Financing Sustainable Entrepreneurship: ESG Measurement, Valuation, and Performance in Token Offerings

Sasan Mansouri* Paul P. Momtaz†‡

June 20, 2021

Click **here** for the latest version.

Abstract

Sustainable Entrepreneurship (SE) targets profitability *and* sustainability goals. A major research gap concerns SE's economic attractiveness for entrepreneurs and investors. The question is ambiguous because sustainability orientation creates costly constraints, while startups cannot fully appropriate their positive externalities. We relate startups' Environment, Society, and Governance (ESG) properties obtained from a machine-learning approach (www.SustainableEntrepreneurship.org) to SE valuation and performance in token offerings. Startups with salient ESG goals are able to raise financing at more favorable valuations, incentivizing entrepreneurs to adopt ESG goals in the first place. However, their post-funding performance is weaker than in conventional startups, suggesting that investors incur a relative financial loss for backing sustainability-oriented entrepreneurs. The funding and post-funding performance is weaker in startups with high degrees of technological, network, and governance formalization.

Keywords: Sustainable Entrepreneurship, Sustainability, ESG, Token Offering, Initial Coin Offering (ICO), Entrepreneurial Finance, Crowdfunding, Machine Learning
JEL Codes: L26, M13, Q01, Q56

*House of Finance, Goethe-University Frankfurt, Theodor-W.-Adorno-Platz 3. 60629 Frankfurt, Germany. mansouri@finance.uni-frankfurt.de

†(Corresponding author.) UCLA Anderson School of Management, Los Angeles, CA 90095, momtaz@ucla.edu

‡House of Finance, Goethe-University Frankfurt, Theodor-W.-Adorno-Platz 3. 60629 Frankfurt, Germany.

1 Introduction

Sustainable Entrepreneurship (SE) is a rapidly growing literature (for excellent recent reviews, see Anand et al., 2021; Johnson and Schaltegger, 2020).[1] SE is characterized by profit-seeking entrepreneurial activity that embraces the broader (non-financial) Environment, Society, and Governance (ESG) goals of our time.[2] A common theme in the literature is that it evokes Schumpeter's (1942) notion of 'creative destruction' to explain how SE may effect sustainable change (e.g., Cohen and Winn, 2007; J. Hall and Vredenburg, 2003; S. L. Hart and Christensen, 2002; S. L. Hart and Milstein, 1999; Senge et al., 2001; and, for a general discussion of Schumpeterian logic applied to SE, Hockerts and Wüstenhagen, 2010; York and Venkataraman, 2010). The literature's tenet is that market failure to solve ESG challenges creates entrepreneurial opportunities.

An important research gap is whether ESG-driven opportunities are *economically* attractive for entrepreneurs in the first place. Schumpeter (1934, 1942) assumed that technological innovations provide entrepreneurs with a *business case* (often associated with more cost-efficient production than incumbents), which is the underlying force behind unfolding 'creative destruction' dynamics. It is ambiguous, however, whether such a business case exists for SE for at least two reasons: (i) ESG goals impose binding restrictions upon entrepreneurs that limit the scope of viable routes to (economic) success, and (ii) entrepreneurs largely fail to internalize ESG rents because they come as positive externalities. Uncertainty about the economic appeal of SE is ubiquitous in the literature. For example, J. K. Hall et al. (2010) refer to SE as a "controversial" field with "major gaps in our knowledge of whether and how this process [i.e., SE] will actually unfold", partly because opportunities for SE "lie beyond the pull of existing markets" (p. 439). Our paper is a first step to address this important gap by posing the following research question:

How (economically) attractive is SE for entrepreneurs and investor?

This question is fundamental for SE scholars and policy-makers alike because a potential lack of economic incentives would suggest the need of government subsidies for entrepreneurs to act as ESG "change agents" (Anand et al., 2021, p. 2), and potentially for SE scholars to adopt a different lens than Schumpeter's (1942).[3]

[1]For earlier reviews, see Bischoff and Volkmann, 2018; Dean and McMullen, 2007; Gast et al., 2017; Kraus et al., 2018; Muñoz and Cohen, 2018; Sarango-Lalangui et al., 2018; Schaefer et al., 2015; Shepherd and Patzelt, 2011; Terán-Yépez et al., 2020.

[2]SE's profit orientation is the key distinguishing factor from social and environmental entrepreneurship that focuses on socio-ecological returns as its primary goal, as Kraus et al. (2018), among others, discuss.

[3]It is important to note that our focus is on the financial rents of SE, as there is no consensual way of how to measure non-financial rents. In the SE context, Anand et al. (2021, p. 12), discuss that "concerns regarding 'how to measure sustainability' emerge as one of the major challenges."

We argue, both theoretically and empirically, that a sufficient condition for SE to effect sustainable change is that sustainability-oriented startups obtain enough funding at sufficiently high valuations relative to conventional startups. The literature on financing SE is very limited, with the notable exception of Vismara (2019).[4] Therefore, reflecting the "multidisciplinary character" of SE (Anand et al., 2021, p. 1), we also borrow from signaling (Ahlers et al., 2015; O. Colombo, 2021; Fisch, 2019), non-economic utility (Barber et al., 2021; Cornell, 2021), and financial markets theory (Fama and French, 2007; Pástor et al., 2020; and, for a review in the ESG context, Gillan et al., 2021) to develop two specific hypotheses relating to the valuation and performance of sustainable startups.

The prospects of non-economic utility is the key feature distinguishing SE from Conventional Entrepreneurship (CE) in entrepreneurial finance markets (Vismara, 2019). In the hypothetical scenario that SE and CE share the same business case, SE should receive higher valuations, with the differential being attributable to investors' ESG-related utility. An '*ESG premium*' on startup value is even in line with Friedman's (1970) famous claim that "the social responsibility of business is to make profits." As long as entrepreneurs have a competitive advantage to jointly achieve economic and ESG goals, then investors should delegate ESG goals to entrepreneurs with specialized skills (O. Hart and Zingales, 2017). For example, it is more efficient for investors to delegate their ESG goals to three specialized startups — one that targets E-goals, another for S-goals, and a third for G-goals — than to tackle all ESG goals jointly themselves. Therefore, under our '***Valuation Premium Hypothesis***' (***VPH***), SE (relative to CE) receives higher valuations. As further discussed in section 3, the *VPH* can be connected to existing evidence that SE is associated with, inter alia, better risk management (Knight, 1997; Kraus et al., 2018), (ii) trust-creating altruism (Momtaz, 2020c; Tilley and Young, 2009), (iii) first-mover advantages (Hockerts and Wüstenhagen, 2010; Lieberman and Montgomery, 1988), and (iv) personal characteristics that are correlated with signals of entrepreneurial quality, such as human, social, and intellectual capital (Ahlers et al., 2015; O. Colombo, 2021; Egri and Herman, 2000; Fisch, 2019; Spence et al., 2011; Vega and Kidwell, 2007).

The flip side of delegated philanthropy is that SE may (economically) underperform in the long run, which is at the core of much controversy in the SE literature (J. K. Hall et al., 2010; Kraus et al., 2018). We label this prediction the '***Post-Funding Underperformance Hypothesis***' (***PFUH***). Financial equilibrium theory argues that investors' higher 'willingness-to-pay' (Barber et al., 2021, p. 1), which is a source of the ESG premium in the first place, has to be followed by lower expected (financial) returns (Fama and French,

[4] Also, see D. Cumming et al. (2016), D. J. Cumming et al. (2017), Guzmán et al. (2020), and Hörisch (2015).

2007; Gillan et al., 2021). Two important aspects deserve elaboration. Lower financial returns (i.e., underperformance) does neither eliminate incentives for entrepreneurs nor for investors to get involved in SE. Entrepreneurs benefit from the ESG premium during the funding stage. Investors sacrifice financial returns for the sake of ESG returns. In aggregate, that is, after adding ESG to financial returns, investors may be better off, depending on their personal preferences for sustainability goals. Therefore, it is helpful to draw a distinction between 'investor value' and 'investor welfare,' only the latter referring to combined economic and ESG rents. To our knowledge, our study is the first to examine the long-term economic performance of SE.[5]

Empirically, we employ a machine-learning (ML) approach to quantify startups' ESG properties, using information disclosed in ICO whitepapers. Specifically, we take advantage of Mikolov et al.'s (2013) powerful semi-supervised word-embedding approach, which trains a neural network to learn the meaning of words and phrases within their respective context. Our approach to finding the ESG-related words and phrases is inspired by Li et al., 2020 in the sense that we define a set of "seed" words/phrases in the first step, and then use the trained word embedding model to find the closest terms to our seeds. We collect all the Financial Times' articles tagged as "ESG investing" or "Moral Money", and focused on their most frequent words and phrases to manually create seed word lists of Environmental (E)-, Social (S)-, and Governance (G)-related terminologies. Our procedure yields a total of 1,495 ESG-related terms consisting of 508, 463, and 524 terms for E, S, and G, respectively. We then measure startups' E, S, and G intensities by measuring the unique counts of the terms from the respective word list in the whitepaper. The sum of the three E, S, and G intensities gives a startup's aggregate ESG score. Manual inspection suggests that our ESG scores are highly performant in identifying the startups with the most salient ESG properties. For replication purposes and as an aid for future SE research, we make our source code available and also developed an easy-to-use web application at www.SustainableEntrepreneurship.org.

Our results support both the VPH and the PFUH. We examine a large sample of 1,043 token offerings over the 2016-2020 period.[6] Token offerings are blockchain-based crowd-

[5]Our study estimates financial undeperformance of SE, that is, investor value. Investor welfare, in contrast, cannot be observed directly, as sustainability preferences are heterogenous across investors and private. Nevertheless, our study can be understood as an upper bound to ESG rents, acknowledging the fact that not the full amount of SE underperformance relative to CE may be attributed to ESG rents, as moral hazard in ESG signaling may also explain part of the underperformance (Momtaz, 2020a; Spence et al., 2011). Other studies that focus on SE outcomes, but with a different focus are Dickel (2017), Djupdal and Westhead (2015), Gregori et al. (2019), Hoogendoorn et al. (2019), Jahanshahi and Brem (2017), Kraus et al. (2017), Lans et al. (2014), Muñoz, Cacciotti, et al. (2018), Mupfasoni et al. (2018), Testa et al. (2019), and Volkmann et al. (2021).

[6]Our paper is fully replicable. The data come from the Token Offerings Research Database (TORD), see

funding campaigns, in which smart contracts govern the exchange of fiat money for tokens between investors and entrepreneurs (Amsden and Schweizer, 2018; Bellavitis et al., 2020; Bellavitis et al., 2021; Fisch, 2019; Giudici and Adhami, 2019; Howell et al., 2020; Huang et al., 2020; Momtaz, 2019, 2020b). Startups with salient ESG properties benefit from substantially higher valuations, supporting the *VPH*. A one-standard-deviation increase in the ESG metric is associated with a 28% increase in the funding amount, which corresponds to around $4.2mmillion (relative to the mean funding amount of $15.2m million in our sample). Further, consistent with the *PFUH*, startups with pronounced ESG properties underperform during the first year after which a token was listed on an exchange platform. A one-standard-deviation increase in the ESG metric is associated at least with a 16% decrease in the first 12-months buy-and-hold abnormal (equally weighted relative to a composite market index) token price performance after the crowdfunding event. Relative to financial utility, non-financial (ESG-related) utility for SE investors amounts to 16-31% of total utility.[7] Both main results are robust to endogeneity concerns related to observed and unobserved heterogeneity.

Given these results, an important next question for entrepreneurs and investors alike in moving forward with SE is whether and how the negative effect on financial performance can be mitigated (Parrish, 2010, for a general discussion of organizational design differences between SE and CE). The excellent review by Kraus et al. (2018) synthesizes the literature, concluding that a high degree of formalization may drive poor SE performance. Formalization refers to all organization structure, such as "control systems and reporting procedures, as well as the formal style of tracking the progress" (Kraus et al., 2018, p. 8). Therefore, the empirical patterns predicted by the *VPH* and the *PFUH* should be negatively moderated by a high degree of formalization. Consistent with this reasoning, technological, network, and governance aspects associated with startup formalization all hurt SE success. This marks a stark contrast to CE. While typical technology startup attributes, such as open-source code, a large social network, and venture capital backing, are typically associated with entrepreneurial success (Fisch, 2019; Fisch and Momtaz, 2020), they can be detrimental in ESG startups. The finding highlights the need for future research to better understand how organizational design can promote, rather than hurt, sustainability-oriented venturing.

The remainder of the paper is organized as follows. Section 2 reviews the existing and multidisciplinary literature on SE and section 3 derives empirical predictions. Section 4

www.paulmomtaz.com/data/tord, and the machine-learning algorithm to quantify ESG properties of our sample startups is made available along this publication.

[7]We view this estimate as an upper bound on ESG-related utility. See also footnote 5.

discusses our machine-learning approach to quantify startups' ESG properties. Section 5 describes our sample and section 6 presents our empirical results. Finally, Section 7 provides a discussion, highlights limitations and potential avenues for future research, and concludes.

2 Related Literature

2.1 Sustainable Entrepreneurship

A consensual definition of sustainable entrepreneurship does not yet exist. However, Anand et al. (2021) and Johnson and Schaltegger (2020) provide excellent recent reviews of the literature.[8] Early studies draw on the concept of "sustainable development," which was introduced in 1987 by the *United Nations' World Commission on Environment and Development* (*WCED*) (e.g., Cohen and Winn, 2007; Dean and McMullen, 2007; J. K. Hall et al., 2010). According to the WCED, sustainable development refers to the striving of society to satisfy its needs without compromising the ability of future generations to satisfy their needs. Some studies draw a strict demarcation line between SE and social and environmental entrepreneurship along the entrepreneurs' distinct objective functions. As reviewed in Kraus et al. (2018), SE's primary goal is to create *positive financial returns* while not harming society and the environment (i.e., *non-negative non-financial returns*), whereas social and environmental entrepreneurship's primary goal is to create *positive non-financial returns*. Further, in contrast to the broader ESG literature in management and economics, the focus of SE has thus far been on E and S goals, thus neglecting G goals. For example, Dean and McMullen (2007) define SE as "the role entrepreneurs can play in creating a more socially and environmentally sustainable economy" (p. 53). For the purpose of our paper, we propose an inclusive definition of SE that embraces all ESG aspects and highlights the dual objective function, as follows:[9]

SE encompasses all entrepreneurial activity that in addition to positive financial returns aims at generating non-negative non-financial returns related to environmental, social, and governance aspects.

[8]Other very helpful reviews of sustainable entrepreneurship include Bischoff and Volkmann (2018), Dean and McMullen (2007), Gast et al. (2017), Kraus et al. (2018), Muñoz and Cohen (2018), Sarango-Lalangui et al. (2018), Schaefer et al. (2015), Shepherd and Patzelt (2011), and Terán-Yépez et al. (2020).

[9]In this sense, our definition abstracts from Cohen and Winn's (2007, p. 35) that focuses mainly on opportunities from environmental degradation, which itself is based on Venkataraman (2019): "*how opportunities to bring into existence 'future' goods and services are discovered, created, and exploited, by whom, and with what economic, psychological, social, and environmental consequences*."

