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Why do video pitches matter in crowdfunding?

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ABSTRACT

Recent research finds that whether or not ventures publish video pitches during crowdfunding campaigns affects their funding success. Little is known, however, about *how* and *why* video pitches help startups achieve higher valuations. To close this gap, we analyze metrics and the content of video pitches published along blockchain-based crowdfunding campaigns (a.k.a. token offerings, initial coin offerings, or ICOs). We confirm that the publication of video pitches increases the funding amount, and present novel evidence on the mechanisms behind this finding. First, the longer the video, the larger its valuation effect. Second, it is the information content that matters in videos, while non-informational content (e.g., music) has no effect. Third, information conveyed in videos vis-à-vis other channels (e.g., white papers) act as informational substitutes. Fourth, investors react positively to buzz words in videos, and this effect is even more pronounced when there are many competing projects. Overall, our results suggest that videos are an important source of information for ICO investors, and investors' limited attention makes videos (and their content, especially buzzwords) more important in "hot" markets.

1. Introduction

Gathering information about firms is crucial for potential investors in order to make informed investment decisions, and even more important in entrepreneurial settings that are typically characterized by high levels of asymmetric information (Adhami et al., 2018; Ahlers et al., 2015; Barg et al., 2021; Block et al., 2021; Colombo et al., 2019; Fisch, 2019; Hu & Ma, 2021; Lambert, 2022; Momtaz, 2020a, 2021d; Vismara, 2018b). To overcome informational asymmetries, investors rely on a broad set of signals to gauge the firm's quality (Ahlers et al., 2015; Vismara, 2018b). Examples of signals (or cues²) are equity retention (Leland & Pyle, 1977), institutional investor backing (Cumming et al., 2021; Fisch & Momtaz, 2020), corporate governance provisions (Giudici & Adhami, 2019), founders' human capital (Colombo & Grilli, 2005; Colombo & Grilli, 2010) or even perceived founder-CEO beauty (Colombo et al., 2020), emotions (Momtaz, 2021a; Momtaz, 2021a), loyalty (Momtaz, 2021b), altruism (Faust et al., 2022; Giudici et al., 2018), and confidence (Huang et al., 2021). The costlier a signal, the better it is for creating "separating equilibria" (Spence, 1978) to distinguish high-quality from low-quality startups. Video pitches are one potential type of costly signal that help inform a scalable crowd of

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² The literature makes a distinction between costly "signals" and "costless" cues, see e.g., Colombo (2021) and Vismara (2018b).

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Study	Sample	Theory	Approach	Findings
Mollick (2014)	 48,526 US-based Kickstarter projects Reward-based and patronage 2009–2012 	Signaling	Dummy for availability of video	 Availability of a video pitch is positively correlated to funding success Video as an indicator for a high- quality project as it shows en- transmo availant properties
Cumming et al. (2017)	 47,139 Indiegogo projects Reward-based 2008 - Oct 2013 	Signaling	Dummy for availability of video	 trepreneur's preparation Video pitch is positively correlated to funding success, with a higher coefficient for cleantech ventures Videos are a costly signal as they require the development of a prototype which can be showcased
Courtney et al. (2017)	 267,295 Kickstarter projects Reward-based Jan 2009 - Dec 2015 	Signaling	Dummy for availability of video and pictures	 Use of media (pictures and video) is positively correlated to funding success, as it demonstrates preparedness and signals project quality Videos are a costly signal as they require the development of a prototype which can be showcased
Scheaf et al. (2018)	 323 Kickstarter projects Reward-based Jan 2010-Dec 2015 	Heuristic information processing	Quality as continuous variable, length and narration time as control variables	 Video quality is positively correlated to funding success Presentation quality is understood as a visual cue used by investors to fill informational voids and shape their impressions Video or narration length was not significant
Li et al. (2016)	 49 Chinese projects on Dajiatou Equity crowdfunding May 2015 	Elaboration likelihood model	Dummy for availability of video	 Availability of a video pitch is positively correlated to funding success
Allison et al. (2017)	 a May 2010 a 383 US-based Kickstarter projects Reward-based Sep - Nov 2011 	Elaboration likelihood model	Dummy for cues based on video and written description	 Findings based on written descriptions and videos Issue-relevant information (e.g., entrepreneurs' education) are more relevant toexperienced investors and when amounts are larger Cues (adopting a group identity or referring to the project as a personal dream) matter most among inexperienced investors and when funding amounts are small
Hu and Ma (2021)	 1139 projects on Y Combinator, MassChallenge, 500 Startups, Techstars, AngelPad Seed accelerators 2010–2019 	Persuasion models allowing for the formation of incorrect beliefs	Positivity score constructed from visual emotions, vocal emotions, textual sentiment	 Positive (passionate and warm) video pitches are positively correlated to funding success Positivity in video pitches is not linked to better long-term performance
Johan and Zhang (2020)	6870 EquiNet projectsEquity crowdfundingJan 2007 - Nov 2016	Signaling, advertising puffery theory	Dummy for availability of video as a control variable	 Video availability is positively correlated with fundraising success Length of qualitative business description ("costless" signal) is correlated with bicker funding

correlated with higher funding.

(continued on next page)

Table 1 (continued)

Study	Sample	Theory	Approach	Findings
Anglin et al. (2018)	 1726 Kickstarter projects Reward-based Before Jun 2012 and in 2016 	Signaling	Dummy for availability of video as a control variable, positive psychological capital language in written text or video pitches	The effect is larger for retail investors Usage of promotional words in the business description is associated with lower funding success. The participation of retail investors moderate the negative effect Video availability is positively correlated with fundraising success Positive psychological capital language in the written firm description is positively related to funding success while positive psychological capital language used in video pitches is
Thapa (2020)	 2000 Kickstarter projects Reward-based 2013–2017 	Information overload theory	Video length and total information as a combination of video length, text length and the number of pictures	 insignificant Video length and total information have a curvelinear relationship with funding success, leading to lower funding probability when too
Parhankangas and Renko (2017)	 656 Kickstarter projects Social and reward-based 2013–2014 	Language expectancy theory	Continuous variables indicate pronouncedness of linguistic styles in videos (all projects have videos)	 much information is provided Linguistic style matters for social entrepreneurs but not commercial ones Language styles with positive impact on funding: Concrete: Easier to understand vs. abstract language Precise: Found to be more transparent while imprecise language is linked to manipulation Interactive: Elicit trust and likability Language styles with negative impact on funding: Psychological distancing: Linked to denome
Kim et al. (2016)	 500 Kickstarter projects Reward-based Mar 2014 - Feb 2016 	Media richness theory	Number of videos in the pitch and video length in seconds as control variables, tone analyser is used to detect emotions and linguistic style	 Linked to deception Linguistic style of the video pitch impacts funding success Analytical and confident speech have a positive impact. Confident speech becomes insignificant when the styles of the text descriptions are included in the representer
Troise et al. (2020)	 243 Italian projects based on 200crowd, ActionCrowd, BackToWork24, CrowdFundMe, In-vestire, Mamacrowd, Muum- lab, Nextequity, Opstart, StarsUp, WeAreStarting Equity crowdfunding Dec 2018–2020 	Social capital theory	Video length in minutes	 included in the regression Video length as a measure of "shared language" is negatively related to the number of investors but does not impact funding raised as % of goal

potential investors in a relatively time-efficient way about the startup (Courtney et al., 2017; Hu & Ma, 2021; Mollick, 2014). It is therefore no surprise that video pitches are seen in an increasingly large number of crowdfunding campaigns, and a number of recent studies controls for the availability of video pitches when estimating determinants of funding success. The purpose of this paper is to shed light on the question of why video pitches matter in crowdfunding. Video pitches are interesting for many reasons. Video pitches typically do not contain additional hard information beyond what startups disclose in their white papers, yet they contain soft information about how founders pitch their project and on which points they decide to focus in a relatively time-constrained video pitch. Video pitches have become the primary way for startups to stand out from the mass of fundraising ventures. Thus, understanding how and why video pitches matter may provide interesting insights into the psychology of crowd-funding markets.

The empirical focus of this paper is blockchain-based crowdfunding, so-called Initial Coin Offerings (ICOs) or token offerings (Bellavitis et al., 2021; Block et al., 2021). In an ICO, a venture raises growth capital from a crowd of investors by selling tokens that can typically be redeemed for the venture's future products and/or services (Momtaz, 2020b). ICOs are a close-to-ideal laboratory to study the role of video pitches in crowdfunding campaigns due to their very high levels of uncertainty (among many others, e.g., An et al., 2019; Belitski & Boreiko, 2021; Bellavitis et al., 2020; Fisch, 2019; Giudici et al., 2020; Hornuf et al., 2021; Howell et al., 2020; Momtaz, 2020a; Momtaz, 2021a) and investors not merely being financially motivated but are keen to back projects that share a common ideology (Fisch et al., 2019), characteristics that may best become apparent in personal video pitches. Thus, the effects of video pitches on crowdfunding success should be salient in ICOs.

