Received: 21 August 2018 | Revised: 19 August 2020 | Accepted: 21 August 2020 | Published on: 14 September 2020

DOI: 10.1002/smj.3235

STRATEGIC MANAGEMENT JOURNAL WILEY

RESEARCH ARTICLE

CEO emotions and firm valuation in initial coin offerings: An artificial emotional intelligence approach

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Funding information
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Abstract

Research Summary: How emotions impact firm valuation is empirically understudied because affective traits are difficult to quantify. However, using artificial emotional intelligence, positive and negative affects can be identified from facial muscle contraction-relaxation patterns obtained from public CEO photos during initial coin offerings, that is, blockchain-based issuances of cryptocurrency tokens to raise growth capital. The results suggest that CEO affects impact firm valuation in two ways. First, CEOs' own firm valuations conform more to those of industry peers if negative affects are pronounced (*conformity mechanism*). Second, investors use CEO affects as signals about firm value and discount when negative affects are salient (*signaling mechanism*). Both mechanisms are stronger in the presence of asymmetric information.

Managerial Summary: The purpose of this paper is to advance our understanding of how CEOs' affective traits influence firm valuation by both, CEOs themselves and investors. The effect of CEO emotions is plausibly particularly pronounced for start-up firms, whose success prospects critically depend on their leaders. My results suggest that CEO emotions impact underpricing in initial coin offerings twofold. First, negative emotions are associated with CEOs choosing an underpricing level that closely conforms to their peer firms' average. Second, investors react to negative CEO emotions by demanding higher discounts on firm value. These effects are more pronounced when there is relatively little public information about the ICO firm. My paper is accompanied by artificial emotional intelligence software for implementation in practice and future research.

KEYWORDS

artificial emotional intelligence (emotion AI), CEO emotions, firm valuation, initial coin offering (ICO), upper echelons theory

JEL CLASSIFICATION

G24; G32; G41; L26; M12; M13

1 | INTRODUCTION

The paper examines how CEO *affects*[1] impact firm valuation in initial coin offerings (ICOs), that is, blockchain-based issuances of cryptocurrency tokens to raise growth capital. Specifically, it addresses three research questions: First, how do CEO affects impact CEOs' own firm valuations? Second, how do CEO affects impact how investors value firms? Third, how do informational asymmetries moderate how CEO affects impact firm valuation by both, CEOs themselves and investors? In this paper, I propose possible answers to all three closely related questions by theoretically and empirically analyzing CEO *affective traits* obtained from a novel artificial emotional intelligence (henceforth, emotion AI) approach.

Many studies conclude that CEOs have a significant impact on firm performance (e.g., Hambrick & Quigley, 2014, 2015).[2] However, research on the role of CEO affects for firm value is "very limited" and "largely remains a blind sport" (Liu et al., 2018, p. 800).[3] This lack is due in large part to difficulties in obtaining reliable data on affective traits, and is thus limited to specific case studies or survey-based evidence, with the latter often being subject to a selectivity bias. For example, Delgado-Garcia and De La Fuente-Sabaté (2010) find survey-based evidence that managers' *negative* affective traits are related to conformist strategies and industry-typical performance in a sample of Spanish savings banks. In a case study, Vuori, Vuori, and

[1]Psychologists use different terms to refer to affects, such as emotions and mood, which can sometimes be difficult to distinguish. Throughout the paper, I follow Forgas (1991) affect who uses *affects* as an inclusive label that refers to emotions and mood.

[2]See, for excellent overviews of CEO attributes that influence firm performance, Liu, Fisher, and Chen (2018) and Wang, Holmes, Oh, and Zhu (2016).

[3]Notable exceptions are Mayew and Venkatachalam (2012) who find a relation between firms' financial future and managerial affective states measured from audio files of earnings conference calls and Blankespoor, Hendricks, and Miller (2017) who use 30-s video clips of IPOs to study investors' cognitive perception of CEOs and how this impacts the pricing of newly issued shares.

Huy (2018) report that the masking of negative emotions causes post-acquisition integration failure in the client relationship marketing sector. Yet, data restrictions on affective traits have precluded a systematic, generalizable study of the relationship between CEO affective traits and firm valuation (Wang et al., 2016). In particular, the gap includes important questions such as whether managerial emotions entail economic value for investors in the form of market signaling and whether such an effect hinges on the level of asymmetric information.

For the purpose of this paper, I employ a novel emotion AI approach to quantify CEO affective traits. The emotion AI uses facial muscle contraction-relaxation patterns obtained from publicly available photo and video material to accurately identify perceived emotions in social interactions (Ekman, 1999; Picard, 2000). The advantage of this approach is that it is easy to implement for all firms and, therefore, allows the compilation of a comprehensive database of managers' affective traits.

ICOs offer an ideal context to use emotion AI in order to examine the relation between CEO affective traits and firm valuation for at least two reasons: First, unlike conventional financing methods, ICO fundraising roadshows happen largely on the internet rather than behind closed doors such as in venture capital transactions, making the emotions that CEOs convey to potential investors readily observable. Second, due to the lack of legal investor protection and information disclosure, ICO investors have close to no *tangible* reference points for their investment decisions (Fisch, 2019; Howell, Niessner, & Yermack, 2019; Momtaz, 2020a), suggesting an increased relative importance of *intangible* investment-relevant information such as CEO affective traits.

