Red Dust Redemption

A bayesian model of dust and stretch with the DEBASS and DES samples

B. Carreres, M. Acevedo, DEBASS collaboration et al.

Oxford Next Generation of SN Survey workshop 2026

Duke Cosmology

Motivations

- DEBASS needs a dust model for cosmology analysis

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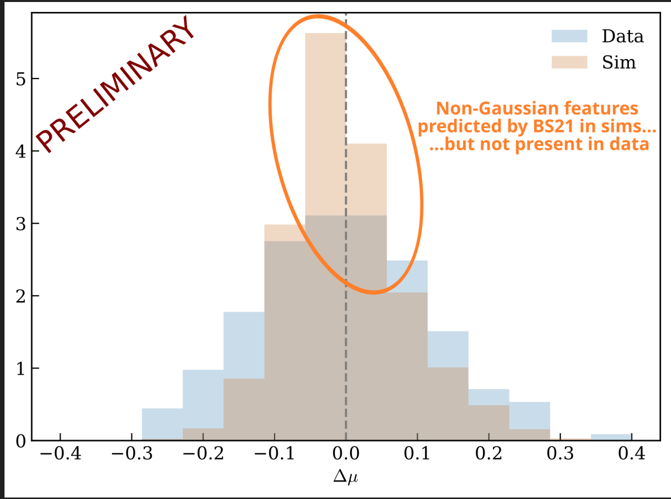
- Cross-validation with other dust models (e.g. Stor…. Sorj… duStBI)
- Interest to understand the low-z non-gaussianities in Hubble Diagram residuals (see *Carreres et al. 2025*)



The (almost) BS21 (*Brout & Scolnic 2021*) model

Dust redden colour:

$$c_{\mathrm{obs}} = c_{\mathrm{int}} + E$$

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(*Nicolas et al. 2021*; *Ginolin et al. 2025*)

$$a_{\mathrm{low}}(1-\delta(z))\mathcal{N}(\mu_{x_1}^{\mathrm{low}}, \sigma_{x_1}^{\mathrm{low}}) + (1 - a_{\mathrm{low}}(1-\delta(z)))\mathcal{N}(\mu_{x_1}^{\mathrm{hi}}, \sigma_{x_1}^{\mathrm{hi}}) \qquad \mathcal{N}_{>1.2}\left(\mu_{R_V}^{\mathrm{loM/hiM}}, \sigma_{R_V}^{\mathrm{loM/hiM}}\right)$$

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(*Nicolas et al. 2021*; *Ginolin et al. 2025*)

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$\theta_{\rm pop}$ $\theta_{\rm glob}$

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$$x_{1,\mathrm{obs}} = x_1$$

θ_{pop} θ_{glob} ϕ $\mathbf{O}$

The dusty likelihood

(*Kelly et al. 2007*; *Stiskalek et al. 2025*)

$$\mathcal{P}(\boldsymbol{\Theta}, \{\phi_i\} | \{\mathbf{o}_i\}) \propto \frac{\mathcal{P}(\boldsymbol{\Theta})}{q(\boldsymbol{\Theta})^{N^{\mathrm{obs}}}} \prod_{i=1}^{N^{\mathrm{obs}}} \mathcal{P}(\mathbf{o}_i | \boldsymbol{\phi}_i, \boldsymbol{\theta}_{\mathrm{glob}}) \mathcal{P}(\boldsymbol{\phi}_i | \boldsymbol{\theta}_{\mathrm{pop}})$$

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Hyper-parameters

Hyper-parameters:

$$\boldsymbol{\Theta} = \begin{cases} \boldsymbol{\theta}_{\text{glob}} & = \{\alpha, \beta, \delta_{M_B}, \sigma_{\text{int}}\} \\ \boldsymbol{\theta}_{\text{pop}} & = \{\tau^{\text{loM/hiM}}, \mu_{R_V}^{\text{loM/hiM}}, \sigma_{R_V}^{\text{loM/hiM}}, \mu_{x_1}^{\text{lo/hi}}, \sigma_{x_1}^{\text{lo/hi}}, a_{\text{low}}\} \end{cases}$$

The dusty likelihood

Latent parameters

$$\mathcal{P}(\boldsymbol{\Theta}, \{\phi_i\} | \{\mathbf{o}_i\}) \propto \frac{\mathcal{P}(\boldsymbol{\Theta})}{q(\boldsymbol{\Theta})^{N^{\text{obs}}}} \prod_{i=1}^{N^{\text{obs}}} \mathcal{P}(\mathbf{o}_i | \phi_i, \boldsymbol{\theta}_{\text{glob}}) \mathcal{P}(\phi_i | \boldsymbol{\theta}_{\text{pop}})$$

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Latent parameters:

$$\phi_i = \{E_i, R_{V,i}, c_{\text{int},i}, x_{1,i}, z_i\}$$

The dusty likelihood

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Hyper-parameters Data

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Data:

$$\mathbf{o}_i = \{m_{B,i}, x_{1,i}, c_i, z_i\}$$

The dusty likelihood

Latent parameters

Hyper-priors

$$\mathcal{P}(\boldsymbol{\Theta}, \{\boldsymbol{\phi}_i\} | \{\mathbf{o}_i\}) \propto \frac{\mathcal{P}(\boldsymbol{\Theta})}{q(\boldsymbol{\Theta})^{N^{\rm obs}}} \prod_{i=1}^{N^{\rm obs}} \mathcal{P}(\mathbf{o}_i | \boldsymbol{\phi}_i, \boldsymbol{\theta}_{\rm glob}) \mathcal{P}(\boldsymbol{\phi}_i | \boldsymbol{\theta}_{\rm pop})$$

Hyper-parameters

Data

Parameter	Description	Prior
Global standardisation parameters		
δ_{M_B}	SN Ia absolute magnitude offset	$\mathcal{N}(0,\ 0.3)$
$\tan^{-1}\alpha$	Stretch–luminosity slope	$\mathcal{U}(0,\ 0.5)$
$\tan^{-1}\beta$	Intrinsic-colour–luminosity slope	$\mathcal{U}(0,\ 1.4)$
$\sigma_{\rm int}$	Achromatic intrinsic scatter	$\mathcal{HN}(0.2)$
Stretch population		
$\mu_{x_1}^{\rm lo/hi}$	Mixture means	$\mathcal{N}([-1.,\ 0.5],\ [1.0,\ 1.0])$
$\sigma_{x_1}^{\rm lo/hi}$	Scatter of faint/bright component	$\mathcal{HN}(1.0)$
$a_{\rm low}$	Mixture weight	$\mathcal{B}(2.0,\ 2.0)$
Intrinsic colour population		
$\mu_{c_{\rm int}}$	Mean intrinsic colour	$\mathcal{N}(-0.1,\ 0.2)$
$\sigma_{c_{\rm int}}$	Scatter in intrinsic colour	$\mathcal{HN}(0.2)$
Host galaxy dust parameters		
$\tau^{\rm loM/hiM}$	E exponential scales	$\mathcal{HC}(0.2)$
$\mu_{R_V}^{\rm loM/hiM}$	Mean dust law slope	$\mathcal{U}(1.2,\ 6.0)$
$\sigma_{R_V}^{\rm loM/hiM}$	Scatter in dust law slope	$\mathcal{HN}(2.0)$

