Davide Sandretto

Essays on Financial Innovations

Expected Returns and Volatility in the Cryptocurrency Market

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Tiivistelmä

Tämä väitöskirja koostuu viidestä esseestä, jotka tarkastelevat kryptovaluuttamarkkinoiden odotettuja tuottoja ja volatiliteettiprofiilia.

Ensimmäinen essee analysoi momentum-kaupankäyntistrategioiden kannattavuutta digitaalisten valuuttojen kontekstissa. Tulokset osoittavat, että pelkkä momentumstrategia ei tuota merkittävää tuottoa yksittäisten kryptovaluuttojen romahdusten vuoksi, mutta riskienhallinta volatiliteettiskaalausmenetelmien avulla parantaa tuottoja huomattavasti sekä faktorimallilla riskikorjattuna että ilman.

Toisessa esseessä tarkastellaan momentum-anomalian ilmenemistä keskittymällä kryptovaluuttoihin, joilla on korkea likviditeetti ja vakaus ajan myötä. Analyysi osoittaa, että momentum ei johdu vakaista digitaalisista valuutoista, vaan valuutoista, jotka saavuttavat vain hetkellisesti korkean likviditeetin.

Kolmas essee tutkii siirtymistä Proof-of-Work (PoW) -konsensusprotokollasta Proof-of-Stake (PoS) -protokollaan sekä sen vaikutusta kryptovaluuttojen volatiliteetin ja energiashokkien väliseen suhteeseen. Tulokset paljastavat merkittävän herkkyyden vähenemisen kryptovaluuttojen reaktiossa energiamarkkinoiden shokkeihin PoS-protokollan käyttöönoton jälkeen, mikä tukee siirtymistä ympäristön kannalta kestävämpään järjestelmään.

Neljäs essee mallintaa kryptovaluuttojen volatiliteettia voimalakijakauman avulla. Havaintojen mukaan altcoineilla on yhteinen riskiprosessi, joka noudattaa voimalakikäyttäytymistä. Tämä viittaa siihen, että riskin hajauttaminen saattaa olla rajallista.

Viides ja viimeinen essee tarkastelee markkinoiden reaktiota uuteen Baselin sääntelykehykseen, joka koskee pankkien altistumista kryptovarojen volatiliteetille. Tapahtumatutkimuksen tulokset osoittavat markkinoiden negatiivisen reaktion, mikä viittaa siihen, että sääntelijöiden linja on mahdollisesti liian tiukka ja että sääntelykehystä voi olla tarpeen tarkistaa.

Tämä väitöskirja täydentää kirjallisuutta arvioimalla perinteisten kaupankäyntistrategioiden kannattavuutta ja kryptovaluuttamarkkinoiden epävarmuutta sekä esittelee mahdollisia riskienhallintatyökaluja.

Asiasanat: kryptovaluuttamarkkinat, odotetut tuotot, volatiliteetti, riskienhallinta.

Abstract

This dissertation consists of five essays that examine expected returns and volatility in the cryptocurrency market.

The first essay analyses the profitability of momentum trading strategies in digital currencies. The results show that a plain momentum strategy does not yield significant returns due to crashes in individual cryptocurrencies, but that risk management through volatility-scaling methods generates substantial gains, both with and without factor model risk adjustment.

The second essay explores how the momentum anomaly manifests when focusing on cryptocurrencies with high liquidity and stability over time. The findings indicate that momentum is not driven by digital currencies with smooth return processes, but rather by those that temporarily reach high liquidity levels.

The third essay investigates the transition from the Proof-of-Work (PoW) to the Proof-of-Stake (PoS) consensus protocol and its impact on the relationship between cryptocurrency volatility and energy shocks. The results reveal a marked decline in the sensitivity of digital currencies to energy market shocks after the adoption of PoS, supporting the shift towards a more environmentally sustainable protocol.

The fourth essay models cryptocurrency volatility using power law distributions. The analysis shows that altcoins share a common risk process that follows power law behaviour, suggesting that the scope for risk diversification is limited.

The fifth essay examines the market reaction to the new Basel framework regulating banks’ exposures to cryptoasset volatility. The event study results indicate a negative market reaction, suggesting that regulators’ stance may be overly stringent and that the framework may warrant revision.

Taken together, this dissertation contributes to the literature by assessing the profitability of traditional trading strategies in cryptocurrency markets, highlighting sources of uncertainty, and identifying potential tools for risk management.

Keywords: cryptocurrency markets, expected returns, volatility, risk management.

Sommario

Questa tesi è composta da cinque saggi che esaminano i rendimenti attesi ed i profili di volatilità nel mercato delle criptovalute.

Il primo saggio analizza la redditività delle strategie di trading basate sul momentum applicate al contesto delle valute digitali. I risultati dimostrano che sebbene una semplice strategia momentum non generi un profitto significativo a causa dei crolli di prezzo di singole criptovalute, una gestione del rischio tramite metodi di volatility-scaling produce rendimenti considerevoli, sia con sia senza aggiustamento per il rischio basato su modelli fattoriali.

Sul tema, il secondo saggio esamina come si manifesti l'anomalia momentum, concentrandosi su criptovalute con elevata liquidità e stabilità nel tempo. L'analisi indica che il momentum non è guidato da valute digitali con un processo dei rendimenti regolare, bensì da criptovalute che raggiungono solo temporaneamente livelli elevati di liquidità.

Il terzo saggio indaga come il passaggio dal protocollo di consenso Proof-of-Work (PoW) al Proof-of-Stake (PoS) impatti la relazione tra la volatilità delle criptovalute e gli shock energetici. I risultati mostrano una riduzione significativa della sensibilità delle valute digitali agli shock del mercato dell'energia in seguito all'adozione del PoS, incoraggiando la migrazione verso questo protocollo ritenuto più sostenibile dal punto di vista ambientale.

Il quarto saggio modella la volatilità delle criptovalute utilizzando distribuzioni a legge di potenza. Si riscontra che le altcoin condividono un processo di rischio comune che segue un comportamento a legge di potenza, implicando che la diversificazione del rischio potrebbe essere limitata.

Infine, il quinto saggio esamina la reazione del mercato delle criptovalute all'implementazione del nuovo framework di vigilanza prudenziale di Basilea per le esposizioni delle banche in cripto-asset. I risultati dell'event study mostrano una reazione negativa del mercato, suggerendo una visione eccessivamente restrittiva da parte dei regolatori e la potenziale necessità di apportare correttivi al framework.

Nel complesso, questa tesi contribuisce alla letteratura esaminando la redditività delle strategie di trading tradizionali e l'incertezza nel mercato delle criptovalute, presentando al contempo potenziali strumenti di mitigazione del rischio.

Parole chiave: mercato delle criptovalute, rendimenti attesi, volatilità, gestione del rischio.

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Turin, September 2025

Davide Sandretto

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Essays

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1 INTRODUCTION

Cryptocurrencies are a new type of digital currency that operates on blockchain technology, an innovative type of distributed ledger. Unlike traditional currencies, they are independent of a central authority and allow for peer-to-peer transactions without the need for intermediaries. The first and most well-known cryptocurrency, Bitcoin, was created in 2009 following distrust in the financial system, which was shaken by the subprime mortgage crisis (Nakamoto, 2009). The idea of a currency not issued by a central authority and therefore immune to its supply interference led to immediate success. Indeed, in almost two decades, the market has grown in a remarkable fashion, now exceeding a valuation of 3,000 billion dollars, with thousands of digital currencies being exchanged[1]. Although originally designed as a medium of exchange, Bitcoin and other Bitcoin-like digital currencies – so called "altcoins" (Grobys, 2024) - struggle to compete with fiat currencies due to their extreme volatility, which classifies them as high-risk assets (Baur and Dimpfl, 2021). Price bubbles (Corbet et al., 2018), recurring defaults (Grobys and Sapkota, 2020), and cases of fraud and market manipulations (Akyildirim et al., 2020) such as the FTX cryptocurrency exchange scandal (Reuters, 2024), are not rare phenomena in this market. Given these unique characteristics, the opportunity to study this emerging financial sector was quickly seized by researchers, leading to investigations into its stylized facts and features (Corbet et al., 2019). However, much remains unexplored, and many aspects that diverge from traditional market dynamics still require further investigation (Härdle et al., 2020).

In recent years, the crypto market has attracted not only retail investors and blockchain enthusiasts but also major institutions, including banks, governments, and mutual funds (BIS, 2023; Elison and Kher, 2023). While a common classification - whether as a currency, digital gold, or a financial asset class - has yet to be firmly established, institutional investors are integrating cryptocurrencies into their portfolios. Their primary motivations include diversification benefits and potential long-term profitability, particularly if digital assets will gain interest due to their underlying technology (Liu et al., 2022). With the Markets in Crypto-Assets Regulation (MiCA) now in force in Europe (European Union, 2023), the new Basel provisions on banks' crypto exposure (BIS, 2024), and the pro-crypto stance of the Trump administration in the U.S. (White House, 2025a, 2025b), cryptocurrencies will become an increasingly integral part of the broader financial ecosystem. As a result, any effort to better understand this market is essential for navigating its future developments.

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[1] Source: coinmarketcap.com as of February 20, 2025.

This dissertation covers various aspects related to the expected returns and volatility profile of the cryptocurrency market, with a particular focus on altcoins, which represent the most relevant digital currencies in terms of market capitalization. The first and second essays analyze the profitability of different momentum strategies, including the novel volatility-adjusted approach proposed by Barroso and Santa-Clara (2015). The third and fourth essays focus on the volatility profile, specifically examining the response to energy shocks following the transition to a less energy-intensive blockchain protocol and identifying a common process that governs the second moment of cryptocurrency returns. Finally, the fifth paper investigates the market reaction to the new Basel framework on banks' cryptoasset exposure. The findings and implications of these studies are valuable for practitioners in the financial and portfolio management industry, as well as regulators, contributing to the growing but still nascent literature on cryptocurrencies.

The remainder of the introductory chapter is organized as follows. Section 2 describes the general contribution of the dissertation, along with the contribution of each paper. Section 3 provides a brief overview of cryptocurrencies and reviews the existing literature on their expected returns and volatility. Section 4 provides summaries of the five essays.

2 CONTRIBUTION OF THE DISSERTATION

This dissertation generally contributes to the recent and growing literature on the cryptocurrency market (Corbet et al., 2019; Härdle et al., 2020). Moreover, it extends the well-established broader literature on asset pricing and volatility behavior by examining a novel and distinctive market, such as that of digital currencies. This emerging market is important for establishing a set of empirical regularities that can serve as stylized facts to confirm old theoretical models or develop new ones (Liu et al., 2022).

The first essay contributes to the inconclusive literature on cryptocurrency momentum in several ways. First, due to recurring bubble formations (e.g., Grobys, 2024; Kyriazis et al., 2020; Wheatley et al., 2019) and the micro-stock illiquidity premium (Fama and French, 2008, 2018), sample specificity may explain the disparate findings on cryptocurrency momentum. Our study addresses these key issues by employing a significantly longer sample period than previous research and focusing on the 30 largest cryptocurrencies by market capitalization. Second, the inconclusiveness regarding the profitability of cryptocurrency momentum could be an artifact of tail events occurring in specific samples. For example, momentum equity strategies are known to suffer from recurring crashes (Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016). We extend this research by examining whether similar patterns affect cryptocurrency momentum strategies. More specifically, we analyze the profitability of Barroso and Santa-Clara's (2015) risk-managed cryptocurrency momentum strategies, which, according to Liu et al. (2019), are not subject to look-ahead bias. Third and finally, we investigate theoretical risk and its implications for cryptocurrency momentum and risk-managed strategies. To explore this issue, we consider Taleb's (2020) assertion that financial data should be modeled using power laws and apply this approach, thereby contributing to the cryptocurrency literature.

The second essay is closely related to the previous one and contributes to the cryptocurrency momentum literature as well. Specifically, this research is the first to examine cryptocurrency momentum within a framework analogous to G10 currency momentum, by analyzing cryptocurrencies with a high degree of liquidity stability over time, providing a foundation for cross-market comparisons. Additionally, this study addresses inconsistencies in prior findings on the profitability of cryptocurrency momentum (e.g., Zaremba et al., 2021). In particular, we extend the work of Grobys et al. (2025) by investigating whether momentum profitability is primarily driven by coins with stable liquidity. Finally, this study builds on the recent work of Aloosh and Bekaert (2022) on foreign exchange rates by differentiating between active and passive cryptocurrency management spaces. In a manner analogous to the foreign exchange market, significant payoffs from momentum strategies associated with coins that are only temporarily available for trading reflect a passive management space.

The third essay examines the impact of transitioning from the Proof-of-Work (PoW) to the Proof-of-Stake (PoS) consensus protocol on the relationship between cryptocurrency volatility and energy shocks. We contribute to the field of sustainable finance by analyzing the environmental implications of this transition. In the context of cryptocurrencies, relatively few studies have explored their sustainability profiles (Corbet et al., 2019). To the best of our knowledge, no prior research has investigated whether shifting to a more sustainable consensus protocol reduces the sensitivity of cryptocurrency volatility to energy shocks. We address this gap using an event study approach, which allows for a causal investigation of this phenomenon by treating protocol switching as a quasi-natural experiment. Finally, this study extends the existing literature on energy shocks and cryptocurrency volatility (Naeem et al., 2023; Okorie and Lin, 2020; Yin et al., 2021) as well as cryptocurrency volatility modeling by applying extended Generalized AutorRegressive Conditional Heteroskedasticity (GARCH)-type specifications (Bouoiyour and Selmi, 2016; Caporale and Zekokh, 2019; Dyhrberg, 2016; Fakhfekh and Jeribi, 2020; Katsiampa, 2017; Katsiampa et al., 2019).

The fourth essay analyzes power law behavior of daily realized variances for the top-10 altcoins by market capitalization. It contributes to the existing literature on modelling the volatility of cryptocurrencies in a number of ways. First, as Kyriazis (2021) observes, previous studies that model the volatility of cryptocurrencies mainly rely upon GARCH-type models to examine volatility dynamics or volatility spillovers. We extend this literature by addressing a more central question: Is variance risk of cryptocurrencies governed by some common process? Acknowledging that cryptocurrencies exhibit extremely heavy tails (e.g., Baur and Dimpfl, 2021) and tail interdependencies (Shahzad et al., 2022; Xu et al., 2021), we model realized cryptocurrency variances as power laws and explore potential commonalities in the second moment of cryptocurrencies. Moreover, we explicitly test standard distributions against power law models. Established literature on realized volatility ascertained that realized asset volatility is close to be lognormally distributed (Andersen et al., 2001; Andersen et al., 2001a, 2001b). We test power-law models using the goodness-of-fit (GoF) test by Clauset et al. (2009). Finally, we propose a new econometric testing procedure derived from blocks bootstraps to test whether a common component in the realized variances of altcoins does exist. A joint test requires the establishment of the covariance matrix of power-law exponents, which is not required in tests for a single data vector. Having estimated the empirical covariance matrix enables us to implement conjoint tests to identify potential cross-sectional power-law behavior. To our knowledge, there are no other test methods available enabling us to examine this issue. Hence, the present study fills an important gap in the econometric literature too (Artico et al., 2020).

Due to the high volatility of cryptocurrencies and the potential for volatility spillovers between traditional financial markets and the crypto market, regulators have increasingly sought to establish regulatory frameworks for this market. In this context, the final essay expands the limited and emerging literature on the impact of regulations on the cryptocurrency market by providing the first evidence of market reactions to the introduction of disclosure and capital requirements for internationally active banks. While prior studies primarily focus on narrow bans or country-specific interventions (Cumming et al., 2024; Koenraadt and Leung, 2024), we analyze the effects of an international regulatory framework, addressing a key limitation in the study by Conlon et al. (2024). Additionally, we extend the broader literature that employs event studies (see, e.g. Bruno et al., 2018; Horváth and Huizinga, 2015; Pancotto et al., 2020) to examine the effects of bank regulation by introducing a novel focus on cryptocurrency markets. Because regulatory changes represent innovations in the intermediary capital ratio (He et al., 2017), we also provide preliminary evidence that shocks to the intermediary capital ratio might affect returns (He and Krishnamurthy, 2013). Finally, this study contributes to the ongoing debate on capital requirements for banks' exposure to cryptoasset risks.

3 BACKGROUND

This section provides a brief overview on the fundamental concepts discussed in the five essays of this dissertation. First, it describes what a cryptocurrency is and its intrinsic value. Then, it highlights the main findings in the literature concerning the risk and return profiles of the cryptocurrency market.

3.1 What is a cryptocurrency and what is its value?

The new MiCA framework, which regulates the market for digital currencies in Europe, defines cryptocurrency (or crypto-asset) as a “digital representation of a value or of a right that is able to be transferred and stored electronically using distributed ledger technology or similar technology” (European Union, 2023). Cryptocurrencies were originally conceived with the ambition of being used as a medium of exchange, aiming to replace traditional fiat currencies (Nakamoto, 2008). The key difference between cryptocurrencies and fiat currencies lies in their underlying structure: digital currencies are not backed by a government or central authority. Instead, they operate on a distributed ledger, commonly referred to as blockchain, where transactions are recorded in a shared database. This system allows for transactions to be executed without the need for intermediaries. As a result, the supply of cryptocurrency is not subject to variation in response to monetary policies implemented by central authorities. Rather, it is regulated by predefined mathematical protocols and algorithms within the blockchain network. The supply is typically limited. For instance, Bitcoin has a maximum supply of 21 million coins that will be reached around the year 2140.

A blockchain requires a consensus protocol, network nodes, and so-called “miners” to function correctly. Starting with network nodes, they are essential participants in the blockchain, as they operate the protocol using a computer and store either part or all the data related to the blockchain transactions. In a permissionless blockchain—a public ledger—anyone can become a node by downloading a portion of the blockchain onto their computer. Conversely, in a permissioned blockchain, only authorized participants are allowed to operate as nodes.

The role of nodes is to validate transactions, ensuring their authenticity and accuracy while preventing the issue of double spending, i.e., the duplication of digital currencies. In essence, their task is to verify the compliance with the blockchain rules. If a transaction does not meet the required standards, it will be rejected, and no reward will be granted to the miners.

Miners are special nodes that play a fundamental role in blockchain operations: processing transactions. When a blockchain receives a transaction request, it is first checked by node validators to determine its legitimacy. If deemed valid, it is placed in the “mempool,” a space where pending transactions wait to be processed. Miners, then, in order to execute these transactions, use powerful hardware with high computational capacity to solve complex mathematical problems. This takes place in a competitive environment, where miners compete against each other. Once a miner successfully finds the solution, they add the verified transactions to a new block, which contains both the new information and references to the previous block, so that the continuity of the blockchain is maintained. Once this process is completed, the nodes verify again whether the transaction complies with the blockchain rules. If the validation is successful, the miner receives a reward for their work, and the transaction is recorded on the blockchain, becoming irreversible and immutable. This ensures that no one can alter the content of the transactions. Remarkably, all transactions are accessible to anyone who participates in the blockchain, making it a transparent system for verifying transaction details. Specifically, anyone can recognize the digital wallet that receives a transaction, but identifying the owner of a digital wallet is a more complex issue. Rarely, it can happen that two miners verify the same block at the same time. This situation, known as "accidental fork," causes the blockchain to momentarily split into two different chains, leading to a divergence of registered transactions. However, this unintentional situation is easily resolved by the blockchain's functionality itself, as miners build subsequent transaction blocks on one of the chains so that the shorter chain is abandoned. In contrast, the blockchain can permanently separate into two different chains when developers intentionally introduce a change in the protocol rules, requiring an upgrade of the blockchain software. This situation can lead to a "hard fork" if some community members (nodes and miners) do not accept the upgrade and decide to continue operating with the older software version. This creates a bifurcation of the chain and results in a different cryptocurrency. An example is Bitcoin Cash, which forked from the Bitcoin blockchain in 2017, after a change in the block size rules. Importantly to note is the difference with a "soft fork", where instead marginal changes are made to the protocol and those who do not update the new version of the software can still operate on the same chain (Jiang et al., 2022).

Finally, the last necessary component is the consensus protocol. While in centralized systems, a few entities hold decision-making power and establish consensus among themselves, in decentralized systems, this process is more complex. In decentralized systems, the network has to elect a leader who is responsible for correctly adding new blocks to the transaction records. However, since this elected individual might behave maliciously, several mechanisms are implemented to make this potential misconduct costly. Consensus algorithms are protocols designed to establish trust and security among network participants (Zhang and Lee, 2020). They ensure that all entities in the system collectively agree on the state of the ledger or the network's transaction records, preventing the addition of blocks that contain conflicting transactions. Thus, consensus protocols permit blockchain updates while guaranteeing that no single entity can disrupt or take control of the entire blockchain system (Xu et al., 2023).

The most well-known consensus protocol is the Proof of Work (PoW) algorithm. Within this protocol, miners solve complex cryptographic puzzles by expending significant computational power in exchange for rewards and transaction fees, typically corresponding in the platform's native currency. Once solved, the miner adds the validated block to the blockchain. This process imposes a computational cost, ensuring that miners must invest resources to successfully append new blocks. Since the validation process performed by network nodes is much simpler than the intensive computations required to miners, the PoW acts as both a barrier and a deterrent against malicious actors attempting to manipulate transactions. As the network always follows the longest chain of transactions (Nakamoto, 2008), a dishonest miner attempting to validate a fraudulent block would need to mine subsequent blocks faster than the rest of the network. Moreover, since nodes and other miners have strong incentives to earn rewards, they would recognize the fake transaction and refuse to build upon the fraudulent block. To succeed in such an attack, the dishonest miner would need to outpace the entire network in both speed and computational power. This scenario, known as a 51% attack, would require control over more than half of the total computational power of the network—an almost impossible feat due to the immense resources required. Thanks to the computational cost imposed by this algorithm, the network is secure against malicious attacks and makes the blockchain reliable and trustworthy.

While the Proof of Work (PoW) consensus mechanism ensures strong security and decentralization, it is not highly scalable. As the network and the number of transactions grow, the mining process becomes increasingly time-consuming, causing transactions to be processed more slowly. This leads to high transaction costs and reduces the attractiveness of the blockchain itself (Zhou et al., 2020). Additionally, the PoW protocol requires considerable energy consumption, which, in most cases, is powered by fossil fuels (de Vries, 2019), making this protocol highly polluting. Estimates indicate that the energy consumption of Bitcoin, which relies on PoW, is equivalent to the entire annual energy consumption of Sweden, with CO_2 emissions comparable to those of Greece and Oman (Kohli et al., 2023).

Addressing some of these issues, a second consensus protocol known as Proof of Stake (PoS) has gained significant popularity. Indeed, recently, relevant cryptocurrencies such as Cardano and Ethereum, have transitioned from a PoW to a PoS protocol. In this system, nodes responsible for mining new blocks in the blockchain do not engage in a competitive process that requires powerful hardware to solve complex puzzles. In contrast, the selection criteria rely on a cryptographic random algorithm that chooses nodes based on the amount of cryptocurrency staked. Therefore, the likelihood of a node being selected as a miner depends on factors such as the quantity of coins it holds, coin age, and randomization. Once the mining process is completed and the block is validated and added to the blockchain, the node receives a reward in coins, similar to the PoW protocol (Hussein et al., 2023). Notably, because the PoS eliminates the competitive process and cryptographic problems are easier to solve, transactions are processed faster, improving system scalability. Additionally, the energy consumption required is significantly lower (Wendl et al., 2023). For instance, the energy consumption of Ethereum was reduced by 99% after the switching from the PoW to the PoS consensus protocol on September 15, 2022[2].

However, there have been growing concerns regarding this consensus algorithm, as the decentralization of the network could be compromised in the long term. This is due to the higher probability of being selected as a miner, which leads to receiving more rewards. These rewards, in turn, increase the node's stake, further amplifying its influence over time. Nonetheless, this mechanism has been both theoretically and empirically disproven. Roşu and Saleh (2021) modeled this issue as a martingale process and demonstrated that a node's stake neither increases nor decreases indefinitely but instead follows a process that converges to a mean equal to its initial value. Additionally, Irresberger and Yang (2023) provided empirical evidence supporting this claim. Another security measure that deters malicious behavior among nodes is the slashing mechanism, which entails the partial or total loss of a node's stake as a penalty for failing to follow protocol rules correctly (Lee and Kim, 2023). This creates a strong incentive for nodes to act honestly. In a PoS blockchain, a 51% attack is highly unlikely, as it would require controlling 51% of the entire cryptocurrency supply. Moreover, a malicious actor would face significant risks, including potential slashing penalties and the devaluation of the compromised blockchain, which in turn could result in a substantial loss of wealth for the attacker.

Finally, several other protocols exist. While some cryptocurrencies adopt a hybrid approach, combining PoS and PoW to leverage the advantages of both mechanisms, others implement alternative protocols such as Proof-of-Authority (PoA), Proof-of-Burn (PoB), and Proof-of-Capacity (PoC). A particularly notable protocol is Delegated Proof-of-Stake (DPoS), in which block validators are elected based on the stakes held by network nodes. Each node selects its preferred validator to confirm transactions

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[2] https://digiconomist.net/ethereum-energy-consumption

and generate new blocks. This protocol makes faster transaction processing compared to the traditional PoS. However, it also results in a higher degree of centralization (Hussein et al., 2023). As of February 2025, cryptocurrencies utilizing PoW account for 65% of the market capitalization, followed by PoS at 15% and DPoS at 3% (CryptoSlate.com).

The first cryptocurrency ever mined was Bitcoin, launched in 2009, according to a white paper authored by Satoshi Nakamoto, an individual or group whose identity remains unknown (Nakamoto, 2008). Bitcoin emerged as an alternative financial instrument following widespread distrust in traditional markets, which had collapsed during the subprime mortgage crisis. Bitcoin quickly gained traction. In 2010, a user exchanged 10,000 BTC for two pizzas, giving Bitcoin its first tangible value. This event is now commemorated annually as Bitcoin Pizza Day on May 22, marking the anniversary of the first real-world Bitcoin transaction (Rehman et al., 2020). By 2011, Bitcoin surpassed the $1 milestone, solidifying its legitimacy as a digital asset. Around the same time, other cryptocurrencies began emerging. In late 2013, Bitcoin reached $100 for the first time, fueled by increasing adoption and media attention (Kraken, 2025). Over the following years, Bitcoin continued to hit higher price levels, further driving public interest. At the end of 2024, following the election of the Trump administration, the cryptocurrency market surged, with Bitcoin surpassing $100,000 for the first time. Bitcoin adoption has also expanded to nations such as El Salvador, which made it a legal tender in 2021 (Patel, 2024), and companies such as Tesla, which accepted Bitcoin as payment for its vehicles (Kovach, 2021). However, both experiments were short-lived, with El Salvador abandoning Bitcoin as legal tender in 2025 (Cointelegraph, 2025) and Tesla discontinuing Bitcoin payments after just a few months (Reuters, 2021). Nonetheless, since Bitcoin's inception in 2009, the cryptocurrency market has experienced super-exponential growth, exceeding a valuation of $3 trillion, with thousands of digital assets actively traded as of February 20, 2025[3].

Are cryptocurrencies mediums of exchange that will replace fiat currencies? Probably not. Considering the aforementioned experiments, Bitcoin and, in general, altcoins do not seem well-suited for widespread exchange. However, concerns among central authorities have led governments to explore competitive alternatives, such as the Central Bank Digital Currency (CBDC) (Bech and Garratt, 2017). A broader adoption of cryptocurrencies has been documented, particularly in illegal activities. It is estimated that one-quarter of Bitcoin users are involved in illicit transactions, including terrorism financing, money laundering, and capital control evasion (Foley et al., 2019). Several factors make large-scale adoption and everyday transactions

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[3] Coinmarketcap.com

difficult. Firstly, cryptocurrencies exhibit ten times higher volatility than traditional exchange rates in both the short and long term, making them an unreliable medium of exchange and eroding trust in their use for payments (Baur and Dimpfl, 2021). Additionally, while blockchain technology itself is secure, cryptocurrencies have faced security risks, primarily due to the hacking of digital wallets where they are stored. These attacks are not related to blockchain vulnerabilities but rather to password breaches and thefts. Initially, hacking incidents were rare and received little attention; however, over time, their frequency and impact have significantly increased (Chen et al., 2023; Grobys, 2021). In February 2025, cryptocurrency exchange Bybit reported a cyberattack in which hackers stole $1.5 billion worth of digital tokens (Reuter, 2025), further contributing to distrust among potential users. Finally, transaction speeds remain uncompetitive compared to traditional payment providers (Hazari and Mahmoud, 2020). While transaction fees are generally lower, they can increase significantly when the blockchain network becomes congested (Kim, 2017).

Another function associated with cryptocurrencies is their role as a store of value. Bitcoin has been often referred to as “digital gold,” serving as a store of value due to its long-term appreciation (Baur et al., 2024; Baur and Dimpfl, 2021; Harvey et al., 2022). However, various studies suggest that during periods of crisis and market shocks, cryptocurrencies behave differently from gold and do not provide a reliable hedge against market downturns (Conlon et al., 2020; Klein et al., 2018).

Are cryptocurrencies therefore useless? The answer depends on the perspective from which they are analyzed. Cryptocurrencies are commonly perceived as either lacking intrinsic value or being driven solely by speculative demand without any fundamental basis. However, what may hold true value is the underlying blockchain technology, which has evolved over the years and found practical applications, such as the tokenization of assets (Gan et al., 2020).

Therefore, it is essential to take a holistic view of the crypto ecosystem. As noted by Härdle et al. (2020), not all cryptocurrencies are the same, and a functional categorization is necessary. While an official and comprehensive classification has yet to be established, we can divide cryptocurrencies into five main categories (Härdle et al., 2020):

- Transaction Mechanisms: this category includes classic cryptocurrencies such as Bitcoin (BTC), Litecoin (LTC), and Monero (XMR), which operate on their own blockchains and are primarily designed as a medium of exchange. These cryptocurrencies do not offer any advanced technological features beyond serving as a decentralized ledger for making transactions.

- Smart Contract Platforms: cryptocurrencies like Ethereum (ETH), Cardano (ADA), and Tezos (XTZ) operate on blockchains that support smart contracts. Smart contracts are pieces of code embedded in the blockchain that are executed automatically when predefined terms and conditions are met, eliminating the need for third-party intermediaries. Once a condition is triggered, the contract self-executes the corresponding clause. Additionally, because of the blockchain, all actions are recorded and verified on a decentralized blockchain ledger. A similar concept in traditional finance is a limit order, which automatically executes a stock purchase when prices reach a predetermined level (Makarov and Schoar, 2022). Smart contracts represent an important technological innovation in blockchain applications.

- Utility token: these cryptocurrencies are often built on top of smart contract blockchains and grant holders the access to specific services or products. An example is the Basic Attention Token (BAT), which allows users to earn rewards for viewing advertisements and permits content creators to pay in BAT to promote their content within a privacy-focused web browser. This category includes tokens launched through Initial Coin Offerings (ICOs), where new projects are financed by issuing tokens to investors.

- Security token: these cryptocurrencies represent stocks, bonds, derivatives, or other financial assets. They are typically issued through Security Token Offerings (STOs).

- Stablecoins: these cryptocurrencies are tailored to keep a stable value, often by being pegged to a fiat currency or commodity. For instance, Tether (USDT) is pegged 1:1 to the U.S. dollar, backed by fiat reserves equivalent to the circulating supply. Other stablecoins, such as Pax Gold (PAXG), are backed by physical assets like gold, as each token represents one ounce of physical gold.

A second, more general classification, based on the risks associated with cryptocurrencies, is outlined in the European MiCA regulation, which defines three main categories:

- E-money tokens: these are crypto-assets designed to maintain a stable value by referencing a single official currency. An example is Tether (USDT), which falls into this category. These tokens must be backed by liquid reserves, deposited in regulated financial institutions, and must be redeemable at any time to ensure stability.

- Asset-referenced tokens: this category includes all other stablecoins and crypto-assets that derive their value from a basket of other assets rather than a single currency. For instance, Pax Gold (PAXG), which is backed by physical gold belongs to this group. However, security tokens are not included in this category, as they are regulated under the MiFID II framework.

- All the others: any cryptocurrency that does not fit into the first two categories falls into this broad classification.

Looking at the first classification, it becomes evident that a certain degree of heterogeneity exists within the crypto world, along with a more concrete level of application. This raises an important question: What is the true value of a cryptocurrency, given that it does not generate any cash flows? While one perspective considers cryptocurrencies mere bubbles or fraudulent schemes driven by speculative demand and enthusiasm (Grobys and Junttila, 2021), another view recognizes their potential intrinsic value, linked to the future innovative applications of blockchain technology (Liu et al, 2022). However, determining this potential intrinsic value is not straightforward. Additionally, the real-world applicability and tangible benefits that cryptocurrencies and blockchain technology can bring to society are still being debated (Makarov and Schoar, 2022). This evolving financial innovation is yet to be fully understood.

3.2 Expected returns in the cryptocurrency market

Since the establishment of modern portfolio theory, with the appealing seminal mean-variance framework introduced by Markowitz (1952), the investigation of asset return determinants has been the central focus in financial literature. Markowitz's insight was particularly compelling: adding an asset with lower returns and similar volatility to a portfolio can improve its return-to-volatility ratio, given a certain level of covariance between them. This concept gave rise to portfolio diversification, whereby holding multiple assets eliminates idiosyncratic volatility. Since this type of risk can be diversified away at no cost, it is not priced in the market as opposed to systematic risk.

Based on this concept, Sharpe (1964), Mossin (1966), and Lintner (1969) developed the Capital Asset Pricing Model (CAPM), in which a one-factor model predicts a positive linear relationship between systematic risk, represented by the market return, and expected returns on assets. Despite the fundamental intuition behind the CAPM, the model fails empirical tests (Fama and French, 2004; Fama and MacBeth, 1973; Friend and Blume, 1970; Jensen, 1968). The validity of the CAPM and its extensions was further questioned when researchers identified patterns in average returns, initially referred to as "anomalies," that these models were unable to explain. The first anomalies were identified in relation to the size of companies (Banz, 1981), book- to-market equity (Chan et al., 1991; Rosenberg et al., 1985; Stattman, 1980), earnings/price (Basu, 1977) and leverage (Bhandari, 1988). Building upon these, Fama and French (1993) developed a three-factor model (FF-3) that extends the CAPM by adding the size and the value effect, i.e., the anomalies whereby small companies tend to have a higher return than large companies, and companies with a high book-to-market ratio outperform the companies with a low book-to-market ratio. Size and value factors are implemented through mimicking portfolios. To construct the latter, securities are first sorted into portfolios (three, five, or ten portfolios, depending on the methodological choice adopted) based on the value of a characteristic associated with higher expected returns. Then, a long-short portfolio is created by taking a long (short) position in the portfolio with high (low) returns. In this way, the risk compensation for such a characteristic is proxied and because the short position finances the long one, the strategy theoretically does not require any cost for an investor (zero-cost strategy). This novel methodological approach introduced in Fama and French's (1993) seminal paper has led researchers to engage in a factor-discovering competition over the past decades.

Indeed, to date, more than 450 anomalies have been discovered, leading to numerous candidate factors to explain securities' expected returns (Hou et al., 2020; Huber et al., 2023). However, researchers advocate for reducing this "zoo of factors" (Cochrane, 2011) to a more parsimonious set of robust predictors with strong theoretical foundations. Achieving this, however, is a difficult task due to redundancy among many of these factors (Kozak et al., 2020). Furthermore, anomalies have been criticized for potential data mining and lack of replicability (Hou et al., 2020). Nevertheless, studies have found a reasonable degree of replication for many of them (Chen and Zimmermann, 2021; Jensen et al., 2023).

Similarly, in the cryptocurrency market, a growing body of literature has explored factor models in attempts to explain expected returns on cryptocurrency. Digital currencies have provided researchers with an opportunity to test well-known and prominent factor models in a new and different market. While cryptocurrency returns are not exposed to traditional equity and currency factors (Liu and Tsyvinski, 2021), a seminal paper by Liu et al. (2022) developed a three-factor model incorporating market, size, and momentum factors to price returns across ten profitable trading strategies. In contrast, Shen et al. (2020) documented a strong reversal effect, arguing that a three-factor model with market, size, and reversal factors outperforms a cryptocurrency-specific CAPM. Similarly, Grobys and Sapkota (2019) found insignificant momentum payoffs, suggesting that traditional momentum strategies may not be effective in crypto markets. Jung and Park (2024) further challenged the Liu et al. (2022) model, showing that a latent factor derived from principal component analysis (PCA) explains much of the remaining return variation and appears to be linked to currency markets. Beyond these, researchers have identified various other anomalies in the cryptocurrency market, including downside risk (Dobrynskaya, 2024), value effects (Liebi, 2022) geopolitical risk (Long et al., 2022), liquidity (Zhang and Li, 2023) and contagion risk (Shahzad et al., 2021) among others. Interestingly, a novel trend factor that subsumes different technical trading signals is shown to be priced in the cross-section of expected cryptocurrency returns, and a model that includes it outperforms previous factor models (Fieberg et al., 2023).

However, cryptocurrency factor modeling remains in its infancy, and much research is still needed to fully understand what drives returns on cryptocurrency. Contradictory results often arise due to differences in methodology and sample specificity (Zaremba et al., 2021). Additionally, an important issue is the influence of small-cap cryptocurrencies, which discount high liquidity premiums and face market frictions such as high transaction costs and short-selling constraints, all of which must be accounted for when implementing trading strategies.

3.3 Volatility in the cryptocurrency market

In portfolio management, the return profile is not the only factor that matters. Indeed, it is typically compared to the measure of uncertainty and risk, known as volatility, which is equally important. Since cryptocurrencies do not have an estimated payoff in terms of dividends or coupons, they are subject to elevated volatility, especially given the presence of short-term speculators (Catalini and Gans, 2019; Cheah and Fry, 2015). This volatility is estimated to be ten times higher than that of the traditional currency market across both short- and long-term horizons, impairing their function as a medium of exchange (Baur and Dimpfl, 2021). Moreover, cryptocurrencies exhibit more extreme values and heavier tail risk than traditional markets (Gkillas and Katsiampa, 2018). Interestingly, Harvey (2014) shows that Bitcoin is about eight times more volatile than the S&P 500 and nearly twenty times more volatile than the U.S. dollar. Due to these unique characteristics, academics have conducted numerous studies investigating the stylized facts and features of cryptocurrency volatility (Ahmed et al., 2024).

The most well-known characteristic is volatility clustering, i.e., large price movements (both upward and downward) tend to be followed by large price movements, and vice versa. This tendency is common in financial traditional markets and is also documented in the cryptocurrency market (Dyhrberg, 2016). Similarly, the cryptocurrency market exhibits volatility persistence, where past volatility influences future volatility, indicating the presence of a long-memory process (Klein et al., 2018). However, this persistence is higher after market shocks than during normal periods (Yaya et al., 2021) and did not diminish after the COVID-19 pandemic, suggesting that market maturity does not mitigate this tendency (Mnif et al., 2020). Interestingly, Grobys (2023) reported evidence for Paretian tails in the volatility process of Bitcoin and documented that volatility persistence is the result of a multifractal behavior.

The literature on asymmetric volatility presents mixed findings. Asymmetric volatility refers to the stylized fact that negative and positive news do not impact volatility with the same magnitude. In traditional markets, bad news tends to have a stronger effect than good news, leading to a greater volatility response (Bekaert and Wu, 2000). However, while several studies have found that Bitcoin and cryptocurrencies in general exhibit a strong asymmetric effect (Bouoiyour and Selmi, 2016; Catania et al., 2018; Klein et al., 2018; Yu, 2019), other studies have reported a symmetric response to positive and negative shocks (Dyhrberg, 2016; Yu et al., 2019). Some researchers have even documented the presence of an inverted asymmetric reaction, where good news is more influential than bad ones (Cheikh et al., 2020; Fakhfekh and Jeribi, 2020). Unsurprisingly, these differences can be associated with divergent samples and models used. However, investor sentiment seems to be a promising key to understanding the inconclusive findings (Güler, 2023).

Furthermore, much effort has been devoted to investigating volatility spillovers. One stream of research has focused on spillovers within the digital currency market, documenting high volatility spillovers among large-cap cryptocurrencies (Katsiampa et al., 2019), with Bitcoin being the most impactful in the transmission mechanism—especially in the case of negative returns rather than positive ones (Ji et al., 2019). In contrast, Shahzad et al. (2022) found that Bitcoin is not the principal transmitter of risk. Analyzing 50 cryptocurrencies using quantile regressions, they show that return spillovers are stronger in the extreme tails of the distribution, with evidence of higher return spillovers from smaller cryptocurrencies. With respect to spillovers between cryptocurrencies and traditional markets, literature documents a potential risk of transmission. For example, Liu and Serletis (2019) found significant transmission of shocks and volatilities between major cryptocurrencies and equity markets. Narayan and Kumar (2024) identified risk spillovers from 33 cryptocurrencies to other markets, such as equities, exchange rates, and commodities. Similarly, Hanif et al. (2022) highlighted the presence of both downside and upside risk spillovers between eight major cryptocurrencies and global and regional equity markets. A similar relationship has been also documented between commodities such as gold, oil, and digital currencies (Ji et al., 2019; Pham et al., 2022). Interestingly, Okorie and Lin (2020) investigated the response of ten cryptocurrencies to crude oil volatility and found that the second moment of cryptocurrency returns is affected by energy shocks, especially given the market's dependence on energy consumption. However, when analyzing tail connectedness, weak relationships are observed between cryptocurrencies and traditional markets during extreme events (Borri, 2019; Jeribi and Fakhfekh, 2021; Lahiani et al., 2021). Finally, mean reversion and structural breaks are also common features of the digital currency market (Borgards and Czudaj, 2021; Mensi et al., 2019). Chu et al. (2017), who conducted a comprehensive horse race of GARCH models, found that for seven most popular cryptocurrencies Integrated GARCH and Glosten-Jagannathan-Runkle GARCH provided the best fit, capturing highly persistent volatility.

The investigation of volatility features is not only important from an academic perspective in studying market phenomena but also for practical applications in the asset management industry and for individual investors. As previously mentioned, cryptocurrencies (especially Bitcoin) have been considered a form of digital gold (Baur et al., 2024; Baur and Dimpfl, 2021; Harvey et al., 2022). However, while gold has well-documented diversification and hedging properties in a well-diversified portfolio (Baur and McDermott, 2010; Jaffe, 1989), cryptocurrencies appear to exhibit different characteristics (Klein et al., 2018). An asset class is typically evaluated in a portfolio based on three main properties: hedging, safe haven, and diversification (Baur and Lucey, 2010). Hedging refers to the absence of correlation or a negative correlation between an asset and a given portfolio on average. A safe haven asset, in contrast, is one that is uncorrelated or negatively correlated with a portfolio during periods of extreme market turmoil. Diversification, on the other hand, refers to an asset that maintains a positive correlation with a portfolio on average but can still provide benefits by reducing overall risk. Early studies have found that cryptocurrencies can serve as effective hedges against the currency market (Kinkyo, 2022), international equities (Gil-Alana et al., 2020) and bonds (Akhtaruzzaman et al., 2020; Liu and Serletis, 2019), since they show a low correlation with these asset classes. Moreover, cryptocurrencies appeared to be resilient during traditional market turbulence, making them a safe haven for investors. For instance, Bouri et al. (2020), using a wavelet value-at-risk analysis spanning the period from 2010 to 2018, found that Bitcoin is the most promising safe haven asset compared to other asset classes such as gold and commodities. Feng et al. (2018) analyzed seven cryptocurrencies across two sub-periods from August 2015 to July 2016 and from August 2016 to August 2017, showing that they were not exposed to financial contagion from the stock market, gold, and commodities, as their tails remained uncorrelated with extreme events in traditional markets. Additionally, their findings highlighted the diversification benefits of including these cryptocurrencies in a stock portfolio. Nevertheless, these studies focused on a period of strong growth in the cryptocurrency market, which was not yet fully mature. Moreover, no extreme events occurred during the selected sample period, leading to an overestimation of cryptocurrencies' potential diversification benefits. Indeed, when analyzing diversification benefits during the market downturn caused by the COVID-19 pandemic, Goodell and Goutte (2021) found that major coins such as Bitcoin, Ethereum, and Litecoin generally did not provide diversification benefits or safe haven properties. Similarly, Conlon and McGee (2020) and Guo et al. (2021) challenged the notion of Bitcoin as a safe haven during the pandemic. Furthermore, Somoza and Didisheim (2022) observed that, after March 2020, the correlation between the stock market and cryptocurrencies became highly positive, diminishing their diversification benefits. This relationship appears to be driven by the trading habits of retail investors, who shift their attention from equities to cryptocurrencies, suggesting that they perceive equities and cryptocurrencies as partial substitutes.

In sum, while the cryptocurrency market shares some similarities with traditional financial markets, it is still young and has plenty of room for future research opportunities, especially as it becomes more integrated into financial markets. Moreover, compared to traditional markets, it has different risk drivers linked to the blockchain technology such as energy, operational and normative risks (Ben Omrane et al., 2024; Griffith and Clancey-Shang, 2023; Roy et al., 2024) that can affect its returns and volatility and need further exploration. Finally, the cryptocurrency industry may benefit from the entry of more “educated” players into the market, such as institutional funds and banks, while its high volatility could be mitigated through new and solid regulations. Studying cryptocurrency volatility is therefore fundamental for making informed decisions and guiding investment choices for retail investors, the financial industry, and policymakers.

4 SUMMARY OF THE ESSAYS

This section summarizes the five interrelated essays investigating the expected returns and volatility profile of the cryptocurrency market.

4.1 Cryptocurrency momentum has (not) its moments

This study analyzes the profitability of cryptocurrency momentum strategies and their volatility-managed counterparts. Evidence on cryptocurrency momentum in the literature is mixed. Grobys and Sapkota (2019) found no evidence of profitability in cryptocurrency momentum strategies. By contrast, Liu et al. (2022) implemented cryptocurrency momentum strategies documenting a large positive payoff of 3% per week. Similarly, there is some controversy surrounding the performance of volatility-managed momentum strategies. Even though scaling past returns using volatility or variance is an intuitive approach that can lead to impressive payoffs (Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016; Moreira and Muir, 2017), it has shortcomings. Liu et al. (2019) argued that volatility-scaling suffers from look-ahead bias. Additionally, Cederburg et al. (2020) conducted a comprehensive empirical investigation using a broad sample of 103 equity portfolios and concluded that volatility management often diminished real-time performance.

Contributing to this literature, we apply momentum strategies to a sample of 30 large-cap cryptocurrencies from 2016 to 2023 to mitigate liquidity confounding effects (Zaremba et al., 2021). We also use Barroso and Santa-Clara's (2015) risk management strategy, which is not subject to look-ahead bias. A long-short portfolio indicates that momentum strategies are not profitable, as they suffer from severe crashes. Even though the presence of severe crashes aligns with the literature on stock price momentum (Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016), we find that these crashes are not due to optionality effects but rather arise from extreme price jumps in a single cryptocurrency in the short leg of the momentum portfolio. When applying volatility management strategies, momentum payoffs restore and increase by a substantial margin. Finally, we assess the theoretical risk of both strategies by means of power law modelling. We document that the theoretical variance of cryptocurrency momentum returns is not finite, meaning that the strategy is highly risky, even after volatility management.

Because our chosen methodology deviates from the established practice of using value-weighted portfolios, and because the idiosyncratic risk of a few coins in a portfolio could have an impact on the obtained results, we perform further tests. That is, we re-examine our analysis using a value-weighting scheme and a larger sample of 2,500 cryptocurrencies. However, we find that the dynamic patterns in these new approaches do not differ from those in our original results. This paper holds important implications for investors seeking to implement momentum strategies in the cryptocurrency market. First and foremost, risk management is critical to earning cryptocurrency momentum profits. Second, even after risk adjustment via volatility scaling, the tail risk of strategies does not change.

4.2 On survivor cryptocurrency momentum

This study is the first to investigate a cryptocurrency-specific analog of currency momentum, as implemented among G10 currencies. Evidence on cryptocurrency momentum is mixed regarding the profitability of this strategy (Grobys and Sapkota, 2019; Liu et al., 2022). Zaremba et al. (2021) emphasized that the inconclusive results in the literature could stem from methodological differences and sample construction, particularly the inclusion of illiquid small coins, which pose significant implementation challenges. Grobys et al. (2025) addressed these challenges by focusing on a rolling investment opportunity set of 30 cryptocurrencies with the highest market capitalizations from 2016 to 2023. Their cryptocurrency momentum strategy was only profitable after excluding extreme values. Among their findings, they document that the turnover of coins in their investment opportunity set averaged 37% annually, highlighting a lack of stability among the top large-cap digital currencies.

Because momentum is typically associated with smooth price movements (Asness et al., 2013), a momentum strategy based on "survivor coins" should theoretically exhibit profitability and a beta-exposure to that strategy might explain cryptocurrency momentum. Survivor coins are defined as free-floating cryptocurrencies that remained among the top 100 altcoins by market capitalization throughout the sample period (January 2017 to August 2024), hence showing stability and liquidity over time. Utilizing them in constructing crypto-momentum, we try to resemble the well-known G10 currency momentum, where only the most liquid and relevant currencies are considered (Aloosh and Bekaert, 2022). Conversely, if no exposure to survivor coins is found, the momentum effect may manifest through cryptocurrencies that gain popularity, suddenly transition from a passive liquidity state to an active one, and then revert to their previous price levels or even default once their popularity fades. Thus, this research is the first to explore cryptocurrency momentum within a framework analogous to G10 currency momentum, specifically by analyzing cryptocurrencies with a high degree of liquidity stability over time, providing a basis for cross-market comparisons. Additionally, this study addresses inconsistencies in prior findings on the profitability of cryptocurrency momentum (Zaremba et al., 2021). Specifically, we extend the work of Grobys et al. (2025) by examining whether momentum profitability is primarily driven by coins with stable liquidity.

We find that only nine coins met this definition. Using these nine coins, we follow the literature on G10 currency momentum and employ tercile and equally-weighted portfolios to construct our Survivor Cryptocurrency Momentum Portfolio (SCMP). This long-short portfolio does not generate significant profits, nor does its trimmed counterpart. Furthermore, a spanning regression on the trimmed momentum strategy proposed by Grobys et al. (2025) shows that both the loading against SCMP and the regression intercept are positive and statistically significant. As the beta coefficient on SCMP is lower than one, this evidence suggests that the profitability of the trimmed plain cryptocurrency momentum portfolio is not an artifact of a leveraged SCMP.

We therefore conclude that the significant payoffs documented for cryptocurrency momentum strategies are likely driven by coins that are only temporarily accessible for trading, falling into a passive investment space (Aloosh and Bekaert, 2022). As a further test, we control for market factor exposure and split our analysis into two subsamples. Yet, our main conclusions remain unchanged. The implications of this study are relevant for investors and asset management firms seeking to implement momentum strategies in the cryptocurrency market. Our findings suggest that such strategies may be impractical in real-world settings, as many coins exist in an environment characterized by low liquidity and instability.

4.3 Does the transition to the Proof-of-Stake consensus protocol tame the response of cryptocurrency volatility to energy shocks?