Using a sample of 232 successfully completed ICOs between August 2015 and April 2018, I find that CEO affects impact firm valuation in two ways. First, consistent with Delgado-Garcia and de la Fuente-Sabaté (2010), negative affects are correlated with CEOs' valuation conformity with industry peers when choosing the underpricing level (*conformity mechanism*). A 1 *SD* is associated with a deviation from industry-average underpricing by 6%. Second, consistent with the notion that perceived affects have signaling value in economic interactions, investors demand more underpricing when CEOs display negative affects (*signaling mechanism*). A 1 *SD* is associated with a discount on firm value that amounts to about 15%. Both figures are statistically and economically significant, indicating that CEO affective traits may be a first-order determinant of firm valuation in ICOs by both, CEOs and investors. Interestingly, CEO positive affects have no significant effect, which is largely consistent with Delgado-Garcia and de la Fuente-Sabaté (2010) and Delgado-Garcia, de la Fuente-Sabaté, and de Quevedo-Puente (2010). Finally, the paper also examines how the level of asymmetric information moderates the affect-valuation relations. The results suggest that the conformity and signaling mechanisms are more pronounced when market participants' information sets are more limited. Again, the results are only significant for negative affects. These results are robust to several sensitivity checks.

My study offers several contributions. First, the paper introduces an emotion AI approach to quantify CEO affective traits from publicly available photo and video material. The method is easy to implement and might encourage future strategy research on CEO affects. Second, the study extends the literature on how negative affects are related to conformist behavior in CEOs (Delgado-Garcia & de la Fuente-Sabaté, 2010) by offering the first evidence that CEO affects also have signaling value in financial markets. Hence, CEO affects impact firm valuation by *both* CEOs and investors. Finally, this study is the first to show that the ramifications of CEO affects are more salient in the presence of asymmetric information.

2 | THEORETICAL BACKGROUND AND HYPOTHESES

2.1 | CEO affects

Much of the psychology literature is concerned with how positive and negative affects influence cognitive processing (e.g., Amabile, Barsade, Mueller, & Staw, 2005). The prominent *dual-force model* submits that negative emotions promote accommodation as the dominant cognitive processing style, leading to error avoidance and conservation. In contrast, positive emotions promote creativity and proactivity (Fiedler (2000, 2001)). Consistent with the model, prior research has found that cognitive processing that is influenced by negative affects often impacts firm outcomes in dynamic environments. For example, a large literature on post-merger integration (PMI) shows that negative emotions impede successful PMIs (Graebner, Heimeriks, Huy, & Vaara, 2017; Vuori et al., 2018).

A related literature in social psychology examines how individuals' affects impact their social environments. Scholarly consensus has been built around two social consequences. First, affects entail *emotional reactions* (Sutton, 1991), for example, CEOs conveying negative affects may cause the same among investors. Second, observed affects may be taken as *emotional cues of deeper motives* (van Kleef, de Dreu, & Manstead, 2004b), suggesting that investors could use negative affects in the CEO as warning signals or *red flags* to stay away from the investment opportunity. Given the lack of corporate governance and legal investor protection, paired with the number of fraudulent ICOs (Böhme, Christin, Edelman, & Moore, 2015; Momtaz, 2020a), *emotional cues* might be an important reference point for investors in ICOs.

2.2 | Initial coin offerings

ICOs represent a novel market for firms to raise growth capital.[4] ICOs combine desirable features of IPOs (e.g., liquidity of issued tokens) and crowdfunding (e.g., attractiveness for both retail and institutional investors). Additionally, firms do not rely on intermediaries to conduct ICOs, suggesting close-to-zero transaction costs. Therefore, ICOs are an attractive new form of financing for the entire cross section of firms, ranging from small start-ups to large multinational corporations. For example, the largest ICO, as of July 2020, raised $4.2 billion in gross proceeds.

In ICOs, firms issue cryptographically secured assets called *tokens* and receive fiat money or major cryptocurrencies such as *Bitcoin* or *Ether* in exchange. Tokens are entries on distributed ledgers, such as *blockchains*, that record all transactions chronologically and publicly. Tokenholders are assigned *keys* that allow them to create new entries on the blockchain to reassign token ownership to someone else. The distinct advantage of the distributed ledger technology is that its publicly available transaction register can be validated by every network participant and validation (or *mining*) happens as a collaborative effort, making the services of traditional financial intermediaries redundant.

ICOs offer an ideal context to study the relation between CEO affects and firm valuation for several reasons. ICOs are characterized by highly asymmetric information (Momtaz, 2020a, 2020c). The lack of legal investor protection and information disclosure laws plausibly leads investors to pay more attention to CEO attributes and behavior. Therefore, if CEO affects impact firm valuation, the effect should be particularly pronounced in ICOs (Colombo, Fisch,

[4]For an introduction to ICOs, see Momtaz (2020b) and Momtaz (2019b).

Momtaz, & Vismara, 2020). Further, ICO fundraising campaigns occur mostly on the internet, not behind closed doors. Thus, an emotion AI approach can be used to extract affects from the publicly available photo and video material.

2.3 | Conceptual framework and hypotheses

Upper echelons theory argues that CEOs' and other top managers' demographic and psychological characteristics influence their corporate decisions through cognition, values, and norms (Hambrick & Mason, 1984). In ICOs, where the roles of founder and CEO usually collide, and where founder-CEOs usually hold most of the equity and hence dominate corporate decision-making, the CEO effect is plausibly most pronounced. Their corporate decisions, conditioned by their affects, impact firm value.

In seminal work, Delgado-Garcia and de la Fuente-Sabaté (2010) propose a conceptual framework that explains how CEO affective traits shape firm outcomes. They provide evidence suggesting that negative (positive) affects may be positively (negatively) related to *strategic conformity*. Hiller and Hambrick (2005, p. 311) refer to strategic conformity as "the degree to which a focal firm looks and behaves like the modal (or typical) firm in its industry." For example, in Delgado-Garcia and de la Fuente-Sabaté's (2010) study of Spanish bank CEOs, strategic conformity refers to the extent to which these banks' asset strategies conform to the industry mean.

