

# Mitigating Malmquist and Eddington Biases in Latent-Inclination Regression of the Tully-Fisher Relation

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## ABSTRACT

When galaxy inclination is treated as a latent variable with a prior distribution function, inference of the Tully-Fisher relation becomes a linear regression problem with both Gaussian and non-Gaussian scatters. Likelihood functions incorporating the Sine scatter of the velocity width, the Gaussian scatter of the dependent variable, and the observational selection function are derived for the forward and the inverse models, where the independent variables are velocity width and luminosity, respectively. Testing on simulated data sets with a Markov Chain Monte Carlo sampling method shows that while Malmquist biases are corrected, the unaccounted Gaussian scatter in the independent variable leads to biased regression coefficients. The biases arise due to the independent variable's scatter shifting the dependent variable's distribution, described here as the generalized Eddington bias. I describe and test two methods that successfully mitigate the Eddington bias: shifting the first moment of the dependent variable before computing the likelihood, or incorporating the Gaussian scatter of the independent variable into the likelihood function of a dual-scatter model. This study provides a framework for unbiased Tully-Fisher inference without inclination correction and underscores the importance of both Malmquist bias and Eddington bias in the calibration of standardizable candles and the estimates of the Hubble constant.

**Keywords:** Linear regression (1945) — Bayesian statistics (1900) — Maximum likelihood estimation (1901) — Scaling relations (2031) — Disk galaxies (391)

## 1. INTRODUCTION

Tully-Fisher relation (TFR) is an empirical correlation between luminosity (or mass) and maximum rotation velocity of spiral galaxies (Tully & Fisher 1977). The tightness of the correlation makes it a remarkable distance indicator in the category of standardizable candles, so it was immediately utilized to measure the Hubble constant  $H_0$  (Sandage & Tammann 1976; Tully & Fisher 1977). In fact, the discovery of the correlation between peak luminosity and rate of decline for Type Ia supernovae, the most popular standardizable candles today, was made possible by distances from the TFR and surface brightness fluctuations (Phillips 1993). But it was soon realized that the TF distances were affected by local peculiar velocities (Tully 1988) and the Malmquist bias (Giraud 1987). The classic Malmquist bias (Eddington 1914; Malmquist 1922) is caused by observational selection effects and the intrinsic scatter in the luminosity of standard candles. The intrinsic scatter of the TFR is expected, as the physical properties of the galaxies are unlikely to be fully captured by rotation velocity alone. When a sample is subdivided in redshift, the Malmquist bias starts to show redshift-dependent behaviors, causing the artifact that measured mean luminosity (and  $H_0$  as a consequence) increases outward (Sandage 1994a,b).

Multiple methods have been proposed to correct for the distance-dependent Malmquist bias: (1) the method of replacing the linewidth-predicted mean luminosity with the analytical mean luminosity that depends on both flux limit and redshift (Sandage 1994a; Butkevich et al. 2005), (2) the method of normalized distances, which enhances the S/N of the luminosity-redshift diagram by shifting galaxies of different luminosities diagonally along the luminosity limit and uses the plateau at lower normalized distances to obtain an unbiased luminosity estimate (Bottinelli et al. 1986, 1988), and (3) the method of maximum likelihood estimation (MLE) that includes the sample selection function in the data likelihood function (Willick 1994; Willick et al. 1997). Among the three, the MLE is the most powerful and versatile method, because it utilizes the full data set, naturally accounts for heteroscedastic measurement errors, and fits the slope, the intercept, and the intrinsic scatter simultaneously. Willick et al. (1997) derived the likelihood functions for the two commonly used unidirectional models: the forward TFR and the inverse TFR, where the independent variable is velocity width and luminosity, respectively. Recent applications of the MLE method on the Cosmicflows-4 (CF4) data include Kourkchi et al. (2022) for the inverse TFR and Boubel et al. (2024) for the forward TFR.

Although the MLE method of unidirectional models accounts for the Malmquist bias, the inferred TF parameters are still biased when the independent variable is measured with error, because it conflicts with the model assumption that the independent variable is free of error. In the next section, I will explain the origin of this additional bias as a generalized Eddington bias (Dyson 1926; Eddington 1940). It is worth noting that this bias is also present in linear regressions using the ordinary least squares (OLS) estimator. The popular methods to mitigate this bias include (1) the bivariate correlated errors and intrinsic scatter (BCES) estimator (Akritas & Bershady 1996) and (2) the Bayesian method of a dual-scatter model (Kelly 2007). The former uses the moments of the data to estimate regression coefficients by correcting the bias in the OLS estimator, while the latter derives the data likelihood function that includes not only the intrinsic scatter and selection function, but also the covariance matrixes of measurement errors and the intrinsic distribution of the independent variable (approximated there as a mixture of Gaussians for mathematical convenience). The Bayesian method mitigates both the Malmquist bias and the generalized Eddington bias, so it is expected to produce unbiased parameter inference for the TFR. But there is one major caveat.

To solve the TFR as a typical linear regression problem, the observational data must be corrected for galaxy inclination so that the scatter around the correlation is Gaussian. Inclination correction is necessary because the observed velocity width is projected along the line of sight and the observed luminosity is attenuated by dust in the plane of the disk and random inclinations cause non-Gaussian scatters in both axes. But inclination estimation with axial ratio is highly uncertain even for well resolved galaxies, because (1) the axial ratio depends the method (isophote fitting vs. surface brightness modeling), the depth of the photometric data, and the bulge-to-disk ratio of the galaxy, and (2) the inclination angle also depends on the assumed edge-on thickness of the disk. As a result, galaxies with lower inclinations (e.g.,  $< 45^\circ - 60^\circ$ ) are often discarded in TF studies because of their larger inclination corrections. Inclination correction also causes correlated errors because the same inclination is used for both luminosity and velocity width. To avoid the problems caused by individual inclination correction, one can model the inclination statistically by treating it as a latent variable. And it is a prime time to develop such methods, because wide-area H I surveys like ALFALFA (Haynes et al. 2018) and WALLABY (Westmeier et al. 2022) continue to produce large samples of H I-selected galaxies at all inclination angles. In Fu (2024), I introduced an iterative latent-inclination method to restore the TFR from the full ALFALFA sample using data uncorrected for inclination. The method is highly efficient and produces a better result than that from inclination-corrected data. But the method requires binning and the biases in the data are

carried directly into the restored TFR. Aiming at unbiased inference of the TFR, I will focus on likelihood-based methods akin to that of Willick et al. (1997) and Kelly (2007).

When inclination is considered a latent variable with a known probability density function (pdf), the inference of the TFR becomes a linear regression problem with both Gaussian and non-Gaussian scatters. Obreschkow & Meyer (2013) proposed an latent-inclination MLE method for the inverse TFR, where luminosity is used to predict velocity width. But they missed an important term in their derivation: the intrinsic distribution function of the independent variable. Even though this term drops out in the likelihood function of the inverse TFR (see § 4.2), its omission led the authors to incorrectly conclude that the scatter of the independent variable can be added in quadrature to the scatter of the dependent variable. On the other hand, while the Malmquist bias can be corrected by the selection function in the likelihood function, the regression coefficients are still biased when measurement error and/or intrinsic scatter in luminosity (the independent variable) are present (which I will show in § 5.3). This is the same bias suffered by the OLS estimator and the MLE method of unidirectional models that I discussed earlier. In this paper, I will develop a Bayesian method of a bidirectional dual-scatter model to mitigate both Malmquist bias and Eddington bias in a linear regression problem where the data have both Gaussian and Sine scatters. I will use simulated data to show that the method produces nearly unbiased results using data uncorrected for inclination.

This paper is organized as follows. In § 2, I describe how observational selection function and luminosity scatter bias the mean luminosity via Malmquist bias, and how the scatter in the independent variable shifts the distribution of the dependent variable through a formula analogous to the Eddington bias. Both biases shift the first moment of the dependent variable away from the true correlation, causing biases in the regression coefficients. In § 3, I describe the data used to constrain the baryonic TFR and introduce the notation system. Next in § 4, I derive the data likelihood functions for the two latent-inclination unidirectional models: the forward and the inverse models. In § 5, I implement the likelihood functions and employ a Markov-Chain Monte Carlo method to sample the posterior pdf of the inferred parameters. Synthetic data of disk galaxies with random sky orientations are then generated to test the numerical methods, to quantify the statistical uncertainties, and to expose the biases of the inferred parameters. As expected, results are biased when the independent variable is measured with error, due to the generalized Eddington bias. Two modifications of the Bayesian method of unidirectional models are then introduced to mitigate the Eddington bias. First, in § 6.1, I reverse the expected Eddington bias in the velocity width data and use the moment-shifted data to constrain the inverse model; and in § 6.2, I introduce

the latent-inclination bidirectional dual-scatter model by incorporating scatter of the independent variable in the likelihood function of the unidirectional models. Both methods yield nearly unbiased parameter inferences using simulated data, confirming the theory in §2. Finally, I summarize the work and discuss future extensions and applications of the methods in §7. The Python functions of the models and the synthetic data generators are made publicly available at [https://github.com/fuhaiastro/TFR\\_biases](https://github.com/fuhaiastro/TFR_biases).

To keep the main text focused on the key concepts and results, I defer extended derivations and numerical considerations to the Appendices. Appendix A supplies the analytical expressions of the conditional pdfs of the models for simple flux-limited samples. Appendix B gives the alternative derivation of the dual-scatter model, starting from the inverse model. Appendix C describes the numerical methods that made the dual-scatter model computationally feasible by accelerating the numerical integrations by three orders of magnitude.

## 2. DISTANCE-DEPENDENT MALMQUIST BIAS AND GENERALIZED EDDINGTON BIAS

There are two important biases in astronomical survey data: the distance-dependent Malmquist bias (Sandage 1994a; Willick 1994), and the Eddington bias of the mean true value (Dyson 1926; Eddington 1940). The Malmquist bias is caused by data censorship and the Gaussian luminosity function of a standard candle. The distance-dependent bias is a generalized form of the classic Malmquist bias that describes the bias of the full sample at all distances (Eddington 1914; Malmquist 1922). On the other hand, the Eddington bias is due to measurement error and gradient in the distribution function of the measurements. The two biases are orthogonal to each other: Malmquist takes the true mean luminosity as known and compare it to the mean of the measured luminosities that survived the selection ( $BM \equiv \langle \tilde{x} \rangle - x$ ), while Eddington takes the measurement as known and compare it to the mean of the unknown true values ( $BE \equiv \tilde{x} - \langle x \rangle$ ). However, the two biases are often conflated because, in the simplest cases, their mathematical outcomes appear similar. The classic Malmquist bias of absolute magnitude for uniformly distributed standard candles with a Gaussian luminosity function of a mean of  $M$  and a standard deviation of  $\sigma_M$  is  $\langle \tilde{M} \rangle - M = -1.382\sigma_M^2$ , and the Eddington bias of apparent magnitude for uniformly distributed sources with constant luminosity and a measurement error of  $\sigma_m$  is  $\langle \tilde{m} \rangle - \langle m \rangle = -1.382\sigma_m^2$ . In both cases, the constant 1.382 is  $0.6 \ln 10$ .

In the following, I describe how each bias affects the distribution of the data and makes the regression coefficients biased. To formulate the problem, consider a family of standardizable candles on an idealized linear correlation:  $y(x) = \beta x + \gamma$ . For galaxies on the TFR,  $y$  would be the logarithmic

luminosity and  $x$  the inclination-corrected logarithmic velocity width. And the inverse function of  $y(x)$  is  $x(y) = (y - \gamma)/\beta$ .

