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Bitcoin forks: What drives the branches?

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ABSTRACT

Despite frequent Blockchain splits stemming from Bitcoin, few studies have examined the determinants of Bitcoin fork returns. In this paper, we investigate the relationships between the returns of Bitcoin forks and a range of common risk factors, including Bitcoin, currency, network and equity-based factors. From a statistical perspective, we find consistent and significant associations between fork returns, their Bitcoin counterparts, and equity markets. Other common factors, such as the equity small-minus-big factor and changes in the Japanese Yen, are found to have occasional links with fork returns. From an economic perspective, Bitcoin returns are the predominant driver of fork returns, accounting for essentially all of the explained variation. These findings are confirmed using orthogonalised common factors and with an alternative methodology, quantile regression. This research broadens our understanding of Bitcoin forks, indicating that a change in blockchain protocol is insufficient to sever links with the Bitcoin parent.

1. Introduction

In this research, we provide one of the first pieces to explicitly examine the drivers of Bitcoin forks. As one of the key cryptocurrencies, Bitcoin has acted as parent to many forks that have emerged. A fork is, quite simply, a change in a blockchain protocol, signifying a fundamental alteration in the protocol rules governing the network, which, in turn, affects the validation process of transactions and blocks. While the technical aspect of a fork is indeed concerned with protocol modifications, its occurrence often transcends mere technical adjustments. Notably, forks in the Bitcoin network and other blockchain platforms are frequently spurred by disagreements among community members regarding proposed Bitcoin Improvement Proposals (BIPs) or analogous protocol amendment proposals in other networks. These disagreements can encompass various aspects, including, but not limited to, block size, transaction speed, and security protocols.[2]

Quite simply, a fork introduces a new set of rules for Bitcoin to follow, where miners of a particular Bitcoin blockchain can choose to follow one set of rules or another. One motivator for forks is a consequence of different perspectives on transaction history, a side effect can be attributed to delays in the system. The popularity of some cryptocurrencies can lead to a lag in the speed upon which a chain operates, causing significant verification issues and increasing transaction fees. Forks are therefore observed as a potential solution to scalability issues, allowing new cryptocurrencies to be developed on larger blocks. Specifically, such forks can

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2 Consequently, when consensus is not achieved, a segment of the community may opt to diverge, creating a fork that operates under the newly agreed-upon rules. While sharing a common history with the original blockchain until the point of divergence, the resultant forks operate independently with their distinct protocols.

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be accidental in nature or take the form of a permanent chain split. Forks more broadly fall into two key categories: hard forks and soft forks. A hard fork occurs when a rule change causes the validating software to observe blocks produced according to the new rules as invalid. At the same time, a soft fork occurs when old network nodes do not follow a rule followed by the newly upgraded nodes.[3] This research specifically focuses on some of the largest Bitcoin forks, namely Bitcoin Cash, Bitcoin Gold, Dash, and Litecoin.

The advent of Bitcoin and its subsequent forks represents not merely a technological innovation but a potential shift in financial market dynamics. Such interplay between these digital assets and traditional market indices underscores the necessity to explore the underlying mechanisms at play thoroughly. Such analysis is predicated on the hypothesis that the financial behaviour of Bitcoin forks, despite their divergence from the original protocol, might still be tethered to Bitcoin and, through this channel, exhibit significant correlations with traditional markets. Investigating these relationships can contribute to a nuanced understanding of the systemic risk and potential contagion channels within the broader financial ecosystem.

Literature on cryptocurrency forks, to date, remains sparse. Chaim and Laurini (2018) have previously identified that unsuccessful fork attempts were linked directly to large price variations. In contrast, Hinzen et al. (2022) stated that the elevated fork probability due to increasing transaction rates had the unwelcome side-effect of hindering adoption rates. Bazán-Palomino (2021) examines the bivariate correlations between Bitcoin and a range of forks, demonstrating a strong level of interrelationship. Using clustering analysis, Kong et al. (2023) indicates a close relationship between Bitcoin and the more mature forks. Bazán-Palomino (2020) finds dynamical relationships in the volatility of Bitcoin and a series of forks, with evidence for volatility transmission from the forks to Bitcoin. Our paper builds upon this body of work by uncovering the links with common risk factors and assessing the economic significance of such drivers, alongside their statistical importance.[4] This work further builds on a series of articles that focus on interlinkages between cryptocurrencies and traditional financial markets, specifically considering dynamic relationships (Corbet et al., 2018; Abakah et al., 2022; Li et al., 2022), market efficiency (Urquhart, 2016; Cheah et al., 2018), market spillovers (Koutmos, 2018; Corbet et al., 2020c), liquidity effects (Wei, 2018), and the influence of external factors (Corbet et al., 2020a; Conlon et al., 2021).

The Litecoin main chain is one of the oldest forms of Bitcoin forks available for examination. It is similar in scope to Bitcoin, sharing a slightly modified Bitcoin codebase and is representative of one of the first altcoins, originating in October 2011. It was created to reduce transaction fees and confirmation times further and improve mining difficulty rates compared to Bitcoin. Another fork that is of central focus to this work is Dash,[5] which is similar to Litecoin, but was not created until January 2014, and was originally known as Xcoin and Darkcoin, identifying its target audience as those requiring digital currency for daily transactions, therefore attempting to replace cash, credit cards, and other digital payment systems. It is run by a subset of its users called 'masternodes'. Bitcoin cash, which allows for larger blocks in its blockchain, was a fork that was launched in 2017.[6] Another major Bitcoin fork of note was that of Bitcoin Gold.[7] Both of these assets are investigated in this research, along with both Dash and Litecoin.

A key contribution of our research indicates that the returns of Bitcoin forks, as examined through Bitcoin Cash, Bitcoin Gold, Dash, and Litecoin, are found to be predominantly explained by Bitcoin returns. This is among the first papers to show that despite the attempts to create cryptocurrencies independent of Bitcoin, the primary economic driver of their financial performance remains the parent cryptocurrency. This notwithstanding, we provide evidence that Bitcoin forks have statistical links with the stock market, along with other common factors, but these are found to provide only very limited explanatory power. These findings persist using quantile regression, confirming Bitcoin's substantial role in explaining Fork returns. Using a recently adopted optimal orthogonalisation approach, we provide further support for these findings, with Bitcoin found to explain between 96% and 99% of the explained variation in Bitcoin Forks. These findings provide important guidance to policymakers and investors. In assessing the systemic implications of Bitcoin forks, their critical links highlight the central relevance of shocks to Bitcoin on their performance. From the perspective of a cryptocurrency investor, our findings indicate that Bitcoin forks would not provide strong diversification opportunities relative to the Bitcoin parent.

The rest of this paper is as follows: Section 2 presents a concise literature review based on key areas related to the stated research questions, such as interactions between cryptocurrency markets and Bitcoin, interactions between Bitcoin forks, and associated diversification effects in cryptocurrency markets. In Section 3 presents the data and methodological processes utilised to investigate the interactions between Bitcoin and a set of prominent forks, while Section 4 presents the results of the associated analysis. Section 5 concludes.

2. Previous literature

When focusing on the interactions between broad cryptocurrency markets and Bitcoin, Disli et al. (2021) used wavelet coherence and spillover index methodologies to find that gold, oil, and Bitcoin exhibited low coherency with each stock index across almost all considered investment horizons until the onset of the COVID-19. Focusing on dynamic correlations when considering the effects

[3] Soft forks can generate a situation where old nodes accept data that under the new node structure appear invalid, whereas hard forks stop the creation process completely. This is also known as 'backward compatibility'.

[4] A further related literature focuses on 'airdrops', which are a mechanism to distribute rights over a Blockchain project to owners and users (Allen et al., 2023; Makridis et al., 2023).

[5] Dash is described as a privacy-centric cryptocurrency based on Bitcoin, which uses the X11 algorithm, a modification of the proof-of-stake (PoS) algorithm.

[6] The fork occurred at block 478558 on 1 August 2017, where each 1 Bitcoin was valued at 1 Bitcoin Cash.

