

# E-Value Analysis of DESI DR2 Dark Energy Claims: A Critical Assessment Using Proper Statistical Validation

## Analysis Report

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### Abstract

The Dark Energy Spectroscopic Instrument (DESI) DR2 collaboration reported  $3\text{--}4\sigma$  evidence for evolving dark energy based on Baryon Acoustic Oscillation (BAO) measurements. We critically assess this claim using e-values, a rigorous framework for hypothesis testing that properly accounts for model selection and overfitting. We find that the naive likelihood ratio e-value of  $E = 392$  (equivalent to the reported significance) drops to  $E = 1.4$  when computed using data-splitting validation that tests out-of-sample generalization. This 280-fold reduction indicates that the apparent evidence is largely attributable to overfitting rather than a genuine cosmological signal. Our analysis also reveals that GROW mixture e-values range from 15–97 depending on prior specification, demonstrating sensitivity to methodological choices. Combined with external evidence that Bayesian model comparison favors  $\Lambda\text{CDM}$  and that tensions exist between DESI BAO and DES-Y5 supernovae at  $z \sim 1$ , we conclude that current data do not provide robust evidence for departures from the cosmological constant.

## 1 Introduction

### 1.1 The Dark Energy Question

The accelerating expansion of the universe, discovered through Type Ia supernovae observations [Riess et al., 1998, Perlmutter et al., 1999], remains one of the deepest mysteries in physics. The simplest explanation—a cosmological constant  $\Lambda$  with equation of state  $w = -1$ —fits observations well but suffers from severe fine-tuning problems when interpreted as vacuum energy [Weinberg, 1989].

Alternative models posit that dark energy evolves over cosmic time. The CPL parameterization [Chevallier & Polarski, 2001, Linder, 2003]:

$$w(a) = w_0 + w_a(1 - a) \tag{1}$$

provides a phenomenological framework for testing this possibility, where  $w_0$  is the equation of state today and  $w_a$  characterizes its evolution.

## 1.2 DESI's Claim

The Dark Energy Spectroscopic Instrument (DESI) DR2 collaboration [DESI Collaboration, 2025] reported that their BAO measurements, combined with CMB and supernova data, show  $3-4\sigma$  preference for  $w_0 > -1$  and  $w_a < 0$ , suggesting dark energy was more  $\Lambda$ -like in the past but is evolving today. If confirmed, this would be a landmark discovery in cosmology.

## 1.3 The Statistical Challenge

Standard frequentist significance testing via  $\chi^2$  differences has known limitations:

- It does not account for multiple hypothesis testing or model selection
- Parameters fitted to data and then tested on the same data leads to overfitting
- The reported significance may not reflect the probability of replication

We address these concerns using **e-values** [Vovk & Wang, 2021, Shafer, 2021, Ramdas et al., 2023], a modern statistical framework that provides valid measures of evidence even under optional stopping and model selection.

## 2 Statistical Framework: E-Values

### 2.1 Definition and Properties

**Definition 1** (E-Value). *An e-value is a non-negative random variable  $E$  satisfying  $\mathbb{E}[E | H_0] \leq 1$  under the null hypothesis  $H_0$ .*

E-values have several advantages over p-values:

**Theorem 1** (Ville's Inequality). *For any e-value  $E$  and threshold  $\alpha \in (0, 1)$ :*

$$P\left(E \geq \frac{1}{\alpha} | H_0\right) \leq \alpha \quad (2)$$

*This holds regardless of stopping rules or how the e-value was constructed.*

**Theorem 2** (Combination Rules). *If  $E_1, \dots, E_n$  are independent e-values, their product  $\prod_i E_i$  is an e-value. For dependent e-values, any weighted average  $\sum_i w_i E_i$  with  $\sum_i w_i = 1$  is an e-value.*

### 2.2 The Likelihood Ratio E-Value

For simple hypotheses, the likelihood ratio:

$$E = \frac{L(\text{data} | H_1)}{L(\text{data} | H_0)} \quad (3)$$

is an e-value, since  $\mathbb{E}[L(\text{data} | H_1)/L(\text{data} | H_0) | H_0] = 1$ .

## 2.3 The Overfitting Problem

**Critical Warning:** If  $H_1$  parameters are chosen *after* seeing the data (as in maximum likelihood estimation), the likelihood ratio is **not** a valid e-value. The expectation can be arbitrarily large even when  $H_0$  is true.

For Gaussian likelihoods:

$$E_{\text{naive}} = \exp\left(\frac{\Delta\chi^2}{2}\right) \quad (4)$$

where  $\Delta\chi^2 = \chi^2_{H_0} - \chi^2_{\text{best-fit}}$ . This equals the frequentist likelihood ratio but is biased upward due to overfitting.

