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ECONOMICS AND BUSINESS

Double Degree

Master's Degree in Finance

Master's Degree in Financial Markets and Investment

The Impact of Different Variables on the Cryptocurrency Market

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THE IMPACT OF DIFFERENT VARIABLES ON THE CRYPTOCURRENCY MARKET

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Study program: Financial Markets and Investment

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Supervisor: Assoc. Ing. Jana Kotlebová, PhD

Bratislava, Pavia 2026 **Bc. Ľubica Lajčiaková**

Declaration of Honour

I hereby honestly declare that I have prepared this Master's thesis independently and that all sources, literature, data, and other materials used in the thesis have been properly listed and acknowledged.

I further declare that I have used artificial intelligence tools in accordance with the principles of academic integrity.

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Date Ľubica Lajčiaková

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ABSTRACT

LAJČIAKOVÁ, Ľubica: *The Impact of Different Variables on the Cryptocurrency Market.* – Bratislava University of Economics and Business. Faculty of Economics and Finance; Department of Banking and International Finance. – Thesis Supervisor: assoc. prof. Ing. Jana Kotlebová, PhD. - Bratislava: NHF EU. University of Pavia; Department of Economics and Management – Lorenzo Trapani, PhD. – Pavia, 2026, 100 pages.

The master's thesis examines the determinants of cryptocurrency volatility in a panel of major cryptocurrencies. It evaluates the role of cryptocurrency-specific characteristics, investor sentiment and macro-financial conditions across different volatility regimes. The empirical analysis uses daily observations for nine cryptocurrencies from January 2020 to December 2025. Volatility is primarily measured by the Garman–Klass range-based estimator, while the Rogers–Satchell estimator is used as a robustness check. The empirical strategy combines fixed-effects panel regression with cryptocurrency and time controls, supplemented by a rolling-window analysis. Driscoll–Kraay standard errors are applied to address heteroskedasticity, serial correlation and cross-sectional dependence. Distributional heterogeneity is further examined through pooled quantile regression with bootstrap inference and cross-quantile coefficient comparisons. The results show that volatility is driven mainly by persistent cryptocurrency-specific market dynamics, liquidity conditions and investor attention measured by Google Trends. These effects vary across volatility regimes and over time, while conventional macro-financial variables display limited and specification-sensitive explanatory power.

Keywords: cryptocurrency, cryptocurrency volatility, determinants, volatility regimes, pooled quantile regression, volatility regimes

ABSTRAKT

LAJČIAKOVÁ, Ľubica: *Vplyv rôznych premenných na trh s kryptomenami.* - Ekonomická univerzita v Bratislave. Národohospodárska fakulta; Katedra bankovníctva a Medzinárodných financií. – Vedúca práce: doc. Ing. Jana Kotlebová, PhD.- Bratislava: NHF EU, Univerzita v Pavii. Katedra Ekonomiky a Manažmentu – Lorenzo Trapani, PhD. - Pavia, 2026, počet strán 100.

Táto diplomová práca skúma determinanty volatility kryptomien na paneli významných ccryptomien. Hodnotí úlohu charakteristík špecifických pre kryptomeny, investorského sentimentu a makrofinančných podmienok v rôznych režimoch volatility. Empirická analýza využíva denné pozorovania deviatich kryptomien za obdobie od januára 2020 do decembra 2025. Volatilita je primárne meraná prostredníctvom Garmanovho-Klassovho estimátora založeného na cenovom rozpätí, pričom Rogersov-Satchellov estimátor slúži ako test robustnosti. Empirická stratégia kombinuje panelovú regresiu s fixnými efektmi a časovým obdobím, a je doplnená o analýzu s rolujúcim oknom. Na zohľadnenie heteroskedasticity, autokorelácie a prierezovej závislosti sú použité Driscollove-Kraayove štandardné chyby. Distribučná heterogenita je ďalej skúmaná prostredníctvom združenej kvantilovej regresie s bootstrapovou inferenciou a porovnávaním koeficientov medzi kvantilmi. Výsledky ukazujú, že volatilita je určovaná najmä perzistentnými trhovými dynamikami špecifickými pre kryptomeny, likviditnými podmienkami a pozornosťou investorov. Vplyv týchto faktorov sa mení naprieč režimami volatility aj v čase, zatiaľ čo konvenčné makrofinančné premenné vykazujú obmedzenú a na špecifikáciu modelu citlivú vysvetľovaciu schopnosť.

Kľúčové slová: kryptomena, volatilita kryptomien, determinanty, režimy volatility, panelová regresia, združená kvantilová regresia

LIST OF ABBREVIATIONS

ADA	Cardano
ADF	Augmented Dickey-Fuller test
API	Application Programming Interface
ASIC	Application-Specific Integrated Circuit
BCH	Bitcoin Cash
BCP	Byzantine Consensus Protocol
BIS	Bank for International Settlements
BNB	Binance Coin
BTC	Bitcoin
CDP	Collateralized Debt Position
CPU	Central Processing Unit
CvaR	Conditional Value-at-Risk
Dapps	Decentralized Applications
DAO	Decentralized Autonomous Organization
DASH	Digital Cash
DCA	Digital Currency Area
DeFi	Decentralized Finance
DLT	Distributed Ledger Technology
DOGE	Dogecoin
DPoS	Delegated Proof-of-Stake
DXY	U.S. Dollar Index
ERC	Ethereum Request for Comments
EPU	Economic Policy Uncertainty
ETH	Ethereum
EVM	Ethereum Virtual Machine
FGI	Fear and Greed Index
FTSE	Financial Times Stock Exchange Index
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GSI	Google Search Index
GSV	Google Search Volume
HAR-RV	Heterogeneous Autoregressive Realized Volatility model
HC1	Heteroskedasticity-consistent standard errors, type 1
ICO	Initial Coin Offering

IPS	Im-Pesaran-Shin test
KPSS	Kwiatkowski-Phillips-Schmidt-Shin test
LINK	Chainlink
LLM	Large Language Model
LM	Lagrange Multiplier
LTC	Litecoin
NFT	Non-Fungible Token
NPoS	Nominated Proof-of-Stake
OHLC	Open, High, Low, Close
P2P	Peer-to-Peer
PoI	Proof-of-Importance
PoS	Proof-of-Stake
PoSA	Proof-of-Stake Authority
PoW	Proof-of-Work
PPI	Producer Price Index
PQR	Pooled Quantile Regression
RDV	Randomized Delegated Voting
S&P 500	Standard & Poor’s 500 Index
SEC	Securities and Exchange Commission
SPV	Simplified Payment Verification
STO	Security Token Offering
TRON	TRON cryptocurrency network
TRX	TRON token
USD	United States Dollar
USDC	USD Coin
USDT	Tether
VaR	Value-at-Risk
VDC	Voting-based Delegated Consensus
VIF	Variance Inflation Factor
VIX	Volatility Index
XMR	Monero
XRP	Ripple
XRPL	XRP Ledger
ZEC	Zcash

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INTRODUCTION

Cryptocurrencies have evolved significantly since 2008, when they first emerged in the aftermath of the financial crisis. It is evident in their market capitalization that has grown tremendously (Liu, 2019) and their increasing recognition among investors, authorities, researchers and the general public as a new investment asset (Wang, 2022).

This evolution is rooted in the concept of a decentralised digital currency, particularly Bitcoin, which was first introduced on the market. Its emergence was a response to the flaws of monetary and payment systems exposed during the financial crisis (Katsiampa, 2019). The growing popularity in the cryptocurrency market derives from unique characteristics of these currencies. Since their value is not based on any tangible asset, but on the trust in the underlying algorithm, that enables them to operate independently of any central authorities, resulting in relatively low transaction costs and secure peer-to-peer payments (Bouteska, 2024).

Despite their potential, cryptocurrencies, mainly Bitcoin, are characterised by extreme price volatility. While this volatility creates opportunities for investors to make a significant profit and attracts high-frequency traders (Ibrahim, 2021, Bouteska, 2024), it also presents challenges for risk management and hedging. Due to the fluctuations in the cryptocurrency market, accurate modelling and forecasting are crucial (Wang, 2022).

Cryptocurrency market movements are influenced by a wide range of factors, including macroeconomic and financial conditions, internal market characteristics, investor sentiment, media attention and technological developments. Although the existing literature on cryptocurrency returns and volatility has grown rapidly, empirical evidence remains mixed. Some studies find that macroeconomic and financial factors, such as stock market movements, exchange rates and financial uncertainty, influence cryptocurrency markets. Other studies suggest that cryptocurrency-specific variables, including past volatility, trading volume, liquidity and investor sentiment, play a more important role. Moreover, many studies focus only on Bitcoin or analyse the average effects of explanatory variables without considering that their influence may differ during periods of low and high volatility.

Therefore, this thesis aims to examine the impact of selected crypto-specific, macroeconomic and financial, and sentiment variables on cryptocurrency market dynamics, with a particular focus on volatility. The analysis investigates whether variables such as lagged volatility, trading volume, illiquidity, market beta, momentum, transaction activity, Google Trends and the Fear and Greed Index significantly affect cryptocurrency volatility. It also examines the role of broader financial variables, including the S&P 500 index, the U.S. Dollar Index and the VIX index.

The empirical analysis is based on a daily panel dataset covering nine selected cryptocurrencies over the period from January 2020 to December 2025. The methodology combines fixed-effects panel regression with pooled quantile regression and a supplementary rolling-window analysis. While the baseline models estimate the average relationship between the selected variables and cryptocurrency volatility, the rolling estimation provides an additional view of how these effects evolve over time, and the pooled quantile regression examines whether they differ across periods of low, medium and high volatility.

The contribution of this thesis lies in providing updated empirical evidence on cryptocurrency volatility using a broader sample of major cryptocurrencies and recent daily data. By combining cryptocurrency-specific factors, sentiment indicators and macroeconomic and financial variables, the thesis provides a more comprehensive view of the determinants of cryptocurrency market dynamics. At the same time, it allows the analysis to distinguish between average effects, changes across volatility regimes, and time variation in the estimated relationships.

The rest of the thesis is structured as follows. Chapter 1 reviews the theoretical background and empirical literature on cryptocurrencies and their market determinants. Chapter 2 defines the objective of the thesis and presents the data, variables and methodology. Chapter 3 presents the empirical results, while the final chapter summarises the main findings, limitations and possible directions for future research.

1 LITERATURE REVIEW

1.1 From Commodity Money to Cryptoassets

Historically, money has been defined by three fundamental economic functions, and that is to serve as a medium of exchange, a unit of account, and as a medium of value. A currency that is effective, must be stable and universally accepted within the jurisdiction (Moin, 2019).

The earliest forms of money were commodity-based with intrinsic value, consisting of precious metals such as gold or silver. During this pre-modern era, money was decentralized. Various independent jurisdictions issued their own coins that varied in purity, therefore they were traded against each other at variable rates. However, after the Peace of Westphalia in 1648, as states wanted to consolidate power and fund national expenditures and operations, they established a monopoly over a mint[1]. This allowed authorities to capture seigniorage[2] and eventually shift to bank money and later to fiat money (Eichengreen, 2018). Fiat money has no intrinsic value; however, it remains functional because it performs the three fundamental functions of money. After the end of the Bretton Woods System in the 1970s, which tied the U.S. dollar to the price of gold, its value is derived from government decree and the public's trust in central banks. (Rabiul, 2018).

Since the second half of the twentieth century, fiat money has shifted toward digitalization. The financial sector was among the first to adopt new information and communication technologies, which greatly transformed the internal operations of banking and financial institutions. This process led to the development of electronic payment systems and the increasing use of cashless transactions. The first wave of digitalization primarily transformed traditional bank deposits into electronic money (Peneder, 2021).

In recent times, digital technology has brought a more significant change away from traditional methods. Brunnermeier et al. (2021) highlight two ways that change how money is structured. The first is "unbundling," where, in the past, a single currency like the Euro

[1] A mint refers to a place or institution where coins are produced and issued.
[2] Seigniorage is a profit gained by the issuer of money from the difference between its nominal value and cost of producing it.

served three key economic roles all at once. Now, thanks to new technology, these roles can be separated because switching between different currencies is becoming easier and less costly. This means people don't have to depend on just one currency for storing value or making transactions. Instead, different currencies can focus on specific functions, creating a digital environment where various currencies with unique roles can thrive and compete with one another.

The second process we observe in Brunnermaier et al. (2021) is “re-bundling.” Re-bundling happens when large digital platform ecosystems combine payment services with social media or e-commerce data. This creates Digital Currency Areas (DCAs), in which the use of specific digital money is tied to a platform’s network rather than to a geographic border. In other words, payment is becoming the centre of platform-based economies, and it has the potential to disrupt the current traditional model, as fintech subsidiaries of payment systems might replace banks.

1.1.1 Centralization

To understand the shift between different forms of money, we have to examine the institutional foundations and their role in the market.

Central banks emerged alongside the development of modern states and financial markets in 1648. Early examples include the Swedish Riksbank, founded in 1668, and the Bank of England, founded in 1694, both of which were initially created to support government finance and manage public debt. During the 19th and early 20th century, central banks assumed responsibility for issuing banknotes, managing exchange rates under the gold standard, and acting as lenders of last resort during financial crises (Monnet, 2023).

M.D.Bordo (2007) describes a central bank as the public authority responsible for implementing policies that influence a country’s money and credit supply. To achieve its goals and affect short-term interest rates, it conducts monetary policy through instruments such as open market operations, discount window lending, or changes in reserve requirements. As the three key goals of modern central banks, he recognizes:

- *Price stability,* which can be interpreted as maintaining an inflation on the low and stable rate by tightening its policy in response to an inflation scare.

- *Stable real economy*, or macroeconomic stability, is associated with high employment and high economic growth of the country.
- *Financial stability* is the last goal, and that includes guaranteeing the efficient functioning of payment systems and reducing the likelihood of financial crises.

Financial stability, according to Bordo (2007), is an increasingly important responsibility of central banks. During the gold standard era, central banks gradually assumed the function of lender of last resort, guided by Bagehot's principle of providing liquidity to solvent, but illiquid institutions. However, before 1914, central banks focused primarily on maintaining gold convertibility and neglected domestic macroeconomic stability. This orientation changed after World War I, as central banks began to pay greater attention to internal objectives such as employment, output, and price stability, amid rising labour and broader social pressures. In the 1920s, the Federal Reserve began to focus on external and internal stability, yet the external still dominated. Unfortunately, their monetary policy led to difficulties between the 1920s and 1930s. At that time, the Fed followed a principle called the real bills doctrine, which held that the quantity of money needed in the economy would be supplied if funds were lent only to banks that present eligible self-liquidating commercial paper as collateral. In 1928, the Fed tightened monetary policy to prevent speculation in the stock market, thus contributing to the Wall Street boom on October 29, 1929, also known as Black Tuesday (Bordo, 2007).

The Great Depression, triggered by the stock market crash, represented the most severe economic collapse of the industrialized world and affected all countries. Market prices, profits, income, trade, and consumers' expenditures declined drastically and unemployment in the USA reached 25% (Dzikevicius, 2009). More critically, from 1930 to 1933, the Fed failed to act as a lender of last resort during multiple bank runs, misinterpreting low nominal interest rates as evidence of monetary easing (Bordo, 2007), further worsened by policies,which raised tariffs on imported goods and triggered measures that caused a massive decline in American trade. The U.S. started using the gold standard after President Roosevelt signed Executive Order 6102, which required holders of significant quantities of gold to sell their gold for $20.67 per ounce. The government profited almost $15 per ounce, since right after the sale, the price of gold increased to $35 per ounce, and the dollar devalued by 69,3% (Dzikevicius, 2009).

The causes of the Depression remain debated. In his work, Dzikevicius (2009) has examined the most severe U.S. financial crises, from the Great Depression to the dot-com bubble, through the lens of the Austrian business cycle theory. From the perspective of Austrian business cycle theory, financial crises originate in central bank monetary intervention. When interest rates are lowered through credit expansion, they no longer reflect consumers' true preferences. This distortion encourages excessive borrowing and investment, leading to unsustainable booms and malinvestment. Once inflationary pressures emerge or credit conditions tighten, these malinvestments are revealed.

From the Austrian view, Hayek and Rothbard argued it was the inevitable result of excessive monetary expansion in the 1920s, with subsequent government interventions only prolonging the downturn (Dzikevicius, 2009). In contrast, Milton Friedman held the monetarist perspective, that the Fed's failure lay in its inaction during the banking panics of 1930–1933, not in the prior expansion (Friedman, 1971).

In the aftermath, as Monnet (2023) explains, formal banking regulation emerged as both a preventive mechanism against crises and a complement to the lender-of-last-resort function, intended also to limit moral hazard by constraining excessive risk-taking. The period from the 1930s to the 1970s, when regulation was most restrictive and financial safety nets such as deposit insurance were introduced, is known as an era when banking crises were almost nonexistent in advanced economies.

After the 1970s, this relative stability gradually deteriorated. According to the data cited by Cunha (2020), the period from 1940 to 1979 recorded only 246 bank failures with deposit insurance losses totalling $134 million, while the decade from 1980 to 1989 alone saw 1,086 bank failures with losses surging to $22,961 million. The deregulatory process and the crises that occurred transformed the banking system from a non-competitive, stable system to a more competitive yet more unstable financial system.

High inflation in the late 1960s pushed market interest rates far beyond the ceilings imposed by Regulation Q, prompting the Depository Institutions Deregulation and Monetary Control Act of 1980, which phased out those ceilings and spurred financial innovation. Its main goal was to increase competition by weakening the regulatory framework. As banks struggled to attract funds, depositors shifted their attention to

unregulated alternatives, particularly Money Market Mutual Funds, which offered higher returns (Trescott, 2021).

The broader dismantling of the post-Depression regulatory framework followed: restrictions on interstate and branch banking were loosened, the separation between commercial and investment banking under the Glass-Steagall Act was weakened, and banks were gradually permitted to expand into securities underwriting, insurance, and other activities. The liberalization of real estate lending and the rise of subprime loans became the root cause of the real estate boom of the 2000s (Cunha, 2020).

In response to growing instability, regulators expanded deposit insurance limit from $40,000 to $100,000 and established the "too-big-to-fail" doctrine, creating government guarantees that raised moral hazard concerns and weakened incentives to monitor banks' risk-taking. Efforts to address these risks through prudential regulation, particularly capital requirements, and introduction of Basel I Accord in 1988, focused narrowly on credit risk while paying little attention to operational, market, and systemic risks (Cunha, 2020). This development reopened the debate on whether monetary and regulatory interventions contribute to instability. The recurrence of many crises after the 1970s suggests that financial regulation did not eliminate systematic risk but shifted the channels through which instability could emerge. During that period, many economists began to question the structure of the central banking system and started exploring ideas of monetary decentralization.

1.1.2 History of Decentralization

The roots of monetary decentralisation can be traced to the work of Austrian economist Friedrich August von Hayek, particularly his proposal for the denationalization of money in 1976. In his work, Hayek challenged the state monopoly over the issuance of money, arguing that government control over the money supply allows authorities to manipulate the money supply, leading to instability. This idea falls within the framework of Austrian Business Cycle Theory. According to Hayek, eliminating the state monopoly would reduce the likelihood of systemic crises. Therefore, he proposed a radical alternative: private entities such as banks, corporations, or even individuals should be able to issue their own currencies, which would compete in the open market (Zou, 2025).

The primary objective of Hayek's work was the creation of a stable currency, not defined by intrinsic value, but by the stability of its purchasing power. He envisioned a system in which currencies would circulate on the market under a distinct name and be traded at variable exchange rates. In such a competitive environment, less reliable currencies would disappear, leaving only the most stable and trustworthy in use. Through this process of competition and market selection, the monetary system is stabilized, allowing the market itself to regulate the money supply (Fantacci, 2019).

An important forerunner to modern cryptocurrencies was the work of David Chaum, whose 1980s paper „Blind Signatures for Untraceable Payments" introduced one of the first coherent visions of digital cash. Chaum designed a privacy-preserving digital money system known as eCash, built around his innovation of cryptographic technique "blind signatures", which allowed a bank to sign a digital coin without seeing its actual contents. Thus preserving the anonymity of the transaction. He implemented this concept commercially through the company DigiCash. Although eCash still relied on a central authority and ultimately failed after DigiCash went bankrupt, Chaum's work proved remarkably generative. It inspired a community of cryptographers and activists connected through an online mailing list and came to be known as the cyberpunks (Nasdaq, 2018).

As Nabben (2022) notes, the cyberpunks emerged in the early 1980s driven by a shared concern over an increasing monitoring of digital communication by the government and institutions. They believed that cryptographic technologies could transform economic relations by enabling anonymous and secure communication over digital networks. Thereby, protecting individual freedom and privacy. This movement was ideologically grounded in the crypto-anarchy articulated by Timothy C. May in his 1988 *Crypto Anarchist Manifesto,* which promoted the view that encrypted peer-to-peer networks would allow individuals to transact freely and, consequently, replace centralised authorities.

To develop these ideas in practice, E.Hughes, T.C. May, and J. Guilmore founded the Cyberpunks Mailing List in 1992, which became a key forum for experimenting with new forms of decentralised electronic money. Over the following years, the mailing list gave rise to several influential proposals, including "e-gold" in 1996, Adam Back's hashcash in 1977, the Proof-of-Stake electronic network called b-money by Wei Dai in 1988, and Nick Szabo's Bit Gold in 2005 (Nabben, 2023).

