Investigating the Hubble Tension with BOSS Full-Shape Power Spectra

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Abstract

I recreate a comparison of fits of BOSS Full-Shape Power spectra using a ΛCDM model and a model including Early Dark Energy that has been proposed to solve the Hubble tension. Both models give comparable fits ($\chi^2 \sim 175$), but convergence of the EDE model is generally poorer. Using only FS data, I find the Early Dark Energy model is able to alleviate the tension by raising the best-fit value of the Hubble constant to $H_0 = 70.58^{+1.6}_{-1.7}$ km/s/Mpc. I cover the details of the power spectrum predictions from the Effective Field Theory of LSS and the Markov Chain Monte Carlo pipeline used for the fits. I finally discuss the inconsistency of my results with those of the reference analysis.

1 Introduction

The tension between the most precise methods of measuring the Hubble constant, H_0, remains one of the principal inconsistencies of the modern standard model of cosmology. Direct measurements of the current expansion rate of the universe using the "standard candles" of Type-Ia supernovae (Riess et al. [2022]) give a generally higher value of H_0 than indirect measurements made with observations of "standard rulers" in the Cosmic Microwave Background ([Planck Collaboration et al., 2020]). The difference between these measurements is now between $4-6\sigma$ [Verde et al., 2019]. While this tension may be resolved by unidentified uncertainties in either measurement, unidentified physics remain an exciting possible solution. Early dark energy (EDE) has been presented as one type of unidentified physics. This model includes an additional field that acts like dark energy in the early universe that raises the expansion rate at early times and thus raises H_0. [D'Amico et al., 2021a] (hereafter Paper I) investigates the impact of two models of EDE on the H_0 tension when including power spectra data from the Baryon Oscillation Spectroscopic Survey (BOSS) with various combinations of other available cosmological data.

1.1 Early Dark Energy

The addition of EDE to the early universe introduces additional degrees of freedom that affect early expansion, and become negligible at later times. I specifically investigate one of the models presented in Paper I: Axion Early Dark Energy, which is simply referred to as EDE by the authors. This model introduces a scalar field ϕ with potential

$$V_n(\phi) = \Lambda^4 \left[1 - \cos\phi/f\right]^n + V_\Lambda \tag{1}$$

or, in terms of a "misalignment angle" $\Theta = \phi/f$ and the axion mass $m = \Lambda^2/f$

$$V_n(\phi) = m^2 f^2 \left[1 - \cos\Theta\right]^n + V_\Lambda \tag{2}$$

There will be some time, with a corresponding redshift z_c, at which the axion field reaches a maximum fraction of the universe's total energy density, given by $f_{\rm EDE}(z_c) \simeq \frac{V_n(\Theta_i)}{\rho_{tot}(z_c)}$. The parameters that dictate the dynamics of this field are then given by $f_{\rm EDE}$, z_c, Θ_i, V_Λ, and n. These can be thought of as describing properties such as the amount of EDE, the time at which EDE begins to decay, and how quickly it does so. I note here that the authors of Paper I investigate only the $n = 3$ case of this EDE model, as does this paper.

The exact mechanism by which EDE increases the inferred value of H_0 is of importance for analyzing any effect on the standard cosmological parameters. The expansion rate of the early universe plasma determines the rate at which its different constituents "freeze out" or decouple from the plasma. By introducing a dark-energy component in the early universe which increases the expansion rate for a time, this decoupling occurs more rapidly than in standard ΛCDM. The sound horizon r_s, which is used as a standard ruler to infer H_0 from the CMB and large-scale structure, is set when photons decouple from the primordial plasma; r_s decreases as a result of this more rapid decoupling. Since the expansion rate in the late universe (i.e. H_0) is increased in kind by the addition of EDE, the observed angular scale of the acoustic oscillations

$$\theta_s = \frac{r_s}{D_A} \sim r_s H_0 \tag{3}$$

is unaffected, as must be the case for this model to make any sense. Further, for this model to successfully resolve the Hubble tension, the change in r_s and H_0 must be of the order of the discrepancy between Direct and Indirect H_0 measurements.

1.2 The Effective Field Theory of Large-Scale Structure

Paper I investigates alleviating the Hubble tension with EDE when including the Full-Shape (FS) of BOSS power spectra, in combination with other data sets. The galaxy power spectrum is a summary statistic describing the anisotropy in the density of galaxies as a function of scale. In the case where real, physical distances to galaxies are known and their distribution is isotropic, the power spectrum is related to the two-point correlation function by a Fourier transform:

$$\xi(r) = \int \frac{d^3k}{2\pi} P(k) e^{i\mathbf{k}\cdot\mathbf{r}} \tag{4}$$

Measurements of galaxy distances using redshifts complicate the use of this statistic, however. Peculiar velocities of galaxies make use of the redshift-distance relation noisy, which "breaks" the isotropy of the matter distribution along the line of sight (Kobayashi et al. 2020). Therefore, the power spectrum measured using redshift measurements, or the *redshift-space* power spectrum (RSPS), is expressed in terms of the magnitude of the wavevectors k perpendicular to the line of sight as well as the cosine of the angle between these and the LOS wavevector $\mu \equiv k_{LOS}/k$. It is convenient to express the resulting power spectrum $P(k,\mu)$ in terms of a multipole expansion using Legendre polynomials:

