1. Light Curve Analysis

1.1. Light curve modeling

To find the best fit to the light curve we developed a modeling package called EXOMOP[1] that uses the analytic equations of Mandel & Agol (2002) to generate a model transit, the Levenberg-Marquardt (LM) non-linear least squares minimization algorithm (Press et al. 1992) to find the best fit, the bootstrap Monte Carlo technique (Press et al. 1992) to calculate robust errors of the LM fitted parameters, a Differential Evolution Markov Chain Monte Carlo (DE-MCMC) (ter Braak 2006) analysis to find the best fit and associated errors, and used both the residual permutation (rosary bead) method (Southworth 2008) and time-averaging method (Pont 2006) to access the importance of red noise in both fitting methods.

We modeled the transit with the DE-MCMC using 20 chains and 20^6 links. The Gelman-Rubin statistic (Gelman & Rubin 2002) was used to ensure chain convergence, as outlined in Ford (2006). We used the Metropolis-Hastings sampler and bayesian inference to characterize the uncertainties because it accounts for non-Gaussian errors and covariances between parameters. Our DE-MCMC model was derived from EXOFAST by Eastman, Gaudi & Agol (2013).

During the analysis, the time of mid-transit (T_c) and planet-to-star radius ($\frac{R_p}{R_*}$) were left as free parameters. Eccentricity (e), argument of periastron (ω), the quadratic limb darkening coefficients (μ_1 and μ_2), and the orbital period (P_b) of the planet were fixed to the values listed in Table 2. In addition, a linear least squares fit was found for the out of transit baseline and was divided out of our transit before modeling. The linear(μ_1) and quadratic(μ_2) limb darkening coefficients in each filter were taken from Claret (2011) using the stellar parameters (T_{eff}= 5340 K, $\log g$= 4.452 (cgs), $[Fe/H]$=0.450) from Torres (2008). We used the fitted parameters from either the LM best-fit model or DE-MCMC best-fit model that produced the lowest scatter in the respective residuals (Transit–Best-fit model). The $\frac{R_p}{R_*}$ and T_c parameters obtained from the EXOMOP analysis and the derived transit durations are summarized in Table 3.

To determine the error in the fitted parameters with the LM method we used the following bootstrap procedure. In step (1), we obtained the best-fit light curves and parameters from the LM non-linear least squares algorithm. In step (2), we multiply the formal errors bars for each data point in the light curve by random Gaussian noise with a standard de-

[1]EXOMOP is avaialbe from http://uaastroclub.org/members/jake-turner/exomop/

viation equal to the original error bars. In step (3), we add the error bars form step (2) to the data. In step (4), we repeat step (1) to find a new best-fit light curve. This process was repeated 10000 times to avoid small-number statistics. When all iterations are finished each fitted parameter from step (4) is subtracted by the original best-fit value and a Gaussian function is fit to the distribution. The standard deviations of the distributions are the 1 sigma uncertainties in the fitted parameters.

In the residual permutation method the best-fit model is subtracted from the data, the residuals are then added to the data points. A new fit is found, and then the residuals are shifted again, with those at the end wrapped around to the start of the data. In this way, every new synthetic data set will have the same bumps and wiggles as the actual data but only translated in time. Usually this process continues until the residuals have cycled back to where they originated. We updated this procedure by allowing for the error bars of the residuals to be taken into account. This is similar to step (2) in the bootstrap procedure described above. This process was repeated 10000 times. This procedure results in a distribution of fitted values for each parameter from which its uncertainty can be estimated using the standard deviation of a Gaussian fit. For each fitted parameter we then defined β_{res} (the scaling factor relative to white noise using the residual permutation method) as $\sigma_{boot}/\sigma_{res}$, where σ_{boot} are the error bars derived from the bootstrap Monte Carlo technique and the σ_{res} are the error bars derived from the residual permutation method.

We implemented the time-averaging method in a similar fashion to that done by Winn (2008). For each light curve we found the best-fitting model and calculated σ_{or}, the standard deviation of the unbinned residuals between the observed and calculated fluxes. Next, the residuals were binned into bins of N points and we calculated the standard deviation, σ_N, of the binned residuals. In our analysis, N ranged from 1 to n/5, where n is the total number of data points in each respective transit. We then used a LM non-linear least squares minimization algorithm to find the RMS of red noise (σ_{red}) and the RMS of white noise (σ_{white}) using the following equation from Pont 2006:

$$\sigma_N = \sqrt{\frac{\sigma_{white}^2}{N} + \sigma_{red}}. \tag{1}$$

The values for σ_{white} and σ_{red} for each transit can be found in Table [INSERT NUMBER]. Using σ_{white} and σ_{red} we estimated β_{tim}, the scaling factor relative to white noise using the time-averaging method, with the following equation from Carter & Winn (2009):

$$\beta_{tim} = \sqrt{1 + \left(\frac{\sigma_{red}}{\sigma_{white}}\right)}. \tag{2}$$

To get the final error bars for the fitted parameters we multiplied σ_{boot} by the largest β

(either β_{tim} or β_{res}) from the residual permutation and time-averaging red noise calculations to account for underestimated error bars due to red noise (Winn 2008). This was only done if the largest β was greater than one. Finally, in cases where the reduced chi-squared (χ_r^2) of the data to the best-fit model was found to be greater than unity we multiplied the error bars above by $\sqrt{\chi_r^2}$ to compensate for the underestimated observational errors (Bruntt 2006; Southworth 2007). The final error bars can be found in Table 2.

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