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

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August 25, 2022

Abstract

Sustainable Entrepreneurship (SE) seeks to attain profitability *and* sustainability goals. A major research gap concerns the economic attractiveness of SE 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.

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

*We thank seminar participants at the Entrepreneurial Finance Association 2021 Annual Meeting, the German Finance Association 2021 Annual Meeting, and the Financial Management Association 2022 Annual European Meeting for helpful comments.

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1 Executive Summary

Prior studies have considered how sustainability-orientated entrepreneurs may help resolve the great Environment, Society and Governance (ESG) challenges of our time. However, few have considered whether sustainability orientation is also financially attractive for entrepreneurs and the investors who back them. Whether sustainability orientation pays is ambiguous because sustainability orientation creates costly constraints, while startups cannot fully appropriate their positive externalities. Understanding the economic implications of sustainable entrepreneurship is not just important for entrepreneurs and investors; it is also important for public policy because a lack of financial incentives would require government subsidies for sustainability-oriented ventures.

The study's goal is to relate startups' ESG properties to their financial performance. A key challenge in our study is that commercial ESG ratings are not available for most private companies. Therefore, we introduce a machine-learning approach to quantify startups' ESG properties from their whitepapers. Our method yields robust ESG scores. In fact, our freely available ESG scores are highly correlated with those of commercial ESG rating agencies (for large firms that are covered by the agencies), demonstrating our approach's external validity. For future research, we make our method available with an easy-to-use interface at (www.SustainableEntrepreneurship.org).

We explore how startups' ESG scores impact their valuations and post-funding performance in blockchain-based crowdfunding campaigns, so-called token offerings or Initial Coin Offerings (ICOs). Our results suggest that startups with salient ESG properties benefit from substantially higher valuations. A one-standard-deviation increase in the ESG metric is associated with a 28% increase in the funding amount. However, startups with pronounced ESG properties underperform in 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 decrease in buy-and-hold abnormal returns of –16% in the first 12-month. Overall, our study contributes to entrepreneurship, entrepreneurial finance, and sustainability research by (i) offering a method to quantify startups' ESG properties, (ii) examining the short-term valuation consequences of startups' sustainability orientation, as well as (iii) its longer-term performance implications.

2 Introduction

Sustainable Entrepreneurship (SE) is a rapidly growing literature (for excellent recent reviews, see Anand et al., 2021; Johnson and Schaltegger, 2020). SE is characterized by

profit-seeking entrepreneurial activity that embraces the broader (non-financial) Environment, Society and Governance (ESG) goals of our time. A common theme in the literature is that it evokes Schumpeter's (1942) notion of 'creative destruction' to explain how SE may affect sustainable change (e.g., Cohen and Winn, 2007; Hall and Vredenburg, 2003; Hart and Christensen, 2002; Hart and Milstein, 1999; Shepherd and Patzelt, 2017; 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) assumes 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, 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 represents a first step towards addressing this important gap by posing the following research question: *How (economically) attractive is SE for entrepreneurs and investors?*

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

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). To fill this gap, we develop two hypotheses related to the valuation and performance of sustainable startups.

The prospect 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 achieve economic and ESG goals together, then investors should delegate ESG goals to entrepreneurs with specialized skills (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 themselves. For these reasons and those in section 4, under our '***Valuation Premium Hypothesis***' (***VPH***), SE receives higher valuations than CE.

The flip side of delegated philanthropy is that SE may (economically) underperform post-funding, which is at the core of much controversy in the SE literature (Hall et al., 2010; Kraus et al., 2018). We label this prediction the '***Post-Funding Underperformance Hypothesis***' (***PFUH***). Financial equilibrium theory argues that investors' greater "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, 2007; Gillan et al., 2021; Pástor et al., 2020). Two important aspects deserve elaboration. Lower financial returns (i.e., underperformance) do not eliminate incentives for entrepreneurs or investors to get involved in SE. The former benefit from the ESG premium during the funding stage, while the latter sacrifice financial returns for the sake of ESG returns. In aggregate, i.e., 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 post-funding financial performance of SE.

Empirically, we employ a machine-learning (ML) approach to quantify startups' ESG properties, using information disclosed in ICO whitepapers. Manual inspection suggests that our ESG scores identify startups' ESG properties well. Even for S&P500 firms, our approach leads to ESG scores that are highly correlated with those of commercial ESG rating agencies, such as *Refinitiv*, underscoring the validity of our approach. For replication purposes and as an aid for future research, our source code is available at our easy-to-use web application www.SustainableEntrepreneurship.org.

Our results support both the VPH and the PFUH. We examine a large sample of 1,043 token offerings over the period 2016-2020.[1] Token offerings are blockchain-based crowdfunding campaigns, in which smart contracts govern the exchange of fiat money for tokens between investors and entrepreneurs (Bellavitis et al., 2020; Bellavitis et al., 2021; Cum-

[1]Our paper is fully replicable. The data come from the Token Offerings Research Database (TORD), see www.paulmomtaz.com/data/tord, and the machine-learning algorithm to quantify ESG properties of our sample startups is made available along with this publication.

ming et al., 2022b; Faust et al., 2022; Fisch, 2019; Giudici and Adhami, 2019; Howell et al., 2020; Huang et al., 2020; Kolbe et al., 2022; Momtaz, 2019, 2020b, 2022a, 2022b). Token offerings are an ideal laboratory to examine the economics of SE. They largely tap pools of individual investors that may be more motivated by non-financial goals than institutional investors (Fisch et al., 2019). 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 $3.4million (relative to the mean funding amount of $11.9million in our sample). Consistent with the *PFUH*, startups with pronounced ESG properties underperform in 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-month 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. Both main results are robust to endogeneity concerns related to observed and unobserved heterogeneity.

The remainder of the paper is organized as follows. Section 3 reviews the existing and multidisciplinary literature on SE and section 4 derives empirical predictions. Section 5 discusses our machine-learning approach to quantify startups' ESG properties. Section 6 describes our sample and section 7 presents our empirical results. Finally, Section 8 provides a discussion, highlights limitations and potential avenues for future research, and concludes the paper.

3 Related Literature

3.1 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. Early studies draw on the concept of "sustainable development," which the *United Nations' World Commission on Environment and Development* (*WCED*) introduced in 1987 (e.g., Cohen and Winn, 2007; Dean and McMullen, 2007; Hall et al., 2010). According to the WCED, sustainable development refers to society striving 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*. Furthermore, in contrast to the broader ESG literature in management and economics, SE has thus far focused 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 (while acknowledging that SE may extend beyond ESG) and highlights the dual objective function, as follows:

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

Existing work on SE is "truly multidisciplinary" (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. For details, we refer the reader to Anand et al. (2021) and Johnson and Schaltegger (2020).

Of immediate relevance to our study's focus, SE outcomes are 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 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) make researchers confront the "major challenge" of coming to a consensus on "how to measure sustainability" (Anand et al., 2021, p. 12). Second, given that SE's historical emergence is tied to entrepreneurial opportunities that result 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).

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 aggregate evidence on the subject is rather limited. Cumming et al. (2016) find a positive relationship between venture capital activity and oil prices in the alternative energy sector ('cleantech'); Cumming et al. (2017) find that reward-based crowdfunding campaigns for cleantech projects on *Indiegogo* 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) find 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 that sustainability-oriented equity-based crowdfunding campaigns are less likely to attract professional investors. Overall, the literature on SE financing is relatively nascent, and a comprehensive analysis 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).

