Blockchain Consensus Protocols, Energy Consumption and Cryptocurrency Prices

Niranjan Sapkota[ab*], Klaus Grobys[ab]

[a] *University of Vaasa, School of Accounting and Finance*

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Abstract

Cryptocurrencies employ different consensus protocols to verify transactions. While the *Proof-of-Work* consensus protocol is the most energy consuming protocol, *Proof-of-Stake* and *Hybrid* consensus protocols have been introduced which consume considerably less energy. We employ portfolio analysis to explore whether energy is a fundamental economic factor affecting cryptocurrency prices. Surprisingly, our results suggest that, on average, cryptocurrencies employing *Proof-of-Work* consensus protocols do not generate returns that are significantly different from those that incorporate *Proof-of-Stake* consensus protocols. Even more surprising is that our results show that cryptocurrencies that incorporate *Hybrid* consensus protocols generated significantly higher average return than the other groups. A possible explanation for that phenomenon may be that investors' demand for cryptocurrencies that they perceive as offering more trust is larger than for those that carry potential risks of blockchain manipulation.

JEL Classification: G12, G14

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* Correspondence to: Department of Accounting and Finance, University of Vaasa, Wolffintie 34, 65200 Vaasa, Finland, Tel.: +358 468 418 558.

E-mail addresses: klaus.grobys@uva.fi (K. Grobys), niranjan.sapkota@uva.fi (N. Sapkota)

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1. Introduction

In the wake of the financial crisis that shook the investors' trust in the financial system, cryptocurrencies were celebrated as an alternative de-centralized medium of exchange. Blockchain technology allows peer-to-peer transactions without going through a financial institution. However, this new technology comes at a cost. In a recent study, De Vries (2019) found that Bitcoin consumed as much electrical energy as all of Hungary in 2018, corresponding to 15 billion U.S. dollar per year. Nowadays there are more than 2,100 cryptocurrencies traded on more than 18,000 exchanges. Knowing that the ever increasing world's energy consumption is a serious problem that has been subject to public debates over many years, the societal impact of cryptocurrencies' energy consumption is vertiginous.[1] Unfortunately, most of the cryptocurrencies do not have an accurate estimate of their electricity consumptions. However, it is known how many cryptocurrencies make use of certain types of consensus protocols[2]. Not all cryptocurrencies that employ *Proof-of-Work* (*PoW*) consensus protocols consume as much electricity as Bitcoin. For example, Ethereum (ETH) and Monero (XMR) also follow the *PoW* consensus protocol, but they consume considerably less electricity than Bitcoin.[3] In general, cryptocurrencies that do not employ *PoW* consensus protocol consume less energy per transactions, as pointed out in Nguyen and Kim (2018). Due to the energy inefficiency of *PoW* mining, *Proof Of Stake* (PoS) a new consensus protocol emerged. *PoS* was first introduced by Sunny King and Scott Nadal in 2012 and later in 2013 Sunny King created the first cryptocurrency Peercoin (PPC) implementing this consensus protocol[4].

According to Bach, Mihalijevic, and Zagar (2018), *PoW* will eventually be replaced by newer and more efficient algorithms. In this regard, De Vries (2019) mentions that Ethereum blockchain has been planning a transition from *PoW* to *PoS*. In terms of energy efficiency, *PoW* and *Hybrid*, which consensus protocol is a mixture of *PoW* and *PoS*, are inefficient, whereas *PoS* is highly efficient (Nguyen and Kim; 2018). Therefore, we can categorize these three consensus mechanisms *PoW*, *Hybrid*, and *PoS* as high-, medium- and low-energy

[1] De Vries (2019) also highlights that even if Bitcoin mining devices could run on renewable energy alone, they would still be discarded as electronic waste at the end of their lifespans. Specifically, the most popular machine on the market, an Application-Specific Integrated Circuit (ASIC) miner, cannot be repurposed because it is hardwired solely for mining Bitcoin, implying that it is likely to wind up with other cast-off electronics in a landfill or incinerator, causing damage to the environment. De Vries' (2019) calculations demonstrate that Bitcoin currently generates as much electronic waste as a small nation, such as Luxembourg.

[2] Table A.2 in the Appendix provides an overview on the number and market capitalization of cryptocurrencies using different consensus mechanism.

[3] See: https://digiconomist.net/ethereum-energy-consumption.

[4] Though PPC is the first cryptocurrency to use *PoS* protocol, it is implemented along with *PoW*, that makes PPC a *Hybrid* coin rather than a pure *PoS* cryptocurrency.

consuming cryptocurrencies, respectively. Furthermore, we would also like to stress out that the optimal level of energy consumption also depends upon mining rewards and fees. Dimitri (2017) argues that, as long as the reward is positive (after deducing the mining costs) the optimal amount of energy consumption differs between miners. Summing up, the energy consumption for *PoW* is considerably higher than for cryptocurrencies incorporating *PoS* and *Hybrid* consensus protocols.[5]

Hayes (2017) argues that in an economy, the cost of production plays an important role to determine the market price. Likewise, in the case of Bitcoin, anything that reduces the cost of production will have a negative influence on its price. He further argues that mining efficiency lowers the marginal cost of production. Taking into consideration the technological progress as energy efficiency and size of the mining network as mining difficulty, he concludes that both of these factors have implications on the cost of production and ultimately on the market value. Similarly, Li and Wang (2017) also confirm the relevance of both the technological and the economic factors on determining the Bitcoin market exchange rates by studying the early and later market. They find that the speculators drive the early market exchange rates, whereas the economic factors drive long-run price dynamics. Furthermore, they confirm that the market price anchors on mining costs, but the impact of mining difficulties diminishes over the long-run as mining technology advances. Interestingly, Bendiksen, Gibbons, and Lim (2018) find that the average marginal costs of Bitcoin creation are significantly lower than the market price of Bitcoin. Contrary to previous studies, Biais, Bisiere, Bouvard, Casamatta and Menkveld (2018) explore the reflection of fundamentals' events on the Bitcoin price and show that a large part of variation in prices does not relate to those fundamental events. They further find that the large fluctuation in Bitcoin prices is driven by the noisy changes in the trust system but not by the fundamentals.

Recently, there are few research papers available studying the relationship between cryptocurrency and energy. In a recent case study, Li, Li, Peng, Cui, and Wu (2019) estimate the electricity consumption of Monero mining. Monero also uses the *PoW* consensus protocol like Bitcoin and Ethereum. By studying different hashing algorithms, they conclude that the mining efficiency largely depends on the hashing algorithms rather than on the consensus mechanism. They also suggest that more studies should be done that investigate the relationship between energy consumption and cryptocurrency mining. Taking into account the financial aspect of cryptocurrency and energy related research, Symitsi and Chalvatzis (2018) analyze

[5] This issue will be discussed in detail in section 2.

the spillover effects between Bitcoin, energy and technology companies and find evidence for short run volatility spillover from technology stocks to Bitcoin, whereas long run volatility spills over from energy stocks to Bitcoin.

