

# PROVABGS Early Data Release: Probabilistic Stellar Mass Function

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## ABSTRACT

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### 1. INTRODUCTION

### 2. THE DESI BRIGHT GALAXY SURVEY EARLY DATA RELEASE

brief description of the DESI BGS early data release and fuji reduction

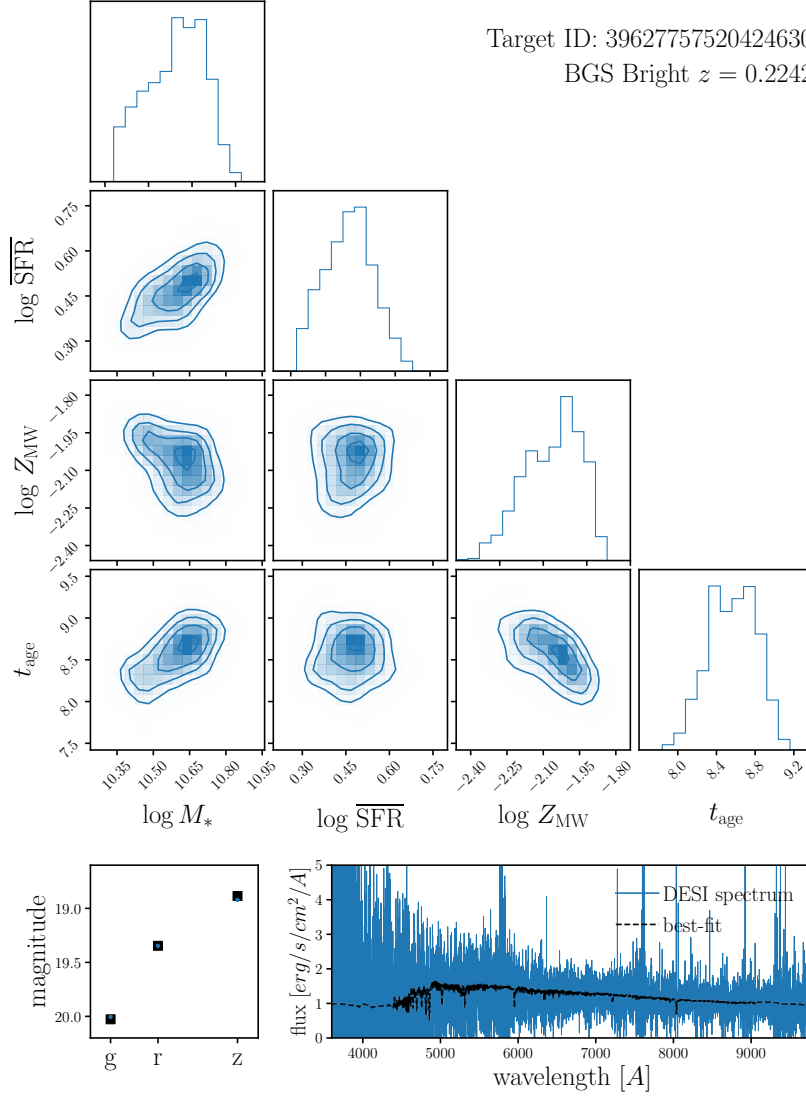
We focus on BGS galaxies at  $z < 0.3$ .

### 3. PROVABGS SED MODELING

For each BGS EDR galaxy, we derive its  $M_*$  and other properties,  $\overline{\text{SFR}}$ ,  $Z_{\text{MW}}$ , and  $t_{\text{age,MW}}$  from DESI photometry and spectroscopy using the PROVABGS SED modeling framework (Hahn et al. 2022). PROVABGS models galaxy SEDs using stellar population synthesis with non-parametric star-formation history (SFH) with a starburst, a non-parametric metallicity history (ZH) that varies with time, and a flexible dust attenuation prescription. The non-parametric SFH and ZH prescriptions are derived from SFHs and ZHs of simulated galaxies in the Illustris hydrodynamic simulation (Vogelsberger et al. 2014; Genel et al. 2014; Nelson et al. 2015) and provide compact and flexibly representations of SFHs and ZHs. For the stellar population synthesis, PROVABGS uses the Flexible Stellar Population Synthesis (FSPS; Conroy et al. 2009, 2010) model with MIST isochrones (Paxton et al. 2011, 2013, 2015; Choi et al. 2016; Dotter 2016), Chabrier (2003) initial mass function (IMF), and a combination of MILES (Sánchez-Blázquez et al. 2006) and BaSeL (Lejeune et al. 1997, 1998; Westera et al. 2002) spectral libraries.

