Cosmology with Type Ia supernovae

Searching for systematics and model independent reconstructions

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For more detail, see the online poster and
Koo et al. 2020, ApJ, 899, 9 (arXiv:2001.10887)
Kazantzidis et al. 2020, arXiv:2010.03491
Koo et al. 2020, arXiv:2009.12045

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Introduction

- Type Ia supernovae (SN Ia) are used as standardizable candles for distance measurement and have become one of important portion of modern cosmology

- The standardization is purely empirical and requires SN Ia light curve fitting model with the number of parameters and hyperparameters

- The light-curve hyperparameters are usually constrained based on assumption of cosmological model

Introduction

- To search for systematics in the SN Ia data, model independent reconstruction is required

- After reconstruction, we can look for features in the data which can be a hint for systematics or new physics

- Also perform model selection and parameter estimation without comparing models

Light-curve hyperparameters

- The Joint Light-curve Analysis (JLA) compilation have light-curve parameters information based on SALT2 fitter
  Betoule et al. 2014
  Guy et al. 2007; Mosher et al. 2014

- $\mu = m_B^\star - (M_B - \alpha X_1 + \beta C)$
  Tripp.1998

- $m_B^\star$, X_1, C are provided light-curve parameters

- α, β, M_B^1, Δ_M are light-curve hyperparameters
  $M_B = M_B^1$ if $M_{\mathrm{stellar}} < 10^{10} M_{\mathrm{sun}}$ (M_{stellar}: Stellar mass of host galaxy)
  $M_B = M_B^1 + \Delta_M$ otherwise

Iterative smoothing method

- The non-parametric method to reconstruct the distance modulus and expansion history of the universe
  Shafieloo et al. 2006, 2018; Shafieloo. 2007; Shafieloo & Clarkson 2010

- Starts from initial guess of distance modulus, but generates model-independent reconstruction of distance modulus with lower χ^2 value after numerous iterations

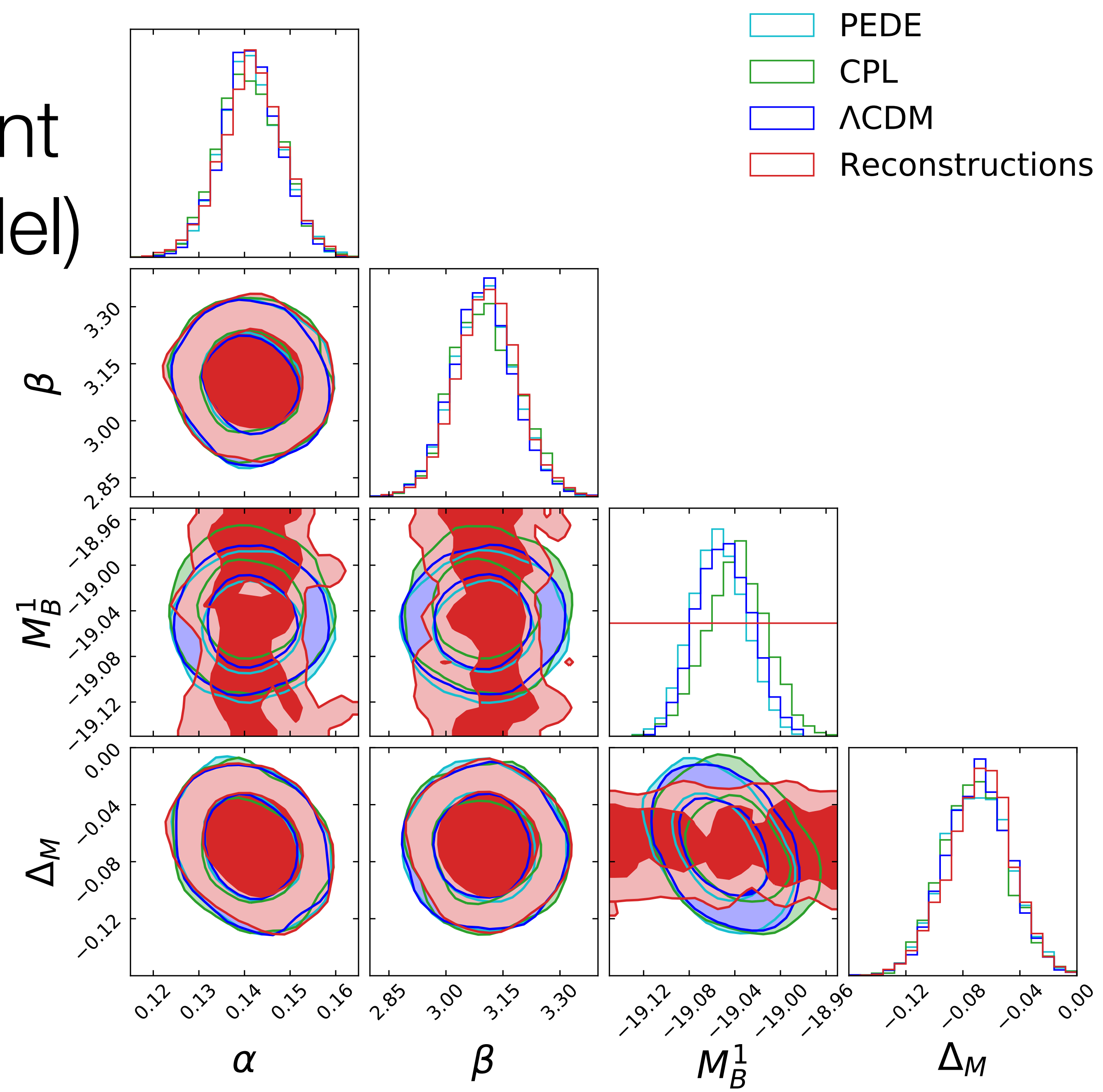
$$\hat{\mu}_{n+1}(z) = \hat{\mu}_n(z) + \frac{\boldsymbol{\delta\mu_n}^T \cdot \mathbf{C}^{-1} \cdot \boldsymbol{W}(z)}{\mathbf{1}^T \cdot \mathbf{C}^{-1} \cdot \boldsymbol{W}(z)}$$ ($\mathbf{C}^{-1}$: inverse of the covariance matrix from JLA)

