

Scale setting the möbius domain wall fermion on HISQ action with M_Ω and the gradient-flow scales

Phys. Rev. D 103, 054511 (2021)

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March 5, 2025

Strategy

Results

Updates

Bayesian model averaging

Backup

Bird's eye view

Strategy

- ▶ Mixed action: möbius domain wall fermions (valence) on highly-improved staggered quarks ($N_f = 2 + 1 + 1$)
- ▶ Work in isosymmetric limit
- ▶ m_Ω for physical scale
- ▶ SU(2) χ PT & Taylor expansions (with model averaging)
- ▶ In addition to w_0 , $\sqrt{t_0}$ calculate improved scales with leading-order discretization effects removed

$$\frac{t^2 \langle E(t) \rangle}{1 + \sum_n C_{2n} \frac{a^{2n}}{t^n}} \Big|_{t=t_{0,\text{imp}}} = 0.3, \quad t \frac{d}{dt} \left(\frac{t^2 \langle E(t) \rangle}{1 + \sum_n C_{2n} \frac{a^{2n}}{t^n}} \right) \Big|_{t=w_{0,\text{imp}}^2} = 0.3$$

Why MDWF on HISQ?

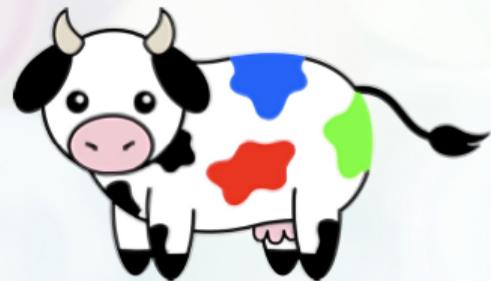
Strategy

- ▶ MDWF circumvents Nielsen-Ninomiya

Why MDWF on HISQ?

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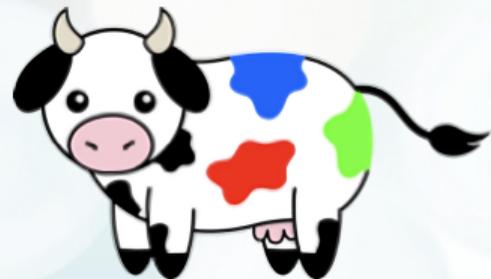
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- ▶ Wanted to bootstrap our action with publicly available data \implies use MILC's HISQ action



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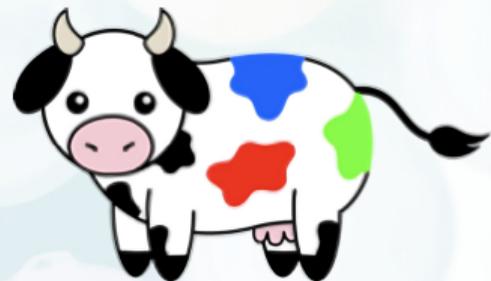
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- ▶ Wanted to bootstrap our action with publicly available data \implies use MILC's HISQ action
- ▶ QUDA provides excellent MDWF solvers: compute time optimized on GPUs such that 95+% of wall clock cycles are spent on MDWF solves, not contractions/smearing



Why MDWF on HISQ?

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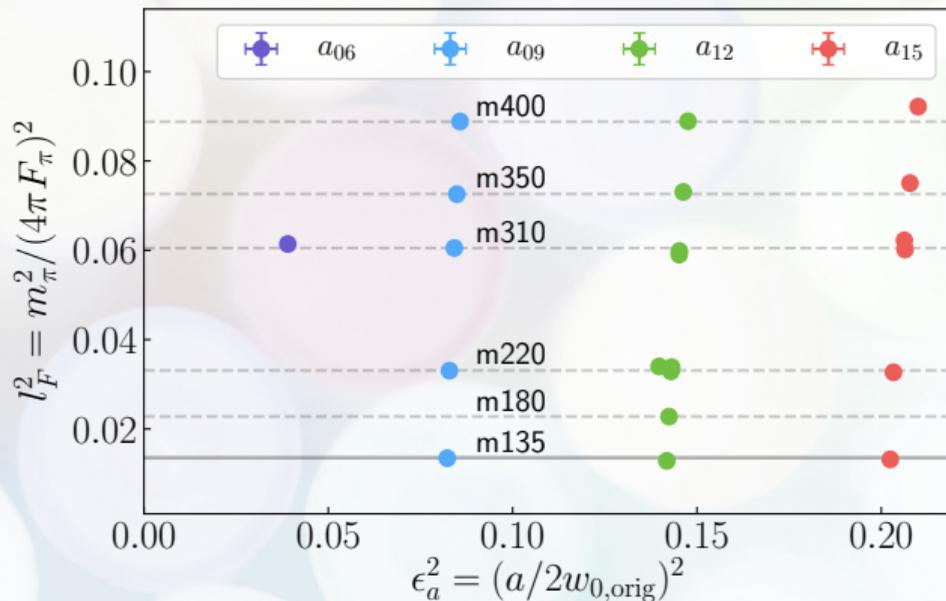
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- ▶ Wanted to bootstrap our action with publicly available data \implies use MILC's HISQ action
- ▶ QUDA provides excellent MDWF solvers: compute time optimized on GPUs such that 95+% of wall clock cycles are spent on MDWF solves, not contractions/smearing
- ▶ Empirically, MDWF requires only around $\sim 1\%$ statistics compared to clover fermions for similar precision \implies offsets cost from simulating 5th dimension, lack of multi-grid solver for MDWF



Lever arms (2020)

Strategy

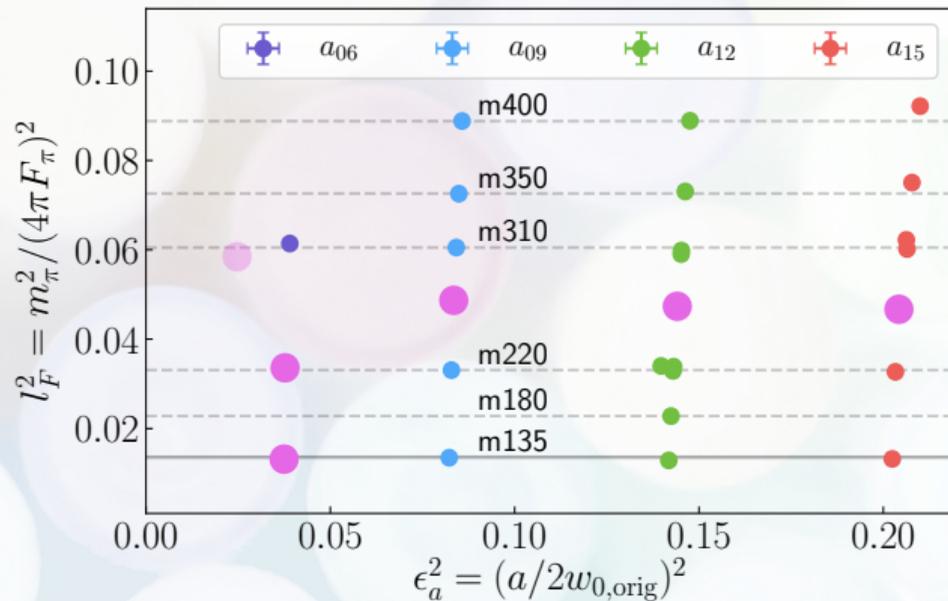
- ▶ 22 ensembles spanning $130 \text{ MeV} \lesssim m_\pi \lesssim 400 \text{ MeV}$, $0.06 \text{ fm} \lesssim a \lesssim 0.15 \text{ fm}$
- ▶ Strange dependence: a12m220ms tuned at $\sim 60\%$ physical strange quark mass
- ▶ Volume dependence: a15m310/L (2.4 fm vs 3.6 fm), a12m310/XL (2.9 fm vs 5.8 fm), a12m310XL/a12m180L/a12m130 (same volume, different m_π)



Lever arms (2025)

Strategy

- ▶ 5_{-0}^{+1} new ensembles
- ▶ 1 at physical pion mass
- ▶ 2_{-0}^{+1} at/below the current finest lattice spacing



Why m_Ω ?

Strategy

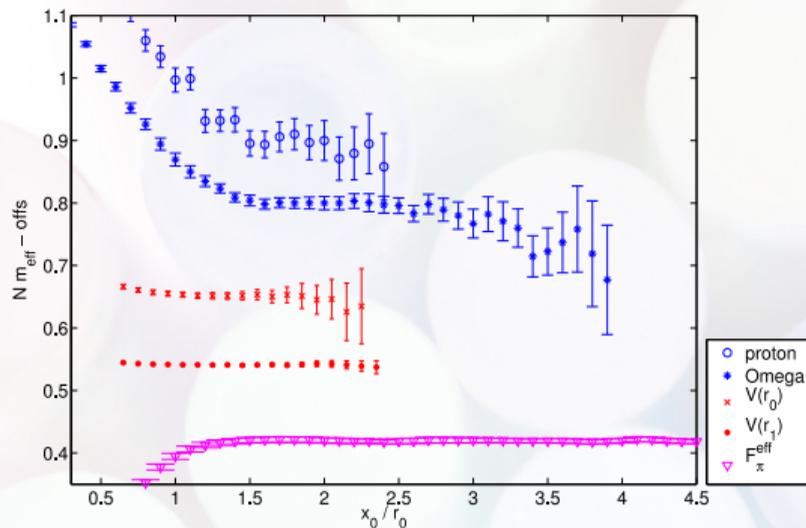
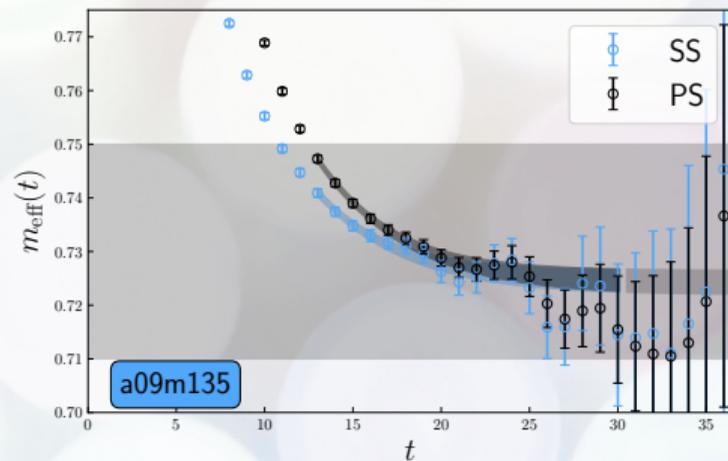


Figure: FLAG (2024)

- ▶ Stable in QCD+QED
- ▶ No valence light quarks \implies milder chiral dependence for extrapolations
- ▶ Favorable Parisi-Lepage scaling compared to other baryons:
 $\text{SNR} \sim e^{-(m_\Omega - 3m_\pi/2)t}$
- ▶ (pre-Edinburgh) Experimental value for m_Ω more precise than decay constants
- ▶ (pre-Edinburgh) Experimental value for F_π contaminated by QED, potential BSM effects

