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Dynamic time series momentum of cryptocurrencies

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ABSTRACT

This paper examines the momentum effect for twenty cryptocurrencies compared to the US stock market. For this purpose, we implement a dynamic modeling approach to define and test momentum periods that follow a formation period for interday and various intraday price levels. We find evidence that large proportions of the asset classes' formation periods are followed by momentum periods, strongly supporting the momentum effect. In particular cryptocurrencies have significantly larger and longer momentum periods in all frequencies which we attribute to the lower derivability of their intrinsic value leading to a higher degree of noise traders in the market. A momentum trading strategy based on the identical approach outperforms a buy-hold strategy for both asset classes, while only cryptocurrencies have higher risk-adjusted returns and lower downside risks than a passive investment. We also find critical price levels during structural elements of the momentum period where the volatility shortly but intensively increases and consequently initiates a price impulse in the direction of the momentum.

1. Introduction

Cryptocurrencies are a truly exceptional form of an asset class. Originally developed as a decentralized digital currency encrypted to the blockchain, cryptocurrencies are nowadays traded for the motive of speculation (Baur et al., 2018). The increased transaction volume of dedicated cryptocurrency exchanges and in particular the introduction of Bitcoin futures at the Chicago Mercantile Exchange transformed cryptocurrencies into a fairly new asset class with distinctive characteristics. Unlike traditional asset classes, cryptocurrencies are entirely decoupled from the real economy, as their fundamental value is not based on cashflows as for stocks or consumption as for commodities. This makes its intrinsic value rather difficult to estimate, which provides an explanation for its exceptional price characteristics such as a significantly high volatility and deep fat tails (Borri, 2019; Klein et al., 2018). In particular the rapid increase and decrease of cryptocurrency prices with its peak in December 2017 gained much attention by investors and also in the financial media over the recent years. However, even after this unparalleled rise and fall, cryptocurrency prices still develop persistently over longer periods into one direction which corresponds to the common definition of the momentum effect.

The momentum effect is one of the most extensively documented financial market anomalies which is persistent over many decades (Asness et al., 2013). The majority of the empirical literature studies cross-sectional momentum which means that past increasing asset prices will outperform past decreasing asset prices (Jegadeesh & Titman, 1993). In contrast, time-series momentum which was first proposed by Moskowitz et al. (2012) is an alternative framework which means that the past performance of an asset price tends to continue in the future. Both phenomenons can be explained by the psychological behavior of investors (see Barberis et al. (1998), Daniel et al. (1998), De Long et al. (1990), Hong and Stein (1999), Tversky and Kahneman (1974) and Grinblatt and Han (2005)). The empirical literature largely confirms the momentum effect for a broad range of traditional assets and data frequencies, however, for the new asset class of cryptocurrencies it shows mixed results. While the majority of the cryptocurrency

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literature provides partial evidence for the momentum effect (see Caporale et al. (2018), Cheng et al. (2019), Tzouvanas et al. (2020)), only a few studies have a clear but contradictory position (see Grobys and Sapkota (2019), Liu and Tsyvinski (2018)). According to the behavioral model of De Long et al. (1990), the momentum effect intensifies with a larger proportion of uninformed noise traders. As noise traders form the largest group of market participants (Baur et al., 2018), we should expect to see clear evidence for the momentum effect in cryptocurrency markets. This motivates us to provide a comprehensive analysis of the momentum effect for the cryptocurrency market by also accounting for different investment strategies represented by various data frequencies. To the best of our knowledge, this is the first study which tests the momentum effect in the cryptocurrency markets for various data frequencies. In addition, we also introduce a dynamic modeling approach for time-series momentum and are therefore in contrast to previous studies able to cover momentum periods from a few minutes to several months for twenty cryptocurrencies. As different frequencies represent different market participants with different investment strategies, the results should reveal the robustness of this financial market anomaly. From the perspective of an investor, the prevalence of the momentum effect is highly relevant, as time-series momentum motivates popular trend following strategies. Hence, we also analyze if the findings of the paper can be exploited to profitably trade cryptocurrencies. We therefore compare a trend following strategy for cryptocurrencies and the US stock market with a buy-hold strategy.

In order to analyze the momentum effect, we compare the number of momentum cycles after a price formation period across cryptocurrencies, the S&P500 stock market index and a stochastic time series imitating geometric Brownian motion. We expect to measure the momentum effect when we are able to identify one or more subsequent momentum cycles which we define as momentum periods. As we do not expect to measure a momentum period for the stochastic time series, it serves as a control group. In the second step, we examine the entire momentum periods and its sub-periods in order to find characteristics of the momentum effect. Finally, we design a momentum trading strategy and compare the risk-return characteristics of both asset classes with those of a buy-hold strategy.

We contribute to the empirical literature by modeling time-series momentum dynamically as a sequence of turning points without the requirement to choose any specific threshold parameter. We calculate turning points based on a smoothing filter algorithm, which indicates price levels at which the investor sentiment changes. First introduced by Borgards and Czudaj (2020), they use the approach to model overreactions as large price changes between two turning points. Both methodologies therefore make use of the favorable properties of turning points but model different market anomalies. In contrast, the existing literature models time-series momentum statically as a return of arbitrarily chosen periods. Since momentum develops dynamically independent of such parameters, the corresponding findings might be biased when relying on such an approach. Therefore, we test the momentum effect with price level data for various intraday frequencies which covers a large spectrum of momentum periods and enables us to find structural differences as different price levels may represent different investment strategies and market participants. Moreover, our methodology allows us to find attributes within periods of time-series momentum. Consequently, our work extends the empirical literature by presenting the persistence and inner mechanics of time-series momentum across the cryptocurrency and equity asset classes for a broad range of data frequencies without the requirement to find adequate model parameters.

We find evidence that price persistence is highly prevalent in both the cryptocurrency and the stock market, strongly supporting the momentum effect. We define time-series momentum dynamically as subsequent momentum cycles, whereas the first momentum cycle is the formation period and the following momentum cycles form the momentum period. Our results show that a large proportion of the cryptocurrencies' and stocks' formation periods are followed by one or more momentum cycles, whereas the stochastic time series unsurprisingly does not exhibit any momentum periods. Our findings can be explained by the theory of noise trader risks proposed by De Long et al. (1990), which implies that overconfident noise traders push up the price and create risks that deter informed traders from arbitraging the mispricing. The ability to derive an intrinsic value of an asset price determines the level of noise traders and informed traders in the market which directly affects the mispricing. This is in line with our finding that cryptocurrencies have more and considerably longer momentum periods than the stock market, as the intrinsic value is in particular difficult to compute for cryptocurrencies. We hypothesize that volatility is the decisive factor for the momentum return, while the momentum duration and the number of momentum cycles are of minor importance. This hypothesis is supported by the finding of critical price levels during momentum cycles, where the price significantly accelerates in the direction of the momentum before it exceeds them. These changing volatility levels can be explained with anchoring effects. The anchoring effect (Tversky & Kahneman, 1974) is a cognitive bias that describes the tendency that a piece of information (the anchor) has a disproportionally large weight in the market participant's decision-making process. As subsequent momentum cycles result in a higher volatility during the momentum period, we conclude that this mechanism significantly contributes to the overall volatility of the asset's time series. This is supported by the higher standard deviation that cryptocurrencies exhibit in contrast to stocks. We also conclude that the momentum effect is prevalent in all data frequencies which underlines the robustness of this financial market anomaly. However, we also find that its prevalence marginally decreases with a higher data frequency which can be again explained with lower volatility levels in higher frequency data. Finally, we show that a momentum strategy based on momentum cycles is able to outperform a buy-hold strategy for both cryptocurrencies and the stock market index, while only cryptocurrencies generate higher risk-adjusted returns than a passive investment.

The remainder of the paper is structured as follows. Section 2 reviews the existing literature on the momentum effect. Section 3 outlines the data and the methodology used in this study. In Section 4, we present and discuss our empirical findings. Section 5 offers concluding remarks.

2. Literature review

The Efficient Market Hypothesis (EMH) refers to the rational behavior of investors which leads to efficient financial markets that reflect all available information in the price of an asset. In effect, efficient markets imply that the assets' price follows a random walk (Fama, 1965) which makes it impossible for investors to gain an edge over the market in the long run. Contradicting the EMH, the empirical literature illustrates various instances of irrational behavior, known as market anomalies. Market anomalies are structural or behavioral biases which lead to price distortion and in turn to inefficient and predictable markets. Ball (2009) provides an overview of various market anomalies including momentum, over- and underreactions, excess volatility, seasonal price patterns and the correlation between future returns and various financial figures such as the dividend yield or the price-to-earnings ratio. Hou et al. (2020) replicates a set of 452 market anomalies for stocks and concludes that in particular momentum is one of the most persisting market anomalies.

The momentum effect is one of the most extensively documented financial market anomalies (see Barberis et al. (1998), Daniel et al. (1998), De Long et al. (1990), De Long et al. (1990), Hong and Stein (1999), Jegadeesh and Titman (1993) and the literature cited therein). Momentum refers to positive autocorrelation in asset prices, which means that increasing (decreasing) prices in the past will continue to increase (decrease) in the future. The implication of the momentum effect is that buying past winners and selling past losers will lead to excess returns, contradicting the EMH. The momentum effect was first documented by Jegadeesh and Titman (1993) (JT) who studied US stocks during the period between 1965 and 1989. JT find that the strategy of selecting stocks based on their past returns generates significantly positive returns over 3 to 12 months holding periods. They find that the EMH can be rejected at the most conservative levels of significance which they confirm in a subsequent study where they enhanced the period to 1997 (Jegadeesh & Titman, 2001). They conclude that the momentum effect is one of the clearest evidence against the EMH. Due to their strong magnitude and persistence, they attribute their results to behavioral explanations rather than systematic risks.

The momentum effect initiated a variety of empirical studies showing the asset prices' tendency to maintain their past returns. Jegadeesh and Titman (2011) provide an overview of the empirical literature on cross-sectional momentum and its behavioral explanations. Rouwenhorst (1998) replicates JT's cross-sectional momentum analysis for 12 European countries in the period from 1980 to 1995 and finds that the returns are correlated with those of JT's study for US stocks. Moskowitz and Grinblatt (1999) measure cross-sectional momentum for portfolios with stocks of the same industry and find that high momentum industries outperform low momentum industries. They conclude that industry momentum better explains the excess returns of cross-sectional momentum strategies than firm-specific factors. Moskowitz et al. (2012) first proposed time-series momentum as an alternative framework, which means that an asset's own past return is a predictor for its future price. While time-series momentum selects an asset based on its own past performance, cross-sectional momentum concentrates on the asset's past relative performance. They find that time-series momentum performed well both in absolute terms and relative to cross-sectional momentum for futures markets in equity indices, bonds, currencies and commodities and also for a diversified portfolio across all asset classes. Huang et al. (2020) analyzes time-series momentum as the predictability of the next month return with the past year return. On the basis of time-series and pooled regression analysis, they conclude contrary that the evidence of time-series momentum is statistically weak but profitable from an investment perspective. While most of the empirical research on the momentum effect has been conducted for global stock markets, other studies document its robustness for other financial markets. Menkhoff et al. (2012) investigate the momentum effect in foreign exchange markets and find a significant difference in the excess returns of past winning and losing currencies. They conclude that cross-sectional momentum outperforms time-series momentum. Miffre and Rallis (2007) model cross-sectional momentum as buying (selling) commodity future contracts in a backwardation (contango) situation of their term structures and validate the momentum effect. Asness et al. (2013) observe the momentum effect for individual stocks, equity indices, currencies, government bonds and commodity futures. They find that momentum excess returns have a high correlation across the asset classes, although the momentum periods are negatively correlated with each other. Asness et al. (2013) results underline the pervasiveness of the momentum effect which Fama and French (2008) crown as the premier market anomaly.