This study examines the impact of transitioning from the Proof-of-Work (PoW) to the Proof-of-Stake (PoS) consensus protocol on the relationship between cryptocurrency volatility and energy shocks. Numerous studies highlight concerns about the substantial energy consumption associated with the cryptocurrency market (de Vries, 2019; Kohli et al., 2023; Sutherland, 2019; D. Zhang et al., 2023). The high energy consumption of cryptocurrencies is primarily driven by the consensus protocol underlying blockchain operations. The standard consensus algorithm adopted by most cryptocurrencies is the PoW protocol, in which block validation is performed by network participants, known as “miners.” These miners engage in a competitive process to solve complex mathematical problems, requiring powerful hardware and high energy expenditure. On the other hand, the PoS protocol eliminates this competitive computational race, significantly reducing energy consumption. To date, some cryptocurrencies have transitioned to PoS, while others—Bitcoin being the most prominent example—still rely on the PoW consensus protocol. Since the PoS protocol requires less energy consumption than PoW, an important question arises: Does transitioning from PoW to the more sustainable PoS consensus protocol affect the sensitivity of cryptocurrency volatility to energy shocks?

The answer to this question is non-trivial, as lower volatility would benefit digital coin holders. Moreover, our results contribute to the field of sustainable finance. In the context of cryptocurrencies, only a few studies have examined their sustainability profiles (Corbet et al., 2019). We also extend the literature on cryptocurrency volatility (Okorie and Lin, 2020; Yin et al., 2021; Naeem et al., 2023) and volatility modeling by employing extended GARCH models (Bouoiyour and Selmi, 2016; Caporale and Zekokh, 2019; Dyhrberg, 2016; Fakhfekh and Jeribi, 2020; Katsiampa, 2017, 2019). Finally, we use the transition to the PoS protocol as a quasi-natural experiment to conduct a causal investigation of this phenomenon. The sample used in this study comprises four cryptocurrencies—Ethereum, Cardano, Toncoin, and Decred—that transitioned from the PoW to the PoS protocol. Cryptocurrency data is sourced from CoinMarketCap, while crude oil (WTI) data is obtained from the U.S. Energy Information Administration. Consistent with earlier research, we use the return on crude oil as a proxy for energy input in crypto mining (Naeem et al., 2022, 2023). Results from GARCH and TGARCH models document an overall diminished sensitivity to energy shocks. Moreover, by re-estimating the GARCH and TGARCH models to include oil innovations in the conditional volatility function as a new measure of oil shocks, our robustness checks strongly corroborate the main findings. Our findings suggest that digital currencies still using the PoW mechanism should consider migrating to PoS, as this shift can benefit stakeholders by reducing the uncertainty of cryptocurrency price fluctuations.

4.4 A common component in cryptocurrency risk: Evidence from realized altcoin variances

The fourth essay employs power laws to model daily realized variances for the top 10 altcoins by market capitalization. A recent survey by Kyriazis (2021) documents that the vast majority of studies apply GARCH-type models to specify volatility dynamics and volatility spillovers. In this regard, the large number of available GARCH specifications enables the identification of the most appropriate model to explain fluctuations in market values. However, this advantage of GARCH-type models can also be a disadvantage. Mandelbrot (2008) stresses that models can be overfitted to explain shifting volatility patterns by incorporating parameters that change daily or even more frequently. Consequently, GARCH-type models often yield results that are model- or sample-specific. An anecdotal example is the study by Bouoiyour and Selmi (2015), who observe that while Threshold GARCH (TGARCH) is optimal for modeling Bitcoin volatility from December 2010 to June 2015, EGARCH is more appropriate from January 2015 to June 2015. Similarly, other studies present model specification-driven results (Bouoiyour and Selmi, 2016; Baur et al., 2018; Bouri et al., 2017; Catania et al., 2018; Dyhrberg, 2016; Klein et al., 2018).

To address this issue, Mandelbrot (2008) recommends building better models by identifying market properties that remain relatively constant over time. Consistently, this study examines if the risk of cryptocurrencies, measured in terms of realized variances, follows a power-law behavior and explores whether a time-invariant commonality exists to explain it. We extend the literature on volatility dynamics and volatility spillovers by analyzing this issue, given that cryptocurrencies exhibit extremely heavy tails (e.g., Baur and Dimpfl, 2021) and tail interdependencies (Shahzad et al., 2022; Xu et al., 2021). Moreover, we explicitly test standard distributions against power-law models and propose a new econometric testing procedure, derived from block bootstraps, to jointly test potential cross-sectional power-law behavior. Using daily range-based variance estimators following Parkinson (1980), we estimate the realized variance of the top 10 altcoins by market capitalization, retrieving data from CoinMarketCap. We find that kurtosis values for realized altcoin variances strongly suggest the presence of heavy tails and a Pareto-type distribution and that up to 30% of the realized variance distributions follow a power-law process. Our findings also indicate that the variance of variance is undefined for altcoins. Next, after estimating the covariance matrix of power-law exponents using block bootstraps, we test whether the power-law behavior manifests in a common cross-sectional component. We document that the optimal power-law exponent governing the cross-section of realized altcoin variances is $\hat{\alpha}$ =2.1, closely corresponding to the traditional Pareto 80/20 rule. Finally, restricting the sample to altcoins that remained among the top 20 altcoins by market capitalization at the end of our sample period, we find evidence of a time-invariant common component manifested in a cross-sectional power-law exponent governing realized altcoin variances. Sample split tests, conducted as robustness checks, confirm these findings.

Our results have practical implications for the professional management of crypto assets, as they suggest that risk diversification across cryptocurrencies may be more limited than previously believed.

4.5 “Don’t stop me now”: the cryptocurrency market reaction to the new Basel framework

The last essay investigates the cryptocurrency market’s reaction to the implementation of the new Basel framework on banks’ exposures to cryptoassets.

In response to the rapid evolution of the crypto market, the Basel Committee on Banking Supervision (BCBS) has introduced a new prudential treatment for banks’ exposures to cryptoassets, set to be in effect on January 1, 2026. An important issue in the crypto market lies in its potential to transmit systemic instability to other asset classes and the broader traditional financial system. For instance, Narayan and Kumar (2024) identify volatility spillovers from 33 cryptocurrencies to other markets, such as equities, exchange rates, and commodities. Similarly, Hanif et al. (2022) highlight the presence of both downside and upside risk spillovers between eight major cryptocurrencies and global and regional equity markets. Even though banks are only marginally exposed to cryptocurrency positions, this exposure is increasing due to a growing interest from banks in participating in this market (BIS, 2023). Given that banks are central to the financial system and have the capacity to propagate risks throughout the broader economy (Kaminsky and Reinhart, 2000), regulation is essential. However, while regulation can benefit both traditional and crypto markets by creating a more transparent environment and encouraging the participation of institutional investors (Conlon et al., 2024), overly rigid rules may hinder their growth. This is what we seek to understand by analyzing how the crypto market reacted to this new prudential standard. This study is the first to explore cryptocurrency market dynamics and investor sentiment in response to the introduction of the prudential treatment regulating banks’ exposures to cryptoassets. It thus expands the limited and emerging literature on the impact of regulations on the cryptocurrency market. While previous studies focus on narrow bans or nation-specific interventions (Cumming et al., 2024; Koenraadt and Leung, 2024), we analyze the impact of an international regulatory framework, addressing the limitations of Conlon et al. (2024). Furthermore, we extend the broader literature that uses event studies to analyze the effects of bank regulation (Horvath and Huizinga, 2015; Bruno et al., 2018; Pancotto et al., 2020), adding a novel focus on cryptocurrency markets. Because regulatory changes represent innovations in the intermediary capital ratio (He et al., 2017), we also provide preliminary evidence that shocks to the intermediary capital ratio might affect returns (He and Krishnamurthy, 2013). Finally, this study contributes to the ongoing debate on capital requirements for banks’ exposure to cryptoasset risks.

We follow the sampling approach of Conlon et al. (2024) and retrieve financial data for 37 cryptocurrencies from CoinMarketCap. To investigate the cryptocurrency market’s reaction to the introduction of the Basel cryptoasset framework, we employ the event study methodology using the market model approach. While our results show an initial positive market reaction to the announcement of the new framework—possibly signaling the expectation of increased institutional involvement—the crypto market reacted negatively as more details on transparency and capital requirements were released. This finding suggests that the new Basel framework may be considered too severe, as it imposes punitive weightings and highly stringent capital requirements, discouraging banks from engaging in crypto-related activities. Using log returns and varying the length of estimation windows as robustness checks does not affect our results.

Our findings suggest that while the general principle of “same risk, same activity, same treatment” is welcomed by stakeholders, the current regulation appears overly stringent. Therefore, certain aspects and calibrations could be reviewed to ensure that banks retain the ability to offer cryptoasset products and services to their customers.

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Cryptocurrency momentum has (not) its moments

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Abstract
This paper explores the tail behavior of cryptocurrency momentum strategies and the profitability of volatility-managed momentum portfolios. Our main results derived from using a sample of large-cap cryptocurrencies and equal-weighted momentum portfolios indicate that cryptocurrency momentum is subject to severe crashes. Even a single cryptocurrency can cause insignificant momentum portfolio returns. In line with the literature on volatility-managing equity portfolios, our findings suggest that volatility management is a useful tool for mitigating cryptocurrency momentum crashes. Further corroborative evidence suggests that cryptocurrency momentum appears to be a phenomenon associated with large-cap cryptocurrencies.

Keywords Cryptocurrencies · Efficient markets · Momentum · Volatility scaling · Tail risk

JEL Classification G10 · G11 · G14 · G15

1 Introduction

Stock price momentum, first documented by Jegadeesh and Titman (1993), has received enormous attention among scholars. This simple trading strategy—a zero-investment portfolio that is long past winner stocks and short past loser stocks—not only holds in expanded samples (Jegadeesh and Titman 2001) but is pervasive across unrelated asset classes (Asness et al. 2013) and holds up to scientific

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Extended author information available on the last page of the article replications (Hou et al. 2020). Unfortunately, momentum strategies suffer from reoccurring crashes or drawdowns that are so severe that it can take more than a decade to recover (Barroso and Santa-Clara 2015; Daniel and Moskowitz 2016). To remedy the problem of momentum crashes, several studies have proposed to scale past returns using volatility or variance (Barroso and Santa-Clara 2015; Daniel and Moskowitz 2016; Moreira and Muir 2017). Despite this intuitively appealing approach, volatility scaling has shortcomings. Liu et al. (2019) have argued that volatility scaling suffers from look-ahead bias. Also, Cederburg et al. (2020) conducted a comprehensive empirical investigation using a broad sample of 103 equity portfolios and concluded that volatility management often diminished real-time performance. Contrarily, Liu et al. (2019) found that the approach proposed by Barroso and Santa-Clara (2015) was not subject to look-ahead bias and yielded reliable results. In sum, some controversy surrounds the performance of volatility-managing momentum strategies.

In recent years, momentum strategies have been applied to cryptocurrencies. Using monthly return data on cryptocurrencies, Grobys and Sapkota (2019) investigated the profitability of crypotcurrency momentum strategies. Unlike Asness et al. (2013), who documented momentum across different asset classes, the authors did not find support for cryptocurrency momentum using monthly returns from 2014 to 2018. By contrast, Liu et al. (2022) implemented cryptocurrency momentum strategies using weekly data from 2014 to 2020 and documented large positive payoffs of 3% per week. Also, in an earlier study, Liu et al. (2020) implemented a cryptocurrency momentum strategy from 2015 to 2018 sample and reported outsized average payoffs of 36% per week. However, confirming the findings in Grobys and Sapkota (2019), Shen et al. (2020) found that, regardless of the momentum strategy using weekly data from 2013 to 2019, insignificant negative returns on cryptocurrency portfolios occurred. Thus, no consensus exists on cryptocurrency momentum profits.

Motivated by this literature, the present study re-examines cryptocurrency momentum strategies using weekly observations in the period 2016 to 2023. To control for liquidity, we focus on the top 30 cryptocurrencies with the highest market capitalization. From a practical standpoint, if an investor seeks to implement cryptocurrency momentum strategies in a market dominated by only a few coins, they must be tradable in the real world. Of particular interest, we examine the magnitudes of momentum crashes for cryptocurrency strategies by comparing the payoffs of the plain strategy with various trimming approaches. Potential increases in the statistical significance of cryptocurrency momentum payoffs after trimming would suggest that their performance depends on the tails of the distribution. Additionally, we explore the profitability of various volatility-managed approaches to scale cryptocurrency momentum payoffs. These analyses yield further insights into how volatility management affects the tail risk of cryptocurrency momentum profits.

Our study contributes to relevant literature in several ways. First, as discussed earlier, since studies on cryptocurrency momentum are inconclusive, it is possible that sample specificity explains disparate findings on cryptocurrency momentum. In this regard, the market for cryptocurrencies is notorious for recurring bubble formations (e.g., Grobys 2024a; Kyriazis et al. 2020; Wheatley et al. 2019) that can generate (seemingly) significant cryptocurrency momentum payoffs. Furthermore, it is a well-known stylized fact that the profitability of momentum strategies is more pronounced among microstocks (Fama and French 2008, 2018). Is the profitability of cryptocurrency momentum driven by micro-cryptocurrencies, which would be difficult to implement in practice due to liquidity problems? Our study addresses these important questions by using a considerably longer sample period than earlier studies and focusing on 30 large cryptocurrencies with the highest market capitalization.

Second, potential profitability of cryptocurrency momentum could be driven by extreme events arriving with low probability. That is, inconclusiveness about the profitability of cryptocurrency momentum could be an artifact of tail events that occurred in some samples. As already mentioned, momentum equity strategies are plagued by recurring crashes (Barroso and Santa-Clara 2015; Daniel and Moskowitz 2016). We extend this research by exploring this issue for cryptocurrency momentum strategies. More specifically, we investigate the profitability of Barroso and Santa-Clara's (2015) risk-managed cryptocurrency momentum strategies. According to Liu et al. (2019), these strategies are not subject to look-ahead bias.

Third, and last, we document evidence that sheds light on the implied risk associated with cryptocurrency momentum and risk-managed strategies. As noted in Taleb (2020), power laws provide a simple yet useful methodological framework to derive the implied risk of payoff series. Specifically, the power law exponent gives us via extrapolation information on the implied risk—that is, the lower the economic magnitude of the power law exponent, the higher is the implied risk of the strategy. Even if large standard deviations (viz. crashes) were not observed, power law functions allow us to form probabilistic assessments about the potential arrival of crashes.[1] Hence, contributing to the literature on cryptocurrency momentum (i.e., Liu et al. 2020, 2022; Zaremba et al. 2021), we explore the implied risk of cryptocurrency momentum strategies by modeling the tail returns of cryptocurrency momentum as power laws.

Using large-capitalization cryptocurrencies and implementing cryptocurrency momentum for various sample periods, we find profits of 1.74% per week from January 2016 to July 2020.[2] These raw payoffs are only nominally significant at the 10% level, which suggests that results in Liu et al. (2022) are possibly attributable to small-cap cryptocurrencies lacking liquidity. In the ex post July 2020 sample period, the average return on cryptocurrency momentum is negative and statistically insignificant consistent with Grobys and Sapkota (2019) and Shen et al. (2020). For the overall sample, cryptocurrency momentum produced an insignificant average raw payoff of 0.90% per week.

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[1] Previously documented by Mandelbrot (1963) for cotton price changes, Lux and Alfarano (2016) argued that the power law behavior of financial assets is a stylized fact. In this respect, Mandelbrot's proposed Lévy-stable hypothesis has been subject to extensive investigations across asset classes for over five decades. Interestingly, a recent study of Grobys (2024b) explores the momentum variance risk for stock price momentum and documents that the realized variance risk is infinite.

[2] Note that this sample mainly overlaps with the sample used in Liu et al. (2022), and the end of the chosen sample coincides with the end of the sample used in Liu et al. (2022).

What explains these ambiguous findings? Using various trimming techniques, we find that cryptocurrency momentum is subject to severe crashes. For example, in December 2020 corresponding to the ex post sample period used in Liu et al. (2022), cryptocurrency momentum crashed by −255.23%. Even though the presence of severe crashes is in line with the literature on stock price momentum (Barroso and Santa-Clara 2015; Daniel and Moskowitz 2016), we find that this crash is *not* related to market reversals but instead to an extreme price jump in a single cryptocurrency in the short leg of the portfolio. Excluding this single event by means of data trimming increases the weekly average return on cryptocurrency momentum to 1.51% per week for the overall sample with a *t*-statistic of 2.63 (i.e., significant at the 1% level). Likewise, risk-managed techniques increase the average payoffs by a substantial margin. Indeed, most of our risk-managed strategies increase the weekly average raw return by more than 200% compared to plain strategy payoffs. Upon risk adjustment of payoffs using asset pricing factors, including a cryptocurrency market factor and plain cryptocurrency momentum factor, risk-managed payoffs as measured by the intercepts of the regression models are statistically significant at the 5% level. These findings are consistent with earlier studies on risk-managed stock price momentum (e.g., Barroso and Santa-Clara 2015; Moreira and Muir 2017).

Finally, our empirical evidence reveals that one single outlier corresponds to 37% of the overall compounded return of the cryptocurrency momentum strategy. Using power laws to model the returns on cryptocurrency momentum shows that the variance of this strategy is statistically undefined as implied by a power law exponent of $\alpha < 3$. This finding suggests that the returns on cryptocurrency momentum are as risky as the returns on cotton price changes (Mandelbrot 1963) or venture capital (Lux and Alfarano 2016). Remarkably, risk-managing cryptocurrency momentum does not significantly change the tail risk of cryptocurrency momentum (i.e., the power law exponents are statistically the same for both the plain strategy and various risk-managed counterparts). Based on this evidence, we conclude that cryptocurrency momentum is riskier than previously believed.

2 Literature review

2.1 Cryptocurrency momentum

Since the seminal paper by Jegadeesh and Titman (1993), momentum has continued to be one of the most persistent anomalies in the asset pricing literature. This investment strategy involves taking a long position in assets that have performed well in the recent past and a short position in assets that have performed poorly. Several theoretical models that highlight investors' behavioral biases, including Barberis et al. (1998), Daniel et al. (1998), Hong and Stein (1999), and others, have sought to explain momentum.

A growing number of studies have investigated the momentum strategy in the cryptocurrency market. One of the pioneering studies in this area was by Grobys and Sapkota (2019). They analyzed a dataset consisting of 143 cryptocurrencies from 2014 to 2018. Employing portfolio analysis across different time windows ranging from 2 to 12 months, as well as evaluating time series momentum effects (Moskowitz et al. 2012), their findings indicated an insignificant payoff for the momentum strategy in the cryptocurrency market.

Liu et al. (2020) used a dataset of 78 cryptocurrencies to identify the common risk factors that explain their returns. Among the factors studied, including market and size, they found that a momentum factor well explains average returns in both time series and cross-sectional analyses. In contrast with Grobys and Sapkota (2019), they identified a positive payoff for a one-year momentum strategy that tends to diminish as the market capitalization of coins increases.

Liu and Tsyvinski (2021) identified a strong influence of time series momentum within one-to-four week horizons. Unlike equity market momentum, they argued that cryptocurrencies do not show an interaction between momentum and investor attention that could arise from a common latent mechanism. In their subsequent study, Liu et al. (2022) expanded their analysis by demonstrating that a three-factor model with market, size, and momentum factors explains the cross section of cryptocurrency returns. They utilized a dataset of 1827 coins with market capitalization over 1 million USD from the beginning of 2014 to July 2020 and sorted portfolios using a one-to-four week formation period. In their analysis, they documented that a long/short momentum strategy produced significant average payoffs of roughly 3% excess weekly returns. Using similar weekly formation periods and the 2000 largest cryptocurrencies, Dobrynskaya (2023) arrived at similar conclusions.

However, Shen et al. (2020) reported contrasting results. They collected data for 1786 coins from 2013 to 2019 using equally weighted portfolios and a weekly updated momentum strategy. Their results documented a negative momentum payoff increasing from larger to smaller cryptocurrencies. Moreover, consistent with the presence of a reversal effect, Borgards and Czudaj (2020) showed that persistent price overreactions occurred for twelve cryptocurrencies.

On the whole, empirical evidence on cryptocurrency momentum is inconclusive. Zaremba et al. (2021) have pointed out that mixed results may stem from differences in methodological approaches and sample construction. Moreover, they documented a liquidity dependency of cryptocurrency returns, especially for the smaller ones. Notably, small coins often exhibit extremely illiquid characteristics, which could pose significant challenges, especially when attempting to implement strategies that short cryptocurrencies. Hence, liquidity constraints can contribute to mixed evidence also.

2.2 Risk-managed strategy

Although the stock price momentum anomaly continues to persist, it can suffer from periods of poor performance. In the equity market, research has demonstrated that, during economic and financial downturns, the high returns of momentum strategies tend to diminish. This downtrend appears to occur in the wake of large market declines followed by rebounds. As argued by Daniel and Moskowitz (2016), the returns on the stock price momentum strategy can be viewed as a written call option on the market. The intuition is that, during a market decline, high-beta stocks tend to suffer more significant losses compared to low-beta stocks, which tend to fare relatively better. For this reason, the portfolio strategy tends to be long low-beta past winners and short high-beta past losers. However, when the market rebounds, high-beta stocks experience rapid increases in returns. These returns can lead to losses for the momentum strategy due to the portfolio's conditional large negative beta with respect to the market (Grundy and Martin 2001).

Seminal work by Barroso and Santa-Clara (2015) demonstrated that crashes can be mitigated by managing the risk of the strategy. To do so, they scaled long/short momentum portfolio returns by the inverse of their six-month realized variance and a target constant. Using this simple approach, they documented an improvement in the strategy that not only diminished the impact of the worst crashes but also improved the overall performance in normal periods, nearly doubling the Sharpe ratio. The performance of the risk-managed strategy was robust to different subsamples and different international markets. Moreover, they found that the turnover of this strategy was comparable to that of a plain momentum strategy, thereby avoiding high transaction costs that makes the strategy feasible for real world implementation.

Moreira and Muir (2017) investigated the performance of different volatility-managed strategies using a similar approach. They constructed stock portfolios for market, momentum, value, profitability, return-on-equity (ROE), investment, and betting-against-beta (BAB) factors using the previous one-month realized variance and a scaling factor. They showed that these portfolios achieve higher risk-adjusted returns compared to their naive counterparts and generate substantial alphas when regressed on a broad range of asset pricing factors. They also emphasized the effectiveness of these strategies, demonstrating strong evidence of a relationship between past volatility and current volatility, which tends to increase as the time horizon shortens.

However, this volatility scaling approach is not without criticism. Liu et al. (2019) identified a look-ahead bias in the scaling factor of Moreira and Muir (2017) related to the constant chosen in order to obtain the same full-sample variance. Upon correcting this issue, they found that risk-managed portfolios did not outperform the market in the sample period from 1936 to 2017. Furthermore, they observed that these portfolios exhibited an unattractive high maximum drawdown, which could make them less appealing to investors. Subsequently, they replicated their analysis by considering the volatility-targeting strategy of Barroso and Santa-Clara (2015). Although this approach does not suffer from look-ahead bias, as the constant is specified ex ante, the authors once again found evidence that volatility-managed portfolios did not outperform the market.

Another study by Cederburg et al. (2020) studied the performance of volatility-managed portfolios using a comprehensive set of 103 equity strategies with mixed results. They found that these portfolios do not consistently provide significantly higher payoffs than their plain momentum counterparts (e.g., 50 of them failed to outperform). While they obtained a positive alpha from spanning regressions in sample, the instability of the parameters in out-of-sample tests indicated a less impressive Sharpe ratio for the strategy. It should be noted that they used the look-ahead bias approach of Moreira and Muir (2017) to construct their portfolios.

More recently, Angelidis and Tessaromatis (2023) suggested that the disappearing profitability of volatility-managed portfolios may be linked to a reduction in arbitrage costs. After the implementation of trading and information rule changes in the USA during the early 2000s, which enhanced market liquidity, volatility management strategies became redundant.

3 Data

We download cryptocurrency data from coinmarketcap.com, a leading source commonly used in the literature. To determine the investment opportunity set for each year, we retrieve the price time series of the 30 cryptocurrencies with the highest market capitalization at the end of December[3] of the previous year from December 2015 to December 2022. We make this choice to obtain a sample of liquid cryptocurrencies that are tradable in the real world and, therefore, avoid issues associated with smaller coins that likely alter momentum strategy payoffs (Fama and French 2008, 2018; Zaremba et al. 2021).[4] The final sample contains daily prices and market capitalization data denominated in US dollars for 89 unique cryptocurrencies. Table 10 in Appendix provides the list of all sample coins by year. Using these data, we construct equal-weighted long/short portfolios from the first week of January 2016 to the fourth week of December 2023, viz. 416 weekly observations.

A potential data issue is that the composition of the investment opportunity set may not systematically include 30 coins each year. Some of the top cryptocurrencies in the earlier years defaulted over time and were thereafter no longer tracked by coinmarketcap.com. To mitigate this potential survivor bias, we retrieve missing observations from other sources, such as finance.yahoo.com and coincodex.com, in order to complete data series as much as possible. Any remaining missing data, for which we could not obtain information, are excluded from the sample. Additionally, we exclude stablecoins from the investment set. These coins are tethered to another asset class to maintain a stable value. For this reason, they do not provide a return and are not a relevant investment opportunity.

It is worth mentioning that, on average, the turnover of coins in the investment opportunity set is 37% annually. This high turnover underlines the considerable difference in the stability between the equity market and the cryptocurrency market. Only 8 cryptocurrencies—namely, Bitcoin (BTC), Ethereum (ETH), XRP (XRP), Dogecoin (DOGE), Litecoin (LTC), Monero (XMR) and Stellar (XLM)—maintained their positions in the top 30 from 2015 to 2022.

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[3] To do so, we utilize Cryptocurrency Historical Data Snapshots provided by coinmarketcap.com. The website offers a historical overview of the market for each week. Since these data are not provided daily, we select for each year the top 30 coins based on the data from the last Sunday of December.

[4] Note that this is also in line with the literature on foreign exchange rates that often focuses on the G10 currencies due to liquidity issues (Assness et al., 2013). Using the G10 currencies to form momentum portfolios leaves us with three equal-weighted currencies in both the long and short leg.

4 Empirical analysis

4.1 Portfolio sorts

Using 30 large cryptocurrencies in December of the previous year, we sort all available cryptocurrencies into quintiles based on their past 30-day returns. We skip the most recent daily price quotation to compute the previous month's formation period (FP) return on cryptocurrency *i*:

$$r_{i,t}^{FP} = \frac{100\left(p_{i,j-1,t} - p_{i,j-30,t}\right)}{p_{i,j-30,t}}, \tag{1}$$

where $p_{i,j-1,t}$ denotes the closing price of cryptocurrency i on the previous trading day j-1 for a given week t, $p_{i,j-30,t}$ denotes the closing price of cryptocurrency i in the past 30 trading days for a given week t, and $r_{i,t}^{FP}$ is the corresponding formation period return on cryptocurrency i in week t. The momentum portfolio is long (short) cryptocurrencies with the highest (lowest) formation period returns. Using quintile sorts, our momentum portfolio is long on portfolio group 5 ("winners") and short on portfolio group 1 ("losers"). We hold the equal-weighted zero-cost portfolio one week ahead and rebalance our portfolio at the beginning of each week. This plain momentum approach ensures that the investment opportunity set consists of

Table 1 Descriptive statistics for the cryptocurrency market and momentum factor

Sample	Sample 1		Sample 2		Sample 3	
Return vector	Momentum	Market	Momentum	Market	Momentum	Market
Mean	0.90	1.70	1.74	2.72	−0.19	0.40
Median	1.38	0.83	1.33	1.69	1.44	0.18
Maximum	61.34	65.11	61.34	62.72	22.08	65.11
Minimum	−255.28	−34.41	−73.86	−34.41	−255.28	−30.34
Std. deviation	17.20	11.78	14.42	13.28	20.21	9.40
Skewness	−8.02	1.18	−0.27	0.88	−11.14	1.72
Kurtosis	121.81	8.50	10.18	6.31	141.19	15.20
Jarque–Bera (JB)	249,133.90	621.56	505.30	137.08	148,582.10	1217.95
(p-value JB)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	416	416	234	234	182	182

This table reports the descriptive statistics of the cryptocurrency market and momentum factors. The market factor is an equal-weighted portfolio of cryptocurrencies consisting of the top 30 cryptocurrencies based on their market capitalization. Using quintile sorts and these top 30 cryptocurrencies, the momentum factor is a strategy that is long cryptocurrencies with the highest return in the 1-month formation period and short those with the lowest return in the 1-month formation period. We skip 1 trading day between the holding period and formation period. This strategy employs equal-weighted asset allocations and is rebalanced weekly. The weekly data sample is from the first week of January 2016 to the fourth week of December 2023 period comprised of 416 observations. Sample 1 corresponds to the overall period (i.e., January 2016 to December 2023), sample 2 covers the subperiod from the first week of January 2016 to the last week of July 2020, and sample 3 spans the subperiod from the first week of August 2020 to the last week of December 2023

Table 2 Portfolio sorts for the momentum factor

Portfolio	P1	P2	P3	P4	P5	(P5-P1)
Panel A. Portfolio sorts for sample 1						
$\bar{r}_i$	1.46	1.30	1.37	1.88	2.36	0.90
$\bar{r}_i^{FP}$	– 19.60	– 6.30	2.68	14.28	64.14	(1.06)
Panel B. Portfolio sorts for sample 2						
$\bar{r}_i$	1.91	2.39	2.49	2.95	3.66	1.74*
$\bar{r}_i^{FP}$	– 20.96	– 5.43	5.46	20.29	88.39	(1.85)
Panel C. Portfolio sorts for sample 3						
$\bar{r}_i$	0.87	– 0.10	– 0.07	0.50	0.68	– 0.19
$\bar{r}_i^{FP}$	– 17.84	– 7.40	– 0.90	6.56	32.96	(– 0.13)

This table reports the portfolio sorts for the cryptocurrency momentum factor. Using quintile sorts and the top 30 cryptocurrencies in terms of their market capitalization, the momentum factor is a strategy that is long cryptocurrencies with the highest return in the 1-month formation period and short those with the lowest return in the 1-month formation period. We skip 1 trading day between the holding period and formation period. This strategy employs equal-weighted asset allocations and is rebalanced weekly. Portfolio 1 (P1) corresponds to the loser portfolio, and portfolio 5 (P5) corresponds to the winner portfolio. The average return for portfolio $i = \{1,2,3,4,5\}$ is denoted as $\bar{r}_i$, whereas the average portfolio return for the formation period (FP) is denoted as $\bar{r}_i^{FP}$. The weekly data sample is from the first week of January 2016 to the fourth week of December 2023 comprised of 416 observations. Sample 1 corresponds to the overall period (e.g., January 2016 to December 2023), sample 2 covers the subperiod from the first week of January 2016 to the fourth week of July 2020, and sample 3 spans the subperiod from the first week of August 2020 to the fourth week of December 2023. The *t*-statistics for the zero-cost portfolios are given in parenthesis

*Statistically significant on a 10% level

the same assets for a given year. At the end of December of each year, we re-assess which cryptocurrencies are in the top 30 in terms of market capitalization.

Descriptive statistics for both the cryptocurrency momentum portfolio and the market factor are reported in Table 1. The results from our portfolio sorts are shown in Table 2. The weekly data sample is from the first week of January 2016 to the fourth week of December 2023 period comprising 416 weekly observations. Sample 1 corresponds to the overall sample period (i.e., January 2016 to December 2023), sample 2 covers the subperiod from the first week of January 2016 to the fourth week of July 2020, and sample 3 spans the subperiod from the first week of August 2020 to the fourth week of December 2023. In Table 1, we see that the market factor outperformed the momentum strategy in these three sample periods. Notice that the momentum strategy performed remarkably well at 1.74% per week in sample 2, which ends in the fourth week of July 2020 as in Liu et al. (2022). Table 2 indicates that this payoff is significant at the 10% level. As expected, Table 2 documents that the average formation period returns are linearly increasing from portfolio group 1 (loser) to group 5 (winner) for all samples. Holding period returns also linearly increase for samples 1 and 2, but this pattern does not hold for sample 3. Concerning the latter subperiod, if we exclude one discontinuity that occurred at the end of December 2020, Figs. 1 and 2 show that the cumulative returns on the cryptocurrency momentum portfolio are linearly increasing. Of particular note, the aforementioned one-week discontinuity manifests a large momentum crash equal to – 255.28%.

4.2 Trimming

To further investigate whether the poor performance of cryptocurrency momentum is attributable to an outlier, we apply various trimming approaches to the data. Specifically, trimming 1 is a procedure that shrinks the distribution between the 5th and 95th percentiles, trimming 2 shrinks the distribution between the 1st and 99th percentiles, and trimming 3 excludes only the largest observation in terms of absolute value (i.e., – 255.28%). We report the corresponding descriptive statistics for sample 1 (overall sample period) in Table 3. Regardless of the trimming procedure, now the average raw return of the cryptocurrency momentum portfolio is highly significant at a 1% level. These results confirm that the poor overall performance of the

Fig. 1 Cumulative returns on the cryptocurrency momentum strategy. Using quintile sorts and the top 30 cryptocurrencies in terms of their market capitalization, the momentum factor is a strategy that is long cryptocurrencies with the highest return in the 1-month formation period and short those with the lowest return in the 1-month formation period. We skip 1 trading day between the holding period and formation period. This strategy employs equal-weighted asset allocations and is rebalanced weekly. This figure plots the evolution of the cumulative returns for the zero-cost momentum portfolio from the first week of January 2016 to the last week of December 2023

Fig. 2 Cumulative returns on the cryptocurrency market factor and the momentum portfolio. The market factor is an equal-weighted portfolio of cryptocurrencies consisting of the top 30 cryptocurrencies based on their market capitalization. Using quintile sorts and the top 30 cryptocurrencies, the momentum factor is a strategy that is long cryptocurrencies with the highest return in the 1-month formation period and short those with the lowest return in the 1-month formation period. We skip 1 trading day between the holding period and formation period. This strategy employs equal-weighted asset allocations and is rebalanced weekly. This figure plots the evolution of the cumulative returns for the market factor and momentum portfolio from the first week of January 2016 to the last week of December 2023

cryptocurrency momentum strategy in the sample period in Liu et al. (2022) is due to an extreme heavy tail produced from a single outlier arriving in the end of the year 2020. Interestingly, given that the Jarque–Bera test in Table 3 does not reject the null hypothesis of normally distributed cryptocurrency momentum portfolio returns (p-value 0.18), we infer that returns between the 5th and 95th percentiles are normally distributed. The critical question that remains is: How can cryptocurrency momentum crash risk be managed?

4.3 Risk-managed cryptocurrency momentum

Appendix Figure 6 plots the evolution of a rolling time window of the standard deviation of four momentum portfolio returns over our weekly sample from January 2016 to the fourth week of December 2023. In line with earlier studies on momentum crashes, the realized volatility process of cryptocurrency momentum exhibits persistent periods of high and low volatility. Following Barroso and Santa-Clara (2015), we implement a risk-managed cryptocurrency momentum portfolio as follows:

$$r_{j,t}^{RM,MOM} = \frac{c}{\hat{\sigma}_{t,j}} r_{t}^{MOM}, \tag{2}$$

Table 3 Descriptive statistics after trimming

Method	Trimming 1	Trimming 2	Trimming 3
Mean	1.33***	1.47***	1.51***
(*t*-statistic)	(3.94)	(3.23)	(2.63)
Median	1.38	1.38	1.39
Maximum	18.93	43.22	61.34
Minimum	−13.70	−31.14	−73.86
Std. deviation	6.54	9.22	11.73
Skewness	0.23	0.40	−0.28
Kurtosis	3.14	5.54	13.34
Jarque–Bera (JB)	3.48	120.20	1855.04
(*p*-value JB)	(0.18)	(0.00)	(0.00)
Observations	374	408	415

This table reports the descriptive statistics of the cryptocurrency momentum factor after trimming the data. Using quintile sorts and the top 30 cryptocurrencies in terms of their market capitalization, the momentum factor is a strategy that is long cryptocurrencies with the highest return in the 1-month formation period and short those with the lowest return in the 1-month formation period. We skip 1 trading day between the holding period and formation period. This strategy employs equal-weighted asset allocations and is rebalanced weekly. The weekly data sample is from the first week of January 2016 to the fourth week of December 2023 comprised of 416 observations. Trimming 1 is a procedure that shrinks the distribution between the 5th and 95th percentiles, trimming 2 shrinks the distribution between the 1st and 99th percentiles, and trimming 3 excludes only the largest observation measured in terms of the absolute economic magnitude. The *t*-statistics for the payoffs of the trimmed zero-cost portfolios are given in parenthesis

*** Statistically significant on a 1% level

where c denotes a scaling factor corresponding to the target level of volatility, r_t^{MOM} denotes the return on the plain momentum strategy in week t as described in Sect. 4.1, $r_{j,t}^{RM,MOM}$ denotes the return on the risk-managed momentum portfolio of strategy j in week t, and $\widehat{\sigma}_{t,j}$ is the estimated standard deviation of the momentum portfolio between week $t-j$ and week $t-1$ with $j \in \{4,8,12\}$ defined as:

$$\hat{\sigma}_{t,j} = \sqrt{\sum_{k=1}^{j} \frac{\left(r_{t-k}^{MOM}\right)^2}{j}}. \tag{3}$$

In Fig. 3, we plot the time series evolution of the scaling factor, or $\frac{c}{\widehat{\sigma}_{t,j}}$, used for volatility-managing cryptocurrency momentum payoffs (i.e., $j = 8$ in association with $c = 10$ from the second week of April 2016 to the fourth week of December 2023). Similar to the results documented by Barroso and Santa-Clara, as shown in Fig. 3, the scaling factor leverages (deleverages) the cryptocurrency momentum payoffs when past volatility was low (high). Subsequently, we risk adjust the

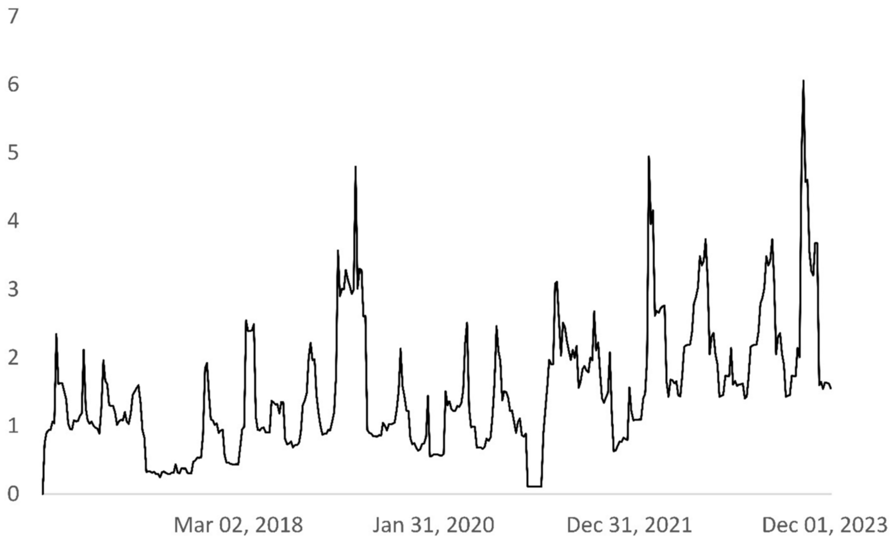

Fig. 3 Evolution of a scaling factor used for volatility-managing cryptocurrency momentum payoffs. Using quintile sorts and the top 30 cryptocurrencies in terms of their market capitalization, the momentum factor is a strategy that is long cryptocurrencies with the highest return in the 1-month formation period and short those with the lowest return in the 1-month formation period. We skip 1 trading day between the holding period and formation period. This plain momentum strategy employs equal-weighted asset allocations and is rebalanced weekly. Risk-managed (RM) cryptocurrency momentum strategies ($r_{j,t}^{RM,MOM}$) scale plain momentum returns as follows: $r_{j,t}^{RM,MOM} = \frac{c}{\hat{\sigma}_{t,j}} r_t^{MOM}$, where c is scaling factor corresponding to the target level of volatility, and $\hat{\sigma}_{t,j}$ is the estimated standard deviation of the momentum portfolio between week $t-j$ and week $t-1$ with $j \in \{4,8,12\}$. This figure plots the evolution of the scaling factor derived from $j = 8$ in association with $c = 10$. The weekly data sample is from the second week of April 2016 to the last week of December 2023 period comprised of 404 observations

risk-managed cryptocurrency momentum payoffs using the following factor regression model:

$$r_{j,t}^{RM,MOM} = \alpha_j + \beta_{j,1} r_t^{Mkt} + \beta_{j,2} r_t^{MOM} + \varepsilon_{j,t}, \tag{4}$$

where r_t^{Mkt} denotes the cryptocurrency market factor in week t, which is simply an equal-weighted portfolio of our cryptocurrencies used for implementing the momentum strategy, r_t^{MOM} denotes the return on the plain cryptocurrency momentum strategy in week t, $\epsilon_{j,t}$ denotes a white noise error at time t, and $\theta_j = (\alpha_j, \beta_{j,1}, \beta_{j,2})$ is a vector of estimated parameters.

Descriptive statistics in Table 4 are shown for risk-managed cryptocurrency momentum portfolios using $c = 10$ to implement the scaling factor. In the sample period April 2016 to December 2023, we observe that the mean weekly payoffs for most risk-managed cryptocurrency momentum strategies are greater than cryptocurrency market returns at 1.59% per week and higher than the plain strategy at 0.71% per week. Specifically, using an 8-week rolling time window strategy to estimate the past realized volatility of the cryptocurrency momentum

Table 4 Descriptive statistics for volatility-managed cryptocurrency momentum portfolios

Factor/strategy	Market factor	r_t^{MOM}	$r_{1,t}^{RM,MOM}$	$r_{2,t}^{RM,MOM}$	$r_{3,t}^{RM,MOM}$
Mean	1.59***	0.71	2.40*	1.86**	1.33
(t-statistic)	(2.69)	(0.83)	(1.81)	(2.09)	(1.45)
Median	0.78	1.28	1.81	1.44	1.28
Maximum	65.11	61.34	124.95	70.11	78.22
Minimum	− 34.41	− 255.28	− 335.26	− 226.30	− 262.64
Std. Dev	11.87	17.25	26.69	17.93	18.47
Skewness	1.20	− 8.16	− 4.55	− 4.67	− 6.93
Kurtosis	8.52	123.48	68.75	68.22	106.45
Jarque–Bera (JB)	609.62	248,847.00	74,162.62	73,082.99	183,380.10
(p-value JB)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	404	404	404	404	404

Using quintile sorts using the top 30 cryptocurrencies, the momentum factor is a strategy that is long cryptocurrencies with the highest return in the 1-month formation period and short those with the lowest return in the 1-month formation period. We skip 1 trading day between the holding period and formation period. This plain momentum strategy employs equal-weighted asset allocations and is rebalanced weekly. Risk-managed (RM) cryptocurrency momentum strategies ($r_{j,t}^{RM,MOM}$) scale plain momentum returns as follows: $r_{j,t}^{RM,MOM} = \frac{c}{\hat{\sigma}_{t,j}} r_t^{MOM}$, where c is scaling factor corresponding to the target level of volatility and $\hat{\sigma}_{t,j}$ is the estimated standard deviation of the momentum portfolio between week $t-j$ and week $t-1$ with $j \in \{4,8,12\}$. This table reports the descriptive statistics for the volatility-managed momentum portfolios. The weekly data sample is from the second week of April 2016 to the fourth week of December 2023 comprised of 404 observations

*** Statistically significant on a 1% level, ** statistically significant on a 5% level, * statistically significant on a 10% level

portfolio, we obtain risk-managed raw payoffs that are statistically significant at a 5% level with an impressive 1.86% per week. Moreover, a strategy using a 4-week rolling time window shows even higher payoffs at 2.40% per week, but significance drops to the 10% level. Whereas Table 1 shows that the kurtosis of the plain cryptocurrency momentum strategy equals 121.81, risk-managed counterparts in Table 4 exhibit lower kurtosis values ranging from 68.22 (strategy using $j = 8$) to 106.45 (strategy using $j = 12$). This evidence suggests that risk managing the cryptocurrency momentum strategy diminishes the occurrence of crashes, which has been reported for risk-managed momentum strategies in the equity market (e.g., Barroso and Santa-Clara 2015).

The regression results reported in Table 5 show that risk management of cryptocurrency momentum generates risk-adjusted returns ranging between 0.76% and 1.69% per week with t-statistics from 2.00 to 3.21 that are significant at the 5% level or lower. The R-square values range from 71 to 83 percent, i.e., most of risk-managed cryptocurrency return variation is explained by the market factor and plain momentum factors. Consistent with earlier risk-managed equity momentum studies, the loadings with respect to the cryptocurrency market factor are economically low but statistically significant.

Table 5 Risk adjusting the volatility-managed cryptocurrency momentum portfolio

Strategy	$\widehat{\alpha}_j$	$\widehat{\beta}_{j,1}$	$\widehat{\beta}_{j,2}$	R^2
$r_{1,t}^{RM,MOM}$	1.69*** (2.32)	$-$0.12** ($-$1.96)	1.29*** (30.74)	0.71
$r_{2,t}^{RM,MOM}$	1.32*** (3.21)	$-$0.07** ($-$2.05)	0.91*** (37.94)	0.79
$r_{3,t}^{RM,MOM}$	0.76** (2.00)	$-$0.07** ($-$2.30)	0.97*** (43.58)	0.83

The market factor (r_t^{Mkt}) is an equal-weighted portfolio of cryptocurrencies consisting of the top -30 cryptocurrencies based on their market capitalization. Using quintile sorts using these top 30 cryptocurrencies, the momentum factor is a strategy that is long cryptocurrencies with the highest return in the 1-month formation period and short those with the lowest return in the 1-month formation period. We skip 1 trading day between the holding period and formation period. This plain momentum strategy employs equal-weighted asset allocations and is rebalanced weekly. Risk-managed (RM) cryptocurrency momentum strategies ($r_{j,t}^{RM,MOM}$) scale plain momentum returns as follows: $r_{j,t}^{RM,MOM} = \frac{c}{\widehat{\sigma}_{t,j}} r_t^{MOM}$, where c is scaling factor corresponding to the target level of volatility and $\widehat{\sigma}_{t,j}$ is the estimated standard deviation of the momentum portfolio between week $t-j$ and week $t-1$ with $j \in \{4,8,12\}$. This table reports the results for the following regression: $r_{j,t}^{RM,MOM} = \alpha_j + \beta_{j,1} r_t^{Mkt} + \beta_{j,2} r_t^{MOM} + \varepsilon_{j,t}$, where $\varepsilon_{j,t}$ denotes a white noise error, $c = 10$, and $\theta_j = (\alpha_j, \beta_{j,1}, \beta_{j,2})$ is the vector of parameters to be estimated. The weekly data sample is from the second week of April 2016 to the fourth week of December 2023 comprised of 404 observations. This table reports the point estimates for the regression models, and t-statistics are given in parentheses

*** Statistically significant on a 1% level, ** statistically significant on a 5% level

4.4 Further analysis: power laws governing cryptocurrency momentum returns

In Sect. 4.2, we found that 90% of the cryptocurrency momentum return distribution is normally distributed. A natural question is: What is the distribution of the remaining 10%? In Appendix Fig. 7 in Appendix, we illustrate the impact of momentum crashes by computing the compounded returns of two cryptocurrency momentum return series. Graphially displaying our findings, the blue (red) line in Appendix Fig. 7 shows the evolution of compounded cryptocurrency momentum returns using all observed data (excluding the most extreme return corresponding to $-$255.28%). Strikingly, one outlier—a single observation corresponding to 0.24% of sample observations—contributes 37% of the overall compounded return. Hence, it is clear that the distribution of the most extreme 5% of cryptocurrency momentum returns is far from normal.

In line with these data, we posit that the distribution of cryptocurrency momentum returns is governed by a power law capable of generating high impact events with low probability. Following Taleb (2020), who advocated to model financial market data using power laws, we model the absolute amount of cryptocurrency momentum returns as:

$$p(x) = Cx^{-\alpha}, \tag{5}$$

where $C = (\alpha - 1)x_{MIN}^{\alpha-1}$ with $\alpha \in \left\{\mathbb{R}_+ | \alpha > 1\right\}$, x denotes the absolute amount of return for a cryptocurrency momentum strategy (e.g., plain or risk managed) provided that $x \in \left\{\mathbb{R}_+ | x_{MIN} \le x < \infty\right\}$, x_{MIN} is the minimum observation governed by the power law and α is the magnitude of the corresponding power law exponent. Given the functional form of Eq. (5), it can be shown that conditional moments of order k, or $E\left[x | x > x_{MIN}\right]$, are defined as:

$$E\left[X^k | x > x_{MIN}\right] = \frac{(\alpha - 1)}{(\alpha - 1 - k)} x_{MIN}^k. \tag{6}$$

From this relation, we see that the theoretical mean (variance) only exists for $\alpha > 2$ $(\alpha > 3)$.

Following White et al. (2008) and Clauset et al. (2009), who argued that maximum likelihood estimation (MLE) is the optimal method for calculating power law exponents, the tail exponents $\widehat{\alpha}$ can be estimated as follows:

$$\hat{\alpha} = 1 + N\left(\sum_{i=1}^{N} \ln\left(\frac{x_i}{x_{MIN}}\right)\right)^{-1}, \tag{7}$$

where $\widehat{\alpha}$ denotes the MLE estimator, $N \le T$ is the number of observations greater than x_{MIN}, and other notation is as before. Like Clauset et al. (2009), we select x_{MIN} by minimizing the distance between the power law model and the empirical data, or Kolmogorov–Smirnov distance (D). This distance is defined as the maximum distance between the cumulative density functions (CDFs) of the data and the fitted model:

$$D = MAX_{x \ge x_{MIN}} |S(x) - P(x)|, \tag{8}$$

where $S(x)$ represents the cumulative distribution function (CDF) of the data for observations with values greater than or equal x_{MIN}, $P(x)$ is the CDF for the power law model that provides the best fit to the data in the range of $x \ge x_{MIN}$, $N \le T$ is the number of observations greater than x_{MIN}, and other notation is as before. In this regard, Clauset et al. (2009) have shown that the standard deviation for estimated power law exponents is:

$$\sigma = \frac{\hat{\alpha} - 1}{\sqrt{N}} + O\left(\frac{1}{N}\right). \tag{8}$$

Summary statistics for the estimated power law exponents are presented in Table 6. A number of new insights into risk-managed momentum strategies are revealed. First, regardless of whether or not risk management is implemented, the estimated power law exponents are close to $\widehat{\alpha} \approx 3$. Upon testing the following hypotheses:

$$H_0 : \alpha \le 3 \text{ versus } H_0 : \alpha > 3,$$

the evidence in Table 6 fails to reject the null hypothesis. Based on Eq. (6), we infer that the variance of cryptocurrency momentum returns is statistically undefined. Second, applying the goodness-of-fit (GoF) test in Clauset et al. (2009), we cannot reject the power law null model regardless of the strategy analyzed.[5] Overall, this evidence suggests that even though the vast majority of observations are governed by a thin-tailed distribution (e.g.., the normal distribution), the tails of the distribution are governed by a power law process with $\alpha \approx 3$ implying the absence of variance or higher moments.

