Event Studies with Crypto Asset Returns

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ABSTRACT

This paper provides the first empirical evidence of how the unique properties of crypto-asset returns impact event-study test performance. Employing a simulation approach with actual price data from 1877 unique crypto-assets over the period of January 1st, 2015 to June 30th, 2018 reveals that both parametric procedures and non-parametric procedures often result in significant statistical errors. In the presence of event-day clustering, only the Generalized Rank T-Test is both powerful and well specified. To estimate abnormal returns, the market-model with a value-weighted index produces test statistics with distributions closest to expectation. The empirical evidence provided by the simulation then used in the first ever crypto-asset based event-study. Specifically, the event study investigated allegations of insider trading by the worlds largest crypto-asset exchange Binance.com. A total of 44 unique listing announcements during the period of September 2017 to June 2018. produce a statistically significant two day return of 13.6% (CAR(0,1)). However, the GRANK-T test fails to reject the null hypothesis of no insider trading during the three days preceding the announcements. Guidance and future applications of event-studies with crypto-asset returns are discussed.

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1. Introduction

Miss-specification in event-studies primarily occurs when there is either, a bias in the abnormal return estimation model or a violation of the test statistic assumptions (or both). Literature has addressed these concerns for a wide variety of financial assets returns (Corrado, 2011). However, the magnitude of the departures from normality previously investigated pail in comparison to the extremely skewed, highly leptokurtic, return characteristics of crypto-assets. Therefore, the applicability of previous evidence is an unexplored empirical question. While, the argument can be made that non-parametric tests are appropriate, without empirical evidence they cannot be assumed to be well-specified (Campbell et al, 2010).

Crypto-Assets, which broadly includes all types of tokens and crypto-currencies were invented in 2009 with the bitcoin blockchain outlined by Nakamoto (a pseudonym, 2008) in a whitepaper distributed on a cryptography email-list. Within 10 years, at the end of 2017, accelerating growth has resulted in over 1500 different crypto-assets with a combined market capitalization exceeding $800bn USD (Coinmarketcap.com). This rapid growth could be seen as reflective of how transformational of an impact blockchain technology is expected to have in society (Gartner level 5 classification). However, there is also a widespread belief, supported with empirical evidence (Griffen and Shams, 2018), that a substantial part of the growth stems from the non-policed[1] and mostly anonymous nature of crypto-assets. These contrasting beliefs highlight the main contribution of this work. This papers simulation based empirical evidence qualifies the use of crypto-asset returns in event-studies, enabling future research to make inferences vital to exploring both explanations.

As the first study to explore the use of crypto-asset returns in event-studies, considerable guidance was drawn from the earliest literature in this area. Using the simulation approach pioneered by Brown and Warner (1985) the performance of five parametric test statistics and four non-parametric test statistics are assessed for daily crypto-asset returns. These are examined under three different approaches to calculating abnormal returns and compared with value-weighted and equal-weighted market indices.

[1] It is a common misconception that the crypto-asset market is unregulated. Existing regulations including those relating to security offerings, fraud, money laundering, market manipulation, misrepresentation and others in most cases directly apply to crypto-assets.

The results of the simulations indicate that the non-normality of crypto-asset returns impact the performance of most specifications. Due to the contrasting skewness of the market index and crypto-asset returns, the market-adjusted abnormal return model should be avoided. The market-model with a value weighted index, was found to have tests statistics with distributions that most closely resembled expectations. When there is no-event day clustering the recommended parametric test is the BMP test and the recommend non-parametric test are the GRANK-T and G-SIGN statistics. However, with event-day clustering the GRANK-T is the only suitable test with sufficient power to detect abnormal returns.

The remainder of the paper is as follows, the motivation and supporting literature is discussed in the section below. The experimental design is presented in section three. Section four presents the results, followed by the discussion and limitations. Section six applies the findings to investigate insider trading by the exchange Binance. The paper concludes by summarizing the findings and presenting guidance for future researchers.

2. Motivation and Literature Review

2.1 Motivation

Event-study methodology has a storied history with impacts extending beyond literature and into criminal trials. In some circumstances it has become the preferred or even required methodology to determine wrong-doing in the eyes of the court (Fisch et al, 2017). This highlights the necessity to develop robust event-study methodologies. In western society is commonly argued that *it is better that 1000 guilty men go free than one innocent man be wrongly convicted.* If the underlying data or event-study methodology used as evidence in court results in miss-specifications that cause an increase in type one errors, then it is of considerable value to society to insure against this.

Ginni Rometty, CEO and Chair of IBM believes *once widely adopted, Blockchain will transform the world* (2016). A robust event-study methodology for crypto-assets will enable considerable insights as the transformation process unfolds. While many research questions cannot yet be defined, I identify several fruitful avenues for researchers in the near future. It is likely public corporations will continue to follow Kodaks lead in developing their own crypto-assets. Insights can be gained examining when these crypto-assets become listed on an exchange or included in a crypto-index. Initial Coin Offerings (ICO), Blockchain Crowdsales (Amsden and

Schweizer, 2018) and Security Token Offerings represent a new mechanism for corporations or ventures to raise capital and have similarities to event-studies in IPO literature. The subsequent treasury spending of the proceeds raised can be examined from a signaling perspective and departures of founders or hiring of new members is pertinent to investigating management questions. Token burning events have similarities to conventional literature examining share repurchases. Outside of the corporate finance domain, the framework provided by this study will be vital to examine blockchain forks (when a network splits into two such as Bitcoin and Bitcoin cash), blockchain security (such as a 51% attack), airdrops (providing the crypto-asset for free to spur adoption), the value of switching consensus mechanisms and broadly in the domain of law.

2.1 Conventional Literature

The history of event-studies dates back to the early 1930s, (MacKinlay, 1997) with the first known study by Dolley (1933) examining the impact of stock splits. The event study methodology that was employed was what we now call the random walk hypothesis in that the best prediction of tomorrows price is todays price. Therefore, the predicted return is equal to zero and the event study calculated how often the price increased or decreased following the event. The literature that followed would soon point out this methodology was flawed because it did not consider underlying movements in the general stock market, therefore erroneously producing statistically significant findings. In principle accounting for general market movements appears straightforward, in practice it remains the core research question addressed in recent literature. Although crypto-assets are categorically different, the underlying research question this paper address's is exactly this. How to account for changes in prices that are unrelated to the event itself.

Conventional literature can be broadly separated by which of the event-study stages it addresses. The first stream concerns the estimation of expected returns had the event not occurred so that abnormal returns can be calculated. This stream has a rich history, with the more recent developments being the introduction of SMB, HML pricing factors (Fama and French, 1993) and momentum factors (Carhart, 1997). However, these are statistical models derived from the historical returns of securities with unknown applicability to crypto-assets. For a detailed discussion on the issues of these in event-studies see Ahern (2009). Fortunately, the event-study literature preceding the discovery of pricing factors provides insights for crypto-assets. The mean adjusted model, market adjusted model and market model examined in Brown and Warner (1985) seminal study can be applied in a variety of situations including crypto-assets.

The second stream of literature concerns determining statistical significance of the abnormal returns. Theoretically under perfect conditions a simple t-test can be used, in practice the unique characteristics of each study must be considered when formulating a statistical test (MacKinlay, 1997). Departures from normality do not always cause concerns. For example, while daily returns are generally non-normal, the impact has been shown under certain circumstance to be minimal in random samples (Brown and Warner, 1985). However, when there is event induced variance an adjustment is required (Boehmer, Musumeci and Poulsen, 1991). Similarly, failure to control for cross-correlation when it is present can result in over rejection of the null hypothesis of no abnormal returns (Kolari and Pynnönen, 2010). Ahern (2009) further demonstrates that omitted variable bias can occur depending on sample selection. The proposed mechanisms to overcome these concerns are summarized in table 1 and discussed in detail in the experimental design section.

[Insert table 1 about here]

2.1 Crypto-Asset Literature.

A critical assumption of event-studies are that event-studies rely on some form of market efficiency. That is, that prices change as a result of traders making rational decisions based on the arrival of new material information. A review of theoretical models and quantitative tests literature support that market efficiency in the context of crypto-assets is similar to that of traditional markets.

Theoretical Models.

Numerous researchers are developing theoretical models which may have an impact on crypto-asset prices and returns. In Cong, Li and Wang (2018), the issue of user-base externalities is modeled into asset-pricing theory. The model suggests that crypto-assets accelerate adoption of a platform and that price depends on the amount of users, platform productivity, the agents transaction needs and similar to traditional securities expectation of price appreciation. Li and Mann (2018) propose a similar model that shows that ICOs leverage the network effect and thus prices should be expected to also reflect this externality.

Quantitative Tests

Wei (2018) in a brief analysis, test for market efficiency of 456 cryptocurrencies found a positive relationship between market efficiency and crypto-asset liquidity. In the lowest 20% of liquid crypto-assets, they document a Hurst exponent value of 0.41, below the cutoff of 0.45 indicating presence of time-series mean reversion. However, as the Hurst tests for long memory of returns its impact on short-term event studies is minimal. Encouragingly, for the 60% most liquid crypto-assets the Hurst scores range from 0.46 to 0.53 indicating the returns are essentially a random walk (0.50=RW). In comparison with the earlier results that found market inefficiencies (Urquhart, 2016), this can be taken as evidence of the crypto-asset market maturing over time.

Ciain et al (2018), take a different approach and investigate the interdependencies between bitcoin and 16 alt-coins. They provide evidence that in the short-term the majority of altcoins (15/16) are cointegrated with bitcoin prices. However, in the long-term the relationship disappears with evidence of only 25% being cointergrated. The relevance of this is questionable, as the study used returns priced in USD[2]. The results they found are expected because industry participants do not view prices in terms of USD but rather in terms of BTC. Therefore, the cointegration in altcoin prices is likely a manifestation of the trading environment rather than evidence of market inefficiency.

3. Experimental Design

This paper employs the standard approach to investigate the theoretical performance among event-study specifications by conducting simulations utilizing the actual pricing data. This approach is flexible enough to address the different research questions of this paper while ensuring the results are transferable to actual event-studies. Brown and Warner (1985) used this approach in concluding that the non-normality of the daily stock returns does not always result in loss of accuracy or miss-specifications of tests when used in event-studies. Similar to Brown and Warner, the overall purpose of the simulation is to determine under what situations the simpler and less computational heavy statistical tests can be used by researchers despite crypto-assets returns

[2] The data source they use is Coinmarketcap.com which reports prices in USD by converting the price feeds they receive by the prevailing BTC/USD market rate resulting in considerable translation bias.

exhibiting substantial deviations from normality. In addition, establish the limitations so that future researchers can account for them.

Results of the simulations are judged on the basis of Type 1 and Type 2 errors. A testing procedure is only considered well-specified if the non-normality, autocorrelation, cross-correlation inherent in crypto-asset data does not materially impact the type 1 error. Among the properly specified tests, the robustness is judged on its power in minimizing type 2 errors. The same approach is used to judge among different methodologies in calculating the excess return or benchmark selection. Returns are determined by $LN(P_t / P_{t-1})$, note that when the specification introduces abnormal return it presented as the nominal number but computed as above. The simulations are conducted in the software program R with the package event studies (Schimmer, Levchenko, and Müller, 2015).

3.1 General Notation

Unless otherwise defined, the following notation applies throughout the specifications. The return of crypto-asset i on day t is noted as R_{it}. The crypto-asset market return on day t is noted as R_{mt}. Abnormal returns for crypto-asset i on day t is noted as $AR_{i,t}$. The average abnormal returns across the sample for day t is found by dividing the sum of $AR_{i,t}$ by the number of crypto-assets in the sample and is noted as $AAR_{,t}$. The cumulative abnormal return for crypto-asset i is found by summing the $AR_{i,t}$ the event period and is noted by $CAR_{i,}$. The averaged cumulative abnormal return across the sample is found by dividing the sum of $CAR_{i,}$ by the number of crypto-assets in the sample and is noted as $CAAR_{.}$ The first day of the estimation period is noted by $T0$, the last day of the estimation window is $T1$ and the last day of the event window is $T2$. The total number of days in the event window is noted as $EvtW$ and in the estimation window is $EstW$. M_i is the number of non-missing observations for crypto-asset i.

3.2 Abnormal Return Models

The proper approach to calculating crypto-asset returns is still an open research question. Without adequate evidence for any specific crypto-currency factor pricing model, this study implements the primary methodologies used in Brown and Warner (1985). The methods of calculating abnormal returns of crypto-assets are the Market model (MM), Market-adjusted model (MAM) and the mean adjusted model (CPMAM).

