Comovement and Instability in Cryptocurrency Markets*

Pierangelo De Pace
Pomona College

Jayant Rao
Claremont Graduate University

July 7, 2020

Abstract

We analyze the extent of comovement between daily price returns of nine major cryptocurrencies during the first three main phases of their development, from April 2013 to November 2018. We assess its evolution using bivariate and multivariate modelling approaches, and detect pronounced time variation. Generally, comovement is initially low and positive, but increases between early 2017 and late 2018. We then adopt a right-tail version of the Augmented Dickey-Fuller unit root test to identify periods of mildly explosive behavior (statistical instability) in the Network Value to Transactions (NVT) ratio (a measure of the dollar value of cryptocurrency transaction activity relative to network value) of six cryptocurrencies. We show evidence of significant mild explosiveness in all of them. At the end of 2017 and in 2018, several cryptocurrencies experience often simultaneous instability associated with rising NVT ratios. Instability is a dominant feature of these markets.

JEL Classification: C58, G1, G10, G11, G12

Keywords: Cryptocurrencies, Asset Pricing, Comovement, NVT Ratio, Mild Explosiveness

*Pierangelo De Pace (corresponding author): Pomona College, Department of Economics. 425 N College Avenue, Carnegie 205; Claremont, CA 91711, USA; Email: pierangelo.depace@pomona.edu; Phone: +1 909 621 8744. Jayant Rao: Claremont Graduate University, Economic Sciences Department; 150 E 10th Street; Claremont, CA 91711, USA; Email: jayant.rao@cgu.edu; Phone: +1 909 344 7085. We are grateful to Graham Bird, Marc Gronwald, Massimo Guidolin, Marco Lorusso, Francesco Ravazzolo, Tom Willet, and the participants of several conferences for many constructive suggestions and remarks.

1 Introduction

Cryptocurrencies (or virtual currencies) are relatively new forms of currencies that generally allow (i) electronic payments between individuals without financial intermediation and (ii) transactions without fees. Typically, they offer anonymity. From a technical point of view, the key innovation that these currencies introduce is the implementation of cryptographic identification protocols into a "distributed ledger". Cryptocurrencies work on digital records thanks to which it is possible to track and validate all payments at any point in time. By design, they can be used in a decentralized payment system that (i) is not necessarily controlled by central banks nor any other financial institutions and (ii) is able to prevent "double spending". Compared with "conventional" currencies, cryptocurrencies are still a relatively limited monetary phenomenon. However, from an investment point of view, for several reasons, they have become quite relevant. Over the years, they have attracted attention from the media, investors, practitioners, academic economists, monetary authorities, governments, and regulators. Since its launch in January 2009, Bitcoin (BTC) has been the most well-known and widely used cryptocurrency.[1]

Academic research on cryptocurrencies was very sparse until not long ago. Lately, however, a rich collection of research papers and articles examining the many properties and characteristics of cryptocurrencies has been written, circulated, and published. Such research has been spurred by growing interest in Bitcoin and other virtual currencies also as novel and potentially lucrative investment vehicles and by months of turbulence and high volatility in virtual currency markets. Especially in 2018, many cryptocurrencies, and Bitcoin in particular, were affected by extensive distress. Some turmoil occurred also in 2019. Therefore, it is not surprising that significant empirical work in this infant, but expanding, literature has concerned cryptocurrency prices and their unstable dynamics.

Questions about what the characteristics of cryptocurrency prices are and whether their market is built on speculation are numerous. Cheah and Fry (2015) empirically document the presence of bubbles in Bitcoin; Corbet et al. (2018a) look for bubbles in Bitcoin and Ethereum (ETH, another major cryptocurrency); Hafner (2018) finds evidence of bubbles in eleven dominant cryptocurrencies; and Bouri et al. (2019) search for bubbles in a set of seven leading cryptocurrencies (Bitcoin; Ripple, XRP; Ethereum; Litecoin, LTC; Nem, XEM; Dash, DASH; and Stellar Lumens, or just Stellar, XLM).[2] According to Fry and Cheah (2016), from an economic point of view, Bitcoin is, paradoxically, interesting due to its lack

[1] Multiple have been the interpretations of Bitcoin's nature: a new type of currency, a commodity like gold, an alternative asset, or an innovative technology.

[2] Ethereum is a global, open-source platform for decentralized applications and Ether is its native currency. Ripple is an independent digital asset that is native to the Ripple Consensus Ledger, which employs the decentralized cryptocurrency known as XRP. As it is customary, and unless it is noted otherwise, we conveniently use the words "Ethereum" or "Ether" and "Ripple" or "XRP" interchangeably to refer to the two cryptocurrencies.

of clarity. Fry (2018) develops bespoke rational bubble models for cryptocurrencies, shows that liquidity risks generate heavy-tails in Bitcoin and other cryptocurrency markets, provides evidence of bubbles in Bitcoin and Ethereum, and argues that the lack of economic clarity may even cause cryptocurrency prices to collapse completely. Indeed, some recent research classifies Bitcoin as a speculative asset, rather than a genuine currency (Baek and Elbeck, 2015). Gandal et al. (2018) demonstrate that, in late 2013, suspicious trading activity likely caused an unprecedented surge in the Bitcoin price, which increased from US$150 to more than US$1000 in just two months; and conclude that unregulated cryptocurrency markets remain vulnerable to manipulation today. Budish (2018) outlines a simple theoretical model in which he demonstrates that Bitcoin would be even more prone to a "majority attack", if it became sufficiently economically important – for example, if it became a store of value akin to gold. He also argues that there are intrinsic limitations to how economically important Bitcoin can become. Bolt and Van Oordt (2019)'s theoretical framework shows that the price of a cryptocurrency depends positively on the volume of payments for goods and services with that virtual currency (transaction value or volume) and on the quantity of virtual currency held in a speculative position; and negatively on the velocity of a cryptocurrency and on its total quantity in circulation. It implies that a speculative position reduces the quantity of virtual currency available to facilitate real payments and, therefore, increases the value of that currency. This model predicts that, as a cryptocurrency becomes more established, its price becomes less sensitive to the impact of shocks to speculators' beliefs. This prediction undermines the conventional wisdom that high price volatility will prevent widespread use of a virtual currency. Cheng and Dai (2020) find carry trade activities under the disguise of Bitcoin transactions on US dollar and Chinese yuan Bitcoin exchanges in the period following the financial crisis of 2007-09. Finally, Bhambhwani et al. (2019) challenge the popular notion that cryptocurrency markets are simply plagued with bubbles and speculative trading, and statistically determine that two main factors drive, instead, cryptocurrency prices in the long run: trustworthiness of the blockchain of a cryptocurrency (measured by its computing power) and the adoption of the blockchain itself (measured by the size of its network).

From a slightly different angle, Urquhart (2016), Nadarajah and Chu (2017), Tiwari et al. (2018), and Khuntia and Pattanayak (2018) study the efficiency properties of Bitcoin. Makarov and Schoar (2019) argue that cryptocurrency markets exhibit periods of large and recurrent arbitrage opportunities across exchanges, and find that Bitcoin, Ethereum, and Ripple prices may differ across exchanges for weeks. Gkillas and Katsiampa (2018) examine the tail behavior of major cryptocurrencies; they find Bitcoin Cash (BCH) to be the riskiest cryptocurrency and Bitcoin and Litecoin to be the least risky. Urquhart (2017) investigates Bitcoin price clustering. Phillip et al. (2018) write about some unique statistical features of cryptocurrencies. Yermack (2015) discusses to what extent Bitcoin can be considered a currency.

Several authors investigate the relationship between the price returns of limited sets of cryptocurrencies and the returns of conventional assets. One of the objectives is to shed light on the possible ways, if any, cryptocurrencies can be included in investment portfolios. Studying the relationship between virtual currencies and other assets, or financial and macroeconomic variables, may be useful to investors, forecasters, economists, and policy makers, especially if one ponders the possibility that cryptocurrencies may, in principle, become economically and financially significant in the future. Bouri et al. (2017), Corbet et al. (2018b), Selmi et al. (2018), Platanakis et al. (2018), for example, describe the hedging and diversification benefits of Bitcoin and other virtual currencies. Koutmos (2018) analyzes the relationship between transaction activity and Bitcoin price returns. Liu and Tsyvinski (2018) show that the returns of Bitcoin, Ripple, and Ethereum have low exposures to traditional asset classes (stocks, currencies, and commodities) and to common macroeconomic factors. They find that the behavior of these currencies is not driven by their function as stakes in the future of blockchain technology (similar to stocks), nor as units of account (similar to currencies), nor as store of value (similar to some metal commodities). They also demonstrate that cryptocurrency returns can be predicted by two factors specific to their markets (momentum and investors attention) and that supply factors (mining costs, price-to-dividend ratios, or realized volatility) are not useful for predicting their dynamics. Borri (2019) studies conditional tail-risk in Bitcoin, Ethereum, Ripple, and Litecoin, and finds that, unconditionally and conditionally, cryptocurrencies are highly correlated with one another, but poorly correlated with other global assets, including gold. He also shows that cryptocurrencies could exhibit attractive returns and hedging features.[3]

To our knowledge, despite the growing attention to cryptocurrencies as digital assets, the existing literature is still lacking convincing and comprehensive empirical evidence on their mixed second moment properties, on the instability that seems to be embedded in cryptocurrency markets, and on most aspects of these currencies as new investment options. In this paper, we fill some of these gaps by considering cryptocurrencies as a separate asset class, of interest for investment purposes.[4] We are concerned with two of their many characteristics, (i) the way their prices move with respect to each other and (ii) their unstable dynamic behavior. First, unlike previous academic research, we empirically examine the extent of price return comovement *within* a broad set of nine dominant cryptocurrencies. We define comovement

[3]Bitcoin and other virtual currencies seem to exhibit the characteristics of alternative or speculative assets. Their correlation with traditional currencies and financial assets is usually low. They are often viewed as diversifiers, safe haven investments, and hedging instruments, a role typically played by gold.

[4]Some recent research is currently trying to determine if, indeed, cryptocurrencies represent a new asset class. Bianchi et al. (2020) claim that, under a rational stochastic discount factor framework, the variables that usually forecast stocks, bonds, and commodities ought to also be able to forecast cryptocurrencies. They fail to find evidence of predictability of cryptos from a rather large (and crypto-biased) set of forecast variables, which implies that cryptocurrencies are really not predictable. Such evidence is in favor of a segmentation of the class of cryptocurrencies from other securities. This segmentation is evidence of cryptocurrencies being a true, novel asset class.

as the correlation coefficient between price returns and, pair by pair, model its time evolution by means of bivariate and multivariate econometric methods. Second, using state-of-the-art recursive methods, we look for and date-stamp periods of statistical instability (which could be seen as distress) in a subset of six cryptocurrency markets. Gronwald (2020) points out that a number of recent papers looking for bubbles in cryptocurrencies are problematic due to an insufficient consideration of their fundamental value. To partially address this issue, he conducts an investigation on bubbles in Bitcoin, Ethereum, Ripple, and Litecoin by expressing Ethereum, Ripple, and Litecoin prices in terms of Bitcoin prices (assuming that Bitcoin is the leading cryptocurrency), and by implementing methods similar to those that we adopt in this work. We concur with his argument. As such, different from what has been done in this strand of the literature, we do not base our empirical scrutiny on mere price data. Rather, we propose the adoption of a new and innovative, yet easily computable, measure of cryptocurrency relative value, the Network Value to Transactions (NVT) ratio. As we explain in Section 2, this measure allows for convenient and direct (although somewhat imperfect) utility comparisons across cryptoassets, even more so than prices do. The application of appropriate econometric methods for the detection of statistical instability on this novel variable may help identify, if not always the formal presence of bubbles, at least the occurrence of distress and turmoil, but also corrections, in cryptocurrency markets.

Because of the absence of a solid theory of cryptocurrency prices and because of a currently poor grasp of how such prices are related to each other, we are reluctant to start out with explicit hypotheses to be then tested empirically. The consideration of how technologically different many cryptocurrencies are lead us to believe that the degree of comovement across their price returns should be generally expected to be low. In a broad financial sense, many of the existing cryptocurrencies could be seen as substitutes, as they compete against each other for market share in a currently small but expanding market. Their degree of substitution may vary, depending on technological overlap or improvement and target consumers (Bitcoin and Litecoin can be thought of as perfect substitutes; Ripple, Ethereum, and Bitcoin have different target consumers). If so, their degree of price comovement could be expected to be negative, or positive and low, if one considers the fact some of them work on similar blockchain technologies.[5] The informal observation of how cryptocurrencies have evolved since their inception suggests that many may be found to be characterized by frequent and pronounced episodes of distress. We explore certain patterns in the data without resorting to any specific conjectures nor speculations. The ultimate goal is to provide a comprehensive set of clear and statistically robust empirical facts about virtual currency

[5]Ethereum powers a blockchain platform for company building and smart contract implementation, which allows companies to enter the market without creating their own blockchain ecosystems. Ripple creates a bridge between traditional markets (banks) and the broad cryptocurrency ecosystem. Litecoin is designed for fast, almost immediate transactions. Monero is based on different hashing algorithms, which represent a departure from the traditional mining process.

price dynamics. The general objective is then twofold: (i) to help determine if, how, and to what extent such currencies can be bundled together in investment portfolios; and (ii) to offer some observational guidance for the formulation of more solid theoretical foundations of cryptocurrency behaviors. After all, even policymakers moved from neglect, to banning, to showing some interest in the blockchain technology and cryptocurrencies. As a matter of fact, a thorough understanding of the empirical features of cryptocurrency markets may be also useful for protecting financial stability.

We work on a daily dataset of nine major cryptocurrencies: Bitcoin, Ripple, Ethereum, Bitcoin Cash, Stellar, EOS, Litecoin, Cardano (ADA), and Monero (XMR). Our samples of data are cryptocurrency-specific, given that virtual currencies are launched on the market at different points in time. The earliest data point is Bitcoin and Litecoin's and goes back to April 28, 2013. Our panel of time series is terminated in late November 2018, in correspondence of the concluding days of what may be considered, as we explain later, a major phase of cryptocurrency market development. As we carry out our empirical analysis, we provide statistical evidence of pronounced time variation in the comovement of cryptocurrency price returns. Generally low to moderately positive, we find it to be drastically increasing for all pairs of cryptocurrencies between early 2017 and late 2018. We also detect statistically significant unstable behavior, or distress, in the subset of six cryptocurrencies for which this specific empirical investigation is possible. The periods of turmoil that we identify are numerous, but not necessarily synchronized across cryptocurrencies. However, we show that several major cryptocurrencies (including Bitcoin and Litecoin) experience significant and almost simultaneous distress in the second half of 2018. We argue, and provide relevant empirical evidence, that instability is an extensively common trait of cryptocurrency markets.

The rest of this paper is organized as follows. In Section 2, we describe the dataset. In Section 3, we explain how we measure the comovement of cryptocurrency price returns, outline how we model its time evolution, and present the empirical results. In Section 4, based on some very recent econometric literature, we provide a statistical definition of instability (turmoil and/or distress) in a variable of interest, summarize the econometrics that we implement to detect and date-stamp periods of unstable dynamics in the cryptocurrency NVT ratios in the sample, and report the empirical outcomes. We conclude with a brief discussion of our findings and some of their implications in Section 5.

2 Data Overview

According to *CoinMarketCap* (an online platform that tracks cryptocurrency capitalization), total cryptocurrency market capitalization reaches a peak of about US$800B in January 2018 (it is still at US$30B in April 2017), at a time when Bitcoin's dominance is about 35%, after steadily fluctuating above 80%

for years until February 2017.[6] By the end of November 25, 2018 (the day that we elect as the end of our sample of data), 2071 cryptocurrencies and other electronic coins and tokens are traded on the global market and their total market capitalization is US$129.4B. On that day, Bitcoin represents 53.93% of the market and its price is US$4009.97. The corresponding dominance figures for the other cryptocurrencies are: Ripple 11.68% (second most dominant cryptocurrency overall, price: US$0.374551), Ethereum 9.31% (third cryptocurrency, price: US$116.45), Bitcoin Cash 2.49% (fourth cryptocurrency, price: US$184.58), Stellar 2.36% (fifth cryptocurrency, price: US$0.159607), EOS 2.35% (sixth cryptocurrency, price: US$3.35), Litecoin 1.42% (seventh cryptocurrency, price: US$30.89), Cardano 0.76% (ninth cryptocurrency, price: US$0.037725), and Monero 0.75% (tenth cryptocurrency, price: US$58.05). Together, these cryptocurrencies account for 85.04% of the total market.

Conditions change rapidly in these markets. For example, by the end of June 9, 2019, 2225 cryptocurrencies and other electronic coins and tokens are traded on the global market, with a total market capitalization of US$244.1B. Bitcoin takes the lion's share again and now represents 55.80% of the market; its price is US$7688.08. The corresponding dominance figures for the other cryptocurrencies in the sample are: Ripple 6.71% (third most dominant cryptocurrency overall, price: US$0.388266), Ethereum 10.14% (second cryptocurrency, price: US$233.09), Bitcoin Cash 2.78% (fifth cryptocurrency, price: US$381.17), Stellar 0.95% (tenth cryptocurrency, price: US$0.119915), EOS 2.32% (sixth cryptocurrency, price: US$6.17), Litecoin 2.93% (fourth cryptocurrency, price: US$115.13), Cardano 0.84% (eleventh cryptocurrency, price: US$0.079470), and Monero 0.58% (thirteenth cryptocurrency, price: US$83.78). At this time, these nine cryptocurrencies account for 83.04% of the total market.

A few months later, on September 22, 2019, the 2379 cryptocurrencies in the market exhibit a total capitalization of US$265.4B. Bitcoin has a dominance of 67.1% and trades at US$10070.39, just hours before suddenly collapsing to about US$8000. On this day, the nine cryptocurrencies that we include in the sample of the present study represent 86.61% of the total market.

These markets are very volatile, their structure changes frequently, and many cryptocurrency emerge and vanish on a daily basis. Following their full development has become a difficult, maybe virtually impossible, task. As far as we can tell, the evolution and characteristics of the entire cryptocurrency market have not been studied. In our empirical investigation, an extended daily dataset of cryptocurrency prices (expressed in U.S. dollars) is collected from *Coin Metrics*, a recently founded provider of cryptoasset market and network data. Samples are cryptocurrency-specific, given that virtual currencies are designed and introduced into the market at different times. All time series end on 11/25/2018. The

[6]Cryptocurrency market capitalization – one way to assess the size of the market – is computed by multiplying the total of all issued coins derived from mining (circulating supply of cryptocurrencies) by the current cryptocurrency market price.

starting dates are 04/28/2013 for Bitcoin (2038 daily observations), 08/04/2013 for Ripple (1940 daily observations), 08/07/2015 for Ethereum (1207 daily observations), 07/31/2017 for Bitcoin Cash (483 daily observations), 08/05/2014 for Stellar (1574 daily observations), 07/01/2017 for EOS (513 daily observations), 04/28/2013 for Litecoin (2038 daily observations), 10/01/2017 for Cardano (421 daily observations), and 05/21/2014 for Monero (1650 daily observations).[7] Bitcoin reaches parity with the U.S. dollar in February 2011, before the beginning of our sample. In 2013, when our panel of data starts, several rivaling cryptocurrencies emerge. By May 2013, the cryptocurrency market counts ten digital currencies, including Litecoin. Another major crypto asset joins in August 2013, in the name of Ripple.

