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Article

The Crowdfunding of Altruism

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Abstract: This paper introduces a machine learning approach to quantify altruism from the linguistic style of textual documents. We apply our method to a central question in (social) entrepreneurship: How does altruism impact entrepreneurial success? Specifically, we examine the effects of altruism on crowdfunding outcomes in Initial Coin Offerings (ICOs). The main result suggests that altruism and ICO firm valuation are negatively related. We, then, explore several channels to shed some light on whether the negative altruism-valuation relation is causal. Our findings suggest that it is not altruism that *causes* lower firm valuation; rather, low-quality entrepreneurs select into altruistic projects, while the marginal effect of altruism on high-quality entrepreneurs is actually positive. Altruism increases the funding amount in ICOs in the presence of high-quality projects, low asymmetric information, and strong corporate governance.

Keywords: altruism; machine learning; crowdfunding; token offerings; Initial Coin Offering; entrepreneurial finance

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1. Introduction

Altruism refers to the willingness to sacrifice one's own resources to improve the welfare of others. As such, altruism is an unconditional act of kindness. In economics, human altruism is a relatively recent discovery (Fehr and Fischbacher 2003). Altruism had no place in neoclassical economics that assumes self-interest to be the primary motivation of people (e.g., Jensen and Meckling 1976). Yet, an established and growing literature shows that altruism is an essential source of motivation (Fehr and Schmidt 2006). In fact, global preferences for altruism may be time-varying. A number of recent reports conclude that altruistic preferences are growing in importance recently (EUROSIF Report 2021; Riedl and Smeets 2017). Therefore, it is important to understand the role of altruistic preferences in the broad cross-section of economic activity.

The role of altruism in entrepreneurial finance is relatively understudied, however. Although there are some excellent studies (e.g., André et al. 2017; Bretschneider and Leimeister 2017; Giudici et al. 2018; Hörisch and Tenner 2020, which we discuss in Section 2.1.3), these exceptions are rare. The lack of studies on the role of altruism in entrepreneurial finance, in particular crowdfunding, is surprising given that crowdfunding allows entrepreneurs to tap a relatively large crowd with heterogeneous preferences (and often non-financial preferences), which plausibly makes crowdfunding the primary choice of entrepreneurs in need of funding for altruistic projects. Our study aims to contribute to filling this gap.

The effect of altruism on crowdfunding outcomes is ex-ante ambiguous. Although altruistic projects may attract larger crowds than purely profit-oriented projects (namely, financial and non-financial investors) and, therefore, may expect higher funding amounts, altruism imposes a constraint on the business model that could depress project valuations. Thus, whether altruistic projects' crowdfunding campaigns result in a valuation premium or a discount is an empirical question, which is important for both entrepreneurs and investors, as well as from a public policy perspective. As the degree of altruism represents an endogenous choice on the part of the entrepreneur, and it is up to the investor to choose to invest in altruistic projects, it is important to understand the value implications of such projects. From a public policy perspective, it is relevant to understand whether altruism is sustainable in the crowdfunding market as it may create positive externalities that can be enjoyed by society at large. Finding that the crowdfunding market marginalizes altruistic projects would render altruistic entrepreneurship a policy variable for potential subsidy programs.

In this study, we will address the following research question: How does altruism affect crowdfunding success? We answer the research question by developing a machine learning approach to quantify the degree of entrepreneurs' altruism from textual documents, which we then relate to the funding amount in entrepreneurs' fundraising campaigns. We also investigate the sensitivity of the altruism-fundraising relation in several additional tests. We detail our empirical approach as well as the additional hypotheses next.

Our altruism score for each Initial Coin Offering (ICO) is derived from their white paper using a sophisticated Natural Language Processing (NLP). Our NLP approach consists of two steps: (i) creating an altruism dictionary, and (ii) applying the dictionary to ICO white papers. Specifically, we obtain an initial dataset of 39,634 short messages from Twitter between July 2017 and July 2021 with the hashtag "#altruism." The tweets allow us to identify the most frequently used words in relation to altruism, which we employ as seed words. Next, we create a meaningful word-vector representation of the seed words, using Mikolov et al.'s (2013a) word embedding approach called "word2vec," which uses a neural network to learn word and word group associations within contextual data. The corpus used for training the word2vec model consists of a dataset of 800 Financial Times articles with the hashtag "#altruism" in addition to the standard pre-trained word2vec model of Google News. This exercise results in a list of 206 altruism-related dictionary terms that we use to calculate white paper-specific altruism scores that, intuitively, relate the terms' frequency to the white paper length.

We test four hypotheses. The first one acknowledges the ambiguous valuation effects of altruism in crowdfunding. Altruistic projects could raise more funding in ICOs, for example, because altruism may improve reputation (Fehr and Fischbacher 2003; Nowak and Sigmund 1998), intrinsic motivation (Christensen-Salem et al. 2021; Fehr and Schmidt 2006), and enlarges the pool of potential crowd-investors (Fisch et al. 2019) by also sending non-financial signals, (Momtaz 2022b) among other benefits. On the other hand, it is ex-ante equally reasonable to expect that altruistic projects raise less funding in ICOs because altruism imposes a constraint on the business model that could, inter alia, result in foregone profits (Tan et al. 2005), and could also be regarded as a value-decreasing deviation from social norms in the crowdfunding context (Kawamura and Kusumi 2020). Thus, *Hypothesis 1a/1b* agnostically predicts that altruistic projects yield higher/lower ICO valuations. The remaining hypotheses predict that the marginal effects of altruism are positive in high-quality startups (*Hypothesis 2*), in firms with strong corporate governance (*Hypothesis 3*), and when informational asymmetries are not very pronounced (*Hypothesis 4*).

The empirical results support the hypotheses. Specifically, our overarching finding is that altruism has a negative effect on the ICO funding amount in the average project. A one standard deviation increase in the altruism score reduces the average ICO funding amount of $12.2 million by $1.54 million, which corresponds to a relative decrease of 12.6%. However, we reject the notion that it is altruism per se that has a causally negative effect on ICO valuations. We find that altruism's marginal effect on ICO valuations is positive in high-quality firms (as measured by the ICO firms' expert ratings), in the presence of strong corporate governance (also measured via NLP based on the ICO white papers), and in firms with low levels of asymmetric information (proxied by the length of the ICO white paper). Overall, our results suggest that it is not altruism that causes lower ICO firm valuations; rather, low-quality entrepreneurs select altruistic projects, while the marginal effect of altruism on high-quality entrepreneurs might actually be positive.

Our study makes at least two empirical contributions to the growing altruism literature in entrepreneurial finance. First, we investigate the role of altruism in token offerings or ICOs. ICOs are blockchain-based crowdfunding campaigns in which entrepreneurs issue digital assets, i.e., tokens, in exchange for venture capital (e.g., Bellavitis et al. 2020, 2021; Boreiko and Risteski 2021; Fisch 2019; Fisch et al. 2019; Giudici and Adhami 2019; Giudici et al. 2020; Hornuf et al. 2021; Huang et al. 2020; Momtaz 2020, 2021a, 2021b, 2022a). ICOs are an ideal context to examine the role of altruism because the average ICO investor's preferences extend beyond purely financial ones (Fisch et al. 2019), thus making the role of altruism particularly salient. To the best of our knowledge, this study is the first to examine the role of altruism in ICOs. Second, most previous studies have relied on ad-hoc ways to measure altruism or on highly-specialized contexts, both ways potentially suffer from low external validity. Our study proposes a machine learning approach to quantify altruism from heterogeneity in entrepreneurs' linguistic styles. As such, our approach is more objective and can easily be applied to other contexts. To facilitate future research, we discuss our machine learning approach in detail in Section 4.

The remaining part of the paper is structured as follows: Section 2 provides some background on ICOs and reviews the related literature on altruism in finance and entrepreneurship; Section 3 derives our hypotheses; Section 4 describes our machine learning approach to quantify altruism for startups; Section 5 elaborates on the data and variables we used in our analysis; and Section 6 presents our empirical approach, as well as the results. Finally, Section 7 concludes with a summary of our key results, theoretical contributions and practical implications, as well as potential avenues for future research.

2. Background

2.1. Altruism in Economics and Finance

2.1.1. Explaining Altruistic Behavior and Cooperation Theoretically

In classic and neo-classic economic theory, individuals are commonly described as homo economicus, i.e., rationally and selfishly maximizing their personal utility. Conflicting with this assumption is altruistic behavior, broadly speaking the intentional increasing of someone else's utility at a personal cost (Tan et al. 2005), which can be observed in a number of situations. Over time, multiple theories have emerged in an attempt to explain this puzzle. These theories should not be seen as competing but rather as complementary, explaining different drivers of altruism (Khalil 2004).

A commonly accepted, albeit selfishly motivated concept to trigger seemingly altruistic behavior is reciprocity and reputation building (Becker 1976; Khalil 2004). Individuals are likely to reciprocate, that is, to reward others for altruistic behavior and punish selfish behavior in order to incentivize cooperation (Axelrod and Hamilton 1981; Hirshleifer and Rasmusen 1989; Taylor 1977). This is in line with rational agents taking into account future utility. Incurring the costs of altruistic behavior today is part of a rational profit maximization strategy if the costs are outweighed by the profits achieved through future cooperation (Khalil 2004). Although reciprocity explains altruistic behavior and cooperation in a number of situations, it fails in one-time or anonymous interactions (Khalil 2004).

Becker (1976) assumed that altruistic behavior stems from the beneficiary's utility being included in the benefactor's utility function. Thus, maximization of personal utility may imply increasing the utility of others. This form of altruism is often observed within families and closely related to the concept of kin selection in evolutionary biology, but it may also extend to friends or strangers (Bergstrom 1995; Khalil 2004). Becker's (1976) theory allows explaining altruistic behavior without violating the assumption of personal utility maximization, even in one-time interactions where no reputation gain can be expected (Khalil 2004). A criticism voiced by Khalil (2004) is that the concept also allows for free-riding. Altruistic individuals only benefit from the utility of others, not from the altruistic act itself. Thus, it might be optimal to let others help the person in need but personally avoid the costs of helping.