The mean adjusted model (CPMAM) calculates each securities abnormal return as:

$$AR_{it} = R_{it} - \overline{R}_i \tag{1}$$

Where

$$\overline{R}_i = \frac{1}{T_1 - T_0} \sum_{t \in [T_0, T_1]} R_{it}$$

The market adjusted model (MAM) is determined by :

$$AR_{it} = R_{it} - R_{mt} \tag{2}$$

The market model (MM) is determined by :

$$AR_{it} = R_{it} - (\alpha_i + \beta_i * R_{mt}) \tag{3}$$

where β_i is a regression coefficient measuring the sensitivity of R_{it} to the market returns

3.3 Parametric Tests.

3.3.1 Cross-Sectional test (Csect-T)

The cross-sectional test was one of the earliest and most basic methods of testing a null hypothesis of zero average abnormal returns of a sample. This method expands the capabilities of the T-test by enabling the simultaneous testing of a multiple events. The test statistic of the cross-sectional test (Csect-t) for day t is:

$$t_{AAR_t} = \sqrt{N} \frac{AAR_t}{S_{AAR_t}} \tag{4}$$

Where the variance is determined by:

$$S^2_{AAR_t} = \frac{1}{N-1} \sum_{i=1}^{N} 1 \, (AR_{i,t} - AAR_t)^2 \tag{5}$$

To examine multi day events the null hypothesis of zero cumulative average abnormal returns, the test statistic of the cross-sectional test is:

$$t_{CAAR} = \sqrt{N} \frac{CAAR}{S_{CAAR}} \tag{6}$$

Where the variance is found by:

$$S^2_{CAAR} = \frac{1}{N-1}\sum_{i=1}^{N} 1\,(CAR_i - CAAR)^2 \tag{7}$$

3.3.2 Patell Test (PATELL)

The Cross-Sectional test primary limitation is its proneness to security specific volatility throughout the estimation period (Patell 1976). This is due to the test providing equal weights to the abnormal returns of all observations. Patell (1976) devised a methodology to correct for such by standardizing the AR of constituent in the sample. The unadjusted estimation period variance of the residuals (in the sense of deviations from predictions, not the residuals of OLS regression) of crypto-asset *i* is found by:

$$S^2_{AR_i} = \frac{1}{M_i - 2}\sum_{t=T_0}^{T_1}\left(AR_{i,t}\right)^2 \tag{8}$$

Since the above is out of sample, the standard error is then adjusted by the forecast error of the event window. The adjustment to the variance is as follows:

$$S^2_{AR_{i,t}} = S^2_{AR_i}\left(1 + \frac{1}{M_i} + \frac{(R_{m,t} - \overline{R}_m)^2}{\sum_{t=T_0}^{T_1} 1\,(R_{m,t} - \overline{R}_m)^2}\right) \tag{9}$$

To account for the security specific volatility each abnormal return is standardized by:

$$SAR_{i,t} = \frac{AR_{i,t}}{S_{AR_{i,t}}} \tag{10}$$

Where ASAR is the average scaled abnormal returns on day *t*, calculated as:

$$ASAR_t = \sum_{i=1}^{N} SAR_{i,t} \tag{11}$$

Since the number of observations varies between crypto-assets in the sample, the test statistic will have an expected value of zero with a variance close to one, calculated as:

$$S_{ASAR_t}^2 = \sum_{i=1}^{N} 1 \frac{M_i - 2}{M_i - 4} \tag{12}$$

The Patell test statistic is then calculated by:

$$z_{Patell,t} = \frac{ASAR_t}{S_{ASAR_t}} \tag{13}$$

To test the null hypothesis of zero cumulative average abnormal returns over the event window. The cumulative scaled abnormal returns are the sum of Equation (10),as determined by:

$$CSAR_i = \sum_{t=T_1+1}^{T_2} 1\, SAR_{i,t} \tag{14}$$

Since the number of observations varies between crypto-assets in the sample, the test statistic will have an expected variance of

$$S_{CSAR_i}^2 = EvtW. \frac{M_i - 2}{M_i - 4} \tag{15}$$

With the Patell's test statistic as:

$$z_{Patell} = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} 1 \frac{CSAR_i}{S_{CSAR_i}} \tag{16}$$

3.3.3 Adjusted Patell Test

Inherent in Patell test is the assumption of no correlation among the residuals of the abnormal returns. Even the smallest levels of correlation in residuals across security-events will lead to over rejecting the null hypothesis. Moreover, the misspecification magnifies as the number of securities in the sample increases (Kolari and Pynnönen's, 2010).

The test statistic for the adjusted Patell test is:

$$z_{adjusted\ Patell,t} = z_{Patell,t} \sqrt{\frac{1}{1+(N-1)\bar{r}}} \tag{17}$$

Where $z_{Patell,t}$ is the Patell test statistic and $\bar{r}$ is defined as the average of the sample cross-correlation of the estimation period abnormal returns. The adjusted Patell test can be used to test the null hypothesis of zero cumulative average abnormal returns "*assuming the square-root rule holds for the standard deviation of different return periods"* (Kolari and Pynnönen's, 2010). It is calculated by;

$$z_{Adj\ Patell} = z_{Patell}\sqrt{\frac{1}{1+(N-1)\bar{r}}} \tag{18}$$

3.3.4 Boehmer, Musumeci and Poulson Test (BMP)

The improvement in the Patell statistic implicitly requires the same variance for the scaled abnormal returns. As a result, when event-induced variance inflation exists, the denominator in the Patell statistics is artificially too low implying a greater likelihood of type one errors. In order to account for the presence of type one errors, Boehmer, Musumeci and Poulson (1991) developed, a more robust approach that estimated event-day volatility to standardize abnormal returns.

To test the null hypothesis of zero averaged abnormal returns on the test statistic for the BMP test is calculated by:

$$z_{BMP,t} = \frac{ASAR_t}{\sqrt{N}S_{ASAR_t}} \tag{19}$$

where $ASAR_t$ is determined in equation (11)and the scaled variance is determined by

$$S^2_{ASAR_t} = \frac{1}{N-1}\sum_{i=1}^{N} 1\left(SAR_{i,t} - \frac{1}{N}\sum_{l=1}^{N} SAR_{l,t}\right)^2 \tag{20}$$

To test the null hypothesis of zero cumulative average abnormal returns the BMP statistic is calculated by:

$$z_{Adjusted\ BMP} = \sqrt{N}\frac{\overline{SCAR}}{S_{\overline{SCAR}}} \tag{21}$$

Note the minor difference between Patell and BMPs scaling of cumulative abnormal returns. In Patells, the returns are each scaled and then aggregated (denoted as CSAR). In BMP, the CAR values are first determined and then scaled. The difference overcomes the sensitivity to the day of the event within the event window resulting from event induced volatility that Patells has. The scaled cumulative abnormal returns for crypto-asset i are calculated as shown in in Kolari and Pynnönen's, (2011) by

$$SCAR_i = \frac{CAR_i}{\left(s_{CAR_i}\right)_{*(mm,mam\ or\ CPmam)}} \tag{22}$$

The scaling is done with Mikkelson and Partch (1998) correction (S_{CAR_i} determined in Appendix 1) for serial correlation in the returns. To account for event-induced volatility the $SCAR_i$ in equation (22) is re-standardized (denoted with *) by the cross-sectional standard deviation as:

$$SCAR_i^* = \frac{SCAR_i}{S_{SCAR}} \tag{23}$$

The averaged scaled cumulative abnormal returns is:

$$\overline{SCAR_t} = \frac{1}{N}\sum_{i=1}^{N} SCAR_{i\ 0}^* \tag{24}$$

With a variance of

$$S_{\overline{SCAR_t}}^2 = \frac{1}{N-1}\sum_{i=1}^{N} 1 \left(SCAR_i - \overline{SCAR_t}\right)^2 \tag{25}$$

3.3.5 Adjusted BMP Test

As the BMP is simply a variation of the Patell test, the BMP test is also exposed to cross-sectional correlation of the scaled abnormal returns (Kolari and Pynnönen's, 2010). Kolari and Pynnönen's (2010) propose an adjusted BMP test statistic. The adjusted BMP test statistics for the null hypothesis of zero average abnormal returns is calculated as:

$$z_{BMP,t} = z_{BMP,t}\sqrt{\frac{1-\bar{r}}{1+(N-1)\bar{r}}} \qquad (26)$$

Similar to their previous modification to the Patell test, the adjusted BMP test adjusts $z_{BMP,t}$ calculated in equation (19) with the average of the sample cross-correlation of the scaled abnormal returns $\bar{r}$. The adjustment process to test the null hypothesis of zero cumulative average abnormal returns is the same as above. The adjusted BMP statistic adjusts z_{BMP} in equation (21) as calculated as:

$$z_{Adj\ BMP} = z_{BMP}\sqrt{\frac{1-\bar{r}}{1+(N-1)\bar{r}}} \qquad (27)$$

3.4 Non- Parametric tests.

3.4.1 Rank Test (RANK)

One of the most popular nonparametric tests used in event-studies is Corrado's (1989) rank test which transforms the daily returns into ordered ranks. The rank statistic using rank Z for testing the null hypothesis of zero abnormal returns on a single day is:

$$t_{rank,t} = \frac{\overline{K}_t - 0.5}{s_{\overline{K}}} \qquad (28)$$

Where $K_{i,t}$ is a standardization of the ranks by the number of non-missing values M_i+1 shown in equation (29) and the average standardized ranks is shown in (30) :

$$K_{i,t} = \frac{rank(AR_{i,t})}{1+M_i+NM_{EvtW}} \qquad (29)$$

$$\overline{K}_t = \frac{1}{N_t}\sum_{i=1}^{N_t}\left(\frac{rank(AR_{i,t})}{1+M_i+NM_{EvtW}}\right) \qquad (30)$$

Where the denominator of the test statistic is determined over the entire observation period as:

$$S_{\overline{K}}^2 = \frac{1}{(EstW)+(\text{EvtW})} \sum_{t=T_0}^{T_2} \frac{N_t}{N} \left(\overline{K}_t - 0.5\right)^2 \quad (31)$$

To test event windows of multiple days, Campbell and Wasley's (1993) definition of the test is required. The rank statistic for testing the null hypothesis of zero cumulative abnormal returns over the multiday period is:

$$t_{rank} = \sqrt{(\text{EvtW})} \left(\frac{\overline{K}_{T_1,T_2} - 0.5}{S_{\overline{K}}} \right) \quad (32)$$

Where the mean rank across firms and time in the event window is found by;

$$\overline{K}_{T_1,T_2} = \frac{1}{EvtW} \sum_{t=T_1+1}^{T_2} \overline{K}_t \quad (33)$$

3.4.2 Generalized Rank Test (GRANK-T)

Despite findings by Corrado's (1989) and Campbell and Wasley's (1993) that the rank test is well specified and powerful when tested on NYSE stocks and Nasdaq stocks, the test loses power over longer event windows. The test also omits any adjustments for event induced variance. Kolari and Pynnönen's, (2011) develop the generalized rank T-test to account for cross-correlation of returns and returns of serial correlation. It does so by condensing the event window into a single observation known as a "*cumulative event day*". To test the abnormality of the *cumulative event day*, the demeaned standardized abnormal ranks of each crypto-asset *i* are calculated by

$$U_{i,t} = \frac{rank(GSAR_{i,t})}{(\text{EstW})+2} - 0.5 \quad (34)$$

The generalized standardized abnormal returns (GSAR) are calculated in equation (23) and equation (10) and utilized in the rank determination as :

$$GSAR_{i,t} = \begin{Bmatrix} SCAR_i^* & \text{for t in event window} \\ SAR_{i,t} & \text{for t in estimation window} \end{Bmatrix} \quad (35)$$

The average rank of a particular time t, is done by

$$\overline{U}_t = \frac{1}{N_t} \sum_{i=1}^{N_t} 1\, U_{i,t} \tag{36}$$

Defining the observation window as consisting of the estimation window and the *cumulative event day*. The variance of the ranks used in the denominator of equation (39) is calculated by

$$S_{\overline{U}}^2 = \frac{1}{(\text{EstW}) - 1} \sum_{t \in ObsW} \frac{N_t}{N} * \overline{U}_t^{(2)} \tag{37}$$

It should be noted, setting t equal to zero indicates day zero when testing a single day and the *cumulative event day* if testing an event window. This is one of the appealing factors as a single test statistic can be used for both single and cumulative null hypothesis. The generalized rank test (GRANK-T) is t-distributed the number of days in the estimation period minus one degrees of freedom. The test statistic is given by Kolari and Pynnönen's, (2011) and is calculated as:

$$t_{grank} = Z \left(\frac{(\text{EstW}) - 1}{(\text{EstW}) - Z^2} \right)^{\frac{1}{2}} \tag{38}$$

Where

$$Z = \frac{\overline{U_0}}{S_{\overline{U}}} \tag{39}$$

<u>3.4.3 Generalized Rank Z (GRANK-Z)</u>

Kolari and Pynnönen's, (2011) demonstrated that for a sufficiently large sample size, a simplified test statistic could be used. This test allows for the generalized rank to converge under the null hypothesis of zero cumulative average abnormal returns to a standard normal distribution, as the sample size increases. The primary drawback compared to the GRANK-T is the ability to control for cross sectional correlations.

The generalized rank Z (GRANK-Z) stat:

$$z_{grank} = \frac{\overline{U_0}}{S_{\overline{U_0}}} = \sqrt{\frac{12N((\text{EstW})+2)}{(\text{EstW})}}\, \overline{U_0} \tag{40}$$

The manipulation is to obtain the standard error of $\overline{U_0}$ is done by:

$$S^2_{\overline{U_0}} = \frac{(\text{EstW})}{12N((\text{EstW}) + 1)} \tag{41}$$

3.4.4 Generalized Sign Test (G-SIGN)

With a high skewness inherent in several crypto-asset return distributions, the final testing method examine in this study was the Cowan, A.R.'s (1992) generalized sign test (generalized sign Z). The generalized sign Z expects that under the null hypothesis of zero abnormal returns, the proportion of crypto-assets with positive abnormal returns is expected to be a similar proportion ($\hat{p}$) of positive abnormal returns from the estimation period,

$$\hat{p} = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{(\text{EstW})} \sum_{t=T_0}^{T_1} \varphi_{i,t} \tag{42}$$

where $\varphi_{i,t}$ is a binomial factor with a value of 1 representing if the sign is positive and a value of 0 otherwise for crypto-asset *i* at time *t*. If the positive CAR is significantly higher than expected from the estimation window, the null hypothesis of zero cumulative abnormal returns is rejected, as tested by the generalized sign test statistic of:

$$z_{sign} = \frac{(w - N\hat{p})}{\sqrt{N\hat{p}(1 - \hat{p})}} \tag{43}$$

where w is the number of crypto-assets demonstrating positive cumulative abnormal returns over the event period. The test stat assumes a normal approximation of the binomial distribution with parameters ($\hat{p}$) and N.

