

Methods Used to Study Bitcoin Price Behaviour, 2000–2026: A Review and Directions for Future Research

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ABSTRACT

While the Bitcoin study has rapidly grown, there has been relatively little study of the dominant methods applied to Bitcoin research and the methods that are underused and deserve more research attention. This note outlines the techniques used in analysing Bitcoin price, returns and volatility. The following 6 queries were executed in Google Scholar for the time span 2000-2026, which resulted in 127 records, which were kept for the 110 studies after screening, each of which was coded under one primary method family. A quantitative design was used in more studies (102 studies; 92.7%) compared to qualitative (5 studies; 4.5%) and mixed designs (3 studies; 2.7%). None of the included studies existed before 2014, and 2026 appears in 54 studies, a period where it appears only to a limited extent. The largest method family was machine learning forecasting, while none of the qualitative studies in the sample involved primary data collection. The note highlights the methods that were not found, or were hardly found, in the reviewed sample and believes that methods employed in qualitative social research such as interviews, focus groups, Delphi panels, document analysis, case studies, and netnography of online Bitcoin investor communities are relevant to Bitcoin, given that its price is driven by investor beliefs, narratives and regulatory developments that statistical modeling cannot adequately capture.

Keywords: Bitcoin, research methods, literature review, time series analysis, qualitative research, research gaps

1. INTRODUCTION

Bitcoin has progressed in just the last 20 years from a technical proposal (Nakamoto, 2008) to an asset studied in economics, finance, computer science and law. Initial research showed it was not based on traditional fundamentals and was very speculative (Ciaian et al., 2016; Kristoufek, 2015), and that the market was not informationally efficient (Bariviera, 2017; Urquhart, 2016).

This growth brings up a point that is rarely discussed in individual studies – what are the predominant methodologies, and what are the ones that have been overlooked? As such, this note outlines the methods used in research published between 2000–2026, categorises them as quantitative, qualitative or mixed, and recognises gaps in methodological application which can be solved by future research.

2. RESEARCH CONTEXT

The significant volatility and non-stationarity of the bitcoin price, plus the repeated booms, crashes, halving and regulatory events, have led to a continuous demand to forecast and model bitcoin volatility. The questions of why these episodes happen, what market participants think about market cycles, and the impact that regulation has on prices also require different approaches, but these have yet to be fully implemented. For the present note we therefore rely on bibliographic data, and not price data.

3. METHODOLOGY

Six queries were designed to capture the principal strands of Bitcoin price research (Table 1) and were executed in Google Scholar on 13 May 2026, with results restricted to 2000–2026. The first 20 results for each query were recorded, and a second retrieval of the first query yielded seven additional records. Because the search was conducted on 13 May 2026, 2026 represents a partial publication year in this review.

Table 1
Search Queries, Records Retrieved and Studies Included

Search query	Source	Records	Included
1. Bitcoin price time series analysis trend seasonality	Google Scholar	27	25
2. Bitcoin price ARIMA GARCH volatility	Google Scholar	20	19
3. Bitcoin price seasonal decomposition	Google Scholar	20	14
4. Bitcoin price structural breaks bubbles	Google Scholar	20	19
5. Bitcoin halving price effect	Google Scholar	20	19
6. Bitcoin calendar effects day-of-the-week returns	Google Scholar	20	14
Total		127	110

Note. Searches were restricted to 2000–2026. Records = records retrieved; Included = studies retained after screening. Eight duplicate and nine off-topic records were removed. Each study is counted under the first query that returned it.

Studies were initially de-duplicated – if a study was returned by two or more queries, it was only kept one time, in the first query that returned it, and eight copies were deleted. The titles and search summaries were then screened and included based on the inclusion criteria. Studies that analysed, modelled or discussed the Bitcoin price, returns or volatility were included, while studies on other tokens/markets were excluded as off-topic (nine records). Of these 127, 119 were unique records and 110 of these contained studies (Table 1). In Tables 2 and 3, each included study had only one study method family, even if more than one method was used, in order to count each study only one time. Studies were categorized as quantitative (numerical data analysed statistically), qualitative (account/ textual material analysed interpretatively, such as reviews or comments) or mixed (both). All 110 studies are provided in a study-level coding (coded-studies spreadsheet).

