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Initial coin offerings (ICOs): market cycles and relationship with bitcoin and ether

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Abstract We apply a vector autoregression (VAR) model to investigate the market cycles of Initial Coin Offerings (ICOs) as well as their relationships with bitcoin and ether. Our sample covers 104 weekly observations between January 2017 and December 2018. Our results show that ICO market cycles exist and that shocks to the growth rates of ICO volumes are persistent. In addition, shocks in cryptocurrency returns have a substantial and positive effect on ICO volumes. In contrast, the volatility of cryptocurrency returns does not significantly affect ICO volumes. Our results are robust to using (i) the number of successfully completed ICO campaigns instead of ICO volumes and (ii) ICO data from a different data source. Our study has implications for financial practice, in particular for cryptocurrency investors and entrepreneurial firms conducting ICOs.

Keywords Initial coin offering (ICO) · Blockchain · Cryptocurrency · Distributed ledger technology · Entrepreneurial finance · Bitcoin · Ether · Vector autoregression (VAR) model

JEL classifications G11 · E22 · O16 · L26

1 Introduction

Cryptocurrencies are digital currencies that rely on a distributed ledger technology (DLT) (Fisch 2019). They emerged with the invention of bitcoin in 2008. Cryptocurrencies, such as bitcoin or ether, have recently gained momentum, and a hype has emerged around them. The market capitalization of cryptocurrencies has skyrocketed, and public awareness has grown considerably. Bitcoin prices reached a peak of approximately US$19,361 per bitcoin in December 2017. This hype, together with the diffusion of DLT, has promoted Initial Coin Offerings (ICOs) as a new financing instrument for entrepreneurial firms (Adhami et al. 2018; Amsden and

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Schweizer 2018; Boreiko and Sahdev 2018; Fisch 2019; Huang et al. in press).

In an ICO, DLT-based ventures create their own cryptocurrency and distribute it among investors against, for instance, bitcoin or ether (Fisch 2019). The ICO website CoinSchedule.com records that from 2013 to 2018, more than US$28.0 billion has been raised in 1601 ICO campaigns, which highlights the relevance of ICOs for the proliferation of entrepreneurial finance. In this context, our study examines the following three research questions: First, to what extent are ICO shocks persistent, and do ICO market cycles exist? Second, how do bitcoin and ether returns influence ICO volumes and vice versa? Third, how does volatility in cryptocurrency markets influence ICO volumes?

To address our research questions, we collected a dataset that covers ICO volumes as well as bitcoin and ether prices over a period of 104 weeks from January 2017 to December 2018. Our data sources are CoinSchedule.com (Fisch 2019) and icodata.io (Boreiko and Sahdev 2018) for ICOs and CoinMarketCap (Fisch 2019) for bitcoin and ether prices in USD. We expect to find evidence of a persistent effect of past ICO volumes influencing subsequent ones. Such an effect would be in line with the market cycle literature on initial public offerings (IPOs) (e.g., Lowry and Schwert 2002). Furthermore, both bitcoin and ether have the highest market capitalization (according to CoinMarketCap in February 2019) and are consequently the leading cryptocurrencies. Most ICOs are token-based and require the investor to exchange either bitcoin or ether for tokens. Thus, if the bitcoin or ether price is high, this leads to a higher amount raised in the corresponding ICO. Moreover, high bitcoin and ether prices may be indicators of a positive market momentum and the potential hype that is characteristic of the cryptocurrency and DLT sphere. As a result, we expect bitcoin or ether returns to be the leading indicators of subsequent ICO volumes. Furthermore, Urquhart (2018) highlights the volatility of cryptocurrencies as a pricing factor of these. Consequently, one would expect that the volatility of cryptocurrency markets would influence subsequent ICO volumes as well.

To test our predictions, we apply a vector autoregression (VAR) model to the three time series under consideration. We apply two different recursive schemes to identify the effects of (i) shocks on the growth rate of ICO volumes, (ii) shocks on bitcoin returns, and (iii) shocks on ether returns for all the variables in the VAR. Since there is substantial co-movement in the returns of both cryptocurrencies, we extract a common cryptocurrency factor as part of our further analysis. Finally, we also account for the potential effects of volatility in the cryptocurrency market on ICOs by augmenting the VAR with variables for bitcoin volatility and ether volatility in another extension. Our results show that shocks to the growth rates of ICO volumes are indeed persistent and that ICO market cycles exist. In addition, shocks in cryptocurrency returns have a substantial and positive effect on these volumes. In contrast, the volatility of cryptocurrency returns does not significantly affect ICO volumes. Our results are robust to using (i) the number of successfully completed ICO campaigns instead of ICO volumes and (ii) to using ICO data from a different source.

Our study contributes to the small but growing literature on ICOs (e.g., Adhami et al. 2018; Amsden and Schweizer 2018; Boreiko and Sahdev 2018; Fisch 2019). It presents evidence for market cycles in ICO markets and shows that ICO volumes are connected to returns from bitcoin and ether. Most of the ICO research so far has focused on ICO campaigns and the success determinants of ICOs (e.g., Adhami et al. 2018; Fisch 2019). To the best of our knowledge, our study is the first to analyze how the returns from one ICO influence the returns of subsequent ICOs and how these returns are driven by the overall cryptocurrency climate. Our study connects ICO research to the literature on IPO drivers and trends (Doidge et al. 2017; Gao et al. 2013; Signori and Vismara 2018). This literature has shown that IPO market cycles exist (Lowry 2003; Lowry and Schwert 2002; Lowry et al. 2010). Furthermore, our study is also related to the literature on the funding dynamics of crowd-based venture financing (Hornuf and Schwienbacher 2018; Thies et al. 2018; Vismara 2018). This literature has focused on reward and equity crowdfunding through platforms as intermediaries and has shown that there exist specific funding dynamics *within* funding campaigns. Our study adds to this literature by showing that there also exist funding dynamics *between* different campaigns.

Our results have implications for financial practice, in particular for ventures seeking to conduct an ICO. Such ventures can tell from our results that market timing is an important factor that determines the success of an ICO. Such ventures should be aware of the spillover and hype effects and carefully decide when to start their ICO campaign. A start during a “hot” ICO market period will lead to increased volumes compared to a start in other periods. Our results further suggest not only that past ICO volumes matter but also that bitcoin and ether returns can have substantial effects. Volatility in cryptocurrency markets appears not to play a role in ICO returns. Therefore, ICO investors appear to be relatively immune to increases in investment risk resulting from volatile cryptocurrency markets. An explanation for this behavior could be that ICO investors do not primarily invest for speculative and financial reasons (Fisch et al. 2018).

The remainder of the paper is organized as follows: Sect. 2 introduces the study context; Sect. 3 summarizes the related literature; Sect. 4 presents our data and econometric model; Sect. 5 shows our baseline results; Sect. 6 includes further analyses and robustness tests; and Sect. 7 concludes the paper.

2 Context and background

2.1 Technology as an enabler of new ways of financing entrepreneurial ventures

Technology has led to the emergence of new players in entrepreneurial finance (Block et al. 2018a). Platform-based crowdfunding in its diverse forms, ranging from equity- and reward-based to donation-based funding, has received a great deal of attention (for reviews of the literature, see Mochkabadi and Volkmann (in press).Moritz and Block (2015). Platform-based crowdfunding has become available only through technologies such as the internet and social media. FinTech credit through e-commerce platforms, such as Alibaba, is another example where technology has mitigated local credit supply frictions and changed the financing of entrepreneurial ventures (Hau et al. 2018). Haddad and Hornuf (in press) show that FinTech start-ups and financial innovations are more likely to occur in countries with a larger number of secure internet servers and mobile telephone subscriptions. Similarly, by analyzing the data of 915 ICOs, Huang et al. (in press) found that ICOs take place more frequently in countries with advanced digital technologies and more developed investment-based crowdfunding platforms. Generally, the diffusion of technology-induced financial innovations provides new ways of assessing risk and dealing with financial information. The innovations also allow for easier participation of nonprofessional investors in new venture financing, thus providing greater liquidity and reducing monitoring costs. On the negative side, they can also lead to a higher contagion risk that results from a greater connectedness through securitization.

