



## Seasonality in the Cross-Section of Cryptocurrency Returns

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### ABSTRACT

This study presents the first attempt to examine the cross-sectional seasonality anomaly in cryptocurrency markets. To this end, we apply sorts and cross-sectional regressions to investigate daily returns on 151 cryptocurrencies for the years 2016 to 2019. We find a significant seasonal pattern: average past same-weekday returns positively predict future performance in the cross-section. Cryptocurrencies with high same-day returns in the past outperform cryptocurrencies with a low same-day return. This effect is not subsumed by other established return predictors such as momentum, size, beta, idiosyncratic risk, or liquidity.

### 1. Introduction

The cross-sectional seasonality effect is one of the most powerful and pervasive asset pricing anomalies. First discovered by Heston and Sadka (2008), it implies that assets with the highest (lowest) average same-calendar month return tend to overperform (underperform) in the future. Importantly, the cross-sectional seasonality effect holds not only for monthly intervals but also for higher frequency data, such as daily returns.<sup>1</sup> In other words, the average same-weekday return in the past is positively related to future performance in the cross-section. Put simply, if an investor plans to invest on Monday, she should check which assets delivered the highest returns on Mondays in the past.

Though initially documented in the United States, this anomaly has subsequently been demonstrated in international equities, stock market indices, commodities, government bonds, and anomaly-based factor strategies for periods extending

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<sup>1</sup> See, Heston, Korajczyk, and Sadka (2010), Keloharju, Linnainmaa, and Nyberg (2016, 2019), Bogousslavsky (2016), Hirshleifer, Jiang, and Meng (2020).

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as long as two centuries.<sup>2</sup> Nonetheless, despite sufficient availability of daily data, one new asset class has so far escaped the attention of the academic community: cryptocurrencies. The major target of this paper is to fill this gap.

Cryptocurrencies constitute a fresh and important asset class. Although they date back only to 2009, their total market capitalization exceeds USD 239 billion.<sup>3</sup> Investor involvement and capital flows to cryptocurrency markets have spurred interest in predicting cryptocurrency returns. Several studies have attempted to reproduce cross-sectional known anomalies from the equity universe, such as momentum (Tzouvanas, Kizys, and Tsend-Ayush 2019; Grobys and Sapkota 2019), moving averages (Grobys, Ahmed, and Sapkota 2019), size effect (Liu, Liang, and Cui 2020; Shen, Urquhart, and Wang 2019), liquidity (Deng et al. 2019), or beta and liquidity (Sovbetov 2018). These patterns cast significant doubt on the informational efficiency of cryptocurrency markets. A few papers have even taken attempts to formalize asset pricing models for the cryptocurrency markets (Liu and Tsyvinski 2018; Liu, Liang, and Cui 2020; Liu, Trsyvinski and Wu 2019; Shen, Urquhart and Wang 2019). Nevertheless, the full multidimensional structure of cryptocurrency returns is yet to be understood. The examination of the cross-sectional seasonality in this asset class will help to shed some light on these issues.

Why does the cross-sectional seasonality effect exist in asset prices? Current literature leans toward behavioural mispricing to explain this phenomenon. As pointed out by Keloharju, Linnainmaa, and Nyberg (2019), systematic changes in investors' demand for risky assets could disassociate security prices from their fundamentals. For instance, if investors favor small firms over big firms at the beginning of the week, excess demand could predictably drive valuations higher every Monday. This seasonal predictability can emanate from different sources, such as sentiment (Hirshleifer, Jiang, and Meng 2020), recurring inflows and outflows (Heston, Korajczyk, and Sadka 2010), or trading patterns within a population (Bogousslasky 2016). As investor psychology and behavioural biases are similar everywhere, regardless of the asset class, they could lead to the development of analogous return patterns in cryptocurrency markets. Therefore, our study aims to be the first to test the daily seasonality effect in the cross-section of cryptocurrency returns.

To achieve this, we investigate 151 cryptocurrencies for the period from August 2016 to December 2019. We apply portfolio sorts and cross-sectional regressions to determine whether the average past same-weekday return predicts future cryptocurrency returns in the cross-section.

Our findings provide evidence in support of the existence of the cross-sectional seasonality effect in cryptocurrency markets: average same-weekday returns positively predict future performance in the cross-section. An equal-weighted (value-weighted) long-short quintile portfolio buying (selling) cryptocurrencies with the highest (lowest) average same-weekday returns displays a statistically and economically significant mean daily return of 0.31% (0.43%). This effect is not subsumed by other popular return-predictive signals.

