

Interpretable Machine Learning for Dynamical Dark Energy: From Phenomenological to String-Inspired Models

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Based on 2606.17951 w/
Arora, Borghetto, De Felice, Malhotra, Mukohyama, Tasinato
+(WIP)

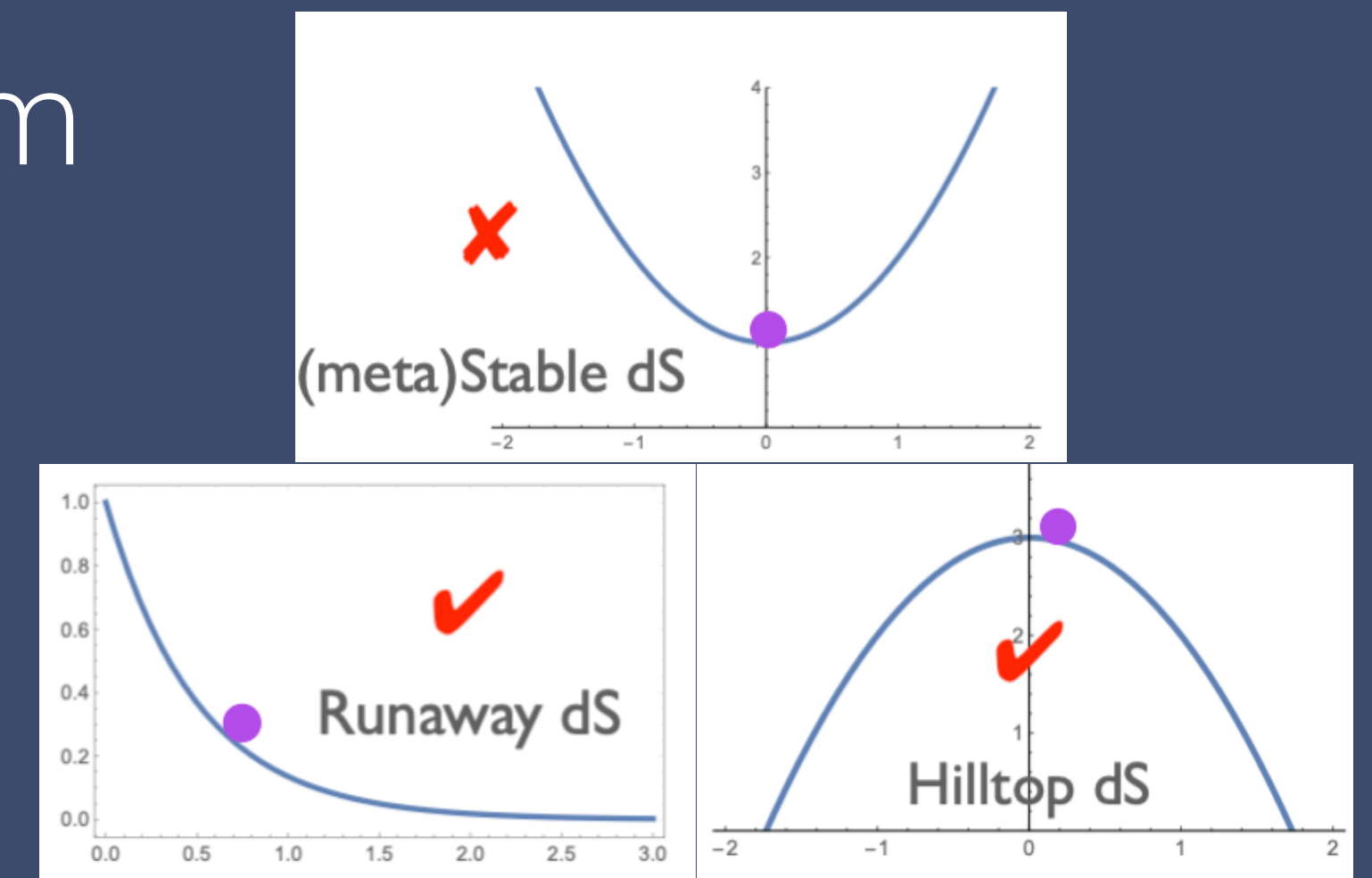
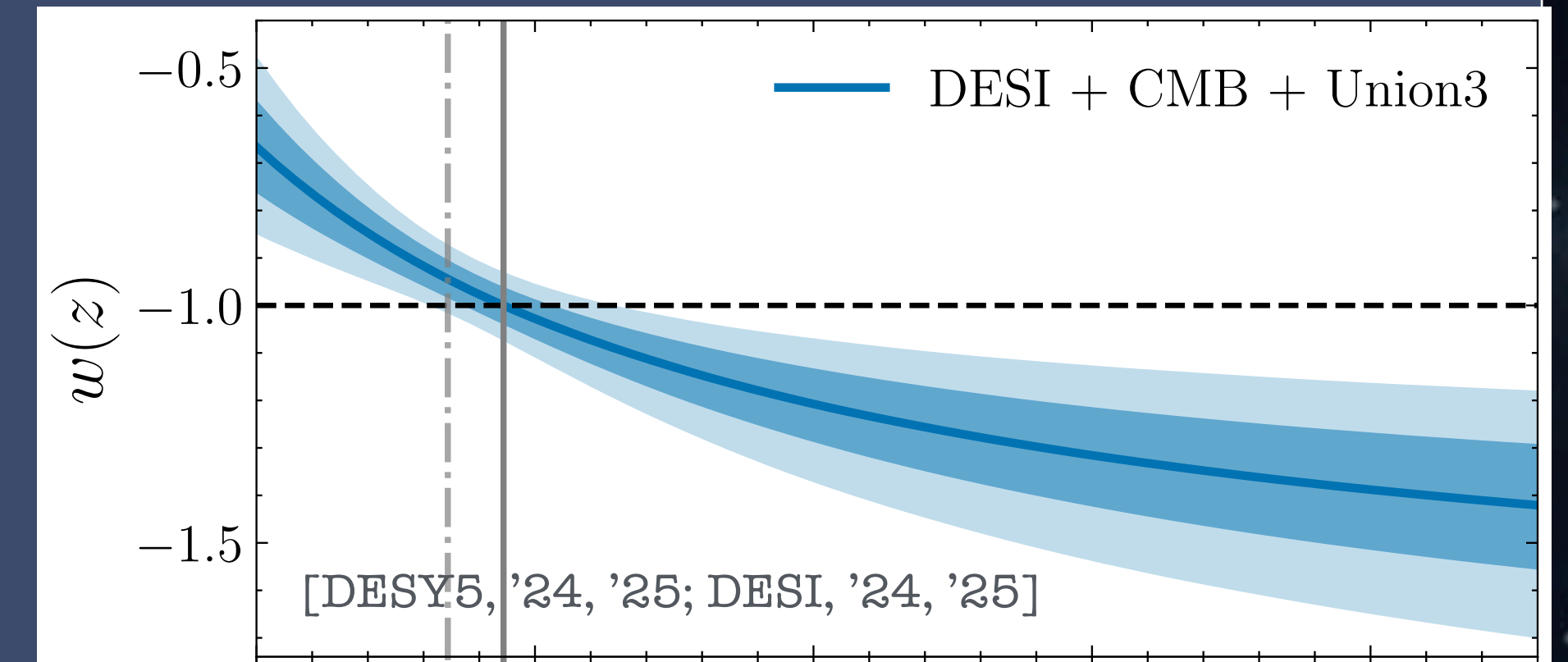
Borghetto, Maharana, Malhotra, Quevedo, Tasinato, Villa

PASCOS 2026: Particles, Strings, and Cosmology, Sheffield, UK

Motivation

- Recent Dark Energy surveys are finding intriguing deviations from a constant energy density. Preferred region seems to indicate a crossing of *phantom divide*, $w_{\text{DE}}(a) < -1$
- On the other hand, recently proposed quantum gravity constraints suggest de Sitter (constant dark energy) might be inconsistent with quantum gravity.