Our theoretical framework relies on signaling theory and related "video as information" arguments. Our overarching hypothesis is that the availability of a video pitch is positively related to ICO firm valuation. This follows from the argumentation that video pitches are a widely observable signal and relatively costly for low-quality ventures (i.e. creating convincing video content from a project with little substance is costly), thereby potentially leading to a "separating equilibrium" in which high-quality ventures are more likely to publish video pitches. Additional hypotheses predict that the marginal effect of video pitch length on ICO firm valuation is positive, and that video pitches' informational (and not non-informational) content drives the positive video pitch-valuation relation.

Testing these hypotheses in our hand-collected ICO sample, we find strong support for all these predictions. Specifically, the availability of a video pitch is associated with a 133% higher ICO firm valuation. This strong association holds in both univariate and multivariate analyses. It is also noteworthy that only 54% of all sample ICO firms have video pitches, suggesting that it is a relatively costly signal.

To better understand the role of video pitches' content, we deconstruct the videos into narrative (i.e informational) and musical (i. e. non-informational) content. In line with our "video as information" reasoning, we confirm that the positive video pitch valuation relation is indeed mainly driven by the informational channel. Musical content does not significantly affect ICO firm valuation. Thus, the evidence suggests that video pitches can increase firm valuations because they offer useful information for potential investors.

Given that video pitches seem to inform the crowd's investment decisions, an important next question is whether other factors help make videos even more effective. We test three such potential mechanisms. First, we examine the dialectic relation between video pitches and white papers as an alternative information source and find, consistent with our expectation, that video pitches and white papers act as informational substitutes. Second, assuming that videos feed into investment decision-making heuristics, we find support for an additional conjecture that crypto-specific jargon (or crypto buzz words) in video pitches are positively related to ICO firm valuation. Third, the effect of crypto-specific jargon on ICO firm valuation is even more pronounced in "hot" markets.

Overall, our paper shows that video pitches matter for crowdfunding success in ICOs. They matter because they inform the crowd's investment decisions, and this effect can be amplified in the presence of otherwise thin information about a venture, by the use of crypto-specific jargon, and in "hot" markets.

The rest of the paper is organized as follows: Section 2 provides some background on ICOs and reviews the related literature on video pitches in crowdfunding. Section 3 derives our hypotheses. Section 4 elaborates on the data and variables we used in our analysis, and Section 5 presents our empirical approach, as well as the results. Finally, Section 6 concludes with a summary of our key results, theoretical contributions and practical implications, as well as potential avenues for future research.

2. Background

This section provides a discussion of the related literature on video pitches in the broader crowdfunding context as well as some background on blockchain technology and initial coin offerings.

2.1. Video pitches in crowdfunding

Table 1 shows an overview of existing literature on video pitches and linguistic style in the context of equity and reward-based crowdfunding. The availability of a video has largely been identified as a positive determinant of funding success, with videos often being theorized as a costly signal or visual cue.

Existing research falls roughly into three broad areas: Studies that view videos as signals of venture quality, studies viewing video as visual cues, and those exploring the impact of certain linguistic styles in company presentations. First, the signaling perspective started with Mollick's (2014) seminal study. Mollick (2014) uses a dummy variable for the availability of a video pitch in his sample of 48,526 US-based crowdfunding campaigns on *Kickstarter* from 2009 to 2012 and finds that the dummy is positively correlated with funding success. Similarly, Cumming et al. (2017) also find a positive correlation between the availability of a video pitch and the project's funding success, which is more pronounced for cleantech ventures. They used a dataset consisting of 47,139 campaigns launched on *Indiegogo* from 2008 until 2013. Courtney et al.'s (2017) approach is slightly different, combining the availability of videos and pictures into one dummy variable for the use of media which was also positively correlated with funding success. The sample used is the largest so far with 267,295 *Kickstarter* campaigns over the 2009–15 period.

The second literature stream draws on the concept of heuristic information processing and on the elaboration likelihood model³ to explain the video's function as visual cue. Scheaf et al. (2018) find video quality to be positively related to the campaign's funding success, supporting their theory of video pitches being visual cues impacting the investors' heuristic information processing. Video and narration length were included as control variables but did not show a significant effect. Scheaf et al. (2018) also find the video quality to positively interact with costly signals such as media coverage and patents. The studied sample includes 323 projects on *Kickstarter* from 2010 to 2015. Li et al. (2016) focus on equity crowdfunding, using a sample of 49 Chinese projects obtained from *Dajiatou*. In line with previous research, they use a dummy variable for the availability of a video pitch and find that it is positively correlated with funding success. The authors draw on the elaboration likelihood model and theorize the video to be a peripheral cue. Allison et al.'s (2017) approach is slightly different, viewing the video and the written business description as a mean to transport cues (i.e., adopting a group identity or referring to the project as a personal dream), they explore the impact on different types of investors. The study uses dummy variables for the existence of the aforementioned cues in the video or written company description and is based on a sample of 383 US-based *Kickstarter* campaigns from September to November 2011. Experienced investors placing larger amounts were found to rely more on issue-relevant information, processed through the central route, while inexperienced investors investing smaller amounts relied heavier on peripheral cues.

A third literature stream studies the impact of linguistic styles used in company presentations, drawing on a heterogeneous set of explanations. Hu and Ma (2021) study a sample of 1139 projects applying to seed accelerators between 2010 and 2019. In contrast to crowdfunding, accelerator programs are funded by professional instead of retail investors. Nonetheless, a positive video pitch, based on visual emotions, vocal emotions and textual sentiment, was found to be positively correlated with funding success, albeit not being correlated with a better long-term performance of the startup. Johan and Zhang (2020) use a dataset of 6870 equity crowdfunding projects from Equinet in the time period 2007-16 to study the impact of qualitative business information as a costless signal and promotional language used in the written business description. Video availability and the length of the written qualitative business description were found to be positively correlated with funding success, while the use of promotional language had a negative impact. The negative impact was mitigated for retail investors. Anglin et al. (2018) use a sample of 1726 reward-based campaigns on Kickstarter to show that positive psychological capital language used in the written firm description is positively correlated with funding success, while positive psychological capital language used in video pitches is insignificant. The results further show a positive relation between the availability of a video pitch and funding success. Thapa (2020) studies 2000 Kickstarter projects from 2013 to 2017, showing that video length and total information as a combination of video length, text length and the number of pictures have a curvelinear relationship with funding success, implying a lower funding probability if too much information is provided. Parhankangas and Renko (2017) explore the impact of linguistic styles on different audiences and find that concrete, precise, and interactive language is positively correlated with funding success of social campaigns while psychological distancing shows a negative correlation. For reward-based projects, none of the linguistic styles were significantly different from zero. The varying impact of linguistic styles is attributed to the lack of clearly defined expectations in social crowdfunding, forcing the entrepreneur to rely more on linguistic styles. The study is based on 656 Kickstarter campaigns from 2013 to 2014. Kim et al. (2016) use a sample of 500 Kickstarter projects from 2014to 2016 to explore the impact of emotions and linguistic styles using a tone analyzer and find analytical speech to have a positive impact. Troise et al. (2020) draw on social capital theory and use the video length as a measure of "shared language." They find a negative correlation with the number of investors per campaign, but failed to find a significant effect for the funding amount as a % of the set goal. Their sample consists of 243 Italian equity crowdfunding campaigns from 2018 to 2020 based on 11 crowdfunding platforms.

Overall, these studies shed light on the role of video pitches in crowdfunding, but they have two important limitations. First, the studies have in common that they focus largely on the availability of video pitches, which leaves several important aspects about video pitches, such as its length, informational content and external factors, largely unexplored. Second, most studies focus on reward-based crowdfunding. This is a unique setting, as backers are repaid with discounts on the sales price of the finished product. Thus, backers are likely future customers with a desire to bring the product to life, rather than financially motivated investors as in most other funding forms. The impact of signals, cues, and linguistic styles varies depending on the receiver (Allison et al., 2017; Johan & Zhang, 2020; Parhankangas & Renko, 2017; Scheaf et al., 2018), making it difficult to transfer findings from reward-based crowdfunding to settings with financially motivated investors. Our paper's purpose is to overcome these limitations.

2.2. Blockchain technology and cryptocurrencies

Cryptocurrencies leverage blockchain and distributed ledger technology to store transaction data immutably and prevent double spending. On blockchains, data is stored in "blocks" which are linked to the previous and following block through cryptographic methods (Natarajan et al., 2017). When combined with distributed ledger technology, the blockchain is stored in a decentralized network across multiple data stores (Nakamoto, 2022; Natarajan et al., 2017). A consensus mechanism, often a simple majority, guarantees that the blockchain is identical (and hence verified) across the entire network (Nakamoto, 2022). This innovation enables secure transactions between anonymous parties, removing the need for a trusted intermediary (Natarajan et al., 2017).

