Financial Uncertainty and the Cross-Section of Cryptocurrency Returns

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Abstract

This paper evaluates the sensitivity of cryptocurrency returns to various measures of uncertainty. We identify that crypto returns react primarily to financial uncertainty, while remaining insensitive to macro or real uncertainty. Portfolio analysis yields a significant premium which is equivalent to the cryptocurrency size factor. This premium is driven by the outperformance (underperformance) of cryptocurrencies with a negative (positive) financial uncertainty beta. Using a series of novel taxonomy indices, we show that the uncertainty premium is greater in coins with speculative rather than transactional features. We provide evidence that larger investors overvalue cryptocurrencies with positive betas, as they can be used to hedge financial uncertainty in their portfolios.

Keywords: Cross-Section of Cryptocurrency Returns; Financial Uncertainty; Taxonomy; Bitcoin.

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1 Introduction

Aggregate uncertainty shocks can reduce the value of assets due to either diminished future cash flows or increased discount rates (Bernanke, 1983; Pastor and Veronesi, 2012).[1] Jurado, Ludvigson and Ng (2015) supports this by providing evidence that economic uncertainty significantly affects the future consumption and investment choices of economic agents. As a result, any aggregate uncertainty influencing an asset's economic fundamentals is expected to be reflected in its returns. Empirically, we see economic uncertainty priced across stocks in both the US (Brogaard and Detzel, 2015; Bali, Brown and Tang, 2017) and international (Brogaard, Dai, Ngo and Zhang, 2020) markets, as well as in stock options (Kelly, Pástor and Veronesi, 2016) and corporate bonds (Bali, Subrahmanyam and Wen, 2021).

Prior studies on uncertainty and asset prices focus on financial securities that have underlying economic value (earnings, coupon payments, etc.) and depend on the state of the aggregate economy through various economic channels (cash flows, discount rates, etc.). However, cryptocurrencies demonstrate pronounced price volatility, often independent of changes in their underlying fundamentals (Biais, Bisiere, Bouvard, Casamatta and Menkveld, 2023). Cryptocurrencies exhibit frequent arbitrage opportunities due to price discrepancies across exchanges (Makarov and Schoar, 2020), and their valuations are significantly influenced by network effects—where the value and utility of a cryptocurrency increase as more users adopt and use it. This creates a positive feedback loop enhancing liquidity, utility, and demand for

[1] Throughout this paper, the term 'uncertainty' shall refer to unpredictability of economic outcomes (e.g., the volatility of conditional forecasts) potentially driven by possible changes in the policies implemented by the governing bodies (e.g., regulation of financial markets, among many other factors; see Pastor and Veronesi (2012)). This form of uncertainty is distinct from Knightian uncertainty (Knight, 1921), which implies a complete lack of any quantifiable knowledge about some possible occurrence.

the cryptocurrency, as discussed by Cong, He and Li (2021) and Cong, Li and Wang (2021). Despite these unique valuation drivers, cryptocurrencies remain largely disconnected from traditional economic indicators.

The Securities and Exchange Commission's (SEC's) recent approval of cryptocurrency exchange-traded funds (ETFs) and the rise of crypto mutual funds (Bianchi and Babiak, 2022) highlights the growing institutional and retail demand for cryptocurrency assets, underscoring the need to understand which internal and external factors influence their returns. Given the distinctive traits of cryptocurrencies, coupled with the heightened interest they have garnered from financial market participants, it is crucial to investigate whether their returns are swayed by macroeconomic, real, or policy uncertainty—factors that predominantly impact underlying economic fundamentals. Alternatively, considering their interlinkages with financial markets, it is imperative to evaluate whether coin returns are susceptible to financial uncertainty. If they are, we should also assess whether coins with speculative features—typically held for their risk and return properties—are more useful as a hedge than those with transactional features, which are typically held for use as a means of transaction or currency.

Motivated by these earlier studies, we seek to identify the types of uncertainty priced in the cross-section of cryptocurrency returns.[2] Using our initial sample of 618 coins from April 2014 to December 2021, we estimate each cryptocurrency's prior 24-month co-movement with various uncertainty indices via their uncertainty beta (β_{UNC}) (Bali et al., 2017). We consider a large set of uncertainty indices and metrics to determine those that are most relevant for the cryptocurrency markets, including the Ludvigson, Ma and Ng (2021) Economic Financial

[2] Throughout this study, the terms 'coin', 'cryptocurrency', and 'crypto(s)' are used interchangeably.

Uncertainty (FINU) index; the Jurado et al. (2015) economic uncertainty index - Total Macroeconomic Uncertainty (MACU); the Economic Policy Uncertainty index (POLU) of Baker, Bloom and Davis (2016); and the option-based volatility measure (VIX). The idea of uncertainty being priced within cryptos is in line with Zhang, Li, Xiong and Wang (2021), who identify that downside risk is priced in the cross-section of crypto returns, and Cai and Zhao (2024), who suggests that during periods of uncertainty, crypto investors are more sensitive to coins with high returns.

Our findings indicate that cryptocurrency returns react solely to the financial uncertainty index — which tends to spike during stock market crashes. Cryptos appear resilient to other forms of uncertainty, including macroeconomic, policy, and the VIX. A portfolio strategy using the High−Low (H−L) approach reveals that coins in the bottom tercile (Low) of financial uncertainty beta (β_{FINU}) outperform those in the top tercile (High) by a substantial 21% per month (H−L alpha). Although large in absolute terms, the magnitude of the effect is similar to that seen in the cryptocurrency coin size (Small minus Big) strategy by Liu, Tsyvinski and Wu (2022) at 25% per month, while much smaller than observed by Benedetti and Kostovetsky (2021) when investigating first month returns of newly issued coins, being 48%. Using the framework of Fama and MacBeth (1973), we observe that, as expected, β_{FINU} is negatively related to one-month ahead returns in excess of the cryptocurrency risk factors: market (CMKT), size (SMB), and momentum (CMOM) (Liu et al., 2022), and additional coin specific factors. That is, higher uncertainty beta coins that increase during heightened uncertainty yield lower average returns. In addition, it provides evidence that financial uncertainty is priced in the cross-section of portfolio crypto returns, as well as the cross-section of individual coin returns.

Our findings can be interpreted within the downside risk framework of Ang, Chen and Xing (2006), who demonstrate that assets' sensitivities to market downturns are crucial determinants of expected returns. In our study, we observe a negative relationship between cryptocurrencies' financial uncertainty beta (β_{FINU}) and their expected returns. This suggests that cryptocurrencies with higher β_{FINU}—meaning they co-move positively with financial uncertainty and perform better when it increases—offer hedging benefits against adverse market conditions. Consequently, investors are willing to accept lower expected returns on these cryptocurrencies due to their desirable hedging properties against downside risk. This dynamic is particularly relevant in the context of the cryptocurrency market; as traditional financial assets might be more exposed to common economic factors, cryptocurrencies—given their decentralized and novel nature—can offer unique diversification benefits.

Furthermore, our empirical findings suggest that only financial uncertainty significantly affects cryptocurrency returns, while macroeconomic, policy uncertainty and the VIX do not. This can be attributed to the unique characteristics of cryptocurrencies—they are decentralized, and not directly linked to any single economic or governmental policy, making them less sensitive to macroeconomic or policy-specific uncertainties. Financial uncertainty directly impacts investment flows into cryptocurrencies by encompassing factors such as credit conditions, market liquidity, and financial market stress. During periods of heightened financial uncertainty, investors may reallocate assets, increasing demand for cryptocurrencies and influencing their prices. Studies such as Corbet, Lucey, Urquhart and Yarovaya (2019) and Bouri, Hussain Shahzad and Roubaud (2020) support this view by highlighting that cryptocurrencies respond more to financial market dynamics than to macroeconomic factors

Moreover, the lack of significant impact from macroeconomic and policy uncertainties on cryptocurrency returns can be further understood by considering the intrinsic attributes of cryptocurrencies. Unlike traditional assets, cryptocurrencies do not generate cash flows, dividends, or interest payments, and their valuations are not derived from underlying economic activities or corporate earnings (Biais et al., 2023). Instead, their value is largely driven by supply and demand dynamics within the crypto market itself, technological developments, and investor sentiment. Macroeconomic indicators such as GDP growth, unemployment rates, or inflation, which typically influence the performance of conventional financial assets, have limited direct relevance to cryptocurrencies (Corbet et al., 2019). Additionally, policy uncertainties, often arising from governmental decisions and regulatory changes, may have a delayed or diffuse effect on cryptocurrencies due to their decentralized and borderless nature (Bouri et al., 2020). The global and digital character of cryptocurrencies dilutes the impact of localized economic or policy events, rendering macroeconomic and policy uncertainties less influential on their returns. This distinct separation underscores why financial uncertainty, which directly affects investor behavior and capital flows in financial markets, emerges as the primary uncertainty factor priced into cryptocurrency returns.

We further validate FINU, by orthogonalizing the measure relative to other uncertainty measures like macroeconomic, political, and market volatility indices, we find that the orthogonalized FINU beta remains negative and significant. This indicates that financial uncertainty uniquely affects cryptocurrency returns, independent of other forms of uncertainty. Additionally, employing a continuous measure of β_{FINU}, we observe a negative linear relationship with expected returns, consistent with traditional asset pricing models (Bali et al., 2017). Using a Generalized Method of Moments approach to address potential endogeneity concerns, the negative significance of β_{FINU} persists.

Our findings indicate that a coin's β_{FINU} exhibits autocorrelation for approximately 18 months and can predict one-month-ahead returns. This underscores the dynamic nature of the cryptocurrency market, suggesting that investors should rebalance their portfolios monthly to capture the H−L alpha. Although the coins' β_{FINU} are more transient compared to those of stocks and bonds, the monthly H−L portfolio strategy requires less frequent adjustments than the weekly rebalancing needed to capture the cryptocurrency three-factor alphas identified by Liu et al. (2022).

In the second part of our paper, we develop a novel taxonomy to categorize cryptocurrencies based on their core features. We find that the financial uncertainty premium (Low β_{FINU} minus High β_{FINU}) is large and significant for coins with speculative features—such as proof-of-work mechanisms and limited supply—indicating that these coins are more likely to be integrated into broader asset portfolios as a hedge against financial uncertainty. However, coins with transactional features (such as tokens and those with uncapped supply) show no significant variation across high and low β_{FINU} portfolios.

To observe this, we hand collect an array of taxonomic attributes for each coin, including their consensus mechanism, token status, mineability, transaction anonymity, presence of a white paper, and block generation speed. As a guide to create the taxonomy, we rely on the coin features reported in Howell, Niessner and Yermack (2020), Liu and Tsyvinski (2021), and Lyandres, Palazzo and Rabetti (2022).

We discover a significant return to the H−L strategy when examining subsamples of coins that share taxonomic features, which make them useful as speculative investments. These features include a proof of work consensus algorithm, operation as a unit of account in their own blockchain (nontoken), an official white paper, a restricted or finite supply of coins, nonanonymous transaction features, and a block generation time exceeding 30 seconds. Coins with speculative features exhibit a significant financial uncertainty premium, indicating that these coins provide hedging benefits against financial uncertainty, consistent with the downside risk framework proposed by Ang et al. (2006).

In contrast, features associated with transactional utility, such as anonymity, a proof-of-stake consensus algorithm, and token status, do not appear to generate significant returns to the H−L β_{FINU} strategy. Building on the framework presented by Biais et al. (2023), we propose that transactional cryptocurrencies derive their value primarily from their utility as a medium of exchange rather than as vehicles for price appreciation or as instruments for hedging against financial uncertainty.

To further validate our taxonomy, we construct a continuous Taxonomy Index that quantifies the degree to which each cryptocurrency exhibits speculative or transactional features. This index assigns positive values to speculative attributes— and negative values to transactional characteristics. Additionally, we apply K-means clustering to classify cryptocurrencies into speculative and transactional groups based on their core features.

Our analysis using the Taxonomy Index and K-means clustering reinforces our earlier findings. We observe that coins classified as speculative exhibit a significant financial uncertainty premium, with higher returns associated with lower financial uncertainty exposure. Specifically, speculative coins in the low β_{FINU} portfolios yield substantial positive excess returns, while those in the high β_{FINU} portfolios do not. In contrast, transactional coins do not show significant variation in returns across different levels of financial uncertainty beta. These results confirm that our taxonomy effectively differentiates between coins in terms of their sensitivity to financial uncertainty, providing robust frameworks for investors to identify cryptocurrencies that may serve as effective hedging instruments or function primarily as mediums of exchange.

Next, we provide evidence that large investors accept lower returns by investing in overvalued cryptocurrencies with a high positive β_{FINU} because these coins can act as a portfolio hedge.[3] We employ a unique data set of cryptocurrency transactions to test whether the mean trade size increases with a coin's financial uncertainty β. We uncover a positive relation between average trade size and β_{FINU}, with high β_{FINU} coins experiencing 42% larger mean trade size relative to low beta coins. Moreover, we do not see a similar effect for MACU, highlighting that crypto investors primarily focus on financial, not macro, uncertainty. We also employ our taxonomic indices and find that the hedging behavior is most prominent in the most speculative groups of coins. Given that mean trade size differs based on their financial uncertainty beta, we suggest that larger investors incorporate information from the FINU index into their overall asset allocation strategies, including cryptocurrencies. Specifically, we provide evidence that institutions/large investors use high β_{FINU} cryptocurrencies as a hedge in their broader financial portfolios and consequently receive lower returns (Campbell, 1993).

Finally, we conduct a series of additional robustness tests tailored specifically for cryptocurrency markets to clarify the profitability of the H$-$L strategy. In light of the unique challenges presented by the COVID-19 pandemic, we segment our data into pre- and post-2020 periods. We evaluate the robustness of the 1-month forward-looking FINU measure by analyzing the impacts of 3- and 12-month forward-looking FINU on monthly returns (Lud-

[3] Bali et al. (2017) claims that institutions use high β_{UNC} stocks as a hedge against macro uncertainty. In doing so, they accept lower future returns.

vigson et al., 2021). We exclude Bitcoin from the sample—an essential step—as its market value accounts for an average of 50% of the sample weight. We further limit the sample to coins that have existed for at least two years. In accordance with Liu et al. (2022), we use Bitcoin as the short portfolio, as it may be difficult to open a short position in many of the coins in the sample (due to the limitations of trading platforms or the absence of derivatives), and we finally limit the sample to the top 50 coins by market capitalization to address liquidity concerns. Intriguingly, the efficacy of the H−L strategy is robust across all additional specifications.

