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**The triangle of ICOs, Bitcoin and Ethereum: A time series
analysis / Christian Masiak/Joern H. Block/Tobias Masiak/
Matthias Neuenkirch**

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The Triangle of ICOs, Bitcoin and Ethereum: A Time Series Analysis

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Abstract

We analyse the triangle of Initial Coin Offerings (ICO) and cryptocurrencies, namely Bitcoin and Ethereum. So far, little is known about the relationship between ICOs, bitcoin and Ether prices. Hence, we employ both bitcoin and Ether prices but also the ICO amount to measure the future development of raised capital in ICOs. First, our results indicate that an ICO has an influence on the subsequent ICO. Second, not only bitcoin prices but also Ether prices play a considerable role with regard to the output of ICO campaigns. However, the effect of Ethereum is of shorter duration on ICO compared to Bitcoin on ICO. A further finding is that the cryptocurrency Bitcoin positively influences Ether. The implications of these findings for investors and entrepreneurial firms are discussed.

Keywords: blockchain, cryptocurrency, entrepreneurial finance, initial coin offering, ICO

JEL Classifications: G11, E22, M13, O16

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1 Introduction

Entrepreneurial innovative firms regularly suffer from financial constraints and access to finance problems, which limit both their growth and survival rate. Among others, asymmetric information, agency conflicts, insufficient collateral, and high transaction costs for capital providers (e.g., Nanda and Rhodes-Kropf 2017; Popov and Udell 2012; Ryan et al. 2014) are reasons for a lack of financing for these entrepreneurial firms. Nevertheless, a large number of different players have entered the market, such as crowdfunding, family offices, accelerators, or venture debt lenders due to problems faced by entrepreneurial innovative firms (see Block et al. 2018 for a summary of new players in entrepreneurial finance). A completely new financing approach, however, has recently emerged in the market, namely initial coin offering (ICO), which is based on the blockchain technology introduced by Satoshi Nakamoto in his white paper about Bitcoin in 2008. In an ICO, entrepreneurial firms are able to create an own cryptocurrency and offer the so-called tokens¹ to investors (“the crowd”) in exchange for capital. According to coinschedule, entrepreneurial innovative firms have raised more than \$11.3 billion in approximately 556 ICO campaigns since 2016, highlighting the considerable relevance of the emerging new financing instrument. Whereas prior literature has extensively analyzed the returns and market cycles of Initial Public Offerings (IPOs) using time series analyses (e.g., Bali and Hovakimian 2009; Lowry and Schwert 2002), little is known about the dynamics of ICOs and the effects between cryptocurrencies and ICOs. This is an important oversight as This paper fills this gap in the literature and employs ICOs and two cryptocurrencies (Bitcoin and Ethereum) market cycles.

The sample period starts from January 2017 and ends in April 2018 including 68 weekly observations. By using VAR models, we address our threefold research question: First, we examine whether the outcome of past ICO campaigns have an impact on subsequent ICO campaigns. Second, we analyze the effect of bitcoin and Ether prices on the outcome of an ICO (and vice versa). Third, we shed light on the effects of bitcoin on Ether prices (and vice versa). We expect that a shock to ICOs has a positive effect on the following campaigns in line with the financing literature on IPOs (e.g., Lowry and Schwert 2002). ICOs, however, are often token-based. For instance, an ICO uses an ERC-20 token and is consequently related to platforms and

¹ Tokens represent either a specific asset or utility that is based on a blockchain. Tokens can represent any kind of tangible or intangible asset, such as commodities, cryptocurrencies or loyalty points.

cryptocurrencies such as Ethereum. Moreover, private and institutional investors often have to exchange either Ethereum or Bitcoin to receive tokens of an ICO campaign. Hence, we expect an effect of shocks (hypes) in Bitcoin or Ethereum on the success of ICOs, as ICO campaigns normally require cryptocurrencies (e.g., Bitcoin, Ethereum).

The present study is most closely related to a set of papers that uses VAR models to analyze market cycles of IPOs (e.g., Doidge et al. 2017; Lowry et al. 2010). Our results show that market cycles exist regarding ICO campaigns and cryptocurrencies. First, the outcome of past ICO campaigns positively influences the subsequent ICO campaigns. Second, both bitcoin and Ether prices positively influence the outcome of an ICO, whereas an ICO has a negative effect on cryptocurrencies (bitcoin and Ether). Moreover, bitcoin has a positive effect on Ether prices.

The remainder of the paper is organized as follows: Section 2 provides background information on ICO and cryptocurrencies. Section 3 introduces the data employed and explains the econometric methodology. Section 4 shows and discusses the empirical results while Section 5 concludes with the paper's implications, its limitations, and avenues for future research.

2 Theoretical background

2.1 Cryptocurrencies and initial coin offerings

Cryptocurrencies are a digital currency and application of the blockchain technology in which all rules and regulations are programmed in a cryptographic algorithm (Benedetti and Kostovetsky 2018). In other words, a cryptocurrency is a currency that is secured and made unique by cryptography. The vast majority of cryptocurrencies are based on a peer-to-peer network and a blockchain respectively where all transactions are recorded and validated as a kind of ledger. Similar to fiat, we can use cryptocurrencies to either buy or sell products and services. Whereas bitcoin and Ether are the most famous cryptocurrencies, these cryptocurrencies represent similar to gold, Euro, U.S. Dollar, Japanese yen or any further fiat, a medium of value exchange. In the case of cryptocurrencies, the value is based on the supply and demand that is requested by its users, as it is not backed by government or any other institutions. However, in comparison to fiat, cryptocurrencies possess transaction anonymity. Furthermore, cryptocurrency users can transfer a value without an intermediary and without geographic limitation that leads to a reduction of transaction costs. The invention of Bitcoin resulted in the creation of further coins

such as Ripple, IOTA or EOS. Currently, more than 1,500 different coins exist that are also traded and listed on websites (see coinmarketcap.com for a comprehensive list of coins and the respective market cap, price and circulating supply).

