

From Environmental Concerns to Market Moves: How Environmental Awareness Shapes Cryptocurrency Returns?

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Abstract

Environmental concerns may influence cryptocurrency prices. Investors' information acquisition regarding environmental issues linked to cryptocurrency mining plays an important role in the pricing of cryptocurrencies. The volume of Google searches for environmental issues related to cryptocurrency mining significantly and negatively affects future cryptocurrency returns. This impact is more pronounced for Proof-of-Work (PoW) cryptocurrencies, which are known for their high energy consumption, compared to Proof-of-Stake (PoS) cryptocurrencies. This study provides important insights into how environmental awareness influences cryptocurrency markets, offering a novel perspective on market prices in the context of sustainability.

Keywords: Cryptocurrency; Environmental Concerns; Google Trends; Information Gathering; Investor Attention

1. Introduction

Non-financial factors, such as environmental concerns, have gained significant attention in the recent investment decision-making process. Growing concerns over the environmental impact of cryptocurrency mining have led environmentally conscious investors to reassess their investment in the crypto market. Elon Musk suspended Tesla vehicle purchases using Bitcoin, citing environmental concerns,² while Sen. Ed Markey drew a parallel between

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² In May 2021, Tesla's CEO Elon Musk announced the suspension of Bitcoin as a payment method for purchasing Tesla vehicles. Musk cited the need for Bitcoin mining to shift towards more sustainable energy sources as one of the

Bitcoin and “digital coal” rather than “digital gold” (C-SPAN, 2022). Furthermore, Treasury Secretary Janet Yellen expressed concerns about the energy consumption of crypto mining and illicit finance facilitated through cryptocurrencies.³ In early 2024, the cryptocurrency markets experienced a notable rally, with Bitcoin surging to unprecedented levels. This phenomenon has captured the attention of investors and market analysts. Against this backdrop, understanding the role of investor attention and its impact on cryptocurrency returns has become increasingly important. This paper aims to examine the impact of investors' environmental concerns on the cryptocurrency market.

To examine how investors' environmental concerns influence the cryptocurrency market, it is important to first measure the public's level of environmental concern over time. Traditional methods to measure investor sentiment often rely on surveys. For example, government agencies often resort to polling to assess public opinions, but the need for representative samples makes it challenging and costly to conduct frequent surveys necessary to capture timely changes in public opinion (Brown, 1999; Fisher and Statman, 2000). Measuring public concerns is a challenging issue, especially in an era where vast volumes of information consume the attention of its recipients, resulting in attention scarcity. In fact, these huge information piles can hinder even computer programs. In the case of ChatGPT, or any generative pre-trained transformer, the program needs to be trained on a large dataset of text conversations, which could be time-consuming. In the financial field, gathering information can shed light on investor attention and concerns. Goetzmann (2022) emphasizes the need to understand how investors gather information about corporate behavior. Researchers have also navigated vast information volumes to measure investor attention. (Ben-Rephael et al., 2017; Wang, 2017; Bajo et al., 2016). Brown (1999) utilizes data from the American Association of Individual Investors (AAII) Sentiment Survey and discovers that unusual levels of investor sentiment are associated with increased volatility in closed-end investment funds. Fisher and Statman (2000) also leverage the AAI survey data and find a negative relationship between investor sentiment and future stock returns. Outside academia, government agencies and institutions often resort to polling and surveys to assess public opinions, but the need for representative samples makes it challenging and costly to conduct frequent surveys necessary to capture timely changes in public opinion.

Given the difficulties in identifying individual concerns and opinions on issues of interest, we propose a methodology to improve the precision of measuring public attention and its direction. Our methodology aligns with the ideas described in Vaswani et al. (2017) and Szczygielski et al. (2024). In our study, we explore how different search term combinations, like "environment" and "crypto," reflect investor concerns about cryptocurrencies. By analyzing various combinations such as "environment" and "green" with "crypto," we construct a composite index of search trends. This index captures investor concerns, and we show that the index has a significant impact on future cryptocurrency returns. Our findings suggest that environmental concerns linked to cryptocurrencies are a strong predictor of their market performance.

reasons for this decision. To view his announcement, see <https://twitter.com/elonmusk/status/1392602041025843203/photo/1>.

³ “It’s an extremely inefficient way of conducting transactions, and the amount of energy that’s consumed in processing those transactions is staggering,” said Janet Yellen, the Treasury Secretary. Previously, Yellen had shown support for environmentally-conscious measures, including the implementation of a carbon tax. For her detailed comments, see <https://www.nytimes.com/2021/02/23/business/dealbook/janet-yellen-dealbook.html>.

This study contributes to the literature in two important ways. First, to the best of our knowledge, this paper is the first to explore the impact of environmental concerns on cryptocurrency mining using Google Trends data, a topic previously unaddressed in the literature. Despite scholars' long-standing debates about cryptocurrencies' sustainability and volatility, discussions regarding a measure for the public's opinion on sustainability topics and how this measure can forecast cryptocurrency returns remain limited. In the wake of the recent rally in Bitcoin's price, which has pushed it to record highs, the financial stakes associated with cryptocurrency investments have significantly increased. This rally highlights the important need to understand how external factors can impact cryptocurrency prices. Our study introduces an innovative measure that can likely forecast movements in the cryptocurrency market, offering potential economic benefits.

Second, our paper proposes that the combination of search terms and a composite index based on these combinations can accurately measure public opinion and attention in a timely and cost-effective manner. Prior research on investors' information-gathering efforts using Google Trends data has relied on search keywords chosen in a somewhat arbitrary manner, lacking a systematic methodology for selecting among numerous potential search term candidates. Our research adopts a more structured approach to refine the search term selection process. Additionally, our method for measuring investor opinions with enhanced accuracy through a composite index of search trends can be extended to study other markets, including stocks, bonds, and real estate. Policymakers can also use our method, employing search term combinations and composite indices developed in this paper, to identify potential market crashes early.

The remainder of the paper is organized as follows. Section 2 describes the background, the literature review, and the hypotheses. Section 3 discusses the data. Sections 4 and 5 describe the empirical strategy and the empirical results. Section 6 explores the implications of our findings and suggests directions for future research. We conclude in Section 7.

2. Background, Literature, and Hypotheses

2.1. Crypto Mining and Costs

Cryptocurrency mining is the process of verifying groups of transactions and combining them into blocks using blockchain technology.⁴ This blockchain is a distributed public ledger of transaction blocks that are duplicated across the entire network. To safeguard data, information from previous blocks is hashed using mathematical algorithms. Bitcoin mining, in particular, employs the double SHA-256 hash function in cryptography to execute its proof of work (PoW). While the double SHA-256 hash function is a computationally intensive technique, it is easy to verify and helps to prevent tampering with blocks in the chain. To draw an analogy, many Bitcoin miners attempt to solve a complex mathematical puzzle simultaneously. Approximately every 10 minutes, one miner successfully solves the puzzle, produces a valid block, and adds it to the Bitcoin blockchain. The miner who successfully solves the puzzle is then credited a certain amount of Bitcoin for their contribution, and a new cycle begins. The built-in Bitcoin protocol regularly adjusts puzzle difficulty to maintain a

⁴ To view the current mined blocks, see this link: <https://www.blockchain.com/btc/blocks>.

consistent interval between block creation in the blockchain. The whole process of solving these puzzles and adding new blocks is known as PoW.⁵

However, due to its growing popularity and public attention, Bitcoin has become increasingly associated with significant energy consumption and a large carbon footprint from its mining (Edwards et al., 2019). According to the Cambridge Bitcoin Electricity Consumption Index (CBECI), using the hash rate of May 2021, Bitcoin miners are estimated to consume 114.56 terawatt-hours (TWh) of energy annually. To put this into perspective, it is equivalent to about 3% of the annual electricity consumption in the United States and exceeds the 93.35 terawatt-hours consumed by the Philippines, which has a population of over 108 million. Other cryptocurrencies, such as Ethereum and Litecoin, add an additional 50% to the energy consumption of Bitcoin (de Vries, 2021). Assuming an implied carbon intensity of 500 grams of CO₂ per kilowatt-hour for Bitcoin mining (Stoll et al., 2019), the energy consumption of 114.56 terawatt-hours is equivalent to a carbon footprint of over 57 million metric tons of CO₂. Further, other payment systems use far less energy and emit far less greenhouse gas. A 2021 IMF report states that a single Bitcoin transaction may emit as much carbon as 1.8 million Visa transactions (International Monetary Fund, 2021). More recent data confirm that the discrepancy in energy efficiency still exists. Table A1 compares the energy consumption per transaction and daily transaction volumes between Bitcoin and Visa. The disparity in energy efficiency persists, as shown in more recent data. Bitcoin consumes 567.4 kWh per transaction, processing 255,757 transactions daily as of December 2022 (Blockchain.com, 2022). In stark contrast, Visa transactions require just 0.0015 kWh each while handling 528.76 million transactions daily, according to Visa's 2022 report (Visa Inc., 2022, 2023). This comparison underscores Bitcoin's significant energy usage and carbon footprint, highlighting the environmental inefficiency of PoW mechanisms relative to traditional financial systems. Last but not least, the ever-increasing crypto mining activities have caused global chip shortages, while broken specialized mining equipment adds to global waste.

Cryptocurrency mining is an energy-intensive process. Miners must make repeated attempts (hashes) to find the right value for the nonce, a critical block component, in order to produce a valid hash value. A valid hash value must be less than the set target, which begins with n leading zeros, with the number of leading zeros determining the mining difficulty. For instance, when the mining difficulty is set at $n=40$, up to 2^{40} attempts may be required to find the right PoW. There are no shortcuts to solving the mining puzzle other than trying random values, or in other words, the fastest solution that we know of is by brute force. Miners attempt as many different hashes as possible in a short amount of time until they find a value that is valid. The mining difficulty changes with the collective hash rate of the mining network, which is a measure of the computational power of a blockchain network. The number of hashes per second that a mining equipment's hash rate specifies is linked to energy consumption. As computing hardware becomes more powerful or the number of miners increases, mining difficulty adjusts automatically, maintaining an average block time of 10 minutes. Similarly, if many miners quit mining at once, the difficulty of the puzzle decreases to match the new hash rate. In May 2021, the total estimated Bitcoin hash rate surpassed 100 billion terahashes per

⁵ Although an important design parameter, the 10-minute time span between block creation is selected arbitrarily in Satoshi's white paper. However, longer or shorter time spans have their advantages and disadvantages, and as a result, some altcoins have been created with different time spans. For an insightful discussion, see <https://bitcointalk.org/index.php?topic=79837.0>.

10-minute block.⁶ Given the significant environmental concerns regarding Bitcoin mining, investors are debating how to balance the potential economic profits of investing in Bitcoin with the environmental damage caused by its transactions. Cryptocurrencies can switch from energy-intensive PoW protocols to more energy-friendly proof of stake (PoS) protocols. For example, on September 15, 2022, Ethereum completed the “Merge” that cut energy use by 99.95% according to the Ethereum Foundation. The Ethereum network has completed its transition from the PoW consensus mechanism to the PoS mechanism, aiming to address concerns about the high energy consumption associated with PoW mining. The migration to a less energy-intensive system in 2022 aims to boost network adoption and differentiate it from the energy-intensive Bitcoin. However, the Bitcoin community remains steadfast on the PoW protocols.