Furthermore, PROVABGS provides a Bayesian inference framework for inferring full posterior probability distributions of the SED model parameter:  $p(\theta | \mathbf{X}^{\text{photo}}, \mathbf{X}^{\text{spec}})$ , where  $\mathbf{X}^{\text{photo}}$  represents the photometry and  $\mathbf{X}^{\text{spec}}$  represents the spectroscopy. In total,  $\theta$  has 13 parameters:  $M_*$ , 6 parameters specifying the SFH ( $\beta_1, \beta_2, \beta_3, \beta_4, f_{\text{burst}}, t_{\text{burst}}$ ), 2 parameters specifying ZH ( $\gamma_1, \gamma_2$ ), 3 parameters specifying dust attenuation ( $\tau_{\text{BC}}, \tau_{\text{ISM}}, n_{\text{dust}}$ ), and a nuisance parameter for the fiber aperture effect. Posteriors have distinct advantages over point estimates because they accurately estimate uncertainties and degeneracies among galaxy properties. Furthermore, as we later demonstrate, they are essential for principled population inference: *e.g.* SMF.

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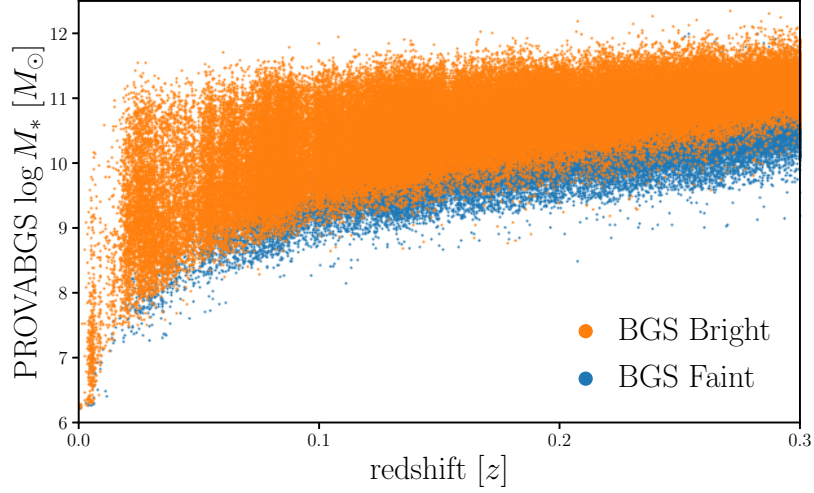


**Figure 1.**

In practice, accurately estimating a 13 dimensional posterior requires a large number ( $\gtrsim 100,000$ ) SED model evaluations, which would require prohibitive computational resources. To address this challenge, PROVABGS samples the posterior using the [Karamanis & Beutler \(2020\)](#) ensemble slice Markov Chain Monte Carlo (MCMC) sampling with the ZEUS Python package<sup>1</sup>. PROVABGS further accelerates the inference by using neural emulators for the SED models. The emulators are accurate to subpercent level and  $> 100\times$  faster than the original SED model based on FSPS ([Kwon et al. 2022](#)). With ZEUS and neural emulation, deriving a posterior takes  $\sim 5$  min per galaxy with PROVABGS. Moreover, [Hahn et al. \(2022\)](#) demonstrated PROVABGS can accurately infer  $M_*$  overall the full expected  $M_*$  range of BGS, using forward modeled synthetic DESI observations.

In Figure 1,

<sup>1</sup> <https://zeus-mcmc.readthedocs.io/>



**Figure 2.**

Figure 2,

#### 4. RESULTS

We are interested in estimating the SMF of BGS galaxies from their individual marginalized posteriors,  $p(M_* | \mathbf{X}_i)$ , derived using PROVABGS (Section 3).

we're going to do population inference in a hierarchical bayesian framework and use a normalizing flow.

why? because it produces unbiased inference.

why do we use normalizing flows?