A third concept, as described by Etzioni (1986), assumes the existence of moral utility stemming from altruistic or "morally correct" behavior in addition to the commonly considered utility gained from pleasure. Hence, regardless of the beneficiary's utility or possible reciprocity, altruistic individuals would gain utility from altruistic actions. Closely related to moral utility is strong reciprocity (Gintis et al. 2008). Strong reciprocity goes beyond reciprocity as individuals may reward or punish the behavior of others out of "fairness" considerations, even if it is not part of a long-term profit maximization strategy and comes at a personal cost (Fehr and Fischbacher 2003; Gintis et al. 2008).

2.1.2. Experimental Evidence of Altruistic Behavior and Cooperation

The theories reviewed in Section 2.1.1 illustrate the various drivers of altruistic behavior, even including selfish components. These drivers are difficult to observe in real-life situations. Thus, studies often rely on experiments in the form of simple strategic games to separate these motives and study them individually.

One approach to exclude selfish motives, such as reciprocity, is to conduct simple one-shot games that do not allow for the possibility of reputation building. Eckel and Grossman (1996) followed this approach when letting participants play anonymous dictator games[1] and found that participants altruistically gave away money to others. The given amounts increased if the recipient was perceived to be needy, hinting at "fairness" considerations (Thaler (1988)). This experimental setup can be compared to anonymous donations.

If experiments allow for the option of reciprocity, e.g., through repeated games, altruistic behavior in the form of cooperation between participants increases substantially. Gächter and Falk (2002) showed this when comparing one-round with repeated gift-exchange games.[2] The level of cooperation (amount returned by the participant in the second round) was significantly higher in repeated games when participants would face consequences for their choices in the following rounds.

Strong reciprocity may take the form of altruistic rewards or altruistic punishment. Altruistic rewards have been documented in anonymous trust games[3] (Berg et al. 1995), gift-exchange games (Fehr et al. 1993), and sequentially played prisoner's dilemma games[4] (Hayashi et al. 1999). An important aspect of the experimental setup is that games are played sequentially, giving one player the opportunity to react to the other's cooperation or defection but not repeatedly, avoiding cooperation based on reciprocity. Strong reciprocity in the form of altruistic punishment can be witnessed in ultimatum games[5], as conducted by Güth et al. (1982). Although rational profit maximization would suggest accepting any offer in one-shot games, low offers that were perceived as "unfair", i.e., generally below 25% (Fehr and Fischbacher 2003), were likely to be rejected. The rejection came at a cost to the recipient but led the proposer to increase the offer in the next round, when facing a new player, by around 7% (Fehr and Fischbacher 2003). Thus, the rejection can be considered an altruistic act towards future players. Both altruistic rewarding and punishing are also observed when stakes are high (Cameron 1999; Fehr et al. 2002; Slonim and Roth 1998) and may be carried out by third parties (Fehr and Fischbacher 2004) that were not directly affected by the preceding actions. In group settings, altruistic punishment has been shown to enable cooperation by incentivizing selfish group members to cooperate as well (Fehr and Gächter 2002; Ostrom et al. 1992; Yamagishi 1986), making it an important mechanism in social interactions (Rilling et al. 2002).

In order to improve understanding of the motives behind strong reciprocity, Rilling et al. (2002) let participants play sequential prisoner's dilemma games while using functional Magnetic Resonance Imaging (fMRI) to measure brain activity. Mutual cooperation between humans led to increased activity in reward-related brain areas. Singer et al. (2004) obtained similar results in an experiment using fMRI while showing participants faces of others who had previously cooperated and not cooperated in one-shot prisoner's dilemma games.

Seymour et al. (2007) found that not only altruistic rewarding but also altruistic punishment leads to an activation of reward-related brain areas.[6]

2.1.3. Altruism in Finance

Despite the common understanding that financial investors are profit-driven, altruistic trends have emerged in traditional financial markets, as well as the crowdfunding sector. In traditional markets, altruistic investor behavior is visible in the growing domain of socially responsible or ESG-based investment strategies (EUROSIF Report 2021). Socially responsible firms are expected to not solely maximize profits but also consider their contribution to socially desirable goods, e.g., environmental protection and fair working conditions. Investors in socially responsible firms may be driven by altruistic considerations or the expectations that other investors are altruistic, leading to relatively high valuations of socially responsible firms. Riedl and Smeets (2017) examined administrative data collected from a fund provider, survey responses from the respective investors, and their behavior in experiments and found that socially responsible investors primarily act out of altruistic motives followed by social signaling. Financial motives do not seem to play an important role as investors expect lower returns and higher fees on socially responsible funds. Previous studies analyzing investors' motivations have found mixed results (Bauer and Smeets 2015; Nilsson 2008).

The impact of a firm's social responsibility on its market performance depends on the investors' priorities. A preference of altruistic investors for socially responsible firms could lead to an increase in investments and better market performance. This effect could, however, be offset by solely profit-seeking investors reducing their investments in the respective company. Research on the magnitude of both effects remains inconclusive. Although some studies find socially responsible firms to perform on par with the market or even better (Bauer et al. 2005; Derwall et al. 2005; Edmans 2011; Kempf and Osthoff 2007), others find socially responsible firms to underperform (Fabozzi et al. 2008; Hong and Kacperczyk 2009). Revelli and Viviani (2015) found in a metastudy that social responsibility can be considered to be neither a strength nor a weakness.

In the crowdfunding space, studies clearly identify altruism as an important driver of funding decisions. Altruism in its strongest form is displayed in social campaigns. Similar to donations, investors fund projects helping people in need or contributing to the social good, without receiving a return of any form (Mollick 2014). Reward-based crowdfunding campaigns aim to fund the development of a product and reward investors with a discount on the purchase price (Mollick 2014). Although investors may be partly driven by selfish motives, such as the wish to purchase the product (Gerber and Hui 2013; Steigenberger 2017) or the expectation of recognition from others (Bretschneider and Leimeister 2017), the altruistic desire to support a good cause remains an important factor driving funding decisions (Bretschneider and Leimeister 2017; Gerber and Hui 2013; Gleasure and Feller 2016; Steigenberger 2017) and campaigns are more likely to be successful in regions with high levels of altruism among the population (Giudici et al. 2018). Financial considerations appear to be insignificant with monetary incentives potentially even crowding out altruistic investors (Cecere et al. 2017). A similar effect can be seen in microlending-based crowdfunding, where investors react positively to campaigns being framed as an opportunity to help others but less positively if they are framed as business opportunities (Allison et al. 2015). André et al. (2017) explain the investors' willingness to altruistically support campaigns through strong reciprocity, the rewarding of socially beneficial behavior of others. Prosocial behavior or environmental orientation of ventures have been found to increase funding success (Berns et al. 2020; Hörisch and Tenner 2020) supporting the idea of reciprocity.

2.2. Initial Coin Offerings (ICOs)

Defining ICOs.[7] ICOs are peer-to-peer venture financing transactions that have evolved from crowdfunding by applying blockchain technology to issue and exchange digital assets, so-called *tokens*, which represent stakes in startup companies (Fisch 2019; Howell et al. 2020; Momtaz 2020). Smart contracts are the basis of the automation of the trustless transactions between entrepreneurs and investors (Amsden and Schweizer 2018; Fisch et al. 2020). To raise financing with an ICO, startup firms sell cryptographically protected digital assets, known as tokens or coins, to interested parties. Tokens can be assigned different types of values and rights. Cryptocurrency tokens are used as a mere medium of exchange, such as Bitcoin; security tokens may include control and voting rights; and utility tokens are similar to vouchers, redeemable for one unit of the company's future product or service (Howell et al. 2020; Lambert et al. 2021). Most ICOs offer utility tokens (Bellavitis et al. 2020) but regulatory developments regarding ICOs have initiated a gradual transition to security token offerings (Bellavitis et al. 2021; Lambert et al. 2021; Momtaz 2021e). The ICO market has evolved steadily since the first ICO of MasterCoin in July 2013, reaching a record aggregate funding amount of $12.3 billion raised by 2598 firms in 2018 (Bellavitis et al. 2021). Unlike other forms of startup financing, ICOs cover the full range of "ticket sizes", from micro-cap (<$100,000) to mega-cap (>$1,000,000,000 such as the $4+ billion EOS campaign) financings.

ICO characteristics. There are both advantages and disadvantages to ICOs. Positive features include disintermediation of peer-to-peer transactions and liquidity of the issued tokens, which may be traded in liquid post-ICO markets. Disadvantages are information asymmetry and commercial as well as legal uncertainty.

Blockchain technology enables disintermediation, particularly through smart contracts which allow entrepreneurs and investors to automate trustless transactions (De Domenico and Baronchelli 2019; Fisch 2019). Therefore, transaction surpluses are redistributed exclusively to entrepreneurs and investors, as opposed to intermediaries (e.g., banks in IPOs). Disintermediation potentially further democratizes markets for entrepreneurial finance by lowering both supply- and demand-side entry hurdles (Fisch et al. 2020), leading to more efficient markets due to a higher participation rate. Moreover, since tokens are exchangeable at near-zero transaction costs and with limited trading delays due to blockchain technology, ICO after-markets are characterized by high liquidity. Liquid ICO aftermarkets reduce discounts for startups associated with illiquidity (Barg et al. 2021; Hou and Howell 2012) and provide investors with quick opportunities to exit (Fisch and Momtaz 2020; Momtaz 2020). Improved trading of stakes in startups might increase the efficiency of entrepreneurial financial markets (e.g., through (fair) token valuations derived from equilibrium prices on liquid token exchanges that are informative to the market; see Momtaz 2021c), improving the allocation of capital to the entrepreneurial projects that perform best and potentially promoting long-term economic growth (Acs and Szerb 2007; Audretsch 2018; Wennekers and Thurik 1999).