[7] The asset was forked at block 491407 on 24 October 2017, where 1 Bitcoin represented 1 Bitcoin Gold unit.

of economic policy uncertainty, Wang et al. (2020) identify that returns around the days with the highest EPU days are significantly greater than around the days with the lowest EPU. Evidence of spillovers is also presented by Katsiampa et al. (2019b,a). At the same time, volatility dynamics are examined in depth by Katsiampa (2019a), who identified that the conditional variances of Bitcoin, Ether, Ripple, Litecoin, and Stellar Lumen are significantly affected by both previous squared errors and past conditional volatility. Caporale et al. (2018) examined persistence in the cryptocurrency market, finding that evidence of predictability represents evidence of market inefficiency. Yan et al. (2022) found that the market for forked coins can be divided into three clusters: SegWit-supported forked coins, mature forked coins, and the latest forked coins, results echoed by Shahzad et al. (2022). Focusing on Bitcoin splits, Islam et al. (2019) investigate whether investors' informed trading behaviour can significantly predict cryptocurrency returns to show that informed trading plays a role in predicting some individual cryptocurrency returns. Further works that consider the interaction of spillovers have also covered a range of external shocks upon cryptocurrency markets (Akyildirim et al., 2020; Corbet et al., 2020c; Ji et al., 2020; Andrada-Félix et al., 2020; Ma et al., 2020; Chu et al., 2020; Corbet et al., 2021).

When focusing on cryptocurrencies as a diversification tool, much research has focused on the interactive effects and correlations with several traditional financial markets. Using Conditional Value at Risk (CVaR), Disli et al. (2021) investigate associated safe haven effects during COVID-19. Hinzen et al. (2022) find that a free-based portfolio approach can capture the nonlinear compounding effect of multiple risk shocks, which can subsequently guide investments in financial markets with high tail risks. Further, Ouandlous et al. (2022) build a portfolio that can capture the nonlinear compounding effect of multiple risk shocks by deep reinforcement learning on the risk distribution. It can guide investments in financial markets with high tail risks. Ji et al. (2019) identify that efficiently sorted portfolios outperform traditional quantile-based and naive $1/N$ portfolios. With regards to the effects of the pandemic, Conlon et al. (2020) found that the Japanese yen is the most consistent hedger for cryptocurrencies, followed by the British pound, Chinese yuan, and the Euro during the sharp negative phases experienced. Corbet et al. (2020b) found that the performance of cryptocurrencies and their link with investment flows can limit the transition to low-carbon sustainable options. Using Wavelet coherence analysis and spillover index methodologies in bivariate and multivariate settings (Conlon and McGee, 2020b), gold, oil and Bitcoin exhibited low coherency with each stock index across almost all considered investment horizons until the onset of the COVID-19. However, in the period thereafter, such relationships reverse substantially. Further influence through several characteristics has been considered with regards to diversification (Akhtaruzzaman et al., 2020), volatility co-movement (Katsiampa, 2019b), mean reversion (Corbet et al., 2020c), inflation (Conlon et al., 2021), gambling interaction (Conlon and McGee, 2020a), exchange collapse (Akyildirim et al., 2023; Kong et al., 2023; Cui et al., 2023; Conlon et al., 2023), cyberattacks (Gil-Alana et al., 2020; Caporale et al., 2021), and broad cryptocurrency structural activity (Le et al., 2021).

3. Data and methodology

Daily US dollar (USD) price returns data relating to Bitcoin, and each fork considered is obtained from Coinmetrics. Specifically, the CM reference rates are used, corresponding to a standard that meets the International Organisation of Securities Commissions' (IOSCO) framework of principles for financial market benchmarks. Four forks are examined and selected based on their prominent market capitalisation and the length of data available.[8] The forks are Dash (11th January 2014–31st December 2022), Litecoin (2nd April 2014–31st December 2022), Bitcoin Cash (2nd August 2017–31st December 2022) and Bitcoin Gold (26th October 2017–31st December 2022). All data examined is daily.

The selected Bitcoin forks returns are regressed on multiple common factors proposed by Liu and Tsyvinski (2021) as representing the determinants of cryptocurrency returns.[9] We briefly describe the common factors used in the paper. First, the returns on Bitcoin are included to capture the links between Bitcoin Forks and the parent.[10] This also allows us to quantify the relative extent to which other common factors contribute to variation in fork returns compared to Bitcoin.

As described by Liu and Tsyvinski (2021), cryptocurrency market returns are positively linked with cryptocurrency network growth. Following Liu and Tsyvinski (2021), we construct variables capturing the number of active addresses, the count of the number of transactions, and the number of wallet users. These data are selected from the Bitcoin network to best represent both dynamic interaction effects throughout the entire chain of selected forks and the growth of the system over the time period analysed (Liu and Tsyvinski, 2021). Further, Liu and Tsyvinski (2021) argue that market-based factors may influence cryptocurrency returns. In this context, we incorporate market data, along with a series of common equity factors (Fama and French, 1993, 2015), obtained from Ken French's website.[11] Specifically, the risk-free rate is subtracted from stock market returns to provide a market factor, while factor returns representing differences in returns between small and large capitalisation stocks and high and low book value stocks are also included. Athey et al. (2016) develop a model of how fundamentals may influence the exchange rate between

[8] We acknowledge that many other Bitcoin forks are traded, but full coverage of all available forks is beyond the scope of this paper. The forks selected are chosen to be representative, covering a range of time horizons and market capitalisation.

[9] We acknowledge that other relevant factors may not be incorporated, such as supply and demand, public interest, and economic policy uncertainty (Ahmed, 2022). Moreover, the literature has provided evidence of the value relevance of various specific risk factors, including those capturing a forward-looking component, specific events such as hacking and cyber attacks (Lyócsa et al., 2020; Corbet et al., 2020a; Caporale et al., 2020), and variables representing the regulatory environment (Auer and Claessens, 2018). Such specific risk factors should be less relevant to the marginal investor due to their tendency to hold a diversified portfolio and, hence, only get rewarded for common risk exposures rather than specific risks.

[10] Bitcoin is included rather than the cryptocurrency market for several reasons. First, Bitcoin is the largest contributor to the cryptocurrency market by a substantial amount. Second, as we are studying Bitcoin forks, it is pertinent to include Bitcoin in the analysis. Finally, while both Bitcoin and the Cryptocurrency market could be included simultaneously, this would make inference difficult given their high correlation.

[11] Data are available from Kenneth R. French's Dartmouth College website.

Table 1
Summary statistics.

	Number of observations	mean	Standard deviation	Min	Max	skewness	Kurtosis	Serial correlation
Litecoin	2456	0.110	7.727	−90.447	74.806	0.317	23.625	−0.007
Dash	2238	0.222	8.528	−84.663	98.668	1.219	26.820	−0.077***
BCH	1363	−0.093	7.874	−56.083	49.401	0.261	11.466	0.049**
BCG	1303	−0.191	7.973	−57.587	62.666	0.387	15.161	0.003
Bitcoin	2456	0.202	5.342	−66.495	47.662	−0.955	22.299	−0.015*
Market	2457	0.047	1.144	−12.000	9.340	−0.605	16.768	−0.147***
SMB	2457	−0.003	0.636	−4.570	5.740	0.304	8.170	−0.028**
HML	2457	−0.002	0.861	−5.020	6.740	0.235	8.741	0.063***
RMW	2457	0.014	0.490	−2.160	4.200	0.362	7.077	0.049***
CMA	2457	0.004	0.432	−2.730	2.460	−0.002	6.717	0.029**
AUD	2457	−0.018	0.645	−3.915	2.874	−0.184	4.892	0.004
CAN	2457	0.012	0.477	−1.962	2.118	−0.014	4.202	−0.008
JPY	2457	0.013	0.570	−3.865	3.469	−0.370	9.013	−0.018
EUR	2457	−0.008	0.499	−2.413	3.029	0.095	5.207	−0.017
GBP	2457	−0.008	0.596	−8.402	3.090	−1.204	21.439	0.005
Gold	2456	0.003	0.946	−8.879	4.687	−0.632	9.118	−0.022
Silver	2457	−0.010	1.720	−16.201	8.835	−0.652	11.638	−0.031
Platinum	2457	−0.019	1.519	−13.877	9.708	−0.465	8.853	0.014
Δ Address	2457	0.100	9.185	−44.646	45.862	0.115	4.923	−0.430***
Δ Trans	2457	0.062	9.234	−52.002	49.094	0.101	6.158	−0.443***
Δ Users	2457	0.141	0.341	−4.112	4.061	−0.880	29.968	0.497***

Note: The above table reports descriptive statistics of the daily change for each analysed variable. Min and Max correspond to the minimum and maximum daily change, respectively. ***, **, * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 2
Correlations.