While originally developed to store transaction data of the cryptocurrency *Bitcoin*, blockchain technology has been further enhanced to support a wide array of smart contracts, allowing for a range of applications and services (e.g., decentralized financing)

³ The elaboration likelihood model states that a change in attitude may result from critical thinking, the central route, or from reliance on heuristics, the peripheral route, depending on the individual's motivation and ability for critical thinking (Petty & Cacioppo, 1986).

(Howell et al., 2020; Zetzsche et al., 2020). One of the most popular smart-contract applications are Initial Coin Offerings (ICOs). As further elaborated below, ICOs automate the fundraising process by wiring tokens to the backer in exchange for the backer's funding amount in an automated way, creating trust in the market and making typical intermediaries, such as crowdfunding platforms or venture capital funds, redundant. Most ICOs offer utility tokens, although recent regulatory developments have spurred the rise of security tokens (Bellavitis et al., 2021; Lambert et al., 2021; Momtaz, 2021f). Utility tokens represent claims much like "corporate coupons" on the venture's future assets, while security tokens are much like traditional equity securities that rely on blockchain technology.

2.3. Initial coin offerings (ICOs)

2.3.1. Defining ICOs

In ICOs, firms raise growth capital by selling their tokens or coins to investors in exchange for fiat money or other established cryptocurrencies (Fisch, 2019).⁴ While the first ICO dates back to 2013, broader public interest started in 2017 when cryptocurrency prices gained momentum. The same year, startups raised \$7bn through ICOs. In 2018, the amount increased to \$19.7bn. Since then, the ICO market cooled down in line with the broader cryptocurrency market, raising over \$4bn in 2019 (Bellavitis et al., 2020). Despite the ICO market's high volatility, its size is substantial, making ICOs an important funding channel for startups in the blockchain sector (e. g., Fisch, 2019; Gan et al., 2021; Momtaz, 2020a). Very large ICOs (e.g., EOS with over \$4bn) even reach the size of initial public offerings (IPOs) or large VC funding rounds (Colombo et al., 2020).

ICOs are set apart from traditional forms of financing by a unique set of characteristics. These offer advantages to the fundraising venture but also pose risks for investors. Blockchain technology provides security across a network of anonymous parties and removes the need for a trusted intermediary to secure the transaction. Transferring funds directly from ICO investors to firms lowers transaction costs (e.g., Kaal & Dell'Erba, 2017; Momtaz, 2021a; Momtaz, 2022). However, financial intermediaries are able to reduce asymmetric information between investor and venture, lowering the risk faced by the investor (Benveniste & Spindt, 1989; Hornuf et al., 2021; Momtaz, 2020a). The absence of intermediaries forces investors to rely on the information firms chose to provide (Boreiko & Risteski, 2021).

Having gained popularity only in 2017, ICOs are a new, rapidly evolving form of fundraising with regulation lagging behind (Bellavitis et al., 2021). The ventures' digital nature further reduces geographical restrictions, allowing firms to evade regional regulation (Bellavitis et al., 2021). While reducing bureaucracy as well as preparation time (e.g., Gan et al., 2021) and allowing funds to be raised from a global pool of investors (e.g., Bellavitis et al., 2021; Momtaz, 2020a), the lack of oversight also hampers litigation and gives rise to fraudulent and malignant behaviour (e.g., Hamrick et al., 2018; Hornuf et al., 2021; Momtaz, 2020a). This is further fuelled by the anonymity associated with blockchain technology and online fundraising. Hornuf et al. (2021) identified 20% of ICOs, in the studied sample of 1,393 campaigns, to be fraudulent.

In addition, ICO investors face the risks associated with early-stage financing. Products or services may not yet be developed when the ICO takes place. In this case, tokens will refer to a future service or profit whose realization is highly uncertain (e.g., Kaal & Dell'Erba, 2017). This risk is amplified by the general uncertainty regarding the adoption of blockchain technology (e.g., Natarajan et al., 2017).

2.3.2. Characteristics of ICO investors

The largest blockchains are public and easily accessible through blockchain explorers. To ensure anonymity, an ideological pillar of blockchain technology, the two parties of a transaction are only referred to by their pseudonymous wallet addresses, not revealing any information about the holders' identities (Nakamoto, 2022). Know-your-customer (KYC) procedures, required for common crypto exchanges such as Coinbase or Binance and certain ICOs, link the wallet addresses to their holders undermining the anonymity of blockchain. This information is, however, not publicly available. Research on ICO investors therefore relies either upon anonymised public transaction data from blockchains or on surveys.

Studies using public data found that ICOs tend to be financed by a large number of investors contributing small amounts. Fahlenbrach and Frattaroli (2021) find ICOs in their sample to attract on average 4,700 investors with a median contribution of \$1203. Boreiko and Risteski (2021) studied a different sample with an average of 1600 investors per ICO each contributing on average \$5625. Both studies show the average contribution to be larger than in crowdfunding (Boreiko & Risteski, 2021; Fahlenbrach & Frattaroli, 2021).

Fisch et al. (2019) conducted a survey with 517 respondents to gain an understanding of ICO investors' characteristics and motives. The vast majority of respondents were male with only 39% having a professional background in technology. The main motives to participate in ICOs were found to be enthusiasm for the technology and the prospect of financial gains. Before making an investment decision, investors do not appear to fully exhaust the available information. Only 31.5% of respondents read the white paper in detail, while the majority only skims it or tries to grasp the general content. The findings are in line with the common assumption that ICO investors are unsophisticated retail investors (e.g., Bellavitis et al., 2020; Benedetti & Kostovetsky, 2021; Fisch & Momtaz, 2020).

⁴ Chapter 2.3 draws on the institutional background chapter in Colombo et al. (2020).

2.4. Reducing asymmetric information

Information asymmetries pose a key hurdle to efficient markets and capital allocation. With investors being cautious and presuming a firm is of bad quality unless suggested otherwise, information asymmetries leave high-quality firms underfunded unless they are able to credibly convey information about their quality to investors (Akerlof, 1978; Vismara, 2018b).

Information is transmitted through different channels. While verifiable facts and figures, e.g., revenue or net income, may simply be stated in official documents, credibility issues arise when communicating more elusive concepts, which are not easily verifiable by a third party, such as firm quality or the management's expectation about the firm's future. To establish credibility, widely observable and costly signals may be emitted supporting the firms' claims (Spence, 1978 for excellent reviews of signaling theory in the entrepreneurial finance context, see Colombo, 2021; Vismara, 2018b). Effective costly signals will be comparably cheap to send for high-quality firms but costly to imitate for low-quality ones (Certo, 2003), inducing a "separating equilibrium", a state in which only high-quality firms choose to send the signal, allowing investors to infer the sender's quality from the observed signal (Spence, 1978).

In addition to analytical analysis, investors may also rely on heuristic information processing to form investment decisions, making heuristic cues a third channel for the transmission of information. Heuristics are simple, quasi-automatically (e.g., Kahneman, 2003) and effortlessly applied rules used to quickly (Gilovich et al., 2002; Kahneman, 2003) categorize people, objects or situations into "good" or "bad" (e.g., Kahneman, 2003). In contrast to analytical, bottom-up information-processing styles, judgements derived from heuristics are not differentiated and **non-issue-relevant** cues (Ambady & Rosenthal, 1993; Judge et al., 2009), e.g., the entrepreneur's clothing (Clarke, 2011), may serve as proxies for missing information or information that is difficult to obtain (e.g., Kahneman & Frederick, 2002). These characteristics facilitate decision making under high risk and ambiguity (Andersen et al., 1996; Scheaf et al., 2018) and may be used by firms to persuade investors in settings with high levels of information asymmetry.

3. Hypotheses

ICOs are characterized by very high levels of asymmetric information as projects are typically very early-stage and founders are young and have no track records (among many others, e.g., An et al., 2019; Bellavitis et al., 2020; Fisch, 2019; Howell et al., 2020; Momtaz, 2021a), moral hazard and outright fraud are thought to be very pronounced (Giudici et al., 2020; Hornuf et al., 2021; Momtaz, 2020a), and there is general commercial and legal uncertainty about the industry's prospects (Adhami et al., 2018; Bellavitis et al., 2020; Bellavitis et al., 2020; Bellavitis et al., 2021; Fisch, 2019; Huang et al., 2020; Momtaz, 2020b; Zetzsche et al., 2020). This is paired with a lack of an institutional framework that could provide a minimum level of investor protection and mandatory disclosure standards (Bellavitis et al., 2021).

