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Solving the puzzle of discrepant variability on monthly time scales implied by SDSS and CRTS datasets

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ABSTRACT

We present an improved photometric error analysis for the 7,100 CRTS (Catalina Real-Time Transient Survey) optical light curves for quasars from the SDSS (Sloan Digital Sky Survey) Stripe 82 catalog. SDSS imaging survey has provided a time-resolved photometric dataset which greatly improved our understanding of the quasar optical continuum variability: data for monthly and longer timescales are consistent with a damped random walk (DRW). Recently, newer data obtained by CRTS provided puzzling evidence for enhanced variability, compared to SDSS results, on monthly time scales. Quantitatively, SDSS results predict about 0.06 mag root-mean-square variability for timescales below 50 days, while CRTS data show about a factor of two larger rms, for spectroscopically confirmed SDSS quasars. Our analysis presented here has successfully resolved this discrepancy as due to slightly underestimated photometric uncertainties provided by the CRTS image processing pipelines. As a result, the correction for observational noise is too small and the implied quasar variability is too large. The CRTS photometric error correction factors, derived from detailed analysis of non-variable SDSS standard stars that were re-observed by CRTS, are about 20-30%, and result in a quasar variability behavior implied by the CRTS data that is fully consistent with earlier SDSS results. An additional analysis based on independent light curve data for the same objects obtained by the Palomar Transient Factory provides further support for this conclusion. In summary, the quasar variability constraints on weekly and monthly time scales from SDSS, CRTS and PTF surveys are mutually compatible, as well as consistent with DRW model.

1 INTRODUCTION

Variability can be used to both select and characterize quasars in sky surveys (for a recent overview see Lawrence 2016). Although various time scales of variability can be linked to physical parameters, such as accretion disk viscosity, or corona geometry (Kelly et al. 2011; Graham et al. 2014), the physical mechanism remains elusive. Most viable explanations for observed variability include accretion disk instabilities (Kawaguchi et al. 1998), surface thermal fluctuations from magnetic field turbulence (Kelly et al. 2009), and coronal x-ray heating (Kelly et al. 2011, see Kozłowski 2016 for a review).

The diversity of physical scenarios available to explain the origin of quasar variability results in a variety of ways to characterize it. The two most widely used approaches to describing variability of quasars include structure function (SF) analysis and light curve fitting based on damped random walk (DRW, also known as the Ornstein–Uhlenbeck process) model (Kelly et al. 2007; MacLeod et al. 2011). SF analysis essentially measures the width of the magnitude difference distribution as a function of the time separation, Δt. The DRW model approach is better suited for well-sampled light curves with a typical cadence of days (Zu et al. 2013; Kozłowski 2016), whereas an ensemble SF analysis is better for sparsely sampled light curves (Hawkins 2002; Vanden Berk et al. 2004; de Vries et al. 2005); for a review and discussion see Kozłowski (2016). For sparsely sampled CRTS (the Catalina Real-time Transient Survey) light curves analyzed here (see §2.2), the SF approach is more robust than fitting DRW model parameters.

The observed SF is often characterized by a simple power law (Schmidt et al. 2010). If the probed time scales are long enough (∼ years), the power law flattens above a characteristic timescale, τ (Ivezić et al. 2004; Kelly et al. 2007; MacLeod et al. 2010). This timescale may correspond to a transition from the stochastic thermal process that drives the variability to the physical response of the disk that successfully dampens the amplitude on longer timescales (Collier & Peterson 2001; Kelly et al. 2007; Kelly et al. 2009;

Kelly et al. 2011; Lawrence 2016). In the context of DRW model, the expected SF is described by

$$\mathrm{SF}(\Delta t) = \mathrm{SF}_\infty \; [1 - \exp(-\Delta t/\tau)]^{1/2}, \tag{1}$$

where SF_∞ is the asymptotic value of the structure function (for $\Delta t \ll \tau$, $\mathrm{SF}(\Delta t) \propto \Delta t^{1/2}$).

Most studies found that $\tau > 100$ days (MacLeod et al. 2010; Kozłowski 2016). Recently, Graham et al. (2014) found a characteristic time scale in quasar's rest frame of about 54 days, using the Slepian Wavelet Variance (SWV) analysis of CRTS light curves. This short timescale implies much stronger variability on monthly time scales than observed in SDSS data: SDSS results from MacLeod et al. (2010) predict about 0.06 mag root-mean-square (rms) variability for timescales below 50 days, while this CRTS-based analysis implies about a factor of two larger rms. These discrepancies have serious implications for physical interpretations of quasar variability: observed time scales are directly related to physical processes and increased variability levels call in question DRW as a viable model for describing quasar light curves (MacLeod et al. 2010; Kozłowski 2016).