Our results contribute to three strains of literature. First, we add to studies of the cross-sectional seasonality anomaly. To our knowledge, we are the first to extend the cross-sectional seasonality anomaly to cryptocurrencies. Second, we extend research on different seasonality effects in cryptocurrencies (Baur et al. 2019; Kaiser 2019; Aharon and Qadan 2019; Caporale and Plastun 2019). Whereas individual daily seasonalities may be insufficiently strong to appear in statistical tests, the cross-sectional seasonality aggregates them all in a single signal. Hence, it shows an alternative perspective to the evidence on seasonal patterns. Third, we add to the streams of literature attempting to replicate equity anomalies in the cryptocurrency universe and to examine the multidimensional nature of their returns (Grobys, Ahmed, and Sapkota 2019; Tzouvanas, Kizys, and Tsend-Ayush 2019; Grobys and Sapkota 2019; Liu, Liang, and Cui 2019; Poyser 2019; Shen, Urquhart, and Wang 2019; Sovbetov 2018). We extend the currently known signal universe with a new return predictive variable for cryptocurrencies. In consequence, not only do our findings provide new insights into asset pricing in cryptocurrency markets from a theoretical perspective, they may also potentially be utilized in practical investment strategies and may help investors to shape their cryptocurrency portfolios.

The remainder of the article proceeds as follows. Section 2 presents the data and variables used in this study. Section 3 demonstrates our research methods. Section 4 reports and discusses the results. Finally, Section 5 concludes the study.

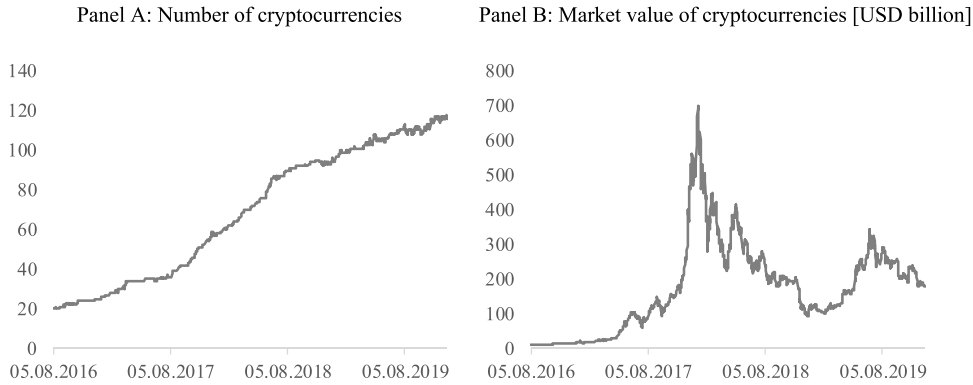
## 2. Data and Variables

Following Grobys and Sapkota (2019), we base our analysis on data retrieved from <https://coinmarketcap.com>. We obtain daily closing prices for a total of 151 cryptocurrencies quoted in U.S. dollars. Each series qualifies as a cryptocurrency and is traded on at least one public exchange.<sup>4</sup> As the study is concerned with the seasonality effect, reasonably liquid and tradeable cryptocurrencies are required. Hence, we select the largest cryptocurrencies by market capitalization, as of 16 December 2019. Consequently, we begin with Bitcoin and proceed to obtain data for the largest 150 cryptocurrencies that follow. For cross-sectional tests, we require at least 20 cryptocurrencies at any given point in time and exclude observations for which market value and turnover are non-positive, and the price does not exceed 0.005 USD. The study period for daily returns runs from 5 August 2016 to 16 December 2019 and is dictated

<sup>2</sup> See, for international equities: Heston and Sadka (2010), Li, Zhang, and Zheng (2018); for equity indices and commodities: Keloharju, Linnainmaa, and Nyberg (2016); for government bonds: Zaremba (2019); for factor strategies: Keloharju, Linnainmaa, and Nyberg (2016), and Zaremba (2017); for long-run historical datasets: Baltussen, Swinkels, and van Vliet (2019).

<sup>3</sup> Data for January 2020 obtained from [www.coinmarketcap.com](http://www.coinmarketcap.com).

<sup>4</sup> See <https://coinmarketcap.com> for full listing criteria. The key requirement for listing is that each cryptocurrency is based upon 1) consensus algorithms, distributed ledgers and peer-to-peer technology, 2) is publicly traded on at least one exchange, 3) has a functional website and 4) has a public representative.



**Fig. 1. Research Sample.** This figure presents data describing the research sample over the study period. Panel A displays the number of cryptocurrencies, and Panel B their total market value expressed in billions of USD. Panel A: Number of cryptocurrencies. Panel B: Market value of cryptocurrencies [USD billion]

by data availability: the 5th of August, 2016, is the first date when the criterion of a minimum 20 cryptocurrencies is met. Notably, given the novelty of cryptocurrencies, the precise number increases gradually along with market development.