While the empirical literature largely confirms the anomaly's validity and robustness for traditional asset classes, the majority of the empirical literature on cryptocurrencies shows only partially evidence for the momentum effect and the minority even represents a clear but contrary position. Liu and Tsyvinski (2018) show significant time-series momentum for the cryptocurrencies Bitcoin, Ethereum and Ripple for various defined daily and weekly returns. To the best of our knowledge, it is the only study which completely confirms the momentum effect for cryptocurrencies. Caporale et al. (2018) examine the degree of market efficiency for the cryptocurrencies Bitcoin, Litecoin, Ripple and Dash for the period 2013 to 2017. Applying rescaled range analysis and fractional integration long-memory methods, they find price persistence for all cryptocurrencies, indicating signs of predictability and market inefficiency. However, they also observe that its degree changes over the time towards market efficiency. Tzouvanas et al. (2020) observe the momentum effect for a portfolio of twelve daily cryptocurrency prices. They show evidence for the momentum effect for short-term portfolios which becomes less significant over the longer term. Cheng et al. (2019) apply detrended fluctuation analysis to the cryptocurrencies Bitcoin, Ethereum, Ripple and Eos. While their results show a significant momentum effect for Bitcoin and Ethereum, they were also able to confirm the overreaction hypothesis for the other two cryptocurrencies at large fluctuations. Caporale and Plastun (2020) model time-series momentum for 3 cryptocurrencies after a 1 day formation period of abnormal returns. They partially find existence of the momentum effect during and after the day of the overreaction, however they also present signs of overreacting behavior on both days. Liu et al. (2020) model time-series momentum as one-year returns for 78 cryptocurrencies and perform cross-sectional regressions as proposed by Fama and MacBeth (1973). They find that market capitalization and momentum are able to explain the variation of the cryptocurrency mean returns and provide evidence for the momentum effect of smaller capitalized cryptocurrencies. In contrast to the literature outlined above, Grobys and Sapkota (2019) do not find any evidence for the momentum effect in the cryptocurrency markets. Equivalent to Fama and French (2008), they use monthly price data of 143 cryptocurrencies over the period from 2014 to 2018 to model time-series and cross-sectional momentum for fixed monthly formation periods. As they define time series momentum as the next month's return of a long or short position depending on the past cumulative monthly performance, their approach also considers positive and negative momentum periods but relies on predefined past returns over longer observation periods contrary to our paper. Kosc et al. (2019) model time-series momentum as the cryptocurrency portfolio of the highest quarter weekly returns while the cryptocurrencies of the lowest quarter weekly returns refer to the contrarian portfolio. They find clear evidence for short-term overreacting behavior but not for the momentum effect in any parameter constellation. In terms of trading the momentum effect, Chu et al. (2020) implement a time-series and a cross-sectional signal-based momentum strategy for 7 cryptocurrencies. Although the short-term momentum strategies are able to generate positive returns, they are outperformed by a passive portfolio strategy. In contrast to Chu et al. (2020), Hudson and Urquhart (2019) find higher risk-adjusted returns for the momentum strategies than passive strategies when applying various technical trading rules to daily Bitcoin prices. As they are not able to confirm their returns to out-of-sample periods, the validity of the momentum effect cannot be finally concluded.

In reliance on static modeling approaches, the empirical literature on cryptocurrencies examines the momentum effect in particular for interday price levels. In contrast, our dynamic modeling approach enables us to study momentum periods from a few minutes to several months for a broad range of cryptocurrencies. In addition, to the best of our knowledge, this is the first study which analyzes the inner dynamics of the momentum period.

3. Data and methodology

3.1. Data

We use price data for twenty cryptocurrencies denominated in US dollar with the highest market capitalization as of December 31, 2019. The cryptocurrency coins include Bitcoin (BTCUSD), Ripple (XRPUSD), Dash (DSHUSD), Eos (EOSUSD), Ethereum Classic (ETCUSD), Ethereum (ETHUSD), Iota (IOTUSD), Litecoin (LTCUSD), Neo (NEOUSD), Monero (XMRUSD), Stellar Lumens (XLMUSD), Zcash (ZECUSD), Metaverse ETP (ETPUSD), 0x (ZRXUSD), Tezos (XTZUSD), Bitcoin SV (BSVUSD), LEO (LEOUSD), Bitcoin Gold (BTGUSD), Tron (TRXUSD) and Batcoin (BATUSD).[1] The data was obtained from the Bitfinex cryptocurrency exchange (https://www.bitfinex.com) and consists of the open, high, low and close prices (OHLC henceforth) of the 1 day (1D), 1 h (1 h) and 5 min (5 m) frequencies respectively. The sample period starts from January 1, 2014 to December 31, 2019 and covers the whole listing period at the Bitfinex exchange for the majority of the cryptocurrencies except for Bitcoin and Litecoin. Data gaps of the price time series have been filled with the last available price.

In addition, we rely on the Standard & Poors 500 index (S&P500) OHLC price data for a frequency of 5 min. We upsampled its 5 m OHLC data to the corresponding frequencies of the cryptocurrencies in order to obtain equivalent data. The data set was sourced from the Chicago Board Options Exchange (CBOE, https://www.cboe.com), the world's largest options exchange. It covers the same 6-year sample period from January 1, 2014 to December 31, 2019. As the momentum effect is extensively documented for stock markets, the S&P500 data serves as a benchmark to illustrate its prevalence for the new asset class of cryptocurrencies. Table 1 provides the descriptive statistics of the respective close price log changes for the 1 day and 1 h frequency. It shows that cryptocurrency and stock market returns are non-Gaussian due to positive or negative skewness and excess kurtosis observed in many cases.

Finally, we compute a stochastic time series for all applied frequencies which simulates geometric Brownian motion. The drift and diffusion components of the stochastic time series are derived from the respective Bitcoin time series as it represents the cryptocurrency with the highest market capitalization. The stochastic time series functions as a control group for both asset classes, as we do not expect to see the momentum effect for the stochastic time series.

3.2. Methodology

This section presents the methodology to model time-series momentum dynamically. Time-series momentum is defined as a period of positively autocorrelated asset prices, which means that the price constantly increases or decreases over a period. The period consists of a formation period at the beginning which is able to predict the subsequent momentum period at the end. Fig. 1 illustrates time-series momentum as a period of increasing prices.

In order to structure time-series momentum, we introduce the concept of a momentum cycle. A positive (negative) momentum cycle is a set of two consecutive, increasing (decreasing) peak and trough turning points of the price time series. As turning points indicate price levels at which the investor sentiment changes, a pair of increasing (decreasing) turning points represents a change of the equilibrium price on a higher (lower) level. A positive (negative) momentum cycle is therefore a period, where the investor sentiment changes on both the resistance and the support side on higher (lower) equilibrium price levels. We identify turning points by a moving-average smoothing filter algorithm which is extensively explained in Borgards and Czudaj (2020). The smoothing filter

[1] In order to check whether the point of time of the sample selection is relevant for our analysis, we have compared our sample of cryptocurrencies with the sample of the twenty cryptocurrencies that have the highest market capitalization as of December 31, 2017 and December 31, 2018. First, the sample composition does not change significantly over the time as the same 16 (17) cryptocurrencies are also in the 2017 (2018) sample. Moreover, they represent the clear majority of the sample market capitalization (2017: 95.86%, 2018: 98.24%). Second, although the cryptocurrency markets comprise of a myriad of individual cryptocurrencies, only a few cryptocurrencies account for the majority of the total market capitalization. Even in our sample the five highest capitalized cryptocurrencies have a 90.22% (2017: 84.40%, 2018: 86.67%) share of the sample market capitalization. We therefore conclude that our sample consistently represents the cryptocurrencies with the highest market capitalization over the entire sample period.

Table 1
Descriptive statistics.

