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with Maria Giovanna Dainotti, Adrià Gómez-Valent and Marina Migliaccio arXiv: 2402.13115

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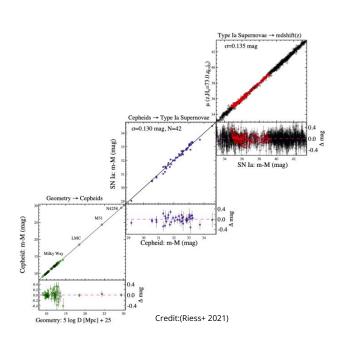
Climbing the ladder

Standard candles, such as Supernovae of Type Ia (SNIa), constitute a well-established tool to measure cosmic distances, which in turn are used to constrain cosmological parameters of fundamental importance



The **cosmic distance ladder** played a pivotal role in the discovery of the late-time cosmic acceleration and has gained much relevance in the discussion of the Hubble tension





Current data on SNIa cover up to z~2.5

To broaden the investigation to higher redshifts one of most promising observables are Gamma-Ray Bursts

Why?

- → Transient but extremely energetic phenomena in our universe (more luminous than SNIa!)
- → Can probe the universe up to z ~9.4

How?

They exhibit characteristics that suggest they are potentially standardizable candles and this allows their use to extend the distance ladder beyond SNIa.

To standardize GRBs and use them as cosmological tools, it is necessary to find tight and intrinsic relations between parameters of their light curves (or spectra) and their luminosity (or energy) (e.g. Amati+ 2002, Ghirlanda+ 2004, Yonetoku+ 2004, Dainotti+ 2008, Bernardini+ 2012..)

Problem 1

- → The spread in the GRBs observed luminosities due to the not yet well-defined nature of their origins (e.g. core collapse of a massive star, neutron stars-black hole system merger..)
- → Reliability of the relations after the truncation and selection effect tests

We focus on

The 3D Dainotti correlation (Dainotti+ 2016): Fundamental plane relation between the peak prompt luminosity, the rest-frame end time of the plateau phase, and its corresponding luminosity

$$\log L_{\rm X} = C_o + a \log T_{\rm X}^* + b \log L_{\rm peak}$$

$$L_{\rm X} = 4\pi D_L^2 F_{\rm X} K_{\rm plateau}$$

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 $L_{\rm peak} = 4\pi D_L^2 F_{\rm peak} K_{\rm prompt}$

- It is supported by a fundamental physical process, the magnetar emission (Rowlinson+ 2014; Bernardini+ 2015; Stratta+ 2018, Dall'Osso+ 2023)
- It overcomes selection biases that could invalidate the reliability of the relations themselves (Dainotti+ 2013, 2017)

Problem 2

→ The *circularity problem* if a cosmological model is assumed during the calibration

Two solutions

- → **Simultaneous fitting**: fit simultaneously the correlation parameters and the parameters of a cosmological model of interest from GRB observations.
- → Calibration with low-redshift probes, given that objects at the same redshift should have the same luminosity distance regardless of the underlying cosmology

$$D_L(z) = c(1+z) \int_0^z \frac{dz'}{H(z')}$$

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Cosmic chronometers (CCH)

Direct measurements of H(z) using massive and passively-evolving galaxies and the differential age technique (Jimenez & Loeb 2002)

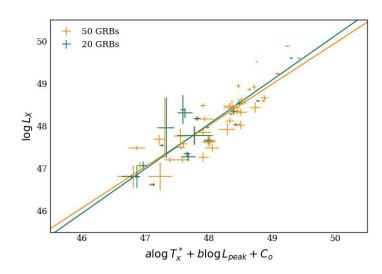
$$H(z) = \frac{\dot{a}}{a} = \frac{-1}{1+z} \frac{dz}{dt}$$

- → Independent of the local distance ladder calibrators
- → Does not rely on any particular cosmological model
- crucial in light of the Hubble tension
- → Both statistical and systematics errors are estimated (Moresco+ 2020)
- → Can act as calibrators for the cosmic ladders (Favale+ 2023)

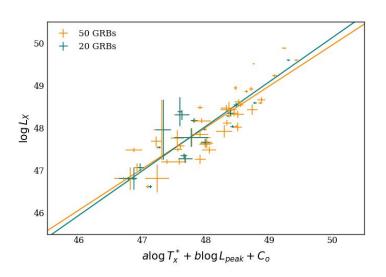
Platinum sample (Dainotti+ 2020)

GRBs with well-defined plateau properties that obey the fundamental plane relation

Select a sub-sample of 20 long GRBs in $0.553 \le z \le 1.96$ to match the CCH range