Existing work on SE is "truly multidisciplinary" (J. K. Hall et al., 2010, p. 441). In terms of the entrepreneurial lifecycle, a substantial and rapidly growing literature with heterogeneous perspectives has emerged, dealing with antecedents of SE, SE opportunity recognition and execution, and SE outcomes, although outcomes are the least studied aspect of SE (Anand et al., 2021).[10]

Antecedents of SE can be distinguished at the individual and the contextual level (Anand et al., 2021; Kraus et al., 2018). *Individual antecedents* include the entrepreneur's personal intent and characteristics (Kimuli et al., 2020; Kuckertz and Wagner, 2010), with the consensus that sustainability-oriented entrepreneurs have salient moral and altruistic preferences (Ploum et al., 2018; Vuorio et al., 2018), display self-efficacy (Muñoz, Janssen, et al., 2018), sustainability-oriented values, beliefs, and motivations (Jahanshahi and Brem, 2017; Mupfasoni et al., 2018; Spence et al., 2011), education and capabilities (Obrecht, 2011, 2016) and, in particular, prior knowledge (Mupfasoni et al., 2018). *Contextual antecedents* include environmental regulations, consumer awareness, and demand (Hooi et al., 2016), other institutional enablers, such as social norms and market incentives (Meek et al., 2010; Pacheco et al., 2010; Shepherd and Patzelt, 2011), as well as local embeddedness, stakeholder involvement, and collaborations (Schaltegger et al., 2018).

SE opportunity-identification processes are often analyzed through the lens of business model choices (e.g., hybrid (Davies and Chambers, 2018), transformative (Binder and Belz, 2017; Hahn et al., 2018), and sustainability-focused (Breuer et al., 2018) business models; and for an excellent overview, see Schaltegger et al., 2016). Sustainable business model studies often investigate trade-offs between financial and non-financial, ESG-related returns, although the evidence is mixed (Anand et al., 2021; Schaltegger et al., 2016). In a widely-cited contribution, Parrish (2010) interviewed 32 individuals and concludes that sustainability-oriented entrepreneurs have to employ "perpetual reasoning" to "succeed in a competitive market context" while conventional entrepreneurs can employ "exploitative reasoning," which leads to implications about organizational design choices for SE that "diverge in important ways from the conventional principles of entrepreneurship" (p. 510).

[10] Johnson and Schaltegger (2020) propose an alternative classification of the literature by SE processes, and SE challenges and opportunities. SE processes can span macro-social and global contexts, such as reducing economic inequality, fighting poverty and climate change (Muñoz and Cohen, 2017; Stål and Bonnedahl, 2016; Yunus et al., 2010)), within and between markets, such as counteracting the degradation of natural resources (Cohen and Winn, 2007; Dean and McMullen, 2007), and the timeline of venture development, such as SE formation, execution, and managing the "triple bottom line" (Binder and Belz, 2017; Choi and Gray, 2008; Parrish, 2010; Stubbs, 2017). SE challenges and opportunities can be summarized a the macro level, such as poverty and climate change (Mair and Marti, 2009; Shepherd and Patzelt, 2011), at the meso level, such as helping local communities, e.g., with micro-financing or with ideas to reverse environmental degradation (Cohen and Winn, 2007; Dean and McMullen, 2007), and at the micro level, such as the resource mobilization and joint venturing initiatives (Desa, 2012; York et al., 2016).

Finally, outcomes of SE is arguably the least studied and most segmented field in the literature. SE outcomes refer to the performance of sustainability-oriented ventures in terms of the 'triple bottom line' (i.e., people, planet, profit). Although Anand et al. (2021) stress that there "is a need to engage more closely with the outcomes of SE activity" (p. 15), there are a few studies that tackle the outcome question. These studies fall broadly into two areas: *ESG impact* and *SE financing and investing performance*.

First, the *'ESG impact'* area is concerned with the contributions SE makes to ESG goals (e.g., Dickel, 2017; Djupdal and Westhead, 2015; Hoogendoorn et al., 2019; Jahanshahi and Brem, 2017; Kraus et al., 2017; Lans et al., 2014; Muñoz, Cacciotti, et al., 2018; Mupfasoni et al., 2018; Testa et al., 2019; Volkmann et al., 2021). The literature is limited in two important ways. First, the very nature of ESG goals (i.e., very long-term, partly subjective and context-dependent, and highly inter-dependent) confront researchers with the "major challenge" of coming to a consensus on the question "how to measure sustainability" (Anand et al., 2021, p. 12). Second, given the SE's historical emergence that is tied to entrepreneurial opportunities that emerge from market failure to prevent environmental degradation (e.g., Cohen and Winn, 2007; Dean and McMullen, 2007), most of the work on ESG impact is limited to environmental impact (Anand et al., 2021).[11]

Second, and most important for the focus of our study, the *'SE financing and investing performance'* area "has a relatively short history" (Böckel et al., 2020, p. 433). The reason is that traditional players in the entrepreneurial finance market are often exclusively interested in financial rents (Block et al., 2018; Vismara, 2016), and thus "the lack of financing is a key obstacle that keeps the potential of sustainable entrepreneurship from being unleashed" but "crowdfunding is expected [...] to remove this obstacle" (Böckel et al., 2020, p. 435). A number of studies looks at the financing of SE, but the aggregate evidence on the subject is rather limited. D. Cumming et al. (2016) find a positive relationship between venture capital activity and oil prices in the alternative energy sector ('cleantech'); D. J. Cumming et al. (2017) find that reward-based crowdfunding campaigns on *Indiegogo* of cleantech projects are more successful if the projects are not-for-profit and have a video pitch, whereas, using an overlapping sample from the same crowdfunding platform, Hörisch (2015) finds no relationship between environmental orientation and crowdfunding success; Calic and Mosakowski (2016) finds some support for a positive relation between sustainability orientation and reward-based crowdfunding success in technology and film/video projects on *Kickstarter*; finally, Vismara (2019) shows

[11]Böckel et al. (2020) contest the environment-bias argument in Anand et al. (2021), and argue that the society bias is more pronounced. Nevertheless, both reviews have in common that the governance aspect is entirely missing from the SE literature.

that sustainability-oriented equity-based crowdfunding campaigns are less likely to attract professional investors. Overall, the literature on financing SE is relatively nascent, and a comprehensive examination of the subject may help address several important voids in the literature, such as the "research gap related to the post-funding phase" (Böckel et al., 2020, p. 433).

2.2 ESG Investing

Sustainable (or impact) investing describes the practice of investors to take ESG considerations into account when making investment and portfolio decisions. Sustainable investing is experiencing soaring growth (Gillan et al., 2021; Pástor et al., 2020). This is mainly driven by large net capital inflows that investment funds experience from institutional investors. For example, in 2019, mutual funds received more than $20 billion in net capital inflows, which icnrease fourfold from the year before.[12] Further, the Principles of Responsible Investments (PRI) initiative had $86 trillion assets under management in 2019 (up from $6.5 trillion in 2006), and more than 3,0000 instititutional players in the financial market have commited to the initiative in 2019.[13] Accordingly, most S&P500 firms have realized the increased demand of ESG, and 86% have published separated sustainability or responsibility reports in 2018 (up from 20% in 2011) (Gillan et al., 2021).[14]

The ESG literature is limited in a number of important ways. First, measures of ESG are offered by several data providers, and the between-provider correlation is very low. Thus, there is substantial disagreement as to how ESG is measured, and as to how different ESG components are weighted to arrive at a composite measure. Second, it is also not clear over what time horizon ESG activities should be measured. Most ESG activities are long-term, however, to observe a significant impact of ESG measures may take longer than a lifetime (e.g., activities aimed at stopping climate change). Third, ESG is a relatively recent phenomenon, and hence the market may be transitioning to a new equilibrium, and therefore it is not clear whether current studies measure a new steady state or simply a transitory, temporary state during the dynamic adjustment process. Fourth, it is not clear in what direction causality runs. That is, it is not clear whether the underlying mechanism is 'doing well by doing good' or 'doing good by doing well.' Finally, ESG has been studied in many asset classes, such as stocks, bonds, bank loans, and real estate. However, ESG is still largely missing from the entrepreneurial finance literature (with some notable exceptions,

[12] https://www.morningstar.com/articles/961765/sustainable-fund-flows-in-2019-smash-previous-records

[13] https://www.morningstar.com/articles/961765/sustainable-fund-flows-in-2019-smash-previous-records

[14] https://www.ga-institute.com/press-releases/article/flash-report-86-of-sp-500-indexR-companies-publish-sustainabilit html

such as D. Cumming et al., 2016; D. J. Cumming et al., 2017; Vismara, 2019).

2.3 Token Offerings

Token offerings or Initial Coin Offerings (ICOs) are blockchain-based crowdfunding campaigns, in which investors wire fiat money or other cryptocurrencies via the blockchain and receive tokens from the fundraising venture. The transaction is fully automated by a smart contract, often on the Ethereum blockchain (ERC20). Tokens are often categorized in three ways: (i) cryptocurrency tokens, such as *Bitcoin*, are mere mediums of exchange, (ii) utility tokens are payment instruments that investors can redeem for a product or service of the issuing venture once developed and on the market, and (iii) security tokens are equity-like instruments that give investors control rights. Shortly after the offering, projects typically list their tokens on liquid exchange platforms, enabling investors to trade tokens with one another (Adhami et al., 2018; Bellavitis et al., 2020; Fisch, 2019; Momtaz, 2020a, 2020b). To our knowledge, we are among the first to look at token offerings to examine the funding success and post-funding performance of SE vs. CE projects.[15]

Token offerings are an ideal playing field to shed more light on the financing of sustainability-oriented startups for at least two reasons. First, the market for token offerings is predominantly populated by individual investors with simultaneous financial and non-financial investment goals (Fisch et al., 2019). Like in crowdfunding (e.g., Giudici et al., 2018), token offerings were born out of disappointment with the fairness of traditional financial markets (Fisch et al., 2020; Howell et al., 2020; Nakamoto, 2019). Therefore, investors in token offerings may be particularly sensitive to the sustainability orientation of potential investment objects. Second, unlike any other entrepreneurial finance mechanism, institutional features surrounding token offerings facilitate a quantitative analysis of ESG and startup valuation and performance. Specifically, (i) it is standard practice that projects in token offerings publish extensive whitepapers disclosing important information, such as how they aim to solve ESG challenges, and (ii) the post-offering listing of tokens on exchange platforms enables to track the financial performance of the projects on a daily basis and in an transparent way by observing equilibrium prices formed by supply-and-demand dynamics in liquid markets. As Böckel et al. (2020), among others, discuss, the post-funding performance of sustainability-oriented startups is an important "research gap" (p. 433). Thus, fair prices obtained from liquid token exchange markets that provide a transparent measure of post-funding performance can help close this gap.

[15] See, also, Guzmán et al. (2020), for a concurrent study with the more narrow focus on global warming.

3 Hypotheses

3.1 ESG and Funding

Like conventional entrepreneurs, sustainable entrepreneurs identify an entrepreneurial opportunity and tap entrepreneurial finance markets for funding. Unlike conventional entrepreneurs, however, sustainable entrepreneurs' funding success is not only determined by the future expected cash flows that investors may receive in the future but also by the expected non-financial utility (Block et al., 2021; Vismara, 2019). The literature offers two potential reasons as to why sustainable entrepreneurs may benefit from higher valuations during the funding stage: the economics of delegated philanthropy and the signaling value associated with ESG properties.

The economics of delegated philanthropy. Friedman's (1970) famous proclaimation that 'the social responsibility of business is to increase its profits' is often used as an argument against ESG/CSR initiatives. However, Friedman's (1970) theoretical argument is based on sophisticated assumptions: (i) markets are competitive, (ii) the regulatory framework is able to internalize external costs, (iii) companies do not have a competitive advantage vis-à-vis their shareholders to do good, and (iv) companies cannot influence regulation. Under these assumptions, corporate ESG initiatives do not add investor value. However, these assumptions are usually violated in reality, potentially providing ESG strategies with a business case.

For example, if investors also have ESG preferences and financially profitable activities cannot be perfectly separated from ESG-detrimental ones (i.e., a violation of Friedman's third assumption), then companies should indeed maximize investor "welfare" (as compared to "value") (O. Hart and Zingales, 2017). In these situations, and in line with Friedman (1970), companies should augment the business objective and include ESG goals in addition to the financial return. An example for such 'delegated philantrophy' would be a startup involved in the production of 3-D printers that enable customers to produce assault rifles. Assuming that investors have a preference for anti-gun legislation, the startup could pay investors a dividend, which they themselves could then donate to anti-gun initiatives. However, it would be more efficient if the startup would not sell its 3-D printers to facilitate the production of guns in the first place. While this hurts profits, it serves the greater social goal of the anti-gun movement, and could maximize total (financial and non-financial) shareholder utility (O. Hart and Zingales, 2017).

Empirical evidence suggests that 'doing well by doing good' can work. Traditional financial markets theory assumes equilibria to be driven by investor preferences for future consumption (Fama and French, 2007). However, if investors incorporate ESG preferences into their utility models, then valuations and expected returns can deviate from the equilibrium suggested by the standard models (Cornell, 2021; Pástor et al., 2020). Therefore, investors with ESG preferences drive up demand for ESG assets, which increases their prices, lets cost of capital decrease, and therefore makes it cheaper to invest in ESG projects. If consumers incorporate ESG considerations also into their 'willingness-to-pay' models (Barber et al., 2021), ESG companies would also profit from higher cash inflows. Additionally, Edmans (2011) finds that employee satisfaction (a measure of G in ESG) increases corporate productivity, and Lins et al. (2017) and Albuquerque et al. (2020) report that ESG policies create trust and loyalty among customers, which acts as an insurance during economic downturns. Therefore, the economics of delegated philanthropy suggests that, under certain assumptions, sustainability-oriented entrepreneurs may receive higher valuations thanks to the add-on non-financial utility they generate for investors with pronounced ESG preferences.

ESG-related signaling. Several papers have established the importance of signaling venture quality for the funding success in token offerings (e.g., Fisch, 2019; Momtaz, 2020b). Building on these findings, we explore additional signaling dimensions that are proprietary to sustainable entrepreneurship. There are at least five such arguments. First, a key concern for investors in token offerings is moral hazard on the part of the entrepreneur who signals her quality (Momtaz, 2020a) and outright fraud (Hornuf et al., 2021). Sustainability orientation on the part of the entrepreneur may signal non-financial motives which reduces investor concerns and creates trust. Second and similarly, the ESG orientation signals management team's awareness for broader issues than just the narrow business scope, which may help foresee and prevent adverse events. Thus, sustainability orientation may be correlated with broad awareness for strategic developments, and therefore valuable from a risk management perspective (Kraus et al., 2018). Third, given that crypto markets are relatively strongly populated by younger generations and these generations have been shown to have pronounced ESG orientations (more so than older generations), sustainable entrepreneurs may create a sense of identification among these younger investment groups (Fisch et al., 2019; Kraus et al., 2018; Spence et al., 2011). Fourth, sustainability orientation may act as an insurance mechanism. Given the highly dynamic and competitive token offerings market, a key risk for entrepreneurs and investors is early project competition (or imitation). The ESG profile of sustainable entrepreneurs may help preserve the USP and help retain customer base or growth share (when a similar but non-ESG competitor threatens), thereby reducing this source of risk (Anand et al., 2021; Johnson and Schaltegger, 2020). Finally and very importantly, ESG awareness has been shown to be correlated with human, social, and intellectual capital, which are first-order determinants of funding success in startup financing (Ahlers et al., 2015; Fisch, 2019; Spence et al., 2011).