The number and values of assets in our sample are reported in Figure 1. Our sample size is comparable to that of Grobys and Sapkota (2019) who consider 143 cryptocurrencies and also obtain data from <https://coinmarketcap.com>. Table A1 in the Online Appendix provides a detailed list and descriptive statistics for all cryptocurrencies comprising the sample.

Our basic return-predictive variable is depicted as *SEAS*, representing the weekly cross-sectional seasonality effect. Following Keloharju, Linnainmaa, and Nyberg (2016), we calculate it as the average daily return over the previous 20 weeks:

$$SEAS_{i,t} = \frac{1}{20}(R_{i,t-7} + R_{i,t-14} + \dots + R_{i,t-140}) \quad (1)$$

where  $R_{i,t-n}$  is the log-return on a cryptocurrency  $i$  on day  $t-n$ . If cross-sectional patterns from different asset markets hold in cryptocurrencies, we would expect *SEAS* to be positively correlated with future returns in the cross-section. Besides *SEAS*, we also consider several additional control variables that are demonstrated to predict future performance in asset markets and cryptocurrencies (see, e.g., Tzouvanas, Kizys, and Tsend-Ayush 2019; Grobys and Sapkota 2019; Liu, Liang, and Cui 2019; Shen, Urquhart, and Wang 2019; Sovbetov 2018). By doing so, we aim to assure that the cross-sectional seasonality effect is a truly independent phenomenon in the cryptocurrency market and not a manifestation of another anomaly. *MV* is the natural logarithm of the market value of a cryptocurrency on day  $t-1$ . Momentum, *MOM*, is measured as the mean daily return on days  $t-140$  to  $t-2$ , i.e., over the last 20 weeks. Note that the measurement window for *MOM* matches our *SEAS* estimation window. This ensures that the *SEAS* effect is driven by the same-weekday returns, and not by other-weekday returns over the measurement periods. The market beta (*BETA*) and idiosyncratic volatility (*IVOL*) are derived from a one-factor regression of daily cryptocurrency excess returns on the value-weighted cryptocurrency market portfolio excess return, estimated over the trailing 20 weeks. The turnover, *TURN*, is the ratio of daily dollar trading volume to capitalization derived from a rolling 20-week period. Finally, the Amihud (2002) illiquidity measure, *ILLIQ*, is computed following Wei (2018) as the ratio of the absolute daily price change to trading volume averaged over weeks  $t-10$  to  $t-1$ .

### 3. Methods

Following the propositions of Fama (2015) that both time-series and cross-sectional tests provide unique insights and complement each other, we apply the two most common tests in asset pricing literature: portfolio sorts and cross-sectional regressions in the style of Fama and MacBeth (1973).

#### 3.1. Time-Series Tests

Starting with portfolio time-series tests, for each day of the study period, we rank all cryptocurrencies on *SEAS*. Subsequently, we sort them into quintiles and form equal-weighted and value-weighted quintile portfolios. Next, we also construct long-short spread portfolios, which buy (sell) the quintiles of cryptocurrencies with the highest (lowest) *SEAS* value. The mean return on this long-short portfolio serves as a simple and intuitive check of the cross-sectional pattern in cryptocurrency returns.

We evaluate portfolio returns with three different factor models:

$$R_{p,t} = \alpha_{F1} + \beta_{MKT}MKT_t + \varepsilon_{F1,t}, \quad (2)$$

$$R_{p,t} = \alpha_{F3} + \beta_{MKT}MKT_t + \beta_{SMB}SMB_t + \beta_{UMD}UMD_t + \varepsilon_{F3,t}, \quad (3)$$

$$R_{p,t} = \alpha_{F7} + \beta_{MKT}MKT_t + \beta_{SMB}SMB_t + \beta_{UMD}UMD_t + \beta_{BET}BET_t + \beta_{ILLIQ}ILLIQ_t + \beta_{TURN}TURN_t + \beta_{IVOL}IVOL_t + \varepsilon_{F7,t} \quad (4)$$

where  $R_{p,t}$  is the daily excess return on an examined portfolio  $p$  on day  $t$ ,  $\varepsilon_t$  is the error term, and  $\alpha_{F1}$ ,  $\alpha_{F3}$ , and  $\alpha_{F7}$  represent abnormal returns (“alphas”) for one-, three-, and seven-factor models.  $\beta_{MKT}$ ,  $\beta_{SMB}$ ,  $\beta_{UMD}$ ,  $\beta_{BET}$ ,  $\beta_{ILLIQ}$ ,  $\beta_{TURN}$ , and  $\beta_{IVOL}$  are measures of exposure to the market (*MKT*), small-minus-big (*SMB*), up-minus-down (*UMD*), beta factor (*BET*), illiquidity (*ILLIQ*), turnover (*TURN*), and idiosyncratic risk (*IVOL*) factors, respectively.