Asset	Mean	Median	SD	Minimum	Maximum	Skewness	Kurtosis	No. obs.	Sample Period
(a) 1 day									
XLMUSD	−0.00372	−0.00524	0.04996	−0.17791	0.27071	0.36699	2.59831	610	05/01/2018–01/01/2020
BTCUSD	0.00103	0.00106	0.0395	−0.22565	0.24016	−0.27815	4.87444	2191	01/01/2014–01/01/2020
DSHUSD	−0.00013	−0.00155	0.06104	−0.23245	0.35995	0.58511	4.54399	1034	03/03/2017–01/01/2020
EOSUSD	0.00091	−0.0018	0.08312	−0.35714	0.94162	1.82508	20.47396	914	07/01/2017–01/01/2020
ETCUSD	0.00047	−0.00173	0.06694	−0.4456	0.5296	0.11872	8.7279	1254	07/26/2016–01/01/2020
ETHUSD	0.00177	−0.00092	0.05787	−0.31145	0.25874	−0.031	3.37124	1393	03/09/2016–01/01/2020
IOTUSD	−0.00127	−0.00226	0.07559	−0.40577	0.39411	0.1541	4.63716	933	06/12/2017–01/01/2020
LTCUSD	0.00026	−0.00142	0.05854	−0.53193	0.59026	0.72338	13.29615	2191	01/01/2014–01/01/2020
NEOUSD	−0.00149	−0.00165	0.06824	−0.29586	0.33808	0.2373	3.17438	846	09/07/2017–01/01/2020
XMRUSD	0.00144	0.00014	0.0626	−0.2884	0.42829	0.33529	4.65295	1127	11/30/2016–01/01/2020
XRPUSD	−0.00054	−0.00295	0.06828	−0.37556	0.63136	1.94446	16.83548	957	05/19/2017–01/01/2020
ZECUSD	−0.00419	−0.00497	0.09549	−1.86191	1.08943	−5.15996	139.85364	1159	10/29/2016–01/01/2020
ETPUSD	−0.0025	−0.00366	0.0875	−0.66073	0.6523	−0.19835	12.6453	833	09/20/2017–01/01/2020
ZRXUSD	−0.00337	−0.00524	0.06635	−0.32311	0.24569	−0.01615	1.79946	723	01/08/2018–01/01/2020
XTZUSD	−0.00015	−0.00144	0.05972	−0.27096	0.20874	0.20653	1.85179	471	09/17/2018–01/01/2020
BSVUSD	−0.00196	−0.00309	0.08325	−0.58059	0.52164	0.27187	16.46237	414	11/13/2018–01/01/2020
LEOUSD	−0.00115	−0.00203	0.02933	−0.0866	0.12114	0.61423	3.46064	226	05/20/2019–01/01/2020
BTGUSD	−0.00374	−0.00272	0.07373	−0.45843	0.74444	1.09463	18.04116	799	10/24/2017–01/01/2020
TRXUSD	−0.00237	−0.00266	0.0617	−0.23466	0.26233	0.087	1.94432	707	01/24/2018–01/01/2020
BATUSD	−0.00203	−0.00171	0.06754	−0.3618	0.26025	−0.16439	2.28004	723	01/08/2018–01/01/2020
S&P500	0.00031	0.0006	0.00779	−0.07502	0.06246	−0.52047	11.94365	1866	01/02/2014–01/01/2020
(b) 1 h									
XLMUSD	−0.00015	0.00000	0.01191	−0.11505	0.12367	0.17500	9.24684	14652	05/01/2018–01/01/2020
BTCUSD	0.00004	0.00005	0.00901	−0.42667	0.28212	−1.75584	136.97315	52607	01/01/2014–01/01/2020
DSHUSD	0.00000	−0.00001	0.01387	−0.15883	0.25958	0.71615	18.06901	24822	03/03/2017–01/01/2020
EOSUSD	0.00004	−0.00007	0.01751	−0.28621	0.40041	0.72452	38.62828	21943	07/01/2017–01/01/2020
ETCUSD	0.00002	0.00000	0.01482	−0.46444	0.20634	−1.14976	50.06766	30096	07/26/2016–01/01/2020
ETHUSD	0.00008	0.00000	0.01255	−0.23750	0.14886	−0.32465	19.28073	33439	03/09/2016–01/01/2020
IOTUSD	−0.00002	0.00000	0.01849	−0.33145	0.69315	2.17267	106.47164	22397	06/12/2017–01/01/2020
LTCUSD	0.00001	0.00000	0.01256	−0.25113	0.20031	−0.15939	29.59570	52607	01/01/2014–01/01/2020
NEOUSD	−0.00005	−0.00014	0.01600	−0.23496	0.28992	0.59301	21.22267	20319	09/07/2017–01/01/2020
XMRUSD	0.00006	0.00000	0.01437	−0.23583	0.21359	−0.02168	16.24824	27053	11/30/2016–01/01/2020
XRPUSD	−0.00003	−0.00012	0.01538	−0.18564	0.29297	1.17188	30.78626	22974	05/19/2017–01/01/2020
ZECUSD	−0.00023	−0.00007	0.02678	−1.07418	1.07418	−3.00870	449.44810	27832	10/29/2016–01/01/2020
ETPUSD	−0.00009	0.00000	0.02173	−0.41162	0.26441	−0.36561	22.47374	20001	09/20/2017–01/01/2020
ZRXUSD	−0.00014	0.00000	0.01688	−0.13018	0.35064	1.39407	29.28032	17352	01/08/2018–01/01/2020
XTZUSD	−0.00003	0.00000	0.01606	−0.27024	0.17139	−0.13928	16.83916	11312	09/17/2018–01/01/2020
BSVUSD	−0.00047	−0.00025	0.04826	−4.47441	0.37380	−79.96217	7424.93942	9949	11/13/2018–01/01/2020
LEOUSD	−0.00005	0.00000	0.00672	−0.05497	0.05914	0.42491	14.65144	5439	05/20/2019–01/01/2020
BTGUSD	−0.00015	0.00000	0.01678	−0.25679	0.42031	1.20059	52.30525	19198	10/24/2017–01/01/2020
TRXUSD	−0.00010	0.00000	0.01450	−0.12542	0.21008	0.50525	14.93782	16976	01/24/2018–01/01/2020
BATUSD	−0.00009	0.00000	0.01996	−0.19716	0.23291	0.35196	11.54814	17354	01/08/2018–01/01/2020
S&P500	0.00002	0.00000	0.00173	−0.03037	0.02541	−0.74733	22.33582	35830	01/02/2014–01/01/2020

Note: The table reports the mean, median, standard deviation (SD), minimum value, maximum value, skewness, kurtosis and the number of observations (No. obs.) for the 1 day (Panel (a)) and 1 h (Panel (b)) close price log changes of the 21 assets. The cryptocurrency price data covers the respective listing period at the Bitfinex cryptocurrency exchange in the period from January 01, 2014 to December 31, 2019.

algorithm requires a sensitivity parameter κ which modifies the number of identified turning points. Corresponding to Borgards and Czudaj (2020), we also use a sensitivity parameter κ of 5 which results in a sufficient number of turning points to model time-series momentum across the three frequencies.

In Fig. 1 the period between the turning points T1 to T4 form a momentum cycle as both peaks T2 and T4 as well as both troughs T1 and T3 increase respectively. Since the previous turning point T-2 does not meet the conditions of a positive momentum cycle, the momentum cycle T1–T4 is defined as the formation period. In a formation period the price initially leaves a random walk and drifts in a certain direction. Our intention is to measure whether the formation period, defined as the first momentum cycle, is able to predict the asset price development after the turning point T4 which is commonly referred to as time-series momentum. We consequently define the series of all subsequent momentum cycles as the momentum period as long as the momentum cycle definition holds true. As a momentum cycle represents a stepwise increase or decrease of the equilibrium price, its last turning point is chained with the subsequent momentum cycle. In Fig. 1 the formation period T1–T4 is followed by the momentum period T4–T12 which consists of four momentum cycles (T3–T6, T5–T8, T7–T10 and T9–T12) and ends in the turning point T12 as it does not meet its definition. All momentum cycles together constitute time-series momentum which we modeled dynamically by the use of momentum cycles as their structural elements. Our concept of a momentum cycle has the benefit that the duration of the time-series momentum is allowed to vary and does not need to be predefined. This seems reasonable since all leading behavioral explanations of the momentum effect like conservatism bias, the disposition effect, delayed overreactions or self-attribution bias (Jegadeesh & Titman, 2011) do not depend on the time.

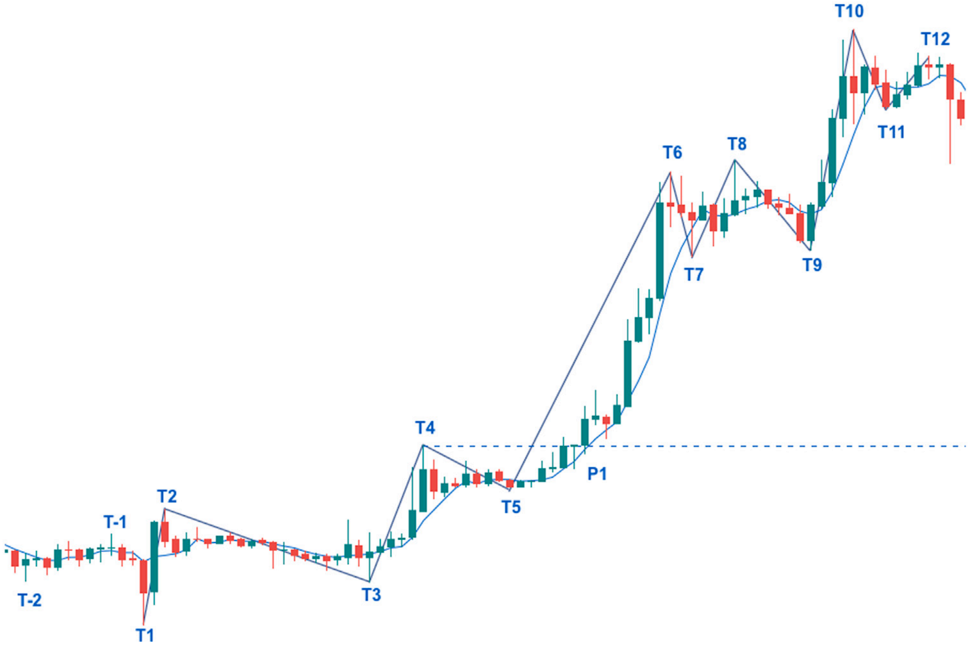

Fig. 1. Formation and momentum period of the Bitcoin-USD price. *Note:* The dark blue line connects the turning points, calculated with a sensitivity parameter κ of 5. The entire dark blue line T1–T12 marks the time-series momentum, whereas the starting period T1–T4 is the formation period and the ending period T4–T12 forms the momentum period. The dotted line marks the illustrated price level of the turning point P4, which the price exceeds in P1 and separates the increasing price development T5–T6 into two sub-periods T5–P1 and P1–T6. Each bar represents the Bitcoin-USD price development within 1 h for the period from August 31, 2019 10:00 to September 4, 2019 02:00. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Based on our definition of time-series momentum, we calculate the number of consecutive momentum cycles for each OHLC time series per asset and frequency. After subtracting the first momentum cycle which is the formation period, we receive the momentum period, expressed as the number of ever-increasing or ever-decreasing equilibrium price changes. Consistent with the EMH, we do not expect any momentum periods for the stochastic time series in any constellation. This result would demonstrate that our modeling approach does not reveal time-series momentum, where it does not exist. In contrast, the distribution of the total number of consecutive momentum cycles provides an indication of whether the momentum effect can be identified and to what extent across the asset classes.

As the empirical literature largely confirms the momentum effect for US stock markets, our intention is to compare its prevalence with cryptocurrency markets. In the following we present how we analyze the structural elements of our dynamic modeling approach, the momentum period and the momentum cycle.

First, we additionally calculate the mean return, duration and slope of the momentum period across both asset classes per frequency and direction (positive or negative). The return is defined as the log change of the starting turning point to the ending turning point. The duration is the number of data points within the momentum period while the slope is measured as the average return per frequency unit. In order to check if the momentum periods of both asset classes have comparable characteristics, we test the null hypothesis that their respective mean values come from the same distribution. As the momentum period return, duration and slope are not normally distributed,[2] we use the non-parametric Mann–Whitney-U test for multiple independent groups. The Mann–Whitney-U test statistic is calculated as

$$U = n_1 n_2 + \frac{n_2(n_2+1)}{2} - \sum_{i=n_1+1}^{n_2} R_i, \tag{1}$$

where n_1 is the sample size of the first asset class, n_2 denotes the sample size of the second asset class and R_i represents the rank of the sample size. We compute the p-values as the level of statistical significance for the Mann–Whitney-U test whereas lower p-values indicate a stronger evidence that both asset class characteristics do not come from the same distribution.