In an investment environment characterized by these levels of uncertainty and information scarcity, signalling is a key strategy to establish credibility. Video pitches are widely observable, as they are prominently featured on *ICObench*, and costly (Courtney et al., 2017; Mollick, 2014), two characteristics required for signals to be effective and induce a "separating equilibrium" (Spence, 1978). The costs of a video pitch are a combination of the production expenses ⁵ and the costs related to the creation of the video's content. While the production costs may already serve as a deterrent for fraudulent campaigns, we expect the main costs for low-quality ventures to lie in content creation. Showcasing a product (e.g., in the form of screenshots) or presenting a roadmap creates little additional costs if a venture has already reached a minimum development stage, but it may require substantial time and effort if a venture does not have a sound concept or prototype yet, leading to a "separating equilibrium" (Courtney et al., 2017).⁶

In addition to signalling a venture's quality, video pitches act as visual cues, influencing investors' heuristic information processing (Scheaf et al., 2018). Considering the high uncertainty and the sparse information environment surrounding ICOs, as well as most investors' lack of technical expertise (Fisch et al., 2019) impeding critical analysis, we expect ICO investors to be particularly susceptible to visual cues, such as video pitches, to facilitate a heuristic assessment of the venture.

Hypothesis 1: The availability of a video pitch is associated with higher ICO firm valuation.

The impact a video's length has on the funding outcome is not evident. A signal's strength typically increases with its emission costs (Spence, 1978), and while the video production expenses increase with the video's length,⁷ the costs of content creation such as developing a prototype or roadmap do not. Assuming the main costs lie in content creation, the video's signalling strength is unlikely to increase with length.

Besides signalling preparedness and a certain upfront investment, video pitches also transport visual cues used by investors in heuristic information processing. The main advantage of heuristics is the speed at which a judgement can be formed (Gilovich et al., 2002; Kahneman, 2003) even under insufficient information (Andersen et al., 1996; Scheaf et al., 2018). Studies generally find that the test subjects' reactions to thin slices of information, such as pictures or very short videos, are correlated to outcomes of, e.g., elections (e.g., Ambady & Rosenthal, 1992, Ambady & Rosenthal, 1993; Benjamin & Shapiro, 2006; Hu & Ma, 2021; Rosenberg et al., 1986; Todorov et al., 2005). Hu and Ma (2021), however, show that rating cues across an entire crowdfunding video pitch, as opposed to only a thin slice, is a stronger predictor of funding success, indicating that investors incorporate all available cues and refine their judgment

⁵ Approximately \$1,000-\$5000 per minute, as per https://dmakproductions.com/blog/how-much-does-video-production-cost/.

⁶ Some crowdfunding platforms provide tips for how to produce convincing video pitches and low-quality ventures could hire professional video makers. Although these points may reduce the market's efficiency in creating separating equilibria, the marginal costs for producing high-quality videos are still higher in low-quality ventures. We thank an anonymous reviewer for the comment.

⁷ https://dmakproductions.com/blog/how-much-does-video-production-cost/

over the duration of the video.

White paper length, often used as a proxy for disclosed information, has also been found to be positively correlated to ICO success (e.g., Fisch, 2019). Both findings suggest that, given a scarce information environment, reducing asymmetric information through additional or longer disclosures positively impacts funding outcomes. Hence, we expect longer video pitches to increase ICO funding success:

Hypothesis 2: The length of a video pitch is positively associated with ICO firm valuation.

While a number of studies focus on cues in video pitches, such as presentation quality or linguistic style (Anglin et al., 2018; Hu & Ma, 2021; Kim et al., 2016; Parhankangas & Renko, 2017; Scheaf et al., 2018), little is known about the investor's perception of the video's informational content. In the context of ICOs, this might be due to white papers commonly being considered the primary source of information about the venture (Florysiak & Schandlbauer, 2021).

There is, however, reason to believe that the video pitch's informational content also contributes to funding success. Video pitches transport key information about the project in a comprehensible and time-efficient way, minimizing the effort required from the investor. Despite the information provided in crowdfunding or ICO campaigns being relatively scarce compared to, e.g., initial public offerings, retail investors pay limited attention to the information available (Buttice et al., 2021; Liu et al., 2020) and are at risk of becoming overwhelmed by lengthy company descriptions or white papers (Moy et al., 2018; Thapa, 2020). As invested amounts are often small, it is also not economically viable to put significant resources into due diligence (Vismara, 2018b). Thus, investors might find watching videos more convenient than reading white papers. Additionally, the time constraints of videos limit the information which can be shared, revealing what the team considers to be the focus of the venture and the strengths worth highlighting.

Building on the "video pitch as information" argument, different video contents should result in different valuation outcomes. Specifically, informational content should increase ICO firm valuations, while non-informational content should not entail such an effect. In the context of ICO video pitches, the content can be decomposed into narrative and musical parts. While the former is informational, musical content is mainly a tool to induce (non-informational) sensation.

Hypothesis 3: The association of informative content to ICO valuation is stronger compared to non-informative content and ICO valuation. Besides being considered to be the primary source of information about the venture (Florysiak & Schandlbauer, 2021), the white paper also serve as a signal demonstrating that effort was put into the development of a viable product and business concept (Florysiak & Schandlbauer, 2021), as well as showcasing the team's technological expertise (Fisch, 2019). Hence, white papers and video pitches are very similar with regard to their signalling properties and informative functions. Hu and Ma (2021) found ventures' quality indicators to be substitutable, i.e., for crowdfunding projects with high-quality video pitches, investors lowered the bar on other quality indicators. Given the similarities between ICO video pitches and white papers, we expect to see substitution effects as well. That is, a more informative white paper should reduce the value of a video pitch and vice versa.

Hypothesis 4: Video pitches and white papers are substitutes in the ICO investment process.

Our final hypothesis pertains to the linguistic style in video pitches, particularly the use of crypto-specific buzz words. Cryptospecific jargon (e.g., "Bitcoin" or "blockchain") has been very prominent in news headlines, especially during bull markets. Prior research suggests that adding hyped words to a company's name increases investor interest. Jain and Jain (2019) report that firms adding "blockchain" to their name during cryptocurrency bull markets experience abnormal equity returns, even if they are not primarily active in the blockchain sector. A similar pattern has been observed during the 1997–2003 dotcom era (Cooper et al., 2001; Emshwiller, 1999; Lee, 2001).

Besides referencing a hyped industry or technology, using crypto-specific jargon commonly seen in headlines may induce a sense of familiarity. Familiarity has been found to reduce the perceived risk (Zajonc, 1968; Zajonc, 1980), also in a financial context (Weber et al., 2005). Even perceived familiarity induced by word fluency was found to have this effect (Dohle & Montoya, 2017; Song & Schwarz, 2009) and positively impact stock market performance (e.g., Alter & Oppenheimer, 2006; Green & Jame, 2013). While these studies have focused on names, it is likely that the use of familiar jargon in video pitches or company descriptions has a similar effect on perceived risk. This effect should be particularly prominent for ICOs, given most investors' lack of technological expertise (Fisch et al., 2019).

With the number of ICOs increasing sharply in "hot" markets (often there are more than 900 ICOs at once, see (Bellavitis et al., 2021)), investors' limited attention may make them particularly susceptible to crypto-specific jargon to be used as a heuristic in the investment decision-making process in those market cycles.

Hypothesis 5a: Video pitches with frequent usage of crypto-specific jargon are associated with higher ICO firm valuations. **Hypothesis 5b:** The valuation effect of crypto-specific jargon in video pitches is more pronounced during "hot" markets.

4. Data

Most of our data come from *ICObench*, and are supplemented with specific variables from *LinkedIn* (e.g., team members' educational background), *GitHub* (e.g., open-source code), and the *Token Offerings Research Database (TORD)*.⁸ We use the TORD to compile specific data on ICO offering terms and ICO firm characteristics. For the video metrics and content, we use the *YouTube* data API to obtain information on video pitches as well as their transcriptions. Finally, we use the *Bitcoin Historical Data* from *Kaggle* to construct proxies of overall market performance.⁹

⁸ TORD is is the most comprehensive publicly available token offerings database and available from www.paulmomtaz.com/data/tord.

⁹ https://www.kaggle.com/mczielinski/bitcoin-historical-data.

4.1. Variables

4.1.1. Dependent Variable

Our dependent variable is the *Funding amount*, (*log*) raised during the ICO, a commonly used proxy for ICO success (e.g., Fisch, 2019; Momtaz, 2020b).

4.1.2. Main independent variables

Video availability (dummy): Dummy variable which equals one if the ICO venture provides a video, and zero otherwise.

We use several variables to measure the informational content of video pitches: Video length, which we consider to be total duration, and its decomposition into narration and musical content, as well as crypto-specific language.

Duration-related constructs:

- Video length, in seconds (log): The variable is derived by taking the natural logarithm of one plus the video length in seconds.
- Video length, in # of words (log): The variable is derived by taking the natural logarithm of one plus the number of words in the video.
- Narration portion of the video, in seconds (log): This is defined as the natural logarithm of one plus the seconds in which the video is playing a narration.
- Music portion of the video, in seconds (log): This variable is defined as the natural logarithm of one plus the seconds of music played without narrative content. (In an alternative specification, we define the proxy as the natural logarithm of one plus the number of lines in the video transcript, where we do not have any narrative content.)