Overall, our findings suggest that cryptocurrency valuations reflect known coin-specific risks (market, size, and momentum) and exogenous financial uncertainty. Unlike traditional securities, the value of cryptocurrencies is not driven by macroeconomic variables. For instance, spikes in macro or real uncertainty do not elicit significant reactions in cryptocurrency prices, consistent with teh arguments of Biais et al. (2023) that crypto prices are influenced by factors other than traditional economic drivers. Interestingly, whereas no apparent direct economic linkage, such as earnings or cash flows, exists between stocks and cryptos, financial contagions from equity markets can still influence crypto valuations. For example, during heightened financial uncertainty, such as stock market downturns, the demand for hedging increases. This increase propels investors toward cryptocurrencies with high β_{FINU} as a safeguard, resulting in buying pressure. Conversely, those with a low β_{FINU} may face selling pressure. These reactions often cause transient over or undervaluation in coins.

In summary, we contribute to the literature by identifying how financial uncertainty, not other forms of uncertainty, are priced in the cross-section of cryptocurrency returns, a topic that has been largely unexplored to date. Second, we introduce a novel taxonomy for categorizing cryptocurrencies based on their utility as speculative or transactional coins and show how this affects the sensitivity of their returns to financial uncertainty. Last, our study contributes to practical knowledge by shedding light on how large investors may be using high beta cryptocurrencies as a hedge against financial uncertainty, causing them to be overvalued. Our insights may be pertinent for institutions that have hedging requirements during periods of financial uncertainty and provide useful evidence for policymakers on the interlinkages of cryptocurrencies to the broader financial market, particularly in the wake of large, notable collapses, including Silicon Valley Bank (SVB) and the FTX exchange.

2 Cryptocurrency risk factors

Cryptocurrencies (coins) represent a new and unusual type of financial asset—they are unregulated (Howell, Niessner and Yermack, 2020) and widely used in illegal activities (Foley, Karlsen and Putniņš, 2019). Due to the lack of explicit cashflows, they are challenging to value (Chod and Lyandres, 2021; Cong, He and Li, 2021), and thus, their asset pricing features are still not fully understood.

Prior theoretical work on cryptocurrency valuations suggests several factors as important determinants of cryptocurrency returns. One group of papers focuses on the novelties brought about by blockchain technology and the related features of the cryptocurrencies (Cong, He and Li, 2021; Sockin and Xiong, 2023). These studies contend that the underlying technologies on which cryptocurrencies are built (e.g., mining and mining dynamics) are fragile; therefore, cryptocurrencies may not represent a reliable investment (Easley, O'Hara and Basu, 2019; Cong, He and Li, 2021; Pagnotta, 2022; Hinzen, John and Saleh, 2022). In general, such factors driving the prices of crypto assets are referred to as production factors (Liu and Tsyvinski, 2021).

A second set of studies emphasizes the economic value of coin, which typically derives from the network effects and product ecosystems created through the sale of tokens and coins (Cong, He and Li, 2021; Sockin and Xiong, 2023; Pagnotta, 2022; Iyengar, Saleh, Sethuraman and Wang, 2023; Biais et al., 2023). Much of this research claims that the economic value of cryptocurrency is derived from its ability to create product ecosystems (the network effect) that are expected to bring future cash inflows into the underlying project. As such, a coin's economic value can be derived from any future cash inflows, as is the case with stocks and bonds (Biais et al., 2023). Liu and Tsyvinski (2021) claim that these risk and cashflow factors are indeed incorporated into crypto prices; however, the production factors do not, suggesting that economic factors drive cryptocurrency returns entirely. They also claim that very little value or risks are embedded in the various production technologies of cryptocurrencies, such as mining features, payment system uses, transaction speeds (average block time), and transaction fee amounts.

Another set of studies analyzes whether cryptocurrencies exhibit any well-known pricing anomalies prevalent in stock markets (market, size, momentum, etc.). For example, two recent papers by Liu and Tsyvinski (2021) and Liu et al. (2022) estimate the valuations of the cryptocurrency market at both the time series and cross-section. These studies find that cryptocurrency returns have low exposure to risk factors in traditional financial markets[4], these returns can be predicted by cryptocurrency-specific time-series factors, such as time-

[4] For example, cryptocurrency returns are not significantly correlated with aggregate consumption or production growth (Liu and Tsyvinski, 2021), which are considered important drivers of equity returns.

series momentum and investor attention (Liu and Tsyvinski, 2021), as well as the following cross-sectional risk factors: cryptocurrency market, size, and momentum. Hu, Parlour and Rajan (2019) identify that most cryptocurrency returns have positive correlations with Bitcoin returns, suggesting that Bitcoin may serve as 'the market' risk factor for cryptocurrency assets. Borri (2019) shows that cryptocurrency returns are exposed to both the skewness and tail risks prevalent in the crypto markets.

In our study, we concentrate on the impact of aggregate financial uncertainty on the cross-sectional pricing of cryptocurrency returns. We take as given the abovementioned cross-sectional risk factors (the cryptocurrency market, size, and momentum factors proposed by Liu et al. (2022)), and we control for these factors in our cryptocurrency returns models. We then show that the Ludvigson et al. (2021) financial uncertainty index is a systematically priced risk factor in the cross-section of cryptocurrency returns.

Our analysis builds on the theoretical and economic arguments made by asset pricing studies that link uncertainty to various financial assets, such as stocks (Pastor and Veronesi, 2012; Brogaard and Detzel, 2015; Bali et al., 2017), bonds (Bai, Bali and Wen, 2019; Bali et al., 2021), and equity options (Kelly et al., 2016). We also rely on the hedging argument originally made by Merton (1973) and Ang et al. (2006), and adopted to policy uncertainty literature by Bali et al. (2017).

This propensity explains the pronounced negative uncertainty premium associated with high β_{FINU} cryptocurrencies attributable to current elevated hedging demands vis-à-vis future returns.

3 Data and sample selection

In this section, we describe our data collection process—including uncertainty indices, market data, taxonomy creation, and the proprietary trade dataset for various cryptocurrencies. We also present descriptive statistics for our uncertainty indices and cryptocurrency variables.

3.0.1 The nature of the uncertainty indices

The Jurado et al. (2015) macroeconomic uncertainty indices (henceforth known as JLN) quantify aggregate uncertainty as the conditional volatility of the purely *unforecastable* component of the future value of a time series of economic indicators. Constructing each of the JLN uncertainty indices begins with selecting multiple time series representing a range of economic activities. Forecasts are built for each data series utilizing autoregressive models. Subsequently, forecast errors are obtained by calculating the differences between each series's actual and predicted values. Then, these forecast errors are squared and averaged to produce a composite measure of macro uncertainty depending on the underlying time series data used.

To construct the macro uncertainty index (MACU), JLN uses information from 132 different macroeconomic time series. These macroeconomic variables include real output and income, employment, consumer spending, housing starts, inventories, capacity utilization measures, and price indices, among others. The MACU index focuses on both real (production, wages, and employment) and nominal (inflation and money growth) activities.[5]

[5] For a detailed breakdown of this methodology and the full variable list used to create each of the JLN indices, refer to Jurado et al. (2015) and Ludvigson et al. (2021).

Building upon the JLN framework, Ludvigson et al. (2021) developed a distinct financial uncertainty index (FINU) that isolates uncertainty originating specifically from financial markets, separate from macroeconomic uncertainty. The FINU index uses time series data from 147 financial variables and valuation ratios. These financial variables includes indicators such as the dividend-price ratio, term spreads on corporate and treasury bonds, and a broad cross-section of portfolio equity returns, including the Fama and French (1993) factors.[6] All JLN indices are available monthly from July 1960 to December 2021.

The POLU index of Baker et al. (2016) is a news-based uncertainty index that is constructed using newspaper coverage of uncertainty-related words from 10 of the largest global newspapers.[7] When constructing the index, the authors conduct monthly searches in each publication for terms related to economic and policy uncertainty.[8] See Baker et al. (2016) for further details.[9] The POLU index tends to be more volatile than the JLN indices, because the daily or monthly political bickering in the newspapers is more dynamic than the macro or financial indicators comprising the JLN indices. However, similar to JLN (see Bali et al., 2017), the POLU index is priced in the cross-section of stock returns (Brogaard and Detzel, 2015); thus, it has the potential to affect cryptocurrency returns as well.

[6] Our qualitative conclusions are unchanged if instead of FINU, we use TFINU measure introduced by Ludvigson et al. (2021), which extends FINU by incorporating health- and COVID-19-related risks into the financial uncertainty measure.

[7] These papers include USA Today, the Miami Herald, the Chicago Tribune, the Washington Post, the Los Angeles Times, the Boston Globe, the San Francisco Chronicle, the Dallas Morning News, the Houston Chronicle, and the Wall Street Journal.

[8] Uncertainty terms include 'uncertainty' or 'uncertain', the terms 'economic' or 'economy', and one or more of the following terms: 'congress', 'legislation', 'white house', 'regulation', 'federal reserve', or 'deficit'.

[9] The POLU index is available at various frequencies; however, we use the monthly time series to be consistent with the frequencies of the other uncertainty indices. To address changes over time in the volume of articles for a given newspaper (briefly, "paper"), the index's authors divide the raw count of policy uncertainty articles by the total number of articles in the same paper and month. This number is then normalized to ensure that each paper has a unit standard deviation from January 1985 through December 2009. Next, the normalized values are summed over papers in each month to obtain a multipaper index. Finally, the multipaper index is normalized with a consistent value from January 1985 through December 2009.

As per Bloom (2009), we also investigate the role of the VIX on cryptocurrency returns. VIX is derived from the prices of out-of-the-money put options on the S&P 500 stock index that are set to expire over the next 30 days. Thus, VIX captures forward-looking expectations of volatility and tail risk in the equity market (Bekaert and Hoerova, 2014). In the context of our study, VIX provides insights into broader market sentiment and the degree of risk aversion among investors. Given the high volatility inherent in cryptocurrency returns, it is plausible that the market conditions and sentiment captured by VIX can have a significant impact on cryptocurrency prices.

3.0.2 Uncertainty indices: data collection and descriptive statistics

We extract monthly time series data for the one-month-ahead economic uncertainty indicators—Financial Uncertainty (FINU) and Macroeconomic Uncertainty (MACU)[10]—from the JLN online data set.[11] Additionally, we retrieve the Political Uncertainty (POLU) index from the Economic Policy Uncertainty website,[12] and the Volatility Index (VIX), and the monthly 3-month Treasury bill rate (used as a proxy for the risk-free rate) from the Federal Reserve Bank of St. Louis's FRED economic data set.

Table 1 presents the descriptive statistics and correlations among the uncertainty measures. In Panel A of Table 1, we see that FINU tends to be slightly higher than MACU, with a similar amount of variation. POLU, and VIX appear to be both higher in terms of nominal value and volatility than FINU, indicating that political uncertainty and market

[10] Although these indices forecast uncertainty one month into the future, we use lagged values in our regression models to capture the impact of past predicted uncertainty on current returns. The estimated uncertainty betas, therefore, reflect the relationship between past (one-month-ahead predicted) uncertainty and current cryptocurrency returns.

[11] Available at https://www.sydneyludvigson.com/macro-and-financial-uncertainty-indexes.

[12] Available at https://www.policyuncertainty.com/twitter_uncert.html.

volatility tend to fluctuate more dramatically. In Panel B, we observe that the correlation between FINU and MACU is 0.681, indicating a moderate level of co-movements between these indices. FINU exhibits slightly higher correlations with POLU and VIX, at 0.739 and 0.701, respectively, suggesting a stronger association with political uncertainty and market volatility.

[Insert Table 1 here]

Figure IA1 plots the time series of FINU alongside MACU, POLU, and VIX. These plots show that FINU frequently leads MACU, indicating that changes in financial uncertainty may forecast shifts in macroeconomic uncertainty. The financial markets appear to respond more swiftly to uncertainty than broader economic measures. While FINU closely tracks the fluctuations in POLU and VIX, its behavior is less reactive during periods of heightened uncertainty, reflecting its broader composition of economic variables. POLU and VIX, on the other hand, are more sensitive to immediate uncertainty-generating events; POLU reflects political shocks in a timely manner and VIX reacts quickly to market stress as it captures short-term volatility expectations. Additionally, the fact that VIX is a single-market measure derived from S&P 500 index options contrasts with the broader, more diversified nature of FINU.

[Insert Figure IA1]

3.1 Cryptocurrency data

We obtain cryptocurrency market data, such as price and trading volume, from the BNC-supported Nasdaq API.[13] We collect time series market capitalization data from Coinmarketcap.com. Our sample period of cryptocurrency market data runs from April 2014 to December 2021. A cryptocurrency is included in the sample if it has market data available during this period prior to 2022. We select cryptocurrencies with market capitalization greater than $5 million to mitigate liquidity constraints and the potential for delisting of coins during the sample period.[14] In addition, we exclude observations for which the β_{UNC} exceeds $-/+10$).[15]

To determine whether coins with speculative or transactional features affect the role of uncertainty in crypto returns, we construct a unique taxonomy of cryptocurrencies. We begin the taxonomy formation using BNC's data on cryptocurrency characteristics.[16] These characteristics contain information on the consensus mechanism, hash algorithm, average block time, transaction anonymity, smart contract support, genesis date, and maximum and total circulating supply. We build upon the BNC taxonomy with data from the following cryptocurrency websites: Coinmarketcap.com and Advfn.com, and we manually scrape the respective coin's white paper. We collect whitepapers from different sources, including the cryptocurrency's website, GitHub account, or Coinmarketcap.com. We comprehensively

[13] Brave New Coin (BNC) is a data and research company that focuses on the blockchain and cryptographic assets industry. It collects market data from centralized exchanges for all publicly traded cryptocurrencies. While both Aspris, Foley, Svec and Wang (2021) and Makridis, Fröwis, Sridhar and Böhme (2023) show that the volumes traded in decentralized exchanges are growing, they are still relatively minor compared to centralized exchanges.

[14] We are concerned with intermarket linkages between the crypto and broader financial market; thus, very small coins do not possess the liquidity to accommodate large investors such as institutions.

[15] The β filter reduces the sample by less than 1% and prevents extreme outliers from influencing the results.

[16] Using extensive holdings data and industry knowledge, BNC develops a general taxonomy for cryptographic assets.

describe the taxonomic characteristics in the results section of the main paper, and in Tables A1 and A2.