A universally accepted definition of *ICO* does not exist (e.g., Fisch et al. 2018). Therefore, we provide a broad definition of ICO that covers the main characteristics and enables the distinction to other financial instruments in the entrepreneurial finance literature. In general, entrepreneurial firms raise capital in an ICO by selling tokens to investors (“the crowd”). Similar to an IPO, entrepreneurial firms offer their tokens (instead of shares) in an ICO for the first time to the public. Furthermore, compared to classical crowdfunding projects, the main difference of ICOs is also the medium of raising capital for a project, namely issuing tokens on a blockchain.

A large number of different token types exist that allows private and institutional investors to invest in projects/firms by exchanging fiat to cryptocurrencies for receiving currency, utility, security, asset, reputation or other types of tokens. All tokens have similarities, such as a peer-to-peer network, verification of transactions based on a ledger, such as the blockchain, or for example, a tangle, a directed acyclic graph as proposed in the IOTA protocol for storing transactions or data. In general, three main token types exist, namely currency tokens, equity tokens and utility tokens. First, currency tokens or coins are digital tokens, which initially emerged with Bitcoin in 2008 by Satoshi Nakamoto. Currency tokens refer to a digital medium of value exchange. Therefore, currency tokens are also labeled as “coins”, highlighting the use as a currency and leading to the term “Initial Coin Offering” (Fisch 2018). Second, equity tokens (or security tokens) represent ownership rights of an asset, such as debt or company stock. In other words, the entrepreneurial firm starts an ICO by employing blockchain technology and smart contracts and issues share or voting rights over the blockchain. However, depending on the token that is offered in the ICO, regulations may be applied, as for example for equity tokens that symbolize shares in a company. Based on the Howey test, equity tokens fall under the regulatory scope of U.S. SEC since these tokens are categorized as securities under securities law. Third, utility tokens (also app coins or app tokens) represent a further token type, which entrepreneurial firms can offer in an ICO. Utility tokens provide users with access to a product or service (similar to a reward-based crowdfunding). Therefore, investors can fund the development of the blockchain project and gain access to the specific service or product in the future. As utility

tokens are not a typical investment, these tokens have not been regulated by the government yet. Hence, the popularity of these tokens has increased considerably over the last months.

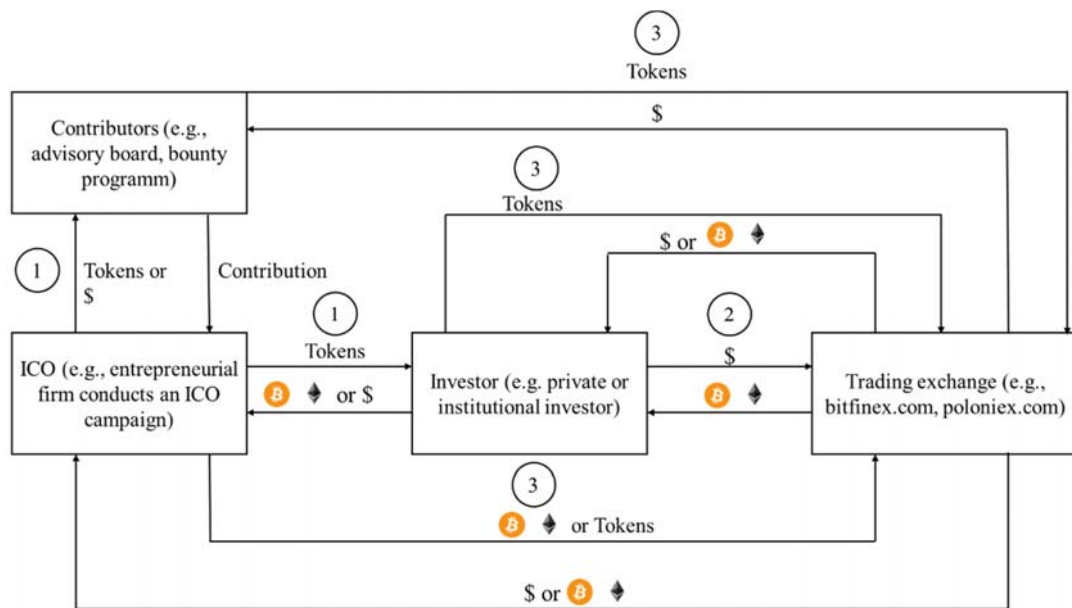
Less popular among investors and entrepreneurial firms are asset tokens or reputation/reward tokens. While asset tokens represent a physical asset or product, for instance, an investment into gold holdings, reputation tokens give a reward to users that are active on a platform, for example publishing content in the social network Steemit. Nevertheless, all past and future ICOs have in common that the buyers of the tokens speculate about an increase in the value of the purchased tokens, with the possibility of securing or selling these tokens in secondary markets. Moreover, it is noteworthy to mention that tokens often have not a counter-value at the time of the ICO and the technological nature of blockchain technology means that ICOs are not applicable to every entrepreneurial firm or venture. Hence, investors face both high information asymmetries and a high risk of an investment failure.