Our study concerns the financing of new ventures by means of ICOs. This financing instrument became available through the diffusion of DLT, e.g., blockchain. The next section describes in detail how new ventures can use ICOs to raise money and how this funding instrument is connected to established cryptocurrencies, such as bitcoin and ether.

2.2 Cryptocurrencies and ICOs

Cryptocurrencies are digital currencies and applications of DLT, in which all rules and regulations are programmed using 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 in a ledger. Similarly, to fiat currencies, they can be used to buy or sell products and services. Bitcoin and ether are among the most important cryptocurrencies and represent an accepted medium of value exchange (Fisch 2019). Their respective value is based on supply and demand and is not influenced by governments and/or central banks.

In an ICO, DLT-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. A token represents an asset or a utility that is based on DLT. There are three main types of tokens: currency tokens, equity tokens, and utility tokens. Currency tokens (e.g., bitcoin, ether, or ripple) 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 (Fisch 2019). Equity tokens or security tokens (e.g., the DAO) represent ownership rights to an asset, such as debt or company stock. Utility tokens, also known as app coins or app tokens (e.g., the joy or EndChain token), provide users with access to a product or a service (such as reward-based crowdfunding) (Fisch 2019). They allow investors to fund the development of a DLT project and gain access to a specific service or a product in the future. In general, the buyers of tokens normally speculate that their value will increase and that they will be able to secure or sell them in secondary markets.

Since the ICO market is unregulated and different types of tokens exist, ICO campaigns differ substantially from each other. Nevertheless, the main actors in every ICO campaign are the venture (capital seeker) that initiates the ICO campaign, the investors (the crowd), the trading exchanges (intermediaries), and the contributors (e.g., external participants that work for the ICO campaign). An ICO campaign typically consists of three stages, which can last several months and offer specific incentives to investors (Benedetti and Kostovetsky 2018).

Pre-ICO phase. An entrepreneurial firm intends to launch an ICO campaign. In preparation, the firm usually publishes a white paper and launches a website to inform potential investors about the ICO campaign (Fisch 2019). A white paper is an (electronic) document that provides key information about the ICO campaign and that is similar to a business plan (Fisch 2019). However, white papers are published voluntarily and are not subject to particular standards or specific guidelines. Whereas some white papers contain detailed information about the technology, others simply focus on financing aspects, the project team or the product itself. Furthermore, the entrepreneurial firm normally announces an advisory board (to signal the quality of the ICO project) and hires experts (e.g., marketing experts, legal advisors) for conducting the ICO campaign, in exchange for either capital or a considerable number of tokens. In particular, smaller firms lacking finance and resources tend to purchase external expertise in order to indicate their quality commitment to potential investors and to differentiate their ICO from other campaigns. To test market acceptance, firms conducting an ICO often offer private sales or presales. Private discussions or pitches from the venture to potential investors create interest in the ICO campaign and a willingness to invest (in a private sale) before the actual start of the ICO. At this stage, investors are usually able to invest fiat instead of cryptocurrencies (e.g., bitcoin or ether), which simplifies the process for both the investors and capital seekers, since they do not need to change fiat to cryptocurrencies. In the case of a public presale, firms conducting an ICO also try to gauge the market acceptance of their ICO as well as the smoothness of the ICO process (e.g., transfer of cryptocurrency investments to the accounts of the venture). In general, investors use trading exchanges, such as bitfinex.com, to exchange fiat (e.g., dollars or euros) for cryptocurrencies (mostly ether) in order to invest in the ICO. Investors in the private sale or presale phase typically receive discounts on the token price.

Main ICO phase. To promote the ICO campaign, the venture usually provides bonus schemes for ICO investors. As a result, early investors in the main ICO phase receive more tokens for the same token price. To receive tokens, potential private or institutional investors typically have to invest with cryptocurrencies. Some investors already possess a considerable amount of cryptocurrencies. If they do not, these investors generally use trading exchanges to exchange fiat for cryptocurrencies. Interestingly, the venture itself can decide the duration of the ICO campaign and extend the time for collecting money.

Post-ICO phase. After an ICO campaign, several actors (investors, ventures, contributors) aim to exchange tokens for fiat, and transactions involving tokens, fiat, and cryptocurrencies rise significantly. In particular, a venture that has conducted an ICO needs fiat in order to make investments and develop the product or service based on DLT. Trading exchanges offer the opportunity to change tokens to fiat or other cryptocurrencies. To trade tokens, ICOs have to be listed on a trading exchange, which typically takes time (often several months). In addition to the ICO firms, investors aim to increase the value of the tokens that they receive and sell them if their value rises considerably. The same is true for contributors to an ICO campaign. In particular, smaller ventures lack resources and often do not have specialists to conduct an ICO campaign for them. Therefore, ICO experts are hired to conduct the ICO campaign and are normally paid in tokens. Moreover, the majority of ICO campaigns involve advisory boards that signal technical and economic expertise. The members of these boards are typically rewarded with tokens. Like the investors, the contributors will typically sell the tokens after the ICO campaign if their value rises sharply.

3 Related literature

We have identified four specific research streams that are relevant to our study. These research streams deal with the funding dynamics and market cycles of ICOs, cryptocurrencies, IPOs, and crowdfunding.

Funding dynamics and market cycles of ICOs. Research on ICOs thus far has focused mainly on the campaign or project level. Little research has been carried out at the overall market level that is the focus of our study. Adhami et al. (2018) analyzed the determinants of ICO success using a hand-collected dataset from 253 ICO campaigns. In particular, the publicly available code source of the ICO, the presale of tokens, and the offering of tokens that allows investors to access a specific service positively influence the success of an ICO. Fisch (2019) analyzed 423 ICOs between 2016 and 2018. He found that high-quality source codes and technical white papers 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 team size) positively influences an ICO's success, whereas venture uncertainty (e.g., short white papers, not being on social media channels such as Telegram or GitHub) has a negative effect on ICO success. Boreiko and Sahdev (2018) analyzed ICO campaigns from different ICO listing sites and found that successful ICOs focus more on self-compliance, listing on ICO aggregation sites and selling fewer tokens to the developers of the ICO campaign, and that they have prior venture capital participation. Moreover, the coverage of a specific ICO on the ICO tracking list positively influences the success of an ICO, whereas the average rating of an ICO on the aggregated ICO sites has no effect on the success of an ICO (Boreiko and Vidusso 2018). Other working papers, such as Conley (2017), Enyi and Le (2017), Venegas (2017), and Yadav (2017), do not analyze empirical data but rather focus on the legal nature of cryptocurrencies and ICOs or on a theoretical analysis of token types. Therefore, the majority of working papers to date have primarily focused on either technical descriptions of ICO campaigns or the determinants of success by analyzing a single project or campaign characteristics. Thus far, few studies exist on the macrolevel drivers of ICOs. The only paper that we are aware of is Huang et al. (in press), who analyze the geographical determinants of ICOs. They find that ICOs occur more frequently in countries with more developed financial systems and public equity markets as well as advanced and pervasive digital technologies. Moreover, ICO-friendly regulations as well as the availability of investment-based crowdfunding platforms lead to higher ICO rates.