While previous studies are mostly considering a single digital currency and a single consensus protocol as a case study exploring either energy efficiency or energy as a fundamental market driving force for the pricing of cryptocurrencies (Hayas, 2017; Li and Wang, 2017; Bendiksen et al., 2018; Biais et al., 2018; Symitsi and Chalvatzis, 2018; Li, et al., 2019), there is no paper available that takes a portfolio perspective across cryptocurrencies. Our paper fills this gap in the literature. Specifically, for each of the three groups of consensus protocols – *PoW*, *Hybrid*, and *PoS* – we retrieve weekly cryptocurrency price data for 20 cryptocurrencies that exhibited the highest market capitalization as of January 3, 2016. By this, we ensure that our cryptocurrencies exhibit a high level of liquidity. We form equal-weighted portfolios of high-, medium- and low-energy consuming cryptocurrencies that correspond to the group of *PoW*, *Hybrid* or, respectively, *PoS* consensus protocols. Since cryptocurrencies incorporating the *PoW* consensus protocol are more risky than the other groups because their mining costs are more exposed to changes in energy prices, finance theory suggests that they should compensate investors with higher returns. Hence, we test whether the differences between those average portfolio returns are statistically different from each other. According to finance theory, we would expect that our *PoW* portfolio would generate significantly higher portfolio average returns than the *Hybrid* or *PoS* portfolio if energy is a fundamental risk factor affecting the cryptocurrency market. In the same manner, we would also expect that our *Hybrid* portfolio would generate significantly higher portfolio average returns than the *PoS* portfolio. Moreover, we investigate the statistical properties of our three portfolios in more detail and test different autoregressive models for determining the data generating processes. Since finance theory suggests that in an efficient market past price information should not embed information for future returns, we would expect not to find any autocorrelations if the cryptocurrency market exhibited weak-form market efficiency.

Our paper fills some important gaps in the literature. First, our study extends the current literature that investigates the role of economic fundamentals for pricing cryptocurrencies. For instance, our paper extends Biais et al. (2018), and Li et al. (2019) in taking a market-wide perspective. While Biais et al. (2018) and Li et al. (2019) focus on Bitcoin and Montero as single cryptocurrencies only, we employ Fama and French's (2008, 2015, 2017) portfolio analysis enabling us to make much more generalized, that is, market-wide conclusions. As Sensoy (2019) finds that liquidity is positively related to market efficiency in cryptocurrency markets, we control for market liquidity by accounting only for those twenty cryptocurrencies that exhibit the highest market capitalization in each group. Moreover, our study empirically tests Hayes' (2017) and Li and Wang's (2017) argument that fundamental factors are drivers of cryptocurrencies' price dynamics. So far there is no consensus achieved yet on the energy efficiency as a market fundamental for cryptocurrencies. While one group of scholars argue that mining cost plays an important role in determining the market price (e.g. Hayes, 2017; Li and Wang, 2017; Symitsi and Chalvatzis, 2018), another group of scholars argues that mining costs do not matter in the long-run (e.g., Dimitri, 2017; Bendiksen et al., 2018). Our paper explores this issue from a new angle.

In doing so, our paper is the first that employs portfolio analysis which has been used to investigate, for instance, the carry trade or momentum effect in traditional currency markets (Lustig, Roussanov, and Verdelhan, 2011; Menkhoff, Sarno, Schmeling, and Schrimpf, 2012a; 2012b), and more recently, the momentum effect in cryptocurrencies (Grobys and Sapkota, 2019). Finally, our paper contributes to the literature that tests the market efficiency of cryptocurrencies. While some scholars argue that Bitcoin is an efficient market (e.g., Tiwari et al., 2018; Bariviera, 2017; Nadarajah and Chu, 2017; Wei, 2018), other scholars take a contrary view, that is, they argue that Bitcoin is an inefficient market (e.g., Zhang et al., 2018; AI-Yahyaee et al., 2018; Urquhart, 2016). Our paper adds to this literature by taking a market-wide perspective similar like Grobys and Sapkota (2019) who employ the whole cross section of cryptocurrencies. In contrast to Grobys and Sapkota (2019) who use monthly return data, we first employ higher frequented weekly data, and second we analyze our well-diversified energy risk portfolios by running autoregressive models to determine return predictability.

Our results show that cryptocurrencies that employ *PoW* consensus protocol do, on average, not generate higher average returns than cryptocurrencies that either employ *Hybrid* or *PoS* consensus protocols. This finding is in favor of the Dimitri (2017) and Bendiksen et al. (2018) who argue that mining costs are not relevant for pricing cryptocurrencies in the long-term. Surprisingly, our findings indicate that cryptocurrencies that employ *Hybrid* consensus protocol generated during our sample period significantly higher average returns than cryptocurrencies that employ either *PoW* or *PoS* consensus protocols. Further subsample analysis provides evidence that this effect is not sample-specific. One possible explanation for our finding could be that the market participators' demand for cryptocurrencies incorporating *Hybrid* technology is relatively higher than for cryptocurrencies that incorporate either *PoS* or *PoW* consensus protocols. The *Hybrid* consensus protocol has the purpose to create a balance between the miners and the stakeholders for improving the governance of the underlying cryptocurrency. Therefore, cryptocurrencies incorporating *Hybrid* consensus protocols are possibly considered as 'more trustworthy'. This result has some important societal implications: First, potential issuers of new cryptocurrencies might benefit from knowing investor preferences. Second, cryptocurrencies that run on *Hybrid* consensus protocols appear to provide, at least on average, better risk-return profiles which is important for the finance industry aiming at optimizing investment vehicles. Third, policy makers need to understand that optimal governance comes at a cost: Even though cryptocurrencies that incorporate *Hybrid* consensus protocol are not as energy-efficient as the peers using *PoS* consensus protocols, they appear to provide optimal governance from the market participators' point of view.

Moreover, we find that our portfolios sorted by energy consumption exhibit strong patterns of higher-order autocorrelations. Since autocorrelation implies return predictability, our study is in line with the literature arguing that cryptocurrencies are inefficient (Zhang et al., 2018; AI-Yahyaee et al., 2018; Urquhart, 2016). Finally, we find strong evidence for time-series momentum which is contrary to Grobys and Sapkota (2019) who do not find any evidence for either cross-sectional or time-series momentum. The main difference between our study and Grobys and Sapkota (2019) is that we employ weekly data while Grobys and Sapkota (2019) employ monthly data. As our findings indicate return autocorrelations up to three weeks, our results are somewhat not comparable Grobys and Sapkota's (2019) study.

Our paper is organized as follows. The next section takes a closer look at consensus protocols of cryptocurrencies. The third section presents the empirical analysis and the last section concludes.

2. Background

There are now more than 2,100 cryptocurrencies traded at over 18,000 cryptocurrency exchanges around the world with Bitcoin market capitalization dominance of 56%[6]. Bitcoin, the first decentralized digital currency, follows the *PoW* consensus mechanism[7]. There are currently 500 cryptocurrencies in the market running on *PoW* protocols. Due to Bitcoin, the *PoW* cryptocurrency sector dominance based on market capitalization is slightly over 75%[8]. Employing the *PoW* protocol, miners on the networks compete against each other to keep the

[6] Coinmarketcap.com (as of 7.5.2019)
[7] In *PoW*, unique cryptographic puzzle is the 'Proof' and the energy consumption and other resources used to solve this puzzle is the 'Work'. For more see, Nakamoto (2008).
[8] https://cryptoslate.com/cryptos/proof-of-work/ (as of 7.5.2019)

transactions by using a huge amount of electricity. Whoever solves the complicated cryptographic puzzles gets the reward. Since there is a unique solution for each transaction, only one miner is rewarded for every puzzle solved. Unfortunately, *PoW* in not an energy efficient consensus protocol.