Since the ICO market is relatively unregulated and different token types exist, ICO campaigns differ substantially from each other. Nevertheless, main actors in every ICO campaign are the venture/entrepreneurial firm (capital seekers) that starts an ICO campaign, investors (the crowd), trading exchanges (intermediaries) and contributors (e.g., participants that work for the ICO campaign). Figure 1 summarizes the ICO process including the key actors and action steps. First, a venture/entrepreneurial firm intends an ICO campaign. Therefore, the firm publishes, for instance, a white paper and launches a website to inform potential investors about the aim of the ICO campaign. Typically, the entrepreneurial firm announces an advisory board but also hires experts (e.g., marketing experts, legal advisors) for conducting the ICO campaign in exchange for either capital or a considerable amount of tokens. In particular, smaller firms with a lack of finance and resources purchase external expertise in order to signal a high quality to potential investors and to differentiate the own ICO from other campaigns. Private or institutional investors receive tokens of the ICO campaign in exchange for cryptocurrencies, such as bitcoin or Ether. Second, some investors already possess a considerable amount of cryptocurrencies. If not, these investors generally use trading exchanges, such as bitfinex.com, to exchange fiat (e.g., dollars or Euros) to cryptocurrencies in order to invest in the ICO.² Third, transactions of tokens, fiat, and cryptocurrencies arise after an ICO campaign. Typically, an entrepreneurial firm or venture of an ICO campaign aims at fiat currencies in order to conduct investments and develop

² It is noteworthy to mention that investors are sometimes able to invest fiat money in exchange for tokens in an ICO campaign.

the product or service based on blockchain technology.³ Trading exchanges offer the opportunity to change tokens or cryptocurrencies to fiat or cryptocurrencies. This will be, however, only possible if the ICO is listed on the trading exchange. Nevertheless, ventures can exchange the collected cryptocurrencies (e.g., mostly Ether or bitcoin) to fiat. In comparison, investors will aim at an increase of value of the received tokens and will sell the tokens if value considerably rises. The same is true for contributors of an ICO campaign. In particular, smaller ventures have a lack of resources and often do not have specialists for conducting an ICO campaign. Hence, these experts are hired for an ICO campaign and payed with either tokens or fiat. Moreover, the majority of ICO campaigns includes an advisory board. The members are typically rewarded with tokens and shall signal the technical and economic expertise of the corresponding ICO campaign. Similar to investors, the contributors will typically sell the tokens if value sharply rises.

Figure 1: Mechanism of ICO campaigns



³ However, ventures are often not able to directly sell the total amount of tokens. To signal the integrity of the ICO campaign, venture typically lock a certain amount of tokens for the team of the venture (approximately between 6 – 24 months).

2.2 Related literature

Although ICO has achieved a remarkable success by raising more than \$11.3 billion in ICOs since 2016, little has been published in peer-reviewed work to date on ICO mechanisms and the connection to bitcoin and Ether prices. Adhami et al. (2018) has analyzed the determinants of an ICO success by a hand-collected dataset of 253 ICO campaigns. In particular, the public available code source of the ICO, a presale of tokens, and the offering of tokens that allow investors to access a specific service positively influences the success of an ICO. Fisch (2018) has analyzed in his working paper 233 ICOs between 2016 and 2017. Social (e.g., twitter followers of the ICO campaign), human (e.g., team size), and intellectual (e.g., publication of the code) capital variables have a positive effect on the amount raised in an ICO. According to the analysis of Amsden and Schweizer (2018), venture quality (e.g., large ICO team size) positively influences the ICO's access, whereas venture uncertainty (e.g., short whitepapers, not being on social media channels such as Telegram or Github) have a negative effect on ICO success. Further working papers, such as Conley (2017), Enyi and Le (2017), Venegas (2017) or Yadav (2017), do not analyze empirical data but rather focus on the legal nature of cryptocurrencies and ICOs or a theoretical analysis of token types. Hence, the majority of working papers has primarily focused on either technical descriptions of ICO campaigns or the determinants of success by analyzing single project characteristics.

The mechanisms of the novel entrepreneurial financing instrument require, however, a detailed investigation whether the same underlying dynamics of other financing instruments (e.g., crowdfunding, IPO, venture capital) apply to ICOs. Prior research, for instance, has extensively analyzed market cycles, timing of an IPO and equity returns of IPOs using time series analyses and revealed that IPO volume fluctuates considerably over time (e.g., Lowry 2003). According to Lowry and Schwert (2002), high IPO returns on the first day lead to high IPO activity by about six months. In other words, more firms go public after recognizing high initial returns of other firms. Yung et al. (2008) argue that positive shocks lead to more firms going public. IPOs issued during hot quarters, for instance, are more likely to delist than those in cold quarters. Subsequent research find similar results: IPO volume is sensitive to contemporaneous IPOs and if firms in a particular industry goes public, it reveals information about the entire growth prospects of the specific industry and affects IPO market cycles (e.g., Alti 2005; Benveniste et al. 2003). Furthermore, some prior studies use VAR model to identify market cycles of IPOs. Lowry (2010)

shows that IPO initial returns fluctuates considerably over time and is significantly higher during “hot” IPO markets. By analyzing U.S. firms between 1975 and 2012, Doidge et al. (2017) reveal a considerable decline in publicly listed companies in the U.S. in 2010 compared to 1975.

3 Data and econometric methodology

3.1 Data

Our data set covers 68 weekly observations for the period from 2 January 2017 to 16 April 2018,⁴ and consists of three variables: (i) the cumulative amount raised in ICO campaigns, (ii) the price of bitcoin, and (iii) the price of Ether. All three variables are measured in logs. We use two different data sources. First, CoinSchedule provides a comprehensive list of ICOs, which has been used in previously newspaper outlets (e.g., Economist, New York Times) and working/conference papers (e.g., Fisch 2018). Beside the amount raised in the ICO in USD, CoinSchedule further includes information about the date of the ICO and the website of the corresponding ICO campaign. Second, CoinMarketCap provides information with regard to daily bitcoin and Ether prices in USD. Due to the granted permission of API calls, we have access to daily bitcoin and Ether prices.

