JOURNAL OF FINANCIAL AND QUANTITATIVE ANALYSIS

doi:10.1017/S002210902400022X

https://doi.org/10.1017/S002210902400022X Published online by Cambridge University Press

Variance Decomposition and Cryptocurrency Return Prediction

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Abstract

This article examines how realized variances predict cryptocurrency returns in the cross section using intraday data. We find that cryptocurrencies with higher variances exhibit lower returns in subsequent weeks. Decomposing total variances into signed jump and jump-robust variances reveals that the negative predictability is attributable to positive jump and jump-robust variances. The negative pricing effect is more pronounced for smaller cryptocurrencies with lower prices, less liquidity, more retail trading activities, and more positive sentiment. Our results suggest that cryptocurrency markets are unique because retail investors and preferences for lottery-like payoffs play important roles in the partial variance effects.

I. Introduction

Cryptocurrencies have recently emerged as a nonnegligible asset class. The aggregate market capitalization of cryptocurrencies exceeded 2 trillion U.S. dollars (USD) in 2021.[1] This remarkable growth has been accompanied by unusually large price fluctuations with extreme returns.[2] Our analyses corroborate these findings, revealing that the annualized weekly volatility of cryptocurrencies frequently

We thank Dexin Zhou, Olivier Scaillet, Fabio Trojani, Narayan Jayaraman, Sudheer Chava, and seminar participants at the University of Geneva, the University of Georgia, Baruch College, Australian Finance and Banking Conference, Midwest Finance Association annual meeting, SKKU International Conference, and Joint Conference with the Allied Korea Finance Associations for their helpful discussions, comments, and encouragement. We particularly thank George Pennacchi (the editor) and an anonymous referee for their constructive suggestions and comments.

[1]Market capitalization data are from www.coinmarketcap.com. Participation in cryptocurrency markets has become widespread. Surveys indicate that 22% of institutional investors already own cryptocurrencies and that 11% of the American population holds Bitcoin (see https://cointelegraph.com/news/hbus-survey-almost-12-of-us-cryptocurrency-holders-are-long-term-investors).

[2]Scaillet, Treccani, and Trevisan (2020) and Liu and Tsyvinski (2021) document high kurtosis (e.g., 15–100 for daily data) and frequent jumps. In fact, Bitcoin prices collapsed, with a nearly 50% drop on Mar. 12, 2020. On Apr. 30, 2020, Bitcoin prices increased by 18% within 24 hours.

https://doi.org/10.1017/S002210902400022X Published online by Cambridge University Press

exceeds 100%. High volatility with extreme returns can arise because the equilibrium prices of cryptocurrencies reflect sunspots that drive high extrinsic volatility even when fundamentals are constant (Biais, Bisiere, Bouvard, Casamatta, and Menkveld (2023)). This high volatility raises a fundamental question in finance: how do realized volatilities (or variances) play a role in cryptocurrency return prediction in the cross section? Addressing this critical question is the primary objective of our study because it has substantial implications for risk assessments, investment strategies, and portfolio management in cryptocurrencies.

In light of the exceptionally wide ranges and heavy tails of cryptocurrency return distributions, we take a comprehensive approach by considering not only the traditional realized variance measure but also decomposed partial variances that separately account for normal and nonnormal returns, including signed jumps. This decomposition is motivated because cryptocurrency market participants may perceive and evaluate uncertainty differently when they face extreme positive or negative returns (Barberis and Xiong ((2009), (2012))). This consideration is particularly relevant for cryptocurrency markets because of the lack of observable fundamental information and the active participation of retail investors compared to established financial markets. Furthermore, the directions of jumps have differential impacts on risk and returns (Patton and Sheppard (2015)).[3] By employing the decomposed variances, our analysis elucidates how realized partial variances affect cryptocurrency return prediction.

Notably, in cryptocurrency markets, variances are dramatically time-varying. Figure 1 illustrates this feature by depicting the 10th, 50th, and 90th percentiles for the weekly realized variances of individual cryptocurrencies and Bitcoin. For example, the weekly variances of Bitcoin range from 0.01 to 0.08 in 2017, with three discernible peaks in 2018. This evidence emphasizes the critical importance of frequently updating cryptocurrency return variances when identifying the effect of variances on future returns. Therefore, we use intraday cryptocurrency data to estimate variances. Leveraging recent advances in the financial econometrics literature, we sum the squared high-frequency returns from the different segments of individual cryptocurrencies' return distributions. Our study extends the literature by addressing such distinctive characteristics of individual cryptocurrency markets and uncovering novel evidence regarding the return predictability of decomposed variances.[4]

We document that cryptocurrencies with high realized variances tend to provide substantially lower excess returns in subsequent weeks than those with low variances. In Figure 2, cryptocurrencies with the lowest (highest) variances have an average excess return of 0.1% (−3.6%) in subsequent weeks. The weekly return differential amounts to 3.7% (193% per annum), which is significant at the

[3]Using parts of the return distribution for measuring risks is similar to using the lower partial moment measures of Price, Price, and Nantell (1982), although our decomposition is driven by extreme returns.

[4]Borri and Santucci de Magistris (2022) use high-frequency data on Bitcoin to find that jumps account for a large portion of the daily variation in Bitcoin returns and adopt a parametric estimation method to show that the conditional skewness and kurtosis of Bitcoin returns are priced using daily data. Our study differs in that we rely on high-frequency data of 100 cryptocurrencies to decompose individual cryptocurrencies' realized variances over time and discover the significant return predictability of decomposed variances.

FIGURE 1

Weekly Variance over Time

Figure 1 illustrates how weekly variances change during the sample period from Oct. 2015 to June 2023. Graph A shows the 10th, 50th, and 90th percentiles of individual cryptocurrency variances in the cross section. Graph B provides weekly variances for bitcoin.

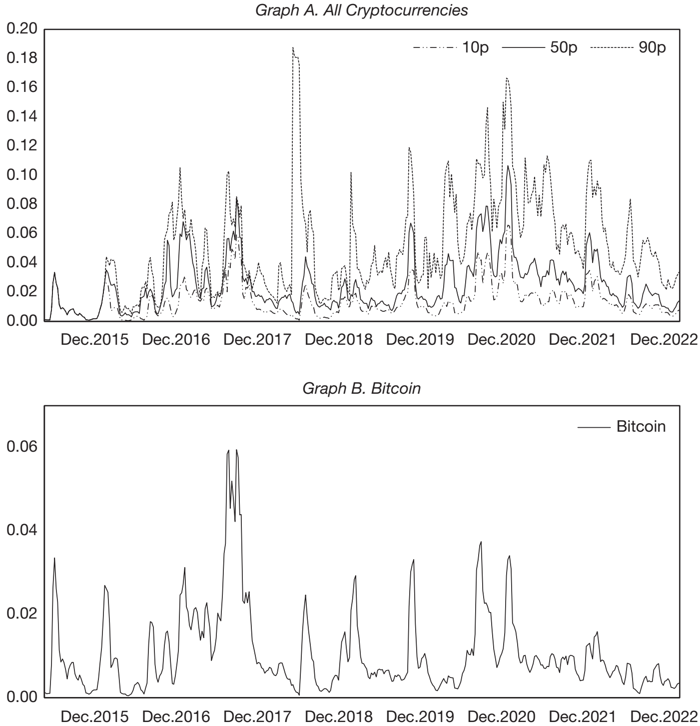
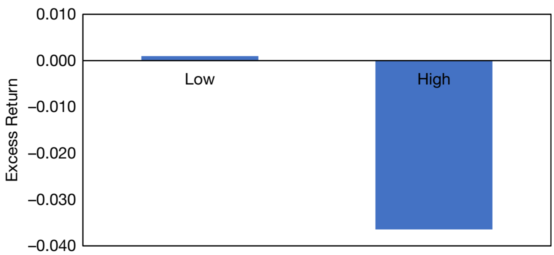


FIGURE 2

Variances and Future Excess Returns

Figure 2 shows the effect of variances on excess returns in the subsequent week. At the end of every week, the cryptocurrencies are sorted on their variances, and tercile portfolios are constructed. For each sorted portfolio, we compute the equal-weighted average of excess returns in the subsequent weeks. We compare the average excess returns of low-variance portfolios with those of high-variance portfolios.



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1% level.[5] This figure provides equal-weighted (EW) average returns, but value-weighted (VW) averages yield consistent results.

To investigate the underlying drivers of this negative return predictability, we decompose the total variance into variances associated with positive jumps, negative jumps, and non-jump returns. By using detected jumps and separated variances, we discover that positive jump and jump-robust variances are significantly and negatively related to excess returns in subsequent weeks. The return prediction of (total) variances stems from return components that are not associated with negative jumps. These variance effects are robust to model specifications, the common risk factors of Liu, Tsyvinski, and Wu (2022), business cycles, and overall market conditions and are not totally attributable to the skewness effect.

The negative relationship between variances and future returns contradicts the traditional risk and return tradeoffs, which typically imply a positive relation in classical asset pricing theories with rational investors. Instead, our finding is in line with behavioral finance studies on speculative retail trading because more individual and retail investors participate in cryptocurrency markets than in other well-established financial markets (Kogan, Makarov, Niessner, and Schoar (2023)).[6] The substantial participation of retail investors allows asset prices to deviate from fundamental values (De Long, Shleifer, Summers, and Waldmann (1990)) and can increase volatility, as shown by Foucault, Sraer, and Thesmar (2011), Xiong and Yu (2011), and Pedersen (2022). Retail investors prefer holding and trading highly volatile securities and are willing to undertake risk that may yield low returns (Han and Kumar (2013)). In fact, the key drivers of high volatility and extreme positive returns are the important lottery features favored by investors.

Specifically, cryptocurrencies with high total and positive jump variances tend to have smaller sizes, lower prices, and wider bid–ask spreads (BASs) than those with low variances. Such cryptocurrencies have significantly larger trading volumes than those with low variances, which suggests a significant disagreement about the future prices of high-variance cryptocurrencies. The retail trading proportion (RTP) and positive investor sentiment tend to be greater for high-variance cryptocurrencies than for low-variance cryptocurrencies. Furthermore, our realized variance measures effectively forecast the lottery properties of individual cryptocurrencies, which makes our findings consistent with the cumulative prospect theory elaborated by Barberis and Huang (2008).[7] Considering Xiong and Yu

[5]This significant spread remains intact after controlling for the cryptocurrency pricing factors of Liu, Tsyvinski, and Wu (2022). Our variance estimation differs from that of Liu et al. (2022), who employ daily returns. Estimation using lower-frequency return data requires an assumption that volatility is stable over a longer estimation horizon. These authors indicate that return volatility is an insignificant pricing factor (we obtain consistent results). Generally, the empirical relation between equity returns and volatility has not been strong. However, Bollerslev, Li, and Zhao (2020) use high-frequency data and identify significant relations.

[6]According to the financial statements of Coinbase, a cryptocurrency exchange platform company, 95% of the total transaction revenues came from retail investors' trading in 2020. Many news articles also support this idea. In addition, see, for example, https://www.wsj.com/articles/bitcoin-prices-pass-50-000-for-first-time-since-may-11629729934 and https://www.bloomberg.com/news/articles/2021-12-21/crypto-funds-explode-in-2021-led-by-proshares-bitcoin-strategy-etf-bito.

[7]Investors who prefer lottery-like returns are willing to pay higher prices for assets with lottery features. Positive jumps represent lottery-like returns in that they are characterized by extremely large

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(2011), we test whether our results arise because of short-selling constraints. However, we do not find supporting evidence.