According to the Bitcoin Energy Consumption Index (2019), Bitcoin comes at the 44th position compared to the world's biggest energy consuming nation. Moreover, one Bitcoin transaction consumes as much electricity as 100,000 VISA (another payment system that is, however, centralized) transactions. The Bitcoin network is expected to consume as much electricity as Denmark by 2020. Furthermore, there are different types of costs associated with mining, such as energy, warehouse maintenance, supercomputers, and mining software.[9]

Due to the high energy consumption of the *PoW* consensus protocol, the *PoS* consensus protocol has been introduced. Nowadays, there are over 400 cryptocurrencies operating with the *PoS* consensus protocol with market capitalization dominance of 6%[10]. Considering *PoS*, this consensus protocol compares the fraction of the asset owned by miners and rewards them based on their percentage of the stake. Instead of relying on the massive power to incentivize the network, *PoS* relies simply on the proportion of wealth miners are staking relative to everyone else. Therefore, in *PoS* consensus protocols all the active miners get their reward based on their stake. As a result, this protocol is far more energy efficient than the *PoW* consensus protocol.

Besides from being energy efficient *PoS* has many potential benefits over *PoW* consensus protocols, increased overall security, more decentralized and transparent pooling consensus are other examples. Moreover, *PoW* is vulnerable to a so-called '51% attack', meaning whoever holds 51% of the entire network's computing power can manipulate the blockchain for their own sake, preventing new transactions from being confirmed. On the other hand, having 51% of a cryptocurrency-specific network's stake, one can manipulate the blockchain, too. As a consequence, a pure *PoS* system can also be unstable, and 51%-stakeholders could easily generate fake timestamp history for fake blocks. As a result, a *Hybrid* of *PoS/PoW* consensus protocol has been implemented by many cryptocurrencies to create a balance between the miners and the stakeholders in order to provide an improvement of the governance for the respective cryptocurrency[11].

[9] https://digiconomist.net/bitcoin-energy-consumption.

[10] https://cryptoslate.com/cryptos/proof-of-stake/ (as of 7.5.2019)

[11] Table A.1 in Appendix provides an overview about the basic difference between *PoW*, *PoS* and *Hybrid* consensus protocol.

More specifically, according to the Bitcoin Energy Consumption Index 2019, the estimated annual electricity consumption of Bitcoin is 61.74 TWh whereas the estimated consumption for Ethereum is almost ten times lower even though they both use the same consensus protocol. However there is no exact estimation of how much (less) energy the *PoS* consensus protocol uses. Comparatively, *PoW* uses thousands of heavily powered supercomputers with millions of investments in infrastructures and energy. On the other hand, operating with the *PoS* consensus protocol, one is able to stake with something as simple as Raspberry Pi which uses around 950 mA (5.0 W) of energy with estimated 43.95 KWh annually[12]. For example, if miners of one cryptocurrency using the *PoS* consensus protocol uses one million of these mini computers for minting, it will still consume 1000 times less energy than Bitcoin and almost 100 times less than Ethereum.

3. Methodology

Depending on the consensus protocols' energy consumptions, cryptocurrencies can be divided into three groups: 1) *PoW*, 2) *Hybrid*, and 3) *PoS*. Cryptocurrencies with *PoW* consensus protocol are the highest energy-consuming cryptocurrencies, whereas cryptocurrencies with *PoS* consensus protocol are the lowest energy-consuming ones. We start our analysis by retrieving weekly data for twenty cryptocurrencies that have the highest market capitalization as of January 3, 2016 for each of those three groups of cryptocurrencies. The three data sets of cryptocurrencies are reported in Table 1. Due to their enormous market capitalizations, we also consider a data set that excludes Bitcoin, Litecoin and Ethereum from the sample. This data set that we refer to as *PoW*^{b} group, contains 17 cryptocurrencies and exhibits a total market capitalization of USD 45,388,634. The total market capitalizations of the *Hybrid* and *PoS* group are USD 36,089,983 and USD 36,229,758. Considering these three groups of cryptocurrencies (e.g., *PoW*^{b}, *Hybrid*, *PoS*) that comprise a total of 57 cryptocurrencies, the relative share in terms of market capitalization for the *PoW*^{b}, *Hybrid* and *PoS* group corresponds to 38%, 31% and 30%. As a consequence, the market capitalizations of our three groups are roughly similar. For each employed cryptocurrency, we retrieve weekly data from January 1, 2016 until December 31, 2018.[13]

[12] See more at https://www.raspberrypi.org/forums/viewtopic.php?t=18043

[13] In choosing weekly data, we follow Gutierrez and Kelley (2008). In weekly terms, we can retrieve 156 observations which makes statistical inference more accurate compared to employing monthly data.

3.1. Cryptocurrency portfolios based on energy consumption and hypothesis testing

We start our analysis by forming equal-weighted portfolios for each group. The cumulative return evolutions are plotted in Figure 1. From Figure 1 we observe that the cumulative return evolutions of our *PoW* and *PoW*^{b} groups are very similar due to the chosen equal-weighting scheme which is common practice in studies that analyze traditional currencies. Interestingly, cryptocurrencies that employ *Hybrid* consensus protocols generated considerably higher returns than the other groups. In Table 2, we report the descriptive statistics of our cryptocurrency portfolios. For our hypothesis tests, we employ simple *t*-statistics of the zero-cost portfolios (*PoW-PoS*), (*PoW*^{b}*-PoS*), (*PoW-Hybrid*) and (*Hybrid-PoS*). If energy as an economic fundamental factor was a driver of cryptocurrencies and finance theory holds, we would expect that all those formulated zero-cost portfolios would generate positive payoffs. The rationale here is that the higher the energy consumption of the underlying consensus protocol, the more risky is the corresponding asset because mining coins becomes more costly, and hence, increases the cost of production. Rational investors would only be willing to keep the more risky assets in their portfolio if they are rewarded with higher returns.

However, the data shows that the corresponding point estimates of the zero-cost portfolios are -0.54%, -0.33%, -9.12% and 8.58% per week with corresponding *t*-statistics of -0.49, -0.27, -2.76 and 2.50. The *t*-statistics of the return differences of the (*PoW-PoS*) and (*PoW*^{b}*-PoS*) groups imply that high energy-consuming cryptocurrencies do not generate higher average returns than low energy-consuming cryptocurrencies, irrespective of whether or not we include the three cryptocurrencies that exhibit the highest market capitalizations (Bitcoin, Litecoin, Ethereum). On the one hand, this is a surprising result because finance theory suggests that assets that carry a higher risk should compensate the investors with a higher return. The *PoW* cryptocurrency portfolio is considerable higher exposed to changes in the price for energy. For instance, if the price for energy increases the mining costs will, in turn, increase as well. In this regard, this result is contrary to Hayes (2017) and Li and Wang (2017) who argue that economic factors drive long-run price dynamics of cryptocurrencies. On the other hand, this result is in line with Biais et al. (2018) who document that a large part of variation in Bitcoin prices does not relate to economic fundamentals' events.