To summarize, the above rationale might theoretically justify a sustainability premium for high-ESG ventures. The financing of SE may be positively influenced in three ways: (i) SE may receive more funds thanks to an expanded market size (i.e., high-ESG otherwise-non-investors), (ii) SE may steal investors away from CE but otherwise similar ventures, and (iii) SE may benefit from increased willingness-to-invest among high-ESG investors thanks to the non-financial utility they may receive. Such a sustainability premium could be particularly pronounced in the token offerings context, which is arguably populated by investors with salient non-financial preferences (Fisch et al., 2019; Schückes and Gutmann, 2020).

H1: *The relation between ESG properties and startup firm valuation is positive.*
(The Valuation Premium Hypothesis, VPH)

3.2 ESG and Post-Funding Performance

How does sustainable entrepreneurship perform after the fundraising campaign compared to conventional entrepreneurship? As J. K. Hall et al. (2010) discuss, "while the case for entrepreneurship as a panacea for transitioning towards a more sustainable society is alluring, there remain major gaps in our knowledge of whether and how this process will actually unfold." The financial performance is such a "major gap," as we are not aware of any study that has looked at the relationship between ESG and long-term financial performance in the entrepreneurial context. Indeed, Böckel et al.'s (2020, p. 433) recent review of studies in the intersection of crowdfunding and sustainability concludes that there exists a major "research gap related to the post-funding phase." Even more generally, the post-financing performance of token offerings and crowdfunding is probably the "least explored" topic (Vanacker et al., 2019, p. 237), not even considering the question of sustainability.

Not many, but a few notable studies look at the post-funding performance of crowdfunded startups. Mollick and Kuppuswamy (2014) report that reward-based crowdfunded ventures on *Kickstarter* over the 2009-2012 period added on average 2.2 new employees (with a standard deviation greater than 9) and 32% of the firms had revenues in excess of $100,000. Iyer et al. (2016) studies lending-based crowdfunding and reports a post-funding default rate of 30%, which clearly exceeds the average return, thus indicating that lending-based crowdfunding campaigns underperform traditional lending markets. Signori and Vismara (2018) look at 212 crowdfunding campaigns and show that only 3 of them exited successfully through an acquisition. Walthoff-Borm et al. (2018) provide very interesting findings by comparing equity-based crowdfunding campaigns on *Seedrs* and *Crowdcube* in the UK. They report lower financial performance, measured as returns on assets, relative to non-crowdfunded startups. Importantly, they are able to compare the returns in ventures in which investors become direct shareholders to those in which they become indirect shareholders (i.e., *Seedrs* uses a nominee structure in which the platform holds and manages the shares). They find that direct shareholdings, which is more comparable to our token offerings context, are more likely to loose and less likely to invest in intangibles. Thus, Walthoff-Borm et al. (2018) is the only crowdfunding study that might suggest that startups with salient ESG attributes (i.e., intangible goals) might underperform post-funding.

Studies on the long-term performance of token offerings are also rare. Momtaz (2021b) studies the performance of crypotcurrencies issued in token offerings over a three-year holding period, and reports that larger ventures underperform. To the possible extent that the sustainability premium (which inflates venture size via the sustainability-related valuation premium) contributes, this finding may suggest that sustainable entrepreneurs are more likely to underperform. Fisch and Momtaz (2020) study the involvement of institutional investors on the post-ICO performance of ventures, and find that the relationship is positive. Given that institutional investors focus on financial performance and shy away from ESG startups (Vismara, 2019), the finding may also indicate that ventures focusing on ESG may underperform. However, we have to attest to the lack of work on the post-funding performance of crowdfunded startups, and acknowledge that the existing work in entrepreneurial finance is *at best* vaguely indicative of SE underperformance.

Given this lack of prior work to build upon, we draw on the broader ESG investing literature (for a review, see Gillan et al., 2021).[16] The overarching tenet is that ESG commitment poses a *binding constraint* that may restrict managerial agility and therefore depress financial performance (Barber et al., 2021; Cornell, 2021). This may be of partic-

[16] It is important to note that there is also no consensus on the performance question in the sustainability literature itself (Anand et al., 2021). Two examples. First, on the one hand, sustainability-oriented ventures may perform better thanks to an increased market size (i.e., gaining high-ESG preference customers), while, on the other hand, they may underperform because they loose low-ESG groups that are, e.g., not willing to pay more for ESG products (Hörisch, 2015; Kraus et al., 2018). Second, some argue that ESG provides intrinsic motivation to entrepreneurs that may boost performance, while others argue that ESG-driven entrepreneurs are "dreamers" and unlikely to be successful businessmen (Edmans, 2011). In both cases, the net effect of sustainability orientation is not clear, which makes the topic "controversial" (J. K. Hall et al., 2010, p. 439).

ular importance in the entrepreneurial context, where hypothesis testing and frequently changing directions is of paramount importance (Johnson and Schaltegger, 2020; Kraus et al., 2018). Thus, a number of studies argues that sustainability is at odds with the prevalent capitalist organization of society (e.g., Balakrishnan et al., 2003).

The consensus in the ESG investing literature is clear: High-ESG investments *under*perform (Gibson et al., 2020; Liang and Renneboog, 2017; Renneboog et al., 2008). This is because ESG commitment creates a binding restriction on portfolio choice which leads to underdiversification, which in turn hurts the risk-return trade-off. Mechanically, equilibrium asset pricing theory suggests that high valuations are related to lower expected returns (Campbell et al., 2012; Fama and French, 2007). For this reasons, if there is a sustainability premium, as hypothesized in ***H1***, then the long-run performance of sustainable entrepreneurs should be negative. We illustrate our two main predictions in Figure 1.

H2: *The relation between ESG properties and post-funding performance is negative.*
(The Post-Funding Underperformance Hypothesis, PFUH)

[Place Figure 1 about here.]

3.3 Technological, Network-, and Governance-Related Formalization

Prior work on sustainable entrepreneurship shows that the integration of sustainability aspects into the venture model creates a high degree of formalization (Kraus et al., 2018). For example, control systems, reporting procedures, process disclosure requirements, and policies that track behavior, such as those efforts associated with obtaining CO_2-neutrality or green certificates from environmental non-profit organizations, all counteract with entrepreneurial flexibility to foster intuitive management styles that help manage the start-up process in an agile manner to reduce execution risk (Kraus et al., 2018; Spence et al., 2011).

The high degree of formalization is "counterintuitive and potentially disadvantageous" and can "potentially be hazardeous" (Kraus et al., 2018, p. 8) for the success and survival of ventures for several reasons. First, formalization requires venture teams to adhere to policies and standards put in place, which has a prolonging effect on the time horizon after which the venture can start harvesting the fruits of its efforts. In particular, in the highly dynamic and competitive startup space, when sustainable entrepreneurs have more uncertain and long-term goals than conventional entrepreneurs, the high degree of formalization poses the risk for the venture to 'die along the way' (Spence et al., 2011). Second, prior work shows that sustainable entrepreneurs are more risk averse (Weerawardena and Mort, 2006), which reflects an attitude that is often associated with lower entrepreneurial success because entrepreneurial exploration inherently requires substantial risk taking (S. P. Kerr et al., 2017; W. R. Kerr et al., 2014). The high degree of formalization in sustainable ventures may amplify an entrepreneur's risk aversion, as policies and standards may to some extent provide a narrative that justifies not taking additional risk (Spence et al., 2011). Thus, various dimensions of formalization, such as technical, network, and governance formalization, may be negatively related to the relations between sustainability orientation and ventures' valuations and performances.

H3a: *The proposed positive relationship in **H1** is less pronounced when the sustainable entrepreneur's degree of technological, network-, and governance-related formalization is high.*

H3b: *The proposed negative relationship in **H2** is more pronounced when the sustainable entrepreneur's degree of technological, network-, and governance-related formalization is high.*

4 Quantifying Startups' ESG Properties

4.1 ESG Measurement in Existing Studies

The measurement of startups' ESG properties is relatively ad-hoc in existing studies, and a unified framework is missing so far from the literature. For example, Vismara (2019) regresses the dummy variable "sustainability orientation" on the funding amount in crowdfunding campaigns, which is based on whether the projects' descriptions include at least one of the following terms: "sustainability," "sustainable," "ecological," "eco-innovation," "eco-efficient," "eco-effective," "eco-design," "ecology," "environmental," "green," "renewable," "cradle to cradle," "dematerialization," "backcasting," "biomimicry," "jugaad innovation," circular economy," and "closed-loop production;" Hörisch (2015) uses entrepreneurs' self-classification as "environmentally oriented" on crowdfunding platform *Indigogo*; and Guzmán et al. (2020) regress the global frequency of Google searches with the search term "global warming" without any concrete reference to their specific sample.

We hope to address this problem by offering an integrated machine-learning approach that quantifies startups' ESG properties from text data (e.g., press releases, whitepapers, *Github* documentation, text on their own website as well as on others, such as *Crunchbase*, among others). The advantage of a broad adoption of our approach would be the comparability of results across ESG studies (Gentzkow et al., 2019; Li et al., 2020; Loughran and McDonald, 2020), as well as a reduction in the subjectivity of ESG measurement in the literature (Berg et al., 2020; Dimson et al., 2020).

4.2 ESG Measurement: A Machine-Learning Approach

Our goal is to measure startups' ESG properties in a relatively objective way from text data (i.e., the information disclosed by startups during their fundraising campaigns). Our approach is in the spirit of the broader "text as data" literature in economics, as reviewed in Gentzkow et al. (2019), which relies on word counts based on topic-specific dictionaries (or word lists). Therefore, our task involves two steps:

1. Creation of an ESG-specific dictionary in the startup context
2. Measuring the (normalized) frequency of ESG cues for each startup ("ESG scores")

For brevity, we defer a comprehensive discussion of our machine-learning approach to the Internet Appendix, and summarize here only the main tenets relevant for understanding our approach and interpreting the results reported in section 6.

4.2.1 ESG Dictionary

An important motivation for creating a novel ESG dictionary using a machine-learning approach comes from the observation that existing ESG ratings are highly subjective, leading to very low correlations between different ratings (Berg et al., 2020; Dimson et al., 2020). Additionally, given the non-standardized nature of startup information disclosure, existing (corporate) ESG ratings cannot be reliably applied to startups. Therefore, our machine-learning approach both (i) helps mitigate the subjectivity bias in ESG ratings and (ii) introduces a replicable "text as data"-based method that allows to derive reliable ESG ratings for startups.

In a first step, we use the Stanford CoreNLP pipeline (Manning et al., 2014) to obtain a dependency representation of each sentence in all whitepapers to help the machine learn the grammatical structure of information that startups typically publish in whitepapers. In particular, we teach the machine to identify "collocations," such as *initial_coin_offering*, which treats conjugate terms as one term. These collocations become important in our second step, as we use a one-hidden-layer neural network (i.e., *word2vec* based on Mikolov et al., 2013[17]) to train the model to predict neighboring collocations,

[17] For a critical discussion of *word2vec*, see Nissim et al. (2020).

which help to quantify language by creating vectors of real numbers for any dictionary word. For example, using this approach, one could find the closest vector for "ICO" as follows: ICO = STO − security token + utility token.

Following Li et al. (2020), we aid the machine in the creation of the ESG dictionary by providing seed words as initial starting points. Specifically, we collect all available *Financial Times* (*FT*) articles with the tags "ESG Investing" or "Moral Money." We follow a standard bag-of-word approach and extract the most frequent bi-grams and tri-grams (two- and three-word combinations) that appeared in the pre-selected *FT* corpus. We then manually go through these bi-/tri-grams and map them to the best-fitting E, S, or G dimension of ESG. Given *FT*'s focus on larger corporations, we manually add terms like 'kyc' and 'whitelist' (as examples for the G dimension). For replication purposes (and potential modification in future studies), we make available the full list of seed words in the Internet Appendix. Our seed words consist of 70 E-, 38 S-, and 46 G-related terms. We also test the sensitivity of our main results to ESG scores obtained from dictionaries with other seed words.

For any term t of the seed words in any of the ESG dimensions j, we obtain a vector representation with the size of 300 (the size of the hidden layer in our *word2vec* model) as $V^t_{j\in\{E,S,G\}} = [x^t_1, x^t_2, ..., x^t_{300}]$. We then calculate the average vector for each {E, S, G} dimensions as $\bar{V}^{j\in\{E,S,G\}} = \frac{1}{N}\sum_1^N [x^t_1, x^t_2, ..., x^t_{300}]$ where N is the size of seed words for the dimension j. This leaves us with three vectors of $\bar{V}^E$, $\bar{V}^S$, and $\bar{V}^G$. Finally, we perform a cosine similarity between $\bar{V}^j$ and the vector of all the terms in our whitepapers database, which leaves us with a total of 1,495 ESG-related terms consisting of 508, 463, and 524 terms in the respective ESG dimensions. Figure 2 illustrates the word-clouds corresponding to the E, S, and G word lists.

[Place Figure 2 about here.]

4.2.2 ESG Score

Using our ESG dictionary, we quantify the E, S, and G dimensions by counting the number of distinct occurrences of our dictionary words in whitepapers, normalized to the size of the word list. Specifically, for token offering i, we measure each dimension ζ of ESG as:

$$\zeta_i = \frac{\sum_t 1_{c(t)_i > 0}}{c(n)} \text{ for } \zeta \in \{\text{E, S, G}\} \tag{1}$$

where $c(t)_i$ denotes the count of term t in whitepaper i and $c(n)$ is the size of the corresponding word list. Thus, our approach adapts that of Loughran and McDonald (2020) to account for the non-standardized nature of whitepapers relative to the highly standardized and regulated use of language in corporate disclosure reports analyzed by Loughran and McDonald (2020). The aggregate ESG score of startup i is then simply described by the sum of its components:

$$ESG_i = \sum_{\{E_i, S_i, G_i\}} \zeta_i \tag{2}$$

4.2.3 Sanity Checks

We perform manual sanity checks to make sure our approach identifies startups' ESG properties reliably. The results are very reconfirming. For example, the startup with the highest environmental score in our sample is *WPP Energy* (funding amount: $59M). *WPP Energy* is "a Swiss Company that over the last decade has established itself as a repository for disruptive energy and environmental technologies through exclusive global licenses." Similarly, the second-highest environmental score in our sample belongs to *Greencoin* (funding amount: $6M), which is "the first decentralized platform based on sustainable green systems to solve real problems in the world, connecting green systems manufacturers and local Installation companies or certified individuals directly with buyers." A careful examination of *WPP Energy*'s and *Greencoin*'s whitepapers shows that these startups are indeed concerned with addressing salient environmental problems. Similarly, we confirm that our approach correctly identifies the S (e.g., the startups *HARA* and *Ubricoin*) and G (e.g., the startups *SMART VALOR* and *Chainium*) dimensions of ESG.

4.2.4 Web Application

In an effort to facilitate the use of our ESG machine-learning approach in future research, we have created a web app that computes ESG scores for text data based on our Python code via simple copy&paste:

www.SustainableEntrepreneurship.org

The Python source code as well as a comprehensive and relatively technical documentation of our machine-learning approach for ESG measurement in the entrepreneurial context is provided in the Internet Appendix.

5 Methods

5.1 Data Sources

Our sample is based on the *Token Offerings Research Database* (*TORD*).[18] The *TORD* offers the most comprehensive publicly available token offerings database, and therefore addresses some of the key concerns about token offerings data limitations (for a comprehensive discussion of these concerns, see section 6.4 in Momtaz, 2020a). We exclude Security Token Offerings (STOs) and Initial Exchange Offerings (IEOs) to avoid biases from various confounding factors in our empirical analyses that would relate to the governance of these alternative token and offering types, and therefore sample only from utility-token ICOs. For these ICOs, we manually collect whitepapers from the firms' websites, *ICObench*, and the internet archive via the *Wayback Machine* (https://web.archive.org/). Finally, we collect post-ICO token prices from *CoinMarketCap*. We include only token offerings with a complete set of variables, as described in section 5.2, in our final sample. Our final sample consists of 1,043 token offerings.