Our article contributes to the literature on the relation between volatility and future returns. The literature indicates that the negative relationship between volatility and future returns can result from the preference for lottery features and that many investors are not fully diversified (e.g., Fama and MacBeth (1973), Hou and Moskowitz (2005), Ang, Hodrick, Xing, and Zhang (2006), Fu (2009), Huang, Liu, Rhee, and Zhang (2010), and Hou and Loh (2016)). Specifically, our article demonstrates that the negative return predictability is associated with both jump-robust and positive jump variances but not with negative jump variances in cryptocurrency markets. Kilic and Shaliastovich (2019) examine the role of implied and realized semivariances in aggregate stock and bond returns and support that our inference methods can identify the nonlinear effect of unusually high uncertainty on returns.

Our article extends the growing literature that examines cryptocurrencies as an asset class.[8] Liu et al. (2022) show that only the standard deviation of price volume predicts future returns. Borri, Massacci, Rubin, and Ruzzi (2022) find that volatility risk is positively priced, while Bianchi and Babiak (2021) show that their realized or idiosyncratic volatility generates a significantly negative return. More broadly, our study is related to studies that characterize return distributions and factor structures in cryptocurrency markets. Our findings of high volatility and large jumps echo those of Yermack (2015) and Scaillet et al. (2020), who study Bitcoin returns. Jia, Liu, and Yan (2021) and Borri and Santucci de Magistris (2022) investigate the effects of higher moments on cryptocurrency returns. Cong, Karolyi, Tang, and Zhao (2022) provide a 5-factor model to consider additional value and network adoption premiums.[9] Sockin and Xiong (2023) present a model that supports the empirical results in the literature.

Our study builds on the literature on realized return moments and jump risk measures. Andersen, Bollerslev, Diebold, and Ebens (2001a) support the approach of estimating realized variances with intraday data. Amaya, Jacobs, and Vasquez (2015) investigate the relation between firm-level realized return moments and subsequent returns. Bollerslev et al. (2020) examine the stock return predictability of realized jump variance components. Lee and Wang (2019) demonstrate the pricing of negative jumps in sovereign currency markets.[10] Our study is the first

payoffs and a low probability. High volatility allows investors to anticipate a high probability of large returns.

[8]Our article is broadly related to the literature on cryptocurrency markets, the economics of cryptocurrencies and blockchain technology, or valuation models for digital currencies. However, we focus on discovering novel empirical evidence on risk and returns and discussing relevant pricing models.

[9]As additional references, Liu and Tsyvinski (2021) analyze the time-series features of return distributions by using daily data on three cryptocurrencies. Shams (2020) studies return correlations. Borri (2019) uses $CoVar$ to measure the conditional tail risk of four cryptocurrencies by employing daily data. Another strand of studies provides evidence of manipulation or dispersion in cryptocurrency prices across exchanges (e.g., Griffin and Shams (2020), Makarov and Schoar (2020), Li, Shin, and Wang (2021), and Borri and Shakhnov (2022)).

[10]Many studies document the important role of jumps in pricing equities, bonds, options, or sovereign currencies (e.g., Merton (1976), Piazzesi (2005), and Chernov, Graveline, and Zviadadze (2018)).

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to utilize cryptocurrency markets as a unique laboratory, documenting cryptocurrencies' special characteristics.

Finally, our work contributes to the behavioral finance literature on speculative trading in financial markets. For cryptocurrency markets, characterized by the active participation of retail investors, we show that investor sentiment is important and that investors' lottery (or gambling) preference exists in these highly uncertain markets. For other financial markets, Baker and Wurgler (2006) show that highly volatile stocks are prone to fluctuations in sentiment. Han and Kumar (2013) show low returns for volatile assets with lottery features such as low prices, high variances, and positive skewness. Boyer, Mitton, and Vorkink (2010) and Bali, Cakici, and Whitelaw (2011) use expected idiosyncratic skewness and maximum returns and find that these features are associated with low expected returns.

The remainder of this article is organized as follows: Section II explains the variance decomposition with signed jumps and the estimation approaches. Section III introduces the high-frequency data used for this study and the estimation results. Section IV investigates how the decomposed variances predict future cryptocurrency returns. Section V discusses potential explanations for our findings. Section VI concludes the article.

II. Inference Methods

In this section, we describe our model of cryptocurrency price processes and explain our inference methods for the total and decomposed variances of individual cryptocurrencies. As cryptocurrency markets operate 24 hours a day in real time, we assume that cryptocurrency prices follow a continuous-time model. We employ a general asset pricing framework with diffusion and jump components to accommodate various forms of nonnormality, such as unusual volatility and heavy tails, often observed in cryptocurrency return data. Specifically, the ith cryptocurrency price is set to follow a generic jump-diffusion model that accommodates the potential intraday volatility and jump patterns:

$$(1) \qquad dc_{i,t} = \mu_{i,t}dt + \sigma_{i,t}dB_{i,t} + Y_{i,t}dJ_{i,t},$$

where $dc_{i,t}$ is the instantaneous change in the natural logarithmic price $c_{i,t}$ of the ith cryptocurrency at time t. The drift $\mu_{i,t}$ and diffusion $\sigma_{i,t}$ are bounded processes, and $B_{i,t}$ is a standard Brownian motion. $Y_{i,t}$ and $dJ_{i,t}$ are the jump size and arrival indicator, respectively.[11] We denote the intraday logarithmic return between discrete times $t(j-1)$ and $t(j)$ by $r_{i,t(j)} = c_{i,t(j)} - c_{i,t(j-1)}$ for cryptocurrency i.

We relate realized total variances and decomposed variances to returns in subsequent weeks. Similar analyses can be performed at different frequencies and return horizons. The total variance is defined as the sum of squared intraday returns in week w,

[11] Our statistical inference is based on discrete samples over a time horizon of $[0,T]$. We assume that there are n discrete observations for each cryptocurrency over the time horizon. In particular, we observe the ith cryptocurrency price $c_{i,t}$ only at discrete times $0 \le t(0) < t(1) < \ldots < t(n) \le T$, and for simplicity, we assume that $t(j+1) - t(j) = \Delta t$ for all js. The total number of weeks within $[0,T]$ is set to be $\tilde{w}$, so that $[0,T] = \cup_{w=1}^{\tilde{w}} W_w$ with the weekly time interval W_w for week w.

(2) $$\text{Total variance}: TV_{i,w} = \sum_{t(j)\in W_w} r^2_{i,t(j)}.$$

Andersen, Bollerslev, Diebold, and Labys (2001b) indicate that as the sampling frequency goes to infinity, this realized total variance converges to the quadratic variation composed of the integrated diffusive variance and jump components as follows:

(3) $$TV_{i,w} = \sum_{t(j)\in W_w} r^2_{i,t(j)} \to \int_{s\in W_w} \sigma^2_{i,s} ds + \sum_{\tau\in W_w} Y^2_{i,\tau}.$$

This total variance measure does not differentiate signed jump variances from diffusive variances. In this article, we recommend decomposing realized total variances into jump robust and signed jump variances by using jump detection tests that identify the arrival times of individual cryptocurrency jumps. In particular, we estimate the diffusive variance term $\int_{s\in W_w} \sigma^2_{i,s} ds$ by using the jump-robust variance estimator, while the jump variance term $\sum_{\tau\in W_w} Y^2_{i,\tau}$ (which can be decomposed into $\sum_{\tau\in W_w, Y_{i,\tau}>0} Y^2_{i,\tau}$ and $\sum_{\tau\in W_w, Y_{i,\tau}<0} Y^2_{i,\tau}$) by using our signed jump variance estimators $JV^{(+)}_{i,w}$ and $JV^{(-)}_{i,w}$ as follows:

(4) $$\text{Jump robust variance}: JRV_{i,w} = \sum_{t(j)\in W_w} r^2_{i,t(j)} I(|T_{i,t(j)}| < \zeta),$$

$$\text{Positive jump variance}: JV^{(+)}_{i,w} = \sum_{t(j)\in W_w} r^2_{i,t(j)} I(|T_{i,t(j)}| > \zeta) \times I(r_{i,t(j)} > 0),$$

$$\text{Negative jump variance}: JV^{(-)}_{i,w} = \sum_{t(j)\in W_w} r^2_{i,t(j)} I(|T_{i,t(j)}| > \zeta) \times I(r_{i,t(j)} < 0),$$

$$\text{Jump variance}: JV_{i,w} = JV^{(+)}_{i,w} + JV^{(-)}_{i,w} = \sum_{t(j)\in W_w} r^2_{i,t(j)} I(|T_{i,t(j)}| > \zeta),$$

where $I(a)$ is an indicator function that equals 1 if a is true. ζ is the rejection criterion for the Lee and Mykland (2008) jump test statistic $T_{i,t(j)}$ for cryptocurrency i at time $t(j)$.[12] We use all intraday return data within a time horizon to approximate the true latent diffusive and jump variances in that period.[13] Our jump variance measures are separated according to the signs of jumps to identify signed jumps' exclusive impact on future returns.[14]

We apply the Lee and Mykland (2008) method or its variant because it is important for us to distinguish individual jumps with different signs within a testing interval. The basic intuition behind this method is to discriminate between diffusive and jump returns by comparing instantaneous returns with the local volatility estimated over the preestimation window of size K. If absolute returns are

[12]We use the standard Gumbel distribution for the rejection criteria, following Lee and Mykland (2008). As cryptocurrency markets may exhibit time-of-day patterns in volatility, following Lee and Wang (2020), we control for the intraday volatility pattern to mitigate concerns regarding the misclassification of jumps.

[13]Because our main analyses are performed at the weekly level, our notation is written with a weekly interval. However, the notation can be generalized to other fixed time intervals.

[14]In this study, we do not separate systematic jumps from idiosyncratic jumps.

significantly larger than the estimated local volatility, they are identified as jumps.[15] To support our application for the purpose of this study, we assess the finite sample performance of our jump variance estimators with simulation studies.[16] We find that the estimation error of the proposed jump variance estimators decreases as we use higher-frequency data. Moreover, jumps in volatility do not significantly affect the power to detect extremely large jumps, which is our main interest for this study.

III. Data

We obtain intraday data from Kaiko, which has collected high-quality tick-by-tick quotes and prices from liquid cryptocurrency exchanges since 2014.[17] Many studies (e.g., Makarov and Schoar (2020), Li et al. (2021)) also use Kaiko for cryptocurrency prices.

To construct an unbiased sample with the largest cross section, we examine all cryptocurrencies that have intraday data longer than nine months and are traded on Coinbase, which is ranked as the top exchange in Kaiko's overall evaluation (e.g., data quality and popularity).[18] The minimum sample period of nine months is chosen because our inference requires a sufficient estimation horizon for detecting jumps and computing decomposed realized variances. Kaiko's order book data provide intraday bid and ask quotes (and volumes) for 198 cryptocurrencies. We exclude stable coins (e.g., Tether). Adopting simple coin selection criteria, our sample comprises 100 cryptocurrencies with various characteristics and includes a delisted coin.[19] Accordingly, survivorship bias is not critical. We also confirm the minimal effect of delisting on our results by following Liu et al. (2022). Our results are confirmed with data from other cryptocurrency exchanges, such as Bitfinex and Bittrex.

The sample period is from Oct. 2015 to June 2023 and includes the failure of large financial institutions such as the FTX or Terra-Luna crash and the crypto winter.[20] From these data, the first return appears in Oct. 2015 for BTC, which is

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[15]Most other jump tests depend on the integrated quantities over an interval during which the jump presence can be recognized but do not indicate the direction, arrival time, or size of each jump or the number of jumps within the interval. The design of the tests proposed by Andersen et al. (2007) is similar to ours except for the rejection criteria. Therefore, the results of the two tests are not expected to differ if the rejection regions are chosen similarly. See Barndorff-Nielsen and Shephard (2006), Andersen et al. (2007), Jiang and Oomen (2008), and Aït-Sahalia and Jacod (2009) for alternative approaches.

