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Institutional investors and post-ICO performance: an empirical analysis of investor returns in initial coin offerings (ICOs)

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ABSTRACT

We examine the role of institutional investors in initial coin offerings (ICOs). Taking a financial investor's perspective, we assess the determinants of post-ICO performance via buy-and-hold abnormal returns (BHAR) in a sample of 565 ICO ventures. Conceptually, we argue that institutional investors' superior screening (selection effect) and coaching abilities (treatment effect) enable them to partly overcome the information asymmetry of the ICO context and extract informational rents from their ICO investments. We find that institutional investor backing is indeed associated with higher post-ICO performance. Disentangling selection and treatment effects econometrically, we find that both of these effects explain the positive impact institutional investors have on post-ICO performance. Overall, our results highlight the importance of institutional investors in the ICO context.

1. Introduction

An initial coin offering (ICO) (i.e., token offering) is a novel mechanism of entrepreneurial finance that enables ventures to raise capital by selling tokens to a crowd of investors (e.g., Fisch, 2019; Howell et al., 2019; Momtaz, 2020a). Tokens are cryptographically protected digital assets implemented on a blockchain, which is a novel approach to recording and transmitting data across a network in an immutable manner (Li and Mann, 2018; Natarajan et al., 2017). Blockchain technology is a disruptive technological innovation with vast potential (e.g., Yermack, 2017).

The funding of ventures building on such innovative technologies is a prime topic in entrepreneurial finance that receives close attention from both theory and practice (e.g., Block et al., 2018; Howell et al., 2019). The acquisition of financial resources is a key challenge for innovative ventures because of high uncertainty, information asymmetry, and asset intangibility (e.g., Gompers and Lerner, 2001; Leland and Pyle, 1977). Institutional investors (e.g., venture capitalists, hedge funds) are crucial to overcoming these challenges and financing innovative ventures (e.g., Brav and Gompers, 1997).

Institutional investors deliberately invest in growth markets and focus on new technologies (e.g., Gompers, 1995; Rosenbusch et al., 2013). ICO ventures fit this description and should thus be attractive targets for institutional investors. Indeed, prior research acknowledges an increasing engagement of institutional investors in new digital finance markets (Huang et al., 2019) and ICOs

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specifically (Howell et al., 2019). Recent studies associate backing by institutional investors with ICO success (e.g., Boreiko and Vidusso, 2019; Howell et al., 2019). In addition, institutional investors' rising interest in ICOs is supported by a plethora of anecdotal evidence (e.g., Kastelein, 2017; Russell, 2018), and industry reports indicate that institutional investors' funding of ICOs increased from $1.0 billion in 2017 to $3.9 billion in 2018. This includes investments by renowned investors such as Sequoia Capital and Andreessen Horowitz, which each participated in deals exceeding $100 million (Diar, 2018).

While institutional investments in ICOs are surging, we know little about the (financial) performance of these investments, the ability of institutional investors to select high-potential ventures (selection effect), or their ability to develop them into outperformers (treatment effect). This is a critical research gap since institutional investors are primarily financially motivated and seek returns (e.g., Gompers et al., 2020; Krishnan et al., 2011). Therefore, understanding institutional investors' participation and value-added in ICOs is crucial for ICO investors, ICO ventures seeking financing, financial intermediaries, and policymakers. Specifically, knowledge about institutional investors' engagement in ICOs is vital for an evidence-based evaluation of the development and significance of the blockchain sector from an economic perspective. Hence, we assess the following overarching research question: how does institutional investor backing affect post-ICO performance?

To answer this research question, we draw on a unique feature of the ICO context: the possibility to trade tokens in secondary markets after the ICO's completion. This aftermarket trading adds a speculative function for ICO investors and resembles the trading of shares after an IPO (e.g., Momtaz, 2020d; Fisch, 2019; Lyandres et al., 2019). For investors, the possibility of selling tokens facilitates their exit and increases liquidity (Momtaz, 2019; Howell et al., 2019). From a research perspective, post-ICO trading enables the measurement of ventures' immediate post-backing (financial) performance (e.g., Krishnan et al., 2011; Ritter and Welch, 2002). Conceptually, we argue that institutional investors possess superior screening and coaching abilities that allow them to mitigate the information asymmetry present in the ICO context. In contrast to retail investors, institutional investors can thus extract informational rents from their ICO investments.

Empirically, we assess ventures' post-ICO performance via buy-and-hold abnormal returns using a sample of 565 ICO ventures. To gain a nuanced understanding of the link between institutional investments and post-ICO performance, we differentiate selection and treatment effects by employing a restricted control function approach (cf., Bertoni et al., 2011; Colombo and Grilli, 2008, 2010). Thus, we disentangle the effect that institutional investors select ICO ventures that would achieve superior performance regardless of their involvement (selection effect) from institutional investors' ability to influence post-ICO performance due to superior coaching abilities (treatment effect). We find an overall positive association between backing by institutional investors and post-ICO performance. Specifically, we find that institutional investors fund ventures with higher observable quality at the time of the ICO (selection) and higher post-ICO performance (treatment). Our results are robust across different specifications (inverse Mills ratio, propensity score matching) and measurements (i.e., liquidity, different holding periods). In summary, our results suggest that institutional investors serve as value-increasing intermediaries in the emerging blockchain sector.

Our findings contribute to the nascent research on ICOs. Existing empirical studies mainly investigate the determinants of ICO success (e.g., Fisch, 2019; Howell et al., 2019). Another substream of ICO research quantifies post-ICO investor returns in the short and long run (e.g., Benedetti and Kostovetsky, 2018; Drobetz et al., 2019; Lyandres et al., 2019). We combine these substreams by introducing institutional investments as a determinant of post-ICO performance. Our findings underline the importance of institutional investors in the ICO-sphere, whose presence future studies should account for.

Additionally, we contribute to the prior research on the relationship between institutional investor backing and aftermarket performance, which is mainly investigated in the IPO context (e.g., Brav and Gompers, 1997; Krishnan et al., 2011; Levis, 2011). However, prior findings are equivocal and sensitive to factors such as time, geography, and industry (Da Rin et al., 2013). Since the ICO sector represents a new industrial setting, it is unclear whether and how the findings documented in IPOs apply to ICOs. We show that the ICO sector features similar dynamics as the IPO context, echoing the findings of Howell et al. (2019). We also add to the important substream of research that disentangles selection from treatment effects in entrepreneurial finance (e.g., Chemmanur et al., 2011; Sørensen, 2007). We find that institutional investors initially select ventures with higher observable quality and add value post-investment. This finding is in line with an established set of evidence obtained in more traditional funding settings (e.g., Chemmanur et al., 2011; Guo and Jiang, 2013; Sørensen, 2007) but partly contrasts with findings obtained in the European context (e.g., Bertoni et al., 2011; Colombo and Grilli, 2010).

From a practical standpoint, our findings inform ventures about the potential benefits of attracting institutional investors instead of solely relying on a crowd of retail investors. As such, entrepreneurs may consider designing their ICO to specifically appeal to institutional investors, which involves a careful trade-off between the benefits and costs of institutional investor backing (e.g., discounts on token prices, loss of control). Additionally, our findings are important to other ICO investors who seek to optimize their investment decisions. For policymakers, our findings indicate that stimulating investments by institutional investors may be beneficial to realize the technological potential and long-term survival of this market. Since institutional investors often dislike regulatory uncertainty (Kastelein, 2017), reducing regulatory voids may be vital to stimulating institutional investments.

2. Background and prior literature

2.1. ICOs as a new means of entrepreneurial finance

In an ICO, ventures raise capital by selling tokens to a crowd of investors (Fisch, 2019). Tokens are cryptographically protected digital units of value that provide value to investors via a utility, currency, or security function (e.g., Howell et al., 2019). For example, utility tokens can be used to purchase a product or service in the future or as a medium of exchange among users on the ICO venture's platform. In contrast, security tokens resemble traditional securities investments and entitle their holder to shares of ownership, dividends, or other financial benefits. During an ICO, investors (e.g., retail investors, institutional investors) can buy these tokens at a predefined price directly from the ICO-conducting venture. Thus, ICO investors provide the venture with early-stage financing that is usually available to the venture directly and immediately (e.g., Fisch, 2019; Howell et al., 2019; Momtaz, 2020a).

ICOs are controversial (e.g., Lyandres et al., 2019; Momtaz, 2020a). Because they are often unregulated (e.g., Chen and Bellavitis, 2020; Huang et al., 2019), ICOs enable startups to raise large amounts of capital while avoiding the costs of compliance and intermediaries. Conversely, the absence of regulation leads to an increased investment risk due to malignant behavior because tokens often have no current counter-value, do not lead to any legal entitlement, and because there is considerable potential for fraud (e.g., Momtaz, 2020a; Howell et al., 2019; Lyandres et al., 2019). For example, Momtaz (2020a) shows that the absence of institutions verifying signals about venture quality ex ante or punishing biased signals ex post creates a moral hazard in signaling, whereby poor-quality ventures expropriate retail investors by exaggerating their true quality. Due to the high investment risk and potential for fraud, some jurisdictions, such as China and South Korea, have banned ICOs (Russell, 2018; for an event study of the market impact of these regulatory bans, see Momtaz, 2020d). In the United States, the Securities and Exchange Commission (SEC) issued a warning to investors but also pointed out the innovative potential of ICOs (SEC, 2017).

Despite regulatory uncertainties, the number of ICOs and the funding raised have exploded since 2017. The overall funding volumes achieved in ICOs are substantial and far exceed those of crowdfunding (e.g., Chen et al., 2020; Fisch, 2019). For example, the largest ICOs raised more than $1 billion in funding (as of May 2020). In addition, the ICO market is characterized by high volatility and bubble behavior (e.g., Drobetz et al., 2019; Corbet et al., 2018). Thus, after reaching record highs in 2018, the ICO sector declined in 2019.

Fig. 1 displays the aggregate monthly number of ICOs (panel a) and the aggregate monthly funding amount (panel b) for the ICOs included in our study. Fig. 1 illustrates the remarkable rise of the ICO sector since 2017, which reached its peak in 2018 and regressed in 2019 (for a comprehensive illustration of the ICO market's development until Q3 2019, see Howell et al., 2019).

2.2. Prior research on (financial) post-ICO performance

Investors can trade tokens on specialized token exchanges after an ICO's successful completion. In addition to the token's primary utility or security function, token trading in a secondary market adds a speculative function for ICO investors and distinguishes ICOs from other traditional forms of entrepreneurial finance (e.g., Fisch, 2019; Lyandres et al., 2019; Momtaz, 2020d, 2019). Indeed, realizing financial returns via the sale of tokens is crucial for ICO investors. In a survey of 517 ICO investors, Fisch et al. (2019) show that the “future sale of the token at a higher price (at a later point in time)” is ICO investors' most important reason for investing in ICOs, surpassing motives such as gaining an equity stake or the intention to use the token in its intended utility function.

The trading of tokens in the aftermarket resembles the post-IPO trading of newly issued shares. Because of this similarity, prior post-ICO performance research heavily draws on IPO research (e.g., Momtaz, 2019b). This IPO research frequently uses aftermarket performance measures as an indicator of ventures' (financial) performance that are of crucial importance to IPO investors (e.g., Krishnan et al., 2011; Levis, 2011; Ritter, 1991). For example, studies on post-ICO performance use performance measures derived from the IPO context such as buy-and-hold returns or first-day returns (e.g., Lyandres et al., 2019; Momtaz, 2020a, 2020d). While these studies document the similarities between IPOs and ICOs (e.g., the existence of underpricing), important differences exist. First, in contrast to shares, tokens usually do not entitle investors to a stake of ownership in the company. Second, ICO ventures are often in very early stages. Third, ICOs do not use underwriters, and the transaction costs are small (e.g., Howell et al., 2019; Momtaz, 2019).

Relatedly, tokens' aftermarket prices are very volatile (e.g., Lyandres et al., 2019; Momtaz, 2019b), which is why ICO investments are often described as high-risk investments (e.g., SEC, 2017). Hence, such investments attract investors with a high risk-return profile (e.g., Fisch et al., 2019; Howell et al., 2019), which is particularly characteristic of institutional investors like venture capitalists or hedge funds (e.g., Block et al., 2019; Puri and Zarutskie, 2012).

Multiple studies assess venture's (longer-term) post-ICO performance and provide equivocal conclusions. For example, Benedetti and Kostovetsky (2018) use a sample of ICOs that occurred between 2013 and April 2018 and find that post-ICO performance is positive when using unweighted buy-and-hold returns. However, the positive effect becomes insignificant when the buy-and-hold returns are adjusted market tokens measure. Using a similar approach, Momtaz (2019b) documents positive buy-and-hold abnormal returns for the mean ICO that occurred between 2013 and April 2018. However, the effect is negative when assessing the median ICO, which suggests that the positive returns obtained when assessing mean values are due to very profitable outliers. Momtaz (2019b) concludes that most ICOs destroy value for investors. Similarly, Lyandres et al. (2019) investigate a sample of ICOs carried out between 2013 and November 2018 and find that post-ICO performance (i.e., cumulative returns of listed tokens) is positive on average. However, the median performance is negative and ranges from −31% to −69%, depending on the period under investigation (from 30 days to 365 days of trading).