5.2 Variables

Our independent variables are the startups' ESG properties, which we derive using a machine-learning approach from the startups' whitepapers. Our machine-learning approach is also available through an easy-to-use web app at www.SustainableEntrepreneurship.org, where future researchers can paste textual information about startups to obtain ESG scores.[19] We describe the independent variable construction in detail in section 4 and in the Internet Appendix. Hence, we focus below on the definitions of our dependent and control variables.

5.2.1 Dependent Variables

Our two dependent variables are the *valuation* of the startup during the funding stage and the *post-funding financial performance*.

Funding valuation. Following exsting studies on ICO performance (e.g., Fisch, 2019), we operationalize startup valuation as the logarithmic funding amount in $ million acquired during the token offering.

[18] We use Version 1 of the TORD, retrieved on April 1st, 2021 at www.paulmomtaz.com/data/tord.

[19] In our study, we have normalized the ESG scores (mean = 0, standard deviation = 1), so that they are easy to interpret.

Post-funding performance. We operationalize the post-funding performance with the 12-month Buy-and-Hold Abnormal Returns (BHARs), following Fisch and Momtaz (2020) and Momtaz, 2021b. Specifically, we compute the 12-month return for each startup with regard to the listing date and subtract the performance of an equally-weighted market benchmark for the same investment period. The equally-weighted market benchmark is based on all tokens that are tracked on *Coinmarketcap*. The equally-weighted market benchmark has the important advantage that it deals with the size anomaly in market returns associated with the Bitcoin- and Ether-related dominance in value-weighted market benchmarks, as described in Momtaz (2021b).

5.2.2 Control Variables: Venture Characteristics

We control for the following venture characteristics: Whitepaper length, team size, rating, technical experience, minimum viable product, open source code, and # industries.

Whitepaper length. The natural logarithm of total words in any given whitepaper, which is often used as a proxy for the total available information on a project (e.g., Fisch, 2019).

Team size. The number of team members, which is a first-order determinant of success in token offerings (Fisch, 2019; Momtaz, 2020b).

Rating. The overall project rating based on the consensus of industry experts on ICObench, and is an important predictor of success in token offerings (Bellavitis et al., 2020; Fisch, 2019; Momtaz, 2020b). The scale runs from 1 ("low quality") to 5 ("high quality").

Technical experience. This is the percentage of team members with a technical background. The variable is hand-collected from team members' professional network profiles, such as *LinkedIn*.

Minimum viable product. This is a dummy variable for whether a startup has a minimum viable product available.

Open source code. Coded as a dummy variable for whether the startup discloses come of its code on *Github*, which is often used as a proxy for a venture's technological sophistication (Fisch, 2019).

Industries. We use *ICObench* industry classifications to measure the potential industries the focal venture targets as the logarithm of one plus the number of the industries, which is a proxy for diversification (Fisch and Momtaz, 2020).

5.2.3 Control Variables: Offering Characteristics

We control for the following offering characteristics: Soft and hard caps, pre-sale, whitelist, bonus, bounty, ERC20.

Soft cap. A dummy variable for whether the startup in a token offering has announced a soft cap. A soft cap is the minimum funding amount at which the offering is deemed successful, and funding campaigns that fail to reach the soft cap typically redeem investor money and end the project.

Hard cap. dummy variable for whether the startup in a token offering has announced a hard cap. A hard cap is the maximum funding amount that a startup accepts. If the hard cap is reached, the offering will end and excess funding will be return to investors.

Pre-sale. A dummy variable indicating if the actual token offering was preceded by a pre-sale event.

Whitelist. A dummy indicating if the token offering has an activated whitelist.

Bonus. A dummy variable for whether the startup is offering a bonus structure, which typically involves discounted or free tokens if individual wallet addresses invest above and beyond a certain pre-determined investment amount.

Bounty. A dummy variable for whether the token offering offers a bounty program, which rewards individuals (mostly in the form of free tokens) for marketing activity that promotes the offering and the startup.

ERC20. A dummy variable for whether the token offering relies on the technical ERC20 standard.

5.2.4 Control Variables: Market Characteristics

We control for whether token offerings are launched during bull or bear markets, with market stagnation serving as the base case.

Bull market. A dummy variable for whether the token offering took place during a bull market, i.e., prior to the so-called "crypto winter."

Bear market. A dummy variable for whether the token offering took place during a bear market, i.e., during the "crypto winter."

5.3 Summary Statistics

Summary statistics and bivariate correlations for all our main variables are in Table 1. The average startup in our sample raises $15.2 million during the token offering with a team of 12.9 people and an average rating of 3.4 (out of 5). More than 4 out of the 12 team members have a technical background. Two-thirds of all startups publish code on *Github*, but only one-fifth of all startups has a minimum viable product at the time of the token offering. These sample statistics resemble those in related studies (e.g., Bellavitis et al., 2020; Fisch, 2019; Howell et al., 2020; Huang et al., 2020; Momtaz, 2020a).

The bivariate correlations indicate that the *aggregate* ESG score is positively correlated with the funding amount ($\rho = 0.238$) and negatively with the post-funding performance ($\rho = -0.107$). The *disaggregated* ESG scores shed further light on what sustainability aspects matter for the funding amount and the post-funding performance. The funding amount is positively correlated with E ($\rho = 0.098$), S ($\rho = 0.213$), and G ($\rho = 0.240$), indicating that environmental aspects are the least correlated with the funding amount among all ESG aspects. The post-funding performance is negatively correlated with E ($\rho = -0.045$), S ($\rho = -0.094$), and G ($\rho = -0.110$), again with E having the weakest correlation with the post-funding performance among all ESG aspects. Overall, these correlations are in line with our two overarching hypotheses. It is also reconfirming that all disaggregated ESG scores are consistent in terms of their correlation coefficients' signs. For brevity, we note that the remaining correlations are largely consistent with those reported in existing studies (e.g., Fisch and Momtaz, 2020).

[Place Table 1 about here.]

Table 2 shows means for the full sample in the first column and for subsamples with above-mean ESG scores in the remaining columns. In line with our two main hypotheses, the average funding amount is $400,000 higher in high-ESG startups, with the difference being statistical significant at the 1% level; and, the post-funding underperformance, measured as the 12-month holding period return adjusted by an equally-weighted market benchmark, is 16% higher, although the difference is not statistical significant in the univariate comparison.

We also shed some light on whether there is "selection on observables" in our sample by comparing the means for our control variables in the full sample with those in the subsamples. Indeed, we find some statistical significant differences between the full sample and the highly sustainable subsamples. For example, the number of team members in high-ESG startups is larger by more than two persons on average, with the difference being highly statistical significant. Moreover, high-ESG startups set higher soft and hard caps, and are more likely to conduct a pre-sale and have a whitelist. Further, they are less likely to conduct the token offering during a bull market and more likely to conduct it during a bear market, possibly indicating that sustainable startups are less sensitive to market opportunism.

Overall, these significant differences between low- and high-ESG startups suggest that we need to control for selection issues in our sample. Next, we discuss three ways in which we control for selection based on to observed and unobserved heterogeneity.

[Place Table 2 about here.]

5.4 Econometric Approach

Our goal is to estimate the causal effect startups' ESG properties have on their funding success and post-funding performance. In addition to OLS models, we rely on several two-stage approaches.[20] These models control for observed and/or unobserved heterogeneity, which is often pronounced in entrepreneurial finance.[21]

Specifically, we are interested in the causal effect that startup i's ESG score, ESG_i, has on the dependent variable, $DV_i \in$ {Valuation$_i$, Performance$_i$}, controlling for a vector of independent variables, Ω_i:

$$DV_i = \beta ESG_i + \mathit{\Omega}_i \gamma + \varepsilon_i, \quad DV_i \in \{\text{Valuation}_i, \text{Performance}_i\} \tag{3}$$

To address the potential endogeneity problem associated with $E[\Omega_i, \varepsilon_i] \neq 0$, our first stage explicitly models the selection of startups into their ESG commitment. Specifically, we model the probability that startup i has a high ESG score above the median, $hiESG_i$, by a vector of exogenous control variables that possibly influence the selection mechanism, $\mathit{\Omega}_i^{(s)}$:

$$hiESG_i = \mathit{\Omega}_i^{(s)} \delta + \xi_i \tag{4}$$

We use the results from equation 4 to control for observed and unobserved heterogeneity in two distinct ways.

First, we compute inverse Mills ratios for each startup i's selection based on observable factors (IMR_i):

$$IMR_i = \frac{\phi\left(\frac{\mathit{\Omega}_i^{(s)}\delta}{\sigma_\xi}\right)}{\mathit{\Phi}\left(\frac{\mathit{\Omega}_i^{(s)}\delta}{\sigma_\xi}\right)} \tag{5}$$

We then use IMR_i in the second step to construct the following IMR estimator, where

[20] The techniques used in our study have been employed before in similar contexts (e.g., Bertoni et al., 2011; M. G. Colombo and Grilli, 2010; Fisch and Momtaz, 2020).

[21] For example, Momtaz (2021a) finds that unobserved heterogeneity in startups' time-to-funding by venture capitalists is so pronounced that it severely biases common time-to-event models.

λ tests the null hypothesis that there is no selection effect:

$$DV_i^{IMR} = \beta ESG_i + \lambda IMR_i + \Omega_i \gamma + v_i, \quad DV_i^{IMR} \in \{\text{Valuation}_i^{IMR}, \text{Performance}_i^{IMR}\} \quad (6)$$

Second, we use Generalized Residuals (GRs) as instrumental variables for startups' ESG scores (Gourieroux et al., 1987), thereby controlling for unobserved heterogeneity by explicitly modeling any endogeneity in the error term. Consistent with Gourieroux et al. (1987), we define the generalized residual as:

$$GR_i = hESG_i \times \frac{\phi\left(-\Omega_i^{(s)}\delta\right)}{1-\Phi\left(-\Omega_i^{(s)}\delta\right)} + (1-hESG_i) \times \frac{-\phi\left(\Omega_i^{(s)}\delta\right)}{\Phi\left(-\Omega_i^{(s)}\delta\right)} \quad (7)$$

where $\phi(.)$ and $\Phi(.)$ denote the probability density and the cumulative density functions of the standard normal distribution, respectively. We restrict the standard deviation of the error term for startups with above-median ESG scores ($\sigma_{\varepsilon,\ hiESG=1}$) to be equal to that of startups with below-median ESG scores ($\sigma_{\varepsilon,\ hiESG=0}$). The restriction ensures that GR_i can be added as an instrumental variable to equation 3.

6 Results

6.1 ESG and Funding

The main results for the VPH are in Table 3. All models include quarter-year and country fixed effects to absorb both time-related and geographical variation. All reported standard errors are robust. The R^2 in all our models exceeds 30%, which is slightly higher than in previous studies (e.g., Fisch, 2019).

Our baseline (OLS) regression results are in column (1), with the the log of the funding amount in \$ million as the dependent variable. The coefficient on the normalized ESG score is 0.25, with a p-value $<$ 1%, suggesting that an increase in the ESG score by one standard deviation increases the average funding amount of \$15.2 million by \$4.2 million. Thus, a one-standard-deviation increase in the ESG score increases the average funding amount by 28%, strongly supporting the VPH that there is a sustainability-related valuation premium in token offerings.

For the control variables, the coefficients are largely consistent with those reported in prior studies (e.g., Bellavitis et al., 2020; Fisch, 2019; Huang et al., 2020; Momtaz, 2020a). Specifically, we find that (i) the whitepaper length, (ii) the expert rating, (iii) team size, and (iv) the presence of a whitelist are significantly positively related to the funding amount, while (v) open source code has a negative association with the funding amount. For sensitivity checks, we show a control model excluding the normalized ESG score in column (2). Both the signs and the magnitudes of the coefficients are similar in columns (1) and (2).

Given the evidence of startups' selection into ESG levels, we perform a two-stage approach in columns (3)-(5). Column (3) contains a first-stage Heckman selection model, which predicts the conditional probability that a startup chooses to have an above-median ESG score. Whitepaper length, team size, and bear markets positively predict token offerings of high-ESG startups, while open source code's marginal effect is negative. We use the first-stage results to obtain IMRs and GRs, as described in section 5.4. We include IMRs as an additional control in column (4). The coefficient on the normalized ESG score is almost unchanged (0.250 in column (1) vs. 0.251 in column (4)). We also find that the IMR is statistically insignificant (unreported), indicating that "selection on observables" is not biasing the marginal effect of the normalized ESG score on the log of the funding amount. Finally, we use the GR as an instrumental variable for the normalized ESG score in column (5) to also address concerns about "selection on unobservables." This reduces the coefficient on the normalized ESG score to 0.211. Thus, unobserved heterogeneity may inflate the sustainability-related valuation premium in token offerings to some extent. Nevertheless, the valuation premium is still economically very significant in the IV model in column (5). In particular, an increase in the ESG score by one standard deviation increases the average funding amount of \$15.2 million by \$3.6 million, corresponding to a relative effect of 23%. Overall, our baseline result is very robust to controlling for both observed and unobserved heterogeneity, and therefore provide strong support for the VPH (Hypothesis 1).

[Place Table 3 about here.]

Our machine-learning approach to ESG measurement also allows to disaggregate the ESG score into its components E, S, and G. Table 4 shows the regression results with the disaggregated ESG scores. Column (1) reprints the ESG coefficient from our baseline model in column (1) of Table 3 for comparison. Columns (2), (3), and (4) report regression coefficients for the disaggregated and normalized E, S, and G scores, respectively. All disaggregated scores are statistically significant at least at the 5% level in these models. The E score coefficient is 0.137 (p-value < 0.01), the S score coefficient is 0.179 (p-value < 0.05), and the G score coefficient is 0.162 (p-value < 0.01). However, testing the effect of the three disaggregated scores simultaneously in column (5) shows that only the

E (0.115) and the G (0.126) score are statistically significant at least at the 10% level. Therefore, ceteris-paribus increases by one standard deviation in E and in G are associated with increases in the average funding amount of 12% and 13%, respectively.

Table 4 also reports Variance Inflation Factors (VIFs). All VIFs for the ESG variables are below 3, with the highest VIF being 2.95 for the S score in the simultaneous model in column (5). Additionally, the VIFs for all other control variables are clearly below 5, which is a commonly agreed threshold (e.g., Leitterstorf and Rau, 2014), and therefore indicate that multicollinearity is not a concern in our analyses.

[Place Table 4 about here.]

Our final tests repeat the analyses in Tables 3 and 4 for Propensity Score Matched (PSM) samples. The rationale is that the PSM approach improves on the IMR-based "selection on observables" control approach if the selection process does not follow a normal distribution. This is because the *conditional independence assumption*[22] inherent in the IMR approach would be violated (e.g., Dehejia and Wahba, 2002; Rosenbaum and Rubin, 1983). Our PSM approach employs a one-to-one nearest-neighbor matching with two different selection cutoffs: 80% and 70%. That is, the PSM samples are based on selection models that predict whether a startup's ESG score is higher than the 80th and 70th percentile, leading to different subsample sizes of 627 and 939 observations, respectively.