Furthermore, the *t*-statistics of the return differences of the (*PoW-Hybrid*) and (*Hybrid-PoS*) that cryptocurrencies with *Hybrid* consensus protocol generated, on average, higher average returns than the *PoW*, *PoW*^{b} or *PoS* group. One could argue that the results could be driven by outlier because we observe from Table 2 that in particular the hybrid group is highly positively skewed. Therefore, we trim the data set and cut off the most extreme four observations on the right and left tail corresponding to 5% of the sample. The observations that were cut-off from the sample are reported in Table A.1 in the appendix. Then we again employ a simple *t*-test of the zero-cost portfolios (*PoW-PoS*), (*PoW^b-PoS*), (*PoW-Hybrid*) and (*Hybrid-PoS*). The point estimates of the zero-cost portfolios are -0.99%, -0.92%, -5.97% and 5.22% per week with corresponding *t*-statistics of -1.41, -1.24, -4.94 and 4.49. The robustness check shows that even though the economic magnitude of the point estimates of the zero-cost portfolios is lower, the *t*-statistics are considerable higher for the *(PoW-Hybrid*) and (*Hybrid-PoS*) portfolio. As our previous conclusion remain unchanged, our findings are not driven by outliers. Finally, Biais et al. (2018) argue that the large fluctuation in Bitcoin prices is driven by the noisy changes in the trust system but not by the fundamentals. If trust is a driver of cryptocurrencies, a possible explanation for the phenomenon could be that investors' relative demand is higher for cryptocurrencies incorporating *Hybrid* consensus protocol than for *PoW* or *PoS* consensus protocol because *Hybrid* consensus protocols are less likely to be subject to manipulation.

3.2. Statistical analysis of the data generating cryptocurrency portfolio processes

The next step in our portfolio analysis was to explore the data generating processes of our *PoW*, *PoW^b*, *Hybrid* and *PoS* portfolios in more detail. To investigate any potential autocorrelation, we employed the standard Akaike information criterion (AIC) to assess the optimal lag-order.[14] In Table 3 we report the estimated autoregressive model accounting for the optimal lag-order with respect to the AIC. Surprisingly, we find that all portfolios have in common that the second lag is highly statistically significant, whereas the first lag is not. Moreover, each cryptocurrency portfolio has a different autoregressive profile. The results reported in Table 2 also reveal that the stability conditions are fulfilled for all cryptocurrency portfolios (see Lütkepohl and Krätzig, 2004, p.23). To investigate whether the regression residuals exhibit any remaining autocorrelation, we employ the LM test for autocorrelation. Specifically, for each model we perform the LM test for autocorrelation successively for one to five lags. Depending on the model, the corresponding test statistics are under the null hypothesis distributed as chi-square with one to five degrees of freedom. The results are reported in Table 4. The LM tests reveal that there is no evidence of any remaining autocorrelation in the regression residuals which indicates that the chosen lag-order (see Table 3) is indeed appropriate for modeling the underlying data generating process. This result has some important implications. First of all,

[14] To estimate the optimal lag-order, we chose a maximum lag length of 12 weeks.

some studies document that cryptocurrency markets move toward efficiency. Specifically, Vidal-Tomás and Ibañez (2018) and Sensoy (2019) argue that Bitcoin has become more efficient over time. Moreover, Bariviera (2017) documents Bitcoin's informational efficiency since 2014, whereas Sensoy (2019) finds Bitcoin markets have become more informationally efficient at the intraday level since the beginning of 2016. In another study, Nadarajah and Chu (2017) report that Bitcoin returns do satisfy the efficient market hypothesis. Further, the study of Khuntia and Pattanayak (2018) supports Vidal-Tomás and Ibañez (2018) and Sensoy (2019) in finding that Bitcoin exhibits market efficiency over time, validating the adaptive market hypothesis. In contrast to those studies, we use a more recent sample which is from 2016–2018. Since our findings indicate higher order autocorrelation, our results provide strong evidence that cryptocurrency markets are inefficient. As we employ only the cryptocurrencies that exhibit the highest market capitalizations at the time of portfolio formation one cannot argue that our results would be driven by either micro-cryptocurrencies.

3.3. Implementing time series momentum strategies

Another implication of autocorrelation among cryptocurrency portfolios is potential time series momentum.[15] Moskowitz, Ooi, and Pedersen, (2012) proposed the time series momentum strategy that performs well even in different market scenarios. Therefore, we estimate time series momentum (TSMOM) as defined by

$$r_{t,t+1}^{TSMOM,s} = sign(r_{t-K}^{s}) \cdot r_{t,t+1}^{s},$$

where r_{t-K}^{s} is the return of security *s* over the past K months and $r_{t,t+1}^{s}$ is next month's return which indicates taking a long position when the sign of the cumulative past $K-$month return is positive and a short position otherwise. First, we implement strategies for $K = \{12, 9, 6, 3\}$ and employ the whole cross section of 60 cryptocurrency. From the left hand side of Panel A of Table 5 we observe that all strategies generated statistically significant average payoffs ranging from 4.09% per week for $K = 3$ to 5.84% per week for $K = 12$. The payoffs are statistically significant on at least a 5% level. Another interesting finding is that the payoff of the TSMOM portfolios are linear increasing as we move from $K = 3$ to $K = 12$. One explanation for that phenomenon could be that some individual cryptocurrencies may have

[15] It is important to note that all significant parameter estimates are positive, irrespective of which lag or which model we consider.

higher order autocorrelation that exceeds the order of five. Therefore, employing a cumulative return window of 12 weeks instead of three might account more precise information. One could raise the concern that the results could be driven by outliers. To address this concern, we trim the data and cut-off 5% of the observations, that is, the most extreme observations from the right and left tail of the distribution. The results are reported on the right hand side of Panel A of Table 5. Even though the portfolios' average payoffs are lower after trimming, the *t*-statistics increase and show that all average payoffs are statistically significant on at least a 1% level.

Another issue that one may wonder is to what extent are the results driven by Bitcoin, Litecoin and Ethereum because those three cryptocurrencies are dominating the overall market in terms of market capitalization (see Table 1.a). To address this issue, we exclude those three cryptocurrencies from the sample and repeat the previous analysis. The results are reported on the left hand side of Panel B of Table 5. The results are virtually the same. Next, we again trim the data and cut off 5% of the observation that are the most extreme ones. The observations that were cut off are reported in Table A.2 in the appendix. The results for the trimmed data excluding Bitcoin, Litecoin and Ethereum are reported on the right hand side of Panel B of Table 5. The conclusions remain unchanged.

3.4. Controlling for the Hybrid cryptocurrency effect

In section 2.1 we have shown that, over the 2016–2018 sample period, cryptocurrencies running on *Hybrid* consensus protocols generated, on average, significant higher returns than cryptocurrencies that were implemented with either *PoS* or *PoW* consensus protocols. The question arises as to whether momentum payoffs are exposed to this cross-sectional phenomenon and if so, to which extent. To investigate this issue in more detail, we regress the payoffs of our time series momentum strategies on the zero-cost portfolio that is long on the cryptocurrency portfolio comprising cryptocurrencies with *Hybrid* consensus protocol and short on the portfolio of cryptocurrencies comprising *PoS* consensus protocols.[16] The regression equation is then simply given by

$$r_{t,t+1}^{TSMOM,s} = c + \gamma\left(R_{Hybrid,t+1} - R_{PoS,t+1}\right) + e_{t+1},$$

[16] One could also implement the short leg as a strategy as $0.5 \cdot PoW + 0.5 \cdot PoS$ or alternatively $0.5 \cdot PoW^{b} + 0.5 \cdot PoS$.

where $r_{t,t+1}^{TSMOM,s}$ denotes momentum payoff of the respective strategy s at time $t+1$, $R_{Hybrid,t+1}$ is the return of the portfolio comprising cryptocurrencies with *Hybrid* consensus protocol, $R_{PoS,t+1}$ is the return of the portfolio comprising cryptocurrencies with *PoS* consensus protocol and e_{t+1} denotes the error term. We estimate the time series regressions using a Newey-West (1987) covariance estimator with five lags. We report the result for the whole data set and for the data set excluding Bitcoin, Litecoin and Ethereum in Table 6. From Table 6 we observe that depending on the time series momentum strategy the exposures against the *Hybrid*-factor, as defined here as $\left(R_{Hybrid,t+1} - R_{PoS,t+1}\right)$, vary between 0.33 and 0.37. The corresponding robust *t*-statistics indicate that those exposures are statistically significant on any level. This result implies that our time series momentum strategies are investment strategies that are in essence invested in cryptocurrencies with *Hybrid* consensus protocol. As the intercepts become insignificant, after controlling for our *Hybrid*-factor, time series momentum strategies implemented in cryptocurrencies time series momentum strategies do not generate returns in excess of our *Hybrid*-factor.

