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Seasonality in cryptocurrencies

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A B S T R A C T

Considering a relatively large cross-section of ten cryptocurrencies, we test for the existence of well-known equity seasonality patterns with respect to cryptocurrency returns, volatility, trading volume and a spread estimator. Whilst we do not observe consistent and robust calendar effects in cryptocurrency returns and consequently cannot reject the weak-form market efficiency, we do observe robust patterns in trading activity. As such, trading volume, volatility and spreads are on average lower in January, on weekends and during the summer months. Besides, we also report a strong impact on the direction and significance of monthly seasonality patterns due to the stark market sell-off in January 2018, which has to be accounted for.

1. Introduction

This study takes a closer look at seasonality effects for cryptocurrencies, also referred to as calendar effects. Thereby, we provide an alternative perspective to the ongoing debate on the degree of market efficiency for cryptocurrencies and investigate well documented patterns in equity returns. Specifically, we test for the (i) Monday effect, (ii) weekend effect, (iii) January effect, (iv) turn-of-the-month effect and (v) Halloween effect among cryptocurrencies. As trading on crypto markets takes place continuously, in contrast to stock markets which are closed over the weekend, insight on the existence of a Monday and weekend effect is of particular interest. Furthermore, we extend our analysis beyond patterns in returns by also considering trading volume, daily volatility in line with Roger and Satchell (1991) and a recently introduced spread estimator by Abdi and Ranaldo (2017).

Urquhart (2016) provides first evidence on the degree of market efficiency for Bitcoin, as the most prominent representative of the cryptocurrency market, and concludes that Bitcoin is not weakly efficient, however shows a tendency of becoming more efficient in terms of a random behavior of returns. Building on these findings, Nadarajah and Chu (2017) run multiple test and conclude, by applying a power transformation of Bitcoin returns, that Bitcoin is largely weak form efficient over their full observation period and across sub-periods. Most recently, Phillip et al. (2018) document mild leverage effects, varying degrees of kurtosis, volatility clustering and predictable patterns in cryptocurrency returns. Additionally, market efficiency is also considered from the perspective of arbitrage possibilities. In this respect, a recent working paper by Hattori and Ishida (2018) tests for arbitrage activities by investors in the Bitcoin Future Market and report findings in support of market efficiency. Previous working papers on arbitrage activities have largely documented the existence of arbitrage opportunities and thereby argued for some degree of market inefficiency (see Makarov and Schoar, 2018; Reynolds et al., 2018). For a holistic literature review on empirical findings concerning cryptocurrencies and their role as an asset class, the reader is referred to Corbet et al. (2018b).

Baur et al. (2017) are the first to take a closer look at seasonality patterns in Bitcoin prices and trading volume from seven global crypto exchanges and find no consistent or persistent evidence of seasonality patterns in Bitcoin returns between December 2010 and

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Table 1
Descriptive statistics.

	Price		Return				Size	Volume	Volatility	Spread	obs
	max	min	mean	std	skew	kurt					
Panel A: Full sample											
BTC	19,497.40	68.43	0.09	1.94	−0.18	10.80	31,086.59	1359.04	4.21	1.12	1,872
BTCcash	3,923.07	213.15	0.09	4.51	0.58	7.03	19,033.51	951.55	10.57	2.71	315
ADA	1.11	0.02	0.32	5.25	2.53	16.58	7115.29	213.13	12.08	2.76	255
DASH	1550.85	0.31	0.18	3.65	3.03	43.85	899.16	26.74	8.35	2.32	1,580
ETH	1396.42	0.43	0.22	3.56	−3.52	66.37	19,167.97	714.21	7.54	1.99	1,041
IOTA	5.37	0.16	0.09	4.38	0.16	5.35	4013.44	99.45	12.07	3.02	365
LTC	358.34	1.16	0.07	2.99	1.78	28.20	1446.01	139.66	5.69	1.49	1,872
NEO	187.41	0.11	0.42	4.65	1.49	13.09	2119.41	94.87	11.35	3.15	595
XRP	3.38	0.00	0.11	3.45	2.01	29.92	5237.10	187.74	5.67	1.63	1,774
XLM	0.90	0.00	0.14	3.66	1.95	17.26	928.17	24.83	8.92	2.57	1,408
Panel B: Sample excluding 2018											
BTC	19,497.40	68.43	0.12	1.91	−0.14	11.90	18,701.69	629.52	4.08	1.07	1,709
BTCcash	3923.07	213.15	0.50	5.43	0.57	5.89	15,287.93	1110.19	13.15	2.94	152
ADA	0.72	0.02	1.60	7.19	2.20	11.04	3135.26	69.99	16.45	3.83	92
DASH	1550.85	0.31	0.24	3.73	3.15	44.54	501.92	16.98	8.48	2.33	1,417
ETH	826.82	0.43	0.28	3.70	−3.72	67.55	9076.87	316.62	7.64	2.00	878
IOTA	5.37	0.16	0.39	5.03	0.15	4.88	2853.25	110.08	14.12	3.26	202
LTC	358.34	1.16	0.10	3.00	1.88	29.82	704.28	86.08	5.54	1.46	1,709
NEO	77.22	0.11	0.64	5.01	1.55	12.70	736.71	43.38	12.05	3.25	432
XRP	2.30	0.00	0.16	3.45	2.26	32.12	1882.30	71.76	5.38	1.57	1,611
XLM	0.36	0.00	0.17	3.63	2.14	18.76	154.39	8.93	8.75	2.58	1,245