Funding dynamics and market cycles of cryptocurrencies. A number of previous studies deal with the market efficiency and price dynamics of bitcoin. Brauneis and Mestel (2018) find that bitcoin is the most efficient cryptocurrency by virtue of being the least predictable. Using VAR and impulse response results, Urquhart (2018) shows that the attention received by bitcoin is influenced both by the volatility and volume that were realized the previous day. Applying different GARCH models, Katsiampa (2017) demonstrates that the bitcoin market is highly speculative and that the optimal model for predicting bitcoin prices is the AR-CGARCH. Moreover, Urquhart (2017) finds price clustering in bitcoin at round numbers. Using data from 2013 to 2017, Caporale et al. (2018) analyzed four different cryptocurrencies, namely, bitcoin, litecoin, ripple, and dash. The results show that these cryptocurrencies are persistent, which implies that a bullish (bearish) market remains bullish (bearish). Bariviera (2017) and Bariviera et al. (2017) analyze the volatility of bitcoin prices and returns between 2011 and 2017. The results show that the bitcoin returns' time series has been white noise since 2014, whereas the volatility of the daily bitcoin returns has been persistent during the time period (2011–2017). Moreover, Bariviera (2017) finds a long memory in price volatility. In addition, prior research has analyzed and compared cryptocurrencies with each other or with other financial markets. Ji et al. (in press) focus on the spillovers of bitcoin volatility into a number of other financial assets, such as bonds, commodities, and currencies. In general, the bitcoin market appears to be relatively isolated. It is noteworthy to mention, however, that Chinese equities and energy commodities can explain approximately 16% and 18% of the bitcoin price volatility during the bear market time of the bitcoin (Ji et al. in press). This is in line with Corbet et al. (2018), who show that cryptocurrencies are interconnected but disconnected from other financial markets, such as the S&P500 or the gold market. In addition to finding interdependencies between bitcoin and ether volatilities, Katsiampa (in press) shows that ether appears to be an appropriate hedge against bitcoin. With regard to the high volatility of cryptocurrencies, it has been suggested that a potential herding effect exists, in the sense that cryptocurrency investors imitate solely the investment decisions of other investors. Using the daily returns of a large number of different cryptocurrencies (65 cryptocurrencies in total) between 2015 and 2017, Vidal-Tomás et al. (in press) find a herding effect during down markets. Moreover, altcoins, which are new alternative cryptocurrencies launched after bitcoin, are herding with the largest cryptocurrencies (e.g., bitcoin, ripple, litecoin, dash). Additionally, investors take into account not only bitcoin (the largest cryptocurrency in terms of market capitalization) but also other cryptocurrencies when making an investment decision. Bouri et al. (in press) support the findings of Vidal-Tomás et al. (in press) but show that herding behavior in cryptocurrencies can vary over time.

Funding dynamics and market cycles of IPOs. The overall number of IPOs has been going down for many years. While in the 1980s and 1990s in the US an average of 310 companies per year conducted an IPO, the numbers have decreased sharply to approximately 100 per year in the period after 2000. Both Gao et al. (2013) and Signori and Vismara (2018) attribute this decline to the higher attractiveness of trade sales and being acquired, relative to the benefit of conducting an IPO and operating as an independent firm. In fact, many innovative market entrants see being acquired by an incumbent as an attractive exit option and as the prize for having successfully developed a radical innovation (Henkel et al. 2015). Despite the overall decline in IPO markets, market cycles also exist. A number of prior studies have 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 a high IPO activity for about 6 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 issued 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 it also affects IPO market cycles (e.g., Benveniste et al. 2003). Furthermore, some prior studies use VAR models to identify the market cycles of IPOs. Lowry et al. (2010) show that IPO returns fluctuate considerably over time and are significantly higher during hot IPO markets. Using a VAR model, Doidge et al. (2017) demonstrate a considerable decline in the number of listed companies in the USA in 2010 compared to 1975.

Funding dynamics and market cycles of crowdfunding. ICOs and crowdfunding campaigns share some similarities (Fisch 2019). In both cases, an entrepreneurial firm seeks funding from a broad crowd of (mostly unprofessional) investors. The literature on the dynamics of crowdfunding and on crowdfunding cycles has focused more on the funding dynamics *within* crowdfunding campaigns (e.g., Burtch et al. 2013; Crosetto and Regner 2018; Hornuf and Schwienbacher 2018; Hornuf and Neuenkirch 2017; Kuppuswamy and Bayus 2017) and less on the funding dynamics *between* crowdfunding campaigns. It has been argued that individual crowdfunding investors base their investment decisions on information conveyed by the investment behavior of other crowd investors, which leads to information cascades (Vismara 2018). The typical funding pattern within a crowdfunding campaign is U-Shaped (Kuppuswamy and Bayus 2017). Crowdfunders typically invest in crowdfunding projects at the beginning and the end of a project. Hornuf and Schwienbacher (2018) show that the allocation mechanism of the crowdfunding platform matters and that it influences funding dynamics: a first-come mechanism leads to an L-shaped pattern, whereas an auction mechanism leads to a U-shaped pattern. Hornuf and Neuenkirch (2017) show that in addition to campaign characteristics, the investor sophistication, progress in funding, herding, and the stock market volatility influence the backers’ willingness to pay in crowdfunding campaigns.

With regard to funding dynamics between different crowdfunding campaigns, it has been suggested that a potential “blockbuster effect” exists, where a popular and widely visible campaign steals investors away from other campaigns (Doshi 2014). This would lead to a substitutive relationship between different campaigns. However, there are also arguments for a complementary relationship. Using a theoretical model, Parker (2014) shows that under the condition of imperfect information about the quality of projects (information), cascades between projects can form. To the best of our knowledge, no empirical research has tested this argument. Another mechanism for complementarity is proposed by Thies et al. (2018). They argue that network effects drive the evolution of a crowdfunding platform and show that increasing the number of projects on a platform increases both the installed base of funders (cross-side network effects) and the number of other entrepreneurs on the platform (same-side network effects).

4 Data and econometric methodology

4.1 Data

Our dataset covers 104 weekly observations for the period from January 1, 2017 to December 30, 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 research (e.g., Fisch 2019). In addition to the amount raised in an 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.

Fig. 1 shows the evolution of these variables over time, and Table 1 displays the descriptive statistics. The prices of bitcoin and ether show a clear upward trend during the first half of the sample period (i.e., until the end of 2017). Thereafter, we observe a continuous decline in both series until the end of the sample period. Similarly, the cumulative amount raised in the ICO campaigns increases rapidly between July 2017 and July 2018. Towards the end of the sample period, however, the boom in ICOs appears to have halted.

The series exhibit stochastic trends, because the null hypothesis of a unit root cannot be rejected in all three cases (see also the bottom of Table 1). Consequently, we check whether the variables have common stochastic trends; that is, we test for potential cointegrating relationships among the three variables. For this purpose, we estimate a VAR in log-levels with five lags as favored by the information criteria. A Johansen (1995) test indicates a maximum number of zero cointegrating vectors according to the Trace Statistic (29.90; 5% Osterwald-Lenum (1992) critical value: 34.55) and the Maximum-Eigenvalue Statistic (19.90; 5% Osterwald-Lenum (1992) critical value: 23.78). Accordingly, we continue with an analysis of the series in log-differences.[2]

Fig.2 shows the evolution of the growth rates of the amounts raised in ICO campaigns over time. In line with the findings from Fig. 1, we observe large growth rates in the second half of 2017 and the first half of 2018 but not thereafter. Fig.3 shows bitcoin returns and ether returns over the same time period. Here, the growth rates are on average positive in 2017 and negative in 2018. The most striking finding, however, is the substantial co-movement between both cryptocurrency returns. This is further highlighted by the large bivariate correlation ($\rho = 0.58$), which can be found in Table 2. In contrast, there is no significant contemporaneous correlation between cryptocurrencies and ICOs. The average growth rate of the ICO volume is 4.24%. Among the cryptocurrencies, ether exhibits stronger average growth rates (2.69%) than bitcoin (1.35%) but is also more volatile with a standard deviation of 20.10 compared to 13.83. All three series are integrated of order 1 as indicated by the unit root tests. Therefore, the subsequent econometric analysis will be carried out in log-differences.

4.2 Econometric methodology

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

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

where X_t is the 3×1 vector of endogenous variables including (i) the growth rate of ICO volumes, (ii) bitcoin returns, and (iii) ether returns; δ is the 3×1 vector of intercepts; U_t is the 3×1 vector of nonstructural error terms; and the $\boldsymbol{A}_i$ are 3×3 parameter matrices. The information criteria favor a VAR(4) model, which also does not exhibit any serial correlation in the error terms of all of the equations.

One problem with the least squares estimation of Eq. (1) is the potential correlation of the error terms across equations. Without a proper transformation of the reduced-form VAR, we are not able to identify the effects of changes, for example, the effect of changes in bitcoin on ICOs, as typically the other variable (i.e., ether) co-moves with the changes in bitcoin. Therefore, in order 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

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

[2] One caveat that has to be mentioned with regard to the cointegration analysis is the relatively short sample that consists of only 104 weekly observations. This might make it difficult to statistically detect a long-run equilibrium between, for instance, the two cryptocurrencies.