2.2. Measuring Investors’ Concerns Using Search Volume Data

The existing literature employs various methods to measure opinions and sentiment. For example, Jiang, Lee, Martin, and Zhou (2019) construct a managerial sentiment index based on the aggregated textual tone found in corporate financial disclosures. Their findings indicate that managerial sentiment serves as a negative predictor of future aggregate stock market returns. Serafeim (2020) uses a measure of public sentiment momentum around corporate sustainability issues, derived by TruValue Labs from various platforms, including NGOs and media, and finds that the valuation premium for a company's sustainability performance increases with positive public sentiment momentum. Our research takes the importance of public sentiment as suggested by Serafeim (2020) a step further by emphasizing the role it plays not only in traditional markets but also in the emerging digital asset sector. Furthermore, our results also underscore Serafeim (2020)'s finding that negative public sentiment increases a company’s perceived risk, leading to a greater discount rate for the company. In the context of cryptocurrencies, we find that negative investor sentiment regarding environmental issues can lead to significant price drops. Thus, our approach extends the use of public sentiment analysis to a wider range of financial assets.

In this study, we leverage Google Trends data to measure investors' environmental concerns, as it reflects their information-gathering efforts. Google Trends serves as a reliable measure of public engagement with a subject, given its status as one of the most widely used search engines worldwide and its extensive repository of publicly accessible data from a diverse array of sources. One shortcoming of the Google Trend data is that the value is a normalized value and is not the raw search volumes performed for each query; raw search volumes would be misleading given Google’s increased popularity over time. That is to say, the Google Trends data is computed by comparing the number of searches relative to all searches in the same region and time period, then the data is normalized so that the highest value is 100, and all other values are scaled relative to the highest value. In short, Google combines all of the search volume data into a single measure of popularity. According to Google Trends FAQs: “Each data point is divided by the total searches of the geography and time range it represents to compare relative popularity. The resulting numbers are then scaled on a range of 0 to 100 based on a topic’s proportion to all searches on all topics.”

⁶ The Total Hash Rate (TH/s) is an estimate of the number of terahashes per second that the Bitcoin network has executed within the past 24 hours. For the most updated hash rate, see <https://www.blockchain.com/charts/hash-rate>.

Numerous academic studies have examined investors' information-gathering efforts using Google Trends data. Search engine data has been employed to forecast general economic indicators (McLaren and Shanbhogue, 2011) and housing market trends (Wu and Brynjolfsson, 2009). More specifically, Da et al. (2011) introduce a novel measure of investor attention by utilizing search frequency in the Google Search Volume Index (SVI). They find that an increase in SVI predicts higher stock prices within the subsequent two weeks, followed by a price reversal within the year. Search trends data have also been used to forecast general economic indicators (McLaren and Shanbhogue, 2011) and housing market trends (Wu and Brynjolfsson, 2009). Da et al. (2015) analyze daily Internet search volume from households related to concerns such as "recession," "unemployment," and "bankruptcy" to reveal the level of investor sentiment. Their sentiment measure predicts short-term return reversals, volatility, and mutual fund flows. Preis et al. (2013) examine a set of 98 search terms such as "debt," "stock," and "inflation," associated with financial markets. They find that strategies based on search volume data outperform random strategies in returns. Kristoufek (2013) uses data from Google Trends and Wikipedia to identify a positive connection between search queries and the bubble and bust cycles of Bitcoin prices, suggesting that the pool of Google search users partially overlaps with the pool of Bitcoin investors. Garcia et al. (2014) study Bitcoin bubbles using search queries and social media data as proxies for the digital behaviour of investors and find positive feedback loops between social media use and the user base.

2.3. The Impacts of Environmental Concerns and Hypothesis

In this section, we develop our hypothesis. Environmental concerns have gained attention due to growing worries about climate change and shifting investor preferences. The investment management industry has increasingly adopted sustainability criteria for screening potential investments. Recent academic literature shows that sustainable stocks outperform traditional ones and that firms with higher corporate social responsibility (CSR) ratings enjoy a lower cost of capital (Ghoul et al., 2011). Fulton et al. (2012) suggest that firms that prioritize reducing their environmental impact are associated with higher risk-adjusted returns and benefit from a lower cost of capital, suggesting that the market views these sustainable companies as low risk. Krüger (2015) highlights investor reactions to positive CSR-related news, particularly those concerning legal or economic-related events. Eccles et al. (2014) find that high-sustainability companies outperformed their counterparts in the long run.

As environmental concerns grow, a key question arises: Could these worries influence cryptocurrency prices? The energy-intensive nature of crypto mining has alarmed investors and regulators alike. Given this, one might expect that heightened focus on environmental issues could lead to "negative investor attention" and potentially drive down cryptocurrency values. Research conducted by Liu and Tsyvinski (2021) and Sockin and Xiong (2023) documents that elevated levels of negative investor attention tend to predict a downturn in future cumulative coin market returns. This aligns with a theoretical model proposed by Cong et al. (2019). They argue that the equilibrium market value of cryptocurrencies is determined by the aggregate demand from heterogeneous users, which is analyzed using a dynamic asset-pricing model. Consequently, we propose the following hypothesis:

Hypothesis 1: Environmental concerns have a negative impact on cryptocurrency returns.

In examining the relationship between environmental concerns and cryptocurrency returns, we also investigate the magnitude of this impact across different cryptocurrencies. Blockchain technology encounters obstacles to expansion due to high energy consumption and scalability issues. To address these challenges, researchers suggest adopting energy-efficient methods, such as PoS, as opposed to the more energy-intensive PoW. While PoW provides greater security, PoS offers a more environmentally friendly and energy-efficient alternative by requiring participants to stake cryptocurrency as collateral, thereby eliminating the need for complex calculations. The energy-intensive process required to mine cryptocurrencies like Bitcoin has long been a point of concern, and some in the blockchain industry think they have a solution: Proof of Stake. This new method of blockchain verification ensures trustworthiness without the need for energy-intensive hardware. The system is already in use by some cryptocurrencies and could potentially lead to greater adoption of the technology due to its energy efficiency. PoS consumes considerably less energy, sometimes up to 99.99% less. As a result, we expect that environmental concerns, as measured by Google Trends searches, will have a greater impact on PoW-based cryptocurrencies.

Hypothesis 2: Environmental concerns have a greater impact on the returns of PoW-based cryptocurrencies relative to non-PoW-based cryptocurrencies.

3. Data

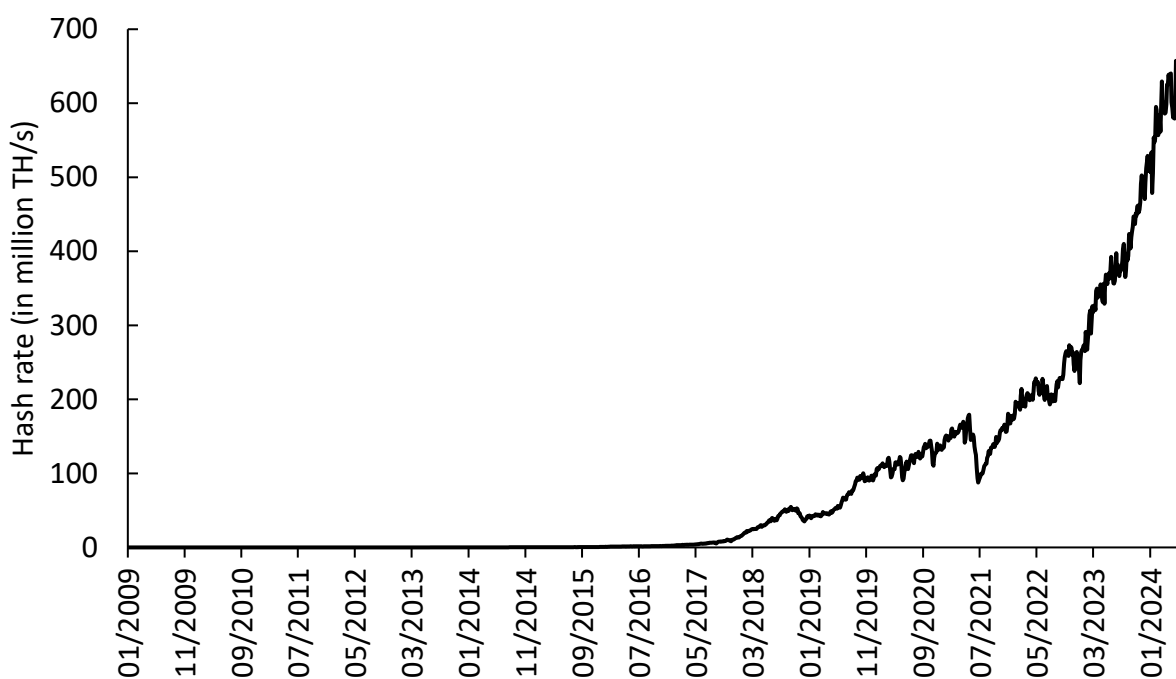
We collect pricing data for the top 20 cryptocurrencies, including Bitcoin and Ethereum, based on market capitalization, from CoinMarketCap.com. The data obtained includes the date, prices (open, close, high, low), trading volume, and market capitalization. Note that exchanges that are not regulated tend to have more fake volume (Jain et al., 2019). To identify the level of public attention and concerns surrounding cryptocurrencies and their impact on the environment, we retrieve worldwide search trend data on some basic search terms: “bitcoin,” “ethereum,” and “esg” using Google Trends (from <https://trends.google.com/>). Additionally, to capture and analyze the public attention and sentiments related to the environment and cryptocurrencies more precisely, we retrieve worldwide search trend data on other variations of the search term “environment crypto”, which include “environmental crypto”, “carbon crypto”, “green crypto”, “energy crypto”, “social crypto”, “governance crypto”, “pollution crypto”, “emissions crypto”, and “emission crypto.” We collect data on the search term “social crypto” because social issues intersect with environmental concerns, especially in PoW cryptocurrencies. For example, the social implications of mining activities, such as how energy consumption contributes to the unequal allocation of resources globally, can impact investor sentiment. We retrieved the weekly data on July 14, 2024, for an eight-year period from July 2016 to July 2024.

4. Analysis of Energy Consumption and Revenue in Bitcoin Mining

As mainstream financial institutions turn their attention to virtual assets, they are concerned with the cryptocurrency industry’s environmental impact. To estimate the energy consumed by Bitcoin mining, we look at the hash rate, which is the number of calculations per second that can be performed during mining. The hash rate is directly linked to the computational power used to mine Bitcoin and process transactions. Figure 1 illustrates the estimated number of terahashes per second on the Bitcoin network from January 2009 to July

2024. As of July 2024, the average hash rate on the Bitcoin mining network is around 600 million terahashes per second. The spikes in 2021 and 2024 coincided with the Bitcoin price run-ups during those periods. As Bitcoin mining becomes more profitable, there is typically an increase in mining activity, resulting in a higher hashrate.