The time evolution of the nine cryptocurrency prices in the sample is represented in Figure 1. The trajectories look similar and, to a noticeable extent, synchronized. In a first major phase, prices stay flat and low across all cryptocurrencies for a relatively long period of time. This period is characterized by low traded quantities for all virtual currencies. Almost simultaneously, between the end of 2016 and the beginning of 2017, a new major phase emerges. During this phase, all crypto prices increase rapidly. Bitcoin's price picks up a little earlier, in 2015 already, but the most sizeable upwards acceleration unfolds during the first weeks of 2017. In all cases, these prices reach their respective peaks between the end of 2017 and the beginning of 2018, when, at the onset of a third major phase, they begin to swiftly decline to much lower levels. The decline becomes slower by the spring of 2018, when the evolution of prices starts exhibiting frequent upwards swings with many small local spikes. Prices settle by the end of our sample, in late November 2018.

At approximately this time, total cryptocurrency market capitalization reaches its lowest point in years, after the sharp increase that begins in January 2017 and the similarly sharp collapse that initiates about one year later. Market capitalization picks up again in the months that follow (as prices do), fluctuating well below its January 2018 maximum. The days between late November and early December 2018 virtually mark the beginning of a new major phase in the evolution of cryptocurrency markets.

In the upper panel of Table 1, we report some basic summary statistics concerning the daily price returns of the nine virtual currencies that we include in our study. These statistics are computed over each cryptocurrency's individual sample. Note that cryptocurrencies are traded world-wide also on non-business days. One fact is of particular relevance: cryptocurrencies have large and volatile returns. The eight positive mean returns vary between 9.4 basis points (bps) and 30.6bps per day (Litecoin and Ethereum, respectively). The only negative mean return is Bitcoin Cash's; over its specific sample, this

[7] Not all cryptocurrencies are created equal. One distinguishing characteristic concerns their supply: while Ethereum, Stellar, EOS, and Monero have unlimited supply, the supply of Bitcoin, Ripple, Bitcoin Cash, Litecoin, and Cardano is limited by design. As we write, Bitcoin and Bitcoin Cash have already reached levels of circulating supply that are close to their respective upper bounds.

cryptocurrency exhibits an average return of -13.5bps. Volatilities, as measured by the sample standard deviations, fluctuate between 438.4bps (Bitcoin) and 999.6bps (EOS). The nine price returns fluctuate widely; their sample ranges are 63% for Bitcoin, 161% for Ripple, 178% for Ethereum, 88% for Bitcoin Cash, 104% for Stellar, 139% for EOS, 134% for Litecoin, 108% for Cardano, and 101% for Monero.

These returns exhibit pronounced excess kurtosis – a consequence of the frequent occurrence of extreme realizations. The kurtosis coefficients are comparable to typical values in the distributions of other financial asset price data collected at the same frequency. In many cases, unlike typical equity returns, we see large and usually positive skewness coefficients, which may reflect the presence of larger extrema on the positive side than on the negative side (see the reported sample maxima and minima). Exceptions are Bitcoin and, especially, Ethereum with their negative skewness coefficients. The empirical distributions of these returns are not Gaussian. Because of the large variations in their dynamics, none of the nine mean returns are likely to be statistically significant – i.e., none of them are at least two standard deviations above or below zero.[8] Bitcoin's average return is barely 1.70 standard deviations above zero.

In the same panel of the same table, we report the ratio between the mean and the standard deviation of the time series of each cryptocurrency returns – i.e., what we call mean-per-standard-deviation index. A risk-averse investor may want to look at this indicator to have a sense of the reward-to-risk ratio embedded in each virtual currency. According to this metric, Bitcoin, Ethereum, and Stellar exhibit a better risk-return trade-off than the other cryptocurrencies over their individual samples (0.038, 0.039, and 0.031, respectively). Ripple, EOS, and Monero's measured trade-offs are just a bit lower with their respective 0.028, 0.023, and 0.025. The worst performers are Bitcoin Cash, Litecoin, and Cardano, whose specific estimated indices are -0.015, 0.014, and 0.014.

The lower panel of Table 1 shows the thirty-six correlation coefficients of all cryptocurrency pairs. The nine virtual currencies in the sample are all positively correlated, with correlation coefficients ranging from 0.205 to 0.652. In general, a correlation coefficient that, in absolute value, lies between 0.50 and 1.00 defines a strong or high correlation. If it lies between 0.30 and 0.49, it defines a medium or moderate correlation. If it lies below 0.30, it defines a small or low correlation. From an investment perspective, if an asset is negatively correlated with another asset, putting them together in a portfolio tends to reduce the risk of that portfolio. If an asset has a weak positive correlation with another asset, then it is called a diversifier. An asset that is uncorrelated (negatively correlated) with another asset is said to be a weak (strong) hedge. Finally, an asset that is uncorrelated (negatively correlated) with another asset during times of distress is considered a weak (strong) safe haven.[9] In our dataset of price returns, we have

[8] Uncertainty around the mean is roughly measured by the ratio between the sample standard deviation of price returns and the square root of the number of observations in the sample.

[9] Gold, for example, has often been considered a hedge and a safe haven.

three low correlations: between Ethereum and Ripple (0.205), between Ethereum and Stellar (0.229), and between Monero and Ripple (0.208). These currencies could be seen as diversifiers of one another. We also have twenty-four moderate correlations and nine strong correlations.

Investors, practitioners, and even policymakers are not just interested in unconditional correlations between asset price returns. Rather, they often want to know what correlation coefficients look like in different states of the market and to be fully aware of the extent of their time variation. For example, investors might want to be informed of how the different returns in their cryptocurrency portfolios are related to each other at times of distress or turmoil with rising prices, or when the markets are experiencing a downward correction – i.e., when an investment portfolio is likely to need a change in its composition. These simple considerations further motivate the way we organize and develop our empirical investigation.

In the first part of this work, we adopt a bivariate statistical approach based on Tang and Xiong (2012) and a multivariate one based on Engle and Sheppard (2001) and Engle (2002) to analyze the comovement of nine cryptocurrency daily price returns, all derived as the first differences of the natural logarithm of daily prices. In the second part, we look for periods of instability in cryptocurrency markets. As we describe in Section 4, we adopt similar econometric techniques as in Cheah and Fry (2015), Corbet et al. (2018a), Hafner (2018), and Bouri et al. (2019). Unlike these authors, who all search for instability in cryptocurrency prices and/or price indices, we do so by examining the statistical properties of different data.[10] Following the statistical methodologies proposed in Phillips and Yu (2011) and Phillips et al. (2015), we identify periods of mildly explosive behavior in the time series of the NVT ratio of six of the cryptocurrencies in the sample, namely Bitcoin, Ethereum, Bitcoin Cash, Stellar, Litecoin, and Cardano.

In the equities world, we can measure the valuation of a stock by looking, for example, at the price-to-earnings ratio, which is a measure able to quantify a company's share price relative to how much money the company makes (or earnings per share). In the cryptocurrencies world, things are not as straightforward, given that these assets do not have any connection to profits or earnings. The purpose of the NVT ratio is simply to detect whether a cryptocurrency is overvalued or undervalued.

As suggested in *Coin Metrics*, for each of these six cryptocurrencies, we construct these ratios by dividing market capitalization levels (i.e., the total market value of all tokens in circulation expressed in U.S. Dollars) by associated transaction volumes (i.e., an estimate of the value of on-chain transaction activity drawn from block explorers and blockchains, expressed in U.S. Dollars).[11] As its creators mention,

[10] See Trimborn and Härdle (2018) for details about the most commonly used cryptocurrency price index, known as CRIX.

[11] According to *Coin Metrics*, at least as we write this paper: (i) Monero has no transaction value data because it uses confidential transactions and it is cryptographically impossible to know the size of such transactions; (ii) EOS has breaks in the transaction value data because there were periods of it being offline; and (iii) Ripple data is irregular and it is near impossible to run a fully validating node; given that we can only rely on their application programming interface (API), which is rather limited, it is not recommended to use such data for an academic study.

the NVT metric is intended to capture the efficacy of a currency at manifesting the property of being a medium of exchange.[12] It measures the dollar value of cryptoasset transaction activity relative to network value and compares how units of on-chain transactions are priced in the market across different networks. For a cryptocurrency to intermediate effectively, it must have sufficient on-chain volumes.

On the one hand, a high NVT ratio (or an NVT ratio that increases quickly over time) generally indicates that the currency is expensive (or is getting more expensive) relative to its actual transaction volume. It could indicate optimism on the part of investors, who might be assuming that transaction volumes (and hence utility) will increase in the future, or (maybe ongoing) overvaluation of the cryptocurrency. On the other hand, a low NVT ratio (or a rapidly falling NVT ratio) may be a sign of (perhaps ongoing) undervaluation, or pessimism about the future prospects of the currency. Specifically, it could either mean that a cryptocurrency transaction volume may decline in the near future (especially if current volume is higher than its normal level), or that the asset is simply undervalued. The NVT ratio could be compared to a conventional price-to-earnings ratio. Of course, cryptocurrency volumes (i.e., transaction activity) are not analogous to earnings; rather, they represent a measure of the underlying demand or utility of a cryptocurrency. Equity investors would like a company to exhibit strong earnings before they buy a stock; likewise, crypto investors would like to see a healthy amount of transaction activity on its network before they decide to invest in a virtual currency.

However, the NVT ratio is not a perfect measure of the relative value of a cryptocurrency. In its standard and original formulation, it relies on a flawed market capitalization indicator and is constructed on a generally problematic measure of transaction volumes.[13] As extensively documented in *Coin Metrics*, for most cryptocurrencies, getting accurate estimates of the actual economic throughput of public blockchains is not trivial. Due to the existence of mixers, self-churn, privacy enhancements, spam, and change outputs, raw estimates of transactional value are often misstated by a factor of five, ten, or more. To partially address these issues, for the computation of the NVT ratios, we make use of *Coin Metrics*'s recently released adjusted transaction volume estimates (expressed in U.S. Dollars), which are produced by means of a proprietary algorithm. From the perspective of the blockchain, all transactions are equally valid; however, for an economist or investor, this new (and different) measure is claimed to be more useful because it is able to isolate the most meaningful economic transactions of each currency. Despite these caveats, NVT ratios still represent a straightforward way to look at the relative utility of competing cryptoassets in a more or less comparable manner.

All NVT ratio time series end on 11/25/2018. They start on 04/28/2013 for Bitcoin (2038 daily

[12] The NVT ratio was initially named MTV (Market to Transaction Value) ratio.

[13] Furthermore, as the creators of the NVT ratio repeatedly emphasize, their indicator is strongly dependent on the assumption that different cryptoassets are roughly comparable in the prevalence of change outputs.

observations), 08/07/2015 for Ethereum (1207 daily observations), 08/03/2017 for Bitcoin Cash (480 daily observations), 11/02/2015 for Stellar (1120 daily observations), 04/28/2013 for Litecoin (2038 daily observations), and 10/02/2017 for Cardano (420 daily observations).

3 Measuring the Comovement of Cryptocurrency Price Returns

We study the dynamic comovement of $M = 9$ cryptocurrency price returns in two different, albeit complementary, ways. First, we model the evolution of their unconditional correlations with a bivariate rolling regression approach. However, this methodology only considers two price returns at a time and, as such, is not able to exploit all the dynamic (simultaneous and non-simultaneous) interrelations that are present in the full set of returns in the sample. To address this issue, we then analyze the dynamic (un)conditional correlations between price returns by estimating a battery of dynamic conditional correlation multivariate generalized autoregressive conditional heteroskedasticity (DCC MV-GARCH) models, which also allow for the estimation of corresponding time-varying conditional volatilities. This way, we are able to capture and utilize at once all the information embedded in our sample of cryptocurrency prices.

3.1 Rolling Unconditional Correlations

We adopt a bivariate approach to compute rolling unconditional correlations between cryptocurrency price returns, as in Tang and Xiong (2012). First, we rescale all daily cryptocurrency price returns by subtracting their respective means and dividing by their respective standard deviations, $r^*_{m,t} = \frac{r_{m,t}-\overline{r}_m}{\sqrt{\frac{\sum_{t=1}^{T}(r_{m,t}-\overline{r}_m)^2}{T-1}}}$. Then, we regress the rescaled returns of cryptocurrency x, $r^*_{x,t}$, on the rescaled returns of cryptocurrency z, $r^*_{z,t}$, with $x, z = 1, 2, ..., M$ and $x \neq z$. $\widehat{\widetilde{\rho}}_{xz}$ obtained from regression $r^*_{x,t} = \mu + \widetilde{\rho}_{xz} r^*_{z,t} + \eta_t$ is the estimated unconditional correlation between the two cryptocurrency price returns. We assess the time-variation in the correlation coefficients between all pairs of price returns by estimating rolling regressions with fixed windows of lengths equal to 30 and 60 days. We correct for autocorrelation in the residuals by computing Newey-West standard errors, based on a Bartlett kernel and a fixed bandwidth, which are used to derive reliable rolling (approximately) 95% confidence intervals for $\widetilde{\rho}_{xz}$.

3.2 Dynamic (Un)Conditional Correlations

The bivariate rolling correlations that we discuss in Section 3.1 can only provide a partial picture of comovement between cryptocurrency price returns, as they fail to take into account the cross-dynamics within the full set of virtual currencies in the sample and, to an extent, are susceptible to changes when different lengths for the rolling windows are selected. We focus again on the time dimension of the data and, to check the robustness of the previous results, we assess how (un)conditional correlations between cryptocurrency price returns evolve over the years by working in a multivariate setting.

We estimate $M-1=8$ DCC MV-GARCH models, as in Engle and Sheppard (2001) and Engle (2002). Each time, we first estimate a univariate GARCH model for each returns series and then derive a multivariate conditional correlation estimator from the transformed residuals of the first-stage models. The resulting conditional correlation coefficients, at each point in time, are a function of past correlations and of the history of the conditional volatility of each returns series. The implemented multivariate GARCH models assume that, respectively, $S = M, M-1, M-2, ..., 2$ demeaned cryptocurrency price returns are conditionally multivariate normal with expected value equal to zero and time-varying covariance matrix, H_t. A dynamic conditional correlation DCC(J,K) MV-GARCH(P,Q) model is estimated on the transformed returns $\widehat{r}_{m,t} = r_{m,t} - \overline{r}_m$, where $\overline{r}_m = \frac{\sum_{t=1}^{T} r_{m,t}}{T}$. Let $\overline{r} = (\overline{r}_1, \overline{r}_2, ..., \overline{r}_S)'$, $\widehat{r}_t = (\widehat{r}_{1,t}, \widehat{r}_{2,t}, ..., \widehat{r}_{S,t})'$, $\widehat{r}_t \sim \mathcal{N}(0, H_t)$, and $H_t = D_t R_t D_t$. D_t is the $S \times S$ diagonal matrix of time-varying conditional standard deviations from S univariate GARCH models. $\sqrt{h_{m,t}}$ is the m^{th} element of the main diagonal of D_t and R_t is a time-varying conditional correlation matrix.[14] Each $h_{m,t}$ follows a univariate GARCH model, $h_{m,t} = \omega_m + \sum_{p=1}^{P_m} \alpha_{m,p} \widehat{r}^2_{m,t-p} + \sum_{q=1}^{Q_m} \beta_{m,p} h_{m,t-q}$, for $m = 1, 2, ..., S$.[15] For each price return, P_m and Q_m are integers between 1 and 30 that do not need to be the same and whose selection is based on the Schwarz Information Criterion. In this work, $P = (P_1, P_2, ..., P_S)'$ and $Q = (Q_1, Q_2, ..., Q_S)'$.

$U_t = \left(1 - \sum_{j=1}^{J} \gamma_j - \sum_{k=1}^{K} \delta_k\right) \overline{U} + \sum_{j=1}^{J} \gamma_j (\widehat{\varepsilon}_{t-j} \widehat{\varepsilon}'_{t-j}) + \sum_{k=1}^{K} \delta_k U_{t-k}$ is the conditional dynamic correlation process used to model the data. $\widehat{\varepsilon}_t \sim \mathcal{N}(0, R_t)$ is the vector of standardized residuals from the multiple OLS regressions $\widehat{r}_t = \theta + \epsilon_t$. $\overline{U}$ is the unconditional covariance of the standardized residuals from the first-stage estimation. We assume that $R_t = (U_t^*)^{-1} U_t (U_t^*)^{-1}$, where

$$U_t^* = \begin{bmatrix} \sqrt{u_{11,t}} & 0 & 0 & ... & 0 \\ 0 & \sqrt{u_{22,t}} & 0 & ... & ... \\ ... & ... & ... & ... & ... \\ ... & ... & ... & ... & 0 \\ 0 & ... & 0 & 0 & \sqrt{u_{SS,t}} \end{bmatrix},$$

such that U_t^* is a diagonal matrix composed of the square root of the diagonal elements of U_t. Under suitable conditions, the elements of R_t have the form $\rho^*_{xz,t} = \frac{u_{xz,t}}{\sqrt{u_{xx,t} u_{zz,t}}}$, with $x, z = 1, 2, ..., S$. In our

[14] Multivariate normality for $\widehat{r}_t$ is not strictly required for consistency and asymptotic normality of these estimators. If returns have non-normal innovations, the DCC estimator is a quasi-maximum likelihood estimator and is still consistent.

[15] GARCH restrictions for the non-negativity of the conditional variances and for their non-unit root behavior are imposed.

application, $\widehat{\theta} = 0$ and $\widehat{r}_t = \widehat{\epsilon}_t$. It follows that $U_t = \left(1 - \sum_{j=1}^{J} \gamma_j - \sum_{k=1}^{K} \delta_k\right) \overline{U} + \sum_{j=1}^{J} \gamma_j (\widehat{r}^*_{t-j} \widehat{r}^{*\prime}_{t-j}) + \sum_{k=1}^{K} \delta_k U_{t-k}$, where $\widehat{r}^*_t$ is standardized $\widehat{r}_t$. In other words, in this context, the conditional dynamic correlations that we estimate by this procedure are equivalent to unconditional dynamic correlations. Note that R_t can also be constant and equal to R. In such a case, the DCC(J,K) MV-GARCH(P,Q) model becomes a constant conditional correlation (CCC) MV-GARCH(P,Q) model (Bollerslev, 1990).[16]

3.3 Empirical Results (1)

The rolling correlations, based on 30-day windows, between price returns for all pairs of cryptocurrencies in the sample are plotted in Figures 2, 3, and 4. In each panel, the solid thin lines represent the estimated rolling correlations; the dashed lines represent the upper and lower bounds of the corresponding 95% confidence bands; the solid bold lines are correlation trends derived from the application of a standard Hodrick-Prescott filter. The estimated correlations based on 60-day rolling windows are similar to the correlations based on 30-day rolling windows for all pairs of cryptocurrencies.[17]

The eight estimated DCC(1,1) MV-GARCH(P,Q) models are reported in Tables 2 and 3. Each model is based on a different set of two to nine cryptocurrency price returns and is estimated on different common samples, from the shortest (when all cryptocurrencies are included) to the longest (when only two cryptocurrencies are included). In all models, a Wald test rejects the null hypothesis that the adjustment parameters γ and δ in the DCC equation are jointly equal to zero at conventional levels. Similarly, likelihood ratio tests suggest that an assumption of time-varying (un)conditional correlations between price returns is more appropriate than an assumption of non-time-varying (un)conditional correlations. These tests empirically justify our preference for DCC over CCC models. Also taken individually, all adjustment parameters are statistically significant. The point estimates of the γ parameter range between 0.036 – in a model based on the full set of cryptocurrencies, but estimated on the shortest common sample – and 0.114 – in a model based on only two cryptocurrencies (Bitcoin and Litecoin), but estimated on the longest common sample. As matter of fact, such point estimates monotonically increase, as S decreases. In a specular manner, the point estimates of the δ parameter range between 0.877 – in the model based on only Bitcoin and Litecoin – and 0.961 – when we include the full set of cryptocurrencies in the sample and proceed with estimation on a short sample. These point estimates monotonically decrease, as S decreases. In all cases, the time series of dynamic correlations are estimated to be very autocorrelated, even though they do not appear to be integrated nor to exhibit unit-root behavior.