Fitting the Ω correlators

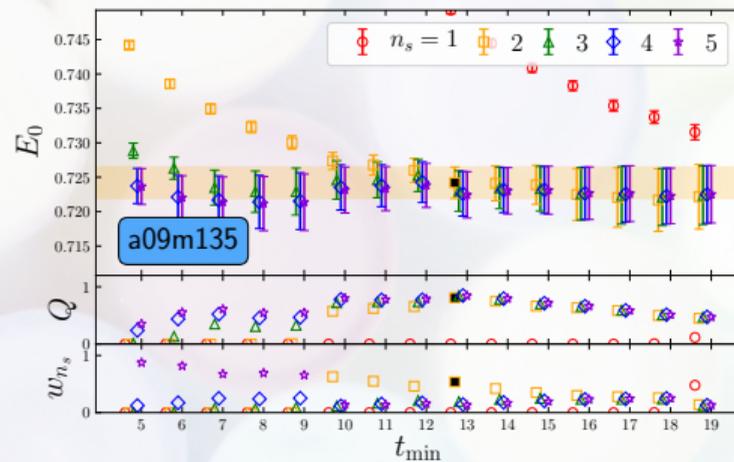
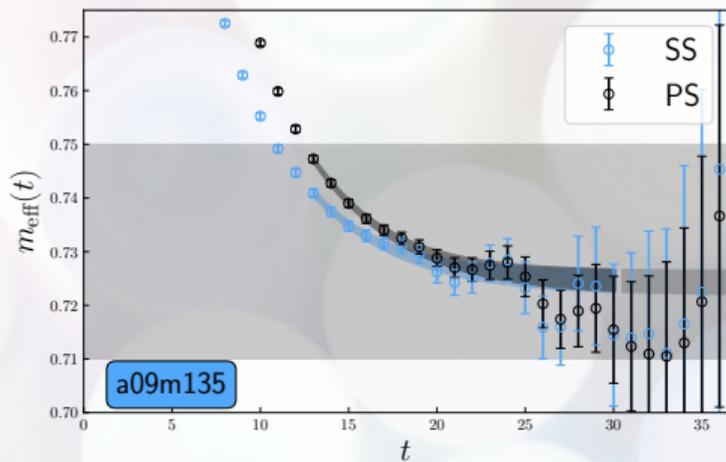
Strategy



- ▶ Two different combinations of source/sinks, fit simultaneously

Fitting the Ω correlators

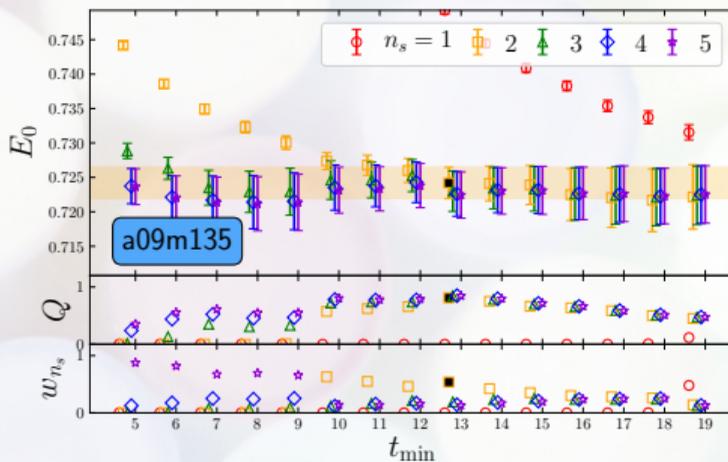
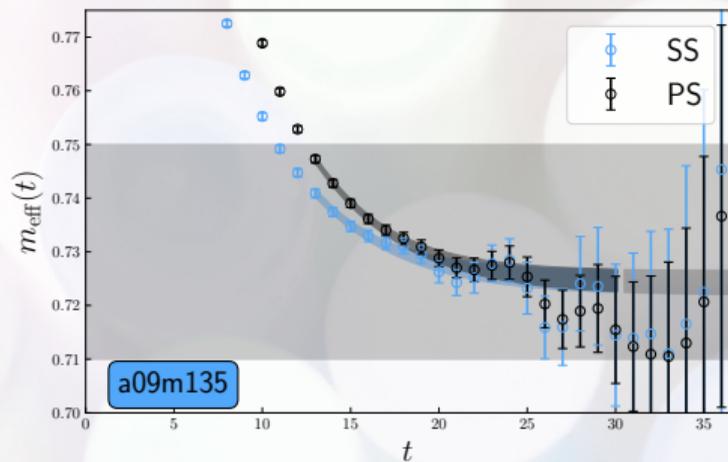
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- ▶ Two different combinations of source/sinks, fit simultaneously
- ▶ Check for stability using multi-state fits up to $N = 5$

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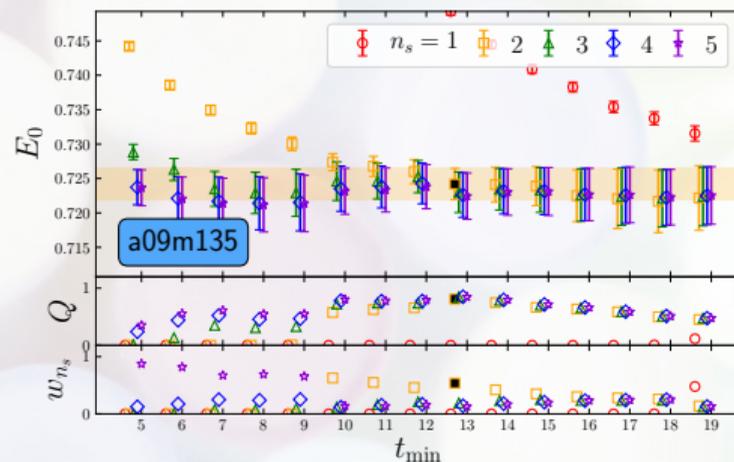
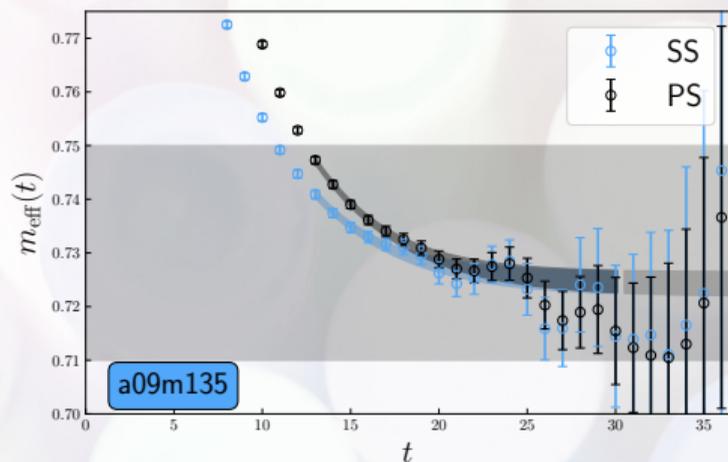
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- ▶ Two different combinations of source/sinks, fit simultaneously
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- ▶ Stabilize fits with wide priors, e.g. $\delta E \sim \log \mathcal{N}(2m_\pi, m_\pi^2)$

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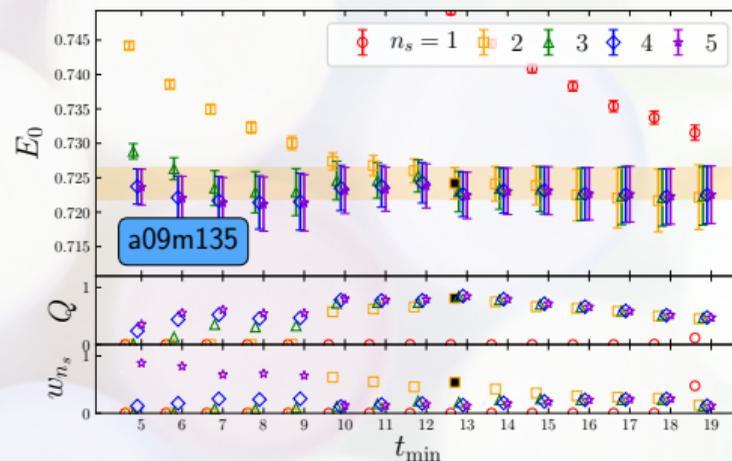
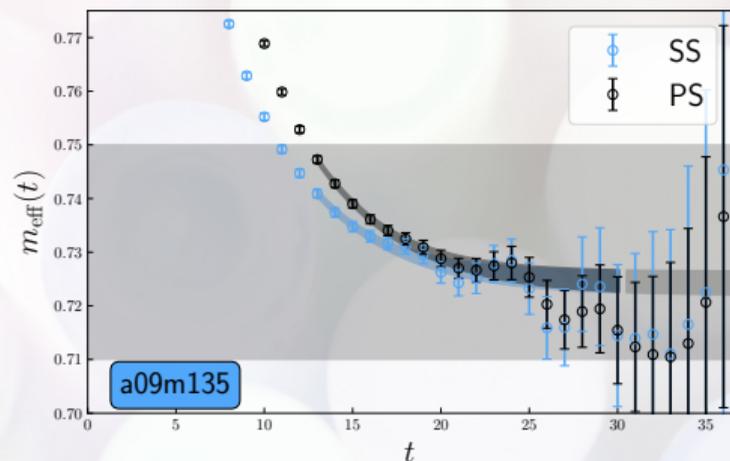
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Fitting the Ω correlators

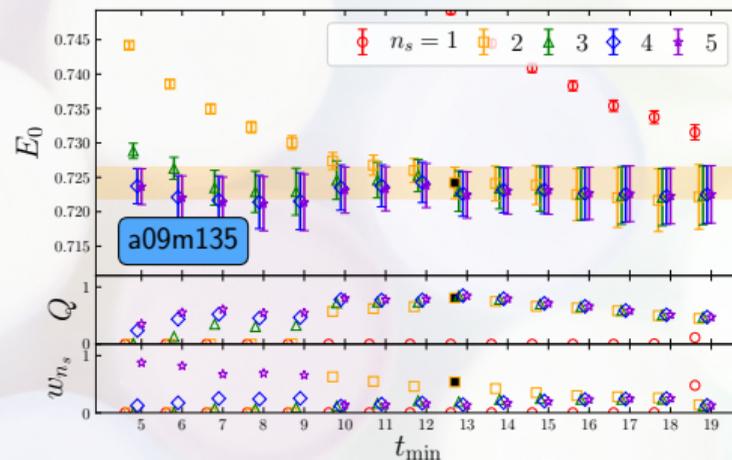
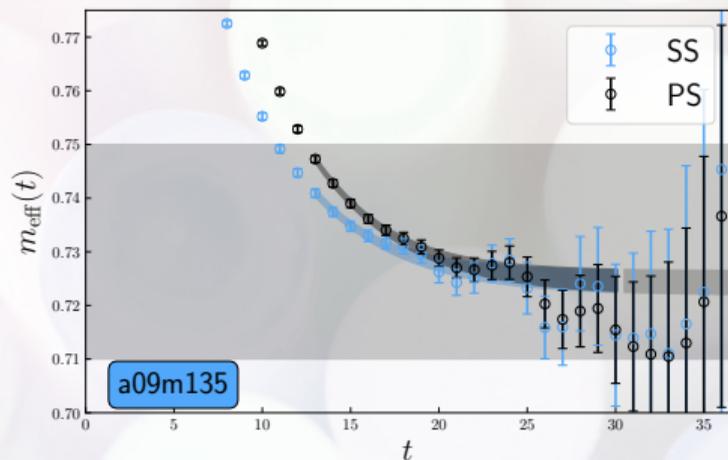
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Strategy

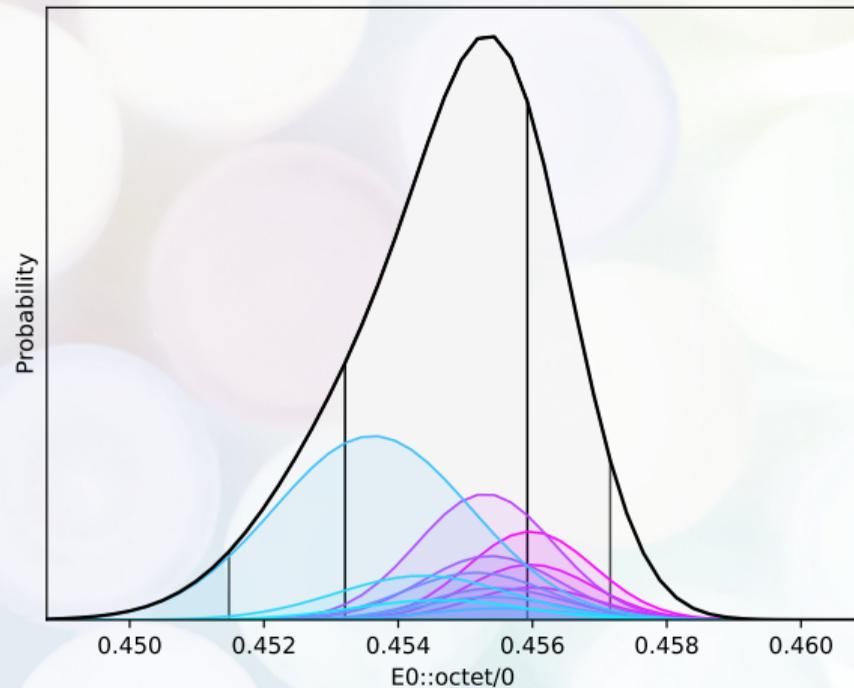


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- ▶ Use Bayes factors & relative stability for model selection
- ▶ Try to optimize t_{\min}^{phys} over all ensembles simultaneously
- ▶ Cross-checks with 3+ people

Some systematic errors

Strategy

- ▶ Model selection is not a replacement for model average!

