Good Volatility, Bad Volatility, and the Cross Section of Cryptocurrency Returns

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Abstract

This paper examines the distributional properties of cryptocurrency realized variation measures (RVM) and the predictability of RVM on future returns. We show the cryptocurrency volatility persistence and the importance of the asymmetry on volatility forecasting. Signed jumps variations contribute around 18% of the cryptocurrency return quadratic variations. The realized signed jump (RSJ) strongly predicts the cross-sectional future excess returns. Sorting the cryptocurrencies into portfolios sorted by RSJ yields statistically and economically significant differences in future excess returns. This jump risk premium remains significant after controlling for cryptocurrency market characteristics and existing risk factors. The standard cross-sectional regression convinces the cryptocurrency return predictability from RSJ by controlling multiple cryptocurrency characteristics. The investor attention explains the predictability of realized jump risk in future cryptocurrency returns.

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1 Introduction

The rapid growth on cryptocurrency market captures the attention of the economists by raising the question that whether cryptocurrency is a real currency or not Yermack (2015). Since then, an increasing number of researches focus on understanding the unique features of cryptocurrency market. One group (Pagnotta and Buraschi, 2018; Biais et al., 2020; Cong et al., 2021b) considers the user adoption creating externality to the cryptocurrency performance, which is referred to as the "network effect". Another set of papers argue that the price of cryptocurrency is linked the cost of mining the coins (Cong et al., 2021a; Sockin and Xiong, 2020). Liu and Tsyvinski (2021); Liu et al. (2021) standardize the return and risk analysis on the cryptocurrency market and show the uniqueness of cryptocurrency market features. The extant work demonstrates the distinguish between the return and risk of the cryptocurrencies and that of the traditional asset classes, including equities, bonds, foreign exchange currency and futures.

In this paper, we examine the volatility risk and jump risk embedded in the cryptocurrency market. The volatility risk and jump risk have certain implications on understanding the unique return and risk patterns of the cryptocurrency, as this new type of asset has a much higher volatility and extreme event probability[1]. We use the high-frequency tick data on cryptocurrencies and explore the volatility and jump behavior in high-frequency dimension.

Our paper is tightly related to two tranches of the extant literatures. The first group of papers treat the cryptocurrency as a new asset class and use the conventional return and risk framework to understand this new market. We extend the work of Liu and Tsyvinski (2021); Liu et al. (2021) by adopting the high-frequency data from the cryptocurrency and examine whether the high-frequency transactions are informative to predict the return patterns of the cryptocurrencies. This paper is also associated with the recent development on the signed jumps using good volatility and and volatility framework. Our work follows the

[1]See, for instance, Table 1 of Liu and Tsyvinski (2021).

methodological development by Patton and Sheppard (2015) and extends the use of jump risk in explaining equity market (Bollerslev et al., 2020), option market (Feunou and Okou, 2019) and CDS market (Zhang et al., 2009). In addition, the work connects with the field on using jump risk premium to predict asset prices, especially on equity returns Bollerslev and Todorov (2011); Bollerslev et al. (2015), option prices (Pan, 2002; Broadie et al., 2007; Andersen et al., 2015) and credit spreads (Wright and Zhou, 2009; Cremers et al., 2008).

We include 51 most active individual USD-based cryptocurrencies, which cover 92.21% of the market capitalization[2]. Our sample covers the most commonly known and traded examples including Bitcoin, Ethereum, Tether, and Ripple. Using the high-frequency prices, we construct the high-frequency-based volatility measures, including good and bad volatilities, and signed jumps (Patton and Sheppard, 2015). For cryptocurrencies, jumps variations contribute about 17.94% of the quadratic variations on average. The significant proportion of jump variation suggests incremental information embodied in the jumps.

Using this data sample, we forecast the realized volatility (RV) of cryptocurrencies by the panel heterogeneous autoregression (HAR) model (Patton and Sheppard, 2015). Similar to the stock market observation, the cryptocurrency volatility is persistent. The persistence on the cryptocurrency market is within a shorter time range compared to the well-studied volatility persistence for equity. We find a unique property of cryptocurrencies: the good volatility (positive semivariance or the volatility of positive returns) is more important than the bad volatility (negative semivariance or the volatility of negative returns) in the prediction of future RV. Higher good volatility (or higher signed jump variation) leads to higher future market RV and thus future uncertainty on the cryptocurrency market. On the other hand, higher bad volatility (or smaller signed jump variation) leads to less future volatility[3].

Our findings reveal the volatility properties of cryptocurrencies with hard-to-value fundamentals. Given the past positive returns (or jumps) are hard be interpreted as fundamental

[2]The statistic is calculated using the daily market capitalization report from `https://coinmarketcap.com/`. We excluded the cryptocurrencies with a market capitalization of fewer than 1 million dollars.

[3]Patton and Sheppard (2015) show that, for the equity market, bad volatility is more important for volatility forecasting and greater bad volatility is associated with higher future volatility.

improvement, investors weigh heavily on past performance, especially salient returns (jumps) to bet on future performance. As a result, greater good volatility (or signed jumps) attract more investors' attention (Sockin and Xiong, 2020; Liu and Tsyvinski, 2021) and they are bet on future performance with little fundamental support, which in turn leads to higher uncertainty. We document a strong signed jump reversion on cryptocurrencies, which motivates us to explore the relation between signed jumps and the cross-sectional cryptocurrency returns.

We adopt the portfolio analysis on cryptocurrency returns using the constructed realized variation measures (RVM). The single sorted portfolio returns show that the RVMs negatively predict the future excess return of the cryptocurrencies. To rule out the possibility of the signed jump risk premium being explained by alternative effects, we perform the single sorted portfolio analysis with control variables by forming the residual future returns conditioned on the explanatory power from these control variables. We identify the jump risk premium as an independent risk source over alternative effects, including the short-term mean reversion (Corbet and Katsiampa, 2020), realized volatility (Ahn and Kim, 2020) and the "salience effect" (Bordalo et al., 2013). This negative relation (between RVMs and future returns) is valid with the control of some of the known risk factors using double-sorted portfolio analysis. The average portfolio return difference between the quintile groups with highest and lowest realized signed jump remains to be economically and statistically significant with the control of market beta, market capitalization and momentum factors. Next, we convince the connection between RVMs and the future returns using the standard Fama-MacBeth regression. The regression results reinforce the relation shown in the portfolio analysis, and the realized signed jump is among the strongest future return predictor in various regression specifications. Finally, we explore the plausible sources of jump risk premium on the cryptocurrency market. Using the short-term trading volume surprise and the Google search frequency, we find that the investor attention and sentiment supports the predictability of realized signed jumps on future returns.

We contribute to the extant literature by using the non-parametric RVMs estimated from the high-frequency cryptocurrency prices to predict the future cryptocurrency returns. This paper provides the financial econometric insights on understanding the RVMs on the transaction-level price of the cryptocurrency market. The new evidence from these realized measures supplement the field on using good volatility and bad volatility to predict the asset prices (Feunou and Okou, 2019; Bollerslev et al., 2020). This work also contributes to the prediction on future return on cryptocurrency market using the empirical asset pricing approaches (Liu et al., 2021). The RVMs, especially the realized signed jump, contain useful information to predict the future excess returns on cryptocurrency market.

The rest of the paper is organized as follows. Section 2 describes the cryptocurrency and related data that we use in the empirical analysis. Section 3 demonstrates the persistence of realized volatility and realized signed jumps in explaining the cross-sectional realized variation. We show the empirical framework and the analytic results in Section 4. We conclude our findings in Section 5.

2 Data

For the cryptocurrency daily return and market capitalization, we retrieve from `Coinmarketcap.com` following similar researches (Liu and Tsyvinski, 2021; Liu et al., 2021). We collect the daily prices of cryptocurrencies from January 3rd, 2017 to June 30th, 2021. The dataset contains cryptocurrency symbol, prices[4], trading volume, and market capitalization. In contract to the centralized trading assets (stocks, futures and options), cryptocurrencies trade on electric exchanges usually twenty-four hours a day and seven days a week. In other words, there is generally no exchange close time for cryptocurrency market. We include all calendar days with cryptocurrency transactions, and the daily returns are calculated using whole day close price from 0:00:00.000 am to 23:59:59.999 pm UTC.

The tick-level data is from `FirstRateData.com`. The data vendor provides the high-

[4]The website provides the daily open, close, high and low prices of cryptocurrencies. We use the daily close price for the return related calculations.

frequency prices and trading volume for 53 most actively traded cryptocurrencies. We excluded 2 cryptocurrencies that are not U.S. dollar based. We collect the price and corresponding trading volume for each transaction, and construct the one-minute-level volume-weighted return. The first available date for Bitcoin is from April 1st, 2013, and the individual cryptocurrency data update to July 20th, 2021. The cryptocurrencies with high frequency prices in this dataset cover on average 92.21% of the total market capitalization reported on `Coinmarketcap.com`[5]. The summed daily market capitalization of the cryptocurrencies with high-frequency data in our sample cover 81.10% to 99.93% of the total capitalization on the market.

In our sample, the daily average return for the 51 cryptocurrencies is 0.05%, with a standard deviation of 1.28%. The skewness and kurtosis of the daily cryptocurrency returns are 0.123 and 5.343. The cryptocurrency returns demonstrate a higher volatility and higher tail risk comparing with that of stock returns. The average trading volume is $38.18 million and the average market capitalization is $8.76 billion.

3 Good Volatility, Bad Volatility and Signed Jumps

We introduce the approach of computing the non-parametric realized variation measures in this section. After showing the descriptive summary of the realized variation measures, we forecast the realized volatility and realized jumps using the panel model. Comparing to the equity market, cryptocurrency market demonstrate a shorter range volatility persistence and a strong realized jump mean reversion.

