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Abstract

There is growing interest in blockchain technologies and the prospects of adopting some form of digital money in the future. Governments and regulators around the world, as well as market participants, are exploring what implications these can have on our financial system. Additionally, there is an ever-increasing pressure by regulators on firms and investors to mitigate any environmental and social externalities which their activities may cause. These two fundamental trends have given rise to, among other assets, so-called "ESG cryptocurrency." These "ESG coins" aim to be more ESG conscious in terms of their overall environmental and societal impact compared to mainstream crypto coins such as bitcoin. In light of these trends, the objectives of this study are threefold. First, to discuss these trends and the motivations for ESG crypto coins. Second, to explore the price behaviors of these coins and, specifically, to examine whether there is herding and feedback trading behaviors which drive their price dynamics. Finally, and given the two aforementioned objectives, to discuss whether these coins are speculative in nature, or, whether there is some merit to these being the future of "green money" in our financial system.

Keywords:
Cryptocurrencies; Environmental, Social and Governance (ESG); Feedback Trading; Herding Behavior; Option-Implied Skewness; Volatility Modeling

"*Today's blockchains may be masterworks of coding, but they are also fiendishly complex, energy-hungry and, perhaps counterintuitively, centralized. Despite years of work, crypto developers are still trying to fully overcome the trade-offs inherent in the technology.*" – The Economist (2022)

1. Introduction

Blockchain technology and cryptocurrencies are now ubiquitous in global financial markets and are a focal topic of conversation amongst not only financial market participants and regulators, but also professionals from a wide range of fields, such as engineering and healthcare (Andolfatto and Martin, 2021; Hargaden et al., 2019; Hasselgren et al., 2020). The future of cryptocurrencies is a hotly debated topic in politics and amongst the general public (Noll, 2023). On one hand, there seems to be a growing acceptance of cryptocurrencies by major regulators, as evidenced by the Securities and Exchange Commission (SEC), approving, on Wednesday 10th January 2024, the first 11 US-listed exchange traded funds (ETFs) to track bitcoin, including products from major financial institutions such as Blackrock (See: Lang and McGee, 2024)[1]. On the other hand, policy makers have recently responded to 'climate action failure' by focusing on the negative environmental impact of traditional cryptocurrencies, and by calling for sweeping new regulations for the cryptocurrency industry, which include mandating that cryptocurrency companies disclose their energy use and emissions – as advocated by United States (US) senator Elizabeth Warren (Warren, 2022).

Against this backdrop, and in recent years, Environmental, Social and Corporate Governance (ESG) investments have garnered intense interest from investors, who may be motivated by moral, ethical or risk and return benefits. Analysis of survey evidence of institutional investors by Krueger et al. (2020) supports the notion that a majority of investors consider that climate risks, particularly those related to regulation, are having material impacts on their portfolios. In terms of investors' motivations, worldwide survey evidence by BNP Paribas (2021) suggests that institutional investors are primarily motivated to engage in ESG because of brand and reputation concerns (59% of survey respondents), the potential for higher long-term returns (45% of survey respondents), and reductions in investment risk (39% of survey respondents).

In terms of growth trends in ESG investing, US sustainable funds witnessed a 35% increase in flows between 2020 and 2021 (Morningstar, 2022a), while in Europe sustainable funds increased by 71% over the same period (Association of the Luxembourg Fund Industry, 2022).[2] Figure 1 shows interest over

[1] Analysts from Standard Chartered predicted during the first week of announcement that demand for these ETFs could attract $50 billion to $100 billion in 2024 alone (Lang and McGee, 2024).
[2] In terms of the worldwide distribution of ESG investment, Morningstar's Global Sustainable Fund Flows report for Q4 2022 (Morningstar, 2022b) suggests that Europe remains the most developed and diverse world region when it comes to sustainable

time using Google Trends™ from January 2004 to March 2023 for the topic "Environmental, Social and Corporate Governance" and the search term "ESG." Currently, web-search popularity and interest in ESG is at the highest level it has ever been. Consistent with this, Figure 2 shows the notable growth in green assets from 2013 to 2021. These include corporate green bonds[3], which are bonds whose proceeds go towards environmentally sustainable and climate-friendly projects, and green loans, which are loans issued to finance environmentally friendly projects. This growth in green assets is especially evident since the SARS-CoV-2 (Covid-19) pandemic began.

[Figure 1 here.]

[Figure 2 here.]

Within ESG investing, much recent focus is on the effects of climate change, and, specifically, on climate-related physical and transition risks. For instance, on the investor side, the Net Zero Asset Managers initiative now has 301 asset managers with $59 trillion assets under management. Becoming a signatory to this initiative represents a commitment to supporting the objective of net zero greenhouse gas emissions by 2050. Moreover, there has also been considerable attention given to climate concerns by regulators and policy makers (Bauer et al., 2023). Examples of recent initiatives and legislative changes include the Sustainable Finance Disclosure Regulation (SFDR) within the European Union (EU), which has been applicable since March 10, 2021 ((Regulation (EU) 2019/2088)). SFDR requires asset managers and financial advisors selling financial products into the EU to explain how sustainability is incorporated into their investments, as well as disclose any adverse impacts their investments choices may have on social and environmental objectives. There are also key international initiatives, such as the Task Force on Climate-related Financial Disclosure (TCFD), which, since its inception in 2017, has set out international guidelines for augmenting the extent and quality of disclosure of climate-related financial information, with the goal of encouraging investments that align with objectives of suitability and net zero emissions. These initiatives are perhaps unsurprising, given that at a country-level estimates by 13 US federal agencies predict that climate change could lead to a reduction of 10% in total economic output in the US by 2100 (Hong et al., 2020).

The attention on the climate is also reflected in recent ESG research. Bolton and Kacperczyk (2021) show that investors in US stock markets price carbon risk, with investors requiring higher returns to compensate for exposure to carbon emissions risk. Ilhan et al. (2021), using data on options markets,

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investments, with 83% ($2,078 billion) of total worldwide sustainable fund assets as of year-end of 2022. By comparison, the United States, in second place, captures 11% ($286 billion) of total assets.

[3] As Flammer (2021) highlights, although corporate green bonds were virtually non-existent in 2013, between 2013 and 2018, 11,189 bonds from 400 unique public and private firms were issued. The green bond market has grown further since. Data from the Climate Bonds Initiative complied by S&P Global (2023) reveals that the value of green bonds issued globally in billions of US dollars between 2017 and 2022 has more than tripled since 2018.

demonstrate that the cost of protection from downside tail risks is higher for more carbon-intensive firms, and that this effect is intensified during periods in which the public's attention to climate change is exacerbated. Zhang (2023) presents evidence of recent shifts in investor preferences around climate concerns in many countries, which can lead to stronger green returns in those countries, as well as a decline in the performance of carbon-intensive firms in the US. Seemingly consistent with the findings of Ilhan et al. (2021) and Zhang (2023), both Pástor et al. (2022) and Ardia et al. (2022) find that green assets have delivered strong returns in recent years, which they attribute to increased attention towards climate concerns.

Given the momentum in ESG-related regulatory policies, the acute market attention on ESG-related issues, and the surge of financial products and markets centered on ESG, we now, and for the first time, see discussions and innovations pertaining to ESG spilling over into the world of cryptocurrencies. Specifically, there have been calls by government authorities around the world to regulate energy-intensive cryptocurrencies, like bitcoin, given the harm they are purported to have on the environment (Truby, 2018). According to Walker (2021, p. 2), "*...cryptocurrencies and ESG principles are far from compatible and any mainstream fund manager or pension fund seeking to place a portion of their portfolio in crypto risks severely undermining their ESG credentials...*" This view may no longer be the norm, especially since the emergence of novel cryptocurrencies which aim to be more "ESG compliant," whether in terms of their environmental externalities, or their governance structures.

Motivated by these recent trends, this study aims to achieve the following three objectives. First, to discuss more rigorously the emergence of ESG crypto coins. Section 2 focuses on this objective and critically discusses the ESG crypto coins, their consensus algorithms, their environmental impacts, their ESG scores, and the literature on herding behavior with regards to cryptocurrency markets. The crypto coins discussed in Section 2 are also the coins that are eventually used in our study sample and are, in turn, discussed more in Section 3.

Second, our study explores the price behaviors of our sampled ESG coins and, specifically, examines whether there is herding and feedback trading behaviors which drive their price dynamics. Motivated by the asset pricing frameworks of Shiller (1984) and Sentana and Wadhwani (1992), as well as the findings of King and Koutmos (2021), among others, we build and implement a feedback trading model to test whether there are herding behaviors present in ESG coins. Our model allows us to assess the direction of such behaviors in order to see whether investors and traders are engaging in 'trend chasing' behaviors, or, whether they are exhibiting 'contrarian' behaviors in their trading patterns. Trend chasing behaviors consist of buying (selling) when there is a crypto coin price increase (decrease) on the prior trading day. Likewise, contrarian trading consists of buying (selling) when there is a crypto coin price decrease (increase) on the prior trading day. As discussed further in Section 4, our framework also integrates bitcoin's option-implied skewness as a measure of investors' forward-looking expectations of crash risk in cryptocurrency markets on aggregate. By doing so, we then gauge whether feedback trading patterns shift or are amplified in the presence of bitcoin crash risk expectations. From a risk management perspective, there is a large body of literature that shows the usefulness of option-implied information, such as skewness, in forecasting returns and investor behaviors in underlying assets (Christoffersen et al., 2013). It is thus beneficial to see whether bitcoin's crash expectations shift feedback trading patterns in our sampled ESG coins, especially given recent literature that models bitcoin's (informational) dominance in the crypto universe (Koutmos, 2018; Wang and Ngene, 2020). Section 4 thus builds and discusses the feedback trading model that we use to ascertain whether herding behaviors drive the prices of ESG crypto coins, and the direction of this price movement.

Finally, and consistent with our study's third objective, we discuss in Section 5 whether these so-called ESG crypto coins can become a viable form of 'green money' in the future. We show in our analysis the pitfalls of these crypto coins and how, similarly with what is found with traditional asset classes, their prices can also be impacted by herding behaviors. Such speculative pressures are of particular concern, given that these are relatively new assets that can experience bubble-like behaviors in the future. There is already a growing body of literature that shows similar budding digital markets, such as those for non-fungible tokens (NFTs) and decentralized finance (DeFi), are riddled with prices bubbles that are highly correlated with market hype and speculative behaviors (Wang et al., 2022).

Finally, Section 6 concludes our study and provides a roadmap for future research into these ESG crypto coins. It furthermore reiterates some of the concerns raised by policymakers regarding the ESG performance of cryptocurrencies and specifically their negative impacts on the environment, as well as wider concerns regarding social and governance aspects.

2. Motivating Evidence

2.1. The rise of ESG coins and the future of green money

Climate change is often cited by government authorities as a chief threat to the environment and to public health (Cifuentes-Faura, 2022). Given the purported relation between manmade carbon emissions, resulting from economic activity and energy consumption, and the climate, policymakers have been keen to regulate energy-intensive crypto assets such as bitcoin. For example, the White House (2022) estimates that crypto assets contribute up to 0.8% of total greenhouse gas emissions in the US, and asserts that:

> "*...crypto-assets can require considerable amounts of electricity usage, which can result in greenhouse gas emissions, as well as additional pollution, noise, and other local impacts to*

communities living near mining facilities. Depending on the energy intensity of the technology and the sources of electricity used, the rapid growth of crypto-assets could potentially hinder broader efforts to achieve…climate commitments to reach net-zero carbon pollution..."

Similarly, the European Central Bank (ECB) is highly critical of the "outsized carbon footprint" of some crypto assets, which it emphasizes have comparable energy consumption to countries such as Spain, Austria and the Netherlands, as well as the Three Gorges Dam in China (European Central Bank, 2022).

Much of the criticism surrounding crypto assets[4], and cryptocurrency markets at large, specifically, has been levied at bitcoin which employs the proof-of-work (PoW) consensus algorithm and because of the sizeable amount of energy the bitcoin network requires to verify transactions. Although precise estimates of energy consumption and environmental footprints for cryptocurrencies are difficult to quantify, it has been estimated that bitcoin requires 707 kilowatt-hours of power per transaction (Forbes Advisor, 2022). De Vries et al. (2022) estimate that as of 2021 the carbon footprint of bitcoin was equivalent to 65.4 megatons of CO_2 (MtCO2) per annum – a figure comparable to that of Greece. Under bitcoin's PoW algorithm, while multiple miners compete to solve a cryptographic puzzle and commit energy resources in the process, only one miner can be the first to verify a transaction and receive a bitcoin reward in the process. Comparable criticism has also been given to the second largest cryptocurrency (in terms of total market capitalization), ethereum, which utilized the same PoW consensus algorithm up until its high-profile switch to Proof-of-Stake (PoS) in September 2022, and had an energy consumption in kilowatt-hours 11 times lower than bitcoin (prior to its switch to PoS) (Forbes Advisor, 2022). From an environmental footprint perspective, ethereum's switch to PoS from PoW is important because PoS is known to be far more energy efficient than PoW, with ethereum now estimated to be 99.988% more energy efficient and have a 99.992% lower carbon footprint than before under PoW (Crypto Carbon Ratings Institute, 2022).

This discussion raises important questions about the sustainability of such crypto assets and whether there should be an efficient method to reduce their energy consumption, or, to mitigate their harmful social impacts in an effort to make them more "climate and society friendly" (de Vries, 2018). Concurrently, such concerns have inspired the rapid emergence of so-called "ESG coins," which is the subject of our study. These novel ESG crypto coins employ next-generation consensus algorithms with

[4] There are also many high-profile failures of cryptocurrency exchanges and hedge funds themselves, such as the November 2022 failure of FTX Trading Ltd (FTX), which is surrounded by allegations of fraud including against founder Sam Bankman-Fried. Although the initial response to the FTX exchange crash was a flight away from cryptocurrencies in general to safe havens such as gold and silver commodities (Yousaf et al., 2023), cryptocurrencies have proved highly resilient and have now more than fully recovered from this shock. To take bitcoin as an example, by January 18th, 2023, it had regained the value it held prior to the FTX exchange crash with market commentators speculating that declining yields on government securities would lead investors towards riskier assets including cryptocurrencies (see for example: Alpher, 2023). Most recently, by January 18th, 2024, the total market capitalization of cryptocurrencies had more than doubled from a figure of $740 billion USD in November 2022 to $1.6 trillion USD in January 2024 (Glover, 2024).

low environmental footprints and have well-stated visions to contribute positively to society. These include addressing important social-environmental issues, such as protecting valuable and at-risk ecosystems, climate change mitigation, and helping drive financial inclusion. Moreover, they are characterized by having stronger transparent governance structures and significantly lower environmental footprints.

The emergence of ESG coins represents a significant step towards a more sustainable future within the cryptocurrency sector and signals a growing recognition of the importance of green alternatives within the industry. From the perspective of meeting climate and sustainability targets they can help to transform the cryptocurrency industry in the medium- to long-term while immediately demonstrating that sustainability can be achieved within the cryptocurrency sector. This is underlined by the emergence of key initiatives such as the 'Crypto Climate Accord', which, inspired by the Pairs Climate Accord, seeks to "*...accelerate the development of digital #ProofOfGreen solutions and set a new standard for other industries to follow...*", with an objective of blockchains being 100% renewably powered by 2030 (Crypto Climate Accord, 2024 p.1). By utilizing ESG coins, and more generally green cryptocurrencies, individuals can potentially reduce their carbon footprint and contribute to lowering overall emissions, without sacrificing potential investment opportunities. This inherent eco-friendliness thus may align with climate change objectives and policies, and promote the development of a more sustainable financial infrastructure (Xiao et al., 2024).