On the one hand our results are in line with Asness, Moskowitz, and Pedersen (2013), who explore the pervasiveness of the momentum phenomenon as they argue that momentum payoffs are positively co-moving across otherwise unrelated asset markets. Our results especially extend the study of Menkhoff, Sarno, Schmeling, and Schrimpf (2012) who explore different momentum strategies implemented among traditional currency. Our results are, however, contrary to recent findings of Grobys and Sapkota (2019) because they do not find any momentum effects in cryptocurrencies. It is noteworthy that our study is different from Grobys and Sapkota (2019) as they use monthly data and we employ weekly data. Gutierrez and Kelley (2008), who also use weekly data in investigating short-term momentum in equities and find strong patterns of momentum effects. Gutierrez and Kelley's (2008) findings are, however, different from Jegadeesh and Titman (1993) Jegadeesh (1990) who employ monthly data implying different data frequencies incorporate different types of information.

3.5. Long-Short investment strategy and Bitcoin futures

From a more practical point of view, one could wonder if such a long-short investment strategy could actually be implemented under real life conditions. Bitcoin Futures contracts have been introduced by the Chicago Mercantile Exchange (CME) and the Chicago Board Options Exchange (CBOE) in December 2017. Since Bitcoin is implemented using *PoW* consensus protocol, we proxy the *PoW* portfolio simply by Bitcoin futures and construct a trading strategy that is short on Bitcoin and long on the portfolio of cryptocurrencies using *Hybrid* consensus protocol. The cumulative return of this strategy is plotted in Figure 3. Figure 3 shows that the zero-cost strategy is almost linear increasing over the sample period. The average return is estimated at 11.65% per week with a *t*-statistic of 3.26 indicating statistical significance on any level. One could wonder to which extent this result is driven by outliers. To address this issue, we cut off 5% of the most extreme observation on the left hand and right hand tail. The observations that were cut off are reported in Table A.3. in the appendix. After trimming the data, the average payoff is still 7.39% per week with a *t*-statistic of 5.35 suggesting that our result is not an artefact due to outliers.

4. Conclusion

The mining process of cryptocurrencies consumes an enormous amount of energy. So far there is no consensus achieved yet as to whether energy is a market fundamental for pricing cryptocurrencies. If energy, as an economic factor, has an impact on the market values of cryptocurrencies and energy plays a role in determining cryptocurrency prices, we would expect that our well-diversified portfolio of cryptocurrencies that incorporate the high energy-consuming *PoW* consensus protocols generated, on average, higher returns than our well-diversified portfolio of cryptocurrencies that incorporate the low energy-consuming *PoS* consensus protocol. However, we do not find such evidence.

Surprisingly, our results demonstrate that our well-diversified portfolio of cryptocurrencies that incorporate the medium energy-consuming *Hybrid* consensus protocol generated considerably higher average returns than our *PoW* or *PoS* portfolios. One important implication of our findings is that energy consumption does not seem to play role for pricing cryptocurrencies. Moreover, the price of cryptocurrencies is mostly determined by its demand side because the supply side is controlled for by the cryptocurrency-specific algorithm. Since cryptocurrencies that incorporate *Hybrid* consensus protocols generated significantly higher average returns than cryptocurrencies incorporating *PoW* or *PoS* protocols, our results imply that investors' relative demand for those cryptocurrencies that incorporate *Hybrid* protocols is greater than investors' relative demand for cryptocurrencies employing *PoW* or *PoS* protocols.

A possible explanation for that phenomenon is that investors perceive cryptocurrencies that employ *Hybrid* protocols as 'more trustworthy' than the others. Even if it is unlikely that the blockchain of cryptocurrencies employing *PoW* or *PoS* protocols is manipulated by a miner that either holds 51% of the entire network's computing power or a miner having 51% of a cryptocurrency-specific network's stake, market participators may still overestimate the risk for market manipulation. Psychologically, investors tend to overestimate events having small probabilities and individuals are according to prospect theory in general risk-averse. As a consequence, the investors' demand for cryptocurrencies that incorporate *Hybrid* consensus protocol is relatively larger because they involve a lower risk of manipulation. However, other explanations are possible as well and future research is needed to elaborate more on this issue.

Another important question that is recently intensively discussed in the literature is whether cryptocurrency markets are efficient. So far there is no consensus achieved yet on whether cryptocurrency markets are efficient. Our findings provide evidence that cryptocurrencies exhibit, on a portfolio level, strong patterns of higher-order autocorrelation. We also found strong effects of time series momentum. Both results imply that cryptocurrency markets are not efficient.

Finally, our results have some practical implications also. On the one hand, *PoW* consensus protocols rely on competitions among miners and, as a consequence, only those that have the highest computational power get rewarded. On the other hand, *PoS* consensus protocols ensure that miners get rewarded in relation to their stake in that cryptocurrency implying co-operation. That is why from an energy-efficiency point of view, *PoS* consensus protocol is energy-efficient. Taking the governance perspective, the *PoS* consensus protocol appears to be less appealing than the *Hybrid* consensus protocol because the *PoS* consensus protocol does not eliminate completely the potential risk of manipulation, whereas the *Hybrid* consensus protocol appears to be superior from a governance point of view. Future research is strongly recommended to investigate the trade-off between energy consumption and governance in more detail.

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Figure 1. Cumulative returns of cryptocurrency portfolios sorted by energy consumption

This table plots the evolution of the cumulative returns for the *PoW*, *PoW*[b], *Hybrid*, and *PoS* portfolio group. The sample period is from January 1, 2016 until December 31, 2018.