3.1 An Empirical Model for Signed Jump

We model the log cryptocurrency price by continuous jump-diffusion process:

$$dc_t = \mu_t dt + \sigma_t dW_t + J_t dq_t,$$

[5] To be included in the sample, the market capitalization needs to exceed $1 million.

where $c_t \equiv log(C_t)$ with C_t as cryptocurrency price. W_t is the standard Brownian motion and dq_t is the Poisson process with jump intensity λ_t. J_t follows normal distribution with mean μ_J and variance σ_J, measuring the jump size of the underlying process. We denote the returns as:

$$r_{t,j} = c_{t,j\cdot\delta} - c_{t,(j-1)\cdot\delta},$$

where $c_{j\cdot\delta}$ is the log asset price at day t and time $j \cdot \delta$. We take δ, the length of time interval, as 5 minutes in our empirical study. m denotes the total number of time intervals within the trading hours. As shown in Barndorff-Nielsen and Shephard (2004), the realized variance and bipower variation of asset returns are

$$\begin{aligned} RV_t &= \sum_{j=1}^{m} r_j^2 \xrightarrow{\delta\downarrow 0} \int_{t-1}^{t} \sigma_s^2 \mathrm{d}s + \int_{t-1}^{t} J_s^2 \mathrm{d}q_s, \\ BV_t &= \frac{\pi}{2}\frac{m}{m-1}\sum_{j=1}^{m} |r_{t,j}||r_{t,j-1}| \xrightarrow{\Delta\downarrow 0} \int_{t-1}^{t} \sigma_s^2 \mathrm{d}s. \end{aligned}$$

Following the recent development on the good volatility and bad volatility framework (Patton and Sheppard, 2015), we separate the RV by the sign of the return for the high-frequency data and obtain the following positive and negative semivariances (or good and bad volatilities):

$$\begin{aligned} RV_t^+ &= \sum_{j=1}^{m} r_j^2 \mathbf{1}_{r_j>0} \xrightarrow{\delta\downarrow 0} \int_{t-1}^{t} \sigma_s^2 \mathrm{d}s + \int_{t-1}^{t} J_s^2 \mathbf{1}_{J_s>0} \mathrm{d}q_s, \\ RV_t^- &= \sum_{j=1}^{m} r_j^2 \mathbf{1}_{r_j<0} \xrightarrow{\delta\downarrow 0} \int_{t-1}^{t} \sigma_s^2 \mathrm{d}s + \int_{t-1}^{t} J_s^2 \mathbf{1}_{J_s<0} \mathrm{d}q_s, \end{aligned}$$

Correspondingly, we obtain the signed jump measure with

$$SJ_t = RV_t^+ - RV_t^- \xrightarrow{\delta\downarrow 0} \int_{t-1}^{t} J_s^2 \mathbf{1}_{J_s>0} \mathrm{d}q_s.$$

Following Patton and Sheppard (2015), we measure the positive and negative signed jumps as $SJ_t^+ = SJ_t \mathbf{1}_{SJ_t>0}$ and $SJ_t^- = SJ_t \mathbf{1}_{SJ_t<0}$. Based on the statistic of the cryptocurrency returns, the volatility are much higher than that of the traditional asset, and jumps on both the positive and negative end are with high probability. The signed jump variation captures the cross sectional return (better than the unsigned jumps) when the volatility of particular cryptocurrency has heterogeneous pattern. We obtain three measures from the intra-day returns

$$
\begin{aligned}
RSJ_t &= SJ_t / RV_t, \\
RSK_t &= \sqrt{n} \sum_{j=1}^{n} r_j^3 / RV_t^{3/2}, \\
RKT_t &= n \sum_{j=1}^{n} r_j^4 / RV_t^2.
\end{aligned}
$$

3.2 Descriptive Analysis of RV and SJ

We report the summary statistics and correlations of various volatility and jump variation measures in following Table 1 and 2. Panel A of Table 1 summarizes the average values of realized volatility (RV), bi-power variation (BV), positive and negative realized semivariances (RV^+ and RV^-), signed jumps (SJ), and positive and negative signed jumps (SJ^+ and SJ^-). Since we have scaled the high-frequency returns by 100, all volatility or jump variation measures are scaled by 10000.

[Insert Table 1 here.]

[Insert Table 2 here.]

The mean of daily RV of Bitcoin is 36.29, suggesting a daily volatility (square root of the mean of RV) of 6.02%. The average (equal-weighted) means of daily RV of the 51 most-traded cryptocurrencies is 1134.57 and the average of volatility is 26.71%. Overall, cryptocurrencies are highly volatile and the Bitcoin is relatively stable among them. By comparing BV and RV, we find about 10.63% of the total quadratic variation of Bitcoin attributing to the jump variation. On average, jump variations represent 17.94% quadratic variations of all 51 cryptocurrencies. Compared to equities, Patton and Sheppard (2015) shows that jump variation only represents about 2% (13%) of quadratic variation for the

S&P 500 ETF (105 individual firms). The significant proportion of jump variations for cryptocurrencies suggests the importance of examining the predictive power of signed jumps.

Panel B of Table 1 report the first-order auto-correlations. For the volatility measures (RV, BV, RV^+ and RV^-), the auto-correlations are around 0.5 for Bitcoin, which indicating volatility clustering effect for Bitcoin[6]. The volatility persistence is not consistent for all cryptocurrencies, though. As shown in the Table 1, the auto-correlation for RV can be as low as 0.0012. For measures of signed jump variations (SJ, SJ^+, and SJ^-), the auto-correlations range from 0.0094 to 0.0821 for the Bitcoin, suggesting no signed jump persistence. For all cryptocurrencies the auto-correlation of SJ can be as low as -0.3593, indicating a weak signed jump reversal for certain cryptocurrencies.

3.3 Persistence of RV of Cryptocurrencies

We examine some statistical properties of the 51 most actively traded cryptocurrencies from the volatility perspective. we propose the panel heterogeneous autoregression (HAR) model using the following specifications (Patton and Sheppard, 2015):

$$\overline{RV}_{h,i,t+h} = \mu_i + \phi_d RV_{i,t} + \phi_w \overline{RV}_{w,i,t} + \phi_m \overline{RV}_{m,i,t} + \epsilon_{i,t+h}, \tag{1}$$

$$\overline{RV}_{h,i,t+h} = \mu_i + \phi_d^+ RV_{i,t}^+ + \phi_d^- RV_{i,t}^- + \phi_w \overline{RV}_{w,i,t} + \phi_m \overline{RV}_{m,i,t} + \epsilon_{i,t+h}, \tag{2}$$

$$\overline{RV}_{h,i,t+h} = \mu_i + \phi_d^+ RV_{i,t}^+ + \phi_d^- RV_{i,t}^- + \gamma RV_{i,t} \mathbf{1}_{r_{i,t}<0} + \phi_w \overline{RV}_{w,i,t} + \phi_m \overline{RV}_{m,i,t} + \epsilon_{i,t+h}, \tag{3}$$

$$\overline{RV}_{h,i,t+h} = \mu_i + \phi_J SJ_{i,t} + \phi_c BV_{i,t} + \phi_w \overline{RV}_{w,i,t} + \phi_m \overline{RV}_{m,i,t} + \epsilon_{i,t+h}, \tag{4}$$

$$\overline{RV}_{h,i,t+h} = \mu_i + \phi_J^+ SJ_{i,t}^+ + \phi_J^- SJ_{i,t}^- + \phi_c BV_{i,t} + \phi_w \overline{RV}_{w,i,t} + \phi_m \overline{RV}_{m,i,t} + \epsilon_{i,t+h}. \tag{5}$$

The dependent variable is h-day average future realized volatility ($\frac{1}{h}\sum_{j=1}^{h} RV_j$) and we use $h = 1, 7, 30, 90$ to represent the future 1-day, 1-week, 1-month and 1-quarter realized volatility respectively since cryptocurrencies are traded 7 days a week. On the right-hand side, we have $\overline{RV}_{w,i,t} = \frac{1}{6}\sum_{j=1}^{6} RV_{i,t-j}$ and $\overline{RV}_{m,i,t} = \frac{1}{23}\sum_{j=7}^{29} RV_{i,t-j}$ to represent past 1-week and 1-month average realized volatility excluding $RV_{i,t}$.

[6] The first-order auto-correlation of daily RV for the S&P 500 ETF is 0.633 (Patton and Sheppard, 2015).

Eq. (1) represents the standard panel HAR model for realized volatility forecasting. If volatility persistence also exist in the cryptocurrency market, we expect ϕ_d, ϕ_w and ϕ_m to be significantly positive. Decomposing realized volatility ($RV_{i,t}$) into good and bad volatilities ($RV_{i,t}+$ and $RV_{i,t}-$) leads to Eq. (2). If the market react homogeneously to $RV_{i,t}+$ and $RV_{i,t}-$, we would expect $\phi_d = \phi_d^+ = \phi_d^-$. Eq. (3) extend Eq. (2) with a cross term of realized volatility $RV_{i,t}$ and the dummy of negative daily return $\mathbf{1}_{r_t<0}$. If $RV_{i,t}+$ and $RV_{i,t}-$ already capture the asymmetric volatilities of market increase and decrease, we would expect γ to be insignificant.

Eq. (4) examine the effect of signed jump variations $SJ_{i,t}$ on future realized volatility by replacing $RV_{i,t}$ in Eq. (4) with $BV_{i,t}$ and incorporating $SJ_{i,t}$. Given previous studies of the equity market, ϕ_J is negative, indicating that positive (negative) jumps lead to smaller (greater) volatility. Eq. (5) further extend Eq. (4) by decomposing $SJ_{i,t}$ into positive and negative signed jumps ($SJ_{i,t}^+$ and $SJ_{i,t}^-$). We expect that $SJ_{i,t}^+$ and $SJ_{i,t}^-$ have heterogeneous effect on future volatility.

Following Table 3 compares the estimation results of forecasting future 1-day, 1-week, 1-month and 1-quarter realized volatilities with past realized volatility measures as specified in Eq. (1), (2) and (3). The volatility is persistent within relatively shorter time range. ϕ_m is not significant for future 1-day, 1-week, 1-month or 1-quarter volatility forecasting. ϕ_d is strongly significantly for $h = 1$ and $h = 7$, with t-statistics greater than 9. For $h = 30$ and $h = 90$, ϕ_d is significant with t-statistics greater than 2. By decomposing $RV_{i,t}$, we find that good volatility has a significant positive effect while bad volatility has weakly significant (or insignificant) negative effect for $h = 1$ and $h = 7$. For $h = 30$ and $h = 90$, both ϕ_d^+ and ϕ_d^- are insignificant. Moreover, we reject (fail to reject) the hull hypothesis $\phi_d = \phi_d^+ = \phi_d^-$ at 0.05 level for $h = 1$ and $h = 7$ ($h = 30$ and $h = 90$). In addition, γ is insignificant for all forecasting horizon, indicating that $RV_{i,t}^+$ and $RV_{i,t}^-$ have already capture the asymmetry effects on volatility forecasting and $RV_{i,t}\mathbf{1}_{r_{i,t}<0}$ provide little incremental information.

[Insert Table 3 here.]