2.3. Institutional investors and aftermarket performance

While prior studies provide initial insights into the direction and magnitude of post-ICO performance, the determinants of post-ICO performance remain mostly unexplored. To address this gap, we draw on prior IPO research, in which the relationship between the presence of institutional investors and post-IPO performance is a recurring theme. Despite a plethora of empirical studies, the findings are mixed and document a positive, neutral, and negative relation between institutional investor backing and ventures' aftermarket performance.

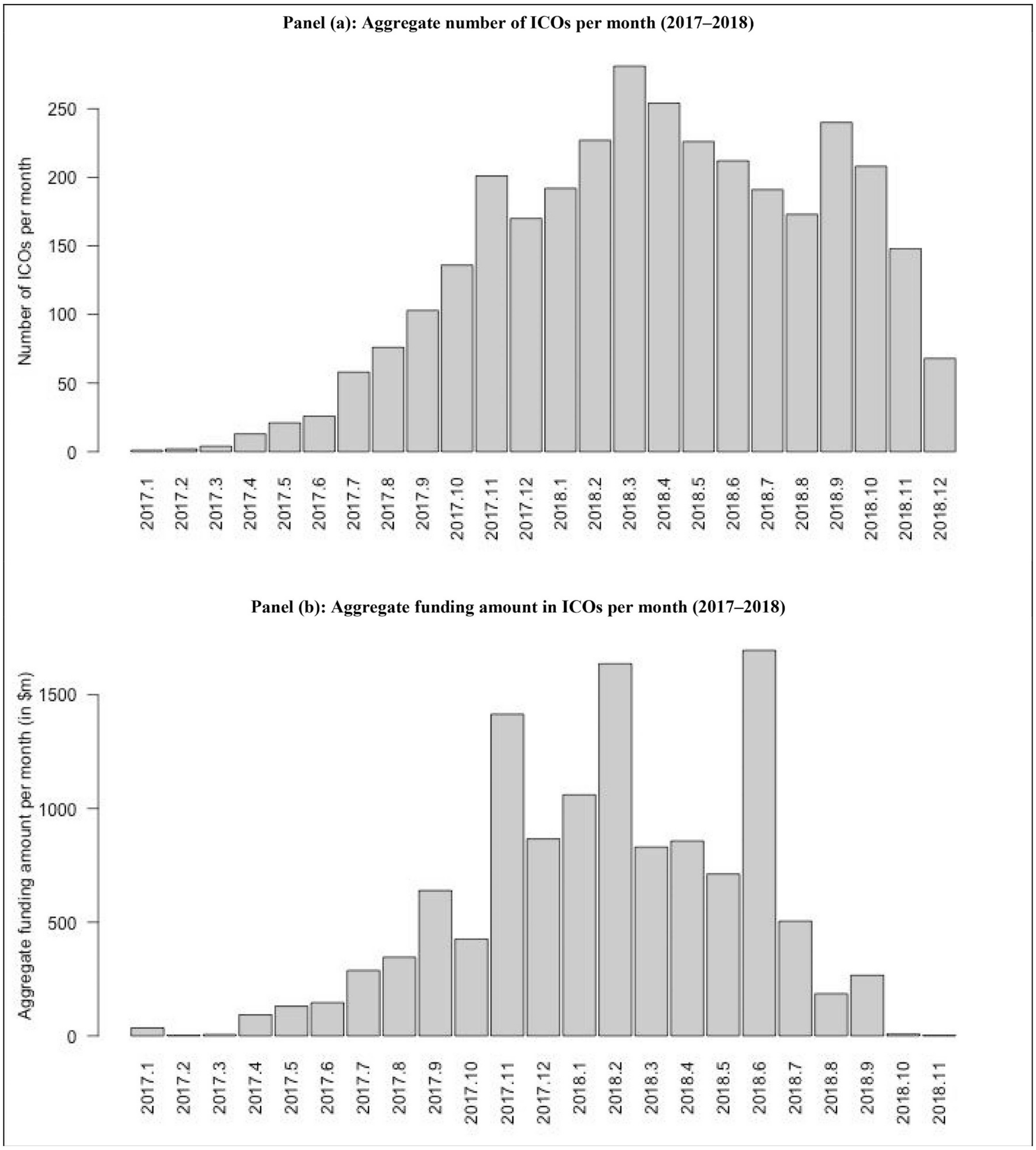

Fig. 1. Aggregate number of ICOs (panel a) and monthly funding amount (in $m) (panel b) from 2017 until 2018 based on the ICOs included in our sample. Data source: ICObench.

Brav and Gompers (1997) find that IPOs backed by institutional investors outperform those not backed by institutional investors. However, the long-term performance differential is sensitive to the estimation method used. Similarly, Field and Lowry (2009) relate higher institutional ownership to higher long-term IPO performance. In contrast, other studies find no significant long-term performance difference between IPOs with and without financing by institutional investors (e.g., Brau et al., 2004; Krishnan et al., 2011; Levis, 2011). A final set of studies documents a lower performance of VC-backed IPOs compared to IPOs without the involvement of institutional investors. For example, Lee and Wahal (2004) find that IPOs backed by institutional investors show higher degrees of underpricing and thus leave more “money on the table”.

Reconciling these divergent findings, Da Rin et al. (2013) conclude that the effect of institutional investor backing on ventures' aftermarket performance is sensitive to various factors, such as time (e.g., period of analysis) and geography (e.g., US vs. European data). Ritter (2017) corroborates this conclusion and shows that the performance differential between IPOs with and without financing by institutional investors in the US has changed over time. While IPOs backed by institutional investors outperformed IPOs not backed by institutional investors until 1998, the relationship has turned around since then.

3. Theory

Prior research shows that funding by institutional investors can (but does not have to) affect aftermarket performance. We extend findings obtained in IPOs to the context of ICOs. Given the equivocal nature of prior research and the novelty of the ICO context, it is unclear whether and how the presence of institutional investors affects post-ICO performance. The following section outlines our theoretical considerations on why financing by institutional investors should lead to superior post-ICO performance.

3.1. Institutional investors and the exploitation of information inefficiencies

In efficient capital markets, a venture's aftermarket value reflects its "true value". Hence, investors cannot select undervalued stocks to realize above-market returns (e.g., Fama, 1970; Malkiel, 2003). Consequently, the aftermarket performance of ventures backed by institutional investors and ventures not backed by institutional investors should be the same (Brav and Gompers, 1997).

However, markets are rarely fully efficient (e.g., Malkiel, 2003). Often, information asymmetry introduces inefficiencies because some market participants lack information that other market participants possess (Leland and Pyle, 1977). Information asymmetry is a key characteristic in markets for entrepreneurial finance in which entrepreneurs have an informational advantage over investors who often find it difficult or impossible to assess a venture's true quality (e.g., Leland and Pyle, 1977; Gompers and Lerner, 2001). In the presence of such market inefficiencies, informationally advantaged market participants can extract informational rents (e.g., Chemmanur et al., 2009; Demiralp et al., 2011; Schenone, 2010). Informational inefficiencies and the resulting extraction of informational rents explain prior findings on nonzero aftermarket performance (e.g., Benzoni and Schenone, 2010; Brav and Gompers, 1997; Ritter, 1991).

Institutional investors have a better understanding of a firm's underlying quality and can thus better exploit information asymmetries than retail investors (e.g., Chemmanur et al., 2009; Lee and Wahal, 2004; Schenone, 2010). The ability of institutional investors to create value and realize above-market returns is generally attributed to a screening and coaching function (e.g., Brav and Gompers, 1997; Gompers et al., 2020; Megginson et al., 2019).

The screening function refers to institutional investors' selection of portfolio ventures ("selection effect"). In contrast to retail investors, institutional investors typically assess portfolio ventures in a more professional and sophisticated way. They can spend a substantial amount of time and resources on assessing the quality of the ventures they seek to invest in, for example, by carrying out extensive due diligence and by implementing effective contracting (e.g., Cumming et al., 2017; Kaplan and Stromberg, 2001; Gompers et al., 2020). By carefully screening investment opportunities, institutional investors can alleviate information asymmetries and invest in high-quality ventures (e.g., Chemmanur et al., 2011; Gompers and Lerner, 2001). The professional investment selection process is also one of the main factors as to why investments by institutional investors can convey a "certification effect" to third parties. Financing by institutional investors signals venture quality and certifies legitimacy to other potential resource providers (e.g., employees, suppliers, cooperation partners, financial intermediaries), which facilitates further performance increases (e.g., Colombo et al., 2019; Hsu, 2004; Megginson and Weiss, 1991).

In addition to carefully screening ventures, institutional investors perform a coaching function ("treatment effect"). Institutional investors typically offer bundles of value-adding services to their portfolio ventures that include professional coaching activities, access to the institutional investor's network, and strategic advice (e.g., Cumming et al., 2005b; Cumming et al., 2017; Hellmann and Puri, 2002; Puri and Zarutskie, 2012). Additionally, institutional investors monitor a venture's progress and cut off ventures from new financing in the case of negative information about future returns (e.g., Gompers, 1995). Thus, coaching and monitoring by institutional investors increase venture quality in a way that is difficult to observe to outsiders. This, in turn, further increases the informational advantages that institutional investors have over retail investors (Demiralp et al., 2011).

3.2. Institutional investors in the ICO context

Institutional investors' screening and coaching activities enable them to overcome informational asymmetries when investing in new ventures. In contrast to retail investors, institutional investors can profit from a privileged position that may enable them to extract informational rents (e.g., Chemmanur et al., 2009; Demiralp et al., 2011; Schenone, 2010). While information asymmetries cannot be exploited in efficient markets, in keeping with Momtaz (2020a), we posit herein that the ICO market is a market in which institutional investors can extract informational rents (i.e., above-market returns). Momtaz (2020a) shows that the ICO market is highly inefficient in that (mostly unsophisticated) investors are largely unable to see beyond "cheap talk" by ICO firms, and those inefficiencies vanish only gradually through information exchange in the aftermarket.

Institutional investors' screening abilities enable them to partially overcome the substantial informational asymmetry present in the ICO context. First, the amount of objective information available in ICOs is low because formal disclosure requirements barely exist (e.g., Blaseg, 2018; Huang et al., 2019; Momtaz, 2020b). Since the ICO sector relies on voluntary information disclosure, ventures produce biased or fake information to increase their chances of funding (e.g., Fisch, 2019; Momtaz, 2020a). Due to their resourceful and professional screening approach, institutional investors are able to collect additional information and verify the accuracy of the information provided by ventures. In contrast, similarly, exhaustive screening is difficult for retail investors (Brav and Gompers, 1997). Second, the ICO market is characterized by a high number of competing ICOs (e.g., Lyandres et al., 2019; Masiak et al., 2019; Drobetz et al., 2019). Institutional investors have the resources to simultaneously screen a large number of ventures thoroughly, while retail investors are limited in this regard (e.g., Block et al., 2019; Gompers et al., 2020; Momtaz, 2020a). Third, investments by institutional investors certify venture quality and thereby reduce information asymmetry for other investors (e.g., Hsu, 2004; Megginson and Weiss, 1991). However, such certification requires the communication of an institutional investor's participation in an ICO. Due to the pseudonymity of ICOs, investor identities remain unknown, and such information is rarely publicized (Fisch, 2019; Kastelein, 2017). Hence, the traditional certification provided by institutional investors is not as pronounced in the ICO context.

Institutional investors' coaching function further amplifies their informationally advantaged position in the ICO context. Institutional investors can add more value to ventures in (very) early stages because such ventures more often lack resources and are in greater need of coaching (e.g., Bertoni et al., 2011; Sapienza et al., 1996). This is particularly true for ICO ventures, which are usually in very early stages and often do not yet have a developed project (e.g., Benedetti and Kostovetsky, 2018; Fisch, 2019; Momtaz, 2019, 2020d). Additionally, ICO ventures are very technology-driven and may thus lack business expertise (e.g., Fisch, 2019). Professionalizing their business model and introducing these ventures to VCs' business networks may be particularly salient (e.g., Bertoni et al., 2011; Gompers, 1995). Finally, institutional investors' monitoring intensifies with increasing information asymmetry (Sapienza et al., 1996). Institutional investors more closely monitor firms to identify negative information and cut business ties as early as possible (Gompers, 1995). Also, institutional investors might increase their involvement since a higher value-added may increase the informational rents that they can extract in the aftermarket (e.g., Chemmanur et al., 2009; Demiralp et al., 2011; Schenone, 2010).

We assume that institutional investors perform similar screening and coaching activities in ICOs based on conceptual arguments. To date, no systematic information exists on what institutional investors actually do in ICOs. To substantiate our conceptual arguments, we collected initial evidence on institutional ICO investments by conducting 17 quantitative interviews with institutional ICO investors. The evidence we collected in the interviews suggests the presence of selection and treatment effects in the ICO context, similar to more traditional funding settings. The interviews are described in more detail in the Appendix.