Equation (2) represents the one-factor model, accounting only for the market risk factor, where  $MKT_t$  is the excess return on the value-weighted portfolio of all the cryptocurrencies in the sample.

The three-factor model (3) also includes the small-minus-big and up-minus-down factors, where  $SMB_t$  and  $UMD_t$  represent daily returns on long-short value-weighted quintile portfolios. *SMB* buys (sells) cryptocurrencies of the smallest (biggest) total market value. *UMD* goes long (short) the cryptocurrencies with the highest (lowest) *MOM*. This model is similar to Carhart’s (1997) four-factor model from the equity universe<sup>5</sup> and also corresponds with the three-factor models proposed by Liu, Liang, and Cui (2019) and Shen, Urquhart, and Wang (2019)<sup>6</sup>

Finally, equation (4) is the broadest and accounts for all the variables outlined in Section 2. Specifically, this seven-factor model also incorporates the  $BET_t$ ,  $ILLIQ_t$ ,  $TURN_t$ , and  $IVOL_t$  factor returns calculated analogously to *UMD*, i.e., as daily returns on the long-short value-weighted quintile portfolios going long (short) the cryptocurrencies with the highest (lowest) *BETA*, *ILLIQ*, *TURN*, and *IVOL*.

### 3.2. Cross-Sectional Tests

In addition to the time-series tests, we examine the seasonality effect with cross-sectional regressions in the spirit of Fama and MacBeth (1973). In this framework, we want to ascertain the predictive power of the *SEAS* variable for the cross-section of returns. To this end, for each day of the study period, we run the following regression:

$$R_i = \gamma_0 + \gamma_{SAME} SAME_i + \sum_{j=1}^n \gamma_K K_i^j + \varepsilon_i \tag{5}$$

where  $R_i$  denotes the excess return on cryptocurrency  $i$ ; *SAME* denotes the cross-sectional seasonality (defined as in Section 2);  $K$  is the set of control variables as outlined in Section 2;  $\gamma_0$ ,  $\gamma_{SAME}$ , and  $\gamma_K$  are estimated daily regression coefficients; and  $\varepsilon_i$  represents the random error term. Our default method applies cross-sectional regressions to raw excess returns. Nevertheless, for robustness, we follow Avramov, Kaplanski, and Subrahmanyam (2019) and replace raw excess returns with risk-adjusted returns in the spirit of Brennan, Chordia, and Subrahmanyam (1998). Specifically, risk-adjusted returns are calculated using a rolling 140-day regression following equation (3), similar to the benchmark-adjusted returns in Jacobs (2015).

## 4. Results

### 4.1. Portfolio Sorts

Table 1

Table 2 presents returns on portfolios from one-way sorts on *SEAS*. A quick overview reveals that the high-*SEAS* portfolios outperform low-*SEAS* portfolios, and differences are statistically significant. The equal-weighted (value-weighted) spread portfolio formed on *SEAS* delivers a mean daily return of 0.31% (0.43%) with a corresponding  $t$ -value of 2.05 (2.06). Notably, the returns remain strong and significant even after applying factor models (2) to (4). The seasonality long-short portfolios continue to produce significant risk-adjusted profits in all specifications. For example, the three-factor model alpha ( $\alpha_{F3}$ ) on the equal-weighted (value-weighted) long-short portfolio amounts to 0.30% (0.45%) with a  $t$ -value of 2.01 (2.26). The alphas remain significant even when we apply all the seven factors incorporated in the model (4). Furthermore, the spread portfolios do not exhibit strong and robust exposure to the other risk factors considered, such as *MKT*, *SMB*, and *UMD*. In summary, Table 2 provides evidence supporting the cross-sectional effect in the cryptocurrency market. Cryptocurrencies with high average same-day-of-the-week returns markedly outperform cryptocurrencies with low average same-day-of-the-week returns.

### 4.2. Cross-Sectional Regressions

Table 3 displays average slope coefficients from the regressions of raw excess returns (Panel A) and risk-adjusted returns (Panel B) on *SEAS* and other control variables. The results corroborate the strong predictive abilities of the average past same-weekday return

<sup>5</sup> Note that the model (3) and the models of Liu, Liang, and Cui (2019) and Shen, Urquhart, and Wang (2019) do not incorporate the high-minus-low (HML) factors because there is no single broadly acknowledged value factor or proxy for value in the cryptocurrency market.