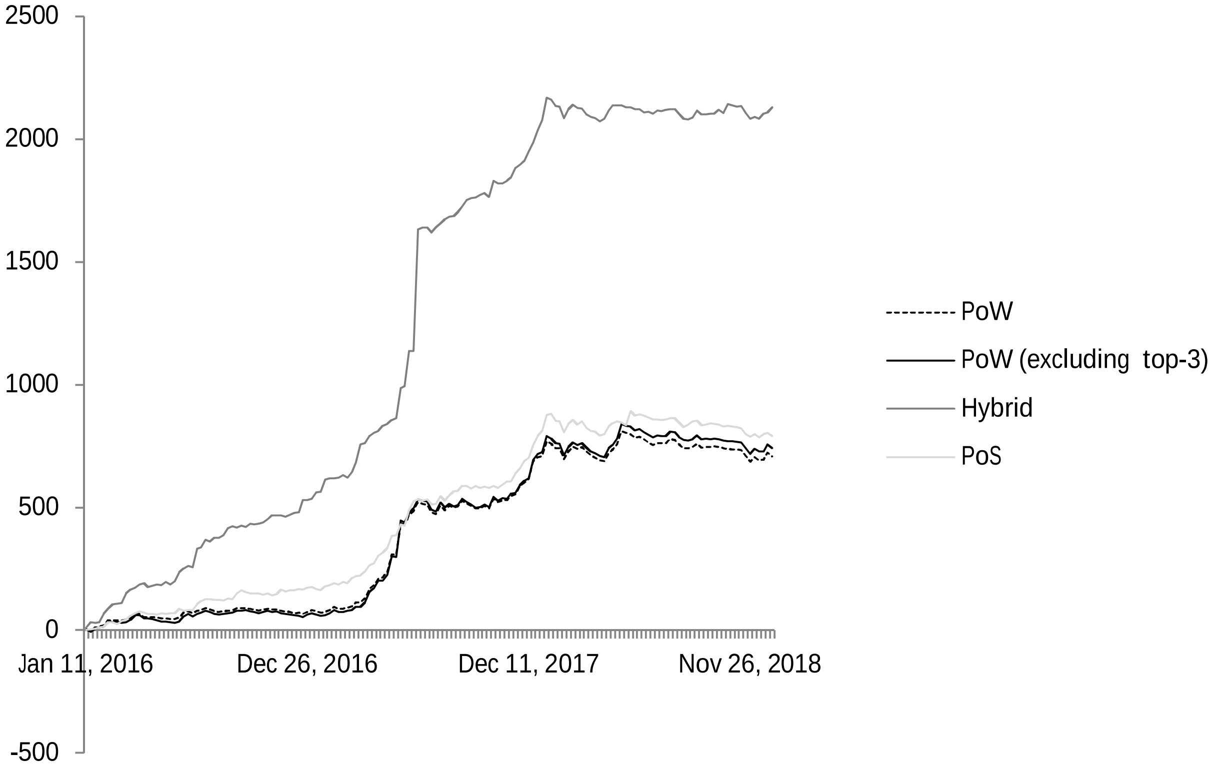

Figure 2. Cumulative returns of time series momentum payoffs

This table plots the evolution of the cumulative returns for the different time-series momentum portfolios. The sample period is from March 28, 2016 until December 31, 2018.

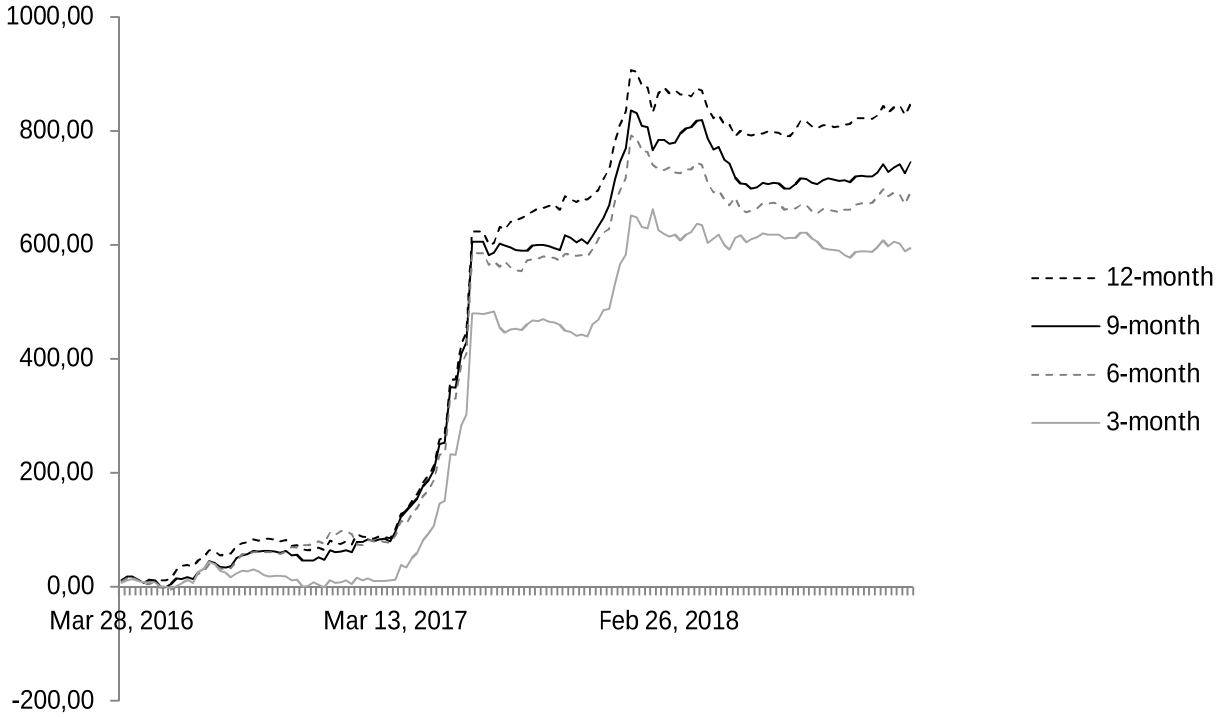

Figure 3. Cumulative return of long/short portfolios based on Bitcoin futures

This table plots the evolution of the cumulative returns for a strategy that is short on Bitcoin and long on a portfolio that consists of cryptocurrencies that incorporate *Hybrid* consensus protocols. The sample period is from January 1, 2016 until December 31, 2018.