The dusty likelihood

Latent parameters

Hyper-priors

SALT measured parameters conditioned on latent parameters and global hyperparameters

$$\mathcal{P}(\boldsymbol{\Theta}, \{\phi_i\} | \{\mathbf{o}_i\}) \propto \frac{\mathcal{P}(\boldsymbol{\Theta})}{q(\boldsymbol{\Theta})^{N^{\rm obs}}} \prod_{i=1}^{N^{\rm obs}} \mathcal{P}(\mathbf{o}_i | \boldsymbol{\phi}_i, \boldsymbol{\theta}_{\rm glob}) \mathcal{P}(\boldsymbol{\phi}_i | \boldsymbol{\theta}_{\rm pop})$$

Hyper-parameters

Data

$$\mathcal{P}(\mathbf{o}_i | \boldsymbol{\phi}_i, \boldsymbol{\theta}_{\rm glob}) = \underbrace{\frac{1}{\sqrt{2\pi |C_i|}} \exp\left[-\tfrac{1}{2} \Delta\mathbf{o}(\boldsymbol{\phi}_i, \boldsymbol{\theta}_{\rm glob})^T C_i^{-1} \Delta\mathbf{o}(\boldsymbol{\phi}_i, \boldsymbol{\theta}_{\rm glob})\right]}_{\text{SALT parameters likelihood}} \underbrace{\frac{1}{\sqrt{2\pi\sigma_z^2}} \exp\left[-\frac{1}{2} \frac{(z_i - z_i^{\rm pred})^2}{\sigma_z^2}\right]}_{\text{Redshift likelihood}}$$

SALT parameters likelihood

Redshift likelihood

The dusty likelihood

$$\mathcal{P}(\boldsymbol{\Theta}, \{\phi_i\} | \{\mathbf{o}_i\}) \propto \frac{\mathcal{P}(\boldsymbol{\Theta})}{q(\boldsymbol{\Theta})^{N^{\mathrm{obs}}}} \prod_{i=1}^{N^{\mathrm{obs}}} \mathcal{P}(\mathbf{o}_i | \boldsymbol{\phi}_i, \boldsymbol{\theta}_{\mathrm{glob}}) \mathcal{P}(\boldsymbol{\phi}_i | \boldsymbol{\theta}_{\mathrm{pop}})$$

Hyper-parameters: $\boldsymbol{\Theta}$

Latent parameters: ϕ_i

Data: $\mathbf{o}_i$

Hyper-priors: $\mathcal{P}(\boldsymbol{\Theta})$

SALT measured parameters conditioned on latent parameters and global hyperparameters: $\mathcal{P}(\mathbf{o}_i | \boldsymbol{\phi}_i, \boldsymbol{\theta}_{\mathrm{glob}})$

Latent parameters conditioned on population parameters (BS21 for dust + N21 for stretch): $\mathcal{P}(\boldsymbol{\phi}_i | \boldsymbol{\theta}_{\mathrm{pop}})$

The dusty likelihood

$$\mathcal{P}(\boldsymbol{\Theta}, \{\boldsymbol{\phi}_i\} | \{\mathbf{o}_i\}) \propto \frac{\mathcal{P}(\boldsymbol{\Theta})}{q(\boldsymbol{\Theta})^{N^{\mathrm{obs}}}} \prod_{i=1}^{N^{\mathrm{obs}}} \mathcal{P}(\mathbf{o}_i | \boldsymbol{\phi}_i, \boldsymbol{\theta}_{\mathrm{glob}}) \mathcal{P}(\boldsymbol{\phi}_i | \boldsymbol{\theta}_{\mathrm{pop}})$$

Hyper-parameters: $\boldsymbol{\Theta}$

Latent parameters: $\boldsymbol{\phi}_i$

Data: $\mathbf{o}_i$

Hyper-priors: $\mathcal{P}(\boldsymbol{\Theta})$

Selection function renormalisation because we don't observe the whole SN population…. ($q(\boldsymbol{\Theta})^{N^{\mathrm{obs}}}$)

SALT measured parameters conditioned on latent parameters and global hyperparameters ($\mathcal{P}(\mathbf{o}_i | \boldsymbol{\phi}_i, \boldsymbol{\theta}_{\mathrm{glob}})$)

Latent parameters conditioned on population parameters (BS21 for dust + N21 for stretch) ($\mathcal{P}(\boldsymbol{\phi}_i | \boldsymbol{\theta}_{\mathrm{pop}})$)

(*Kelly et al. 2007*; *Stiskalek et al. 2025*)

$$q(\boldsymbol{\Theta}) = \int \Phi\left(\frac{m_{\mathrm{lim}} - m_B^{\mathrm{pred}}(\boldsymbol{\phi}, \boldsymbol{\theta}_{\mathrm{glob}})}{\sqrt{\sigma_{\mathrm{sel}}^2 + \sigma_{m_B^{\mathrm{obs}}}^2}}\right) \mathcal{P}(\boldsymbol{\phi} | \boldsymbol{\Theta}) d\boldsymbol{\phi}$$

The dusty likelihood

Latent parameters

Hyper-priors

SALT measured parameters conditioned on latent parameters and global hyperparameters

$$\mathcal{P}(\boldsymbol{\Theta}, \{\boldsymbol{\phi}_i\} | \{\mathbf{o}_i\}) \propto \frac{\mathcal{P}(\boldsymbol{\Theta})}{q(\boldsymbol{\Theta})^{N^{\rm obs}}} \prod_{i=1}^{N^{\rm obs}} \mathcal{P}(\mathbf{o}_i|\boldsymbol{\phi}_i, \boldsymbol{\theta}_{\rm glob})\,\mathcal{P}(\boldsymbol{\phi}_i|\boldsymbol{\theta}_{\rm pop})$$

Hyper-parameters

Data

Selection function renormalisation because we don't observe the whole SN population….