Table 4 compares the estimation results of of forecasting future volatilities with signed jumps (Eq. (4) and (5)). ϕ_J is uniformly positive, with a 0.05 significant level, for $h = 1$ and $h = 7$. Contrary to equities (Patton and Sheppard, 2015), greater (smaller) signed jumps lead to greater (smaller) future realized volatilities. Decomposing the positive and negative signed jumps, we find that ϕ^J- is significantly positive for all forecasting horizons while ϕ_J^+ is insignificant. The positive effect of $SJ_{i,t}^-$ on future volatility suggests that when the market of cryptocurrencies is dominated by negative jumps, future volatility tends to decrease.

[Insert Table 4 here.]

We thus confirm the volatility persistence for cryptocurrencies from the above empirical evidence. Compared with equities, the volatilities of cryptocurrencies are persistent within a shorter time range. Today's volatility only has a strongly significant (0.01 level) positive effect on future 1-day and 1-week volatility. We find that good volatility (positive semivariances) has to lead to greater future (1-day and 1-week) volatilities while bad volatility (negative semivariances) leads to smaller future volatilities. Unlike the well-studied asymmetry of equity prices, i.e. equity price decrease is associated with greater future volatility, our results reveal the "inverse" asymmetry for cryptocurrencies. The volatility of positive (negative) returns leads to greater (smaller) future volatilities. Consistently, the empirical results of the signed jump also show that greater signed jump variation leads to greater volatility. This run against the previous inception of the equity market that the equity market could be more (less) volatile when negative (positive) jumps dominate the market.

[Insert Table 5 here.]

Table 5 summarizes the estimation results of forecasting one-day ahead good volatility ($RV_{i,t+1}^+$), bad volatility ($RV_{i,t+1}^-$), and signed jumps ($SJ_{i,t+1}$) with past good/bad volatilities ($RV_{i,t}^+$, $RV_{i,t}^-$), signed jump measures ($SJ_{i,t}$, $SJ_{i,t}^+$ and $SJ_{i,t}^-$). We find that both the one-day ahead good and bad volatilities are positively associated with current good volatility while current bad volatility is weakly and negatively related to both the one-day ahead good and bad volatilities. The results suggest that there is no good (or bad) volatility persistence. When today's good volatility is higher (bad volatility is lower), tomorrow's volatility, including good and bad, is higher (lower). Table 5 also shows that one-day ahead signed jump variation is negatively related to the current signed jump variation, suggesting a jump reversal, which is consistent with our findings in the following part of jump-sorted portfolio returns. Consistently, current good (bad) volatility is negatively (positively) related to future signed jump variations.

To conclude, cryptocurrency, which is a more lottery-like asset compared to the equity, has non-fundamental feature and is hard to value through discounting the future cash flows. Investor attention could be attracted by positive returns, especially by the positive jumps (Sockin and Xiong, 2020; Liu and Tsyvinski, 2021). We cannot attribute the positive returns of cryptocurrencies to fundamental improvements like equities. Investors bet on the higher future prices of cryptocurrencies without any guarantee of future cash flow (or earning growth). Cryptocurrency investors weigh heavily on past-performance-based information such as momentum or technical analysis (Liu and Tsyvinski, 2021; Detzel et al., 2021). Our results show that greater good volatility (or signed jump variation) lead to greater future market uncertainty (as measured by $RV_{i,t+1}$, $RV^+_{i,t+1}$ and $RV^-_{i,t+1}$) and smaller signed jumps ($SJ_{i,t+1}$). On the other hand, bad volatility (negative signed jumps variations) discourage investors from joining the cryptocurrency market. When negative returns or jumps dominate today, we expect a less volatile market and positive jumps (jump reversal). Our findings are aligned with the salience theory (Bordalo et al., 2013; Cosemans and Frehen, 2021) that investors overvalue (undervalue) cryptocurrencies with salient upsides (downside). The significant jump reversal suggests the following study of signed jumps and the cross-sectional returns.

4 Signed Jumps and the Cross Sectional Cryptocurrency Returns

After constructing the understanding the realized variation measures from the cryptocurrency market, we use realized jump, skewness and kurtosis measures (RSJ, RSK and RKT) and examine their cross sectional predictability to the future cryptocurrency returns.

Similar to the stock market, the single-sorted portfolio demonstrates a significant negative relation between the realized variation measures and the future cryptocurrency returns. This negative relation is still valid when we control for the short-term mean reversion effect. We then examine this negative relation using double-sorted portfolio controlling for the existing risk factors on cryptocurrency markets documented by Liu et al. (2021). We corroborate these findings using the cross-sectional return predictability regressions that control for realized variation measures and other cryptocurrency characteristics.

4.1 Descriptive Analysis

Panel A of Table 6 summarizes the realized variation measure along with other cryptocurrency characteristics. The RSJ measure has scaled mean of -0.0059, reflecting a large tail jump risk associated with the negative returns. The high-frequency returns are skewed to the right and strongly reject the normality distribution. The cryptocurrencies in our sample have an averaged market beta of 0.71, indicating that most of the actively traded cryptocurrencies slightly underact to the market returns. The correlation coefficients are displayed in the Panel B of Table 6. From the correlation table, we find the RSJ is strongly associated with the RSK, and positively correlated with market capitalization, mean reversion, trading volume, the realized volatility, and idiosyncratic volatility. The RSJ is negatively relative to the RKT, market beta, momentum factor and the illiquidity measure.

In Table 7, we present the variable mean value by sorting the realized variation measures (RSJ, RV, RSK and RKT). The sorted quintile portfolio averages convince the correlation pattern across the independent variables. For instance, Panel A and Panel C display the positive correlation between RSJ and RSK, as the portfolio averages show a monotonic increase on both variables. Besides, the RSJ and RST are negatively connected with momentum and positively connected with idiosyncratic volatility.

4.2 Single Portfolio Sorting

At each trading day[7], we sort the cryptocurrencies into quintile portfolios based on the realized variation measures (RSJ, RSK and RKT) from the high-frequency transactions during the day. We then calculate the equal-weighted and value-weighted returns over the subsequent trading day for each portfolio. All strategies are rebalanced on daily basis.

In Panel A of Table 8 presents the average future return of each portfolio by sorting the realized signed jump. Both equal-weighted portfolio and value-weighted portfolio demonstrate a strong monotonically decreasing returns from the group 1 (lowest RSJ) to the group 5 (highest RSJ). In value-weighted portfolios, the difference in average daily returns between the portfolio with highest RSJ and lowest RSJ is -34.0 basis points (with Newey-West adjusted t-statistic = -2.931). As for the equal-weighted portfolio, the average daily return decreases from 45.1 basis points in the lowest RSJ portfolio to -39.3 basis points in the highest RSJ portfolio. The difference on the average daily returns reaches 84.4 basis points (with Newey-West adjusted t-statistic = -7.103).

[Insert Table 8 here]

We examine if the average daily return difference orients from the systematic risk. We use the stock market risk factors by Fama and French (1993) and Carhart (1997) and the the cryptocurrency market risk factors by Liu et al. (2021). Panel A of Table 8 reports the alpha from the Fama-French-Carhart 4-factor model in "FFC4" column and from the Liu-Tsyvinski-Wu 3-factor model in "LTW3" column. We observe a similar monotonically decreasing pattern on the alpha estimate comparing to the unconditional portfolio sorting.

[7] Most of the coins and tokens are traded 24 hours a day and seven days a week.

For the value-weighted returns, the FFC4 alpha reduces from 24.7 basis points in lowest RSJ portfolio to -9.4 basis points in the highest RSJ portfolio. The difference on the alpha in quintile groups is -34.1 basis points, and the difference becomes 42.6 basis point after controlling for the LTW3 factors. As for the equal-weighted portfolios, the difference of average daily returns between the lowest and highest RSJ is -85.8 basis points (with t-statistic = -5.737) using FFC4 factors and is -93.0 basis points (with t-statistic = -7.758) using LTW3 factors.

The portfolio returns by sorting RSK and RKT are presented in Panel B and Panel C in Table 8. We obtain a generally decreasing returns from the lowest RSK/RKT portfolio to the portfolio with highest RSK/RKT. The economic magnitude of the average return difference is slightly smaller than that of the RSJ portfolios. The average daily return is 21.2 basis points lower in the highest RSK portfolio than that of the lowest RSK portfolio with value-weighted basis (t-statistic=-3.500). The FFC4 and LTW3 alphas are -8.1 basis points and -13.9 basis points, respectively. The average daily return difference is insignificantly -20.4 basis points in case of value-weighted portfolio sorting by RKT. The portfolio sorting results show decreasing average return generally with the increase on RKT, but the impact is smaller and insignificant.

To illustrate the future return predictability using realized variation measures, we construct the long-short portfolios using the single-sorted approach. We initiate the portfolio with the wealth of $1 at the beginning of 2017. On daily basis, we rebalance this cryptocurrency portfolio using the high-frequency transactions during the day. The portfolio has long position on the cryptocurrencies with lowest realized variation measures, and has short position on the cryptocurrencies with highest realized variation measures. Figure 1 plots the portfolio value executing this investment strategy. The best performance is from the long-short portfolio using RSJ as the rebalancing signal. The end of period (June 30th, 2021) wealth for value-weighted (equal-weighted) RSJ portfolio is $30.74 ($115.92), for RSK portfolio $3.75 ($4.58) and almost zero for RKT portfolio. Though with high rate of return during the sample period, the volatility is relatively high for the cryptocurrency portfolio, causing the Sharpe ratio of value-weighted (equal-weighted) RSJ portfolio being 2.06 (3.37).

[Insert Figure 1 here]

4.3 Single Portfolio Sorting with Controls

The empirical evidence in Table 8 shows that the jump risk premium exists in the cross-sectional cryptocurrency returns. One may argue that this jump risk premium is not a standalone risk factor, and the jump risk premium could potentially be explained by other attributes. Thus we continue to validate the identification of jump risk premium as a standalone risk source by sorting the portfolios using RSJ with controls. The returns are first regressed by the individual control variable, and the residuals are sorted in single portfolio by RSJ.

The main alternative explanation of the jump risk premium is the short-term mean reversal. We define the mean reversion by the lagged one day cryptocurrency return. We examine the excess return residuals controlled by the mean reversion and check the predictability of RSJ on the residual returns. Next, since the realized signed jump is computed from the realized volatility, we use the RV as the control variable in the single portfolios sorted by RSJ. Lastly, investors may emphasize more of the asset returns with more significant bias from the benchmark return. The effect is referred to as the "salience theory" (ST) (Bordalo et al., 2012, 2013) and is empirically validated on the stock market (Cosemans and Frehen, 2021). We follow the salience effect measure constructed in Cosemans and Frehen (2021) and implement on the cryptocurrency market. We then use the ST measure as one of the control variable in the single sorted portfolios.