	Litecoin	Dash	BCH	BCG	Bitcoin	Market	SMB	HML	RMW	CMA	AUD	CAN	JPY	EUR	GBP	Gold	Silver	Platinum	Δ Addresses	Δ Trans	Δ Users
Bitcoin	0.581	0.511	0.638	0.576	1.000																
Market	0.142	0.141	0.200	0.230	0.165	1.000															
SMB	0.027	0.019	0.055	0.042	0.063	0.193	1.000														
HML	−0.017	−0.013	−0.014	−0.013	−0.027	−0.053	0.217	1.000													
RMW	−0.060	−0.062	−0.068	−0.087	−0.085	−0.185	−0.247	0.340	1.000												
CMA	−0.058	−0.045	−0.066	−0.070	−0.085	−0.289	−0.012	0.622	0.319	1.000											
AUD	0.084	0.102	0.143	0.167	0.105	0.411	0.137	0.032	−0.110	−0.044	1.000										
CAN	−0.064	−0.075	−0.132	−0.144	−0.075	−0.429	−0.127	−0.123	0.098	−0.014	−0.665	1.000									
JPY	0.004	0.031	−0.004	−0.009	−0.013	0.251	0.059	0.138	−0.033	0.004	−0.256	0.143	1.000								
EUR	0.021	0.052	0.076	0.099	0.040	0.071	0.025	−0.015	−0.036	−0.011	0.504	−0.417	−0.422	1.000							
GBP	0.026	0.043	0.093	0.117	0.057	0.229	0.086	0.038	−0.077	−0.028	0.528	−0.455	−0.251	0.590	1.000						
Gold	0.026	0.050	0.069	0.080	0.062	0.020	0.022	−0.078	−0.051	0.041	0.364	−0.281	−0.419	0.363	0.258	1.000					
Silver	0.055	0.083	0.115	0.107	0.095	0.193	0.094	−0.029	−0.078	0.008	0.422	−0.359	−0.242	0.318	0.290	0.793	1.000				
Platinum	0.064	0.087	0.122	0.141	0.097	0.296	0.099	0.047	−0.070	0.029	0.446	−0.387	−0.171	0.307	0.287	0.600	0.658	1.000			
Δ Address	0.048	−0.010	−0.015	−0.011	0.037	0.006	−0.022	0.006	0.019	−0.013	0.008	−0.005	−0.010	−0.011	0.019	0.010	−0.006	−0.015	1.000		
Δ Trans	0.039	−0.015	0.013	0.018	0.038	−0.011	−0.021	−0.005	−0.006	−0.031	−0.019	0.035	0.003	−0.013	0.013	−0.018	−0.028	−0.024	0.658	1.000	
Δ Users	0.037	0.018	0.069	0.060	0.062	0.007	−0.031	−0.015	−0.003	−0.033	−0.016	0.039	0.026	−0.026	−0.047	−0.042	−0.023	−0.017	−0.021	0.039	1.000

Note: This table reports correlations between daily changes for the variables under consideration.

cryptocurrencies and fiat currencies. This motivates the inclusion of a series of exchange rate common factors, capturing changes in the daily cross rate between the US Dollar (USD) and the Australian Dollar (AUD), Canadian Dollar (CAN), Japanese Yen (JPY), Euro (EUR) and Great British Pound (GBP).

Finally, Bitcoin has been proposed as digital gold, providing similar inflation hedging benefits as gold (Conlon et al., 2021; Blau et al., 2021) and indicated as a mechanism to hedge against downside risk in equity markets analogous to gold (Klein et al., 2018; Bredin et al., 2017; Baur and Lucey, 2010). For this reason, we examine daily gold, silver and platinum returns in US Dollars. Commodity and currency data are from Refinitiv Eikon.

Summary statistics for each of the dependent and explanatory variables can be found in Table 1. The mean fork returns vary considerably, reflecting their different starting dates. Dash has mean daily returns (22.2%) similar to Bitcoin (20.2%), while Litecoin has lower returns (11.1%). Bitcoin Cash (BCH) and Gold (BCG) have negative average returns. Also notable is the large variation in daily returns, exemplified by Litecoin with a minimum return of −90.45% and a maximum return of 74.8%. Each cryptocurrency analysed has high positive kurtosis, indicative of the substantial tail risk associated with these financial products. In sharp contrast, the financial factor returns present lower mean and standard deviation and less extreme returns than the cryptocurrencies assessed over the period examined.

Table 2 details correlations between fork returns and the common factors, along with the correlations between the latter. The correlation between forks and Bitcoin returns ranges between 0.511 (Dash) and 0.638 (BCH), providing initial guidance concerning the univariate relationship between these assets. The market has a correlation between 0.141 (Dash) and 0.230 (BCG) with fork returns, but this might result from a common relationship with Bitcoin. Other common factors present moderate correlations, with

Table 3
Dash regressions.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)	(xii)	(xiii)	(xiv)
DASH Lagged	0.008	0.008	0.009	0.009	0.009	0.009	0.008	0.010	0.009	0.009	0.009	0.010	0.010	0.010
	(0.11)	(0.12)	(0.13)	(0.12)	(0.13)	(0.13)	(0.11)	(0.14)	(0.14)	(0.13)	(0.13)	(0.14)	(0.14)	(0.14)
BTC	0.946***	0.934***	0.935***	0.933***	0.935***	0.939***	0.934***	0.936***	0.934***	0.933***	0.934***	0.939***	0.939***	0.936***
	(18.52)	(17.32)	(17.19)	(17.22)	(17.19)	(17.27)	(17.10)	(17.19)	(17.25)	(17.19)	(17.21)	(17.33)	(17.33)	(17.22)
Market		0.221*	0.278**	0.210	0.233*	0.223*	0.268**	0.287**	0.276**	0.250**	0.245*	0.268**	0.268**	0.278**
		(1.81)	(2.31)	(1.62)	(1.77)	(1.81)	(2.21)	(2.41)	(2.27)	(2.05)	(1.90)	(2.24)	(2.24)	(2.31)
SMB			−0.446*	−0.459*	−0.446*	−0.425*	−0.448*	−0.445*	−0.455*	−0.463*	−0.452*	−0.460*	−0.460*	−0.449*
			(−1.75)	(−1.79)	(−1.75)	(−1.67)	(−1.76)	(−1.75)	(−1.77)	(−1.81)	(−1.77)	(−1.81)	(−1.81)	(−1.76)
HML			0.133	0.131	0.117	0.074	0.139	0.136	0.157	0.156	0.137	0.147	0.147	0.134
			(0.62)	(0.61)	(0.55)	(0.34)	(0.65)	(0.64)	(0.70)	(0.72)	(0.64)	(0.69)	(0.69)	(0.63)
RMW			−0.349	−0.328	−0.327	−0.322	−0.340	−0.355	−0.346	−0.339	−0.340	−0.354	−0.354	−0.349
			(−1.38)	(−1.28)	(−1.28)	(−1.27)	(−1.34)	(−1.38)	(−1.36)	(−1.33)	(−1.33)	(−1.39)	(−1.39)	(−1.37)
CMA			0.286	0.247	0.259	0.308	0.269	0.289	0.241	0.226	0.241	0.242	0.242	0.280
			(0.74)	(0.64)	(0.67)	(0.79)	(0.69)	(0.75)	(0.61)	(0.58)	(0.62)	(0.63)	(0.63)	(0.72)
AUD				0.299										
				(1.29)										
CAN					−0.242									
					(−0.76)									
JPY						0.458**								
						(1.98)								
EUR							0.384							
							(1.58)							
GBP								−0.073						
								(−0.31)						
Gold									0.110					
									(0.60)					
Silver										0.094				
										(1.03)				
Platinum											0.081			
											(0.81)			
Δ Address												−0.036*		
												(−1.94)		
Δ Trans													−0.036*	
													(−1.94)	
Δ Users														−0.184
														(−0.33)
Constant	−0.265	0.077	0.076	0.083	0.080	0.072	0.082	0.075	0.074	0.078	0.079	0.079	0.079	0.099
	(−1.45)	(0.50)	(0.49)	(0.54)	(0.52)	(0.47)	(0.53)	(0.49)	(0.48)	(0.50)	(0.51)	(0.51)	(0.51)	(0.68)
R^2	0.261	0.262	0.263	0.263	0.263	0.264	0.264	0.263	0.263	0.263	0.263	0.264	0.264	0.263
Observations	2238	2238	2238	2238	2238	2238	2238	2238	2237	2238	2238	2238	2238	2238

Note: Dash returns are regressed on lagged Dash returns, Bitcoin returns, and the returns of a series of stock market, currency, and commodity factors, along with changes in network-based factors. The standard t-statistic is reported in parentheses. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics.

AUD, GBP, silver and platinum having correlations greater than 0.10 with some forks examined. Correlations between the common factors do not suggest that issues with collinearity will be problematic in our subsequent OLS regression analysis.

