Does soft information in expert ratings curb information asymmetry? Evidence from crowdfunding and early transaction phases of Initial Coin Offerings

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Does soft information in expert ratings curb information asymmetry? Evidence from crowdfunding and early transaction phases of Initial Coin offerings

Tong Wang [a,*], Sheng Zhao [b], Mengqiu Zhou [a]

[a] *Business school, 29 Buccleuch Place, University of Edinburgh, EH8 9JS, United Kingdom*
[b] *Xi'an Jiaotong-Liverpool University, Suzhou Dushu Lake Science and Education Innovation District, Suzhou Industrial Park, Suzhou 215123, PR China*

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ABSTRACT

An Initial Coin Offering is the Initial Public Offering of the crypto sector. By issuing crypto tokens in exchange for funds, Initial Coin Offering is a popular way to raise capital for products or services typically associated with cryptocurrencies by issuing crypto tokens in exchange for funds. Initial Coin Offering has gained a lot of attention in the past few years; however, its lack of regulation has raised transparency and investor protection concerns from public agencies. This paper examines the role of soft information in third-party expert ratings and how it can mitigate information asymmetry in the financial markets. Expert ratings normally contain two types of information: hard information – a summary of public, numerically-measured information, and soft information – containing expert insights, rumours, and private conversations. Taking advantage of the special dual-rating system of a leading Initial Coin Offering rating platform, we successfully isolate soft information from expert ratings. We find that soft information reduces information asymmetry between issuers and investors, measured by the amount of raised funds in the crowdfunding phase and the underpricing levels in the early transaction phase. We also test the long-term survival rates and market price trends of issued tokens and conclude that soft information also plays a crucial role for investors in predicting the long-term performance of tokens. A heterogeneity analysis further shows that the soft information provided by expert ratings is more influential in countries or regions with low business environment indices.

1. Introduction

Information asymmetry shapes financial activities from various perspectives. In the initial offering process of financial products, in particular, a series of factors play significant roles, such as the limited knowledge held by investors (Chahine et al., 2020), behaviour of product issuers (Cohen & Dean, 2005), and administrative reasons (Kao & Chen, 2020). A large body of literature has well documented how information asymmetry influences the performance of Initial Public Offerings (IPO) (Lowry et al., 2010) and how some capital-market factors mitigate such impact (Michala, 2019). With the emergence and development of modern IT techniques, studies of information asymmetry have been extended to newly constructed digital financial products, such as peer-to-peer loan markets (Lin et al., 2013; Wang et al., 2021) and the digital banking service (Gomber et al., 2017), in order to investigate how the rise of the fintech

* Corresponding author.
E-mail addresses: twang210@ed.ac.uk (T. Wang), Sheng.Zhao@xjtlu.edu.cn (S. Zhao).

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industry is associated with information asymmetry. Among those new products, the initial coin offering (ICO) is a type of fintech instrument, which attracts an increased interest in the research fields of financial markets, corporate governance, and regulation. As a new form of financing tool that raises funds by selling crypto tokens initiated by blockchain-based companies in exchange for fiat or cryptocurrencies, Initial Coin Offering (ICO) markets have some unique features in relation to traditional IPO markets. For example, in most cases, ICO issuers are not selling equity tokens but utility ones; ICOs are generally less regulated, have shorter maturity and rely more on special social media-based marketing channels (Ofir & Sadeh, 2020). Other characteristics of ICO markets, such as retail investor denomination (Fisch & Momtaz, 2020) and commitment creditability (Howell et al., 2020) also affect the risk of information asymmetry in ICO offerings/transactions.

To tackle information asymmetry in ICO markets, some information intermediary platforms, such as icorating.com, have adopted an expert-rating system, which aims to provide a more straightforward indicator to the market to fill the information gap between investors and issuers. Some researchers focus on the information delivered by ICO in-market factors; for example, the issuer-team information (Giudici & Adhami, 2019) and signals provided by documents published by the issuers (Zhang et al., 2019; Chen, 2019); Howell et al., 2020). However, since external financial intermediaries play an important role for investors to access ICO information, classic theorists find that financial intermediaries reduce the cost of gathering and transferring information and thus decrease information asymmetry in financial markets (Ferguson & Lam, 2021). Professional rating providers (particularly credit rating agencies), as one of the categories of a financial information intermediary, profoundly impact the magnitude of information asymmetry (Tang, 2009; Hu et al., 2019). Parallel to the role of credit rating agencies in the traditional IPO market (An & Chen, 2008), the ICO rating agents provide rating services for ICO markets. The literature has well documented the role of rating in the reduction of information asymmetry problems (Roosenboom et al., 2020), as well as in the prediction and determinants of future ICO performances (Boreiko & Vidusso, 2019).

As stated above, these ratings (traditional credit ratings and ICO ratings) are intended to reduce information asymmetry by providing investors with summarized and clear information. However, it remains unexplored as to how the information gap is reduced: specifically, which is the more valuable ingredient contained within the ratings; soft information (the insight of experts), or hard information (a comprehensive summary of objective information)?[1] In most cases, ratings are released and presented to the public in a simplified format (for instance, AAA, A1 etc.). It is thus not explicitly known whether these ratings are derived from hard or soft information. Previous scholars (for instance, D'Aurizio et al., 2015, Fisch & Momtaz, 2020) have applied a series of extraction and identification measures but have mainly focused on bank-lending or online-lending activities: the soft information role in financial-product offering markets is less pronounced.

In this paper, we take advantage of a unique dataset of ICO markets to discuss the role of hard and soft information in reducing information asymmetry, respectively. In our dataset, each of the ICO projects has two ratings: an expert rating to summarize the views of experts, and a benchmark rating, which is an algorithm-creating score to summarize the hard information. The co-existence of these two types of ratings provides us with an opportunity to separate and quantify the predictive power of hard and soft information. Our results show that the soft information element in expert ratings plays a significant role in reducing ICO information asymmetry, while hard information does not.

This paper combines the records of ICOs that were posted and raised between 2015 and 2020 from icorating.com, with the record of token prices from coinmarketcap.com. Two categories of indicators are constructed to assess the magnitude of information asymmetry: first, the attributes that reflect ICO performances in the crowd-sale period (mainly following Ahlers et al., 2015; Chen, 2019); and second, underpricing indexes that measure information asymmetry during the transaction period (mainly following Cook et al., 2006; Fisch & Momtaz, 2020; Zhang et al, 2019). We empirically show that expert ratings are significantly associated with information asymmetry indicators while the algorithm-creating rating score, which only contains hard information, does not significantly predict ICO performances after controlling for other publicly observable parameters. This specifies that hard information components in rating scores do not solve information asymmetry. In order to further examine the soft information component, we employ a two-stage regression analysis. We compute the residuals after regressing expert ratings (mixed information) by algorithm-creating ratings (only hard information) along with publicly observed control variables. Next, we use these residuals to proxy the soft information and find that it is significantly associated with the ICO token performance in the market and thus implies a reduction of information asymmetry. This finding is consistently robust with different measures of information asymmetry. We further find that during the transaction period, the predictability of soft information tends to vanish with a longer time window after the ICO is completed. In order to supplement the claim that hard information does not impact information transmission, we employ 2SLS (two-stage least square) and 2SRI (two-stage residual inclusion) methods showing that after removing soft information, expert ratings are not significantly associated with ICO performance. We seek to further understand whether soft information predicts ICO performances by providing extra information to the market or by providing biased suggestions for investors who are misled to over-invest in what changes the short-run performance measures (as discussed by Goldstein & Huang, 2020). To that end, we conduct an additional test finding that the long-term survival of ICOs still can be substantially explained by extra information provided by expert ratings. This shows that the informative expert ratings do not work by misleading investors to invest in bad-quality projects but rather by providing additional information (further to the hard information in algorithm-creating ratings) on the ICO fundamentals. Moreover, the heterogeneity test shows that the soft information in expert ratings is more important for ICOs which are registered in regions/countries with a poorer business environment. By definition, a poor business environment implies that transparency and credibility of hard information are

[1] Hard information refers to number-based, easy-to-obtain and impersonal information, while soft information refers to the opposite, which means text-based, hard-to-obtain and personalized information (Liberti & Petersen, 2019).

major concerns, and investors thus rely more on the soft information in expert ratings.

This paper contributes to the literature in three aspects. First, this paper adds to the literature about the role of soft information in ratings and financial activities (Liberti & Petersen, 2019). The significance of soft information in financial decisions has been widely documented. Soft information is commonly measured by firm ownership structure (D'Aurizio et al., 2015), textual analyses of financial documents (Dorfleitner et al., 2016; Jiang et al., 2018; Liu et al., 2020) and some specific information disclosure designs, such as the compulsory loan-scoring system (Chen et al., 2015). These methods mainly work for lending markets and are restricted to the specific arraignments of the banking/online lending activities. In the rating field (besides the common findings that credit ratings play an essential role in the financial market), whether this role originates from the soft information or from summarising the hard information is less pronounced. To address this question, we separate the impact of soft information from mixed information sources. The empirical results suggest that soft information is significant in both the ICO crowdfunding and early transaction stages, but hard information is not.

Second, this paper provides new insights into ICO market efficiency. Since the emergence of blockchain technology, a large body of literature has been added to analyse the determinants of ICO market performances (Howell et al., 2020; Fisch & Momtaz, 2020; Cerchiello et al., 2019). Our results show that the long-term predictive power of soft information declines, implying that information revelation theories still apply in ICO markets. That is, market trading mitigates the information gap between the insider and the outsider (Barclay & Hendershott, 2003; Brogaard et al., 2014), although ICO markets are less regulated and heavily rely on voluntary information disclosure.

Third, we contribute to the growing discussion on the effectiveness of rating services on reducing information asymmetry in financial markets. Rating services, represented by commercial credit ratings, provide an external channel by which to reduce information asymmetry in equity markets (Tang, 2009), lending markets (Wittenberg-Moerman, 2008) and bond markets (Yang et al., 2017). However, with concerns about the conflict of interests originating from issuer-paid models (Cornaggia & Cornaggia, 2013) and the incentives of credit rating providers to inflate ratings (Stolper, 2009; Behr et al., 2018), the malfunction of credit ratings is a commonly discussed topic. In this paper, we apply the data from ICO markets to show that expert ratings (as a non-paid rating service) successfully reduce information asymmetry by providing personalised opinions beyond hard information. We also find that this function persists during the offering and early-transaction period but disappears in the long term.

Finally, our study provides important international implications. We find that soft information in expert ratings has heterogeneous predictive power in different countries or regions with different quality of business environments. In particular, soft information plays a more significant role in financial markets where the business environments are poorer. This fits the literature on the relationship between functions of credit ratings and the local institutional environment (Butler & Fauver, 2006; Poon & Chan, 2008), and our study provides new empirical evidence in the ICO markets.

This paper is organised as follows. Section 2 introduces the institutional background of ICO markets, including the fund-raising process, transaction models around the ICO date and the corresponding rating system. Section 3 summarizes the related literature on ICO performance, expert ratings and soft information extraction. Our research hypotheses are also discussed in this section. Section 4 provides the data description and variable construction. Section 5 presents the main empirical results and discusses their statistical and economic implications. We also report the robustness checks and the additional tests regarding the international implications in Section 6. Section 7 concludes.

2. Institutional background

An initial coin offering (ICO) is a new form of financing tool that raises funds by selling digital tokens initiated by blockchain-based companies in exchange for fiat or cryptocurrency. In contrast to traditional funding models, start-ups can use ICOs to circumvent the strict and regulated funding process required by venture capitalists or banks. After the ICO completes, the tokens can usually be exchanged between investors or converted into other cryptocurrencies or fiat currencies on a cryptocurrency exchange in a secondary market. The typical ICO process consists of two phases. The first is the crowdfunding (or crowd sales) stage, before which issuer teams post general project ideas on cryptocurrency forums (such as Bitcointalk) to attract public interest and gather feedback. The issuers then publish white papers describing the project outline, technical details, team members, and the funding plan (Zhang et al., 2019). In the formal ICO sales phase, projects usually set a soft cap and a hard cap: if the soft cap is achieved within the defined fundraising period, the ICO is considered to be a successful project; otherwise, the money is usually returned to investors, which means the project has failed. Meanwhile, the token sale is regarded as completed and successful once the raised amount reaches the hard cap. After an ICO is successfully funded, its tokens are typically traded on a cryptocurrency exchange, which is the second phase of an ICO project. The offer price of tokens is determined by the issuers and the cryptocurrency exchange rate. The price at which cryptocurrency exchanges trade is determined by bid and ask prices in an auction system, similar to the price at which securities exchanges trade.