4. Research design

4.1. Sample construction

We retrieved our core data from ICObench, an ICO database that is commonly used due to its wide coverage (e.g., Huang et al., 2019; Lyandres et al., 2019). We collected all utility-token ICOs that ended between August 2015 and December 2018. ICObench deletes some failed ICOs from their database, as do many other data sources. Therefore, we backfilled missing data with information retrieved from other sources, such as CoinSchedule, Coingecko, and ICOalert. Furthermore, we hand-collected other relevant control variables used in prior ICO studies from various sources, such as venture websites, Twitter, GitHub, and LinkedIn. Using this labor-intensive approach, we were able to identify an initial sample of 2905 ICOs with complete information.

We then collected data on institutional investor backing via a list of institutional investors provided by CryptoFundResearch (www.cryptofundresearch.com). This list includes approximately 750 institutional investors (mostly VCs and hedge funds) and the ICOs they invested in. CryptoFundResearch is the most comprehensive list of investments by institutional investments and is featured in notable outlets such as Bloomberg (Kharif, 2019). We used the list as of August 14, 2019. While the list is useful for identifying institutional investors, the investor details included are limited. Therefore, we manually complemented the list by researching each investment to ensure that the investment took place during the ICO and not as an aftermarket transaction (i.e., neither on an exchange platform nor as a private transaction) and that institutional investors purchased tokens (instead of equity). Additionally, we manually verified and added data on the institutional investors themselves, which we collected from investors' websites and LinkedIn.

Our post-ICO performance data come from CoinMarketCap, the most established source for aftermarket data in the ICO context (e.g., Lyandres et al., 2019; Drobetz et al., 2019; Momtaz, 2020a). We retrieved all performance data available until April 2019. However, only a fraction of all ICO ventures in our sample listed their tokens within this time frame; thus, the subsample of ventures with performance data contains 565 firms.

In summary, our final sample consists of all 2905 firms that completed their ICOs between August 2015 and December 2018, for which all required control variables are available. A total of 565 out of the 2905 (19.4%) sample firms had their tokens listed as of April 2019. Institutional investors backed 322 (189) of the 2905 (565) firms in our sample.

Note that a significant reduction in sample size is common in studies relying on post-ICO performance data. For example, Lyandres et al.'s (2019) initial sample of 4441 ICOs reduces to 582 when using an aftermarket performance measure similar to ours. Similarly, Benedetti and Kostovetsky's (2018) sample reduces from 2390 to 283 ICOs. While the reduction in sample size of 2905 ICOs to 565 firms is not a concern specific to our study, it is a limitation that we discuss in the final section.[1]

4.2. Variables

We summarize all the variables, their descriptions, and data sources in Table 1.

4.2.1. Dependent variable: post-ICO performance (BHAR)

Since the seminal contribution of Ritter (1991), buy-and-hold abnormal returns (BHAR) are a standard measure for the long-term performance of IPO returns (e.g., Brav and Gompers, 1997; Krishnan et al., 2011; Ritter and Welch, 2002). BHAR measure wealth

[1] An advantage of having a relatively large initial sample is that we can rely on more information to estimate our selection model.

Table 1
Description of variables and data sources.

Variable	Description	Data source(s)
Dependent variable used in main analysis		
Post-ICO performance (BHAR)	Buy-and-hold abnormal returns (BHAR) over the first six months of trading after the token's exchange listing date.	Coinmarketcap
Independent variable		
Institutional investor backing	Dummy variable equal to one if an institutional investor invested in the venture, zero otherwise.	CryptoFundResearch, venture websites
Control variables: venture characteristics		
Expert rating (avg.)	Average of all expert ratings of the whole project at the time of the ICO. Ratings scale from 1 (“low quality”) to 5 (“high quality”).	ICObench
GitHub	Dummy variable equal to one if the startup discloses its source code on GitHub, zero otherwise.	GitHub
Platform	Dummy variable equal to one if the venture intends to create a new platform, zero otherwise.	ICObench
# Industries	Number of distinct industries the ICO addresses (proxy for diversification).	ICObench
Control variables: ICO characteristics		
Ethereum	Dummy variable equal to one if the venture uses a standard of the Ethereum platform, zero otherwise.	ICObench
Token supply (log.)	Number of tokens (log.) created in the smart contract used in the token offering.	ICObench
Promotion: presale	Dummy variable equal to one if a pre-ICO took place prior to the actual ICO, zero otherwise.	ICObench
Promotion: free tokens	Dummy variable equal to one if the venture distributes some tokens for free, zero otherwise.	Venture websites
Promotion: reward program	Dummy variable equal to one if the venturehas a token reward program in place, zero otherwise.	Venture websites
Investor restrictions	Dummy variable equal to one if the venture used a Know-Your-Customer (KYC) process or a whitelist during the ICO.	ICObench
Twitter activity (log.)	Number of Tweets sent during the ICO (in logged form).	Twitter
# Competing ICOs	Number of token offerings with overlapping fundraising periods.	ICObench
Market volatility	Change in overall crypto market returns on an equally-weighted portfolio on all tokens listed on one of the 26 major exchange platforms measured between the dates of the launch and the end of the focal ICO.	Coinmarketcap
Control variables: venture's human capital characteristics		
Team size	Number of team members at the start of the ICO (i.e., team members excluding advisors).	ICObench
Techincal team members	Number of team members with a college degree in a technical field (e.g., engineering, computer science).	LinkedIn
Ph.D.	Dummy variable equal to one if the at least one team member holds a Ph.D., zero otherwise.	LinkedIn
Crypto industry experience	Number of team members with prior crypto industry experience.	Linkedin
CEO age	CEO's age.	LinkedIn
Control variables: institutional investor characteristics		
SEC-registered investor	Dummy variable equal to one if the institutional investor is registered with the SEC, zero otherwise.	CryptoFundResearch
Crypto-specific investor	Dummy variable equal to one the institutional investor exclusively invests in crypto-markets, zero otherwise	CryptoFundResearch
Dependent variables used in further analyses		
Liquidity (log.)	Growth in liquidity over the first six months after the token's exchange listing.	Coinmarketcap
Funding amount (log.)	Total gross proceeds raised in the ICO (in $m, log.).	ICObench, venture websites
ICO duration (log.)	Number of days (log.) between ICO's start and end.	ICObench
# Exchange listings (log.)	Number of token exchanges (log.) a token is listed on within six months after ICO ends.	ICObench, venture websites

gains for investors who purchase tokens during the ICO and then hold them for a given time horizon. Hence, BHAR are of crucial importance to institutional investors because they are primarily interested in realizable returns (e.g., Krishnan et al., 2011).

In line with prior post-ICO performance research, we use winsorized BHAR as our main measure of post-ICO performance (e.g., Benedetti and Kostovetsky, 2018; Lyandres et al., 2019; Momtaz, 2019b). Such measures based on aftermarket returns are particularly appropriate when other measures of financial performance are not available (e.g., return on assets, profit margins) (DeCarolis and Deeds, 1999). This is the case in the ICO context, where histories of earnings or tangibles rarely exist (e.g., Fisch, 2019; Howell et al., 2019; Momtaz, 2020a).

IPO research typically measures BHAR over the first three years of aftermarket trading. In contrast, ICO research usually uses a window of six months for reasons of data availability and due to the recency of the ICO phenomenon. In line with Lyandres et al. (2019), we thus refer to BHAR as a measure of “longer-term” instead of “long-term” post-ICO performance. In summary, our dependent variable ('post-ICO performance (BHAR)') measures wealth gains for investors who hold tokens for 180 days after the first day of trading.

In line with the IPO literature (e.g., Chambers and Dimson, 2009), we define the BHAR as the 180-day raw return corrected by the value-weighted (market capitalization) market return. Technically:

$$BHAR_i = \frac{P_{i,t=180} - P_{i,t=1}}{P_{i,t=1}} - \sum_{j=1,j\neq i}^{n} \frac{MktCap_{j,t=180}}{\sum_{j=1}^{n} MktCap_{j,t=180}} \times \frac{P_{j,t=180} - P_{j,t=1}}{P_{j,t=1}} \tag{1}$$

where $P_{i,\ t}$ denotes the token price of firm i on day t, and $MktCap_{j,\ t}$ denotes the market capitalization of firm j on day t (and $j \neq i$).

The choice of the market-capitalization-based benchmark to adjust returns deserves further motivation.[2] First, Momtaz (2019b) explores the measurement of long-term cryptocurrency returns and finds that the market-capitalization-based benchmark is preferable because other benchmarks, such as the volume-weighted or the equally-weighted benchmark, are more susceptible to rapid market movements due to irregular trading activity. For example, several mini-cap ICO firms experience extreme returns of more than 300% in only one day. Considering these firms in the construction of the return benchmark without weighting by market capitalization could introduce severe inconsistencies. Second, market capitalization is affected by boom-and-bust cycles in the token market (Chen et al., 2020). A failure to account for these overall market cycles could lead to a bias of our findings by spurious correlations. Since we are primarily interested in the ability of firms backed by institutional investors to outperform the market, adjusting BHAR using a market-capitalization-based benchmark seems to be the most appropriate approach.

4.2.2. Independent variable: institutional investor backing

Our independent variable 'institutional investor backing' is a dummy variable equal to one if the ICO received an investment by an institutional investor (e.g., venture capitalists, hedge fund) and zero otherwise (e.g., Brav and Gompers, 1997; Colombo and Grilli, 2010; Howell et al., 2019). The data were retrieved from CryptoFundResearch and were manually extended and verified to ensure a high degree of accuracy.

4.2.3. Control variables

We include a variety of control variables to rule out confounding influences on post-ICO performance. The control variables concern venture characteristics, ICO characteristics, ventures' human capital characteristics, and institutional investor characteristics. Our control variables resemble those used in prior ICO research (e.g., Fisch, 2019; Howell et al., 2019; Lyandres et al., 2019; Momtaz, 2020d). We obtained data on the control variables from ICO-compiling sites (i.e., ICObench), ventures' websites, and social media sites (i.e., LinkedIn, Twitter).

4.2.3.1. Venture characteristics

4.2.3.1.1. Expert ratings (avg.). ICObench allows experts to rate ICOs and makes these ratings publicly available. Expert ratings can serve as endorsements by third parties and constitute credible signals of venture quality (e.g., Mollick and Nanda, 2016). Since signals alleviate information asymmetries, expert ratings play a crucial role in the highly uncertain ICO context (Momtaz, 2020d). To rule out a similar effect on post-ICO performance, we control for each ICO's expert ratings. Expert ratings on *ICObench* comprise the dimensions "team", "vision", and "product" and range from 1 ("low quality") to 5 ("high quality"). We average the score across the three dimensions.[3]

4.2.3.1.2. GitHub (dummy). ICOs occur in the technology-intensive blockchain sector. Prior research underlines the importance of technological signals for venture success (e.g., Fisch, 2019; Lyandres et al., 2019; Momtaz, 2020a) and indicates that ICO investors are technologically motivated (e.g., Fisch et al., 2019). To demonstrate technological capabilities, ICO ventures often publish their source code on GitHub. This source code is one of the core assets of the venture and enables a detailed technological due diligence. Prior studies associate open source code with higher ICO success (e.g., Adhami et al., 2018; Giudici and Adhami, 2019) and post-ICO operating performance (Howell et al., 2019). We thus include a dummy variable that captures whether the venture's source code is available on GitHub or not.

4.2.3.1.3. Platform (dummy). Institutional investors consider a venture's business model as one of the primary factors in investment decisions (e.g., Gompers et al., 2020). Additionally, institutional investors prefer to invest in portfolio ventures with high growth potential (e.g., Block et al., 2019; Puri and Zarutskie, 2012). Due to the presence of network externalities, platform-based business models are capable of rapid growth and large scale. Additionally, platform-based business models are common in the ICO context (e.g., Howell et al., 2019). Since multi-sided platform-based businesses might be more appealing to institutional investors,

[2] A related question is whether BHARs are the preferred way to measure returns to tokenholders at all. An alternative approach might be to look at abnormal returns from Fama and French (1993, 2015) factor models. However, existing research does not find that there is a pronounced factor structure in the token market (Li and Yi, 2019). Hence, the Fama-French approach to measure abnormal returns will not work well in the ICO context.

[3] Acknowledging the concern that expert ratings may be endogenous, we perform a Durbin Wu Hausman (DWH) test for endogeneity. In the first stage, we model the expert rating as a function of venture and human capital characteristics. If expert ratings are endogenous to institutional investors' choice to purchase tokens, there should be systematic variation in the error term. Thus, we extract the DWH residual from the first stage and include it in the second stage, our main model, as described in Section 4.3. The DWH residual is insignificant, suggesting that expert ratings are not endogenous in our model.

and since network externalities might positively affect their post-ICO performance, we include a dummy variable that controls for the presence of a platform business. We derive the variable from ICObench's industry categorization.

