J. Int. Financ. Markets Inst. Money 71 (2021) 101289

Contents lists available at ScienceDirect

Journal of International Financial Markets, Institutions & Money

journal homepage: www.elsevier.com/locate/intfin

Speculation and lottery-like demand in cryptocurrency markets

Klaus Grobys [a,*,1], Juha Junttila [b,1]

[a] University of Vaasa, School of Accounting and Finance, P.O. Box 700, FI-65101 Vaasa, Finland
[b] University of Jyväskylä, School of Business and Economics, P.O. Box 35, FI-40014 Jyväskylä, Finland

A R T I C L E I N F O

Article history:
Received 18 May 2020
Accepted 6 January 2021
Available online 9 January 2021

JEL classification:
G01
G12
G14

Keywords:
MAX
Lottery-like demand
Cryptocurrency
Financial technology
Gambling

A B S T R A C T

This is the first paper that explores lottery-like demand in cryptocurrency markets. Since recent research provides evidence that cryptocurrency returns appear to be short-memory processes, we modify Bali, Cakici and Whitelaw's (2011) and Bali, Brown, Murray, and Tang's (2017) MAX measure and employ a weekly forecast horizon and daily log-returns from the previous week to calculate the metric for our portfolio sorts. From an econometric point of view, this study proposes statistical tests that are robust to unknown dynamic dependency structures in the cryptocurrency data. Our results show that average raw and risk-adjusted return differences between cryptocurrencies in the lowest and highest MAX quintiles exceed 1.50% per week. These results are robust after controlling for Bitcoin risk or potential microstructure effects. Our findings are important also from a theoretical point of view because they suggest that parallel to stock markets, similar behavioral mechanisms of underlying investor behavior are present also in new virtual currency markets.

1. Introduction

Bali, Cakici and Whitelaw (2011) adopt extreme positive returns as a proxy for lottery-like payoffs. Their finding indicates that stocks that exhibited the highest daily return (sample maximum of the daily returns) over the prior month (MAX) produced significantly lower returns over the subsequent one-month holding period. This negative MAX-effect has also been found in international equity markets (Walkshäusl, 2014; Chan and Chui, 2016). Bali et al. (2011) argue that individual investor portfolios lack diversification due to the investors' preferences for lottery-type stocks, which implies that this lottery-like demand could cause the negative idiosyncratic volatility premium. The authors show that after controlling for the MAX-effect, the negative effect of idiosyncratic volatility on stock returns vanishes. Hung and Yang (2018) argue that many stock markets are subject to daily price limits and therefore propose a modified MAX measure. Their findings confirm earlier studies in that stocks with highest (lowest) modified MAX experience lower (higher) future returns, indicating that stocks with highest (lowest) modified MAX tend to be overpriced (underpriced).

In a recent paper, Asness et al. (2020) argue that because a stock's beta is the product of the correlation and volatility, a stock can have a high MAX simply because of high volatility or high skewness. Hence, higher than second moments of the return distribution play a specific role in the analysis of the MAX-effect. To decompose these effects, they propose a scaled MAX (SMAX) that goes long on stocks with low MAX return divided by estimated ex-ante volatility and short on stocks with

* Corresponding author.
E-mail addresses: kgrobys@uva.fi (K. Grobys), juha-pekka.junttila@jyu.fi (J. Junttila).
[1] We would like to thank Savva Shanaev for useful comments. Moreover we would like to thank Ji Wu, Andrew Urquhart, Syed Riaz Mahmood Ali, and Richard Mcgee for encouraging comments. We are also grateful for having received insightful comments from the participants of the 3rd Cryptocurrency Research Conference (ICMA Centre, University of Reading).

https://doi.org/10.1016/j.intfin.2021.101289
1042-4431/

the opposite feature. The authors emphasize that the SMAX factor captures lottery-like demand in a manner that is not as mechanically related to volatility but more so to the overall shape of the underlying return distribution. Their findings confirm earlier studies as they imply that lottery-like demand play a significant role in stock markets.

Given this strong evidence of lottery-like demand in equity markets, it is surprising to note that there are yet no studies available investigating lottery-like demand in cryptocurrency markets. This is curious as many scholars argue that cryptocurrency markets are more likely to be subject to speculation than having the purpose of being a medium of exchange. In this regard, using a wide range of econometric models, one strand of literature affirms reoccurring speculative bubble behavior in cryptocurrency markets (Cretarola and Figá-Talamanca, 2020; Geuder et al., 2019; Chaim and Laurini, 2019; Fry, 2018). Moreover, Baur et al. (2018, p.178) who explore whether Bitcoin is mainly used as an alternative currency or rather as a speculative investment conclude: "Bitcoin is mainly used as a speculative investment despite or due to its high volatility and large returns."

Motivated by this current literature, our paper explores another dimension of speculative behavior in cryptocurrency markets, that is, lottery-like demand. This study employs a set of 20 cryptocurrencies to implement the analysis of the MAX-effect over the January 2016–December 2019 period that exhibit the highest market capitalizations in these markets as of January 2, 2016. Specifically, at the beginning of each week, the cryptocurrencies are sorted into quintiles by the maximum of the daily returns during the last seven trading days prior to portfolio formation. The first quintile comprises those cryptocurrencies that have the lowest daily maximum return within the last week, whereas the fifth quintile comprises the ones that exhibit the highest daily maximum return over the same period. The zero-cost strategy is long on the fifth and short on the first quintile. This strategy is updated at the beginning of each week. Even though cryptocurrency markets are traded 24/7, as a robustness check, a second strategy is implemented where a one-day delay between portfolio formation and asset allocation is implemented. To risk-adjust the payoffs, we regress the zero-cost portfolio returns on the excess returns of Bitcoin, which is employed as cryptocurrency market factor in our analysis. Statistical inference is based on blocks bootstraps using different block lengths.

This study contributes in some important aspects to current literature. First, this paper adds to literature investigating lottery-like demands in asset markets. While earlier studies exclusively focus on equity markets (Bali et al., 2011, 2017; Walkshäusl, 2014; Chan and Chui, 2016; Hung and Yang, 2018; Asness et al., 2020), this is the first research that investigates this theme in cryptocurrency markets. This is an important issue for at least two reasons: First, as of March 2020, the overall market capitalization of the cryptocurrency market is more than USD 260 billion.[2] In this regard, Fry and Cheah (2016, p.350) highlight that "from an economic perspective the sums of money involved are substantial." Our paper differs from Bali et al.'s (2011) and Bali et al.'s (2017) from a methodological point of view because we employ weekly forecast horizons. This choice is motivated by the recent literature on cryptocurrency research documenting that the data on their valuation and returns appear to be short-memory processes (Grobys et al., 2020), and moreover, monthly data would not provide enough observations for the relevant, recent period of their market expansion (Shen, Urquhart, and Wang, 2020). Furthermore, cryptocurrency markets are well-known for their speculative nature (Cretarola and Figà-Talamanca, 2020; Geuder et al., 2019; Chaim and Laurini, 2019; Fry, 2018; Baur et al., 2018). Hence, the question arises of whether virtual currency markets are subject to any of the same market forces or pricing anomalies as equity markets. This paper fills this important gap in the literature.

Second, this paper adds to the relatively new strand of literature investigating cross-sectional patterns in cryptocurrency returns. In this regard, one strand of the literature explores potential risk factors in cryptocurrency markets such as size and momentum (Shen et al., 2020; Grobys and Sapkota, 2019; Liu et al., 2020; Li et al., 2019), whereas another strand of the literature investigates the profitability of technical trading rules (Gerritsen et al., 2019; Corbet et al., 2019; Miller et al., 2019). This study adds to this literature by exploring the MAX-effect. In doing so, this study also contributes to the ongoing discussion on the efficiency of the cryptocurrency market because the literature has not yet achieved a consensus. In this regard, Kristoufek and Vosvrda (2019) provide an excellent summary of the current discussion. Our paper takes a new perspective and hypothesizes that if the cryptocurrency markets were efficient, information about the past maximum daily cryptocurrency returns would not predict subsequent returns.

Finally, another contribution of this study is that it proposes a simple econometric test for the risk-adjustment of the strategy's payoffs. This is an important issue because the results of standard statistical inference can be misleading in the presence of non-normality, as already pointed out in an early paper by Affleck-Graves and McDonald (1989). A more recent stream of literature on blocks bootstrap shows that test statistics based on bootstraps are statistically more reliable than standard test statistics. In this regard, Liu et al. (2019), who test the out-of-sample return predictability, propose a new statistical bootstrap-based test for the directional accuracy of stock returns and show that their test offers both more correct size and better power than the standard test. Moreover, Huang, Li, Wang, and Zhou (2020) re-assess established stylized facts of the well-known Time Series Momentum (TSM) effect and compare the t-statistics in a pooled regression framework with nonparametric bootstraps. Their findings indicate that while the standard t-statistic in a pooled regression appears large, it is not statistically reliable as it is less than the critical values of block bootstraps.[3] The test proposed in our study addresses the

[2] According to coinmarketcap.com, the total market capitalization in the cryptocurrency market was USD 260.3 billion as of March 5, 2020.

[3] In the statistical literature, recent studies show that employing bootstrapping improves inference for predictive quantile regressions with persistent predictors and conditionally heteroskedastic errors (Fan and Lee, 2019), yields better approximations of the critical values derived for testing for an unknown change in mean in time series settings with weekly dependent observations (Peštová and Pešta, 2018), and provides reliable test statistics for linear errors-in-variables (EIV) models that contain measurement errors in the input and output data (Pešta, 2017; Platanakis, 2018).

statistical inference problem because it is based on a blocks bootstrap procedure that is appropriate in the presence of unknown (dynamic) dependency structures in the cryptocurrency data.