$$\mathbf{1}^T = (1,\cdots,1), \quad \boldsymbol{W}_i(z) = \exp\left(-\frac{\ln^2(\frac{1+z}{1+z_i})}{2\Delta^2}\right), \quad \boldsymbol{\delta\mu_n}|_i = \mu_i - \hat{\mu}_n(z_i)$$

$$\chi^2_n = \boldsymbol{\delta\mu_n}^T \cdot \mathbf{C}^{-1} \cdot \boldsymbol{\delta\mu_n}$$

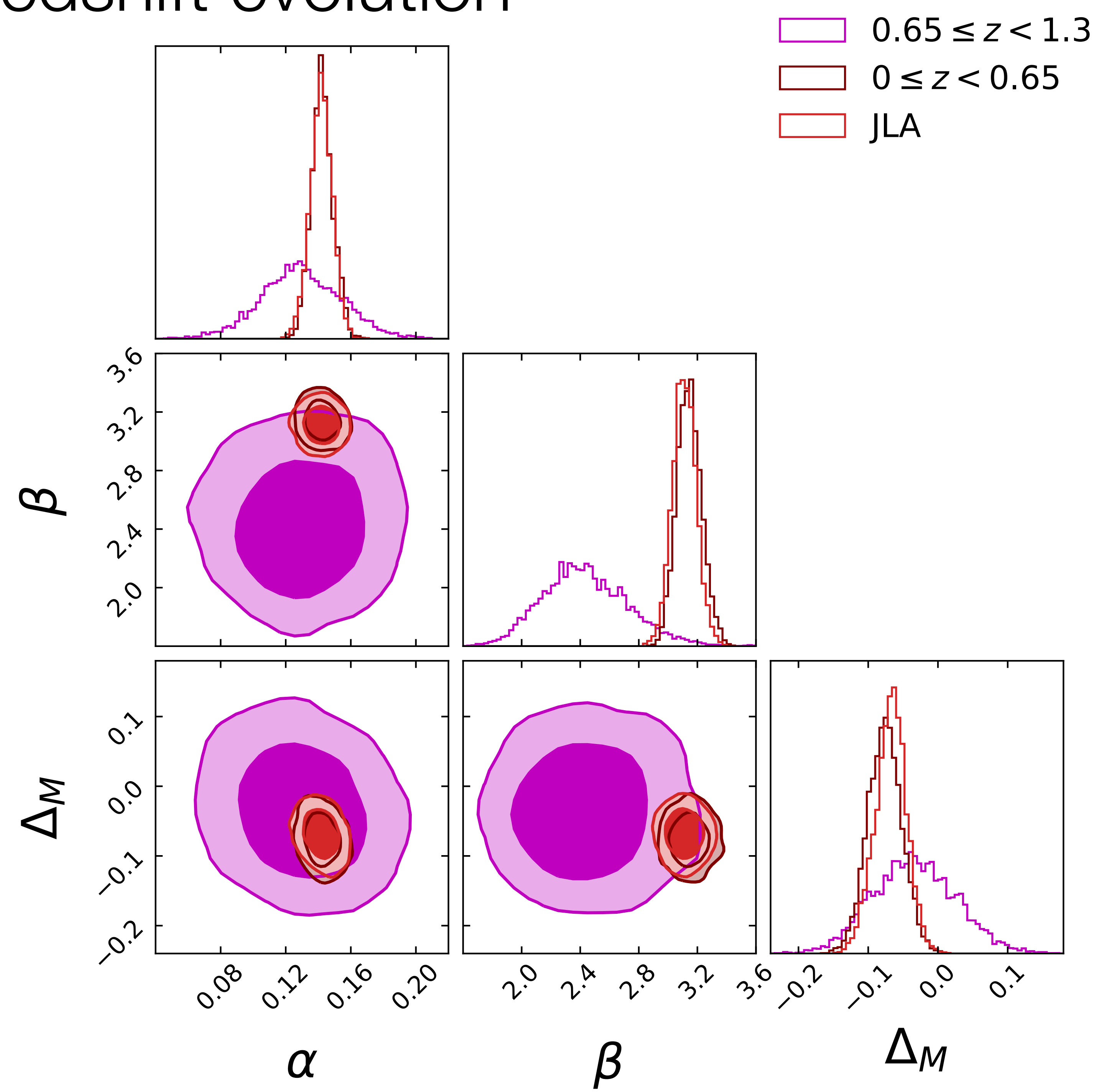
Constraints

- Assume 3 models for comparison
- Contours are all consistent (No dependence on model)



Constraints (Reconstructions)

- No clear redshift evolution



Looking for features in SN Ia data

- Pantheon: Based on SALT2 fitter, more recent than JLA, includes more SNe Ia, considers more uncertainties
  Scolnic et al. 2018

- Oscillating features in Pantheon data at $z<0.5$ around the best-fit ΛCDM model

- See how generic such behavior is found at many Monte Carlo realizations of the data (using full covariance matrix of the Pantheon data)

Looking for features in SN Ia data

Bin	z Range	$\mathcal{M} \pm 1\sigma$ error	$\Delta\sigma_{\mathcal{M}}$	$\Omega_{0m} \pm 1\sigma$ error	$\Delta\sigma_{\Omega_{0m}}$
Full Data	$0.01 < z < 2.26$	23.81 ± 0.01	-	0.29 ± 0.02	-
1st	$0.01 < z < 0.13$	23.78 ± 0.03	1.14	0.07 ± 0.17	1.35
2nd	$0.13 < z < 0.25$	23.89 ± 0.06	1.48	0.56 ± 0.19	1.34
3rd	$0.25 < z < 0.42$	23.75 ± 0.06	0.99	0.18 ± 0.11	1.05
4th	$0.42 < z < 2.26$	23.85 ± 0.06	0.69	0.33 ± 0.06	0.50