[16]The details of the simulation studies are reported in Appendix A of the Supplementary Material. A theoretical justification for our variance decomposition based on asymptotic properties is available from the authors.

[17]Trading volumes are also provided by Kaiko. See Makarov and Schoar (2020) for the details of Kaiko.

[18]As indicated by Makarov and Schoar (2020), many nonintegrated cryptocurrency exchanges exist in parallel across countries. The majority of these exchanges function like regulated equity markets, but they lack provisions to ensure the best price for trading. Because this unusual feature increases price deviations across cryptocurrency exchanges, the use of cryptocurrency price data from multiple exchanges can result in contamination with frictions from different exchanges and thus is undesirable for our study.

[19]The list of cryptocurrencies is provided in Appendix B of the Supplementary Material.

[20]The crypto winter refers to a bear market with significant declines in prices and market capitalization. Our results continue to hold with data from shorter sample periods and different exchanges.

the starting time of our sample period.[21] These cryptocurrencies account for approximately 80% of the total market capitalization of all cryptocurrencies as of 2023.[22]

A. Intraday Cryptocurrency Returns and Jumps

We choose the 15-minute interval to compute intraday returns because of the tradeoff between the following considerations. First, the accuracy of the price data can suffer from measurement errors that result from microstructure noise in data sampled too frequently. Second, a lower sampling frequency can hinder the consistent estimation of realized moments.[23] For each interval, we select the latest observation to construct evenly spaced data. We remove quotes that do not change for 3 consecutive intervals because these quotes might be inactive. We perform this filtering process for bid and ask quotes and construct mid quotes (i.e., mid = 0.5 × (bid+ask)).[24] Using the mid quotes, we compute log returns.

Table 1 summarizes the 15-minute returns of the 25 selected sample cryptocurrencies.[25] Bitcoin has the largest number of observations and the longest sample period. Notably, cryptocurrency markets are extremely volatile. Standard deviations range from 0.27% to 1.25%, which implies annualized standard deviations greater than 100%. Interestingly, the skewness ranges from −1.34 to 1.71. The dispersed skewness implies that some cryptocurrencies provide lottery-like returns, while others have crash-like returns. The kurtosis is higher than 9, indicating that it is important to analyze the tails of the return distributions.

We implement the variance decomposition and estimate weekly realized measures using detected jumps.[26] Table 2 summarizes the jump detection results for the 25 selected sample cryptocurrencies.[27] The average jump frequency is

[21]The order book data start in Apr. 2015, but observations in the early period are extremely sparse.

[22]We provide details about our sample construction and filtering procedure in Appendix C of the Supplementary Material.

[23]Like sovereign currency markets, cryptocurrency markets allow 24-hour trading and have real-time trading features. Therefore, we follow Lee and Wang ((2019), (2020)) in terms of the sampling frequency.

[24]We follow the realized variance literature by using mid-quotes as the measures of true prices. Mid-quotes are generally less noisy than transaction prices because they do not suffer from bid–ask bounce effects. See Bandi and Russell (2006) for details. Following Andersen et al. (2001a) and Lee (2012), who suggest the problems of bid–ask bounce effects, we filter out observations when large returns are canceled out. We confirm the reliability of our data by comparing our mid-quotes with daily transaction data on coinmarketcap.com.

[25]The summary statistics for the 100 cryptocurrencies are provided in Appendix B of the Supplementary Material.

[26]The Lee and Mykland jump test requires setting a window size K to estimate the instantaneous volatility using the first $K-1$. The window size K must be large enough to ensure that the jump effect disappears for a consistent volatility estimation. In this study, we use $K=156$ for our 15-minute frequency, as recommended by Lee and Mykland (2008). We identify jumps with a 5% significance level. Our results are robust when we use a 1% significance level and filter out small jumps by using a 10% false discovery rate.

[27]The jump detection results for the 100 cryptocurrencies are provided in Appendix B of the Supplementary Material.

TABLE 1

Summary Statistics

Table 1 shows the summary statistics of cryptocurrency data. Column Cryptocurrency lists the abbreviated names of the cryptocurrencies in the sample. Column No. of obs shows the number of 15-minute return observations after data filtering. Column Start indicates the months in which the earliest observations appear in the sample. Columns under 15-min return provide the mean, standard deviation, skewness, and kurtosis of the 15-minute returns for the 25 selected cryptocurrencies. Columns Market cap., Volume, Price, and BAS show the unconditional averages of market capitalization, daily trading volumes (in billions of USD), prices per coin (in USD), and percentage BASs, respectively. Row Avg. 100 shows the averages across the 100 sample cryptocurrencies.

			15-Min Return							
Cryptocurrency	No. of Obs.	Start	Mean (%)	Std. Dev. (%)	Skew	Kurt	Market Cap ($B)	Volume ($B)	Price ($)	BAS (%)
BTC	263,892	Oct. 2015	0.0023	0.3983	−0.188	19.076	270.99	17.82	15,517.00	0.011
ETH	229,770	July 2016	0.0022	0.5168	−0.068	15.162	100.31	8.96	1,003.27	0.030
LTC	216,697	Oct. 2016	0.0012	0.5936	0.016	15.027	4.67	1.55	91.74	0.067
BCH	190,108	Dec. 2017	−0.0003	0.5673	0.053	15.242	8.00	1.92	416.19	0.043
ETC	161,484	Aug. 2018	−0.0001	0.6249	0.069	16.790	2.10	0.80	19.88	0.092
ZRX	160,121	Oct. 2018	−0.0010	0.6995	0.071	24.108	0.39	0.06	0.50	0.136
XRP	64,229	Feb. 2019	0.0005	0.5197	−0.109	20.925	15.87	1.79	0.28	0.064
XLM	149,494	Mar. 2019	−0.0002	0.5553	−0.001	16.177	2.75	0.28	0.16	0.072
EOS	135,076	Apr. 2019	0.0014	0.5601	−0.095	14.771	3.33	1.43	3.09	0.138
REP	119,864	Apr. 2019	−0.0064	0.7078	0.188	20.966	0.20	0.02	16.54	0.292
LINK	139,040	June 2019	0.0010	0.6488	0.015	11.856	3.74	0.68	12.20	0.079
XTZ	129,846	Aug. 2019	0.0003	0.6640	0.023	11.500	1.80	0.14	2.60	0.146
ALGO	132,270	Aug. 2019	−0.0007	0.7436	0.002	23.743	2.54	0.20	0.60	0.090
DASH	131,336	Sept. 2019	−0.0010	0.5870	−0.016	13.990	1.14	0.26	102.48	0.120
OXT	111,485	Dec. 2019	−0.0065	0.8280	0.489	17.496	0.12	0.03	0.26	0.146
ATOM	119,789	Jan. 2020	0.0004	0.6997	0.022	11.126	2.97	0.40	13.87	0.083
KNC	116,027	Feb. 2020	−0.0003	0.7623	0.103	13.128	0.17	0.03	1.46	0.115
OMG	94,855	May. 2020	0.0002	0.7718	0.182	11.982	0.56	0.19	4.30	0.142
MKR	106,360	June 2020	−0.0007	0.6037	0.048	12.437	1.06	0.08	1,528.35	0.071
COMP	104,874	June 2020	−0.0012	0.6993	−0.107	11.129	0.98	0.13	187.46	0.076
LRC	96,365	Sept. 2020	−0.0024	0.8149	0.276	14.184	0.40	0.08	0.56	0.087
ZEC	88,913	Dec. 2020	0.0000	0.6522	0.002	12.724	0.84	0.26	102.28	0.076
ADA	78,975	Mar. 2021	−0.0014	0.5473	0.036	12.444	15.03	1.05	0.95	0.031
DOGE	71,844	June 2021	−0.0041	0.5537	0.071	15.383	5.67	0.67	0.13	0.048
ZEN	59,632	Sept. 2021	−0.0049	0.5999	−0.160	12.542	0.23	0.02	30.28	0.147
Avg. 100	81,626		−0.0052	0.7370	0.187	16.443	5.44	0.49	773.57	0.192

0.55%, which intuitively implies that approximately one jump occurs every two days. The jump frequency in cryptocurrency markets is similar to that in typical sovereign currency markets. Interestingly, the sizes of cryptocurrency jumps are relatively large. The average of the medians of positive (negative) jump sizes is 3.2% (−2.9%), which is more than 10 times larger than that in sovereign currency markets.[28] This comparison highlights the importance of jumps in cryptocurrency returns. This large jump size is consistent with the findings of Liu and Tsyvinski (2021), who show that cryptocurrencies tend to have extreme returns in their distributions.

The frequencies and sizes of jumps are considerably dispersed across individual cryptocurrencies. The jump frequencies range from 0.22% (SUSHI) to 2.06% (BTRST) of the available return observations, and the median positive jump sizes range from 0.1% (RAI) to 4.9% (RGT). The ranges of the jump sizes are wider than those of sovereign currency markets. These findings indicate that cross-sectional differences in jump measures could play a role in cryptocurrency pricing. Overall,

[28]Lee and Wang (2019) report that the median positive (negative) jump size ranges from ±0.1% to ±0.3%, with an average of ±0.24%.

TABLE 2

Summary Statistics of Cryptocurrency Jumps

Table 2 summarizes the results of jump detection tests in cryptocurrency markets. To identify jumps, we apply the approach of Lee and Mykland (2008) and adjust the intraday volatility patterns of individual cryptocurrencies, following Lee and Wang (2020). Column Cryptocurrency lists the currency codes of the 25 sample cryptocurrencies. For each cryptocurrency, we provide the number of filtered jumps and the jump frequencies relative to the available observations (% jp). For signed jumps, we report the 25th, 50th, and 75th percentiles of positive and negative jump sizes in the last 6 columns. The numbers in columns % jp, positive jump size, and negative jump size are in percentage terms. Row Avg. 100 shows the averages across the 100 sample cryptocurrencies.