On the downside, ICOs are characterized by high levels of asymmetric information. There are several reasons for information asymmetry including the relatively young average age of blockchain-experienced entrepreneurs and, consequently, the lack of a solid track record. Additionally, startup firms often sell tokens before being able to present crowd-investors with a fully developed product or service. The nonexistence of mandatory disclosure requirements and the absence of intermediaries result in difficulties in signaling or certifying project quality (Fisch 2019; Fisch and Momtaz 2020; Howell et al. 2020; Momtaz 2021c). Furthermore, ICO companies are known to embellish information about their underlying quality. The pronounced information asymmetry in ICOs may result in various challenges, such as adverse selection and moral hazard (Chod and Lyandres 2021; Gan et al. 2021; Howell et al. 2020; Momtaz 2021c, 2021d). In addition to information asymmetry, there is commercial uncertainty related to often immature business models, technical challenges regarding the underlying blockchain technology, and industry-wide token adoption at large (Allen et al. 2020; Fisch 2019; Harvey et al. 2021; Howell et al. 2020). Lastly, utility tokens are not regulated by securities law and the applicable jurisdiction in globally distributed token platform transactions may be difficult to determine, hindering the pursuit of legal actions in cases of fraud or deception (Block et al. 2021; Hornuf et al. 2021; Howell et al. 2020).

ICO issuers and investors. Established facts about both ICO issuers or ICO investors are limited. At the time of the ICO, the typical venture is between one and three years old, employs 15 team member with backgrounds in technology or finance, selects its headquarter considering geographical aspects and tax optimization strategies, tends to publish its source code online but does not hold patents on its technology, and uses social media as the primary channel to promote the ICO (Adhami et al. 2018; An et al. 2019; Fisch 2019; Howell et al. 2020; Huang et al. 2020; Momtaz 2020). Momtaz (2021d) further finds that loyal founders (i.e., relatively longer tenure at previous workplaces) are associated with ICO success and Colombo et al. (2020) show that the founder's attractiveness is linked to higher funding amounts.

Evidence on ICO investor characteristics is sparse, largely due to the pseudo-anonymous nature of blockchain technology. Fahlenbrach and Frattaroli (2021) find that the average ICO is backed by 4700 investors, each contributing $1500. Using a different sample, Boreiko and Risteski (2021) find the average ICO to be backed by only 1600 investors with individual contributions of $5625. In both cases, contributions are substantially higher than in traditional crowdfunding campaigns (Cumming et al. 2021). Surveying ICO investors regarding their technological, ideological, and financial motives for investing, Fisch et al. (2019) find that technological enthusiasm and anticipated financial gains, as well as ideological judgments, are among the important factors driving investments. Similarly, Mansouri and Momtaz 2021 show that investors fund projects with a social and environmental orientation. Investors gather value-relevant information not only from the ventures' white papers (Fisch et al. 2019) but also from experts' ratings (Barth et al. 2021; Bourveau et al. 2019) and the ventures' video pitches (Kolbe et al. 2021).

3. Hypotheses

From a social perspective, altruism in firms is a positive trait as it increases contributions to public goods in the form of donations, support of socially desirable concepts, or the development of products and technologies aimed at benefiting society.

A good reputation, based on altruistic behavior, may also be rewarded by business partners, governments, or consumers in the form of favorable treatment (Fehr and Fischbacher 2003; Nowak and Sigmund 1998) leading to an economic benefit. The essence of altruism, however, incurring costs or foregoing profits in order to benefit others (Tan et al. 2005) is not easily compatible with financial profit maximization. Hence, altruistic behavior by firms is likely to reduce financial profit, potentially violating the firm's obligation to act in the best interest of its shareholders (Friedman 2007). This is of particular importance for early-stage financing. In contrast to established firms, many early-stage ICO ventures are not yet profitable with investors speculating on the firm's growth potential and future profits (Howell et al. 2020). The success of a startup is far from guaranteed and the founder's ability and determination are often seen as one of the key drivers (Davis et al. 2017; MacMillan et al. 1985). Although altruistic ambitions in established firms may slightly reduce profits, an altruistic founding team, which lacks focus on growth and the generation of profits, potentially decides between the success and failure of the startup.

As altruistic behavior impacts firms in various ways, we also expect the investor's willingness to fund altruistic startups to be impacted by various motives. (a) Sympathizing with the venture's cause and a desire to contribute might increase the investor's willingness to participate in the ICO. In this scenario, the investor would display altruism as described by Becker (1964) and personally profit from the utility gains of others. (b) Investors may also act under strong reciprocity and altruistically reward startups for their behavior (Berg et al. 1995; Fehr et al. 1993; Gintis et al. 2008; Hayashi et al. 1999). Altruistic behavior and the contribution to public goods increase the generosity of others (Fehr and Fischbacher 2003; Nowak and Sigmund 1998). As altruistic startups claim to contribute to social goods, investors may altruistically reward them in the form of higher initial funding. Under these two motives, ICO investors' behavior would resemble that of crowdfunding investors and we would expect a firm's altruistic tendencies to have a positive effect on funding success. (c) Lastly, financial motives are likely to be an important factor. If a financially motivated investor assumes the firm's financial performance to be worse due to its altruistic ambitions, his investments would decrease. The opposite would be true if the investor assumes other investors to be highly altruistic and supportive of the firm, leading to a financial outperformance. On traditional financial markets, the evidence regarding the financial performance of socially responsible firms is mixed (e.g., Bauer et al. 2005; Derwall et al. 2005; Fabozzi et al. 2008; Hong and Kacperczyk 2009), but investors appear to assume an underperformance (Riedl and Smeets 2017), which is likely also the case for startups. If investors were primarily driven by financial motives, we would expect an underperformance of altruistic ventures.

With these opposing effects, the overall impact of altruism on investors' funding decisions is ambivalent and depends on the firm's ability to combine altruism with profit generation and the individual investor's values and motives. Fisch et al. (2019) found in a survey that ICO investments are driven by both ideological and financial motives. Given this ambiguity, we refrain from making a prediction regarding the overall impact:

Hypothesis 1a: *Altruistic projects raise less funds in ICOs.*

Hypothesis 1b: *Altruistic projects raise more funds in ICOs.*

We expect the trade-off investors face between utility gained from supporting altruistic ventures and possible financial losses to be reduced for high-quality ventures. High-quality is commonly understood to be characterized by a sound business plan, a path to profit or revenue generation and a good management team. Thus, investors are more likely to believe in the firm's ability to combine altruistic ambitions with revenue generation, reducing the fear of a substantially worse financial performance. In this case, non-financial utility gains might outweight potential financial losses, resulting in a positive marginal effect of altruism:

Hypothesis 2: *The marginal effect of altruism in high-quality ventures is positive.*

A crucial aspect influencing the utility investors to gain from supporting an altruistic venture is the venture's trustworthiness (Colombo et al. 2020). Altruistic behavior is difficult to quantify compared to net income, stock returns, or exchange rate appreciation (similar to environmental or social orientation, see Mansouri and Momtaz 2021). Hence, verifying claims regarding altruistic actions is challenging. The venture's founding team often holds a large number of tokens which can lead to substantial financial gains if the exchange rate appreciates. This creates a moral hazard problem with the founders having an incentive to divert from the communicated altruistic path and focus on their personal profit maximization (Leland and Pyle 1977; Momtaz 2021c). Additionally, fraudulent campaigns are easier to create when disguised as altruistic ventures contributing to a social cause (Hornuf et al. 2021). When framed as a social venture, an original product and a sound business plan, both of which require creativity, skills, and effort, are not needed. Thus, we hypothesize:

Hypothesis 3: *The marginal effect of altruism is positive in ventures with strong corporate governance.*

Startup financing, including ICOs, is generally negatively impacted by a high level of information asymmetry (e.g., Adhami et al. 2018; Barg et al. 2021; Block et al. 2021; Fisch 2019; Momtaz 2021b), hindering the investor's assessment of the firm's quality and future potential. We believe this issue to be of particular importance when considering altruistic ventures. As outlined in ***H1***, economic success in the form of profit maximization and the altruistic motive to improve the utility of others or create social goods is not naturally aligned. Studying the business concept allows the investor to understand whether the venture is able to combine both aims or will sacrifice one. Thus, we expect the firm's ability to reduce asymmetric information to have a positive impact on the marginal effect of altruism:

Hypothesis 4: *The marginal effect of altruism is positive in ventures with low levels of asymmetric information.*

4. Quantifying Startups' Altruism

When quantifying altruism, we rely on textual information from the startups' white papers and follow a "dictionary" method, one of the standard approaches used in economic literature to quantify an attribute via textual analysis (Loughran and McDonald 2016). This method requires the researchers to first, define a set of relevant terms, i.e., the dictionary, and second, measure their relative frequencies within a text.

4.1. Altruism Dictionary

Our approach to create an altruism dictionary is methodologically similar to Li et al. (2021) and Mansouri and Momtaz (2021). We use a semi-supervised machine learning method that creates a word-list in two steps. In the first step, we define a small set of hand-picked "seed words" that are associated with altruism. In the second step, the machine expands our word-list by finding the most similar words to the seed words, in the context of a business-related text[8].

4.1.1. Seed Words

To compile a list of seed words, we start with the most frequent terms in tweets containing the hashtag "#altruism". Twitter users add a hashtag when they want to relate their tweet to a specific topic, enabling other users to find the tweet when searching for the hashtag. Using Twitter data offers several advantages. First, the data is easily accessible using publicly available APIs. Second, as the crypto community is very active on Twitter, our textual data has a crypto-related context[9]. Third, hashtags are labeled and identified by humans, therefore, the chance of misclassifying the words is lower. On the downside, tweets commonly contain slang and emojis, requiring additional cleaning of the data and manual checks.