<sup>6</sup> Our model departs from Liu, Liang, and Cui (2019) and Shen, Urquhart, and Wang (2019) in two minor ways. First, instead of two-way sorts, we use simple one-way sorts to form factors. This is aimed at assuring that the factor portfolios are built identically as the evaluated portfolios so that any abnormal return is driven by the underlying return predictive variable rather than the portfolio construction technique. Second, our *UMD* factor is based on a 20-week sorting period—shorter than, e.g., Liu, Liang, and Cui (2019) who use 52 weeks. This is aimed at aligning the *MOM* sorting period with the *SAME* variable. Nonetheless, this choice does not qualitatively affect our findings, and our results also hold for different formation periods such as 5, 10, 25, or 52 weeks.

**Table 1**

**Statistical Properties of the Research Sample.** The table reports the basic statistical properties of the variables used in the study. *R* denotes the daily log-return. The other variables are abbreviated as follows: *SEAS* is the average past same-weekday returns; *BETA* is the cryptocurrency market beta; *MV* is the market value (expressed in USD million); *MOM* (momentum) is the mean daily return through the past 20 weeks. *TURN* is the turnover ratio; *IVOL* is the idiosyncratic volatility; and *ILLIQ* is the Amihud illiquidity measure. *Panel A* presents descriptive statistics. *Panel B* displays the time-series average of the daily pairwise correlation. The values above (below) diagonal are Pearson product-moment (Spearman rank-based) coefficients. The asterisks \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The table is based on 84514 cryptocurrency-day observation, and the average number of cryptocurrencies in the sample is 68.

	R	SEAS	BETA	MV	MOM	TURN	IVOL	ILLIQ
<i>Panel A: Descriptive Statistics</i>								
Average	-0.001	0.000	0.945	2510.326	-0.044	8.370	0.076	1.822
Std. deviation	0.095	0.023	0.409	14892.917	1.112	15.706	0.048	16.164
Skewness	0.469	0.287	-0.477	10.188	0.932	4.608	1.479	0.033
Kurtosis	26.097	4.070	2.641	122.436	1.708	27.203	3.261	1.902
Minimum	-1.596	-0.159	-2.023	0.159	-7.989	0.007	0.000	0.000
1st quartile	-0.027	-0.013	0.751	20.091	-0.808	1.363	0.042	0.003
Median	0.000	0.000	0.991	73.667	-0.223	3.329	0.063	0.024
3rd quartile	0.021	0.011	1.189	349.895	0.547	8.417	0.097	0.158
Maximum	2.058	0.201	3.832	326502.486	5.689	163.295	0.385	1329.808
<i>Panel B: Correlation Coefficients</i>								
R		0.012** (2.10)	0.000 (-0.10)	0.003 (1.38)	-0.015*** (-3.27)	-0.005 (-1.31)	-0.004 (-0.97)	0.006 (1.25)
SEAS	0.010** (2.11)		0.017*** (3.38)	0.014*** (8.17)	0.240*** (55.22)	0.010** (2.20)	0.015*** (3.50)	-0.001 (-0.25)
BETA	-0.003 (-0.54)	0.008* (1.66)		0.050 (0.81)	0.024 (0.29)	0.095* (1.72)	-0.064 (-0.73)	-0.238* (-1.82)
MV	0.000 (-0.01)	0.056*** (16.24)	0.210*** (6.42)		0.058 (1.62)	-0.026 (-0.71)	-0.246*** (-3.52)	-0.091*** (-4.25)
MOM	-0.019*** (-4.20)	0.241*** (65.34)	0.015 (0.19)	0.182*** (8.39)		0.064 (0.98)	0.086*** (4.19)	0.014 (0.42)
TURN	0.000 (-0.05)	0.014*** (3.26)	0.166*** (3.50)	0.259*** (8.66)	0.070 (1.57)		0.029 (0.70)	-0.246*** (-10.18)
IVOL	-0.021*** (-4.12)	0.024*** (6.34)	-0.024 (-0.48)	-0.493*** (-22.80)	0.143*** (5.93)	0.295*** (4.75)		0.339*** (10.05)
ILLIQ	-0.010** (-1.96)	-0.034** (-8.56)	-0.244** (-7.42)	-0.875*** (-72.16)	-0.091*** (-2.91)	-0.579*** (-8.46)	0.492** (12.67)	

for future payoffs in the cross-section. In the single-factor regression (specification [1]), the slope coefficient on *SEAS* is positive and significant, and the relevant *t*-statistics are 2.32 and 2.04 for the raw and risk-adjusted returns, respectively. The seasonality effect explains, on average, 3.55% of the cross-sectional variation in returns.