	Jump Frequency				Positive Jump Size (%)			Negative Jump Size (%)		
Cryptocurrency	Total	Positive	Negative	% jp	25p	50p	75p	25p	50p	75p
BTC	2,180	1,037	1143	0.826	0.0083	0.0129	0.0192	−0.0212	−0.0141	−0.0094
ETH	1,318	639	679	0.574	0.0125	0.0185	0.0262	−0.0263	−0.0197	−0.0138
LTC	1,091	526	565	0.503	0.0171	0.0235	0.0325	−0.0327	−0.0235	−0.0176
BCH	1,025	517	508	0.539	0.0170	0.0229	0.0320	−0.0306	−0.0221	−0.0164
ETC	968	466	502	0.599	0.0175	0.0252	0.0342	−0.0341	−0.0244	−0.0165
ZRX	840	364	476	0.525	0.0188	0.0278	0.0431	−0.0392	−0.0255	−0.0183
XRP	380	203	177	0.592	0.0133	0.0186	0.0261	−0.0295	−0.0208	−0.0130
XLM	594	248	346	0.397	0.0156	0.0207	0.0276	−0.0286	−0.0191	−0.0144
EOS	675	307	368	0.500	0.0175	0.0228	0.0312	−0.0314	−0.0231	−0.0162
REP	1,048	532	516	0.874	0.0224	0.0320	0.0441	−0.0399	−0.0283	−0.0204
LINK	366	151	215	0.263	0.0191	0.0258	0.0351	−0.0366	−0.0259	−0.0176
XTZ	444	197	247	0.342	0.0205	0.0283	0.0399	−0.0333	−0.0260	−0.0180
ALGO	451	183	268	0.341	0.0232	0.0362	0.0535	−0.0431	−0.0295	−0.0211
DASH	462	205	257	0.352	0.0180	0.0264	0.0365	−0.0338	−0.0249	−0.0177
OXT	843	493	350	0.756	0.0220	0.0331	0.0476	−0.0426	−0.0281	−0.0198
ATOM	311	128	183	0.260	0.0217	0.0285	0.0409	−0.0373	−0.0263	−0.0193
KNC	416	190	226	0.359	0.0228	0.0335	0.0444	−0.0384	−0.0266	−0.0188
OMG	314	154	160	0.331	0.0235	0.0322	0.0460	−0.0393	−0.0275	−0.0175
MKR	387	180	207	0.364	0.0169	0.0247	0.0332	−0.0311	−0.0239	−0.0172
COMP	273	95	178	0.260	0.0253	0.0362	0.0438	−0.0407	−0.0305	−0.0235
LRC	365	178	187	0.379	0.0254	0.0383	0.0545	−0.0422	−0.0333	−0.0228
ZEC	261	92	169	0.294	0.0195	0.0270	0.0412	−0.0344	−0.0251	−0.0180
ADA	291	131	160	0.368	0.0171	0.0228	0.0310	−0.0280	−0.0204	−0.0139
DOGE	425	193	232	0.592	0.0184	0.0241	0.0338	−0.0288	−0.0218	−0.0164
ZEN	221	85	136	0.371	0.0197	0.0264	0.0367	−0.0365	−0.0264	−0.0202
Avg. 100	420	206	214	0.550	0.0228	0.0320	0.0446	−0.0395	−0.0285	−0.0205

the numbers of positive and negative jumps are similar, and the distributions of positive and negative jump sizes are not discernibly different. These symmetries are also observed in other financial markets.

B. Weekly Realized Variances

We use the intraday return and detected jump data summarized in the previous subsection to compute the weekly decomposed variances and return measures. To construct weekly spans, we follow the approach of Liu et al. (2022). Our choice of weekly analyses is also consistent with that of Amaya et al. (2015) and Bollerslev et al. (2020), who aggregate intraday data to construct realized risk measures over longer horizons and examine how these measures are related to subsequent equity returns in the cross section.

We describe our weekly realized variances, which are estimated as explained in Section II. Panel A of Table 3 shows the summary statistics of the weekly realized variances. The mean weekly realized total variance is 0.146, which corresponds to an annualized standard deviation of 138%. To put this into perspective, this annualized realized volatility can be compared with that of other financial asset markets. For example, the annualized realized volatility in sovereign currency markets ranges from 5.3% to 19.2%, with a mean of 12.25% (Lee and Wang (2019)).

TABLE 3

Summary Statistics of Weekly Realized Variances

Table 3 reports the summary statistics of the decomposed variances estimated with intraday data. The variance is defined as the sum of squared 15-minute returns and is estimated from the previous month of observations. The positive (negative) jump variance is defined as the sum of squared positive (negative) jump sizes and is estimated from the previous month of observations. The total jump variance is the sum of the positive and negative jump variances. The jump-robust variance is estimated from observations without a jump. Panel A reports the first 4 central moments (Mean, Stdev, Skew, and Kurt), 25th percentile (25p), median (Median), and 75th percentile (75p). Panel B shows the pairwise correlations between these measures.

Panel A. Distributional Characteristics

		Jump Variance			
	Total Variance	Positive	Negative	Total	Jump-Robust Variance
Mean	0.146	0.010	0.008	0.018	0.127
Std. dev.	0.161	0.015	0.010	0.024	0.154
Skew	6.031	3.671	5.073	3.736	6.752
Kurt	91.738	25.338	67.674	24.953	110.573
25p	0.058	0.002	0.003	0.006	0.047
Median	0.103	0.005	0.005	0.010	0.087
75p	0.179	0.012	0.010	0.021	0.155

Panel B. Correlation Matrix

		Jump Variance		
	Total Variance	Positive	Negative	Total
Positive jump variance	0.420			
Negative jump variance	0.339	0.640		
Total jump variance	0.425	0.934	0.873	
Jump–robust variance	0.981	0.248	0.175	0.239

In addition, regarding U.S. stock markets, Andersen et al. (2001a) indicate that the mean of the annualized standard deviation is 28%, and Amaya et al. (2015) show that the median of annualized realized volatility is approximately 45%. This comparison suggests unusually high volatility in cryptocurrency markets.

Because cryptocurrency returns have substantial jump components, the mean of the jump-robust variances drops to 0.127. The mean jump variances appear relatively small because jumps are rare events; thus, jump variances often take a value of 0. However, when jumps occur, the jump variances dominantly contribute to the total variances. Symmetric jumps allow positive and negative jump variances to have similar distributions.

Panel B of Table 3 shows the correlations of these weekly realized variances. The jump-robust variances are highly correlated with the total variances because jump returns are rare. The correlation coefficient of these 2 variances is 0.98, which implies that they carry similar information. The positive and negative jump variances are positively correlated, with a correlation coefficient of 0.64, indicating that positive jumps are occasionally accompanied by negative jumps. Because jumps tend to be detected during volatile periods, total variances are positively correlated with jump variances (i.e., the correlation coefficients are greater than 0.33). However, the relatively low correlation coefficients imply that signed jump variances capture information that differs from that captured by total and jump robust variances.

To examine how our weekly realized variance measures change over time and to assess whether there are cross-sectional differences in these measures, we plot the 10th, 50th, and 90th percentiles of the weekly realized variances. We provide the

https://doi.org/10.1017/S002210902400022X Published online by Cambridge University Press

time-series plots for the total, positive jump, negative jump, and jump-robust variances in Graphs A–D of Figure 3, respectively. The percentiles for realized decomposed variances are clearly time-varying within relatively short horizons compared to those observable in stock markets. The total variances peak in 2018 because of turbulence in cryptocurrency markets.[29] The positive and negative jump variances are relatively high in 2018 and after 2021, and multiple peaks with large cross-sectional variations occurred in 2016, as bullish cryptocurrency markets attracted major market players, setting the stage for their growth.[30] Bullish and bearish markets consecutively occurred in the 2020s, which widened the cross-sectional variations in jump variances. Because the total and jump-robust variances are estimated with almost the same observations except for rare jumps, they yield similar patterns (Graphs A and D). Overall, all variance measures dynamically change over time with discernible cross-sectional dispersion. Therefore, it is important to frequently update these risk measures for cryptocurrency markets to capture the time-varying features and pricing effects.

IV. Return Prediction with Variances

In this section, we investigate cryptocurrency return predictability, showing significantly negative spreads in returns to variance-sorted portfolios. Sorting analyses enable us to assess return predictability with selected variance measures and show the economic magnitudes of predictable returns. Then, we further support our findings by using cross-sectional predictability regressions that simultaneously control for multiple variance measures.

A. Sorting Analyses

In this subsection, we compare the returns of total variance-sorted portfolios. At the end of every week (week w), we sort individual cryptocurrencies on total variances and construct tercile portfolios. The total variance measures are estimated with intraday observations from week $w-3$ to w. Then, we compute equal-weighted (EW) and value-weighted (VW) returns in the subsequent week for each portfolio. We consider a long-short portfolio that purchases cryptocurrencies in the top tercile and sells cryptocurrencies in the bottom tercile.[31]

In Panel A of Table 4, we report the weekly returns of the total variance-sorted portfolios. The rows labeled “Excess return” show the clear negative relation between the realized total variances and the average subsequent returns. The portfolios with the highest total variances (High portfolios) provide significantly

[29]After substantial attention was given to cryptocurrency markets in 2017, there were hacking events (Corbet, Cumming, Lucey, Peat, and Vigne (2020)), and many governments (e.g., Korea, Japan, and the U.S.) announced the strengthening of regulations on cryptocurrency markets.

[30]For example, Standard Chartered initiated investments in cryptocurrency markets.

[31]Although we use long-short portfolios for comparison purposes, there is a potential concern that some cryptocurrencies are difficult to short-sell. Therefore, following Liu et al. (2022), we assume that Bitcoin is shorted and confirm that our results are robust.

FIGURE 3

Time-Series of Weekly Realized Variances

Figure 3 illustrates how the weekly decomposed variances change during the sample period from Oct. 2015 to June 2023. Graphs A–D are for the total, positive jump, negative jump, and jump-robust variances, respectively. These decomposed variance measures are estimated from the previous month of observations. In each panel, we provide the 10th, 50th, and 90th percentiles of decomposed variances in the cross section.