One of the earliest contributions was Hashcash, proposed by Adam Back in 1997, which introduced a mechanism known as Proof-of-Work. Originally designed to combat automated abuse of internet services such as email spam, the system required the sender's computer to solve a cryptographic puzzle demanding a moderate amount of CPU effort before a message could be transmitted. Although this action was negligible for users sending occasional emails, it became expensive for spammers who sent thousands of emails within a short period of time (Sheikh & Banday, 2021), using cryptographic hash functions such as SHA1, SHA256, or SHA3 (Back, 2002). Though Hashcash was not itself a currency, the logic under the algorithm was a building block in subsequent proposals.

That same logic appeared in Wei Dai's b-money proposal published the following year in 1998. Dai envisioned an anonymous digital cash system in which participants performing computational work would be rewarded with newly created units of currency, thus extending Hashcash's principle into an economic incentive. All transactions would be broadcast to and verified by the entire network, maintaining a shared ledger without central authority. Alongside this fully decentralised first proposal, Dai also described a second, more practical variant, in which a subset of participants referred to as servers would maintain transaction records and process payments. However, the requirement was to deposit a specified amount as a guarantee against misconduct. One proposal maximally decentralised and the other more efficient but reliant on a servers, reflected on a broader challenge the community had to resolve, and that is to build a system that was both trustless and practical (Dai, 1998).

It was this challenge that Nick Szabo engaged most directly in developing Bit Gold, described by Elliott (2018) as the first-cryptocurrency, developed in 1998 and formally published in 2005. Whereas Back had focused on computational effort as a tool against abuse, and Dai had extended it into monetary reward mechanism, Szabo approached the design of digital money by considering the properties of physical gold itself, observing that its value derives partly from difficulty and the cost of mining it. He then drew an analogy between this scarcity and the effort required to solve cryptographic puzzles, and proposed a system in which each solved puzzle would be linked to the previous one, forming a timestamped record of work that prevented network to move to next puzzle without first being verified. This structure directly addressed the problems of double-spending and double-mining that had undermined earlier proposals. Yet Bit Gold still fell short of a

complete solution. It relied on a few participants to validate records, leaving it vulnerable to Sybil attacks, in which a malicious actor could create multiple fake identities to gain influence over the network, and as a result it was never implemented in practice.

What these proposals reveal, taken together, is not a sequence of independent inventions but a cumulative effort to solve the same underlying problem from different angles. Haschash established that computational power could function as a decentralised mechanism and was incorporated in design of blockchain, B-money showed how that effort could be converted into monetary value, while Bit Gold demonstrated that chaining those records cryptographically could prevent manipulation, what was incorporated in an idea of blockchain as well. Each proposal identified something essential, that would continue until eventually Satoshi Nakamoto's 2008 white paper synthesised these ideas into what became Bitcoin (Maleh, 2022).

1.1.3 The Rise of Bitcoin

The modern fiat system faced a significant crisis during the 2008 global financial collapse. As central banks sought to stabilize economies through unconventional expansionary measures, such as quantitative easing, public trust in the banking system declined. As questions were once again raised about the efficacy and stability of fiat money, the situation created an opportunity to introduce Bitcoin. In October 2008, an individual or a group operating under the pseudonym Satoshi Nakamoto published the whitepaper *"Bitcoin: A Peer-to-Peer Electronic Cash System"*. Nakamoto's proposal was revolutionary. It combined cryptographic security with a distributed ledger technology that records transactions across a decentralised, peer-to-peer network. More precisely, he called it blockchain. This system relies on cryptographic algorithms, eliminating the need for trusted third parties such as banks. Thus, the launch of the Bitcoin network's genesis block on January 3rd, 2009, marked the birth of the modern cryptocurrency market and the beginning of a hybrid monetary ecosystem where private digital tokens and public fiat money coexist (Golacik, 2024).

Following the emergence of Bitcoin, we observed significant growth in the cryptocurrency market. The first new cryptocurrency after Bitcoin was developed in 2011 by Vincent Durham and was called Namecoin. All cryptocurrencies developed after Bitcoin are

typically referred to as alternative coins or, more commonly, altcoins (Luo, 2023). Today, on the cryptocurrency market is thousands of such altcoins. Each of them has different characteristics (Baker, 2023). CoinMarketCap lists 9,353 active cryptocurrencies with a combined market capitalization of around 3.79 trillion dollars, and Bitcoin maintains the largest market share among them (CoinMarketCap, 2025).

1.2 Cryptoassets

Many authorities refer to cryptoassets as ”tokens” (Ocampo, 2023). By Global Digital Finance tokens represent legal embodiment of a share of an asset, set of permissions, or a set of claims held by a bearer of the token (GDF, 2018). They exist in a physical or a digital form. In physical form, we can envision them as lottery ticket, in more traditional physical form, examples could include insertable coins into slot machines or bingo cards. Representations of digital tokens, that public uses day-to-day are QR codes or discount codes (Linden, 2023). Broadly, digital tokens can be defined as digital representations of assets, tangible or intangible, and this process is known as *tokenization.* With the emergence of blockchain technology, the concept of tokenization has evolved even further (Baker, 2023), and it led to development of cryptoassets.

To categorize cryptoassets, authorities often classify them according to their underlying economic characteristics, that is economic function of the token (Ocampo, 2023). Based on this approach, Ocampo in his paper identifies stablecoins, global stablecoins, security tokens, utility tokens, governance tokens and native tokens, which he also calls cryptocurrencies. However, this is not the only possible classification. Baker in his book distinguishes cryptocurrencies, stablecoins, utility tokens, security tokens and tokenised assets.

Given the diversity, this thesis will adopt the categorization proposed by W.K. Hardle and co-workers (2019), who distinguish seven groups of cryptoassets. First is the *transaction mechanisms*, which were primarily designed to function as “stores of value”. Bitcoin is an example of this class, often called as digital gold due to its fixed supply and role as a hedge against fiat currency volatility. Another example is Litecoin, sometimes described as digital silver (Baker, 2023). These currencies also serve distinct roles within the market. As

another example, we could pinpoint Ripple, or XRP, which is primarily utilized for cross-border transactions, whereas Monero and Z-Cash function as privacy coins.

The second class consists of tokens that enable *distributed computation*. They were designed to extend its functionality beyond the exchange of money. Unlike simple payment coins, these tokens power networks capable of executing smart contracts. Primary representation is Ethereum, another are Solana, Cardano, TRON or Avalanche.

Third class represents utility tokens. Programmable blockchain assets designed to provide access to specific services and products (Hardle et al., 2019). These tokens function as the internal currency for localized digital economies. In some models, like Filecoin or Mana, they are used as payments, while in others, like ALEX, they can use a dual-token design. One token is used for payment, and another nontransferable token is a special reward granting additional benefits.

Security tokens represent digital versions of traditional financial instruments, such as stocks, bonds, derivatives or real estate. They are typically issued via Security Token Offerings (STOs). From an economic perspective, they are important as they can speed up settlements, automate processes, allow assets to be divided into smaller shares, and expand access to a broader range of investors. The most prominent infrastructure is ERC-1400 (Baker, 2023).

Fifth and sixth classes are fungible and non-fungible tokens (NFTs). Fungible tokens are standardized, where each unit is identical and interchangeable. For instance, Ethereum's ERC-20. NFTs are, by contrast, unique and non-interchangeable. They are a digital representation of unique items or agreements (Hardle et al., 2019).

Stablecoins form the final category of cryptoassets. These assets aim to minimize the extreme volatility often seen in other cryptocurrencies, where prices can fluctuate by more than 20% within a single day, by pegging their value to a reference point such as a fiat currency or commodity. Such stability is crucial for a currency to fulfil the three fundamental functions of money: a store of value, a unit of account, and a medium of exchange. Stablecoins are generally classified into four main types according to their collateralization and stabilization methods (Moin, 2019):

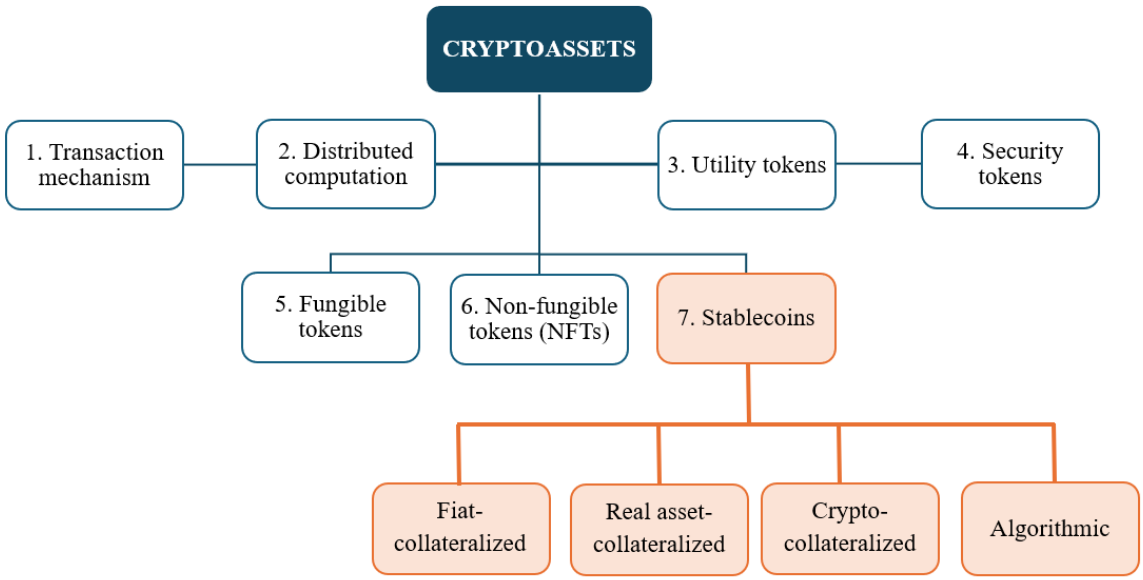
I. Fiat-Collateralized Stablecoins achieve price stability by maintaining a 1:1 reserve of traditional national currencies, such as the US dollar, held in bank accounts. Leading examples like Tether (USDT) and USDC. Other examples include LBCPeg tied to the pound sterling, Fedcoin or Eurocoin. Though these systems introduce significant centralization risks and a dependency on legacy financial institutions.

II. Real Asst-Collateralized Stablecoins are backed by physical commodities like gold or real estate. Projects such as Digix and Swiss Real Estate allow users to hold a digital representation of tangible assets. However, storing and auditing physical assets often leads to greater centralization and lower scalability than with purely digital assets.

III. Crypto-Collateralized Stablecoins were designed for decentralized operation and are backed by other cryptocurrencies. Because the underlying collateral is volatile, protocols like Maker DAO's DAI employ "leveraged loans" and require over-collateralization to protect the system against rapid market swings. Users must lock up collateral in the form of different cryptoassets in the collateralized debt position (CDP).

IV. Algorithmic (Uncollateralized) Stablecoins use mathematical algorithms to expand or contract the token supply in response to price swings. An example is the Basis projects (Moin, 2019, Hardle et al., 2019).

Figure 1 Classification of cryptoassets by function and stablecoin design



Source: Own elaboration

1.2.1 Characteristics of Cryptoassets

Cryptoassets share certain common features, but they differ in their technical design and intended purpose. Some are mainly used as means of payment or store of value, while others have broader roles within blockchain ecosystems. For example, Ethereum was created as a platform for computation and decentralized applications (DApps) (Baker, 2023).

Despite these differences, the market remains dominated by a few key players, with Bitcoin and Ethereum making up a large portion of the total market cap. Although Bitcoin is viewed as digital cash with significant price volatility, many users treat Bitcoin as an investment or a store of value rather than as a daily exchange medium (Baker, 2023). In his paper, Bauer (2017) has analysed Bitcoin public ledger and found out, that one third of Bitcoins are held by investors who received them, but do not send them to anyone. Thus, he concluded only a minority of Bitcoin users use it as medium of exchange, most of investors are holding it.

Another common feature of cryptoassets is their high volatility. Among them, stablecoins are the ones that tackle volatility the best (Rajapaksa, 2025). Understanding what drives volatility and its patterns is therefore essential. According to Arikan (2021), variables affecting the value of cryptocurrencies can be categorized as external and internal, with internal being economic and technological infrastructure. Therefore, it is important to state the distinctive characteristics of major cryptocurrencies, as these play a crucial role in shaping their volatility and their overall market behaviour.

P. Ciaian states that although the cryptocurrency market is known for high volatility, little is known about its price formation mechanisms and altcoin interdependencies. According to Baker (2023) prices of major cryptoassets tend to move together, suggesting a relatively high degree of correlation across the market. P. Ciaian and co-workers (2018) came to the conclusion that in the short run, Bitcoin’s price distortion can affect the prices of the altcoins. However, Bitcoin has only a limited impact on the prices of other cryptoassets in the long run.

1.2.1.1 Blockchain and Distributed Ledger

The concept of blockchain is based on a shared ledger, which is a distributed ledger technology (DLT) that is maintained across a peer-to-peer (P2P) network and regularly updated by its participants, known as nodes (Olbrecht & Pieters, 2023). DLT describes decentralized digital systems that enable computers to share, update, and synchronize records across various networks without relying on a central trusted authority (BIS, 2017). Blockchain offers key features such as decentralization, transparency, autonomy, and security (Tasdelen, 2024).

Blockchain technology was introduced by Bitcoin, or more precisely, Bitcoin brought blockchain into practice, as it is not entirely new but combines existing technologies, such as timestamping, Merkle trees, Byzantine fault tolerance, Proof-of-Work (PoW), hashcash, and bit gold (Baker, 2023). In practice, blockchain records transactions in blocks that are chronologically linked, creating a continuous chain of records. Before transactions are grouped into a block, they are verified by nodes. The process of validating and adding new blocks is governed by the consensus mechanism used by a particular blockchain network (Jamwal, 2024).

As blockchain technology evolved, various projects began modifying the original architecture to fix specific limitations or add new features. A key result of this evolution was the rise of forks, allowing existing blockchain protocols to be adapted or expanded into new networks. We can differentiate between hard and soft forks. A soft fork is a change in the blockchain rules that allows nodes using an older version to accept new blocks, while a hard fork introduces rules incompatible with the previous version. Nodes that do not update their software cannot validate newly created blocks. As an example, Bitcoin Cash and Bitcoin Gold are hard forks of Bitcoin (Vujičić, 2018).

Ethereum, the second-largest cryptocurrency by market share, revolutionized the cryptocurrency market by introducing smart contracts. These autonomous scripts, stored on the blockchain, are executed within the Ethereum Virtual Machine (EVM) and are vital for building decentralised applications (DApps) on the Ethereum platform, as the blockchain has a built-in Turing-complete programming language. This makes Ethereum far more than just a platform for cryptocurrency transactions (Jamwal, 2024). Tasdelen (2024) states that

this development has impacted the entire market by fostering a diverse ecosystem of tokens and decentralized (DeFi) platforms.

We should note that not all blockchain-based projects gain relevance through technological innovations. Some projects built on simple blockchain infrastructures have achieved broader market recognition. A prominent example is Dogecoin, whose blockchain was not particularly innovative, being derived from Litecoin, which itself was based on Bitcoin. Despite its limited technical innovation, Dogecoin has achieved significant popularity (Cary, 2021).

1.2.1.2 Transactions and Consensus Mechanism

Transactions serve as the core building blocks, facilitating the transfer of coins. They are executed when the keys used in the process are generated. We can explain transaction process on the Bitcoin. For the transaction process, the user needs a wallet, whether physical or digital, to store coins and tokens. Then he can generate a private and a public key. The private key is used to sign the transaction. Public key, generated from the private key, verifies the transaction. Since the public key is large, it is hashed with a hash function. Then it is encoded to get Bitcoin address. To transfer coins, the sender needs to input the receiver's Bitcoin address (Mueller et al., 2018).

Each transaction presents a public entry in the blockchain. Transactions are hashed in Merkle tree, which is a binary tree with many leaf nodes and the root of leaf nodes. Bitcoin introduced Simplified Payment Verification (SPV), allowing nodes to store only the block headers of the longest chain (Vujičić, 2018).

The transaction process is generally similar on different blockchain networks, the main difference lies in the way the block is validated and accepted into the network. This is performed by the consensus mechanism (Jamwal, 2024). Various types of consensus mechanisms exist:

- Proof-of-Work (PoW) was a key element of Bitcoin’s blockchain. In the PoW system, miners compete to validate transactions by trying random numbers (a nonce) to find a specific combination of letters and numbers called a hash. Once the miner finds the correct hash value, it is verified by other nodes, and the block is

added to the chain of blocks forming the blockchain. Bitcoin adjusts the hash difficulty, so the average time to find a block is approximately 10 minutes for all nodes. Thus, the nodes with lower computer power also have a chance to win the race (Olbrecht, 2023). PoW is used by many cryptocurrencies, including Litecoin, Monero, or Dogecoin. While Bitcoin relies on the SHA-256 hashing algorithm, Dogecoin employs Scrypt, and Monero uses RandomX, which is optimized for Central Processing Units (CPUs) to discourage Application-Specific Integrated Circuits (ASIC)[3] dominance, therefore promoting greater mining decentralization (Monero, 2025).

- Proof-of-Stake is used by altcoins such as Ethereum and Solana. It was first proposed in Peercoin to address the centralization issues and energy waste. In PoS, miners do not compete to solve complex mathematical puzzles, but they are selected based on their stake and the duration they have held their coins (Tesdalen, 2024). Coin age is calculated by multiplying the number of coins by the number of days they have been held. Therefore, according to Xion et al. (2025), PoS can lead to the concentration of coins and may become more centralized over time. Ethereum has previously used PoW called Etash, then in 2022 completed its transition to PoS in an event known as The Merge. The Merge reduced ETH issuance by around 90%, often called the "triple halving", and significantly lowered energy consumption by 99.9%, from 112 TWh to 0.01 TWh per year. Although it did not decrease gas fees or increase transaction speed, it marked a key step toward Ethereum's sustainability and long-term scalability (CoinMarketCap, 2025).
- PoSA, DPoS, and NPoS are different types of Proof-of-Stake consensus. Each has unique features. In Proof-of-Stake Authority, which coin such as BNB uses, a predefined trusted authority selects validators. A small group of delegates, chosen by token holders through voting, helps ensure consensus and verify transactions in Delegated Proof of Stake, advancing toward greater decentralization. Nominated Proof-of-Stake works on a similar selection process. Users nominate delegates with their stake, and afterwards the protocol selects a large set of delegates and distributes the stakes (Tasdelen, 2024).

[3] Specialized mining hardware.

- Proof-of-Activity is a hybrid consensus mechanism that combines elements of PoW and PoS. Similarly to PoW, miners compete in mining to earn token rewards. The block does not include transactions, only the transaction title and the block reward address. The transaction title indicates which validator was randomly selected to sign the block and add it to the blockchain. This approach lowers the chance of the attacks as it is not possible to predict who is a validator at the next iteration (Terjanian et al., 2024).
- Proof of Importance builds on PoS but evaluates nodes not only by the amount of tokens they hold, but also by their overall activity and contribution to the network. PoI aims to distribute influence and reduce the concentration of power among the wealthiest users (Terjanian et al., 2024).
- Byzantine Consensus Protocol is a way for a blockchain network to verify transactions by making sure most participants, precisely 80%, agree on what is valid, even if some participants act dishonestly. It is based on the Byzantine Generals Problems. The idea that a system must still reach the same correct decision despite a small number of "traitors". XRPL validates transactions through a unique Federated Consensus mechanism, the BCP mechanism, in which independent validators agree on the order and outcome of transactions. This new system enables rapid and low-cost transactions (Ciaian et al., 2018).

Terjanian et al. (2024) note that considerable progress has been made in the development of consensus mechanisms that aim to improve scalability, strengthen security, decentralization, and reduce transaction latency. The number of modified models has grown. We have highlighted some of the most notable ones, but there are many others as well, including Proof-of-Burn, Proof-of-Concept, and voting-based algorithms like Proof-of-Vote, VDC, and RDV (Xiong et al., 2025).

Some of the cryptocurrencies do not operate on their own blockchains. In instance, Tether functions as a token built on existing networks such as Bitcoin, Ethereum, Avalanche, or Bitcoin Cash, with its security supported by the underlying hashing algorithms of these blockchains (CoinMarketCap, 2025).