The estimated dynamic (un)conditional correlations are plotted in Figures 5, 6, and 7. Each panel

[16] Without loss of generality and to ensure convergence of the implemented algorithm(s), J and K are set equal to 1.

[17] The empirical outcomes based on 60-day rolling windows are reported in Figures OA1, OA2, and OA3 (Online Appendix).

is based on one of the eight DCC(1,1) MV-GARCH(P,Q) models that we consider. For each specific pair of cryptocurrencies, we report the dynamic correlations derived from the model that we estimate on the longest available common sample of data. The solid thin lines represent the estimated dynamic correlations; the solid bold lines are correlation trends extracted from the application of a standard Hodrick-Prescott filter. The horizontal dashed lines represent the constant correlations estimated in each case from a CCC MV-GARCH(P,Q) model. The remaining two dashed lines represent the upper and lower bounds of the corresponding 95% confidence bands. Very informally, the fact that all estimated dynamic (un)conditional correlations move outside the confidence bands at some point over the sample is additional statistical evidence against the adoption of CCC models and against the assumption of constant (un)conditional correlations. In all cases, the dynamic correlations that we derive from this multivariate modelling approach appear to be qualitatively identical to the rolling correlations that we estimate in the previously described bivariate setting.

Correlations are almost always positive. Between 2013 and 2016, when we are able to compute them, they are moderate or low and often close to zero. They are negative occasionally, notably between Ethereum and Litecoin and between Ethereum and Bitcoin in the first half of 2016, and between Bitcoin Cash and Cardano from the end of 2017 to the beginning of 2018. These findings are unsurprising, given that cryptocurrencies are, in general, independently created and are based on slightly different platforms, technologies, and protocols. Thus, they exhibit different features, characteristics, and limitations. Moreover, to an extent, they compete against each other for market share. An evident exception is the correlations between Bitcoin and Litecoin price returns, which, on average, stay high and positive over the entire period, between 2013 and the end of 2018. As a matter of fact, the Litecoin network was launched in October 2011 as a fork of the Bitcoin Core client − i.e., the free and open-source software that serves as a Bitcoin node (the set of which forms the Bitcoin network).[18] Another exception is, perhaps, the correlations between Ripple and Stellar price returns, consistently positive and often strong throughout the sample.[19] Virtually all correlations drastically go up between the beginning of 2017 and the end of 2018, when they remain positive, even though, in most cases, noticeably flex downwards. This evidence corroborates the view that, until the end of 2016, most virtual currencies in the sample were diversifiers of each other. Some of them could even be seen as weak hedges. However, given the sharp comovement increases in the last two years of data, these conclusions do not seem to hold at the end of 2018.

The dynamic (un)conditional variances from the eight DCC(1,1) MV-GARCH(P,Q) models are plotted in Figure 8. For each cryptocurrency, we report the dynamic variances from the model that we

[18]The Bitcoin Core client provides a wallet that verifies payments. It is considered to be Bitcoin's reference implementation.
[19]Stellar shares similarities with Ripple and was founded by one of Ripple's co-founders.

estimate on the longest common sample. All cryptocurrency price returns exhibit time-varying volatility, several periods of high variance, and pronounced volatility clustering. In almost all cases, the evolution of the estimated variances follows a typical shape. At the beginning of their respective samples, when or close to when these virtual currencies are introduced, high levels of variance prevail. Such levels may reflect the presence of significant uncertainty during the early stages of development of these cryptocurrencies, possibly related to whether they will be recognized and accepted by the market. Variances later decline to lower levels, as cryptocurrencies consolidate their positions. Volatilities experience a general increase in 2017, with expanding media coverage, the introduction of what will soon become major currencies (Bitcoin Cash and EOS in July; Cardano in October), and the launch of Bitcoin futures contracts in December. At this time, concerns about extended regulation measures for cryptocurrencies mount and spread world-wide. The second half of 2017 records the closing of online crypto exchanges in China. An exception to the aforementioned patterns is Ethereum: the dynamic (un)conditional variance of its price returns, albeit with some inevitable variations, evolves in a more or less stable fashion over the sample.

4 Detecting Instability in Cryptocurrency Markets

Failing to recognize unstable dynamics in cryptocurrency markets, as in any other markets, may have serious implications on investments and economic policies. Identifying bubbles, turmoil, and/or periods of distress, especially in real time, is not easy. Recently, several tests for the empirical detection of bubbles in price data have been developed. Some of these tests are based on a combination of econometric techniques and theoretical arguments derived from asset pricing theory. The main idea behind some of these statistical tools is that, if a bubble develops at some point in time in a given market, *relative* prices should exhibit, at least locally and temporarily, an explosive dynamic behavior.

Empirical strategies for bubble detection are found in Phillips and Yu (2011) and Phillips et al. (2015), who show how to formally date-stamp bubbles in asset price data, and have been applied widely in many contexts over the last few years.[20] They propose a rolling right-tail variation of the Augmented Dickey-Fuller (ADF) unit root test in which, under the null hypothesis, the time series of interest has a unit root and, under the alternative, the time series has, at least locally, a root larger than one – i.e., that time series is representable as a mildly explosive stochastic process. Phillips et al. (2015) maintain that, if the null is rejected, a version of their procedure based on recursive and flexible windows can be used, under general regularity conditions, as a date-stamping strategy able to consistently estimate the origination

[20]See, for example, Contessi et al. (2020) for an application on U.S. fixed income markets; Chen and Xie (2017) for an empirical exercise on dividend yields from European and Pacific Rim countries; and Chen and Wu (2018) for a study on government debts.

and termination of multiple bubbles in long time series. Through simulations, they demonstrate that their strategy outperforms Phillips and Yu (2011)'s approach.

Even if cryptocurrencies lack clear measures of fundamental values, they are often associated with speculative bubbles. However, the difficulty itself of measuring their fundamental value is, in practice, one of the main practical problems, when it comes to the detection of bubbles in these markets.[21] It follows that tests for speculative bubbles in crypto markets inevitably have to rely upon strong assumptions about the dynamics of the unobserved fundamentals. More broadly, though, and depending on the specific context, Phillips et al. (2015)'s empirical strategy can be useful to identify episodes of distress, exuberance, and collapse; as well as structural breaks, periods of regime change, or incidents of panic, correction, and turmoil. In this paper, we show that the periods of mildly explosive behavior that we detect in the six cryptocurrency NVT ratios in the sample, especially when such ratios exhibit an upward sloping trajectory, often corresponds to well-known episodes of turmoil in cryptocurrency markets. We argue that such episodes can be viewed as financial distress or panic, sometimes maybe even bubbles.

4.1 Testing for Mildly Explosive Behavior

The formal statistical test for the detection of mild explosiveness is based on a reduced-form equation, $y_t = \mu + \delta y_{t-1} + \sum_{i=1}^{p} \phi_i \Delta y_{t-i} + \varepsilon_t$, where y_t is the time series of interest. In this work, y_t is the moving average of a cryptocurrency NVT ratio over rolling windows of 30 or 60 days. μ is an intercept, p is the maximum number of lags that we want to allow (30, if the moving average is based on a 30-day rolling window; 60, if it is based on a 60-day rolling window), and ε_t is a conventional error term. The testing strategy is a right-tail variation of the standard ADF unit root test. As in Phillips et al. (2015), the null and alternative hypotheses are, respectively, $H_0 : \delta = 1$ and $H_1 : \delta > 1$. The original sample interval of T observations is rescaled to the compact interval $[0, 1]$. The δ coefficient, estimated by ordinary least squares over the (rescaled) sample $[r_1, r_2] \subseteq [0, 1]$, and its corresponding ADF test statistic are denoted by δ_{r_1,r_2} and ADF_{r_1,r_2}, respectively. The (fractional) window size of the regression is defined as $r_w = r_2 - r_1$. The Generalized Supremum ADF ($GSADF$) test is derived from a recursive procedure in which the ADF test statistic is calculated over (overlapping) rolling windows of increasing sizes and moving starting points (i.e., over a forward rolling and expanding sample). Each iteration of this recursive approach produces an estimated equation over a different (rescaled) sample and an associated ADF test statistic. The $GSADF$ test statistic is computed as *supremum* ADF_{r_1,r_2}, over all possible windows,

[21] The model presented and the empirical analysis conducted by Cheah and Fry (2015) for the early years of Bitcoin, until 2014, suggest that the fundamental value of Bitcoin is zero.

$GSADF\left(r_0\right) = \sup\limits_{\substack{r_2 \in [r_0,1] \\ r_1 \in [0, r_2 - r_0]}} \left\{ADF_{r_1,r_2}\right\}$, where r_0 is the smallest sample window width fraction (we set it to 10%) and 1 is the largest window width fraction (corresponding to the full sample size) in the recursion.

The critical values are simulated. First, we generate a random sample of T observations from a null model. As in Phillips et al. (2015), it is a random walk with an asymptotically negligible drift, $y_t = dT^{-\eta} + \theta y_{t-1} + e_t$, $e_t \sim N\left(0, \sigma^2\right)$, $\theta = d = \eta = 1$, where η is a localizing coefficient that controls the magnitude of the drift as $T \longrightarrow \infty$ and e_t is a normal error term. Second, we recursively estimate the initial reduced-form equation by least squares over the sample generated by the null model using the aforementioned recursive mechanism, and store the resulting $GSADF$ test statistic. Third, we repeat first and second steps 1000 times. The p-value for the computed test statistic is $p\left(\widehat{\tau}\right) = \frac{1}{1000}\sum_{j=1}^{1000} I\left(\tau_j > \widehat{\tau}\right)$, where $\widehat{\tau}$ is the sample $GSADF$ statistic, $I\left(\cdot\right)$ is an indicator function such that $I\left(\tau_j > \widehat{\tau}\right) = 1$ if $\tau_j > \widehat{\tau}$ and $I\left(\tau_j > \widehat{\tau}\right) = 0$ if $\tau_j \leqslant \widehat{\tau}$, and $\left\{\tau_j\right\}_{j=1}^{1,000}$ is the sequence of simulated $GSADF$ statistics.

4.2 Date-Stamping Periods of Mildly Explosive Behavior

Under general regularity conditions, if the null hypothesis of the test is rejected, we can consistently estimate origination and termination of periods of mild explosiveness by means of a recursive ADF test based on backward expanding samples and on an algorithm that works specularly to the one that we outlined in the previous subsection. The end point of each sample, r_2, now moves backwards, whereas the start point is allowed to vary from 0 to $r_2 - r_0$. For each r_2, we obtain a sequence of ADF test statistics, $\left\{ADF_{r_1,r_2}\right\}_{r_1 \in [0, r_2 - r_0]}$. The Backward Supremum ADF test statistic is the supremum of the ADF test statistic sequence over this interval, $BSADF_{r_2}\left(r_0\right) = \sup\limits_{r_1 \in [0, r_2 - r_0]} \left\{ADF_{r_1,r_2}\right\}$.

An estimate of the beginning $\left(\widehat{r}_e\right)$ of a period of mild explosiveness (as fraction of the full sample) is given by $\widehat{r}_e = \inf\limits_{r_2 \in [0,1]} \left\{r_2 : BSADF_{r_2}\left(r_0\right) > cv_{r_2}^{\beta_T}\right\}$, where $cv_{r_2}^{\beta_T}$ is the $100\left(1 - \beta_T\right)\%$ critical value of the $BSADF$ test statistic based on Tr_2 observations and β_T is a real number between 0 and 1 that indicates the level of significance of the test, in this paper set to a conventional 10%. An estimate of the termination $\left(\widehat{r}_f\right)$ of a period of mild explosiveness is determined as $\widehat{r}_f = \inf\limits_{r_2 \in [\widehat{r}_e, 1]} \left\{r_2 : BSADF_{r_2}\left(r_0\right) < cv_{r_2}^{\beta_T}\right\}$. The origination (termination) date is the observation in correspondence to which the $BSADF$ statistic exceeds (falls below) the critical value of the $BSADF$ statistic. $GSADF$ test and $BSADF$ test statistics are related to each other as $GSADF\left(r_0\right) = \sup\limits_{r_2 \in [r_0, 1]} \left\{BSADF_{r_2}\left(r_0\right)\right\}$.

4.3 Empirical Results (2)

Table 4 shows the outcome of the battery of $GSADF$ tests that we run on the 30-day and 60-day moving averages of the NVT ratios in the sample. It includes information about the cryptocurrency-specific periods over which we are able to derive such variables. These tests signal the presence of mild explosiveness in all six cryptocurrencies that we consider, namely Bitcoin, Ethereum, Bitcoin Cash, Stellar, Litecoin, and Cardano. The periods of mildly explosive behavior that we estimate are graphically represented in Figures 9 and 10 as grey overlays on each NVT ratio time series. We also plot the sequences of $BSADF$ test statistics and the corresponding simulated critical values, which are needed to date-stamp the occurrence of mild explosiveness. In Table 5, we spell out all date-stamped periods, their lengths (in days), and whether they are associated with generally rising or declining NVT ratios.

When a cryptocurrency price rallies upwards significantly, whether a bubble is occurring or not depends on whether transaction activity follows suit and supports the new valuation. If it does, then the NVT ratio stays low, which is evidence against the presence of a bubble. However, if the transaction volume fails to support the higher valuation implied by the new price level and, instead, falls away after the rally, the NVT ratio will explode, at least temporarily. This dynamic behavior would signal the presence of a bubble. One could then expect a market crash in the near future, because of the currently unsustainable price level. A specular argument applies when the price level declines and transaction activity does not follow suit. An overall (possibly explosive) drop in the NVT ratio will then occur, which would suggest the presence of an ongoing correction. The expectation, in this case, would be that of a new rally in the near future. All six cryptocurrencies exhibit multiple periods of mild explosiveness in their NVT ratios. In the next few paragraphs, we briefly provide an overview of these episodes.

Ethereum. This cryptocurrency is not affected much by distress. Over a sample of a little more than three years, only one period of instability is detected in the 30-day moving-average time series of its NVT ratio, between October and November 2017. Such period covers 3.30% of the observations in the sample over which the statistical procedure that we describe in Sections 4.1 and 4.2 is able to produce results (henceforth: *the relevant sample observations*). In this instance, Ethereum's mild explosiveness is associated with a rising NVT ratio. The NVT ratio increase is so moderate that the presence of actual financial turmoil in this virtual currency is debatable. However, the simultaneous acceleration in the way the price of Ethereum moves up seems to suggest ongoing distress (maybe a bubble), even though the transaction activity concerning this currency appears, all in all, to follow suit, at least to an extent.

Three periods of instability are, instead, detected in the 60-day moving-average time series of the NVT ratio. These three spells correspond to 14.98% of the relevant sample observations. During the first two periods, which are different from the spell of instability identified in the 30-day moving average of its NVT ratio, Ethereum experiences a correction with unstable dynamics in its (falling) NVT ratio between February and April 2016, and then again between August and September of the same year.

Overall stable prices during these months indicate that the NVT ratio correction is likely driven by an increasing transaction activity. The August-September 2016 spell comes shortly after an attacker exploits Ethereum's Decentralised Anonymous Organisation (DAO, a board of directors with anonymous participants) and steals an amount of currency equal to US$50M. The Ethereum Foundation comes forward to reverse the attack and a soft fork is first implemented, unfortunately with no success. A hard fork is later performed and the lost funds are recovered.

Maybe, the relative absence of instability in Ethereum shows that this currency could be a long-term player, capable (at least in principle) of challenging Bitcoin in its role of most dominant cryptocurrency. Bitcoin is initially created as a potential alternative to fiat currencies, but Ethereum actually provides the technological infrastructure for many tokens. As such, the theoretical utility of Ethereum could be greater than that of Bitcoin. In fact, Ethereum, which is released only in the second half of 2015, becomes the number two cryptocurrency in the market relatively quickly.

Bitcoin. Statistical instability is much more common in the remaining five cryptocurrencies. Over a time span of almost five and a half years, Bitcoin is characterized by several long periods of turmoil. The two moving-average time series of Bitcoin's NVT ratio exhibit mild explosiveness five times each. In the 30-day moving average, 44.03% of the relevant sample observations corresponds to periods of instability; the corresponding proportion in the 60-day moving average is 34.04%. In both cases, three occurrences of instability are associated with a rising NVT ratio. A mildly explosive correction in the $30-$day moving average of Bitcoin's NVT ratio develops between February and March 2014. A significant long-lasting period of distress accompanied by an increasing NVT ratio occurs between April and October 2014. These two phases follow the first major cryptocurrency exchange hack. In February 2014, Mt.Gox, which becomes the largest cryptocurrency exchange in 2013, at its peak handling 70% of all Bitcoin transactions, has 850000 BTC stolen from it. As of today, it represents the largest theft of BTC in Bitcoin history (current date value would be above US$3B). After the theft, the BTC price plummets by 50% and does not recover to its initial price till late 2016.[22]

2017 is a busy year for Bitcoin. It reaches the US$1000 mark, keeps ascending and, by June, is worth over US$3000. A rising number of miners means higher fees and more time spent processing transactions. Some demand an increase in block size and, in August, Bitcoin Cash is created via a fork in the network. For the remainder of 2017, Bitcoin is on an upswing. By October, it tops US$6000. By the end of November 2017, it is at nearly US$10000. At the end of December, it hits a peak of US$19783.

Another spell of turmoil goes hand in hand with a generally rising NVT ratio during a period of almost

[22] Cryptocurrency exchange hacks have remained ever-present since, though rarely of Mt.Gox's size.

nine months between March and the end of November 2018. 2018 is a rough year for Bitcoin investors, especially those who assume that its price will keep increasing. Many sell their coins while they can, as the price steadily drops until the end of the year.

Bitcoin Cash. The analysis of the 30-day moving average of its NVT ratio shows that distress is experienced seven times in just about fifteen months (54.17% of the relevant sample observations). Unstable dynamics are found five times in the 60-day moving-average time series (65.26% of the relevant sample observations). Shortly after its launch in August 2017, between October and December 2017, Bitcoin Cash's already declining NVT ratio is affected by mild explosiveness. The almost contemporaneous increase in the price of this cryptocurrency suggests the presence of a proportionally larger increase in the level of its transaction activity, possibly due to a growth in the popularity of this currency in the months following its inception. Two lengthy spells of distress associated with a rising NVT ratio (and rapidly declining prices, a price correction) are seen between January and April 2018 and then between July (perhaps even June) and September 2018. September, October, and November 2018 are characterized by a mildly explosive collapse of Bitcoin Cash's NVT ratio, associated with a steadily falling price level.