The results for the PSM samples are in Table 5. Panels A and B regress on the aggregate and disaggregated ESG scores, respectively. Columns (1)-(2) and (3)-(4) report results for the baseline model and for the IV model, respectively. For brevity, we note that the results are consistent. The marginal effect of the aggregate and normalized ESG score ranges between 0.186 and 0.222, with a p-value always lower than 5%. The marginal effects of the disaggregated and normalized E score ranges between 0.105 and 0.126, with a p-value always below 10%. The coefficents for the S and G scores are not consistently statistically significant. Therefore, the sustainability-oriented valuation premium in token offerings is mostly driven by the environmental component.

[Place Table 5 about here.]

6.2 ESG and Post-Funding Performance

Tests of the PFUH (Hypothesis 2) are in Table 6. The dependent variable in all models is the 12-month BHAR relative to an equally-weighted market benchmark. Panel A regresses

[22] That is, conditional on IMR_i, the ESG scores must be independent of the other control variables.

on the aggregate normalized ESG score, while Panel B regresses on the disaggregated normalized E, S, and G scores. Both panels contain the baseline model and the IMR model. Only Panel A contains the IV model (because GRs cannot be simultaneously calculated for each of the three ESG dimensions in Panel B).

The evidence supports the PFUH that startups with salient ESG properties underperform the market. An increase in the aggregate ESG score by one standard deviation is associated with an underperformance of 16.3% over the first year of token trading in columns (1) and (2). Interestingly, the estimated underperformance in column (3) is clearly higher, with a marginal effect of ESG on BHAR of −37.3%, suggesting that unobserved heterogeneity attenuates true underperformance.

In contrast to the dominance of the *environmental* component in the valuation premium (Hypothesis 1), we find in Panel B of Table 6 that the *governance* component drives the post-funding underperformance. Only the disaggregated G component is consistently statistically significant at least at the 10% level in Panel B. An increase by one standard deviation in the G dimension is associated with 19.2% (column 1) to 19.6% (column 2) post-funding underperformance. The E and S dimensions are not statistically significant and also economically insignificant, with coefficients ranging from −2.7% to −0.2%. Overall, these results support our second hypotheses that sustainability-oriented startups underperform the market post-funding, with the effect being mostly attributable to the governance dimension in ESG.

[Place Table 6 about here.]

6.3 The Moderating Effect of Formalization

The results so far suggest that entrepreneurs benefit from sustainability-orientation in the form of a premium during the funding stage and investors incur a financial loss post-funding. Our third hypothesis posits that formalization (i.e., binding constraints) has a negative moderating effect on both funding and post-funding performance. The rationale is that sustainability-orientation already imposes binding constraints onto the startup whose effects other constraints may magnify. Binding constraints reduce entrepreneurial flexibility and the scope of experimentation (e.g., March, 1991), therefore, ***H3a*** and ***H3b*** posits that formalization is associated negatively with the ESG-funding and and ESG-performance relations articulated in the ***VPH*** and ***PFUH***.

The results of the moderation tests are in Table 7. We use three proxies for the formalization. For technological formalization, proxy 1 is a dummy indicator for whether the startup open-sourced its code on *GitHub*. For network formalization, proxy 2 is the log of the number of followers in *Twitter*. For governance formalization, proxy 3 is a dummy equal to one if the startup is VC-backed. These variables have been introduced before in the token offerings literature (e.g., Fisch, 2019; Fisch and Momtaz, 2020).

Columns (1)-(3) and (4)-(6) regress the log of the funding amount and the 12-month BHAR, respectively. For the valuation models, we find that all formalization proxies have a strong direct effect on startups' valuations, as well as negative moderating effects, with the interactions with the network and governance proxies being statistically significant at least at the 10% level. For the performance models, we find only partial support for our hypothesis. Only the governance-related formalization proxy has a statistically significant direct effect on the 12-month BHAR (p-value $< 1\%$), while only the technology-related formalization proxy has a statistically significantly negative moderating effect. In particular, ceteris paribus, the post-funding underperformance increases by 33.2% if the startup increases its ESG score by one standard deviation while having open-sourced some of its platform code. Overall, the results in Table 7 provide partial support for the moderating effects posited by ***H3a*** and ***H3b***.

For brevity, Table 7 does not report the coefficients for our control variables as they resemble those shown in Table 3. Note that the R^2 increases significantly compared to the unmoderated specifications in Table 3 and Table 6.

[Place Table 7 about here.]

For brevity, we defer our robustness checks to the Internet Appendix. Specifically, we test the sensitivity of our results to the inclusion of additional control variables, which has the advantage of absorbing more variation, while the limited availability of additional variables reduces our sample size substantially. Our main results do not qualitatively change in these specifications. For example, controlling for the percentage of tokens distributed in the token offering (token retention often serves as a signal for project quality, see Leland and Pyle, 1977, does not affect the ESG-valuation relation. Importantly, we also report robustness tests for different ESG scores, by altering the initial seed words we provide the machine in order to compile the ESG dictionary. Again, our results are very robust. All these tests are discussed in detail in the Internet Appendix.

7 Discussion and Concluding Remarks

7.1 Summary of Main Results

We test two overarching hypotheses in this paper. The ***Valuation Premium Hypothesis*** (***VPH***) posits that Sustainable Entrepreneurship (SE), relative to Conventional Entrepreneurship (CE), achieves higher valuations in entrepreneurial finance markets. The ***Post-Funding Underperformance Hypothesis*** (***PFUH***) posits that SE (financially) underperforms CE in the long run. The empirical context are utility token offerings or Initial Coin Offerings (ICOs). Token offerings provide an ideal laboratory to test these hypotheses because (i) the information disclosed in whitepapers can be used to quantify startups' ESG properties, and (ii) tokens are often listed on exchange platforms after the offering, providing a transparent measure of financial performance (Fisch and Momtaz, 2020). Examining a sample of 1,043 token offerings over the 2016-2020 period, we find support for both the *VPH* and the *PFUH*. For the *VPH*, we find that a one-standard-deviation increase in our ESG metric is associated with a 26% increase in the funding amount. This corresponds to $1 million (relative to the mean funding amount of $3.8 million in our sample). For the *PFUH*, we find that a one-standard-deviation increase in our ESG metric is associated with a 16% decrease in the first 12-months buy-and-hold abnormal (equally weighted relative to a composite market index) token price performance. Relative to financial utility, non-financial (ESG-related) utility for SE investors amounts to 17-27% of total utility.

Additional analyses investigate the moderating role of technology-, network-, and governance-related formalization at the startup level on the relationships articulated in the *VPH* and the *PFUH*. Formalization refers broadly to all organizing that imposes dependencies and constraints onto the startup (Kraus et al., 2018). The contingency effects of formalization are important. Technological, network, and governance aspects associated with startup formalization all hurt the valuation and performance of sustainability-oriented startups in our sample. These findings are consistent with predictions in the SE literature, as synthesized in Kraus et al. (2018), albeit puzzling. Attributes, such as open-source code, large social networks, and venture capital backing, are associated with success in conventional startups (Fisch, 2019; Fisch and Momtaz, 2020), yet they impede success in sustainability-oriented startups, suggesting that organizing SE may need to meet fundamentally different requirements than CE (Parrish, 2010).

Our results are robust to endogeneity concerns related to observed and unobserved heterogeneity in our sample, and insensitive to various modifications of our empirical baseline model.

7.2 Theoretical Contributions and Practical Implications

Our study contributes to the SE literature in several important ways. First, at the most abstract level, the sustainability-related valuation premium suggests that entrepreneurs have an economic incentive to launch sustainability-oriented projects or to introduce ESG aspects to existing ones. The existence of the sustainability premium also implies that Schumpeterian logic may apply (Schumpeter, 1934, 1942), and that the demand for ESG creates entrepreneurial opportunity, potentially leading to a replacement of conventional businesses with sustainability-oriented ones. As such, entrepreneurs may act as "change agents" for sustainability-oriented change (Anand et al., 2021, p. 2). Our finding thus addresses a major question around SE, potentially helping to resolve much of the "controversy" around the incentives of SE in the literature (J. K. Hall et al., 2010, p. 439).

Second, our study helps close the"research gap related to the post-funding phase" of SE (Böckel et al., 2020, p. 433). SE's financial underperformance suggests that investors in ESG startups are willing to pay for non-financial sustainability-related returns. Viewing the financial underperformance as an upper bound for the non-financial utility from ESG, our study suggests that non-financial utility constitutes 17-27% of total utility in sustainability-oriented entrepreneurial activity. It is worth noting that even after one year of post-funding underperformance, the average ESG startup still trades at a valuation premium of up to 10%. Therefore, despite the underperformance and the opportunity to exit the investment anytime in liquid token markets, investors remain invested in ESG startups, again highlighting the importance of non-financial utility for SE investors.

Finally, our study contributes to the emerging SE literature by highlighting the importance of binding constraints (Pástor et al., 2020; Renneboog et al., 2008). The results that both the valuation premium and the post-funding performance are negatively influenced by technology-, network-, and governance-related formalization underscore the importance of delegated philanthropy in solving problems associated with SE's binding constraints (Kraus et al., 2018). O. Hart and Zingales (2017) relax Friedman's (1970) assumptions to show that sustainability likely has a business case outside of neoclassical models, and that delegated philanthropy can reduce SE execution risk associated with the rigidity of binding constraints. The more specialized the delegation of ESG problems to various ventures, the more successful the ventures in terms of funding and post-funding performance because granular delegation reduces binding constraints for individual startups. Nevertheless, delegation, underperformance, and moderating formalization all suggest that SE is no "no brainer," and that more work, particularly on organizing SE (Parrish, 2010), is necessary to understand when SE is beneficial for entrepreneurs and investors, and why.

Three distinct practical implications emerge from our study. First, from a public policy perspective, our results that entrepreneurs have an economic incentive for sustainability-oriented venturing and get funded suggest that Schumpeter's (1942) notion of 'creative destruction' seems to be applicable to the SE context, thus the SE market should sustain itself without the need for government subsidies. Second, SE investors need to expect financial losses relative to CE. Thus, SE may only attract investors whose personal ESG preference can compensate financial underperformance. Third, and arguably most importantly, entrepreneurs need to cautiously weigh the pros and cons of various organizational designs, and consider that organizing that is optimal for CE may not be optimal for SE (Parrish, 2010).

7.3 Avenues for Further Research

Our study is a first step to understand the financial aspects surrounding SE activity that matter for entrepreneurs and investors alike. Given the vast and growing interest in SE, as evidenced by the large number of recent reviews (for a recent overview, see Anand et al., 2021, chapter 2.1), and the necessarily high level of abstraction in our analysis, it seems very likely that a vivid literature around the financial aspects of sustainability-oriented venturing is about to emerge. Some avenues for potentially fruitful further research are suggested below:

1. *Financial returns to SE.* Our study focused on token offerings, a market that is predominantly populated by relatively young generations with high ESG preferences (Fisch et al., 2019; Kraus et al., 2018; Spence et al., 2011). Also, given the recency of token offerings, our analysis of 'long-run' returns does not extend beyond a one-year period. This gives rise to a number of interesting questions. First, do our results of an ESG premium followed by underperformance hold in other contexts, in particular in those with institutional investors, such as venture capitalists, whose limited partnership agreements often require them to focus exclusively on financial returns? Second, how long do investors bear SE underperformance, and is there a point of financial loss at which investors abandon sustainability-oriented startups? Third, our study is set in a time period that experiences relatively high demand for ESG. This raises the question how our results would change with a lower aggregate demand for ESG.

2. *ESG returns to SE.* Our study estimated the financial rents associated with SE for entrepreneurs and investors. While our underperformance measure can be viewed

as an upper bound for investors' ESG rents, it leaves a number of open questions. For example, relative to financial rents, how important are ESG rents for investors in sustainability-oriented startups, and to what extent are investors willing to sacrifice financial rents for ESG goals? Of course, as Anand et al. (2021, p. 12) correctly observe, "how to measure sustainability" is a "major challenge." This is owed partly to the subjectivity of many ESG rents (e.g., normative dimensions of ESG, such as relative economic equality), partly to the longevity of many ESG goals (e.g., climate change), and partly to the difficulty associated with quantifying ESG rents, among others. Our view is that, moving forward, case studies seem a possibility to understand cause-and-effect in SE.

3. *Disaggregating ESG.* Similarly, our study employed a machine-learning approach to quantify ESG properties of startups. We also decomposed ESG into E, S, and G. However, an even more granular approach may help unveil contingency aspects of SE (e.g., E is composed of many grand challenges itself, such as climate change, air and water pollution, solar energy and other renewable energies, and carbon footprints of new and old technologies). Our machine-learning algorithm, which we publish as open source along with this paper, can easily be modified to measure more granular components of ESG in future research.

4. *Organizing SE.* Our study of how a high degree of formalization associated with technology, network, and governance aspects, which are all associated with success in conventional startups, can be detrimental in sustainability-oriented startups raises the important question of the optimal organizational design in SE. Parrish (2010) discusses how organizational design in CE and SE might be fundamentally different, employing an inductive approach based on 32 qualitative interviews. Yet, the research on concrete, practically implementable forms of startup structure conducive to SE success is very limited.

References

Adhami, S., Giudici, G., & Martinazzi, S. (2018). Why do businesses go crypto? an empirical analysis of initial coin offerings. *Journal of Economics and Business*, *100*, 64–75.

Ahlers, G. K., Cumming, D., Günther, C., & Schweizer, D. (2015). Signaling in equity crowdfunding. *Entrepreneurship theory and practice*, *39*(4), 955–980.

Albuquerque, R., Koskinen, Y., Yang, S., & Zhang, C. (2020). Resiliency of environmental and social stocks: An analysis of the exogenous covid-19 market crash. *The Review of Corporate Finance Studies*, *9*(3), 593–621.

Amsden, R., & Schweizer, D. (2018). Are blockchain crowdsales the new'gold rush'? success determinants of initial coin offerings. *Success determinants of initial coin offerings (April 16, 2018)*.

Anand, A., Argade, P., Barkemeyer, R., & Salignac, F. (2021). Trends and patterns in sustainable entrepreneurship research: A bibliometric review and research agenda. *Journal of Business Venturing*, *36*(3), 106092.

Balakrishnan, U., Duvall, T., & Primeaux, P. (2003). Rewriting the bases of capitalism: Reflexive modernity and ecological sustainability as the foundations of a new normative framework. *Journal of Business Ethics*, *47*(4), 299–314.

Barber, B. M., Morse, A., & Yasuda, A. (2021). Impact investing. *Journal of Financial Economics*, *139*(1), 162–185.

Bellavitis, C., Cumming, D., & Vanacker, T. (2020). Ban, boom, and echo! entrepreneurship and initial coin offerings. *Entrepreneurship Theory and Practice*, 1042258720940114.

Bellavitis, C., Fisch, C., & Wiklund, J. (2021). A comprehensive review of the global development of initial coin offerings (icos) and their regulation. *Journal of Business Venturing Insights*, *15*, e00213.

Berg, F., Koelbel, J. F., & Rigobon, R. (2020). *Aggregate confusion: The divergence of esg ratings*. MIT Sloan School of Management.

Bertoni, F., Colombo, M. G., & Grilli, L. (2011). Venture capital financing and the growth of high-tech start-ups: Disentangling treatment from selection effects. *Research policy*, *40*(7), 1028–1043.

Binder, J. K., & Belz, F.-M. (2017). Developing sustainable opportunities: Merging insights from social identity and structuration theory. *Academy of Management Proceedings*, *2017*(1), 14167.

Bischoff, K., & Volkmann, C. K. (2018). Stakeholder support for sustainable entrepreneurship-a framework of sustainable entrepreneurial ecosystems. *International Journal of Entrepreneurial Venturing*, *10*(2), 172–201.