We find 39,634 tweets with the hashtag "#altruism" between July 2017 and July 2021 and clean the textual data following the common steps in the literature. First, we remove any usernames and mentions as well as emojis, URLs, and numerical content in the tweets. We then identify and drop stop words using the list of stop words provided in the NLTK library in Python (Bird et al. 2009). Finally, we drop titles, such as "Mr.", "Mrs.", "Dr.", as well as punctuation and symbols, including the # sign.

In the next step, we follow a bag-of-words analysis and list the most frequent words in our corpus of cleaned texts. Out of the 50 most frequently used words, we manually select 31 (e.g., 'altruism', 'charity', 'help', and 'philanthropy') as our seed words. Please see Table A2 for the full list of seed words.

4.1.2. Word Embedding

Word embeddings are techniques to represent words in a vector space, so that machines "learn" a language and, depending on the training set, learn to vectorize words in a specific context. This enables the researcher to calculate the similarity of the words based on their vector proximity measures, such as cosine similarity.

We train a word embedding model using the popular word2vec (Mikolov et al. 2013a) algorithm developed by researchers at Google. Word2vec trains a neural network model with only one hidden layer[10] by predicting the neighboring words in a window of 5 words. Each input word would be represented as a vector of size 300, i.e., the hidden layer size, which will be used to predict the next word. After the training, the trained weights of such a neural network would be able to create a vector of real numbers for any input word of the corpus.

We use the Gensim python library (Rehurek and Sojka 2010) for the training of our word2vec model. We download 800 Financial Times articles tagged in the topic of altruism and build a *universe* of words based on all words appearing in this corpus. This enables us to filter for words that are not used outside the context of business language. To avoid the bias of training on a small sample of only 800 articles, we intersect our vectors with the standard pre-trained word2vec model of Google News, which is trained on a dataset of around 100 billion words (Mikolov et al. 2013b)[11].

Next, we use the trained word2vec model on our universe to find the top 10 most similar words to the seed words we defined in the previous subsection. More precisely, we measure the cosine similarity for the vector of each of the 31 seed words to the vectors of all words in the universe, and select the top 10 similar words to each seed word. In line with Li et al. (2021), we manually examine the selected words and remove those that are not relevant for our measurement, resulting in a list of 206 words for our final dictionary. Figure 1 shows the word cloud for our altruism dictionary. For a complete list please see Table A2.

Figure 1. Wordcloud of the altruistic word list.

4.2. Altruism Score

We determine a venture's altruism score using a dictionary method, i.e., counting the frequency of the words from our previously defined dictionary in a white paper and setting it into relation to the total length of the white paper. Specifically, for each ICO, the altruism score is calculated as follows:

$$A_i = (\sum_t c(t)_i)/c(n)_i, \tag{1}$$

where $c(t)_i$ is the count of term t in white paper i and $c(n)_i$ is the total number of words in white paper i.

4.3. Sanity Check

To check the reliability of our altruism score, we manually review the ICOs that achieve the highest altruism scores based on our approach.

Figure 2 shows the word clouds based on the white papers of our top three altruistic ICOs. Life Change is a "decentralized Christian platform that provides a safe and secure environment for people of all faith to socialize, transact, communicate, and grow together in the knowledge of Christ" ICObench (2017). The word cloud of Life Change includes words such as 'church', 'life', 'change', 'spiritual', and 'need'. The second top score belongs to Christ Coins.[12] This project has the purpose of rewarding "people who read the Bible, post/view content and interact with the community on the Life Change Platform. The rewards may then be used to supplement personal income, invested for potential future gains, tithed to churches, or used to support global missions and humanitarian efforts"ICObench (2017). The word cloud of Christ Coins include words such as 'god', 'spiritual', 'help', 'social', 'rights', 'rebuild', and 'contribution'.

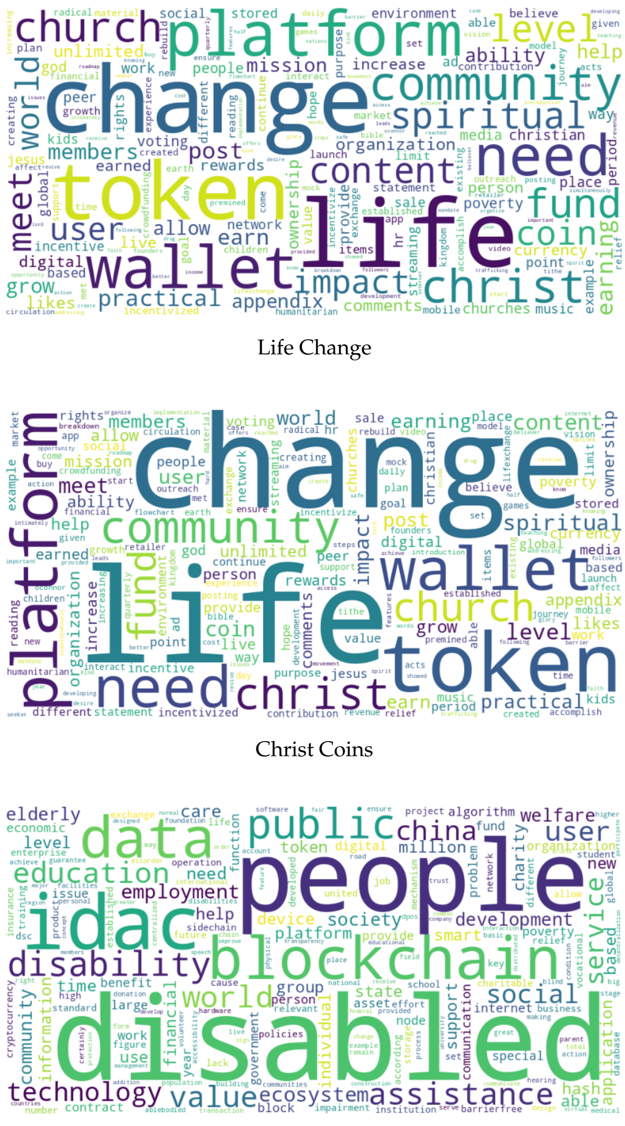

Figure 2. Wordcloud of ICOs with the highest altruistic score.

The third ICO venture with the highest altruism score is International Disability Chain, IDAC, a project with the vision of creating a "cryptocurrency ecosystem with a fully transparent and decentralized donating platform" ICObench (2018). The word cloud of IDAC includes 'disabled', 'people', 'elderly', 'disability', 'social', 'education', 'service', 'welfare', and 'poverty'.

The other top altruistic projects are Human Coin and NamaCoin. Human Coin provides a platform to track donations online and rank social projects as well as philanthropists

ICObench (2018), and NamaCoin provides solar panels to power, e.g., atmospheric water generators in developing countries ICObench (2019).

5. Data

5.1. Data Sources

Our sample of utility token ICOs is based on ICObench, LinkedIn, GitHub, and the most comprehensive publicly accessible database, the Token Offerings Research Database TORD[13]. In particular, we use TORD to collect data on ICO offering terms and firm characteristics. The database used is limited to utility token ICOs and excludes Security Token Offerings (STOs) and Initial Exchange Offerings (IEOs) to avoid distortions caused by various confounding factors of alternative token and offering types. The final sample of 980 white papers is limited to token offerings for which the necessary data for further analysis is available.

5.2. Variables

5.2.1. Dependent Variable

Funding amount, in $ (log): The dependent variable is the ICO success, measured by the amount of funds raised during the ICO (e.g., Fisch 2019). The natural logarithm is used to account for the variable's skewness (Colombo et al. 2020).

5.2.2. Independent Variables:

Altruism score (z-standard): We construct an altruism score as detailed in the previous section. To ease the interpretation of the coefficients, the score is z-standardized, i.e., the arithmetic mean is subtracted from each measured value and the result is divided by the standard deviation.

5.2.3. Other Independent Variables: Control Variables

A broad set of control variables is included to eliminate confounding explanations.[14]

The first category of control variables is related to the venture's characteristics:

Expert rating: Expert ratings are published on ICObench and are considered to serve as an external "validation" of the project in an otherwise highly uncertain environment (Lee et al. 2022; Momtaz 2020). The rating scale ranges from 1 to 5 with 5 being the best score.

Governance score: The governance score is taken from Mansouri and Momtaz (2021) and is based on the occurrences of words linked to good corporate governance in the venture's white paper. For a detailed description, please see Mansouri and Momtaz (2021).

White paper length, in # words (log): This variable serves as a proxy for the informational content of the white paper and the overall level of asymmetric information (Fisch 2019). It is constructed by taking the natural logarithm of one plus the number of words in the venture's white paper.

Team size, in # FTE: Social capital may be approximated by the number of team members (Fisch 2019; Lyandres et al. 2019; Momtaz 2020).

Team members with technical background, in %: The team's technical background is measured by the number of members with a degree in a tech-related field, divided by the total team size (Mansouri and Momtaz 2021). The team's education is obtained from LinkedIn.

Minimum viable product (dummy): This variable is one if the venture has developed a minimum viable product, and zero otherwise.

Open source (dummy): This variable is one if the project's code has been published on Github. Publishing the code increases transparency and may be used as a signal to demonstrate technological capabilities (Fisch 2019).

 # Industries (log): Horizontal diversification is measured by the number of industries a venture targets. The variable is constructed by taking the natural logarithm of one plus the number of target industries as reported on ICObench (Fisch and Momtaz 2020).

Team members with PhD, in # FTE: This variable is the number of team members with a PhD degree. The team's education is obtained from LinkedIn.

Team members with crypto background, in %: The team's crypto background is measured by the number of members with previous experience in cryptocurrency-related domains divided by the total number of team members. The team's experience is obtained from LinkedIn.

The second category of control variables is related to the offering characteristics.

Soft cap (dummy): This variable is one if a soft cap has been announced, and zero otherwise. A soft cap is the minimum amount of funds to be raised in the ICO. Failing to reach this threshold will result in the investors being refunded (Mansouri and Momtaz 2021).