3.2 ESG Investing

Sustainable (or impact) investing describes the practice of investors considering ESG when making investment and portfolio decisions. Sustainable investing is experiencing soaring growth in terms of both practice and research (Gillan et al., 2021; Pástor et al., 2020). However, the sustainable investing literature is limited in a number of important ways. First, several data providers offer ESG metrics, and the between-provider correlation is very low (Berg et al., 2020). Thus, there is substantial disagreement as to how ESG is measured, and different components are weighted to arrive at a composite measure. Second, as ESG is a relatively recent phenomenon and the market may be transitioning to a new equilibrium, it is unclear whether current studies measure a new steady state or simply a transitory, temporary state during the dynamic adjustment process. Third, the direction of causality is unclear, i.e., 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, such as Cumming et al., 2016; Cumming et al., 2017; Vismara, 2019).

3.3 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. 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 an issuing venture's product or service once it is developed and on the market, and (iii) security tokens are equity-like instruments that give investors control rights. Shortly after the offering, projects often 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; Momtaz et al., 2022).

Token offerings are an ideal playing field to shed more light on the financing of sustainability-oriented startups for at least two reasons. First, individual investors with simultaneous financial and non-financial investment goals predominantly populate the market for token offerings (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) listing tokens on exchange platforms post-offering enables the project's financial performance to be tracked on a daily basis and in a transparent way by observing equilibrium prices formed by supply-and-demand dynamics in liquid markets. As Böckel et al. (2020) 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.

4 Hypotheses

4.1 ESG and Funding

Like their conventional counterparts, 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 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 proclamation that 'the social responsibility of business is to increase its profits' is often used as an argument against ESG/CSR (i.e., Corporate Social Responsibility) 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") (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 philanthropy' would be a startup involved in the production of 3-D printers that enable customers to produce assault rifles. Assuming that investors prefer 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 (Hart and Zingales, 2017).

Empirical evidence suggests that 'doing well by doing good' can work. Traditional financial market theory assumes that investor preferences for future consumption determine

the financial market equilibrium (Fama and French, 2007). However, if investors incorporate ESG preferences into their utility models (for evidence of this, see Shepherd et al., 2009; Shepherd et al., 2013), 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 ultimately makes it cheaper to invest in ESG projects. If consumers incorporate ESG considerations into their 'willingness-to-pay' models (Barber et al., 2021) as well, 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 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 establish the importance of signaling venture quality for the funding success in token offerings (e.g., Fisch, 2019; Momtaz, 2020b, 2021a). 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 in signaling (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 (Kraus et al., 2018), effectively lowering start-up related ex ante risk levels. 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 younger generations are well represented on crypto markets and empirical studies show that these generations 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). Sixth, ESG could be regarded as an investment in product differentiation, which might result in startups being able to appropriate higher profit margins after product launch (e.g., Albuquerque et al., 2019). 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 may theoretically justify a sustainability premium for high-ESG ventures. SE financing 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 context of token offerings, which is arguably populated by investors with salient non-financial preferences (Fisch et al., 2019; Schückes and Gutmann, 2020).

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

4.2 ESG and Post-Funding Performance

How does sustainable entrepreneurship perform after the fundraising campaign compared to conventional entrepreneurship? As 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 one such "major gap," as we are not aware of any study that has examined the relationship between ESG and post-funding financial performance in the entrepreneurial context. Indeed, Böckel et al.'s (2020, p. 433) recent review of studies at the intersection of crowdfunding and sustainability concludes that a major "research gap related to the post-funding phase" exists. 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* in the period 2009-2012 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, 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 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 lose and less likely to invest in intangibles. Thus, Walthoff-Borm et al. (2018) is the only crowdfunding study that may suggest that startups with salient ESG attributes (i.e., intangible goals) may underperform post-funding.

Studies on the post-funding performance of token offerings are also rare. Momtaz (2021b) studies the performance of cryptocurrencies 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 ventures' post-ICO performance, 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 (Pástor et al., 2020, and for a review, see Gillan et al., 2021). 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 particular importance in the entrepreneurial context, where product market-related hypothesis testing and frequently changing directions is of paramount importance (Johnson and Schaltegger, 2020; Kraus et al., 2018). Thus, many studies argue that sustainability is at odds with capitalist societies (e.g., Balakrishnan et al., 2003).

In the ESG investing literature, the consensus is clear: High-ESG investments *un-*

*der*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 under-diversification and, in turn, hurts the risk-return trade-off. Moreover, equilibrium asset pricing theory suggests that high valuations are mechanically related to lower expected returns (Campbell et al., 2012; Fama and French, 2007). For these reasons, if there is a sustainability premium, as hypothesized in ***H1***, then sustainable entrepreneurs should have a negative post-funding performance.

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

5 Quantifying Startups' ESG Properties

5.1 ESG Measurement in Existing Studies

Existing studies measure startups' ESG properties relatively ad-hoc, 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 the crowdfunding platform *Indiegogo*; 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, e.g., *Crunchbase*). Broad adoption of our approach would increase the comparability of results across ESG studies (Li et al., 2020; Loughran and McDonald, 2020), and reduce subjectivity of ESG measurement in the literature (Berg et al., 2020; Dimson et al., 2020).

5.2 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. Creating an ESG-specific dictionary in the startup context
2. Measuring the (normalized) prevalance of ESG cues for each startup ("ESG scores")

For brevity, we defer a comprehensive discussion of our machine-learning approach to the Internet Appendix A, as well as to our source code website on *GitHub*. Here, we summarize the main tenets relevant for understanding our approach and interpreting the results reported in section 7.

5.2.1 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 derives 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 every whitepaper 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 to train the model to predict neighboring collocations, 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 provide seed words as initial starting points to help the machine to create the ESG dictionary. Specifically, we collect all available *Financial Times* (*FT*) articles with the tags "ESG Investing" or "Moral Money." We follow a standard bag-of-words approach and extract the most frequent bi-grams and tri-grams (two and three-word combinations) that appeared in the pre-selected *FT* corpus. Then, we 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), the full list of seed words is available in the Internet Appendix Table I.A.1. 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, and find robust results.

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 1 illustrates the word clouds corresponding to the E, S and G word lists.

[Place Figure 1 about here.]

5.2.2 ESG Score

We use our ESG dictionary to 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:

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

5.2.3 Sanity Checks

We perform manual sanity checks to make sure that our approach identifies startups' ESG properties reliably. The results are 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." Careful examinations of *WPP Energy*'s and *Greencoin*'s whitepapers show 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. Note that we not only conducted sanity checks for those startups with the highest and lowest ESG scores, rather, we manually checked ESG-related word clouds for each of the 1,043 ICOs in our sample. Additionally, we checked the average ESG scores by industry. In particular, we observed that E is most pronounced in Energy and Manufacturing, S is most pronounced in Health and lowest in Casinos/Gambling, and G is most pronounced in Banking and in Legal and least pronounced in Manufacturing, which is consistent with reasonable ex ante expectations (e.g., Berg et al., 2020; Dorfleitner et al., 2015).

5.2.4 Web Application

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

www.SustainableEntrepreneurship.org

The Python source code as well as comprehensive and relatively technical documentation of our machine-learning approach for measuring ESG in the entrepreneurial context is provided in the Internet Appendix A, as well as on our *GitHub* project page.

5.2.5 External Validity of ESG Scores from www.SustainableEntrepreneurship.org

We are also able to demonstrate the external validity of our method. In particular, we compare how our ESG scores from www.SustainableEntrepreneurship.org correlate – out-

of-sample – with the ESG and CSR scores from the leading commercial ESG rating agency, *Refinitiv* for all S&P500 firms, and find very strong relations. To demonstrate the validity of our ESG scores for publicly listed firms, we obtained all SEC EDGAR publications by S&P500 firms, as well as *Refinitiv*'s ESG and CSR scores for these firms. We then used the method at www.SustainableEntrepreneurship.org to calculate ESG scores for the S&P500 firms. We show that our ESG scores and *Refinitiv*'s are strongly related in Figure 2. This demonstrates that our approach to quantify firms' ESG properties is valid beyond our narrowly defined empirical context of tokenized startups, and can plausibly be used in other settings, such as other, non-tokenized startups (see Cumming et al., 2022a, for a first use case) or even large, publicly-listed firms.