Although, owing to their rapid emergence and a lack of available data, there is a paucity of existing evidence on ESG coins, the recent literature on green cryptocurrencies is informative as to the potential benefits of environmentally friendly cryptocurrencies from the perspective of the environment as well as for investors. Recent research stresses the important role that green cryptocurrencies should pay in the transition to a more sustainable and environmentally friendly future (e.g., Xiao et al., 2024). Moreover, this literature demonstrates that environmental cryptocurrencies may contain safe haven properties during adverse conditions (Ren and Lucey, 2022), exhibit weak correlations with conventional cryptocurrencies (Pham et al., 2022) and stable tail risk across time, as well as possessing key diversification benefits in optimal portfolios (Naeem et al., 2023; Ali et al., 2024). Overall, this literature is illustrative of green cryptocurrencies possessing perhaps fundamentally different characteristics compared to environmentally 'harmful' cryptocurrencies (Ren and Lucey, 2022).

With respect to governance issues our ESG coins generally perform much better than many traditional cryptocurrencies such as bitcoin. For example, although bitcoin has not, to date, been plagued by any major security or privacy issues, or faces any major legal or regulatory challenges the blockchain is controlled by a small number of mining pools (Kondor et al., 2014). Thus, instead of being decentralized the market is highly centralized (Kondor et al., 2014). Such issues are important as they undermine some of the main benefits that decentralized governance and data-infrastructure in blockchains can bring (Halaburda, 2018), which include mitigating expropriation and privacy risks, censorship, lock-in effects and the extent of bargaining power from the platform sponsor (Catalini and Gans, 2019).

The Executive Order by President Biden on March 9, 2022, titled "Ensuring Responsible Development of Digital Assets," has raised questions about what form money will take in the near future (Exec. Order No. 14067). Moreover, uncertainty regarding the future of money has inspired a small recent interdisciplinary literature that speculates on the future use of cryptocurrencies and digital currency as 'green money' (e.g., Siqueira et al., 2020; King et al., 2021; Larue et al., 2022).

When synthesizing the existing literature, it is important to articulate that although the terms 'cryptocurrency' and 'digital currency' have been used somewhat interchangeably (e.g., Velde, 2013), 'digital currency' is now generally accepted to mean a digital form of existing fiat currency issued by central banks[5]. Commonly, this means Central bank digital currency (CBDC), which many countries and country blocks have been actively researching in recent years. Two examples are the European Central Bank, who has both put forward detailed plans for the introduction of a digital Euro (see: European Central Bank, 2023), and the G7 group of countries (see: G7 United Kingdom, 2021). CBDC can be defined as "*...a digital asset that only the central bank may issue or destroy, that is traded at par against banknotes and reserves, that is available 24/7, that may be used in peer-to-peer transactions and that circulates on digital media that are at least partially different from existing media..."* (Banque de France, 2022).

An important similarity between 'digital currency' and 'cryptocurrency' is in the use of the underlying blockchain technology. However, there are some major differences. Unlike CBDC, cryptocurrencies are not centrally administered by central banks or governments and are instead decentralised. Consequently, they do not benefit from state or central bank protection, thus undermining their potential use as fiat (Velde, 2013; Yermack, 2015; Gandal et al., 2018; King and Koutmos, 2021). In other words, they differ from CBDCs in that no trust needs to be placed in a traditional centralized authority (King et al., 2021). Furthermore, although CBDC currencies, as digital forms of existing fiat, generally embody the main characteristics that money is widely thought to need to possess, including common acceptance as a means of payment and exchange, a unit of account, and a store of value, cryptocurrencies do not share these properties (Yermack, 2015; King et al., 2021). For example, cryptocurrencies are notoriously volatile and generally perform very poorly as stores of value (Yermack, 2015). These sentiments are also largely shared by policy makers. For instance, a recent Joint Statement on cryptocurrencies by, collectively, the Federal Reserve, the Federal Deposit Insurance Corporation (FDIC), and the Office of the Comptroller of the Currency (OCC), raises awareness on a variety of key

[5] We thank an anonymous reviewer for making this point.

issues such as the significant volatility of crypto assets and their possible contagion risks with the rest of the financial system (Federal Reserve et al., 2023).

When making predictions regarding the future, it is difficult to separate the hyperbole surrounding cryptocurrencies from the realistic likelihood they will be adopted as alternative fiat currencies. Based on the previous discussion, what would seem a more likely scenario is that the increased adoption of ESG coins will accelerate the progress of the crypto sector towards greener blockchains. While we anticipate that this could increase demand for cryptocurrencies generally as investable assets and perhaps alternative forms of payments, it is difficult to predict that they could displace traditional forms of fiat. Instead, it would seem more likely that the positive influence that ESG coins will have on reducing the environmental impact of the crypto industry through improvements to the sustainability of blockchains will instead accelerate the diffusion of CBDC. If in the future specific ESG coins become more widely accepted, they may begin to present potential competition to CBDCs as alternative form of 'money'. However, even given this, it is worth considering the "choice in currency" framework of Hayek (1976), according to which individuals would be expected to naturally choose between currency alternatives based on their ability to function as fiat as well as their ability to guarantee a sustainable future.

Given these observations, we argue that CBDC appears to have a relatively clearer path towards becoming a greener form of future money. Although the environmental impact of CBDC depends on the way it is implemented, including the underlying blockchain technology, policy makers are keen to embed sustainability principles into CBDC designs. For example, the G7 group of countries has established the principle that "*...the energy usage of any CBDC infrastructure should be as efficient as possible to support the international community's shared commitments to transition to a 'net zero'..."* (G7 United Kingdom, 2021, p.11), and argues "*...that energy usage should be factored into the design and implementation of any CBDC from the outset...*" (p. 12). Moreover, as a further area of development, the idea of specific green central bank digital currencies (CBDC) has been mooted by policy makers such as the United States Congress Committee on Financial Services (US House of Representatives, 2021) although it is not clear how these will unfold.

Two crucial issues that must we must address prior to any empirical implementation of our feedback trading model are how to identify ESG coins and how do we differentiate them based on their ESG performance. In the limited related literature on green cryptocurrencies (Ali et al., 2024), existing studies have attempted to circumvent this issue by focusing on comparing 'more' to 'less' energy efficiency cryptocurrencies based on their estimated energy consumptions (e.g., Gallersdörfer et al., 2020; Ren and Lucey, 2022). In our study, we address this issue by exploiting the recent availability of ESG ratings data for cryptocurrencies from 'Green Crypto Research', which is "*...the world's 1st ESG rating* *for cryptos...*" and aims to "*...support professional investors in evaluating the relative environmental, social, and governance risks of crypto assets...*" in a comparable way to traditional investable assets such as equities, real estate, and bonds (Green Crypto Research, 2024, p.1). In doing so, we are also able to go beyond the confines of these recent studies, to consider not just the 'green performance' of cryptocurrencies, but also their wider ESG performance, which therefore allows us to go beyond pure energy use considerations.

ESG coins include well-known coins, such as XRP and Cardano, as well as newer and lesser-known coins, such as Bitcoin Green (BITG). To begin discussion of ESG coins, and to also introduce the sampled coins used in this study, which we discuss in greater depth in Section 3, we present our ten sampled ESG coins in Table 1. This table shows each of the sampled coins' overall ESG rating, as well as a rating for each of the ESG pillars (Environment, Social and Governance, respectively). As mentioned, the ratings are provided by the firm Green Crypto Research (greencryptoresearch.com), which, first, assigns ratings independently to each of the three pillars on a rising scale from D to A+ and afterwards computes a composite ESG rating that is based on the average across the three ESG pillars. The "Environment" pillar score is based on (i) energy consumption, (ii) pollution and waste, and (iii) aspiration to achieve net zero. The "Social" pillar score is based on (i) social impact, (ii) asset distribution, and (iii) entry and usage barriers. Finally, the "Governance" pillar score is based on (i) network diversification, (ii) network security and incidents, (iii) governance issues.

As shown in Table 1, Solana, Cardano, Avalanche, and Tezos, respectively, are rated as 'A' for their overall ESG rating. Ripple has the lowest overall ESG rating of 'C,' while the remainder of the coins (Polkadot, Tron, EOS, and Alogorand, respectively) earned an overall rating of 'B.' Of all the coins, Tezos is the only ESG coin in our sample to receive an 'A+' on the social pillar, whereby social performance is captured by how evenly-distributed assets are, how low transaction fees are, and the strength of the social vision of its underlying blockchain.

[Table 1 here.]

Figure 3 and Table 2 summarize the environmental impact of each of the sampled ESG coins in terms of CO_2 emissions, electronic waste, power consumption per transaction, and overall power consumption, respectively. In Figure 3, bitcoin, the most well-known cryptocurrency in circulation (and largest in terms of market capitalization) is also shown for the sake of comparison. As can be seen, bitcoin exhibits the largest negative impact on the environment relative to the ESG coins.

[Figure 3 here.]

[Table 2 here.]

While Table 2 summarizes the consensus algorithms of each of the respective sampled ESG coins, Table 3 provides a more in-depth discussion of each of the coins' consensus algorithms and what implications they may have on each of the three pillars of ESG. As can be seen from Table 3, the majority of our sampled coins utilize some form of the proof-of-stake (PoS) consensus algorithm, which is viewed as an environmentally safer alternative to, say, proof-of-work (PoW). For example, bitcoin green, a climate-investment blockchain platform that utilizes PoS, is focused around providing incentives that reward users for taking personal actions that reduce their carbon footprint, as well as providing a platform that make it easy to originate and trade transparent carbon credits.

[Table 3 here.]

2.2. Price behaviors of ESG crypto coins

Despite their seemingly good intentions, ESG coins may not be stable assets for investors or the general public, especially if their market and price dynamics are prone to herding and feedback trading behaviors. Such herding and feedback trading behaviors are the focal point of our study. Herding, whether applied to ESG investments or other asset classes, describes the behavior of a group of investors who may trade in one direction for a period of time, characterized by the tendency for some informed investors to mimic the behavior of others even if it is contrary to their own beliefs. As King and Koutmos (2021, p.79) argue: "...herding and feedback trading behaviors are important to identify and quantify...because they have the potential to instigate a plethora of phenomena, such as excess volatility, momentum and reversals..."

Recent literature explores price behaviors in ESG assets, including price anomalies and herding. For example, Ciciretti Dalò and Ferri (2021) examine whether ESG funds engage in herding or anti-herding behavior. They find that they engage in an anti-herding strategy, which results in higher risk-adjusted returns, and, surprisingly, that the higher risk-adjusted performance is associated with lower systematic risk exposure. Gavrilakis and Floros (2023) focus on herding behavior and returns in the equity markets of six European countries. They observe evidence of herding behavior in three countries (Portugal, Italy and Greece) during the Covid-19 pandemic, and in Greece and France over their full sample period of 2010 to 2020. Thus, they conclude that herding is more present during adverse market conditions when there is more trading volume and volatility, which corresponds with market inefficiency and asset mispricing. Similarly, Rubbaniy et al. (2021) find evidence of herding behavior for constituents of the MSCI USA ESG leader index between 2007 and 2020, irrespective of market conditions. As the authors argue, such herding behaviors in ESG investments are problematic as they can lead to mispricing of assets, with negative implications for market inefficiency and portfolio diversification. Finally, a recent stream of research provides evidence that air pollution can intensify cognitive biases amongst stock market participants. Specifically, both Huang et al. (2020) and Li et al. (2021) demonstrate that air pollution can exacerbate the disposition effect (a cognitive bias relating to the tendency to sell assets that have appreciated in value while holding onto losers to long) among investors in financial markets.

Also relevant to this discussion is a growing literature that looks at price behaviors within cryptocurrency markets[6]. King and Koutmos (2021) find evidence of both herding and contrarian-type behaviors, contingent on the cryptocurrency market examined, and that these drive price dynamics. A number of studies also show that price behaviors can vary over time and with respect to market conditions (e.g., Bouri et al., 2017; Bouri et al., 2019; King and Koutmos, 2021; Karaa et al., 2021; Ren and Lucey, 2022). For instance, Karaa et al. (2021) find that positive feedback trading is present in the bitcoin market and that the extent of feedback trading is influenced by several noise-related factors. Other studies demonstrate that herding tends to increase in response to uncertainty (e.g., Bouri et al., 2017; Bouri et al., 2019). More recently, Koutmos (2023) examines the sentiment-return relation for bitcoin and finds that both positive and negative sentiment influences bitcoin price changes, while Bonaparte and Bernile (2023) use sentiment data to investigate whether the prospect of the introduction of cryptocurrency regulations impact the price, volatility and trading of seven cryptocurrencies. They find that while it does not impact long-term prices, it does impact volatility and trading volume.

A handful of recent studies examine aspects relevant to the environmental performance of cryptocurrencies. Pham et al. (2022) investigate the tail dependence between carbon prices and seven cryptocurrencies – which they split into green and non-green based on the consensus algorithm used. Analyzing periods of low and high volatility, they find that there are typically low levels of spillovers between cryptocurrencies and carbon prices during periods of low volatility but high spillovers during periods of high volatility, such as during the Covid-19 pandemic. Classifying cryptocurrencies into two groups based on their energy consumption, Ren and Lucey (2022) examine the hedge- and safe-haven property of clean energy indices during periods of extreme volatility in cryptocurrency markets. They present evidence consistent with the idea that clean energy stocks can act as safe havens during such periods – especially for high energy consumption cryptocurrencies but are not effective direct hedges. Finally, and closest to our study, several papers look at herding behavior between high and lower energy consumption cryptocurrencies. Ren and Lucey (2022) find that herding is common amongst less environmentally friendly cryptocurrencies but not present in environmentally friendly cryptocurrency markets. Ren and Lucey (2022) present evidence that more energy efficient cryptocurrencies herd with high energy consumption cryptocurrencies during positive economic conditions, but that herding is only evident amongst high energy consumption cryptocurrencies. Finally, Sharif et al. (2023) examine

[6] Importantly, while it may be imagined that a considerable volume of trading activity in cryptocurrency markets may be algorithmic, an analysis of bitcoin market microstructure by Dyhrberg et al. (2018) supports the notion that a majority of bitcoin trades conducted are in fact executed by retail investors and are non-algorithmic, which increases the scope for cognitive biases amongst market participants to drive price dynamics.

correlations and spillovers amongst five cryptocurrencies, that they define as “dirty,” based on their use of the PoW consensus algorithm (bitcoin, ethereum, bitcoin cash, ethereum classic, and litecoin), and five they define as “green” (cardano, ripple, iota, stellar, and nano), with green economy indices. They show that total connectedness is highest between green economy indices and clean cryptocurrencies.

The above findings have implications for our understanding of price behaviors in cryptocurrency markets – and specifically for ESG coins. Notably, there is reason to conjecture that the extent to which herding behaviors are presents in ESG cryptocurrencies may first depend on both well-known behavioral biases, which, as discussed, have been observed broadly for major cryptocurrencies (e.g., King and Koutmos, 2021), as well as the specific motivations of investors, which may be different based on preferences for ESG. For example, worldwide survey evidence of institutional investors by BNP Paribas (2021) reveals that 80% of investors who hold ESG-focused investments hold crypto investments, compared to only 22% who do not hold ESG themed assets. Yet 96% of the 80% of investors who hold both ESG investments and crypto asset considered it important or very important that major cryptocurrencies reduce their environmental footprint.