It is not obvious whether these discrepancies are due to various problems with CRTS and/or SDSS datasets (inadequate sampling, incorrect estimates of photometric errors, etc), or perhaps are due to different analysis methods (SWV vs. SF analysis). Here we reanalyze these CRTS data using the same SF method as used by MacLeod et al. (2010) to analyze SDSS data, and investigate the origin of these discrepant timescales and variability levels. We argue that the most likely explanation of these discrepancies are slightly under-estimated photometric errors for CRTS light curve data.

2 DATA SETS

We study stars and quasars selected from the sky region known as SDSS Stripe 82 (S82; a ~300 deg^2 large region along the Celestial Equator: $22^h24^m < \mathrm{RA} < 04^h08^m$ and $|\mathrm{Dec}| < 1.27°$). We utilize both SDSS and CRTS photometric data.

2.1 Sloan Digital Sky Survey (SDSS)

We use two SDSS catalogs, with five-band near-simultaneous photometry for 9,258 quasars, and 1,006,849 standard stars (non-variable stars, as implied by the repeated SDSS photometry, see Ivezić et al. 2007). The quasar catalog[1] includes spectroscopically confirmed quasars from the SDSS Data Release 7 (Abazajian et al. 2009), based on the SDSS Quasar Catalog IV (Schneider et al. 2008), and was compiled by MacLeod et al. (2011). The standard stars catalog[2] was constructed as described in Ivezić et al. (2007).

[1] http://www.astro.washington.edu/users/ivezic/cmacleod/qso_dr7/Southern.html
[2] http://www.astro.washington.edu/users/ivezic/sdss/catalogs/stripe82.html

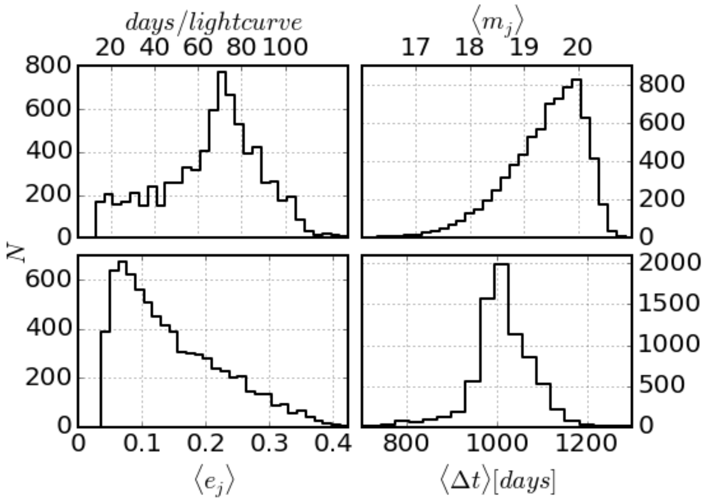

Figure 1. The distribution of properties of 7,601 CRTS quasar light curves for objects that were observed on at least 10 distinct nights (epochs). The distribution of the number of distinct nights is shown in the upper-left panel. Within that sample, 96% of light curves are longer than 7 years. The upper-right panel shows the mean day-averaged CRTS magnitude, $\langle m_j \rangle$ (see eq. 3). The bottom-left panel shows the mean day-averaged error, $\langle \sigma_j \rangle$ (see eq. 4). We use only quasars with light curve averaged error smaller than 0.3, leaving 7,108 quasars in the sample. The bottom-right panel shows the mean time difference $\langle \Delta t \rangle$ between day-averaged epochs. All means here are calculated per lightcurve.

2.2 Catalina Real-time Transient Survey (CRTS)

The main goal of CRTS was to find near-Earth objects. Its short intra-night cadence (4 exposures per night) was designed to allow a rapid follow-up (Graham et al. 2015), and white light (without filter) light curves maximize the sensitivity for faint objects. Three survey telescopes (0.7m Catalina Sky Survey Schmidt in Arizona, 1.5m Mount Lemmon Survey telescope in Arizona, and the 0.5m Siding Spring Survey Schmidt in Australia) were equipped with identical, 4kx4k CCDs (see Djorgovski et al. (2011) for technical details). Although in principle white light magnitudes can be calibrated to Johnson's V band zero point (Drake et al. 2013), this step was unnecessary in our analysis.