Hard cap (dummy): This variable is one if a hard cap has been announced, and zero otherwise. A hard cap is the maximum amount of funds that will be accepted. Upon reaching the hard cap, no more tokens will be given out and the ICO ends automatically (Mansouri and Momtaz 2021).

Pre-sale (dummy): This variable is one if a pre-sale was offered before the ICO and zero otherwise. Investors participating in pre-sales are able to purchase tokens at a discount to the ICO price.

Whitelist (dummy): Dummy variable with one indicating that a venture has an active whitelist. Joining a whitelist ahead of an ICO typically requires a KYC procedure and ensures investors that they are entitled to participate in the offering.

KYC (dummy): This variable is one if the completion of a Know-Your-Customer (KYC) procedure is required before participating in the ICO as an investor, and zero otherwise.

Bonus (dummy): Dummy variable with one indicating the existence of a bonus program. Under bonus programs, rewards such as discounts or free tokens are offered to individual wallet addresses investing more than a certain threshold during the ICO.

Bounty (dummy): This variable is one if a bounty program exists, and zero otherwise. Bounty structures offer rewards (typically free tokens or discounts) to individuals promoting the ICO.

ERC-20 standard (dummy): Dummy variable with one indicating compliance with ERC-20, a technical standard for utility tokens on the Ethereum blockchain. The standard facilitates compatibility between tokens and various external applications. Leveraging the Ethereum blockchain further reduces the operational risks linked to a proprietary blockchain.

5.3. Summary Statistics

Table 1 displays the summary statistics for all variables. The average venture in the dataset of 1047 token-issuing companies raises $12.2 million during the token offering with an average rating of 3.4 (out of 5). The team consists of an average of 13.4 people, of which 0.7 have a PhD. On average, 34.7% of the team members have previous experience in the crypto space. The sample statistics are similar to those in related studies (Mansouri and Momtaz 2021; Momtaz 2021c).

We observe an average altruism score of 0.023, before z-standardization, meaning that 2.3% of the words in the white papers of our sample ICOs are among the words in our altruism dictionary. The altruism score has a standard deviation of 0.01 and a maximum of 0.096.

Table 1. Summary statistics.

	Mean	Std. Dev.	Q1	Median	Q3
Altruism score (z-standard)	0.0	1.0	−0.7	−0.1	0.5
Funding amount, in $m	12.2	26.9	1.6	5.2	15.0
Expert rating	3.4	0.6	3.0	3.4	3.9
White paper length, in # words (log)	8.1	0.6	7.8	8.2	8.5
Team size, in # FTE	13.4	7.9	8.0	12.0	18.0
Team members with technical background, in %	27.2	19.8	12.5	25.0	39.1
Minimum viable product (dummy)	0.2	0.4	0.0	0.0	0.0
Open source (dummy)	0.7	0.5	0.0	1.0	1.0
# Industries (log)	1.3	0.5	0.7	1.4	1.6
Team members with PhD, in # FTE	0.7	1.1	0.0	0.0	1.0
Team members with crypto background, in %	34.7	23.0	16.7	33.3	50.0
Soft cap (dummy)	0.6	0.5	0.0	1.0	1.0
Hard cap (dummy)	0.9	0.3	1.0	1.0	1.0
Pre-sale (dummy)	0.5	0.5	0.0	1.0	1.0
Whitelist (dummy)	0.3	0.5	0.0	0.0	1.0
KYC (dummy)	0.5	0.5	0.0	0.0	1.0
Bonus (dummy)	0.0	0.1	0.0	0.0	0.0
Bounty (dummy)	0.3	0.5	0.0	0.0	1.0
ERC-20 standard (dummy)	0.8	0.4	1.0	1.0	1.0

Explanation: The table shows the summary statistics of the variables used in this study. The sample consists of 980 ICOs between 2016 and 2020. Altruism score is z-standardized (mean = 0 and standard deviations = 1). All variables are defined in Section 5.2.

Table 2 shows the bivariate correlations among the variables. The highest correlation among our variables is 0.536 which is much lower than the generally agreed threshold of $\rho = 0.7$ (Leitterstorf and Rau 2014).

Table 2. Correlation matrix.

	1.	**2.**	**3.**	**4.**	**5.**	**6.**	**7.**	**8.**	**9.**	**10.**	**11.**	**12.**	**13.**	**14.**	**15.**	**16.**	**17.**	**18.**	**19.**
Key Variables:																			
1. Altruism score (z-standard)																			
Dependent variables:																			
2. Funding amount, in $m	0.014																		
Control variables: Venture characteristics:																			
3. Expert rating	−0.001	−0.006																	
4. White paper length, in # words (log)	0.028	0.074	0.273																
5. Team size, in # FTE	0.049	0.068	0.381	0.275															
6. Team members with technical background, in %	−0.019	−0.033	−0.090	0.028	−0.030														
7. Minimum viable product (dummy)	−0.023	−0.105	0.345	0.048	0.181	−0.038													
8. Open source (dummy)	0.023	−0.110	0.372	0.134	0.140	0.025	0.230												
9. # Industries (log)	0.022	−0.067	0.231	0.054	0.144	−0.045	0.226	0.110											
10. Team members with PhD, in # FTE	−0.005	−0.012	0.128	0.189	0.320	0.142	0.059	0.035	0.038										
11. Team members with crypto background, in %	−0.050	0.067	0.123	0.060	0.048	0.165	0.080	0.065	−0.016	0.076									
Control variables: Offering characteristics:																			
12. Soft cap (dummy)	0.047	−0.060	0.240	0.087	0.156	−0.123	0.239	0.170	0.157	0.012	−0.050								
13. Hard cap (dummy)	0.012	−0.022	0.225	0.132	0.128	−0.048	0.119	0.134	0.088	0.014	0.008	0.357							
14. Pre-sale (dummy)	−0.004	−0.086	0.239	0.090	0.178	−0.081	0.109	0.103	0.157	0.086	−0.001	0.216	0.187						
15. Whitelist (dummy)	0.082	0.002	0.234	0.163	0.222	−0.003	0.204	0.086	0.147	0.104	0.023	0.167	0.116	0.092					
16. KYC (dummy)	0.044	−0.006	0.355	0.175	0.281	−0.033	0.297	0.127	0.228	0.128	0.015	0.249	0.191	0.135	0.536				
17. Bonus (dummy)	−0.015	−0.016	0.025	−0.006	0.024	0.042	0.049	0.050	0.060	0.036	0.012	−0.025	0.005	−0.009	0.039	0.084			
18. Bounty (dummy)	0.046	−0.080	0.264	0.070	0.162	−0.059	0.448	0.177	0.220	0.038	0.044	0.231	0.152	0.174	0.207	0.310	0.041		
19. ERC-20 standard (dummy)	0.001	−0.020	0.117	0.041	0.095	−0.012	0.120	0.039	0.108	0.057	0.016	0.070	0.070	0.068	0.101	0.145	0.025	0.110	

6. Empirical Analyses

6.1. Main Result: Altruism and ICO Firm Valuation

With this paper, we aim to understand the impact of altruism on firm valuations in ICOs and its interaction with other venture qualities. To address the first part of our question, we regress the *Altruism score* as defined in Section 5 on the *Funding amount* received during the ICO:

$$Funding\ amount_i = \beta_0 + \beta_1 \cdot Altruism\ score_i + \beta_2 \cdot X_i + \lambda_t + \mu_c + \varepsilon_i, \quad (2)$$

with X_i denoting a rich set of control variables (as described in Section 5.2.3) to eliminate confounding explanations. In line with nascent literature (e.g., Howell et al. 2020; Momtaz 2020), we also include time fixed effects, λ_t, and country fixed effects, μ_c, in our regression. This will remove common time trends, as well as country-specific factors.

Table 3 shows the results of this analysis, with columns (1) to (4) showing the regression results with different fixed effects specifications. The *Altruism score* is negatively related to the *Funding amount* raised during the ICO at a 10% significance level, for all the specifications. In the richest specification, in column (4), the coefficient is −0.133, meaning that an increase in the *Altruism score* by one standard deviation leads to a 12.6% decrease in the *Funding amount*. 12.6% translate to around \$1.54m for the ICOs in our sample. This result supports the idea that (ICO) investors are primarily financially motivated, and non-financial utility gained from supporting a good cause is not able to outweigh potential foregone profits. Thus, we accept ***H1a*** (and reject ***H1b***).

In addition to the statistical significance of the altruism score, in line with the literature, we find several control variables to have a significant impact on the ICO success. These include (i) the white paper length, (ii) the expert rating, (iii) the venture's team size, as well as (iv) the percentage of team members with previous experience in the crypto sector, and (v) the open source dummy.

Table 3. Main Results.