For the Malmquist bias, random Gaussian scatter is in the luminosity axis,  $\tilde{y} = y(x) + \epsilon_y$ , where the random variable  $\epsilon_y$  is drawn from a normal distribution with zero mean and a standard deviation of  $\sigma_y$ . So the conditional pdf of  $\tilde{y}$  at a given  $x$  is a Gaussian:

$$p(\tilde{y}|x) = \frac{1}{\sqrt{2\pi}\sigma_y} \exp\left(-\frac{[\tilde{y} - y(x)]^2}{2\sigma_y^2}\right) \quad (1)$$

When the sample is selected above a logarithmic luminosity limit of  $y_l$  that depends on distance ( $y_l = \text{const.} + 2 \log D_L$ ), the selection function and the luminosity dispersion  $\sigma_y$  shifts the mean luminosity of the observed sample relative to the correlation-predicted mean luminosity according to the distance-dependent Malmquist bias (e.g., Willick 1994; Butkevich et al. 2005):

$$\begin{aligned} y(x) - \langle \tilde{y} \rangle_x &= \frac{\int_{y_l}^{\infty} [y(x) - \tilde{y}] p(\tilde{y}|x) d\tilde{y}}{\int_{y_l}^{\infty} p(\tilde{y}|x) d\tilde{y}} \\ &= -\sigma_y \sqrt{\frac{2}{\pi}} \frac{\exp[-(y_l - y(x))^2 / (2\sigma_y^2)]}{\text{erfc}[(y_l - y(x)) / (\sqrt{2}\sigma_y)]} \end{aligned} \quad (2)$$

Now suppose the scatter is in the  $x$ -axis instead,  $\tilde{x} = x(y) + \epsilon_x$ , where the random variable  $\epsilon_x$  is drawn from a normal distribution with zero mean and a standard deviation of  $\sigma_x$ . In this case, there is no selection function, but the mean  $y$  will still be shifted from the correlation-predicted value, because the distribution of  $y$  at a given  $\tilde{x}$  is altered from a Gaussian according to Bayes' rule:

$$p(y|\tilde{x}) = \frac{p(\tilde{x}|y)p(y)}{p(\tilde{x})} \quad (3)$$

where the conditional pdf of  $\tilde{x}$  at a given  $y$  is a Gaussian:

$$\begin{aligned} p(\tilde{x}|y) &= \frac{1}{\sqrt{2\pi}\sigma_x} \exp\left(-\frac{[\tilde{x} - x(y)]^2}{2\sigma_x^2}\right) \\ &= \frac{1}{\sqrt{2\pi}\sigma_x} \exp\left(-\frac{[y(\tilde{x}) - y]^2}{2(\beta\sigma_x)^2}\right) \end{aligned} \quad (4)$$

The bias of the mean  $y$  at a given  $\tilde{x}$  due to the scatter in  $\tilde{x}$  can be expressed as:

$$\begin{aligned} y(\tilde{x}) - \langle y \rangle_{\tilde{x}} &= \int [y(\tilde{x}) - y] \frac{p(\tilde{x}|y)p(y)}{p(\tilde{x})} dy \\ &= \int [y(\tilde{x}) - y] \frac{1}{\sqrt{2\pi}\sigma_x} \exp\left(-\frac{[y(\tilde{x}) - y]^2}{2(\beta\sigma_x)^2}\right) \frac{p(y)}{p(\tilde{x})} dy \\ &= \frac{\beta^2 \sigma_x}{\sqrt{2\pi} p(\tilde{x})} \int \frac{d}{dy} \left[ \exp\left(-\frac{[y(\tilde{x}) - y]^2}{2(\beta\sigma_x)^2}\right) \right] p(y) dy \end{aligned} \quad (5)$$

The symmetry between  $y$  and  $y(\tilde{x})$  allows the chain rule:

$$\begin{aligned} y(\tilde{x}) - \langle y \rangle_{\tilde{x}} &= -\frac{\beta^2 \sigma_x}{\sqrt{2\pi} p(\tilde{x})} \int \frac{d}{dy(\tilde{x})} \left[ \exp \left( -\frac{[y(\tilde{x}) - y]^2}{2(\beta \sigma_x)^2} \right) \right] p(y) dy \\ &= -\frac{\beta \sigma_x^2}{p(\tilde{x})} \int \frac{d}{d\tilde{x}} [p(\tilde{x}|y)p(y)] dy \end{aligned} \quad (6)$$

The final result is obtained by applying Leibniz's rule to take the derivative out of the integral:

$$\begin{aligned} y(\tilde{x}) - \langle y \rangle_{\tilde{x}} &= -\frac{\beta \sigma_x^2}{p(\tilde{x})} \frac{d}{d\tilde{x}} \left( \int p(\tilde{x}|y)p(y) dy \right) \\ &= -\beta \sigma_x^2 \frac{d \ln p(\tilde{x})}{d\tilde{x}} \end{aligned} \quad (7)$$

The result is analogous to the Eddington bias of the mean true value (Dyson 1926; Eddington 1940):

$$\tilde{x} - \langle x \rangle_{\tilde{x}} = -\sigma^2 \frac{d \ln p(\tilde{x})}{d\tilde{x}} \quad (8)$$

where  $\tilde{x}$  is the measured value,  $\langle x \rangle_{\tilde{x}} = \int x p(x|\tilde{x}) dx$  the mean of the true values that could have produced the measured value,  $\sigma$  the measurement error, and  $p(\tilde{x})$  the distribution function of the measured values. In fact, the Eddington bias is a special case of Eq. 7 for  $\beta = 1$  and  $\gamma = 0$ . Hence, I will call it the generalized Eddington bias.

The equations above show that Malmquist bias and Eddington bias are driven by different sample characteristics: the former on the luminosity limit and the luminosity dispersion, while the latter on the dispersion of the independent variable and its distribution function. They operate on the data simultaneously and cause the inferred regression coefficients to deviate from the truth by shifting the moment of the data from the location predicted by the true correlation. Eddington bias leads to biased regression coefficients in the following way. When  $p(\tilde{x})$  is a simple exponential distribution function,  $p(\tilde{x}) \propto \exp(\tilde{x}/x_0)$ , the Eddington bias is a constant, implying a vertical shift of the best-fit relation from the truth, causing the intercept to change while keeping the same slope. For other distributions (e.g., Schechter function), the Eddington bias varies with  $\tilde{x}$ , leading both the slope and the intercept to drift away from the truth. Malmquist bias affects the regression coefficients in a more complicated way because the bias depends not only on luminosity scatter and flux limit, but also on redshift and the unknown true correlation. Therefore, from a forward modeling perspective, correcting the biases in inferred parameters requires statistical models that build in the relevant sample characteristics ( $\sigma_x, \sigma_y, y_l$ ).

### 3. FORMULATION OF THE PROBLEM

The TFR has various empirical forms. The luminosity axis could be absolute magnitude, stellar mass, or baryonic mass;

and the velocity axis could be line widths from neutral hydrogen (H I), molecular gas (CO), or ionized gas ([O II]). I will formulate the problem using the TFR between baryonic mass and H I line width, because (1) the addition of gas mass to stellar mass tends to reduce the curvature of the correlation (e.g., McGaugh et al. 2000; Kourkchi et al. 2022) and (2) H I is the best tracer of the maximum rotation velocity thanks to its extended spatial distribution. This choice does not restrict the application of the methods to only baryonic TFR, since the derived expressions can be easily adjusted to suit magnitude-based TFRs.

The baryonic TFR is a power-law correlation between the baryonic mass (stellar + gas) and the edge-on rotation velocity. In logarithmic, it is a linear relation with two coefficients ( $\beta, \gamma$ ):

$$\log M_b = \beta [\log W - \log \sin(\text{inc}) - 2.5] + \gamma \quad (9)$$

where  $\log M_b$  is the logarithmic baryonic mass in solar mass ( $M_\odot$ ) and  $\log W - \log \sin(\text{inc})$  is the observed velocity width ( $W$  in  $\text{km s}^{-1}$ ) corrected for the inclination angle (inc). The relation is anchored at  $\log V_0 = 2.5$  dex (or  $V_0 = 316 \text{ km s}^{-1}$ ), so that the intercept  $\gamma$  is the baryonic mass of spirals with edge-on velocity width of  $316 \text{ km s}^{-1}$ .

The baryonic mass is calculated as the *apparent* baryonic mass multiplied by the square of the luminosity distance, which in logarithmic is:

$$\log M_b = \log m_b + 2 \log D_L \quad (10)$$

The apparent mass ( $\log m_b$ ) includes the  $4\pi$  term and is calculated using the H I 21 cm flux ( $S_{21}$  in  $\text{Jy km s}^{-1}$ ) and apparent magnitude in an optical/near-IR filter ( $m_\lambda$ ) using the following relation:

$$m_b = 2.356 \times 10^5 K_g S_{21} + 10^{-0.4(m_\lambda - M_{\lambda,\odot} - 25)} (M/L)_\lambda \quad (11)$$

where  $K_g$  is the atomic-to-ISM conversion factor (typically assumed to be 1.33),  $M_{\lambda,\odot}$  is the absolute magnitude of the Sun (Willmer 2018), and  $(M/L)_\lambda$  is the color-estimated mass-to-light ratio in solar units ( $M_\odot/L_\odot$ ). The latter two must be in the same filter as the galaxy magnitude, as indicated by the subscript  $\lambda$ .

For most galaxies, distance is not a direct observable, but rather an inferred quantity from the observed redshift and a cosmological model. At low redshift ( $z < 0.1$ ), the redshift-derived luminosity distance can be accurately calculated using the Taylor expansion form of Caldwell & Kamionkowski (2004):

$$D_L \approx \frac{cz}{H_0} \left[ 1 + \frac{1}{2}(1 - q_0)z - \frac{1}{6}(1 - q_0 - 3q_0^2 + j_0)z^2 \right] \quad (12)$$

where  $cz$  is the cosmological redshift in  $\text{km s}^{-1}$ ,  $H_0 = 70 \text{ km s}^{-1} \text{ Mpc}^{-1}$  is the assumed Hubble constant,  $q_0 = -\frac{\ddot{a}a}{\dot{a}^2} =$



$\Omega_{m,0}/2 - \Omega_{\Lambda,0}$  is the deceleration parameter, and  $j_0 = -\frac{\ddot{a} \cdot a^2}{\dot{a}^3} = \Omega_{m,0} + \Omega_{\Lambda,0}$  is the cosmic jerk. When adopting  $\Omega_{m,0} = 0.315$ ,  $\Omega_{\Lambda,0} = 0.685$  from Planck Collaboration et al. (2020),  $q_0 = -0.53$  and  $j_0 = 1$ .

In the following, I will use shorthand symbols for the logarithmic of the apparent mass, the distance squared, the velocity width ratio, and the sine of the inclination:

$$\begin{aligned} m &\equiv \log m_b \\ d &\equiv 2 \log D_L \\ w &\equiv \log W - 2.5 \\ i &\equiv \log \sin(\text{inc}) \end{aligned} \quad (13)$$

With these shorthands, the TFR in Eq. 9 can be rewritten as:

$$m + d = \beta(w - i) + \gamma \quad (14)$$

I will also use  $(\tilde{m}, \tilde{w}, \tilde{d})$  to indicate measured values (with errors) and  $(m, w, d)$  to indicate the true values. Similarly,  $\tilde{\theta}$  and  $\theta$  represent the inferred value and the true value of parameter  $\theta$ , respectively. And the bias of the inferred parameter is defined as  $B_\theta \equiv \tilde{\theta} - \theta$ .

The data available to the astronomer are  $\{\tilde{m}_i, \tilde{w}_i, \tilde{d}_i\}_{k=1}^N$  for a sample of  $N$  galaxies that survived the observational selection function  $S(\tilde{m}, \tilde{w})$ . The goal of parameter inference is to optimally utilize these data to constrain the TF parameters  $(\beta, \gamma)$ , ideally free of statistical and selection biases.

It is important to mitigate the biases because a biased  $\gamma$  directly leads to a biased Hubble constant ( $H_0$ ). Two separate samples are needed to estimate  $H_0$ : a larger and more distant redshift sample and a smaller and closer zero-point sample. The distances of the former are calculated using an assumed value of  $H_0$ , and the distances of the latter are from standard candles on the lower rung of the distance ladder (e.g., Cepheids). The TF coefficients  $(\beta, \gamma)$  are estimated using the redshift sample, while the zero-point sample determines the intercept ( $\gamma_{ZP}$ ) with Cepheid distances assuming the same slope  $\beta$ . Since it is fair to assume that both samples follow the same TFR, any difference between the intercepts from the two samples ( $\gamma$  and  $\gamma_{ZP}$ ) implies a deviation between the actual value of  $H_0$  and the assumed Hubble constant ( $70 \text{ km s}^{-1} \text{ Mpc}^{-1}$ ):

$$\log(H_0/70) = 0.5(\gamma - \gamma_{ZP}) \quad (15)$$

As a result, the bias in  $\gamma$  will directly transfer to the inferred Hubble constant:

$$B_{H_0} \approx 35 \ln 10 B_\gamma = 4.84(B_\gamma/0.06) \text{ km s}^{-1} \text{ Mpc}^{-1} \quad (16)$$

A bias of 0.06 dex (or 0.15 mag) in the intercept would lead to a bias of  $\sim 5 \text{ km s}^{-1} \text{ Mpc}^{-1}$  in the Hubble constant, comparable to the current ‘‘Hubble tension’’ (e.g. Riess et al. 2024).

Note that  $B_\gamma$  is only one of the two biases involved in the Hubble constant; the other is the bias of  $\gamma_{ZP}$  from the zero-point sample. It is thus critical to use the same statistical model for the redshift and the zero-point samples, in addition to consistent measurements of rotation velocities and masses (or luminosities) across the two samples (Bradford et al. 2016). If the biases of the intercepts from the two samples are equal, they will cancel out and the resulting  $H_0$  estimate would be unbiased. Unfortunately, that is unlikely to happen, because the biases depend on the following sample characteristics that usually do not match between the two samples: (1) the observational selection function, (2) the measurement errors of the dependent and the independent variables, and (3) the distribution function of the independent variable. Therefore, to reduce bias in determining the Hubble constant, one need to analyze both the redshift sample and the zero-point sample with statistical models that incorporate their specific characteristics to correct for their different biases.

#### 4. DERIVATION OF THE LIKELIHOOD FUNCTIONS

To begin the Bayesian inference process, I derive the data likelihood functions for two commonly assumed generative models: the forward model ( $w$  as independent variable that predicts  $m+d$ ) and the inverse model ( $m+d$  as the independent variable that predicts  $w$ ) in this section.

##### 4.1. The Forward Model

The forward generative model uses velocity width ( $w-i$ ) to predict the mass ( $m+d$ ). It also assumes Gaussian dispersion along the mass axis. By using  $w$  as an independent variable, its measurement error is inherently ignored in the forward model. To make this explicit in the notation and to distinguish the forward model with the dual-scatter model in § 6.2, I use  $w$  in place of  $\tilde{w}$  in this subsection. In addition, the residual redshift noise propagated into the distance parameter  $\tilde{d}$  is ignored and  $d$  is used in place of  $\tilde{d}$  to make this assumption explicit. But I will later comment on how to properly include redshift noise in the likelihood function.

Given the TFR in Eq. 14, the forward model can be expressed as:

$$\tilde{m} = \beta(w - i) - d + \gamma + \epsilon_{im} + \epsilon_{em} \quad (17)$$

where the random variables represent the intrinsic dispersion ( $\epsilon_{im}$ ) and the measurement error ( $\epsilon_{em}$ ), and they are drawn from Gaussian distributions with zero means and standard deviations of  $\sigma_{im}$  and  $\sigma_{em}$ , respectively.