3. Sample data

Given the focus on ESG investing, and especially ESG-inspired crypto assets, we examine whether herding and feedback trading behaviors are present in such markets. This is important since, as discussed, herding and feedback behaviors can result in excess volatility and price bubbles. Our ten sampled ESG crypto coins are, respectively, Polkadot (DOT), Solana (SOL), Cardano (ADA), Ripple (XRP), Avalanche (AVAX), Tron (TRX), EOS (EOS), Algorand (ALGO), Tezos (XTZ), and Bitcoin Green (BITG). While these ESG coins were introduced in Table 1, along with their respective ESG ratings, Table 4 shows their intraday trading summary statistics for their respective sample ranges (lowest price, highest price, average price, average volume, and average market capitalization).[7] Of all the ESG coins, DOT, SOL and ADA have market capitalizations in excess of 15 billion USD. Altogether, the ten ESG coins in our sample have a combined market capitalization in excess of 81 billion USD. It is important to note that while Table 4 ranks these coins based on the size of their average market capitalization, the sample ranges for each coin differ depending on their inception dates (as shown in the third column of the table). For

[7] The data are sourced from *https://coinmarketcap.com* and consist of daily closing prices for the ten sampled ESG coins. Since these coins trade in several exchanges around the world simultaneously, an obvious challenge is selecting exchanges that are liquid, safe, and most representative of the aggregate market. The advantage to using data from *CoinMarketCap* for empirical testing is that its price data are calculated as the volume-weighted average of all prices reported across the various exchange markets. This gives an average price that, arguably, may be most representative of the aggregate market (Koutmos and Payne, 2021). Unlike traditional assets which trade only on weekdays, cryptocurrencies trade all seven days of the week.

example, AVAX, DOT, and SOL, respectively, have the shortest sample ranges relative to the remaining coins.

[Table 4 here.]

All the ESG coins show a wide degree of variance in their price behaviors. For example, EOS, which has the largest average trade volume of all the sampled coins, experienced a minimum price of \$0.48 and a maximum price of \$22.89. Figure 4 shows time series plots of the price and trade volumes of each of the sampled ESG coins. All the sampled coins showed relatively high volatility during the height of the Covid-19 pandemic, with some coins losing over 50% of their value within a short period of time before experiencing sharp price reversions.

[Figure 4 here.]

From Figure 4 we can see a high degree of price volatility for all our ten sampled ESG coins. This type of volatility risk is not typically found in traditional asset classes, such as equities and bonds. Yet, such volatility may also be alluring for investors and speculators alike. Table 5 shows summary statistics of the unconditional four moments of each of the coins' returns, computed as the logarithmic first-differences of their respective closing prices, P: $100 * \ln{(P_t/P_{t-1})}$. The mean returns, in absolute terms, tend to be higher than what is typically observed for traditional asset classes.[8] For example, the highest mean return is 0.3596 (SOL) while the lowest is -0.3132 (BITG). Of all the sampled coins, the mean return of DOT is closest to zero (-0.0042). All the sampled coins are highly leptokurtic, suggesting they have thicker tails and, consequently, higher tail risks when compared to normally distributed return series. Of all the coins, DOT, SOL, EOS, ALGO, and XTZ, respectively, are negatively skewed. The Sharpe ratio is estimated for each of the sampled ESG coins' return series, R, as $(R_t - r_f)/\sigma$ whereby r_f denotes the risk-free rate.[9] The denominator for the Sharpe ratio is the unconditional standard deviation of the respective coins' returns, σ. The value-at-risk (VaR) for the coins' returns is estimated as follows: $\text{VaR} = W\left(\mu\Delta t - n\sigma\sqrt{\Delta t}\right)$ whereby μ is the mean return; W is the value of the portfolio invested; n is the number of standard deviations depending on the confidence level; σ is the standard deviation of returns; Δt is the time window (Signer and Favre, 2002).

[Table 5 here.]

While not directly comparable given the sampled coins' differing sample ranges, it appears BITG, SOL, AVAX, TRX, EOS, ADA, ALGO, XRP, DOT, and XTZ (in that order) are the riskiest of the coins

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[8] All the sampled ESG coins' return series are stationary and do not contain a unit root (unit root test results not tabulated for brevity but available upon request). This permits for empirical implementation of the herding and feedback regression analysis that is described in Section 4.

[9] See *http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html* for data on the risk-free rate, r_f. We use moving-average approaches to extrapolate weekend data (to correspond with our sampled coins' trading dates, which are 7 days a week), in order to estimate the Sharpe and modified Sharpe ratios in Table 5.

given their VaR estimates, while SOL, TRX, ADA, AVAX, XRP, DOT, XTZ, EOS, ALGO, and BITG (in that order) have the highest Sharpe ratios. However, considering the pronounced higher moment risks (skewness and kurtosis risks) these coins exhibit in their return distributions, it is possible our VaR and Sharpe measures downplay their risks.

Given the non-Gaussian nature of our sampled coins' price changes, it is important to integrate higher moment risks beyond only the first two moments. As Signer and Favre (2002) demonstrate, VaR model estimations that overlook higher moment risks, such as excess kurtosis ("fat tails"), may provide an incomplete picture of the downside risks of the underlying asset in question. From an asset pricing perspective, and from the view of a risk-averse investor, fat tails in an asset's return distribution is undesirable since this implies a relatively higher probability of extreme (negative) returns. In order to incorporate such higher moment risks, Table 5 also shows each sampled coins' modified VaR (MVaR) and modified Sharpe ratio, respectively (Gregoriou and Gueyie, 2003). The MVaR can be expressed as follows (using some of the same notation as the VaR discussed earlier):

$$\text{MVaR} = W\left[\mu - \{z_c + \frac{1}{6}(z_c^2 - 1)S + \frac{1}{24}(z_c^3 - 3z_c)K - \frac{1}{36}(2z_c^3 - 5z_c)S^2\}\sigma\right] \quad (1)$$

whereby W is the value of the portfolio invested in the sampled cryptocurrency; z_c is the critical value for the probability $(1-\alpha)$ and is -1.96 for a 95% probability; μ is the mean return; σ is the standard deviation of returns; S is skewness in returns; K is excess kurtosis in returns. The physical skewness and kurtosis of the coins' returns are estimated as follows:

$$S = \frac{1}{T}\sum_{t=1}^{T}\left(\frac{R_t - \bar{R}}{\sigma}\right)^3 \quad (2)$$

$$K = \frac{1}{T}\sum_{t=1}^{T}\left(\frac{R_t - \bar{R}}{\sigma}\right)^4 - 3 \quad (3)$$

After computing the coins' MVaR, we can proceed to estimate their respective modified Sharpe ratios:

$$\text{Modified Sharpe Ratio} = (R_{\text{t}} - r_{\text{f}})/\text{MVaR} \quad (4)$$

From Table 5, and for every one of the sampled coins, we see that MVaR estimates are higher than VaR estimates. BITG, followed by XRP, ALGO, XTZ, SOL, EOS, DOT, TRX, AVAX, and ADA (in that order) showed the most pronounced differences. Inspection of the modified Sharpe ratios shows that, of all the coins, SOL, TRX, ADA, AVAX, and XRP (in that order) provide the most favorable reward-to-risk profile for investors (given their respective sample ranges). In particular, and for these five specific coins, their modified Sharpe ratio estimates are lower than that of their Sharpe ratio estimates. This is to be expected since their MVaR estimates, which serves as the denominator in the modified Sharpe ratio shown in equation (4), is higher than their respective VaR estimates. A key message from this analysis is that although cryptocurrencies, such as our sampled ESG coins, may show periods of unsurpassed growth, they pose large downside (tail) risks for investors. This message is also consistent with the findings of Fry (2018), who documents heavy tails in cryptocurrency markets.

The question thus becomes, given these ESG coins' large downside risks and price volatilities, whether herding and feedback behaviors are present in such markets and, if so, what impact do they exert on their respective price dynamics? The next section proceeds in building our analytical framework that is used to explore this question.

4. Analytical framework

In order to begin exploring the question of whether herding and feedback traders are present in ESG coin markets we develop an empirical framework based on the models of Merton (1980), Shiller (1984) and Sentana and Wadhwani (1992). Sub-section 4.1., first, builds a base model, as in Sentana and Wadhwani (1992), to identify whether feedback traders are present in ESG coin markets, and, second, extends this model to entertain the possibility that such feedback trading can shift depending on the sign of past ESG coin returns. Sub-section 4.2. further develops our feedback trading model to accommodate for the possibility that investors' forward-looking expectations of aggregate cryptocurrency market crash risk can further drive, or, alter, feedback trading behaviors in ESG coin markets. We utilize a measure for bitcoin's option-implied skewness for this purpose. From a risk management perspective, option-implied skewness can help capture and forecast investors' forward-looking crash risk expectations (Christoffersen et al., 2013). In addition, and given that derivatives markets for most cryptocurrencies in circulation (such as our sampled ESG coins) have yet to be developed, bitcoin remains the (informationally) dominant cryptocurrency within the crypto universe. As shown by others, what happens in bitcoin markets can quickly spillover into other cryptocurrencies (Koutmos, 2018; Wang and Ngene, 2020).

4.1. Model Setup

Building on Sentana and Wadhwani (1992), our framework assumes the trading activity of two types of heterogeneous investors; the first type are mean-variance (MV) optimizers who trade in order to maximize their expected mean-variance utility. Their decisions are conditional upon the means and variances of returns across time and their demand function for a given ESG coin can be described empirically as follows:

$$MV_t = \left[E_{t-1}(R_t) - r_f\right] / (\theta * Var(R_t))\,;\ \theta > 0\ or\ \theta < 0 \tag{5}$$

where MV_t is the fraction of a given ESG coin, which mean-variance optimizers hold at time t. $E_{t-1}(R_t)$ is the expected return conditional on information available as of $t-1$ while, and as discussed in footnote

(7), r_f denotes the risk-free rate. Relative risk aversion can be ascertained by the coefficient θ. Consistent with theoretical asset pricing, it should be positive in sign and statistically significant. The conditional variance of the coins' returns at time t is denoted by $Var(R_t)$. From an asset pricing perspective, θ reflects the nature of the risk-return tradeoff and, theoretically, should be positive if investors are rational mean-variance maximizers. We have no a priori expectation to believe that there is a positive risk-return tradeoff for our sampled ESG coins, however, and if we assume the coefficient θ is positive, the product of $\theta * Var(R_t)$ reflects the risk premium at time t. Thus, the demand for ESG coins by such mean-variance maximizers is driven by the degree of volatility risk, $Var(R_t)$, whereby their demand rises when their expected returns, $E_{t-1}(R_t) - r_f$, also rise.

The second group of traders exhibit feedback, or herding-type of behaviors ($Herd$). Such traders engage in 'trend chasing,' or, 'momentum' behaviors, and their demand for ESG coins depends on lag returns, R_{t-1}, and can be described as follows:

$$Herd_t = \rho\left(R_{t-1} - r_f\right);\ \rho > 0\ or\ \rho < 0 \tag{6}$$

where $Herd_t$ is the fraction of coins they hold at time t. The fact that their demand function is conditional solely upon lagged returns is not necessarily over-simplistic. This is because there is a plethora of investment websites that utilize momentum tactics (based on past prices) to provide buy and sell recommendations for cryptocurrency traders.[10] Theses websites may contribute to amplify herding and feedback trading behaviors at any given time. Hudson and Urquhart (2021) illustrate how technical trading strategies, many of which are actively used in equity markets and which use past prices in order to predict where prices are going in the future, can be successfully used in cryptocurrency markets.

Thus, equation (6) posits that herding and feedback traders execute trade decisions on the basis of lag returns, R_{t-1}. The coefficient ρ is essential in telling us the direction of such herding behavior. For example, if the coefficient ρ is positive, it indicates that herders are following positive feedback, or trend chasing and momentum strategies by buying when there are recent price increases and selling when there are recent price decreases. Such behavior may be irrational, especially if investors are trying to mimic one another, or, it may be rationally explainable since it can result in the triggering of electronic stop-loss orders. It may also be the result of distress selling following significant price declines and investors' unwillingness to accept heightened price volatility. Regardless of the reason, it is a form of herding that can produce bubble-like behaviors in asset prices, or sway prices in a direction that is unrelated to fundamental value. Conversely, if ρ is negative, it shows that investors are buying when there are recent

[10] An example of such a website is *https://www.tradingview.com/symbols/DOTUSD/technicals/* for Polkadot (DOT). This website makes recommendations based on, among other momentum indicators, moving average techniques. Such websites also encourage investors to share, or, post their trade positions and to chat with other investors. Despite having some educational value and their good intentions, these websites can also encourage herding and feedback behaviors, whereby investors begin mimicking one another.

price decreases and selling when there are recent price increases. A negative sign for ρ can reflect contrarian-like behaviors or "buy low and sell high" type of strategies.

Given equations (5) and (6), in equilibrium, and at any time for a given ESG coin, it is required that all available coins are held by these two heterogeneous groups:

$$MV_t + Herd_t = 1 \tag{7}$$

If we proceed to substitute equations (5) and (6), respectively, into equation (7), we have the following:

$$\left[E_{t-1}(R_t) - r_f\right]/(\theta * Var(R_t)) + \rho\left(R_{t-1} - r_f\right) = 1 \tag{8}$$

Equation (8) can be recast as a regression equation with a stochastic residual term if we set $r_t = R_{t-1} - r_f$ and $r_t + \varepsilon_t = E_{t-1}(R_t) - r_f$. When substituting these into equation (8), we now have the following:

$$r_t = \theta\sigma_t^2 - \rho(\theta * Var(r_t))(r_{t-1}) + \varepsilon_t \tag{9}$$

Consistent with theoretical asset pricing, and the notion that investors are risk-averse mean-variance optimizers, it is expected that θ is positive in its sign. If it is positive, this denotes a positive risk-return tradeoff (Merton, 1980).

If we look at the term $-\rho(\theta * Var(r_t))(r_{t-1})$, it implies that if there is positive feedback trading (i.e. herders are present in the market and engaging in trend chasing behaviors), and, therefore the parameter ρ is positive and significant, it will induce a negative autocorrelation pattern in the return series for the given ESG coin. This negative autocorrelation will be proportional to the conditional variance, $Var(r_t)$. Let us consider how negative autocorrelation patterns can shift according to the conditional variance of a given ESG coin's price changes. On the one hand, and for example, herders who 'chase trends' during high volatility periods (when $Var(r_t)$ is relatively high) may cause a relatively greater negative return autocorrelation than when they engage in such behavior during, say, low volatility periods (when $Var(r_t)$ is relatively low). Conversely, a negative sign for ρ, denoting that herders buy during recent price declines and sell during recent prices appreciations, results in positive autocorrelation since we now have $-\left(-\rho(\theta * Var(r_t))(r_{t-1})\right)$.

We can algebraically simplify equation (9) and, consistent with asset pricing and market microstructure theory, when including a coefficient to account for autocorrelation resulting from non-synchronous trading and other such market frictions (Lo and MacKinlay, 1990), we can write the following:

$$r_t = b_0 + b_1 Var(r_t) + (b_2 + b_3 Var(r_t))(r_{t-1}) + \varepsilon_t \tag{10A}$$

Equation (10A) is now expressed in a tractable model that can be used to detect herding (feedback) behaviors, whereby $b_1 = \theta$ and $b_3 = -\rho(\theta)$. The constant term, b_0, is included as is convention when testing asset pricing regressions. Economically, the constant may serve to account for information content not subsumed in other coefficients. As mentioned, b_2 serves as the autocorrelation coefficient. Given the overall structure of equation (10A), the model simplifies to the classic Merton (1980) intertemporal capital asset pricing model (ICAPM) when herding investors are not present in the market (i.e., $b_3 = 0$).