4.5 Robustness checks

A recent study of Hou et al. (2020) finds that the vast majority of asset pricing studies fails scientific replication and therefore calls for re-examining documented results using a "similar but not identical statistical model." The results documented in the present study are derived from 30 large-cap cryptocurrencies used to construct both an equal-weighted cryptocurrency market factor and an equal-weighted cryptocurrency momentum factor. Consequently, a reader could argue first that our chosen methodology deviates from the established practice to use value-weighted portfolios of assets. Second, because our methodology results in portfolios with only six constituents, a reader could argue that our cryptocurrency momentum portfolio could be subject to a significant exposure to idiosyncratic risk. Fisher and Lorie (1970) and Surz and Price (2000) document that the minimum number of assets required to reach reasonable diversification levels corresponds to 30 constituents. Therefore, one could argue that the large tail risk for our cryptocurrency momentum strategy could be a manifestation of lacking diversification.

Hence, to address these concerns, we follow Zaremba et al (2021) and obtain additional data on cryptocurrencies from coinmarketcap.com, a commonly used data provider for research on the pricing of cryptocurrencies. The data provided from coinmarketcap.com are volume weighted averages of prices across 200 crypto-exchanges. We match the data sample with the sample used in our main analysis and retrieve daily data from January 1, 2016, until December 31, 2023, a total of 2919 daily observations of 2500 cryptocurrencies. Following Liu et al. (2021), we exclude cryptocurrencies with less than 1 million market capitalization and we cater for outliers by filtering the returns of less than − 99% or greater than + 200%. The market index of cryptocurrencies is the value weighted cross-section average of returns. For the computation of the momentum factor, we divide the coins into deciles based on the past seven days returns while skipping the last one day to avoid short reversal effects (see Zaremba et al. 2021) and form value-weighted portfolios for each momentum group. The momentum factor is the return difference between the top and the bottom momentum portfolios. Data retrieval and portfolio constructions are detailed in Zaremba et al. (2021). Note that using (a) an expanded data set, (b)

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[5] The GoF test assuming the power law hypothesis as the null model is described in Clauset et al. (2009).

value-weighted portfolios, and (c) a similar but not identical methodology to form the cryptocurrency momentum portfolio ensures that our robustness checks are in line with the requirements for a scientific replication (see Hou et al. 2020).

Next, because the vast majority of asset pricing studies in cryptocurrency research employs weekly data (e.g., Liu et al. 2020, 2022; Shen et al. 2020)—and to make the results derived from using value-weighted portfolios comparable to results derived from our main analysis—we transform daily data into weekly data by summing up seven consecutive returns leaving us with 416 weekly observations covering the sample from the first week of January 2016 until the last week of December 2023. In Fig. 4, we plot the cumulative returns on our equal-weighted cryptocurrency market factor used in our main analysis and the value-weighted cryptocurrency market factor over the sample from January 2016 to December 2023. From Fig. 4, we observe that until the end of 2019 both indices exhibit virtually the same cumulative return paths, whereas afterward the value-weighted index appears to exhibit a drift. Unsurprisingly, principal component analysis (unreported) suggests that the returns on both cryptocurrency indices exhibit one dominant eigenvalue corresponding to $\lambda = 1.41 > 1$, explaining 70.65% of the overall variation. This strongly suggests that both indices share a common stochastic component despite of being derived from (a) different weighting schemes and (b) different number of constitutes.

Next, in Fig. 5 we plot the evolution of the cumulative returns on both the equal-weighted cryptocurrency momentum factor derived from 30 coins, the value-weighted cryptocurrency momentum factor derived from a data set comprising 2500 coins, and the value-weighted cryptocurrency market factor derived from a data set comprising 2500 coins. Again, the sample is from January 2016 to December 2023. From visual inspection of Fig. 5, a few interesting issues arise: First, regardless the weighting scheme or number of constitutes used to form cryptocurrency momentum portfolios, cryptocurrency momentum strategies appear to be subject to severe crashes. Second, crashes across cryptocurrency momentum strategies do not coincide—and neither do they seem to be related to market reversals. Third, the value-weighted cryptocurrency momentum factor derived from a data set comprising 2500 coins underperforms both the value-weighted market index and the equal-weighted counterpart by a substantial margin.

We continue our analysis by evaluating the descriptive statistics for our value-weighted cryptocurrency portfolios. In Table 7, we report the descriptive statistics of the value-weighted cryptocurrency market factor, the value-weighted cryptocurrency momentum factor, and the value-weighted cryptocurrency momentum factor after trimming the data. We use the same trimming procedures as outlined in Sect. 4.2. Table 7 provides some interesting insights. First, it becomes evident that the value-weighted cryptocurrency momentum portfolio produces statistically significantly negative returns corresponding to − 3.40% per week. Second, although trimming somewhat increases average returns, average returns remain statistically significantly negative regardless the trimming approach adopted, with average payoffs ranging between − 1.18% and − 2.69% per week. Third, using trimming 1, the payoff distribution comprising 90% of the value-weighted cryptocurrency momentum returns is statistically distributed as normal, as indicated by the Jarque–Bera test exhibiting a p-value > 5%. Interestingly, this result is in line with our result documented earlier for the equal-weighted cryptocurrency momentum strategy. Fourth, the value-weighted cryptocurrency momentum portfolio is subject to crashes manifested in extreme negative returns: Specifically, 1% of the observed return distribution exhibits payoffs ranging between −154.75% and −297.30%. Risk managing only partially remedies this issue.

Then we implement various risk-managing strategies as outlined in Sect. 4.3. The results are reported in Table 8. From Table 8, we observe that even though risk managing successfully removes the crashes as indicated by payoff minimum ranging between −1.12% and −1.82% per week for risk-managed value-weighted cryptocurrency momentum portfolios, average payoffs remain statistically significantly negative, with average payoffs ranging between −0.02% and 0.03% and corresponding t-statistics ranging between −2.71 and −3.50 indicating statistical significance on a 1% level. Unsurprisingly, risk adjusting the volatility-managed value-weighted cryptocurrency momentum portfolio does not result in positive average returns as implied by the results documented in Table 11 in appendix.

Finally, we explore the tail risk associated with various value-weighted cryptocurrency momentum strategies. To do so, we estimate power law models as outlined in Sect. 4.4 for the plain value-weighted cryptocurrency momentum strategy and various risk-managed counterparts. The results are reported in Table 9. Strikingly, the estimated power law exponent for the plain strategy is $\widehat{\alpha} = 2.4462$ which is in line with the estimate for the equal-weighted counterpart corresponding to $\widehat{\alpha} = 2.8653$ (see Table 6). Moreover, the GoF tests do not reject the power law null hypothesis for any strategy as indicated by p-values ranging between 0.3960 and 0.9200. Again, these results corroborate the results documented for equal-weighted portfolios. Furthermore, only for the strategy using $j = 4$, the hypothesis $\alpha > 3$ can be rejected on a common 5% level, as indicated by $\widehat{t} = 1.7279 > 1.65$.

Overall, whereas equal-weighted cryptocurrency momentum using only 30 coins with highest market capitalization and value-weighted cryptocurrency momentum using a data set comprising 2500 coins produce different average payoffs, the results of our robustness checks reveal at least two important commonalities: First, regardless the weighting scheme or number of coins included, cryptocurrency momentum strategies are subject to crash risks that are different from momentum crashes documented in the literature on equities (Daniel and Moskowitz 2016). Second, regardless the weighting scheme or number of coins included, the tail risk of the plain strategies is qualitatively the same.

5 Discussion

5.1 Comparisons to earlier studies

Our main analysis indicates that a momentum strategy implemented within the cryptocurrency market does not yield a significant payoff. This result mainly occurs because the distribution of cryptocurrency momentum returns has severe fat tails and, as such, extreme negative events nullify the efficacy of such a strategy. This fact aligns with prior literature on momentum crashes, which asserts that this anomaly is

Table 6 Estimated power law exponents for various cryptocurrency momentum strategies

	r_t^{MOM}	$r_{1,t}^{RM,MOM}$	$r_{2,t}^{RM,MOM}$	$r_{3,t}^{RM,MOM}$
$\widehat{\alpha}$	2.8653	2.9437	3.3036	3.2685
x_{MIN}	9.8708	25.5242	21.4018	16.4004
$\widehat{\sigma}$	0.1897	0.2803	0.3700	0.3017
N (in %)	107 (25.72%)	55 (13.35%)	44 (10.78%)	63 (15.59%)
p-value (GoF)	0.9820	0.8210	0.7970	0.5290
$\widehat{t}$	−0.7101	−0.2009	0.8205	0.8900

Using maximum likelihood estimation (MLE), the tail exponents $\widehat{\alpha}$ are estimated for various cryptocurrency momentum strategies as follows: $\widehat{\alpha} = 1 + N\left(\sum_{i=1}^{N}\ln\left(\frac{x_i}{x_{MIN}}\right)\right)^{-1}$, where x denotes the absolute amount of return on a cryptocurrency momentum strategy (e.g., plain or risk managed), $\widehat{\alpha}$ denotes the MLE estimator, and $N \leq T$ is the number of observations greater than x_{MIN}. In line with Clauset et al. (2009), we select x_{MIN} by minimizing the distance between the power law model and the empirical data defined as Kolmogorov–Smirnov distance (D), which is maximum distance between the cumulative density functions (CDFs) of the data and the fitted model: $D = MAX_{x \geq x_{MIN}} |S(x) - P(x)|$, where $S(x)$ represents the cumulative distribution function (CDF) of the data for observations with values greater than or equal x_{MIN} and $P(x)$ is the CDF for the power law model that provides the best fit to the data in the range of $x \geq x_{MIN}$, $N \leq T$ is the number of observations greater than x_{MIN}, and other notation is as before. Clauset et al. (2009) showed that the standard deviation for estimated power law exponents is defined as: $\sigma = \frac{\widehat{\alpha}-1}{\sqrt{N}} + O(\frac{1}{N})$. This table reports the estimates for power law functions and corresponding descriptive statistics. In our notation, r_t^{MOM} denotes the return on the plain equal-weighted cryptocurrency momentum strategy, whereas $r_{i,t}^{RM,MOM}$ denotes the return on risk-managed equal-weighted cryptocurrency momentum strategy i. The statistic $\widehat{t}$ tests the following hypotheses: $H_0 : \alpha \leq 3$ against $H_1 : \alpha > 3$. Given a significance level of 5% and a one-sided test, the null hypothesis is rejected if $\widehat{t} > 1.65$.

susceptible to substantial negative movements (Barroso and Santa-Clara 2015; Daniel and Moskowitz 2016). However, we find that outliers tend to exhibit considerably larger economic magnitudes compared to those observed in the equity market. As documented in Daniel and Moskowitz's study (2016), the lowest monthly returns for stock price momentum occurred in 1932 with a decline of −74.36%. Similarly, Barroso and Santa-Clara (2015) computed a maximum decline of −91.59% in 1932. In our case, the momentum portfolio experienced a crash of −255% at the end of 2020, which is three times larger than the largest equity momentum crash. What can explain this large disparity in crash risk?

Cryptocurrencies represent a novel asset class distinct from traditional financial assets in that they lack an intrinsic economic value based on tangible assets (Corbet et al. 2019). Their value is derived from their underlying algorithms that facilitate transaction tracing and, in turn, is linked to the level of trust in this emerging technology. It is important to note that unlike other asset classes, cryptocurrencies do not offer promises of future payments or dividends that render them inherently riskier investments. Indeed, as pointed out by Chaim and Laurini (2019), cryptocurrencies show very high levels of unconditional volatility, suffer from large outliers that are mostly right-skewed, and have leptokurtic return distributions. Moreover, Baek and Elbeck (2015) showed that Bitcoin is 26 times more volatile than the S&P 500

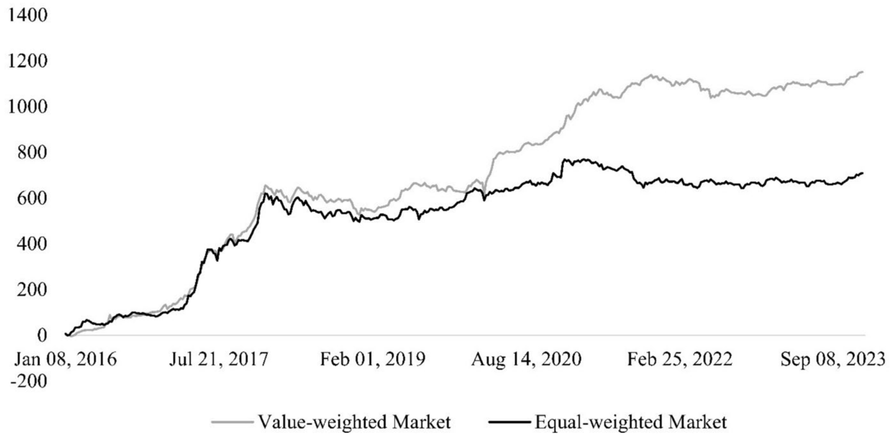

Fig. 4 Cumulative returns on the equal-weighted and value-weighted cryptocurrency market factor. This figure plots the evolution of the cumulative returns for the equal-weighted cryptocurrency market factor derived from 30 coins and the value-weighted cryptocurrency market factor derived from a data set comprising 2500 coins. The sample is from the first week of January 2016 to the last week of December 2023

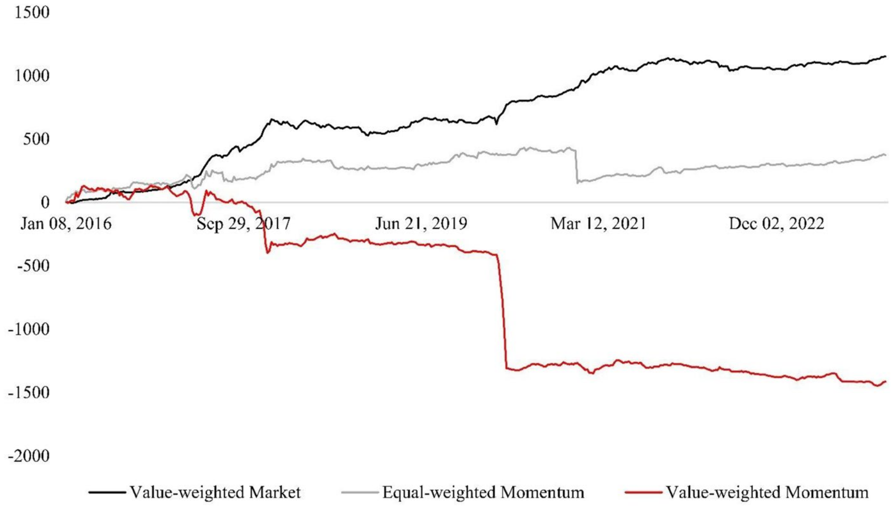

Fig. 5 Cumulative returns on different cryptocurrency momentum factors and the value-weighted cryptocurrency market factor. This figure plots the evolution of the cumulative returns for the equal-weighted cryptocurrency momentum factor derived from 30 coins, value-weighted cryptocurrency momentum factor derived from a data set comprising 2500 coins, and value-weighted cryptocurrency market factor derived from a data set comprising 2500 coins. The sample is from the first week of January 2016 to the last week of December 2023

index, and their returns appear to be internally driven by buyers and sellers rather than influenced by fundamental economic factors. Consistent with the latter, Grobys and Junttila (2021) found evidence of a lottery-like demand in digital currencies markets guided by speculation. Investors' influence can contribute to bubbles

Table 7 Descriptive statistics for value-weighted portfolios

	Market	Cryptocurrency momentum strategies			
	Factor	Plain strategy	Trimming 1	Trimming 2	Trimming 3
Mean	2.77***	− 3.40***	− 1.18***	− 1.99***	− 2.69**
(*t*-statistic)	(5.08)	(− 2.54)	(− 2.91)	(− 2.69)	(− 2.36)
Median	1.87	− 1.02	− 1.02	− 1.02	− 0.95
Maximum	53.09	69.10	15.79	49.63	69.10
Minimum	− 50.35	− 297.30	− 21.81	− 143.47	− 242.36
Std. deviation	11.12	27.28	7.82	14.99	23.17
Skewness	0.15	− 5.96	− 0.24	− 3.14	− 4.91
Kurtosis	6.31	55.81	2.76	27.87	45.41
Jarque–Bera (JB)	191.13	50,798.31	4.39	11,184.78	32,765.55
p-value (JB)	0.00	0.00	0.11	0.00	0.00
Observations	416	416	374	408	415

This table reports the descriptive statistics of the value-weighted cryptocurrency market factor, the value-weighted cryptocurrency momentum factor, and the value-weighted cryptocurrency momentum factor after trimming the data. Using a data set comprising 2500 coins, the value-weighted cryptocurrency market factor at time t corresponds to the value weighted cross-section average of returns. For the value-weighted momentum factor, we divide the coins into deciles based on the past seven days returns, skipping the last day to avoid short reversal (see Zaremba et al (2021), and form value-weighted portfolios for each momentum group. The momentum factor is the return difference between the top and the bottom momentum portfolios. Daily data are transformed into non-overlapping weekly data by summing up seven consecutive holding period returns. The weekly data sample is from the first week of January 2016 to December 2023 comprised of 416 observations. Trimming 1 is a procedure that shrinks the distribution between the 5th and 95th percentiles, trimming 2 shrinks the distribution between the 1st and 99th percentiles, and trimming 3 excludes only the largest observation measured in terms of the absolute economic magnitude. The t-statistics are given in parenthesis

*** Statistically significant on a 1% level, ** Statistically significant on a 5% level

in cryptocurrency prices. Their speculative behavior, combined with the absence of a central authority regulating the supply and potential network effects, makes this phenomenon highly probable (Wei and Dukes 2021). Not surprisingly, the market for cryptocurrencies may experience severe price fluctuations and extreme outliers.

Aside from the magnitude of these events, the mechanisms through which they occur in the context of cryptocurrency are substantially different. Equity momentum crashes typically originate during times of market decline followed by a rebound. This phenomenon arises because the momentum portfolio during prolonged recessions, as discussed earlier, tends to be long on firms with low conditional beta on the market and short on those with high beta. Subsequently, when the market rebounds, the short positions in the portfolio yield extreme negative returns. According to Daniel and Moskowitz (2016), these extreme negative returns occur because momentum effectively embeds a written (short) call option on the market. This optionality effect, as described by Daniel et al. (2018), follows Merton's (1974) framework, wherein a stock can be considered as a call option on the underlying firm's assets in the presence of debt. During a recession, past losers experience significant value

Table 8 Descriptive statistics for volatility-managed value-weighted cryptocurrency momentum portfolios

Factor/strategy	Market factor[a]	$r_t^{MOM(VW)}$	$r_{1,t}^{RM,MOM(VW)}$	$r_{2,t}^{RM,MOM(VW)}$	$r_{3,t}^{RM,MOM(VW)}$
Mean	2.79***	− 3.77***	− 0.03***	− 0.02***	− 0.03***
(t-statistic)	(4.99)	(− 2.78)	(− 2.71)	(− 3.18)	(− 3.50)
Median	1.84	− 1.08	− 0.01	− 0.01	− 0.01
Maximum	53.09	69.10	0.49	0.40	0.42
Minimum	− 50.35	− 297.30	− 1.82	− 1.12	− 1.34
Std. deviation	11.26	27.22	0.19	0.15	0.15
Skewness	0.15	− 6.20	− 2.69	− 1.85	− 2.80
Kurtosis	6.17	57.50	24.47	13.23	21.29
Jarque–Bera (JB)	170.12	52,587.63	8247.01	1989.64	6159.96
(p-value JB)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	404	404	404	404	404

Risk-managed (RM) value-weighted cryptocurrency momentum strategies ($r_{j,t}^{RM,MOM(VW)}$) scale plain value-weighted cryptocurrency momentum returns as follows: $r_{j,t}^{RM,MOM(VW)} = \frac{c}{\hat{\sigma}_{t,j}} r_t^{MOM(VW)}$, where c is scaling factor corresponding to the target level of volatility and $\hat{\sigma}_{t,j}$ is the estimated standard deviation of the momentum portfolio between week $t-j$ and week $t-1$ with $j \in \{4,8,12\}$. This table reports the descriptive statistics for the volatility-managed value-weighted cryptocurrency momentum portfolios. The weekly data sample is from the second week of April 2016 to December 2023 comprised of 404 observations

***Statistically significant on a 1% level

[a] This table uses the value-weighted cryptocurrency market factor

losses, which causes their stocks to behave like at- or out-of-the-money call options on the firm's assets. The convexity of their payoffs results in slight changes in value for even large downward moves in their underlying assets, whereas the opposite occurs for upward moves, i.e., when the market rises. Even though the aforementioned mechanism may not be directly applicable in their context, Daniel and Moskowitz (2016) note that index futures, commodities, fixed income securities, and currency momentum exhibit option-like behavior.

Contrarily, in the case of cryptocurrency portfolios, crash risk originates from a *single* cryptocurrency that experiences a significant price surge, thereby impacting the short leg of the portfolio. For example, the cryptocurrency Mindol (MIN) experienced a price increase from 0.54 USD to 7.86 USD on December 23, 2020. This movement of 1400% explains how a short-leg portfolio of 6 cryptocurrencies can produce a loss of the cryptocurrency momentum strategy corresponding to − 255%. Thus, as demonstrated when applying trimming techniques, this single currency movement accounts for the insignificant payoff of cryptocurrency momentum. Of course, this crash is substantially different from the optionality effect documented in the equity market. Hence, we conclude that cryptocurrency

Table 9 Estimated power law exponents for various value-weighted cryptocurrency momentum strategies

	$r_t^{MOM(VW)}$	$r_{1,t}^{RM,MOM(VW)}$	$r_{2,t}^{RM,MOM(VW)}$	$r_{3,t}^{RM,MOM(VW)}$
$\widehat{\alpha}$	2.4462	4.3428	2.8936	3.0419
x_{MIN}	7.6821	0.3697	0.1132	0.1291
$\widehat{\sigma}$	0.1194	0.7771	0.2725	0.2225
N (in %)	163 (40.35%)	21 (5.20%)	120 (29.70%)	93 (23.02%)
p-value (GoF)	0.6400	0.4160	0.3960	0.9200
$\widehat{t}$	−4.6382***	1.7279**	−0.4969	0.1883

Using maximum likelihood estimation (MLE), the tail exponents $\widehat{\alpha}$ are estimated for various value-weighted cryptocurrency momentum strategies as follows: $\widehat{\alpha} = 1 + N\left(\sum_{i=1}^{N}\ln\left(\frac{x_i}{x_{MIN}}\right)\right)^{-1}$, where x denotes the absolute amount of return on a value-weighted cryptocurrency momentum strategy (e.g., plain or risk-managed), $\widehat{\alpha}$ denotes the MLE estimator and $N \leq T$ is the number of observations greater than x_{MIN}. In line with Clauset et al. (2009), we select x_{MIN} by minimizing the distance between the power law model and the empirical data defined as Kolmogorov–Smirnov distance (D), which is maximum distance between the cumulative density functions (CDFs) of the data and the fitted model: $D = MAX_{x \geq x_{MIN}} |S(x) - P(x)|$, where $S(x)$ represents the cumulative distribution function (CDF) of the data for observations with values greater than or equal x_{MIN} and $P(x)$ is the CDF for the power law model that provides the best fit to the data in the range of $x \geq x_{MIN}$, $N \leq T$ is the number of observations greater than x_{MIN}, and other notation is as before. Clauset et al. (2009) showed that the standard deviation for estimated power law exponents is defined as: $\sigma = \frac{\widehat{\alpha}-1}{\sqrt{N}} + O(\frac{1}{N})$. This table reports the estimates for power law functions and corresponding descriptive statistics. In our notation, $r_t^{MOM(VW)}$ denotes the return on the plain value-weighted cryptocurrency momentum strategy, whereas $r_{i,t}^{RM,MOM(VW)}$ denotes the return on risk-managed value-weighted cryptocurrency momentum strategy i. The statistic $\widehat{t}$ tests the following hypotheses: $H_0 : \alpha \leq 3$ against $H_1 : \alpha > 3$. Given a significance level of 5% and a one-sided test, the null hypothesis is rejected if $\widehat{t} > 1.65$.

*** Statistically significant on 1 % level,** Statistically significant on a 5% level

momentum crashes are not related to market reversals but rather arise from an extreme price jump in a single cryptocurrency.[6]

Could the crash risk be an artifact of using equal-weighted portfolios and 30 coins only? Expanding the data set to 2500 coins and using value-weighted cryptocurrency momentum portfolios, the results from our robustness checks show that the crash risk associated with cryptocurrency momentum is not a manifestation of potential exposure to some idiosyncratic risk. On the other hand, our results are in line with Zaremba et al. (2021) who scrutinized the momentum and reversal effects in cryptocurrencies. The authors found that only the 2% of cryptocurrencies that exhibit the highest market capitalization produce return momentum, whereas 98% of

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[6] Note also from Figs. 2 and Appendix Fig. 7 that the cryptocurrency market was in a clear upwards move ex ante the cryptocurrency momentum crash which supports our claim that the market did not experience any reversal when the crash occurred.

the remaining coins—representing only a small fraction of the total market capitalization—exhibit average momentum payoffs that are negative.

5.2 Implications

The unprofitability of the momentum strategy can be mitigated by implementing some type of risk management. By adopting the non-look-ahead biased strategy proposed by Barroso and Santa-Clara (2015), we can effectively avoid crashes and achieve impressive returns that cannot be explained by the market factor or its plain counterpart. These economically significant payoffs are in line with previous literature on equity markets. Also, they are consistent with the recent findings by Angelidis and Tessaromatis (2023), who found that a volatility-managed strategy is effective in a high-cost arbitrage environment. However, while this strategy enhances risk-adjusted returns, it does not change the tail risk behavior of the momentum portfolio.

A reader might argue that the three risk-managed cryptocurrency momentum strategies all have lower kurtosis and larger skewness than the un-managed momentum strategy which seems inconsistent with our results derived from power laws. However, while the kurtosis of the plain cryptocurrency momentum portfolio is 123.48, as documented in Table 4, the risk-managed counterparts still exhibit extremely heavy tails manifested in kurtosis values that exceed 3 by a substantial margin: Specifically, from Table 4 we observe that the lowest kurtosis value is achieved for strategy $r_{2,t}^{RM,MOM}$ exhibiting a kurtosis value of 68.22. For comparison, the excess kurtosis of the Chi-square (exponential) distribution with one degree of freedom—which exhibits considerably heavier tails than the standard normal—is 12 (6). It is evident that standard distributions cannot generate the heavy tails we observe for risk-managed cryptocurrency momentum strategies. A manifestation of the empirical result that kurtosis values decrease after risk-managing cryptocurrency momentum is that power law exponents for the returns on risk-managed cryptocurrency momentum strategies exhibit economic magnitudes that are larger than $\widehat{\alpha} = 2.8653$ which is the estimated tail exponent for the plain strategy. It is important to note that a lower (higher) tail exponent suggests more (less) extreme outliers. However, the results documented in Table 6 suggest that, statistically, the hypothesis that $\alpha < 3$ cannot be rejected for any strategy regardless risk management.

Next, employing power laws to model the returns of cryptocurrency momentum and its risk-managed counterpart, we observe that the theoretical variance of both strategies is statistically undefined as implied by a power law exponent of $\alpha < 3$. This result is in line with recent research documenting that the realized variance risk of stock price momentum is infinite (Grobys 2024b). Hence, because the variance is not finite, a major implication is that traditional statistical methodologies may lead to invalid inferences.

Is risk-managed cryptocurrency momentum profitable? If the theoretical variance is undefined, despite impressive cryptocurrency momentum returns using volatility scaling, these payoffs are subject to considerable uncertainty. Whereas Moreira and Muir (2017) concluded that risk management expands the mean–variance frontier, our results suggest that we can only make clear inferences about a *mean-only space*; that is, volatility scaling likely increases average payoffs but no theoretically defined variance exists.

6 Conclusion

The momentum anomaly has been subject of extensive studies in the asset pricing literature. However, published research is inconclusive regarding its applicability to digital currencies. This paper explored the feasibility of a momentum strategy implemented in the cryptocurrency market and investigated whether volatility risk management can enhance its risk-adjusted returns. To do so, we collected cryptocurrency data for the top 30 coins in terms of market capitalization at year end and constructed equally weighted cryptocurrency momentum portfolios based on weekly rebalancing. Our sample spanned from the first week of January 2016 to the fourth week of December 2023, resulting in 416 weekly return observations.

We found that cryptocurrency momentum did not yield a significant payoff due to a severe crash. Unlike the equity market, this crash was idiosyncratic to a single cryptocurrency and, therefore, not subject to an optionality effect as documented by Daniel and Moskowitz (2016) for stocks. In an effort to control crash risk, we implemented risk management strategies based on past return volatility scaling. Using different past volatility windows, impressive risk-managed payoffs from 1.86% to 2.40% per week were generated. After risk adjusting momentum returns using a factor model, consistent with equity market studies, significant payoffs persisted.

Using power laws to model tail returns of cryptocurrency momentum and risk-managed counterparts, further analyses indicated that the theoretical variance is undefined (i.e., power law exponent $\alpha < 3$). For this reason, traditional statistical methodologies can yield invalid inferences. Additionally, because risk management does not change the tail risk of cryptocurrency momentum, we conclude that this strategy is subject to considerable uncertainty that implies greater risk than previous cryptocurrency research has suggested.

Our findings have important implications for investors seeking to implement momentum strategies in the cryptocurrency market. First and foremost, risk management is critical to earning cryptocurrency momentum profits. Second, even after risk adjustment via volatility scaling, investors should be aware that tail risk can still be very high due to undefined return variance. Future research is recommended to investigate the performance of volatility-scaling risk management for other cryptocurrency anomalies. For example, Liu et al. (2022) constructed zero-cost strategies based on 24 cryptocurrency characteristics broadly classified into four groups, including size, volume, volatility, and momentum. Hence, future studies are encouraged to explore the profitability and the tail risk of zero-cost strategies derived from other characteristics apart from past return performance.

Appendix

See Figs. 6 and 7, Tables 10 and 11.

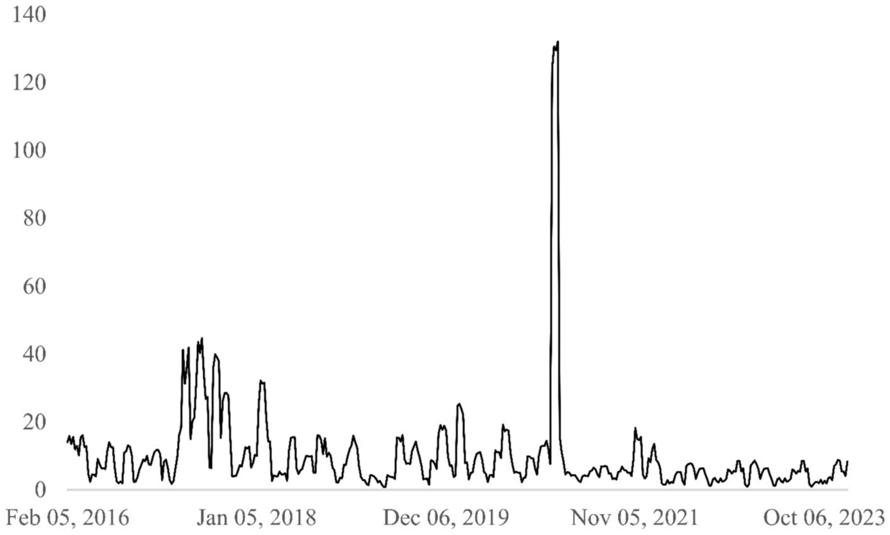

Fig. 6 Realized volatility of the cryptocurrency momentum portfolio using a rolling time window of 4 weeks. This figure shows the evolution of a rolling time window of the standard deviation of four consecutive momentum portfolio returns over the weekly sample January 2016 to December 2023

Fig. 7 Compounded return on the cryptocurrency momentum portfolio. This figure shows the evolution of the compounded return on cryptocurrency momentum portfolio returns over the weekly sample January 2016 to December 2023. The blue line shows the evolution of compounded cryptocurrency momentum returns, whereas the red line shows the evolution of compounded cryptocurrency momentum returns excluding the most extreme return corresponding to − 255.28%

Table 10 Investment opportunity set

Panel A. Top 30 Cryptocurrencies—27 December 2015				Panel B. Top 30 Cryptocurrencies—25 December 2016				Panel C. Top 30 Cryptocurrencies—31 December 2017				Panel D. Top 30 Cryptocurrencies—30 December 2018			
Rank	Name	Symbol	Market Cap	Rank	Name	Symbol	Market Cap	Rank	Name	Symbol	Market Cap	Rank	Name	Symbol	Market Cap
1	Bitcoin	BTC	$6,348,303,535.49	1	Bitcoin	BTC	$14,396,198,729.33	1	Bitcoin	BTC	$237,466,518,547.07	1	Bitcoin	BTC	$67,475,512,827.39
2	XRP	XRP	$212,734,466.03	2	Ethereum	ETH	$626,189,615.98	2	XRP	XRP	$89,121,967,114.06	2	XRP	XRP	$15,076,740,856.33
3	Litecoin	LTC	$152,353,682.59	3	XRP	XRP	$232,006,578.41	3	Ethereum	ETH	$73,170,132,771.99	3	Ethereum	ETH	$14,560,066,114.19
4	Ethereum	ETH	$64,913,889.24	4	Litecoin	LTC	$213,168,549.82	4	Bitcoin Cash	BCH	$42,774,236,530.93	4	Bitcoin Cash	BCH	$2,869,903,437.91
5	Dash	DASH	$16,121,933.07	5	Monero	XMR	$132,525,971.58	5	Cardano	ADA	$18,659,588,487.38	5	EOS	EOS	$2,430,234,521.47
6	Dogecoin	DOGE	$14,837,666.78	6	Ethereum Classic	ETC	$93,536,872.97	6	Litecoin	LTC	$12,663,197,417.17	6	Stellar	XLM	$2,250,048,215.08
7	Peercoin	PPC	$9,872,343.12	7	Dash	DASH	$69,834,088.36	7	IOTA	IOTA	$9,869,763,787.81	7	Litecoin	LTC	$1,912,263,647.77
8	BitShares	BTS	$8,999,976.20	8	MaidSafeCoin	MAID	$44,717,207.22	8	NEM	XEM	$9,306,424,139.90	8	Tether**	USDT	$1,893,629,500.50
9	Stellar	XLM	$8,319,858.32	9	NEM	XEM	$32,455,741.19	9	Dash	DASH	$8,189,388,164.00	9	Bitcoin SV	BSV	$1,553,228,295.25
10	MaidSafeCoin	MAID	$6,532,958.12	10	Steem	STEEM	$31,444,070.65	10	Stellar	XLM	$6,442,724,493.37	10	TRON	TRX	$1,329,143,863.30
11	Nxt	NXT	$6,435,492.48	11	Augur	REP	$30,404,634.00	11	Monero	XMR	$5,426,210,002.08	11	Cardano	ADA	$1,122,116,467.72
12	Bytecoin	BCN	$5,575,055.92	12	Iconomi*	ICN	$29,921,653.84	12	EOS	EOS	$5,041,642,753.40	12	IOTA	IOTA	$1,002,877,280.23
13	Namecoin	NMC	$5,541,075.54	13	Dogecoin	DOGE	$24,708,711.86	13	Neo	NEO	$4,937,436,141.97	13	Monero	XMR	$806,939,516.43
14	Monero	XMR	$4,746,216.19	14	Factom	FCT	$21,824,198.16	14	Qtum	QTUM	$4,603,333,032.82	14	BNB	BNB	$784,234,811.60
15	Factom	FCT	$3,973,903.24	15	Waves	WAVES	$20,314,945.28	15	Bitcoin Gold	BTG	$4,380,775,196.80	15	Dash	DASH	$698,091,182.88
16	GridCoin	GRC	$3,318,853.66	16	Stellar	XLM	$17,845,296.56	16	Verge	XVG	$3,208,728,455.06	16	NEM	XEM	$619,220,627.98
17	Rubycoin	RBY	$3,242,739.75	17	DigixDAO	DGD	$16,789,319.99	17	TRON	TRX	$2,942,336,038.18	17	Ethereum Classic	ETC	$568,817,905.13
18	Emercoin	EMC	$2,497,094.42	18	Lisk	LSK	$14,298,781.50	18	Nano	XNO	$2,885,869,971.17	18	Neo	NEO	$527,716,102.54
19	Clams	CLAM	$2,130,115.66	19	Zcash	ZEC	$13,741,401.91	19	Ethereum Classic	ETC	$2,765,755,613.58	19	Maker	MKR	$347,476,493.39
20	BlackCoin	BLK	$1,961,088.04	20	Swiscoin*	SCN	$12,459,317.54	20	BitConnect	BCC	$2,593,243,079.16	20	Zcash	ZEC	$332,048,193.21
21	YbCoin*	YBC	$1,889,851.70	21	EDC Blockchain	EDC	$11,893,201.05	21	Lisk	LSK	$2,377,903,943.13	21	Waves	WAVES	$309,381,632.54
22	MonaCoin	MONA	$1,591,595.30	22	GameCredits	GAME	$11,857,561.08	22	OmiseGO	OMG	$2,029,570,238.64	22	Tezos	XTZ	$302,665,930.63
23	Counterparty	XCP	$1,498,862.55	23	Xenixcoin*	XEN	$11,624,658.54	23	ICON	ICX	$2,017,629,553.50	23	Dogecoin	DOGE	$278,470,304.32
24	Startcoin	START	$1,395,709.41	24	BitShares	BTS	$11,047,151.13	24	Ardor	ARDR	$1,718,412,421.71	24	USD Coin**	USDC	$249,383,514.72
25	NeuCoin*	NEU	$1,379,275.02	25	Ardor	ARDR	$10,862,223.99	25	BitShares	BTS	$1,714,041,929.34	25	Bitcoin Gold	BTG	$238,520,472.35
26	NEM	XEM	$1,350,448.76	26	LoMoCoin*	LMC	$9,790,908.08	26	Populous	PPT	$1,536,709,576.52	26	VeChain	VET	$233,909,929.16
27	Global Currency Reserve	KWD	$1,325,873.75	27	Bytecoin	BCN	$8,276,082.86	27	Zcash	ZEC	$1,495,222,601.73	27	TrueUSD**	TUSD	$207,286,489.45
28	BitcoinDark*	BTCD	$1,290,322.82	28	Golem	GLM	$7,800,898.11	28	Tether**	USDT	$1,384,856,529.14	28	Qtum	QTUM	$206,333,378.42
29	AmberCoin	AMBER	$1,254,452.07	29	Emercoin	EMC	$7,663,821.18	29	Stratis	STRAX	$1,384,480,444.68	29	OmiseGO	OMG	$199,283,833.25
30	Novacoin	NVC	$1,139,684.13	30	Gulden	NLG	$7,606,658.43	30	Waves	WAVES	$1,259,664,154.05	30	Zilliqa	ZIL	$194,575,018.05

Table 10 (continued)

Panel E. Top 30 Cryptocurrencies—29 December 2019				Panel F. Top 30 Cryptocurrencies—27 December 2020				Panel G. Top 30 Cryptocurrencies—26 December 2021				Panel H. Top 30 Cryptocurrencies—25 December 2022			
Rank	Name	Symbol	Market Cap	Rank	Name	Symbol	Market Cap	Rank	Name	Symbol	Market Cap	Rank	Name	Symbol	Market Cap
1	Bitcoin	BTC	$134,570,835,775.06	1	Bitcoin	BTC	$488,213,268,382.01	1	Bitcoin	BTC	$960,899,995,734.94	1	Bitcoin	BTC	$324,093,186,300.92
2	Ethereum	ETH	$14,698,483,422.09	2	Ethereum	ETH	$77,828,069,141.05	2	Ethereum	ETH	$483,620,188,465.02	2	Ethereum	ETH	$149,169,092,950.40
3	XRP	XRP	$8,536,136,120.35	3	Tether**	USDT	$20,729,387,121.49	3	BNB	BNB	$91,239,389,442.48	3	Tether**	USDT	$66,243,849,258.58
4	Tether**	USDT	$4,125,339,508.86	4	XRP	XRP	$12,851,124,973.13	4	Tether**	USDT	$78,020,576,206.34	4	USD Coin**	USDC	$44,348,890,607.38
5	Bitcoin Cash	BCH	$3,874,556,156.19	5	Litecoin	LTC	$8,439,551,136.23	5	Solana	SOL	$61,170,181,005.50	5	BNB	BNB	$38,894,316,962.85
6	Litecoin	LTC	$2,783,708,411.61	6	Bitcoin Cash	BCH	$6,290,438,770.71	6	Cardano	ADA	$48,735,884,302.66	6	XRP	XRP	$17,438,570,226.36
7	EOS	EOS	$2,548,344,835.55	7	BNB	BNB	$4,839,330,613.85	7	XRP	XRP	$43,789,189,735.81	7	Binance USD**	BUSD	$17,393,414,909.52
8	BNB	BNB	$2,200,851,434.24	8	Chainlink	LINK	$4,833,804,693.48	8	USD Coin**	USDC	$42,392,023,711.45	8	Dogecoin	DOGE	$10,076,566,956.65
9	Bitcoin SV	BSV	$1,813,274,573.35	9	Cardano	ADA	$4,804,453,143.56	9	Terra	LUNC	$36,262,543,327.79	9	Cardano	ADA	$8,945,785,641.41
10	Stellar	XLM	$926,843,557.23	10	Polkadot	DOT	$4,592,307,413.22	10	Polkadot	DOT	$30,943,660,939.69	10	Polygon	MATIC	$6,944,943,117.07
11	TRON	TRX	$916,441,896.99	11	USD Coin**	USDC	$3,582,730,027.76	11	Avalanche	AVAX	$28,024,471,317.76	11	Dai	DAI	$5,847,586,517.37
12	Tezos	XTZ	$911,327,053.77	12	Stellar	XLM	$3,170,263,194.62	12	Dogecoin	DOGE	$25,210,069,507.96	12	Polkadot	DOT	$5,168,182,598.74
13	Cardano	ADA	$888,882,223.76	13	Bitcoin SV	BSV	$3,113,350,011.74	13	SHIBA INU	SHIB	$21,036,265,565.30	13	TRON	TRX	$5,042,409,485.27
14	UNUS SED LEO	LEO	$823,580,467.65	14	Wrapped Bitcoin	WBTC	$3,035,975,344.15	14	Polygon	MATIC	$20,411,914,262.07	14	Litecoin	LTC	$4,976,584,253.49
15	Cosmos	ATOM	$813,804,080.92	15	Monero	XMR	$2,798,785,869.76	15	Cronos	CRO	$15,811,859,284.42	15	Shiba Inu	SHIB	$4,551,453,927.84
16	Monero	XMR	$813,746,410.83	16	EOS	EOS	$2,549,025,780.05	16	Binance USD**	BUSD	$14,632,314,648.34	16	Solana	SOL	$4,180,006,175.80
17	Huobi Token	HT	$678,721,856.55	17	NEM	XEM	$2,123,154,048.23	17	Wrapped Bitcoin	WBTC	$13,129,214,895.89	17	Uniswap	UNI	$3,929,874,440.08
18	Chainlink	LINK	$665,841,558.77	18	TRON	TRX	$2,067,107,839.20	18	Uniswap	UNI	$11,745,630,155.55	18	Avalanche	AVAX	$3,637,468,062.45
19	Neo	NEO	$652,749,972.22	19	Tezos	XTZ	$1,510,425,125.03	19	Litecoin	LTC	$10,806,756,315.88	19	UNUS SED LEO	LEO	$3,447,947,960.08
20	MINDOL	MIN	$638,796,576.01	20	UNUS SED LEO	LEO	$1,354,911,353.37	20	Chainlink	LINK	$10,745,755,661.49	20	Wrapped Bitcoin	WBTC	$3,100,946,665.40
21	Ethereum Classic	ETC	$541,875,099.12	21	THETA	THETA	$1,346,225,507.91	21	Algorand	ALGO	$10,216,971,621.55	21	Chainlink	LINK	$3,040,866,462.10
22	999	999	$523,189,674.97	22	Cronos	CRO	$1,273,375,675.08	22	TerraUSD**	USTC	$9,952,448,734.27	22	Toncoin	TON	$2,969,682,082.98
23	USD Coin**	USDC	$520,939,799.33	23	Dai	DAI	$1,106,811,793.68	23	NEAR Protocol	NEAR	$9,724,360,291.45	23	Monero	XMR	$2,646,679,380.68
24	HedgeTrade	HEDG	$516,827,656.56	24	Neo	NEO	$1,064,818,715.88	24	Dai	DAI	$9,371,280,978.02	24	Cosmos	ATOM	$2,583,178,816.23

Table 10 (continued)

Panel E. Top 30 Cryptocurrencies—29 December 2019				Panel F. Top 30 Cryptocurrencies—27 December 2020				Panel G. Top 30 Cryptocurrencies—26 December 2021				Panel H. Top 30 Cryptocurrencies—25 December 2022			
25	IOTA	IOTA	$468,403,923.48	25	Dash	DASH	$1,061,465,798.16	25	Bitcoin Cash	BCH	$8,564,343,857.77	25	Ethereum Classic	ETC	$2,244,205,310.39
26	Maker	MKR	$448,314,261.26	26	VeChain	VET	$1,061,121,307.65	26	TRON	TRX	$8,309,592,456.12	26	Bitcoin Cash	BCH	$1,952,616,106.12
27	Cronos	CRO	$441,270,132.30	27	Celsius	CEL	$1,016,716,288.48	27	Cosmos	ATOM	$7,285,398,828.95	27	Stellar	XLM	$1,928,352,970.45
28	Dash	DASH	$413,310,785.85	28	Cosmos	ATOM	$1,003,531,564.11	28	Stellar	XLM	$7,206,705,407.49	28	Cronos	CRO	$1,510,925,684.13
29	Ontology	ONT	$348,595,243.81	29	Filecoin	FIL	$992,839,784.49	29	Decentraland	MANA	$7,050,454,756.85	29	OKB	OKB	$1,388,940,572.39
30	VeChain	VET	$310,542,537.66	30	Revain	REV	$989,937,349.40	30	Axie Infinity	AXS	$6,551,674,566.11	30	ApeCoin	APE	$1,297,707,700.33

This table reports the investment opportunity set for each year, which consists of the 30 cryptocurrencies with the highest market capitalizations as of the last Sunday of December. The data span from December 2015 to December 2022. An asterisk (*) indicates that a cryptocurrency has been excluded from the sample due to a lack of related data. A double asterisk (**) identifies a stablecoin that has been excluded from the sample

Table 11 Risk adjusting the volatility-managed value-weighted cryptocurrency momentum portfolio

Strategy	$\widehat{\alpha}_j$	$\widehat{\beta}_{j,1}$	$\widehat{\beta}_{j,2}$	R^2
$r_{1,t}^{RM,MOM(VW)}$	−0.0106 (−1.25)	−0.0008 (−1.02)	0.0034*** (11.06)	0.25
$r_{2,t}^{RM,MOM(VW)}$	−0.0083 (−1.42)	−0.0008 (−1.62)	0.0034*** (15.84)	0.41
$r_{3,t}^{RM,MOM(VW)}$	−0.0095 (−1.63)	−0.0012** (−2.33)	0.0036*** (17.16)	0.46

The market factor ($r_t^{Mkt(VW)}$) is a value-weighted portfolio of cryptocurrencies derived from a data set comprising 2,500 coins. Risk-managed (RM) value-weighted cryptocurrency momentum strategies ($r_{j,t}^{RM,MOM(VW)}$) scale plain value-weighted cryptocurrency momentum returns as follows: $r_{j,t}^{RM,MOM(VW)} = \frac{c}{\widehat{\sigma}_{t,j}} r_t^{MOM(VW)}$, where c is scaling factor corresponding to the target level of volatility and $\widehat{\sigma}_{t,j}$ is the estimated standard deviation of the value-weighted cryptocurrency momentum portfolio between week $t-j$ and week $t-1$ with $j \in \{4,8,12\}$. This table reports the results for the following regression: $r_{j,t}^{RM,MOM(VW)} = \alpha_j + \beta_{j,1} r_t^{Mkt(VW)} + \beta_{j,2} r_t^{MOM(VW)} + \varepsilon_{j,t}$, where $\varepsilon_{j,t}$ denotes white noise error, $c = 10$, and $\theta_j = (\alpha_j, \beta_{j,1}, \beta_{j,2})$ is the vector of parameters to be estimated. The weekly data sample is from the second week of April 2016 to the fourth week of December 2023 comprised of 404 observations. This table reports the point estimates for the regression models, and t-statistics are given in parentheses

***Statistically significant on a 1% level

**Statistically significant on a 5% level

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Declarations

Conflict of interest The authors declare that they have no interests to declare.

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On survivor cryptocurrency momentum*

Klaus Grobys[1], Davide Sandretto[2], Janne Äijö[3]

Abstract

Motivated by the significant illiquidity observed in the cryptocurrency market—exemplified by phenomena such as "defaulted coins"—this study is the first to investigate a cryptocurrency-specific analog of currency momentum, as implemented among G10 currencies. We analyze nine free-floating cryptocurrencies that remained within the top 100 altcoins by market capitalization during the sample period, spanning January 2017 to August 2024. Using weekly data, we evaluate two cryptocurrency momentum strategies: one focused solely on survivor coins and another utilizing the largest 30 coins for a given year (referred to as "plain cryptocurrency momentum"). Our main findings are as follows: (a) Cryptocurrency momentum is not evident when applied to survivor coins; (b) plain cryptocurrency momentum is profitable only after the dataset is trimmed; (c) the profitability of trimmed plain cryptocurrency momentum does not result from leveraging survivor coin-based cryptocurrency momentum; (d) even after trimming, the profitability of plain cryptocurrency momentum is highly sample-dependent.

Keywords: Cryptocurrency momentum, Survivor cryptocurrencies, Liquidity.

JEL codes: C59, G10, G14, G15, G19.

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1. Introduction

The study of cryptocurrency momentum was first introduced by Grobys and Sapkota (2019), who investigated the profitability of various momentum strategies using monthly returns on 143 cryptocurrencies from 2014 to 2018. Their findings revealed no statistically significant momentum payoffs. Conversely, Liu et al. (2020) observed substantial average weekly payoffs of 36% when employing a cryptocurrency momentum strategy over a 2015–2018 sample of 78 coins. Shen et al. (2020) used weekly return data on 1,786 coins from 2013 to 2019 and corroborated the findings of Grobys and Sapkota (2019), documenting insignificant average returns. Liu et al. (2022) extended this analysis to 1,827 coins spanning 2014–2020 and found statistically significant average payoffs of 3% per week. Interestingly, Zaremba et al. (2021) emphasized that inconclusive results in the literature could stem from methodological differences and sample construction, particularly the inclusion of illiquid small coins, which pose significant implementation challenges.