Stellar. In less than three years, five periods of turmoil are detected in the 30-day moving average of its NVT ratio (27.47% of the relevant sample observations); the 60-day moving-average becomes mildly explosive six times (42.57% of the relevant sample observations). These episodes are generally characterized by an increasing NVT ratio. Some turbulence is found in mid-2016, when a mildly explosive increase in the NVT ratio is associated with a basically stable price level. Unstable dynamics with increasing NVT ratios are also identified between June and November 2017; this time, they accompany the probable formation of a bubble, as Stellar's price goes up steeply between October 2017 and the end of the same year. Between March and September 2018, Stellar exhibits spells of instability, a rising NVT ratio, and a slowly falling price level.

Litecoin. The 30-day and 60-day moving averages of this currency's NVT ratio exhibit unstable dynamics four and five times, respectively, over a span of almost five and a half years. These occurrences of instability cover 19.45% and 24.40% of the corresponding relevant sample observations. After almost six months of distress, between October 2014 and April 2015, a generally rising NVT ratio, and stable prices, the most recent spell of turmoil accompanied by an increasing NVT ratio develops between March and November 2018. This spell represents a long episode of correction, characterized by a sharply declining price level, after the peak of early 2018. At the end of the sample, Litecoin's distress does not appear to have come to an end, yet. Additional, and brief, episodes of mildly explosive corrections in Litecoin's NVT ratio are found in mid-2016 and between the end of 2017 and the beginning of 2018. It must be noted that, in May 2017, Litecoin implements some relevant technological improvements in its platform and that Coinbase (the largest Bitcoin exchange) adds support to Litecoin. The combination of these two events likely contributes to the price shoot up that we start observing by the end of 2017.

Cardano. In about thirteen months, five and four spells of distress are found, respectively, in the 30-day and 60-day moving averages of Cardano's NVT ratio. Such spells extend over 52.12% and 72.48% of the relevant sample observations. They are associated with an increasing NVT ratio and falling prices at the beginning of 2018 and, then again, between April and November 2018. In these cases, Cardano is likely experiencing an even larger fall in its transaction activity. An NVT ratio mildly explosive adjustment occurs in March and April 2018, as the price level follows suit in the decline.

Across all six cryptocurrencies, we detect twenty-seven episodes of turmoil in the 30-day moving-average time series of their NVT ratios; eighteen of them are associated with increasing NVT ratios. In the 60-day moving-average time series, we find twenty-eight periods of distress; fourteen of them are associated with rising NVT ratios. Barring Bitcoin's, the 60-day moving averages of the remaining five NVT ratios are characterized by proportionally longer periods of mild explosiveness than their 30-day moving-average counterparts. Overall, the six cryptocurrencies are in a state of instability for significant portions of their samples. This specific finding casts doubts on their usefulness as store of value (as conventional currencies) and may discourage risk-averse investors from looking at them as viable investment options.

For most part of 2018, Bitcoin, Litecoin, and Cardano appear to be in an almost synchronized state of distress accompanied by increasing NVT ratios and rapidly falling prices, probably evidence of a correction in these currencies. During the final months of 2018, Bitcoin Cash experiences some turmoil, too, which is, however, associated with falling NVT ratio and price level, probably a sign of collapsing transaction activity. At the same time, Stellar's NVT ratio stays flat, after the turbulence of mid-2018. The significant and protracted distress that we detect in 2018 in several of these currencies is coincident with the generally rising price return correlations that we document in Section 3.3.

In Table 6, we report summary statistics concerning the price returns of the six cryptocurrencies in this section. We split the individual samples into three subsamples corresponding to three different currency-specific states of the world: (a) instability associated with a generally rising NVT ratio, (b) instability associated with a generally declining NVT ratio, and (c) no instability. In the upper panel, a descriptive investigation is conducted over the subsamples determined from the analysis of the 30-day moving averages of the six NVT ratios. In the lower panel, the same investigation is conducted over the subsamples determined from the analysis of the 60-day moving averages of the same NVT ratios. There are no clear-cut regularities. However, with just two exceptions, both of them regarding Cardano, the assumption of normal returns is rejected in all other cases. At least pointwise, mean returns are usually the greatest when instability is associated with a declining NVT ratio – i.e., state of the world (b) – or when no instability is occurring – i.e., state of the world (c). They are generally the lowest in state of the world (a) – i.e., when mild explosiveness accompanies generally increasing NVT ratios. These returns are, on average, usually negative in state of the world (a), as opposed to states (b) and (c), when, instead, their means are positive in most cases. Volatility is higher in states of the world (b) and (c) than in state (a). Negative skewness (which is not the norm) is more likely to be found in state of the world (a).

An investor with some tolerance for risk would probably hold a portfolio composed of these six virtual currencies during periods of explosively declining NVT ratios. In terms of average returns, a second best would be to hold these currencies when there is no instability in their NVT ratios. These two qualitative conclusions also hold, if one looks at the trade-off between reward and risk embedded in the mean-per-standard-deviation index. Across the six cryptocurrencies that we analyze, the best average performance is found when the virtual currencies experience instability and exhibit a declining NVT ratio. The second best average performance is, again, detected during periods of no statistical instability.

5 Conclusions

In this paper, we conduct a comprehensive empirical examination of the price dynamics of an extended set of nine major cryptocurrencies. We focus on the degree of comovement of price returns and carefully study its time evolution by adopting a bivariate modelling approach and a multivariate one. Moreover, we test cryptocurrency markets for signs of statistical instability using a state-of-the-art testing and date-stamping algorithm. Cryptocurrency markets change quickly and it is, in general, challenging to find long-run regularities. Nonetheless, the evidence that we provide generates two general takeaways.

First, from an investment point of view, most virtual currencies in the sample are diversifiers of each other and some of them may be even seen as weak hedges until the end of 2016. This claim is based on the finding that almost all estimated dynamic correlations between cryptocurrency price returns are either moderately positive or positive and low, often close to zero, from the beginning of the sample through late 2016. The pronounced comovement increases that we document in the last two years of data, between the beginning of 2017 and the end of 2018, suggest that those previous claims should probably be reconsidered, as they do not seem to hold steady over time. Second, consistent with the conventional wisdom, we find most cryptocurrencies to often exhibit pervasive signs of turbulence for significant portions of their samples. Several spells of distress may likely be bubbles. We also determine that, for most part of 2018 and by the end of the same year, Bitcoin, Litecoin, and Cardano appear to be in an almost synchronized and very noticeable state of turmoil, probably a significant market correction.

On the one hand, despite being based on different technologies and protocols, and created with slightly diverse objectives, in the last few years in the sample, several cryptocurrencies have been characterized, to a non-negligible extent, by evidently common price behaviors.[23] The predominance of Bitcoin is suggestive of the fact that the world-wide financial transactions that concern this specific virtual currency might have non-trivial spillover effects on the price evolution of other (even major) cryptocurrencies.[24] Perhaps, investors consider cryptocurrencies as a group rather than individual projects with unique trajectories, and only a few of them make investment decisions based on intensive research. If investors have correlated demands across cryptocurrencies, a common component might drive cryptocurrency prices. Currencies that exhibit similar investor bases might also exhibit strong comovement in their returns. Likely, retail investors tend to be exposed to behavioral biases. It is, however, a fact that investors must first buy Bitcoin or Ethereum before they can exchange these for the desired cryptocurrency. These factors are, maybe, what has been pushing the dominance of Bitcoin over the market, resulting in a "follow the leader" behavior. A formal factor analysis may shed some light on the validity of some of these assertions.

On the other hand, the growing empirical literature on cryptocurrency price dynamics, the casual and informal observation of cryptocurrency behaviors, and the elements and patterns that we document in the present work leave no or little doubt on the existence of frequent occurrences of distress in these markets. Even though some work has already been done on the topic, it is still difficult to claim anything certain about what drives prices in and across cryptocurrency markets; what determines cryptocurrency values; and what factors, if any, represent the common denominator(s) of these seemingly unrelated assets. Yet, our comovement analysis suggests that, in the last couple of years of data in the sample, several major virtual currencies might have been affected by common shocks in a fairly similar fashion.

References

Baek, C. and Elbeck, M. (2015). Bitcoins as an investment or speculative vehicle? A first look. *Applied Economics Letters*, 22(1):30–34.

Bhambhwani, S., Delikouras, S., and Korniotis, G. M. (2019). Do fundamentals drive cryptocurrency prices? *Working Paper*.

Bianchi, D., Guidolin, M., and Pedio, M. (2020). Dissecting time-varying risk exposures in cryptocurrency markets. *Working Paper*.

[23] If supply side factors and technological features are essential drivers of the underlying value of a cryptocurrency, currencies with similar characteristics should exhibit high comovement in price returns.

[24] Using GARCH-in-mean models, Liu and Serletis (2019) find statistically significant evidence of shock transmission among the leading cryptocurrencies and spillover effects from cryptocurrency markets to other financial markets in the United States, as well as in other major economies.

Bollerslev, T. (1990). Modelling the coherence in short-run nominal exchange rates: A multivariate generalized Arch model. *The Review of Economics and Statistics*, 72(3):498–505.

Bolt, W. and Van Oordt, M. R. (2019). On the value of virtual currencies. *Journal of Money, Credit and Banking*, forthcoming.

Borri, N. (2019). Conditional tail-risk in cryptocurrency markets. *Journal of Empirical Finance*, 50:1–19.

Bouri, E., Molnár, P., Azzi, G., Roubaud, D., and Hagfors, L. I. (2017). On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier? *Finance Research Letters*, 20:192–198.

Bouri, E., Shahzad, S. J. H., and Roubaud, D. (2019). Co-explosivity in the cryptocurrency market. *Finance Research Letters*, 29:178–183.

Budish, E. (2018). The economic limits of Bitcoin and the blockchain. *National Bureau of Economic Research Working Paper Series*, 24717.

Cheah, E.-T. and Fry, J. (2015). Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin. *Economics Letters*, 130:32–36.

Chen, S.-W. and Wu, A.-C. (2018). Is there a bubble component in government debt? New international evidence. *International Review of Economics & Finance*, 58:467–486.

Chen, S.-W. and Xie, Z. (2017). Detecting speculative bubbles under considerations of the sign asymmetry and size non-linearity: New international evidence. *International Review of Economics & Finance*, 52:188–209.

Cheng, J. and Dai, Y. (2020). Is Bitcoin a channel of capital inflow? Evidence from carry trade activity. *International Review of Economics & Finance*, 66:261–278.

Contessi, S., De Pace, P., and Guidolin, M. (2020). Mildy explosive dynamics in U.S. fixed income markets. *European Journal of Operational Research*, Forthcoming.

Corbet, S., Lucey, B., and Yarovaya, L. (2018a). Datestamping the Bitcoin and Ethereum bubbles. *Finance Research Letters*, 26:81–88.

Corbet, S., Meegan, A., Larkin, C., Lucey, B., and Yarovaya, L. (2018b). Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics Letters*, 165:28–34.

Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics*, 20(3):339–350.

Engle, R. F. and Sheppard, K. (2001). Theoretical and empirical properties of dynamic conditional correlation multivariate GARCH. *National Bureau of Economic Research Working Paper Series*, 8554.

Fry, J. (2018). Booms, busts and heavy-tails: The story of Bitcoin and cryptocurrency markets? *Economics Letters*, 171:225–229.

Fry, J. and Cheah, E.-T. (2016). Negative bubbles and shocks in cryptocurrency markets. *International Review of Financial Analysis*, 47:343–352.

Gandal, N., Hamrick, J., Moore, T., and Oberman, T. (2018). Price manipulation in the Bitcoin ecosystem. *Journal of Monetary Economics*, 95:86–96.

Gkillas, K. and Katsiampa, P. (2018). An application of extreme value theory to cryptocurrencies. *Economics Letters*, 164:109–111.

Gronwald, M. (2020). How explosive are cryptocurrency prices? *Working Paper*.

Hafner, C. M. (2018). Testing for bubbles in cryptocurrencies with time-varying volatility. *Journal of Financial Econometrics*, pages 1–17. nby023.

Khuntia, S. and Pattanayak, J. (2018). Adaptive market hypothesis and evolving predictability of Bitcoin. *Economics Letters*, 167:26–28.

Koutmos, D. (2018). Bitcoin returns and transaction activity. *Economics Letters*, 167:81–85.

Liu, J. and Serletis, A. (2019). Volatility in the cryptocurrency market. *Open Economies Review*, 30(4):779–811.

Liu, Y. and Tsyvinski, A. (2018). Risks and returns of cryptocurrency. *National Bureau of Economic Research Working Paper Series*, 24877.

Makarov, I. and Schoar, A. (2019). Trading and arbitrage in cryptocurrency markets. *Journal of Financial Economics*, forthcoming.

Nadarajah, S. and Chu, J. (2017). On the inefficiency of Bitcoin. *Economics Letters*, 150:6–9.

Phillip, A., Chan, J. S., and Peiris, S. (2018). A new look at cryptocurrencies. *Economics Letters*, 163:6–9.

Phillips, P. C. B., Shi, S., and Yu, J. (2015). Testing for multiple bubbles: Historical episodes of exuberance and collapse in the S&P 500. *International Economic Review*, 56(4):1043–1078.

Phillips, P. C. B. and Yu, J. (2011). Dating the timeline of financial bubbles during the subprime crisis. *Quantitative Economics*, 2(3):455–491.

Platanakis, E., Sutcliffe, C., and Urquhart, A. (2018). Optimal vs naïve diversification in cryptocurrencies. *Economics Letters*, 171:93–96.

Selmi, R., Mensi, W., Hammoudeh, S., and Bouoiyour, J. (2018). Is bitcoin a hedge, a safe haven or a diversifier for oil price movements? A comparison with gold. *Energy Economics*, 74:787–801.

Tang, K. and Xiong, W. (2012). Index investment and the financialization of commodities. *Financial Analysts Journal*, 68(6):54–74.

Tiwari, A. K., Jana, R., Das, D., and Roubaud, D. (2018). Informational efficiency of Bitcoin — An extension. *Economics Letters*, 163:106–109.

Trimborn, S. and Härdle, W. K. (2018). CRIX an index for cryptocurrencies. *Journal of Empirical Finance*, 49:107–122.

Urquhart, A. (2016). The inefficiency of Bitcoin. *Economics Letters*, 148:80–82.

Urquhart, A. (2017). Price clustering in Bitcoin. *Economics Letters*, 159:145–148.

Yermack, D. (2015). Chapter 2 - Is Bitcoin a real currency? An economic appraisal. *Handbook of Digital Currency*, pages 31–43.

A Figures

Figure 1: Cryptocurrency Daily Prices (in U.S. Dollars)

