GAMMA-RAY BURST FLARES: X-RAY FLARING. II.

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ABSTRACT

We present a catalog of 498 flaring periods found in gamma-ray burst (GRB) light curves taken from the online Swift X-Ray Telescope GRB Catalogue. We analyzed 680 individual light curves using a flare detection method developed and used on our UV/optical GRB Flare Catalog. This method makes use of the Bayesian Information Criterion to analyze the residuals of fitted GRB light curves and statistically determines the optimal fit to the light curve residuals in an attempt to identify any additional features. These features, which we classify as flares, are identified by iteratively adding additional “breaks” to the light curve. We find evidence of flaring in 326 of the analyzed light curves. For those light curves with flares, we find an average number of \( \sim 1.5 \) flares per GRB. As with the UV/optical, flaring in our sample is generally confined to the first 1000 s of the afterglow, but can be detected to beyond 10\(^5\) s. Only \( \sim 50\% \) of the detected flares follow the “classical” definition of \( \Delta t/t \leq 0.5 \), with many of the largest flares exceeding this value.

Key word: gamma-ray burst: general

Online-only material: color figures, machine-readable table

1. INTRODUCTION

The Swift (Gehrels et al. 2004) mission has revolutionized the study of gamma-ray burst (GRB) afterglows due to its rapid response time and automated GRB response algorithms. Swift is comprised of three instruments that work together, and all contribute their unique capabilities to this the study of GRBs. The Burst Alert Telescope (BAT; Barthelmy et al. 2005) first detects the GRB and causes the satellite to perform an autonomous slew to the GRB position, generally within \( \sim 100 \) s of the GRB trigger. The X-Ray Telescope (XRT; Burrows et al. 2005a) and UV/Optical Telescope (UVOT; Roming et al. 2000, 2004, 2005) then begin an automated sequence of observations designed to localize the position of the GRB to less than an arcsecond and follow the decay of the afterglow. Swift has triggered on and localized an X-ray counterpart for over 700 GRBs, increasing the number of afterglow localizations by approximately an order of magnitude from the pre-Swift era. The rapid localizations and follow-up provided by Swift has resulted in several exciting new discoveries about the properties of the GRB afterglow, including the “canonical” X-ray light curve (Nousek et al. 2006), which is observed in a number of GRBs (e.g., Hill et al. 2006; Evans et al. 2009). Also discover early in the Swift mission was the presence of X-ray flares in the early afterglow (e.g., Burrows et al. 2005b; Romano et al. 2006).

Flares in GRB afterglows had been seen prior to their observation by the XRT (e.g., Piro et al. 1998, 2005), but only in three X-ray afterglows. The XRT observations have shown that flares are seen in all phases of the canonical X-ray light curve and are quite common, appearing in approximately 50% of the XRT afterglows (O’Brien et al. 2006). These flares are observed as superimposed excesses deviating from the underlying light curve. Through the study of individual flares in GRBs 050406 (Romano et al. 2006), 050502B (Falcke et al. 2006), 050713A (Morris et al. 2007), 050724 (Campana et al. 2006), and 050904 (Cusumano et al. 2007), it has been shown that X-ray flares are observed in both long and short GRBs, appear to come from a distinctly different emission mechanism than the underlying afterglow, and can be observed out to beyond 10\(^5\) s from the initial GRB trigger (e.g., Swenson et al. 2010). These studies also point toward a likely internal shock source for the flares, though the actual source of the flares still remains in question and may be caused by one of many different mechanisms including instabilities in the ejecta, stored electromagnetic energy, or collision with the extrastellar medium (Zhang et al. 2006).

