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Abstract

We apply time series analysis to investigate the market cycles of Initial Coin Offerings (ICOs) as well as bitcoin and Ether. Our results show that shocks to ICO volumes are persistent and that shocks in bitcoin and Ether prices have a substantial and positive effect on these volumes – with the effect of bitcoin shocks being of shorter duration than that of Ether shocks. Moreover, higher ICO volumes cause lower bitcoin and Ether prices. Finally, bitcoin shocks positively influence Ether but not the other way round. Our study has implications for financial practice, in particular for cryptocurrency investors and entrepreneurial firms conducting ICOs.

Keywords: blockchain, cryptocurrency, entrepreneurial finance, initial coin offering, bitcoin, Ether, time series analysis

JEL Classifications: G11, E22, O16

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1 Introduction

Cryptocurrencies are digital currencies that rely on blockchain technology. They emerged with the invention of bitcoin in 2008. Cryptocurrencies, such as bitcoin or Ether, have gained momentum recently and a hype has emerged around them. The market capitalization of cryptocurrencies has sky-rocketed and public awareness has considerably grown. Bitcoin prices reached a peak of approximately 19,361 USD per bitcoin in December 2017. This hype, together with the diffusion of blockchain technology, has furthered Initial Coin Offerings (ICOs) as a new financing instrument for entrepreneurial firms with blockchain-based business models.

In an ICO, blockchain-based ventures typically create their own cryptocurrency and distribute it among investors against bitcoin or Ether. Since 2016, more than $12.0 billion has been raised in 767 ICO campaigns, highlighting the relevance of ICOs for the proliferation of entrepreneurial finance. In this context, our study examines the following interrelated research questions: First, to what extent do market cycles with ICOs exist? More specifically, are ICO volumes persistent? Can we observe indications of spillover effects and bubbles? Second, to what degree do market cycles of bitcoin and Ether prices influence ICO volumes and vice versa?

To address our research questions, we collect a data set that covers ICO volumes, bitcoin and Ether prices over a period of 68 weeks from January 2017 to April 2018. Our data sources are CoinSchedule for ICOs and CoinMarketCap for bitcoin and Ether prices in USD. We expect to see market cycles, as well as evidence of persistence, in that past ICO volumes influence subsequent ones. Such an effect would be in line with the financing literature on Initial Public Offerings (IPOs) (e.g., Lowry and Schwert 2002). Most ICOs are token-based and require the investor to exchange cryptocurrencies such as bitcoin and Ether for tokens. Hence, we expect bitcoin or Ether prices to be a leading indicator for subsequent ICO volumes. To test our predictions, we apply a recursively identified vector autoregression (VAR) model to the three time series under consideration.

Our results show that shocks to ICO volumes are indeed persistent and that shocks in bitcoin and Ether prices have a substantial and positive effect on ICO volumes – with the effect of bitcoin shocks on ICO volumes being of shorter duration than the effect of Ether. Moreover, higher ICO volumes cause lower Ether and bitcoin prices. Finally, bitcoin shocks positively influence Ether but not the other way round, supporting the notion that bitcoin is the leading cryptocurrency. Our results are robust when considering the number of ICOs rather than ICO volumes.

Our study contributes to research on cryptocurrencies (e.g., Boehme et al. 2015; Cheah and Fry 2015; Urquhart 2018), ICOs (Adhami et al., 2018), and how these transformative innovations are used to finance blockchain-based ventures (Csóka and Herings 2017; Iansiti and Lakhani 2017). It also contributes to the literature on crowd-based venture financing (Lin and Viswanathan 2015; Younkin and Kuppuswamy 2017). Our results have implications for financial practice, particularly for cryptocurrency investors and entrepreneurial firms seeking to conduct an ICO. The latter group can see from our results that market timing is an important factor determining the success of an ICO, and that not only past ICO volumes matter in this regard, but also that bitcoin and Ether prices have substantial effects.