The rationale for decomposing total video duration into its narration and music parts is that narration can be regarded as a proxy for informative content, whereas musical content usually serves the purpose of triggering emotional reactions on the part of the viewers (i. e., the investors).

Crypto-specific language: This variable was constructed to evaluate the linguistic style of videos, as well as the specificity of the employed language. It captures the density of crypto buzz words. We identified common crypto buzz words by looking at the headlines of *Financial Times* articles tagged with the term "cryptocurrencies," and then compiled a dictionary of the words used most often. Our list consists of terms such as '(Bit)coin', 'crypto(currency)', 'blockchain', 'digital(ized)', 'finance', 'trading', 'money', 'exchange', and 'ether(ium)'. The variable is defined as the count of occurrences of these words in the video divided by the total number of words. We focused only on those transcripts with at least one hundred words in order to avoid extreme skewness that could result from a small denominator.

4.1.3. Control Variables

We include several control variables to rule out a number of confounding explanations.¹⁰

The first set of controls relates to the firm characteristics and the information provided to investors:

White paper length, in # words (log): The natural logarithm of one plus the number of words in the venture's white paper, serving as a proxy for its informational content (e.g., Fisch, 2019).

Expert rating: *ICObench* provides expert ratings on a scale from 1 (low quality) to 5 (high quality). The resulting average rating is often viewed to provide "certification" of a project's legitimacy (Lee et al., 2021; Momtaz, 2020b).

Team size, in # FTE: The number of team members serves as a proxy for social capital and has been found to impact valuations (Fisch, 2019; Lyandres et al., 2019; Momtaz, 2020b).

Technical background, in %: Number of team members with a technical background as a percentage of the entire team. The team members' backgrounds are obtained from *LinkedIn*.

Minimum viable product (dummy): The variable is coded as a dummy, which is one if a minimum viable product exists, and zero otherwise.

Open source (dummy): Open source code may signal a venture's technological ability (Fisch, 2019). It is coded as a dummy variable, which equals one if the code is publicly available on *GitHub*.

Industries (log): The logarithm of one plus the number of industries targeted by the venture as per *ICObench*'s industry classification, serving as a proxy for horizontal diversification (Fisch & Momtaz, 2020).

The second set of control variables relates to ICO characteristics:

Soft cap (dummy): Failing to reach the soft cap, the minimum amount ventures expect to raise during the ICO, results in investors being refunded (Mansouri & Momtaz, 2021). The variable is coded as a dummy variable, with one indicating the announcement of a soft cap.

Hard cap (dummy): Reaching the hard cap, the maximum amount of funding accepted, ends the offering automatically (Mansouri & Momtaz, 2021). The variable is coded as a dummy variable, with one indicating the announcement of a hard cap.

Pre-sale (dummy): Pre-sales allow investors to purchase tokens at a discount before the ICO. It is coded as a dummy variable, which is one if a pre-sales is offered, and zero otherwise.

¹⁰ The control variables are largely similar to the ones used by Mansouri and Momtaz (2021)

Table 2
Descriptive Statistics and Correlations.

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.	19.	20.
Mean	6.506	0.000	0.000	0.000	0.000	0.000	0.000	3.254	11.668	24.953	0.259	0.618	1.299	0.637	0.853	0.508	0.348	0.102	0.348	0.814
SD	7.613	1.000	1.000	1.000	1.000	1.000	1.000	0.625	7.374	20.630	0.438	0.486	0.509	0.481	0.354	0.500	0.476	0.302	0.476	0.389
Q1	0.000	_	-	_	_	-	-	2.800	6.000	8.333	0.000	0.000	0.693	0.000	1.000	0.000	0.000	0.000	0.000	1.000
		0.563	0.510	0.455	0.796	0.707	0.536													
Median	0.000	_	_	_	_	_	0.083	3.250	11.000	23.077	0.000	1.000	1.386	1.000	1.000	1.000	0.000	0.000	0.000	1.000
		0.065	0.066	0.055	0.796	0.306														
Q3	15.063	0.418	0.371	0.394	0.587	0.415	0.628	3.800	16.000	37.500	1.000	1.000	1.609	1.000	1.000	1.000	1.000	0.000	1.000	1.000
 Funding amount (log) 																				
Video length, in seconds (log)*	0.099																			
 Narration portion of video, in seconds (log)* 	0.099	0.873																		
4. Video length, in # words (log)*	0.097	0.857	0.954																	
5. Music portion of video, in seconds (log)*	-0.019	0.093	_	_																
· · · · · ·			0.136	0.188																
6. Crypto-specific language*	0.034	_	_	_	_															
		0.175	0.174	0.189	0.033															
7. White paper length, in # words (log)*	0.133	0.154	0.098	0.086	0.019	_ 0.108														
8. Expert rating	0.217	0.107	0.027	0.026	-	-	0.289													
O Theory along in # FTF	0.175	0.040	0.015	0.000	0.022	0.014	0.001	0.410												
9. Team size, in # FTE	0.175	0.042	0.015	0.009	-	-	0.321	0.410												
10 Technical background in 0/	0.042	0.006	0.066	0.060	0.024	0.068	0.045		0.051											
10. Technical background, in %	0.043	0.026	0.066	0.069		_ 0.007	0.045	-	0.051											
11 Minimum wighle and dust (dumma)	0.116	0.070	0.009	0.006	0.022		0.087	0.028 0.373	0.204	0.051										
11. Minimum viable product (dummy)	- 0.116	0.070	0.009	0.006	0.018	-	0.087	0.373	0.204	-0.051										
12. Open source (dummy)	0.072	0.020		_	_	0.032 0.003	0.093	0.404	0.171	0.017	0.188									
12. Open source (duminy)	0.072	0.020		_ 0.059	- 0.021	0.003	0.093	0.404	0.171	0.017	0.100									
13. # Industries (log)	- 0.018	0.016	0.047	-	0.021	0.007	0.070	0.221	0.161	-0.011	0 100	0.145								
13. # muustries (log)	- 0.018	0.010		_ 0.034	_ 0.006	0.007	0.070	0.221	0.101	- 0.011	0.100	0.145								
14. Soft cap (dummy)	- 0.041		0.032	0.034	0.000	0.017	0.073	0.231	0.151	- 0.060	0 101	0.159	0 1 2 7							
14. Son cap (duminy)	- 0.041	0.052		_ 0.055	 0.020	0.017	0.073	0.231	0.151	- 0.000	0.191	0.156	0.12/							
15. Hard cap (dummy)	0.081	0.032	0.048	0.003	0.020	_	0.081	0.248	0.149	-0.018	0 1 4 2	0.120	0 104	0 420						
13. Hard cap (duiling)	0.081	0.007	0.007	0.004	0.001		0.081	0.240	0.149	- 0.018	0.142	0.130	0.104	0.436						
16. Pre-sale (dummy)	0.053	_	0.007	_	0.001	0.042	0.065	0.229	0.128	- 0.051	0.077	0 1 1 0	0 1 3 4	0 1 8 5	0 154					
10. Pre-sale (duilinity)	0.055		 0.078	_ 0.074	0.052	0.028	0.005	0.229	0.120	- 0.031	0.077	0.110	0.134	0.165	0.134					
17. Whitelist (dummy)	- 0.043		0.078	0.074	_	_	0.181	0.228	0.216	0.043	0.195	0 102	0 160	0.152	0 1 4 9	0.075				
17. Wintenst (duniny)	- 0.043	0.029	0.032	0.054		 0.028	0.101	0.220	0.210	0.043	0.195	0.102	0.109	0.152	0.140	0.075				
18. Bonus (dummy)	- 0.257	0.010	0.041	0.053	-	0.028	0.044	0.040	0.060	- 0.005	0 1 9 0	0.017	0.070	0.062	0.052	_	0.138			
18. Bolius (dullilly)	- 0.237	0.019	0.041	0.055	_ 0.014	 0.058	0.044	0.040	0.000	- 0.005	0.160	0.017	0.079	0.002	0.055		0.138			
10 Pounty (dummy)	- 0.079				0.014	0.038	0.070	0.285	0.176	- 0.040	0 202	0.155	0 1 9 0	0 102	0 1 4 2		0.184	0 1 0 2		
19. Bounty (dummy)	- 0.079	_ 0.019	 0.022	0.023	- 0.002	0.035	0.070	0.200	0.170	- 0.040	0.393	0.155	0.160	0.192	0.142	0.130	0.164	0.103		
20. ERC-20 standard (dummy)	- 0.038	0.019	0.022	0.025	0.002	0.001	0.034	0.094	0.076	- 0.007	0.040	0.022	0.057	0.074	0.060	0.052	0.079	0.021	0.007	
20. ENG-20 Standard (dunning)	- 0.038	0.017	_ 0.004	_ 0.003	0.000	0.001	0.034	0.094	0.070	- 0.007	0.008	0.033	0.057	0.074	0.002	0.052	0.078	0.021	0.067	
		0.017	0.004	0.003																

* indicates variable was z-standardized (mean = 0, standard deviation = 1).