Studying large numbers of flares from several different bursts and analyzing their bulk properties allows us to try and better constrain the physical process by which flares are created. Several previous studies have been performed on XRT light curves, analyzing groups of X-ray flares. The earliest studies by Falcone et al. (2007) and Chincarini et al. (2007) found flares in 33 of the first 110 GRBs observed by Swift. These studies showed that late-time internal shocks were necessary to explain 10 of the observed flares and that some sort of central engine activity was the preferred method for a majority of the flares. Follow-up studies performed by (Chincarini et al. 2009, 2010) and (Margutti et al. 2010) showed that X-ray flaring may have some correlation with the GRB prompt emission, that flares evolve over time, and that they were likely caused by late-time internal dissipation processes.

Morris (2008) did incorporate the BAT, XRT, and UVOT data for the flare sample used by Falcone et al. (2007) and Chincarini et al. (2007) and showed that whereas the afterglow could be fit by a simple absorbed power law, the spectral energy distribution of the flaring periods could not. (Roming et al. 2006) attempted to perform a study analyzing flares in the UV/optical, but was severely limited due to the low significance of UV/optical flares compared to X-ray flares.

Realizing the need for more detected flares in the UV/optical, in our first paper (Swenson et al. 2013), we presented a catalog of flares found in the UV/optical from the collection of light curves presented in the Second Swift/UVOT GRB Afterglow Catalog, an expansion on the First Swift/UVOT GRB after Catalog (Roming et al. 2009). These flares were
found using a new algorithm developed specifically for the purpose of performing a blind, systematic search for flares in GRB afterglows. This search resulted in the discovery of 119 potential flaring periods in 68 GRB afterglows, many of which were previously undetected. This study showed that flares in the UV/optical are much more common than previously thought.

As mentioned previously, many of the studies on X-ray flares were limited in their reach due to limitations in their data sets. Falcone et al. (2007) and Chincarini et al. (2007) were limited by the time that Swift had been operating. Chincarini et al. (2009) limited their data set to GRBs with redshift measurements to study the actual energetics. Chincarini et al. (2010) limited their study to only flares found within the first 1000 s of the GRB afterglow, and Margutti et al. (2010) used only a sample of nine exceptionally bright X-ray flares. An additional study by Margutti et al. (2011) investigated the average flaring component of 44 GRBs with known redshift. More importantly, that study illustrated the difficulty of identifying late-time flares due to the decaying nature of the GRB afterglow. Using a 2σ threshold for flare detection, they calculated the necessary peak flare flux needed to be detectable and showed that at late times the flare-to-continuum flux ratio must increase (see their Figure 1 for an example) in order for flares to remain detectable. We know that late-time flares do exist (e.g., Swenson et al. 2010), but only those few that are easily detectable have been investigated. There has yet to be a blind, systematic search for X-ray flares performed on a data set that was not preselected to match some criteria.

The precise nature of the GRB central engine is still largely unknown and many of the previous studies on GRB flares have indicated a likely connection between flaring and the central engine, making the study of GRB flares crucial to our understanding of GRBs. Having a complimentary X-ray catalog using the algorithm developed in Swenson et al. (2013) would address the limitations mentioned in the previous X-ray studies and allow for more stringent constraints on the origin of GRB flares through cross-correlation of the X-ray and UV/optical.

In this paper, we present the results from a blind, systematic search for flares in XRT light curves. Using the method described in Swenson et al. (2013), we have constructed the most complete catalog of X-ray flares to date and provide the temporal details of each flare, including $T_{\text{peak}}$, $\Delta t$, and the strength of the flare relative to the underlying light curve. In a forthcoming paper, we will perform our cross-correlation analysis of this catalog and our UV/optical flare catalog.

This paper is organized as follows. In Section 2, we describe our data set as well as our methodology for identifying flares. In Section 3, we present our catalog of GRB flares observed by the XRT, and in Section 4, we discuss the implications drawn from the catalog.

2. METHODOLOGY

For the purposes of this study, we will use the publicly available XRT light curves from the online Swift/XRT GRB Catalogue (Evans et al. 2007, 2009). We downloaded the light curves for the time period covering 2005 January through 2012 December, as well as the best-fit parameters for each burst. We calculated the light curve residuals using the best-fit parameters and perform our flare-finding analysis on these residuals.