[Place Figure 2 about here.]

5.2.6 Limitations of the Machine-Learning Approach to Quantify ESG Properties

Given that our machine-learning approach is central to our study, it is important to discuss its limitations. First, there are semantic ambiguities that can affect our ESG scores at two different layers in the machine-learning process: (i) Input terms more related to crypto than ESG potentially dilute our ESG dictionary, while input terms that are very closely related to ESG might miss information that are tangentially relevant to ESG; and (ii) the purely mechanical output term selection could include terms that are not necessarily relevant for ESG (e.g., "pension funds"). Hence, we check the sensitivity of our results to various modifications of input and output terms, as shown below. Second, we use the *word2vec* NLP model, but there are model-specific parameters that may differ in other machine-learning algorithms, such as *LSTM* and (self-)attention models, which could potentially lead to different ESG dictionary terms.

6 Methods

6.1 Data Sources

Our sample is based on the *Token Offerings Research Database* (*TORD*).[2] *TORD* offers the most comprehensive publicly available token offerings database, and therefore addresses some of the key concerns about data limitations in regards to token offerings (for a comprehensive discussion of these concerns, see section 6.4 in Momtaz, 2020a). Our empirical

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

analyses exclude Security Token Offerings (STOs) and Initial Exchange Offerings (IEOs) to avoid biases from various confounding factors that would relate to the governance of these alternative token and offering types, and therefore only sample 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 and the startups' market capitalizations from *CoinMarket-Cap*. We only include token offerings with a complete set of variables, as described in section 6.2, in our final sample. Our final sample consists of 1,043 token offerings.

6.2 Variables

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

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 first described in Momtaz (2021b).

6.2.2 Independent Variables

Our independent variables are the startups' ESG properties, which we derive from their whitepapers using a machine-learning approach. We describe the independent variable construction in detail in section 5 and in the Internet Appendix A.

6.2.3 Control Variables

For brevity, we define our control variables in Table A1 in the appendix.

6.3 Summary Statistics

Table 1 provides summary statistics and bivariate correlations for all of our main variables. The average startup in our sample raises $11.9 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, of all the ESG aspects, environmental aspects are the least correlated with the funding amount. The post-funding performance is negatively correlated with E ($\rho = -0.045$), S ($\rho = -0.094$) and G ($\rho = -0.110$), with E again being the most weakly correlated ESG aspect with the post-funding performance. 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 differences for subsamples with above-mean ESG scores relative to the full sample in the remaining columns. In line with our two main hypotheses, the average funding amount is higher in high-ESG startups, with the difference being statistically 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 statistically 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 statistically significant differences between the full sample and the highly sustainable subsamples. For example, high-ESG startups have, on average, more than two additional team members, with the difference being highly statistically significant. Moreover, high-ESG startups set higher soft and hard caps, and are more likely to

conduct a pre-sale and have a whitelist. Furthermore, 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 two ways in which we control for selection based on observed and unobserved heterogeneity.

[Place Table 2 about here.]

6.4 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.[3] These models control for observed and/or unobserved heterogeneity, which is often pronounced in entrepreneurial finance.

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

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

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, $\Omega_i^{(s)}$:

$$hiESG_i = \Omega_i^{(s)} \delta + \xi_i \tag{4}$$

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):

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

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

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

7 Results

7.1 ESG and Funding

Figure 3 illustrates the univariate relation between our ESG score and the funding amount, in $ million. The binned scatter plot (# bins = 20) indicates a linear ESG-valuation relation. Given the strength of the unconditional relation, the graphical evidence suggests that ESG may be prime determinant of ICO firm valuations. Next, we examine the robustness of this relation in a multivariate model.

[Place Figure 3 about here.]

Table 3 shows the main results for the VPH. 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 of 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 log of the funding amount in $ million as the dependent variable. The coefficient of the normalized ESG score is

0.25, with a p-value $< 1\%$, suggesting that a one standard deviation increase in the ESG score increases the average funding amount of \$11.9 million by \$3.4 million, or 28%. This strongly supports the VPH that there is a sustainability-related valuation premium in token offerings.

The coefficients of the control variables 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 the (i) whitepaper length, (ii) expert rating, (iii) team size, and (iv) 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 6.4. We include IMRs as an additional control in column (4). The coefficient of 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 of 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 \$11.9 million by \$2.8 million, corresponding to a relative effect of 23%. Overall, our baseline result is robust to controlling for both observed and unobserved heterogeneity, and therefore supports the VPH (Hypothesis 1).

[Place Table 3 about here.]

Our machine-learning approach to ESG measurement can also 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. A plausible explanation for the non-significant S dimension in the disaggregated tests is that the E, S, and G dimensions are interrelated, and cross-correlations render some dimensions non-significant, which is acknowledged as a common problem in the ESG literature (Dorfleitner et al., 2015).

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), indicating 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* 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 percentiles, leading to different subsample sizes of 627 and 939 observations, respectively.

Table 5 presents the results for the PSM samples. 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 coefficients for the S and G scores are not consistently statistically significant. Therefore, the environmental component largely drives the sustainability-oriented valuation premium in token offerings.

[Place Table 5 about here.]

7.2 ESG and Post-Funding Performance

Figure 4 illustrates the univariate relation between our ESG score and post-funding performance, measured as 12-month BHAR. The binned scatter plot indicates a linearly negative ESG-performance relation. Given the strength of the unconditional relation, the graphical evidence suggests that ESG may be prime determinant of the identified post-ICO underperformance. Next, we examine the robustness of this relation in a multivariate model.

[Place Figure 4 about here.]

Table 6 displays the tests of the PFUH (Hypothesis 2). The dependent variable in all of the models is the 12-month BHAR relative to an equally-weighted market benchmark. Panel A regresses 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. Columns (1) and (2) show a one-standard-deviation increase in the ESG score is associated with a 16.3% underperformance over the first year of token trading. Interestingly, the estimated underperformance in column (3) is clearly higher (-37.3%), suggesting that unobserved heterogeneity attenuates true underperformance.

In contrast to the dominance of the *environmental* component in the valuation premium, Panel B of Table 6 shows 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. A one-standard-deviation increase 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 PFUH 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.]

7.3 Post-hoc Analyses: Underlying Theoretical Mechanisms

7.3.1 Technology, Network, and Governance

Given the supporting evidence for the ***VPH*** and the ***PFUH***, an important next question for entrepreneurs and investors alike in moving forward with SE is whether and how the

ESG-valuation and -performance relations are driven and, therefore, can be influenced by organizational design choices (Kraus et al., 2018; Parrish, 2010). In particular, the excellent review by Kraus et al. (2018) argues that several fundamental entrepreneurial decisions that are typically believed to drive success in CE are possibly detrimental to SE. The rationale is that sustainability-orientation already imposes binding constraints onto the startup, the effects of which may be magnified by other constraints. Binding constraints reduce entrepreneurial flexibility and the scope of experimentation (e.g., March, 1991). In the following, we test three distinct channels associated with Kraus et al.'s (2018) argument: technological-, network-, and governance-related constraints.

Table 7 presents the results of these post-hoc moderation tests. For the technological dimension, proxy 1 is a dummy indicator for whether the startup open-sourced its code on *GitHub*. For the network dimension, proxy 2 is the log of the number of followers on *Twitter*. For the governance dimension, proxy 3 is a dummy equal to one if the startup is backed by a VC. These variables have been introduced before in the token offerings literature (e.g., Colombo et al., 2021; 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 the 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 proxy has a statistically significant direct effect on the 12-month BHAR (p-value $< 1\%$), while only the technology-related proxy has a statistically significantly negative moderating effect. In particular, ceteris paribus, if the startup increases its ESG score by one standard deviation while having open-sourced some of its platform code, then the post-funding underperformance increases by 33.2%. Overall, the results in Table 7 provide partial support for the argument in Kraus et al. (2018) that several entrepreneurial design choice typically associated with success in CE might be detrimental to SE.