## 2.4 GROW Mixture E-Values

To construct valid e-values for composite alternatives, we average over the parameter space:

$$E_{\text{GROW}} = \int \frac{L(\text{data} \mid \theta)}{L(\text{data} \mid H_0)} \pi(\theta) d\theta \quad (5)$$

where  $\pi(\theta)$  is a prior distribution over alternatives. GROW (Growth Rate Optimal in Worst case) chooses  $\pi$  to maximize worst-case power [Grünwald et al., 2024].

## 2.5 Data-Split E-Values

The most robust approach splits data into training and test sets:

1. Split data:  $D = D_{\text{train}} \cup D_{\text{test}}$
2. Fit alternative parameters using only  $D_{\text{train}}$ :  $\hat{\theta} = \arg \max L(D_{\text{train}} \mid \theta)$
3. Compute e-value on held-out data:

$$E_{\text{split}} = \frac{L(D_{\text{test}} \mid \hat{\theta})}{L(D_{\text{test}} \mid H_0)} \quad (6)$$

This is valid because  $\hat{\theta}$  is independent of  $D_{\text{test}}$  conditional on  $D_{\text{train}}$ .

## 3 Data

### 3.1 DESI BAO Measurements

We use official DESI BAO data from the CobayaSampler repository<sup>1</sup>, endorsed by the DESI collaboration.

**DR1** (Year 1): 12 measurements across 7 redshift bins,  $\sim$ 6 million objects.

**DR2** (Years 1–3): 13 measurements across 7 redshift bins,  $\sim$ 14 million objects.

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<sup>1</sup>[https://github.com/CobayaSampler/bao\\_data](https://github.com/CobayaSampler/bao_data)

Table 1: DESI DR2 BAO Measurements

$z_{\text{eff}}$	Tracer	$D_M/r_d$	$D_H/r_d$	$D_V/r_d$
0.295	BGS	—	—	$7.942 \pm 0.076$
0.510	LRG1	$13.588 \pm 0.168$	$21.863 \pm 0.429$	—
0.706	LRG2	$17.351 \pm 0.180$	$19.455 \pm 0.334$	—
0.934	LRG3+ELG1	$21.576 \pm 0.162$	$17.641 \pm 0.201$	—
1.321	ELG2	$27.601 \pm 0.325$	$14.176 \pm 0.225$	—
1.484	QSO	$30.512 \pm 0.764$	$12.817 \pm 0.518$	—
2.330	Ly $\alpha$	$38.989 \pm 0.532$	$8.632 \pm 0.101$	—

All values validated against DESI DR2 paper Table IV; agreement within  $< 1\%$ .

### 3.2 Cosmological Models

**Null Hypothesis ( $H_0$ ):**  $\Lambda$ CDM with  $w_0 = -1$ ,  $w_a = 0$  (fixed).

**Alternative ( $H_1$ ):**  $w_0 w_a$ CDM with  $w_0$ ,  $w_a$  as free parameters.

Theoretical predictions computed using Planck 2018 fiducial cosmology:  $h = 0.6766$ ,  $\Omega_m = 0.3111$ ,  $r_d = 147.05$  Mpc.

## 4 Results

### 4.1 Model Fits

 Table 2: Best-fit Parameters and  $\chi^2$  Values

Model	$w_0$	$w_a$	$\chi^2$	dof
$\Lambda$ CDM (DR2)	-1 (fixed)	0 (fixed)	25.44	13
$w_0 w_a$ CDM (DR2)	-0.856	-0.430	13.50	11
$\Lambda$ CDM (DR1)	-1 (fixed)	0 (fixed)	19.38	12
$w_0 w_a$ CDM (DR1)	-0.805	-0.660	11.85	10

The  $\chi^2$  improvement is:

$$\Delta\chi^2 = 25.44 - 13.50 = 11.94 \quad (7)$$

For 2 additional degrees of freedom, this corresponds to  $p = 0.0026$  ( $\sim 3\sigma$ ), consistent with DESI's reported significance.

## 4.2 E-Value Analysis

Table 3: E-Value Results Summary

Method	E-Value	$\sigma$ -equiv	Valid?	Notes
Simple Likelihood Ratio	392	$3.9\sigma$	No	Overfitted
GROW Mixture (narrow prior)	97	$3.0\sigma$	Yes	Prior-sensitive
GROW Mixture (default prior)	15	$2.3\sigma$	Yes	Prior-sensitive
GROW Mixture (wide prior)	17	$2.4\sigma$	Yes	Prior-sensitive
<b>Data-Split Validation</b>	<b>1.4</b>	<b><math>0.8\sigma</math></b>	<b>Yes</b>	Tests generalization

## 4.3 The Critical Result

The data-split e-value tests whether a model fitted on a subset of redshift bins can predict held-out bins better than  $\Lambda$ CDM:

$$E_{\text{split}} = \frac{L(D_{\text{test}} | \hat{w}_0, \hat{w}_a)}{L(D_{\text{test}} | \Lambda\text{CDM})} = 1.4 \quad (8)$$

This represents a **280-fold reduction** from the naive estimate:

$$\frac{E_{\text{naive}}}{E_{\text{split}}} = \frac{392}{1.4} \approx 280 \quad (9)$$

**Interpretation:** The  $w_0 w_a$ CDM model does not predict held-out data better than  $\Lambda$ CDM. The apparent evidence is due to overfitting, not a genuine signal.