In this study we used a sample of 7,932 spectroscopically confirmed S82 quasars from the Data Release 2, based on the list by MacLeod et al. (2011). The majority (96%) of CRTS quasar light curves span the time of 7-9 years, with typical sampling of 1 to 4 observations per night, 70 observing nights on average, and the mean interval between two succesive observing nights of 1026 days (see Fig. 1). We also use CRTS light curves for 52,133 randomly chosen 10% subsample of the S82 standard stars from Ivezić et al. (2007).

2.3 Preprocessing

It is common to bin the data to reduce noise, by averaging over timescales shorter than what is required by the science goals. In this study, the hourly timescale of intra-night variability of CRTS light curves, with ~ 4 epochs each night, is much shorter than the timescales of interest (of the order of tens of days). We day-averaged all CRTS light curves following a procedure similar to Charisi et al. (2016). We adopt a convention that an index i runs over intra-night observations, and an index j separates distinct observing nights. Thus the day-averaged timestamp is :

$$t_j = \langle t_{ij} \rangle = N^{-1} \sum_{i=1}^{N} t_{ij} \tag{2}$$

where N is the number of observations per night. We similarly replace each set of N brightness measurements from the j-th night by their mean weighted by the inverse square of error:

$$m_j = \langle m_{ij} \rangle = \frac{\sum_{i=1}^{N} w_{i,j} m_{i,j}}{\sum_{i=1}^{N} w_{i,j}} \tag{3}$$

with weights $w_{i,j} = err_{i,j}^{-2}$, where $err_{i,j}$ are photometric uncertainty (colloquially, "error") estimates for individual photometric data points computed by the CRTS photometric pipeline.

Finally, we estimate the error on the weighted mean m_j by the inverse square of the sum of weights:

$$err_j = \left(\sum_{i=1}^{N} w_{i,j} \right)^{-1/2}, \tag{4}$$

and to avoid implausibly small error estimates, we add in quadrature 0.01^m to err_j if $err_j < 0.02^m$ (note that for homoscedastic errors, $err_{i,j} = \overline{err}$, $err_j = \overline{err}/\sqrt{N}$).

2.4 Final Sample Selection

We have selected both quasars and stars using a combination of information from SDSS and CRTS. To find magnitude difference between different observing nights, we first require that the raw light curves must have more than 10 photometric points (raw epochs). This step reduces the sample size from the initial 52,131 stars and 7,932 quasars to 49,385 stars and 7,707 quasars. After day-averaging, we also remove light curves with less than 10 observing nights (day-averaged epochs), leaving 48,250 stars and 7,601. In addition, we require that the light curve-average of nightly errors $\langle err_j \rangle < 0.3^m$ (see Fig. 1); this step removes fewer than 10% of light curves. Our final samples include 42,864 stars and 7,108 quasars.

A crucial part of our analysis below is a test of photometric uncertainties computed by the CRTS photometric pipeline using repeated CRTS observations of non-variable stars. In order to test for possible systematic effects with respect to magnitude (most notably the increase of photometric noise towards the faint end) and color, we first select subsamples from three magnitude bins, using the SDSS r magnitudes: *bright:* 17-18, *medium:* 18-18.5, and *faint:* 18.5-19. We note that the faint completeness limit of the SDSS spectroscopic quasar sample is $r \sim 19$, and that the CRTS white light magnitudes are strongly correlated with the SDSS r magnitudes. Furthemore, we split the stellar sample using SDSS color measurements into the "blue" ($-1< g-i <1$) and "red" ($1< g-i <3$) subsamples. Table 1 shows the number of objects in each type-magnitude bin.

Table 1. Count of stars and quasars, selected by their SDSS r magnitudes and $g-i$ colors.

r mag.	red stars	blue stars	quasars
17-18	2993	2795	185
18-18.5	2087	1400	333
18.5-19	2327	1496	747
total	7407	5691	1265

3 ANALYSIS

The structure function (SF) is a well-studied approach to characterizing light curves (Ivezić et al. 2004; Vanden Berk et al. 2004; de Vries et al. 2005; MacLeod et al. 2010; Graham et al. 2013; Kozłowski 2016). SF for a light curve is a measure of the width of the magnitude difference distribution, as a function of the time separation, Δt (see below for a discussion of how to account for observational errors). SF is closely related to auto-correlation function and the frequency power spectrum (for a detailed discussion, see Ivezić et al. 2014). For two (day-averaged) epochs j and k, with $j > k$, the magnitude difference is computed as $\Delta m_{j,k} = m_j - m_k$, the time difference is $\Delta t_{j,k} = t_j - t_k$, and the combined magnitude measurement error (measurement uncertainty for $\Delta m_{j,k}$) is $e_{j,k} = (err_j^2 + err_k^2)^{1/2}$ (where err_j is defined by eq. 4).

