Online Appendix for

“Variance Decomposition and Cryptocurrency Return Prediction”

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To keep the main text brief, we provide this online appendix to further support our empirical results and to expand on the details of the summarized points in the main text.

This online appendix includes multiple appendixes, which are located in the order of the main text. Online Appendix A supports our empirical application of jump variance estimators by checking their finite sample performance. Online Appendix B provides the summary statistics and jump detection results for all 100 sample cryptocurrencies and the full names. Online Appendix C elaborates upon the approaches for constructing samples and filtering intraday data. Online Appendix D compares the results of using the measures that we introduce in this paper with those of employing alternative measures. Online Appendix E supplements the contemporaneous sorting analyses with characteristics by regressing price increases and partial variances on characteristic variables. Online Appendix F defines the variables used in this paper. Each appendix contains the corresponding figure and table.

O. Appendix A. Monte Carlo simulation

As indicated in the main text, taking the total realized variance as the estimator of integrated variance (volatility) is a common approach in the literature. In this paper, we suggest further decomposing total realized variances into jump-robust and (signed) jump variances by applying jump detection tests that identify the arrivals of individual cryptocurrency jumps (with different signs). To support the empirical application of our jump variance estimators for our study, in this appendix, we examine our measures' finite sample performance by using Monte Carlo simulation. The purpose of this simulation study is to prove that the proposed estimators converge to the true jump variances that we aim to identify in the model. By definition, the performance of our jump variance estimators depends on the performance of the jump tests because the estimators use cryptocurrency returns in the time intervals during which jump tests detect jump arrivals. Therefore, we design this simulation to study the effectiveness of our jump detection tests and the estimation errors that can be made by using our jump variance estimator(s). In sum, the overall results show that our jump variances perform well in estimating return variations associated with jumps under general market conditions.

For return generation, we use the Euler-Maruyama scheme, which is widely used to simulate data from continuous-time models. To avoid starting value effects, we discard the first five hundred observations from the burn-in period every time we generate a time series. We generate intraday data over one trading day from the general model in Section II as

$$dc_{i,t} = \mu_{i,t}dt + \sigma_{i,t}dB_{i,t} + Y_{i,t}dJ_{i,t}, \tag{9}$$

where the stochastic volatility model is specified as the following square root processes:

$$d\sigma_{i,t}^2 = \kappa(\theta - \sigma_{i,t}^2)dt + \omega\sigma_{i,t}dW_{i,t}. \tag{10}$$

The terms $dB_{i,t}$ and $dW_{i,t}$ are standard Brownian motion processes. $Y_{i,t}$ and $dJ_{i,t}$ denote the jump size and jump arrival indicator for the i-th cryptocurrency price at time t, respectively, as indicated in Subsection II.A. The jump sizes are selected relative to the volatility level $\sigma_{i,t-}$ immediately before jump time t. Because we assume that volatility is stochastic, the jump sizes are also time varying and are set at $5\sigma_{i,t-}$, $3\sigma_{i,t-}$, $1\sigma_{i,t-}$, $0.5\sigma_{i,t-}$ and $0.25\sigma_{i,t-}$. We ignore the drift term in this simulation by setting $\mu_{i,t} = 0$ because the magnitudes of the drift terms, compared to those of the diffusion and jump terms, are negligible at intraday levels. We use the parameters for the volatility process from Li, Wells and Yu (2008): $\kappa = 0.0162$, $\theta = 0.8465$, and $\omega = 0.47$. We consider the full 24 trading hours per day and simulate 10,000 paths of the log price process $c_{i,t}$. We consider various sampling frequencies of 5 minutes, 15 minutes, 30 minutes, 1 hour, 2 hours, 3 hours, 6 hours, and 12 hours.

The results from this simulation study are reported in Table OA. Panel A shows that as we increase the sampling frequency, the likelihood of detecting true jump arrivals by our jump tests approaches 100%. As long as the goal of the application is to detect rare and extremely large jumps, our jump variance estimators are expected to perform well when we use high-frequency intraday data. Panel B confirms this expectation, indicating that the mean squared error (MSE) of the jump variance estimator significantly decreases as we increase the sampling frequency within a day. Because of this result, we use 15-minute cryptocurrency returns and confirm our results with different intraday return data.

Table OA
Finite sample performance of the jump variance estimator.

This table shows the results of simulation analyses to present the performance of the jump variance estimators used in our study. Considering that the performance of jump variance estimators depends on the performance of jump tests in detecting jump arrivals, we first examine how likely it is that our jump tests detect true jump arrivals and report the results in Panel A. Then, we investigate the estimator error that can be made by applying our jump variance estimators and report the results in Panel B. The number of simulations is set to 10,000. The jump sizes are set relative to the stochastic volatility level $\sigma_{i,t-}$ immediately before jump time t. We consider various intraday sampling frequencies. The estimation error is measured by the mean squared error (MSE).

Panel A. Likelihood of detecting true jump arrival

	Jump sizes relative to volatility level				
Sampling Frequency	$5 \times \sigma_{i,t-}$	$3 \times \sigma_{i,t-}$	$1 \times \sigma_{i,t-}$	$0.5 \times \sigma_{i,t-}$	$0.25 \times \sigma_{i,t-}$
12 hours	0.9656	0.9628	0.9566	0.9389	0.6846
6 hours	0.9878	0.9885	0.9867	0.9815	0.9440
3 hours	0.9961	0.9955	0.9943	0.9930	0.9862
2 hours	0.9969	0.9971	0.9955	0.9965	0.9911
1 hour	0.9989	0.9983	0.9980	0.9977	0.9972
30 minutes	0.9990	0.9993	0.9992	0.9990	0.9988
15 minutes	0.9996	1.0000	1.0000	0.9996	0.9994
5 minutes	1.0000	1.0000	1.0000	1.0000	1.0000