3.5 Data Collection

Crypto-Asset data

Crypto-Assets, as a whole, represent a relatively new asset-class which presented numerous problems during the data collection process. To date there does not exist any database similar to CRSP or DataStream used in previous literature. In the absence of a database it was first attempted to retrieve the pricing data from the exchanges that each crypto-asset trades on. Unfortunately, this proved infeasible as many exchanges blocked access to non-registered users with terms excluding

Canadians due to regulatory laws. To overcome these issues, previous literature investigating cryptocurrencies have primarily used Coinmarketcap.com (Ciain et al, 2017). However, Coinmarketcap.com contains two fatal flaws that would have induced bias into the analysis. First, the data would have substantial survivorship bias as the website removes all evidence of a crypto-asset once it makes the decision to delist them. Second, the website does not provide the prices in terms of BTC resulting in considerable translation error[3] as most crypto-assets trade in terms of BTC.

Following an analysis of similar aggregation sites, Coingecko.com was selected due to the following reasons. I) among the largest coverage of the crypto-asset universe with 1887 crypto-assets as of June 30th, 2018 ii) free from survivorship bias and translation error and iii) matches the data source used by the benchmark index. Coingecko calculates each crypto-assets price based on a volume weighted average among all trading pairs at all supported exchanges.

Benchmark Data

Index calculation methodologies for traditional assets have a rich history in literature. However, none of which can be directly applied to cryptocurrencies. To the best of my knowledge, the CRIX index (Trimborn and Hardle, 2018) is the only cryptocurrency index created based on a methodology that has undergone a peer-review. The CRIX index is value weighted with a dynamic number of constituents to account for the fast-changing nature of cryptocurrencies. Data for the CRIX index (Trimborn and Hardle, 2018) was requested and graciously provided for the analysis. To test the performance of using an equal-weighted benchmark the analysis used the equal weighted top 100 index from cryptoz.ai. It was selected as it was the only equal weighted index that covered the entire sample period.

4. Results

Table 2 Panel A reports the descriptive statistics of the daily price returns of the entire sample. Among all crypto-assets there are a total of 637,497 unique crypto-asset daily prices. The returns are grouped in rows by the amount of daily price points in the dataset. As expected, the returns exhibit substantial deviations from normality, with substantial excess kurtosis and positive

[3] During much of the time period examined the largest exchanges (such as Bittrex.com) did not have USD or any FIAT currency based trading pairs. All prices from the exchanges such as this are recorded in BTC. The USD prices listed on sites like Coinmarketcap.com translate it to USD based on prevailing BTC/USD rates from other exchanges.

skewness. Several of the outrageous returns were verified for accuracy and found to be the result of two issues. The first is the presence of "pump and dump" market manipulation (Hamrik et al, 2018). The second is due to exchanges altering the tickers used for a particular crypto-asset or altering the trading pair currencies without notifying Coingecko. As a result, the recorded in prices in the dataset often jump significantly. Given that one issue represents true price changes, while the other was a data issue to be conservative the extreme points could not be removed from the analysis. The trimmed means highlight how outlier driven the daily returns are.

[insert Table 2 about here]

Table 2 Panel B reports the descriptive statistics of the daily returns of the index. Compared to the crypto-asset returns, the index has positive average returns and negative skewness. The extreme volatility of the crypto-asset market as a whole highlight the challenges of conducting event-studies. The most obvious implication that must be considered throughout the specifications is the contrasting skewness of crypto-assets and index returns.

4.1 Impact of Data Skewness

Prior to examining test specifications, it is beneficial to understand how the contrasting skewness impacts each abnormal return model. The most severely impacted model is the market-adjusted model. On any given day we would expect to subtract the median of the market return from the median of the crypto-assets return to determine the abnormal return. Where the median of the market is expected to be larger than its assumption of the mean return and the median of the crypto-assets return is expected to be lower than its mean. The result compounds and produces a negative bias in the abnormal return estimates. Moreover, the issue worsens rather than improves by using a greater the number of days in the event-window as the mean returns are also contrasting. This conclusion is evident in table 4 (VW) and table 7 (EW) models. As the number of days in the event window increase the CAAR becomes increasingly negative. This biases the test statistics, resulting in over rejection of the null

The comparison period mean adjusted model is similarly biased in that on any given day we would expect to subtract the mean of the crypto-assets estimation period return, from the median of the crypto-assets return to determine the abnormal return. As a result of the positive skewness the estimation period mean return is expected to be greater than the median and on a single day will result in a negative bias in the abnormal return. However, unlike the MAM this bias naturally corrects itself as the number of days in the event-window increases.

Finally, the market model is expected to be the least impacted as the intercept term of the regression should adjust, so that given the mean index return the fitted line predicts the mean crypto-asset return. This is evident in table 3 (VW) and table 6 (EW) as none of the CARs are statistical different from zero. An important caveat to this, is the assumption that the market model does not have any omitted variable bias.

4.2 Simulated Test Statistics

In this section the results are based on 250 simulations, each with 50 randomly selected crypto-assets with replacement. Prior to randomization, crypto-assets which have been forked or ICOd within the previous 70 days are removed. Second, following previous literature (Campbell et al, 2010) the universe is further restricted to only select securities that have at least 5 days of available post event-day-price data. Samples are then drawn from the resulting subset of 431 995 crypto-asset daily price pairs. The results are shown in tables 3-7.

[insert table 3-7 about here]

Under the null hypothesis of no abnormal returns, the distribution of the simulated test statistics of the parametric tests and that of GRANK-Z should be approximately distributed N(0,1). The non-parametric distributions of GRANK-T and RANK should be as discussed in the methodology section, however with a 100-day estimation period they should approach normality and for brevity are assumed do so for the purpose of this discussion. Regardless of the abnormal return model or the benchmark calculation the simulations show that the statistics are significantly impacted from the data characteristics of crypto-assets.

Using the value-weighted market model (table 3) for discussion, several conclusions can be made. Comparing the kurtosis of the Patell and the BMP test statistics it is evident that the event day volatility adjustment is vital in crypto-asset event-studies. The Cross-sectional test appears to be well specified, although the excess Kurtosis is negative across all panels likely indicating that the test will have low power. Surprisingly, the ten day event windows seems to cause issues for the Patell, adj-PATELL, GRANK-T and GRANK-Z statistics that would be expected to also be present in the twenty day window but are not. The most likely explanation of this is the relatively small simulation size (250 simulations) combined with the previously mentioned extreme data issues. Comparing to the other specifications it appears that contrary to traditional stocks (Corrado and Truong, 2008) a value-weighted index results in better test statistics than an equal-weighted market model.

4.3 Rejection frequencies

The rejection frequencies with zero abnormal return are shown in tables 8 through 11. Table 8, Table 10 panel A and Table 11 panel A simulations are done with the previously described randomization. In Table 9 (Table 10 panel B), the randomization adds the additional steps of randomly selecting a day and selecting one of the largest 100 crypto-assets on that day. This is repeated with replacement to select 50 (10,25,50 or 100) crypto-assets. Panel B of table 11 conducts a simulation for which there are clustered event days. The randomization once again first selects a single day. In the next step it randomly selects (10, 25, 50 or 100) crypto-assets from that day. With the exception of the Patell and adj-Patell statistics the majority are relatively robust to miss-specification for the single day and three-day event windows. Additional implications are presented in the discussion section.

[insert Table 8 to 11 about here]

The power of the tests to detect introduced abnormal returns are shown in tables 12 through 15. Each seeded return used is simulated 250 times with 50 sample crypto-assets. The seeded returns of -10%, -3%, -1%, 1%, 3% and 10% are given at the top of each column for the preferred market model specifications. The CPMAM and MAM specifications test only -10%, -3%, 3% and 10% introduced abnormal returns.

[insert Table 12 to 15 about here]

5.0 Discussion

The contribution of this study is best understood from the context of a researcher conducting an event-study. The normal process selects the methodology that both accounts for the underlying data characteristics and enables the most precise estimation of the variance used to determine the test statistic. Given the non-normality of crypto-asset returns, without any empirical evidence the proper approach is to implement adjustments for cross-sectional dependence and event-induced volatility. These adjustments reduce the ability to detect abnormal returns. As shown in the simulated results of the Csect test, the adjustments are so severe detecting abnormal returns of -10% and +10% results in type ii errors in the range of 90% seen in tables 12-15. Moreover, absent empirical evidence the researcher is unaware of the power of the test to detect abnormal returns. Each of these are discussed below.

5.1 Estimation precision

Understanding the relationship between each of the test-statistics provides a guideline for which situations allow more precise estimations. When the residuals of the *cumulative scaled* abnormal returns are uncorrelated, then the adj-PATELL will be equivalent to the PATELL. Similarly. if the residuals of the *scaled cumulative* abnormal returns are uncorrelated, then adj-BMP reduces to the BMP. Correlated residuals can result from event-day clustering and omitted variable bias in the selected abnormal return model. Table 11 Panel B, shows that in the presence of event-day clustering it is highly recommend to use the adjusted versions defined by Kolari and Pynnönen (2010). However, if there is no event day clustering as in Panel A the standard BMP approach can be used with caution.

The BMP will be approximately the same as the PATELL, when there is no event-induced variance inflation. Under this condition forgoing the variance adjustment can provide a more precise estimation. However, as seen in both table 10 and table 11 the PATELL test is prone to type 1 errors. As a result researchers should strongly consider against using the PATELL under any circumstance.

Kolari and Pynnönen (2011) for ease of estimation, define the GRANK-Z as an approximation that can be used for the GRANK-T under the assumption that returns are not cross-correlated. Similar to the parametric tests the simulations results of table 11 reveal that in the case of crypto-assets it is advised against using the GRANK-Z when the event days are clustered. The type 1 error increases as the sample size increases. Unfortunately, event-day clustering has an even greater impact on the generalized sign test. With rejection rates reaching 17.6%-21.2% in a sample size of 100.

5.2 Power of test statistics

As expected from the discussion on the issues of skewness in the market adjusted model, the result is an greater ability to detect negative abnormal returns than positive ones. As shown in table 14 (-3% and +3%) for both the parametric tests and non-parametric tests the type ii error is significantly larger (lower rejections of Null hypothesis) in the right tail. In table 14, the tests for the CPMAM model have significantly greater power to detect 3% abnormal returns when considering the event day. This power decreases significantly when testing for cumulative abnormal returns. Moreover, for all tests the power to detect cumulative abnormal returns in the right tail is significantly greater. This can be explained by the positive skewness and excess kurtosis of the crypto-assets returns, as the number of days within the event-window increases the likelihood that at least one of those returns is from the fat-right tail increases.

The results of the preferred market model specification are shown in table 12 and table 13. The PATELL and adj-PATELL statistics should not be used due to the type 1 error seen in the middle columns with zero abnormal return. Moving outwards to the 1% seeded returns we quickly see that the best performing tests are the G-Sign and GRANK-T. However, as discussed in the previous section the G-Sign test is prone to type 1 errors when event days are clustered. Therefore, the final recommendation is to use the GRANK-T test when possible.

5.3 Limitations

There are two primary limitations that should be addressed in future research. The first is that the methodology only considers exchange-based volume of crypto-assets trades. Incorporating the volume (transactions) that occur through the blockchain network itself will be required to make complete and accurate inferences. The other primary limitations of this study relate to the market indexes. As previously highlighted the study employed the CRIX and EW100 indexes as the market returns, both of which are maintained by third parties. In addition to concerns of accuracy in the methodologies of the indexes themselves, the use of third party indexes increases the potential for calculation errors. For instance, this may explain the relatively poorer performance of the equal weighted index. The value-weighted CRIX index is calculated using the same source of data as the crypto-asset returns. However, the EW100 index uses a different source of data which it is possible that "closing" of each day due to time zone differences do not match that of the individual crypto-assets. Moreover, the index returns do not fully represent the market as the CRIX only includes 30 constituents and the EW100 only includes 100 crypto-assets. A lack of data limits this studies ability to purse the obvious solution to these concerns of creating a new market index. Specifically, the dataset was unable to consistently determine the weightings[4] of constituents for value-weighted and unable to account for "forks[5]" for equal weighted index calculations. Nonetheless, the viability of commercial indexes as examined in this paper is an important contribution as it enables their use in event-studies of future researchers.

The secondary limitations include the number of simulations and underlying data accuracy. The number of simulations while consistent with early literature (Brown and Warner, 1985) is about one fourth (250) the amount used in recent literature (Kolari and Pynnönen, 2010). Given the presence of a substantial number of extreme data points in the sample its possible that results could change with an increased simulation size. The extreme data points were the result of both true market movements (pump and dump) and data transcription errors by the exchanges. Although this study was unable to distinguish between the two, recent literature suggests that it may be possible to use machine learning to predict pump and dump schemes (Xu and Livshits, 2018) which may overcome this limitation.