In our study, we employ data on average daily trade size, denominated in U.S. dollars, for a subset of the cryptocurrencies. These data are expected to reflect the categories of investors engaged in trading on a given day, whether by large institutional investors/whales or smaller individual investors. The trade size helps us determine whether coins with a high uncertainty beta predominantly attract substantial institutions or minor individual traders. The method is adapte from equity market research, with Lee and Radhakrishna (2000) using trade size to differentiate between institutional and household trading. We source our data from Messari.io, drawing from Coinmetric's database, including daily network activity from April 2014 to December 2021 for 60 leading cryptocurrencies by market capitalization. This data set reflects approximately 78% of our sample's total market capitalization as of December 31, 2021. We report the coins present in the trade data set in Appendix IA2.

3.2 Cryptocurrency descriptive statistics

Panel A of Table 2 presents annual averages for the cryptocurrency dataset, including the total count of coins, their average market-capitalization weighted monthly return (RT), dollar market capitalization in millions (MKTCAP), and the mean age of the coins in years (AGE). In 2015, we have 12 cryptocurrencies in our sample, with the number of coins reaching as high as 583 by the end of 2021. We report the descriptive statistics following the calculation of the respective uncertainty beta, requiring at least one year of prior data. Thus, this drops all coins in 2014. The average size of the coins in our sample varies significantly over time. The sample becomes populated with newly issued cryptocurrencies as the crypto market experiences boom and bust cycles. Due to the requirement that information on the underlying cryptocurrency characteristics is manually collected, we cannot work with the thousands of cryptocurrencies listed on popular websites, many of which lack trading volume and have a market capitalization lower than the $5 million cutoff. As such, our sample is more similar to existing academic cryptocurrency studies such as (Howell et al., 2020) and Liu and Tsyvinski (2021). For example, the average return of 0.105 per month (0.024 per week) in our sample is comparable to the returns reported in Liu et al. (2022).

In Table 2, Panel B, we report descriptive statistics by FINU tercile. For the β_{FINU}, there is a clear progression from low to high terciles, moving from -2.040 to 0.385. The result suggests that all coins tend to be more negatively related to FINU, which is expected, as asset values should fall on average when uncertainty increases. Interestingly, MKTCAP is the largest for the medium tercile, mainly because it contains the three most popular coins—Bitcoin, Ethereum, and Solana. The β_{FINU} of the coin and their β relative to CMKT, CSMB, and CMOM appear to be negatively related.

[Insert Table 2 here]

In Table 2, we report the descriptive statistics of the R^2 from regressions of coin by coin monthly excess returns on the financial uncertainty and Liu and Tsyvinski (2021) factors. This allows us to identify which factors have the greatest average effect on coin returns across the sample. FINU yields the highest explanatory power (0.084), above any uncertainty metrics and the Liu and Tsyvinski (2021) factors.

4 Empirical Results

In this section, we use portfolio sorts to demonstrate that financial uncertainty (FINU) is priced in the cross-section of coin returns in excess of the established cryptocurrency three factors. In addition, we report that other forms of uncertainty (UNC: MACU, POLU, and VIX) do not have a strong effect on the crypto markets.

4.1 Univariate portfolio analysis: uncertainty indices

Following Bali et al. (2017), we construct the uncertainty β_{UNC} for each coin each month. The beta is calculated by running rolling monthly regressions of excess returns (coin return less risk-free rate) on each uncertainty index (UNC) using data from the previous 24 months. To be included in the results, a cryptocurrency must have a minimum of 12 consecutive monthly observations leading up to the formation period.[17]

To form portfolios, we sort cryptocurrencies into market-capitalization-weighted tercile portfolios based on their estimated β_{UNC} at the start of each month. Tercile one (LOW_UNC) includes cryptocurrencies with the lowest β_{UNC}, while terciles two (MED_UNC) and three (HIGH_UNC) contain those with medium and high β_{UNC} values, respectively. This sorting process results in three portfolios for each month in our sample period. We then calculate the market-capitalization-weighted excess returns for each portfolio over the subsequent month. Repeating this process each month generates a time series of monthly returns for each uncertainty tercile portfolio.

To evaluate the relationship between uncertainty betas and future returns, we regress

[17] Prior studies (Bali et al., 2017) use 60-month rolling periods when calculating β_{UNC}. However, due to the limited lifetime of cryptocurrencies, we employ a 24-month window. Our results are qualitatively similar when we use an 18- or 30-month window.

the time series of monthly excess returns for each uncertainty tercile portfolio on known cryptocurrency risk factors. These are the market (CMKT), size (CSMB), and momentum (CMOM) factors, of Liu et al. (2022). Table 3 presents the results for each tercile portfolio for all uncertainty metrics. The final row (H−L) shows the difference in coefficients between the HIGH_FINU and LOW_FINU portfolios.[18] Standard errors are computed per Newey and West (1987), aligning with Liu and Tsyvinski (2021).

[Insert Table 3 here]

Within Table 3, Panel A, Column 1, the LOW_FINU portfolio exhibits a significant positive return of approximately 30.4%, while the HIGH_FINU portfolio's 9.3% is not statistically significant. Most importantly, the differential portfolio of HIGH minus LOW (H−L) β_{FINU} yields a significant -21.1% per month return. In Column 4, when accounting for all three crypto factors, the H−L portfolio maintains a statistically significant return. Considering the challenges associated with short selling in the cryptocurrency market, as outlined by Garfinkel, Hsiao and Hu (2023), the strategy of focusing solely on long positions, as demonstrated in Column 4, generates a substantial monthly return of 0.211%. This return is realistically achievable for investors despite the limitations imposed by short-selling constraints.[19]

Having established the importance of financial uncertainty, we now examine whether other forms of uncertainty are also priced in the cross-section of cryptocurrency returns. In Table 3, Panel A, Columns 5–8, we observe that the H−L portfolio returns for MACU are insignificantly different from zero, suggesting that macroeconomic uncertainty does not

[18] The portfolio method we employ is very similar to Ang et al. (2006).
[19] We address short-selling limitations further in Section 7 and Table 8 by using Bitcoin as the short portfolio.

influence crypto returns. In Panel B, Columns 1–4, although POLU generates significant returns for the H−L portfolio, however, this significance does not persist under the stricter regression framework of Fama and MacBeth (1973) employed in Table 4. The H−L returns for the VIX portfolios are also non-significant in columns 5-8. These findings reveal that crypto investors do not demand significant excess returns to hold coins with low uncertainty betas when the source of uncertainty is macroeconomic, policy-oriented, or market volatility-related. Furthermore, the HIGH_UNC portfolios tend to exhibit positive but statistically insignificant returns, indicating that crypto investors are not penalized by lower returns for holding such high-uncertainty portfolios. This suggests that uncertainty measures that rely on non-financial sources (e.g., news-based, macroeconomic, or market volatility indices) are not priced in the cryptocurrency market.

The results in Table 3 support our claim that certain interlinkages exist between the traditional financial market and the crypto markets, as the hedging utility of high beta coins leads them to be overvalued relative to low beta coins. For example, the returns of individual cryptocurrencies in the LOW_FINU portfolio are negatively correlated with financial uncertainty (i.e., they decrease in value during periods of uncertainty). Hence, to hold these cryptocurrencies uncertainty-averse investors demand extra compensation in the form of higher expected returns, which is present given that this portfolio yields 30.4% per month. On the other hand, individual crypto returns in HIGH_FINU are positively correlated with FINU (i.e., they increase in value during periods of uncertainty), which can be used as a hedging instrument against spikes in uncertainty. Thus, investors are willing to pay higher prices (and accept lower future returns) for HIGH_FINU cryptocurrencies, as they do so for stocks and bonds with high sensitivity to uncertainty (Bali et al., 2017, 2021) as they have hedging utility (Ang et al., 2006).

The only form of uncertainty priced in the cryptocurrency market appears to be the unexplained component of the 147 financial indicators that form the financial uncertainty index (FINU) of Ludvigson et al. (2021). Thus, factors that surprise equity investors seem to spill over to affect crypto market participants. Since equity and cryptocurrency markets do not appear to have any economic fundamentals in common (no earnings or cash flow linkages), such spillovers could be financial and could occur only if cryptocurrencies were part of a more extensive portfolio with an equity component. In line with claims of Ang et al. (2006), when equity traders are surprised (or uncertain) about the financial valuation of equities, they may use other assets (cryptocurrencies) with high β_{FINU} as a hedge. Doing so can create a temporary overvaluation of these financial instruments that corrects itself in the future - this is evident as the high β_{FINU} portfolio has relatively lower future returns.

4.2 Fama-Macbeth regressions

The portfolio sorts in Table 3 reveal a negative relationship between the current month's financial uncertainty beta and the subsequent month's cryptocurrency returns. We employ the Fama and MacBeth (1973) regression method as per Bali et al. (2017) to substantiate these results. The coin-month level Fama–Macbeth approach allows us to assess if all four forms of uncertainty are priced in the cross-section of individual cryptocurrencies as well as the cross-section of cryptocurrency portfolios.

$$\begin{aligned} Rt_{i,t} = \beta_0 + \beta_1 UNC_{i,t,u} + \beta_2 CMKT_{i,t} + \beta_3 CSMB_{i,t} + \beta_4 CMOM_{i,t} \\ + \beta_5 CDOWN_{i,t} + \beta_6 AMIHUD_{i,t} + \beta_7 RISK_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{1}$$

In this model, $Rt_{i,t}$ represents the return of the coin i in month t in excess of the risk-free rate. The independent variables include: $UNC_{i,t,u}$, which captures the uncertainty indices beta for the respective index u; $CMKT_{i,t}$, the beta of the cryptocurreny market factor; $CSMB_{i,t}$, the beta of the crypto size factor; $CMOM_{i,t}$, the beta to the crypto momentum factor; $CDOWN_{i,t}$, the coins downside risk beta (Ang et al., 2006); $AMIHUD_{i,t}$, the illiquidity measure from Amihud; and $RISK_{i,t}$, the prior 180-day standard deviation of daily returns. The standard errors are adjusted using the approach of Newey and West (1987) with one month lag.

In Table 4, Panel A, we present the time-series averages of the slope coefficients from market-capitalization-weighted Fama–MacBeth regressions. The dependent variable is the monthly excess return. The key independent variable is the tercile rank of the current month's uncertainty betas (β_{UNC}).[20] As control variables, we include the coin's 24-month rolling β relative to the three cryptocurrency risk factors(CMKT, CSMB, and CMOM)and various other coin-specific factors (AMIHUD, CDOWN, and RISK).[21] The regressions are run at a monthly frequency from April 2014 to December 2021. To address potential issues related to heteroskedasticity and autocorrelation, we employ Newey and West (1987) standard errors with one lag.

Table 4 reports the Fama–Macbeth results for each uncertainty index. In columns 1–5 of Panel A, we find that our measure of financial uncertainty beta (β_{FINU}) relates negatively (significant at the 1% level) to the next month's excess returns even after implementing the more rigorous Fama-MacBeth method and the inclusion of coin controls. In economic terms,

[20] We follow Liu and Tsyvinski (2021), who sort crypto betas each month into terciles to prevent extreme observations from skewing the results within their Fama–Macbeth regressions.

[21] Zhang et al. (2021) shows that the downside risk beta influences coin returns. This beta measures the sensitivity of a cryptocurrency's returns to market downturns.

moving from the top to the bottom tercile of β_{FINU} corresponds to an increase in expected monthly excess returns of approximately 0.198% to 0.320%. This finding confirms that FINU is priced in the cross-section of cryptocurrency returns.

In short, Table 4, reveals that the sensitives of MACU, POLU, and VIX (β_{MACU}, β_{POLU}, β_{VIX}) are not significantly related to future excess returns, unlike equities where they are priced in the cross section(Pastor and Veronesi, 2012).

The lack of significance of these uncertainty measures in the cryptocurrency market may reflect the unique nature of cryptocurrencies as decentralized assets that operate independently of central banks and national economies. Cryptocurrencies are not tied to any specific country's economic performance or monetary policy, making them less sensitive to macroeconomic and policy uncertainties that affect national financial assets. Instead, they are more influenced by global financial market dynamics and investor sentiment, which are encapsulated in financial uncertainty indices. Moreover, cryptocurrencies are characterized by high volatility, speculative trading, and the absence of intrinsic value derived from cash flows or earnings (Corbet et al., 2019). These attributes make them less responsive to macroeconomic indicators like GDP growth, inflation, or interest rates. Studies by Bouri et al. (2020) demonstrate that cryptocurrencies can act as hedges or safe havens during periods of financial market turmoil, but are less effective against economic policy uncertainties. Liu et al. (2022) suggests that cryptocurrency returns are primarily driven by cryptocurrency-specific risks and factors unique to the digital asset ecosystem rather than broader economic variables. This notion is further supported by Cong, He and Li (2021), who highlight that the valuation and adoption of cryptocurrencies are influenced by network effects and technological advancements—factors not directly captured by traditional macroeconomic or policy uncertainty measures.

[Insert Table 4 here]

4.3 Alternative FINU specifications

Having established the significant effect of financial uncertainty on cryptocurrency returns, we now explore alternative specifications to validate the robustness of our results. Specifically, we orthogonalize FINU with respect to other uncertainty indices to isolate its unique impact, examine the continuous measure of β_{FINU}, employ a Generalized Method of Moments (GMM) approach to address potential endogeneity concerns, and analyze the persistence of β_{FINU} over time through autocorrelation analysis to assess different cryptocurrencies effectiveness as a hedge.

We first create an orthogonalized measure of financial uncertainty, denoted as $\text{FINU}^{\text{Orthog}}$, to ensure that our results are not driven by correlations with other uncertainty indices. We regress the nominal values of FINU on MACU, POLU, and VIX, and use the residuals from this regression as the orthogonalized measure. This process isolates the component of financial uncertainty that is independent of macroeconomic, political, and market volatility uncertainties. We then calculate $\beta_{\text{FINU}}^{\text{Orthog}}$, which reflects the coin's 24-month rolling β relative to the orthogonalized measure. We report the results in Table IA1.

In Table IA1, Panel A, Columns 1-3, we see that the $\beta_{\text{FINU}}^{\text{Orthog}}$, is significant and only slighter lower than the β_{FINU} at -0.136. This finding reinforces that financial uncertainty, independent of other forms of uncertainty, is indeed priced in the cross-section of cryptocurrency returns. We also include the continuous value $\beta_{\text{FINU}}^{\text{Cont}}$ to align with methods more typically used in equities research Bali et al. (2017). As with the tercile measure employed in Table 4, the continuous measure is negative and significant, supporting our expectation that FINU has a negative linear relationship with crypto returns.

