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RESEARCH ARTICLE

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Optimal timing of ESG-aligned blockchain adoption: a market-based decision and forecasting framework

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ABSTRACT

We propose a market-based decision-support framework to guide the adoption of ESG-aligned blockchain technologies. This treats the cost of financing such technologies as a function of investor sentiment and applies sentiment forecasts to determine when adoption is economically optimal. We implement our framework using a novel set of blockchain ESG scores, data from the cryptocurrency markets and an investor sentiment proxy to identify periods when investors favour ESG features in blockchain technology. Our analysis reveals that blockchains with high ESG scores generate higher cryptocurrency returns than their lower-rated counterparts in times of optimistic market sentiment. However, they underperform in challenging market times. We also find that higher ESG scores are associated with higher market volatility. Governance and environmental factors have the strongest effect on investor preferences. On the basis of these findings, we model the adoption decision as a real-options timing problem and compute the sentiment level above which adoption is optimal. We find that delaying adoption until sentiment improves yields substantially greater value than adopting immediately. Overall, our work provides operational insights into how decision-makers can strategically integrate ESG features when introducing emerging technologies.

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KEYWORDS
ESG; blockchain; sentiment forecasting; portfolio selection

PRACTITIONER SUMMARY

Our paper proposes a market-based framework to help firms decide when to adopt responsible (ESG-aligned) blockchain technologies. It uses ESG ratings for major blockchains, data from the cryptocurrency markets and an index of investor sentiment to show that responsible blockchains are more attractive to investors in optimistic markets. We also find that governance, followed by environmental features, matters most for investors. Based on these findings, we develop a decision-support tool that uses investor sentiment forecasts to determine when adopting an ESG-aligned blockchain is financially attractive. Our framework provides a practical optimisation tool to help decision-makers with the strategic rollout of responsible blockchain technologies. Our results indicate that firms engaging in such technologies should plan financing activities to occur in optimistic market conditions, when investor appetite for ESG assets is strongest. As governance appears to matter most for investors, firms should prioritise strong governance features in blockchain adoption, such as transparency and accountability, and not just environmental features. From an investor perspective, our work suggests portfolio selection strategies that adjust exposure to ESG assets in line with the underlying market sentiment.

1. Introduction

The rapid adoption of digital technologies, such as Artificial Intelligence and Blockchain, has been coupled with concerns about their environmental, social and governance (ESG) implications. For example, AI data centres and larger blockchain networks have exceeded several countries in energy consumption, which has raised questions about their environmental footprint. In addition, governance failures, such as the collapse of the popular cryptocurrency exchange FTX, highlight that accountability and transparency matter in digital innovation.

The introduction of ESG-aligned technologies is a potential solution to these challenges. However, these often involve significant economic costs, making the adoption decision a non-trivial optimisation problem. In this context, this paper develops a market-based decision-support and forecasting framework to determine the optimal timing for adopting an ESG-aligned blockchain platform. In this manner, it adds to a developing literature on the strategic adoption of blockchain technologies (e.g., Chen et al., 2025; Choi, 2021; Fan et al., 2022; Ji et al., 2022; Zhang, Dong, et al., 2023).

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We model the decision of when to adopt an ESG-aligned blockchain as an optimal timing problem using a real-options approach. Motivated by evidence from the equity markets, we consider that the cost of financing the blockchain is a function of cryptocurrency market sentiment, which drives investor preferences for ESG-aligned technologies.[1] In this setting, adoption occurs when the sentiment crosses an endogenous threshold. We show how decision-makers can exploit sentiment forecasts to plan investment in sustainable blockchain technologies. In this manner, we contribute to the literature on the Operations-Finance Interface (OFI), which explores how operations and finance can be integrated to create firm value.

Our focus on blockchain allows the assessment of investor preferences for sustainable technologies using detailed ESG and market data, which are not readily available for other emerging technologies. We measure the ESG performance of 28 public blockchain networks with distinct underlying technologies and governance structures by leveraging a new dataset of ESG scores provided by Green Crypto Research. These scores are based on objective and transparent principles, consistent with conventional ESG ratings. They can also be decomposed into environmental, social and governance components. This is important, as different ESG dimensions may have varying importance for investors and decision-makers, while technologies often exhibit significant variation in performance across dimensions. For example, the Bitcoin network ranks low in the environmental category because of its high electricity consumption, while it ranks highly in terms of governance, as it promotes high decentralisation. Based on the available scores, we create a time-varying ESG profile for each blockchain, which provides a holistic overview of its sustainability features. As such, we differ from previous research that primarily uses energy consumption as a proxy for blockchain sustainability (e.g., Duan et al., 2023; Husain et al., 2023; Lobão, 2022; Pham et al., 2023; Ren & Lucey, 2022a, 2022b).

Since each of the considered blockchains is associated with a publicly traded cryptocurrency, we analyse the link between the cryptocurrency's market performance and the ESG performance of the underlying blockchain. This allows us to infer investor preferences for ESG characteristics in blockchain technology. In this way, our work contributes to a large literature that has developed around the relationship between ESG and investment performance. While the literature identifies a positive link between ESG and corporate financial performance (e.g., see Brooks & Oikonomou, 2018, and Atz et al., 2023), the evidence on the relationship between ESG and market returns remains mixed (for a survey of the literature, see Kräussl et al., 2024). For example, Kempf and Osthoff (2007), Statman and Glushkov (2009) and In et al. (2019) document higher risk-adjusted returns for firms with stronger sustainability practices. In contrast, Bolton and Kacperczyk (2021), Hsu et al. (2023) and Garel et al. (2024) report that green stocks underperform brown stocks. Hartzmark and Sussman (2019) and Aswani et al. (2024) find no strong link between sustainability and investment performance. Our work extends this literature by providing fresh evidence from the digital asset markets and by focusing on the value of ESG at the technology level rather than the firm or the fund level.

A key feature of our approach is that it accommodates dynamic investor preferences for ESG assets. This is important as a growing body of literature reports time-varying demand for ESG investments in traditional financial markets. For instance, Pástor et al. (2022) suggest that while green investments may initially produce lower expected returns, changes in investor preferences towards sustainability can lead to higher returns. Bansal et al. (2022) provide evidence that in good economic times investors prefer socially responsible stocks and reward them with higher returns, while in bad economic times low social-responsibility stocks perform better. Cho (2023) confirms this finding in an emerging market. The findings of Bansal et al. (2022) and Cho (2023) align ESG assets with luxury goods, suggesting that investor preferences for such assets are stronger in the absence of binding wealth constraints. Motivated by this evidence, we hypothesise that investor demand for blockchains with strong ESG qualities will be higher when market conditions are favourable and investor sentiment is optimistic. During such periods, we expect that the performance of cryptocurrencies associated with higher ESG scores will exceed that of their lower-rated counterparts.

To assess investor preferences for ESG features in blockchain technology, our work relies on a zero-cost portfolio (*HML*) that is long in cryptocurrencies with above-median ESG scores and short in cryptocurrencies with below-median scores. A significant positive return for the *HML* portfolio is indicative of investors valuing strong ESG characteristics in blockchain technology. We evaluate the performance of this portfolio using daily returns from January 2022 to February 2024, the period for which we have access to ESG scores. In the full sample, the performance of the *HML* portfolio is not statistically different from zero, in line with previous research that reports mixed evidence on the performance of sustainable investments. However, we find that the performance of the *HML* portfolio is significantly and positively correlated with the overall cryptocurrency market. This suggests that the value placed on ESG attributes is affected by the overall market conditions.

Motivated by this finding, we examine the performance of the *HML* portfolio across periods with different market conditions and investor sentiment. We adopt the Crypto Fear and Greed Index as a proxy of cryptocurrency market sentiment and identify periods of negative, neutral and positive investor sentiment, based on the Bayesian Estimator of Abrupt change, Seasonality, and Trend (BEAST) by Zhao et al. (2019). In line with our hypothesis, we show that the *HML* portfolio generates a significant positive annualised return of 129% in the period of optimistic sentiment (greed). In contrast, during the period of negative sentiment (fear), the *HML* portfolio produces a negative return of −53%. Our findings hold if we control for market risk and remain robust to additional specifications of the *HML* portfolio we consider. Overall, our analysis provides evidence of time-varying investor demand for digital technologies with strong ESG qualities.

We further seek to identify potential drivers of the time-varying investor preferences we observe. First, we consider the role of size. Previous literature suggests that firm size plays a moderating role in the performance of ESG-focused stocks (In et al., 2019), while size is an established risk factor in cryptocurrency returns (Liu et al., 2020). We find that during the period of positive sentiment, the outperformance of cryptocurrencies with high ESG scores is primarily driven by those with larger market capitalisations. Second, we explore whether the observed pattern in the *HML* portfolio returns is driven by changes in risk levels across time. Using an EGARCH volatility model, we find that the variance of the portfolio of cryptocurrencies with high ESG scores is significantly higher than that of the portfolio with lower ESG scores across all periods in our sample. This result contrasts with previous studies which typically report lower volatility for ESG stocks (e.g., Broadstock et al., 2021; Cerqueti et al., 2021; Lööf et al., 2022). It indicates that the time-varying performance of cryptocurrencies with high ESG scores is not driven by their risk profile.

We determine which ESG dimensions of blockchain technology matter most for investors. We find that the outperformance of cryptocurrencies with high ESG scores during periods of positive market sentiment is mainly driven by the governance component of ESG, followed by the environmental component. The social component instead has no significant impact on portfolio returns. This suggests that investors' ESG concerns about blockchain technology are mainly driven by governance and environmental issues.

Based on our portfolio analysis, we solve the optimal adoption timing problem assuming that the cost of capital associated with adopting an ESG-aligned blockchain is a decreasing function of investor sentiment. This reflects stronger investor appetite for ESG assets under favourable market conditions. To forecast sentiment dynamics, we apply a bounded stochastic process, which we fit to the series of the Crypto Fear and Greed Index. Solving the optimal timing problem using Monte Carlo simulation allows us to identify sentiment thresholds for technology adoption. Under our assumptions, we find that waiting to adopt until investor sentiment improves yields a 63% premium over immediate investment. This result shows how sentiment-driven financing conditions can impact operational decisions, supporting an OFI-based approach to digital innovation.

The remainder of this work is organised as follows. Section 2 presents a review of the literature that drives our main hypothesis. Section 3 describes our decision-support framework while the portfolio performance analysis is presented in Section 4. Section 5 presents the solution to the optimal adoption-timing model while Section 6 concludes the paper.

2. Literature review

2.1. ESG and blockchain adoption

While blockchain is often associated with bitcoin and other cryptocurrencies, its applications extend across several industries. Supply chain management, finance, healthcare and other fields have been rapidly adopting blockchain technology to improve security, efficiency and trust in the way information and transactions are handled (Tandon et al., 2021). The World Economic Forum expects that up to 10% of the global GDP could be stored on blockchain networks by 2027.[2] However, being an emerging technology, blockchain requires adopters to balance complex trade-offs between operational benefits, economic costs, stakeholder attitudes, regulatory compliance and sustainability. In this context, a developing strand in the operational research literature has been aiming to support technology adoption decisions under such trade-offs. For example, Choi (2021) proposes a framework for identifying how the risk attitudes of supply chain agents affect the benefits of introducing blockchain in supply chain finance. Ji et al. (2022) explore the optimal timing of blockchain adoption in the supply chain as a function of consumer sensitivity to the technology. In a similar fashion, Fan et al. (2022) study blockchain adoption outcomes in relation to the traceability awareness of consumers. Zhang, Dong, et al. (2023) investigate the benefits of blockchain adoption as a function of demand volatility and operational and selling costs. In an e-commerce setting, Chen et al. (2025) explore how financial constraints affect blockchain introduction strategies.