Grobys et al. (2025) addressed these challenges by focusing on a rolling investment opportunity set of 30 cryptocurrencies with the highest market capitalizations from 2016 to 2023. Their cryptocurrency momentum strategy was only profitable after trimming extreme values. The authors argued that unprofitability in cryptocurrency momentum arises from extreme price moves in single coins, which distort portfolio returns. Moreover, they document that the turnover of coins in their investment opportunity set was 37% annually, on average, highlighting a considerable stability issue in the digital currency market. Is the stability of coins relevant for momentum profitability? If smooth price movements are essential for profitability—consistent with the notion of momentum as a pervasive phenomenon (Asness et al., 2013)—cryptocurrency momentum portfolios composed of "survivor coins" should theoretically exhibit profitability. This suggests that the profitability of other momentum strategies might result from leveraged exposure to survivor coin momentum. In other words, the profitability of Grobys et al. (2025) momentum portfolio, after excluding extreme values, might mainly be driven by the momentum effect of survivor coins. Conversely, if this hypothesis does not find empirical support, the momentum effect may manifest through other cryptocurrencies that gain popularity and suddenly transition from a passive management state to an active one, then reverting to their previous price levels or even defaulting, once their popularity vanishes. Intuitively, in such instances, a momentum strategy would be profitable as it would take long positions on these coins until they lose popularity and revert, at which point they would be shortened. However, this process may not be monotonic, potentially causing drawdowns in the strategy.

This study examines the profitability of cryptocurrency momentum implemented in a time-invariant liquidity space defined by survivor coins. Survivor coins are free-floating cryptocurrencies that remained among the top 100 altcoins by market capitalization throughout the sample period (January 2017 to August 2024), thereby demonstrating stability and liquidity over time. Following the literature on G10 currency momentum, we construct a momentum portfolio by going long on the coins with the highest cumulative returns over the previous month and short on those with the lowest cumulative returns. The zero-cost portfolio is rebalanced weekly. We analyze the strategy's profitability on raw and trimmed data (removing outliers within the 2.5th and 97.5th percentiles). Additionally, we evaluate the profitability of a "plain cryptocurrency momentum portfolio," formed using the top 30 coins by market capitalization at the end of each calendar year. We further investigate whether the profitability of this strategy is attributable to leveraged exposure against the survivor cryptocurrency momentum portfolio by regressing its payoffs on survivor coin momentum. Robustness checks include controlling for the cryptocurrency market factor, implementing regression models on trimmed data, and conducting sample-split tests.

This study makes several key contributions to the growing literature on cryptocurrency momentum. First, by focusing on survivor coins, this study isolates the effects of liquidity and stability, which are fundamental for understanding momentum effects in cryptocurrency markets. Illiquidity and discontinuities—features of defaulted coins—introduce noise and complexity to estimate momentum payoffs. For example, Grobys (2024) emphasizes that cryptocurrencies undergoing sharp declines in liquidity fail to exhibit stable data-generating processes, undermining the reliability of statistical estimations.[1] By narrowing the focus to survivor coins, this research ensures a robust analysis by examining coins with higher stability in data-generating processes and consistent market relevance. Second, this research is the first to explore cryptocurrency momentum within a framework analogous to G10 currency momentum, providing a basis for cross-market comparisons. Survivor coins share some characteristics with G10 currencies, such as sustained growth and liquidity over time. These similarities may enable us to carry out a comparative analysis between these two distinct markets in terms of investor behavior.

Third, this study addresses inconsistencies in prior findings on the profitability of cryptocurrency momentum (e.g., Zaremba et al., 2021). Specifically, we extend the work by Grobys et al. (2025) by analyzing whether momentum profitability is mainly generated by coins with stable liquidity. Finally, this study relates to the recent work of Aloosh and Bekaert (2022) on foreign exchange rates by distinguishing between active and passive cryptocurrency management spaces. In a manner analogous to the foreign exchange market, significant payoffs in momentum strategies associated with coins that are only temporarily available for trading reflect a passive management space. Conversely, survivor coin momentum represents an active space, characterized by stability and sustained market activity. This distinction provides valuable insights into the practical implementation of momentum strategies in cryptocurrency markets.

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[1] Unsurprisingly, the literature on currency momentum often focuses on the G10 currencies due to three key factors: (a) their market capitalization, (b) high levels of liquidity, and (c) the absence of extreme discontinuities (Colacito et al., 2018; Greenwood-Nimmo et al., 2016). Lee and Wang (2020) report that the jump frequency of currencies exceeds that of the U.S. stock market, with non-G10 currencies exhibiting even higher discontinuity frequencies. These jumps have severe implications, as they can trigger the collapse of trading strategies, such as carry trades. Statistically, the data-generating processes of G10 currencies should align closely with those of survivor coins. Intuitively, for a coin to maintain its position among the top 100 cryptocurrencies by market capitalization, its growth rate must correspond to the overall growth of the cryptocurrency market capitalization. Recent studies, such as those by Harris et al. (2022) and Aloosh and Bekaert (2022), have explored momentum portfolios among G10 currencies. Aloosh and Bekaert (2022) coined the term "Deutsche Bank momentum factor" to describe the momentum portfolio implemented among the G10 currencies. This term underscores the potential relevance of applying similar frameworks to highly liquid and stable cryptocurrencies, providing a basis for deeper comparative analysis.

We find that survivor coins are indeed rare. According to CoinMarketCap, out of the 100 coins with the highest market capitalization as of December 2016, only nine coins remain in the top 100 in 2024: Bitcoin, Ethereum, XRP, Dogecoin, Litecoin, Stellar, Ethereum Classic, Monero, and Neo. Note that we do not include Tether USD because it is a stablecoin pegged to the US dollar, not a free-floating coin. Using these nine coins, we follow the literature on G10 currency momentum and employ tercile and equally-weighted portfolios to form our Survivor Cryptocurrency Momentum Portfolio (SCMP). Over our sample period from January 2017 to August 2024, SCMP generated an average payoff of 0.36% per week, which was statistically insignificant. Data trimming does not change this result. These findings are in line with the literature on G10 currency momentum, which documents insignificant average payoffs in the post-financial crisis period (Harris et al., 2022).

Furthermore, using the coins ranked among the top 30 in terms of market capitalization, the evidence suggests that plain cryptocurrency momentum produced a statistically significant average payoff of 0.93% per week after trimming. This result aligns with a recent study by Grobys et al. (2025), which documents that the legs of such a cryptocurrency portfolio sometimes include coins subject to extreme price moves. An extreme price move in a single cryptocurrency can cause a cryptocurrency momentum crash, rendering average returns insignificant. However, once outliers are excluded, cryptocurrency momentum generates statistically significant average payoffs (Grobys et al., 2025).

Additionally, using trimmed data on the plain cryptocurrency momentum portfolio and regressing this portfolio on SCMP, our results show that both (a) the loading against SCMP and (b) the regression intercept are positive and statistically significant. As the beta coefficient on SCMP is lower than one, this evidence suggests that the profitability of the trimmed plain cryptocurrency momentum portfolio is not an artifact of leveraged SCMP. While Grobys et al. (2025) indicate that the unprofitability of a plain cryptocurrency momentum portfolio can be caused by an extreme price move by a single cryptocurrency, our findings show that the average payoffs of the trimmed plain cryptocurrency momentum portfolio cannot be explained by its exposure to SCMP. Hence, our study concludes that the outsized and significant average payoffs documented for cryptocurrency momentum strategies must be an artifact of coins that are only temporarily accessible for trading, thus forming a 'passive' cryptocurrency management space.

The remainder of this study is structured as follows: Section 2 describes the data. Section 3 outlines the methodology. Section 4 presents the results, and Section 5 concludes with a discussion of the implications and avenues for future research.

2. Data

Cryptocurrency data were collected from CoinMarketCap, a widely recognized source in the traditional literature (Liu et al., 2022). Specifically, the dataset includes prices for nine survivor coins: Bitcoin (BTC), Ethereum (ETH), XRP (XRP), Dogecoin (DOGE), Litecoin (LTC), Stellar (XLM), Ethereum Classic (ETC), Monero (XMR), and Neo (NEO). Survivor coins are defined as free-floating cryptocurrencies that consistently ranked among the top 100 in terms of market capitalization throughout the sample period, spanning January 2017 to August 2024. This ranking serves as a proxy for high liquidity and stability over time. Tether USD (USDT), a stablecoin pegged to the US dollar, was excluded from the sample due to its unique nature and fixed valuation.

Descriptive statistics for these nine cryptocurrencies are presented in Table A.1, while Table A.2 provides a comparison of their market capitalizations as of December 2016 and December 2023. Notably, these nine coins accounted for approximately 96% of the total market capitalization at the end of 2016. Although this share decreased by 2023, it remained significant at approximately 67%, with Bitcoin and Ethereum continuing to dominate market share.

To construct tercile survivor cryptocurrency momentum portfolios, we utilized weekly price data spanning from the first week of January 2017 to the fourth week of August 2024, resulting in a dataset comprising 398 weekly observations. Additionally, to create quintile plain cryptocurrency momentum portfolios, we adopted the methodology of Grobys et al. (2025), retrieving data for the top 30 cryptocurrencies by market capitalization over the same period. This approach yielded a comparable dataset of 398 weekly observations. The investment opportunity set of 30 coins was re-evaluated annually at the end of December, covering the period from December 2016 to December 2023. This is consistent with established methodologies in the literature.

3. Empirical analysis

3.1. Implementing cryptocurrency momentum strategies

Using our set of survivor coins, we sort them into three groups based on their past 30-day returns. Following Grobys et al. (2025), we skip the most recent daily price quotation to compute the previous month's formation period (FP) return on survivor coin *i*:

$$r_{i,t}^{FP} = \frac{100(p_{t,j-1} - p_{t,j-30})}{p_{t,j-30}}, \tag{1}$$

where $p_{t,j-1}$ denotes the closing price of survivor coin *i* on the previous trading day for a given week *t*, $p_{t,j-30}$ denotes the closing price of survivor coin *i* in the past 30 trading days for a given week *t*, and $r_{i,t}^{FP}$ is the corresponding formation period return on survivor coin *i* in week *t*. The survivor coin momentum portfolio is long (short) on the three survivor coins with the highest (lowest) formation period returns. We hold the equal-weighted zero-cost survivor coin portfolio (SCMP) one week ahead and rebalance our portfolio at the beginning of each week. Our weekly data sample is from the first week of January 2017 to the fourth week of August 2024, comprising 398 observations. We report the average holding period returns, average formation period returns and average zero-cost portfolio return in Panel A of Table 1. We observe from Panel A of Table 1 that whereas the average formation period returns monotonically increase as we move from the loser group to the winner group from -8.25% to 44.30% per week, the average returns do not. The zero-cost SCMP strategy produced an average return of 0.36% per week with a *t*-statistic of 0.58, suggesting that the average payoff is statistically not different from zero.

Next, following Grobys et al. (2025), we also consider a cryptocurrency momentum portfolio consisting of 30 large-cap cryptocurrencies exhibiting the highest market capitalization in the previous December, for each given year. Since this strategy comprises more assets than our survivor coin portfolio, we employ quintile sorts. We refer to this strategy as the plain cryptocurrency momentum strategy (PCMP). Again, PCMP is a zero-cost portfolio long (short) on the coins with highest (lowest) formation period returns. We hold the equal-weighted PCMP one week ahead and rebalance our portfolio at the beginning of each week. Note that the implementation of this strategy and the corresponding coins used are detailed in Grobys et al. (2025). Using the same sample, we report the average holding period returns, average formation period returns and average zero-cost portfolio return in Panel B of Table 1. We observe from Panel B of Table 1 that the average zero-cost portfolio returns increase linearly as we move from the loser group to the winner group from 1.60% to 2.17% per week. Similarly, as documented in Grobys et al. (2025), the zero-cost PCMP produced an average return of 0.56% per week with a *t*-statistic of 0.68, suggesting that the average payoff is statistically not different from zero.

What could be the explanation for insignificant average returns of these strategies? In Table 2, we report the descriptive statistics of these two cryptocurrency momentum strategies along with the descriptive statistics of the market factor, which is the equal-weighted average return on our 30 large-cap cryptocurrencies used for implementing the PCMP. We observe from Table 2 that the maximum drawdown is -211.74% for PCMP and “only” -56.28% for SCMP. Also, the kurtosis values for both strategies are 80.67 and 27.46 indicating the presence of extremely heavy tails. Next, in Figure 1 we plot the cumulative returns on these two cryptocurrency momentum strategies. Figure 1 visualizes that both strategies SCMP and PCMP are subject to crashes which are, however, considerably more pronounced for PCMP as opposed to SCMP.

3.2. Trimming the return data on cryptocurrency momentum strategies

Following Grobys et al. (2025), we explore whether the unprofitability of our cryptocurrency momentum strategies is driven by "outliers." To investigate this issue, we trim the return data by shrinking the return distributions between the 2.5th and 97.5th percentiles. The descriptive statistics are documented in Table 3. Strikingly, the trimmed data on PCMP suggest that the average payoff corresponding to 0.93% per week is statistically significant on a common 5% level (*t*-statistic 2.40). This confirms Grobys et al. (2025), who document that the average return on such a large-cap cryptocurrency momentum strategy becomes statistically significant after trimming the data. On the other hand, trimming does not change the profitability of SCMP: After trimming the average return on this strategy is -0.10% per week and statistically not different from zero (*t*-statistic -0.30). Interestingly, this result suggests that the unprofitability of the SCMP is not an artifact of extreme events. Furthermore, this result lines up nicely with the literature on G10 currency momentum documenting that the momentum strategy implemented among the G10 currencies produces insignificant average payoffs (e.g., Harris et al., 2022). Since G10 currencies and survivor coins have similar liquidity characteristics, a comparison can be drawn. G10 currencies, for instance, account for approximately 89% of global trading volume, which makes them an ideal data sample for analysis (Aloosh and Bekaert, 2022; Colacito et al., 2018). Indeed, a high liquidity condition leads to greater market efficiency, as it minimizes common frictions such as high trading costs, search frictions, and demand pressures (Cochrane, 2001). Similarly, as argued in our study, survivor coins exhibit stability in the data-generating process and popularity in the cryptocurrency market—both may be manifested in maintaining high trading volumes over time as observed from Table A.2 in the appendix—which contribute to a more efficient market environment.

3.3. Can some exposure to survivor cryptocurrency momentum portfolio explain the returns on the plain cryptocurrency momentum strategy?

A natural question that arises is as to whether the returns on PCMP are an artifact of leveraging the SCMP. To explore whether some exposure to SCMP could explain the returns on PCMP, we regress the returns on PCMP on an intercept term and SCMP as follows:

$$r_t^{MOM\,30} = a_j + \beta_1 r_t^{MOM9} + \varepsilon_t, \tag{2}$$

where $r_t^{MOM\,30}$ denotes the return on PCMP at time *t*, r_t^{MOM9} denotes the return on SCMP at time *t*, a_j and β_1 measure the regression intercept and PCMP's exposure to SCMP, and ε_t denotes an error term that is assumed to be a white noise process. As a robustness check, we also control for the market factor as follows:

$$r_t^{MOM\,30} = a_j + \beta_1 r_t^{MOM9} + \beta_2 r_t^{MKT} + \varepsilon_t, \tag{3}$$

In Eq. (3), r_t^{MKT} denotes the return on the cryptocurrency market factor where β_2 measures PCMP's exposure to this factor and all other notation is as before. We estimate a correlation of -0.02 between the market factor and SCMP, suggesting no collinearity-related issues in the estimation. The regression results using the whole data are reported in Table 4. We observe from Table 4 that $\hat{\beta}_1 = 0.25$ regardless whether or not the cryptocurrency market factor is accounted for. The point estimate is statistically significant on any level regardless the regression model specification. Interestingly, the loading against the market factor is statistically significantly negative which appears to be a universal feature for momentum strategies and has been documented repetitively in the literature on equity market momentum. However, the results documented in Table 4 provide strong evidence that (a) PCMP is not leveraged on SCMP as $\hat{\beta}_1 < 1$ regardless the model specification and (b) the average risk-adjusted payoff of PCMP does not reach statistical significance after controlling for SCMP or SCMP and the cryptocurrency market factor. To check the robustness of our findings, we use the trimmed data on the returns on PCMP and re-run the regression models of Eqs. (1) and (2). The results are documented in Table 5. From Table 5, we observe that the average returns using the trimmed data on PCMP remain statistically significant regardless the regression model specification. Interestingly, we see that $\hat{\beta}_1 = 0.14$ regardless whether or not the cryptocurrency market factor is accounted for. Whereas the point estimate is statistically significant on any level, the economic magnitude is lower than using the untrimmed data. Because we only use the trimmed data on PCMP, the fact that $\hat{\beta}_1$ decreases might be explained by a decreasing co-variance between trimmed PCMP and SCMP. That is, the profitability of trimmed PCMP must stem from coins that exhibit different properties than survivor coins which are (a) highly liquid and (b) stable. Since the PCMP comprises coins that are large but the vast majority of coins exits the group of selected coins on an annual basis, the PCMP must arise from coins that eventually end up in "default," which casts doubt on the practical feasibility of this investment strategy.

3.4. Additional tests

To shed additional light on the profitability of cryptocurrency momentum, we implement sample split tests. For the implementation of our sample split tests, we only use the trimmed data on PCMP which produced statistically significant average for the whole sample. Sample 1 covers the subperiod from the first week of January 2017 to the third week of October 2020. Sample 2 covers the subperiod from the fourth week of October 2020 to the fourth week of August 2024. Again, we run the regression models outlined in Eqs. (1) and (2). The results are documented in Tables A.3 and A.4 in the appendix. Surprisingly, from Table A.3 in association with Table A.4 it becomes evident that trimmed PCMP produces only significant risk-adjusted average returns in sample 2. This result suggests that the seeming profitability of the cryptocurrency momentum strategy is subject to sample-specificity. Is the documented profitability of cryptocurrency a myth? Future research is encouraged to elaborate more on this issue.

4. Discussion

4.1. Alignment with Earlier Studies

This study demonstrates that only a small subset of cryptocurrencies exhibit characteristics of liquidity and stability in terms of relative market capitalization. By examining the top 100 cryptocurrencies by market capitalization from January 2017 to December 2023, we find that only nine coins have maintained their positions over time, reflecting growth aligned with the overall market.

Our analysis of survivor coins reveals structural parallels with G10 currencies. Between 2017 and 2024, survivor coins constituted approximately 82% of the cryptocurrency market's total capitalization, comparable to G10 currencies, which represent 89% of global currency trading volume (Aloosh and Bekaert, 2022). Given these similarities, we implemented a momentum strategy across these prominent cryptocurrencies, mirroring a G10 currency framework. Consistent with Harris et al. (2022), who observed a lack of significant profitability in G10 currency momentum post-financial crisis, we find similar results when applying momentum strategies to this liquid and stable cryptocurrency subset. These findings hold true even after excluding extreme observations.

Furthermore, our results align with those of Zaremba et al. (2021), who reported substantial variation in return patterns among cryptocurrencies based on market size. Their findings indicate that the largest 2% of cryptocurrencies—accounting for 94% of market capitalization—exhibit momentum effects, while small- and medium-cap cryptocurrencies tend to display reversal effects. With an average of 1,126 cryptocurrencies in their dataset, approximately 23 coins demonstrate momentum behavior. Zaremba et al. (2021) applied a 2% winsorization to the return distribution, making their results comparable to our trimmed plain momentum portfolio, which exhibits positive and significant payoffs for the top 30 largest-cap cryptocurrencies.

However, unlike prior studies (e.g., Zaremba et al., 2021; Shen et al., 2020; Liu et al., 2022), this research explicitly accounts for the stability of cryptocurrencies in maintaining liquidity over time, a critical factor for momentum strategy implementation. Previous studies employed static approaches, retrospectively assessing cryptocurrency liquidity based on market capitalization at a single point in time. By contrast, we adopt a dynamic approach, reassessing the investment opportunity set annually to capture time-variant changes in market capitalization. This approach reveals that momentum strategies based on trading survivor coins are unprofitable and that PCMP returns are not leveraged by survivor momentum strategies. Consequently, the significant payoffs observed in trimmed momentum portfolios of large-cap cryptocurrencies appear driven by temporary upward trends, which subside as coins revert to their prior market capitalization levels, placing them in a passive management state. These findings cast doubt on the practical applicability of momentum trading strategies in the cryptocurrency market.

4.2. Limitations

One potential concern could be that our methodology introduces survivorship bias, as the tested strategies rely on information unavailable at the time of trading (i.e., whether a coin ultimately survives or not). While this critique is valid, we argue that rational investors would avoid strategies that fail to generate significant payoffs in the first place. Even in this chosen setting, our evidence demonstrates that momentum strategies implemented among survivor coins do not yield statistically significant payoffs, consistent with results for G10 currencies (Harris et al., 2022).

Another potential critique could be that our study examines several cryptocurrency momentum specifications, including alternative samples and data preparation procedures, which may overlap with earlier research. For instance, Fieberg et al. (2024) explored over 20,000 cryptocurrency momentum specifications, including diverse samples and winsorizing techniques. However, Fieberg et al. (2024) neither offer a comparative analysis with G10 currency momentum nor address the stability issues in cryptocurrency, as highlighted by Grobys (2024). Consequently, their results may reflect a "passive management space," as described by Aloosh and Bekaert (2022). Further research is needed to address these limitations and advance knowledge in this area.

5. Conclusion

The literature on cryptocurrency momentum remains inconclusive (Grobys et al., 2025). Particular attention must be paid to the role of small coins, as they can lead to biased inferences due to their high illiquidity premiums and trading constraints (Zaremba et al., 2021). Despite this, even cryptocurrencies with high market capitalization can experience extreme price volatility, resulting in sharp drops in market capitalization or, in some cases, default (Grobys and Sapkota, 2020), impairing the profitability of momentum strategies. Aloosh and Bekaert (2022) argue that large price discontinuities, along with the associated illiquidity, create a "passive management space" for investors seeking to implement momentum strategies. If momentum is truly pervasive, as previous research suggests (Asness et al., 2013), its profitability may be driven by cryptocurrencies that remain in an "active management space," such as survivor coins. Alternatively, the momentum factor could be attributable to coins that experience temporary price surges before reverting to baseline levels.

To test this hypothesis, we analyze nine survivor coins—cryptocurrencies that remained in the top 100 by market capitalization between January 2017 and August 2024. We also examine a broader set of the top 30 coins to compute the plain cryptocurrency momentum portfolio, following the methodology of Grobys et al. (2025). To construct zero-cost long-short portfolios, we create tercile and quintile portfolios, respectively, for a total of 398 weekly observations spanning from January 2017 to August 2024.

Our results show that the survivor cryptocurrency momentum portfolio does not generate significant payoffs, even when we eliminate 5% of extreme observations. These results align with the literature on G10 currencies (Harris et al., 2022). In contrast, the PCMP shows positive and significant payoffs only when data is trimmed, consistent with the findings of Grobys et al. (2025). Additionally, regressing the SCMP on the PCMP reveals that the returns of the PCMP are not an artifact of leveraging the SCMP. These results, which are robust to market factor exposure and sample-splitting tests, suggest that the significant payoffs documented for cryptocurrency momentum strategies are likely driven by coins that are only temporarily accessible for trading.

The implications of this study are relevant for investors and asset management firms looking to implement momentum strategies in the cryptocurrency market. Our findings suggest that such strategies may be infeasible in practice, as many coins fall into a space characterized by low liquidity and stability. Furthermore, with the prominent entrance of banks and financial intermediaries into this market, as sanctioned by the upcoming crypto-asset framework developed by the Basel Committee (Bank for International Settlements, 2022), this research suggests that traditional financial products of the forex market, such as the Deutsche Bank index (Aloosh and Bekaert, 2022), may offer limited appeal in terms of payoffs. Future research should further investigate the sample-specific nature of cryptocurrency momentum returns and explore the determinants of non-survivor coin returns. Moreover, other risk factors, such as size and value, could be examined within this highly liquid subset of survivor coins. In this regard, Liebi (2022) documented that the value factor is priced into the cryptocurrency market, with its premium being most pronounced among small coins. This evidence suggests that liquidity may play a fundamental role in determining the value premium's significance and magnitude.

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Figure 1. Cumulative returns on the cryptocurrency momentum strategies.

Using tercile (quintile) sorts and the top 9 (30) cryptocurrencies, the momentum factor is a strategy that buys cryptocurrencies with the highest return in the 1-month formation period and shorts those with the lowest return in the 1-month formation period. We skip 1 trading day between the holding period and the formation period. This strategy employs equal-weighted asset allocations and is rebalanced weekly. This figure plots the evolution of the cumulative returns on both momentum portfolios from the first week of January 2017 to the fourth week of August 2024.

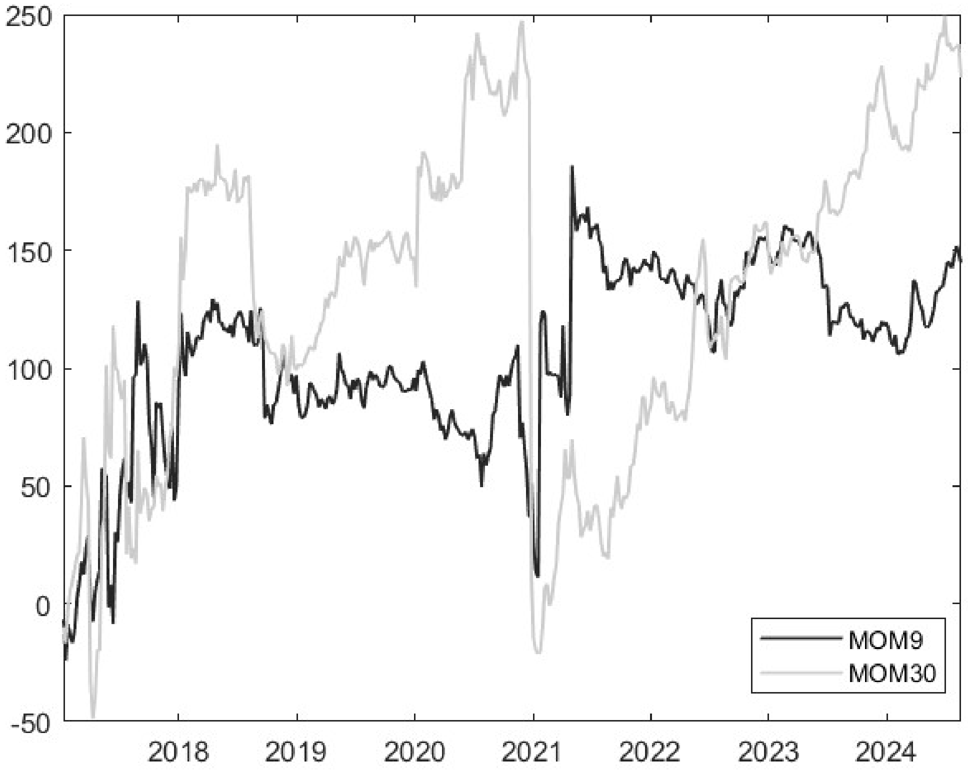

Table 1. Portfolio sorts for the momentum factor.

This table reports the portfolio sorts for the cryptocurrency momentum factor. Using tercile (quintile) sorts for the top 9 (30) cryptocurrencies in terms of their market capitalization, the momentum factor is a strategy that takes a long position in cryptocurrencies with the highest return in the 1-month formation period and a short position in those with the lowest return in the 1-month formation period. We skip 1 trading day between the holding period and the formation period. This strategy employs equal-weighted asset allocations and is rebalanced weekly. In tercile sorting Portfolio 1 (P1) corresponds to the loser portfolio, and portfolio 3 (P3) corresponds to the winner portfolio, while in quintile sorting portfolio 5 (P5) corresponds to the winner portfolio. The average return for portfolio i={1,2,3,4,5} is denoted as $\bar{r}_i$, whereas the average portfolio return for the formation period (FP) is denoted as $\bar{r}_i^{FP}$. The weekly data sample is from the first week of January 2017 to the fourth week of August 2024, comprising 398 observations. The *t*-statistics for the zero-cost portfolios are given in parenthesis.

Panel A. Sorted momentum portfolios for top 9 coins

Portfolio	P1	P2	P3	(P3-P1)
$\bar{r}_i$	1.83	2.45	2.20	0.36
$\bar{r}_i^{FP}$	-8.25	6.73	44.30	(0.58)

Panel B. Sorted momentum portfolios for top 30

Portfolio	P1	P2	P3	P4	P5	(P5-P1)
$\bar{r}_i$	1.60	1.19	1.49	1.88	2.17	0.56
$\bar{r}_i^{FP}$	-17.69	-5.09	3.95	16.22	62.68	(0.69)

Table 2. Descriptive statistics for the cryptocurrency market and momentum factor.

This table reports the descriptive statistics of the cryptocurrency market and momentum factors. The market factor is an equal-weighted portfolio of cryptocurrencies consisting of the top 30 cryptocurrencies based on their market capitalization. Using tercile (quintile) sorts and these top 9 (30) cryptocurrencies, the momentum factor is a strategy that takes a long position in cryptocurrencies with the highest return in the 1-month formation period and a short position in those with the lowest return in the 1-month formation period. We skip 1 trading day between the holding period and the formation period. This strategy employs equal-weighted asset allocations and is rebalanced weekly. The weekly data sample is from the first week of January 2017 to the fourth week of August 2024, and it comprises 398 observations.

	Momentum (30 coins)	**Momentum (9 coins)**	**Market**
Mean	0.56	0.36	1.67***
(t-statistic)	(0.69)	(0.58)	(2.72)
Median	0.89	-0.41	0.83
Max	64.85	107.13	65.11
Min	-211.74	-56.28	-34.41
Std. Dev.	16.12	12.47	12.24
Skewness	-5.76	2.77	1.09
Kurtosis	80.67	27.46	7.70
Jarque-Bera test (JB)	102235.90	10431.92	445.31
p-value (JB)	0.00	0.00	0.00
Observations	398	398	398

*** Statistically significant on a 1% level.

Table 3. Descriptive statistics for the trimmed momentum factor.

This table reports the descriptive statistics of the cryptocurrency momentum factor after trimming the data. Using tercile (quintile) sorts and the top 9 (30) cryptocurrencies in terms of their market capitalization, the momentum factor is a strategy that takes a long position in cryptocurrencies with the highest return in the 1-month formation period and a short position in those with the lowest return in the 1-month formation period. We skip 1 trading day between the holding period and the formation period. This strategy employs equal-weighted asset allocations and is rebalanced weekly. The weekly data sample is from the first week of January 2017 to the fourth week of August 2023, comprising 398 observations. We apply a trimming procedure that shrinks the distribution between the 2.5th and 97.5th percentiles, The *t*-statistics for the payoffs of the trimmed zero-cost portfolios are given in parenthesis.

	Momentum (30 coins)	**Momentum (9 coins)**
Mean	0.93**	-0.10
(*t*-statistic)	(2.40)	(-0.30)
Median	0.89	-0.41
Max	21.81	27.49
Min	-19.24	-21.42
Std. Dev.	7.56	6.56
Skewness	0.13	0.10
Kurtosis	3.34	4.78
Jarque-Bera test (JB)	2.86	50.52
p-value (JB)	0.24	0.00
Observations	378	378

** Statistically significant on a 5% level.

Table 4. Risk-adjusting the cryptocurrency momentum portfolio.

This table reports the results for the following regression:

$$r_t^{MOM\ 30} = a_j + \beta_1 r_t^{MOM9} + \beta_2 r_t^{MKT} + \varepsilon_t$$

where $r_t^{MOM\ 30}$ is the momentum factor computed utilizing the top 30 cryptocurrencies in term of market capitalization, r_t^{MOM9} is the momentum factor computed utilizing the top 9 cryptocurrencies in terms of market capitalization, $r_t^{MKT}$is the market factor computed as an equal-weighted portfolio of cryptocurrencies consisting of the top -30 cryptocurrencies. ε_t denotes a white noise error. The weekly data sample is from the first week of January 2017 to the fourth week of August 2024, comprising 398 observations. Using quintile sorts on these top 30 cryptocurrencies, the momentum factor is a strategy that takes a long position in cryptocurrencies with the highest return in the 1-month formation period and a short position in those with the lowest return in the 1-month formation period. We skip 1 trading day between the holding period and the formation period.

Strategy	$r_t^{MOM\ 30}$	$r_t^{MOM\ 30}$
$\hat{a}_j$	0.47	0.75
	(0.59)	(0.94)
$\hat{\beta}_1$	0.25***	0.25***
	(3.95)	(3.92)
$\hat{\beta}_2$		-0.16**
		(-2.55)
R^2	0.04	0.05

***,** Statistically significant on a 1% and 5% level, respectively.

Table 5. Risk-adjusting the trimmed cryptocurrency momentum portfolio.

This table reports the results for the following regression:

$$r_t^{TMOM\ 30} = a_j + \beta_1 r_t^{MOM9} + \beta_2 r_t^{MKT} + \varepsilon_t$$

where $r_t^{TMOM\ 30}$ is the trimmed momentum factor computed utilizing the top 30 cryptocurrencies in terms of market capitalization, r_t^{MOM9} is the momentum factor computed utilizing the top 9 cryptocurrencies in terms of market capitalization, r_t^{MKT} is the market factor computed as an equal-weighted portfolio of cryptocurrencies consisting of the top -30 cryptocurrencies. ε_t denotes a white noise error. The weekly data sample is from the first week of January 2017 to the fourth week of August 2024, comprising 378 trimmed observations. Using quintile sorts on these top 30 cryptocurrencies, the momentum factor is a strategy that takes a long position in cryptocurrencies with the highest return in the 1-month formation period and a short position in those with the lowest return in the 1-month formation period. We skip 1 trading day between the holding period and the formation period.

Strategy	$r_t^{TMOM\ 30}$	$r_t^{TMOM\ 30}$
$\hat{a}_j$	0.85**	0.88**
	(2.24)	(2.30)
$\hat{\beta}_1$	0.14***	0.14***
	(4.18)	(4.16)
$\hat{\beta}_2$		-0.05
		(-1.32)
R^2	0.04	0.05

***,** Statistically significant on a 1% and 5% level, respectively.

Appendix.

Table A1. Descriptive statistics for the 9 survivor cryptocurrencies.

This table reports the descriptive statistics for the 9 survivor coins, with daily returns spanning from January 2017 to August 2024.

Coins	Bitcoin (BTC)	Dogecoin (DOGE)	Ethereum (ETH)	Ethereum Classic (ETC)	Litecoin (LTC)	Monero (XMR)	Neo (NEO)	Stellar (XLM)	XRP (XRP)
Mean	0.22	0.52	0.33	0.28	0.24	0.23	0.40	0.36	0.39
Median	0.13	-0.04	0.08	0.00	0.03	0.21	0.05	-0.05	-0.08
Maximum	25.25	355.57	33.66	58.04	66.77	53.80	122.69	106.08	179.37
Minimum	-37.17	-40.26	-42.35	-39.73	-36.18	-41.39	-37.23	-33.63	-46.01
Std. Dev.	3.79	9.77	5.03	6.16	5.55	5.33	7.40	7.24	7.43
Skewness	-0.05	18.30	0.36	1.14	1.39	0.53	3.42	4.34	6.98
Kurtosis	10.15	632.89	9.94	13.46	18.66	14.75	48.41	53.35	139.84
Jarque-Bera	5967.99	46428341.00	5682.19	13369.40	29502.52	16235.77	245971.50	304471.10	2206640.00
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Observations	2799	2799	2799	2799	2799	2799	2799	2799	2799

Table A2. Survivor coins and market capitalization.

This table provides the market capitalization for the 9 surviving cryptocurrencies as of December 2016 and December 2023, along with a comparison to the total market capitalization for both years.

Cryptocurrency	Mkt Capitalization as of December 2016	% of total mkt capitalization	Mkt Capitalization as of December 2023	% of total mkt capitalization
Bitcoin (BTC)	14,396,198,729.33	87.86%	827,811,209,384.41	47.74%
Ethereum (ETH)	626,189,615.98	3.82%	274,194,287,336.35	15.81%
XRP (XRP)	232,006,578.41	1.42%	33,283,785,350.85	1.92%
Litecoin (LTC)	213,168,549.82	1.30%	5,390,137,464.63	0.31%
Monero (XMR)	132,525,971.58	0.81%	3,032,945,820.76	0.17%
Ethereum Classic (ETC)	93,536,872.97	0.57%	3,172,554,930.65	0.18%
Dogecoin (DOGE)	24,708,711.86	0.15%	12,746,626,943.45	0.74%
Stellar (XLM)	17,845,296.56	0.11%	3,643,117,124.30	0.21%
Neo (NEO)	7,339,395.58	0.04%	982,991,919.33	0.06%
Total	15,743,519,722.09	96.08%	1,164,257,656,274.73	67.15%

Table A3. Risk-adjusting the trimmed cryptocurrency momentum portfolio - subsample 1.

This table reports the results for the following regression:

$$r_t^{TMOM\,30} = a_j + \beta_1 r_t^{MOM9} + \beta_2 r_t^{MKT} + \varepsilon_t$$

where $r_t^{TMOM\,30}$ is the trimmed momentum factor computed utilizing the top 30 cryptocurrencies in terms of market capitalization, r_t^{MOM9} is the momentum factor computed utilizing the top 9 cryptocurrencies in terms of market capitalization, r_t^{MKT} is the market factor computed as an equal-weighted portfolio of cryptocurrencies consisting of the top -30 cryptocurrencies. ε_t denotes a white noise error. The weekly data sample is from the first week of January 2017 to the fourth week of August 2024, comprising 398 observations. Sample 1 covers the subperiod from the first week of January 2017 to the third week of October 2020. Using quintile sorts on these top 30 cryptocurrencies, the momentum factor is a strategy that takes a long position in cryptocurrencies with the highest return in the 1-month formation period and a short position in those with the lowest return in the 1-month formation period. We skip 1 trading day between the holding period and the formation period.

Strategy	$r_t^{TMOM\,30}$	$r_t^{TMOM\,30}$
$\hat{a}_j$	0.25	0.32
	(0.44)	(0.58)
$\hat{\beta}_1$	0.21***	0.20***
	(3.75)	(3.66)
$\hat{\beta}_2$		-0.11**
		(-2.16)
R^2	0.07	0.10

***,** Statistically significant on a 1% and 5% level, respectively.

Table A4. Risk-adjusting the trimmed cryptocurrency momentum portfolio - subsample 2.

This table reports the results for the following regression:

$$r_t^{TMOM\ 30} = a_j + \beta_1 r_t^{MOM9} + \beta_2 r_t^{MKT} + \varepsilon_t$$

where $r_t^{TMOM\ 30}$ is the trimmed momentum factor computed utilizing the top 30 cryptocurrencies in terms of market capitalization, r_t^{MOM9} is the momentum factor computed utilizing the top 9 cryptocurrencies in terms of market capitalization, r_t^{MKT} is the market factor computed as an equal-weighted portfolio of cryptocurrencies consisting of the top -30 cryptocurrencies. ε_t denotes a white noise error. The weekly data sample is from the first week of January 2017 to the fourth week of August 2024, comprising 398 observations. Sample 2 covers the subperiod from the fourth week of October 2020 to the fourth week of August 2024. Using quintile sorts on these top 30 cryptocurrencies, the momentum factor is a strategy that takes a long position in cryptocurrencies with the highest return in the 1-month formation period and a short position in those with the lowest return in the 1-month formation period. We skip 1 trading day between the holding period and the formation period.

Strategy	$r_t^{TMOM\ 30}$	$r_t^{TMOM\ 30}$
$\hat{a}_j$	1.37***	1.36***
	(2.66)	(2.63)
$\hat{\beta}_1$	0.10**	0.10**
	(2.41)	(2.41)
$\hat{\beta}_2$		0.04
		(0.71)
R^2	0.03	0.03

***,** Statistically significant on a 1% and 5% level, respectively.

Does the transition to the Proof-of-Stake consensus protocol tame the response of cryptocurrency volatility to energy shocks?*

Abstract

This study investigates the impact of transitioning from the Proof-of-Work (PoW) to the Proof-of-Stake (PoS) consensus protocol on the relationship between cryptocurrency volatility and energy shocks. Specifically, we exploit the random nature of the transition to the PoS consensus algorithm as a quasi-natural experiment. We analyze this issue for the volatility processes of four digital currencies with high market capitalization using GARCH models. Our cross-sectional findings reveal a significant reduction in the sensitivity of digital currencies to energy market shocks following the adoption of PoS. These findings advocate for the migration from the energy-intensive PoW consensus protocol to the more environmentally sustainable PoS protocol.

Keywords: Cryptocurrency, Energy shocks, Volatility, Proof of Stake, Proof of Work.

JEL codes: C59, G10, G14, G15, G19.

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1. Introduction

Since the inception of Bitcoin, the cryptocurrency market has experienced remarkable growth over the past decade. As of June 2024, the digital currency market has reached a total market capitalization of roughly 2.5 trillion dollars and now encompasses more than 10,000 coins (Source: coinmarketcap.com, accessed on June 20, 2024). The proliferation of cryptocurrencies has captivated both the academic community and the financial industry due to their dual role as digital currencies and highly rewarding, yet volatile, investment assets (Corbet et al., 2019).

On the other hand, cryptocurrencies have also received significant attention from policymakers and the broader community concerning their carbon footprint. Assessing the precise environmental impact of cryptocurrencies is challenging (Sutherland, 2019). Nevertheless, numerous studies highlight concerns about the substantial energy consumption associated with the cryptocurrency market (de Vries, 2019, 2020; Kohli et al., 2023; Sutherland, 2019; Zhang et al., 2023). It is estimated that activities related to mining digital currencies account for 1 to 2 percent of total U.S. electricity consumption (U.S. Energy Information Administration, 2022). Moreover, research by Kohli et al. (2023) reveals that the energy consumption of Bitcoin mining alone surpasses that of Sweden, with its CO2 emissions approaching those of Greece and Oman. Although renewable energy sources could potentially be used to meet part of the energy demands of the cryptocurrency market, their instability due to seasonal variability makes them less attractive to miners, who thus are forced to rely on fossil fuels (de Vries, 2019).

The high energy consumption of cryptocurrencies is primarily a function of the consensus protocol underlying blockchain operations. This innovative technology relies on a decentralized public ledger that records all transactions and data of network participants. Each transaction forms part of a block, which must be validated by nodes (network members) using hardware with immense computing power to solve a complex cryptographic puzzle. Upon solving these mathematical equations, the validated block is added to the chain, and the validator receives a reward in the form of a predetermined amount of cryptocurrency. A key characteristic of this process is that once a block is validated, it becomes immutable, and the transaction cannot be reversed, ensuring the security and transparency of the technology. The energy required for this validation process is contingent on the consensus protocol employed by the digital coin.

The standard consensus algorithm adopted by most cryptocurrencies is the Proof-of-Work (PoW) protocol. This mechanism involves the validation of blocks by network participants known as "miners," who engage in a competitive process to solve complex mathematical problems. The probability of a miner successfully validating a block is directly proportional to their computational power and energy expenditure. As cryptocurrency mining intensifies, the complexity of these problems escalates, requiring more computing power and, consequently, higher energy consumption. A graphical illustration of this issue is presented in Figure 1 for Bitcoin.

In response to the high energy demands and environmental concerns associated with PoW, the blockchain community has developed an alternative consensus protocol known as Proof-of-Stake (PoS). Under the PoS mechanism, block validation is carried out by validators who are randomly selected from the network participants based on the quantity of coins they have staked. The probability of being chosen as a validator increases with the amount of staked coins.

Unlike PoW, PoS eliminates the competitive aspect of block validation. There is no need for extensive computational resources or specialized hardware, as the cryptographic puzzles involved are simpler and independent of network size. This lack of competition and reduced need for high-powered machinery significantly decreases the energy consumption associated with PoS. Consequently, the PoS protocol is less CO2-intensive, making it a more environmentally sustainable option compared to PoW (Bouraga, 2021; Leslie, 2020; Sriman et al., 2021; Truby et al., 2022). Data on electricity consumption and CO_2 emissions reported by the Crypto Carbon Ratings Institute (CCRI) consistently confirm this fact. Indeed, while PoW cryptocurrencies such as Bitcoin and Dogecoin consume 149.7 TWh and 3.9 TWh of electricity respectively, emitting 73.9 Mt and 1.9 Mt of CO_2 annually, Ethereum and Cardano, which rely on PoS, consume significantly less—only approximately 6 GWh and 0.7

GWh of electricity—and emit 1.9 Mt and 0.2 Mt of CO_2, respectively. The statistics also indicate that Ethereum's transition to PoS has led to a 99% reduction in its energy consumption and carbon emissions (carbon-ratings.com, 2023). However, despite these encouraging figures, energy demand is correlated with the size of the network, and therefore the PoS protocol is still more impacting than traditional centralized systems (Sedlmeir et al., 2020). Interested readers are referred to the study of Wendl et al. (2023) for a complete literature review on the energy consumption of PoW and PoS consensus protocols.

To date, the majority of cryptocurrencies—including Bitcoin as the most prominent example—still rely on the PoW consensus protocol. Despite facing resistance from miners, who find their mining activity profitable, some developers have decided to move towards adopting PoS. Ethereum, among others, represented a significant turning point by completing its transition to this consensus mechanism on September 15, 2022. Despite some initial surprise within the community of users, the founders always believed that PoS was the most suitable option for this digital currency. They argued that this protocol's features could reduce the high energy requirements of the blockchain, ensure its efficiency, and enhance network scalability (Coindesk, 2022; Beincrypto, 2024).

Since the PoS protocol still requires energy—yet, to a substantially lesser extent than PoW—a question that arises is: Does a move from PoW to the more sustainable PoS consensus protocol affect the sensitivity of cryptocurrency volatility to energy shocks? An answer to this question is not trivial, since lower volatility would benefit digital coin holders. Indeed, it is well known that cryptocurrencies are extremely volatile and subject to recurring bubbles, as speculative behaviors drive this market (Fry & Cheah, 2016). On the other hand, energy shocks play an important role in heightening asset volatility. As documented by Park and Ratti (2008), oil price shocks account for roughly 6% of the volatility in real returns on stocks in both the US and Europe. Moreover, commodity uncertainty is a priced state variable in economies that affects asset payoffs and investor portfolio choices (Bakshi &

Chen, 1996; Christoffersen & Pan, 2018). Similar volatility dynamics are documented in the cryptocurrency market (Naeem et al., 2023).

To address our research question, we analyze the sensitivity to energy shocks in the conditional volatility process of four major cryptocurrencies that switched from a PoW to a PoS consensus algorithm. In doing so, we utilize GARCH models within a quasi-natural experimental setting.

Our study contributes to the existing literature in several ways: First, we contribute to the field of sustainable finance by examining the environmental impact of transitioning from PoW to PoS consensus protocols. Given the strong interest from institutions and the broader community, the financial industry, and other sectors, must consider the sustainable impact of its externalities. In the context of cryptocurrencies, few studies have examined their sustainability profiles (Corbet et al., 2019). Ren and Lucey (2022) analyze the herding behavior of green and dirty cryptocurrencies, concluding that there is no evidence of herding patterns among investors of clean coins. Pham et al. (2022) investigate the tail dependence among carbon prices, green cryptocurrencies, and non-green ones. They argue that green cryptocurrencies highlight diversification potential against both carbon markets and non-green cryptocurrencies, offsetting their risk during extreme downward market movements. Moreover, green coins can better diversify different global and regional equity portfolios than their non-green counterparts (Ali et al., 2024). To the best of our knowledge, no prior study has analyzed the potential reduction in the sensitivity of cryptocurrency volatility to energy shocks after the transition to a more sustainable consensus protocol. This is not a trivial issue because lower volatility in the returns of green cryptocurrencies would suggest a strong case for stakeholders in PoW cryptocurrencies to consider switching to the PoS model.

Second, the opportunity to conduct an event study allows for a causal investigation of this phenomenon. This approach is more robust than others, such as constructing portfolios of PoW and PoS coins, which might lead to misleading inferences due to potential spurious correlations. We utilize a unique opportunity to study this issue as a quasi-natural experiment, because different coins transitioned at different dates, enabling us to treat the cross-section of switches as a quasi-natural experiment. This methodological approach is particularly valuable because it allows us to analyze the same cryptocurrency in a counterfactual way, where the only feature that has changed is the consensus protocol.

Third, we contribute to the literature on energy shocks and cryptocurrency volatility. Previous studies have generally analyzed the response to energy shocks on different cryptocurrencies without distinguishing the effects of energy consumption levels. Okorie and Lin (2020) show unidirectional and bidirectional volatility spillover between the crude oil market and both the top 5 and bottom 5 cryptocurrencies based on market capitalization. Naeem et al. (2023) find a positive correlation between oil prices and cryptocurrencies regardless of market conditions, showing that rising fluctuations in oil demand shocks lead to significant movements in cryptocurrencies. However, Yin et al. (2021), using GARCH-MIDAS models to investigate the connection between the volatility of Bitcoin, Ethereum, and XRP and oil shocks, report contrasting results. They find a negative relationship between oil shocks and the long-term volatility of cryptocurrencies, which vanished when controlling for macroeconomic proxies, indicating that cryptocurrency volatility is mainly affected through the macroeconomic channel. We differentiate from the aforementioned studies by focusing on the impact of energy shocks—proxied by crude oil—on the volatility of cryptocurrencies that have switched to a green protocol.

Finally, we also contribute to the extensive literature on cryptocurrency volatility modeling by examining our research question using extended GARCH-type specifications. A consistent body of literature has investigated the volatility of cryptocurrencies—especially Bitcoin—adopting various GARCH-type models, including Threshold GARCH, Asymmetric-Power GARCH, Component with Multiple Threshold GARCH, Exponential GARCH, and Markov-Switching GARCH models, among others (Bouoiyour and Selmi, 2016; Caporale and Zekokh, 2019; Dyhrberg, 2016; Fakhfekh and Jeribi, 2020; Katsiampa, 2017, 2019). For a complete literature review on the volatility of cryptocurrency, refer to the paper by Kyriazis (2021). Following the earlier literature, we adopt GARCH and TGARCH models in our analysis, as these are considered benchmark models for modeling the volatility of financial assets. From a methodological point of view, our study adds to the literature by proposing two novel approaches to this stream of research. First, we employ a modified version of the GARCH and TGARCH models, which accounts for a dummy variable that considers the volatility response to energy shocks after the consensus algorithm transition. Second, we propose a novel chi-squared joint test that allows us to jointly test the overall volatility response to energy shocks—as traditional event study approaches are not suitable for our analysis.

Our results show that after adopting the PoS consensus protocol, the cryptocurrencies in our sample experienced a significantly reduced sensitivity to energy shocks. More specifically, our estimates suggest that while not all cryptocurrencies exhibit a significant negative effect individually, the joint test of their coefficients using our novel test provides evidence for an overall significant reduction in response to oil fluctuations. Running a TGARCH model as a robustness check, our results hold, and we notice that the leverage effect of negative news on cryptocurrency volatility is only marginally supported by our analysis. These mixed findings align with the previous literature. For example, Grobys (2021) did not observe asymmetric patterns in the volatility processes of Ethereum and Bitcoin, whereas Baur and Dimpfl (2018) found a positive asymmetric response for a set of 20 cryptocurrencies. Conversely, Yu (2019) documented a negative leverage effect. Finally, by re-estimating the GARCH and TGARCH models to include oil innovations in the conditional volatility function as a new measure of oil shocks, the findings derived from our robustness checks strongly corroborate our main results.