The results show that the difference between returns on cryptocurrency portfolios with the highest and lowest maximum daily returns is -1.54% per week. While the negative relationship confirms the results from the previous equity market studies (Bali et al., 2011, 2017; Walkshäusl, 2014; Chan and Chui, 2016; Hung and Yang, 2018; Asness et al., 2020), the economic magnitude is considerably higher in the case of cryptocurrency markets. The return difference in raw returns is statistically significant at a 1% risk level. Trimming the data by cutting of 5% of the payoff distribution neither lowers the spread nor diminishes its statistical significance. Controlling for Bitcoin risk increases the spread by 21 basis points per month. The results are robust because accounting for potential the microstructure issues does not change the results. Consistent with earlier literature focusing on equity markets, this evidence suggests that investors may be willing to pay more for cryptocurrencies that exhibit extreme positive returns, and thus, these cryptocurrencies exhibit lower returns in the future. These findings have important implications from a theoretical point of view because they suggest that similar behavioral mechanisms of underlying investor behavior as in the stock markets are present even in the new virtual currency markets (Tversky and Kahneman, 1992; Barberis and Huang, 2008; Brunnermeier et al., 2007).

2. Literature review

In a fundamental study on the gambling behavior in stock markets, Kumar et al. (2016) show that correlated trading by gambling-motivated investors generates excess return co-movement among stocks with lottery features. Inspired by Kumar (2009), they use US data from 1980 to 2005 and measure the attractiveness of a stock as a gambling object using an LIDX lottery index and assign all stocks from the CRSP into vigintiles (20 bins) each year by price, idiosyncratic volatility, and idiosyncratic skewness. Bin 20 contains stocks from the lowest price group and the highest volatility, and skewness groups. For each stock, the price, volatility, and skewness vigintile bin scores are added to produce a score between 3 and 60, and the score is then scaled between 0 and 1. A higher value of LIDX for a stock indicates that the stock is more attractive to investors who enjoy speculative trading and gambling. The authors show that lottery-like stocks co-move strongly with one another, and this return co-movement is strongest among lottery stocks located in regions where investors exhibit stronger gambling propensity. Looking directly at investor trades, they also find that investors with a greater propensity to gamble trade lottery-like stocks more actively and that those trades are more strongly correlated. Finally, they give empirical evidence that time variation in general gambling enthusiasm and income shocks from fluctuating economic conditions induce a systematic component in investors' demand for lottery-like stocks.

In a recent paper, Alkan and Guner (2018) use daily market data and quarterly book value data on stocks listed on Borsa Istanbul, excluding REITs and stocks in the 'Emerging market and Watch-list' market segments for the period from January 3, 2000 to June 30, 2016. By proxying the lottery-like preferences with demand for stocks with extreme positive returns (MAX), they find that 'high-MAX' stocks significantly underperform 'low-MAX' stocks. This holds also after controlling for a series of potential explanatory return characteristics. The negative relationship between MAX and expected returns seem to be driven by stocks strongly preferred by individual investors and strengthens following the periods of high investor sentiment. The MAX discount increased during the period of temporary short-sale restrictions at Borsa Istanbul, but overall, they stress a limits-to-arbitrage explanation for the observed MAX anomaly.

Nguyen and Truong (2018) use a sample of U.S. stocks over the period 1973–2015 and find that quarterly earnings announcements account for more than 18% of the total maximum daily returns in the high MAX portfolio, but maximum daily returns as triggered by earnings announcements do not entail lower future returns. The idea of MAX-type pricing does not pertain when conditioning MAX returns on earnings announcements, and the earnings announcement dependent MAX returns do not indicate a probability of future large short-term upward returns. Furthermore, excluding earnings announcement related MAX returns in constructing the lottery demand factor results in not only a larger lottery demand premium but also superior factor model performance.

Additionally, Chichernea et al., (2019) analyze the role of investors' heterogeneous preferences for skewness effects to the negative correlation between idiosyncratic volatility (IVOL) and mean returns. Using data on all common stocks covered by the CRSP traded on New York Stock Exchange, American Stock Exchange, and NASDAQ, they compute institutional holdings based on 13F filings for all firms covered by the Thomson Reuters. The monthly sample starts from 1980 and ends in 2016, and they exclude the so called penny stocks (i.e., stocks with a lagged price under a $1). Their results reveal that the IVOL puzzle is stronger within stocks held primarily by agents with a preference for lottery-like payoffs and during economic downturns, when the demand for lottery-like payoffs is high. Hence, their results support theories that suggest lottery preferences could be a significant source of the IVOL puzzle.

Finally, Brown, Lu, Ray and Teo (2018) use an extensive, hand-collected data set on hedge fund manager vehicle purchase records and details from various websites covering the period 2006–2012. The authors show that motivated by sensation seeking, hedge fund managers who own powerful sports cars take on more investment risk but do not deliver higher returns, resulting in lower Sharpe ratios, information ratios, and alphas. Moreover, sensation-seeking managers trade more frequently, actively, and unconventionally, and prefer lottery-like stocks. They also show that some investors are themselves susceptible to sensation seeking and that sensation-seeking investors fuel the demand for sensation-seeking hedge fund managers. While investors perceive sensation seekers to be less competent, they do not fully appreciate the superior investment skills of sensation-avoiding fund managers.

Even though a considerable strand of literature dealing with lottery-like demand in equity market settings exists, it is surprising to note that there is no study available that explores this issue in cryptocurrency markets, which are known to be highly speculative in their nature. This is the first study that addresses this issue.

3. Data

Daily data for the following cryptocurrencies were retrieved from coinmarketcap.com: Bitcoin (BTC), Ripple (XRP), Litecoin (LTC), Ethereum (ETH), Dash (DASH), Dogecoin (DOGE), Peercoin (PPC), BitShares (BTS), Stellar (XLM), Nxt (NXT), MaidSafeCoin (MAID), Namecoin (NMC), Factom (FCT), Bytecoin (BCN), Monero (XMR), Rubycoin (RBY), Emercoin (EMC), Clams (CLAM), BlackCoin (BLK), MonaCoin (MONA), and NEM (XEM)[4] These cryptocurrencies comprise 99% of the overall market capitalization as of January 2, 2016. Since we employed Bitcoin as the market factor, we excluded this cryptocurrency from the main analysis. As a consequence, the 20 cryptocurrencies that we use in our sorts are between rank 2 and 21 in terms of market capitalizations as of January 2, 2016. As we employ only large cap cryptocurrencies – speaking in relative terms – we control ex-ante for liquidity. The daily data set used in this study starts on January 1, 2016 and ends on December 31, 2019, resulting in 1463 daily observations. As cryptocurrencies are traded 24/7, weekly non-overlapping returns were calculated as the return over seven trading days leaving us with 209 observations as

$$r_{i,t} = log\left(\frac{P_{i,j7-7}}{P_{i,j7-14}}\right),$$

where i refers to the cryptocurrency considered, $j \in \{1, 2, 3, \cdots, 208, 209\}$ is an indicator mapping to the daily matrix, and $t \in \{1, 2, 3, \cdots, 208, 209\}$ indicates the weekly time dimension of the data matrix. Note that the price vectors $\boldsymbol{P}_i$ have dimension $\boldsymbol{P}_i \in M_{1456,1}$. This means, as an example, we compound the log-return of cryptocurrency i for the last week of our sample (i.e.,$t = 209$) as $r_{i,209} = log(P_{i,1456}/P_{i,1449})$. Moreover, data for the weekly US risk-free rate for the same sample period are downloaded from Kenneth French's website. All cryptocurrency data are denoted in terms of US dollars. The excess returns for all the cryptocurrencies are calculated by subtracting the US risk-free rate from the raw return observations. In our analysis we use weekly data since monthly data would not provide enough observations as pointed out by (Shen, Urquhart, and Wang, 2020) and in accordance with Platanakis et al. (2018) and Platanakis and Urquhart's (2019) research.[5] Descriptive statistics for the weekly raw cryptocurrency returns are reported in Table A1 in the appendix.

4. Empirical framework

4.1. Statistical inference and blocks bootstraps

A wide range of recent literature suggests (dynamic and other) dependency structures in cryptocurrencies such as speculative bubble formation (Cretarola and Figà-Talamanca, 2020; Geuder et al, 2019; Chaim and Laurini, 2019; Fry, 2018), regime switches and volatility clustering (Ardia et al., 2019; Caporale and Zekokh, 2018; Conrad et al., 2018; Chu et al., 2017; Dyhrberg, 2016; Katsiampa, 2017), and seasonal patterns (Aharon and Qadan, 2019; Baur et al., 2019; Caporale and Plastun, 2019). To provide an illustrative example of these issues, we plot the time series evolution of daily log-returns of the cryptocurrency Ethereum in Fig. A1 in the appendix. Visual inspections show very clear patterns of alternating periods of low and high volatility regimes (e.g., volatility clustering), which is a stylized fact of financial markets. We also plot the bounds for 2.5% and 97.5% of the empirical distribution.

In this regard, Fig. A1 reveals that there are often considerable spikes (both positive and negative) in the time series, indicating that the cryptocurrency is prone to outliers and extreme events. Furthermore, in the calendar year 2017 – during the formation of the Bitcoin-bubble –Ethereum generated average daily log-returns of 1.23%, which with a t-statistic of 3.33 indicated statistical significance on any level. In the calendar year 2018, however, – during the burst of the Bitcoin-bubble – Ethereum generated average daily log-returns of -0.44%, which were with a t-statistic of -1.51 statistically not different from zero. This empirical fact could be evidence for a regime switch in the first moment of the time series of Ethereum log-returns. The duration of clusters in the first and second moment needs to be taken into account to make accurate

[4] Since data for YbCoin (market capitalization USD 1903017 as of January 2, 2016) were not available, YbCoin was replaced by MonaCoin (market capitalization USD 1627740 as of January 2, 2016).

[5] Using weekly data instead of monthly data used in earlier studies (e.g., Bali et al., 2011; Bali et al., 2017; Asness et al., 2020; Hung and Yang, 2018) also meets the requirements of a scientific replication as asked for by Hou et al., 2020, who investigated 452 asset pricing anomalies and found that most anomalies fail to meet currently acceptable standards for empirical finance. They emphasize that the crux is that unlike natural sciences finance is mostly observational in nature. Therefore, it is critical to evaluate the reliability of published results against 'similar, but not identical', specifications. This paper satisfies the requirements of scientific replication in line with Hamermesh (2007) because it (*i*) uses a sample period that is different from earlier paper and (*ii*) considers a different asset market. Second, it uses a similar but not identical model: While earlier studies employ monthly data, this study uses weekly data (due to the data limitation pointed out).

statistical inference. It is noteworthy that the other cryptocurrencies used in our sample (unreported) exhibit very similar features, which is perhaps not surprising as Borri (2019) points out that cryptocurrencies appear to be highly correlated.