Next, we estimate the relationship between excess monthly returns, key uncertainty measures, and market factors using a market-capitalization weighted two-step Generalized Method of Moments (GMM) model with robust standard errors. The dependent variable is excess monthly returns, and the independent variables include financial uncertainty (β_{FINU}) and the controls used in Table 4. The GMM model incorporates multiple lags of each independent variable as instruments, allowing us to address potential endogeneity concerns. We report the results in Table IA1, Panel A, Columns 7–9. Like the Fama-Macbeth specification, β_{FINU} remains negative and significant with and without the inclusion of controls.

[Insert Table IA1 here]

Investors are compensated for holding cryptocurrencies with a high β_{UNC} in the previous month. However, such investors may also want to plan further ahead, which is a difficult task in rapidly changing cryptocurrency markets. Therefore, knowing whether β_{FINU} is a persistent or evolving characteristic is crucial for medium- to long-term portfolio allocation and hedging decisions. Our next analysis aims to understand the temporal dynamics of financial uncertainty in cryptocurrency markets and assess the suitability of these cryptocurrencies as potential hedging tools against financial uncertainty.

Next, we examine whether a coin's FINU beta becomes more stable over time. To assess the persistence of the uncertainty beta, we examine the autocorrelation of the contemporary month's uncertainty beta to the n-months-ahead β_{FINU} using the Fama–MacBeth framework.

Within Table 5, Panel B, Column 1, we see that β_{FINU} is autocorrelated as far back as 24 months. However, with the inclusion of the Liu and Tsyvinski (2021) three factors, β_{FINU} only exhibits significant autocorrelation for up to 18 months. Thus, the financial uncertainty beta of cryptocurrencies appears transient. In comparison, Bali et al. (2017) observes that stock level β_{UNC} tends to be autocorrelated out to five years. The transient nature of β_{FINU} in cryptocurrencies has important implications for investors. It indicates that the hedging benefits of high β_{FINU} coins may not be stable over long horizons, necessitating more frequent portfolio adjustments. This aligns with the cryptocurrency market's dynamic and rapidly evolving nature, as highlighted by Liu and Tsyvinski (2021), who use weekly data to capture market movements more effectively. These insights are valuable for investors seeking to incorporate cryptocurrencies into their portfolios as hedging instruments against financial uncertainty.

5 The cryptocurrency taxonomy

In this section, we establish a novel categorization (taxonomy) of cryptocurrencies based on their underlying features, denoting them as speculative or transactional. Our goal is to understand whether a coin's underlying features determine the effect of financial uncertainty on its subsequent returns. For this purpose, we construct novel measures of a cryptocurrencies speculative nature.

5.1 The importance of the cryptocurrency taxonomy

Building on the popular classification of cryptocurrency as a 'digital currency' or a 'digital commodity', we categorize features based on their core technology. We distinguish between cryptocurrencies with 'speculative' features, which have characteristics that make them more suited for investment and might be sensitive to financial uncertainty or used as a hedge, and cryptocurrencies with 'transactional' features, which have characteristics of a currency and are thus less likely to be sensitive to exogenous uncertainty.[22] We use the following cryptocurrency characteristics to form the taxonomy: consensus mechanism, token status, mineability, transaction anonymity, presence of a white paper, and block generation speed. The classification is guided by the taxonomy development framework proposed by Nickerson, Varshney and Muntermann (2013), and the features are described in depth in Appendix A1.

Given the utility of different features and their associated clientele, the risk-return trade-offs are expected to differ considerably between speculative and transactional cryptocurrencies. Cryptocurrencies with features typically associated with speculative assets may strongly correlate with financial uncertainty, acting as alternative investments during market downturns. Investors may be more likely to use speculative cryptocurrencies as a hedge, as they have features typically associated with traditional financial assets. Cryptocurrencies with features well suited for payment transactions, can act as a medium of exchange. As a result, they may be less useful as a financial hedge and, thus, they are less likely to exhibit sensitivity to financial uncertainty.

Cryptocurrencies with speculative features, similar to Bitcoin and Litecoin, often employ

[22] Although all cryptocurrencies can be used for speculation or transactions, we make the distinction based on the structural features of the cryptocurrencies. Thus, in a relative sense, the features make them more appropriate/efficient for the stated role.

a proof-of-work consensus algorithm—this ensures heightened security. They tend to have slower block speeds, reflecting a prioritization of network stability over efficiency.[23] Such cryptocurrencies also exhibit a nonanonymous blockchain, which improves traceability and trust in the investment context (Cole, Dyhrberg, Foley and Svec, 2022); a finite supply, which offers potential scarcity-driven appreciation; mineability, which signifies an inherent value derived from computational work; and iv) are usually non-tokens, often backed by comprehensive whitepapers (Biryukov, Khovratovich and Pustogarov, 2014), ensuring transparency and detailed insights for potential investors.[24] These attributes collectively mark them as prime investment assets for those looking to hedge against market uncertainties or capitalize on potential price appreciation.

On the other hand, cryptocurrencies with transactional features, akin to Ethereum and Monero, mirror the conventional attributes of fiat currencies. They often employ a proof of stake consensus algorithm, optimizing for energy efficiency and scalability; facilitate anonymous transactions, ensuring user privacy akin to cash transactions; feature faster block speeds, emphasizing transactional throughput; are typically non-mineable, reflecting their use-case-centered design rather than computational value extraction; the absence of a whitepaper often indicates a more practical, application-focused ethos (Buterin, 2013).

[23] While we classify cryptocurrencies with a proof of work consensus algorithm as speculative due to their emphasis on security over efficiency, some might argue that this consensus method does not inherently dictate a coin's speculative nature, as proof of work is merely a transaction validation method. However, historically, cryptocurrencies employing proof of work have been subject to greater price volatility and have been popularly used as investment assets rather than mediums of exchange. Additionally, the energy-intensive nature of proof of work makes transactions more costly and slower, detracting from its utility as a transactional currency.

[24] A white paper is a document that outlines the purpose of the cryptocurrency, the proposed technology, and the management of the project (Florysiak and Schandlbauer, 2022). It often serves as a roadmap for the project's future development and can be a determinant of its transparency and trustworthiness (Florysiak and Schandlbauer, 2022), as well as its long-term value and survival (Cahill and Liu, 2021; Thewissen, Shrestha, Torsin and Pastwa, 2022)

Predominantly geared toward transactions, these cryptocurrencies, exemplified by privacy-centric tokens such as Zcash and Monero, may be less influenced by financial uncertainty. As Biais et al. (2023) points out, their valuation is more tied to their transactional utility than to traditional financial fundamentals, emphasizing their role as cash equivalents.

Next, we explore whether features of the underlying cryptocurrency's design affect their sensitivity to financial uncertainty and alter subsequent returns. Can one use such features to improve the hedging capacity of their portfolio against uncertainty? This issue is relevant since Bali et al. (2017) finds that bivariate portfolio sorts based on uncertainty betas, and any other relevant factor (e.g., investment, ROE, book-to-market, etc.) provides useful insights into the stock factors that can absorb the alpha and, hence, explain the sensitivity of a stock to uncertainty. We extend this analysis for cryptocurrencies to determine the taxonomic factors that can make them useful for hedging financial uncertainty and/or can benefit from the H−L strategy.

To test our claims, we segment data on the abovementioned eight coin taxonomic characteristics as dummy variables: POW, POS, token, mineable, white paper, anonymous, infinite supply, and blockchain speed above 30 seconds.[25] Appendix A1 further describes these features, and Appendix A2 reports the proportion of cryptocurrencies by taxonomic features.[26]

Table 5 reports the results of first splitting the data into pairs based on each of the

[25] Numerous other consensus mechanisms exist in the blockchain landscape and within the taxonomic dataset, including, but not limited to, Proof of Burn, Proof of Space, and various forms of Byzantine Fault Tolerance. For our analysis, we split the sample on POW and POS due to their predominant presence as they account for over 65% of our unweighted sample and exceed 85% when value-weighted.

[26] While characteristics such as stablecoin status may provide a discernible distinction, they represent less than 3% of our sample and, thus, are not separately categorized in our analysis. In unreported analysis, removing stablecoins does not qualitatively affect the results.

eight coin characteristics. We then run portfolio sort regressions akin to those in Table 3 of excess return on the tercile portfolios (low, medium, high) for β_{FINU} and adjust standard errors according to Newey and West (1987). For example, we separate non-POW and POW cryptocurrencies to inspect whether each group generates a significant HIGH−LOW return. In Table 6, Columns 1 and 2 of Panel A, we observe that while cryptocurrencies with a POW consensus algorithm are a good hedge against financial uncertainty (they yield significant H−L returns), the non-POW are not. Similarly, the portfolios of cryptocurrencies with speculative features such as non-POS (Column 3), non-token (Column 5), and mineable (Column 8) all have significant variations in the high and low portfolios. In Panel B of Table 6, we continue to see positive and significant differences for cryptocurrencies with speculative features, which include cryptocurrencies with a white paper (Column 2), a finite supply (Column 3) that are nonanonymous (Column 5), and have a block time greater than 30 seconds (Column 7).[27]

Table 6, Panels A and B show that portfolios comprising cryptocurrencies with transactional features, such as proof of stake, tokens, nonmineability, absence of whitepapers, infinite supply, and anonymity, do not exhibit significant H−L returns. Notably, it is more than just a statistical nonsignificance; the economic significance of the POS and Token portfolios is almost zero.

[Insert Table 5 here]

Our taxonomy highlights distinct characteristics of cryptocurrencies, offering investors a deeper understanding of the features that can be advantageous during turbulent financial

[27] Ibikunle, Mollica and Sun (2024) provide signifcant evidence on the mechanisms by which anonymity can be deployed in blockchains.

times. Cryptocurrencies with speculative traits are more sensitive to FINU, positioning them as prime candidates for hedging portfolios. The cryptocurrencies with speculative features in the high tercile of FINU generate the most substantial returns. In contrast, cryptocurrencies with transactional attributes do not demonstrate significant returns in the H−L portfolio, suggesting a disconnect from the broader financial markets.

5.2 Taxonomy index

Building on our previous findings that a cryptocurrencies design features influence its sensitivity to financial uncertainty, we aim to quantify this relationship by developing a novel continuous index that positions cryptocurrencies along the speculative-transactional spectrum. This approach allows us to capture the degree to which specific characteristics contribute to a cryptocurrencies classification, providing a more nuanced understanding of how these features affect returns in the presence of financial uncertainty.

We employ two methods to create these continuous indices. The first method involves constructing a Taxonomy Index using specific cryptocurrency characteristics identified in our taxonomy. As discussed earlier and identified in their returns, cryptocurrencies with attributes such as POW consensus mechanisms, mineability, and the presence of a white paper tend to be used for speculative purposes and exhibit greater returns to the H−L portfolio. In contrast, cryptocurrencies with features like POS, infinite cryptocurrency supply, anonymity, and faster block times are designed to facilitate day-to-day monetary transactions and thus, they show lower returns to the H−L portfolio.

We define the speculation index as the sum of the relevant indicators.

$$\begin{aligned}\text{Taxonomy Index} = &(\text{POW} + \text{Mineable} + \text{White Paper}) \\ &- (\text{POS} + \text{Token} + \text{Infinite Supply} \\ &+ \text{Anonymity} + \text{Block Time} < 30\,\text{seconds})\end{aligned} \tag{2}$$

Higher values of this index indicate that a cryptocurrency has more speculative features, while lower (or negative) values suggest that it is more transactional in nature. This continuous measure allows us to assess the extent to which a cryptocurrencies features align with speculative purposes and analyze how this alignment affects its sensitivity to financial uncertainty.

The second method involves applying K-means clustering, an unsupervised machine learning algorithm widely used for classification tasks in finance (Dang, Chen, Yu, Chen and Yang, 2022; Herman, Zsido and Fenyves, 2022). K-means clustering partitions the data into K distinct, non-overlapping clusters by minimizing the within-cluster variation. Specifically, we set $K = \{2, 4, 7\}$ to categorize cryptocurrencies into clusters representing speculative and transactional cryptocurrency groups.

The algorithm solves the following optimization problem:

$$\arg\min_{C_1,\ldots,C_K} \sum_{k=1}^{K} \sum_{i \in C_k} |x_i - \mu_k|^2 \tag{3}$$

where x_i is the vector of taxonomic features for cryptocurrency i, and μ_k is the centroid of cluster C_k. The algorithm iteratively updates the cluster assignments and centroids until convergence is achieved.

After K-means clustering, we examine the characteristics of the cryptocurrencies within each cluster to label them as speculative or transactional, based on the predominant features present. This data-driven approach allows us to validate our Taxonomy Index classifications and ensure robustness in our categorization. By employing both the Taxonomy Index and K-means clustering, we provide robust frameworks for classifying cryptocurrencies along the speculative-transactional spectrum. This dual approach enhances the validity of our analysis by cross-validating the results obtained from two distinct methodologies. Table A2, Panels B and C, report the taxonomic features of the indices sorted into quartiles.

To test the effect of the taxonomy indices on the returns to financial uncertainty, we split the sample of cryptocurrencies into four groups based on their Taxonomy Index and K-Means clustering index scores, respectively. [28] Within each group, we perform univariate portfolio sorts based on the financial uncertainty beta (β_{FINU}) as per Table 5 and report the results in Table 6.

[Insert Table 6 here]

In Table 6, for the highly speculative group (quartile 4) identified by the Taxonomy Index, the difference in returns between the high and low β_{FINU} portfolios (H$-$L) is significant at -25.1%, indicating that cryptocurrencies with lower exposure to financial uncertainty yield higher returns among speculative cryptocurrencies. For the more transactional groups (quartile 1-3), the *LOW_FINU* and the *HIGH_FINU* portfolios exhibit no statistically significant difference. Thus, the result supports our earlier findings that financial uncertainty does

[28] This approach allows us to maintain sufficient sample sizes in each group for robust statistical analysis. The return and trade size results are robust between median (2) and septile (7) sorts. However, using finer partitions, such as deciles, would significantly reduce the number of cryptocurrencies in each category, undermining the reliability of the results due to limited sample sizes.

not impact the returns of transactional cryptocurrencies, and the effect of this uncertainty is focused on the cryptocurrencies with the most speculative features.

Similarly, the results obtained using the K-means clustering index (cluster 4) corroborate these findings. The H−L returns for the speculative group are significant at −23.2%, reinforcing that speculative cryptocurrencies with lower financial uncertainty exposure offer higher returns. In contrast, the other more transactional cluster does not exhibit significant H−L returns.