Note: This table presents the descriptive statistics for the ten crypto coins considered in this study. Panel A provides statistics on the full availability of each coin, and Panel B excludes all observation from 2018. The coins considered are: Bitcoin (BTC), Bitcoin Cash (BCC), Cardano (ADA), DASH (DASH), Ethereum (ETH), IOTA (MIOTA), Litecoin (LTC), NEO (NEO), Ripple (XRP), Stellar (XLM). The coins where selected on the basis of being the largest by market capitalization as of June 2018 and gathered from www.coinmarketcap.com. Statistics are provided for prices, log returns, market-capitalization (size), trading volume (volume), volatility and the spread estimator.

October 2017. However, they do observe a significant weekend effect in trading volume, which aligns well with previous evidence on currency markets. We add to the existing literature in five main ways: (i) we test for seasonality patterns across various crypto-currencies – not just Bitcoin, (ii) we consider additional seasonality patterns, (iii) we extend our analysis by also considering patterns in daily volatility and spreads, (iv) we implement a state-of-the-art GARCH(1,1) model to test for seasonality in cryptocurrency returns, and (v) we explicitly consider the impact of the 2018 sell-off in cryptocurrency markets.

2. Data

To analyze seasonality patterns in crypto coins, we utilize daily data from coinmarketcap.com. We focus on the largest coins by market capitalization with a sufficiently long historic price series as to estimate seasonality patterns. The application of daily returns, quotes in USD and a focus on the largest cryptocurrencies is in line with previous research and, thereon provides a solid basis for comparison (see Urquhart (2016); Nadarajah and Chu (2017); Phillip et al., (2018)). Furthermore, sufficient market-capitalization and liquidity are also relevant criteria to be considered by institutional investors and/or to qualify for the construction of a crypto fund under the regulation of the AIFM Directive by most authorities. Specifically, we include the following coins in our analysis: Bitcoin (BTC), Bitcoin Cash (BCC), Cardano (ADA), DASH (DASH), Ethereum (ETH), IOTA (MIOTA), Litecoin (LTC), NEO (NEO), Ripple (XRP), Stellar (XLM). As of June 2018, these coins are the largest by market capitalization. Our observation period varies in terms of the start date – with Bitcoin as the longest time-series starting in April 28th, 2013 – and ends for all coins on June 12th, 2018.

Table 1 reports the descriptive statistics for the ten considered cryptocurrencies across the full sample (Panel A) and when excluding observation from 2018 (Panel B). In line with Phillip et al. (2018) we observe inconsistent characteristics on the distribution of log returns across alternative coins. Whilst we observe high average returns, standard deviations and kurtosis across the board, skewness is negative for BTC and ETH only. Furthermore, we observe a tendency where trading volume and volatility increase on average with the maturity of the coin – indicated by the number of available observations – whereas spreads tend to decrease in the age of the coin.

3. Methodology

As the basis of our analysis, we build on four metrics to analyze the existence of seasonality patterns in cryptocurrencies. First, we examine seasonality patterns with respect to log returns where the return of a crypto coin i is calculated as

$$R_{i,t} = \log(P_{i,t}/P_{i,t-1})$$

where P denotes the price of a coin i at time t. Second, we consider trading volume as an indicator of investors trading activity on crypto markets. Thereon, we can observe if investors show patterns of lower trading activity during weekends, holidays or specific months of the year. Furthermore, trading volume indicates the level of activity on the markets and with respect to a specific cryptocurrency, as well as being a proxy for market liquidity.