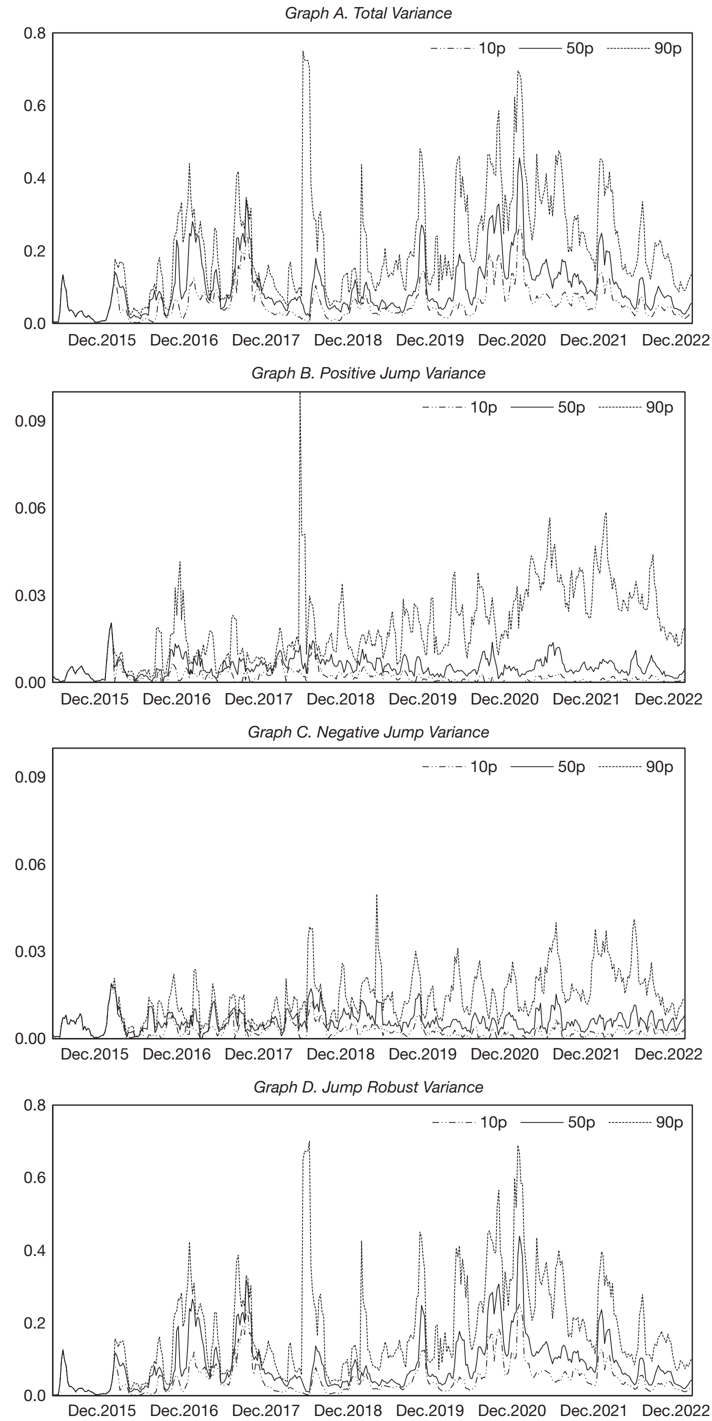

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TABLE 4

Excess Returns of Cryptocurrencies Sorted by Decomposed Variances

Table 4 shows the relationship between the decomposed variances and subsequent excess returns. At the end of every week, we sort the 100 sample cryptocurrencies on the estimated (total) variance, positive and negative jump variances, or jump-robust variance and then construct tercile portfolios. We estimate the total and decomposed variance measures by using the previous month of observations. For each sorted portfolio, we compute excess returns in the subsequent week. The portfolios are constructed with equal-weights (EW) and value-weights (VW). In Panels A–D, we report the results for the portfolios sorted by the total, positive jump, negative jump, and jump-robust variances. In each panel, we report the average excess returns, standard deviation, and Sharpe ratio for the excess returns. In addition, we provide the alphas of the time-series regressions of the portfolio returns on the 3-factor model of Liu, Tsyvinski, and Wu (2022). Column Low (High) concerns portfolios with the lowest (highest) sorting measures. Column H–L shows the differences between the values of High and Low portfolios (the standard deviations and Sharpe ratios in this column are for longing High portfolios and shorting Low portfolios). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Low	Mid	High	H–L
Panel A. Total Variance				
Total variance	0.021	0.034	0.052	0.031***
Excess return (EW)	0.001	−0.007	−0.036	−0.037***
Standard deviation	0.108	0.130	0.128	0.063
Sharpe ratio	0.009	−0.052	−0.285	−0.589
Alpha	0.013	0.010	−0.012	−0.024***
Excess return (VW)	0.008	0.000	−0.022	−0.030***
Standard deviation	0.098	0.132	0.146	0.093
Sharpe ratio	0.084	−0.001	−0.147	−0.321
Alpha	0.021	0.003	−0.006	−0.027***
Panel B. Positive Jump Variance				
Positive jump variance	0.001	0.002	0.004	0.003***
Excess return (EW)	−0.001	−0.004	−0.037	−0.036***
Standard deviation	0.119	0.117	0.127	0.054
Sharpe ratio	−0.007	−0.036	−0.291	−0.672
Alpha	0.010	0.011	−0.011	−0.021***
Excess return (VW)	0.007	0.007	−0.016	−0.023***
Standard deviation	0.103	0.107	0.137	0.078
Sharpe ratio	0.066	0.061	−0.117	−0.291
Alpha	0.017	0.016	−0.009	−0.026***
Panel C. Negative Jump Variance				
Negative jump variance	0.001	0.002	0.003	0.002***
Excess return (EW)	−0.005	−0.004	−0.032	−0.027***
Standard deviation	0.118	0.124	0.121	0.051
Sharpe ratio	−0.044	−0.035	−0.267	−0.531
Alpha	0.006	0.013	−0.008	−0.014***
Excess return (VW)	0.011	0.000	−0.012	−0.023***
Standard deviation	0.103	0.116	0.130	0.079
Sharpe ratio	0.106	0.002	−0.093	−0.292
Alpha	0.017	0.016	−0.003	−0.020***
Panel D. Jump-Robust Variance				
Jump–robust variance	0.019	0.030	0.046	0.027***
Excess return (EW)	−0.001	−0.008	−0.033	−0.032***
Standard deviation	0.110	0.127	0.129	0.063
Sharpe ratio	−0.010	−0.062	−0.258	−0.512
Alpha	0.011	0.007	−0.008	−0.020***
Excess return (VW)	0.008	−0.001	−0.017	−0.026***
Standard deviation	0.098	0.129	0.143	0.090
Sharpe ratio	0.086	−0.006	−0.121	−0.286
Alpha	0.021	0.004	0.001	−0.020***

lower excess returns in subsequent weeks than those with the lowest total variances (Low portfolios). Specifically, the differentials between the weekly excess returns of High and Low portfolios are −3.7% and − 3.0% for EW and VW portfolios, respectively, which are statistically significant at the 1% level. Unlike excess returns, the standard deviations of High and Low portfolios are similar.

To investigate whether these return differences result from exposure to systematic risk factors, we compute alphas by regressing weekly excess returns on the three factors of Liu et al. (2022). The differentials between the alphas of High and Low portfolios remain negative and significant for both the EW and VW portfolios. Therefore, the negative relation between the total variances and subsequent returns cannot be explained solely by systematic factors.

Our results are partly inconsistent with those of Liu et al. (2022) in that these authors show insignificantly negative return differentials in subsequent weeks for volatility-sorted portfolios. These different results arise because these authors use daily data for variance/volatility estimations, while we employ intraday data. In fact, using the daily data of our sample coins, we obtain consistent results. By using higher-frequency observations for variance estimations, we can measure variances more precisely and better capture variances' time-varying features because the variance estimates are more frequently updated with recent data over shorter horizons and are less vulnerable to the smoothing effect of older data. As noted in Section III, variances in cryptocurrency markets are clearly time-varying, and their cross-sectional variations change dramatically over short horizons. We incorporate this fact with high-frequency data and clearly demonstrate the significant role of realized variances in cryptocurrency return prediction, which has not been studied in the literature.

To examine which types of variances contribute to the return prediction, we perform additional sorting analyses by using positive jump, negative jump, and jump-robust variances. This variance decomposition with signed jump and non-jump returns differentiates the impact of extreme variations from nonnormal return distributions.[32] The sorting analysis results using these decomposed variances are reported in Panels B–D of Table 4.

In Panel B of Table 4, High positive jump variance portfolios have 3.6% (2.3%) lower excess returns for EW (VW) portfolios than do Low positive jump variance portfolios. The alphas for High positive jump variance portfolios are also significantly lower than those for Low positive jump variance portfolios. These results indicate that positive jump variances significantly contribute to the negative return predictability of total variances.

Panel C of Table 4 shows the results for negative jump variance-sorted portfolios, which are similar to those for positive jump variance-sorted portfolios in Panel B. The similarity results from the positive correlation of positive and negative jump variances. Our regression analyses in the next subsection clarify the exclusive effects of these variables with simultaneous controls. Finally, Panel D presents the results for jump-robust variance-sorted portfolios. The overall results in Panel D are similar to those presented in Panel A because the total and jump robust variances are similar, except for occasional jump arrivals.

[32]Bollerslev, Medeiros, Patton, and Quaedvlieg (2021) propose a similar variance decomposition with partial (co)variance measures, which enables the multiple decompositions of realized variances.

https://doi.org/10.1017/S002210902400022X Published online by Cambridge University Press

B. Cross-Sectional Regression Analyses

The sorting analyses could ignore the potential confounding effects of various independent variables. In this subsection, we address this concern by conducting a series of standard Fama and MacBeth (FMB) (1973) cross-sectional regressions with individual cryptocurrencies. These analyses expand our findings and simultaneously control for multiple factors and cryptocurrency characteristics. Our choice of regression models is motivated by Amaya et al. (2015), who use FMB regressions to identify the relationship between weekly realized central moments and stock returns in subsequent weeks. Our regression models are also consistent with those of Bali et al. (2011), who adopt FMB regressions to investigate the relationship between maximum daily returns and subsequent monthly returns.[33]

We first test the effect of the total variance measure on subsequent returns. Specifically, for each week in our sample, we run the following cross-sectional regression:

$$rx_{i,w+1} = \gamma_{0,w} + \gamma_{1,w} TV_{i,w} + c'_w X_{i,w} + \varepsilon_{i,w+1}, \tag{5}$$

where $rx_{i,w+1}$ is the excess return of cryptocurrency i over week $w+1$. The first variable of interest $TV_{i,w}$ and the vector of control variables $X_{i,w}$ are measured at the end of week w. After estimating the slope coefficients for each week in the sample, we take the time-series averages of the coefficient estimates to check whether the independent variables can significantly predict excess returns in the subsequent week.

Table 5 shows the related estimates and corresponding t-statistics.[34] As shown in column 1, the coefficients of realized total variances are significantly negative. To compare our intraday data-based measure with the daily return-based volatility measure of Liu et al. (2022), we use the standard deviations of daily returns as independent variables in column 2. Consistent with the result of Liu et al. (2022), the volatilities estimated with daily data provide insignificantly negative coefficients. This comparison elucidates the importance of using intraday data for capturing volatility effects in cryptocurrency markets. Column 3 shows that the negative relationship between total variances and future returns is robust to cryptocurrency-specific control variables such as lagged returns and cryptocurrency sizes. These controls are employed because of the momentum and size factors of Liu et al. (2022).[35]

Then, we use multiple independent variables to test the effect of the decomposed variances on subsequent returns. Specifically, we conduct the following cross-sectional regression:

[33]Bali et al. (2011) employ daily data, while we use intraday data, similar to Amaya et al. (2015). The regression frequency of Bali et al. (2011) is monthly, while ours is weekly, as is that of Amaya et al. (2015).

[34]That is, we report $\hat{\gamma}_l = (1/\tilde{w})\sum_{w=1}^{\tilde{w}} \hat{\gamma}_{l,w}$ with $l=0,1$ or $l=0,1,2,3$, where $\tilde{w}$ is the total number of weeks. We use the Newey–West standard errors. Our results are robust to lag length selection.

[35]Our results indicate that the lagged return effects differ across return horizons or sample periods. For example, columns 3 and 4 of Table 6 show that 1-month and 1-quarter lagged returns are significant, while 1-week lagged returns are insignificant in Table 7, which also shows that the lagged return effects are sensitive to sample periods.

TABLE 5

Return Prediction with Decomposed Variances

Table 5 shows how decomposed variances are related to excess returns in the subsequent week. We estimate the coefficients of the following Fama–MacBeth (FMB) regression:

$$rx_{i,w+1} = \gamma_{0,w} + \gamma_{1,w} TV_{i,w} + c'_w X_{i,w} + \varepsilon_{i,w+1} \text{ or}$$

$$rx_{i,w+1} = \gamma_{0,w} + \gamma_{1,w} JV^{(+)}_{i,w} + \gamma_{2,w} JV^{(-)}_{i,w} + \gamma_{3,w} JRV_{i,w} + c'_w X_{i,w} + \varepsilon_{i,w+1},$$

where $rx_{i,w}$ is the excess return of cryptocurrency i in week w. $TV_{i,w}$, $JV^{(+)}_{i,w}$, $JV^{(-)}_{i,w}$, and $JRV_{i,w}$ are the total, positive jump, negative jump, and jump-robust variances, respectively. These decomposed variances are estimated with the previous month of observations (i.e., observations from week $w-3$ to week w). For comparison, we replace $TV_{i,w}$ with the volatility estimated from 1-month daily return data (column 2). $X_{i,w}$ is the vector of control variables such as lagged excess returns and natural logarithmic market capitalization. Then, we report the time-series averages of the estimated coefficients and the corresponding t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	1	2	3	4	5	6
Constant	0.012	−0.005	−0.054**	0.014*	0.120	−0.033
t-stat.	1.57	−0.47	−2.10	1.81	1.53	−1.29
Total variance	−0.221***		−0.171***			
t-stat.	−7.77		−5.62			
Jump variance				−0.669***		
t-stat.				−4.71		
Positive jump variance					−1.470***	−1.492***
t-stat.					−5.24	−4.69
Negative jump variance					0.626	0.791
t-stat.					1.07	1.31
Jump–robust variance				−0.152***	−0.151***	−0.091**
t-stat.				−4.83	−4.41	−2.00
Volatility (daily data)		−0.134				
t-stat.		−0.86				
Lagged return			0.006			0.003
t-stat.			0.44			0.16
Market capitalization			0.003***			0.002**
t-stat.			3.13			2.11
Adj. R^2	0.115	0.092	0.186	0.163	0.200	0.266

$$(6) \qquad rx_{i,w+1} = \gamma_{0,w} + \gamma_{1,w} JV^{(+)}_{i,w} + \gamma_{2,w} JV^{(-)}_{i,w} + \gamma_{3,w} JRV_{i,w} + c'_w X_{i,w} + \varepsilon_{i,w+1},$$

where $JV^{(+)}_{i,w}$, $JV^{(-)}_{i,w}$, and $JRV_{i,w}$ are the positive jump, negative jump, and jump robust variances, respectively, as defined in Section II. These decomposed variances are estimated with 1 month of observations. We conduct weekly cross-sectional regressions and then report the time series means of the coefficient estimates and t-statistics.