The paper is organized as follows: Section 2 provides a description of the data. Section 3 presents the methodology and results of our statistical analyses. Section 4 discusses the empirical results, while Section 5 concludes.

2. Data

We downloaded data on the following cryptocurrencies from coinmarketcap.com: Ethereum, Cardano, Toncoin, and Decred. After thorough research across coin websites, media sources, and social media, we identified only these four coins that made the transition from Proof-of-Work (PoW) to Proof-of-Stake (PoS). The small sample size reflects the rarity of such transitions. However, we do not rule out the possibility that other small-cap coins, for which information on such transitions is more difficult to obtain, may have also made the switch. This should not be a concern, as our focus is on large coins relevant to the market and less prone to liquidity frictions, which could otherwise make the volatility response to energy shocks noisier.

These cryptocurrencies adopted the PoS consensus protocol on 15.09.2022[1], 29.07.2020[2], 28.06.2022[3], and 29.08.2023[4]. Since the event days are non-overlapping and associated with random market environments, we consider the transition from PoW to PoS as an opportunity to study the consensus protocol change as a quasi-natural experiment. In Table 1, we report the specific dates when the respective cryptocurrencies switched from a PoW to a PoS consensus mechanism. The ex-ante sample refers to the 180 days preceding the event date, whereas the ex-post sample refers to the 180 days following the event date. In Table 2, we present the corresponding descriptive statistics for the cryptocurrencies for the ex-ante and ex-post event samples. We also provide the descriptive statistics for crude oil (WTI) obtained from the US Energy Information Administration. In our study, we use the return on crude oil as it is an often-used energy proxy for crypto mining (Naeem et al., 2022, 2023)

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[1] https://ethereum.org.

[2] https://www.coindesk.com/tech/2020/07/30/cardano-introduces-proof-of-stake-with-shelley-hard-fork/.

[3] https://www.coindesk.com/business/2022/06/28/final-toncoin-mined-ahead-of-transition-to-proof-of-stake/.

[4] https://www.cypherpunktimes.com/decred-journal-september-2023/.
Decred switched to the BLAKE3 hashing algorithm, which implemented a new block reward split as 89% PoS, 1% PoW, 10% Treasury. This has virtually nullified the dependence on the PoW system.

3. Empirical Analysis

To explore whether a change from PoW to PoS consensus protocol has an effect on the sensitivity of cryptocurrency volatility to energy shocks, we employ the following extended GARCH(1,1) model specification:

$$RET_{i,t} = c_i + \varepsilon_{i,t}, \tag{1}$$

$$\varepsilon_{i,t} = \sqrt{\left(\alpha_i + \beta_i \varepsilon_{i,t-1}^2 + \gamma_i \sigma_{i,t-1}^2 + \delta_i \left(RET_{Oil,t}^D\right)^2 + \theta_i d_{i,t} \left(RET_{Oil,t}^D\right)^2\right)}\, \epsilon_{i,t}, \tag{2}$$

where $RET_{i,t}$ in the mean equation denotes the returns on cryptocurrency i at time t, and c_i denotes the corresponding regression intercept, whereas $\varepsilon_{i,t}$ is assumed to be governed by a conditional volatility process. Considering the conditional volatility equation, $\varepsilon_{i,t-1}^2$ and $\sigma_{i,t-1}^2$ are defined as the squared residual of the mean equation and the conditional variance at time $t-1$, $RET_{Oil,t}^D$ denotes the de-meaned return on oil at time t, $d_{i,t}$ is a dummy variable that has a value of 0 before the event for cryptocurrency i, and a value of 1 after the event, whereas $\epsilon_{i,t}$ is assumed to be a white noise error term, such as $\epsilon_{i,t} \sim N(0,1)$. In the variance equation, the parameters for α_i, β_i, γ_i, δ_i, and θ_i are estimated via quasi-maximum likelihood estimation. Note that in our model specification, squared de-meaned returns on crude oil, $\left(RET_{Oil,t}^D\right)^2$, serve as a proxy for measuring the contemporaneous effect of energy shocks on the conditional cryptocurrency volatility. Specifically, θ_i measures how the conditional cryptocurrency volatility i responds to energy shocks *after* adopting the PoS consensus protocol. The GARCH models are estimated via maximum-likelihood estimation. We hypothesize in H_1 that the adoption of the PoS consensus protocol should result in a *lowered* sensitivity of conditional cryptocurrency volatilities to energy shocks. That is, we test the following hypothesis pair:

$$H_0\colon\ \theta_i = 0\ \forall\ i = \{ETH, ADA, TON, DCR\} \quad \text{vs.} \quad H_1\colon\ \theta_i < 0\ \forall\ i = \{ETH, ADA, TON, DCR\}.$$

Given the size of our sample, traditional event study methodologies are not suitable for drawing inferences. Therefore, to draw cross-sectional conclusions, we implement the following novel test statistic which is designed to test hypothesis jointly:

$$\lambda_0 = \begin{pmatrix} \hat{\theta}_1 \\ \hat{\theta}_2 \\ \hat{\theta}_3 \\ \hat{\theta}_4 \end{pmatrix}^T \begin{pmatrix} \hat{\sigma}^2_{\hat{\theta}_1} & 0 & 0 & 0 \\ 0 & \hat{\sigma}^2_{\hat{\theta}_2} & 0 & 0 \\ 0 & 0 & \hat{\sigma}^2_{\hat{\theta}_3} & 0 \\ 0 & 0 & 0 & \hat{\sigma}^2_{\hat{\theta}_4} \end{pmatrix}^{-1} \begin{pmatrix} \hat{\theta}_1 \\ \hat{\theta}_2 \\ \hat{\theta}_3 \\ \hat{\theta}_4 \end{pmatrix}, \qquad (3)$$

where $\hat{\theta}_1$, $\hat{\theta}_2$, $\hat{\theta}_3$, $\hat{\theta}_4$ are point estimates obtained from Eq. (2), and $\hat{\sigma}^2_{\hat{\theta}_1}$, $\hat{\sigma}^2_{\hat{\theta}_2}$, $\hat{\sigma}^2_{\hat{\theta}_3}$, $\hat{\sigma}^2_{\hat{\theta}_4}$ are the corresponding estimated parameter variances derived from the GARCH-model specification. Note that our proposed test in Eq. (3) requires $COV(\hat{\theta}_i, \hat{\theta}_j) = 0$ for $i \neq j$. We argue that this holds in our research due to the quasi-experimental setting; that is, the event days do not coincide and, as a consequence, $COV(\hat{\theta}_i, \hat{\theta}_j) = 0$ for $i \neq j$ holds. Using a significance level of 5 percent, we reject the null hypothesis if $\hat{\lambda}_0 > 9.49$ because the test statistic λ_0 is under the null hypothesis distributed as $\chi^2(4)$.

In Table 3 we report the point estimates for the GARCH(1,1) model outlined in Eqs. (1) and (2). The point estimates for θ_i vary between -0.18 (Ethereum and Toncoin) and -0.64 (Decred) with corresponding t-statistics varying between -1.60 and -1.96 indicating that for only some coins the change from PoW to PoS resulted in a decreased uncertainty with respect to energy shocks. However, implementing the joint test, we find that $\hat{\lambda}_0 = 13.11 > 9.49$ implying that the overall effect across the cryptocurrencies that adopted PoS is indeed statistically significantly negative.

Next, there is a vast amount of literature postulating that negative news affect asset volatility in a more pronounced manner than positive news. To model this issue, we mode error term of Eq. (1) using the Threshold GARCH (TGARCH) model specification as proposed by Glosten et al. (1993):

$$\varepsilon_{i,t} = \sqrt{\left(\alpha_i + \beta_{0i}\varepsilon^2_{i,t-1} + \beta_{1i}d_{1,i,t}\varepsilon^2_{i,t-1} + \gamma_i\sigma^2_{i,t-1} + \delta_i\left(RET^D_{Oil,t}\right)^2 + \theta_i d_{2,i,t}\left(RET^D_{Oil,t}\right)^2\right)}\,\epsilon_{i,t}, \qquad (4)$$

whereas the mean equation is defined as in Eq. (1), $\varepsilon_{i,t}$ in Eq. (4) is assumed to be governed by a conditional volatility process. That is, $\varepsilon_{i,t-1}^2$ is defined as the squared residual of the mean equation at time $t-1$, and $d_{1,i,t}$ is a dummy variable that has a value of 0 if $\varepsilon_{i,t} > 0$, and a value of 1 if $\varepsilon_{i,t} < 0$. Furthermore, $RET_{Oil,t}^D$ denotes the de-meaned return on oil at time t, $d_{i,t}$ is a dummy variable that has a value of 0 before the event for cryptocurrency i and a value of 1 after the event, whereas $\epsilon_{i,t}$ is assumed to be a white noise error term, such as $\epsilon_{i,t} \sim N(0,1)$. In the variance equation, the parameters for α_i, β_i, β_{1i}, γ_i, δ_i, and θ_i are estimated via quasi-maximum likelihood estimation. We then collect the point estimates $\hat{\theta}_1$, $\hat{\theta}_2$, $\hat{\theta}_3$, $\hat{\theta}_4$ from Eq. (4) as well as the corresponding $\hat{\sigma}_{\hat{\theta}_1}^2$, $\hat{\sigma}_{\hat{\theta}_2}^2$, $\hat{\sigma}_{\hat{\theta}_3}^2$, $\hat{\sigma}_{\hat{\theta}_4}^2$ derived from the modified TGARCH-model specification and re-estimate the test statistic given in Eq. (3) which is then denoted as λ_1.

In Table 4 we report the point estimates for the TGARCH(1,1) model outlined in Eqs. (1) and (4). The point estimates for θ_i vary between -0.18 (Toncoin) and -3.32 (Decred) with corresponding t-statistics varying between -1.73 and -5.98. Strikingly, for the vast majority of cryptocurrencies considered, the change from PoW to PoS resulted in a statistically significantly decreased uncertainty with respect to energy shocks. Implementing the joint test, we find that $\hat{\lambda}_1 = 67.55 > 9.49$ which suggests that the overall effect across the cryptocurrencies that adopted PoS is indeed statistically significantly negative. Overall, after controlling for the often-postulated leverage effect of bad news on asset volatility, our main results remain unchanged. Interestingly, we observe from Table 4 that the evidence for the leverage effect of bad news is mixed: Whereas $\hat{\beta}_1$ for Cardano is estimated at $\hat{\beta}_1 = 0.07$ with a *t*-statistic of 1.81 indicating only marginal significance on a 10 percent level, for other cryptocurrencies we do not find such evidence.

Next, one could be concerned about potential autocorrelation of the returns on oil. In Table 5 we report the results from the following regressions:

$$RET_{Oil,t} = c_{Oil} + \rho RET_{Oil,t-1} + \varepsilon_{Oil,t}, \qquad (5)$$

where $RET_{Oil,t}$ is the return on oil at time t, c_{Oil}, and ρ are parameters to be estimated, and $\varepsilon_{Oil,t}$ denotes an error term that is assumed to be a white noise process. Using the overall samples—that is, the ex-ante and ex-post event samples together—the regression results are reported in Table 5. We see from Table 5 that for two-out-of-four samples, the estimated first-order autocorrelation parameter is statistically significant. Therefore, we re-define the energy shocks as the squared innovations from Eq. (5), that is, $\varepsilon_{Oil,t}^2$, and re-estimate the GARCH(1,1) model using Eq. (6) in association with Eq. (1):

$$\varepsilon_{i,t} = \sqrt{\left(\alpha_i + \beta_i \varepsilon_{i,t-1}^2 + \gamma_i \sigma_i^2 + \delta_i \varepsilon_{Oil,t}^2 + \theta_i d_{i,t} \varepsilon_{Oil,t}^2\right)} \epsilon_{i,t}, \tag{6}$$

where $\varepsilon_{Oil,t}^2$ denotes the squared residual from Eq. (5) and all other notation is as before. Again, we collect the point estimates $\hat{\theta}_1, \hat{\theta}_2, \hat{\theta}_3, \hat{\theta}_4$ from Eq. (6) as well as the corresponding $\hat{\sigma}_{\hat{\theta}_1}^2, \hat{\sigma}_{\hat{\theta}_2}^2, \hat{\sigma}_{\hat{\theta}_3}^2, \hat{\sigma}_{\hat{\theta}_4}^2$ derived from the modified GARCH-model specification and re-estimate the test statistic given in Eq. (3) which is then denoted as λ_2.

In Table 6 we report the point estimates for the modified GARCH(1,1) model outlined in Eqs. (1) and (6). The point estimates for θ_i vary between -0.18 (Ethereum and Toncoin) and -2.61 (Decred) with corresponding *t*-statistics varying between -1.60 and -6.99. Implementing the joint test, we find that $\hat{\lambda}_2 = 58.32 > 9.49$ which corroborates with our main findings suggesting that the overall effect across the cryptocurrencies that adopted PoS is indeed statistically significantly negative.

As a final robustness check, we incorporate $\varepsilon_{Oil,t}$, as outlined in Eq. (5), using a TGARCH(1,1) model specification where the mean equations are given as in Eq. (1) and the conditional volatility is modelled as follows:

$$\varepsilon_{i,t} = \sqrt{\left(\alpha_i + \beta_{0i} \varepsilon_{i,t-1}^2 + \beta_{1i} d_{1,i,t} \varepsilon_{i,t-1}^2 + \gamma_i \sigma_{i,t-1}^2 + \delta_i \varepsilon_{Oil,t}^2 + \theta_i d_{2,i,t} \varepsilon_{Oil,t}^2\right)} \epsilon_{i,t}, \tag{7}$$

where $\varepsilon_{Oil,t}^2$ denotes the squared residual from Eq. (5) and all other notation is as detailed earlier. We collect the point estimates $\hat{\theta}_1, \hat{\theta}_2, \hat{\theta}_3, \hat{\theta}_4$ from Eq. (7) as well as the corresponding $\hat{\sigma}_{\hat{\theta}_1}^2, \hat{\sigma}_{\hat{\theta}_2}^2, \hat{\sigma}_{\hat{\theta}_3}^2, \hat{\sigma}_{\hat{\theta}_4}^2$

derived from the modified TGARCH-model specification and re-estimate the test statistic given in Eq. (3) which is then denoted as λ_3.

In Table 7 we report the point estimates for the modified TGARCH(1,1) model outlined in Eqs. (1) and (7). The point estimates for θ_i vary between -0.18 (Toncoin) and -3.20 (Decred) with corresponding *t*-statistics varying between -1.60 and -6.52. Implementing the joint test, we find that $\hat{\lambda}_3 = 51.23 > 9.49$ which again supports our main results. Overall, our findings suggest that adopting the PoS consensus protocol has the overarching effect that cryptocurrency volatility is less sensitive to energy shocks. This result holds regardless of the model specification.

4. Discussion

4.1. Alignment with Previous Research

Baur and Dimpfl (2018), who employ Glosten et al.'s (1993) Threshold GARCH (TGARCH) model to explore asymmetric volatility responses for a set of 20 cryptocurrencies, find that for virtually all coefficients measuring asymmetries in volatility responses, the coefficient is negative. Their result implies that negative shocks increase volatility less than positive shocks, which contrasts with the positive coefficient generally reported in stock markets. Conversely, in our analysis, we obtain mixed evidence supporting the leverage effect. Indeed, only the coefficient β_1 for Cardano suggests a greater weight on negative news, whereas for Decred, the effect is negative, indicating that its volatility is more sensitive to positive news, as documented by Baur and Dimpfl (2018). No asymmetric response was found for Ethereum and Toncoin. The different outcomes may be an artifact of different time periods and short samples. The sample specificity of results can also be noted in the literature. For instance, while Baur and Dimpfl (2018) find a positive asymmetry volatility response for 20 cryptocurrencies, studies by Klein et al. (2018), Yu (2019), and Catania et al. (2018) show a higher sensitivity of volatility to past negative news for Bitcoin and other major cryptocurrencies in different periods between 2011 and 2018. Interestingly, Bouri et al. (2017), who use a TGARCH model, find that the asymmetry effect of Bitcoin volatility changed over time.

Moreover, our results contrast with those of Kliber and Będowska-Sójka (2024). While the authors find no significant difference in the correlation patterns between PoW and PoS cryptocurrencies with the oil energy index, we find that such a difference indeed does exist. Specifically, our analysis shows that the volatility is lower for cryptocurrencies transitioning to the PoS protocol. This discrepancy may be attributed to the different methodological approaches employed. Kliber and Będowska-Sójka (2024) utilize portfolio analysis and plain correlation methods, whereas we adopt a quasi-experimental approach accounting for potential endogeneity.

4.2. Implications

This study has important implications for cryptocurrency stakeholders. Several studies suggest the external intervention of regulators to influence and incentivize the transition to PoS (Di Febo et al., 2021; Shanaev et al., 2020; Wendl et al., 2023). Regulations could involve measures to reduce the profitability of mining activities. For instance, economic measures might include higher taxation on the profits of non-environmentally compliant cryptocurrencies or increased taxes on mining hardware. Additionally, promoting greater awareness of the environmental impact of PoW coins through information provided by centralized exchanges could further incentivize the transition.

Complementing these measures, our results demonstrate a strong internal incentive to adopt a more sustainable consensus mechanism. The PoS consensus protocol enhances decentralization and scalability by allowing a larger network of validators, thanks to its lower hardware and energy requirements, while also supporting faster transactions for users (Khan et al., 2021). Moreover, as demonstrated in the present research, PoS-based networks offer greater stability due to their reduced sensitivity to energy shocks. This stability may attract a broader range of users and create a sustainable environment for participants, developers, and validators. Regarding the security of this protocol, PoS blockchains should avoid falling into a “rich-get-richer” dynamic. This occurs because the PoS model is believed to induce wealth concentration, creating a centralizing effect where wealthier participants are more likely to be chosen to validate blocks and receive rewards. Roşu and Saleh (2021) were the first to provide a theoretical model against this issue, in which the share of an investor with a buy-and-hold strategy evolves according to a martingale. This means that while wealthier investors are more likely to earn rewards, they also face proportionally larger losses in shares if not selected, leading to long-term stability of shares around their initial value. This theoretical model was later supported by empirical findings from Irresberger and Yang (2023). The authors found that increases in concentration are not due to unfair advantages large stakes may have in PoS protocols, but rather due to other validators entering or leaving the consensus process.

We believe that the transition to the PoS protocol holds several benefits and economic incentives for crypto stakeholders. First, blockchain users are likely to favor PoS systems as their operations would be less impacted by price fluctuations driven by energy market volatility. Cryptocurrencies were initially envisioned as payment alternatives, yet their extreme volatility prevents them from serving this purpose without a high risk of value loss (Sangari & Mashatan, 2024). Thus, reduced exposure to price volatility caused by energy shocks in a PoS network can make a cryptocurrency more appealing compared to others. Additionally, lower volatility stabilizes the price of gas fees, i.e., the transaction fees paid to validators to process a transaction (Koutmos, 2023). Stable gas fees would make PoS blockchains more attractive for various operations, such as the execution of smart contracts.

Developers also have strong economic incentives to adopt PoS due to the enhanced scalability it offers (Khan et al., 2021). PoS makes block validation easier compared to PoW. As a result, gas fees—determined by the supply and demand of transactions—are expected to be lower and more stable (Kreppmeier et al., 2023). Consequently, the combination of stability, scalability, and energy efficiency makes PoS systems more appealing and sustainable for ongoing development and adoption.

On the other hand, miners may initially perceive the transition to PoS as a threat to their activity. Indeed, a transition to PoS would render their hardware investments obsolete. Nonetheless, as demonstrated by Islam et al. (2023), the long-term profitability of mining is unsustainable, as both power consumption and capital investment can erode profit margins. The competitive cycle of continually upgrading hardware to mine more blocks increases costs exponentially, which becomes unsustainable unless the cryptocurrency's price rises accordingly. In the long term, miners stand to gain from PoS's stability, as it ensures a more predictable profit margin without the need for constant hardware investments and high energy costs. While miners may focus on short-term gains, they ultimately have a strong economic incentive to support the shift to PoS for long-term profitability. Furthermore, reduced volatility resulting in more stable returns improves the reward-to-risk ratio. This, in turn, could make cryptocurrencies more attractive to other stakeholders such as potential investors.

Our findings also have implications for the asset management industry, suggesting that institutions can improve their portfolio diversification strategies by investing in cryptocurrencies utilizing PoS blockchains. This approach can mitigate exposure to volatility dynamics resulting from energy shocks. Further implications derived from our results extend to innovative financing methods such as Initial Coin Offerings (ICOs). This new financing channel democratizes financial investments, allowing broader access to acquire funding for businesses compared to traditional approaches (e.g., IPO), while also significantly reducing costs by eliminating the need for third-party intermediaries. As documented by Campino et al. (2022), a project’s success in terms of capital raised is negatively impacted by cryptocurrency return volatility, among other factors. Moreover, Lyandres et al. (2022) show that higher volatility negatively affects post-ICO operating performance. Thus, our results suggest that ICO projects should leverage PoS cryptocurrencies, as these can reduce coin volatility and potentially enhance project success rates.

4.3. Limitations

Our study presents some limitations that warrant acknowledgment. Firstly, we analyze the transition effect exclusively for four cryptocurrencies with high market capitalization. To enhance the generalizability of our findings, future research should consider a larger sample that includes digital currencies with lower market capitalizations. As more coins presumably switch to the PoS mechanism, future studies could also re-examine this issue using methodologies that require a larger sample size. While our proposed chi-squared joint test is suitable for small samples, traditional event study approaches may be more appealing for investigating this issue using larger datasets.

Additionally, our research followed the mainstream literature by employing extended GARCH-type models to investigate the research question. However, other models have been proposed in the literature that could potentially offer an alternative design to explore the dynamics of cryptocurrency volatility. For instance, future studies could consider additional volatility characteristics such as non-linearities, exponential effects, regime-switching, and dynamics related to structural breaks.

Finally, one might question whether the effect on volatility had been discounted prior to the event day due to the transition announcement. It is possible to argue that events of this nature, known as "forks," do not always culminate successfully, and the associated uncertainty may mitigate any potential discounting effect. Given the decentralized nature of blockchain networks, such events require community consensus and significant collaborative efforts among developers and validators, hence, holding inherent uncertainties. Even though switching a consensus protocol may result from a governance decision, it does not necessarily reflect the unified will of the entire community, which is called upon to approve the change. In this regard, analyzing this phenomenon by setting the event window around the announcement day could provide additional valuable insights. However, since this exceeds the scope of the present study, this is left for future research.

5. Conclusion

Recently, there have been growing concerns about the environmental sustainability of digital currencies. The PoW consensus mechanism is increasingly viewed as unsuitable to meet current carbon footprint reduction targets. However, the alternative PoS algorithm appears as a promising avenue to mitigate blockchain energy consumption. To date, only a handful of cryptocurrencies have transitioned to PoS—with the majority still reliant on PoW.

This study examines the impact of the change of consensus protocol on the volatility sensitivity of four high market capitalization cryptocurrencies—Ethereum, Cardano, Toncoin, and Decred—to energy shocks. Using data from coinmarketcap.com, we utilize the random transition features of these coins as a quasi-natural experimental setting. By employing extended GARCH and TGARCH models to assess cryptocurrency volatility, we find evidence of a significant negative overall effect. This implies that following the transition to PoS, cryptocurrencies demonstrate diminished sensitivity of their volatility to energy shocks, proxied by oil shocks.

Our findings suggest that digital currencies still using the PoW mechanism should consider migrating to PoS, as this shift can benefit stakeholders by reducing the uncertainty of cryptocurrency price changes. Since cryptocurrencies are notorious for extremely high levels of price change uncertainty, this is not a trivial issue. Future research could extend our study by analyzing a larger sample of cryptocurrencies or employing other volatility models to depict volatility dynamics.

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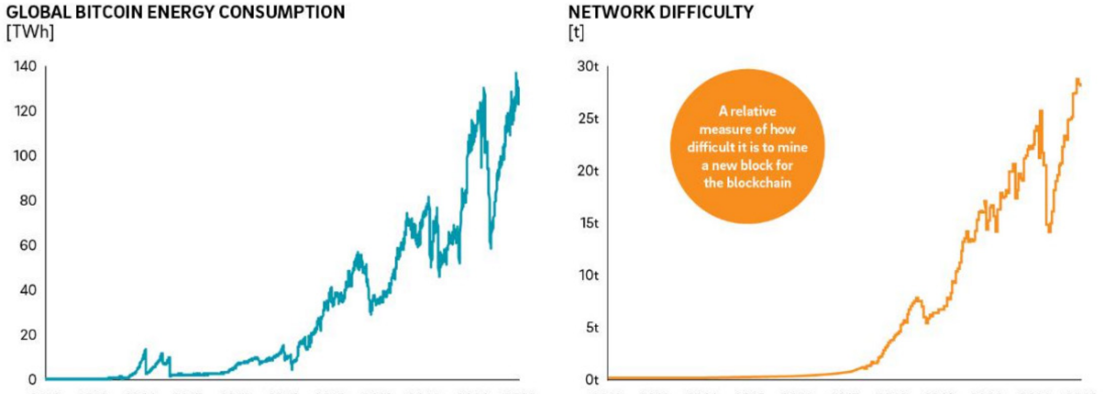
Figure 1. Bitcoin network complexity and energy consumption.

This figure reports a comparison of the energy consumed by the Bitcoin blockchain and its relative measure of complexity in mining a new block.
Source: Vaughan et al. (2022)



GLOBAL BITCOIN ENERGY CONSUMPTION
[TWh]

NETWORK DIFFICULTY
[t]

Source University of Cambridge, Blockchain.com, Roland Berger

Table 1. Event dates

This table reports the specific date when a cryptocurrency switched from a Proof of Work (PoW) to a Proof of Stake (PoS) consensus mechanism. The ex-ante sample refers to the preceding 180 days from the event date, while the ex-post sample refers to the subsequent 180 days after the event date.

Cryptocurrency	**Event Day**	**Ex-ante sample**	**Ex-post sample**
Cardano	29.07.2020	31.01.2020 – 28.07.2020	30.07.2020 – 25.01.2021
Toncoin	28.06.2022	30.12.2021 – 27.06.2022	29.06.2022 – 25.12.2022
Ethereum	15.09.2022	19.03.2022 – 14.09.2022	16.09.2022 – 14.03.2023
Decred	29.08.2023	02.03.2023 – 28.08.2023	30.08.2023 – 25.02.2024

Table 2. Descriptive statistics.

Descriptive statistics for the price returns of Cardano (ADA), Toncoin (TON), Ethereum (ETH), Decred (DCR), and West Texas Intermediate (WTI) from coinmarketcap.com and the US Energy Information Administration. The ex-ante sample refers to the returns of the past 180 days from the event date, while the ex-post sample refers to the returns of the next 180 days after the event date.

Cryptocurrency	Cardano		WTI_C		Toncoin		WTI_T		Ethereum		WTI_E		Decred		WTI_D	
Sample period	**Ex-ante**	**Ex-post**	**Ex-ante**	**Ex-post**	**Ex-ante**	**Ex-post**	**Ex-ante**	**Ex-post**	**Ex-ante**	**Ex-post**		**Ex-post**	**Ex-ante**	**Ex-post**	**Ex-ante**	**Ex-post**
Mean	0.0078	0.0069	0.0027	0.0017	-0.0045	0.0052	0.0024	-0.0017	-0.0021	0.0016	-0.0008	-0.0009	-0.0025	0.0032	0.0003	-0.0001
Median	0.0048	0.0046	0.0000	0.0012	-0.0038	-0.0002	0.0023	-0.0004	-0.0014	-0.0014	0.0005	-0.0004	-0.0032	0.0024	0.0007	0.0003
Maximum	0.2019	0.2849	0.5309	0.0491	0.2073	0.2673	0.0856	0.0504	0.1793	0.1811	0.0669	0.0504	0.2126	0.2844	0.0409	0.0579
Minimum	-0.3957	-0.1736	-0.5134	-0.0526	-0.1712	-0.1495	-0.1199	-0.0792	-0.1665	-0.1746	-0.0792	-0.0589	-0.1238	-0.1135	-0.0534	-0.0553
Std. Dev.	0.0628	0.0627	0.0892	0.0165	0.0557	0.0520	0.0251	0.0208	0.0485	0.0365	0.0226	0.0180	0.0398	0.0409	0.0162	0.0159
Skewness	-0.9003	0.5876	0.9893	-0.1577	0.7558	0.7304	-0.3340	-0.4351	0.0206	-0.2191	-0.4544	-0.1519	1.1143	2.8246	-0.5526	-0.2223
Kurtosis	12.5250	5.3438	19.1805	4.2425	5.6251	7.1433	7.2422	4.0771	4.7442	9.7168	4.4134	4.0786	8.1847	21.6134	4.1963	4.6850
Jarque-Bera	700.8405	51.2700	1981.8590	12.2560	68.4387	143.9517	137.5481	14.3001	22.7016	337.9160	21.0596	9.3656	237.5317	2822.0190	19.7844	22.6511
Probability	0.0000	0.0000	0.0000	0.0022	0.0000	0.0000	0.0000	0.0008	0.0000	0.0000	0.0000	0.0093	0.0000	0.0000	0.0001	0.0000
Observations	179	179	179	179	179	179	179	179	179	179	179	179	179	179	179	179

Table 3. Estimates for a generalized conditional heteroskedasticity model accounting for de-demeaned returns on oil.

This table reports the estimated parameters for the following generalized conditional heteroskedasticity (GARCH) model:

$$RET_{i,t} = c_i + \varepsilon_{i,t},$$

$$\varepsilon_{i,t} = \sqrt{\left(\alpha_i + \beta_i \varepsilon^2_{i,t-1} + \gamma_i \sigma^2_{i-1} + \delta_i \left(RET^D_{Oil,t}\right)^2 + \theta_i d_{i,t} \left(RET^D_{Oil,t}\right)^2\right)}\, \epsilon_{i,t},$$

Considering the mean equation, $RET_{i,t}$ denotes the returns on cryptocurrency *i* at time *t*, and c_i denotes the corresponding regression intercept, whereas $\varepsilon_{i,t}$ is assumed to be governed by a conditional volatility process, where $\varepsilon^2_{i,t-1}$ ($\sigma^2_{i,t-1}$) are defined as the squared residual (conditional variance) of the mean equation at time $t-1$, $RET^D_{Oil,t}$ denotes the de-meaned return on oil at time *t*, $d_{i,t}$ is a dummy variable that has a value of 0 before the event for cryptocurrency *i* and a value of 1 after the event, whereas $\epsilon_{i,t}$ is assumed to be a white noise error term, such as $\epsilon_{i,t} \sim N(0,1)$. In the variance equation, the parameters for α_i, β_i, γ_i, δ_i, and θ_i are estimated via quasi-maximum likelihood estimation.

Coin	$\hat{c}_i$	$\hat{\alpha}_i$	$\hat{\beta}_i$	$\hat{\gamma}_i$	$\hat{\delta}_i$	$\hat{\theta}_i$
Ethereum	0.10	1.32**	0.15***	0.78***	0.12	-0.18
	(0.45)	(2.48)	(4.49)	(15.47)	(0.87)	(-1.60)
Cardano	0.68**	5.15**	0.11***	0.78***	-0.00	-0.29**
	(2.00)	(2.41)	(3.26)	(10.42)	(-0.15)	(-1.96)
Toncoin	0.03	4.83***	0.16***	0.72***	-0.10	-0.18*
	(0.12)	(4.15)	(3.81)	(13.00)	(-1.61)	(-1.94)
Decred	-0.16	2.71***	0.56***	0.45***	0.46	-0.64*
	(-0.88)	(4.98)	(10.75)	(9.19)	(1.26)	(-1.73)

*, **, *** denotes statistical significance on a 10%, 5%, or 1% level.

Table 4. Estimates for a threshold generalized conditional heteroskedasticity model accounting for de-demeaned returns on oil.

This table reports the estimated parameters for the following threshold generalized conditional heteroskedasticity (TGARCH) model:

$$RET_{i,t} = c_i + \varepsilon_{i,t},$$

$$\varepsilon_{i,t} = \sqrt{\left(\alpha_i + \beta_{0i}\varepsilon_{i,t-1}^2 + \beta_{1i}d_{1,i,t}\varepsilon_{i,t-1}^2 + \gamma_i\sigma_{i,t-1}^2 + \delta_i\left(RET_{Oil,t}^D\right)^2 + \theta_i d_{2,i,t}\left(RET_{Oil,t}^D\right)^2\right)}\,\epsilon_{i,t}.$$

Considering the mean equation, $RET_{i,t}$ denotes the returns on cryptocurrency *i* at time *t*, and c_i denotes the corresponding regression intercept, whereas $\varepsilon_{i,t}$ is assumed to be governed by a conditional volatility process where $\varepsilon_{i,t-1}^2$ ($\sigma_{i,t-1}^2$) are defined as the squared residual (conditional variance) of the mean equation at time $t-1$, and $d_{1,i,t}$ is a dummy variable that has a value of 0 if $\varepsilon_{i,t} > 0$, and a value of 1 if $\varepsilon_{i,t} < 0$. Furthermore, $RET_{Oil,t}^D$ denotes the de-meaned return on oil at time *t*, $d_{2,i,t}$ is a dummy variable that has a value of 0 before the event for cryptocurrency *i* and a value of 1 after the event, whereas $\epsilon_{i,t}$ is assumed to be a white noise error term, such as $\epsilon_{i,t} \sim N(0,1)$. In the variance equation, the parameters for α_i, β_i, β_{1i}, γ_i, δ_i, and θ_i are estimated via quasi-maximum likelihood estimation.

Coin	$\hat{c}_i$	$\hat{\alpha}_i$	$\hat{\beta}_{0,i}$	$\hat{\beta}_{1,i}$	$\hat{\gamma}_i$	$\hat{\delta}_i$	$\hat{\theta}_i$
Ethereum	-0.01	13.23**	-0.02	0.05	0.58***	-0.42***	-0.49***
	(-0.04)	(2.87)	(-0.26)	(0.85)	(3.53)	(-27.03)	(-5.98)
Cardano	0.62*	4.82**	0.10***	0.07*	0.77***	-0.00	-0.26*
	(1.85)	(2.38)	(3.22)	(1.81)	(10.57)	(-0.07)	(-1.73)
Toncoin	0.02	4.67***	0.14***	0.02	0.73***	-0.11	-0.18**
	(0.07)	(4.11)	(2.93)	(0.36)	(13.37)	(1.60)	(-1.96)
Decred	0.16	5.84***	1.20***	-1.08***	0.09	3.15***	-3.32***
	(0.90)	(6.86)	(9.14)	(-6.98)	(1.53)	(4.70)	(-5.00)

*, **, *** denotes statistical significance on a 10%, 5%, or 1% level.

Table 5. Oil returns autocorrelation.

To explore whether the returns on oil are autocorrelated, we run the following regressions:

$$RET_{Oil,t} = c_{Oil} + \rho RET_{Oil,t-1} + \varepsilon_{Oil,t},$$

where $RET_{Oil,t}$ is the return on oil at time t, c_{Oil}, and ρ are parameters to be estimated, and $\varepsilon_{Oil,t}$ denotes an error term that is assumed to be a white noise process. Using the overall samples—that is, the ex-ante and ex-post event samples together—the regression results are reported in this table.

Sample	CARDANO 31.01.2020 - 25.01.2021	TONCOIN 30.12.2021 - 25.12.2022	ETHEREUM 19.03.2022 - 14.03.2023	DECRED 02.03.2023 - 25.02.2024
WTI_{t-1}	-0.1238**	0.0796	0.0737	0.1232**
	(0.019)	(0.132)	(0.166)	(0.019)
Constant	0.0024	0.0004	-0.0009	0.0001
	(0.469)	(0.749)	(0.634)	(0.940)
R-squared	0.0153	0.0063	0.0054	0.0152
Observations	359	359	359	359

*, **, *** denotes statistical significance on a 10%, 5%, or 1% level

Table 6. Estimates for a generalized conditional heteroskedasticity model accounting for oil innovations.

This table reports the estimated parameters for the following generalized conditional heteroskedasticity (GARCH) model:

$$RET_{i,t} = c_i + \varepsilon_{i,t},$$

$$\varepsilon_{i,t} = \sqrt{(\alpha_i + \beta_i \varepsilon^2_{i,t-1} + \gamma_i \sigma^2_{i,t-1} + \delta_i \varepsilon^2_{Oil,t} + \theta_i d_{i,t} \varepsilon^2_{Oil,t})}\epsilon_{i,t},$$

Considering the mean equation, $RET_{i,t}$ denotes the returns on cryptocurrency *i* at time *t*, and c_i denotes the corresponding regression intercept, whereas $\varepsilon_{i,t}$ is assumed to be governed by a conditional volatility process defined where $\varepsilon^2_{i,t-1}$ ($\sigma^2_{i,t-1}$) are defined as the squared residual (conditional variance) of the mean equation at time $t-1$, and $\varepsilon_{Oil,t}$ are the regression residuals from the following regression:

$$RET_{Oil,t} = c_{Oil} + \rho RET_{Oil,t-1} + \varepsilon_{Oil,t},$$

where $RET_{Oil,t}$ is the return on oil at time *t*, c_{Oil}, and ρ are parameters to be estimated, and $\varepsilon_{Oil,t}$ denotes an error term that is assumed to be a white noise process. Furthermore, $d_{i,t}$ denotes a dummy variable that has a value of 0 before the event for cryptocurrency *i* and a value of 1 after the event, whereas $\epsilon_{i,t}$ is assumed to be a white noise error term, such as $\epsilon_{i,t} \sim N(0,1)$. In the variance equation, the parameters for α_i, β_i, γ_i, δ_i, and θ_i are estimated via quasi-maximum likelihood estimation.

Coin	$\hat{c}_i$	$\hat{\alpha}_i$	$\hat{\beta}_i$	$\hat{\gamma}_i$	$\hat{\delta}_i$	$\hat{\theta}_i$
Ethereum	0.14	1.28**	0.15***	0.78***	0.13	-0.18
	(0.67)	(2.49)	(4.49)	(15.67)	(0.91)	(-1.60)
Cardano	0.64*	5.17**	0.11***	0.77***	-0.00	-0.27*
	(1.87)	(2.42)	(3.27)	(10.43)	(-0.16)	(-1.93)
Toncoin	0.05	4.90***	0.16***	0.72***	-0.09	-0.18*
	(0.17)	(4.11)	(3.79)	(12.69)	(-1.38)	(-1.79)
Decred	-0.20	7.83***	0.80***	-0.08**	2.37***	-2.61***
	(-1.33)	(8.60)	(10.56)	(-2.46)	(6.53)	(-6.99)

*, **, *** denotes statistical significance on a 10%, 5%, or 1% level.

Table 7. Estimates for a threshold generalized conditional heteroskedasticity model accounting for oil innovations.

This table reports the estimated parameters for the following threshold generalized conditional heteroskedasticity (TGARCH) model:

$$RET_{i,t} = c_i + \varepsilon_{i,t},$$

$$\varepsilon_{i,t} = \sqrt{\left(\alpha_i + \beta_{0i}\varepsilon_{i,t-1}^2 + \beta_{1i}d_{1,i,t}\varepsilon_{i,t-1}^2 + \gamma_i\sigma_{i,t-1}^2 + \delta_i\varepsilon_{Oil,t}^2 + \theta_i d_{2,i,t}\varepsilon_{Oil,t}^2\right)}\epsilon_{i,t}.$$

Considering the mean equation, $RET_{i,t}$ denotes the returns on cryptocurrency *i* at time *t*, and c_i denotes the corresponding regression intercept, whereas $\varepsilon_{i,t}$ is assumed to be governed by a conditional volatility process where $\varepsilon_{i,t-1}^2$ ($\sigma_{i,t-1}^2$) are defined as the squared residual (conditional variance) of the mean equation at time $t-1$, and $\varepsilon_{Oil,t}$ are the regression residuals from the following regression:

$$RET_{Oil,t} = c_{Oil} + \rho RET_{Oil,t-1} + \varepsilon_{Oil,t},$$

where $RET_{Oil,t}$ is the return on oil at time *t*, c_{Oil}, and ρ are parameters to be estimated, and $\varepsilon_{Oil,t}$ denotes an error term that is assumed to be a white noise process. Furthermore, $d_{1,i,t}$ is a dummy variable that has a value of 0 if $\varepsilon_{i,t} > 0$, and a value of 1 if $\varepsilon_{i,t} < 0$. Moreover, $d_{2,i,t}$ is a dummy variable that has a value of 0 before the event for cryptocurrency *i* and a value of 1 after the event, whereas $\epsilon_{i,t}$ is assumed to be a white noise error term, such as $\epsilon_{i,t} \sim N(0,1)$. In the variance equation, the parameters for α_i, β_{0i}, β_{1i}, γ_i, δ_i, and θ_i are estimated via quasi-maximum likelihood estimation.

Coin	$\hat{c}_i$	$\hat{\alpha}_i$	$\hat{\beta}_{0,i}$	$\hat{\beta}_{1,i}$	$\hat{\gamma}_i$	$\hat{\delta}_i$	$\hat{\theta}_i$
Ethereum	0.05	2.32**	0.05	0.20***	0.70***	0.24	-0.27
	(0.22)	(2.77)	(1.35)	(3.08)	(9.09)	(1.21)	(-1.60)
Cardano	0.59*	4.84**	0.10***	0.07*	0.76***	-0.00	-0.25*
	(1.73)	(2.40)	(3.22)	(1.82)	(10.58)	(-0.08)	(-1.72)
Toncoin	0.04	4.78***	0.15***	0.02	0.72***	-0.10	-0.18*
	(0.13)	(4.05)	(2.94)	(0.26)	(12.95)	(1.34)	(-1.80)
Decred	0.15	6.55***	1.32***	-1.18***	0.02	3.03***	-3.20***
	(0.86)	(8.22)	(8.75)	(-6.59)	(0.46)	(6.23)	(-6.52)

*, **, *** denotes statistical significance on a 10%, 5%, or 1% level.

A common component in cryptocurrency risk: Evidence from realized altcoin variances*

Klaus Grobys[1], James W. Kolari[2], Davide Sandretto[3]

Abstract

This paper employs power laws to model daily realized variances for the top-10 altcoins by market capitalization. To conduct a joint test, we propose a novel methodology based on blocks bootstraps to estimate the covariance matrix of power-law exponents. Empirical tests provide strong evidence for market risk behavior manifested in a common power-law exponent governing the cross section of realized altcoin variances. These and other results suggest that, although altcoin variance risk exhibits idiosyncratic features, a common risk component exists in the altcoin cryptocurrency market.

JEL Classification: F31, C22, G11, G12, G13, G15.
Key Words: Bitcoin; cryptocurrency; Pareto distributions; power laws; second moment; variance.

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1. Introduction

What do we know about the (variance) risk of cryptocurrencies? In a survey on volatility analyses of cryptocurrencies, Kyriazis (2021) documents that the vast majority of studies apply GARCH-type models to specify volatility dynamics and volatility spillovers. In this respect, the large number of available GARCH specifications enables identification of the most appropriate model to explain fluctuations in market values. However, this advantage of GARCH-type models can be a disadvantage also. Mandelbrot (2008) stresses that models can be overfitted to explain shifting volatility patterns via the use of parameters that change by day and even more frequently. Subsequently, GARCH-type models oftentimes deliver results that are *model*- or *sample-specific*.

As an example, Grobys (2021) investigates the impact of hacking incidents on Bitcoin volatility. Based on normally-distributed innovations in the EGARCH model specification, he finds that hacking incidents result in higher levels of Bitcoin return volatility on the day after the hacking occurred. However, based on *t*-distributed innovations allowing for heavy tails, EGARCH results suggest that hacking incidents do not affect Bitcoin return volatility on the day after hacking.[1] Similarly, many studies find that volatility interdependencies depend on the chosen model specification.[2] Turning to sample specificity, Bouoiyour and Selmi (2015) observe that, while Threshold GARCH (TGARCH) is optimal in the period December 2010 to June 2015 to model Bitcoin volatility, EGARCH is most appropriate from January 2015 to June 2015.[3] In light of these and other studies, considerable ambiguity surrounds the appropriate choice of volatility models for cryptocurrencies.

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[1] Despite evidence of heavy tails in financial data, Sun and Zhou (2014, p. 288) document that the innovation term assumed in the often applied GARCH(1,1) model follows a standard normal distribution.

[2] An extensive literature on GARCH model specification exists. Interested readers are referred to the following studies of different financial assets: Bouoiyour and Selmi (2016), Dyhrberg (2016), Bouri et al. (2017), Baur et al. (2018), Catania et al. (2018), Klein et al. (2018), Canh et al. (2019), Kyriazis et al. (2019), Omane-Adepong and Alagidede (2019), Tiwari et al. (2019), Yu (2019), Akyildirim et al. (2020), Cheikh et al. (2020), Fakhfekh and Jeribi (2020).

[3] For further discussion and evidence on the sample-specificity of GARCH-type models in studies of financial assets, see also Chu et al. (2017), Peng et al. (2018), Caporale and Zekokh (2019), Charles and Darné (2019), Gyamerah (2019), Katsiampa (2019), Troster et al.(2019), Cheikh et al. (2020), Fakhfekh and Jeribi (2020), Hattori (2020), Kyriazis (2021), Fung et al. (2022), and Chen et al. (2023).

In an attempt to remedy this problem, Mandelbrot (2008) recommends that better models can be built by identifying market properties that are relatively constant over time. Consistent with this reasoning, the present study seeks to: (1) ascertain to what extent the risk of cryptocurrencies measured in terms of realized variances is subject to power-law behavior, and (2) explore whether a commonality exists that helps to explain potential power-law behavior. Numerous studies (e.g., Bubák et al., 2011; Andersen et al., 2003; Andersen et al., 2004) document that realized variances contain information that standard models, such as generalized auto-regressive conditional heteroskedasticity (GARCH) models, cannot discern. For this reason, departing from previous literature, we model the realized variance processes of cryptocurrencies by means of Parkinson's (1980) range-based realized variance estimator. Using the well-known maximum likelihood estimation approach by Clauset et al. (2009), we fit power-law models to realized cryptocurrency variances. To draw cross-sectional inferences, we propose a novel procedure for testing whether potential power-law behavior in the realized variance processes of cryptocurrencies shares a common component manifested in a power-law exponent governing the whole cross section of realized cryptocurrency variances. If so, our results would suggest that: (1) cryptocurrencies are riskier than suggested by standard models; and (2) risk diversification is more limited for cryptocurrencies than previously believed. Since institutional investors have entered the market for cryptocurrencies to manage large funds, the existence of potentially hidden risk exposures is not a trivial issue.[4]

The present study contributes to existing literature in a number of ways. First, as Kryiazis (2021) observes, previous studies that model the volatility of cryptocurrencies mainly rely upon GARCH-type models to examine volatility dynamics or volatility spillovers. We extend this literature by addressing a more central question: Is variance risk of cryptocurrencies governed by some common

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[4] A recent report by Ernst and Young documents that institutions invest increasing amounts of the assets under management (AUM) in crypto/digital assets. According to their analyses, 45% of financial institutions with more than $500 billion in AUM responded that they allocate more than 1% of their portfolio to crypto assets. These survey findings suggest that a large amount of capital invested in the market for cryptocurrencies is attributable to traditional institutional investors (see https://www.ey.com/en_us/financial-services/how-institutions-are-investing-in-digital-assets).

process? Acknowledging that cryptocurrencies exhibit extremely heavy tails (e.g., Baur and Dimpfl, 2021) and tail interdependencies (e.g., Xu et al., 2021; Shahzad et al., 2022), we model realized cryptocurrency variances as power laws. In a recent study, Grobys (2024) reports evidence on the power-law behavior of cryptocurrency returns. Using co-fractality analysis, he detects the presence of strong co-dependencies in power-law behavior. Consistent with this evidence, Lux and Alfarano (2016) comment that power laws in returns and volatility are closely related to one another as joint characteristics of financial data.

Second, we explore potential commonalities in power-law behavior in the second moment of cryptocurrencies.[5] As discussed earlier, the rationale for using realized variances, as opposed to GARCH-type models, is that these models tend to provide sample- or model-specific estimates. Additionally, seminal work by Mandelbrot (1963) documents power-law behavior of cotton price changes. Subsequent research extended his methods to the power-law behavior of other asset classes. For example, West (2017) reports evidence that stock market returns follow a power law as determined by its exponent or fractal dimension. Motivated in part by these studies, investment companies began to hire physicists, mathematicians, and computer scientists (viz., quants) to apply these concepts to professional investment strategies. Lux and Alfarano (2016) observe that the majority of studies on power laws in finance focus on the intrinsic dynamics of speculative interaction in financial markets (e.g., the rational expectation bubble theory). However, contrary to Mandelbrot's undefined variance processes, they note that researchers gradually converged to the consensus belief that power-law exponents of financial assets typically satisfy the conditions required for finite variances. Here we explore this issue for cryptocurrency markets due to well-documented evidence that cryptocurrencies: (1) are about tenfold riskier than traditional currencies (Baur and Dimpfl,

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[5] Grobys et al. (2021) examine the volatility of stable cryptocurrencies (e.g., stablecoins) and their stochastic interdependencies with Bitcoin volatility. Using power laws to model the volatility processes, the authors find that stablecoins are statistically unstable as indicated by power-law exponents of $\hat{\alpha} < 3$. The present study extends their analyses to the potential power-law behavior of realized altcoin variances.

2021), and (2) exhibit re-occurring bubbles that result in crashes (e.g., Geuder et al., 2019; Kyriazis et al., 2019; Wheatley et al., 2019).

Third, we explicitly test standard distributions against power law models. Published studies generally find that realized asset volatility is close to lognormally distributed (e.g., Andersen et al., 2001; Andersen et al., 2001a, 2001b). We initially test whether the distribution governing realized altcoin variances is log-normal versus $\chi^2(1)$. Since this test assumes that the distributions are standardized with defined theoretical mean and variance, we test power-law models using the goodness-of-fit (GoF) test by Clauset et al. (2009) also.

Fourth, and last, we propose a new econometric testing procedure derived from blocks bootstraps to test data series.[6] Specifically, a joint test requires the establishment of the covariance matrix of power-law exponents, which is not required in tests for a single data vector. After estimating the empirical covariance matrix, we implement joint tests to identify potential cross-sectional power-law behavior. To our knowledge, no previous test methods enable joint tests employing multiple time series data vectors. Hence, the present study fills an important gap in the econometric literature (e.g., Artico et al., 2020).

Using daily range-based variance estimators in line with Parkinson (1980), we find that kurtosis values for realized altcoin variances vary between 88.73 and 1661.75, which strongly suggests the presence of heavy tails. Computing the ratio of the share of the top-20 percent of largest capitalization observations on the cumulative total shows that this metric varies between 67.17 percent and 94.48 percent. Since this finding is indicative of a Pareto 80/20 distribution (i.e., the share of the top-20 percent comprise 80 percent on the cumulative total), we hypothesize that realized cryptocurrency variances behave approximately as a Pareto-type distribution. Indeed, upon estimating the power-law exponents for the top-10 altcoins, we obtain estimated exponents between $\hat{\alpha} = 1.97$ and $\hat{\alpha} = 2.92$.