4. KEY FINDINGS

Among the 110 included studies, 102 (92.7%) employed quantitative methods, 5 (4.5%) qualitative methods and 3 (2.7%) mixed methods (Table 2). In this review, “qualitative” denotes narrative, conceptual and review papers rather than primary interview or focus-group studies.

Table 2
Studies by Type of Methodology

Methodology of the studies	Number of studies	Share of studies (%)
Quantitative	102	92.7
Qualitative	5	4.5
Mixed	3	2.7
Total	110	100.0

Note. The types of studies are qualitative = narrative, conceptual and review studies; mixed = text sentiment analysis combined with statistical or machine-learning models. Percentages may not add up to 100 due to rounding.

Although the search window began in 2000, no included study predated 2014; thereafter, the literature expanded markedly, from 2 studies in 2009–2016 to 18 in 2017–2020, 34 in 2021–2023 and 54 in 2024–2026 (Table 3), with two further studies undated. Due to the nature of a partial year (2026), the count for 2024–2026 should not be directly compared with previous full-years. The first studies used the methodology of transaction-network analysis and econometric models (Ciaian et al., 2016; Kondor et al., 2014). Forecasting models started to appear from 2017, first in ARIMA and Prophet specifications (Yenidoğan et al., 2018) and later in neural networks (Uras et al., 2020). In 2024–2026, machine learning was the most common approach taken, and was used in conjunction with decomposition or GARCH models.

Table 3
Primary Method Family by Publication Period

Method family	Type	2009–16	2017–20	2021–23	2024–26	Total
Machine learning / deep learning	Quant.	0	3	8	16	27
GARCH-family volatility	Quant.	0	2	5	7	14
Regression, causality, VAR, cointegration	Quant.	1	4	3	3	11
Event study / quasi-experimental	Quant.	0	1	2	9	12
Calendar-anomaly tests	Quant.	0	0	2	5	9 ^a
ARIMA, Prophet and structural time-series	Quant.	0	4	2	2	8
Bubble and structural-break tests	Quant.	0	1	4	3	8
Decomposition and spectral (STL, EMD/VMD, wavelet)	Quant.	0	0	3	3	6
Long-memory, fractal and efficiency tests	Quant.	0	1	0	0	1
Theoretical and simulation models	Quant.	0	1	1	2	4
Regime-switching models	Quant.	0	0	1	0	1
Network analysis	Quant.	1	0	0	0	1
Text sentiment analysis + statistical model	Mixed	0	1	0	2	3
Narrative, conceptual or review	Qual.	0	0	3	2	5
Total		2	18	34	54	110

Note. Only the main method family is counted in each study. The 2024–26 column covers only part of 2026 (search conducted 13 October 2026). Quant. = quantitative; Qual. = qualitative; ARIMA = autoregressive integrated moving average; GARCH = generalised autoregressive conditional heteroskedasticity; VAR = vector autoregression; STL = seasonal-trend decomposition using loess; EMD = empirical mode decomposition; VMD = variational mode decomposition. ^aIncludes two undated studies.

Seasonal decomposition has been primarily used as a pre-processing phase for forecasting, with very limited examples being found of other applications with respect to characterising long-run structure (Poyser, 2019). Only one study in the sample used a regime switching model (Chan et al., 2023) and studies of the bubbles and structural breaks used explosive-root and related tests (Cretarola & Figà-Talamanca, 2021).

The qualitative group was indirect, and small. Only one of the five qualitative studies collected primary data by interviews, and all were narrative, conceptual or review papers (e.g., Taskinsoy, 2021). The three mixed-

methods studies developed automated sentiment scores from social media text, which were more akin to text mining than to integrated mixed method studies (Raju & Tarif, 2020).