Second, we analyze the individual momentum cycles as they form the building blocks of the momentum period. In particular the price level of the second turning point within a momentum cycle plays an important role, as its exceeding determines whether the momentum period is continued or not. In Fig. 1 the turning point T4 marks the second turning point of the momentum cycle T3–T6. The exceeding of its price level at the point P1 means that the next peak turning point T6 will be higher than the last turning point T4 which corresponds to the confirmation of a new momentum cycle and the continuation of the momentum period.

[2] We confirmed the normal distribution with a D'Agostino-Pearson omnibus test for normality. The results are available upon request.

Table 2
Consecutive momentum cycles.

Frequency	1D			1 h			5 m		
Momentum cycle	Crypto-currencies	S&P500	Stochastic time series	Crypto-currencies	S&P500	Stochastic time series	Crypto-currencies	S&P500	Stochastic time series
(a) Positive momentum cycles									
0	55.342	54.167	100.000	59.321	67.713	100.000	68.369	73.441	100.000
1	24.932	12.500	0.000	22.726	21.973	0.000	20.415	19.173	0.000
2	9.589	20.833	0.000	10.527	7.175	0.000	7.183	5.162	0.000
3	6.575	8.333	0.000	4.510	2.392	0.000	2.604	1.446	0.000
4	1.918	4.167	0.000	1.769	0.448	0.000	0.886	0.591	0.000
5	0.274	0.000	0.000	0.710	0.149	0.000	0.330	0.078	0.000
6	0.548	0.000	0.000	0.229	0.149	0.000	0.147	0.109	0.000
7	0.274	0.000	0.000	0.153	0.000	0.000	0.040	0.000	0.000
8	0.548	0.000	0.000	0.044	0.000	0.000	0.018	0.000	0.000
9	0.000	0.000	0.000	0.000	0.000	0.000	0.004	0.000	0.000
10	0.000	0.000	0.000	0.011	0.000	0.000	0.003	0.000	0.000
11	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000
(b) Negative momentum cycles									
0	52.078	70.968	100.000	57.484	72.578	100.000	67.173	79.302	100.000
1	22.992	25.806	0.000	24.747	20.197	0.000	21.050	16.005	0.000
2	11.357	3.226	0.000	10.735	5.583	0.000	7.488	3.227	0.000
3	6.371	0.000	0.000	4.134	1.149	0.000	2.764	1.120	0.000
4	3.324	0.000	0.000	1.778	0.328	0.000	0.975	0.231	0.000
5	2.770	0.000	0.000	0.622	0.000	0.000	0.352	0.099	0.000
6	0.554	0.000	0.000	0.322	0.000	0.000	0.110	0.016	0.000
7	0.277	0.000	0.000	0.122	0.000	0.000	0.059	0.000	0.000
8	0.000	0.000	0.000	0.033	0.164	0.000	0.013	0.000	0.000
9	0.000	0.000	0.000	0.011	0.000	0.000	0.012	0.000	0.000
10	0.277	0.000	0.000	0.011	0.000	0.000	0.002	0.000	0.000

Note: The table reports the percentage of the consecutive momentum cycles per frequency and momentum direction for the 20 cryptocurrencies and the S&P500 index for the period from January 01, 2014 to December 31, 2019.

We hypothesize that the previous peak (trough) turning point has an impact on the price development of a trough (peak) turning point to the next peak (trough) turning point within a momentum cycle. We therefore separate every increasing (decreasing) turning point to turning point period of a positive (negative) momentum cycle into two sub-periods at the price level of the previous peak (trough) turning point. For each sub-period we calculate the log return, standard deviation, duration and slope based on the 5 m frequency time series. In order to indicate a relation of both sub-periods, we calculate a ratio of both sub-period figures, whereas a ratio higher than 1 means that the figure of the first sub-period exceeds the one of the second sub-period. In Fig. 1 we see that the price level of the previous peak turning point T4 separates the increasing price development T5–T6 into two sub-periods at the point P1. As the second sub-period P1–T6 has obviously a larger log return than the first sub-period T5–P1, the return ratio is below unity for this momentum cycle. In general, a ratio that is significantly different from 1 indicates that the price level of the previous turning point has an impact on the price development within the momentum cycle and consequently determines the degree of time-series momentum. We calculate for each ratio the mean, median and standard deviation per frequency and direction across all cryptocurrencies and the S&P500. In order to test the null hypothesis that their mean values come from the same distribution, we apply the non-parametric Mann–Whitney-U test to find individual characteristics of the asset classes.

4. Empirical findings

4.1. Dynamic time series momentum

Table 2 illustrates the percentage of consecutive momentum cycles in a momentum period for the cryptocurrencies, the S&P500 index and the stochastic time series per frequency and direction.

Based on the described methodology, the first line represents the formation period and shows the proportion of all single momentum cycles which are not followed by a momentum period. All subsequent lines show the proportion of multiple consecutive momentum cycles which implies that a momentum period can be identified. For example, 55.3% (54.2%) of the positive cryptocurrency (S&P500) formation periods are not followed by another momentum cycle in the daily frequency, which is always the case for the stochastic time series. This also means that time-series momentum can be clearly detected for 44.7% (45.8%) of the cryptocurrency (S&P500) momentum cycles. Conversely, the stochastic time series does never exhibit time-series momentum in all frequencies and momentum directions. This result was expected because the stochastic time series simulates a random walk which represents the price in an efficient market that does not have time-series momentum per definition. It also indicates the quality of our modeling approach, as it shows that our method does not measure time-series momentum when there is none. In addition, it also shows that cryptocurrency and stock market prices do not follow a pure random walk.

Our results reveal that time-series momentum can be clearly shown for cryptocurrencies and the S&P500 in each frequency and direction as large proportions of their formation periods are followed by momentum periods. In addition, the more consecutive

Table 3
Momentum period characteristics.

Frequency	1D				1 h				5 m			
	Crypto-currencies	S&P500	Difference	p-value	Crypto-currencies	S&P500	Difference	p-value	Crypto-currencies	S&P500	Difference	p-value
(a) Positive momentum cycles												
Return	22.611	3.637	18.973***	0.0009	4.234	0.544	3.689***	0.0000	1.250	0.161	1.089***	0.0000
Duration	24.250	28.363	−4.113 (ns)	0.1079	21.729	21.300	0.428 (ns)	0.1447	18.567	17.882	0.684***	0.0000
No. momentum cycles	1.761	2.090	−0.328 (ns)	0.0752	1.691	1.453	0.237***	0.0001	1.471	1.402	0.069***	0.0000
Return per duration	0.920	0.128	0.792***	0.0000	0.195	0.025	0.169***	0.0000	0.070	0.009	0.061***	0.0000
Return per momentum cycle	12.600	1.739	10.860***	0.0001	2.495	0.374	2.121***	0.0000	0.858	0.115	0.742***	0.0000
Duration per momentum cycle	13.668	13.565	0.102 (ns)	0.4569	12.805	14.652	−1.847**	0.0077	12.524	12.753	−0.228***	0.0001
(b) Negative momentum cycles												
Return	29.351	1.724	27.627***	0.0000	3.942	0.406	3.535***	0.0000	1.250	0.155	1.095***	0.0000
Duration	30.519	12.333	18.185***	0.0007	21.851	18.640	3.210***	0.0001	19.268	17.099	2.169***	0.0000
No. momentum cycles	2.128	1.111	1.017**	0.0083	1.670	1.365	0.304***	0.0000	1.487	1.320	0.166***	0.0000
Return per duration	0.947	0.139	0.807***	0.0000	0.181	0.021	0.159***	0.0000	0.066	0.009	0.057***	0.0000
Return per momentum cycle	13.961	1.552	12.409***	0.0000	2.356	0.297	2.058***	0.0000	0.854	0.117	0.737***	0.0000
Duration per momentum cycle	14.635	11.100	3.535*	0.0209	13.046	13.653	−0.607 (ns)	0.2322	12.934	12.948	−0.013***	0.0002

Note: The table reports the mean return, duration, number of momentum cycles and derived ratios of the momentum periods per frequency and momentum direction for the 20 cryptocurrencies and the S&P500 index for the period from January 01, 2014 to December 31, 2019. It also shows the mean differences as well as the p-values of the Mann–Whitney-U test. The asterisks represent the level of significance, where***,**,* indicates that the test statistic is significant at the 0.1%, 1% and 5% level respectively while ns means that the test statistic is not significant.

momentum cycles an asset price has, the less the probability that another momentum cycle will follow which can be demonstrated by the constantly decreasing proportions of consecutive momentum cycles for all assets, frequencies and directions. Both results show that momentum periods are no sporadic and rare exceptions but happen regularly with varying levels of intensity which provides evidence for the momentum effect.

We find that cryptocurrencies have a significantly higher percentage of momentum periods than the S&P500 with the exception of daily positive momentum periods where both levels are comparable. Moreover, cryptocurrencies have almost more than twice as many consecutive momentum cycles than the S&P500. For instance, the longest number of positive, consecutive momentum cycles for cryptocurrencies (S&P500) in the 5 m frequency is 6 (11), which is equivalent to all other frequencies and directions. This result that time-series momentum is more prevalent and pronounced for cryptocurrencies can be explained with the noise trader risk model of De Long et al. (1990). Their behavioral model implies that noise traders excessively increase or decrease the price of an asset and therefore create risks for fundamental traders reluctant to adjust the mispricing. This situation is given as Baur et al. (2018) find that noise traders are the largest group of market participants in the cryptocurrency markets.

Furthermore, our results show that the momentum effect slightly attenuates the higher the frequency for both asset classes. For 47.9% (29.0%) of the initial negative momentum cycles of cryptocurrencies (S&P500) in the 1D frequency, time-series momentum can be found which decreases to a lower level of 32.8% (20.7%) in the 5 m frequency. Interestingly, the lengths of the momentum periods, expressed as the number of momentum cycles, are longer in the higher frequencies for both asset classes. Both results indicate that time-series momentum is more stable but less prevalent in the higher frequencies which we trace back to the presence of different market participants with different investment strategies in the different frequencies. As the percentage of time-series momentum is still large in the higher frequencies, our results do not imply that the market efficiency increases with a higher frequency. We therefore conclude that the results confirm the robustness of the momentum effect for cryptocurrencies.

Finally, we do not find significant differences between positive and negative time-series momentum in particular for cryptocurrencies. Table 2 shows that cryptocurrencies have a slightly larger proportion of negative time-series momentum while the reverse is true for the S&P500. This result can be observed for each frequency, however the imbalance is in particular pronounced for the S&P500. For example for daily frequencies, cryptocurrencies (S&P500) have 3.3% (16.8%) more negative (positive) time-series momentum. This asymmetric behavior of the S&P500 can be explained by the empirical stylized fact that stock returns usually have persistent negative skewness and excess kurtosis over longer periods (Cont, 2001) which can be confirmed by Table 1 in the Data Section for the S&P500. This shows that negative price changes are faster than positive price changes for the S&P500 which leads us to conclude that time-series momentum is a constant process of consecutive price adjustments where the likelihood of overvaluing or undervaluing information is less than for faster price changes.