We extend the literature by providing guidance on blockchain adoption with a focus on the sustainability features of the underlying technology. This is important as concerns have arisen about the environmental, social and governance (ESG) implications of blockchain platforms. The Bitcoin network, for example, is often criticised for its high energy consumption and climate impact (Corbet et al., 2021; Corbet & Yarovaya, 2020; Zhang, Chen, et al., 2023). At the same time, failures in popular blockchain projects, such as FTX, Terra and Celsius, have exposed governance risks in blockchain-based applications. In response to these issues, more sustainable blockchain platforms have been proposed.[3] However, their adoption often comes with additional costs and complexities. Firms engaging with ESG-aligned blockchains need to consider how their investors balance trade-offs between short-term costs and long-term value derived from ESG qualities. In this context, this paper develops a decision-support framework to evaluate investor preferences towards ESG characteristics in blockchain technology and to determine the optimal timing of adoption.

We differ from previous studies on blockchain adoption by taking a market-based perspective and employing information from the cryptocurrency markets. A cryptocurrency is a digital asset that operates on a public blockchain and is traded in specialised digital exchanges. In recent years, cryptocurrencies have been established as an alternative investment asset (Corbet et al., 2019) with the Securities and Exchange Commission (SEC) approving the first Bitcoin ETF in the US in 2024. Investors typically assess the value of cryptocurrencies based on the attributes of the underlying blockchain, which may include efficiency, transaction costs, speed, among others (Zimmerman, 2020). However, it remains an open question whether the ESG features of blockchain technology act as a value driver for investors. Our analysis aims to answer this question.

Previous research on the link between blockchain sustainability and cryptocurrency prices has focused on the energy demand associated with blockchain networks, classifying them as *green/clean* or *dirty*. This distinction is based on the algorithm used for processing blockchain transactions (e.g., Duan et al., 2023; Husain et al., 2023; Lobão, 2022; Pham et al., 2023; Ren & Lucey, 2022a, 2022b). For example, Bitcoin uses a Proof-of-Work (PoW) algorithm which is energy-intensive (Corbet & Yarovaya, 2020). In contrast, the Ethereum network recently adopted a Proof-of-Stake (PoS) algorithm which is more energy-efficient. In this context, bitcoin would be considered a dirty cryptocurrency while the Ethereum cryptocurrency would be considered a green cryptocurrency. The literature has examined the performance of green cryptocurrencies as diversifiers or hedges against different types of risk (Esparcia et al., 2024; Husain et al., 2023; Pham et al., 2022; Ren & Lucey, 2022a; Sharif et al., 2023).[4] Results appear to be mixed and to vary depending on the specific periods and risks analysed.

In this work, we extend our focus beyond the energy consumption of different blockchains and examine whether the broader environmental, social and governance implications of blockchain technology are considered by investors. This is important as a blockchain may achieve energy efficiency at the expense of other attributes, such as transparency or security. For example, while some PoS algorithms are known for their lower energy consumption compared to PoW alternatives, they may promote centralisation, as larger stakeholders tend to exert more control (Saad et al., 2021). In this context, the next section explores the literature on investor preferences for ESG assets and provides the foundation for our framework.

2.2. ESG and investor preferences

Bloomberg Intelligence estimates that the value of ESG assets will exceed \$40 trillion by 2030.[5] However, investor demand for ESG assets appears to vary across markets and time periods. For instance, Morningstar found that in 2023, U.S. sustainable funds actually saw their first yearly drop.[6] In light of this evidence, we identify factors that may drive changes in investor preferences towards ESG assets by looking at both managerial theoretical frameworks and empirical evidence from the literature.

Stakeholder theory suggests that firms should consider the interests of all stakeholders, such as employees, customers, the society and the environment, and not just that of the shareholders (Freeman, 1984). Within this framework, a high ESG rating may indicate a firm's commitment to provide wider benefits that go beyond short-term performance, but instead they add value in the longer term (Clarkson, 1995). For example, firms that engage in sustainable practices can better meet demands from clients and regulators for responsible corporate behaviour. In this context, investors will prefer firms with high ESG performance.

An alternative theoretical framework for assessing investor preferences towards ESG can be developed under agency theory (Jensen & Meckling, 1976). Within this framework, managers may use ESG activities in order to achieve objectives that are not consistent with value maximisation. For example, ESG activities can be used to mislead stakeholders about the firm's focus on sustainability, a practice known as "greenwashing" (Hemingway & Maclagan, 2004). In such cases, the adoption of ESG activities may negatively impact the value of the firm, especially when it does not lead to measurable outcomes with regards to sustainability and business responsibility (Fatemi et al., 2018).

Several empirical studies link ESG engagement to improved corporate financial performance in support of the stakeholder theory (see Brooks & Oikonomou, 2018, and Atz et al., 2023, for reviews of the literature). However, the contribution of sustainability initiatives to superior financial performance is not always recognised by shareholders as the evidence about the relationship between ESG performance and market returns is mixed (Aswani et al., 2024; Brooks & Oikonomou, 2018; Kräussl et al., 2024). For example, focusing on environmental sustainability, Bolton and Kacperczyk (2021), Hsu et al. (2023) and Garel et al. (2024) find that brown stocks are associated with higher returns than green stocks. In contrast, Kempf and Osthoff (2007), Statman and Glushkov (2009), In et al. (2019) and Broadstock et al. (2021) report that firms with strong ESG commitment produce higher returns. Quaye et al. (2025) also find that green firms outperform brown firms in environments where the majority of firms undertake green initiatives.

Investors may not always reward ESG initiatives with higher valuations for several reasons. First, ESG activities can be costly. Andreou and Kellard (2021) highlight that being environmentally proactive may require resources which introduce significant economic costs to the firm. Investors with a short-term horizon may overweight these costs in their decision-making over potential sustainability benefits (Starks et al., 2017). Second, in line with agency theory, underperformance of ESG investments may be indicative of investor aversion to greenwashing risk (Fatemi et al., 2018). Third, a link between high ESG scores and lower returns may be due to differences in the risk between ESG and non-ESG assets. In particular, the risk of ESG stocks may be lower, if ESG practices serve as a protective mechanism against reputation and regulatory risk. Lower risk in ESG stocks can lead to investors accepting lower returns for such stocks, as Cornell (2021) explains. Empirically, Ilhan et al. (2021) and Hoepner et al. (2024) demonstrate that firm activities that benefit the environment are associated with lower downside risk. Broadstock et al. (2021) and Lööf et al. (2022) provide international evidence that non-ESG stocks were more volatile in the COVID-19 period.

The conflicting evidence about the link between ESG and investment performance in previous studies could also be explained by time-varying investor preferences towards sustainability. On the basis of an equilibrium model, Pástor et al. (2022) argue that unexpected shifts in the demand for green assets (for example, due to a regulatory change) can generate high realised returns for green stocks, which are expected to be followed by lower returns. Bansal et al. (2022) alternatively argue that investors may treat social responsibility similarly to luxury goods, i.e., allocate more of their wealth to highly rated socially responsible investment (SRI) stocks during good economic times. This is because individuals and households experience growth in their financial well-being and they can afford to expand their portfolio by incorporating stocks with high SRI ratings. SRI can become less affordable in bad economic times due to wealth constraints, and, as a result, demand for SRI may be lower. Cho (2023) confirms the findings of Bansal et al. (2022) in the Korean market. Motivated by this evidence, we formulate the following hypothesis that underlies the framework presented in the next section:

H1. Investors prefer blockchains with high ESG ratings under favourable market conditions and positive sentiment.

3. A market-based decision-support framework for ESG-aligned technology adoption

3.1. The optimal adoption timing problem

We develop a decision-support framework that offers blockchain adopters a market-based tool to determine the optimal timing of the introduction of ESG-aligned blockchain technologies based on sentiment forecasts. This model can support decision-makers with timing the introduction of sustainable technologies to coincide with favourable financing conditions.

We consider a firm interested in adopting a new ESG-aligned blockchain platform. Motivated by evidence from the equity markets covered in the previous section, we consider that the cost of capital associated with the platform is a function of the underlying market sentiment as follows:

$$r(S_t) = r_0 - \delta S_t, \quad (1)$$

Where S_t is a measure of sentiment at time t taking values in $(-1,1)$, $r_0 > 0$ is the base cost of capital when sentiment is neutral and δ is the sensitivity of the cost of capital to sentiment.[7] We impose that $r_0 > |\delta|$, which ensures that $r(S_t) > 0$. When S_t approaches 1, investors are characterised by extreme optimism, while when S_t approaches -1, we observe extreme pessimism. $S_t = 0$ represents neutral sentiment. If δ is positive, investors require a higher return when market sentiment is negative, and a lower return when sentiment is positive. If δ is negative, the relationship between sentiment and cost of capital is reversed.

Let I_0 and C_0, respectively, be the adoption cost and the expected annual cash flow associated with the considered blockchain technology. For expositional purposes, we assume that these are constant and independent of S_t. If the firm adopts the technology at time t and the project's discount rate is locked at $r(S_t)$, then the net present value (NPV) from the adoption is given by

$$V(t) = \frac{C_0}{r(S_t)} - I_0. \quad (2)$$

If δ is positive, the added value from adoption is higher when investor sentiment becomes more optimistic. In contrast, if δ is negative, the value of adoption is lower in optimistic periods.

Assuming that the opportunity to invest in the technology expires at time T, the firm's objective is to select the optimal adoption time τ^* that leads to the maximum expected discounted NPV:

$$\tau^* \in \arg\max_{\tau \in \mathcal{T}_0} \mathbb{E}\left[\max\left(\frac{C_0}{r(S_\tau)} - I_0, 0\right) e^{-r_f \tau}\right], \quad (3)$$

Where r_f is the risk-free rate, assumed to be constant in $[0, T]$, $\mathcal{T}_0$ is the set of admissible stopping times in $[0, T]$, and the expectation is taken under the risk-neutral measure. The above optimal timing problem captures the decision of whether to invest in the new technology immediately or postpone adoption to a future time when investor preferences may be more favourable towards ESG.

The option to defer the adoption of the technology until market sentiment becomes more optimistic adds strategic flexibility to the firm's decision-making process. This is particularly valuable in uncertain market conditions when investor preferences about ESG shift over time. The value of flexibility, i.e., the value of the real option to wait (V_{RO}) before introducing the technology, is then given by

$$V_{RO} = \mathbb{E}\left[\max\left(\frac{C_0}{r(S_{\tau^*})} - I_0, 0\right) e^{-r_f \tau^*}\right] \text{-} \max\left(\frac{C_0}{r(S_0)} - I_0, 0\right). \quad (4)$$

V_{RO} is the additional economic benefit from strategically delaying the adoption of the technology until investors show a stronger appetite for ESG.

To empirically implement this framework and determine the optimal adoption time $\tau^* \in [0, T]$, it is essential for the firm to first evaluate how ESG characteristics and market sentiment affect the perceived value of the considered blockchain technology. To this end, we propose an approach that combines dynamic ESG profiling at the technology level, portfolio analysis linking ESG to market performance and structural decomposition of investor sentiment to assess how market sentiment influences investor preferences for ESG-aligned blockchains.

3.2. Blockchain ESG profiling

We use a new dataset of blockchain ESG scores to create a time-varying ESG profile for the period from January 2022 to February 2024 for several popular blockchains. This is provided by Green Crypto Research (GCR).[8] GCR is a non-profit organisation that offers the first ESG ratings for over 80 blockchains and tokens globally. Using a set of transparent standards consistent with traditional sustainability rating agencies (e.g., MSCI, Sustainalytics, and Bloomberg) and European sustainability regulations, GCR provides ratings on a letter scale (D− to A+) and scores (from 0 to 100) for the overall ESG profile of each blockchain-based project as well as its environmental, social and governance dimensions. Each rating is independently reviewed by at least two experts. The ratings and scores are derived using around 100 qualitative and quantitative data points that cover environmental factors (e.g., power consumption, electronic waste, carbon footprint), social factors (e.g., social impact, asset distribution, accessibility) and governance factors (e.g., network security, diversification, governance issues).