Block, J. H., Colombo, M. G., Cumming, D. J., & Vismara, S. (2018). New players in entrepreneurial finance and why they are there. *Small Business Economics*, *50*(2), 239–250.

Block, J. H., Hirschmann, M., & Fisch, C. (2021). Which criteria matter when impact investors screen social enterprises? *Journal of Corporate Finance*, *66*, 101813.

Böckel, A., Hörisch, J., & Tenner, I. (2020). A systematic literature review of crowdfunding and sustainability: Highlighting what really matters. *Management Review Quarterly*, 1–21.

Breuer, H., Fichter, K., Lüdeke-Freund, F., & Tiemann, I. (2018). Sustainability-oriented business model development: Principles, criteria and tools. *International Journal of Entrepreneurial Venturing*, *10*(2), 256–286.

Calic, G., & Mosakowski, E. (2016). Kicking off social entrepreneurship: How a sustainability orientation influences crowdfunding success. *Journal of Management Studies*, *53*(5), 738–767.

Campbell, J. Y., Lo, A. W., & MacKinlay, A. C. (2012). *The econometrics of financial markets*. princeton University press.

Choi, D. Y., & Gray, E. R. (2008). The venture development processes of "sustainable" entrepreneurs. *Management Research News*.

Cohen, B., & Winn, M. I. (2007). Market imperfections, opportunity and sustainable entrepreneurship. *Journal of business venturing*, *22*(1), 29–49.

Colombo, M. G., & Grilli, L. (2010). On growth drivers of high-tech start-ups: Exploring the role of founders' human capital and venture capital. *Journal of business venturing*, *25*(6), 610–626.

Colombo, O. (2021). The use of signals in new-venture financing: A review and research agenda. *Journal of Management*, *47*(1), 237–259.

Cornell, B. (2021). Esg preferences, risk and return. *European Financial Management*, *27*(1), 12–19.

Cumming, D., Henriques, I., & Sadorsky, P. (2016). cleantech'venture capital around the world. *International Review of Financial Analysis*, *44*, 86–97.

Cumming, D. J., Leboeuf, G., & Schwienbacher, A. (2017). Crowdfunding cleantech. *Energy Economics*, *65*, 292–303.

Davies, I. A., & Chambers, L. (2018). Integrating hybridity and business model theory in sustainable entrepreneurship. *Journal of Cleaner Production*, *177*, 378–386.

Dean, T. J., & McMullen, J. S. (2007). Toward a theory of sustainable entrepreneurship: Reducing environmental degradation through entrepreneurial action. *Journal of business venturing*, *22*(1), 50–76.

Dehejia, R. H., & Wahba, S. (2002). Propensity score-matching methods for nonexperimental causal studies. *Review of Economics and statistics*, *84*(1), 151–161.

Desa, G. (2012). Resource mobilization in international social entrepreneurship: Bricolage as a mechanism of institutional transformation. *Entrepreneurship theory and practice*, *36*(4), 727–751.

Dickel, P. (2017). The impact of protectability and proactiveness on the environmental performance of new ventures. *Corporate Governance: The International Journal of Business in Society*.

Dimson, E., Marsh, P., & Staunton, M. (2020). Divergent esg ratings. *The Journal of Portfolio Management*, *47*(1), 75–87.

Djupdal, K., & Westhead, P. (2015). Environmental certification as a buffer against the liabilities of newness and smallness: Firm performance benefits. *International Small Business Journal*, *33*(2), 148–168.

Edmans, A. (2011). Does the stock market fully value intangibles? employee satisfaction and equity prices. *Journal of Financial economics*, *101*(3), 621–640.
Egri, C. P., & Herman, S. (2000). Leadership in the north american environmental sector: Values, leadership styles, and contexts of environmental leaders and their organizations. *Academy of Management journal*, *43*(4), 571–604.
Fama, E. F., & French, K. R. (2007). Disagreement, tastes, and asset prices. *Journal of financial economics*, *83*(3), 667–689.
Fisch, C. (2019). Initial coin offerings (icos) to finance new ventures. *Journal of Business Venturing*, *34*(1), 1–22.
Fisch, C., Masiak, C., Vismara, S., & Block, J. (2019). Motives and profiles of ico investors. *Journal of Business Research*.
Fisch, C., Meoli, M., & Vismara, S. (2020). Does blockchain technology democratize entrepreneurial finance? an empirical comparison of icos, venture capital, and reits. *Economics of Innovation and New Technology*, 1–20.
Fisch, C., & Momtaz, P. P. (2020). Institutional investors and post-ico performance: An empirical analysis of investor returns in initial coin offerings (icos). *Journal of Corporate Finance*, *64*, 101679.
Friedman, M. (1970). The social responsibility of business is to increase its profits. *The New York Times Magazine*, *(13 September)*, 32–33.
Gast, J., Gundolf, K., & Cesinger, B. (2017). Doing business in a green way: A systematic review of the ecological sustainability entrepreneurship literature and future research directions. *Journal of Cleaner Production*, *147*, 44–56.
Gentzkow, M., Kelly, B., & Taddy, M. (2019). Text as data. *Journal of Economic Literature*, *57*(3), 535–74.
Gibson, R., Glossner, S., Krueger, P., Matos, P., & Steffen, T. (2020). Responsible institutional investing around the world. *Swiss Finance Institute Research Paper*, (20-13).
Gillan, S. L., Koch, A., & Starks, L. T. (2021). Firms and social responsibility: A review of esg and csr research in corporate finance. *Journal of Corporate Finance*, 101889.
Giudici, G., & Adhami, S. (2019). The impact of governance signals on ico fundraising success. *Journal of Industrial and Business Economics*, *46*(2), 283–312.
Giudici, G., Guerini, M., & Rossi-Lamastra, C. (2018). Reward-based crowdfunding of entrepreneurial projects: The effect of local altruism and localized social capital on proponents' success. *Small Business Economics*, *50*(2), 307–324.
Gourieroux, C., Monfort, A., Renault, E., & Trognon, A. (1987). Generalised residuals. *Journal of Econometrics*, *34*(1-2), 5–32.
Gregori, P., Wdowiak, M. A., Schwarz, E. J., & Holzmann, P. (2019). Exploring value creation in sustainable entrepreneurship: Insights from the institutional logics perspective and the business model lens. *Sustainability*, *11*(9), 2505.
Guzmán, A., Pinto-Gutiérrez, C., & Trujillo, M.-A. (2020). Attention to global warming and the success of environmental initial coin offerings: Empirical evidence. *Sustainability*, *12*(23), 9885.
Hahn, T., Figge, F., Pinkse, J., & Preuss, L. (2018). A paradox perspective on corporate sustainability: Descriptive, instrumental, and normative aspects. *Journal of Business Ethics*, *148*(2), 235–248.

Hall, J., & Vredenburg, H. (2003). The challenges of innovating for sustainable development. *MIT Sloan management review*, *45*(1), 61–68.

Hall, J. K., Daneke, G. A., & Lenox, M. J. (2010). Sustainable development and entrepreneurship: Past contributions and future directions. *Journal of business venturing*, *25*(5), 439–448.

Hart, O., & Zingales, L. (2017). Companies should maximize shareholder welfare not market value. *ECGI-Finance Working Paper*, (521).

Hart, S. L., & Christensen, C. M. (2002). The great leap: Driving innovation from the base of the pyramid. *MIT Sloan management review*, *44*(1), 51.

Hart, S. L., & Milstein, M. B. (1999). Global sustainability and the creative destruction of industries. *MIT Sloan Management Review*, *41*(1), 23.

Hockerts, K., & Wüstenhagen, R. (2010). Greening goliaths versus emerging davids—theorizing about the role of incumbents and new entrants in sustainable entrepreneurship. *Journal of business venturing*, *25*(5), 481–492.

Hoogendoorn, B., Van der Zwan, P., & Thurik, R. (2019). Sustainable entrepreneurship: The role of perceived barriers and risk. *Journal of Business Ethics*, *157*(4), 1133–1154.

Hooi, H. C., Ahmad, N. H., Amran, A., & Rahman, S. A. (2016). The functional role of entrepreneurial orientation and entrepreneurial bricolage in ensuring sustainable entrepreneurship. *Management research review*.

Hörisch, J. (2015). Crowdfunding for environmental ventures: An empirical analysis of the influence of environmental orientation on the success of crowdfunding initiatives. *Journal of cleaner production*, *107*, 636–645.

Hornuf, L., Kück, T., & Schwienbacher, A. (2021). Initial coin offerings, information disclosure, and fraud. *Small Business Economics*, 1–19.

Howell, S. T., Niessner, M., & Yermack, D. (2020). Initial coin offerings: Financing growth with cryptocurrency token sales. *The Review of Financial Studies*, *33*(9), 3925–3974.

Huang, W., Meoli, M., & Vismara, S. (2020). The geography of initial coin offerings. *Small Business Economics*, *55*(1), 77–102.

Iyer, R., Khwaja, A. I., Luttmer, E. F., & Shue, K. (2016). Screening peers softly: Inferring the quality of small borrowers. *Management Science*, *62*(6), 1554–1577.

Jahanshahi, A. A., & Brem, A. (2017). Sustainability in smes: Top management teams behavioral integration as source of innovativeness. *Sustainability*, *9*(10), 1899.

Johnson, M. P., & Schaltegger, S. (2020). Entrepreneurship for sustainable development: A review and multilevel causal mechanism framework. *Entrepreneurship Theory and Practice*, *44*(6), 1141–1173.

Kerr, S. P., Kerr, W. R., & Xu, T. (2017). Personality traits of entrepreneurs: A review of recent literature.

Kerr, W. R., Nanda, R., & Rhodes-Kropf, M. (2014). Entrepreneurship as experimentation. *Journal of Economic Perspectives*, *28*(3), 25–48.

Kimuli, S. N. L., Orobia, L., Sabi, H. M., & Tsuma, C. K. (2020). Sustainability intention: Mediator of sustainability behavioral control and sustainable entrepreneurship. *World Journal of Entrepreneurship, Management and Sustainable Development*.

Knight, G. A. (1997). Cross-cultural reliability and validity of a scale to measure firm entrepreneurial orientation. *Journal of business venturing*, *12*(3), 213–225.

Kraus, S., Burtscher, J., Niemand, T., Roig-Tierno, N., & Syrjä, P. (2017). Configurational paths to social performance in smes: The interplay of innovation, sustainability, resources and achievement motivation. *Sustainability*, *9*(10), 1828.

Kraus, S., Burtscher, J., Vallaster, C., & Angerer, M. (2018). Sustainable entrepreneurship orientation: A reflection on status-quo research on factors facilitating responsible managerial practices. *Sustainability*, *10*(2), 444.

Kuckertz, A., & Wagner, M. (2010). The influence of sustainability orientation on entrepreneurial intentions—investigating the role of business experience. *Journal of business venturing*, *25*(5), 524–539.

Lans, T., Blok, V., & Wesselink, R. (2014). Learning apart and together: Towards an integrated competence framework for sustainable entrepreneurship in higher education. *Journal of Cleaner Production*, *62*, 37–47.

Leitterstorf, M. P., & Rau, S. B. (2014). Socioemotional wealth and ipo underpricing of family firms. *Strategic Management Journal*, *35*(5), 751–760.

Leland, H. E., & Pyle, D. H. (1977). Informational asymmetries, financial structure, and financial intermediation. *The journal of Finance*, *32*(2), 371–387.

Li, K., Mai, F., Shen, R., & Yan, X. (2020). Measuring corporate culture using machine learning. *The Review of Financial Studies*.

Liang, H., & Renneboog, L. (2017). On the foundations of corporate social responsibility. *The Journal of Finance*, *72*(2), 853–910.

Lieberman, M. B., & Montgomery, D. B. (1988). First-mover advantages. *Strategic management journal*, *9*(S1), 41–58.

Lins, K. V., Servaes, H., & Tamayo, A. (2017). Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis. *the Journal of Finance*, *72*(4), 1785–1824.

Loughran, T., & McDonald, B. (2020). Measuring firm complexity. *Available at SSRN 3645372*.

Mair, J., & Marti, I. (2009). Entrepreneurship in and around institutional voids: A case study from bangladesh. *Journal of business venturing*, *24*(5), 419–435.

Manning, C. D., Surdeanu, M., Bauer, J., Finkel, J., Bethard, S. J., & McClosky, D. (2014). The Stanford CoreNLP natural language processing toolkit. *Association for Computational Linguistics (ACL) System Demonstrations*, 55–60. http://www.aclweb.org/anthology/P/P14/P14-5010

March, J. G. (1991). Exploration and exploitation in organizational learning. *Organization science*, *2*(1), 71–87.

Meek, W. R., Pacheco, D. F., & York, J. G. (2010). The impact of social norms on entrepreneurial action: Evidence from the environmental entrepreneurship context. *Journal of Business Venturing*, *25*(5), 493–509.

Mikolov, T., Sutskever, I., Chen, K., Corrado, G., & Dean, J. (2013). Distributed representations of words and phrases and their compositionality. *arXiv preprint arXiv:1310.4546*.

Mollick, E. R., & Kuppuswamy, V. (2014). After the campaign: Outcomes of crowdfunding. *UNC Kenan-Flagler Research Paper*, (2376997).

Momtaz, P. P. (2019). Token sales and initial coin offerings: Introduction. *The Journal of Alternative Investments*, *21*(4), 7–12.

Momtaz, P. P. (2020a). Entrepreneurial finance and moral hazard: Evidence from token offerings. *Journal of Business Venturing*, 106001.

Momtaz, P. P. (2020b). Initial coin offerings. *Plos one*, *15*(5), e0233018.

Momtaz, P. P. (2020c). Initial coin offerings, asymmetric information, and loyal ceos. *Small business economics*, 1–23.

Momtaz, P. P. (2021a). Econometric models of duration data in entrepreneurship with an application to start-ups' time-to-funding by venture capitalists (vcs). *Journal of Applied Statistics*, 1–22.

Momtaz, P. P. (2021b). The pricing and performance of cryptocurrency. *The European Journal of Finance*, *27*(4-5), 367–380.

Muñoz, P., Cacciotti, G., & Cohen, B. (2018). The double-edged sword of purpose-driven behavior in sustainable venturing. *Journal of Business Venturing*, *33*(2), 149–178.

Muñoz, P., & Cohen, B. (2017). Mapping out the sharing economy: A configurational approach to sharing business modeling. *Technological Forecasting and Social Change*, *125*, 21–37.

Muñoz, P., & Cohen, B. (2018). Entrepreneurial narratives in sustainable venturing: Beyond people, profit, and planet. *Journal of Small Business Management*, *56*, 154–176.

Muñoz, P., Janssen, F., Nicolopoulou, K., & Hockerts, K. (2018). Advancing sustainable entrepreneurship through substantive research. *International Journal of Entrepreneurial Behavior & Research*.

Mupfasoni, B., Kessler, A., & Lans, T. (2018). Sustainable agricultural entrepreneurship in burundi: Drivers and outcomes. *Journal of Small Business and Enterprise Development*.

Nakamoto, S. (2019). *Bitcoin: A peer-to-peer electronic cash system* (tech. rep.). Manubot.

Nissim, M., van Noord, R., & van der Goot, R. (2020). Fair is better than sensational: Man is to doctor as woman is to doctor. *Computational Linguistics*, *46*(2), 487–497.

Obrecht, J.-J. (2011). On the relevance of the concept of entrepreneurial capabilities. *International Journal of Entrepreneurship and Small Business*, *13*(2), 107–125.