The ability of our Taxonomy index and K-means clustering index to effectively differentiate between speculative and transactional cryptocurrencies in terms of their sensitivity to financial uncertainty has important implications. For investors seeking to hedge against financial uncertainty, the ability to properly identify speculative cryptocurrencies with low β_{FINU} may enhance investor's portfolio performance by capturing higher expected returns associated with bearing uncertainty risk. Furthermore, understanding the distinct roles of different cryptocurrencies can inform portfolio construction and risk management strategies, particularly given the growing integration of digital assets into broader financial markets.

6 Mechanism: Large investor hedging

In this section, we analyze the mechanism by which cryptocurrencies with a high uncertainty beta become overvalued (See section 4). We partition cryptocurrencies based on the taxonomy indices to assess if the hedging behavior is constrained to speculative cryptocurrencies. This mechanism is based on the hedging-based rationale of Ang et al. (2006) and is empirically supported by previous research from Campbell (1993); Bali et al. (2017).

We argue that the overvaluation in high β_{FINU} cryptocurrencies is driven by their utility as a cross-market hedge and that some investors use this hedging tool to protect against the financial risk in the equity or bond markets. This argument implies that these traders' portfolios are large enough to include both traditional financial assets (such as stocks and bonds) and cryptocurrencies. When these traditional financial assets are shocked by financial uncertainty, investors seek hedging instruments, which we argue can be found, among others, in the cryptocurrency markets.[29] Natural candidates for traders with substantial enough portfolios to hold both traditional and crypto assets are large traders (potentially hedge funds or so-called 'whales' in the crypto markets).

To provide support for this mechanism, we use the trade-size data from subsection 3.1 to determine whether high-β_{FINU} cryptocurrencies are more commonly traded by large investors, as we expect their average trade size (TRADE_MEAN) to surpass that of low beta cryptocurrencies. The data set includes the mean daily trade size for 60 of the largest cryptocurrencies by market capitalization. We report the full list of cryptocurrencies in Appendix IA2. To act as a counterfactual, we also test whether trade size is related to β_{MACU} to determine if investors are sensitive to macroeconomic uncertainty.

Importantly, most of the HIGH_FINU cryptocurrencies are not necessarily the largest in terms of market capitalization. Table A3 in the Appendix lists the top 50 cryptocurrencies by mean market capitalization across the sample and shows their average β_{FINU} and their tercile (HIGH_, MED_, or LOW_UNC). The results in Table A3 make it clear that hedging

[29] Our argument does not imply that all financial uncertainty faced by all the traders is hedged with high uncertainty beta cryptocurrencies. For our argument to hold true, only a fraction of the traders in the traditional financial markets need to be hedging with cryptocurrencies. This fraction should be high enough to make a difference in the cryptocurrency markets, which are arguably still in their nascent stage and not as large in trading volume or market capitalization as other financial markets.

demand (HIGH_FINU) is not necessarily correlated with the market capitalization of the cryptocurrency (correlation between TRADE_MEAN and market capitalization is +0.038). For example, the top three cryptocurrencies by market capitalization (Bitcoin, Ethereum, and Solana) are not in the high FINU tercile and, thus, they are not necessarily useful as a hedge against financial uncertainty. Our hedging claims are related only to HIGH_FINU tercile cryptocurrencies. According to Table A3, they include cryptocurrencies such as Hex, Polkadot, Avalanche, and Aave.

To assess the relationship between trade size and financial uncertainty, we regress each cryptocurrencies monthly log mean trade size on dummies for HIGH_FINU, MED_FINU, LOW_FINU, and controls that are likely to affect trade size, such as market capitalization (MKTCAP), dollar trading volume for that month (DOL_VOL), lagged monthly return (LAG_RT), Amihud (2002) illiquidity during that month (AMIHUD), return volatility during the prior 12 months (RETVOL), and cryptocurrency fixed effects. We cluster the standard errors at the year-month level. The difference between the high and low terciles is reported in the bottom row of Table 7. In addition, we repeat the regressions using the MACU beta terciles to assess whether trade size is affected by macro uncertainty.

In Columns 1–3 in Panel A of Table 7, we report the coefficients for FINU terciles, while for Columns 4–6, we report the results for MACU. In Columns 1–3, the coefficient for H−L is statistically significant, ranging between 0.419 and 0.582. We see that high FINU beta cryptocurrencies have trade sizes at least 41% larger than those of low beta cryptocurrencies. These results hold even with the inclusion of cryptocurrency controls and fixed effects. The difference in trade size between terciles bolsters our claim that they are likely executed by larger investors. This finding suggests a possible hedging or strategic trading preference by such entities, influenced by a cryptocurrencies sensitivity to financial uncertainty. In Columns 4–6, we observe that the H−L coefficient for MACU is insignificant, suggesting that investors do not have a strong sensitivity to macro uncertainty in cryptocurrencies. The finding that macro uncertainties do not affect investor behavior or subsequent returns provides further evidence that certain interlinkages exist between the traditional financial and cryptocurrency markets.

Next, we analyze the differences in trade sizes for each quartile of the taxonomy indices. We first partition the cryptocurrencies into quartiles based on the taxonomic index, and K-means clusters. We then repeat the above analysis to determine the difference in the high and low FINU terciles. In Table 7, Panel B, we see significant positive coefficients from the H−L test only for quartile 4 and cluster 4. Meanwhile, we see slight negative H−L coefficients for quartiles 2 and 3, and for cluster 2. These results reveal that large traders rely on the most speculative set of cryptocurrencies to hedge their financial uncertainty. [30]

Overall, we provide evidence reinforcing our claim that large traders (perhaps institutional investors) are trading more frequently in cryptocurrencies with high uncertainty β, particularly those with speculative features, which increases the current demand for such cryptocurrencies. As this overvaluation corrects, we observe the negative relation between the next month's returns and the financial uncertainty beta reported in Tables 3 and 4. The results in Table 7 make it clear that this overvaluation is caused in part by large transactions/investors. We consider this pattern as evidence that high beta cryptocurrencies are used as a hedging tool with larger portfolio of financial assets — as they increase in price

[30] These results are qualitatively similar using sorts from two to seven groups, in which the most speculative group is the most positive and significant

during financial shocks. To the best of our knowledge, this is the first academic evidence demonstrating that certain cryptocurrencies are used as a hedge against a surprise crash in the equity or bond markets (cross-market hedging against financial uncertainty).

[Insert Table 7 here]

7 Robustness tests

As the cryptocurrency market is relatively new, it has a series of unique qualities that may influence our analysis. To bolster the credibility of our findings, this section provides additional tests aimed at ensuring the robustness of our results. These tests include segmenting the data into the pre- and post-COVID-19 period, using additional Ludvigson et al. (2021) thee-month and 12-month ahead FINU measures, removing Bitcoin from the sample, requiring cryptocurrencies to be at least two years of age, using Bitcoin as the short portfolio, focusing on the top 50 largest cryptocurrencies in terms of market capitalization, and applying the H−L strategy net of transaction costs.

These robustness tests are reported in Table 7, where we first sort cryptocurrencies each month into terciles based on their one-month-ahead FINU beta and then use them to predict future excess returns. In Table 7, Panel A, Columns 1-4, we segment the data to account for the volatility surges amidst the COVID-19 era. Consequently, the data are split into two periods: the pre-COVID-19 period [2014, 2020) represented in Table 8, Panel A, Columns 1 and 2, and the post-COVID-19 period [2020, 2021] for Columns 3 and 4. Notably, the alpha is more pronounced in the post-COVID-19 phase (-0.281) than in the pre-COVID-19 era (-0.181), further corroborating the strategy's efficacy, as it continues to yield significant profits during extreme uncertainty.

Next, we focus on the dynamic effects of FINU whereby we regress the excess returns on forward-looking FINU for three and up to 12 months into the future. In Table 7, Panel A, Columns 5-8, we report the results of portfolio sort regressions using 3-, and 12-month ahead FINU index. The findings, alongside the prior results, indicate that the H−L portfolio stays significant for 1-, 3-, and 12-month ahead FINU measures. However, generating conclusions from the forward-looking FINU measures is difficult, as one-month ahead FINU correlates with three months ahead FINU and 12-month ahead FINU at 99.84% and 97.58%, respectively.

In Columns 1 and 2 of Panel B in Table 7, we display the results after removing Bitcoin from the sample. This is of key importance as the excess returns are market-capitalization-weighted, and the removal of Bitcoin removes between 92% (in 2014) and 50% (in 2021) of the sample in the cross-section. Similarly, for Columns 3 and 4 in Panel B of Table 7, we remove all cryptocurrencies younger than two years of age.[31] The results are qualitatively similar to those in Table 3, as the H−L strategy remains significant for all specifications.

Despite the profitability of a long-only strategy in the low tercile, a legitimate concern is that taking a short position in many of the cryptos in the sample (Garfinkel et al., 2023) is infeasible. As per Liu and Tsyvinski (2021), we employ Bitcoin rather than the High β_{FINU} portfolio to act as the short portfolio. In Table 7, Panel B, Columns 5 and 6, we find that the returns to the Bitcoin minus Low (BTC−Low) strategy remain significant and are slightly larger than the H−L strategy at −0.235 versus −0.211 for the entire sample.

[31] The average age of the cryptocurrencies in the full sample declines during the period from 3.2 (in 2014) to 1.3 years (in 2021).

Another potential concern is that our results are driven by extremely small cryptocurrencies, even though our returns are value-weighted. Table 7, Panel B, Columns 7 and 8 provide the results of tests in which we include only the largest 50 cryptocurrencies in the sample (or fewer in the early years when there are less than 50 cryptocurrencies). Despite limiting the sample, the results are indistinguishable from the full sample results, as market-capitalization weighting already adjusts for cryptocurrency size.

Finally, we consider the effect of trading costs on the strategy's profitability. We follow Liu and Tsyvinski (2021) and consider the transaction fees, bid-ask spreads, and margin fees. We use upper bound calculations for these costs at 0.2% for platform transaction fees (0.4% for two legs), 0.5% for bid-ask spread (1% for two legs), and 1.4% to maintain a month-long short position in BTC. Given that our strategy yields approximately 21.1% per month, a reduction of 2.8% per month to 18.3% remains both sizable and statistically significant.

[Insert Table 7 here]

8 Conclusion

This paper explores the relationship between cryptocurrency returns and various forms of uncertainty. Cryptocurrency returns exhibit a significant response to financial uncertainty while remaining largely unaffected by other forms of uncertainty like macroeconomic, policy, or VIX. This unique relation underlines the distinct nature of cryptocurrencies, as they do not have underlying fundamentals like cash flows or dividends and are not tied to traditional economic indicators. This makes them less susceptible to external economic shocks but they are influenced by the broader financial markets.

Our study contributes to the evolving field of cryptocurrency research by introducing financial uncertainty as a pivotal risk factor. This complements existing models like the Liu and Tsyvinski (2021) three-factor model, by showing that financial uncertainty is systematically priced into the cross-section of cryptocurrency portfolios and coins. Thus, FINU is a vital part of any 'n-factor' asset-pricing model tailored toward such crypto assets.

We next conduct a taxonomic analysis to understand why certain cryptocurrencies are more sensitive to financial uncertainty than others. We create several novel taxonomic indices based on blockchain characteristics. Using these indices we show that the coins' returns that are most affected by financial uncertainty are those that have speculative features. This contrasts coins with transactional features that are insensitive to financial uncertainty.

Our paper also demonstrates that coins with high sensitivity to financial uncertainty (high β_{FINU}) tend to be overvalued (yield lower average returns). This suggests that these coins are being used as a hedge against financial risks emanating from traditional stock or bond markets. We also document larger trade sizes among high FINU beta cryptocurrencies, which points to the involvement of large financial institutions or major crypto-market players in a cross-market hedging strategy. This result is particularly noteworthy as it establishes a potential link between traditional financial markets and the cryptocurrency markets, suggesting significant spillover effects in line with investor hedging (Ang et al., 2006).

Looking ahead, our research opens new avenues for investigating other emerging digital assets, such as non-fungible tokens (NFTs). It may be interesting to assess whether these newer forms of assets also exhibit sensitivity to broader macroeconomic and financial uncertainties. This research can further clarify the evolving dynamics of digital assets within the larger financial ecosystem.

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Table 1: Uncertainty metrics

This table provides descriptive statistics and correlations for the monthly uncertainty (UNC) metrics. The UNC metrics include Economic Financial Uncertainty (FINU), Total Macroeconomic Uncertainty (MACU), Economic Policy Uncertainty (POLU), and the option-based volatility measure (VIX). Panel A presents the descriptive statistics. Panel B details the correlations, and the p-values are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The data span from April 2014 to December 2021.

Panel A: Descriptives

	Mean	SD	Min	25th	50th	90th	Max
FINU	0.895	0.156	0.676	0.778	0.866	1.016	1.436
MACU	0.686	0.167	0.525	0.583	0.617	0.732	1.268
POLU	1.033	0.989	0.221	0.467	0.717	1.199	5.482
VIX	1.733	0.667	1.010	1.318	1.564	1.924	5.414

Panel B: Correlations

	FINU	MACU	POLU	VIX
FINU	1.000			
MACU	0.681***	1.000		
	(0.000)			
POLU	0.739***	0.820***	1.000	
	(0.000)	(0.000)		
VIX	0.701***	0.776***	0.821***	1.000
	(0.000)	(0.000)	(0.000)	

Table 2: Descriptive statistics

This table presents the descriptive statistics for the sample following the calculation of β_{FINU}. Panel A displays the end-of-year coin values for quantity of coins (Coins), market capitalization-weighted monthly coin return (RT), coin market capitalization in millions (MKTCAP), and mean coin age in years (AGE). The bottom row is the average of the values across the sample. Panel B provides descriptive statistics for the FINU beta terciles, which include cryptocurrency market capitalization (MKTCAP), and the β of the three crypto factors: market (β_{CMKT}), size (β_{CSMB}), and momentum (β_{CMOM}). Panel C reports the descriptive statistics for the R^2 from regressions of monthly returns for each coin on the uncertainty indices and the factors outlined by Liu and Tsyvinski (2021). The data span from April 2014 to December 2021.