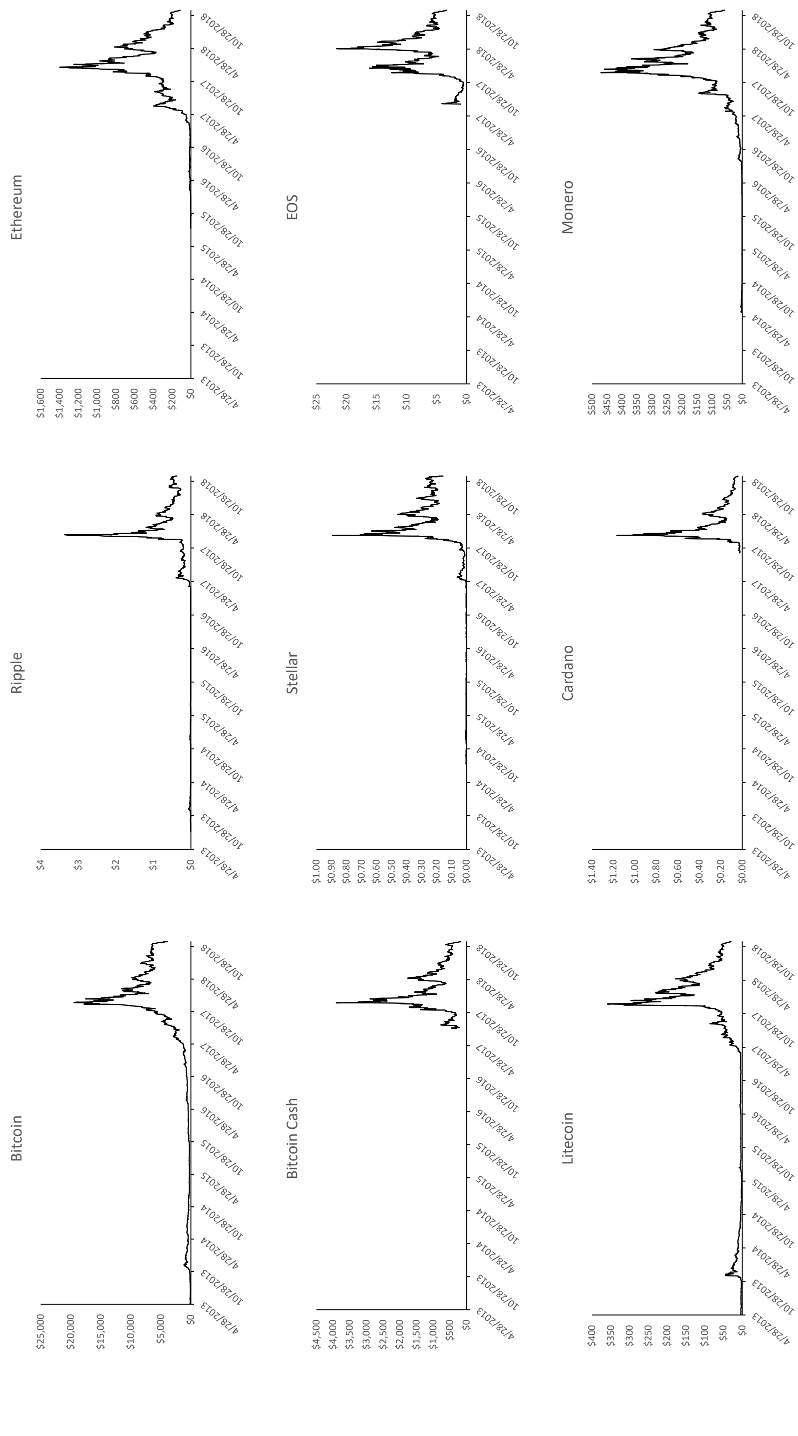
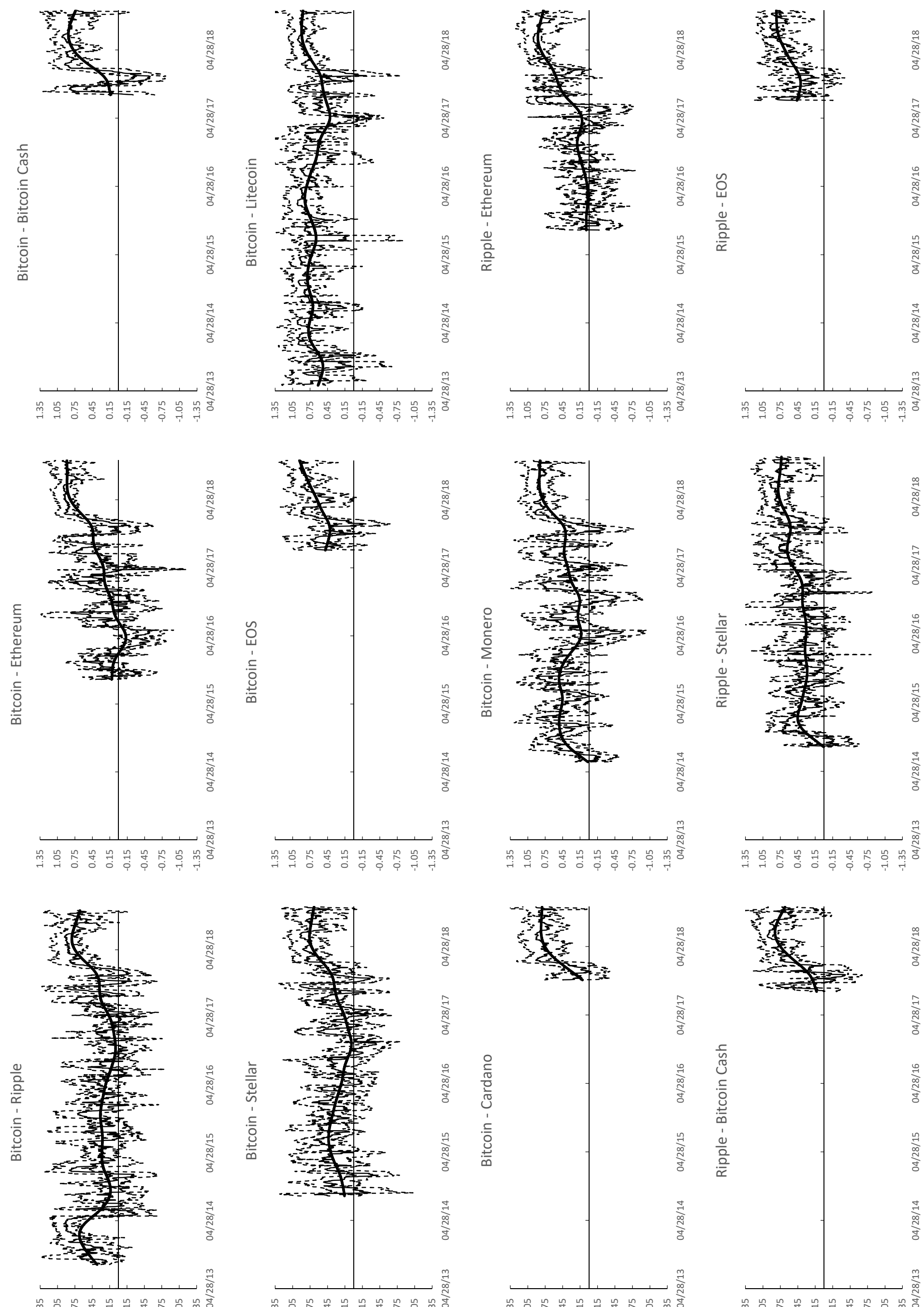
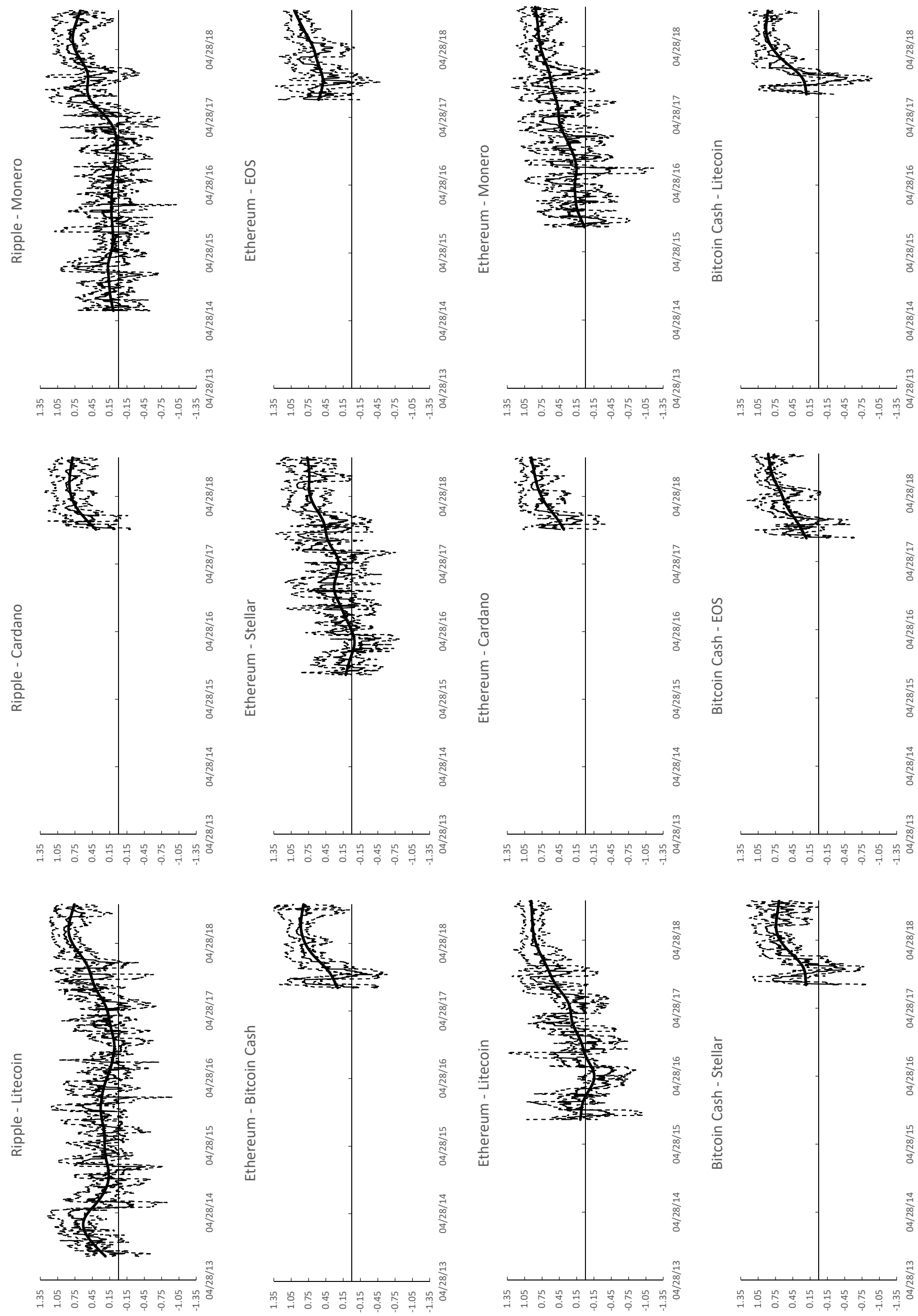


Figure 2: Rolling Correlations (30-Day Rolling Windows) of Cryptocurrency Daily Price Returns (1)



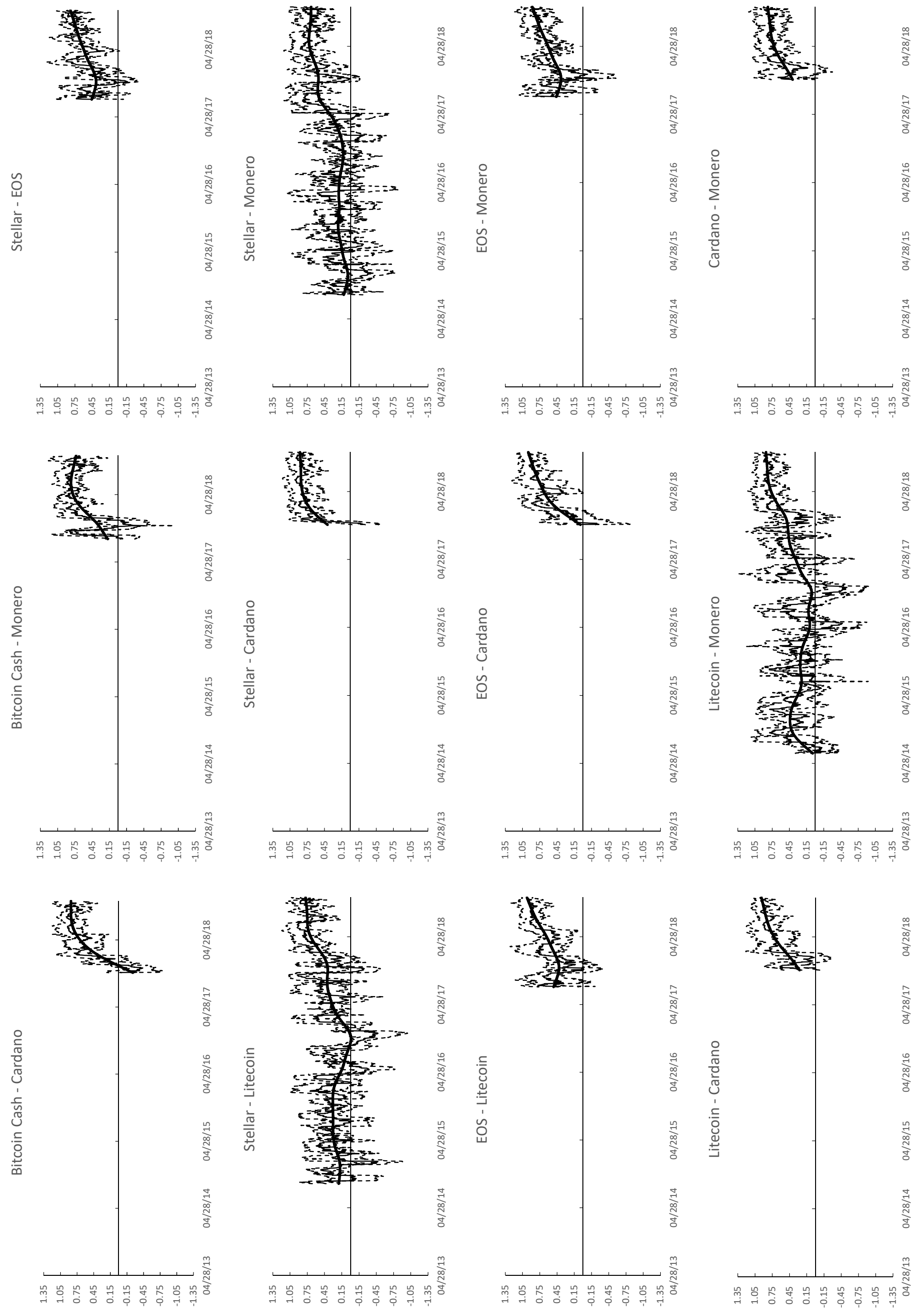
Notes. Rolling correlations derived as described in Tang and Xiong (2012), based on 30-day windows, between the price returns of all pairs of cryptocurrencies in the sample. The solid thin lines represent the estimated rolling correlations; the dashed lines represent the upper and lower bounds of the corresponding 95% confidence bands; the solid bold lines are correlation trends derived from the application of a standard Hodrick-Prescott filter.

Figure 3: Rolling Correlations (30-Day Rolling Windows) of Cryptocurrency Daily Price Returns (2)



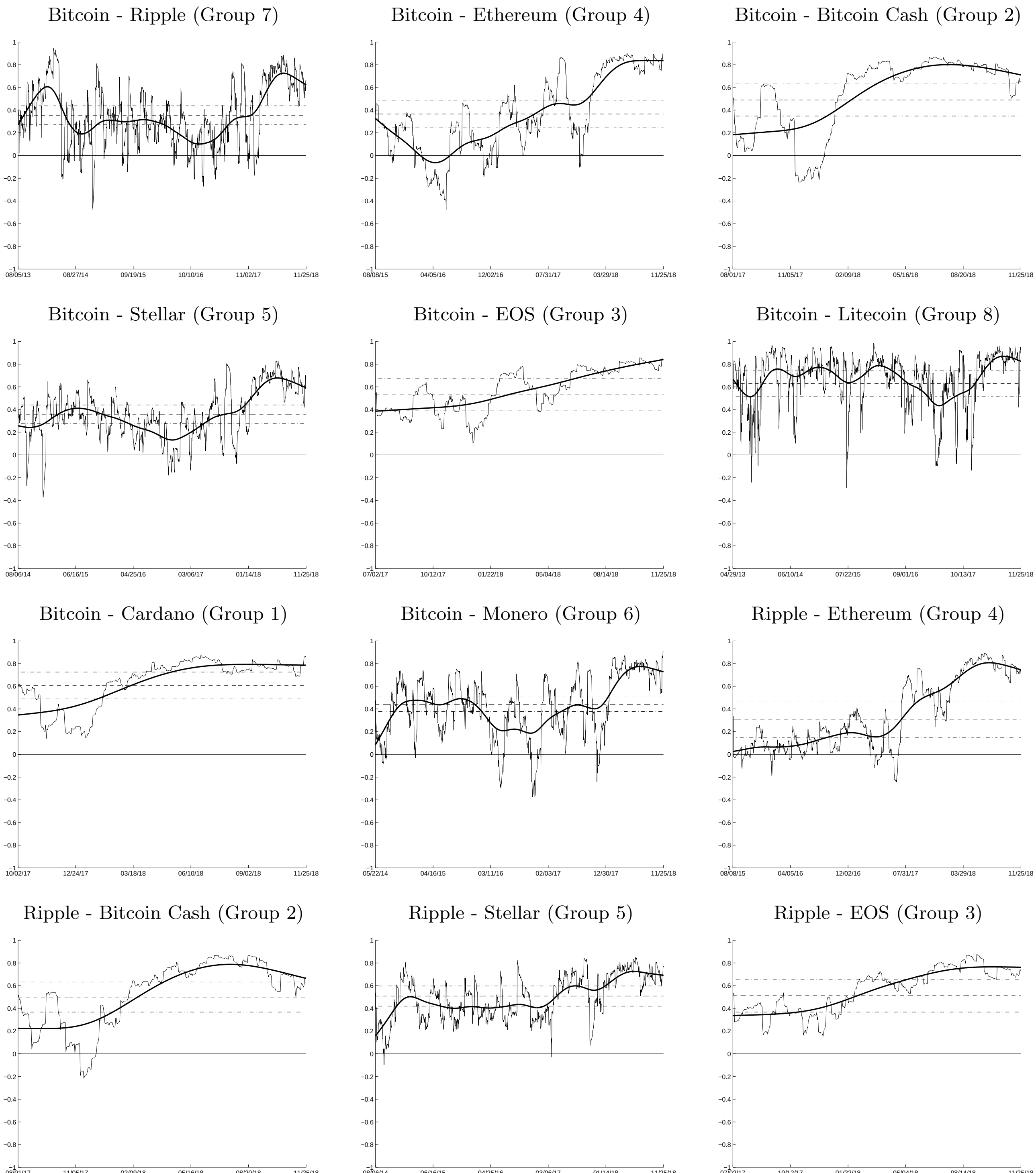
Notes. Rolling correlations derived as described in Tang and Xiong (2012), based on 30-day windows, between the price returns of all pairs of cryptocurrencies in the sample. The solid thin lines represent the estimated rolling correlations; the dashed lines represent the upper and lower bounds of the corresponding 95% confidence bands; the solid bold lines are correlation trends derived from the application of a standard Hodrick-Prescott filter.

Figure 4: Rolling Correlations (30-Day Rolling Windows) of Cryptocurrency Daily Price Returns (3)



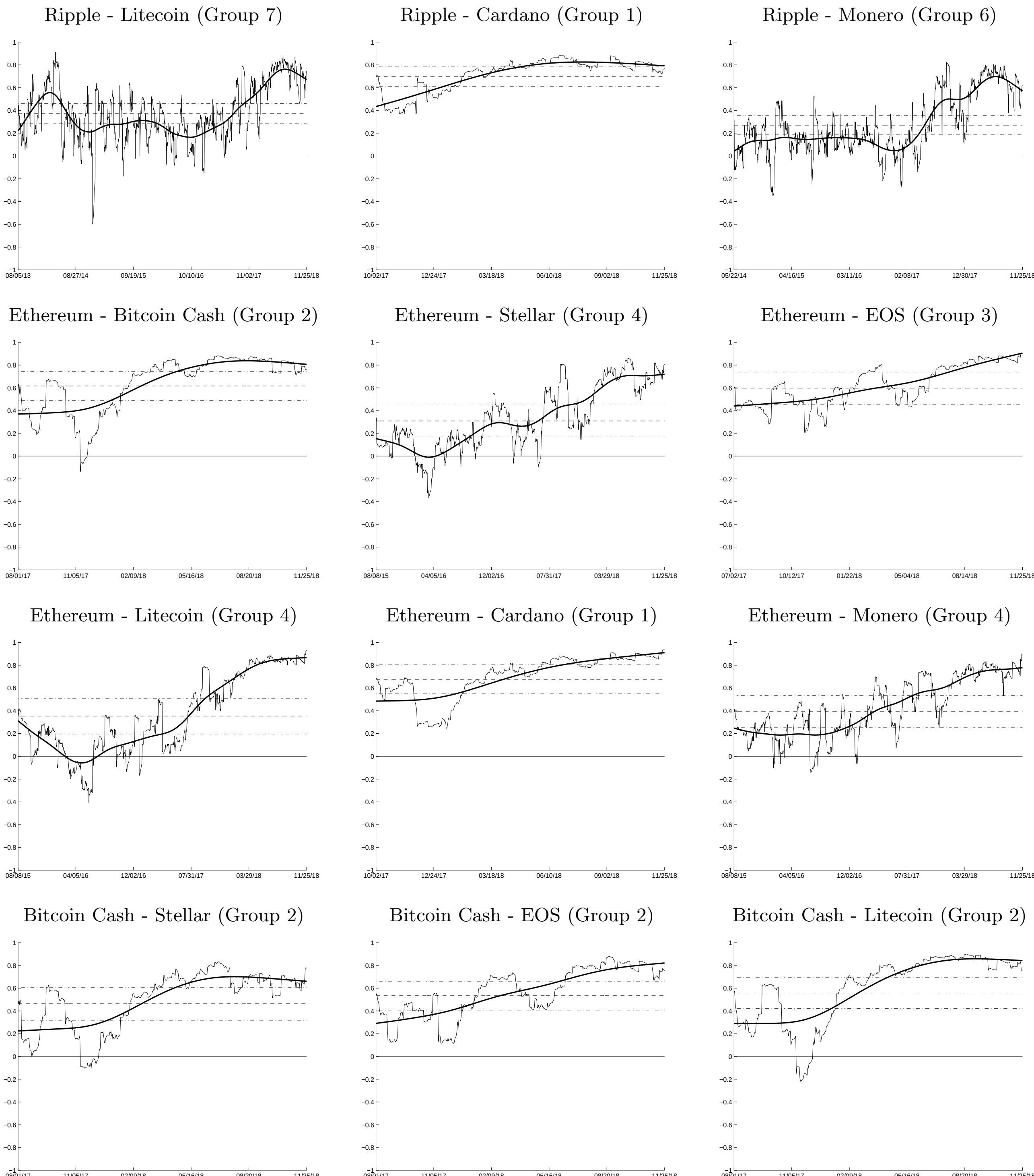
Notes. Rolling correlations derived as described in Tang and Xiong (2012), based on 30-day windows, between the price returns of all pairs of cryptocurrencies in the sample. The solid thin lines represent the estimated rolling correlations; the dashed lines represent the upper and lower bounds of the corresponding 95% confidence bands; the solid bold lines are correlation trends derived from the application of a standard Hodrick-Prescott filter.