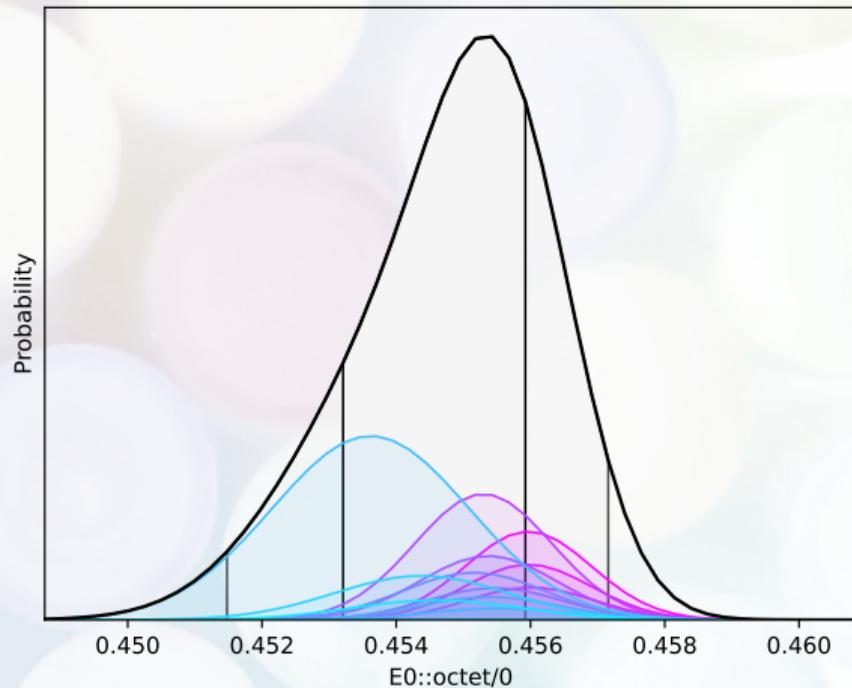


Example from CLS ensemble B450

Some systematic errors

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- ▶ Model selection is not a replacement for model average!
- ▶ Law of large numbers does not necessarily apply to systematic errors \implies posterior will often be non-Gaussian

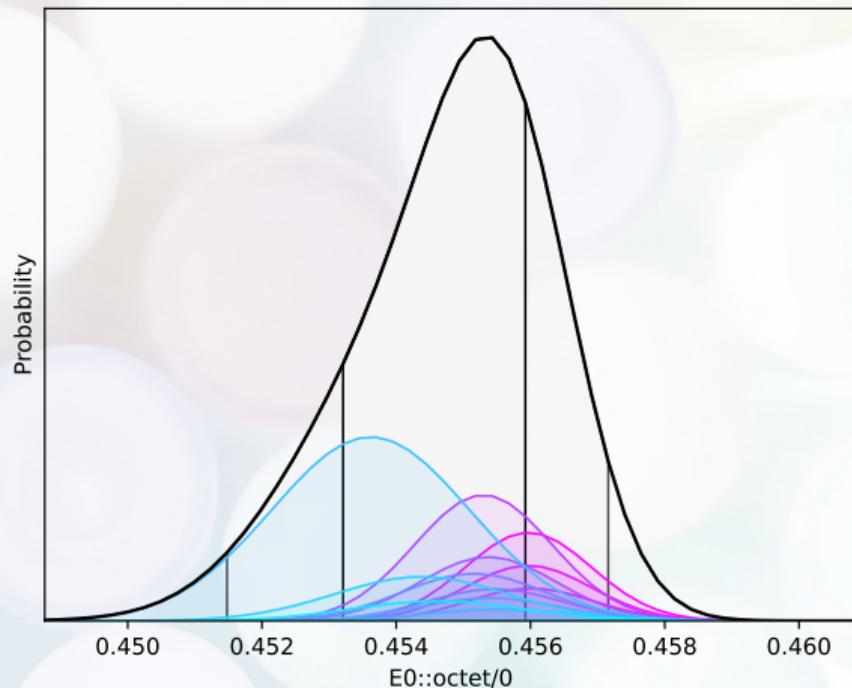


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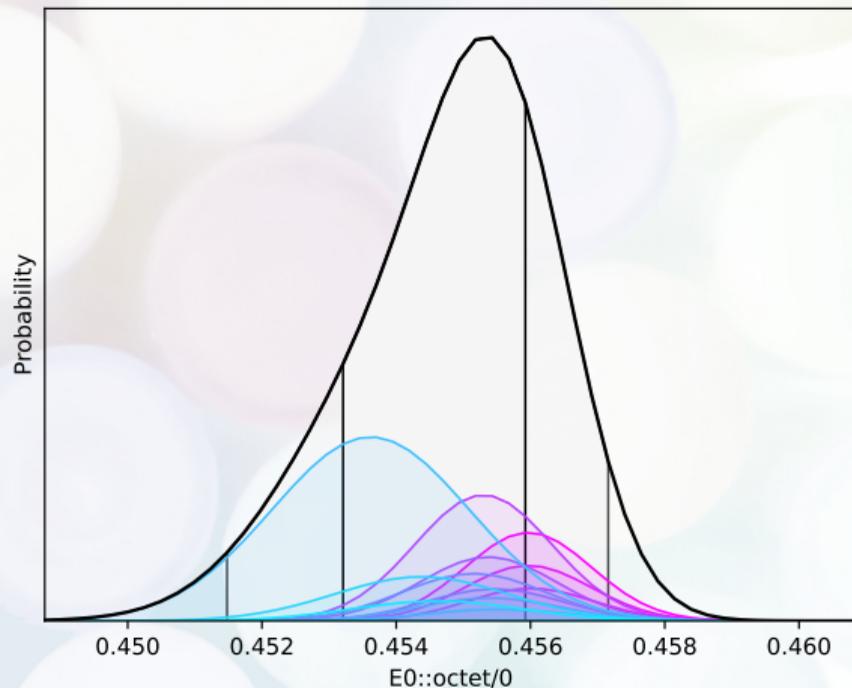


Example from CLS ensemble B450

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- ▶ Law of large numbers does not necessarily apply to systematic errors \implies posterior will often be non-Gaussian
- ▶ Not sufficient to simply quote statistical/systematic errors – we must chain correlations forward
- ▶ Generalized linear least squares is unbiased, but *nonlinear* least squares is not



Example from CLS ensemble B450

Backbone for the analysis: choosing the appropriate effective field theory

Strategy

- ▶ Mixed-action EFT not advantageous per previous studies (e.g., F_K/F_π)
- ▶ SU(3) heavy baryon χ PT converges too slowly \implies use SU(2) heavy baryon χ PT with only pions as degrees of freedom
- ▶ Fix ensembles near physical value of strange quark masses so that Taylor corrections are sufficient

Parameterizing the chiral dependence

Strategy

Generically write $O = O^{\chi} + O^{m_{qs} \neq m_{qs}^*} + O^{\text{disc}}$

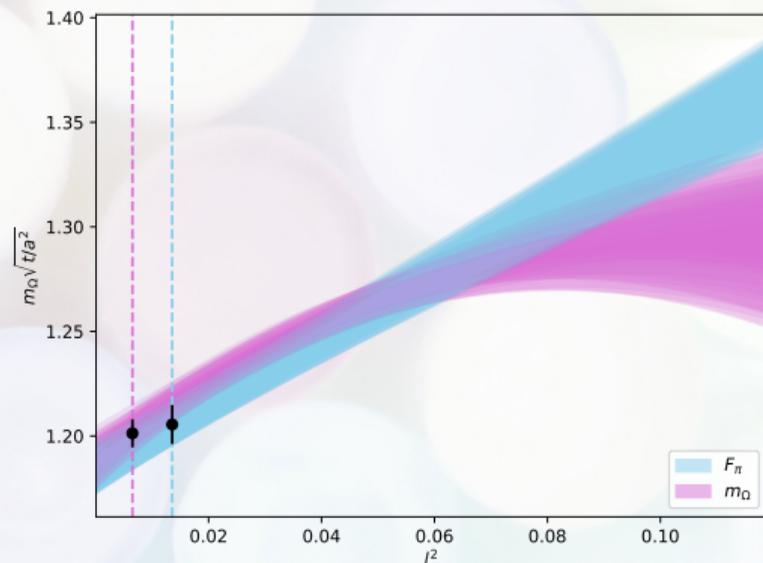
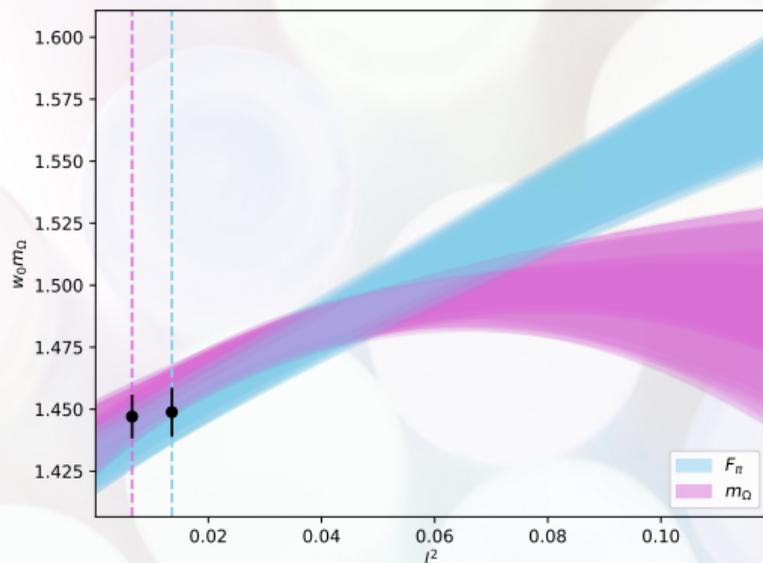
- ▶ SU(3) heavy baryon χ PT converges slowly \implies use SU(2) heavy baryon χ PT w/ Taylor corrections for strange quark mass mistuning
- ▶ Ω baryon has no terms non-analytic in m_{π}^2 until $\mathcal{O}(m_{\pi}^4)$, no odd powers of m_{π}^2 until $\mathcal{O}(m_{\pi}^7)$ \implies no odd powers of m_{π} for $m_{\Omega} w_0$ to working order

$$m_{\Omega}^{\chi} = m_0 \left\{ \begin{array}{l} 1 + \alpha_2 \frac{m_{\pi}^2}{\Lambda_{\chi}^2} + \frac{m_{\pi}^4}{\Lambda_{\chi}^4} [\alpha_4 \lambda_{\pi} + \beta_4] + \frac{m_{\pi}^6}{\Lambda_{\chi}^6} [\alpha_6 \lambda_{\pi}^2 + \beta_6 \lambda_{\pi} + \gamma_6] + \dots \end{array} \right\}$$
$$w_0^{\chi} = w_{0,\text{ch}} \left\{ \begin{array}{l} 1 + k_1 \frac{m_{\pi}^2}{\Lambda_{\chi}^2} + \frac{m_{\pi}^4}{\Lambda_{\chi}^4} [k_2 \lambda_{\pi} + k_3] + \dots \end{array} \right\}$$

where $\lambda_{\pi} = \log(m_{\pi}^2/\mu^2)$ (and we take $\mu = \Lambda = \{4\pi F_{\pi}, m_{\Omega}\}$)