It is important to note that standard econometric tests do not account for these issues. Due to the overwhelming evidence of cryptocurrency returns' non-normality (see also Table 2 for our data), this paper employs one type of (non-parametric) blocks bootstrap simulation of the reported t-statistics that is robust to unknown dependency structures in the cryptocurrency data.[6] The reported t-statistics from all our empirical analyses can be therefore referred to as heteroscedasticity-and-auto correlation-robust (HAC) t-statistics. It is important to stress that the chosen block length in our blocks bootstrap addresses the issue of persistent regimes in the first and second moment as well as the reoccurrence of outliers in the data.

First, $\boldsymbol{X}$ is denoted as the regressor matrix that has the dimension $T \times K$ with $K \in \{1, 2\}$, and T refers to the number of observations. Specifically, $\boldsymbol{X}$ can be either simply a $T \times 1$ vector of ones – if we are estimating the t-statistics of the raw payoffs – or a $T \times 2$ matrix that has a vector of ones in the first column and a vector of Bitcoin excess returns in the second column – if we are estimating the risk-adjusted payoffs. Moreover, we denote the $T \times 1$ vector of MAX-payoffs as $\boldsymbol{Y}$ and then construct the block matrix $\boldsymbol{W} = [\boldsymbol{XY}]$. We start the algorithm to create $b = 1, \cdots, B$ samples of matrices $\boldsymbol{W}_1, \cdots, \boldsymbol{W}_B$ as follows: In each run b, we randomly draw with replacement a block with expected block length h from the matrix $\boldsymbol{W}$**.** For instance, if the first randomly drawn block length is n, we draw randomly with replacement with probability $1/(T-n)$ a block that has the dimension $n \times (K+1)$ from the rows $1, 2, \cdots, (T-n)$ of the matrix $\boldsymbol{W}$. This block is used to create a new matrix $\boldsymbol{W}_b$ and, hence, is the first block of dimension$n \times (K+1)$ in $\boldsymbol{W}_b$**.**

If the second randomly drawn block length is m, we randomly draw with replacement with probability $1/(T-m)$ a block from the rows $1, 2, \cdots, (T-m)$ of $\boldsymbol{W}$ that has the dimension $m \times (K+1)$ and which is stacked below the first block of observations in $\boldsymbol{W}_b$**.** This procedure is stopped when the matrix $\boldsymbol{W}_b$ has more than T rows. All rows after T are cut-off so that $\boldsymbol{W}_b$ has the same dimension as $\boldsymbol{W}$. Using random block lengths that follow a geometric distribution ensures that the $(K+1)$ data series' in $\boldsymbol{W}_b$ exhibit ergodicity.

Second, for each run b the OLS estimators are calculated as $\widehat{\boldsymbol{\beta}}_b = (\boldsymbol{X}_b{}'\boldsymbol{X}_b)^{-1}\boldsymbol{X}_b{}'\boldsymbol{y}_b$, where

$\boldsymbol{Y}_b = \begin{bmatrix} y_{1b} \\ y_{2b} \\ \vdots \\ y_{Tb} \end{bmatrix}$, and $\boldsymbol{X}_b$ can be either $\boldsymbol{X}_b = \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix}$, or $\boldsymbol{X}_b = \begin{bmatrix} 1 & x_{1b} \\ 1 & x_{2b} \\ \vdots & \vdots \\ 1 & x_{Tb} \end{bmatrix}$.

Note that $\boldsymbol{X}_b$ and $\boldsymbol{Y}_b$ are retrieved from $\boldsymbol{W}_b = [\boldsymbol{X}_b\boldsymbol{Y}_b]$**.** Specifically,

$\boldsymbol{W}_b = \begin{bmatrix} 1 & y_{1b} \\ 1 & y_{2b} \\ \vdots & \vdots \\ 1 & y_{Tb} \end{bmatrix}$, or $\boldsymbol{W}_b = \begin{bmatrix} 1 & x_{1b} & y_{1b} \\ 1 & x_{2b} & y_{2b} \\ \vdots & \vdots & \vdots \\ 1 & x_{Tb} & y_{Tb} \end{bmatrix}$, respectively. Hence, $\widehat{\boldsymbol{\beta}}_b$ is either a scalar or a 2×1 vector. Each $\widehat{\boldsymbol{\beta}}_b$ is stacked in a vector $\widehat{\boldsymbol{\theta}}_b$ such that either $\widehat{\boldsymbol{\theta}}_b{}' = (\widehat{\alpha}_1, \widehat{\alpha}_2, \cdots, \widehat{\alpha}_B)$ or $\widehat{\boldsymbol{\theta}}_b{}' = \left(\widehat{\alpha}_1, \widehat{\beta}_1, \widehat{\alpha}_2, \widehat{\beta}_2, \cdots, \widehat{\alpha}_B, \widehat{\beta}_B\right)$.

Third, the bootstrap population parameter mean vector is estimated by

$$\bar{\widehat{\boldsymbol{\theta}}}_b = \frac{1}{B}\sum\nolimits_{b=1}^{B} \widehat{\boldsymbol{\theta}}_b$$

and the bootstrap population covariance matrix of $\sqrt{T}\left(\widehat{\boldsymbol{\theta}}_{\boldsymbol{b}} - \widehat{\boldsymbol{\theta}}\right)$ is estimated by

$$\widehat{\boldsymbol{C}}^* = \frac{T}{B}\sum\nolimits_{b=1}^{B} \left(\widehat{\boldsymbol{\theta}}_b - \bar{\widehat{\boldsymbol{\theta}}}_b\right)\left(\widehat{\boldsymbol{\theta}}_b - \bar{\widehat{\boldsymbol{\theta}}}_b\right)'$$

On the main diagonal of the blocks bootstrap covariance matrix $\widehat{\boldsymbol{C}}^*$ are the bootstrapped variances for the corresponding estimated parameters in $\widehat{\boldsymbol{\theta}}$ which denotes the estimated parameter vector based on the actual data. Dividing each element in $\widehat{\boldsymbol{\theta}}$ by the square root of the corresponding element of the main diagonal in $\widehat{\boldsymbol{C}}^*$ provides our HAC-robust estimates of the t-statistics. Note also that in constructing $\boldsymbol{W}_b$, we use in each given run b a randomly drawn block length h that follows a geometric distribution, that is, h $GEO(p)$. Using a random block length of $h = 20$, we calculate$p$ according to the definition $E[h] = \frac{1-p}{p}$ for the geometric distribution. Hence, we use $p = 0.0476$ for drawing random blocks from $\boldsymbol{W}_b$. Employing a random block length that follows a geometric distribution ensures that the time series in the bootstrapped matrices $\boldsymbol{W}_b$ are ergodic (Godfrey, 2009, p.201). Finally, our blocks bootstrap approach makes use of $B = 1000$ bootstrap replications. It is noteworthy that Godfrey (2009, p.123) emphasizes that experiments have shown that this blocks bootstrap methodology can lead to much more accurate statistical inferences than the kernel-based method for estimating variance.

[6] Note that the descriptive statistics reported in Table A.1. in the appendix strongly support the evidence documented in the current literature. Specifically, virtually all cryptocurrency returns exhibit excess kurtosis and a high level of skewness.

4.2. Sorting the portfolios

Unlike Bali et al. (2011) who use monthly data, we start our empirical analysis by sorting all twenty cryptocurrencies at the beginning of each week by the maximum daily log-return during the last week (i.e., seven days) in an increasing order from lowest to highest daily maximum log-return. The rationale of this approach is that first of all Bali et al.'s (2011) findings indicate that average raw return differences in the stock markets between the low MAX and high MAX equity portfolios are −0.98% per month for stocks with the maximum return in the first half of the month versus −0.95% per month for those with the maximum return in the second half of the month. This implies that this effect is not driven by a certain week within the previous month. As a result, the MAX-effect should persist even when using data of the most recent previous week. The second issue why we employ weekly data for the analysis of holding period returns is simply data availability. In this regard, Shen et al. (2020), who propose a three factor pricing model for the cryptocurrency market, argue that monthly data would not provide enough observations in the case of most recent cryptocurrency market data for all the smaller cryptocurrencies than Bitcoin. Finally, recent research on the profitability of technical trading rules implemented on cryptocurrency markets documents that cryptocurrencies appear to be short-memory processes (Grobys et al., 2020).

Next, the cryptocurrencies are allocated into five portfolio groups. The first quintile comprises those cryptocurrencies that have the lowest daily maximum log-return within the last week, whereas the fifth quintile comprises those cryptocurrencies that exhibit the highest daily maximum log-return over the same period. The zero-cost strategy is long on the fifth and short on the first quintile, and the allocation is updated based on this strategy at the beginning of each week.

Tables 1 and 2 report the estimated average point estimates for each quintile, the zero-cost portfolio, the trimmed zero-cost portfolio and the descriptive statistics of the portfolio distributions. The cumulative returns of the zero-cost portfolio are plotted in Fig. 1. From Fig. 1 we observe that the cumulative returns virtually linearly decrease across time. Moreover, we learn from Table 1 that the average predicted return linearly decreases as we move from lowest to highest maximum daily return portfolio, which confirms the corresponding literature in equity market research (Bali et al., 2011, 2017; Walkshäusl, 2014; Chan and Chui, 2016; Hung and Yang, 2018; Asness et al., 2020). The zero-cost portfolio generates −1.54% weekly average returns with a HAC-robust t-statistic of −2.68 indicating statistical significance even on a 1% level. While the eco-

Table 1
Predicted raw returns. A set of twenty cryptocurrencies is employed and sorted at the beginning of each week by the maximum daily log-return during the last week in an increasing order from lowest to highest daily maximum log-return. The cryptocurrencies are then allocated to five portfolio groups. The first quintile comprises those cryptocurrencies that have the lowest daily maximum log-return within the last week, whereas the fifth quintile comprises those cryptocurrencies that exhibit the highest daily maximum log-return over the same period. The zero-cost strategy is long on the fifth and short on the first quintile. This strategy is updated at the beginning of each week. Trimmed data denotes the spread where 2.50% of each tail is cut off. The sample period is from January 2016 until December 2019. HAC-robust t-statistics are given in parentheses.