	Funding Amount, in \$ (log)			
	(1)	**(2)**	**(3)**	**(4)**
Altruism score (z-standard)	−0.124 *	−0.133 *	−0.121 *	−0.133*
	(0.068)	(0.075)	(0.069)	(0.077)
Expert rating	0.373 ***	0.395 ***	0.388 ***	0.425 ***
	(0.122)	(0.129)	(0.118)	(0.122)
White paper length, in # words (log)	0.401 ***	0.377 ***	0.400 ***	0.396***
	(0.110)	(0.110)	(0.109)	(0.109)
Team size, in # FTE	0.037 ***	0.035 ***	0.037 ***	0.036 ***
	(0.009)	(0.010)	(0.009)	(0.010)
Team members with technical background, in %	0.001	−0.001	−0.001	−0.004
	(0.004)	(0.004)	(0.004)	(0.004)
Minimum viable product (dummy)	−0.411 ***	−0.465 ***	−0.077	−0.126
	(0.156)	(0.164)	(0.182)	(0.188)
Open source (dummy)	−0.458 ***	−0.437 ***	−0.431 ***	−0.417***
	(0.126)	(0.134)	(0.122)	(0.129)
# Industries (log)	−0.229 *	−0.200	−0.201	−0.170
	(0.123)	(0.136)	(0.124)	(0.134)
Team members with PhD, in # FTE	−0.017	0.016	−0.036	−0.008
	(0.054)	(0.057)	(0.055)	(0.058)

Table 3. *Cont.*

	Funding Amount, in $ (log)			
	(1)	**(2)**	**(3)**	**(4)**
Team members with crypto background, in %	0.011 ***	0.011 ***	0.008 ***	0.008***
	(0.003)	(0.003)	(0.003)	(0.003)
Soft cap (dummy)	−0.306 **	−0.350 **	−0.177	−0.190
	(0.129)	(0.142)	(0.128)	(0.139)
Hard cap (dummy)	0.182	0.006	0.181	0.045
	(0.180)	(0.192)	(0.192)	(0.202)
Pre-sale (dummy)	−0.293 **	−0.286 **	−0.234 **	−0.204 *
	(0.119)	(0.126)	(0.119)	(0.123)
Whitelist (dummy)	0.186	0.131	0.261 *	0.206
	(0.142)	(0.148)	(0.141)	(0.147)
KYC (dummy)	−0.080	−0.086	0.165	0.218
	(0.159)	(0.168)	(0.163)	(0.168)
Bonus (dummy)	0.008	0.017	0.095	0.305
	(0.348)	(0.337)	(0.646)	(0.651)
Bounty (dummy)	−0.353 **	−0.308 **	−0.210	−0.119
	(0.148)	(0.157)	(0.145)	(0.152)
ERC-20 standard (dummy)	−0.169	−0.207	−0.157	−0.193
	(0.135)	(0.145)	(0.138)	(0.148)
Observations	980	980	975	975
Adjusted R^2	0.125	0.147	0.165	0.197
Quarter_FE	No	No	Yes	Yes
Country_FE	No	Yes	No	Yes

Explanation: The table shows the results from regressions based on Equation (2). The dependent variable is the natural logarithm of the funding amount (in $). The altruism score is z-standardized (mean = 0 and standard deviations = 1). All control variables are defined in Section 5.2. The sample consists of 980 ICOs between 2016 and 2020. Huber–White robust standard errors are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

6.2. Additional Results: Moderating Mechanisms

After establishing a correlation between the venture's altruistic tendencies and the funding success, we consider interaction terms with several firm characteristics to understand *why* altruism has a negative impact on funding success and which factors might have a mitigating effect.

6.2.1. Venture Quality

As venture quality is not directly observable, we consider the *Expert rating* published on ICObench as a proxy. The rating is constructed based on the assessment of the venture by external experts in the crypto space. Despite not being linked to long-term outperformance of the coin (Fisch and Momtaz 2019), it is correlated with a higher funding success (Lee et al. 2022; Momtaz 2020), suggesting that investors see the rating as a "quality certificate" for ICOs. To test how the marginal impact of altruism depends on venture quality, we amend the main regression as shown in Equation (2) to include an interaction term with the *Expert rating*, leading to the following equation:

$$\begin{aligned} Funding\ amount_i = {} & \beta_0 + \beta_1 \cdot Altruism\ score_i + \beta_2 \cdot Altruism\ score \times Expert\ rating_i \\ & + \beta_3 \cdot X_i + \lambda_t + \mu_c + \varepsilon_i, \end{aligned} \tag{3}$$

The regression results of this analysis are shown in Table 4. The interaction term $Altruism \times Expert\ rating$ has a positive and statistically significant coefficient in all fixed-effect specifications. Based on the richest specification in column (4), considering two startups which only differ in their respective expert ratings by one point, the marginal effect of altruism on firm valuation would be 0.175 higher for the high-quality venture. Economically, the above example suggests that the high-quality venture can increase its funding amount relative to the low-quality venture by 19.2% by raising its altruism score by one standard deviation. This finding, in line with ***H2***, indicates that investors expect high-quality ventures to be able to combine altruism with profit making.

Table 4. Moderation: Expert rating as a proxy for venture quality.

	Funding Amount, in $ (log)			
	(1)	(2)	(3)	(4)
Altruism score (z-standard) × Expert rating	0.191 **	0.210 **	0.168 *	0.175 *
	(0.087)	(0.094)	(0.089)	(0.097)
Altruism score (z-standard)	−0.766 **	−0.842 **	−0.687 **	−0.724 *
	(0.325)	(0.355)	(0.333)	(0.372)
Expert rating	0.360 ***	0.390 ***	0.374 ***	0.418 ***
	(0.122)	(0.129)	(0.117)	(0.122)
White paper length, in # words (log)	0.401 ***	0.374 ***	0.398 ***	0.392 ***
	(0.109)	(0.110)	(0.108)	(0.109)
Team size, in # FTE	0.037 ***	0.036 ***	0.037 ***	0.036 ***
	(0.009)	(0.010)	(0.009)	(0.010)
Team members with technical background, in %	0.001	−0.002	−0.001	−0.004
	(0.004)	(0.004)	(0.004)	(0.004)
Minimum viable product (dummy)	−0.404 ***	−0.453 ***	−0.081	−0.125
	(0.156)	(0.164)	(0.182)	(0.188)
Open source (dummy)	−0.452 ***	−0.434 ***	−0.426 ***	−0.415 ***
	(0.126)	(0.133)	(0.122)	(0.129)
# Industries (log)	−0.232 *	−0.205	−0.204 *	−0.175
	(0.122)	(0.135)	(0.124)	(0.134)
Team members with PhD, in # FTE	−0.018	0.014	−0.035	−0.007
	(0.054)	(0.057)	(0.055)	(0.058)
Team members with crypto background, in %	0.010 ***	0.011 ***	0.007 ***	0.008***
	(0.003)	(0.003)	(0.003)	(0.003)
Soft cap (dummy)	-0.303 **	−0.345 **	−0.177	−0.190
	(0.129)	(0.142)	(0.129)	(0.139)
Hard cap (dummy)	0.169	−0.013	0.162	0.024
	(0.179)	(0.190)	(0.191)	(0.201)
Pre-sale (dummy)	−0.288 **	−0.281 **	−0.234 **	−0.205 *
	(0.119)	(0.126)	(0.119)	(0.123)
Whitelist (dummy)	0.166	0.114	0.244 *	0.192
	(0.142)	(0.148)	(0.141)	(0.147)
KYC (dummy)	−0.072	−0.079	0.169	0.219
	(0.160)	(0.168)	(0.163)	(0.169)
Bonus (dummy)	0.012	0.019	0.066	0.270
	(0.365)	(0.334)	(0.662)	(0.656)
Bounty (dummy)	−0.352 **	−0.307 *	−0.210	−0.119
	(0.148)	(0.157)	(0.146)	(0.153)
ERC-20 standard (dummy)	−0.167	−0.202	−0.159	−0.191
	(0.135)	(0.145)	(0.139)	(0.148)
Observations	980	980	975	975
Adjusted R^2	0.129	0.151	0.167	0.199
Quarter_FE	No	No	Yes	Yes
Country_FE	No	Yes	No	Yes

Explanation: The table shows the results from regressions based on Equation (3). The dependent variable is the natural logarithm of the funding amount (in $). The altruism score is z-standardized (mean = 0 and standard deviations = 1). All control variables are defined in Section 5.2. The sample consists of 980 ICOs between 2016 and 2020. Huber-White robust standard errors are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

6.2.2. Corporate Governance

In order to test how corporate governance influences the investor's judgement of altruistic ventures, we follow the same approach as in Equation (3) but now consider the venture's *Governance score* as defined in (Mansouri and Momtaz 2021). We obtain:

$$\begin{aligned} Funding\ amount_i = &\beta_0 + \beta_1 \cdot Altruism\ score_i \\ &+ \beta_2 \cdot Altruism\ score \times Governance\ score_i \\ &+ \beta_3 \cdot X_i + \lambda_t + \mu_c + \varepsilon_i, \end{aligned} \tag{4}$$

The results of this analysis are shown in Table 5. The coefficient of the interaction term *Altruism score* × *Governance score* is positive and statistically significant at the 1% level for all the specifications. Based on column (4), given two identical ventures which differ in their governance score by one standard deviation, the marginal effect of a one standard deviation increase in the altruism score would be 23.3% higher for the venture with better corporate governance. This finding supports the idea that investors gain more utility from financing altruistic ventures if trust in the venture fulfilling its claims is higher (***H3***).

Table 5. Moderation: Corporate governance.