4.2.3.1.4. # Industries. When listing an ICO, ventures can choose any number of industry categories that apply to the ICO. ICObench includes 29 industry categories. The categories with the highest numbers of ICOs include "platforms" and "cryptocurrency", while the least prevalent categories include "legal" and "arts". Building on this categorization, we include the number of distinct industries the ICO addresses, which serves as a proxy for diversification. We include this control variable because a higher number of industries indicates a broader scope of future applications by the venture's products, which could affect post-ICO performance.

4.2.3.1.5. Country dummies. Several country-level characteristics determine the prevalence of ICOs and the evolution of digital finance more generally (e.g., Howell et al., 2019; Huang et al., 2019). For example, ICO regulation is an essential country-level factor that shapes the dynamics and success of ICOs. While some countries entertain more ICO-friendly regulations, ICOs are banned in several jurisdictions (e.g., Momtaz, 2020d; Fisch et al., 2019). Relatedly, countries such as Switzerland try to establish clusters for blockchain ventures. Hence, ICOs from these countries might constitute more attractive investments (Fisch, 2019). To control for any location-specific effects, we include a set of country fixed effects that control for the ICO venture's location (i.e., US, China, Russia, Switzerland, and Singapore).

4.2.3.2. ICO characteristics

4.2.3.2.1. Ethereum (dummy). Ethereum is a blockchain technology that ICO ventures can build on. The Ethereum standard (ERC20) is the most common token standard (as of 2020). Its advantages include greater interoperability with other tokens, a more advanced infrastructure, and access to network externalities (Fisch, 2019; Howell et al., 2019). Prior studies document a positive association between the Ethereum standard and ICO success (Momtaz, 2020d; Fisch, 2019). Hence, we include a dummy variable to capture whether an ICO builds on the Ethereum standard or not.

4.2.3.2.2. Token supply (log.). ICO ventures can freely determine the token supply created and sold in their ICO. Even though the token supply is arbitrary, prior research associates a higher token supply with higher amounts of funding (Fisch, 2019; Momtaz, 2020a). Usually, a higher number of tokens corresponds to a lower price per token. An explanation is that buying a high quantity of cheap tokens with the hope that they reach high payoffs is akin to lottery-type stocks, which are particularly attractive to risk-affine investors (e.g., Brav and Gompers, 1997; Fisch, 2019). Thus, we include token supply as a control variable.

4.2.3.2.3. Promotional activities. ICO ventures often conduct a range of ICO-specific promotional activities to encourage investors to buy and trade tokens. Since these promotional activities intend to increase ICO success, we control for three of the most common ICO promotions (Fisch, 2019; Howell et al., 2019; Momtaz, 2020a). First, a presale (or pre-ICO) often precedes the actual ICO in which a limited number of discounted tokens are offered to early investors. Research in crowdfunding underlines the importance of attracting early investors for funding success and argues that attracting early investors is particularly beneficial for accelerating campaigns and increasing the funding collected (e.g., Vismara, 2018). Another function of a presale is to fund the costs of promoting the ICO (Howell et al., 2019). Hence, we the variable 'promotion: presale (dummy)' captures whether a presale preceded the ICO or not). Second, ventures frequently distribute small amounts of tokens for free in so-called "airdrops" ('promotion: free tokens (dummy)'). These free token promotions intend to build interest by increasing the dissemination of tokens and encouraging investors to trade tokens (Howell et al., 2019). Third, ICOs frequently implement reward programs (i.e., "bounty programs") in which rewards are offered for promoting and engaging with an ICO ('promotion: reward program (dummy)'). These rewards include cash rewards or discounts on tokens.

4.2.3.2.4. Investor restrictions (dummy). ICOs frequently implement investor restrictions, such as know-your-customer (KYC) processes or whitelists. The implementation of a KYC process or a whitelist forces investors to register before they can participate in the ICO. While a whitelist usually refers to a simple preregistration process, a KYC process requires a more thorough identification and verification of investors. The implementation of investor restrictions reduces the pool of potential investors and increases transaction costs (e.g., Momtaz, 2020d; Blaseg, 2018). On the positive side, such investor restrictions enable ventures to identify their investors, which is difficult in the ICO context (Fisch, 2019). This potentially allows ventures to establish longer-term investor relationships (Li and Mann, 2018). To capture confounding effects, we include a dummy variable that measures whether at least one restriction is in place (i.e., KYC and/or whitelist).

4.2.3.2.5. Twitter activity (log.). A high level of social media activity (e.g., on Twitter) signifies a venture's intention of communicating more frequently with a crowd of potential investors. Thus, a higher level of Twitter activity helps ventures to reduce informational asymmetries that investors face when investing in ICOs (Fisch, 2019). Indeed, prior ICO research documents a positive association between Twitter activity and funding raised (e.g., Fisch, 2019) and post-ICO performance (e.g., Benedetti and Kostovetsky, 2018). Hence, we control for the venture's activity on social media via the number of Tweets sent during the ICO. We include the variable in logged form due to its skewness.

4.2.3.2.6. # Competing ICOs. A large number of ICOs simultaneously compete for investments (e.g., Drobetz et al., 2019; Lyandres et al., 2019; Masiak et al., 2019). An increasing number of competing ICOs might hamper an individual ICO's possibilities to acquire funding and influence subsequent ICO outcomes. This is, for example, because investors often do not have the resources to simultaneously screen a large number of ventures (e.g., Block et al., 2019; Gompers et al., 2020). In contrast, institutional investors can screen a large number of investments at the same time. Thus, a crowded market characterized by a higher number of competing ICOs might enable institutional investors to extract additional information returns. We thus control for the number of concurrent ICOs at the beginning of each focal ICO.

4.2.3.2.7. Market volatility. The ICO market is dynamic, fast-paced, and volatile (e.g., Corbet et al., 2018; Drobetz et al., 2019;

Momtaz, 2019b). The high volatility of token prices in the aftermarket affects the BHAR investors can realize. To account for such time-related effects, we include a control variable that captures the change in the overall crypto market returns on an equally weighted portfolio. We calculate these returns based on all tokens listed on one of the 26 major exchange platforms, measured between the dates of the launch and the end of the focal ICO.

4.2.3.2.8. Time dummies. To account for other time-related differences, such as bubble behavior and general market swings, we include quarter-year dummies in all of our models (e.g., Fisch, 2019; Howell et al., 2019; Lyandres et al., 2019),

4.2.3.3. Ventures' human capital characteristics. Prior research in entrepreneurial finance shows that founder and team characteristics are crucial selection criteria for institutional investors (e.g., Block et al., 2019; Gompers et al., 2020). Research in the ICO context suggests a similar importance. For example, Giudici and Adhami (2019), Colombo et al. (2020), and Momtaz (2020a, 2020b, 2020c) associate various human capital characteristics (e.g., team size, higher academic degrees of the venture's core team) with higher ICO success. Similarly, Howell et al. (2019) show that founders with crypto experience and a technical background influence post-ICO operating performance.

Thus, we include a set of control variables referring to ventures' human capital characteristics to account for a potential influence on institutional investors' investment decisions and post-ICO performance. First, we control for ventures' team size ('team size'), which reflects the number of team members the venture reported at the start of the ICO, excluding advisors. Second, to account for individuals' technical expertise, we control for the number of team members with a college degree in a technical field (e.g., engineering, computer sciences) ('technical team members'). Third, to capture differences due to a higher level of formal education, we construct a dummy variable that captures whether at least one team member holds a Ph.D. ('Ph.D.'). Fourth, we control for individuals' domain-specific experience by capturing the number of team members with prior crypto industry experience ('crypto industry experience'). Finally, we include a control variable that captures CEO age ('CEO age'), as the CEO is also the founder in most ICOs.

4.2.3.4. Institutional investor characteristics. A final set of control variables refers to institutional investors' characteristics because such investor-specific characteristics can affect institutional investors' screening and coaching abilities. Characteristics associated with performance outcomes include the investor type of institutional investor (e.g., Chemmanur et al., 2009), the institutional investor's reputation (e.g., Krishnan et al., 2011), and the institutional investor's experience (Guo and Jiang, 2013).

To account for the institutional investor's reputation in the ICO context, we consider whether the institutional investor is registered with the SEC ('SEC-registered investor'). Investors registered with the SEC underwent an approval process, speaking to their seriousness. SEC registration also implies compliance with US securities laws and broad information disclosure requirements. The signals of SEC-registered investors may thus be more valuable to market participants. To account for the institutional investor's experience, we include a variable that captures whether the investor itself states its sole investment focus is on the crypto industry ('crypto-specific investor'). A clear focus may be associated with higher crypto-related skill sets (e.g., technology), more dedicated human resources, and social capital. Therefore, those investors may more significantly affect ventures' post-ICO performance.

4.2.4. Additional dependent variables used in further analyses

In addition to return-based measures, prior IPO research shows that institutional investors seek liquidity. Overall, higher liquidity is associated with lower risk because it enables investors to exit their investments more easily (e.g., Cumming et al., 2005a; Cumming et al., 2011; Eckbo and Norli, 2005). In line with prior ICO research, we thus use liquidity ('liquidity (log.)') as another post-ICO performance measure (e.g., Howell et al., 2019; Lyandres et al., 2019).

ICOs provide investors with early access to liquidity due to the transferability of tokens, which they can easily trade on cryptocurrency exchanges (Momtaz, 2019). The liquidity differs sharply between institutional investors' usual equity investments, which are often relatively illiquid and is another parallel between ICOs and IPOs (Momtaz, 2020d; Howell et al., 2019). Institutional investors' interest in liquidity was reaffirmed in our interviews with institutional investors (see Appendix). Fourteen out the 17 institutional investors interviewed indicated that they consider token liquidity as an important metric when assessing ICO investments.

In additional analyses, we examine the effects of institutional investor backing on measures of ICO success in the primary market. These measures include the amount of funding raised in the ICO ('funding amount (log.)'), the duration of the ICO in days ('ICO duration (log.)'), and the number of token exchanges the token is listed on within six months after the ICO ('# exchange listings (log.)'). These variables are in line with many prior studies on ICO success (e.g., Fisch, 2019; Howell et al., 2019; Momtaz, 2020c, 2020d) and are included in logged form due to their skewness.

4.3. Method

4.3.1. Potential endogeneity in ventures' institutional investor backing

Our empirical focus is on estimating the extent to which institutional investors affect post-ICO performance. A potential endogeneity issue arises since institutional investors may produce private information about venture quality when screening potential investment targets, which leads them to select higher-quality investments in the first place. This selection effect may bias any treatment effect (i.e., the institutional investor's actual effect on post-ICO performance) because our econometrical model relies on publicly available information.

Prior research shows that disentangling such selection and treatment effects is vital for enabling causal inference (for a methodological survey, see Appendix 1 in Colombo and Grilli, 2008; for empirical applications, see Bertoni et al., 2011; Chemmanur et al., 2011; Guo and Jiang, 2013). These studies indicate that a failure to account for institutional investors' selection of high-quality ventures can lead to an overestimation of the actual effect institutional investors have on venture performance.

In particular, Bertoni et al. (2011, p. 1033) note that the performance of new technology-based ventures is "closely related to unobservable characteristics such as innovative business ideas, development of a unique technology, or a team of smart owner-managers." If such unobservable characteristics affect post-ICO performance and the likelihood of obtaining institutional investor backing, we might mistakenly conclude that institutional investors may cause post-ICO outperformance (spurious correlation). Moreover, if institutional investors can identify ICO ventures with better performance prospects, a significant coefficient may not indicate that institutional investors cause higher post-ICO performance but the opposite (reverse causality) (for related studies, see Colombo and Grilli, 2005, 2008, 2010).

4.3.2. Econometrical approach

We seek to estimate the effect of institutional investor backing for firm *i* ($INST_i$) on post-ICO performance ($BHAR_i$), controlling for a vector of independent variables, Ω_i:

$$BHAR_i = \beta INST_i + \Omega_i \gamma + \varepsilon_i \tag{2}$$

Several methodological approaches exist to account for institutional investors' selection based on unobservable characteristics. In line with prior studies (e.g., Colombo and Grilli, 2005, 2008), we employ (1) a restricted control function (rCF) approach, (2) an inverse Mills ratio (IMR) approach, and (3) a propensity score matching approach.