Obrecht, J.-J. (2016). Sustainable entrepreneurship education: A new field for research in step with the'effectual entrepreneur'. *International Journal of Entrepreneurship and Small Business*, *29*(1), 83–102.

Pacheco, D. F., Dean, T. J., & Payne, D. S. (2010). Escaping the green prison: Entrepreneurship and the creation of opportunities for sustainable development. *Journal of Business Venturing*, *25*(5), 464–480.

Parrish, B. D. (2010). Sustainability-driven entrepreneurship: Principles of organization design. *Journal of Business Venturing*, *25*(5), 510–523.

Pástor, L., Stambaugh, R. F., & Taylor, L. A. (2020). Sustainable investing in equilibrium. *Journal of Financial Economics*.

Ploum, L., Blok, V., Lans, T., & Omta, O. (2018). Toward a validated competence framework for sustainable entrepreneurship. *Organization & environment*, *31*(2), 113–132.

Renneboog, L., Ter Horst, J., & Zhang, C. (2008). Socially responsible investments: Institutional aspects, performance, and investor behavior. *Journal of banking & finance*, *32*(9), 1723–1742.

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, *70*(1), 41–55.

Sarango-Lalangui, P., Santos, J. L. S., & Hormiga, E. (2018). The development of sustainable entrepreneurship research field. *Sustainability*, *10*(6), 2005.

Schaefer, K., Corner, P. D., & Kearins, K. (2015). Social, environmental and sustainable entrepreneurship research: What is needed for sustainability-as-flourishing? *Organization & environment*, *28*(4), 394–413.

Schaltegger, S., Beckmann, M., & Hockerts, K. (2018). Collaborative entrepreneurship for sustainability. creating solutions in light of the un sustainable development goals. *International Journal of Entrepreneurial Venturing*, *10*(2), 131–152.

Schaltegger, S., Hansen, E. G., & Lüdeke-Freund, F. (2016). Business models for sustainability: Origins, present research, and future avenues.

Schückes, M., & Gutmann, T. (2020). Why do startups pursue initial coin offerings (icos)? the role of economic drivers and social identity on funding choice. *Small Business Economics*, 1–26.

Schumpeter, J. A. (1934). *The theory of economic development*. Harvard University Press, Cambridge.

Schumpeter, J. A. (1942). *Capitalism, socialism and democracy*. Harper, New York.

Senge, P. M., Carstedt, G., & Porter, P. L. (2001). Next industrial revolution. *MIT Sloan management review*, *42*(2), 24–38.

Shepherd, D. A., & Patzelt, H. (2011). The new field of sustainable entrepreneurship: Studying entrepreneurial action linking "what is to be sustained" with "what is to be developed". *Entrepreneurship theory and practice*, *35*(1), 137–163.

Signori, A., & Vismara, S. (2018). Does success bring success? the post-offering lives of equity-crowdfunded firms. *Journal of Corporate Finance*, *50*, 575–591.

Spence, M., Gherib, J. B. B., & Biwolé, V. O. (2011). Sustainable entrepreneurship: Is entrepreneurial will enough? a north–south comparison. *Journal of Business Ethics*, *99*(3), 335–367.

Stål, H. I., & Bonnedahl, K. (2016). Conceptualizing strong sustainable entrepreneurship. *Small Enterprise Research*, *23*(1), 73–84.

Stubbs, W. (2017). Sustainable entrepreneurship and b corps. *Business Strategy and the Environment*, *26*(3), 331–344.

Terán-Yépez, E., Marın-Carrillo, G. M., del Pilar Casado-Belmonte, M., & de las Mercedes Capobianco-Uriarte, M. (2020). Sustainable entrepreneurship: Review of its evolution and new trends. *Journal of Cleaner Production*, *252*, 119742.

Testa, S., Nielsen, K. R., Bogers, M., & Cincotti, S. (2019). The role of crowdfunding in moving towards a sustainable society. *Technological Forecasting and Social Change*, *141*, 66–73.

Tilley, F., & Young, W. (2009). Sustainability entrepreneurs. *Greener Management International*, (55).

Vanacker, T., Vismara, S., & Walthoff-Borm, X. (2019). What happens after a crowdfunding campaign? *Handbook of research on crowdfunding*. Edward Elgar Publishing.

Vega, G., & Kidwell, R. E. (2007). Toward a typology of new venture creators: Similarities and contrasts between business and social entrepreneurs. *New England Journal of Entrepreneurship*.

Venkataraman, S. (2019). The distinctive domain of entrepreneurship research. *Seminal ideas for the next twenty-five years of advances*. Emerald Publishing Limited.

Vismara, S. (2016). Equity retention and social network theory in equity crowdfunding. *Small Business Economics*, *46*(4), 579–590.

Vismara, S. (2019). Sustainability in equity crowdfunding. *Technological Forecasting and Social Change*, *141*, 98–106.

Volkmann, C., Fichter, K., Klofsten, M., & Audretsch, D. B. (2021). Sustainable entrepreneurial ecosystems: An emerging field of research. *Small Business Economics*, *56*(3), 1047–1055.

Vuorio, A. M., Puumalainen, K., & Fellnhofer, K. (2018). Drivers of entrepreneurial intentions in sustainable entrepreneurship. *International Journal of Entrepreneurial Behavior & Research*.

Walthoff-Borm, X., Vanacker, T. R., & Collewaert, V. (2018). Equity crowdfunding, shareholder structures, and firm performance. *Corporate Governance: An International Review*, *26*(5), 314–330.

Weerawardena, J., & Mort, G. S. (2006). Investigating social entrepreneurship: A multidimensional model. *Journal of world business*, *41*(1), 21–35.

York, J. G., O'Neil, I., & Sarasvathy, S. D. (2016). Exploring environmental entrepreneurship: Identity coupling, venture goals, and stakeholder incentives. *Journal of Management Studies*, *53*(5), 695–737.

York, J. G., & Venkataraman, S. (2010). The entrepreneur–environment nexus: Uncertainty, innovation, and allocation. *Journal of business Venturing*, *25*(5), 449–463.

Yunus, M., Moingeon, B., & Lehmann-Ortega, L. (2010). Building social business models: Lessons from the grameen experience. *Long range planning*, *43*(2-3), 308–325.

Exhibits

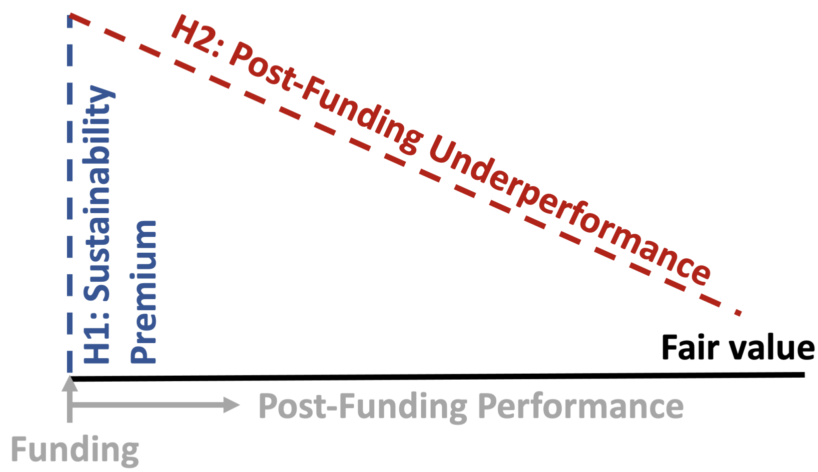

Figure 1: Illustration of Main Predictions

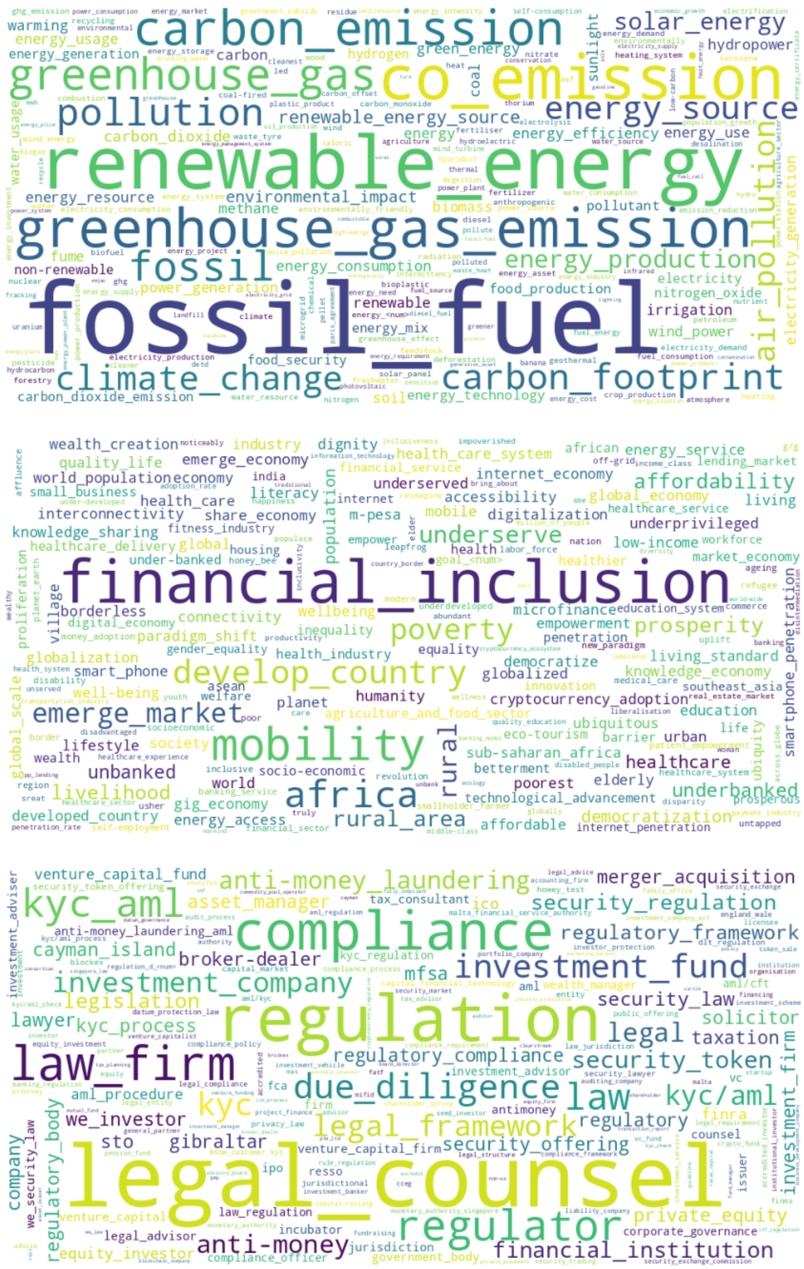

Figure 2: Relative Importance of Terms in ESG Dictionary by {E,S,G} Dimension

Table 1: Descriptive statistics and correlations

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.	19.	20.	21.	22.
Mean	0.000	0.000	0.000	0.000	15.158	-0.534	8.100	3.393	12.924	0.254	0.203	0.661	1.291	0.619	0.884	0.540	0.312	0.008	0.313	0.802	0.325	0.688
SD	1.000	1.000	1.000	1.000	1.912	1.163	0.661	0.587	7.952	0.202	0.403	0.474	0.489	0.486	0.320	0.499	0.463	0.087	0.464	0.399	0.469	0.463
Q1	-0.726	-0.478	-0.668	-0.768	14.215	-1.012	7.775	3.000	7.000	0.091	0.000	0.000	0.693	0.000	1.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000
Median	-0.072	-0.277	-0.044	-0.083	15.429	-0.346	8.151	3.400	12.000	0.250	0.000	1.000	1.099	1.000	1.000	1.000	0.000	0.000	0.000	1.000	0.000	1.000
Q3	0.586	0.058	0.579	0.655	16.524	-0.085	8.496	3.900	17.000	0.375	0.000	1.000	1.609	1.000	1.000	1.000	1.000	0.000	1.000	1.000	1.000	1.000
Key variables:																						
1. ESG Score (normalized)																						
2. E-Score (normalized)	0.648																					
3. S-Score (normalized)	0.894	0.419																				
4. G-Score (normalized)	0.815	0.217	0.651																			
Dependent variables:																						
5. Funding amount, in $m	0.238	0.098	0.213	0.240																		
6. BHAR, 12-mo (equally weighted)	-0.107	-0.045	-0.094	-0.110	0.058																	
Control variables: Venture characteristics:																						
7. Whitepaper length, in (log-words)	0.657	0.309	0.655	0.562	0.226	-0.071																
8. Expert rating	0.219	0.055	0.212	0.232	0.112	-0.079	0.292															
9. Team size, in # FTE	0.297	0.068	0.292	0.316	0.169	-0.034	0.289	0.397														
10. Technical background, in %	0.001	-0.010	0.010	0.000	0.086	0.025	0.069	-0.034	0.050													
11. Minimum viable product (dummy)	0.058	0.064	0.040	0.038	-0.100	-0.138	0.054	0.344	0.180	-0.043												
12. Open source (dummy)	0.054	0.033	0.082	0.011	-0.072	-0.114	0.140	0.363	0.146	0.037	0.221											
13. # Industries (log)	0.064	0.072	0.045	0.040	-0.065	-0.180	0.070	0.240	0.160	-0.016	0.213	0.106										
Control variables: Offering characteristics:																						
14. Soft cap (dummy)	0.141	0.097	0.122	0.114	-0.109	-0.107	0.078	0.219	0.144	-0.120	0.219	0.160	0.169									
15. Hard cap (dummy)	0.126	0.066	0.110	0.119	-0.016	-0.027	0.130	0.225	0.131	-0.038	0.131	0.126	0.093	0.363								
16. Pre-sale (dummy)	0.123	0.083	0.094	0.115	-0.050	-0.094	0.108	0.237	0.179	-0.054	0.117	0.102	0.174	0.207	0.176							
17. Whitelist (dummy)	0.180	0.090	0.145	0.186	0.055	-0.150	0.175	0.238	0.229	0.018	0.195	0.084	0.156	0.161	0.121	0.094						
18. Bonus (dummy)	-0.030	-0.033	-0.007	-0.035	-0.005	0.028	-0.019	0.008	0.024	-0.001	-0.017	0.017	0.032	-0.022	0.032	-0.007	0.036					
19. Bounty (dummy)	0.067	0.079	0.059	0.025	-0.119	-0.163	0.062	0.258	0.153	-0.062	0.430	0.160	0.215	0.222	0.167	0.183	0.203	0.012				
20. ERC-20 standard (dummy)	0.050	0.002	0.033	0.077	-0.063	-0.147	0.030	0.102	0.088	-0.017	0.108	0.034	0.099	0.080	0.067	0.057	0.080	0.016	0.102			
Control variables: Market characteristics:																						
21. Bull market (dummy)	-0.150	-0.119	-0.131	-0.107	0.131	0.226	-0.093	-0.261	-0.204	0.112	-0.305	-0.116	-0.203	-0.341	-0.234	-0.205	-0.396	-0.014	-0.380	-0.235		
22. Bear market (dummy)	0.149	0.097	0.113	0.141	-0.022	-0.245	0.083	0.183	0.200	0.012	0.149	0.051	0.177	0.266	0.202	0.168	0.314	-0.036	0.293	0.210	-0.638	

Table 2: Are ESG startups different?