Figure 1. Daily Bitcoin mining hash rate



We further examine the energy requirements of the hardware used by Bitcoin miners and provide a summary of the computing capability and power consumption of three different Bitcoin miners in Table 1. For example, the Bitmain Antminer S19j Pro can achieve a performance of up to 104 terahashes per second while consuming approximately 3,068 watts of power. Assuming all mining activities were conducted using the Antminer S19j Pro, the estimated annual energy consumption would be around 26.0 terawatt-hour. Considering the less efficient legacy mining hardware and assuming that they can achieve only a quarter of the efficiency of the latest generation of hardware, the estimated annual energy consumption would be comparable to the power consumption of Sweden.

Determining the amount of carbon emissions associated with Bitcoin mining is a complicated task. While household and industrial energy consumption requires proximity to power plants, Bitcoin can be mined anywhere. Bitcoin miners are not bound by locations, and they have the flexibility to use power sources that are untenable for most other applications. The profitability of Bitcoin mining has led to increased investment in renewable energy sources such as hydro-power and solar, making them more efficient and practical for mining. The Cambridge Centre for Alternative Finance (CCAF) estimated that 39% of Bitcoin's energy consumption was carbon neutral in 2020. To one extreme, Song and Aste (2020) argue that the energy costs of Bitcoin mining have never really increased, while Das and Dutta (2020) find a

significant negative relationship between Bitcoin's energy consumption and miners' revenue, especially during periods of low or volatile miners' revenues.

Table 1. Bitcoin mining gigs and power consumption

We obtain mining hardware data from <https://www.asicminervalue.com/miners/>. To calculate annualized energy consumption, we use the hash rate as of July 15, 2021, to determine maximum energy usage. Country-level annual energy consumption data is from Statista for the year 2021.

Panel A. Crypto-mining energy consumption				
Mining Model	Release date	Hashrate	Power consumption	Annualized energy consumption if Bitcoin is mined using this model.
		up to 104 TH/s		26.0 terawatt-hours
Antminer S19j Pro	Q3, 2021	TH/s	~3,068 W	
Avalonminer 1246	Q1, 2021	up to 90 TH/s	~3,420 W	33.5 terawatt-hours
Whatsminer M31S+	Q4, 2020	up to 80 TH/s	~3,360 W	37.1 terawatt-hours
Panel B. Country energy consumption				
				177 terawatt-hours
Sweden				
USA				3,930 terawatt-hours

Bitcoin miners earned an average of \$46 million per day in December 2021. Approximately 98.5% of the revenue was in the form of Bitcoins earned per block, and 1.5% in processing fees. Kaiser and Stöckl (2020) document herding behavior as a factor in explaining price bubbles of the cryptocurrency market, with increased miner revenue attracting new miners and investments to the Bitcoin mining industry. Cong et al. (2021) model decentralized mining in centralized pools and find that while centralized mining increases energy consumption, it does not undermine the decentralization required for public blockchains. The diversification of individual miners across pools and the endogenous fees charged by pools generally sustain decentralization, while larger pools are better at internalizing their externality on global hash rates, charge higher fees, and attract fewer miners, resulting in slower growth. Risk sharing leads to the rise of mining pools, but not necessarily further consolidations of pools (hence over-concentration).

5. The Impact of Information Acquisition on Cryptocurrency Returns

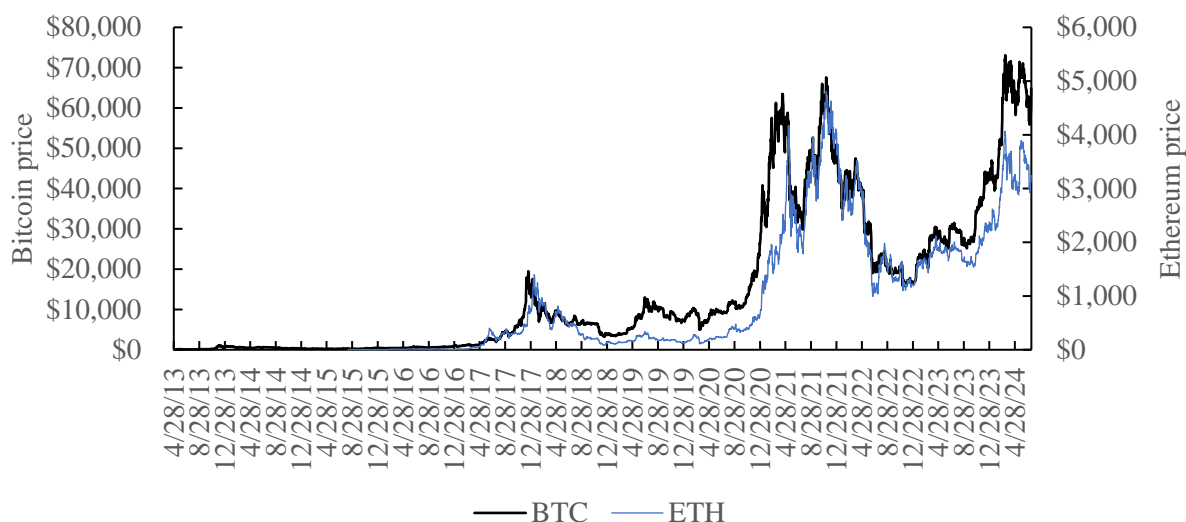
5.1. Graphical Analysis

This section investigates the impact of information acquisition on cryptocurrency returns, focusing on the environmental concerns as reflected by Google Trends data. Figure 2 (a) shows that Bitcoin price peaks generally precede those of Ethereum. The first significant peak in Bitcoin prices occurred on December 16, 2017, at \$19,497.40, followed by a months-long decline before another rise in December 2020, culminating in another peak of \$63,503.46

on April 13, 2021. Ethereum's first major price peak, at \$1,396.42, happened on January 14, 2018, nearly a month after Bitcoin's December 2017 peak. This price also declined for several months before rising alongside Bitcoin in December 2020 and peaking once more at \$4,168.7 on May 11, 2021, roughly a month after Bitcoin's April 2021 peak.

Figure 2. Google search trends over time for crypto and environmental issues

(a) Bitcoin and Ethereum historical prices



5.2. Main Empirical Analysis

5.2.1. Screening of Keywords and the Construction of a Composite Index

Recognizing that users have diverse preferences when choosing keywords to express their views on a particular topic, we aim to develop a composite variable that offers greater predictive power than individual search terms. The key step in creating this variable is identifying search terms that accurately reflect users' concerns. To achieve this, we employ a two-stage process to select the candidate search terms with the highest predictive power, following the method proposed by Yang et al. (2015):

- (1) The initial step in our analysis involves compiling a comprehensive list of the most commonly used keywords associated with environmental concerns in cryptocurrency mining. We aim to identify these search terms as objectively as possible. To create this keyword set, we consider various aspects of environmental issues, including emissions and pollution, aided by related keyword recommendations from Google for guidance. This approach results in a collection of ten sets of search terms, allowing us to capture the breadth of environmental discussions surrounding cryptocurrency mining.
- (2) In the absence of prior assumptions about which keyword searches best represent environmental concerns related to cryptocurrency mining, in the second step, we rely on the data to identify the keywords with the best predictive power among our set of ten. To do this, we calculate the correlation between Bitcoin returns and the lagged weekly Google trend search volumes for each of the ten sets using data from the first

130 weeks of our 420-week sample. The objective of this test is to identify keyword combinations with lagged search volumes that show the strongest negative correlation with Bitcoin return trends over time. By restricting our analysis to the first 130 weeks, we preserve the remaining data from weeks 131-420 for out-of-sample testing, which helps us evaluate the predictive power of the new composite variable. This approach addresses the potential issue that a model performing well on in-sample data may not necessarily yield accurate predictions on new, unseen, out-of-sample data. Thus, in section 5.2.2, we use out-of-sample testing to validate the robustness of our method and to determine whether its predictive power extends beyond the specific in-sample data on which it was trained.

In Panel A of Table 2, we present the correlations between Bitcoin returns and lagged weekly Google Trends searches for the ten individual keyword combinations, denoted as $\rho_{R_{BTC,t},GT_{esg\&crypto}_{t-1}}$. Our analysis reveals varying levels of correlation across different search keywords. On average, the correlations between Bitcoin returns and the lagged Google Trends search keywords are -0.124, while the median correlation is -0.138. We focus on keywords with correlation values below this median, focusing on terms like “environmental crypto”, “carbon crypto”, “green crypto”, “energy crypto”, and “social crypto”, which have the most negative correlation values. Interestingly, shorter keywords tend to have more negative values for $\rho_{R_{BTC,t},GT_{esg\&crypto}_{t-1}}$. This suggests that the general population prefers shorter search terms when looking for information related to their environmental concerns about cryptocurrency mining, and this finding is consistent with the preference of internet users for shorter search terms in general (Spink et al., 2001).

Table 2. Construction of a Google Trends composite index and its impact on cryptocurrency returns.

Panel A. Correlations

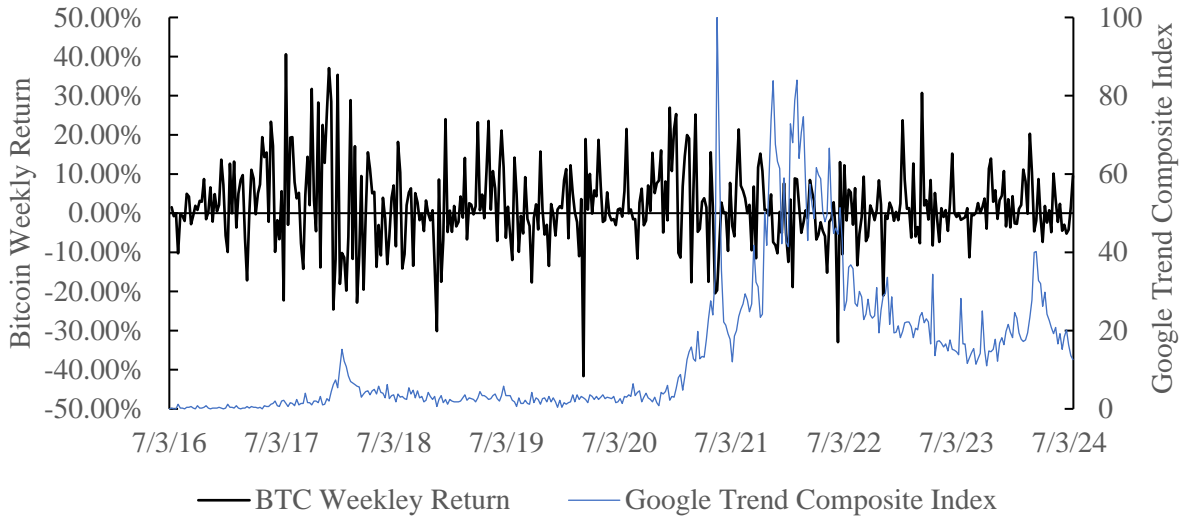
#	Search Term Combination	$\rho_{R_{BTC,t},GT_{esg\&crypto}_{t-1}}$
1	environmental crypto	-0.174
2	carbon crypto	-0.141
3	green crypto	-0.208
4	energy crypto	-0.151
5	environment crypto	-0.135
6	social crypto	-0.243
7	governance crypto	-0.055
8	pollution crypto	-0.007
9	emissions crypto	-0.127
10	emission crypto	0.002

Using the methodology developed by Yang et al. (2015), we aggregate search data into a comprehensive web search index from lagged Google Trends search volumes for five selected keywords. This index, known as the composite index, is calculated by averaging the weekly Google Trends search volumes for these keywords. Yang et al. (2015) show that using lagged search data significantly improves forecasting performance. In our subsequent analyses, we focus on this composite index to determine whether it accurately captures environmental concerns about cryptocurrency mining and exhibits predictive capability. In Figure 2(b), we present the weekly Bitcoin returns alongside our newly created Google Trend Composite Index.