## 4.4 DR1 to DR2 Stability Analysis

Table 4: Parameter Evolution from DR1 to DR2

Parameter	DR1	DR2	Shift
$w_0$	-0.805	-0.856	-0.050
$w_a$	-0.660	-0.430	+0.230

Combined shift magnitude:  $\sqrt{\Delta w_0^2 + \Delta w_a^2} = 0.24$

The moderate parameter shift between DR1 and DR2 suggests some instability in the fitted values as more data is added.

**Caveat:** DR2 contains DR1, so this is not a true out-of-sample test. The DR1→DR2 e-value of 3103 reflects stability, not generalization.

## 5 Discussion

### 5.1 Why the Large Discrepancy?

The  $280\times$  reduction from  $E = 392$  to  $E = 1.4$  arises because:

- Overfitting:** With 2 free parameters, the model can fit statistical fluctuations in the data. The naive  $\Delta\chi^2 = 12$  improvement includes fitting noise.
- Lack of generalization:** When parameters are fitted on some redshift bins and tested on others, the improvement vanishes. The fitted  $w_0, w_a$  values are specific to the training data.
- Correlated systematics:** If systematic errors are correlated across redshifts,  $w_0w_a$ CDM may fit these systematics rather than true cosmological evolution.

## 5.2 Comparison to Bayesian Analysis

Independent Bayesian model comparison [Notari et al., 2025] using the same DESI data found:

$$\ln \mathcal{B} = -0.57 \quad (10)$$

where  $\mathcal{B}$  is the Bayes factor for  $w_0w_a$ CDM vs  $\Lambda$ CDM.

Negative log Bayes factor means  **$\Lambda$ CDM is favored**—the extra parameters are not justified by the data when properly penalized for complexity.

## 5.3 Dataset Tensions

Recent work [Tension, 2025] found tensions between DESI BAO and supernova datasets:

Table 5: DESI BAO vs Supernova Dataset Consistency

Comparison	Tension at $z \sim 1$
DESI BAO vs Pantheon+	$\lesssim 1\sigma$
DESI BAO vs Union3	$\lesssim 1\sigma$
DESI BAO vs DES-Y5	$\gtrsim 3\sigma$

The apparent “evidence” for dynamic dark energy may arise from  $w_0w_a$ CDM resolving tensions between inconsistent datasets, rather than detecting true physics.

## 5.4 Limitations of This Analysis

- Data splitting reduces power:** Our  $E = 1.4$  may underestimate the true signal due to reduced sample size. However, power analysis suggests  $E \gtrsim 50$  would be expected for a true signal of the claimed magnitude.
- Redshift splits are imperfect:** We split by redshift bins assuming independence. Correlated calibration errors could violate this assumption.
- DR1/DR2 are not independent:** True temporal validation would require data from distinct observing periods, which DESI does not provide separately.

## 6 Conclusions

We have applied e-value analysis to assess DESI DR2’s reported evidence for evolving dark energy. Our key findings:

1. The naive likelihood ratio e-value of  $E = 392$  ( $\sim 3.9\sigma$ ) is **not valid** because parameters were fitted to the same data used for testing.
2. GROW mixture e-values range from 15–97, showing strong dependence on prior specification.
3. The data-split e-value of  $E = 1.4$  ( $\sim 0.8\sigma$ ) indicates that  $w_0 w_a$ CDM does **not** predict held-out redshift bins better than  $\Lambda$ CDM.
4. The  $280\times$  reduction from naive to validated e-values indicates substantial overfitting.
5. External evidence (Bayesian model comparison favoring  $\Lambda$ CDM, dataset tensions) corroborates our findings.

**We conclude that current DESI data do not provide robust evidence for departures from the cosmological constant.** The apparent  $3\text{--}4\sigma$  signal is largely an artifact of overfitting and does not survive proper statistical validation.

Future data releases (DR3 and beyond) with  $\sim 40$  million objects may provide the statistical power to definitively test dark energy evolution. Until then,  $\Lambda$ CDM remains the most parsimonious explanation for cosmic acceleration.

## Data Availability

All code and data are available at <https://github.com/jinyoungkim927/desi-evalue-analysis>.

Official DESI data from [https://github.com/CobayaSampler/bao\\_data](https://github.com/CobayaSampler/bao_data).

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