1.3 Factors Affecting the Cryptocurrency Market

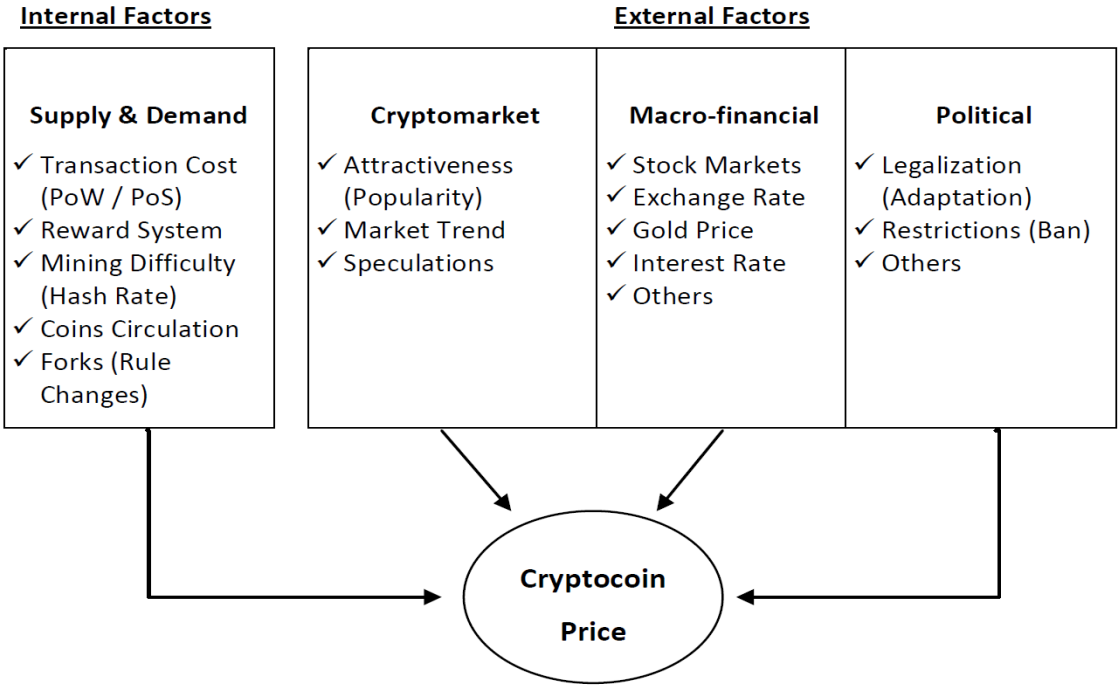
Cryptocurrency markets represent a specific segment of financial markets characterized by rapid growth, high uncertainty, and distinctive price dynamics. Unlike traditional financial assets, cryptocurrencies emerged outside established regulatory structures and valuation metrics (Long et al., 2025). In this regard, Yermack (2015) and Baur et al. (2018) describe cryptocurrencies primarily as speculative assets, whose market behaviour differs significantly from traditional assets. Saleh (2019) emphasizes that their extreme volatility increases the importance of understanding the drivers of price movements. According to Long(2025) and González (2025), understanding market determinants in this kind of environment is essential not only for investors, but also for market stability and efficiency.

Colbet et al. (2018), Akylidirim et al. (2020), and Platankis and Urquhart (2020) state the relationship between traditional financial assets and cryptocurrencies is weak, thus they react to a different set of factors. Colbet et al. (2018) also note that Bitcoin is a unique asset class whose price is detached from traditional macroeconomic fundamentals. Liu and Tsyvinski (2020) reached the same conclusion, cryptocurrencies have relatively low exposure to traditional market factors.

Ciaian (2018), in his research on Bitcoin prices, identifies key determinants such as supply and demand, investor attractiveness, and global macro-financial trends, which many researchers agree on. However, his work aims to address a gap in the understanding of altcoin price formation, arguing that previous studies have overlooked the interdependencies between Bitcoin and altcoin prices, as well as the relative significance of external factors.

Broader classification of the factors is offered by Sovbetov (2018), drawing on Poyser (2017), which distinguishes between internal and external price factors, as showed in Figure 2. Sovbetov extends the first classifications, showing importance of the more complex factors structure.

Figure 2 Classification of the cryptocurrency market factors



Source: Sovbetov, 2018

Research (González et al., 2025; Bakhtiar et al., 2023) agrees that, for a long time, cryptocurrencies lacked a standard valuation framework typically used in equity, bond, or commodity markets and a clear understanding of intrinsic value. Bakhtiar et al. (2023) propose that valuation should incorporate not only market data, but also fundamental and sentiment-based indicators, including consensus mechanisms, the presence of smart contracts and stablecoins, supply type, Google Search Index and FGI.

The literature on cryptocurrency factors is still relatively young. Recent literature treats the cryptocurrency market as a multidimensional system, where price is influenced by a set of macroeconomic, financial, technological, and behavioural factors (González, 2025). Dunbar (2022) uses standard Sharpe Simple Index Model, while Liu et al. (2022) use multi-factor model including size and momentum, and Koutmos (2020) concluded it is difficult to find factors affecting Bitcoin returns. According to González (2025), a suitable approach is to use factor models, which aim to uncover latent factors behind observed returns. It is a statistical method that examines correlations among observed variables to detect and quantify latent factors. However, the selection of the appropriate number of factors is challenging. Using a few factors oversimplifies the model and fails to identify all the factors, while using too many leads to overfitting.

1.3.1 Macroeconomics and Financial Factors

The impact of macroeconomic indicators on the cryptocurrency market is a subject of empirical debate, that also focuses on whether Bitcoin functions as a safe-haven asset or a speculative risk asset. Kawamoto et al. (2023) argue that rising Producer Price Index (PPI) levels indicate inflationary pressures, prompting investors to seek lucrative alternatives. However, Scharnowski (2024) emphasizes that Bitcoin's high price volatility and its lack of a long-term value function, comparable to gold, often lead investors toward traditional government bonds during periods of uncertainty. Additionally, Naeem et al. (2021) and Abakah et al. (2020) further analyse influence of interest rate and debt market on the cryptocurrency market. identify an inverse relationship between Treasury yields and Bitcoin returns, showing that higher yields increase the attractiveness of low-risk bonds and reduce investor demand for cryptocurrencies. On the other hand, Ali et al. (2024) argue that declining yields encourage investors to shift toward alternative high-growth opportunities, including cryptocurrencies. Lin et al. (2025) suggest that investor should closely monitor the PPI, USD exchange rates, and bond yields.

The role of foreign exchange serves as another critical determinant. Taghizadeh-Hesary et al. (2022), Umar et al. (2021) and Sharma et al. (2023) observe that an appreciating dollar typically triggers capital outflows from cryptocurrency market as investors prioritize dollar-denominated assets. Wei et al. (2024) and Yousef et al. (2024) state that a rising USD/CNY exchange rate triggers concerns about global outlook, thus leading to selling Bitcoin. Equally, Kong et al. (2024) found that USD depreciation correlates with increased investor confidence and a higher demand for risky assets, consequently driving up Bitcoins returns. On the other hand, Kristjanpoller and Bouri (2019) examined the cross-correlation between major fiat currencies and crypto, concluding their asymmetric relationship, that remain persistent over time with most cases displaying multifractal properties.

The literature employs various GARCH-type models to identify these complex relationships. Cermak (2019) used GARCH including macroeconomic determinants as stock market indexes, exchange rate, short-term interbank rate and long-term government bond yields across countries that trade crypto the most. He confirmed its significance except in Japan. Dyhrberg (2018) using asymmetric GARCH found that BTC can serve as short-term hedge against the FTSE index and the US dollar. Sovbetov (2018) identified a

weak positive long-run relationship between the S&P 500 and major cryptocurrencies, although he mentions this relationship disappears in the short run.

1.3.2 Cryptocurrency Market Specific Factors

Internal market determinants, specifically market size, beta, and momentum, have been identified as primary drivers of expected returns (Chen and Zimmermann, 2019; Feng et al., 2020). Analyzing these dynamics, Sovbetov (2018) found that the cryptocurrency beta exerts a significant long-run multiplier of 0.79 on BTC and 0.38 on ETH at 1% significance level. In contrast, smaller assets as LTC, DASH and XMR show long-run impacts of 0.34, 0.11 and 0.25, respectively, at a 5% significance level. He also suggested that BTC and ETH exhibit heighten sensitivity to market fluctuations in the short term.

The relevance of these internal determinants also varies across different categories of cryptoassets. González (2025) found that the cryptocurrency market is generally driven by up to two global factors, one of them being strongly linked to Bitcoin. However, stablecoins appear to be influenced by a wider range of variables. Besides internal market dynamics, their valuation is also shaped by the characteristics of the underlying assets to which they are pegged. Moreover, market microstructure and liquidity play a central role in the price formation. This view is further supported by Sovbetov (2018), who noted that trading volume has a significant long-run impact, especially on Bitcoin, underlining the importance of liquidity.

A similar perspective is offered by Będowska-Sójka (2026), who examines the internal characteristics that determine whether the cryptocurrency remains tradable or turns into an untradable „zombie“ asset. The study identifies three groups of predictors. First is basic market variables such as prices, trading volume and market capitalization, second is advanced statistical indicators such as long memory, alpha-stable tail index, and Value-at-Risk, and last one is categorical variables capturing asset specific technological features. Overall, the findings suggest that the long viability and performance of cryptocurrencies depend also on internal trading conditions, liquidity, and risk structure. He also discovered that simple models based on price and volume often outperform complex predictors like assets age, consensus mechanism, or social media presence, with only significant categorical predictor is classification of an asset as a „coin“ or a „token“.

Studies using machine learning further emphasize the role of these variables. For example, Cakici et al.(2024) highlight factors as past alpha, illiquidity, and momentum. Lastly, Wang et al. (2023) show a crucial role of previous trading information and lagged volatility.

1.3.3 Technological and Fundamental Factors

The technological architecture and network effects of a cryptocurrency are primary determinants of its long-term value and price divergence. Gandal and Halaburda (2016) observed that while early market behaviour treated Bitcoin and altcoins as generic financial assets, the later emergence of strong network effects created a significant divergence favouring Bitcoin. Osterrieder et al. (2017) suggest that cryptocurrencies sharing the same underlying technology exhibit similar non-normal statistical properties and extreme value behaviours. However, both of these research papers have not included interdependencies between Bitcoin and altcoins.

Fundamental factors of cryptocurrencies is rooted in the asset's technical characterises. Existing papers include supply factors, hashing algorithms and longevity. Hayes (2015) examined 66 cryptocurrencies using cross-sectional data and regression analysis. He identified that the type of algorithm, specifically Scrypt and SHA-256, significantly impact value. His analysis suggests that the Scrypt algorithm often carries higher value in altcoins due to its higher computing power requirements, which increases security against hacking. In a subsequent study, Hayes (2016) demonstrated that 81% of Bitcoin's price is associated with its marginal cost of production.

The choice of consensus mechanism represents another critical fundamental driver. Sharif et al. (2023) used a quantile spillover index to find a stronger connection between green economy indices and PoS cryptocurrencies compared to PoW models. He identified PoS cryptocurrencies as potential "safe harbours" for diversifications. Bakhtiar et al. (2023) research paper further broadened the impact of fundamental factors, examining consensus mechanisms, smart contracts, and Initial Coin Offerings (ICOs). They identified significant positive impact on daily returns, while inflationary supply had a negative effect during the period between 2015-2017. Investors should also pay attention particularly to a consensus mechanism and ICO when making investment decisions as they have shown significant effect on cryptocurrencies.

Bhambhwani et al. (2019) established a positive and statistically significant relationship between price, computing power, and network size. This is supported by Easley et al. (2018), who developed a game-theoretic model to explain the transition of Bitcoin from a mining-based structure to a market-based ecology, emphasizing the role of transaction fees and trading volume. Furthermore, Cong et al. (2018) highlight how mining pools act as a centralizing force through risk sharing. Gronwald (2023) used standard GARCH models and combined jump-GARCH models to reveal that extreme price movements are more evident in the BTC market rather then commodities, such as gold or crude oil. He states the reason is that total supply of Bitcoin is fixed, while commodities face short-run supply uncertainty. Finally, Cretarola and Figa-Talamanca (2017) suggest that these technical indicators effectively function as measure of confidence, where asset and derivative prices are directly influenced by the reliability of the underlying technology.

1.3.4 Sentiment, Media Attention and Investor Behaviour

The influence of market sentiment, defined by Baker and Wurgler (2007) as the collective mood and expectations of investors, is a foundational pillar in understanding cryptocurrency valuation. Unlike traditional financial markets, where asset prices are grounded in transparent financial reporting, the cryptocurrency ecosystem relies almost exclusively on online communities and social media platforms for information distribution (Akylidrim et al., 2021; Milas et al., 2021). This environment is particularly sensitive to the influence of retail investors, who heavily depend on sentiment-driven discussions on platforms such as X and Reddit, rather than institutional analysis (Beckers, 2019; Smales, 2022). Consequently, Rognone et al. (2020) argue that social media sentiment exerts a far more immediate and potent influence on cryptocurrency prices than on traditional financial assets.

The speculative nature of cryptocurrencies has led many stakeholders to investigate the formation of “speculative bubbles”, price escalations driven by market sentiment rather than underlying fundaments. According to Bakhtiar et al. (2023) there have been observations that new market participants usually approach Bitcoin as speculative investment with little intention to utilize it as a medium of payment. This speculative pressure is directly measurable through social media, Mei et al. (2018) found that a single positive forum post containing the term Bitcoin is associated with a 0.00353% increase in

its price on the following day. Long et al. (2025) used Granger causality tests to show that sentiment significantly drives the volatility of BTC, ETH and DOGE, while volatility at the same time reshapes future sentiment. He captured this interconnectedness by the Total Connectedness Index, that distinguishes betweet currencies that receive sentiment shocks and those that transmit them.

At some categories, sentiment almost entirely replaces underlying fundaments, most notably in Non-Fungible Tokens (NFTs) and “memecoins”. Kong (2024) observes that the NFT market on Solana is highly volatile and driven by external factors, such as public commentary and market sentiment. The absence of trading regulations heightens these price fluctuations and therefore, exposing investors to significant risk.

The distinction between sentiment and technology driven volatility is further clarified by Doan (2025), who analysed volatility and risk profits of Solana, Dogecoin and Polygon. He used GARCH model to examine their volatility. The results indicated that Solana exhibited relatively moderate volatility spikes, implying greater market stability then other two altcoins, what has been accounted to its technological advancement. At the risk analysis, using Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR) methods, Solana again showed moderate risk levels, suggesting its market was influenced by a broader set of factors. However, Dogecoin has highest volatility compared to Solana and Polygon, and parameters indicated high persistence of volatility. For Dogecoin, market events, non-fundamental factors, played significant role. Social media and support from high-profile figures influenced its price. Another reason mentioned, was the origin of Dogecoin as meme and limited use beyond speculative trading.

A primary tool for measuring media attention is the Google Search Index (GSI) or Google Search Volume (GSV). Lin (2021) identified a significant relationship where past cryptocurrencies returns drive future investor attention, however the reverse dependency is weak. In terms of measuring market fear, Hoang and Baur (2021) argue that GSV is more credible because it is inclusive of the global population, whereas the Financial Stress Index used by Gaies et al. may not be representative as it is limited to the U.S. Analysing historical datasets from 2009 to 2023, Bakhtiar et al. (2023) concluded that while GSI remains crucial for selection of assets, its importance has weakened, suggesting that technological advancements may be making the cryptocurrency market less vulnerable to

traditional bubble behaviour. However, Fear and Greed Index (FGI) remains a critical factor for market timing, as demonstrated by the negative returns associated with period of fear during the pandemic. To identify early warnings of market bubble periods, Agosto et al. (2022) used a backward superior covariate-augmented Dickey-Fuller test to show that news volume and Google queries are not as significant as polarised version of investor's sentiment, especially to provide more accurate warning signal of market bubbles.

Methodologically, the analysis has evolved from simple dictionary-based models ti artificial intelligence (AI). Early research used general dictioneries like the General Inquirer or DICTION (Tetlock, 2007). However, the field has shifted toward machine learning complex models such as Convolution Neural Networks and Long Short-Termy Memory (Yang et al., 2016). The most recent breakthrough is the emergence of Large Language Models (LLM). Researchers such as Liang et al. (2022) and Zeng et al.(2022) demonstrate that LLMs outperform traditional models in detecting emotional inclinations.

1.3.5 Regulation and Policy Factors

While characteristics such as decentralization, anonymity, and payment irreversibility offer many advantages for users, Sovbetov (2018) argues that they also attract illicit activities, including money loundering, drug trafficking, and weapons procurement. This association in cybercrime has required intervention from regulatory authorities, including the SEC, FBI, and the Department of Homeland Security (DHS). A landmark regulatory shift occurred in March 13 by issuing rules defining virtual currency exchanges and administrators as money service businesses. The practical impact was shown shortly after, when DHS froze a major account of Mt.Gox.

Beyond direct legal enforcement, the regulatory landscape is often captured through the Economic Policy Uncertainty (EPU) index. Demir et al. (2018) found that EPU index significantly improves the predictive accuracy of Bitcoin returns, suggesting that investors react to the future government actions. The relationship is further examined by Papadamount et al. (2021) who examined the EPU's influence across a wider spectrum of assets. Their findings indicate that the EPU index affects the mean returns of approximately half of all investigated cryptocurrencies, revealing non-linear effects across

every quantile of volatility. They suggest that the speculative motivation remains independent of the broader economic environment, even when policy fluctuates.

2 THE OBJECTIVE AND METHODOLOGY

The previous chapter reviewed the theoretical part and empirical literature on the cryptocurrency market and identified main groups of factors that were linked to the cryptocurrency volatility. Since the cryptocurrency market represents multidimensional system in which several assets are observed over time and are influenced by variety of determinants, a panel framework was considered to be the most appropriate choice. This is also consistent with recent literature, which applies panel regression models in the analysis of cryptocurrency valuation and return dynamics (Lin et al.,2025; Bakhtiar et al.,2023).

2.1 The Objective

The main objective of this thesis is to examine how selected crypto-specific, macroeconomic and financial, and sentiment variables affect cryptocurrency market dynamics in a panel framework. The analysis focuses on cryptocurrency volatility. Given the main objective, two partial objectives are defined:

- the first partial objective is to identify how selected determinants affect daily cryptocurrency volatility measured by Garman-Klass volatility estimator in the baseline panel setting, while also using a rolling-window fixed-effects estimation to analyse how these relationships evolve over time
- the second objective, in order to investigate volatility more closely, is to assess whether effects of the selected variables vary across different volatility regimes. Particularly, what role do determinants play in low, medium and high-volatility periods.

2.2 Data and Variables

The empirical analysis is based on a daily panel dataset covering the period from January 1st, 2020 to December 31st, 2025. The dataset is organised in long format, where each observation represents one cryptocurrency on one trading day. This structure thus preserves time variation within each cryptocurrency and the cross-sectional heterogeneity across different coins.

The sample consists of 9 selected cryptocurrencies, namely Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), TRON (TRX), Dogecoin (DOGE), Cardano (ADA), Bitcoin Cash (BCH), Chainlink (LINK), Zcash (ZEC). The selection was based on market capitalization, with the selected coins belonging to the upper section of the market ranking at the coinmarketcap.com, specifically within ranks 1 to 16 during our analysis. Stablecoins were excluded from the sample, as their price and volatility dynamics differ from those of standard cryptocurrencies, and would distort the analysis. In addition, some coins with higher market share were not included because all of the sufficient data were not available for full sample period.

The use of multiple cryptocurrencies is important as the thesis does not aim to explain the behaviour of one coin only, but rather to analyse cryptocurrency market dynamics across a broader section of assets. This approach makes it possible to account for differences in liquidity, trading activity, and other characteristics, while also capturing the effects of common external factors (González, 2025).

The choice of daily data is based on the nature of the crypto markets, which are highly dynamic. In addition, the selected sample period covers different market phases, including periods of trending behaviour, corrections and periods of high volatility. It is therefore suitable for the analysis as it studies the behaviour of cryptocurrencies under different market conditions.

The data used in empirical analysis were obtained through APIs using the Python programming language. The sources are listed in Table n.1. For variables that were constructed or transformed, the reported source refers to the original data from which the final variables were derived.

Table 1 Description of variables used in empirical analysis

Variable	Type	Description	Source
$\boldsymbol{ln_gkvol_{i,t}}$	Dependent	Daily log Garman-Klass volatility	Binance
$\boldsymbol{ln_rsvol_{i,t}}$	Dependent	Daily log Rogers-Satchell volatility	Binance
$\boldsymbol{ln_gkvol_{i,t-1}}$	Crypto-specific	Lagged log volatility	Binance
$\boldsymbol{ln_gkvol_ma7_{i,t-1}}$	Crypto-specific	Lagged short-run log volatility proxy	Binance
$\boldsymbol{ln_vol_{i,t-1}}$	Crypto-specific	Quote asset trading volume in USDT	CoinMarketCap
$\boldsymbol{ln_illiq_{i,t-1}}$	Crypto-specific	Log illiquidity measure	CoinMarketCap, Binance

$\boldsymbol{mom_7_{i,t-1}}$	Crypto-specific	Log short-horizon momentum	Binance
$\boldsymbol{beta_7_{i,t-1}}$	Crypto-specific	Log short-horizon beta	CoinMarketCap, Binance
$\boldsymbol{ln\ _tx_per_address_{i,t-1}}$	Sentiment	Log daily number of transactions per active address	Coin Metrics
$\boldsymbol{gt_{i,t-1}}$	Sentiment	Google Trends Index for each coin	Google Trends
$\boldsymbol{fgi_{i,t-1}}$	Sentiment	Crypto Fear & Greed Index	Alternative.me
$\boldsymbol{dxy_ret_{i,t-1}}$	Macro-financial	Log return on the U.S. Dollar Index	Yahoo
$\boldsymbol{vix_chg_{i,t-1}}$	Macro-financial	Log change in Volatility Index	Yahoo
$\boldsymbol{spx_ret_{i,t-1}}$	Macro-financial	Log return on the S&P 500 Index	Yahoo

Source: Own processing

2.2.1 Dependent Variables

The empirical analysis uses two main dependent variables, namely daily Garman-Klass volatility and daily Rogers-Satchell volatility.