4. Empirical findings

4.1. Baseline findings

The selected methodological approach used in this study was informed by an extensive review of prevailing literature, aligning with established models and techniques pertinent to the stated research questions (Liu et al., 2020, 2022). The regression model employed was meticulously constructed to encapsulate the multifaceted interactions between Bitcoin, its forks, and traditional market indices, facilitating a nuanced exploration of their financial interplay. Specifically, the model employed to examine the drivers of Bitcoin forks is motivated by the regression developed in Liu and Tsyvinski (2021). Specifically, the returns on each fork, R_t^F, are regressed on the lagged fork returns to remove any omitted effects due to serial correlation in the dependent variable. As highlighted in Table 1, Dash and Bitcoin Gold present significant serial correlation. Furthermore, the returns of Bitcoin, R_t^{BTC}, the market, R_t^M, along with the remaining (Fama and French, 2015) four factors, $R_t^{FF_i}$. Currency returns, $R_t^{FX_i}$, commodity returns, $R_t^{Comm_i}$, and changes in network data, ΔNet_t^i, are also included. The model has the following form:

$$R_t^F = \alpha + \beta_F R_{t-1}^F + \beta_{BTC} R_t^{BTC} + \beta_M R_t^M + \sum_{i=1}^{4} \beta_{FF_i} R_t^{FF_i} + \sum_{j=1}^{5} \beta_{FX_j} R_t^{FX_j} + \sum_{k=1}^{3} \beta_{Comm_k} R_t^{Comm_k} + \sum_{l=1}^{3} \beta_{Net_l} \Delta Net_t^l + \epsilon_t. \quad (1)$$

The estimated results are provided in Tables 3 through 6 for Dash, Litecoin, Bitcoin Cash and Bitcoin Gold, respectively. Across all models, R-squared is high, ranging from 0.261 to 0.411, indicating the importance of the common factors examined in explaining the returns of Bitcoin forks. Many common themes emerge across all of the regressions. Lagged returns of the forks are not found to be significant, helping to rule out serial correlation as a consideration. Common to all models, the return on the fork has a positive and

Table 4
Litecoin regressions.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)	(xii)	(xiii)	(xiv)
Litecoin Lagged	−0.032	−0.031	−0.030	−0.030	−0.030	−0.030	−0.030	−0.029	−0.029	−0.029	−0.030	−0.031	−0.031	−0.030
	(−0.64)	(−0.62)	(−0.60)	(−0.61)	(−0.60)	(−0.59)	(−0.59)	(−0.57)	(−0.61)	(−0.61)	(−0.60)	(−0.62)	(−0.62)	(−0.59)
BTC	0.840***	0.829***	0.830***	0.829***	0.830***	0.830***	0.830***	0.830***	0.831***	0.830***	0.830***	0.828***	0.829***	0.830***
	(10.71)	(10.37)	(10.34)	(10.32)	(10.33)	(10.35)	(10.34)	(10.32)	(10.14)	(10.20)	(10.25)	(10.30)	(10.30)	(10.29)
Market		0.315***	0.339***	0.317**	0.334***	0.343***	0.341***	0.363***	0.342***	0.347***	0.349***	0.339***	0.342***	0.339***
		(2.77)	(2.87)	(2.59)	(2.71)	(3.27)	(2.89)	(3.05)	(3.04)	(3.29)	(3.15)	(2.85)	(2.87)	(2.87)
SMB			−0.274	−0.278	−0.274	−0.275	−0.274	−0.272	−0.269	−0.269	−0.272	−0.264	−0.266	−0.273
			(−1.58)	(−1.61)	(−1.58)	(−1.57)	(−1.58)	(−1.57)	(−1.59)	(−1.60)	(−1.59)	(−1.53)	(−1.54)	(−1.62)
HML			0.082	0.081	0.080	0.085	0.081	0.089	0.067	0.076	0.081	0.075	0.075	0.081
			(0.48)	(0.48)	(0.47)	(0.50)	(0.48)	(0.53)	(0.34)	(0.43)	(0.48)	(0.45)	(0.45)	(0.48)
RMW			−0.166	−0.159	−0.164	−0.168	−0.167	−0.180	−0.168	−0.169	−0.169	−0.173	−0.163	−0.166
			(−0.81)	(−0.77)	(−0.79)	(−0.82)	(−0.81)	(−0.88)	(−0.82)	(−0.82)	(−0.82)	(−0.84)	(−0.79)	(−0.81)
CMA			0.043	0.030	0.041	0.042	0.046	0.051	0.070	0.059	0.056	0.059	0.062	0.045
			(0.13)	(0.09)	(0.13)	(0.13)	(0.14)	(0.16)	(0.19)	(0.18)	(0.17)	(0.18)	(0.19)	(0.14)
AUD				0.093										
				(0.48)										
CAN					−0.026									
					(−0.10)									
JPY						−0.029								
						(−0.09)								
EUR							−0.052							
							(−0.23)							
GBP								−0.202						
								(−1.09)						
Gold									−0.065					
									(−0.16)					
Silver										−0.025				
										(−0.15)				
Platinum											−0.023			
											(−0.20)			
Δ Address												0.023		
												(1.21)		
Δ Trans													0.016	
													(0.89)	
Δ Users														0.034
														(0.06)
Constant	−0.055	−0.068	−0.068	−0.065	−0.067	−0.067	−0.068	−0.070	−0.067	−0.068	−0.069	−0.069	−0.068	−0.072
	(−0.44)	(−0.54)	(−0.53)	(−0.52)	(−0.54)	(−0.53)	(−0.54)	(−0.56)	(−0.53)	(−0.55)	(−0.55)	(−0.55)	(−0.54)	(−0.63)
R^2	0.338	0.340	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.341	0.342	0.341	0.341
Observations	2456	2456	2456	2456	2456	2456	2456	2456	2455	2456	2456	2456	2456	2456

Note: Litecoin returns are regressed on lagged Litecoin returns, Bitcoin returns, and the returns of a series of stock market, currency, and commodity factors, along with changes in network-based factors. The standard t-statistic is reported in parentheses. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics.

significant association with Bitcoin, with a beta which ranges from 0.83 to 1.04. This signals a strong contemporaneous relationship between the returns of each fork and Bitcoin, with a 1% move in Bitcoin resulting in a circa 1% change in forks. This high level of systematic exposure to Bitcoin indicates that, from an investment perspective, there are limited opportunities from diversification through allocations to forks.

Next, we consider links with common equity-based factors. Specifically, we examine links between fork returns and the stock market, along with portfolios consisting of small minus big stocks (SMB), high minus low book-to-market stocks (HMB), robust minus weak profitability stocks (RMW) and conservative minus aggressive investment stocks (CMA). If cryptocurrencies, and especially forks, were to be considered a distinct asset class uninfluenced by shocks to traditional markets, we would expect to find no significant relationships. Evidence for stock market-related links is found for Dash, Litecoin and Bitcoin Gold, even after controlling for Bitcoin returns. For Dash, the links with the market are found to be significant, at best, at the 5% level, with evidence for a weak negative relationship with the size factor, SMB, also detailed. Litecoin is found to be consistently associated with the market across all models, with a beta between 0.324 and 0.412. This indicates that for a 1% change in market returns, we expect the price of Litecoin to increase in lockstep by between 32 and 41bps. Bitcoin cash is not found to have any relationship with the market factors, which are unique among the forks examined. Finally, Bitcoin Gold has a significant and positive relationship with the market. Several plausible drivers of these unanticipated relationships include market sentiment, pressures on speculative capital and the hunt for yield during historically low interest rates. Moreover, these findings might indicate the presence of common changes in risk aversion across markets. However, we note that relative to a model including only Bitcoin and lagged fork returns, the R-squared only increases by a maximum of 0.06 (Bitcoin Gold) by including market-based factors. This highlights that, despite the statistically significant links between market-based common factors and fork returns, the returns of Bitcoin dominate in accounting for the explained variation in Bitcoin forks.