Importantly, *SEAS* remains a significant predictor of cross-sectional returns even when we control for additional variables, such as *BETA*, *MV*, *MOM*, *TURN*, *IVOL*, and *ILLIQ*, in bivariate regressions (specifications [2] to [7]). This confirms that seasonality is not some other asset pricing effect “in disguise”, but an independent phenomenon providing incremental information about future returns. Even when we account for all the control variables jointly (specification [8]), the role of *SEAS* remains strong and significant, with a corresponding *t*-value exceeding 2.7<sup>7</sup>.

We note that the *SEAS* coefficient remains significant even when we control for *MOM*. This is important, as the *MOM* variable incorporates the average return on the same day of the week and also on other weekdays. This confirms that *SEAS* is not simply driven by high or low past average returns, but by returns on specific days: the same day of the week. In fact, the coefficients on *MOM* are negative, suggesting that the other weekday returns are negatively correlated in the cross-section with future returns. This is in line with the observations of Keloharju, Linnainmaa, and Nyberg (2016) and Keloharju et al. (2019), who document that whereas the average same-calendar month (or weekday) return correlates positively, the average other-calendar month negatively predicts future payoffs<sup>8</sup>.

#### 4.3. Further Robustness Checks

Finally, we corroborate our results with a battery of additional robustness checks. We apply them to the portfolio sorts from Section 4.1. First, instead of using only quintile portfolios, we also perform sorts using decile and tercile portfolios. Second, we run the analysis limiting the sample to only the 20 or 30 largest cryptocurrencies on day *t*-1 in terms of market capitalization. We also

<sup>7</sup> For robustness, we also experiment with modelling the examined relationship with quantile regression. The tests yield consistent signs of the *SAME* coefficient, but the significance depends on the choice of the  $\tau$  parameter. The detailed results are available upon request.

<sup>8</sup> Although the *MOM* variable already encompasses all the other-weekday returns, for robustness, we also extend specification [8] to explicitly include an additional variable representing the average other-weekday return. The conclusions are robust and the slope coefficient for *SAME* remains positive and significant for both raw and risk-adjusted returns.