While equation 10A will enable empirical testing of the presence of mean-variance optimizers and herding (feedback) traders, we are also interested in testing whether there exists an asymmetry in their behavior with respect to periods of negative returns. In other words, do negative returns (price declines in ESG coins) exacerbate herding behaviors? Thus, we refer to equation 10A as our "base model" and extend it in order to account for this possible asymmetric behavior. To accomplish this, and consistent with Koutmos (1997), we include the following term to equation (10A) in order to form our "extended model" as follows:

$$r_t = b_0 + b_1 Var(r_t) + \big(b_2 + b_3 Var(r_t)\big)(r_{t-1}) + b_4 |r_{t-1}| + \varepsilon_t \qquad (10B)$$

As mentioned, if b_3 is negative and statistically significant, there is evidence of herding, or, trend chasing, behaviors. Now, with the newly added term $b_4|r_{t-1}|$, we can examine whether lagged negative returns amplify herding. Specifically, if $b_4 > 0$, then negative returns indeed amplify herding (positive feedback) behaviors. The coefficient on r_{t-1} is therefore:

$$[b_2 + b_3 Var(r_t) + b_4] \text{ for } r_{t-1} \geq 0, \text{ and}$$
$$[b_2 + b_3 Var(r_t) - b_4] \text{ for } r_{t-1} < 0 \qquad (11)$$

Finally, an important consideration is the conditional volatility model to be used in order to estimate equations (10A) and (10B), respectively. To accomplish this, we use the component generalized autoregressive conditional heteroskedasticity (CGARCH) model of Engle and Lee (1999). The CGARCH is advantageous relative to other GARCH-type models in that it allows for the modeling of the short-run (transitory) and long-run (permanent) components of volatility, respectively:

$$\text{CGARCH(1,1): } \sigma_{i,t}^2 = m_t + \delta_3\,(\varepsilon_{t-1}^2 - m_{t-1}) + \delta_4(\sigma_{t-1}^2 - m_{t-1})$$
$$m_t = \delta_0 + \delta_1(m_{t-1} - \delta_0) + \delta_2(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) \qquad (12)$$

The long-run component is defined as m_t and is a function of past volatility, whereby its trend is determined by the forecasting error, $\varepsilon_{t-1}^2 - \sigma_{t-1}^2$. The coefficient δ_2 quantifies the initial impact of a shock in returns, while δ_1 measures the persistence of the shock. The short-run volatility component is defined as the difference between the total conditional variance and its long-run component, $\sigma_t^2 - m_t$, and where the coefficient δ_4 quantifies the initial impact of a shock, δ_3 measures the degree of its persistence. To ensure non-negativity in the total conditional variance, σ_t^2, it is assumed that $\delta_0 > 0$, $\delta_3 > 0$, $\delta_4 > \delta_2 > 0$, $1 > \delta_2 > (\delta_3 + \delta_4) > 0$, and $m_t > 0$. The CGARCH specification in equation (12) reduces to the standard GARCH(1,1) if either $\delta_3 = \delta_4 = 0$ or if $\delta_1 = \delta_2 = 0$. To estimate the conditional volatility of our sampled ESG coins, we adopt a first order lag structure since, consistent with existing evidence, lower-order GARCH models are sufficient in terms of effectively modeling the volatility properties of asset returns (Bollerslev et al., 1992).[11]

Several distributions have been proposed in the literature for GARCH standardized residuals (Bollerslev et al., 1992). Oftentimes, the standard normal distribution is used. The disadvantage to this approach is that standardized GARCH residuals most often display leptokurtic properties, thereby producing biased, or, unreliable, tests statistics (Antoniou et al., 2005). Thus, and as has been suggested in prior literature, we use the generalized error distribution (GED), which has the following density function:

$$f(\mu_t, \sigma_t, v) = (v/2)[\Gamma(3/v)]^{1/2}[\Gamma(1/v)]^{-3/2}(1/\sigma_t)exp(-[\Gamma(3/v)/\Gamma(1/v)]^{v/2}|\varepsilon_t|\sigma_t|) \quad (13)$$

whereby $\Gamma(.)$ represents the gamma function and v represents a scale parameter that is to be estimated endogenously. For example, for $v = 2$, the GED yields a normal distribution. Likewise, for $v = 1$ it yields a Laplace distribution. Finally, the log likelihood over each of the ESG coins' sample period, is expressed as:

$$L(\theta) = \sum_{t=1}^{T} \log f(\mu_t, \sigma_t, v) \quad (14)$$

whereby μ and σ are the conditional mean and conditional standard deviation, respectively. Given the high degree of nonlinearities in the parameters of the log likelihood function, numerical maximization techniques are needed. This study uses the algorithm of Berndt et al. (1974) for estimations.

Finally, it is important to note that the base model (equation (10A)) and our extended model (equation (10B)) are estimated using the permanent volatility component and the total volatility component, respectively, for each of the sampled ESG coins. This is advantageous because it checks for robustness in the results, as well as allowing for the possibility that feedback traders may behave differently depending on the volatility component. Since the permanent component of volatility tends to be driven by macroeconomic, and more systematic, risk factors, we may see differences in the behavior of our two heterogeneous groups of investors (MV and $Herd$). The total volatility component also includes the short-run component, which is transitory in nature and can either increase, or, decrease, the total volatility. Taken together, the above analysis will help us in better understanding the price behaviors of these ESG coins.

4.2. Role of Bitcoin Market Crash Risk Expectations

To better understand the nature of feedback trading from yet another angle, we further develop our feedback trading framework to accommodate for the possibility that investors' forward-looking expectations of aggregate cryptocurrency market crash risk plays a role in driving feedback traders in

[11] Results for varying CGARCH ordering structures, as well as for a variety of other GARCH-type models, are available upon request. Regardless of the GARCH-type specification utilized, the core findings of our study remain robust. For brevity, results are tabulated for only the CGARCH in Tables 6A and 6B, respectively, because the CGARCH allows for the estimations of our "base" and "extended" models using the long-run and total conditional variance, respectively.

ESG coin markets. As mentioned, option-implied information, such as skewness, can help capture and forecast investors' forward-looking crash risk expectations (Christoffersen et al., 2013). In addition, it is important to bear in mind that options markets can serve as an important medium of price discovery for their underlying spot markets, especially given that investors who possess private information are likely to use such markets to maximize their returns. In the words of Black (1975, p. 41), "...Since an investor can usually get more action for a given investment in options than he can by investing directly in the underlying stock, he may choose to deal in options when he feels he has an especially important piece of information..."

In this study, we focus on bitcoin's option-implied skewness for the following three reasons. First, because option-implied information has been shown to reflect investors' sentiment, behaviors, and their forward-looking expectations (Christoffersen et al., 2013; Seo and Kim, 2015). Second, and because option-implied skewness has been shown to reflect investors' expectations on future crash risk, it has served as an important input in various risk management and portfolio selection models (Dennis and Mayhew, 2002; DeMiguel et al., 2013). Finally, it has been shown that, despite the large number of cryptocurrencies in circulation, bitcoin remains the informationally dominant cryptocurrency within the crypto universe (Koutmos, 2018; Wang and Ngene, 2020). For example, Koutmos (2018) demonstrates how bitcoin is the dominant contributor of spillovers among several of the largest cryptocurrencies in circulation.

Taken together, these three reasons motivate incorporating bitcoin's option-implied skewness into our feedback model in order to gauge whether it plays any role in how feedback traders behave in our sampled ESG coin markets. Thus, in order to quantify bitcoin's option-implied skewness, our study utilizes the framework by T3 Index Pty Ltd. (*https://t3index.com*).[12] This skewness index, SI, is defined as follows:

$$SI = 100 - 10S \tag{15}$$

whereby S represents the fair payoff of a 30-day arithmetic skew swap from a portfolio of bitcoin options. S is interpolated (or extrapolated) from adjacent bitcoin monthly options' price skewness, S_1 and S_2:

$$S = wS_1 + (1 - w)S_2 \tag{16}$$

whereby $w = (t_2 - t_M)/(t_2 - t_1)$ and where t_M denotes the number of seconds within the 30-day period. t_1 and t_2 denote the time (also in seconds) to the near- and next-term expiration, respectively. Thus,

[12] The full white paper documentation of the methodology as well as its model assumptions is publicly available here: *https://t3index.com/indexes/bitskew/*. T3 Index provides several option-implied methodologies that are cited in the popular financial press and which receive investor attention. For example, this recent *Bloomberg* article cites T3 Index following the market uncertainty caused by the FTX debacle: *https://www.bloomberg.com/news/articles/2024-03-07/bitcoin-btc-volatility-spike-heralds-an-early-test-of-us-etf-demand*.

skewness estimates, $S_{1,2}$, can be estimated using an approximation for the arithmetic skewness swap as follows:

$$S_{1,2} = \left[2 * \left\{3 * \sum_i (K_i - F)\Delta K_i p_i + (p^c_{ATM} - p^p_{ATM})^3\right\}\right] / \left[2 * \sum_i \Delta K_i p_i - (p^c_{ATM} - p^p_{ATM})^2\right]^{3/2} \quad (17)$$

and whereby p^c_{ATM} and p^p_{ATM} denote the price (in USD) of at-the-money (ATM) call and put options, respectively. The strike is represented by K, and (K_{ATM}) represents the point which linearly interpolated call and put prices intersect. From this, we can calculate the forward price, F, as follows: $F = K_{ATM} + (p^c_{ATM} - p^p_{ATM})$. The parameter ΔK_i represents half the difference of strikes on both sides of K_i, and can be expressed as follows: $\Delta K_i = (K_{i+1} - K_{i-1})/2$. To estimate equation (17) a BTC option put and call options are ordered on the basis of their strikes, K (from lowest to highest) and their corresponding prices are gathered for the analysis: for a call option (if $K_i > K_{ATM}$) and for a put option (if $K_i < K_{ATM}$). In the event that $K_i \cong K_{ATM}$, an average is taken of p^c_{ATM} and p^p_{ATM}.

A time series plot of bitcoin's option-implied skewness is shown in Figure 5. While this is discussed more in Section 5 of our study, especially in the context of our feedback model, there is a notable observation that can be made. In the days surrounding the collapse of the FTX exchange bitcoin's option-implied skewness reached a record high, indicating investors' heightened crash risk expectations for bitcoin. The vertical red line in Figure 5 corresponds with November 2, 2022. This was arguably the initial date within the FTX debacle timeline. On this day, CoinDesk reported that the balance sheet for Alameda Research, which was FTX's sister company, was comprised heavily of FTX's native crypto token (FTT).[13] In the days following this article, bitcoin's option-implied skewness reached the highest level within the sample period for this specific skewness measure (July 1, 2020 until March 4, 2023). As is discussed further in the proceeding section, this sample period is utilized and, for purposes of this study, to investigate whether investors' expectations of bitcoin crash risk play any role in the feedback trading behaviors of our sampled ESG coins.

[Figure 5 here.]

To incorporate the information content of option-implied skewness in equation (17), we modify and re-cast our feedback trading model in equation (10A). As in equation (10A), and using Sentana and Wadhwani (1992) as our theoretical foundation, we modify our feedback trading model in similar vein to, among others, Chau et al. (2011) and Chau et al. (2016), with an inclusion of a dummy variable, D_t, to account for whether there is a rise ($D_t = 1$) or decline ($D_t = 0$) in bitcoin's option-implied skewness on trading day t relative to trading day $t - 1$:

[13] See the CoinDesk article here: *https://www.coindesk.com/business/2022/11/02/divisions-in-sam-bankman-frieds-crypto-empire-blur-on-his-trading-titan-alamedas-balance-sheet/*.

$$r_t = b_{0,D}D_t + b_{0,ND}(1 - D_t) + b_{1,D}D_tVar(r_t) + b_{1,ND}(1 - D_t)Var(r_t) + D_t\big(b_{2,D} + b_{3,D}Var(r_t)\big)(r_{t-1}) + (1 - D_t)\big(b_{2,ND} + b_{3,ND}Var(r_t)\big)(r_{t-1}) + \varepsilon_t \quad (18)$$

As in equation (10A), equation (18) is estimated using the CGARCH model in equation (12), along with the GED distribution for the CGARCH residuals (in equation (13)) and the log likelihood in equation (14). In addition, equation (18) is estimated using the permanent component of volatility as well as the total component, respectively.

The interpretations for the parameters in equation (18) are analogous to the parameters in equation (10A). The important distinction is whether the parameter is estimated when there is a rise ($D_t = 1$) or decline ($D_t = 0$) in bitcoin's option-implied skewness on trading day t relative to trading day $t - 1$. The parameters with subscript D, which include $b_{0,D}$ (the constant), $b_{1,D}$ (the behavior of mean-variance optimizing traders), $b_{2,D}$ (the autocorrelation coefficient), and $b_{3,D}$ (the behavior of feedback traders), are estimated on trading days for which there is a rise in bitcoin's option-implied skewness. Alternatively, parameters with the subscript ND (no dummy) represent (and with similar interpretation) trading days for which $D_t = 0$.

By estimating equation (18), we can be decipher whether (a) the parameters are of similar sign and significance across trading days when bitcoin's option-implied skewness rises as opposed to when it declines; (b) whether the parameters exhibit differences in their signs or significance depending on fluctuations in bitcoin's option-implied skewness. If we see (a), it suggests that ESG coin traders may not be driven, or influenced, by expectations of a bitcoin price crash. However, if they are influenced by such a prospect, it is possible we will see (b) transpire for our sampled ESG coins. Furthermore, and given the distinctions in our sampled ESG coins' blockchains, we do not anticipate, a priori, to see consistent patterns across all our ESG crypto markets.

5. Discussion of findings

The volatility components for each of the ESG coins' price changes is shown in Figure 6, estimated from the CGARCH in equation (12). There are at least three observable commonalities across the ESG coins' volatility dynamics.

[Figure 6 here.]

First, there is a strong correlation between the permanent and total components of volatility. This is to be expected, given that, theoretically, the permanent component reflects changes in macro-level risk factors and expectations. Within equation (12), the permanent component, m_t, is a determining component for the total conditional variance, $\sigma_{i,t}^2$. The short-run (transitory) component, defined as $\sigma_t^2 -$

m_t, takes unique patterns for each of the ESG coins. For example, for DOT, the short-run component experiences downward shocks relatively more, thus adjusting the total volatility downward at various points in time (such as around April 2021). For other coins, such as SOL, the transitory component experiences more upward shocks.

Second, and for those ESG coins for which the sample range covers the December 2017 period (ADA, XRP, TRX, and EOS), there are notable rises in the permanent and total volatilities of the respective coins. This coincides with the introduction of bitcoin futures by the CBOE and CME, respectively, on December 10, 2017 and December 18, 2017. During this period, bitcoin's price lost approximately 30% of its value within only a few trading days. This was a time when investor sentiment for crypto assets reached a low point, and a time when bearish investors could utilize futures to push bitcoin's price down. As Hale et al. (2018) notes, "...[the] one-sided speculative demand came to an end when the futures for bitcoin started trading…with the introduction of bitcoin futures, pessimists could bet on a bitcoin price decline, buying and selling contracts with a lower delivery price in the future than the spot price…" (p. 2). This negative sentiment impacted all crypto assets by some varying degree, given that bitcoin's market capitalization alone presently accounts for nearly half the total market capitalization of all crypto assets in circulation.

Third, and at the height of the Covid-19 pandemic in 2020-21, all our sampled coins experienced rises in their total volatilities. This was a time when investor uncertainty rose, and, just from January 2020 to March 2020, major indices (such as the S&P 500) lost nearly 30% of their value. For some coins (like SOL) the volatility persistence during this time period is relatively higher than other coins (such as, for example, TRX and BITG).

These volatility dynamics are important to understand since, as mentioned, volatility herding (feedback) traders' impact on coins' negative autocorrelation patterns will be proportional to the conditional variance. In our case, and in this study, we consider the conditional permanent volatilities, and conditional total volatilities, separately. A suitable starting point for our discussion is the base model results (which corresponds with equation (10A)). In Tables 6A and 6B, respectively, we show estimation results for the permanent conditional volatility component, and, the total conditional volatility, respectively.

[Table 6A here.]

[Table 6B here.]

In Table 6A, for the base model and when the permanent conditional volatility component is used for $Var(r_t)$ in equation (10A), we see evidence for a positive risk-return tradeoff for four out of the eight sampled coins; SOL, ADA, XRP, and TRX, respectively. For these coins, the coefficient b_1 is positive and statistically significant, suggesting that traders in these markets are mean-variance optimizers and that the permanent conditional volatility component is important in their buying and selling decisions. It is important to note that for traditional asset classes and equity-linked index funds, there tends to be an insignificant, or, negative, risk-return tradeoff due to the so-called volatility feedback effect that is commonly observed in empirical asset pricing (Koutmos, 2015).