In addition, the forward model also requires parameterizing the distribution function of edge-on rotation velocity ( $w-i$ ) of the galaxy population (hereafter ‘‘velocity function’’). Given the TFR that links velocity with mass, the velocity function is closely linked to the mass function, which

is normally parameterized as a Schechter function:

$$\frac{dn}{d(m+d)} = \phi_* 10^{(\alpha+1)(m+d-M_*)} \exp(-10^{m+d-M_*}) \quad (18)$$

where  $\alpha$  is the faint-end slope,  $M_*$  the characteristic mass (above which the exponential drop-off commences). Normally the normalization factor  $\phi_*$  is in units of  $\text{Mpc}^{-3} \text{dex}^{-1}$ ; for the purpose here, I redefine  $\phi_*$  as the factor that normalizes the distribution function to unity so that it becomes a properly normalized pdf  $p(m+d)$ .

Substituting  $m+d$  with  $\beta(w-i)+\gamma$ , one obtains the corresponding velocity function:

$$\frac{dn}{d(w-i)} = \beta \phi_* 10^{(\alpha+1)[\beta(w-i)-v_*]} \exp[-10^{\beta(w-i)-v_*}] \quad (19)$$

where  $v_* = M_* - \gamma$ , which equals the characteristic logarithmic velocity multiplied by  $\beta$ . Notice the extra  $\beta$  in front of  $\phi_*$  because  $d(m+d) = \beta d(w-i)$ .

In the following, I will start by expressing the joint probability of  $(\tilde{m}, d, w, i)$ , then marginalize it over  $i$  to obtain the joint probability of the observables  $(\tilde{m}, d, w)$ , and finally using the joint probability and the selection function to calculate the conditional probability of  $\tilde{m}$ , which makes up the likelihood function.

The joint probability that a galaxy has the three observables  $(\tilde{m}, \tilde{d}, w)$  and an inclination  $i$  can be factorized using the multiplication rule:

$$p(\tilde{m}, d, w, i) = p(\tilde{m}|w, i, d) p(w|i) p(i) p(d) \quad (20)$$

When choosing these factors, I have considered relations between the variables and have made the following assumptions:

- the velocity function parameters does not evolve over the redshift range covered by the sample, so that  $p(w|i)$  does not depend on distance.
- inclination and distance are independent variables, so that  $p(i, d) = p(i) p(d)$ .

The particular set of conditional pdfs are straightforward to express. The first term is obtained by marginalizing the joint pdf  $p(\tilde{m}, m|w, i, d)$  over  $m$ , which is a convolution of two Gaussians:

$$\begin{aligned} p(\tilde{m}|w, i, d) &= \int_{-\infty}^{\infty} p(\tilde{m}|m) p(m|w, i, d) dm \\ &= \frac{1}{\sigma_m \sqrt{2\pi}} \exp \left[ -\frac{[\tilde{m} + d - \beta(w-i) - \gamma]^2}{2\sigma_m^2} \right] \end{aligned} \quad (21)$$

Per the convolution theorem of Gaussians, the variance of the convolved Gaussian,  $\sigma_m^2$ , is the sum of the variances from intrinsic dispersion and measurement error:

$$\sigma_m^2 = \sigma_{im}^2 + \sigma_{em}^2 \quad (22)$$

Note that the likelihood-based method naturally handles heteroscedastic measurement errors, because different values of  $\sigma_{em}$  can be supplied for each source while treating  $\sigma_{im}$  as a constant parameter that describes the whole sample.

The second term is the probability of projected velocity given the inclination and the velocity function and it can be expressed by the normalized Schechter distribution function in Eq. 19:

$$p(w|i) = \beta \phi_* 10^{(\alpha+1)[\beta(w-i)-v_*]} \exp[-10^{\beta(w-i)-v_*}] \quad (23)$$

The velocity function is a critical component of the forward model because the term depends on  $i$  so it does not drop out in the conditional pdf in Eq. 30 below.

The third term is the prior pdf of the inclination parameter. Assuming isotropic random orientation on the sky, the pdf of inclination angle  $\text{inc}$  is a sine function:  $p(\text{inc}) = \sin(\text{inc})$  for  $0 < \text{inc} < \pi/2$ . The pdf of  $i \equiv \log \sin(\text{inc})$  can then be derived using the pdf identity  $p(i)di = p(\text{inc})d\text{inc}$ , and the result is:

$$p(i) = \ln 10 \frac{10^{2i}}{\sqrt{1-10^{2i}}} \quad (24)$$

Note that  $i \leq 0$  given its definition.

The last term is the probability of observing a galaxy at a given distance. It is proportional to the integrated galaxy volume density at the distance  $n(d)$  (i.e., the redshift distribution) multiplied by the survey volume  $\Omega D_L^2 dD_L$ . Expressed in distance parameter  $d$ , the probability is:

$$p(d) \propto 10^{3d/2} n(d) \quad (25)$$

When one ignores the difference between the redshift-inferred distance  $\tilde{d}$  and the true distance  $d$  (as assumed here), this term drops out in the conditional pdf in Eq. 30 below. But if one opts to account for this difference (e.g., Willick et al. 1997), the following term needs to be multiplied to the joint pdf in Eq. 28 below to obtain  $p(\tilde{m}, w, \tilde{d}, d, i)$ :

$$p(\tilde{d}|d) = \frac{1}{\sigma_d \sqrt{2\pi}} \exp \left[ -\frac{(\tilde{d}-d)^2}{2\sigma_d^2} \right] \quad (26)$$

where the standard deviation is proportional to the ratio between the velocity noise ( $\sigma_{cz}$ ) and the redshift:

$$\sigma_d \approx \frac{2}{\ln 10} \frac{\sigma_{cz}}{cz} \quad (27)$$

and an additional marginalization over  $d$  is required when calculating the joint pdf of the three observables in Eq. 29. Note that because of the additional  $d$ -dependent terms in  $p(d)$ , the marginalization over  $d$  is not as simple as the marginalization over  $m$  in Eq. 21. For this reason, it is incorrect to absorb this integral over  $d$  by simply adding  $\sigma_d^2$  to  $\sigma_m^2$  in Eq. 22.

Combining the terms defined above, the joint probability can be written is:

$$p(\tilde{m}, w, d, i) = p(d) \times \frac{\ln 10 \cdot 10^{2i}}{\sqrt{1 - 10^{2i}}} \times \frac{1}{\sigma_m \sqrt{2\pi}} \exp \left[ -\frac{[\tilde{m} + d - \beta(w - i) - \gamma]^2}{2\sigma_m^2} \right] \times \beta \phi_* 10^{(\alpha+1)[\beta(w-i)-v_*]} \exp[-10^{\beta(w-i)-v_*}] \quad (28)$$

which can then be marginalized over  $i$  to obtain the joint probability of the three observables:

$$p(\tilde{m}, w, d) = \int_{-\infty}^0 p(\tilde{m}, w, d, i) di \quad (29)$$

The observational selection function,  $S(\tilde{m}, w)$ , truncates the joint pdf,  $p(\tilde{m}, w, d)$ , so that the resulting pdf is no longer normalized. To account for  $S(\tilde{m}, w)$  and the associated Malmquist bias, one shall compute the conditional pdf of  $\tilde{m}$  by normalizing the truncated joint pdf with the pdf marginalized over  $\tilde{m}$ :

$$p(\tilde{m}|w, d) = \frac{S(\tilde{m}, w)p(\tilde{m}, w, d)}{\int_{-\infty}^0 S(\tilde{m}, w)p(\tilde{m}, w, d) d\tilde{m}} = \frac{S(\tilde{m}, w) \int_{-\infty}^0 p(\tilde{m}|w, i, d)p(w|i)p(i) di}{\int_{-\infty}^0 S(\tilde{m}, w) \int_{-\infty}^0 p(\tilde{m}|w, i, d)p(w|i)p(i) di d\tilde{m}} \quad (30)$$

Notice that the distance distribution function,  $p(d)$ , has cancelled out in the division. When the sample is simply flux-limited by a step function, the integral over  $\tilde{m}$  on the denominator becomes an error function, making it much faster to evaluate. I provide the full expression of the conditional pdf for flux-limited samples in Eq. A3 in Appendix A.

The data likelihood function ( $\mathcal{L}$ ) is defined as the probability of the data given the model. For the forward model, the data are  $\{\tilde{m}_k\}_{k=1}^N$  and the model is the combination of the model parameters  $\theta \equiv (\beta, \gamma, \sigma_m, v_*, \alpha)$  and the independent variables  $\{w_k, d_k\}_{k=1}^N$ . It is thus the product of the conditional probabilities in Eq. 30 of all valid data points. In practice, its logarithmic is preferred:

$$\ln \mathcal{L} = \sum_{k=1}^N \ln p(\tilde{m}_k | w_k, d_k) \quad (31)$$

#### 4.2. The Inverse Model

The inverse model uses mass ( $m + d$ ) to predict velocity width ( $w - i$ ) and assumes Gaussian dispersion along the velocity axis:

$$\tilde{w} - i = (m + d - \gamma) / \beta + \epsilon_{iw} + \epsilon_{ew} \quad (32)$$

where the random variables represent the intrinsic dispersion in velocity ( $\epsilon_{iw}$ ) and measurement error ( $\epsilon_{ew}$ ). By using  $m + d$

as the independent variable, its measurement error is inherently ignored in the inverse model, so I use  $m$  and  $d$  in place of  $\tilde{m}$  and  $\tilde{d}$  in this subsection.

Starting by factorizing the joint pdf:

$$p(\tilde{w}, m, d, i) = p(\tilde{w}|m, d, i)p(m|d)p(d)p(i) \quad (33)$$

Similar to the forward model, the first term is obtained by marginalizing the joint pdf  $p(\tilde{w}, w|m, d, i)$  over  $w$ :

$$p(\tilde{w}|m, d, i) = \int_{-\infty}^{\infty} p(\tilde{w}|w)p(w|m, d, i)dw = \frac{1}{\sigma_w \sqrt{2\pi}} \exp \left[ -\frac{[\tilde{w} - i - (m + d - \gamma) / \beta]^2}{2\sigma_w^2} \right] \quad (34)$$

where the variance  $\sigma_w^2$  is the sum of the variances from intrinsic dispersion and measurement error:

$$\sigma_w^2 = \sigma_{iw}^2 + \sigma_{ew}^2 \quad (35)$$

The second term is the normalized mass function in Eq 18:

$$p(m|d) = \phi_* 10^{(\alpha+1)(m+d-M_*)} \exp(-10^{m+d-M_*}) \quad (36)$$

For simplicity, I assume that the baryonic mass function is independent of inclination angle, implying that intrinsic dust extinction has been corrected for when calculating the stellar-mass-to-light ratio using color. The last two terms of the joint pdf are the same as in Eqs. 24 and 25. Therefore, the joint pdf can be written as:

$$p(\tilde{w}, m, d, i) = p(d) \times \frac{\ln 10 \cdot 10^{2i}}{\sqrt{1 - 10^{2i}}} \times \frac{1}{\sigma_w \sqrt{2\pi}} \exp \left[ -\frac{[\tilde{w} - i - (m + d - \gamma) / \beta]^2}{2\sigma_w^2} \right] \times \phi_* 10^{(\alpha+1)(m+d-M_*)} \exp(-10^{m+d-M_*}) \quad (37)$$

which can then be marginalized over  $i$  to obtain the joint probability of the three observables:

$$p(\tilde{w}, m, d) = \int_{-\infty}^0 p(\tilde{w}, m, d, i) di \quad (38)$$

The conditional probability of  $\tilde{w}$  is then obtained by normalization:

$$p(\tilde{w}|m, d) = \frac{S(m, \tilde{w})p(\tilde{w}, m, d)}{\int_{-\infty}^0 S(m, \tilde{w})p(\tilde{w}, m, d) d\tilde{w}} = \frac{S(m, \tilde{w}) \int_{-\infty}^0 p(\tilde{w}|m, i, d)p(i) di}{\int_{-\infty}^0 S(m, \tilde{w}) \int_{-\infty}^0 p(\tilde{w}|m, i, d)p(i) di d\tilde{w}} \quad (39)$$

where both the mass distribution function,  $p(m|d)$ , and the distance distribution,  $p(d)$ , have dropped out. Hence, only

the three TFR model parameters are constrained by the inverse model:  $\theta \equiv (\beta, \gamma, \sigma_w)$ . When the selection function depends only on  $m$  [i.e.,  $S(m, \tilde{w}) = S(m)$ ], it also drops out from the expression:

$$\begin{aligned} p(\tilde{w}|m, d) &= \int_{-\infty}^0 p(\tilde{w}|m, d, i) p(i) di \\ &= \frac{\ln 10}{\sigma_w \sqrt{2\pi}} \int_{-\infty}^0 \frac{10^{2i}}{\sqrt{1-10^{2i}}} \exp \left[ -\frac{[\tilde{w}-i-(m+d-\gamma)/\beta]^2}{2\sigma_w^2} \right] di \end{aligned} \quad (40)$$

I provide the full expression of the conditional pdf for flux-limited samples in Eq. A5 in Appendix A.