Our analysis employs ESG scores instead of ratings, as they offer a more detailed assessment of the ESG characteristics of each blockchain. Scores are largely independent of short-term price movements and contemporaneous investor sentiment, as the rating methodology does not employ price data, while scores are updated every 3–6 months. This allows us to interpret ESG scores as an external input to our models and not an outcome of market movements. We apply a set of filters to our dataset. First, we exclude tokens from the analysis as our focus is on the ESG features of the blockchain technologies themselves. Second, we omit blockchains that do not have a score in 2022 as including them would restrict the time period in our analysis. We end up with 28 blockchains with an ESG profile consisting of daily observations for the total ESG score as well as the individual scores for the environmental, social, and governance components. We present the blockchains we consider in our work in Table A1 of the Appendix.[9]

Panel A in Table 1 reports descriptive statistics for the blockchain ESG scores. It presents the average, median, minimum and maximum score across blockchains over time, the average range across blockchains and the standard deviation of the cross-sectional mean. We observe that the mean overall ESG score is 61, while the individual environmental, social and governance pillars exhibit average values of 80, 76, and 69, respectively. The median scores are close to the average scores in all categories, except for the environmental category where the median exceeds the average considerably. This is largely driven by a small subset of cryptocurrencies with low environmental scores, mainly due to high energy consumption. It also results in a larger variation in the environmental score across blockchains compared to the social and governance pillars. Finally, variation over time is slightly higher for the total ESG score and the governance score compared to the environmental score and the social score, as the range values indicate. This suggests that blockchains are more likely to make changes to their governance structure over time instead of their environmental or social features.

We also present the top 10 and bottom 10 blockchain networks according to their overall ESG score and their score for each individual ESG component in Panel B of Table 1. We observe that performance can vary considerably across the three components. For example, Bitcoin ranks in the top 10 in terms of its governance score and in the bottom 10 in terms of its environmental and social scores. Green Crypto Research highlights high energy usage and entry and usage barriers as respective drivers of the relatively low environmental and social scores. Lack of legal, regulatory and security issues is cited as one of the factors contributing to Bitcoin's strong governance score. This example is indicative of the complex trade-offs blockchain platforms face in balancing performance across different ESG pillars.

3.3. Portfolio construction

Our portfolio construction approach relies on data from the cryptocurrency markets. Each of the blockchains considered is associated with a main cryptocurrency that is publicly traded on digital exchanges. The comparative performance of these cryptocurrencies, in relation to the ESG profiles of the underlying blockchains, can reveal investor preferences for ESG features in blockchain technology. We source daily price data from CoinMarketCap for the period from January 2022 to February 2024, which matches the timeframe for which we have available ESG scores. We also draw daily market capitalisation data from the same source.[10] We use the Royalton CRIX Crypto Index from S&P Global and the three-month Treasury bill rate to respectively proxy the overall cryptocurrency market and the risk-free rate.[11]

For each day in our sample, we allocate cryptocurrencies of blockchains with above-median scores to an equally-weighted portfolio labelled as *High_ESG*. In a similar manner, we assign cryptocurrencies with below-median scores to an equally-

Table 1. ESG scores.

Panel A: Descriptive statistics

	N (blockchains)	Average	Median	Min	Max	Range	St dev. of average score
ESG score	28	60.976	61.500	93	10	8.929	22.900
Environmental score	28	79.899	96.000	100	10	7.464	27.640
Social score	28	75.863	77.000	97	40	6.000	14.524
Governance score	28	68.826	68.500	100	10	9.250	21.315

Panel B: Top and bottom 10 blockchains for each category

ESG score		Environmental score		Social score		Governance score	
Top 10	Bottom 10	Top 10	Bottom 10	Top 10	Bottom 10	Top 10	Bottom 10
SOL	BTC	SOL	BTC	MATIC	XMR	DOT	XMR
AVAX	XMR	EOS	XMR	CRO	DOGE	ADA	DOGE
ADA	DOGE	MATIC	ETC	XTZ	THETA	SOL	BCH
XTZ	ETC	ALGO	LTC	SOL	XRP	AVAX	LTC
MATIC	LTC	HBAR	DOGE	AVAX	BNB	ETH	THETA
ALGO	BCH	NEAR	BCH	ADA	HBAR	NEAR	ETC
NEAR	THETA	BNB	ETH	VET	ETH	XTZ	HBAR
VET	XRP	VET	FTM	ALGO	FTM	MATIC	ZIL
ATOM	HBAR	CRO	ZIL	LTC	BTC	ATOM	XLM
DOT	ZIL	XLM	XRP	TRX	XLM	BTC	CRO

This table provides details on the ESG scores provided by Green Crypto Research for the period from January 2022 to February 2024. Panel A presents summary statistics for the total ESG score and the scores for each individual ESG dimension, i.e., environmental, social and governance. It reports the number of blockchains in our sample and the average, median, minimum and maximum score across time and blockchains. It also gives the cross-sectional mean of the range and the cross-sectional standard deviation of the time-series mean score. Panel B lists the names of the top 10 and bottom 10 blockchain cryptocurrencies for each ESG dimension.

weighted portfolio labelled as *Low_ESG*. If $\mathcal{H}_t$ and $\mathcal{L}_t$ are respectively the sets of cryptocurrencies included in the *High_ESG* and *Low_ESG* portfolios at day *t*, then the daily returns of each portfolio are given by:

$$r_{\mathrm{t}}^{\mathrm{High}} = \frac{1}{N_H} \sum_{i \in \mathcal{H}_t} r_{i,t}, \quad r_t^{\mathrm{Low}} = \frac{1}{N_L} \sum_{i \in \mathcal{L}_t} r_{i,t} \tag{5}$$

Where N_H and N_L are the number of assets in each portfolio. We assume equal weights instead of value weights to prevent portfolios from being dominated by Bitcoin and Ethereum, which have significantly higher market capitalisations. We split our set of cryptocurrencies using the median as the cut-off point to ensure a higher level of diversification (i.e., up to 14 cryptocurrencies in each of the two portfolios).[12]

Our decision-support framework employs a zero-cost portfolio strategy we denote *HML* (high-minus-low*). HML* takes a long position in the *High_ESG* portfolio and a short position in the *Low_ESG* portfolio.[13] The daily return of the *HML* portfolio is then given by

$$r_{\mathrm{t}}^{HML} = r_{\mathrm{t}}^{\mathrm{High}} - r_t^{\mathrm{Low}} \tag{6}$$

Significantly positive r_{t}^{HML} suggests that investors value ESG features in blockchain technology. Conversely, if *HML* is associated with negative returns, we infer that investors have lower demand for blockchains with high ESG scores.

Our portfolio construction approach can be considered as a special case of portfolio selection that incorporates non-price-based criteria, i.e., ESG scores (e.g., see Gasser et al., 2017; Aouni et al., 2018; Lindquist et al., 2022; Steuer & Utz, 2023; Sahamkhadam & Stephan, 2024). Similar types of portfolio strategies have been considered for the stock market. For example, Kempf and Osthoff (2007) examine whether incorporating SRI criteria in stock portfolios can lead to significantly positive returns using a trading strategy of buying shares with strong SRI ratings and selling shares with weak SRI ratings. In et al. (2019) explore a strategy that consists of a long position in carbon-efficient firms and a short position in carbon-inefficient firms. Quaye et al. (2025) assess the performance of high-minus-low green-revenue-factor portfolios across five economies.

3.4. Investor sentiment

A key feature of our framework is that it can accommodate dynamic investor preferences for sustainability, which vary across market conditions. It uses investor sentiment to identify different market states as sentiment is a key driver of price dynamics in the cryptocurrency markets. For example, Bouteska et al. (2022), Anamika et al. (2023) and Koutmos (2023) report that investor sentiment is a significant driver of bitcoin returns. As a measure of sentiment in the cryptocurrency markets, we adopt the Crypto Fear and Greed Index (CFGI).[14] The index evaluates market trends and investor behaviour in the cryptocurrency markets based on price volatility, market momentum/volume, social media analysis, surveys, Bitcoin dominance and investor attention to the market. As such, it captures both market conditions and investor psychology. It is updated daily and ranges between 0 and 100, where values close to 0 indicate highly negative sentiment ("extreme fear") and values close to 100 indicate highly positive sentiment ("extreme greed"). A value around 50 is indicative of neutral sentiment. CFGI has been used in recent studies to study the relationship between investor sentiment and cryptocurrency prices (e.g., Gaies et al., 2023; Mokni et al., 2022; Wang et al., 2024).

To identify periods of positive, negative, or neutral sentiment, our work employs the Bayesian Estimator of Abrupt change, Seasonality, and Trend (BEAST) by Zhao et al. (2019).[15] BEAST is a time-series decomposition algorithm which is applied for robust identification of breakpoints in the time-series data. While alternative approaches generally rely on a single best model, BEAST applies Bayesian model averaging to leverage information across several models and jointly model nonlinear trend, seasonal structure and abrupt changes. These properties make it well suited to cryptocurrency market sentiment which is characterised by seasonal patterns with sharp shocks (e.g., regulatory events).

By applying the BEAST method to the daily CFGI values, we detect three distinct market states, i.e., an initial period of highly negative sentiment (fear period), a neutral sentiment period and a final period of highly positive sentiment (greed period). These are presented in Figure 1. We interpret the greed period as "good times" and the fear period as "bad times" in the cryptocurrency markets throughout our analysis. The estimated break dates are 14 January 2023 and 25 October 2023. The fear period is characterised by the collapse of high-profile projects, such as Terra and FTX, which resulted in negative market sentiment. The neutral period captures a consolidation phase after the FTX failure, where prices stabilised. Finally, the greed period is characterised by optimism, supported by expectations of a Bitcoin ETF approval, increasing participation by institutional investors and declining macroeconomic uncertainty.

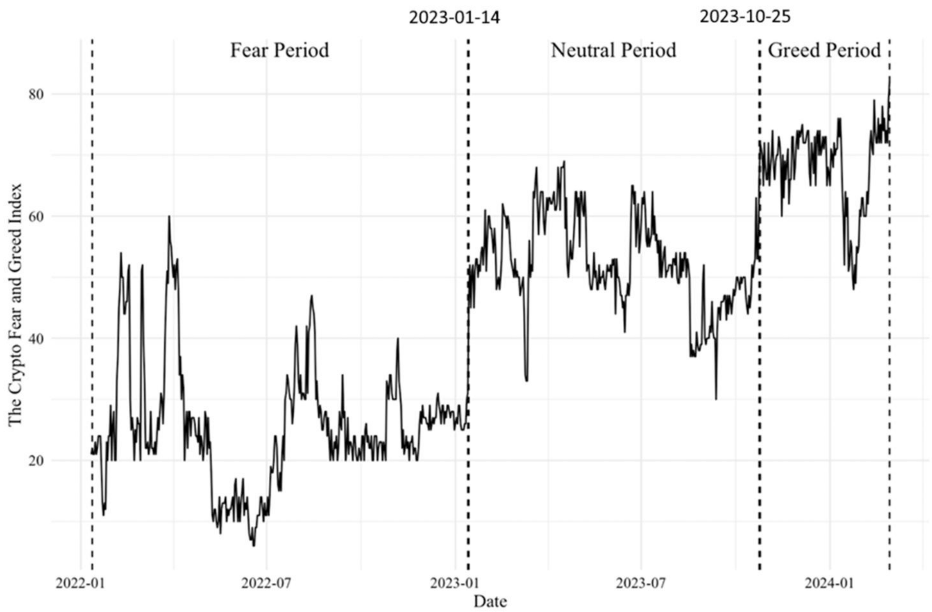


Figure 1. Crypto Fear and Greed Index. This figure illustrates the time series of the Crypto Fear and Greed Index (CFGI) from January 2022 to February 2024. It highlights three distinct periods, each corresponding to different market sentiment, along with the transition dates.

Table 2. Portfolio returns.