Next, we consider an easily to derive daily estimator of the bid-ask spread when quote data is not available, by following the suggested method by Abdi and Ranaldo (2017). Thereon, the spread estimate is derived as follows:

$$S_{i,t} = \sqrt{4 \times (C_{i,t} - M_{i,t}) \times (C_{i,t} - M_{i,t+1}), 0}$$

Where $C_{i,t}$ is again the day's closing price of coin I at time t and $M_{i,t}$ is the daily mid-range price. However, due to estimation errors the standard form can become negative. Therefore, we follow Corwin and Schultz (2012) and set negative monthly estimates to zero and then calculate the spread (Abdi and Ranaldo, 2017, p. 4447). As such, the spread estimator also provides some intuition on the liquidity of the coins considered in this study.

Finally, we estimate daily volatility according to Roger and Satchell (1991) on the basis of high, low and closing prices. Consequently, the daily volatility of a coin i is estimated as follows:

$$Vol_{i,t} = \sqrt{\log(H_{i,t}/L_{i,t}) \times \log(H_{i,t}/O_{i,t}) + \log(L_{i,t}/C_{i,t}) \times \log(L_{i,t}/O_{i,t})}$$

Where H is the day's highest price, L the day's lowest price, O the day's opening price and C the day's closing price at time t. As part of our robustness checks we also consider taking the squared daily return as a volatility estimate. Results are directionally identical but statistically less significant.

4. Empirical evidence

Motivating the existence of seasonality patterns in crypto markets and deriving hypothesis in line with the existing literature for equity markets is not straight forward for a number of reasons. First of all, the possibility to trade 24/7 and the existence of weekday effects in trading should be mutually exclusive; Yet, behavioral factors are likely to influence trading behavior on crypto markets and weekends might be perceived as “free time” after all. In contrast, the fact that private trading is not the primary profession of many crypto investors, can result in increased trading activity over weekends. Second, for the predominant period of our sample crypto markets were dominated – possibly still are – by private rather than institutional traders. This notion has recently been supported by Corbet et al. (2018) in that the concentration of price discovery in the sport market rather than the futures market is predominantly attributable to unsophisticated/non-institutional investors. As such, insights from this study also yield interesting insight for more mature markets (equity, bonds, alternatives, etc.) on whether seasonality patterns are dominantly driven by institutional trading. Along these lines, effects such as window dressing can also be precluded. At the same time, seasonality patterns – commonly traded on by technical traders – are likely to play a much stronger role given the dominance of technical trading due to a lack of fundamental information for decision making. Consequently, the motivation for the existence of seasonality patterns in crypto markets is not as straight forward, however provides multifold insight on the efficiency of crypto markets and investor behavior in general.

4.1. Monday and weekend effect

Both the Monday and Weekend effect can be classified as day-of-the-month patterns. The Monday effect refers to the tendency of Monday returns to be negative or lower compared to the rest of the week. The weekend effect, often used interchangeably with the Monday effect, is observed separately in this study on the basis of continues trading over the weekends in cryptocurrency markets. As such we are interested if trading patterns on Saturdays and Sundays deviate from working days and thereby deviate from the classical specification of the weekend effect, which is concerned with the Monday-Friday return difference (Ülkü and Rogers, 2018).

Table 2 presents the results for the Monday effect (Panel A) and weekend effect (Panel B). Our initial hypothesis of lower/negative Monday returns is not confirmed. We find mixed results for the considered coins and only statistically significant and positive for Bitcoin. Thereon, a clear inference on crypto-market efficiency is not possible. This is potentially routed in the fact that the market is dominated by private investors. As Ülkü and Rogers (2018) show for equities, the Monday effect is basically an institutional investors phenomenon, which could explain the mixed results observed for cryptocurrencies, where trading was largely dominated by private traders and only recently institutional investors entered the market.

