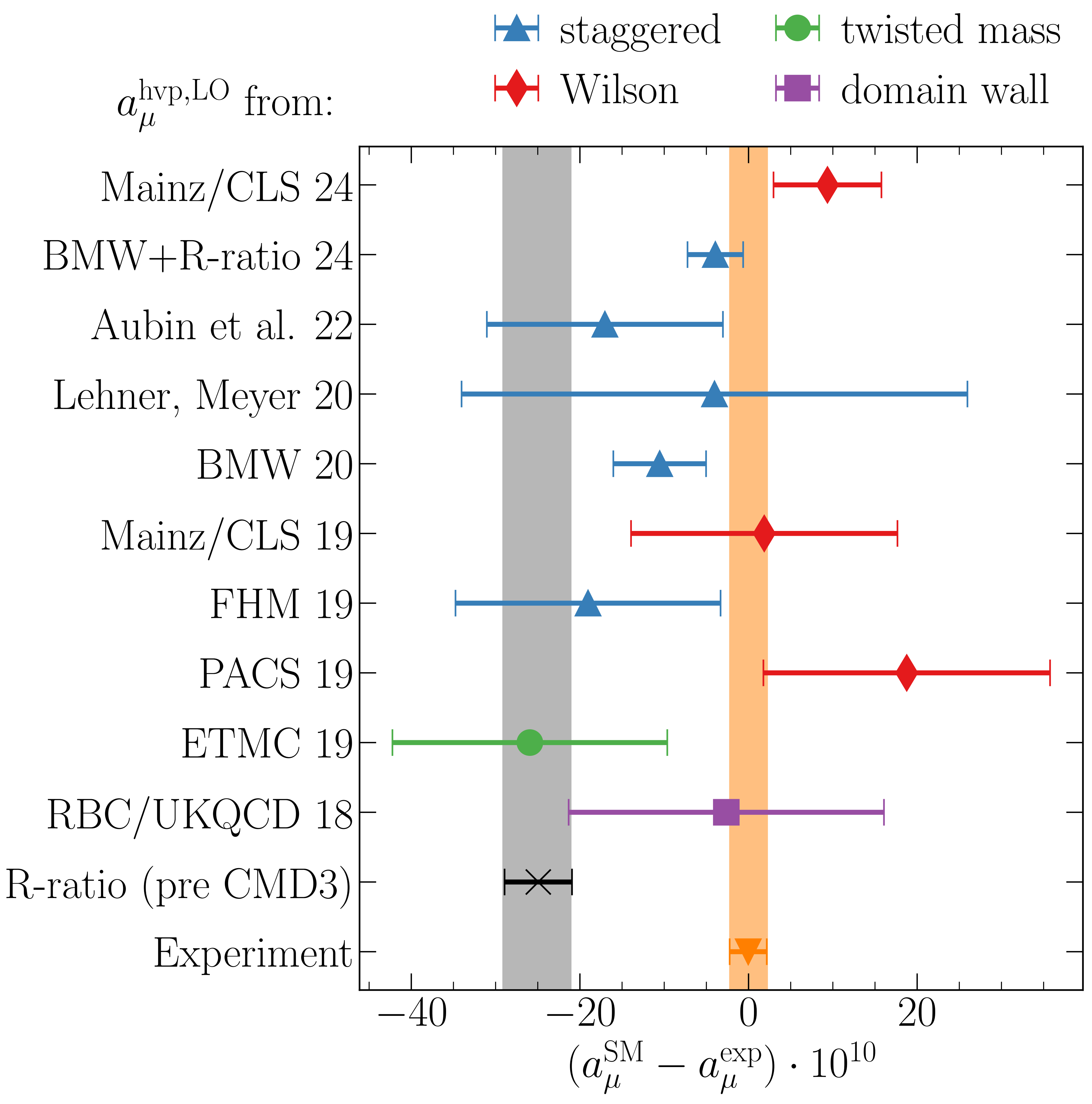


- Compute contributions to $a_\mu^{\rm hvp}$ in isoQCD (Mainz world) by combinations with $(a_\mu^{\rm hvp})^{\rm SD}$ and $(a_\mu^{\rm hvp})^{\rm ID}$.
- We (will) publish the derivatives w.r.t. the input that defines our scheme. See [Portelli] for a comparison of schemes.
- $a_\mu^{\rm hvp,l}$ determined to 0.8% precision
- Excellent compatibility of Mainz/CLS 19 with Mainz/CLS 24.