Metric	Low (L)	Group 2	Group 3	Group 4	High (H)	(H-L)	(H-L)[a]
Average return	1.33	1.38	0.55	1.08	−0.22	−1.54***	−1.89***
(HAC-robust t-statistic)						(−2.68)	(−2.83)
Past MAX	3.18	5.23	7.27	10.24	21.39		
Past VOLA	1.33	1.66	1.97	2.50	4.42		

Table 2
Descriptive portfolio statistics. We employ a set of twenty cryptocurrencies and sorted them at the beginning of each week by the maximum daily log-return during the last week in an increasing order from lowest to highest daily maximum log-return. The cryptocurrencies are then allocated to five portfolio groups. The first quintile (L) comprises those cryptocurrencies that have the lowest daily maximum log-return within the last week, whereas the fifth quintile (H) comprises those cryptocurrencies that exhibit the highest daily maximum log-return over the same period. The zero-cost strategy (H-L) is long on the fifth and short on the first quintile. This strategy is updated at the beginning of each week. This table reports the descriptive statistics of the quintile portfolios, where mean is each group's sample average, median is each group's value corresponding to the 50% of the sorted observations in that corresponding sample, minimum and maximum denote each group's lowest and highest weekly return over the sample period, std.dev. is each group's standard deviation over the sample period, skewness and kurtosis measure each group's third and fourth central moment, whereas Jarque-Bera denotes each group's Jarque-Bera test statistic (assuming normality under the null hypothesis) and the last row denoted as probability is the p-value corresponding to each group's Jarque-Bera test statistic. The sample period is from January 2016 until December 2019.

Metric	Low (L)	Group 2	Group 3	Group 4	High (H)	(H-L)
Mean	1.33	1.38	0.55	1.08	−0.22	−1.54
Median	1.19	0.13	−0.20	−0.39	−1.18	−1.89
Maximum	51.11	48.19	58.93	64.89	70.15	59.87
Minimum	−38.22	−48.44	−59.93	−46.53	−72.09	−40.81
Std. Dev.	13.23	13.90	13.33	15.47	16.80	14.21
Skewness	0.34	0.41	0.11	0.72	0.67	0.73
Kurtosis	4.21	5.06	6.01	5.77	6.69	6.30
Jarque-Bera	16.80	42.42	79.21	84.57	133.25	112.93
Probability	0.00	0.00	0.00	0.00	0.00	0.00

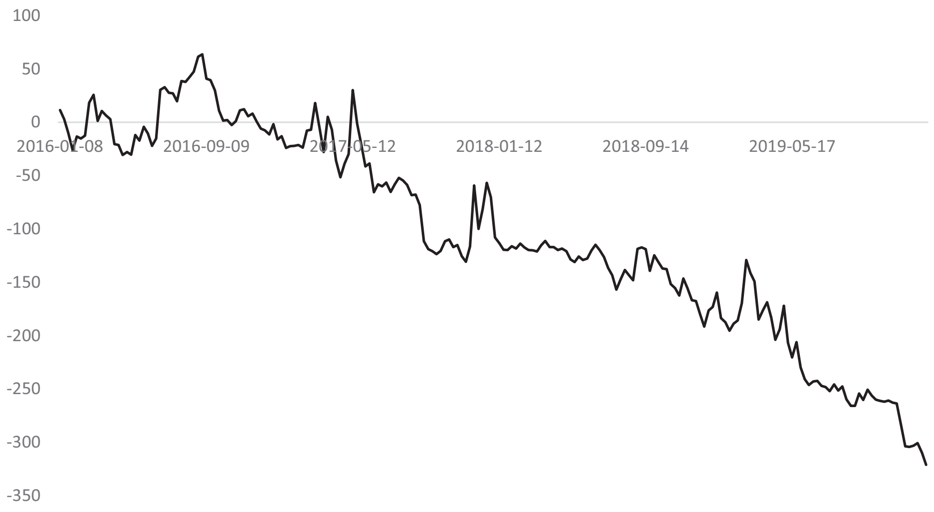

Fig. 1. Cumulative returns. This figure plots the cumulative returns of the zero-cost MAX portfolio over time. The sample period is from January 2016 until December 2019.

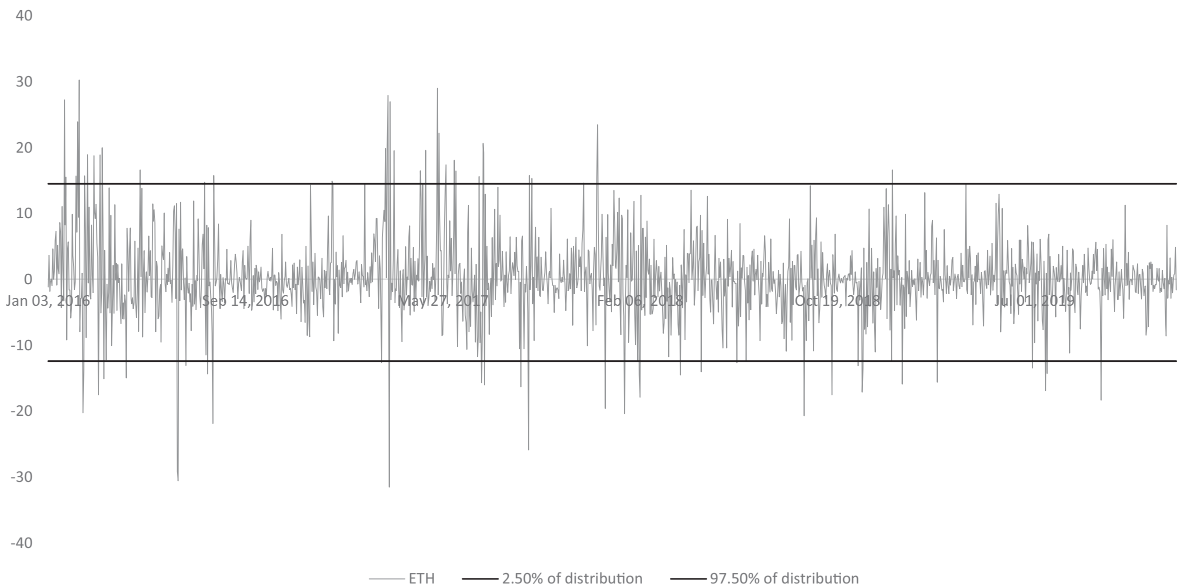

Fig. A1. This table plots the daily log-returns of the cryptocurrency Ethereum over the sample period. The bounds for 2.5% and 97.5% of the empirical distribution are also provided. The sample is from January 2, 2016 until December 31, 2019.

nomic magnitude as reported here exceeds the spread documented by Bali et al. (2011) and Bali et al. (2017) by a large margin, our findings confirm both their and Asness et al.'s (2020) findings in that the past volatility of the high MAX portfolio is highly correlated with past idiosyncratic volatility of individual cryptocurrency portfolio groups.

Indeed, the past portfolio volatility is strictly linearly increasing as we move from the lowest to the highest MAX group. It may be surprising that the average of the past MAX which ranges from 3.18% to 21.39% average daily maximum return, is very close to the figures documented by Bali et al. (2011) who report figures between 1.30% and 23.60%. This finding is perhaps related to the sorting procedure as Bali et al. (2011) use deciles and we employ quintiles. Furthermore, one could argue that the enormous payoff might be attributed to a few observations in the tails. To address this concern, we trim the data and cut-off 2.50% of the observations on both the left- and right-hand tail of the payoff distribution. From Table 1 we observe that the average payoff even increases after trimming, which strongly suggests that this pattern cannot be attributed to the rare observations in the tails.

Recent research argues that cryptocurrency returns are highly correlated with each other (Borri, 2019). One may wonder whether the payoff of the zero-cost strategy can be explained by an exposure against the market risk. To address this concern, we regress the zero-cost portfolio returns on the excess returns of Bitcoin, that is,

$$MAX_t = \alpha + \beta BTC_t^{ex} + u_t, \tag{1}$$

where MAX_t denotes the return on the zero-cost portfolio that is long on those cryptocurrencies that had the lowest maximum daily log-return in the last week prior to portfolio formation and short on those cryptocurrencies that had the highest daily log-return in the last week prior to portfolio formation. Moreover, BTC_t^{ex} denotes Bitcoin returns in excess of the US risk-free tate, α and β are parameters to be estimated and u_t is an ergodic stationary stochastic process that is assumed to be distributed as $u_t\left(0, \sigma_{u_t}^2\right)$. The point estimate for α is -1.75 per week with corresponding HAC-robust t-statistic of -2.70 indicating statistical significance even on a 1% significance level. Next, one could wonder how sensitive our results are with respect to the chosen random block length of $h = 20$ in the blocks bootstrap procedure. In Table A3 in the appendix, we report the corresponding HAC-robust t-statistics for various block lengths $h = \{10, 15, 20, 25, 30\}$. Our results are robust with respect to the changes in the random block length in the bootstrap simulation.

As mentioned in Bali et al. (2011), investors may pay high prices for assets that have experienced extreme positive returns in the past in the expectation that this behavior will reoccur in the future. Hence, the question arises whether these expectations are rational. While Bali et al. (2011) explore this issue by examining the average month-to-month portfolio transition matrix, our data span requires an investigation of the week-to-week portfolio transition matrix. Specifically, in our research context the portfolio allocation transition matrix indicates the average probability that a cryptocurrency in quintile i in the current week will move to quintile j in the subsequent week. The results are reported in Table 5. Since we operate with 209 weekly observations and we need one month for determining the previous week MAX values, the reported figures are the averages across 207 transitions. If the maximum daily returns are completely random, then each entry in the matrix should equal 0.2 (20%) as a high or low maximum return in one week should not provide any information about the maximum return in the following week.