Visualizing the chiral dependence (improved scales)

Strategy



► Despite having very different trajectories, both results agree at physical point

“Fixing” the renormalization scale

Strategy

- ▶ Chiral logs depend on the renormalization scale: $\lambda_l = \log(m_\pi^2/\mu^2)$
- ▶ One natural choice is to use the pion decay constant in the SU(2) limit, $\mu_0 = 4\pi F_0$
- ▶ Consider instead $\mu^{\text{ens}} = 4\pi F_\pi^{\text{ens}}$, with F_π taken on a given lattice ensemble.

$$F_\pi = 1 + \underbrace{\alpha \frac{m_\pi^2}{\Lambda^2} + \beta \frac{m_K^2}{\Lambda^2} - \frac{m_\pi^2}{\Lambda^2} \lambda_l - \frac{1}{2} \frac{m_K^2}{\Lambda^2} \lambda_K}_{\text{NLO}} + \dots$$
$$\implies \log \left(\frac{m_\pi^2}{\mu_0^2} \frac{\mu_0^2}{(\mu^{\text{ens}})^2} \right) = \log \left(\frac{m_\pi^2}{\mu_0^2} \right) - 2\delta_{F_\pi}^{\text{NLO}} + \mathcal{O}(m^4, m^4 \lambda, m^4 \lambda^2, a^2, a^2 \alpha_S)$$

- ▶ To working order, we can absorb these terms into the N³LO terms
- ▶ But at higher order, these corrections potentially become important

Parameterizing the strange quark mass mistuning

Strategy

Generically write $O = O^X + O^{m_{q_s} \neq m_{q_s}^*} + O^{\text{disc}}$

- ▶ All but what ensemble tuned near the strange quark mass \implies a Taylor expansion for strange dependence should suffice

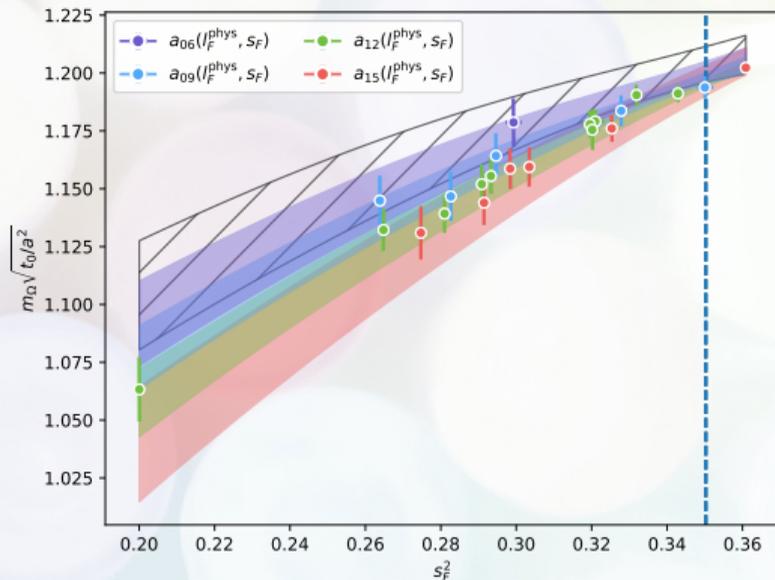
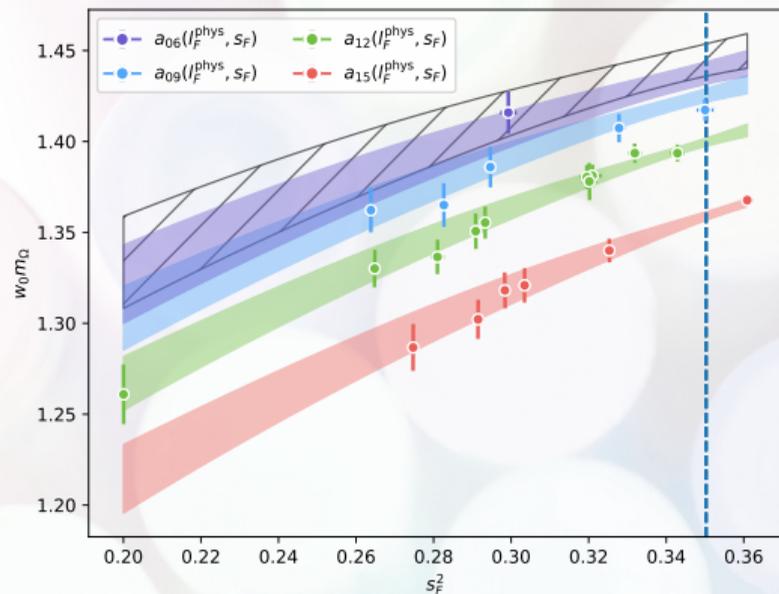
$$m_{\Omega}^{m_{q_s} \neq m_{q_s}^*} = c'_s s_{\Lambda}^2 + c'_{ss} s_{\Lambda}^4 + c'_{sss} s_{\Lambda}^6 + \dots$$

$$w_0^{m_{q_s} \neq m_{q_s}^*} = c''_s s_{\Lambda}^2 + c''_{ss} s_{\Lambda}^4 + c''_{sss} s_{\Lambda}^6 + \dots$$

where $s_{\Lambda}^2 = (2m_{\pi}^2 - m_K^2)/\Lambda_{\chi}^2$

Strange quark mass mistuning

Strategy



Representative model: N³LO w/ chiral logs, $\Lambda = 4\pi F_\pi$

Parameterizing the discretation effects (w/o FV corrections)

Strategy

Generically write $O = O^X + O^{m_{qs} \neq m_{qs}^*} + O^{\text{disc}}$

- ▶ Similar Taylor expansion for a -dependence, but now must also include **radiative corrections** from the Symanzik effective theory

$$m_{\Omega}^{\text{disc}} = \tilde{d}'_a \epsilon_a^2 \alpha_S + d'_a \epsilon_a^2 + d'_{aa} \epsilon_a^4 + d'_{aaa} \epsilon_a^6 \dots$$
$$w_0^{\text{disc}} = \tilde{d}''_a \epsilon_a^2 \alpha_S + d''_a \epsilon_a^2 + d''_{aa} \epsilon_a^4 + d''_{aaa} \epsilon_a^6 \dots$$

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More generally, $\delta_a^{\text{Symanzik}} \sim a^2 \alpha_S^{n+\gamma}$

- ▶ $n = 0$ for MDWF, $n = 1$ for HISQ
- ▶ γ unknown for our action

Proxies for the lattice spacing

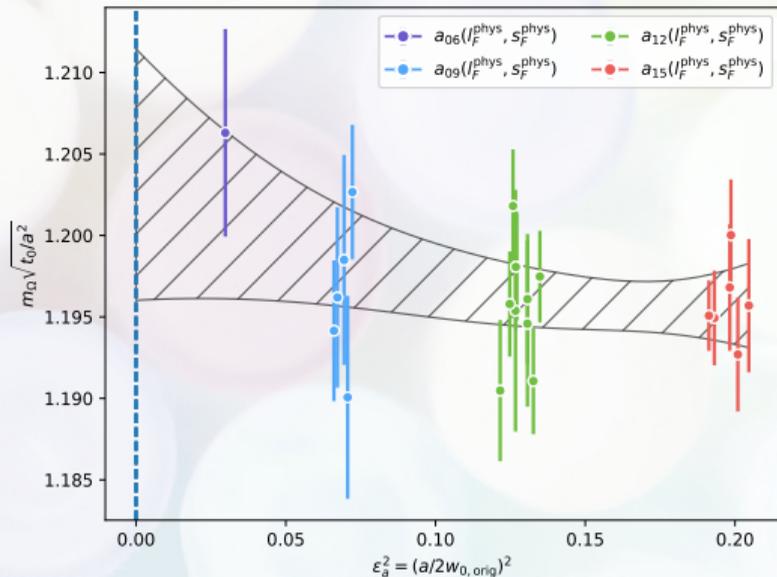
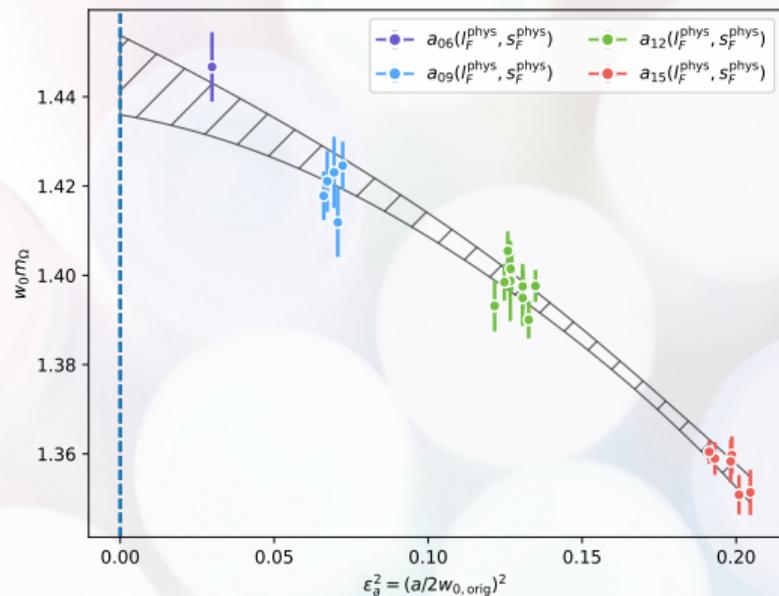
Strategy

- ▶ We define our small parameters such that $l_\Lambda^2 \sim s_\Lambda^2 \sim \epsilon_a^2$
- ▶ In previous work (for F_K/F_π) we parameterized the lattice dependence via $\epsilon_{a,\text{fixed}}^2 = \frac{a^2}{(2w_{0,\text{orig}})^2}$
- ▶ But in this work, in order to give all the gradient flow scales equal footing, we also consider the parameterization

$$\epsilon_{a,\text{var}}^2 = \begin{cases} \frac{a^2}{(2w_{0,\text{orig}})^2}, & y = w_{0,\text{orig}} m_\Omega \\ \frac{a^2}{(2w_{0,\text{imp}})^2}, & y = w_{0,\text{imp}} m_\Omega \\ \frac{a^2}{4t_{0,\text{orig}}}, & y = \sqrt{t_{0,\text{orig}}} m_\Omega \\ \frac{a^2}{4t_{0,\text{imp}}}, & y = \sqrt{t_{0,\text{imp}}} m_\Omega \end{cases}$$