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[6] In our research context, such multiple empirical networks are cryptocurrencies, and here we focus on how potential power-law behavior is manifested in the dynamics of uncertainty processes of cryptocurrencies measured in terms of their realized variances.

These findings indicate that the variance of variance is undefined for altcoins. Subsample analysis shows that these estimates vary between $\hat{\alpha} = 1.83$ and $\hat{\alpha} = 3.19$ in the first subsample and $\hat{\alpha} = 1.86$ and $\hat{\alpha} = 2.63$ in the second subsample. Interestingly, power-law behavior is not necessarily restricted to tail regions; indeed, our findings for the full sample indicate that up to 30 per cent of the realized variance distributions are governed by a power-law process.

Using block bootstraps to estimate the covariance matrix of power-law exponents shows that the correlation between power-law exponents varies between -0.2799 and 0.2478 with corresponding *t*-statistics of -9.21 and 8.09 indicating significance at any level. These results strongly suggest that the covariance matrix needs to be taken into account when multiple empirical networks are subject to joint tests. Strikingly, testing whether power-law behavior is manifested in a common cross-sectional component, we find that the range for the cross-sectional, power-law exponent is between $\hat{\alpha} = 2.0$ and $\hat{\alpha} = 2.2$. The optimal power-law exponent governing the cross section of realized altcoin variances is $\hat{\alpha} = 2.1$, which closely corresponds to the traditional Pareto 80/20. Is the cross-sectional power-law behavior stable over time? Using the full sample of top-10 altcoins, we reject this hypothesis. Corroborating this inference, some altcoins that exhibited their highest market capitalization as of January 1, 2016 were close to default by the end of the sample period on October 3, 2023.

Finally, restricting the sample to those altcoins that were still among the top-20 altcoins by market capitalization at the end of our sample period, we find that: (1) there exists a common component manifested in a cross-sectional power-law exponent governing realized altcoin variances; (2) the power-law behavior does not change over time; and (3) the optimal exponent governing uncertainty in the market for highly-capitalized altcoins is $\hat{\alpha} \approx 2.1 - 2.3$. Relatedly, we show that neither the lognormal nor the $\chi^2(1)$ distribution are able to describe the data-generating processes of realized altcoin variances. Instead, the evidence points to a failure to reject the power-law null model for the majority of realized altcoin variances.

The study is organized as follows. Section 2 overviews the methodology. Section 3 reports the empirical results. Section 4 provides discussion. The last section concludes.

2. Methodology

2.1. Data

Following Liu et al. (2022), we collect data from coinmarketcap.com for the top-10 altcoins in terms of their market capitalization as of January 1, 2016. Specifically, we download data for the period January 1, 2016 to October 3, 2023 for the following altcoins: Bitcoin (BTC), Ripple (XRP), Litecoin (LTC), Ethereum (ETH), Dogecoin (DOGE), Peercoin (PPC), BitShares (BTS), Stellar Lumen (XLM), Nxt (NXT), and MaidSafeCoin (MAID).[7] In Table A.1 in the Appendix, we report the corresponding market capitalizations as of January 1, 2016 and October 3, 2023. The overall market capitalization of these altcoins equaled USD 7,010.67 million as of January 1, 2016 or 98.41 percent of overall cryptocurrency market capitalization. Due to the high concentration of the cryptocurrency market, the top-10 altcoins can be regarded as representative of the market.[8] Since the overall market capitalization of these coins was 80.75 percent of total market capitalization at the end of the sample period (e.g., October 3, 2023), we infer that our sample of selected coins remains representative of the market over time for the most part.[9] Even so, the market capitalizations of NXT and MAID, which were close to zero near the end of the sample period, indicate that these coins are illiquid and therefore lack representativeness. Overall, only 5-out-of-10 altcoins as of January 1, 2016 continued to be in the top-20 cryptocurrencies in terms of market capitalizations by the end of the sample period. We will return to this issue in discussion of forthcoming results.

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[7] Like Grobys et al. (2020) we exclude Dash to include only non-privacy cryptocurrencies. Due to offering the function *optional privacy* (PrivateSend), Dash is not completely non-private. We replace Dash with MAID.

[8] Using a sample of highly liquid coins is consistent with research on traditional currencies that often focuses on the G10 currencies. These currencies comprise about 70% of the total traded volume of foreign exchange (Grobys and Heinonen, 2017).

[9] The market capitalization of the overall market for cryptocurrencies was USD 1.09 trillion as of October 3, 2023. However, the market for stablecoins with a market capitalization of USD 123.03 billion is included in this figure. Dropping stablecoins, total market capitalization of our cryptocurrencies is 966.25 billion.

2.2. Realized variances

As in Grobys (2023), we employ Parkinson's (1980) range-based variance estimator and compute annualized daily realized variances as:

$$\sigma_{i,t}^{2} = T\frac{1}{4\ln(2)}\left(\ln\left(H_{i,t}\right) - \ln\left(L_{i,t}\right)\right)^{2}, \tag{1}$$

where $H_{i,t}$ and $L_{i,t}$ denote the highest and lowest price for altcoin *i* on trading day *t*, and $\sigma_{i,t}^{2}$ denotes cryptocurrency i's corresponding annualized daily variance, where $T = 365$ as cryptocurrencies are traded 365 trading days per annum. According to Chou et al. (2010), range-based volatility estimators are more efficient and contain more information than changes in closing prices. Hence, they provide a reasonable way to model the uncertainty in the cryptocurrency market.[10] Descriptive statistics for realized cryptocurrency variances are reported in Table 1.

As shown in Table 1, realized cryptocurrency variances exhibit extremely heavy tails manifested by kurtosis values between 88.73 and 1661.75. Unsurprisingly, the Jarque-Bera test rejects normality for all realized cryptocurrency variances. It is noteworthy that the largest 20 percent of realized cryptocurrency variance observations account for between 67.17 and 94.48 percent of the cumulative totals.[11] Because the traditional Pareto 80/20 distribution postulates that the largest 20 percent of observations comprise 80 percent of the cumulative total, we infer that realized cryptocurrencies variance tend to follow a Pareto-type distribution.

2.3. Main analyses

2.3.1 Power laws

To investigate the heaviness of the altcoin variance tails, altcoin variances are modeled using the following power-law function:

$$p(x) = Cx^{-\alpha}, \tag{2}$$

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[10] See Groby (2021; 2023) for applications of range-based volatility measures to foreign exchange rate risk.

[11] The cross-sectional average of these variances is 77.42 percent.

where $C = (\alpha - 1)x_{MIN}^{\alpha-1}$ with $\alpha \in \{\mathbb{R}_+ | \alpha > 1\}$, x denotes the respective annualized daily altcoin variance provided that $x \in \{\mathbb{R}_+ | x_{MIN} \leq x < \infty\}$, x_{MIN} is the minimum value governed by the power-law process, and α is the magnitude of the corresponding tail exponent.[12] Regarding the latter exponent, Taleb (2020) emphasizes that α of a power-law function captures via extrapolation low-probability deviations not seen in the data; nonetheless, it plays a disproportionately large role in determining the theoretical mean of the process. Further, it can be shown that the conditional expectation of the altcoin variance, defined in this context as $E[x|x > x_{MIN}]$, is given by:

$$E[x|x > x_{MIN}] = \int_{x_{MIN}}^{\infty} xd\ p(x)x = \frac{(\alpha-1)}{(\alpha-2)} x_{MIN}. \tag{3}$$

The second moment, or $E[X^2]$ corresponding to the variance of the altcoin variance, is defined as:

$$E[X^2|x > x_{MIN}] = \int_{x_{MIN}}^{\infty} x^2\ p(x)dx = \frac{(\alpha-1)}{(\alpha-3)} x_{MIN}^2. \tag{4}$$

Higher moments of order k are analogously defined as:

$$E[X^k|x > x_{MIN}] = \frac{(\alpha-1)}{(\alpha-1-k)} x_{MIN}^k. \tag{5}$$

From equations (4) and (5), it is evident that the theoretical mean only exists for $\alpha > 2$, whereas the variance only exists for $\alpha > 3$.

2.3.2. Maximum likelihood estimation

Following White et al. (2008) and Clauset et al. (2009), who emphasize that MLE is the most accurate estimation methodology for estimating power-law exponents, the tail exponents are estimated as:

$$\hat{\alpha} = 1 + N\left(\sum_{i=1}^{N} \ln\left(\frac{x_i}{x_{MIN}}\right)\right)^{-1}, \tag{6}$$

where $\hat{\alpha}$ denotes the MLE estimator, N is the number of observations exceeding x_{MIN}, and other notations are as before. Clauset et al. (2009) observe that determining the corresponding values for α

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[12] Following Clauset et al. (2009), to simplify notation, index *i* for an individual altcoin is dropped.

and x_{MIN} is necessary for estimating the most suitable power-law model. Moreover, Clauset et al. (2009) derive the standard deviation of the estimated power-law exponent as:

$$\hat{\sigma} = \frac{\hat{\alpha}-1}{\sqrt{N}} + O(\frac{1}{N}). \tag{7}$$

From equation (7), we see that the MLE estimator depends on the chosen x_{MIN}, such that there are different possible MLE estimators from which to choose. Which is the most suitable candidate for x_{MIN}?

Clauset et al. (2009) point out that practitioners often plot $\hat{\alpha}/x_{MIN}$ and choose the value for x_{MIN} beyond which $\hat{\alpha}$ is stable. However, this approach is rather subjective and can be sensitive to noise or fluctuations in the tail of the distribution. To overcome these problems, Clauset et al. (2009) propose to select $\hat{\alpha}$ based on the optimal Kolmogorov-Smirnov (KS) distance *D*. This metric measures the maximum distance between the cumulative density functions (CDFs) of the data and the fitted power-law model as defined by:

$$D = MAX_{x \geq x_{MIN}} |S(x) - P(x)|, \tag{8}$$

where $S(x)$ is the CDF of the data for the observation with a value of at least x_{MIN}, and $P(x)$ denotes the CDF for the power-law model that best fits the data in the region $x \geq x_{MIN}$. The estimate for x_{MIN} ($\hat{x}_{MIN}$) is the value of x_{MIN} that minimizes *D*. Results documented in Clauset et al. (2009) show that their proposed technique to estimate α is superior to traditional log-log regression approaches. Unfortunately, their proposed approach is only applicable to a single data series.

2.3.3. Blocks bootstraps for estimating the covariance matrix for power-law exponents

Thus far we have reviewed methodologies proposed in the literature to estimate power-law exponents for single data series. Moreover, the statistical approach proposed by Clauset et al. (2009) does not account for potential dependency structures in the data. In the presence of autocorrelation (for example), $\hat{\sigma}$ will be biased. Departing from previous literature, in order to test for a common component of power-law behavior, we seek to estimate the covariance matrix of $\hat{\alpha}_1$, $\hat{\alpha}_2$, $\hat{\alpha}_3$, …, $\hat{\alpha}_N$.

For this purpose, we propose a blocks bootstrap procedure. Denoting block length as m, a blocks bootstrap procedure is implemented wherein $E[m] = \sqrt{T}$. Subsequently, the Tx1 data vectors of altcoin variances $i = 1, \ldots, N$ (denoted as $\boldsymbol{x}_i$) are stacked into matrix $\boldsymbol{W}$:

$$\boldsymbol{W} = [\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_N].$$

The blocks of dimension *m*xK are randomly drawn from matrix $\boldsymbol{W}$ with respect to the time dimension $t = 1, \ldots, T$. Blocks are governed by a geometric distribution; that is, $m \sim GEO(p)$ with $E[m] = \frac{(1-p)}{p}$. According to Godfrey (2009), this procedure ensures stationarity.

In our analysis, we use $E[m] = 53$ and $p = 0.0185$ as $\sqrt{T} \approx 53$. The rationale for choosing an expected block length of $\sqrt{T}$, as opposed to $T^{1/3}$ that Godfrey cites as typical for bootstrapping variances, is that partial autocorrelation functions (unreported) indicate dependencies beyond $T^{1/3}$.[13] Employing randomly selected block lengths, the blocks drawn from $\boldsymbol{W}$ vary in length. The randomly drawn blocks m, which have dimension *m*xK from data matrix $\boldsymbol{W}$, are stacked in matrix $\boldsymbol{W}_b$ as:

$$\boldsymbol{W}_b = \begin{bmatrix} m_1 \\ m_2 \\ m_3 \\ \vdots \end{bmatrix}.$$

The bootstrap procedure is stopped when the length of the artificial matrix $\boldsymbol{W}_b$ exceeds the length *T*. Observations that exceed *T* are cut off so that every artificial data matrix $\boldsymbol{W}_b$ has the same length as the original data matrix $\boldsymbol{W}$. This process corresponds to one iteration b of our blocks bootstrap procedure. Employing this approach, for each iteration b, the Tx1 vectors $\boldsymbol{x}_{b,1}$, $\boldsymbol{x}_{b,2}$, …, $\boldsymbol{x}_{b,N}$ are extracted from matrix $\boldsymbol{W}_b$, and MLE estimators are estimated as discussed earlier:

$$[\ddot{\alpha}_{b,1} \quad \ddot{\alpha}_{b,2} \quad \cdots \quad \ddot{\alpha}_{b,N}].$$

This blocks bootstrap procedure is performed for $b = 1, \ldots, 1000$ iterations, and point estimates for α are stacked in BxN matrix $\widehat{\boldsymbol{\alpha}}_{BOOT}$:

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[13] For example, the realized variance for MAID shows statistically significant (at the 5% level) partial autocorrelation for lag 39 (i.e., the point estimate is 0.110). Surprisingly, 8-out-of-10 realized altcoin variances exhibit statistically significant (at the 5% level) partial autocorrelation for lag order exceeding $T^{1/3} \approx 14$.

$$\widehat{\boldsymbol{\alpha}}_{BOOT} = \begin{pmatrix} \ddot{\alpha}_{1,1} & \ddot{\alpha}_{1,2} & \cdots & \cdots & \ddot{\alpha}_{1,N} \\ \ddot{\alpha}_{2,1} & \ddot{\alpha}_{1,2} & \cdots & \cdots & \ddot{\alpha}_{2,N} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \ddot{\alpha}_{B,1} & \ddot{\alpha}_{B,2} & \dots & \dots & \ddot{\alpha}_{B,N} \end{pmatrix}.$$

The corresponding bootstrapped standard errors $\hat{\sigma}_{BOOT,i}$ are then given by:

$$\hat{\sigma}_{BOOT,i} = \sqrt{\frac{1}{B}\sum_{b=1}^{B}\left(\ddot{\alpha}_{b,i} - \bar{\ddot{\alpha}}_{b,i}\right)^2}.$$

Godfrey notes that this approach is robust to unknown dependency structures in the data that are commonly observed for financial assets. More importantly, our blocks bootstrap approach retains potential (unknown) co-dependencies potentially contained in the data. Using the matrix $\widehat{\boldsymbol{\alpha}}_{BOOT}$ allows us to compute the covariances between $\ddot{\alpha}_i$ and $\ddot{\alpha}_j$ for $i, j = 1, \dots, N$ as:

$$\hat{\sigma}_{BOOT,i,j} = \frac{1}{B}\sum_{b=1}^{B}\left(\ddot{\alpha}_{b,i} - \bar{\ddot{\alpha}}_{b,i}\right)\left(\ddot{\alpha}_{b,j} - \bar{\ddot{\alpha}}_{b,j}\right) \text{ with } i \neq j.$$

If covariances between power-law exponents are significant, they need to be taken into account when implementing statistical tests for marketwide commonalties across the altcoin variances.

2.3.4. Is there a common component governing power-law behavior across altcoin variances?

To explore whether a common component governing power-law behavior of altcoin variances exists, the following test statistic is proposed:

$$\hat{\lambda} = (\ddot{\boldsymbol{\alpha}} - q\mathbf{1})'\widehat{\boldsymbol{\Sigma}}^{-1}(\ddot{\boldsymbol{\alpha}} - q\mathbf{1}), \tag{10}$$

where the covariance matrix $\widehat{\boldsymbol{\Sigma}} = COV(\widehat{\boldsymbol{\alpha}}_{BOOT})$ has the dimension NxN, $\ddot{\boldsymbol{\alpha}}$ is a Nx1 vector collecting the estimated average of power-law exponents for realized altcoin variances obtained via blocks bootstraps, $\mathbf{1}$ is a Nx1 vector consisting of ones, and q is the hypothesized cross-sectional power-law exponent. The estimated test statistic (denoted as $\hat{\lambda}$) is under the null hypothesis distributed as $\chi^2(N)$. The test statistic is iteratively estimated within the interval $q = (1.5, 2.2, \dots, 2.5)$. This range of values is an economically important interval of power-law exponents.

Rejecting the null hypothesis for all possible exponents (e.g., $\boldsymbol{\alpha}' \neq q\mathbf{1}\ \forall\ q = (1.5, 1.6,\ \ldots, 2.5)$) would indicate that the realized altcoin variances exhibit heterogenous sources of risk manifested in altcoin-specific risk dynamics rather than a common source of risk. On the other hand, accepting the null hypothesis only for $q \leq 2$ would imply that realized altcoin variances are governed by a common component manifested in a cross-sectional power-law exponent generating common power-law behavior. This outcome would indicate that the theoretical variance of the cross section of altcoin variances is statistically undefined. On the other hand, while accepting the null hypothesis for $2 < q \leq 3$ would likewise imply that realized altcoin variances are governed by a common, cross-sectional power-law exponent, now the theoretical variance of the cross section of realized altcoin variances is statistically defined, but higher theoretical moments (e.g., the variance of realized altcoin variance) remain statistically undefined. Accepting the null hypothesis for $q > 3$ would imply that realized altcoin variances are governed by a common, cross-sectional power-law exponent and theoretical mean, variance, and third moment are defined. An important implication here is that standard methodologies, such as OLS, could be employed for the purpose of statistical inferences (Fama, 1963). Finally, if our hypothesis is rejected for all hypothesized cross-sectional power-law exponents, the results would imply that realized altcoin variances do not share some common power-law behavior.

2.3.5. Is cross-sectional power-law behavior of realized altcoin variance invariant over time?

Mandelbrot (2008) criticizes the problem of sample-specific parameter estimates obtained from GARCH-type models. In his words, "…many recent models of price variation try to explain the obviously shifting pattern of volatility by inserting parameters that change by the day, hour, and second; such are the GARCH family …" Mandelbrot (2008, p. 242) Relevant to the present study: Is potential power-law behavior in the cross section of realized altcoin variances subject to change? To address this question, let us define K as the dimension of non-overlapping subsamples and N as the number of realized altcoin variances. Also, let the vector $\ddot{\boldsymbol{\alpha}}$ be defined as $\ddot{\boldsymbol{\alpha}} = (\ddot{\boldsymbol{\alpha}}_1, \ddot{\boldsymbol{\alpha}}_2, \dots, \ddot{\boldsymbol{\alpha}}_K)'$, where $\ddot{\boldsymbol{\alpha}}_j$ with $j = 1, \dots, K$ are Nx1 vectors of estimated sample averages of power-law exponents obtained via blocks bootstraps for subsample j. Moreover, we specify $\boldsymbol{q}$ as a NKx1 vector consisting of the corresponding cross-sectional exponent to be tested, and $\widehat{\boldsymbol{\Sigma}}_{\widehat{\alpha}}$ is the estimated NKxNK covariance matrix of $\ddot{\boldsymbol{\alpha}} = (\ddot{\boldsymbol{\alpha}}_1, \ddot{\boldsymbol{\alpha}}_2, \dots, \ddot{\boldsymbol{\alpha}}_K)'$ obtained via blocks bootstrap defined as:

$$\widehat{\boldsymbol{\Sigma}}_{\widehat{\alpha}} = \begin{pmatrix} \widehat{\boldsymbol{\Sigma}}_{\widehat{\alpha}_1} & \mathbf{0} & \dots & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \widehat{\boldsymbol{\Sigma}}_{\widehat{\alpha}_2} & \dots & \mathbf{0} & \mathbf{0} \\ \vdots & \vdots & & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \vdots & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} & \widehat{\boldsymbol{\Sigma}}_{\widehat{\alpha}_K} \end{pmatrix},$$

where $\widehat{\boldsymbol{\Sigma}}_{\widehat{\alpha}_j}$ are NxN covariance matrices obtained via blocks bootstraps for subsample j, and $\mathbf{0}$ defines NxN matrices consisting of zeros. Thus, the following test statistic is proposed:

$$\hat{\lambda} = (\ddot{\boldsymbol{\alpha}} - \boldsymbol{q})' \widehat{\boldsymbol{\Sigma}}_{\widehat{\alpha}}^{-1} (\ddot{\boldsymbol{\alpha}} - \boldsymbol{q}), \tag{11}$$

with $\boldsymbol{q} = q\mathbf{1}$ wherein $\mathbf{1}$ is the NKx1 vector of ones, and q is the hypothesized cross-sectional and time-frequency invariant power-law exponent. The estimated test statistic (denoted as $\hat{\lambda}$) is under the null hypothesis distributed as $\chi^2(NK)$. Again, the test statistic is iteratively estimated within the interval $q = (1.5, 2.2, \ldots, 2.5)$. The interpretation of potential outcomes is essentially the same as elaborated in the previous section. As detailed earlier, rejecting the null hypothesis could either imply that realized altcoin variances exhibit heterogenous sources of risk or that potential cross-sectional power-law behavior changes over time or both. Contrarily, acceptance of the null hypothesis implies that cross-sectional power-law behavior is invariant over time.

2.4. Additional analyses

2.4.1 Changing the block length

How sensitive are our main results with respect to changes in the expected block length? Since Godfrey (2009) documents that a block length of $T^{1/3}$ is typically recommended for bootstrapping variances, we implement the blocks bootstrap procedure described earlier with an expected block length of $E[m] = T^{1/3} = 14 \approx \sqrt{2833}$ and $p = 0.0667$ for the geometric distribution. We again obtain point estimates in terms of sample averages of the bootstrapped power-law exponents and stack them into a `Nx1` vector denoted as $\dot{\boldsymbol{\alpha}}$. Writing the corresponding estimated covariance matrix obtained via blocks bootstraps as $\dot{\boldsymbol{\Sigma}} = COV(\dot{\boldsymbol{\alpha}}_{BOOT})$, we test whether there exists a common component governing power-law behavior of altcoin variances by using the following test statistic:

$$\hat{\lambda} = (\dot{\boldsymbol{\alpha}} - q\mathbf{1})'\dot{\boldsymbol{\Sigma}}^{-1}(\dot{\boldsymbol{\alpha}} - q\mathbf{1}), \tag{12}$$

where the covariance matrix $\dot{\boldsymbol{\Sigma}} = COV(\dot{\boldsymbol{\alpha}}_{BOOT})$ has the dimension `NxN`, $\dot{\boldsymbol{\alpha}}$ is a `Nx1` vector of estimated sample averages of power-law exponents obtained from blocks bootstraps, $\mathbf{1}$ is a `Nx1` vector of ones, and q is the hypothesized cross-sectional power-law exponent. The estimated test statistic (denoted as $\hat{\lambda}$) is under the null hypothesis distributed as $\chi^2(N)$. The test statistic is iteratively estimated within the interval $q = (1.5, 2.2, \ldots, 2.5)$. Results derived from this test are interpreted in the same manner as before.

2.4.2. Testing alternative distributions against the power-law model

Despite strong evidence of extremely heavy tails, some readers could be skeptical about whether the power-law model is plausible. Earlier literature documents that realized asset volatility is close to a log-normal distribution (e.g., Andersen et al., 2001; Andersen et al., 2001a & 2001b). There are different ways to investigate this issue. Taleb (2020) observes that a typical manifestation of heavy-tailed financial market data is that the probability of an observation being within one standard deviation of the mean is between 75 and 95 percent, whereas the corresponding probability derived from the thin-tailed normal distribution is 68 percent. Since events exceeding "one-sigma" appear to play an important role in heavy-tailed financial market data, we use the following one-sigma test to investigate whether the distribution governing realized altcoin variances is log-normal or $\chi^2(1)$:

$$\lambda = \frac{\left(x_{\leq \pm 1\sigma} - m_{\leq \pm 1\sigma}\right)^2}{m_{\leq \pm 1\sigma}} + \frac{\left(x_{> \pm 1\sigma} - m_{> \pm 1\sigma}\right)^2}{m_{> \pm 1\sigma}}, \tag{1}$$

where $m_{\leq \pm 1\sigma}$ denotes the expected number of observations occurring within one standard deviation from the mean of a chosen distribution, which can be either log-normal or $\chi^2(1)$, $m_{> \pm 1\sigma}$ denotes the expected number of observations exceeding one standard deviation from the mean, and $x_{\leq \pm 1\sigma}$ and $x_{> \pm 1\sigma}$ are the corresponding values for the observed distribution of some realized altcoin variance. Pearson (1900) demonstrates that this type of test statistic is under the null hypothesis distributed as $\chi^2(1)$ for $T \to \infty$. Consequently, our one-sigma test is implemented using both distributions successively under the null hypothesis and the power law model under the alternative.

Since an important feature of the one-sigma test is that the distributions are standardized implying that the theoretical mean and variance of the underlying distributions are defined, power-law models are tested using the goodness-of-fit (GoF) test by Clauset et al. (2009) (i.e., $\alpha < 3$ suggests that the variance is undefined). The GoF test can be summarized as follows. First, recall that the Kolmogorov-Smirnov (KS) distance is the maximum distance between the cumulative density functions (CDFs) of the data and the fitted power-law model defined earlier as:

$$D = MAX_{x \geq x_{MIN}} |S(x) - P(x)|,$$

where $S(x)$ is the CDF of the data for the observation with a value of at least x_{MIN}, and $P(x)$ is the CDF for the power-law model that best fits the data in the region $x \geq x_{MIN}$. The estimate $\hat{x}_{MIN}$ is then the value of x_{MIN} that minimizes *D*. Using the parameter vector $(\hat{\alpha}, \hat{x}_{MIN})$ that optimizes *D* (Table 2), the GoF test generates a *p*-value that quantifies the plausibility of the power-law null hypothesis. That is, this test compares *D* with the distance measurements for comparable synthetic data sets drawn from the hypothesized power-law model. The *p*-value is then defined as the fraction of synthetic distances that is larger than the empirical distance. Employing a standard significance level of 5%, the power-law null hypothesis is not rejected for *p*-values exceeding 5%, as the difference between the empirical data and the model can be attributed to statistical fluctuations.[14] In the present study, power-law model parametrizations based on the original data sets are used as hypothesized power-law models when implementing the GoF tests (see section 2.3.2 and Table 2).

3. Empirical Results

3.1. Main results

Using Clauset et al.'s (2009) MLE procedure, estimated power-law exponents based on daily realized altcoin variance data for the sample period January, 1, 2016 to October, 3, 2023 are reported in Panel A of Table 2. We observe from Panel A that estimated power-law exponents vary between $\hat{\alpha} = 1.8659$ for realized XLM variance and $\hat{\alpha} = 2.9173$ for realized BTC variance. For only 2-out-of-10 realized altcoin variances (viz., realized BTC and BTS variance), $\hat{\alpha}$ is less than two standard deviations below $\alpha = 3$, which implies that for the vast majority of realized altcoin variances the second theoretical conditional moment (e.g., the conditional variance of realized altcoin variance) is statistically undefined. Surprisingly, substantial parts of the distributions between 4.06 and 31.73 percent of the realized variance distributions are governed by a power-law process. Hence, because the tail region of distributions covers only approximately 5 percent, we infer that it is difficult to defend Paretian tails. Our results indicate that, for 5-out-of-10 realized altcoin variances, more than 20 percent of the distributions are governed by power laws.

Panels B and C in Table 2 report the point estimates for power-law exponents for an earlier and later subsample based on non-overlapping daily realized altcoin variance data from January 1, 2016 to November 11, 2019 and November 12, 2019 to October 3, 2023, respectively. The results obtained from these subsamples confirm the findings that $\hat{\alpha}_i < 3 \; \forall \; i = 1, \dots, N$, such that substantial parts of the realized altcoin variance distributions are governed by power-law processes.

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[14] The implementation of this test is detailed in Clauset et al. (2009, pp., 675 − 678).

Since the MLE approach proposed by Clauset et al. (2009) is derived under the assumption of independently distributed observations (IID), $\hat{\sigma}$ in equation (7) is subject to underestimation in the presence of unknown dependency structures (i.e., volatility clustering). Moreover, their approach is not designed for implementing joint tests in multiple network settings. For these reasons, we earlier proposed using a blocks bootstraps approach. Specifically, we implement a blocks bootstraps procedure with randomly chosen block lengths that is governed by a geometric distribution and $E[m] = \sqrt{T}$.[15] For the full sample, we use $p = 0.0185$ as $\sqrt{T} \approx 53$, whereas for the non-overlapping subsamples, we set $p = 0.0256$ as $\sqrt{T} \approx 38$.

Panel A of Table 3 reports the descriptive statistics for estimated power-law exponents derived from blocks bootstraps denoted as $\ddot{\alpha}_i$, where $= 1, \dots, N$. We observe that the sample means for $\ddot{\alpha}_i$, which are unbiased estimators for α_i, are close to the point estimators derived from Clauset et al.'s (2009) approach for all $i = 1, \dots, N$. The economic magnitudes of the robust standard deviations (denoted as $\hat{\sigma}_{BOOT,i}$) are considerably larger than $\hat{\sigma}_i$. As an example, we see from Panel A of Table 2 that $\hat{\sigma}_{BTC} = 0.1841$, whereas Panel A of Table 3 shows that $\hat{\sigma}_{BOOT,BTC} = 0.365$. Indeed, the robust standard deviation for the estimated power-law exponent for realized Bitcoin variances is about twice as large as the standard deviation derived under the IID assumption. Using robust standard deviations, we see that point estimators $\hat{\alpha}_i$ are within 95% confidence intervals for $\ddot{\alpha}_i \; \forall \; i = 1, \dots, N$. As an example, the 95% confidence interval for $\ddot{\alpha}_{BTC}$ is $[1.8293, 3.2601]$, wherein $\hat{\alpha}_{BTC} = 2.9173$ falls within this interval. Not surprisingly, this empirical evidence holds across all point estimators, as point estimators $\hat{\alpha}_i$ are unbiased.

Panels B and C of Table 3 report the descriptive statistics for power-law exponents derived from blocks bootstraps for the earlier and later subsamples based on data from January 1, 2016 to November 11, 2019, and November 12, 2019 to October 3, 2023, respectively. The results obtained

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[15] Godfrey (2009) points out that blocks bootstraps with randomly chosen block lengths generate stationary data.

from both subsamples confirm the finding that $\ddot{\alpha}_i < 3 \; \forall \; i = 1, \dots, N$, which strongly corroborates our findings in Table 2.

Next, Table 4 reports the estimated correlation matrix for power-law exponents retrieved via blocks bootstraps. The vast majority of correlations are statistically significant even at a 1% significance level with correlations varying between $\hat{\rho}_{\ddot{\alpha}_{MAID},\ddot{\alpha}_{XLM}} = -0.2799$ and $\hat{\rho}_{\ddot{\alpha}_{DOGE},\ddot{\alpha}_{ETH}} = 0.2694$. Thus, we infer that the covariance matrix for power-law exponents needs to be taken into account when implementing joint tests.

To explore whether a common component governing power-law behavior of realized altcoin variances exists, we use the Nx1 vector $\ddot{\boldsymbol{\alpha}}$ of unbiased estimators for power-law exponents, and the estimated NxN covariance matrix $\hat{\boldsymbol{\Sigma}} = COV(\hat{\boldsymbol{\alpha}}_{BOOT})$ to estimate the test statistic λ as in Equation (10). We do this iteratively for the interval $q = (1.5, 2.2, \dots, 2.5)$, which includes economically important cross-sectional power-law exponents. Under the null hypothesis, the reference test statistic is distributed as $\chi^2(10)$. Recall that the null hypothesis suggests the presence of a common power-law exponent that governs the cross section of realized altcoin variances.

Table 5 reports the results. Strikingly, we observe that the null hypothesis cannot be rejected for $2.0 \leq q \leq 2.2$. Whereas the optimum is $q = 2.1$ as the p-value is the highest at 0.2241, we cannot reject the hypothesis that $q = 2.0$, which implies that realized altcoin variances are governed by a common power-law behavior due to uncertainty with no defined theoretical mean. On the other hand, the optimal value of $q = 2.1$ suggests that the cross-sectional exponent governing the common power-law behavior of realized altcoin variances corresponds to the same exponent governing the traditional Pareto 80/20 distribution.[16] Even though the theoretical conclusions are different, the practical implications are virtually the same – namely, even though the theoretical mean may exist, in finite samples we do not observe it.

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[16] Note that the mean of the traditional Pareto 80/20 distribution is—at least theoretically—defined.

Does the common power-law behavior of realized altcoin variance change over time? To explore this issue, we utilize the two non-overlapping subsamples discussed earlier. Again, we use blocks bootstraps to estimate both the two `Nx1` vectors of subsample-specific point estimates denoted as $\ddot{\boldsymbol{\alpha}}_1$ and $\ddot{\boldsymbol{\alpha}}_2$ and corresponding covariance matrices denoted as $\widehat{\boldsymbol{\Sigma}}_{\widehat{\alpha}_1}$ and $\widehat{\boldsymbol{\Sigma}}_{\widehat{\alpha}_2}$, respectively.[17] We implement the test λ in equation (11) on an iterative basis for the interval $q = (1.5, 2.2, \ldots, 2.5)$. Under the null hypothesis, the reference test statistic is distributed as $\chi^2(20)$. Recall that the null hypothesis suggests the presence of a common power-law exponent that governs the cross section of realized altcoin variances, which is hypothesized to be invariant over time. Table 6 reports the results. Surprisingly, regardless of which cross-sectional power-law exponent is tested, we observe that the null hypothesis is rejected.

It is possible that the lack of representativeness for half of the top-10 altcoins near the end of the sample period led to illiquidity[18] that explains our findings in Table 6. To explore this issue, we implement the test in Equation (10) for both subsamples independently. The results are reported in Tables A.5 and A.6 in the Appendix. As documented in Table A.5, the results for the first subsample confirm the presence of a common exponent governing the cross section of realized altcoin variances as the null hypothesis cannot be rejected for $1.9 \leq q \leq 2.4$. However, the results from Table A.6 for the second subsample indicate that the null hypothesis is rejected regardless of which q is tested.

To investigate further, we restrict the sample of altcoins to include only BTC, XRP, LTC, ETH, and DOGE. These altcoins were in the top-10 as of January 1, 2016 and later remained in the top-20 near the end of the sample (see Table A.1). Excluding stablecoins, these five altcoins accounted for 80.42 percent of the overall market capitalization for cryptocurrencies as of October 3, 2023. Using these representative altcoins and nonoverlapping subsamples, we repeat tests for whether the cross-

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[17] The estimated correlation matrices for the first and second subsample obtained via blocks bootstraps are reported in Tables A.3 and A.4 in the appendix.

[18] For instance, the daily trading volumes for MAID and NXT were considerably less than USD 1000 towards the end of the sample.

sectional power-law behavior of realized altcoin variance is subject to change over time. Notably, as shown in Table 7, the null hypothesis cannot be rejected for $2.1 \leq q \leq 2.3$. This inference implies that: (1) there exists a common exponent that governs the power-law behavior of the cross section of the realized variances of representative altcoins; (2) this power-law behavior is invariant over time; and (3) the power-law behavior is close to the traditional Pareto 80/20 distribution.

3.2. Additional results

Even though we argued that a block length of $\sqrt{T}$ is more suitable in our research context due to partial autocorrelation functions suggesting that realized altcoin variances are relatively long-memory processes, we next evaluate how sensitive our results are with respect to changes in block length. To begin, we use a block length of $T^{1/3}$, which is often recommended for bootstrapping variances, and implement the blocks bootstrap procedure with an expected block length of $T = 14 \approx \sqrt{2833}$ and $p = 0.0667$ for the geometric distribution. As unbiased estimators, we use the Nx1 vector of average point estimates retrieved from bootstrapped power-law exponents and denote the vector as $\dot{\boldsymbol{\alpha}}$. The corresponding estimated covariance matrix obtained via blocks bootstraps is denoted as $\dot{\boldsymbol{\Sigma}} = COV(\dot{\boldsymbol{\alpha}})$. The descriptive statistics and the correlation matrix are reported in Tables A.7 and A.8 in the Appendix. Comparing these descriptive statistics with those reported in Table 3, we observe that both average point estimates for power-law exponents and robust standard deviations are virtually the same. We again test whether there exists a common component governing cross-sectional power-law behavior of realized altcoin variances using the test statistic λ as in Equation (12). The results are reported in Appendix Table A.9. Since the null hypothesis cannot be rejected for $2.0 \leq q \leq 2.1$, this evidence supports our main results – namely, realized altcoin variances are governed by a common power-law exponent that is very close to the traditional Pareto 80/20 distribution.

Finally, because earlier literature suggests that realized asset volatility is close to a log-normal distribution, we investigate whether often-used distributions in financial economics, such as the log-normal, can accurately generate the data for realized altcoin variances. First, we use the one-sigma test to compare the log-normal against power laws. It can be shown that a fraction of 0.8189 is within one standard deviation from the mean for a standardized lognormal distribution (LGN). Appendix Table A.10 reports the fractions of realized altcoin variances within one standard deviation from the mean. These fractions vary between 0.9386 and 0.9951 that is considerably larger than predicted by the log-normal model. As expected, under the null hypothesis of log-normal, the estimated test statistics indicate that the log-normal is clearly rejected for all realized altcoin variances (i.e., $\hat{\lambda} \geq 273.6199 > 3.8415 = \chi^2_{0.95}(1)$ with all p-values equal to 0.0000). Next, we test the null hypothesis of $\chi^2(1)$. It can be shown that a fraction of 0.8797 is within one standard deviation from the mean for a standardized $\chi^2(1)$ distribution. In Appendix Table A.10, we see that even the $\chi^2(1)$ distribution is rejected for all realized altcoin variances (i.e., $\hat{\lambda} \geq 100.7633 > 3.8415 = \chi^2_{0.95}(1)$ with all p-values equal to 0.0000).

Since the one-sigma test requires that the second moment of the underlying distribution exists, this test cannot be used to test power laws with exponent $\alpha < 3$ as the null hypothesis. Therefore, we implement the GoF tests as described in section 2.4.2 using the parametrizations in Table 2. Based on 1000 replications, the estimated p-values for the GoF tests in Appendix Table A.10 suggest that the power-law null model cannot be rejected for the majority of realized altcoin variances. Summarizing our findings, power laws describe the data-generating processes for realized altcoin variance more accurately than standard distributions.

4. Discussion

4.1. How do the results line up with earlier literature?

Seminal work by Mandelbrot (1963) documents that cotton price changes do not exhibit a finite variance. However, as surveyed by Lux and Alfarano (2016), the consensus in the financial economics literature gradually converged to the insight that power-law exponents of financial assets typically satisfy the conditions required for finite variances. Our research on cryptocurrencies is more consistent with Mandelbrot. In sum, we cannot reject the hypothesis that the cross-sectional power-law exponent is $\alpha \approx 2$, which implies that the theoretical mean of realized variance processes is statistically undefined.

A possible explanation to reconcile our findings with extant literature is that intraday data is used to compute daily variances, whereas the vast majority of studies used the absolute amount of returns. In this regard, we chose the Parkinson (1980) estimator as price range variance estimators contain more information than simple closing price changes (Chou et al., 2010). Future research is warranted on this issue.

It is noteworthy that Grobys (2023) examines the power-law behavior of realized foreign exchange rate variances and finds relatively low estimated power-law exponents similar to our cryptocurrency analyses. Comparatively, bootstrapped point estimates in Grobys (2023) indicate that estimated power-law exponents for realized foreign exchange rate variances are $\hat{\alpha}_i < 3 \, \forall \, i = 1, \dots, 9$ versus $\ddot{\alpha}_i < 3 \, \forall \, i = 1, \dots, 10$ in the present study. Thus, both studies provide evidence that second theoretical moments of realized variance processes do not exist. Even though many studies postulate that realized volatility is close to lognormally-distributed (e.g., Andersen et al., 2001; Andersen et al., 2001a & 2001b), our findings are more consistent with Grobys (2023) as the power-law null hypothesis cannot be rejected for cryptocurrencies.

4.2. Implications

Our findings have important implications to statistical tests of asset variances. As a simple example, we use the point estimator derived from Clauset et al.'s (2009) approach and the corresponding standard deviation derived from the IID assumption. In Table 2 we see that $\hat{\alpha}_{BTC} = 2.9173$ and $\hat{\sigma}_{BTC} = 0.1841$. Upon testing the following hypotheses:

$$H_0\colon \alpha_{BTC} \leq 2 \text{ versus } H_1\colon \alpha_{BTC} > 2,$$

the corresponding test statistic as derived by Clauset et al. (2009), which follows a normal distribution under the null hypothesis, is estimated at $\hat{\lambda} = 4.9826$. Because $\hat{\lambda} = 4.9826 > 1.6449$, we would reject the null hypothesis.[19] On the other hand, upon testing the following hypotheses:

$$H_0\colon \alpha_{BTC} > 3 \text{ versus } H_1\colon \alpha_{BTC} \leq 3,$$

the corresponding test statistic is estimated at $\hat{\lambda} = 0.4492$. Given that $\hat{\lambda} = 0.4492 < 1.6449$, we would not reject the null hypothesis. The implication of these statistical tests is that we would mistakenly assume that realized Bitcoin variance exhibited a finite second moment (e.g., variance of realized variance). Following the mainstream of empirical researchers, we would believe that standard statistical methodologies such as OLS are valid for statistical inference. However, using our cross-sectional test that accounts for the covariance matrix of power-law exponents, or Equations (10) and (11), we found that upon testing the cross-sectional exponent, the hypothesis $q = 2.0$ could not be rejected. Consequently, the theoretical mean of the realized altcoin variance processes does not exist. As pointed out by Fama (1963), application of standard methodologies based on OLS in this research environment would yield misleading results. Our results reveal that an important reason for why the literature on studying the volatility dynamics of cryptocurrencies documents inconclusive results is that the theoretical variances of realized cryptocurrency variances is infinite.

4.3. Limitations

In our analyses, we focused on the top-10 altcoins by market capitalization. This approach is in line with studies on foreign exchange rates that often investigate the G10 currencies as highly liquid, tradable, and representative of the foreign exchange rate market (i.e., about 70 percent of the overall traded volume). Like earlier studies on altcoins (e.g., Zhang et al., 2018; Grobys et al., 2020), we studied highly liquid altcoins. Unexpectedly, only 5-out-of-10 altcoins maintained their

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[19] Note that 1.6449 is the critical value for a one-sided test using the standard normal distribution and a significance level of 5%.

representativeness in terms of market capitalization and liquidity. Since the market for altcoins is more concentrated than those of other assets, the top-5 altcoins still represented 80.42 percent of the overall market at the end of the sample period (October 3, 2023). We found that only representative altcoins exhibit invariance of power-law behavior over time; conversely, non representative altcoins had heterogenous power-law behavior due to illiquidity (i.e., lack of trading).

Further GoF tests indicated that power-law model was rejected for five altcoin realized variance processes. This finding does not mean that those realized altcoin variances are not governed by power laws. As pointed out by Taleb (2012), because it can take a long time for fractal processes to reveal their true properties, absence of evidence for power-law behavior does *not* imply evidence of absence of power-law behavior. From another perspective, although GoF tests reject the power-law null model for ETH (for instance), the maximum of the realized variance distribution corresponds to a 20-sigma event. Since standard distributions are typically not able to generate such large standard deviations, this anecdotical evidence supports a power law.

Lastly, the present study employed the Parkinson-estimator to model realized altcoin variances. However, several other range-based estimators are available (e.g., Garman-Klass, Rogers-Satchell, and Yang-Zhang estimators). In this regard, studies are inconclusive about the choice of range-based estimators. Grobys (2023) finds that for 7-out-of-9 realized foreign exchange rate variances, the maximums are higher when using the Garman-Klass (1980) estimator as opposed to the Parkinson estimator. Since recent evidence suggests that the Parkinson-estimator appears to be less inflated than the Garman-Klass estimator, we followed Grobys (2023) and chose the former.

5. Conclusion

Previous studies employed standard methodologies, such as GARCH-type models, to investigate uncertainty in the cryptocurrency market. A potential problem with this approach is the common assumption of normality; however, if the population variance is infinite, these models will yield misleading results. The present study explored the risk of altcoin cryptocurrencies that have similar features to Bitcoin. Using a set of 10 altcoins with the highest market capitalizations as of January 1, 2016, we modeled their risk in terms of realized altcoin variances via power laws.

Our findings revealed that realized altcoin variances exhibit strong patterns of power-law behavior with relatively low estimated power-law exponents. A manifestation of power-law behavior is the reoccurrence of extreme events. For this reason, we developed a new blocks bootstraps procedure to examine whether there exists a common component manifested in a cross-sectional exponent generating statistically the same power-law behavior across all realized altcoin variances. Our tests provided strong evidence for such a commonality. Surprisingly, the common exponent governing cross-sectional power-law behavior was estimated at $\alpha \approx 2.1$, which is the same exponent governing the traditional Pareto 80/20 distribution. Even though the optimal exponent appears to be close to $\alpha \approx 2.1$, we could not reject $\alpha = 2.0$, such that the theoretical mean of realized altcoin variances is undefined.

Because most studies of financial assets employ these models, future research is recommended to replicate and extend our analyses of cryptocurrencies. Additionally, our findings have practical implications to the professional management of crypto assets in the sense that risk diversification may be more limited than previously believed. Given fractal-like behavior in the second moment of cryptocurrencies, an interesting issue is the potential presence of co-fractality for realized cryptocurrency variances. We leave this research for future study.

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Table 1. Descriptive statistics of daily range-based variances using the Parkinson-estimator

Publicly available intraday prices for Bitcoin (BTC), Ripple (XRP), Litecoin (LTC), Ethereum (ETH), Dogecoin (DOGE), Peercoin (PPC), BitShares (BTS), Stellar (XLM), Nxt (NXT), and MaidSafeCoin (MAID) are downloaded from coinmarketcap.com. The sample period is from January, 1, 2016 to October, 3, 2023 (i.e., 2,833 daily observations). To estimate annualized daily variances, the following range-based variance estimator proposed by Parkinson (1980) is employed:

$$\sigma_{i,t}^2 = T\frac{1}{4\ln{(2)}}\left(\ln(H_{i,t}) - \ln(L_{i,t})\right)^2,$$

where $H_{i,t}$ and $L_{i,t}$ denote the highest and lowest price for cryptocurrency i on trading day t, and $\sigma_{i,t}^2$ is cryptocurrency i's annualized realized variance, where $T = 365$ for trading days per annum. This table reports the descriptive statistics.

	BTC	XRP	LTC	ETH	DOGE	PPC	BTS	XLM	NXT	MAID
Mean	0.5684	2.3534	0.9560	0.9975	1.7442	8.4430	1.9236	1.7373	2.5739	1.9964
Median	0.2072	0.4578	0.3353	0.3423	0.3623	0.5679	0.5890	0.4666	1.0011	0.8644
Maximum	41.3489	892.4544	61.7451	47.4243	296.4681	6591.5460	108.7633	191.8660	102.0344	181.9652
Minimum	0.0017	0.0000	0.0028	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Std. Dev.	1.4420	21.8405	2.5455	2.3392	7.7485	143.7444	5.1473	6.3677	5.8931	5.0107
Skewness	12.8426	33.7012	10.7076	8.1128	23.0477	38.7615	8.6342	15.2005	7.6248	19.0235
Kurtosis	279.4432	1255.5330	176.7608	105.1014	777.6592	1661.7460	113.4139	349.4434	88.7345	607.1096
Jarque-Bera	9098717.0000	186000000.0000	3618145.0000	1261626.0000	71087251.0000	325000000.0000	1474274.0000	14276812.0000	895105.1000	43249995.0000
(p-value JB)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Top-20%/total	0.7250	0.7583	0.8281	0.7310	0.7322	0.7132	0.6717	0.9448	0.7881	0.8499
Observations	2833	2833	2833	2833	2833	2833	2833	2833	2833	2833

Table 2. Estimated power-law exponents for daily variances based on the Parkinson-estimator

Cryptocurrency variances are modeled using the following power-law function:

$$p(x) = Cx^{-\alpha},$$

where $C = (\alpha - 1)x_{MIN}^{\alpha-1}$ with $\alpha \in \{\mathbb{R}_+ | \alpha > 1\}$, x denotes the respective annualized daily cryptocurrency variance provided $x \in \{\mathbb{R}_+ | x_{MIN} \leq x < \infty\}$, x_{MIN} is the minimum value governed by the power-law process, and α is the magnitude of the corresponding tail exponent. Following White et al. (2008) and Clauset et al. (2009), the tail exponents are estimated as:

$$\hat{\alpha} = 1 + N\left(\sum_{i=1}^{N} \ln\left(\frac{x_i}{x_{MIN}}\right)\right)^{-1},$$

where $\hat{\alpha}$ denotes the MLE estimator, N is the number of observations exceeding x_{MIN}, and other notations are as before. The estimate $\hat{\alpha}$ is selected based on the optimal Kolmogorov–Smirnov (KS) distance D measuring the maximum distance between the cumulative density functions (CDFs) of the data and the fitted power-law model:

$$D = MAX_{x \geq x_{MIN}} |S(x) - P(x)|,$$

where $S(x)$ is the CDF of the data for the observation with a value of at least x_{MIN}, and $P(x)$ is the CDF for the power-law model that best fits the data in the region $x \geq x_{MIN}$. Estimate $\hat{x}_{MIN}$ is then the value of x_{MIN} that minimizes D. This table reports the estimates $\hat{\alpha}$, $\hat{x}_{min}$, $\hat{\sigma}$, and N in terms of its percentage (%) of the total observations as well as the p-value of a goodness-of-fit (GoF) test. The sample period is from January, 1, 2016 to October, 3, 2023 (i.e., 2833 daily observations). The estimates for the whole sample are reported in Panel A of Table 2, whereas the estimates for the first subsample (viz., January, 1, 2016 to November, 11, 2019) and second subsample (viz., November, 12, 2019 to October, 3, 2023) are reported in Panels B and C, respectively.

Panel A. Estimates derived from daily variances based on the Parkinson-estimator and the full sample.

	BTC	XRP	LTC	ETH	DOGE	PPC	BTS	XLM	NXT	MAID
$\hat{\alpha}$	2.9173	2.1651	2.0040	2.2053	2.5496	2.1164	2.7761	1.8659	2.2152	1.9675
$\hat{\sigma}$	0.1841	0.0487	0.0440	0.0474	0.1111	0.0377	0.1276	0.0347	0.0692	0.0365
$\hat{x}_{min}$	2.6180	2.0177	1.5889	1.0128	2.7122	1.7748	5.5867	2.0529	2.9636	1.1722
N in%	0.0406	0.2090	0.1927	0.2344	0.0724	0.3173	0.0713	0.2319	0.1147	0.2577

Panel B. Estimates derived from daily variances based on the Parkinson-estimator and the first subsample.