In the present context, prior work on new securities issues suggests that underpricing may be associated with benefits for the issuer (Ljungqvist, 2007). Indeed, Drobetz, Momtaz, and Schröder (2019) find that ICO underpricing measured on the first day of trading explains token returns up to at least 6 months after the listing. Therefore, the CEO's decision problem at the time of the listing is to choose the right underpricing level. The conformity argument would imply the market's average underpricing level as a reference point.[5]

The degree of CEO conformity is determined by affects in at least two ways. First, affective traits impact *cognitive processing*. Fiedler's (2000, 2001) dual-force model maintains that cognitive processing styles are conditioned by the decision makers' affect structures. On the one hand, negative affective traits promote accommodation as the dominant cognitive processing style, leading to error avoidance and conservation. Therefore, conformity may result from dominant negative affects (e.g., Elsbach & Barr, 1999). On the other hand, positive affective traits promote creativity and proactivity, which is associated with deviation from norms, leading to less conformity (e.g., Mittal & Ross, 1998).

Second, affective traits also at least partially determine *risk preferences*. Negative affects are strongly associated with high risk aversion; for example, Delgado-Garcia et al. (2010) show that negative affective traits in Spanish bank CEOs are related to lower risk taking. In contrast, positive affects generally motivate decision makers to make riskier decisions (Isen & Patrick, 1983). Thus, lower risk aversion associated with positive affects may reduce conformity to industry standards (i.e., increase deviations from the norm).[6]

[5]This study of conformity adds to the existing literature (e.g., Delgado-Garcia et al., 2010) in several novel ways. For example, unlike prior studies, my focus on *underpricing conformity* helps quantifying the effect of conformity on firm value.

[6]Underpricing conformity is not only driven by affective determinants but also by structural determinants, such as "windows of opportunity" (Drobetz et al., 2019). Because there may be real costs associated with the choice of underpricing, the impact of negative affect may be more pronounced than that for positive affect. I thank an anonymous reviewer for pointing this out.

Hypothesis (H1a). *The level of a CEO's negative affects is positively related to the level of an ICO's underpricing conformity.*

Hypothesis (H1b). *The level of a CEO's positive affects is negatively related to the level of an ICO's underpricing conformity.*

Affective traits may also have signaling value. Signaling is important for the functioning of capital markets because it allows firms to transfer information about their *quality* to potential investors in environments which often feature asymmetric information (Campbel & Kracaw, 1980; Healy & Palepu, 2001; Leland & Pyle, 1977). Connelly et al. (2011, p. 43), define quality as "the underlying, unobservable ability of the signaler to fulfill the needs or demands of an outsider observing the signal." Hence, by providing information about ICO firms' abilities, signals have a direct impact on how investors value ICO firms. Positive signals may cause a valuation premium, whereas negative signals may lead to a valuation discount.

Investors may process CEO affects as signals about fundamental firm value because they may provide information about intentions and quality (Stiglitz, 2000). First, investors may infer CEOs' personal intentions from affective traits obtained from observed facial expressions. CEO intentions are key determinants of investment decisions involving young firms due to moral hazard. Leland and Pyle (1977, p. 731) argue that "borrowers [i.e., ICO firms] cannot be expected to be entirely straightforward about their characteristics [...] since there may be substantial rewards for exaggerating positive qualities." Indeed, Momtaz (2020a) shows that manifestations of moral hazard are quite pronounced in the ICO market due to the absence of regulation and intermediaries. Thus, the value of signals that allow investors to infer CEOs' true intentions may be particularly high in ICOs. In two related studies, van Kleef, de Dreu, and Manstead (2004a); van Kleef et al. (2004b) show that individuals take affects into account in negotiations, responding more to negative affects as they indicate the opposing parties' reservation to make concessions. Affects are more relevant for negotiation outcomes when the opposing parties have higher power; that is, when the negotiator has little influence. Therefore, CEO affective traits may be an important signal in the ICO context where a crowd of individually relatively powerless investors bargains with ICO firms about a fair valuation and financial incentives.

Second, investors may take affects as signals of CEO quality. Positive affects are associated with an opportunity-seeing attitude that leads to higher risk-taking than negative affects when there is upside potential (Delgado-Garcia et al., 2010; Isen & Patrick, 1983). As per Fisch, Masiak, Vismara, and Block (2019), ICO firms are embedded in an environment of high technological, regulatory, and industry uncertainty, as well as, overall, strong dynamics of change. This context plausibly calls for managerial abilities associated with creativity and flexibility (attributed to positive affects) to respond to an ever-changing business environment (Fisch et al., 2019). Therefore, ICO investors may put a premium on positive affects and discount negative affects.

Overall, CEO affects may impact investors' firm valuations in ICOs by providing signals about the CEOs' true intentions and their quality, and by affecting investors' personal mood structures (and, hence, their beliefs about an ICO firm's quality).

Hypothesis (H2a). *The level of a CEO's negative affects is positively related to an ICO's underpricing level.*

Hypothesis (H2b). *The level of a CEO's positive affects is negatively related to an ICO's underpricing level.*

Agency problems due to highly asymmetric information are very pronounced in ICOs (Momtaz, 2020a, 2020c). Healy and Palepu (2001) argue that possible solutions to agency problems between CEOs and investors are contracting, information disclosure, corporate governance, information intermediaries, and an active market for corporate control, none of which are available in the ICO market to the extent of more established financial markets (Howell et al., 2019).

Informational asymmetries surrounding ICOs plausibly moderate both CEOs' degree of conformity and investors' reaction to CEO affects. First, the conformity mechanism may even be more pronounced in the presence of highly asymmetric information because asymmetric information induces uncertainty on the part of CEOs about how investors will assess the ICO. This may, on the one hand, amplify error-avoiding behavior due to negative affects and, on the other hand, amplify riskier underpricing behavior due to positive affects (Elsbach & Barr, 1999; Fiedler, 2001; Isen & Patrick, 1983). These effects are further increased due to selective perception of reconfirming information (Johnson & Tversky, 1983). That is, in information-scarce contexts, perception biases may further lead investors to under- or overweight the few pieces of available information and hence amplify the behavioral consequences of information asymmetries, such as underpricing conformity and level in the ICO context. Second, the signaling mechanism may be more pronounced because affects as signals for potential agency costs will become more important in the presence of highly asymmetric information.