Our flare-finding analysis follows the same basic methodology set forth in Swenson et al. (2013). We processed the calculated residuals $^3$ using the breakpoints analysis function (Zeileis et al. 2003) within the publicly available R (R Core Team 2014) package strucchange (Zeileis et al. 2002). The breakpoint analysis determines the optimal number of “breakpoints” that are required to best explain any features that may remain in the residuals of the GRB light curve. This is done by simultaneously minimizing both the residual sum of squares and the Bayesian Information Criterion (BIC; Schwarz 1978) over several iterative fits to the light curve. For the purposes of our analysis, we used the guidelines provided by Kass & Raftery (1995) and require $\text{BIC}_1 - \text{BIC}_{\text{min}} > 6$ as the criterion for determining the preferred fit to the light curve residuals.

We performed 10,000 Monte Carlo iterations for each GRB light curve, each time varying the data points based on a Poisson distribution to account for measurement error and then determining the optimal number of breakpoints and grouping those breakpoints into potential flares. For each potential flare, we identify the following parameters: $T_{\text{start}}$, $T_{\text{peak}}$, and $T_{\text{stop}}$, the start, peak, and end times of each flare, respectively, each nominally associated with an individually identified breakpoint. Due to the higher density of data points, and therefore timing resolution, our determinations of $T_{\text{start}}$ and $T_{\text{stop}}$ will be more precise than for the UV/optical flares, but we will continue to refer to them as “limits” because there are still instances of poor timing resolution and gaps in the data that prevent us from determining a more accurate breakpoint. We calculated $\Delta t/T$, defined as $(T_{\text{stop}} - T_{\text{start}})/T_{\text{peak}}$, and the peak flux ratio using the measured flux at $T_{\text{peak}}$ and an interpolation of the flux of the underlying light curve at the same time. We also provide a confidence measure, which we define as the fractional number of times that a particular flare was recovered during the 10,000 simulations.

It should be noted that the Monte Carlo simulations being employed add a further noise component in addition to the statistical error already present in the data. The simulated light curves used for breakpoint detection are therefore conservative relative to the observed light curve, and the breakpoints identified are found to be significant in spite of the additional noise component, making them robust. Additionally, the calculated confidence measure should be viewed as a lower limit, as many of the weaker flares may suffer in their detection fraction due to the noise introduced in the Monte Carlo simulations.

A few minor changes in the actual processing of the data were required, as opposed to the UV/optical data set. Due to the much higher density of data points available in many of the X-ray light curves, as opposed to the relatively sparsely sampled UV/optical light curves, we were forced to limit the number of potential breakpoints identified to 75 per light curve. By default, the analysis iteratively adds additional breakpoints between every data point in the light curve, beginning with the strongest (i.e., most likely) breakpoint. This process is computationally intensive, and adding an arbitrarily large number of additional breakpoints increases the processing time exponentially. By limiting the number of breakpoints to 75, we are allowing for a minimum of 25 individual flares per light curve. Our results presented in this paper show that no burst had more than nine

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$^3$ We perform our analysis on the fitted light curve residuals to speed up the flare-finding process. The accuracy of the initial light-curve fit does not contribute significantly to the results of our analysis. Analysis performed on a subset of light curves, rather than on the residuals, showed that we recover a fit consistent with those provided by Evans et al. (2007, 2009), but which required approximately twice as many CPU cycles to recover both the general fit to the light curve, as well as any flares.
individual flares identified, so the truncation of the analysis had no effect on the end results.

For the sake of consistency, we assume that the fits provided by the Swift-XRT GRB Catalogue (Evans et al. 2007, 2009) are correct in fitting just the underlying light curve and not the flares (see footnote 3). This assumption may result in the identification of a “flare” during the fast initial decay phase of the canonical light curve (Nousek et al. 2006). Because there is no data prior to the start of the XRT observations, we cannot conclusively differentiate between observations that start during the canonical fast initial decay phase versus those that may start during the decay of a flare. A large number of XRT observations begin during the fast initial decay phase and the Swift-XRT GRB Catalogue does not always fit that initial steep decay as part of the light curve, particularly if the observed portion of the phase is extremely short. In these cases, our flare analysis will identify the initial steep decay as being part of a flare, which may or may not be the case.