Panel A: Descriptive statistics

	N days	Average	St. Dev.	Sharpe ratio	Skewness	Kurtosis	Correlation with *MRKT*	Average market cap ($B)
High_ESG	778	−0.007	0.725	−0.085	−0.512	6.741	0.846	12.044
Low_ESG	778	0.111	0.634	0.088	−0.503	7.023	0.868	58.708
HML	778	−0.118	0.244	−0.710	0.216	4.388	0.261	35.561
MRKT	778	0.279	0.612	0.365	−0.116	11.765		

Panel B: Average portfolio returns

	High_ESG	*Low_ESG*	*HML*
Full sample	−0.007	0.111	−0.118
	(−0.014)	(0.256)	(−0.706)
Fear period	−0.929	−0.396	−0.533**
	(−1.091)	(−0.512)	(−2.230)
Neutral period	0.044	0.260	−0.216
	(0.067)	(0.473)	(−0.862)
Greed period	2.531**	1.244*	1.287***
	(2.555)	(1.655)	(2.669)

This table presents results from our portfolio analysis. Panel A reports descriptive statistics for a portfolio of cryptocurrencies with high ESG score (*High_ESG*) and a portfolio of cryptocurrencies with low ESG score (*Low_ESG*). *HML* is a portfolio that is long on *High_ESG* and short on *Low_ESG*. *MRKT* represents the CRIX index which is our proxy for the cryptocurrency market. Return statistics are annualised. Panel B reports average annualised returns for each portfolio and associated *t*-statistics in parentheses for the full-sample as well as three subsamples. These correspond to highly positive market sentiment (greed period), neutral market sentiment (neutral period) and highly negative market sentiment (fear period). Significance levels are indicated by ***, **, and *, i.e., 1%, 5%, and 10%, respectively.

4. Portfolio performance

In this section, we study how investors value ESG features in blockchain technologies. To this end, we analyse the risk-return properties of the *High_ESG*, *Low_ESG* and *HML* portfolios across the whole sample and distinct market conditions. We also adapt our analysis to identify which ESG dimensions have a stronger impact on investor preferences.

4.1. ESG scores and market returns

Panel A of Table 2 presents annualised descriptive statistics for the *High_ESG*, *Low_ESG* and *HML* portfolio returns, as well as the market portfolio (*MRKT*) proxied by the CRIX index. The *High_ESG* portfolio exhibits a negative average return in our sample while the average return of the *Low_ESG* portfolio is positive. However, these are not significant as the respective *t*-statistics in Panel B indicate. The volatility of the *High_ESG* portfolio is also higher in the full sample (0.73 vs 0.63). As a result, the Sharpe ratios for the *High_ESG* and *Low_ESG* portfolios are −0.085 and 0.088, respectively. Both portfolios exhibit similar levels of skewness and kurtosis which are consistent with non-normal distributions. They are also strongly correlated with the overall cryptocurrency market, which is characterised by high levels of correlation among cryptocurrencies.

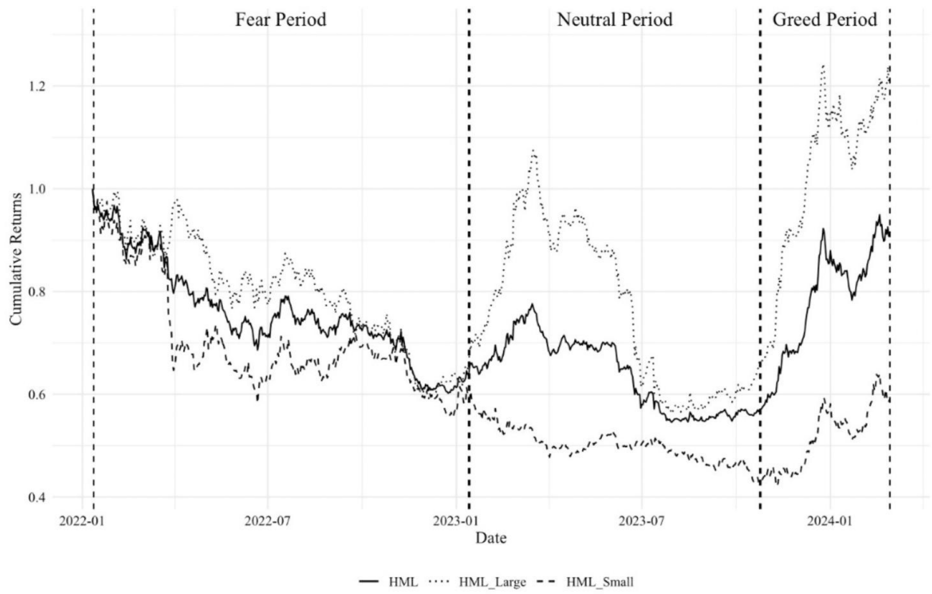


Figure 2. Cumulative returns of HML portfolios. The figure plots the cumulative return for a portfolio (*HML*) that is long on a portfolio of cryptocurrencies with high ESG score and short on a portfolio of cryptocurrencies with low ESG score. It also plots cumulative returns for a portfolio that includes only cryptocurrencies with above median market capitalisation (*HML_Large)* and a portfolio that includes only cryptocurrencies with below median market capitalisation (*HML_Small*). The figure indicates three periods representing positive (greed), neutral and negative (fear) market sentiment.

Examining the performance of the *HML* strategy, we observe in Panel B of Table 2 that the average return is not statistically significant in the full sample. This is consistent with previous research offering mixed evidence on investor preferences for ESG assets (e.g., Aswani et al., 2024; Kräussl et al., 2024). However, we find a significant positive correlation of 0.26 between *HML* and the market portfolio, as reported in Panel A. This indicates that cryptocurrencies with high ESG scores tend to outperform those with low ESG scores when the overall market is performing well. This finding suggests that investor preferences for blockchains with high ESG scores vary with market conditions.

To explore this further, we test whether the average return of the *HML* strategy changes across the three time periods with distinct investor sentiment, i.e., the fear period, neutral period and greed period. As shown in the last three rows of Panel B, *HML* produces a statistically significant negative average return in the fear period of around −53% and a statistically significant positive average return in the greed period of around 129%. The neutral period return is not statistically significant. The results suggest that investors reward ESG attributes with higher valuations when conditions are favourable and sentiment is positive. However, they tend to prefer cryptocurrencies with lower ESG scores when there is negative market sentiment. Figure 2 shows how the *High_ESG* and *Low_ESG* portfolios perform in terms of cumulative returns across the three periods we consider. Overall, our results support hypothesis H1 by indicating that investors prefer blockchains with high ESG scores during periods of strong market optimism.

4.2. The moderating role of size

Previous literature identifies size as a moderating factor in the performance of firms that engage in ESG activities. For example, In et al. (2019) find that the outperformance of carbon-efficient firms is mainly driven by firms with high market capitalisation. In addition, size is an established risk factor in the cross-section of cryptocurrency returns (e.g., see Liu et al., 2020). In this context, we explore whether our results vary across different levels of market capitalisation. To this end, we sort the cryptocurrencies in the *High_ESG* and *Low_ESG* portfolios based on their capitalisation and divide each portfolio into two portfolios, i.e., one with cryptocurrencies with above-median market value and the other with below-median market value. This results in four distinct portfolios: *Small_High_ESG*, *Small_Low_ESG*, *Large_High_ESG*, and *Large_Low_ESG*. We then repeat our return analysis for these four portfolios, with the results presented in Table 3 and Figure 2.

In the full sample, all four portfolios produce insignificant returns in line with our previous results. Focusing on the fear period, we observe that the difference between *Large_High_ESG* and *Large_Low_ESG* is similar to the difference between *Small_High_ESG* and *Small_Low_ESG*. However, focusing on the greed period shows that the outperformance of the cryptocurrencies with high ESG scores is primarily driven by those with high market

Table 3. Returns of portfolios sorted by ESG score and size.

Panel A: Full sample			
	High_ESG	*Low_ESG*	Difference
Large	0.146	0.072	0.074
	(0.293)	(0.170)	(0.332)
Small	−0.172	0.150	−0.323
	(−0.337)	(0.320)	(−1.582)
Panel B: Fear period			
	High_ESG	*Low_ESG*	Difference
Large	−0.926	−0.383	−0.543
	(−1.057)	(−0.513)	(−1.619)
Small	−0.932	−0.408	−0.525*
	(−1.100)	(−0.487)	(−1.749)
Panel C: Neutral period			
	High_ESG	*Low_ESG*	Difference
Large	0.404	0.218	0.186
	(0.632)	(0.396)	(0.557)
Small	−0.348	0.301	−0.649**
	(−0.495)	(0.522)	(−2.259)
Panel D: Greed period			
	High_ESG	*Low_ESG*	Difference
Large	2.633***	1.041	1.592***
	(2.914)	(1.408)	(2.659)
Small	2.426**	1.450*	0.977
	(2.127)	(1.706)	(1.585)

This table displays the average returns for portfolios of cryptocurrencies sorted by ESG score and size (market capitalisation) for the full sample as well as three subsamples. These respectively correspond to periods of highly positive market sentiment (greed period), neutral market sentiment (neutral period) and highly negative market sentiment (fear period). *t*-statistics are in parentheses. Significance levels are indicated by ***, **, and *, i.e., 1%, 5%, and 10%, respectively.

Table 4. Market model coefficients.

Panel A: Full sample			
	High_ESG	*Low_ESG*	*HML*
Excess return (α)	−0.0008	0.0015	−0.0005
	(−1.0798)	(0.8466)	(−1.2173)
Market risk (β)	1.0027***	1.0159***	0.1035***
	(44.2615)	(13.2317)	(7.5050)
Panel B: Fear period			
	High_ESG	*Low_ESG*	*HML*
Excess return (α)	−0.0008	0.0005	−0.0014**
	(−0.8924)	(0.7525)	(−2.2081)
Market risk (β)	1.1451***	1.0516***	0.0935***
	(48.3345)	(53.0066)	(5.3651)
Panel C: Neutral period			
	High_ESG	*Low_ESG*	*HML*
Excess return (α)	−0.0012	−0.0004	−0.0010
	(−0.9049)	(−0.4081)	(−1.4348)
Market risk (β)	0.7096***	0.6084***	0.1012***
	(15.8625)	(16.5977)	(4.4613)
Panel D: Greed period			
	High_ESG	*Low_ESG*	*HML*
Excess return (α)	0.0015	−0.0013	0.0026*
	(0.8466)	(−1.1699)	(1.9406)
Market risk (β)	1.0159***	0.8708***	0.1451**
	(13.2317)	(19.0687)	(2.5756)

This table presents the estimated coefficients of the market model in Eq. (7). The coefficients are presented for a portfolio of cryptocurrencies with high ESG score (*High_ESG*), a portfolio of cryptocurrencies with low ESG score (*Low_ESG*) and a portfolio that is long on *High_ESG* and short on *Low_ESG*. The CRIX index is our proxy for the cryptocurrency market. *t*-statistics are in parentheses. Significance levels are indicated by ***, **, and *, i.e., 1%, 5%, and 10%, respectively.

capitalisation. During the greed period, the difference in the annualised returns between the *Large_High_ESG* and *Large_Low_ESG* portfolios is 159% and significant at the 1% level. In the same period, the *Small_High_ESG* and *Small_Low_ESG* portfolios yield statistically similar returns. These results imply that sustainable blockchain technologies are more attractive to investors when they are associated with larger and more established platforms. We attribute this to stronger disclosure practices and higher-quality ESG data that can improve confidence among ESG investors. Our results are consistent with previous evidence by In et al. (2019) that the potential outperformance of high-ESG stocks between 2005 and 2015 mostly comes from large- and mid-cap firms.