Hypothesis (H3). *The proposed relationships in Hypotheses (H1a), (H1b), (H2a), and (H2b) are more pronounced in ICOs with higher levels of asymmetric information.*

3 | METHODS

3.1 | Sample

The sample consists of ICOs that took place between April 2015 and June 2018. I merge data from five sources, with the deal data being retrieved from *ICObench*.[7] Additional firm level controls are obtained from firms' websites. Trading data to construct the measures of underpricing is obtained from *CoinMarketCap*. CEO attributes are sampled from their social network profiles (e.g., LinkedIn). Photo material to extract affects is based on web searches, in which each photo is manually validated and matched to the CEO. The final sample consists of 232 ICOs, with listed tokens as of April 2019.

3.2 | Emotion AI approach to quantify affects from CEO photos around ICOs

The measurement of CEO affects is based on an *emotion AI* approach (see, for an overview of the available methods, Martinez & Du, 2012). Emotion AI draws on research in cognitive science. Notably, Ekman et al. (1987) and Ekman (1999) show that the facial expressions of affects are universal and can thus be reliably classified across cultures and contexts. In the facial action

[7]For an excellent overview of available ICO databases and their relative merits, see Lyandres, Palazzo, and Rabetti (2019).

coding system, Ekman and Friesen (1978) code facial expressions as a function of facial muscle contraction-relaxation patterns, which allows to train emotion AI to be able to map the system of cues obtained from facial expressions to seven basic emotions: happiness, sadness, surprise, fear, anger, disgust, and contempt.[8]

3.3 | Identification of fundamental affect structure: Positive and negative affects

The emotion AI provides estimates for the presence of the seven basic emotions, as identified by Ekman (1999) (happiness, sadness, surprise, fear, anger, disgust, and contempt). Specifically, it computes likelihoods that individuals in photos show certain affects. As Ekman (1999) points out, more than these seven basic emotions exist, but only these are encoded in facial muscles and can thus be detected. Nevertheless, evidence surveyed in Watson, Clark, and Tellegen (1988) indicates that, irrespective of scales used (self-rated or perceptions from facial expressions by others), studies of affective structure consistently identify two dimensions of affect: one is associated with positive affect and the other with negative affect.

Therefore, to account for the fact that affect is a multifaceted concept and to identify the dominant affect components, I follow the factor-analytical framework used by Watson et al. (1988), as implemented by Delgado-Garcia and de la Fuente-Sabaté (2010). Specifically, a principal component analysis is performed on all seven basic affects identified with the emotion AI. Two affects, disgust and contempt, have weak primary loadings (below 0.3) on the appropriate factor and are hence excluded. There are two dominant components that account for almost 70% of the common variation. The emotions anger, fear, sadness, and surprise have strong primary loadings on the first component (negative affect), while relatively low secondary loadings on the second component. Happiness loads strongly on the second component (positive affect), and less so on the first component. Cronbach's alpha reliabilities are consistently above .7, indicating internal consistency. Thus, the two dominant dimensions of affect structure for each CEO in my sample have been identified. I use the factor scoring weights to construct the two main independent variables, negative affect and positive affect, that can be used in regression analyses.

3.4 | Affective states or affective traits?

By proposing novel AI-based measures of negative and positive affect, two questions emerge: Do the measures measure affective states or affective traits of the sample CEOs, and to what extent are the measures comparable to other measures of affect frequently used in management research such as those based on the Positive Affect and Negative Affect Schedule (PANAS) by Watson et al. (1988)? To address these questions it is important to note that both the emotion AI and PANAS are based on momentary evaluations of affect and are thus designed to measure

[8]The emotion AI approach relies on various machine-learning algorithms to quantify emotions. The machine-learning algorithms, in turn, rely on curated databases of pre-classified faces. Various databases exist and are available for research purposes, such as JAFFE, CK+, MultiPIE, MMI, DISFA, FERA, SFEW, and FER2013 (see Mollahosseini, Chan, & Mahoor, 2016). Other databases are commercially available; for example, the database from Microsoft's Project Oxford is used in the present study. The precision of emotional AI has significantly improved over the last decade. Recent algorithms assign mostly the same emotional states to portrayed humans as human evaluators do (Howard, Zhang, and Horvitz (2017)).

affective states. However, Tellegen (1985) and many others have found that affective states identified with PANAS strongly correspond to affective *traits*. Therefore, finding a sufficiently strong correlation between the AI-based measures of negative and positive affect and those measured with PANAS would suggest the identification of affective *traits*.

To compare the AI-based and PANAS-based measures, the PANAS survey was sent with a brief demographic questionnaire and a description of the research project to the CEOs of listed firms in the sample. First contact was made in February 2019 and follow-up messages were sent to unresponsive CEOs 4 weeks after this (up to a total of three reminders overall). The mediums of communication were email and private messaging through professional networks. CEOs were promised anonymity and advanced access to the study results to improve the conscientiousness and reliability of the responses (Delgado-Garcia & de la Fuente-Sabaté, 2010; Hambrick, Geletkanycz, & Fredrickson, 1993). Out of the total 232 CEOs of listed firms, 21 had replied by June 2019. To increase the number of respondents, I expanded the reach to CEOs of unlisted firms until the total number of responses reached 50 in September 2019. The PANAS subsample was compared to the full sample along several CEO (e.g., age, education) and firm (e.g., funding amount) dimensions to ensure representativeness. The comparison did not indicate statistical differences at the 5% level.