Initially, the index's level remains relatively low but experiences a sharp rise starting in mid-2020, indicating increased and sustained concern over the environmental impact of cryptocurrency mining. Notably, spikes in the index often precede declines in Bitcoin's returns. This trend may suggest that growing investor concerns about the environmental impact of mining may negatively affect Bitcoin prices.

Figure 2. Google search trends over time for crypto and environmental issues

(b) Search trends



5.2.2 The Impact of the Composite Index on Cryptocurrency Returns

In this section, we rely on out-of-sample testing to examine the relationships between the Google Trends composite index related to environmental concerns of cryptocurrency mining and future cryptocurrency returns. We regress cryptocurrency returns on the lagged weekly composite index. We estimate the following model for Bitcoin and Ethereum returns separately:

$$R_{i,t} = \alpha + \beta_1 GT_composite_{t-1} + \beta_2 GT_crypto_{i,t-1} + \beta_3 GT_esg_{t-1} + \beta_4 R_{i,t-1} + \beta_5 R_{SPY,t-1} + \beta_6 R_{SUSA,t-1} + \epsilon_{i,t} \quad (1)$$

where $GT_composite_{t-1}$ refers to the lagged weekly Google Trends searches using the composite index which captures environmental concerns about cryptocurrency mining. $GT_crypto_{i,t-1}$ denotes the weekly Google Trends searches using keywords “bitcoin” or “ethereum,” with subscript i taking the values BTC or ETH respectively. GT_esg_{t-1} is the lagged weekly Google trend searches using the keyword “esg.” ESG stands for environmental, social, and governance. We use the search term “esg” due to its brevity and common usage in search behaviors. As a concise acronym, “esg” is likely one of the first terms investors input into search engines when exploring environmental concerns related to cryptocurrencies. Using lagged weekly Google trend searches for the keyword “environment” for the variable GT_esg_{t-1} yields similar regression results. We also control for the following lagged return variables, $R_{i,t-1}$ represents the lagged weekly cryptocurrency return, $R_{SPY,t-1}$ represents the

lagged S&P 500 index return, and $R_{SUSA,t-1}$ corresponds to the iShares MSCI USA ESG Select ETF. At last, ϵ is the error term. The coefficient β_1 captures the effect of investors' environmental concerns related to cryptocurrency mining on cryptocurrency returns. Given the close relationship between the stock market, macroeconomic uncertainty, and the Bitcoin market, we incorporate stock market returns as a control variable, using the S&P 500 index return as a proxy. This follows the approach of Conlon and McGee (2020) and Pal and Mitra (2019), who identify a weak correlation between stock markets and cryptocurrency returns. Moreover, we include the returns of the iShares ESG ETF as another control variable in our analysis, in response to the findings of Naeem and Karim (2021) concerning the tail dependence between cryptocurrencies and green financial assets.

To estimate Equation (1), we conduct three sets of tests to confirm its suitability for our empirical analysis. First, we assess whether the residuals of our OLS regression model exhibit autocorrelation, which could bias our estimates and invalidate the model. We used the Breusch-Godfrey test to check for serial correlation up to 20 lags in the residuals (Breusch, 1978; Davidson & MacKinnon, 1993; Godfrey, 1978). The null hypothesis of the Breusch-Godfrey test is that there is no autocorrelation in the residuals up to the specified lag order. If the null hypothesis is rejected, it indicates the presence of autocorrelation, necessitating consideration of a different model, such as an ARIMA model, which can properly handle such time series data. This test is particularly useful because it can detect higher-order autocorrelation, not just first-order, providing a more comprehensive assessment of autocorrelation in the model. As shown in Table A2, the test results fail to reject the null hypothesis across all lag orders. This indicates that the residuals from the OLS model do not exhibit autocorrelation, suggesting that a more complex time-series model like ARIMA is not necessary. The absence of serial correlation supports the appropriateness of the OLS model for our analysis.

Second, we use the Breusch-Pagan test to check for heteroskedasticity in the residuals (Breusch & Pagan, 1979; Cook & Weisberg, 1983). Heteroskedasticity can lead to inefficient estimates and affect the validity of our standard errors. The null hypothesis of the Breusch-Pagan test is that the residuals have constant variance (homoscedasticity). If we reject the null hypothesis, it would indicate that heteroskedasticity is present. As presented in Table A3, the test results for both cryptocurrencies indicate that we fail to reject the null hypothesis of homoscedasticity (constant variance), indicating that there is no evidence of heteroskedasticity. This further validates the use of OLS, as the assumption of homoscedasticity is satisfied.

Third, we test if the residuals are normally distributed by using the Skewness/Kurtosis test for normality (D'agostino et al., 1990). This test assesses whether the distribution of the residuals deviates from a normal distribution by examining both skewness (asymmetry) and kurtosis (tailedness). Normally distributed residuals are important for making valid inferences from the OLS model. The null hypothesis of the Skewness/Kurtosis test is that the residuals are normally distributed. Table A4 presents the test results for both cryptocurrencies. The p-values for both cryptocurrencies are greater than 0.05, leading us to fail to reject the null hypothesis. This finding supports the assumption that the residuals are normally distributed, which is important for valid hypothesis testing and accurate construction of confidence intervals within the OLS regression analysis framework.

Panel B of Table 2 presents the out-of-sample regression results examining how Google Trends affect cryptocurrency returns using Equation (1). The first column results show that the lagged composite term has a negative and significant effect on Bitcoin returns, with the coefficient of the composite term, β_1 , being negative and significant at the 1% level. This

suggests that even after accounting for other variables, investor attention to environmental concerns continues to play a crucial role in predicting future Bitcoin returns. This result can be interpreted as follows: when investors express environmental concerns regarding cryptocurrencies, as evidenced by increased search volume, it negatively affects future Bitcoin prices. These results support *Hypothesis 1*, suggesting that heightened investor attention to environmental concerns predicts lower future cryptocurrency returns.

Table 2. Construction of a Google trends composite index and its impact on cryptocurrency returns.

Panel B. Impact of Google Trends on Cryptocurrency Returns: Bitcoin and Ethereum (Pre- and Post-Merge)

	$R_{BTC,t}$	$R_{ETH,t}$	
		Before the Merge	After the Merge
$GT_composite_{t-1}$	-0.187*** (0.048)	-0.495** (0.201)	-0.030 (0.173)
$GT_Bitcoin_{i,t-1}$	0.129** (0.058)		
$GT_Ethereum_{i,t-1}$		0.138 (0.144)	-0.122 (0.087)
GT_esg_{t-1}	-0.029 (0.031)	0.100 (0.089)	-0.045 (0.096)
$R_{i,t-1}$	-0.023 (0.061)	-0.046 (0.121)	0.086 (0.113)
$R_{SPY,t-1}$	2.258* (1.270)	3.904 (3.885)	3.416 (2.422)
$R_{SUSA,t-1}$	-2.149* (1.272)	-3.652 (3.930)	-2.819 (2.210)
Constant	3.040 (1.844)	-1.030 (4.148)	8.357 (7.522)
Observations	289	130	97
R^2	0.069	0.075	0.084

For our Ethereum sample, we divided it into two distinct periods: the PoW period before September 15, 2022, and the PoS period after the Merge. Given the significance of this event, it provides an excellent opportunity to test our hypothesis regarding the influence of environmental concerns on cryptocurrency returns. We estimated our model separately for each period to rigorously examine any differences in the relationship between environmental concerns and Ethereum's returns. Given the extended and highly publicized nature of Ethereum's transition from PoW to PoS, it is essential to consider the period between July 2021, when EIP-3675 was introduced, and September, 2022, when the Merge was finalized, as a transition period rather than a pure PoW period.

During this time, investors and the broader cryptocurrency community were fully aware of the impending shift to PoS, as they were regularly informed through official channels, including Ethereum Improvement Proposals, developer conferences, and blog posts. This anticipation likely influenced investor behavior and market dynamics, making it a period of significant adjustment rather than a stable PoW phase. As a result, excluding this transition period from the study is justified to maintain the accuracy and reliability of our analysis, allowing us to focus on the distinct PoW and PoS phases before and after this transition.

In the second and third columns of Table 2 Panel B, we found a significant negative relationship between environmental concerns during the PoW period, as captured by the coefficient of the composite variable. Specifically, the coefficient for the composite variable, β_1 , is -0.495, which is statistically significant at the 5% level. This result aligns with our hypothesis that the energy-intensive nature of PoW mining made Ethereum more vulnerable to environmental concerns.

After the transition to PoS, the relationship between environmental concerns and Ethereum's returns changed notably. The coefficient for the composite variable, β_1 , dropped to -0.030 and was no longer statistically significant. This indicates that the sensitivity of Ethereum's returns to environmental concerns has substantially decreased following the switch to PoS. This result supports the expectation that by significantly reducing its energy consumption, Ethereum has become less exposed to negative investor sentiment driven by environmental issues. The results of this analysis strongly support our hypothesis that the environmental impact of cryptocurrencies plays a critical role in their evaluation and pricing. The significant decrease in the influence of environmental concerns on Ethereum's returns post-Merge underscores the effectiveness of the transition to PoS in mitigating this specific market risk. This finding not only provides empirical evidence that aligns with the broader narrative of environmental sustainability becoming increasingly important to investors but also reinforces the argument that cryptocurrencies with lower environmental footprints, like those using PoS, are less vulnerable to shifts in investor sentiment driven by environmental awareness. The R^2 values range from 6.9% and 8.4% for regressions in Table 2.

5.2.3. Non-Linear Effects of Environmental Concerns on Cryptocurrency Returns

In this section, we examine the non-linear relationship between environmental concerns and cryptocurrency returns. We first separate the variable $GT_composite_{t-1}$ into two distinct variables: Lower $GT_composite_{t-1}$ and Upper $GT_composite_{t-1}$. This separation is based on whether the $GT_composite_{t-1}$ value falls above or below its median. This approach allows us to differentiate the effects of varying levels of environmental concern on cryptocurrency returns, accounting for any non-linearity in this relationship, as the influence of environmental

concerns on cryptocurrency returns might differ depending on whether the concern is relatively low or high.