In the following, we analyze the characteristics of the momentum periods for both asset classes. As the stochastic time series does not reveal any momentum period, we do not longer consider it hereafter. Momentum periods are the core of our dynamic modeling approach because their characteristics allow us to draw conclusions about the prevalence and quality of the momentum effect. As our intention is to uncover differences and similarities between cryptocurrency and stock markets, we compare three basic measurements of momentum periods with each other: vertical change, horizontal change and slope. Table 3 reports the mean log return, duration and number of momentum cycles as well as derived ratios of the asset classes' momentum periods for each frequency and direction.

The mean log return represents the vertical change while duration and number of momentum cycles indicate the mean horizontal change of a price. The slope is calculated as the mean ratio of the vertical and horizontal change. Confirming our findings, the results impressively provide evidence for the momentum effect since the horizontal and vertical change always differs significantly from zero for all asset classes, frequencies and directions.

First, the momentum return is significantly larger for cryptocurrencies than for the S&P500 in each frequency and direction. By using the Mann–Whitney-U test, we test the null hypothesis that their respective mean returns come from the same distribution. Across all frequencies and directions, each *p*-value is lower than 0.001 which is clearly below the 0.1% significance level, indicating that the chance to find a U-statistic as extreme or even more extreme than the one observed is considerably less than 0.1%, if the null hypothesis is true. Across all frequencies and directions, cryptocurrency momentum returns are at least six times higher than the stock market returns, for daily negative momentum periods even seventeenfold higher. This impressive disparity is equivalent to the relation of the asset classes' mean standard deviation as shown in Table 1 in the Data Section. In absence of momentum, an asset price increases and decreases symmetrically around its mean which changes in times of momentum when one side fluctuates more than the other side. When considering momentum as a period of asymmetric price fluctuations, a higher standard deviation leads to a higher momentum return. We therefore conclude that the standard deviation of a cryptocurrency price time series directly affects the intensity of time-series momentum.

Second, the momentum duration and the number of momentum cycles are significantly larger for cryptocurrencies than for the S&P500 in negative momentum periods, however only partially for positive momentum periods. Both figures represent the horizontal change of the momentum period, either as a unit of the frequency or as a dynamic structural element of the momentum period. They are highly correlated as can be seen from the result that the mean duration of a momentum cycle is in a narrow corridor between eleven and fourteen units of the respective frequency for each asset class, frequency and direction. This again demonstrates that our modeling approach is able to dynamically measure the vertical as well as the horizontal change of time-series momentum. The mean number of momentum cycles always differs significantly from unity which means that the momentum period is longer than the formation period on average, clearly showing the momentum effect for all asset classes, frequencies and directions. Although cryptocurrencies have a significantly longer momentum duration, in particular for negative momentum periods, their difference is not as extreme as for the momentum returns. In the intraday frequencies, cryptocurrencies have a 1.02 to 1.17 times longer momentum duration. We therefore conclude that the momentum duration is comparable across both asset classes, frequencies and directions, being no striking feature of cryptocurrencies. As a consequence of our results that cryptocurrencies have a considerably larger momentum return with evenly momentum duration, the mean price slope within a momentum period, expressed as return per duration and return per momentum cycle, is also significantly higher for cryptocurrencies in each frequency and direction.

Third, when comparing the momentum effect across frequencies and directions, we find no clear differences. The momentum return, standardized to the highest frequency in order to be comparable, is considerably larger for the 5 m frequency. However, this is not surprising, as each momentum cycle consists of countermovements which are obviously larger in higher frequencies. For the purpose of comparing the momentum returns, we need to consider the number of momentum periods which we analyze in greater detail in the next section when applying a simple trading strategy. Although we find that the duration and number of momentum cycles is larger in the lower frequencies of both asset classes, their differences are negligible. The only exception are negative momentum periods for the S&P500 in the 1D frequency which are significantly smaller than those of the cryptocurrencies and other frequencies independent of the direction. This can be explained by the fact that the S&P500 nearly constantly increased more than 70% in the observation period, where negative momentum periods were rare and unextended.

Fourth, we perform a variety of robustness checks to test for time and asset specific factors. First, we calculate the results of Table 3 again for the same period but excluding the period from January 01, 2017 to December 31, 2017 in order to measure the impact of the cryptocurrency bubble that heavily affected the prices of all cryptocurrencies.[3] The results explicitly show that the mean cryptocurrency returns in positive and negative momentum cycles of all frequencies are only marginally lower than the returns of Table 3. Furthermore, the statistical significances of the differences to the S&P500 returns also remain virtually unchanged. Both results clearly confirm our findings, leading us to conclude that the cryptocurrency bubble does not explain the prevalence of time-series momentum on the cryptocurrency markets. Second, we test the effects of privacy coins on our results by excluding them from our set of cryptocurrencies. While cryptocurrencies are pseudonyms but not completely private as transactions are publicly observable on the blockchain, privacy coins are cryptocurrencies which encrypt their transactions using zero-knowledge proofs or similar private technology. In order to measure the influence of the transactions' observability, we calculate the results again for the entire period without the privacy coins in our set of cryptocurrencies (i.e. Monero, Dash and Zcash).[4] As all momentum period figures remain almost constant to those of Table 3, we provide evidence that the observability of transactions is no explanatory factor for time-series momentum. Third, as cryptocurrencies are highly correlated in particular with the price of Bitcoin (see also Zhang et al. (2018) and Aslanidis et al. (2019)), we calculate the momentum period returns of all individual cryptocurrencies in our sample relative to the returns of Bitcoin for all frequencies and directions.[5] Confirming the high correlation, we find that all cryptocurrencies in all frequencies and directions have the same-directed positive, absolute momentum period returns. Interestingly, around 90% and more of the individual cryptocurrencies have even higher returns than Bitcoin with lower-frequency positive momentum periods as the only exception. Our findings therefore robustly demonstrate that time-series momentum is also prevalent on asset level.

Finally, we also apply the original time series momentum trading strategy of Moskowitz et al. (2012) to our set of cryptocurrencies with a 1 day price frequency. As the results need to be comparable to our findings, we calculate the mean return and measure whether it is equal to zero on the basis of the same lookback and holding periods as in Moskowitz et al. (2012). We have added the results as Table A.4 in the Appendix section of the paper. Our results broadly confirm the findings of Grobys and Sapkota (2019) as 75% of the formation and momentum period combinations yield to mean returns that are either negative or statistically not different from zero. However, the remaining 25% of the mean returns show that the time series momentum effect can be observed. Interestingly, momentum periods with a length of 24 days are positive and statistically significant for most of the defined formation periods which exactly corresponds to our results in Table 3 (i.e. the mean duration of positive momentum cycles is 24.25). This explicitly underlines that our method dynamically captures momentum periods without the requirement to predefine formation or

[3] See Appendix Table A.1 for details.

[4] See Appendix Table A.2 for details.

[5] See Appendix Table A.3 for details.

Table 4
Momentum cycle ratios.

	Cryptocurrencies				S&P500					
	Mean	Median	Std. dev.	PRL1	Mean	Median	Std. dev.	PRL1	Diff. median	p-value
A. Positive momentum/1 day										
Return	1.580	0.912	2.163	44.565	0.996	0.625	1.001	33.333	0.286	0.10477 (ns)
Standard deviation	1.583	1.380	0.986	80.451	0.946	0.743	0.856	13.044	0.637	0.00000***
Duration	1.630	0.682	3.034	39.855	4.439	1.845	5.420	62.500	−1.163	0.00292**
Slope	9.873	1.683	26.694	64.493	2.408	0.542	6.453	12.500	1.141	0.00000***
B. Positive momentum/1 h										
Return	2.114	1.152	3.894	54.985	0.643	0.395	0.561	26.667	0.757	0.00282**
Standard deviation	2.258	1.503	7.116	86.207	1.340	1.402	0.531	76.923	0.102	0.32399 (ns)
Duration	1.415	0.531	2.401	36.858	12.021	0.385	44.085	20.000	0.146	0.11801 (ns)
Slope	168.992	2.082	2.359	74.018	10.242	2.053	16.746	66.667	0.029	0.31832 (ns)
C. Positive momentum/5 min										
Return	1.556	0.823	2.650	43.084	1.318	0.888	1.406	45.179	−0.065	0.33182 (ns)
Standard deviation	1.473	1.231	1.132	65.596	1.264	1.188	0.678	60.968	0.042	0.00002***
Duration	1.522	0.514	4.036	35.208	2.182	0.797	7.863	44.904	−0.283	0.00037***
Slope	5.035	1.718	18.617	66.202	3.030	1.319	5.678	60.055	0.398	0.00041***
D. Negative momentum/1 day										
Return	1.592	0.858	2.530	44.461	1.600	0.910	1.990	47.170	−0.052	0.22379 (ns)
Standard deviation	1.537	1.261	1.447	68.090	1.648	1.461	0.823	79.630	−0.200	0.0067**
Duration	1.645	0.535	4.435	36.405	1.761	0.547	4.635	38.113	−0.011	0.28795 (ns)
Slope	6.467	1.736	83.671	66.458	3.794	1.779	5.645	70.943	−0.044	0.22574 (ns)
E. Negative momentum/1 h										
Return	2.771	1.013	17.503	50.350	1.264	0.899	1.228	42.297	0.113	0.00001***
Standard deviation	3.083	1.139	47.729	56.355	129.026	1.057	1234.220	53.586	0.082	0.00000***
Duration	1.595	1.013	2.148	52.335	1.726	1.001	2.256	55.862	0.012	0.00001***
Slope	3.777	1.112	117.398	53.795	1.355	0.922	1.604	44.864	0.189	0.00000***
F. Negative momentum/5 min										
Return	2.536	1.058	13.766	52.035	1.398	0.901	1.564	48.066	0.157	0.00013***
Standard deviation	19.311	1.202	2106.650	59.074	95.266	1.126	1018.400	57.762	0.076	0.00000***
Duration	1.595	1.036	2.277	51.387	1.653	1.034	2.149	52.970	0.002	0.00531**
Slope	2.738	1.191	31.219	56.341	1.435	1.001	1.471	52.832	0.190	0.00000***

Note: The table reports characteristics of the return, standard deviation, duration and slope momentum cycle ratios per frequency and momentum direction for the 20 cryptocurrencies and the S&P500 index for the period from January 01, 2014 to December 31, 2019. It also shows the median differences as well as the p-values of the Mann–Whitney-U test. The asterisks represent the level of significance, where***,**,* indicates that the test statistic is significant at the 0.1%, 1% and 5% level respectively while ns means that the test statistic is not significant.

momentum periods. The results of Table A.4 show that the parameter-based modeling approach of Moskowitz et al. (2012) does not measure time series momentum efficiently which leads to the illustrated mixed results. In contrast, we find clear evidence that price persistence is highly prevalent in the cryptocurrency markets which leads us to conclude that our modeling approach more efficiently measures time series momentum.