Several key features of ICO markets differ from traditional IPO practices. First, ICO issuers are mostly small, opaque, emerging growth enterprises, and most ICO issuers have not followed up on the specific planning of a project, its progress, or the use of project funds. Second, ICO markets are dominated by retail investors, with limited participation by institutional investors (Fisch & Momtaz, 2020). Third, ICO markets are highly fragmented and unregulated. Most issuers only disclose information through a white paper that has no mandatory disclosure requirement and is not subject to regulation or audit requirements. As a consequence, the authenticity of the information cannot be easily verified by investors. In both phases, investors are free to make decisions by either participating in the crowdfunding process or buying/selling the listed tokens in the trading process. However, the information investors rely on for ICO investment decisions is restricted, compared with the traditional IPO. Unlike the investor-protection practice applied widely in the traditional financial product offering market, the information disclosure requirements of the ICO are non-standard and not under official authorisation (Hornuf et al., 2021). Therefore, the key reference for potential investors to make financial decisions in ICO markets is the fundamental financial data and wording descriptions in the white papers (Fisch et al., 2019; Samieifar & Baur, 2021).

The features of ICO markets highlight the need for more external participants, especially rating service providers, to be involved in offering ICO investors more information advantages. Besides the public information provided by the issuers, potential investors are able to consult the feedback provided by ICO rating scores from multiple sources. Many rating organisations (represented by ICO-rating) and individual experts (represented by ICObench) participate in the quality control of ICO projects by providing online rating reports. These rating platforms offer certification for the quality of ICOs and a variety of ICO evaluations, including algorithmic-creating and expert-posting ratings. ICO listing websites sprang up in 2017, with over 100 online platforms offering ICO listing information and rating services by the end of 2020. They gather a range of ICO experts to provide analysis and rating services to attract users. These platforms also evaluate experts' rating quality and monitor the authenticity of their personal information, professional backgrounds and experience.

The two rating systems studied in this paper are the Benchy and Expert rating systems, listed on icobench.com. Benchy rating (BR, hereafter) uses a set of more than 30 predefined parameters (in four categories: team information, ICO information, product information, and social media information) to evaluate whether an issuer has disclosed certain items of information that are considered important to ICO investors. It provides an algorithm-based score (between 0 and 1) for each of the parameters based on the overall availability of the disclosure of the four categories and generates an overall BR (from 1 to 5). Expert rating (ER, hereafter) is a weighted average of the rating scores of several unpaid crypto experts selected to rate ICOs and the weights for each expert are determined by ICObench, based on the quantity and quality of the expert's previous contributions to the crypto community. Interestingly, so as to be consistent with the platform's algorithmic ratings (BR), ICObench encourages experts to include the same criteria in their ratings as the benchmark ratings (that is, team rating, vision rating and product rating), which matches the categories of parameters that create BR. Hence, ER and BR share a similar set of hard information (the public parameters); however, ER also includes soft information provided by rating experts. This unique rating system in ICO markets should provide researchers with an opportunity to extract the soft-information component of ER based on the fundamental hard information benchmark of BR. Our econometric design to do this is presented in Section 4.

3. Literature and hypotheses

3.1. Related literature on information asymmetry in ICO markets

Information asymmetry is a common problem in financial product offering markets. The literature has well and widely documented the importance of information asymmetry in traditional IPO markets. The information gap is created or magnified by several behavioural factors, such as the tendency of firm owners to screen their inside information before publishing it to the public (Tong et al., 2013), the lack of legitimacy of top managers (Cohen & Dean, 2005), the shortage of independent firm boards (Chahine & Filatotchev, 2008), and restrictions on information disclosure (Bukh et al., 2005). The commonly recognised practice for reducing information asymmetry for IPOs is to provide the investors with additional information sources, such as pre-IPO auditing results (Bédard et al., 2008; Kao, & Chen, 2020), the opinions of expert analysts (Bouzouita et al., 2015), and the information enhancement provided by credit ratings (An & Chan, 2008).

As an emerging and innovative way of raising funds for firms, fintech products in particular, have received significant attention from academia in terms of the information asymmetry problem for them. Lin et al (2013) focus on peer-to-peer online markets and find that personal connections play a key role for the information asymmetry in lending decision-making. Wang et al. (2021) show that geographical factors also determine information quality in the peer-to-peer lending process. For ICO markets, information asymmetry is discussed on both sides: the issuer and the investor. On the issuer side, scholars focus on the role of documents disclosed by issuers in determining information asymmetry. Fisch (2019) finds that releasing the source code reduces information asymmetry. Zhang et al. (2019) raise the readability of white papers as the essential determinant. The creditability of issuer documents also tackles information asymmetry (Chen 2019). Guidici & Adhami (2019) find that team size and the member expertise of the issuers significantly influence information transmission in the ICO process. On the investor side, it is widely argued that the high proportion of retail investors is the main driver of information asymmetry (Fisch & Momtaz, 2020). Fisch et al. (2019) analyse the heterogeneity of investors in the context of financial decision-making.

Regarding the measure of information asymmetry in ICO markets, scholars apply-two categories of measures to reflect information asymmetry in the ICO crowdfunding process and in the ICO transaction process, respectively. For the crowdfunding process, the success of ICO fund-raising (i.e., the funds raised exceed the hard-cap or soft cap) is viewed as an example of less information asymmetry. Roosenboom et al. (2020) empirically find that the success of the ICO is typically determined by the quantity of information provided to investors. Howell et al., (2020) and Gan et al. (2021) follow Roosenboom's view and apply the success of ICOs as a proxy for lower information asymmetry. For the transaction process, underpricing (i.e., the transaction price in the first few days is higher than the ICO price) is normally applied to measure the degree of information asymmetry. Following the literature of IPO markets, the occurrence and magnitude of underpricing after the IPO indicate the information gap between different market participants (Cheung & Krinsky, 1994). This theory has been applied in the discussion of ICO markets where the underpricing is also linked with information asymmetry (Felix & von Eije, 2019; Michala, 2019), although some scholars do not fully agree that underpricing is a fair reflection of the information gap (Benedetti & Kostovetsky, 2021). In the empirical design of this paper, we apply both categories of measurement (i.e., the failure of the crowdfunding period and underpricing during the transaction period) to indicate a higher level of information asymmetry.

3.2. Related literature on the role of rating services in the reduction of information asymmetry

Starting from the early 1900s, rating services have been regarded as a crucial instrument for reducing information asymmetry by providing investors with expert opinions about underlying securities. The credit rating sector is the rating service that attracts the highest level of attention in the literature. Tang (2009) proxies credit market information asymmetry using credit rating refinements' data. He et al. (2011) examine the effect of rating changes on stock market information asymmetry. Besides the traditional equity and bond securities, credit ratings also affect the markets of innovative financial products, such as asset-backed securities (Faltin-Traeger et al., 2010; Moreira & Zhao, 2018) or more complicated securities, such as CDO (Griffin & Tang, 2011; Mählmann, 2012). Recent studies focus on the role of credit ratings in emerging markets, such as the Korean share market (Yang et al., 2017) and the Chinese bond market (Hu et al., 2019). This work concludes that credit rating services profoundly change the behaviours of market participants and influence market information asymmetry. Furthermore, some factors are explored to explain the heterogeneous quality of credit ratings, such as the expertise of applied modelling methods (Huang et al., 2004; Bonsall IV et al., 2017), the information source used by the rating team (Hilscher & Wilson, 2017), governmental regulations (Behr et al., 2018), and so on. The conflict of interests in the credit rating industry, which originated as the issuer-paid model, is well documented as another reason for a low-quality rating (Xia, 2014). A common practice in the credit rating industry is that the entities that issue bonds/equities pay the rating agencies for a rating. Such issuer-paid models are significantly associated with inflated rating levels, which are higher than the fundamentals of rated firms (Frenkel, 2015). Interestingly, scholars find that even the inflated ratings are still informative for investors (Goldstein & Huang, 2020) and have prediction power for firms' default risk (Zhao et al., 2021).

For ICO markets, the rating system differs from the traditional credit rating industry. It is un-paid, publicly available without a solicitation fee for investors and hence is free from potential conflict of interests. Bourveau et al. (2022) and Lee et al. (2021) found that expert ratings correlate with the success of ICOs and the long-term performance of the secondary market. Florysiak & Schandlbauer (2019) show that the higher the numerical reviewer score, the lower the probability of fraud. Roosenboom et al. (2020) find that expert ratings are a valuable tool to overcome information asymmetry as a factor that influences the success of ICOs. ICOs with positive expert ratings are more likely to be successful in raising funds and perform more effectively afterwards. Liu et al. (2021) explain the reason for the information asymmetry reduction by showing that expert ratings embed value-related information summarised by a group of experts, which follows the discussion on the *wisdom of crowds*[2] in financial markets (Ray, 2006), especially for fintech products (Yum et al., 2012). Concerns about the quality of multiple-source rating systems in ICO markets have been raised by Boreiko & Vidusso (2019), who point out that even though expert ratings may predict the success of ICOs, the information quality varies significantly with providers. In this paper, we examine the information source of expert ratings by splitting the information increment into two components – hard information-based and soft information-based – to further discuss how ICO rating systems tackle information asymmetry.

3.3. Related literature on soft information in financial activities

Hilscher & Wilson (2017) specify that the malfunction of rating scores results from an insufficient information source. They raise the concern that if the ratings only reflected public-observing information (i.e., hard information), they would not help to reduce the information gap and thus perform poorly in predicting the performances of rated entities. Generally, the function of hard and soft information in financial markets is of considerable academic attention. Petersen (2004) believes that with the development of information technology, hard information should play a more important role in financial decisions. However, recent research regarding different financial market sectors finds that the importance of soft information in communicating information among different financial participants has not been weakened. Agarwal & Hauswald (2010) investigate the accessibility of private information, which is measured by the borrower-lender physical distance as the soft information. They find that it is strongly correlated with banks' lending behaviour. D'Aurizio et al. (2015) find that soft information matters substantially in lending behaviour by protecting borrowers from having their funding cut by bankers during periods of recession. Chen et al. (2015) find that investors respond more rapidly to soft information than hard information in lending markets. Besides the traditional financial behaviour, the literature also finds that the power of soft information is non-negligible in the fintech market, in which soft information is more likely to be accessed (Sheng, 2021). For the peer-to-peer lending market, textual information extracted from a loan document is applied as a measure of soft information, and a strong relationship between that and the P2P performances is broadly examined and found on a consistent basis (Dorfleitner et al., 2016; Jiang et al., 2018; Wang et al., 2019). Other types of soft information in P2P lending have also been explored, such as borrowers' appearance (Duarte et al., 2012), chat records between borrowers and lenders (Xu & Chau, 2018), borrowers' birthplace (Wang et al., 2021), and so on. The research on the role of soft information in ICO markets has also been raised, focusing primarily on the role of white papers (Fisch et al., 2019; Samieifar & Baur, 2021) in the information transmission channels. Little previous research has concerned soft information in the ratings of ICOs.