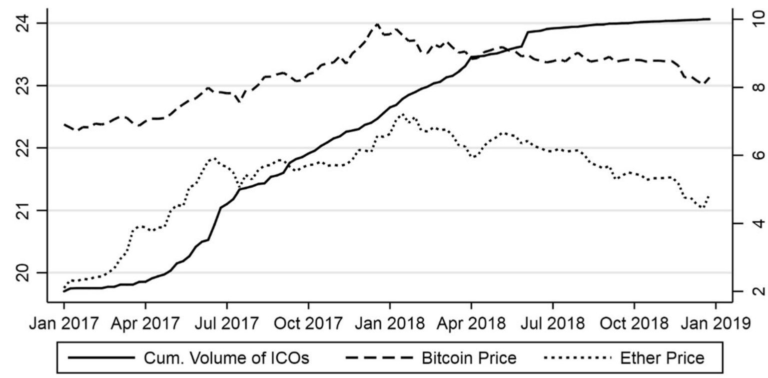

Fig. 1 ICO volumes, bitcoin prices, and ether prices over time (in logs). The figure shows the amount raised in ICO campaigns (left axis) as well as the prices of bitcoin and ether (both on right axis). All variables are in logs

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 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:

Table 1 Descriptive statistics in log-levels

	ICO	Bitcoin	Ether
Mean	22.30	8.39	5.38
Standard deviation	1.57	0.82	1.25
Minimum	19.70	6.71	2.10
Maximum	24.06	9.86	7.22
Unit root test	− 1.85 [0.35]	− 1.99 [0.29]	− 2.69 [0.08]

Table 1 displays descriptive statistics for the amount raised in ICO campaigns as well as the prices of bitcoin and ether in log-levels (see also Fig. 1). Figures in brackets are p values of Augmented Dickey and Fuller (1979) tests with a constant and one lag. The unit root tests have been conducted in two consecutive steps. First, tests with a deterministic trend and a constant term have been carried out with the lag length being determined by the minimum Schwarz criterion. The deterministic trends are not significant at the 5% level in the case of all three tests. Second, tests with a constant term have been carried out with the lag length being determined by the minimum Schwarz criterion. The constant term is found to be significant in the case of all three tests. Number of observations: 104

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

Since P has no nonzero 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 regarding the instantaneous relationships among the three variables. We propose to order ICOs first, followed by bitcoin and ether. This implies that, first, 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 returns 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 (Fisch et al. 2018). Therefore, ICOs are the slowest-moving variable and are 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 (Ciaian and Rajcaniova 2018). As part of our robustness test, however, we also interchange the ordering of bitcoin and ether (see Sect. 6.1).

5 Baseline results

5.1 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 3. The Granger causality tests, that is, tests for the joint exclusion of all four lags for

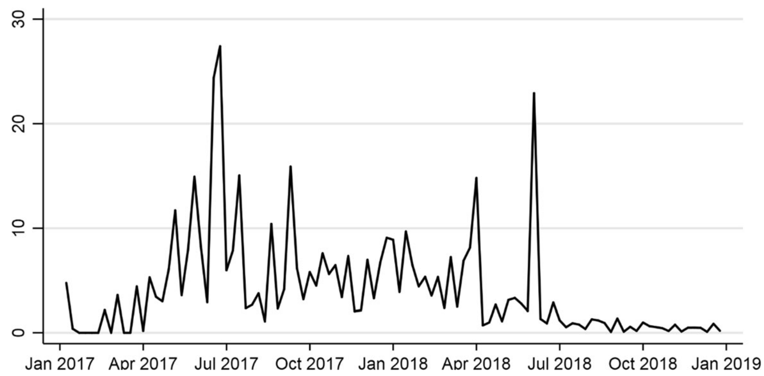

Fig. 2 Growth rates of ICO volumes over time (in percent). The figure shows the growth rate (in percent) of the amount raised in ICO campaigns

any one variable from the equation of another variable, indicate that we find a simple Granger causal relationship from ether to bitcoin ($F(4, 86) = 4.32$ [0.00]). In addition, bitcoin and ether jointly—but not individually—Granger cause the growth rates of ICO volumes ($F(8, 86) = 3.39$ [0.00]). This lack of an individual Granger causal relationship from both cryptocurrencies to ICOs is further indicative of potential collinearity issues.

In general, there are very few significant estimates in Table 3. However, as already stated in Sect. 4.2, such an analysis of the reduced-form of Eq. (1) neglects contemporaneous relations across the variables. Indeed, we find nonzero bivariate correlations in the residuals of Eq.(1). For instance, in the case of bitcoin and ether, the conditional correlation is quite substantial ($\rho = 0.56$), which indicates that we cannot interpret the residuals as true shocks to 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 12 weeks thereafter.

5.2 Impulse response functions

Fi.4 shows the impulse response functions (solid lines) alongside the 95% confidence bands (dashed lines). To answer our first research question, we first focus on the impulse responses in the top left figure. Here, we find that shocks to ICOs are persistent, implying that a bullish (bearish) market remains bullish (bearish) for 4 weeks. Shocks to both cryptocurrencies, in contrast, are not persistent as their responses become insignificant 1 week after the shock. We observe a positive and significant reaction of ICOs to shocks in both cryptocurrencies. Shocks to bitcoin have a significant and pronounced impact on ICOs after 4 to 8 weeks, with a peak effect of 1.45 percentage points (pp). In contrast, shocks to ether only trigger a significant increase in ICOs of 0.99 pp. after 4 weeks. Although we do not find any significant response of ether to ICOs, bitcoin returns significantly increase by 1.88 pp. 5 weeks after ICO shocks. Therefore, with respect to our second research question, we can conclude that shocks in both cryptocurrency returns have a substantial and positive effect on ICO volumes, whereas the opposite effect is found to be limited.

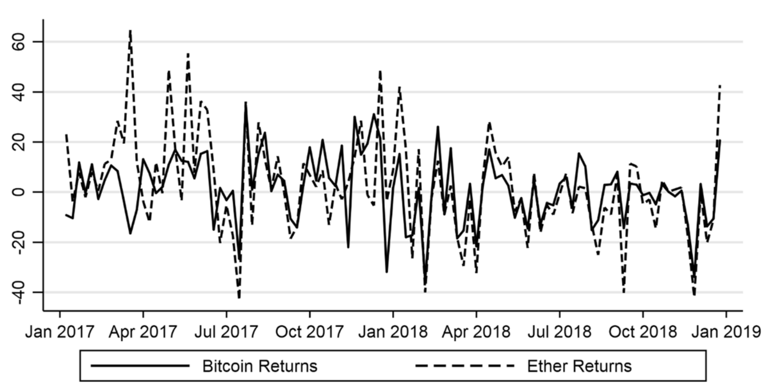

Fig. 3 Bitcoin returns and ether returns over time (in percent). The figure shows the returns of bitcoin and ether in percent

Table 2 Descriptive statistics in log-differences

	ICO	Bitcoin	Ether
Mean	4.24	1.35	2.69
Standard deviation	5.14	13.83	20.10
Minimum	0.00	− 35.35	− 43.10
Maximum	27.40	34.70	64.64
Unit root test	− 5.02 [0.00]	− 6.63 [0.00]	− 5.41 [0.00]
Correlation with ICO	1.00		
Correlation with bitcoin	− 0.12 [0.23]	1.00	
Correlation with ether	− 0.08 [0.43]	0.58 [0.00]	1.00

The table displays descriptive statistics for the growth rates of the amount raised in ICO campaigns as well as the returns of bitcoin and ether (see also Figs. 2 and 3). All variables are measured in percent. Figures in brackets are (i) p values of Augmented Dickey Fuller tests with a constant and one lag according to the minimum Schwarz criterion and (ii) p values of bivariate correlations. Number of observations: 103

6 Further analyses and robustness tests

6.1 Alternative ordering and cryptocurrency factor

As our first robustness test, we change the ordering in the impulse response analysis. ICOs are (still) ordered first, followed by ether and bitcoin. Fig. 5 shows the selected impulse responses for this modified ordering. We still observe a positive and significant reaction of ICOs to shocks in both cryptocurrencies. However, the effects of ether on ICOs are more pronounced in this alternative ordering as ICOs significantly increase 4 to 7 weeks after a shock in ether, with a peak effect of 1.63 pp.[3] In contrast, shocks to bitcoin only trigger a significant increase in ICOs of 0.56 pp. after 8 weeks. The effect of ICO shocks on bitcoin remains the same as in the baseline ordering (1.88 pp. after 5 weeks).