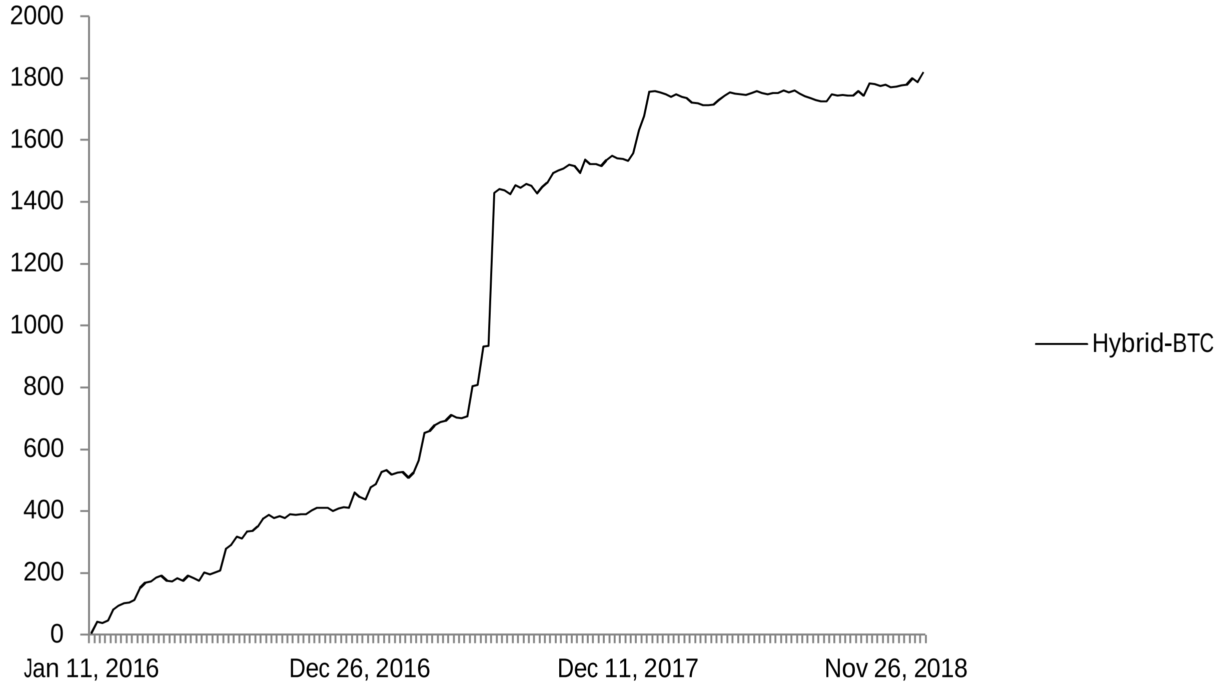

Table 1. Top 20 Coins using PoW, PoS and Hybrid Consensus Protocols

This table reports the top 20 cryptocurrencies using *PoW*, *PoS* and *Hybrid* (*PoW/Pos*) consensus protocol as of Jan 3, 2016. It is generated using the historical snapshot available at coinmarketcap.com.

S.No.	PoW Coins	Symbol	Market Cap	PoS Coins	Symbol	Market Cap	Hybrid Coins	Symbol	Market Cap
1	Bitcoin	BTC	6467437080	BitShares	BTS	8591688	Dash	DASH	19794713
2	Litecoin	LTC	152873521	Nxt	NXT	6863998	Peercoin	PPC	9756959
3	Ethereum	ETH	73843278	Factom	FCT	5646935	Emercoin	EMC	2729184
4	Dogecoin	DOGE	14940681	NuShares	NSR	3176456	Novacoin	NVC	1162587
5	Namecoin	NMC	6073338	Rubycoin	RBY	2763547	I0Coin	I0C	697337
6	Bytecoin	BCN	5582979	Clams	CLAM	2199047	ReddCoin	RDD	577185
7	Monero	XMR	5295952	BlackCoin	BLK	2000105	Diamond	DMD	484841
8	GridCoin	GRC	3206756	GlobalCurrency	GCR	1387263	I/O Coin	IOC	310983
9	MonaCoin	MONA	1627740	StorjcoinX	SJCX	687999	CloakCoin	CLOAK	201995
10	Startcoin	START	1561435	MintCoin	MINT	661925	WhiteCoin	XWC	70092
11	Tether	USDT	951600	NuBits	USNBT	849743	Bitstar	BITS	62056
12	Primecoin	XPM	900600	SolarCoin	SLR	522662	BeanCash	BITB	53056
13	VeriCoin	VRC	796319	Rimbit	RBT	330286	LiteDoge	LDOGE	42925
14	DigiByte	DGB	740007	Blocknet	BLOCK	312057	UltraCoin	UTC	31851
15	DNotes	NOTE	711592	FairCoin	FAIR	247002	Capricoin	CPC	27313
16	GameCredits	GAME	666554	HyperStake	HYP	173539	Kobocoin	KOBO	27149
17	Quark	QRK	647684	BitBay	BAY	141822	Sprouts	SPRTS	25115
18	WorldCoin	WDC	581449	AudioCoin	ADC	129387	Amsterdam	AMS	13420
19	PayCoin	XPY	581404	Orbitcoin	ORB	122492	SuperCoin	SUPER	12954
20	BoostCoin	BOST	522544	NavCoin	NAV	121805	BitSend	BSD	8268
	Total Market Cap		45388634*			36929758			36089983
	Market Cap Share		38,33 %			31,19 %			30,48 %

* Excluding Bitcoin, Litecoin and Ethereum

Table 2. Descriptive statistics of cryptocurrency portfolios sorted by energy consumption

This table reports the descriptive statistics for four cryptocurrency portfolios ranked by energy consumption. The sample period is from January 1, 2016 until December 31, 2018.

	PoW	PoW[b]	HYBRID	PoS
Mean	4.5354	4.7480	13.6552	5.0736
Median	0.2240	-0.2533	6.4679	2.8859
Maximum	130.9860	147.4168	492.9698	66.7729
Minimum	-44.0888	-45.3746	-45.8466	-45.6972
Std. Dev.	19.5048	21.2037	45.4339	16.4352
Skewness	2.4676	2.7013	7.8663	0.9413
Kurtosis	14.8132	16.5463	81.2525	5.5172
Jarque-Bera	1065.4040	1382.4810	41411.3300	64.2257
Probability	0.0000	0.0000	0.0000	0.0000

[b] Excluding the Bitcoin, Litecoin and Ethereum.

Table 3. Estimated autoregressive models

This table reports the parameter estimates for different autoregressive models. The optimal lag-order is determined using the Akaike Information Criterion. Newey-West (1987) *t*-statistics accounting for five lags are given in parenthesis. The sample period is from January 1, 2016 until December 31, 2018.

Variable	constant	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	R-squared
PoW	2.45** (2.30)	-0.03 (-0.56)	0.29** (2.22)	0.21*** (2.75)	-	-	0.13
PoW[b]	2.66** (2.27)	-0.04 (-0.71)	0.29** (2.35)	0.21** (2.60)	-	-	0.13
HYBRID	10.06** (2.33)	-0.00 (-0.12)	0.26*** (2.76)	-	-	-	0.07
PoS	2.83*** (2.90)	0.09 (1.08)	0.21*** (2.81)	0.15*** (3.15)	-0.15 (-1.16)	0.14** (2.41)	0.12

**Statistically significant on a 5% level.
*** Statistically significant on a 1% level.
[b] Excluding the Bitcoin, Litecoin and Ethereum.

Table 4. LM test statistics for remaining autocorrelation

This table reports different LM test statistics for the regression residuals of table 3. Under the null hypothesis the test statistics are asymptotically distributed as chi-square distribution with one to five degrees of freedom. The corresponding critical values for the 5% significance levels are 3.84, 5.99, 7.82, 9.49, and 11.07. The corresponding p-values are given in parentheses.

Model/Lags	1	2	3	4	5
PoW	1.87 (0.1716)	1.88 (0.3915)	2.75 (0.4316)	3.80 (0.4343)	3.91 (0.5611)
PoW[b]	2.00 (0.1577)	2.00 (0.3684)	2.91 (0.4065)	4.22 (0.3767)	4.35 (0.4995)
HYBRID	0.45 (0.5046)	2.45 (0.2942)	2.56 (0.4644)	2.99 (0.5594)	3.01 (0.6991)
PoS	1.79 (0.1807)	2.65 (0.2665)	2.87 (0.4115)	3.61 (0.4604)	4.63 (0.4619)

Table 5.a. Descriptive statistics of different time series momentum strategies

This table reports the descriptive statistics for different cryptocurrency momentum portfolio using the untrimmed data set and trimmed data. The trimmed data cuts-off the most extreme observations on the right and left hand tail of the distribution corresponding to 5% of the empirical probability distribution. The sample period is from March 28, 2016 until December 31, 2018.

	untrimmed data set				trimmed data			
Statistic/strategy	**12-week**	**9-week**	**6-week**	**3-week**	**12-week[b]**	**9-week[b]**	**6-week[b]**	**3-week[b]**
Mean	5.8406*** (3.25)	5.1375*** (2.89)	4.7690*** (2.72)	4.0946** (2.40)	4.0765*** (4.48)	3.3978*** (3.73)	2.7740*** (3.22)	2.4013*** (2.81)
Median	2.1003	1.2360	0.6012	0.3523	2.1003	1.2360	0.6012	0.3523
Maximum	177.5289	176.9290	178.4604	177.2945	47.0611	45.7703	48.5731	43.1194
Minimum	-43.6178	-40.6550	-32.3301	-36.0245	-19.1971	-22.9566	-19.8712	-17.0311
Std. Dev.	21.6429	21.3942	21.1121	20.5486	10.6520	10.6530	10.0834	9.9986
Skewness	4.3059	4.3729	4.8064	4.8256	1.2205	1.0119	1.2830	1.4688
Kurtosis	31.7670	32.8757	36.0594	38.0875	5.8958	5.7910	7.2381	6.2550
Jarque-Bera	5447.7940	5854.6400	7161.3580	8000.8420	81.8794	67.8476	140.1137	109.7399
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

**Statistically significant on a 5% level.
*** Statistically significant on a 1% level.
[b]These data are trimmed and exclude the four most extreme time series observations on the left and right tail of the corresponding return distributions.