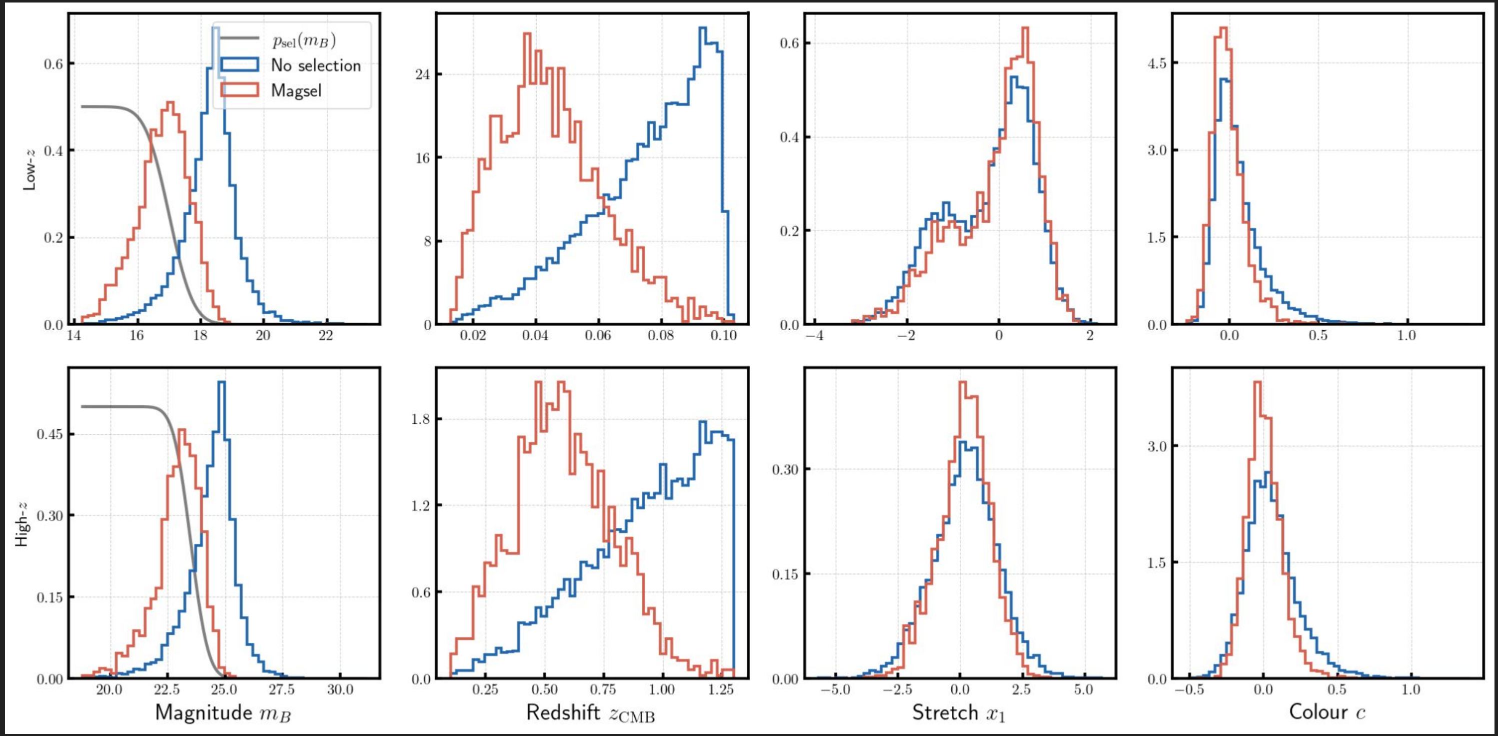
Latent parameters conditioned on population parameters (BS21 for dust + N21 for stretch)

Implemented in python using `numpyro`, sampled using the NUTS algorithm.

A first test with “toy sims”

2 samples of 2000 SNe Ia: low-z 0.015 < z < 0.1; high-z 0.1 < z < 1.2. Fiducial selection on mB.
Errors:

- Low-z – fixed to median of DEBASS
- High-z – Linear function of z, fitted from DES data



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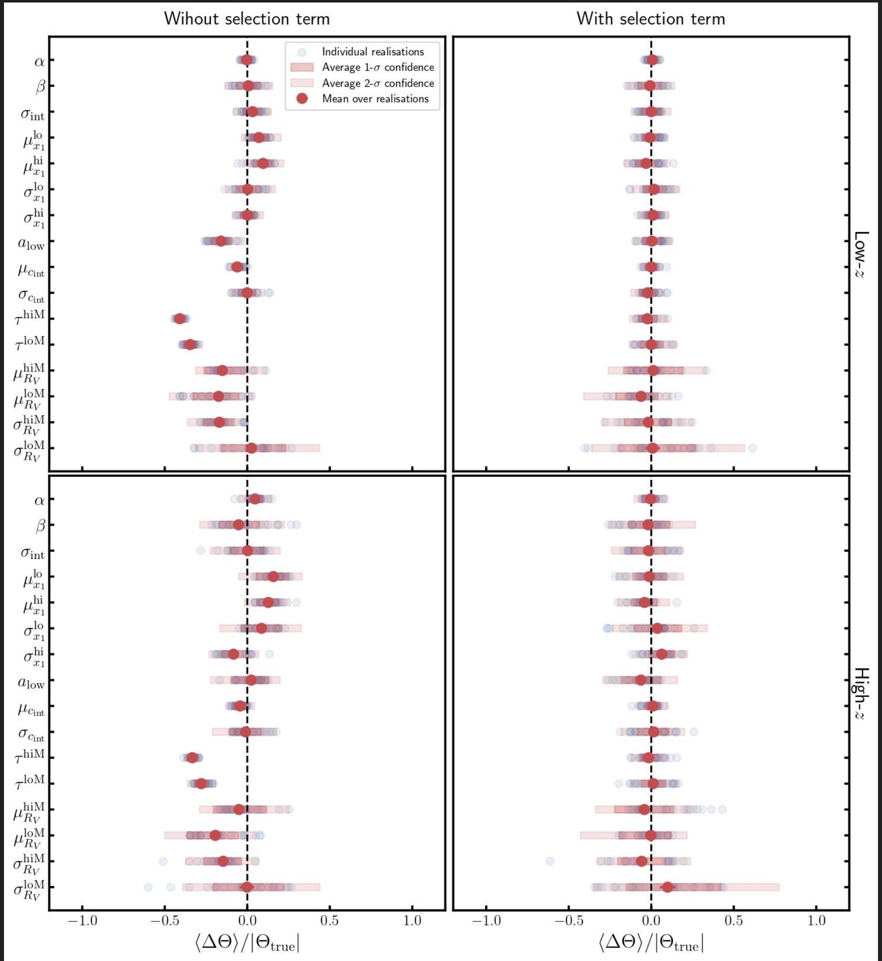
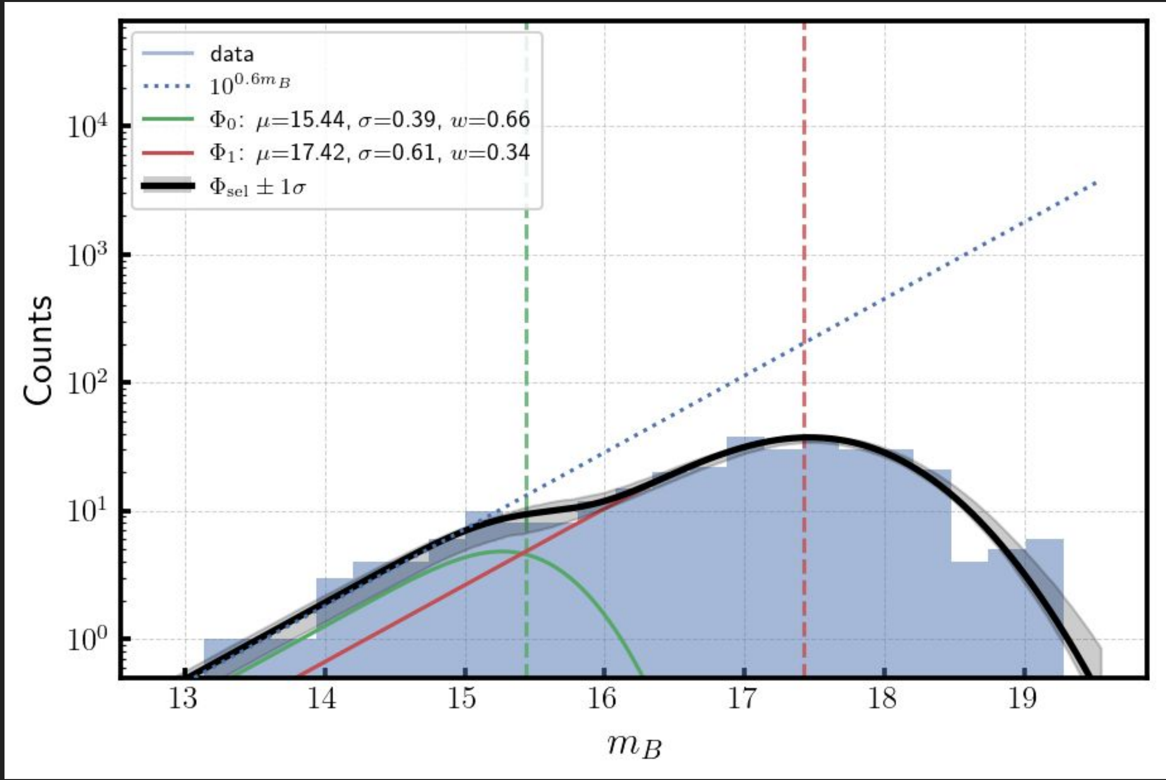