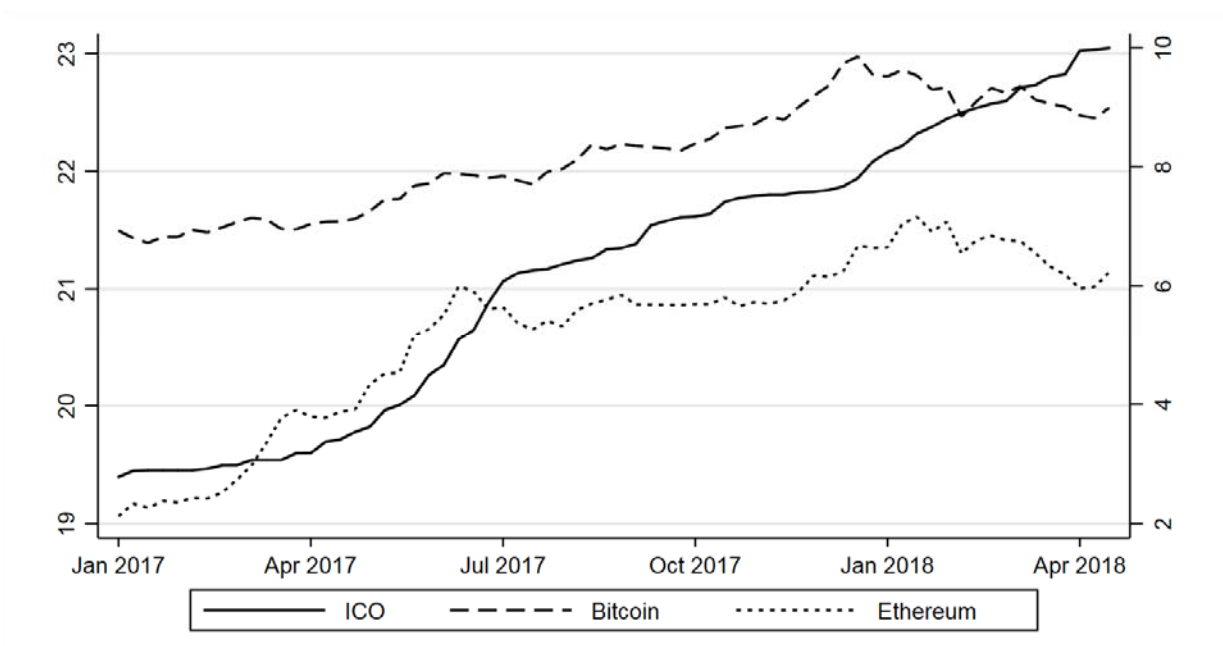
Figure 2 shows the evolution of these variables over time and Table A1 in the Appendix displays descriptive statistics. All three variables exhibit a clear upward trend. The strongest average growth rate can be found for Ethereum (6.55% per week), followed by the ICO indicator (5.93% per week), and Bitcoin (4.42% per week).

To avoid spurious relationships between the variables in the empirical analysis below, we remove the linear deterministic trends. In addition, we test for non-stationarity of the de-trended series with the help of an Augmented Dickey-Fuller (1979) test. The null hypothesis of non-stationarity can be rejected for all three variables at the 5% significance level.⁵ Figure 3 shows the evolution of the de-trended variables over time.

⁴ The start data is chosen to ensure enough variation in the indicator for ICO campaigns, which is (still) rather slow-moving in the second half of 2016.

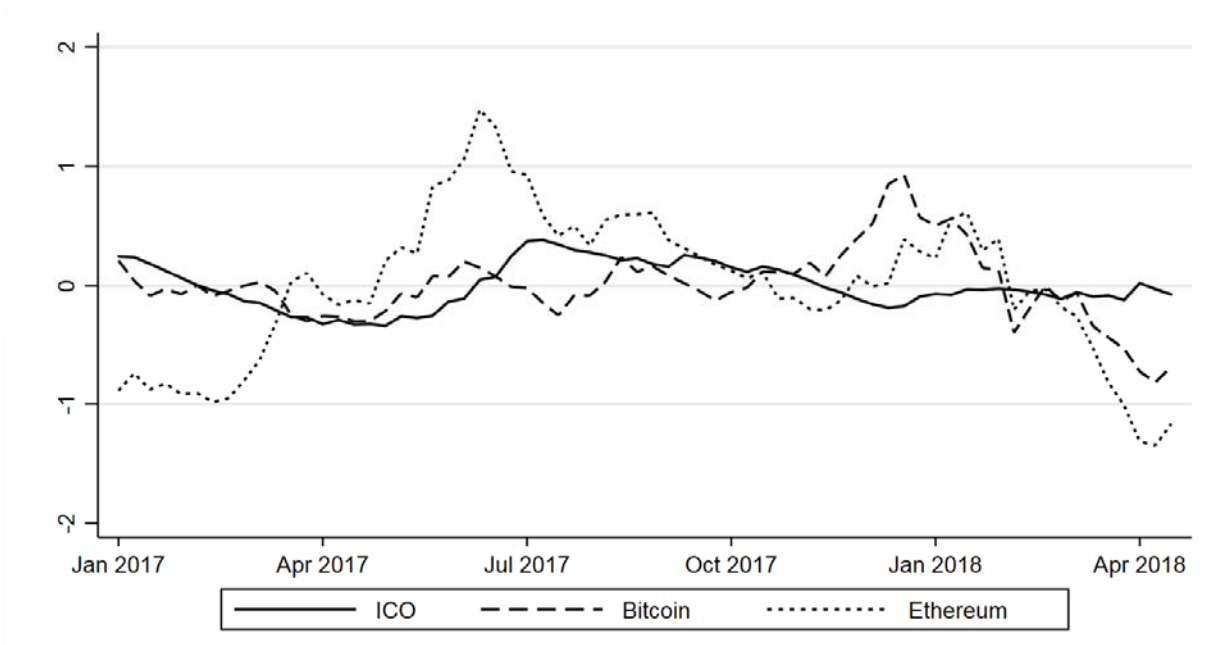
⁵ The test statistics are -2.48 (ICO), -2.16 (Bitcoin), and -2.33 (Ethereum). The critical value is -1.95 . Lag length selection (three lags) is based on the Schwert (1989) rule.