**Table 2**  
Performance of Portfolios from One-Way Sorts on Average Past Same-Weekday Returns

The table reports the performance of portfolios from one-way sorts on *average past same-weekday returns (SEAS)*. The *High (Low)* portfolio contains the quintile of firms with the highest (lowest) *SEAS*, and *H-L* denotes the zero-investment strategy going long (short) the *High (Low)* portfolio.  $\bar{R}$  is the mean daily excess return, *Vol* is the standard deviation, *Skew* is skewness, and *Kurt* is kurtosis.  $\alpha_{F1}$ ,  $\alpha_{F3}$ , and  $\alpha_{F7}$  indicate the intercepts from the one-factor, three-factor, and seven-factor models (equations [2] to [4]), respectively.  $\beta_{MKT}$ ,  $\beta_{SMB}$ ,  $\beta_{UMD}$ ,  $\beta_{BETA}$ ,  $\beta_{ILLIQ}$ ,  $\beta_{TURN}$ , and  $\beta_{IVOL}$  are measures of exposure to the market (*MKT*), small-minus-big (*SMB*), up-minus-down (*UMD*), beta (*BETA*), illiquidity (*ILLIQ*), turnover (*TURN*), and idiosyncratic risk (*IVOL*) factors, respectively. The measures of exposure are estimated using the seven-factor model (equation 4).  $R^2$  denotes the time-series adjusted  $R^2$  coefficient of determination. The numbers in parentheses are *Newey-West (1987)* adjusted *t*-statistics. Panels *A* and *B* report the results for the equal-weighted and value-weighted portfolios, respectively.  $\bar{R}$ , *Vol*,  $\alpha_{F1}$ ,  $\alpha_{F3}$ ,  $\alpha_{F7}$ , and  $R^2$  are presented as percentages. The asterisks \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Panel A: Equal-weighted portfolios						Panel B: Value-weighted portfolios					
	Low	2	3	4	High	H-L	Low	2	3	4	High	H-L
<i>Descriptive statistics</i>												
$\bar{R}$	-0.04 (-0.25)	0.13 (0.86)	0.15 (0.94)	0.09 (0.53)	0.27 (1.62)	0.31** (2.05)	-0.19 (-0.94)	0.16 (0.99)	0.11 (0.69)	0.13 (0.89)	0.24 (1.32)	0.43** (2.06)
<i>Vol</i>	5.51	5.24	5.34	5.31	5.87	5.03	7.03	5.73	5.24	5.16	6.83	7.18
<i>Skew</i>	-0.55	-0.48	-0.34	-0.35	0.01	0.57	-0.30	-0.79	0.45	0.29	0.62	0.25
<i>Kurt</i>	2.42	3.38	4.26	2.38	2.77	5.15	6.99	10.80	7.69	8.47	7.06	7.90
<i>Abnormal returns</i>												
$\alpha_{F1}$	-0.17 (-1.52)	0.00 (-0.04)	0.01 (0.13)	-0.05 (-0.47)	0.14 (1.18)	0.31** (2.03)	-0.35** (-2.34)	0.02 (0.18)	-0.03 (-0.32)	-0.01 (-0.10)	0.10 (0.72)	0.45** (2.16)
$\alpha_{F3}$	-0.27*** (-2.82)	-0.08 (-0.93)	-0.07 (-0.76)	-0.11 (-1.18)	0.03 (0.29)	0.30** (2.01)	-0.400*** (-2.75)	0.010 (0.07)	-0.060 (-0.72)	-0.030 (-0.36)	0.060 (0.43)	0.450** (2.26)
$\alpha_{F7}$	-0.22** (-2.36)	-0.07 (-0.91)	-0.06 (-0.74)	-0.11 (-1.18)	0.08 (0.80)	0.30** (2.04)	-0.27** (-2.07)	0.02 (0.17)	-0.05 (-0.55)	-0.03 (-0.38)	0.16 (1.17)	0.43** (2.10)
<i>Factor exposures</i>												
$\beta_{MKT}$	0.96*** (27.47)	1.00*** (33.17)	0.98*** (29.56)	0.99*** (36.05)	0.99*** (24.75)	0.04 (0.82)	1.06*** (24.11)	1.03*** (23.83)	1.01*** (28.85)	1.03*** (31.05)	0.93*** (19.48)	-0.14** (-2.11)
$\beta_{SMB}$	0.31*** (6.29)	0.31*** (7.24)	0.35*** (8.3)	0.29*** (6.61)	0.37*** (7.57)	0.06 (1.17)	0.04 (0.98)	0.04 (1.24)	0.12*** (4.17)	0.06*** (2.67)	0.10* (1.91)	0.06 (1.03)
$\beta_{UMD}$	-0.08*** (-3.96)	-0.06*** (-3.55)	-0.05*** (-2.60)	-0.03* (-1.87)	-0.04 (-1.33)	0.04 (1.05)	-0.09*** (-2.65)	-0.01 (-0.45)	-0.03 (-1.30)	0.00 (-0.05)	0.00 (0.06)	0.10 (1.58)
$\beta_{BET}$	0.03 (0.80)	0.02 (1.06)	0.07** (2.48)	0.04 (1.38)	0.03 (0.85)	0.00 (0.03)	0.03 (0.85)	-0.01 (-0.54)	0.00 (-0.06)	-0.01 (-0.49)	0.02 (0.69)	-0.01 (-0.15)
$\beta_{ILLIQ}$	-0.03 (-0.44)	-0.06 (-1.10)	-0.05 (-0.89)	-0.02 (-0.49)	-0.04 (-0.77)	-0.01 (-0.16)	-0.03 (-1.20)	-0.02 (-0.57)	-0.04** (-2.11)	0.02 (1.11)	0.02 (0.42)	0.05 (0.87)
$\beta_{TURN}$	0.05 (1.12)	0.03 (0.94)	0.03 (0.80)	0.07** (2.26)	-0.01 (-0.28)	-0.06 (-1.08)	-0.09** (-2.48)	0.03 (1.30)	-0.04 (-0.73)	0.01 (0.71)	0.02 (0.63)	0.11** (2.00)
$\beta_{IVOL}$	0.16*** (4.66)	-0.04 (-1.33)	-0.05 (-1.43)	-0.05 (-1.51)	0.18*** (5.45)	0.02 (0.45)	0.24*** (6.53)	0.05*** (3.26)	0.02 (1.56)	0.00 (0.39)	0.23*** (8.05)	-0.01 (-0.15)
$R^2$	63.06	69.71	69.32	66.68	62.32	0.69	55.93	57.18	64.58	67.79	47.58	2.53

remove 10% of the largest and smallest cryptocurrencies at time  $t-1$ , as well as repeat our calculations excluding Bitcoin from the sample. Third, we check alternative filtering procedures, such as minimum coin prices, ranging from 0.1 USD to 0.4 USD. Fourth, we consider the *SEAS* variable based on alternative estimation windows, such as 10 weeks. Fifth, we investigate the performance of the *SEAS*-based portfolios within subperiods (i.e., the study period split in half). Sixth, we explore the role of individual days of the week and reproduce results while excluding different weekdays (Monday, Tuesday... etc.) from the sample. Seventh, we also examine different minimum coin prices, ranging from 0.1 USD to 0.4 USD.