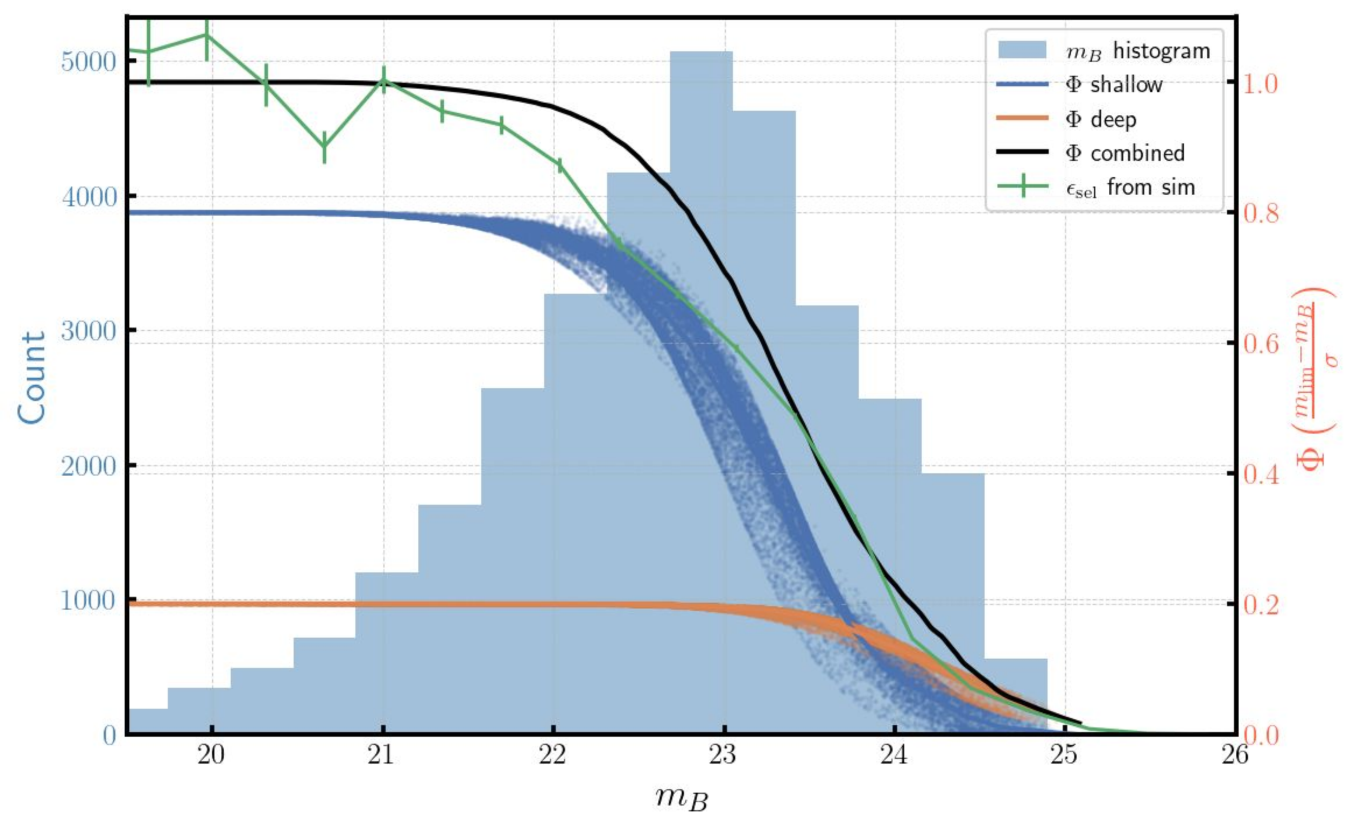
Calibration of the selection function for DEBASS

Fit using low-z approximation: $\mathcal{P}(m_B) = 10^{0.6 m_B}\Phi\left(\frac{m_{\rm lim} - m_B}{\sigma_{\rm sel}}\right)$



Calibration of the selection function for DES

Computed from *Kessler et al. 2015* mag limit values



Full validation on SNANA sims

Simulations are set up, already done few tests.
I now need to run the fit on more sims.

Preliminary results on DEBASS and DES data !

Preliminary

Global parameters:

	Red Dust Red.		Ref. (Vincenzi+2024/BS21)	
	DES	DEBASS	DES	Low-z
α	0.167 ± 0.005	0.148 ± 0.008	0.170 ± 0.004	0.137 ± 0.008
β_{int}	1.8 ± 0.2	1.9 ± 0.4	2.0 ± 0.2	2.0 ± 0.2
σ_{int}	0.096 ± 0.005	0.098 ± 0.009	–	–

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Dust parameters:

		Red Dust Red.		Ref. (BS21)	
		DES	DEBASS	DES	Low-z
$\mu_{c_{\rm int}}$		-0.063 ± 0.005	-0.065 ± 0.010	-0.084 ± 0.004	-0.084 ± 0.004
$\sigma_{c_{\rm int}}$		0.044 ± 0.003	0.045 ± 0.007	0.042 ± 0.002	0.042 ± 0.002
μ_{R_V}	$\log M < 10$	2.5 ± 0.1	2.6 ± 0.2	2.8 ± 0.4	2.8 ± 0.4
	$\log M > 10$	1.6 ± 0.2	1.8 ± 0.2	1.5 ± 0.3	1.5 ± 0.3
σ_{R_V}	$\log M < 10$	0.4 ± 0.1	0.2 ± 0.2	1.3 ± 0.2	1.3 ± 0.2
	$\log M > 10$	0.6 ± 0.1	0.5 ± 0.2	1.3 ± 0.2	1.3 ± 0.2
τ	$\log M < 10$	0.13 ± 0.01	0.11 ± 0.02	0.12 ± 0.02	$0.01^{+0.05}_{-0.01}$
	$\log M > 10$	0.124 ± 0.008	0.23 ± 0.04	0.15 ± 0.02	0.19 ± 0.08

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Stretch parameters:

	Red Dust Red.		Ref. (Ginolin et al. 2025)
	DES	DEBASS	ZTF
a_{low}	0.84 ± 0.09	0.72 ± 0.10	0.81 ± 0.14
$\mu_{x_1,\mathrm{lo}}$	-1.15 ± 0.09	-1.34 ± 0.12	-1.24 ± 0.18
$\mu_{x_1,\mathrm{hi}}$	0.34 ± 0.04	0.52 ± 0.09	0.42 ± 0.08
$\sigma_{x_1,\mathrm{lo}}$	0.59 ± 0.06	0.49 ± 0.09	0.73 ± 0.09
$\sigma_{x_1,\mathrm{hi}}$	0.64 ± 0.03	0.60 ± 0.07	0.54 ± 0.05

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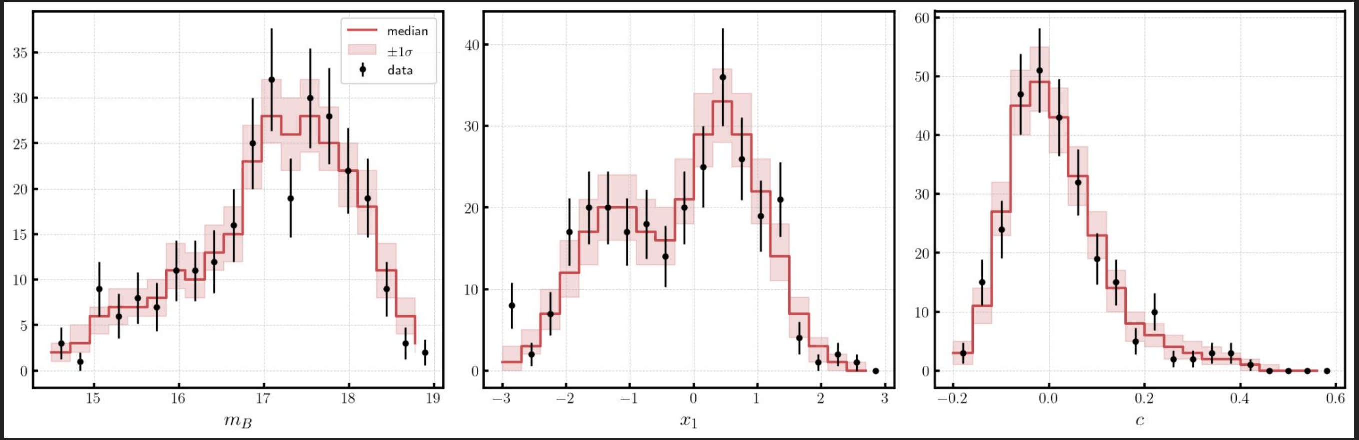
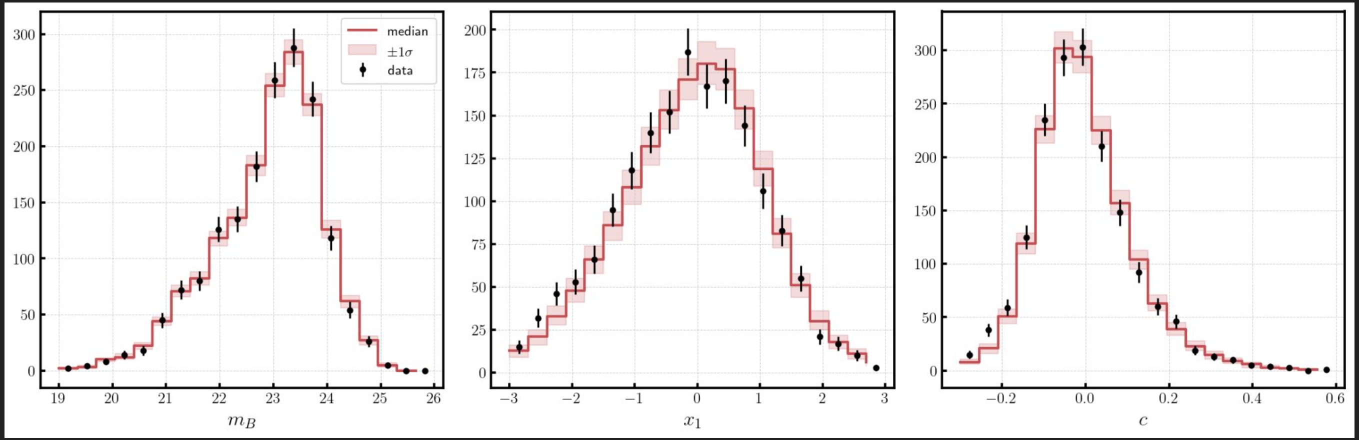
Preliminary

DEBASS



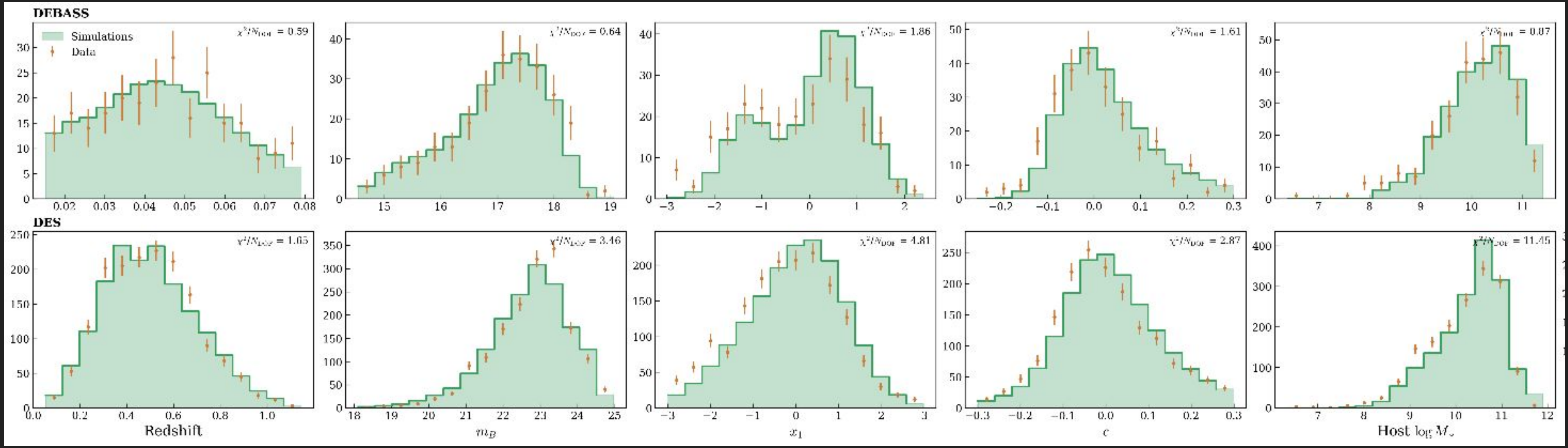
DES



Preliminary results on DEBASS and DES data !

Preliminary

Plots by **M. Acevedo**
(DUKE PhD, soon on the job market !)