2 Context and Theoretical Background

2.1 Cryptocurrencies and ICOs

Cryptocurrencies are digital currencies and applications of blockchain technology, in which all rules and regulations are programmed in a cryptographic algorithm. The vast majority of cryptocurrencies are based on a peer-to-peer network and a blockchain, where all transactions are recorded and validated as a ledger. Similar to fiat currencies, they can be used to buy or sell products and services. Bitcoin and Ether are one of the most important cryptocurrencies and – as with gold, Euro, U.S. Dollar, Japanese yen or any further fiat currency – represent a widely accepted medium of value exchange. In the case of cryptocurrencies, the value is simply based on supply and demand, and is not influenced by government and/or central banks. Furthermore, cryptocurrency users can transfer a value without intermediaries or geographic limitations.

In an ICO, blockchain-based ventures generally raise capital by selling tokens (rather than shares, as in an IPO) to investors in exchange for cryptocurrencies (e.g., bitcoin, or Ether) or fiat. Tokens represent an asset or utility that is based on a blockchain. There are three main types of token, namely currency tokens, equity tokens, and utility tokens. First, currency tokens or coins are digital tokens, which were initially introduced along with Bitcoin in 2008 by Satoshi Nakamoto. Currency tokens refer to a digital medium of value exchange. Second, equity tokens (or security tokens) represent ownership rights to an asset, such as debt or company stock. In line with the Howey test, equity tokens fall under the regulatory scope of the U.S. SEC, since they are categorized as securities under securities law. Third, utility tokens (also known as app coins or app tokens) provide users with access to a product or service (similar to reward-based crowdfunding). They allow investors to fund the development of a blockchain project and gain access to the specific service or product in the future. Since utility tokens are not a typical investment, these tokens are not yet regulated. They are nevertheless very popular in ICOs. Regardless of the type of token used, the common link between all past and future ICOs is that the buyers of the tokens generally speculate that their value will increase, and that they will be able to secure or sell them in secondary markets.

2.2 Related literature

The two pieces of literature most closely related to our study deal with market cycles of cryptocurrencies and IPOs.

Brauneis and Mestel (2018) find that bitcoin is the most efficient cryptocurrency by virtue of being the least predictable. Using vector autoregression and impulse response results, Urquhart (2018) shows that the attention received by bitcoin is influenced by both the volatility and volume realized the previous day. Applying different GARCH models, Katsiampa (2017) reveals that the bitcoin market is highly speculative and the optimal model for predicting bitcoin prices is the AR-CGARCH. Urquhart (2017) finds price clustering in bitcoin at round numbers. Furthermore, Corbet et al. (2018) show that cryptocurrencies are interconnected, but disconnected from other financial markets such as the S&P500 or gold.

Prior research has used time series analyses to evaluate IPO market cycles, timing, and equity returns (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 once they see other firms obtaining high initial returns. 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 finds similar results: IPO volume is sensitive to contemporaneous IPOs, and if firms in a particular industry go public, this is indicative of the overall growth prospects of the specific industry and affects IPO market cycles (e.g., Benveniste et al. 2003). Furthermore, some prior studies use VAR models to identify market cycles of IPOs. Lowry et al. (2010) shows that initial IPO returns fluctuate considerably over time and are significantly higher during hot IPO markets. Using a VAR model, Doidge et al. (2017) reveal a considerable decline in publicly listed companies in the U.S. in 2010 compared to 1975.

To date, no research exists about the triangle of ICOs, bitcoin and Ether, and how their market cycles interact.