Panel B. Performance of the jump variance estimator measured by the MSE

	Jump sizes relative to volatility level				
Sampling Frequency	$5 \times \sigma_{i,t-}$	$3 \times \sigma_{i,t-}$	$1 \times \sigma_{i,t-}$	$0.5 \times \sigma_{i,t-}$	$0.25 \times \sigma_{i,t-}$
12 hours	0.000398	0.000405	0.000388	0.000377	0.000234
6 hours	0.000192	0.000191	0.000197	0.000185	0.000169
3 hours	0.000092	0.000094	0.000093	0.000093	0.000091
2 hours	0.000059	0.000061	0.000061	0.000061	0.000060
1 hour	0.000030	0.000030	0.000031	0.000031	0.000030
30 minutes	0.000015	0.000015	0.000015	0.000015	0.000015
15 minutes	0.000007	0.000007	0.000007	0.000008	0.000008
5 minutes	0.000003	0.000003	0.000002	0.000003	0.000003

O. Appendix B. Summary statistics for all sample cryptocurrencies

In this appendix, we provide the summary statistics for all 100 sample cryptocurrencies. Table OB1 shows the four central moments of 15-minute returns and the unconditional averages of market capitalization, daily trading volumes in billion U.S. dollars (USD), prices per coin in USD, and percentage bid-ask spreads (BASs). Table OB2 presents the number of filtered jumps, the jump frequencies relative to the available observations, and the distributions of jump sizes. In these tables, we provide the abbreviated and full names of the sample cryptocurrencies.

Table OB1
Summary statistics (all sample coins).
This table shows the summary statistics of the cryptocurrency data. Column Cryptocurrency lists the abbreviated and full names of the cryptocurrencies in the sample. Column # 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 each sample cryptocurrency. Columns Market cap., Volume, Price, and BAS show the unconditional averages of market capitalization, daily trading volumes in billion U.S. dollars (USD), prices per coin in USD, and percentage bid-ask spreads (BASs), respectively. Row Avg.100 shows the averages across the 100 sample cryptocurrencies.

Crypto currency	# obs	Start	15-min return Mean (%)	Stdev (%)	Skew	Kurt	Market cap ($B)	Volume ($B)	Price ($)	BAS (%)
1inch (1INCH)	68,474	Apr. 2021	-0.0043	0.6519	-0.214	12.320	0.52	0.13	1.75	0.19
aave (AAVE)	88,379	Dec. 2020	0.0000	0.6842	0.008	11.520	2.32	0.29	187.47	0.06
ach (Alchemy Pay)	66,572	Aug. 2021	-0.0059	0.9386	0.577	16.242	0.10	0.03	0.04	0.11
ada (Cardano)	78,975	Mar. 2021	-0.0014	0.5473	0.036	12.444	15.03	1.05	0.95	0.03
agld (Adventure Gold)	55,573	Sep. 2021	-0.0060	0.8321	0.314	13.859	0.07	0.03	0.90	0.34
algo (Algorand)	132,270	Aug. 2019	-0.0007	0.7436	0.002	23.743	2.54	0.20	0.60	0.09
amp (Amp)	58,889	Jun. 2021	-0.0115	0.7391	0.231	15.512	0.81	0.02	0.03	0.17
ankr (Ankr Network)	78,597	Mar. 2021	-0.0044	0.7041	0.121	14.203	0.30	0.06	0.06	0.08
arpa (ArpaCoin)	49,385	Oct. 2021	-0.0053	0.7322	0.283	15.443	0.05	0.03	0.06	0.28
asm (Assemble Protocol)	54,380	Oct. 2021	-0.0086	0.9920	0.439	21.955	0.03	0.01	0.04	0.56