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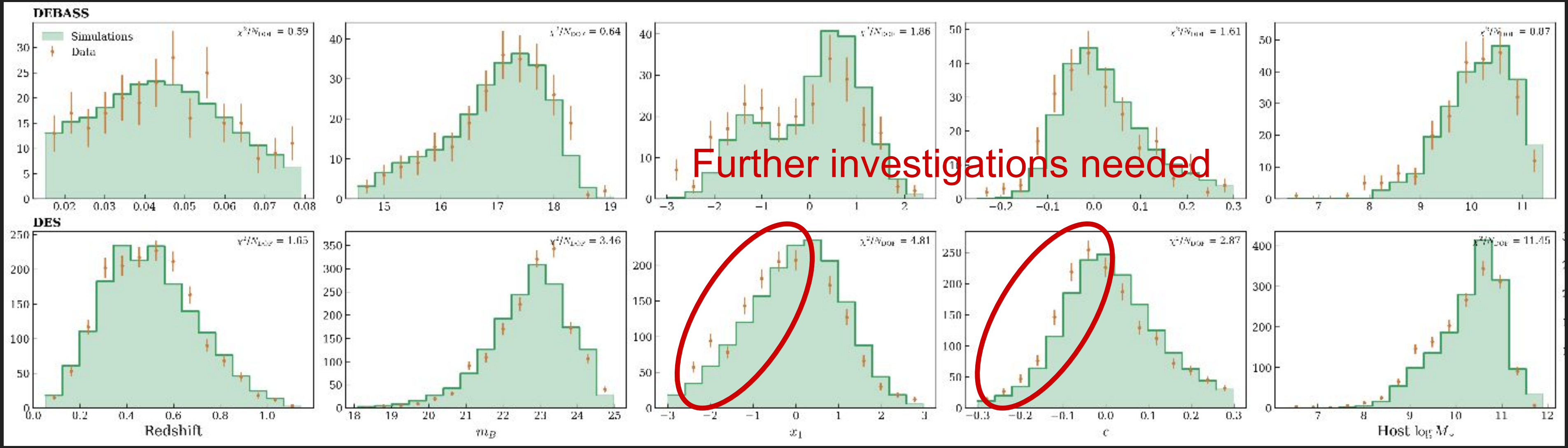

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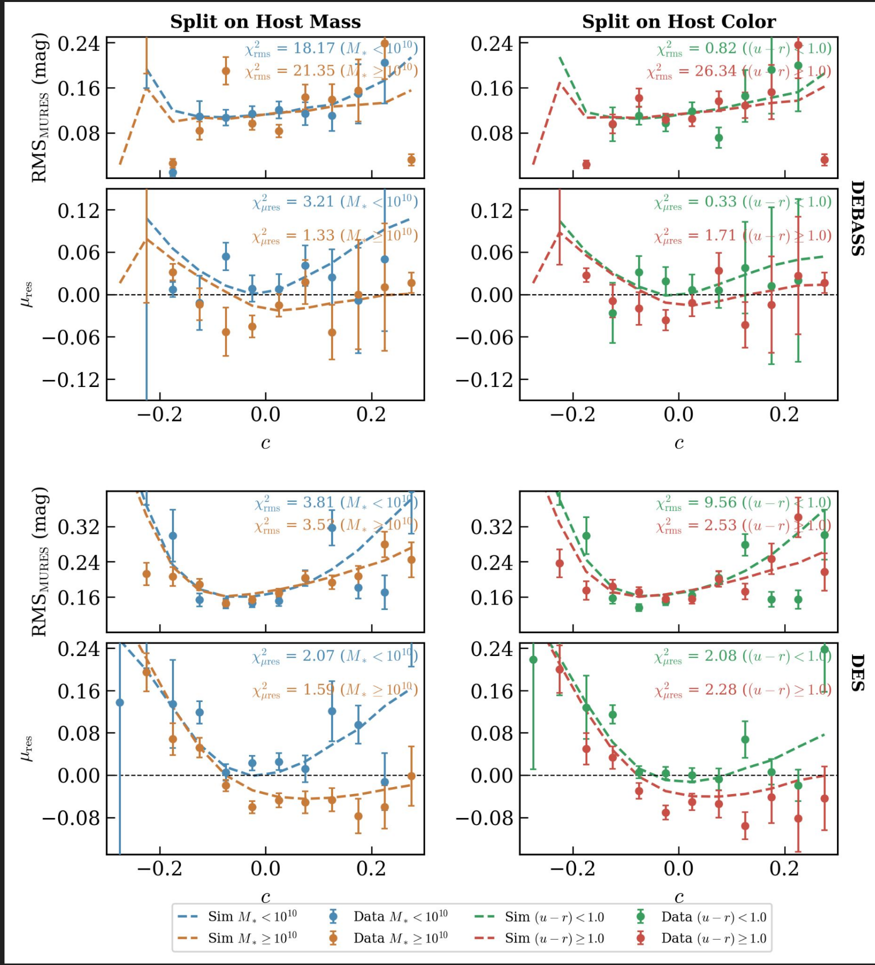
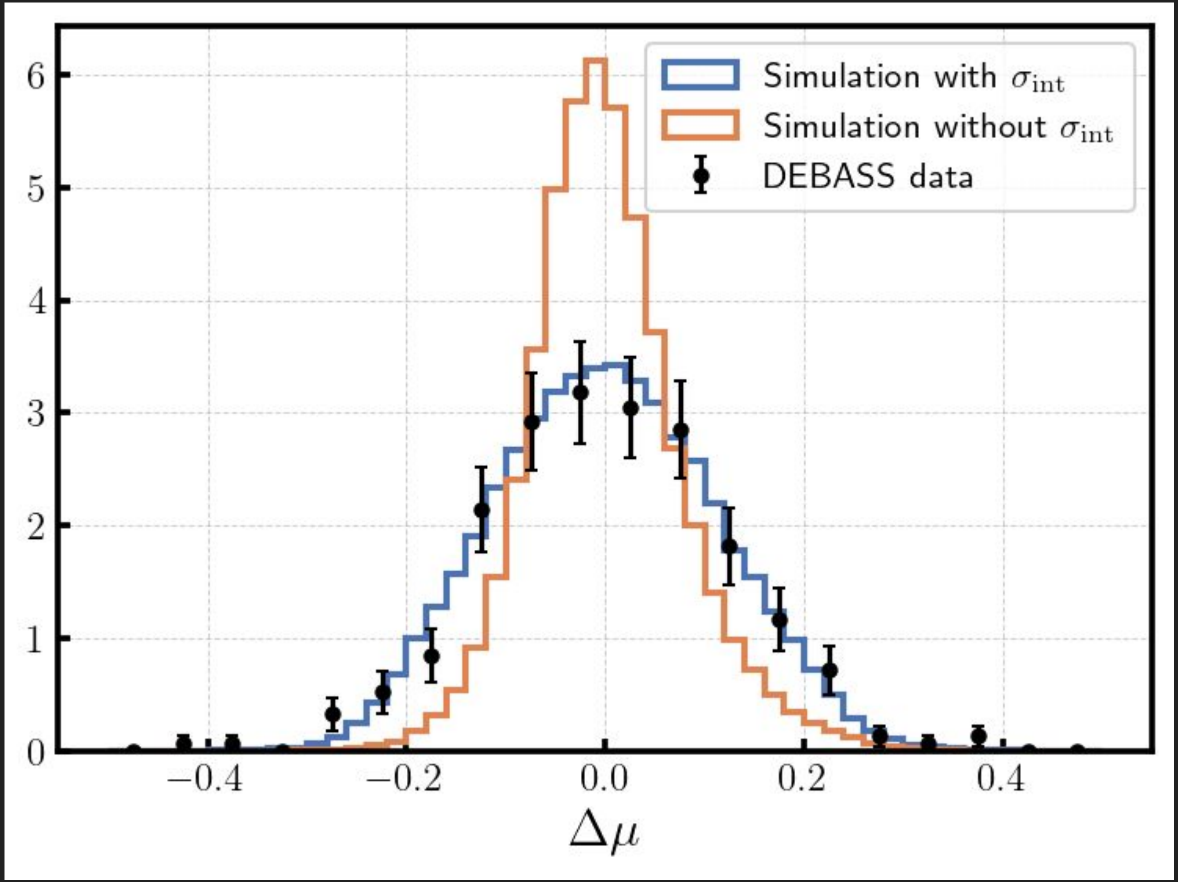