Lattice spacing dependence

Strategy



Representative model: N³LO w/ chiral logs, $\Lambda = 4\pi F_\pi$, $\epsilon_a = \epsilon_{a,\text{fixed}}$

Finite volume corrections

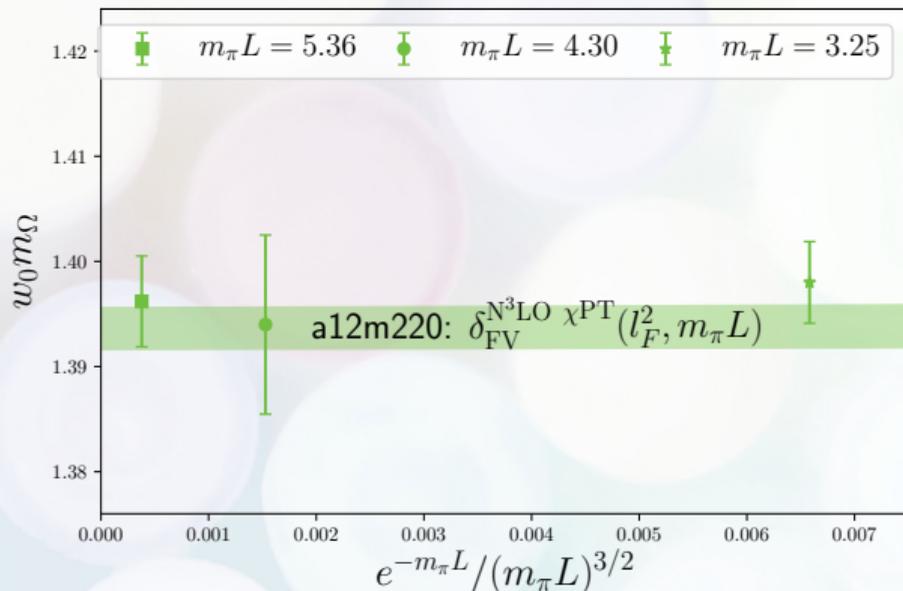
Strategy

Correct for finite volume by modifying the tadpole integral:

$$\log\left(\frac{m^2}{\mu^2}\right) \rightarrow \log\left(\frac{m^2}{\mu^2}\right) + 4k_1(mL)$$

where $k_1(mL) \sim e^{-ML}/(mL)^{3/2}$

- ▶ Determined corrections to $N^3\text{LO}$
- ▶ k_1 has no free parameters
- ▶ Conclusion: F.V. corrections are negligible



Putting it all together

Strategy

Generically write $O = O^X + O^{\text{disc}} + O^{m_{qs} \neq m_{qs}^*}$

► Expand everything, remembering the cross-terms

$$w_0 m_\Omega = c_0 + \delta_{ls,\Lambda}^{\text{NLO}} + \delta_{ls,\Lambda}^{\text{N}^2\text{LO}} + \delta_{ls,\Lambda}^{\text{N}^3\text{LO}} + \delta_{a,\Lambda}^{\text{NLO}} + \delta_{a,\Lambda}^{\text{N}^2\text{LO}} + \delta_{a,\Lambda}^{\text{N}^3\text{LO}}$$

where

$$\begin{aligned} \delta_{ls,\Lambda}^{\text{NLO}} &= l_\Lambda^2 c_l + s_\Lambda^2 c_s, & \delta_{a,\Lambda}^{\text{NLO}} &= d_a \epsilon_a^2 + d'_a \alpha_S \epsilon_a^2, \\ \delta_{ls,\Lambda}^{\text{N}^2\text{LO}} &= l_\Lambda^4 (c_{ll} + c_{ll}^{\text{ln}} \lambda_\pi) + l_\Lambda^2 s_\Lambda^2 c_{ls} + s_\Lambda^4 c_{ss}, & \delta_{a,\Lambda}^{\text{N}^2\text{LO}} &= d_{aa} \epsilon_a^4 + \epsilon_a^2 (d_{al} l_\Lambda^2 + d_{as} s_\Lambda^2), \\ \delta_{ls,\Lambda}^{\text{N}^3\text{LO}} &= l_\Lambda^6 (c_{lll} + c_{lll}^{\text{ln}} \lambda_\pi + c_{lll}^{\text{ln}^2} \lambda_\pi^2) + l_\Lambda^4 s_\Lambda^2 \lambda_\pi c_{lls}^{\text{ln}} & \delta_{a,\Lambda}^{\text{N}^3\text{LO}} &= d_{aaa} \epsilon_a^6 + \epsilon_a^4 (d_{aal} l_\Lambda^2 + d_{aas} s_\Lambda^2) \\ &+ l_\Lambda^4 s_\Lambda^2 c_{lls} + l_\Lambda^2 s_\Lambda^4 c_{lss} + s_\Lambda^6 c_{sss}, & &+ \epsilon_a^2 (d_{all} l_\Lambda^4 + d_{als} l_\Lambda^2 s_\Lambda^2 + d_{ass} s_\Lambda^4). \end{aligned}$$

25 unknown LECs! Can we fit all of these terms?

Example Models

Strategy

- Instead of fitting the full expression, consider various truncations & model average

$$w_0 m_\Omega = \underbrace{c_0}_{\text{LO}} + \underbrace{\delta^{\text{NLO}}(I_F, S_F)}_{\text{chiral NLO}} + \underbrace{\delta_{a,F}^{\text{NLO}}}_{\text{disc NLO}}$$

$$w_0 m_\Omega = \underbrace{c_0}_{\text{LO}} + \underbrace{\delta^{\text{NLO}}(I_F, S_F)}_{\text{chiral NLO}} + \underbrace{\delta^{\text{N}^2\text{LO}}(I_F, S_F)}_{\text{chiral N}^2\text{LO}} + \underbrace{\delta_{\text{ln}}^{\text{N}^2\text{LO}}}_{\text{chiral log N}^2\text{LO}}$$
$$+ \underbrace{\delta_{a,F}^{\text{NLO}}}_{\text{disc NLO}} + \underbrace{\delta_{a,F}^{\text{N}^2\text{LO}}}_{\text{disc N}^2\text{LO}} + \underbrace{\delta_{L,F}^{\text{N}^2\text{LO}}}_{\text{FV N}^2\text{LO}}$$

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Setting priors with empirical Bayes

Strategy

- ▶ Stabilize fits with priors
- ▶ Because we tune to the physical strange quark mass, light quark mass dependence can be guesstimated by eye
- ▶ Assume higher-order LECs are of similar size
- ▶ But what about the rest?

Setting priors with empirical Bayes

Strategy

Let $M = \{\Pi, f\}$ denote a model. Per Bayes's theorem:

$$p(\Pi|D, f) = \frac{p(D|\Pi, f)p(\Pi|f)}{p(D|f)}$$

Assuming a uniform distribution for the hyperpriors $p(\Pi|f)$:

$$\text{peak of } p(D|\Pi, f) \implies \text{peak of } p(\Pi|D, f)$$

where $p(D|\Pi, f) = \int d\theta P(D|\theta, \Pi, f)P(\theta|\Pi, f)$ is the marginal likelihood function

- ▶ Implemented in `lsqfit` via `lsqfit.empbayes_fit`

Setting priors with empirical Bayes

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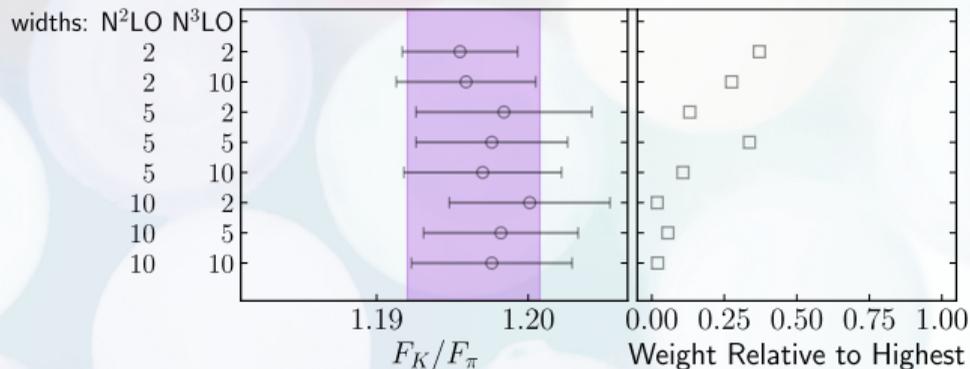
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- ▶ Shouldn't use for everything – only use for discretization terms
- ▶ Tune each model independently



Results

Model averaging

Results

Weight fits with Bayes factor:

- ▶ like a likelihood ratio, but Bayesian
- ▶ automatically penalizes more complicated models