We compute SF as a function of time difference $\Delta t_{j,k}$ (hereafter, Δt for brevity and similarly, Δm for $\Delta m_{j,k}$ and e for $e_{j,k}$) by binning (Δt, Δm, e) data along Δt axis. With a median number of data points per light curve of 70, on average we generate $\sum_{j=2}^{70}(j-1) = 2,415$ (Δt, Δm, e) data points. This large number allows us to simply use 200 linearly spaced bins of Δt, which provide adequate time resolution while ensuring sufficiently large number of Δm values per bin.

Given that we suspect data and data processing problems as a plausible explanation for discrepant results between SDSS-based and CRTS-based studies, we first study variability in the observed frame (the available SDSS redshifts for all object enable analysis in the rest frame, too).

The top two panels in Fig. 2 show the standard deviation for Δm, and the robust standard deviation ($\sigma_G = 0.741(q_{75} - q_{25})$, where q_{25} and q_{75} are 25% and 75% quartiles) estimate computed from the interquartile range, as a function of Δt for quasars, and separately for blue and red stars. The latter is somewhat smaller than the former, which indicates mild non-Gaussianity of Δm distributions. For Δt below about 100 days, all three subsamples show similar behavior, while for longer time scales quasars show appreciably larger scatter of observed Δm, presumably due to intrinsic variability. In order to estimate the intrinsic variability, these "raw" measurements need to be corrected for the effects of observational (measurement) errors, as described next.

3.1 Effects of Observational Errors on Structure Function

Given a bin with M values of (Δt_i, Δm_i, e_i), $i = 1...M$, SF will correspond to the rms width of the Δm_i distribution, σ_{tot}, *only if* all e_i are negligibly small compared to the true SF value. When measurement uncertainties are homoscedastic, $e_i = \bar{e}$, then simply SF $= (\sigma_{tot}^2 - \bar{e}^2)^{1/2}$. In a general case of heteroscedastic uncertainties, the correction for the effects of observational errors is more involved because each value Δm_i is drawn from a *different* Gaussian distribution whose width is given by $\sigma_i = (\mathrm{SF}^2 + \mathrm{e}_\mathrm{i}^2)^{1/2}$. Indeed, in this general case the distribution of all Δm_i in a given bin *need not be a Gaussian at all!*

We refer the reader for a detailed discussion of how to estimate SF in a general case to Ivezić et al. (2014), and here briefly summarize the gist of their maximum likelihood method. The likelihood of a set of M measurements Δm_i is given by

$$p(\{\Delta m_i\}|\mathrm{SF},\mu,\{\mathrm{e_i}\}) = \prod_{\mathrm{i=1}}^{\mathrm{M}} \frac{1}{\sqrt{2\pi}\sigma_\mathrm{i}} \exp\left(\frac{-(\Delta\mathrm{m_i}-\mu)^2}{2\sigma_\mathrm{i}^2}\right), \quad (5)$$

where $\{.\}$ denotes a set of values and μ is introduced to account for possible systematic photometric errors between observing epochs that define the bin's Δt_i values. We note that this expression is only an approximation to the true likelihood because it assumes that measurement errors for Δm_i are uncorrelated. This assumption is, strictly speaking, not true because different Δm_i values can be based on the same individual magnitude measurements.

There is no closed form solution for maximizing the likelihood given by eq. 5 and we estimate SF numerically, using code[3] from *astroML* python module (Vanderplas et al. 2012). With the aid of Bayes Theorem and using uniform priors for SF and μ, the logarithm of the posterior pdf for SF and μ becomes

$$L_p(SF,\mu) = \mathrm{const.} - \frac{1}{2}\sum_{i=1}^{M}\left(\ln(\mathrm{SF}^2+\mathrm{e_i^2}) + \frac{(\Delta\mathrm{m_i}-\mu)^2}{\mathrm{SF}^2+\mathrm{e_i^2}}\right). \quad (6)$$

We evaluate L_p on a grid[4] of μ and SF first, find its maximum which yields the maximum a posteriori (MAP) estimates for SF and μ, and then marginalize over μ to find the posterior pdf for SF:

$$p(\mathrm{SF}) = \int_0^\infty \mathrm{p}(\mathrm{SF},\mu|\{\Delta\mathrm{m_i}\},\{\mathrm{e_i}\})\mathrm{d}\mu, \quad (7)$$

which is used to estimate the uncertainty (the credible region) of MAP estimate for SF. When there is no strong evidence for intrinsic variability, SF tends to zero.

