Asset Pricing on Blockchain:

Slow moving capital, momentum, and bubbles of cryptocurrencies

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David (Dexin) Hou*   Jennifer (Jie) Li†   Li Liao‡   Hong Zhang§

Abstract

Blockchain-technologies have limited scalability in processing transactions. We argue that this feature has a profound influence on the pricing of blockchain-based assets. In periods when capital goes beyond the processing capacity of a blockchain, impediments to trade dominate price dynamics and create bubble-crash patterns. Even in the normal stage of a blockchain, information dissemination could be constrained by slow verification of transactions—momentum arises as a consequence. Hence momentum and bubbles may reflect two distinctive stages of crypto slow moving capital. Analysis based on a sample of 1392 cryptocurrencies from 2013 to 2018 lends support to the above notion. Particularly, momentum works for normal-stage (but not for impediment-stage) cryptocurrencies. Bubbles and crashes are more likely to occur among impediment-stage (as opposed to normal-stage) cryptocurrencies. Our results shed new lights on the asset pricing foundation of blockchain-based products.

Key words: Blockchain, Slow moving capital, Momentum, Bubbles, Cryptocurrency, FinTech

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* PBC School of Finance, Tsinghua University, 43 Chengfu Road, Haidian District, Beijing, PR China 100083, Email: houdx.14@pbcsf.tsinghua.edu.cn

† Shanghai Advanced Institute of Finance, Shanghai Jiao Tong University, 211 Huaihai West Road, Xuhui District, PR China 200000; E-mail: jli6@saif.sjtu.edu.cn

‡ PBC School of Finance, Tsinghua University, E-mail: liaol@pbcsf.tsinghua.edu.cn

§ PBC School of Finance, Tsinghua University, Email: zhangh@pbcsf.tsinghua.edu.cn

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Introduction

Blockchain is at the core of the new wave of Fintech evolution. Since the initial offering of the first blockchain-based cryptocurrency (Bitcoin) in 2009, more than one thousand cryptocurrencies have been released based on similar or improved blockchain platforms. Blockchain and its related infrastructures are also widely believed to be disruptive to a wide range of industries.[1] Despite the far-reaching breakthroughs that blockchain may potentially bring, the asset pricing implications of blockchain-based financial assets are surprisingly gloomy. Take cryptocurrencies as an example. Although cryptocurrencies are embedded with many novel properties compared to traditional assets, what attracts the public attention is the wave of crypto bubbles and crashes with unpreceded magnitudes and intensities (e.g., Corbet, Brian Lucey, Larisa Yarovaya 2017). As noticed by Bloomberg, for instance, the crypto market had scared away investors by its record 80% plunge during the "Great Crypto Crash" in early 2018, which is worse even than the epic Dot-Com crash.[2] These observations challenge the academic world to explore the pricing foundation of blockchain and explain the potential difference between cryptocurrencies and traditional assets, if any.

Our paper aims to address this issue by examining the asset pricing implications of one of the most fundamental features of blockchain technologies: limited scalability or limited capacity in processing transactions. This feature is rooted deeply in blockchain, which typically underpins *decentralized digital ledgers* based on peer-to-peer networks, public key cryptography, and consensus mechanism. Consequently, validating data authenticity as well as transactions becomes a costly task.[3] As argued in Cong and He (2019), there is a fundamental tension between decentralized consensus and information dissemination. From asset pricing's perspective, the property limits the speed and scale at which capital can flow. Figure 1 provides an intuitive example by plotting the ratio of pending transactions over and recorded ones for Bitcoin. When the ratio is high, capital cannot really flow—we see that this scenario occurs quite frequently.

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[1] Indeed, blockchain and its related infrastructures, such as decentralized distributed ledgers and network-based trust (e.g., Harvey 2016; Tasca 2016), are also widely believed to be disruptive to a wide range of industries, ranging from sharing economy such as AirBnB to the financial industry, and may even challenge the regulatory systems adopted in major developed economies (Raskin and Yermack 2016; also see Schneider et. al, 2016 for a recent industry report and Gao et. al., 2019 for a recent case study).

[2] https://www.bloomberg.com/news/articles/2018-09-12/crypto-s-crash-just-surpassed-dot-com-levels-as-losses-reach-80.

[3] With decentralized digital ledgers, transactions on a blockchain are not stored in a single location but hosted by millions of computers simultaneously, accessible to anyone on the network but safe from hackers. The consensus mechanism, which aims to protect the network of decentralized distributed ledgers from fraudulence, is typically established based on proof-of-work (PoW) or Proof-of-Stake (PoS) protocols, whose capacity in processing transactions is limited compared to centralized protocols. The first few generations of blockchains such as those used by Bitcoin and Ethereum, can handle a smaller number of transactions per second (TPS) compared to Visa. Bitcoin, Ethereum and Visa's TPS numbers are 7, 50, and 24000. Some more recent cryptos claim to have a much higher TPS. However, concerns on their network security arise as a consequence.

We argue that limited scalability and its resulting slow moving capital provides a fundamental framework to understand the price dynamics of cryptocurrencies. In particular, two different regimes of market conditions may distort the pricing of cryptocurrencies differently. First of all, the literature (see, e.g., Duffie, Garleanu, and Pedersen 2007, 2009; Duffie 2010) suggests that significant impediments to capital movements give rise to sharp price shifts and reversals, creating bubble-crash types of price dynamics. We refer to the regime as an *impediment stage* when there is no confusion, and expect the same implications apply to blockchain-based assets.

But even in the absence of major impediments to capital, which we can refer to as a *normal stage*, asset prices can nonetheless be affected by the speed at which information can be disseminated on a blockchain. To see the intuition, consider the case when a piece of new information arrives (e.g., the value of a blockchain increases due to more users or investors it attracts, as discussed in Sockin and Xiong 2018; Cong, Li, and Wang 2019). Although some informed investors observe and want to trade on this information, the lack of liquidity originated from limited scalability and slow verification of transactions could hinder their speed of trading—informed investors, for instance, may choose to strategically release their information through multiple periods of trading (e.g., Kyle 1985; Holden and Subrahmanyam, 1992). Asset prices in this case can exhibit positive autocorrelation, or *momentum*.

Based on the above arguments, one intriguing pricing implication of blockchain-based assets is that both momentum and bubbles can naturally arise as a consequence of blockchain-based slow moving capital. Perhaps even more importantly, the two types of price dynamics reflect—and therefore occur alternately but not simultaneously—in two distinctive stages of blockchain-based slow moving capital. If we focus on a large cross section of blockchain assets, then bubbles and momentum should be observed in the subsample of impediment-stage assets and normal-stage assets, respectively. For instance, for the subsample of assets in their impediment stage, the intensity of observing a bubble or a crash is high, but that for momentum is not—the positive price autocorrelation of momentum is likely to be dominated by the large-scale reversals. By contrast, the probability of witnessing a sudden crash for the subsample of normal-stage assets would be smaller compared to impediment-stage assets. One interesting implication of the above arguments is that blockchain-based momentum may not be associated with more crash risk, because momentum mostly occurs in a normal stage whereas crash risk is intuitively higher in the impediment stage. This feature differs drastically from momentum of most traditional assets, such as stocks, that are traded in more liquid markets (e.g., Daniel and Moskowitz 2016).

We test the above intuition based on the complete set of cryptocurrencies, the most noticeable blockchain-based assets. Following Griffin and Shams (2018), we download pricing and market cap information from *coinmarketcap.com*, our major database. We then use *cryptocompare.com* and

Yahoo!Finance to further augment the sample and verify the information. Our final sample consists of 1392 cryptocurrencies in the sample period from 2013 to 2018. As a robustness check, we also follow Makarov and Schoar (2019) to use exchange-level pricing information for a set of 268 cryptocurrencies provided by *Kaiko.com*.

We conduct three steps of analysis to assess momentum, bubble, and their relationship in the crypto market. In the first step, we classify cryptocurrencies into two different groups representing the two different stages (i.e., normal vs. bubble) of assets, and we examine whether impediment-stage assets are exposed with higher crash risk in spirit of Greenwood, Shleifer, and You (2018). More explicitly, for each quarter, we classify a cryptocurrency as an impediment-stage asset if it has experienced either a price run-up that belongs to the top quintile (i.e., top 20%) of all cryptocurrencies, or a price drawdown that belongs to the top quintile of all cryptocurrencies, or both, and we classify the rest cryptocurrencies as normal-stage assets (our results are robust to the threshold).[4] We find that the two stages are relatively stable, and that impediment-stage cryptocurrencies identified in one quarterly are likely to experience a much higher probability of large price jumps and crashes in the following quarter. This observation confirms that blockchain assets are more vulnerable to crash risk in bubble stage.