Table 9 presents the portfolio returns from sorting RSJ with the control on mean reversion, realized volatility and salience theory. In Panel A, the control variable is one day lagged return as short-term mean reversion. The difference between high and low RSJ portfolios is

-1.303% with t-statistic of -8.283. The statistical and economic significance is stronger than that of the single sorted portfolio without controlling for mean reversion. This indicates that the jump risk premium we identified is a standalone risk source distinguishing from the mean reversion effect. The similar pattern is observed from Panel B of Table 9. The risk premium magnitude and the statistical significance are higher after controlling the realized volatility. This observation convinces the advantage of using signed volatility instead of the using RV directly as a excess return predictor.

[Insert Figure 9 here]

Panel C of Table 9 shows the risk premium difference and statistical significance similar to the unconditional single sorted portfolios on RSJ. This is not a denial of salience effect on the cryptocurrency market. Instead, the jump risk premium may capture an independent risk source from the salience effect estimated from the daily return deviation with respect to the market return. Overall, the single portfolio sorting results show that the risk premium identified from RSJ is independent to the major plausible alternative explanations on the negative relation between RSJ and future excess return.

4.4 Double Portfolio Sorting

We perform the double-sorted portfolio analysis to examine the return predictability controlling for known cryptocurrency market risk factors Liu et al. (2021). Table 10 reports the average returns using unconditional sorting on RSJ controlling for the cryptocurrency market risk factors proposed in Liu et al. (2021).

[Insert Table 10 here]

Panel A of Table 10 presents the average daily return in the five-by-five portfolios sorted by RSJ and the market beta. The market beta of cryptocurrencies is the sensitivity of individual cryptocurrency return with respect to the cryptocurrency market return. The row “High - Low” calculates the difference between the quintile portfolios with highest and lowest RSJ in each of the market beta portfolios. All the quintile portfolios conditioning on market beta predict negative return spread on RSJ. Under value-weighted regime, the average daily return difference on RSJ is -69.3 basis points (with t-statistic = -3.834) in the lowest market beta group and -67.2 basis points (with t-statistic = -2.902) in highest market beta group. The “in-between” market beta groups demonstrate a smaller magnitude on return difference from RSJ ranking and weaker statistical significance. We obtain a similar pattern from equal-weighted portfolio on RSJ sorted with the market beta controlled.

Liu et al. (2021) show a strong size effect on the cryptocurrency return pattern. In Panel B of Table 10, we control the market capitalization of cryptocurrencies and investigate the return predictability from RSJ. The return difference pattern is largely asymmetric depending on the size of the cryptocurrency. The difference of RSJ return predictability is strongest in the quintile portfolio with the small market capitalization. The average daily return difference between highest and lowest RSJ reached 108.1 basis points (with t-statistic=-5.099) in the smallest size group, using value-weighted regime. This is much higher than the magnitude of -18.1 basis points in the largest size group, where the average return difference is insignificant (with t-statistic=-1.499). The empirical evidence confirms a strong negative relation between RSJ and future returns conditioning on the presence of size effect on cryptocurrency returns.

Lastly, we show the double-sorted portfolio returns on RSJ and momentum. Liu et al. (2021) document a strong momentum factor on cryptocurrency market from one week up to four weeks. In Panel C of Table 10, we report the portfolio sorting excess returns on RSJ with the control of four-week momentum. That is, the portfolio is sorted by the cumulative return from day $t-28$ to day $t-2$, and unconditionally sorted by RSJ. The value weighted portfolio has average daily excess return difference of -84.0 basis points with robust t-statistic of -4.235 between the highest and lowest RSJ portfolios. The average daily excess return becomes -23.9 basis points with robust t-statistic of -1.688 with the highest momentum portfolio. The future return predictability is stronger for the portfolio with relative smaller past month return. We obtain a similar pattern using equal-weighted portfolio, where magnitude of the return difference among quintile portfolios and the statistical significance are larger.

4.5 Fama-MacBeth Regressions

The single-sorted and double-sorted portfolio analyses establish a strong negative relation between realized variation measures and the future cryptocurrency returns. The portfolio analysis allows up to one control factor to explain the potential source of the sign jump risk premium. We reinforce the portfolio analysis by running the standard Fama and MacBeth (1973) cross-sectional type predictive regressions, where we control multiple cryptocurrency characteristics at the same time.

We conduct the regression using daily return data with the following specification:

$$\text{CReturns}_{i,t+1} = \alpha + \beta \cdot \Lambda_{i,t} + \lambda \cdot \text{RSJ}_{i,t} + \epsilon_{i,t}, \tag{6}$$

where $\text{CReturns}_{i,t}$ is the individual cryptocurrency return, $\Lambda_{i,t}$ contains the known risk factors on cryptocurrency (market, size and momentum) and control variables, and RSJ denotes the realized signed jump. We also examine RSK and RKT in the regression to evaluation the predictability of realized variation measures on future returns.

Besides the realized variation measure, key independent variables include the return sensitivity with respect to market return (BETA), the market capitalization (SIZE), the cumulative return from day $t-28$ to day $t-1$ as the momentum factor (MOM), the simple return from day $t-1$ as the mean-reverting factor (REV), the logarithm of trading volume (VOLM), the idiosyncratic volatility estimated from the volatility of residual from market model using the past month daily returns (IVOL), and the Amihud (2002) measure using the high-frequency transactions during the day (ILLIQ).

Panel A of Table 11 reports the univariate Fama-MacBeth regression coefficients between one-day ahead cryptocurrency returns and each of the individual control variable. Among the realized variation measures, RSJ, RSK and RKT have negative and statistically significant coefficients. The estimated coefficients are consistent with the main conclusion from the single-sorted and double-sorted portfolio analyses. RV has negative but insignificant coefficient. Among the control variables, momentum factor's coefficient is positive and significant, whereas the one-day lagged return is strongly negatively associated with the future return. Besides, market beta, idiosyncratic volatility and illiquidity measure have positive coefficient, and the market capitalization has negative coefficient. The direction of the coefficient is generally consistent with the work by Liu et al. (2021).

Panel B of Table 11 displays the multivariate regression analysis on realized variation measures and the control variables. In specification I to IV, each of the realized variation measure is combined with the full set of control variables. While momentum and mean reversion factors remain to be strongly significant in these regression, the RSJ becomes the only statistically significant realized variation measures among the four. When we remove the mean reversion factor, the RSK and RKT are statistically significant in specification V and VI. From the regression results from VII to X, we conclude that the one-day lagged return is the mainly competing factor with the realized variation measure. In the full control regression XI, RSJ remains to be the strongest risk factor among the four realized variation measures. The RSK is weakly significant. The market sensitivity, momentum and mean reversion are statistically significant. The RSJ remains to be significant in all regression specifications.

4.6 Source of the Jump Premium on Cryptocurrency Market

We continue to explore the plausible sources for the jump risk premium on the cryptocurrency market. In the stock market case, the source of the equity price jumps is largely the news of the underlying firms (Maheu and McCurdy, 2004; Lee and Mykland, 2008; Bajgrowicz et al., 2016; Jeon et al., 2021). The timing of the news coincides with most of the jumps on the equity market. In the cryptocurrency case, the non-fundamental feature makes it hard to connect the news directly related to the price of the underlying cryptocurrency.

Rognone et al. (2020) find that the news on Bitcoin is related the Bitcoin price, but the prices rise regardless on the news sentiment. Lyócsa et al. (2020) argue that the Bitcoin realized variance is not very sensitive to the scheduled macroeconomic news, but relates to the Bitcoin specific news such as the Bitcoin market regulation and the hacking of Bitcoin exchange.

Both Rognone et al. (2020) and Lyócsa et al. (2020) focus on the Bitcoin as one representative cryptocurrency on the whole market. The reaction of Bitcoin price and volatility (and thus its jump component) to the news demonstrates significant distinguish with that of foreign currencies and stocks. In addition, the investor attention and the sentiment in reaction to the news play an increasing important role in explaining the jump behaviors on the cryptocurrency market.

We focus on exploring the formation of the cross-sectional cryptocurrency jumps and how does the jump premium connect with the cryptocurrency returns. In earlier discussion, we show that the realized signed jump is negatively connected with the future cryptocurrency returns. In this section, we examine the source of the jumps on the cryptocurrency market. Based on the work of Rognone et al. (2020) and Lyócsa et al. (2020), the investor attention from the news becomes a impacting factor on cryptocurrency realized volatility. On the return side, the "network factors" are positively related to the future cryptocurrency returns (Cong et al., 2021b; Sockin and Xiong, 2020; Liu and Tsyvinski, 2021).

We select two cryptocurrency market measures to proxy the investor attention and investor sentiment. First, we construct the trading volume shock, defining by the difference between the most recent daily trading volume and the moving average of the past 30 days. The volume shock measurement compares the short-term trading volume with the relative long-term one, reflecting the bias of short-term popularity of the cryptocurrency comparing to the equilibrium one. Second, we collect the Google web page search frequency for the cryptocurrencies in our data sample within the sample period. A sentiment index is computed using the web search frequencies to address the cross-sectional attention towards the individual cryptocurrencies.

Table 12 displays the Fama-MacBeth regressions with the investor attention and sentiment measures included. To examine the asymmetric effect from the productivity of RSJ on future returns, we construct the interaction terms between RSJ and investor attention measures respectively. The coefficient interaction terms is statistically significant, with expected sign given the estimated parameters for RSJ and the individual investor attention measures. This indicates that the investor attention and sentiment magnify the impact of RSJ on predicting the future cryptocurrency returns.

[Insert Figure 12 here]

More specifically, when using the trading volume shock measure, the short-term trading popularity positively predicts the future excess return. This is consistent with the conclusion from Liu and Tsyvinski (2021) on the Bitcoin market[8]. The interaction term has negative and significant coefficient, indicating that the economic magnitude of the impact from RSJ on future return is higher with there is more "abnormal" trading volume in the short term. In specification (2), the frequency on Google search is positively related to the future return, which is consistent with the main conclusion of Sockin and Xiong (2020). The interaction term (between RSJ and Google search index) is negatively significant from the model estimation. This indicates that the predictability of RSJ on future returns is stronger when the corresponding cryptocurrency is more popular.

Overall, the empirical evidence from Table 12 provides a reasonable source of the jumps on the cryptocurrency market. The investor attention contributes to the magnitude of the jump risk premium in the cross-sectional cryptocurrency returns. The realized signed jumps have a more pronounced impact on future excess return when the investor attention is higher.