Therefore, when ordering bitcoin (ether) second, the effect of bitcoin (ether) shocks on ICOs is stronger. Nevertheless, both cryptocurrencies positively affect the growth rates of ICO volumes in both orderings. Due to the high degree of correlation of bitcoin returns and ether returns ($\rho = 0.58$) and the high degree of correlation in the residuals of the bitcoin equation and the ether equation in the VAR analysis ($\rho = 0.56$), it makes sense to extract a common "cryptocurrency factor" (CF) using a principal component analysis of bitcoin returns and ether returns. The first component indeed explains 79% of the variation in the cryptocurrency returns. Therefore, despite the nonexistence of a long-run cointegrating relationship between the prices of the two cryptocurrencies, their returns exhibit a pronounced short-run co-movement.

To obtain a clearer picture of the relationship between ICOs and cryptocurrency returns, we estimate a bivariate VAR with the growth rate of ICO volumes and the standardized cryptocurrency factor (CF).[4] We detect a simple Granger causal relationship from the CF on ICOs ($F(4, 90) = 6.43$ [0.00]) but not the other way around. Fig. 6 shows the selected impulse responses for this bivariate VAR where the CF is ordered after the ICOs. Confirming the findings of Table 3, we find that a shock in the CF leads to a significant increase in ICOs for 4, 5, 7, and 10 weeks after the shock with a maximum effect of 1.79 pp.

[3] Note that the effect is significant after four, five, and seven weeks.

[4] Descriptive statistics for the standardized CF are as follows: mean: 0; standard deviation: 1; minimum: − 2.69; maximum: 2.29; Augmented Dickey and Fuller (1979) test with a constant and one lag (p value in brackets): − 5.92 [0.00].

[5] Both volatility measures are integrated of order 0. The Augmented Dickey and Fuller (1979) test statistics (with p values in brackets) are as follows: bitcoin volatility: − 4.46 [0.00]; ether volatility: − 6.08 [0.00].

[6] Ether volatility to bitcoin returns: $F(4, 78) = 3.27$ [0.02]; ether volatility to ether returns: $F(4, 78) = 3.97$ [0.01].

[7] We do not report the impulse responses of shocks in the three key variables as these are virtually unaffected by this modification. All omitted results are available upon request from the corresponding author.

[8] The number of successfully completed ICO campaigns (in logs) is integrated of order 1. The Augmented Dickey-Fuller (1979) test statistics (with p values in brackets) are as follows: Log-levels: 1.83 [1.00]; Log-differences: − 3.39 [0.01]. The bivariate correlation with the indicator for the volume of ICO campaigns is $\rho = 0.65$.

Table 3 Estimates of VAR model

	1: ICO		2: Bitcoin		3: Ether	
ICO_{t-1}	0.181	(0.094)	− 0.233	(0.293)	− 0.784	(0.442)
ICO_{t-2}	− 0.084	(0.091)	0.404	(0.283)	*0.846*	*(0.426)*
ICO_{t-3}	*0.353*	*(0.090)*	− 0.235	(0.280)	− 0.383	(0.422)
ICO_{t-4}	0.156	(0.093)	0.406	(0.288)	0.293	(0.435)
$Bitcoin_{t-1}$	− 0.020	(0.036)	0.154	(0.112)	0.114	(0.169)
$Bitcoin_{t-2}$	0.055	(0.036)	0.048	(0.111)	0.020	(0.168)
$Bitcoin_{t-3}$	0.004	(0.036)	0.022	(0.113)	0.119	(0.170)
$Bitcoin_{t-4}$	0.065	(0.035)	0.016	(0.110)	0.241	(0.166)
$Ether_{t-1}$	0.016	(0.026)	− 0.073	(0.081)	0.046	(0.122)
$Ether_{t-2}$	0.004	(0.026)	0.089	(0.081)	0.236	(0.123)
$Ether_{t-3}$	0.023	(0.026)	0.148	(0.081)	0.140	(0.122)
$Ether_{t-4}$	*0.052*	*(0.025)*	*− 0.300*	*(0.079)*	*−0.316*	*(0.119)*
Constant	*1.320*	*(0.612)*	0.056	(1.902)	1.840	(2.866)
R^2	0.44		0.25		0.20	
Portmanteau: $Chi^2(8)$	1.41	[0.99]	2.68	[0.95]	4.64	[0.80]

The table shows the coefficients (with standard errors in parentheses) for the estimation of Eq. (1) using least squares. Coefficients in italics are significant at the 5% level. The line headed "Portmanteau" shows statistics for a test of the null hypothesis of no serial correlation (with p-values in brackets). Number of observations: 99

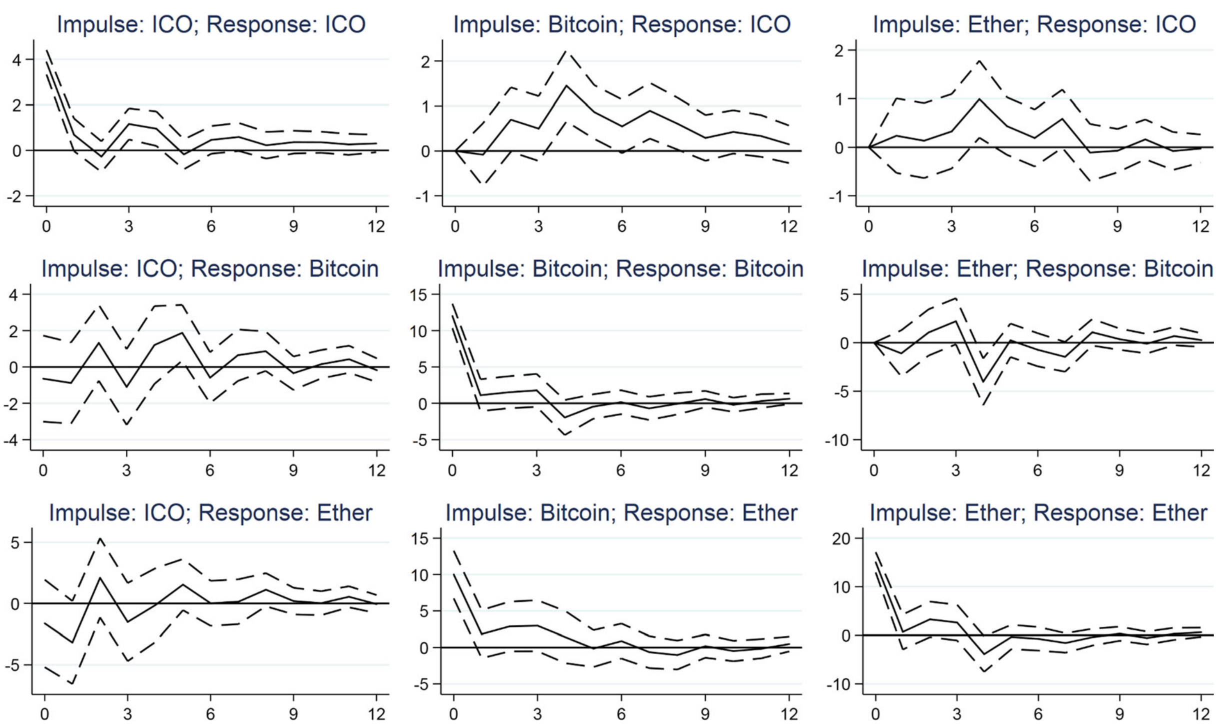

Fig. 4 Impulse responses of VAR model. The figure shows the impulse responses (solid lines, in percentage points) to a one standard deviation shock in the ICO growth rates (left panel), bitcoin returns (middle panel), and ether returns (right panel), alongside. the corresponding 95% confidence bands (dashed lines). Cholesky decomposition is based on the following ordering: (i) ICO, (ii) bitcoin, and (iii) ether