The data likelihood function is obtained from the conditional pdf in the same manner as in the forward model:

$$\ln \mathcal{L} = \sum_{k=1}^N \ln p(\tilde{w}_k | m_k, d_k) \quad (41)$$

## 5. IMPLEMENTATION AND TESTING

This section describes how I implement the latent-inclination likelihood functions in a Bayesian framework (§ 5.1), generate synthetic TF galaxy samples with random sky orientations (§ 5.2), and test the method with synthetic data sets (§ 5.3). The testing reveals the biases of inferred parameters when the independent variable is measured with error, as expected from § 2. For measurement errors and sample sizes typical for the ALFALFA sample, the biases are much greater than the inferred statistical uncertainties and they scale with the scatter of the independent variable.

### 5.1. Parameter Inference

The Bayesian theorem uses the data likelihood function  $\ln \mathcal{L}$  to update the prior knowledge of the model to provide the posterior distribution of the model parameters given the data ( $D$ ):

$$\ln p(\theta|D) = \ln \mathcal{L} + \ln p(\theta) - \ln p(D) \quad (42)$$

where  $p(\theta)$  is the prior pdf of the model parameters and  $p(D)$  is the Bayesian evidence of the model as a whole.

When prior knowledge is insufficient or ignored, the priors are assumed to be flat within specified bounds:

$$p(\theta) = \prod_{j=1}^n \frac{1}{\Delta \theta_j} \quad (43)$$

where  $n$  is the number of parameters. When such bounded flat priors are assumed, the posterior peaks at the parameters that maximizing the data likelihood, making the Bayesian inference essentially the same as MLE.

The evidence is defined as the marginalized probability of the data ( $D$ ) over all model parameters ( $\theta$ ) of a given model:

$$p(D) = \int p(D|\theta) p(\theta) d\theta \quad (44)$$

It is often challenging to evaluate the evidence accurately because it is a multi-dimensional integral that requires calculations of the data likelihood function over the entire parameter space. But it can be safely ignored for the purpose of parameter inference, because it is a constant for a given model and a given data set. In addition, Markov-Chain Monte Carlo (MCMC) algorithms do not require *normalized* pdf to sample the parameter space at frequencies proportional to the pdf, making them the favored method for Bayesian inference.

I employ the affine-invariant MCMC ensemble sampler implemented in the Python code `emcee`<sup>2</sup> (Foreman-Mackey et al. 2013) to sample the posterior pdfs. The ensemble approach is naturally parallelizable, inherently handles correlated parameters, and minimizes the need for manual tuning of step sizes for poorly scaled parameters. Standard procedure to set up the sampler is followed. The number of walkers is set to an integer number of CPU cores and is set between two and three times the number of free parameters. Starting from random initial positions within the bounds, the walkers proceed until the length of the chains exceeds 50 times the estimated autocorrelation length ( $l$ ; typically between 40 and 200 steps). After discarding the initial  $2l$  steps (“burn-in”) and thinning the chains by keeping one step for every  $l/2$  steps, the chains from all walkers are combined to form the final parameter array, whose distribution functions should trace the posterior pdfs of the parameters given the data. For each model parameter, I quote the best-fit value and the  $1\sigma$  (68%) credible interval given by the 50th, 16th, and 84th percentiles of the marginalized cumulative distribution function.

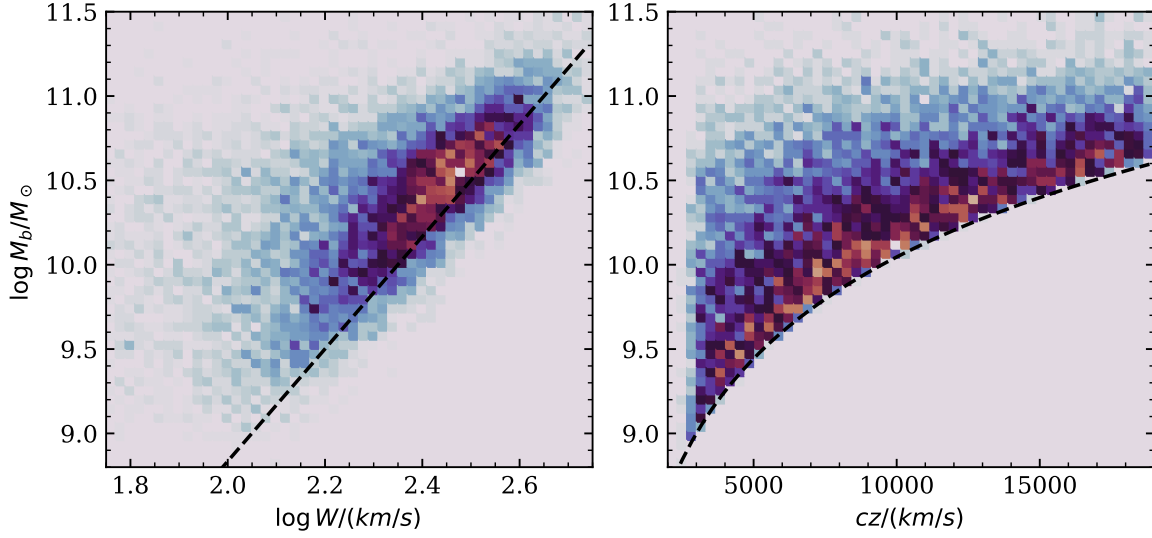
### 5.2. Simulated Data for Testing

To test whether the models in § 4 can recover unbiased parameter estimation, I simulate three samples of galaxies where the ground truth of the model parameters are known. I start the process by random sampling of the velocity function in narrow redshift intervals. This is necessary because other than the Schechter function parameters, the survey volume and the redshift distribution also change the probability of sampling a galaxy with a particular rotation velocity, and both of these factors could vary with redshift. So the first step is to divide the user-set redshift range into a fine grid of equal intervals ( $\delta cz$ ), then for each redshift, a subsample is generated following the procedure below:

1. The redshift grid center,  $cz_0$ , represents the true cosmological redshift of the simulated subset, i.e., all galaxies in this subset are at the same true distance  $d(cz_0)$ , calculated using Eq. 12.
2. The initial subsample size for each  $cz_0$  is calculated as  $N_0 = a(cz_0)^{2+n} \delta cz$ , where  $a$  is a scale factor and  $n$  is

<sup>2</sup> <https://emcee.readthedocs.io>





**Figure 1.** Distributions of synthetic sample C in baryonic mass vs. projected line width (left) and baryonic mass vs. redshift (right). The dashed line in the left panel shows the prescribed TFR and the dashed curve in the right panel shows the mass limit as a function of redshift.

**Table 1.** Input Parameters vs. Inferred Parameters

Parameter	Synthetic Data Set		
	A	B	C
Input Parameters (Truth)			
$\sigma_m$	0.15	0.0	0.15
$\sigma_w$	0.0	0.045	0.045
$\gamma$	10.50	10.50	10.50
$\beta$	3.33	3.33	3.33
$v_*$	0.3	0.3	0.3
$\alpha$	-1.27	-1.27	-1.27
$m_l$	5.736	5.736	5.736
$N$	10,132	10,111	10,147
Inferred Parameters from Forward Model			
$\gamma$	$10.502^{+0.004}_{-0.004}$	$10.444^{+0.004}_{-0.003}$	$10.450^{+0.005}_{-0.005}$
$\beta$	$3.355^{+0.031}_{-0.031}$	$3.094^{+0.024}_{-0.025}$	$3.164^{+0.039}_{-0.037}$
$\sigma_m$	$0.162^{+0.003}_{-0.003}$	$0.145^{+0.003}_{-0.003}$	$0.210^{+0.004}_{-0.004}$
$v_*$	$0.264^{+0.033}_{-0.033}$	$0.273^{+0.033}_{-0.030}$	$0.248^{+0.040}_{-0.037}$
$\alpha$	$-1.206^{+0.039}_{-0.040}$	$-1.225^{+0.042}_{-0.043}$	$-1.181^{+0.046}_{-0.043}$
Inferred Parameters from Inverse Model			
$\gamma$	$10.560^{+0.004}_{-0.003}$	$10.500^{+0.003}_{-0.003}$	$10.554^{+0.005}_{-0.004}$
$\beta$	$3.587^{+0.025}_{-0.024}$	$3.337^{+0.023}_{-0.024}$	$3.593^{+0.029}_{-0.029}$
$\sigma_w$	$0.046^{+0.001}_{-0.001}$	$0.046^{+0.001}_{-0.001}$	$0.062^{+0.001}_{-0.001}$

NOTE—The fitted parameters are assumed to have flat priors within the following bounds:  $10 < \gamma < 11$ ,  $2.5 < \beta < 4.5$ ,  $0.001 < \sigma_m < 0.3$ ,  $0.001 < \sigma_w < 0.1$ ,  $-1 < v_* < 1$ , and  $-2 < \alpha < 0$ . For both the forward and the dual-scatter models, the standard mass limit  $m_l$  is fixed to the input value.

the power-law index of the integrated galaxy volume density. Both parameters can be adjusted to change

the redshift distribution and the size of the final sample after the selection function is applied.

3. *Optional:* Random redshifts perturbed by velocity noise,  $\{cz_i\}_{i=1}^{N_0}$ , are drawn around  $cz_0$  following a normal distribution with a mean of  $cz_0$  and a standard deviation of  $\sigma_{cz}$ :  $N(cz_0, \sigma_{cz}^2)$ . Distances,  $\{\tilde{d}_i\}$ , are then calculated from  $\{cz_i\}$  using Eq. 12. The velocity noise is thus propagated into  $\{\tilde{d}_i\}$ .
4. Intrinsic edge-on velocities,  $\{v_i\}$ , are drawn from the Schechter function in Eq. 19 with specified parameters ( $v_*, \alpha$ ) using the inverse transform sampling method. The default sampling range is  $-3.5 < \beta v - v_* < 1.5$ .
5. Intrinsic masses,  $\{M_i\}$ , are calculated from the edge-on velocities using an idealized TFR:  $M_i = \beta v_i + \gamma$ . The exact linear relation between  $\{v_i\}$  and  $\{M_i\}$  makes sampling the intrinsic velocity function equivalent to sampling the intrinsic mass function in Eq. 18, as long as  $M_*$  is set to equal  $v_* + \gamma$ .
6. Apparent masses,  $\{\tilde{m}_i\}$ , are calculated from the idealized TFR mass by subtracting the true distance and adding Gaussian scatters:  $\tilde{m}_i = M_i - d(cz_0) + \epsilon_m$ . The random scatter  $\epsilon_m$  is drawn from a normal distribution with a standard deviation of  $\sigma_m$ :  $N(0, \sigma_m^2)$ .
7. Projected velocities,  $\{\tilde{w}_i\}$ , are calculated from the edge-on velocities by adding random inclinations and Gaussian scatters:  $\tilde{w}_i = v_i + \log \sin \epsilon_i + \epsilon_w$ . To simulate samples with isotropic random orientations, the cosine of the inclination angle,  $\cos \epsilon_i$ , is drawn from a uniform distribution between 0 and 1, which then allow  $\sin \epsilon_i$  to be computed as  $\sqrt{1 - \cos^2 \epsilon_i}$ . The random scatter in

$w$  is drawn from a normal distribution with a standard deviation of  $\sigma_w$ , i.e.,  $\epsilon_w \sim N(0, \sigma_w^2)$ .

8. Finally, the observational selection function,  $S(\tilde{m}, \tilde{w})$ , is applied to the simulated data set, and the survived subsample is kept.

For simplicity, I use homoscedastic scatters in the simulated data (i.e.,  $\sigma_m$  and  $\sigma_w$  are both constants for the entire sample), although the Bayesian methods can handle heteroscedastic measurement errors by separating the constant intrinsic dispersion from the heteroscedastic measurement errors. It is worth noting that the frequently reported increase in mass/magnitude dispersion among slow rotators in a TF sample is mainly due to the smearing of the luminosity limit across the redshift range of the sample (see Fig. 1 for example). Dispersion measurements in mass/magnitude near these luminosity limits should be deemed as upper limits, thus they do not offer evidence for heteroscedastic intrinsic dispersion in the TFR.

Three synthetic samples were generated for testing. They assume modest levels of scattering that are typically expected in galaxy samples like the ALFALFA or CF4:

- A.  $\sigma_m = 0.15, \sigma_w = 0$  (no scatter in  $w$ )
- B.  $\sigma_m = 0, \sigma_w = 0.045$  (no scatter in  $m$ )
- C.  $\sigma_m = 0.15, \sigma_w = 0.045$  (scatters in both axes)

Samples A and B match the assumptions of the forward model and the inverse model, respectively, and Sample C represents the more realistic case where scatters are present in both axes. The ratio of the dispersions,  $\sigma_m/\sigma_w$ , matches the assumed slope of the TFR ( $\beta = 3.33$ ) to ensure equal contributions.

The other model parameters are shared across the samples:

- The velocity noise due to residual peculiar motion is ignored ( $\sigma_{cz} = 0$ ) to avoid the additional marginalization over the true distance, as explained in § 4.1.
- The selection function depends only on the apparent logarithmic mass ( $\tilde{m}$ ) and is a step function with a detection limit at  $m_l = 5.736$ , appropriate for the ALFALFA sample.
- The power-law index of the galaxy density is set to  $n = -1$  to produce a flatter redshift distribution, and the sampling scale factor is set to produce  $\sim 10,000$  galaxies over the redshift range between  $4,000 < cz < 18,000 \text{ km s}^{-1}$  above the detection limit. The sample size and its redshift distribution are comparable to those of HI-selected galaxy samples like the ALFALFA and CF4.

- The TF parameters are set to  $\beta = 3.33$  and  $\gamma = 10.5$ , similar to the values found in Kourkchi et al. (2022).
- The Schechter function parameters for the intrinsic velocity and mass distributions are set to  $\alpha = -1.27$ ,  $v_* = 0.3$ , and  $M_* = v_* + \gamma = 10.8$ . These values are consistent with the tabulated baryonic mass function of Papastergis et al. (2012).