Figure 5: Dynamic (Un)Conditional Correlations of Cryptocurrency Daily Price Returns (1)



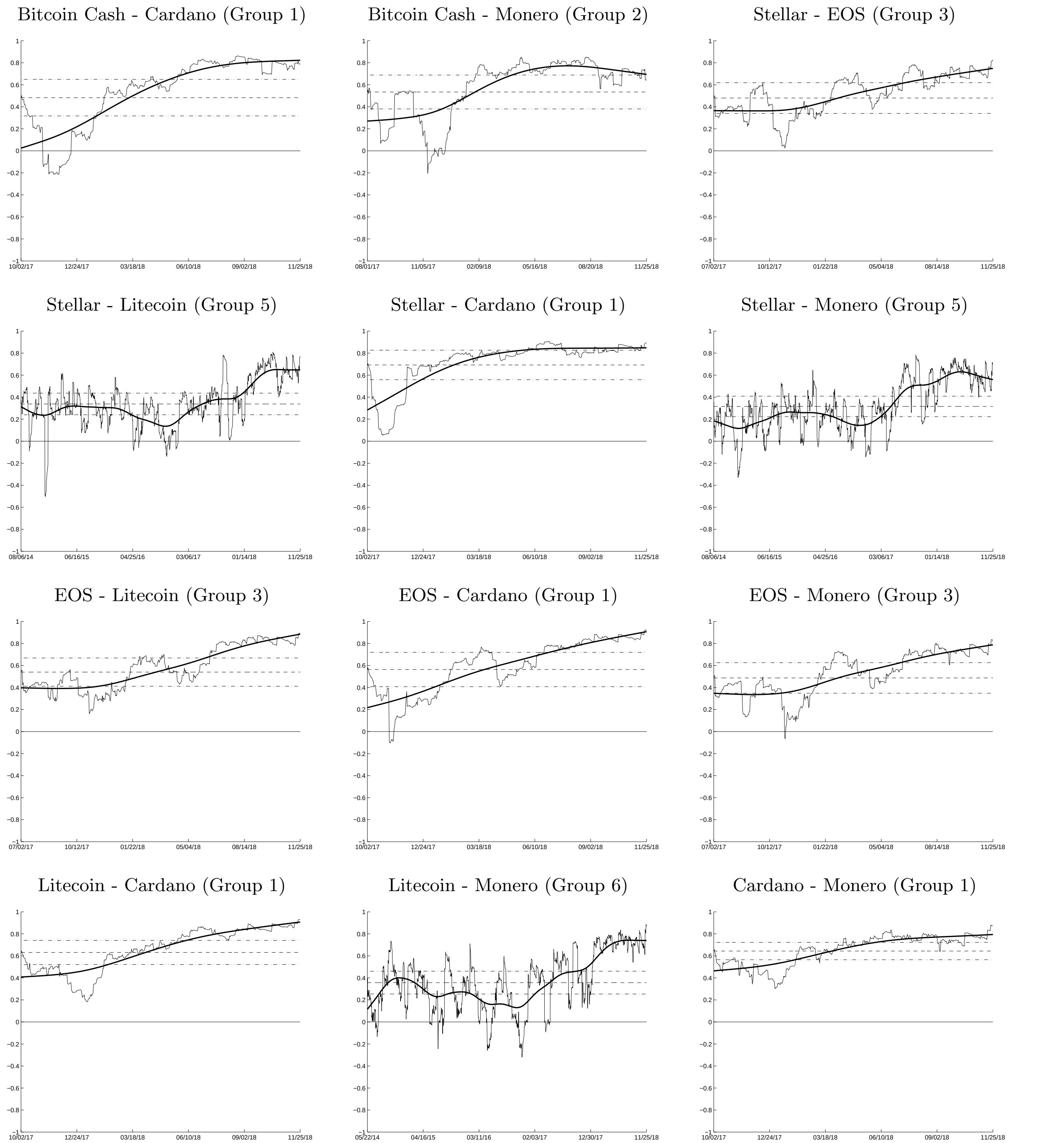
Notes. Dynamic (un)conditional correlations derived as described in Engle and Sheppard (2001) and Engle (2002) for all pairs of cryptocurrency price returns. Each panel is based on one of the eight DCC(1,1) MV-GARCH(P,Q) models that we consider. For each specific pair of cryptocurrencies, we report the dynamic correlations from the model that we estimate on the longest available common sample of data (the estimation group number is indicated for each plot). The solid thin lines represent the estimated dynamic correlations; the solid bold lines are correlation trends derived from the application of a standard Hodrick-Prescott filter; the horizontal dashed lines in the middle represent the constant correlations estimated in each case from a CCC MV-GARCH(P,Q) model; the remaining two dashed line respectively represent the upper and lower bounds of the corresponding 95% confidence bands. The complete set of results is available upon request.

Figure 6: Dynamic (Un)Conditional Correlations of Cryptocurrency Daily Price Returns (2)



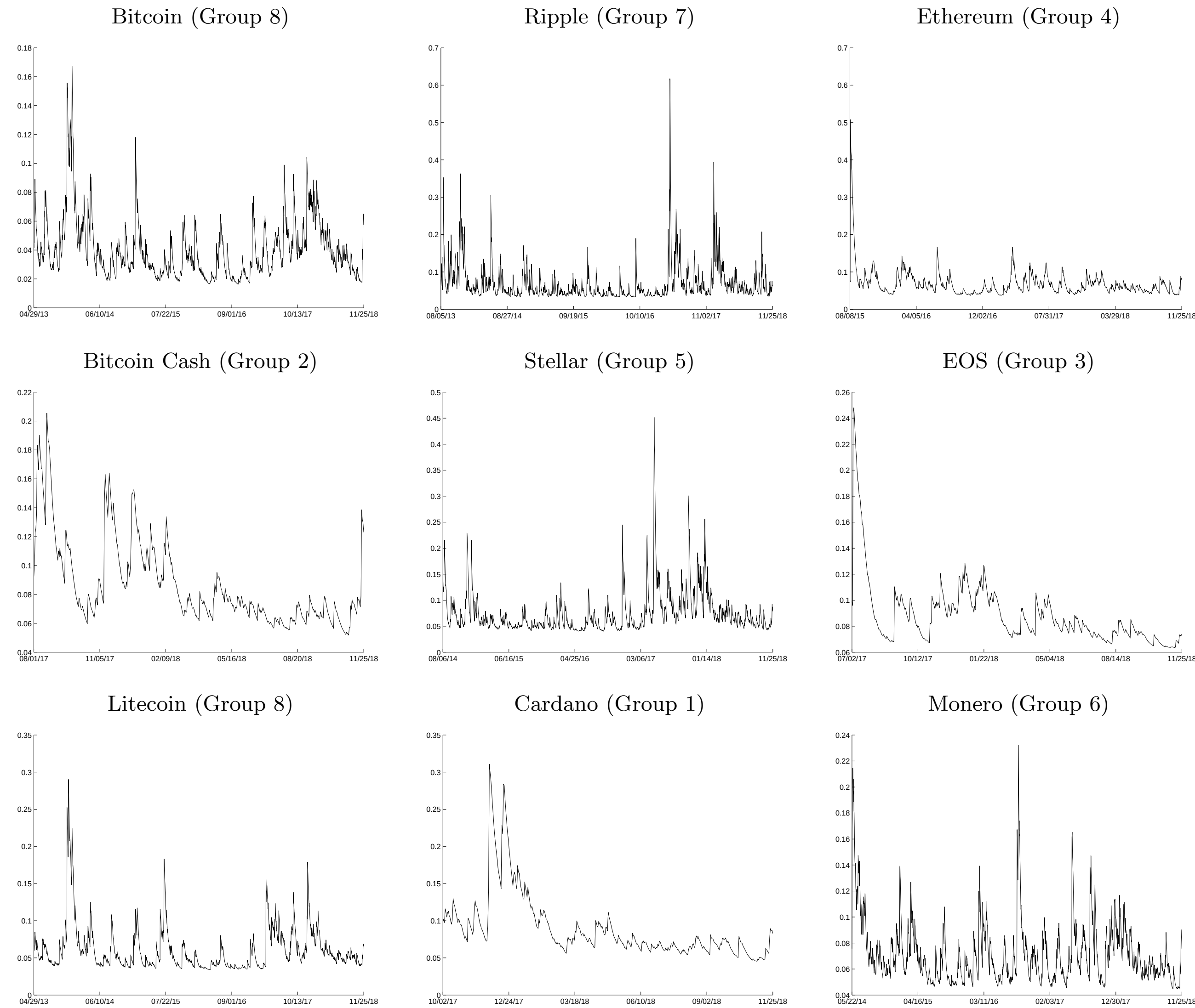
Notes. Dynamic (un)conditional correlations derived as described in Engle and Sheppard (2001) and Engle (2002) for all pairs of cryptocurrency price returns. Each panel is based on one of the eight DCC(1,1) MV-GARCH(P,Q) models that we consider. For each specific pair of cryptocurrencies, we report the dynamic correlations from the model that we estimate on the longest available common sample of data (the estimation group number is indicated for each plot). The solid thin lines represent the estimated dynamic correlations; the solid bold lines are correlation trends derived from the application of a standard Hodrick-Prescott filter; the horizontal dashed lines in the middle represent the constant correlations estimated in each case from a CCC MV-GARCH(P,Q) model; the remaining two dashed line respectively represent the upper and lower bounds of the corresponding 95% confidence bands. The complete set of results is available upon request.

Figure 7: Dynamic (Un)Conditional Correlations of Cryptocurrency Daily Price Returns (3)



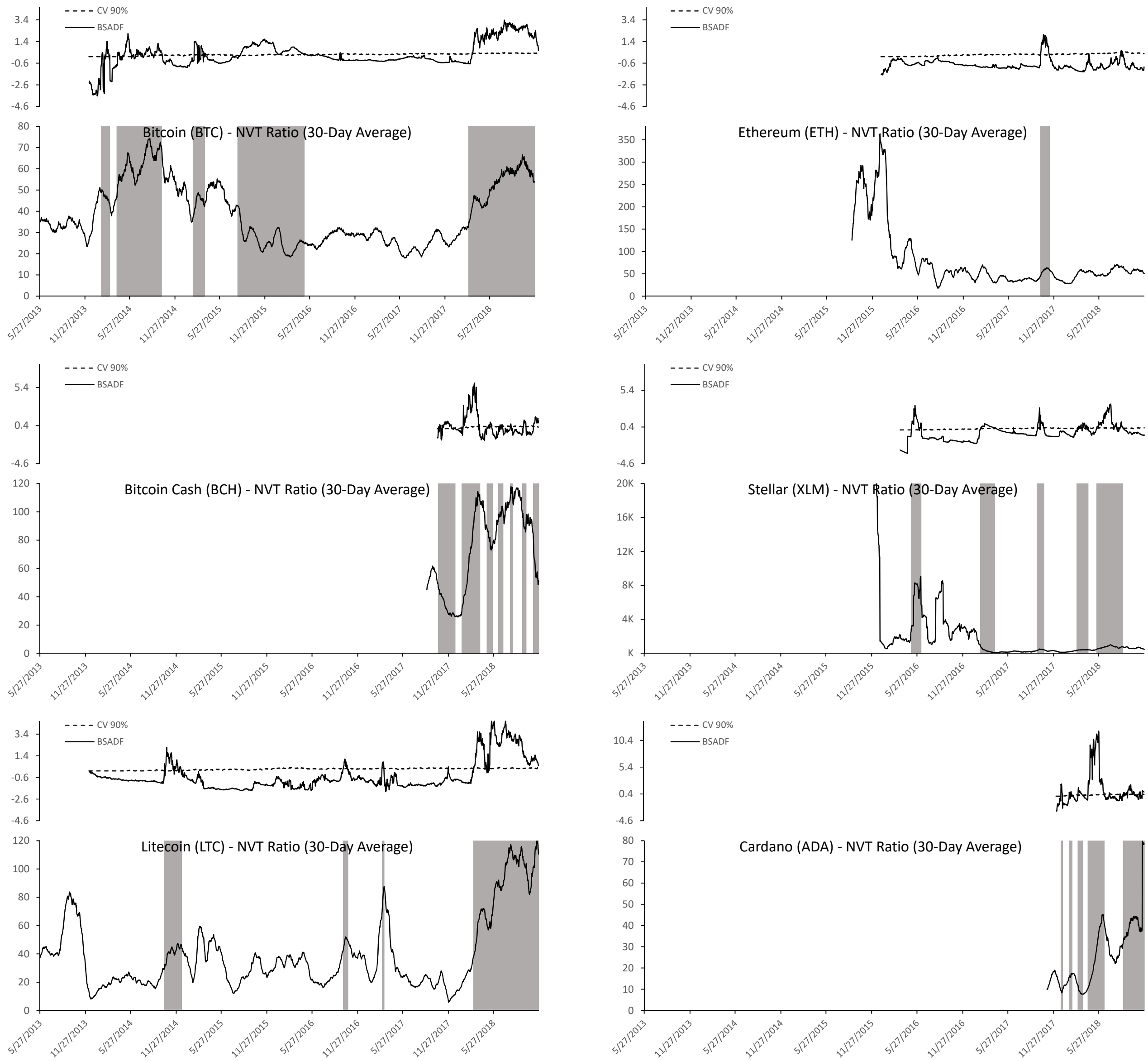
Notes. Dynamic (un)conditional correlations derived as described in Engle and Sheppard (2001) and Engle (2002) for all pairs of cryptocurrency price returns. Each panel is based on one of the eight DCC(1,1) MV-GARCH(P,Q) models that we consider. For each specific pair of cryptocurrencies, we report the dynamic correlations from the model that we estimate on the longest available common sample of data (the estimation group number is indicated for each plot). The solid thin lines represent the estimated dynamic correlations; the solid bold lines are correlation trends derived from the application of a standard Hodrick-Prescott filter; the horizontal dashed lines in the middle represent the constant correlations estimated in each case from a CCC MV-GARCH(P,Q) model; the remaining two dashed line respectively represent the upper and lower bounds of the corresponding 95% confidence bands. The complete set of results is available upon request.

Figure 8: Dynamic (Un)Conditional Variances of Cryptocurrency Daily Price Returns



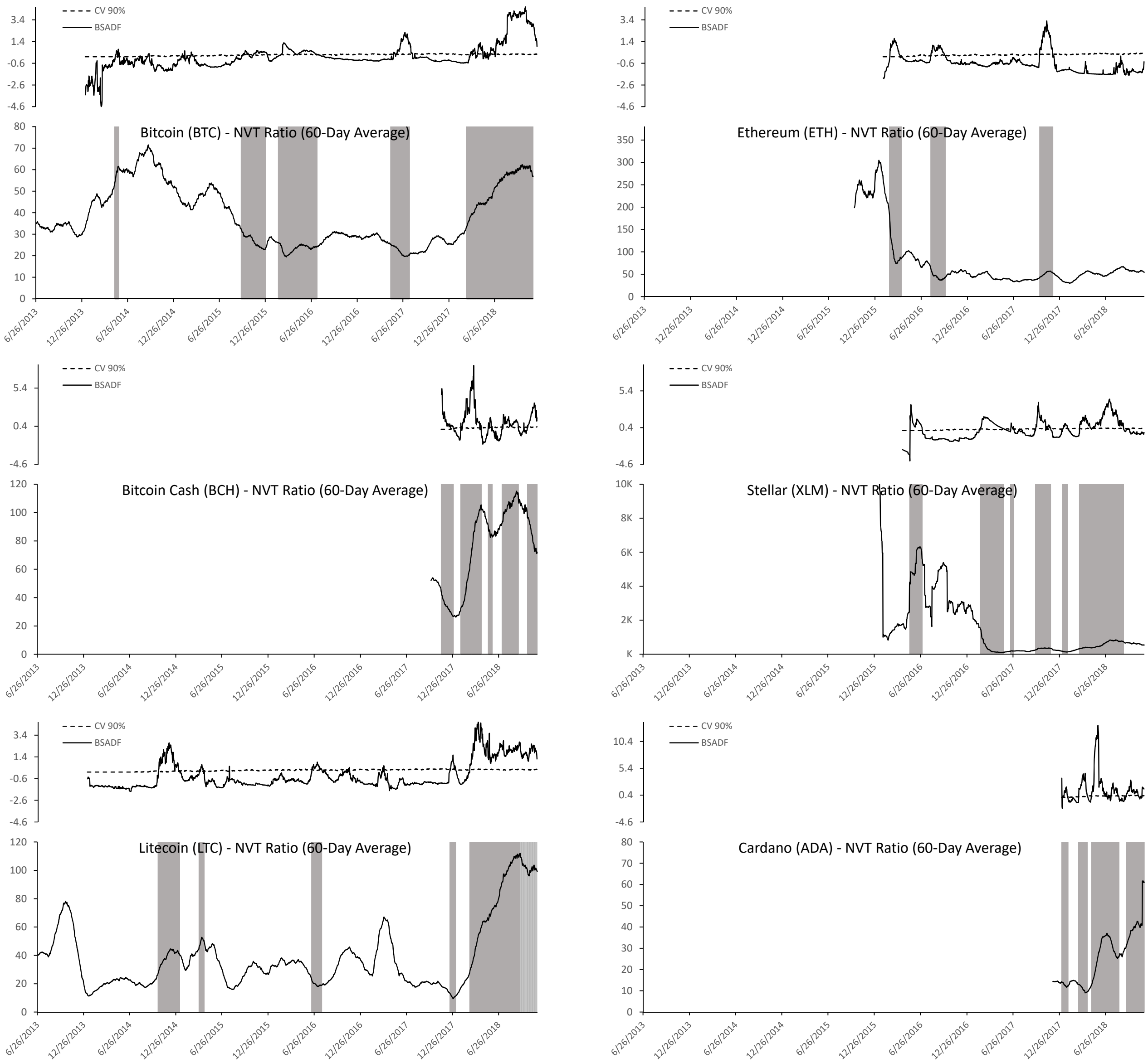
Notes. Dynamic (un)conditional variances derived as described in Engle and Sheppard (2001) and Engle (2002) for all cryptocurrency price returns. Each panel is based on one of the eight DCC(1,1) MV-GARCH(P,Q) models that we consider. For each specific cryptocurrency, we report the dynamic variance from the model that we estimate on the longest available common sample of data (the estimation group number is indicated for each plot). The complete set of results is available upon request.

Figure 9: Mildly Explosive Behavior in Cryptocurrency NVT Ratios (30-Day Average)



Notes. Date-stamping periods of mildly explosive behavior in six major cryptocurrencies. Sequence of $BSADF$ test statistics and corresponding sequence of critical values in the upper panel of each plot. Shaded areas represent periods of mildly explosive behavior in the time series of cryptocurrency NVT ratios (30-day average). Level of the testing procedure: 10%.