6. Application: Insider Trading at Binance.com

The original inspiration of this study was the desire to investigate market manipulation, insider trading and fraud in the unpoliced crypto-asset world. Following the empirical evidence provided by the simulations these research questions can now be addressed. Although not the direct purpose of the study it is beneficial to conduct an actual event-study to illustrate the aforementioned findings. The chosen event-study is to determine if there is evidence of insider trading preceding the announcement of a crypto-assets listing on what is now the worlds largest crypto-asset exchange Binance.

The date of the announcements that Binance intends to list a crypto-asset was collected from binance.com for the period of September 2017 and June 2018. This resulted in a total of 67 different crypto-assets. However, several of the assets had less than 40 trading days prior to the

[4] A key differentiator of crypto-assets is the concept of mining rewards increasing the outstanding supply. Although these can be approximated by an inflation rate, the inflation rates do not remain constant instead often varying dynamically as a function of network hash rates.
[5] A blockchain fork is when a crypto-currency splits into two distinct crypto-assets. In such cases investors now own 1 of each crypto-asset. Therefor to accurately calculate the assets return on the day it forks, knowledge of all forks must be known.

announcement and were dropped from the analysis. The remaining sample consisted of a total for 44 announcements which is similar to the sample size in the simulation.

The first stage of the event-study determined the average abnormal returns for the 5 days preceding and following the announcement. As shown in figure 1, the event appears to have caused significant price movements with the averaged abnormal returns exceeding 8% on the day following the announcement

[insert figure 1 about here]

The CAR(-5,5) results shown in panel (A) of table 16 highlight the difficulty of performing event studies on cryptocurrencies. Despite seemingly clear evidence from both the returns in figure 1 and a market perception that gaining a listing on Binance is considered to be a positive event, many of the statistical measures fail to reject the null at a 5% level of significance. Moreover, the only one that does (PATELL) as found in the simulation results likely did so because of the event-induced volatility. It should be noted that there was several occurrences where the announcements included more than one crypto-asset. This likely resulted in cross-correlation in abnormal return residuals. As suggested by the simulation analysis, in such a case of event-day clustering the preferred test-statistic is the GRANK-T. Examining the AARs of day -3,-2,-1 in table 17 and the CAR(-3,-1) in table 16 we fail to reject the null hypothesis of zero abnormal return for any of the days leading up to the announcement. At 95% significance the GRANK-T test does not indicate evidence of insider trading prior to announcements. Despite the briefness, this example highlights the significant contribution of the simulation results for regulators pursuing market manipulation.

[insert table 16 and 17 about here]

Conclusion

This study was the first to explore the suitability of utilizing crypto-asset returns to conduct event studies. Using the simulation approach pioneered by Brown and Warner (1985) the performance of five parametric and four non-parametric test statistics were examined under three different abnormal return models and two index specifications. The results of the simulations indicate that the non-normality of crypto-asset returns impacts the performance of most specifications. Due to the contrasting skewness of the market index and crypto-asset returns the market-adjusted model should be avoided. The market-model with a value weighted index, was found to have tests statistics with distributions that most closely resembled expectations. When there is no-event day clustering the recommended parametric test is the BMP test and the recommend non-parametric test are the GRANK-T and G-SIGN statistics. However, with event-day clustering the GRANK-T is the only suitable test that maintains significant power. The results of the simulation proved vital at avoiding type one error in an exploratory event-study of insider trading prior to announcements made by the exchange Binance. Overall, the findings should give confidence to future researchers that crypto-asset returns can be used in event-studies.

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Appendix

Appendix A: Mikkelson and Partch (1988) equations

Mikkelson and Partch (1988) correction of (S_{CAR_i}) for equation (23). Note that NM_{EvtW} indicates the number non-missing days in the Event Window.

Market Model:

$$S_{CAR_i}^2 = S_{AR_i}^2 \left(+ \frac{NM_{EvtW}^2}{M_i} + \frac{\left(\sum_{t=T_1+1}^{T_2} 1 \left(R_{m,t} - \overline{R}_m \right) \right)^2}{\sum_{t=T_0}^{T_1} 1 \left(R_{m,t} - \overline{R}_m \right)^2} \right)$$

Comparison Period Mean Adjusted Model:

$$S_{CAR_i}^2 = S_{AR_i}^2 \left(NM_{EvtW} + \frac{NM_{EvtW}^2}{M_i} \right)$$

Market Adjusted Model:

$$S_{CAR_i}^2 = S_{AR_i}^2 * NM_{EvtW}$$

Tables and Figures

Table 1: Summary of Test Statistics

	Test	Prone to	Improvement	Drawback
Parametric	CSect-T	Low power		
	Patell	Over rejection of null when cross-correlation in residuals	Standardized abnormal returns to account for security specific volatility	The PATELL test assumes that scaled abnormal returns have the same variance.
	Adj-Patell		Accounts for cross-correlation in abnormal return residuals	
	BMP	Over rejection of null when cross-correlation in residuals	Removes dependency of the order of days in Patell	Same as Patell
	Adj-BMP		Same as Adj-Patell	
		Prone to	**Improvement**	**Drawback**
Non-Parametric	Sign	Low Power	Accounts for Skewness	
	Rank	Low power	Accounts for non-normality	Poor performance over longer event windows
	Generalized Rank T-test. (GRANK-T)		Uses the idea of BMP to create a single *cumulative event day*, which is then ranked. Overcomes the loss of power as days in the event window increase.	Computationally difficult
	Generalized Rank Z-test (GRANK-Z)	Over rejection of null when cross-correlation in residuals	Reduced computational requirements	

Table 2: Descriptive Statistics

Panel A: Daily Crypto-Asset Returns

Descriptive Statistics for Equally Weighted Average Daily Returns by Individual Crypto Assets										
Number of price points	Total	Average Return	Average 5% Trim	Average Median Return	Average Min	Average Max Return	Average Kurtsosis	Average Skewness	% Min < - 1.00	%Max > 1.00
Entire sample	1887	-0.66%	-0.88%	-0.73%	-1.399	1.496	22.971	0.469	39.7%	44.6%
>50	1785	-0.61%	-0.84%	-0.69%	-1.448	1.552	23.744	0.492	41.3%	46.4%
>100	1593	-0.49%	-0.73%	-0.63%	-1.483	1.608	24.842	0.535	42.4%	48.5%
>500	359	-0.12%	-0.42%	-0.35%	-1.931	2.124	47.548	0.643	63.8%	74.7%
>1000	203	-0.03%	-0.33%	-0.30%	-1.911	2.104	50.559	0.743	59.6%	72.9%

Panel A presents the average descriptive statistics among the crypto-asset daily price returns in the entire sample. The rows are separated by the number of price points in the dataset an individual crypto-asset has. With the exception of the final two columns the averages presented are the unweighted averages of each individual Crypto-Assets descriptive statistics. The final two columns indicate the percentage of the Crypto-Assets included in that row which had at least one day where $LN(P_t/P_{t-1})$ was less than and greater than one.

Panel B: Daily Index Returns

Index	Average Return	Median	Standard Deviation	Minimum	Maximum	Kurtosis	Skewness
Panel A Index							
CRIX	0.0028	0.0032	0.0399	-0.2533	0.1985	6.5559	-0.7908
EW100	0.0033	0.0033	0.0513	-0.4583	0.4478	12.4100	-0.4505
Panel B Comparable References							
VW10	0.0022	0.0023	0.0390	-0.2373	0.1832	6.0219	-0.8466
VW20	0.0023	0.0024	0.0392	-0.2383	0.1837	6.0587	-0.8942
VW50	0.0023	0.0023	0.0393	-0.2371	0.1817	6.0332	-0.9065
VW100	0.0023	0.0024	0.0393	-0.2383	0.1811	6.0333	-0.9159
EW 10	0.0025	0.0015	0.0472	-0.2950	0.2122	5.7770	-0.5740
EW20	0.0029	0.0012	0.0469	-0.2933	0.1847	4.0765	-0.6015
EW50	0.0029	0.0017	0.0475	-0.2935	0.2715	5.3839	-0.4470

Source: Cryptoz.ai for all except CRIX. Crix is as described in Trimborn, S., & Härdle, W. K. (2018).

Panel B presents the average daily returns of indexes during sample period beginning on January 1st 2015 and ending on June 30th 2018. The CRIX index is value weighted with dynamic constituents that adjust for thinly traded tokens. The EW100, is an equally weighted index of the top 100 cryptocurrency based by estimated market capitalization. Similarly EW(10,20,50) represented equally weighted returns based on the top 10, 20 and 50 crypto-assets. VW(10,20,50,100) represent the value-weighted returns for the same constituents as the equally weighted indexes. Rebalancing is done at the beginning of each month, retrieved from Cryptoz.ai.

Table 3: Simulated test statistics for Market Model-Value Weighted Entire Sample

Market Model

Panel A	Mean		Median	Std	Kurtosis	Skewness
AAR (0)	-0.006		-0.008	0.087	4.692	-0.187
RANK	-0.019		-0.012	1.030	2.874	0.170
PATELL	0.006		0.019	6.628	123.067	-8.783
adj-PATELL	0.005		0.019	6.628	122.997	-8.778
Csect T	-0.069		-0.127	0.972	2.321	0.185
adj-BMP	0.020		0.018	0.967	2.443	-0.005
GRANK-T	0.098	*	0.150	0.998	3.103	-0.268
G-SIGN	-0.004		-0.013	1.030	2.970	0.196
GRANK-Z	0.099	*	0.139	0.988	3.083	-0.199
Panel B	**Mean**		**Median**	**Std**	**Kurtosis**	**Skewness**
CAR(-1,+1)	0.008		-0.004	0.121	4.421	0.213
PATELL	0.183		0.041	2.971	29.709	1.921
adj-PATELL	0.181		0.043	2.890	21.547	1.112
Csect T	0.003		-0.072	0.970	2.181	0.022
BMP	0.050		0.060	0.967	2.384	-0.012
adj-BMP	0.032		0.031	1.036	2.351	-0.112
RANK	0.024		-0.026	0.820	2.839	0.161
GRANK-T	0.013		-0.023	0.953	3.375	-0.147
G-SIGN	-0.091	*	-0.060	0.897	3.118	-0.014
GRANK-Z	0.015		-0.022	0.938	3.228	-0.091
Panel C	**Mean**		**Median**	**Std**	**Kurtosis**	**Skewness**
CAR(−5,+5)	0.000		0.000	0.164	3.208	0.066
PATELL	0.790	***	0.365	2.733	29.552	4.337
adj-PATELL	0.772	***	0.345	2.712	33.235	4.537
Csect T	-0.031		-0.003	0.975	2.550	0.027
BMP	0.226	***	0.432	0.970	2.835	-0.174
adj-BMP	0.299	***	0.463	0.969	2.387	-0.226
RANK	-0.006		-0.007	0.738	2.569	0.055
GRANK-T	-0.157	**	-0.047	1.110	3.163	-0.319
G-SIGN	-0.204	***	-0.129	0.992	3.147	-0.179
GRANK-Z	-0.156	**	-0.051	1.089	3.117	-0.321
Panel D	**Mean**		**Median**	**Std**	**Kurtosis**	**Skewness**
CAR(−10,+10)	-0.002		-0.002	0.204	4.113	-0.230
PATELL	0.206		0.459	7.656	205.860	-13.481
adj-PATELL	0.175		0.462	8.384	212.573	-13.837
Csect T	-0.054		-0.009	0.959	2.388	-0.066
BMP	0.301	***	0.394	1.037	3.596	-0.269
adj-BMP	0.345	***	0.520	1.051	2.622	-0.272
RANK	-0.081	**	-0.126	0.773	2.959	0.197
GRANK-T	-0.075		-0.024	1.089	4.136	-0.200
G-SIGN	-0.103	**	-0.079	0.947	3.179	-0.004
GRANK-Z	-0.073		-0.026	1.081	3.731	-0.125

*,**,*** indicate significance at the 10%, 5% and 1%.

Descriptive statistics of the simulated test statistics values (tables 3 to 7). Calculation methodology described following table 7.