Slide by Simon Kuberski, 7th Plenary Workshop on $(g-2)_\mu$ KEK Sep 2024

New Mainz/CLS result

The leading-order hadronic vacuum polarization contribution



- The estimate of IB corrections allows to compute a **preliminary** a_μ^{hvp}.
- Our result supports the no new physics scenario.
- Ongoing work to compute IB corrections. So far
  - no IB in scale setting
  - electroquenched approximation
  - **preliminary estimate**

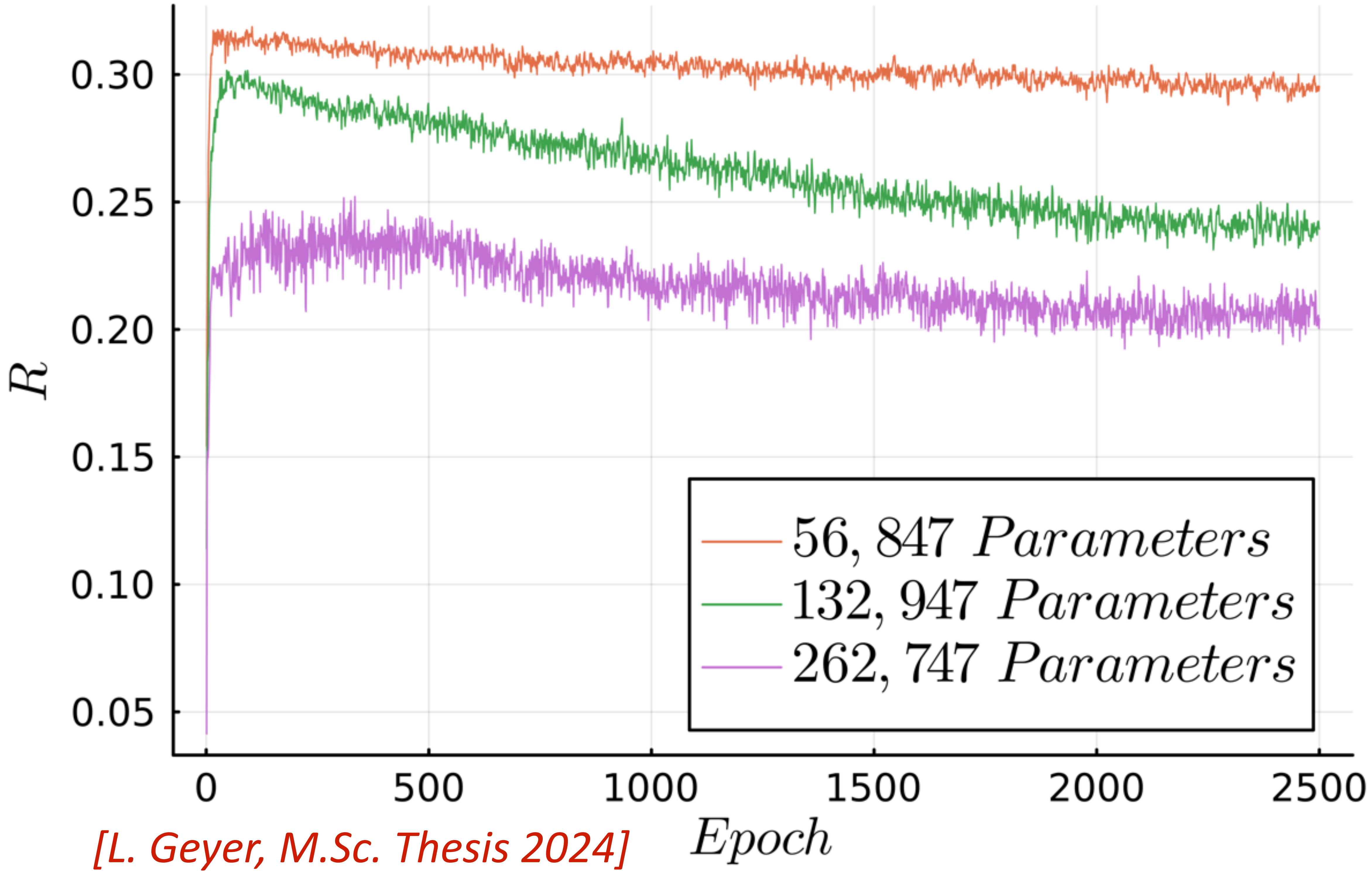
Slide by Simon Kuberski, 7th Plenary Workshop on $(g-2)_\mu$ KEK Sep 2024

Summary and conclusions

- Machine-learning models with bias correction are able to reproduce exact calculations with comparable statistical precision
- No "noise reduction" observed in all models studied so far
- Saving in computer time can be substantial, but depends strongly on the observable
- Using ML for QED part leads to 50% reduction in numerical effort for computing baryon masses including isospin-breaking corrections
- Rest-eigen part of vector correlator:
  bias correction dominates the total uncertainty; less CPU time produces a larger error
- Outlook: optimise setup to increase correlations between $O_{\rm appx}$ and O

Backup

Grid search and R-score



[L. Geyer, M.Sc. Thesis 2024]

Models with increasing complexity lead to overfitting

$$R_k = 1 - \frac{\sum_{i=1}^{47}(v_{\mathrm{t},k,i}^{\mathrm{ER}} - v_{\mathrm{p},k,i}^{\mathrm{ER}})^2}{\sum_{i=1}^{47}(v_{\mathrm{t},k,i}^{\mathrm{ER}} - \hat{v}_{\mathrm{t},i}^{\mathrm{ER,tr}})^2}, \quad R_k \in (-\infty, 1].$$