$$P_\ell(k) = \frac{2\ell+1}{2} \int P(k,\mu) L_\ell(\mu) d\mu \tag{5}$$

Cosmological analysis using these Power spectra is difficult due to the non-linear effects on smaller scales and biases introduced by tracers of the matter distribution (galaxies). The Effective Field Theory of Large-Scale Structure (EFTofLSS) was developed recently to account for these effects and model the RSPS. The EFT introduces higher-order corrective terms to the predictions of linear theory and 1-loop perturbation theory so that the RSPS can be written

$$P_\ell(k) = P_\ell^{\rm lin}(k) + P_\ell^{\rm 1-loop}(k) + P_\ell^{\rm ctr}(k) + P_\ell^{\rm stoch}(k) \tag{6}$$

where the first term terms constitute the standard 1-loop perturbation theory prediction. This model introduces 10 nuisance parameters: 4 galaxy biases b_i, 3 associated with non-linearity $c_{t,i}$, and 3 associated with noise $c_{\epsilon,i}$. While these are interesting as they are related to galaxy properties, we aim to marginalize over them when performing an analysis of cosmological parameters.

2 Data And Methods

2.1 BOSS Full-Shape Power Spectra

In this paper, I attempt to recreate the results of Paper I regarding the Axion Early Dark Energy model fitting only BOSS DR12 Full-Shape power spectra. These data are publicly available ([D'Amico et al., 2022]), and include monopole and quadrupole ($\ell = 0, 2$) power spectra for the two BOSS sky cuts (see Fig. 6 of [Alam et al., 2015]). Data from each sky is binned into two effective redshifts of $z_{\text{eff}} = \{0.38, 0.61\}$, for a total of 8 power spectra in all Figure 1.

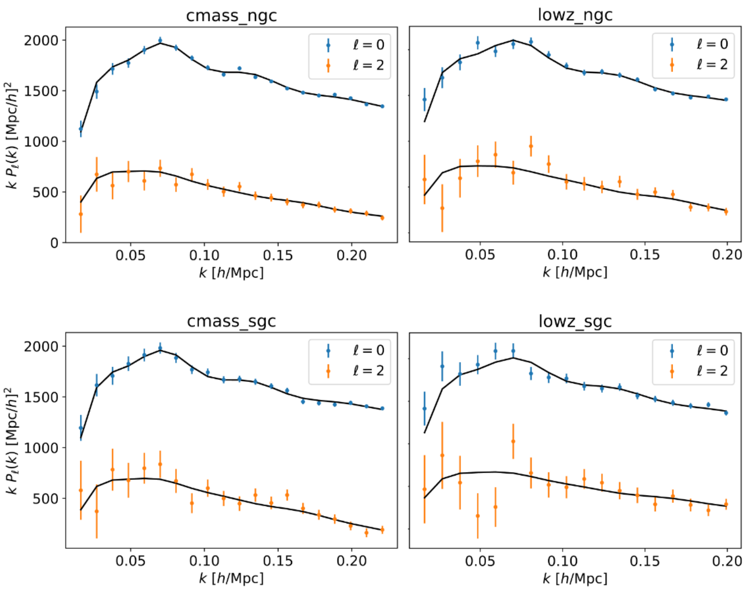

Figure 1: The monopole and quadrupole spectra for each of the BOSS DR12 skies. Each multipole has 20 data points, so there are 160 data points fit in total. Example EFT predictions are plotted over these in black.

2.2 Likelihood

Models for the power spectra are computed using the publicly available `CLASS_EDE` and PyBird: Python code for Biased tracers in Redshift space ([D'Amico et al., 2021b]). `CLASS_EDE` is a modified version of the Cosmic Linear Anisotropy Linear Solving System (`CLASS`), a Boltzmann code used to compute linear power spectra (i.e. the first term in eq. (6)) for a given cosmology ([Hill et al., 2020]). This modified version incorporates EDE parameters into these predictions. PyBird then computes the remaining EFT terms for the provided linear spectrum. PyBird also handles computation of the likelihood of the BOSS FS data given the model parameters, which is assumed to be a Gaussian distribution:

$$\mathcal{L}(D|\theta_n, \theta_C) = \exp\left\{-\frac{1}{2}(\mathrm{P}_\ell^{\mathrm{EFT}}(\mathrm{k}) - \mathrm{P}_\ell^{\mathrm{D}}(\mathrm{k}))\mathrm{C}^{-1}(\mathrm{P}_\ell^{\mathrm{EFT}}(\mathrm{k}) - \mathrm{P}_\ell^{\mathrm{D}}(\mathrm{k}))^{\mathrm{T}}\right\} \tag{7}$$