Table 4: Simulated test statistics for Market Adjusted Model- Value Weighted Entire Sample

Market Adjusted Model

Panel A	Mean	Median	Std	Kurtosis	Skewness
AAR (0)	-0.001	-0.005	0.084	4.831	0.171
RANK	0.005	0.024	0.992	2.750	-0.062
PATELL	0.027	-0.124	4.481	59.627	-3.794
adj-PATELL	0.027	-0.124	4.484	59.518	-3.780
Csect T	-0.100 *	-0.132	1.000	2.309	-0.038
adj-BMP	-0.157 ***	-0.102	1.003	2.197	-0.143
GRANK-T	0.131 **	0.281	0.988	2.982	-0.516
G-SIGN	0.046	0.030	0.971	2.835	0.034
GRANK-Z	0.132 **	0.278	0.984	2.876	-0.483
Panel B	**Mean**	**Median**	**Std**	**Kurtosis**	**Skewness**
CAR(-1,+1)	0.002	-0.003	0.115	4.750	0.270
PATELL	-0.184	-0.246	2.443	27.688	-2.390
adj-PATELL	-0.207	-0.245	2.638	35.468	-3.223
Csect T	-0.067	-0.037	1.010	2.424	-0.134
BMP	-0.210 ***	-0.292	0.993	2.693	0.061
adj-BMP	-0.277 ***	-0.335	0.990	2.778	0.105
RANK	0.000	-0.034	0.772	3.437	0.016
GRANK-T	-0.142 **	-0.092	1.017	3.830	-0.277
G-SIGN	-0.233 ***	-0.260	0.975	3.424	0.153
GRANK-Z	-0.136 **	-0.095	1.006	3.675	-0.223
Panel C	**Mean**	**Median**	**Std**	**Kurtosis**	**Skewness**
CAR(−5,+5)	-0.020 **	-0.028	0.151	3.430	0.116
PATELL	-0.079	-0.294	1.895	18.692	2.871
adj-PATELL	-0.098	-0.280	1.851	17.234	2.637
Csect T	-0.269 ***	-0.223	1.060	2.629	-0.178
BMP	-0.413 ***	-0.373	1.044	2.344	-0.234
adj-BMP	-0.462 ***	-0.511	1.061	2.279	-0.093
RANK	-0.147 ***	-0.139	0.727	2.857	-0.122
GRANK-T	-0.606 ***	-0.390	1.137	2.834	-0.441
G-SIGN	-0.524 ***	-0.514	1.026	2.753	-0.072
GRANK-Z	-0.599 ***	-0.417	1.122	2.634	-0.392
Panel D	**Mean**	**Median**	**Std**	**Kurtosis**	**Skewness**
CAR(−10,+10)	-0.020 **	-0.038	0.165	3.054	0.104
PATELL	-0.351 ***	-0.377	1.486	4.761	-0.219
adj-PATELL	-0.338 ***	-0.350	1.461	4.489	0.031
Csect T	-0.247 ***	-0.326	1.038	2.486	-0.067
BMP	-0.410 ***	-0.466	1.057	2.658	-0.137
adj-BMP	-0.464 ***	-0.498	1.048	2.353	-0.093
RANK	-0.052	-0.103	0.754	3.419	0.104
GRANK-T	-0.572 ***	-0.496	1.066	3.086	-0.181
G-SIGN	-0.494 ***	-0.535	0.937	2.698	0.167
GRANK-Z	-0.569 ***	-0.500	1.059	2.976	-0.109

*,**,*** indicate significance at the 10%, 5% and 1%.

Descriptive statistics of the simulated test statistics values (tables 3 to 7). Calculation methodology described following table 7.

Table 5: Simulated test statistics Comparison Period Mean Adjusted Model Entire Sample

Comparison Period Mean Adjusted Model					
Panel A	**Mean**	**Median**	**Std**	**Kurtosis**	**Skewness**
AAR (0)	-0.005	-0.008	0.086	4.681	-0.146
RANK	0.010	-0.031	1.032	2.973	0.126
PATELL	-0.005	-0.021	6.197	118.732	-8.594
adj-PATELL	-0.005	-0.021	6.196	118.591	-8.585
Csect T	-0.064	-0.098	0.984	2.140	0.070
adj-BMP	0.001	-0.018	0.965	2.447	-0.025
GRANK-T	0.124 **	0.195	1.032	2.964	-0.284
G-SIGN	-0.038	-0.099	1.078	3.035	-0.058
GRANK-Z	0.128 **	0.194	1.021	2.924	-0.283
Panel B	**Mean**	**Median**	**Std**	**Kurtosis**	**Skewness**
CAR(-1,+1)	0.010 *	0.000	0.119	4.746	0.300
PATELL	0.144	0.040	2.606	16.246	-0.009
adj-PATELL	0.145	0.041	2.625	15.290	-0.318
Csect T	0.024	-0.004	0.962	2.386	-0.056
BMP	0.044	0.041	0.977	2.635	-0.086
adj-BMP	0.003	0.063	1.040	2.427	-0.165
RANK	0.034	-0.004	0.774	2.868	0.077
GRANK-T	-0.032	-0.001	1.005	3.470	-0.325
G-SIGN	-0.190 ***	-0.144	0.923	3.480	-0.157
GRANK-Z	-0.030	0.000	0.995	3.279	-0.269
Panel C	**Mean**	**Median**	**Std**	**Kurtosis**	**Skewness**
CAR(−5,+5)	-0.002	-0.006	0.163	3.095	0.099
PATELL	0.613 ***	0.363	2.200	17.823	3.098
adj-PATELL	0.586 ***	0.346	2.122	16.879	2.901
Csect T	-0.089 *	-0.047	1.047	2.618	-0.152
BMP	0.194 ***	0.324	0.994	2.598	-0.227
adj-BMP	0.228 ***	0.338	0.983	2.591	-0.144
RANK	-0.057	-0.065	0.747	2.662	0.024
GRANK-T	-0.306 ***	-0.231	1.189	2.983	-0.349
G-SIGN	-0.327 ***	-0.412	0.948	2.952	0.132
GRANK-Z	-0.310 ***	-0.241	1.171	2.856	-0.352
Panel D	**Mean**	**Median**	**Std**	**Kurtosis**	**Skewness**
CAR(−10,+10)	0.013	-0.001	0.191	3.597	-0.119
PATELL	0.013	0.384	7.418	229.346	-14.771
adj-PATELL	-0.004	0.382	7.961	232.563	-14.924
Csect T	0.006	-0.006	0.983	2.381	-0.071
BMP	0.303 ***	0.384	1.045	3.025	-0.284
adj-BMP	0.298 ***	0.409	1.055	2.691	-0.311
RANK	-0.068 *	-0.101	0.736	2.839	0.034
GRANK-T	-0.201 ***	-0.138	1.125	3.866	-0.331
G-SIGN	-0.168 ***	-0.163	0.943	3.124	-0.114
GRANK-Z	-0.193 ***	-0.132	1.102	3.356	-0.256

*,**,*** indicate significance at the 10%, 5% and 1%.

Descriptive statistics of the simulated test statistics values (tables 3 to 7). Calculation methodology described following table 7.

Table 6: Simulated test statistics Market Model Equally Weighted Entire Sample

Equal weighted market model					
Panel A	**Mean**	**Median**	**Std**	**Kurtosis**	**Skewness**
AAR (0)	0.002	-0.005	0.089	8.994	0.721
RANK	-0.077 *	-0.018	0.894	3.053	0.033
PATELL	0.576 **	0.027	4.448	26.250	2.648
adj-PATELL	0.576 **	0.027	4.445	26.201	2.656
Csect T	-0.049	-0.084	0.982	2.073	-0.022
adj-BMP	-0.001	0.027	0.956	2.648	-0.126
GRANK-T	0.131 ***	0.188	0.842	3.846	-0.135
G-SIGN	-0.055	-0.043	0.908	2.743	0.080
GRANK-Z	0.133 ***	0.194	0.828	3.611	-0.190
Panel B	**Mean**	**Median**	**Std**	**Kurtosis**	**Skewness**
CAR(-1,+1)	-0.002	-0.004	0.123	5.113	0.087
PATELL	0.708 ***	0.130	3.603	12.962	2.177
adj-PATELL	0.734 ***	0.123	3.742	13.012	2.192
Csect T	-0.029	-0.067	1.030	2.153	0.039
BMP	0.013	0.163	1.053	2.385	-0.331
adj-BMP	-0.012	0.198	1.090	2.357	-0.271
RANK	-0.100 **	-0.053	0.869	3.031	-0.045
GRANK-T	-0.008	0.111	1.003	2.571	-0.342
G-SIGN	-0.188 ***	-0.217	0.955	2.666	-0.020
GRANK-Z	-0.014	0.117	0.979	2.496	-0.342
Panel C	**Mean**	**Median**	**Std**	**Kurtosis**	**Skewness**
CAR(−5,+5)	-0.006	-0.013	0.120	25.056	0.198
PATELL	-0.223 ***	-0.187	1.030	2.289	-0.107
adj-PATELL	-0.311 ***	-0.317	1.097	2.101	-0.189
Csect T	-0.283 ***	-0.290	1.003	2.829	0.133
BMP	-0.063	-0.071	0.846	2.722	-0.077
adj-BMP	-0.200 ***	-0.206	1.020	2.741	-0.283
RANK	-0.202 ***	-0.196	1.032	2.866	-0.303
GRANK-T	-0.173	-0.297	2.851	22.154	-0.094
G-SIGN	-0.315 ***	-0.291	1.051	2.267	-0.172
GRANK-Z	-0.266 ***	-0.175	1.334	2.580	-0.201
Panel D	**Mean**	**Median**	**Std**	**Kurtosis**	**Skewness**
CAR(-10,+10)	-0.007	-0.019	0.148	3.538	0.316
PATELL	-0.176	0.144	10.121	215.681	-14.182
adj-PATELL	-0.221	0.145	10.624	217.657	-14.278
Csect T	-0.133 **	-0.171	1.007	2.669	0.113
BMP	0.077	0.108	1.023	2.512	-0.162
adj-BMP	0.064	0.139	1.039	2.639	-0.190
RANK	-0.136 ***	-0.128	0.738	2.625	-0.127
GRANK-T	-0.215 ***	-0.169	1.114	3.140	-0.240
G-SIGN	-0.244 ***	-0.189	0.939	2.854	0.056
GRANK-Z	-0.203 ***	-0.165	1.094	3.152	-0.224

*,**,*** indicate significance at the 10%, 5% and 1%.

Descriptive statistics of the simulated test statistics values (tables 3 to 7). Calculation methodology described following table 7.

Table 7: Simulated test statistics Market Adjusted Model Equally Weighted Entire Sample

Equally Weighted Market Adjusted Model					
Panel A	**Mean**	**Median**	**Std**	**Kurtosis**	**Skewness**
AAR (0)	0.003	-0.004	0.093	4.818	0.108
RANK	-0.046	-0.089	0.987	3.019	0.142
PATELL	-0.056	-0.216	4.040	33.047	-2.360
adj-PATELL	-0.056	-0.217	4.044	33.005	-2.357
Csect T	-0.030	-0.050	0.967	2.024	-0.001
adj-BMP	-0.141 **	-0.187	0.975	2.356	-0.138
GRANK-T	0.226 ***	0.304	0.928	2.960	-0.051
G-SIGN	-0.007	0.002	1.000	3.117	0.000
GRANK-Z	0.218 ***	0.300	0.902	2.679	-0.073
Panel B	**Mean**	**Median**	**Std**	**Kurtosis**	**Skewness**
CAR(-1,+1)	-0.012 **	-0.012	0.104	4.685	0.221
PATELL	-0.170	-0.299	2.789	22.422	-0.230
adj-PATELL	-0.173	-0.297	2.851	22.154	-0.094
Csect T	-0.223 ***	-0.187	1.030	2.289	-0.107
BMP	-0.315 ***	-0.291	1.051	2.267	-0.172
adj-BMP	-0.311 ***	-0.317	1.097	2.101	-0.189
RANK	-0.063	-0.071	0.846	2.722	-0.077
GRANK-T	-0.202 ***	-0.196	1.032	2.866	-0.303
G-SIGN	-0.283 ***	-0.290	1.003	2.829	0.133
GRANK-Z	-0.200 ***	-0.206	1.020	2.741	-0.283
Panel C	**Mean**	**Median**	**Std**	**Kurtosis**	**Skewness**
CAR(−5,+5)	-0.029 ***	-0.020	0.155	3.707	-0.256
PATELL	-0.394 ***	-0.420	1.851	8.199	0.075
adj-PATELL	-0.384 ***	-0.404	1.869	7.727	0.398
Csect T	-0.306 ***	-0.134	1.102	2.669	-0.362
BMP	-0.470 ***	-0.471	1.052	2.490	-0.185
adj-BMP	-0.499 ***	-0.606	1.033	2.546	-0.044
RANK	0.065 *	0.031	0.752	3.227	-0.138
GRANK-T	-0.481 ***	-0.378	1.193	4.030	-0.472
G-SIGN	-0.421 ***	-0.426	1.025	2.931	0.023
GRANK-Z	-0.470 ***	-0.397	1.152	3.666	-0.457
Panel D	**Mean**	**Median**	**Std**	**Kurtosis**	**Skewness**
CAR(−10,+10)	-0.034 ***	-0.045	0.193	5.432	-0.144
PATELL	-0.316 ***	-0.464	1.516	5.512	0.756
adj-PATELL	-0.315 ***	-0.504	1.537	5.299	0.657
Csect T	-0.313 ***	-0.291	1.063	2.683	-0.095
BMP	-0.510 ***	-0.505	1.176	2.910	-0.290
adj-BMP	-0.512 ***	-0.556	1.157	2.611	-0.158
RANK	0.272 ***	0.330	0.684	3.065	-0.040
GRANK-T	-0.302 ***	-0.281	1.237	3.018	-0.343
G-SIGN	-0.341 ***	-0.319	1.073	2.525	0.047
GRANK-Z	-0.309 ***	-0.268	1.224	3.041	-0.379

*,**,*** indicate significance at the 10%, 5% and 1%.

Descriptive statistics of the simulated test statistics values (tables 3 to 7). Calculation methodology described following table 7.

Description statistics of the observed test values shown in Tables 3 to 7.