3 Data and Econometric Methodology

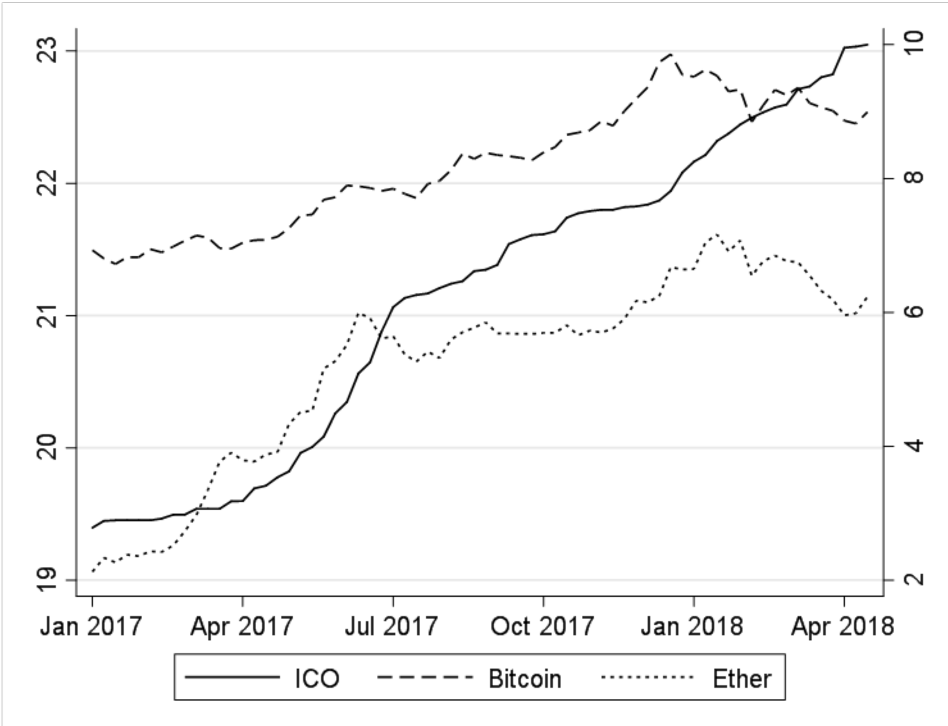
3.1 Data

Our data set covers 68 weekly observations for the period from 2 January 2017 to 16 April 2018,[1] 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, and has been used in previous media articles (e.g., Economist). Beside the amount raised in the ICO in USD, CoinSchedule includes information about the date of the ICO and the website of the corresponding ICO campaign. Second, CoinMarketCap provides information on daily bitcoin and Ether prices in USD. As we have permission to access API calls, we can retrieve daily bitcoin and Ether prices.

Figure 1 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 Ether (6.55% per week), followed by the ICO indicator (5.93% per week), and bitcoin (4.42% per week).

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

Figure 1: ICO volumes, bitcoin prices, and Ether prices over time (in logs)

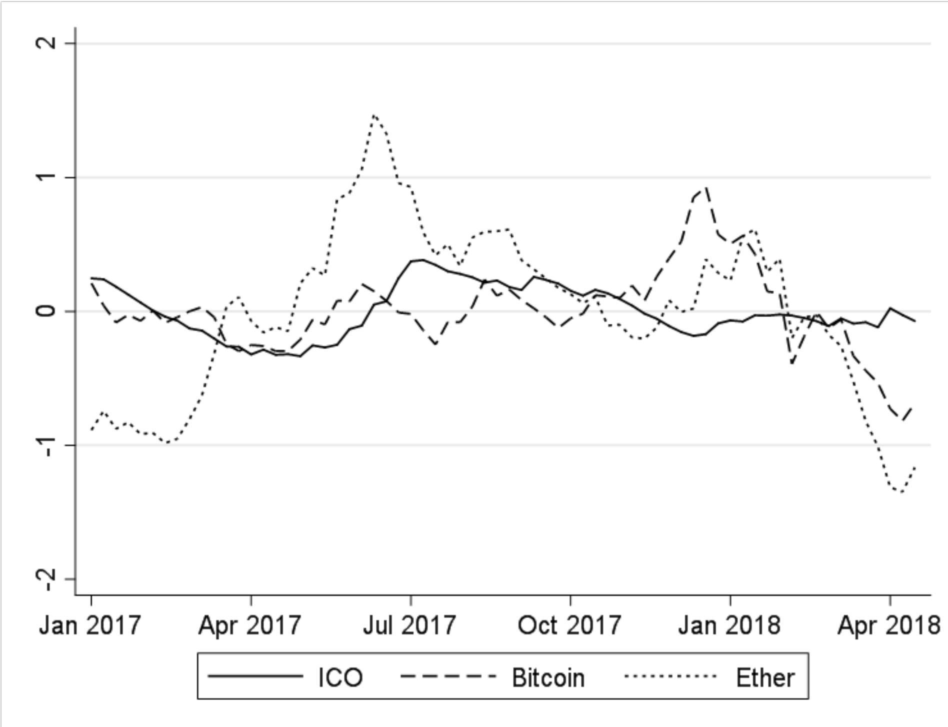


Notes: Figure 1 shows the amount raised in ICO campaigns (left axis) as well as the prices of bitcoin and Ether (both on right axis). All variables are in logs.