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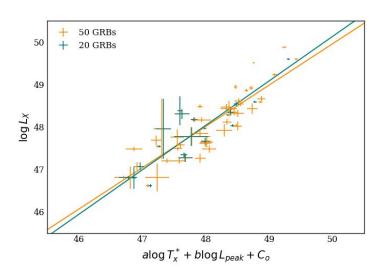
- Gaussian Processes (GP)
 bayesian reconstruction tool
- + **MCMC** analysis

$$D_{L}(z) = c(1+z) \int_{0}^{z} \frac{dz'}{H(z')}$$

$$\chi^{2}(a, b, C_{o}, \sigma_{int}) = \sum_{i=1}^{N} \frac{[\log D_{L}^{\text{obs}}(z_{i}) - \log D_{L}^{\text{th}}(z_{i}, a, b, C_{o})]^{2}}{(\sigma_{\text{obs},i}^{2} + \sigma_{int}^{2})}$$

$$\log D_{L}^{\text{th}} = a_{1} \log T_{X}^{*} + b_{1} (\log F_{\text{peak}} + \log K_{\text{prompt}}) + c_{1} + d_{1} (\log F_{X} + \log K_{\text{plateau}})$$

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Results - GP reconstruction

GP is designed to perform data-driven reconstruction of smooth trends from Gaussian distributed data

$$f(x) \sim GP(\mu(x), D[K(x, \tilde{x}), C])$$

Advantages:

- → works under very minimal assumptions no need for a model
- encodes the assumptions on the covariance between points at which we do not have data
- → outcomes are agnostic estimates of functions of interest

$$\bar{f}^* = \mu^* + K(X^*, X)[K(X, X) + C]^{-1}(y - \mu)$$

$$cov(f^*) = K(X^*, X^*) - K(X^*, X)[K(X, X) + C]^{-1}K(X, X^*)$$

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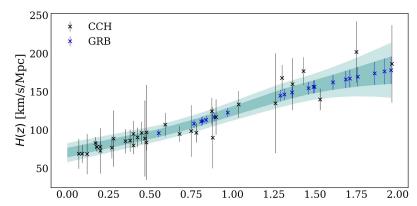
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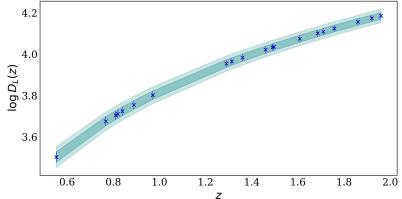
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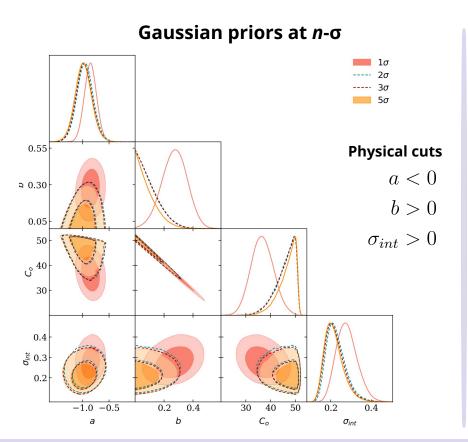
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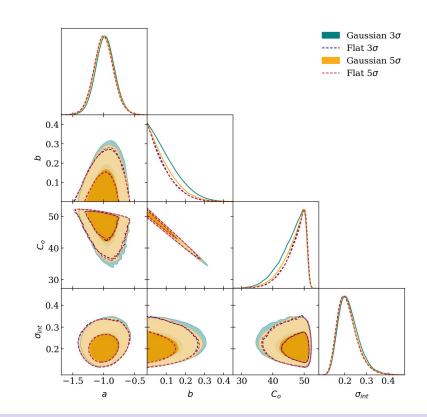
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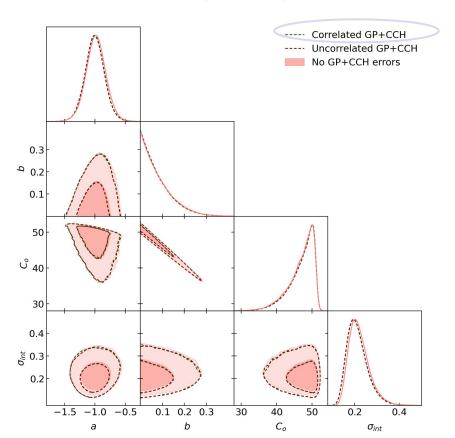