4.3. Controlling for market risk

To this point, our analysis has focused on average portfolio returns. We further explore if the observed differences in the market performance between high- and low-ESG-ranked blockchains hold if we consider risk-adjusted returns. We obtain risk-adjusted returns for the *High_ESG*, *Low_ESG*, and *HML* portfolios by applying a market model:

$$r_t - r_{f,t} = \alpha + \beta \left(r_{m,t} - r_{f,t}\right) + \varepsilon_t, \qquad (7)$$

Where r_t is the portfolio return at time t, $r_{f,t}$ is the risk-free rate (proxied by the three-month US Treasury bill rate), $r_{m,t}$ is the return on the cryptocurrency market index (CRIX) and ε_t is the error term. Alpha (α) represents the portfolio return adjusted for market risk. The latter is captured by beta (β). We estimate this model using a standard OLS regression. Table 4 reports the results for the full sample and across different time periods.

The results are consistent with our previous findings. In the full sample and the neutral period, the *HML* portfolio does not produce a statistically significant risk-adjusted return. As shown in Panel B, the *Low_ESG* portfolio again significantly outperforms the *High_ESG* portfolio in the fear period as the alpha of *HML* is −0.0014, which is statistically significant at the 5% level. In contrast, the *HML* portfolio produces a risk-adjusted return of 0.0026 in the period of positive sentiment which is significant at the 10% level. The latter result indicates that blockchains with high ESG score attract higher risk-adjusted returns under favourable market conditions. This provides further support for Hypothesis H1.

Another interesting conclusion from Table 4 is that *HML* is consistently associated with a positive beta across all time periods under consideration.

Table 5. Extended market model coefficients.

Panel A: Market model with greed period indicator			
	High_ESG	*Low_ESG*	*HML*
Excess alpha under extreme greed (α_1)	0.0045**	0.0007	0.0038***
	(1.9603)	(0.3571)	(2.6966)
Excess return (α_0)	−0.00128*	−0.0005	−0.0010**
	(−1.6612)	(−0.7383)	(−2.0475)
Market risk (β)	1.0043***	0.9002***	0.1039***
	(42.9109)	(47.0526)	(7.3137)

Panel B: Market model with greed period and fear period indicators			
	High_ESG	*Low_ESG*	*HML*
Excess alpha under extreme greed (α_1)	0.0045*	0.0009	0.0036**
	(1.9257)	(0.4701)	(2.4405)
Excess alpha under extreme fear (α_2)	0.0003	0.0008	−0.0004
	(0.2102)	(0.6896)	(−0.4426)
Excess return (α_0)	−0.0012	−0.0007	−0.0008
	(−1.2279)	(−0.8205)	(−1.1983)
Market risk (β)	0.7892***	0.6811***	0.1079***
	(21.9976)	(23.7487)	(4.7744)

This table presents the estimated coefficients of the extended market models presented in Eqs. (8) (Panel A) and (9) (Panel B). The coefficients are presented for a portfolio of cryptocurrencies with high ESG score (*High_ESG*), a portfolio of cryptocurrencies with low ESG score (*Low_ESG*) and a portfolio that is long on *High_ESG* and short on *Low_ESG*. The CRIX index is our proxy for the cryptocurrency market. *t*-statistics are in parentheses. Significance levels are indicated by ***, **, and *, which represent 1%, 5%, and 10%, respectively.

It appears that cryptocurrencies with stronger ESG features are more sensitive to market movements. We also see that the *HML* beta is higher in the greed period (0.1451) than in the fear period (0.0935). To further explore the effect of time-varying market risk on investor demand for ESG, we consider two extensions of the market model (7), similarly to Bansal et al. (2022). The extended market models are specified as follows:

$$r_t - r_{f,t} = \alpha_0 + \beta_1(r_{m,t} - r_{f,t}) + \alpha_1 I_t^{Greed} + \Upsilon_1\left((r_{m,t} - r_{f,t})I_t^{Greed}\right) + \varepsilon_t \tag{8}$$

and

$$r_t - r_{f,t} = \alpha_0 + \beta_1(r_{m,t} - r_{f,t}) + \alpha_1 I_t^{Greed} + \alpha_2 I_t^{Fear} + \Upsilon_1\left((r_{m,t} - r_{f,t})I_t^{Greed}\right) + \Upsilon_2\left((r_{m,t} - r_{f,t})I_t^{Fear}\right) + \varepsilon_t. \tag{9}$$

In the above, I_t^{Greed} is a variable that indicates highly positive market sentiment (*extreme greed*) taking the value of 1 when the Fear and Greed Index exceeds 66, and 0 otherwise. Similarly, I_t^{Fear} takes the value of 1 when the Fear and Greed Index is less than 34, and 0 otherwise, indicating highly negative market sentiment (*extreme fear*). In this context, the parameters α_1 and α_2 capture the excess risk-adjusted return (excess alpha) in good times and bad times, respectively.

Table 5 reports the estimation results for the two extended models for the full sample. In Panel A, we observe that the excess alpha of the *HML* portfolio under extreme greed is positive and statistically significant at the 1% level. The excess alpha under extreme greed for the *High_ESG* portfolio is 0.0045, which is statistically significant at the 5% level, while the excess alpha for the *Low_ESG* portfolio is not significant. These results confirm that investors experience positive demand shifts towards sustainable blockchain technology when market sentiment is highly positive. We also observe that the unconditional alpha for the first extended market model is negative (−0.001), which shows that outside periods of highly positive market sentiment, investors prefer blockchains with lower ESG scores.

The results in Panel B allow us to compare excess risk-adjusted returns across periods of highly positive and highly negative market sentiment. While the excess HML alpha under extreme greed remains positive and statistically significant, the excess alpha under extreme fear is not statistically significant. This implies that positive shifts in market sentiment have a more pronounced impact on investor demand for ESG-aligned technology than negative shifts.

Overall, our results support our main hypothesis as they imply that investor preferences for blockchains with strong ESG qualities are time-varying, influenced by market conditions and investor sentiment. Investors value ESG more in good times and are more likely to include blockchains with strong ESG characteristics in their portfolios. In such times, adoption of sustainable technologies is more likely to be supported by external capital. However, when the cryptocurrency market conditions are challenging and investors experience negative shifts in their sentiment, ESG features appear to become less of a priority as investors focus on blockchain features with more immediate links to operational or financial gains. As such, under significant economic uncertainty, firms should place greater emphasis on the operational and financial advantages of sustainable technologies, alongside their ESG benefits.

4.4. Portfolio volatility

Previous research finds that firms with good ESG performance are associated with lower risk, especially under challenging market conditions (Broadstock et al., 2021; Cornell, 2021; Hoepner et al., 2024; Ilhan et al., 2021; Lööf et al., 2022). For instance, Broadstock et al. (2021) and Lööf et al. (2022) report lower volatility for stocks with high ESG scores in the COVID-19 period. These studies motivate us to explore whether the lower return of the *High_ESG* portfolio during the fear period is driven by lower risk levels for cryptocurrencies with stronger ESG profiles. To this end, we employ an Exponential GARCH (EGARCH) model to estimate the daily volatility of the *High_ESG* and *Low_ESG* portfolios. The EGARCH model (Nelson, 1991) is a member of the GARCH family of conditional variance models. Its main advantage compared to alternatives is that it can capture the asymmetric impact of positive and negative shocks on the volatility process. As such, it is often used for the estimation of cryptocurrency volatility (e.g., Zhang, Ma, et al., 2023).

We assume the following EGARCH(1,1) specification for the conditional variance σ_t^2 at time t:

$$\ln\left(\sigma_t^2\right) = \omega + \alpha\left[\frac{|\varepsilon_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}}\right] + \gamma\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \beta\ln\left(\sigma_{t-1}^2\right) \tag{10}$$

In the above, ω is the long-term average of the log variance, α assesses the effect of past shocks on current volatility, β measures the persistence of volatility over time and γ represents the leverage parameter, which indicates the type of asymmetric response to past shocks. A large α implies a strong response of volatility to market changes, while a large β suggests that shocks are long lasting. If $\gamma > 0$, positive shocks have a greater impact on the volatility than negative shocks, and vice versa if $\gamma < 0$.

Panel A of Table 6 reports the EGARCH parameters for the *High_ESG* and *Low_ESG* portfolios estimated using the full sample. All estimated parameters are statistically significant. The values of β exceed 0.9 and indicate that the volatility of both portfolios is highly persistent. The volatility of the *High_ESG* portfolio appears to be affected more strongly by past returns as the ARCH parameters (α) show. Consistent with findings from the stock market, both portfolios exhibit significant negative leverage effects (γ). As such, their volatility is affected more by past negative returns than positive returns. The leverage effect is stronger for the *Low_ESG* portfolio (−0.084 versus −0.067).

We further examine whether the volatilities of the *High_ESG* and *Low_ESG* portfolios vary across different market conditions. Panel B in Table 6 presents the average annualised conditional variance of the two portfolios for the full sample as well as for the fear, neutral and greed periods. We also employ a Wilcoxon signed-rank test to assess the statistical significance of the differences in volatility between the two portfolios. The *High_ESG* portfolio exhibits a significantly higher variance across all periods than the *Low_ESG* portfolio. In the fear period, the average annualised variance of the former is 0.655 while that of the latter is 0.516. As expected, the average variance of both portfolios is lower during the greed period, but the *High_ESG* portfolio is still more volatile with an average variance of 0.413 versus 0.286 for the *Low_ESG* portfolio. The higher volatility of the *High_ESG* portfolio in our sample is also illustrated in Figure 3, which depicts the time series of the daily conditional variance for both portfolios across the three periods. We can observe that the *High_ESG* portfolio experiences more prominent volatility spikes compared to the *Low_ESG* portfolio.

Our portfolio volatility results indicate that ESG investing in the cryptocurrency markets is associated with higher risk. The higher variance of high-ESG cryptocurrencies is consistent with their greater sensitivity to market movements and the stronger effect of past returns on their volatility, as indicated by the larger ARCH parameter. This finding contrasts with previous evidence from the stock market. A potential explanation is that high-ESG networks are younger, fast-growing platforms, which are naturally

Table 6. Portfolio volatility.

Panel A: EGARCH estimation results

	High_ESG	*Low_ESG*
Constant (ω)	−0.631***	−0.675***
	(−3.985)	(−4.346)
Volatility persistence (β)	0.904***	0.900***
	(38.447)	(40.265)
Magnitude of shocks (α)	0.318***	0.262***
	(8.279)	(7.794)
Leverage (γ)	−0.067**	−0.084***
	(−2.573)	(−3.553)

Panel B: Average variance

	High_ESG	*Low_ESG*	Difference
Full sample	0.524	0.398	0.126***
Fear period	0.655	0.516	0.139***
Neutral period	0.404	0.295	0.109***
Greed period	0.413	0.286	0.127***

This table presents results from estimating the conditional variance of two portfolios using an EGARCH(1,1) model. The first portfolio includes cryptocurrencies with high ESG scores (*High_ESG*) and the second portfolio includes cryptocurrencies with low ESG scores (*Low_ESG*). Panel A reports the EGARCH parameter estimates. *t*-statistics are shown in parentheses. Panel B reports the annualised average conditional variance for each portfolio for the full sample as well as three subsamples. These respectively correspond to periods of highly positive market sentiment (greed period), neutral market sentiment (neutral period) and highly negative market sentiment (fear period). We test whether the difference in the variances is statistically significant using a Wilcoxon signed-rank test. Significance levels are indicated by ***, **, and *, which represent 1%, 5%, and 10%, respectively.