	Funding Amount, in $ (log)			
	(1)	**(2)**	**(3)**	**(4)**
Altruism score (z-standard) × Governance score (z-standard)	0.177 ***	0.177 ***	0.198 ***	0.209 ***
	(0.060)	(0.066)	(0.059)	(0.065)
Governance score (z-standard)	0.292 ***	0.226 ***	0.278 ***	0.204 ***
	(0.064)	(0.068)	(0.063)	(0.065)
Altruism score (z-standard)	−0.083	−0.092	−0.072	−0.083
	(0.053)	(0.057)	(0.053)	(0.058)
Expert rating	0.355 ***	0.393 ***	0.372 ***	0.422 ***
	(0.120)	(0.128)	(0.115)	(0.120)
White paper length, in # words (log)	0.187	0.212 *	0.196 *	0.247 **
	(0.114)	(0.116)	(0.111)	(0.113)
Team size, in # FTE	0.033 ***	0.032 ***	0.033 ***	0.034 ***
	(0.009)	(0.010)	(0.008)	(0.009)
Team members with technical background, in %	0.002	−0.001	−0.000	−0.004
	(0.004)	(0.004)	(0.004)	(0.004)
Minimum viable product (dummy)	−0.399 **	−0.453 ***	−0.040	−0.089
	(0.157)	(0.166)	(0.183)	(0.190)
Open source (dummy)	−0.402 ***	−0.399 ***	−0.380 ***	−0.385 ***
	(0.125)	(0.133)	(0.121)	(0.129)
# Industries (log)	−0.213 *	−0.189	−0.184	−0.160
	(0.120)	(0.134)	(0.122)	(0.132)
Team members with PhD, in # FTE	−0.013	0.017	−0.033	−0.007
	(0.053)	(0.056)	(0.054)	(0.058)
Team members with crypto background, in %	0.010 ***	0.011 ***	0.007 ***	0.007**
	(0.003)	(0.003)	(0.003)	(0.003)
Soft cap (dummy)	−0.328 **	−0.363 **	−0.193	−0.195
	(0.128)	(0.141)	(0.127)	(0.138)
Hard cap (dummy)	0.168	−0.006	0.170	0.035
	(0.171)	(0.185)	(0.180)	(0.193)
Pre-sale (dummy)	−0.313 ***	−0.305 **	−0.252 **	−0.219 *
	(0.119)	(0.127)	(0.119)	(0.123)
Whitelist (dummy)	0.178	0.126	0.250 *	0.198
	(0.141)	(0.148)	(0.140)	(0.147)
KYC (dummy)	−0.160	−0.153	0.090	0.158
	(0.161)	(0.169)	(0.164)	(0.169)
Bonus (dummy)	0.097	0.085	0.198	0.361
	(0.379)	(0.348)	(0.698)	(0.685)
Bounty (dummy)	−0.320 **	−0.282 *	−0.175	−0.086
	(0.150)	(0.159)	(0.146)	(0.153)
ERC-20 standard (dummy)	−0.186	−0.207	−0.167	−0.182
	(0.131)	(0.141)	(0.133)	(0.142)
Observations	980	980	975	975
Adjusted R^2	0.147	0.162	0.188	0.214
Quarter_FE	No	No	Yes	Yes
Country_FE	No	Yes	No	Yes

Explanation: The table shows the results from regressions based on Equation (4). The dependent variable is the natural logarithm of the funding amount (in $). The altruism score, as well as the governance score, are z-standardized (mean = 0 and standard deviations = 1). All control variables are defined in Section 5.2. The sample consists of 980 ICOs between 2016 and 2020. Huber-White robust standard errors are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

6.2.3. Asymmetric Information

The amount of information available for a specific ICO venture is commonly approximated by the length of the white paper (e.g., Fisch 2019). A longer white paper should include more information about the venture's business plan; thus, reducing information asymmetry between investor and venture. Following this approach, we use *White paper length* to measure information asymmetry and amend the main regression, as shown in Equation (2) to include the interaction term with the venture's white paper length:

$$\begin{aligned} Funding\ amount_i = \ & \beta_0 + \beta_1 \cdot Altruism\ score_i + \beta_2 \cdot Altruism\ score \times White\ paper\ length_i \\ & + \beta_3 \cdot X_i + \lambda_t + \mu_c + \varepsilon_i, \end{aligned} \tag{5}$$

Table 6 shows the results of this analysis. The coefficient of the interaction term *Altruism score* $\times$ *Whitepaper length* is positive and statistically significant at the 1% level for all the specifications. Economically, based on column (4), this implies that for a venture with a 10% longer white paper, an increase in the *Altruism score* by one standard deviation results in a marginal funding increase of 2.54%. These results support ***H4*** and show that investors value altruism if they have sufficient information to verify the venture's quality and business plan, but associate altruism with bad quality (i.e., low financial returns) otherwise.

Table 6. Moderation: Information asymmetry proxied by white paper length.

	Funding Amount, in $ (log)			
	(1)	**(2)**	**(3)**	**(4)**
Altruism score (z-standard)	0.229 ***	0.223 ***	0.232 ***	0.227 ***
× White paper length, in # words (log)	(0.071)	(0.073)	(0.069)	(0.073)
Altruism score (z-standard)	−1.942 ***	−1.905 ***	−1.963 ***	−1.943 ***
	(0.592)	(0.608)	(0.571)	(0.616)
Expert rating	0.345 ***	0.372 ***	0.359 ***	0.399 ***
	(0.121)	(0.128)	(0.116)	(0.120)
White paper length, in # words (log)	0.517 ***	0.488 ***	0.516 ***	0.507***
	(0.113)	(0.116)	(0.110)	(0.115)
Team size, in # FTE	0.036 ***	0.035 ***	0.036 ***	0.035 ***
	(0.009)	(0.010)	(0.009)	(0.009)
Team members with technical background, in %	0.001	−0.001	−0.001	−0.004
	(0.004)	(0.004)	(0.004)	(0.004)
Minimum viable product (dummy)	−0.393 **	−0.438 ***	−0.054	−0.092
	(0.157)	(0.165)	(0.182)	(0.188)
Open source (dummy)	−0.450 ***	−0.431 ***	−0.423 ***	−0.411 ***
	(0.126)	(0.133)	(0.122)	(0.128)
# Industries (log)	−0.229 *	−0.204	−0.202	−0.176
	(0.122)	(0.135)	(0.124)	(0.134)
Team members with PhD, in # FTE	−0.024	0.008	−0.043	−0.015
	(0.054)	(0.056)	(0.054)	(0.058)

Table 6. *Cont.*

	Funding Amount, in $ (log)			
	(1)	(2)	(3)	(4)
Team members with crypto background, in %	0.010 ***	0.011 ***	0.007 ***	0.007**
	(0.003)	(0.003)	(0.003)	(0.003)
Soft cap (dummy)	−0.288 **	−0.330 **	−0.162	−0.173
	(0.128)	(0.141)	(0.128)	(0.138)
Hard cap (dummy)	0.143	−0.034	0.134	−0.003
	(0.178)	(0.189)	(0.190)	(0.200)
Pre-sale (dummy)	−0.289 **	−0.276 **	−0.233 **	−0.197
	(0.119)	(0.126)	(0.118)	(0.123)
Whitelist (dummy)	0.179	0.122	0.252 *	0.194
	(0.141)	(0.148)	(0.141)	(0.146)
KYC (dummy)	−0.101	−0.111	0.138	0.192
	(0.159)	(0.168)	(0.163)	(0.169)
Bonus (dummy)	0.001	0.034	0.090	0.298
	(0.352)	(0.324)	(0.641)	(0.633)
Bounty (dummy)	−0.382 **	−0.338 **	−0.244 *	-0.152
	(0.149)	(0.158)	(0.145)	(0.153)
ERC-20 standard (dummy)	−0.161	−0.201	−0.155	−0.191
	(0.134)	(0.144)	(0.136)	(0.146)
Observations	980	980	975	975
Adjusted R^2	0.135	0.156	0.175	0.206
Quarter_FE	No	No	Yes	Yes
Country_FE	No	Yes	No	Yes

Explanation: The table shows the results from regressions based on Equation (5). The dependent variable is the natural logarithm of the funding amount (in $). The altruism score is z-standardized (mean = 0 and standard deviations = 1) to ease interpretation. All control variables are defined in Section 5.2. The sample consists of 980 ICOs between 2016 and 2020. Huber–White robust standard errors are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

7. Discussion and Conclusion

7.1. Summary of Results

This study seeks to shed light on the crowdfunding of altruistically motivated startups. To measure altruism, we use a machine learning approach to create a score based on the relative frequency of words linked to altruism in white papers. Using a large, hand-collected set of ICO data, we find that a higher altruism score is negatively related to crowdfunding success. The negative impact is economically significant with a one standard deviation increase in the altruism score reducing the average funding amount of $12.2 million by $1.54 million (–12.6%). The finding plausibly indicates that ICO investors are primarily financially motivated and link altruism to a subpar financial performance.

However, we find that several factors mitigate this effect. First, venture quality as measured by the average third-party expert rating provided on ICObench positively moderates the altruism–valuation relation, suggesting that investors value altruism if the fear of poor financial performance is mitigated by a sound business plan and good management team. Second, altruism has a positive marginal effect in firms with good corporate governance. Finally, we also find a reduction in asymmetric information to mitigate the negative financial impact of altruism. With altruism and profit maximization not being naturally aligned, the investment in an altruistic venture presents a trade-off for the investor. A higher level of available information is likely to improve the investor’s ability to assess the magnitude of the trade-off increasing his confidence in the investment.

7.2. Theoretical Contributions and Practical Implications

Previous studies regarding the altruistic (or socially responsible) behavior of firms have largely focused on listed companies with existing ESG-ratings or classification regarding social responsibility. The creation of an altruism score based on texts published by the firm allows us to measure altruistic motivations of companies more precisely and to rate firms even if the amount of publicly available information is very limited, as it is the case for many ICO ventures. Our approach is transparent and easy-to-implement for future research. Our approach may, thus, help to reduce the problem with low external validity of how altruism is operationalized in existing studies.

Innovative startups with altruistic ambitions have a vast potential to positively contribute to society. Thus, their financing is of high importance. The evidence of how socially responsible behavior affects the share price of listed companies is overall ambiguous and does not allow us to draw conclusions regarding the financing of startups. Our findings show that for ICO ventures, a high emphasis on altruistic motives leads to an overall reduction in ICO funding but high expert ratings, good corporate governance, and a reduction in asymmetric information mitigate these effects to some extent.

We further contribute to literature regarding the understanding of ICO investors. While a survey by Fisch et al. (2019) concludes that ideological motives and enthusiasm for the technology are important investment motives next to the financial gains, our results suggest that ICO investors are not solely but primarily driven by financial motives. Our contributions to the understanding of ICO investors are valuable for startups considering ICOs, in particular those with altruistic motivations, as our findings help to improve marketing strategies.

7.3. Avenues for Future Research

ICO investors are often anonymous retail investors. Further research might want to test if our findings are transferable to professional investors. Engelmann and Fischbacher (2009) have shown that reputation gains are an important factor contributing to altruistic behavior or the rewarding thereof. Professional investors are likely to be more concerned with reputation and might be more inclined to support altruistic ventures.

Further, our results suggest that investors avoid altruistic ventures as they fear a worse financial performance. Further research could investigate the impact of altruism on the long-term performance of cryptocurrencies in order to verify whether this fear is justified.