The bottom two panels in Fig. 2 show SF and μ as a function of Δt for quasars, blue and red stars. For Δt below about 1000 days, μ for all three subsamples is within 0.01^m from zero, as expected. On the other hand, SF below about 100 days is in the range 0.05-0.10^m for all three subsamples. In case of quasars, the observed SF$\sim 0.1^m$ for 10 d $< \Delta t <$100 d demonstrates that the difference between SDSS results from MacLeod et al. (2010) (see the yellow dashed line in the third panel) and CRTS results from Graham et al. (2014) is *not* due to different analysis methods (SF vs. SWV, respectively): here we fully reproduce this discrepancy using SF method and CRTS data.

Fig. 2 also indicates a plausible solution to this puzzle: the observed SF for both blue and red stars in the range $10^d < \Delta t < 100^d$ is *unexpectedly* large: the values are in the range 0.05-0.10^m rather than negligible (say, $\lesssim 0.01-0.02^m$).

[3] See http://www.astroml.org/book_figures/chapter5/index.html
[4] The grid size is set using approximate solutions described by Ivezić et al. (2014).

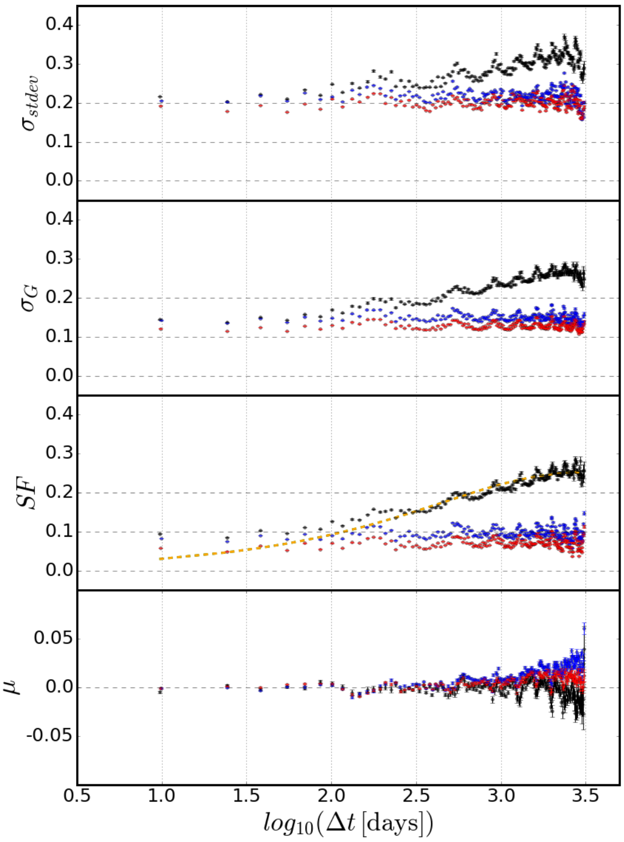

Figure 2. The four panels show various statistics computed for subsamples of 747 CRTS quasars (black points), 1496 "blue" stars (blue points), and 2327 "red" stars (red points), with SDSS r magnitudes in the range 18.5-19. Red and blue stars have SDSS colors $1 < \mathrm{g-i} < 3$ and $-1 < \mathrm{g-i} < 1$, respectively. All pairwise CRTS brightness differences are binned in 200 linearly spaced bins of time difference Δt. For each bin, we compute, from top to bottom: the standard deviation σ_{stdev}, the robust standard deviation estimate σ_G based on the interquartile range , the structure function SF, and the mean value of Δm per bin μ. Both μ and SF are found from the 2D maximum of the log-likelihood L_p on the $[\mu,\mathrm{SF}]$ grid (see eq. 6). The yellow dashed line in the third panel traces the fiducial Damped Random Walk model (see eq. 1).

In other words, more variation is observed in light curves of non-variable stars than can be explained with reported photometric errors. The same result is obtained for all three chosen magnitude bins. Such a behavior could be observed if photometric error estimates computed by the CRTS photometric pipeline are mis-estimated, resulting in an incorrect correction for observational errors. We proceed to perform an independent test of photometric errors using repeated observations of non-variable standard stars.