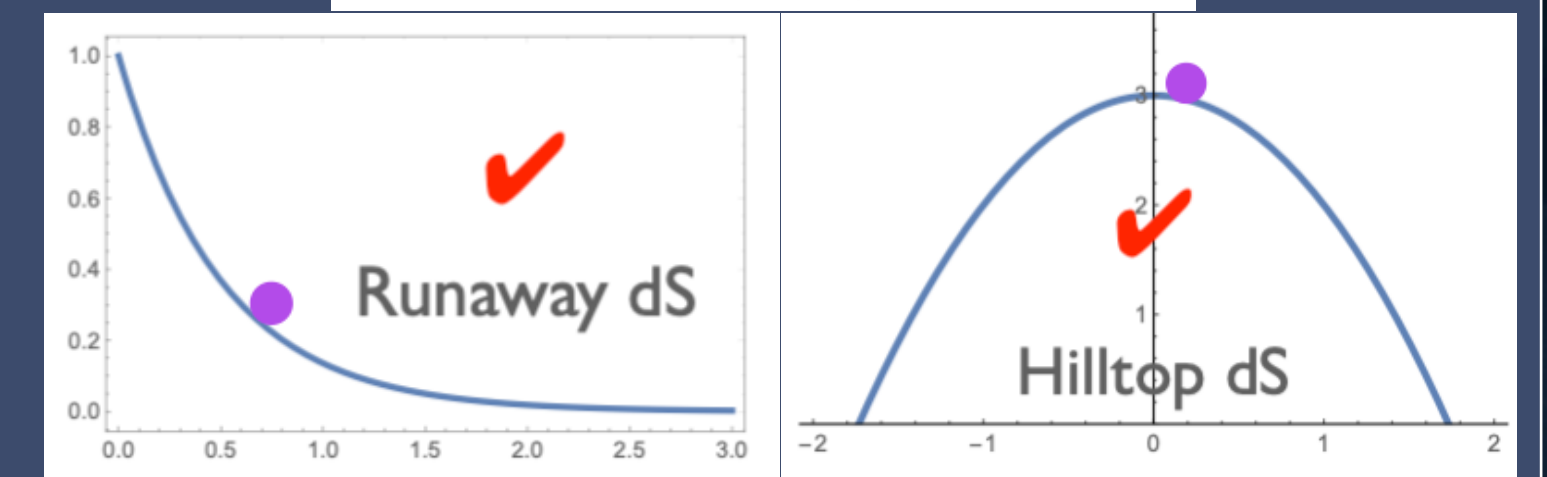
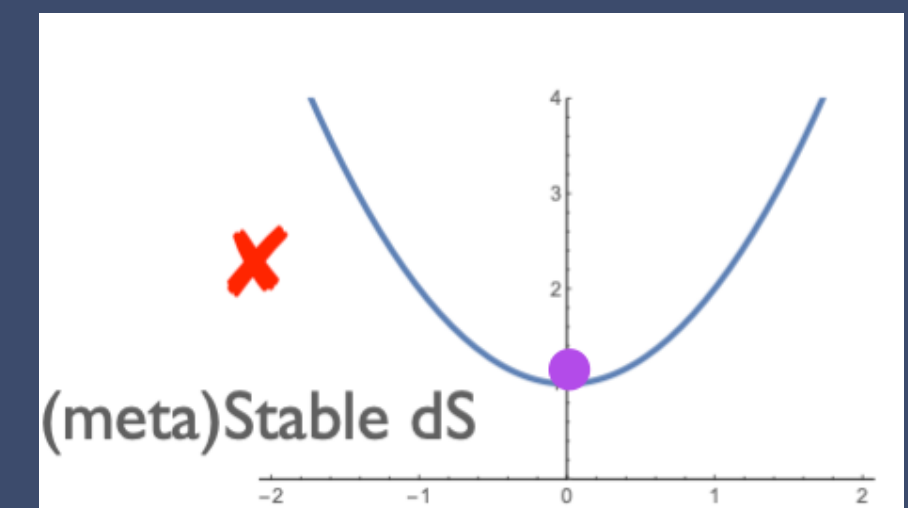
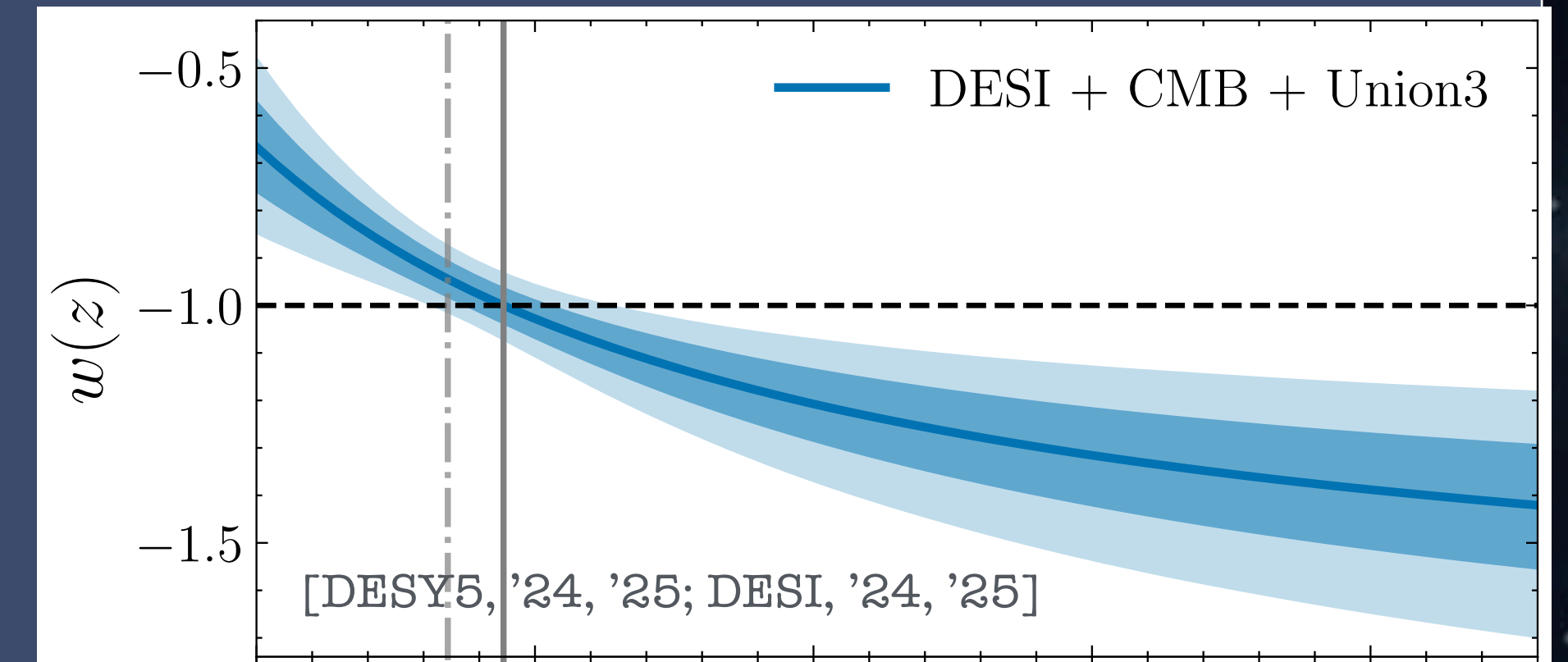
[Danielsson, Van Riet '18; Obied, Ooguri, Spodyneiko, Vafa '18; Garg, Krishnan '18; Ooguri, Palti, Shiu, Vafa '18]