Figure 2: ICO, Bitcoin, and Ethereum over time (in logs)



Notes: Figure 2 shows the amount raised in ICO campaigns (left axis) as well as the prices of bitcoin and Ether (both on right axis). All variables are in logs.

Figure 3: ICO raised, Bitcoin price, and Ethereum price over time (in logs, de-trended)



Notes: Figure 3 shows the amount raised in ICO campaigns as well as the prices of bitcoin and Ether. All variables are in logs and linearly de-trended.

Ethereum is the most volatile series with a standard deviation of 0.64, followed by Bitcoin (0.31) and ICO (0.19). Indeed, we observe stronger booms (e.g., in June 2017 and January 2018) and busts (e.g., in April 2018) in Ethereum than in Bitcoins or ICOs. The pairwise correlation is found to be the strongest between the two cryptocurrencies ($\rho = 0.46$), followed by ICO and Ethereum ($\rho = 0.17$), and ICO and Bitcoin ($\rho = 0.04$). Hence, it appears that the relation between the two cryptocurrencies and the ICO indicator is, if at all, rather modest. However, it remains to be seen if these bivariate contemporaneous relationships hold in a multivariate VAR model that also incorporates dynamics in the connections across variables.

3.2 Econometric Methodology

Our empirical strategy builds on a linear VAR model (Sims 1980), which can be written as follows in its reduced form:

$$X_t = \delta + \sum_{i=1}^p A_i X_{t-i} + U_t \quad (1)$$

X_t is the 3×1 vector of endogenous variables including the linearly de-trended variables for (i) the amount raised in ICO campaigns (in logs), (ii) bitcoin prices (in logs), and (iii) Ether prices (in logs). δ is the 3×1 vector of intercepts, U_t is the 3×1 vector of non-structural error terms, and the A_i are 3×3 parameter matrices. Both the Bayesian information criterion and the Hannan Quinn information criterion favor a lag length of 1 for the three-variable VAR model. However, the residuals of the Ethereum equation exhibit significant autocorrelation at the 5% level. Hence, a VAR(1) is not able to sufficiently capture the dynamics in the system. In contrast, the use of two lags eliminates serial correlation in the error terms of all equations at the 5% level.

One problem with the estimation of Eq. (1) with least squares is the potential correlation in the error terms across equations. Without a proper transformation of the reduced-form VAR we are not able to identify the effects of changes, say, in Bitcoin on ICOs as typically the other variable co-move with changes in Bitcoin. Hence, to identify the effect of pure shocks in one variable on the other variables in the system, we have to transform the reduced-form VAR into a structural VAR. For that purpose, we impose a recursive identification scheme that orthogonalizes the residuals and transforms these into true innovations, which are uncorrelated to each other.

Such a Cholesky decomposition exists for each regular variance covariance matrix Σ_{UU} and relies on a lower triangular matrix P , for which $\Sigma_{UU} = PP'$ holds. Using this triangular matrix, the moving average representation⁶ of Eq. (1) can be transformed as follows:

$$X_t = \mu + U_t - \sum_{i=1}^{\infty} \mathbf{B}_i U_{t-i} \quad (2)$$

$$X_t = \mu + PP^{-1}U_t - \sum_{i=1}^{\infty} \mathbf{B}_i PP^{-1}U_{t-i} \quad (3)$$

Defining $\theta_i = \mathbf{B}_i P$, $\theta_0 = P$, and $W_t = P^{-1}U_t$, we can simplify Eq. (3) as follows:

$$X_t = \mu + \theta_0 W_t - \sum_{i=1}^{\infty} \theta_i W_{t-i} \quad (4)$$

Since P has no non-zero entries above its main diagonal, the transformed contemporaneous residuals of the three equations are no longer correlated with each other and represent true innovations or, put differently, shocks.

Such an identification scheme obviously requires assumptions on the instantaneous relationships across the three variables. We propose to order ICOs first, followed by Bitcoin and Ethereum. This implies, first, that shocks to ICOs can have a contemporaneous effect on the other two variables, whereas the opposite effect is ruled out. Second, shocks to bitcoin can directly move Ether prices, but not vice versa. The theoretical idea is that engaging in ICOs is driven by “longer-term” considerations of the investor, at least compared to buying and selling cryptocurrencies. Hence, ICOs are the slowest-moving variable and only affected with a time lag by shocks to the cryptocurrencies. Bitcoins are considered the benchmark cryptocurrency, which is why we order these before Ethereum and allow for a contemporaneous reaction of Ethereum to shocks in Bitcoin.⁷

4 Empirical results

We start our discussion of the results with the least squares estimates of Eq. (1) in Table 1.

⁶ Every stable VAR of order p can be re-written as vector moving average model of order infinity, that is, the weighted sum of all residuals.

⁷ Note that the results presented in Section 4 are qualitatively similar when applying other recursive schemes. To conserve space, we focus on the results of the theoretically most reasonable scheme and provide all other results on request.

Table 1: Estimates of VAR model

	1: ICO	2: Bitcoin	3: Ethereum
ICO _{t-1}	0.940 (0.122)	-0.801 (0.354)	-0.770 (0.506)
ICO _{t-2}	-0.046 (0.116)	0.735 (0.337)	0.456 (0.482)
Bitcoin _{t-1}	-0.008 (0.050)	1.070 (0.144)	0.119 (0.205)
Bitcoin _{t-2}	-0.003 (0.049)	-0.156 (0.141)	-0.065 (0.201)
Ethereum _{t-1}	0.014 (0.036)	-0.123 (0.104)	0.965 (0.149)
Ethereum _{t-2}	0.041 (0.036)	0.165 (0.105)	0.023 (0.150)
Constant	-0.007 (0.006)	-0.014 (0.017)	-0.008 (0.024)
R ²	0.941	0.825	0.908
Portmanteau: Chi ² (6)	6.70	7.11	11.93

Notes: Table 1 shows the coefficients (with standard errors in parentheses) for the estimation of Eq. (1) using least squares. Coefficients in bold are significant at the 5% level. Line 'Portmanteau' shows statistics for a test of the null hypothesis of no serial correlation. Number of observations: 66.