3.4. Hypothesis development

The literature above has well documented the role of rating services in reducing information asymmetry and the function of soft

[2] The "wisdom of crowds" refers to the phenomenon whereby investors follow a group of experts when making investment decisions under the circumstance of very limited public information that can be relied on.

information in financial decisions. However, we also find that the specific role of soft information in ratings has been less discussed. It is well recognised that rating services provide information for market participants in helping them to make decisions; however, the "information" is derived from a mixed source: hard information, which is relied on by rating agencies when they calculate rating scores, and soft information, which comes from the human insights of raters, private information sources or individual experiences. The hard information component and the soft information component of ratings represent two functions of rating services: collecting and presenting publicly available information, and providing additional information that investors cannot easily recognise. In the ICO market, the latter function should be of greater importance in reducing information asymmetry due to the features of this market (less-regulated, low transparency, a high proportion of retail investors, etc.). Therefore, we raise the hypothesis of this paper as:

H0: In the ICO market, soft information in expert ratings is of more significance in determining information asymmetry than hard information.

Based on previous literature, we test this hypothesis in two phases of ICO: the crowdfunding period and the post-ICO transaction period. In the crowdfunding phase, the low information asymmetry is quantified by a higher amount of raised funds. Thus, we detail our hypothesis H0 in the crowdfunding stage as:

H0-a: The soft information in expert ratings is positively associated with the amount of funds raised in the crowdfunding phase, while the hard information is not.

For the post-ICO period, we regard the occurrence and magnitude of underpricing in the early period of transactions as the proxy of information asymmetry. Based on this, we detail our hypothesis H0 in the early transaction stage as:

H0-b: The soft information in expert ratings is negatively associated with the underpricing of ICOs in the early transaction phase, while the hard information is not.

4. Data and variables

4.1. Variables: Information asymmetry indicators

We measure information asymmetry for both the crowdfunding and transaction stages. For the crowdfunding stage, information asymmetry is measured by the amount of raised funds. Besides, in the formal ICO sales phase, projects usually set a soft cap and a hard cap. If the soft cap is achieved within the defined fundraising period, the ICO is considered successful; otherwise, the money is usually returned to investors. The hard cap is the highest possible amount that each ICO is able to collect. Therefore, we supplement the absolute amount of funds by two additional indicators to measure the information asymmetry: first, the ratio between the raised funds and the hard cap; and second, the dummy of whether the raised funds exceed the soft cap. The selection of these three indicators mainly follows the work of Fisch (2019), Roosenboom et al., (2020) and Lee et al. (2021). In summary, we select ln *(Raised), Soft Cap Hit* and *Funding Percentage* as the measure of information asymmetry in the crowdfunding period.

For the transaction stage, we define the information asymmetry by the measure of underpricing on the first day after the ICO. Underpricing refers to the phenomenon that a new token closes its first day of trading above the set ICO price. A large-sized underpricing on the first trading day indicates a high-level information gap between the inside traders (mainly at the ICO period) and public traders (mainly at the transaction period). The application of underpricing for measuring information asymmetry is originally documented in the IPO market (Beatty & Ritter, 1986; Cheung & Krinsky, 1994) and has been well recognized in the ICO field (Felix & von Eije, 2019; Michala, 2019). To clarify the meaning of underpricing, Ljungqvist & Wihelm (2003) define it as "the percentage difference between the price at which the IPO stock is sold to investors (the issue price) and the price at which the stock is subsequently traded in the market". Felix and von Eije (2019) used the first-day closing price of Coinmarketcap.com as a more credible closing price and corrected the underpricing by subtracting the returns of the ICO market (the largest cryptocurrency index, CCI30). Longer observing windows are also applied to measure underpricing, for instance, 5 days (Chanson et al., 2018). In this paper, we calculate ICO underpricing (UP_i) at different time intervals(i) by referring to the calculation method of IPO underpricing to fully observe the market's response to the information changing with time. To eliminate the potential effects of macro-economic factors, we adjust the absolute underpricing value taking the market situation into consideration and construct a market-corrected underpricing (MUP_i) as our final proxy of information asymmetry:

$$UP_i = \frac{P_{1i} - P_0}{P_0} \tag{1}$$

$$MUP_i = \frac{P_{1i} - P_0}{P_0} - \frac{P_{mi} - P_{m0}}{P_{m0}} \tag{2}$$

P_{1i} is the closing price of the token on the ith day after ICO in CoinMarketCap, and P_0 is the offering price of the ICO project. P_{mi} is defined as the closing price of the cryptocurrency market portfolio on the ith day after ICO, and P_{m0} is defined as the opening price of the cryptocurrency market portfolio (based on CCI30) at the offering date of the ICO. In terms of the selection i, we use 1 day, 5 days and 7 days respectively as the time windows for the baseline test and longer period tests for robustness checks.

4.2. Variables: Rating scores

Among the ICO rating and information platforms, the most recognized rating website is ICObench (icobench.com), which is composed of experts who voluntarily provide the rating of ICOs. ICObench is the largest and most visited ICO rating site and provides a

BR based on an automated algorithmic rating that evaluates over 30 disclosures of projects and ICO features, as well as ER from external cryptographers who volunteer to provide ratings. In this paper we apply these two types of ratings, respectively.

ER is provided by unpaid crypto experts based on a rating methodology that involves evaluating three specific dimensions of an ICO: team, vision and product. It is a weighted average of the ratings of the different crypto experts selected to rate ICOs, where the individual weights of crypto experts are determined by ICObench based on the quantity and quality of their previous contributions to ICObench and other crypto communities. To monitor the effectiveness of ER, ICObench rates the quality of experts according to how well they meet certain criteria. BR uses a set of more than 30 predefined parameters to evaluate whether an issuer has disclosed certain items of information that are considered important to ICO investors. These metrics fall into four categories: team information, ICO information, product information, and social media information. It provides an algorithm-based score (between 0 and 1) for each of the parameters of the ICO based on the overall availability of the disclosure of the four categories and generates an overall BR (from 1 to 5). Therefore, the BR is an objective rating that reflects the quantity and quality of information disclosed by the token issuers. Although some inputs for the algorithm of BR is known, the details of the algorithm are not available (Basu et al., 2021). It should be noted that ER and BR share the same hard information source. To be consistent with the platform's algorithmic ratings (BR), ICObench encourages experts to include the same criteria in their ratings as the benchmark ratings: team ratings should consider whether members have worked on other related projects or whether they have kept the community informed of project progress; vision rating should be based on project goals, market potential, and business strategy; and product ratings should take into account the stage and technology behind the product, strategic and growth options, as well as the promise of understanding the market.

We collect the records of both ratings, which allows us to distinguish between the quantitative processing of BR containing only publicly disclosed information and experts' assessments that contain the experts' human insights or private information. By employing a two-stage regression design, we are able to better observe the soft information component that is contained in ER but not in BR. The soft information in ER reflects the private information possessed by the expert and the professional ability to deal with public information. For example, experts may have a better ability to examine product development disclosures, product source codes and smart contracts to better assess project viability and the return on investment. They can also manage social media activity in order to help assess demand for the platform and tokens, which is a key driver of the intrinsic value of tokens (Bourveau et al., 2019).

4.3. Variables: Control variables

According to previous literature, we add in multiple control variables for the crowdfunding dataset and the transaction dataset, respectively.

4.3.1. Issuer size

The issue size is representative of ex-ante uncertainty (Beatty and Ritter, 1986). In general, the larger the issue size, the higher the information content of the project with true value. IPOs with smaller issue sizes are riskier than IPOs with larger issue sizes (Boonchuaymetta and Chuanrommanee, 2013) in ICOs, while small issue sizes have more uncertain information and are more speculative. Therefore, the larger the issue size, the less information asymmetry will be present (Felix and Eije, 2019).

4.3.2. Issuer retained ratio

In ICOs, the percentage of tokens owned by insiders is another positive signal. In capital offerings, when insiders retain a majority of the company's shares, the token percentage provides a positive signal to investors (Vismara, 2016). Stock ownership retained by board members is associated with improved operating performance (Bhagat and Bolton, 2008). Entrepreneurs who sell a larger share of the firm at the time of IPO are less likely to attract the interest of potential investors (Mcconnell et al., 2008). For the ICO, the higher retention rate of the token by the issuer will convince the market that the incentives of insiders are consistent with those of mass investors (Giudici and Adhami, 2019). Thereby, it is the investors who believe that the issuer is motivated to work hard for the success of the project. The issuer's belief that the value of cryptocurrencies will rise also indicates that the issuer has confidence in the long-term performance of cryptocurrencies (Roosenboom et al., 2020). Therefore, retaining a relatively high amount of cryptocurrency is a high-quality signal that will attract more investors on the issue date.

4.3.3. Duration

Time has an impact on how investors gather and digest information. Duration refers to the number of days to raise capital in an ICO from launch to close. Campaigns with longer durations are less likely to reach their financing goals, as planning for longer durations may indicate a lack of confidence in the project by potential investors (Mollick, 2014). Therefore, longer durations planned for ICO campaigns at launch can negatively affect financing success (Roosenboom et al., 2020), although if the duration is long enough, investors can study the project in detail and make a well-considered decision. However, people are highly sensitive to short-term financial events, and this scenario creates the impression of a limited and exclusive offer. Thus, the shorter the duration of the ICO, the more money the project is likely to raise (Rasskazova et al., 2019).

4.3.4. Market sentiment

Investor sentiment can be defined as the way in which investors form beliefs. Behavioural finance suggests that emotions can influence investors' decisions (Barberis et al., 2005). Burns and Moro (2018), analyse the main factors affecting the performances of ICOs based on investor sentiment (Baker and Wurgler, 2007), and that market sentiment provides insight into a potential return. Drobetz et al. (2019) find that coins listed during periods of negative investor sentiment generate negative returns in the short term.

Dean et al. (2020) argue that in the cryptocurrency market, the prices of tokens are mainly driven by speculative pressure. The markets' perceptions of these tokens are considered as investment drivers. Cheah and Fry (2015) find that positive market sentiment concerning the prospect of ICOs should have an impact on the percentage of ICO financing. Market sentiment may influence ICO success (Benedetti and Kostovetsky, 2021; Fisch, 2019). The better the token market sentiment, the greater the success that can be achieved through financing (Dean et al., 2020). Furthermore, market sentiment affects token underpricing (Loughran and Ritter, 2002). During periods of optimism in the IPO market, investors have a more positive view of the long-term performance of ICOs. As issuers do not take full advantage of this optimism (Ljungqvist and Wilhelm, 2003; Ljungqvist et al., 2006), there may have an increase in underpricing. The same may happen with cryptocurrencies. Therefore, the positive market sentiment may have exacerbated the undervaluation of ICOs.

4.3.5. Milestone

Key project milestones set the path and benchmarks for subsequent business development. Often, proposed future progress is measured through milestones. Milestones express the team and product philosophy and reflect the size and quality of the project (Florysiak and Schandlbauer, 2019). When the development team reaches certain milestones, token owners can decide to release capital over time (Giudici et al., 2020). The project development process is linked to various decision milestones. More milestone disclosures thus reflect more comprehensive progress of the project and facilitate investors to obtain more information on the project and respond positively. Thus, the number of milestones reflects the development of the project to some extent.

4.3.6. Hot market

The demand for capital by firms varies according to macroeconomic conditions, and the number of listed companies in the IPO market changes significantly over time, resulting in "hot" and "cold" market periods. (Pástor & Veronesi, 2005). The hot market period is defined by the high intensity of IPOs. Similar to the IPO market, the ICO market also suffers from hot and cold market changes, with a rise in the number of new ICO listings before the beginning of 2018 and a sharp decline afterwards. The price volatility in 2017 led to synchronised price fluctuations in almost all of the cryptocurrencies on which the platform-based industry relies. Less information content is all that is needed in order to get investors to accept projects of the same quality in a hot ICO market compared with a cold market. Thus, hot and cold market conditions can lead to differences in the amount of information that investors evaluate, which can affect the likelihood of success of the ICO at that stage. (Florysiak & Schandlbauer, 2019). There is also a significant positive correlation between hot issue markets and underpricing (Boonchuaymetta and Bhuanrommanee, 2013). The cyclical pattern of underpricing has existed during hot and cold markets (Ibbotson and Jaffe, 1975; Ritter, 1984). On the one hand, in hot markets, excessive investor optimism leads to a high concentration of IPOs and higher levels of underpricing (Lerner, 1994; Loughran & Ritter, 1995; Baker and Wurgler, 2000). On the other hand, bonds issued by a similar hot market are riskier and therefore underpriced, and ICOs need to compensate for the risk through greater underpricing.