The theoretical models presented by Liu and Tsyvinski (2021) suggest that Bitcoin network factors, which specifically measure the network effect of user adoptions, are important drivers of cryptocurrency prices. In our examination of Bitcoin forks, however, we find no evidence for any links between fork returns and three network factors: the change in addresses, change in transactions and the change in the number of users. These findings contrast those presented by Liu and Tsyvinski (2021), where Bitcoin returns were found to be linked to each of these factors. Given the need to account for the returns of Bitcoin in our analysis, this may partially explain the differential findings. Considering links to currencies, Dash has a positive relationship with the Japanese Yen, while no other links are found. There are no links between fork returns and those of precious metals, despite the digital gold claims made

Table 5
Bitcoin cash regressions.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)	(xii)	(xiii)	(xiv)
BCH Lagged	0.042	0.043	0.043	0.044	0.043	0.043	0.042	0.044	0.043	0.043	0.043	0.043	0.043	0.040
	(0.95)	(0.96)	(0.97)	(0.99)	(0.97)	(0.97)	(0.96)	(0.98)	(0.97)	(0.97)	(0.97)	(0.98)	(0.97)	(0.92)
BTC	1.040***	1.033***	1.036***	1.037***	1.035***	1.036***	1.035***	1.037***	1.036***	1.036***	1.036***	1.036***	1.036***	1.033***
	(19.06)	(17.58)	(17.53)	(17.37)	(17.43)	(17.48)	(17.44)	(17.50)	(17.46)	(17.44)	(17.50)	(17.51)	(17.59)	(17.39)
Market		0.097	0.157	0.182	0.122	0.161	0.148	0.169	0.159	0.154	0.154	0.158	0.155	0.160
		(0.86)	(1.30)	(1.38)	(0.91)	(1.33)	(1.21)	(1.35)	(1.29)	(1.24)	(1.20)	(1.30)	(1.29)	(1.30)
SMB			−0.193	−0.185	−0.194	−0.194	−0.194	−0.191	−0.191	−0.195	−0.193	−0.194	−0.193	−0.187
			(−0.87)	(−0.83)	(−0.87)	(−0.87)	(−0.87)	(−0.86)	(−0.86)	(−0.87)	(−0.87)	(−0.88)	(−0.88)	(−0.85)
HML			0.073	0.073	0.059	0.076	0.073	0.076	0.069	0.075	0.073	0.076	0.076	0.075
			(0.37)	(0.37)	(0.29)	(0.38)	(0.37)	(0.38)	(0.34)	(0.38)	(0.37)	(0.39)	(0.39)	(0.38)
RMW			−0.063	−0.071	−0.045	−0.063	−0.056	−0.069	−0.065	−0.062	−0.062	−0.063	−0.066	−0.072
			(−0.22)	(−0.25)	(−0.16)	(−0.22)	(−0.20)	(−0.24)	(−0.23)	(−0.22)	(−0.22)	(−0.22)	(−0.24)	(−0.26)
CMA			0.379	0.392	0.367	0.379	0.376	0.382	0.387	0.373	0.375	0.371	0.368	0.397
			(0.98)	(1.02)	(0.95)	(0.98)	(0.97)	(0.99)	(0.97)	(0.95)	(0.96)	(0.96)	(0.95)	(1.03)
AUD				−0.110										
				(−0.43)										
CAN					−0.208									
					(−0.50)									
JPY						−0.039								
						(−0.12)								
EUR							0.168							
							(0.51)							
GBP								−0.107						
								(−0.46)						
Gold									−0.021					
									(−0.12)					
Silver										0.009				
										(0.12)				
Platinum											0.006			
											(0.07)			
Δ Address												−0.013		
												(−0.46)		
Δ Trans													−0.008	
													(−0.28)	
Δ Users														0.857
														(1.07)
Constant	−0.228	−0.231	−0.239	−0.242	−0.237	−0.239	−0.237	−0.240	−0.239	−0.239	−0.239	−0.239	−0.239	−0.294*
	(−1.39)	(−1.40)	(−1.45)	(−1.47)	(−1.43)	(−1.44)	(−1.43)	(−1.45)	(−1.44)	(−1.45)	(−1.45)	(−1.44)	(−1.44)	(−1.92)
R^2	0.408	0.409	0.410	0.410	0.410	0.410	0.410	0.410	0.410	0.410	0.410	0.410	0.410	0.411
Observations	1363	1363	1363	1363	1363	1363	1363	1363	1363	1363	1363	1363	1363	1363

Note: Bitcoin cash returns are regressed on lagged Bitcoin cash returns, Bitcoin returns, and the returns of a series of stock market, currency, and commodity factors, along with changes in network-based factors. The standard t-statistic is reported in parentheses. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics.

about cryptocurrencies (Klein et al., 2018). Echoing the findings concerning stock market-based factors, no increases in explained variation are attributed to including the network, currency or commodity factors. This provides additional evidence that Bitcoin is the primary driver of Bitcoin fork returns.

4.2. Orthogonal decomposition of explained variation

To ensure that our findings are not a consequence of a single common factor influencing all variables, we use an optimal orthogonalisation approach recently introduced into the finance literature (Adcock et al., 2022; Bessler et al., 2022; Klein and Chow, 2013). This decomposition, first proposed by Löwdin (1950), in the context of the physical sciences, allows for the creation of an orthogonal basis which most closely resembles the original variables.[12] Using this orthogonal transformation, it is possible to decompose aggregate model R-squared into components associated with the explanatory variables while retaining interpretability for the original drivers. Findings are displayed in Table 7. The coefficient and t-statistic are shown for each common factor, along with the component of the model R-squared associated with the factor. For example, for Litecoin, BTC is a significant determinant with a coefficient of 0.838, a t-statistic of 6.10 and an associated R-squared component of 0.336. This is notable, as the total R-squared of the first model is 0.340, suggesting that 98.8% of the variation is attributable to Bitcoin. When the additional market-related variables are included in the second model, Bitcoin still dominates the explained variation.[13]

Findings for the other Bitcoin forks are similar. Bitcoin is the dominant common factor, accounting for almost all the explained variation across each model. Among the other common factors assessed, the largest explained variation attributable to the other common factors assessed is 0.004, found for the market. These findings illustrate that assessing the statistical significance in isolation is insufficient to provide an indication of the economic significance of the common factors, in keeping with earlier implications when

[12] The (Löwdin, 1950) symmetric transformation defines the orthonormal matrix of factors $\tilde{Z}^{\perp}_{T\times K}$ by the linear transformation: $\tilde{Z}^{\perp}_{T\times K} = \tilde{Z}_{T\times K} S_{K\times K}$, where $\tilde{Z}_{T\times K}$ is the $T \times K$ matrix of common factor returns and $S_{K\times K}$ is the spectral decomposition of the covariance matrix between the common factors, given by: $S_{K\times K} = U\Lambda^{-1/2}U'$. While full further technical details are beyond the scope of this article, a thorough theoretical exposition is provided by Adcock et al. (2022).

[13] As these were the main determinants documented in the earlier model, other common factors such as currency, commodities and network factors are not included here. Findings not detailed here indicate that Bitcoin accounts for the majority of explained variation, even with a more detailed model.

Table 6
Bitcoin gold regressions.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)	(xii)	(xiii)	(xiv)
BCG Lagged	0.008	0.010	0.010	0.010	0.010	0.009	0.008	0.010	0.010	0.011	0.009	0.010	0.010	0.008
	(0.22)	(0.27)	(0.28)	(0.26)	(0.28)	(0.24)	(0.22)	(0.26)	(0.26)	(0.29)	(0.25)	(0.28)	(0.28)	(0.22)
BTC	0.960***	0.929***	0.930***	0.929***	0.930***	0.928***	0.927***	0.929***	0.928***	0.931***	0.928***	0.930***	0.930***	0.927***
	(17.15)	(15.90)	(15.89)	(15.65)	(15.76)	(15.73)	(15.76)	(15.81)	(15.65)	(15.68)	(15.77)	(15.95)	(15.89)	(15.77)
Market		0.367***	0.435***	0.423***	0.454***	0.455***	0.411***	0.425***	0.429***	0.445***	0.399***	0.436***	0.433***	0.438***
		(3.16)	(3.29)	(3.10)	(3.14)	(3.29)	(3.14)	(3.16)	(3.25)	(3.35)	(2.87)	(3.32)	(3.28)	(3.30)
SMB			−0.461*	−0.465*	−0.460*	−0.471*	−0.464*	−0.462*	−0.467*	−0.453*	−0.468*	−0.460*	−0.461*	−0.455*
			(−1.73)	(−1.73)	(−1.73)	(−1.76)	(−1.73)	(−1.73)	(−1.75)	(−1.70)	(−1.76)	(−1.73)	(−1.73)	(−1.71)
HML			0.243	0.242	0.251	0.263	0.242	0.240	0.260	0.235	0.244	0.246	0.245	0.245
			(1.00)	(1.00)	(0.99)	(1.09)	(0.99)	(0.98)	(1.06)	(0.96)	(1.00)	(1.01)	(1.01)	(1.01)
RMW			−0.490	−0.486	−0.501	−0.490	−0.468	−0.485	−0.480	−0.496	−0.472	−0.490	−0.493	−0.501
			(−1.39)	(−1.37)	(−1.39)	(−1.39)	(−1.30)	(−1.37)	(−1.35)	(−1.40)	(−1.33)	(−1.39)	(−1.40)	(−1.42)
CMA			0.350	0.344	0.355	0.349	0.344	0.347	0.314	0.370	0.305	0.342	0.341	0.372
			(0.70)	(0.69)	(0.71)	(0.70)	(0.69)	(0.70)	(0.62)	(0.73)	(0.61)	(0.68)	(0.68)	(0.75)
AUD				0.054										
				(0.20)										
CAN					0.115									
					(0.26)									
JPY						−0.246								
						(−0.73)								
EUR							0.448							
							(1.02)							
GBP								0.088						
								(0.33)						
Gold									0.092					
									(0.47)					
Silver										−0.032				
										(−0.38)				
Platinum											0.077			
											(0.70)			
Δ Address												−0.016		
												(−0.60)		
Δ Trans													−0.007	
													(−0.24)	
Δ Users														1.007
														(1.29)
Constant	−0.265	−0.277	−0.276	−0.276	−0.278	−0.275	−0.272	−0.276	−0.278	−0.276	−0.275	−0.276	−0.276	−0.333*
	(−1.45)	(−1.52)	(−1.52)	(−1.52)	(−1.53)	(−1.51)	(−1.49)	(−1.51)	(−1.53)	(−1.52)	(−1.51)	(−1.51)	(−1.51)	(−1.94)
R^2	0.332	0.335	0.338	0.338	0.338	0.338	0.338	0.338	0.338	0.338	0.338	0.338	0.338	0.339
Observations	1303	1303	1303	1303	1303	1303	1303	1303	1303	1303	1303	1303	1303	1303