Garman-Klass Volatility

The volatility is used to capture the uncertainty of cryptocurrency market behaviour. Given the availability of daily OHLC data, the thesis relies on Garman-Klass volatility estimator. The estimator is calculated as logarithmic volatility. This variable serves as dependent variable in the baseline volatility model and in the pooled quantile regression for volatility. We have computed volatility as:

$$\sigma^2_{GK_{i,t}} = \frac{1}{2}\left[ln\left(\frac{H_{i,t}}{L_{i,t}}\right)\right]^2 - (2ln2 - 1)\left[ln\left(\frac{C_{i,t}}{O_{i,t}}\right)\right]^2 \quad (2.1)$$

$$\ln_\text{gkvol}_{i,t} = \ln(\sigma^2_{GK_{i,t}}) \quad (2.2)$$

where $O_{i,t}$, $H_{i,t}, L_{i,t}$ and $C_{i,t}$ denote the daily open, high, low, and close prices of cryptocurrency *i* on the day *t*.

Rogers-Satchell Volatility

Rogers-Satchell serves as the dependent variable in the robustness check for the baseline volatility model and pooled quantile regression volatility model. The variable is calculated using daily OHLC data and transformed logarithmically. Computation is as follows:

$$\sigma^2_{RS_{i,t}} = \left[ln\left(\frac{H_{i,t}}{C_{i,t}}\right) ln\left(\frac{H_{i,t}}{O_{i,t}}\right) + ln\left(\frac{L_{i,t}}{C_{i,t}}\right) ln\left(\frac{L_{i,t}}{O_{i,t}}\right) \right] \quad (2.3)$$

$$\ln_rsvol_{i,t} = \ln(\sigma^2_{RS_{i,t}}) \quad (2.4)$$

2.2.2 Explanatory Variables

The explanatory variables used in the empirical analysis are divided into three groups, namely crypto-specific variables, macroeconomic and financial variables, and sentiment variables. This classification follows theoretical background discussed in the previous chapter. Although, technological variables such as consensus mechanism were not included in the models as they are largely time-invariant over the sample period. In fixed effects framework that the thesis employs, such variables would be absorbed by individual effects. In order to reduce simultaneity and avoid look-ahead bias, the explanatory variables are included in the models in lagged form, precisely information about variables at time *t-1* is used to explain dependent variables at time *t.*

Crypto-specific Variables

These variables capture the internal market characteristics of individual coins. They are constructed as follows. The variable $ln_gkvol_{i,t-1}$ is shifted by one day within cryptocurrency *i*, in order to capture short-run persistence. Additionally, we have constructed 7-day rolling moving average of log Garman-Klass volatility to capture the persistence over the whole week, models utilize lagged version $ln_gkvol_ma7_{i,t-1}$:

$$ln_gkvol_ma7_{i,t} = \frac{1}{7}\sum_{j=1}^{7} ln_gkvol_{i,t-j} \quad (2.5)$$

Trading volume reflects the intensity of market trading activity and is log-transformed and lagged by one day. Calculation is as follows:

$$ln_vol_{i,t} = \ln(volume_{i,t}) \quad (2.6)$$

Iliquidity indicates how strongly the price moves relative to trading volume, that is, the price impact of trades. It is captured by an Amihud Illiquidity Ratio constructed as a ratio of the absolute daily return to daily trading volume:

$$illiq_{i,t} = \frac{|ret_{i,t}|}{volume_{i,t}} \tag{2.7}$$

Because this variable was strongly right-skewed, its lagged value by one day is transformed logarithmically, however, to allow this transformation with presence of very small values, a positive constant *c* is added:

$$ln_illiq_{i,t-1} = \ln(illiq_{i,t-1} + c) \tag{2.8}$$

The 7-day momentum variable shows whether the cryptocurrency had a tendency to rise or fall over the previous week and is defined as the rolling sums of daily returns:

$$mom_7_{i,t} = \sum_{j=1}^{7} \mathrm{ret}_{i,t-j} \tag{2.9}$$

Market sensitivity is measured by rolling beta coefficients computed with respect to the market cap-weighted cryptocurrency return. First, the market return is constructed as a market-cap weighted average of daily returns across all cryptocurrencies. Then, using this benchmark, the 7-day and 30-day rolling data was constructed:

$$market_return_t = \sum_{i=1}^{N} w_{i,t} ret_{i,t} \tag{2.10}$$

$$w_{i,t} = \frac{MCAP_{i,t}}{\sum_{j=1}^{N} MCAP_{i,t}} \tag{2.11}$$

$$beta_7_{i,t} = \frac{Cov_7(ret_{i,t}, market_return_t)}{Var_7(market_return_t)} \tag{2.12}$$

$$beta_30_{i,t} = \frac{Cov_{30}(ret_{i,t}, market_return_t)}{Var_{30}(market_return_t)}. \tag{2.13}$$

Sentiment Variables

The sentiment group consists of variables that capture investor attention and activity. Analysis is using Crypto Fear and Greed Index, Google Trends Index and variable which

explains how many confirmed transactions were made per active addresses, $ln_tx_per_address_{i,t-1}$. All variables are lagged by one day.

Since a single daily Google Trends data were not available for the full sample period, the data were downloaded in overlapping shorter windows (90 days with 30 days overlapped) and stitched into continuous daily series using overlap-based rescaling. Where appropriate, the series were constructed from two search terms referring to the same cryptocurrency, for example for BTC the data included “bitcoin” and “btc” as search terms. While in cases of ambiguous terminology only the more specific search term was used, for example for LINK was included only “chainlink” search term. The final Google Trends series were normalized to a 0-100 scale and matched to individual coins.

Macro and Financial Variables

The last group consists of macroeconomic and financial variables, which capture the external environment in which cryptocurrency markets operate. Since cryptocurrencies are not fully isolated from development in traditional markets, the analysis includes variables reflecting stock market performance, U.S. dollar movements and market uncertainty. For that reason, analysis includes logarithmic return on S&P 500 Index, logarithmic return on the U.S. Dollar Index and logarithmic changes in the Volatility Index. As these variables are based on traditional financial markets, there are missing data on weekends and public holidays. The missing data were filled using last available value from the previous trading day (forward-fill procedure).

2.3 Methodology

To examine the relationship between the selected explanatory variables and cryptocurrency market dynamics, the empirical analysis applies mean-based panel models and pooled quantile regression models. The baseline part of the analysis focuses on the average effects of selected determinants on cryptocurrency volatility. These baseline models are complemented by pooled quantile regressions, which make it possible to assess whether estimated relationships vary across different parts of the conditional distribution of the dependent variables.

Before estimating the models, dataset was prepared in Python and we have examined:

- the main statistical properties through the descriptive statistics of the selected variables,
- pairwise relationship between selected variables by correlation analysis,
- multicollinearity among selected variables by the Variance Inflation Factor,
- the stationarity of the panel variables using the Im-Pesaran-Shin (IPS) test and Fisher-type panel unit root test,
- stationarity of the time-series variables using Augmented Dickey-Fuller (ADF) test and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test.

2.3.1 Baseline Panel Models for Returns and Volatility

The baseline empirical framework is based on fixed effects panel model. The fixed effects makes it possible to control time-invariant heterogeneity across cryptocurrencies, while still utilizing the time variation in the explanatory variables.

However, even though the analysis is based on daily data, a year_month variable was constructed and used as the time effect in the models. The reason is that daily time fixed effects would absorb a significant part of the variation in the macro-financial and sentiment variables, which are identical across all coins on a given day. The model still preserves the daily variation of the explanatory variables inside each month. Although analysis is using year_month control variable, the actual estimation still comes from daily movements.

The general form of baseline model can be written as:

$$y_{i,t} = \alpha_i + \lambda_t + \beta' X_{i,t-1} + \varepsilon_{i,t} \tag{2.14}$$

- $y_{i,t}$ – dependant variable of cryptocurrency *i* on day *t*
- α_i – cryptocurrency-specific fixed effects
- λ_t – time fixed effects
- $X_{i,t-1}$ – vector of explanatory variables lagged by one day
- $\varepsilon_{i,t}$ – error term

The volatility equations were estimated through a sequence of models. For both dependent variables we have defined models as follows:

- model M1A includes only cryptocurrency-specific explanatory variables,
- model M1B extends model M1A by sentiment variables,
- model M1C extends model M1B by macroeconomic and financial variables, and represents full baseline specification,
- model M1D represents robustness check in which the dependent variable is replaced by Rogers-Satchell volatility, to verify whether the baseline model remains robust to an alternative measure,
- model M1E represents additional robustness check based on a reduced sample excluding Bitcoin to assess whether the relationships are driven by Bitcoin's dominant role or whether they hold across remaining selected coins.

The models are first estimated using HC1 heteroskedasticity-robust standard errors, and then several post-estimation tests are carried out. Hausman test to evaluate between fixed and random effects, Wooldridge test to examine serial correlation, Modified Wald test to examine heteroskedasticity, and Breusch-Pagan LM CD test for cross-sectional dependence.

In case the tests indicate that the panel residuals exhibit some of these features, the baseline models are re-estimated using Driscoll-Kraay standard errors. These estimates are then treated as the main basis.

Finally, the empirical analysis also employs Wald tests for selected groups of explanatory variables. These tests evaluate the joint significance of variable blocks, such as crypto-specific block, sentiments block and macro-financial block, to assess their overall contribution, not only individual coefficients.

2.3.2 Supplementary Rolling-window Analysis

As an additional supplementary step, the empirical analysis also employs a rolling-window fixed-effects estimation. Its purpose is to examine whether the estimated relationships remain stable over time or change across different phases of cryptocurrency market development. More specifically, the model is repeatedly re-estimated on overlapping subsamples using a one-year rolling window and monthly window endpoints, while preserving the same dependent variable and explanatory variables as in the main baseline specification. This approach makes it possible to trace the evolution of the estimated

coefficients over the sample period and to assess whether particular determinants become more relevant during episodes of market stress. The rolling-window analysis is interpreted as a complementary diagnostic exercise rather than as a separate core estimation framework.

2.3.3 Pooled Quantile Regressions for Returns and Volatility

Empirical analysis is further extended by pooled quantile regression (PQR) model for the Garman-Klass volatility estimator. PQR is particularly relevant in cryptocurrency market, where the relationships between variables are often non-linear and may vary across different market conditions.

The general form of the PQR model can be defined as:

$$Q_\tau\left(y_{i,t}\middle|X_{i,t-1}\right) = \alpha_\tau + \beta_\tau{}' X_{i,t-1} \tag{2.15}$$

- $Q_\tau\left(y_{i,t}\middle|X_{i,t-1}\right)$ – the conditional τ-th quantile of the dependent variable,
- $y_{i,t}$ – dependent variable of cryptocurrency *i* on day *t,*
- $X_{i,t-1}$ – vector of explanatory variables lagged by one day,
- α_τ – quantile-specific intercept,
- β_τ – vector of quantile-specific slope coefficients.

The lag structure of baseline model is maintained to reduce simultaneity and to keep the PQR consistent with the overall empirical design. PQR models are estimated for several quantiles, namely 0.1, 0.25, 0.5, 0.75, and 0.9 quantile. These quantiles represent different market states to make it possible to distinguish between normal periods and periods with extreme conditions.

The models are estimated using bootstrap standard errors to get more reliable estimates, since PQR does not estimate the conditional mean but different parts of the distribution. The bootstrap standard errors are computed by repeated resampling over the time dimension, where individual time periods are randomly drawn and re-estimated. A total of 200 iterations is used. In addition, the empirical analysis employs Wald tests across quantiles in order to evaluate how the estimated coefficients differ between quantiles.

2.3.4 Robustness Check

Robustness checks are included in order to verify the stability of the estimated coefficients and to assess whether the main findings depend on the specific model design. In the thesis, two robustness checks are applied.

First, the baseline volatility specification is re-estimated using an alternative dependent variable. While the main model employs logarithmically transformed Garman–Klass volatility, the first robustness check replaces it with logarithmically transformed Rogers–Satchell volatility. Both estimators are based on daily OHLC prices, but they differ in their assumptions, especially with respect to the role of drift. This check therefore makes it possible to examine whether the main results remain stable when volatility is measured in a different way, while keeping the explanatory variables and the sample unchanged.

Second, the baseline specification is re-estimated on a reduced sample excluding Bitcoin. This step is important because Bitcoin remains the dominant cryptocurrency in terms of market capitalization, trading activity, and investor attention, and may therefore disproportionately influence the estimated relationships. By removing Bitcoin from the sample, it is possible to assess whether the identified effects also hold more generally across the broader market of large cryptocurrencies, or whether they are driven mainly by the behaviour of the dominant coin.

Taken together, these robustness checks make it possible to evaluate whether the main conclusions are sensitive to the choice of volatility proxy and to the presence of Bitcoin in the dataset. If the estimated signs, magnitudes, and significance levels remain broadly similar across these alternative specifications, this strengthens the credibility of the baseline results and suggests that the identified relationships are not purely model-specific.

3 RESULTS AND DISCUSSION

The results section starts with the data analysis, in order to obtain a better understanding of the data, before proceeding to the model analysis.

3.1 Preliminary Data Analysis

3.1.1 Descriptive Statistics of the Variables

Table 2 and Table 3 report the descriptive statistics of the variables before and after transformation. Their purpose is to provide an initial overview of the distributional properties of the dataset and to indicate whether further transformation of the variables is justified before the estimation.

Table 2 Descriptive statistics of variables before transformation

Variable	N	Mean	SD	Min	Median	Max	Skew	Kurt
gk_volatility	19728	0.04	0.06	0	0.03	7.46	76.97	8704.79
rs_volatility	19728	0.04	0.08	0	0.03	10.22	95.36	11671.12
gk_volatility_ma7	19728	0.04	0.03	0.01	0.04	1.23	14.6	451.92
volume	19728	7.27 bn	14.51 bn	0.01 bn	1.08 bn	350.97 bn	3.76	28.95
illiquidity	19728	0	0	0	0	0	3.4	14.86
mom_7	19728	2985.39	127575.4	-1382024	0.03	2079798	0.62	44.91
beta_7	19728	0.17	0.44	-0.09	0	1.67	2.49	4.33
tx_per_address	19728	7.49	23.54	0.02	1.25	417.06	5.73	41.24
gt_coin	19728	11.64	10.76	0.05	8.92	100	2.41	9.71
fgi	19728	49.98	22.12	6	50	95	-0.02	-1.07
vix_chg	19728	100.23	7.01	64.25	100	174.04	2.64	19.65
spx_ret	19728	100.04	1.09	88.02	100	109.52	-0.35	21.43
dxy_ret	19728	100	0.37	97.88	100	101.65	-0.21	3.75

Source: Own calculations using Python.

The raw variables show significant heterogeneity across the dataset. This is particularly visible for the volatility estimators, trading volume, and several cryptocurrency-specific variables. Both Garman-Klass volatility and Rogers-Satchell volatility exhibit very low median values, around 0.03, but extremely high maximum values, reaching 7.46 and 10.22, respectively. These variables are also characterised by very high positive skewness and kurtosis. A similar pattern is observed for trading volume and transaction count per active address. As shown in Table 2, the maximum value of transaction count per active address reaches 417.06, indicating periods of intensive network activity. These results suggest that the dataset contains a large number of calm observations, combined with a smaller number

of extreme episodes, which reflects the speculative nature and abrupt regime changes. This behaviour is quite typical for the cryptocurrency markets and in line with the literature (Bouteska, 2024; Yermack, 2015; Baur et al.,2018).

Looking at the Fear and Greed Index centred close to its neutral level suggests that sample covers both fear and greed phases of the market cycle. Values below 50 represent "fear", the uncertainty on the market, whereas values above 50 represent "greed". Google Trends displays a strongly right-skewed distribution, similar to several other crypto-specific variables, implying that investor attention is usually moderate but occasionally surges sharply during periods of intensified investor activity.

Among the macroeconomic and financial variables, strong right-skewness is visible mainly in the Volatility Index. However, the difference between its median and maximum value is not as extreme as in the case of the crypto-specific variables. Thus, this may suggest that VIX could play role in the analysis. On the other hand, S&P 500 and U.S. Dollar Index appear to be distributed more symmetrically.

The descriptive analysis of the raw dataset indicates that variable transformation is clearly necessary. The variables differ considerably in magnitude and contain outliers, which could distort coefficient estimates. In particular, the variable illiquidity due to large number of very small values is logarithmically transformed using small constant *c*.

Table 3 Descriptive statistics of the variables

Variable	N	Mean	SD	Min	Median	Max	Skew	Kurt
ln_gkvol	19728	-6.70	1.31	-12.07	-6.71	4.02	0.14	0.81
ln_rsvol	19728	-6.71	1.34	-12.95	-6.72	4.65	0.14	0.96
ln_gkvol_ma7_l1	19728	-6.70	1.03	-10.32	-6.70	-2.30	0.06	0.46
ln_vol_l1	19728	21.06	1.91	16.21	20.80	26.58	0.26	-0.74
ln_illiq_l1	19728	-20.50	2.31	-32.38	-20.10	-14.84	-0.81	1.67
mom_7_l1	19728	0.83	13.68	-86.11	0.29	178.06	1.18	14.26
beta_7_l1	19728	1.11	0.70	-10.85	1.04	9.93	1.56	24.45
ln_tx_per_address_l1	19728	0.35	1.53	-3.71	0.22	6.03	1.03	1.04
gt_coin_l1	19728	11.64	10.76	0.05	8.92	100.00	2.41	9.71
fgi_l1	19728	49.98	22.12	6.00	50.00	95.00	-0.02	-1.07
vix_chg_l1	19728	0.00	6.58	-44.24	0.00	55.41	1.42	11.30
spx_ret_l1	19728	0.03	1.10	-12.77	0.00	9.09	-0.74	22.58
dxy_ret_l1	19728	0.00	0.37	-2.14	0.00	1.64	-0.24	3.78

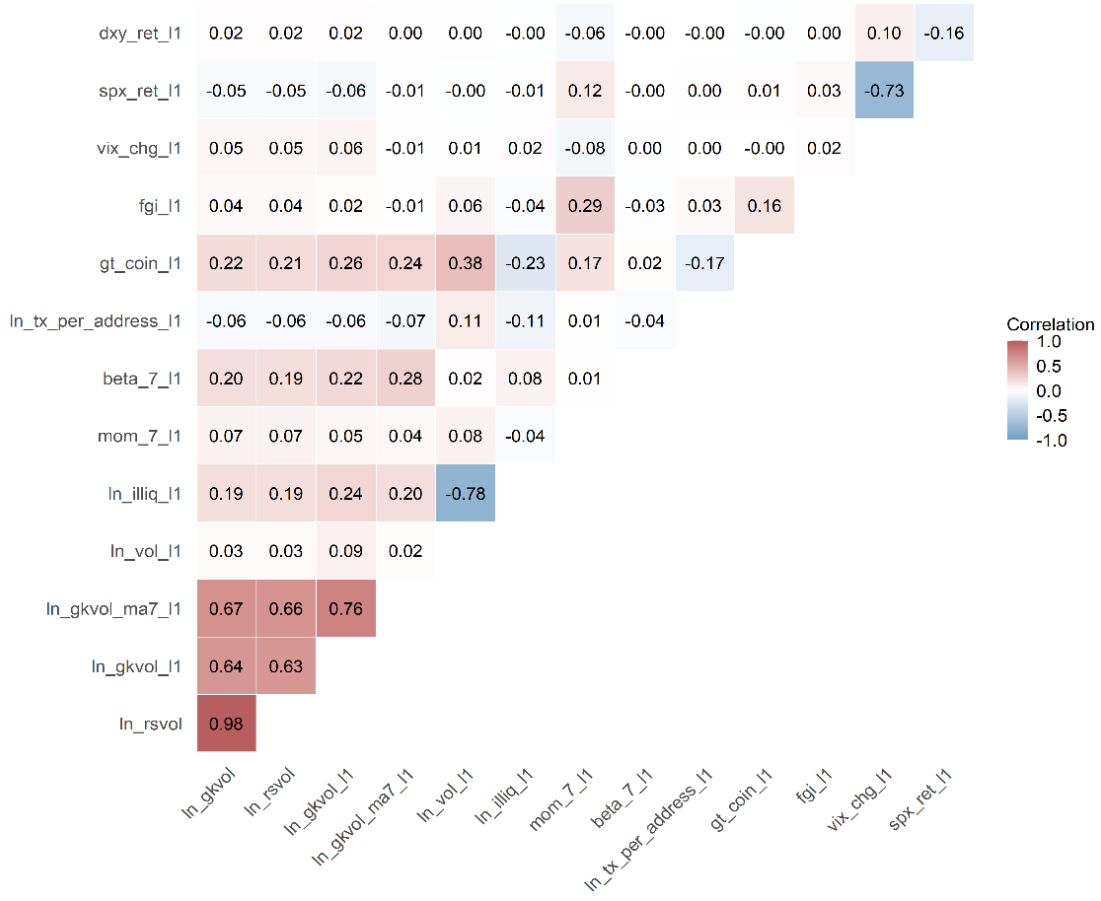
Source: Own calculations using RStudio software.

After the transformation, the distribution of the variables becomes more stable and suitable for the analysis. In particular, the log-transformed volatility, volume, illiquidity, and transaction count per active address show less extreme asymmetry.

3.1.2 Correlation Analysis and Multicollinearity Diagnostics

The next step in data analysis is to examine the relationships among the variables in the same form in which they are used in the models. For this reason, the correlation analysis is based on the transformed variables.