5. DISCUSSION

The findings depict a field that is methodologically deep but narrow: forecasting questions predominate, whereas explanatory questions remain underdeveloped. Statistical tools can establish when a bubble has formed, when a structural break has occurred or when volatility has shifted, but not why these events occur. Methods not identified, or rarely identified, in this review sample are listed in Table 4.

Table 4
Methods Not Identified or Rare in This Review Sample

Method	Type	Number of studies	Potential additional value	Example source
Interviews or focus groups (thematic analysis)	Qual.	0	Participants' views of cycles and halvings	Braun & Clarke (2006)
Delphi expert panels	Qual.	0	Expert consensus on long-run drivers	Linstone & Turoff (1975)
Document and policy analysis	Qual.	0	How regulation shapes market phases	Bowen (2009)
Explanatory sequential mixed methods	Mixed	0	Statistics locate episodes; interviews explain them	Creswell & Plano Clark (2018)
Descriptive STL on long monthly series	Quant.	≤2	Size of trend versus seasonality	Cleveland et al. (1990)
Quantile regression across market phases	Quant.	0	Drivers at extreme gains and losses	–
Survival analysis of bull and bear phases	Quant.	0	Duration and ending of cycles	–
Agent-based simulation	Quant.	0	How trader behaviour produces bubbles	–
Synthetic control / difference-in-differences	Quant.	1	Causal effect of halvings	Virtonen (2025)
Regime-switching models	Quant.	1	Timing of shifts between market states	Chan et al. (2023)

Note. The number of studies is for the 110 studies that were reviewed. A count of 0 does not mean that the method has not been used in the research of Bitcoin, it just means that the method wasn't identified in this sample of the literature.

A combination of the two traditions would be accomplished through explanatory sequential mixed-methods designs (Creswell & Plano Clark, 2018), in which episodes are identified through the analysis of statistics and then explained by the use of qualitative inquiry. Qualitative options are discussed in the Conclusion. Regarding the quantitative, descriptive STL decomposition (Cleveland et al., 1990), quantile regression, survival analysis of market cycles, and agent-based simulation and quasi-experimental designs to reduce events were uncommon or not found in this sample.

6. LIMITATIONS

A few restrictions must be noted. The review was limited to six Google Scholar searches and only the first six pages of each search were checked; due to the ranking of results on Google Scholar based on relevance not completeness, relevant studies may not have been included. Titles and search summaries were used for coding, thus some studies use approaches other than those captured here. Lastly, lack of a method in this review sample does not mean that the method has never been used in Bitcoin research but simply that it is less frequently used in the most prominent research literature.

7. CONCLUSION

Quantitative (92.7%) and qualitative (2.5%) and mixed methods (3.7%) price research methods are used in nearly all of the review sample, with mixed methods and qualitative methods being underused.

There are a number of qualitative methods that are suitable for this topic. They could be explored using semi-structured interviews or focus groups with traders, miners and analysts and analysed thematically (Braun & Clarke, 2006) to shed light on how the participants define the terms 'halving', 'bull run' and 'crash'. Expert consensus could be achieved on the long term determinants of price through the use of Delphi panels (Linstone & Turoff, 1975). Understanding the market phases through document analysis (Bowen 2009) of regulatory statements and exchange-traded fund (ETF) approvals, can help shed light on the influence of policy on market phases. Case studies (Yin, 2018) of isolated incidents, such as the 2017 price surge or the 2022 FTX implosion, could be used to explore events that lead up to a price drop, and netnography (Kozinets, 2020) could be used to document the stories that are shared in online investor communities prior to and during price fluctuations.

They are especially well-suited to the Bitcoin, which produces no cash flows to justify its price, and whose valuation relies heavily on attention, belief and narrative (Ciaian et al., 2016; Kristoufek, 2015; Shiller, 2017; Swartz, 2018). Variables can identify only the process and meaning of why things are the way they are, which can be uncovered through qualitative inquiry (Bansal et al., 2018). In mixed methods designs (Creswell & Plano Clark, 2018), these would allow future studies to describe and explain Bitcoin price behaviour; a combination of qualitative and quantitative methods.

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