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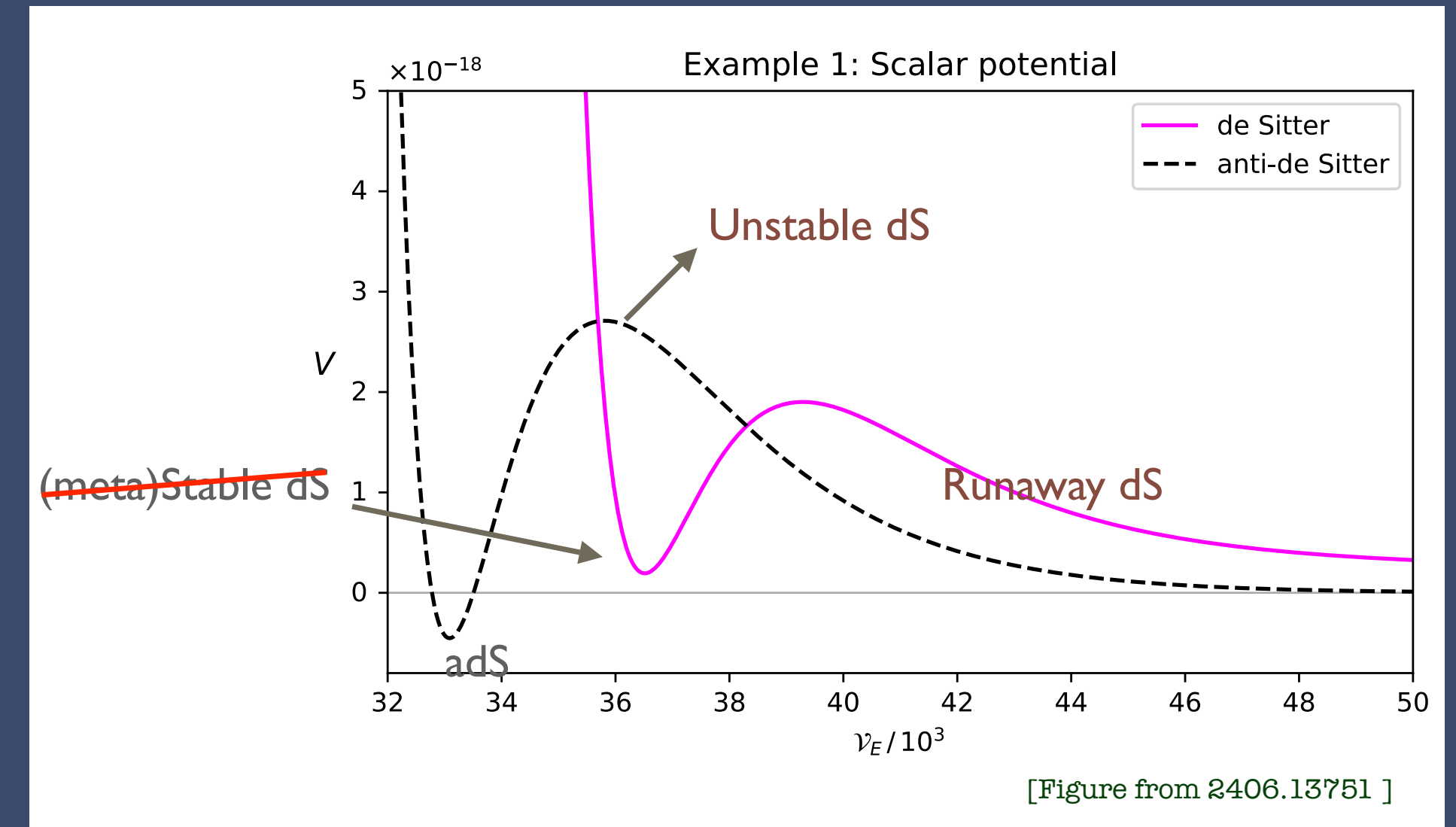


Theoretic and observational constraints suggest dynamical dark energy.

Dynamical Dark Energy: quintessence

[Ratra, Peebles, '88;
Caldwell, Dave, Steinhardt, '98]

- String compactifications naturally contain many scalar fields:
Quintessence emerges naturally in string-inspired settings.
- * *Runaway and hilltop* potentials arise naturally from moduli dynamics (axions, saxions)
- * These models can *satisfy swampland constraints* while remaining *cosmologically viable*.



[Battacharya, Borgetto, Malhotra, Parameswaran, Tasinato & **IZ** '24;
[Aletras et al '24; Akrami, Aletras, Nesseris, '25;
Dinda, Maartens; Chen, Zaldarriaga, '25]

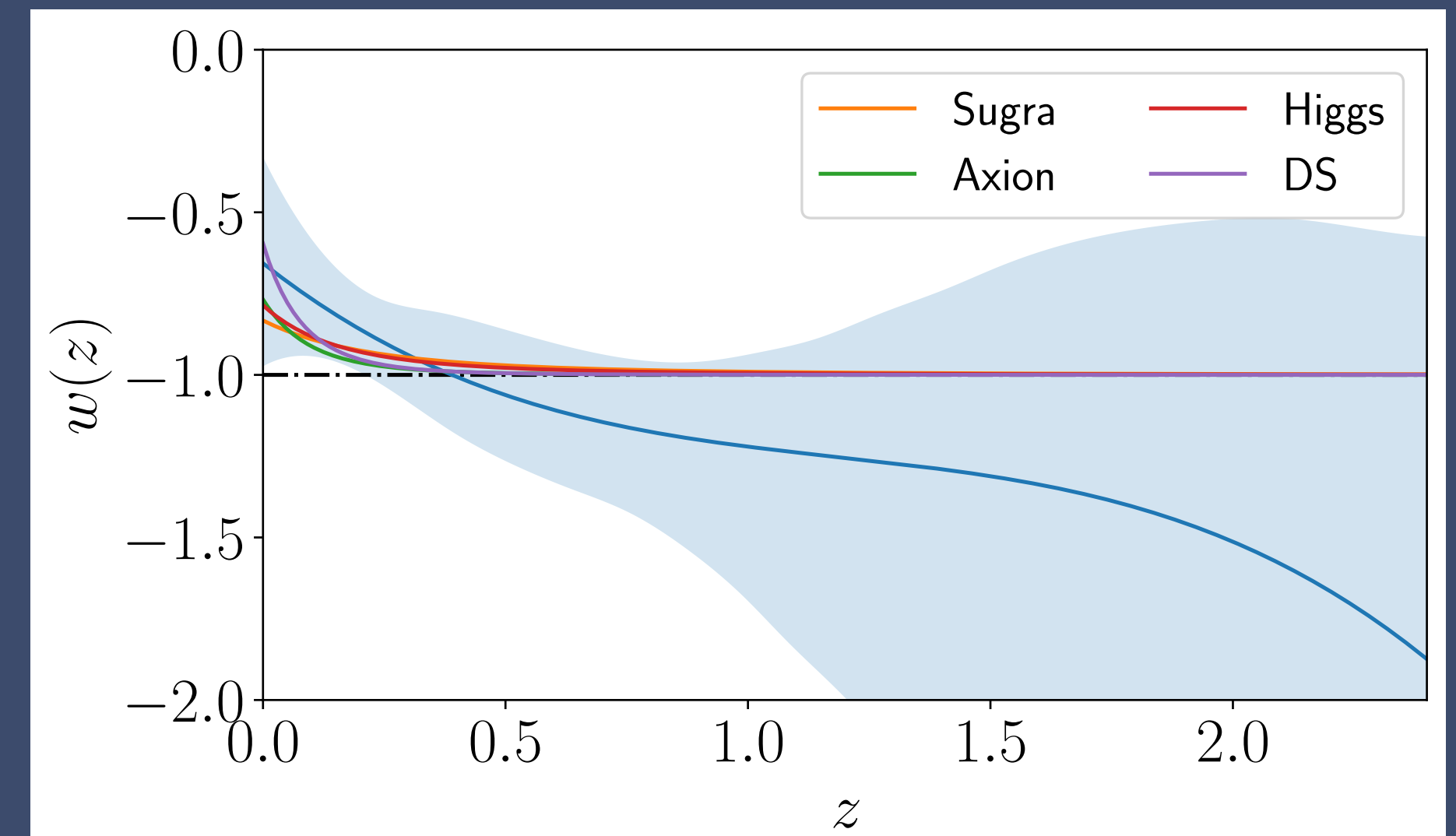
Dynamical Dark Energy: quintessence

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✱ *Runaway and hilltop potentials arise naturally from moduli dynamics (axions, saxions)*

✱ *These models can satisfy swampland constraints while remaining cosmologically viable.*

AIC	Axion	Sugra	Higgs	DS	Λ CDM	CPL	Exp
CMB+DESI+Pantheon+	12409.55	12409.40	12409.07	12408.9	12406.04	12401.70	12407.19
CMB+DESI+Union3	11030.07	11029.49	11030.38	11027.9	11028.69	11019.62	11029.00
CMB+DESI+DESY5	12644.67	12645.65	12644.89	12641.2	12649.01	12637.79	12644.73
hilltop-like						runaway	



[Battacharya, Borgetto, Malhotra, Parameswaran, Tasinato & **IZ** '24;
 [Alesta et al '24; Akrami, Alesta, Nesseris, '25;
 Dinda, Maartens; Chen, Zaldarriaga, '25]

The Phantom-Crossing Problem

- Minimally coupled quintessence cannot cross $w=-1$.