Figure 3 The heatmap of Pearson correlation coefficients for the variables



Source: Own calculations using RStudio software.

Figure 3 presents the correlation matrix in the form of a heatmap. The reported values are Pearson correlation coefficients, which show the direction and strength of the linear relationship between individual variables. The matrix helps to understand the structure of dataset and indicates whether the variables move together positively, negatively, or only weakly. The scale of the correlation coefficients is shown in the legend in the right corner.

Strong positive correlations are represented by dark red colour, while strong negative correlations are shown in blue.

The strongest correlation is observed between two volatility estimators, namely log-transformed Garman-Klass volatility and log-transformed Rogers-Satchell volatility, with a correlation coefficient of 0.98. This result is expected since both variables are alternative estimators of daily price volatility. Their high correlation shows they capture the same volatility dynamics, although they are based on the different assumptions. This also supports the use of Rogers-Satchell volatility only as a robustness check. Thus, both dependent variables have similar correlations with explanatory variables, highest with the volatility-based measures.

A relatively strong relationship can be seen between explanatory variables, precisely lagged volatility and its 7-day moving average, as well as between these two variables and the trading volume. The correlation between *ln_gkvol_l1* and *ln_gkvol_ma7_l1* reaches 0.76, while the correlation between *ln_gkvol_l1* and *ln_vol_l1* is 0.24, and between *ln_gkvol_ma7_l1* and *ln_vol_l1* it is 0.38. This pattern seems right, as periods of higher volatility in cryptocurrency markets are often accompanied by stronger trading activity, since the large price swings attract higher investment attention. For example, speculative trading, as with higher risk comes higher rewards, or portfolio rebalancing to safer assets.

An important result is the strong negative correlation between illiquidity and trading volume, which reaches -0.78. Since illiquidity is calculated using trading volume, this relationship is expected. Also in more liquid periods, trading volume tends to be higher and price impact per unit tends to be lower. In contrast, during periods of thinner market activity, even relatively small trades may have a larger price effect. The negative sign thus corresponds to the expected inverse relationship.

The remaining cryptocurrency-specific variables show mostly low to moderate pairwise correlations. Beta and momentum are weakly related to the other regressors, with beta having strongest positive correlation of 0.28 with 7-day moving average of Garman-Klass volatility and momentum with the Fear and Greed Index reaching positive correlation of 0.29.

The sentiment variable *ln_tx_per_address_l1* displays weak correlations with most of the variables, the strongest is negative relationship with the Google Trends Index. Google Trends Index is moderately positive with volatility variables and volume, which seems logical as periods with higher investor attention are often associated with higher volatility. Bekhtiar et al. (2023) also notes that Google search activity may rise together with speculative interest.

The macro-financial variables are weakly correlated with crypto-specific regressors. The coefficients for the S&P 500, VIX and U.S. Dollar Index are in many cases close to zero. This is not unusual as previous literature reports correlations between cryptocurrencies and traditional financial assets are often relatively low, apart from periods of market stress (Härdle et al., 2018). The strongest relationship within macro block is negative correlation of -0.73 between *spx_ret_l1* and *vix_chg_l1*. This is consistent with standard intuition, that with increasement in uncertainty and implied volatility, equity market declines.

Overall, the correlation matrix does not point to severe pairwise correlation, apart from two volatility estimators. This is not a problem, since these two are dependent variables and are not included in the same model. To verify whether the selected explanatory variables can be included in the models without creating multicollinearity, VIF analysis was conducted.

Table 4 Variance Inflation Factor (VIF) values of the explanatory variables

Variable	VIF_1	VIF_2	VIF_3	VIF_4
ln_gkvol_l1	2.79	2.8	2.83	2.83
ln_gkvol_ma7_l1	2.43	2.47	2.49	2.49
ln_vol_l1	3.24	3.47	3.47	3.47
ln_illiq_l1	3.39	3.39	3.39	3.39
mom_7_l1	1.01	1.12	1.14	1.14
beta_7_l1	1.09	1.09	1.09	1.09
ln_tx_per_address_l1	-	1.08	1.08	1.08
fgi_l1	-	1.12	1.12	1.12
gt_coin_l1	-	1.38	1.38	1.38
spx_ret_l1	-	-	2.18	2.18
dxy_ret_l1	-	-	1.03	1.03
vix_chg_l1	-	-	2.14	2.14

Source: Own calculations using RStudio software.

Table 4 reports Variance Inflation Factor values. The results show that all values remain below 5, which suggest that the multicollinearity is not severe and the explanatory variables can be retained in the estimated models. Highest VIF values are observed for

trading volume, illiquidity and volatility measures, as expected from the correlation matrix analysis.

3.1.3 Unit Root Testing and Stationarity Assessment

Before estimating the models, it is important to verify whether the variables are stationary, since non-stationary variables may lead to false regression results.

Since the dataset has a panel structure and likely heterogeneity across cryptocurrencies, panel data are analysed using the the Im-Pesaran-Shin (IPS) test and the Fisher-type panel unit root test. Both tests were applied to the transformed variables used in the regressions. In both cases, the null hypothesis assumes that the variable contains a unit root and the rejection of the null hypothesis indicates stationarity.

Table 5 Panel unit root testing using IPS and Fisher-type tests

	IPS			**Fisher**		
Variable	**t-stat**	**p-value**	**Result**	**t-stat**	**p-value**	**Result**
ln_gkvol	-55.75	<0.0001	Stationary	1706.17	<0.0001	Stationary
ln_rsvol	-57.83	<0.0001	Stationary	1764.61	<0.0001	Stationary
ln_gkvol_l1	-55.82	<0.0001	Stationary	1707.90	<0.0001	Stationary
ln_gkvol_ma7_l1	-19.34	<0.0001	Stationary	407.211	<0.0001	Stationary
ln_vol_l1	-22.65	<0.0001	Stationary	541.03	<0.0001	Stationary
ln_illiq_l1	-82.76	<0.0001	Stationary	2046.38	<0.0001	Stationary
mom_7_l1	-40.12	<0.0001	Stationary	1179.28	<0.0001	Stationary
beta_7_l1	-43.65	<0.0001	Stationary	1309.09	<0.0001	Stationary
ln_tx_per_address_l1	-27.46	<0.0001	Stationary	708.41	<0.0001	Stationary
gt_coin_l1	-25.25	<0.0001	Stationary	625.34	<0.0001	Stationary
fgi_l1	-12.46	<0.0001	Stationary	204.36	<0.0001	Stationary
vix_chg_l1	-116.18	<0.0001	Stationary	1506.98	<0.0001	Stationary
spx_ret_l1	-112.12	<0.0001	Stationary	1640.45	<0.0001	Stationary
dxy_ret_l1	-112.01	<0.0001	Stationary	1643.87	<0.0001	Stationary

Source: Own calculations using RStudio software.

As reported in Table 5, all variables are found to be stationary according to both panel unit root tests. In all cases, the null hypothesis of a unit root is rejected, indicating that the variables do not show non-stationary behaviour.

The macro-financial variables and the Fear and Greed Index are identical across cryptocurrencies within the same date. Thus their stationarity is additionally verified using time-series unit root tests. More specifically, the Augmented Dickey-Fuller (ADF) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test to ensure the variables are truly

stationary. In the ADF test, the null hypothesis assumes the unit root, while the alternative hypothesis suggests the series has no unit root and therefore is stationary. The KPSS has the hypothesis switched. The null hypothesis indicates stationarity.

Table 6 Time-series unit root testing using ADF and KPSS tests

	ADF			KPSS		
Variable	**Stat**	**p-value**	**Result**	**Stat**	**p-value**	**Result**
fgi_l1	-12.0033	0.01	Stationary	0.0797	0.1	Stationary
vix_chg_l1	-30.9333	0.01	Stationary	0.0031	0.1	Stationary
spx_ret_l1	-28.1727	0.01	Stationary	0.0064	0.1	Stationary
dxy_ret_l1	-26.7599	0.01	Stationary	0.0136	0.1	Stationary

Source: Own calculations using RStudio software.

Table 6 displays time-series unit root tests. From the results we can conclude the variables are stationary. Since all variables are stationary after our transformation, both panel and time-series, no further differencing is needed.

3.2 Baseline Volatility Model Results

This section presents the main estimation results for the baseline volatility models. Firstly, we present the initial baseline estimates of the volatility models. The models are estimated within a fixed-effects framework with coin fixed effects and year-month fixed. At this stage, the inference is based on HC1 robust standard errors.

The baseline analysis is constructed in a stepwise way as mentioned in the Methodology section. Model M1A includes the core market variables related to the volatility persistence and trading condition. Model M1B extends this specification by adding sentiment variables, and model M1C presents full specification model, including macro-financial determinants. In addition, two robustness checks are considered. Model M1D keeps the same explanatory variables as M1C, but replaces dependent variable with logarithmically transformed Rogers-Satchell volatility (*ln_rsvol*) instead of logarithmically transformed Garman-Klass volatility (*ln_gkvol*). This robustness check is included as both estimators are based on the OHLC prices, but they differ in assumptions. The Garman-Klass estimator assumes zero-drift, whereas the Roger-Satchell estimator is drift-independent (Molnár, 2020). Their comparison therefore helps verify whether the main results remain stable across alternative range-based measures of volatility. These estimators are also more appropriate than close-to-close volatility, as they use more information from daily trading

data, while realized volatility would require high-frequency trading intraday data (Meilijson, 2018).

Model M1E employs dependent variable *ln_gkvol*, but excludes Bitcoin from the sample in order to assess whether the estimated relationships are also present across the broader market of large cryptocurrencies and are not driven by the Bitcoin. This approach is suitable for the analysis because, without removing Bitcoin, it would be difficult to determine whether the results reflect the wider market or mainly the behaviour of the dominant coin.

The initial results suggest that most of the selected variables are statistically significant and their estimated sign are in line with the expected economic interpretation. In particular, the estimates point to an important role of the volatility persistence, trading activity, liquidity conditions, and investor-related variables. At the same time, given the nature of daily cryptocurrency panel data, it is necessary to verify whether the standard assumptions of panel regression are satisfied before drawing conclusions.

3.2.1 Diagnostic Testing of the Baseline Volatility Model Specifications

Several diagnostic tests were carried out in order to verify whether the selected panel model was appropriate and whether the main assumptions of panel regression were satisfied.

The diagnostic testing was performed separately for three specifications of the baseline volatility model, namely for the model M1C, M1D and M1E, as they differ significantly.

The selected tests point out main economic issues which usually arise in panel models with daily cryptocurrency data. In a panel of cryptocurrencies observed over time it is expected that the individual coins differ in their unobserved characteristics, that residuals may be serially correlated, that the variance of the error term may differ across coins, and that individual coins may be correlated and thus react jointly to the same market-wide shocks. For this reason, the diagnostic testing focused on four standard tests, namely the Hausman test, the Wooldridge test for autocorrelation in panel data, the modified Wald test for groupwise heteroskedasticity, and the Breusch-Pagan LM CD test for cross-sectional dependence (Hoyos and Sarafidis, 2006; Drukker, 2003; Torres-Reyna, 2007).

Table 7 Diagnostic tests of the baseline volatility model specifications

Test	Model	Statistics	Df	Avg. corr.	p-value	Result
Hausman	M1C	473.60	12	-	<0.001	Prefer FE
	M1D	409.86	12	-	<0.001	Prefer FE
	M1E	466.92	12	-	<0.001	Prefer FE
Wooldridge serial correlation	M1C	3.50	-	-	0.0613	No evidence
	M1D	9.88	-	-	0.0017	Serial correlation
	M1E	3.63	-	-	0.0569	No evidence
Modified Wald heteroskedasticity	M1C	4.37e+07	9	-	<0.001	Heteroskedasticity
	M1D	4.37e+07	9	-	<0.001	Heteroskedasticity
	M1E	3.88e+07	9	-	<0.001	Heteroskedasticity
Breusch-Pagan LM CD	M1C	2.56e+04	36	0.56	<0.001	Cross-sec. dep.
	M1D	2.51e+04	36	0.56	<0.001	Cross-sec. dep.
	M1E	1.93e+04	28	0.56	<0.001	Cross-sec. dep.

Source: Own calculations using Python.

For each model specification, the Hausman test was first used to compare the fixed effects and random effects estimators. This test helps determine whether the individual unobserved effects are correlated with explanatory variables. If this correlation is present, the random effects estimator is no longer appropriate and the fixed effects estimator is the preferred choice. This is relevant in the dataset, since cryptocurrencies differ in characteristics, that are difficult to measure as they are usually time invariant. For example market maturity, technological background, or investor base. The Hausman test is designed for this type of decision. Its null hypothesis assumes that the individual characteristics are not correlated with the regressors and that the difference in coefficients is not systematic (Torres-Reyna, 2007; Hausman; 1978). Looking at the Table 7, the results suggest that fixed effects model is appropriate for all three model specifications. In the Hausman test, the null hypothesis is rejected in M1C, M1D, and M1E at the 1% significance level.

Then, the Wooldridge test was applied to examine whether the residuals have serial correlation. This test is suitable for panel setting because it can be implemented under general conditions and has good size and power properties (Drukker, 2003). Dataset we use is observed at the daily frequency and volatility-related variables, such as *ln_gkvol_l1* and *ln_gkvol_ma7_l1*, may show persistence over time. Serial correlation is thus important to check as it biases standard errors and reduces the efficiency of inference (Torres-Reyna, 2007).

The results provide mixed evidence on serial correlation. For M1D, the null hypothesis of no first-order autocorrelation is rejected and the result indicate the presence of serial correlation in residuals. On the other hand, for M1C and M1E, the p-values are 0.0613 and 0.569, respectively, which means that the null hypothesis is not rejected at the 5% significance level. Therefore, there is no evidence of serial correlation. Although, both p-values are relatively close to the significance level, so the possibility of weak residual persistence is not fully excluded.

Next, the modified Wald test for groupwise heteroskedasticity was used to assess whether the variance of the error term is constant across panel data (Torres-Reyna, 2007). However, since the cryptocurrencies in the sample differ significantly in terms of volume, liquidity, and trading intensity, it would be unrealistic to assume that the variance is constant. The results are thus not surprising and show exactly our assumption. In all three model specifications, the null hypothesis of homoskedasticity is rejected at the 1% significance level, indicating presence of the heteroskedasticity.

Finally, cross-sectional dependence was tested using the Breusch-Pagan Lagrange Multiplier test. According to De Hoyos and Sarafidis, the LM test is appropriate when $N<T$. Therefore, this test was chosen as this assumption fits the structure of the panel dataset used in analysis, which contains a relatively small cross-sectional dimension and a much longer time dimension. The null hypothesis of the test assumes cross-sectional independence of the residuals.

According to the Table 7, the null hypothesis of the Breusch-Pagan LM CD test is rejected in all three model specifications at the 1% significance level. This indicates that the residuals are correlated across cryptocurrencies. The average pairwise correlation is around 0.56 in all three cases. The result is economically reasonable, as large coins often respond together to volatility shocks, broader macro-financial events or common market sentiment.

These findings are important for the next steps of the analysis as they imply that the regression results should be interpreted using an estimation approach that takes in account these features, especially through the use of robust standard errors. For this reason, the main regression model employs standard errors corrected using the approach proposed by Driscoll and Kraay (1998).

3.2.2 Main Baseline Volatility Model Results

Table 8 reports the estimation results of the baseline volatility models, while Figure 4 provides a graphical comparison of the estimated coefficients for the main specification and the robustness checks. All models are estimated using fixed effects with coin fixed effects and year-month fixed effects. Inference is based on Driscoll-Kraay standard errors due to the econometric issues identified in the diagnostic testing.

Table 8 Baseline volatility model estimates

Variable	M1A	M1B	M1C	M1D	M1E
ln_gkvol_l1	0.2402***	0.2315***	0.2252***	0.2329***	0.2358***
	(0.0170)	(0.0168)	(0.0165)	(0.0167)	(0.0168)
ln_gkvol_ma7_l1	0.3343***	0.3372***	0.3427***	0.3579***	0.3276***
	(0.0253)	(0.0251)	(0.0248)	(0.0250)	(0.0248)
ln_vol_l1	0.1323***	0.1178***	0.1183***	0.1150***	0.1212***
	(0.0127)	(0.0126)	(0.0126)	(0.0126)	(0.0125)
ln_illiq_l1	0.0477***	0.0485***	0.0484***	0.0497***	0.0461***
	(0.0075)	(0.0074)	(0.0075)	(0.0078)	(0.0075)
mom_7_l1	0.0035***	0.0018	0.0023**	0.0021*	0.0025**
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0011)
beta_7_l1	0.0413***	0.0418***	0.0412***	0.0345**	0.0359**
	(0.0142)	(0.0142)	(0.0141)	(0.0146)	(0.0141)
ln_tx_per_address_l1		0.0224**	0.0224**	0.0226**	0.0252***
		(0.0093)	(0.0093)	(0.0093)	(0.0093)
gt_coin_l1		0.0078***	0.0078***	0.0087***	0.0081***
		(0.0012)	(0.0012)	(0.0012)	(0.0013)
fgi_l1		0.0046***	0.0042**	0.0044**	0.0045***
		(0.0017)	(0.0017)	(0.0018)	(0.0017)
vix_chg_l1			0.0059*	0.0064*	0.0054
			(0.0035)	(0.0036)	(0.0035)
dxy_ret_l1			0.0260	0.0344	0.0343
			(0.0444)	(0.0448)	(0.0443)
spx_ret_l1			-0.0101	-0.0062	-0.0105
			(0.0253)	(0.0261)	(0.0250)
Observations	19728	19728	19728	19728	17536
R-squared	0.4398	0.4425	0.4441	0.4275	0.4503
Coin FE	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes
SE type	Driscoll-Kraay	Driscoll-Kraay	Driscoll-Kraay	Driscoll-Kraay	Driscoll-Kraay

Source: Own calculations using Python.

The results show that cryptocurrency volatility is primarily associated with its own persistence and with internal market conditions. Focusing on the full baseline specification, Model M1C, both the one-day lag of volatility and the lagged 7-day volatility average are positive and highly statistically significant. Since the dependent variable and these regressors are logarithmically transformed, their coefficients can be interpreted approximately as elasticities. Holding the remaining regressors constant, a 10% increase in one-day lagged volatility is associated with an approximately 2.2% increase in current volatility. A comparable 10% increase in the lagged 7-day volatility average is associated with an approximately 3.3% increase in current volatility. The estimated coefficients are also large compared to the remaining regressors. This suggests that volatility in cryptocurrency markets is strongly persistent, meaning that periods of elevated volatility tend to be followed by further volatile periods rather than by an immediate return to calmer conditions. This result is in line with the literature. Wang et al. (2023) identify lagged volatility as key factors of volatility forecasts, while Katsiampa (2019) reports that the conditional variance of major cryptocurrencies is highly influenced by past shocks and past conditional volatility, which points to strong volatility persistence.

Trading conditions are also economically meaningful. A 10% increase in lagged trading volume is associated with an approximately 1.1% increase in current volatility, while a 10% increase in the illiquidity measure is associated with an approximately 0.5% increase. Thus, stronger trading activity is associated with higher volatility, but lower market liquidity additionally amplifies price movements because a given order flow has a greater price impact. This indicates that volatility rises during periods of stronger market pressure and less stable trading conditions. According to Wang et al. (2023) previous trading information plays a role when forecasting cryptocurrency volatility.

Among the remaining cryptocurrency-specific variables, the coefficient on beta (*beta_7_l1)* is positive and statistically significant in all specifications, which suggests that coins with higher systematic market exposure also tend to exhibit higher volatility. A 0.1 increase in the rolling market beta is associated with an approximately 0.4% increase in current volatility. Momentum (*mom_7_l1*) is positive as well, but its effect is weaker and not fully stable across all models. This indicates that short-term price continuation may matter for volatility, although its role appears smaller than the role of the volatility persistence, trading activity, and liquidity conditions.