[Place Table 7 about here.]

7.3.2 ESG and Startup-related Risk

A fourth mechanism that would explain the ESG-related valuation premium and post-funding underperformance is related to how ESG is associated with startup-related risk. High-ESG startups might have lower risk, which, in turn, would explain why investors

might value them at a premium and why they yield lower returns in the aftermarket (Cumming et al., 2022a). To explore the risk channel, we study how ESG relates to aftermarket risk, measured as the standard deviation in startups' token market capitalization in the first twelve months following the exchange listing. Controlling for all other factors as in Table 6, the regression coefficient on ESG of –0.234 is indicative of the conjecture that ESG is negatively related to venture risk, albeit it is statistically non-significant (SE = 0.388). Nevertheless, regressing the disaggregated ESG scores leads to a negative G coefficient of –0.902 (SE = 0.339), statistically significant at the 1% level. Therefore, while we do not find evidence in support of the conjecture that ESG statistically significant affects startups' risk levels, we do find some significant results for the G dimension, suggesting that adopting governance-related goals may help reduce aftermarket risk. The results are in Table 8.

[Place Table 8 about here.]

7.4 Robustness Checks

Several robustness checks are available in the Internet Appendix for the sake of brevity. First, in Internet Appendix B, 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 with 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. Second, we report robustness tests for different ESG scores in Internet Appendix C, which are based on altered seed word lists to construct the ESG dictionary. Again, our results are very robust. Third, we control for a postential selectivity issue related to the fact that not all startups publish whitepapers, but whitepapers are required to compute ESG scores with our machine-learning approach. Therefore, we run a two-stage least squares tests that predicts the probability of having a whitepaper in the first stage and then computes controls for selection on *observables* and *unobservables* that we include in our second-stage regressions. The results are robust, suggesting that selectivity does not seem be biasing our results. These robustness tests are also reported the Internet Appendix.

Our results are robust to several additional (untabulated) robustness checks, such as (i) a two-stage least squares approach that controls for the potential selection bias into token

exchange listings for our post-funding performance tests, (ii) the inclusion of platform or industry fixed effects, (iii) the elimination of blockchain-related terms from the seed word list used to calculate the G score or to the exclusion of the G dimension from the ESG score overall, (iv) the zero-value imputation of missing information pertaining to ICO firms' funding amounts that did not meet their soft caps to rule out a potential survivorship bias, (v) a post-2018 interaction term with ESG that controls for the increased level of startups ESG scores in more recent sample periods that plausibly relates to a "selling the hype" argument, (vi) the sample reduction for our valuation tests so that observations match exactly with those for our performance tests, (vii) alternative specifications of our bull and bear market controls that are based on indicators for whether the overall crypto market prices moved by positive or negative 20%, respectively, at any given day, and (viii) excluding startups from the energy sector form our sample.

8 Discussion and Concluding Remarks

8.1 Summary of Main Results

This paper tests two overarching hypotheses. The ***Valuation Premium Hypothesis*** (***VPH***) posits that Sustainable Entrepreneurship (SE) achieves higher valuations in entrepreneurial finance markets than Conventional Entrepreneurship (CE) does. The ***Post-Funding Underperformance Hypothesis*** (***PFUH***) posits that SE (financially) underperforms CE post-funding. The empirical context is 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 in the period 2016-2020, we find support for both the *VPH* and *PFUH*. For the *VPH*, we find that a one-standard-deviation increase in our ESG metric is associated with a 28% increase in the funding amount. This corresponds to $3.4 million (relative to the mean funding amount of $11.9 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-month 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 16-31% of total utility.

8.2 Theoretical Contributions and Practical Implications

Our study contributes to the SE literature in several important ways, in particular, by (i) offering a method to quantify startups' ESG properties, as well as testing sustainability-related equilibrium theory in terms of (ii) short-term valuation and (iii) long-term performance implications.

ESG has become increasingly important in entrepreneurial finance (Geczy et al., 2021; Gillan et al., 2021), however, commercial ESG rating agencies are not just in disagreement about how to measure ESG (Berg et al., 2020), they also do not offer ESG ratings for small- and medium-sized enterprises (SMEs). Against this background, our objective, machine-learning-based approach to assess SMEs' ESG properties offers a valuable, albeit not perfect, tool to spur research in the realm of sustainable entrepreneurship. At least two current projects, Cumming et al. (2022a) and Xia and Yan (2022), adopt our method and confirm our overarching results in different empirical contexts.

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 (Hall et al., 2010, p. 439).

Our study also helps close the "research gap related to the post-funding phase" of SE (Böckel et al., 2020, p. 433). Financial underperformance by SEs 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.

Our study reveals three distinct practical implications. First, from a public policy perspective, entrepreneurs have an economic incentive for sustainability-oriented venturing and receive funding, suggesting that Schumpeter's (1942) notion of 'creative destruction'

seems 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 preferences 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).

8.3 Limitations and Avenues for Further Research

Our study represents a first step towards understanding the relevant financial aspects of SE activity that matter for entrepreneurs and investors alike. Next, we suggest some avenues for potentially fruitful further research.

Financial returns to SE. Our study focuses on token offerings, a market predominantly populated by relatively young generations with strong ESG preferences (Fisch et al., 2019; Kraus et al., 2018; Spence et al., 2011), which raises concerns about external validity. Also, given the recency of token offerings, our analysis of post-funding returns is limited to 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, e.g., 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 period when demand for ESG is relatively high. This raises the question of how our results would change with less aggregate demand for ESG.

ESG returns to SE. Our study estimates 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 questions unanswered. 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, a "major challenge" here is "how to measure sustainability". 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), partly to the difficulty associated with quantifying ESG rents, and partly to issues associated with non-transparent ESG reporting standards and "greenwashing" incentives, among others. Moving forward, we believe that case studies offer the best possibility to understand cause-and-effect in SE.

Disaggregating ESG. Similarly, our study employs a machine-learning approach to quantify ESG properties of startups. We also decompose 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). Future research can easily modify our machine-learning algorithm, which we publish as open source along with this paper, to measure more granular components of ESG.

Organizing SE. Our study of how 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 may be fundamentally different. Yet, the research on concrete, practically implementable forms of startup structure conducive to SE success is very limited. At the same time, a related void calls for more research on how regulation can shape entrepreneurial finance with respect to sustainability (e.g., Bellavitis et al., 2021).

8.4 Concluding Remarks

This study has sought to shed light on the role of startups' Environmental, Social, and Governance (ESG) properties for their valuation and post-funding performance in token offerings, using a machine-learning approach to quantify startups' "ESG-ness" from whitepapers. Our results suggests that ESG is positively related to valuation and negatively related to post-funding performance, suggesting that it is economically attractive for entrepreneurs to adopt ESG goals in the first place, while investors incur relative financial losses post-funding. Our study spearheads the emerging literature on how ESG affects entrepreneurial finance and suggests several promising avenues for future research.