Panel A: Decriptives by year

Year	Coins	RT	MKTCAP	AGE
2015	12.507	0.021	59.891	3.204
2016	22.647	0.075	79.403	3.111
2017	120.880	0.496	572.498	2.901
2018	333.528	-0.137	274.275	2.301
2019	321.684	-0.008	90.644	1.955
2020	362.814	0.088	116.259	1.789
2021	583.834	0.203	457.821	1.627
Average	251.128	0.105	235.827	2.413

Panel B: Descriptives by β_{FINU} tercile

β_{FINU} Tercile	β_{FINU}	MKTCAP	β_{CMKT}	β_{CSMB}	β_{CMOM}
Low	-2.040	12.612	0.606	0.390	0.210
Medium	-0.657	45.479	0.482	0.204	0.084
High	0.385	20.164	0.444	0.195	0.071

Panel C: Average coin R^2

	Mean	SD	Min	25th	50th	90th	Max
FINU	0.084	0.111	0.000	0.011	0.042	0.113	0.749
MACU	0.058	0.102	0.000	0.004	0.021	0.063	0.700
POLU	0.063	0.095	0.000	0.009	0.033	0.077	0.936
VIX	0.061	0.083	0.000	0.009	0.035	0.080	0.897
CMKT	0.051	0.081	0.000	0.006	0.026	0.064	0.812
CSMB	0.031	0.080	0.000	0.001	0.005	0.020	0.856
CMOM	0.028	0.067	0.000	0.001	0.008	0.020	0.638

Table 3: Univariate portfolios of coins sorted by uncertainty beta

This table reports coefficients from regressions of market capitalization-weighted excess (return − risk-free rate) monthly cryptocurrency returns for tercile portfolios formed on uncertainty betas using measures: FINU, MACU, POLU, and VIX. Each month, cryptocurrencies are sorted into three portfolios: LOW_UNC (lowest uncertainty betas), MED_UNC (medium uncertainty betas), and HIGH_UNC (highest uncertainty betas). Regressions include the cryptocurrency market factor (CMKT), size factor (CSMB), and momentum factor (CMOM) as explanatory variables. The final row shows the coefficient differences between the highest and lowest uncertainty beta portfolios (H−L). Newey and West (1987) adjusted t-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample period is from April 2014 to December 2021.

Panel A: JLN indices								
	1	2	3	4	5	6	7	8
	FINU				MACU			
LOW_UNC	0.304***	0.193***	0.195***	0.197***	0.166***	0.089*	0.090*	0.086*
	(4.747)	(3.187)	(3.197)	(3.188)	(3.215)	(1.775)	(1.786)	(1.691)
MED_UNC	0.134**	0.023	0.025	0.027	0.095*	0.018	0.019	0.015
	(2.090)	(0.380)	(0.403)	(0.430)	(1.839)	(0.357)	(0.375)	(0.297)
HIGH_UNC	0.093	-0.018	-0.016	-0.014	0.226***	0.149***	0.150***	0.146***
	(1.455)	(-0.291)	(-0.265)	(-0.229)	(4.368)	(2.962)	(2.968)	(2.858)
CMKT		0.965***	0.966***	0.971***		0.671***	0.672***	0.662***
		(6.962)	(6.956)	(6.883)		(5.853)	(5.847)	(5.676)
CSMB			-0.002	0.000			-0.001	-0.004
			(-0.338)	(0.002)			(-0.271)	(-0.563)
CMOM				-0.002				0.003
				(-0.217)				(0.496)
H−L	-0.211**	-0.211**	-0.211**	-0.211**	0.060	0.060	0.060	0.060
	(-2.328)	(-2.548)	(-2.543)	(-2.538)	(0.815)	(0.870)	(0.868)	(0.867)

Table 3: Continued

Panel B: Alternative indices

	1	2	3	4	5	6	7	8
	POLU				VIX			
LOW_UNC	0.313***	0.211***	0.212***	0.212***	0.249***	0.130*	0.132*	0.131*
	(4.268)	(2.932)	(2.940)	(2.905)	(3.532)	(1.941)	(1.958)	(1.919)
MED_UNC	0.149**	0.046	0.048	0.048	0.182**	0.064	0.065	0.064
	(2.026)	(0.644)	(0.662)	(0.657)	(2.587)	(0.949)	(0.969)	(0.943)
HIGH_UNC	0.105	0.003	0.004	0.005	0.160**	0.041	0.043	0.042
	(1.435)	(0.040)	(0.061)	(0.064)	(2.267)	(0.612)	(0.635)	(0.613)
CMKT		0.891***	0.892***	0.893***		1.034***	1.036***	1.033***
		(5.425)	(5.421)	(5.339)		(6.742)	(6.737)	(6.615)
CSMB			-0.002	-0.002			-0.002	-0.003
			(-0.292)	(-0.138)			(-0.345)	(-0.264)
CMOM				-0.000				0.001
				(-0.023)				(0.093)
H−L	-0.208**	-0.208**	-0.208**	-0.208**	-0.089	-0.089	-0.089	-0.089
	(-2.004)	(-2.119)	(-2.115)	(-2.110)	(-0.895)	(-0.974)	(-0.972)	(-0.970)

Table 4: Fama-MacBeth cross-sectional regressions

This table presents the time-series averages of the slope coefficients from Fama and MacBeth (1973) regressions of next month's excess returns on the current month's uncertainty beta (β_{UNC}). The control variables include the beta of the excess market return (β_{MKT}), the beta of the size factor (β_{CSMB}), the beta of the momentum factor (β_{CMOM}), the downside risk beta (β_{DOWN}), the standard deviation of returns over the prior six months (RISK), and the Amihud illiquidity measure (AMIHUD). Panel A reports the results for FINU and MACU, while Panel B reports the results for POLU and VIX. The t-statistics, adjusted using the Newey and West (1987) method with one lag, are provided in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period covers April 2014 to December 2021.

Panel A: JLN measures	1	2	3	4	5	6	7	8	9	10
			FINU					MACU		
β_{UNC}	-0.099**	-0.110**	-0.111**	-0.124**	-0.160***	0.037	0.017	0.001	-0.018	-0.028
	(-2.015)	(-2.412)	(-2.426)	(-2.568)	(-2.861)	(1.019)	(0.480)	(0.024)	(-0.432)	(-0.609)
β_{CMKT}		-0.010	-0.026	-0.042	-0.013		-0.025	-0.038	-0.046	-0.002
		(-0.376)	(-0.887)	(-1.442)	(-0.337)		(-0.902)	(-1.068)	(-1.151)	(-0.034)
β_{CSMB}			-0.319	0.278	0.259			0.073	0.814	0.635
			(-1.471)	(0.858)	(0.837)			(0.264)	(1.642)	(1.219)
β_{CMOM}				-0.919	-1.269*				-1.131	-1.526
				(-1.366)	(-1.786)				(-1.219)	(-1.574)
β_{DOWN}					0.110					-0.159
					(0.538)					(-0.354)
AMIHUD					1.089					6.672
					(0.254)					(1.043)
RISK					0.018					-0.192
					(0.150)					(-1.337)
Constant	0.355***	0.400***	0.414***	0.470***	0.531***	0.066	0.132*	0.138*	0.176*	0.188
	(2.681)	(3.025)	(3.034)	(3.071)	(3.058)	(0.882)	(1.763)	(1.691)	(1.867)	(1.426)
Observations	11,256	11,256	11,256	11,256	11,185	10,664	10,664	10,664	10,664	10,592
R-squared	0.219	0.360	0.437	0.484	0.580	0.253	0.363	0.471	0.525	0.615

Table 4: Continued

	1	2	3	4	5	6	7	8	9	10
Panel B: Alternative indices										
			POLU					VIX		
β_{UNC}	-0.084	-0.096	-0.083	-0.100	-0.091	-0.080	-0.078	-0.075	-0.110	-0.130*
	(-1.635)	(-1.612)	(-1.284)	(-1.279)	(-1.260)	(-1.571)	(-1.514)	(-1.222)	(-1.366)	(-1.765)
β_{CMKT}		0.022	-0.019	-0.000	0.063		-0.021	-0.031	-0.025	0.001
		(0.842)	(-0.544)	(-0.000)	(1.155)		(-0.630)	(-0.920)	(-0.604)	(0.020)
β_{CSMB}			-0.212	0.338	-0.028			-0.420	0.190	0.063
			(-0.978)	(0.954)	(-0.079)			(-1.542)	(0.503)	(0.168)
β_{CMOM}				-0.152	-0.640				-1.091	-1.581*
				(-0.219)	(-0.919)				(-1.232)	(-1.985)
β_{DOWN}					0.548					0.240
					(1.293)					(0.409)
AMIHUD					17.974					13.132
					(1.166)					(0.946)
RISK					0.114					0.095
					(1.127)					(0.965)
Constant	0.356**	0.376**	0.378**	0.426*	0.349	0.329**	0.356**	0.380**	0.463*	0.433**
	(2.336)	(2.189)	(1.994)	(1.870)	(1.636)	(2.245)	(2.237)	(2.064)	(1.990)	(2.114)
Observations	11,564	11,564	11,564	11,564	11,491	11,484	11,484	11,484	11,484	11,412
R-squared	0.212	0.327	0.411	0.458	0.558	0.165	0.290	0.380	0.434	0.537

Table 5: Univariate sorts of coin portfolios by taxonomic features on financial uncertainty

This table displays the results of portfolio regressions of value-weighted (market capitalization) excess monthly cryptocurrency returns on FINU terciles sorted by the cryptocurrency taxonomic characteristics. These characteristic pairs include whether the cryptocurrency is Proof of Work (POW), Proof of Stake (POS), a Token, is Mineable, has a working paper (WP), has an infinite supply, is anonymous, or has a block time greater than or less than 30 seconds. After splitting the coins within the respective category, tercile portfolios are formed for each month by sorting individual cryptocurrencies based on their uncertainty betas, with tercile 1 (LOW_FINU) containing cryptocurrencies with the lowest uncertainty betas and tercile 3 (HIGH_FINU) containing those with the highest uncertainty betas. This table reports the coefficients representing the relation between next month's excess cryptocurrency returns and the financial uncertainty beta (FINU), as well as the crypto market factor (CMKT), size factor (MCAP), and momentum factor (MOM). Coins represent the average number of coins in the partitioned sample. The last row presents the coefficient differences between the highest and lowest uncertainty betas (H−L). Newey and West (1987) adjusted t-statistics with one lag are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is April 2014 to December 2021

Panel A: Taxonomic features 1

	1	2	3	4	5	6	7	8
	NON_POW	POW	NON_POS	POS	NON_Token	Token	NON_Mineable	Mineable
LOW_UNC	0.174***	0.240***	0.252***	0.119*	0.214***	0.155**	0.182**	0.184***
	(2.631)	(3.736)	(3.925)	(1.916)	(3.577)	(2.506)	(2.532)	(3.045)
MED_UNC	0.057	0.102	0.074	0.027	0.059	0.026	0.068	0.109*
	(0.867)	(1.591)	(1.158)	(0.373)	(0.996)	(0.351)	(0.933)	(1.812)
HIGH_UNC	0.070	0.062	0.023	0.111	0.019	0.143*	0.061	0.031
	(1.041)	(0.945)	(0.351)	(1.475)	(0.315)	(1.868)	(0.823)	(0.503)
CMKT	0.741***	0.374***	0.665***	0.671***	0.674***	0.619***	0.785***	0.499***
	(5.060)	(2.632)	(4.674)	(4.793)	(5.082)	(4.348)	(4.929)	(3.733)
CSMB	-0.003	-0.004	-0.004	-0.005	-0.004	-0.001	-0.003	-0.005
	(-0.331)	(-0.403)	(-0.369)	(-0.584)	(-0.426)	(-0.088)	(-0.246)	(-0.526)
CMOM	0.002	0.003	0.002	0.000	0.002	-0.001	0.001	0.003
	(0.206)	(0.321)	(0.226)	(0.020)	(0.264)	(-0.143)	(0.126)	(0.368)
H−L	-0.104	-0.178**	-0.229***	-0.009	-0.195**	-0.012	-0.120	-0.153*
	(-1.150)	(-2.028)	(-2.607)	(-0.091)	(-2.379)	(-0.129)	(-1.216)	(-1.852)

Table 5: Continued

Panel B: Taxonomic features 2

	1	2	3	4	5	6	7	8
	NO_WP	WP	Finite	Infinite	Non_ Anony- mous	Anonymous	Block_Time >30s	Block_Time <30s
LOW_UNC	0.132***	0.224***	0.208***	0.314***	0.233***	0.180**	0.257***	0.224***
	(2.705)	(3.489)	(3.371)	(3.001)	(3.647)	(2.537)	(4.149)	(3.114)
MED_UNC	-0.004	0.085	0.071	0.022	0.063	-0.028	0.091	0.006
	(-0.067)	(1.324)	(1.148)	(0.200)	(0.997)	(-0.372)	(1.484)	(0.074)
HIGH_UNC	0.099*	0.021	0.023	0.099	0.030	0.011	0.033	0.045
	(1.686)	(0.317)	(0.372)	(0.818)	(0.470)	(0.122)	(0.530)	(0.593)
CMKT	0.329***	0.755***	0.713***	0.565**	0.698***	0.987***	0.592***	0.683***
	(2.980)	(5.297)	(5.215)	(2.379)	(4.938)	(5.324)	(4.320)	(4.247)
CSMB	-0.003	-0.004	-0.004	-0.006	-0.004	-0.003	-0.004	-0.004
	(-0.406)	(-0.397)	(-0.405)	(-0.355)	(-0.407)	(-0.248)	(-0.427)	(-0.373)
CMOM	0.001	0.002	0.002	0.004	0.002	-0.002	0.002	0.003
	(0.154)	(0.216)	(0.266)	(0.270)	(0.263)	(-0.283)	(0.281)	(0.314)
H−L	-0.033	-0.204**	-0.185**	-0.214	-0.202**	-0.170	-0.223***	-0.179*
	(-0.441)	(-2.313)	(-2.186)	(-1.391)	(-2.315)	(-1.579)	(-2.637)	(-1.782)

Table 6: Univariate sorts of coin portfolios by speculative indexes by financial uncertainty

This table displays the results of portfolio regressions of value-weighted (market capitalization) excess monthly cryptocurrency returns on FINU terciles sorted by the cryptocurrency indexes: Taxonomy index and K-means clustering index into Speculative and Transactional. After splitting the coins in half within the respective category, tercile portfolios are formed for each month by sorting individual cryptocurrencies based on their uncertainty betas, with tercile 1 (LOW_FINU) containing cryptocurrencies with the lowest uncertainty betas and tercile 3 (HIGH_FINU) containing those with the highest uncertainty betas. This table reports the coefficients representing the relation between next month's excess cryptocurrency returns and the financial uncertainty beta (FINU), as well as the crypto market factor (CMKT), size factor (MCAP), and momentum factor (MOM). Coins represent the average number of coins in the partitioned sample. The last row presents the coefficient differences between the highest and lowest uncertainty betas (H−L). Newey and West (1987) adjusted t-statistics with one lag are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is April 2014 to December 2021