When we turn our attention to the coefficient b_3 in the base model, we see strong evidence of positive feedback trading in seven out of the ten sampled ESG coins, namely, DOT, SOL, ADA, XRP, AVAX, EOS, and XTZ, respectively. This is strong evidence that traders in these markets engage in herding behaviors – they buy en masse when prices are rising and, conversely, sell when prices are declining. This type of destabilizing behavior can result in price bubbles and can be amplified when noise rises in the market or the media (Karaa et al., 2021). As mentioned, and given that there is rising popularity and interest crypto investing, whereby investors utilize a range of momentum-type strategies (see footnote (8)), this could lead to excess price volatility in these types of markets and coins.

The coefficient estimates for the extended model (equation (10B)) in Table 6A corroborate some of these arguments. While equation (10B) also checks for the presence of mean-variance optimizers, as well as herding traders, it includes the parameter $b_4|r_{t-1}|$ in order to examine whether lagged negative returns amplify herding. If the coefficient b_4 is positive and significant, then negative returns indeed amplify herding (positive feedback) behaviors. From the results, we see that all the coins which showed evidence of herding behavior in the base model, are also showing evidence of herding in the extended model. In addition, we also see that now TRX is also showing signs of positive feedback trading. Thus, we have a total of eight out of ten coins showing signs that their price behaviors are driven by such momentum-type traders and strategies. Of these eight, three coins (ADA, XRP, and TRX) show that this herding behavior is amplified when past returns are negative.

Finally, and in Table 6B for both the base and extended models, respectively, we generally see confirmation of our aforementioned findings. Table 6B uses the total conditional volatility. As discussed and shown in Figure 6, there is a strong correlation between the permanent volatility component and total volatility. This is to be expected, given that, theoretically, the permanent component reflects changes in macro-level risk factors and expectations. While the total component can experience relatively more variance (given that the short-run component can induce sharp changes in its value), we see qualitatively similar findings. Specifically, there is strong evidence for positive feedback trading, and, with some exceptions, few of the ESG coins show signs of a statistically positive risk-return tradeoff.

When we turn our attention to Tables 7A and 7B, which contain results for the feedback trading model in equation (18) for the permanent volatility component and total volatility, respectively, we see whether investors' crash risk expectations for bitcoin (the dominant cryptocurrency that drives movements in the entire crypto market) plays any role in how the aforementioned groups of traders behave. As mentioned, equation (18) permits us to decipher whether their behaviors appear robust (the model parameters are of analogous sign and magnitude when compared to those in Tables 6A and 6B) or whether we see differences in behavior. The option-implied skewness measure shown in Figure 5 spans from July 1, 2020 until March 4, 2023. Thus, and for specific purposes of Tables 7A and 7B, this now serves as the sample range for all our sampled ESG coins in Table 1, with the exception of DOT and AVAX, which begin on September 2, 2020 and September 22, 2020, respectively. Both these coins' ranges, however, like all the other sampled ESG coins, end on March 4, 2023.

When we do a comparison of Tables 6A and 7A, and while there are qualitative similarities in the findings in terms of which ESG coins see evidence for feedback trading, there are novel nuanced findings that merit discussion. For the feedback trading parameter, b_3, and for Table 7A, we see that all our sampled ESG coins, with the exception of BITG, show evidence that feedback traders are present in such markets and which drive their respective price movements. This general finding is generally compatible with what see from from Table 6A. The difference, now, is that we can infer whether investors' expectations of crash risk in the crypto market plays any role in their behavior. In the cases of DOT, SOL, ADA, TRX, EOS, ALGO, and XTZ, respectively, we see strong evidence of positive feedback trading. These findings are generally compatible with the conclusions we made in Table 6A. A noteworthy finding is the case of XTZ, which shows negative feedback trading during trading days when option-implied skewness rises ($b_{3,D}$) and positive feedback trading when option-implied skewness declines ($b_{3,ND}$). This behavior suggests that feedback traders can behave differently depending on their crash risk expectations of the aggregate crypto market. Of all the aforementioned sampled ESG coins that show evidence of positive feedback trading, and in addition to the unique case of XTZ, XRP (at the 5% level) and AVAX (at the 10% level) show signs of positive feedback trading only during trading days when option-implied skewness rises ($b_{3,D}$).

Overall, and in both Tables 7A and 7B, the frequency of feedback trading parameter significance comes from $b_{3,ND}$ as opposed to $b_{3,D}$. In similar vein, and for mean-variance maximizing traders (b_1), we see that more cases of statistical significance for $b_{1,ND}$ as opposed to $b_{1,D}$. A noteworthy finding when doing a comparison of b_1 between Tables 6A and 6B with Tables 7A and 7B, respectively, is we see a deterioration in the positive risk-return tradeoff that we initially saw in Tables 6A and 6B. Specifically, ADA, XRP, and TRX, which although initially showed evidence of a positive risk-return tradeoff in Tables 6A and 6B, do not show the same conclusion in Tables 7A and 7B. Further inspection shows that, as a result of partitioning between periods of rising (declining) crypto crash risk expectations, some ESG coins show evidence of a negative risk-return tradeoff (as in the case of EOS, ALGO, and BITG, respectively, for $b_{1,ND}$) while SOL shows evidence for a positive risk-return tradeoff (and again for

$b_{1,ND}$). These findings serve as motivation for the need to better understand the nature of the risk-return tradeoff for these ESG coins.

Lastly, the findings tabulated in Table 7B, which uses total conditional volatility, generally echoes much of the findings in Table 7A. Taken together, these findings show that (a) ESG coins generally are susceptible to the same types of speculative positive feedback trading strategies that we see in conventional asset markets, such as equities markets; (b) ESG coins do not show signs of a stable mean-variance tradeoff, which instead can vary on the basis of investors' expectations; (c) Overall, investors' aggregate perceptions of crypto market crash risk can influence their trading behaviors, although this influence is heterogeneous across the sampled ESG markets.[14] Taken together, findings (a) through (c), at a minimum, provide preliminary evidence that these ESG coins, which although contain some unique investment attributes and are not entirely integrated from a market microstructure point of view (given some of the differences we see in trading behaviors across the sampled coins), can be driven largely by speculative pressures, attitudes, and trading strategies. Whether they ultimately serve as the future of 'green money' is to be seen.

6. Summary & concluding remarks

This study discusses a novel strand of growing literature that examines the feasibility of using ESG-inspired cryptocurrencies, which do not pose the types of harmful environmental effects which, say, bitcoin's PoW consensus algorithm imposes given the sizeable amount of energy its network requires to verify transactions and to stay operable. Government authorities and regulators have long argued that such energy-intensive forms of digital money are not sustainable. Thus, alternatives are being proposed, which may or may not be suitable forms of money for the public in the future.

We begin our study by introducing this growing strand of literature, as well as the sampled ESG coins that we empirically examine, and discuss reasons for the growing trend in ESG crypto assets. Like companies and traditional assets which have increasingly become ESG rated, we introduce an ESG rating for cryptocurrencies that is gaining popularity among investors. Specifically, we exploit the recent availability of ESG ratings for cryptocurrencies from the provider 'Green Crypto Research', which provides "*the world's 1st ESG rating for cryptos*" and aims to "*support professional investors in evaluating the relative environmental, social, and governance risks of crypto assets*" in a comparable way to traditional investable assets such as equities, real estate and bonds (Green Crypto Research, 2024 p.1). We then proceed to explore the price behaviors of these coins and, specifically, to examine whether there

[14] These broad findings are qualitatively corroborated when alternatives to the CGARCH volatility model in equation (12) are considered, such as the symmetric GARCH, GJR-GARCH, EGARCH, and PGARCH. These results are available upon request.

is herding and feedback trading behaviors which drive their price dynamics. We show that there is strong evidence for the presence of herding, or, 'feedback', traders, who employ 'bandwagon' type strategies, and buy during recent price appreciations and sell during recent price declines. This type of feedback trading is very prevalent among conventional asset markets, such as equities markets, and has the potential to lead to price bubbles and excess volatility in the future.

Our study contributes to a novel and budding strand of research that examines whether new forms of “green money” can be used in our financial system. While our empirical analysis shows some important statistical properties in the behaviors of ESG coins, more work is undoubtedly needed in areas, more broadly, such as (i) whether it is in the best interest of market participants and the public to make transactions using cryptocurrencies; (ii) the costs and benefits of adopting and exchanging such coins in our financial system; (iii) the economic and non-economic mechanisms which drive the price behaviors of such crypto assets.

We conclude with the caveats argued by Lo and Wang (2014), that money is supposed to serve as a medium of exchange, unit of account, and a store of value, respectively. These are the three functions of money that economists generally agree on. A firm, investor, or household is generally willing to accept fiat money as a method of payment for something of value. Given some of our preliminary results, the case for ESG coins, such as those sampled, becoming the future of green money, may be a weak one. This is especially true given that their price movements appear to be driven by the same types of speculative pressures, attitudes, and trading strategies that we see in conventional asset markets. Instead, it seems more likely that ESG coins will become yet another investment class of cryptocurrencies for investors, and may even become more popular in helping to improve the sustainability of blockchain technology.

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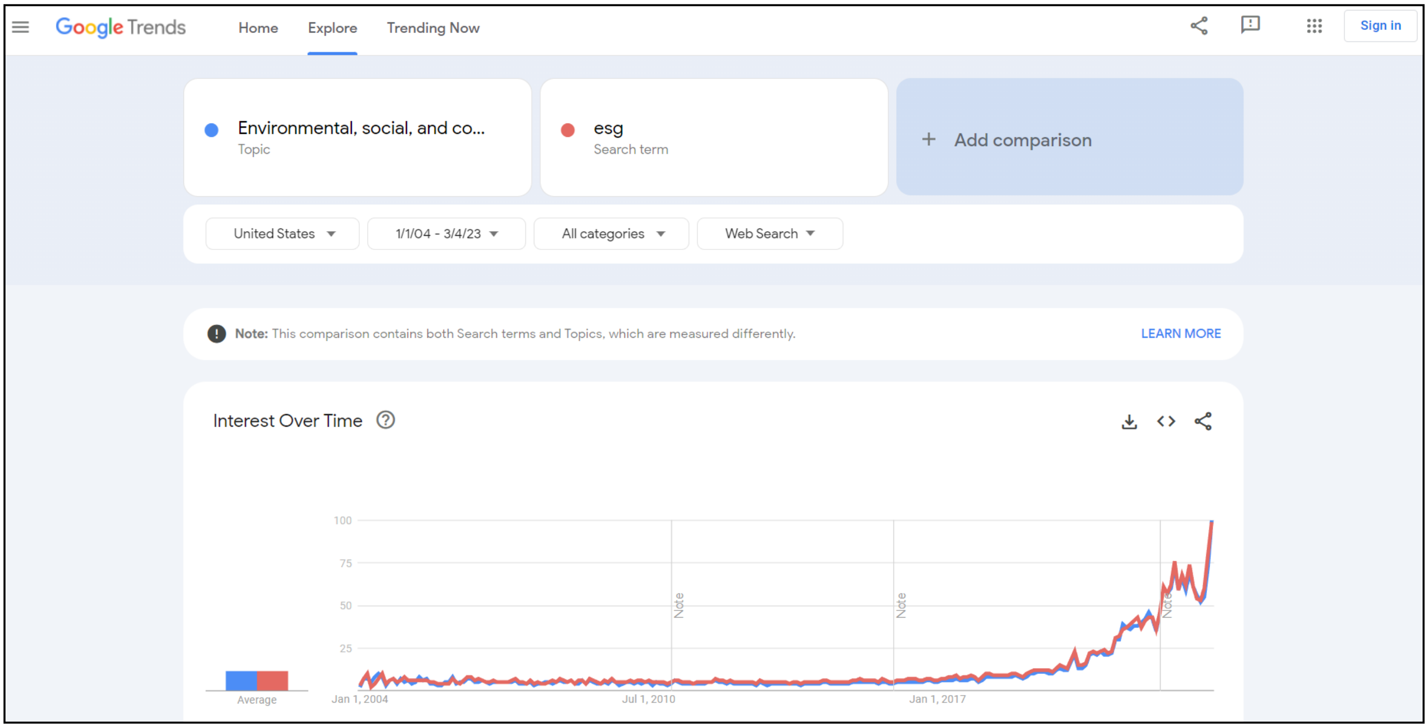
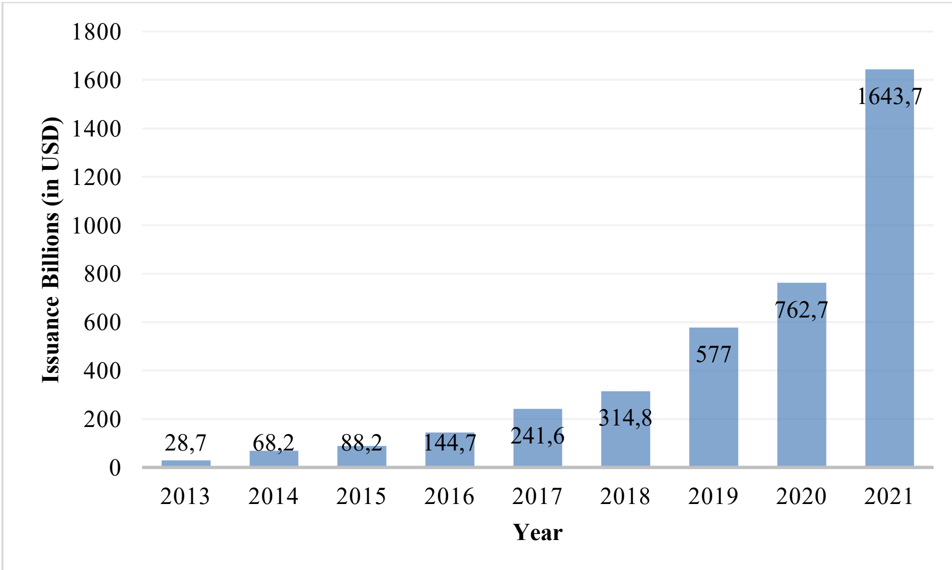
Figure 1
Google Trends™ for ESG, 2004 - 2023



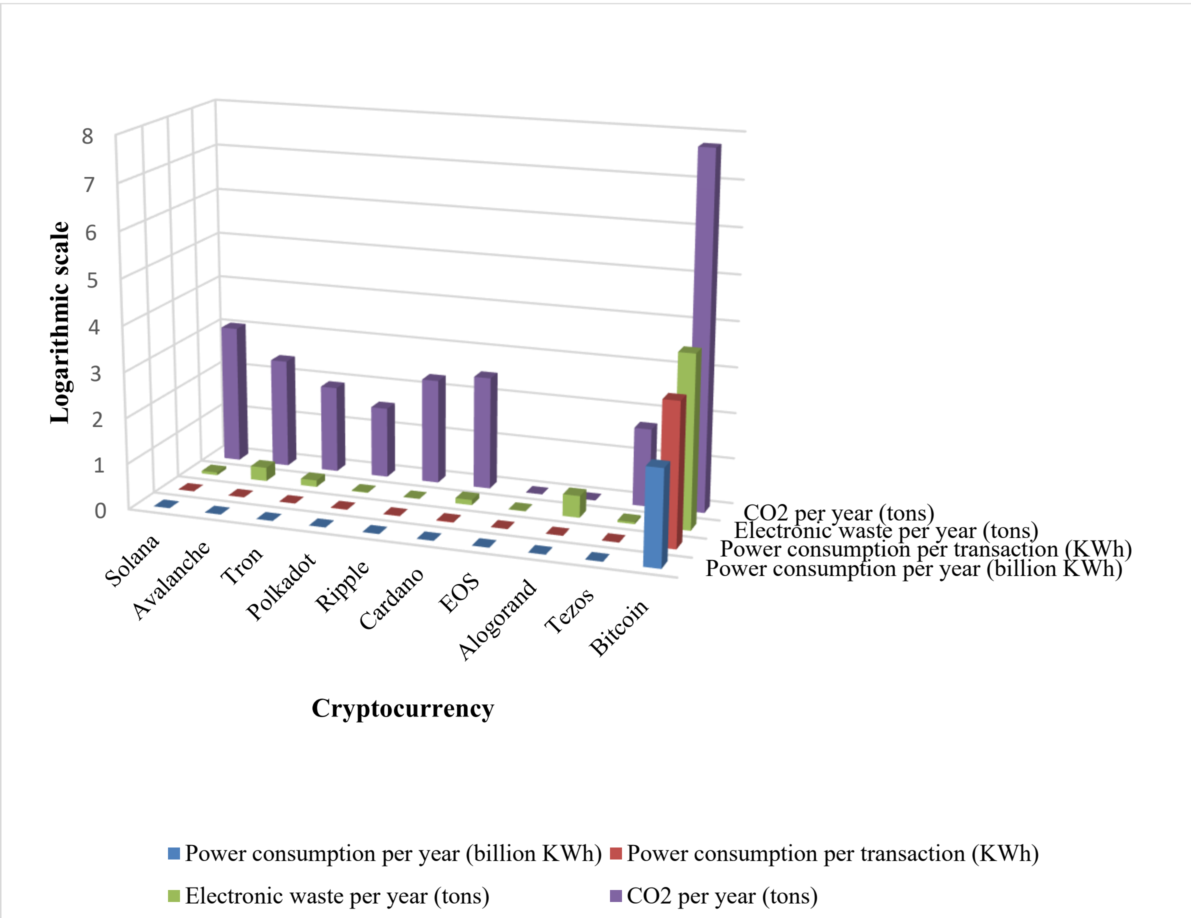
Source: Google Trends™ for the search term "esg" from January 1, 2004 until March 4, 2023.