	BTC	XRP	LTC	ETH	DOGE	PPC	BTS	XLM	NXT	MAID
$\hat{\alpha}$	2.8768	2.4634	2.0942	2.5756	2.0498	1.8298	3.1884	2.1974	2.1396	1.9949
$\hat{\sigma}$	0.2223	0.1289	0.0640	0.1326	0.0523	0.0373	0.3526	0.0746	0.0781	0.0645
$\hat{x}_{min}$	2.5217	4.9514	1.6031	3.0803	0.7104	1.1342	9.1029	2.3054	2.8757	2.1001
N in%	0.0565	0.1017	0.2281	0.1102	0.3114	0.3856	0.0311	0.2006	0.1681	0.1893

Panel C. Estimates derived from daily variances based on the Parkinson-estimator and the second subsample.

	BTC	XRP	LTC	ETH	DOGE	PPC	BTS	XLM	NXT	MAID
$\hat{\alpha}$	2.2066	2.2049	1.8597	2.3493	2.6344	2.4704	2.3699	1.6445	2.3908	1.9232
$\hat{\sigma}$	0.0572	0.0762	0.0446	0.0712	0.1753	0.0723	0.0681	0.0292	0.1445	0.0385
$\hat{x}_{min}$	0.3477	1.8728	0.7345	0.6548	2.4692	2.0172	1.7635	0.8659	2.6641	0.4898
N in%	0.3380	0.1948	0.2936	0.2731	0.0692	0.3112	0.3056	0.3903	0.0748	0.4411

Table 3. Descriptive statistics for bootstrapped power-law exponents

The covariance matrix for power-law exponents is obtained via blocks bootstrap. Denoting the selected block length as m, a blocks bootstrap procedure is implemented such that $E[m] = \sqrt{T}$. The Tx1 data vectors of cryptocurrency variances $i = 1, \dots, N$ (denoted as $\boldsymbol{x}_i$) are stacked into matrix $\boldsymbol{Y}$:

$$\boldsymbol{Y} = [\boldsymbol{x}_1, \boldsymbol{x}_2, \dots, \boldsymbol{x}_N].$$

Blocks m are randomly drawn from matrix $\boldsymbol{Y}$ with respect to the time dimension $t = 1, \dots, T$. Blocks are governed by a geometric distribution, wherein $m \sim GEO(p)$ with $E[m] = \frac{(1-p)}{p}$. Using this procedure, the blocks drawn from $\boldsymbol{Y}$ vary in length. Randomly drawn blocks m that have dimensions mxK from data matrix $\boldsymbol{Y}$ are stacked in matrix $\boldsymbol{Y}_b$ as:

$$\boldsymbol{Y}_b = \begin{bmatrix} m_1 \\ m_2 \\ m_3 \\ \vdots \end{bmatrix}.$$

The procedure is stopped when the length of the artificial matrix $\boldsymbol{Y}_b$ reaches a length exceeding T. Observations exceeding T are cut off; such that every artificial data matrix $\boldsymbol{Y}_b$ has the same length as the original data matrix $\boldsymbol{Y}$. This process corresponds to one iteration b of the blocks bootstrap procedure. Using this blocks bootstrap procedure, for each iteration b, Tx1 vectors, $\boldsymbol{x}_{b,1}, \boldsymbol{x}_{b,2}, \dots, \boldsymbol{x}_{b,N}$ are extracted from matrix $\boldsymbol{Y}_b$, and the MLE estimators are estimated using the procedure described in the text to yield:

$$[\hat{\alpha}_{b,1} \quad \hat{\alpha}_{b,2} \quad \cdots \quad \hat{\alpha}_{b,N}].$$

The procedure is performed for $b = 1, \dots, 1000$ iterations, and point estimates for α are stacked in BxN matrix $\hat{\boldsymbol{\alpha}}_{BOOT}$:

$$\hat{\boldsymbol{\alpha}}_{BOOT} = \begin{pmatrix} \hat{\alpha}_{1,1} & \hat{\alpha}_{1,2} & \cdots & \cdots & \hat{\alpha}_{1,N} \\ \hat{\alpha}_{2,1} & \hat{\alpha}_{1,2} & \cdots & \cdots & \hat{\alpha}_{2,N} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \hat{\alpha}_{B,1} & \hat{\alpha}_{B,2} & \dots & \dots & \hat{\alpha}_{B,N} \end{pmatrix}.$$

This table reports the descriptive statistics for blocks-bootstrapped power-law exponents based on daily data using the variance-estimator by Parkinson (1980) and $E[m] = 53$. The overall sample period is from January, 1, 2016 to October, 3, 2023 (i.e., 2,833 daily observations). Panels A to C report the descriptive statistics for blocks bootstrapped power-law exponents. Estimates for the whole sample are reported in Panel A of Table 3. Estimates for the first subsample (viz., January, 1, 2016 to November, 11, 2019) and second subsample (e.g., November, 12, 2019 to October, 3, 2023) are reported in Panels B and C, respectively.

Panel A. Descriptive statistics for bootstrapped power-law exponents for the full sample.

	$\ddot{\alpha}_{BTC}$	$\ddot{\alpha}_{XRP}$	$\ddot{\alpha}_{LTC}$	$\ddot{\alpha}_{ETH}$	$\ddot{\alpha}_{DOGE}$	$\ddot{\alpha}_{PPC}$	$\ddot{\alpha}_{BTS}$	$\ddot{\alpha}_{XLM}$	$\ddot{\alpha}_{NXT}$	$\ddot{\alpha}_{MAID}$
Mean	2.5447	2.2677	2.0736	2.3180	2.3847	2.1611	2.6015	1.8915	2.1935	2.0631
Median	2.5247	2.2427	2.0518	2.2697	2.3575	2.1317	2.5362	1.8805	2.1856	2.0494
Maximum	4.1370	2.7480	3.0401	3.3833	3.3953	3.6071	3.4203	2.5670	2.8213	2.6085
Minimum	1.8952	1.9329	1.6101	1.9469	1.8764	1.7527	2.1441	1.5097	1.8247	1.7275
Std. Dev.	0.3650	0.1415	0.1896	0.2057	0.1916	0.2116	0.2532	0.1257	0.1545	0.1252
Skewness	0.1812	0.6614	0.5427	1.5484	0.7543	2.0755	0.3708	0.5705	0.5913	0.5706
Kurtosis	2.5079	3.0164	4.0047	5.9962	3.9880	11.2169	1.9833	4.2565	4.0303	3.5221
Jarque-Bera	15.5624	72.9109	91.1356	773.6183	135.5052	3531.1490	65.9901	120.0295	102.5119	65.6202
Probability	0.0004	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000

Panel B. Descriptive statistics for bootstrapped power-law exponents for the first subsample.

	$\ddot{\alpha}_{BTC}$	$\ddot{\alpha}_{XRP}$	$\ddot{\alpha}_{LTC}$	$\ddot{\alpha}_{ETH}$	$\ddot{\alpha}_{DOGE}$	$\ddot{\alpha}_{PPC}$	$\ddot{\alpha}_{BTS}$	$\ddot{\alpha}_{XLM}$	$\ddot{\alpha}_{NXT}$	$\ddot{\alpha}_{MAID}$
Mean	2.5120	2.4038	2.2121	2.4687	2.2068	2.0684	2.6676	2.2224	2.1475	2.0161
Median	2.5628	2.4261	2.1923	2.4927	2.1600	1.8767	2.4971	2.1936	2.1312	2.0012
Maximum	3.7094	3.4350	2.9168	4.8083	3.9004	4.3019	4.3239	3.9504	2.8404	2.6152
Minimum	1.7313	1.6727	1.5271	1.7557	1.8410	1.5365	1.9238	1.7919	1.7756	1.7167
Std. Dev.	0.3589	0.2181	0.2434	0.3736	0.2185	0.5449	0.4110	0.1875	0.1689	0.1302
Skewness	-0.2178	-0.0928	0.1464	0.5869	1.3935	2.1226	0.8995	2.4827	0.8261	0.8774
Kurtosis	2.3419	3.6331	3.1924	3.7290	7.4355	6.3060	3.1764	15.5860	4.1369	4.6310
Jarque-Bera	25.9517	18.1340	5.1165	79.5463	1143.3570	1206.3320	136.1372	7627.6490	167.6065	239.1442
Probability	0.0000	0.0001	0.0774	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000

Panel C. Descriptive statistics for bootstrapped power-law exponents for the second subsample.

	$\ddot{\alpha}_{BTC}$	$\ddot{\alpha}_{XRP}$	$\ddot{\alpha}_{LTC}$	$\ddot{\alpha}_{ETH}$	$\ddot{\alpha}_{DOGE}$	$\ddot{\alpha}_{PPC}$	$\ddot{\alpha}_{BTS}$	$\ddot{\alpha}_{XLM}$	$\ddot{\alpha}_{NXT}$	$\ddot{\alpha}_{MAID}$
Mean	2.3094	2.2063	1.8814	2.4295	2.4652	2.5098	2.3862	1.7061	2.2895	2.0571
Median	2.2748	2.1997	1.8718	2.3952	2.4480	2.4889	2.3523	1.6966	2.2715	2.0509
Maximum	3.5619	2.6539	2.3772	3.4758	3.7405	3.1709	3.3755	2.2271	3.1359	2.7782
Minimum	1.9863	1.8910	1.5417	2.0780	1.9098	2.0609	2.0979	1.3813	1.7709	1.7120
Std. Dev.	0.1709	0.0942	0.1294	0.1745	0.2117	0.1585	0.1590	0.1196	0.1921	0.1376
Skewness	1.7617	0.4311	0.4268	1.6142	0.9097	0.9228	2.2807	0.6301	0.6889	0.6204
Kurtosis	9.4889	3.9362	3.1395	7.5296	5.6229	4.3760	10.6098	4.3945	4.3612	4.3104
Jarque-Bera	2271.6600	67.4874	31.1733	1289.1390	424.5730	220.8349	3279.8420	147.2039	156.3062	135.6996
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000

Table 4. Correlation matrix for blocks-bootstrapped power-law exponents

This table reports the correlation matrix for power-law exponents that is obtained via blocks bootstrap as described in the text. The sample period is from January, 1, 2016 to October, 3, 2023 (i.e., 2,833 daily observations).

Correlation (*t*-Statistic)	$\ddot{\alpha}_{BTC}$	$\ddot{\alpha}_{XRP}$	$\ddot{\alpha}_{LTC}$	$\ddot{\alpha}_{ETH}$	$\ddot{\alpha}_{DOGE}$	$\ddot{\alpha}_{PPC}$	$\ddot{\alpha}_{BTS}$	$\ddot{\alpha}_{XLM}$	$\ddot{\alpha}_{NXT}$	$\ddot{\alpha}_{MAID}$
$\ddot{\alpha}_{BTC}$	1.0000									
	(-----)									
$\ddot{\alpha}_{XRP}$	0.1172***	1.0000								
	(3.7294)	(-----)								
$\ddot{\alpha}_{LTC}$	0.0104	0.1461***	1.0000							
	(0.3282)	(4.6640)	(-----)							
$\ddot{\alpha}_{ETH}$	0.0923***	0.0825***	0.0164	1.0000						
	(2.9274)	(2.6153)	(0.5193)	(-----)						
$\ddot{\alpha}_{DOGE}$	0.1000***	-0.0020	-0.1201***	0.2694***	1.0000					
	(3.1760)	(-0.0644)	(-3.8205)	(8.8358)	(-----)					
$\ddot{\alpha}_{PPC}$	-0.0492	-0.1829***	-0.1955***	0.0964***	0.2097***	1.0000				
	(-1.5577)	(-5.8778)	(-6.2971)	(3.0608)	(6.7768)	(-----)				
$\ddot{\alpha}_{BTS}$	0.0191	0.0294	0.1063***	-0.0884***	-0.1078***	-0.0770**	1.0000			
	(0.6044)	(0.9305)	(3.3761)	(-2.8046)	(-3.4257)	(-2.4382)	(-----)			
$\ddot{\alpha}_{XLM}$	-0.1089***	0.0219	0.2383***	-0.1031***	-0.2023***	-0.1286***	0.0879***	1.0000		
	(-3.4598)	(0.6930)	(7.7519)	(-3.2737)	(-6.5251)	(-4.0964)	(2.7892)	(-----)		
$\ddot{\alpha}_{NXT}$	0.2041***	0.0929***	-0.0876***	0.1280***	0.2040***	0.1528***	-0.0326	-0.2122***	1.0000	
	(6.5864)	(2.9473)	(-2.7781)	(4.0776)	(6.5814)	(4.8837)	(-1.0302)	(-6.8596)	(-----)	
$\ddot{\alpha}_{MAID}$	0.1120***	0.1382***	-0.0828***	0.2209***	0.1806***	0.1967***	-0.0951***	-0.2799***	0.2478***	1.0000
	(3.5591)	(4.4067)	(-2.6232)	(7.1547)	(5.8004)	(6.3386)	(-3.0167)	(-9.2097)	(8.0815)	(-----)

*** Statistically significant at a 1% level.

** Statistically significant at a 5% level.

Table 5. Testing for a common power-law exponent governing the cross section of realized altcoin variances

To explore whether a common component exists that governs the cross-sectional power-law behavior of realized altcoin variances, the following test statistic is used:

$$\hat{\lambda} = (\ddot{\boldsymbol{\alpha}} - q\mathbf{1})'\hat{\boldsymbol{\Sigma}}^{-1}(\ddot{\boldsymbol{\alpha}} - q\mathbf{1}),$$

where the covariance matrix $\hat{\boldsymbol{\Sigma}} = COV(\hat{\boldsymbol{\alpha}}_{BOOT})$ has the dimension `NxN`, $\ddot{\boldsymbol{\alpha}}$ is a `Nx1` vector of estimated average power-law exponents obtained from blocks bootstraps, $\mathbf{1}$ is a `Nx1` vector of ones, and q is the hypothesized cross-sectional power-law exponent. The estimated test statistic (denoted as $\hat{\lambda}$) is under the null hypothesis distributed as $\chi^2(N)$. The test statistic is iteratively estimated within the interval $q = (1.5, 1.6, \ldots, 2.4, 2.5)$. Bold face type indicates statistical significance at a 5% level. The sample period is from January, 1, 2016 to October, 3, 2023.

q	$\hat{\lambda}$	p-value
1.5	**135.6772**	**0.0000**
1.6	**99.3245**	**0.0000**
1.7	**69.3328**	**0.0000**
1.8	**45.7019**	**0.0000**
1.9	**28.4319**	**0.0015**
2.0	17.5229	0.0636
2.1	12.9748	0.2241
2.2	14.7875	0.1400
2.3	**22.961**	**0.0101**
2.4	**37.4958**	**0.0000**
2.5	**58.3912**	**0.0000**

Table 6. Testing for invariance of a cross-sectional power-law exponent governing realized altcoin variances

To explore whether a common exponent governing the realized variances of altcoins is invariant over non-overlapping subsamples, the following estimated test statistic is used:

$$\hat{\lambda} = \left(\begin{bmatrix} \ddot{\boldsymbol{\alpha}}_1 \\ \ddot{\boldsymbol{\alpha}}_2 \end{bmatrix} - q\mathbf{1}\right)' \begin{bmatrix} \widehat{\boldsymbol{\Sigma}}_1 & \mathbf{0} \\ \mathbf{0} & \widehat{\boldsymbol{\Sigma}}_2 \end{bmatrix}^{-1} \left(\begin{bmatrix} \ddot{\boldsymbol{\alpha}}_1 \\ \ddot{\boldsymbol{\alpha}}_2 \end{bmatrix} - q\mathbf{1}\right),$$

where the estimated covariance matrices $\widehat{\boldsymbol{\Sigma}}_1$ and $\widehat{\boldsymbol{\Sigma}}_2$ for subsample 1 and 2 have the dimensions NxN, $\ddot{\boldsymbol{\alpha}}_1$, and $\ddot{\boldsymbol{\alpha}}_2$ are Nx1 vectors of estimated power-law exponents for subsample 1 and 2 obtained from blocks bootstraps, $\mathbf{1}$ is here a 2Nx1 vector of ones, and q is the hypothesized market-wide power-law exponent. The estimated test statistic (denoted as $\hat{\lambda}$) is under the null hypothesis distributed as $\chi^2(2N)$. The test statistic is iteratively estimated within the interval $q = (1.5, 1.6, \ldots,$ 2.4, 2.5). Bold face type indicates statistical significance at a 5% level. The first subsample is form January, 1, 2016 to November, 11, 2019, and the second subsample is from November, 12, 2019 to October, 3, 2023.

q	$\hat{\lambda}$	p-value
1.5	**227.4110**	**0.0000**
1.6	**171.4301**	**0.0000**
1.7	**125.0568**	**0.0000**
1.8	**88.2910**	**0.0000**
1.9	**61.1328**	**0.0000**
2.0	**43.5822**	**0.0017**
2.1	**35.6392**	**0.0170**
2.2	**37.3037**	**0.0101**
2.3	**48.5757**	**0.0004**
2.4	**69.4554**	**0.0000**
2.5	**99.9426**	**0.0000**

Table 7. Testing for a market-wide power-law exponent and invariance using the top-5 altcoins

To explore whether a common exponent governing the realized variances of altcoins is invariant over non-overlapping subsamples, the following estimated test statistic is used:

$$\hat{\lambda} = \left(\begin{bmatrix} \ddot{\boldsymbol{\alpha}}_1 \\ \ddot{\boldsymbol{\alpha}}_2 \end{bmatrix} - q\mathbf{1}\right)' \begin{bmatrix} \hat{\boldsymbol{\Sigma}}_1 & \mathbf{0} \\ \mathbf{0} & \hat{\boldsymbol{\Sigma}}_2 \end{bmatrix}^{-1} \left(\begin{bmatrix} \ddot{\boldsymbol{\alpha}}_1 \\ \ddot{\boldsymbol{\alpha}}_2 \end{bmatrix} - q\mathbf{1}\right),$$

where the estimated covariance matrices $\hat{\boldsymbol{\Sigma}}_1$ and $\hat{\boldsymbol{\Sigma}}_2$ for subsample 1 and 2 have the dimensions NxN, $\ddot{\boldsymbol{\alpha}}_1$, and $\ddot{\boldsymbol{\alpha}}_2$ are Nx1 vectors of estimated power-law exponents for subsample 1 and 2 obtained from blocks bootstraps, $\mathbf{1}$ is here a 2Nx1 vector of ones, and q is the hypothesized market-wide power-law exponent. The estimated test statistic (denoted as $\hat{\lambda}$) is under the null hypothesis distributed as $\chi^2(2N)$. The test statistic is iteratively estimated within the interval $q = (1.5, 1.6, \ldots,$ 2.4, 2.5). Bold face type indicates statistical significance at a 5% level. The first subsample is form January, 1, 2016 to November, 11, 2019, and the second subsample is from November, 12, 2019 to October, 3, 2023.

q	$\hat{\lambda}$	p-value
1.5	**131.3481**	**0.0000**
1.6	**99.1453**	**0.0000**
1.7	**71.9979**	**0.0000**
1.8	**49.9059**	**0.0000**
1.9	**32.8692**	**0.0003**
2.0	**20.8879**	**0.0219**
2.1	13.9619	0.1748
2.2	12.0913	0.2791
2.3	15.2760	0.1222
2.4	**23.5161**	**0.0090**
2.5	**36.8115**	**0.0001**

Table A.1. Market capitalization

Publicly available intraday prices for Bitcoin (BTC), Ripple (XRP), Litecoin (LTC), Ethereum (ETH), Dogecoin (DOGE), Peercoin (PPC), BitShares (BTS), Stellar (XLM), Nxt (NXT), and MaidSafeCoin (MAID) are downloaded from coinmarketcap.com. The sample period is from January 1, 2016 to October 3, 2023 (i.e., 2,833 daily observations). This table reports the rank of each cryptocurrency measured in terms of market capitalization as of January 1, 2016 and October 3, 2023. Also, market capitalization as of October 3, 2023 is reported in terms of USD.

Coin	Rank as of Jan 1, 2016	Market cap as of Jan 1, 2016 (in Mio $)	Rank as of Oct 3, 2023	Market cap as of Oct 3, 2023 (in Mio $)
BTC	1	6529.30	1	538846.47
XRP	2	199.72	5	27973.45
LTC	3	153.91	15	4761.36
ETH	4	71.98	2	196871.99
DOGE	5	15.82	9	8618.69
PPC	6	9.51	784	8.45
BTS	7	8.78	509	27.58
XLM	8	8.46	23	3090.92
NXT	9	6.68	4435	0.00
MAID	10	6.51	5059	0.00
			Total:	780198.09

Table A.2. Correlation matrix

Publicly available intraday prices for Bitcoin (BTC), Ripple (XRP), Litecoin (LTC), Ethereum (ETH), Dogecoin (DOGE), Peercoin (PPC), BitShares (BTS), Stellar (XLM), Nxt (NXT), and MaidSafeCoin (MAID) are downloaded from coinmarketcap.com. To estimate annualized daily variances, the following range-based variance estimator proposed by Parkinson (1980) is employed:

$$\sigma_{i,t}^2 = T \frac{1}{4 \ln{(2)}} \left(\ln(H_{i,t}) - \ln(L_{i,t})\right)^2,$$

where $H_{i,t}$ and $L_{i,t}$ denote the highest and lowest price for cryptocurrency i on trading day t, and $\sigma_{i,t}^2$ is cryptocurrency i's annualized realized variance, where $T = 365$ for trading days per annum. The sample period is from January 1, 2016 to October 3, 2023 (i.e., 2,833 daily observations). This table reports the correlation matrix of realized altcoin variances. The corresponding *t*-statistics are in parentheses.

t-Statistic	BTC	XRP	LTC	ETH	DOGE	PPC	BTS	XLM	NXT	MAID
BTC	1.0000									
	(-----)									
XRP	0.0814***	1.0000								
	(4.3479)	(-----)								
LTC	0.6365***	0.1248***	1.0000							
	(43.9088)	(6.6915)	(-----)							
ETH	0.6531***	0.1339***	0.5692***	1.0000						
	(45.8907)	(7.1869)	(36.8379)	(-----)						
DOGE	0.2476***	0.0984***	0.2827***	0.2366***	1.0000					
	(13.5966)	(5.2590)	(15.6803)	(12.9592)	(-----)					
PPC	0.0092	-0.0016	0.0030	0.0142	0.0009	1.0000				
	(0.4888)	(-0.0852)	(0.1593)	(0.7540)	(0.0495)	(-----)				
BTS	0.4533***	0.2038***	0.4899***	0.4439***	0.3344***	0.0077	1.0000			
	(27.0578)	(11.0766)	(29.9029)	(26.3574)	(18.8797)	(0.4077)	(-----)			
XLM	0.3170***	0.1836***	0.3953***	0.3435***	0.2134***	-0.0018	0.4309***	1.0000		
	(17.7809)	(9.9397)	(22.8970)	(19.4585)	(11.6202)	(-0.0966)	(25.4055)	(-----)		
NXT	0.4100***	0.0773***	0.3514***	0.3503***	0.2010***	-0.0011	0.3574***	0.2955***	1.0000	
	(23.9195)	(4.1248)	(19.9734)	(19.9017)	(10.9171)	(-0.0588)	(20.3615)	(16.4566)	(-----)	
MAID	0.3249***	0.0439**	0.2801***	0.3594***	0.1189***	-0.0043	0.2381***	0.1908***	0.2442***	1.0000
	(18.2791)	(2.3381)	(15.5219)	(20.4924)	(6.3736)	(-0.2285)	(13.0425)	(10.3412)	(13.4015)	(-----)

*** Statistically significant at a 1% level.

** Statistically significant atn a 5% level.

Table A.3. Correlation matrix for blocks-bootstrapped power-law exponents for the first subsample

This table reports the correlation matrix for power-law exponents that is obtained via blocks bootstrap as described in the text. The sample period is from January, 1, 2016 to November, 11, 2019 (i.e., 1,416 daily observations).

Correlation (*t*-Statistic)	$\ddot{\alpha}_{BTC}$	$\ddot{\alpha}_{XRP}$	$\ddot{\alpha}_{LTC}$	$\ddot{\alpha}_{ETH}$	$\ddot{\alpha}_{DOGE}$	$\ddot{\alpha}_{PPC}$	$\ddot{\alpha}_{BTS}$	$\ddot{\alpha}_{XLM}$	$\ddot{\alpha}_{NXT}$	$\ddot{\alpha}_{MAID}$
$\ddot{\alpha}_{BTC}$	1.0000									
	(-----)									
$\ddot{\alpha}_{XRP}$	0.1377***	1.0000								
	(4.3907)	(-----)								
$\ddot{\alpha}_{LTC}$	0.0789**	0.1732***	1.0000							
	(2.5012)	(5.5550)	(-----)							
$\ddot{\alpha}_{ETH}$	0.0864***	0.1108***	0.0772**	1.0000						
	(2.7397)	(3.5232)	(2.4463)	(-----)						
$\ddot{\alpha}_{DOGE}$	0.1082***	0.0513	0.0184	0.1888***	1.0000					
	(3.4370)	(1.6220)	(0.5799)	(6.0723)	(-----)					
$\ddot{\alpha}_{PPC}$	0.0434	-0.0426	0.1280***	-0.0314	0.0209	1.0000				
	(1.3729)	(-1.3471)	(4.0777)	(-0.9926)	(0.6613)	(-----)				
$\ddot{\alpha}_{BTS}$	0.0169	0.0539*	-0.0016	0.0251	-0.1451***	0.0173	1.0000			
	(0.5335)	(1.7064)	(-0.0496)	(0.7931)	(-4.6342)	(0.5481)	(-----)			
$\ddot{\alpha}_{XLM}$	-0.0134	0.0537*	-0.0026	-0.0544*	-0.0284	-0.0401	0.0516	1.0000		
	(-0.4237)	(1.7004)	(-0.0810)	(-1.7208)	(-0.8963)	(-1.2680)	(1.6334)	(-----)		
$\ddot{\alpha}_{NXT}$	0.1209***	0.1328***	0.0920***	0.1482***	0.1527***	0.1216***	0.0901***	-0.0027	1.0000	
	(3.8469)	(4.2323)	(2.9188)	(4.7346)	(4.8804)	(3.8713)	(2.8578)	(-0.0860)	(-----)	
$\ddot{\alpha}_{MAID}$	0.0848***	0.0456	0.0310	0.2237***	0.3385***	0.0600*	-0.0734**	-0.0773**	0.2749***	1.0000
	(2.6895)	(1.4436)	(0.9791)	(7.2519)	(11.3662)	(1.8993)	(-2.3247)	(-2.4481)	(9.0340)	(-----)

*** Statistically significant at a 1% level.
** Statistically significant at a 5% level.
* Statistically significant at a 10% level.

Table A.4. Correlation matrix for blocks-bootstrapped power-law exponents for the second subsample

This table reports the correlation matrix for power-law exponents that is obtained via blocks bootstrap as described in the text. The sample period is from November, 12, 2019 to October, 3, 2023 (i.e., 1,417 daily observations).

Correlation (*t*-Statistic)	$\ddot{\alpha}_{BTC}$	$\ddot{\alpha}_{XRP}$	$\ddot{\alpha}_{LTC}$	$\ddot{\alpha}_{ETH}$	$\ddot{\alpha}_{DOGE}$	$\ddot{\alpha}_{PPC}$	$\ddot{\alpha}_{BTS}$	$\ddot{\alpha}_{XLM}$	$\ddot{\alpha}_{NXT}$	$\ddot{\alpha}_{MAID}$
$\ddot{\alpha}_{BTC}$	1.0000									
	(-----)									
$\ddot{\alpha}_{XRP}$	0.0579*	1.0000								
	(1.8314)	(-----)								
$\ddot{\alpha}_{LTC}$	-0.0640**	0.1688***	1.0000							
	(-2.0268)	(5.4086)	(-----)							
$\ddot{\alpha}_{ETH}$	0.1894***	0.3513***	0.2222***	1.0000						
	(6.0933)	(11.8525)	(7.1999)	(-----)						
$\ddot{\alpha}_{DOGE}$	0.0326	0.0867***	-0.0257	0.2478***	1.0000					
	(1.0308)	(2.7496)	(-0.8130)	(8.0816)	(-----)					
$\ddot{\alpha}_{PPC}$	-0.1175***	0.1528***	0.2093***	0.1839***	0.0422	1.0000				
	(-3.7386)	(4.8846)	(6.7607)	(5.9111)	(1.3346)	(-----)				
$\ddot{\alpha}_{BTS}$	0.0212	0.1421***	0.0094	0.0781**	0.1574***	0.0892***	1.0000			
	(0.6685)	(4.5362)	(0.2971)	(2.4755)	(5.0345)	(2.8276)	(-----)			
$\ddot{\alpha}_{XLM}$	-0.1792***	-0.0407	0.1296***	-0.0501	0.0440	0.0730**	-0.0496	1.0000		
	(-5.7545)	(-1.2881)	(4.1299)	(-1.5858)	(1.3925)	(2.3129)	(-1.5701)	(-----)		
$\ddot{\alpha}_{NXT}$	0.1836***	0.1517***	-0.0010	0.1187***	-0.0713**	-0.0356	-0.0414	-0.0576*	1.0000	
	(5.8989)	(4.8486)	(-0.0304)	(3.7751)	(-2.2590)	(-1.1250)	(-1.3084)	(-1.8217)	(-----)	
$\ddot{\alpha}_{MAID}$	-0.0145	0.1648***	0.3125***	0.1167***	-0.0276	0.0405	0.0542*	0.0418	0.2130***	1.0000
	(-0.4567)	(5.2792)	(10.3938)	(3.7129)	(-0.8710)	(1.2805)	(1.7156)	(1.3222)	(6.8873)	(-----)

*** Statistically significant at a 1% level.
** Statistically significant at a 5% level.
* Statistically significant at a 10% level.

Table A.5. Testing for a cross-sectional power-law exponent using data on the first subsample

To explore whether a common component exists that governs the cross-sectional power-law behavior of realized altcoin variances, the following test statistic is used:

$$\hat{\lambda} = (\ddot{\boldsymbol{\alpha}}_1 - q\mathbf{1})'\hat{\boldsymbol{\Sigma}}_1^{-1}(\ddot{\boldsymbol{\alpha}}_1 - q\mathbf{1}),$$

where the covariance matrix $\hat{\boldsymbol{\Sigma}}_1 = COV(\hat{\boldsymbol{\alpha}}_{BOOT})$ has the dimension `NxN`, $\ddot{\boldsymbol{\alpha}}_1$ is a `Nx1` vector of estimated power-law exponents obtained from blocks bootstraps, $\mathbf{1}$ is a `Nx1` vector of ones, and q is the hypothesized cross-sectional power-law exponent. The estimated test statistic (denoted as $\hat{\lambda}$) is under the null hypothesis distributed as $\chi^2(N)$. The test statistic is iteratively estimated within the interval $q = (1.5, 1.6, \ldots, 2.4, 2.5)$. Bold face type indicates statistical significance at a 5% level. The sample period is from January, 1, 2016 to November, 11, 2019.

q	$\hat{\lambda}$	p-value
1.5	**71.0949**	**0.0000**
1.6	**53.2775**	**0.0000**
1.7	**38.2902**	**0.0000**
1.8	**26.1329**	**0.0036**
1.9	16.8057	0.0787
2.0	10.3086	0.4137
2.1	6.6416	0.7589
2.2	5.8047	0.8318
2.3	7.7978	0.6484
2.4	12.6210	0.2457
2.5	**20.2743**	**0.0268**

Table A.6. Testing for a cross-sectional power-law exponent using data on the second subsample

To explore whether a common component exists that governs the cross-sectional power-law behavior of realized altcoin variances, the following test statistic is used:

$$\hat{\lambda} = (\ddot{\boldsymbol{\alpha}}_2 - q\mathbf{1})'\hat{\boldsymbol{\Sigma}}_2^{-1}(\ddot{\boldsymbol{\alpha}}_2 - q\mathbf{1}),$$

where the covariance matrix $\hat{\boldsymbol{\Sigma}}_2 = COV(\hat{\boldsymbol{\alpha}}_{BOOT})$ has the dimension NxN, $\ddot{\boldsymbol{\alpha}}_2$ is a Nx1 vector of estimated power-law exponents obtained from blocks bootstraps, $\mathbf{1}$ is a Nx1 vector of ones, and q is the hypothesized market-wide power-law exponent. The estimated test statistic (denoted as $\hat{\lambda}$) is under the null hypothesis distributed as $\chi^2(N)$. The test statistic is iteratively estimated within the interval $q = (1.5, 1.6,$ …, 2.4, 2.5). Bold face indicates statistical significance at a 5% level. The sample period is from November, 12, 2019 to October, 3, 2023.

q	$\hat{\lambda}$	p-value
1.5	**156.3161**	**0.0000**
1.6	**118.1526**	**0.0000**
1.7	**86.7666**	**0.0000**
1.8	**62.1581**	**0.0000**
1.9	**44.3271**	**0.0000**
2.0	**33.2736**	**0.0003**
2.1	**28.9975**	**0.0013**
2.2	**31.4990**	**0.0005**
2.3	**40.7779**	**0.0000**
2.4	**56.8344**	**0.0000**
2.5	**79.6683**	**0.0000**

Table A.7. Correlation matrix of power-law exponents derived from blocks bootstraps with expected block length restricted to $T^{1/3}$

The covariance matrix for power-law exponents are obtained via blocks bootstrap. Denoting the selected block length as m, a blocks bootstrap procedure is implemented such that $E[m] = T^{1/3}$. The Tx1 data vectors of cryptocurrency variances $i = 1, \dots, N$ (denoted as $\boldsymbol{x}_i$) are stacked into matrix $\boldsymbol{Y}$:

$$\boldsymbol{Y} = [\boldsymbol{x}_1, \boldsymbol{x}_2, \dots, \boldsymbol{x}_N].$$

Blocks m are randomly drawn from matrix $\boldsymbol{Y}$ with respect to the time dimension $t = 1, \dots, T$. Blocks are governed by a geometric distribution, wherein $m \sim GEO(p)$ with $E[m] = \frac{(1-p)}{p}$. Using this procedure, the blocks drawn from $\boldsymbol{Y}$ vary in lengths. Randomly drawn blocks m that have dimensions mxK from data matrix $\boldsymbol{Y}$ are stacked in matrix $\boldsymbol{Y}_b$ as:

$$\boldsymbol{Y}_b = \begin{bmatrix} m_1 \\ m_2 \\ m_3 \\ \vdots \end{bmatrix}.$$

The procedure is stopped when the length of the artificial matrix $\boldsymbol{Y}_b$ reaches a length exceeding T. Observations exceeding T are cut off; such that every artificial data matrix $\boldsymbol{Y}_b$ has the same length as the original data matrix $\boldsymbol{Y}$. This process corresponds to one iteration b of the blocks bootstrap procedure. Using this blocks bootstrap procedure, for each iteration b, Tx1 vectors, $\boldsymbol{x}_{b,1}, \boldsymbol{x}_{b,2}, \dots, \boldsymbol{x}_{b,N}$ are extracted from matrix $\boldsymbol{Y}_b$, and the MLE estimators are estimated using the procedure described in the text to yield:

$$[\hat{\alpha}_{b,1} \quad \hat{\alpha}_{b,2} \quad \cdots \quad \hat{\alpha}_{b,N}].$$

This blocks bootstrap procedure is performed for $b = 1, \dots, 1000$ iterations, and point estimates for α are stacked in BxN matrix $\hat{\boldsymbol{\alpha}}_{BOOT}$:

$$\hat{\boldsymbol{\alpha}}_{BOOT} = \begin{pmatrix} \hat{\alpha}_{1,1} & \hat{\alpha}_{1,2} & \cdots & \cdots & \hat{\alpha}_{1,N} \\ \hat{\alpha}_{2,1} & \hat{\alpha}_{1,2} & \cdots & \cdots & \hat{\alpha}_{2,N} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \hat{\alpha}_{B,1} & \hat{\alpha}_{B,2} & \dots & \dots & \hat{\alpha}_{B,N} \end{pmatrix}.$$

This table reports the descriptive statistics for blocks-bootstrapped power-law exponents based on daily data using the variance-estimator by Parkinson (1980) and $E[m] = 14$. The overall sample period is from January, 1, 2016 to October, 3, 2023 (i.e., 2,833 daily observations). This table reports the correlation matrix.

Correlation (*t*-Statistic)	$\dot{\alpha}_{BTC}$	$\dot{\alpha}_{XRP}$	$\dot{\alpha}_{LTC}$	$\dot{\alpha}_{ETH}$	$\dot{\alpha}_{DOGE}$	$\dot{\alpha}_{PPC}$	$\dot{\alpha}_{BTS}$	$\dot{\alpha}_{XLM}$	$\dot{\alpha}_{NXT}$	$\dot{\alpha}_{MAID}$
$\dot{\alpha}_{BTC}$	1.0000									
	(-----)									
$\dot{\alpha}_{XRP}$	0.0459	1.0000								
	(1.4530)	(-----)								
$\dot{\alpha}_{LTC}$	-0.0110	0.0826***	1.0000							
	(-0.3469)	(2.6180)	(-----)							
$\dot{\alpha}_{ETH}$	0.0434	0.0441	0.0874***	1.0000						
	(1.3722)	(1.3951)	(2.7716)	(-----)						
$\dot{\alpha}_{DOGE}$	0.0539*	0.1626***	0.0838***	0.2746***	1.0000					
	(1.7052)	(5.2056)	(2.6554)	(9.0227)	(-----)					
$\dot{\alpha}_{PPC}$	0.0417	-0.0957***	-0.0408	0.0350	0.2333***	1.0000				
	(1.3183)	(-3.0374)	(-1.2900)	(1.1052)	(7.5810)	(-----)				
$\dot{\alpha}_{BTS}$	0.0117	-0.0041	0.0890***	0.0022	-0.0250	-0.1050***	1.0000			
	(0.3703)	(-0.1302)	(2.8228)	(0.0680)	(-0.7904)	(-3.3355)	(-----)			
$\dot{\alpha}_{XLM}$	-0.0638**	-0.0473	0.0182	-0.0900***	-0.1153***	-0.0974***	0.0699**	1.0000		
	(-2.0191)	(-1.4955)	(0.5747)	(-2.8563)	(-3.6665)	(-3.0921)	(2.2150)	(-----)		
$\dot{\alpha}_{NXT}$	0.1009***	0.1498***	0.0077	0.0512	0.1503***	0.1094***	0.0063	-0.0826***	1.0000	
	(3.2041)	(4.7872)	(0.2447)	(1.6191)	(4.8030)	(3.4761)	(0.1984)	(-2.6170)	(-----)	
$\dot{\alpha}_{MAID}$	0.0628**	0.0158	0.0477	0.1214***	0.1392***	0.0622**	-0.0648**	-0.1591***	0.1351***	1.0000
	(1.9884)	(0.5001)	(1.5073)	(3.8648)	(4.4396)	(1.9686)	(-2.0498)	(-5.0926)	(4.3076)	(-----)

*** Statistically significant at a 1% level.
** Statistically significant at a 5% level.
* Statistically significant at a 10% level.

Table A.8. Descriptive statistics of power-law exponents derived from blocks bootstrap with expected block length restricted to $T^{1/3}$

This table reports the descriptive statistics of blocks bootstrapped power-law exponents using the procedure outlined in the text. Here the expected block length is restricted to be $E[m] = 14$. The overall sample period is from January 1, 2016 to October, 3, 2023.

	$\dot{\alpha}_{BTC}$	$\dot{\alpha}_{XRP}$	$\dot{\alpha}_{LTC}$	$\dot{\alpha}_{ETH}$	$\dot{\alpha}_{DOGE}$	$\dot{\alpha}_{PPC}$	$\dot{\alpha}_{BTS}$	$\dot{\alpha}_{XLM}$	$\dot{\alpha}_{NXT}$	$\dot{\alpha}_{MAID}$
Mean	2.4936	2.2458	2.0583	2.3222	2.3959	2.1448	2.5817	1.8728	2.1964	2.0309
Median	2.4828	2.2101	2.0450	2.2497	2.3775	2.1284	2.5426	1.8648	2.1865	2.0159
Maximum	3.5586	2.8140	4.2950	3.6500	3.1657	3.8034	3.2900	2.3316	3.0792	2.5751
Minimum	1.9088	1.9633	1.6296	1.9606	1.9802	1.8161	2.1266	1.6397	1.8509	1.7623
Std. Dev.	0.3634	0.1368	0.2087	0.2455	0.1973	0.1475	0.2470	0.0892	0.1525	0.1201
Skewness	0.3360	1.0766	2.6781	1.8971	0.5359	2.8896	0.3513	0.4645	0.8431	0.9161
Kurtosis	2.3113	4.1412	24.7175	7.1259	3.1969	25.3927	1.9822	3.6953	4.9597	4.4857
Jarque-Bera	38.5784	247.4612	20847.4600	1309.0970	49.4723	22284.5800	63.7346	56.1026	278.4826	231.8386
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000

Table A.9. Testing for a market-wide power-law exponent derived from blocks bootstrap with expected block length restricted to $T^{1/3}$

To explore whether a common component exists that governs the cross-sectional power-law behavior of realized altcoin variances, the following test statistic is used:

$$\hat{\lambda} = (\dot{\boldsymbol{\alpha}} - q\mathbf{1})'\dot{\boldsymbol{\Sigma}}^{-1}(\dot{\boldsymbol{\alpha}} - q\mathbf{1}),$$

where the covariance matrix $\dot{\boldsymbol{\Sigma}} = COV(\dot{\boldsymbol{\alpha}}_{BOOT})$ has the dimension NxN, $\dot{\boldsymbol{\alpha}}$ is a Nx1 vector of estimated power-law exponents obtained from blocks bootstraps, $\mathbf{1}$ is a Nx1 vector of ones, and q is the hypothesized market-wide power-law exponent. The estimated test statistic (denoted as $\hat{\lambda}$) is under the null hypothesis distributed as $\chi^2(N)$. The test statistic is iteratively estimated within the interval $q = (1.5, 1.6, \ldots, 2.4, 2.5)$. Bold face type indicates statistical significance at a 5% level. The sample period is from January, 1, 2016 to October, 3, 2023.

q	$\hat{\lambda}$	p-value
1.5	**149.2048**	**0.0000**
1.6	**105.7781**	**0.0000**
1.7	**70.8017**	**0.0000**
1.8	**44.2756**	**0.0000**
1.9	**26.2000**	**0.0035**
2.0	16.5746	0.0844
2.1	15.3997	0.1181
2.2	**22.6751**	**0.0120**
2.3	**38.4008**	**0.0000**
2.4	**62.5769**	**0.0000**
2.5	**95.2034**	**0.0000**

Table A.10. Testing standard distributions and hypothesized power-law models

The following one-sigma-test is employed to test whether the data-generating process governing cryptocurrency variances is distributed as log-normal, $\chi^2(1)$, or a power law:

$$\lambda = \frac{(x_{\leq \pm 1\sigma} - m_{\leq \pm 1\sigma})^2}{m_{\leq \pm 1\sigma}} + \frac{(x_{> \pm 1\sigma} - m_{> \pm 1\sigma})^2}{m_{> \pm 1\sigma}},$$

where $m_{\leq \pm 1\sigma}$ denotes the expected number of observations occurring within one standard deviation from the mean of some specified distribution, $m_{> \pm 1\sigma}$ denotes the expected number of observations exceeding one standard deviation from the mean, and $x_{\leq \pm 1\sigma}$ and $x_{> \pm 1\sigma}$ are the observed values for the distribution of a chosen cryptocurrency variance. Pearson (1900) shows that this type of test statistic is distributed as $\chi^2(1)$ for $T \longrightarrow \infty$. Note that it can be shown that a fraction of 0.8189 is within one standard deviation from the mean for a standardized lognormal distribution (LGN), whereas the corresponding figure for a standardized $\chi^2(1)$ distribution is 0.8797. For testing power-law models, the goodness-of-fit (GoF) test by Clauset et al. (2009) is employed as summarized in the text. Power-law model parametrizations based on the original data sets (Table 2) are used as hypothesized power-law models for running the GoF tests. Bold face type indicates that the null hypothesis cannot be rejected at a 5% significance level. The tests are implemented for daily data within the full sample from January 1, 2016 to October 3, 2023.

	BTC	XRP	LTC	ETH	DOGE	PPC	BTS	XLM	NXT	MAID
$prob(x \leq \pm 1\sigma)$	0.9446	0.9474	0.9686	0.9386	0.9492	0.9411	0.9538	0.9951	0.9640	0.9894
$H_0: \sigma_{i,t}^2 \sim LGN$	301.7460	315.4578	428.0073	273.6199	324.1823	285.0346	347.4232	592.7932	402.1673	555.3920
(p-value)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$H_0: \sigma_{i,t}^2 \sim \chi^2(1)$	112.6915	122.7143	211.4944	92.8104	129.1954	100.7633	146.8267	356.2408	190.2207	322.2129
(p-value)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
p-value for GoF test[a] $\left(H_0: \sigma_{i,t}^2 \sim PL(\hat{\alpha}, \hat{\sigma}_{i,min}^2)\right)$	**0.8350**	0.0090	0.0000	0.0000	**0.1970**	0.0010	**0.4300**	**0.5250**	**0.3670**	0.0020

“Don’t stop me now”: the cryptocurrency market reaction to the new Basel framework

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Abstract

This study investigates the cryptocurrency market reaction to the implementation of the new Basel framework on banks’ exposures to cryptoassets. Using an event study methodology, we analyze the market response to eight key steps of the Basel Committee’s work program, from the release of the first statement to the publication of the final framework. While the first statement declaring the intention of monitoring banks’ exposures to cryptoassets led to a positive market reaction, the following publications on the disclosure and capital requirements for banks led to negative market responses. Our results suggest that the new Basel framework may be perceived as highly stringent, discouraging banks from engaging in crypto-related activities. This study provides valuable implications for regulators, highlighting the potential need for adjustments to the framework.

Keywords: Cryptocurrency, Banks, Basel framework.

JEL codes: E50, G2, G14, G15.

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1. Introduction

Although the cryptocurrency market has grown significantly in recent years, it has been underexplored how cryptocurrencies can be integrated into the traditional financial system and the existing regulatory frameworks. In response to the rapid evolution of the crypto market, in 2019 the Basel Committee on Banking Supervision (BCBS) started to build up a new prudential treatment for banks' exposures to cryptoassets that will enter into force in January 1, 2026. The Basel regulation is part of a global ongoing activity set up by numerous standard-setting bodies and international organizations—such as the European Security and Markets Authority (ESMA), the Committee on Payments and Market Infrastructures (CPMI), and the International Organization of Securities Commissions (IOSCO)—to address several issues arising from cryptoassets. Such organizations are focused on investor protection, market integrity, anti-money laundering, bank exposure, and financial stability monitoring (Financial Stability Board, 2019).

In this paper, we investigate the cryptocurrency market reaction to the introduction of the Basel cryptoasset regulatory framework. Understanding how the cryptoasset market reacted to the development of the new Basel prudential standard critical insights into investor sentiment and offers valuable feedback to regulators for future adjustments. Indeed, further modifications to the standard might be made by the Basel Committee if the continuous monitoring of the bank-crypto interactions reveals substantial issues. Despite the virtuous aim of protecting the financial system from this asset class, the new prudential treatment developed by the Basel Committee was not totally welcomed by the international financial press and the institutional stakeholders who joined the consultation phases, as they considered the requirements imposed on banks too restrictive. A strong negative market reaction would reflect significant opposition to the measures imposed by this new framework. Such a response could be interpreted as a signal of institutional investors being excluded from this market, with potential consequences for its future growth and maturity. On the other hand, a positive reaction would indicate favorable acceptance of the framework as a step toward greater participation by major players. This could bring potential benefits to the market, such as improved liquidity, stability, and transparency (Conlon et al., 2024).

We answer our research question by conducting an event study on the impact of the development of the prudential standard on banks' cryptoasset exposures upon the cryptocurrency market. In particular, we analyze the market reaction to different key phases of the release of the BCBS' prudential regulatory framework, starting from the 2019 Committee's first announcement of the intention of monitoring banks' exposure to cryptoassets and introducing prudential treatment, until the publication of the final standard in 2024.

Our results show an initial positive market reaction to the announcement of the new framework, which can be considered as a sign of the potential significant presence by incumbents and, consequently, a universal recognition of cryptocurrencies as an asset class by the entire banking and financial system. However, after this first positive response, the crypto market negatively reacted as more details on transparency and capital requirements were released. This result suggests that the new Basel framework might have been considered too severe, mainly because it imposes punitive weighting and highly stringent capital requirements, pushing the banking system away from the crypto activity.

To the best of our knowledge, our paper is the first to explore the crypto market dynamics in response to the introduction of the prudential treatment that disciplines the banks' exposures to cryptoassets. We thus contribute to the existing literature in several ways. First, we expand the limited and emerging literature on the impact of regulations on the cryptocurrency market by providing the first evidence of market reaction to the development of disclosure and capital requirements for banks. While previous studies focused on narrow bans or nation-specific interventions (BIS, 2018; Cumming et al., 2024; Koenraadt & Leung, 2024), we analyze the impact of an international regulatory framework, addressing the limitation of the study by Conlon et al. (2024). Second, we extend the broader literature that uses event studies to analyze the effects of bank regulation, adding a novel focus on cryptocurrency markets (Horvath & Huizinga, 2015; Bruno et al., 2018; Pancotto et al., 2020). Finally, we enrich the debate on the capital requirements for banks' exposure to cryptoassets, which has been very heated during the consultation phases, by revisiting some concerns expressed by stakeholders.

Our results provide relevant insights for policymakers to refine the prudential regulatory framework, since the market reaction has been negative. The stakeholders' responses to the BCBS consultations suggest that a robust regulation, sound risk management, and ongoing supervisory oversight are appreciated. However, the general principle of "same risk, same activity, same treatment" should be applied also to the crypto market and some technical aspects and calibration could be reviewed to not reduce the banks' ability to offer cryptoasset products and services to the banks' customers (ICMA, 2022; WFE, 2022).

The remainder of the paper is organized as follows. Section 2 revises the related literature and Section 3 reports the timeline of the Basel regulatory developments. Section 4 describes the data and Section 5 illustrates the methodology. Section 6 presents the results and provides some robustness checks. Section 7 concludes the paper.

2. Literature review

The cryptocurrency market has experienced a significant growth in size and relevance within the financial context in recent years. As of the end of December 2024, the overall market capitalization exceeds 3 trillion USD, and more than 10,000 digital coins are traded[1]. A decade before, the market was valued at just 6 billion USD, with roughly 500 coins available.

Despite this success, cryptocurrencies have been found to be highly volatile, thus failing to serve their original function as a medium of exchange (Baur & Dimpfl, 2021). Indeed, digital coins often experience bubbles, high tail risks, and severe crashes. Enoksen et al. (2020) reported the presence of several pricing bubbles across eight large-cap cryptocurrencies, especially during the period from

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[1] Source: coinmarketcap.com.