	1	2	3	4	5	6	7	8
	Taxonomic Index				K-means clustering			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4	Cluster 1	Cluster 2	Cluster 3	Cluster 4
LOW_FINU	0.083	0.129*	0.032	0.210***	0.134*	0.084	0.119*	0.218***
	(1.254)	(1.945)	(0.590)	(3.121)	(1.736)	(1.330)	(1.784)	(3.248)
MED_FINU	-0.071	-0.020	0.020	0.005	-0.075	0.071	0.009	0.017
	(-1.031)	(-0.291)	(0.363)	(0.07)	(-0.800)	(1.068)	(0.132)	(0.251)
HIGH_FINU	0.108	0.054	0.061	-0.041	0.047	0.047	0.117**	-0.014
	(1.435)	(0.809)	(1.282)	(-0.61)	(0.499)	(0.674)	(2.007)	(-0.208)
CMKT	0.786***	0.829***	0.645***	1.108***	1.259***	0.644***	0.456***	0.855***
	(5.327)	(5.797)	(5.353)	(7.212)	(6.394)	(4.504)	(3.251)	(5.598)
CSMB	-0.003	0.001	0.003	0.002	0.008	-0.003	-0.003	0.001
	(-0.347)	(0.075)	(0.446)	(0.159)	(0.662)	(-0.328)	(-0.352)	(0.065)
CMOM	-0.002	-0.004	-0.004	-0.003	-0.010	0.000	-0.002	-0.003
	(-0.246)	(-0.610)	(-0.765)	(-0.359)	(-0.980)	(0.053)	(-0.307)	(-0.332)
H-L	0.025	-0.074	0.028	-0.251***	-0.087	-0.037	-0.002	-0.232**
	(0.262)	(-0.828)	(0.410)	(-2.772)	(-0.744)	(-0.413)	(-0.019)	(-2.576)

Table 7: Trade size by uncertainty tercile

Panel A reports the regression results for the log average monthly trade size (TRADE_MEAN (Log)) on tercile sorts for Economic Financial Uncertainty (FINU) and Total Macro Uncertainty (MACU) uncertainty betas for a sub-sample of cryptocurrencies. Panel B reports the regression results for trade size on FINU sorted by the taxonomic indices: manual index and K-means clustering index. The regressions include a set of control variables, market capitalization (MKTCAP), dollar trading volume (DOL_VOL), past month returns (LAG_RT), the Amihud (2002) illiquidity measure (AMIHUD), return volatility (RISK) and coin fixed effects. Standard errors are clustered at the year-month level. The t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample covers the period from April 2014 to December 2021.

Panel A: Trade size by uncertainty tercile

	1	2	3	4	5	6
	Trade mean (Log)					
	FINU			MACU		
LOW_UNC	0.603***	0.530***	3.618***	0.993***	0.833***	3.183***
	(4.624)	(3.876)	(19.055)	(5.131)	(4.278)	(22.566)
MED_UNC	1.198***	1.073***	3.896***	1.055***	0.839***	3.388***
	(8.025)	(7.568)	(23.098)	(7.190)	(5.703)	(22.826)
HIGH_UNC	1.185***	1.088***	4.038***	1.090***	0.887***	3.220***
	(6.715)	(6.145)	(25.676)	(6.598)	(4.776)	(23.679)
MKTCAP		0.000***	0.000***		0.000***	0.000***
		(8.627)	(11.171)		(9.141)	(11.780)
DOL_VOL		0.000	0.000		0.000	0.000
		(0.553)	(0.317)		(0.256)	(0.357)
LAG_RT		0.504***	0.495***		0.437***	0.362***
		(4.508)	(4.853)		(3.568)	(3.729)
AMIHUD		-0.000	-0.000		-0.000	-0.000
		(-1.461)	(-0.575)		(-1.597)	(-0.489)
RISK		-0.008	0.270		0.205	1.360***
		(-0.084)	(1.594)		(1.420)	(8.847)
Observations	1,952	1,952	1,952	1,821	1,821	1,821
R-squared	0.209	0.243	0.713	0.199	0.233	0.745
Coin F.E	NO	NO	YES	NO	NO	YES
H-L	0.582***	0.558***	0.419***	0.097	0.054	0.037
	(4.822)	(4.393)	(4.847)	(0.741)	(0.430)	(0.586)

Table 7: Continued

Panel B: Trade size by financial uncertainty tercile by taxonomy indices

	1	2	3	4	5	6	7	8
	TRADE_MEAN (Log)							
	Taxonomic Index				K-means clustering			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4	Cluster 1	Cluster 2	Cluster 3	Cluster 4
LOW_FINU	1.608	4.7***	0.586	2.333***	3.415***	3.122***	2.333***	1.869
	(0.819)	(10.823)	(0.631)	(12.835)	(44.339)	(5.189)	(13.184)	(0.823)
MED_FINU	1.606	4.376***	0.583	2.635***	3.297***	2.593***	2.63***	1.94
	(0.818)	(10.294)	(0.628)	(15.003)	(37.998)	(4.412)	(15.384)	(0.855)
HIGH_FINU	2.342	4.414***	0.184	2.844***	3.229***	2.606***	2.837***	2.537
	(1.206)	(11.54)	(0.200)	(15.322)	(22.429)	(5.396)	(15.711)	(1.129)
MKTCAP	0.000***	0.000	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(7.919)	(1.191)	(7.211)	(6.331)	(7.919)	(6.331)	(11.191)	(7.211)
DOL_VOL	0.000	0.000***	0.000***	-0.000***	0.000	-0.000***	0.000***	-0.000***
	(1.181)	(4.213)	(4.321)	(4.314)	(1.181)	(4.314)	(4.213)	(4.321)
LAG_RT	-0.107	0.353***	-0.034	0.272***	-0.095	0.068	0.084***	0.274***
	(-0.588)	(7.511)	(-1.259)	(6.326)	(-0.495)	(0.544)	(3.818)	(6.683)
AMIHUD	-0.000	-0.001	-0.000	-0.001	-0.000	-0.001	-0.001	-0.000
	(0.212)	(1.010)	(1.234)	(1.050)	(0.212)	(-1)	(-1)	(1.234)
RISK	0.691***	-0.246	0.248***	0.474***	0.691***	-0.478	0.189***	0.482***
	(3.075)	(-1.123)	(4.203)	(3.564)	(5.075)	(-1.423)	(3.375)	(3.736)
Obs	447	341	503	732	337	241	660	785
Adj R-Sq	0.836	0.935	0.748	0.772	0.824	0.908	0.900	0.777
Coin F.E	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
H-L	0.239	-0.285*	-0.402*	0.510***	0.170	-0.516**	-0.186	0.504***
	(1.008)	(-1.748)	(-1.856)	(8.947)	(0.637)	(-2.481)	(-1.398)	(9.010)

Table 8: Robustness tests

For each month, tercile portfolios are formed by sorting individual cryptocurrencies based on their financial uncertainty betas. Tercile 1 (LOW_FINU) comprises cryptocurrencies with the lowest uncertainty betas, while tercile 3 (HIGH_FINU) includes those with the highest uncertainty betas. The table presents coefficients from regressions of the next month's value-weighted (by market capitalization) excess cryptocurrency returns on the Financial Uncertainty beta (FINU), alongside the cryptocurrency market factor (CMKT), size factor (CSMB), and momentum factor (CMOM). The final row reveals the coefficient differences between the highest and lowest uncertainty betas (H−L). Panel A reports the results for partitions of the sample prior to and subsequent to the Covid-19 period; it also includes FINU measures three months and 12 months ahead. Panel B shows the outcomes when Bitcoin is excluded from the sample, when coins have a minimum of two years of age, when Bitcoin is utilized as the short portfolio, and when considering only the top 50 coins by market capitalization. The bottom row (BTC−L) of Panel B, represents the coefficient of Bitcoin minus the LOW portfolio. Newey and West (1987) adjusted t-statistics are provided in parentheses. Asterisks *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period extends from April 2014 to December 2021.

Panel A: Time variation

	1	2	3	4	5	6	7	8
	Pre 2020		Post 2020		Three-month ahead FINU		12-month ahead FINU	
LOW_FINU	0.260***	0.139*	0.410***	0.175*	0.287***	0.220***	0.198***	0.139***
	(3.189)	(1.725)	(4.188)	(1.826)	(4.721)	(3.733)	(4.500)	(3.369)
MED_FINU	0.127	0.007	0.150	-0.084	0.169***	0.092	0.093**	0.026
	(1.559)	(0.082)	(1.537)	(-0.880)	(2.780)	(1.563)	(2.111)	(0.636)
HIGH_FINU	0.078	-0.042	0.129	-0.106	0.094	0.023	0.106**	0.045
	(0.961)	(-0.521)	(1.315)	(-1.107)	(1.546)	(0.390)	(2.400)	(1.070)
CMKT		0.922***		0.513*		0.817***		0.683***
		(4.738)		(1.933)		(6.168)		(7.348)
CSMB		-0.034		0.653**		-0.002		-0.001
		(-1.504)		(2.321)		(-0.228)		(-0.117)
CMOM		0.032		-0.003		0.001		0.001
		(1.468)		(-0.429)		(0.084)		(0.199)
H−L	-0.181	-0.181*	-0.281**	-0.281**	-0.193**	-0.197**	-0.092	-0.095*
	(-1.575)	(-1.692)	(-2.031)	(-2.467)	(-2.245)	(-2.449)	(-1.470)	(-1.673)

Table 8: Continued

Panel B: Liquidity restictions	1	2	3	4	5	6	7	8
	Excluding Bitcoin (BTC)		Excluding coins <2 years of age		BTC short		Top 50 coins	
LOW_FINU	0.304***	0.201***	0.285***	0.167**	0.207***	0.208***	0.301***	0.196***
	(4.667)	(3.166)	(4.198)	(2.571)	(3.959)	(3.944)	(4.763)	(3.216)
MED_FINU	0.131**	0.029	0.128*	0.010	0.037	0.038	0.124*	0.020
	(2.021)	(0.452)	(1.882)	(0.152)	(0.706)	(0.723)	(1.969)	(0.321)
HIGH_FINU	0.116*	0.013	0.079	-0.039	-0.004	-0.002	0.095	-0.010
	(1.777)	(0.202)	(1.165)	(-0.597)	(-0.072)	(-0.047)	(1.502)	(-0.162)
BTC					-0.013	-0.012		
					(-0.272)	(-0.243)		
CMKT		0.929***		0.968***	0.862***	0.866***		0.948***
		(6.403)		(6.826)	(8.375)	(8.277)		(6.795)
CSMB		0.001		0.000	-0.002	-0.001		-0.001
		(0.071)		(0.048)	(-0.564)	(-0.146)		(-0.157)
CMOM		-0.002		-0.002		-0.001		-0.001
		(-0.224)		(-0.295)		(-0.187)		(-0.137)
H−L	-0.188**	-0.188**	-0.206**	-0.206**	-0.211***	-0.211***	-0.206**	-0.206**
	(-2.043)	(-2.202)	(-2.145)	(-2.366)	(-2.670)	(-2.928)	(-2.306)	(-2.510)
BTC−L					-0.235***	-0.220***		
					(-3.068)	(-3.155)		

Table A1: Description of cryptocurrency taxonomic features

This table provides a description of the taxonomic features of the cryptocurrencies within the study.

Feature	Category	Description
Proof of Work (POW)	Speculative	Proof of Work (POW) is a consensus mechanism used by many blockchains. Miners solve computationally intensive puzzles, often using the SHA-256 algorithm, which produces a unique 256-bit hash from input data. By varying a nonce and hashing the block's content, miners seek a hash value below a predefined target. Once found, the solution is broadcasted for verification. If confirmed by other nodes, the block is appended to the blockchain, and the miner is rewarded. This mechanism ensures network security by making malicious alterations costly in computational terms.
Proof of Stake (POS)	Transactional	A consensus mechanism where the process of validating and recording transactions is more energy-efficient than POW. Validators are chosen to create new blocks based on the number of coins they hold and are willing to 'stake' as collateral. In Proof of Stake, validators propose the next block based on their stake in the system. The larger their stake, the more frequently they are selected. Validators are incentivized to act honestly; malicious behavior could lead to a loss of their staked coins. This mechanism is thus less computationally intensive than POW.
Non-Token	Speculative	A cryptocurrency that operates with a distinct blockchain, focusing solely on its native coin for all operations and transactions within its blockchain.
Token	Transactional	Tokens are digital cryptographic units of value or representation, minted on blockchains. They can emulate various forms of assets - from tangible commodities to intangible rights. Tokens often comply with specific standards, like ERC-20 or ERC-721 on the Ethereum platform, which prescribe their creation, transfer, and interaction protocols. Depending on the use-case, tokens can symbolize ownership (like shares), access rights to a specific service, or even unique digital assets (as in the case of Non-Fungible Tokens). Their issuance and functionality are typically governed by smart contracts on their respective blockchains.
Non-Mineable	Transactional	Cryptocurrencies whose issuance doesn't rely on computational mining processes. Instead, their supply is typically predefined and distributed via methods like initial coin offerings, airdrops, staking rewards, or direct allocations.
Mineable	Speculative	Cryptocurrencies produced via mining. Miners perform cryptographic computations, and upon successfully adding a block to the blockchain, they are rewarded with the cryptocurrency.
White Paper	Speculative	A technical document issued by blockchain and cryptocurrency projects. It details the project's purpose, technical specifications, mechanism designs, and sometimes the tokenomics.
Finite Supply	Speculative	Cryptocurrencies that have a predetermined maximum limit on the total number that can ever exist. The code of such cryptocurrencies contains this limit, ensuring no more can be created once the cap is reached.
Infinite Supply	Transactional	Cryptocurrencies without a hard-coded supply cap. The issuance rate and method vary, but there's no coded upper limit to the number of tokens or coins that can be produced.
Non-Anonymous Blockchain	Speculative	Blockchains that log and display transaction details in a transparent manner. While wallet addresses are pseudonymous, transaction details like amounts and timestamp are openly available.
Anonymous Blockchain	Transactional	Blockchains designed with enhanced privacy protocols. Techniques such as coin mixing, zero-knowledge proofs, or stealth addresses may be utilized to obscure transaction details.
Block Time >30 seconds	Speculative	The interval at which a new block is added to a blockchain exceeds 30 seconds. This duration is a result of the blockchain's design parameters and consensus rules.
Block Time <30 seconds	Transactional	The interval for adding a new block to the blockchain is under 30 seconds. This is typically seen in blockchains designed for high-speed transactions or specific use-cases demanding rapid confirmations.