The PANAS subsample consists of 50 CEOs who responded to 20 affect-related items on the PANAS scale.[9] PANAS-based measures of affect are obtained following the procedure in Watson et al. (1988) precisely, as implemented in Delgado-Garcia and de la Fuente-Sabaté (2010). The PCA revealed two dominant components, with all 20 descriptors having strong primary and low secondary loadings for the appropriate factors. The first component is associated with negative affect, while the second is associated with positive affect. For both affects, alpha reliabilities exceeded the .7 cutoff. Hence, the factor weighting scores were used to construct PANAS-based measures of positive affect and negative affect. The pairwise correlation coefficient for the PANAS- and AI-based measures of negative affect was 0.64, whereas the corresponding coefficient for positive affect was 0.51. This suggests that both PANAS- and AI-based measures share a substantial amount of common variation. Thus, the emotion AI has identified positive and negative affective *traits* from the facial expressions of the sample CEOs during the fundraising process, which can further be used as regressors to analyze the emotion-valuation relation in ICOs.

3.5 | Variables

3.5.1 | Independent variables

The above identification of CEO affective traits based on the novel emotion AI approach yields two independent variables: negative affect and positive affect, which are mean-centered and

[9]Ten items are related to positive affects: enthusiastic, interested, determined, excited, inspired, alert, active, strong, proud, and attentive. The other 10 items are related to negative affects: scared, afraid, upset, distressed, jittery, nervous, ashamed, guilty, irritable, and hostile. CEOs were asked to evaluate each descriptor on a five-point scale (i.e., 1 = very slightly or not at all, 2 = a little, 3 = moderately, 4 = quite a bit, and 5 = very much). Furthermore, CEOs were asked to evaluate the scale for how they felt during the pre-ICO phase, which is the time period for which AI-based measures of the CEOs' structures of affect have been compiled. However, Watson et al. (1988, p. 1065) argue that "even momentary moods are, to a certain extent, reflections of one's general affective level," the identification of which, namely affective traits, is precisely the objective of this section.

expressed in *SD*. Summary statistics and pair-wise correlations with other variables are shown in Table 1.

3.5.2 | Dependent variables

There are two key dependent variables. For the tests of the conformity mechanism, *underpricing conformity* is defined as the deviations in absolute value from the market's average underpricing level. This figure is multiplied by negative one to be consistent with the definition of conformity in Delgado-Garcia and de la Fuente-Sabaté (2010). For the tests of the signaling mechanism, *underpricing level* is defined as the difference between the closing and opening price divided by the opening price on the first day of trading (Momtaz, 2020b).[10]

3.5.3 | Moderator

To test the hypotheses that the valuation-affect relation is moderated by informational asymmetries, the word count for each ICO whitepaper is used as a proxy for the level of asymmetric information. The whitepaper is the main source of information in ICOs and has been used to proxy for the level of asymmetric information in the ICO context in several studies (e.g., Fisch, 2019; Howell et al., 2019; Lyandres et al., 2019). The rationale is that longer whitepapers (measured by word count) contain more information. The variable is scaled (specifically, the natural logarithm of word count is divided by its maximum value and multiplied by −1) so that the shortest whitepaper has the highest value, consistent with stronger informational asymmetry.

3.5.4 | Control variables

Several controls related to the CEOs' backgrounds and to firm and ICO characteristics are employed.

3.5.5 | CEO age

CEO age is defined as the length of time a CEO has lived until the focal ICO measured in years. Information on CEO age is obtained from firms' websites and social network profiles.

3.5.6 | Female CEO

Female CEO is a dummy variable which is equal to one if the CEO is female, and zero otherwise.

[10]The measure is consistent with IPO underpricing (Ljungqvist, 2007), assuming that the full extent of underpricing is realized at the end of the first trading day. The assumption appears to be reasonable because online token exchanges impose no restrictions on daily price fluctuations. Alternative measures are discussed in the robustness section.

TABLE 1 Summary statistics

	Mean	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Underpricing conformity	−4.4%	13.9%	1														
2. Underpricing level	7.6%	27.7%	**0.72**	1													
3. Negative affect	0	1	**0.17**	**0.15**	1												
4. Positive affect	0	1	−0.09	0.02	0	1											
5. Asymmetric information	0.81	0.07	0.07	0.08	**−0.17**	**−0.14**	1										
6. CEO age	35.7	6.0	0.02	−0.04	−0.03	−0.01	**−0.16**	1									
7. Female CEO	0.06	0.24	−0.11	−0.10	0.11	**0.16**	−0.08	**−0.16**	1								
8. Formal education	0.36	0.48	**0.23**	0.07	0.12	0.06	−0.02	0.06	0.01	1							
9. Average tenure	2.51	1.91	−0.01	−0.11	**0.19**	**−0.16**	**0.22**	**0.28**	0.01	−0.01	1						
10. CEO cryptoexperience	0.58	0.49	0.03	−0.09	**−0.21**	0.06	**−0.36**	0.15	0.01	**0.18**	−0.07	1					
11. Ethereum blockchain	0.84	0.37	0.05	0.14	0.10	**−0.24**	−0.09	−0.03	0.01	0.07	−0.08	0.09	1				
12. VC backing	0.36	0.49	**−0.26**	**−0.19**	0.04	0.10	−0.01	−0.12	−0.08	**−0.26**	0.06	**−0.19**	0.02	1			
13. Financing needs	16.46	0.77	**−0.21**	**−0.20**	0.12	0.07	0.12	0.05	0.03	**−0.19**	**0.17**	0.04	−0.05	**0.38**	1		
14. Time-to-market	21.42	22.10	**0.13**	**−0.14**	−0.07	**−0.19**	**0.18**	**−0.15**	−0.00	−0.08	**0.58**	**−0.31**	**0.14**	0.03	**0.21**	1	
15. Platform-market size	9.84	9.51	−0.09	**0.16**	0.02	0.04	**0.24**	**0.15**	−0.01	0.06	0.05	−0.11	−0.12	**−0.23**	**−0.21**	**−0.14**	1
16. News density	4.88	10.03	−0.12	0.02	−0.09	0.11	0.12	0.10	−0.05	−0.07	−0.11	**−0.17**	0.07	0.11	**0.16**	0.11	**0.21**

Note: # obs. = 232. Coefficients with statistical significance (i.e., *p*-value <.05) are displayed in bold characters.