Table 3 Sample Splits.

	Sample Mean for Startups		Differences in Subsamples
	without Video	with Video	
Funding amount (log)	5.513	7.345	1.832 * **
Whitepaper length, in # words (log)	-0.092	0.078	0.170 * **
Expert rating	3.079	3.403	0.324 * **
Team size, in # FTE	10.695	12.492	1.797 * **
Technical background, in %	26.325	23.793	- 2.532 * **
Minimum viable product (dummy)	0.216	0.296	0.080 * **
Open source (dummy)	0.556	0.671	0.115 * **
# Industries (log)	1.249	1.342	0.092 * **
Soft cap (dummy)	0.592	0.676	0.084 * **
Hard cap (dummy)	0.815	0.886	0.070 * **
Pre-sale (dummy)	0.450	0.557	0.106 * **
Whitelist (dummy)	0.319	0.372	0.054 * **
Bonus (dummy)	0.100	0.103	0.002
Bounty (dummy)	0.308	0.381	0.073 * **
ERC-20 standard (dummy)	0.800	0.827	0.027 * **
Observations	1088	1286	

Explanation: The table presents a t-test between two subsamples of ICO campaigns, with and without video pitches. The first two columns present the means of the variables for each subsample. The third column shows the differences of the first two columns and the t-tests on the equality of means. Variables are defined in Section 4.1.3. The variable *White paper length, in # words* is z-standardized (mean = 0 and standard deviations = 1). The sample comprises 1,286 ICOs with a video pitch and 1,088 ICOs without one, all taking place between 2016 and 2020. * ** , * *, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Whitelist (dummy): Whitelists allow investors to ensure ex ante that they are entitled to participate in the ICO before its official start. Typically, a KYC procedure is required to join the whitelist. It is coded as a dummy variable, with one indicating that a venture has an active whitelist.

Bonus (dummy): Bonus programs offer rewards (typically in the form of free tokens or discounts) to individual wallet addresses investing more than a certain amount (Mansouri & Momtaz, 2021). It is coded as a dummy variable, which is one if a bonus program is offered, and zero otherwise.

Bounty (dummy): Bounty programs offer rewards (typically in the form of free tokens or discounts) to investors for promoting the ICO. It is coded as a dummy variable, with one indicating that a bounty program exists.

ERC-20 standard (dummy): This is the technical token standard for utility tokens introduced by *Ethereum*. Compliance with the standard increases the compatibility of the token with external applications, while reducing operational risks associated with an own blockchain technology; thus, making adoption easier and likely influencing the funding success (e.g., Fisch & Momtaz, 2020). It is coded as a dummy variable, with one indicating the compliance with the ERC-20 standard.

4.2. Summary Statistics

Summary statistics and bivariate correlations are in Table 2.¹¹ To ease the economic interpretation of our main results, we z-standardize (i.e., mean = 0, standard deviation = 1) all the main variables in our analyses, i.e., Video length, in seconds, Video length, in # words, Narration portion of video, Music portion of video, Crypto-specific language, as well as Whitepaper length and BTC monthly return.

The average ICO in our sample raises \$5.16 million (6.51 for the logged values), receives an expert rating of 3.254 (out of 5), and has a team consisting of 11.668 individuals of which 24.953% have an educational background in a technical field. About every fourth (i.e., 25.9%) startup has a minimum viable product (henceforth, MVP) and 61.8% of all startups have published open-source code on *GitHub*. These statistics are broadly similar to those found in related studies (e.g., Bellavitis et al., 2020; Fisch, 2019; Howell et al., 2020; Huang et al., 2020; Momtaz, 2020a).

The correlations show that the *Funding amount* is positively correlated with several video metrics, in particular *Video length* and *Narration portion of video* but not with *Music portion of video*. This is suggestive evidence that videos primarily play an informational role in ICOs, echoing the findings from related studies (e.g., <u>Cumming et al., 2017</u>) that the availability of a video pitch and fundraising success are positively related in the crowdfunding context.

Among our video related variables, we see high correlations between *Video length, in # words, Video length, in seconds* and *Narration portion of video*. Although such high correlations are natural by construction, we observe a very low correlation ($\rho = 0.09$) between the *Music portion of video* and *Video length, in seconds*, suggesting a high heterogeneity in the way musical elements added in the creation of the video pitches in our sample. In all of our regression settings, correlations among the independent variables are not high enough to

¹¹ Because we always use the largest possible number of observations in our subsequent regression analyses, the number of observations differs across our models. For the summary statistics and correlations in Table 2, we therefore always consider the largest possible number of observations.

Main Results: Video Pitches and ICO Firm Valuation.

	Funding amount (log)				
	(1)	(2)	(3)	(4)	(5)
Video availability (dummy)	0.846 * **				
	(0.286)				
Video length, in seconds (log)		0.475 * *			
		(0.197)			
Narration portion of video, in seconds (log)			0.452 *		
			(0.237)		
Music portion of video, in seconds (log)				0.168	
				(0.244)	0.467.*
Video length, in # words (log)					0.467 *
Music portion of transprint in # lines (loc)					(0.260) 0.167
Music portion of transcript, in # lines (log)					
White paper length, in # words (log)	0.508 * **	0.431 *	0.476 *	0.518 *	(0.240) 0.475 *
white paper length, in # words (log)	(0.145)	(0.220)	(0.280)	(0.285)	(0.280)
Expert rating	2.867 * **	2.896 * **	2.667 * **	2.691 * **	2.670 * **
Expert fating	(0.281)	(0.411)	(0.513)	(0.513)	(0.514)
Team size, in # FTE	0.132 * **	0.106 * **	0.120 * **	0.120 * **	0.121 * **
	(0.021)	(0.030)	(0.037)	(0.037)	(0.037)
Technical background, in %	0.001	0.007	0.012	0.013	0.012
rechinear background, in 70	(0.007)	(0.010)	(0.013)	(0.013)	(0.013)
Minimum viable product (dummy)	- 1.160 * **	- 0.910 *	- 0.772	- 0.707	- 0.775
r f f f f f f f f f f f f f f f f f f f	(0.377)	(0.506)	(0.633)	(0.634)	(0.635)
Open source (dummy)	- 0.041	0.140	- 0.007	- 0.070	0.014
	(0.302)	(0.437)	(0.535)	(0.539)	(0.537)
# Industries (log)	-0.310	-0.182	0.460	0.444	0.469
-	(0.280)	(0.381)	(0.475)	(0.476)	(0.475)
Soft cap (dummy)	- 0.451	0.263	- 0.054	-0.085	- 0.040
	(0.335)	(0.462)	(0.572)	(0.577)	(0.574)
Hard cap (dummy)	1.865 * **	1.871 * **	2.846 * **	2.869 * **	2.818 * **
	(0.446)	(0.694)	(0.872)	(0.870)	(0.872)
Pre-sale (dummy)	0.162	0.006	0.234	0.158	0.206
	(0.292)	(0.398)	(0.495)	(0.497)	(0.497)
Whitelist (dummy)	- 0.679 * *	-0.481	- 0.466	-0.368	-0.437
	(0.314)	(0.435)	(0.542)	(0.544)	(0.545)
Bonus (dummy)	- 5.836 * **	- 6.830 * **	- 7.141 * **	- 7.152 * **	- 7.178 * **
	(0.342)	(0.489)	(0.606)	(0.612)	(0.607)
Bounty (dummy)	-0.235	0.220	0.139	0.142	0.140
	(0.324)	(0.445)	(0.548)	(0.548)	(0.548)
ERC-20 standard (dummy)	-0.165	-0.161	-0.736	-0.758	-0.735
	(0.354)	(0.506)	(0.632)	(0.635)	(0.633)
Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	2374	1279	855	855	855
Adjusted R ²	0.277	0.277	0.290	0.287	0.290

Explanation: The table shows the results from regressions based on Equation 1. The dependent variable is natural logarithm of the funding amount (in \$). Variables of interest, i.e., *Video length, in seconds, Narration portion of video, in seconds, Music portion of video, in seconds, Video length, in # words, Music portion of transcript, in # lines, and White paper length, in # words* are z-standardized (mean = 0 and standard deviations = 1). All control variables are defined in Section 4.1.3. The sample consists of ICOs between 2016 and 2020. In columns (2) - (5), we restrict the sample to only those campaigns providing a video pitch. All specifications include country and quarter-year fixed effects. Huber-White robust standard errors are in parentheses. * ** , * *, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

raise a multicollinearity issue.¹²

5. Empirical analyses

5.1. Main results: video pitches and ICO firm valuation

Prefacing our regression analyses, it is important to highlight that ventures choosing to publish a video pitch vary significantly along a number of relevant covariates from those that do not to publish a video pitch. This observation is important because empirical studies of crowdfunding differ in the scope of confounding factors they control for, and therefore, it is no surprise that evidence on

¹² The maximum correlation among the independent variables is $\rho = 0.4$ between the dummy for open-source and the experts' ratings. This is much lower than the generally agreed threshold of $\rho = 0.7$ (Leitterstorf & Rau, 2014)

Additional results: informativeness of video pitches.