- Possible resolutions:

- ✳ Scalar-tensor theories [Boisseau, Esposito-Farese, Polarski, Starobinsky, '00]

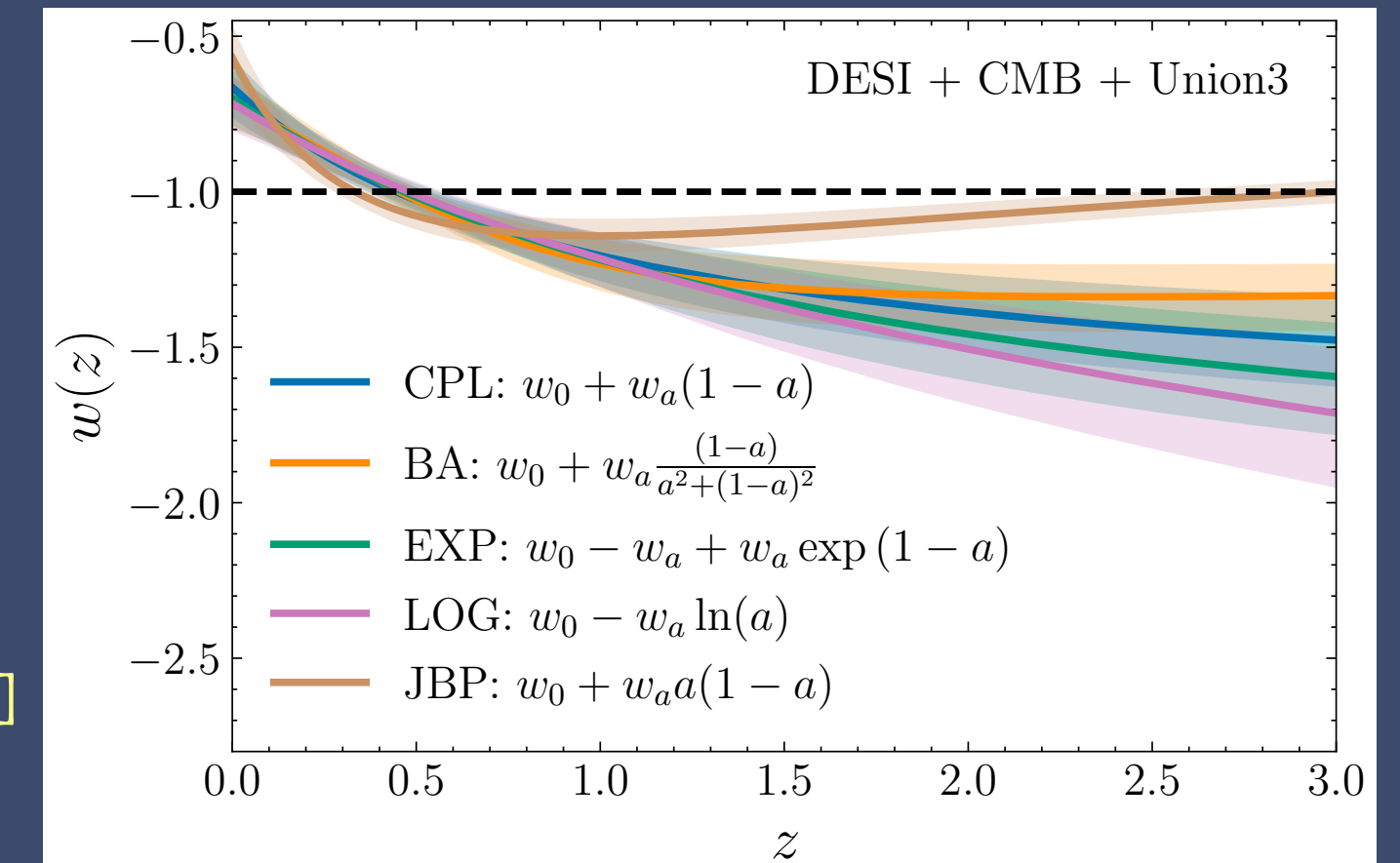
- ✳ Coupled quintessence [Stefancic, '03; Huey, Wandelt, '04; Das, Corasantini, Khoury, '05]

Arise naturally in string theory: scalar-tensor theories; D-brane disformal couplings; coupled moduli to towers of states...

[Gasperini, Piazza, Veneziano, '01; Koivisto, Wills, **12**, '14; Agrawal, Obied, Vafa, '19]

String-inspired models cosmologically viable.

[Smith et al., '24; Chakraborty, Chanda, Das, Dutta, '25; Khoury, Lin, Trodden, '25; Bedroya, Obied, Vafa, Wu, '25; Wang, Cai, Guo, Wang, '25]



Phenomenological Result

- String-inspired quintessence can partly reproduce dynamical evolution hinted by observations. Simple hilltop and runaway thawing models generally fit less well than CPL.
- String-inspired coupled quintessence models can perform well.
- This motivates a more data-driven and model-flexible approach.
- Interpretable Machine Learning: Symbolic Regression
 - ▶ Reconstruct equation of state
 - ▶ Reconstruct scalar potential

Exhaustive Symbolic Regression (ESR)

Exhaustive Symbolic Regression (ESR) *is an algorithm that, given a set of operators, generates all possible functions up to a specified complexity.*

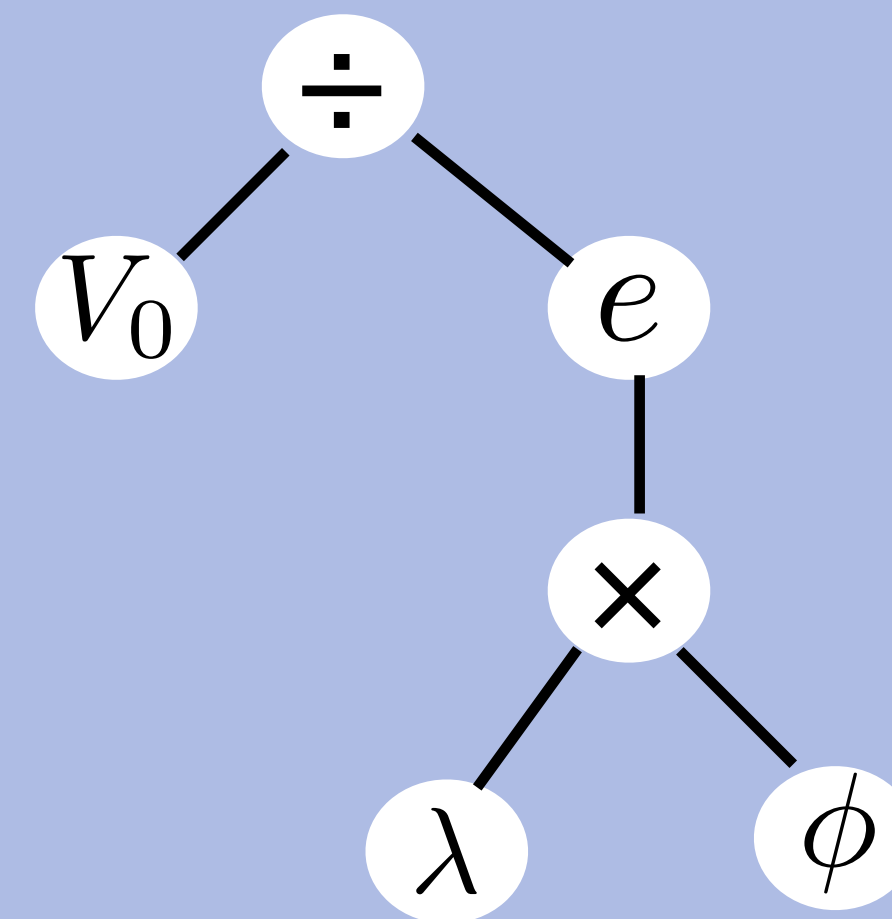
[Bartlett, Desmond, Ferreira, Sousa, '23-24]