In summary, we find considerable differences of the momentum periods across the asset classes, however not for the various frequencies and directions which again underlines the robustness of the momentum effect. In particular, we find that the standard deviation of an asset time series plays an important role in explaining the differently-sized momentum returns of both asset classes. We will analyze this result in more detail in the next section by use of the smallest structural elements of time-series momentum, the momentum cycles.

As a consequence of our finding that in particular the return characterizes the cryptocurrency and stock market's momentum periods, we further analyze the transitions of the chained momentum cycles in more detail. For example, in Fig. 1 of the Methodology Section we consider the two consecutive momentum cycles T3–T6 and T5–T8 in order to examine the chained transition period T5-T6. According to our modeling approach, this transition period plays an important role because an exceeding of the price over the previous turning point provides a confirmation of a new momentum cycle and therefore a higher momentum return. In Fig. 1, the price exceeds the level of the previous turning point T4 at the point P1, thus confirming the following momentum cycle T5–T8. We hypothesize that the previous turning point affects the price development of the transition period in the way that the price evolves differently before and after its exceeding. For our following analysis, we analyze all transition periods for all consecutive momentum cycles across all asset classes, frequencies and directions. We therefore calculate for both sub-periods of the transition period (before and after the price level exceeding) the log return, standard deviation, duration as well as the slope and calculate their ratios, where the preceding sub-period return marks the numerator and the subsequent sub-period return the denominator. In Fig. 1, the return ratio of the transistion period T5–T6 is significantly smaller than 1 as the log return of T5–P1 is considerably lower than the subsequent log return P1–T6.

Table 4 presents descriptive statistics of the return ratio, standard deviation ratio, duration ratio and slope ratio for each asset class, momentum direction and frequency.

For example, the mean return ratio of cryptocurrencies during positive momentum cycles in the 1 h timeframe is 2.114 which means that the log return in the preceding sub-period is 2.114 times larger than the log return of the subsequent sub-period. In

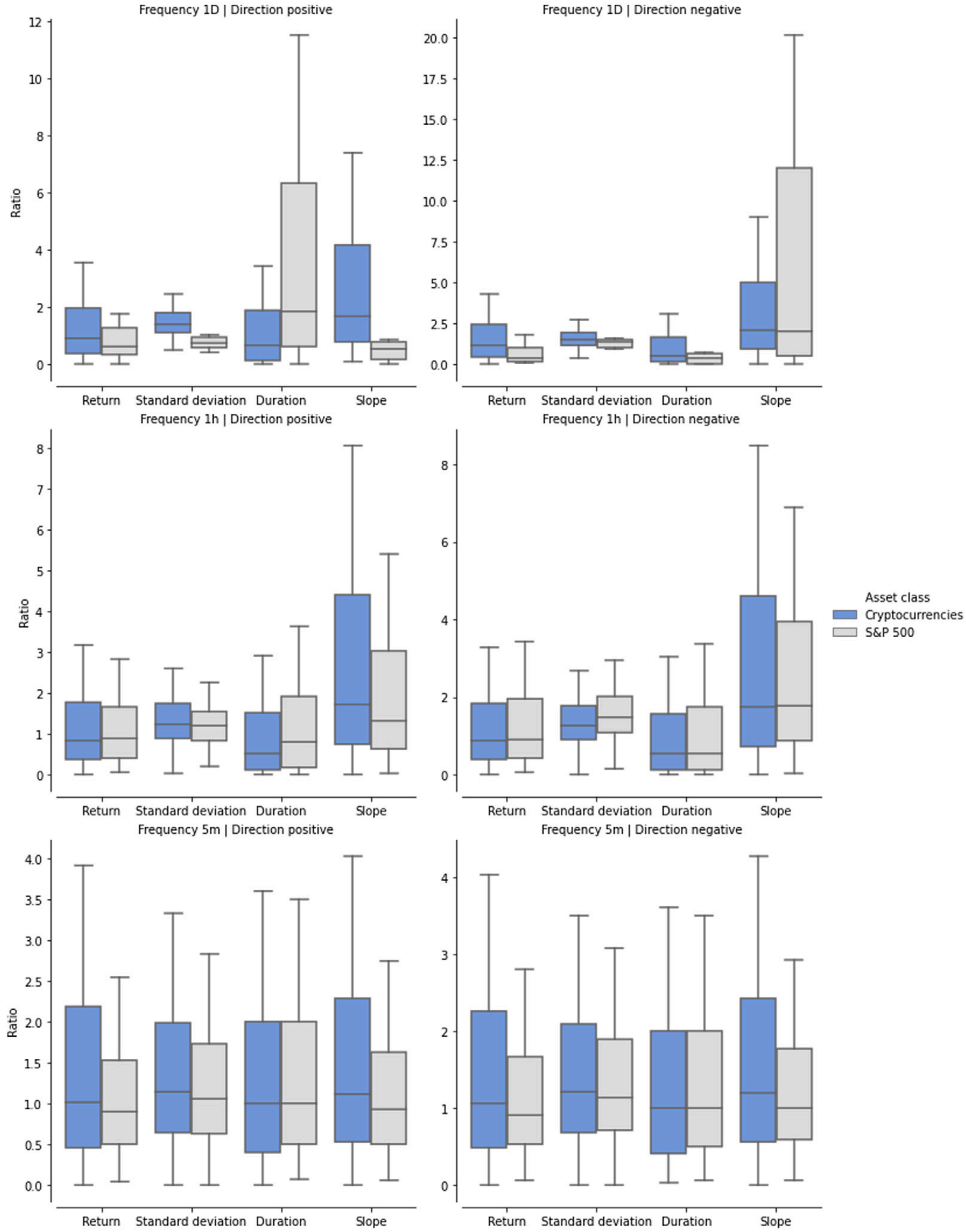

Fig. 2. Distribution of the momentum cycle ratios. *Note:* The figure shows the distribution of the return, standard deviation, duration and slope ratios of all positive and negative momentum cycles per frequency across the 20 cryptocurrencies and the S&P500 index for the period from January 01, 2014 to December 31, 2019.

contrast, the corresponding mean return ratio of the S&P500 is 0.643 which is significantly lower indicated by the *p*-value below the 1% significance level that we calculated for the Mann–Whitney-U test described in the Methodology section. As ratios can vary widely if either the denominator or the numerator is sufficiently low, nearly all ratios have large standard deviations, so that we additionally rely on the median ratio and its asset class difference. Finally, we present the percentage of ratios that are larger than 1 (PRL1) in order to better assess the ratio distribution. Fig. 2 graphically illustrates the high dispersion as well as the asset classes' median ratios for all frequencies and directions.

First, the standard deviation and slope of the price decreases significantly, as soon as the price exceeds the price level of the previous turning point. For cryptocurrencies, the median (PRL1) is for every frequency and direction considerably larger than 1

(50%) which is partially the case for the S&P500. In addition, both figures are always higher for cryptocurrencies in each frequency and direction except for daily negative momentum cycles. This result can be explained by the anchoring effect (Tversky & Kahneman, 1974) which is a cognitive bias that describes the tendency that a piece of information (the anchor) has a disproportionally large weight in the market participant's decision-making process. In advance of the price exceeding, the previous turning point marks the anchor as it represents the current extreme point of a momentum period. We therefore assume that market participants regard the extreme point as a confirmation of the momentum period. In advance of its exceeding, the uncertainty of the momentum continuation leads to an intense price development which can be seen in our results in the form of a higher standard deviation and slope of the preceding sub-period. As soon as the price exceeds the extreme point and therefore confirms the momentum period, both figures decrease significantly as the uncertainty regarding the future price development seems to be reduced.

Second, the return and duration of the preceding sub-period does not differ significantly from the subsequent sub-period as our results show inconsistent median ratios and PRL1 for cryptocurrencies across the frequencies and directions. For the S&P500 the median return ratio and return PRL1 is lower than 1 (50%) in each constellation. We therefore conclude that the anchoring effect, triggered by the previous turning point, leads to an intense price stimulus in advance of the renewed momentum confirmation which does not have a sustainable effect on the subsequent price development. This can be shown in our results as the return and duration of the subsequent sub-period is not consistent when the standard deviation and slope is low.

Third, our results do not change substantially across the various frequencies. Fig. 2 shows that the dispersion is larger for the higher frequencies which can be explained by their higher number of observations. In particular for the S&P500, we find 10 negative momentum cycles in the 1D frequency as the price increases nearly over the entire observation period. Overall, the anchoring effect (Tversky & Kahneman, 1974) can be clearly identified over the various frequencies. This is an impressive result, because different market participants, acting in the different frequencies with different investment strategies, are highly exposed to this robust cognitive bias. In addition, we find asymmetric results between positive and negative momentum cycles of both asset classes in the intraday frequencies. While the slope ratios are higher for positive momentum cycles, the duration ratios are considerably higher for negative momentum cycles. As the standard deviation ratios are always higher for positive momentum cycles, it means for both asset classes that a negative price exceedance results in a sharper price decrease. It also means that a positive, subsequent price movement is slower but longer on average. This asymmetric behavior might again be explained by the negative skewness and excess kurtosis of both asset classes over longer periods which lead to faster negative price changes.

In summary, when extrapolating from our momentum cycle results to the momentum effect, our findings reveal that momentum consists of multiple price impulses that decay instantly as soon as its confirmation is renewed.

4.2. Trading strategy

In this section, we design a trading strategy which exploits our empirical findings for trading time-series momentum. The trading strategy relies on the same dynamic modeling approach as described in the Methodology Section. This means that an investor enters a long (short) position when a new positive (negative) formation period has been formed in order to benefit from the expected price increase (decrease) of the subsequent momentum period. In Fig. 1 of the Methodology Section an investor would open a long position after the realization of the turning point T4. He would then hold the position as long as the momentum cycle conditions are valid which would be after the realization of the turning point T12 in Fig. 1. Therefore, our parameter-less, dynamic momentum strategy can be regarded as a kind of trading rule as shown in Grobys et al. (2020). We assume trading fees of 0.2% per trade[6] and calculate our results before (gross-of-fees) and after (net-of-fees) its deduction, respectively. For reasons of simplicity we start by abstracting from slippage as the difference of the expected price of a trade and the price at which the trade is executed. Table 5 Panel (a) and (b) report the results of our momentum trading strategy and compare them with those of a buy-hold strategy in Panel (c).