On the other hand, a reason for the significantly positive Monday return of Bitcoin, and the corresponding evidence of a “reverse Monday effect”, might be its maturity.[1] Olson et al. (2007) suggest a five-stage life cycle with respect to the pattern of changes in the Monday effect, starting with the discovery, public awareness, disappearance, reappearance and overshooting, and finally both anomaly and reverse anomaly disappear. The fast communication of individual traders through channels like Reddit is likely to speed up the process of going through the different stages or, alternatively result in an overshooting at the second stage already. If this was true, we should observe significant negative Monday returns for earlier years of Bitcoin trading. Thereon, we exclude all observations of 2017 and 2018 and indeed observe a significantly (t-stat: 2.475) negative Bitcoin Monday return of −0.12% (non-Monday return +0.31%).

With respect to our additional measures, Foster and Viswanathan (1990) report significantly higher trading costs and intra-day volatility as well as lower trading volume for Mondays. We observe no significant evidence for the Monday effect in volatility, spreads

[1] Evidence for the existence of a reverse Monday/weekend effect was previously reported by Mehdian and Perry (2001), Gu (2004) and Cho, Linton and Whang (2007).

Table 2
Day-of-the-week effects.

	Return		Volatility		Spread		Volume		Obs.
	mean	t-stat	mean	t-stat	mean	t-stat	mean	t-stat	
Panel A: Monday effect									
Bitcoin	0.32	2.10**	4.28	0.30	1.05	−0.55	1,277.05	−0.42	268
	0.05		4.20		1.13		1,372.72		1604
Bitcoin Cash	−0.56	−1.05	9.25	−0.94	2.28	−0.75	790.97	−1.00	45
	0.20		10.79		2.78		978.31		270
Cardano	0.35	0.04	10.91	−0.64	1.87	−1.04	187.50	−0.61	37
	0.32		12.27		2.91		217.48		218
Dash	−0.10	−1.27	8.58	0.33	2.38	0.20	24.33	−0.64	226
	0.23		8.31		2.31		27.14		1354
Ethereum	0.05	−0.63	6.88	−1.29	1.53	−1.78*	707.86	−0.07	149
	0.25		7.65		2.07		715.27		892
IOTA	0.53	0.78	12.81	0.71	3.04	0.02	91.51	−0.31	52
	0.02		11.95		3.02		100.77		313
Litecoin	0.13	0.33	5.73	0.11	1.40	−0.54	127.13	−0.54	268
	0.06		5.68		1.51		141.76		1604
NEO	0.87	0.95	12.01	0.69	3.88	1.29	108.11	0.81	85
	0.35		11.24		3.03		92.66		510
Ripple	−0.11	−1.09	5.46	−0.44	1.60	−0.12	139.04	−1.10	254
	0.15		5.70		1.64		195.86		1520
Stellar	0.37	0.97	8.89	−0.05	2.24	−1.20	23.06	−0.31	201
	0.10		8.93		2.62		25.13		1207
Panel B: Weekend effect									
Bitcoin	0.08	−0.15	3.88	−2.12**	1.14	0.26	1,220.04	−1.11	534
	0.09		4.34		1.11		1,414.73		1337
Bitcoin Cash	0.26	0.42	9.92	−0.50	2.72	0.01	897.34	−0.54	90
	0.02		10.51		2.72		975.72		224
Cardano	0.70	0.72	11.85	−0.04	2.09	−1.17	210.03	−0.14	72
	0.18		11.92		3.00		215.26		182
Dash	0.13	−0.36	8.05	−0.59	2.09	−1.07	25.85	−0.37	452
	0.20		8.42		2.37		27.12		1127
Ethereum	0.05	−0.98	6.82	−2.14**	1.95	−0.24	614.44	−1.61	298
	0.29		7.80		2.01		755.23		742
IOTA	0.25	0.43	10.28	−2.67***	2.72	−0.78	74.77	−1.49	104
	0.03		12.78		3.15		109.61		260
Litecoin	0.12	0.47	5.19	−1.98**	1.48	−0.08	123.03	−1.10	534
	0.05		5.89		1.50		146.33		1337
NEO	0.68	0.86	10.38	−1.53	2.38	−2.09**	79.37	−1.49	170
	0.32		11.70		3.45		101.30		424
Ripple	−0.05	−1.22	4.90	−2.59***	1.57	−0.41	153.75	−1.19	506
	0.17		5.98		1.66		201.35		1267
Stellar	0.09	−0.32	8.33	−1.49	2.47	−0.44	19.91	−1.34	402
	0.16		9.14		2.58		26.82		1005