Complexity:

number of connected nodes
in *tree* representation of
mathematical expression

[Petersen et al. '21]

$$V = V_0 e^{-\lambda \phi}$$



$\{\times, /, \exp, a_0, a_1, x\}$

Complexity = 6

SPIDER - Symbolic regression Pipeline for Dark Energy Reconstruction

[Borghetto, Malhotra, Arora, De Felice, Mukohyama, Tasinato, **IZ**, '26]

Generation
(ESR)



CAMB/
CLASS



Fitting

SPIDER

1. Choose a set of operators, e.g. $(+, -, \times, /, \exp, \sin)$, a variable, x and free parameters, a_i
2. Fix the complexity, i.e. the number of operators allowed in each expression.
3. Generate a library of unique functions, $f(x, a_i)$, composed of all (simplified) the possible combinations of the operators, variable and free parameters.
4. Use CAMB/CLASS with CMB, SN and DESI DR2 data as likelihoods.
5. Sort and rank functions by the total χ^2 and compared against the benchmarks Λ CDM and CPL parametrisation.

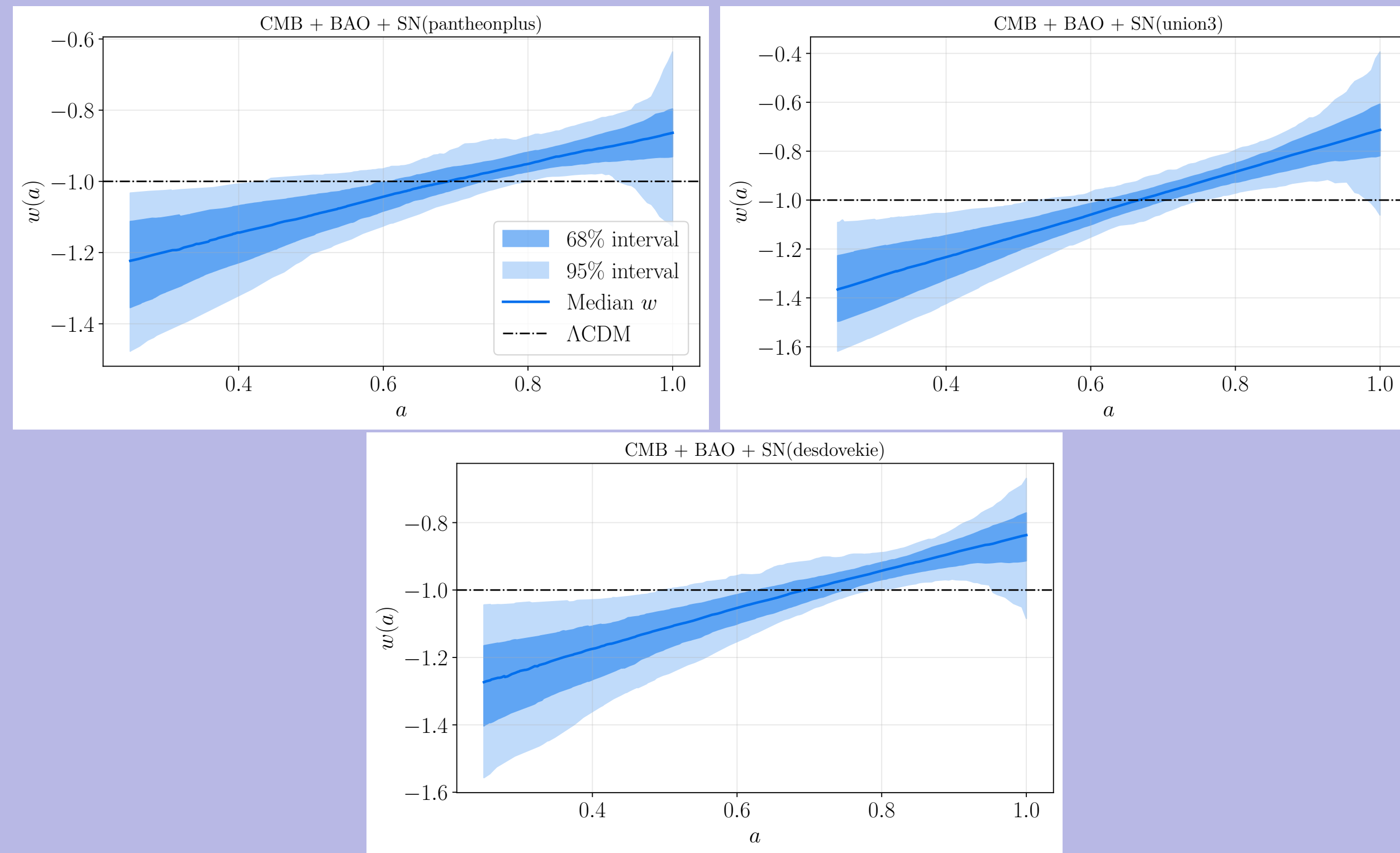
Equation of state reconstruction: VCDM

[Borghetto, Malhotra, Arora, De Felice, Mukohyama, Tasinato, **12**, '26]

- We use **SPIDER** to reconstruct the equation of state $w(a)$
- We do this in a minimally *modified gravity* model, know as VCDM:
[De Felice, Doll, Mukohyama, '20]
In VCDM, the cosmological constant Λ in the standard Λ CDM model is generalised to a function $V(\phi)$, where ϕ is a non-dynamical auxiliary field.
- Given the eos, the function V can be found from the theory.

Results: VCDM

1. Spline reconstruction of $w(a)$



Cosmological data
CMB + BAO + SN

Bayesian spline
reconstruction of $w(a)$

Qualitative information
smooth, monotonic,
low-complexity evolution

SPIDER

Operator basis
 $\{+, -, \times, /, \sqrt{}, \text{pow}, \text{exp}\}$
complexity $cl = 4$

ESR generation
candidate analytic
functions $w(a; c_i)$

VCDM + CLASS
background and
perturbations

Cobaya fitting
 $\chi^2_{\min}$ and
posterior constraints

Model selection
rank candidates
compare with CPL,
 Λ CDM

Marginalised spline reconstruction with 2, 3, and 4 nodes: smooth phantom behaviour

Results: VCDM

	CPL 95% CI
	CPL: $w = w_0 + w_a(1 - a)$, $\chi^2 = 1039.2$
	BA: $w = w_0 + w_a(1 - a)/(a^2 + (1 - a)^2)$, $\chi^2 = 1039.7$
	JBP: $w = w_0 + w_a a(1 - a)$, $\chi^2 = 1041.1$
	EXP: $w = w_0 - w_a + w_a e^{1-a}$, $\chi^2 = 1039.9$
	LOG: $w = w_0 - w_a \ln(a)$, $\chi^2 = 1039.5$
	F24: $w = a - w_0 $, $\chi^2 = 1045.8$
	F42: $w = \frac{w_0}{\sqrt{a}}$, $\chi^2 = 1039.7$
	F79: $w = w_0 + a^2$, $\chi^2 = 1044.0$
	F83: $w = w_0 e^{-a}$, $\chi^2 = 1040.3$
	Λ CDM: $\chi^2 = 1053.2$