Our second step of analysis focuses on crypto momentum that can be generated from the above two groups of cryptocurrencies. Given the relative short time period, we use weekly information to construct momentum portfolios. For instance, we will demonstrate our results mostly based on the momentum strategy with 2-week ranking period and 2-week holding period (the 2week-2week strategy). Following Daniel and Moskowitz (2016), we mainly examine market-cap value-weighted (VW) returns for crypto-momentum strategies. This VW methodology is economically appealing in examining crypto-momentum, because it mitigates the potential concern that a few very small and illiquid cryptocurrencies may have huge influences in relevant trading strategies due to their volatile price movements. Based on these specifications, we split our sample into two groups of assets based on the before-ranking period classification of normal vs. bubble stages, and we separately report momentum return for these two groups of assets.

Our empirical results are striking. We find that momentum can generate highly significant return in and only in the group of normal-stage cryptocurrencies. The weekly return of the 2week-2week VW momentum strategy among normal-stage cryptocurrencies can be as high as 6.7%. By contrast, the same strategy would lead to an insignificant -0.76% return for impediment-stage cryptocurrencies. Moreover, when we test momentum strategies with different durations of ranking and holding periods, we find that the above distinction remains highly significant. To differentiate the momentum strategy based on normal-stage

[4] Note that, since we cannot directly observe pending transaction for most cryptocurrencies, we proxy for the impediment stage by the occurrence of a bubble (or a negative bubble).

cryptocurrencies from traditional momentum, we refer to the former as *enhanced momentum* when there is no confusion.

While these observations lend support to the notion that momentum and bubbles are two distinctive asset pricing distortions for blockchain-based assets, we conduct one more test to further illustrate the potential relationship between momentum and crash. More explicitly, we follow Daniel and Moskowitz (2016) to estimate the market exposure of the normal momentum portfolio in bear markets (i.e., down-market betas). We first find that the 2-week-2-week momentum portfolio of normal-stage cryptocurrencies exhibits insignificant market beta, when we directly regress momentum returns on the VW crypto market return. Importantly, the market exposure of normal-stage crypto momentum in down-market is insignificantly, implying that the positive return of normal-stage crypto-momentum is not associated with higher market crash risk. This observation differs drastically from both equity and currency momentum (both have significant negative down-market betas in Daniel and Moskowitz 2016), but is consistent with our working hypothesis based on slow moving capital.

Our last step of analysis aims to shed more light on blockchain-based asset pricing by conducting a list of additional tests and robustness checks. We first ask whether the formation of the impediment stage could indeed be related to some characteristics of investors. To examine this potential link, we regress the indication function of bubbles on Google search and its changes. We find that larger Google search and positive changes in Google search of a cryptocurrency in a quarter is positively associated with the likelihood for the asset to fall into an impediment stage in the following quarter, other things being equal. This observation is consistent with search-based argument. In particular, more attention from investors will not drastically relax the trading capacity of blockchain—but it potentially signals that, since more investors are interested in the asset, the fraction of high-valuation investors might increase. This increase in high-valuation investors will precisely give rise to for formation of bubble in search-based models.

Next, we notice that different cryptocurrencies may be launched for different purposes. The recent guideline issued by Swiss Financial Market Supervisory Authority (FINMA), for instance, classifies cryptocurrencies into three categories: payment tokens, utility tokens, and asset tokens.[5] Based on the purposes of the cryptocurrencies in our sample (e.g., Digital Currency, Smart Contract, 3D Printing; there are 92 subcategories in total in our sample), we can roughly classify cryptocurrencies into three categories, including *Digital Currency*, *Usage*, and *Others*. Among the three, the category of *Digital Currency* is in spirit the closest to traditional assets (i.e., fiat currencies), whereas the other two categories are more remote

[5] The FINMA 16 February 2018 guideline, which is available at the following link: https://www.finma.ch/en/~/media/finma/dokumente/dokumentencenter/myfinma/1bewilligung/fintech/wegleitung-ico.pdf?la=en.

to traditional asset classes. We find that the latter two categories can generate significant enhanced momentum return, while the effect with the latter assets become less significant (but with proper sign). This result further suggests that blockchain-based assets may be subject to different pricing distortions compared to traditional assets.

We finally conduct a list of robustness checks. We confirm that our main empirical finding is not driven by a few small and illiquid assets by replicating our results on the sample largest cryptocurrencies (top 500 in terms of market cap). Next, since cryptocurrencies may have different prices across different exchanges (e.g., Makarov and Schoar 2019), we examine whether our results are robust to exchange-level returns as opposed to market-level returns (the latter is reported in most online databases averaged across exchanges) by using returns obtained from the largest exchange of any particular crypto (in trading volume prior to the holding period) according to *Kaiko.com*. We get consistent results, though the statistical level is smaller due to smaller cross section of this sample. Finally, additional tests show that our results are robust to alternative threshold of enhanced momentum strategy as well as different durations of the bear market. Using different bubble threshold (e.g., when bubble threshold is defined as top 30% price run-ups or drawdowns, or as an absolute return threshold such as 300% weekly return), for instance, does not change our finding that momentum based on none-bubble experienced assets can both generate returns and have positive skewness. In addition, although we demonstrate the relationship between bubbles and momentum based on the 2-week-2-week strategy, our analysis is also robust to a wide list of cryptocurrency momentum strategies.

We contribute to the emerging literature on blockchain and cryptocurrency pricing. A few recent studies aim to model the exchange rates of cryptocurrencies (Bolt and van Oordt 2016), the influence of cost of production (Hayes 2016), investor attractiveness (Rajcaniova and d'Artis Kancs 2016), as well as market designs related to trading (Katya and Park 2016), transaction fees (Easley, O'Hara, and Basu, 2017), and information disclosure (Cong and He, 2018). On the empirical side, recent studies examine different perspectives of cryptocurrency trading as well as their implications, such as the sensitivity of Bitcoin/USD exchange rate to economic fundamentals and technological factors (Li and Wang 2016), the price efficiency of Bitcoin (Urquhart 2016; Ghyselsy and Nguyenz 2018), anomalies (Hubrich, 2017; Rohrbach, Suremann, and Osterrieder 2017; Liu, Tsyvinski, and Wu 2019), risk-return tradeoff (Liu and Tsyvinski 2018); arbitrage (Makarov and Schoar 2019), bubbles (Corbet, Brian Lucey, Larisa Yarovaya 2017), price manipulation in Boicoin trading (Griffin and Shams 2018; Gandal, Hamrick, Tyler Moore, and Oberman 2018), as well as the network effect (Gandal and Halaburda 2016; Cong, Li, and Wang 2019) and membership/fee considerations (Sockin and Xiong 2018). Our main contribution is to explore the asset pricing foundation of blockchain based on its most challenging bottleneck of limited capacity in processing transactions. This feature allows us to understand blockchain-based financial assets on a solid theoretical ground (e.g., Rubinstein and Wolineky 1985, Duffie, Garleanu, and Pedersen 2007, 2009, Duffie 2010).

In doing so, we also contribute to the literature on momentum. While it is generally agreed that momentum cannot be explained by traditional asset pricing factors, its economic sources are still under debate. Barberis et al. (1998), Daniel et al. (1998), Hong and Stein (1999), and Grinblatt and Han (2005) argue that momentum can be generated by behavioral biases. Berk et al. (1999), Johnson (2002), and Sagi and Seasholes (2007), on the other hand, provide rational explanations.[6] Some more recent research also links momentum to distress risk (Garlappi and Yan, 2011; and Agarwal and Taffler, 2008), long-term risk (Zurek, 2008), cultural difference (Chui et al., 2010) and institutional investors (Vayanos and Woolley, 2013). Burnside, Eichenbaum, and Rebelo (2011) survey the literature on currency momentum and conclude that existing risk factors cannot explain currency momentum. In the literature, the intuition of momentum crash (Daniel and Moskowitz 2016) is at the heart of our analysis, because it allows us to examine the relationship between momentum and crash risk. We show that observations from the cryptocurrency market strongly favor asset pricing theories that can synchronize both momentum and the dynamics of bubbles/crashes.

The remainder of the paper is organized as follows. Section II presents our variables and summary statistics. Section III reports the baseline relationship between bubble experience and momentum. Section IV presents additional robustness checks. Section V concludes.

II. Data and Variable Construction

We now describe the sources of our data and the construction of our main variables.