4.3.7. Presale

Prior to the start of an ICO, the ICO will test market demand and estimate prices through a presale. Early investors who participate in the presale are often able to receive bonuses to encourage early participation and generate momentum for subsequent public offerings. Typically, the investment threshold is higher, and the sale size is smaller than in a subsequent public sale. The aim is to demonstrate to the public that the project team can have a group of cornerstone investors who are bullish about the project's prospects (Roosenboom et al., 2020). When the main financing begins, the project already has a certain amount of funding in place, which allows investors to signal that the upcoming ICO will generate interest in the market (Rasskazova and Rasskazov, 2019). Presales thus tend to have a positive impact on ICO performances.

Besides the common factors influencing both the crowdfunding and transaction periods of ICO, we also control for some specific factors for each of the two phases.

For the crowdfunding period:

4.3.8. Hard cap

The hard cap is the maximum financing limit set by the project. The financing demand is necessary to control for the scale effect in the returned model of ICO companies (Momtaz, 2021). The hard cap can be used to measure financing demand (Fisch, 2019). A higher hard cap means that the number of investors participating in the project is greater. This may send negative signals to the market. Financing goals are also negatively associated with success in the context of reward-based crowdfunding (Mollick, 2014). ICOs tend to set high hard caps that they are unlikely to reach (Ofir and Sadeh, 2020). However, higher hard caps are negatively associated with ICO success (Roosenboom et al., 2020). A large hard cap may deter investors from raising capital because they are concerned about the difficulty of doing so, while a high hard cap also requires a lot of money to be spent on marketing campaigns (Rasskazova et al., 2019). Similarly, research currently underway in IPOs suggests that underpricing is a quality signal used by issuers who know the true value better than investors (Welch, 1989).

4.3.9. KYC (Know Your Customer certificate)

KYC is the process of determining whether a customer is eligible for a given transaction (Ostern and Riedel, 2020). It initially originated from the traditional financial sector but has been widely used in ICOs. In traditional financial markets, KYC requirements are set by national legislation, regulatory documents issued by banking regulators, and international organizations, such as the FATF.[3] The introduction of KYC into the crypto market is due to the extreme ease and inadequate regulation of holding ICOs. Regulatory requirements for ICOs vary from country to country. According to the U.S. securities and exchange commission, providing KYC documents is mandatory. Only after filing KYC documents can an ICO legally allow investors to participate in an ICO. Most countries have not yet developed regulatory standards for ICOs. Companies launching an ICO need KYC to earn the trust of regulators. This amounts to a set of rules and regulations created by startups raising capital from token sales without legal regulation to deal with illegal operations, such as ICO scams, fraud and money laundering. If ICOs had sufficient KYC details, then it would make ICOs more legitimate, thus making it easier for investors and founders to establish credibility with banks.[4] Therefore, the availability of KYC certification will also influence investors' judgement of ICO quality and send credible signals to the market.

There are also factors working only during the transaction period.

4.3.10. Trading volume

When stock prices adjust to market value, they are eventually reflected not only in the level of underpricing but also in trading volume. Miller and Reilly (1987) find that the level of IPO underpricing affects the size of the trading volume. Schultz and Zaman (1994) find a similar relationship between trading volume and the level of underpricing. Thus, the trading volume may be an important (control) variable for ICO underpricing, and its signal may positively affect the level of ICO underpricing (Felix and Eije, 2019).

4.3.11. Isbonus

During the crowdfunding period, early investors usually receive pricing discounts, which may benefit their early transaction premium. Fahlenbrach & Frattaroli (2014) found that over half of early investors received presale discounts. The existence of presale discounts allows a certain group of investors to "lock" their profits in by selling the tokens on the secondary market and thus change their trading behaviour.

The definition and description of all of the variables for this paper are displayed in Table 1.

4.4. Sample description

We construct our dataset from three websites: icobench.com, coinmarketcap.com and icoholder.com. We collect the rating information and fundamental information of ICO projects listed online from August 1, 2015 to August 1, 2020 from ICObench(icobench.com), and merge it with the records listed during the same period from ICOHolder(icoholder.com). We also collect the transaction information that has tracked all of the above projects within one year since they were listed on CoinMarketCap (coinmarketcap.com). The market portfolio index of cryptocurrencies is also collected from CCI30 (cci30.com). Due to the different monetary units involved in different ICO projects, we convert all variables with different currency units into U.S. dollars. The cryptocurrency exchange rate data is collected from CoinMarketCap, and the fiat currency exchange rate data is from the London Stock Exchange. The exchange rate of other cryptocurrencies and fiat currencies to the U.S. dollar is converted according to their closing price on the end day of relative ICO projects (UTC time).

In the calculation of underpricing, we use CCI30 as the benchmark to compute the market adjustment of underpricing. At the same time, we adjust the data dimension with large values, such as trading volume, to make the regression coefficients a reasonable demonstration. In order to solve the problem of skewness of data distribution, a natural logarithm form is used for numerical data, such as issue size, raised amount and hard cap.

Due to the technical errors of the websites, some collected data may be misrecorded. Thus, we eliminate the extreme values and outliers in the data screening. For example, ICOs generally last for about two months, but some projects in the data collection have a duration of more than one year. We suspect that the website did not make a detailed distinction between multi-round fundraising and single-round fundraising when recording data. Therefore, we exclude data of ICO projects of an unreasonable duration. However, we retain the true reflection of the market according to the actual situation. When dealing with underpricing data, it is true that the first-day trading volatility in the cryptocurrency market is considerable, leading to seemingly extreme data values. For example, cryptocurrencies dramatically plunge in price after the trade, resulting in the order of magnitude gap between their offering price and their first-day closing price. However, such volatility is also a feature of the cryptocurrency market, so it is retained. Throughout the data screening, we restore the true situation of the market and only eliminate the apparently extreme values that do not conform to the market rules. In the end, we construct a dataset of 504 ICO project samples for the study of information asymmetry for the crowdfunding period and another dataset of 244 samples for the study of information asymmetry for the transaction period. The summary statistics are reported in Tables 2 and 3 for crowdfunding data and transaction data, respectively.

We realize that with the missing values of some control variables, the final sample (504 ICOs) is only a subset of the original sample (761 ICOs). This may raise a concern that some missing ICOs may have a lower rating score than those kept in the final dataset. To

[3] FATF refers to the Financial Action Task Force, an intergovernmental organization founded in 1989 on the initiative of the G7 to develop policies to combat money laundering.

[4] CoinFactory report: https://medium.com/@CoinFactory/why-kyc-is-necessary-for-an-ico-c4616e98504d.

Table 1
Variable definition.

Information asymmetry	Definition
Crowdfunding period	
Ln(Raised)	The natural logarithm of the amount of money an ICO raised during its crowdfunding duration (in US dollars)
Soft cap hit	Dummy equal to 1 if the ICO successfully reached its minimum funding target and 0 otherwise
Funding percentage	The percentage of the total amount raised as a percentage of the hard cap
Transaction period	
MUP(i): Underpricing Market adj (i days)	The market-corrected underpricing level of an ICO token on the i-day after it is listed on an exchange
Ratings	
ICObench rating	
Expert Rating	A weighted average of the ratings of different crypto experts who rate ICOs
Benchy Rating	A predefined set of more than 30 parameters was used to assess whether the issuer had disclosed certain items of information deemed important to ICO investors
Control variables	
Issue size	The natural logarithm of the number of coins offered multiplied by the offer price (in US dollars)
Issuer retained ratio	The number of cryptocurrencies of the project not offered in the ICO divided by the total number of project cryptocurrencies
Duration	Number of planned for the ICO campaign at the time of its launch
Market sentiment	Market sentiment is equal to the 30-day return of the CCI30 index measured at the listing day
Ln(Milestones)	The nature logarithm of number of milestones of the project team
Ln(Hard cap)	The nature logarithm of maximum funding limit set by the project
Ln(raised)	The natural logarithm of the amount of money an ICO raised during its crowdfunding duration (in US dollars)
Hot market	Dummy with a value of 1 if the ICO happened between July and December 2017, otherwise 0
Trading volume	The trading volume at the listing day (in US dollars)
Presale	Dummy with a value of 1 if coins were available for sale before the official ICO, otherwise 0
Isbonus	Dummy with a value of 1 if early investors get discounts within the ICO period, otherwise 0
KYC	Dummy with a value of 1 if the ICO get the KYC (Know-Your-Customer) certificate, otherwise 0

Table 2
Summary statistics of ICO crowdfunding dataset.

Variable	Obs	Mean	Std. Dev.	Min	Max	
Information asymmetry						
Ln(Raised)	504	15.05	1.710	7.132	20.17	
Soft cap hit	504	0.349	0.477	0.000	1.000	
Funding percentage	504	0.278 0.701 0	1.42	0.353	0.003	1.000
Ratings						
Expert Rating (From 1 to 5)	504	3.448	0.597	1.800	4.700	
Benchy Rating (From 1 to 5)	504	3.309	0.556	1.800	4.800	
Control variables						
Issue size	504	16.87	1.527	8.006	23.51	
Issuer retained ratio	504	0.459	0.201	0.000	0.982	
Duration	504	34.17	15.68	1.000	70.00	
Market sentiment	504	0.045	0.486	−0.570	2.064	
Ln(Milestones)	504	2.211	0.393	0.693	3.434	
Ln(Hard cap)	504	17.22	1.560	1.946	23.03	
Hotmarket	504	0.167	0.373	0.000	1.000	
Presale	504	0.502	0.500	0.000	1.000	
KYC	504	0.524	0.500	0.000	1.000	

Note:
1 The minimum value of the data in the funding percentage is 0. There are projects that set a high hard cap and raise very little money, resulting in a small percentage of capital raised without reaching a value above the thousandth percentile, and the default value of the data in the stata software is the thousandth percentile after the decimal point, so it is shown as 0 but not actually. This explanation also applies to the case where the minimum value of issuer retained ratio is 0.
2 Variables that are not labeled with units have no real meaningful units because the natural logarithmic values are taken in the study.

address this concern, we draw density histograms of rating score distributions for both the raw and the final samples (see Fig. 1) and find that the shapes of rating distribution (for both the Benchy rating and expert rating) of the two samples are nearly the same. This also implies that the sample that we used for regression is unlikely to create a selection bias.

Table 3
Summary statistics of ICO transaction dataset.

Variable	Obs	Mean	Std. Dev.	Min	Max
Information asymmetry					
MUP(1)	238	0.957	5.573	−1.183	44.60
MUP(5)	236	1.322	11.35	−1.025	161.8
MUP(7)	234	1.395	11.47	−1.062	161.8
Ratings					
Expert Rating (From 1 to 5)	244	3.469	0.600	1.800	4.500
Benchy Rating (From 1 to 5)	244	3.303	0.614	1.800	4.500
Control variables					
Issue size	244	19.31	2.02	12.90	25.33
Issuer retained ratio	244	0.495	0.208	0.037	0.950
Ln(Raised)	244	15.35	1.520	11.61	18.50
Duration	244	45.67	48.46	1.000	379.0
Hot market	244	0.131	0.338	0.000	1.000
Trading volume	244	137.6	454.7	0.000	4306
Presale	244	0.570	0.496	0.000	1.000
Isbonus	244	0.516	0.501	0.000	1.000

Note:
1. The observation numbers of underpricing data are slightly fewer for a longer time window because some of the ICOs did not last for day i so the records are missing.
2. Variables that are not labeled with units have no real meaningful units because the natural logarithmic values are taken in the study.