Complexity: 4

Operators:

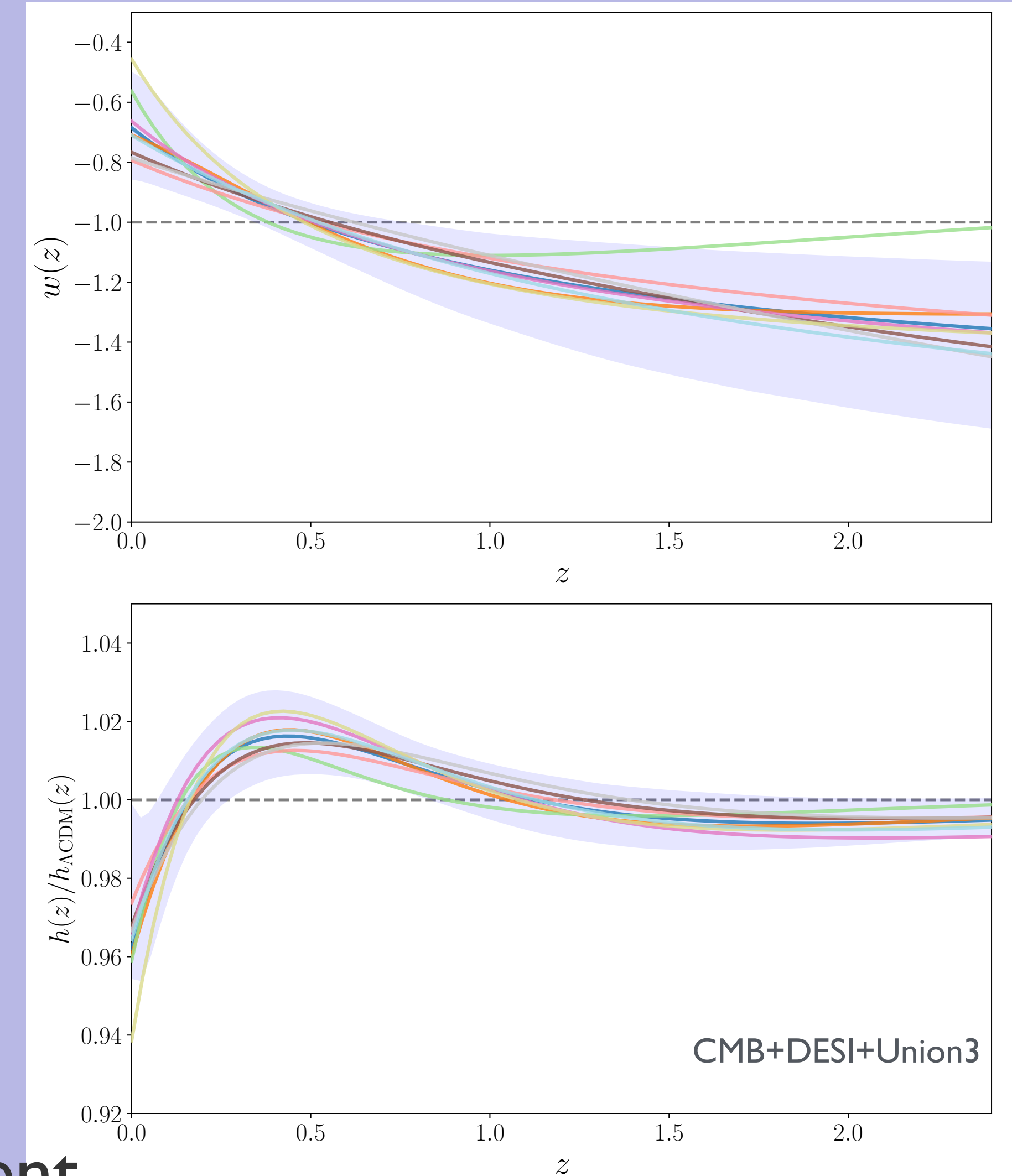
$\{+, -, \times, /, \sqrt{}, \text{power}, \text{exp}\}$

Performance:

close or better than
CPL

Human found (CPL, BA, JBP, EXP, LOG): two
parameter parametrisations

ML found (F24, F42, F79, F83): **one** parameter
parametrisations. F42 (SR): allows analytic treatment



Results: VCDM

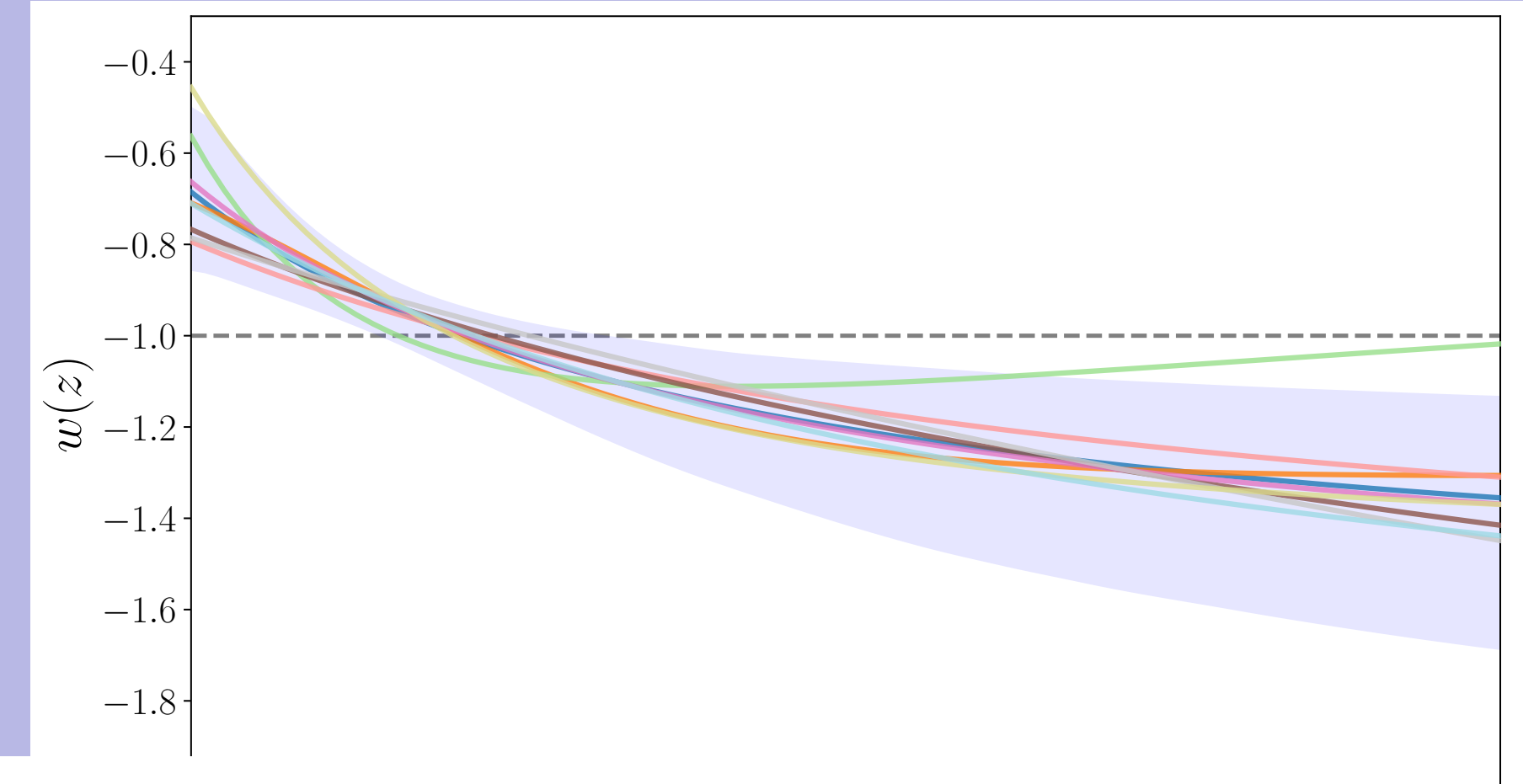
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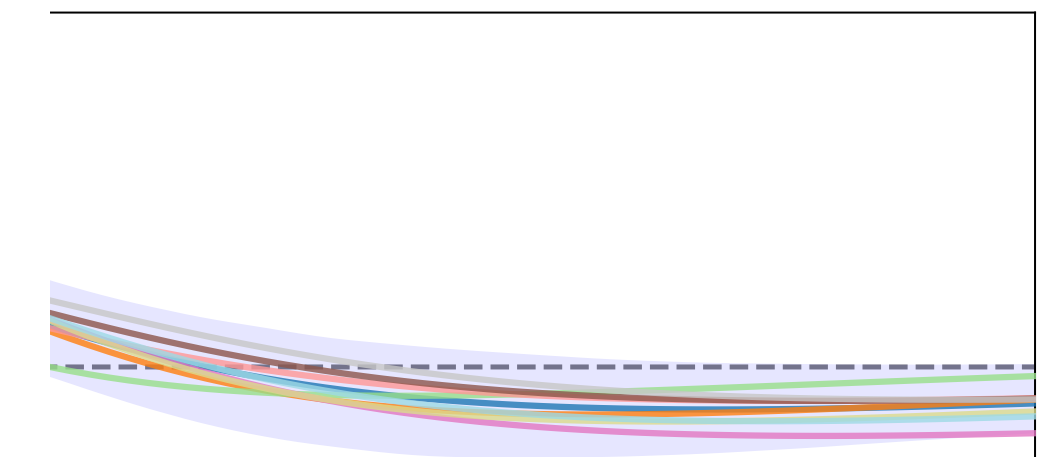
$\{+, -, \times, /, \sqrt{}, \text{power}, \text{exp}\}$