Table 3 presents the results. The coefficients for both the Lower $GT_composite_{t-1}$ and the Upper $GT_composite_{t-1}$ are negative and significant at the 1% level in the first column where the dependent variable is Bitcoin returns, suggesting that both lower and higher levels of environmental concern negatively affect Bitcoin returns. For the Ethereum sample, the results show notable differences before and after the transition from PoW to PoS. During the PoW period, only the coefficient for Upper $GT_composite_{t-1}$ is negative and significant at the 1% level. This suggests that higher levels of environmental concern had a more consistent and significant negative impact on Ethereum returns during the PoW period. However, in the PoS period, neither Lower $GT_composite_{t-1}$ and the Upper $GT_composite_{t-1}$ are significant, indicating that the transition to a more energy-efficient system has effectively decreased the impact of environmental concerns on Ethereum's returns. The R^2 values in these regressions range from 7.6% to 8.7%, showing improved explanatory power compared to the results in Table 2.

Table 3. Non-Linear Effects of Environmental Concerns on Cryptocurrency Returns

	$R_{BTC,t}$	$R_{ETH,t}$	
		Before the Merge	After the Merge
Lower $GT_composite_{t-1}$	-0.313*** (0.086)	-0.950 (1.281)	0.057 (0.295)
Upper $GT_composite_{t-1}$	-0.196*** (0.050)	-0.491*** (0.175)	0.013 (0.203)
$GT_Bitcoin_{i,t-1}$	0.164** (0.064)		
$GT_Ethereum_{i,t-1}$		0.127 (0.151)	-0.122 (0.085)
GT_esg_{t-1}	-0.009 (0.031)	0.095 (0.094)	-0.049 (0.112)
$R_{i,t-1}$	-0.016 (0.061)	-0.050 (0.132)	0.092 (0.112)
$R_{SPY,t-1}$	2.373* (1.270)	3.659 (4.148)	3.296 (2.631)
$R_{SUSA,t-1}$	-2.224* (1.273)	-3.404 (4.251)	-2.713 (2.296)
Constant	2.382 (1.873)	-0.117 (5.109)	7.449 (9.273)
Observations	289	130	97
R^2	0.087	0.076	0.085

5.2.4. Crypto Mining Type and the Impact of Search Combinations

High energy consumption and scalability challenges persist as obstacles to expanding the applications of blockchain technology. In response to these concerns, some researchers propose adopting the PoS mechanism and other energy-efficient approaches, rather than the PoW mechanism, to reduce the energy consumption of blockchains. Both types of crypto mining verify cryptocurrency transactions. PoW requires miners to solve complex mathematical problems to validate the blockchain's accuracy and to approve the records and transactions organized in a block before adding it to the blockchain. The PoW process is more secure but also more energy-intensive compared to non-PoW mining, including PoS mining. PoS provides consensus and security by requiring participants to prove its trustworthiness through staking, which refers to the use of cryptocurrency coins as collateral by miners to win the right to validate and extend the blocks. If everything is accurate, the miner will be rewarded with the right to process new blocks of transactions. However, if issues such as fraud arise, the miner who added the problematic block is penalized by forfeiting all or part of his staked coins. PoS reduces the mining difficulty of each node and accelerates the mining process. While PoS cannot guarantee fairness, it is more energy efficient than PoW. In the context of proof-of-stake mining, rich nodes often become richer, consequently diminishing the appeal of other nodes. This lower energy consumption results from the absence of complex mathematical problem-solving in PoS, allowing it to scale up more effortlessly to accommodate large transaction volumes. Given the difference in energy consumption between coins relying on PoW and PoS, we anticipate that the Google Trends variable, which proxies for environmental concerns about cryptocurrencies, will have a larger impact on the future returns of PoW coins. Panel A of Table 4 displays the top 20 cryptocurrencies, as of December 31, 2021, and their mining types on that date. This group includes two PoW cryptocurrencies, 17 non-PoW cryptocurrencies, and Ethereum.

Table 4. Crypto mining type and the impact of Google trends on cryptocurrency returns using the composite index

Cryptocurrency	Mining type	Cryptocurrency	Mining type
BTC	Proof of work	AVAX	Proof of stake
	Proof of work (before the Merge)		
ETH	Proof of stake (after the Merge)	DOGE	Proof of work
USDT	Proof of reserves	SHIB	Proof of stake
BNB	Proof of authority	MATIC	Proof of stake
SOL	Proof of stake	BUSD	Tokenization
USDC	Tokenization	LINK	Proof of stake
ADA	Proof of stake	CRO	Proof of stake
XRP	Consensus, proof of correctness	WBTC	Proof of reserves
LUNA	Proof of stake	UST	Proof of stake
DOT	Proof of stake	UNI	Proof of stake

Table A5 highlights the disparities in energy consumption across different cryptocurrency mining methods. PoW cryptocurrencies, such as Bitcoin and pre-Merge

Ethereum, have the highest energy consumption per transaction at 500 kWh and 70 kWh, respectively. In contrast, PoS cryptocurrencies, like Cardano (ADA) and Polkadot (DOT), consume significantly less energy, at 0.22 kWh and 0.003 kWh per transaction, respectively. Other non-PoW methods also show lower energy usage; for instance, Binance Coin (BNB) with proof of authority uses 0.015 kWh, and Ripple (XRP) with proof of correctness requires only 0.0079 kWh per transaction. These numbers underscore the substantial environmental impact of PoW cryptocurrencies compared to their non-PoW counterparts. Bitcoin's popularity compared to other cryptocurrencies has increased its environmental impact as it remains the dominant force in the market. Despite the existence of over 13,000 cryptocurrencies, Bitcoin continues to lead, largely due to its first-mover advantage, widespread acceptance, and extensive pool of users. As of 2024, the daily trading volume of Bitcoin fluctuates around \$42 billion, reflecting its robust liquidity. In comparison, the combined average daily trading volume of all non-PoW cryptocurrencies is approximately \$150 billion. This dominance is also reflected in its market capitalization, which is around \$1.3 trillion, compared to Ethereum's market cap of \$0.29 trillion and Tether's market cap of \$0.11 trillion. Due to its energy inefficiency and popularity, Bitcoin's overall energy consumption is significant, accounting for 60% to 77% of global crypto-asset electricity use as of August 2022, according to the White House Office of Science and Technology Policy (The White House, 2022).

Given the discrepancies in energy usage among different cryptocurrencies, we test the differences in the impact of the Google Trends searches on returns of cryptocurrencies with different mining types by repeating our regression in Equation (1), with cryptocurrency returns as the dependent variable and lagged search volume as the independent variables. For Ethereum, we categorize it as a PoW currency before the Merge and as a PoS currency afterward. Due to the lengthy and widely publicized transition from PoW to PoS, we exclude Ethereum observations between July 2021—when EIP-3675 was introduced—and September 2022, when the Merge was completed. During this transition period, although Ethereum technically remained a PoW currency, investors and the broader cryptocurrency community were fully aware of the upcoming shift to PoS.

For the group of non-PoW cryptocurrencies, our regressions include both the lagged coin return, denoted as $R_{i,t-1}$, and the lagged Bitcoin return, denoted as $R_{BTC,t-1}$, as control. This methodology is underpinned by two key considerations. Firstly, as the most influential cryptocurrency, Bitcoin continues to dominate the market. Its position might impact the future returns of non-PoW cryptocurrencies, making it important to account for Bitcoin's past performance when analyzing these assets. Our second justification is related to Milunovich (2022), who examines the linkages and transmission of price fluctuations across PoW and PoS cryptocurrencies. His findings suggest that, on an average, Bitcoins export greater uncertainty than the non-PoW coins. In light of this, the influence that Bitcoin's returns might exert on non-PoW cryptocurrency returns is an important consideration. Thus, our analysis controls for the lagged return of Bitcoin in our regression of non-PoW cryptocurrencies.

Table 4 Panel B presents the results. When regressing cryptocurrency returns on the composite term and control variables, the coefficient for the lagged composite term, β_1 , is -0.283 for PoW coins versus -0.095 for non-PoW coins, with both coefficients significant at the 1% level. This result is consistent with the fact that mining PoW coins consumes more energy and that investors' searches for environmental concerns and cryptocurrency issues reflect their concerns about the mining of PoW coins, potentially explaining the negative relationship.

Table 4. Crypto mining type and the impact of Google trends on cryptocurrency returns using the composite index

	PoW=1	PoW=0
$GT_composite_{t-1}$	-0.284*** (0.064)	-0.095*** (0.021)
$GT_crypto_{i,t-1}$	0.188*** (0.072)	0.132*** (0.026)
GT_esg_{t-1}	0.053 (0.056)	-0.037** (0.016)
$R_{i,t-1}$	0.045 (0.075)	0.033 (0.041)
$R_{BTC,t-1}$		0.741*** (0.035)
$R_{SPY,t-1}$	5.798*** (2.084)	-0.721 (0.584)
$R_{SUSA,t-1}$	-5.280*** (1.875)	0.847 (0.561)
Constant	-1.433 (2.467)	0.865 (1.137)
Testing the difference in β_1 between PoW=1 and PoW=0 groups		
Chi2(1)		8.07
P-value		0.005
Observations	604	3,857
R^2	0.044	0.192

For cryptocurrencies using non-PoW mechanisms to verify and extend blocks, the sign and significance of coefficients for the composite term are smaller than those for cryptocurrencies using PoW mechanisms. In fact, a Chi-square test for the difference in the coefficients for the composite term, β_1 , yields a Chi-square statistic of 8.07 with a p-value of 0.005. These results indicate that the coefficients of the composite term for the PoW sample and non-PoW sample are significantly different. The composite term appears to capture

investor concerns about cryptocurrency mining more accurately, particularly among investors in the PoW coins that consume more energy, showing a stronger impact for PoW relative to non-PoW cryptocurrencies. The results support our *Hypothesis 2*.

Table 4. Crypto mining type and the impact of Google trends on cryptocurrency returns using the composite index

	PoW=1	PoW=0
Lower $GT_composite_{t-1}$	-0.408*** (-3.175)	-0.155*** (-4.171)
Upper $GT_composite_{t-1}$	-0.258*** (-3.724)	-0.108*** (-4.959)
$GT_crypto_{i,t-1}$	0.200** (2.415)	0.153*** (5.435)
GT_esg_{t-1}	0.074 (1.245)	-0.029* (-1.747)
$R_{i,t-1}$	0.040 (0.533)	0.028 (0.688)
$R_{BTC,t-1}$		0.738*** (21.141)
$R_{SPY,t-1}$	6.221*** (2.936)	-0.595 (-1.013)
$R_{SUSA,t-1}$	-5.676*** (-2.979)	0.723 (1.287)
Constant	-1.642 (-0.623)	0.600 (0.512)
Observations	602	3,850
R^2	0.043	0.194

Interestingly, for cryptocurrencies utilizing non-PoW methods to verify and extend blocks, the lagged search volume for the keyword “bitcoin” has a positive and significant impact on weekly cryptocurrency returns. The coefficient for the Google Trends keyword “bitcoin” is 0.741 and statistically significant at the 1% level. This findings can be attributed to Bitcoin's status as the most well-established cryptocurrency, which continues to dominate the market.