All approaches start with a selection equation, which models the probability that firm *i* receives institutional investor backing by a vector of exogenous control variables affecting the selection mechanism, $\Omega_i^{(s)}$:

$$INST_i = \Omega_i^{(s)} \delta + \xi_i \tag{3}$$

4.3.2.1. Restricted control function (rCF). We first employ a restricted control function (rCF) approach (Imbens and Wooldridge, 2007). The rCF approach may lead to more consistent parameter estimates in our performance models because institutional investor backing might be endogenous to several variables, such as expert ratings. The rCF approach helps to deal with the endogeneity possibly generated by spurious correlations or reverse causality, leading to the "experimental average treatment effect" (Heckman, 1990; Colombo and Grilli, 2008) of institutional investor backing on post-ICO performance. The advantage of the rCF approach over IMR and matching approaches is that, rather than assuming that the conditioning set of relevant control variables is sufficiently complete, the rCF method models omitted variables (Heckman and Navarro-Lozano, 2004). Another advantage is that the generalized residual obtain from the first stage can be regarded as an explicit test for endogeneity (Colombo and Grilli, 2008). The idea is to control for the endogeneity in the error term in a two-stage process. First, the selection equation (Eq. (4)) produces a generalized residual ($GENRES_i$). Consistent with Gourieroux et al. (1987), we define the generalized residual as:

$$GENRES_i = INST_i \times \frac{\phi(-\Omega_i^{(s)}\delta)}{1 - \Phi(-\Omega_i^{(s)}\delta)} + (1 - INST_i) \times \frac{-\phi(\Omega_i^{(s)}\delta)}{\Phi(-\Omega_i^{(s)}\delta)} \tag{4}$$

where $\phi(.)$ and $\Phi(.)$ denote the probability density and the cumulative density functions of the standard normal distribution, respectively. We restrict the standard deviation of the error term for ventures with institutional investor backing ($\sigma_{\varepsilon,\ INST=1}$) to be equal to that of ventures that did not receive institutional investor backing ($\sigma_{\varepsilon,\ INST=0}$). This restriction is necessary so that $GENRES_i$ can be added as a single control variable to Eq. (2), which leads to the following rCF estimator, in which θ tests the null hypothesis that there is no selection effect:

$$BHAR_i^{rCF} = \beta INST_i + \theta GENRES_i + \Omega_i \gamma + u_i \tag{5}$$

4.3.2.2. Inverse Mills ratio. The second approach uses an inverse Mills ratio. We employ this approach for two reasons. First, it relaxes the restriction of the equality of the error term's standard deviation implemented in the rCF approach. Second, it provides another robustness check for the rCF approach because, provided that there is no relevant omitted variable, it relaxes assumptions about the separability of outcomes, the exogeneity of regressors, and the need of exclusion restrictions (Heckman and Navarro-Lozano, 2004). For a more technical comparison of the various approaches, Colombo and Grilli (2008, Appendix 1) and Heckman and Navarro-Lozano (2004) provide an excellent discussion. The inverse Mills ratio (IMR_i) is defined as follows:

$$IMR_i = \frac{\phi\left(\frac{\Omega_i^{(s)}\delta}{\sigma_\xi}\right)}{\Phi\left(\frac{\Omega_i^{(s)}\delta}{\sigma_\xi}\right)} \tag{6}$$

This leads to the following IMR estimator, where λ tests the null hypothesis that there is no selection effect:

$$BHAR_i^{IMR} = \beta INST_i + \lambda IMR_i + \Omega_i \gamma + v_i \tag{7}$$

Table 2
Descriptive statistics and correlations.

		1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.
	# Observations	565	2905	2905	2905	2905	2905	2905	2905	2905	2905	2905	2905
	Mean	0.265	0.111	3.150	0.881	0.567	2.930	0.881	13.94	0.512	0.411	0.381	0.243
	Standard deviation	3.800	0.314	0.797	0.324	0.496	2.310	0.324	8.310	0.500	0.492	0.483	0.429
1.	Performance (BHAR)												
2.	Institutional investor	0.06											
3.	Expert rating (avg.)	−0.06	0.04										
4.	GitHub	−0.04	0.03	0.22									
5.	Platform	−0.05	0.13	0.17	0.01								
6.	# Industries	−0.09	−0.08	0.25	0.03	0.35							
7.	Ethereum	0.00	0.02	0.04	0.02	0.02	−0.01						
8.	Token supply (log.)	−0.02	−0.21	0.25	0.06	0.03	0.16	0.00					
9.	Promotion: presale	−0.14	0.00	0.26	0.06	0.13	0.18	0.03	0.12				
10.	Promotion: free tokens	0.01	−0.07	0.34	0.04	0.06	0.16	−0.04	0.16	0.20			
11.	Promotion: reward program	−0.11	−0.01	0.42	0.07	0.14	0.23	0.02	0.26	0.12	0.29		
12.	Investor restrictions	−0.09	−0.07	0.31	0.04	0.05	0.18	0.01	0.10	0.16	0.20	0.25	
13.	Twitter activity (log).	−0.03	0.15	0.20	0.02	0.06	0.04	0.00	0.08	−0.03	0.10	0.08	0.07
14.	# Competing ICOs	−0.27	−0.05	0.18	0.09	0.05	0.18	0.07	0.67	0.15	0.17	0.25	0.13
15.	Market volatility	−0.01	0.05	−0.17	0.00	−0.01	−0.14	0.00	−0.15	−0.12	−0.14	−0.24	−0.18
16.	Team size	0.00	0.07	0.44	0.10	0.09	0.13	0.04	0.15	0.11	0.18	0.16	0.20
17.	Teachincal team	−0.11	0.08	0.27	0.03	0.08	0.10	0.00	0.07	0.03	0.12	0.10	0.16
18.	Ph.D.	0.05	0.08	0.10	0.01	0.04	0.08	0.02	0.01	0.02	0.02	0.01	0.11
19.	Industry experience	−0.11	0.04	0.29	0.01	0.08	0.10	−0.03	0.07	0.06	0.16	0.13	0.14
20.	CEO age	0.11	−0.03	0.10	−0.06	−0.06	0.00	−0.01	0.03	0.04	0.03	0.03	0.11
21.	SEC registered investor	0.03	0.23	0.00	0.01	−0.01	−0.03	−0.04	−0.03	−0.03	−0.04	−0.04	−0.04
22.	Crypto-specific investor	0.14	0.63	0.08	0.03	0.03	−0.04	0.00	−0.04	−0.06	0.02	−0.09	0.01
23.	Liquidity (log.)	0.37	0.27	0.06	0.05	−0.02	−0.09	0.04	−0.03	−0.03	0.09	0.00	−0.04
24.	Funding amount (in $mil)	−0.06	0.20	0.02	−0.07	0.05	−0.05	0.01	−0.05	−0.01	0.02	0.00	0.01
25.	ICO duration (in days)	−0.06	−0.16	0.04	−0.03	−0.06	0.06	0.00	0.08	−0.04	0.08	0.06	0.03
26.	# Exchange listings (log.)	0.32	0.28	−0.06	−0.04	−0.05	−0.09	0.00	−0.02	−0.14	0.01	−0.11	−0.09

(*continued on next page*)

Table 2 (*continued*)

		13.	14.	15.	16.	17.	18.	19.	20.	21.	22.	23.	24.	25.	26.
	# Observations	2905	2905	2905	2905	2905	2905	2905	2905	2905	2905	565	1081	1081	10-81
	Mean	4.840	282.9	1.013	8.949	1.163	0.156	2.179	33.82	0.010	0.065	1.960	13.90	59.40	0.4-02
	Standard deviation	1.510	124.9	0.467	6.212	1.236	0.405	3.741	6.430	0.070	0.246	5.350	34.50	71.70	1.210
1.	Performance (BHAR)														
2.	Institutional investor														
3.	Expert rating (avg.)														
4.	GitHub														
5.	Platform														
6.	# Industries														
7.	Ethereum														
8.	Token supply (log.)														
9.	Promotion: presale														
10.	Promotion: free tokens														
11.	Promotion: reward program														
12.	Investor restrictions														
13.	Twitter activity (log).														
14.	# Competing ICOs	0.00													
15.	Market volatility	−0.03	−0.27												
16.	Team size	0.20	0.09	0.03											
17.	Teachincal team	0.13	0.03	−0.05	0.46										
18.	Ph.D.	0.10	0.00	−0.04	0.18	0.24									
19.	Industry experience	0.14	0.03	0.00	0.32	0.33	0.16								
20.	CEO age	0.14	−0.09	0.11	0.02	−0.05	0.06	0.06							
21.	SEC registered investor	0.00	−0.05	−0.04	0.01	0.01	0.01	0.00	0.04						
22.	Crypto-specific investor	0.06	−0.08	−0.10	0.07	0.07	0.05	0.02	−0.05	0.24					
23.	Liquidity (log.)	−0.04	−0.06	0.01	0.08	−0.02	0.02	−0.04	0.03	0.21	0.32				
24.	Funding amount (in $mil)	0.02	0.00	0.01	0.01	0.05	0.02	0.04	0.03	0.34	0.11	0.09			
25.	ICO duration (in days)	0.03	0.06	−0.15	0.08	−0.05	−0.04	0.00	0.11	−0.04	−0.10	−0.12	−0.06		
26.	# Exchange listings (log.)	−0.03	−0.27	0.11	0.05	0.03	0.01	−0.01	−0.07	0.17	0.30	0.36	0.12	−0.11	

4.3.2.3. Propensity score matching. The rCF and IMR approaches should control for selection-related endogeneity provided that we have sufficient controls to model the selection mechanism. However, both approaches could still be biased if, for example, the remaining selection process is not normally distributed. This is because the conditional independence assumption, which is implicit in our selection models, could be violated (i.e., we assume that institutional investor backing is independent of the other control variables conditional on $GENRES_i$ or IMR_i).

To address this concern, we employ propensity score matching (PSM) using a nearest-neighbor algorithm (e.g., Dehejia and Wahba, 2002; Rosenbaum and Rubin, 1983). Hence, the model only considers those ventures without institutional investor backing (our "control group") that are the most similar to those ventures with institutional investor backing (our "treatment group"). The approach assumes that ventures with similar observable characteristics are also more similar in their unobservable characteristics. Therefore, the conditional independence assumption is less likely to be violated in this matched sample, alleviating endogeneity concerns.

5. Empirical results

5.1. Descriptive statistics

Table 2 displays summary statistics for our full sample ($N = 2905$ ICOs) and the subsamples of ventures with post-ICO performance data ($N = 565$, main analysis) and ICO success data ($N = 1081$, additional analysis). Regarding our independent variable, 322 of the 2905 ICOs (11.1%) obtained institutional investor backing. The number of ventures with institutional investor backing in the subsample of 565 ventures with post-ICO performance data is 189 (33.5%).

5.1.1. Dependent variable: post-ICO performance (BHAR)

The mean ICO in our sample yields a six-month BHAR of 26.5%, with a standard deviation of 3.8. The average BHAR is significantly different from zero at the 1%-level. This positive effect is in line with prior findings (e.g., Lyandres et al., 2019; Momtaz, 2019b) and indicates that investors may be able to extract informational rents in ICOs.

5.1.2. Control variables: venture characteristics

The mean expert rating of the sample ICOs is 3.2 (SD = 0.8), based on *ICObench*'s ratings from 1 ("low quality") to 5 ("high quality"). A total of 88.1% of all ICO ventures publish their code as open source on GitHub, which is in line with other studies (Fisch, 2019). Additionally, 56.7% of the ICOs have a platform-based business model and select an average of 2.9 industry categories on ICObench.

5.1.3. Control variables: ICO characteristics

The Ethereum standard serves as the basis for 88.1% of the sampled ICOs, underlining its pioneering role in the ICO context. The overall token supply (log.) is 13.9 on average, which corresponds to 1.1 million tokens. The standard deviation of 8.3 indicates a high skewness. Regarding promotional activities, more than half of the ICOs (51.2%) conduct a presale (or pre-ICO), 41.1% of the ICO ventures offer free token promotions, and 38.1% entertain a reward program. Less than one quarter of all sample firms (24.3%) implement investor restrictions in the form of a KYC process or a whitelist. Ventures post an average of 126 messages on Twitter during their ICO (log. = 4.8), and the average ICO takes place simultaneously with 283 competing ICOs (i.e., ICO durations have at least a partial overlap). Finally, we observe that the average market volatility is 1.0, with a moderate standard deviation of 0.5.

5.1.4. Control variables: ventures' human capital characteristics

The average ICO core team comprises 8.9 members, out of which 1.2 members have an educational background in a technical field. An average of 2.2 team members report experience in the crypto-sector before the focal ICO and there is at least one core-team member with a Ph.D. in 15.6% of the ICO firms. The average CEO is 33.8 years old, with a standard deviation of 6.4 years.

5.1.5. Control variables: institutional investor characteristics

In the full sample, only 1% of the firms are backed by an institutional investor registered with the SEC. This implies that almost 10% of all institutional investors in ICOs are registered with the SEC, and, in the subsample of firms with available post-ICO performance data, the coverage of SEC-registered institutional investors is 16%. Also, 6.5% of the firms obtained backing from an institutional investor that focuses exclusively on the crypto-sector. Among the firms that have successfully obtained institutional investor backing, this applies to 70 out of 322 firms.

5.1.6. Additional dependent variables used in further analyses

We track ICO liquidity as a further measure of aftermarket performance. The average liquidity (log.) is 2.0 with a standard deviation of 5.4. Another set of additional dependent variables refers to ICO success. The average funding amount ($13.9 million) resembles those reported in related ICO studies (e.g., Fisch, 2019; Momtaz, 2020d). Finally, the average ICO duration is 59.4 days, and approximately every other ICO firm lists its tokens on token exchanges within six months after completing the ICO.