Additionally, due to the number of data points contained in some of the brightest X-ray light curves, the process of iteratively fitting every data point requires a large number of CPU cycles, and completing the normal 10,000 Monte Carlo iterations would have required several years of computational time. In those cases, we limited the number of iterations to 1000 Monte Carlo simulations and report our confidence measure as the fraction of times the flare was identified during the 10,000 Monte Carlo simulations. The first column identifies whether the identified feature comes from an overlapping “flaring period.”

Notes. Flares are listed in chronological order by GRB date, then sorted by confidence. All times are relative to the time of the initial burst trigger. \(\Delta t/t\) is calculated as \((T_{\text{stop}} - T_{\text{start}})/T_{\text{peak}}\). \(T_{\text{start}}\) and \(T_{\text{stop}}\) are lower and upper limits, respectively. Flux ratio is calculated as the flux at the flare peak time divided by the extrapolated flux of the underlying light curve at the same time, normalized using the flux of the underlying light curve, and is a lower limit of the actual peak flux ratio. The confidence measure represents the fraction of times the flare was identified during the 10,000 Monte Carlo simulations. The confidence measure is calculated as \((T_{\text{stop}} − T_{\text{start}})/T_{\text{peak}}\). \(T_{\text{start}}\) and \(T_{\text{stop}}\) are lower and upper limits, respectively. Flux ratio is calculated as the flux at the flare peak time divided by the extrapolated flux of the underlying light curve at the same time, normalized using the flux of the underlying light curve, and is a lower limit of the actual peak flux ratio. The confidence measure represents the fraction of times the flare was identified during the 10,000 Monte Carlo simulations. The first column identifies whether the identified feature comes from an overlapping “flaring period.”

Our analysis identifies a specific data point in the light curve as being associated with these quantities. The large number of digits reported for \(T_{\text{peak}}\), \(T_{\text{start}}\), and \(T_{\text{stop}}\) are not reflective of our confidence in their determination, but are rather the timestamp associated with the data point identified. We have chosen not to round these values for two reasons: (1) any rounding decision we make would be arbitrary, and (2) the relative effect of the rounding on each value would differ depending on the size of the value. This also prevents the introduction of an arbitrary bias to the data.

(This table is available in its entirety in a machine-readable form in the online journal. A portion is shown here for guidance regarding its form and content.)

### Table 1

| Flaring Period | Source Name | \(z\) | \(T_{\text{peak}}\) \(\text{(s)}\) | \(T_{\text{start LL}}\) \(\text{(s)}\) | \(T_{\text{stop LL}}\) \(\text{(s)}\) | \(\Delta t/t\) | Flux Ratio Lower Limit | Confidence |
|----------------|-------------|------|-----------------|-----------------|-----------------|-------------|----------------------|-----------|
| N              | GRB 050128  | 720.13 | 686.15          | 784.77          | 0.14            | 0.43        | 0.5163               |
| N              | GRB 050128  | 293.30 | 278.18          | 305.28          | 0.09            | 0.34        | 0.4182               |
| N              | GRB 050219A | 129.10 | 126.20          | 131.46          | 0.04            | 0.66        | 0.7269               |
| N              | GRB 050219A | 262.85 | 245.68          | 295.79          | 0.19            | 0.72        | 0.6922               |
| N              | GRB 050219A | 164.02 | 159.94          | 169.35          | 0.06            | 0.46        | 0.5689               |
| N              | GRB 050318A | 1.44  | 32447.35        | 32878.65        | 0.13            | 1.75        | 0.3661               |
| N              | GRB 050319A | 3.24  | 1438.08         | 1510.20         | 0.09            | 0.88        | 0.7775               |
| N              | GRB 050401A | 2.9   | 139.69          | 134.29          | 151.31          | 0.12        | 0.40                 | 0.5326    |
| N              | GRB 050401A | 173.49 | 169.78          | 187.33          | 0.10            | 0.39        | 0.3651               |
| N              | GRB 050406A | 210.50 | 112.65          | 354.36          | 1.15            | 20.42       | 0.9250               |

Notes.