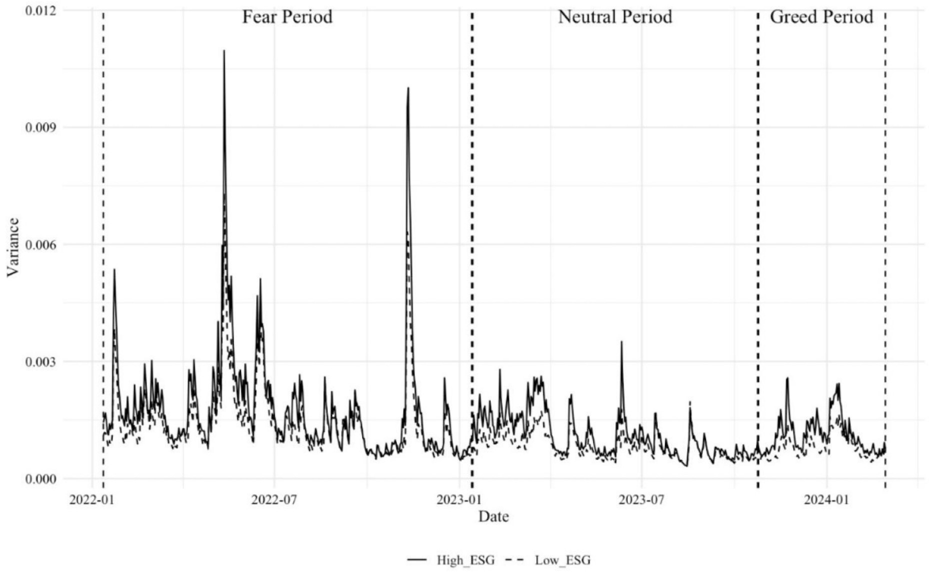


Figure 3. Portfolio variance. The figure displays the daily conditional variance of two cryptocurrency portfolios: one with high average ESG score (*High_ESG*) and one with a low average ESG score (*Low_ESG*). The conditional variance is estimated using an EGARCH(1,1) model over the period January 2022–February 2024. The figure indicates three periods representing positive (greed), neutral and negative (fear) market sentiments.

associated with higher risk. In the equity markets, ESG is instead more common among mature firms with strong disclosure practices, which tend to be less volatile. Overall, the time-varying performance of ESG-aligned blockchains cannot be fully explained by differences in risk profiles. This supports our alternative explanation of dynamic investor preferences that depend on underlying market conditions and sentiment.

4.5. Which ESG dimensions matter most to investors?

We adapt our analysis to determine whether any dimensions of ESG are more important to blockchain investors than others. To this end, we repeat our tests using pairs of portfolios that are constructed using the scores assigned to each ESG component. For example, the analysis for the governance component assumes a *High_G* portfolio, which contains cryptocurrencies with above-median governance score and a *Low_G* portfolio, which consists of cryptocurrencies with below-median governance score. Panel A in Tables 7–9 presents the average returns for portfolio pairs with high and low environmental, social and governance scores, respectively, along with their difference (*HML*) across the full sample and the fear, neutral, and greed periods. Panel B reports the respective results based on the first extended market model, as in Eq. (8).

We find that the reported time-varying investor preferences for responsible blockchain technology are primarily driven by the environmental and governance components of ESG. The portfolio of cryptocurrencies with high environmental scores significantly outperforms that with low environmental scores in terms of annualised average return in the greed period by about 91%, while underperforming by about 76% in the fear period. Similarly, the difference between the portfolio of high governance scores and that of low governance scores is significantly positive, with a 139% annualised return, in the greed period and significantly negative, with a −42% annualised return, in the fear period. For both ESG dimensions, the *HML* portfolio generates a statistically significant positive excess alpha under highly positive market sentiment. In contrast, the portfolios created using social scores do not significantly differ in terms of market performance. This indicates that the social dimension of ESG may be less important to blockchain investors. This is consistent with evidence from the equity markets. According to the ESG Global Survey 2021 by BNP Paribas (2021), investors view the social dimension as the most challenging to analyse and quantify, as it lacks in data quality in terms of other dimensions. As a result, S performance tends to have a weaker effect on market returns (e.g., see Galema & Gerritsen, 2025). Our results reveal a similar pattern in the cryptocurrency markets where investor attention focuses on environmental and governance issues, such as energy consumption and security of blockchain platforms, as social performance is not as well-defined and attracts less media coverage.

We also observe that, in good times, governance performance matters more for investors than environmental or social performance, as the governance-based *HML* portfolio yields higher average returns

Table 7. Results using environmental scores.

Panel A: Average returns			
	High_E	*Low_E*	*HML_E*
Full sample	0.0139	0.2159	−0.2020
	(0.0273)	(0.4685)	(−1.0551)
Fear period	−1.0517	−0.2883	−0.7634**
	(−1.1766)	(−0.3592)	(−2.3731)
Neutral period	0.2254	0.2078	0.0176
	(0.3616)	(0.3422)	(0.0755)
Greed period	2.5888**	1.6791**	0.9097*
	(2.5205)	(1.9616)	(1.9325)

Panel B: Market model with greed period indicator			
	High_E	*Low_E*	*HML_E*
Excess alpha under extreme greed (α_1)	0.0042*	0.0009	0.0032*
	(1.7024)	(0.4638)	(1.9585)
Excess return (α_0)	−0.0012	−0.0003	−0.0011**
	(−1.4499)	(−0.3790)	(−1.9827)
Market factor (β)	1.0040***	0.9474***	0.0565***
	(39.5513)	(45.8793)	(3.3640)

This table presents results for three cryptocurrency portfolios: one with a high average environmental score (*High_E*), one with a low average environmental score (*Low_E*) and a portfolio that is long on *High_E* and short on *Low_E* (*HML_E*). Panel A reports average annualised returns for each portfolio over the full sample and three subsample periods representing positive (greed), neutral, and negative (fear) market sentiments. Panel B shows the estimated coefficients from our first extended market model (Eq. (8)), using the CRIX index as the cryptocurrency market proxy. *t*-statistics are in parentheses. Significance levels are indicated by ***, **, and *, i.e., 1%, 5%, and 10%, respectively.

Table 8. Results using social scores.

Panel A: Average returns			
	High_S	*Low_S*	*HML_S*
Full sample	0.0423	0.0266	0.0157
	(0.0874)	(0.0601)	(0.1062)
Fear period	−0.7556	−0.5839	−0.1717
	(−0.8968)	(−0.7505)	(−0.7865)
Neutral period	0.0987	0.1121	−0.0134
	(0.1641)	(0.1908)	(−0.0687)
Greed period	2.1849**	1.6073**	0.5775
	(2.1952)	(2.1603)	(1.2087)

Panel B: Market model with greed period indicator			
	High_S	*Low_S*	*HML_S*
Excess alpha under extreme greed (α_1)	0.0028	0.0026	0.0001
	(1.2784)	(1.3511)	(0.1088)
Excess return (α_0)	−0.0010	−0.0009	−0.0002
	(−1.3006)	(−1.4038)	(−0.4620)
Market risk (β)	0.9824***	0.9175***	0.0647***
	(43.8174)	(46.7023)	(5.0415)

This table presents results for three cryptocurrency portfolios: one with a high average social score (*High_S*), one with a low average social score (*Low_S*) and a portfolio that is long on *High_S* and short on *Low_S* (*HML_S*). Panel A reports average annualised returns for each portfolio for the full sample and three subsample periods representing positive (greed), neutral, and negative (fear) market sentiments. Panel B shows the estimated coefficients from our first extended market model (Eq. (8)), using the CRIX index as the cryptocurrency market proxy. *t*-statistics are in parentheses. Significance levels are indicated by ***, **, and *, i.e., 1%, 5%, and 10%, respectively.

Table 9. Results using governance scores.

Panel A: Average returns			
	High_G	*Low_G*	*HML_G*
Full sample	0.0471	0.0657	−0.0186
	(0.0980)	(0.1459)	(−0.1168)
Fear period	−0.8808	−0.4588	−0.4221*
	(−1.0637)	(−0.5770)	(−1.8364)
Neutral period	0.1108	0.2342	−0.1234
	(0.1829)	(0.3898)	(−0.5515)
Greed period	2.5792***	1.1904*	1.3888***
	(2.5304)	(1.6676)	(2.8528)

Panel B: Market model with greed period indicator			
	High_G	*Low_G*	*HML_G*
Excess alpha under extreme greed (α_1)	0.0040*	0.0011	0.0028**
	(1.9208)	(0.5472)	(2.1023)
Excess return (α_0)	−0.0011	−0.0006	−0.0007
	(−1.5882)	(−0.8662)	(−1.4561)
Market risk (β)	0.9871***	0.9164***	0.0705***
	(46.3003)	(43.1682)	(5.1832)

This table presents results for three cryptocurrency portfolios: one with a high average governance score (*High_G*), one with a low average governance score (*Low_G*), and a portfolio that is long on *High_G* and short on *Low_G* (*HML_G*). Panel A reports average annualised returns for each portfolio over the full sample and three subsample periods. These respectively represent positive (greed), neutral, and negative (fear) market sentiments. Panel B shows the estimated coefficients from our first extended market model (Eq. (8)), using the CRIX index as the cryptocurrency market proxy. *t*-statistics are in parentheses. Significance levels are indicated by ***, **, and *, i.e., 1%, 5%, and 10%, respectively.

in the greed period. This result is consistent with previous work for the stock market where the governance element of ESG appears to have a stronger effect on market performance compared to the environmental and social elements (e.g., Broadstock et al., 2021; Pedersen et al., 2021). In the context of blockchain technology, attractive governance features, such as transparency, trust, security and decentralisation, appear to matter for investors, and should be prioritised by technology adopters.

5. Solving the optimal adoption-timing problem

In this section, we draw from our portfolio analysis to solve the optimal adoption-timing problem (3). As our results indicate, investor preferences for ESG-aligned blockchain technologies are time-varying, affected by the underlying market sentiment. Such technologies tend to attract more investment in periods of optimistic sentiment, and less during periods of fear. This implies that investing in ESG-aligned blockchain technologies will tend to command a lower cost of capital when sentiment is favourable, because investors show a stronger appetite for ESG assets. Alternatively, when sentiment is negative, the cost of capital will tend to be higher. These findings infer a positive sentiment sensitivity of the cost of capital (δ) in Eq. (1).

Given that the sentiment process S_t is stochastic, we need to forecast sentiment dynamics before solving the optimal timing problem. To this end, we model S_t as a bounded stochastic process by letting $S_t = \tanh(Z_t)$, where Z_t is a latent variable following an Ornstein–Uhlenbeck process with the following specification:

$$dZ_t = \kappa\left(\overline{Z} - Z_t\right)dt + \sigma dW_t, \quad (11)$$

Where $\overline{Z}$ is the long-term mean of Z_t, $\kappa > 0$ is the speed of mean reversion, $\sigma > 0$ is the volatility, and W_t is a standard Wiener process. This specification ensures that S_t remains bounded at (−1,1). Ornstein–Uhlenbeck processes are widely used in Finance as they can capture mean reversion parsimoniously (e.g., see Maller et al. 2009).

We fit the sentiment forecasting model to the available data for the Crypto Fear and Greed index (CFGI) over the period January 2022–February 2024. We first normalise the sentiment index to the interval [−1, 1] so that $S_t = -1$ corresponds to an index value of 0 (extreme fear), $S_t = 0$ corresponds to an index value of 50 (neutral sentiment) and $S_t = 1$ corresponds to an index value of 100 (extreme greed). We then transform S_t to its latent representation $Z_t = \operatorname{arctanh}(S_t)$ and estimate the parameters $\kappa, \overline{Z}$ and σ using maximum-likelihood estimation.

We explore the solution of optimal timing problem (3) under the following assumptions. First, we consider a technology that can be introduced at any time within a period [0,1], corresponding to a calendar year. The cost of adoption is $I_0 = 10$ and does not change over this period. When the technology is adopted, it is expected to generate an annual cashflow $C_0 = 1$ perpetually. The baseline cost of capital associated with the technology, under neutral investor sentiment, is $r_0 = 8\%$ while the risk-free rate is $r_f = 3\%$. The sensitivity of the cost of capital to sentiment is positive, as inferred by our portfolio analysis, taking a value $\delta = 0.02$.