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Exhibits

Figure 1: Relative Importance of Terms in ESG Dictionary by {E,S,G} Dimension

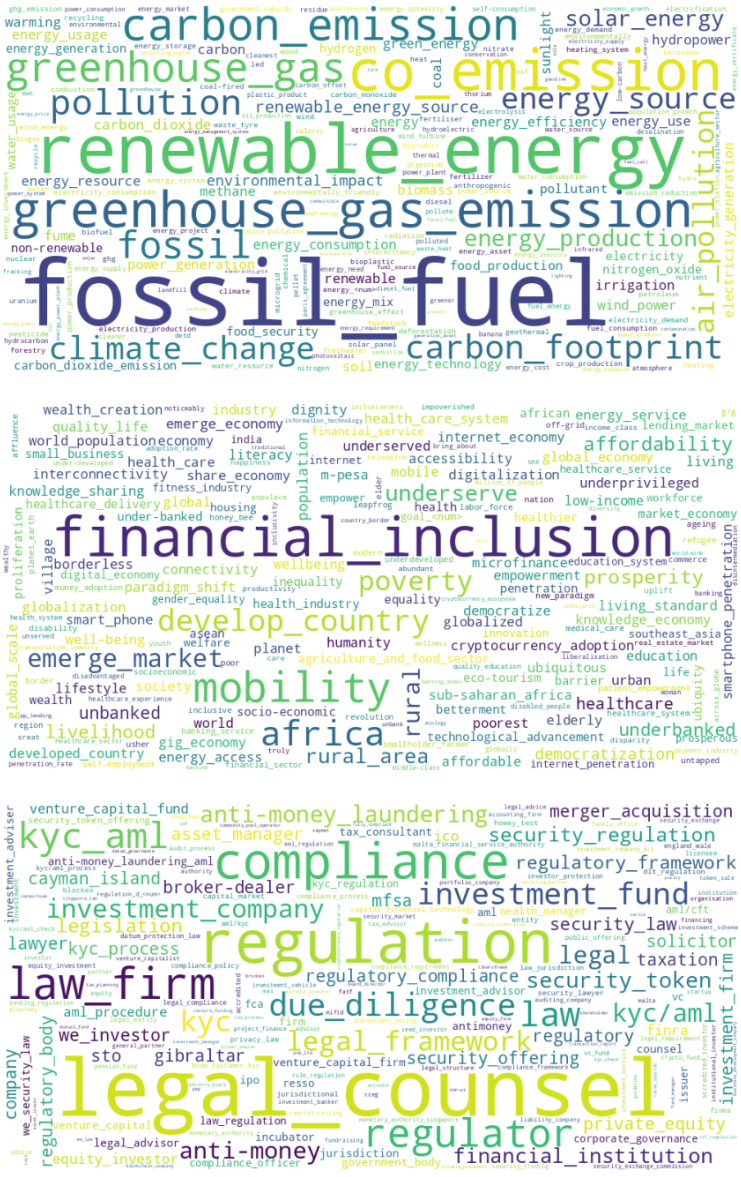

Figure 2: The External Validity of ESG Scores from www.SustainableEntrepreneurship.org

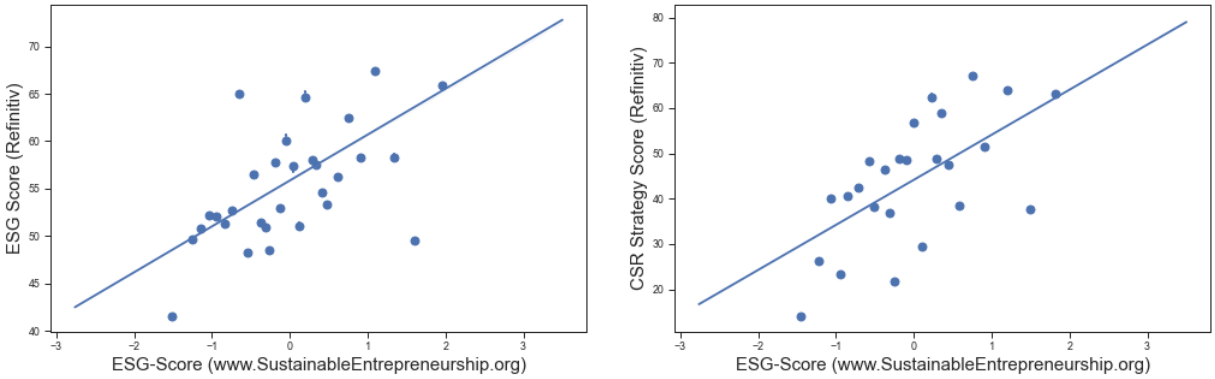

Figure 3: The Valuation of Sustainable Entrepreneurs

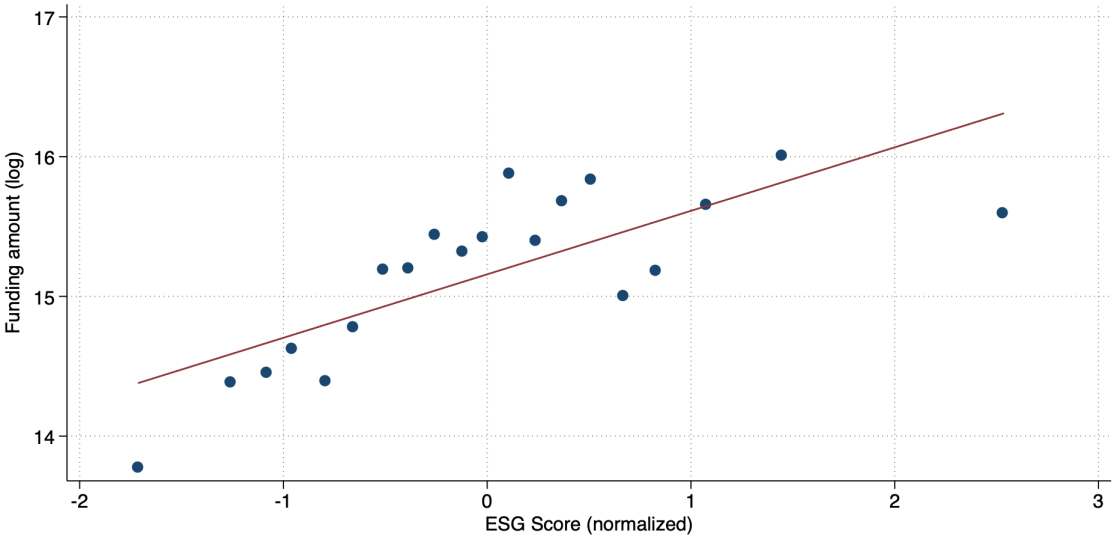

Table 1: Descriptive statistics and correlations

	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 (log)	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[1]	*...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 (log)	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***

[1] High-ESG = Startups with above-median ESG score.

Table 3: The Sustainability Premium

Column	(1)	(2)	(3)	(4)	(5)
Model:	Main	Control	Selection	IMR[2]	IV[3]
Dependent variable:	Valuation[1]	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[2]	✗	✗	✗	✓	✗
IV[3]	✗	✗	✗	✗	✓
Quarter-year FEs	✓	✓	✓	✓	✓
Country FEs	✓	✓	✓	✓	✓

[1] Valuation = Funding amount (log).
[2] IMR = Inverse Mills Ratio
[3] IV = Instrumental Variable

Explanations: These are results from regressions of startup valuation on the ESG score. The dependent variable is natural logarithm of the funding amount (in $ million). Our econometric identification approach is detailed in Section 6.4. 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 as an Instrumental Variable (IV) for the ESG score. Control variables are defined in Section 6.2. The sample consists of 1,043 token offerings 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	✓	✓	✓	✓	✓
Quarter-year FEs	✓	✓	✓	✓	✓
Country FEs	✓	✓	✓	✓	✓

* VIF = Variance Inflation Factor.

Explanations: These are results from regressions of startup valuation on the ESG score and its components. The dependent variable is natural logarithm of the funding amount (in $ million). Our econometric identification approach is detailed in Section 6.4. 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 as an Instrumental Variable (IV) for the ESG score. Control variables are defined in Section 6.2. The sample consists of 1,043 token offerings 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. The table also shows Variance Inflation Factors (VIFs) for the ESG score and its components, as well as the highest VIF for the control variables. Control variables are similar to those reported in Table 3 and therefore suppressed here for brevity.