[8] Liu and Tsyvinski (2021) use four measures to proxy the network factor, including the number of wallet users, active addresses, transaction count and payment count on the Bitcoin market. We select the trading volume shock to better connect the jump behavior and the capital market variable for each individual cryptocurrencies

5 Conclusion

We continue the work of Liu and Tsyvinski (2021) and Liu et al. (2021) on using the empirical asset pricing approach to understand the return predictability of the cryptocurrency market. We first use the high-frequency transaction data to analyze the persistence of the realized volatility on this new asset class. We confirm the volatility persistence with a relatively shorter time range comparing to the equity market. We also document that good volatility is more important for volatility forecasting, and higher good volatility (bad volatility) is associated wither higher (smaller) future realized volatility. In addition, the signed jump demonstrates a strong mean reversion pattern on the cryptocurrency market.

From the persist realized variation measures, we construct the realized signed jump and the realized skewness/kurtosis measures to capture the future cryptocurrency return. We examine the return predictability from cryptocurrency realized variation measures. The single-sorted portfolio analysis shows a strong negative relation between the future excess cryptocurrency return and realized signed jump. The signed jump risk premium is independent to the short term mean reversion, realized volatility and salience effect on the cryptocurrency market. This pattern is confirmed by double-sorted portfolio using control variables from existing risk factor documented in Liu et al. (2021). The jump risk premium is both economically and statistically significant in the cross-sectional cryptocurrency returns. The standard Fama-MacBeth regression supports that RSJ is the strongest future return predictors among the realized variation measures and contributes to the future return predictability along with the other risk factors on the cryptocurrency market. We further explore the source of the jumps on the cryptocurrency markets, and find that the invest attention contributes to the jump risk premium in prediction of the future excess returns.

The literature on cryptocurrency risk and return is growing rapidly. From empirical asset pricing prospective, understanding the unique features of cryptocurrency return pattern is vital to disentangle this new asset class, especially in comparison with the returns of existing asset class such as stocks, options, bonds and foreign currencies. From financial econometric prospective, obtaining high quality cryptocurrency price data, especially the prices in different frequency, lay the foundation to explore the return and volatility dynamics.

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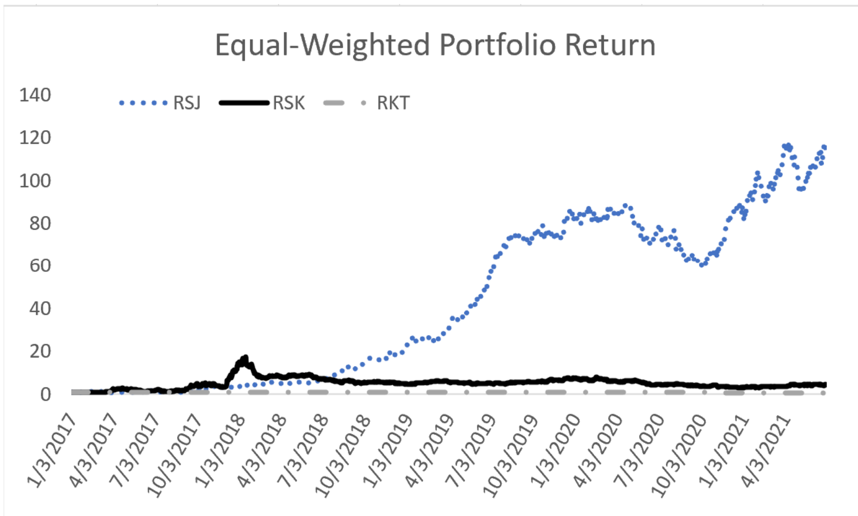

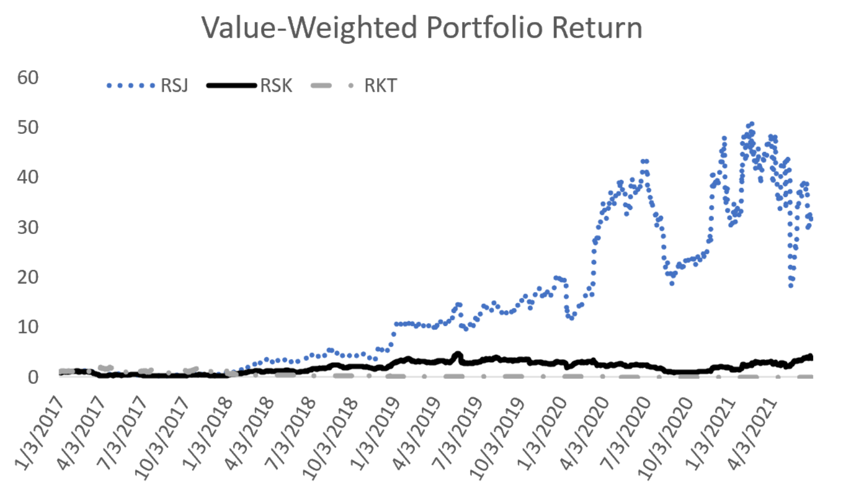

Figure 1: The top graph illustrates the cumulative return on equal-weighted long-short portfolio on realized variation measures (RSJ, RSK and RKT). The bottom graph illustrates the cumulative return on value-weighted long-short portfolio on realized variation measure. Both portfolios start with \$1 at January 3rd, 2017, rebalance on daily basis, and accrue up to June 30th, 2021.

Table 1: Summary statistics of daily realized volatility and jump variations

Table 1 summarizes the average values and auocorrelations of realized volatility (RV), bi-power variation (BV), positive and negative realized semivariances (RV^+ and RV^-), signed jumps (SJ), and positive and negative signed jumps (SJ^+ and SJ^-). All measures of volatility and jump variation are scaled by 1000. The Bitcoin column shows the the summary statistics for the Bitcoin and The right four columns contain the mean, 5% quantile, median, and 95% quantile from the panel of all 51 most-traded cryptocurrencies. Panel A summarizes the statistics for realize variation measures and panel B summarizes the first-order auto-correlations.

Panel A: Realized Variation Measures

	Bitcoin	All cryptocurrencies			
	Mean	Mean	$Q_{.05}$	Median	$Q_{.95}$
RV	36.2932	1134.5777	38.2565	540.8617	5954.4623
BV	32.4336	931.063	34.3568	484.9304	4645.9787
RV^+	18.1336	568.1212	19.0153	268.2304	2978.427
RV^-	18.1596	566.4565	19.2412	272.6313	2976.0353
SJ	-0.026	1.6647	-10.8321	-0.1937	17.7035
SJ^+	1.4781	16.4641	0.2325	6.3502	72.8044
SJ^-	-1.5042	-14.7994	-52.5093	-7.457	-0.228

Panel B: Auto-correlation

	Bitcoin	All cryptocurrencies			
	Mean	Mean	$Q_{.05}$	Median	$Q_{.95}$
RV	0.5397	0.3873	0.0012	0.3688	0.8491
BV	0.5033	0.3749	0.0019	0.3617	0.8394
RV^+	0.4968	0.3855	0.0012	0.3421	0.8485
RV^-	0.5611	0.3853	0.0011	0.3871	0.8494
SJ	0.0094	-0.0598	-0.3593	-0.0275	0.1701
SJ^+	0.0258	0.0868	-0.0044	0.0604	0.2596
SJ^-	0.0821	0.1025	-0.0031	0.065	0.3018

Table 2: Correlation of daily realized volatility and jump variations.

Panel A of reports the correlations among realized volatility (RV), bi-power variation (BV), positive and negative realized semivariances (RV^+ and RV^-), signed jumps (SJ), and positive and negative signed jumps (SJ^+ and SJ^-) for Bitcoin. Panel B reports the equal weighted average of the correlations of those variables for the panel of 51 most-traded cryptocurrencies.

Panel A: Bitcoin							
	RV	BV	RV^+	RV^-	SJ	SJ^+	SJ^-
RV	1.0000						
BV	0.9946	1.0000					
RV^+	0.9896	0.9937	1.0000				
RV^-	0.9892	0.9742	0.9577	1.0000			
SJ	0.0618	0.1269	0.205	-0.0853	1.0000		
SJ^+	0.4974	0.5574	0.6068	0.3753	0.8245	1.0000	
SJ^-	-0.6092	-0.5807	-0.5142	-0.6928	0.5764	0.0129	1.0000

Panel B: All Cryptocurrencies							
	RV	BV	RV^+	RV^-	SJ	SJ^+	SJ^-
RV	1.0000						
BV	0.9897	1.0000					
RV^+	0.9966	0.9849	1.0000				
RV^-	0.9961	0.9875	0.9858	1.0000			
SJ	0.0345	0.026	0.0887	-0.022	1.0000		
SJ^+	0.4388	0.4252	0.4799	0.3932	0.6926	1.0000	
SJ^-	-0.4124	-0.4098	-0.3734	-0.4495	0.6623	0.0441	1.0000

Table 3: Estimation results of Panel HAR Model with Good and Bad Volatilities

For forecasting horizon $h=1$, $h=7$, $h=30$ and $h=90$, we report the estimation results of panel HAR models specified as Eq. (1), (2) and (3). Eq. (1) examine the volatility persistence. Eq. (2) and (3) examine the effect of good and bad volatility separately. All models include currency fixed effect. *,** and *** represent 10%, 5% and 1% levels of significance respectively and the t-statistics are reported in the bracket.

$$Eq.(1): \quad \overline{RV}_{h,i,t+h} = \mu_i + \phi_d RV_{i,t} + \phi_w \overline{RV}_{w,i,t} + \phi_m \overline{RV}_{m,i,t} + \epsilon_{i,t+h},$$

$$Eq.(2): \quad \overline{RV}_{h,i,t+h} = \mu_i + \phi_d^+ RV_{i,t}^+ + \phi_d^- RV_{i,t}^- + \phi_w \overline{RV}_{w,i,t} + \phi_m \overline{RV}_{m,i,t} + \epsilon_{i,t+h},$$

$$Eq.(3): \quad \overline{RV}_{h,i,t+h} = \mu_i + \phi_d^+ RV_{i,t}^+ + \phi_d^- RV_{i,t}^- + \gamma RV_{i,t}\mathbf{1}_{r_{i,t}<0} + \phi_w \overline{RV}_{w,i,t} + \phi_m \overline{RV}_{m,i,t} + \epsilon_{i,t+h}.$$