The results from these tests, reported in Table A2 of the Online Appendix, do not contradict or qualitatively differ from our baseline findings. For the sake of brevity, we do not report detailed outcomes in this article.<sup>9</sup>

### 5. Concluding Remarks

Our study aims to examine the cross-sectional seasonality effect of *Keloharju, Linnainmaa, and Nyberg (2016)* in the cryptocurrency market. Having examined 151 cryptocurrencies for the period August 2016 to December 2019, we demonstrate a strong and sizeable seasonality phenomenon. Cryptocurrencies with the high (low) average same-weekday returns in the past continue to overperform (underperform) in the future. This effect is robust to different types of tests and under alternative specifications.

Not only do our findings provide new insights into asset pricing in the cryptocurrency market and cast doubt on the informational efficiency of cryptocurrency markets, they could be also potentially be used to construct practical investment strategies. The seasonality pattern could serve as a foundation of an efficient cryptocurrency picking approach.

A limitation of our study is the relatively short sample period. Nevertheless, this inherent feature of this novel asset class cannot

<sup>9</sup> The detailed results are available upon request.



**Table 3**

## Cross-Sectional Regressions

The table reports the average slope coefficients (multiplied by 100) of the cross-sectional regressions following Fama and MacBeth (1973). The dependent variables are daily cryptocurrency raw excess returns (Panel A) and risk-adjusted returns (Panel B). The independent variables are the average past same-weekday return (*SEAS*), market beta (*BETA*), the natural logarithm of the market value (*MV*), turnover ratio (*TURN*), idiosyncratic volatility (*IVOL*), and Amihud's illiquidity ratio (*ILLIQ*).  $\bar{R}^2$  is the average cross-sectional coefficient of determination expressed as a percentage. The numbers in parentheses are Newey-West (1987) adjusted *t*-statistics. The asterisks \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Panel A: Raw excess returns</i>								
SEAS	0.060** (2.32)	0.059** (2.33)	0.063** (2.44)	0.073*** (2.73)	0.054** (2.10)	0.072*** (2.74)	0.068* (2.60)	0.094* (3.30)
BETA		-0.001 (-0.55)						0.000 (0.15)
MV			0.000*** (-2.87)					0.000*** (-2.17)
MOM				-0.354*** (-3.79)				-0.002*** (-2.99)
TURN					0.010 (-0.58)			0.03* (1.70)
IVOL						-0.006 (-0.62)		-0.019* (-1.83)
ILLIQ							0.000* (1.77)	0.000 (1.21)
R <sup>2</sup>	3.55	7.49	5.67	7.23	6.26	7.38	8.00	22.20
<i>Panel B: Risk-adjusted returns</i>								
SEAS	0.053** (2.04)	0.053** (2.05)	0.052** (2.00)	0.068** (2.46)	0.049* (1.84)	0.058** (2.20)	0.006** (2.34)	0.079*** (2.72)
BETA		-0.001 (-0.74)						-0.001 (-0.92)
MV			0.000*** (-3.03)					0.000* (-1.88)
MOM				-0.349*** (-4.34)				-0.002*** (-3.44)
TURN					-0.005 (-0.30)			0.023 (1.29)
IVOL						-0.005 (-0.60)		-0.021* (-1.91)
ILLIQ							0.000* (1.93)	0.000 (1.39)
R <sup>2</sup>	3.62	7.45	4.81	6.73	6.37	6.84	7.50	21.00

be overcome. The external validity of our findings could be verified in the future with the use of longer samples and fresher data.

The investigation of the topics discussed in this article could be extended in at least two important directions. The first essential unanswered question relates to the exact mechanism of the development of the seasonality effect in the cryptocurrency market. The second question is how this effect can be exploited by market practitioners.

**CRedit authorship contribution statement**

**Huaigang Long:** Data curation, Formal analysis, Investigation, Methodology, Software, Visualization. **Adam Zaremba:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing - original draft, Writing - review & editing. **Ender Demir:** Writing - review & editing. **Jan Jakub Szczygielski:** Resources, Writing - review & editing. **Mikhail Vasenin:** Data curation, Resources.

**Supplementary materials**

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.frl.2020.101566](https://doi.org/10.1016/j.frl.2020.101566).

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