First, the momentum strategy has a considerably higher return, risk and risk-adjusted return for cryptocurrencies compared to the S&P500 in each frequency and momentum direction. Furthermore, cryptocurrencies have a larger percentage of momentum trades which are defined as trades where the time-series momentum consists of at least one momentum cycle after the formation period. Regarding the realized return, cryptocurrencies have a higher profit per trade and a larger total return, although they have less trades on average than the S&P500 in each frequency and direction. After deducting trading fees, only positive long momentum trades in the 1D frequency are profitable for the S&P500, while cryptocurrencies do always generate a positive total net return in the 1D and 1 h frequencies. In contrast, the cryptocurrency momentum strategy is consistently exposed to higher risk levels, defined as the mean maximum drawdown. Nevertheless, cryptocurrency returns always compensate the taken risks, indicated by the higher return over maximum drawdown figures for each frequency and direction. As opposed to mean reversion trading strategies, where the counter-reaction of an overreaction is traded, momentum trading strategies have less winning trades but higher returns per trade (Conrad & Kaul, 1998). This means that winning trades of a momentum strategy are more sensitive to the profitability of the whole strategy. We therefore determine the proportion of the largest winner returns that make up the total gross return which we name percentage of breakeven trades. For example, 8.2% (4.9%) of the largest cryptocurrency (S&P500) long momentum returns in the 1 h frequency make up the total gross return of 492.1% (59.4%). This means that a lower proportion of the S&P500 winner trades was responsible for reaching the breakeven point of the momentum strategy. As a consequence a lower proportion implies a higher risk due to a greater dependency on the largest winner trades. With only the exception of long momentum trades in the

[6] See https://www.bitfinex.com/fees for a detailed overview of the trading fees at the Bitfinex cryptocurrency exchange.

Table 5
Momentum trading strategy and buy-hold strategy results.

	1D			1 h			5 m		
	Crypto-currencies	S&P500	Difference	Crypto-currencies	S&P500	Difference	Crypto-currencies	S&P500	Difference
(a) Long momentum trades									
Gross profit per trade	7.248	1.360	5.888	0.996	0.089	0.907	0.093	0.013	0.079
Net profit per trade	6.848	0.960	5.888	0.596	−0.311	0.907	−0.307	−0.387	0.079
Total number of trades	18.25	24	−5.75	457.85	669	−211.15	4729.55	6431	−1701.45
Number of momentum trades	8.15	11	−2.85	186.25	216	−29.75	1496	1708	−212
Percentage of momentum trades	45.864	45.833	0.031	39.310	32.287	7.023	28.002	26.559	1.443
Total return gross	134.477	32.640	101.837	492.052	59.360	432.692	727.852	84.990	642.862
Total return net	127.177	23.040	104.137	308.912	−208.240	517.152	−1163.970	−2487.410	1323.440
Maximum drawdown gross	−15.409	−2.475	−12.934	−26.954	−3.015	−23.939	−138.574	−3.393	−135.182
Maximum drawdown net	−16.519	−5.998	−10.521	−42.322	−208.761	166.439	−1004.960	−2498.200	1493.240
Return over maximum drawdown gross	13.763	13.189	0.574	51.532	19.687	31.845	49.584	25.052	24.532
Return over maximum drawdown net	12.144	3.841	8.302	19.413	−0.998	20.410	−1.371	−0.996	−0.376
Percentage of breakeven trades	17.498	25.000	−7.502	8.231	4.933	3.299	2.901	1.524	1.378
(b) Short momentum trades									
Gross profit per trade	10.581	0.124	10.457	1.002	0.033	0.969	0.066	0.001	0.065
Net profit per trade	10.181	−0.276	10.457	0.602	−0.367	0.969	−0.334	−0.399	0.065
Total number of trades	18.05	31	−12.95	449.95	609	−159.05	4543.4	6073	−1529.6
Number of momentum trades	8.65	9	−0.35	191.3	167	24.3	1491.45	1257	234.45
Percentage of momentum trades	49.477	29.032	20.445	41.470	27.422	14.048	29.168	20.698	8.470
Total return gross	180.702	3.850	176.852	448.198	20.350	427.848	647.536	3.400	644.136
Total return net	173.482	−8.550	182.032	268.217	−223.250	491.467	−1169.820	−2425.800	1255.980
Maximum drawdown gross	−13.768	−7.169	−6.599	−14.182	−3.397	−10.786	−157.830	−18.131	−139.699
Maximum drawdown net	−14.806	−17.696	2.891	−26.755	−223.472	196.717	−1025.000	−2436.080	1411.080
Return over maximum drawdown gross	18.608	0.537	18.071	53.498	5.991	47.507	35.444	0.188	35.256
Return over maximum drawdown net	16.366	−0.483	16.849	23.355	−0.999	24.354	−1.299	−0.996	−0.303
Percentage of breakeven trades	21.243	3.226	18.017	8.947	1.642	7.305	2.878	0.016	2.861
(c) Buy-hold									
Total return gross	185.959	177.486	8.473	190.756	176.207	14.549	196.595	176.375	20.220
Maximum drawdown gross	−90.207	−20.833	−69.374	−91.913	−20.934	−70.980	−92.489	−21.176	−71.313
Return over maximum drawdown gross	2.094	8.519	−6.426	2.124	8.417	−6.293	2.180	8.329	−6.149

Note: The table reports the return, risk and risk-adjusted characteristics of the momentum trading strategy and a buy-hold strategy per frequency and momentum direction for the 20 cryptocurrencies and the S&P500 index for the period from January 01, 2014 to December 31, 2019.

1D frequency, cryptocurrencies are less dependent on their largest winner trades, having a more balanced return distribution and therefore a lower risk profile.

Second, the momentum strategy outperforms a buy-hold strategy for cryptocurrencies while the opposite is true for the S&P500. Although the sum of the long and short total returns are positive for both asset classes, they are only higher for cryptocurrencies compared to a buy-hold strategy. Interestingly, the risk is nearly always lower for the momentum strategies in both asset classes which leads to higher risk-adjusted returns for cryptocurrencies in each constellation as well as for the S&P500 when trading positive time-series momentum. Even after deducting a trading fee of 0.2% per trade, the trading strategy would still be significantly profitable for cryptocurrencies in the lower frequencies which is never the case for the S&P500. In the 5 m frequency, the trading fees eat up the mean gross profit per trade of both asset classes so that the net profit per trade is always negative.

We conclude that the findings of our present paper can be better exploited for cryptocurrencies compared to equity markets. However, it should also be noted that the selection of the observation period and the transaction fees have a major impact on the profitability of the momentum trading strategy. In particular the observation period of the S&P500 covers the longest bull run in the US stock market history,[7] which makes negative momentum periods harder to find. In general, we show that even when following a fairly simple trading strategy without any external parameters and also accounting for transaction costs, it is still possible to generate excess returns on cryptocurrency markets due to the presence of the momentum effect. Interestingly, a cryptocurrency investor is also able to considerably reduce the downside risk when invested into an active trading strategy of a lower frequency instead of a passive investment.

5. Conclusion

Our paper tests the momentum effect for twenty cryptocurrencies and the S&P500 stock market index. We model time-series momentum dynamically as consecutive momentum cycles which follow an initial price formation period. In the first step, we

[7] See https://www.wsj.com/articles/global-markets-calmer-after-two-hectic-days-11583899913 for a newspaper article in the Wall Street Journal as of 11.03.2020.

compare the number of momentum cycles for both asset classes with a stochastic time series imitating geometric Brownian Motion. As the stochastic time series never exhibits a momentum cycle, we measure the momentum effect when we are able to identify one or more subsequent momentum cycles which we define as momentum periods. In the second step, we analyze all momentum periods and sub-periods to identify characteristics of the momentum effect. Assuming that an investor trades the respective momentum periods, we compare the risk-return characteristics of both asset classes with those of a buy-hold investment in the final step.

We find broad evidence in favor of the momentum effect for a variety of assets and frequencies which confirms this extensively discussed market anomaly in the empirical literature for the new asset class cryptocurrencies. Our results show for both asset classes that a large proportion of their formation periods are followed by one or more momentum cycles, forming the momentum period. In particular cryptocurrencies have longer and larger momentum periods which is in line with the theory of noise trader risks of De Long et al. (1990). Here, overconfident noise traders push up the price and create risks that deter informed traders from arbitraging the mispricing. As the intrinsic value of the cryptocurrencies is more difficult to compute, we assume that its level of noise traders is higher than for stock markets, leading to a higher prevalence of the momentum effect. We also find for both asset classes critical price levels during momentum cycles where the price develops more intense before its exceeding which we attribute to anchoring effects. As the price development around these critical price levels is largely responsible for the stacked momentum cycles, we conclude that momentum periods are made up of such multiple price impulses. By testing the momentum effect for various frequencies, we are able to cover momentum periods from a few minutes to several months for twenty cryptocurrencies. This large spectrum of momentum periods represents different market participants with different investment strategies, so that our results reveal the robustness of this financial market anomaly. Finally, we show that a momentum strategy based on momentum cycles is able to outperform a buy-hold strategy for both cryptocurrencies and the stock market index, while only cryptocurrencies have higher risk-adjusted returns and lower downside risks than a passive investment. This makes cryptocurrencies in particular interesting for trading the momentum effect.

To the best of our knowledge, this is the first study which models time-series momentum dynamically as a sequence of turning points which are not based on any specific threshold parameter. Moreover, our approach allows us to draw conclusions with regard to the inner mechanics of time-series momentum across cryptocurrency and stock markets. Our present paper is one of the few in the academic literature which finds clear and unequivocal evidence of time-series momentum for a broad range of cryptocurrencies and frequencies. In summary, we hypothesize that the prevalence of time-series momentum is a function of the derivability of the asset's intrinsic value. The better investors can assess the intrinsic value, the less they consider the previous extreme point in their decision-making process which means a lower level of anchoring and less intensive price impulses. In line with the theory of noise trader risks, low price impulses would be arbitraged by informed traders so that the momentum effect does not occur. This hypothesis would explain the prevalence of time-series momentum for cryptocurrencies as well as for stock markets and in particular why cryptocurrencies have considerable longer and larger momentum periods. Moreover, this hypothesis explains why the momentum effect can also be observed for fixed income (Zaremba et al., 2019) and real estate markets (Beracha & Skiba, 2011) where future cash flows are more tangible to predict, but their prevalence and intensity is significantly lower than for equity or cryptocurrency markets. As we have clearly found that the momentum effect holds for various cryptocurrencies, future research might also analyze the inner mechanics of the momentum effect for other asset classes with the same dynamic modeling approach.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Table A.1
Momentum period characteristics excluding the cryptocurrency bubble formation period.