We generate 100,000 forward paths of the sentiment process using the estimated parameters with 365 daily time steps and the sentiment initially assumed to be neutral ($S_0 = 0$). Each step represents a potential decision point for the adoption of the considered technology. Panel A of Figure 4 illustrates 5 simulated paths of the sentiment process. We then solve the optimal stopping problem *via* dynamic programming using backward induction on a (t, Z) grid. For each node of the grid, we compare the NPV from immediate adoption to the conditional expectation of the value from delaying the adoption for one more day. If the first exceeds the latter, then the firm proceeds with the immediate adoption of the technology and the node is marked as “adopt now.” Based on this process, we determine an option exercise boundary $S^*(t)$, which identifies the minimum sentiment value that will trigger adoption on day t. Finally, for each simulated sentiment path, we determine the optimal adoption timing τ^* as the first day the observed sentiment crosses $S^*(t)$. If this crossing does not occur before T, then the firm will adopt at time T, if the NPV is positive. Panel B of Figure 4 presents the discounted NPV and τ^* for each sentiment path of Panel A.

As can be seen in Table 10, the option value (V_{RO}) is around 63% of the immediate NPV. This highlights that the flexibility to introduce an ESG-aligned blockchain technology when investors favour sustainable investments is of significant value to the firm. The value of flexibility varies with the underlying sentiment parameters as Figure 5 indicates. First, the option premium increases with the sensitivity of the cost of capital to investor sentiment (δ). This is because the more sensitive the cost of capital is to sentiment, the more valuable the option to wait for stronger positive sentiment becomes. Second, the added value from delaying adoption is larger when investor sentiment is more volatile, as high volatility is expected to create more opportunities for investor sentiment to exceed the adoption trigger $S^*(t)$ at a future time t.

Figure 6 (Panel A) presents the exercise trigger $S^*(t)$, i.e., the minimum sentiment level for each t that will lead the firm to immediately adopt the technology considered. When the sentiment S_t is above the curve, then the NPV from immediate adoption of the blockchain technology exceeds the value of waiting, and adoption takes place. Otherwise, the firm should wait and reassess the next day. The exercise trigger $S^*(t)$ starts at 0.588, as can be seen in Table 10, corresponding to a value of 79 for CFGI. This gradually reduces over time. Earlier on, the trigger is higher as the firm has a relatively large window to exploit opportunities for future sentiment swings. As time passes, these opportunities shrink, and the option premium is lower. At the final decision date, the option expires and the firm will adopt the technology if the NPV is positive or reject it otherwise.

Panel B of Figure 6 presents the distribution of the optimal adoption time across paths. The mean adoption time is 0.48 years (Table 10). The probability of adoption in the first three months is around 31% while the probability of adoption in the last three months is around 25%. The larger adoption rate in the first few months is due to the large volatility of investor sentiment in the cryptocurrency markets, which leads to positive spikes above the adoption trigger early in the period. We also observe that around 9% of the paths do not cross the trigger, and investment takes place on the final date.

6. Conclusions

6.1. Summary

This study proposes a market-based decision-support framework to identify investor preferences for

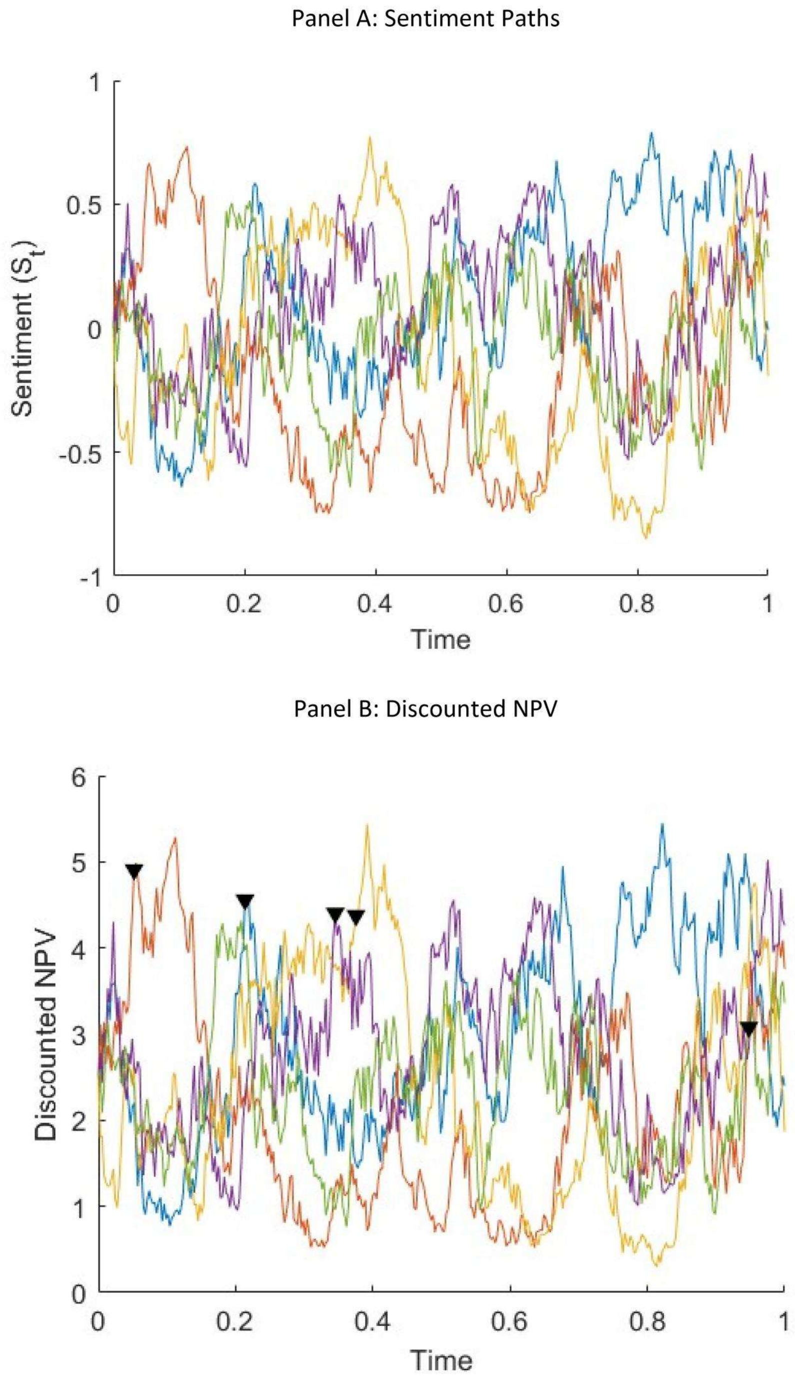


Figure 4. Sentiment process and NPV. Panel A illustrates five paths for the sentiment process obtained using simulation. Panel B illustrates the associated discounted net present value (NPV) of adoption over time for each sentiment path in Panel A. The marks show the first date the sentiment value exceeds the adoption trigger $S^*(t)$.

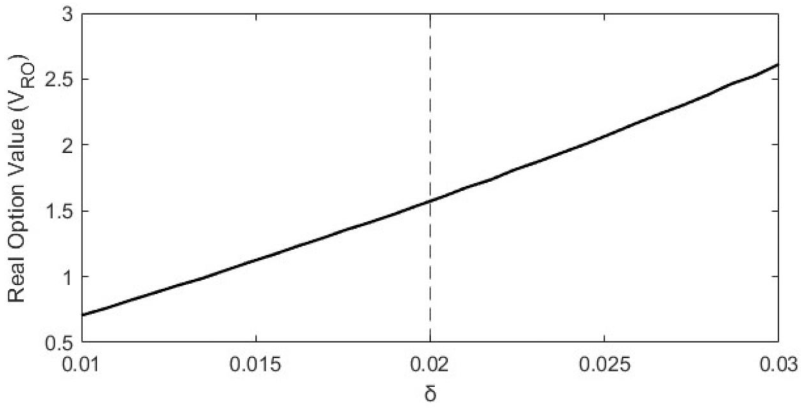
Table 10. Real option valuation.

Variable	Estimate
Immediate NPV $(V(0))$	2.500
Option premium (V_{RO})	1.572
Initial exercise trigger $S^*(0)$.	0.588
Mean τ^* (yrs)	0.482
Prob($\tau^* \leq$ 3 m)	0.311
Prob($\tau^* \geq$ 9 m)	0.253

This table summarises the results from solving the real option valuation problem as described in section 5. It reports the NPV from adopting the considered technology at time 0, the premium of the option to wait for adoption and the trigger for exercising the option to adopt at time 0. It also reports the mean adoption time in years, the probability of adopting in the first three months and the probability of adopting in the last three months.

ESG-aligned technologies and to determine the optimal timing for adopting such technologies. The framework uses a novel set of blockchain ESG scores, data from cryptocurrency markets and a measure of investor sentiment to identify when investors favour ESG features in blockchain. Our analysis indicates that cryptocurrencies with high ESG scores outperform lower-rated cryptocurrencies during times of favourable market conditions and investor optimism. In contrast, during periods of negative market sentiment, cryptocurrencies on

Panel A: Sensitivity to δ



Panel B: Sensitivity to σ

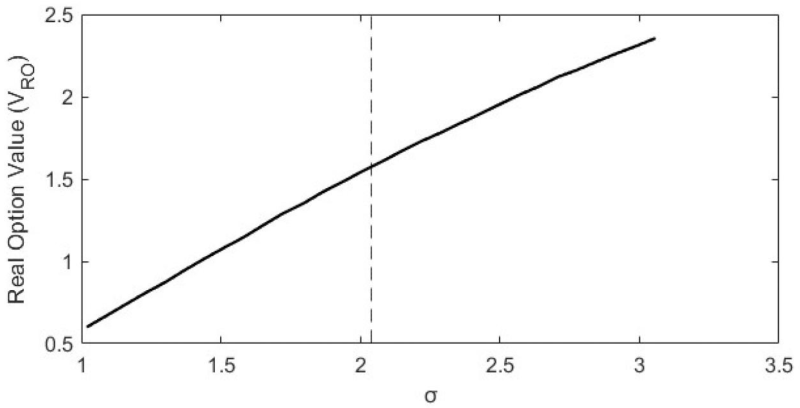


Figure 5. Sensitivity of the Real Option Value to sentiment parameters. This figure shows how the premium from the option to delay the adoption of the ESG-aligned technology changes with the sensitivity of cost of capital to the sentiment (δ) and the volatility (σ) in the OU process (11). The dashed lines show the baseline values of the parameters based on the calibrated parameters.

ESG-aligned blockchains tend to underperform. Our results suggest that while investors value strong ESG performance in emerging technologies in "good times," they tend to prioritise factors that have a clearer link to their wealth during market downturns. Among the three ESG components, governance and environmental factors have the strongest impact on investor preferences. We also find that higher ESG scores are associated with higher market volatility. Building on these findings, we develop a real-options model for determining the optimal roll-out of ESG-aligned technologies based on sentiment forecasts. This implies that the strategic deferral of technology adoption until investors have a stronger appetite for ESG assets can yield significant economic benefits.

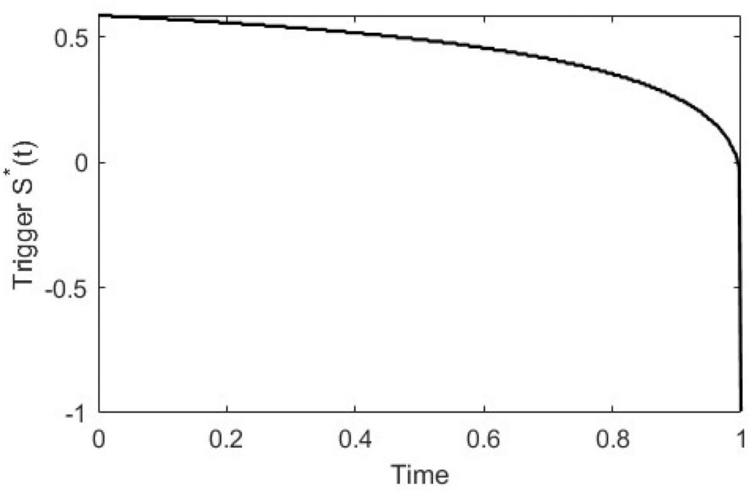
6.2. Theoretical and managerial implications

The paper contributes to the Operations-Finance Interface (OFI) literature by linking market-based evidence with real-options modelling in the context of technology adoption. While traditional operations management models treat financing conditions as exogenous, we instead endogenise the cost of capital by modelling it as a function of the market sentiment. In this way, we determine how investor preferences and ESG valuations drive adoption timing within a stochastic optimisation framework.