A look to non-gaussianities



Preliminary

Takeaways

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- The scatter due to dust doesn’t seem to be enough to explain the scatter of low-z DEBASS data. Addition of a gray scatter seems needed.

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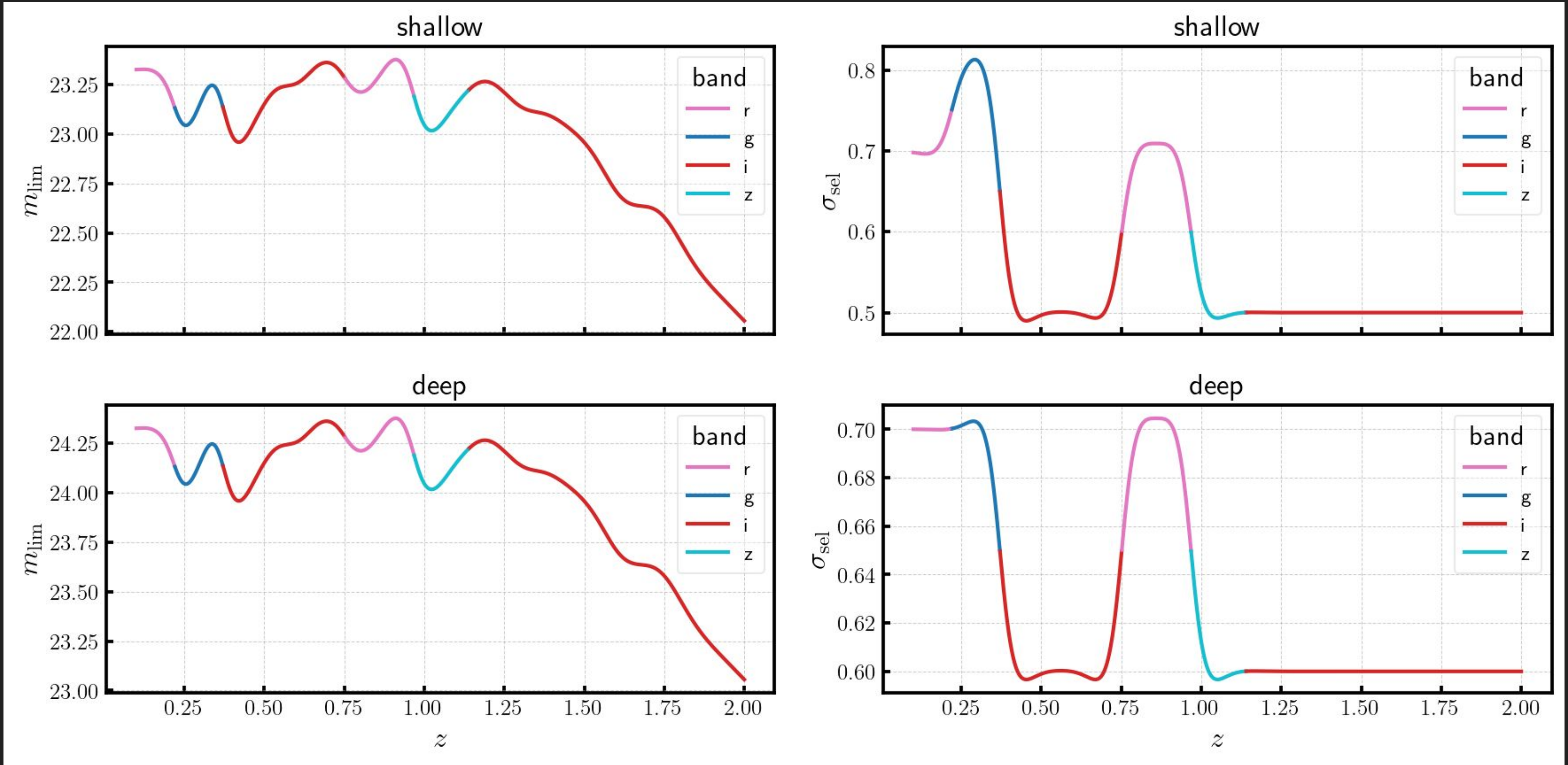
- Red Dust Redemption offers a cross-check to existing models
- Preliminary results mostly agree with BS21 / Ginolin+2025 and show good modeling of the scatter
- The scatter due to dust doesn’t seem to be enough to explain the scatter of low-z DEBASS data. Addition of a gray scatter seems needed.
- Full validation on SNANA simulations and improvement of the DES selection are in progress