A. Sample and Data Sources

Trading data for cryptocurrencies come from "coinmarketcap.com". For any particular cryptocurrency, we directly download its weekly price quoted in USD from "coinmarketcap.com". Weekly return of each cryptocurrency is then constructed as its weekly price appreciation measured in USD. Since many cryptocurrency exchanges start to operate after March 2013, our main sample period is from Apr 1, 2013 to Feb 2018. We augment this main data source with *cryptocompare.com* and *Yahoo!Finance*. In particular,

[6] More debates can be found in Conrad and Kaul (1998), Jegadeesh and Titman (2001, 2002), Grundy and Martin (2001), Lewellen (2002), Chordia and Shivakumar (2002, 2006), Pastor and Stambaugh (2003), Vassalou and Apedjinou (2003), Cooper et al. (2004), George and Hwang (2004), Korajczyk and Sadka (2004), Liu and Zhang (2008), Avramov et al. (2007), Novy-Marx (2012) and others.

we add to the sample of *coinmarketcap.com* additional cryptocurrencies that are included in both databases with consistent return information—i.e., with 0.99 correlation between the weekly returns reported in these two databases. Our final sample consists of 1392 cryptocurrencies in the sample period from 2013 to 2018. As a robustness check, we also follow Makarov and Schoar (2019) to use exchange-level pricing information for a set of 268 cryptocurrencies provided by *Kaiko.com*.

It is worth mentioning two properties of our data. First, even though the first cryptocurrency, Bitcoin was released in 2009, the number of cryptocurrencies before our testing period is quite limited. Figure 1 plots the number of cryptocurrencies traded in all the exchanges. We can see that the popularity of cryptocurrency, in terms of the number of assets traded in the market, booms in the year of 2014. To ensure the number of cryptocurrencies used in our tests, we do not extend our period before 2013. Secondly, we mainly focus on the price appreciation in USD of cryptocurrency in computing return. This method is consistent with the way we construct equity momentum. If we treat cryptocurrency as currencies, however, we may also want to control for interest rates in constructing currency momentum (see, e.g., Burnside, Eichenbaum, and Rebelo 2011). However, interest rates for USD is persistently low in our testing period, whereas cryptocurrencies do not have monetary policies associated with them. The magnitude of interest rates of a typical currency is also dwarfed by the magnitude of cryptocurrency return. Interest rates, in this regard, is economically unimportant to cryptocurrency momentum.

B. Main Characteristics of Crypto-currency Momentum

Table 1 tabulates the main characteristics of a list of leading cryptocurrencies, as well as a market-capitalization-weighted (VW) index of all the cryptocurrencies. In our sample period, for instance, Bitcoin (BTC) has an average weekly return of 3%, with a weekly Sharpe Ratio of 0.19. The return of ETH, which is released in 2015 as a potential competitor to BTC, has a better weekly return of 8% and a Sharpe Ratio of 0.34. The VW index is somewhat in between, with a weekly return of 4% and a Sharpe Ratio of 0.27.

III. Asset Bubbles and Momentum

Since the general description of crypto-momentum suggests the existence of both similarities and differences between the cryptocurrency market and the equity market, the economic question becomes how to understand these similarities and differences. We argue that the framework of Daniel and Moskowitz (2016) is particularly important to understand crypto-momentum due to one of the most phenomenal observations in the cryptocurrency market: the existence of vast bubbles with unpreceded magnitudes and intensities (e.g., Corbet, Brian Lucey, Larisa Yarovaya 2017). In this section, we therefore examine how bubble experience affects the characteristics of momentum portfolios.

A. Bubbles and Crashes Predicted By Historical Bubble-Experience Indicator

We start with the question of whether crypto-currencies crash could be predicted by historical impediment-stage indicator. To answer this question, we classify a cryptocurrency as a impediment-stage asset if it has experienced either a price run-up that belongs to the top quintile (i.e., top 20%; our results are robust to this threshold) of all cryptocurrencies in a given period, or a price drawdown that belongs to the top quintile of all cryptocurrencies, or both. We then examine whether future bubble stages can be predicted by historical impediment-stage indicators in the following panel specification:

$$D_{i,t+1}(Bubble) = \alpha_0 + \beta_1 * D_{i,t}(Bubble) + \beta_2 * D_{i,t}(Normal) + \varepsilon_{it}, \quad (1)$$

where the dependent variable $D_{i,t+1}(Bubble)$ is dummy variable indicating the occurrence of a bubble (i.e., the occurrence of either a large top-quintile price run-up or a large bottom-quintile price drawdown) for cryptocurrency i in quarter $t + 1$ (i.e., measured in a 13-week period). The two independent variables $D_{i,t}(Bubble)$ and $D_{i,t}(Normal)$ indicate whether cryptocurrency i is in an impediment stage or normal stage in quarter t. An impediment stage is defined as the occurrence of either a large price run-up or a large price drawdown in quarter t that belong to the top 20% price run-ups or drawdowns experienced by all cryptocurrencies. Hence, equation (1) essentially asks whether bubble stages persist over time, except that it separately measures price run-ups and price drawdowns as the two components of future bubble stage.

Table 2 shows the results for the panel regression. Panel A presents the results for OLS panel regression and panel B presents the results for logistic panel regression. In both panels, the bubble-experience indicator is positively correlated with the bubble or crash dummy in the coming quarter while the normal-period indicator is negatively correlated with the bubble or crash dummy in the coming quarter. This indicates that both bubble and crash are less likely to appear during normal periods while more likely to appear during bubble periods.

B. Momentum Portfolios Based on Normal/Impediment-stage Cryptocurrencies

In this sub-section, we take further look at momentum portfolios constructed based on normal/impediment-stage assets. The momentum portfolios are constructed in the following way: we split the winner and loser portfolios of the 2-week-2-week strategy into two groups according to whether a cryptocurrency has experienced a phenomenal pricing bubble prior to the holding period. We use run up and drawn down fluctuation of crypto currencies price to measure the existence of a bubble. Based on 20%-80% threshold, we effectively split the 2-week-2-week momentum into two sub-momentum strategies, one concentrates on the buying/selling of cryptocurrencies with bubble experience and one on those without. We then report return, t statistics market-adjusted performance, market beta, and skewness for the two sub-momentum strategies.

Table 3 shows the main results. For the group that have experienced normal periods, the winner minus loser portfolio generates a return of 6.77% with t statistics 2.45. Both the winner and loser portfolios obtain positive skewness. For the group that have experienced bubble periods, the winner minus loser portfolio generate a non-significant negative return. The winner minus loser portfolio obtained negative skewness. This indicates that momentum strategy is not working for impediment-stage cryptocurrencies.

C. Enhanced Momentum Strategies based on Normal-Stage Cryptocurrencies

Previous results suggest that momentum strategies work for normal-stage cryptocurrencies but not impediment-stage assets. We further look at performance of the momentum strategies generated by normal-stage cryptocurrencies (i.e., enhanced momentum) for different ranking periods and normal periods.

Table 4 reports the momentum alphas that can be generated during normal periods in the cryptocurrency market. To avoid any potential problem associated with ICOs, we exclude the first week of trading return for each cryptocurrency (we do this also for the VW index). Including this week does not change our main conclusions. In order to control for the common trend and volatility associated with the cryptocurrency market, we further use the VW cryptocurrency market return to adjust for momentum returns. This table then tabulates the market-adjusted crypto-momentum based on a wide range of combinations of ranking and holding periods.

We can see that crypto-momentum delivers significant return for a wide range of ranking and holding periods. The 6-week ranking period/1-week holding period momentum strategy (i.e. the 6-week-1-week momentum strategy), for instance, can deliver a weekly market-adjusted return of 9.15%, with a t-statistics of 2.37. More generally, combinations with a ranking period between 1 to 6 weeks and a holding period between 1 to 2 weeks can generate positive returns. This observation suggests that momentum is an important anomaly that can help us understand the asset pricing grounds of the cryptocurrency market, just as it is for the equity market.

D. Bear Market Betas of Enhanced Momentum Strategies

Economically, equity momentum portfolios typically exhibit negative beta and negative skewness. But for cryptocurrency portfolios, enhanced momentum strategies actually have positive beta and skewness. What could explain such drastically different properties of cryptocurrency momentum? To understand this question, in Table 5 we follow Daniel and Moskowitz (2016) to further estimate the bear-market betas of the momentum portfolio. We run the following regression:

$$\tilde{R}_{WML,t} = (\alpha_0 + \alpha_B * I_{B,t-1}) + (\beta_0 + I_{B,t-1}(\beta_B + \tilde{I}_{U,t}\beta_{B,U})) * \tilde{R}_{Mkt,t} + \tilde{\epsilon}_t,$$

where the key dependent variable $\tilde{R}_{WML,t}$ is the WML return in week t, $\tilde{R}_{Mkt,t}$ represents market-capitalization-weighted (VW) index of all the cryptocurrencies in week t, $I_{B,t-1}$ denotes an ex ante bear market indicator that equals one if the cumulative VW index return in the past 7 weeks is negative and is zero otherwise, $I_{U,t}$ is a contemporaneous, i.e., not ex ante, up-market indicator variable that is one if the excess VW index return is greater than the risk-free rate in week t, and is zero otherwise. Given that the duration of crashes in the cryptocurrency market is not as long as the equity market, the down-market is estimated as negative market return in the 7-week period prior to the holding period (we will provide robustness checks on this horizon in later sections).