Figure 2
Growth in Green Investment Worldwide



Source: Authors' calculations and from Bloomberg. This figure displays the increasing trend of worldwide green asset issuance between 2013 and 2021 in USD.

Figure 3
Cryptocurrency Environmental Impact



Source: Authors' calculations and from Green Crypto Research (URL: *greencryptoresearch.com*). The figure displays the estimated annual consumption of power per year, power consumption per transaction, electronic waste per year, and CO_2 emissions per year for the sampled cryptocurrencies with the exception of Bitcoin Green (due to data unavailability). Bitcoin is also shown in the figure for the sake of comparison. All data are presented in logarithmic form.

Figure 4
Time Series Plots of Price and Volume Levels (both in USD)

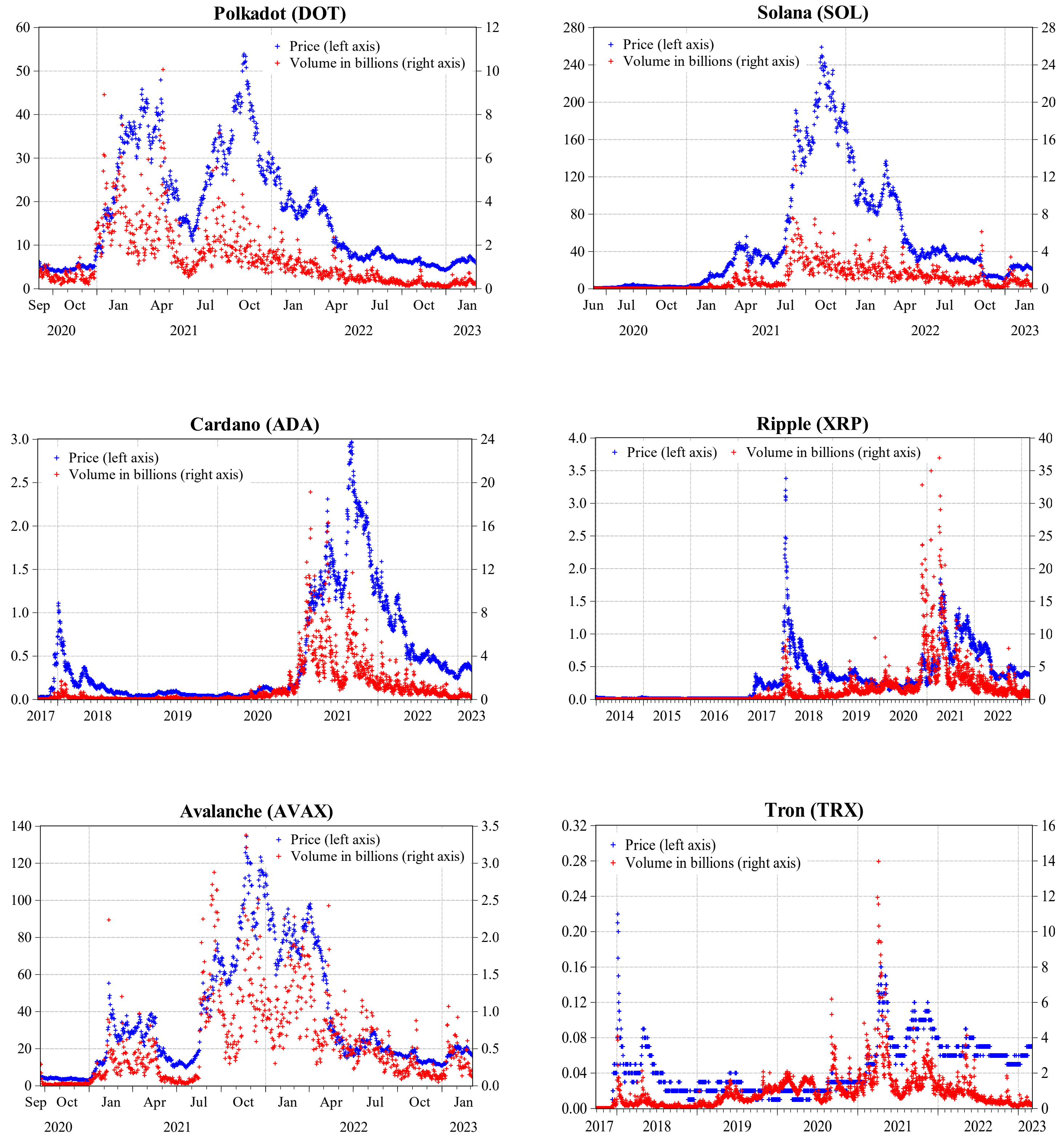
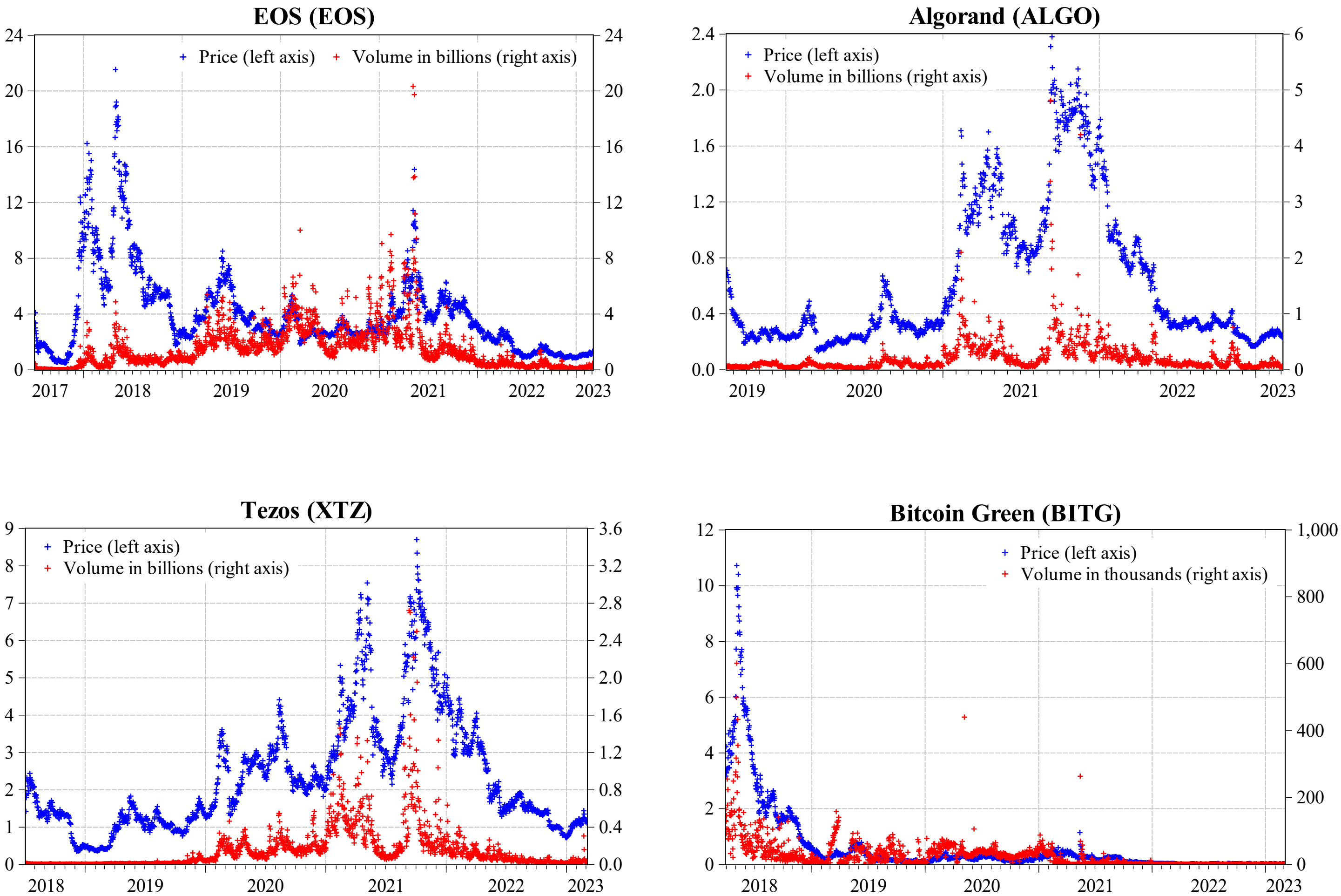


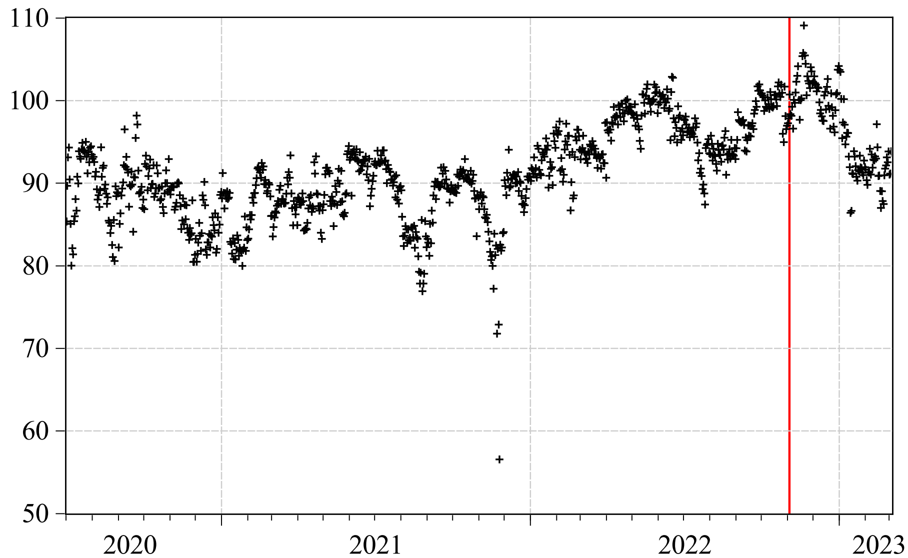
Figure 4 (Cont.)

Time Series Plots of Price and Volume Levels (both in USD)



Source: This figure shows time series plots of each sampled ESG coins' price series (left axis and in blue) and trade volume (right axis and in red). Data are sourced from CoinMarketCap (*https://coinmarketcap.com*) and consist of daily closing prices for the ten sampled ESG coins. Since these coins trade in several exchanges around the world simultaneously, the advantage to using data from CoinMarketCap is that its price data are calculated as the volume-weighted average of all prices reported across the various exchange markets. Unlike traditional assets which trade only on weekdays, cryptocurrencies, such as our sampled ESG coins, trade all seven days of the week.

Figure 5
Time Series Plot of Bitcoin Option-Implied Skewness



Source: Authors' calculations and T3 Index Pty Ltd. (*https://t3index.com*). The sample period for this option-implied skewness measure is from July 1, 2020 until March 4, 2023. The vertical red line corresponds with November 2, 2022, as this is the day that arguably began the timeline for the FTX debacle.