Descriptive statistics of the simulated test statistics values. All panels are based on 250 simulations each with 50 randomly selected crypto-assets, with replacement, from during the period of January 1st 2015 to June 30th 2018. Event-day abnormal returns are determined by as described in the title of the tables. The market index is the value weighted CRIX or equal weighed EW100 index. Panel (A) shows the descriptive statistics of the test statistics when the specification is testing the abnormal returns of a single day (0), Panel (B) the descriptive statistics of the test statistics when the specification is testing for cumulative abnormal returns over a three day event period (-1,+1). Panel (C) the descriptive statistics of the test statistics when the specification is testing for cumulative abnormal returns over a ten day event period (-5,+5). Panel (D) the descriptive statistics of the test statistics when the specification is testing for cumulative abnormal returns over a ten day event period (-10,+10). An estimation windows from -100 to -11 days is used for calibrating the parameters of the market model and the standard deviations and signs necessary for determining test statistics. The rank test calculates ranks across the entire observation period (Panel A: -100,+0), (Panel B: -100,+1), (Panel C: -100,+5), (Panel D: -100,+10). Randomization for Panel A, B and C, first excludes crypto-assets which have been forked or ICOd within the previous 70 days. Second, the universe is further subsetted to only select securities that have at least 5 days of available post event-day-price data. Randomization for Panel D, extends the requirement to observe at least 90 previous days since initial fork/ico. The parametric test statistics of Csect-T, PATELL, BMP, Adj-PATELL, adj-BMP are calculated based on the specifications described in section *Parametric Tests* and defined in Brown and Warner(1985), Patell (1976), Boehmer et al (1991) and Kolari and Pynnönen (2010,2010). When the null hypothesis is no abnormal returns, the test statistics across all parametric tests should be normally distributed N(0,1). The non-parametric tests of RANK, GRANK-T and GRANK-Z are calculated by the specifications shown on page 12 and defined in Corrado and Zivney(1992), Kolari and Pynnönen (2011, 2011). The G-SIGN is defined for a single day event as in Cowan(1992) and as defined in Kolari and Pynnönen (2011) for multiday events. When the null hypothesis is no abnormal returns, the test statistic of GRANK-Z should be ~N(0,1). The RANK test according the Corrado (2011) also has a mean of zero and a variance of one. The GRANK-T test is expected to be Student *t* distributed.

Table 8: Rejection frequencies with zero abnormal performance (entire sample)

Rejection rates with zero abnormal performance												
	AAR(+0)			CAR(-1, 1)			CAR(-5, 5)			CAR(-10,10)		
HO:	Left	Right	2-Tail	Left	Right	2-Tail	Left	Right	2-Tail	Left	Right	2-Tail
Panel (A) VW Market Model Abnormal Returns												
PATELL	0.104	0.144	0.248	0.108	0.144	0.252	0.028	0.171	0.199	0.080	0.228	0.308
Csect T	0.052	0.040	0.092	0.036	0.028	0.064	0.044	0.036	0.080	0.044	0.028	0.072
G-SIGN	0.052	0.068	0.120	0.052	0.024	0.076	0.092	0.032	0.124	0.048	0.024	0.072
BMP	0.044	0.044	0.088	0.036	0.040	0.076	0.016	0.032	0.048	0.036	0.068	0.104
RANK	0.048	0.056	0.104	0.020	0.028	0.048	0.012	0.012	0.024	0.012	0.020	0.032
GRANK-T	0.048	0.052	0.100	0.044	0.048	0.092	0.120	0.040	0.159	0.064	0.040	0.104
adj-PATELL	0.104	0.144	0.248	0.108	0.148	0.256	0.028	0.167	0.195	0.084	0.220	0.304
adj-BMP	0.044	0.044	0.088	0.036	0.044	0.080	0.016	0.056	0.072	0.032	0.080	0.112
GRANK-Z	0.052	0.052	0.104	0.040	0.044	0.084	0.108	0.036	0.143	0.072	0.048	0.120
Panel (B) VW Market Adjusted Abnormal Returns												
PATELL	0.120	0.132	0.252	0.116	0.124	0.240	0.068	0.104	0.171	0.128	0.076	0.204
Csect T	0.060	0.020	0.080	0.052	0.040	0.092	0.088	0.016	0.104	0.076	0.024	0.100
G-SIGN	0.028	0.048	0.076	0.068	0.052	0.120	0.139	0.004	0.143	0.084	0.020	0.104
BMP	0.084	0.020	0.104	0.068	0.032	0.100	0.096	0.024	0.120	0.128	0.020	0.148
RANK	0.044	0.048	0.092	0.016	0.016	0.032	0.016	0.008	0.024	0.016	0.012	0.028
GRANK-T	0.060	0.028	0.088	0.060	0.036	0.096	0.183	0.016	0.199	0.136	0.016	0.152
adj-PATELL	0.120	0.132	0.252	0.116	0.124	0.240	0.060	0.104	0.163	0.128	0.080	0.208
adj-BMP	0.084	0.020	0.104	0.068	0.024	0.092	0.108	0.024	0.131	0.128	0.016	0.144
GRANK-Z	0.056	0.040	0.096	0.056	0.040	0.096	0.191	0.016	0.207	0.136	0.012	0.148
Panel (C) Comparison period abnormal returns												
PATELL	0.100	0.156	0.256	0.092	0.140	0.232	0.032	0.151	0.183	0.076	0.212	0.288
Csect T	0.036	0.036	0.072	0.028	0.044	0.072	0.048	0.032	0.080	0.040	0.032	0.072
G-SIGN	0.064	0.056	0.120	0.052	0.020	0.072	0.064	0.020	0.084	0.072	0.020	0.092
BMP	0.044	0.040	0.084	0.032	0.036	0.068	0.028	0.052	0.080	0.040	0.084	0.124
RANK	0.052	0.064	0.116	0.012	0.020	0.032	0.008	0.008	0.016	0.012	0.004	0.016
GRANK-T	0.060	0.044	0.104	0.048	0.044	0.092	0.135	0.032	0.167	0.092	0.032	0.124
adj-PATELL	0.100	0.156	0.256	0.096	0.140	0.236	0.032	0.155	0.187	0.076	0.208	0.284
adj-BMP	0.044	0.040	0.084	0.044	0.032	0.076	0.028	0.048	0.076	0.028	0.080	0.108
GRANK-Z	0.064	0.048	0.112	0.060	0.036	0.096	0.135	0.032	0.167	0.092	0.032	0.124
Panel (D) EW Market Model Abnormal Returns												
PATELL	0.139	0.190	0.329	0.139	0.190	0.329	0.072	0.172	0.244	0.132	0.164	0.296
Csect T	0.036	0.020	0.056	0.036	0.020	0.056	0.048	0.040	0.088	0.044	0.024	0.068
G-SIGN	0.032	0.036	0.067	0.032	0.036	0.067	0.080	0.020	0.100	0.060	0.044	0.104
BMP	0.028	0.024	0.052	0.028	0.024	0.052	0.036	0.040	0.076	0.048	0.040	0.088
RANK	0.036	0.020	0.056	0.036	0.020	0.056	0.028	0.004	0.032	0.072	0.060	0.132
GRANK-T	0.024	0.024	0.048	0.024	0.024	0.048	0.084	0.032	0.116	0.056	0.044	0.100
adj-PATELL	0.139	0.190	0.329	0.139	0.190	0.329	0.080	0.168	0.248	0.132	0.164	0.296
adj-BMP	0.028	0.024	0.052	0.028	0.024	0.052	0.040	0.036	0.076	0.048	0.040	0.088
GRANK-Z	0.020	0.024	0.044	0.020	0.024	0.044	0.084	0.024	0.108	0.064	0.060	0.124
Panel (E) EW Market Adjusted Abnormal Returns												
PATELL	0.172	0.168	0.340	0.120	0.103	0.223	0.148	0.076	0.224	0.148	0.084	0.232
Csect T	0.032	0.020	0.052	0.073	0.027	0.100	0.116	0.008	0.124	0.088	0.024	0.112
G-SIGN	0.052	0.036	0.088	0.087	0.023	0.110	0.124	0.012	0.136	0.124	0.036	0.160
BMP	0.044	0.016	0.060	0.087	0.003	0.090	0.140	0.008	0.148	0.176	0.024	0.200
RANK	0.048	0.056	0.104	0.023	0.010	0.033	0.016	0.012	0.028	0.004	0.024	0.028
GRANK-T	0.020	0.044	0.064	0.067	0.013	0.080	0.148	0.016	0.164	0.132	0.032	0.164
adj-PATELL	0.172	0.168	0.340	0.127	0.100	0.227	0.144	0.076	0.220	0.140	0.096	0.236
adj-BMP	0.044	0.016	0.060	0.100	0.007	0.107	0.136	0.008	0.144	0.160	0.012	0.172
GRANK-Z	0.020	0.044	0.064	0.063	0.010	0.073	0.140	0.012	0.152	0.140	0.032	0.172

Simulated rejection frequencies with zero abnormal returns (tables 8 to 11). Calculation methodology described following table 11.

Table 9: Rejection frequencies with zero abnormal performance (TOP 100)

	AAR(+0)			CAR(-1, 1)			CAR(-5, 5)			CAR(-10,10)		
HO:	AAR < 0	AAR > 0	AAR≠0	CAAR <	CAAR >	CAAR≠0	CAAR <	CAAR >	CAAR≠0	CAAR <	CAAR >	CAAR≠0
Panel (A) VW Market Model Abnormal Returns												
PATELL	0.128	0.172	0.300	0.139	0.198	0.337	0.167	0.315	0.482	0.104	0.296	0.400
Csect T	0.024	0.016	0.040	0.040	0.044	0.083	0.052	0.020	0.072	0.108	0.028	0.136
G-SIGN	0.044	0.048	0.092	0.044	0.032	0.075	0.040	0.052	0.092	0.068	0.048	0.116
BMP	0.028	0.040	0.068	0.028	0.052	0.079	0.016	0.084	0.100	0.032	0.108	0.140
RANK	0.024	0.036	0.060	0.032	0.040	0.071	0.016	0.016	0.032	0.048	0.020	0.068
GRANK-T	0.016	0.024	0.040	0.048	0.044	0.091	0.028	0.040	0.068	0.080	0.080	0.160
adj-PATELL	0.128	0.172	0.300	0.139	0.210	0.349	0.163	0.319	0.482	0.112	0.300	0.412
adj-BMP	0.028	0.040	0.068	0.032	0.071	0.103	0.020	0.092	0.112	0.024	0.136	0.160
GRANK-Z	0.016	0.028	0.044	0.056	0.048	0.103	0.028	0.040	0.068	0.080	0.076	0.156
Panel (B) VW Market Adjusted Abnormal Returns												
PATELL	0.192	0.148	0.340	0.180	0.113	0.293	0.068	0.104	0.171	0.219	0.131	0.351
Csect T	0.016	0.012	0.028	0.047	0.013	0.060	0.088	0.016	0.104	0.135	0.000	0.135
G-SIGN	0.048	0.048	0.096	0.033	0.030	0.063	0.139	0.004	0.143	0.100	0.028	0.127
BMP	0.060	0.044	0.104	0.047	0.023	0.070	0.096	0.024	0.120	0.179	0.024	0.203
RANK	0.048	0.060	0.108	0.013	0.027	0.040	0.016	0.008	0.024	0.024	0.052	0.076
GRANK-T	0.048	0.044	0.092	0.030	0.027	0.057	0.183	0.016	0.199	0.100	0.024	0.124
adj-PATELL	0.192	0.148	0.340	0.180	0.117	0.297	0.060	0.104	0.163	0.239	0.108	0.347
adj-BMP	0.060	0.044	0.104	0.050	0.027	0.077	0.108	0.024	0.131	0.167	0.024	0.191
GRANK-Z	0.052	0.056	0.108	0.033	0.030	0.063	0.191	0.016	0.207	0.175	0.024	0.199
Panel (C) Comparison period abnormal returns												
PATELL	0.132	0.176	0.308	0.156	0.200	0.356	0.303	0.127	0.430	0.120	0.276	0.396
Csect T	0.036	0.012	0.048	0.028	0.008	0.036	0.092	0.024	0.116	0.068	0.048	0.116
G-SIGN	0.048	0.048	0.096	0.032	0.020	0.052	0.096	0.016	0.112	0.044	0.016	0.060
BMP	0.052	0.048	0.100	0.044	0.024	0.068	0.159	0.020	0.179	0.028	0.072	0.100
RANK	0.064	0.048	0.112	0.036	0.028	0.064	0.048	0.020	0.068	0.016	0.036	0.052
GRANK-T	0.064	0.044	0.108	0.052	0.052	0.104	0.104	0.020	0.124	0.080	0.068	0.148
adj-PATELL	0.132	0.176	0.308	0.168	0.208	0.376	0.307	0.131	0.438	0.124	0.260	0.384
adj-BMP	0.052	0.048	0.100	0.044	0.048	0.092	0.171	0.024	0.195	0.032	0.080	0.112
GRANK-Z	0.072	0.040	0.112	0.052	0.036	0.088	0.100	0.012	0.112	0.072	0.060	0.132

Simulated rejection frequencies with zero abnormal returns (tables 8 to 11). Calculation methodology described following table 11.

Rejection frequencies are based on 250 simulations, each with N randomly selected crypto-assets with replacement from the largest 100 crypto-assets based upon size during the period of January 1st 2015 to June 30th 2018.