We apply the above test to the raw 5-week-2-week momentum portfolio as well as to the two sub-momentum strategies conditioning on the bubble-experience of cryptocurrencies. The raw cryptocurrency momentum portfolio exhibits an average negative market beta if we directly regress momentum returns on the VW market return. This property is similar to that of the equity momentum. However, when we apply similar tests to the two sub-momentum strategies conditioning on the bubble experience of cryptocurrencies, we find limited significance.

E. Relation between Bubble Experience and Investor Attention

In this subsection, we first ask whether the formation of the impediment stage could indeed be related to some characteristics of investors. To examine this potential link, we regress the indication function of bubbles on Google search and its changes in the following regression:

$$D_{i,t+1}(Bubble) = \alpha + \beta_1 * Google_{i,t-1} + \beta_2 * \Delta\%Google_{i,t-1} + \beta_3 * M_{i,t-1} + \varepsilon_{i,t}$$

where the dependent variable$D_{i,t+1}(Bubble)$ is dummy variable. Bubble is defined as the crypto currencies relative price emerging big run up in the coming quarter (13 weeks). $Google_{i,t-1}$ is defined as the maximum weekly Google Search volume of specific crypto currency in the last quarter (13week). $\Delta\%Google_{i,t-1}$ is the maximum change rate of weekly Google Search volume of specific crypto currency in the last quarter (13week). $M_{i,t-1}$ is the relative control variables. We control for crypto currency and week fixed effects.

Table 6 shows the results for the relation between investor attention and bubble experience. We find that larger Google search and positive changes in Google search of a cryptocurrency in a quarter is positively associated with the likelihood for the asset to fall into an impediment stage in the following quarter, other things being equal. This observation is consistent with search-based argument. In particular, more attention from investors will not drastically relax the trading capacity of blockchain—but it potentially signals that, since more investors are interested in the asset, the fraction of high-valuation investors might increase. This increase in high-valuation investors will precisely give rise to for formation of bubble in search-based models.

IV. Additional Analysis and Robustness Checks

Our last step of analysis conducts a list of additional tests and robustness checks in order to shed new light on the economic foundation of crypto-momentum. We first apply our tests to different types of crypto currencies according to their main usage obtained from https://coincheckup.com. We then conduct robustness checks on the threshold of enhanced momentum strategy as well as different durations of the bear market. We finally show that the main conclusions apply to different combination of ranking/holding periods.

A. Enhanced Momentum for Different Types of Cryptocurrencies

One important feature in the cryptocurrency market is that different cryptocurrencies may be launched for different purposes. In particular, cryptocurrencies can be launched not only as a digital currency or a method of payments, but also a token for the usage of certain technology or service. Zetzsche et al. (2018), for instance, examines a dataset of more than 300 ICO White Papers and classifies the corresponding cryptocurrencies into four categories of software usage token, community token, currency token, and equity token. The recent guideline issued by Swiss Financial Market Supervisory Authority FINMA classifies tokens into three categories: payment tokens, utility tokens, and asset tokens. Depending on their different purposes, some cryptocurrencies may be similar to traditional assets whereas others may not. It is therefore interesting to examine whether the aforementioned momentum could be somehow associated with these purposes.

To achieve this goal, we use https://coincheckup.com to recognize the major purposes of available cryptocurrencies, which allows us to classify cryptocurrencies into broad categories. More explicitly, about 1008 cryptocurrencies in our sample can be matched with Coincheckup.com, with their purposes classified into 92 subcategories ranging from digital currency to Smart Contract and to even 3D printing. Based on subcategory information, we roughly classify cryptocurrencies in our sample into three broad categories: *Digital Currency* (including Payments), *Usage*, and *Others*.[7] Although the classification is not perfect, it roughly follows the guideline of FINMA and is also in spirit consistent with Zetzsche et al. (2018). It also highlights the linkage between cryptocurrencies and traditional assets: while cryptocurrencies classified as *Digital Currency* may behave as currencies, the other two types could be more distant to traditional assets. Although cryptocurrencies in *Usage* could be associated with R&D type of activities, they differ from classical securities of stocks or bonds. The category of *Others* includes financial intermediation and other purposes of cryptocurrencies that are difficult to qualify; such subtlety may reflect the expanding boundary of the cryptocurrency market.

In Table 7, we effectively split the 2-week-2-week enhanced momentum into three sub-momentum strategies, concentrating on the buying/selling of cryptocurrencies according to the performances of three strategies. Interestingly, we find that enhanced crypto-momentum based on *Digital Currency* tokens exhibit very similar properties to momentum crash—its positive return of momentum is associated with negative skewness. This similarity suggests that the asset pricing properties of *Digital Currency* tokens are indeed not that different from those of currencies. By contrast, cryptocurrencies in *Usage* and *Others* exhibit both positive enhanced momentum return and positive skewness, which differs from the typical behavior of equity momentum. Overall, we see that momentum return is associated with negative skewness for cryptocurrencies that are more similar to traditional securities (i.e., *Digital Currency*) and positive skewness for those that are not (i.e., *Usage*, and *Others*). This observation suggests that asset pricing for the bulk of new type of cryptocurrencies may indeed be different.

[7] Ten sub-categories, including Digital Currency, Payments, Multi-Currency Wallet, Payments Service Provider, Micro payments, Marijuana, Debit Card, Payment Gateway, Remittance, Market-Pegged, are classified as *Digital Currency/Payments*. Next, 69 sub-categories are classified as *Usage* tokens, including Platform, Smart Contracts, Privacy, Anonymity, Gaming, Token Issuance, Exchange, Build Dapps, Gambling, Social Network, Blockchain As A Service, Crowdfunding, Cybersecurity, Social Media, Data Storage, Media & Publishing, Messaging, Entertainment, Prediction Market, Advertising, Internet Decentralization, Mining, Voting, Intellectual Property Registration, Governance Integrated, Interoperability Between Blockchains, Decentralized Banking, Computing, Decentralized Exchange, Scientific Research, Identity Management, Healthcare, Environment Friendly, Artificial Intelligence, Adults, Personal Data Monetizing, Insurance, Networking, Charity, Enterprise, Freelancing, Online Reputation Management, Ticketing, Telecom, Virtual Reality, Arts, Recruitment, Fundraising, Education, Web Domain Registration, Search, Document Storage, Savings, Artists, Augmented Reality, Cryptos categorized as Blockchain Incubator, Database Services, Auctions, Marketing, Cloud Hosting, Invoicing, Supercomputer, 3d Printing, Search Engine, Terminal, Startup Accelerator, Speech Recognition, Lending, Identification. *Others* contains the subcategories of Trading, Real World Assets, Marketplace, Unclear, Unlcear Project Or Product Status, loyalty programme, fund, investments, Energy, real estate, N/A, Industrial Production, as well as the rest of cryptocurrencies not belong to *Currency/Payments* or *Usage*, as well as cryptocurrencies that are in our sample but not reported in Coincheckup.com (excluding these unmatched cryptocurrencies will not change our main findings). Note that a cryptocurrency may have multiple purposes and thus appear in both *Digital Currency/Payments* and *Usage*. Bitcoin, for instance, is associated with Digital Currency, Cyber Security, and P2P Lending. Hence it appears in both groups.

B. Top 500 Marketcap Coins VW Momentum and Kaiko VW Momentum

In this subsection, we show that our results are robust to different groups of crypto-currencies. We split the winner and loser portfolios of the 2-week-2-week strategy into two groups according to whether a crypto currency has experienced a phenomenal pricing bubble prior to the holding period. We use run up and drawn down fluctuation of crypto currencies price to measure the existence of a bubble. Based on 20%-80% threshold, we effectively split the 2-week-2-week momentum into two sub-momentum strategies, one concentrates on the buying/selling of crypto currencies with bubble experience and one on those without. We then report return, market-adjusted performance, market beta, and skewness for the two sub-momentum strategies.

Table 8 shows both the results for Top 500 Marketcap Coins VW Momentum and Kaiko VW Momentum. The first sample means to further address the concern that momentum could be related to small and illiquid assets. Consistent with our findings, momentum based on none-bubble experienced assets can both generate returns and have positive skewness. By focusing on the top 500 cryptocurrencies with the largest market cap, our results basically rule out this particular concern.