Results - Impact of the prior choice



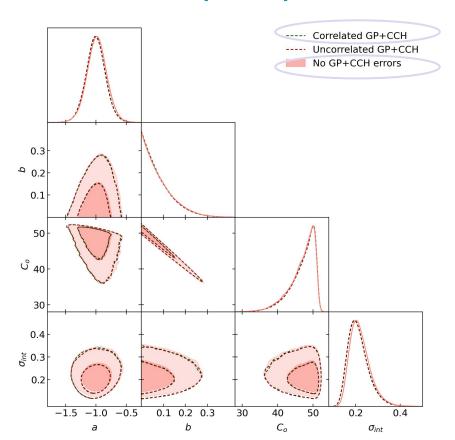


Results - Impact of the modelling of CCH uncertainties & covariance



$$\ln \mathcal{L} = -\frac{N}{2} \ln(2\pi) - \frac{1}{2} \ln \det(C_{\mathrm{T}}) - \frac{1}{2} \sum_{i,j=1}^{N} \Delta_{i}^{T} (C_{\mathrm{T}}^{-1})_{ij} \Delta_{j}$$

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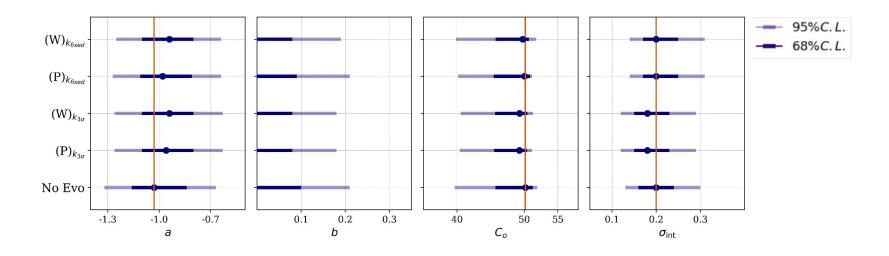
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Results - Redshift evolution corrections

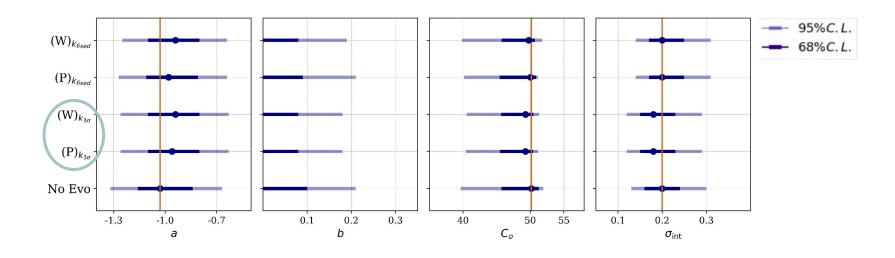
$$\log L_{\rm X} - k_{L_x} \log(1+z) = a_{ev} (\log T_{\rm X}^{\star} - k_{T_{\rm X}^{\star}} \log(1+z)) + b_{ev} (\log L_{\rm peak} - k_{L_{\rm peak}} \log(1+z)) + C_{o,ev}$$
(Efron & Petrosian (1992) method)



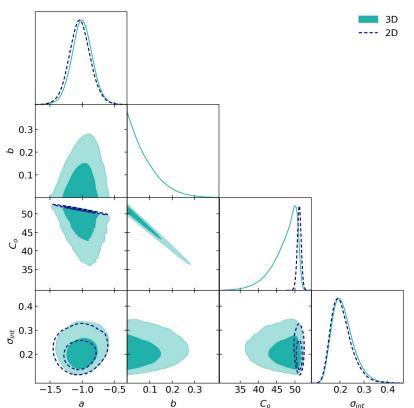
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(Efron & Petrosian (1992) method)



Results - 2D vs 3D Dainotti relation



$$\log L_{\rm X} = C_o + a \log T_{\rm X}^*$$

2D Dainotti correlation (Dainotti+ 2008)

		a	b	C_o	$\sigma_{ m int}$
3D relation	Mode values	-1.03	< 0.21	50.17	0.20
3D relation	Mean	-1.00 ± 0.16	< 0.21	$47.05^{+4.21}_{-1.35}$	$0.21^{+0.03}_{-0.05}$
OD 1	Mode values	-1.07		51.19	0.19
2D relation	Mean	-1.04 ± 0.16		51.16 ± 0.53	$0.21^{+0.03}_{-0.05}$