Frequency	1D				1 h				5 m			
	Crypto-currencies	S&P500	Difference	p-value	Crypto-currencies	S&P500	Difference	p-value	Crypto-currencies	S&P500	Difference	p-value
(a) Positive momentum cycles												
Return	18.496	3.732	14.764***	0.0009	3.601	0.601	2.999***	0.0000	1.110	0.171	0.938***	0.0000
Duration	24.010	28.222	−4.211 (ns)	0.1079	21.233	21.983	−0.749 (ns)	0.1447	18.369	18.199	0.170***	0.0000
No momentum cycles	1.762	2.111	−0.349 (ns)	0.0752	1.652	1.497	0.154***	0.0001	1.454	1.409	0.045***	0.0000
Return per duration	0.760	0.132	0.628***	0.0000	0.171	0.027	0.143***	0.0000	0.064	0.009	0.054***	0.0000
Return per momentum cycle	10.228	1.767	8.460***	0.0000	2.180	0.401	1.778***	0.0000	0.775	0.121	0.653***	0.0000
Duration per momentum cycle	13.569	13.368	0.200 (ns)	0.4569	12.815	14.682	−1.867**	0.0077	12.536	12.912	−0.376***	0.0001
(b) Negative momentum cycles												
Return	31.455	2.910	28.545***	0.0000	3.729	0.443	3.286***	0.0000	1.155	0.166	0.989***	0.0000
Duration	31.546	18.600	12.946***	0.0007	21.887	18.815	3.071***	0.0001	19.199	17.525	1.674***	0.0000
No momentum cycles	2.178	1.200	0.978**	0.0083	1.664	1.368	0.295***	0.0000	1.474	1.337	0.136***	0.0000
Return per duration	0.981	0.156	0.825***	0.0000	0.171	0.023	0.148***	0.0000	0.062	0.009	0.052***	0.0000
Return per momentum cycle	14.814	2.425	12.389***	0.0000	2.241	0.323	1.917***	0.0000	0.800	0.124	0.676***	0.0000
Duration per momentum cycle	14.797	15.500	−0.702*	0.0209	13.120	13.746	−0.626 (ns)	0.2322	12.988	13.099	−0.111***	0.0002

Note: The table reports the mean return, duration, number of momentum cycles and derived ratios of the momentum periods per frequency and momentum direction for the 20 cryptocurrencies and the S&P500 index for the period from January 01, 2014 to December 31, 2019, excluding the period from January 01, 2017 to December 31, 2017. It also shows the mean differences as well as the p-values of the Mann–Whitney-U test. The asterisks represent the level of significance, where***,**,* indicates that the test statistic is significant at the 0.1%, 1% and 5% level respectively while ns means that the test statistic is not significant.

Table A.2
Momentum period characteristics excluding the privacy coins Monero, Dash and Zcash.

Frequency	1D				1 h				5 m			
	Crypto-currencies	S&P500	Difference	p-value	Crypto-currencies	S&P500	Difference	p-value	Crypto-currencies	S&P500	Difference	p-value
(a) Positive momentum cycles												
Return	23.086	3.637	19.448***	0.0009	4.166	0.544	3.622***	0.0000	1.252	0.161	1.091***	0.0000
Duration	24.220	28.364	−4.143 (ns)	0.1114	21.429	21.301	0.128 (ns)	0.1745	18.461	17.883	0.577***	0.0000
No momentum cycles	1.779	2.091	−0.311 (ns)	0.0876	1.665	1.454	0.210***	0.0001	1.468	1.402	0.065***	0.0000
Return per duration	0.941	0.128	0.812***	0.0000	0.195	0.026	0.169***	0.0000	0.071	0.009	0.062***	0.0000
Return per momentum cycle	12.674	1.740	10.934***	0.0001	2.493	0.374	2.118***	0.0000	0.862	0.115	0.747***	0.0000
Duration per momentum cycle	13.476	13.565	−0.088 (ns)	0.4073	12.819	14.653	−1.833**	0.0098	12.464	12.753	−0.289***	0.0000
(b) Negative momentum cycles												
Return	30.187	1.724	28.462***	0.0000	3.903	0.407	3.496***	0.0000	1.257	0.155	1.101***	0.0000
Duration	30.788	12.333	18.454***	0.0007	21.702	18.641	3.060***	0.0001	19.195	17.099	2.095***	0.0000
No momentum cycles	2.161	1.111	1.049**	0.0070	1.669	1.365	0.304***	0.0000	1.483	1.321	0.162***	0.0000
Return per duration	0.965	0.140	0.825***	0.0000	0.181	0.022	0.159***	0.0000	0.067	0.009	0.058***	0.0000
Return per momentum cycle	14.089	1.552	12.537***	0.0000	2.334	0.298	2.036***	0.0000	0.863	0.118	0.745***	0.0000
Duration per momentum cycle	14.488	11.100	3.388*	0.0233	12.955	13.654	−0.695 (ns)	0.2637	12.917	12.948	−0.031***	0.0000

Note: The table reports the mean return, duration, number of momentum cycles and derived ratios of the momentum periods per frequency and momentum direction for 17 non-privacy cryptocurrencies (Bitcoin, Ripple, Eos, Ethereum Classic, Ethereum, Iota, Litecoin, Neo, Stellar Lumens, Metaverse ETP, 0x, Tezos, Bitcoin SV, LEO, Bitcoin Gold, Tron and Batcoin) and the S&P500 index for the period from January 01, 2014 to December 31, 2019. It also shows the mean differences as well as the p-values of the Mann–Whitney-U test. The asterisks represent the level of significance, where***,**,* indicates that the test statistic is significant at the 0.1%, 1% and 5% level respectively while ns means that the test statistic is not significant.

Table A.3
Absolute and relative momentum period returns per cryptocurrency.

Frequency	1D				1 h				5 m			
Momentum period	Positive		Negative		Positive		Negative		Positive		Negative	
Return	Absolute	Relative	Absolute	Relative	Absolute	Relative	Absolute	Relative	Absolute	Relative	Absolute	Relative
Bitcoin	24.255	–	15.208	–	2.782	–	1.962	–	0.722	–	0.683	–
Stellar Lumens	7.840	−16.415	24.660	9.453	2.755	−0.027	3.190	1.228	0.940	0.218	1.094	0.411
Dash	16.833	−7.423	22.828	7.621	4.448	1.666	3.644	1.683	1.127	0.405	1.139	0.456
Eos	29.223	4.968	24.854	9.646	5.735	2.953	4.639	2.677	1.368	0.646	1.286	0.603
Ethereum Classic	19.555	−4.700	26.792	11.584	4.795	2.014	3.756	1.795	1.275	0.553	1.267	0.585
Ethereum	36.095	11.840	32.019	16.812	4.532	1.750	3.660	1.698	1.126	0.404	1.049	0.367
Iota	49.131	24.876	45.291	30.084	5.736	2.954	5.125	3.163	1.432	0.710	1.390	0.707
Litecoin	15.239	−9.016	22.552	7.344	3.774	0.992	3.088	1.127	1.194	0.472	1.127	0.445
Neo	17.125	−7.130	28.449	13.242	4.303	1.521	5.137	3.176	1.457	0.735	1.319	0.637
Monero	10.498	−13.757	22.765	7.558	4.729	1.948	4.026	2.065	1.278	0.556	1.178	0.495
Ripple	15.723	−8.532	22.365	7.158	4.589	1.807	3.995	2.033	1.184	0.462	1.105	0.423
Zcash	32.417	8.162	28.266	13.059	4.675	1.894	4.819	2.857	1.316	0.594	1.338	0.656
Metaverse ETP	36.512	12.257	37.320	22.113	5.964	3.182	4.002	2.040	1.759	1.037	1.785	1.103
0x	27.689	3.434	38.974	23.766	4.561	1.780	5.129	3.167	1.506	0.784	1.325	0.643
Tezos	11.670	−12.585	12.928	−2.280	3.795	1.013	3.818	1.856	1.134	0.412	1.479	0.797
Bitcoin SV	24.235	−0.020	69.300	54.093	4.334	1.552	4.142	2.180	1.401	0.679	1.248	0.566
LEO	2.855	−21.400	2.475	−12.733	1.560	−1.222	1.786	−0.175	0.406	−0.315	0.392	−0.291
Bitcoin Gold	20.492	−3.763	54.358	39.151	3.911	1.130	4.181	2.220	1.460	0.738	1.433	0.750
Tron	31.777	7.522	26.464	11.256	3.710	0.928	4.151	2.190	1.235	0.513	1.258	0.576
Batcoin	23.049	−1.206	29.163	13.956	3.993	1.211	4.593	2.631	1.692	0.970	2.123	1.440
Mean non-Bitcoin	22.524	−1.731	30.096	14.888	4.310	1.529	4.046	2.085	1.278	0.556	1.281	0.598
Std. non-Bitcoin		11.510		14.644		1.020		0.817		0.291		0.334
% Outperformer		36.8%		89.5%		89.5%		94.7%		94.7%		94.7%

Note: The table reports the absolute momentum period returns per cryptocurrency, frequency and momentum direction for the period from January 01, 2014 to December 31, 2019. It also shows the momentum period returns relative to the returns of Bitcoin. % Outperformer indicates the percentage of individual cryptocurrencies which have higher momentum period returns than those of Bitcoin.

Table A.4
Mean momentum period returns calculated with predefined formation and momentum periods.

	Momentum period							
Formation period	1	3	6	9	12	24	36	48
1	−0.0030 ns	0.0014 ns	−0.0003 ns	−0.0018 ns	−0.000 ns	−0.0031 ns	−0.0061 ns	−0.0152 ns
3	0.0001 ns	0.0035 ns	0.0060 ns	0.0038 ns	0.0127 ns	0.0312**	0.0272*	0.0116 ns
6	0.0007 ns	0.0065 ns	0.0055 ns	0.0042 ns	0.0139*	0.0334***	0.0213 ns	0.0178 ns
9	−0.0002 ns	−0.0014 ns	−0.0020 ns	0.0046 ns	0.0126 ns	0.0266**	0.0053 ns	−0.0012 ns
12	0.0004 ns	0.0053 ns	0.0123**	0.0199***	0.0284***	0.0335***	0.0125 ns	−0.0015 ns
24	0.0029 ns	0.0122***	0.0210***	0.0332***	0.0365***	0.0257**	−0.0077 ns	−0.0366**
36	0.0030 ns	0.0080**	0.0118**	0.0108 ns	0.0095 ns	−0.0178 ns	−0.0554***	−0.0793***
48	−0.0006 ns	−0.0003 ns	−0.0071 ns	−0.0113 ns	−0.0191**	−0.0609***	−0.0911***	−0.1128***

Note: The table reports the mean momentum period log returns calculated with predefined daily formation and momentum periods. They are calculated on the basis of our sample of 20 cryptocurrencies for the period from January 01, 2014 to December 31, 2019. The asterisks represent the level of significance whether the mean return is equal to zero, where***,**,* indicates that the test statistic is significant at the 0.1%, 1% and 5% level respectively while ns means that the test statistic is not significant. For example, after a formation period of 1 day, the mean log return of the subsequent 1 day momentum period would be −0.3% which is statistically not different to a return of 0.0%.

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