	Sample mean for all startups	*Differences in subsamples: Δ All startups − ...*			
		*...high-ESG**	*...high-E*	*...high-S*	*...high-G*
Key variables:					
ESG Score (normalized)	0.0	0.773^{***}	0.594^{***}	0.749^{***}	0.689^{***}
E-Score (normalized)	0.0	0.388^{***}	0.493^{***}	0.333^{***}	0.207^{***}
S-Score (normalized)	0.0	0.707^{***}	0.549^{***}	0.821^{***}	0.57^{***}
G-Score (normalized)	0.0	0.705^{***}	0.375^{***}	0.578^{***}	0.806^{***}
Dependent variables:					
Funding amount, in $m	15.158	15.559^{***}	15.411^{***}	15.517^{***}	15.546^{***}
BHAR, 12-mo (equally weighted)	-0.534	-0.658	-0.622	-0.599	-0.602
Control variables:					
Venture characteristics:					
Whitepaper length, in (log-words)	8.1	8.453^{***}	8.419^{***}	8.467^{***}	8.416^{***}
Expert rating	3.393	3.513^{***}	3.5^{***}	3.529^{***}	3.521^{***}
Team size, in # FTE	12.924	15.063^{***}	14.199^{***}	15.137^{***}	15.084^{***}
Technical background, in %	25.438	25.203	24.853	25.273	25.047
Minimum viable product (dummy)	0.203	0.216	0.22	0.228	0.22
Open source (dummy)	0.661	0.658	0.691	0.685	0.663
# Industries (log)	1.291	1.319	1.322	1.328	1.305
Offering characteristics:					
Soft cap (dummy)	0.619	0.669^{***}	0.667^{***}	0.679^{**}	0.673^{**}
Hard cap (dummy)	0.884	0.918^{**}	0.907	0.911^{***}	0.914^{***}
Pre-sale (dummy)	0.54	0.6^{**}	0.571	0.574	0.6^{**}
Whitelist (dummy)	0.312	0.388^{***}	0.352	0.376^{**}	0.396^{***}
Bonus (dummy)	0.008	0.004	0.004	0.006	0.004
Bounty (dummy)	0.313	0.335	0.346	0.347	0.329
ERC-20 standard (dummy)	0.802	0.824	0.797	0.814	0.825
Market characteristics:					
Bull market (dummy)	0.325	0.266^{**}	0.268^{**}	0.267^{**}	0.269^{**}
Bear market (dummy)	0.688	0.759^{***}	0.736^{**}	0.739^{**}	0.758^{***}

* High-ESG = Startups with above-median ESG score.

Explanations: Variables are defined in Table A1 in the appendix. The sample consists of 1,043 ICOs between 2016 and 2020. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3: The Sustainability Premium

Column	(1)	(2)	(3)	(4)	(5)
Model:	Main	Control	Selection	IMR	IV
Dependent variable:	Valuation*	Valuation	$\mathbb{1}_{\text{High-ESG}}$	Valuation	Valuation
Key variables:					
ESG Score (normalized)	0.250***			0.251***	0.211**
	(0.067)			(0.067)	(0.103)
Venture characteristics:					
Whitepaper length, in (log-words)	0.251**	0.492***	0.391***	0.242**	0.289**
	(0.122)	(0.115)	(0.035)	(0.122)	(0.147)
Expert rating	0.490***	0.485***	0.022	0.484***	0.490***
	(0.112)	(0.114)	(0.029)	(0.113)	(0.105)
Team size, in # FTE	0.031***	0.034***	0.006***	0.031***	0.031***
	(0.008)	(0.008)	(0.002)	(0.008)	(0.008)
Technical background, in %	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.004)	(0.004)	(0.001)	(0.004)	(0.003)
Minimum viable product (dummy)	0.001	-0.014	-0.061	0.007	-0.001
	(0.181)	(0.183)	(0.042)	(0.182)	(0.170)
Open source (dummy)	-0.351***	-0.385***	-0.125***	-0.328**	-0.356***
	(0.128)	(0.128)	(0.031)	(0.131)	(0.122)
# Industries (log)	-0.143	-0.147	-0.003	-0.151	-0.143
	(0.127)	(0.129)	(0.031)	(0.128)	(0.119)
Offering characteristics:					
Soft cap (dummy)	-0.206	-0.182	0.023	-0.206	-0.203
	(0.134)	(0.135)	(0.034)	(0.135)	(0.126)
Hard cap (dummy)	-0.035	-0.051	-0.021	-0.051	-0.037
	(0.199)	(0.201)	(0.049)	(0.200)	(0.187)
Pre-sale (dummy)	-0.149	-0.134	0.040	-0.155	-0.147
	(0.122)	(0.122)	(0.029)	(0.123)	(0.115)
Whitelist (dummy)	0.223*	0.246*	0.035	0.227*	0.227*
	(0.130)	(0.131)	(0.035)	(0.130)	(0.122)
Bonus (dummy)	0.111	0.087	-0.109	0.137	0.107
	(0.603)	(0.600)	(0.110)	(0.607)	(0.565)
Bounty (dummy)	-0.175	-0.179	-0.009	-0.177	-0.176
	(0.150)	(0.151)	(0.035)	(0.151)	(0.141)
ERC-20 standard (dummy)	-0.183	-0.189	0.003	-0.186	-0.184
	(0.139)	(0.141)	(0.035)	(0.140)	(0.131)
Market characteristics:					
Bull market (dummy)	-0.010	-0.010	0.029	-0.024	-0.010
	(0.189)	(0.189)	(0.058)	(0.190)	(0.177)
Bear market (dummy)	0.107	0.149	0.114*	0.094	0.113
	(0.233)	(0.232)	(0.061)	(0.233)	(0.218)
Observations	1043	1043	1043	1039	1043
R^2	0.313	0.306	0.408	0.315	0.313
IMR	✗	✗	✗	✓	✗
IV	✗	✗	✗	✗	✓
Quarter-year FEs	✓	✓	✓	✓	✓
Country FEs	✓	✓	✓	✓	✓

* Valuation = Funding amount (log.).

Explanations: These are regression results of valuation on the ESG score. The dependent variable is natural logarithm of the funding amount (in $ million). In column (3), the dependent variable is a dummy indicating whether the token offering has an above-median ESG score. Column 4 shows the results for the Inverse Mills Ratio (IMR) approach. Column 5 uses the Generalized Residuals (GR) as an instrumental variable for the ESG score. Control variables are defined in Table A1 in the appendix. The sample consists of 1,043 ICOs between 2016 and 2020. All specifications include country and quarter-year fixed effects. Huber-White robust standard errors are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Decomposing the Sustainability Premium

Column	(1)	(2)	(3)	(4)	(5)
Dependent variable: Valuation = funding amount (log.)					
ESG Score (normalized)	0.250***				
	(0.067)				
E-Score (normalized)		0.137***			0.115**
		(0.051)			(0.056)
S-Score (normalized)			0.179**		0.074
			(0.071)		(0.084)
G-Score (normalized)				0.162***	0.126*
				(0.062)	(0.069)
Observations	1043	1043	1043	1043	1043
R^2	0.313	0.310	0.310	0.309	0.314
VIF* [ESG]	2.16				
VIF [E]		1.27			1.41
VIF [S]			2.15		2.95
VIF [G]				1.82	2.28
VIF [argmax(controls)]	4.63	4.63	4.63	4.62	4.64
Controls	✓	✓	✓	✓	✓

* VIF = Variance Inflation Factor.

Explanations: These are regression results of valuation on the ESG score and its components. The dependent variable is natural logarithm of the funding amount (in $ million). Control variables are defined in Table A1 in the appendix. The sample consists of 1,043 ICOs between 2016 and 2020. All specifications include country and quarter fixed effects. VIF stands for Variance Inflation Factor. Huber-White robust standard errors are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Propensity Score Matched (PSM) Samples

Column	(1)	(2)	(3)	(4)
Model:	PSM		GR/IV*	
Selection cutoff:	80%ile	70%ile	80%ile	70%ile
Dependent variable: Funding amount (log)				
Panel A: ESG composite				
ESG Score (normalized)	0.195***	0.186***	0.222**	0.262***
	(0.065)	(0.061)	(0.103)	(0.100)
Controls	✓	✓	✓	✓
GR	✗	✗	✓	✓
Observations	627	939	627	939
R^2	0.296	0.253	0.296	0.252
Panel B: ESG decomposition				
E-Score (normalized)	0.126**	0.110**	0.124**	0.105*
	(0.059)	(0.056)	(0.060)	(0.056)
S-Score (normalized)	0.059	0.050	0.054	0.034
	(0.091)	(0.084)	(0.095)	(0.089)
G-Score (normalized)	0.100	0.126*	0.094	0.109
	(0.074)	(0.068)	(0.082)	(0.075)
Controls	✓	✓	✓	✓
GR	✗	✗	✓	✓
Observations	627	939	627	939
R^2	0.299	0.256	0.299	0.256

Note: * indicates that columns (3) and (4) are based on the IV model in panel A and on the inclusion of the GR as a simple control in panel B.

Explanations: These are regression results of valuation on the ESG score and its components. The dependent variable is natural logarithm of the funding amount (in $ million). Panels A and B regress on the aggregate and disaggregated ESG scores, respectively. Columns (1)-(2) and (3)-(4) report results for the baseline model and for the IV model, respectively. The PSM approach employs a one-to-one nearest-neighbor matching with two different selection cutoffs: 80% and 70%. That is, the PSM samples are based on selection models that predict whether a startup's ESG score is higher than the 80th and 70th percentile, leading to different subsample sizes of 627 and 939 observations, respectively.

Table 6: The Performance of Sustainable Entrepreneurs

Column	(1)	(2)	(3)
Model:	Main	IMR	GR
Dependent variable: BHAR, 12 months			
Panel A: ESG composite			
ESG Score (normalized)	-0.163*	-0.163*	-0.373**
	(0.091)	(0.092)	(0.155)
Controls	✓	✓	✓
IMR	✗	✓	✗
GR	✗	✗	✓
Observations	302	300	302
R^2	0.368	0.377	0.357
Panel B: ESG decomposition			
E-Score (normalized)	-0.024	-0.027	.
	(0.083)	(0.084)	.
S-Score (normalized)	-0.015	-0.007	.
	(0.138)	(0.142)	.
G-Score (normalized)	-0.192*	-0.196*	.
	(0.110)	(0.111)	.
Controls	✓	✓	.
IMR	✗	✓	.
GR	✗	✗	.
Observations	302	300	.
R^2	0.372	0.382	.

Explanations: Panel A (B) shows regression results of long-run performance on the ESG score (ESG score's components). The dependent variable is the 12-month Buy-and-Hold Abnormal Return (BHAR) after the token listing date relative to an equally-weighted composite crypto-market benchmark. Column 2 shows the result for the propensity score matching approach. In column 3, we control for the calculated inverse Mills ratios as in the equation 6. Column 4 presents the result of the second stage of a 2sls approach where we instrument the startups' ESG scores with the generalized residuals described in the equation 7. Control variables are defined in Table A1 in the appendix. The sample consists of 1,043 ICOs between 2016 and 2020. All specifications include country and quarter fixed effects. Huber-White robust standard errors are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7: The Moderating Effect of the Degree of Formalization

Column	(1)	(2)	(3)	(4)	(5)	(6)
Model	Valuation			Performance		
Dependent variable:	Funding amount (log.)			BHAR (12 months)		
ESG	0.255**	0.776**	0.312***	0.087	0.461	-0.196*
	(0.129)	(0.333)	(0.070)	(0.148)	(0.396)	(0.101)
Formalization (Proxy 1)	-0.351***			-0.197		
	(0.128)			(0.160)		
Formalization (Proxy 2)		0.166***			0.035	
		(0.039)			(0.043)	
Formalization (Proxy 3)			1.092***			0.594***
			(0.137)			(0.186)
ESG $\times$ Formalization (Proxy 1)	-0.007			-0.332*		
	(0.141)			(0.174)		
ESG $\times$ Formalization (Proxy 2)		-0.068*			-0.068	
		(0.039)			(0.046)	
ESG $\times$ Formalization (Proxy 3)			-0.533***			0.005
			(0.116)			(0.176)
Controls	✓	✓	✓	✓	✓	✓
Observations	1043	1008	1043	302	290	302
R^2	0.313	0.332	0.350	0.378	0.376	0.401

Explanations: These are regression results of valuation and performance on the ESG score. In columns (1)-(3), The dependent variable is natural logarithm of the usd raied in the ICO. In column (4)-(6), the dependent variable is the 12 months buy-and-hold abnormal return after the ICO. We use three proxies for the formalization. Proxy 1 is the dummy indication if the ICO open sourced its code in GitHub. Proxy 2 is the number of followers in Twitter. Proxy 3 is a dummy equals one if the ICO is VC-backed. Control variables are defined in Table A1 in the appendix. The sample consists of 1,043 ICOs between 2016 and 2020. All specifications include country and quarter fixed effects. Huber-White robust standard errors are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix

Table A1:
Variable definitions

Variable	Description	Sources
	Panel A: Dependent variables	
Funding amount (log.)	The funding amount raised in an ICO in $m (log.).	ICObench, ICO-drops, CoinSchedule, company websites
Buy-and-Hold Abnormal Return (BHAR), 12-mo (equally weighted)	The excess return of the token over a holding period of t months after its first trading day, computed by adjusting the raw return by the equally-weighted market benchmark following the method by Momtaz (2021b). The equally-weighted index is constructed based on all cryptocurrencies with available price data.	Coinmarketcap
	Panel B: ESG variables	
E-Score (normalized)	The count of distinct occurrences of terms in our environmental word list, normalized by total terms in the word list	Company websites, Internet Archive
S-Score (normalized)	The count of distinct occurrences of terms in our social word list, normalized by total terms in the word list	Company websites, Internet Archive
G-Score (normalized)	The count of distinct occurrences of terms in our governance word list, normalized by total terms in the word list	Company websites, Internet Archive
ESG Score (normalized)	Sum of the Environmental, Social, and Governance scores	Company websites, Internet Archive
	Panel C: Control variables: Venture characteristics:	
Whitepaper length, in (log-words)	natural logarithm of count of words in the whitepaper	Company websites, Internet Archive
Expert rating	ICO rating in the ICObench platform	ICObench
Team size, in # FTE	The number of team members.	ICObench
Technical background, in %	The number of technical experience of all team members in years.	LinkedIn
Minimum viable product (dummy)	A dummy variable that equals one if the firm has a minimum viable product	ICObench
Open source (dummy)	A dummy variable that equals one if the firm publishes open source code on GitHub, and zero otherwise.	GitHub
# Industries (log)	The logarithm of one plus the number of the industries in which the ICO is active.	ICObench
	Panel D: Control variables: Offering characteristics:	
Soft cap (dummy)	A dummy indicating if the ICO has a soft cap goal	ICObench
Hard cap (dummy)	A dummy indicating if the ICO has a hard cap goal	ICObench
Pre-sale (dummy)	A dummy variable that equals one if the firm conducted a Pre-ICO sale, and zero otherwise.	ICObench
Whitelist (dummy)	A dummy indicating if the ICO has an activated whitelist	ICObench
Bonus (dummy)	A dummy variable that equals one if the firm has a bonus program in place, and zero otherwise.	ICObench
Bounty (dummy)	A dummy variable that equals one if the firm has a bounty program in place, and zero otherwise.	ICObench
ERC-20 standard (dummy)	A dummy variable that equals one if the tokens have an ERC20 standard, and zero otherwise.	ICObench
	Panel E: Control variables: Market characteristics:	
Bull market (dummy)	A dummy variable for whether the token offering took place during a bull market, i.e., prior to the so-called "crypto winter."	

Bear market (dummy)	A dummy variable for whether the token offering took place during a bear market, i.e., during the “crypto winter.”