From column 4 of Table 5, we show the results using decomposed variances as independent variables to identify which variance component significantly contributes to the negative predictability of the realized total variance. To represent the role of jumps without considering signs, we decompose total variances into jump and jump-robust variances. Column 4 shows that the coefficient of jump variances is -0.669 and that of jump-robust variances is -0.152. Both coefficients are significant at the 1% level. Column 5 indicates that the negative relation of jump variances to subsequent returns mainly results from positive jump variance effects. In particular, positive jump variances continue to have significantly negative coefficients, while negative jump variances have positive coefficients. The negative return prediction of positive jump and jump-robust variances is maintained after controlling for lagged returns and market capitalization, as shown in column 6. These results imply that cryptocurrencies with higher variances tend to provide lower returns in subsequent periods and that this predictive relationship is amplified if positive jump variances are high.

From these analyses, we propose two key takeaways. First, it is important to account for the unique characteristics of cryptocurrency markets with unusually high volatility. Our realized variance measures capture short-term volatility dynamics and accommodate frequent updates with high-frequency data, which allows for the identification of unique variance effects. Another important and interesting point is that the negative return prediction results from return distributions beyond the left tail. This relationship could contrast with the classical risk and return trade-off, which is typically represented by the positive relation between risk measures (e.g., variances) and returns. In the next section, we explore the possible connection of our findings with previous studies that present this negative relationship.

C. Robustness Tests

In this subsection, we address the concern that the return predictability of positive jump and jump-robust variances is attributable to our selection of dependent variables or omitted variables in the regressions. We also investigate how our results are affected by aggregate cryptocurrency uncertainty, average liquidity in cryptocurrency markets, and business cycles. We prove that our results are robust to model specifications and market conditions.

First, we test whether our results are sensitive to the choice of subsequent return horizons for dependent variables. We consider the 2 alternatives of 2-week and 1-month excess returns as dependent variables by replacing $rx_{i,w+1}$ with $rx_{i,w+1:w+2}$ or $rx_{i,w+1:w+4}$ in equation (6), where $rx_{i,w+1:w+k}$ represents the excess returns of cryptocurrency i from weeks $w+1$ to $w+k$. Columns 1 and 2 of Table 6 present the results of applying equation (6) with the replaced dependent variables. We continue to find that positive jump and jump-robust variances yield negative coefficients, which are significant at the 1% level.[36]

In the second set of robustness checks, we consider additional control variables of lagged returns with alternative horizons while keeping the same dependent variables of subsequent-week returns as in our main regression specification. This set of robustness tests is motivated by Jegadeesh (1990), Lehmann (1990), and Jegadeesh and Titman (1993), who document short-term return reversals at weekly and monthly horizons and return momentum at 6-month to 12-month horizons in stock markets. Given our relatively short sample period, we use lagged 1-month and 1-quarter returns, instead of lagged 1-week returns, as control variables. We report the results in columns 3 and 4 of Table 6. These alternative controls are intended to capture momentum or reversal effects that may exist in cryptocurrency markets. We conclude that our main findings remain consistent.

[36]We perform additional tests with other horizons and find consistent results.

TABLE 6

Robustness Test

Table 6 shows the robustness of the decomposed variance effect. We use the following Fama–MacBeth (FMB) regression:

$$rx_{i,w+1} = \gamma_{0,w} + \gamma_{1,w} JV_{i,w}^{(+)} + \gamma_{2,w} JV_{i,w}^{(-)} + \gamma_{3,w} JRV_{i,w} + c_w' X_{i,w} + \varepsilon_{i,w+1},$$

where $rx_{i,w}$ is the excess return of cryptocurrency i in week w. $JV_{i,w}^{(+)}$, $JV_{i,w}^{(-)}$, and $JRV_{i,w}$ are the positive jump, negative jump, and jump-robust variances, respectively. These decomposed variances are estimated from the previous month of observations (i.e., observations from week $w-3$ to week w). $X_{i,w}$ is the vector of control variables such as lagged excess returns and natural logarithmic market capitalization. For the part denoted "Dependent variable," we replace the dependent variable with 2-week excess returns (column 1) and 1-month excess returns (column 2). For the part denoted "Control: Long-term," we control for the potential return momentum/reversal effect and maximum return effect, employing the lagged excess returns over periods from week $w-3$ to week w (i.e., 1-month returns) for column 3 and those from week $w-11$ to w (i.e., 1-quarter returns) for column 4. For the part denoted "Control: Maximum," we use the maximum 15-minute excess returns in week w for column 5 and the maximum one-day returns during the period from week $w-3$ to week w for column 6. In this table, we report the time-series averages of the estimated coefficients and the corresponding t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable		Control: Long-Term		Control: Maximum	
	1	2	3	4	5	6
Constant	−0.090*	−0.192**	−0.023	−0.001	−0.021	−0.024
t-stat.	−1.88	−2.24	−0.96	−0.04	−0.87	−0.98
Positive jump variance	−2.693***	−4.562***	−1.588***	−1.343***	−1.268***	−1.266***
t-stat.	−5.05	−6.32	−5.20	−4.01	−4.02	−3.15
Negative jump variance	1.139	−0.333	0.960	0.889	0.740	0.908
t-stat.	1.02	−0.25	1.53	1.44	1.22	1.49
Jump–robust variance	−0.169**	−0.234**	−0.104***	−0.126***	−0.117***	−0.159***
t-stat.	−2.19	−2.13	−2.57	−3.17	−2.89	−3.91
Lagged return (or Max)	0.036	0.082**	0.059**	0.156***	−0.200***	0.051
t-stat.	1.32	2.32	2.00	3.43	−3.27	1.13
Market capitalization	0.005***	0.011***	0.002*	0.001	0.002*	0.002*
t-stat.	2.80	3.50	1.80	0.73	1.82	1.79
Adj. R^2	0.281	0.288	0.271	0.267	0.250	0.260

Because (jump) variances can be high when maximum returns are high, one might raise the question of whether our findings are related to maximum return effects. To distinguish our findings from the maximum return effects, we control for the maximum 15-minute returns in week w and maximum daily returns in the previous month. As columns 5 and 6 of Table 6 indicate, neither the 15-minute nor one-day maximum return weakens our results. This result suggests that our decomposed variance measures capture the aspects of historical return variations that are different from one extreme realized return.[37]

We also investigate whether our results are robust to changes in aggregate cryptocurrency market uncertainty, average liquidity in cryptocurrency markets, and business cycles. We compute weekly cryptocurrency market volatility by following the approach of Menkhoff, Sarno, Schmeling, and Schrimpf (2012) that is used for foreign currency markets. For average illiquidity, we adopt an approach similar to that of Chordia, Roll, and Subrahmanyam (2001) by taking the average of the illiquidity measures of Amihud (2002) across cryptocurrencies. Using the medians of these measures, we construct high- and low-volatility or illiquidity subsamples. To consider business cycles, we separate our sample into

[37]Univariate regression with 1-day maximum returns yields a significantly negative coefficient, which is consistent with the results of Bali et al. (2011). By adding positive jump variances, we find that the effect of the maximum returns becomes weaker than that of the univariate regression result.

TABLE 7

Time-Series Subsample Analyses

Table 7 shows how the effects of decomposed variances on subsequent excess returns depend on market conditions. We construct time series subsamples depending on the overall volatility and illiquidity of cryptocurrency markets and business cycles. Cryptocurrency market volatility is defined as the means of the average absolute values of 15-minute log cryptocurrency returns across individual cryptocurrencies during the corresponding week, following Menkhoff et al. (2012). Cryptocurrency market illiquidity is captured by the averages of individual weekly Amihud (2002) illiquidity measures. The High (Low) period subsample is obtained by excluding the 20% of weeks with the lowest (highest) volatility or illiquidity measures. Business cycles are separated considering NBER business cycles (i.e., in our sample, the former (latter) period is before (after) Aug. 2021, and the former period includes recession periods). We apply the following Fama–MacBeth (FMB) regression to these time series subsamples:

$$rx_{i,w+1} = \gamma_{0,w} + \gamma_{1,w} JV_{i,w}^{(+)} + \gamma_{2,w} JV_{i,w}^{(-)} + \gamma_{3,w} JRV_{i,w} + c'_w X_{i,w} + \varepsilon_{i,w+1},$$

where $rx_{i,w}$ is the excess return of cryptocurrency i in week w. $JV_{i,w}^{(+)}$, $JV_{i,w}^{(-)}$, and $JRV_{i,w}$ are the positive jump, negative jump, and jump-robust variances, respectively. These decomposed variances are estimated from the previous month of observations (i.e., observations from week $w-3$ to week w). $X_{i,w}$ is the vector of control variables such as lagged excess returns and natural logarithmic market capitalization. Then, we report the time-series averages of the estimated coefficients and the corresponding t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Market Volatility		Market Illiquidity		Sample Period	
	Low	High	Low	High	Former	Latter
Constant	−0.032**	−0.034**	−0.035**	−0.036***	0.034*	−0.100***
t-stat.	−2.37	−2.36	−2.26	−3.86	1.92	−11.61
Positive jump variance	−1.032***	−1.890***	−1.477***	−1.504***	−2.098***	−0.877***
t-stat.	−8.38	−7.36	−7.96	−8.15	−7.52	−8.91
Negative jump variance	−0.443**	1.860***	0.457*	1.009***	2.199***	−0.638***
t-stat.	−2.14	5.10	1.74	3.73	5.39	−4.67
Jump–robust variance	−0.076***	−0.105***	−0.028	−0.099***	−0.148***	−0.032*
t-stat.	−4.77	−3.25	−1.49	−3.92	−4.50	−1.83
Lagged return	−0.003	0.007	−0.008	0.008	0.020	−0.015*
t-stat.	−0.30	0.51	−0.76	0.80	1.38	−1.94
Market capitalization	0.002***	0.002***	0.002***	0.002***	−0.000	0.004***
t-stat.	3.96	3.70	2.97	6.78	−0.25	13.34
Adj. R^2	0.228	0.301	0.238	0.281	0.361	0.170

two subsamples, the latter of which starts in Aug. 2021 (i.e., the subsample for the former period includes recession periods). We choose this separation because the National Bureau of Economic Research (NBER) indicates that the peak during our sample period occurs in Feb. 2020 and because the two subsamples can be of similar sizes. Then, we apply the FMB regressions of equation (6) to each subsample.

Table 7 shows the results. In the columns denoted Market volatility, the variance effects of this article are significant for both the high- and low-volatility subsamples. As the columns under Market illiquidity indicate, the return predictability of positive variances is robust, while that of jump-robust variances is significant only for the period with high levels of market illiquidity. This result implies that the effect of variances from extreme price movements (i.e., positive jumps) can be dominant in less liquid markets. The last two columns for business cycles indicate that our findings are robust regardless of the business cycle or subsample period. Overall, our results are robust to sample selection and market conditions such as market volatility and illiquidity.