The input parameters and the final sample sizes between  $4,000 < cz < 18,000$  ( $N$ ) are listed in Table 1. As an example, Fig. 1 shows the distributions of synthetic sample C in the plane of mass vs. projected velocity width and mass vs. redshift. The former illustrates the combination of Sine scatter and Gaussian scatters, while the latter illustrates the observational selection function.

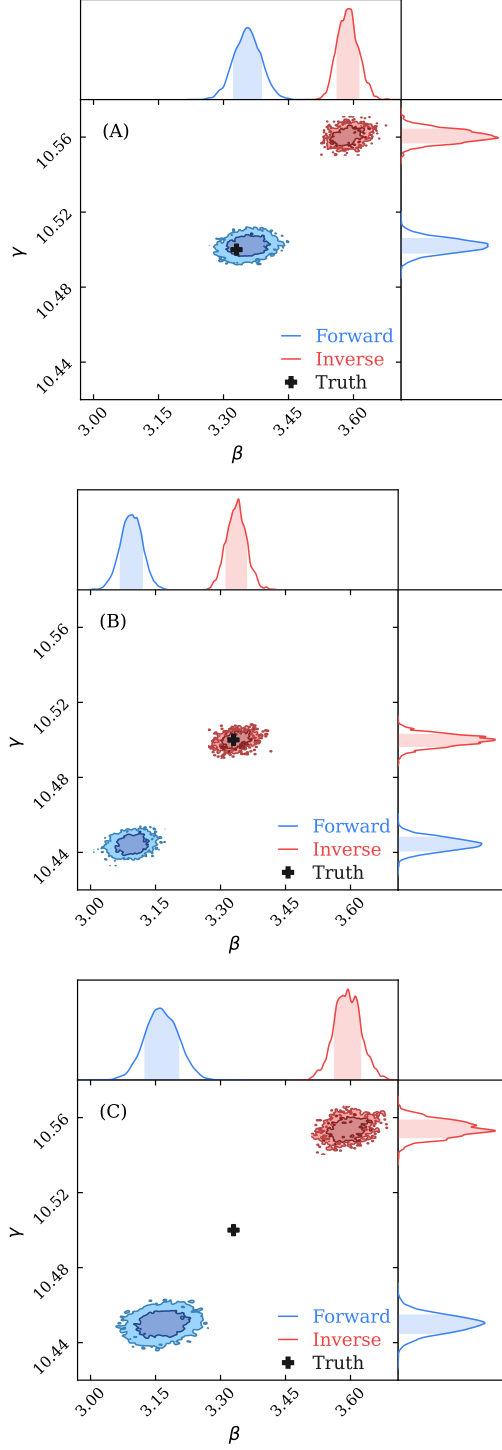
### 5.3. Testing on Simulated Data

The expectation of testing the models with synthetic samples with different dispersion parameters is that when the generative model of the model matches that of the simulated data, the model should produce unbiased parameter estimation; otherwise, the model may produce a biased estimation because of the generalized Eddington bias (§ 2). The testing in this subsection thus serves two purposes: (1) to validate the implementation of the likelihood functions in the code, and more important, (2) to quantify the level of biases when the assumed model mismatches the true model that generated the data.

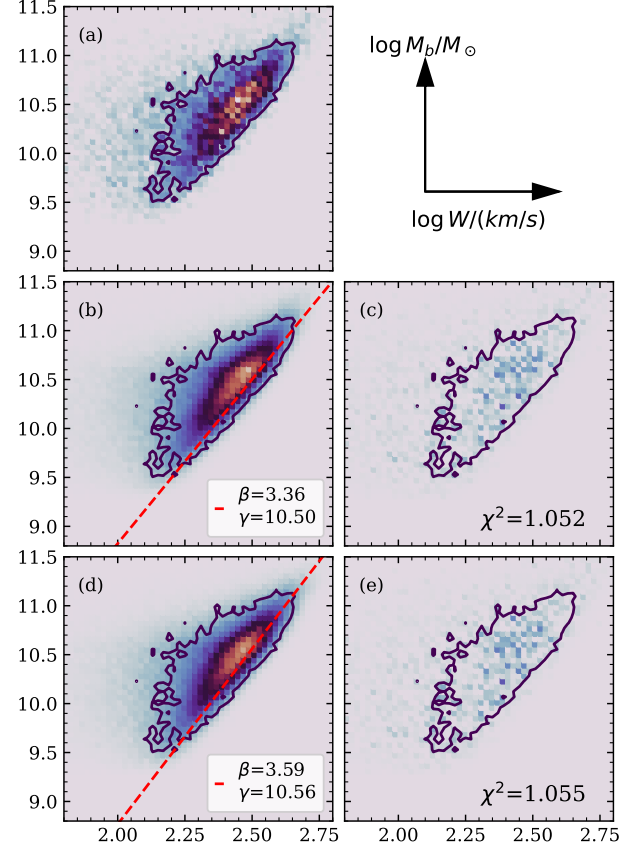
Assuming bounded flat priors for all parameters, I run the forward and the inverse models on the three synthetic samples and the inferred parameters are compared to the input parameters in Table 1. The MCMC-sampled posterior pdfs of the two key parameters (TF slope  $\beta$  and intercept  $\gamma$ ) are presented in Fig. 2. As expected, the forward model recovers the truth using Sample A, and the inverse model recovers the truth using Sample B. This finding provide confidence in the derived likelihood functions of the two models and their implementation in the code. On the other hand, significant biases are observed when the forward model is used on Samples B and C (where  $\sigma_w \neq 0$ ), and when the inverse model is used on Samples A and C (where  $\sigma_m \neq 0$ ).

The directions of the biases are that the forward model underestimate both parameters while the inverse model overestimate them. The amount of biases ( $B_\gamma \simeq \pm 0.06, B_\beta \simeq \pm 0.24$ ) are significantly greater than the statistical uncertainties shown in the marginalized pdfs ( $\sigma_\gamma \simeq 0.004, \sigma_\beta \simeq 0.03$ ). Further experiments show that both biases increase almost linearly with the variance of the independent variable (see § 6.3).

It is worth noting that the same biases are present when inclination-corrected data are used; i.e., the bias is not introduced by treating inclination as a latent variable. Instead,



**Figure 2.** MCMC-sampled posterior pdfs from the forward (blue) and the inverse (red) models for samples A, B, and C, respectively. For simplicity, only the two TF parameters are shown: slope ( $\beta$ ) and intercept ( $\gamma$ ). In all posterior plots, the contours in the joint pdfs enclose 68% and 95% of the volume, the highlighted regions in the marginalized pdfs show the credible intervals defined by the 16th and the 84th percentiles, and the black crosses indicate the truth. Biases appear whenever the data contains scattering in the model-assumed independent variable.

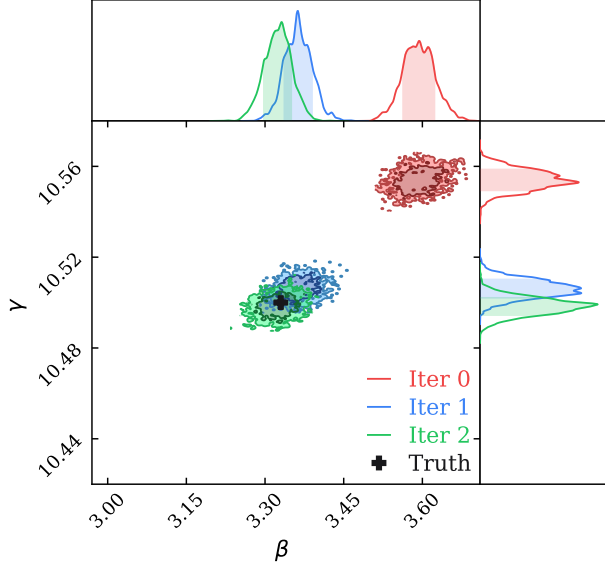


**Figure 3.** The distribution of mass vs. projected line width of the input data (a) is compared with those generated using the best-fit parameters of the forward model (b) and the inverse model (d). In all panels, the same contour is plotted, which encloses bins containing a minimum of 9 objects in panel a. In this example, the input data are from sample A, so the forward model inferred the correct TF parameters. However, both models fit the data equally well (see the residuals in c and e), making it difficult to use a goodness-of-fit parameter such as the reduced  $\chi^2$  to select the model.

it is a feature of unidirectional regression models. As mentioned earlier, it is well known that the OLS estimate of the regression slope is biased to zero when the independent variable is measured with error (e.g., Akritas & Bershadsky 1996). Since least-squares is a maximum likelihood estimator, the same biases are expected in unidirectional MLE methods that neglect the error of the independent variable, regardless whether the data are corrected for inclination or not.

Despite of the biased parameter estimation, both models fit the input data equally well for all three input samples. I demonstrate this with sample A in Fig. 3, where synthetic samples  $20\times$  larger than the input sample are generated using the best-fit parameters of the two models<sup>3</sup>, and their distribu-

<sup>3</sup> Unconstrained  $\sigma$  is set to zero and unconstrained Schechter function parameters are set to the truth values.



**Figure 4.** Posterior pdfs from the inverse model after iterative Eddington bias corrections. Sample C is used as the input data and iteration 0 is before any bias correction, so it is the same as the posterior of the inverse model in Fig. 2c. In subsequent iterations,  $\beta$  and  $\log M_*$  are updated using the result from the previous iteration, and  $\{\tilde{w}_k\}_{k=1}^N$  are bias corrected using  $\{\tilde{m}_k + d_k\}_{k=1}^N$  using Eq. 51. When the correct  $\sigma_m$  is specified, unbiased parameter inference of the TFR is obtained after just a few iterations.

tions are compared with that of the input sample. The model residuals show statistical fluctuations comparable to the Poisson noise, as indicated by the reduced  $\chi^2$  values around unity. The slight difference in the  $\chi^2$  values between the two models is actually due to the stochastic nature of the simulated model samples. This finding shows that the goodness-of-fit cannot be used to tell which model is better supported by the data. Instead of model selection, one should focus on methods that can mitigate the biases.

## 6. UNBIASED PARAMETER INFERENCE

This section introduces mainly two latent-inclination methods that can mitigate both Malmquist bias and Eddington bias in the inference of the TFR. The first method shifts the dependent variable using the predicted Eddington bias from Eq. 7 (§ 6.1), and the second method incorporates the scatter of the independent variable in the likelihood function of a bidirectional dual-scatter model (§ 6.2). Technically, there is a third method—choosing an empirical unbiased anchor point for the correlation (§ 6.3)—but it only reduces the bias of the intercept parameter.

### 6.1. Shifting the Moment of the Dependent Variable

In § 2, I have explained that the generalized Eddington bias is caused by the scatter in the independent variable and the gradient of its distribution function. It is thus expect that,

when the predicted Eddington bias of the dependent variable is corrected for using Eq. 7, the inferred parameters will be no longer biased.

For calibrating the TFR using inclination-corrected data, one could choose to correct either  $x$  for the inverse model, or  $y$  for the forward problem. But when the inclination angle is considered a latent variable, one can only correct  $\tilde{w}$  for the inverse model. This is because to correct  $\tilde{m}$  for the forward model using Eq. 7 requires knowing the inclination-corrected velocity width ( $x \equiv \tilde{w} - i$ ).

For the forward relation, the Eddington bias of the mean  $y$  due to scatters in  $\tilde{x}$  is given by Eq. 7:

$$y(\tilde{x}) - \langle y \rangle_{\tilde{x}} = -\beta \sigma_x^2 \frac{d \ln p(\tilde{x})}{d \tilde{x}} \quad (45)$$

For the inverse relation, the Eddington bias of mean  $x$  due to scatters in  $\tilde{y}$  is:

$$x(\tilde{y}) - \langle x \rangle_{\tilde{y}} = -\frac{\sigma_y^2}{\beta} \frac{d \ln p(\tilde{y})}{d \tilde{y}} \quad (46)$$

To remove the bias, one can shift the value of individual  $x$ :

$$x_c = x - \frac{\sigma_y^2}{\beta} \frac{d \ln p(\tilde{y})}{d \tilde{y}} \quad (47)$$

so that the mean of  $x_c$  matches the  $\tilde{y}$ -predicted  $x$ :

$$x(\tilde{y}) - \langle x_c \rangle_{\tilde{y}} = x(\tilde{y}) - \langle x \rangle_{\tilde{y}} + \frac{\sigma_y^2}{\beta} \frac{d \ln p(\tilde{y})}{d \tilde{y}} = 0 \quad (48)$$

If  $\tilde{y}$  follows a Schechter function:

$$p(\tilde{y}) \propto 10^{(\alpha+1)(\tilde{y}-y_*)} \exp(-10^{\tilde{y}-y_*}) \quad (49)$$

then the Eddington bias correction in  $x$  is:

$$x_c = x - \frac{\ln 10}{\beta} \sigma_y^2 [(\alpha+1) - 10^{\tilde{y}-y_*}] \quad (50)$$

For the case of the inverse TFR, the bias correction in  $\tilde{w}$  is:

$$\tilde{w}_c = \tilde{w} - \frac{\ln 10}{\beta} \sigma_m^2 [(\alpha+1) - 10^{(\tilde{m}+d)-M_*}] \quad (51)$$

which shows that the correction depends on four parameters ( $\sigma_m, \beta, M_*, \alpha$ ) and the observed mass of the galaxy. The mass of the galaxy is available in the data, but how to determine the four parameters?