3.5.7 | Formal education

Formal education is coded as a dummy variable that takes a value of one if the CEO has a post-graduate degree (e.g., Master's, MBA, PhD), and zero otherwise.

3.5.8 | Average tenure

Average tenure is defined as a CEO's cumulative work experience divided by her number of previous appointments. The measure can be viewed as a proxy for agency conflicts (Momtaz, 2020c).

3.5.9 | Industry experience

Industry experience is a cryptoindustry specific measure that is coded as an indicator variable equal to one if the CEO has prior experience in the cryptoindustry, and zero otherwise.

3.5.10 | Ethereum blockchain

I also control for whether ICO tokens are created on the *Ethereum* blockchain, which has been shown to be a first-order determinant of ICO success as it provides a technical standard for the token design (Fisch, 2019; Howell et al., 2019).

3.5.11 | VC backing

VC backing is a dummy variable equal to one if at least one VC fund has invested, and zero otherwise. The variable is included because Fisch and Momtaz (2020) show that VC backing and ICO firm performance are significantly positively related. The information on VC backing come from several sources, including Crunchbase, CryptoFundList, whitepapers, and project websites.

3.5.12 | Financing needs

The funding amount (log.) is used to control for firms' financing needs. The variable controls for a size effect in the return pattern of ICO firms (Momtaz, 2019a). However, the results are similar when other measures of financing needs are used, such as soft- or hardcaps (Fisch, 2019).

3.5.13 | Time-to-market

The variable is defined as the time from company founding to the first day of the ICO in months. The results are very similar when I use other variable definitions such as the time-to-listing (from company founding or from ICO end) or the ICO duration.

3.5.14 | Platform-market size

Platform-market size is proxied by the token supply (log.); that is, the number of tokens issued.

3.5.15 | News density

News density is defined as the average number of Tweets per day by the firm measured in the year prior to the ICO. The variable controls for investor attention to each ICO (Fisch, 2019).

4 | EMPIRICAL RESULTS

4.1 | Main results

Descriptive statistics and correlations are in Table 1. Underpricing conformity and level average at −4.4 and 7.6%, respectively. Negative and positive affects are expressed by their *SD*. Negative affect and both underpricing conformity and level are significantly (p-values =.009 and =.022) and positively correlated. The correlation coefficients ($\rho = 0.17$ and $\rho = 0.15$) suggest that an increase of 1 *SD* in negative affect is related to an increase in underpricing conformity and level by 17 and 15%, respectively. Positive affect is not significantly correlated with the dependent variables.[11]

The main results are in Table 2, with tests of the conformity mechanism in Columns (1)–(3) and tests of the signaling mechanism in Columns (4)–(6).

The control models in Columns (1) and (4), with no variable related to CEO affective traits or asymmetric information, show that, first, underpricing conformity is significantly related to CEO age, gender, and formal education and, second, the underpricing level is negatively correlated with CEO average tenure and former cryptoexperience.

Tests of Hypotheses (H1a), (H1b), (H2a), and (H2b) are in Columns (2) and (5), respectively. Negative affective traits have a significantly positive effect on underpricing conformity and underpricing level, providing empirical support for Hypotheses (H1a) and (H2a). The results suggest that a 1 *SD* increase in negative affect is associated with an increase in underpricing conformity and underpricing level by 6.01% (p-value =.026) and 15.54% (p-value =.030), respectively. Interestingly, the results suggest an asymmetry in how affective traits influence underpricing. While negative affect is significantly positive in the underpricing conformity and level regressions, positive affect is never significant. The evidence fails to reject the null in Hypotheses (H1b) and (H2b). All other variables are largely consistent with the control models.

I test Hypothesis (H3) in Columns (3) and (6). Again, negative affective traits have a significantly positive effect on underpricing conformity and underpricing level that is consistent in magnitude with the coefficients reported in Columns (2) and (5). Moreover, the interaction effect of negative affect and informational asymmetries is significantly positive in both models, with coefficients of 0.0716 (p-value =.013) and 0.1793 (p-value =.006) in Columns (3) and (6), respectively. The results are also economically meaningful. For example, in Column (6), a 1 *SD*

[11]Consistent with the *IPO* underpricing literature, multicollinearity is tested using variance inflation factors (Leitterstorf & Rau, 2014). None of the VIFs crosses the threshold of 10, with almost all being below 2. The results suggest that multicollinearity is not an issue in my analyses.

TABLE 2 CEO emotions and firm valuation in ICOs: Testing the conformity and signaling mechanisms

	Conformity mechanism			Signaling mechanism		
	(1)	(2)	(3)	(4)	(5)	(6)
CEO affective traits						
Negative affect		**0.0601** (0.0269)	**0.0582** (0.0278)		**0.1554** (0.0711)	**0.1366** (0.0527)
Positive affect		0.0122 (0.0224)	0.0158 (0.0554)		−0.0165 (0.0278)	−0.0521 (0.0640)
Moderating role of asymmetric information						
Asymmetric information proxy			0.0286 (0.1540)			0.1674 (0.1781)
× Negative affect			**0.0716** (0.0286)			**0.1793** (0.0647)
× Positive affect			−0.0160 (0.0613)			0.0607 (0.0709)
CEO background						
CEO age	**0.0071** (0.0025)	**0.0093** (0.0037)	**0.0076** (0.0031)	0.0054 (0.0039)	0.0051 (0.0050)	0.0103 (0.0059)
Female CEO	**−0.1468** (0.0384)	**−0.1760** (0.0622)	**−0.1229** (0.0558)	−0.0710 (0.0986)	−0.0231 (0.1073)	0.0178 (0.1109)
Formal education	**0.0707** (0.0212)	**0.0773** (0.0366)	**0.0755** (0.0348)	0.0418 (0.0498)	**0.0821** (0.0254)	0.0765 (0.0406)
Average tenure	−0.0022 (0.0109)	−0.0067 (0.0122)	−0.0192 (0.0175)	**−0.0334** (0.0141)	**−0.0349** (0.0119)	**−0.0382** (0.0157)
CEO cryptoexperience	−0.0429 (0.0389)	−0.0373 (0.0469)	−0.0470 (0.0690)	**−0.0911** (0.0201)	−0.0763 (0.0411)	−0.0315 (0.0798)
Firm and ICO characteristics						