D. Comparison with the Realized Skewness Effect

The variance effects in this article might be linked to the skewness effect, which also implies a negative relationship between skewness and subsequent returns (Amaya et al. (2015)). Jia et al. (2021) and Borri and Santucci de Magistris (2022) document the effects of coskewenss and realized skewness on the cross section of cryptocurrency returns, respectively. To clarify how the variance effect in this article is related to the skewness effect, we compare these two effects. We first check with our data that the skewness effect exists in cryptocurrency markets. Then, we compare our decomposed variance effects with the skewness effect.[38]

Following Amaya et al. (2015), we use lagged skewness as the main explanatory variable and volatility and kurtosis as control variables. We run the following Fama–MacBeth (FMB) regression:

$$rx_{i,w+1} = \lambda_{0,w} + \lambda_{1,w} LSkew_{i,w} + \lambda_{2,w} Vol_{i,w} + \lambda_{3,w} Kurt_{i,w} + c'_w X_{i,w} + \varepsilon_{i,w+1}, \tag{7}$$

where $LSkew_{i,w}$, $Vol_{i,w}$, and $Kurt_{i,w}$ are the weekly realized skewness, volatility, and kurtosis of returns, respectively.[39]

We report the results in Table 8. In column 1, we run a univariate regression that uses only realized skewness and show that cryptocurrencies with high realized skewness tend to have low excess returns in subsequent weeks, which is consistent with the findings of Amaya et al. (2015). We include volatility and kurtosis in column 2 and add lagged returns and market capitalization in column 3. We continue to find that high realized skewness significantly predicts low future returns. As column 4 shows, this negative relationship is robust to the additional controls of jump-robust volatility and kurtosis. Therefore, the skewness effect appears to exist in cryptocurrency markets, as it does in U.S. equity markets.

We compare the return predictability of skewness with that of positive jump variances by conducting horse-race regressions. As columns 5 and 6 of Table 8 show, the coefficients of realized skewness become insignificant after controlling for the decomposed partial variances. Jump-robust and positive jump variances continue to exhibit negative and statistically significant coefficients, which indicates that the realized variances, including positive jump variances, are more important return predictors in cryptocurrency markets than is realized skewness. Interestingly, in highly uncertain cryptocurrency markets, high realized variances are more important and preferred characteristics than high realized skewness as long as they are not associated with extreme negative returns.

V. Exploration of Mechanism for Return Predictability

The negative relation between variances and future cryptocurrency returns contrasts with the positive risk–return tradeoffs that traditional finance theories suggest (e.g., Merton (1987)). However, considering other asset markets that share similar characteristics and investors with cryptocurrency markets, our findings can be explained by behavioral finance studies on speculative retail trading with lottery preferences. In this section, we explore several economic mechanisms and discuss

[38]In Appendix D of the Supplementary Material, we also use alternative jump variance measures instead of skewness.

[39]We use jump-robust volatilities instead of jump-robust variances to be consistent with the FMB regression specification of Amaya et al. (2015). When we use variances or jump-robust variances instead of volatilities or jump-robust volatilities, we find essentially the same results.

https://doi.org/10.1017/S002210902400022X Published online by Cambridge University Press

TABLE 8

Comparison of Positive Jump Variance Effects with Skewness Effects

Table 8 shows the return predictability with skewness, which is compared with that with positive jump variances. We employ the following Fama–MacBeth (FMB) regression:

$$rx_{i,w+1} = \lambda_{0,w} + \lambda_{1,w} LSkew_{i,w} + \lambda_{2,w} Vol_{i,w} + \lambda_{3,w} Kurt_{i,w} + c'_w X_{i,w} + \varepsilon_{i,w+1},$$

where $rx_{i,w}$ is the excess return of cryptocurrency i in week w. $LSkew_{i,w}$, $Vol_{i,w}$, and $Kurt_{i,w}$ are the realized weekly skewness, volatility (i.e., the square root of the variance), and kurtosis of the returns, respectively. These realized moments are estimated from the previous month of observations. To compare the positive jump variance effects with the skewness effects, we replace $Vol_{i,w}$ with the jump-robust volatility (i.e., the square root of the jump-robust variance) and the positive and negative jump variances. $X_{i,w}$ is the vector of control variables such as lagged excess returns and natural logarithmic market capitalization. Then, we report the time-series averages of the estimated coefficients and the corresponding t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	1	2	3	4	5	6
Constant	−0.016	0.063***	0.025	0.065***	0.043***	−0.002
t-stat.	−1.73	6.16	0.80	6.08	3.69	−0.08
Skewness	−0.286***	−0.007	−0.009*	−0.009*	0.005	0.002
t-stat.	−7.52	−1.46	−1.86	−1.84	0.82	0.23
Volatility		−0.049***	−0.039***			
t-stat.		−8.76	−5.88			
Jump-robust volatility				−0.052***	−0.035***	−0.018**
t-stat.				−8.08	−4.80	−2.24
Kurtosis		−0.002**	−0.001**	−0.002***	−0.001	−0.000
t-stat.		−2.21	−2.17	−2.85	−1.00	−0.20
Lagged return			0.005			0.001
t-stat.			0.34			0.06
Market capitalization			0.001			0.001
t-stat.			1.12			1.19
Positive jump variance					−1.632***	−1.672***
t-stat.					−3.75	−3.57
Negative jump variance					1.019	0.715
t-stat.					1.31	0.94
Adj. R^2	0.041	0.173	0.244	0.173	0.253	0.319

related studies in the literature to enhance our understanding of the potential drivers of our findings.

A. Retail Investor Trading

We consider speculative retail trading as one explanation because Kogan et al. (2023) show that retail investors actively participate in cryptocurrency markets. According to Han and Kumar (2013), retail investors are drawn toward stocks with speculative features (e.g., high volatility and skewness) and are willing to undertake risk that may yield lower returns. Barberis and Huang (2008) demonstrate investors' preference for lottery-type returns. Barberis and Xiong (2012) present a model in which investors' risk-seeking behavior allows investors to prefer holding and trading highly volatile securities because of a greater chance of realizing large gains. Our finding for cryptocurrency markets is closely related to these studies.

For formal tests, we gauge retail investors' trading activities by modifying the RTP of Han and Kumar (2013) to accommodate our weekly studies using cryptocurrency market data. Specifically, we acknowledge a notably wide dispersion in the right-skewed distribution of trading volumes. Given the unique nature of cryptocurrency markets, we establish the 90th percentile of volumes, which is 22 million dollars, across all sample cryptocurrencies as the threshold for characterizing retail investors' trading activities.[40] We also use characteristic variables such as market capitalization, prices, and percentage BASs because Han and Kumar (2013) document that retail investors tend to favor stocks with low market capitalization and low prices, which tend to be less liquid. Daily dollar trading volumes are employed to check for trading activities associated with high variances.

We examine the cross-sectional differences in these characteristics of variance-sorted portfolios. This approach is similar to that used in asset pricing studies that explain the negative risk and return relationship in stock markets by considering firm or portfolio characteristics (Fu (2009), Brandt, Brav, Graham, and Kumar (2010)) and price pressures resulting from illiquidity (Avramov, Chordia, and Goyal (2006)). To be consistent with our sorting analyses in Section IV, at the end of week w, we sort cryptocurrencies on one of decomposed variances and construct tercile portfolios. For each portfolio, we compute the equal-weighted averages of the characteristics in week w.[41]

Table 9 shows the time-series averages of the characteristic variables for the sorted portfolios. Using the total variance-sorted portfolios, Panel A indicates that retail trading activities are significantly greater for cryptocurrencies with high total variances than for those with low total variances. Cryptocurrencies with high total variances tend to have smaller market sizes, lower prices, and wider BASs than those with low total variances. These results are consistent with those of Han and Kumar (2013). Interestingly, the largest trading volumes of High total variance portfolios result mainly from High positive jump variance portfolios, which show the most discernible differences in trading volumes (Panel B). High positive jump variance portfolios also have higher RTPs than other portfolios, which implies that cryptocurrencies with high positive jump variances attract retail transactions.

The literature documents similar return predictability of extreme volatility in other asset markets in which retail investors actively participate. Xiong and Yu (2011) study asset price bubbles in China's warrant markets with the limited presence of institutional investors, finding that warrant bubbles are accompanied by trading frenzy and large volatility and highlighting the role of short-selling constraints and heterogeneous beliefs in explaining the price bubbles (i.e., resale option theory). Our evidence of large trading volumes for High (positive jump) variance portfolios indicates that cryptocurrency investors indeed tend to disagree about the future prices of cryptocurrencies with high variances. However, our variance effects are unlikely to result from overpricing because of short-selling constraints. For our tests, we measure short-selling availability by using the trading volumes of associated futures contracts to initiate short-selling positions.[42] As Table 9 shows, High variance portfolios tend to exhibit larger futures trading

[40]We utilize dollar volumes at 5-minute intervals. Considering that approximately 90–95% of Coinbase's revenues originate from retail investors, we use the 90th percentile of 5-minute trading volumes. We perform additional tests using the 50th and 95th percentiles as alternative thresholds and confirm the robustness.

[41]We report the contemporaneous characteristics for simplicity; the predictive analyses are consistent.

[42]We collect daily futures trading volumes and the volume of futures buyers (those taking the counterparty positions for sellers at prevailing market prices). These futures trading volume data are from binance.com.

TABLE 9

Characteristics of Decomposed Variance-Sorted Portfolios

Table 9 shows the characteristics of decomposed variance-sorted portfolios. At the beginning of every week, we sort the 100 sample cryptocurrencies based on the estimated (total) variance, positive and negative jump variances, or jump-robust variance and construct tercile portfolios. We estimate the total and decomposed variance measures by using the previous month of observations. For each sorted portfolio, we provide the average market capitalization (in billions of USD), daily trading volume (in billions of USD), prices (in USD), BAS, and RTP of Han and Kumar (2013) in the corresponding week. In addition, we report sentiments for individual cryptocurrencies. We use the number of buy opinions (relative to market capitalization) and the percentage of buy opinions relative to total opinions on Twitter and Telegram. To examine the possibility of short selling, we also consider the futures trading volume (in millions of USD) and volumes that buyers take the sellers' futures prices (in millions of USD). In each panel, column Low (High) presents portfolios with the lowest (highest) sorting measures. Column H–L shows the differences between the values of High and Low portfolios. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Low	Mid	High	H–L
Panel A. Total Variance				
Size/trade variable				
Market capitalization ($B)	39.2	2.2	0.9	–38.3***
Daily trading volume ($B)	11,704	21,263	23,957	12,253***
Price ($)	3,124	227	261	–2,863***
Bid–ask spread	0.001	0.001	0.002	0.001***
RTP	0.913	0.958	0.952	0.039***
Sentiment				
No. of Twitter buy /market cap	181.147	311.487	598.336	417.188***
% of Twitter buy	25.389	24.965	25.923	0.534
No. of Telegram buy /market cap	36.410	109.980	280.846	244.437***
% of Telegram buy	23.347	18.089	16.142	–7.205
Short selling availability				
Futures volumes ($M)	660	772	1358	698***
Futures buyers' volume ($M)	320	375	666	346***
Panel B. Positive Jump Variance				
Size/trade variable				
Market capitalization ($B)	26.9	15.2	1.5	–25.4***
Daily trading volume ($B)	1,552	16,045	39,133	37,581***
Price ($)	2,308	1,121	294	–2,014***
Bid–ask spread	0.001	0.001	0.002	0.001***
RTP	0.933	0.938	0.956	0.023***
Sentiment				
No. of Twitter buy /market cap	169.808	278.230	639.958	470.151***
% of Twitter buy	25.484	25.524	25.416	–0.068
No. of Telegram buy /market cap	52.182	78.820	278.874	226.692***
% of Telegram buy	21.929	19.907	15.941	–5.988
Short selling availability				
Futures volumes ($M)	587	1302	935	348***
Futures buyers' volume ($M)	286	633	458	172***
Panel C. Negative Jump Variance				
Size/trade variable				
Market capitalization ($B)	28.2	12.0	2.7	–25.5***
Daily trading volume ($B)	8,594	22,304	25,823	17,229***
Price ($)	2,368	954	381	–1,986***
Bid–ask spread	0.001	0.001	0.002	0.001***
RTP	0.935	0.927	0.960	0.025***
Sentiment				
No. of Twitter buy /market cap	239.442	278.201	568.234	328.792***
% of Twitter buy	25.182	25.586	25.556	0.374
No. of Telegram buy /market cap	51.585	51.797	296.433	244.848***
% of Telegram buy	21.361	19.777	16.545	–4.816
Short selling availability				
Futures volumes ($M)	736	1114	960	225***
Futures buyers' volume ($M)	358	543	469	112***
Panel D. Jump-Robust Variance				
Size/trade variable				
Market capitalization ($B)	38.9	2.4	1.0	–37.9***
Daily trading volume ($B)	19,248	26,639	11,064	–8,184***
Price ($)	3,114	195	299	–2,816***
Bid–ask spread	0.001	0.001	0.002	0.001***
RTP	0.920	0.951	0.951	0.031***