In Table 4 Panel C, we again break down the composite variable into Lower $GT_composite_{t-1}$ and Upper $GT_composite_{t-1}$ to explore potential non-linear effects. For

PoW coins, the coefficients are -0.408 for the Lower $GT_composite_{t-1}$ and -0.258 for the Upper $GT_composite_{t-1}$, both significant at 1% level. Non-PoW coins show coefficients of -0.155 and -0.108, also significant at 1% level. These findings reveal that even when accounting for non-linear relationships, PoW coins remain more sensitive to environmental concerns than non-PoW coins, regardless of whether the $GT_composite_{t-1}$ value is above or below the median.

5.3. Robustness checks

To confirm that the observed relationship between the lagged volume of Google searches for environmental concerns related to cryptocurrency mining and future cryptocurrency returns is not confounded by events directly impacting both price dynamics and search behavior, it is important to exclude observations surrounding significant cryptocurrency-related events. By excluding the weeks surrounding these events, we mitigate the risk that our results are driven by market reactions to these events rather than by the underlying relationship between environmental awareness and cryptocurrency returns. Therefore, we conducted a thorough investigation and identified several key events that could have driven both price dynamics and search interest simultaneously. Below is the list of the events we identified within our sample period:

1. New York's Denial of Air Quality Permit to Greenidge Generation (June 30, 2022)

This event marked a significant regulatory action where the New York State Department of Environmental Conservation denied a permit renewal for a Bitcoin mining facility due to environmental concerns. The decision was a critical precedent in state-level regulation of cryptocurrency operations, particularly highlighting the environmental impact of PoW mining. Given the direct connection between the event and environmental issues in cryptocurrency mining, it likely spurred increased search interest and influenced market perceptions, making it important to exclude this event from our analysis.

2. Executive Order 14067 - Ensuring Responsible Development of Digital Assets (March 9, 2022)

This executive order from President Biden focused national attention on the energy and environmental impacts of cryptocurrencies. By directing federal agencies to study these impacts and develop corresponding policies, the order had the potential to shift market sentiment and increase public interest, as reflected in Google search trends. The high-profile nature of this directive and its direct relevance to environmental concerns in the cryptocurrency sector justify its exclusion from the main analysis to avoid confounding the results.

3. White House Report on Cryptocurrency Energy Usage (September 8, 2022)

The White House Office of Science and Technology Policy's report on cryptocurrency energy usage presented detailed assessments and policy recommendations aimed at reducing the environmental impact of crypto mining. The release of this report was a major event that likely influenced both market behavior and public interest, particularly regarding environmental sustainability in the cryptocurrency industry. Given its significant impact on the narrative

surrounding crypto and environmental issues, it was necessary to exclude this period to maintain the integrity of our analysis.

4. EU Parliament's Vote on MiCA Regulation (April 20, 2023)

The European Parliament's approval of the Markets in Crypto-Assets (MiCA) regulation introduced a comprehensive framework for regulating the cryptocurrency market within the EU, with specific provisions addressing environmental impact. This vote was a landmark event in the regulatory landscape, likely driving both market movements and heightened search activity related to cryptocurrency and environmental concerns. Given the substantial implications of this regulation, it was critical to exclude its influence from our study.

5. China's Crypto Mining Crackdown (May 5, 2021)

A significant event related to the environmental impact of crypto mining occurred when China intensified its crackdown on cryptocurrency mining operations. The Chinese government expressed concerns over the environmental impact of Bitcoin mining, particularly its high energy consumption and carbon footprint. This move led to increased global awareness about the environmental sustainability of cryptocurrency mining.

We then excluded these time periods from our sample and re-estimated the model. The results are presented in Table A6. Notably, our results remained consistent with the original estimates, suggesting that the observed relationship is robust and not an artifact of these specific events. This approach increases the credibility of our results and supports our conclusions, which are based on broader, more generalizable trends in the data.

At last, we apply the Newey-West method in our time-series data. Table A7 shows that the lagged composite variable remains a strong predictor of Bitcoin returns, with a significant negative coefficient of -0.187 at the 1% level. For Ethereum, the coefficient during the PoW period is -0.495, also significant at the 1% level, but drops to -0.030 and becomes insignificant post-Merge. These results confirm that environmental concerns significantly impact cryptocurrencies using energy-intensive PoW mechanisms, with diminished effects after Ethereum's shift to PoS.

6. Implications and Future Directions

By analyzing search volume data from a large population, it becomes clear that the general public is paying attention to publicity regarding the environmental impact of cryptocurrency mining. In this paper, we explore public perception of the issue by analyzing search trends linked to various combinations of search terms. Our methodology aligns with the ideas described in Vaswani et al. (2017), as we examine the relationship between two words to understand their combined meaning and context. We created a composite index because individuals tend to use search terms interchangeably, without making any meaningful distinction between them. For example, an individual who is concerned about the environmental impact of cryptocurrency mining may use combinations of search terms such as "environment crypto," "carbon crypto," or "green crypto." Some may choose the shorter search term or simply use the first one that comes to mind. However, all three search term

combinations address a similar subject matter, namely the impact of cryptocurrencies on the environment. Given the unpredictable nature of the choice of search terms, a composite of search trend data that captures the trend in various search term combinations can more comprehensively reflect changes in public opinion over time, as opposed to relying on the trend data of a single search term combination like “environment crypto.” In this way, our paper not only discovers a relationship between investor concerns and cryptocurrency prices but also proposes that a composite measure based on various combinations of search terms can more accurately measure public opinion and attention. This approach may warrant further studies in the future. One potential application would be measuring investors' opinions on the impact of geopolitical risks on commodity prices, potentially leading to economic gains. Beyond financial markets, politicians, policymakers, corporate executives, and advertisers might want to measure the direction of public opinion on a policy or product in a timely manner. Given that the Google Trends data can tell the search volume in the region users specify, political candidates can use the methods proposed in our paper to investigate the public opinion locally or country-wide on a potential policy and adjust their positions according to shifts in public opinion. Similarly, corporate executives can use our methods to examine public opinion on a newly launched product and base decisions for future launches on timely feedback from the public.

7. Conclusion

Cryptocurrencies, as a new asset class, offer diversification benefits to portfolios that include traditional assets like stocks and bonds. However, their significant price volatility raises concerns for both investors and governments. This paper examines how growing public awareness of cryptocurrency mining's environmental impact may influence future cryptocurrency returns. Using Google trends to analyze multiple search terms, we capture investor concern, which is important when considering cryptocurrency investments. Our research reveals that the degree to which investors acquire information, as shown by search trends, could predict future returns. We also find that this impact differs between cryptocurrencies mined via PoW and other methods, highlighting public recognition of varying energy demands. Our findings align with Walker's (2021) assertion that cryptocurrencies and environmental sustainability currently conflict.

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Supplementary Materials: Tables and Figures

Figure 1. Daily Bitcoin mining hash rate

We obtain Bitcoin mining hash rate data from <https://www.blockchain.com/charts/>. The hash rate measures the number of calculations performed per second during the mining process, directly reflecting the computational power required to mine Bitcoin and process transactions.

Figure 2. Google search trends over time for crypto and environmental issues

We obtain cryptocurrency price data from <https://coinmarketcap.com> and search trend data from <https://trends.google.com/trends/>. The search trend data shows the level of interest compared to its highest point during the specified region and period. A value of 100 denotes the peak level of popularity for the search term, whereas a score of 0 indicates insufficient data for the search term.

Table 1. Bitcoin mining gigs and power consumption

We obtain mining hardware data from <https://www.asicminervalue.com/miners/>. To calculate annualized energy consumption, we use the hash rate as on July 15, 2021, to determine maximum energy usage. Country-level annual energy consumption data is from Statista for the year 2021.

Table 2. Construction of a Google trends composite index and its impact on cryptocurrency returns.

We include ten different combinations of cryptocurrency and environmental keywords in our Google Trends searches. Worldwide search trend data was retrieved on July 2024, for an eight-year period from July 2016 to July 2024 from <https://trends.google.com/>.

Panel A presents the correlation coefficients between Bitcoin returns and lagged weekly Google trend searches over the first 130-week period. We then construct a composite index $GT_composite$, which is the average weekly Google Trends search volume for the top five search term combinations that exhibit the most negative correlations with next week's bitcoin returns.

In Panel B, we use data from the last 290-week period to run the following model, testing the impact of Google Trends on cryptocurrency returns.

$$R_{i,t} = \alpha + \beta_1 GT_composite_{t-1} + \beta_2 GT_crypto_{i,t-1} + \beta_3 GT_esg_{t-1} + \beta_4 R_{i,t-1} + \beta_5 R_{SPY,t-1} + \beta_6 R_{SUSA,t-1} + \epsilon_{i,t} \quad (1)$$

The dependent variable $R_{i,t}$ is the return during week t for crypto i , which refers to bitcoin (BTC) and Ethereum (ETH), respectively. The Independent variable $GT_composite_{t-1}$ is the lagged, average weekly Google Trends search volume for the top five search term combinations that exhibit the most negative correlations with next week's bitcoin returns.

Control variables include $GT_crypto_{i,t-1}$, the lagged weekly Google trend searches using keywords “Bitcoin” or “Ethereum”, GT_esg_{t-1} , the lagged weekly Google trend searches using the keyword “esg”, $R_{i,t-1}$, the lagged crypto return, and lagged returns for market indices. We include two lagged market indices: the SP500 index ($R_{SPY,t-1}$) and the iShares MSCI USA ESG Select ETF ($R_{SUSA,t-1}$). ϵ is the error term. Robust standard errors are in parenthesis below the coefficient. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3. Non-Linear Effects of Environmental Concerns on Cryptocurrency Returns

We include ten different combinations of cryptocurrency and environmental keywords in our Google Trends searches. Worldwide search trend data was retrieved on July 2024, for an eight-year period from July 2016 from <https://trends.google.com/>.