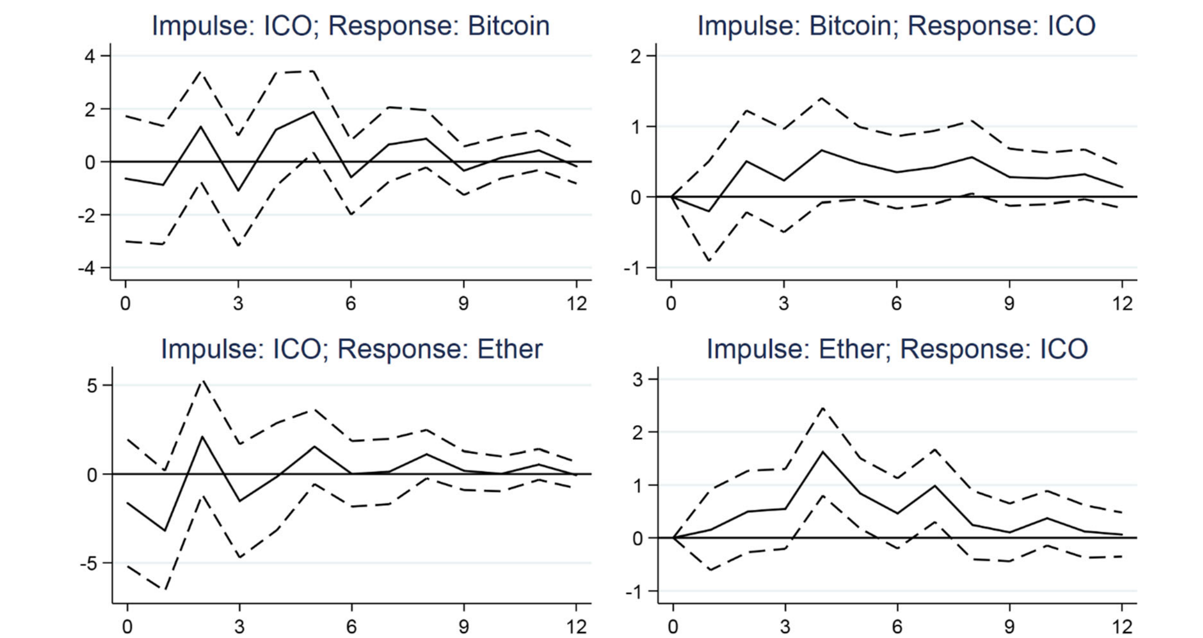

Fig. 5 Impulse responses of VAR model: Alternative ordering. The figure shows selected responses (solid lines, in percentage points) to a one standard deviation shock in the ICO growth rates (left panel), bitcoin returns (upper right figure), and ether returns (lower right figure), alongside the corresponding 95% confidence bands (dashed lines). Cholesky decomposition is based on the following ordering: (i) ICO, (ii) ether, and (iii) bitcoin. Full set of impulse responses is available from the corresponding author

6.2 Cryptocurrency volatility

Previous research has documented that the volatility of cryptocurrencies is an important pricing factor for these currencies (Urquhart 2018). Therefore, we examine whether their volatility also affects the growth rates of ICOs. For that purpose, we create weekly volatility measures for both cryptocurrencies based on the standard deviation of their returns over the past seven days.[5] Next, we include four lags of both variables as exogenous regressors in the VAR model. We detect a significant Granger causal relationship for the volatility of ether to both cryptocurrencies.[6] However, there is no significant Granger causal relationship of bitcoin volatility in any equation or a Granger causal relationship from ether volatility on ICOs. Fig. 7 shows the dynamic multipliers of one standard deviation innovations in lagged bitcoin volatility and lagged ether volatility.[7] Both bitcoin volatility and ether volatility are indeed found to influence the returns of both cryptocurrencies, although this relationship is very short-lived. However, as an answer to our third research question, we find no significant impact of both cryptocurrency volatility measures on ICO growth rates.

6.3 An alternative ICO indicator

As part of our robustness tests, we replace the indicator for the cumulative amount of money raised (volume) in ICO campaigns by the number of successfully completed ICO campaigns (also in log-differences).[8] As with our baseline model, we estimate a VAR(4) model and obtain the impulse responses based on the same recursive ordering. Fig. 8 shows the results. Compared to the baseline results in Fig. 3, shocks to ICOs are even more persistent when considering the number of successfully completed campaigns rather than their volume, as the response becomes insignificant only after 13 weeks (not shown in Fig. 8). Our key results of a positive reaction of the ICO indicator to shocks in either bitcoin

[5] Both volatility measures are integrated of order 0. The Augmented Dickey and Fuller (1979) test statistics (with p values in brackets) are as follows: bitcoin volatility: − 4.46 [0.00]; ether volatility: − 6.08 [0.00].

[6] Ether volatility to bitcoin returns: $F(4, 78) = 3.27$ [0.02]; ether volatility to ether returns: $F(4, 78) = 3.97$ [0.01].

[7] We do not report the impulse responses of shocks in the three key variables as these are virtually unaffected by this modification. All omitted results are available upon request from the corresponding author.

[8] The number of successfully completed ICO campaigns (in logs) is integrated of order 1. The Augmented Dickey-Fuller (1979) test statistics (with p values in brackets) are as follows: Log-levels: 1.83 [1.00]; Log-differences: − 3.39 [0.01]. The bivariate correlation with the indicator for the volume of ICO campaigns is $\rho = 0.65$.

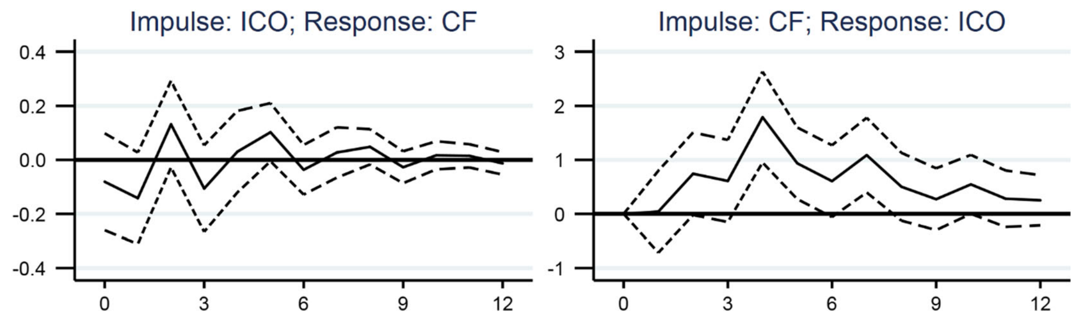

Fig.6 Impulse responses of VAR model: Cryptocurrency factor. The figure shows selected impulse responses (solid lines, in percentage points) to a one standard deviation shock in the ICO growth rates (left panel) and the cryptocurrency factor (right panel), alongside the corresponding 95% confidence bands (dashed lines). Cholesky decomposition is based on the following ordering: (i) ICO and (ii) cryptocurrency factor (CF). Full set of impulse responses is available from the corresponding author on request

(significant after 2, 4, 5, 7, and 10 weeks with a peak effect of 0.39 pp) or ether (significant after 7 weeks with an effect of 0.21 pp) are robust to this modification. In addition, we find a positive reaction of bitcoin returns to ICO shocks on impact and 5 weeks after the shock.

6.4 Alternative ICO data

Finally, we rerun the baseline analysis with data on ICO volumes from a different source (icodata.io).[9] Fig. 9 shows the results. Compared to the baseline results in Fig. 3, the significance of the results is much more pronounced. Shocks to ICOs are persistent up to 7 weeks after the shock. The positive effect of bitcoin shocks on ICOs is significant 2 to 8 weeks after the shock, with a peak effect of 1.58 pp. ICOs also react significantly to ether shocks after 4 and 5 weeks, with a maximum impact of 1.70 pp. Finally, the short-lived effect of ICOs on bitcoin returns (1.71 pp. after 5 weeks) is also replicated in this extension.