We learn from Table 5 that the elements (1,1) and (5,5) both exceed 20%. Table 5 also illustrates the corresponding t-statistic of the hypothesis that the transition probability (i, j) is equal to 20%. We see that the transition probabilities (1,1) and (5,5) are both statistically significant even on a 1% significance level. While Bali et al. (2011) document that stocks in decile 10 (which indicates the group exhibiting the maximum daily return in the last month) have a 35% chance of appearing in the same decile next month, our results strongly support Bali et al.'s (2011) because 34% of all cryptocurrencies that are in quintile 5 (indicating the cryptocurrencies group exhibiting the maximum daily return in the last week) appear on average in the same group next week. It is noteworthy that the chance of cryptocurrencies that were in the high MAX portfolio end up again in the same portfolio is even higher than the transition probabilities (5,1) and (5,2) taken together. This result strongly indicates that cryptocurrencies that have experienced extreme positive returns in the past are more likely to generate extreme positive returns in the future than generating extreme negative returns. This, in turn, implies that investors' expectations appear to be rational.

4.3. Is lottery-like demand priced in the cross section of cryptocurrency returns?

Bali et al. (2011) point out that a different way to examine the persistence of extreme positive daily returns is to look at firm-level cross-sectional regressions of MAX on lagged predictor variables. Investigating this issue in the U.S. stock market, for each month they run a regression across firms of the maximum daily return within that month on the maximum daily return from the previous month and seven lagged control variables. These control variables have in earlier literature been found to be associated with the cross section of expected equity market returns. Specifically, they control for beta, size, book-to-market ratio, momentum, reversal, illiquidity and idiosyncratic volatility.

The current literature on cryptocurrencies documents a short term reversal effect in the cross section of cryptocurrencies (Shen, Urquhart, and Wang, 2020; Grobys and Sapkota, 2019). Moreover, Bali et al. (2011) highlight that the MAX-effect is strongly related to idiosyncratic volatility and reversals. Motivated by these two suggestions, also operational in the case of cryptocurrencies, we employ at a cryptocurrency-level cross-sectional regressions by first regressing the excess returns of each cryptocurrency i on its maximum daily return in week t-1 (MAX), the excess return of week t-1 (reversal, denoted by $CRYPTO_{i,t-1}^{ex}$), and the idiosyncratic volatility in week t-1 measured by the individual weekly volatility of cryptocurrency i. The corresponding regressions are then given by

$$CRYPTO_{i,t}^{ex} = \alpha_i + \beta_{i,1} MAX_{i,t-1}^{ex} + \beta_{i,2} CRYPTO_{i,t-1}^{ex} + \beta_{i,3} IVOL_{i,t-1}^{ex} + e_{i,t} \tag{2.1}$$

where $CRYPTO_{i,t}^{ex}$ denotes the weekly excess log-return of cryptocurrency i at time t, $MAX_{i,t-1}^{ex}$ denotes the maximum daily excess log-return of cryptocurrency i at time t-1, $IVOL_{i,t-1}^{ex}$ denotes the idiosyncratic weekly volatility of cryptocurrency i at time t-1, $e_{i,t}$ is a cryptocurrency-specific white noise term assumed to be distributed as $e_t\left(0, \sigma_{e_t}^2\right)$ and α_i, $\beta_{i,1}$, $\beta_{i,2}$, $\beta_{i,3}$ are parameters that are estimated of this dynamic model. The point estimates are reported in Table A5 in the appendix. Consistent with Bali et al. (2011), the time series average sensitivity against MAX, that is, $\sum_{i=1}^{K} \hat{\beta}_{i,1}$ is negative and estimated at

-0.1938. To assess the cross-sectional impact on pricing the cryptocurrencies, we place the estimated betas in a regressor matrix $\boldsymbol{B}$, and stack the sample averages of cryptocurrency excess returns in a vector denoted $\mathbf{z}$. Specifically,

$$\boldsymbol{B} = \begin{bmatrix} 1 & \hat{\beta}_{1,1} & \hat{\beta}_{1,2} & \hat{\beta}_{1,3} \\ 1 & \hat{\beta}_{2,1} & \hat{\beta}_{2,2} & \hat{\beta}_{2,3} \\ \vdots & \vdots & \vdots & \vdots \\ 1 & \hat{\beta}_{K,1} & \hat{\beta}_{K,2} & \hat{\beta}_{K,3} \end{bmatrix}, \text{ and } \boldsymbol{z} = \begin{bmatrix} \sum_{t=1}^{T} CRYPTO_{1,t}^{ex} \\ \sum_{t=1}^{T} CRYPTO_{2,t}^{ex} \\ \vdots \\ \sum_{t=1}^{T} CRYPTO_{K,t}^{ex} \end{bmatrix}.$$

Then, the parameter vector of cross-sectional risk-premiums, $\boldsymbol{\lambda}$, is estimated as

$$\widehat{\boldsymbol{\lambda}} = (\boldsymbol{B}'\boldsymbol{B})^{-1}\boldsymbol{B}'\boldsymbol{z} \tag{2.2}$$

yielding $\widehat{\boldsymbol{\lambda}} = (0.39, 3.47, 4.43, 0.51)'$. Using blocks bootstrap as described in Section 4.1, defining $\boldsymbol{W} = [\boldsymbol{Bz}]$, and employing a random block length of $h = 3$ and $B = 1000$ bootstrap replications, the corresponding HAC-robust covariance matrix $\widehat{\boldsymbol{C}}_{\lambda}^{*}$, given by $\widehat{\boldsymbol{C}}_{\lambda}^{*} = \frac{T}{B}\sum_{b=1}^{B}\left(\widehat{\boldsymbol{\lambda}}_b - \bar{\widehat{\boldsymbol{\lambda}}}_b\right)\left(\widehat{\boldsymbol{\lambda}}_b - \bar{\widehat{\boldsymbol{\lambda}}}_b\right)'$ is then estimated to be

$$\widehat{\boldsymbol{C}}_{\lambda}^{*} = \begin{bmatrix} 0.0236 & -0.0529 & -0.0458 & -0.0114 \\ -0.0529 & 0.8152 & -0.3338 & 0.2126 \\ -0.0458 & -0.3338 & 1.9599 & -0.1933 \\ -0.0114 & 0.2126 & -0.1933 & 0.0629 \end{bmatrix}$$

Hence, the corresponding vector of HAC-robust t-statistics, $\boldsymbol{t}_{\widehat{\lambda}}$ are estimated as $\boldsymbol{t}_{\widehat{\lambda}} = (2.54, 3.83, 3.18, 2.03)$.[7] This result has some important implications. First, lottery-like demand is clearly priced in the cross section of cryptocurrency log-returns. Higher exposure to beta risk associated with MAX is positively related to the cross section of expected cryptocurrency returns. The economic magnitude of the risk premium is close to the risk premium related to the reversal's beta risk. Second, idiosyncratic volatility appears to matter as well but the economic magnitude is small and the t-statistic is – even if indicating statistical significance on a common 5% – considerably smaller than the risk premium related to MAX and reversals. Third, this model is capable of explaining 61% of the variation in cross-sectional average returns. The explanatory power of this model is considerably higher than that of Shen et al.'s (2020) three-factor model that produces an R-square value of (only) 16%.

4.4. Other robustness checks

Even though cryptocurrency markets are – unlike equity markets – traded 24/7, one could wonder if the results are robust if a one-day delay between portfolio formation and allocation is implemented. For instance, in momentum research, Jegadeesh and Titman (1993) propose in their seminal paper to implement a one-week delay between the portfolio formation period and the holding period to account for microstructure issues such as bid-ask spread, price pressure, and lagged reaction effects. Since cryptocurrencies appear to be short memory processes, as documented by Grobys et al. (2020), we address this issue by implementing the MAX strategy by discounting the most recent past trading day when determining the maximum daily log-return in the previous week. The results are reported in Tables 3 and 4. The results are virtually the same. Again, we regress the zero-cost strategy that skips one day between formation and holding period on the Bitcoin excess returns. The results are reported in Table A4 in the appendix and confirm our previous findings. We also report the corresponding HAC-robust t-statistics for various random block length variations as in Section 4.2. Our results remain unchanged.

Another concern could be a potential survivorship bias. However, a survivorship bias in our study's research context would be to view the performance of existing cryptocurrencies or funds in the market as a representative comprehensive sample without regarding those that had been unsuccessful. This, in turn, would bias our results in terms of overestimation of our MAX strategy's performance. Our study explicitly accounts for the survivorship bias because it uses cryptocurrencies that exhibited at the beginning of the sample, that is, on January 2, 2016, the highest market capitalization. This information had been, however, available to the naïve investor.

Furthermore, as pointed out by Ahmed, Grobys, and Sapkota (2020), one could argue that the rank of market capitalizations of our set of cryptocurrencies could be too volatile during the sample period, which could cast doubt on the reliability of our results. To investigate this issue, we report in Table A6 the rank of our cryptocurrencies in terms of market capitalization in the beginning and at the end of the sample. The rank correlation is estimated at 0.4496 with a t-statistic of 7.24 statistically significant on any level. This result confirms the findings of Ahmed et al. (2020) who explore the profitability of technical trading implemented among ten large cap cryptocurrencies that exhibit the so-called 'privacy function'. The

[7] Note that the standard OLS estimates for the t-statistics are estimated as $\boldsymbol{t}_{\widehat{\lambda}} = (3.34, 6.99, 4.12, 4.06)$. These estimates are, however, upwards biased. There are different alternatives to address this issue e.g. in monthly data. One application of Fama's and MacBeth's (1973) cross-sectional regressions employs a rolling time window of 60 observations to estimate the betas and consecutively estimates the corresponding lambda vector. The problem with this approach is that our sample does not provide enough observations to generate reasonable estimates. Hence, given our research setting, bootstrapping serves as a reasonable choice for estimating the covariance matrix. The advantages of bootstrapping are detailed by Godfrey (2009).