First,  $M_*$  and  $\alpha$  are the Schechter function parameters of the mass distribution that include dispersions. The mass function of the galaxy sample can be measured using luminosity-function estimators that correct for the Malmquist bias, e.g., the  $C^-$  method (Lynden-Bell 1971), followed by a Schechter function fit to the discrete distribution. Alternatively, the parameters ( $M_*, \alpha$ ) can be inferred using the



forward model, because the model infers  $v_*$  and  $\alpha$ , and  $M_* = v_* + \gamma$ . It is safe to use  $v_*$  and  $\alpha$  from the forward model because (1) they are mildly biased (unlike  $\beta, \gamma$ ), i.e., their deviations from the truth are within twice the statistical error (see the blue curves in Fig. 5), and (2) the Eddington bias correction is relatively insensitive to these parameters.

Next,  $\beta$  is the slope of the TFR, which is a key parameter to be determined by the model. Using it as an input parameter thus requires an iterative process. The iterative process starts from the results of the forward model and the inverse model without Eddington bias correction. The former provides  $v_*$ ,  $\alpha$ , and the upper limit on  $\sigma_m$ , the latter provides  $\beta_j$  and  $\gamma_j$  for  $j = 0$ , where the subscripts indicate that they are the initial guess values and will be updated in subsequent iterations. For a specified value of  $\sigma_m$ , the line widths are then corrected for the Eddington bias using Eq. 51 with parameters  $(\sigma_m, \beta_j, v_* + \gamma_j, \alpha)$ . The subsequent runs of the inverse model uses Eddington-bias-corrected line widths ( $\tilde{w}_c$ ) as the input data and produce updated values of  $\beta_j$  and  $\gamma_j$ . Fig. 4 illustrates the iterative process and shows that results converge in just a few iterations.

Finally,  $\sigma_m$  is the mass dispersion that includes both measurement error and intrinsic dispersion. This is the only parameter that needs to be specified by the user based on prior knowledge of the data. In the worse case, one can use the forward model to estimate the total dispersion of the data in the  $m$ -direction ( $\sigma_m^t$ ), which gives the upper limit of  $\sigma_m$ :  $0 < \sigma_m < \sigma_m^t$ . Therefore, the bias-corrected results must lie somewhere between the two extremes defined by the forward and the inverse models without corrections (e.g., see Fig. 2 for Sample C). Underestimating  $\sigma_m$  causes under-correction of the Eddington bias, so the TF parameters  $\beta$  and  $\gamma$  will be biased high although their deviations from the truth are reduced compared to the uncorrected inverse model. On the other hand, overestimating  $\sigma_m$  causes over-corrections of the Eddington bias, so the TF parameters overshoot the truth and will be biased low as they approaches those inferred from the forward model. Therefore, the primary limitation of this method is that the inferred parameters will be unbiased only when the correct value of  $\sigma_m$  is prescribed.

## 6.2. The Bidirectional Dual-Scatter Model

In this subsection, I introduce the dual-scatter model where I expand the likelihood function of the latent-inclination forward model by including scatters of the independent variable  $w$ . In Appendix B, I expand the likelihood function of the inverse model by including scatters in  $m$ . It is shown there that the results are mathematically equivalent, making the model bidirectional.

Similar to § 4.1, I start by factorizing the joint pdf. When  $w$  and  $m$  are independent<sup>4</sup> and the intrinsic scatter is along the  $m$ -axis (as in the forward model), the joint probability of the dual-scatter model can be decomposed as:

$$\begin{aligned} p(\tilde{m}, \tilde{w}, d, w, i) &= p(\tilde{m}, \tilde{w}, d | w, i) p(w, i) \\ &= p(\tilde{m} | d, w, i) p(\tilde{w} | w) p(d) \times p(w | i) p(i) \\ &= p(\tilde{w} | w) p(\tilde{m}, w, d, i) \end{aligned} \quad (52)$$

where  $p(\tilde{m}, w, d, i)$  is given by Eq. 28, and the new term,  $p(\tilde{w} | w)$ , is a Gaussian:

$$p(\tilde{w} | w) = \frac{1}{\sigma_w \sqrt{2\pi}} \exp \left[ -\frac{(\tilde{w} - w)^2}{2\sigma_w^2} \right] \quad (53)$$

The joint pdf of the observables  $(\tilde{m}, \tilde{w}, d)$  is then calculated by marginalizing Eq. 52 over  $w$  and  $i$ :

$$\begin{aligned} p(\tilde{m}, \tilde{w}, d) &= \int_{-\infty}^{\infty} \int_{-\infty}^0 p(\tilde{m}, \tilde{w}, d, w, i) di dw \\ &= \frac{\beta \phi_* p(d)}{2\pi \sigma_m \sigma_w} \int_{-\infty}^{\infty} \int_{-\infty}^0 \frac{\ln 10 \cdot 10^{2i}}{\sqrt{1 - 10^{2i}}} \\ &\quad \times \exp \left[ -\frac{(\tilde{w} - w)^2}{2\sigma_w^2} \right] \exp \left[ -\frac{(\tilde{m} + d - \beta(w - i) - \gamma)^2}{2\sigma_m^2} \right] \\ &\quad \times 10^{(\alpha+1)[\beta(w-i)-v_*]} \exp(-10^{\beta(w-i)-v_*}) di dw \end{aligned} \quad (54)$$

Accounting for the selection function  $S(\tilde{m}, \tilde{w})$ , the conditional pdf of  $\tilde{m}$  is:

$$p(\tilde{m} | \tilde{w}, d) = \frac{S(\tilde{m}, \tilde{w}) p(\tilde{m}, \tilde{w}, d)}{\int_{-\infty}^{\infty} S(\tilde{m}, \tilde{w}) p(\tilde{m}, \tilde{w}, d) d\tilde{m}} \quad (55)$$

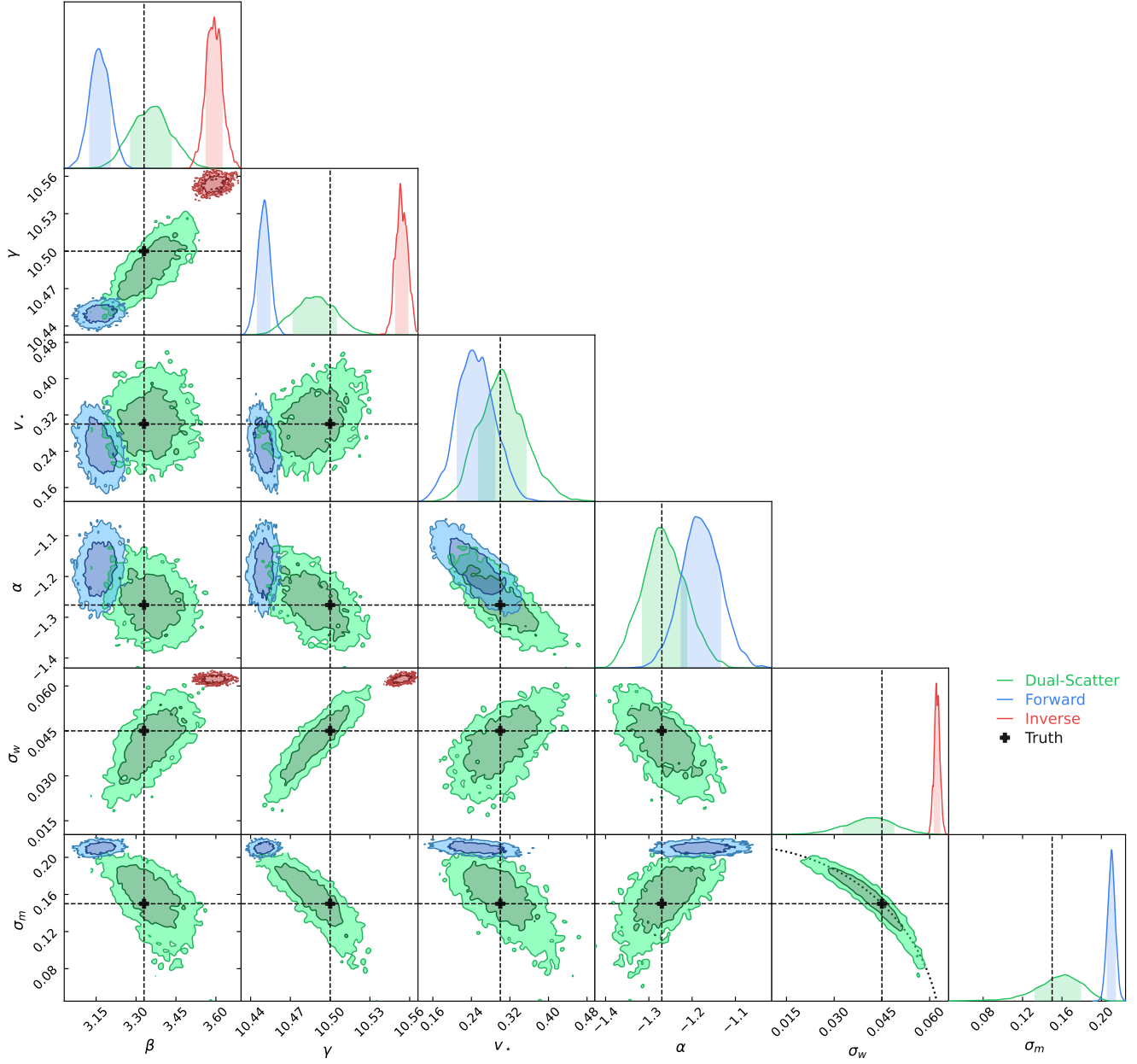
And the data likelihood function is composed of the above conditional pdfs:

$$\ln \mathcal{L} = \sum_{k=1}^N \ln p(\tilde{m}_k | \tilde{w}_k, d_k) \quad (56)$$

Like the forward model, when the selection function is a step function of  $\tilde{m}$ , the integral over  $\tilde{m}$  on the denominator of Eq. 55 becomes an error function. This replacement reduces the triple integral to a double integral. I provide the full expression of the conditional pdf in Eq. A4 in Appendix A.

However, even after this simplification, evaluating the likelihood function remains computationally expensive because each data point still requires calculating two double integrals. In Appendix C, I describe a Fast Fourier Transform (FFT) method to compute the double integrals. Additional acceleration is achieved by vectorizing the conditional pdf function and leveraging the integrated Graphics Processing Unit

<sup>4</sup> This is a valid assumption because correlated measurement errors in TFR data are introduced by inclination correction.



**Figure 5.** MCMC-sampled posterior pdfs from the dual-scatter model (*green*) compared to those from the forward model (*blue*) and the inverse model (*red*). The data are from sample C, whose input parameters are indicated by black dashed lines and the black crosses. The dual-scatter model produces relatively unbiased inferences for all parameters, gives more realistic statistical uncertainties, and reveals parameter degeneracies. For example, the two  $\sigma$ 's are tightly correlated on an ellipse:  $\sigma_m^2 + \beta^2 \sigma_w^2 = \sigma_l^2$ , as indicated by the dotted curve in the panel.

(GPU). Together, the computation time is reduced by three orders of magnitude when compared to direct integration, making the dual-scatter model even faster than the forward model, when the latter is run on the CPU.

The dual-scatter model is applied on the three synthetic data sets described in § 5.2. The results are tabulated in Table 2. Since Sample C includes comparable amounts of scatters in both axes, I opt to show its MCMC-sampled posterior pdfs in Fig. 5. The results from the dual-scatter model can be summarized as follows:

- The marginalized posteriors show that the best-fit (median) parameters are relatively unbiased for all three samples, i.e., they lie within  $1\sigma$  from the truth.
- The statistical uncertainties of the inferred parameters are larger compared to those from the forward and the inverse model: the TF parameters ( $\beta, \gamma$ ) show  $2\text{--}3\times$  larger uncertainties, the dispersion parameters ( $\sigma_m, \sigma_w$ ) show  $2\text{--}8\times$  greater uncertainties, while the Schechter parameters ( $v_*, \alpha$ ) show comparable uncertainties.

**Table 2.** Inferred Parameters from the dual-scatter model

Parameter	Synthetic Data Set		
	A	B	C
$\gamma$	$10.500^{+0.007}_{-0.005}$	$10.481^{+0.007}_{-0.009}$	$10.488^{+0.016}_{-0.016}$
$\beta$	$3.386^{+0.042}_{-0.036}$	$3.242^{+0.038}_{-0.040}$	$3.357^{+0.074}_{-0.077}$
$\sigma_m$	$0.149^{+0.005}_{-0.011}$	$0.054^{+0.030}_{-0.032}$	$0.158^{+0.020}_{-0.025}$
$\sigma_w$	$0.011^{+0.009}_{-0.007}$	$0.042^{+0.003}_{-0.005}$	$0.041^{+0.007}_{-0.008}$
$\nu_*$	$0.300^{+0.033}_{-0.031}$	$0.329^{+0.030}_{-0.033}$	$0.303^{+0.050}_{-0.048}$
$\alpha$	$-1.236^{+0.038}_{-0.040}$	$-1.318^{+0.044}_{-0.040}$	$-1.266^{+0.053}_{-0.048}$

- The joint posteriors show significant correlations among parameters. In particular, the two dispersion parameters are tightly correlated on an ellipse:  $\sigma_m^2 + \beta^2 \sigma_w^2 = \sigma_t^2$ . These covariances explain the larger uncertainties of the inferred parameters.