3.2 Tests of Observational Errors Using Non-variable Stars

Assuming that standard stars from SDSS are truly non-variable, if (Gaussian) photometric error estimates computed by the CRTS photometric pipeline are correct, then the distribution of $\chi_i = \Delta m_i/e_i$ for stars should be distributed as a unit Gaussian, N(0,1). Deviations of the distribution width for stars from unity indicate incorrect photo-

Table 2. The robust distribution widths for χ for blue stars.

mag	σ_G
17 - 18	0.087
18 - 18.5	1.107
18.5 - 19	1.288

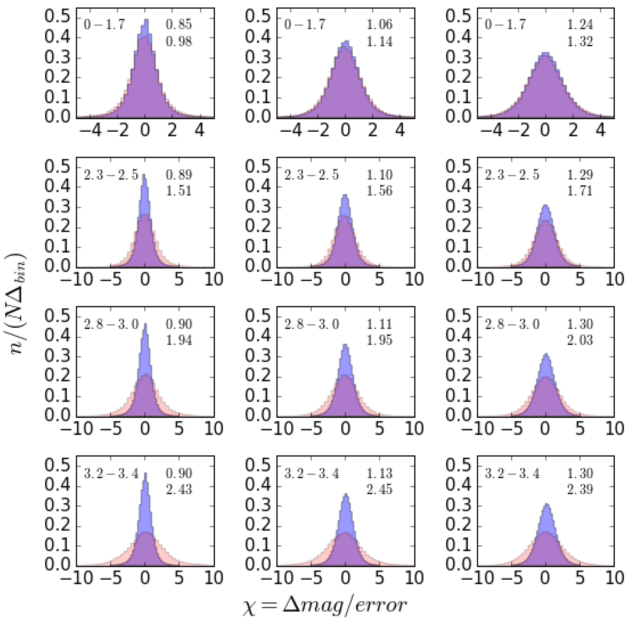

Figure 3. Histograms show CRTS-based $\chi = \Delta m/\text{error}$ for blue stars (blue shading) and quasars (red shading), split into bins of $\log \Delta t$ (rows) and SDSS r magnitude (columns). Vertically, from top to bottom, $\log \Delta t$: $0 < \log \Delta t < 1.7$ ($t < 50$ days), $2.3 < \log \Delta t < 2.5$, $2.8 < \log \Delta t < 3.0$, and $3.2 < \log \Delta t < 3.4$ (indicated by numbers in the upper left corner of each subplot). Horizontally, from left to right, the SDSS r magnitude bins are: 17−18, 18−18.5, and 18.5 − 19. The numbers in the upper-right corner of each subplot are the robust width of χ distributions determined using interquartile range (σ_G); upper value for blue stars and lower value for quasars.

metric error estimates. For quasars, we expect that the width should exceed unity because of their intrinsic variability, and that the width should increase with Δt. We perform this test in Fig. 3, where we show χ distributions for both blue stars and quasars, and for a grid of Δt and magnitude bins.

For the shortest Δt bin (<50 days), the distributions for stars and quasars appear indistinguishable for all three magnitude bins. This similarity immediately argues that there is no detected intrinsic variability for quasars. Furthermore, the width of χ distributions for stars appears to be a function of magnitude, with very little dependence on Δt. The distribution widths for stars in each magnitude bin (all Δt values), obtained using robust width estimator σ_G, are listed in Table 2. For example, the bin with $18.5 < r < 19$, which contains the majority of quasars, appears to have underestimated photometric errors by a factor of 1.3 on average. The same conclusion is derived using red stars. For small Δt, where quasar SF is intrinsically small, quasar SF will be thus significantly over-estimated, while for large Δt, where quasar SF is intrinsically large, the effect on SF will be small. We extend this qualitative conclusion to a more quantiative analysis in the next section.