Table 5.b. Descriptive statistics of different time series momentum strategies excluding Bitcoin, Litecoin and Ethereum

This table reports the descriptive statistics for different cryptocurrency momentum portfolio using the untrimmed data set and trimmed data. The data set excludes Bitcoin, Litecoin and Ethereum when implementing the momentum strategies. The trimmed data cuts-off the most extreme observations on the right and left hand tail of the distribution corresponding to 5% of the empirical probability distribution. The sample period is from March 28, 2016 until December 31, 2018.

	untrimmed data set				**trimmed data**			
Statistic/strategy	**12-week**	**9-week**	**6-week**	**3-week**	**12-week**[b]	**9-week**[b]	**6-week**[b]	**3-week**[b]
Mean	5.9707*** (3.21)	5.2727*** (2.87)	4.8860*** (2.69)	4.1547** (2.34)	4.1088*** (4.42)	3.4477*** (3.72)	2.8014*** (3.19)	2.3748*** (2.71)
Median	2.1498	1.2782	0.8633	0.1245	2.1498	1.2782	0.8633	0.1245
Maximum	185.8179	185.1864	186.7984	185.5712	47.1799	45.8212	48.7715	43.0308
Minimum	-43.9765	-40.8578	-32.9985	-36.4867	-20.4995	-23.3220	-19.9503	-18.3225
Std. Dev.	22.4212	22.1504	21.8863	21.3493	10.8845	10.8471	10.2639	10.2624
Skewness	4.4225	4.4952	4.9134	4.9222	1.1995	1.0025	1.2498	1.4606
Kurtosis	32.9569	34.1708	37.3207	39.1820	5.7590	5.6745	7.0168	6.1719
Jarque-Bera	5894.5460	6358.5230	7699.9440	8494.8950	76.3038	63.7816	127.7652	106.1410
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

**Statistically significant on a 5% level.
*** Statistically significant on a 1% level.
[b]These data are trimmed and exclude the four most extreme time series observations on the left and right tail of the corresponding return distributions.

Table 6. Controlling for the Hybrid cryptocurrency effect

This table reports the parameter estimates for regression equations that regress different momentum strategies on the Hybrid-factor which is a portfolio that is long on cryptocurrencies that incorporate Hybrid consensus protocols and short on cryptocurrencies that incorporate PoS consensus protocols. Newey-West (1987) *t*-statistics accounting for five lags are given in parenthesis. The sample period is from March 28, 2016 until December 31, 2018.

Strategy	constant	(Hybrid-PoS)	R-squared
12-month	2.82 (1.42)	0.36*** (26.04)	0.53
9-month	2.10 (1.06)	0.36*** (29.72)	0.55
6-month	1.81 (1.13)	0.35*** (17.14)	0.53
3-month	1.27 (0.75)	0.33*** (10.73)	0.51
12-month[a]	2.81 (1.38)	0.37*** (26.33)	0.54
9-month[a]	2.10 (1.04)	0.37*** (30.19)	0.56
6-month[a]	1.79 (1.12)	0.37*** (17.13)	0.54
3-month[a]	1.19 (0.70)	0.35*** (10.83)	0.52

[a] Excluding Bitcoin, Litecoin and Ethereum.
*** Statistically significant on a 1% level.

Appendix

Table A.1. Comparisons between PoW, PoS, and Hybrid Consensus Protocols

Criteria	PoW	PoS	Hybrid (PoW + PoS)
Energy Efficiency	No	Yes	No
Modern Hardware	Very Important	No need	Important
Forking	When two nodes find the suitable nonce at the same time	Very difficult	Probably
Double Spending attack	Yes	Difficult	Yes, but less serious than in PoW
Block creating speed	Low, depends on variant	Fast	Low, depends on variant
Pool mining	Yes, but it can be prevented	Yes, and it is difficult to prevent	Yes
Example	Bitcoin (BTC), Litecoin (LTC)	BitShares (BTS), Nextcoin (NXT)	Dash (DASH), Peercoin (PPC)

Source: Nguyen and Kim (2018)

Table A.2. Comparison of PoW, PoS and Hybrid Cryptocurrencies Based on their Numbers and Market Capitalization

Panel A: Including Bitcoin, Ethereum, and Litecoin

	PoW	PoS	Others	Total
Number of Cryptocurrencies	517	402	1222	2141
Percentage (%)	24.14	18.78	57.08	100
Market Capitalization ($ in B)	141.38	10.86	36.40	188.64
Dominance (%)	75.14	5.77	19.09	100

Panel B: Excluding Bitcoin, Ethereum, and Litecoin

Number of Cryptocurrencies	514	402	1222	2138
Percentage (%)	24.04	18.80	57.16	100
Market Capitalization ($ in B)	12.48	10.86	36.57	59.91
Dominance (%)	20.83	18.12	61.05	100

Note. This table is generated using the information available at cryptoslate.com as of 7.5.2019. Panel B excludes three largest cryptocurrencies under PoW protocol. 'Others' includes Hybrids, dPoS and other consensus protocol cryptocurrencies.

Table A.2. Trimmed observations for energy-sorted cryptocurrency portfolios

(PoW-PoS)	(PoW^b-PoS)	(Hybrid-PoW)	(Hybrid-PoS)
-62.6284	-62.5129	-459.372	-56.8231
-26.2100	-29.8355	-107.789	-38.5675
-25.8078	-28.2217	-74.8582	-31.6448
-25.7638	-25.6716	-63.8474	-27.2312
27.88344	30.27623	24.7859	72.3571
30.63994	33.7027	35.82428	78.75633
57.07233	64.70682	52.2831	82.02508
87.16298	103.5939	53.16028	487.2559

Table A.3. Trimmed observations for cryptocurrency momentum portfolios

12-week	9-week	6-week	3-week
177.5289	176.929	178.4604	177.2945
100.4631	97.91368	96.34356	81.66023
72.01109	66.20229	73.25367	68.439
61.89667	59.80724	60.48544	51.3516
-24.11458	-23.78528	-20.45539	-18.07823
-24.28796	-24.64637	-21.93967	-28.09708
-31.46949	-32.33011	-22.35219	-31.80449
-43.61776	-40.65498	-32.33011	-36.02447

Table A.4. Trimmed observations for investment strategy using Bitcoin futures

zero-cost strategy
495.6029
124.6176
97.55845
89.2479
-15.843
-18.9803
-23.309
-25.5998