We follow the same approach as [Hahn et al. \(2022\)](#) to estimate:

$$p(\phi | \{\mathbf{X}_i\}) = \frac{p(\phi) p(\{\mathbf{X}_i\} | \phi)}{p(\{\mathbf{X}_i\})} \quad (1)$$

$$= \frac{p(\phi)}{p(\{\mathbf{X}_i\})} \int p(\{\mathbf{X}_i\} | \{\theta_i\}) p(\{\theta_i\} | \phi) d\{\theta_i\}. \quad (2)$$

$$= \frac{p(\phi)}{p(\{\mathbf{X}_i\})} \prod_{i=1}^N \int p(\mathbf{X}_i | \theta_i) p(\theta_i | \phi) d\theta_i \quad (3)$$

$$= \frac{p(\phi)}{p(\{\mathbf{X}_i\})} \prod_{i=1}^N \int \frac{p(\theta_i | \mathbf{X}_i) p(\mathbf{X}_i)}{p(\theta_i)} p(\theta_i | \phi) d\theta_i \quad (4)$$

$$= p(\phi) \prod_{i=1}^N \int \frac{p(\theta_i | \mathbf{X}_i) p(\theta_i | \phi)}{p(\theta_i)} d\theta_i. \quad (5)$$

We estimate the integral using  $S_i$  Monte Carlo samples from the individual posteriors  $p(\theta_i | \mathbf{X}_i)$ :

$$\approx p(\phi) \prod_{i=1}^N \frac{1}{S_i} \sum_{j=1}^{S_i} \frac{p(\theta_{i,j} | \phi)}{p(\theta_{i,j})}. \quad (6)$$

BGS provides two samples: BGS Bright and Faint. Galaxies in BGS Bright are selected based on a  $r < 19.5$  flux limit, while the ones in BGS Faint are selected based on a fiber-magnitude and color limit and  $r < 20.0175$  flux limit. Since neither of these samples are volume-limited and complete as a function of  $M_*$ , we must include the selection effect when estimating the SMF. We do this by including weights derived from  $z_i^{\max}$ , the maximum redshift that galaxy  $i$  could be placed and still be included in the BGS samples. We derive  $z_i^{\max}$  for every galaxy using by redshifting the SED predicted by the best-fit parameters. We then derive  $V_i^{\max}$ , the comoving volume out to  $z_i^{\max}$ , and weights  $w_i = w_{i,\text{comp}}/V_i^{\max}$ . We modify Eq. 1 to include  $w_i$ :

$$p(\phi | \{\mathbf{X}_i\}) \approx \frac{p(\phi)}{\prod_{i=1}^N p(\mathbf{X}_i)^{w_i}} \prod_{i=1}^N \left( \int p(\mathbf{X}_i | \theta_i) p(\theta_i | \phi) d\theta_i \right)^{w_i} \quad (7)$$

$$\approx \frac{p(\phi)}{\prod_{i=1}^N p(\mathbf{X}_i)^{w_i}} \prod_{i=1}^N \left( \sum_{j=1}^{S_i} \frac{p(\theta_{i,j} | \phi)}{p(\theta_{i,j})} \right)^{w_i} \quad (8)$$

$$\approx \frac{p(\phi)}{\prod_{i=1}^N p(\mathbf{X}_i)^{w_i}} \prod_{i=1}^N \left( \sum_{j=1}^{S_i} \frac{q_\phi(\theta_{i,j})}{p(\theta_{i,j})} \right)^{w_i}. \quad (9)$$

In practice, we do not derive the full posterior  $p(\phi | \{\mathbf{X}_i\})$ . Instead we derive the maximum a posteriori (MAP) hyperparameter  $\phi_{\text{MAP}}$  that maximizes  $p(\phi | \{\mathbf{X}_i\})$  or  $\log p(\phi | \{\mathbf{X}_i\})$ . We expand,

$$\log p(\phi | \{\mathbf{X}_i\}) \approx \log p(\phi) + \sum_{i=1}^N w_i \log \left( \sum_{j=1}^{S_i} \frac{q_\phi(\theta_{i,j})}{p(\theta_{i,j})} \right). \quad (10)$$