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.[2] Figure 2 shows the evolution of the de-trended variables over time.

[2] 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 volumes, bitcoin price, and Ether price over time (in logs, de-trended)



Notes: Figure 2 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.

Ether 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 Ether than in bitcoin or ICOs. The correlation between pairs is found to be the strongest in the two cryptocurrencies ($\rho = 0.46$), followed by ICO and Ether ($\rho = 0.17$), and ICO and bitcoin ($\rho = 0.04$). Hence, it appears that the relation between the two cryptocurrencies and the ICO indicator is, at best, rather modest. However, it remains to be seen whether 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 in its reduced form as follows:

$$X_t = \delta + \sum_{i=1}^{p} \boldsymbol{A}_i X_{t-i} + U_t \tag{1}$$

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 $\boldsymbol{A}_i$ 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 Ether 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 least-squares estimation of Eq. (1) 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-moves 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. To do so, we impose a recursive identification scheme that orthogonalizes the residuals and transforms these into true innovations, which are uncorrelated to each other.

A Cholesky decomposition of this nature 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 representation[3] of Eq. (1) can be transformed as follows:

$$X_t = \mu + U_t - \sum_{i=1}^{\infty} \boldsymbol{B}_i U_{t-i} \tag{2}$$

$$X_t = \mu + PP^{-1}U_t - \sum_{i=1}^{\infty} \boldsymbol{B}_i PP^{-1} U_{t-i} \tag{3}$$

Defining $\boldsymbol{\theta}_i = \boldsymbol{B}_i P$, $\boldsymbol{\theta}_0 = P$, and $W_t = P^{-1}U_t$, we can simplify Eq. (3) as follows:

$$X_t = \mu + \boldsymbol{\theta}_0 W_t - \sum_{i=1}^{\infty} \boldsymbol{\theta}_i W_{t-i} \tag{4}$$

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 shocks.

This kind of identification scheme obviously requires assumptions on the instantaneous relationships across the three variables. We propose to order ICOs first, followed by bitcoin and Ether. 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

[3] Every stable VAR of order p can be rewritten as a vector moving average model of order infinity, that is, the weighted sum of all residuals.

Ether prices, but not vice versa. The theoretical idea is that investors who engage in ICOs are driven by "longer-term" considerations, at least compared to buying and selling cryptocurrencies. Hence, ICOs are the slowest-moving variable and only affected by shocks to the cryptocurrencies with a time lag. Bitcoin is considered the benchmark cryptocurrency, which is why we order it before Ether and allow for a contemporaneous reaction of Ether to shocks in bitcoin.[4]

4 Empirical Results

4.1 Results of VAR Model and Granger Causality Tests

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

Table 1: Estimates of VAR model

	1: ICO		2: Bitcoin		3: Ether	
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)
$Ether_{t-1}$	0.014	(0.036)	–0.123	(0.104)	**0.965**	**(0.149)**
$Ether_{t-2}$	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. The line headed 'Portmanteau' shows statistics for a test of the null hypothesis of no serial correlation. Number of observations: 66.

Most of the variation in the three variables can be explained by their lagged value(s). Solely in the case of bitcoin, we detect a statistically significant, albeit offsetting, influence of lagged values on the ICO indicator. Granger causality tests, that is, tests for joint exclusion of both lags for any one variable from the equation of another variable, indicate that we find a simple Granger causal relationship from Ether 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 Ether prices (F(2,59) = 3.04).

[4] 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 can provide all other results on request.

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 Ether, the conditional correlation is quite substantial ($\rho = 0.59$). The correlations between ICO and bitcoin ($\rho = -0.20$), and ICO and Ether ($\rho = -0.11$), also indicate that we cannot interpret the residuals as true shocks to any 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 one of the variables transmits through the system on impact and for the 26 weeks thereafter.

4.2 Impulse Response Functions

Figure 3 shows the impulse responses functions (solid lines) alongside the 95% confidence bands (dashed lines). As indicated by the impulse responses on the main diagonal, shocks to any 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 Ether.