where $P_\ell^{\mathrm{EFT}}(k)$ and $P_\ell^{D}(k)$ are the prediction and observation for a given multipole of the RSPS in a given k bin, and C^{-1} is the covariance matrix of the data. I denote the model parameters as either nuisance θ_n or cosmological θ_C. The data covariance is estimated using a set of 2048 mock simulations of the BOSS Sky patches, referred to as "Patchy" mocks ([Kitaura et al., 2016]). The nuisance parameters are expected to be of $\mathcal{O}(1)$, and Gaussian priors with zero mean and a standard deviation of 2 are placed on all of these except for b_1 and c_2; these are given flat priors: $b_1 \in [0, 4]$, $c_2 \in [-10, 10]$. These priors are motivated by the physical restriction that EFT terms must be less dominant than lower-order terms. The only prior placed on ΛCDM cosmology is $\omega_b \sim \mathcal{N}(0.02268, 0.00038)$ from Big Bang Nucleosynthesis constraints. I assume the default flat priors from `CLASS_EDE`, $f_{\mathrm{EDE}} \in [0.001, 0.5]$, $log_{10}(z_c) \in [3.0, 4.3]$, $\Theta_i \in [0.1, 3.1]$ for the varied EDE parameters.

Ultimately, the above likelihood will be marginalized over to analyze cosmological parameters; that is, we are interested in computing the integral $\mathcal{L}(D|\theta_C) = \int d\theta_n \mathcal{L}(D|\theta_n, \theta_C)$. For parameters that appear in the likelihood at no higher than quadratic order, and have Gaussian priors, such an integral is an analytic Gaussian integral(see [d'Amico et al., 2020] for further details). This is the case for all but the two EFT parameters with flat priors (b_1 and c_2). Performing this computation leaves us with a "partially marginalized" likelihood with only 2 nuisance parameters for each sky, which is more efficient to work with when running a Markov Chain Monte Carlo fitting routine.

2.3 Sampling

Following the methods of Paper I, I sample the posteriors of the model RSPS parameters using the MCMC sampler MontePython ([Brinckmann and Lesgourgues, 2019]), which PyBird provides an EFT-BOSS likelihood for. In the interest of time and following the example of ([d'Amico et al., 2020]), I have chosen to sample only a subset of the ΛCDM cosmological model parameters: The dimensionless Hubble constant h, the cold dark matter energy density ω_{cdm}, and the amplitude of the primordial power spectrum A_s. The remaining cosmological parameters, n_s and ω_b I fix to the Planck 2018 best-fit values. In line with this, I initialize the varying cosmological parameters at Planck 2018 best-fit values. The two non-analytically-marginalized EFT parameters for each sky are initialized at values of $b_1 = 2$ and $c_2 = 0$. The EDE parameters, f_{EDE}, z_c, Θ_i, are initialized at the values given in ([Hill et al., 2020]), and V_Λ has been fixed at a value of 1 for convenience.

I fit the BOSS FS data with a base ΛCDM model and a EDE model. For each of these fits, I use the default Metroplis-Hastings algorithm implemented in MontePython to run 5 chains in parallel with 20,000 total steps and an acceptance rate ~ 0.23 for a final total chain length of $\sim 5,000$. When analyzing these chains I discard half of the chains as burn-in, which is well beyond the point the likelihood values appear to converge.

3 Results and Discussion

The resulting posteriors for the cosmological parameters shared between the base ΛCDM and EDE models are shown in Figure 2. We can first immediately see that the uncertainties in the EDE fit are slightly larger than those from the ΛCDM fit. This is likely due to worse convergence. This is likewise the case for the ΛCDM posterior of A_s, which is broad and multi-modal. Investigating the Gelman-Rubin convergence statistic ([Gelman and Rubin, 1992]) for each run supports this conclusion: the GR statistic is slightly higher generally for every parameter in the EDE run, and is highest for A_s in the ΛCDM run. Given more time, it would be desirable to run these chains to a level consistent with the criteria of Paper I of $R < 0.005$.