Since the first two terms are constant, we derive  $\phi_{\text{MAP}}$  by maximizing

$$\max_{\phi} \sum_{i=1}^N w_i \log \left( \sum_{j=1}^{S_i} \frac{q_\phi(\theta_{i,j})}{p(\theta_{i,j})} \right). \quad (11)$$

We use ADAM optimizer and determine the architecture of the normalizing flow through experimentation.

paragraph summarizing the weights that we use: vmax, spectroscopic completeness weights,

#### 4.1. The Probabilistic Stellar Mass Function

### ACKNOWLEDGEMENTS

It's a pleasure to thank

### APPENDIX

#### A. SPECTROSCOPIC COMPLETENESS

Spectroscopic galaxy surveys, such as BGS, do not successfully measure the redshift for all of the galaxies they target. As a result, this spectroscopic incompleteness must be accounted for when

measuring galaxy population statistics such as the SMF. In this appendix, we present how we estimate the spectroscopic incompleteness for BGS and derive the weights we use to correct for its impact on the SMF.

For BGS, spectroscopic incompleteness is primarily driven by fiber assignment and redshift failures. DESI uses 10 fiber-fed spectrographs with 5000 fibers but targets more galaxies than available fibers. For instance, the BGS Bright and Faint samples have  $\sim 860$  and  $530$  targets/deg<sup>2</sup>, respectively. For the 8 deg<sup>2</sup> field-of-view of DESI, this roughly correspond to 11,000 targets, significantly more than the 5000 available fibers. DESI only measures the spectra of targets that are assigned fibers. In fact, of the 5000, a minimum of 400 ‘sky’ fibers are dedicated to measuring the sky background for accurate sky subtraction and an additional 100 fibers are assigned to standard stars for flux calibration ?.

Furthermore, each fiber is controlled by a robotic fiber positioner on the focal plane. These positioners can rotate on two arms and be positioned within a circular patrol region of radius 1.48 arcmin (????). Although the patrol regions of adjacent positioners slightly overlap, the geometry of the positioners cause higher incompleteness in regions with high target density (?). To mitigate the incompleteness from the fiber assignment, BGS will observe its footprint with four passes. With this strategy, BGS achieves  $\sim 80\%$  fiber assignment completeness (?).

To estimate fiber assignment completeness, we run the fiber assignment algorithm (?) on BGS targets 128 separate times. For each BGS galaxy,  $i$ , we count the total number of times out of 128 that the galaxy is assigned a fiber:  $N_{i,FA}$ . Then to correct for the fiber assignment incompleteness, we assign correction weights

$$w_{i,FA} = \frac{128}{N_{i,FA}} \quad (A1)$$

to each BGS galaxy.

Although we measure a spectrum for each galaxy assigned a fiber, we do not accurately measure a redshift for every spectra. This redshift measurement failure significantly contributes to spectroscopic incompleteness. For BGS, redshift failure of an observed galaxy spectrum depends mainly on fiber magnitude and a statistic, TSNR2. Fiber magnitude is derived from the predicted flux of the BGS object within a 1.5'' diameter fiber; we use  $r$ -band fiber magnitude  $r_{\text{fiber}}$ . TSNR2 roughly corresponds to the signal-to-noise ratio of the spectrum and is used to calibrate the effective exposure times in DESI observations

In Figure 3, we present the redshift success rate of BGS Bright galaxies as a function of  $r_{\text{fiber}}$  and TSNR2.

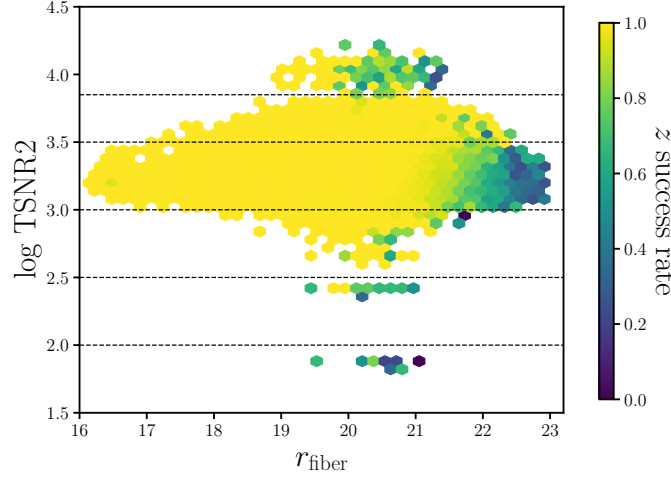
$$f_{z\text{-success}}(r_{\text{fiber}}) = \frac{1}{2} (1 - \text{erf}(c_0(r_{\text{fiber}} - c_1))) \quad (A2)$$