atom (Cosmos)	119,789	Jan. 2020	0.0004	0.6997	0.022	11.126	2.97	0.40	13.87	0.08
avax (Avalanche)	60,069	Sep. 2021	-0.0023	0.5888	0.004	10.570	7.75	0.51	40.84	0.06
axs (Axie Infinity)	63,161	Aug. 2021	-0.0048	0.6271	0.250	13.614	1.93	0.30	39.41	0.12
badger (Badger DAO)	43,220	Oct. 2021	-0.0067	0.6605	0.283	11.017	0.12	0.02	8.30	0.32
bal (Balancer)	88,571	Oct. 2020	-0.0010	0.6357	-0.253	9.974	0.20	0.05	17.27	0.16
band (Band Protocol)	99,088	Aug. 2020	-0.0029	0.7843	0.017	11.578	0.14	0.05	5.57	0.12
bat (Basic Attention Token)	73,999	Apr. 2021	-0.0021	0.6091	-0.017	12.079	0.52	0.11	0.56	0.15
bch (Bitcoin Cash)	190,108	Dec. 2017	-0.0003	0.5673	0.053	15.242	8.00	1.92	416.19	0.04
bnt (Bancor)	77,769	Dec. 2020	-0.0013	0.5485	-0.173	12.038	0.25	0.03	2.38	0.21
bond (BarnBridge)	58,181	Jun. 2021	-0.0134	0.8376	0.658	19.046	0.06	0.02	11.82	0.27
btc (Bitcoin)	263,892	Oct. 2015	0.0023	0.3983	-0.188	19.076	270.99	17.82	15,517.00	0.01
btrst (Braintrust)	46,563	Sep. 2021	-0.0131	0.7803	0.235	31.846	0.23	0.00	2.98	0.31
chz (Chiliz)	69,606	Jun. 2021	-0.0023	0.6381	0.133	12.121	0.84	0.22	0.21	0.11
clv (Clover)	27,408	Jul. 2021	-0.0083	1.0971	0.723	18.628	0.07	0.02	0.60	0.55
comp (Compound Coin)	104,874	Jun. 2020	-0.0012	0.6993	-0.107	11.129	0.98	0.13	187.46	0.08
coti (COTI)	61,137	Aug. 2021	-0.0038	0.6872	-0.013	12.846	0.12	0.03	0.19	0.14
crv (Curve DAO Token)	78,420	Mar. 2021	-0.0003	0.7369	0.114	10.490	0.74	0.19	1.91	0.10
ctsi (Cartesi)	73,959	May. 2021	-0.0063	0.7874	0.282	14.966	0.13	0.03	0.37	0.14
dash (Digital Cash)	131,336	Sep. 2019	-0.0010	0.5870	-0.016	13.990	1.14	0.26	102.48	0.12
ddx (DerivaDAO)	37,028	Sep. 2021	-0.0225	1.0613	0.447	23.295	0.07	0.00	2.18	0.80
doge (Dogecoin)	71,844	Jun. 2021	-0.0041	0.5537	0.071	15.383	5.67	0.67	0.13	0.05
dot (Polkadot)	70,964	Jun. 2021	-0.0016	0.5304	-0.077	11.275	15.69	1.20	14.87	0.05
enj (Enjin Coin)	67,704	Apr. 2021	-0.0039	0.7402	-0.007	11.162	0.49	0.09	1.20	0.21
eos (Eos)	135,076	Apr. 2019	0.0014	0.5601	-0.095	14.771	3.33	1.43	3.09	0.14
etc (Ethereum Classic)	161,484	Aug. 2018	-0.0001	0.6249	0.069	16.790	2.10	0.80	19.88	0.09
eth (Ethereum)	229,770	Jul. 2016	0.0022	0.5168	-0.068	15.162	100.31	8.96	1,003.27	0.03
farm (Harvest Finance)	64,821	Jul. 2021	-0.0096	0.7227	0.632	21.175	0.06	0.01	81.15	0.17
fet (Fetch AI)	65,552	Jul. 2021	-0.0019	0.8350	0.406	12.278	0.16	0.03	0.33	0.14
fil (Filecoin)	88,894	Dec. 2020	-0.0010	0.6099	0.146	14.300	3.49	0.60	33.18	0.06
forth (Ampleforth Governance Token)	58,318	Apr. 2021	-0.0161	0.9642	0.719	20.215	0.08	0.02	9.60	0.32
grt (The Graph)	86,741	Dec. 2020	-0.0008	0.8287	0.076	12.083	1.70	0.17	0.52	0.09
gtc (Gitcoin)	55,492	Jun. 2020	-0.0042	0.8714	0.125	12.066	0.09	0.02	5.49	0.41
icp (Internet Computer)	74,552	May. 2021	-0.0053	0.7339	0.111	12.122	4.23	0.20	25.00	0.07
iotx (IoTeX)	64,761	Aug. 2021	-0.0056	0.7859	0.251	22.902	0.23	0.03	0.07	0.24