Table 5: Propensity Score Matched (PSM) Samples

Column	(1)	(2)	(3)	(4)
Model:	PSM		IV/GR[1]	
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	✓	✓	✓	✓
Quarter-year FEs	✓	✓	✓	✓
Country FEs	✓	✓	✓	✓
IV	✗	✗	✓	✓
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	✓	✓	✓	✓
Quarter-year FEs	✓	✓	✓	✓
Country FEs	✓	✓	✓	✓
Generalized Residual (GR)	✗	✗	✓	✓
Observations	627	939	627	939
R^2	0.299	0.256	0.299	0.256

[1] 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 results from regressions of startup valuation on the ESG score (Panel A) and its components (Panel B) based on Propensity Score Matched (PSM) samples. Models (1) and (3) match the 20% highest ESG score startups, and models (2) and (4) match the 30% highest ESG score startups to expand the PSM sample size. Columns (1) and (2) are baseline OLS regressions, while columns (3) and (4) are based on our instrumental variable (IV) model in Panel A and on the inclusion of the generalized residual (GR) in Panel B. Everything else is as in the regressions in Table 3 and Table 4.

Figure 4: The Performance of Sustainable Entrepreneurs

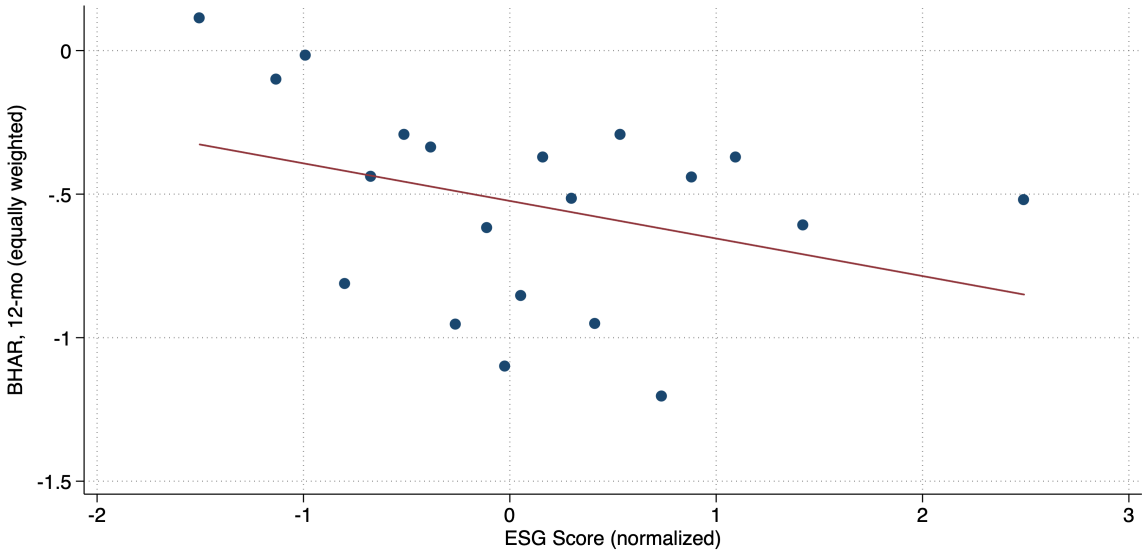

Table 6: The Performance of Sustainable Entrepreneurs

Column	(1)	(2)	(3)
Model:	Main	IMR	IV/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	✓	✓	✓
Quarter-year fixed effects	✓	✓	✓
Country fixed effects	✓	✓	✓
IMR	✗	✓	✗
IV	✗	✗	✓
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	✓	✓	.
Quarter-year fixed effects	✓	✓	.
Country fixed effects	✓	✓	.
IMR	✗	✓	.
GR	✗	✗	.
Observations	302	300	.
R^2	0.372	0.382	.

Explanations: These are results from regressions of the long-run performance on the ESG score in Panel A and on its components in Panel B. 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. Model (1) is the baseline model, model (2) conditions on observable heterogeneity, and model (3) controls for unobserved heterogeneity. Control variables are defined in Section 6.2. The sample size is reduced because either tokens have not been listed and therefore we do not observe token price performance or because tokens have been listed less than 12 months ago. 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: Moderating Effects of Technology, Network, and Governance

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 × Formalization (Proxy 1)	-0.007			-0.332*		
	(0.141)			(0.174)		
ESG × Formalization (Proxy 2)		-0.068*			-0.068	
		(0.039)			(0.046)	
ESG × Formalization (Proxy 3)			-0.533***			0.005
			(0.116)			(0.176)
Controls	✓	✓	✓	✓	✓	✓
Quarter-year fixed effects	✓	✓	✓	✓	✓	✓
Country fixed effects	✓	✓	✓	✓	✓	✓
Observations	1043	1008	1043	302	290	302
R^2	0.313	0.332	0.350	0.378	0.376	0.401

Explanations: These are moderation results from regressions of startup valuation on the ESG score, interacted with proxies for technology, network, and governance proxies. The dependent variable is natural logarithm of the funding amount (in $ million) in columns (1)-(3) and the 12-month BHAR in columns (4)-(6). Proxy 1 is the dummy indicator for whether the token offering firm open-sourced its code on *GitHub*. Proxy 2 is the log-number of followers in Twitter. Proxy 3 is a dummy that equals one if the token offering is backed by a venture capital fund. Control variables are defined in Section 6.2. The sample consists of 1,043 token offerings 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 8: ESG and Startup-related Risk

Model:	(1)	(2)
Dependent variable: σ(Market cap.), 12-mo		
ESG Score (normalized)	–0.234	
	(0.388)	
E-Score (normalized)		0.107
		(0.177)
S-Score (normalized)		0.373
		(0.446)
G-Score (normalized)		–0.902***
		(0.339)
Controls	✓	✓
Quarter-year fixed effects	✓	✓
Country fixed effects	✓	✓
Observations	311	311
R^2	0.357	0.382

Explanations: These are results from regressions of the market capitalisation's volatility on the ESG score. The dependent variable is the logarithm of 12-month volatility(standard deviation) of the startup's market capitalisation after the token listing date. Control variables are defined in Section 6.2. The sample size is reduced because either tokens have not been listed and therefore we do not observe token performance or because tokens have been listed less than 12 months ago. 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: Control Variable Definitions

Panel A: Control Variables – Venture Characteristics	
Whitepaper length	The natural logarithm of total words in any given whitepaper, which is often used as a proxy for the total information available about 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 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).
Panel B: Control Variables – Offering Characteristics	
Soft cap	A dummy variable for whether the startup has announced a soft cap in its token offering. 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	A dummy variable for whether the startup has announced a hard cap in a token offering. 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 returned 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 active whitelist.
Bonus	A dummy variable for whether the startup offers 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.
Panel C: Control Variables – Market Characteristics	
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."
Panel D: Quarter-year and Country Fixed Effects	
In keeping with previous studies (e.g., Fisch and Momtaz, 2020), we include quarter-year and country fixed effects. Quarter-year effects help control for the high volatility in the token market as well as time-variation in startups' ESG profiles, as "selling the hype" has become more prominent in recent periods, while country fixed effects are relevant to control for jurisdiction-level confounding factors, such as geography (Huang et al., 2020) and regulation (Bellavitis et al., 2021). In robustness tests, we also experiment with industry fixed effects.	

INTERNET APPENDIX

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

A Quantifying Startups' ESG Properties

A Machine-Learning Approach: Detailed Description

Textual analysis in economics, finance and accounting literature is mainly applied using a dictionary count approach, in which researchers rely on predefined word lists to extract information from textual data (Gentzkow et al., 2019). Should we rely on humans or machines to create these word lists?[4] The advantage of human wisdom in creating these word lists comes at the cost of subjectivity and requires substantial transparency. In the context of ESG measurement, subjectivity plays a crucial role as many of the available ESG scoring databases provide inconsistent ratings (Berg et al., 2020; Dimson et al., 2020).