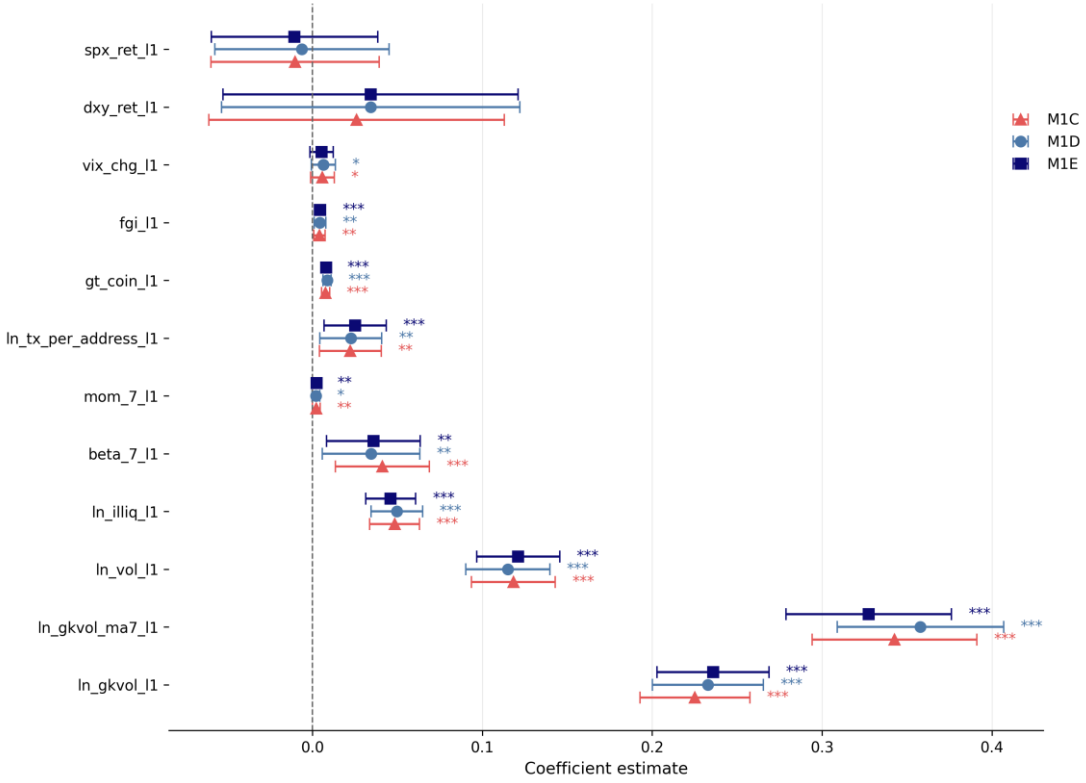
After adding sentiment variables, the core market coefficients remain stable, which supports the robustness of the baseline specification. The transaction-based variable *ln_tx_per_address_l1* is positive and significant in all models where it is included, suggesting that more intensive network activity is associated with higher future volatility. A 10% increase in this measure is associated with an approximately 0.2% increase in volatility. The same applies to the other added variables. Both Google Trends (*gt_coin_l1*) and the Fear and Greed Index (*fgi_l1*) enter with positive and statistically significant coefficients, indicating that higher investor attention and stronger market sentiment are associated with higher volatility. Google Trends is measured on a 0–100 scale. Therefore, a 10-point increase in coin-specific search interest is associated with an approximately 8.1% increase in current volatility. A 10-point increase in the Fear and Greed Index, corresponding to a movement towards a more greedy market sentiment, is associated with an approximately 4.3% increase in volatility. This result is consistent with Long et al. (2025), who show that market sentiment consistently affects both short- and long-term cryptocurrency volatility and may increase market volatility through stronger trading activity.

The macro-financial variables provide a more mixed picture. Changes in the VIX (*vix_chg_l1*) are positive and weakly significant in Models M1C and M1D, which suggests that higher global financial uncertainty may be associated with higher cryptocurrency volatility. Economically, a 10% increase in the VIX is associated with around a 0.1% increase in cryptocurrency volatility. However, this effect is no longer statistically significant in Model M1E after Bitcoin is excluded from the sample. By contrast, S&P 500 returns (*spx_ret_l1*) and U.S. Dollar Index returns (*dxy_ret_l1*) do not appear statistically significant in any of the main specifications. This suggests that, in the present dataset, volatility is explained more by internal crypto-market dynamics and investor behaviour than by the included macro-financial controls.

The robustness checks confirm that the main results are not sensitive to the specific model design. In model M1D, the signs, magnitudes, and significance levels of the coefficients remain similar to those in model M1C. This indicates that the main conclusions do not depend on one specific range-based volatility estimator. In model M1E, the coefficient pattern remains mostly unchanged as well. Lagged volatility, its moving average, trading volume, illiquidity, beta, transaction activity, Google Trends, and the Fear and Greed Index

all remain positive, while the macro-financial variables stay weak or insignificant. This suggests that the estimated relationships are not driven only by Bitcoin, but are also present across the broader sample of large cryptocurrencies.

Figure 4 Comparison of coefficient estimates across models M1C, M1D and M1E



Source: Own calculations using Python.

Figure 4 illustrates this result. The coefficient estimates for Models M1C, M1D, and M1E are visually very close for most explanatory variables, and the confidence intervals overlap substantially. The largest and most stable effects are observed for lagged volatility, the 7-day moving average of volatility, trading volume, and illiquidity. By contrast, the macro-financial variables are clustered around zero, what visually confirms their weaker explanatory role in the model.

Overall, the baseline volatility models suggest that the volatility of major cryptocurrencies is shaped primarily by internal market dynamics, especially its own persistence, trading activity, liquidity conditions, and investor behaviour. The explanatory power of the models remains relatively stable across specifications, with the R-squared ranging from 0.4398 to 0.4503, which indicates a moderate but consistent ability of the selected variables to explain changes in volatility. However, the impact of the explanatory variables is unlikely

to be linear. For this reason, pooled quantile regression is estimated to examine how the magnitude and statistical significance of the explanatory variables change across different volatility regimes.

3.2.2.1 Wald Tests of Joint Significance for Blocks of Explanatory Variables

In addition to the interpretation of individual coefficients, Wald tests of joint significance were conducted for the main blocks of explanatory variables. The purpose of these tests is to examine whether a given group of regressors is jointly relevant for the model. explanatory variables may not appear statistically significant on their own, but they may contribute to the explanatory power when they are considered together within one block.

The explanatory variables were grouped into three blocks. The first block contains the crypto-specific variables, the second block includes the sentiment variables, and the third block covers the macro-financial variables. For each block, the null hypothesis assumes that all coefficients in the group are jointly equal to zero. Meaning, the block has no explanatory power in the model. The alternative hypothesis assumes that at least one of the coefficients in the block differs from zero, so the block is relevant. The tests are evaluated at the 5% significance level.

Table 9 Wald tests of joint significance for blocks of explanatory variables

Model	Block	Wald statistic	df	p-value	Decision (5%)
M1A	Crypto-specific	2573.973	6	0.0000	Reject H0
	Sentiment	-	-	-	-
	Macro-financial	-	-	-	-
M1B	Crypto-specific	2255.641	6	0.0000	Reject H0
	Sentiment	56.010	3	0.0000	Reject H0
	Macro-financial	-	-	-	-
M1C	Crypto-specific	2235.961	6	0.0000	Reject H0
	Sentiment	54.621	3	0.0000	Reject H0
	Macro-financial	8.203	3	0.0420	Reject H0
M1D	Crypto-specific	2134.011	6	0.0000	Reject H0
	Sentiment	62.024	3	0.0000	Reject H0
	Macro-financial	8.346	3	0.0394	Reject H0
M1E	Crypto-specific	2158.823	6	0.0000	Reject H0
	Sentiment	54.838	3	0.0000	Reject H0
	Macro-financial	7.699	3	0.0527	Do not reject H0

Source: Own calculations using Python.

The results in the Table 9 show a clear pattern for the crypto-specific variables. In all models, the null hypothesis is strongly rejected, with very large Wald statistics and p-

values effectively equal to zero. This confirms that the crypto-specific block is jointly significant throughout all specifications. This result is in line with the baseline model estimates.

Same conclusion holds for the sentiment block. In all models where sentiment variables are included, the null hypothesis is again rejected at the 5% level. This means that the sentiment-related variables are jointly significant and add explanatory value to the model.

The macro-financial block provides a more complex result. In models M1C and M1D, the null hypothesis is rejected at the 5% significance level, which suggests that the macro-financial variables are jointly significant in these models. At first sight, this may seem somewhat stronger than what is visible from the individual coefficient estimates, where only the VIX variable appears weakly significant, while the remaining macro-financial controls are not individually significant. However, this is not contradictory. The Wald test does not assess the variables one by one, but evaluates whether they are jointly relevant as a group. This means that the macro-financial variables may carry explanatory power when considered together, even though their separate effects appear weaker. Therefore, macro-financial block may still improve the model.

However, in model M2E the null hypothesis for the macro-financial block is not rejected at the 5% significance level, with a p-value of 0.0527. Although this result is close to the threshold, the macro-financial variables cannot be considered jointly significant once Bitcoin is excluded from the sample. This may indicate that part of the explanatory power of the macro-financial block in the previous specifications was linked to Bitcoin itself. Such an interpretation is economically reasonable, since Bitcoin remains the dominant cryptocurrency and is often viewed as the main channel through which broader market conditions are reflected in the crypto market (Ciaian, 2018).

3.3 Supplementary Rolling-window Analysis in Time

Figure 5 complements the main results by showing how the estimated effects evolved over time in a rolling fixed-effects specification. The purpose of this figure is to illustrate whether the relationships identified in the main models remained stable throughout the sample or changed during major market episodes.

The figure suggests that the strongest and most persistent effects over time are related to the internal volatility process. Across the sample, volatility persistence remains the dominant mechanism, which confirms that cryptocurrency volatility is not driven by isolated shocks only, but tends to carry over across market phases. At the same time, the relative importance of the explanatory variables changes across major periods of market stress, which indicates that the transmission of volatility is time-dependent.

The first major shift is visible around the COVID-related market crash in March 2020. In this phase, the strongest movements are concentrated in variables linked to broad market stress, liquidity conditions, and external financial pressure. The model suggests that the macro-variables are in fact impactful in distressed eras. The initial pandemic shock affected cryptocurrency volatility not only through internal market dynamics, but also through a sudden tightening of trading conditions and a strong spillover from global uncertainty.

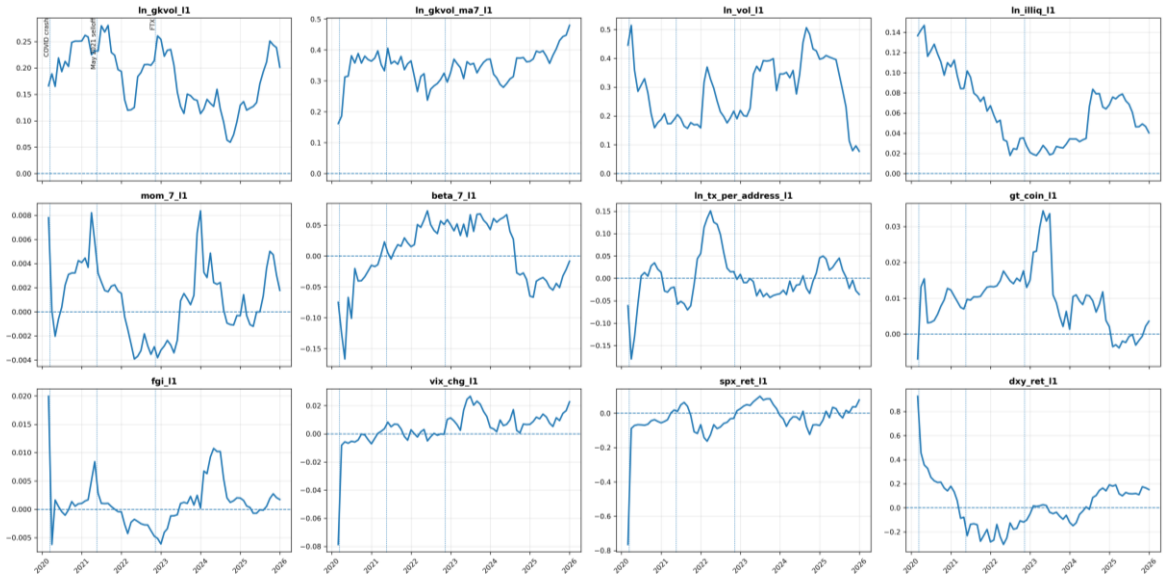
A different pattern emerges around the broad cryptocurrency sell-off in May 2021. In this period, the figure points more clearly to the importance of market-intrinsic mechanisms, especially volatility persistence, trading activity, and investor attention. Compared with the COVID shock, the May 2021 episode appears less driven by external financial conditions and more by developments specific to the cryptocurrency market itself. This is consistent with the idea that once the market moved out of the initial global crisis phase, volatility was increasingly shaped by speculative dynamics, higher trading intensity, and stronger investor focus on individual cryptoassets.

The next important shift appears around the FTX collapse in late 2022. Here, the figure again suggests a strengthening of internal market factors, but in a different form than in 2021. During the FTX episode, the most relevant role appears to be played by volatility persistence and liquidity-related conditions, while several secondary variables become less stable. This indicates that the shock was transmitted mainly through fragility inside the crypto market itself. Rather than reflecting a broad macro-financial event, this period seems to represent a market-specific breakdown in confidence, where volatility was amplified above all by its own recent history and by worsening trading conditions.

In the later part of the sample, the figure suggests a gradual normalization of several secondary effects. Compared with the earlier crisis episodes, the relationships become less

dominated by abrupt external shocks and more concentrated around the core internal drivers already identified in the baseline and quantile regressions. This supports the broader interpretation of the thesis that cryptocurrency volatility is primarily shaped by persistent market-intrinsic mechanisms, while the influence of sentiment and macro-financial variables becomes stronger mainly in selected periods of market stress.

Figure 5 Time variation in rolling FE coefficient estimates



Source: Own calculations using Python.

3.4 Pooled Quantile Regression

Pooled quantile regression was employed to complement the baseline panel estimates, in order to examine whether the effects of the explanatory variables differ across volatility regimes. Since we expect the explanatory variables to have non-linear effects, quantile regression makes it possible to study how these relationships change at different points of the conditional distribution of the dependent variable (Koenker and Hallock, 2001).

To preserve consistency with the baseline analysis, the pooled quantile regressions were estimated on the same transformed daily panel dataset and with the same variable definitions as in the baseline models. The main quantile specification therefore corresponds to the baseline volatility model based on log-transformed Garman-Klass volatility (*ln_gkvol*), and the robustness checks were constructed in the same way as before, so that the comparison across modelling approaches remains the same. This also means that the

quantile analysis relies on the same lag structure and the same explanatory variables as the baseline fixed-effects models.

The quantile regression was estimated for five selected quantiles, namely the lower tail, lower-middle part, median, upper-middle part, and upper tail of the volatility distribution. That is 0.10, 0.25, 0.50, 0.75, and 0.90. This choice makes it possible to compare the behaviour of the explanatory variables across relatively calm periods, intermediate states, and more volatile regimes. The median quantile serves as a natural midpoint, while the 10th and 90th quantiles provide information about the lower and upper parts of the volatility distribution. The 0.25 and 0.75 were chosen to provide a more detailed view of how the effects of explanatory variables evolve.

For a clearer interpretation of the pooled quantile regression results, the estimated quantiles were linked to specific volatility intervals. Since the dependent variable is the logarithmically transformed Garman–Klass volatility *(ln_gkvol*), the quantile bounds were converted back into percentage volatility values.

Table 10 Quantiles and corresponding volatility percentages

Quantile	Volatility (%)
0.10	1.55%
0.25	2.32%
0.50	3.50%
0.75	5.27%
0.90	7.90%

Own calculations.

For each quantile, the model was first estimated on the full pooled sample. In a second step, bootstrap standard errors were computed to get more reliable inference, since in quantile regression it is less straightforward. Bootstrap methods are widely used to estimate standard errors and confidence intervals through repeated resampling (stata.com, 2026).

In the empirical analysis, bootstrap standard errors were calculated by resampling dates, not individual observations. All unique dates in the sample were identified and the data were divided into date blocks. In each bootstrap repetition, the same number of dates as in the original sample was randomly drawn with replacement, and all cryptocurrency observations from those selected dates were used to create a new sample. This approach keeps together the observations from the same day, which is important because

cryptocurrencies may react jointly to common daily shocks. If single observations were resampled separately, this daily structure would be lost. This approach is better aligned with our dataset.

For each quantile, 200 bootstrap repetitions were used. This number was chosen as a compromise between computation time and reliable inference, since the quantile model had to be re-estimated many times. The bootstrap standard errors were computed as the standard deviation of the estimated coefficients across successful repetitions. The 95% bootstrap confidence intervals were then obtained from the 2.5th and 97.5th percentiles of the bootstrap estimates (stata.com, 2026).

Table 11 Pooled Quantile Regression Results for Cryptocurrency Volatility

Variable	0.1	0.25	0.5	0.75	0.9
const	-1.7855***	-1.6169***	-1.2813***	-0.7122***	-0.1041
	(0.1663)	(0.1199)	(0.1123)	(0.1534)	(0.2016)
ln_gkvol_l1	0.2387***	0.2414***	0.2418***	0.2790***	0.3274***
	(0.0190)	(0.0165)	(0.0190)	(0.0196)	(0.0293)
ln_gkvol_ma7_l1	0.6374***	0.5956***	0.5660***	0.5030***	0.4306***
	(0.0227)	(0.0218)	(0.0225)	(0.0256)	(0.0404)
ln_vol_l1	0.0475***	0.0419***	0.0417***	0.0349***	0.0285**
	(0.0134)	(0.0094)	(0.0108)	(0.0118)	(0.0120)
ln_illiq_l1	0.0590***	0.0515***	0.0514***	0.0525***	0.0546***
	(0.0118)	(0.0084)	(0.0094)	(0.0105)	(0.0097)
mom_7_l1	0.0043***	0.0052***	0.0047***	0.0023	0.0002
	(0.0012)	(0.0010)	(0.0011)	(0.0015)	(0.0014)
beta_7_l1	-0.0080	0.0014	0.0166	0.0273	0.0306
	(0.0185)	(0.0146)	(0.0182)	(0.0205)	(0.0255)
ln_tx_per_address_l1	-0.0163***	-0.0146***	-0.0087	0.0012	0.0132
	(0.0062)	(0.0049)	(0.0054)	(0.0066)	(0.0085)
gt_coin_l1	0.0033**	0.0030***	0.0035***	0.0053***	0.0057***
	(0.0013)	(0.0009)	(0.0010)	(0.0014)	(0.0018)
fgi_l1	0.0004	0.0008	0.0011	0.0012	0.0017
	(0.0008)	(0.0007)	(0.0008)	(0.0010)	(0.0013)
vix_chg_l1	0.0097**	0.0102***	0.0091**	0.0028	-0.0007
	(0.0046)	(0.0037)	(0.0039)	(0.0043)	(0.0048)
spx_ret_l1	0.0345	0.0328*	0.0200	-0.0278	-0.0676*
	(0.0210)	(0.0183)	(0.0268)	(0.0320)	(0.0380)
dxy_ret_l1	-0.0283	-0.0025	0.0057	0.0659	0.0980
	(0.0414)	(0.0360)	(0.0488)	(0.0644)	(0.0677)

*Notes: The table reports quantile regression coefficients. Bootstrap standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.*
Source: Own calculations using Python.

Table 11 reports the results of the pooled quantile regression for the main volatility specification. The model was estimated on the same transformed dataset as the baseline model.

Overall, the pooled quantile regression indicates that the estimated relationships are not fully uniform across the conditional volatility distribution. The 0.10 and 0.90 quantiles correspond approximately to daily volatility levels of 1.55% and 7.90%, respectively. The results should therefore be interpreted as conditional associations in relatively low- and high-volatility states rather than as strictly separated market regimes.

The clearest heterogeneity concerns volatility persistence. At the 0.10 quantile, a 10% increase in one-day lagged volatility is associated with an approximately 2.3% increase in current volatility, while at the 0.90 quantile the corresponding association rises to approximately 3.2%. The difference between the lower and upper quantiles is statistically significant. By contrast, the effect of the 7-day volatility average declines from approximately 6.3% at the 0.10 quantile to approximately 4.2% at the 0.90 quantile for a comparable 10% increase. This difference is also statistically significant. These results suggest that the broader recent volatility environment is relatively more important in calmer market conditions, whereas the most immediate volatility shock becomes more important when volatility is already elevated.

This interpretation is consistent with Corsi (2009), who models financial-market volatility as a combination of components acting at different time horizons. In his HAR-RV model, daily volatility is linked to the daily, weekly and monthly volatility components. He observes so called volatility cascade view, where elevated volatility tends to carry over rather than disappear immediately.

Trading volume and illiquidity remain positive throughout the estimated distribution. The point estimate for trading volume declines from 0.0475 at the 0.10 quantile to 0.0285 at the 0.90 quantile. Economically, a 10% increase in trading volume is associated with approximately 0.5% higher volatility at the lower quantile and approximately 0.3% higher volatility at the upper quantile. However, the pairwise coefficient tests do not confirm that this difference is statistically significant. Illiquidity has a stable effect across the

distribution. A 10% increase in illiquidity is associated with approximately 0.6% higher volatility at the lower quantile and approximately 0.5% higher volatility at the upper quantile. The positive effect of illiquidity indicates that weaker liquidity conditions and a higher price impact of trades are systematically connected with higher volatility. This interpretation is also in line with market microstructure literature, where trading volume and liquidity are commonly viewed as important indicators of market stability and trading frictions (Będowska-Sójka, 2025).