7 Conclusions

7.1 Main results and implications for financial practice

Our study is the first to analyze the connection of ICOs to the bitcoin and ether cryptocurrencies and is closely related to a set of papers that use VAR models to analyze cryptocurrencies, stock returns, and IPOs (e.g., Doidge et al. 2017; Lowry et al. 2010; Garlappi and Song 2016). In our VAR model, we use the growth rate of the amount raised by ICO campaigns, bitcoin returns, and ether returns between January 2017 and December 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 4 weeks. Therefore, a hype surrounding one ICO positively influences subsequent ICOs, which is in line with the respective IPO literature (e.g., Lowry and Schwert 2002). Second, innovations in either bitcoin or ether positively influence ICOs up to 8 weeks after the shock. This may be an indication of the hype surrounding the entire cryptocurrency and ICO sphere and the spillover effects of cryptocurrencies on ICOs. Prior literature on financing (e.g., crowdfunding and IPO, or secondary markets), for instance, found a significant effect of media content on the stock market (e.g., Gurun and Butler 2012; Tetlock 2007). The media and news hype surrounding cryptocurrencies in the year 2017 (e.g., "ICOs: the new gold rush", "Bitcoin rally continues as futures forecast even higher prices") may thus have had a positive effect on ICOs. In particular, high returns and success stories of bitcoin investors may attract the attention of other potential investors. In fact, media attention to bitcoin measured with data from Google Trends is influenced by the volatility and volume realized on the previous day (Urquhart 2018). Additionally, the crypto and ICO market may be driven by irrational herding behavior. As with crowdfunding, an ICO is considerably publicized in media channels, which may lead to social contagion processes. Therefore, investors may simply follow others without considering all the facts or their

[9] The indicator for ICOs based on this source (in logs) is also integrated of order 1. The Augmented Dickey-Fuller (1979) test statistics (with p values in brackets) are as follows: Log-level: 0.97 [1.00]; Log-differences: −4.91 [0.01]. The bivariate correlation with the original indicator for the volume of ICO campaigns is ρ= 0.54.

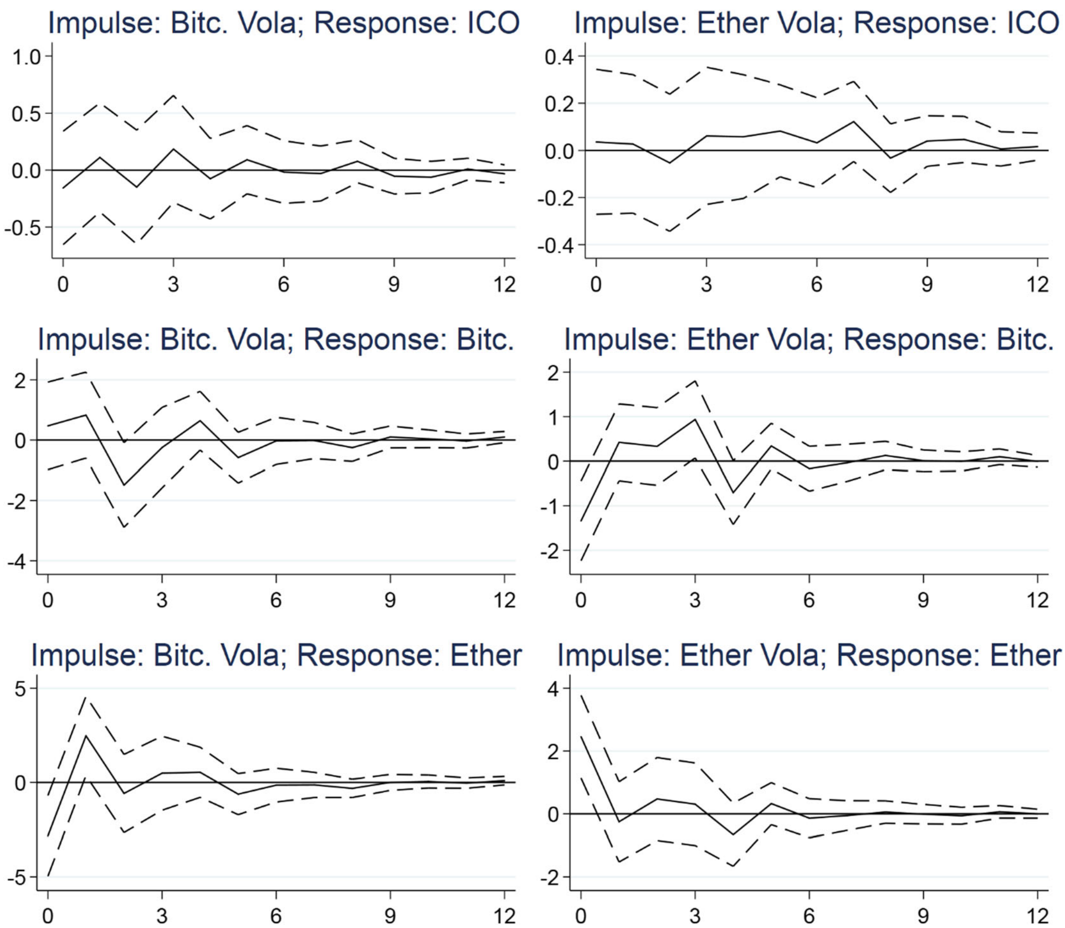

Fig. 7 Dynamic multipliers of VAR model controlling for cryptocurrency volatility. The figure shows the dynamic multipliers (solid lines, in percentage points) to a one standard deviation innovation in lagged bitcoin volatility (left panel) and lagged ether volatility (right panel), alongside the corresponding 95% confidence bands (dashed lines)

own experience (e.g., Simonsohn and Ariely 2008). Third, we find only a very limited effect of the growth rates of ICO volumes on cryptocurrency returns and no significant effect at all for the volatility of cryptocurrency on ICO volumes. Finally, our results are robust to using (i) the number of successfully completed ICO campaigns instead of ICO volumes and (ii) ICO data from a different source.

Our results also have implications for financial practice, in particular for entrepreneurial firms seeking to conduct an ICO. Such firms can tell from our results that market timing is an important factor that determines the success of an ICO and that not only do past ICO volumes matter in this regard but also bitcoin and ether returns have substantial effects. The cryptocurrency market is currently facing both lower bitcoin and ether prices. Two alternative strategies may be appropriate for entrepreneurial firms conducting an ICO that depend on the status of the ICO campaign in these declining cryptocurrency markets. First, entrepreneurial firms that have already started the campaign may focus on signaling the quality of the product/service based on DLT to guarantee the success of the ICO campaign. In other words, entrepreneurial firms have to compete with other capital seekers by highlighting the quality and feasibility of the project, such as the technological capability of the project and a high-quality source code (e.g., Fisch 2019). Second, entrepreneurial firms that have not yet started the campaign may postpone the start of the ICO campaign in times of declining bitcoin or ether prices and ICO volumes, and they may choose an alternative starting date. Our results also have implications for cryptocurrency