The effects of ICO shocks on both cryptocurrencies are negative, which is in line with the mechanism of ICOs. Both firms conducting an ICO and the remaining actors in an ICO campaign (e.g., contributors, entrepreneurial firms) normally aim to sell tokens in secondary markets afterwards, in order to receive fiat. Thus, a shock in an ICO leads to a decline in 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 Ether 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 to the ICO indicator, which amounts to 4.6 bps. Hence, shocks to the ICO indicator lead to reactions of more than twice the size in the case of Ether and of roughly one-and-a-half times the size in the case of bitcoin.

Turning to the reaction of ICOs to the cryptocurrencies, we observe a positive and significant reaction to shocks in both variables. Innovations in Ether have a highly significant and pronounced effect on ICOs after three to 14 weeks, with a peak effect of 3.7 pp after nine weeks. In contrast, shocks to bitcoin only trigger a significant response five to eleven weeks after the event, with a maximum increase of 3.4 pp after eleven weeks. When we account for the size of the shocks (12.9 pp for bitcoin and 15.2 for Ether), we can see that their effect on ICOs is only roughly a quarter of the original size. Hence, innovations in ICOs tend to drive change in cryptocurrencies rather than the other way round.

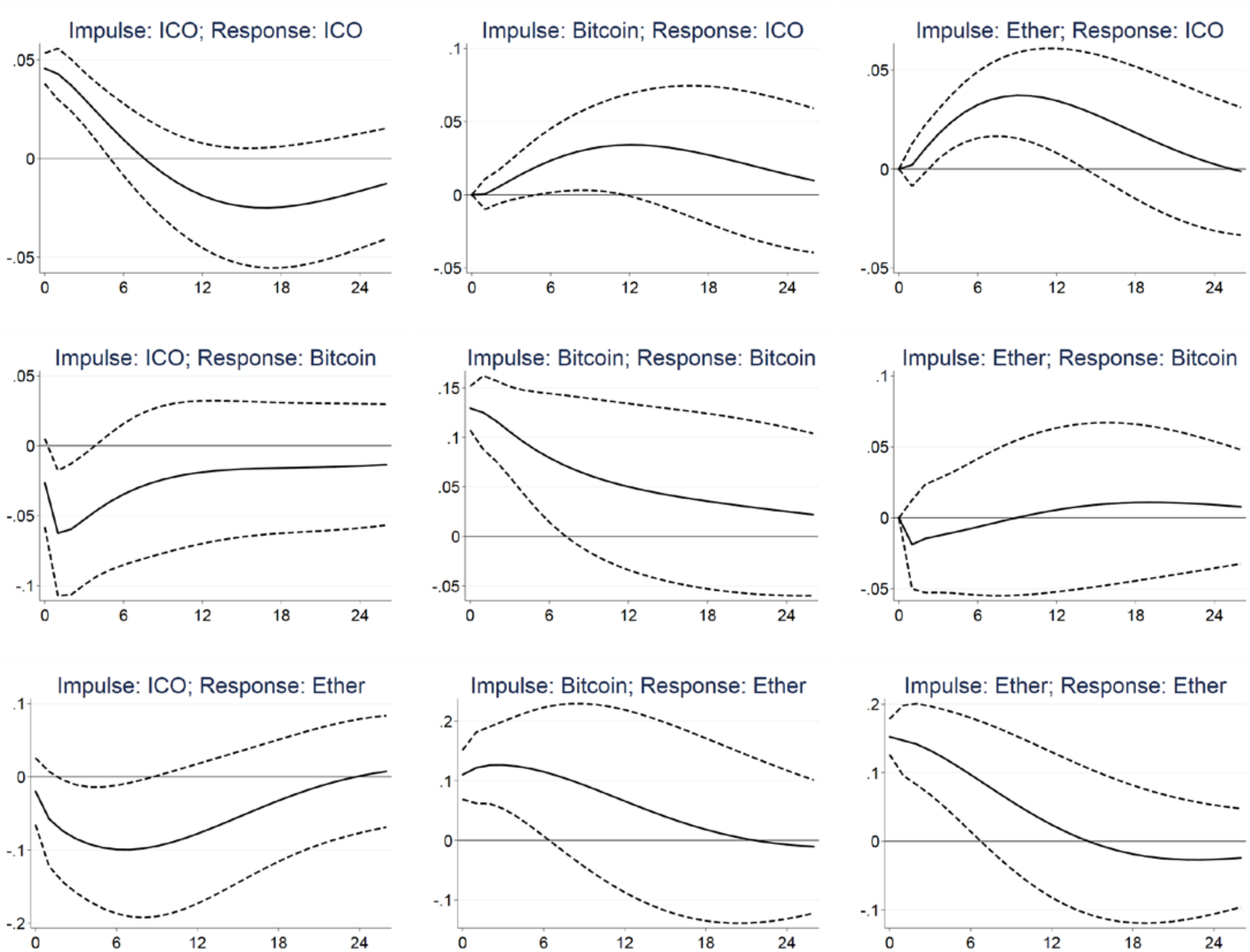
Finally, we take a closer look at the relationship between the two cryptocurrencies. In line with the idea that bitcoin is the benchmark, we detect no significant effects of shocks in Ether prices on bitcoin prices at any horizon under consideration. In contrast, shocks to bitcoin exert a significant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