Kazantzidis. Koo. Nesseris. Shafieloo. Perivolaropoulos. 2020

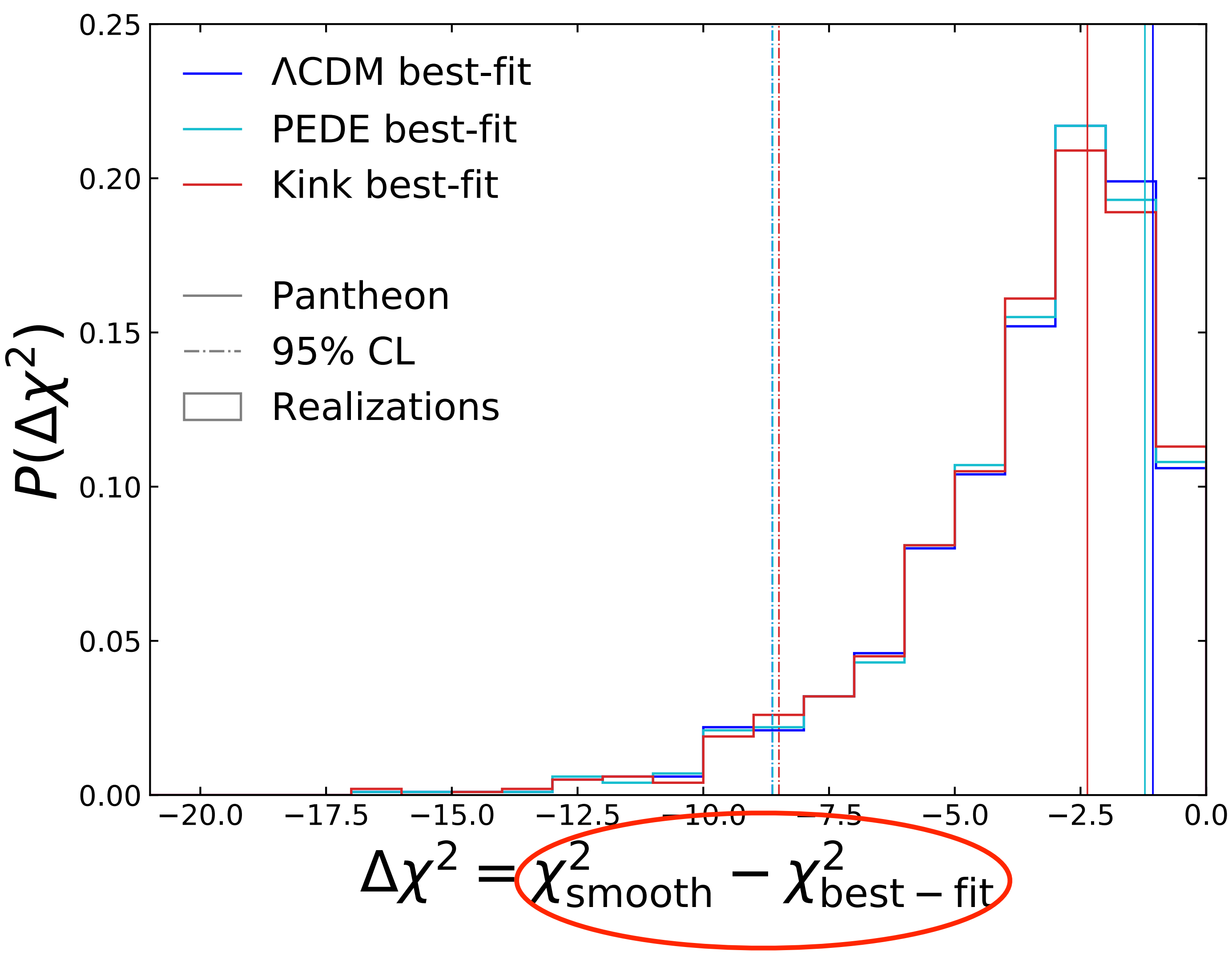
- Large $\boldsymbol{\sigma}$ deviation of the redshift binned best-fit parameter values from their full dataset best-fit values
- Such features occur in 4-5% of Pantheon-like simulations
- Might be a hint to possible systematic or new physics

Direct model testing

- Model testing using bayesian evidence depends on comparing models
- We try to test consistency of a model and the data without comparing different models
- Estimate likelihood distribution of $\Delta\chi^2$ using iterative smoothing method for model selection and parameter estimation