Most of the variation in either of the three variables can be explained by their lagged value(s). Only in the case of Bitcoin, we detect a statistically significant, albeit offsetting, influence of lagged values of the ICO indicator. Granger causality tests, that is, tests for joint exclusion of both lags of either variable in the equation of another variable, indicate that we find a simple Granger-causal relationship from Ethereum to ICO ($F(2,59) = 10.11$) at the 1% level. Two other Granger causal relationships can be found at the 10% level, as lagged values of the ICO indicator significantly predict both, Bitcoin prices ($F(2,59) = 2.56$) and Ethereum prices ($F(2,59) = 3.04$).

However, as already stated in Section 3.2, such an analysis of the reduced-form of Eq. (1) neglects contemporaneous relations across the variables. Indeed, we find non-zero bivariate correlations in the residuals of Eq. (1). In the case of Bitcoin and Ethereum, the conditional correlation is quite substantial ($\rho = 0.59$). But also the correlations between ICO and Bitcoin ($\rho = -0.20$) and ICO and Ethereum ($\rho = -0.11$) indicate that we cannot interpret the residuals as true shocks to either of these variables. Consequently, we rely on the Cholesky decomposition and the MA representation in Eq. (4) to demonstrate what happens when a shock to either of the variables transmits through the system on impact and for the 26 weeks thereafter. Figure 3 shows these impulse responses functions (solid lines) alongside the 95% confidence bands (dashed lines).

As indicated by the impulse responses on the main diagonal, shocks to either of the three variables are persistent, implying that a bullish (bearish) market remains bullish (bearish) for four

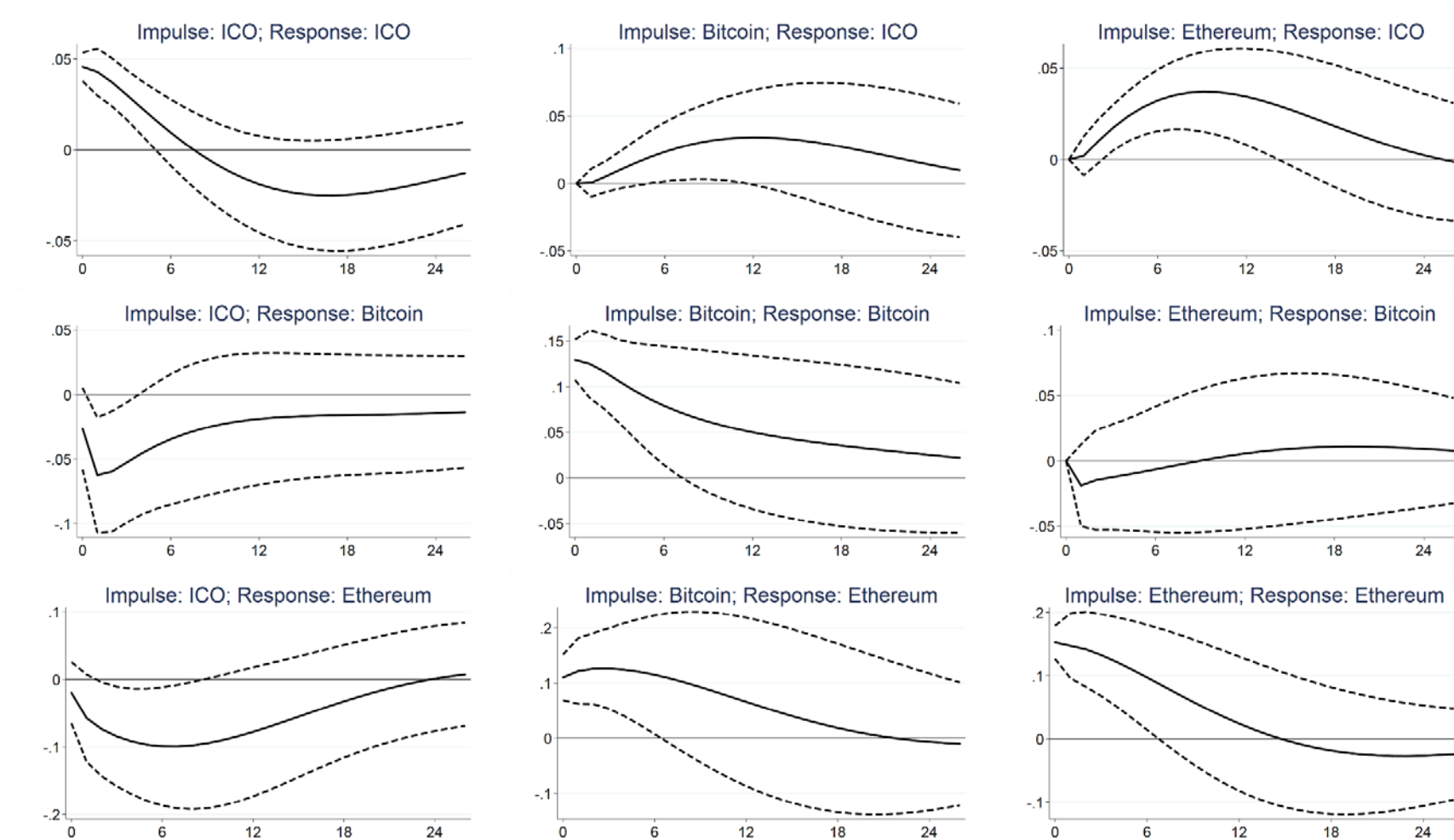
weeks in the case of ICOs, seven weeks in the case of Bitcoin, and six weeks in the case of Ethereum.