4.3 Robustness Tests

As part of our robustness tests, we replace the indicator for the cumulative amount of money raised (volume) in ICO campaigns by the cumulative number of successfully completed ICO campaigns (also linearly de-trended). As with 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 the cryptocurrencies and the ICO indicator.

We no longer detect a negative response of Ether after shocks to the ICO indicator. Similarly, there is no positive reaction to bitcoin shocks in terms of the number of successful ICO campaigns. 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 ICOs to Ether 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.

Figure 3: Impulse responses of VAR model



Notes: Figure 3 shows the impulse responses (solid lines, in percentage points) to 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) Ether.

5 Conclusions and Implications for Financial Practice

Our study is the first to identify market cycles in and shocks to ICOs and cryptocurrencies, and is closely related to a set of papers that uses VAR models to analyze market cycles of cryptocurrencies and IPOs (e.g., Doidge et al. 2017; Lowry et al. 2010). In our VAR model, we use amounts raised by ICO campaigns, bitcoin and Ether prices between January 2017 and April 2018. Our main results are as follows: 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 one ICO positively influences subsequent ICOs, which is in line with the respective literature (e.g., Lowry and Schwert 2002). Second, the effect of ICO shocks on both bitcoin and Ether prices are negative. Furthermore, shocks to ICOs have a stronger and more persistent effect on Ether than on bitcoin. An explanation for this phenomenon may be related to the fact that the vast majority of ICOs are based on the Ethereum platform, and investors therefore require Ether rather than bitcoin to invest. Third, innovations in either Ether or bitcoin positively influence ICOs three to 14 weeks after the shock. In general, innovations in ICOs are seen to drive change in cryptocurrencies than the reverse. According to the mechanism of ICO campaigns, investors, contributors, and the actual venture conducting the ICO typically aim to exchange tokens for cryptocurrencies and, in particular, fiat money. A shock to ICOs therefore negatively influences cryptocurrency prices. Finally, shocks to bitcoin prices influence Ether prices more strongly than the other way round. Bitcoin, as the first and leading cryptocurrency in terms of market capitalization, thus partly determines Ether prices. In summary, market cycles of ICOs, bitcoin and Ether are seen to exist and interact.

Our results are relevant for cryptocurrency investors and blockchain-based ventures seeking to obtain entrepreneurial finance through an ICO. First, market timing matters when planning an ICO campaign. Entrepreneurial firms intending to conduct an ICO should be aware of the spillover and hype effects, and use this knowledge to choose the optimum time to launch their ICO campaign. The decision to kick off during hot ICO and cryptocurrency markets will most probably lead to higher volumes in the respective ICO campaign. Second, the interplay between cryptocurrencies and ICOs is of particular relevance for cryptocurrency investors. After a successful ICO campaign, such as Telegram that collected approximately 1.7 billion USD, prices in cryptocurrencies may decrease considerably. Investors should therefore be aware of blockbuster ICOs when looking to buy or sell cryptocurrencies.