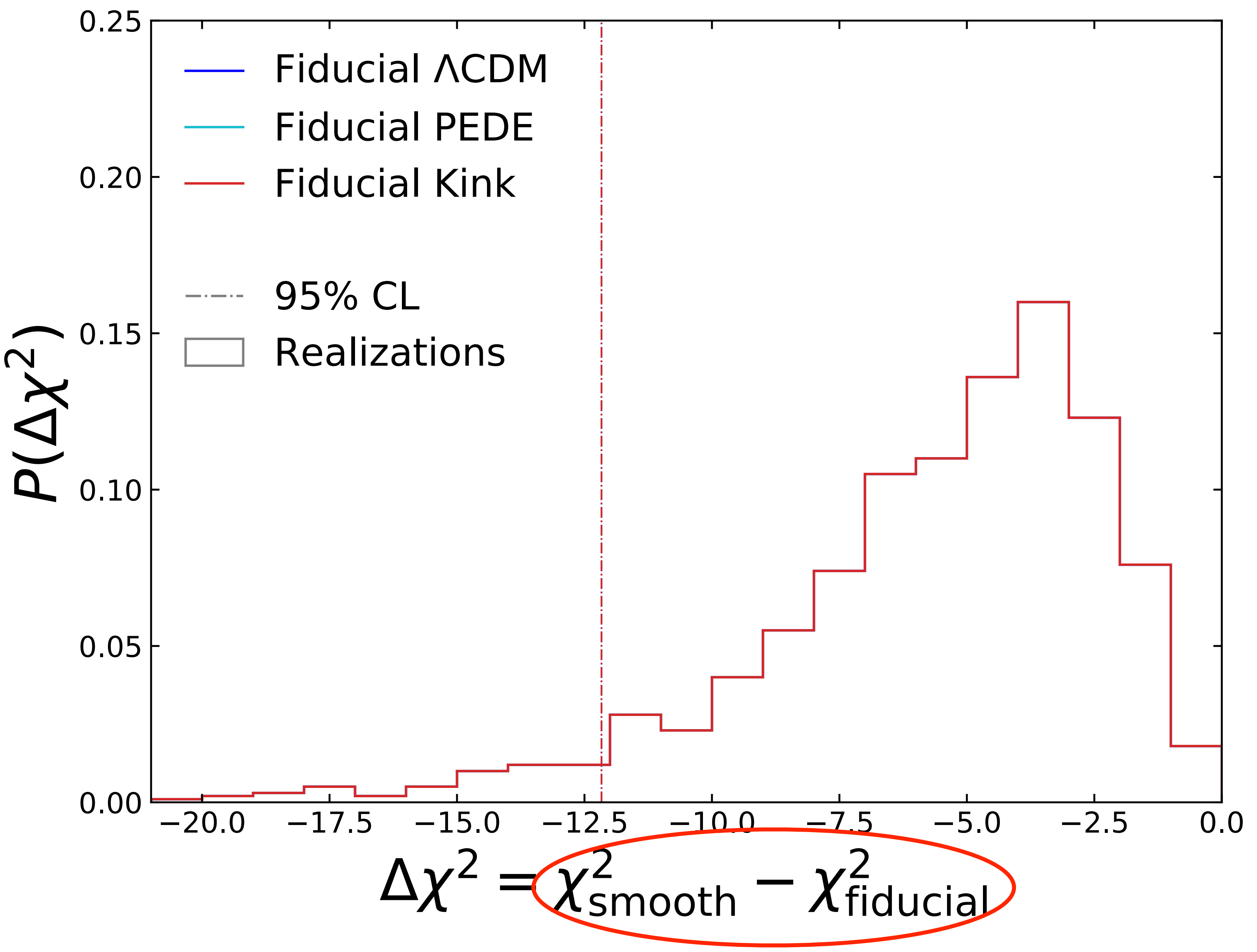
Model selection

- 1000 Pantheon-like mock realizations
- No dependence on cosmological models that are used for simulation