The effect of ICO shocks on both cryptocurrencies are negative, which is in line with the mechanism of ICOs described in Figure 1. Both firms conducting an ICO and the remaining actors in an ICO campaign (e.g., contributors, entrepreneurial firms) normally aim at selling tokens in secondary markets to receive fiat after an ICO. Thus, a shock in ICO consequently lead to a decline of cryptocurrency prices. We observe a significant compression of Bitcoin prices one to three weeks after the shock with a maximum effect of 6.2 percentage points (pp) after one week. The negative reaction of Ethereum becomes significant after two weeks and remains so until eight weeks after the shock. Here, the maximum contraction of 10 pp is found after seven weeks. To put these figures into perspective, we need to account for the size of the shock in the ICO indicator, which amount to 4.6 bps. Hence, shocks to the ICO indicator lead to reactions of more than twice its size in the case of Ethereum and of roughly one-and-a-half the size in the case of Bitcoin.

Turning to the reaction of ICOs to either of the cryptocurrencies, we observe a positive and significant reaction to shocks in both variables. Innovations in Ethereum have a highly significant and pronounced effect on ICOs three to 14 weeks after the shocks with a peak effect of 3.7 pp after nine weeks. In contrast, shocks to Bitcoin only trigger a significant responses five to eleven weeks after the shock with a maximum increase of 3.4 pp after eleven weeks. Accounting for the size of the shocks (12.9 pp for Bitcoin and 15.2 for Ethereum) illustrates that the effect of shocks to cryptocurrencies on ICOs is only roughly a quarter of their size. Hence, innovations in ICOs rather drive changes in cryptocurrencies than the other way around.

Finally, we take a closer look at the relationship between both cryptocurrencies. In line with the idea that Bitcoin is the benchmark cryptocurrency, we detect no significant effects of shocks in Ethereum prices on Bitcoin prices at any horizon under consideration. In contrast, shocks to Bitcoin exert a significant positive effect on Ethereum on impact until six weeks after the shock. The peak effect of 12.6 pp is found after three weeks and amount to roughly one standard deviation in the triggering variable.

Figure 3: Impulse responses of VAR model



Notes: Figure 3 shows the impulse responses (solid lines, in percentage points) to a one standard deviation shock in the ICO indicator (left panel), bitcoin prices (middle panel), and Ether prices (right panel) alongside the corresponding 95% confidence bands (dashed lines). Cholesky decomposition is based on the following ordering: (i) ICO, (ii) Bitcoin, and (iii) Ethereum.

As part of our robustness tests, we replace the indicator for the cumulative amount of money raised in ICO campaigns by the cumulative number of successfully completed ICO campaigns (also linearly de-trended). Similar to our baseline model, we also estimate a VAR(2) model and obtain the impulse responses based on the same recursive ordering. Figure A1 in the Appendix shows the results. In the following discussion, we focus on the dynamic relationships between either of the cryptocurrencies and the ICO indicator.

We no longer detect a negative response of Ethereum after shocks to the ICO indicator. Similarly, there is no positive reaction in the number of successful ICO campaigns to Bitcoin shocks. The only two results that carry over from the baseline model are the negative response of Bitcoin to ICO shocks and the positive reaction of ICO to Ethereum shocks. Hence, it appears that the total amount of money raised in ICO campaigns is the better indicator for explaining the dynamic relationship between ICOs and the two cryptocurrencies.

5 Conclusions and Implications

Our paper is among the first to identify market cycles in and shocks to ICO and cryptocurrencies. In our VAR model, we use recent amounts raised by ICO campaigns, bitcoin and Ether prices between January 2017 and April 2018. First, we find evidence that a bullish (bearish) market in the case of ICOs remains bullish (bearish) for approximately four weeks, whereas shocks to bitcoin and Ether prices are persistent for seven and six weeks, respectively. Hence, a hype in ICOs positively influences subsequent ICOs which is in line with the finance literature on IPOs (e.g., Lowry and Schwert 2002). Thus, entrepreneurial firms and ventures intending an ICO should be aware of the spillover and hype effect and carefully decide the timing of their ICO start.

Second, ICO shocks on both bitcoin and Ether prices are negative. In general, this is bad news for investors investing in cryptocurrencies before a successful ICO campaign, such as Telegram, as prices in cryptocurrencies may decrease considerably after an ICO shock. Furthermore, shocks to ICOs have generally a much stronger effect on Ethereum than on Bitcoin. An explanation for this phenomenon may be related to the fact that the vast majority of ICOs is based on the Ethereum platform and investors hence require Ether rather than bitcoin to invest in an ICO campaign.

Third, innovations in either Ethereum or Bitcoin positively influences ICOs three to 14 weeks after the shock. Innovations in ICOs, however, tend to rather drive changes in cryptocurrencies than vice versa. According to the aforementioned mechanism and processes of ICO campaigns (see Section 2.2), investors, contributors and the venture itself conducting an ICO typically aim at exchanging tokens to both cryptocurrencies and particularly fiat. Therefore, a shock to ICOs negatively influences cryptocurrency prices. Finally, shocks to bitcoin prices particularly influences Ether prices than the other way around. Bitcoin as the first and leading cryptocurrency in terms of market capitalization, hence, partly determines the prices of Ether. In summary, the hype effect surrounding ICOs and cryptocurrencies identified in this paper is an important step towards solving the puzzle of the high amount raised in past ICO campaigns. Future research should consequently be aware of the relationship between ICOs and Bitcoin/Ether when investigating either the mechanism of cryptocurrencies or ICO campaigns. Future research may further improve the understanding of the new emerging financing instrument to mitigate imbalances in financing for innovative entrepreneurial firms and prevent future bubbles.