Table 2 also shows the correlations for all variables. Since all correlation coefficients of the control variables are below 0.7, regression coefficients should not be severely biased. For confirmation, we compute generalized variance inflation factors (GVIFs) for each of our regression models. Specifically, we use Fox and Monette's (1992) measure of $GVIF^{1/2 \times C}$, where C denotes the number of coefficients. Mathematically, this measure compares correlations among the regressors to the “utopian ellipsoid” of uncorrelated regressors. The highest GVIF measure we obtain in the selection model is 1.9. The highest GVIF measure in the main analysis is 2.3. Moreover, the measure is below 3.0 in all other models. Hence, multicollinearity does not seem to be an issue in our study.

5.2. Main results: post-ICO performance (BHAR)

5.2.1. Regression results

Table 3 displays our main results for the effect of institutional investor backing on post-ICO performance (i.e., six-month BHAR). Column (1) shows the selection model, column (2) shows the control model, and column (3) shows the performance model using the rCF approach. All models include country and quarter-year fixed effects as well as robust standard errors.

The selection model (1) predicts the likelihood that an ICO venture obtains institutional investor backing, given a vector of observable characteristics. For example, the results show that a venture's expert rating (avg.) has a significantly positive effect on the probability of institutional investor backing with a coefficient estimate of 0.3134 ($p < .01$). This implies that a one-point-standard-deviation increase over the average expert rating increases the probability of attracting institutional investor financing by 56.3% (= 0.3134 + 0.3134 × 0.797). Furthermore, platform-based business models increase the likelihood of obtaining institutional investments by 37.7%, while serving an additional industry reduces the odds by 5.0%. Moreover, ventures backed by institutional investors provide a lower token supply (−2.3%), are less likely to conduct a presale (−19.2%), and offer reward programs less often (−34.5%). Instead, institutional investor-backed ICO ventures are more active in promoting their ICO on Twitter. Furthermore, team members with educational backgrounds in a technical field and those with a Ph.D. significantly increase the probability of institutional investor backing. No significant effects emerge regarding open source code on GitHub, Ethereum-based tokens, free token promotions, investor restrictions, the number of competing ICOs, market volatility, team size, industry experience, and CEO age.

Based on these results, we estimate the generalized residual (Gourieroux et al., 1987), which we include in the performance model to account for the endogeneity of institutional investor backing (as outlined in Section 4.3). The rCF model in column (3) shows a highly significant effect for the generalized residual ($p < .01$). Importantly, the coefficient is positive, which indicates the presence of a selection effect and suggests that institutional investors can indeed identify high-quality ICO ventures. Additionally, we find that the post-ICO performance of institutional investor-backed ICOs exceeds that of ventures without such backing by a rate of 1.3 ($p < .01$) after controlling for the selection effect via the generalized residual. Hence, the contribution of institutional investor backing to post-ICO outperformance amounts to 129%, indicating a substantial treatment effect.

Regarding the control variables, we find that platforms, investor restrictions, competing ICOs, market volatility, and the number of technical team members have a negative effect on post-ICO performance, while BHAR increase with token supply, reward programs, CEO age, and crypto-specific institutional investors. Note that the significances of the controls in column (3) differ from those in column (2). This implies that neglecting the existing endogeneity in post-ICO performance and institutional investor backing produces substantially biased parameter estimates.

5.2.2. Graphical evidence for different holding periods (1 to 12 months)

Our main dependent variable considers BHAR for a fixed holding period of six months after the initial listing date. While we choose the time horizon of six months based on sample size considerations and in line with prior ICO research, BHAR might be sensitive to different holding periods (e.g., Lyandres et al., 2019; Momtaz, 2019b). Also, time-series data on post-ICO performance can enable insights into the timing and intensity of value creation attributable to institutional investors.

Therefore, we compute a monthly outperformance measure for different holding periods ranging from one to twelve months, which reflects the difference between the average BHAR of ventures with and without institutional investor backing. Fig. 2 illustrates the evolution of outperformance by ICO ventures with institutional investor backing. Overall, the graphical evidence suggests that institutional investor-backed ICO ventures achieve performance increases of 50–75%. The outperformance increases steadily over the first six to seven months, and then remains at that level for longer holding periods. This shows that most of the average outperformance associated with institutional investor backing is realized in the first six months, suggesting that our time horizon choice of six months in the main analysis covers most of the value creation attributable to institutional investors.

5.2.3. Robustness tests using inverse Mills ratio and propensity score matching

The combined results of column (3) and Fig. 2 suggest that institutional investors are able to identify high-quality ICOs and further contribute to their outperformance. To ensure the robustness of these findings, we reestimate the performance model (i.e., column 3) using two alternative econometric approaches: the inverse Mills ratio (IMR) and propensity score matching (PSM).

The IMR specification is presented in column (4) of Table 3 and is identical to column (3) with the exception that the generalized residual is replaced with the IMR. This approach leads to three main findings. First, the coefficient of institutional investor backing is still significant and positive ($p < .01$), but its magnitude is slightly decreased. Second, the control variables are mostly consistent with those reported for the rCF model in column (3). Third, substituting the generalized residual by an IMR results in a partial loss of explanatory power (R^2).

PSM results are displayed in column (5) of Table 3. Note that these models also include the IMR as a control for selection. However, they improve on the conditional independence assumption by eliminating non-institutional-investor-backed ICO ventures that do not sufficiently resemble institutional-investors-backed ICO firms. While we use a one-to-one nearest-neighbor matching

Table 3
Main analysis: institutional investor backing and post-ICO performance (buy-and-hold abnormal returns, 6 months).

Column	(1)	(2)	(3)	(4)	(5)
Dependent variable	Institutional inv.	Post-ICO performance (BHAR)			
Model	Probit	Control	Restricted CF	IMR	PSM
Institutional investor (dummy)			1.290***	1.158***	1.0043***
			(0.2521)	(0.2103)	(0.1996)
Generalized residual	No	No	Yes*** (+)	No	No
Inverse Mills ratio	No	No	No	Yes** (+)	Yes*** (+)
Expert Rating (avg.)	0.3134***	1.3186	−0.6353	−0.7134	−0.7187*
	(0.05998)	(1.9057)	(0.8271)	(0.6649)	(0.3850)
GitHub (dummy)	0.0922	−1.2946	−1.1953	−0.9642	1.6771*
	(0.1321)	(1.9984)	(1.5768)	(1.0074)	(0.8983)
Platform (dummy)	0.3766***	−2.4165	−1.2487***	−1.2659***	−1.5086***
	(0.0743)	(1.9461)	(1.0372)	(0.4033)	(0.3597)
# Industries	−0.0500**	0.1189	0.4536	0.3017	0.6659
	(0.0203)	(0.4196)	(0.5843)	(0.4025)	(0.3238)
Ethereum (dummy)	0.0487	1.6423	1.1077	1.3368	1.3815*
	(0.1056)	(1.6808)	(1.1486)	(1.0247)	(0.7629)
Token supply (log.)	−0.0231***	0.01044	0.1781	0.1962*	0.2637***
	(0.0041)	(0.0650)	(0.1576)	(0.1093)	(0.0790)
Promotion: presale	−0.1919*	1.2823*	1.9761**	2.0664***	2.5393***
	(0.1196)	(0.6905)	(0.9887)	(0.7186)	(0.8002)
Promotion: free tokens (dummy)	0.0140	1.568**	0.4762	0.3779	0.5184
	(0.0844)	(0.7771)	(0.6841)	(0.5259)	(0.8229)
Promotion: reward program (dummy)	−0.3449***	−0.9965	1.4487	1.6635	2.0084***
	(0.1103)	(0.8751)	(0.9736)	(1.1545)	(0.6672)
Investor restrictions (dummy)	−0.0581	−0.3343	−0.4685	−0.4210	−0.6735**
	(0.1116)	(0.5496)	(0.4002)	(0.3672)	(0.3351)
Twitter activity (log.)	0.1416***	−0.2985	−0.5089	−0.8406*	−2.1610***
	(0.0214)	(0.3617)	(0.5166)	(0.4917)	(0.6136)
# Competing ICOs	0.0005	−0.0411***	−0.0487***	−0.0539***	−0.0613***
	(0.0007)	(0.0124)	(0.0097)	(0.0100)	(0.0072)
Market volatility	0.0005	−1.4702**	−1.5281**	−1.1311**	−1.0822**
	(0.0942)	(0.6638)	(0.6735)	(0.5516)	(0.5377)
Team size	−0.0111	0.0327	0.0413	0.0879	0.0622
	(0.0092)	(0.0373)	(0.0376)	(0.0698)	(0.0532)
Technical team	0.0813**	−0.3621*	−0.4231**	−0.3992**	−0.4054**
	(0.0403)	(0.1976)	(0.1996)	(0.1965)	(0.1987)
PhD (dummy)	0.2223**	0.4703	0.2767	0.3562	0.4598
	(0.0936)	(0.5390)	(0.5494)	(0.4316)	(0.6687)
Industry experience	−0.0039	−0.0892	−0.0793	−0.02153	−0.1069
	(0.0131)	(0.0956)	(0.0963)	(0.0588)	(0.1237)
Age	−0.0086	0.0772*	0.1020**	0.1654**	0.1900**
	(0.0078)	(0.0449)	(0.0465)	(0.0817)	(0.0942)
SEC registered investor (dummy)			−6.3263	−3.2677	−2.981
			(4.3862)	(4.2473)	(2.5516)
Crypto-specific investor (dummy)			3.4812*	2.5912*	1.9993*
			(1.9719)	(1.3884)	(1.0951)
Country/quarter-year fixed effects	Yes/yes	Yes/yes	Yes/yes	Yes/yes	Yes/yes
No. observations	2905	565	565	565	378
(McFadden) R2	(0.321)	0.118	0.145	0.130	0.135

This table presents 2SLS regression results. Model (1) is the first-stage and regresses a dummy for institutional investor backing on a vector of control variables. Model (2) regresses the second-stage dependent variable on all control variables to compare the parameter estimates of the controls to those in Models (3), (4), and (5). Model (3) employs a restricted control function approach and includes the generalized residual as a control. Model (4) includes the inverse Mills ratio. Finally, Model (5) replicates Model (4) with a propensity score matching. All variables are defined in Table 1. All models include robust standard errors. CF = Control function. IMR = Inverse Mills ratio. PSM = Propensity score matching.

* $p < .10$.
** $p < .05$.
*** $p < .01$.

model, the results are robust when using one-to-three and one-to-five nearest-neighbor matchings (not reported). The PSM results resemble those reported in column (4) and underline the robustness of our main analysis. Overall, the IMR- and PSM-based robustness tests support the results from the rCF approach, suggesting that the selection and treatment effects of institutional investors on post-ICO performance are significantly positive.

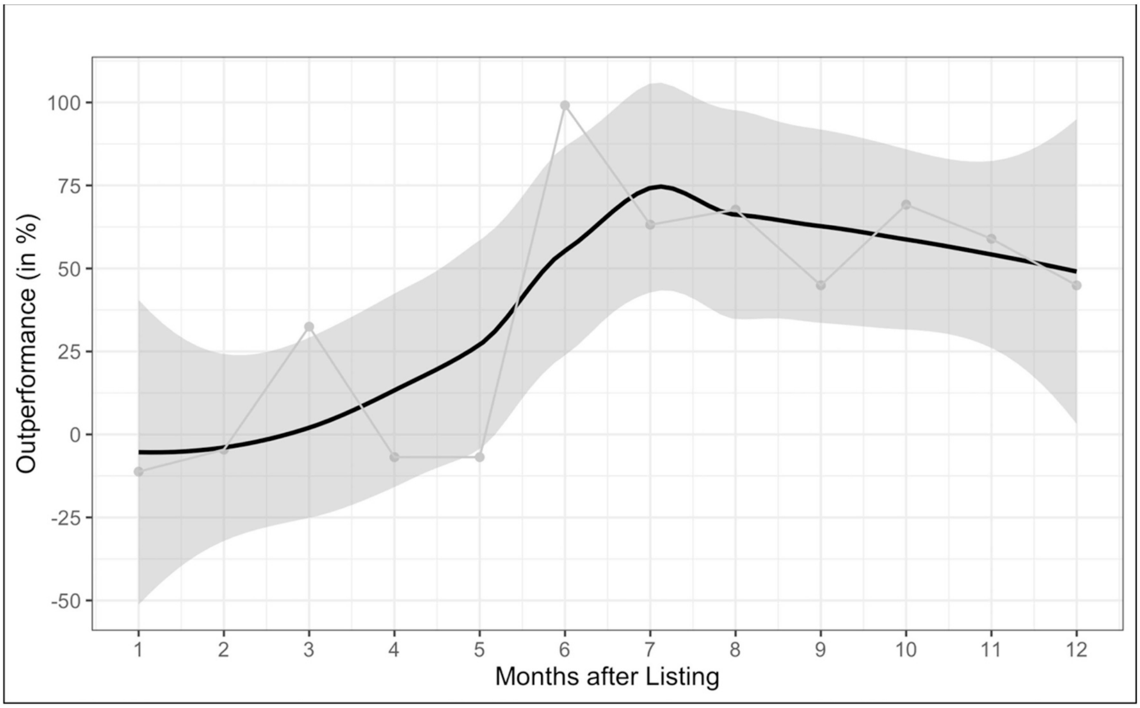

Fig. 2. Outperformance of startup firms with institutional investor backing relative to firms without institutional investor backing over first 12 months after the exchange listing.