The second sample test means to address the issue that, since cryptocurrencies may have different prices across different exchanges (e.g., Makarov and Schoar 2019), what most online databases report as market-level returns (averaged across exchanges) may not be tradable. To address this issue, we examine whether our results are robust to exchange-level returns by using returns obtained from the largest exchange of any particular crypto according to *Kaiko.com*. In particular, across all the exchanges that a cryptocurrency traces against U.S. dollar, we always choose one exchange which has the largest trading volume on this asset in the week right before the holding period of a particular momentum strategy. We get consistent results from this sample with a somewhat lower statistical level. The reduced statistical level is reasonable, because this sample has a much smaller cross section (a total of 268 cryptos). But the message is unambiguous that normal-stage (impediment-stage) cryptocurrencies generate significant (insignificant) momentum return.

C. Robustness Checks based on Cross-referenced Sample and Stocks

Table 9 provides two more robustness checks. The first is again on the sample of cryptocurrencies we have used. Instead of using *cryptocompare.com* and *Yahoo!Finance* to augment the sample of cryptocurrencies provided by *coinmarketcap.com*, we now use the two samples to provide a cross-reference to the latter database. In particular, for each cryptocurrency reported by *coinmarketcap.com*, we ask if we can 1) find the same asset in either *cryptocompare.com* or *Yahoo!Finance*, and 2) if the weekly return of the asset as reported in *coinmarketcap.com* has a correlation of 0.99 or above with the return reported in *cryptocompare.com* or *Yahoo!Finance*. If both criteria are satisfied, we put this cryptocurrency into the sample we call as “The Sample of Cross-Reference”.

We then focus on the sample of top 500 cryptocurrencies that can survive this enhanced scrutiny. Compared to our main sample as well as the sample used in Panel A of Table 8, this sample contains less number of assets but with higher quality of return numbers. We then apply the sample enhanced momentum test to this sample of cryptocurrencies, and report the results in Panel A of Table 9. The layout is similar to that of Table 8. Again, we see that normal-stage crypto momentum is positive, whereas impediment-stage crypto momentum is largely negative (though insignificant).

We then provide a Placebo test of our results. We have argued that the difference between normal-stage crypto momentum and impediment-stage crypto momentum arises due to the limited capacity for blockchains to process information and capital. If this intuition is correct, traditional assets not severely subject to such a property should not demonstrate a similar pattern. Panel B of the table therefore applies the similar tests to the U.S. stock market. We can see that stocks do not exhibit as significant a pattern as cryptocurrencies, suggesting that the joint distribution of momentum and bubbles is quite unique feature of blockchains. Of course, we expect other OTC markets to exhibit this property as well, a prediction that goes beyond the scope of our current paper.

D. Momentum Portfolios Using Various Ranking Threshold

In this robustness check, we show that our results are robust to alternative threshold of enhanced momentum strategy. We split the winner and loser portfolios of the 2-week-2-week strategy into two groups according to whether a cryptocurrency has experienced a phenomenal pricing bubble prior to the holding period. We use run up and drawn down fluctuation of crypto currencies price to measure the existence of a bubble. Based on 30%-70% threshold and 10%-90% threshold, we effectively split the 2-week-2-week momentum into two sub-momentum strategies, one concentrates on the buying/selling of cryptocurrencies with bubble experience and one on those without. We then report return, market-adjusted performance, market beta, and skewness for the two sub-momentum strategies.

Table 10 presents the results of the momentum portfolio returns for both normal/bubble periods. Using different bubble threshold (e.g., when bubble threshold is defined as top 30% price run-ups or drawdowns, or as an absolute return threshold such as 300% weekly return), for instance, does not change our finding that momentum based on none-bubble experienced assets can both generate returns and have positive skewness.

V. Conclusion

Limited capacity in processing transactions presents one of the most fundamental technical challenges to blockchain-based financial applications (e.g., Bitcoin). We argue that this property also has profound impacts on asset prices by limiting the speed and scale at which capital can flow, which may distort prices in generating in normal days and bubbles/crashes in high-tension periods.

Consistent with this notion, we find that momentum strategy works for normal-stage cryptocurrencies but not for impediment-stage ones. Moreover, contrary to equity-momentum, crypto-momentum is not associated with higher crash risk. If anything, crash risk is associated with, and can be predicted by, the impediment stage of cryptocurrencies. Our results are robust to a list of additional tests, alternative samples, as well as alternative definitions of normal-stage vs. impediment-stage.

Our results have important normative implications. In particular, they suggest that limited capacity in processing transactions and the resulting slow moving capital may provide a potential asset pricing foundation to understand the market of cryptocurrencies and blockchain-based financial assets.

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Table 1: Summary Statistics: Crypto Currencies and the VW index

This table tabulates the main characteristics of a list of leading crypto currencies, including Bitcoin, Litecoin, Ripple, Dogecoin, Dash and Ethereum, as well as a market-capitalization-weighted (VW) index of all the crypto currencies. The consistent price and market cap data (5th May 2013-1st June 2018) is from: https://coinmarketcap.com/, 1392 crypto currencies constitute the whole sample.

	BTC	LTC	XRP	DOGE	Dash	ETH	VW
First Date	2013/5/5	2013/5/5	2013/8/18	2013/12/29	2014/2/23	2015/8/16	2013/5/5
Observations	249	249	234	215	207	130	249
Mean	0.03	0.04	0.06	0.03	0.06	0.08	0.04
t-value	3.00	2.11	2.38	1.99	3.19	3.85	4.42
Max	0.66	2.92	3.90	1.71	1.94	0.90	0.90
Min	-0.33	-0.42	-0.41	-0.43	-0.50	-0.36	-0.34
STD	0.13	0.27	0.37	0.25	0.29	0.23	0.15
Sharp ratio	0.19	0.13	0.16	0.14	0.22	0.34	0.27
Kurtosis	3.58	54.85	54.75	18.16	18.46	2.50	7.44
Skewness	1.02	6.00	6.24	3.38	3.59	1.47	1.44
P=5%	-0.16	-0.21	-0.23	-0.21	-0.18	-0.19	-0.15
P=10%	-0.12	-0.14	-0.16	-0.16	-0.14	-0.14	-0.10
P=25%	-0.04	-0.07	-0.08	-0.07	-0.07	-0.07	-0.03
P=50%	0.02	0.00	-0.01	-0.01	0.00	0.03	0.02
P=75%	0.08	0.06	0.07	0.06	0.11	0.14	0.09
P=90%	0.17	0.23	0.27	0.24	0.30	0.40	0.20
P=95%	0.27	0.39	0.55	0.42	0.54	0.57	0.26

Table 2: Crypto Currencies Crash Is Predicted By Historical Bubble-Experience Indicator

This table present the result of the following panel specification:

$$D_{i,t+1}(Bubble) = \alpha_0 + \beta_1 * D_{i,t}(Bubble) + \beta_2 * D_{i,t}(Normal) + \varepsilon_{it},$$

where the dependent variable $D_{i,t+1}(Bubble)$ is dummy variable indicating the occurrence of a bubble (i.e., either a large top-quintile price run-up, or a large bottom-quintile price drawdown, or both) for cryptocurrency i in quarter $t+1$ (i.e., measured in a 13-week period).. The two independent variables $D_{i,t}(Bubble)$ and $D_{i,t}(Normal)$ indicate whether cryptocurrency i is in an impediment stage or normal stage in quarter t. An impediment stage is defined as the occurrence of either a large price run-up or a large price drawdown in quarter t that belong to the top 20% price run-ups or drawdowns experienced by all cryptocurrencies.