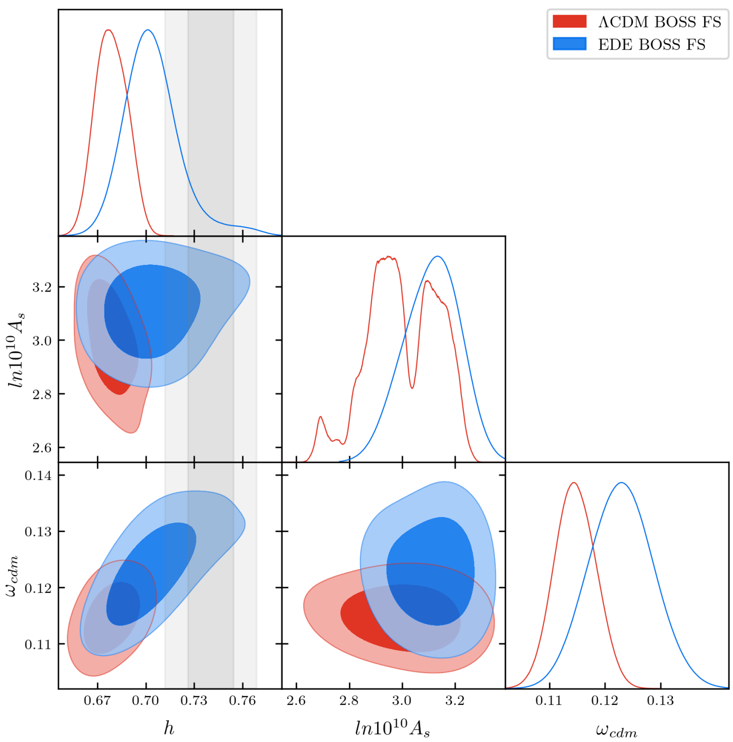

Figure 2: Posteriors of the cosmological parameters common to both the ΛCDM and EDE models. The value of h associated with the SH0ES measurement of $H_0 = 74.03 \pm 1.42$ km/s/Mpc is shown as a gray band.

Despite these issues, the key result is evident from the 1-D posterior of h: the fit with EDE shifts

Model	H_0 best-fit	$-\ln \mathcal{L}_{\min}$	$\chi^2_{\min}$	Worst $R-1$
ΛCDM	$67.45^{+1.2}_{-1.3}$ km/s/Mpc	87.66	175.3	0.7465
EDE	$70.58^{+1.6}_{-1.7}$ km/s/Mpc	87.49	175	2.385

Table 1: H_0 best-fit and minimum log-likelihood and chi-squared values from both the ΛCDM and EDE runs. I also include the worst value of the $R-1$ convergence statistic, which is for A_s in ΛCDM and $\Theta_{i,\mathrm{scf}}$ in EDE.

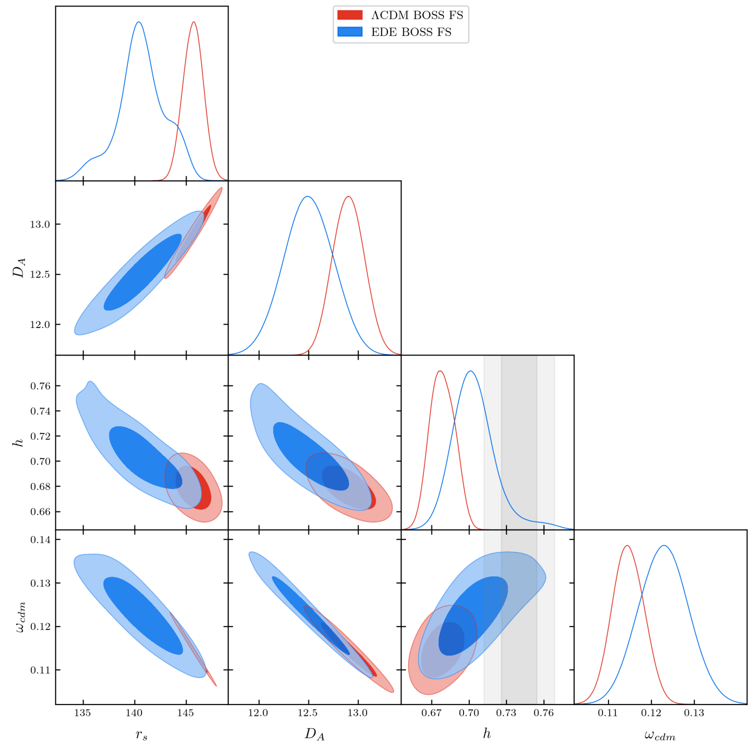

Figure 3: Posteriors including the derived parameters r_s and D_A for both fits.

the mean value closer to the SH0ES measurement. However, there is still slight tension with the distance ladder measurement in either case. This is consistent with the results of Paper I which do not include FS data (see their Figure 4), interestingly. The combination of Planck+FS data actually results in a greater tension with SH0ES than in base ΛCDM in Paper I (their figure 5). In this regard, my results are more consistent with prior EDE studies that do not include FS data.

Figure 3 also shows the posteriors of the derived parameters D_A and r_s (the angular diameter distance and the sound horizon at recombination) for the sake of comparing with the physical reasoning behind EDE raising the inferred value of h. As we might expect from the discussion in Section 1.1, h and r_s are inversely related. The shift of r_s to a lower value is then able to raise h accordingly, but as r_s is fairly well determined by the ΛCDM fit already, the shift is small. This case is stronger in the reference analysis, as the combination of Planck+FS+BAO+SN data used there breaks the $r_s - H_0$ degeneracy.

Lastly, I present the posteriors of the parameters in the EDE model in Figure 4. We see that h and $f_{\rm EDE}$ are directly related, as we should expect from the effect of including EDE. This fit favors a small but non-zero for $f_{\rm EDE}$, largely agreeing with fit from Paper I.