Backups


shallow
deep
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z
23.25
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23.00
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0.7
0.6
0.5
0.70
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0.66
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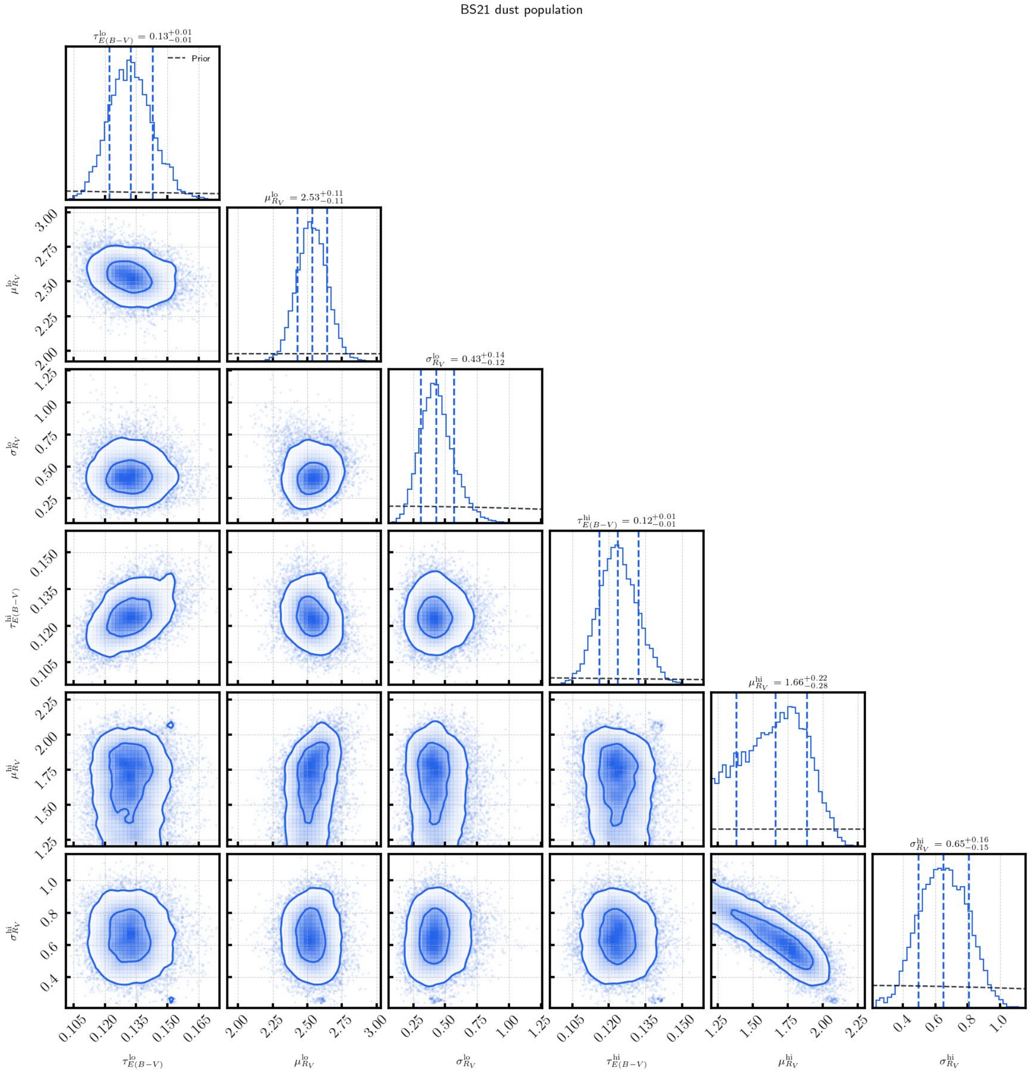
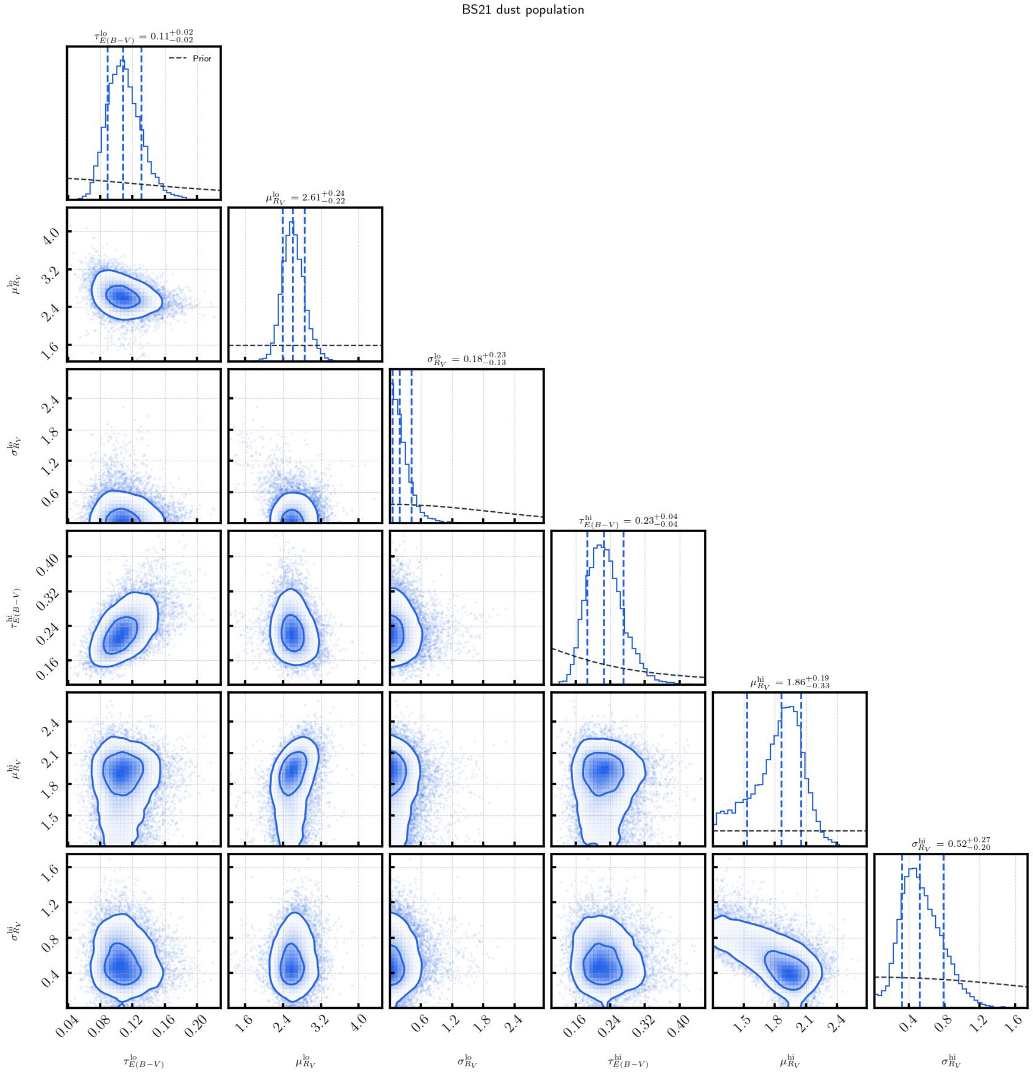
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00

Backups


BS21 dust population
$\tau^{\rm lo}_{E(B-V)} = 0.13^{+0.01}_{-0.01}$
Prior
$\mu^{\rm lo}_{R_V} = 2.53^{+0.11}_{-0.11}$
$\sigma^{\rm lo}_{R_V} = 0.43^{+0.14}_{-0.12}$
$\tau^{\rm hi}_{E(B-V)} = 0.12^{+0.01}_{-0.01}$
$\mu^{\rm hi}_{R_V} = 1.66^{+0.22}_{-0.28}$
$\sigma^{\rm hi}_{R_V} = 0.65^{+0.16}_{-0.15}$
$\tau^{\rm lo}_{E(B-V)}$
$\mu^{\rm lo}_{R_V}$
$\sigma^{\rm lo}_{R_V}$
$\tau^{\rm hi}_{E(B-V)}$
$\mu^{\rm hi}_{R_V}$
$\sigma^{\rm hi}_{R_V}$

Backups


BS21 dust population
$\tau^{lo}_{E(B-V)} = 0.11^{+0.02}_{-0.02}$
Prior
$\mu^{lo}_{R_V} = 2.61^{+0.24}_{-0.22}$
$\sigma^{lo}_{R_V} = 0.18^{+0.23}_{-0.13}$
$\tau^{hi}_{E(B-V)} = 0.23^{+0.04}_{-0.04}$
$\mu^{hi}_{R_V} = 1.86^{+0.19}_{-0.33}$
$\sigma^{hi}_{R_V} = 0.52^{+0.27}_{-0.20}$
$\tau^{lo}_{E(B-V)}$
$\mu^{lo}_{R_V}$
$\sigma^{lo}_{R_V}$
$\tau^{hi}_{E(B-V)}$
$\mu^{hi}_{R_V}$
$\sigma^{hi}_{R_V}$