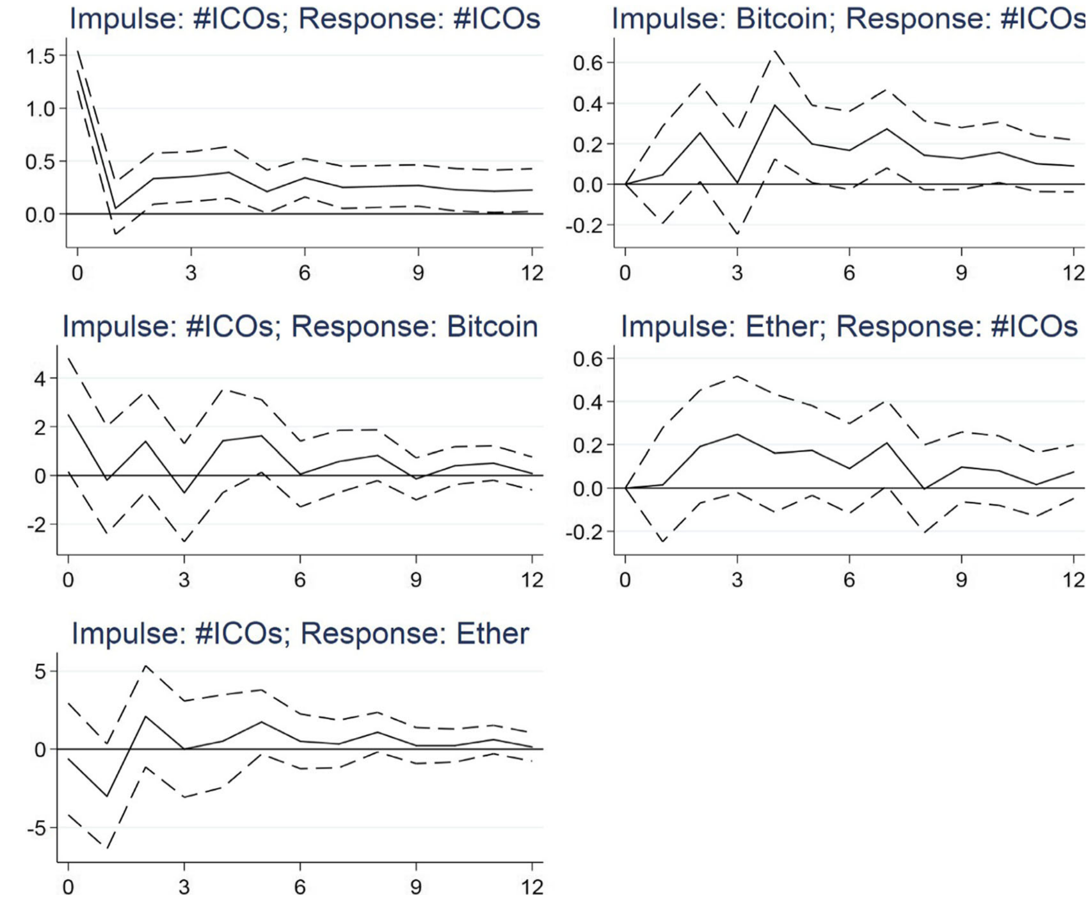

Fig. 8 Impulse responses of VAR model with number of ICOs. The figure shows the impulse responses (solid lines, in percentage points) to a one standard deviation shock in the ICO growth rates (left panel), bitcoin returns (upper right figure), and ether returns (middle right figure), alongside the corresponding 95% confidence bands (dashed lines). Cholesky decomposition is based on the following ordering: (i) ICO, (ii) bitcoin, and (iii) ether. Full set of impulse responses is available from the corresponding author

investors. Investors who want to diversify their portfolio and reduce investment risks should be cautious about investing in both ICOs and established cryptocurrencies (such as ether or bitcoin), as the returns from these assets are correlated with each other. Moreover, our finding regarding the persistence of the shocks of ICO returns represents evidence of a market inefficiency. This suggests that trend-trading strategies can be used to generate abnormal profits (Caporale et al. 2018). From a regulatory standpoint, evidence for herding and persistence makes the occurrence of systematic risk that could jeopardize market stability more likely, which is often an important concern for policy-makers. Stricter market regulation that reduces herding and promotes market efficiency might be needed (Bouri et al. in press). Such regulations could provide investors with more security by decreasing the speculative component.Asset valuation becomes more accurate (Vidal-Tomás et al. in press).

7.2 Limitations and future research

Future research could further improve our understanding of this new emerging financing instrument. First, the study primarily focuses on three different market cycles (ICO, bitcoin, ether) due to the connection between ICOs and cryptocurrencies, but it neglects exogenous variables (e.g., specific ICO campaign characteristics) to a certain extent. Therefore, future research might further investigate the characteristics of ICO campaigns, following studies such as that of Fisch (2019). Second, since ICOs are a particular type of crowdsale and have specific mechanisms that are linked to crowdfunding,

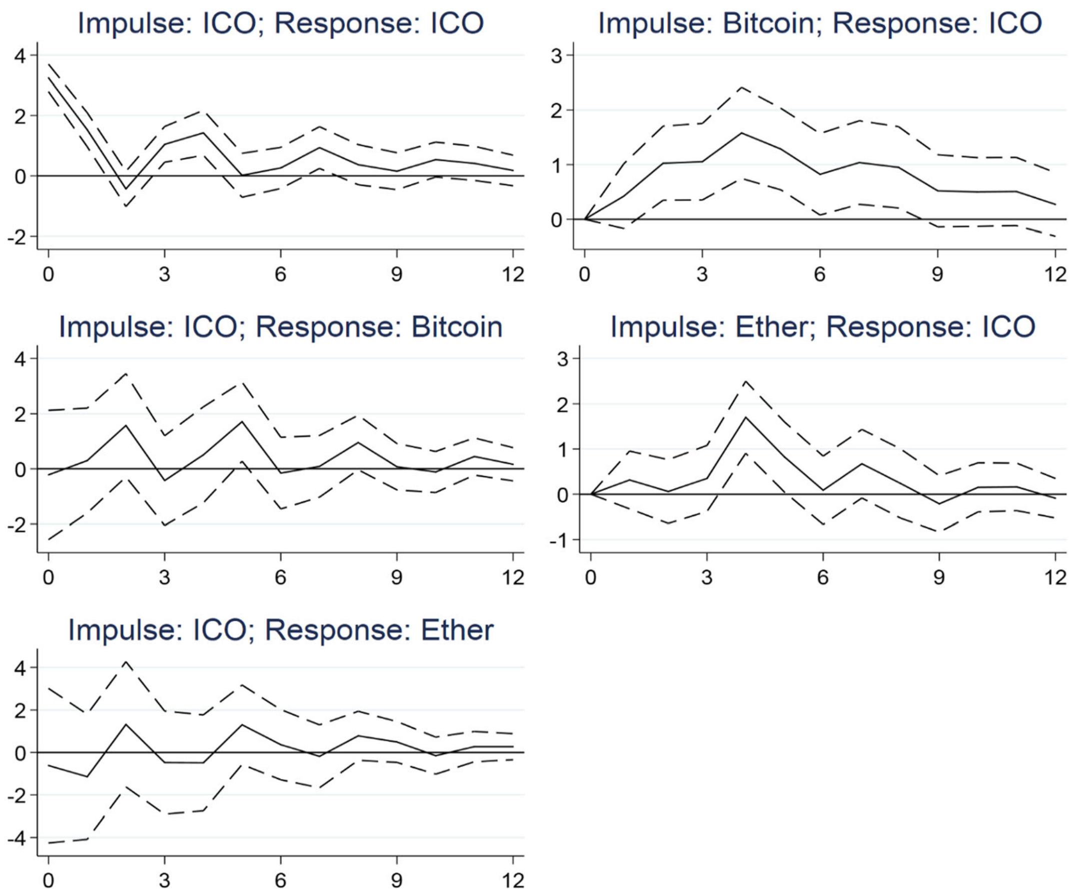

Fig. 9 Impulse responses of VAR model with alternative ICO data. The figure shows the impulse responses (solid lines, in percentage points) to a one standard deviation shock in the ICO growth rates (left panel), bitcoin returns (upper right figure), and ether returns (middle right figure), alongside the corresponding 95% confidence bands (dashed lines). Cholesky decomposition is based on the following ordering: (i) ICO, (ii) bitcoin, and (iii) ether. Full set of impulse responses is available from the corresponding author

different mechanisms explored in crowdfunding could be transferred to ICO research. For instance, similarly to crowdfunding (e.g., Block et al. 2018b), ventures regularly post updates during an ICO campaign. However, little is known about the effects of these updates on social media channels (e.g., Reddit, Steemit, Telegram) and blogs posted by the venture on the success of the ICO campaigns. Third, the number of ICO campaigns has risen sharply since the beginning of 2018 but has declined considerably in the second half of 2018. Therefore, future research might examine the robustness of the results by analyzing future ICO campaigns since both new datasets and ICO listing websites are available (e.g., ICOHOLDER). The results of using other ICO aggregation websites may differ significantly since the different ICO listing sites appear to contain varying numbers of ICOs (Boreiko and Sahdev 2018). Finally, the majority of ICO campaigns are traded on trading exchanges such as bitfinex. Whereas this study analyzes the effect of ICOs, bitcoin, and ether returns on the volume of ICOs in a campaign, future research could investigate the effect of such variables on the current returns and volatilities after trading begins on trading exchanges.

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