(continued on next page)

TABLE 9 (continued)

Characteristics of Decomposed Variance-Sorted Portfolios

Panel D. Jump-Robust Variance (continued)				
Sentiment				
No. of Twitter buy /market cap	239.160	293.993	552.437	313.278***
% of Twitter buy	25.556	25.097	25.678	0.123
No. of Telegram buy /market cap	47.538	100.089	277.792	230.255***
% of Telegram buy	22.797	18.068	16.582	−6.215
Short selling availability				
Futures volumes ($M)	675	724	1389	714***
Futures buyers' volume ($M)	327	351	681	354***

volumes than Low variance portfolios, which implies that cryptocurrencies with high variances tend to have fewer short-selling constraints.

B. Investor Sentiment

Baker and Wurgler (2006) show that investor sentiment affects the cross section of stock returns. These authors find that when sentiment is high, "riskier" stocks with high volatility tend to earn lower returns and confirm their prediction that highly volatile stocks are difficult to value and to arbitrage, making these stocks especially prone to fluctuations in sentiment. This effect is stronger for small, young, unprofitable, non-dividend-paying, extreme growth, and distressed stocks. As Sockin and Xiong (2023) also discuss the importance of sentiment in cryptocurrency markets, in this subsection, we check whether our variance effects are related to sentiment.

Considering Vosoughi, Roy, and Aral (2018) and Duz Tan and Tas (2021), we use daily coin-level sentiment measures from Twitter. We supplement our analyses with Telegram sentiment measures.[43] We employ the numbers and percentages of buy opinions and examine the relationship between these sentiment and our realized variance measures in the cross section. As Table 9 shows, more positive sentiment is shared among investors for cryptocurrencies with higher variances, particularly with positive jump variances. This finding implies greater enthusiasm for cryptocurrencies with high positive jump variances and is consistent with the active participation of retail investors in the previous subsection. In addition, our cryptocurrency market results support the model of Pedersen (2022), in which speculative investors learn about market sentiment through social network platforms, further increasing prices.

C. Cryptocurrencies as Lotteries

In this subsection, we support that the variance effect is consistent with cumulative prospect theory based on investors' preferences for lottery-like returns (e.g., Barberis and Huang (2008)). The key insight of this theory is that investors may favor assets with ex ante return distributions with rare but extremely high returns and thus would be willing to pay higher prices for such assets, which results

[43]We collect daily investor sentiment data from intotheblock.com via cryptocompare.com, which provides the number of buy, sell, and neutral opinions. We appreciate that the referee informs us of the data source.

in low subsequent returns. Accordingly, investors with lottery preferences are attracted by and seek out cryptocurrencies with observable measures that can help them predict lottery-type returns in the future. We hypothesize that positive jump and jump-robust variances can predict future lottery returns because positive jumps share common features with lottery-type returns (i.e., unusually large payoffs with low probability) and because high variances increase the likelihood of realizing lottery-type returns as long as they are not associated with extremely negative jumps.

A widely accepted measure for lottery-like returns in the literature is skewness (e.g., Boyer et al. (2010), Barberis, Mukherjee, and Wang (2016)). Therefore, to support our explanation, we test whether our key variance measures (i.e., positive jump and jump-robust variances) can predict future skewness. If this condition holds, these variance measures can be negatively related to subsequent returns, as documented in this article. We perform an empirical test similar to that of Boyer et al. (2010). Specifically, we estimate the following regression model:

$$Skew_{i,w+1} = \psi_0 + \psi_1 LSkew_{i,w} + \psi_2 JV_{i,w}^{(+)} + \psi_3 JV_{i,w}^{(-)} + \psi_4 JRV_{i,w} + c'X_{i,w} + e_{i,w+1}, \tag{8}$$

where $Skew_{i,w}$ is the weekly realized skewness of cryptocurrency i in week w. $LSkew_{i,w}$ is the realized skewness estimated from the previous month of observations (i.e., observations from week $w-3$ to week w). $X_{i,w}$ is the vector of control variables, such as weekly kurtosis, lagged excess returns, natural logarithmic market capitalization, and fixed effects.

Table 10 shows that lagged skewness does not provide significant coefficients in a robust manner. This evidence is consistent with that of Boyer et al. (2010), who also show that lagged realized skewness is not a strong predictor of future skewness for stocks. However, we find that both positive jump and jump-robust variances significantly predict skewness in the subsequent week. Column 3 shows that both positive jump and jump-robust variances have significantly positive coefficients, which indicates that one can expect to observe greater skewness for cryptocurrencies with higher positive jump and jump-robust variances realized in the current period. In the remaining columns, we continue to find robust results. This finding has important implications in practice because investors can expect future skewness by using our decomposed realized variances, which can be estimated with available data.

D. Nondiversifiable Factors

Our variance measures are computed without a specific assumption of a factor model and thus include systematic and idiosyncratic components. In this subsection, we discuss whether our finding of the negative return prediction of variances is related to nondiversifiable components. This discussion is related to that of Ang, Hodrick, Xing, and Zhang (2009), who document that stocks with recent past high idiosyncratic volatility have low future average returns and that not easily diversifiable factors underlie their idiosyncratic volatility effects.

TABLE 10

Prediction of Weekly Skewness

Table 10 shows whether weekly skewness can be predicted by lagged weekly skewness or decomposed variances. To investigate this possibility, we use the following panel regression:

$$Skew_{i,w+1} = \psi_0 + \psi_1 LSkew_{i,w} + \psi_2 JV_{i,w}^{(+)} + \psi_3 JV_{i,w}^{(-)} + \psi_4 JRV_{i,w} + c' X_{i,w} + e_{i,w+1},$$

where $Skew_{i,w}$ is the realized weekly skewness of cryptocurrency i in week w and is estimated from the observations in week w. $LSkew_{i,w}$ is the realized skewness estimated from the previous month of observations (i.e., observations from week $w-3$ to week w). $JV_{i,w}^{(+)}$, $JV_{i,w}^{(-)}$, and $JRV_{i,w}$ are the positive jump, negative jump, and jump-robust variances, respectively. These decomposed variances are estimated from the previous month of observations (i.e., observations from week $w-3$ to week w). $X_{i,w}$ is the vector of control variables such as weekly kurtosis, lagged excess returns, natural logarithmic market capitalization, and fixed effects. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	1	2	3	4	5	6	7
Constant	−0.048***	−0.170***	−0.239***	−0.343***	−0.270***	−0.376***	−0.083***
t-stat.	−4.96	−13.47	−15.02	−2.99	−10.21	−3.07	−0.25
Skewness	0.224***				0.136***	0.132***	−0.039
t-stat.	11.18				5.25	4.96	−1.35
Positive jump variance		11.127***	9.043***	10.391***	4.322***	5.517***	2.842**
t-stat.		11.80	9.32	10.15	3.46	4.20	1.99
Negative jump variance		−0.966	−0.196	−1.585	3.887**	2.466	1.089
t-stat.		−0.67	−0.14	−1.03	2.42	1.44	0.61
Jump–robust variance			0.649***	0.647***	0.684***	0.692***	0.414***
t-stat.			10.50	9.75	10.01	9.30	5.61
Kurtosis					0.004*	0.004**	0.004
t-stat.					1.93	1.97	1.67
Lagged return				−0.196***		−0.213***	−0.116**
t-stat.				−4.19		−4.57	−2.42
Market capitalization				0.005		0.005	0.002
t-stat.				0.87		0.85	0.13
Fixed effects	No	No	No	No	No	No	Yes
Adj. R^2	0.014	0.024	0.031	0.032	0.034	0.035	0.069

In Section IV, for our cryptocurrency return prediction, we examine the excess returns and alphas of variance-sorted portfolios, accounting for the three factors of Liu et al. (2022). In Table 4, both the returns and alphas of High total and positive jump variance portfolios are significantly lower than those of Low portfolios. This implies that the negative relation between realized variances and subsequent returns cannot be fully explained by these existing systematic factors. Given this context, we further investigate whether idiosyncratic components mainly contribute to the return predictability of total and positive jump variances.

To this end, we compute the correlations among the 3-factor alphas of cryptocurrencies constituting each variance-sorted portfolio.[44] We find that High total and positive jump variance portfolios exhibit average correlations of −0.3% and 0.1%, respectively. Moreover, the correlations observed in High total and positive jump variance portfolios are significantly lower than those in Low and Mid portfolios.[45] The significantly low correlations of High total and positive jump variance cryptocurrencies suggest that the returns of cryptocurrencies in High portfolios tend to be more idiosyncratic than those in Low portfolios. Combined with the significant

[44]We report the results obtained using the 3-factor model alphas and confirm the consistency of our conclusions using market model alphas.

[45]The differentials are statistically significant at the 1% level. For total (positive jump) variance-sorted portfolios, the correlations of Low and Mid portfolios are 2% and 1% (2% and 0.4%), respectively.

alpha differentials reported in our sorting analyses, these findings reveal that idiosyncratic components play important roles in our main finding of the total and positive jump variance effects in cryptocurrency markets. These additional findings distinguish the dynamics of cryptocurrency markets from those of equity markets.

VI. Conclusion

The remarkable growth in cryptocurrency markets has been accompanied by unusually large price fluctuations, generating return distributions with exceptionally wide ranges and heavy tails. We study how realized variances associated with different parts of return distributions affect future cryptocurrency returns. Using high-frequency returns, we decompose total variances into jump-robust, positive jump, and negative jump variances.

Our cross-sectional analyses reveal that cryptocurrencies with high total variances tend to exhibit low excess returns in subsequent weeks. The weekly return spread between cryptocurrencies in the lowest and highest tercile portfolios is 3.7% (193% per annum). This negative return prediction is attributable to jump-robust and positive jump variances. Interestingly, this result is more pronounced for cryptocurrencies with smaller sizes, lower prices, less liquidity, and more retail trading activities and is affected by investor sentiment. Our results can be explained by the overpricing of such cryptocurrencies that results from the risk-taking behavior of retail investors seeking highly volatile assets with the potential for large gains. In addition, our findings support the impact of retail investors' active participation on cryptocurrency markets.

Our article contributes to the literature by adopting comprehensive intraday cryptocurrency data to precisely measure variances and identifying how decomposed partial variances can be used to distinguish their differential impact on future returns. We show that it is important to frequently capture the dynamic nature of cryptocurrency market volatility by using high-frequency data. Our study provides important implications for assessing risks in highly volatile asset markets.

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S002210902400022X.

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