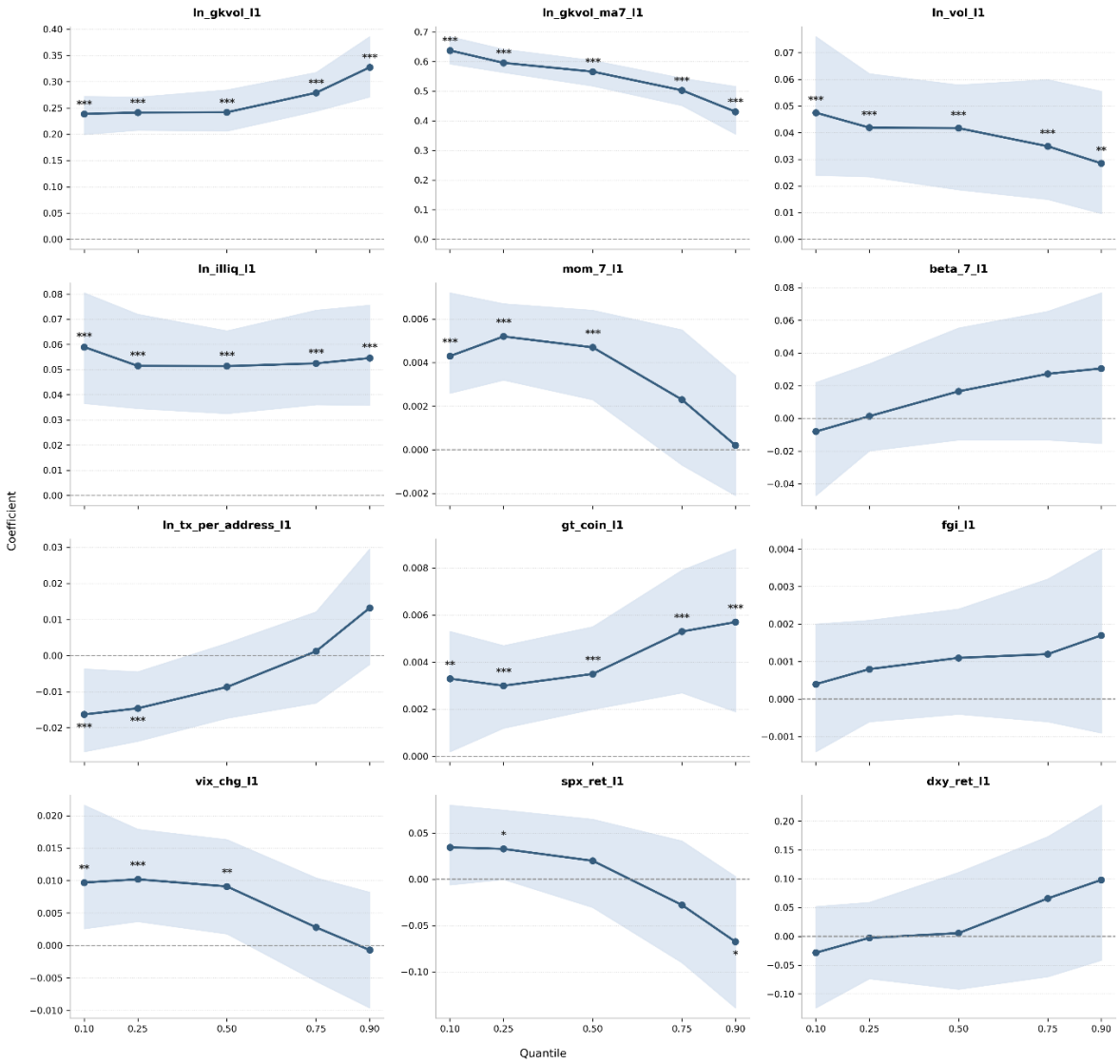
Google Trends is positive and statistically significant at all quantiles. A 10-point increase in coin-specific search interest is associated with approximately 3.4% higher volatility at the 0.10 quantile and approximately 5.9% higher volatility at the 0.90 quantile. The evidence strongly supports a positive relationship between investor attention and volatility across the full distribution. This result is consistent with the broader literature, which emphasizes that investor attention and sentiment play an important role in cryptocurrency market dynamics. Long et al. (2025) similarly conclude that market sentiment consistently affects cryptocurrency volatility.

By contrast, the Fear and Greed Index (*fgi_l1*) is not statistically significant at any quantile. This suggests that, once the other explanatory variables are controlled for, this broader sentiment indicator does not provide additional explanatory power for volatility in the pooled quantile model. One possible reason is that the effect of market sentiment is already captured more directly by Google Trends, which is coin-related and therefore closer to the behaviour of investors in specific cryptocurrency markets. In this sense, the two sentiment measures may not carry the same type of information.

The macro-financial variables provide a mixed and clearly regime-dependent picture. Changes in the VIX (*vix_chg_l1*) are positive and significant at the 0.10, 0.25, and 0.50 quantiles, but become insignificant at the 0.75 and 0.90 quantiles. This may suggest that global financial uncertainty matters more when cryptocurrency volatility is relatively low or moderate, whereas in already highly volatile states, internal crypto-market dynamics dominate. The coefficient on S&P 500 returns (*spx_ret_l1*) is only weakly significant and changes sign across the distribution, while the U.S. Dollar Index (*dxy_ret_l1*) remains insignificant throughout. Taken together, these results indicate that macro-financial variables do not appear to be stable drivers of cryptocurrency volatility in the same way as

internal market variables. This partly differs from studies that find a stronger role of macroeconomic factors for Bitcoin volatility, but it is consistent with the view that their influence may depend on the sample, the volatility proxy, and the market regime considered (Dempere, 2019).

Figure 6 Quantile Regression Coefficient Paths with 95% Confidence Bands



Source: Own calculations using Python.

Figure 6 adds an important visual dimension to the quantile regression results. It shows not only the direction of the estimated effects, but also their stability across the distribution through the width of the confidence bands. The figure makes it clear that some variables follow a smooth pattern across quantiles, while others become flatter or more uncertain in the upper part of the distribution. This is particularly useful for distinguishing between variables whose effects change gradually across volatility regimes and those whose role

becomes less precisely estimated at higher quantiles. In this sense, the figure complements the regression table by highlighting where the coefficients are both economically meaningful and statistically more stable.

Concerning the width of the confidence bands in Figure 5, they provide an additional information about the precision of the estimated effects. In general, narrower bands indicate that the coefficient estimates are more precisely estimated across bootstrap replications, while wider bands signal uncertainty. In the present results, the core volatility variables and the main market-related regressors tend to have relatively narrower bands, which supports the view that their effects are more robust across the distribution. By contrast, wider bands are more visible for several macro-financial variables and for some coefficients in the upper quantiles, suggesting that their effects are estimated with lower precision.

A particularly visible feature of the figure is that the confidence bands tend to widen towards the upper part of the volatility distribution for several variables. This may suggest that, in more volatile market conditions, the relationships become less stable and the estimates are more sensitive to the specific observations in the upper tail. In practical terms, this means that although some coefficients may still show a certain direction, the degree of certainty surrounding their exact size becomes lower. This pattern is especially noticeable for variables such as *spx_ret_l1* and *dxy_ret_l1,* where the confidence bands become considerably wider in the highest quantiles, but it can also be observed for *beta_7_l1* and *ln_tx_per_address_l1*. By contrast, variables such as *ln_gkvol_l1, ln_gkvol_ma7_l1, ln_vol_l1,* and *gt_coin_l1* retain comparatively more stable patterns, which further supports their stronger and more consistent role in explaining volatility across different market states.

3.4.1 Pairwise Coefficient Differences

Table 12 shows that the statistically significant differences across quantiles are not spread evenly across all explanatory variables, but are concentrated mainly in the variables that describe the internal dynamics of volatility itself. The clearest shifts can be seen when the upper quantile is compared with the lower and median parts of the distribution. This confirms that the structure of the model changes especially when the market moves into the

highest volatility regime, rather than gradually across the whole distribution. In other words, the lower and middle parts of the volatility distribution appear to be relatively similar, while the upper tail behaves more differently.

Overall, the strongest evidence of coefficient instability is related to the volatility persistence variables. This suggests that the mechanism through which past volatility affects current volatility is not constant across market states. The upper part of the distribution is therefore not only more volatile in level terms, but also different in how strongly it reacts to its own recent history. A smaller but still visible pattern can be observed for some market-based and macro-financial variables, where the significant differences again appear mainly in comparisons that include the highest quantile. This indicates that their role becomes more distinct only once the market enters more extreme conditions.

By contrast, for several other regressors the estimated coefficients do vary numerically across quantiles, but these differences are not statistically significant. This means that, although their effect may appear slightly stronger or weaker across the distribution, the changes are not large enough to conclude that their role truly differs between volatility regimes. Taken together, the table suggests that the most meaningful regime shifts are concentrated in the core volatility process itself, while a large part of the remaining explanatory variables retains a more stable effect across the distribution.

Table 12 Pairwise Coefficient Differences Across Quantiles

Variable	0.10 vs 0.50	0.10 vs 0.90	0.50 vs 0.90
ln_gkvol_l1	-0.0031	-0.0888***	-0.0856***
	(0.0194)	(0.0315)	(0.0251)
ln_gkvol_ma7_l1	0.0715***	0.2069***	0.1354***
	(0.0221)	(0.0448)	(0.0373)
ln_vol_l1	0.0058	0.0190	0.0132
	(0.0131)	(0.0177)	(0.0126)
ln_illiq_l1	0.0076	0.0045	-0.0032
	(0.0109)	(0.0154)	(0.0107)
beta_7_l1	-0.0246	-0.0386	-0.0140
	(0.0215)	(0.0300)	(0.0236)
mom_7_l1	-0.0004	0.0041**	0.0045***
	(0.0011)	(0.0016)	(0.0012)
ln_tx_per_address_l1	-0.0075	-0.0295***	-0.0220**
	(0.0064)	(0.0095)	(0.0084)

gt_coin_l1	-0.0002	-0.0024	-0.0022
	(0.0012)	(0.0019)	(0.0015)
fgi_l1	-0.0007	-0.0014	-0.0006
	(0.0007)	(0.0012)	(0.0010)
vix_chg_l1	0.0006	0.0104*	0.0097*
	(0.0037)	(0.0059)	(0.0046)
spx_ret_l1	0.0144	0.1021***	0.0876**
	(0.0237)	(0.0391)	(0.0316)
dxy_ret_l1	-0.0341	-0.1263*	-0.0923
	(0.0437)	(0.0743)	(0.0600)

*Notes: The table reports bootstrap-based pairwise differences in pooled quantile regression coefficients across selected quantiles of the volatility distribution. Bootstrap standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.*
Source: Own calculations using Python.

3.4.2 Robustness Check

The pooled quantile regression results were supplemented by two robustness checks in order to assess whether the main distributional patterns depend on the selected volatility proxy or on the inclusion of Bitcoin in the sample. The first check replaces Garman–Klass volatility with Rogers–Satchell volatility, while the second re-estimates the Garman–Klass specification after excluding Bitcoin. Overall, the robustness results do not change the main interpretation of the quantile analysis. Instead, they confirm that the most important changes across volatility regimes are related to volatility persistence, liquidity conditions, and investor attention.

First, the Rogers–Satchell robustness check provides an important test of whether the main results depend on the way daily volatility is measured. The Garman–Klass estimator used in the main analysis is derived under the assumption of zero drift, meaning that it assumes no strong systematic upward or downward movement of prices within the trading day. By contrast, the Rogers–Satchell estimator is drift-independent. It is therefore more appropriate when a volatile day is also characterised by a clear directional price movement, such as a strong intraday increase or decline.

The results remain broadly similar under the Rogers–Satchell measure. In particular, the immediate lag of volatility becomes stronger towards the upper quantiles, while the effect of the 7-day volatility average declines. This suggests that the main result is not caused only by directional intraday movements that may affect the Garman–Klass estimator.

Instead, the shift from broader recent volatility conditions towards more immediate volatility shocks in the upper tail remains visible even when the volatility measure controls for drift.

The liquidity-related results are especially stable across the two measures. Illiquidity remains positive and statistically significant throughout the distribution, while trading volume is mainly relevant in the lower and middle quantiles. This suggests that the relationship between liquidity conditions and volatility does not depend on whether a volatile day involves a strong upward or downward price trend. Rather, lower liquidity appears to increase volatility because trades have a larger price impact and the market is less able to absorb order flow, regardless of the direction of the price movement.

Some smaller differences are visible for transaction activity, broader sentiment, and selected macro-financial variables. For example, transaction activity becomes positive in the highest Rogers–Satchell quantile, whereas its effect is weaker in the main Garman–Klass specification. This may indicate that network activity is more closely connected with extreme directional price movements than with volatility measured only as a broad intraday range. However, these differences do not change the main conclusion that volatility persistence, liquidity conditions, and investor attention remain the most robust determinants across both volatility measures.

The second robustness check excluding Bitcoin provides further support for the main results. The two volatility persistence variables preserve the same pattern as in the full sample: the effect of the immediate lag increases towards the upper quantile, while the influence of the 7-day moving average gradually declines. Illiquidity and Google Trends also remain positive and statistically significant across almost the entire distribution. Trading volume continues to be positively related to volatility, and its effect remains statistically significant even in the upper quantile. This suggests that the importance of market activity and liquidity is not driven only by Bitcoin, but is also present across the remaining major cryptocurrencies.

The exclusion of Bitcoin affects mainly the strength of some individual coefficients rather than the overall structure of the results. In particular, transaction activity remains negative for a larger part of the distribution than in the full-sample model, while the effects of momentum and the macro-financial variables remain limited mainly to selected quantiles.

Therefore, Bitcoin appears to influence some of the more specific market relationships, but it does not determine the central mechanism identified in the analysis.

Overall, the robustness checks support the reliability of the main pooled quantile regression findings. The exact significance of several secondary variables changes across specifications, which means that their effect should not be overstated. However, the key result remains unchanged: cryptocurrency volatility is governed by different mechanisms across volatility regimes. Lower and middle volatility states are more closely related to the broader recent volatility environment and trading conditions, whereas the upper tail is shaped more strongly by immediate volatility shocks, liquidity fragility, and investor attention.

CONCLUSION

This thesis examined the determinants of cryptocurrency volatility using a daily panel dataset of nine major cryptocurrencies over the period from January 2020 to December 2025. The analysis focused on crypto-specific, sentiment-related, macroeconomic, and financial variables. The empirical strategy combined fixed-effects panel regression, a supplementary rolling-window analysis, and pooled quantile regression in order to examine the average determinants of volatility, their development over time, and their behaviour across different volatility regimes.

The first partial objective was to identify the main determinants of daily cryptocurrency volatility in the baseline panel framework. The results show that volatility is explained mainly by internal cryptocurrency market dynamics. The strongest and most stable effects were found for lagged volatility, the 7-day moving average of volatility, trading volume, and illiquidity. This indicates that cryptocurrency volatility is persistent and closely connected to the trading environment of the market.

Sentiment variables also contributed to the explanation of volatility, especially Google Trends. Its positive and statistically significant effect suggests that higher investor attention toward a specific cryptocurrency is connected with higher volatility. By contrast, the macro-financial variables showed a weaker and less stable effect. Changes in the VIX were relevant in some specifications, while S&P 500 returns and U.S. Dollar Index returns were not stable predictors of cryptocurrency volatility. Overall, volatility is explained more consistently by crypto-specific variables and investor attention than by broader financial conditions.

The supplementary rolling-window analysis adds a time perspective to these relationships. It shows that the importance of the explanatory variables changes across major market episodes. During broader stress events, such as the COVID-related shock, the role of external uncertainty and trading conditions becomes more visible, whereas during cryptocurrency-specific disruptions, such as the 2021 sell-off and the FTX collapse, the dominant role is played mainly by internal volatility persistence, liquidity conditions, and investor attention. At the same time, the rolling estimates confirm that the core importance of volatility-related variables remains present throughout the sample.

The second partial objective was to examine whether the effects of the selected variables differ across volatility regimes. The pooled quantile regression confirms that the determinants of volatility are not constant across the distribution. In lower and middle volatility regimes, volatility is shaped mainly by the broader recent volatility environment, trading volume, illiquidity, Google Trends, and, to some extent, VIX changes. In the upper part of the distribution, the structure of the results changes more clearly. The immediate lag of volatility becomes more important, while the effect of the 7-day moving average becomes weaker. At the same time, Google Trends becomes more influential in the upper tail, and illiquidity remains positive and stable. This suggests that high-volatility periods are driven more strongly by recent shocks, liquidity fragility, and investor attention.

The pairwise coefficient comparisons support this interpretation. The largest and most statistically significant differences across quantiles are concentrated mainly in the volatility persistence variables, especially when the highest quantile is compared with the lower and median parts of the distribution. This confirms that the upper tail of cryptocurrency volatility behaves differently from normal market conditions.

The robustness checks confirm the reliability of the main findings. This suggests that the results are not dependent on a single volatility estimator and are not driven only by the dominant position of Bitcoin.

The findings of this thesis contribute to the existing literature by analysing cryptocurrency volatility in a broader panel setting and by combining average-effect estimation, time variation in the estimated relationships, and quantile-based analysis. The results show that the same variable may have a different role depending on whether the market is in a relatively calm state or in a period of elevated uncertainty, and also depending on the specific phase of market development. This distinction represents the main added value of the thesis. While baseline panel models identify the general determinants of volatility, the rolling analysis shows how their relative importance evolves over time, and the quantile results reveal that the drivers of volatility depend on where the market is located in the volatility distribution.

In this way, the thesis provides a more detailed interpretation of cryptocurrency risk. It shows that risk management based only on average effects may overlook the factors that become relevant precisely when volatility is highest and when investors are most exposed

to sudden losses. For investors, this implies that risk assessment should consider not only changes in trading volume or market sentiment, but also the current volatility regime, liquidity conditions, and the broader market phase. Overall, the findings contribute to a better understanding of cryptocurrency volatility as a regime-dependent and time-varying process shaped mainly by internal market mechanisms and investor attention rather than by stable macro-financial effects.

Limitations and Directions for Future Research

Several limitations should be considered when interpreting the results of this thesis. First, the empirical sample includes nine major cryptocurrencies observed between January 2020 and December 2025. These assets represent an important and relatively established part of the cryptocurrency market, but they do not cover its full diversity. Smaller cryptocurrencies, newly issued tokens, decentralised finance projects, stablecoins, or meme coins may react differently to changes in liquidity, market sentiment, and external financial conditions. Therefore, the findings should be interpreted mainly in relation to larger cryptocurrencies with relatively long trading histories and sufficient data availability.

A further limitation concerns the measurement of volatility. The main analysis uses daily Garman–Klass volatility, while Rogers–Satchell volatility is applied as an alternative measure in the robustness check. Both estimators use open, high, low, and close prices and therefore capture more information than a simple close-to-close measure. However, they are still based on daily observations. Cryptocurrency markets operate continuously, and important price changes may occur within a few minutes or hours, especially during periods of market stress, liquidations, exchange problems, or major announcements. Future research could therefore use intraday data and realised volatility measures in order to examine whether the identified relationships also hold at a higher frequency.

The selected explanatory variables should also be understood as proxies for wider market mechanisms. Google Trends and the Fear and Greed Index provide useful information about investor attention and sentiment, but they cannot capture all dimensions of market behaviour. For example, social media discussions, news sentiment, large-holder activity, exchange inflows and outflows, derivatives-market positioning, funding rates, or liquidation data may contain additional information about future volatility. Similarly, the macro-financial block includes the S&P 500, the U.S. Dollar Index, and the VIX, but other

variables, such as interest rates, inflation announcements, bond yields, monetary policy decisions, or regulatory news, could also influence cryptocurrency markets.

The use of traditional financial variables also creates a practical limitation because stock-market and foreign-exchange data are not available during weekends and public holidays, unlike cryptocurrency prices, which are traded continuously. In the present analysis, missing observations were filled using the most recent available value in order to maintain a consistent daily dataset. Although this is a reasonable solution, it may not fully reflect the exact timing through which information from traditional financial markets is transmitted to cryptocurrency markets.

The pooled quantile regression also has certain limitations. Its main advantage is that it shows how the relationship between volatility and its determinants differs across lower, middle, and upper parts of the distribution. However, the pooled model focuses on common patterns across the selected cryptocurrencies and may not fully capture differences in the behaviour of individual coins. Although this issue is partly addressed through cryptocurrency fixed effects in the baseline models and through the robustness check excluding Bitcoin, future research could estimate coin-specific quantile models or compare groups of cryptocurrencies based on market size, liquidity, technological design, or consensus mechanism.

Overall, future research could extend the dataset over a longer period, include a wider set of cryptoassets, and focus more directly on the impact of specific regulatory, technological, or market-wide events.

Despite these limitations, the analysis provides a broader view of the factors associated with cryptocurrency volatility across cryptocurrencies. Future research could build on these findings by combining higher-frequency market data with more detailed sentiment, on-chain, and derivatives-market indicators.

RESUMÉ

Táto diplomová práca sa zaoberá analýzou vplyvu vybraných premenných na dynamiku trhu s kryptomenami, pričom sa zameriava najmä na volatilitu vybraných kryptomien. Kryptomeny predstavujú relatívne nové finančné aktíva, ktoré sa od tradičných mien a finančných nástrojov odlišujú svojou decentralizovanou povahou, fungovaním na princípe blockchainovej technológie a vysokou mierou cenovej volatility. Práve výrazné cenové výkyvy vytvárajú na jednej strane príležitosti na dosiahnutie nadpriemerných výnosov, no na druhej strane zvyšujú riziko investorov a komplikujú efektívne riadenie portfólia. Z tohto dôvodu je dôležité analyzovať faktory, ktoré môžu ovplyvňovať správanie kryptomenového trhu a najmä zmeny jeho volatility.

Vznik kryptomien súvisí s postupnou digitalizáciou finančného systému a snahou vytvoriť alternatívu k tradičnému centralizovanému menovému systému. Historicky boli peniaze postupne transformované od komoditných foriem cez bankové peniaze až po súčasné fiat meny. Ich fungovanie je založené najmä na dôvere verejnosti v štát a centrálne banky, ktoré zabezpečujú emisiu peňazí, regulujú peňažnú zásobu a prostredníctvom menovej politiky sledujú cenovú a finančnú stabilitu. Kryptomeny priniesli nový pohľad na fungovanie peňazí, pretože ich existencia nie je založená na centrálnej autorite, ale na decentralizovanej sieti používateľov a kryptografických pravidlách.