×2 : Expand to N²LO or N³LO

×2 : w/ or w/o chiral logs

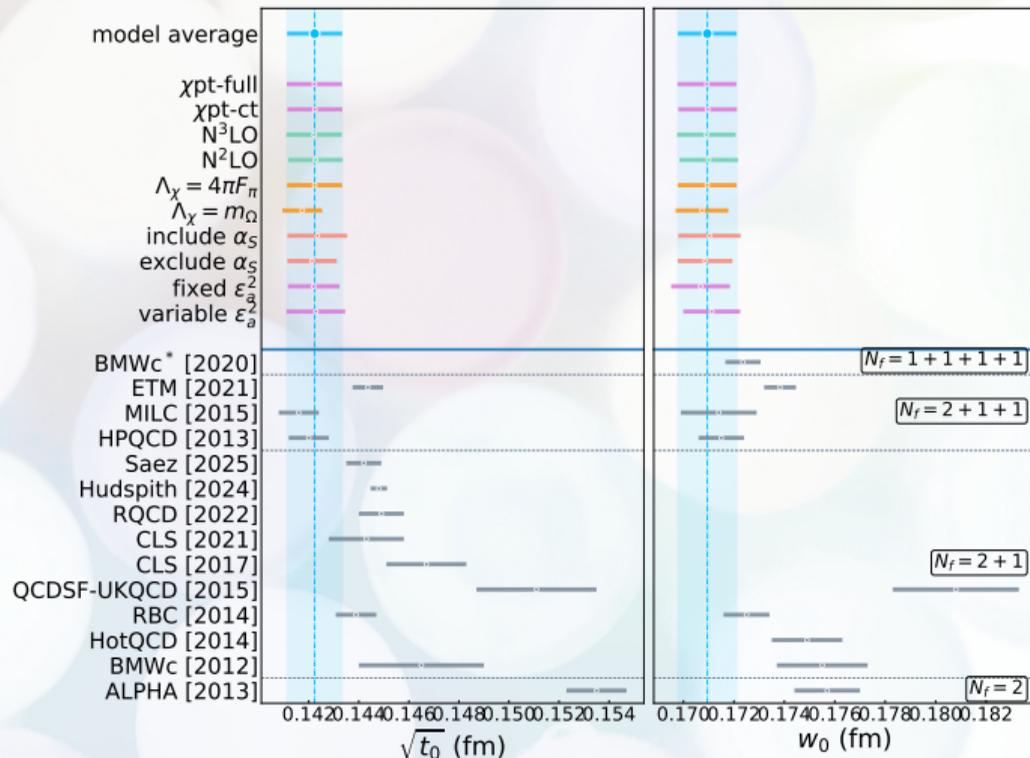
×2 : incl./excl. F.V. corrections

×2 : incl./excl. $\alpha_S a^2$

×2 : $\Lambda = 4\pi F_\pi, M_\Omega$

×2 : $\epsilon_a = \epsilon_{a,\text{fixed}}, \epsilon_{a,\text{var}}$

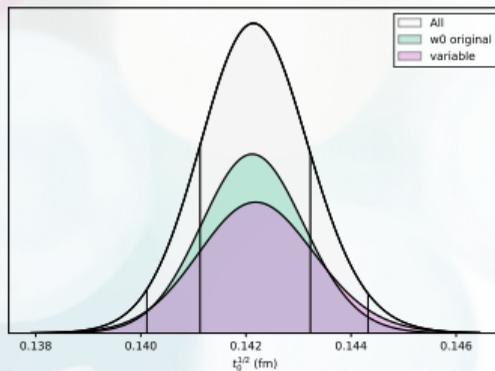
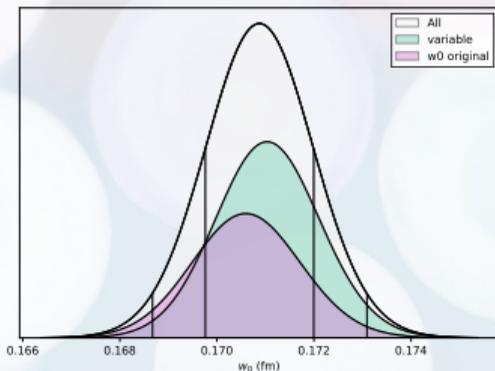
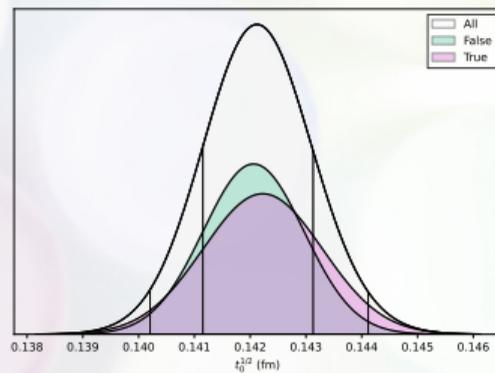
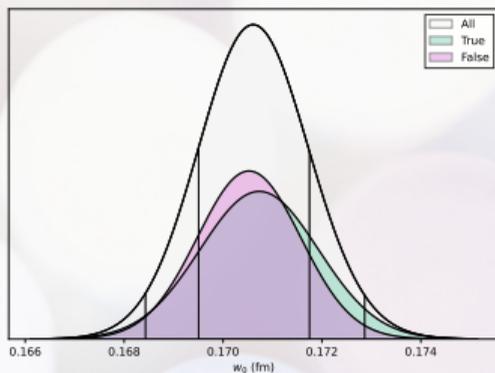
64 : total choices



Most important variations

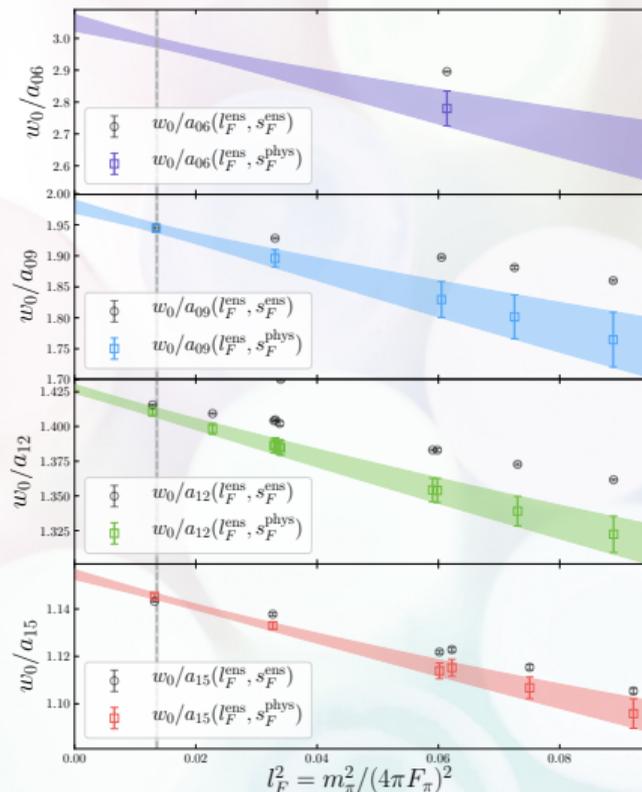
Results

- ▶ Models with $\Lambda_\chi = 4\pi F_\pi$ have much greater weight than $\Lambda_\chi = M_\Omega$
- ▶ Next largest variations come from including/excluding radiative $a^2\alpha_S$ discretization term (top), choice of $\epsilon_{a,\text{variable}}$ vs $\epsilon_{a,\text{fixed}}$ (bottom)



Measuring the lattice spacings

Results



We can determine the lattice spacing (in physical units) on each ensemble by fitting the N²LO expression for each lattice spacing

$$\frac{w_0}{a} = \frac{w_{0,\text{ch}}}{a} \left\{ 1 + k_l l_F^2 + k_s s_F^2 + k_a \epsilon_{a,\text{ch}}^2 + k_{ll} l_F^4 + k_{lln} l_F^4 \ln(l_F^2) + k_{ls} l_F^2 s_F^2 + k_{ss} s_F^4 + k_{aa} \epsilon_{a,\text{ch}}^4 + k_{al} l_F^2 \epsilon_{a,\text{ch}}^2 + k_{as} s_F^2 \epsilon_{a,\text{ch}}^2 \right\}$$

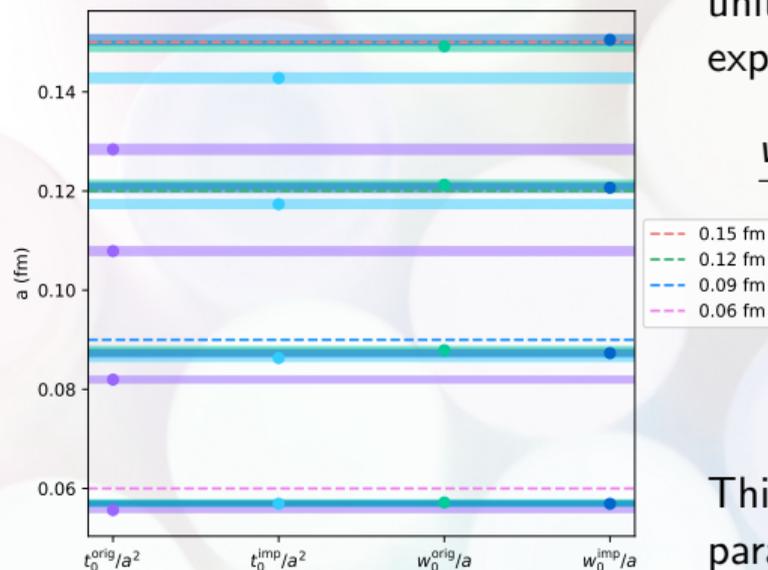
This requires us to use a different expansion parameter for ϵ_a

$$\epsilon_{a,\text{ch}} = \frac{1}{(2w_{0,\text{ch}}/a)}.$$

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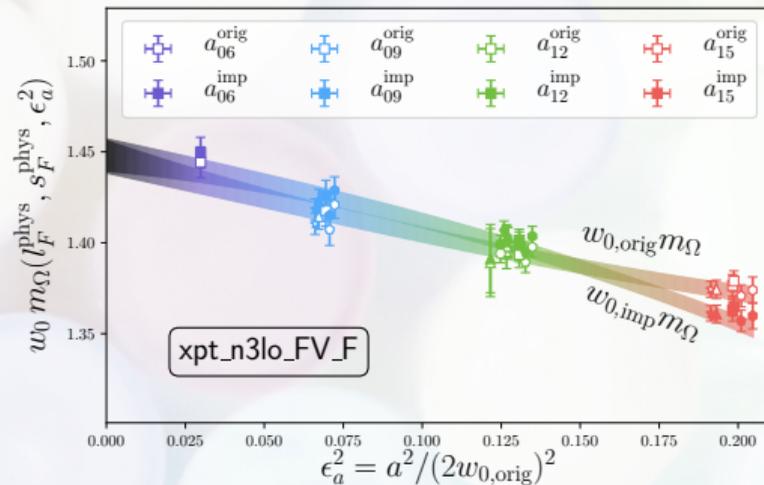
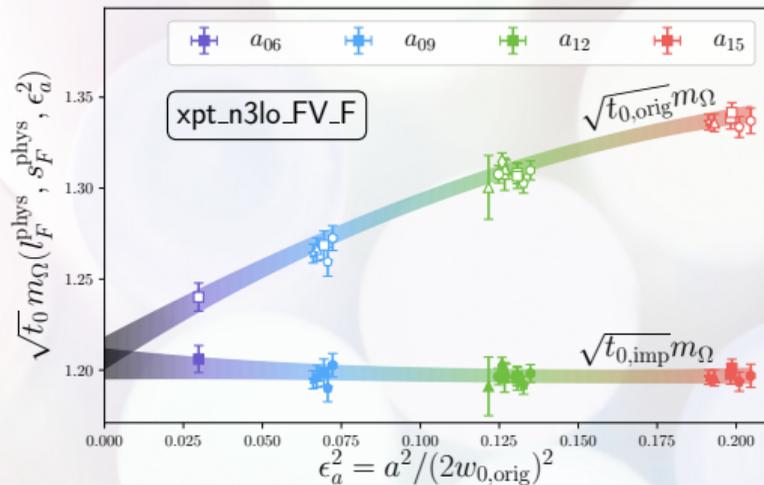
This requires us to use a different expansion parameter for ϵ_a

$$a = w_0 / (w_{0,\text{ch}} / a)$$

$$\epsilon_{a,\text{ch}} = \frac{1}{(2w_{0,\text{ch}} / a)}$$

Continuum approach for different gradient flow scales

Results



- ▶ Although $\sqrt{t_{0,\text{orig}}}$ and $\sqrt{t_{0,\text{imp}}}$ agree in the continuum, their approaches are quite different!