- Flares are listed in chronological order by GRB date, then sorted by confidence. All times are relative to the time of the initial burst trigger.
- \(\Delta t/t\) is calculated as \((T_{\text{stop}} − T_{\text{start}})/T_{\text{peak}}\). \(T_{\text{start}}\) and \(T_{\text{stop}}\) are lower and upper limits, respectively. Flux ratio is calculated as the flux at the flare peak time divided by the extrapolated flux of the underlying light curve at the same time, normalized using the flux of the underlying light curve, and is a lower limit of the actual peak flux ratio. The confidence measure represents the fraction of times the flare was identified during the 10,000 Monte Carlo simulations.
- \(T_{\text{peak}}\), \(T_{\text{start LL}}\), and \(T_{\text{stop LL}}\) are not reflective of our confidence in their determination, but are rather the timestamp associated with the data point identified. We have chosen not to round these values for two reasons: (1) any rounding decision we make would be arbitrary, and (2) the relative effect of the rounding on each value would differ depending on the size of the value. This also prevents the introduction of an arbitrary bias to the data.

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### 3. RESULTS

Here, we present the results of our analysis of the 680 XRT GRB light curves taken from the online Swift-XRT GRB Catalogue (Evans et al. 2007, 2009) spanning 2005 January through 2012 December. We detect 498 unique potential flaring periods, for which we can distinguish start and stop times, detected in 326 different light curves. A number of these identified flares are actually multiple superimposed flares contained within a shared “flaring period.” Because of the high density of data points in the X-ray light curves, we are able to resolve periods of multiple overlapping flares. Due to the overlapping, we cannot uniquely identify the start or stop of the individual flares within the larger “flaring period.” We are limited to identifying only the start and stop times of the entire period containing the overlapping flares. For the sake of simplicity and completeness, we will include these flaring periods in our analysis and simply refer to these flaring periods as “flares.” Table 1 provides the following information for each potential flare: (1) Whether or not the flare is isolated or is part of a larger flaring period, (2) GRB Name, (3) the GRB redshift (blank if unknown), (4) the flare peak time, defined as the data point most often identified as the flare peak during the Monte Carlo simulations, as well as limits on (5) \(T_{\text{start}}\) and (6) \(T_{\text{stop}}\), defined as the last and first data points, respectively, that are well fit by the underlying light curve. (7) A limit on \(\Delta t/t\) based on the peak time, \(T_{\text{start}}\) and \(T_{\text{stop}}\), and (8) the ratio of the peak flux during the flaring period, relative to the flux of the underlying light curve at the same time, using the observed flux at the flare peak time and an interpolation of the flux of the underlying light curve. The flux ratio is normalized using the flux of the underlying light curve to allow for direct comparison of each flare across all light curves. Finally, (9) the confidence measure of the detected flare indicating the fractional number of times the flare was recovered during the 10,000 Monte Carlo simulations.

We previously discussed the difficulty in identifying flares, particularly at late times in the light curve due to the degradation of the underlying afterglow. In Table 1, we present all potential flares found by our analysis, regardless of their confidence, meaning that a small number may be related to statistical fluctuations or non-flaring activity. This was done in an attempt to eliminate bias from our conclusions, as well as those from subsequent studies that use this data.

### 4. DISCUSSION

Our analysis shows that at least 47% of the analyzed XRT light curves contain possible flaring episodes. This percentage
is very similar to previous studies (e.g., O'Brien et al. 2006; Chincarini et al. 2010), in spite of our detection of a significantly larger number of total flares and, specifically, a larger number of small, weak flares. This may indicate that X-ray GRB afterglows come in two varieties; those with flares and those without.