In summary, compared to the forward model, including the scatter of the independent variable  $w$  requires multiplication of another Gaussian function of  $\tilde{w} - w$  and an additional marginalization over  $w$  in both the numerator and the denominator of the conditional pdf that makes up the likelihood function. The added complexity makes the MCMC sampling significantly more computationally expensive, motivating innovative applications of numerical methods and GPU acceleration. The resulting posteriors show nearly unbiased parameter estimation, more realistic estimates of the uncertainties, and strong degeneracy between the two dispersion parameters. The degeneracy is a feature of the mathematical problem, so it cannot be eliminated, but its effects decreases as the sample size increases.

### 6.3. The Unbiased Anchor Point

The TFR is typically anchored at  $\log V_0 = 2.5$ , which is an arbitrary choice. In this subsection, I describe the existence of a preferred anchor point at which the inferred intercepts of both the forward and the inverse models are unbiased.

By simulating a number of data sets that share the same TFR ( $\beta = 3.33, \gamma = 10.5$ ) and observational selection function but have different amount of scatters in the independent variable, I find the following power-law relations between the biases of the regression coefficients and the standard deviation of the independent variables:

$$\begin{aligned}
 B_\gamma &= \begin{cases} -0.058(\sigma_w/0.05)^{1.8} & \text{forward model} \\ +0.060(\sigma_m/0.15)^{1.8} & \text{inverse model} \end{cases} \\
 B_\beta &= \begin{cases} -0.246(\sigma_w/0.05)^{1.8} & \text{forward model} \\ +0.237(\sigma_m/0.15)^{1.8} & \text{inverse model} \end{cases} \quad (57)
 \end{aligned}$$

The biases of both coefficients scale with the standard deviation of the independent variable following the same power

law, making their ratio constant regardless of the amount of scatter. This finding suggests an empirical way to reduce the generalized Eddington bias by choosing an anchor location other than the default  $\log V_0 = 2.5$ . Because of the constant bias ratio  $B_\gamma/B_\beta$ , the true TFR (unbiased) and the inferred TFRs (biased) all converge at a single point at:

$$\begin{aligned}
 \log V_0 &= 2.5 - \frac{B_\gamma}{B_\beta} \\
 \gamma_0 &= \gamma - \beta \frac{B_\gamma}{B_\beta} \quad (58)
 \end{aligned}$$

This converging point is the preferred anchor position because the intercepts of all the inferred TFRs are unbiased at this point.

This unbiased anchor location depends on sample characteristics and the TFR but it can be determined empirically using the differences between the inferred parameters from the forward model and the inverse model on the same data. Take Sample C as an example, using the inferred TF parameters listed in Table 1, I calculate that  $\Delta B_\gamma / \Delta B_\beta = 0.25$ , so the unbiased anchor point is  $\log V_0 = 2.25$ . Using this empirically estimated unbiased anchor point will minimize the bias of the inferred intercept:  $\gamma_0 = 9.67$  for both the forward and the inverse models despite of their different slopes.

## 7. SUMMARY AND DISCUSSION

Utilizing linear regression methods on the determination of the TFR requires the observed data to be corrected for inclination. But the current method to estimate inclination angle from galaxy morphology is highly uncertain and requires well-resolved images. This paper shows that by treating the inclination as a latent variable with a known distribution function, one can infer the TF parameters using data uncorrected for inclinations. Unlike traditional linear regression analysis, which considers only Gaussian scatters from intrinsic dispersion and measurement errors, the latent-inclination inference of the TFR is a linear regression problem with both Gaussian scatters and non-Gaussian scatters (from random sky orientation). Extensions of linear regression methods are thus needed to tackle the TFR problem. I focus on likelihood-based methods in this paper mainly because they can account for Malmquist bias by including observational selection function.

I derive the likelihood functions of the latent-inclination method for two unidirectional models that neglect the measurement errors of the independent variable: the forward model (velocity width as independent variable) and the inverse model (mass as independent variable). Both likelihood functions are implemented with a MCMC-sampler and are tested on simulated galaxy samples with random orientations and with random Gaussian scatters in mass and velocity. I find that, when the independent variable has significant scatters, the inferred regression coefficients are biased (Fig. 2),

although biased models demonstrate similarly good quality of fit to the data (Fig. 3). The biases of both coefficients increase with the scatter of the independent variable  $B_\theta \propto \sigma_x^{1.8}$ . The bias of the intercept directly impact the Hubble constant: for example, using the inverse TFR model, neglecting a scatter of 0.15 dex in luminosity would lead to an overestimate of the Hubble constant by  $\sim 5 \text{ km s}^{-1} \text{ Mpc}^{-1}$  (Eq. 16), comparable to the “Hubble tension”.

Evidently, the measurement error of the independent variable ( $x$ ) does not simply propagate into the dependent variable ( $y$ ) through the correlation as  $\sigma_y = \beta \sigma_x$ , because that would not lead a bias in the slope and intercept. Instead, it shifts the first moment of  $y$  at each  $x$  by altering the conditional pdf  $p(y|x)$  according to Bayes’ rule. I derive the analytical form of the bias and found it similar to the Eddington bias (Eq. 7).

Methods aimed at unbiased parameter inference must include both (1) the scatter of the dependent variable and the selection function to account for Malmquist bias, and (2) the scatter and the distribution function of the independent variable to account for the Eddington bias of the dependent variable. Given this knowledge, I introduce two methods that mitigate both biases:

- Shifting the dependent variable by reversing the expected amount of Eddington bias (*Moment Shifting*),
- Incorporating the scatter of the independent variable in the likelihood function (*Dual-scatter Model*).

Testing on synthetic data sets shows that both methods can effectively reduce or eliminate both the Malmquist biases and the Eddington biases (Figs. 4 and 5). Each method has its own strengths and limitations, and it is a trade-off between efficiency and accuracy:

- The moment-shifting method can iteratively determine most of the required parameters for bias correction, but the dispersion parameter of the independent variable must be specified *a priori*.
- The dual-scatter model is the most versatile and is recommended for most scenarios. It fits both dispersion parameters simultaneously, produces more realistic estimates of parameter uncertainties, and reveals covariances among model parameters. But it is the most computationally expensive method, requiring innovative numerical techniques to expedite and even leveraging GPUs to accelerate (Appendix C).

Technically, there is one additional method: defining the intercept of the TFR at an unbiased anchor point (§ 6.3). The unbiased anchor method takes advantage of the correlation between the biases of the regression coefficients, and once

the TFR is redefined at the preferred anchor point, the inferred intercept from both the forward and the inverse models will be unbiased. However, the inferred slope will still be biased and the anchor point depends on the characteristics of the sample. The latter makes it difficult to apply the method on the Hubble constant estimate, because the unbiased intercepts of the redshift and the zero-point samples are defined at two different anchor points.

The next step is to apply the latent-inclination methods on actual data. Currently there are two major data sets for TF studies in the nearby Universe ( $cz < 20,000 \text{ km s}^{-1}$ ): the ALFALFA sample of  $\sim 31,500$  galaxies<sup>5</sup> (Haynes et al. 2018; Durbala et al. 2020) and the CF4 BTF-Distances catalog of  $\sim 10,000$  galaxies<sup>6</sup> (Kourkchi et al. 2022). The ALFALFA sample is naturally suited for the latent-inclination methods because it is a  $7000 \text{ deg}^2$  H I survey from a single instrument (Arecibo ALFA) and it includes galaxies at all inclinations. In contrast, the CF4 sample is a compilation of H I surveys from seven radio telescopes and excludes galaxies with estimated inclination less than  $45^\circ$ . Some of the compiled subsamples in CF4 were selected to be edge-on systems, causing a spike near  $90^\circ$  in the distribution of measured inclinations. The ALFALFA sample is also preferred because of Malmquist bias: a single observational selection function that describes the full data set can be used in the likelihood function. For a heterogeneous sample like the CF4, the complex selection effects from various instruments are unlikely to be captured by a single post facto selection function. Instead, each constituent subsample should be separately analyzed using their own selection function, and the final result would be a weighted average of the results from the subsamples.

Applications of the methods on the ALFALFA data also face challenges. First, the H I flux limit increases with line width. Like all spectroscopic line surveys with fixed integration time per target, ALFALFA is more sensitive to narrower lines because the same amount of signal is spread over fewer spectroscopic channels. The line flux limits set gas mass limits, making the latter also depending on the line width. Second, both the total H I flux and the optical photometry become unreliable for the nearest galaxies. The former can be easily addressed by using the special catalog for extended sources (Hoffman et al. 2019). But to address the latter, one needs to replace the automatic photometry from pipelines with more involved asymptotic photometry (Courtois et al. 2011) for a large sample of galaxies. Because of the inclination cutoff at  $45^\circ$ , only 43% (13,617) of the ALFALFA

<sup>5</sup> The ALFALFA sample contains 25,432 high S/N H I detections (Code 1) and 6,068 low S/N detections with prior optical detection (Code 2).

<sup>6</sup> The CF4 catalogs are available in the Extragalactic Distance Database: <https://edd.ifa.hawaii.edu>.



sample are included in the CF4 Initial Candidates catalog, leaving 57% of the sample without asymptotic photometry.

So far I have focused the discussion on the linear baryonic TFR. Depending on the available data, the investigator may want to use a different form of the TFR. Fortunately, the expressions derived for the baryonic TFR can be easily modified to other empirical forms of the TFR:

- To apply the methods on magnitude-based TFR, only a simple modification is required: compute  $m$  as  $-0.4$  times the apparent magnitude at wavelength  $\lambda$  (i.e.,  $m \equiv -0.4m_\lambda$ ) to convert the decreasing magnitude scale defined by Pogson’s ratio to an increasing decade scale. With this conversion, the best-fit intercept parameter  $\gamma$  is related to the fiducial absolute magnitude  $M_\lambda^0$  as:  $M_\lambda^0 = -2.5\gamma - 25$ .
- To apply the methods on non-linear TFR (e.g., to capture the curvature of the  $i$ -band TFR at the luminous end), one can replace the linear relation in Eq. 14 with more complex functions of  $(w-i)$  like a polynomial.

The presented model has made the following simplifications to keep the discussion focused on the Sine scatter of the velocity width and the Gaussian scatters of logarithmic mass and velocity width: (1) the redshifts are assumed to have been corrected for peculiar velocities, (2) the residual velocity noise is ignored, and (3) the apparent baryonic mass is assumed to be unaffected by galaxy inclination (i.e., either gas mass dominates or stellar mass extinction is accounted for by the color-derived mass-to-light ratio). Below I describe future extensions of the model to relax these assumptions.

To incorporate velocity noise in the likelihood function requires multiplying a Gaussian function of  $\tilde{d}-d$  to the joint pdf and an additional marginalization over the true distance  $d$  (§ 4.1). In addition, models that simultaneously fit the scale parameters of a peculiar velocity model and the velocity noise have been developed previously for TFR studies using inclination-corrected data (e.g., Willick et al. 1997; Boubel et al. 2024). The same methodology can be applied to the latent-inclination models.

For magnitude-based TFRs, to account for the inclination-dependent internal extinction in the forward and the dual-scatter model, one needs to replace  $\tilde{m}$  with its extinction-corrected counterpart  $\tilde{m} - 0.4A(\text{inc})$  in  $p(\tilde{m}|w, i, d)$  (Eq. 21).

A common way to parameterize the extinction is  $A(\text{inc}) = \tau \log[\sec(\text{inc})]$  (e.g., Shao et al. 2007). The extinction-corrected mass is then  $\tilde{m} - 0.2\tau \log(1 - 10^{2i})$  (where  $i \equiv \log[\sin(\text{inc})]$  as defined in Eq. 13), and the conditional pdf becomes:

$$p(\tilde{m}|w, i, d) = \frac{1}{\sigma_m \sqrt{2\pi}} \times \exp \left[ -\frac{[\tilde{m} - 0.2\tau \log(1 - 10^{2i}) + d - \beta(w-i) - \gamma]^2}{2\sigma_m^2} \right] \quad (59)$$

The replacement adds  $\tau$  (the face-on extinction) as a new parameter and changes the subsequent calculation of the conditional pdf  $p(\tilde{m}|w, d)$  (Eq. 30) and  $p(\tilde{m}|\tilde{w}, d)$  (Eq. 55) that make up the likelihood functions.

To account for the inclination-dependent extinction in the inverse model, one needs to replace  $m$  with  $m - 0.2\tau \log(1 - 10^{2i})$  in both  $p(\tilde{w}|m, d, i)$  and  $p(m|d)$  (Eqs. 34 and 36). This replacement makes the mass function term,  $p(m|d)$ , to depend on the inclination, so it can no longer be cancelled out in the conditional pdf in Eq. 39.

Finally, I note that although the latent-inclination Bayesian methods were developed for fitting the TFR, the likelihood-based methodology is quite general and can be modified to tackle other linear regression problems with both Gaussian and non-Gaussian scatters. The main requirement is that the prior pdf of the latent parameter is known, whether analytically as a function or numerically as a table.

The Python functions and an example Jupyter notebook are made publicly available at the accompanying GitHub repository: [https://github.com/fuhaiastro/TFR\\_biases](https://github.com/fuhaiastro/TFR_biases).