We use data from January 2019 to July 2024 to run the following model, testing the impact of Google Trends on cryptocurrency returns.

$$R_{i,t} = \alpha + \beta_1 GT_composite_{t-1} + \beta_2 GT_crypto_{i,t-1} + \beta_3 GT_esg_{t-1} + \beta_4 R_{i,t-1} + \beta_5 R_{SPY,t-1} + \beta_6 R_{SUSA,t-1} + \epsilon_{i,t} \quad (1)$$

The dependent variable $R_{i,t}$ is the return during week t for crypto i , which refers to bitcoin (BTC) and Ethereum (ETH), respectively. The variable $GT_composite_{t-1}$ is the lagged, average weekly Google Trends search volume for the top five search term combinations that exhibit the most negative correlations with next week’s bitcoin returns. We separate the variable $GT_composite_{t-1}$ into two distinct variables: Lower $GT_composite_{t-1}$ and Upper $GT_composite_{t-1}$. This separation is based on whether the $GT_composite_{t-1}$ value falls above or below its median. Control variables include $GT_crypto_{i,t-1}$, the lagged weekly Google trend searches using keywords “Bitcoin” or “Ethereum”, GT_esg_{t-1} , the lagged weekly Google trend searches using the keyword “esg”, $R_{i,t-1}$, the lagged crypto return, and lagged returns for market indices. We include two lagged market indices: the SP500 index ($R_{SPY,t-1}$) and the iShares MSCI USA ESG Select ETF ($R_{SUSA,t-1}$). ϵ is the error term. Robust standard errors are in parenthesis below the coefficient. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4. Crypto mining type and the impact of Google trends on cryptocurrency returns using the composite index

We obtain data on the top 20 cryptocurrencies ranked by market capitalization from <https://coinmarketcap.com> on December 31, 2021. We classify the cryptocurrencies into two categories: PoW=1 for proof of work cryptocurrencies and 0 otherwise. Panel A displays the top 20 cryptocurrencies by market capitalization. In Panel B, using data from January 2019 to July 2024, we run the following model to test the impact of Google Trends on cryptocurrency returns.:

$$R_{i,t} = \alpha + \beta_1 GT_composite_{t-1} + \beta_2 GT_crypto_{i,t-1} + \beta_3 GT_esg_{t-1} + \beta_4 R_{i,t-1} + \beta_5 R_{SPY,t-1} + \beta_6 R_{SUSA,t-1} + \epsilon_{i,t} \quad (1)$$

The dependent variable $R_{i,t}$ is the return during week t for crypto i , which refers to one of the 20 cryptocurrencies, respectively. The Independent variable $GT_composite_{t-1}$ is the lagged, average weekly Google Trends search volume for the top five search term combinations that exhibit the most negative correlations with bitcoin returns. Control variables include $GT_crypto_{i,t-1}$, the lagged weekly Google trend searches using keywords “Bitcoin”, GT_esg_{t-1} , the lagged weekly Google trend searches using the keyword “esg”, $R_{i,t-1}$, the lagged crypto return, and lagged returns for market indices. We include two lagged market indices: the SP500 index ($R_{SPY,t-1}$) and the iShares MSCI USA ESG Select ETF ($R_{SUSA,t-1}$). ϵ is the error term. For the PoW=0 sample, we add bitcoin return, $R_{BTC,t-1}$, as an additional control variable in the regressions. Robust standard errors are shown in parenthesis below the coefficient. The Chi-square statistic tests the difference in coefficient β_1 for PoW=1 vs. PoW=0 samples. In Panel C, we repeat the regression performed in Panel B but allow for non-linear effects. We separate the variable $GT_composite_{t-1}$ into two distinct variables: Lower $GT_composite_{t-1}$ and Upper $GT_composite_{t-1}$. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix

From Environmental Concerns to Market Moves: How Environmental Awareness Shapes Cryptocurrency Returns

Appendix Section 1 Regulating Cryptocurrency's Environmental Impact

The intersection of cryptocurrency and environmental sustainability is gaining attention as mining operations, particularly those using PoW mechanisms, face global scrutiny. These energy-intensive activities, with their heavy carbon footprints, have spurred regulatory actions aimed at mitigating their environmental impact.

Firstly, the rapid expansion of cryptocurrency mining operations in the United States has led to a substantial increase in electricity consumption, estimated to account for 0.6% to 2.3% of total U.S. electricity demand. This surge in energy usage has prompted significant concerns among policymakers regarding its potential impact on electricity costs, grid reliability, and carbon emissions.⁷ In response to these concerns, the U.S. Energy Information Administration (EIA) has announced plans to conduct a mandatory survey to systematically assess cryptocurrency mining's electricity consumption. The findings from this survey are expected to inform future planning and public education efforts, providing critical data to guide regulatory interventions.

Moreover, the White House Office of Science and Technology Policy (OSTP) has released a fact sheet addressing the climate and energy implications of crypto-assets within the United States. The OSTP report underscores the substantial electricity usage and environmental impacts of crypto-assets, particularly those utilizing the energy-intensive PoW consensus mechanism. To mitigate these impacts, the OSTP recommends the development of performance standards and the promotion of less energy-intensive technologies. The overall goal of these recommendations is to align the development of crypto-assets with the U.S. objectives of reducing greenhouse gas emissions, advancing environmental justice, and achieving a sustainable clean energy future.⁸

Also in the context of U.S. policy, the Biden administration has proposed the Digital Asset Mining Energy (DAME) excise tax as a measure to address the significant economic and environmental costs associated with cryptomining. The tax, set at 30% of the electricity costs used in cryptomining after a phase-in period, aims to hold cryptomining firms accountable for the negative externalities they impose on society, such as local pollution, increased greenhouse gas emissions, and elevated energy prices. This excise tax is part of a broader effort to mitigate climate change, reduce energy costs, and promote the responsible

⁷ See "Tracking electricity consumption from U.S. cryptocurrency mining operations", U.S. Energy Information Administration, February 1, 2024. <https://www.eia.gov/todayinenergy/detail.php?id=61364>

⁸ See "FACT SHEET: Climate and Energy Implications of Crypto-Assets in the United States", The White House Press Release, September 8, 2022. <https://www.whitehouse.gov/ostp/news-updates/2022/09/08/fact-sheet-climate-and-energy-implications-of-crypto-assets-in-the-united-states/>

development of digital assets. The tax is projected to generate \$3.5 billion in revenue over the next decade.⁹

At the state level, a cryptocurrency mining law signed in 2022 in the State of New York establishes a two-year moratorium on issuing certain permits to specific mining operations. This legislative measure reflects growing recognition of the need to balance the economic benefits of cryptocurrency mining with its environmental and social costs.¹⁰

In the international context, a UN study conducted during the 2020–2021 period revealed that approximately 67% of the energy consumed by the global Bitcoin mining network was derived from fossil fuels.¹¹ This study highlights the urgent need for regulatory interventions and technological advancements to mitigate the environmental impacts of cryptocurrency mining. The study further emphasizes the importance of addressing the inequities and injustices arising from the largely unregulated digital currency sector. It suggests that governments should explore alternative, more energy-efficient digital currencies and implement stricter regulations to monitor and reduce the environmental footprint of cryptocurrencies.¹²

Finally, also in the international context, an article published by the International Monetary Fund (IMF) explores potential solutions to reduce the carbon footprint of cryptocurrencies, with a particular focus on the PoS model. Unlike miners in a PoW system, "validators" in a PoS system do not engage in competitive mining, thereby requiring minimal computing power. This could potentially reduce energy consumption by over 99%. However, the article notes that it is unlikely that Bitcoin, the largest cryptocurrency, will transition away from PoW due to its established infrastructure and network effects.¹³

As the cryptocurrency market evolves, so will the regulatory frameworks addressing these concerns. Future policy development may focus on reducing energy consumption through technological innovations while also considering the broader impacts on market stability and investor behavior.

⁹ See “The DAME tax: Making cryptominers pay for costs they impose on others.” The White House. May 2, 2023. <https://www.whitehouse.gov/cea/written-materials/2023/05/02/cost-of-cryptomining-dame-tax/>

¹⁰ See “Cryptocurrency Mining Law.” New York State Department of Environmental Conservation. 2024. <https://dec.ny.gov/environmental-protection/climate-change/statutes-regulations-policies#:~:text=Signed%20in%202022%2C%20the%20cryptocurrency,of%2Dwork%20authentication%20methods%20to>

¹¹ See “UN study reveals the hidden environmental impacts of Bitcoin: Carbon is not the only harmful by-product.” United Nations University Institute for Water, Environment and Health. October 24, 2023. <https://www.unwater.org/article/un-study-reveals-hidden-environmental-impacts-bitcoin-carbon-not-only-harmful-product>

¹² Certain countries, such as China and India, have either prohibited or heavily restricted cryptocurrency mining to redirect energy consumption toward conventional business sectors and lower carbon emissions. Nevertheless, government policies and investor sentiments may shift in response to significant developments in green energy usage for cryptocurrency mining. Consequently, investors should monitor the proportion of alternative energy sources, such as wind and solar, used in cryptocurrency mining and adjust their investment strategies accordingly.

¹³ See “Cleaning up crypto”, International Monetary Fund., September, 2021. <https://www.imf.org/en/Publications/fandd/issues/2021/09/how-to-make-cryptocurrencies-cleaner-and-greener>

Table A1. Crypto mining type and their energy consumption

This table compares the energy consumption per transaction and the daily transaction volumes of Bitcoin (BTC) and Visa in 2022. The data is sourced from the 2022 Visa Environmental, Social & Governance Report, Blockchain.com, and Digiconomist.

Transaction method	Energy consumption per transaction (kWh)	Number of transactions processed in per day
BTC	567.4	255,757
Visa	0.0015	528.76 million

Table A2. The Breusch-Godfrey LM Tests for Autocorrelation

The Breusch-Godfrey LM Test for Autocorrelation detects the presence of autocorrelation in the residuals of a regression model, which is violates one of the key assumptions of the OLS regression. A significant test statistic would indicate that the residuals are not independent, suggesting the presence of autocorrelation.

Lags(p)	Bitcoin			Ethereum		
	F	df	Prob > F	F	df	Prob > F
1	3.001	(1, 280)	0.1143	0.262	(1, 280)	0.6091
2	1.523	(2, 278)	0.2198	0.393	(2, 278)	0.6756
3	1.315	(3, 276)	0.2699	0.449	(3, 276)	0.7184
4	1.05	(4, 274)	0.3815	0.777	(4, 274)	0.541
5	0.862	(5, 272)	0.5074	0.647	(5, 272)	0.664
6	0.748	(6, 270)	0.6112	1.27	(6, 270)	0.2713
7	0.778	(7, 268)	0.606	1.228	(7, 268)	0.2874
8	0.73	(8, 266)	0.6648	1.171	(8, 266)	0.3167
9	0.668	(9, 264)	0.7379	1.04	(9, 264)	0.4087
10	0.631	(10, 262)	0.7872	1.563	(10, 262)	0.1177

Table A3. The Breusch–Pagan Test for Heteroskedasticity

The Breusch-Pagan test for heteroskedasticity tests the presence of heteroskedasticity in the residuals of a regression model. If the test statistic, which follows a chi-square distribution, is significantly greater than zero, it would indicate that the residual variance is not constant and heteroskedasticity is present.