Figure 10: Mildly Explosive Behavior in Cryptocurrency NVT Ratios (60-Day Average)



Notes. Date-stamping periods of mildly explosive behavior in six major cryptocurrencies. Sequence of $BSADF$ test statistics and corresponding sequence of critical values in the upper panel of each plot. Shaded areas represent periods of mildly explosive behavior in the time series of cryptocurrency NVT ratios (60-day average). Level of the testing procedure: 10%.

B Tables

Table 1: Summary Statistics of Cryptocurrency Daily Price Returns

	BTC	XRP	ETH	BCH	XLM	EOS	LTC	ADA	XMR
Mean	0.165%	0.214%	0.306%	-0.135%	0.252%	0.226%	0.094%	0.138%	0.192%
Median	0.192%	-0.273%	-0.103%	-0.633%	-0.318%	-0.217%	0.000%	-0.484%	-0.140%
Maximum	36.140%	101.096%	40.346%	42.969%	70.404%	100.412%	82.456%	84.819%	56.767%
Minimum	-26.742%	-60.171%	-137.399%	-44.925%	-33.342%	-38.772%	-51.927%	-23.274%	-44.048%
Range	62.882%	161.267%	177.745%	87.894%	103.746%	139.184%	134.383%	108.093%	100.815%
Std. Dev.	4.384%	7.771%	7.866%	9.245%	8.161%	9.996%	6.739%	9.807%	7.567%
Skewness	-0.139	2.002	-4.126	0.485	1.917	2.304	1.733	2.755	0.584
Kurtosis	11.045	29.307	82.120	8.301	17.287	23.831	28.411	21.372	8.859
Mean per Std. Dev.	0.038	0.028	0.039	-0.015	0.031	0.023	0.014	0.014	0.025
Jarque-Bera	5500.451	57209.610	317986.500	583.254	14341.090	9710.608	55826.100	6438.264	2452.421
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Observations	2037	1939	1206	482	1573	512	2037	420	1649

	BTC	XRP	ETH	BCH	XLM	EOS	LTC	ADA
XRP	0.342							
	15.992							
	0.000							
ETH	0.352	0.205						
	13.049	7.276						
	0.000	0.000						
BCH	0.405	0.393	0.556					
	9.704	9.369	14.656					
	0.000	0.000	0.000					
XLM	0.323	0.519	0.229	0.316				
	13.549	24.067	8.175	7.301				
	0.000	0.000	0.000	0.000				
EOS	0.486	0.462	0.590	0.464	0.439			
	12.554	11.751	16.509	11.465	11.049			
	0.000	0.000	0.000	0.000	0.000			
LTC	0.652	0.335	0.344	0.473	0.313	0.507		
	38.842	15.670	12.709	11.758	13.060	13.281		
	0.000	0.000	0.000	0.000	0.000	0.000		
ADA	0.457	0.595	0.544	0.338	0.615	0.459	0.469	
	10.503	15.155	13.242	7.354	15.954	10.557	10.845	
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	
XMR	0.435	0.208	0.334	0.492	0.305	0.491	0.349	0.541
	19.615	8.636	12.277	12.383	12.672	12.734	15.099	13.166
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes. Samples: 04/28/2013-11/25/2018 for Bitcoin, 08/05/2013-11/25/2018 for Ripple, 08/08/2015-11/25/2018 for Ethereum, 08/01/2017-11/25/2018 for Bitcoin Cash, 08/06/2014-11/25/2018 for Stellar, 07/02/2017-11/25/2018 for EOS, 04/29/2013-11/25/2018 for Litecoin, 10/02/2017-11/25/2018 for Cardano, and 05/22/2014-11/25/2018 for Monero. In the lower panel, at each intersection, the first number is the unconditional correlation coefficient between the corresponding two cryptocurrency price returns. The second number is a t test statistic for the null hypothesis that the correlation coefficient is equal to zero. The third number is the corresponding p-value.

Table 2: DCC MV-GARCH Models for Cryptocurrency Daily Price Returns (1)

GARCH Equations	Group 1 (S=9) 10/02/2017 BTC	XRP	ETH	BCH	XLM	EOS	LTC	ADA	XMR
ω	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.0000)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)
α_1	0.062	0.140	0.054	0.064	0.055	0.031	0.079	0.111	0.064
	(0.0248)	(0.0659)	(0.0327)	(0.0426)	(0.0452)	(0.0483)	(0.036)	(0.1013)	(0.0273)
β_1	0.925	0.837	0.887	0.914	0.938	0.964	0.886	0.876	0.909
	(0.0264)	(0.0575)	(0.0632)	(0.0598)	(0.0386)	(0.0631)	(0.0532)	(0.1014)	(0.0376)
DCC Equation									
γ	0.036								
	(0.0041)								
δ	0.961								
	(0.0049)								

GARCH Equations	Group 2 (S=8) 08/01/2017 BTC	XRP	ETH	BCH	XLM	EOS	LTC	XMR
ω	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.0000)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0000)	(0.0001)	(0.0001)
α_1	0.068	0.129	0.066	0.086	0.062	0.019	0.096	0.081
	(0.0308)	(0.0683)	(0.0318)	(0.0413)	(0.029)	(0.0103)	(0.0312)	(0.0392)
β_1	0.918	0.834	0.838	0.886	0.935	0.979	0.872	0.882
	(0.035)	(0.0764)	(0.0605)	(0.0564)	(0.0235)	(0.0126)	(0.0428)	(0.055)
DCC Equation								
γ	0.038							
	(0.0061)							
δ	0.958							
	(0.0081)							

GARCH Equations	Group 3 (S=7) 07/02/2017 BTC	XRP	ETH	XLM	EOS	LTC	XMR
ω	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.0000)	(0.0002)	(0.0002)	(0.0001)	(0.0003)	(0.0001)	(0.0002)
α_1	0.084	0.130	0.090	0.058	0.051	0.098	0.078
	(0.0482)	(0.0696)	(0.0332)	(0.032)	(0.0289)	(0.0301)	(0.0393)
α_2	0.901	0.826	0.804	0.938	0.890	0.866	0.887
	(0.0553)	(0.0829)	(0.069)	(0.0285)	(0.0506)	(0.0407)	(0.0585)
β_1							
β_2							
DCC Equation							
γ	0.039						
	(0.0075)						
δ	0.958						
	(0.0106)						

GARCH Equations	Group 4 (S=6) 08/08/2015 BTC	XRP	ETH	XLM	LTC	XMR
ω	0.000	0.000	0.000	0.000	0.000	0.000
	(0.0000)	(0.0002)	(0.0001)	(0.0003)	(0.0001)	(0.0002)
α_1	0.138	0.346	0.133	0.203	0.070	0.112
	(0.0336)	(0.1928)	(0.0586)	(0.0882)	(0.0189)	(0.0408)
α_2						
β_1	0.860	0.626	0.829	0.772	0.893	0.828
	(0.0313)	(0.1484)	(0.0768)	(0.1088)	(0.0236)	(0.0679)
β_2			0.000			
			(0.001)			
DCC Equation						
γ	0.041					
	(0.0094)					
δ	0.955					
	(0.0122)					

GARCH Equations	Group 5 (S=5) 08/06/2014 BTC	XRP	XLM	LTC	XMR
ω	0.000	0.000	0.000	0.000	0.000
	(0.0000)	(0.0002)	(0.0003)	(0.0001)	(0.0002)
α_1	0.136	0.404	0.198	0.084	0.113
	(0.0296)	(0.1664)	(0.0798)	(0.021)	(0.0359)
α_2	0.000				
	(0.0049)				
β_1	0.855	0.568	0.768	0.872	0.826
	(0.0313)	(0.1167)	(0.1105)	(0.0293)	(0.0626)
β_2					
DCC Equation					
γ	0.053				
	(0.0135)				
δ	0.932				
	(0.0225)				

Notes. As in Engle and Sheppard (2001) and Engle (2002), the estimates in the GARCH Equations correspond to $h_{m,t} = \omega_m + \sum_{p=1}^{P_m} \alpha_{m,p}\widehat{r}_{m,t-p}^2 + \sum_{q=1}^{Q_m} \beta_{m,p} h_{m,t-q}$ for $m = 1, 2, ..., S$, where S is the number of cryptocurrencies in each estimation group (in this table, $S = 9, 8, 7, 6, 5$) and $\widehat{r}_m$ is the demeaned price returns. For each m, P_m and Q_m are integers between 1 and 30 chosen according to the Schwarz Information Criterion. The estimates in the DCC Equations are based on the process $U_t = \left(1 - \sum_{j=1}^{J} \gamma_j - \sum_{k=1}^{K} \delta_k\right)\overline{U} + \sum_{j=1}^{J} \gamma_j (\widehat{r}_{t-j}^{*} \widehat{r}_{t-j}^{*\prime}) + \sum_{k=1}^{K} \delta_k U_{t-k}$, where $\widehat{r}_t^{*}$ is $\widehat{r}_t = (\widehat{r}_{1,t}, \widehat{r}_{2,t}, ..., \widehat{r}_{S,t})'$ standardized by the corresponding standard deviations, and $\overline{U}$ is the unconditional covariance of the standardized residuals resulting from the first-stage estimation. Standard errors are reported in parentheses. Estimation samples start on the date indicated under the group number and all end on 11/25/2018.

Table 3: DCC MV-GARCH Models for Cryptocurrency Daily Price Returns (2)

	Group 6 (S=4) 05/22/2014				Group 7 (S=3) 08/05/2013			Group 8 (S=2) 04/29/2013	
GARCH Equations	BTC	XRP	LTC	XMR	BTC	XRP	LTC	BTC	LTC
ω	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.0000)	(0.0002)	(0.0001)	(0.0001)	(0.0000)	(0.0002)	(0.0001)	(0.0000)	(0.0001)
α_1	0.135	0.326	0.086	0.117	0.116	0.329	0.065	0.127	0.087
	(0.0281)	(0.1905)	(0.021)	(0.0343)	(0.0313)	(0.152)	(0.0262)	(0.0369)	(0.0158)
α_2	0.000				0.000		0.000		
	(0.0054)				(0.006)		(0.0094)		
α_3							0.000		
							(0.0065)		
α_4							0.000		
							(0.0103)		
α5							0.039		
							(0.0391)		
β_1	0.856	0.637	0.868	0.830	0.881	0.668	0.871	0.868	0.889
	(0.0292)	(0.1598)	(0.03)	(0.0518)	(0.0354)	(0.1253)	(0.0142)	(0.0404)	(0.0141)
β_2									
DCC Equation									
γ	0.060				0.076			0.114	
	(0.0162)				(0.0176)			(0.0327)	
δ	0.931				0.910			0.877	
	(0.0224)				(0.0223)			(0.0363)	

Notes. As in Engle and Sheppard (2001) and Engle (2002), the estimates in the GARCH Equations correspond to $h_{m,t} = \omega_m + \sum_{p=1}^{P_m} \alpha_{m,p}\widehat{r}^2_{m,t-p} + \sum_{q=1}^{Q_m} \beta_{m,p} h_{m,t-q}$ for $m = 1, 2, ..., S$, where S is the number of cryptocurrencies in each estimation group (in this table, $S = 4, 3, 2$) and $\widehat{r}_m$ is the demeaned price returns. For each m, P_m and Q_m are integers between 1 and 30 chosen according to the Schwarz Information Criterion. The estimates in the DCC Equations are based on the process $U_t = \left(1 - \sum_{j=1}^{J}\gamma_j - \sum_{k=1}^{K}\delta_k\right)\overline{U} + \sum_{j=1}^{J}\gamma_j(\widehat{r}^*_{t-j}\widehat{r}^{*\prime}_{t-j}) + \sum_{k=1}^{K}\delta_k U_{t-k}$, where $\widehat{r}^*_t$ is $\widehat{r}_t = (\widehat{r}_{1,t}, \widehat{r}_{2,t}, ..., \widehat{r}_{S,t})'$ standardized by the corresponding standard deviations, and $\overline{U}$ is the unconditional covariance of the standardized residuals resulting from the first-stage estimation. Standard errors are reported in parentheses. Estimation samples start on the date indicated under the group number and all end on 11/25/2018.

Table 4: Right-Tail Augmented Dickey-Fuller (ADF) Tests on Cryptocurrency NVT Ratios

Cryptocurrency NVT Ratio (30-Day Average)	GSADF Test Statistic	Sample	Size of Test	Critical Values Bitcoin	Critical Values Ethereum	Critical Values Bitcoin Cash	Critical Values Stellar	Critical Values Litecoin	Critical Values Cardano
Bitcoin	3.374337***	05/27/2013 - 11/25/2018	1%	2.554494	2.792815	2.799835	2.639787	2.652179	2.799072
Ethereum	2.026782*	09/05/2015 - 11/25/2018	5%	2.199994	2.171908	2.201178	2.165129	2.188547	2.235417
Bitcoin Cash	5.988520***	09/01/2017 - 11/25/2018	10%	1.995449	1.959356	1.987084	1.906535	1.948615	2.011380
Stellar	3.513114***	12/01/2015 - 11/25/2018							
Litecoin	4.647609***	05/27/2013 - 11/25/2018							
Cardano	12.13353***	10/31/2017 - 11/25/2018							

Cryptocurrency NVT Ratio (60-Day Average)	GSADF Test Statistic	Sample	Size of Test	Critical Values Bitcoin	Critical Values Ethereum	Critical Values Bitcoin Cash	Critical Values Stellar	Critical Values Litecoin	Critical Values Cardano
Bitcoin	4.593047***	06/26/2013 - 11/25/2018	1%	2.571528	2.738997	2.874361	2.602233	2.571528	2.931101
Ethereum	3.299823***	10/05/2015 - 11/25/2018	5%	2.215061	2.193453	2.200594	2.191365	2.215061	2.253935
Bitcoin Cash	8.359869***	10/01/2017 - 11/25/2018	10%	1.963333	1.960699	1.946608	1.984789	1.963333	1.989439
Stellar	4.274055***	12/31/2015 - 11/25/2018							
Litecoin	4.717897***	06/26/2013 - 11/25/2018							
Cardano	13.37575***	11/30/2017 - 11/25/2018							

Notes. Right-tail ADF tests, as described in Phillips et al. (2015), that we run individually on the NVT ratios of six cryptocurrencies. We find statistical evidence of mildly explosive behavior in all six cryptocurrencies. *** denotes statistical significance at the 1% level; * denotes statistical significance at the 10% level. Schwarz Information Criterion is used to select optimal lag in test regressions. 30 days is maximum lag length considered on 30-day average of computed NVT ratios; 60 days is maximum lag length considered on 60-day average of computed NVT ratios. Critical values: simulated using 1000 replications. Initial window size: 10% of full sample.

Table 5: Periods of Mildly Explosive Behavior in Cryptocurrency NVT Ratios

Cryptocurrency	Periods of Mildly Explosive Behavior (NVT Ratio, 30-Day Average)	Periods of Mildly Explosive Behavior (NVT Ratio, 60-Day Average)
Bitcoin [5(3), 5(3)]	02/02/2014 - 03/06/2014 (33 days)	**05/06/2014 - 05/21/2014* (16 days)**
	04/06/2014 - 10/02/2014* (180 days)	09/21/2015 - 12/26/2015 (97 days)
	02/09/2015 - 03/26/2015* (46 days)	**02/16/2016 - 07/18/2016* (154 days)**
	08/09/2015 - 05/04/2016 (270 days)	05/08/2017 - 07/21/2017 (75 days)
	03/03/2018 - 11/25/2018* (268 days)	**03/06/2018 - 11/25/2018* (265 days)**
Ethereum [1(1), 3(1)]	**10/05/2017 - 11/08/2017* (35 days)**	02/22/2016 - 04/07/2016 (46 days)
		08/03/2016 - 09/28/2016 (57 days)
		10/08/2017 - 11/28/2017* (52 days)
Bitcoin Cash [7(3), 5(2)]	10/18/2017 - 12/23/2017 (67 days)	11/11/2017 - 12/28/2017 (48 days)
	01/21/2018 - 04/02/2018* (72 days)	**01/27/2018 - 04/17/2018* (81 days)**
	05/02/2018 - 05/22/2018 (21 days)	05/16/2018 - 05/31/2018 (16 days)
	06/18/2018 - 07/04/2018* (17 days)	**07/10/2018 - 09/11/2018* (64 days)**
	08/04/2018 - 08/12/2018* (9 days)	10/18/2018 - 11/25/2018 (39 days)
	09/22/2018 - 10/05/2018 (14 days)	
	11/05/2018 - 11/25/2018 (21 days)	
Stellar [5(4), 6(3)]	**05/04/2016 - 06/11/2016* (39 days)**	**05/14/2016 - 07/01/2016* (49 days)**
	02/06/2017 - 04/03/2017 (57 days)	02/16/2017 - 05/19/2017 (93 days)
	09/22/2017 - 10/17/2017* (26 days)	**06/16/2017 - 06/28/2017* (13 days)**
	03/01/2018 - 04/13/2018* (44 days)	**09/23/2017 - 11/20/2017* (59 days)**
	05/19/2018 - 08/30/2018* (104 days)	01/08/2018 - 01/26/2018 (19 days)
		03/15/2018 - 09/04/2018* (174 days)
Litecoin [4(4), 5(3)]	**10/12/2014 - 12/17/2014* (67 days)**	**10/17/2014 - 01/09/2015* (85 days)**
	10/01/2016 - 10/17/2016* (17 days)	**03/28/2015 - 04/16/2015* (20 days)**
	03/06/2017 - 03/12/2017* (7 days)	06/16/2016 - 07/25/2016 (40 days)
	03/10/2018 - 11/25/2018* (261 days)	12/15/2017 - 01/06/2018 (23 days)
		03/04/2018 - 11/25/2018* (267 days)
Cardano [5(3), 4(2)]	12/27/2017 - 01/01/2018 (6 days)	01/04/2018 - 01/28/2018 (25 days)
	01/29/2018 - 02/08/2018* (11 days)	03/12/2018 - 04/14/2018 (34 days)
	03/05/2018 - 03/22/2018 (18 days)	**05/02/2018 - 08/17/2018* (108 days)**
	04/14/2018 - 06/17/2018* (65 days)	**09/17/2018 - 11/25/2018* (70 days)**
	09/03/2018 - 11/25/2018* (84 days)	

Notes. Periods of mildly explosive behavior in six major cryptocurrencies, as graphically represented in Figures 9 and 10. During the periods in bold and with an asterisk, the corresponding cryptocurrencies exhibit mild explosiveness and generally rising NVT ratios. The remaining are periods during which the corresponding cryptocurrencies experience mild explosiveness and generally falling NVT ratios. We provide information about the length (expressed in days) of the estimated periods of mild explosiveness. In the first column, in square brackets next to the name of each cryptocurrency, we report the following sequence of numbers, $[A\,(B)\,,\ C\,(D)]$: A is the number of periods of mild explosiveness that we detect in the time series of the 30-day moving average of a cryptocurrency NVT ratio; B is the number of periods of mild explosiveness in that cryptocurrency market, which are associated with a generally rising NVT ratio; C is the number of periods of mild explosiveness that we detect in the time series of the 60-day moving average of a cryptocurrency NVT ratio; D is the number of periods of mild explosiveness in that cryptocurrency market, which are associated with a generally rising NVT ratio.