Table OB1
Summary statistics (all sample coins, continued).

Crypto currency	# obs	Start	Mean (%)	15-min return Stdev (%)	Skew	Kurt	Market cap ($B)	Volume ($B)	Price ($)	BAS (%)
jasmy (Jasmy)	56,425	Oct. 2021	-0.0067	0.9691	0.475	15.532	0.20	0.13	0.03	0.17
keep (Keep Token)	53,060	Jun. 2021	-0.0117	0.8218	0.242	19.801	0.20	0.02	0.37	0.26
knc (Kyber Network)	116,027	Feb. 2020	-0.0003	0.7623	0.103	13.128	0.17	0.03	1.46	0.12
link (ChainLink)	139,040	Jun. 2019	0.0010	0.6488	0.015	11.856	3.74	0.68	12.20	0.08
lpt (Livepeer)	65,917	Jun. 2021	-0.0078	0.7126	0.038	14.997	0.32	0.02	16.80	0.20
lrc (Loopring)	96,365	Sep. 2020	-0.0024	0.8149	0.276	14.184	0.40	0.08	0.56	0.09
ltc (Litecoin)	216,697	Oct. 2016	0.0012	0.5936	0.016	15.027	4.67	1.55	91.74	0.07
mana (Decentraland)	75,960	Apr. 2021	-0.0024	0.6967	0.192	13.467	0.93	0.19	1.23	0.08
mask (Mask Network)	57,353	Jul. 2021	-0.0038	0.9049	0.405	12.468	0.18	0.09	5.45	0.35
matic (Matic Network)	80,399	Mar. 2021	-0.0007	0.7557	-0.073	26.172	4.85	0.54	1.14	0.04
mir (Mirror Protocl)	64,287	May. 2021	-0.0144	0.8324	0.571	20.950	0.13	0.03	1.67	0.17
mkr (Maker)	106,360	Jun. 2020	-0.0007	0.6037	0.048	12.437	1.06	0.08	1,528.35	0.07
mln (Enzyme)	67,428	Jun. 2021	-0.0109	0.6735	0.468	25.940	0.05	0.00	52.34	0.17
nkn (NKN)	75,198	Apr. 2021	-0.0053	0.7894	0.089	13.601	0.08	0.01	0.23	0.14
nmr (Numeraire)	96,091	Aug. 2020	-0.0102	0.7907	0.631	19.595	0.09	0.01	28.69	0.16
nu (NuCypher)	73,003	Dec. 2020	-0.0060	0.9749	0.436	18.910	0.20	0.05	0.36	0.20
ogn (Origin Protocol)	73,659	Apr. 2021	-0.0058	0.7926	0.060	12.058	0.13	0.05	0.48	0.21
omg (OmiseGO)	94,855	May. 2020	0.0002	0.7718	0.182	11.982	0.56	0.19	4.30	0.14
orn (Orion Protocol)	59,227	Aug. 2021	-0.0085	0.6585	0.317	15.959	0.12	0.01	3.02	0.26
oxt (Orchid)	111,485	Dec. 2019	-0.0065	0.8280	0.489	17.496	0.12	0.03	0.26	0.15
perp (Perpetual Protocol)	54,088	Oct. 2021	-0.0094	0.7222	0.313	13.930	0.26	0.02	3.17	0.27
pla (PlayDapp Token)	63,188	Aug. 2021	-0.0080	0.7346	0.177	22.585	0.20	0.06	0.63	0.26
poly (Polymath)	62,822	Jul. 2021	-0.0073	0.7336	0.447	26.572	0.14	0.02	0.33	0.30
qnt (Quant)	70,421	Jun. 2021	-0.0013	0.7279	0.223	12.981	0.80	0.02	139.68	0.11
quick (QuickSwap)	64,169	Aug. 2021	-0.0113	0.7066	0.290	24.280	0.09	0.02	166.42	0.30
rad (Radicle)	40,183	Sep. 2021	-0.0197	0.9760	0.583	16.641	0.13	0.02	5.04	0.44
rai (Rai Reflex Index)	3,754	Aug. 2021	-0.0049	0.2697	-1.338	25.152	0.04	0.00	2.92	0.64
rari (Rarible)	33,261	Oct. 2021	-0.0195	1.1606	0.199	17.226	0.04	0.00	7.25	0.57
ren (Ren)	93,807	Oct. 2020	-0.0025	0.7998	-0.024	10.924	0.23	0.04	0.40	0.11
rep (Augur)	119,864	Apr. 2019	-0.0064	0.7078	0.188	20.966	0.20	0.02	16.54	0.29
req (Request Network)	59,605	Aug. 2021	-0.0113	0.8079	0.728	19.626	0.09	0.01	0.17	0.18
rgt (Rari Governance Token)	34,609	Sep. 2021	-0.0128	1.1810	0.611	21.721	0.11	0.00	16.17	0.57
rlc (iExec RLC)	69,368	May. 2021	-0.0042	0.7968	0.074	13.966	0.10	0.01	2.31	0.23
rly (Rally)	44,522	Jul. 2021	-0.0098	0.8733	1.706	50.526	0.22	0.01	0.25	0.32
shib (Shiba Inu)	59,288	Sep. 2021	0.0010	0.7420	0.628	32.800	8.44	1.10	0.00	0.12
skl (SKALE Network)	72,439	Mar. 2021	-0.0052	0.8148	0.022	11.673	0.31	0.04	0.19	0.18
snx (Synthetix Network Token)	87,599	Dec. 2020	-0.0003	0.7602	0.039	10.257	0.50	0.06	7.06	0.09
sol (Solana)	70,755	Jun. 2021	-0.0017	0.6460	0.084	12.256	15.20	1.08	68.14	0.04
storj (Storj)	69,457	Mar. 2021	-0.0053	0.7762	0.096	13.376	0.16	0.04	0.90	0.26
sushi (Sushi)	75,380	Mar. 2021	-0.0028	0.7009	-0.010	10.524	0.68	0.25	5.27	0.17
trb (Tellor Tributes)	73,914	May. 2021	-0.0030	0.7505	-0.023	13.102	0.05	0.03	27.77	0.16
tribe (Tribe)	40,963	Aug. 2021	-0.0079	0.4960	0.389	26.994	0.21	0.01	0.55	0.24
tru (TrueFi)	58,764	Aug. 2021	-0.0118	0.8603	0.376	15.483	0.07	0.01	0.19	0.26
uma (UMA)	95,853	Sep. 2020	-0.0089	0.7807	0.524	16.737	0.51	0.04	8.26	0.13
uni (Uniswap)	96,279	Sep. 2020	0.0001	0.6784	0.025	11.746	7.36	0.47	12.73	0.07
wbtc (Wrapped Bitcoin)	93,708	Oct. 2020	0.0008	0.3755	-0.059	13.031	4.82	0.15	34,096.31	0.10
wcfg (Wrapped Centrifuge)	23,013	Oct. 2021	-0.0385	1.2544	0.479	16.385			0.47	0.65
xlm (Stellar)	149,494	Mar. 2019	-0.0002	0.5553	-0.001	16.177	2.75	0.28	0.16	0.07
xrp (Ripple)	64,229	Feb. 2019	0.0005	0.5197	-0.109	20.925	15.87	1.79	0.28	0.06
xtz (Tezos)	129,846	Aug. 2019	0.0003	0.6640	0.023	11.500	1.80	0.14	2.60	0.15
xyo (XYO Network)	52,624	Sep. 2021	-0.0077	0.9156	0.566	16.526	0.08	0.00	0.02	0.25
yfii (DFI.money)	54,960	Sep. 2021	-0.0066	0.7134	-0.030	27.228	0.16	0.08	1,963.18	0.19
yfi (yearn.finance)	97,232	Sep. 2020	-0.0020	0.6745	0.014	11.974	0.66	0.24	21,157.01	0.07
zec (Zcash)	88,913	Dec. 2020	0.0000	0.6522	0.002	12.724	0.84	0.26	102.28	0.08
zen (Horizen)	59,632	Sep. 2021	-0.0049	0.5999	-0.160	12.542	0.23	0.02	30.28	0.15
zrx (0x)	160,121	Oct. 2018	-0.0010	0.6995	0.071	24.108	0.39	0.06	0.50	0.14
Avg.100	81,626		-0.0052	0.7370	0.187	16.443	5.44	0.49	773.57	0.19

Table OB2

Summary statistics of cryptocurrency jumps (all sample coins).

This table 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 100 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 six 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.