$$w_{\text{SR}}(a) = \frac{w_0}{\sqrt{a}}$$



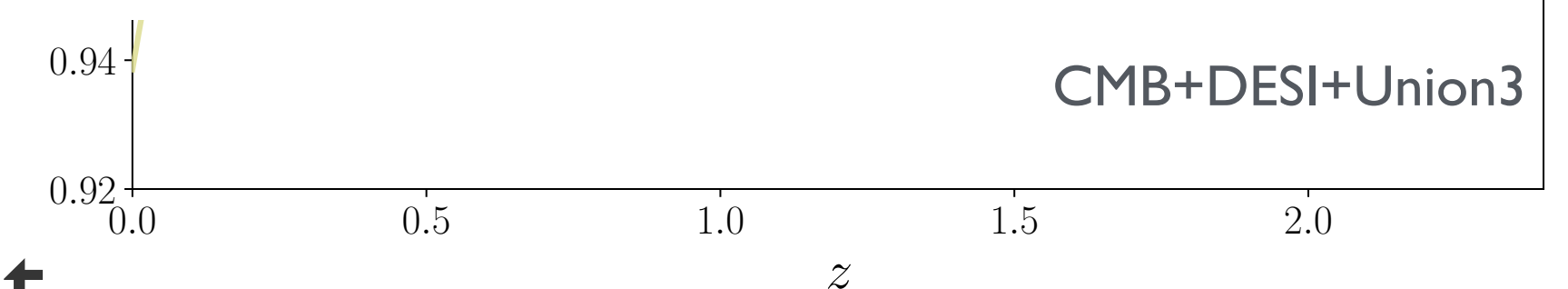
Model	N_{DE}	χ^2	$\Delta\chi^2_{\mathcal{M}-\text{SR}}$	$\log \mathcal{Z}$	$\log B_{\mathcal{M},\text{SR}}$
Λ CDM	-	1053.2	13.5	-543.56 ± 0.34	-4.64
CPL	2	1039.2	-0.5	-540.58 ± 0.35	-1.52
BA	2	1039.7	-0.0	-541.55 ± 0.34	-2.64
JBP	2	1041.1	1.4	-540.97 ± 0.29	-2.06
EXP	2	1039.9	0.2	-541.02 ± 0.36	-2.11
LOG	2	1039.5	-0.2	-541.08 ± 0.35	-2.17
SR	1	1039.7	0	-538.91 ± 0.29	0
F83	1	1040.3	0.6	-538.74 ± 0.32	0.17

1.0 1.5 2.0
 z



Human found (CPL, BA)
parameter parametrisati

ML found (F24, F42, F79, F83): **one** parameter
parametrisations. F42 (SR): allows analytic treatment



Coupled Quintessence Reconstruction

[WIP w/Borghetto, Malhotra, Maharana, Quevedo, Tasinato, Villa]

- We explore phantom crossing modelling generic coupled quintessence via a *time dependent potential*: $V(\phi, a)$

$$V_{\text{eff}}(\phi, a) = V_1(\phi) + \frac{\rho_m^0}{a^3} (F(\phi, a) - 1)$$

DE eos:

$$w_{\text{eff}}(t) = \frac{\frac{\dot{\phi}^2}{2} - V(\phi, t) - \frac{1}{3H} \frac{\partial V}{\partial t}}{\frac{\dot{\phi}^2}{2} + V(\phi, t)}$$

- $V_{\text{eff}}(\phi, a) = V_0 e^{-\lambda\phi} + \frac{\rho_m^0}{a^3} [f(\phi) - 1]$

- $V_{\text{eff}}(\phi, a) = V_0 e^{-\lambda\phi} + \frac{\rho_m^0}{a^3} \left[\frac{f(\phi)}{a^n} - 1 \right]$