Figure 6
Time Series Plots of CGARCH Volatility Components

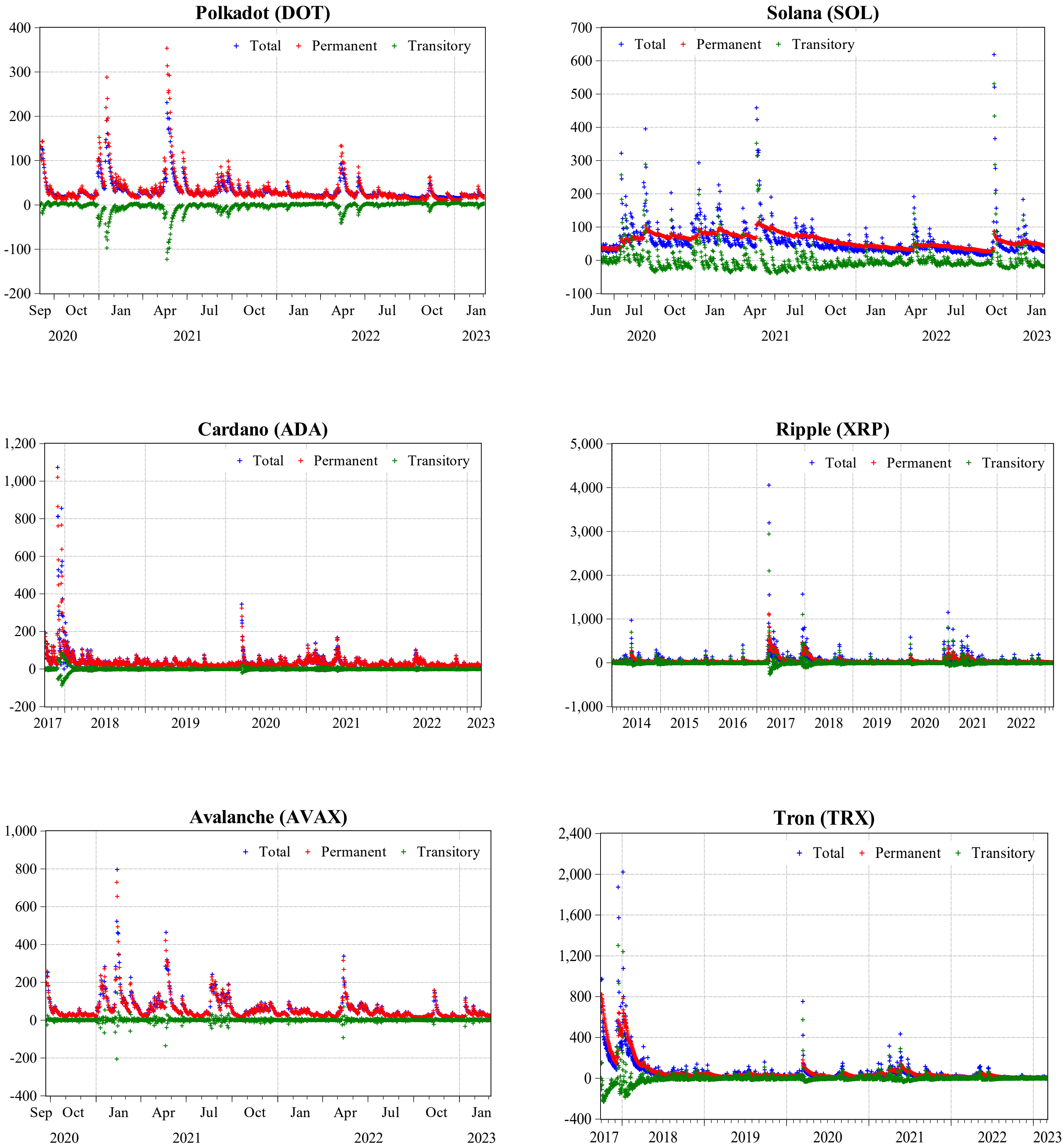
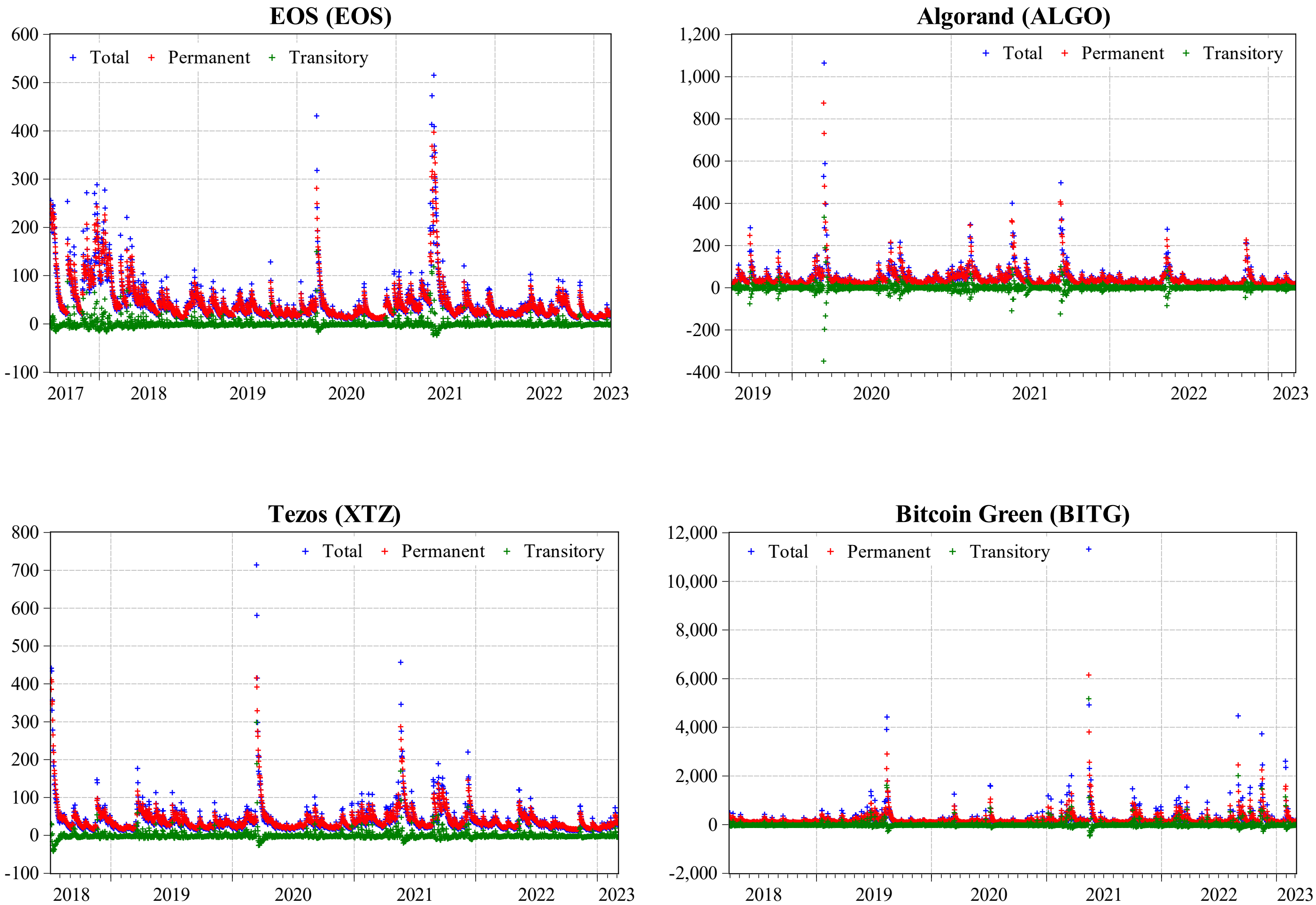


Figure 6 (Cont.)
Time Series Plots of CGARCH Volatility Components



Source: This figure shows time series plots of each sampled ESG coins' return volatilities from the CGARCH model in equation (12). The total, permanent, and transitory volatility components are in blue, red, and green, respectively. Price data used to calculate each ESG coins' returns are from CoinMarketCap (*https://coinmarketcap.com*) and consist of daily closing prices for the ten sampled ESG coins.

Table 1
Sampled Cryptocurrencies and their ESG Ratings

Crypto	Abbrev.	ESG rating	Environment	Social	Governance	Website
Polkadot	DOT	B	A+	B+	A+	https://polkadot.network/
Solana	SOL	A	A+	A-	A-	https://solana.com/
Cardano	ADA	A	A-	A-	A+	https://cardano.org/
Ripple	XRP	C	A+	C+	B-	https://ripple.com/
Avalanche	AVAX	A	A+	A-	A-	https://www.avax.network/
Tron	TRX	B	A+	B+	B	https://tron.network/
EOS	EOS	B	A+	B	B	https://eos.io/
Algorand	ALGO	B	A+	A-	B+	https://www.algorand.com/
Tezos	XTZ	A	A+	A+	B+	https://tezos.com/
Bitcoin Green	BITG	No data	No data	No data	No data	https://bitgreen.org/

Notes: This table reports on the ESG ratings for each of the sampled cryptocurrencies used in this study. These ratings are compiled by the authors and are sourced from Green Crypto Research (URL: *greencryptoresearch.com*) (Data as of January 1, 2023). Each ESG pillar is rated independently first on a rising scale from D to A+ and then a composite ESG rating is computed based on the average across the three ESG pillars. The “Environment” pillar score is based on (i) energy consumption, (ii) pollution and waste, and (iii) aspiration to achieve net zero. The “Social” pillar score is based on (i) social impact, (ii) asset distribution, and (iii) entry and usage barriers. The “Governance” pillar score is based on (i) network diversification, (ii) network security and incidents, (iii) governance issues. The last column provides the website URL for each of the sampled cryptocurrencies.

Table 2
Sampled Cryptocurrencies and their "Green" Credentials

Crypto	**Abbrev.**	**Blockchain Since**	**Consensus algorithm**	**Power consumption per year (billion KWh)**	**Power consumption per transaction (KWh)**	**Electronic waste per year (tons)**	**CO2 per year (tons)**
Polkadot	DOT	2020	Nominated proof-of-stake (NPoS)	0.0001	0.017	0.03	35
Solana	SOL	2020	Proof of history (PoH)	0.002	0.0005	0.15	1,100
Cardano	ADA	2017	Proof-of-Stake (PoS)	0.001	0.03	0.3	300
Ripple	XRP	2012	Ripple Protocol consensus algorithm (RPCA)	0.0005	0.008	0.004	200
Avalanche	AVAX	2020	Proof-of-Stake (PoS)	0.0005	0.007	1	250
Tron	TRX	2018	Delegated proof of stake (DPoS)	0.0002	0.00003	0.4	80
EOS	EOS	2018	Proof-of-Stake (PoS)	0.0006	0.00043	0.02	0
Alogorand	ALGO	2019	Proof-of-Stake (PoS)	0.0005	0.00001	2	0
Tezos	XTZ	2018	Proof-of-Stake (PoS)	0.0001	0.00001	0.1	50
Bitcoin Green	BITG	2021	Proof-of-Stake (PoS)	No data	No data	No data	No data

Notes: This table reports the sampled cryptocurrencies used in this study (first and second columns). The third column reports the year in which the cryptocurrencies had a blockchain while the fourth column reports on their consensus algorithm (Table 3 provides more description on the respective consensus algorithms). The last four columns report on each of the cryptocurrencies' consumption per year (in billion of KWh), consumption per transaction (in KWh), electronic waste per year (in tons), and CO2 emissions per year (in tons), respectively. The data for this table are compiled by the authors using Green Crypto Research (URL: *greencryptoresearch.com*) (Data as of January 1, 2023), with the exception of the limited data on Bitcoin Green, which is sourced from Crunchbase (URL: *https://www.crunchbase.com/organization/bitcoin-green-bitg*).

Table 3
Sampled Cryptocurrencies and their Consensus Algorithms

Consensus algorithm	Cryptos	Description of the relevant blockchain consensus algorithm
Proof-of-Stake (PoS)	Cardano, EOS, Avalanche, Alogorand, Tezos, and Bitcoin Green	Cryptocurrencies such as Cardano, EOS, Avalanche, Alogorand, Tezos, and Bitcoin Green, which use the Proof-of-Stake (PoS) algorithm are much more environmentally friendly when compared to those that employ Proof-of-Work (PoW), which is used by Bitcoin, and, until very recently, Ethereum. One of the key differences is that to fulfill the role of verifiers (of block transactions) 'miners' are required to stake a certain number of units of cryptocurrency tokens. This has implications for the ability of users to add malicious blocks to the blockchain. Specifically, under PoW someone would have to control more than 51% of the computing power of the network. In contrast under PoS (and its variants below), this could be achieved by owning more than 51% of the cryptocurrency on the network. Moreover, rather than 'mining' under Proof-of-Stake (PoS) new blocks are 'forged' by the verifiers who have staked their own cryptocurrency tokens. Typically, verifiers (validator nodes) are rewarded with a transaction fee for their role in successfully forging new blocks.
Nominated proof-of-stake (NPoS)	Polkadot	Nominated proof-of-stake (NPoS) is similar to PoS. The most significance difference relates to who is able to validate blocks - with only nominated nodes permitted to do so under NPoS. Polkadot is one cryptocurrency that utilizes this consensus algorithm.
Delegated proof-of-stake (DPoS)	Tron	Like NPoS, Delegated Proof-of-Stake (DPoS) also shares many similarities to PoS. For example, like PoS and NPoS validators under DPoS are rewarded with a transaction fee for successfully verifying transactions. A key distinguishing feature from PoS, is the existence of a democratic voting system (with an individual's voting power determined by the number of cryptocurrency units held) to determine who produced new blocks, which differ from the stake pools under PoS.
Proof-of-history (PoH)	Solana	Proof of history (PoH) possesses several technological innovations that facilitate more efficient transactions. One of the key distinguishing features of PoH over consensus mechanisms discussed, is that network nodes possess their own internal clocks that serve to measure the passage of time and verify events. This proof is based on a verifiable delay function (VDF) that hashes incoming events and determines when they happened. Individual nodes can then separately evaluate the sequence of hashes and establish time, without the need to verify time with other nodes. In this way PoH, addresses a specific challenge which relates to determining the precise instance an event occurred. Most blockchains approach this issue by requiring a network consensus to be reached that establishes that time has passed and the order of transactions.
Ripple protocol consensus algorithm (RPCA)	Ripple	The Ripple Protocol consensus algorithm (RPCA) differs from the above protocols in several important ways. First, the RPCA blockchain was specifically developed with the objective of facilitating fast and low-cost international transfer of funds. Second, unlike other blockchains which are considered as 'public' or as largely decentralized, Ripple represents a 'permissioned' blockchain, which means it is much more centralized. In practice, Ripple is controlled and managed by only a small number of organizations.

Notes: This table provides a brief description of the relevant blockchain consensus algorithm for each of the sampled cryptocurrencies used in this study. The five consensus algorithms that underlie our sampled cryptocurrencies are, respectively, proof-of-stake (PoS), nominated proof-of-stake (NPoS), delegated proof-of-stake (DPoS), proof-of-history (PoH), and Ripple protocol consensus algorithm (RPCA). Of all the consensus algorithms, six out of our ten sampled cryptocurrencies use PoS (Cardano, EOS, Avalanche, Alogorand, Tezos, and Bitcoin Green, respectively).

Table 4
Intraday Trading Summary Statistics

Cryptocurrency	Abbrev.	Sample Range	No. of Obs.	Lowest Price	Highest Price	Avg. Price	Avg. Volume	Avg. Market Cap.
1. Polkadot	DOT	09/02/2020 — 03/04/2023	N = 914	$3.62	$55.00	$17.28	$1,329,506,097	$16,857,772,573
2. Solana	SOL	06/02/2020 — 03/04/2023	N = 1,006	$0.55	$260.06	$51.84	$1,158,259,709	$16,053,795,023
3. Cardano	ADA	10/02/2017 — 03/04/2023	N = 1,980	$0.02	$3.10	$0.48	$1,097,159,249	$15,193,298,051
4. Ripple	XRP	12/27/2013 — 03/04/2023	N = 3,355	< $0.01	$3.84	$0.32	$1,490,996,620	$13,852,481,235
5. Avalanche	AVAX	09/22/2020 — 03/04/2023	N = 894	$2.79	$146.22	$35.32	$559,436,501	$8,082,621,506
6. Tron	TRX	09/28/2017 — 03/04/2023	N = 1,984	< $0.01	$0.30	$0.04	$956,999,208	$3,485,164,051
7. EOS	EOS	07/03/2017 — 03/04/2023	N = 2,071	$0.48	$22.89	$3.96	$1,508,368,948	$3,461,168,463
8. Algorand	ALGO	08/15/2019 — 03/04/2023	N = 1,298	$0.10	$2.83	$0.63	$210,025,114	$2,655,348,480
9. Tezos	XTZ	07/04/2018 — 03/04/2023	N = 1,705	$0.31	$9.18	$2.35	$151,747,039	$1,856,664,266
10. Bitcoin Green	BITG	03/29/2018 — 03/04/2023	N = 1,802	$0.01	$12.30	$0.61	$29,044	$3,315,302

Notes: This table reports intraday trading summary statistics on the sampled cryptocurrencies used in this study. The frequency of the data is daily (7-days-a-week). Cryptocurrency abbreviations (tickers) are shown in the second column while the third and fourth columns, respectively, indicate the sample range and number of observations. The remaining five columns are denominated in USD ($) and report the lowest, highest and average price observed over each of the cryptocurrencies' respective sample range, along with the average trading volume and market capitalization, respectively.

Table 5
Unconditional Moments and Risk-Return Metrics

Cryptocurrency	Mean	Std. Dev.	Skew.	Kurt.	VaR	Modified VaR	Sharpe	Modified Sharpe
1. Polkadot	-0.0042	6.2902	-0.1402	9.3726	-12.3330	-16.7846	-0.0007	-0.0003
2. Solana	0.3596	7.8616	-0.3227	8.7018	-15.0491	-20.8329	0.0457	0.0173
3. Cardano	0.1295	6.7395	1.8290	26.1973	-13.0799	-16.0834	0.0192	0.0081
4. Ripple	0.0782	6.4504	1.6641	36.4504	-12.5646	-21.0314	0.0121	0.0037
5. Avalanche	0.1260	7.4248	0.4228	9.7776	-14.4266	-17.7356	0.0170	0.0071
6. Tron	0.1579	7.0787	1.8110	27.3547	-13.7164	-17.5622	0.0223	0.0090
7. EOS	-0.0584	6.7095	-0.0688	10.5645	-13.2090	-18.2948	-0.0087	-0.0032
8. Algorand	-0.0883	6.5370	-0.7623	13.9547	-12.9008	-20.9757	-0.0135	-0.0042
9. Tezos	-0.0306	6.2330	-0.6426	11.6744	-12.2473	-18.7695	-0.0049	-0.0016
10. Bitcoin Green	-0.3132	13.6745	1.3296	25.0910	-27.1152	-38.5549	-0.0229	-0.0081

Notes: This table reports on the unconditional moments (mean, standard deviation, skewness and kurtosis, respectively) for the log returns (in percentages) of each of the sampled cryptocurrencies used in this study. The last four columns of this table show the risk-return metrics for each of the sampled cryptocurrencies; specifically, the value-at-risk (VaR), modified VaR (MVaR), Sharpe ratio, and modified Sharpe ratio, respectively (see equations (1) through (4)).