2017 to 2018, which is consistent with the previous results by Corbet et al. (2018). Baur & Dimpfl (2021) also found that Bitcoin's volatility is ten times higher than that of major exchange rates, and Dai et al. (2023) show that cryptocurrency crashes occur with a higher probability and to a greater extent than the ones observed in the equity market.

One further issue of the crypto market lies in its potential transmission of systemic instability to other asset classes. Narayan & Kumar (2024) identify risk spillovers from 33 cryptocurrencies to other markets, such as equities, exchange rates, and commodities. Similarly, Hanif et al. (2022) highlight the presence of both downside and upside risk spillovers between 8 major cryptocurrencies and global and regional equity markets. However, the famous case of the FTX bankruptcy, one of the leading cryptocurrency exchanges, seems to undermine the reliability of this evidence since it marked an important decline in the crypto market, but not in traditional markets (Yousaf et al., 2023).

Nonetheless, it is plausible that increased banks' exposure to cryptocurrencies, followed by a subsequent market downfall, would significantly affect the systemic risk. Indeed, banks have a central role in the financial system and the capacity to propagate their risks throughout the broader economy (Kaminsky & Reinhart, 2000). Even though banks' balance sheets are only marginally exposed to cryptocurrency positions, this exposure is increasing due to a growing interest from banks in participating in this market.[2] As a result, in 2019 the Basel Committee published a statement declaring its intention to monitor banks' exposures to cryptoassets and introduce a prudential treatment for such exposures. As written in the related newsletter, "*the Committee is of the view that the continued growth of cryptoasset trading platforms and new financial products related to cryptoassets has the potential to raise financial stability concerns and increase risks faced by banks*" (BIS, 2019a).

Considering that cryptocurrencies were ideologically designed as decentralized instruments, independent of mechanisms governing the traditional banking and financial system, the introduction of the new prudential regulation is critical for this market. Indeed, it has been shown that news

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[2] For instance, a recent report by BIS (2023a) highlighted that the reported exposure of surveyed banks grew by 30% between the end of 2021 and June 2022.

regarding policy statements made by regulatory bodies, central banks, relevant international institutions, and standard-setting bodies had a significant impact on cryptocurrency valuations and trading volumes between 2015 and 2018 (BIS, 2018). More specifically, the new Basel framework represents a further step of the global regulatory activity on the cryptoasset market, aiming to integrate cryptocurrencies into the consolidated Basel regulatory system. On the one hand, the integration into the conventional financial system could be welcomed, since it would promote a robust capital framework and appropriate risk management practices, together with a clear set of engagement rules for institutional investors. On the other hand, it could be considered a breach of the original nature of cryptocurrencies, as they are designed to function outside the established regulatory architecture. In this context, it appears extremely relevant to investigate how the cryptocurrency market reacted to the announcements of the introduction of this regulatory framework.

3. Timeline of the Basel cryptoasset framework

The potential threat to the solidity and stability of the financial system has driven different regulators to develop legislative frameworks.[3] In particular, the Basel Committee on Banking Supervision has developed the "Prudential Treatment of Cryptoasset Exposures," a framework designed to guide banks in managing risks associated with this emerging asset class to be implemented by 1 January 2026. On March 13, 2019, the Basel Committee published a newsletter declaring its intention to monitor banks' direct and indirect exposures to cryptoassets, alongside a promise to introduce a prudential treatment for such exposures (BIS, 2019a). In more details, the Committee expected that banks authorized to buy cryptoassets or provide related services adopted at least the following tools: due diligence, governance and risk management, disclosure, and supervisory dialogue.

On December 12 of the same year, being aware that the crypto market was immature, lacked standardization, evolved constantly and was very risky—not only in terms of traditional risk such as

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[3] A prominent example is the European Union's Markets in Crypto-Assets (MiCA) regulation (EU, 2023a).

market, credit, liquidity, and operational risks, but also in terms of fraud and cyber risk, money laundering and terrorist financing—the Committee released a discussion paper merely raising questions to seek stakeholder inputs for designing the new prudential framework (BIS, 2019b). In the first section of the discussion paper, the Committee reviewed the key features, economic functions, and potential sources of value of cryptoassets, as well as the channels of bank exposures to them and their rising risks. In the second section, the document provided general principles to design a prudential treatment for cryptoassets, following the fundamental rule "same risk, same activity, same treatment". It also displayed an illustrative example of a potential capital and liquidity treatment for high-risk cryptoassets, suggesting different capital absorption for exposures in the trading and banking book, no possibility of using cryptos as collateral for credit risk mitigation, and an unfavorable liquidity risk treatment both in the short and long term.

Based on the feedback received, the Committee published a consultative document on June 10, 2021, proposing a general structure of the prudential treatment of banks' cryptoasset exposures (BIS, 2021). Cryptoassets were categorized into two main groups based on their underlying potential risks. The Group 1 included tokenized traditional assets (Group 1a) and cryptocurrencies with effective stabilization mechanisms, such as stablecoins (Group 1b). Group 1 cryptoassets meet in full a set of classification conditions, such as having a value which is effectively and continually linked to an underlying traditional asset or a pool of traditional assets, ensuring full transferability and full redeemability continuously. In addition, entities that execute redemptions, transfers, or the settlement finality of the cryptoasset must be regulated and supervised. As a result, such coins share characteristics similar to traditional assets and can be treated under the general principle "same risk, same activity, same treatment". Therefore, the proposal was to subject them to the same capital requirements set out in the standard Basel framework for credit risk and market risk, according to standardized or internal model-based approaches. However, to address operational risks arising from the rapid evolution of the cryptoassets and the technologies they rely on, the consultative document considered the possibility of introducing an additional capital charge, and welcomed the feedback from stakeholders on the design and calibration of such measure. The second group of cryptoassets, which includes Bitcoin,[4] was instead represented by all the other cryptocurrencies, which failed to meet any of the above-mentioned classification conditions. Due to their higher risk profile, they were subject to a higher capital requirement that was a risk weight of 1,250% applied to the greater of the absolute value of the aggregate long positions and short positions to which the bank is exposed, to ensure that the bank holds a capital at least equal to its exposure on cryptoassets. At this stage, the consultative document was not proposing any new regulatory treatment related to the leverage ratio, the large exposures framework, or the liquidity ratio requirements, which followed the traditional Basel rules.

With a second consultation in June 2022, the Basel Committee divided the Group 2 cryptoassets into two subgroups. Group 2a included cryptoassets that do not meet the classification conditions for Group 1 but satisfy different hedging recognition criteria, with a capital requirement of 100% of the net exposure to these assets. Group 2b comprised all the other cryptocurrencies. Moreover, the second consultation introduced a 1% Tier 1 capital exposure limit for Group 2 cryptoassets (BIS, 2022a). By December 2022, the final standard was approved and added as a new chapter of the consolidated Basel Framework, with an initial implementation date of January 2025 (BIS, 2022b). The structure of the standard was substantially unchanged with respect to the proposal set out in the second consultation, but following some stakeholders' feedback, the Committee defined a new calibration for the Group 2 exposure limit.[5]

Finally, after reviewing disclosure requirements and prudential amendments through two public consultations – the first one focusing on the disclosure templates on October 17, 2023 (BIS, 2023b)

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[4] All the cryptocurrencies included in our sample are part of the Group 2 cryptoassets. The two stablecoins Thether and Pax Gold are included in this group as they might not meet all the technical requirements of the prudential framework.

[5] "The first modification will result in exposures being measured as the higher of the gross long and gross short position in each cryptoasset, rather than the aggregate of the absolute values of long and short exposures, as proposed in the second consultation. This change will ensure that banks that take steps to hedge exposures are not penalised under the limit. The second modification relates to the capital consequences of a breach of the limit. To reduce cliff effects, the Committee has agreed that the consequence of breaching the limit of 1% will be for the Group 2b capital treatment to apply to only the amount by which the limit is exceeded, rather than to all Group 2 exposures. However, to ensure that banks have a strong incentive to not significantly exceed the 1% threshold, a new 2% limit will be introduced which, if breached, will result in the whole of Group 2 exposures being subject to the Group 2b capital treatment". BIS (2022b), p.7.

and the second one on December 14, 2023 (BIS, 2023c) – the Basel Committee issued a revised standard on July 17, 2024, to be implemented by January 1, 2026, along with final disclosure requirements (BIS, 2024a).

4. Data

While other event studies on cryptocurrencies have focused either on a few relevant coins (Yue et al., 2021; Zhou, 2024) or included all the coins available during the analyzed sample period (Cumming et al., 2024; Koenraadt & Leung, 2024), we follow the sampling approach of Conlon et al. (2024), as we want to analyze coins that are (i) relevant to the overall cryptocurrency market and (ii) representative within specific categories based on the functionality of digital assets. We opted for this sampling approach because including only a few relevant coins would fail to capture different reactions due to the varying features of cryptocurrencies, and considering all the coins available in the market could introduce contamination of returns caused by illiquidity and other frictions well-documented in the literature (Zaremba et al., 2021).

Following Conlon et al. (2024)[6], we analyze the impact of the new Basel framework on the returns of 37 cryptocurrencies. We collect daily cryptocurrency prices from Coinmarketcap.com, a leading source of cryptocurrency data that aggregates information from 250 exchanges based on volume-weighted average prices (Liu et al., 2022). Drawing the price time series from the start of the estimation window on October 1, 2018, to the last event on July 31, 2024, we obtain a total of 2,131 daily observations. Following Härdle et al. (2020), we divide the 37 cryptocurrencies in our sample into 4 categories: stablecoins, digital currencies, smart contract platforms, and utility tokens. Stablecoins refer to cryptocurrencies tailored to maintain a stable value, often by being pegged to a fiat currency or commodity, while digital currencies include coins that operate on their own blockchains and are primarily designed as a medium of exchange. Smart contract platforms operate

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[6] Conlon et al. (2024) used a sample of 40 cryptocurrencies from 2019 to 2023. For 3 of these coins, price data before 1 January 2019 are not available, therefore we are not able to include them in our analysis.

on blockchains that support smart contracts, hence permitting greater functionality within the blockchain ecosystem. Finally, utility tokens refer to cryptocurrencies that are often built on top of smart contract blockchains and grant holders the access to specific services or products. Table A.1 in the appendix lists the coins in our sample, along with their market capitalization and categorization. Table 1 reports the descriptive statistics for each coin return. We observe that coin return distributions are heavy-tailed, with Kurtosis values ranging from 8.09 for Cardano (ADA) to 733.09 for Dogecoin (DOGE), hence higher than the standard value of 3 posited by the Gaussian distribution. Furthermore, the Jarque-Bera test results (Jarque & Bera, 1980) indicate the rejection of the null hypothesis of normal distribution for every coin in our sample.

5. Methodology

To investigate the cryptocurrency market reaction to the introduction of the Basel cryptoasset framework, we employ the event study methodology. This approach is particularly well-suited for analyzing market reactions to regulatory interventions (Moenninghoff et al., 2015; Pancotto et al., 2020). The event study methodology requires precise identification of the event dates to isolate the effect of specific news on market movements. To this end, we identified the relevant publications from the Bank for International Settlements (BIS) webpage that document the Basel Committee's work. Table 2 summarizes the key event dates when these reports were made public, covering a total of 8 events. The key dates range from the first communication via a newsletter on March 13, 2019, to the final revised framework released on July 17, 2024.

Following the classical event study methodology (see, e.g., Brown & Warner, 1985; Henderson, 1990; MacKinlay, 1997), we first need to determine the abnormal returns generated by the event. The abnormal returns are the difference between the realized returns and the expected returns, i.e., the returns one would have expected if no event had occurred over the selected event window (MacKinlay, 1997). In order to estimate normal returns, we make use of the market model. This approach consists of calculating expected returns by regressing coin returns on a market index through OLS estimation. Thereafter, the expected returns are subtracted from the realized returns to obtain abnormal returns:

$$AR_{i,j} = R_{i,j} - \widehat{a_\imath} - \widehat{\beta_\imath} R_{m,t} \tag{1}$$

$$R_{i,s} = a_i + \beta_i R_{m,s} + \varepsilon_{i,s} \qquad \text{for s} \in [\text{T,t}] \tag{2}$$

where $R_{i,s}$ is the daily return of coin *i* at time *s* in the estimation window defined as $(P_{i,s} - P_{i,s-1})/P_{i,s-1}$, $R_{m,s}$ is the market return calculated as the value-weighted average of returns of the cryptocurrencies in our sample. This is a good proxy for the overall cryptocurrency market, as the total market capitalization in October 2018 was approximately $220 billion, while the market capitalization of the cryptocurrencies in our sample was around $200 billion. $AR_{i,j}$ is the daily abnormal return of coin *i* at time *j* in the event window, and $R_{i,j}$ is the daily return of coin *i* at time *j* in the event window.

The estimation window is usually set to be a period prior to the event window (MacKinlay, 1997). To avoid any influence from the event itself, it is common practice to exclude the event period from the estimation window and skip a range of days close to the event window (Miyajima & Yafeh, 2007; Pancotto et al., 2020). Defining *t*= 0 as the day of the event for each coin, we set an estimation window that spans from *T*= -100 to *t*= -11 for a total of 90 days, skipping 10 days preceding the event (Li & Ongena, 2015). Moreover, we examine symmetric event windows of 10, 6, and 2 days around the event (centered at day 0) to account for potential information leakage or lagged market reactions. As robustness checks, we also evaluate the sensitivity of our results to longer estimation windows.

Once abnormal returns are estimated, they must be aggregated over the event window in order to draw overall inferences about the event of interest. By doing so, we obtain the Cumulative Abnormal Return (CAR) for each coin *i*:

$$CAR_i(j_1, j_2) = \sum_{j=j_1}^{j_2} AR_{i,j} \tag{3}$$

where j_1 indicates the event window starting day and j_2 indicates the event window ending day.

Finally, CARs must be aggregated cross-sectionally in order to test coins' reaction to the event:

$$CAAR(j_1,j_2) = \frac{1}{37}\sum_{i=1}^{37} CAR_i(j_1,j_2) \quad (4)$$

where $CAAR(j_1,j_2)$ is the Cumulative Average Abnormal Return for the event window j_1,j_2.

To test whether the CAAR of an event is statistically significant, we first perform the standard t-test, where standard errors are estimated from the time series of mean excess returns (Brown & Warner, 1985). Secondly, we use the Boehmer et al. (1991) test, which is robust to event-induced variance—a phenomenon that violates the constant variance assumption of returns, as events often increase return variance. Additionally, we evaluate the statistical significance of our outcomes using the generalized rank test proposed by Kolari & Pynnonen (2011). This test addresses the issue of non-normal return distributions and offers several desirable statistical properties, such as robustness to cross-correlation caused by event-day clustering (i.e., when the event occurs on the same day for all securities), autocorrelation of abnormal returns, and event-induced volatility.

Lastly, we analyze which characteristics might have influenced the cryptocurrencies' reaction to the announcements through a multivariate regression of CARs (Li & Ongena, 2015). We consider the market capitalization of a cryptocurrency (Chokor & Alfieri, 2021), retrieving the data from coinmarketcap.com. Moreover we include binary variables corresponding to the cryptocurrency categories to capture possible different responses based on the coin's functionality.

We run the following OLS regression on CARs, using the (-3,3) and (-5,5) estimation windows:

$$CAR_{i,t} = \alpha_0 + \beta_1 Size_{i,t} + \beta_2 Category_{i,t} + \varepsilon_{i,t} \quad (5)$$

where $CAR_{i,t}$ is the cumulative abnormal return for cryptocurrency *i* at time *t* and $Size$ is a vector of four binary variables corresponding to the quartiles of the average market capitalization observed for cryptocurrency *i* during the event window *t*. *Category* is a vector of dummies that includes stablecoins (omitted in the regression), digital currencies, smart contract platforms and utility tokens. We employ robust clustered standard errors at cryptocurrency level.

6. Results and Discussion

6.1 Univariate analysis

Table 3 presents the Cumulative Average Abnormal Returns (CAARs) for the 37 cryptocurrencies in our sample around the Basel Committee's announcements of eight distinct regulatory events. We observe that, across all the events of interest, the standard t-test statistic frequently rejects the null hypothesis, with the Boehmer et al. (1991) test yielding similar outcomes. However, to make more robust inferences, we rely on the Kolari & Pynnonen (2011) test, which demonstrates higher power than traditional testing procedures and accounts for statistical issues by inflating standard errors.

Our results reveal a positive market reaction to the newsletter release on March 13, 2019 (event 1). While abnormal returns on the event day are close to zero, CAARs over wider event windows are positive and economically meaningful. Moreover, statistical significance is attested at the 5% significance level in the [-1, 1] and [-5, 5] event windows. This positive reaction could be attributed to the opening of the cryptocurrency market to institutional investors, who are likely to make significant capital allocations and improve market liquidity.

No significant market reaction was registered following the publication of a discussion paper on December 12, 2019 (event 2). Given that the document had a clear consultative intent and the prudential proposal was not defined in detail, the market likely took a "wait-and-see approach," waiting to understand the design of the prudential treatment, after the discussion with all the stakeholders. Conversely, we observe a rather large market reaction to the publication of the first consultation paper on June 10, 2021 (event 3), when the Basel Committee released a draft containing detailed regulatory proposals. For nearly all the event windows, we find statistically significant CAARs, even at the 1% confidence level. Specifically, CAARs range from -10.75% over the event window [-1,1] to -17.56% over the [-5, 5] window. These results convey the strong negative reaction of the market to the strict proposal of the Basel Committee. While at first glance the market may have perceived the new regulatory framework as an opening for banks to operate in the cryptocurrency sector, the proposal of a risk weight of 1,250%—among others—seems to have created a hostile environment for such activities (Walker & Stafford, 2021).

No significant negative market reaction was observed on June 30, 2022 (event 4), when the Basel Committee published its second consultation paper. This paper introduced technical adjustments, including the recognition of hedging criteria for a new Group 2a and an exposure limit to Group 2 of 1% of a bank's Tier 1 capital. Across all the event windows, CAARs are not statistically significant, indicating that the market had likely priced in the Basel Committee's strict view after the first consultation. Regarding the publication of the final standard on December 16, 2022 (event 5), we document another negative reaction, both on the event day and over wider windows. This event marked the Basel Committee's definitive stance and it set the implementation date of January 1, 2025 for the new framework.

Finally, with respect to the remaining events, we find weaker market reactions. Notably, following the consultation on banks' disclosure on October 17, 2023 (event 6), we observe that only CAARs over the [-1, 1] window decreased significantly by -3.47%. This reaction may, however, be confounded by the adoption of a new directive by the EU Council on the same day, introducing regulations on cryptocurrency transactions and advance tax rulings for high-net-worth individuals (European Union, 2023b).

Overall, our results highlight a negative impact of the new Basel framework on the cryptocurrency market. Consistent with the findings by Conlon et al. (2024), regulatory measures are not well received by this market. Additionally, the delayed responses observed in 6- and 10-day event windows are in line with the findings of Joo et al. (2020) and Shanaev et al. (2020), who highlight the relative inefficiency of cryptocurrency markets compared to traditional financial markets, resulting in slower information flow. The negative market reaction could also suggest that investors discounted a future lower demand for cryptoassets by banks, as the opportunity cost of holding these assets has become burdensome, considering a minimum capital charge of 100% of the exposure.

6.2 Multivariate analysis

After assessing the overall reaction of the cryptocurrencies to the regulatory announcements, we analyze whether coin characteristics might have led to a heterogeneous response. To do this, we regress each cryptocurrency's CARs on a set of characteristics, considering all the events except the first one, which recorded a positive reaction. Table 4 provides the descriptive statistics for the variables employed in the analysis. We observe that for the seven events, the average CARs is -4% for the [-3,3] window and -5% for the [-5,5] window. Moreover, 27% of the observations are associated with the digital currencies category, 32% with smart contract platforms, and 35% with utility tokens, while the remaining 5% are linked to stablecoins.

Table 5 presents the results of the multivariate regression analyses. In line with Chokor & Alfieri (2021), the cryptocurrency size quartiles show a monotonically negative association with CARs over both event windows, suggesting that higher capitalized cryptocurrencies experienced more negative cumulative abnormal returns. Moreover, we observe a heterogeneous reaction to the announcements across cryptocurrency categories. Specifically, considering that the omitted category is stablecoins, whose returns are nearly zero, we document a negative and significant reaction for digital currencies, with CARs of -3% and -4.7% over the event windows [-3,3] and [-5,5], respectively. Interesting, smart contract platform cryptocurrencies and utility tokens show even more negative average CARs, ranging from -5.4% to -8.4% over the two event windows. These findings open to several cautious interpretations. Since smart contract platform cryptocurrencies and utility tokens have a more practical and innovative nature than digital currencies, which serve only a transactional function, their more pronounced reaction could be due to investors who discount the higher costs banks may face in investing in this market in the future. Indeed, because of the interest shown by banks in smart contracts and tokenization services (Lee, 2021; BIS, 2024b; Bloomberg, 2024; World Economic Forum, 2024) this framework might have made investments in cryptocurrencies offering such features too costly and triggered this stronger negative reaction.

Our results line up with concerns raised by stakeholders during the consultation phases. For instance, stakeholders expressed strong opposition to the 1,250% capital weight assigned to Group 2 cryptocurrencies and advocated for the adoption of tools already established for other high-risk asset classes, such as the 400% capital weight applied to speculative unlisted equity (American Bankers Association, 2021; Coinbase, 2021; State Street, 2021). Additionally, criticisms were raised regarding the lack of granularity in Group 2, which could be further subdivided and have different risk weights applied based on coins' characteristics (European Banking Federation, 2021). For example, it is peculiar that the regulator compared the risk of meme coins like Dogecoin to that of Ethereum, which supports smart contracts and can be used for tokenization services (Howell et al., 2020; Khan et al., 2022).

This market presents high risk and potential contagion effects that could lead to detrimental outcomes, therefore caution is essential in imposing lenient capital requirements in order to prevent a possible shattering financial crisis. However, banks could be an important player in this market by implementing more effective risk management tools. By offering services related to cryptoassets, banks could also provide better product control and increased transparency to investors, but with the current framework, these activities may be disincentivized.

This new regulation would seem to reflect the first Basel framework developed in 1988, in which the requirements were overly general and simplistic, leading to a lack of granularity in the treatment of activities and, hence, to subsequent revisions (Jobst, 2007). Drawing a parallel with the original Basel standard, we contend that there is room for revisions of the current framework, particularly concerning the risk weights assigned to Group 2 cryptoassets. Additionally, if no significant risks emerge from exposure to these assets, a future increase in the Tier 1 exposure limit should be considered. We also recommend a risk weighting scheme that more accurately reflects the various applications, types, and characteristics that may influence the inherent risks of these assets.

6.3 Robustness checks

In this sub-section, we perform several robustness checks that vary in two main dimensions. Firstly, in lieu of computing simple returns for the calculation of abnormal returns, we adopt continuously compounded returns. Thus, we replicate our model in equation (1), considering returns calculated as follows:

$$R_{i,t} = ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \tag{6}$$

This methodological choice is recommended to better conform to the assumption of normal return distribution (Henderson, 1990). Nonetheless, studies indicate that this estimation approach does not produce outcomes that significantly diverge (Thompson, 1988; Brown & Warner, 1985).

Secondly, we analyze the sensitivity of our findings to different estimation windows. The length of the estimation window can affect the calculation of normal returns and, consequently, the magnitude of abnormal returns. In this regard, we apply two estimation windows of 120 and 150 days preceding the event window. Specifically, we set in equation (2) estimation windows of T=-130, t=-11 and T=-160, t=-11, respectively. We compute a total of five different versions of CAARs for each event, given the interaction among our two methodological designs (i.e., return type and estimation window length).

Concerning the first robustness check, in Table 6, we report the descriptive statistics for log returns for all the coins in our sample. We observe that return normality issues are reduced. Nevertheless, the values for kurtosis and skewness still diverge from those of a Gaussian distribution. Again, we reject the normality assumption for every coin in the Jarque-Bera test. Table 7 presents the CAARs calculated using log returns over an estimation period of 90 days. We observe that, across all the events, our conclusions remain consistent. Regarding the second set of robustness checks, we find that neither the log-return specification nor the length of the estimation window qualitatively affects our findings.[7]

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[7] For brevity, results are not reported here, but they are available on request.

7. Conclusions

In this paper, using an event study approach, we examine the crypto market reaction to the Basel Committee's announcements of a new prudential treatment for banks' exposure to cryptoassets. We find that the release of the first newsletter was positively received by the market, suggesting that investors might have perceived potential benefits from the expected increased participation by financial institutions. However, as more details were unveiled, investors' reaction turned negative. Indeed, our results show negative CAARs in all the events where relevant new details were released. Specifically, we observe a negative reaction, with CAARs ranging from -10.75% to -17.56% over different event windows, when the first consultation paper was released in June 2021. This evidence is consistent with the view that the prudential treatment appears excessively stringent to investors, potentially disincentivizing significant participation by banks. This vision is also confirmed by the stakeholders' comments and the international financial press. Furthermore, a negative market reaction took place in December 2022, when the Basel Committee released the definitive stance and defined the implementation date for the new framework as January 1, 2025. Overall, our results show a negative crypto market reaction to the implementation of the new Basel framework. Indeed, despite the preliminary positive market reaction that welcomed the idea of adopting the same Basel framework already in use for the other assets, the following negative investors' response provides relevant insights for future adjustment to the current framework. Moreover, we observe a heterogeneous reaction when analyzing the cross-section of CARs, with cryptocurrencies featuring greater technological innovation and functionality showing more negative abnormal returns. Consistently, this may reflect a discounted expectation of lower banks' participation in assets in which they would otherwise have a greater interest and involvement.

Our findings suggest that while the general principle of "same risk, same activity, same treatment" is welcomed by stakeholders, the current regulation appears overly stringent, particularly regarding the 1,250% capital weight for Group 2 cryptocurrencies and the lack of granularity within such group. Therefore, some technical aspects and calibration could be revised to ensure that banks retain the ability to offer cryptoasset products and services to their customers. In this regard, regulators could consider a lower weight capital requirement for Group 2 cryptocurrencies, aligning it with the risk weights already applied to other particularly risky assets, such as speculative unlisted equity. Furthermore, regulators should consider a more granular subdivision of Group 2 based on parameters related to the cryptocurrencies' characteristics, e.g. their different functional nature.

This study acknowledges some limitations regarding the data sample used for the analysis. Although we followed the literature by considering relevant cryptocurrencies at the beginning of 2019 and analyzing them across the events (Conlon et al., 2024; Chokor & Alfieri, 2021**),** we did not take into consideration the response of other coins that emerged over time and may have later become relevant to the market.

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Table 1. Descriptive statistics for cryptocurrency returns

This table reports descriptive statistics for the 37 cryptocurrencies in our sample from October 1st 2018 to July 31st 2024. The total daily observations are 2,131.

Coin ID	Coin Name	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera test	Probability JB test
ADA	Cardano	0.0020	0.0003	0.3224	-0.3957	0.0514	0.3962	8.0850	2351.6790	0.00
BAT	Basic Attention Token	0.0016	0.0004	0.4566	-0.4022	0.0552	0.7036	11.1430	6063.4790	0.00
BCH	Bitcoin Cash	0.0014	-0.0005	0.5842	-0.4296	0.0566	1.5076	21.9592	32723.4300	0.00
BNT	Bancor	0.0012	-0.0004	0.5134	-0.4127	0.0574	1.1430	15.7266	14845.3200	0.00
BTC	Bitcoin	0.0017	0.0007	0.1875	-0.3717	0.0345	-0.3469	12.4589	7986.9430	0.00
BTG	Bitcoin Gold	0.0017	-0.0009	1.0469	-0.4198	0.0599	3.6139	57.7618	270911.7000	0.00
CVC	Civic	0.0026	0.0010	1.4456	-0.4251	0.0803	5.3531	79.0901	524254.8000	0.00
DASH	Dash	0.0005	0.0008	0.5704	-0.3722	0.0530	1.0487	18.7360	22377.4100	0.00
DOGE	Dogecoin	0.0043	-0.0007	3.5557	-0.4026	0.1008	21.5879	733.0902	47494292.0000	0.00
EOS	EOS	0.0004	0.0004	0.5521	-0.3960	0.0536	0.4229	14.9185	12676.4200	0.00
ETC	Ethereum Classic	0.0018	0.0000	0.4226	-0.3973	0.0556	1.0763	13.9479	11053.6400	0.00
ETH	Ethereum	0.0022	0.0009	0.2595	-0.4235	0.0441	-0.2950	10.7285	5334.3970	0.00
FUN	FunFair	0.0010	-0.0010	0.9067	-0.5013	0.0609	2.8837	40.3185	126610.9000	0.00
ICX	ICON	0.0011	0.0009	0.4202	-0.4466	0.0596	0.0954	8.8399	3031.4510	0.00
LRC	Loopring	0.0025	0.0003	0.6353	-0.4389	0.0710	1.7387	16.0065	16094.4600	0.00
LSK	Lisk	0.0010	-0.0001	0.5595	-0.4233	0.0569	0.6852	13.5738	10094.0500	0.00
LTC	Litecoin	0.0012	0.0006	0.3083	-0.3618	0.0478	0.0092	9.6628	3941.6960	0.00
MANA	Decentraland	0.0029	0.0006	1.5474	-0.4673	0.0720	5.3434	107.2346	974849.4000	0.00
MKR	Maker	0.0024	0.0000	0.5262	-0.5588	0.0563	1.0697	18.9695	23050.5300	0.00
NEO	Neo	0.0013	0.0013	0.4137	-0.3723	0.0548	0.2698	10.0806	4477.4100	0.00
OMG	OMG Network	0.0008	-0.0002	0.7105	-0.4302	0.0648	1.2612	17.7198	19803.6800	0.00
QTUM	Qtum	0.0015	0.0023	0.4941	-0.4405	0.0587	0.5614	12.5076	8138.1300	0.00
REP	Augur	0.0009	-0.0007	0.8034	-0.4906	0.0694	2.3431	29.5973	64762.6300	0.00
SNT	Status	0.0016	0.0009	0.8728	-0.3418	0.0632	3.2463	44.5906	157332.9000	0.00
TRX	TRON	0.0019	0.0019	0.3969	-0.4074	0.0459	0.1768	13.3287	9483.5240	0.00
USDP	Pax Dollar	0.0000	0.0000	0.0501	-0.0509	0.0037	0.1221	41.0607	128630.4000	0.00
USDT	Tether	0.0000	0.0000	0.0548	-0.0512	0.0032	0.7865	86.1098	613524.4000	0.00
UTK	XMoney	0.0026	-0.0007	0.9780	-0.3748	0.0735	2.1289	24.9566	44415.3200	0.00
VET	VeChain	0.0020	0.0002	0.3484	-0.4606	0.0578	0.2442	8.5922	2797.9200	0.00
XLM	Stellar	0.0008	0.0000	0.7492	-0.3363	0.0521	2.6993	38.7570	116113.9000	0.00
XMR	Monero	0.0012	0.0023	0.4119	-0.4139	0.0456	-0.3982	16.4820	16195.5300	0.00
XRP	Ripple	0.0014	-0.0002	0.7308	-0.4233	0.0542	2.3372	33.8640	86521.9900	0.00
XTZ	Tezos	0.0013	0.0009	0.3578	-0.4552	0.0558	0.1045	9.1597	3372.7670	0.00
XVG	Verge	0.0017	-0.0002	0.9160	-0.4168	0.0714	2.6247	28.6957	61073.2100	0.00
ZEC	Zcash	0.0008	0.0000	0.2876	-0.4169	0.0530	-0.0741	8.4296	2619.5440	0.00
ZIL	Zilliqa	0.0017	0.0009	0.9479	-0.4321	0.0656	2.4053	35.6969	96980.6400	0.00
ZRX	0x Protocol	0.0016	-0.0002	0.5965	-0.3727	0.0617	1.2829	15.7997	15131.5000	0.00

Table 2. Key event dates

This table reports the key dates of the ongoing development of the Basel Committee on Banking Supervision (BCBS) design of the prudential treatment for banks' exposures to cryptoassets. Each date is the publication date of the corresponding type of document.

#	Date	Type	Brief Description
1	13/03/2019	Newsletter https://www.bis.org/publ/bcbs_nl21.htm	It announces for the first time the BCBS prudential expectations related to banks' exposures to cryptoassets and related services.
2	12/12/2019	Discussion paper https://www.bis.org/bcbs/publ/d490.pdf	It puts forward the BCBS basic idea on the prudential treatment for cryptoassets to seek further input from stakeholders.
3	10/06/2021	First consultation paper https://www.bis.org/bcbs/publ/d519.pdf	It consists of a preliminary proposal on the prudential treatment for cryptoassets. It defines two groups of cryptoassets, each of them with different capital requirements.
4	30/06/2022	Second consultation paper https://www.bis.org/bcbs/publ/d533.pdf	It consists of the revised proposal of the previous consultation paper aiming at addressing the issues raised by respondents. New introduction of Group 2a and 1% Tier 1 capital exposure limit for Group 2 cryptoassets.
5	16/12/2022	Final standard https://www.bis.org/bcbs/publ/d545.htm	It is the final standard of the prudential treatment of cryptoassets exposure, a new chapter of the consolidated Basel Framework, to be implemented by 1 January 2025.
6	17/10/2023	Consultation on banks' disclosure https://www.bis.org/bcbs/publ/d556.pdf	It consists of a set of standardized disclosure templates subject to consultation among banks and market participants.
7	14/12/2023	Consultation on standard amendments https://www.bis.org/bcbs/publ/d567.pdf	It includes various amendments to the standard on banks' exposures to cryptoassets.
8	17/07/2024	Final standard revised https://www.bis.org/bcbs/publ/d579.htm	It is the final disclosure framework for banks' cryptoasset exposures to be implemented by 1 January 2026.

Table 3. Event study results.
This table reports the market reaction to each announcement event related to the Basel cryptoasset exposure framework, defined by CAARs in %. We compute abnormal returns through the market model. The event windows [0], [-1,1], [-3,3], [-5,5] correspond to the event day, 2 days, 6 days, and 10 days around the event date, respectively. The estimation window is set to be from T=-100 to t= -11, equal to 90 days before the event day. Statistical significance is tested based on standard t-test, Boehmer et al. (1991) test accounting for event-date clustering standard errors and Kolari & Pynnonen (2011) test accounting for non-parametric data and event-induce variance.
*** denotes significance at the 1% level; ** denotes significance at the 5% level; * denotes significance at the 10% level.

			Window			
#	**Date**		**[0]**	**[-1,1]**	**[-3,3]**	**[-5,5]**
1	13/03/2019	CAAR	-0.29%	4.41%	3.05%	6.19%
	Newsletter	t-test (p-value)	0.580	**0.000*** **	**0.035** **	**0.001*** **
		BMP (p-value)	0.790	**0.000*** **	**0.039** **	**0.002*** **
		KP (p-value)	0.816	**0.020** **	0.110	**0.040** **
2	12/12/2019	CAAR	-0.26%	1.08%	-1.00%	-5.21%
	Discussion paper	t-test (p-value)	0.629	0.249	0.493	**0.007*** **
		BMP (p-value)	0.631	0.238	0.612	**0.000*** **
		KP (p-value)	0.964	0.780	0.849	0.192
3	10/06/2021	CAAR	-0.79%	-10.75%	-16.02%	-17.56%
	First consultation	t-test (p-value)	0.479	**0.000*** **	**0.000*** **	**0.000*** **
		BMP (p-value)	0.118	**0.000*** **	**0.000*** **	**0.000*** **
		KP (p-value)	0.648	**0.016** **	**0.006*** **	**0.008*** **
4	30/06/2022	CAAR	-0.28%	1.08%	2.30%	-2.26%
	Second consultation	t-test (p-value)	0.711	0.420	0.272	0.398
		BMP (p-value)	0.953	0.159	**0.004*** **	**0.018** **
		KP (p-value)	0.932	0.503	0.403	0.545
5	16/12/2022	CAAR	-2.38%	-1.93%	-6.46%	-6.72%
	Final standard	t-test (p-value)	**0.000*** **	**0.008*** **	**0.000*** **	**0.000*** **
		BMP (p-value)	**0.000*** **	**0.000*** **	**0.000*** **	**0.000*** **
		KP (p-value)	**0.053* **	0.242	**0.043** **	**0.086* **
6	17/10/2023	CAAR	0.17%	-3.47%	-2.75%	-1.06%
	Consultation on banks' disclosure	t-test (p-value)	0.773	**0.001*** **	**0.093* **	0.610
		BMP (p-value)	0.858	**0.000*** **	**0.000*** **	0.518
		KP (p-value)	0.813	**0.035** **	0.293	0.682
7	14/12/2023	CAAR	0.92%	2.75%	4.37%	3.16%
	Standard amendments	t-test (p-value)	0.120	**0.009*** **	**0.008*** **	0.126
		BMP (p-value)	0.230	0.982	0.141	0.787
		KP (p-value)	0.624	0.690	0.752	0.809
8	17/07/2024	CAAR	1.08%	0.95%	-2.27%	-1.23%
	Final standard revised	t-test (p-value)	**0.029** **	0.263	**0.094* **	0.477
		BMP (p-value)	**0.037** **	0.326	**0.003*** **	0.404
		KP (p-value)	0.544	0.840	0.435	0.622

Table 4. Descriptive statistics for the multivariate analysis of CARs.
This table reports the summary statistics for the dependent and independent variables employed in the multivariate analysis of CARs. The number of observations is 259.

	Mean	StDev	Min	Max
CARs [-3,3]	-0.04	0.10	-0.36	0.61
CARs [-5,5]	-0.05	0.11	-0.50	0.51
Size 1st quartile [-3,3]	0.25	0.43	0.00	1.00
Size 2nd quartile [-3,3]	0.25	0.44	0.00	1.00
Size 3rd quartile [-3,3]	0.25	0.43	0.00	1.00
Size 4th quartile [-3,3]	0.25	0.43	0.00	1.00
Size 1st quartile [-5,5]	0.24	0.43	0.00	1.00
Size 2nd quartile [-5,5]	0.24	0.43	0.00	1.00
Size 3rd quartile [-5,5]	0.25	0.43	0.00	1.00
Size 4th quartile [-5,5]	0.27	0.44	0.00	1.00
Stablecoins	0.05	0.23	0.00	1.00
Digital Currencies	0.27	0.44	0.00	1.00
Smart Contract Platforms	0.32	0.47	0.00	1.00
Utility Tokens	0.35	0.48	0.00	1.00

Table 5. Multivariate analysis of CARs.

This table reports the multivariate analysis of CARs including all the announcements. The dependent variables are the CARs associated with the event windows [-3,3] and [-5,5]. We control for the average coin size during an event and its category. Stablecoins dummy variable is omitted. Event 1 is excluded as it has a contrasting sign compared to the other events.

	(1) CARs [-3,3]	(2) CARs [-3,3]	(3) CARs [-5,5]	(4) CARs [-5,5]
Digital Currencies		-0.030**		-0.047***
		(0.013)		(0.015)
Smart Contract Platforms		-0.054***		-0.063***
		(0.013)		(0.013)
Utility Tokens		-0.065***		-0.084***
		(0.015)		(0.015)
Size 2nd quartile [-3,3]	-0.033*	-0.042**		
	(0.018)	(0.019)		
Size 3rd quartile [-3,3]	-0.053***	-0.062***		
	(0.017)	(0.016)		
Size 4th quartile [-3,3]	-0.046**	-0.069***		
	(0.019)	(0.019)		
Size 2nd quartile [-5,5]			-0.029	-0.041*
			(0.020)	(0.020)
Size 3rd quartile [-5,5]			-0.044**	-0.056***
			(0.020)	(0.019)
Size 4th quartile [-5,5]			-0.043*	-0.068***
			(0.022)	(0.021)
Observations	259	259	259	259
R-squared	0.055	0.088	0.048	0.086

Note: Robust and clustered standard errors at cryptocurrency level in parentheses*** p<0.01, ** p<0.05, * p<0.1

Table 6. Descriptive statistics for cryptocurrency log returns

This table reports descriptive statistics for the 37 cryptocurrencies in our sample from October 1st 2018 to July 31st 2024. The total daily observations are 2,131.

Coin ID	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera test	Probability JB test
ADA	0.0007	0.0003	0.2794	-0.5037	0.0513	-0.2162	10.1638	4573.4080	0.00
BAT	0.0001	0.0004	0.3761	-0.5145	0.0548	-0.1019	11.4339	6319.4480	0.00
BCH	-0.0001	-0.0005	0.4601	-0.5613	0.0556	0.0275	19.1796	23244.1400	0.00
BNT	-0.0005	-0.0004	0.4144	-0.5322	0.0566	-0.0233	15.8109	14572.6800	0.00
BTC	0.0011	0.0007	0.1718	-0.4647	0.0350	-1.1215	20.4363	27441.4200	0.00
BTG	0.0000	-0.0009	0.7163	-0.5444	0.0566	1.1017	26.2285	48339.8000	0.00
CVC	-0.0001	0.0010	0.8943	-0.5536	0.0718	1.8817	29.2811	62585.4300	0.00
DASH	-0.0009	0.0008	0.4513	-0.4655	0.0526	-0.1253	15.5587	14009.8100	0.00
DOGE	0.0014	-0.0007	1.5164	-0.5151	0.0688	5.9972	126.4111	1365098.0000	0.00
EOS	-0.0011	0.0004	0.4396	-0.5042	0.0540	-0.6498	15.1617	13282.9800	0.00
ETC	0.0003	0.0000	0.3525	-0.5064	0.0548	0.0930	13.6071	9993.0240	0.00
ETH	0.0012	0.0009	0.2307	-0.5507	0.0448	-1.1224	17.4089	18882.0700	0.00
FUN	-0.0007	-0.0010	0.6454	-0.6958	0.0583	0.6596	26.4148	48834.9500	0.00
ICX	-0.0007	0.0009	0.3508	-0.5918	0.0602	-0.7128	11.8581	7147.6080	0.00
LRC	0.0002	0.0003	0.4918	-0.5778	0.0684	0.5983	12.4869	8118.4310	0.00
LSK	-0.0006	-0.0001	0.4443	-0.5505	0.0568	-0.3342	13.7701	10339.0200	0.00
LTC	0.0001	0.0006	0.2687	-0.4491	0.0483	-0.7004	12.5486	8269.9400	0.00
MANA	0.0007	0.0006	0.9351	-0.6298	0.0660	1.3449	29.5122	63053.5300	0.00
MKR	0.0008	0.0000	0.4228	-0.8182	0.0561	-0.7501	30.3654	66692.8000	0.00
NEO	-0.0003	0.0013	0.3462	-0.4656	0.0551	-0.5024	11.2583	6145.2420	0.00
OMG	-0.0013	-0.0002	0.5368	-0.5624	0.0638	0.0247	13.3918	9588.7120	0.00
QTUM	-0.0002	0.0023	0.4015	-0.5808	0.0588	-0.4809	14.2456	11311.0100	0.00
REP	-0.0014	-0.0007	0.5897	-0.6745	0.0670	0.2579	21.9563	31930.1200	0.00
SNT	-0.0002	0.0009	0.6274	-0.4182	0.0598	1.0738	22.1534	32982.9800	0.00
TRX	0.0008	0.0019	0.3342	-0.5232	0.0463	-0.7838	17.3403	18477.7900	0.00
USDP	0.0000	0.0000	0.0489	-0.0522	0.0037	-0.0995	41.3382	130510.8000	0.00
USDT	0.0000	0.0000	0.0534	-0.0526	0.0032	0.3851	85.4879	604213.0000	0.00
UTK	0.0001	-0.0007	0.6821	-0.4697	0.0704	0.6586	13.1495	9300.7060	0.00
VET	0.0003	0.0002	0.2989	-0.6173	0.0582	-0.5572	12.4185	7986.7580	0.00
XLM	-0.0004	0.0000	0.5592	-0.4100	0.0501	0.9674	21.5679	30944.7600	0.00
XMR	0.0001	0.0023	0.3450	-0.5342	0.0468	-1.6448	24.3510	41437.8700	0.00
XRP	0.0000	-0.0002	0.5486	-0.5505	0.0525	0.4487	24.5882AA	41453.0200	0.00
XTZ	-0.0003	0.0009	0.3059	-0.6073	0.0564	-0.7354	13.5284	10034.3400	0.00
XVG	-0.0006	-0.0002	0.6502	-0.5391	0.0677	0.9643	16.5563	16647.7800	0.00
ZEC	-0.0006	0.0000	0.2528	-0.5394	0.0537	-0.7764	11.7370	6992.0310	0.00
ZIL	-0.0004	0.0009	0.6668	-0.5658	0.0632	0.4914	18.0362	20160.5500	0.00
ZRX	-0.0003	-0.0002	0.4678	-0.4663	0.0605	0.2475	11.8813	7025.4130	0.00

Table 7. Event study results: robustness checks

This table reports the market reaction to each announcement event related to the Basel cryptoasset exposure framework, defined by CAARs. We compute abnormal returns through the market model and consider log returns. The event windows [0], [-1,1], [-3,3], [-5,5] correspond to the event day, 2 days, 6 days, and 10 days around the event date, respectively. The estimation window is set to be from T=-100 to t= -11, equal to 90 days before the event day. Statistical significance is tested based on standard t-test, Boehmer et al. (1991) test accounting for event-date clustering standard errors and Kolari & Pynnonen (2011) test accounting for non-parametric data and event-induce variance.

*** denotes significance at the 1% level; ** denotes significance at the 5% level; * denotes significance at the 10% level.

			Window			
#	**Date**		**[0]**	**[-1,1]**	**[-3,3]**	**[-5,5]**
1	13/03/2019	CAAR	-0.26%	4.24%	2.91%	5.97%
	Newsletter	t-test (p-value)	0.601	**0.000*****	**0.035****	**0.001*****
		BMP (p-value)	0.807	**0.000*****	**0.048****	**0.002*****
		KP (p-value)	0.826	**0.019****	0.108	**0.039****
2	12/12/2019	CAAR	-0.28%	1.08%	-0.87%	-5.09%
	Discussion paper	t-test (p-value)	0.590	0.240	0.544	**0.007*****
		BMP (p-value)	0.604	0.228	0.687	**0.001*****
		KP (p-value)	0.950	0.779	0.905	0.216
3	10/06/2021	CAAR	-0.56%	-10.24%	-14.60%	-15.43%
	First consultation	t-test (p-value)	0.590	**0.000*****	**0.000*****	**0.000*****
		BMP (p-value)	0.286	**0.000*****	**0.000*****	**0.000*****
		KP (p-value)	0.799	**0.019****	**0.007*****	**0.010*****
4	30/06/2022	CAAR	-0.21%	1.34%	2.83%	-1.40%
	Second consultation	t-test (p-value)	0.770	0.278	0.143	0.570
		BMP (p-value)	0.903	**0.095***	**0.001*****	**0.057***
		KP (p-value)	0.905	0.452	0.342	0.666
5	16/12/2022	CAAR	-2.51%	-2.04%	-6.58%	-6.99%
	Final standard	t-test (p-value)	**0.000*****	**0.004*****	**0.000*****	**0.000*****
		BMP (p-value)	**0.000*****	**0.000*****	**0.000*****	**0.000*****
		KP (p-value)	**0.058***	0.220	**0.043****	**0.068***
6	17/10/2023	CAAR	0.18%	-3.37%	-2.60%	-0.81%
	Consultation on banks' disclosure	t-test (p-value)	0.740	**0.001*****	**0.091***	0.677
		BMP (p-value)	0.872	**0.000*****	**0.002*****	0.346
		KP (p-value)	0.801	**0.032****	0.258	0.632
7	14/12/2023	CAAR	0.82%	1.21%	2.79%	1.67%
	Standard amendments	t-test (p-value)	0.140	0.213	**0.067****	0.387
		BMP (p-value)	0.253	0.634	0.172	0.971
		KP (p-value)	0.643	0.506	0.807	0.741
8	17/07/2024	CAAR	1.14%	1.04%	-2.27%	-1.32%
	Final standard revised	t-test (p-value)	**0.022****	0.223	**0.096***	0.446
		BMP (p-value)	**0.026****	0.263	**0.002*****	0.304
		KP (p-value)	0.530	0.814	0.405	0.569

Appendix

Table A.1. Coins market capitalization

This table reports the rank of each cryptocurrency measured in terms of market capitalization as of October 1st 2018 and July 31st 2024. Market capitalization is reported in terms of USD.

Cryptocurrency	Category	Market cap as of October 2018 (in $)	Market cap as of July 2024 (in $)
BTC	Digital Currencies	114,298,799,169.34	1,346,858,598,263.73
ETH	Smart Contract Platform	23,161,718,295.12	393,322,680,889.11
XRP	Digital Currencies	19,250,423,140.09	33,685,454,186.45
BCH	Digital Currencies	8,998,850,691.53	8,224,838,106.85
EOS	Smart Contract Platform	5,219,176,098.86	851,908,025.05
XLM	Utility Tokens	4,610,262,538.69	2,941,900,955.86
LTC	Digital Currencies	3,409,619,931.88	5,320,509,845.55
USDT	Stablecoins	2,796,926,995.61	114,407,348,239.48
ADA	Smart Contract Platform	2,194,940,618.06	14,628,361,406.16
XMR	Digital Currencies	1,872,936,437.84	3,033,284,038.51
TRX	Smart Contract Platform	1,767,001,348.97	12,072,243,564.54
DASH	Digital Currencies	1,508,482,116.14	316,520,911.90
NEO	Smart Contract Platform	1,174,063,615.80	814,307,680.74
ETC	Smart Contract Platform	1,145,479,643.60	3,354,045,303.90
XTZ	Smart Contract Platform	800,339,724.02	766,832,016.56
VET	Smart Contract Platform	725,134,061.09	2,215,290,921.05
DOGE	Digital Currencies	647,783,256.69	18,900,820,199.87
ZEC	Digital Currencies	622,770,590.81	523,583,089.73
OMG	Utility Tokens	487,162,789.31	36,845,520.16
BTG	Digital Currencies	463,956,448.32	468,960,972.30
MKR	Utility Tokens	453,022,299.66	2,452,532,155.06
ZRX	Utility Tokens	395,865,633.55	317,719,570.49
LSK	Smart Contract Platform	368,009,952.00	147,477,849.52
QTUM	Smart Contract Platform	341,218,558.62	282,904,568.74
ZIL	Smart Contract Platform	284,385,712.94	320,280,548.34
ICX	Smart Contract Platform	261,453,323.83	169,775,395.90
XVG	Digital Currencies	236,411,895.58	70,866,378.40
BAT	Utility Tokens	175,539,106.13	294,033,101.40
REP	Utility Tokens	140,411,615.37	7,834,200.40
SNT	Utility Tokens	138,737,639.92	97,657,391.55
LRC	Utility Tokens	86,325,035.05	207,886,512.39
BNT	Utility Tokens	85,152,424.79	74,714,709.12
FUN	Utility Tokens	81,737,093.37	39,862,279.83
MANA	Utility Tokens	79,900,847.40	641,716,475.13
CVC	Utility Tokens	42,312,519.13	109,961,307.55
USDP	Stablecoins	24,191,408.72	114,390,907.64
UTK	Utility Tokens	17,293,465.51	24,205,185.70