Table A2: Descriptives of taxonomic features

This table reports the end-of-year coin values and characteristics for the sample, such as the number of coins (Coins), proportion of tokens (Token), the ratio of coins accompanied by a whitepaper (WP), fraction of coins with unlimited supply (Infinite), share of anonymous coins (Anonymous), and the percentage of coins exhibiting block times less than 30 seconds (Block_Time<30s). The bottom row is the average of the values across the sample. The data covers the period of April 2014 to December 2021.

Panel A: Taxonomy features by year	Coins	POW	POS	Token	Mineable	WP	Infinite	Anonymous	Block_ Time <30s
2015	12.507	0.537	0.060	0.104	0.672	0.896	0.134	0.000	0.224
2016	22.647	0.540	0.080	0.080	0.620	0.947	0.147	0.133	0.273
2017	120.880	0.475	0.097	0.106	0.558	0.922	0.198	0.074	0.263
2018	333.528	0.412	0.307	0.360	0.351	0.823	0.167	0.105	0.405
2019	321.684	0.362	0.283	0.558	0.223	0.796	0.095	0.066	0.581
2020	362.814	0.347	0.300	0.576	0.200	0.774	0.079	0.072	0.565
2021	583.834	0.326	0.305	0.631	0.176	0.765	0.067	0.066	0.551
Average	251.128	0.428	0.204	0.345	0.400	0.846	0.127	0.074	0.409
Panel B: Taxonomy features by taxonomic index									
Quartile 1	129	0.000	0.863	0.769	0.000	0.818	0.162	0.083	0.781
Quartile 2	129	0.002	0.147	0.835	0.000	0.649	0.053	0.019	0.597
Quartile 3	128	0.549	0.140	0.719	0.026	0.826	0.027	0.012	0.669
Quartile 4	128	0.722	0.048	0.091	0.687	0.822	0.101	0.139	0.218
Panel C: Taxonomy features by K-means clusters									
Cluster 1	236	0.279	0.302	0.904	0.000	1.000	0.000	0.004	1.000
Cluster 2	86	0.000	0.821	0.018	0.021	0.887	0.316	0.131	0.295
Cluster 3	108	0.207	0.124	0.896	0.000	0.131	0.018	0.010	0.072
Cluster 4	84	0.876	0.000	0.000	0.992	0.765	0.155	0.209	0.133

Table A3: Financial uncertainty beta by size rank

This table reports the uncertainty beta characteristics of the top 50 cryptocurrencies by market capitalization (Size). This table includes their average βFINU, tercile FINU Rank (rank of Economic Financial Uncertainty), and the discrete FIN Tercile (LOW, MED, HIGH) across the sample. The data cover the period of April 2014 to December 2021.

Size	Name	β_{FINU}	FINU Rank	FINU Tercile	Size	Name	β_{FINU}	FINU Rank	FINU Tercile
1	Bitcoin	-0.415	2.284	MED	26	Bitcoin Sv	0.453	2.680	HIGH
2	Ethereum	-1.064	2.185	MED	27	Vechain	-0.937	1.069	LOW
3	Solana	-0.019	2.167	MED	28	Cosmos	-0.750	1.143	LOW
4	Polkadot	3.604	3.000	HIGH	29	FTX Token	-0.389	2.067	MED
5	Hex	6.582	3.000	HIGH	30	Kusama	2.523	3.000	HIGH
6	Avalanche	2.747	3.000	HIGH	31	Stellar	-2.325	1.475	LOW
7	Cardano	-1.663	1.308	LOW	32	Tezos	0.200	2.700	HIGH
8	Xrp	-2.399	1.288	LOW	33	Thorchain	1.287	3.000	HIGH
9	Binance USD	-0.012	2.714	HIGH	34	Leo Token	0.114	2.632	HIGH
10	Terra	-2.311	1.000	LOW	35	Ethereum Classic	-1.573	1.981	MED
11	Bitcoin Cash	-1.143	1.683	MED	36	Kadena	-9.269	1.000	LOW
12	Wrapped Bitcoin	-0.303	1.938	MED	37	Celo	0.288	3.000	HIGH
13	Filecoin	-0.281	2.000	MED	38	Monero	-1.045	2.229	MED
14	Bitcoin Bep2	2.639	3.000	HIGH	39	Iota	-1.317	1.791	MED
15	Elrond	4.819	3.000	HIGH	40	Neo	-1.637	1.789	MED
16	Near	2.871	3.000	HIGH	41	Nem	-2.107	1.763	MED
17	Dai	-0.006	2.833	HIGH	42	Curve Dao Token	3.833	3.000	HIGH
18	Chainlink	-0.152	2.475	HIGH	43	Stacks	-0.770	1.273	LOW
19	Litecoin	-0.997	2.088	MED	44	SNT	-1.007	1.417	LOW
20	Polygon	-0.990	1.600	LOW	45	Celsius	-0.450	2.182	MED
21	Dogecoin	-1.941	1.630	LOW	46	Dash	-1.972	2.040	MED
22	Helium	-1.537	1.000	LOW	47	Bittorrent	-0.794	1.400	LOW
23	Algorand	-0.579	1.294	LOW	48	Huobi Token	-0.334	1.939	MED
24	Eos	-1.383	1.500	LOW	49	Maker	-0.038	2.083	MED
25	Aave	6.186	3.000	HIGH	50	Sushiswap	6.359	3.000	HIGH

Table IA1: Robust FINU

This table presents the results of cross-sectional regressions of cryptocurrencies' excess returns on alternative measures of financial uncertainty and various control variables. Columns 1–6 report the time-series averages of the slope coefficients from Fama and MacBeth (1973) regressions, while columns 7–9 display estimates from the Generalized Method of Moments (GMM). In columns 1–3, the key independent variable is the tercile sorts of orthogonalized financial uncertainty beta ($\beta_{\text{FINU}}^{\text{Orthog}}$), which is generated by orthogonalizing FINU relative to the other three uncertainty indices (MACU, POLU, VIX). Columns 4–6 use the continuous financial uncertainty beta ($\beta_{\text{FINU}}^{\text{Cont}}$). T-statistics, adjusted using the Newey-West (1984) method with one lag, are reported in parentheses below the coefficients. Columns 7–9 present GMM estimation results using tercile sorts of the financial uncertainty beta (β_{FINU}). Panel B displays the average slope coefficients for 6-month, 12-month, 18-month, and 24-month-ahead βFINU. The control variables include the beta of the excess market return (β_{CMKT}), the beta of the size factor (β_{CSMB}), the beta of the momentum factor (β_{CMOM}), the downside risk beta (β_{DOWN}), the Amihud illiquidity measure (AMIHUD), and the standard deviation of returns over the prior six months (RISK). t-statistics are reported in parentheses below the coefficients. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table IA1: Continued

Panel A: Robust FINU	1	2	3	4	5	6	7	8	9
				FMB				GMM	
$\beta^{\text{Orthog}}_{\text{FINU}}$	-0.105**	-0.120***	-0.136**						
	(-2.214)	(-2.805)	(-2.353)						
$\beta^{\text{Cont}}_{\text{FINU}}$				-0.064**	-0.066**	-0.093**			
				(-2.030)	(-2.006)	(-2.280)			
β_{FINU}							-0.046***	-0.064**	-0.073***
							(-2.646)	(-2.448)	(-2.663)
β_{CMKT}		-0.086**	-0.090**		-0.061*	-0.030		1.033***	1.223***
		(-2.325)	(-2.174)		(-1.942)	(-0.952)		(3.495)	(4.263)
β_{CSMB}		0.190	0.433		0.042	0.161		-0.108	-0.104
		(0.587)	(1.225)		(0.168)	(0.498)		(-1.356)	(-1.519)
β_{CMOM}		-1.006	-1.250		-0.835	-0.597		-0.002	-0.000
		(-1.341)	(-1.595)		(-1.304)	(-0.823)		(-0.381)	(-0.051)
β_{DOWN}			-0.063			0.025			-0.000
			(-0.258)			(0.123)			(-0.852)
AMIHUD			-3.601			-0.526			-0.000*
			(-1.158)			(-0.310)			(-1.702)
RISK			-0.046			0.030			-0.030
			(-0.363)			(0.276)			(-0.522)
Constant	0.363***	0.492***	0.560***	0.081***	0.117***	0.097**	0.091***	0.091***	0.093***
	(2.721)	(3.364)	(2.806)	(3.085)	(3.689)	(2.362)	(16.702)	(12.741)	(12.569)
Observations	11,078	11,078	11,008	11,256	11,256	11,185	9,762	9,762	9,762
R-squared	0.243	0.482	0.588	0.240	0.496	0.596	-	-	-

Table IA1: Continued

Panel B: Autocorrelation of financial uncertainty beta		
	1	2
n-months-ahead β_{FINU}	Univariate FMB	FF3 FMB
n=6	0.447***	0.362***
	(8.110)	(6.931)
n=12	0.461***	0.270***
	(6.338)	(5.873)
n=18	0.227**	0.096**
	(2.178)	(2.233)
n=24	0.211**	0.011
	(2.229)	(0.348)

Table IA2: Coin list trade data set

This table reports the list of coins by ticker that are covered by the transaction data.

Bitcoin	Civic	Loom Network
Ripple	EOS	TrueUSD
Dogecoin	Lisk	Huobi Token
Dash	Populous	Tezos
Stellar	Bitcoin Cash	Gemini Dollar
Litecoin	0x	Bitcoin SV
Monero	Gas	Grin
Ethereum	DigiByte	HedgeTrade
Ethereum Classic	Decentraland	FTX Token
Waves	Chainlink	Wrapped Bitcoin
Augur	Enigma	Binance USD
Golem	Cardano	Dai
Vertcoin	NEO	Paxos Gold
Gnosis	Power Ledger	Yearn. finance
Zcash	Bitcoin Gold	Serum
Decred	Dragonchain	Balancer
BAT	QASH	SushiSwap
Verge	Maker	Aave
OmiseGO	Polymath	Algorand

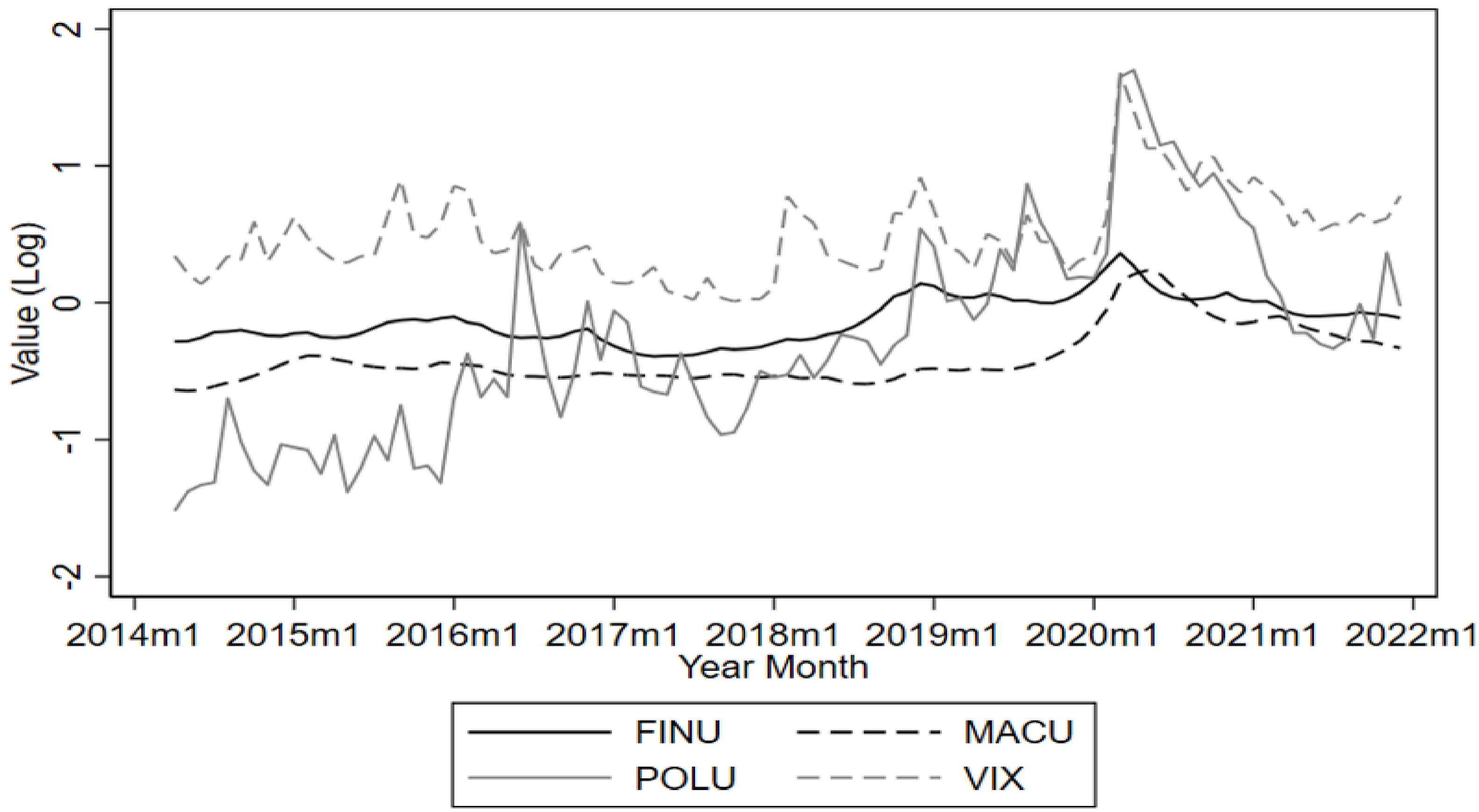

Figure IA1: This figure illustrates the time-series variation in the Ludvigson et al. (2021) Economic Financial Uncertainty (FINU), the Jurado et al. (2015) Total Macro Uncertainty (MACU) indices. In addition, it includes the Baker et al. (2016) POLU measure and the volatility index (VIX).