5.2.4. Sensitivity tests: ICObench's industry classification scheme

Two of our control variables (i.e., '# industries' and 'platform (dummy)') are derived from ICObench's industry classification scheme. Because this scheme is not related to known industry categories, we further assess the robustness of our results with respect to the classifications scheme.

First, we exclude '# industries' and report the results for the main effects for the rCF, IMR, and PSM models in panel A of Table 4. Second, we exclude 'platform (dummy)' and reestimate our models. The results are reported in panel B of Table 4. Third, we include all industry classifications according to ICObench's scheme ($n = 29$) as indicator variables, while exluding '# industries' for reasons of multicollinearity. The results are reported in Panel C of Table 4.

Altogether, we find that our main results do not change in magnitude and significance across the different model specifications, which underlines their robustness.

5.2.5. Heterogeneous treatment effects model: venture capitalists (VC) versus hedge funds

VCs and hedge funds dominate the group of institutional investors in our sample. In previous analyses, we pool these different investor types for the benefit of statistical power. We now perform a heterogeneous treatment effects analysis, in which we split the sample into ICOs backed by VCs and those firms backed by hedge funds. We use information included in CryptoFundResearch to distinguish investors. We then run the rCF and IMR model specifications with six-month BHAR as the dependent variable for the two subsets. The PSM specification is omitted due to small sample size. All control variables are included but not displayed for the sake of brevity; they are qualitatively similar to those reported in Table 3.

The results reported in Table 5 are consistent with our main results. Both VC and hedge funds are able to select higher-quality ICO firms, as evidenced by the significantly positive generalized residuals and IMRs. Further, both VCs and hedge funds make significant contributions to ICO firms' longer-term development. The quantitative estimates of outperformance in terms of BHAR are largely in line with those reported in Table 3. This implies that both VCs and hedge funds lead to significant selection and treatment effects on post-ICO performance. Also, pooling VC and hedge funds to increase statistical power does not appear to bias the overall results for institutional investors because the quantitative effects of both investor types are similar.

5.3. Additional analyses

5.3.1. Additional secondary market measure: liquidity

To enable more holistic insights into the relationship between institutional investor backing and post-ICO performance, Table 6 uses *liquidity (*log.*)* as the dependent variable and also considers the first six months of trading.

The results show that the liquidity of institutional investor-backed ICOs exceeds that of ICOs without backing by institutional investors by a rate of 2.0. This suggests that institutional investors can scale ICO ventures to a level that drives the superior

Table 4
Sensitivity tests for ICObench's industry classification scheme for post-ICO performance (buy-and-hold abnormal returns, 6 months).

Panel A. Excluding '# industries'			
Column	(1)	(2)	(3)
Dependent variable	Post-ICO performance (BHAR)		
Model	Restricted CF	IMR	PSM
Institutional investor (dummy)	1.294***	1.155***	1.0040***
	(0.2522)	(0.2098)	(0.1991)
Generalized residual	Yes*** (+)	No	No
Inverse Mills ratio	No	Yes** (+)	Yes*** (+)
Controls	Yes	Yes	Yes
No. observations	565	565	378
R^2	0.144	0.129	0.133
Panel B. Excluding 'platform (dummy)'			
Column	(1)	(2)	(3)
Dependent variable	Post-ICO performance (BHAR)		
Model	Restricted CF	IMR	PSM
Institutional investor (dummy)	1.264***	1.149***	1.0026***
	(0.2503)	(0.2071)	(0.1958)
Generalized residual	Yes*** (+)	No	No
Inverse Mills ratio	No	Yes** (+)	Yes*** (+)
Controls	Yes	Yes	Yes
No. observations	565	565	378
R^2	0.142	0.127	0.131
Panel C. Controlling for all 29 industries according to ICObench's classification			
Column	(1)	(2)	(3)
Dependent variable	Post-ICO performance (BHAR)		
Model	Restricted CF	IMR	PSM
Institutional investor (dummy)	1.2511***	1.097***	0.9863***
	(0.2304)	(0.1924)	(0.1902)
Generalized residual	Yes*** (+)	No	No
Inverse Mills ratio	No	Yes** (+)	Yes*** (+)
Controls	Yes	Yes	Yes
No. observations	565	565	378
R^2	0.151	0.135	0.142

This table presents robustness checks to ensure that ICObench's industry classification scheme (and the control variables derived from it) does not confound the relation between institutional investor backing and post-ICO performance. Panel A drops the control variable that measures the number of industries that the ICO firm operates in according to ICObench ('# industries'). Panel B drops 'platform (dummy)'. Panel C includes dummy variables for all 29 sectors, according to ICObench's industry classification scheme (while dropping '# industries' to mitigate multi-collinearity concerns). Because the control variables are very similar to those reported in Table 3, we suppress the corresponding coefficients. The first stage is very similar to that shown in Table 3, Model (1), and therefore also suppressed. Models (1), (2), and (3) are identical to columns (3), (4), and (5) in Table 3, with the exception of the modifications described above. Models (1), (2), and (3) employ a restricted control function, inverse Mills ratio, and propensity score matching approach, respectively. All variables are defined in Table 1. All models include robust standard errors. CF = Control function. IMR = Inverse Mills ratio. PSM = Propensity score matching.

** $p < .05$.

*** $p < .01$.

performance (for theory linking liquidity via network effects to performance, see, e.g., Li and Mann, 2018). Again, we document evidence of existing selection-related endogeneity. Both the generalized residual and the inverse Mills ratio are statistically significant ($p < .01$). Additionally, the generalized residual is positive, supporting the previous finding that institutional investors identify and invest in better ICO ventures.

For the control variables, we find that platforms and competing token offerings have a negative effect on the liquidity increase after sixth months. In contrast, free token promotions and crypto-specific institutional investors spur liquidity. Furthermore, the model explains between one-sixth and one-fourth of the variation in token liquidity (R^2).

Table 5

Heterogeneous treatment effects analysis for post-ICO performance (buy-and-hold abnormal returns, 6 months).

Column	(1)	(2)	(3)	(4)
Dependent variable	Post-ICO performance (BHAR)			
Subsample	Venture capital backing		Hedge fund backing	
Model	Restricted CF	IMR	Restricted CF	IMR
Institutional investor (dummy)	1.4379**	1.5270***	0.7296*	0.9172***
	(0.6951)	(0.5857)	(0.4370)	(0.3506)
Generalized residual	Yes (+)	No	Yes* (+)	No
Inverse Mills ratio	No	Yes* (+)	No	Yes** (+)
Controls	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Quarter-year fixed effects	Yes	Yes	Yes	Yes
No. observations	509	509	429	429
R^2	0.136	0.133	0.167	0.170

This table presents a heterogeneous treatment effects analysis for institutional investors disaggregated into VCs and hedge funds. The first stage is very similar to that shown in Table 3, Model (1), and therefore suppressed. Models (1) and (2) regresses the second-stage dependent variable on all control variables, including a variable for the type of institutional investor that is equal to one if a VC was involved, and zero otherwise. Models (3) and (4) regresses the second-stage dependent variable on all control variables, including a variable for the type of institutional investor that is equal to one if a hedge fund was involved, and zero otherwise. Models (1) and (3) employ a restricted control function approach and include the generalized residual as a control. Models (2) and (4) include the inverse Mills ratio as a control. All variables are defined in Table 1. All models include robust standard errors. CF = Control function. IMR = Inverse Mills ratio.

* p < .10.

** p < .05.

*** p < .01.

5.3.2. Primary market measures

Prior ICO research often focuses on the determinants of ICO success (e.g., Adhami et al., 2018; Fisch, 2019; Momtaz, 2020b, 2020c, 2020d). As an additional analysis, we examine how institutional investor backing affects (1) the funding raised in ICOs, (2) ICO duration, and (3) the number of exchanges tokens listed after the ICO. Table 7 shows the results. Overall, the results provide supporting evidence that institutional investors play an essential role in ICO success. Institutional investor-backed ICO firms raise higher funding amounts in less time and are listed on more exchange platforms. We use a sample of 1081 ICO ventures for these analyses. This is because we try to leverage the maximum number of observations in each model to minimize concerns related to sample selectivity.

5.3.2.1. Funding amount. Panel A of Table 7 shows that the presence of institutional investors in ICOs significantly increases the funding raised (i.e., institutional investor-backed ICO firms raise $4.5 m more according to the rCF specification). The estimated effect is lower when we omit the generalized residual in columns (2) and (3) and instead rely on a Heckman correction and a PSM approach ($2.3 m). In total, the effect institutional investors have on the funding amount in ICOs is also economically significant, given that the average funding amount in the entire sample is $13.9 m.

5.3.2.2. ICO duration. Panel B of Table 7 focuses on ICO duration in days (log.) as the dependent variable. Institutional investor backing is associated with a significant reduction in the time it takes ICO firms to complete the ICO. The parameter estimates for institutional investor backing are weaker in columns (2) and (3). The significantly positive generalized residual indicates that institutional investors preferably invest in those ICO firms that require less time-to-market and reduce the time-to-market further.

5.3.2.3. Number of exchange listings. Finally, Panel C of Table 7 shows the results for the number of exchange listings (normalized) (log.). Institutional investors play an important role in increasing the presence of their investment targets on token exchange listings. The finding may explain why institutional investor-backed ICO firms experience significant increases in token liquidity since the additional exchange listings are related to access to new markets.

6. Conclusion

6.1. Summary and concluding remarks

We find that institutional investor backing is associated with higher post-ICO performance. This indicates that institutional investors are able to realize above-market financial returns (i.e., BHAR) in ICOs. In line with our theoretical predictions, we attribute this result to institutional investors' superior screening (selection effect) and coaching abilities (treatment effect), which enable them to extract informational rents in the ICO market by overcoming information asymmetries. By further disentangling selection and

Table 6
Additional analysis: institutional investor backing and liquidity (6 months).

Column	(1)	(2)	(3)	(4)	(5)
Dependent variable	Institutional inv.	Liquidity (log.)			
Model	Probit	Control	Restricted CF	IMR	PSM
Institutional investor (dummy)			2.0318***	1.9474***	2.0348***
			(0.2597)	(0.2867)	(0.2213)
Generalized residual	No	No	Yes*** (+)	No	No
Inverse Mills ratio	No	No	No	Yes*** (+)	Yes*** (+)
Expert Rating (avg.)	0.3236***	0.7025***	−0.2863	−0.3491	−0.9348*
	(0.0612)	(0.2024)	(0.4166)	(0.4292)	(0.4905)
GitHub (dummy)	0.0946	0.3961	0.4293	0.5456	0.7839*
	(0.1384)	(0.4954)	(0.4627)	(0.4798)	(0.4226)
Platform (dummy)	0.3865***	−0.3581	−1.1692***	−1.2037***	−1.5435***
	(0.0866)	(0.2894)	(0.3423)	(0.3599)	(0.3076)
# Industries	−0.0519**	−0.0722	0.0145	−0.0320	−0.0249
	(0.0248)	(0.0972)	(0.0956)	(0.0973)	(0.0851)
Ethereum (dummy)	0.0495	0.2768	0.2179	0.0434	−0.0819
	(0.1204)	(0.3967)	(0.3649)	(0.3785)	(0.3381)
Token supply (log.)	−0.0266***	−0.0087	0.0349	0.0536**	0.0870***
	(0.0048)	(0.0164)	(0.0229)	(0.0247)	(0.0245)
Promotion: presale	−0.1980*	0.0594	0.5561	0.8619*	1.2676**
	(0.1191)	(0.4480)	(0.4988)	(0.5036)	(0.5347)
Promotion: free tokens (dummy)	0.0090	1.0594***	0.8680***	0.7616***	0.9724***
	(0.0855)	(0.2819)	(0.2724)	(0.2783)	(0.2567)
Promotion: reward program (dummy)	−0.3759***	−0.4151	0.6479	1.1119**	1.7494**
	(0.1025)	(0.3987)	(0.5439)	(0.5312)	(0.7937)
Investor restrictions (dummy)	−0.0585	−0.1860	−0.4419	−0.4668	−0.4722
	(0.1040)	(0.4187)	(0.3896)	(0.4040)	(0.3865)
Twitter activity (log.)	0.1594***	−0.0886	−0.1635	−0.3620***	−0.5189***
	(0.0273)	(0.0990)	(0.1216)	(0.1187)	(0.1049)
# Competing ICOs	0.0007	−0.0032*	−0.0033*	−0.0046**	−0.0069***
	(0.0008)	(0.0018)	(0.0018)	(0.0022)	(0.0020)
Market volatility	0.0005	−0.1680	−0.0657	−0.1089	−0.1344
	(0.0942)	(0.4418)	(0.2030)	(0.1973)	(0.2056)
Team size	−0.0111	0.0552	0.0820	0.0820	0.0820
	(0.0092)	(0.0533)	(0.0508)	(0.0672)	(0.0738)
Technical team	0.0813**	−0.0979	−0.2229	−0.1764	−0.3008
	(0.0403)	(0.2825)	(0.3394)	(0.2697)	(0.4105)
PhD (dummy)	0.2223**	0.1630	−0.4248	−0.1723	−0.2248
	(0.0936)	(0.7697)	(0.7419)	(0.4263)	(0.5195)
Industry experience	−0.0039	−0.2269*	−0.1993	−0.2809	−0.2567
	(0.0131)	(0.1369)	(0.2100)	(0.2942)	(0.3305)
Age	−0.0086	0.0015	0.0315	0.0617	0.1116
	(0.0078)	(0.0640)	(0.0961)	(0.1088)	(0.1626)
SEC registered investor (dummy)			−0.4791	−0.6551	−0.4936
			(0.6382)	(0.7471)	(0.9326)
Crypto-specific investor (dummy)			0.8497**	0.7936**	1.0492**
			(0.4098)	(0.4001)	(0.5094)
Country/quarter-year fixed effects	Yes/yes	Yes/yes	Yes/yes	Yes/yes	Yes/yes
No. observations	2905	565	565	565	378
(McFadden) R2	(0.321)	0.151	0.257	0.212	0.247