Crypto	Jump frequency				Positive jump size (%)			Negative jump size (%)		
currency	Total	Positive	Negative	% jp	25p	50p	75p	25p	50p	75p
1inch (1INCH)	213	85	128	0.311	0.0243	0.0342	0.0438	-0.0421	-0.0299	-0.0234
aave (AAVE)	235	98	137	0.266	0.0209	0.0319	0.0414	-0.0367	-0.0270	-0.0189
ach (Alchemy Pay)	407	242	165	0.611	0.0245	0.0344	0.0539	-0.0433	-0.0305	-0.0221
ada (Cardano)	291	131	160	0.368	0.0171	0.0228	0.0310	-0.0280	-0.0204	-0.0139
agld (Adventure Gold)	338	181	157	0.608	0.0243	0.0340	0.0494	-0.0441	-0.0307	-0.0232
algo (Algorand)	451	183	268	0.341	0.0232	0.0362	0.0535	-0.0431	-0.0295	-0.0211
amp (Amp)	335	193	142	0.569	0.0227	0.0300	0.0421	-0.0402	-0.0291	-0.0205
ankr (Ankr Network)	364	160	204	0.463	0.0229	0.0337	0.0439	-0.0365	-0.0261	-0.0204
arpa (ArpaCoin)	186	93	93	0.377	0.0311	0.0407	0.0576	-0.0439	-0.0364	-0.0277
asm (Assemble Protocol)	647	328	319	1.190	0.0283	0.0391	0.0588	-0.0514	-0.0349	-0.0245
atom (Cosmos)	311	128	183	0.260	0.0217	0.0285	0.0409	-0.0373	-0.0263	-0.0193
avax (Avalanche)	171	65	106	0.285	0.0173	0.0280	0.0366	-0.0318	-0.0227	-0.0178
axs (Axie Infinity)	276	132	144	0.437	0.0240	0.0324	0.0434	-0.0367	-0.0265	-0.0213
badger (Badger DAO)	150	87	63	0.347	0.0263	0.0346	0.0479	-0.0359	-0.0283	-0.0224
bal (Balancer)	224	73	151	0.253	0.0211	0.0267	0.0342	-0.0370	-0.0281	-0.0222
band (Band Protocol)	293	122	171	0.296	0.0294	0.0369	0.0476	-0.0451	-0.0330	-0.0245
bat (Basic Attention Token)	225	72	153	0.304	0.0209	0.0264	0.0363	-0.0316	-0.0235	-0.0159
bch (Bitcoin Cash)	1,025	517	508	0.539	0.0170	0.0229	0.0320	-0.0306	-0.0221	-0.0164
bnt (Bancor)	284	104	180	0.365	0.0166	0.0224	0.0306	-0.0286	-0.0212	-0.0147
bond (BarnBridge)	490	285	205	0.842	0.0280	0.0368	0.0560	-0.0443	-0.0328	-0.0247
btc (Bitcoin)	2180	1037	1143	0.826	0.0083	0.0129	0.0192	-0.0212	-0.0141	-0.0094
btrst (Braintrust)	960	483	477	2.062	0.0149	0.0226	0.0377	-0.0322	-0.0201	-0.0137
chz (Chiliz)	253	121	132	0.363	0.0223	0.0310	0.0411	-0.0362	-0.0274	-0.0197
clv (Clover)	120	81	39	0.438	0.0334	0.0458	0.0643	-0.0493	-0.0339	-0.0237
comp (Compound Coin)	273	95	178	0.260	0.0253	0.0362	0.0438	-0.0407	-0.0305	-0.0235
coti (COTI)	182	74	108	0.298	0.0245	0.0311	0.0416	-0.0430	-0.0326	-0.0210
crv (Curve DAO Token)	207	89	118	0.264	0.0236	0.0313	0.0428	-0.0392	-0.0297	-0.0222
ctsi (Cartesi)	293	167	126	0.396	0.0278	0.0350	0.0476	-0.0442	-0.0323	-0.0245
dash (Digital Cash)	462	205	257	0.352	0.0180	0.0264	0.0365	-0.0338	-0.0249	-0.0177
ddx (DerivaDAO)	544	288	256	1.469	0.0196	0.0338	0.0512	-0.0452	-0.0311	-0.0183
doge (Dogecoin)	425	193	232	0.592	0.0184	0.0241	0.0338	-0.0288	-0.0218	-0.0164
dot (Polkadot)	180	58	122	0.254	0.0178	0.0258	0.0311	-0.0326	-0.0212	-0.0141
enj (Enjin Coin)	171	57	114	0.253	0.0306	0.0389	0.0513	-0.0418	-0.0310	-0.0209
eos (Eos)	675	307	368	0.500	0.0175	0.0228	0.0312	-0.0314	-0.0231	-0.0162
etc (Ethereum Classic)	968	466	502	0.599	0.0175	0.0252	0.0342	-0.0341	-0.0244	-0.0165
eth (Ethereum)	1318	639	679	0.574	0.0125	0.0185	0.0262	-0.0263	-0.0197	-0.0138
farm (Harvest Finance)	595	334	261	0.918	0.0203	0.0296	0.0435	-0.0375	-0.0246	-0.0180
fet (Fetch AI)	262	159	103	0.400	0.0303	0.0381	0.0521	-0.0468	-0.0343	-0.0251
fil (Filecoin)	423	217	206	0.476	0.0219	0.0290	0.0374	-0.0365	-0.0268	-0.0184
forth (Ampleforth Governance Token)	491	302	189	0.842	0.0295	0.0416	0.0623	-0.0465	-0.0350	-0.0271
grt (The Graph)	227	93	134	0.262	0.0281	0.0334	0.0456	-0.0449	-0.0344	-0.0231
gtc (Gitcoin)	180	83	97	0.324	0.0333	0.0429	0.0590	-0.0520	-0.0406	-0.0317
icp (Internet Computer)	222	90	132	0.298	0.0242	0.0326	0.0440	-0.0363	-0.0287	-0.0201
iotx (IoTeX)	395	201	194	0.610	0.0210	0.0315	0.0456	-0.0423	-0.0295	-0.0202

Table OB2
Summary statistics of cryptocurrency jumps (all sample coins, continued).