	Funding amount (log)					
	(1)	(2)	(3)			
Video length, in seconds (log)	0.481 * *					
	(0.194)					
Narration portion of video, in seconds (log)		0.448 *				
		(0.232)				
Video length, in # words (log)			0.461 *			
			(0.263)			
White paper length, in # words (log)	0.438 * *	0.534 * *	0.534 *			
	(0.215)	(0.260)	(0.261)			
Video length, in seconds (log)	-0.231					
\times White paper length, in # words (log)	(0.164)					
Narration portion of video, in seconds (log)		- 0.436 * **				
\times White paper length, in # words (log)		(0.167)				
Video length, in # words (log)			- 0.390			
\times White paper length, in # words (log)			(0.199)			
Controls	Yes	Yes	Yes			
Quarter Fixed Effects	Yes	Yes	Yes			
Country Fixed Effects	Yes	Yes	Yes			
Observations	1279	855	855			
Adjusted R ²	0.278	0.293	0.292			

Explanation: These are results from regressions of startup valuation on video pitch related variables as outlined in Equation 2. The dependent variable is natural logarithm of the funding amount (in \$). All control variables are defined in Section 4.1.3, and the coefficients are not shown for the sake of brevity. *Video length, in seconds, Narration portion of video, in seconds, Video length, in # words* and *White paper length, in # words* are z-standardized (mean = 0 and standard deviations = 1). The sample consists of token offerings between 2016 and 2020 with a video pitch. All specifications include country and quarter-year fixed effects. Huber-White robust standard errors are in parentheses. * ** , * *, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

whether video pitches matter for crowdfunding success are mixed, such as in Mollick (2014) vs. Troise et al. (2020). Table 3 shows tests of differences in means for our dependent variable and for all covariates we control for. Note that the funding amount (log) that startups with video pitches receive is 33% higher than that of startups without video pitches. For the controls, it is striking to observe that out of our 14 controls, 13 controls are significantly different between the subsamples of startups with vs. without video pitch. Thus, it is important to condition the empirical link between the availability of a video pitch and the funding amount on the largest-possible set of controls in order to identify an unbiased marginal effect. This was precisely the rationale as to why we focused the data gathering effort on a broad set of variables to control for differences between startups (compare Section 4).

With the importance of covariates for the video pitch-valuation relation in mind, we specify the following multivariate regression model in which we regress the *Funding amount* (*log*) raised by ICO firm *i* on a dummy variable indicating whether a video pitch is available and on the full set of our controls. Formally:

Funding amount_i =
$$\beta_0 + \beta_1 \cdot Video availability_i + \beta_2 \cdot X_i + \lambda_t + \mu_c + \varepsilon_i$$
, (1)

where β_1 is the coefficient of interest, and *Video availability i* is a dummy indicating the availability of a video pitch, and X_i contains the controls as discussed in Section 4.1. Additionally, we follow the tradition in empirical ICO studies (e.g., Howell et al., 2020; Momtaz, 2020b) and absorb time trends using quarter-year fixed effects, λ_p and country specific variations with country fixed effects, μ_c .

The coefficient of *Video availability* in column (1) of Table 4 is statistically significant at the 1% level, suggesting that the marginal effect of publishing a video pitch in an ICO campaign, in line with *H1*, increases the funding amount on average by 133% (i.e., 133% = $e^{0.846}$ –1). Column (2) replaces *Video availability* with the continuous variable *Video length, in seconds*. The coefficient is also statistically significantly positive. For example, a startup with a 10% longer video pitch than the average is associated with a valuation premium of 4.75% in our sample. Thus, video pitches are significantly positively related to ICO firm valuation, providing empirical support for *H2*.

Our data also allows us to decompose video content into narration (i.e., a proxy for informational content) and music (i.e., a proxy for non-informational content). The results are interesting and go beyond existing evidence insofar as our results suggest that it is only the narrative (i.e., informational) content that drives the identified effect between video pitches and ICO firm valuations. The coefficient of *Narration portion of video* is significantly positive in column (3), while the coefficient of *Music portion of video* is not statistically different from zero in column (4). To be sure, in column (5), we test the *Video length, in # words* and *Music portion of transcript, in the # lines*. Indeed, we find that the video as a whole matters, while the amount of musical content is statistically non-significant. Therefore, these results provide empirical support for *H3* (*H3a* and *H3b*), indicating that the positive video pitch-valuation relation is driven by informational video content, but not by non-informational video content.¹³

For the control variables, we find – largely consistent with related studies (e.g., Adhami et al., 2018; Bellavitis et al., 2020; Fisch,

¹³ The music in a video pitch could be specially value relevant for a startup projects in the art and entertainment industries. Our results are robust for inclusion of a dummy indicating whether a project is categorized as 'Art' or 'Entertainment' by the ICOBench platform.

Additional Results: The Role of Video Pitches in "Hot" Markets.

	Funding amount (log)					
	(1)	(2)	(3)			
Crypto-specific language	0.435 *	0.401	0.425 *			
	(0.246)	(0.263)	(0.251)			
BTC monthly return		-0.0511	- 0.364			
		(0.265)	(0.318)			
Crypto-specific language		0.491 *	0.454 *			
× BTC monthly return		(0.289)	(0.273)			
Controls	Yes	Yes	Yes			
Time Fixed Effects	Month		Year			
Country Fixed Effects	Yes	Yes	Yes			
Observations	811	814	814			
Adjusted R ²	0.293	0.184	0.214			

Explanation: These are results from regressions of startup valuation on video pitch related variables as outlined in Equations 3 and 4. The dependent variable is the natural logarithm of the funding amount (in \$). *Crypto-specific language* is the frequency of crypto-related jargon in the video pitch, and *BTC monthly return* is the monthly buy-and-hold return on *Bitcoin*. All control variables are defined in Section 4.1.3, and the coefficients are not shown for the sake of brevity. Both the *Crypto-specific language* and *BTC monthly return* variables are z-stan-dardized (mean = 0 and standard deviations = 1). The sample consists of token offerings between 2016 and 2020 with a video pitch. All specifications include country fixed effects. In columns (1) and (3) we absorb time trends with month year and year fixed effects, respectively. Huber-White robust standard errors are in parentheses. * ** , * *, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

2019; Momtaz, 2020a) – that (i) the white paper length is significantly positively related to the funding amount, (ii) expert rating also positively, and statistically significantly, predict ICO success, (iii) the team size is also positively associated with the funding amount, (iv) the dummy indicator for the minimum viable product, however, is negatively related to the funding amount, (v) if the ICO firm has defined a hard cap before the ICO, this has a positive marginal effect on the funding amount, (vi) the presence of a whitelist is negatively correlated with the funding amount, and (vii) a bonus program is also negatively related to the funding amount.

Finally, note that the adjusted R-squared ranges from 27.7% to 29.0% and is therefore comparable (and slightly above) those explained variations in related studies (e.g., Adhami et al., 2018; Fisch, 2019; Huang et al., 2020; Momtaz, 2020a, Momtaz, 2020b).

5.2. Additional results: mechanisms why video pitches matter

Showing the importance of the video pitches for the startups' valuation raises a natural question why these video pitches are important. In this subsection, we explore two channels through which video pitches affect the valuation. We first discuss the informativeness of the video pitches as a disclosure source, and second, the role of video pitches during the bull market for crypto assets.

5.2.1. Informativeness of video pitches

In order to test **H4** and understand the relationship between information contents of video pitches and the white papers, we extend the model introduced in equation 1 by including the interaction term with the *White paper length*. More specifically, for ICO *i*, we have:

Funding
$$amount_i = \beta_0 + \beta_1 \cdot Video informativeness_i + \beta_2 \cdot White paper length, in words_i + \beta_3 \cdot Video informativeness × White paper length, in words_i + \beta_4 \cdot X_i + \lambda_t + \mu_c + \varepsilon_i,$$
(2)

where Video informativeness interchangeably refers to the Video length, in seconds, Narration portion of video, in seconds and Video length, in # words. X_{i_b} , λ_t , and μ_c are as in Eq. (1).

The results of the regressions are shown in Table 5. The coefficients of the interaction term are negative in all the three specifications. Column (2) shows the interaction of *Narration portion of the video* and *White paper length* to be negative at a significance level of 1%. A one standard deviation increase in *White paper length* almost entirely wipes out the positive effect of *Narration portion of the video*. The interaction term of *Video length, in # words* and *White paper length*, shown in column (3) is negative as well at a significance level of only 10%. These findings support the H4, that the importance of videos diminishes for lengthier white papers.