In our analysis of the bulk properties of the detected X-ray flares, we have followed the same method used in Swenson et al. (2013) and divided the flares into three groups: “gold,” “silver,” and “bronze.” Our comparisons to UV/optical flares will also come from our analysis in Swenson et al. (2013).

The gold group is defined as those flares with confidence measures greater than 0.7 and $\Delta t/t < 0.5$. This group constitutes those flares which satisfy the somewhat “classical” definition of a flare in terms of duration and have a good recoverability rate. This group contains 127 flares. The silver group allows for longer flares and lower confidence, expanding the parameters to confidence measures greater than 0.6 and $\Delta t/t < 1.0$. This group contains 115 flares after excluding overlap from the gold group. The remaining flares that do not qualify for either the gold or silver and are grouped together in the bronze, which contains 256 flares.

Of the 326 X-ray light curves with flares, the average number of flares per GRB is $\sim 1.5$. Figure 1 shows the distribution of flares per GRB for the gold, silver, and bronze groups, shown in black, blue, and red, respectively. GRB 100728A had the most resolved flares of the analyzed bursts, with nine, and five other GRB light curves had five or more flares.

The flare peak times range from 48 s after the trigger of GRB 110119A to over 400 ks for GRB 090902B; 82% of all detected flares peaked before 1000 s, nearly matching the percentage seen in the UV/optical light curves. We suspect that this similarity to the UV/optical flares is not coincidental and that many of these flares may be correlated, or at the very least, caused by a similar mechanism that is active during the early stages of the GRB. This issue will be looked at in depth in our next paper correlating the UV/optical and X-ray flares. Figure 2 shows the distribution of $T_{\text{peak}}$ for the three groups of flares.

The groups were created so as to reflect this understanding, to reflect the recoverability rate of $T_{\text{peak}} \leq 1000$ s is immediately obvious in all three groups, and all three groups appear to originate from a similar parent distribution peaking between 300 s and 500 s after the trigger.

The duration of the flares, recognizing that a number of the $T_{\text{start}}$ and $T_{\text{stop}}$ values are only limits, varies from $\Delta t/t = 0.02$ to over 100 (though the extremely large values are due to observing gaps in the data). Only $\sim 50\%$ of the flares exhibited $\Delta t/t < 0.5$, whereas this number was at least 80% for the UV/optical flares. This difference between the duration of the X-ray and UV/optical flares may be due to the UV/optical flares being generally fainter than those seen in the X-ray. If we only see the peak of the flare in the UV/optical, then our measured duration for the flare will be biased relative to the X-ray where we see more of the flare rise and decay. Figure 3 shows the distribution of $\Delta t/t$ for the three groups of flares. Ioka et al. (2005) showed that it is difficult to achieve rapid variability, defined as $\Delta t/t \leq 1$, in the external shock, so an internal shock model has been favored to explain the $\Delta t/t \ll 1$ seen in most flares. However, Figure 3 shows a significant number of possible flares that exhibit $\Delta t/t > 1$. For this work, we are reporting all potential features detected by our flare finding algorithm, and we treat them as potential flares. It is possible, however, that a portion of our detected features, in particular, those with $\Delta t/t > 1$, are due to other processes, such as the emergence of the reverse shock, and are not flares. It is also possible that these are flares caused by processes other than internal shocks. An interesting relationship between the gold, silver, and bronze groups needs to be pointed out when interpreting Figure 3. There is a continuous distribution of potential flares that spreads across all three groups, which we believe provides evidence to the likelihood of the bronze group containing a high percentage of real flares, despite their $\Delta t/t$ value. The decision to split the detected flares into three groups was based on our prior understanding of flare properties from the previous studies mentioned earlier, namely, that the majority of flares exhibit $\Delta t/t \ll 1$. The groups were created so as to reflect this understanding, to reflect the recoverability rate...
for each flare, and also to allow for direct comparison with the UV/optical flares presented in Swenson et al. (2013). Because the flares do not meet the criteria for the gold group, they spill over into the silver and bronze groups. This can be seen by the abrupt cut-off, based on our group criteria, in the gold group at $\Delta t/t = 0.5$ and the subsequent continuation of the distribution in the silver group between $0.5 < \Delta t/t \leq 1.0$ and the excess tail extending into the bronze group at $\Delta t/t > 1.0$. These large flares comprise the majority of the silver group, with the remaining flares being distributed at $\Delta t/t < 0.5$. The primary distribution of the bronze flares, removing the extended tail from the gold and silver groups, can be see at $\Delta t/t < 1.0$ and peaking at $\Delta t/t \sim 0.1$. This work is now challenging the understanding of what constitutes an X-ray flare by finding a significant number of large potential flares exhibiting $\Delta t/t > 0.5$ and, as Figure 3 shows, a significant tale in the distribution with $\Delta t/t > 1.0$.