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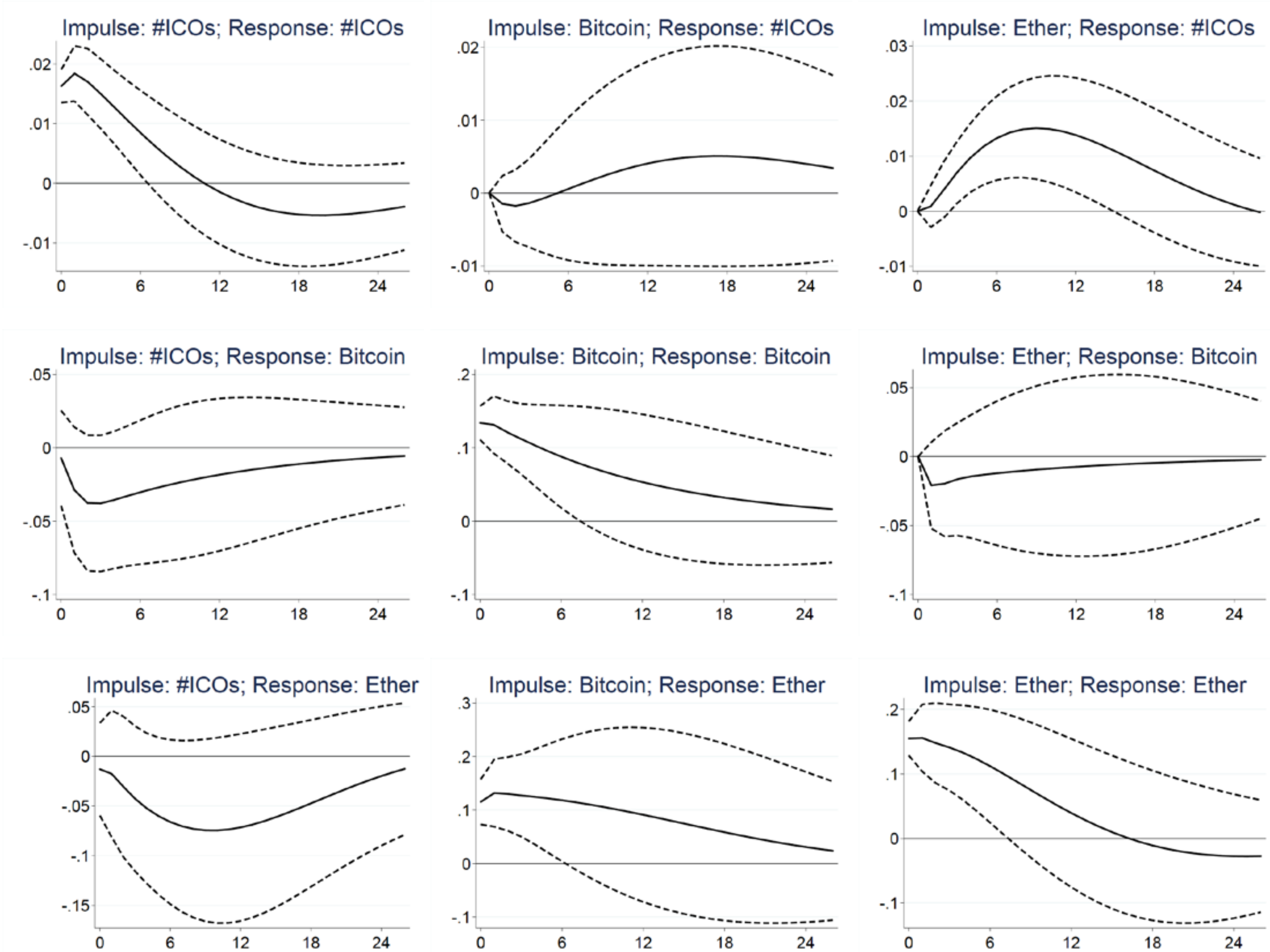
Appendix

Table A1: Descriptive Statistics

	ICO	Bitcoin	Ether
Level			
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 Ether	0.898	0.913	1
Deterministic Trend	0.059	0.066	0.044
De-Trended			
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 Ether	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 Ether 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 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) Ether.