Crypto currency	Jump frequency Total	Positive	Negative	% jp	Positive jump size (%) 25p	50p	75p	Negative jump size (%) 25p	50p	75p
jasmy (Jasmy)	228	136	92	0.404	0.0311	0.0445	0.0613	-0.0464	-0.0336	-0.0270
keep (Keep Token)	574	291	283	1.082	0.0238	0.0348	0.0499	-0.0454	-0.0335	-0.0222
knc (Kyber Network)	416	190	226	0.359	0.0228	0.0335	0.0444	-0.0384	-0.0266	-0.0188
link (ChainLink)	366	151	215	0.263	0.0191	0.0258	0.0351	-0.0366	-0.0259	-0.0176
lpt (Livepeer)	283	127	156	0.429	0.0274	0.0382	0.0487	-0.0419	-0.0314	-0.0226
lrc (Loopring)	365	178	187	0.379	0.0254	0.0383	0.0545	-0.0422	-0.0333	-0.0228
ltc (Litecoin)	1091	526	565	0.503	0.0171	0.0235	0.0325	-0.0327	-0.0235	-0.0176
mana (Decentraland)	235	92	143	0.309	0.0200	0.0302	0.0425	-0.0349	-0.0242	-0.0169
mask (Mask Network)	174	82	92	0.303	0.0360	0.0479	0.0631	-0.0531	-0.0432	-0.0334
matic (Matic Network)	215	88	127	0.267	0.0181	0.0268	0.0374	-0.0371	-0.0254	-0.0171
mir (Mirror Protocl)	483	292	191	0.751	0.0244	0.0342	0.0503	-0.0426	-0.0308	-0.0229
mkr (Maker)	387	180	207	0.364	0.0169	0.0247	0.0332	-0.0311	-0.0239	-0.0172
mln (Enzyme)	807	396	411	1.197	0.0176	0.0291	0.0417	-0.0361	-0.0233	-0.0158
nkn (NKN)	309	124	185	0.411	0.0306	0.0376	0.0495	-0.0451	-0.0340	-0.0254
nmr (Numeraire)	965	536	429	1.004	0.0204	0.0326	0.0472	-0.0366	-0.0256	-0.0174
nu (NuCypher)	588	320	268	0.805	0.0291	0.0436	0.0621	-0.0543	-0.0376	-0.0239
ogn (Origin Protocol)	243	101	142	0.330	0.0230	0.0365	0.0506	-0.0427	-0.0310	-0.0216
omg (OmiseGO)	314	154	160	0.331	0.0235	0.0322	0.0460	-0.0393	-0.0275	-0.0175
orn (Orion Protocol)	397	236	161	0.670	0.0229	0.0321	0.0432	-0.0392	-0.0317	-0.0227
oxt (Orchid)	843	493	350	0.756	0.0220	0.0331	0.0476	-0.0426	-0.0281	-0.0198
perp (Perpetual Protocol)	316	173	143	0.584	0.0224	0.0297	0.0399	-0.0359	-0.0263	-0.0190
pla (PlayDapp Token)	474	214	260	0.750	0.0170	0.0294	0.0446	-0.0424	-0.0267	-0.0177
poly (Polymath)	690	343	347	1.098	0.0212	0.0304	0.0465	-0.0418	-0.0301	-0.0202
qnt (Quant)	225	116	109	0.320	0.0239	0.0313	0.0428	-0.0382	-0.0284	-0.0209
quick (QuickSwap)	664	336	328	1.035	0.0218	0.0315	0.0439	-0.0389	-0.0253	-0.0189
rad (Radicle)	380	223	157	0.946	0.0278	0.0402	0.0520	-0.0506	-0.0325	-0.0237
rai (Rai Reflex Index)	28	17	11	0.746	0.0005	0.0007	0.0018	-0.0024	-0.0013	-0.0005
rari (Rarible)	271	145	126	0.815	0.0328	0.0455	0.0664	-0.0598	-0.0442	-0.0309
ren (Ren)	281	120	161	0.300	0.0270	0.0386	0.0530	-0.0486	-0.0348	-0.0267
rep (Augur)	1048	532	516	0.874	0.0224	0.0320	0.0441	-0.0399	-0.0283	-0.0204
req (Request Network)	509	312	197	0.854	0.0227	0.0333	0.0514	-0.0408	-0.0271	-0.0198
rgt (Rari Governance Token)	399	208	191	1.153	0.0357	0.0493	0.0684	-0.0561	-0.0397	-0.0300
rlc (iExec RLC)	289	142	147	0.417	0.0258	0.0331	0.0441	-0.0419	-0.0313	-0.0208
rly (Rally)	337	185	152	0.757	0.0243	0.0410	0.0627	-0.0453	-0.0310	-0.0224
shib (Shiba Inu)	354	189	165	0.597	0.0200	0.0305	0.0456	-0.0354	-0.0252	-0.0182
skl (SKALE Network)	206	82	124	0.284	0.0277	0.0382	0.0498	-0.0451	-0.0350	-0.0262
snx (Synthetix Network Token)	212	97	115	0.242	0.0244	0.0338	0.0463	-0.0414	-0.0324	-0.0241
sol (Solana)	205	102	103	0.290	0.0200	0.0268	0.0338	-0.0390	-0.0288	-0.0203
storj (Storj)	257	106	151	0.370	0.0225	0.0349	0.0486	-0.0410	-0.0282	-0.0199
sushi (Sushi)	164	67	97	0.218	0.0242	0.0339	0.0481	-0.0417	-0.0303	-0.0246
trb (Tellor Tributes)	241	102	139	0.326	0.0287	0.0404	0.0505	-0.0455	-0.0351	-0.0237
tribe (Tribe)	455	235	220	1.111	0.0140	0.0204	0.0320	-0.0286	-0.0206	-0.0132
tru (TrueFi)	360	202	158	0.613	0.0304	0.0425	0.0551	-0.0515	-0.0380	-0.0275
uma (UMA)	694	400	294	0.724	0.0236	0.0348	0.0490	-0.0398	-0.0281	-0.0201
uni (Uniswap)	244	99	145	0.253	0.0217	0.0316	0.0424	-0.0383	-0.0290	-0.0214
wbtc (Wrapped Bitcoin)	509	237	272	0.543	0.0101	0.0141	0.0192	-0.0199	-0.0147	-0.0101
wcfg (Wrapped Centrifuge)	249	144	105	1.082	0.0348	0.0478	0.0680	-0.0656	-0.0446	-0.0336
xlm (Stellar)	594	248	346	0.397	0.0156	0.0207	0.0276	-0.0286	-0.0191	-0.0144
xrp (Ripple)	380	203	177	0.592	0.0133	0.0186	0.0261	-0.0295	-0.0208	-0.0130
xtz (Tezos)	444	197	247	0.342	0.0205	0.0283	0.0399	-0.0333	-0.0260	-0.0180
xyo (XYO Network)	330	184	146	0.627	0.0273	0.0387	0.0523	-0.0416	-0.0307	-0.0219
yfii (DFI.money)	377	170	207	0.686	0.0220	0.0322	0.0492	-0.0448	-0.0312	-0.0211
yfi (yearn.finance)	253	95	158	0.260	0.0241	0.0331	0.0451	-0.0391	-0.0261	-0.0205
zec (Zcash)	261	92	169	0.294	0.0195	0.0270	0.0412	-0.0344	-0.0251	-0.0180
zen (Horizen)	221	85	136	0.371	0.0197	0.0264	0.0367	-0.0365	-0.0264	-0.0202
zrx (0x)	840	364	476	0.525	0.0188	0.0278	0.0431	-0.0392	-0.0255	-0.0183
Avg.100	420	206	214	0.550	0.0228	0.0320	0.0446	-0.0395	-0.0285	-0.0205

O. Appendix C. Sample construction and data filtering procedure

As noted in the introduction, cryptocurrency markets are relatively new and rapidly growing. We rely on intraday data that are long enough across multiple cryptocurrencies to meet our goal of analyzing return predictability. Because Kaiko provides reliable intraday data and because existing studies such as Makarov and Schoar (2020) employ intraday data from Kaiko, we collect data from Kaiko.