Aside from research related to altruism in ICOs, we also see the applicability of the altruism score to a variety of other firms and settings, allowing for a comparison of different funding dynamics regarding altruistic firms depending on the market.

7.4. Concluding Remarks

Using our unique Natural Language Processing (NLP)-based altruism score, we answer the following research question: How does altruism affect crowdfunding success in Initial Coin Offerings (ICOs)? We find that altruism, on average, is negatively associated with funding success. However, our paper highlights the relevance of a venture's quality, corporate governance, and level of information asymmetry when entrepreneurs raise funds for altruistic projects, as these characteristics have positive moderation effects on the altruism–valuation relation.

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Appendix A

Table A1. Variable definitions.

Control Variables	Definition
Venture Characteristics	
Expert rating	Overall project rating based on the consensus of industry experts on ICObench, scale from 1(low quality) to (high quality)
White paper length, in # words (log)	Natural logarithm of one plus the total words in any given white paper
Team size, in # FTE	Number of team members, full time equivalence
Team members with technical background, in %	Number of team members with with a degree in a tech-related field divided by total team size
Minimum viable product (dummy)	Dummy variable specifying whether a venture has a minimum viable product
Open source (dummy)	Dummy variable specifying whether a venture discloses it's code on GitHub
# Industries (log)	Utilization of ICObench industry classifications to measure the potential industries targeted by the company, defined as the logarithm of one plus the number of industries
Team members with PhD, in # FTE	Number of team members with PhD
Team members with crypto background, in %	Number of team members with experiences in cryptocurrency related domains divided by total team size
Offering Characteristics	
Soft cap (dummy)	Dummy variable specifying whether a venture has announced a soft cap in its token offering, soft cap: minimum funding amount required for the offer to be successful
Hard cap (dummy)	Dummy variable specifying whether a venture has announced a hard cap in its token offering, hard cap: maximum amount of funding that a startup will accept
Pre-sale (dummy)	Dummy variable specifying whether the actual token offering was preceded by a pre-sale event
Whitelist (dummy)	Dummy variable specifying whether the token offering includes an active whitelist
KYC (dummy)	Dummy variable specifying whether the token offering includes a know your customer (KYC) process
Bonus (dummy)	Dummy variable specifying whether the token offering includes a bonus structure(e.g., discounted, of free token if investor reaches certain investment amount)
Bounty (dummy)	Dummy variable specifying whether the token offering includes a bounty program (e.g., discounted, or free tokens for promoting marketing activities of the investor)
ERC-20 (dummy)	Dummy variable specifying whether the token offering is based on ERC-20 technical standard

Table A2. ML seed words and similarity scores.

Seed Word	Word Vectors (Similarity to the Seed)									
altruism	('altruistic', 0.68)	('benevolence', 0.59)	('selfishness', 0.54)	('voluntarism', 0.53)	('humanitarianism', 0.53)	('compassion', 0.53)	('altruists', 0.53)	('altruistically', 0.53)	('idealism', 0.52)	
altruist	('altruistic', 0.50)	('altruism', 0.50)	('egotist', 0.49)	('virtuous', 0.49)	('amoral', 0.48)	('beneficent', 0.48)	('altruists', 0.47)			
aware	('cognizant', 0.73)	('unaware', 0.69)	('mindful', 0.66)	('concerned', 0.63)						
bible	('biblical', 0.45)	('christ', 0.40)								
charity	('charities', 0.79)	('charitable', 0.72)	('fundraiser', 0.55)	('fundraising', 0.54)	('fundraisers', 0.51)	('underprivileged', 0.49)	('philanthropic', 0.48)	('donate', 0.47)	('donations', 0.47)	('donating', 0.47)
community	('communities', 0.69)	('outreach', 0.49)	('organizations', 0.48)	('society', 0.47)	('congregation', 0.46)	('families', 0.46)	('organization', 0.43)			
conscious	('cognizant', 0.52)	('mindful', 0.49)	('consciously', 0.49)	('conscientious', 0.47)	('aware', 0.45)	('consciousness', 0.42)	('wise', 0.38)			
donate	('donating', 0.83)	('donated', 0.74)	('donation', 0.73)	('donates', 0.69)	('donations', 0.61)	('contribute', 0.51)	('charity', 0.47)			
ego	('egos', 0.79)	('egotism', 0.59)	('narcissism', 0.55)	('egotist', 0.53)	('narcissistic', 0.49)					
empathy	('compassion', 0.74)	('empathetic', 0.63)	('sympathy', 0.62)	('affection', 0.57)	('humility', 0.55)	('solicitousness', 0.55)	('emotion', 0.54)	('kindness', 0.53)	('admiration', 0.51)	
ethic	('ethos', 0.71)	('philosophy', 0.61)	('mentality', 0.58)	('individualism', 0.56)	('principles', 0.54)	('ideals', 0.54)	('spirit', 0.53)	('tenets', 0.53)	('mindset', 0.52)	
give	('giving', 0.74)	('gave', 0.74)	('gives', 0.67)	('given', 0.64)						
good										
happy	('happier', 0.62)									
heart	('hearts', 0.59)	('kidney', 0.47)	('lung', 0.47)	('lungs', 0.42)						
help	('helping', 0.64)	('helps', 0.58)	('helped', 0.56)	('needed', 0.50)	('empower', 0.50)					
human	('humans', 0.59)	('humankind', 0.56)	('mankind', 0.53)	('humanity', 0.52)	('animal', 0.49)	('beings', 0.46)	('natural', 0.44)			
kind										
love	('loved', 0.69)	('loves', 0.66)	('hate', 0.60)	('loving', 0.58)	('affection', 0.56)					
need	('needed', 0.73)	('needs', 0.66)	('needing', 0.62)							
peace	('unity', 0.53)	('peaceful', 0.51)	('democracy', 0.51)	('harmony', 0.49)	('democratic', 0.47)	('justice', 0.45)				
people	('individuals', 0.58)	('others', 0.55)	('youths', 0.52)	('children', 0.51)						
philanthropy	('philanthropic', 0.84)	('charitable', 0.64)	('philanthropists', 0.64)	('philanthropically', 0.57)	('philanthropist', 0.57)	('entrepreneurship', 0.52)	('charities', 0.50)	('generosity', 0.50)	('voluntarism', 0.50)	('entrepreneurial', 0.49)
religion	('religions', 0.74)	('religious', 0.72)	('spirituality', 0.59)	('morality', 0.58)	('ideology', 0.57)	('christianity', 0.53)				
revolution	('revolutions', 0.70)	('revolutionary', 0.62)	('revolt', 0.56)	('uprisings', 0.54)	('uprising', 0.53)	('revolts', 0.51)	('movement', 0.48)			
self	('narcissistic', 0.42)	('narcissism', 0.39)	('ego', 0.36)	('selfishness', 0.34)	('centredness', 0.34)	('oneself', 0.33)				
share	('sharing', 0.43)	('shared', 0.42)								
social	('societal', 0.54)	('sociological', 0.48)	('welfare', 0.47)	('socially', 0.47)	('interpersonal', 0.46)	('activism', 0.44)				
thank	('thanking', 0.78)	('thanked', 0.75)	('grateful', 0.70)	('thankful', 0.63)	('gratitude', 0.63)	('appreciate', 0.57)				
volunteer	('volunteering', 0.79)	('volunteers', 0.79)	('volunteered', 0.64)	('outreach', 0.48)	('mentors', 0.48)	('donations', 0.45)	('mentoring', 0.45)	('donation', 0.43)	('donate', 0.43)	
world	('globe', 0.69)	('global', 0.57)	('planet', 0.51)	('global', 0.57)	('worldwide', 0.56)	('globally', 0.54)	('worlds', 0.53)	('planet', 0.51)		

Explanation: The table lists the words in our altruism dictionary. On the left, 31 seed words are shown and on the right, up to 10 of the most similar words in the universe of our trained word2vec model are shown. The cosine similarity scores are printed next to each word.

Notes

1 A "dictator" is given money that she can allocate between herself and a recipient.

2 Players are divided into "firms" and "workers." Firms choose a salary to offer the worker. Subsequently, workers choose an effort level. The effort is costly for workers but leads to a payoff for firms.

3 Two players obtain the same initial amount of money. Player A can decide to give a portion of her money to player B, followed by B having the opportunity to pay back A. In each transfer, the amounts are increased by the experimenter.

4 Two players choose whether to cooperate or to defect. The payoff structure is characterized by defection being the dominant strategy, despite mutual cooperation having a higher payoff. In sequential prisoners' dilemmas, player B observes A's choice before making his own.

5 Similar to dictator games, one person can divide a given amount of money between themselves and the other player. The other person has then the option to accept or decline the offer. In case it is declined, no money will be given out to either player (Güth et al. 1982).

6 Altruism is present in many experiments across the (social) sciences, not just economics, but also health-related studies, e.g., Diener et al. (2018).

7 This section draws on Momtaz (2021a, 2022b).

8 In a supervised setting, researchers rely on a labeled dataset and let the algorithm detect the words that correlate with the labeled attribute. In an unsupervised setting, e.g., in topic modeling, the algorithm comes with a group of words that could potentially be used to measure an attribute. Our approach is a middle ground as we do not have any external reliable metric for labeling altruism in the texts that could be used for the supervision.

9 The word 'Crypto' appears 799 times in our corpus of tweets.

10 Compared to "deep" neural networks where researchers stack many layers of neurons, word2vec has a "shallow" structure.

11 This model contains 300-dimensional vectors for 3 million words and phrases, trained on a subset of the Google News dataset. The model is publicly available at https://drive.google.com/file/d/0B7XkCwpI5KDYNlNUTTlSS21pQmM (accessed on 1 September 2021)

12 Christ Coins are the currency used on the Life Change Platform. Despite the link, both are listed as separate projects on ICObench.

13 www.paulmomtaz.com/data/tord (accessed on 15 June 2021).

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

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