	$h=1$			$h=7$			$h=30$			$h=90$		
	Eq. (1)	Eq. (2)	Eq. (3)	Eq. (1)	Eq. (2)	Eq. (3)	Eq. (1)	Eq. (2)	Eq. (3)	Eq. (1)	Eq. (2)	Eq. (3)
ϕ_d	0.730***			0.410***			0.831**			0.630**		
	[9.425]			[9.299]			[2.499]			[2.248]		
ϕ_d^+		5.095**	5.391**		1.737**	1.969**		2.764	2.749		2.119	2.105
		[2.544]	[2.528]		[2.530]	[2.440]		[1.611]	[1.358]		[1.547]	[1.324]
ϕ_d^-		-3.619*	-4.042*		-0.912	-1.242		-1.095	-1.073		-0.852	-0.833
		[-1.830]	[-1.905]		[-1.354]	[-1.522]		[-0.840]	[-0.646]		[-0.871]	[-0.668]
γ			0.163			0.127			-0.008			-0.008
			[1.637]			[1.422]			[-0.028]			[-0.037]
ϕ_w	0.146***	0.141***	0.133***	0.363***	0.361***	0.355***	1.547*	1.544*	1.545*	0.698*	0.697*	0.697*
	[2.726]	[2.726]	[2.683]	[3.048]	[3.029]	[3.146]	[1.778]	[1.776]	[1.799]	[1.771]	[1.768]	[1.802]
ϕ_m	0.008	0.007	0.004	-0.027	-0.027	-0.030	-0.616	-0.617	-0.616	-0.173	-0.173	-0.173
	[0.864]	[0.786]	[0.403]	[-0.743]	[-0.747]	[-0.741]	[-1.557]	[-1.557]	[-1.537]	[-0.974]	[-0.974]	[-0.955]
R^2	0.6219	0.6331	0.6391	0.4846	0.4859	0.4906	0.4046	0.4049	0.4049	0.1201	0.1202	0.1202

Table 4: Estimation results of Panel HAR Model with Signed Jump Variations.

For forecasting horizon $h = 1$, $h = 7$, $h = 30$ and $h = 90$, we report the estimation results of panel HAR models specified as Eq. (4) and (5). Eq. (4) examine the effect of signed jump $SJ_{i,t}$ after controlling the bi-power variation $BV_{i,t}$. Eq. (5) decomposing signed jump variations into positive and negative jump variations. All models include currency fixed effect. *,** and *** represent 10%, 5% and 1% levels of significance respectively and the t-statistics are reported in the bracket.

$$Eq.(4): \quad \overline{RV}_{h,i,t+h} = \mu_i + \phi_J SJ_{i,t} + \phi_c BV_{i,t} + \phi_w \overline{RV}_{w,i,t} + \phi_m \overline{RV}_{m,i,t} + \epsilon_{i,t+h}, \tag{7}$$

$$Eq.(5): \quad \overline{RV}_{h,i,t+h} = \mu_i + \phi_J^+ SJ_{i,t}^+ + \phi_J^- SJ_{i,t}^- + \phi_c BV_{i,t} + \phi_w \overline{RV}_{w,i,t} + \phi_m \overline{RV}_{m,i,t} + \epsilon_{i,t+h}. \tag{8}$$

	$h=1$		$h=7$		$h=30$		$h=90$	
	Eq. (4)	Eq. (5)	Eq. (4)	Eq. (5)	Eq. (4)	Eq. (5)	Eq. (4)	Eq. (5)
ϕ_J	5.027**		1.701**		2.733		2.110	
	[2.394]		[2.326]		[1.551]		[1.505]	
ϕ_J^+		3.633		0.191		-1.625		-1.201
		[1.290]		[0.293]		[-1.366]		[-1.525]
ϕ_J^-		7.421***		4.297***		10.222**		7.800**
		[7.195]		[7.831]		[2.351]		[2.207]
ϕ_c	0.922***	0.939***	0.517***	0.535***	1.064**	1.116**	0.814**	0.853**
	[9.551]	[9.770]	[9.969]	[10.502]	[2.521]	[2.612]	[2.259]	[2.339]
ϕ_w	0.153***	0.146***	0.368***	0.359***	1.545*	1.521*	0.693*	0.675*
	[3.010]	[2.855]	[3.191]	[3.046]	[1.778]	[1.754]	[1.773]	[1.733]
ϕ_m	0.009	0.011	-0.026	-0.024	-0.614	-0.608	-0.172	-0.167
	[0.806]	[0.991]	[-0.741]	[-0.686]	[-1.561]	[-1.556]	[-0.971]	[-0.955]
R^2	0.6339	0.6358	0.4869	0.4896	0.4072	0.4096	0.1211	0.1218

Table 5: Forecasting ahead Good/Bad Volatilities and Signed Jumps.

We report the estimation results of forecasting 1-day ahead good volatility ($RV^+_{i,t+1}$), bad volatility ($RV^-_{i,t+1}$), and signed jumps ($SJ_{i,t+1}$) with past good/bad volatilities ($RV^+_{i,t}$, $RV^-_{i,t}$), signed jump measures ($SJ_{i,t}$, $SJ^+_{i,t}$ and $SJ^-_{i,t}$) and other control variables. All models include currency fixed effect. *,** and *** represent 10%, 5% and 1% levels of significance respectively and the t-statistics are reported in the bracket. The regression equations are specified as follows and the dependent variable $y_{i,t+1}$ could be $RV^+_{i,t+1}$, $RV^-_{i,t+1}$ and $SJ_{i,t+1}$ respectively.

$$y_{i,t+1} = \mu_i + \phi^+_d RV^+_{i,t} + \phi^-_d RV^-_{i,t} + \phi_w \overline{RV}_{w,i,t} + \phi_m \overline{RV}_{m,i,t} + \epsilon_{i,t+h},$$
$$y_{i,t+1} = \mu_i + \phi_J SJ_{i,t} + \phi_c BV_{i,t} + \phi_w \overline{RV}_{w,i,t} + \phi_m \overline{RV}_{m,i,t} + \epsilon_{i,t+h},$$
$$y_{i,t+1} = \mu_i + \phi^+_J SJ^+_{i,t} + \phi^-_J SJ^-_{i,t} + \phi_c BV_{i,t} + \phi_w \overline{RV}_{w,i,t} + \phi_m \overline{RV}_{m,i,t} + \epsilon_{i,t+h}.$$

	$RV^+_{i,t+1}$	$RV^+_{i,t+1}$	$RV^+_{i,t+1}$	$RV^-_{i,t+1}$	$RV^-_{i,t+1}$	$RV^-_{i,t+1}$	$SJ_{i,t+1}$	$SJ_{i,t+1}$	$SJ_{i,t+1}$
$RV^+_{i,t}$	2.397**			2.698**			-0.302**		
	[2.550]			[2.539]			[-2.365]		
$RV^-_{i,t}$	-1.660*			-1.959*			0.299**		
	[-1.789]			[-1.866]			[2.392]		
$SJ_{i,t}$		2.363**			2.664**			-0.301**	
		[2.391]			[2.397]			[-2.361]	
$SJ^+_{i,t}$			1.582			2.051			-0.469*
			[1.239]			[1.333]			[-1.774]
$SJ^-_{i,t}$			3.704***			3.717***			-0.013
			[7.183]			[7.193]			[-0.275]
$BV_{i,t}$		0.460***	0.470***		0.462***	0.469***		-0.002	0.000
		[9.505]	[9.811]		[9.593]	[9.730]		[-0.933]	[0.425]
$\overline{RV}_{w,i,t}$	0.071***	0.077***	0.073***	0.070***	0.076***	0.073***	0.001	0.001	-0.000
	[2.733]	[3.012]	[2.853]	[2.719]	[3.007]	[2.856]	[0.608]	[0.546]	[-1.185]
$\overline{RV}_{m,i,t}$	0.004	0.004	0.006	0.004	0.004	0.005	0.000	0.000	0.000
	[0.811]	[0.828]	[1.040]	[0.761]	[0.784]	[0.943]	[0.710]	[0.700]	[1.311]
R^2	0.632	0.6329	0.6352	0.6336	0.6343	0.6357	0.0902	0.0900	0.1354

Table 6: Summary Statistics on Portfolio Analysis

Table 6 presents the summary statistics of the main variables. The sample consists of the 51 most active cryptocurrencies with market capitalization over $1 million within the sample period from January 2017 to June 2021. RSJ, RV, RSK and RKT are the signed jump, realized volatility, realized skewness, and realized kurtosis, respectively. BETA denotes the beta with respect to the market return. SIZE is the market capitalization of the cryptocurrency. MOM is the compound return of day $t-7$ through day $t-2$. REV denotes the lagged one day return. VOLM is the logarithm of trading volume. IVOL denotes the idiosyncratic volatility estimated from the market model. ILLIQ denotes the illiquidity level using the daily Amihud (2002) measure.

Panel A: Description											
	RSJ	RV	RSK	RKT	BETA	SIZE	MOM	REV	VOLM	IVOL	ILLIQ
N	67,058	67,058	67,058	67,058	64,280	64,344	64,335	64,335	64,101	64,280	64,093
Mean	-0.0059	0.0043	-0.0503	15.1610	0.7108	20.3798	0.0224	0.0005	18.1031	1.0006	0.0091
Std. Dev.	0.1757	0.0023	0.9971	36.3482	0.5153	2.0112	0.1280	0.0128	2.6701	0.5286	0.0477
Panel B: Correlation											
RSJ	1.0000	0.0190	0.6803	-0.0092	-0.0096	0.0095	-0.0055	0.0113	0.0120	0.0075	-0.0353
RV		1.0000	0.0253	0.0700	0.2597	-0.1937	0.0979	0.0372	-0.2471	0.4590	0.0825
RSK			1.0000	-0.0206	0.0026	-0.0185	-0.0175	-0.0050	-0.0198	0.0244	-0.0253
RKT				1.0000	-0.0184	-0.0323	0.0141	0.0073	-0.0083	-0.0652	-0.0024
BETA					1.0000	-0.1464	-0.0521	-0.0269	-0.2862	-0.0059	0.0544
SIZE						1.0000	0.0498	0.0179	0.8064	-0.1268	-0.2439
MOM							1.0000	0.4024	0.0897	0.0865	-0.0366
REV								1.0000	0.0474	0.0257	-0.0191
VOLM									1.0000	-0.2450	-0.3371
IVOL										1.0000	0.0843
ILLIQ											1.0000

Table 7: Portfolio Characteristics Sorted by Realized Variation Measures

Table 7 shows the time-series average of value-weighted portfolio characteristics sorted by RSJ (Panel A), RV (Panel B), RSK (Panel C) and RKT (Panel D). The sample consists of the 51 most active cryptocurrencies with market capitalization over $1 million within the sample period from January 2017 to June 2021. RSJ, RV, RSK and RKT are the signed jump, realized volatility, realized skewness, and realized kurtosis, respectively. BETA denotes the beta with respect to the market return. SIZE is the market capitalization of the cryptocurrency. MOM is the compound return of day $t-7$ through day $t-2$. REV denotes the lagged one day return. VOLM is the logarithm of trading volume. IVOL denotes the idiosyncratic volatility estimated from the market model. ILLIQ denotes the illiquidity level using the daily Amihud (2002) measure.