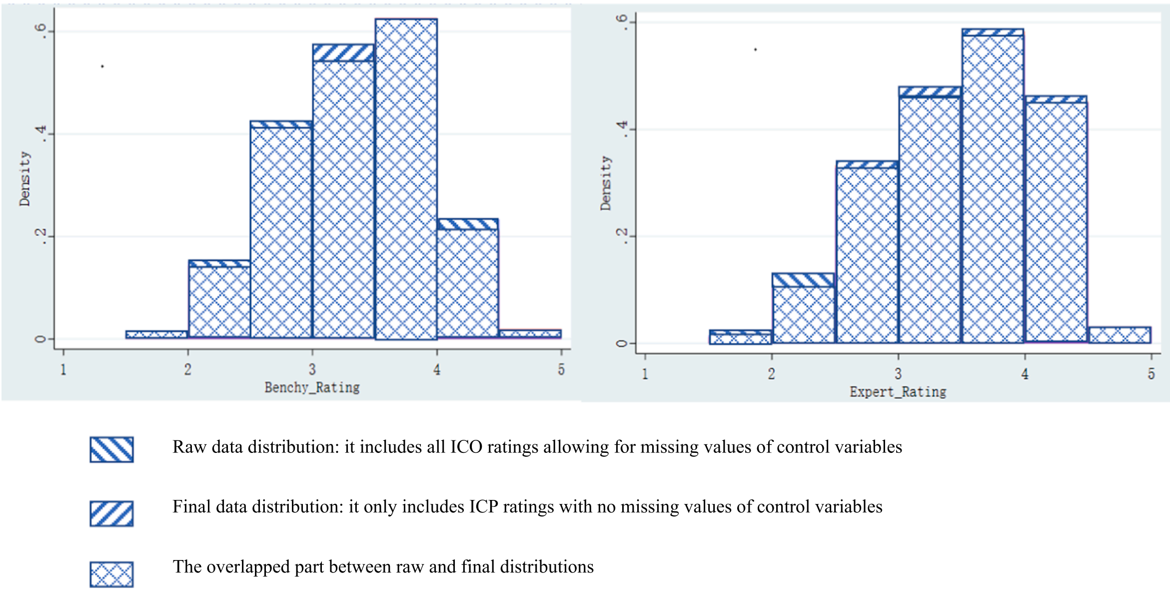

Fig. 1. Histograms of distribution density of Benchy rating score and Expert rating score for raw data and final data.

5. Empirical results

5.1. Expert ratings and Benchy ratings to predict ICO performances

We firstly regress the indicators of ICO performance by the two types of ratings (i.e., ER, which contains a mixed information source and BR, which reflects only hard information). To control for potential information that is not included in the rating score, we also add the control variables into the regression design. The general regression function is written as:

$$PerformanceMeasure = ExpertRating/BenchyRating + Controls + \lambda + \varepsilon \tag{3}$$

For the crowdfunding period data, *performancemeasure* is proxied by the amount of raised funds, the dummy indicating whether this amount hits the soft cap and the percentage of this amount out of the hard cap. For the transaction period data, *performancemeasure* is is defined by the market-adjusted underpricing with time windows of 1 day, 5 days and 7 days respectively. *ExpertRating*, and *BenchyRating*, control variables have been defined and discussed in Table 1. λ refers to year fixed effect, which controls for the common shocks of time-variant, ICO-invariant unobserved factors. To make more robust time controls, we also replace the year fixed effects with quarter and month fixed effects and find similar results.

The regression results of crowdfunding data and transaction data are displayed in Tables 4 and 5, respectively. For the crowdfunding period data, we find a significantly different predictive power of ER and BR for information asymmetry. The first three columns of Table 4 show that after controlling for the public variables, the score of ER is still significantly and positively related to a better ICO crowdfunding performance. This significant predictive power is consistent among the three measures we construct. Besides the statistical significance (at a significance level of 10 %), we find that the economic significance, represented by the estimate parameters, is also pronounced: first, the estimate of ER for ln*(raised)* is 0.468, which indicates that if the ER score is one-mark higher (from 1 to 5), the average amount of funds successfully raised in the ICO increases for approximately 47 %; second, the estimate of ER for *soft-cap-hit* is 0.067, which indicates that if the ER score is one-mark higher (from 1 to 5), we should see a 6.93 % ($e^{0.067}-1$) increase in the odds of the raised funds hitting the soft cap; and third, the estimate of ER for *funding percentage* is 0.079, which indicates that if the ER score is one-mark higher (from 1 to 5), the ratio that successfully raised funds out of the hard cap for this ICO increases by approximately 8 %. On the contrary, from the last three columns of Table 4, we find that the predictive power of algorithm-created BR is not significant for all measures of ICO performance at a significance level of 10 %. This evidence shows that only the ratings that have soft information ingredient (i.e., the ER that have mixed information sources) reduce the information asymmetry for the crowdfunding of ICOs. This is consistent with hypothesis that we propose.

Table 5 shows the parallel test results for the transaction period. The reduction of information asymmetry (i.e., a lower market-adjusted underpricing) is significantly related to a higher-level expert rating only for a 1-day transaction window after the ICO completes but not for longer transaction periods (5 days and 7 days). In column 2 of Table 5, the estimate of ER is −1.237, significant at a level of 6 %. The economic implication of the size of this parameter is also reasonable: if the ER score is 1 mark higher, the corresponding underprice decreases by around 1.2 %. Since a lower underpricing is the proxy of a lower level of information asymmetry, this evidence shows that the ER contains more information for the first-day transaction, which is expected by our hypothesis. However, if the time window is longer (5 days or 7 days), the significance of ER disappears (see columns 2 and 3 of Table 5). This implies that the information advantage of ER shrinks with time. This finding is consistent with literature that studies the shock of credit ratings on financial product transaction prices, showing that the shock only lasts for a couple of trading days and gets weaker with time for stocks (Norden & Weber, 2004; Choy et al., 2006), bonds (Jorion & Zhang, 2007) and asset-backed securities (Moreira & Zhao, 2018). Similar to the crowdfunding results, from the last three columns of Table 5 we find that the BR is not significant for any time window to predict the ICO underpricing. It shows that BR provides little additional information regarding the ICO underpricing after controlling for the publicly-observed information.

The results for control variables in Table 4 also fit the expectation for crowdfunding data. *Issue size* shows a significant positive association with ICO performances. This indicates that the larger the issuance scale of the project, the smaller the degree of information asymmetry, so it is easier to win the trust of investors and obtain financing success. In addition, the *Duration* of ICO is negatively correlated with the raised amount, which is consistent with the analysis of behavioural economics. People are highly sensitive to short-term financial events. Hence, the shorter the ICO duration, the more funds the project raises. The *issuer retained ratio* has a positive relationship with the raised amount, which is also consistent with previous studies. A higher issuer retained ratio makes the market believe that the incentives of insiders are consistent with those of mass investors (Giudici and Adhami, 2019). Therefore, the issuer retained ratio is correlated and reliable with the probability of ICO success. In addition, we also find that the number of *milestones* also positively relates to the raised amount. On the one hand, *milestones* reflect investors' attention to the project's progress, while on the other hand, they are also a monitoring window for outside investors. Projects with more milestones reflect better project quality, more recognition from investors and more funding. *Market sentiment* and *hot market* also positively predict the performances of ICOs, but the *hot market* is not as predicted by previous studies, which may be due to two factors that counterbalance each other: the high number of ICOs mixed in the hot market increases the ratio of fraudulent projects to failed ones. We also find that in *hot market* phases, higher information content predicts a higher possibility of successful ICOs. In terms of the transaction period, the significance of control variables is weaker than that in the crowdfunding period. We find from Table 5 that the amount of raised funds in the crowdfunding period is slightly negatively correlated with the underpricing.[5] A possible reason may be that a relatively good performance in the crowdfunding phase implies a lower level of information asymmetry, which is consequently evidenced by a lower level of underpricing in the transaction phase. We also find that the variable *presale* is negatively related to underpricing, which means that if an ICO is available to be transacted before the official offering (mainly by institutional investors), the information asymmetry in the post-ICO

[5] We acknowledge an issue of systematically different levels of adjusted R-squares in Table 4 and Table 5. For the crowdfunding data regressions (Table 4), the adjusted R-squares are all positive with a reasonably high levels which indicates a sufficient aggregate explanatory power of ICO fundamentals for the performances. But for the transaction data regressions (Table 5), the adjusted R-squares are positive but small for 1-day cases and even are negative for cases with longer windows. The low explanatory power for transaction data may be attributed into two aspects. First, from the statistical perspective, the sample size for the transaction data is much smaller than that of crowdfunding data due to the fact that the majority of firms who want to have ICOs were not able to successfully get their ICOs listed and hence are not included in the tests for the post-ICO performances. This is consistent with the findings of other scholars such as Fisch & Momtaz (2020) and Benedetti & Kostovetsky (2021). With a small sample size but a relatively large number of independent variables, both the R-squared and adjusted R-squared may mis-measure the explanatory power of the independent variables (Akossou & Palm, 2013). Furthermore, from the financial perspective, in Table 5 we mainly use pre-ICO fundamentals, including the pre-ICO ratings as independent variables to explain the post-ICO performances, while the pre-ICO fundamentals have been reflected by the first day's token price. Therefore, the explanatory power of pre-ICO fundamentals should be lower than that for crowdfunding period. Especially for observation windows longer than 1 day, the relevance of pre-ICO information with the transaction prices further fade away, therefore we sometimes observe negative adjusted R-squared.

Table 4
Regression of information asymmetry with ratings_Crowdfunding.

Dependent	Ln(Raised)	Soft cap hit	Funding percentage	Ln(Raised)	Soft cap hit	Funding percentage
Expert Rating	0.468***	0.067*	0.079*			
	(0.000)	(0.079)	(0.086)			
Benchy Rating				0.186	0.005	0.039
				(0.172)	(0.223)	(0.445)
issue_size	0.412**	0.041***	0.110***	0.425***	0.044***	0.112**
	(0.000)	(0.007)	(0.000)	(0.000)	(0.004)	(0.000)
issuer_ratained_ratio	1.441***	0.034	0.216	1.533***	−0.049	0.231*
	(0.000)	(0.751)	(0.102)	(0.000)	(0.647)	(0.081)
duration	−0.007*	−0.001	−0.003	−0.007*	−0.001*	−0.003
	(0.081)	(0.120)	(0.134)	(0.0081)	(0.149)	(0.134)
market_sentiment	0.179	0.102*	0.045	0.183	0.102*	0.046
	(0.301)	(0.060)	(0.496)	(0.301)	(0.060)	(0.486)
log_milesone	−0.301*	−0.038	−0.068	−0.254	−0.029	−0.061
	(0.084)	(0.474)	(0.303)	(0.150)	(0.584)	(0.356)
log_hardcap	0.059	−0.069***	−0.287***	0.062	−0.069***	−0.287***
	(0.220)	(0.000)	(0.000)	(0.197)	(0.000)	(0.000)
Hotmarket	0.256	−0.174**	−0.046	0.212	−0.282**	−0.053
	(0.308)	(0.024)	(0.628)	(0.404)	(0.018)	(0.577)
Presale	0.199	0.019	0.045	0.223	0.024	0.048
	(0.156)	(0.659)	(0.396)	(0.117)	(0.577)	(0.365)
KYC	−0.008	0.054	−0.079	0.078	0.074	−0.068
	(0.960)	(0.271)	(0.189)	(0.645)	(0.139)	(0.266)
Platform FE	Yes	Yes	Yes	Yes	Yes	Yes
N	504	504	504	504	504	504
adj. R2 (PseudoR2)	0.237	0.077	0.349	0.217	0.071	0.346

p-values in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5
Regression of information asymmetry with ratings_transaction.