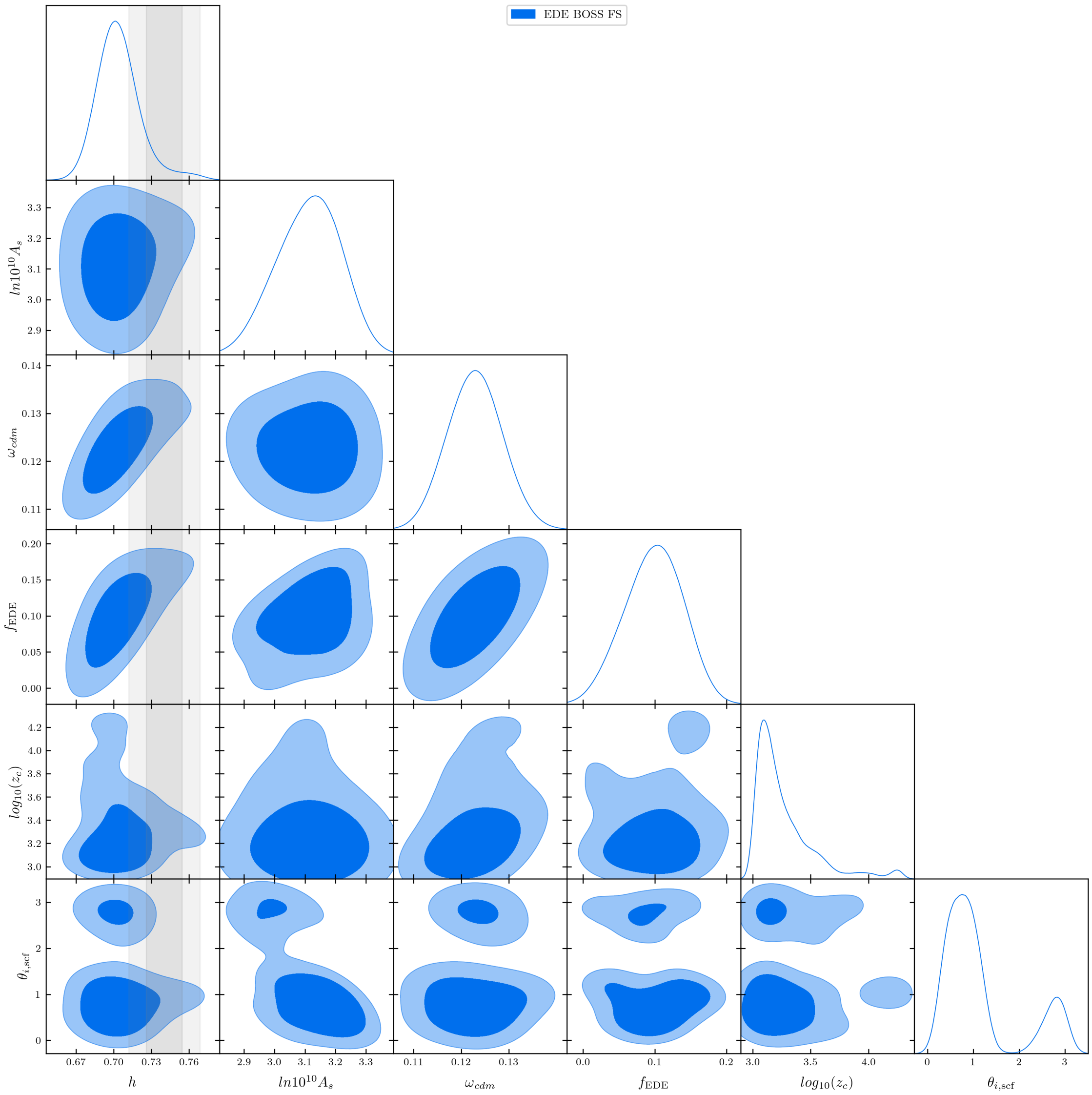

Figure 4: Posteriors of all of the cosmological parameters for the EDE model.

4 Conclusion

In this paper, I review the details of a cosmological analysis using fits of EFTofLSS predictions to the BOSS redshift-space power spectrum and recreate some of the results regarding the alleviation of the Hubble tension with the Axion Early Dark Energy model. I find that the EDE model can ease the tension when fitting only BOSS data. The best-fit values of H_0 for fits with ΛCDM and EDE are found to be $H_0 = 67.45^{+1.2}_{-1.3}$ km/s/Mpc and $H_0 = 70.580.7^{+1.6}_{-1.7}$ km/s/Mpc, with EDE decreasing the tension with the SH0ES measurement from 3.4σ to 1.6σ. This result is inconsistent with the results of Paper I, where the tension was found to increase when fitting the EDE model with a combination of data that includes the BOSS FS. In addition to poorer chain convergence in my fits, this disagreement can be attributed to inconsistency between the FS data and the combination of Planck+FS+BAO+SN data used in the reference analysis. In light of these results, it would be interesting to repeat this study with more robust convergence requirements. It would also be interesting to study differences when using different combinations and subsets of the data used in Paper I.