This table presents 2SLS regression results. Model (1) is the first-stage and regresses a dummy for institutional investor backing on a vector of control variables. Model (2) regresses the second-stage dependent variable on all control variables to compare the parameter estimates of the controls to those in Models (3), (4), and (5). Model (3) employs a restricted control function approach and includes the generalized residual as a control. Model (4) includes the inverse Mills ratio in the spirit of Heckman (1979). Finally, Model (5) replicates Model (4) with a propensity score matching. All variables are defined in Table 1. All models include robust standard errors. CF = Control function. IMR = Inverse Mills ratio. PSM = Propensity score matching.

* $p < .10$.
** $p < .05$.
*** $p < .01$.

treatment effects, we find that both selection and treatment effects are complementary in explaining the overall positive effect on post-ICO performance.

Our results underscore the importance of institutional investors in the ICO-sphere and contribute to nascent research on ICOs (e.g., Chen et al., 2020; Fisch, 2019; Howell et al., 2019; Momtaz, 2020a). Our findings are intriguing because the idea of bypassing financial intermediaries is the backbone of blockchain technology (e.g., Fisch et al., 2019; Howell et al., 2019). However,

Table 7
Additional analysis: impact of institutional investor backing on measures of ICO success.

Panel A. Effect of institutional investor backing on the funding amount			
Column	(1)	(2)	(3)
Dependent variable	Funding amount (log.) (normalized)		
Model	Restricted CF	IMR	PSM
Institutional investor (dummy)	1.5022***	0.8263***	0.8391***
	(0.5181)	(0.2198)	(0.1900)
Generalized Residual	Yes** (+)	No	No
Inverse Mills Ratio	No	Yes*** (+)	Yes** (+)
Controls	Yes	Yes	Yes
No. observations	1081	1081	901
R^2	0.299	0.295	0.583

Panel B. Effect of institutional investor backing on ICO duration (log.) (normalized)			
Column	(1)	(2)	(3)
Dependent variable	ICO duration (log.) (normalized)		
Model	Restricted CF	IMR	PSM
Institutional investor (dummy)	−0.6853***	−0.2512***	−0.2176***
	(0.1304)	(0.0771)	(0.0542)
Generalized residual	Yes*** (+)	No	No
Inverse Mills ratio	No	Yes (+)	Yes (+)
Controls	Yes	Yes	Yes
No. observations	2905	2905	2263
R^2	0.404	0.399	0.624

Panel C. Effect of institutional investor backing on the number of exchange listings			
Column	(1)	(2)	(3)
Dependent variable	# Exchange listings (log.) (normalized)		
Model	Restricted CF	IMR	PSM
Institutional investor (dummy)	3.054***	2.388***	1.957***
	(1.0197)	(0.1930)	(0.2128)
Generalized residual	Yes*** (+)	No	No
Inverse Mills ratio	No	Yes*** (+)	Yes*** (+)
Controls	Yes	Yes	Yes
No. Observations	2905	2905	2263
R^2 (adj. R^2)	0.353	0.334	0.655

This table presents additional 2SLS regression results. Panel A uses log-transformed and normalized Funding Amount (in USD) as the dependent variable. Panel B uses log-transformed and normalized ICO Duration (in days) as the dependent variable. Panel B uses log-transformed and normalized Number of Exchange Listings as the dependent variable. The first-stage model is omitted here for brevity, as it is identical to that reported in Table 3. Model (1) employs a restricted control function approach and includes the generalized residual as well as the Inverse Mills ratio as controls. Model (2) only includes the inverse Mills ratio in the spirit of Heckman (1979). Finally, Model (3) replicates Model (2) with a propensity score-matched sample to further mitigate differences in the sample distributions of ventures that received VC financing and those that have not. All models include the control variables described in Table 1 as well as country fixed effects and year fixed effects. All models include robust standard errors. CF = Ccontrol function. IMR = Inverse Mills ratio. PSM = Propensity score matching.

** $p < .05$.
*** $p < .01$.

disintermediation may induce market inefficiencies due to moral hazard and information asymmetries. In line with Momtaz (2020a), our findings indicate that intermediaries (e.g., institutional investors) may find substantial financial gains from eliminating such inefficiencies.

Our findings also contribute to research on the relationship between institutional investor backing and aftermarket performance (e.g., Brav and Gompers, 1997; Chemmanur et al., 2011) and the particular substream of research that focuses on disentangling selection and treatment effects to improve causal inferences (e.g., Colombo and Grilli, 2005, 2010; Bertoni et al., 2011). Our findings document the importance of selection and treatment effects in the ICO context, which is in line with prior research in more traditional funding settings (e.g., Chemmanur et al., 2011; Guo and Jiang, 2013; Sørensen, 2007). However, the importance of selection and treatment effects is not uniform; studies in the European context generally attribute performance after institutional investments to a treatment effect, while a selection effect seems to be absent (e.g., Bertoni et al., 2011; Colombo and Grilli, 2010). A potential explanation is that ventures with great prospects self-select out of the market for institutional investments because they can raise sufficient funds independently and do not want to lose corporate control to institutional investors (e.g., Colombo and Grilli, 2010). Such self-selection does not seem to take place in the ICO context.

6.2. Limitations and avenues for future research

We operationalize institutional investor backing as a dummy variable and with little differentiation. However, the relation between institutional investor backing and ventures' post-ICO performance might partially depend on further characteristics of the institutional investor and the investment itself. These include the amount invested, the value-added activities performed by the investor (e.g., operational coaching, board seats, access to networks, nothing), and the investor's exit strategy (e.g., timing and method of exit). Unfortunately, despite manually researching each investment thoroughly, we were not able to gather such information reliably. This is mainly because ICO ventures and institutional investors do not disclose such information on their websites and because established investor databases do not contain this information (yet). Since more details on institutional investments will become available going forward, future research may make important contributions by investigating institutional investors' involvement in a more nuanced way. This includes, for example, assessing factors that moderate the effect of institutional investor backing on performance or exploring factors such as timing and exit strategies of institutional investors. Additionally, institutional investments typically syndicate their investments to mitigate risk (Gompers et al., 2020). Since ICOs entail high investment risk, syndication should become more likely. Hence, investigating the particularities of syndication in the novel ICO context might be an essential topic for future research.

Similarly, ICOs can impose trading restrictions on their tokens after the ICO. During these lockup periods (also known as vesting periods), investors and the ventures' team, which typically retains a share of the ventures' tokens, cannot sell their tokens (Howell et al., 2019). In IPOs, lockup periods are a commonly used commitment device that typically serves as an indicator of venture quality and alleviates moral hazard problems (e.g., Arthurs et al., 2009; Brav and Gompers, 2003). Hence, lockup periods could be associated with increased ICO performance in the primary and secondary markets. In contrast, lockup periods limit investors' exit options and decrease liquidity in the short run, which might deter institutional investors and negatively impact post-ICO performance. Against this background, future research can build on the vast literature on lockups in corporate finance and assess the existence, structure, and duration of ICO lockup periods and its implications.

Additionally, prior research questions the reliability and informative content of prices surrounding cryptocurrencies and tokens, which we base our dependent variable on. For example, fraudulent trading activity exists that has a significant influence on prices (e.g., Corbet et al., 2018; Howell et al., 2019). This evidence is in line with practitioner reports that indicate that most tokens artificially enlarge their trading volumes to appeal to investors (Baydakova, 2019). This manipulative behavior might bias our results, and the extent of this limitation is difficult to assess because the market is very opaque (Gandal et al., 2018). However, ICO research typically draws on such measures of aftermarket performance because other performance measures are difficult (or impossible) to obtain (e.g., Lyandres et al., 2019; Momtaz, 2019b). Additionally, the concern is alleviated by the evidence shown in Fig. 2, which suggests that our sample is not characterized by short-lived spikes in investor returns that are typically used in related work as evidence of manipulative activity.

Finally, limitations concern our study's external validity. For example, our performance measures are only available for a subset of ICO ventures. One reason for the unavailability of data is that ventures are not forced to list their tokens on exchanges. Another reason for the reduction in sample size is that the overlap between the different data sources we use is limited. For example, while ICObench (our starting point) covers many ICOs, even if very little data are available, not all of these ventures are listed by Coinmarketcap (our data source for performance data). We expect that both issues will fade with time as more data become available in a standardized format. Relatedly, most data providers delete ICOs from their records if they are unsuccessful or turn out to be fraudulent. While we invested much effort into mitigating these issues in our data construction process, we cannot rule out a certain bias in our sample related to missing data. This is an issue in all ICO studies (for a thorough discussion, see Momtaz, 2020a). Again, future research should have access to more comprehensive and reliable data, which will enable a replication of our findings to assess their reliability.

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Appendix A. Qualitative evidence on institutional investors in ICOs

Institutional investors are associated with superior portfolio firm performance due to screening and coaching abilities (e.g., Chemmanur et al., 2011; Sørensen, 2007). We assume that institutional investors perform similar screening and coaching activities in ICOs, which ultimately lead to higher post-ICO performance. However, while recent evidence suggests that institutional investors increasingly invest in ICOs, no systematic information exists on what institutional investors actually do in ICOs.

We collect initial evidence on institutional ICO investments by conducting 17 quantitative interviews with institutional ICO investors. The main goal of this interview-based approach is to provide some legitimacy to our conceptual considerations regarding the presence of selection and treatment effects. In contrast to explorative interviews, our interviews were structured, and every interviewee received a similar set of questions to facilitate comparisons.

Our interviews focused on the characteristics and activities performed by institutional investors in ICOs and took place in 2019. The interviewees are from the US (12), Europe (3), and other countries (2) (China, Canada). The investors' firms employ an average of 5.3 investment professionals, and the average investors possess an investment experience of 11.8 years. The average investment experience in the crypto industry is 3.5 years. This includes ICOs.

First, we asked respondents about their selection process when considering ICO ventures. The respondents told us that they spend a considerable time on screening investments. While some investors spend 3 to 5 days, 13 of the 17 investors spend more than 10 (and up to 180) days on gathering information and conducting due diligence before investing in an ICO. Also, most investors consider a wide set of information sources in their screening process. The most important information sources are the venture's source code and white paper. In addition, the most important factors that institutional investors consider when investing in ICOs are the ventures' technical sophistication, team quality, and the novelty of the product proposed. These factors largely resemble factors identified in venture capital research (e.g., Gompers et al., 2020) and indicate that institutional investors assess ICO ventures using similar criteria than more traditional ventures.

Second, we asked respondents about the value-added activities they perform in ICOs to gather preliminary evidence on the presence of treatment effects. Overall, 14 of the 17 interviewees stated that they do provide a value-adding function in ICOs. Specifically, most of the respondents engage in coaching activities and provide strategic and operational advice to their portfolio ventures. In addition, three interviewees mentioned that they provide a certification effect to their portfolio ventures. Other responses include the provision of resources, technical analyses, and enabling access to the institutional investor's network. Overall, these value-added activities closely resemble the coaching, monitoring, and certification activities described in more traditional funding settings (e.g., Chemmanur et al., 2011; Colombo et al., 2019; Gompers et al., 2020).

The evidence collected in the interviews suggests the presence of selection and treatment effects in the ICO context is similar to more traditional funding settings. Another interesting finding is a lack of interest in acquiring ownership in portfolio ventures. Only 3 of 17 investors have ownership targets and all of them are below 20%. Additionally, most institutional investors (11 of 17) try to negotiate private deals when investing in ICOs. The most important item in these negotiations is the extent of token discounts, while the acquisition of board seats and dividends are the least important items.

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