Dependent	MUP(1)	MUP(5)	MUP(7)	MUP(1)	MUP(5)	MUP(7)
Expert Rating	−1.237*	−2.399	−1.811			
	(0.066)	(0.183)	(0.159)			
Benchy Rating				−0.469	−0.110	−0.102
				(0.383)	(0.848)	(0.859)
issue_size	0.267	0.606	0.614	0.236	0.534	0.535
	(0.153)	(0.207)	(0.209)	(0.192)	(0.211)	(0.215)
log_raised	−0.836	−2.478*	−2.428*	−0.877	−2.473*	−2.475*
	(0.558)	(0.114)	(0.122)	(0.547)	(0.115)	(0.123)
issuer_ratained_ratio	0.002	0.013	0.013	0.002	0.013	0.012
	(0.820)	(0.500)	(0.509)	(0.783)	(0.499)	(0.513)
duration	0.001	0.001	0.000	0.001	0.001	0.000
	(0.178)	(0.335)	(0.461)	(0.176)	(0.385)	(0.440)
trading_volume	3.213	1.357	8.244	4.075	1.720	7.310
	(0.548)	(0.846)	(0.296)	(0.433)	(0.810)	(0.331)
market_sentiment	−1.455*	−1.301	−1.306	−1.043	−0.524	−0.451
	(0.097)	(0.157)	(0.238)	(0.189)	(0.498)	(0.636)
hotmarket	−0.734	0.419	0.453	−0.978	−0.084	−0.043
	(0.407)	(0.772)	(0.757)	(0.242)	(0.940)	(0.971)
Presale	−0.627**	−0.725**	−0.767**	−0.683***	−0.800**	−0.857**
	(0.042)	(0.075)	(0.054)	(0.031)	(0.069)	(0.052)
isbonus	0.464	0.757	0.668	0.428	0.639	0.510
	(0.527)	(0.446)	(0.528)	(0.553)	(0.484)	(0.592)
Platform FE	Yes	Yes	Yes	Yes	Yes	Yes
N	238	236	234	238	236	234
adj. R^2	0.010	−0.033	−0.028	−0.002	−0.039	−0.035

p-values in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

period would be much less.

In sum, the baseline tests show that the ER, which contain mixed information sources (soft information and hard information), are predictive for the information asymmetry during the crowdfunding and early transaction phases of ICOs, while the algorithm-creating ratings (BR) do not have such predictive power. We conclude that the ratings that only reflect hard information should not provide any extra information for ICOs but the ratings that reflect a mixture information do. In the next step, we employ a 2-stage regression design to extract the soft information component from the ER to confirm that it is the soft information component in the ER that provides extra information to market participants.

5.2. Extraction of soft information in expert ratings and the prediction of ICO performance

In order to isolate the soft information from ER and explore the role of ER in solving information asymmetry in greater detail, we refer to the method of information decomposition in the bond rating market (Agarwal and Hauswald, 2010). We use a two-stage regression method to separate the soft information components in ER and explore the mechanism of expert rating to solve information asymmetry.

We apply the same design of outcome variables with baseline tests: for the crowdfunding phase, we use *ln*(*raised*), *soft cap hit* and *funding percentage* to measure information asymmetry and for the transaction phase, we employ MUP(1), MUP(5) and MUP(7), respectively. The selection of control variables is also consistent with that in the baseline test.

The test is done in two steps:

Step1: Soft information is obtained by residual decomposition of ER:

$$ExpertRating = BenchyRating + Controls + \lambda + \delta(Soft\_Information) \quad (4)$$

where *ExpertRating*, *BenchyRating*, *Controls* and λ are identically defined as the baseline regressions (Eqs. (3) and (4)). δ(*Soft_information*) is the estimated residual used in the second step to proxy the soft information component in the *ExpertRating*. It quantifies the variations in ER that are not able to be explained by BR (hard information-driven ratings) and open information in the market.

Step 2: we replace *ExpertRating*, the key independent variables of baseline test Eq. (3), by the soft information proxy, which is collected in the first step to re-run the key regressions:

$$PerformanceMeasure = \delta(Soft\_Information) + Controls + \lambda + \varepsilon \quad (5)$$

where *PerformanceMeasure*, *Controls*, λ are defined in Eq. (3) and δ(*Soft_Information*) is computed in Eq. (5).

The regression results are shown in Table 6 (for the crowdfunding phase) and Table 7 (for the transaction phase). From the results of the first stage regressions in both tables, we find a significant relationship between BR and ER: the estimate of BR is significantly positive for both phases. This implies that experts give rating scores based on the hard information source, which is reflected by BR. The sizes of estimates are around 0.74 (0.746 for the crowdfunding data and 0.741/0.739/0.734 for the transaction data, with 1-day, 5-day and 7-day windows, respectively). This indicates that when controlling for the fundamental information of ICOs, if the BR is 1-mark higher, the average ER would increase by about 0.74 marks. In the second stage test, we find that the residuals of the first stage

Table 6
2-stage regression, crowdfunding.

Stage	1st	2nd		
Dependent	Expert Rating	Ln(Raised)	Soft cap hit	Funding percentage
δ (Soft_Information)		0.512***	0.334*	0.117**
		(0.000)	(0.086)	(0.020)
Benchy Rating	0.746***			
	(0.000)			
issue_size	0.035*	0.451***	0.251***	0.118***
	(0.052)	(0.000)	(0.000)	(0.000)
issuer_ratained_ratio	0.232*	1.575***	−0.307**	0.240*
	(0.068)	(0.000)	(0.094)	(0.068)
duration	0.001	0.006	0.001	−0.002
	(0.617)	(0.134)	(0.868)	(0.318)
market_sentiment	0.008	0.235	0.555**	0.058
	(0.901)	(0.180)	(0.036)	(0.380)
log_milesone	0.144**	−0.248	−0.143	−0.060
	(0.023)	(0.152)	(0.573)	(0.356)
log_hardcap	0.005	0.027	−0.418***	−0.295***
	(0.781)	(0.574)	(0.000)	(0.000)
Hotmarket	−0.124	0.104	−1.041**	−0.077
	(0.178)	(0.680)	(0.011)	(0.418)
Presale	0.088*	0.253*	0.150	0.055
	(0.085)	(0.069)	(0.456)	(0.300)
KYC	0.335***	0.188	0.363	−0.044
	(0.000)	(0.223)	(0.101)	(0.448)
Platform FE	Yes	Yes	Yes	Yes
N	504	504	504	504
adj. R2 (PseudoR2)	0.154	0.238	0.076	0.352

p-values in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7
2-stage regression, transaction.

Stage	1st			2nd		
Dependent	Benchy Rating	Benchy Rating	Benchy Rating	MUP(1)	MUP(5)	MUP(7)
δ (Soft_Information)				−2.740**	−4.132	−4.230
				(0.023)	(0.212)	(0.211)
Benchy Rating	0.741***	0.739***	0.734***			
	(0.000)	(0.000)	(0.000)			
issue_size	0.015	0.015	0.016	0.202	0.502	0.503
	(0.169)	(0.161)	(0.150)	(0.245)	(0.225)	(0.226)
log_raised	−0.006	−0.012	0.001	−0.759	−2.253*	−2.243*
	(0.956)	(0.908)	(0.995)	(0.591)	(0.131)	(0.140)
issuer_ratained_ratio	−0.001**	−0.001**	−0.001**	0.001	0.013	0.013
	(0.045)	(0.054)	(0.081)	(0.841)	(0.505)	(0.518)
duration	0.000	0.001	0.001	0.001	0.001	0.001
	(0.507)	(0.212)	(0.424)	(0.157)	(0.417)	(0.454)
trading_volume	−0.480	−0.360	0.632	4.554	1.638	7.141
	(0.408)	(0.523)	(0.226)	(0.390)	(0.823)	(0.379)
market_sentiment	−0.195***	−0.195***	−0.211***	−0.877	−0.491	−0.419
	(0.002)	(0.001)	(0.001)	(0.203)	(0.486)	(0.634)
hotmarket	0.101**	0.103***	0.096**	−1.102	−0.117	−0.077
	(0.039)	(0.037)	(0.051)	(0.196)	(0.921)	(0.949)
preico	0.047***	0.045***	0.049***	−0.682**	−0.801**	−0.859**
	(0.003)	(0.005)	(0.002)	(0.033)	(0.073)	(0.054)
isbonus	−0.020	−0.022	−0.020	0.354	0.616	0.487
	(0.657)	(0.619)	(0.662)	(0.633)	(0.514)	(0.622)
Platform FE	Yes	Yes	Yes	Yes	Yes	Yes
N	244	242	240	238	236	234
adj. R2	0.680	0.675	0.680	0.012	−0.024	−0.019

p-values in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

regressions are consistently informative regarding explaining the crowdfunding performances (see the last three columns of Table 6). Estimates of $\delta(Soft\_Information)$ are significantly positive with a significance level of 10 % for all three measures of ICO information asymmetry. This evidence supports the hypothesis that it is the soft information component of ER that matter in the reduction of information asymmetry for the ICO crowdfunding period. In terms of the transaction period, we find similar results with the baseline test: the soft information (proxied by $\delta(Soft\_Information)$ only works to explain underpricing for the 1-day transaction window but not for the longer windows (5-day and 7-day windows).

To summarize, our results support the hypothesis that the soft information in ER play significant roles in the determination of ICO information asymmetry. After identifying the significant predictive power of ER, we separate the soft information from the ER and examine its predicative power through a two-stage regression. The hard information (i.e., open market information) and soft information (i.e., human insights, experts' private information or professional ability) in ER are isolated by residual decomposition. By observing the relationship of the soft information component in ER and ICO performances, we find that the soft information in ER significantly predicts the information asymmetry indicators of ICO crowdfunding and transactions. The experts, on the one hand, similar to credit rating providers for firms (Byoun et al., 2014) or for banks (Nakamura & Roszbach 2018), may contact the stakeholders of the projects or private social networks to source private information. On the other hand, experts have greater professional ability to better identify market information and process public data so as to better assess the project quality. This part of soft information differs from open market information and is not easy to capture by ordinary investors. Therefore, ER help the ICO market to solve the problem of information asymmetry by providing incremental information to the market, providing investors with reasonable opinions and reliable forecasts in the development of projects.

5.3. *The mechanism of soft information to determine information asymmetry: long-term performances*

So far, we have found evidence showing that the soft information component in the ER is associated with a reduction in information asymmetry of ICOs. However, there are two potential economic interpretations for this empirical finding: either the ER provide solid information about the fundamentals of the ICO projects, which cannot be accessed by the hard information providers, or the ER mislead retail investors to invest in poor quality projects, which cause the ICOs to overperform in the crowdfunding and early transaction phases. In the former case, the ER function well as an information provider, while in the latter case, ratings are still informative but are biased (Goldstein & Huang, 2020). The "informative but biased" case is particularly critical in cryptocurrency transaction due to the effect of the "wisdom of crowds" (Lee et al., 2021). This concept follows that of Lee et al. (2021), who state that if ER are consistently higher than BR for the same projects, there should be a possibility of biased ER: we therefore check the observations in our sample and find that 49.2 % ER are higher than BR (with the remaining 30.2 % ER equal to BR and 20.6 % are lower than BR). This provides some early warning signals of the "informative but biased" explanation. In order to examine which economic interpretation better suits our empirical results, we conduct an additional analysis to test whether the ICOs that received higher-than-

Benchy ER perform better in the long run. We follow a two-stage regression design. In the first stage, we collect residuals of ER after being regressed by BR and control variables. The residuals measure the soft information provided by the ER, and a higher value of residuals indicates a more optimistic ER score (controlling for the hard information of BR and control variables). In the second stage, we take the residuals as the independent variables and set the dependent variable as the dummy variable indicting long-term survival (equal to 1 if the ICO still exists in the market 360 days after ICO completes and equal to 0 otherwise). In summary, the two steps can be written as:

$$\text{Step 1}: ExpertRating = BenchyRating + Controls + \lambda + \delta(Soft\_Information) \tag{6}$$

$$\text{Step 2}: Survial(360days) = \delta(Soft\_Information) + Controls + \lambda + \varepsilon \tag{7}$$

We apply this two-stage regression design with the sample data for the projects with a completion of ICOs. The results are shown in Table 8. The estimate of our interests is the parameter on $\delta(Soft\_Information)$ of the second step. The results show that in the second stage the coefficient on $\delta(Soft_{Information})$ is significantly positive with a significance level of 5 %. This reflects that the soft information of ER has a long-term prediction power: a higher ER (compared with the benchmark of BR and ICO fundamentals) is related to a higher survival chance in one year. Based on the assumption that the 1-year performance reflects the true fundamentals of ICOs, the result strengthens the statement that the ER reduce the information asymmetry by providing more information to reflect the true fundamentals of ICOs. Due to data limitation, we cannot rule out the biased rating assumption, but at least our results indicate that the soft information contained in the ER is information revealing.