To construct an unbiased sample with the largest cross-section, we examine all cryptocurrencies that have available data longer than nine months and are traded on Coinbase, which is ranked as the top exchange in Kaiko's overall evaluation (e.g., quality and popularity).[1] The minimum sample period is chosen because our variance measures require estimation horizons. Kaiko's order book data provide intraday bid and ask quotes (and volumes) for 198 cryptocurrencies (as of 2022). We exclude stable coins (e.g., Tether) and cryptocurrencies with only a short sample period. Adopting simple coin selection criteria, our sample comprises 100 cryptocurrencies with various characteristics and includes a delisted coin.

To filter out 15-minute interval data, we follow two papers that study sovereign currency markets (i.e., Lee and Wang, 2019, 2020) because sovereign currency markets share many similar characteristics with cryptocurrency markets. For example, both cryptocurrency and sovereign currency markets trade continuously throughout the day. Specifically, we remove quotes that do not change for three consecutive time intervals because these quotes might be inactive. We perform this filtering process for bid and ask quotes and then construct mid

[1] An early version of this paper used the data of cryptocurrencies on Bitfinex and Bittrex and shows results consistent with those in this paper. To avoid concerns resulting from the different operating mechanisms of various exchanges, this paper employs data only from Coinbase because this exchange provides a wider cross-section than the other two exchanges.

quotes (i.e., mid$= 0.5 \times$ (bid+ask)).

Using the mid quotes, we compute 15-minute log returns (i.e., $r_{i,t(j)} = c_{i,t(j)} - c_{i,t(j-1)}$, where $c_{i,t(j)}$ is the logarithm of the mid quote of the i-th cryptocurrency at time $t(j)$). Following Andersen et al. (2001) and Lee (2012), who suggest potential problems resulting from bid-ask bounce effects, we filter out observations when large returns are canceled out by subsequent large returns with the opposite sign (i.e., the sum of two consecutive returns is close to zero, and the magnitude of each return is large). To mitigate the concern that small numbers of extreme observations drive the results, we remove extreme intraday returns if the absolute z-statistics are greater than seven. In addition, we exclude observations belonging to days that have fewer than 30 observations.

O. Appendix D. Comparison with alternative measures

Our positive jump variance measure is comparable to the relative signed jump (RSJ) variation measure of Bollerslev, Li and Zhao (2020), which is defined as the difference between the up and down semivariances divided by the total return variation. These authors find a clear negative relation between the RSJ measure and the average future returns in stock markets. Therefore, the return predictability of positive jump variances may appear consistent with that of the RSJ measure. However, using the RSJ measure, we have difficulty distinguishing whether the significant negative relation results from positive jump or negative jump variation (because the RSJ measure combines these two jump variations). Using our separated positive and negative jump variance measures, we can make the distinction, which can provide the additional benefit of identifying what drives the effects.

Instead of considering the relative differences in semivariances, one can still consider signed jump variations based on signed semivariances by subtracting half of the bipower variation. In this appendix, we confirm the role of positive jump variances in predicting cryptocurrency returns using this alternative measure and compare our findings. To this end, in equation (6) of the main text, we replace positive and negative jump variances with positive and negative semivariances minus half of the bipower variation.

We report the results in Table OD. As column 1 shows, the alternative positive jump variances also provide significantly negative coefficients with the control of jump-robust and alternative negative jump variances. In column 2, the return predictability of the alternative positive jump variance measures is robust to controlling for lagged returns and market capitalization. To compare our positive jump variance measure with the alternative measures, we perform a horse race regression in columns 3 and 4. Interestingly, our positive jump variances have significantly negative coefficients, while the alternative measures lose significance. This finding can occur because our measures are estimated with only positive jumps and capture large price changes more effectively than do the alternative measures.

Table OD

Comparison of positive jump variances with alternative jump variances.

This table shows the return predictability with alternative jump variance measures, which is compared with that with positive jump variances. We employ the following FMB regression:

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

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). The alternative positive (negative) jump variance is defined as the positive (negative) semivariance minus half of the bipower variation (Bollerslev, Li and Zhao, 2020). We first use the alternative jump variances in the regressions and then employ our jump variance measures as defined in Section II. $X_{i,w}$ is the vector of control variables, such as lagged excess returns and natural logarithmic market capitalization. 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.

	1	2	3	4
Constant	0.013	-0.045*	0.009	-0.039
t-stat	1.60	-1.77	1.07	-1.57
Positive variance - 0.5BV	-1.271**	-1.526**	0.690	0.660
t-stat	-4.15	-4.15	0.95	0.92
Negative variance - 0.5BV	-0.322	0.118	0.502	1.402**
t-stat	-0.74	0.26	0.82	2.28
Jump-robust variance	0.131	0.209*	-0.372*	-0.463**
t-stat	1.15	1.71	-1.85	-2.10
Positive jump variance			-1.741***	-1.744***
t-stat			-2.83	-2.98
Negative jump variance			0.612	0.002
t-stat			0.87	0.00
Lagged return		0.018		0.010
t-stat		1.04		0.60
Market capitalization		0.002***		0.002**
t-stat		2.69		2.32
Adj. R^2	0.197	0.262	0.289	0.337

O. Appendix E. Relationship between characteristics and prices

Cryptocurrencies with higher total and positive jump variances have lower returns in the subsequent week. The characteristics that drive this result can be associated with contemporaneous price increases. To investigate this possibility, we contemporaneously regress excess returns or our variance measures on characteristic variables. To be consistent with Section V, we use (log) market capitalization, (log) daily trading volumes, (log) futures volumes, bid-ask spreads (BASs), numbers of buy opinions on Twitter, and retail trading proportions (RTPs). These characteristic variables are estimated with the previous month of observations at the end of every week.