## B. STELLAR MASS COMPLETENESS

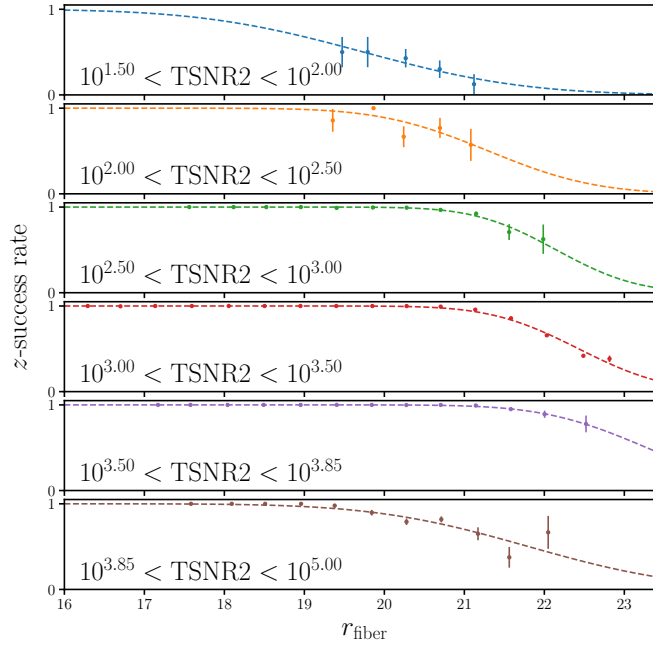
First, we take galaxies with  $i\Delta z < z < (i+1)\Delta z$ .

For each galaxy take their best-fit SED from PROVABGS and artificially redshift it to  $z' = z + \Delta z$ .

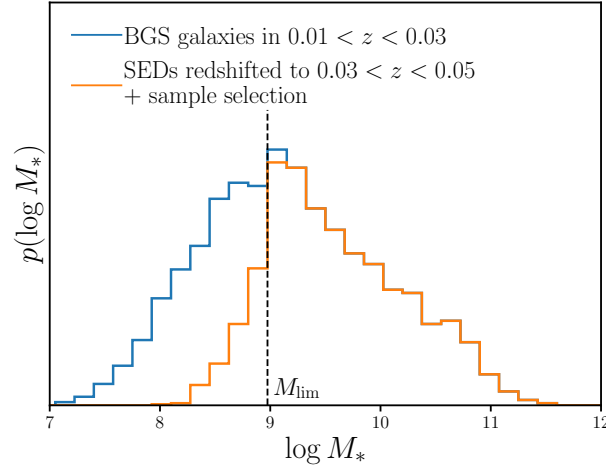
afterward, calculate the  $r$  band magnitude using the best-fit SED and determine whether the galaxy at  $z'$  would be within the target selection.



**Figure 3.** Redshift success rate of BGS Bright galaxies as a function of  $r_{\text{fiber}}$  and TSNR2. TSNR2 is a statistic that roughly corresponds to the signal-to-noise ratio of the observed spectrum. The color map represents the mean redshift success rate in each hexbin. We mark the TSNR2 bins (black dashed) that we use to separately fit the redshift success rate as a function of  $r_{\text{fiber}}$  using Eq. A2. In each TSNR2 bin, redshift success decreases as  $r_{\text{fiber}}$  increases.



**Figure 4.** Redshift success rates of BGS Bright galaxies as a function of  $r_{\text{fiber}}$  in 6 TSNR2 bins. The error bars represent the poisson uncertainties. In each panel, we include the best-fit analytic (Eq. A2) approximation of the redshift success rate (dashed). The best-fit  $c_0$  and  $c_1$  values are derived using  $\chi^2$  minimization. We use this analytic approximation to calculate the spectroscopic completeness weights.



**Figure 5.** blah

We then compare the  $M_*$  distributions and determine the  $M_*$  below which a significant number of galaxies are excluded from the sample.

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