Table 3
Predicted raw returns with skipping one day between formation and holding period. A set of twenty cryptocurrencies is employed and sorted at the beginning of each week by the maximum daily log-return during the last week in an increasing order from lowest to highest daily maximum log-return. In determining the highest daily maximum log-return, the most recent past return is skipped. The cryptocurrencies are then allocated to five portfolio groups. The first quintile comprises those cryptocurrencies that have the lowest daily maximum log-return within the last week, whereas the fifth quintile comprises those cryptocurrencies that exhibit the highest daily maximum log-return over the same period. The zero-cost strategy is long on the fifth and short on the first quintile. This strategy is updated at the beginning of each week. The sample period is from January 2016 until December 2019. HAC-robust *t*-statistics are given in parentheses.

Metric	Low (L)	2	3	4	High (H)	(H-L)	(H-L)[a]
Average return	1.65	1.01	0.98	0.65	−0.17	−1.82**	−2.24***
(HAC-robust *t*-statistic)						(−2.43)	(−2.87)
Past MAX	2.73	4.74	6.66	9.48	19.75		
Past VOLA	1.29	1.59	1.89	2.46	4.33		

*Statistical significant on a 10% level.
** Statistical significant on a 5% level.
[a] Data are trimmed at 5%.

Table 4
Descriptive portfolio statistics with skipping one day between formation and holding period. This table reports the descriptive statistics of the quintile portfolios sorted by the maximum daily log-return during the last week while skipping the most recent past daily log-return. The sample period is from January 2016 until December 2019.

Metric	Low (L)	Group 2	Group 3	Group 4	High (H)	(H-L)
Mean	1.65	1.01	0.98	0.65	−0.17	−1.82
Median	1.24	0.19	−0.29	−0.50	−1.25	−1.95
Maximum	51.11	46.01	62.76	60.87	70.15	62.92
Minimum	−38.22	−48.44	−59.93	−46.53	−72.09	−40.81
Std. Dev.	13.41	13.23	14.20	14.55	16.97	15.01
Skewness	0.35	0.14	0.28	0.36	0.73	0.77
Kurtosis	4.15	4.98	5.86	4.60	6.72	6.38
Jarque-Bera	15.69	34.82	73.81	26.80	138.74	119.36
Probability	0.00	0.00	0.00	0.00	0.00	0.00

Table 5
Transition matrix. This table reports the weekly transition matrix. Each entry denotes the probability of transition from group *i* to *j* in the next week. This table also reports the *t*-statistic of the hypothesis that the transition probability (i, j) is equal to 0.20. The sample period is from January 2016 until December 2019. The *t*-statistics are given in parentheses.

i|*j*	Low (L)	Group 2	Group 3	Group 4	High (H)
Low (L)	0.2705***	0.2017	0.2186	0.1655***	0.1437***
	(4.86)	(0.14)	(1.50)	(−2.94)	(−4.78)
Group 2	0.2089	0.2464***	0.2017	0.2041	0.1389***
	(0.71)	(3.37)	(0.14)	(0.32)	(−5.35)
Group 3	0.2222*	0.2307**	0.1896	0.1932	0.1643***
	(1.73)	(2.33)	(−0.81)	(−0.51)	(−2.94)
Group 4	0.1643***	0.1812	0.2150	0.2258**	0.2138
	(−3.25)	(−1.56)	(1.15)	(2.00)	(1.07)
High (H)	0.1341***	0.1401***	0.1751**	0.2114	0.3394***
	(−5.63)	(−5.08)	(−2.04)	(0.94)	(8.84)

* Statistical significant on a 10% level.
** Statistical significant on a 5% level.
*** Statistical significant on a 1% level.

authors find that the rank correlation of their set of cryptocurrencies is 0.77 and statistically significant over the 2016–2018 period. Hence, in line with Ahmed et al. (2020) we infer that even though there is variation in market capitalizations across time, the rank among the large cap cryptocurrencies is, on average, fairly stable confirming the reliability of our results.

Next, one could wonder whether the results would change if we included Bitcoin in the sample due to its overwhelming market dominance. First, we chose an equal-weighted scheme for the portfolios which is in line with the literature on traditional currencies. That means that even if Bitcoin was included and allocated to either long or short leg, its return would have only 25% of the overall portfolio weight. Nevertheless, to get more clarity on this issue, we next include Bitcoin in the sample and exclude NEM from the sample. We again employ portfolio sorts and allocate all cryptocurrencies into five portfolio groups. The first quintile comprises those cryptocurrencies that have the lowest daily maximum log-return within the last week, whereas the fifth quintile comprises those cryptocurrencies that exhibit the highest daily maximum log-return over the same period. The zero-cost strategy is long on the fifth and short on the first quintile, and the allocation is updated based on this strategy at the beginning of each week. The results are reported in Table A7 in the appendix. The results are virtually the same and our conclusions remain unchanged.

Finally, one could wonder to which extend the reported statistical significances would change if we used traditional heteroscedasticity-and-autocorrelation-robust (HAC) *t*-statistics such as those proposed in Newey and West (1987). To address this issue, we report in Table A8 in the appendix the raw and risk-adjusted MAX-payoffs as reported in Tables 1, 3, A3 and A4, respectively, using (*i*) standard *t*-statistics, (*ii*) our proposed HAC-robust *t*-statistics using a random block length of $h = 20$, and heteroscedasticity-and-autocorrelation-robust *t*-statistics as proposed by Newey and West (1987) using three different lag-lengths l with l={1,3,5}. From Table A8. we observe that using standard *t*-statistics that do not account for any dependency structures in the data would suggest that only the risk-adjusted MAX strategy implemented by skipping the most recent past trading day and calculating the maximum daily log-return between trading day when determining the maximum daily log-return in the previous week generates an average payoff significant on a 5% level (*t*-statistic −2.08). Using Newey and West (1987) covariance estimators, accounting for one lag suggests that only risk-adjusted MAX strategies generate average payoffs significant on a 5% level (*t*-statistic −2.14 in both cases). As we move to the Newey and West (1987) covariance estimators accounting for five lags, we obtain similar levels of statistical significance as we obtain using our proposed heteroscedasticity-and-autocorrelation-robust test statistics using a random block length of $h = 20$. The findings of our analysis are in line with Godfrey (2009), who argues that asymptotically valid tests such as the HAC-robust *t*-tests as proposed by Newey and West (1987) may involve severe size distortions, especially when the data set is small and the data are fat-tailed and highly skewed. Moreover, it is important to stress that using Newey and West (1987) covariance estimators, we lose (due to the lag structure) information that could be important for statistical inference. As an example, cryptocurrency data suggest latent regimes in the first moment that last considerably longer than five weeks (see Section 4.1.). This is not accounted for when using Newey and West (1987) covariance estimators. Using blocks bootstraps in association with a randomly chosen block length we first (*i*) ensure, that latent regimes in the first and/or second moment in that data generating process are preserved, and second (*ii*) we do not lose valuable information in the data.

5. Conclusion

This study investigates lottery-like behavior in new digital financial markets. To account for market liquidity, we obtained data for a set of 20 cryptocurrencies that exhibited the highest market capitalization as of January 2, 2016. We excluded Bitcoin from the main sample because we employed Bitcoin as risk factor in regressions adjusting for market risk. Motivated by the recent literature on cryptocurrency research emphasizing that cryptocurrency markets are rather subject to speculation than medium of exchange, this study contributes to the literature by exploring another type of speculative behavior in cryptocurrency markets, that is, lottery-like demand. The general set-up of this study follows the literature on investigating this issue for equity markets. However, there are also some important differences. For instance, equity market research typically operates with monthly data, whereas our study uses weekly data, as the most recent literature argues first that cryptocurrencies appear to be short-memory processes, and second using lower frequented data – such as monthly data – would not provide enough observations for reasonable statistical inference.

Noting that there is a wide range of literature on cryptocurrencies that indicates excessive tail risks, non-linearities (such as regimes switches), and volatility clustering, we propose an econometric estimation procedure based on blocks bootstraps to account for the poor performance of asymptotical tests in terms of severe size distortions. Confirming earlier studies, the current research finds that the difference between returns on cryptocurrency portfolios with the highest and lowest maximum daily returns is negative. However, the economic magnitude is considerably higher (e.g., −1.54% per week) than the figures documented in equity markets. Hence, our study concluded that investors find cryptocurrencies that exhibit high payoffs desirable and hence, they offer lower future returns. The results are robust.

From a practical point of view, our results may have important implications for portfolio management investing in cryptocurrencies. In this regard, it is important to stress that an essential difference between traditional asset markets (such as equity markets) and cryptocurrency markets is the availability of short-selling.[8] Specifically, investors in cryptocurrency markets face short selling constraints implying that the MAX strategy could only be implemented as a long-only strategy. Therefore, a speculative investment strategy could involve betting on cryptocurrencies exhibiting the lowest maximum return in the week preceding portfolio formation. Exploring the profitability of such investment vehicles is beyond the scope of this paper and hence left for future research.

Finally, our findings are interesting also from a theoretical point of view because they suggest that the similar behavioral mechanisms of underlying investor behavior are present even in digital financial markets. As more data becomes available, future research is encouraged to investigate this issue using monthly data. Moreover, it is reasonable to assume that a lottery-prone investor will be monitoring small-cap cryptocurrencies extensively. Future research is therefore encouraged

[8] To the best of our knowledge, Bitcoin is the only cryptocurrency serving as underlying for financial derivatives. In this regard, Corbet et al. (2018) explore the effects of Bitcoin futures and find that spot volatility has increased following the appearance of futures contracts.

to investigate the MAX-effect for utility tokens or security tokens because these digital financial tools are likely to be subject to even more speculative behavior than the market for cryptocurrencies originally designed for as a medium for transaction.

Appendix

See Table A2.

Table A1
Descriptive statistics. This table reports the descriptive statistics of the cryptocurrencies used in this study. The weekly data is from January 2016 until December 2019.