This study has made use of python ([Van Rossum and Drake, 2009]), jupyter notebooks ([Kluyver et al., 2016]), and the numpy ([Harris et al., 2020]), GetDist ([Lewis, 2019]), and matplotlib ([Hunter, 2007])packages. A github repository with the code required for this paper and some demonstration of the MCMC sampling and plotting routine is available at (`https://github.com/cosweeney/ASTR513.git`)

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References

Adam G. Riess, Wenlong Yuan, Lucas M. Macri, Dan Scolnic, Dillon Brout, Stefano Casertano, David O. Jones, Yukei Murakami, Gagandeep S. Anand, Louise Breuval, Thomas G. Brink, Alexei V. Filippenko, Samantha Hoffmann, Saurabh W. Jha, W. D'arcy Kenworthy, John Mackenty, Benjamin E. Stahl, and WeiKang Zheng. A comprehensive measurement of the local value of the hubble constant with 1 km s-1 mpc-1 uncertainty from the hubble space telescope and the SH0es team. *The Astrophysical Journal Letters*, 934(1):L7, jul 2022. doi: 10.3847/2041-8213/ac5c5b. URL `https://doi.org/10.3847%2F2041-8213%2Fac5c5b`.

Planck Collaboration, N. Aghanim, Y. Akrami, M. Ashdown, J. Aumont, C. Baccigalupi, M. Ballardini, A. J. Banday, and Barreiro. Planck 2018 results. VI. Cosmological parameters. , 641:A6, September 2020. doi: 10.1051/0004-6361/201833910.

Licia Verde, Tommaso Treu, and Adam G. Riess. Tensions between the early and late Universe. *Nature Astronomy*, 3:891–895, September 2019. doi: 10.1038/s41550-019-0902-0.

Guido D'Amico, Leonardo Senatore, Pierre Zhang, and Henry Zheng. The hubble tension in light of the full-shape analysis of large-scale structure data. *Journal of Cosmology and Astroparticle Physics*, 2021(05):072, may 2021a. doi: 10.1088/1475-7516/2021/05/072. URL `https://doi.org/10.1088%2F1475-7516%2F2021%2F05%2F072`.

Guido D'Amico, Yaniv Donath, Matthew Lewandowski, Leonardo Senatore, and Pierre Zhang. The BOSS bispectrum analysis at one loop from the Effective Field Theory of Large-Scale Structure. *arXiv e-prints*, art. arXiv:2206.08327, June 2022. doi: 10.48550/arXiv.2206.08327.

Shadab Alam, Franco D. Albareti, Carlos Allende Prieto, F. Anders, Scott F. Anderson, Timothy Anderton, Brett H. Andrews, Eric Armengaud, Éric Aubourg, Stephen Bailey, Sarbani Basu, Julian E. Bautista, Rachael L. Beaton, Timothy C. Beers, Chad F. Bender, Andreas A. Berlind, Florian Beutler, Vaishali Bhardwaj, Jonathan C. Bird, Dmitry Bizyaev, Cullen H. Blake, Michael R. Blanton, Michael Blomqvist, John J. Bochanski, Adam S. Bolton, Jo Bovy, A. Shelden Bradley, W. N. Brandt, D. E. Brauer, J. Brinkmann, Peter J. Brown, Joel R. Brownstein, Angela Burden, Etienne Burtin, Nicolás G. Busca, Zheng Cai, Diego Capozzi, Aurelio Carnero Rosell, Michael A. Carr, Ricardo Carrera, K. C. Chambers, William James Chaplin, Yen-Chi Chen, Cristina Chiappini, S. Drew Chojnowski, Chia-Hsun Chuang, Nicolas Clerc, Johan Comparat, Kevin Covey, Rupert A. C. Croft, Antonio J. Cuesta, Katia Cunha, Luiz N. da Costa, Nicola Da Rio, James R. A. Davenport, Kyle S. Dawson, Nathan De Lee, Timothée Delubac, Rohit Deshpande, Saurav Dhital, Letícia Dutra-Ferreira, Tom Dwelly, Anne Ealet, Garrett L. Ebelke, Edward M. Edmondson,