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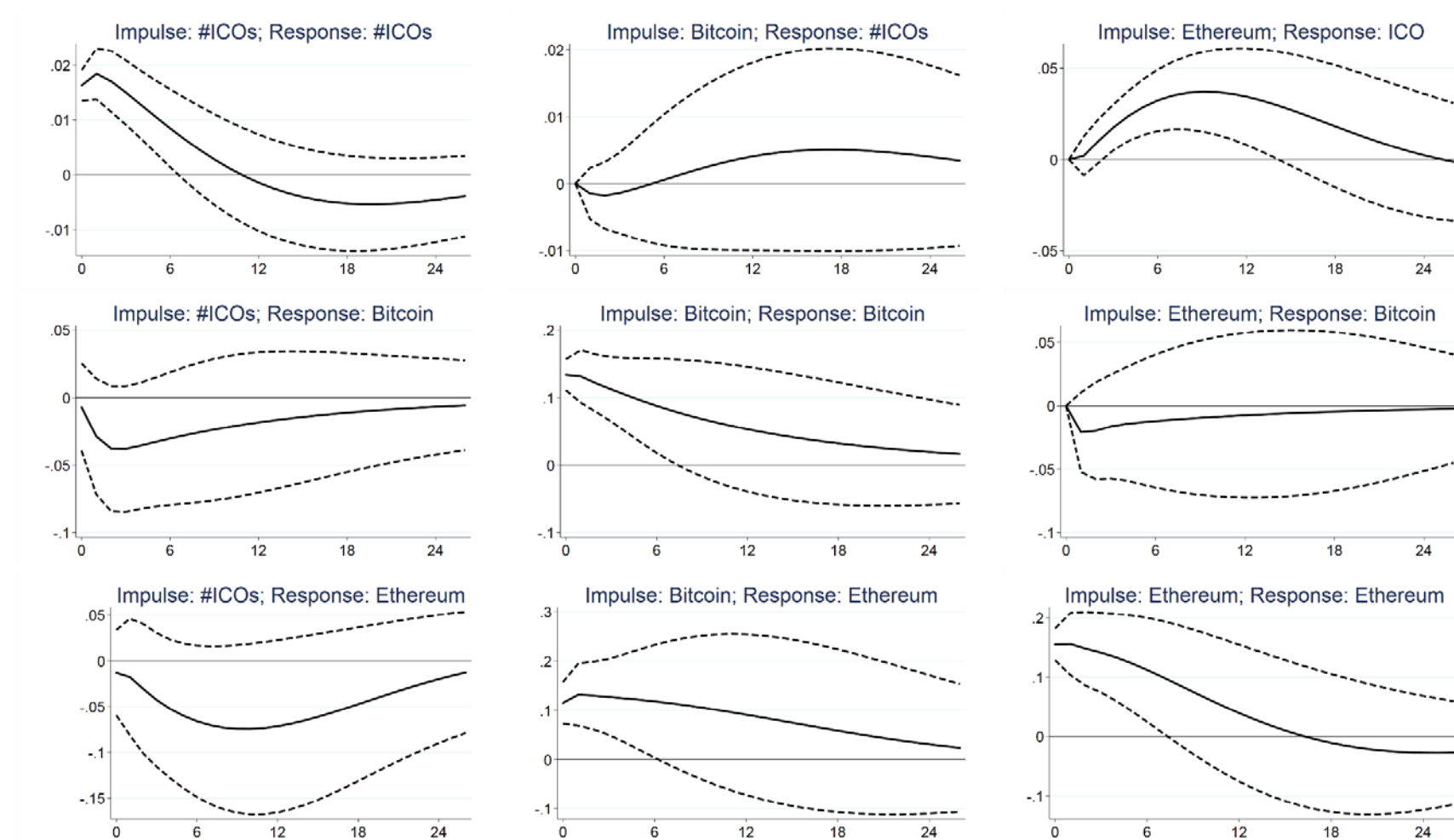
Appendix

Table A1: Descriptive Statistics

	ICO	Bitcoin	Ethereum
<u>Level</u>			
Mean	21.13	8.20	5.21
Standard Deviation	1.19	0.93	1.44
Minimum	19.40	6.72	2.13
Maximum	23.05	9.86	7.16
Correlation with ICO	1	0.931	0.898
Correlation with Bitcoin	0.931	1	0.913
Correlation with Ethereum	0.898	0.913	1
Deterministic Trend	0.059	0.066	0.044
 <u>De-Trended</u>			
Mean	0	0	0
Standard Deviation	0.191	0.315	0.636
Minimum	−0.334	−0.817	−1.348
Maximum	0.384	0.929	1.476
Correlation with ICO	1	0.045	0.174
Correlation with Bitcoin	0.045	1	0.456
Correlation with Ethereum	0.174	0.456	1
Unit Root Test	−2.48	−2.16	−2.33

Notes: The upper part of Table A1 displays descriptive statistics for the amount raised in ICO campaigns as well as the prices of Bitcoin and Ethereum in log-levels (see also Figure 2), whereas the lower part provides the corresponding statistics for the linearly de-trended series (see also Figure 3). All deterministic trends are significant at the 1% level and all unit root tests (with three lags; lag length selection based on Schwert's (1989) rule) are significant at the 5% level.

Figure A1: Impulse responses of VAR model with Number of ICOs



Notes: Figure A1 shows the impulse responses (solid lines, in percentage points) to a one standard deviation shock in the ICO indicator (left panel), bitcoin prices (middle panel), and Ether prices (right panel) alongside the corresponding 95% confidence bands (dashed lines). Cholesky decomposition is based on the following ordering: (i) #ICOs, (ii) Bitcoin, and (iii) Ethereum.