	BITSHARES	BLACKCOIN	BTC	BYTECOIN	CLAMS	DASH	DODGE	EMERCOIN	ETH	FACTOM	LTC
Mean	0.76	0.18	1.30	0.93	−0.39	1.18	1.28	−0.29	2.35	0.61	1.15
Median	−0.79	−0.30	0.60	−1.65	0.00	0.10	−0.99	−1.77	0.83	−1.20	−0.31
Maximum	83.18	47.16	55.91	124.98	61.62	56.47	74.69	82.61	95.98	80.27	104.45
Minimum	−62.48	−80.93	−37.71	−48.26	−97.48	−38.12	−81.43	−82.81	−43.18	−61.35	−63.52
Std. Dev.	20.71	19.74	10.65	22.80	21.07	15.36	18.28	21.11	18.24	19.69	15.85
Skewness	0.82	−0.53	0.47	1.90	−1.03	0.55	0.80	0.72	1.37	0.79	1.46
Kurtosis	5.84	4.78	6.54	9.73	7.06	4.28	7.68	6.38	7.87	5.96	13.02
Jarque-Bera	93.36	37.25	116.72	519.79	180.09	24.60	213.03	117.08	272.03	98.42	947.74
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

	MAIDSAFECOIN	MONACOIN	MONERO	NAMECOIN	NEM	NXT	PEERCOIN	RUBYCOIN	STELLAR	XRP
Mean	0.71	1.07	2.17	0.00	2.32	0.12	−0.43	−0.50	1.55	1.65
Median	0.41	−1.81	0.23	0.75	−0.86	−2.74	−1.31	0.94	−1.79	−1.33
Maximum	52.93	198.76	65.63	96.20	94.85	139.27	61.86	83.95	169.78	135.55
Minimum	−49.95	−58.52	−39.55	−84.43	−58.00	−64.11	−47.66	−105.31	−59.92	−49.53
Std. Dev.	15.94	23.57	16.91	18.74	21.59	21.06	15.03	23.83	22.27	20.67
Skewness	−0.01	3.70	0.91	−0.14	1.42	1.80	0.91	−0.26	2.97	2.68
Kurtosis	3.55	27.75	5.27	9.57	6.95	12.27	6.17	5.67	21.02	14.96
Jarque-Bera	2.64	5810.77	73.68	376.89	206.71	861.43	116.07	64.43	3134.73	1494.74
Probability	0.27	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table A2
Market capitalizations. This table reports the market capitalizations of the set of cryptocurrency used in this study. The market capitalizations are retrieved from coinmarketcap.com as of January 2, 2016.

No	Cryptocurrency	Market Capitalization
0	BTC	6,467,437,080
1	XRP	201,799,631
2	LTC	152,873,521
3	ETH	73,843,278
4	DASH	19,794,713
5	DOGE	14,940,681
6	PPC	9,756,959
7	BTS	8,591,688
8	XLM	8,436,465
9	NXT	6,863,998
10	MAID	6,789,470
11	NMC	6,073,338
13	FCT	5,646,935
13	BCN	5,582,979
14	XMR	5,295,952
15	RBY	2,763,547
16	EMC	2,729,184
17	CLAM	2,199,047
18	BLK	2,000,105
19	MONA	1,627,740
20	XEM	1,573,830

Table A3
Risk-adjusted returns. This table reports the estimated parameters of the time series regression given by $MAX_t = \alpha + \beta BTC_t^{ex} + u_t$, where MAX_t denotes a zero-cost portfolio that is long on those cryptocurrencies that had the lowest maximum daily log-return in the last week prior to portfolio formation and short on those cryptocurrencies that had the highest daily log-return in the last week prior to portfolio formation. Moreover, BTC_t^{ex} denotes Bitcoin returns in excess of the US risk-free rate, α and β are parameters to be estimated and u_t is an ergodic stationary stochastic process. The sample period is from January 2016 until December 2019. HAC-robust *t*-statistics are given in parentheses.

Block length *h*	alpha	beta	*t*-statistic alpha	*t*-statistic beta
10	−1.75**	0.16	−2.42	1.05
15	−1.75**	0.16	−2.55	1.04
20	−1.75***	0.16	−2.70	1.10
25	−1.75***	0.16	−2.81	1.08
30	−1.75***	0.16	−2.70	1.15

** Statistical significant on a 5% level.
*** Statistical significant on a 1% level.

Table A4
Risk-adjusted returns with skipping one day between formation and holding period. This table reports the estimated parameters of the regression given by $MAX_t^* = \alpha + \beta BTC_t^{ex} + u_t$, where MAX_t^* denotes a zero-cost portfolio that is long on those cryptocurrencies that had the lowest maximum daily log-return in the last week prior to portfolio formation and short on those cryptocurrencies that had the highest daily log-return in the last week prior to portfolio formation. In determining the highest daily maximum log-return, this strategy skips the most recent past daily log-return. Moreover, BTC_t^{ex} denotes Bitcoin returns in excess of the US risk-free rate, α and β are parameters to be estimated and u_t is an ergodic stationary stochastic process. The sample period is from January 2016 until December 2019. HAC-robust *t*-statistics are given in parentheses.

Block length *h*	alpha	beta	*t*-statistic alpha	*t*-statistic beta
10	−2.14**	0.25	−2.38	1.31
15	−2.14**	0.25	−2.34	1.32
20	−2.14**	0.25	−2.35	1.32
25	−2.14**	0.25	−2.46	1.36
30	−2.14**	0.25	−2.32	1.36

** Statistical significant on a 5% level.

Table A5
Time series regressions. This table reports the estimated parameters of the time series regression, $CRYPTO_{i,t}^{ex} = \alpha_i + \beta_{i,1} MAX_{i,t-1}^{ex} + \beta_{i,2} REVERSAL_{i,t-1}^{ex} + \beta_{i,3} IVOL_{i,t-1}^{ex} + u_{i,t}$, where $CRYPTO_{i,t}^{ex}$ denotes the weekly excess log-return of cryptocurrency *i* at time *t*, $MAX_{i,t-1}^{ex}$ denotes the maximum daily excess log-return of cryptocurrency *i* at time *t*-1, $IVOL_{i,t-1}^{ex}$ denotes the idiosyncratic weekly volatility of cryptocurrency *i* at time *t*-1, $u_{i,t}$ is a cryptocurrency-specific white noise term and α_i, $\beta_{i,1}$, $\beta_{i,2}$, $\beta_{i,3}$ are parameters that are estimated in this time series model.

Cryptocurrency	Average excess returns	β_{MAX}	$\beta_{Reversal}$	$\beta_{Volatility}$
XRP	1.62	−1.13	0.45	5.18
LTC	1.12	0.55	−0.05	−1.77
ETH	2.32	0.78	−0.10	−2.42
DASH	1.16	0.27	0.05	0.27
DOGE	1.25	−0.78	0.32	3.11
PPC	−0.46	0.23	−0.08	−1.20
BTS	0.73	−0.92	0.39	5.27
XLM	1.52	−0.24	0.17	1.57
NXT	0.10	−1.85	0.44	8.46
MAID	0.68	0.59	−0.08	−0.72
NMC	−0.03	−0.07	−0.08	−0.19
FCT	0.59	0.25	−0.16	0.00
BCN	0.91	−0.55	0.20	2.38
XMR	2.14	0.92	0.01	−2.90
RBY	−0.53	0.08	−0.04	−1.36
EMC	−0.31	−0.73	0.21	2.83
CLAM	−0.41	−0.52	0.21	1.16
BLK	0.16	−0.44	0.04	1.90
MONA	1.04	−0.34	0.06	2.11
XEM	2.29	0.05	0.04	1.25

Table A6
Rank correlations. This table reports the rank correlations of the cryptocurrencies as of the beginning of the sample (e.g., January 2, 2016) and the end of the sample (e.g., December 28, 2019).

Cryptocurrency	Rank as of January 2, 2016	Rank as of December 28, 2019
XRP	2	3
LTC	3	6
ETH	4	2
DASH	5	28
DOGE	6	34
PPC	7	413
BTS	8	105
XLM	9	10
NXT	10	291
MAID	11	130
NMC	12	352
FCT	13	205
BCN	14	92
XMR	15	16
RBY	16	1303
EMC	17	471
CLAM	18	1261
BLK	19	564
MONA	20	93
XEM	21	31

Table A7
Predicted raw returns using Bitcoin in the sample. A set of twenty cryptocurrencies including Bitcoin is employed and sorted at the beginning of each week by the maximum daily log-return during the last week in an increasing order from lowest to highest daily maximum log-return. The cryptocurrencies are then allocated to five portfolio groups. The first quintile comprises those cryptocurrencies that have the lowest daily maximum log-return within the last week, whereas the fifth quintile comprises those cryptocurrencies that exhibit the highest daily maximum log-return over the same period. The zero-cost strategy is long on the fifth and short on the first quintile. This strategy is updated at the beginning of each week. Trimmed data denotes the spread where 2.50% of each tail is cut off. The sample period is from January 2016 until December 2019. HAC-robust *t*-statistics are given in parentheses.

Metric	Low (L)	Group 2	Group 3	Group 4	High (H)	(H-L)	(H-L)[a]
Average return	1.11	1.43	0.62	0.95	−0.26	−1.37**	−1.68***
(HAC-robust *t*-statistic)						(−2.27)	(−2.70)
Past MAX	3.05	5.07	7.06	9.96	20.90		
Past VOLA	1.26	1.60	1.93	2.44	4.36		

** Statistical significant on a 5% level.
*** Statistical significant on a 1% level.
[a] Data are trimmed at 5%.

Table A8
Predicted returns using traditional heteroscedasticity-and-autocorrelation-robust test statistics. This table reports the raw and risk-adjusted MAX payoffs as reported in tables 1, 3, A.3 and A.4, respectively, using (*i*) standard *t*-statistics, (*ii*) our proposed heteroscedasticity-and-autocorrelation-robust test statistics using a random block length of h = 20, and heteroscedasticity-and-autocorrelation-robust test statistics as proposed in Newey-West (1987) using three different lag-lengths l with $l = \{1, 3, 5\}$. The sample period is from January 2016 until December 2019.