Table 6A

Herding and Feedback Estimates using Permanent Conditional Volatility Component

Cryptocurrency	Base Model				Extended Model				
	b_0	b_1	b_2	b_3	b_0	b_1	b_2	b_3	b_4
1. Polkadot	-0.0850 (-0.295)	0.0025 (0.438)	0.0296 (0.628)	-0.9280** (-2.762)	-0.2018 (-0.661)	-0.0026 (-0.356)	0.0279 (0.592)	-0.9150** (-2.722)	0.0668 (1.135)
2. Solana	-1.4738 (-1.892)	0.0317** (2.531)	0.2769** (2.543)	-4.6099** (-3.198)	-1.5055 (-1.932)	0.0275** (2.097)	0.2755** (2.530)	-4.6060** (-3.196)	0.0511 (1.111)
3. Cardano	-0.5445** (-2.892)	0.0202** (6.144)	0.0421 (1.557)	-0.4667** (-5.799)	-0.9532** (-4.542)	0.0121** (3.228)	0.0390 (1.448)	-0.5218** (-6.433)	0.1612** (4.332)
4. Ripple	-0.0931 (-0.700)	0.0042** (2.550)	0.1341** (6.204)	-0.5481** (-10.113)	-0.3019** (-2.147)	-0.0001 (-0.113)	0.1274** (5.898)	-0.5792** (-10.628)	0.1117** (4.438)
5. Avalanche	0.0260 (0.083)	0.0023 (0.434)	0.0535 (0.958)	-0.3439** (-2.576)	-0.0614 (-0.202)	0.0003 (0.044)	0.0538 (0.961)	-0.3561** (-2.536)	0.0397 (0.665)
6. Tron	-0.0133 (-0.074)	0.0031** (2.220)	0.0098 (0.306)	-0.0474 (-0.584)	-0.5639** (-2.815)	-0.0015 (-0.979)	0.0175 (0.549)	-0.1813** (-2.171)	0.2018** (6.022)
7. EOS	0.0687 (0.323)	-0.0026 (-0.799)	0.0291 (0.833)	-0.7054** (-3.058)	0.0067 (0.030)	-0.0055 (-1.389)	0.0286 (0.820)	-0.7014** (-3.041)	0.0451 (1.301)
8. Algorand	-0.1066 (-0.433)	0.0003 (0.085)	-0.0492 (-1.407)	-0.0661 (-0.507)	-0.2527 (-0.939)	-0.0029 (-0.669)	-0.0498 (-1.426)	-0.0468 (-0.356)	0.0649 (1.331)
9. Tezos	-0.2900 (-1.274)	0.0064 (1.540)	0.0238 (0.729)	-0.8806** (-4.069)	-0.3794 (-1.599)	0.0031 (0.637)	0.0211 (0.644)	-0.8324** (-3.794)	0.0527 (1.329)
10. Bitcoin Green	-0.0526 (-0.128)	-0.0014 (-1.133)	-0.2018** (-6.881)	-0.0103 (-0.670)	-0.2004 (-0.322)	-0.0034 (-1.488)	-0.2025** (-6.330)	-0.0107 (-0.568)	0.0703 (1.129)

Notes: This table reports maximum likelihood estimates for the herding and feedback models in equations (10A) and (10B), respectively, for the sampled cryptocurrencies used in this study. The conditional variance is estimated using the permanent volatility components of each of the respective cryptocurrencies using the CGARCH (see equations (12) through (14)). While equation (10A) is the "base model," equation (10B) is the "extended model" and allows for the testing of asymmetric feedback effects (i.e. whether lagged negative returns amplify the behaviors of herding traders). For illustrative purposes, the coefficient b_3 (for both the "base model" and "extended model") is dilated by a factor of 10^3 (i.e. $b_3 * 10^3$). Parentheses show t-statistics whereas (*) and (**) denote significance at the 10% and 5% levels, respectively.

Table 6B

Herding and Feedback Estimates using Total Conditional Volatility

Cryptocurrency	Base Model				Extended Model				
	b_0	b_1	b_2	b_3	b_0	b_1	b_2	b_3	b_4
1. Polkadot	-0.0636 (-0.184)	0.0020 (0.234)	0.0435 (0.853)	-1.4624** (-2.754)	-0.1218 (-0.350)	-0.0065 (-0.592)	0.0411 (0.806)	-1.4377** (-2.707)	0.0746 (1.277)
2. Solana	0.0500 (0.131)	0.0048 (1.014)	0.0717 (1.526)	-0.7370** (-3.522)	0.0317 (0.082)	0.0036 (0.551)	0.0700 (1.474)	-0.7299** (-3.460)	0.0168 (0.268)
3. Cardano	-0.5414** (-2.879)	0.0201** (6.132)	0.0402 (1.489)	-0.4430** (-5.716)	-0.9452** (-4.501)	0.0121** (3.231)	0.0363 (1.352)	-0.4877** (-6.262)	0.1591** (4.247)
4. Ripple	-0.0092 (-0.079)	0.0025** (2.595)	0.1131** (5.694)	-0.1742** (-10.972)	-0.3926** (-2.866)	-0.0030** (-2.123)	0.1012** (5.085)	-0.1684** (-10.623)	0.1682** (5.313)
5. Avalanche	0.0771 (0.239)	0.0013 (0.254)	0.0567 (1.045)	-0.4327** (-2.947)	-0.0390 (-0.121)	-0.0003 (-0.058)	0.0588 (1.073)	-0.4661** (-2.871)	0.0424 (0.805)
6. Tron	-0.2134 (-1.206)	0.0071** (4.760)	0.0014 (0.049)	-0.0582 (-1.477)	-0.5963** (-2.967)	0.0020 (1.018)	0.0010 (0.036)	-0.0716* (-1.817)	0.1610** (3.964)
7. EOS	0.0425 (0.209)	-0.0020 (-0.684)	0.0284 (0.852)	-0.5769** (-3.280)	-0.0187 (-0.090)	-0.0057 (-1.416)	0.0284 (0.855)	-0.5779** (-3.286)	0.0522 (1.376)
8. Algorand	0.0284 (0.120)	-0.0026 (-0.789)	-0.0320 (-0.867)	-0.2333 (-1.201)	-0.1657 (-0.614)	-0.0049 (-1.340)	-0.0357 (-0.964)	-0.1638 (-0.820)	0.0655 (1.500)
9. Tezos	-0.2047 (-0.980)	0.0043 (1.207)	0.0105 (0.346)	-0.5586** (-3.979)	-0.2941 (-1.331)	0.0008 (0.177)	0.0094 (0.308)	-0.5409** (-3.834)	0.0543 (1.238)
10. Bitcoin Green	-0.4298 (-1.172)	0.0004 (0.445)	-0.1928** (-6.815)	-0.0139 (-1.493)	-0.5043 (-1.276)	-0.0001 (-0.115)	-0.1942** (-6.831)	-0.0126 (-1.296)	0.0245 (0.508)

Notes: This table reports maximum likelihood estimates for the herding and feedback models in equations (10A) and (10B), respectively, for the sampled cryptocurrencies used in this study. The conditional variance is estimated using the total volatility components of each of the respective cryptocurrencies using the CGARCH (see equations (12) through (14)). While equation (10A) is the "base model," equation (10B) is the "extended model" and allows for the testing of asymmetric feedback effects (i.e. whether lagged negative returns amplify the behaviors of herding traders). For illustrative purposes, the coefficient b_3 (for both the "base model" and "extended model") is dilated by a factor of 10^3 (i.e. $b_3 * 10^3$). Parentheses show t-statistics whereas (*) and (**) denote significance at the 10% and 5% levels, respectively.

Table 7A

Herding and Feedback Estimates in the Presence of Bitcoin Crash Risk using the Permanent Conditional Volatility Component

Cryptocurrency	$b_{0,D}$	$b_{0,ND}$	$b_{1,D}$	$b_{1,ND}$	$b_{2,D}$	$b_{2,ND}$	$b_{3,D}$	$b_{3,ND}$
1. Polkadot	-0.5106 (-1.148)	-0.0806 (-0.210)	0.0240** (2.560)	-0.0055 (-0.723)	-0.1164 (-1.402)	0.0323 (0.495)	1.8100* (1.909)	-1.1720** (-3.126)
2. Solana	-1.3852 (-1.174)	-2.1990** (-1.969)	0.0278 (1.507)	0.0438** (2.405)	0.0317 (0.187)	0.5192** (3.415)	-1.6340 (-0.737)	-7.4830** (-3.736)
3. Cardano	-0.5095 (-1.001)	-0.3512 (-0.729)	0.0201 (1.389)	0.0167 (1.115)	-0.1168 (-1.362)	0.2226** (2.683)	0.6500 (0.493)	-4.3990** (-3.622)
4. Ripple	0.2165 (0.515)	-0.0430 (-0.108)	0.0063 (0.967)	-0.0060 (-0.847)	0.1589** (2.083)	-0.0086 (-0.105)	-1.0410** (-2.295)	-0.2680 (-0.486)
5. Avalanche	0.3288 (0.674)	-0.2986 (-0.611)	0.0036 (0.643)	0.0017 (0.271)	0.0308 (0.489)	0.0751 (0.983)	-0.3750* (1.683)	-0.2580 (-0.624)
6. Tron	0.3390 (0.965)	0.2621 (0.790)	0.0015 (0.153)	-0.0144 (-1.461)	-0.1668* (-1.879)	0.0372 (0.477)	1.2480 (0.853)	-2.7230** (-2.628)
7. EOS	0.4857 (1.260)	0.1332 (0.385)	-0.0040 (-0.579)	-0.0173** (-2.851)	-0.1750** (-2.444)	0.0937 (1.475)	0.5490 (0.500)	-1.3820** (-4.664)
8. Algorand	-0.3061 (-0.691)	0.4155 (0.950)	0.0134* (1.803)	-0.0180** (-2.223)	-0.1307** (-2.018)	0.0605 (0.827)	0.2940 (0.723)	-1.3820** (-2.380)
9. Tezos	-0.2134 (-0.393)	-0.0502 (-0.105)	0.0096 (0.845)	-0.0081 (-0.777)	-0.2509** (-2.807)	0.0634 (0.902)	2.4270** (2.068)	-1.3950** (-2.447)
10. Bitcoin Green	0.1783 (0.208)	1.2059 (1.333)	-0.0022 (-1.030)	-0.0067** (-2.451)	-0.1022* (-1.737)	-0.2259** (-2.865)	-0.0126 (-0.573)	-0.0562 (-0.710)

Notes: This table reports maximum likelihood estimates for the herding and feedback model in equation (18) for the sampled cryptocurrencies used in this study. These regression estimates, unlike the estimates shown in Tables 6A and 6B, incorporate bitcoin's option-implied skewness (equation (17)). The conditional variance is estimated using the permanent volatility components of each of the respective cryptocurrencies using the CGARCH (see equations (12) through (14)). The sample range used for this table spans from July 1, 2020 until March 4, 2023 (with the exception of DOT and AVAX, which begin on September 2, 2020 and September 22, 2020, respectively). Both these coins' ranges, however, like all the other sampled ESG coins, end on March 4, 2023. For illustrative purposes, the coefficient b_3 (for both the "base model" and "extended model") is dilated by a factor of 10^3 (i.e. $b_3 * 10^3$). Parentheses show t-statistics whereas (*) and (**) denote significance at the 10% and 5% levels, respectively.

Table 7B

Herding and Feedback Estimates in the Presence of Bitcoin Crash Risk using Total Conditional Volatility

Cryptocurrency	$b_{0,D}$	$b_{0,ND}$	$b_{1,D}$	$b_{1,ND}$	$b_{2,D}$	$b_{2,ND}$	$b_{3,D}$	$b_{3,ND}$
1. Polkadot	-0.5536 (-1.035)	-0.0487 (-0.106)	0.0280** (2.000)	-0.0071 (-0.597)	-0.1160 (-1.263)	0.0498 (0.716)	2.2810* (1.620)	-1.8680** (-3.130)
2. Solana	0.3180 (0.576)	-0.4050 (-0.729)	-0.0005 (-0.084)	0.0123* (1.647)	0.0273 (0.411)	0.1403* (1.943)	-0.5780** (-2.214)	-1.0520** (-2.829)
3. Cardano	-0.5705 (-1.140)	-0.3660 (-0.764)	0.0217 (1.548)	0.0171 (1.141)	-0.1358 (-1.600)	0.2166** (2.616)	0.9480 (0.748)	-4.2040** (-3.551)
4. Ripple	0.1580 (0.456)	-0.3609 (-1.117)	0.0078* (1.839)	0.0023 (0.509)	0.1191* (1.939)	-0.0336 (-0.502)	-0.2770** (-2.015)	-0.0790 (-0.418)
5. Avalanche	0.3266 (0.674)	-0.1521 (-0.313)	0.0035 (0.653)	-0.0008 (-0.135)	0.0373 (0.570)	0.0669 (0.840)	-0.4900* (-1.717)	-0.2450 (-0.471)
6. Tron	0.4002 (1.302)	0.0281 (0.099)	-0.0007 (-0.087)	-0.0050 (-0.690)	-0.1027 (-1.450)	-0.0003 (-0.005)	0.0246 (0.045)	-1.0710** (-2.764)
7. EOS	0.4118 (1.077)	0.0215 (0.066)	-0.0021 (-0.301)	-0.0141** (-2.688)	-0.1969** (-2.619)	0.0812 (1.305)	0.7820 (0.997)	-1.0390** (-4.539)
8. Algorand	-0.2940 (-0.668)	0.4090 (0.973)	0.0141* (1.887)	-0.0167* (-2.311)	-0.0525 (-0.801)	0.0403 (0.551)	-0.3680 (-0.739)	-1.2760* (-1.904)
9. Tezos	-0.2616 (-0.550)	-0.0862 (-0.209)	0.0107 (1.144)	-0.0074 (-0.883)	-0.2138** (-2.681)	0.0474 (0.741)	1.5140* (1.866)	-0.9390** (-2.555)
10. Bitcoin Green	-0.1477 (-0.188)	0.6554 (0.803)	-0.0008 (-0.499)	-0.0044* (-1.939)	-0.0962* (-1.677)	-0.2158** (-2.877)	-0.0096 (-0.678)	-0.0426 (-0.842)

Notes: This table reports maximum likelihood estimates for the herding and feedback model in equation (18) for the sampled cryptocurrencies used in this study. These regression estimates, unlike the estimates shown in Tables 6A and 6B, incorporate bitcoin's option-implied skewness (equation (17)). The conditional variance is estimated using the total volatility of each of the respective cryptocurrencies using the CGARCH (see equations (12) through (14)). The sample range used for this table spans from July 1, 2020 until March 4, 2023 (with the exception of DOT and AVAX, which begin on September 2, 2020 and September 22, 2020, respectively). Both these coins' ranges, however, like all the other sampled ESG coins, end on March 4, 2023. For illustrative purposes, the coefficient b_3 (for both the "base model" and "extended model") is dilated by a factor of 10^3 (i.e. $b_3 * 10^3$). Parentheses show t-statistics whereas (*) and (**) denote significance at the 10% and 5% levels, respectively.