Reconstruct $f(\phi)$

optimise n

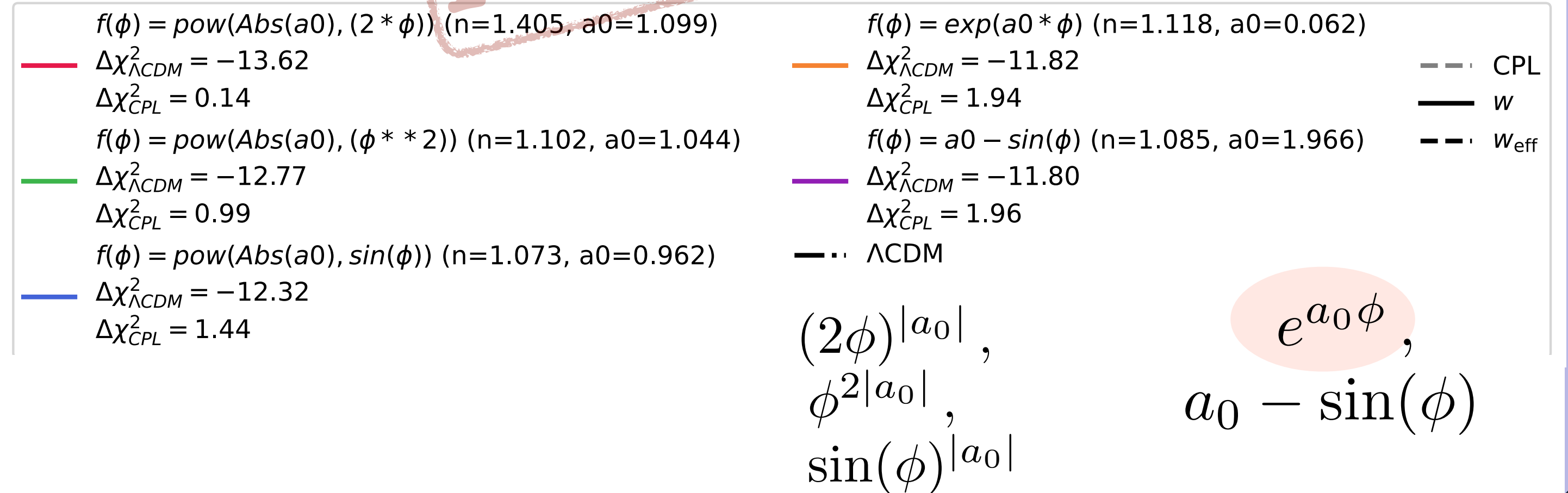
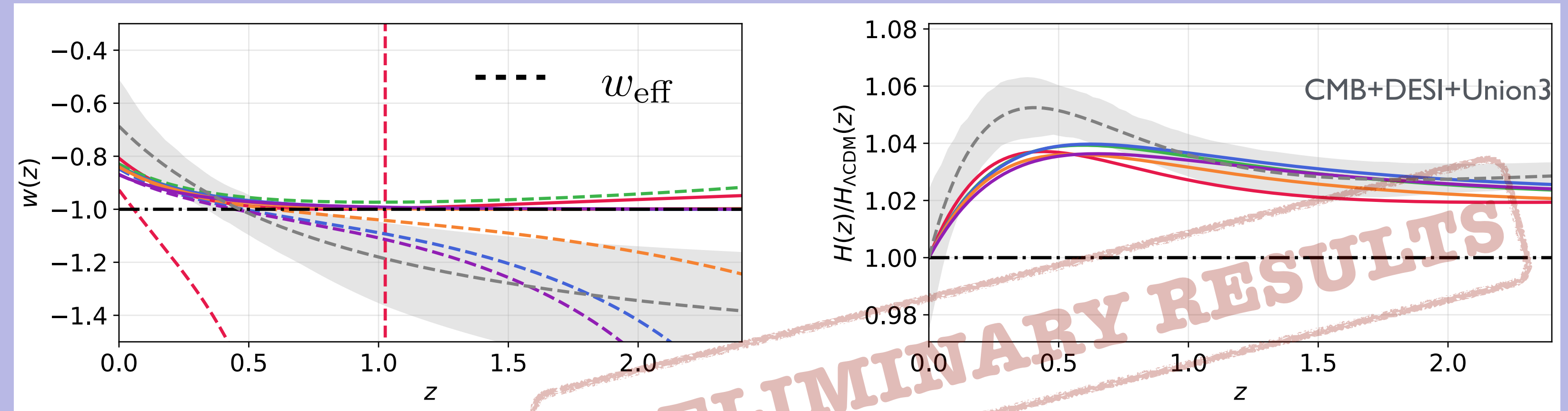


Time dependent potential

Potential: $V_{\text{eff}}(\phi, a) = V_0 e^{-\lambda\phi} + \frac{\rho_m^0}{a^3} [f(\phi) - 1]$

$$w_{\text{eff}}(t) = \frac{\frac{\dot{\phi}^2}{2} - V(\phi, t) - \frac{1}{3H} \frac{\partial V}{\partial t}}{\frac{\dot{\phi}^2}{2} + V(\phi, t)}.$$

- Complexity: 5
- Operators:
 $\{+, -, \times, /, \text{power}, \text{exp}, \text{square}, \text{sin}\}$
- Performance:
 closer to CPL than
 quintessence models



Conclusions

- SR provides an interpretable, model-flexible approach to reconstruct dark energy directly from data. Use cosmological data to guide theory construction.
- Machine learning acts as an interpretable bridge between data and UV-inspired models.
- Connect ML-reconstructed potentials to microscopic string models: p-forms, axions, moduli couplings.
- The objective is not merely fitting data, but identifying physically meaningful structures.

Outlook

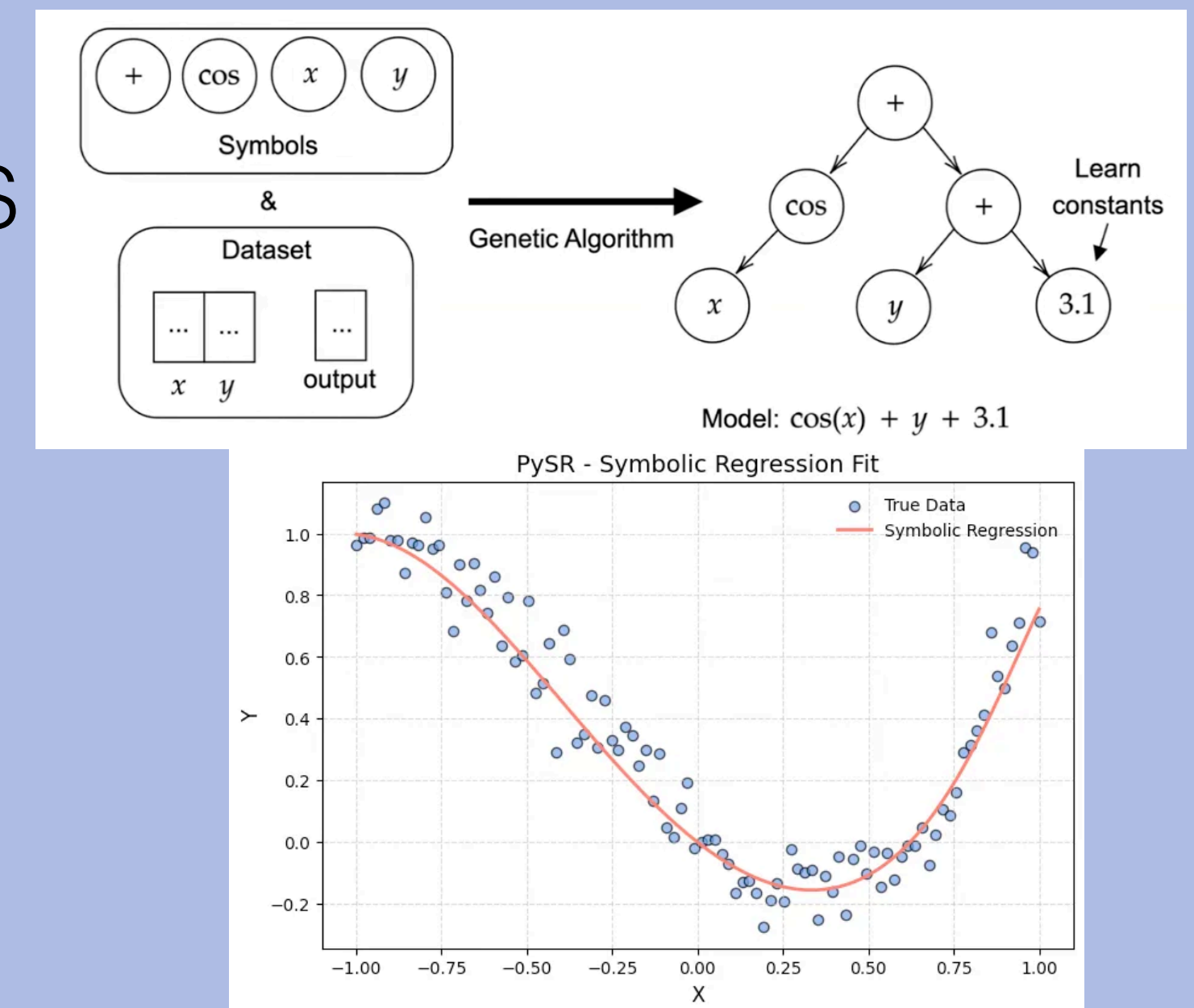
- Future DESI, Euclid, and Rubin data will sharpen the evidence for dynamical dark energy.
- Interpretable ML may help identify robust theoretical structures behind observational trends.

Symbolic Regression (PySR)

SR discovers interpretable analytic expressions that best fit a dataset, balancing accuracy and simplicity.

PySR uses a multi-population evolutionary algorithm:

- **Generate:** random population of expressions
- **Evolve:** mutate and crossover the fittest
- **Select:** keep best by accuracy + simplicity
- **Stop:** at threshold accuracy, time limit, etc



The best equation is the simplest one that fits the data well