Metric	(H-L)[a]	(H-L)[b]	(H-L)[c]	(H-L)[d]
Point estimate	−1.54	−1.75	−1.82	−2.14
Standard *t*-statistic	−1.57	−1.78	−1.75	−2.08
HAC-robust *t*-statistics using our proposed bootstrapping approach and a random block length of$h = 20$	−2.68	−2.70	−2.43	−2.35
HAC-robust *t*-statistics as proposed in Newey-West (1987) using a lag-length of l = 1	−1.89	−2.14	−1.76	−2.14
HAC-robust *t*-statistics as proposed in Newey-West (1987) using a lag-length of l = 3	−2.13	−2.47	−1.82	−2.22
HAC-robust *t*-statistics as proposed in Newey-West (1987) using a lag-length of l = 5	−2.51	−2.77	−2.48	−2.78

[a] In the first column, (H-L) denotes the spread of the raw returns as reported in Table 1.
[b] In the second column, (H-L) denotes the spread of the risk-adjusted returns as reported in Table A3.
[c] In the third column, (H-L) denotes the spread of the raw returns as reported in Table 3.
[d] In the fourth column, (H-L) denotes the spread of the risk-adjusted returns as reported in Table A4.

References

Affleck-Graves, J., McDonald, B., 1989. Non-normalities and tests of asset pricing theories. J. Finance 44, 889–908.
Ahmed, S., Grobys, K., Sapkota, N., 2020. Profitability of technical trading rules among cryptocurrencies with privacy function. Finance Res. Lett. 35, 101495.
Alkan, U., Guner, B., 2018. Preferences for lottery stocks at Borsa Istanbul. J. Int. Financ. Markets Inst. Money 55, 211–223.
Ardia, D., Bluteau, K., Rüede, M., 2019. Regime changes in bitcoin garch volatility dynamics. Finance Res. Lett. 29, 266–271.
Aharon, D.Y., Qadan, M., 2019. Bitcoin and the day-of-the-week effect. Finance Res. Lett. 31, 415–424.
Asness, C., Frazzini, A., Gormsen, N.J., Pedersen, L.H., 2020. Betting against correlation: testing theories of the low-risk effect. J. Financ. Econ. 135, 629–652.
Brown, S., Lu, Y., Ray, S., Teo, M., 2018. Sensation Seeking and Hedge Funds. Journal of Finance 73, 2871–2914..
Bali, T.G., Cakici, N., Whitelaw, R.F., 2011. Maxing out: stocks as lotteries and the cross-section of expected returns. J. Financ. Econ. 99 (2), 427–446.
Bali, T.G., Brown, S.J., Murray, S., Tang, Y., 2017. A lottery demand-based explanation of the beta anomaly. J. Financ. Quant. Anal. 52 (6), 2369–2397.
Baur, D.G., Cahill, D., Godfrey, K., Liu, Z., 2019. Bitcoin time-of-day, day-of-week and month-of-year effects in returns and trading volume. Finance Res. Lett. 31, 78–92.
Baur, D., Hong, K., Lee, A.D., 2018. Bitcoin: medium of exchange or speculative assets?. J. Int. Financ. Markets Inst. Money 54, 177–189.
Barberis, N., Huang, M., 2008. Stocks as lotteries: the implications of probability weighting for security prices. Am. Econ. Rev. 98, 2066–2100.
Borri, N., 2019. Conditional tail-risk in cryptocurrency markets. J. Empirical Finance 50, 1–19.
Brunnermeier, M.K., Gollier, C., Parker, J.A., 2007. Optimal beliefs, asset prices and the preference for skewed returns. Am. Econ. Rev. 97, 159–165.
Caporale, G.M., Plastun, A., 2019. The day of the week effect in the cryptocurrency market. Finance Res. Lett. 31, 258–269.
Caporale, G.M., Zekokh, T., 2018. Modelling Volatility of cryptocurrencies using Markov-switching GARCH Models. CESifo Group Munich. No. 7167.
Chaim, P., Laurini, M.P., 2019. Is Bitcoin a bubble?. Phys. A 517, 222–232.
Chan, Y.-C., Chui, A.C.W., 2016. Gambling in the Hong Kong stock market. Int. Rev. Econ. Finance 44, 204–218.
Chichernea, D.C., Kassa, H., Slezak, S., 2019. Lottery preferences and the idiosyncratic volatility puzzle. Eur. Financ. Manage. 25, 655–683.
Chu, J., Chan, S., Nadarajah, S., Osterrieder, J., 2017. GARCH Modelling of cryptocurrencies. J. Risk Financ. Manage. 10, 17.
Conrad, C., Custovic, A., Ghysels, E., 2018. Long-and short-term cryptocurrency volatility components: a GARCH-MIDAS analysis. J. Risk Financ. Manage. 11, 23.
Corbet, S., Eraslan, V., Lucey, B., Sensoy, A., 2019. The effectiveness of technical trading rules in cryptocurrency markets. Finance Res. Lett. 31, 32–37.
Corbet, S., Lucey, B., Maurice, P., Samuel, V., 2018. Bitcoin Futures—What use are they?. Econ. Lett. 172, 23–27.
Cretarola, A., Figà-Talamanca, G., 2020. Bubble regime identification in an attention-based model for Bitcoin and Ethereum price dynamics. Econ. Lett. 191. 108831.
Dyhrberg, A.H., 2016. Bitcoin, gold and the dollar – a GARCH volatility analysis. Finance Res. Lett. 16, 85–92.
Gerritsen, D.F., Bouri, E., Ramezanifar, E., Roubaud, D., 2019. The profitability of technical trading rules in the Bitcoin market. Finance Res. Lett. (forthcoming).
Geuder, J., Kinateder, H., Wagner, N., 2019. Cryptocurrencies as financial bubbles: the case of Bitcoin. Finance Res. Lett. 31, 179–184.
Godfrey, L., 2009. Bootstrap Tests for Linear Regression Models. Palgrave MacMillan, London.
Grobys, K., Sapkota, N., 2019. Cryptocurrencies and Momentum. Econ. Lett. 180, 6–10.
Grobys, K., Ahmed, S., Sapkota, N., 2020. Technical trading rules in the cryptocurrency market. Finance Res. Lett. 32, 101396.
Fan, R., Lee, J.H., 2019. Predictive quantile regressions under persistence and conditional heteroscedasticity. J Econ. 213, 261–280.
Fry, J., 2018. Booms, busts and heavy-tails: the story of Bitcoin and cryptocurrency markets?. Econ. Lett. 171, 225–229.
Fama, E. F., MacBeth, J. D., 1973. Risk, Return, and Equilibrium: Empirical Tests, Journal of Political Economy 81, 607–636..
Fry, J., Cheah, E.T., 2016. Negative bubbles and shocks in Cryptocurrency markets. Int. Rev. Financ. Anal. 47, 343–352.
Hamermesh, D.S., 2007. Viewpoint: replication in economics. Can. J. Econ. 40, 715–733.
Hou, K., Xue, C., Zhang, L., 2020. Replicating anomalies. Rev. Financ. Stud. 33, 2019–2133.
Huang, D., Li, J., Wang, L., Zhou, G., 2020. Time series momentum: is it there?. J. Financ. Econ. 135, 774–794.
Hung, W., Yang, J.J., 2018. The MAX effect: Lottery stocks with price limits and limits to arbitrage. J. Financ. Markets 41, 77–91.
Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: implications for stock market efficiency. J. Finance 48, 35–91.
Katsiampa, P., 2017. Volatility estimation for bitcoin: a comparison of GARCH models. Econ. Lett. 158, 3–6.
Kristoufek, L., Vosvrda, M., 2019. Cryptocurrencies market efficiency ranking: not so straightforward. Physica A 531, 120853.
Kumar, A., Page, J.K., Spalt, O.G., 2016. Gambling and comovement. J. Financ. Quant. Anal. 51, 85–111.
Kumar, A., 2009. Who gambles in the stock market?. J. Finance 64 (4), 1889–2193.
Liu, W., Liang, X., Cui, G., 2020. Common risk factors in the returns on cryptocurrencies. Econ. Model. 86, 299–305.
Li, Y., Zhang, W., Xiong, X., Wang, P., 2019. Does size matter in the cryptocurrency market?. Appl. Econ. Lett. (forthcoming).
Liu, L., Bu, R., Pan, Z., Xu, Y., 2019. Are financial returns really predictable out-of-sample? Evidence from a new bootstrap test. Econ. Model. 81, 124–135.
Miller, N., Yang, Y., Sun, B., Zhang, G., 2019. Identification of technical analysis patterns with smoothing splines for bitcoin prices. J. Appl. Stat. 46, 2289–2297.
Newey, W.K., West, K.D., 1987. A simple, positive semi-definite, heteroskedsticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.
Nguyen, H.T., Truong, C., 2018. When are extreme daily returns not lottery? At earnings announcements!. J. Financ. Markets 41, 92–116.
Peštová, B., Pešta, M., 2018. Abrupt change in mean using block bootstrap and avoiding variance estimation. Commun. Stat. – Theory Methods 33, 413–441.
Pešta, M., 2017. Block bootstrap for dependent errors-in-variables. Commun. Stat. – Theory Methods 46, 1871–1897.
Platanakis, E., Sutcliffe, C., Urquhart, A., 2018. Optimal vs naïve diversification in cryptocurrencies. Econ. Lett. 171, 93–96.
Platanakis, E., Urquhart, A., 2019. Should investors include bitcoin in their portfolios? A Portfolio Theory approach. British Acc. Rev. (2019). https://doi.org/10.1016/j.bar.2019.100837.
Shen, D., Urquhart, A., Wang, P., 2020. A three-factor pricing model for cryptocurrencies. Finance Res. Lett. 34. 101248.
Tversky, A., Kahneman, D., 1992. Advance in prospect theory: cumulative representation of uncertainty. J. Risk Uncert. 5, 297–323.
Walkshäusl, C., 2014. The MAX effect: European evidence. J. Bank. Finance 42, 1–10.