In this paper, we choose a middle ground. On the one hand, the machine relies on itself in detecting the meaningful phrases in the context of startups' whitepapers (i.e., word embedding via word2vec), and on the other hand, we guide the machine to come up with the terminologies that are most relevant for our purpose, based on a set of seed words.

Our procedure to create the ESG-relevant lexicon is methodologically close to Li et al. (2020). First, we collect whitepaper documents and parse their textual contents. Second, we clean the text by performing standard prepossessing procedures and define the set of words and context-specific phrases. Third, we do word embedding using the word2vec method (Mikolov et al., 2013) to obtain vector representation of all the words and phrases that have appeared in the corpus of whitepapers. Fourth, we define a set of seed words that represent each of the three pillars of ESG. Fifth, we use our trained word2vec model and generate our word lists by finding the closest word and/or phrase to our seed words. In training our word2vec model, we accept all standard assumptions for the hyper-parameter tuning of the model. Specifically, we use the Python package provided by Li et al. (2020), which implements all the previous steps. Finally, we calculate the ESG intensity of each whitepaper using the generated word lists.

A.1 Text prepossessing

Before we feed the corpus (universe of texts) to our word2vec model, we apply standard text prepossessing procedures to ensure the efficiency of our ML training process.

First, we remove line breaks from the text and replace numbers/emails/URLs/phone numbers with the respective tags, i.e., "<num>", "<email>", "<url>", "<phone>".

[4] See (Loughran & McDonald, 2020b) for a comprehensive discussion

Second, we employ the Stanford CoreNLP pipeline (Manning et al., 2014) to generate a dependency representation of each sentence.[5] Figure I.A.1 shows the dependency representation for an example sentence: "The basis for the distribution of GNC in the domain of real economic activity is the loyalty system, this is the most important and central tool of the platform." This helps the machine to better understand the grammatical structure of the sentences, and enables it to form collocations, i.e., a collection of more than one word that tends to appear frequently together, like "initial_coin_offering". We treat these collocations as single words in the following steps.

Third, we remove the stop words, i.e., words that do not add much meaning to a sentence like 'the', 'as', 'of', etc., as well as punctuation marks. Note that this step must follow the creation of collocations, as they could consist of some stop words, such as in "as_well_as".

[Place Figure I.A.1 about here.]

A.2 Word Embedding

Word embedding is a way to mathematically represent words and enables the machine to compare the semantic similarity of the words. Our word embedding approach relies on the revolutionary word2vec method developed by Mikolov et al. (2013). The idea behind word2vec is to use a shallow (only one hidden layer) neural network, which is trained to predict words in the neighborhood of an input word, by exploring all the sentences in the corpus. In other words, during the training phase, an input word is translated to a vector in the hidden layer (a), and then this vector should predict the neighboring word (b). After the training, the trained weights of the neural network for (a) would be able to create a vector of real numbers for any input word of the corpus.[6] If trained on a vast corpus, the results of this seemingly simple algorithm would be very precise. A famous example of a trained word2vec model would be that one could find the vector closest to the vector of word 'Queen' by subtracting the vector of 'man' from the vector of the word 'King' and add the results to the vector of the word 'woman' (i.e., $King - Man + Woman = Queen$).[7]

[5]The CoreNLP pipeline incorporates several steps. The most important steps include 1) tokenization, i.e., breaking down the text to smaller language units like words, 2) lemmatization, i.e., converting a word to its base form (e.g., "coins" to "coin"), and 3) entity chunking, i.e., replacing the entities' names with a proper tag.

[6]The size of this vector is the same as the size of the hidden layer in the neural network. We use the same settings as in Li et al. (2020) and consider a vector of size 300 for the word representations.

[7]Like any other ML framework, word2vec has its limitations. See Nissim et al. (2020) for a discussion on interesting and humorous examples of word2vec predictions.

A.3 Seed Words

As the starting point for measuring ESG intensity of the startup whitepapers, we collect all the available Financial Times (FT) articles with the tag of "ESG Investing" or "Moral Money". We follow a standard bag-of-words approach and extract bi-grams and tri-grams[8] that appear most frequently in the FT corpus. We then manually go through these n-grams and decide if they belong to the E, S or G dimensions of the ESG. As the FT mostly covers the corporate world, it may not necessarily include the governance terms that are important for our context of ICO whitepapers. Therefore, we manually add terms like 'kyc', 'whitelist', 'blockchain', 'utility', 'security_token', etc. for the governance dimension. The full list of our seed words (available in Table I.A.1) consists of 70 Environmental, 38 Social, and 46 Governance related words/n-grams.

A.4 ESG wordlists

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 of the ESG 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 $\bar{V}^G$.

Next, we perform a cosine similarity between $\bar{V}^j$ and the vector of all of the terms in our whitepaper corpus and select the 500 most similar terms for each dimension. If a term appears in more than one dimension, then it is only considered for the dimension that has a higher cosine similarity.[9] Furthermore, some of our seed words have never appeared in the corpus of whitepapers.[10] We did not remove them from our word lists, though not affecting our results at all, as these terms could be relevant for future out-of-sample studies. This leaves us with a total of 1,495 ESG-related terms consisting of 508, 463 and 524 terms in the respective ESG dimensions.

A.5 ESG Score

We quantify the E, S and G dimensions using a dictionary-based approach, by counting the number of distinct occurrences of our respective word list in the ICOs whitepapers, normalized to the size of the word list. Specifically, for ICO i we measure each dimension

[8]Please note that bi-grams and tri-grams are two and three-word combinations of the words that appear in a neighborhood, and are not necessarily a collocation.

[9]This is the reason why some dimensions could have a word list smaller than 500.

[10]This is the reason why some dimensions could have a word list greater than 500.

of the ESG as:

$$E[S\ or\ G]_i = \frac{\sum_t 1_{c(t)_i > 0}}{c(n)}, \tag{8}$$

Where $c(t)_i$ is the count of term t in the whitepaper of ICO i and $c(n)$ is the size of the corresponding *word list*.

According to Loughran and McDonald (2020a), this approach slightly deviates from the norm in accounting and finance literature, where researchers count the total frequency of the words in a word list and normalize it to the total words in the document. In our context, however, this will lead to biases. Unlike corporate disclosures, ICO whitepapers are neither standardized nor regulated, and they vary substantially in length, format and content. Moreover, some ICOs have the words like 'green' or 'human' in their titles, which leads to bias in measuring the environmental or social score if a traditional frequency count method is applied.

Furthermore, we measure the total ESG score of the startup i by adding the three dimensions' intensity, i.e. $ESG_i = E_i + S_i + G_i$.

B Additional Controls

In this section, we check the robustness of our findings by including additional control variables to our baseline model. We control for the following additional controls: # investors, KYC, ICO duration, fiat accepted, % distributed in ICO, Twitter followers, LinkedIn, and crypto experience.

 # Investors. The logarithm of the number of institutional investors, as listed on the *CryptoFundResearch* list.

KYC. A dummy variable that equals one if the firm has a Know-Your-Customer (KYC) procedure, and zero otherwise.

ICO duration. The difference in days between the start and end of the ICO.

Fiat accepted. A dummy variable that equals one if the ICO accept fiat currencies.

Distributed in ICO. The percentage of tokens distributed in the token offering (i.e., 1 - "Distributed in ICO" is the token retention ratio).

Twitter followers. The logarithm of the number of the firm's Twitter followers.

Linkedin. A dummy variable that equals one if the ICO has a Linkedin page.

Crypto experience. The percentage of the team members who have experience in the crypto environments.

Table I.A.2 reports the results of this analysis. Adding the additional controls reduces our observations from 1043 in column (1) to 808 in column (5), which has the highest number of control variables. Our main results do not qualitatively change in these specifications. In all specifications, the coefficient on the normalized ESG score remains statistically significant at least at 5%.