6. Miscellaneous

To show that the results we obtain in this project are consistent, we conduct multiple additional tests to confirm the robustness and show some new findings based on the local business environment.

6.1. Robustness check: Expert ratings with soft information eliminated

So far, we have provided evidence to support the claim that: first, the BR, which represents the public hard information in ratings, does not reduce information; and second, the soft information component, which is represented by the residuals of ER, does. To further test whether the ER continue to work in reducing information asymmetry after eliminating the soft information, we carry out 2SLS/2SRI tests to show that after eliminating the soft information component, the ER do not provide any extra information to reduce information asymmetry.

The general estimation process is as follows. The first step is similar to Eq. (5): we regress ER scores by BR scores and control variables. With the estimated parameters, we compute $\widehat{ExpertRating}$, the estimate of ER score:

$$\widehat{ExpertRating} = BenchyRating + Controls + \lambda \tag{8}$$

$\widehat{ExpertRating}$ only contains the hard information reflected by BR and the control variables. Therefore, we regard it as the proxy of the non-soft information element in the ER. Thus, in the second stage, we regress the ICO information asymmetry by this computed proxy:

$$PerformanceMeasure = \widehat{ExpertRating} + Controls + \lambda + \varepsilon \tag{9}$$

The selection of estimation method (2SLS or 2SRI) depends on the feature of the information asymmetry indicator: if the indicator is a continuous variable, we use 2SLS estimation, but if it is a dummy variable, we employ 2SRI estimation. The results of 2SLS/2SRI test are shown in Table 9 (for crowdfunding) and Table 10 (for transaction).[6] From both tables, we find that in the second stage regression, the estimates of $\widehat{ExpertRating}$ are not significant for either the crowdfunding or transaction phases. It fits the hypothesis we make that the ER do not reduce information asymmetry via the hard information source.

Besides the 2SLS/2SRI regression presented above, we also add different types of time fixed effects in the regressions. For each of the regressions shown in the main context, we replicate it by adding year fixed effect, quarter fixed effect and month fixed effect, respectively, to control for potential variations in market development, macro-conditions or seasonal factors, and we find similar results. Moreover, for the transaction data, we try longer time windows (from 7 days to 180 days) for computing underpricing and find that the rating information is not significantly associated with any underpricing measures longer than 1 day (this is the same conclusion as the main result). To save space, we do not report the regression tables of robustness tests, however they are available upon request.

[6] Several studies based on 2SRI suggest reporting cluster standard errors to solve the autocorrelation problem. In this study, however, we would like to report robust standard errors because ratings are published independently, and they are unlikely to be correlated. In addition, the rule of thumb for minimum clustering size is 50, which is larger than any possible clustering dimension (platform or country) in a small sample. That is, in practice, reporting robust standard errors would be a more reasonable choice for our research.

Table 8
Long-run performances tests.

Stage	1st	2nd
Dependent	Expert Rating	One-year Survival
δ (Soft_Information)		0.128**
		(0.019)
Benchy Rating	0.721***	
	(0.000)	
issue_size	0.015	0.010
	(0.155)	(0.442)
issuer_ratained_ratio	−0.012	0.016
	(0.913)	(0.889)
duration	−0.001*	−0.000
	(0.096)	(0.399)
trading_volume[a]	0.610	−0.102*
	(0.266)	(0.063)
market_sentiment	−0.268	−0.663**
	(0.579)	(0.087)
hotmarket	−0.204***	0.009
	(0.001)	(0.861)
preico	0.104**	0.011
	(0.038)	(0.763)
log_raised	0.045***	−0.003
	(0.005)	(0.800)
isbonus	−0.022	−0.072*
	(0.628)	(0.063)
N	235	235
adj. R2	0.668	−0.019
Platform	Yes	Yes

p-values in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
[a] The coefficients shown in the row of "trading_volume" are 10,000 times their original values.

Table 9
2SLS/2SRI, crowdfunding.

Stage	1st	2nd		
	Expert Rating	Ln(Raised)	Soft cap hit	Funding percentage
Benchy Rating	0.871***			
	(-0.03)			
$\widehat{\text{Expert Rating}}$		0.213	0.047	0.044
		(0.163)	(0.225)	(0.442)
Issue size	0.017	0.421***	0.234***	0.112***
	(-0.011)	(0.000)	(0.079)	(0.000)
Issuer retained ratio	0.148*	1.500***	0.157	0.224*
	(-0.077)	(0.000)	(0.502)	(0.087)
Market sentiment	0.008	0.181	0.522**	0.046
	(-0.039)	(0.296)	(0.263)	(0.484)
Hot market	−0.055	0.224	−0.977	−0.050
	(-0.056)	(0.370)	(0.405)	(0.594)
Presale	0.006	0.222	0.138	0.048
	(-0.031)	(0.111)	(0.203)	(0.360)
Ln(Milestones)	0.049	−0.264	−0.136	−0.063
	(-0.039)	(0.127)	(0.251)	(0.333)
Ln(Hard cap)	0.008	0.061	−0.393*	−0.287***
	(-0.011)	(0.202)	(0.089)	(0.000)
KYC	0.000	0.078	0.327	−0.068
	(-0.036)	(0.630)	(-0.233)	(0.264)
Duration	−0.001	−0.007	0.001***	−0.002
	(-0.001)	(0.115)	(0.006)	(0.131)
Observations	504	504	504	504
adj. R2 (PseudoR2)	0.071	0.230	0.073	0.348
Fixed Effect	Yes	Yes	Yes	Yes

p-values in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10
2SLS/2SRI results, transaction.

Stage	1st			2nd		
Dependent	Benchy Rating	Benchy Rating	Benchy Rating	MUP(1)	MUP(5)	MUP(7)
$\widehat{\text{Expert Rating}}$				−0.633	−0.143	−0.144
				(0.385)	(0.862)	(0.863)
Benchy Rating	0.741***	0.739***	0.734***			
	(0.000)	(0.000)	(0.000)			
issue_size	0.015	0.015	0.016	0.232	0.510	0.511
	(0.169)	(0.161)	(0.150)	(0.192)	(0.201)	(0.205)
log_raised	−0.006	−0.012	0.001	−0.777	−2.262*	−2.248*
	(0.956)	(0.908)	(0.995)	(0.583)	(0.129)	(0.139)
issuer_ratained_ratio	−0.001***	−0.001**	−0.001**	0.001	0.013	0.01
	(0.045)	(0.054)	(0.081)	(0.825)	(0.503)	(0.514)
Duration[a]	0.037	0.073	0.044	0.883	0.696	0.496
	(0.507)	(0.212)	(0.424)	(0.172)	(0.423)	(0.457)
trading_volume	−0.480	−0.360	0.632	4.733	2.318	8.058
	(0.408)	(0.523)	(0.226)	(0.376)	(0.753)	(0.332)
market_sentiment	−0.195***	−0.195***	−0.211***	−1.183	−0.554	−0.485
	(0.002)	(0.001)	(0.001)	(0.184)	(0.531)	(0.653)
hotmarket	0.101***	0.103***	0.0960**	−0.916	−0.0813	−0.0342
	(0.039)	(0.037)	(0.051)	(0.273)	(0.941)	(0.976)
preico	0.0465***	0.0446***	0.0493***	−0.654***	−0.794**	−0.851**
	(0.003)	(0.005)	(0.002)	(0.036)	(0.080)	(0.059)
isbonus	−0.0199	−0.0224	−0.0197	0.405	0.628	0.503
	(0.657)	(0.619)	(0.662)	(0.575)	(0.495)	(0.600)
Platform FE	Yes	Yes	Yes	Yes	Yes	Yes
N	244	242	240	238	236	234
adj. R2	0.680	0.675	0.680	0.010	−0.029	−0.023

p-values in parentheses.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.
[a] The coefficients shown in the row of "Duration" are 1000 times their original values.

6.2. Additional tests: The effect of business environment

Business environment is a key factor to determine the macro level of information asymmetry for ICO crowdfunding and transaction. In countries or regions where the business environment is more transparent or efficient, the information asymmetry between the ICO issuers and traders should be lower and hence investors could rely more on the hard information. In this subsection, we use the World Bank business environment indexes as indicators of general business environment. To make the comparison more robust we apply-two types of business indexes, BIndex_1 and BIndex_2. BIndex_1 measures the "Ease of doing business score"[7] and BIndex_2 is the score of "starting a new business".[8] To tackle with the situation of cross-region listing we take the average values of the indexes among all regions where each ICO is reported to be registered. Inevitably, the inclusion of these indexes reduces the sample size to 418 (originally 504) for crowdfunding data and 241 (originally 244) for transaction data.

Table 11 and Table 12 report the results of the tests following the main designs of this paper but adding BIndex_1 and BIndex_2 as additional control variables. Table 11 presents the baseline results which replicate the Eq. (3). Checking the estimates on ER/BR we find that the finding is consistent with our original conclusion: in most of the cases the expert ratings significantly forecast the ICO performances in crowdfunding period and in the first-day transaction period while the algorithmic rating (Benchy rating) does not provide any new information for the performance forecast. If we check the specific estimates on the business environment index, we find a weakly positive relationship between the regional business index quality and the ICO crowdfunding performances: controlling other factors constant if the ICO is registered in places with higher-quality business environment, the ICO would raise a bigger amount of funds and would be more likely to hit the hard cap. This fits the intuitive sense that investors trust ICOs which are registered in places with better business environments.

Table 12 shows the replicated results of the two-stage tests for the soft information effect (following Eq. (4) and Eq. (5)). We also find similar results with the main tests: the crowdfunding performances and early-stage underpricing (i.e., 1-day window) can be explained by the indicators of soft information, even with the local business environment controlled. Therefore, our main findings in

[7] The ease of doing business score is the simple average of the scores for each of the Doing Business topics: starting a business, dealing with construction permits, getting electricity, registering property, getting credit, protecting minority investors, paying taxes, trading across borders, enforcing contracts and resolving insolvency. The score is computed based on the methodology in the DB17-20 studies for topics that underwent methodology updates.

[8] The score for starting a business is the simple average of the scores for each of the component indicators: the procedures, time and cost for an entrepreneur to start and formally operate a business, as well as the paid-in minimum capital requirement.

Table 11
Including country-level business environment indexes as control variables_Baseline tests.