Daniel J. Eisenstein, Tristan Ellsworth, Yvonne Elsworth, Courtney R. Epstein, Michael Eracleous, Stephanie Escoffier, Massimiliano Esposito, Michael L. Evans, Xiaohui Fan, Emma Fernández-Alvar, Diane Feuillet, Nurten Filiz Ak, Hayley Finley, Alexis Finoguenov, Kevin Flaherty, Scott W. Fleming, Andreu Font-Ribera, Jonathan Foster, Peter M. Frinchaboy, J. G. Galbraith-Frew, Rafael A. García, D. A. García-Hernández, Ana E. García Pérez, Patrick Gaulme, Jian Ge, R. Génova-Santos, A. Georgakakis, Luan Ghezzi, Bruce A. Gillespie, Léo Girardi, Daniel Goddard, Satya Gontcho A. Gontcho, Jonay I. González Hernández, Eva K. Grebel, Paul J. Green, Jan Niklas Grieb, Nolan Grieves, James E. Gunn, Hong Guo, Paul Harding, Sten Hasselquist, Suzanne L. Hawley, Michael Hayden, Fred R. Hearty, Saskia Hekker, Shirley Ho, David W. Hogg, Kelly Holley-Bockelmann, Jon A. Holtzman, Klaus Honscheid, Daniel Huber, Joseph Huehnerhoff, Inese I. Ivans, Linhua Jiang, Jennifer A. Johnson, Karen Kinemuchi, David Kirkby, Francisco Kitaura, Mark A. Klaene, Gillian R. Knapp, Jean-Paul Kneib, Xavier P. Koenig, Charles R. Lam, Ting-Wen Lan, Dustin Lang, Pierre Laurent, Jean-Marc Le Goff, Alexie Leauthaud, Khee-Gan Lee, Young Sun Lee, Timothy C. Licquia, Jian Liu, Daniel C. Long, Martín López-Corredoira, Diego Lorenzo-Oliveira, Sara Lucatello, Britt Lundgren, Robert H. Lupton, III Mack, Claude E., Suvrath Mahadevan, Marcio A. G. Maia, Steven R. Majewski, Elena Malanushenko, Viktor Malanushenko, A. Manchado, Marc Manera, Qingqing Mao, Claudia Maraston, Robert C. Marchwinski, Daniel Margala, Sarah L. Martell, Marie Martig, Karen L. Masters, Savita Mathur, Cameron K. McBride, Peregrine M. McGehee, Ian D. McGreer, Richard G. McMahon, Brice Ménard, Marie-Luise Menzel, Andrea Merloni, Szabolcs Mészáros, Adam A. Miller, Jordi Miralda-Escudé, Hironao Miyatake, Antonio D. Montero-Dorta, Surhud More, Eric Morganson, Xan Morice-Atkinson, Heather L. Morrison, Benôit Mosser, Demitri Muna, Adam D. Myers, Kirpal Nandra, Jeffrey A. Newman, Mark Neyrinck, Duy Cuong Nguyen, Robert C. Nichol, David L. Nidever, Pasquier Noterdaeme, Sebastián E. Nuza, Julia E. O'Connell, Robert W. O'Connell, Ross O'Connell, Ricardo L. C. Ogando, Matthew D. Olmstead, Audrey E. Oravetz, Daniel J. Oravetz, Keisuke Osumi, Russell Owen, Deborah L. Padgett, Nikhil Padmanabhan, Martin Paegert, Nathalie Palanque-Delabrouille, Kaike Pan, John K. Parejko, Isabelle Pâris, Changbom Park, Petchara Pattarakijwanich, M. Pellejero-Ibanez, Joshua Pepper, Will J. Percival, Ismael Pérez-Fournon, Ignasi Pérez-Ràfols, Patrick Petitjean, Matthew M. Pieri, Marc H. Pinsonneault, Gustavo F. Porto de Mello, Francisco Prada, Abhishek Prakash, Adrian M. Price-Whelan, Pavlos Protopapas, M. Jordan Raddick, Mubdi Rahman, Beth A. Reid, James Rich, Hans-Walter Rix, Annie C. Robin, Constance M. Rockosi, Thaíse S. Rodrigues, Sergio Rodríguez-Torres, Natalie A. Roe, Ashley J. Ross, Nicholas P. Ross, Graziano Rossi, John J. Ruan, J. A. Rubiño-Martín, Eli S. Rykoff, Salvador Salazar-Albornoz, Mara Salvato, Lado Samushia, Ariel G. Sánchez, Basílio Santiago, Conor Sayres, Ricardo P. Schiavon, David J. Schlegel, Sarah J. Schmidt, Donald P. Schnei-

der, Mathias Schultheis, Axel D. Schwope, C. G. Scóccola, Caroline Scott, Kris Sellgren, Hee-Jong Seo, Aldo Serenelli, Neville Shane, Yue Shen, Matthew Shetrone, Yiping Shu, V. Silva Aguirre, Thirupathi Sivarani, M. F. Skrutskie, Anže Slosar, Verne V. Smith, Flávia Sobreira, Diogo Souto, Keivan G. Stassun, Matthias Steinmetz, Dennis Stello, Michael A. Strauss, Alina Streblyanska, Nao Suzuki, Molly E. C. Swanson, Jonathan C. Tan, Jamie Tayar, Ryan C. Terrien, Aniruddha R. Thakar, Daniel Thomas, Neil Thomas, Benjamin A. Thompson, Jeremy L. Tinker, Rita Tojeiro, Nicholas W. Troup, Mariana Vargas-Magaña, Jose A. Vazquez, Licia Verde, Matteo Viel, Nicole P. Vogt, David A. Wake, Ji Wang, Benjamin A. Weaver, David H. Weinberg, Benjamin J. Weiner, Martin White, John C. Wilson, John P. Wisniewski, W. M. Wood-Vasey, Christophe Ye'che, Donald G. York, Nadia L. Zakamska, O. Zamora, Gail Zasowski, Idit Zehavi, Gong-Bo Zhao, Zheng Zheng, Xu Zhou, Zhimin Zhou, Hu Zou, and Guangtun Zhu. The Eleventh and Twelfth Data Releases of the Sloan Digital Sky Survey: Final Data from SDSS-III. , 219(1):12, July 2015. doi: 10.1088/0067-0049/219/1/12.