For the sake of brevity, we do not report the coefficients of the control variables, as they are consistent with the analysis in the previous subsection. Adjusted R^2 s are also similar to the main regression analyses in the previous subsection.

5.2.2. The role of video pitches in "Hot" markets

Finally, we explore the role of crypto-specific language on the funding raised testing **H5a**. To do so, we replace *Video informativeness* in Equation 1, with *Crypto-specific language*, i.e., frequency of the crypto related jargon in the video pitch. We then model the funding raised by ICO *i* as:

Funding amount_i =
$$\beta_0 + \beta_1 \cdot Crypto - specific \ language_i + \beta_4 \cdot X_i + \lambda_t + \mu_c + \varepsilon_i$$
, (3)

Column (1) of Table 6 shows the result of this analysis. The coefficient of *Crypto-specific language*, in line with **H5a**, is positive and statistically significant at 10%. Specifically, a one standard deviation increase in the frequency of crypto-specific jargon is associated with an increase in funding by 57.3%.

Next, we verify if this effect is larger for the months in which the *Bitcoin* return is higher. Therefore, we extend the model in equation 3 by including the interaction term with the monthly buy-and-hold return on *Bitcoin*, i.e.,

Funding amount_i =
$$\beta_0 + \beta_1 \cdot Crypto - specific \ language_i + \beta_2 \cdot BTC \ monthly \ return_i + \beta_3 \cdot Crypto - specific \ language_i \times BTC \ monthly \ return_i + \beta_4 \cdot X_i(+\lambda_t) + \mu_c + \varepsilon_i,$$
(4)

with BTC monthly return i being the buy-and-hold return on Bitcoin in the month of firm i's ICO.

The results are shown in columns (2) and (3) of Table 6. Column (2) does not include any time fixed effects, while column (3) includes within year variations. We find the coefficient of the interaction term to be positive and statistically significant at a 10% level in both specifications. These results confirm **H5b**, i.e., the effect of crypto-specific language on valuation increases during the *Bitcoin* bull market.

6. Discussion and conclusion

6.1. Summary of results

This study has sought to shed light on whether and why video pitches matter for crowdfunding success in Initial Coin Offerings (ICOs). Using a large, hand-collected ICO sample, we find that the availability as well as the length of video pitches has a significantly positive effect on the ICO funding amount. The effects are also economically meaningful. For example, conditioning on an extensive set of control variables, we find that ICO firms are able to achieve 133% higher funding amounts when they publish a video pitch. Similarly, increasing the length of a video pitch by, for example, 10% is associated with a marginal effect on the funding amount of 4.75%. Besides, note that only 54% of all ICO firms choose to publish video pitches. In fact, the marginal costs of a video pitch might be prohibitively high in low-quality ventures (e.g., it is costly to create convincing video content from a project with little substance, see also Courtney et al., 2017). Thus, video pitches might serve as an effective device to create a "separating equilibrium" (Leland & Pyle, 1977; Spence, 1978), that helps investors distinguish low- from high-quality ventures.

Analyzing the content of video pitches that we decompose into informational (i.e., narrative) and non-informational (i.e., musical) content, we find that it is the informational content that is driving the positive relation between video pitches and ICO firm valuation, whereas the non-informational content does not entail a significant effect. These results, together with the finding that the length of video pitches is positively associated with the funding amount, strongly suggest that video pitches matter because they inform potential investors' investment decisions. Further, examining the "video as information" argument, we explore the dialectic relation between video pitches and ICO white papers. Our empirical findings suggest that video pitches and white papers are informational substitutes. That is, having a very informative white paper as well as a very informative video pitch increases the funding amount, but the marginal interaction effect of having both is negative.

Finally, we explore the role of linguistic style and the external market environment for the video pitch-valuation relation. In particular, we explore the effect of crypto-specific jargon, and find that ventures that populate video pitches with crypto-specific jargon to convey information are able to raise more funding. Pairing the results with the external market environment, we find that the valuation effect of crypto-specific jargon is even more pronounced in "hot" markets. A potential explanation is that crypto-specific jargon triggers investment decision-making heuristics, and this is most pronounced in "hot" markets when a high number of ICO firms compete for capital from the crowd and investors have only a very limited time to screen each venture.

6.2. Theoretical contributions and practical implications

Our paper makes at least two overarching contributions. First, we add to the growing and important literature on success determinants of ICOs. Prior research identifies mainly human and social capital, technological, governance-related, and emotional signals of venture quality (e.g., Adhami et al., 2018; An et al., 2019; Barth et al., 2021; Bellavitis et al., 2020; Bellavitis et al., 2021; Benedetti & Kostovetsky, 2021; Block et al., 2021; Colombo et al., 2020; Cumming et al., 2021; Drobetz et al., 2019; Fisch & Momtaz, 2020; Fisch, 2019; Florysiak & Schandlbauer, 2021; Giudici & Adhami, 2019; Giudici et al., 2020; Hornuf et al., 2021; Howell et al., 2020; Huang et al., 2020; Lyandres et al., 2019; Momtaz, 2020a; Momtaz, 2020b; Momtaz, 2021a; Momtaz, 2021a, 2021b; Sharma & Zhu, 2020), with video pitches being largely overlooked so far.¹⁴ Our study is the first to show in the ICO context that video pitches are a primary determinant of the funding amount.

Another contribution pertains to the broader role of video pitches in entrepreneurial finance. As reviewed in Table 1, the existing literature has established the availability of a video pitch in entrepreneurial finance markets, especially in crowdfunding (e.g., Cumming et al., 2017; Hu & Ma, 2021), as an important success determinant, but is limited insofar as it is still relatively opaque as to *why* video pitches matter. Our results show that video pitches matter because they a) signal the venture's preparedness, b) convey cues

¹⁴ Nevertheless, video pitches have received some, albeit limited, attention in the crowdfunding literature, which Table 1 shows.

and induce interest or a feeling of familiarity through the use of prominent context-specific jargon, and c) provide information (as opposed to non-informational sentiment) in a convenient format. The informational aspect is of particular relevance as previous literature on ICOs has mainly considered white papers to be the primary informational source (e.g., Florysiak & Schandlbauer, 2021). We show that this is not necessarily the case as video pitches serve a similar purpose and even act as substitute to white papers.

These findings bear important practical implications for startups, investors, and policymakers. First, for ventures, our results are relevant because they may help ventures create more effective ICO campaigns via video pitches (with specific insights into what video content and features matter most). Following the insights about the use of video pitches in this paper will help ventures reduce asymmetric information, ultimately leading to higher firm valuations. Second, for investors, our study suggests that the availability and the length of video pitches may be effective signals of underlying venture quality. This is because the marginal costs of creating video pitches is significantly higher in low-quality ventures, which are therefore less likely to publish convincing video pitches. Third, for policymakers, the evidence in our study suggests that ICO investors, who are mostly small, individual investors with little prior investment experience (Fisch et al., 2019), prefer informational convenience over informational completeness (i.e., video pitches over white papers), which has implications as to how policymakers should best design informational disclosure requirements in ICO markets.

6.3. Avenues for future research

Our paper establishes a positive relation between the availability and length of a video pitch and the ICO fundraising success. Future research could build on this finding and explore in greater detail the impact of certain video characteristics. For example, one interesting aspect could be the video narrator's ability to signal confidence, or to elicit trust, passion or enthusiasm among the viewers (for related research, see e.g., Fisch et al., 2019; Huang et al., 2021; Mitteness et al., 2012; Momtaz, 2021a; Momtaz, 2021a, Momtaz, 2021a; Stroe et al., 2020). Closely related questions worthwhile of exploration are: How does observing the actual entrepreneur and/or expert advisors in a video influence funding success? How do an entrepreneur's personality traits, such as perceived intelligence, passion, enthusiasm, and positive affects in general affect funding success?

A particularity to most video pitches in entrepreneurial finance is that they have a "comments" section, at least when published on *YouTube*. Exploring the crowd's comments to video pitches may paint a more nuanced picture of the psychology of crowdfunding markets, and may shed further light on the effectiveness of signals (e.g., Colombo, 2021) and informational cascades or herding dynamics (e.g., Vismara, 2018a), among many other interesting topics for future research.

6.4. Concluding remarks

In closing, our paper highlights the relevance of video pitches in entrepreneurial finance markets. Video pitches function as costly signals, helping to distinguish low-quality from high-quality projects. They also convey information in a more convenient and accessible way than alternative sources (e.g., the white paper), which minimizes information acquisition costs for investors. Our study contributes to the literature beyond existing work, in particular, our study explores the content of video pitches and links the effect of linguistic style to external market conditions to paint a more nuanced picture of the psychology of crowdfunding markets. As such, our findings have important implications for startups, investors, and policymakers.

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