OLS Panel Regression						
	$\boldsymbol{D_{T+1}}$**(Large Drawdowns)**		$\boldsymbol{D_{T+1}}$**(Large Runups)**		$\boldsymbol{D_{T+1}}$**(Large DD or RUs)**	
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Intercept	0.13***	0.32***	0.19***	0.24***	0.31***	0.53***
	(15.76)	(30.18)	(21.61)	(21.98）	(30.14)	(41.45)
$D_{i,t}(Bubble\ Stage)$	0.18***		0.05***		0.22***	
	(13.63)		(3.57)		(13.22)	
$D_{i,t}(Normal\ Stage)$		-0.18***		-0.06***		-0.22***
		(-13.63)		(-3.57)		(-13.22)
R-squared	0.05	0.05	0.00	0.00	0.05	0.05
Observations	3601	3601	3601	3601	3601	3601

Logistic Panel Regression						
	$\boldsymbol{D_{T+1}}$**(Large Drawdowns)**		$\boldsymbol{D_{T+1}}$**(Large Runups)**		$\boldsymbol{D_{T+1}}$**(Large DD sor RUs)**	
	$\boldsymbol{D_{T+1}}$**(p = Crash)**		$\boldsymbol{D_{T+1}}$**(p = Bubble)**		$\boldsymbol{D_{T+1}}$**(p = Bubble or Crash)**	
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Intercept	-1.88***	-0.77***	-1.47***	-1.18***	-0.80***	0.10**
	(-29.77)	(-13.53)	(-26.80)	(-18.78.)	(-17.23)	(1.97)
$D_{i,t}(Bubble\ Stage)$	1.10***		0.30***		0.90***	
	(12.96)		(3.56)		(12.78)	
$D_{i,t}(Normal\ Stage)$		-1.10***		-0.30***		-0.90***
		(-12.96)		(-3.56)		(-12.78)
Observations	3601	3601	3601	3601	3601	3601

Table 3: Momentum Portfolios Based on Normal/Bubble-experienced Category (Low-High: 80%-20% Ranking)

In this table, we split the winner and loser portfolios of the 2-week-2-week strategy into two groups according to whether a cryptocurrency has experienced a phenomenal pricing bubble prior to the holding period. We use run up and drawn down fluctuation of crypto currencies price to measure the existence of a bubble. Based on 20%-80% threshold, we effectively split the 2-week-2-week momentum into two sub-momentum strategies, one concentrates on the buying/selling of cryptocurrencies with bubble experience and one on those without. We then report return, market-adjusted performance, market beta, and skewness for the two sub-momentum strategies.

Statistic	Normal-Experience (Low Run up, Low Drawn down)						Bubble-Experience (High Run up, High Drawn Down)					
	Loser	2	3	4	Winner	WML	Loser	2	3	4	Winner	WML
$\overline{r-rf}$	1.62%	1.19%	8.68%	3.89%	8.39%	6.77%	4.23%	2.00%	2.38%	4.32%	3.47%	-0.76%
$t(\overline{r-rf})$	1.24	0.85	1.55	1.92	3.03	2.45	1.19	1.88	2.67	3.95	2.48	-0.21
σ	0.19	0.20	0.80	0.29	0.40	0.40	0.51	0.15	0.13	0.16	0.20	0.52
α	0.69%	7.79%	2.89%	0.08%	7.78%	7.09%	3.36%	1.07%	1.50%	3.67%	2.65%	-0.71%
t(α)	0.53	1.36	1.42	0.05	2.76	2.51	0.93	1.02	1.75	3.35	1.89	-0.19
β	0.16	0.16	0.18	0.20	0.11	-0.06	0.15	0.16	0.15	0.11	0.15	-0.01
t(β)	3.59	0.78	2.44	4.03	1.08	-0.56	1.20	4.48	5.09	2.92	2.93	-0.07
Sharp	0.09	0.06	0.11	0.13	0.21	0.17	0.08	0.13	0.19	0.27	0.17	-0.01
Skewnes	1.15	1.77	13.09	5.38	9.38	10.05	10.75	2.14	0.68	1.68	1.09	-10.53
Kurtosis	3.62	9.46	181.47	48.07	113.33	126.39	138.03	13.37	2.01	5.68	1.73	136.57

Table 4: Performance (VW-index adjusted alpha) of Crypto-currency Enhanced Momentum

This table reports the momentum alphas that can be generated in the cryptocurrency market. To avoid any potential problem associated with ICOs, we exclude the first week of trading return for each cryptocurrency (we do this also for the VW index). Including this week does not change our main conclusions. In order to control for the common trend and volatility associated with the cryptocurrency market, we further use the VW cryptocurrency market return to adjust for momentum returns. This table then tabulates the market-adjusted crypto-momentum based on a wide range of combinations of ranking and holding periods.

Ranking period	**Holding period**					
	1week	2week	3week	1month	5week	6week
1week	12.11%	10.42%	8.68%	5.62%	4.12%	7.51%
	(1.55)	(1.86)	(1.63)	(2.21)	(1.98)	(1.48)
2week	8.53%	7.09%	-2.90%	-6.31%	2.63%	5.99%
	(2.59)	(2.51)	(-0.45)	(-0.7)	(2.29)	(2.15)
3week	7.31%	6.72%	-10.16%	-6.54%	2.91%	8.21%
	(2.81)	(4.02)	(-0.74)	(-0.64)	(1.56)	(1.97)
1month	6.51%	4.60%	3.46%	3.40%	10.27%	10.15%
	(3.85)	(3.23)	(2.29)	(2.1)	(1.54)	(1.54)
5week	3.82%	19.60%	14.05%	11.70%	9.31%	8.40%
	(2.11)	(1.33)	(1.42)	(1.55)	(1.54)	(1.64)
6week	9.15%	20.56%	27.81%	21.16%	17.33%	16.28%
	(2.39)	(1.32)	(1.22)	(1.24)	(1.26)	(1.29)

Table 5: Down-Market Betas for Enhanced Momentum Strategies (Bear Market Period: 7 Weeks)

In this table, we follow Daniel and Moskowitz (2016) to further estimate the down-market betas of the momentum portfolio:

$$\widetilde{R}_{WML,t} = (\alpha_0 + \alpha_B * I_{B,t-1}) + (\beta_0 + I_{B,t-1}(\beta_B + \tilde{I}_{U,t}\beta_{B,U})) * \widetilde{R}_{Mkt,t} + \tilde{\epsilon}_t$$

where the key dependent variable $\widetilde{R}_{WML,t}$ is the 2-week-2-week WML return in week t, $\widetilde{R}_{Mkt,t}$ represents market-capitalization-weighted (VW) index of all the cryptocurrencies in week t, $I_{B,t-1}$ denotes an ex ante bear market indicator that equals one if the cumulative VW index return in the past 7 weeks is negative and is zero otherwise, $\tilde{I}_{U,t}$ is a contemporaneous, i.e., not ex ante, up-market indicator variable that is one if the excess VW index return is greater than the risk-free rate in week t, and is zero otherwise. Given that the duration of crashes in the cryptocurrency market is not as long as the equity market, the down-market is estimated as negative market return in the 7-week period prior to the holding period. We then split each of the winner/loser portfolios of this strategy into two groups according to whether a cryptocurrency has experienced a phenomenal pricing bubble prior to the holding period, where we use run up and drawn down fluctuation of crypto currencies price to measure bubble-experience. We apply similar tests to the two sub-momentum strategies conditioning on the bubble-experience of cryptocurrencies. Robust t-statistics are reported in parentheses and are based on standard errors clustered by city and year. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Coefficient	Variable	Estimated coefficients (t-statistics)											
		(1)			(2)			(3)			(4)		
		WML			WML			WML			WML		
		All	Normal	Bubble	All	Normal	Bubble	All	Normal	Bubble	All	Normal	Bubble
$\tilde{\alpha}_0$	1	0.06**	0.07**	0.01	0.07**	0.07*	0.03	0.07**	0.07**	0.01	0.07**	0.07*	0.03
		(2.13)	(2.51)	(0.28)	(2.11)	(1.93)	(0.59)	(2.20)	(2.26)	(0.22)	(2.10)	(1.93)	(0.59)
$\tilde{\alpha}_B$	$I_{B,t-1}$				-0.04	0.02	-0.06				-0.02	0.03	-0.11
					(-0.71)	(0.32)	(-0.73)				(-0.26)	(0.39)	(-0.99)
$\tilde{\beta}_0$	$\tilde{R}_{Mkt,t}$	-0.05	-0.06	-0.02	-0.03	-0.05	0.02	-0.03	-0.06	0.03	-0.03	-0.05	0.02
		(-0.52)	(-0.56)	(-0.16)	(-0.27)	(-0.51)	(0.15)	(-0.25)	(-0.55)	(0.24)	(-0.27)	(-0.51)	(0.15)
$\tilde{\beta}_B$	$I_{B,t-1}\tilde{R}_{Mkt,t}$				-0.68	0.00	-1.23	-0.27	-0.02	-1.25	-0.39	0.18	-1.89
					(-1.45)	(0.00)	(-1.89)	(-0.38)	(-0.03)	(-1.25)	(-0.46)	(0.19)	(-1.59)
$\tilde{\beta}_{B,U}$	$I_{B,t-1}\tilde{I}_{U,t}\tilde{R}_{Mkt,t}$							-0.78	0.06	-0.01	-0.55	-0.36	1.25
								(-0.78)	(0.05)	(-0.01)	(-0.40)	(-0.23)	(0.66)
R^2_{adj}		-0.00	-0.00	-0.00	-0.00	-0.01	0.01	0.00	-0.01	0.00	-0.00	-0.02	0.00

Table 6: Relation between Bubble Experience and Investor Attention

This table tests the relation between investor attention and bubble experience. Crypto currency Google Search volume and the growth rate of Google Search volume measure investor attention on cross-section crypto currencies.

$$D_{i,t+1}(Bubble) = \alpha + \beta_1 * Google_{i,t-1} + \beta_2 * \Delta\%Google_{i,t-1} + \beta_3 * M_{i,t-1} + \varepsilon_{i,t}$$

where the dependent variable $D_{i,t+1}(Bubble)$ is dummy variable. Bubble is defined as the crypto currencies relative price emerging big run up in the coming quarter (13 weeks). $Google_{i,t-1}$ is defined as the maximum weekly Google Search volume of specific crypto currency in the last quarter (13week). $\Delta\%Google_{i,t-1}$ is the maximum change rate of weekly Google Search volume of specific crypto currency in the last quarter (13week). $M_{i,t-1}$ is the relative control variables. We control for crypto currency and week fixed effects. The standard errors are clustered by crypto currency and week. ***, **, and * represent statistical significance at 1%, 5% and 10%, respectively.