Guido D'Amico, Leonardo Senatore, and Pierre Zhang. Limits on iw/iCDM from the EFTofLSS with the PyBird code. *Journal of Cosmology and Astroparticle Physics*, 2021(01):006–006, jan 2021b. doi: 10.1088/1475-7516/2021/01/006. URL `https://doi.org/10.1088%2F1475-7516%2F2021%2F01%2F006`.

J. Colin Hill, Evan McDonough, Michael W. Toomey, and Stephon Alexander. Early dark energy does not restore cosmological concordance. , 102(4):043507, August 2020. doi: 10.1103/PhysRevD.102.043507.

Francisco-Shu Kitaura, Sergio Rodríguez-Torres, Chia-Hsun Chuang, Cheng Zhao, Francisco Prada, Héctor Gil-Marín, Hong Guo, Gustavo Yepes, Anatoly Klypin, Claudia G. Scóccola, Jeremy Tinker, Cameron McBride, Beth Reid, Ariel G. Sánchez, Salvador Salazar-Albornoz, Jan Niklas Grieb, Mariana Vargas-Magana, Antonio J. Cuesta, Mark Neyrinck, Florian Beutler, Johan Comparat, Will J. Percival, and Ashley Ross. The clustering of galaxies in the SDSS-III Baryon Oscillation Spectroscopic Survey: mock galaxy catalogues for the BOSS Final Data Release. , 456(4):4156–4173, March 2016. doi: 10.1093/mnras/stv2826.

Guido d'Amico, Jérôme Gleyzes, Nickolas Kokron, Katarina Markovic, Leonardo Senatore, Pierre Zhang, Florian Beutler, and Héctor Gil-Marín. The cosmological analysis of the SDSS/BOSS data from the Effective Field Theory of Large-Scale Structure. , 2020(5):005, May 2020. doi: 10.1088/1475-7516/2020/05/005.

Thejs Brinckmann and Julien Lesgourgues. MontePython 3: Boosted MCMC sampler and other features. *Physics of the Dark Universe*, 24:100260, March 2019. doi: 10.1016/j.dark.2018.100260.

Andrew Gelman and Donald B. Rubin. Inference from Iterative Simulation Using Multiple Sequences. *Statistical Science*, 7:457–472, January 1992. doi: 10.1214/ss/1177011136.

Guido Van Rossum and Fred L. Drake. *Python 3 Reference Manual*. CreateSpace, Scotts Valley, CA, 2009. ISBN 1441412697.

Thomas Kluyver, Benjamin Ragan-Kelley, Fernando Pérez, Brian Granger, Matthias Bussonnier, Jonathan Frederic, Kyle Kelley, Jessica Hamrick, Jason Grout, Sylvain Corlay, Paul Ivanov, Damián Avila, Safia Abdalla, and Carol Willing. Jupyter notebooks – a publishing format for reproducible computational workflows. In F. Loizides and B. Schmidt, editors, *Positioning and Power in Academic Publishing: Players, Agents and Agendas*, pages 87 – 90. IOS Press, 2016.

Charles R. Harris, K. Jarrod Millman, Stéfan J. van der Walt, Ralf Gommers, Pauli Virtanen, David Cournapeau, Eric Wieser, Julian Taylor, Sebastian Berg, Nathaniel J. Smith, Robert Kern, Matti Picus, Stephan Hoyer, Marten H. van Kerkwijk, Matthew Brett, Allan Haldane, Jaime Fernández del Río, Mark Wiebe, Pearu Peterson, Pierre Gérard-Marchant, Kevin Sheppard, Tyler Reddy, Warren Weckesser, Hameer Abbasi, Christoph Gohlke, and Travis E. Oliphant. Array programming with NumPy. *Nature*, 585(7825):357–362, September 2020. doi: 10.1038/s41586-020-2649-2. URL `https://doi.org/10.1038/s41586-020-2649-2`.

Antony Lewis. GetDist: a Python package for analysing Monte Carlo samples. *arXiv e-prints*, art. arXiv:1910.13970, October 2019. doi: 10.48550/arXiv.1910.13970.

J. D. Hunter. Matplotlib: A 2d graphics environment. *Computing in Science & Engineering*, 9(3): 90–95, 2007. doi: 10.1109/MCSE.2007.55.