TABLE 2 (Continued)

	Conformity mechanism			Signaling mechanism		
	(1)	(2)	(3)	(4)	(5)	(6)
Ethereum blockchain	0.0516 (0.0482)	0.0034 (0.0576)	**0.0696** (0.0133)	0.0946 (0.0621)	0.1245 (0.0716)	**0.1384** (0.0420)
VC backing	−0.0364 (0.0422)	−0.0443 (0.0498)	−0.0323 (0.0548)	−0.0197 (0.0545)	−0.0112 (0.0619)	0.0293 (0.0634)
Financing needs	−0.0162 (0.0136)	−0.0038 (0.0207)	−0.0354 (0.0418)	0.0233 (0.0132)	0.0402 (0.0258)	0.0360 (0.0484)
Time-to-market	0.0011 (0.0009)	0.0015 (0.0010)	**0.0025** (0.0010)	0.0011 (0.0011)	**0.0021** (0.0009)	0.0013 (0.0020)
Platform-market size	−0.0004 (0.0020)	−0.0015 (0.0024)	0.0010 (0.0030)	0.0034 (0.0026)	**0.0053** (0.0026)	**0.0064** (0.0030)
News density	−0.0020 (0.0027)	−0.0020 (0.0030)	−0.0042 (0.0020)	−0.0020 (0.0035)	−0.0030 (0.0037)	**−0.0063** (0.0026)
Constant	0.0604 (0.2270)	0.0651 (0.3388)	0.0475 (1.2977)	**0.0535** (0.0292)	**0.0851** (0.0102)	0.0940 (0.0601)
No. observations	232	232	232	232	232	232
Adjusted R^2	.0783	.0894	.1058	.876	.1009	.1156
p-Value	.002	0.000	.000	.001	.000	.000

Note: This table presents the main regression results for the affect-valuation relation in ICOs. Columns (1)–(3) test the conformity mechanism. The dependent variable is the absolute-value deviation from the market's average underpricing level. Columns (4)–(6) test the signaling mechanism. The dependent variable is the underpricing level in %, defined as the difference between the closing and opening price over the opening price on the first day of trading. All variables are defined in the text. Heteroscedasticity-adjusted *SE*s are clustered by quarter-years and shown in parentheses below the coefficients. Coefficients with statistical significance (i.e., *p*-value <.05) are displayed in bold characters.

increase in the asymmetric information measure is associated with a moderating effect on the relation between negative affect and underpricing level of 1.26% (0.07×0.1793). This roughly corresponds to one-tenth of the total effect negative affect has on the underpricing level. The findings indicate that the presence of strongly asymmetric information amplifies the effect of negative affect on underpricing. Again, positive affect is not significant in both underpricing conformity and level regressions, suggesting that positive affect cannot atone for highly asymmetric information. Thus, the results partially support Hypothesis (H3).

Overall, the evidence in Table 2 largely supports Hypotheses (H1a), (H2a), and (H3), but fails to support the others, indicating that negative affect is a substantial driver of underpricing conformity and underpricing level in the ICO context, while positive affect is not.

4.2 | Additional tests and robustness checks

I conduct several sensitivity tests.[12] First, I make sure that spurious market co-movements do not confound the dependent variable by constructing a market-adjusted measure of ICO underpricing. This requires deducting a market-capitalization weighted benchmark from the raw underpricing measure as follows (Momtaz, 2019a):

$$maU_i = \frac{P_{i,1} - P_{i,0}}{P_{i,0}} - \sum_{j=1}^{n} \left[\frac{MC_{j,t}}{\sum_{j=1}^{n} MC_{j,t}} \cdot \frac{P_{j,t} - P_{j,t-1}}{P_{j,t-1}} \right]$$

where maU_i denotes the market-adjusted underpricing for firm i, and $P_{i,0}$ and $P_{i,1}$ denote the opening and closing prices for firm i on the first trading day, respectively. The market benchmark is calculated as the sum of the products of the market capitalization of every digital currency j of more than 1,400 that are listed on *coinmarketcap* on day t over the total market capitalization on day t and the daily raw return of digital currency j on day t. When I rerun my main model with the modified dependent variables based on maU_i, the coefficients on negative affects of 7.26 and 13.28% for the underpricing conformity and level regressions, respectively, are very similar to those reported in Columns (3) and (6) of Table 2. Thus, the results are robust.[13]

Second, because upper echelons theory argues that several CEO attributes may influence corporate performance (Hambrick & Quigley, 2014), I test interactions between CEO affective traits and several demographic variables, such as age. Age has a significantly positive effect only on underpricing level, which is reduced in the presence of negative affect.[14] The main results are robust.

Finally, I examine the impact of the CEO facial width-to-height ratio (fWHR), which has recently gained substantial academic and public attention, with studies that show that higher fWHR due to higher testosterone levels is related to more achievement-striving incentives (and

[12]Details on the test results are documented in the online appendix.

[13]I also make sure that outliers are not an issue by constructing a dummy variable that is equal to one if the underpricing is positive, and zero otherwise. When the dummy is used as the dependent variable, the results are robust (not tabulated but available upon request). The probability of underpricing increases by almost one-half per 1 *SD* increase in negative affect.