	Dependant Variable: $D_{i,t+1}(p = Bubble)$			
Variables	Model 1	Model 2	Model 3	Model 4
Google Search	0.001***	0.001***	0.001***	0.001***
	(5.23)	(9.48)	(5.23)	(9.48)
Δ% Google Search	0.018***	0.014***	0.018***	0.014***
	(8.98)	(6.75)	(8.98)	(6.75)
Risk free rate		-1.43***		-1.43***
		(-16.27)		(-16.27)
Mkt-rf		0.005***		0.005***
		(3.68)		(3.68)
SMB		-0.001		-0.001
		(-0.21)		(-0.21)
HML		0.008*		0.008*
		(2.52)		(2.52)
RMW		0.011*		0.011*
		(2.44)		(2.44)
CMA		-0.004		-0.004
		(-0.99)		(-0.99)
Fixed effect	ICY	ICY	ICY	ICY
Crypto currency	Yes	Yes	Yes	Yes
Week controls	No	No	Yes	Yes
Observations	23365	23365	23365	23365
AdjRsq	-2.16%	-0.71%	-2.16%	-0.71%

Table 7: Different Types of Cryptocurrencies (2-week-2-week Momentum)

In this table, we split the enhanced winner and enhanced loser portfolios of the 2-week-2-week strategy into three groups (Digital Currency & Payments, Usage and Others) according to 92 cryptocurrency sub-categories from https://coincheckup.com/category. 10 sub-categories are classified as Digital Currency & Payments category, 69 sub-categories, such as Platform and Smart Contracts, are classified as Usage category. Others category contains the rest of cryptocurrencies not belong to Digital Currency & Payments category and Usage category in the enhanced winner/loser portfolio. Based on three categories, we effectively split the 2-week-2-week enhanced momentum into three sub-momentum strategies, concentrating on the buying/selling of cryptocurrencies according to the performances of three strategies. We then report return, market-adjusted performance, market beta, and skewness for the three sub-momentum strategies.

Statistic	**Loser**				**Winner**				**WML**			
	Enhanced (All)	Digital Currency	Usage	Others	Enhanced (All)	Digital Currency	Usage	Others	Enhanced (All)	Digital Currency	Usage	Others
$\overline{r-rf}$	1.62%	5.89%	4.97%	2.77%	8.39%	7.26%	6.85%	4.72%	6.77%	1.37%	1.88%	1.95%
$t(\overline{r-rf})$	1.24	2.92	2.96	1.94	3.03	4.3	3.49	2.6	2.45	0.71	1.16	1.06
σ	0.19	0.27	0.23	0.19	0.40	0.23	0.26	0.24	0.40	0.26	0.22	0.25
α	0.69%	4.72%	4.06%	2.08%	7.78%	6.50%	5.98%	3.95%	7.09%	1.78%	1.93%	1.87%
t(α)	0.53	2.32	2.39	1.43	2.76	3.79	3.00	2.14	2.51	0.90	1.15	0.99
β	0.16	0.18	0.14	0.10	0.11	0.11	0.13	0.12	-0.06	-0.06	-0.01	0.01
t(β)	3.59	2.60	2.43	2.14	1.08	2.01	1.96	1.89	-0.56	-0.94	-0.13	0.20
Sharp ratio	0.09	0.22	0.22	0.14	0.21	0.32	0.26	0.19	0.17	0.05	0.09	0.08
Skewness	1.15	3.94	3.54	1.14	9.38	1.65	3.08	1.89	10.05	-0.98	1.27	2.03
Kurtosis	3.62	25.75	25.61	3.62	113.33	3.87	16.61	7.35	126.39	7.99	3.52	11.24

Table 8: Robustness Check on Top 500 Marketcap Coins VW Momentum and Kaiko VW Momentum

In this table, we split the winner and loser portfolios of the 2-week-2-week strategy into two groups according to whether a crypto currency has experienced a phenomenal pricing bubble prior to the holding period. We use run up and drawn down fluctuation of crypto currencies price to measure the existence of a bubble. Based on 20%-80% threshold, we effectively split the 2-week-2-week momentum into two sub-momentum strategies, one concentrates on the buying/selling of crypto currencies with bubble experience and one on those without. We then report return, market-adjusted performance, market beta, and skewness for the two sub-momentum strategies. Two sample are tested for robustness check.

Top 500 Marketcap Coins Sample (VW)

Statistic	Normal-Experience (Low Run up, Low Drawn down)						Bubble-Experience (High Run up, High Drawn Down)					
	Loser	2	3	4	Winner	WML	Loser	2	3	4	Winner	WML
$\overline{r-rf}$	2.16%	2.71%	12.66%	5.86%	6.26%	4.10%	6.21%	2.40%	2.92%	5.63%	4.48%	-1.73%
$t(\overline{r-rf})$	1.74	1.9	1.87	2.92	4.23	2.73	1.62	2.55	3.18	4.25	2.94	-0.45
σ	0.17	0.20	0.92	0.28	0.21	0.21	0.54	0.13	0.13	0.19	0.21	0.54
α	1.37%	1.72%	11.38%	4.93%	5.47%	4.11%	5.09%	1.50%	2.20%	4.91%	3.64%	-1.45%
t(α)	1.10	1.21	1.64	2.42	3.67	2.67	1.31	1.64	2.43	3.68	2.37	-0.37
β	0.13	0.16	0.20	0.15	0.13	0.00	0.19	0.15	0.12	0.12	0.14	-0.05
t(β)	3.06	3.25	0.85	2.13	2.52	-0.03	1.38	4.72	3.79	2.58	2.65	-0.34
Sharp	0.12	0.14	0.14	0.21	0.30	0.19	0.12	0.18	0.23	0.30	0.21	-0.03
Skewnes	1.86	2.14	11.86	3.23	1.99	0.28	10.91	0.80	0.52	2.24	1.05	-11.29
Kurtosis	9.07	9.26	151.93	17.46	7.38	8.42	138.49	3.88	1.50	8.79	2.16	147.21

Kaiko Data Sample (VW)

Statistic	Normal-Experience (Low Run up, Low Drawn down)						Bubble-Experience (High Run up, High Drawn Down)					
	Loser	2	3	4	Winner	WML	Loser	2	3	4	Winner	WML
$\overline{r-rf}$	4.44%	9.28%	4.39%	5.55%	13.37%	8.92%	1.75%	8.22%	4.98%	13.68%	7.09%	5.35%
$t(\overline{r-rf})$	1.67	3.81	2.72	2.24	2.89	2.25	0.44	1.54	1.36	2.07	1.87	1.19
σ	0.21	0.25	0.20	0.27	0.36	0.31	0.30	0.45	0.36	0.54	0.29	0.34
α	3.26%	7.69%	3.07%	4.26%	11.32%	8.06%	-4.01%	7.89%	0.94%	12.00%	2.22%	6.24%
t(α)	1.21	3.09	1.90	1.68	2.41	1.96	-1.08	1.43	0.27	1.74	0.60	1.29
β	0.10	0.14	0.15	0.14	0.17	0.07	0.83	0.03	1.05	0.13	0.70	-0.13
t(β)	1.77	2.27	3.20	2.00	1.76	0.85	4.32	0.26	4.56	0.86	3.68	-0.51
Sharp	0.21	0.37	0.22	0.21	0.37	0.29	0.06	0.18	0.14	0.25	0.25	0.16
Skewnes	1.58	2.80	1.11	5.57	2.20	2.80	1.82	5.58	5.17	5.72	1.42	1.07
Kurtosis	4.68	11.60	2.41	45.52	5.61	9.51	4.49	39.50	36.79	39.88	3.06	4.80

Table 9: Robustness Check on Cross-referenced Top 500 Crypto-Momentum and Stock Momentum

In this table, we conduct robustness checks for two additional samples, including cross-referenced Top 500 cryptocurrencies (cryptocurrencies with the largest market-caps, for which the return reported by Coinmarketcap must have a correlation of 0.99 or above with the return reported in *cryptocompare.com* or *Yahoo!Finance*) and the sample of U.S. stocks (6-month-6-month momentum in this case). We split the winner and loser portfolios of the 2-week-2-week strategy into two groups according to whether a crypto currency has experienced a phenomenal pricing bubble prior to the holding period. We use run up and drawn down fluctuation of crypto currencies price to measure the existence of a bubble. Based on 20%-80% threshold, we effectively split the 2-week-2-week momentum into two sub-momentum strategies, one concentrates on the buying/selling of crypto currencies with bubble experience and one on those without. We then report return, market-adjusted performance, market beta, and skewness for the two sub-momentum strategies.