Quintile	RSJ	RV	RSK	RKT	BETA	SIZE	MOM	REV	VOLM	IVOL	ILLIQ
Panel A: Sorted by RSJ											
1 (LOW)	-0.1785	0.0041	-0.8995	16.6048	0.7468	20.2188	0.0332	0.0005	17.6729	1.0541	0.0146
2	-0.0379	0.0046	-0.2400	13.7872	0.7607	20.5962	0.0338	0.0006	18.1701	1.0607	0.0066
3	-0.0058	0.0049	-0.0393	13.8139	0.7612	20.5906	0.0299	0.0003	18.2203	1.0653	0.0057
4	0.0241	0.0048	0.1339	13.5682	0.7597	20.5628	0.0239	0.0006	18.1676	1.0818	0.0062
5 (HIGH)	0.1538	0.0043	0.7280	15.1718	0.7504	20.1354	0.0139	0.0006	17.6260	1.1049	0.0126
Panel B: Sorted by RV											
1 (LOW)	-0.0169	0.0017	-0.1093	13.6273	0.5787	21.8609	0.0061	0.0000	19.8798	0.5834	0.0034
2	-0.0096	0.0038	-0.0591	10.5012	0.7833	20.5408	0.0131	-0.0001	17.9865	1.0908	0.0059
3	-0.0044	0.0046	-0.0364	11.2185	0.7815	20.2032	0.0242	0.0003	17.6948	1.1515	0.0082
4	0.0016	0.0054	-0.0195	13.4685	0.7862	20.0253	0.0348	0.0007	17.4992	1.2003	0.0105
5 (HIGH)	0.0027	0.0069	-0.0112	23.5793	0.8000	19.7680	0.0791	0.0019	17.2216	1.2408	0.0164
Panel C: Sorted by RSK											
1 (LOW)	-0.1648	0.0041	-0.9785	21.2638	0.7531	20.4181	0.0320	0.0008	17.8960	1.0287	0.0130
2	-0.0418	0.0046	-0.2192	11.6185	0.7628	20.4874	0.0308	0.0005	18.0521	1.0716	0.0076
3	-0.0063	0.0050	-0.0361	9.9610	0.7583	20.5910	0.0298	0.0005	18.2178	1.0751	0.0065
4	0.0256	0.0047	0.1242	10.9966	0.7583	20.4521	0.0202	0.0004	18.0634	1.0802	0.0067
5 (HIGH)	0.1442	0.0043	0.7842	19.0898	0.7506	20.1709	0.0186	0.0006	17.6482	1.0984	0.0121
Panel D: Sorted by RKT											
1 (LOW)	-0.0037	0.0049	-0.0064	3.4419	0.7489	19.9894	0.0196	0.0002	17.4412	1.1074	0.0168
2	-0.0037	0.0047	-0.0177	5.0800	0.7621	20.2988	0.0329	0.0003	17.8502	1.1363	0.0098
3	-0.0050	0.0044	-0.0332	6.9734	0.7652	20.4311	0.0358	0.0007	18.0321	1.1117	0.0075
4	-0.0043	0.0043	-0.0482	10.5661	0.7578	20.5728	0.0364	0.0008	18.1780	1.0553	0.0059
5 (HIGH)	-0.0079	0.0045	-0.1106	44.4268	0.7457	20.7232	0.0365	0.0008	18.2468	0.9735	0.0069

Table 8: Single-sorted Portfolios on Realized Variation Measures

Table 8 presents the average returns of the single-sorted portfolios using the realized variation measures. The sample consists of the 51 most active cryptocurrencies with market capitalization over $1 million within the sample period from January 2017 to June 2021. On each day, the cryptocurrencies are sorted into quintiles according to the realized variation measures computed using the transactions within the day. Each portfolio is held for one day. The "EW Return" and "VW Return" columns report the one-day ahead excess returns of each portfolio with equal-weighted and value-weighted, respectively. The "FFC4" column reports the Fama-French-Carhart 4-factor alpha for the corresponding portfolio. The "LTW" column reports the Liu-Tsyvinski-Wu 3-factor alpha for the corresponding portfolio. The "High - Low" row reports the portfolio average return difference between the highest sorting value portfolio and the lowest sorting value portfolio using the corresponding sorting variable. The "t-Stat" row reports the Newey-West robust t-statistic. Panel A presents the portfolio returns sorted by RSJ, Panel B by RSK and Panel C by RKT.

Panel A: Sorting by RSJ	EW Return	FFC4	LTW3	VW Return	FFC4	LTW3
1 (Low)	0.451	0.436	0.329	0.281	0.247	0.197
2	0.094	0.064	-0.123	0.012	-0.012	0.008
3	-0.002	-0.038	-0.158	0.087	0.049	-0.145
4	-0.023	-0.052	-0.164	-0.021	-0.069	-0.212
5 (High)	-0.393	-0.422	-0.601	-0.060	-0.094	-0.229
High - Low	-0.844	-0.858	-0.930	-0.340	-0.341	-0.426
t-Stat	[-7.103]	[-5.737]	[-7.758]	[-2.931]	[-3.019]	[-3.342]

Panel B: Sorting by RSK	EW Return	FFC4	LTW3	VW Return	FFC4	LTW3
1 (Low)	0.240	0.206	0.046	0.188	0.027	-0.028
2	0.193	0.168	0.000	0.064	0.163	0.027
3	0.021	-0.007	-0.108	-0.005	-0.035	-0.097
4	-0.088	-0.115	-0.241	-0.013	-0.066	-0.156
5 (High)	-0.247	-0.281	-0.454	-0.025	-0.053	-0.167
High - Low	-0.488	-0.487	-0.500	-0.212	-0.081	-0.139
t-Stat	[-4.082]	[-3.295]	[-4.109]	[-3.500]	[-2.877]	[-2.521]

Panel C: Sorting by RKT	EW Return	FFC4	LTW3	VW Return	FFC4	LTW3
1 (Low)	0.137	0.115	-0.050	0.157	0.109	-0.061
2	0.073	0.053	-0.182	0.134	0.118	0.013
3	0.038	0.001	-0.102	0.036	0.005	-0.059
4	-0.024	-0.060	-0.219	0.040	0.003	-0.036
5 (High)	-0.068	-0.095	-0.193	-0.048	-0.072	-0.207
High - Low	-0.205	-0.209	-0.143	-0.204	-0.180	-0.146
t-Stat	[-1.953]	[-1.391]	[-1.339]	[-1.756]	[-1.711]	[-1.714]

Table 9: Single-sorted Portfolios on Realized Variation Measures with Controls

Table 8 presents the average returns of the single-sorted portfolios using the realized variation measures. The sample consists of the 51 most active cryptocurrencies with market capitalization over $1 million within the sample period from January 2017 to June 2021. On each day, the cryptocurrencies are sorted into quintiles according to the realized variation measures computed using the transactions within the day. Each portfolio is held for one day. The "EW Return" and "VW Return" columns report the one-day ahead excess returns of each portfolio with equal-weighted and value-weighted, respectively. The "FFC4" column reports the Fama-French-Carhart 4-factor alpha for the corresponding portfolio. The "LTW" column reports the Liu-Tsyvinski-Wu 3-factor alpha for the corresponding portfolio. The "High - Low" row reports the portfolio average return difference between the highest sorting value portfolio and the lowest sorting value portfolio using the corresponding sorting variable. The "t-Stat" row reports the Newey-West robust t-statistic. Panel A presents the portfolio returns sorted by RSJ controlling for the mean reversal, Panel B by RSJ controlling for the realized volatility and Panel C by RSJ controlling for the salient theory.

Panel A: Sorting by RSJ Controlling REV	EW Return	FFC4	LTW3	VW Return	FFC4	LTW3
1 (Low)	0.684	1.015	0.580	0.440	0.401	0.374
2	0.256	0.549	0.073	0.105	0.292	-0.087
3	0.059	0.403	-0.044	0.131	0.245	0.080
4	-0.052	0.350	-0.150	-0.036	0.060	-0.132
5 (High)	-0.619	-0.088	-0.791	-0.226	0.011	-0.367
High - Low	-1.303	-1.103	-1.371	-0.666	-0.390	-0.740
t-Stat	[-8.283]	[-5.257]	[-7.165]	[-2.931]	[-5.846]	[-6.162]

Panel B: Sorting by RSJ Controlling RV	EW Return	FFC4	LTW3	VW Return	FFC4	LTW3
1 (Low)	0.494	0.876	0.369	0.316	0.335	0.233
2	0.150	0.527	-0.066	0.051	0.305	-0.170
3	0.053	0.531	-0.103	0.126	0.294	0.051
4	0.038	0.572	-0.103	0.022	0.179	-0.099
5 (High)	-0.337	0.399	-0.546	-0.017	0.272	-0.183
High - Low	-0.831	-0.477	-0.916	-0.333	-0.063	-0.417
t-Stat	[-6.993]	[-2.184]	[-7.627]	[-2.869]	[-0.327]	[-3.432]

Panel C: Sorting by RSJ Controlling ST	EW Return	FFC4	LTW3	VW Return	FFC4	LTW3
1 (Low)	0.523	0.904	0.400	0.338	0.350	0.257
2	0.177	0.551	-0.038	0.070	0.316	-0.149
3	0.077	0.550	-0.077	0.143	0.304	0.070
4	0.058	0.588	-0.081	0.037	0.187	-0.081
5 (High)	-0.323	0.407	-0.531	-0.005	0.277	-0.170
High - Low	-0.847	-0.497	-0.931	-0.343	-0.074	-0.427
t-Stat	[-7.128]	[-2.276]	[-7.757]	[-2.963]	[-0.385]	[-3.519]

Table 10: Double-sorted Portfolios on Realized Variate Measures

Table 10 presents the average returns of the double-sorted portfolios of realized variation measures controlling for the Liu-Tsyvinski-Wu three factors on cryptocurrency market. The sample consists of the 51 most active cryptocurrencies with market capitalization over $1 million within the sample period from January 2017 to June 2021. On each day, the cryptocurrencies are sorted into 5×5 groups with unconditional manner on realized signed jumps computed using the transactions within the day and the existing cryptocurrency factors. Each portfolio is held for one day. The one-day ahead excess returns of each portfolio with equal-weighted and value-weighted construction are reported in the grid. The portfolio sorted by RSJ is reported in rows, and the portfolio sorted by the existing factors are reported in columns. The "High - Low" row reports the portfolio average return difference between the highest sorting value portfolio and the lowest sorting value portfolio using the corresponding sorting variable. The "t-Stat" row reports the Newey-West robust t-statistic. Panel A presents the portfolio returns with controlling variable of market beta, Panel B with market capitalization and Panel C by momentum.