The relative strengths of the flares range from a minimum flux ratio of 0.1 to a maximum of several thousand. Figure 4 shows the distribution of flare flux ratios for the three groups. All three groups of flux ratios have long tails that extend into the tens, hundreds, and thousands for the gold, silver, and bronze groups, respectively. The flux ratios shown in Figure 4 show the distributions for those smaller, weaker flares that have previously been less studied. Unlike the UV/optical flares, which had noticeable gaps in the distributions of flux ratios, the X-ray flares show a much more continuous distribution in
Figure 4. Distribution of the logarithmic flare flux ratio, relative to the underlying light curve. The three distributions are the gold (top), silver (middle), and bronze (bottom) distributions described in the text.

(A color version of this figure is available in the online journal.)

We also categorized each flare, grouping them according to which phase of the canonical X-ray light curve (Nousek et al. 2006) it peaked during. We used the light-curve classification provided in the XRT GRB Catalogue (Evans et al. 2007, 2009) to determine whether the light curve was canonical in shape. Figure 6 shows $T_{\text{peak}}$ versus $\Delta \tau$ for flares occurring during the initial fast decay phase (green triangles), the shallow/plateau phase (red squares), and the final decay phase (black diamonds) of the light curve. The majority of light curves do not follow the canonical classification, but, for comparison, we have included flares coming from these light curves (gray circles). As Figure 6 shows, all the flares appear to follow the same evolution in $\Delta \tau$ as the light curve progresses. This same result was seen in our analysis of the remaining flare parameters. This means that either the physical process creating the flares is the same for all phases of the light curve, or multiple flare creation mechanisms are able to produce flares that behave and evolve similarly. Additionally, we analyzed the full XRT GRB Catalogue spanning 2005 January through 2012 December by separating the flaring and non-flaring GRBs into two groups. We then categorized each light curve based on the
light-curve classification given in the XRT GRB Catalogue (“No break,” “One-break,” “Canonical,” and “Oddball”). Analyzing the two distributions of light-curve types with a K-sample Anderson–Darling test (Scholz & Stephens 1987) yields a p-value of >0.95, indicating that the flaring and non-flaring GRBs are highly consistent with belonging to the same parent population. This provides further evidence that the mechanism powering the X-ray afterglow, which defines the eventual light-curve classification, is independent from the mechanism causing the X-ray flaring.

5. CONCLUSIONS

We have analyzed 680 XRT GRB light curves from the online Swift–XRT GRB Catalogue (Evans et al. 2007, 2009) using the flare detection method introduced in Swenson et al. (2013). We detect the presence of 498 unique potential flaring periods, many of them previously unreported. We plan to perform a cross-correlation analysis of the UV/optical flares provided in Swenson et al. (2013) and the X-ray flares reported in this work. By using the multi-wavelength flare information from these two catalogs, we will be able to better constrain the properties of GRB flares and better understand their origin.

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