Results

With a suitable set-up for the GP training in combination with state-of-the-art CCH data and marginalizing over the parameters defining the fundamental plane,

we tested the robustness of the results against

- → Different prior choices
- → Correlations from the GP+CCH reconstruction
- → Corrections due to evolutionary effects
- tightest scatter found for this correlation: $\sigma_{int} = 0.20^{+0.03}_{-0.05}$

→ 3D and 2D relation

parameters compatible with the magnetar model

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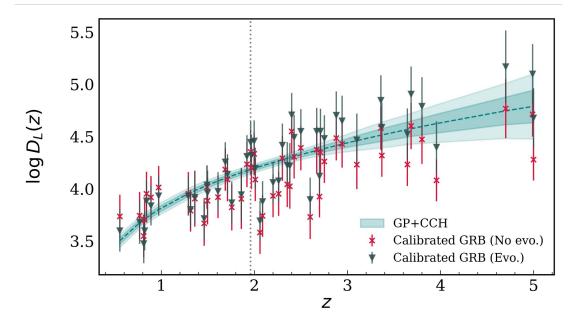
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Cosmological application: extension of the distance ladder



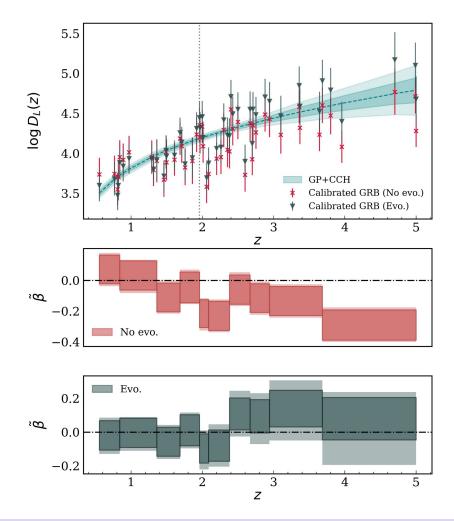
Check tests:

- → the correlation coefficients between the calibration and nuisance parameters of the 20 GRBs involved in the calibration process are negligible;
- → the posterior distributions of the nuisance parameters are highly in accordance with the corresponding prior distributions

To quantify possible deviations from the GP+CCH distance and keep track of the trend at z>2:

$$\beta = \overline{\log D_L^{\text{GRB}}} - \overline{\log D_L^{\text{GP+CCH}}}$$

$$\tilde{\beta}_k = \frac{\sum_{i,j=e_k}^{f_k} \beta_i \omega_{ij}}{\sum_{i,j=e_k}^{f_k} \omega_{ij}}, \qquad \tilde{\sigma}_k = \sqrt{\frac{1}{\sum_{i,j=e_k}^{f_k} \omega_{ij}}}$$



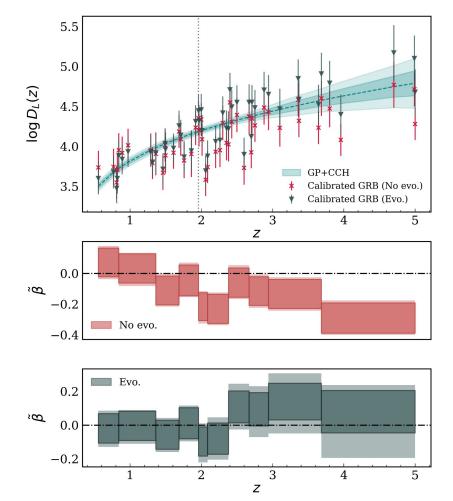
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Physical properties of astrophysical objects at high z are more affected by the Malmquist bias (Malmquist 1922)

Correcting for evolution is also able to cure the negative trend at z>2, already found in previous literature (e.g. Postnikov+ 2014)



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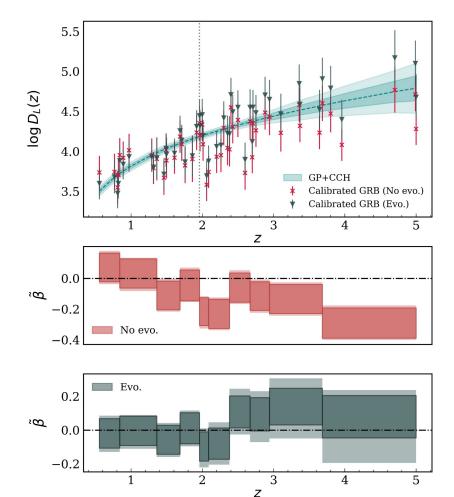
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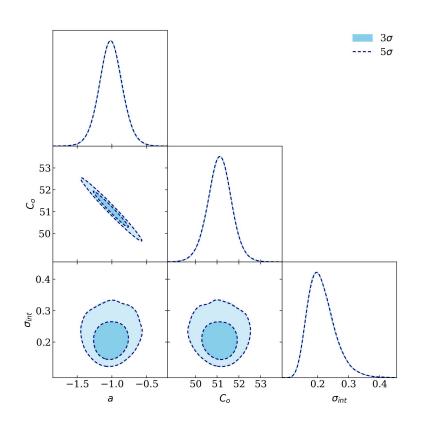
Unbiased luminosity distances up to z=5