[Place Table I.A.2 about here.]

C Other Seed Words

In this section, we address potential concerns that our results could be driven by our manual selection of the seed words. To this end, we repeat the steps in generating our word lists with the exception that we consider only two or three seed words for each dimension of the ESG. Specifically, we set the seed words to be ['environmental', 'climate'] for the E dimension, ['society', 'social_responsibility'] for the S dimension, and ['governance', 'white_paper', 'token'] for the G dimension. Figure I.A.2 illustrates the resulting word lists, and it shows that we are able to capture the most relevant terms needed to construct our ESG word lists with only two or three words.

[Place Figure I.A.2 about here.]

C.1 Other Seed Words and Funding

To test the validity of the word lists created with the small set of seed words, we repeat our baseline (OLS) regression with the log of the funding amount in $ million as the dependent variable, on the ESG score as well as its components derived from these word lists.

Table I.A.3 shows the results of this analysis. In column (1), the coefficient of the normalized ESG score is 0.34, with a p-value $< 1\%$, suggesting that a one standard deviation increase in the ESG score increases the average funding amount of $15.2 million by $6.1 million, or 40%. 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 the 1% level in these models. The E score coefficient is 0.138 (p-value < 0.01), the S score coefficient is 0.212 (p-value < 0.01), and the G score coefficient is 0.321 (p-value < 0.01). However, testing the effect of the three disaggregated scores simultaneously in column (5) shows that only the E (0.123) and the G (0.301) score are statistically significant at least at the 5% level. Thus, ceteris paribus increases by one standard deviation in E and G are associated with 13% and 35% increases in the average funding amount, respectively. These results are in line with the paper's analysis and strongly support the VPH that there is a sustainability-related valuation premium in token offerings.

[Place Table I.A.3 about here.]

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Internet Appendix — Exhibits

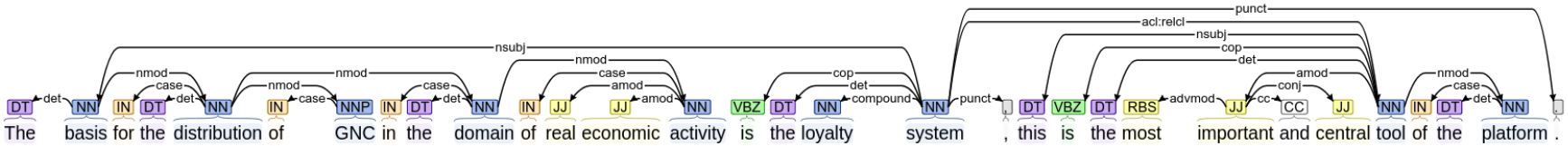

Figure I.A.1: Example of a dependency representation

Figure I.A.2: Robustness Tests: ESG word lists with alternative seed words

Table I.A.1:
Seed Words

E	S	G
climate_change	moral_money	pension_funds
green_bonds	responsible_investing	investment_management
fossil_fuel	development_goals	supply_chain
green_bond	sustainable_development_goals	task_force
carbon_emission	impact_investment	investment_managers
carbon_footprint	social_issues	chief_investment_officer
renewable_energy	uns_sustainable	governance_issues
global_warming	social_impact	private_sector
greenhouse_gas	positive_impact	hedge_funds
climate_risk	essential_forward_thinking	managing_director
energy_source	gender_diversity	shareholder_proposals
green_finance	developing_countries	due_diligence
greenhouse_gas_emissions	decentralized	stakeholder_capitalism
carbon_footprint	defi	retail_investors
paris_climate	democratize	annual_meetings
climate_change_meets	democratization	esg_disclosure
paris_agreement	disintermediation	law_firm
fuel_companies	africa	global_advisors
fossil_fuel_companies	poor	board_members
climate_crisis	catching_up	investors_looking
natural_gas	india	passive_managers
environmental_impact	mobile	institutional_investors
thermal_coal	mobility	advisors
force_climaterelated_disclosures	cell_phone	bounty
green_bond_market	smart_phone	kyc
climaterelated_risks	access	whitelist

green_energy
low_carbon
oil_gas_companies
environmental_issues
carbon_dioxide
zero_emissions
indispensable_energy
bn_green
carbon_pricing
green_deal
carbon_neutral
fight_climate_change
carbon_price
coal_power
green_bonds
fossil_fuel
tackle_climate
lowcarbon_economy
co_emissions
risks_climate
zero_carbon
green_investment
risks_climate_change
green_credentials
reduce_carbon
action_climate
save_planet
green_debt
greenhouse_gases
coal_projects

geography
dispersion
microfinance
micro_finance
impact_investing
equality
inequality
care
income
responsible_investment
impact_investing
csr

blockchain
utility
security_token
token_distribution
intermediary
law
regulation
policy
regulator
token_retention
airdrop
founder
partner
compliance
howey_test
sec
equity
venture_capital
VC
incubator

away_fossil		
climate_accord		
carbon_credits		
first_green		
environmental_standards		
un_climate		
new_green		
netzero_carbon		
solar_wind		
renewable_energy		
global_warming		
sustainable_investing		
sustainable_investment		
sustainable_development		

Table I.A.2: Robustness Tests: Additional Controls

Column	(1)	(2)	(3)	(4)	(5)
	Dependent variable: Valuation, Funding amount (log.)				
ESG	0.276***	0.234***	0.223**	0.198**	0.197**
	(0.085)	(0.088)	(0.097)	(0.099)	(0.100)
GR	-0.356	-0.151	0.192	0.121	0.161
	(0.755)	(0.761)	(0.849)	(0.872)	(0.872)
$Investors$		0.690***	0.605***	0.554***	0.547***
		(0.093)	(0.113)	(0.114)	(0.112)
KYC		0.186	0.257	0.256	0.261
		(0.165)	(0.180)	(0.184)	(0.183)
$ICO\ Duration$		0.002	0.002	0.002	0.002
		(0.001)	(0.002)	(0.002)	(0.002)
$Fiat\ Accepted$			0.427	0.509	0.505
			(0.304)	(0.318)	(0.317)
$Distributed\ in\ ICO$			-0.676*	-0.608	-0.633
			(0.406)	(0.412)	(0.411)
$TwitterFollowers$				0.103**	0.096**
				(0.042)	(0.042)
$Linkedin$					0.058
					(0.180)
$CryptoExperience$					0.507*
					(0.302)
Observations	1043	1039	835	808	808
R^2	0.314	0.345	0.368	0.369	0.372
Controls	✓	✓	✓	✓	✓
Quarter-year FEs	✓	✓	✓	✓	✓
Country FEs	✓	✓	✓	✓	✓

Table I.A.3: Robustness - Seed words

Column	(1)	(2)	(3)	(4)	(5)
Dependent variable: Valuation, Funding amount (log.)					
ESG	0.338***				
	(0.070)				
Environmental		0.138***			0.123**
		(0.052)			(0.059)
Social			0.212***		0.037
			(0.074)		(0.091)
Governance				0.321***	0.301***
				(0.077)	(0.088)
Observations	1043	1043	1043	1043	1043
R^2	0.318	0.310	0.311	0.318	0.322
Controls	✓	✓	✓	✓	✓
Quarter-year FEs	✓	✓	✓	✓	✓
Country FEs	✓	✓	✓	✓	✓

Table I.A.4: Whitepaper-related selectivity: Second stage from 2SLS

Column	(1)	(2)
Dependent variable: Valuation, Funding amount (log.)		
ESG	0.247***	0.247***
	(0.067)	(0.067)
IMR	✓	✗
GR	✗	✓
Observations	1043	1043
R^2	0.309	0.309
Controls	✓	✓
Quarter_FE	✓	✓
Country_FE	✓	✓

THE END OF THE INTERNET APPENDIX