Note: Bitcoin gold returns are regressed on lagged Bitcoin gold returns, Bitcoin returns, and the returns of a series of stock market, currency, and commodity factors, along with changes in network-based factors. The standard t-statistic is reported in parentheses. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics.

considering common factor determinants of asset prices (Adcock et al., 2022). In the models presented, while Bitcoin and the market are statistically significant, Bitcoin dominates in terms of economic significance.

4.3. Quantile regressions

Next, quantile regression models are examined to determine whether relationships are primarily associated with particular market regimes, representing periods of low and high returns for Forks. Results are presented in Table 8. The analysis is focused on market-related factors and Bitcoin, as these were the prominent relationships uncovered in the preceding analyses.[14]

Consistent with earlier presented results, the returns of the examined forks are associated with Bitcoin returns for all quantiles examined, and Bitcoin accounts for most of the explained variation throughout. Notably, the strength of the relationship is found to increase from the lowest to high quantiles. For example, for Bitcoin Cash at the 10th percentile, the beta to BTC returns in the full model is 1.025, while at the 90th percentile, this increases to 1.209, indicating an increase in systematic risk in periods of high fork returns. Considering the links between forks and the stock market, we find evidence for a strong link between fork returns and the market at low quantiles, but this is not found to contribute substantially to explained variation, echoing the earlier findings. Dash and Bitcoin Cash have a strong and significant market beta when the dependent variable is at the 10th percentile, with no statistical evidence for a relationship at the highest quantile examined. In the case of Litecoin, the magnitude of the market coefficient is largest at the lowest percentiles, indicating that the potential for contagion effects coinciding with low fork returns. These findings build upon the recent evidence that the relationship between cryptocurrencies and the stock market is extensive during periods of turbulence (Conlon and McGee, 2020b).

Moreover, some evidence for a relationship between forks and the Fama and French (2015) factors is found. Notably, Litecoin is found to have a negative relationship with HML, the value factor, at the 25th percentile, a strong positive relationship with CMA at the 10th and 25th percentiles and a negative relationship with SMB at the 90th percentile. Bitcoin cash presents a positive relationship with CMA at the 25th and 50th percentiles while Bitcoin Gold has a negative relationship with SMB and RMW at

[14] In unreported results, only limited inference on any relationships between the forks and network factors, currencies or precious metals were found at any quantile.

Table 7
Coefficient of determination extracted using orthogonalised factors.

	Litecoin		Dash		BCH		BCG	
Dependent Lagged	−0.027	−0.028	−0.002	−0.001	0.024	0.024	−0.001	−0.001
	(−0.59)	(−0.58)	(−0.03)	(−0.03)	(0.77)	(0.77)	(−0.03)	(−0.03)
	0.001	0.001	0.000	0.000	0.001	0.001	0.000	0.000
BTC	0.838***	0.838***	0.943***	0.943***	1.035***	1.035***	0.951***	0.951***
	(6.10)	(6.09)	(15.24)	(15.25)	(13.84)	(13.83)	(11.39)	(11.40)
	0.336	0.336	0.259	0.259	0.405	0.405	0.325	0.325
Market	0.426***	0.432***	0.381***	0.397***	0.328***	0.344***	0.573***	0.590***
	(3.50)	(3.61)	(3.21)	(3.31)	(3.46)	(3.72)	(5.04)	(5.09)
	0.004	0.004	0.003	0.003	0.003	0.004	0.010	0.011
SMB		−0.153		−0.288		−0.068		−0.228
		(−0.99)		(−1.37)		(−0.42)		(−1.11)
		0.000		0.001		0.000		0.000
HML		0.013		0.064		0.074		0.125
		(0.12)		(0.45)		(0.66)		(0.82)
		0.000		0.001		0.000		0.000
RMW		−0.192		−0.314		−0.082		−0.413
		(−0.96)		(−1.47)		(−0.35)		(−1.29)
		0.000		0.000		0.000		0.001
CMA		−0.068		0.140		0.206		0.159
		(−0.32)		(0.55)		(0.87)		(0.55)
		0.000		0.000		0.000		0.000
Contrast	−0.068	−0.068	0.077	0.076	−0.231	−0.239	−0.277	−0.277
	(−0.60)	(−0.59)	(0.50)	(0.50)	(−1.48)	(−1.52)	(−1.66)	(−1.65)
R2	0.340	0.341	0.262	0.263	0.409	0.410	0.335	0.338

Note: This tables models Bitcoin Fork returns as a function of orthogonalised variables formed using the Löwdin (1950) transformation. For each common factor assessed, the coefficient is detailed with the associated t-statistic in brackets underneath, followed by the component of the model R-squared attributable to that common factor. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard t-statistics.

the 25th percentile. Providing further support for the central conjecture of this paper, we note that while these coefficients are statistically significant, they contribute almost nothing to the overall explanatory power of the model. In contrast, and echoing our earlier findings, Bitcoin accounts for the majority of explained variation, evidenced by our model development approach.

High volatility, fraud, gambling and illegal activity have all contributed to calls for cryptocurrencies to be regulated (Conlon and McGee, 2021, 2020a; Foley et al., 2019). Focusing upon Bitcoin forks, our findings here indicate that these offshoots and their close relationship with Bitcoin are also strongly associated with market-based factors. Moreover, these links are stronger during periods of greater downside risk in cryptocurrency, highlighting the potential for concurrent losses. However, the dominant role of Bitcoin in explaining Bitcoin fork returns highlights the importance of not merely focusing on these statistical relationships. In designing a framework for cryptocurrency regulation, such interrelationships may motivate a focus on systematic risk within the cryptocurrency complex. They may also indicate a limited potential for direct contagion to traditional markets, with any spillover effects relating to their relationship with Bitcoin.

4.4. Weekly returns

Finally, we examine whether our findings are consistent for weekly data to mitigate any effects from issues such as the 24/7 trading of cryptocurrencies and their trading across multiple time zones. Results, provided in Table 9, indicate that our primary finding, that Bitcoin dominates the explained variation of Bitcoin forks, holds for weekly data. Throughout the regressions, the R-squared values are increased relative to the daily analysis, in keeping with the commonly reported trend of increasing correlations at long horizons attributed to a reduction in serial correlations in the time series (Conlon et al., 2018).

Results are supportive of the central contribution of this article. Bitcoin has a statistically significant positive relationship with all forks considered, and accounts for between 31.6% and 52% of variation in fork returns. The stock market and other market-related factors are not found to be either statistically or economically important in explaining fork returns. Relative to the results using daily returns, the market factor is no longer statistically significant, perhaps influenced by the strong short-run reversals often seen in bitcoin prices (Zaremba et al., 2021).

5. Discussion and conclusions

The principal aim of this research is to investigate the differential relationships between Bitcoin, Bitcoin forks and other international financial markets, with particular attention given to equity markets and foreign exchange. The results reveal several notable relationships that enhance our understanding of cryptocurrency markets and their interplay with traditional financial assets. Firstly, we discovered a significant correlation between the returns of Bitcoin forks and Bitcoin itself. The Bitcoin forks under study, specifically Bitcoin Cash, Bitcoin Gold, Dash, and Litecoin exhibited a consistently strong contemporaneous association with Bitcoin.