As Table OE shows, the prices of cryptocurrencies with low market capitalization and trading volumes tend to increase before they decrease in subsequent weeks. Because positive jumps capture large price increases, regressions that use positive jump variances as dependent variables provide results similar to those using excess returns. In addition, total and positive jump variances provide similar relationships. Interestingly, total and positive jump variances are positively related to futures volumes, which confirms that such cryptocurrencies do not relatively suffer from short-selling constraints.

Table OE
Contemporaneous relationship between characteristics and price increases.

This table shows the results of regressing excess returns, total variances, or positive jump variances on contemporaneous market capitalization, daily trading volumes, futures volumes, bid-ask spreads (BASs), numbers of buy opinions on Twitter, and retail trading proportions (RTPs). Characteristic variables are estimated with the previous month of observations at the end of every week. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Excess returns		Total variances		Pos. jump variances	
	1	2	3	4	5	6
Constant	-0.143***	0.092	-0.092***	-0.795***	0.003	-0.014**
t-stat	-5.51	1.20	-3.59	-11.23	1.11	-2.48
Log market capitalization	-0.011***	-0.037***	-0.048***	-0.035***	-0.002***	-0.003***
t-stat	-6.37	-10.79	-20.00	-9.25	-14.19	-8.89
Log trading volumes	0.016***	0.021***	0.049***	0.076***	0.002***	0.003***
t-stat	9.09	6.85	19.38	17.83	13.14	12.90
Log futures volumes	-0.001	0.009***	0.007***	0.001***	0.0005***	0.0003*
t-stat	-1.15	5.03	11.79	0.66	9.99	1.92
BAS	-8.969***	-9.201***	17.907***	22.421***	-0.231**	-0.254***
t-stat	-6.17	-5.18	15.15	21.15	-2.40	-2.88
Log Twitter buy	0.005***	0.000	-0.007***	-0.001	0.000	0.001***
t-stat	2.87	0.17	-4.30	-0.59	0.01	4.59
RTP	0.006	0.016*	0.004	-0.010	0.000	0.000
t-stat	1.00	1.86	0.44	-1.00	0.42	0.32
Year/coin fixed effects	No	Yes	No	Yes	No	Yes
Adj. R^2	0.082	0.191	0.289	0.592	0.129	0.347

O. Appendix F. Variable definition

In this appendix, we provide the definitions of the variables considered in our analyses.

Given the notation established in Section II, we follow Amaya et al. (2015) for the definitions of realized moments that can be estimated with intraday return data. We obtain the realized variance as equation (5) in the main text, which defines the total variance. The realized volatility is computed as the square root of the realized variance as follows:

$$Vol_{i,w} = \sqrt{Var_{i,w}}. \tag{11}$$

We also consider ex post realized higher moments. The realized skewness is again based on cubed intraday returns standardized by the realized variance as follows:

$$Skew_{i,w} = \frac{\sqrt{N} \sum_{t(j) \in W_w} r_{i,t(j)}^3}{Var_{i,w}^{3/2}}, \tag{12}$$

where N is the total number of observations over the estimation window for week w. When this realized skewness measure is negative (positive), we can interpret the asset return distribution as having a left (right) tail that is fatter than the right (left) tail. Similarly, we consider the realized kurtosis defined as follows:

$$Kurt_{i,w} = \frac{N \sum_{t(j) \in W_w} r_{i,t(j)}^4}{Var_{i,w}^2}. \tag{13}$$

This measure is expected to capture the extremes of the return distributions.

For individual cryptocurrencies, using the notation in Sections II and III, we compute (percentage) BASs defined as follows:

$$BAS_{i,w} = \frac{1}{N} \sum_{t(j) \in W_w} \frac{bid_{i,t(j)} - ask_{i,t(j)}}{mid_{i,t(j)}}, \tag{14}$$

where $bid_{i,t(j)}$ ($ask_{i,t(j)}$) represents the bid (ask) quote of cryptocurrency i at time $t(j)$. $mid_{i,t(j)}$ is the mid quote (i.e., $0.5 \times (bid_{i,t(j)} + ask_{i,t(j)})$) and N is the total number of observations over the estimation window for week w.

To consider market conditions for robustness checks, we employ the overall volatility and illiquidity measures in cryptocurrency markets. We compute the cryptocurrency market volatility ($CVol$) by following the approach of calculating the global foreign exchange volatility of Menkhoff et al. (2012). Specifically, the cryptocurrency market volatility in week w is defined as

$$CVol_w = \frac{1}{N} \sum_{t(j) \in W_w} \sum_{i}^{\kappa_j} \frac{|r_{i,t(j)}|}{\kappa_j}, \tag{15}$$

where κ_j is the number of available cryptocurrencies at time $t(j)$. For the illiquidity measure, we modify the approach of Amihud (2002) because we use intraday data for weekly analyses, while the author uses daily data for monthly analyses. We first estimate the weekly illiquidity for individual cryptocurrencies as follows:

$$ILLIQ_{i,w} = \frac{1}{N} \sum_{t(j) \in W_w} \frac{|r_{i,t(j)}|}{V_{i,t(j)}}, \tag{16}$$

where $V_{i,t(j)}$ is the dollar volume of cryptocurrency i from time $t(j-1)$ to $t(j)$. Then, we take the average of individual illiquidity measures across available cryptocurrencies.

To examine retail investors' transactions, we use the retail trading proportion (RTP) of Han and Kumar (2013). Using 5-minute trading volumes, we define the threshold of dollar transaction volumes for retail trading activities. Specifically, we use the 90th percentile of all cryptocurrencies' 5-minute trading volumes, which is 22 million dollars. If transaction volumes are lower than the bar, the transaction is classified as retail trading. Our threshold allows approximately 90% of total trading volume to be retail trading volume because 90-95% of Coinbase revenues originate from retail investors. We employ the previous month of trading volume data to compute weekly RTP measures.

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