Our work extends recent OR studies that combine financial and operational perspectives in blockchain adoption. For example, Choi (2021) proposes a supply-chain framework where agents' attitudes towards cryptocurrency drive the decision to adopt a blockchain technology. Chen et al. (2025) explore how financing constraints along with blockchain costs jointly affect blockchain strategy decisions. Our paper contributes to this growing literature by identifying investor sentiment as an operationally relevant decision variable, which affects thresholds for ESG-aligned blockchain adoption.

The market-based framework we propose also extends previous work on multi-criteria decision aid (MCDA) approaches for portfolio selection which integrate non-price criteria in investment decisions (e.g., see Aouni et al., 2018). Our portfolio analysis shows that dynamic ESG weighting, which varies with the underlying market conditions, results in

Panel A: Optimal trigger ($S^*(t)$)



Panel B: Histogram of the adoption time (τ*)

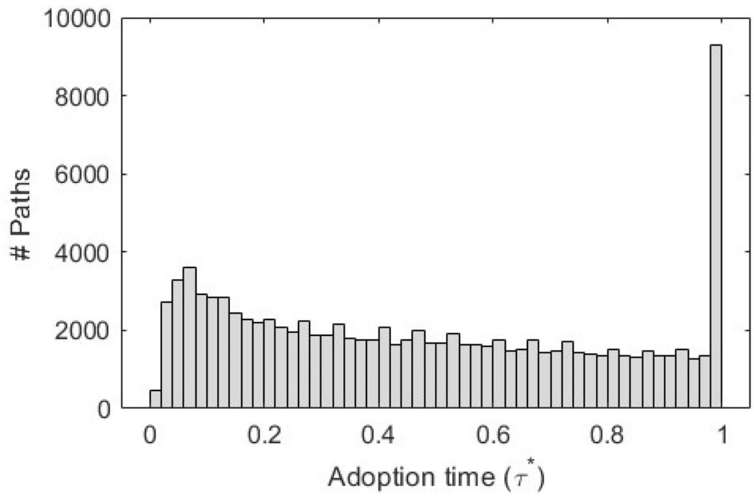


Figure 6. Optimal exercise boundary and distribution of adoption times. Panel A illustrates the option exercise boundary computed using dynamic programming. For each decision date, it shows the exercise trigger $S^*(t)$. This is the minimum sentiment level that will lead to immediate adoption of the technology considered. Panel B shows a histogram of the adoption time τ^*. Using 100,000 simulation paths, it reports the number of paths that adoption takes place within a specific time-window.

strong performance. As such, our work empirically advocates a state-dependent MCDA approach to sustainable investing.

For investors and decision-makers, our framework provides an optimisation tool to support strategic investment in ESG-aligned blockchain technologies. It employs market data and sentiment indices to construct operational decision triggers that inform the timing of adoption. Our analysis suggests that firms engaging in sustainable blockchain initiatives should plan capital raising activities to take place in favourable market conditions, as investors tend to have a more positive stance towards ESG assets then. In times of negative market sentiment, managers should proactively communicate the longer-term value generated by ESG to maintain investor confidence.

Our results also suggest that firms should not only focus on technology that promotes environmental sustainability, as is common in practice. Since governance appears to be the most important element of ESG for investors, firms should also prioritise transparency and accountability when adopting emerging technologies. Finally, from an investor perspective, our analysis advocates multicriteria portfolio strategies that dynamically adjust exposure to ESG-aligned cryptocurrencies, in response to the underlying market sentiment.

6.3. Directions for future research

This study offers several potential pathways for future research. First, future research could apply our framework to explore investor preferences towards ESG-aligned blockchain technologies in longer periods that potentially involve regulatory changes or other factors that affect responsible investing patterns. Second, as ESG-aligned technologies appear to be associated with increased market volatility, further work could focus on developing risk management frameworks that can mitigate risk factors in the adoption of such technologies. Finally, our framework can be transferred to other emerging technologies beyond blockchain if three conditions hold. First, there should exist a tradeable market asset based on which investor preferences can be identified. Second, credible ESG indicators at the technology level are necessary. Third, a measurable and forecastable sentiment proxy that can be used for identifying market states should be available.

Notes

1. For example, Bansal et al. (2022) and Cho (2023) find that investor demand for sustainable assets varies with economic conditions.
2. https://www.weforum.org/stories/2024/01/blockchain-change-world-finance-stablecoins-internet/.
3. See Rani et al. (2024) for a summary of sustainable blockchain applications.
4. Another developing literature investigates the presence of herding behaviour in green cryptocurrency markets in periods of uncertainty (Lobão, 2022; Ren & Lucey, 2022b).
5. https://www.bloomberg.com/company/press/global-esg-assets-predicted-to-hit-40-trillion-by-2030-despite-challenging-environment-forecasts-bloomberg-intelligence/.
6. https://www.morningstar.com/sustainable-investing/us-sustainable-funds-register-first-annual-outflows-2023?campaign_id=4&emc=edit_dk_20240119&instance_id=112927&nl=dealbook
7. While this reduced-form specification of the cost of capital allows us to focus on the effects of market sentiment on blockchain adoption, it is important to acknowledge other factors that may affect financing conditions, such as macroeconomic indicators, interest rates, and regulatory risks. Our framework can be readily extended to incorporate such factors, e.g., by allowing the baseline r_0 to be a function of macroeconomic conditions.
8. We are grateful to Green Crypto Research for offering us access to this dataset.
9. As our sample covers the period from January 2022 to February 2024, it may under-represent newer or delisted projects.
10. While there is significant variation in terms of ESG performance, we observe that our sample is tilted toward more established networks. Indicatively, 26 out of the 28 blockchains we consider were ranked in the Top-100 by market capitalization on 29/02/2024 based on data from Coinmarketcap, which indicates that smaller projects are underrepresented in our sample. To reduce the influence of blockchains associated with very large market capitalisation, we assume equal weights in our portfolio analysis while we also report results for portfolios excluding Bitcoin and Ethereum, which dominate the rest of the networks in terms of market size.
11. Our choice of the CRIX index as a proxy of the overall cryptocurrency market is motivated by its wide market capitalisation coverage and its common use in previous studies for cryptocurrency factor pricing (e.g., see Shah et al. (2021) and Wang & Chong (2021)).
12. We assess the robustness of our findings with respect to the portfolio construction method in two ways. First, we exclude the two most popular blockchains (Bitcoin and Ethereum) which dominate in terms of market capitalisations and tend to have lower levels of volatility. Second, instead of using the median to classify blockchains, we assign those in the top 33% of ESG scores to the *High_ESG* portfolio and those in the bottom 33% in the *Low_ESG* portfolio. Our results for both approaches are qualitatively similar to our main analysis, as shown in Tables A2 and A3 in the Appendix.
13. We note that "HML" here is distinct from the Fama-French HML value factor based on the book-to-market ratio.
14. https://alternative.me/crypto/fear-and-greed-index/.
15. We are grateful to Kaiguang Zhao for making the MATLAB code for the implementation of the BEAST method publicly available at https://uk.mathworks.com/matlabcentral/fileexchange/72515-bayesian-changepoint-detection-time-series-decomposition.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

Data availability statement

ESG data that support the findings of this study are available from Green Crypto Research. Cryptocurrency prices are openly available at CoinMarketCap.com. Data for the Crypto Fear and Greed Index are openly available at Alternative.me.

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Appendix

Table A1. List of Blockchains.This table reports the names and the respective cryptocurrency symbols for the blockchains included in our analysis.

Blockchain	Cryptocurrency Symbol
Cardano	ADA
Algorand	ALGO
Cosmos	ATOM
Avalanche	AVAX
Bitcoin Cash	BCH
Binance Coin	BNB
Bitcoin	BTC
Cronos (crypto.com)	CRO
Dogecoin	DOGE
Polkadot	DOT
EOS.IO	EOS
Ethereum	ETH
Ethereum Classic	ETC
Fantom	FTM
Hedera Hashgraph	HBAR
Huobi Token	HT
Litecoin	LTC
Polygon	MATIC
NEAR Protocol	NEAR
Solana	SOL
Theta Network	THETA
TRON	TRX
VeChain	VET
Stellar Lumens	XLM
Monero	XMR
Ripple	XRP
Tezos	XTZ
Zilliqa	ZIL

Table A2. Results for Portfolios without BTC and ETH.

Panel A: Average returns			
	High_ESG	*Low_ESG*	*HML*
Full sample	0.0100	0.0840	−0.0740
	(0.0200)	(0.1900)	(-0.4229)
Fear Period	−0.8946	−0.4026	−0.4920**
	(-1.0581)	(-0.5102)	(-1.9985)
Neutral Period	0.0269	0.2205	−0.1936
	(0.0401)	(0.3932)	(-0.7252)
Greed Period	2.5723***	1.1811	1.3912***
	(2.4793)	(1.5887)	(2.7040)

Panel B: Market model with greed period indicator			
	High_ESG	*Low_ESG*	*HML*
Excess alpha under extreme greed (α_1)	0.0043*	0.0010	0.0032**
	(1.8547)	(0.5049)	(2.2080)
Excess return (α_0)	−0.0012	−0.0006	−0.0008*
	(-1.5743)	(-0.8172)	(-1.6694)
Market factor (β)	1.0039***	0.9013***	0.1024***
	(42.2285)	(43.7027)	(6.8616)

This table presents results for three cryptocurrency portfolios that do not include BTC and ETH, i.e., one with a high average ESG score (*High_ESG*), one with a low average ESG score (*Low_ESG*) and a portfolio that is long on *High_ESG* and short on *Low_ESG* (*HML*). Panel A reports average annualised returns for each portfolio over the full sample and three subsample periods. These respectively represent positive (greed), neutral, and negative (fear) market sentiments. Panel B shows the estimated coefficients from our first extended market model (Eq. (8)), using the CRIX index as the cryptocurrency market proxy. *t*-statistics are in parentheses. Significance levels are indicated by ***, **, and *, i.e., 1%, 5%, and 10%, respectively.

Table A3. Results for tercile portfolios.

Panel A: Average returns			
	High_ESG	*Low_ESG*	*HML*
Full sample	0.0720	0.1399	−0.0679
	(0.1326)	(0.3022)	(−0.2950)
Fear Period	−0.9667	−0.2781	−0.6886**
	(−1.0266)	(−0.3391)	(−2.0602)
Neutral Period	0.2044	0.3085	−0.1041
	(0.3008)	(0.5067)	(−0.3120)
Greed Period	2.7425***	0.9735	1.7690***
	(2.4146)	(1.2898)	(2.6043)

Panel B: Market model with greed period indicator			
	High_ESG	*Low_ESG*	*HML*
Excess alpha under extreme greed (α_1)	0.0040	0.0004	0.0035*
	(1.5820)	(0.2221)	(1.8269)
Excess return (α_0)	−0.0012	−0.0002	−0.0011*
	(−1.3614)	(−0.3220)	(−1.6931)
Market factor (β)	1.0705***	0.9093***	0.1610***
	(41.3389)	(45.8801)	(8.2080)

This table presents results for three portfolios, i.e., one with cryptocurrencies in the top third of ESG scores (*High_ESG*), one with cryptocurrencies in the bottom third (*Low_ESG*) and a portfolio that is long on *High_ESG* and short on *Low_ESG* (*HML*). Panel A reports average annualised returns for each portfolio over the full sample and three subsample periods. These represent positive (greed), neutral, and negative (fear) market sentiments. Panel B shows the estimated coefficients from our first extended market model (Eq. (8)), using the CRIX index as the cryptocurrency market proxy. *t*-statistics are in parentheses. Significance levels are indicated by ***, **, and *, i.e., 1%, 5%, and 10%, respectively.