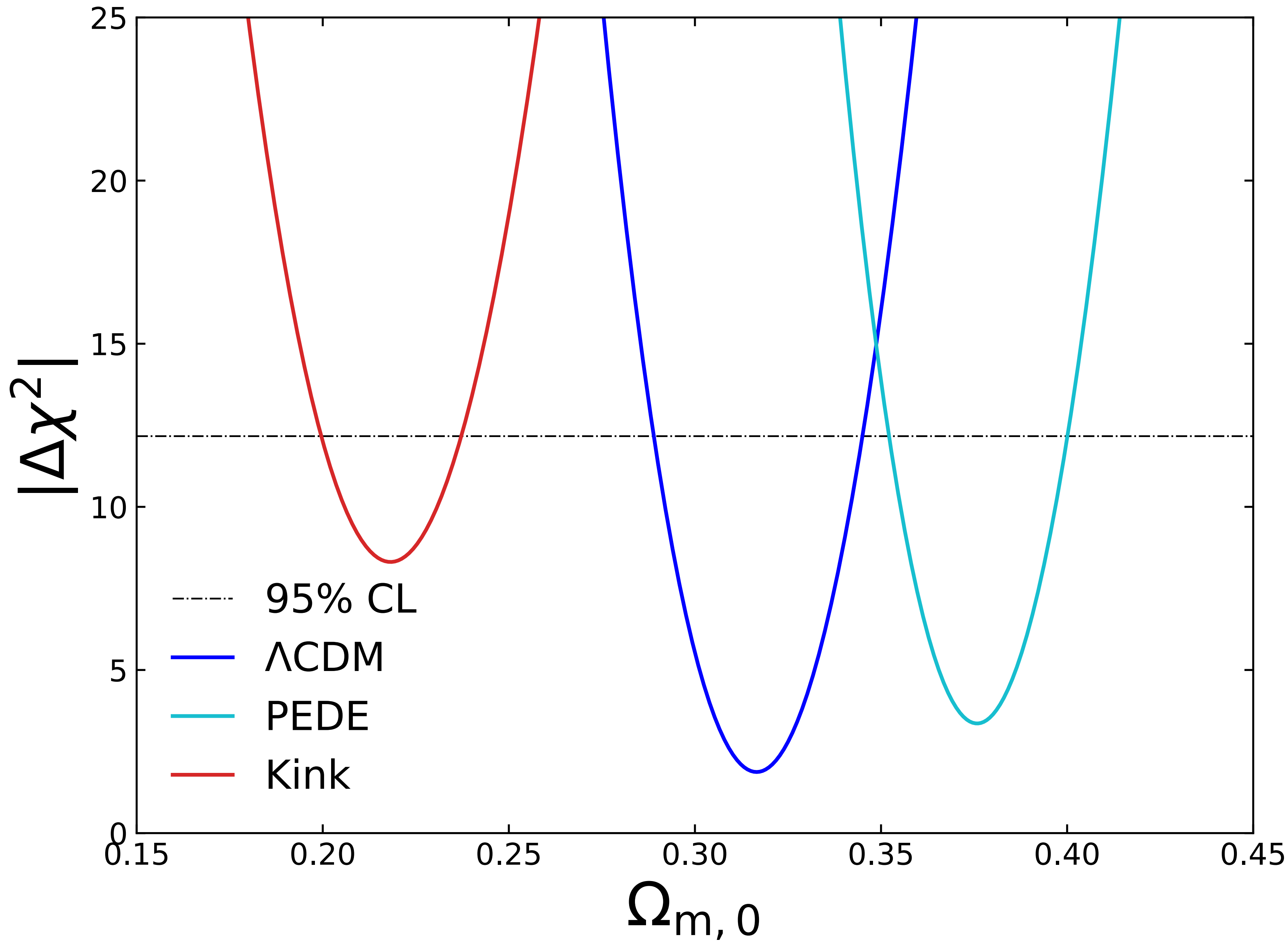
Parameter estimation

- 1000 Pantheon-like mock realizations



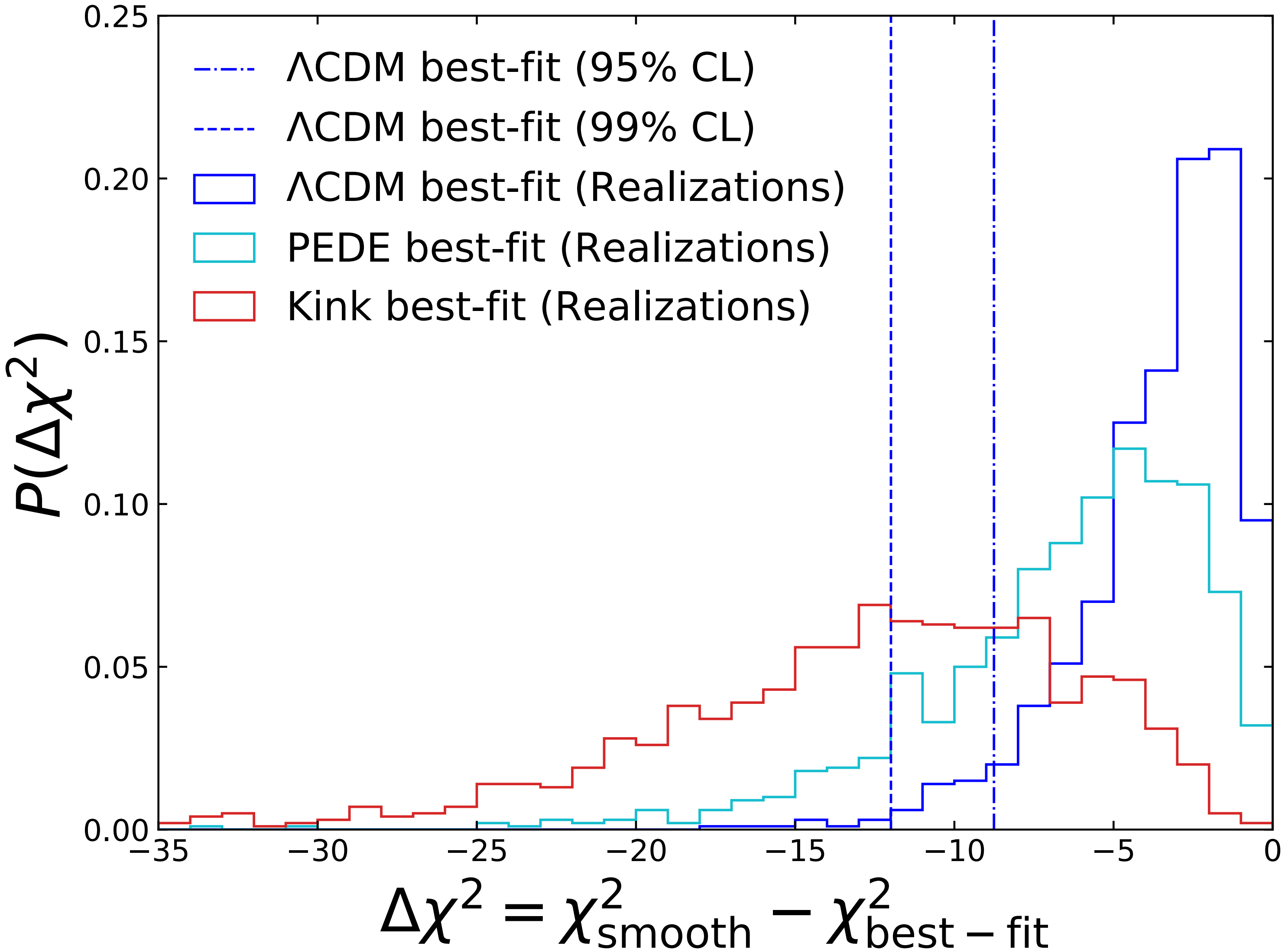
Parameter estimation

- Based on previous 95% CLs from Pantheon



Model selection with future data

- 1000 WFIRST mock realizations, ΛCDM fiducial model
- Estimated Type II errors:



Type II	>95%	>99%
PEDE	24.7%	10.5%
Kink	70.1%	49.5%

Summary

- No model dependence nor redshift evolution of light-curve hyperparameters have found
- 4-5% of Pantheon-like simulations have similar oscillatory features with that in Pantheon data
(systematics or new physics?)
- Model selection and parameter estimation using iterative smoothing method works well
(confronting with Bayesian analysis)

Supplementary slides

Test models for constraining hyperparameters

- ΛCDM: Lambda-cold dark matter model

  $w(z) = -1$ (w: equation-of-state parameter)

- CPL: Chevallier-Polarski-Linder parameterization

  $$w(z) = w_0 + w_a \frac{z}{1+z}$$

  Chevallier. Polarski. 2001; Linder. 2003

- PEDE: Phenomenologically Emergent Dark Energy model

  $$w(z) = -\frac{1}{3\ln 10}(1 + \tanh[\log_{10}(1+z)]) - 1$$

  Li. Shafieloo. 2019

Test data and models for model selection

- WFIRST (simulated): Forecasted peak luminosity values of SNe Ia in WFIRST

- 'kink' model

$$w(z) \;=\; w_0 \;+\; (w_\infty - w_0)\frac{1+\exp(\frac{a_c}{d_m})}{1+\exp(-\frac{a-a_c}{d_m})}\frac{1-\exp(-\frac{a-1}{d_m})}{1-\exp(\frac{1}{d_m})}$$

Corasaniti. Copeland. 2003

- $w_0 = -1,\ w_\infty = -0.5,\ a_c = \frac{2}{3}$, and $d_m = 1$

Holsclaw et al. 2010; Shafieloo et al. 2012