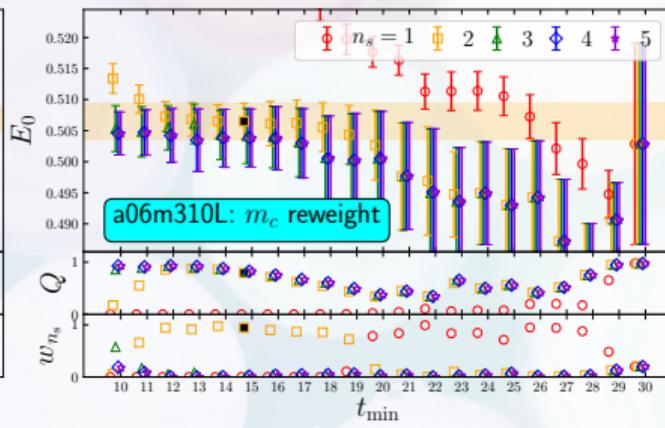
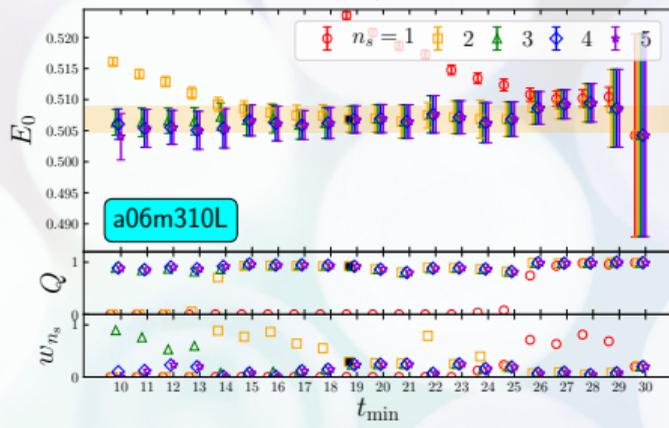
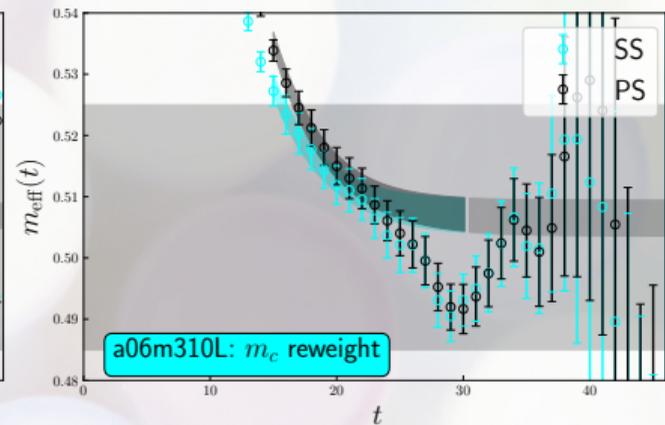
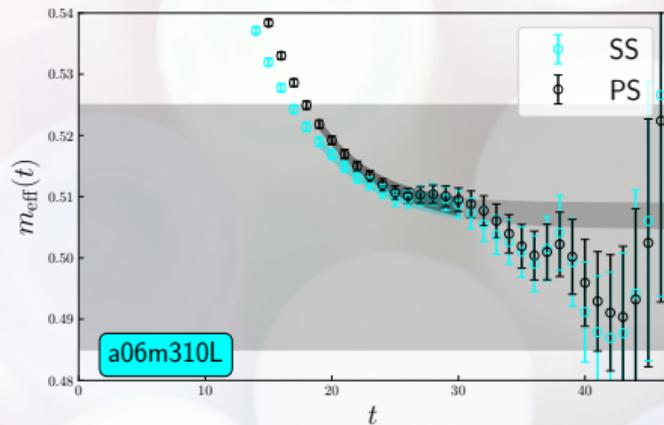
Charm reweighting (1/2)

Results

- ▶ On our finest ensemble, charm quark mass mistuned by about $\sim 10\%$ of the physical value
- ▶ Although this might sound rather mild, the size of the mistuning is \sim the size of the strange quark mass
- ▶ Does the mistuning matter?

Charm reweighting (2/2)

Results



Updates

Ratio of flow scales $\sqrt{t_0}/w_0$ (preliminary)

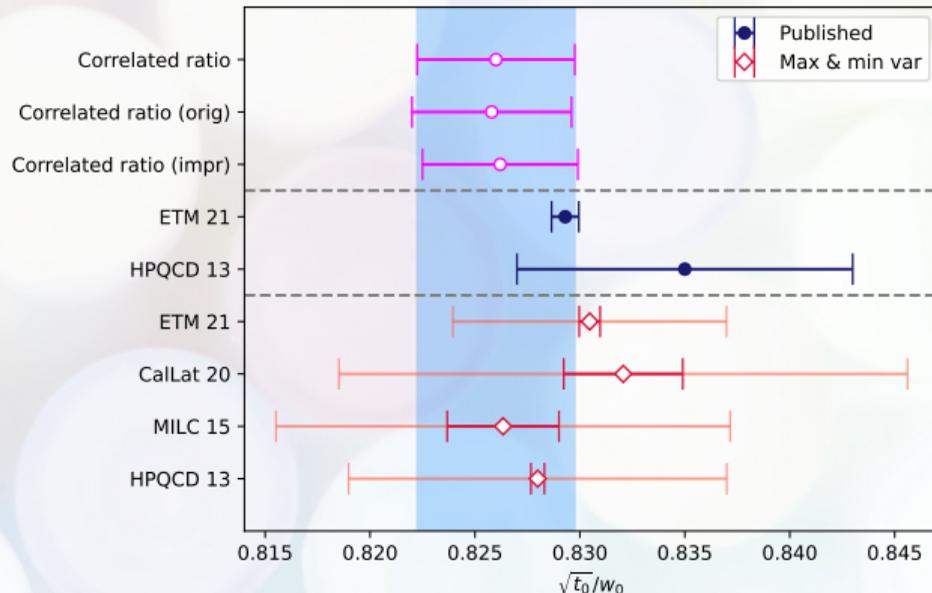
Updates

- ▶ In Callat20, fits for $m_\Omega w_0$ and $m_\Omega \sqrt{t_0}$ were treated separately \rightarrow fit simultaneously to form correlated ratio $\sqrt{t_0}/w_0$ for each model
- ▶ This changes the model weights somewhat, leading to $< 1\sigma$ shifts in w_0 , $\sqrt{t_0}$.

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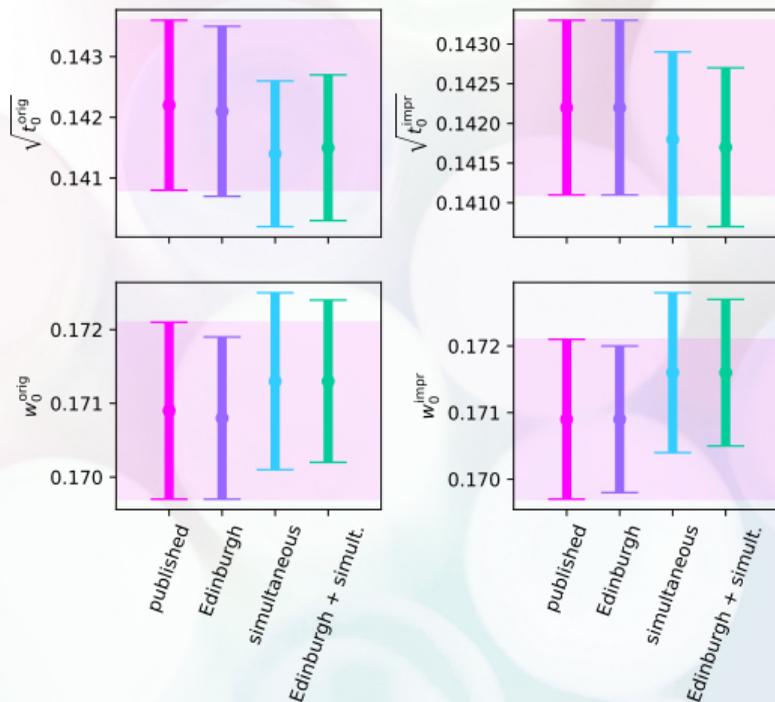


$$\max/\min \text{Var}\left(\frac{X}{Y}\right) = \left(\frac{X}{Y}\right)^2 \left[\left(\frac{\sigma_X}{X}\right)^2 + \left(\frac{\sigma_Y}{Y}\right)^2 \pm 2\frac{\sigma_X\sigma_Y}{XY} \right]$$

Redefining the physical point per the Edinburgh consensus

(preliminary)

Updates



Flag 2015 Edinburgh

$$m_\pi : \quad 134.8(3) \rightarrow 135.0$$

$$m_K : \quad 494.2(3) \rightarrow 494.6$$

$$f_\pi : \quad 130.21(81) \rightarrow 130.5$$

- ▶ Using FLAG as input avoids QED, possible BSM corrections
- ▶ Edinburgh choice reduces physical point uncertainty in error budget, but numbers otherwise nearly identical

Bayesian model averaging

Overview

Bayesian model averaging

The issue of BMA can be roughly split into two parts:

- ▶ The estimation of model weights
- ▶ The procedure for computing the statistical, systematic errors

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Bayesian model averaging

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- ▶ The estimation of model weights
- ▶ The procedure for computing the statistical, systematic errors

We concentrate on the latter point. *Desiderata* for our procedure:

- ▶ Able to separately estimate statistical, systematic errors
- ▶ Able to track correlations between different model-averaged observables
- ▶ Able to chain the results from model-averaged analysis \mathcal{A} to a second model-averaged analysis \mathcal{B}

Quadrature

Bayesian model averaging

Popularized by Neil & Jay:

$$\begin{aligned}\text{Var}[X] &= E[X^2] - E[X]^2 \\ &= E[E[X^2|M]] - E[(E[X|M])]^2 \\ &= \sum_M p(M) \langle X^2 \rangle_M - \left(\sum_M p(M) \langle X \rangle_M \right)^2 \\ &= \sum_M p(M) \text{Var}(X)_M + \sum_M p(M) \langle X \rangle_M^2 - \left(\sum_M p(M) \langle X \rangle_M \right)^2\end{aligned}$$

Quadrature

Bayesian model averaging

Generalization to covariance follows directly from the law of total covariance:

$$\begin{aligned}\mathbb{E}[X] &= \mathbb{E}[\mathbb{E}[X|M]] \\ \text{Cov}(X, Y) &= \underbrace{\mathbb{E}[\text{Cov}(X, Y|M)]}_{\text{EVPC}} + \underbrace{\text{Cov}(\mathbb{E}[X|M], \mathbb{E}[Y|M])}_{\text{CHM}}\end{aligned}$$

(EVPC: expectation value of process covariance; CHM: covariance of hypothetical means)

Is this model averaging?

Quadrature

Bayesian model averaging

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(EVPC: expectation value of process covariance; CHM: covariance of hypothetical means)

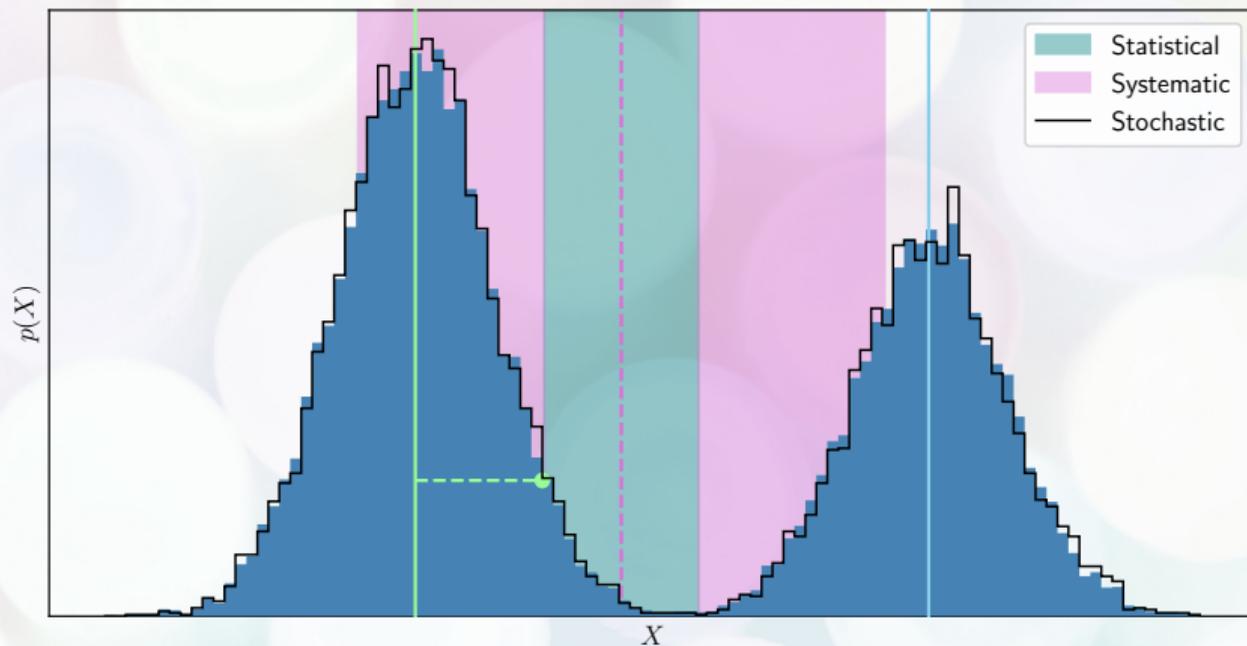
Is this model averaging? Sort of?