[14]The interaction effects of other CEO attributes are also tested (i.e., gender, formal education, average tenure, and industry experience). Only gender significantly interacts with negative affect (amplifying), and statistical power seems weak.

potentially to overconfidence and hubris), which capital market participants have become aware of (Eisenegger, Haushofer, & Fehr, 2011). As He et al. (2019, p. 1014) summarize, "individuals with higher fWHR will exert more efforts and perform better due to their higher achievement drive." If CEO and investor awareness to this widely discussed measure is more pronounced than their awareness of affective traits in ICOs, then fWHR might confound the results. However, the main results are robust. Additionally, I find that fWHR is negatively related to both ICO underpricing conformity and underpricing level.[15]

5 | DISCUSSION AND CONCLUDING REMARKS

This paper explores the relations among CEO affective traits, firm valuation, and the level of asymmetric information in the context of ICOs. Studies on CEO affects are rare in strategy scholarship, due in large part to the difficulty of obtaining reliable estimates of valid constructs (Liu et al., 2018; Wang et al., 2016). Notable exceptions are Delgado-Garcia and de la Fuente-Sabaté (2010) and Delgado-Garcia et al. (2010), who conduct a survey of Spanish bank CEOs to examine how their affects impact strategic and performance conformity and risk aversion, respectively. Therefore, prior work has shown how CEO affects determine their own decision-making, whereas the signaling value of CEO affects for external stakeholders, prior to this study, has largely remained "a blind spot" (Liu et al., 2018, p. 800).

This paper theorizes CEO affects may impact firm valuation in two ways. First, in keeping with Delgado-Garcia and de la Fuente-Sabaté (2010), there may be a *conformity mechanism*; that is, negative affects may cause CEOs in their own firm valuation to conform to greater extent with the valuation of their peers. Second, expanding the theory of CEO affects to market signaling in the spirit of Leland and Pyle (1977), there may be a *signaling mechanism*; that is, investors may discount the firm value when they observe negative affects. Moreover, both conformity and signaling mechanisms should be more pronounced in the presence of asymmetric information.

A methodological novelty of this study is the use of emotion AI to identify CEO affective traits. The main advantage of this approach over others, for example, over the frequently used PANAS survey (Watson et al., 1988), is that it does not require the participation or disclosure of very personal information of the study objects to measure their affect structure. Instead, affects can be identified from patterns in facial muscle contraction and relaxation obtained from photos and videos. Therefore, the method is easy-to-implement and available for all study objects with enough publicly available photo material. Hence, the emotion AI approach may pave the way for more research on the role of CEO affects for strategic decision-making and overall performance.

The empirical results support both the conformity mechanism and the signaling mechanism. CEO negative affects lead to greater underpricing conformity. That is, negative affects are associated with lower absolute-value deviations from market's average underpricing level. A 1 *SD* increase in negative affects corresponds to a lower deviation from the average underpricing level by 6%. Further, CEO affects have substantial signaling value. Investors may require a discount on firm value of about 15% per 1 *SD* increase in negative affects. Interestingly, the

[15]Similarly, I checked whether a CEO's "look of competence" confounds the affects-valuation relationship by using data on the "look of competence" from Colombo et al. (2020). My results are robust when I control for the "look of competence" in my main models and in mediation models. Results are available upon request.

conformity and signaling mechanisms are significant only for negative affects; positive affects do not significantly influence underpricing behavior. While the asymmetry between negative and positive affects is surprising, note that it is consistent with Delgado-Garcia and de la Fuente-Sabaté (2010) and Delgado-Garcia et al. (2010), who find that positive affects do not directly affect performance conformity and risk taking, respectively. One possible explanation for this finding is that facial expressions associated with positive affects are the norm in the ICO context, and negative affects, as deviations from the norm, may be more salient and therefore entail a stronger market reaction. Another potential explanation is that my approach derives the positive affect measure only from one emotional trait, i.e., happiness, which may not be the most relevant positive affect in the ICO context and hence does not possess sufficient explanatory power for the variation in ICO underpricing behavior.[16] The results also indicate that the conformity mechanism and the signaling mechanism are amplified in the presence of asymmetric information. Informational asymmetries further increase CEO conformity with the market's average underpricing level and the discount which investors demand. Supplementary tests show, inter alia, that CEO age also moderates the signaling mechanism.

The results have practical implications to both CEOs and investors. CEOs need to be aware of the economic costs of negative affects. Given average ICO gross proceeds of about $22 million (Howell et al., 2019), a 1 *SD* increase in negative affects may cost the average ICO firm more than $3 million. For (uninformed) investors, because CEO negative affects is associated with greater underpricing conformity, sensing negative affects may lower both the risk of making substantial losses and the chance to make substantial gains.

Several promising avenues for future research have emerged from this study. For example, future studies could apply the emotion AI approach to strategic contexts other than ICOs. Similarly, it seems interesting to better understand whether CEO affects matter to the same extent in contexts in which more tangible investment information (e.g., legal investor protection) is available. The long-term consequences of CEO affects also seems to be a promising direction for further research.

ACKNOWLEDGEMENTS

I thank Marvin Lieberman, Yan Anthea Zhang (the editor), two anonymous reviewers, and seminar participants at the Max Planck Institute for Innovation and Competition and McMaster University for helpful comments. I acknowledge financial support for this research project from the Price Center for Entrepreneurship and Innovation at UCLA. Software to quantify emotions from facial expressions is available from my website: https://www.paulmomtaz.com/code/artificial-emotional-intelligence.

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[16]I thank the editor for pointing this out.

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How to cite this article: Momtaz PP. CEO emotions and firm valuation in initial coin offerings: An artificial emotional intelligence approach. *Strat Mgmt J*. 2021;42:558–578. https://doi.org/10.1002/smj.3235