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*Software:* NumPy (Harris et al. 2020), SciPy (Virtanen et al. 2020), emcee (Foreman-Mackey et al. 2013), PyTorch (Paszke et al. 2019), ChainConsumer (Hinton 2016)

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## APPENDIX

## A. FULL EXPRESSIONS OF THE CONDITIONAL PROBABILITIES

In this Appendix, I provide the full expressions of the conditional pdfs of the forward, the inverse, and the dual-scatter models for a common case of selection function where the sample is only limited by flux and the selection function is a step function:

$$S(\tilde{m}) = \begin{cases} 1, & \text{if } \tilde{m} \geq m_l \\ 0, & \text{otherwise} \end{cases} \quad (\text{A1})$$

This particular selection function significantly simplifies the marginalization of the joint pdf over  $\tilde{m}$ , because the only  $\tilde{m}$ -dependent term is a Gaussian, and its partial integral is the complementary error function (erfc):

$$\begin{aligned} \int_{-\infty}^{\infty} S(\tilde{m}) p(\tilde{m}|w, i, d) d\tilde{m} &= \int_{m_l}^{\infty} p(\tilde{m}|w, i, d) d\tilde{m} \\ &= \int_{m_l}^{\infty} \frac{1}{\sigma_m \sqrt{2\pi}} \exp \left[ -\frac{[\tilde{m} + d - \beta(w - i) - \gamma]^2}{2\sigma_m^2} \right] d\tilde{m} \\ &= \frac{1}{2} \text{erfc} \left[ \frac{m_l + d - \beta(w - i) - \gamma}{\sqrt{2}\sigma_m} \right] \end{aligned} \quad (\text{A2})$$

After this simplification, the conditional pdfs for the forward and the dual-scatter models become:

- The forward model:

$$p(\tilde{m}|w, d) = \frac{\sqrt{2}}{\sqrt{\pi}\sigma_m} \frac{\int_{-\infty}^0 \frac{10^{2i}}{\sqrt{1-10^{2i}}} \exp \left[ -\frac{[\tilde{m} + d - \beta(w - i) - \gamma]^2}{2\sigma_m^2} \right] 10^{(\alpha+1)[\beta(w-i)-v_*]} \exp(-10^{\beta(w-i)-v_*}) di}{\int_{-\infty}^0 \frac{10^{2i}}{\sqrt{1-10^{2i}}} \text{erfc} \left[ \frac{m_l + d - \beta(w - i) - \gamma}{\sqrt{2}\sigma_m} \right] 10^{(\alpha+1)[\beta(w-i)-v_*]} \exp(-10^{\beta(w-i)-v_*}) di} \quad (\text{A3})$$

- The dual-scatter model:

$$p(\tilde{m}|\tilde{w}, d) = \frac{\sqrt{2}}{\sqrt{\pi}\sigma_m} \frac{\int_{-\infty}^0 \frac{10^{2i}}{\sqrt{1-10^{2i}}} \left( \int_{-\infty}^{\infty} \exp \left[ -\frac{(w-\tilde{w})^2}{2\sigma_w^2} \right] \exp \left[ -\frac{[\tilde{m} + d - \beta(w - i) - \gamma]^2}{2\sigma_m^2} \right] 10^{(\alpha+1)[\beta(w-i)-v_*]} \exp(-10^{\beta(w-i)-v_*}) dw \right) di}{\int_{-\infty}^0 \frac{10^{2i}}{\sqrt{1-10^{2i}}} \left( \int_{-\infty}^{\infty} \exp \left[ -\frac{(w-\tilde{w})^2}{2\sigma_w^2} \right] \text{erfc} \left( \frac{m_l + d - \beta(w - i) - \gamma}{\sqrt{2}\sigma_m} \right) 10^{(\alpha+1)[\beta(w-i)-v_*]} \exp(-10^{\beta(w-i)-v_*}) dw \right) di} \quad (\text{A4})$$

For the inverse model, simplifying the conditional pdf does not require a step function, but any function that depends only on  $m$  [i.e.,  $S(m, \tilde{w}) = S(m)$ ]. When this is the case, the selection function on the denominator can be taken out of the integral and cancel out the function on the numerator. And after the cancellation of  $S(m)$ , the denominator becomes unity because both  $p(\tilde{w}|m, i, d)$  and  $p(i)$  are properly normalized pdfs. The result is given below:

$$\begin{aligned} p(\tilde{w}|m, d) &= \frac{S(m) \int_{-\infty}^0 p(\tilde{w}|m, d, i) p(i) di}{\int_{-\infty}^0 \left( \int_{-\infty}^{\infty} S(m) p(\tilde{w}|m, d, i) d\tilde{w} \right) p(i) di} \\ &= \int_{-\infty}^0 p(\tilde{w}|m, d, i) p(i) di \\ &= \frac{\ln 10}{\sigma_w \sqrt{2\pi}} \int_{-\infty}^0 \exp \left[ -\frac{[\tilde{w} - i - (m + d - \gamma)/\beta]^2}{2\sigma_w^2} \right] \frac{10^{2i}}{\sqrt{1-10^{2i}}} di \end{aligned} \quad (\text{A5})$$

### B. DUAL-SCATTER MODEL STARTING FROM THE INVERSE MODEL

Starting from the joint pdf of  $p(\tilde{w}, m, d, i)$  in Eq. 33 and 37:

$$\begin{aligned} p(\tilde{w}, m, d, i) &= p(\tilde{w}|m, d, i)p(m|d)p(d)p(i) \\ &= p(d) \times \frac{\ln 10 \cdot 10^{2i}}{\sqrt{1-10^{2i}}} \frac{1}{\sigma_w \sqrt{2\pi}} \exp \left[ -\frac{[\tilde{w} - i - (m + d - \gamma)/\beta]^2}{2\sigma_w^2} \right] \phi_* 10^{(\alpha+1)[m+d-M_*]} \exp[-10^{m+d-M_*}] \end{aligned} \quad (\text{B6})$$

To account for measurement error in  $m$ , one needs to multiply an additional term because the joint probability including  $\tilde{m}$  is:

$$p(\tilde{w}, \tilde{m}, d, m, i) = p(\tilde{m}|m)p(\tilde{w}, m, d, i) \quad (\text{B7})$$

where the new factor is a Gaussian:

$$p(\tilde{m}|m) = \frac{1}{\sigma_m \sqrt{2\pi}} \exp \left[ -\frac{(\tilde{m} - m)^2}{2\sigma_m^2} \right] \quad (\text{B8})$$

The joint pdf of the observables  $(\tilde{w}, \tilde{m}, d)$  is then calculated by marginalizing the above joint pdf over  $m$  and  $i$ :

$$\begin{aligned} p(\tilde{w}, \tilde{m}, d) &= \int_{-\infty}^0 \int_{-\infty}^{\infty} p(\tilde{w}, \tilde{m}, d, m, i) dm di \\ &= \frac{\phi_* p(d)}{2\pi \sigma_w \sigma_m} \int_{-\infty}^0 \int_{-\infty}^{\infty} \exp \left[ -\frac{[\tilde{w} - i - (m + d - \gamma)/\beta]^2}{2\sigma_w^2} \right] \exp \left[ -\frac{(\tilde{m} - m)^2}{2\sigma_m^2} \right] 10^{(\alpha+1)(m+d-M_*)} \exp[-10^{m+d-M_*}] p(i) dm di \end{aligned} \quad (\text{B9})$$

When substituting  $m$  for  $\beta(w - i) + \gamma - d$  using the idealized TFR in the above equation:

$$\begin{aligned} p(\tilde{w}, \tilde{m}, d) &= \frac{\beta \phi_* p(d)}{2\pi \sigma_w \sigma_m} \int_{-\infty}^0 \int_{-\infty}^{\infty} \exp \left[ -\frac{(\tilde{w} - w)^2}{2\sigma_w^2} \right] \exp \left[ -\frac{[\tilde{m} + d - \beta(w - i) - \gamma]^2}{2\sigma_m^2} \right] 10^{(\alpha+1)[\beta(w-i)-v_*]} \exp[-10^{\beta(w-i)-v_*}] p(i) dw di \end{aligned} \quad (\text{B10})$$

which is equivalent to  $p(\tilde{m}, \tilde{w}, d)$  in Eq. 54. Therefore, the data likelihood function of the dual-scatter model remains the same whether one starts from the forward model or the inverse model.



## C. NUMERICAL ACCELERATION BY FAST FOURIER TRANSFORM AND PYTORCH

For the dual-scatter model with step-like selection function, the conditional pdf that constitutes the likelihood function is (see Eq. A4 in Appendix A):

$$p(\tilde{m}|\tilde{w}, d) = \frac{\sqrt{2}}{\sqrt{\pi}\sigma_m} \frac{\int_{-\infty}^0 \frac{10^{2i}}{\sqrt{1-10^{2i}}} \left( \int_{-\infty}^{\infty} \exp\left[-\frac{(w-\tilde{w})^2}{2\sigma_w^2}\right] \exp\left[-\frac{(\tilde{m}+d-\beta(w-i)-\gamma)^2}{2\sigma_m^2}\right] 10^{(\alpha+1)[\beta(w-i)-v_*]} \exp(-10^{\beta(w-i)-v_*}) dw \right) di}{\int_{-\infty}^0 \frac{10^{2i}}{\sqrt{1-10^{2i}}} \left( \int_{-\infty}^{\infty} \exp\left[-\frac{(w-\tilde{w})^2}{2\sigma_w^2}\right] \operatorname{erfc}\left(\frac{m_l+d-\beta(w-i)-\gamma}{\sqrt{2}\sigma_m}\right) 10^{(\alpha+1)[\beta(w-i)-v_*]} \exp(-10^{\beta(w-i)-v_*}) dw \right) di} \quad (\text{C11})$$

Direct integration of the double integrals on both the numerator and the denominator for each data point is computationally expensive. On a 2021 Macbook Pro with an M1 Pro chip (8 performance CPU cores and 2 efficiency cores), the dual-scatter model with direct integration of 1024 nodes in each integration axis takes  $\sim 17$  min per MCMC step for 16 walkers and 10,147 data points. This is painfully slow and forces one to either reduce the number of nodes or to bin the data points, neither of which is ideal. In this Appendix I describe numerical methods that expedited the computation by thousands of times. These methods can be generalized and applied to similar types of integrals.

The key is to realize that the integral over  $i$  on the numerator of the above equation,

$$\int_{-\infty}^0 \frac{10^{2i}}{\sqrt{1-10^{2i}}} \exp\left[-\frac{(\tilde{m}+d-\beta(w-i)-\gamma)^2}{2\sigma_m^2}\right] 10^{(\alpha+1)[\beta(w-i)-v_*]} \exp(-10^{\beta(w-i)-v_*}) di \quad (\text{C12})$$

is a convolution between:

$$f(i) = \begin{cases} \frac{10^{2i}}{\sqrt{1-10^{2i}}}, & \text{if } i < 0 \\ 0, & \text{otherwise} \end{cases} \quad (\text{C13})$$

and

$$g(w-i) = \exp\left[-\frac{(\tilde{m}+d-\beta(w-i)-\gamma)^2}{2\sigma_m^2}\right] 10^{(\alpha+1)[\beta(w-i)-v_*]} \exp(-10^{\beta(w-i)-v_*}) \quad (\text{C14})$$

The result is a new function of  $w$ :

$$\{f * g\}(w) = \int_{-\infty}^{\infty} f(i)g(w-i)di \quad (\text{C15})$$

which can be calculated on an evenly spaced grid of  $w$  using the convolution theorem:

$$\{f * g\}(w) = \mathcal{F}^{-1}[\mathcal{F}\{f\}(w) \cdot \mathcal{F}\{g\}(w)] \quad (\text{C16})$$

Since the computation of the Fast Fourier Transform (FFT) of  $f$  and  $g$  and the inverse FFT of their product has a total complexity of  $\mathcal{O}(N \log N)$  and direct computation of the convolution integral has a complexity of  $\mathcal{O}(N^2)$ , substantial improvement in computing efficiency can be achieved with FFT-based convolution when  $N$  is a large number. For my implementation in python, I noticed an order-of-magnitude shorter computational time when using an evenly spaced grid of 1,024 nodes between  $-2.5 < w < 2.5$ .

The result can then be supplied to the integral over  $w$  to complete the calculation of the numerator:

$$\int_{-\infty}^{\infty} \{f * g\}(w) \exp\left[-\frac{(w-\tilde{w})^2}{2\sigma_w^2}\right] dw \quad (\text{C17})$$

Notice that even though this second integral is also a convolution, direct evaluation is faster because the convolution result is needed only at a specific value of  $\tilde{w}$  instead of an array of  $\tilde{w}$ . In such cases, FFT methods have no computational advantage over direct evaluation.

The same method can be applied to compute the denominator, simply replace the function of  $g$  as:

$$g(w-i) = \operatorname{erfc}\left(\frac{m_l+d-\beta(w-i)-\gamma}{\sqrt{2}\sigma_m}\right) 10^{(\alpha+1)[\beta(w-i)-v_*]} \exp(-10^{\beta(w-i)-v_*}) \quad (\text{C18})$$

On the same 2021 Macbook Pro, the FFT-powered dual-scatter model takes 1.65 s per MCMC step for 16 walkers and 10,147 data points, which is only  $1.9\times$  and  $7.6\times$  slower than the much simpler forward and inverse models, respectively. Recall that each MCMC step took  $\sim 17$  min without FFT acceleration (i.e.,  $\sim 600\times$  slower).

I achieved an additional  $\sim 4\times$  acceleration by vectorizing the conditional pdf function and leveraging the integrated 16-core Graphics Processing Unit (GPU) with PyTorch's Metal Performance Shaders (MPS) backend (Paszke et al. 2019). The GPU- and FFT-powered dual-scatter model takes 0.44 s per MCMC step, which is even  $2\times$  faster than the simpler forward model on the CPU. The MCMC chains sufficiently converged after  $\sim 6,000$  steps, so the total computing time is  $\sim 0.75$  hr. The PyTorch version of the code is made available along with the NumPy version.