Note: This table reports the results for the Monday effect (Panel A) and weekend effect (Panel B). The first row for each coin represents the mean returns of the effect period (e.g. Monday or weekend) and the second row the non-Monday/ non-Weekend means. Corresponding t-statistics (parenthesis) and significance levels: * 10% level, ** 5% level and *** 1% level. The coins considered are: Bitcoin (BTC), Bitcoin Cash (BCC), Cardano (ADA), DASH (DASH), Ethereum (ETH), IOTA (MIOTA), Litecoin (LTC), NEO (NEO), Ripple (XRP), Stellar (XLM). The coins where selected on the basis of being the largest by market capitalization as of June 2018 and gathered from www.coinmarketcap.com.

and trading volume. Yet, albeit not significant, we do observe a tendency of lower trading volume on Mondays compared to the rest of the week, which is in line with Foster and Viswanathan (1990).

In terms of a differences in returns over the weekend, we observe generally lower trading volume in all considered coins, as well as significantly lower volatility. This indicates, that trading, although possible on seven days of the week, takes place predominantly during working days. Besides, we observe no consistent evidence with respect to a difference in returns and spreads between weekend and non-weekend days.

4.2. January effect

The January effect was first discussed by Rozeff and Kinney (1976) when the authors observed on average higher stock market returns in January compared to the rest of the months, however only among small-cap firms. This anomaly is generally contributed to tax-loss selling, window-dressing, omitted risk-factors, bid-ask bounce, information-release or a combination of all (e.g. Ritter,1988).

Whilst window dressing and the bid-ask bounce appear to be unlikely reasons in the crypto universe, tax-loss selling and tax-gain selling, in that respect, appear more reasonable and are also in-line with higher trading volume in January. In that respect, investors

Table 3
January effect.

	Return		Volatility		Spread		Volume		Obs.
	mean	t-stat	mean	t-stat	mean	t-stat	mean	t-stat	
Panel A: January effect									
Bitcoin	−0.21	−2.04**	5.26	3.28***	1.58	2.65***	2,746.03	5.72***	155
	0.12		4.11		1.08		1,213.19		1717
Bitcoin Cash	−0.75	−1.09	10.24	−0.19	2.68	−0.04	1,362.71	2.08**	31
	0.18		10.61		2.71		906.67		284
Cardano	−0.46	−0.88	15.22	1.56	2.69	−0.07	551.34	8.20***	31
	0.43		11.64		2.77		166.33		224
Dash	−0.01	−0.60	8.37	0.03	2.35	0.08	42.75	3.03***	124
	0.20		8.35		2.32		25.38		1456
Ethereum	0.74	1.50	8.65	1.68*	2.06	0.21	1,765.93	8.60***	93
	0.16		7.43		1.98		611.03		948
IOTA	−0.60	−0.92	12.39	0.23	3.40	0.46	159.42	1.73*	31
	0.16		12.04		2.99		93.88		334
Litecoin	−0.28	−1.55	5.95	0.50	1.86	1.57	200.44	2.07**	155
	0.11		5.66		1.46		133.27		1717
NEO	0.47	0.08	11.64	0.26	3.84	1.02	245.21	8.14***	62
	0.42		11.31		3.07		77.38		533
Ripple	−0.41	−1.98**	6.16	0.82	2.08	1.46	681.99	9.10***	155
	0.16		5.62		1.59		135.76		1619
Stellar	0.05	−0.30	10.12	1.52	2.93	1.01	105.53	11.19***	124
	0.15		8.81		2.53		17.04		1284
Panel B: January effect (excluding 2018)									
Bitcoin	−0.15	−1.65*	4.57	1.33	1.55	2.49**	75.70	−3.02***	124
	0.14		4.04		1.04		680.69		1585
Dash	0.18	−0.17	8.00	−0.40	2.31	−0.04	1.11	−2.86***	93
	0.25		8.52		2.33		18.09		1324
Ethereum	0.84	1.25	7.58	−0.06	1.96	−0.09	10.02	−3.83***	62
	0.23		7.64		2.00		339.92		816
Litecoin	−0.23	−1.28	5.07	−0.79	1.86	1.50	7.92	−2.75***	124
	0.13		5.58		1.43		93.30		1585
NEO	0.02	−0.72	7.34	−2.72***	3.12	−0.13	0.04	−3.26***	31
	0.69		12.41		3.26		46.73		401
Ripple	−0.28	−1.47	3.96	−2.10**	1.95	1.11	0.85	−1.89*	124
	0.20		5.49		1.53		78.31		1487
Stellar	−0.12	−0.83	7.25	−1.62	2.52	−0.15	0.07	−2.28**	93
	0.20		8.87		2.59		9.64		1152