Cross-Referenced Sample of Top 500 Cryptocurrencies (VW)

Statistic	Normal-Experience (Low Run up, Low Drawn down)						Bubble-Experience (High Run up, High Drawn Down)					
	Loser	2	3	4	Winner	WML	Loser	2	3	4	Winner	WML
$\overline{r-rf}$	2.31%	4.31%	2.86%	3.62%	5.36%	3.05%	17.52%	3.53%	9.38%	6.38%	2.47%	-15.05%
$t(\overline{r-rf})$	1.89	2.37	1.81	2.44	3.78	2.12	1.05	2.45	1.39	2.76	1.5	-0.91
σ	0.18	0.28	0.25	0.23	0.21	0.22	2.50	0.22	1.00	0.34	0.25	2.50
α	1.29%	2.68%	1.48%	2.29%	4.34%	3.06%	15.68%	2.32%	8.28%	4.57%	1.56%	-14.12%
t(α)	1.07	1.50	0.95	1.56	3.09	2.08	0.92	1.63	1.20	1.99	0.95	-0.83
β	0.19	0.28	0.24	0.24	0.19	0.00	0.35	0.22	0.20	0.31	0.17	-0.18
t(β)	4.35	4.27	4.20	4.44	3.69	-0.04	0.57	4.19	0.78	3.79	2.87	-0.29
Sharp	0.13	0.16	0.12	0.16	0.25	0.14	0.07	0.16	0.09	0.19	0.10	-0.06
Skewnes	0.95	4.56	7.33	6.78	1.40	0.88	14.84	2.61	13.88	4.93	1.49	-14.85
Kurtosis	3.15	28.42	84.87	75.54	4.13	3.75	222.43	14.19	200.73	38.02	5.02	222.67

Stock Market Sample (VW)

Statistic	Normal-Experience (Low Run up, Low Drawn down)						Bubble-Experience (High Run up, High Drawn Down)					
	Loser	2	3	4	Winner	WML	Loser	2	3	4	Winner	WML
$\overline{r-rf}$	0.53%	0.73%	0.80%	0.85%	0.96%	0.42%	0.81%	0.72%	0.80%	0.96%	1.16%	0.36%
$t(\overline{r-rf})$	1.37	2.32	2.64	2.33	2.15	0.99	1.61	1.7	2.24	2.7	2.23	0.63
σ	0.03	0.03	0.03	0.03	0.04	0.04	0.04	0.04	0.03	0.03	0.05	0.05
α	-0.63%	-0.36%	-0.32%	-0.46%	-0.48%	0.14%	-0.53%	-0.66%	-0.41%	-0.23%	-0.33%	0.20%
t(α)	-2.30	-2.43	-3.80	-3.21	-1.86	0.31	-1.34	-2.72	-2.27	-1.25	-0.87	0.32
β	0.96	0.89	0.93	1.08	1.19	0.23	1.10	1.14	1.00	0.98	1.23	0.13
t(β)	10.71	18.49	33.18	23.06	13.87	1.52	8.47	14.26	16.77	16.00	9.87	0.64
Sharp	0.15	0.26	0.30	0.26	0.24	0.11	0.18	0.19	0.25	0.31	0.25	0.07
Skewnes	-0.15	-0.02	-0.32	-0.23	0.73	2.43	-0.42	-0.24	-0.25	0.15	1.17	2.81
Kurtosis	-0.51	0.47	0.60	2.00	5.30	13.52	0.13	0.71	0.06	0.90	6.83	15.53

Table 10: Robustness Check On Momentum Portfolios Using Various Ranking Threshold

In this table, we split the winner and loser portfolios of the 2-week-2-week strategy into two groups according to whether a cryptocurrency has experienced a phenomenal pricing bubble prior to the holding period. We use run up and drawn down fluctuation of crypto currencies price to measure the existence of a bubble. Based on 30%-70% threshold and 10%-90% threshold, we effectively split the 2-week-2-week momentum into two sub-momentum strategies, one concentrates on the buying/selling of cryptocurrencies with bubble experience and one on those without. We then report return, market-adjusted performance, market beta, and skewness for the two sub-momentum strategies.

Low-High: 70%-30% Ranking

Statistic	Normal-Experience (Low Run up, Low Drawn down)						Bubble-Experience (High Run up, High Drawn Down)					
	Loser	2	3	4	Winner	WML	Loser	2	3	4	Winner	WML
$\overline{r-rf}$	1.09%	2.77%	1.97%	5.18%	6.54%	5.45%	1.44%	2.13%	5.62%	4.79%	28.28%	26.83%
$t(\overline{r-rf})$	0.87	1.62	2.16	2.62	4.69	3.74	0.59	1.58	2.1	2.88	1.25	1.18
σ	0.18	0.25	0.14	0.30	0.20	0.21	0.36	0.20	0.40	0.24	3.34	3.36
α	0.36%	1.44%	1.13%	3.82%	5.93%	5.57%	0.49%	1.04%	4.58%	3.83%	28.90%	28.41%
t(α)	0.29	0.85	1.27	1.93	4.20	3.74	0.20	0.79	1.69	2.29	1.25	1.22
β	0.13	0.22	0.16	0.24	0.11	-0.02	0.17	0.21	0.19	0.17	-0.11	-0.29
t(β)	2.89	3.69	4.90	3.34	2.15	-0.39	1.97	4.45	1.88	2.77	-0.14	-0.34
Sharp	0.06	0.11	0.15	0.17	0.33	0.26	0.04	0.11	0.14	0.20	0.08	0.08
Skewnes	0.78	6.41	1.04	7.09	1.41	1.05	8.59	2.19	10.49	2.93	14.63	14.44
Kurtosis	2.70	63.05	3.23	63.20	2.94	3.29	103.39	9.84	137.57	15.47	214.96	211.48

Low-High: 90%-10% Ranking

Statistic	Normal-Experience (Low Run up, Low Drawn down)						Bubble-Experience (High Run up, High Drawn Down)					
	Loser	2	3	4	Winner	WML	Loser	2	3	4	Winner	WML
$\overline{r-rf}$	0.06%	2.87%	1.94%	5.42%	7.46%	7.40%	6.99%	2.08%	23.87%	6.68%	1.77%	-5.22%
$t(\overline{r-rf})$	0.05	1.67	2.18	2.72	2.92	2.94	1.42	1.07	1.23	2.22	1.06	-1.02
σ	0.18	0.26	0.13	0.30	0.37	0.37	0.70	0.28	2.68	0.42	0.24	0.73
α	-0.88%	1.34%	1.07%	4.08%	6.77%	7.65%	6.19%	0.87%	22.53%	5.52%	1.12%	-5.07%
t(α)	-0.72	0.79	1.25	2.05	2.60	2.98	1.22	0.45	1.13	1.80	0.66	-0.97
β	0.17	0.26	0.17	0.24	0.12	-0.05	0.13	0.22	0.21	0.19	0.11	-0.02
t(β)	3.89	4.29	5.29	3.36	1.34	-0.50	0.76	3.17	0.31	1.80	1.86	-0.14
Sharp	0.00	0.11	0.15	0.18	0.20	0.20	0.10	0.07	0.09	0.16	0.08	-0.07
Skewnes	0.66	6.07	0.34	6.74	9.42	10.33	11.86	3.92	13.70	5.11	2.65	-10.93
Kurtosis	2.10	57.11	2.15	58.56	115.59	133.29	157.09	29.98	188.75	39.13	15.55	142.40

Figure 1: Slow Moving Capital on Bitcoin

This figure plots slow moving capital as well as the price of Bitcoin. Slow moving capital is proxied by the ratio between the number of pending transactions (i.e., transactions that are yet to be verified by Bitcoin miners) and that of verified transactions recorded on the blockchain (left scale). The price of Bitcoin is marked using the right scale.