Bitcoin		Ethereum	
chi2(1)	Prob > F	chi2(1)	Prob > F
0.91	0.3409	0.72	0.3945

Table A4. Skewness and Kurtosis Tests for Normality

The Skewness and Kurtosis tests for normality assess whether the distribution of residuals in a regression model deviates from a normal distribution by examining their skewness and kurtosis. Skewness measures the asymmetry of the distribution, with normal distributions having a skewness of zero. Kurtosis measures the "tailedness" of the distribution, with normal distributions having a kurtosis of three. These tests calculate the skewness and kurtosis of the residuals and testing whether these values significantly differ from those expected under a normal distribution. Significant results from these tests suggest that the residuals are not normally distributed, which can affect the validity of hypothesis tests and confidence intervals in regression analysis. The results below indicate that we cannot reject the null hypothesis of normally distributed residuals.

Bitcoin				Ethereum			
Pr(skewness)	Pr(kurtosis)	Joint Test		Pr(skewness)	Pr(kurtosis)	Joint Test	
		chi2(2)	Prob>chi2			chi2(2)	Prob>chi2
0.0636	0.401	4.17	0.1244	0.5394	0.6218	0.63	0.7316

Table A5. Crypto mining type and their energy consumption

We obtain data on the top 20 cryptocurrencies ranked by market capitalization from <https://coinmarketcap.com> on December 31, 2021. We classify the cryptocurrencies into two categories: PoW=1 for proof of work cryptocurrencies and 0 otherwise. The table displays the the top 20 cryptocurrencies by market capitalization and their energy consumption per transaction. We lists these cryptocurrencies along with their energy consumption per transaction, with data sourced from the Cambridge Centre for Alternative Finance, Digiconomist, the Crypto Carbon Ratings Institute, and the environmental impact reports of each cryptocurrency.

Cryptocurrency	Mining type	Estimated energy consumption per transaction
BTC	Proof of work	500 kWh
ETH	Proof of work (before the Merge)	70 kWh (before the Merge)
	Proof of stake (after the Merge)	0.03kWh (after the Merge)
USDT	Proof of reserves	Depends on the underlying blockchain network
BNB	Proof of authority	0.015 kWh
SOL	Proof of stake	0.000166 kWh
USDC	Tokenization	Depends on the underlying blockchain network
ADA	Proof of stake	0.22 kWh
XRP	Consensus, proof of correctness	0.0079 kWh
LUNA	Proof of stake	between 0.00001 and 0.01 kWh
DOT	Proof of stake	0.003 kWh
AVAX	Proof of stake	0.0005 kWh
DOGE	Proof of work	594 kWh
SHIB	Proof of stake	0.03 kWh
MATIC	Proof of stake	0.00003 kWh
BUSD	Tokenization	Depends on the underlying blockchain network
LINK	Proof of stake	0.03 kWh

CRO	Proof of stake	0.0004 kWh
WBTC	Proof of reserves	0.03 kWh
UST	Proof of stake	Between 0.001 to 0.01 kWh
UNI	Proof of stake	0.03 kWh

Table A6. Robustness Check by Excluding Weeks Surrounding Significant Cryptocurrency-Related Events

We include ten different combinations of cryptocurrency and environmental keywords in our Google Trends searches. Worldwide search trend data was retrieved on July 2024, for an eight-year period from July 2016 from <https://trends.google.com/>.

We use data from January 2019 to July 2024 to run the following model, testing the impact of Google Trends on cryptocurrency returns.

$$R_{i,t} = \alpha + \beta_1 GT_composite_{t-1} + \beta_2 GT_crypto_{i,t-1} + \beta_3 GT_esg_{t-1} + \beta_4 R_{i,t-1} + \beta_5 R_{SPY,t-1} + \beta_6 R_{SUSA,t-1} + \epsilon_{i,t} \quad (1)$$

We exclude specific weeks surrounding significant cryptocurrency- and environmental-related events to prevent the observed relationship between Google search volumes for environmental concerns and cryptocurrency returns from being influenced by these events. The left half of the table presents the results when the week of the event (week t) is excluded, and the right half presents the results when the weeks surrounding the event (weeks $t-1$ to $t+1$) are excluded.

In Panel A, the dependent variable $R_{i,t}$ is the return during week t for crypto i , which refers to bitcoin (BTC) and Ethereum (ETH), respectively. In Panel B, the dependent variable $R_{i,t}$ is the return during week t for crypto i , which refers to one of the 20 cryptocurrencies, respectively. The Independent variable $GT_composite_{t-1}$ is the lagged, average weekly Google Trends search volume for the top five search term combinations that exhibit the most negative correlations with next week's bitcoin returns. Control variables include $GT_crypto_{i,t-1}$, the lagged weekly Google trend searches using keywords "Bitcoin" or "Ethereum", GT_esg_{t-1} , the lagged weekly Google trend searches using the keyword "esg", $R_{i,t-1}$, the lagged crypto return, and lagged returns for market indices. We include two lagged market indices: the SP500 index ($R_{SPY,t-1}$) and the iShares MSCI USA ESG Select ETF ($R_{SUSA,t-1}$). In Panel B, For the PoW=0 sample, we add bitcoin return, $R_{BTC,t-1}$, as an additional control variable in the regressions. The Chi-square statistic tests the difference in coefficient β_1 for PoW=1 vs. PoW=0 samples. ϵ is the error term. Robust standard errors are in parenthesis below the coefficient. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Impact of Google Trends on Cryptocurrency Returns: Bitcoin and Ethereum (Pre- and Post-Merge)

	Dropping week t			Dropping weeks $t-1$ to $t+1$		
	$R_{BTC,t}$	$R_{ETH,t}$		$R_{BTC,t}$	$R_{ETH,t}$	
		Before the Merge	After the Merge		Before the Merge	After the Merge
$GT_composite_{t-1}$	- 0.188*** (0.048)	- 0.512*** (0.160)	0.032 (0.173)	- 0.143*** (0.054)	- 0.574*** (0.167)	0.037 (0.179)
$GT_Bitcoin_{i,t-1}$	0.142** (0.058)			0.081 (0.064)		
$GT_Ethereum_{i,t-1}$		0.135 (0.149)	-0.132 (0.085)		0.198 (0.182)	-0.099 (0.079)
GT_esg_{t-1}	-0.033 (0.032)	0.087 (0.089)	-0.051 (0.112)	-0.008 (0.032)	0.047 (0.097)	-0.083 (0.107)
$R_{i,t-1}$	-0.015 (0.062)	-0.083 (0.129)	0.103 (0.112)	0.012 (0.067)	-0.043 (0.124)	0.150 (0.112)
$R_{SPY,t-1}$	2.234* (1.280)	2.878 (4.203)	3.603 (2.657)	2.211* (1.299)	3.155 (4.191)	2.771 (2.656)
$R_{SUSA,t-1}$	-2.070 (1.281)	-2.584 (4.298)	-2.983 (2.319)	-2.096 (1.300)	-2.868 (4.282)	-2.029 (2.299)
Constant	2.931 (1.858)	-0.370 (3.974)	7.924 (8.261)	2.428 (1.835)	1.102 (4.193)	9.355 (7.975)
Observations	284	129	96	264	127	93
R^2	0.071	0.077	0.084	0.045	0.089	0.089

Panel B. Cryptocurrency returns and mining types

	Dropping week t		Dropping weeks $t-1$ to $t+1$	
	PoW=1	PoW=0	PoW=1	PoW=0
$GT_composite_{t-1}$	-0.278*** (0.065)	-0.100*** (0.021)	-0.253*** (0.073)	-0.096*** (0.022)
$GT_crypto_{i,t-1}$	0.179** (0.074)	0.140*** (0.026)	0.170** (0.083)	0.145*** (0.028)
GT_esg_{t-1}	0.062 (0.057)	-0.044*** (0.016)	0.058 (0.059)	-0.046*** (0.016)
$R_{i,t-1}$	0.052 (0.077)	0.046 (0.041)	0.042 (0.077)	0.044 (0.043)
$R_{BTC,t-1}$		0.756*** (0.035)		0.739*** (0.035)
$R_{SPY,t-1}$	5.591*** (2.077)	-0.760 (0.586)	5.355** (2.082)	-0.883 (0.589)
$R_{SUSA,t-1}$	-5.049*** (1.870)	0.871 (0.564)	-4.796** (1.875)	1.075* (0.567)
Constant	-1.757 (2.491)	1.072 (1.133)	-1.681 (2.516)	0.930 (1.125)
	Testing the difference in β_1 between PoW=1 and PoW=0 groups			
Chi2(1)	6.83		5.36	
P-value	0.009		0.015	
Observations	593	3,783	571	3,634
R^2	0.045	0.200	0.035	0.199

Table A7. Impact of Google Trends on Cryptocurrency Returns with Newey-West Standard Errors

We include ten different combinations of cryptocurrency and environmental keywords in our Google Trends searches. Worldwide search trend data was retrieved on July 2024, for an eight-year period from July 2016 from <https://trends.google.com/>.

We use data from January 2019 to July 2024 to run the following model, testing the impact of Google Trends on cryptocurrency returns.

$$R_{i,t} = \alpha + \beta_1 GT_composite_{t-1} + \beta_2 GT_crypto_{i,t-1} + \beta_3 GT_esg_{t-1} + \beta_4 R_{i,t-1} + \beta_5 R_{SPY,t-1} + \beta_6 R_{SUSA,t-1} + \epsilon_{i,t} \quad (1)$$

The dependent variable $R_{i,t}$ is the return during week t for crypto i , which refers to bitcoin (BTC) and Ethereum (ETH), respectively. The Independent variable $GT_composite_{t-1}$ is the lagged, average weekly Google Trends search volume for the top five search term combinations that exhibit the most negative correlations with next week's bitcoin returns. Control variables include $GT_crypto_{i,t-1}$, the lagged weekly Google trend searches using keywords "Bitcoin" or "Ethereum", GT_esg_{t-1} , the lagged weekly Google trend searches using the keyword "esg", $R_{i,t-1}$, the lagged crypto return, and lagged returns for market indices. We include two lagged market indices: the SP500 index ($R_{SPY,t-1}$) and the iShares MSCI USA ESG Select ETF ($R_{SUSA,t-1}$). ϵ is the error term. Newey–West heteroskedasticity- and autocorrelation- Robust standard errors are in parenthesis below the coefficient. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	$R_{BTC,t}$	$R_{ETH,t}$	
		Before the Merge	After the Merge
$GT_composite_{t-1}$	-0.187*** (0.048)	-0.495*** (0.115)	-0.030 (0.158)
$GT_Bitcoin_{i,t-1}$	0.129** (0.054)		
$GT_Ethereum_{i,t-1}$		0.138 (0.125)	-0.122 (0.079)
GT_esg_{t-1}	-0.029 (0.030)	0.100 (0.096)	-0.045 (0.107)
$R_{i,t-1}$	-0.023 (0.057)	-0.046 (0.118)	0.086 (0.120)
$R_{SPY,t-1}$	2.258* (1.257)	3.904 (4.282)	3.416 (2.675)
$R_{SUSA,t-1}$	-2.149* (1.279)	-3.652 (4.416)	-2.819 (2.276)
Constant	3.040* (1.806)	-1.030 (4.459)	8.357 (8.012)
Observations	289	130	97