Panel A: Baseline for expert ratings

	Crowdfunding data						Transaction data			
Dependent	Ln (Raised)	Soft cap hit	Funding percentage	Ln (Raised)	Soft cap hit	Funding percentage	MUP(1)	MUP(1)	MUP (5)	MUP (5)
Expert Rating	0.398**	0.074*	0.030	0.386**	0.075*	0.029	−1.290*	−1.267*	−1.766	−1.835
	(0.004)	(0.079)	(0.173)	(0.020)	(0.075)	(0.188)	(0.056)	(0.062)	(0.135)	(0.142)
BIndex_1	0.021**	−0.002	0.002**	–	–	–	0.033	–	0.008	–
	(0.020)	(0.505)	(0.046)				(0.499)		(0.880)	
BIndex_2	–	–	–	0.019*	−0.002	0.001	–	0.012	–	0.059
				(0.085)	(0.505)	(0.617)		(0.892)		(0.525)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Platform FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	418	418	418	418	418	418	235	235	233	233
adj. R2	0.263	0.111	0.243	0.259	0.111	0.239	0.006	0.004	−0.039	−0.038

Panel B: Baseline for Benchy ratings

	Crowdfunding data						Transaction data			
Dependent	Ln (Raised)	Soft cap hit	Funding percentage	Ln (Raised)	Soft cap hit	Funding percentage	MUP (1)	MUP (1)	MUP (5)	MUP (5)
Benchy Rating	0.159	0.030	−0.008	0.147	0.031	−0.009	−0.494	−0.472	−0.086	−0.494
	(0.287)	(0.510)	(0.739)	(0.328)	(0.491)	(0.708)	(0.377)	(0.425)	(0.890)	(0.378)
BIndex_1	0.020**	−0.002	0.002	–	–	–	0.028	–	−0.001	–
	(0.027)	(0.510)	(0.650)				(0.578)		(0.986)	
BIndex_2	–	–	–	0.019*	−0.003	0.001	–	0.002	–	0.0280
				(0.085)	(0.506)	(0.620)		(0.979)		(0.578)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Platform FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	418	418	418	418	418	418	235	235	233	233
adj. R2	0.249	0.105	0.240	0.246	0.105	0.236	−0.006	−0.008	−0.045	−0.045

this paper are robust when business environment factors are controlled.

6.3. Additional tests: Heterogeneity analysis for ICOs with different business environments

If an ICO is issued in a place with higher transparency, better market governance or a better practice of rules of law, the by-nature information asymmetry should be lower and hence the role of soft information should be weaker. Therefore, we conduct a heterogeneity analysis based on the local business environment to check whether the estimates on ER and soft information components are only significant for the subsample of poor-environment regions.

We apply the averaged BIndex_1, the ease score for doing business, as the proxy of the local business environment, and split the original sample into two groups: the high-index group where ICOs have a BIndex_1 larger than the sample mean and the low-index group where ICOs have a BIndex_1 smaller than the sample mean. With the two subsamples, we replicate the main tests (baseline tests for expert ratings and two-stage tests for soft information) and the results are shown in Tables 13 and 14.

In Table 13 we report the subsample results for the baseline test (Eq. (3)). We find that the significant estimates on ERs only exist for the low-index group. That is, expert ratings only matter for ICOs in relatively poor-environment regions. In Table 14 we find similar results for the soft information effect (following Eq. (4) and Eq. (5)). The significant effects of soft information on ICO performances only exist in the low-index group, showing that the soft information in expert ratings does substantially reduce the information asymmetry for ICOs, but only in poor-environment regions.

This result implies that from investors' perspectives, the business environment and soft information in expert rating are strategic substitutes. A good business environment reduces investors' reliance on expert ratings, since investors can directly infer useful information from what the ICO issuers disclose. In contrast,e a poor business environment decreases the credibility of the information of the ICO project, and investors thus turn to expert ratings as the major information source.

To sum up, this heterogeneity analysis not only provides additional evidence to support our original hypothesis about the role of expert ratings in reducing the information gap between investors and ICO issuers but also has important international implications for the ICO sectors.

6.4. International implications

Our results have several international implications.

First, ICO trading platforms can be viewed as highly globalised emerging markets, and a growing number of international investors have added crypto tokens to their portfolios. Due to the unregulated nature of token trading, however, information asymmetry becomes an issue, and it is therefore critical to keep investors informed about the true quality of ICO projects. In this vein, our findings

Table 12
Including country-level business environment indexes as control variables_soft information tests.

Panel A: crowdfunding data

Dependent	Business environment index 1				Business environment index 2			
	First Stage	Second Stage			First Stage	Second Stage		
	Expert rating	Ln(Raised)	Soft cap hit	Funding percentage	Expert rating	Ln(Raised)	Soft cap hit	Funding percentage
Benchy rating	0.875***	–	–	–	0.875***	–	–	–
	(0.000)				(0.000)			
Soft information	–	0.425***	0.372*	0.030		0.412***	0.378*	0.029
		(0.004)	(0.086)	(0.212)		(0.005)	(0.081)	(0.228)
BIndex_1	−0.001	0.019**	−0.009	0.002	–	–	–	–
	(0.583)	(0.035)	(0.489)	(0.212)				
BIndex_2	–	–	–	–	−0.001	0.018*	−0.013	0.001
					(0.583)	(0.100)	(0.417)	(0.617)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Platform FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	418	418	418	418	418	418	418	418
adj. R2	0.154	0.262	0.262	0.243	0.154	0.258	0.262	0.239

Panel B: transaction data

Dependent	Business environment index 1			Business environment index 2		
	First Stage	Second Stage		First Stage	Second Stage	
	Expert rating	MUP(1)	MUP(5)	Expert rating	MUP(1)	MUP(5)
Benchy Rating	0.734***	–	–	0.732***	–	–
	(0.000)			(0.000)		
Soft information	–	−2.182*	−4.134	–	−2.156	−4.173
		(0.100)	(0.210)		(0.113)	(0.213)
BIndex_1	0.003	0.024	−0.0040	–	–	–
	(0.372)	(0.615)	(0.945)			
BIndex_2	–	–	–	0.003	−0.003	0.037
				(0.456)	(0.968)	(0.658)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Platform FE	Yes	Yes	Yes	Yes	Yes	Yes
N	241	235	233	241	235	233
adj. R2	0.670	0.009	−0.030	0.670	0.007	−0.029

Table 13
Heterogeneity analysis for country-level business environment indexs_Baseline tests.

Panel A: Subsample: Low BE index group

	Crowdfunding data						Transaction data			
Dependent	Ln (Raised)	Soft cap hit	Funding percentage	Ln (Raised)	Soft cap hit	Funding percentage	MUP(1)	MUP (5)	MUP (1)	MUP (5)
Expert Rating	0.465***	0.071	0.060**	–	–	–	−2.458*	−4.317	–	–
	(0.009)	(0.189)	(0.039)				(0.060)	(0.226)		
Benchy Rating	–	–	–	0.209	0.002	0.016	–	–	0.417	1.394
				(0.270)	(0.972)	(0.606)			(0.651)	(0.407)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Platform FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	255	255	255				91	90	91	90
adj. R2	0.275	0.092	0.277	0.258	0.085	0.265	−0.031	−0.078	−0.069	−0.094

Panel B: Subsample: High BE index group

	Crowdfunding data						Transaction data			
Dependent	Ln (Raised)	Soft cap hit	Funding percentage	Ln (Raised)	Soft cap hit	Funding percentage	MUP (1)	MUP (1)	MUP (5)	MUP (5)
Expert Rating	0.232	0.065	−0.021	–	–	–	−0.565	−0.495	–	–
	(0.216)	(0.066)	(0.035)				(0.547)	(0.525)		
Benchy Rating	–	–	–	0.052	0.063	−0.048	–	–	−0.903	−0.845
				(0.835)	(0.408)	(0.231)			(0.322)	(0.256)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Platform FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	163	163	163	163	163	163	138	137	138	137
adj. R2	0.269	0.225	0.250	0.264	0.223	0.255	−0.010	−0.017	−0.003	−0.010

Table 14
Heterogeneity analysis for country-level business environment indexs_soft information tests.

Panel A: Subsample: Low BE index group

	Crowdfunding data				Transaction data		
Dependent	First Stage	Second Stage			First Stage	Second Stage	
	Expert Rating	Ln(Raised)	Soft cap hit	Funding percentage	Expert Rating	MUP(1)	MUP(5)
Benchy Rating	0.824*** (0.000)	—	—	—	0.804*** (0.000)	—	—
Soft information	—	0.484** (0.012)	−0.355 (0.206)	0.061** (0.050)	—	−9.208** (0.042)	−17.97 (0.159)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Platform FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	255	255	255	255	91	91	90
adj. R2	0.154	0.274	0.085	0.275	0.716	0.075	−0.025

Panel B: Subsample: High BE index group

	Crowdfunding data				Transaction data		
Dependent	First Stage	Second Stage			First Stage	Second Stage	
	Expert Rating	Ln(Raised)	Soft cap hit	Funding percentage	Expert Rating	MUP(1)	MUP(5)
Benchy Rating	0.975*** (0.000)	—	—	—	0.720*** (0.000)	—	—
Soft Information	—	0.239 (0.299)	−0.350 (0.337)	0.025 (0.499)	–	1.500 (0.210)	1.478 (0.120)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Platform FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	163	163	163	163	138	138	137
adj. R2	0.154	0.269	0.225	0.250	0.633	−0.011	−0.017

indicate that industry expert evaluations provide investors with valuable information to safeguard them from low-quality and fraudulent projects. Our findings accord with those of Bourveau et al. (2022), who also emphasise the significance of information disclosure and intermediaries. Our research goes a step further by demonstrating that the distinguishing factor in expert judgments is subjective information.

Second, our results imply that ICO issuers might strategically choose the registered countries and regions. The strategic behaviour of ICO issuers is also observed in Phua et al. (2022). Based on our heterogeneity analysis, soft information in expert ratings is significant only in countries with low business environment indices. A better business environment reduces the information asymmetry between ICO issuers and investors. Therefore, If ICO becomes more important in financial sectors, countries might make an effort to improve their business environment to attract registrations of high-quality ICO projects. Consequently, more international collaboration might be needed to protect investors from scam ICO projects (Zetzsche, 2017).

Third, for national regulatory agencies, our results imply the possibility of international regulatory competition in the ICO industry. To reduce information asymmetry in ICO marketplaces, the current legal framework must be expanded to provide more transparency and credibility to international investors for ICO ventures. In a broad sense, regulation also serves as an informational conduit for investors, since it suggests that the regulated business satisfies the necessary requirements established by governmental bodies. Recent regulatory developments on initial coin offerings (Lockaby, 2018; Bellavitis et al., 2021) indicate that the path of regulation has shifted toward greater openness and information disclosure before an ICO can be issued legally.

7. Conclusion

This paper examines the role of soft and hard information in expert ratings of ICO. We take advantage of the special, double-track rating system of ICObench where Benchy ratings (BR, only hard information included) and Expert ratings (ER, both hard and soft information included) co-exist during the crowdfunding and early transaction phases. By separately testing the effectiveness of BR and ER, we find that for both phases of ICOs, the BR does not reduce information asymmetry while the ER does. We further apply a two-stage regression model to isolate the soft information ingredient in ER and find that soft information matters for information asymmetry. This empirical finding supports our research hypothesis that the soft information component in ER helps to tackle the problem of information asymmetry in ICO markets. To explain the mechanism that causes soft information to affect information channels, we test whether soft information measures predict the long-term survival of completed ICOs: our results show that soft information indeed reflects ICO project fundamentals. As a robustness check, we use the 2SLS/2SRI method and find that after eliminating the soft information component, the impact of ER on ICO information asymmetry disappears.

Our results mainly contribute to the literature on the prediction of ICO performances, the role of rating services in financial markets and the extraction of soft information. We also contribute to the discussion about the international implication of ICO studies: first, our results show that industry expert ratings can provide useful information to protect international investors from low-quality and scam projects; second, Second, ICO issuers might strategically choose the registered countries and regions, which imposes a challenging in tracking scam projects and calls for more international collaboration. Third, for national regulatory agencies, our results imply the possibility of international regulatory competition in the ICO industry.

Due to data (un)availability, we do not address the possible reasons why the Benchy rating (the hard information) fails to determine information asymmetry. Furthermore, we find that the explanatory power of the pre-ICO information for the ICO transaction performances is weaker than that for crowdfunding performances. Future research can be done in two aspects: 1) combining with social media data, our dataset could be used to explore the source of soft information, i.e., whether the soft information in expert ratings rises from the experts' own insight or their social networks; 2) digging into the profiles of experts and explore how well experts' background can explain their accuracy in predicting ICO performance.

CRediT authorship contribution statement

Tong Wang: Conceptualization, Resources, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Sheng Zhao:** Conceptualization, Methodology, Validation, Investigation, Writing – original draft, Formal analysis, Writing – review & editing. **Mengqiu Zhou:** Conceptualization, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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