$$p(X, Y) = \sum_{\mathcal{M}} p(X, Y|\mathcal{M})p(\mathcal{M})$$

Total variance matches the marginal posterior, but none of the other moments are likely to match

Gaussian: Prediction

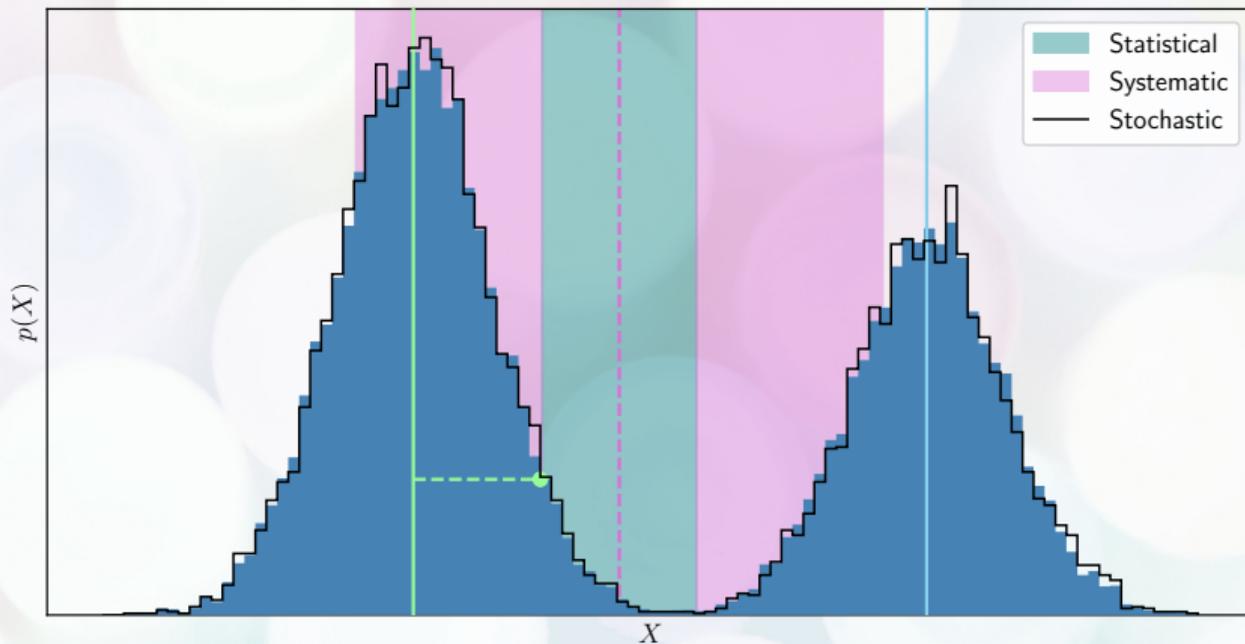
Bayesian model averaging



$$p(X, Y) \xrightarrow{\text{quadrature}} \mathcal{N}(\langle \mathbb{E}[X], \mathbb{E}[Y] \rangle, \text{EVPC}(X, Y) + \text{CHM}(X, Y))$$

Stochastic: Prediction

Bayesian model averaging



- Boyle et al (2024): for each resample, pick a model $M^r \sim p(M)$

Some other options

Bayesian model averaging

Desiderata for BMA:

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- ▶ Able to track correlations between different model-averaged observables
- ▶ Able to chain the results from model-averaged analysis \mathcal{A} to a second model-averaged analysis \mathcal{B}

Some options:

- ▶ Fermilab/HPQCD/MILC [hep-lat/2411.09656]: requires quadrature, higher-order moments lost
- ▶ BMW [hep-lat/2407.10913]: parametric bootstrap; different predictions for statistical & systematic errors; can construct pathological examples
- ▶ Boyle et al [hep-lat/2406.19193]: stochastic, semi-parametric bootstrap; appears to underestimate/overestimate stat/sys errors compared to Fermilab
- ▶ Frison [hep-lat/2302.06550]: fully Bayesian; complicated

Summary & future work

- ▶ Finite volume corrections explicitly worked out to $N^3\text{LO}$, found to be negligible
- ▶ Even in cases of relatively severe charm quark mass mistuning, impact is relatively mild
- ▶ There is no standard procedure for BMA in our community
- ▶ For us, scale setting is our dominant uncertainty when extrapolating in physical units, e.g. in our current effort to measure the nucleon sigma term



Backup

Approximate marginal posterior as a Gaussian mixture:

$$X \sim \sum_M w_M N(\mu_M, \sigma_M) \rightarrow \sum_M w_M N(\mu_M, \sqrt{\lambda} \sigma_M)$$

Let $I(\lambda) = Q(0.84; \lambda) - Q(0.16; \lambda)$ (with Q the quantile function) and

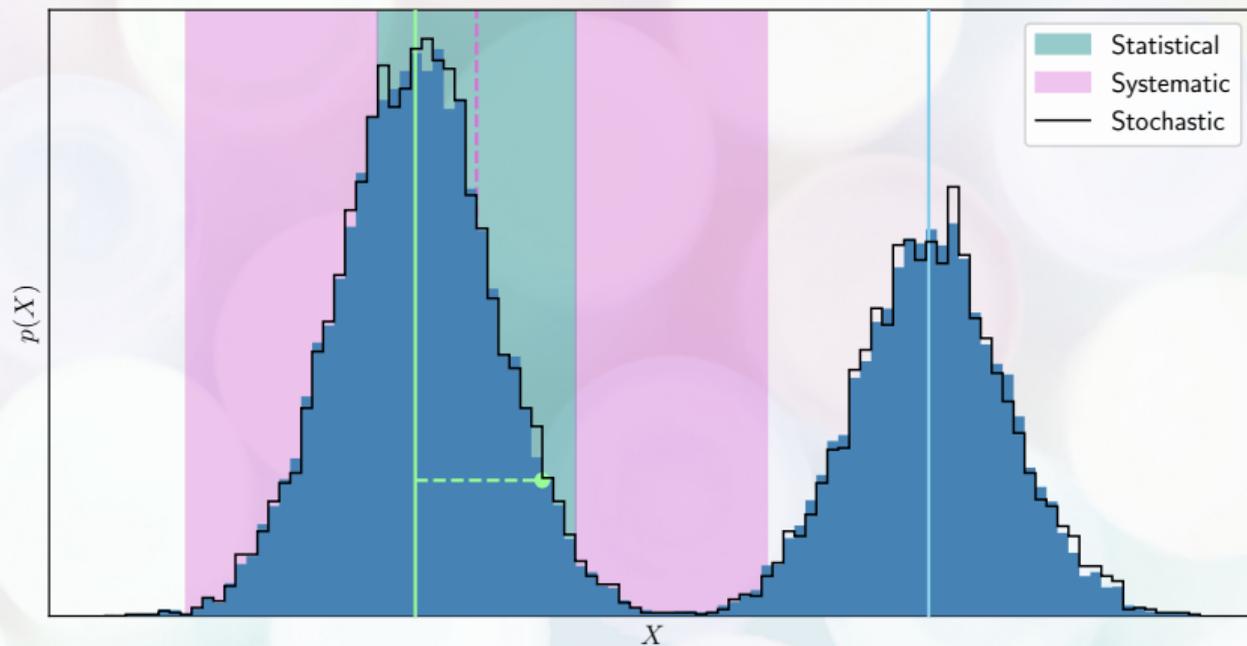
$$\sigma_{\text{sys}}^2 + \lambda \sigma_{\text{stat}}^2 \equiv I(\lambda)^2 / 4.$$

If the relationship between λ and $I(\lambda)^2$ is linear, statistical and systematic errors are uniquely defined by solving for two different values of λ .

Use median for best estimate.

BMW: Prediction

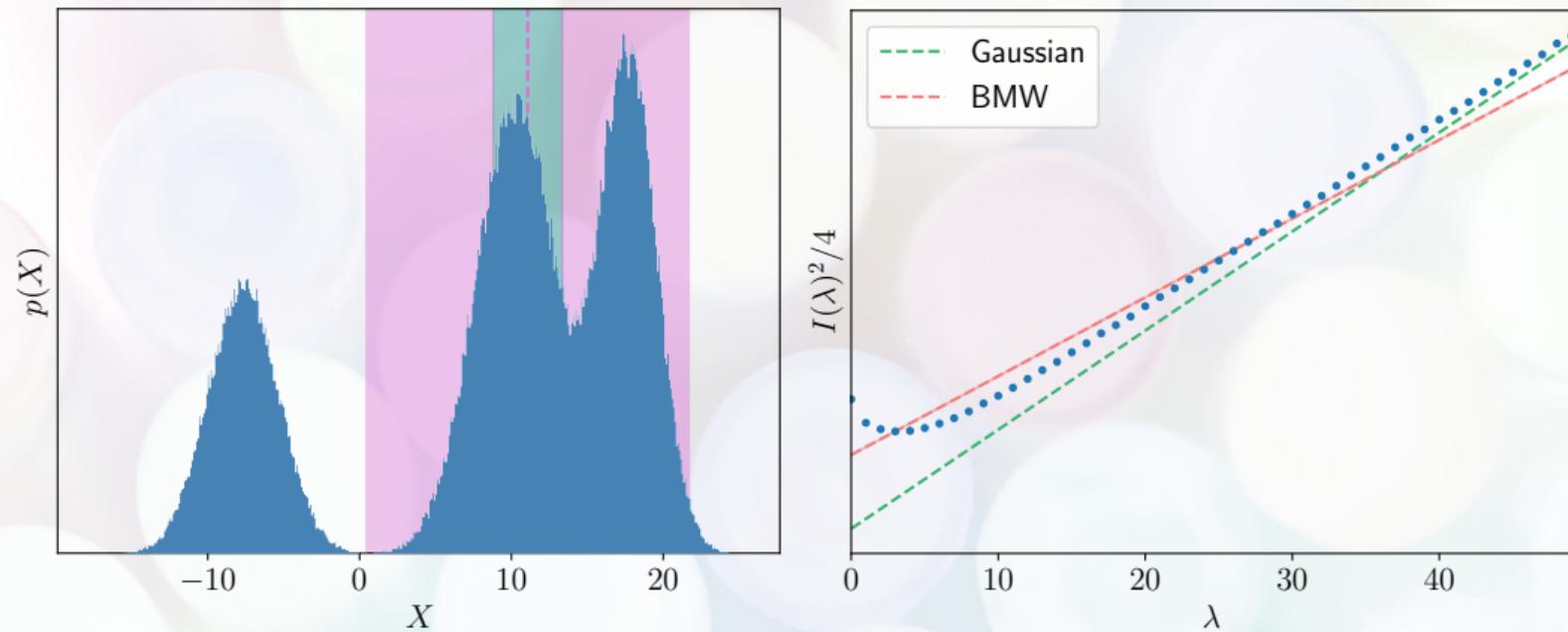
Backup



- ▶ Although error estimated with confidence intervals, this is not a confidence interval

BMW: A pathological example

Backup



► Must check that residuals are normal, but procedures still not guaranteed to match