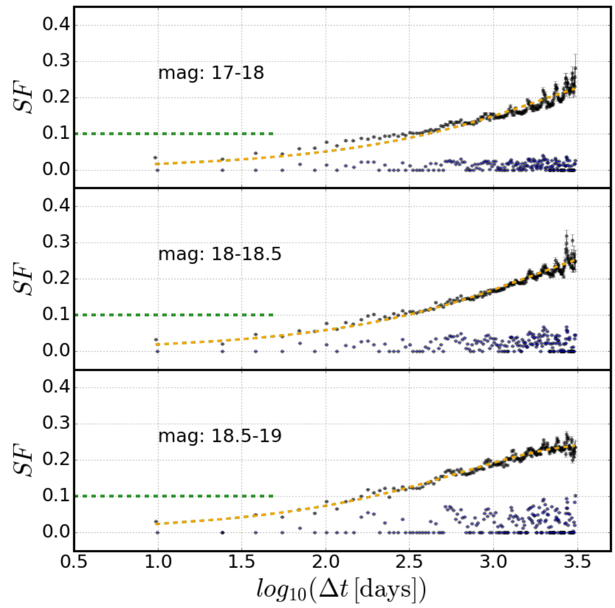

Figure 4. Analogous to the third panel in Fig. 2, except that here SF for blue stars and quasars in all three magnitude bins are shown, and photometric errors are modified by multiplicative correction factors listed in Table 2. Note that SF for stars in vanishing, while SF for quasars at $\log_{10}(\Delta t) < 1.7$ is about twice as small as in Fig. 2.

3.3 Structure Function with Corrected Observational Errors

Informed by the analysis from preceeding section, we assume that correction factors for photometric error estimates are independent of color and are only a function of magnitude. Depending on the magnitude of stars and quasars, we multiply their reported photometric errors by σ_G values listed in Table 2, and repeat SF analysis. By construction, we expect that the width of χ distributions for blue stars will be unity, and that their SF will tend to 0. For quasars, we expect somewhat smaller SF at large Δt and much smaller SF at small Δt, compared to SF values shown in the third panel in Fig. 2.

Fig. 4 shows SF for blue stars and quasars for subsamples from the three selected magnitude bins. As evident, both expectations are born out: for all three magnitude bins, SF for blue stars is essentially vanishing within noise ($\sim 0.05^m$), while SF for quasars at small Δt is about twice smaller than in Fig. 2 and thus consistent with the values based on SDSS data. In Fig. 3.3 we demonstrate that this agreement with SDSS results extends to rest frame analysis, too.

3.4 SF Estimated from PTF Data

Recent PTF (Palomar Transient Factory) Data Release 3 light curves[5] can be used for an independent test of our conclusions derived above. We queried the NASA/IPAC In-

[5] http://www.ptf.caltech.edu/page/lcdb

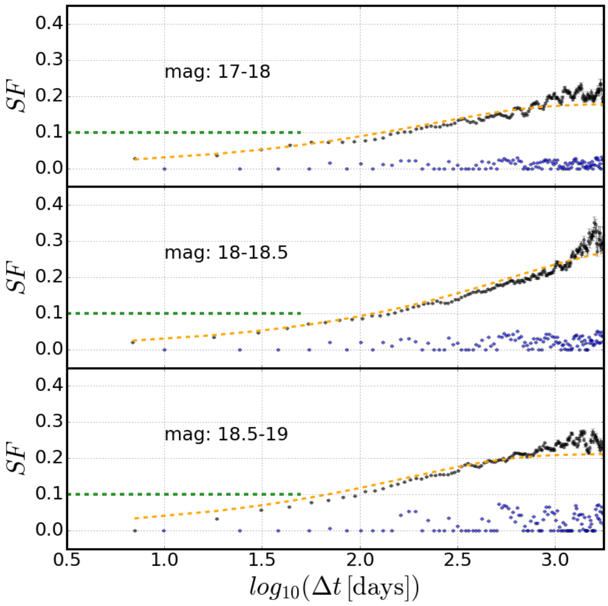

Figure 5. Analogous to Fig. 4, but here for Δt in the quasar rest frame : $t_{rest} = t_{obs}$ / (1+z), using known quasar redshifts from SDSS (MacLeod et al. 2010). The rest frame correction shifts time lags to shorter timescales and produces SF for quasars in agreement with corresponding results obtained by (MacLeod et al. 2010).

Table 3. Count of stars and quasars, selected by their SDSS r magnitudes and $g - i$ colors.

Table 4. Analoguous to 1, except that here the counts of stars and quasars with PTF adequate data are listed.

r mag.	red stars	blue stars	quasars
17-18	1243	1077	90
18-18.5	825	497	160
18.5-19	913	548	377
total	2981	2122	627

frared Science Archive[6] 'PTF Objects' catalog using coordinates for 7,601 spectroscopically confirmed Stripe 82 quasars, and 48,250 standard stars (same as the final samples used for CRTS-based analysis). A positional multi-object search with a matching radius of 2 arcsec, with a flag 'ngoodobs' > 10, resulted in 6,471 quasars and 38,776 stars. For these objects we obtained time series data from the 'PTF Light Curve Table' catalog (we grouped by SDSS coordinates).