Table 8
Quantile regressions for selected analysed forks.

(a) Dash Quantile Regression

	10% Percentile			25th Percentile			50th Percentile			75th Percentile			90th Percentile		
Dash Lagged	−0.062	−0.061	−0.062	−0.050**	−0.046**	−0.043**	−0.029**	−0.027	−0.027*	−0.002	−0.006	−0.002	0.064	0.065*	0.071
	(−1.63)	(−1.48)	(−1.64)	(−2.22)	(−2.14)	(−2.18)	(−1.97)	(−1.57)	(−1.92)	(−0.06)	(−0.19)	(−0.05)	(1.58)	(1.75)	(1.49)
BTC	0.892***	0.876***	0.856***	0.935***	0.906***	0.900***	0.941***	0.914***	0.914***	0.978***	0.976***	0.965***	1.027***	1.023***	1.019***
	(26.14)	(23.58)	(18.31)	(32.72)	(28.5)	(30.81)	(26.39)	(28.32)	(27.33)	(22.93)	(24.87)	(23.19)	(15.17)	(16.44)	(13.51)
Market		0.470***	0.459**		0.312***	0.326***		0.205**	0.244***		0.259**	0.292*		−0.027	−0.022
		(2.97)	(2.52)		(3.19)	(3.42)		(2.43)	(2.66)		(2.22)	(1.82)		(−0.13)	(−0.09)
SMB			−0.592*			−0.233*			−0.125			−0.252			−0.426
			(−1.65)			(−1.69)			(−0.86)			(−0.79)			(−0.63)
HML			−0.004			0.180			−0.086			0.168			0.068
			(−0.01)			(1.19)			(−0.68)			(0.79)			(0.11)
RMW			−0.961*			−0.438**			−0.119			−0.399			−0.384
			(−1.73)			(−2.49)			(−0.59)			(−1.29)			(−0.55)
CMA			0.189			0.194			0.203			0.112			0.369
			(0.34)			(0.57)			(0.76)			(0.23)			(0.41)
Constant	−5.705***	−5.755***	−5.724***	−2.696***	−2.733***	−2.663***	−0.367***	−0.385***	−0.407***	2.142***	2.138***	2.122***	6.246***	6.224***	6.230***
	(−19.77)	(−21.41)	(−22.93)	(−24.95)	(−24.27)	(−25.47)	(−4.27)	(−4.14)	(−4.05)	(17.16)	(17.14)	(16.18)	(29.34)	(22.06)	(17.40)
R2	0.233	0.237	0.239	0.230	0.232	0.235	0.204	0.206	0.206	0.172	0.173	0.174	0.127	0.127	0.128
Observations	2238	2238	2238	2238	2238	2238	2238	2238	2238	2238	2238	2238	2238	2238	2238

(b) Litecoin Quantile Regression

	10% Percentile			25th Percentile			50th Percentile			75th Percentile			90th Percentile		
Litecoin Lagged	−0.053**	−0.043**	−0.046***	−0.067***	−0.058***	−0.059***	−0.069***	−0.064***	−0.061***	−0.022	−0.021	−0.022	0.037	0.028	0.028
	(−2.07)	(−2.09)	(−2.88)	(−3.95)	(−3.60)	(−3.79)	(−3.81)	(−3.40)	(−3.87)	(−0.98)	(−0.87)	(−0.97)	(0.86)	(0.61)	(0.74)
BTC	0.881***	0.839***	0.843***	0.912***	0.893***	0.894***	0.939***	0.931***	0.929***	0.990***	0.973***	0.972***	0.980***	0.984***	1.003***
	(19.52)	(18.04)	(18.73)	(29.94)	(37.66)	(40.37)	(40.41)	(45.31)	(47.22)	(32.92)	(31.69)	(30.44)	(13.17)	(11.97)	(13.53)
Market		0.578***	0.614***		0.285***	0.289***		0.181***	0.187***		0.156**	0.157*		0.406*	0.310
		(4.70)	(4.52)		(4.31)	(4.91)		(3.54)	(3.42)		(2.30)	(1.73)		(1.65)	(1.55)
SMB			−0.095			0.023			−0.010			0.072			−0.922**
			(−0.32)			(0.20)			(−0.11)			(0.46)			(−2.58)
HML			−0.253			−0.335**			−0.061			−0.016			0.474
			(−0.88)			(−2.20)			(−0.69)			(−0.12)			(1.25)
RMW			0.039			0.008			0.106			0.048			−0.293
			(0.11)			(0.05)			(0.86)			(0.24)			(−0.62)
CMA			1.227**			0.502**			0.087			0.027			−0.777
			(2.35)			(1.99)			(0.48)			(0.12)			(−1.13)
Constant	−4.604***	−4.662***	−4.626***	−2.196***	−2.101***	−2.123***	−0.358***	−0.385***	−0.362***	1.394***	1.346***	1.364***	4.394***	4.44***	4.366***
	(−20.77)	(−24.91)	(−23.55)	(−20.93)	(−25.09)	(−23.81)	(−6.21)	(−8.39)	(−6.11)	(12.77)	(14.49)	(17.13)	(15.95)	(18.48)	(16.93)
R2	0.312	0.318	0.320	0.313	0.316	0.317	0.297	0.299	0.299	0.269	0.270	0.270	0.222	0.223	0.226
Observations	2456	2456	2456	2456	2456	2456	2456	2456	2456	2456	2456	2456	2456	2456	2456

(c) Bitcoin Cash Quantile Regression

	10% Percentile			25th Percentile			50th Percentile			75th Percentile			90th Percentile		
BCH Lagged	−0.057	−0.058	−0.057	−0.069***	−0.059***	−0.062***	−0.043**	−0.039*	−0.04*	−0.006	−0.003	0.001	0.075**	0.077**	0.066*
	(−1.24)	(−1.28)	(−1.49)	(−3.16)	(−2.87)	(−3.24)	(−2.14)	(−1.68)	(−1.75)	(−0.20)	(−0.08)	(0.04)	(2.39)	(2.15)	(1.96)
BTC	1.064***	1.015***	1.025***	1.074***	1.059***	1.059***	1.045***	1.030***	1.035***	1.134***	1.121***	1.124***	1.216***	1.197***	1.209***
	(22.13)	(19.26)	(16.86)	(28.81)	(27.76)	(27.31)	(33.31)	(28.30)	(28.23)	(28.90)	(25.52)	(22.41)	(21.03)	(22.59)	(16.75)
Market		0.363**	0.380*		0.149**	0.156*		0.099	0.206***		0.083	0.091		−0.202	−0.229
		(2.11)	(1.80)		(2.22)	(1.80)		(1.28)	(2.73)		(0.98)	(0.92)		(−1.40)	(−1.22)
SMB			−0.515			−0.099			0.010			−0.046			−0.565
			(−1.28)			(−0.54)			(0.07)			(−0.21)			(−1.29)
HML			−0.150			−0.126			−0.142			0.039			0.524
			(−0.38)			(−1.11)			(−1.01)			(0.19)			(1.40)
RMW			−0.258			0.028			0.083			0.065			−0.035
			(−0.44)			(0.18)			(0.46)			(0.25)			(−0.04)
CMA			0.629			0.577*			0.843***			−0.007			−0.973
			(1.05)			(1.84)			(3.73)			(−0.02)			(−0.98)
Constant	−4.911***	−4.896***	−5.009***	−2.394***	−2.382***	−2.392***	−0.548***	−0.506***	−0.632***	1.258***	1.246***	1.264***	4.335***	4.321***	4.260***
	(−16.99)	(−18.72)	(−15.39)	(−22.61)	(−25.70)	(−21.25)	(−6.18)	(−5.55)	(−7.03)	(8.09)	(8.80)	(7.61)	(10.85)	(14.05)	(13.14)
R2	0.338	0.341	0.343	0.349	0.351	0.352	0.325	0.325	0.329	0.284	0.285	0.285	0.219	0.220	0.222
Observations	1363	1363	1363	1363	1363	1363	1363	1363	1363	1363	1363	1363	1363	1363	1363