Table 10: Simulated rejection frequencies as a function of Sample Size

	Sample size = 10 CAAR(-1,1)			Sample size = 25 CAAR(-1,1)			Sample size = 50 CAAR(-1,1)			Sample size = 100 CAAR(-1,1)		
HO:	**PR < 0.05**	**PR > 0.95**	**2-Tail**	**PR < 0.05**	**PR > 0.95**	**2-Tail**	**PR < 0.05**	**PR > 0.95**	**2-Tail**	**PR < 0.05**	**PR > 0.95**	**2-Tail**
Panel (A) Entire Sample												
PATELL	0.075	0.111	0.187	0.120	0.135	0.255	0.124	0.204	0.328	0.160	0.248	0.408
Csect T	0.044	0.016	0.060	0.068	0.020	0.088	0.044	0.048	0.092	0.060	0.024	0.084
G-SIGN	0.060	0.067	0.127	0.068	0.040	0.108	0.068	0.028	0.096	0.088	0.032	0.120
BMP	0.052	0.024	0.075	0.076	0.024	0.100	0.068	0.032	0.100	0.056	0.060	0.116
RANK	0.028	0.008	0.036	0.024	0.024	0.048	0.028	0.016	0.044	0.056	0.020	0.076
GRANK-T	0.063	0.036	0.099	0.092	0.032	0.124	0.084	0.024	0.108	0.036	0.028	0.064
adj-PATELL	0.079	0.111	0.190	0.116	0.135	0.251	0.124	0.208	0.332	0.172	0.248	0.420
adj-BMP	0.052	0.036	0.087	0.080	0.024	0.104	0.068	0.036	0.104	0.044	0.044	0.088
GRANK-Z	0.056	0.024	0.079	0.084	0.036	0.120	0.060	0.028	0.088	0.024	0.032	0.056
Panel (B) TOP 100												
PATELL	0.046	0.040	0.086	0.080	0.066	0.146	0.180	0.224	0.404	0.220	0.288	0.508
Csect T	0.022	0.008	0.030	0.028	0.004	0.032	0.032	0.020	0.052	0.028	0.028	0.056
G-SIGN	0.032	0.016	0.048	0.040	0.022	0.062	0.084	0.048	0.132	0.056	0.068	0.124
BMP	0.042	0.022	0.064	0.036	0.022	0.058	0.032	0.040	0.072	0.020	0.060	0.080
RANK	0.016	0.020	0.036	0.026	0.016	0.042	0.048	0.048	0.096	0.020	0.056	0.076
GRANK-T	0.036	0.016	0.052	0.048	0.018	0.066	0.036	0.064	0.100	0.020	0.064	0.084
adj-PATELL	0.046	0.044	0.090	0.084	0.068	0.152	0.188	0.228	0.416	0.216	0.288	0.504
adj-BMP	0.030	0.026	0.056	0.040	0.026	0.066	0.036	0.048	0.084	0.020	0.052	0.072
GRANK-Z	0.038	0.018	0.056	0.048	0.016	0.064	0.032	0.056	0.088	0.020	0.072	0.092

Simulated rejection frequencies with zero abnormal returns (tables 8 to 11). Calculation methodology described following table 11.

Rejection frequencies are based on 250 simulations, each with N randomly selected crypto-assets with replacement from either the entire sample (Panel A) or from the largest 100 crypto-assets (Panel B) based upon size during the period of January 1st 2015 to June 30th 2018.

Table 11: Clustered simulated rejection frequencies as a function of sample size

	Sample size = 10 CAAR(-1,1)			Sample size = 25 CAAR(-1,1)			Sample size = 50 CAAR(-1,1)			Sample size = 100 CAAR(-1,1)		
HO:	**PR < 0.05**	**PR > 0.95**	**2-Tail**	**PR < 0.05**	**PR > 0.95**	**2-Tail**	**PR < 0.05**	**PR > 0.95**	**2-Tail**	**PR < 0.05**	**PR > 0.95**	**2-Tail**
Panel (A) Non-Clustured												
PATELL	0.075	0.111	0.187	0.120	0.135	0.255	0.124	0.204	0.328	0.160	0.248	0.408
Csect T	0.044	0.016	0.060	0.068	0.020	0.088	0.044	0.048	0.092	0.060	0.024	0.084
G-SIGN	0.060	0.067	0.127	0.068	0.040	0.108	0.068	0.028	0.096	0.088	0.032	0.120
BMP	0.052	0.024	0.075	0.076	0.024	0.100	0.068	0.032	0.100	0.056	0.060	0.116
RANK	0.028	0.008	0.036	0.024	0.024	0.048	0.028	0.016	0.044	0.056	0.020	0.076
GRANK-T	0.063	0.036	0.099	0.092	0.032	0.124	0.084	0.024	0.108	0.036	0.028	0.064
adj-PATELL	0.079	0.111	0.190	0.116	0.135	0.251	0.124	0.208	0.332	0.172	0.248	0.420
adj-BMP	0.052	0.036	0.087	0.080	0.024	0.104	0.068	0.036	0.104	0.044	0.044	0.088
GRANK-Z	0.056	0.024	0.079	0.084	0.036	0.120	0.060	0.028	0.088	0.024	0.032	0.056
Panel (B) Clustered												
PATELL	0.083	0.119	0.202	0.096	0.159	0.255	0.164	0.176	0.340	0.192	0.232	0.424
Csect T	0.052	0.060	0.111	0.032	0.048	0.080	0.072	0.032	0.104	0.052	0.040	0.092
G-SIGN	0.079	0.091	0.171	0.072	0.120	0.191	0.128	0.124	0.252	0.176	0.212	0.388
BMP	0.083	0.095	0.179	0.056	0.076	0.131	0.100	0.088	0.188	0.108	0.112	0.220
RANK	0.052	0.075	0.127	0.028	0.084	0.112	0.040	0.052	0.092	0.064	0.092	0.156
GRANK-T	0.071	0.083	0.155	0.064	0.064	0.127	0.044	0.040	0.084	0.036	0.064	0.100
adj-PATELL	0.083	0.115	0.198	0.080	0.124	0.203	0.128	0.152	0.280	0.140	0.172	0.312
adj-BMP	0.071	0.103	0.175	0.036	0.088	0.124	0.052	0.068	0.120	0.064	0.052	0.116
GRANK-Z	0.067	0.099	0.167	0.080	0.116	0.195	0.128	0.112	0.240	0.104	0.208	0.312

Simulated rejection frequencies with zero abnormal returns (tables 8 to 11). Calculation methodology described following table 11.

Samples of panel (A) as described in common methodology, samples of panel (B), are determined by first choosing a random day and second randomly selecting N crypto-assets <u>without</u> replacement.

Rejection frequencies of various specification with zero abnormal returns (tables 8 to 11)

Simulated rejection frequencies with zero abnormal returns (tables 8 to 11). Rejection frequencies are based on 250 simulations, each with N randomly selected crypto-assets with replacement during the period of January 1st 2015 to June 30th 2018. Randomization for both the entire sample and clustered samples is first done by excluding crypto-assets which have been forked or ICOd within the previous 70 days. Second, the universe is further divided to only select securities that have at least 5 days of available post event day-price data. Samples of panel (A) are than drawn from the resulting subset of 431 995 crypto-asset daily price pairs. The market index is the value weighted CRIX index. Event-day abnormal returns are determined by the one factor market model approach. The event window includes 1 day prior and 1 day after (-1,1).

An estimation windows from -100 to -11 days is used for calibrating the parameters of the market model and the necessary standard deviations and signs necessary for determining test statistics. The rank test calculates ranks across the entire observation period (-100,+1). The parametric test statistics of Csect-T, PATELL, BMP, Adj-PATELL, adj-BMP are calculated based on the specifications described in section *Test Statistics* and defined in Brown and Warner(1985), Patell (1976), Boehmer et al (1991) and Kolari and Pynnönen (2010,2010) respectively. The null hypothesis across all parametric tests is that the mean CAR is zero. The non-parametric tests of RANK, GRANK-T and GRANK-Z are calculated by the specifications shown in *Test Statistics* and defined in Corrado and Zivney(1992), Kolari and Pynnönen (2011, 2011). The G-SIGN is defined for a single day event as in Cowan(1992) and as defined in Kolari and Pynnönen (2011) for multiday events. The null hypothesis of the G-SIGN test is that the proportion of event day abnormal returns having a particular sign is equal to the proportion of estimation-period abnormal returns with that sign. The null hypothesis of the RANK test is that the mean ranking of the abnormal returns in the event period is equal to that of the entire observation period. The null of the GRANK-T and GRANK-Z is that the demeaned standardized abnormal rank of the event period is equal to zero.

Table 12: Seeded abnormal return rejection frequencies Market Model -Value Weighted

Market Model Value Weighted Abnormal Returns								
Panel A: AAR(0)	**HO: AAR < 0**				**HO: AAR > 0**			
Seeded Returns	**-0.1**	**-0.03**	**-0.01**	**0**	**0**	**+0.01**	**+0.03**	**+0.1**
PATELL	0.608	0.256	0.176	0.104	0.144	0.200	0.368	0.528
Csect T	0.072	0.048	0.048	0.052	0.040	0.068	0.052	0.100
G-SIGN	0.992	0.596	0.176	0.052	0.068	0.200	0.460	0.664
BMP	0.392	0.152	0.072	0.044	0.044	0.092	0.244	0.396
RANK	1.000	0.620	0.176	0.048	0.056	0.204	0.552	0.692
GRANK-T	0.692	0.336	0.084	0.048	0.052	0.136	0.500	0.576
adj-PATELL	0.612	0.260	0.176	0.104	0.144	0.200	0.368	0.532
adj-BMP	0.392	0.152	0.072	0.044	0.044	0.092	0.244	0.396
GRANK-Z	0.700	0.332	0.096	0.052	0.052	0.160	0.470	0.560
Panel B: 3-Day CAR	**HO: CAR < 0**				**HO: CAR > 0**			
PATELL	0.464	0.139	0.076	0.108	0.144	0.163	0.200	0.424
Csect T	0.052	0.060	0.040	0.036	0.028	0.052	0.036	0.076
G-SIGN	0.928	0.347	0.116	0.052	0.024	0.108	0.224	0.548
BMP	0.316	0.104	0.040	0.036	0.040	0.064	0.160	0.328
RANK	0.908	0.255	0.084	0.020	0.028	0.064	0.232	0.548
GRANK-T	0.580	0.263	0.100	0.044	0.048	0.116	0.228	0.516
adj-PATELL	0.468	0.147	0.084	0.108	0.148	0.163	0.208	0.420
adj-BMP	0.440	0.163	0.076	0.036	0.044	0.096	0.208	0.376
GRANK-Z	0.700	0.332	0.092	0.052	0.052	0.084	0.336	0.560

Table 13: Seeded abnormal return rejection frequencies Market Model Equally weighted

Market Model Equally Weighted Abnormal Returns								
Panel A: AAR(0)	**HO: AAR < 0**				**HO: AAR > 0**			
Seeded Returns	**-0.1**	**-0.03**	**-0.01**	**0**	**0**	**+0.01**	**+0.03**	**+0.1**
PATELL	0.592	0.292	0.168	0.139	0.190	0.196	0.340	0.728
Csect T	0.100	0.100	0.044	0.036	0.020	0.044	0.092	0.132
G-SIGN	0.996	0.632	0.144	0.032	0.036	0.164	0.620	1.000
BMP	0.408	0.212	0.064	0.028	0.024	0.080	0.260	0.572
RANK	1.000	0.696	0.136	0.036	0.020	0.168	0.636	1.000
GRANK-T	0.688	0.396	0.104	0.024	0.024	0.152	0.512	0.912
adj-PATELL	0.592	0.288	0.168	0.139	0.190	0.196	0.340	0.724
adj-BMP	0.408	0.212	0.064	0.028	0.024	0.080	0.264	0.572
GRANK-Z	0.692	0.392	0.096	0.020	0.024	0.152	0.524	0.920
Panel B: 3-Day CAR	**HO: CAR < 0**				**HO: CAR > 0**			
PATELL	0.388	0.148	0.132	0.124	0.204	0.176	0.196	0.536
Csect T	0.088	0.048	0.064	0.044	0.048	0.064	0.032	0.108
G-SIGN	0.900	0.268	0.084	0.068	0.028	0.112	0.276	0.904
BMP	0.296	0.152	0.072	0.068	0.032	0.096	0.136	0.460
RANK	0.904	0.284	0.072	0.028	0.016	0.076	0.248	0.876
GRANK-T	0.568	0.228	0.100	0.084	0.024	0.088	0.224	0.808
adj-PATELL	0.400	0.140	0.132	0.124	0.208	0.180	0.188	0.532
adj-BMP	0.444	0.196	0.088	0.068	0.036	0.112	0.256	0.632
GRANK-Z	0.552	0.228	0.100	0.060	0.028	0.088	0.220	0.820

Simulated rejection frequencies of seeded abnormal returns (tables 12 to 15). Calculation methodology described following table 15