	1 (Low)	2	3	4	5 (High)	Average
Panel A: Sorted by RSJ Controlling for Market Beta						
Equal-Weighted						
1 (Low)	0.418	0.541	0.028	0.338	0.234	0.312
2	-0.199	0.035	0.126	-0.133	0.312	0.028
3	-0.123	0.085	-0.050	0.037	-0.325	-0.075
4	-0.066	-0.240	-0.165	0.091	0.144	-0.048
5 (High)	-0.572	-0.555	-0.140	-0.411	-0.556	-0.447
High - Low	-0.990	-1.096	-0.167	-0.749	-0.790	-0.758
	[-3.834]	[-3.358]	[-1.550]	[-4.228]	[-2.835]	[-4.501]
Value-Weighted						
1 (Low)	0.328	0.428	-0.014	0.230	0.201	0.235
2	-0.162	0.036	0.098	-0.159	0.203	0.003
3	-0.065	-0.005	-0.023	0.077	-0.245	-0.052
4	-0.057	-0.170	-0.128	-0.004	0.177	-0.036
5 (High)	-0.364	-0.266	-0.064	-0.226	-0.470	-0.278
High - Low	-0.693	-0.695	-0.050	-0.457	-0.672	-0.513
	[-3.372]	[-2.571]	[-0.843]	[-3.324]	[-2.902]	[-3.718]

Panel B: Sorted by RSJ Controlling for Market Capitalization						
Equal-Weighted						
1 (Low)	1.008	0.584	0.173	-0.103	0.117	0.356
2	-0.069	0.415	-0.107	0.040	-0.325	-0.009
3	-0.249	0.019	-0.113	0.074	-0.020	-0.058
4	-0.096	-0.140	-0.090	-0.275	-0.014	-0.123
5 (High)	-0.911	-0.800	-0.304	-0.181	-0.115	-0.462
High - Low	-1.919	-1.384	-0.478	-0.078	-0.232	-0.818
	[-5.042]	[-6.559]	[-1.351]	[-0.114]	[-1.704]	[-4.364]
Value-Weighted						
1 (Low)	0.594	0.487	0.150	-0.056	0.107	0.257
2	-0.025	0.350	-0.049	0.094	-0.261	0.022
3	-0.130	0.058	-0.044	0.106	0.055	0.009
4	-0.069	-0.050	0.014	-0.178	-0.083	-0.073
5 (High)	-0.487	-0.558	-0.183	-0.087	-0.074	-0.278
High - Low	-1.081	-1.045	-0.334	-0.031	-0.181	-0.534
	[-5.099]	[-6.391]	[-1.025]	[0.303]	[-1.499]	[-3.575]

Panel C: Sorted by RSJ Controlling for Momentum						
Equal-Weighted						
1 (Low)	0.261	0.641	0.316	0.330	0.238	0.357
2	-0.175	-0.011	0.031	-0.056	0.289	0.016
3	-0.253	0.045	-0.061	0.007	0.197	-0.013
4	-0.400	-0.142	0.050	0.100	0.256	-0.027
5 (High)	-0.890	-0.478	-0.415	-0.448	-0.150	-0.476
High - Low	-1.150	-1.120	-0.732	-0.779	-0.388	-0.834
	[-4.572]	[-4.224]	[-2.360]	[-4.269]	[-2.055]	[-5.639]
Value-Weighted						
1 (Low)	0.193	0.382	0.216	0.239	0.261	0.258
2	-0.193	-0.032	0.024	-0.063	0.187	-0.015
3	-0.260	0.062	-0.023	-0.003	0.109	-0.023
4	-0.273	-0.145	0.029	0.091	0.230	-0.014
5 (High)	-0.648	-0.373	-0.279	-0.315	0.021	-0.319
High - Low	-0.840	-0.755	-0.494	-0.554	-0.239	-0.577
	[-4.235]	[-3.412]	[-1.800]	[-3.588]	[-1.688]	[-4.905]

Table 11: Fama-MacBeth Cross-Sectional Regressions

Table 11 reports the estimated regression coefficients the t-statistics (in brackets) from Fama-MacBeth cross-sectional regressions for daily cryptocurrency returns. The sample consists of the 51 most active cryptocurrencies with market capitalization over \$1 million within the sample period from January 2017 to June 2021. RSJ, RV, RSK and RKT are the signed jump, realized volatility, realized skewness, and realized kurtosis, respectively. BETA denotes the beta with respect to the market return. SIZE is the market capitalization of the cryptocurrency. MOM is the compound return of day $t-7$ through day $t-2$. REV denotes the lagged one day return. VOLM is the logarithm of trading volume. IVOL denotes the idiosyncratic volatility estimated from the market model. ILLIQ denotes the illiquidity level using the daily Amihud measure.

	RSJ	RV	RSK	RKT	BETA	SIZE	MOM	REV	VOLM	IVOL	ILLIQ
Panel A: Univariate											
	-3.239***	-22.009	-0.316***	-0.008**	0.660	-0.015	1.167***	-0.111***	-0.018	0.014	13.127
	[-6.105]	[-0.967]	[-3.276]	[-2.121]	[0.188]	[-0.750]	[2.749]	[-10.732]	[-1.050]	[0.131]	[1.627]
Panel B: Multivariate											
I	-2.027***				3.918	-0.005	0.991**	-0.110***	-0.007	0.076	-0.122
	[-3.341]				[1.115]	[-0.169]	[2.303]	[-9.416]	[-0.226]	[0.681]	[-0.011]
II		-11.882			4.152	-0.015	0.911**	-0.121***	0.021	0.061	3.864
		[-0.478]			[1.167]	[-0.470]	[2.109]	[-10.612]	[0.640]	[0.529]	[0.353]
III			-0.108		4.577	-0.024	0.932**	-0.120***	0.003	0.043	6.804
			[-1.115]		[1.329]	[-0.747]	[2.142]	[-10.569]	[0.105]	[0.387]	[0.577]
IV				-0.005	4.790	-0.016	0.948**	-0.122***	0.011	0.069	1.521
				[-1.425]	[1.401]	[-0.485]	[2.192]	[-10.850]	[0.348]	[0.607]	[0.135]
V	-6.471***	-14.518	-0.843***	-0.013***							
	[-5.596]	[-0.624]	[-4.326]	[-3.081]							
VI	-6.142***	-24.075	-0.805***	-0.015***	1.423	-0.014	0.547				
	[-4.536]	[-0.987]	[-3.848]	[-2.819]	[0.400]	[-0.631]	[1.258]				
VII	-2.817*	-28.72	-0.457*	-0.011*	4.144	-0.022	0.886**	-0.100***			
	[-1.834]	[-1.180]	[-1.909]	[-1.847]	[1.250]	[-1.016]	[2.074]	[-8.040]			
VIII	-6.516***	-21.016	-0.791***	-0.010**	0.964	-0.015	0.481		0.001		
	[-4.834]	[-0.809]	[-3.781]	[-2.348]	[0.265]	[-0.428]	[1.099]		[0.035]		
IX	-6.574***	-31.458	-0.813***	-0.015***	3.509	-0.020	0.647			0.096	
	[-4.297]	[-1.206]	[-3.594]	[-2.870]	[1.015]	[-0.939]	[1.460]			[0.812]	
X	-6.235***	-25.366	-0.816***	-0.012***	2.290	-0.014	0.825*				8.521
	[-4.452]	[-1.011]	[-3.825]	[-2.731]	[0.637]	[-0.619]	[1.868]				[0.778]
XI	-4.543**	-8.909	-0.543*	-0.005	6.759**	-0.031	0.852*	-0.096***	0.026	0.110	4.303
	[-2.316]	[-0.294]	[-1.854]	[-0.811]	[1.964]	[-0.874]	[1.651]	[-6.978]	[0.687]	[0.920]	[0.357]

Table 12: Fama-MacBeth Cross-Sectional Regressions: Source of the Jumps

Table 12 reports the estimated regression coefficients the t-statistics (in brackets) from Fama-MacBeth cross-sectional regressions for daily cryptocurrency returns. The sample consists of the 51 most active cryptocurrencies with market capitalization over $1 million within the sample period from January 2017 to June 2021. RSJ is the realized signed jump. BETA denotes the beta with respect to the market return. SIZE is the market capitalization of the cryptocurrency. MOM is the compound return of day $t-7$ through day $t-2$. REV denotes the lagged one day return. VOLM is the logarithm of trading volume. IVOL denotes the idiosyncratic volatility estimated from the market model. ILLIQ denotes the illiquidity level using the daily Amihud measure. VOLM SHOCK denotes the trading volume shock, computed by the difference between most recent daily trading volume and the moving average of the past 30 days' trading volume. GOOGLE SEARCH INDEX denotes the web page search frequency on the underlying cryptocurrencies.

	(1)	(2)
RSJ	-3.173***	-2.255***
	[-3.746]	[-3.940]
RSJ $\times$ VOLM SHOCK	-134.603**	
	[-2.196]	
RSJ $\times$ GOOGLE SEARCH INDEX		-1.376***
		[-3.551]
BETA	0.083	0.849
	[0.022]	[0.230]
SIZE	-0.046	-0.045
	[-1.294]	[-1.336]
MOM	0.229	0.635
	[0.462]	[1.476]
REV	-0.114***	-0.105***
	[-8.239]	[-8.470]
VOLM	-0.063*	-0.058*
	[-1.722]	[-1.656]
IVOL	-0.012	0.023
	[-0.096]	[0.192]
ILLIQ	5.431*	4.950
	[1.849]	[1.626]
VOLM SHOCK	0.939*	0.760*
	[1.963]	[1.743]
GOOGLE SEARCH INDEX	0.051***	0.090***
	[6.418]	[5.502]