Table 6: Summary Statistics of Cryptocurrency Daily Price Returns, by Subsample

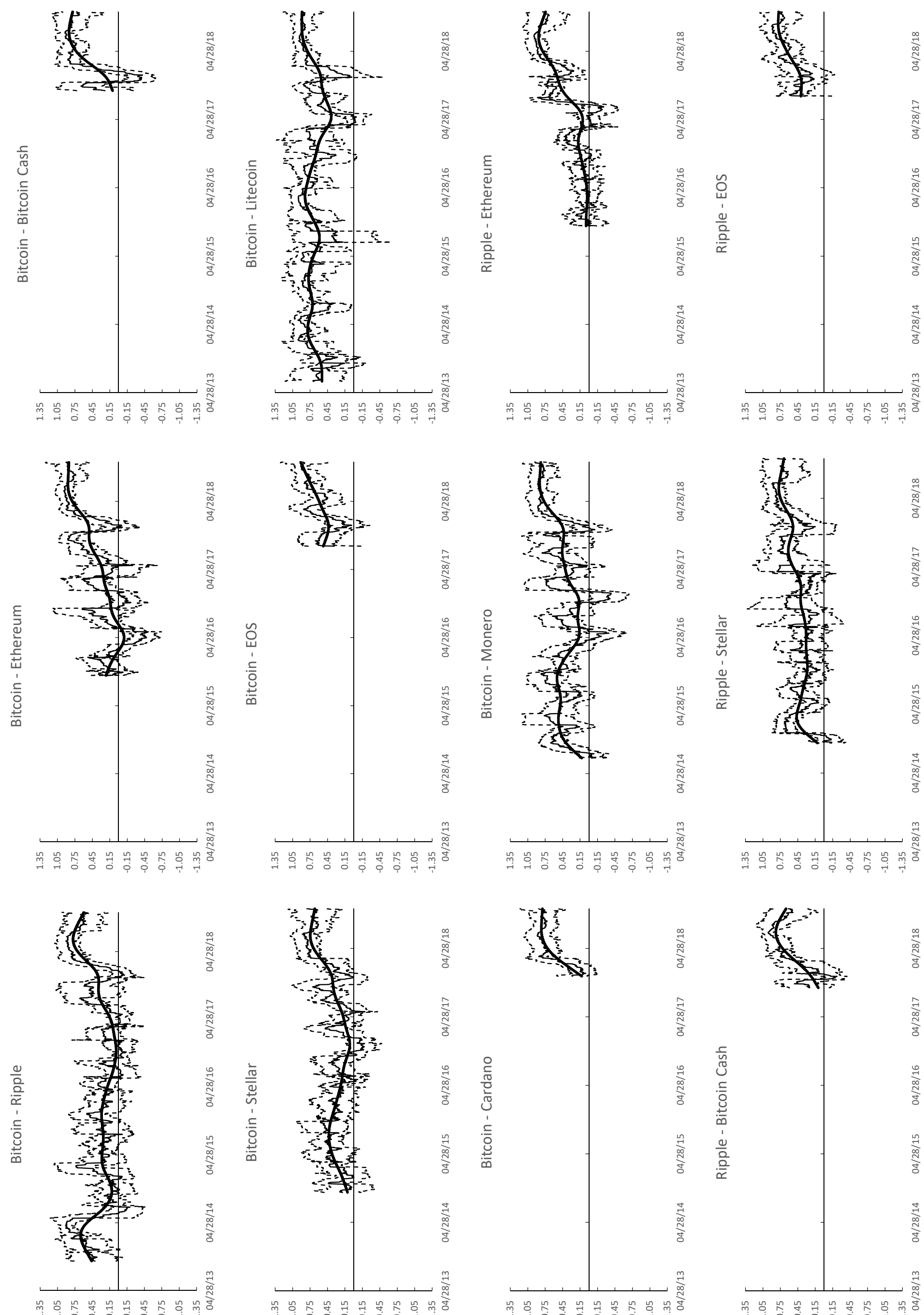
	Bitcoin			Ethereum			Bitcoin Cash			Stellar			Litecoin			Cardano		
	Instability + Rising NVT Ratio	Instability + Declining NVT Ratio	No Instability	Instability + Rising NVT Ratio	Instability + Declining NVT Ratio	No Instability	Instability + Rising NVT Ratio	Instability + Declining NVT Ratio	No Instability	Instability + Rising NVT Ratio	Instability + Declining NVT Ratio	No Instability	Instability + Rising NVT Ratio	Instability + Declining NVT Ratio	No Instability	Instability + Rising NVT Ratio	Instability + Declining NVT Ratio	No Instability
Summary statistics based on the analysis of subsamples, as determined by the date-stamping algorithm applied on the NVT ratios (30-day average)																		
Mean	-0.225%	0.084%	0.231%	0.015%	-	0.474%	-1.426%	0.996%	-0.216%	0.097%	0.949%	0.496%	-0.579%	-	0.125%	-1.167%	0.975%	0.262%
Median	-0.058%	0.112%	0.274%	-0.518%	-	0.000%	-1.417%	-0.575%	-0.032%	-0.536%	-0.618%	-0.278%	-0.279%	-	0.000%	-1.008%	-0.118%	-0.473%
Maximum	14.602%	17.215%	29.077%	10.827%	-	28.629%	29.170%	42.969%	19.049%	65.692%	45.717%	70.404%	11.537%	-	51.845%	22.803%	25.242%	59.714%
Minimum	-19.554%	-16.430%	-26.742%	-5.087%	-	-31.984%	-26.377%	-39.582%	-30.871%	-15.937%	-9.696%	-33.342%	-14.870%	-	-51.927%	-20.697%	-14.960%	-22.374%
Range	34.156%	33.645%	55.819%	15.914%	-	60.613%	55.547%	82.551%	49.920%	81.629%	55.413%	103.746%	26.406%	-	103.772%	43.500%	40.202%	82.088%
Std. Dev.	3.501%	3.353%	4.503%	2.931%	-	6.552%	7.274%	10.889%	6.585%	7.339%	7.906%	9.433%	4.140%	-	6.549%	6.595%	10.261%	9.774%
Skewness	-0.405	-0.381	-0.387	1.492	-	0.184	0.266	0.535	-0.384	3.583	3.366	1.757	-0.578	-	0.322	-0.129	0.622	2.776
Kurtosis	7.165	9.469	10.250	6.998	-	6.282	6.337	6.129	5.881	32.061	19.295	14.677	4.677	-	16.638	4.346	3.045	16.584
Mean per Std. Dev.	-0.064	0.025	0.051	0.005	-	0.072	-0.196	0.091	-0.033	0.013	0.120	0.053	-0.140	-	0.019	-0.177	0.095	0.027
Jarque-Bera	370.512	535.737	2241.339	36.291	-	466.197	46.639	56.025	68.888	7951.165	738.275	4417.437	60.887	-	11325.250	12.523	1.551	1525.403
Probability	0.000	0.000	0.000	0.000	-	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-	0.000	0.002	0.460	0.000
Observations	494	303	1012	35	-	1026	98	123	186	213	57	713	352	-	1458	160	24	170
Summary statistics based on the analysis of subsamples, as determined by the date-stamping algorithm applied on the NVT ratios (60-day average)																		
Mean	-0.107%	0.735%	0.067%	0.850%	1.046%	0.278%	-0.849%	0.180%	-0.177%	0.272%	2.614%	0.122%	-0.778%	-0.692%	0.266%	-1.044%	-0.479%	-0.970%
Median	0.149%	0.628%	0.080%	0.025%	0.091%	-0.090%	-1.049%	-0.694%	-0.077%	-0.437%	0.946%	-0.462%	-0.426%	-0.482%	0.000%	-0.815%	-0.561%	-1.157%
Maximum	12.749%	22.351%	22.148%	14.251%	19.794%	28.629%	29.170%	42.969%	19.049%	65.692%	70.404%	54.261%	11.537%	11.865%	51.845%	14.908%	33.505%	22.803%
Minimum	-14.462%	-11.293%	-23.557%	-7.134%	-20.954%	-31.984%	-26.377%	-39.582%	-30.871%	-26.414%	-33.342%	-32.189%	-23.539%	-20.876%	-51.927%	-18.372%	-22.374%	-20.697%
Range	27.211%	33.644%	45.705%	21.385%	40.747%	60.613%	55.547%	82.551%	49.920%	92.106%	103.746%	86.450%	35.076%	32.741%	103.772%	33.280%	55.879%	43.500%
Std. Dev.	3.206%	4.167%	4.087%	3.855%	6.703%	6.556%	6.526%	11.422%	7.328%	8.003%	13.887%	8.224%	4.286%	6.051%	6.252%	5.383%	9.998%	7.428%
Skewness	-0.503	0.674	-0.484	1.088	0.345	0.149	0.199	0.654	-0.410	2.105	2.274	1.186	-0.813	-0.669	0.681	-0.276	1.011	0.031
Kurtosis	6.378	7.463	8.646	5.018	5.021	6.438	6.937	6.122	5.116	18.295	12.828	10.427	5.975	4.537	16.846	3.766	5.163	3.760
Mean per Std. Dev.	-0.033	0.176	0.016	0.220	0.156	0.042	-0.130	0.016	-0.024	0.034	0.188	0.015	-0.182	-0.114	0.042	-0.194	-0.048	-0.131
Jarque-Bera	225.168	155.759	1606.765	19.070	19.576	436.534	94.589	49.167	28.329	3093.174	547.255	1393.025	178.206	10.908	10863.620	6.617	21.545	2.158
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.004	0.000	0.037	0.000	0.340
Observations	435	172	1175	52	103	880	145	103	132	295	112	550	372	63	1347	178	59	89

Highlights

- We analyze nine major cryptocurrencies between April 2013 and November 2018.
- We estimate the time variation in the correlations of their price returns by means of bivariate and multivariate modelling approaches and find it to be pronounced.
- These correlations, usually positive, are generally increasing between early 2017 and late 2018.
- By means of a right-tail variation of the Augmented Dickey-Fuller test, we identify and date-stamp periods of mildly explosive behavior in cryptocurrency markets.
- We show statistically significant evidence of frequent mild explosiveness in all cryptocurrencies.
- Mild explosiveness is simultaneous in several major cryptocurrencies at the end of 2017 and in 2018.

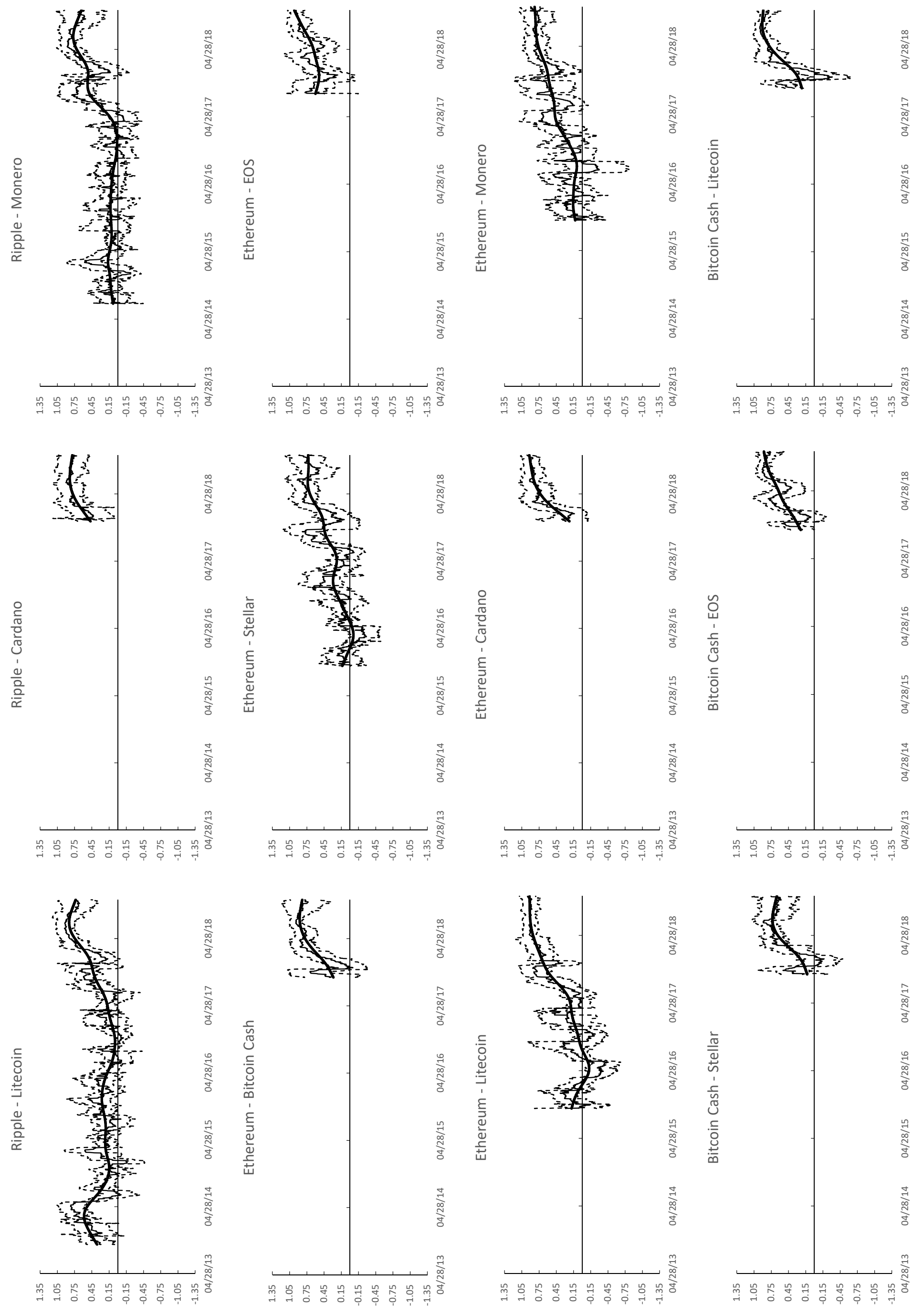
Online Appendix

Figure OA1: Rolling Correlations (60-Day Rolling Windows) of Cryptocurrency Daily Price Returns (1)



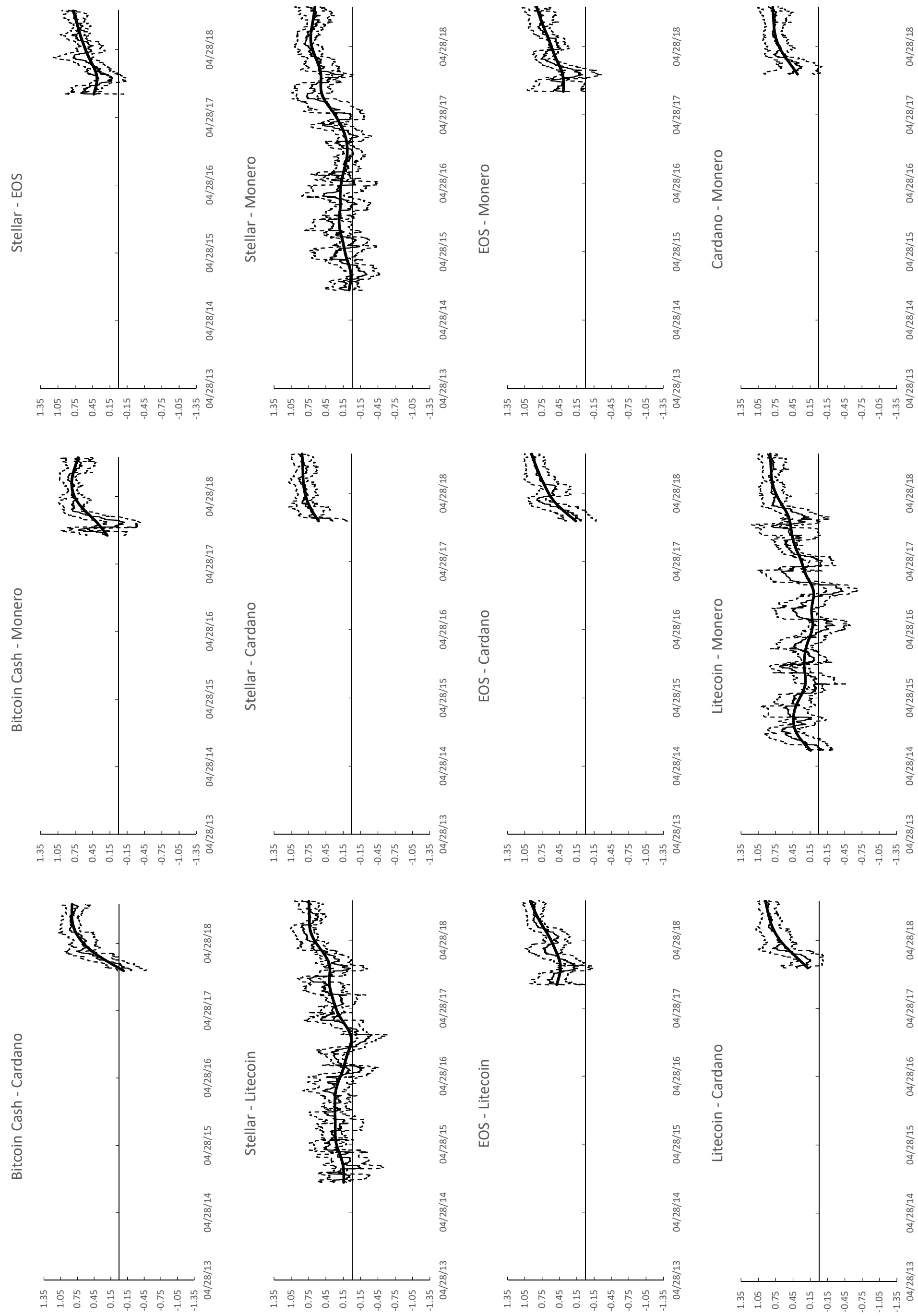
Notes. Rolling correlations derived as described in Tang and Xiong (2012), based on 60-day windows, between the price returns of all pairs of cryptocurrencies in the sample. The solid thin lines represent the estimated rolling correlations; the dashed lines represent the upper and lower bounds of the corresponding 95% confidence bands; the solid bold lines are correlation trends derived from the application of a standard Hodrick-Prescott filter.

Figure OA2: Rolling Correlations (60-Day Rolling Windows) of Cryptocurrency Daily Price Returns (2)



Notes. Rolling correlations derived as described in Tang and Xiong (2012), based on 60-day windows, between the price returns of all pairs of cryptocurrencies in the sample. The solid thin lines represent the estimated rolling correlations; the dashed lines represent the upper and lower bounds of the corresponding 95% confidence bands; the solid bold lines are correlation trends derived from the application of a standard Hodrick-Prescott filter.

Figure OA3: Rolling Correlations (60-Day Rolling Windows) of Cryptocurrency Daily Price Returns (3)



Notes. Rolling correlations derived as described in Tang and Xiong (2012), based on 60-day windows, between the price returns of all pairs of cryptocurrencies in the sample. The solid thin lines represent the estimated rolling correlations; the dashed lines represent the upper and lower bounds of the corresponding 95% confidence bands; the solid bold lines are correlation trends derived from the application of a standard Hodrick-Prescott filter.