Table 14: Seeded abnormal return rejection frequencies - Market Adjusted Model

Market Adjusted Model Value Weighted Abnormal Returns						
Panel A: AAR(0)	**HO: AAR < 0**			**HO: AAR > 0**		
Seeded Returns	**-0.1**	**-0.03**	**0**	**0**	**+0.03**	**+0.1**
PATELL	0.560	0.252	0.120	0.132	0.124	0.672
Csect T	0.072	0.048	0.060	0.020	0.012	0.124
G-SIGN	0.996	0.592	0.028	0.048	0.060	1.000
BMP	0.376	0.212	0.084	0.020	0.016	0.524
RANK	1.000	0.632	0.044	0.048	0.040	1.000
GRANK-T	0.660	0.388	0.060	0.028	0.024	0.932
adj-PATELL	0.560	0.256	0.120	0.132	0.124	0.672
adj-BMP	0.376	0.212	0.084	0.020	0.016	0.524
GRANK-Z	0.668	0.388	0.056	0.040	0.028	0.928
Panel B: 3-Day CAR	**HO: CAR < 0**			**HO: CAR > 0**		
PATELL	0.408	0.136	0.116	0.124	0.088	0.372
Csect T	0.060	0.064	0.052	0.040	0.032	0.084
G-SIGN	0.908	0.372	0.068	0.052	0.244	0.932
BMP	0.328	0.172	0.068	0.032	0.088	0.372
RANK	0.916	0.300	0.016	0.016	0.236	0.868
GRANK-T	0.640	0.268	0.060	0.036	0.168	0.812
adj-PATELL	0.420	0.164	0.116	0.124	0.100	0.356
adj-BMP	0.560	0.292	0.068	0.024	0.084	0.564
GRANK-Z	0.644	0.280	0.056	0.040	0.148	0.812

Table 15: Seeded abnormal return rejection frequencies (Comparison Period Mean Adjusted Model)

Comparison Period Mean Adjusted Model Abnormal Returns						
Panel A: AAR(0)	**HO: AAR < 0**			**HO: AAR > 0**		
Seeded Returns	**-0.1**	**-0.03**	**0**	**0**	**+0.03**	**+0.1**
PATELL	0.548	0.296	0.100	0.156	0.360	0.744
Csect T	0.052	0.120	0.036	0.036	0.124	0.168
G-SIGN	0.996	0.728	0.064	0.056	0.800	1.000
BMP	0.396	0.216	0.044	0.040	0.260	0.600
RANK	1.000	0.736	0.052	0.064	0.756	1.000
GRANK-T	0.648	0.464	0.060	0.044	0.668	0.928
adj-PATELL	0.548	0.300	0.100	0.156	0.360	0.744
adj-BMP	0.396	0.216	0.044	0.040	0.260	0.600
GRANK-Z	0.656	0.460	0.064	0.048	0.656	0.928
Panel B: 3-Day CAR	**HO: CAR < 0**			**HO: CAR > 0**		
PATELL	0.372	0.155	0.092	0.140	0.204	0.568
Csect T	0.052	0.028	0.028	0.044	0.044	0.108
G-SIGN	0.948	0.064	0.052	0.020	0.284	0.960
BMP	0.296	0.028	0.032	0.036	0.156	0.508
RANK	0.968	0.052	0.012	0.020	0.300	0.948
GRANK-T	0.608	0.044	0.048	0.044	0.300	0.848
adj-PATELL	0.384	0.092	0.096	0.140	0.208	0.564
adj-BMP	0.428	0.036	0.044	0.032	0.212	0.648
GRANK-Z	0.604	0.044	0.060	0.036	0.284	0.840

Simulated rejection frequencies of seeded abnormal returns (tables 12 to 15). Calculation methodology described following table 15

Rejection frequencies of various specification with seeded abnormal returns (tables 12 to 15)

Rejection frequencies are based on 250 simulations, each with 50 randomly selected crypto-assets with replacement from during the period of January 1st 2015 to June 30th 2018. Randomization first excludes crypto-assets which have been forked or ICOd within the previous 70 days. Second, the universe is further subsetted to only select securities that have at least 5 days of available post eventday-price data. Samples are than drawn from the resulting subset of 431 995 crypto-asset daily price pairs. The market index is the value weighted CRIX index. Seeded returns are added to the day zero returns for each crypto-asset in each simulation.

Event-day abnormal returns are determined by the one factor market model approach. An estimation windows from -100 to -11 days is used for calibrating the parameters of the market model, the standard deviations and signs necessary for determining test statistics. The rank test calculates ranks across the entire observation period (-100,+1). The parametric test statistics of Csect-T, PATELL, BMP, Adj-PATELL, adj-BMP are calculated based on the specifications described in section *Test Statistics* and defined in Brown and Warner(1985), Patell (1976), Boehmer et al (1991) and Kolari and Pynnönen (2010,2010) respectively. The null hypothesis across all parametric tests is that the mean AAR and CAR is zero. The non-parametric tests of RANK, GRANK-T and GRANK-Z are calculated by the specifications shown in *Test Statistics* and defined in Corrado and Zivney(1992), Kolari and Pynnönen (2011, 2011). The G-SIGN is defined for a single day event as in Cowan(1992) and as defined in Kolari and Pynnönen (2011) for multiday events. The null hypothesis of the G-SIGN test is that the proportion of event day abnormal returns having a particular sign is equal to the proportion of estimation-period abnormal returns with that sign. The null hypothesis of the RANK test is that the mean ranking of the abnormal returns in the event period is equal to that of the entire observation period. The null of the GRANK-T and GRANK-Z is that the demeaned standardized abnormal rank of the event period is equal to zero.

Table 16: Binance listing announcement (CAR) analysis

	CAR	PATELL	Csect T	G-SIGN	BMP	RANK	GRANK-T	adj-PATELL	adj-BMP	GRANK-Z
Panel (a) CAR (-5,5)										
Value weighted	9.3%	1.694 **	1.501 *	1.436 *	1.528 *	-1.033	0.846	1.625 *	1.545 *	1.243
Equal weighted	9.1%	1.612 *	1.470 *	1.142	1.478 *	-1.157	0.763	1.588 *	1.510 *	1.096
Panel (B) CAR (-3,-1)										
Value weighted	4.3%	1.927 **	1.520 *	1.708 **	1.834 **	0.371	0.981	1.850 **	1.447 *	1.411 *
Equal weighted	5.0%	1.979 **	1.819 **	2.320 **	1.957 **	0.529	1.318 *	1.965 **	1.690 **	1.800 **
Panel (C) CAR (0,1)										
Value weighted	13.6%	6.564 ***	2.433 ***	3.522 ***	1.927 **	0.494	1.453 *	6.302 ***	1.511 *	2.093 **
Equal weighted	14.1%	6.820 ***	2.526 ***	3.227 ***	2.048 **	0.548	1.647 *	6.769 ***	1.699 **	2.253 **
Panel (D) CAR (2,4)										
Value weighted	-10.9%	-4.592 ***	-2.287 **	-1.921 **	-2.002 **	-2.909 ***	-1.539 *	-4.409 ***	-1.478 *	-2.219 **
Equal weighted	-11.6%	-5.119 ***	-2.530 ***	-2.518 ***	-2.345 **	-3.126 ***	-1.772 **	-5.081 ***	-1.913 **	-2.426 ***

*,**,*** indicate significance at the 10%, 5% and 1%.

Test statistic values for a sample of 44 announcements of Crypto-Assets listings by Binance.com for the period of September 2017 and June 2018. Panels A-D show the resulting test statistic values for the days indicate in brackets. In all Panels, value weighted refers to calculations using a market model approach with the value weighted CRIX index. The equal weighted refers to to calculations using a market model approach with the equal weighted EW100 index.

An estimation windows from -120 to -11 days is used for calibrating the parameters of the market model, the standard deviations and signs necessary for determining test statistics. The rank test calculates ranks across the entire observation period (-100,+11). The parametric test statistics of Csect-T, PATELL, BMP, Adj-PATELL, adj-BMP are calculated based on the specifications described in section *Test Statistics* and defined in Brown and Warner(1985), Patell (1976), Boehmer et al (1991) and Kolari and Pynnönen (2010,2010) respectively. The null hypothesis across all parametric tests is that the mean CAR is zero. The non-parametric tests of RANK, GRANK-T and GRANK-Z are calculated by the specifications shown in *Test Statistics* and defined in Corrado and Zivney(1992), Kolari and Pynnönen (2011, 2011). The G-SIGN is defined in Kolari and Pynnönen (2011) for multiday events. The null hypothesis of the G-SIGN test is that the proportion of event day abnormal returns having a particular sign is equal to the proportion of estimation-period abnormal returns with that sign. The null hypothesis of the RANK test is that the mean ranking of the abnormal returns in the event period is equal to that of the entire observation period. The null of the GRANK-T and GRANK-Z is that the demeaned standardized abnormal rank of the event period is equal to zero.

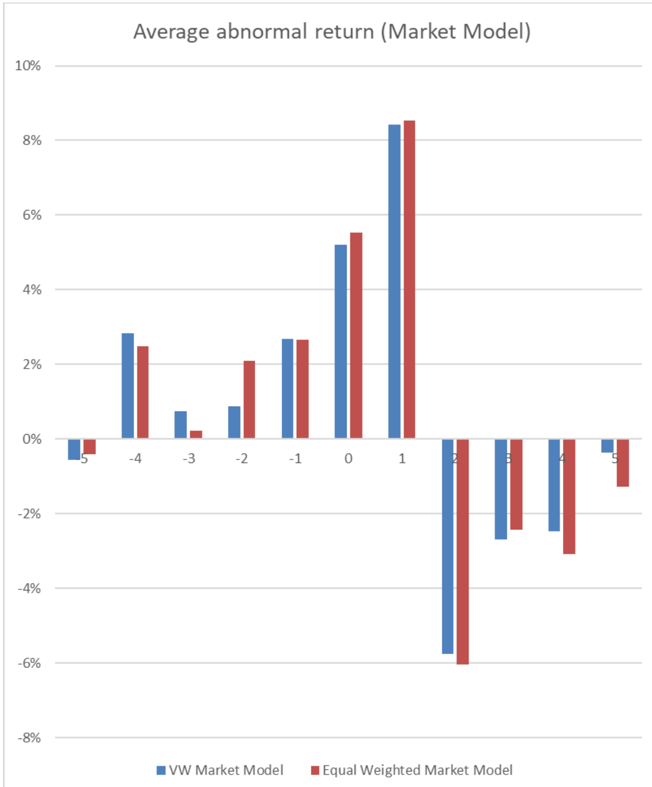
Table 17: Daily average abnormal return of Binance.com listing announcements

Panel (a) Value-Weighted Index										
	CAR	PATELL	Csect T	G-SIGN	BMP	RANK	GRANK-T	adj-PATELL	adj-BMP	GRANK-Z
AAR(-3)	0.8%	1.344 *	-0.409	0.562	1.184	-0.178	-0.123	1.340 *	1.179	-0.177
AAR(-2)	0.9%	0.548	-0.409	0.762	0.672	0.262	0.207	0.546	0.670	0.298
AAR(-1)	2.7%	1.954 **	0.498	1.041	1.190	0.662	0.680	1.948 **	1.185	0.980
AAR(0)	5.2%	1.970 **	0.196	1.972 **	1.484 *	0.570	0.588	1.964 **	1.478 *	0.846
AAR(1)	8.4%	7.308 ***	0.498	1.514 *	1.494 *	0.233	0.662	7.285 ***	1.488 *	0.954
AAR(2)	-5.8%	-5.005 ***	-1.618 *	-1.532 *	-1.553 *	-2.091 **	-1.008	-4.989 ***	-1.547 *	-1.455 *
Panel (b) Equal-Weighted Index										
	CAR	PATELL	Csect T	G-SIGN	BMP	RANK	GRANK-T	adj-PATELL	adj-BMP	GRANK-Z
AAR(-3)	0.2%	0.569	-0.401	0.169	0.552	-0.434	-0.461	0.567	0.550	-0.630
AAR(-2)	2.1%	1.853 **	1.715 **	1.694 **	1.937 **	1.136	1.095	1.846 **	1.928 **	1.493 *
AAR(-1)	2.7%	1.528 *	0.203	1.038	0.879	0.264	0.471	1.523 *	0.875	0.643
AAR(0)	5.5%	2.104 **	0.506	2.219 **	1.611 *	0.778	0.736	2.096 **	1.603 *	1.006
AAR(1)	8.5%	7.538 ***	0.506	1.519 *	1.558 *	0.109	0.748	7.509 ***	1.550 *	1.023
AAR(2)	-6.0%	-5.405 ***	-2.518 ***	-1.710 **	-1.823 **	-2.069 **	-1.063	-5.384 ***	-1.814 **	-1.455 *

*,**,*** indicate significance at the 10%, 5% and 1%.

Test statistic values for a sample of 44 announcements of Crypto-Assets listings by Binance.com for the period of September 2017 and June 2018. An estimation windows from -120 to -11 days is used for calibrating the parameters of the market model, the standard deviations and signs necessary for determining test statistics. The rank test calculates ranks across the entire observation period (-100,+11). The parametric test statistics of Csect-T, PATELL, BMP, Adj-PATELL, adj-BMP are calculated based on the specifications described in section *Test Statistics* and defined in Brown and Warner(1985), Patell (1976), Boehmer et al (1991) and Kolari and Pynnönen (2010, 2010) respectively. The null hypothesis across all parametric tests is that the mean AAR is zero. The non-parametric tests of RANK, GRANK-T and GRANK-Z are calculated by the specifications shown in *Test Statistics* and defined in Corrado and Zivney(1992), Kolari and Pynnönen (2011, 2011). The G-SIGN is defined for a single day event as in Cowan(1992). The null hypothesis of the G-SIGN test is that the proportion of event day abnormal returns having a particular sign is equal to the proportion of estimation-period abnormal returns with that sign. The null hypothesis of the RANK test is that the mean ranking of the abnormal returns in the event period is equal to that of the entire observation period. The null of the GRANK-T and GRANK-Z is that the demeaned standardized abnormal rank of the event period is equal to zero.

Figure 1: Binance Listings average daily abnormal returns



Average Abnormal returns calculated as described in table 17.