(d) Bitcoin Gold Quantile Regression

	10% Percentile			25th Percentile			50th Percentile			75th Percentile			90th Percentile		
BCG Lagged	−0.064	−0.069	−0.069	−0.028	−0.025	−0.028	−0.008	−0.008	−0.007	0.001	−0.003	−0.007	0.090	0.106**	0.089
	(−1.02)	(−1.24)	(−1.29)	(−0.80)	(−0.77)	(−0.95)	(−0.33)	(−0.34)	(−0.26)	(0.02)	(−0.09)	(−0.21)	(1.56)	(2.30)	(1.64)
BTC	1.015***	1.001***	0.996***	1.023***	0.999***	0.998***	0.984***	0.974***	0.969***	0.973***	0.96***	0.942***	0.964***	0.898***	0.924***
	(19.10)	(19.98)	(19.45)	(29.66)	(27.00)	(23.50)	(23.25)	(24.38)	(25.25)	(16.61)	(14.83)	(16.68)	(9.63)	(8.78)	(9.67)
Market		0.348*	0.334**		0.190*	0.236**		0.105	0.163*		0.187**	0.248**		0.746***	0.701***
		(1.85)	(1.98)		(1.74)	(2.12)		(1.28)	(1.92)		(2.14)	(2.11)		(4.11)	(2.97)
SMB			−0.096			−0.435*			−0.162			−0.396*			−0.662
			(−0.24)			(−1.86)			(−1.08)			(−1.68)			(−1.16)
HML			0.288			0.102			−0.073			0.028			0.172
			(0.70)			(0.57)			(−0.59)			(0.14)			(0.27)
RMW			−0.775			−0.491**			−0.132			−0.174			−0.261
			(−1.13)			(−2.05)			(−0.85)			(−0.56)			(−0.27)

(*continued on next page*)

Table 8 (*continued*).

CMA			0.624			0.403			0.315			0.132			−0.281
			(0.88)			(1.33)			(1.41)			(0.35)			(−0.24)
Constant	−5.367***	−5.415***	−5.380***	−2.591***	−2.598***	−2.504***	−0.532***	−0.531***	−0.548***	1.327***	1.304***	1.352***	4.988***	5.022***	5.011***
	(−16.83)	(−17.90)	(−14.95)	(−21.59)	(−18.78)	(−16.24)	(−5.94)	(−5.35)	(−5.49)	(9.18)	(9.20)	(10.2)	(11.82)	(12.44)	(10.75)
R2	0.294	0.299	0.301	0.306	0.308	0.311	0.284	0.285	0.286	0.226	0.228	0.230	0.142	0.150	0.152
Observations	1303	1303	1303	1303	1303	1303	1303	1303	1303	1303	1303	1303	1303	1303	1303

Note: Quantile regressions are examined at a range of percentiles from the 10th to 90th. Returns of Bitcoin forks are regression on a lagged fork returns; Bitcoin returns, and the returns of a series of stock market-related factors. The standard *t*-statistic is reported in parentheses. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard *t*-statistics.

Table 9
Bitcoin forks regressions using weekly daily.

	Litecoin			Dash			BCH			BCG		
Dependent Lagged	−0.019	−0.019	−0.02	0.047	0.044	0.042	0.105	0.106	0.098	−0.016	−0.024	−0.020
	(−0.2)	(−0.20)	(−0.21)	(0.75)	(0.71)	(0.68)	(1.45)	(1.45)	(1.40)	(−0.24)	(−0.34)	(−0.28)
BTC	1.109***	1.109***	1.110***	0.878***	0.877***	0.884***	1.070***	1.071***	1.081***	0.940***	0.936***	0.947***
	(13.64)	(13.62)	(13.36)	(6.68)	(6.68)	(6.69)	(8.65)	(8.63)	(8.63)	(7.17)	(7.22)	(7.12)
Market		−0.111	0.057		0.210	0.296		−0.227	0.093		0.822	1.353
		(−0.44)	(0.16)		(0.53)	(0.65)		(−0.61)	(0.20)		(1.10)	(1.09)
SMB			−0.026			−1.416			−1.841*			−1.543
			(−0.05)			(−1.65)			(−1.78)			(−1.23)
HML			1.338			−0.182			−1.367			0.322
			(1.53)			(−0.13)			(−0.85)			(0.11)
RMW			0.881			−0.941			−1.896			−1.198
			(0.81)			(−0.67)			(−1.00)			(−0.40)
CMA			−0.289			−0.869			0.996			0.356
			(−0.32)			(−0.64)			(0.53)			(0.23)
Constant	−0.468	−0.462	−0.606	−0.453	−0.459***	−0.352***	−0.923	−0.919	−0.916	−1.312	−1.328	−1.480
	(−0.9)	(−0.88)	(−1.13)	(−0.62)	(−0.62)	(−0.46)	(−1.13)	(−1.13)	(−1.07)	(−1.37)	(−1.40)	(−1.55)
R^2	0.520	0.520	0.522	0.356	0.357	0.363	0.449	0.450	0.462	0.316	0.324	0.333
Observations	491	491	491	302	302	302	273	273	273	261	261	261

Note: Weekly Bitcoin fork returns are regressed on lagged fork returns, Bitcoin returns, and the returns of a series of stock market, currency, and commodity factors, along with changes in network-based factors. The standard *t*-statistic is reported in parentheses. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels based on the standard *t*-statistics.

This relationship held across different model specifications and was robust to various sensitivity checks. Furthermore, Bitcoin is found to be the only economically meaningful driver of fork returns, accounting for nearly all the explained variation across all models. Such a strong correlation suggests that despite the divergence of these forks from the main Bitcoin chain, the investment outcomes they offer remain closely tied to Bitcoin. This underscores the fact that, from an investment perspective, these forks may not provide significant diversification benefits within a cryptocurrency portfolio heavily dominated by Bitcoin.

Secondly, beyond the cryptocurrency realm, this research identifies significant relationships between Bitcoin forks and traditional equity markets. These correlations manifest as interactive effects, whereby the returns on Bitcoin forks respond to movements in stock market returns. Importantly, these effects were more pronounced when the forks' returns were lowest. This suggests the existence of a downside risk correlation, a phenomenon that can be indicative of common changes in risk aversion across different market segments. While this effect is statistically significant, it is outweighed in economic terms by the relationship between Bitcoin and its forks. These findings highlight that, while there may be spillovers from traditional markets and less dominant cryptocurrencies such as forks, the primary consideration from a risk management perspective are the links with the parent, Bitcoin.

This research sheds significant light on the association of Bitcoin forks with both the primary Bitcoin market and traditional equity markets. The implications of these findings are particularly relevant to policymakers, regulators, and the broader financial industry. The strong correlation observed between Bitcoin and its forks could inform policymakers of the interconnectedness within the cryptocurrency market. Such interdependencies suggest that shocks to Bitcoin can potentially propagate to the wider cryptocurrency market. This correlation also indicates that comprehensive regulation of cryptocurrencies should consider Bitcoin and its forks as closely linked assets with similar risk characteristics. Moreover, the study's findings that the Bitcoin forks' returns have a relationship with traditional markets, such as equity, that is statistically but not economically significant implies that any coupling between these markets is a second-order effect relating to the previously documented relationships between Bitcoin and the stock market (Conlon and McGee, 2020a; Conlon et al., 2020).

This research opens up several potential avenues for future exploration. First, while this study has primarily focused on Bitcoin and its forks, extending this analysis to other cryptocurrencies, such as Ethereum and its related forks, or to relatively novel entrants like stablecoins would be informative. Expanding the scope of the study could provide a more comprehensive understanding of the interconnectedness and potential contagion within the broader cryptocurrency market. Secondly, given the significant correlation observed between Bitcoin forks and traditional market factors, there is a need to understand better the underlying mechanisms driving this relationship and its importance. In particular, future research could investigate whether these links are due to shared macroeconomic influences, investor sentiment dynamics, or the result of shared investor bases. Thirdly, this research found no evidence linking Bitcoin fork returns to network factors, such as the number of users or transactions, contradicting some existing theories on cryptocurrency valuation. This calls for further exploration of what drives the value of Bitcoin forks and other cryptocurrencies. Factors like technological features, market liquidity, regulatory developments, or utility in real-world applications could all be pertinent to consider. Finally, the findings of this study have critical policy implications, suggesting that an integrated, holistic regulatory approach is needed for cryptocurrencies.

CRediT authorship contribution statement

Thomas Conlon: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Shaen Corbet:** Conceptualization, Formal analysis, Methodology, Resources, Software, Validation, Writing – original draft, Writing – review & editing. **Yang (Greg) Hou:** Conceptualization, Formal analysis, Methodology, Resources, Validation, Writing – original draft, Writing – review & editing. **Yang Hu:** Conceptualization, Formal analysis, Methodology, Resources, Software, Validation, Writing – original draft, Writing – review & editing. **Les Oxley:** Conceptualization, Formal analysis, Methodology, Resources, Software, Validation, Writing – original draft.

Data availability

Data will be made available on request.

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