Note: This table reports the results for the January effect across the full sample of each coin (Panel A) and excluding all observations from 2018 (Panel B). The first row for each coin represents the mean returns for January and the second row the means of non-January months. Corresponding t-statistics (parenthesis) and significance levels: * 10% level, ** 5% level and *** 1% level. The coins considered are: Bitcoin (BTC), Bitcoin Cash (BCC), Cardano (ADA), DASH (DASH), Ethereum (ETH), IOTA (MIOTA), Litecoin (LTC), NEO (NEO), Ripple (XRP), Stellar (XLM). The coins where selected on the basis of being the largest by market capitalization as of June 2018 and gathered from www.coinmarketcap.com.

sell coins that trade for less than they were initial bought for in December to realize a loss – thereby potentially offsetting the positive rally in equities – whereas good performing coins are sold in January to postpone the realization of capital gains (Constantinides, 1984). Whereas, the latter appears more likely as a driver of the January effect for cryptocurrencies, it is still questionable whether retail investors (predominant investor group over the past years) engage in such tax efficient trading mechanisms. In support of this notion, Ritter (1988) referred to tax related buying and selling as the "parking-the-proceeds hypothesis", which he relates to habits of individual (non-institutional) investors. At the same time, the fact that investors in cryptocurrencies are spread across the globe and different countries show different fiscal year ends is likely to dilute such tax effects.

Table 3 provides the results on the January effect for two samples, all available data in Panel A and excluding observation from 2018 in Panel B. We consider the second subset, excluding 2018, based on the large sell-off in January 2018 and thereby ensure that our results are nor driven by this one shock to the market. Overall, we make two central observations: (i) returns in January are on average negative – implying a "reverse January effect", (ii) when excluding 2018 trading volume and volatility is significantly lower in January compared to other months.

First of all, we observe that the sell-off in January 2018 had a strong impact on the observed patterns and has – through significant downward pressure – resulted in negative January returns, high trading volume, a widening of the spread estimator and increased levels of volatility.[2] Excluding the 2018 observation, we observe significantly lower trading volume and volatility across the

[2] The impact of the January 2018 sell-off is particularly strong given the overall short observation period compared to alternative studies on equity markets.

Table 4
Halloween effect.

	Return		Volatility		Spread		Volume		Obs.
	mean	t-stat	mean	t-stat	mean	t-stat	mean	t-stat	
Halloween effect									
Bitcoin	0.09	−0.06	4.87	6.72***	1.27	2.85***	1934.88	7.71***	908
	0.09		3.58		0.98		730.72		963
Bitcoin Cash	0.27	0.82	10.99	1.43	3.00	1.40	1,232.92	5.15***	181
	−0.15		9.46		2.33		572.66		133
Cardano	0.58	1.23	13.45	3.40***	2.80	0.27	265.43	4.91***	181
	−0.31		8.05		2.59		85.69		73
Dash	0.32	1.50	9.43	3.91***	2.52	2.04**	36.48	6.46***	800
	0.04		7.18		2.05		16.77		779
Ethereum	0.40	1.75*	7.70	0.91	2.03	0.37	890.04	4.67***	544
	0.01		7.32		1.95		522.80		496
IOTA	0.39	1.28	12.87	1.90*	3.09	0.25	163.76	6.34***	181
	−0.20		11.26		2.97		36.25		183
Litecoin	0.14	0.91	6.11	2.55**	1.59	1.28	176.66	4.07***	908
	0.01		5.30		1.41		99.29		963
NEO	0.18	−1.55	9.89	−4.68***	2.99	−0.80	115.18	3.83***	362
	0.79		13.55		3.37		63.58		232
Ripple	0.19	1.01	6.33	3.63***	1.82	2.04**	295.98	6.34***	906
	0.03		4.98		1.43		69.62		867
Stellar	0.23	0.95	8.92	0.04	2.56	0.07	39.22	6.42***	725
	0.04		8.90		2.54		9.57		682