We processed these PTF light curves in exactly the same way as the CRTS light curves. We first performed day-averaging, using the weighted error as the measure of uncertainty on day-averaged brightness measurement. We further selected only those objects that have been observed on at least 10 different nights, resulting in samples of 2,753 quasars and 15,714 stars. The counts of magnitude-limited subsamples are listed in Table 4.

The SF results based on PTF light curve data are shown

[6] https://irsa.ipac.caltech.edu

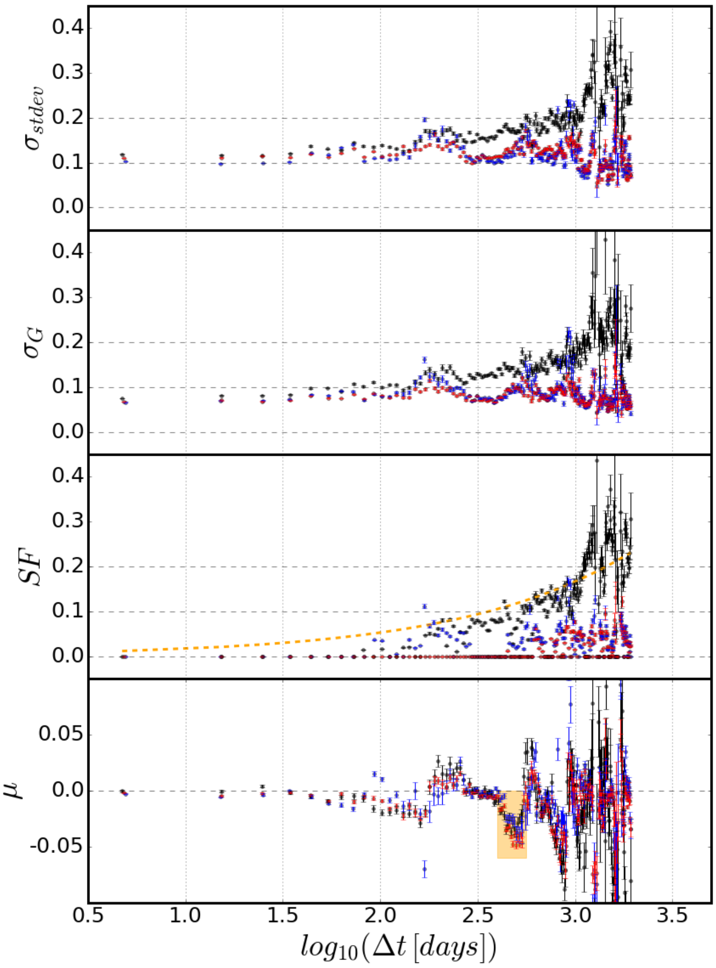

Figure 6. Analogous to Fig. 2, but here the statistics for subsamples of 377 quasars (black points), 548 "blue" stars (blue points), and 913 "red" stars (red points), with adequate PTF light curve data are shown. Note that the mean magnitude difference (μ, the bottom panel) does not stay as close to 0 as for CRTS data – a deviation around $\log_{10} \Delta t \approx 2.7$ might indicate some issues with photometric zeropoint calibration (at the level of 0.02-0.03^m).

in Fig. 6. For these uncorrected PTF data, it is evident that there is no sign of variability for quasars on short timescales (Δt < 100 days) above the SDSS-level of ~0.05^m (unlike for CRTS data, see Fig. 2). Note also that standard stars show no appreciable variability at any time scale (SF≈ 0). Therefore, this PTF-based analysis further supports our conclusion that extraneous quasar variability at short time scales was due to slightly understimated photometric uncertainties.

4 CONCLUSIONS

We analyzed the error properties of the CRTS sample of quasars and standard stars. Using repeated CRTS observations of non-variable stars, we found that the photometric error estimates computed by the CRTS photometric pipeline are slightly under-estimated for the majority of quasars. When quasar light curves are corrected for the impact of observational errors, the resulting corrections are thus too small. For small Δt, where quasar SF is intrinsically small, quasar SF is significantly over-estimated (akin to the subtraction of two large numbers to get a small number, when the second large number is under-estimated). In particular, at time scales of about 50 days, SF is over-estimated by about a factor of two. This behavior provides a plausible explanation for the increased quasar variability level in CRTS light curves reported by Graham et al. (2014), compared to earlier SDSS-based results obtained by MacLeod et al. (2010). An additional analysis based on independent light curve data for the same objects obtained by the Palomar Transient Factory provides further support for this conclusion. We conclude that the quasar variability constraints on weekly and monthly time scales from SDSS, CRTS and PTF surveys are mutually compatible, as well as consistent with DRW model.

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