Conclusions

- Objects like GRBs (or quasars) can definitively be crucial to extend the range of applicability of the cosmic distance ladder method to larger redshifts, provided that improvements in understanding reliability of these alternative probes and the relations that govern their intrinsic properties will keep to be addressed in the future.
- The stability of our results lead us to conclude that the CCH calibration of the Dainotti relation is capable of identifying a valuable set of standardizable candles, as they
 - obey tightly to the fundamental plane with an intrinsic scatter of $\sigma_{int} = 0.20^{+0.03}_{-0.05}$
 - lead to tight constraints of the 2D relation compatible with the physics of this relation, thus supporting its theoretical interpretation
- This set of unbiased luminosity distances can therefore be a candidate for future use in cosmological applications.





Impact of the prior choice on the 2D Dainotti relation

$$\beta = \overline{\log D_L^{\rm GRB}} - \overline{\log D_L^{\rm GP+CCH}}$$

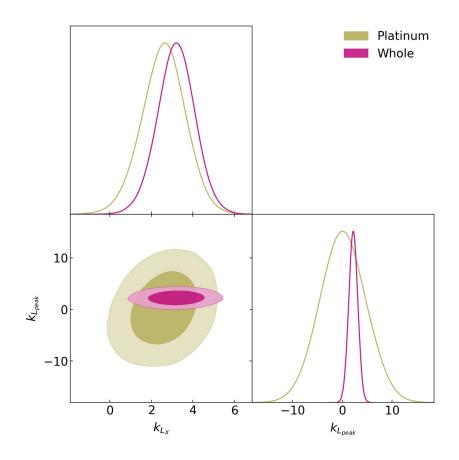
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$$x = \sqrt{\frac{1}{\sum_{i,j=e_k}^{f_k} \omega_{ij}}}$$

binned bias

	FP_{BF}	3σ	5σ
a	-1.03 ± 0.16	(-1.85, -0.2)	(-2.39, 0)
C_o	51.2 ± 0.52	(48, 54)	(47,56)
σ_{int}	0.43 ± 0.08	(0.01, 0.85)	(0, 1.13)

	FP_{BF}	3σ	5σ
a	-0.81 ± 0.17	(-1.68, 0)	(-2.26, 0)
b	0.50 ± 0.17	(0, 1.37)	(0, 1.95)
C_o	24.65 ± 8.91	(-22,71)	(-53,102)
σ_{int}	0.35 ± 0.07	(0, 0.72)	(0, 0.97)



 $K(x, \tilde{x}) = \sigma_f^2 exp \left[-\frac{(x-\tilde{x})^2}{2l^2} \right]$

$$C_{ij} = \frac{1}{N_{real}} \sum_{\mu=1}^{N_{real}} (M_{\mu,i} - \bar{M}_i)(M_{\mu,j} - \bar{M}_j)$$

The covariance matrix on

M = log-luminosity distance reconstruction
with GP+CCH

About Gaussian Processes

$$\bar{f}^* = \mu^* + K(X^*, X)[K(X, X) + C]^{-1}(y - \mu)$$

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Kernel functions: Hyperparameters:

$$ullet$$
 the characteristic length scale of significant changes in $f(x)$

•
$$\sigma_f$$
 the variance, amplitude of significant changes in $f(x)$

$$K(x,\tilde{x}) = \sigma_f^2 exp\left[\left(-\frac{\sqrt{3}|x-\tilde{x}|}{l}\right)\left(1+\frac{\sqrt{3}|x-\tilde{x}|}{l}\right)\right]$$
 Matérn 32 covariance function

$$\ln \mathcal{L} = \ln p(\mathbf{y}|\mathbf{X}, \sigma_f, l) = -\frac{1}{2}(\mathbf{y} - \boldsymbol{\mu})^T [K(\mathbf{X}, \mathbf{X}) + C]^{-1}(\mathbf{y} - \boldsymbol{\mu}) - \frac{1}{2} \ln |K(\mathbf{X}, \mathbf{X}) + C| - \frac{n}{2} \ln 2\pi$$