Note: This table reports the results for the Halloween or "Sell in May" effect across the full sample of each coin. The first row for each coin represents the mean returns for January and the second row the means of non-January months. Corresponding t-statistics (parenthesis) and significance levels: * 10% level, ** 5% level and *** 1% level. The coins considered are: Bitcoin (BTC), Bitcoin Cash (BCC), Cardano (ADA), DASH (DASH), Ethereum (ETH), IOTA (MIOTA), Litecoin (LTC), NEO (NEO), Ripple (XRP), Stellar (XLM). The coins where selected on the basis of being the largest by market capitalization as of June 2018 and gathered from www.coinmarketcap.com.

considered crypto coins. Whilst having previously discussed the positive January returns in equities to be attributable to *tax-loss selling*, one reason for the large sell-off to take place in January 2018 could be for reasons of *tax-gain selling*. According to Chen and Singal (2003, p.78), "…*rational investors sell past winners in January instead of December…[thereby] they can defer taxes by almost one year*". Again, whether or not this indeed reasonable given the international investor base remains questionable.

Second, in both sample we observe consistently negative January returns and significantly so for Bitcoin, even when considering a GARCH(1,1) regression (see Section 5) and when considering each year separately. Thereby, we have to reject the existence of a January effect, but observe a tendency towards a "reverse January effect", which was previously documented for momentum profits by Jegadeesh and Titman (2001, p.706) when including small and low priced stocks. As Bhattacharyya and Chandra (2016, p.5) discuss, penny stocks are commonly characterized by low liquidity, low trading volume, high price volatility, as well as a huge potential for profits for risk seekers due to "*…information asymmetry, low liquidity, and uncertainty related to the fundamentals…*". As such the evidence on a reverse January effect among cryptocurrencies is in line with the empirical evidence on penny stocks, which show similar characteristics.

4.3. Halloween effect

Finally, we take a closer look at the "Halloween" or "sell in May" effect according to which returns from beginning of November to end of April are significantly higher than for the other half of the year. The first empirical evidence was provided by Bouman and Jacobsen (2002), who observe the Halloween effect in 36 out of 37 considered markets and particularly strong in Europe. They challenge their findings in a variety of ways: (i) including transactions costs, (ii) data mining, (iii) compensation for risk, (iv) driven by the January effect, (v) effect is sector specific, (vi) impact of vacation on trading activity, (vii) seasonality in news, and (viii) caused by shift in interest rates or trading volume.

Table 4 reports the results with respect to the Halloween effect. First, we observe a tendency of on average higher returns from November to April, however not statistically significant with the exception of Ethereum. Second, we observe significantly higher volatility, spreads and trading volume over the non-summer month (November–April). For the case of considered coins in this study, there appears to be a link between the risk and return observed for the Halloween effect in that positive returns are accompanied by higher risk and lower returns are accompanied by significantly lower risk (e.g. NEO). Interestingly, with respect to the vacation hypothesis for the Halloween effect, we do document significantly lower trading volume in support of this notion. Consequently, investors tend to trade less during their vacation, which is consistent with lower trading activity over weekends. Besides, we also test for the Halloween effect to be driven by the January effect, but can reject this hypothesis.

5. Robustness checks

We also run our tests with respect to calendar effects in cryptocurrency returns based on a GARCH(1,1) regression approach, following the methodology proposed by Urquhart and McGroarty (2014), but find no material differences. Next, we test for the turn-of-the-month effect but do not find any statistically significant evidence across the set of considered coins. Furthermore, we test the Monday effect as MO vs. TUE–FR, thereby excluding the weekend to be consistent with the existing literature on equity markets, but observe no significant differences. Finally, we also test for "sell in May, but remember to come back in September" variant of the Halloween effect. Again, results are not materially different, but less robust with lower significance levels. A third variation of this anomaly claims superior results when selling end of May and returning in the beginning of October. Indeed, we observe a stronger effect in returns and even significant for DASH and Ethereum, whereas the pattern weakens for volatility and volume. Overall, the results are still in line with the traditional specification. Finally, we also check for sensitivity of the Monday-, weekend- and Halloween effect towards the January 2018 sell-off by rerunning the tests and excluding all 2018 observations and find no material differences.

6. Conclusion

This study contributes to the debate on market efficiency for cryptocurrencies by analyzing well-known seasonality effects, previously documented for traditional asset classes. On the basis of the existence on seasonality patterns in cryptocurrency returns we cannot reject the weak-form efficient market hypothesis. We observe no consistent and significant calendar effect in cryptocurrency returns, with the exception of a robust Monday and reverse January effect for Bitcoin.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.frl.2018.11.007.

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