Prvou a najznámejšou kryptomenou sa stal Bitcoin, ktorý bol predstavený v roku 2008 ako decentralizovaný systém elektronických platieb medzi používateľmi. Jeho fungovanie je založené na technológii blockchain, ktorá predstavuje distribuovanú databázu záznamov o uskutočnených transakciách. Transakcie sú zaznamenávané v jednotlivých blokoch, ktoré sú navzájom prepojené pomocou kryptografických hashovacích funkcií. Vďaka tomu je spätná úprava historických údajov veľmi náročná a systém môže fungovať bez potreby tradičného sprostredkovateľa, akým je napríklad banka.

Postupným vývojom kryptomenového trhu vzniklo veľké množstvo alternatívnych kryptomien, ktoré sa líšia použitou technológiou, konsenzuálnym mechanizmom, účelom využitia alebo spôsobom vytvárania nových jednotiek. Niektoré kryptomeny fungujú najmä ako decentralizovaný prostriedok uchovávania hodnoty alebo platobný nástroj, iné sú spojené s inteligentnými kontraktmi, decentralizovanými aplikáciami alebo službami

decentralizovaných financií. Trh s kryptomenami sa preto postupne stal komplexným prostredím, v ktorom sa stretávajú technologické faktory, trhové mechanizmy, makroekonomické podmienky aj správanie investorov.

Jednou z najvýraznejších charakteristík kryptomenového trhu je jeho vysoká volatilita. Hodnoty kryptomien môžu v krátkom období výrazne rásť alebo klesať, čo je dôsledkom nižšej stability trhu, špekulatívneho správania investorov, rozdielnej miery likvidity, reakcií na správy, reguláciu a zmeny vo všeobecnej ekonomickej situácii. Volatilita je z pohľadu investorov dôležitá, pretože predstavuje mieru neistoty spojenú s budúcim cenovým vývojom. Vyššia volatilita zvyšuje potenciál výnosu, ale zároveň zvyšuje riziko možných strát.

Existujúca odborná literatúra poukazuje na to, že správanie kryptomenového trhu nemožno vysvetliť iba jedným faktorom. Vývoj cien, výnosov a volatility môže byť ovplyvnený kombináciou makroekonomických a finančných premenných, interných charakteristík jednotlivých kryptomien, technologických faktorov, regulácie, investorského sentimentu a mediálnej pozornosti. Výsledky jednotlivých štúdií však nie sú vždy jednotné. Niektoré výskumy potvrdzujú vplyv tradičných finančných premenných, ako sú vývoj akciového trhu, kurz amerického dolára alebo miera globálnej neistoty. Iné štúdie naopak naznačujú, že kryptomeny sú vo väčšej miere ovplyvňované vlastnými vnútornými mechanizmami a správaním investorov.

Makroekonomické a finančné faktory môžu ovplyvňovať kryptomeny najmä prostredníctvom zmien v celkovej ekonomickej neistote, rizikovom apetíte investorov a alokácii kapitálu medzi tradičné a alternatívne aktíva. V práci sú preto zohľadnené premenné reprezentujúce vývoj amerického akciového trhu, pohyby amerického dolára a zmeny indexu volatility VIX. Tieto premenné zachytávajú širšie finančné prostredie, v ktorom sa kryptomenový trh nachádza. Ich vplyv však nemusí byť stabilný, keďže kryptomeny často reagujú na vlastné trhové udalosti a špecifické faktory, ktoré sa v tradičných finančných trhoch nevyskytujú.

Dôležitú skupinu determinantov tvoria aj premenné, ktoré zachytávajú vnútorné charakteristiky kryptomenového trhu. Patrí sem najmä predchádzajúca volatilita, objem obchodovania, likvidita, cenový moment, citlivosť kryptomeny na vývoj celého kryptomenového trhu a aktivita používateľov v sieti. Tieto premenné sú významné, pretože

zachytávajú aktuálny stav jednotlivých kryptomien, intenzitu obchodovania a mieru, do akej môže aj menší obchod ovplyvniť ich cenu. V podmienkach nízkej likvidity môže aj relatívne malá zmena dopytu alebo ponuky vyvolať výraznejší pohyb ceny, čo sa následne prejavuje rastom volatility.

Ďalším významným faktorom je investorský sentiment a pozornosť investorov. Kryptomenový trh je vo veľkej miere ovplyvňovaný online komunitami, sociálnymi sieťami, diskusiami na internetových platformách a vyhľadávaním informácií. Keďže pri mnohých kryptomenách nie je možné aplikovať tradičné metódy oceňovania využívané pri akciách alebo dlhopisoch, správanie investorov a ich očakávania môžu mať výraznejší vplyv na cenový vývoj. V práci je sentiment zachytený prostredníctvom Crypto Fear and Greed Indexu, Google Trends indexu a ukazovateľa transakčnej aktivity v rámci jednotlivých kryptomenových sietí.

Hlavným cieľom diplomovej práce je preskúmať, ako vybrané kryptomenové, makroekonomické a finančné premenné a premenné zachytávajúce sentiment vplývajú na dynamiku trhu s kryptomenami v panelovom rámci. Analýza sa sústreďuje predovšetkým na volatilitu kryptomien. Čiastkovým cieľom práce je identifikovať determinanty dennej volatility kryptomien v základnom panelovom modeli a následne preskúmať, či sa vplyv jednotlivých premenných mení v období nízkej, strednej a vysokej volatility.

Empirická analýza je založená na dennom panelovom súbore údajov za obdobie od 1. januára 2020 do 31. decembra 2025. Vzorka obsahuje deväť vybraných kryptomien, konkrétne Bitcoin, Ethereum, Ripple, TRON, Dogecoin, Cardano, Bitcoin Cash, Chainlink a Zcash. Výber kryptomien bol založený najmä na ich trhovej kapitalizácii a dostupnosti dostatočne dlhého časového radu údajov. Stablecoiny neboli do vzorky zahrnuté, pretože ich cenová a volatilná dynamika je odlišná od štandardných kryptomien a mohla by skresliť výsledky analýzy.

Závislou premennou v práci je denná volatilita kryptomien. Na jej výpočet bol použitý Garmanov-Klassov odhad volatility, ktorý využíva denné údaje o otváracej, maximálnej, minimálnej a uzatváracej cene kryptomeny. Ako kontrolný a robustnostný prístup bol použitý aj Rogersov-Satchellov odhad volatility. Využitie dvoch alternatívnych ukazovateľov umožňuje overiť, či hlavné výsledky nie sú závislé iba od jednej konkrétnej metódy merania volatility.

Vysvetľujúce premenné boli rozdelené do troch základných skupín. Prvú skupinu tvoria kryptomenové premenné, medzi ktoré patrí oneskorená volatilita, sedemdňový priemer volatility, objem obchodovania, ukazovateľ nelikvidity, cenový moment, trhová beta a počet transakcií pripadajúcich na aktívnu adresu. Druhú skupinu predstavujú sentimentové premenné, konkrétne Fear and Greed Index a Google Trends index pre jednotlivé kryptomeny. Tretiu skupinu tvoria makroekonomické a finančné premenné, medzi ktoré patrí výnos indexu S&P 500, výnos amerického dolárového indexu a zmena indexu VIX. Všetky vysvetľujúce premenné boli do modelov zahrnuté s jednodňovým oneskorením, aby sa znížil problém simultánnosti a aby sa pri interpretácii výsledkov zachoval predikčný charakter modelu.

Pred samotným odhadom modelov bola vykonaná deskriptívna analýza dát, korelačná analýza, testovanie multikolinearity a testovanie stacionarity. Na overenie stacionarity panelových premenných boli použité IPS a Fisherove testy jednotkového koreňa. Pri časových radoch spoločných pre všetky kryptomeny boli aplikované ADF a KPSS testy. Analýza potvrdila vhodnosť transformovaných premenných pre následné ekonometrické modelovanie.

Základná empirická analýza využíva panelové modely s fixnými efektmi kryptomien a časovými efektmi na úrovni roku a mesiaca. Fixné efekty umožňujú kontrolovať špecifické a časovo nemenné charakteristiky jednotlivých kryptomien, napríklad rozdiely v technológii, veľkosti trhu alebo dlhodobej úrovni likvidity. Modely boli odhadované postupne. Prvá špecifikácia obsahovala iba kryptomenové premenné, druhá bola rozšírená o sentimentové premenné a úplná špecifikácia zahŕňala aj makroekonomické a finančné faktory. Na základe diagnostických testov boli pre hlavné výsledky použité Driscollove-Kraayove štandardné chyby, ktoré zohľadňujú prítomnosť heteroskedasticity, sériovej korelácie a možnej závislosti medzi kryptomenami.

Výsledky základných panelových modelov ukazujú, že volatilita hlavných kryptomien je ovplyvňovaná najmä vlastnými internými trhovými charakteristikami. Významnú úlohu zohráva predchádzajúca volatilita a jej sedemdňový priemer, čo naznačuje, že volatilita kryptomien má výraznú perzistenciu. Obdobia zvýšenej volatility majú tendenciu pretrvávať aj v nasledujúcich dňoch. Zároveň sa potvrdil pozitívny a štatisticky významný

vplyv objemu obchodovania a nelikvidity. Vyšší objem obchodov a horšie likviditné podmienky sú spojené s vyššou volatilitou kryptomien.

Výsledky ďalej ukazujú, že význam majú aj premenné zachytávajúce širšiu vnútornú aktivitu kryptomenového trhu. Trhová beta, cenový moment a transakčná aktivita vykazujú pozitívny vzťah s volatilitou. To naznačuje, že volatilita jednotlivých kryptomien nie je ovplyvnená iba ich vlastnými cenovými pohybmi, ale aj citlivosťou na vývoj celého kryptomenového trhu a intenzitou aktivity používateľov v ich sieťach.

V prípade sentimentových premenných sa potvrdila najmä dôležitosť Google Trends indexu. Vyšší záujem používateľov o konkrétnu kryptomenu, meraný intenzitou jej vyhľadávania, je spojený s vyššou volatilitou. Tento výsledok podporuje predpoklad, že investorská pozornosť a online záujem môžu prispievať k výraznejším cenovým pohybom. Fear and Greed Index bol v základných panelových modeloch významný, avšak jeho výsledky sa pri kvantilovej regresii nepotvrdili vo všetkých režimoch volatility. Naznačuje to, že všeobecný sentiment celého kryptomenového trhu nemusí zachytávať dynamiku jednotlivých kryptomien rovnako presne ako ukazovateľ vyhľadávania konkrétnej kryptomeny.

Makroekonomické a finančné premenné mali v porovnaní s kryptomenovými a sentimentovými premennými slabší vplyv. Zmena indexu VIX vykazovala iba obmedzený pozitívny vplyv, zatiaľ čo výnos indexu S&P 500 a zmeny amerického dolárového indexu neboli v základných modeloch stabilne štatisticky významné. Waldove testy však ukázali, že makrofinančné premenné môžu mať v niektorých špecifikáciách spoločný vysvetľujúci význam. Ich vplyv sa však po vylúčení Bitcoinu zo vzorky oslabil, čo môže poukazovať na osobitné postavenie Bitcoinu ako dominantnej kryptomeny, prostredníctvom ktorej sa širšie finančné podmienky výraznejšie premietajú do kryptomenového trhu.

Doplnková analýza s posúvajúcim sa časovým oknom ukázala, že význam jednotlivých premenných sa menil v čase. Počas COVID-19 šoku v marci 2020 sa výraznejšie prejavil vplyv externého stresu, neistoty a obchodných podmienok. V tomto období boli makrofinančné premenné a likviditné podmienky viditeľnejšie než v pokojnejších fázach trhu. Naopak, počas výpredaja kryptomien v roku 2021 a pri kolapse FTX v roku 2022 dominovali najmä oneskorená volatilita, sedemdňový priemer volatility, nelikvidita a investorská pozornosť. Časová analýza teda ukázala, že makrofinančné faktory neboli

úplne bezvýznamné, ale ich vplyv sa prejavoval skôr epizodicky, najmä počas širších stresových udalostí.

Pooled kvantilová regresia bola použitá na preskúmanie toho, či sa vplyv jednotlivých determinantov mení v rôznych režimoch volatility. Modely boli odhadnuté pre kvantily 0,10, 0,25, 0,50, 0,75 a 0,90, ktoré reprezentujú relatívne pokojné, stredné a vysoko volatilné trhové podmienky. Na zabezpečenie spoľahlivejšej inferencie boli použité bootstrapové štandardné chyby, pričom bootstrapovanie prebiehalo na úrovni jednotlivých dátumov. Tento prístup zachováva spoločné denné šoky, ktoré môžu ovplyvňovať všetky sledované kryptomeny naraz.

Výsledky kvantilovej regresie potvrdili, že vplyv determinantov volatility nie je rovnaký vo všetkých trhových podmienkach. Bezprostredne oneskorená volatilita získava výraznejší vplyv najmä vo vyšších kvantiloch volatility. To znamená, že ak je trh už v období zvýšenej neistoty, aktuálna volatilita je vo väčšej miere ovplyvňovaná nedávnym cenovým šokom. Naopak, v obdobiach nižšej a strednej volatility má výraznejšiu úlohu širšie krátkodobé prostredie zachytené sedemdňovým priemerom volatility.

Objem obchodovania ostáva pozitívne spojený s volatilitou naprieč celým rozdelením, jeho vplyv však smerom k najvyšším kvantilom slabne. Nelikvidita si naopak zachováva relatívne stabilný pozitívny vplyv aj vo vysoko volatilných obdobiach. Tento výsledok naznačuje, že v extrémnejších trhových podmienkach je dôležité nielen množstvo uskutočnených obchodov, ale aj schopnosť trhu absorbovať tieto obchody bez výrazného cenového pohybu.

Google Trends index je pozitívny a štatisticky významný vo všetkých analyzovaných kvantiloch, pričom jeho vplyv rastie smerom k hornému okraju rozdelenia volatility. Tento výsledok ukazuje, že investorská pozornosť je obzvlášť dôležitá v obdobiach silných trhových výkyvov. Naopak, Fear and Greed Index sa v pooled kvantilovej regresii neukázal ako štatisticky významný. Možným vysvetlením je, že všeobecný sentiment trhu už nedokáže priniesť dodatočnú informáciu po zohľadnení konkrétnej pozornosti investorov venovanej jednotlivým kryptomenám.

Zistenia práce ukazujú, že volatilita hlavných kryptomien je formovaná predovšetkým ich vlastnou trhovou dynamikou, likviditnými podmienkami, intenzitou obchodovania a

investorskou pozornosťou. Makroekonomické a finančné premenné síce môžu v určitých podmienkach ovplyvňovať kryptomenový trh, ich úloha je však menej stabilná a slabšia v porovnaní s vnútornými charakteristikami kryptomien. Výsledky zároveň potvrdzujú, že vzťahy medzi jednotlivými premennými a volatilitou nie sú lineárne a menia sa podľa aktuálneho režimu volatility.

Práca prináša širší pohľad na determinanty kryptomenovej volatility tým, že analyzuje viacero kryptomien súčasne a kombinuje panelovú regresiu s pooled kvantilovou regresiou. Jej prínos spočíva najmä v rozlíšení medzi priemerným vplyvom determinantov volatility a ich vplyvom v rôznych trhových situáciách. Zistenia môžu byť využiteľné pre investorov, ktorí pri riadení rizika zohľadňujú likviditu, intenzitu obchodovania a sentiment na trhu, ale aj pre ďalší výskum zameraný na dynamiku kryptomenového trhu.

Medzi obmedzenia práce patrí najmä výber obmedzeného počtu kryptomien, dostupnosť údajov a skutočnosť, že niektoré technologické charakteristiky kryptomien sú počas sledovaného obdobia relatívne stabilné, a preto ich nie je možné plne zachytiť vo fixných efektových modeloch. Priestor pre budúci výskum predstavuje rozšírenie vzorky o ďalšie kryptomeny, využitie vysokofrekvenčných dát, podrobnejšie skúmanie regulačných udalostí alebo zapojenie alternatívnych ukazovateľov sentimentu založených napríklad na sociálnych sieťach a spravodajstve.

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APPENDICES

Appendix A. Initial Baseline Fixed-Effects Estimates with HC1 Robust Standard Errors

Variable	M1A	M1B	M1C	M1D	M1E
ln_gkvol_l1	0.2402***	0.2315***	0.2252***	0.2329***	0.2358***
	(0.0092)	(0.0092)	(0.0092)	(0.0095)	(0.0097)
ln_gkvol_ma7_l1	0.3343***	0.3372***	0.3427***	0.3579***	0.3276***
	(0.0133)	(0.0134)	(0.0134)	(0.0139)	(0.0141)
ln_vol_l1	0.1323***	0.1178***	0.1183***	0.1150***	0.1212***
	(0.0120)	(0.0120)	(0.0120)	(0.0123)	(0.0125)
ln_illiq_l1	0.0477***	0.0485***	0.0484***	0.0497***	0.0461***
	(0.0059)	(0.0059)	(0.0059)	(0.0061)	(0.0062)
mom_7_l1	0.0035***	0.0018***	0.0023***	0.0021***	0.0025***
	(0.0003)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
beta_7_l1	0.0413***	0.0418***	0.0412***	0.0345***	0.0359***
	(0.0109)	(0.0109)	(0.0109)	(0.0114)	(0.0109)
ln_tx_per_address_l1		0.0224*	0.0224*	0.0226*	0.0252**
		(0.0117)	(0.0117)	(0.0121)	(0.0119)
gt_coin_l1		0.0078***	0.0078***	0.0087***	0.0081***
		(0.0011)	(0.0011)	(0.0012)	(0.0012)
fgi_l1		0.0046***	0.0042***	0.0044***	0.0045***
		(0.0008)	(0.0008)	(0.0008)	(0.0008)
vix_chg_l1			0.0059***	0.0064***	0.0054***
			(0.0015)	(0.0015)	(0.0016)
dxy_ret_l1			-0.0101	-0.0062	-0.0105
			(0.0098)	(0.0099)	(0.0104)
spx_ret_l1			0.0260	0.0344*	0.0343*
			(0.0181)	(0.0186)	(0.0192)
Observations	19728	19728	19728	19728	17536
R-squared	0.512	0.514	0.516	0.5	0.503
Coin FE	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes
SE type	HC1	HC1	HC1	HC1	HC1

*Notes: Standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Source: Own calculations using Python.*

Appendix B. Pooled Quantile Regression Robustness Check: Rogers–Satchell Volatility

Variable	0.1	0.25	0.5	0.75	0.9
const	-1.9736***	-1.5686***	-1.1288***	-0.4575***	0.1266
	(0.1861)	(0.1437)	(0.1139)	(0.1412)	(0.2326)
ln_gkvol_l1	0.2478***	0.2481***	0.2530***	0.2862***	0.3286***
	(0.0216)	(0.0169)	(0.0174)	(0.0202)	(0.0296)
ln_gkvol_ma7_l1	0.6277***	0.5962***	0.5619***	0.5066***	0.4472***
	(0.0261)	(0.0225)	(0.0216)	(0.0262)	(0.0378)
ln_vol_l1	0.0562***	0.0393***	0.0310**	0.0251**	0.0186
	(0.0156)	(0.0104)	(0.0104)	(0.0096)	(0.0143)
ln_illiq_l1	0.0607***	0.0505***	0.0467***	0.0513***	0.0508***
	(0.0131)	(0.0090)	(0.0083)	(0.0084)	(0.0113)
mom_7_l1	0.0053***	0.0050***	0.0046***	0.0021	-0.0017
	(0.0013)	(0.0011)	(0.0012)	(0.0015)	(0.0017)
beta_7_l1	-0.0107	0.0056	0.0236*	0.0262	0.0303
	(0.0204)	(0.0174)	(0.0143)	(0.0203)	(0.0267)
ln_tx_per_address_l1	-0.0141**	-0.0100**	-0.0061	0.0061	0.0172**
	(0.0067)	(0.0049)	(0.0050)	(0.0063)	(0.0087)
gt_coin_l1	0.0013	0.0031***	0.0035***	0.0056***	0.0063***
	(0.0014)	(0.0010)	(0.0011)	(0.0013)	(0.0018)
fgi_l1	0.0007	0.0009	0.0013	0.0013	0.0022*
	(0.0009)	(0.0008)	(0.0008)	(0.0009)	(0.0013)
vix_chg_l1	0.0118**	0.0107***	0.0085**	0.0052	-0.0018
	(0.0046)	(0.0038)	(0.0040)	(0.0038)	(0.0053)
spx_ret_l1	0.0421*	0.0357*	0.0193	-0.0229	-0.0732*
	(0.0228)	(0.0213)	(0.0249)	(0.0291)	(0.0394)
dxy_ret_l1	0.0007	-0.0022	0.0099	0.0793	0.1083
	(0.0458)	(0.0407)	(0.0468)	(0.0548)	(0.0722)

*Notes: The dependent variable is log Rogers–Satchell volatility. Bootstrap standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.*
Source: *Own calculations using Python.*

Appendix C. Pooled Quantile Regression Robustness Check: Excluding Bitcoin

Variable	0.1	0.25	0.5	0.75	0.9
const	-2.7155***	-2.2602***	-1.8260***	-1.1776***	-0.8914***
	(0.2352)	(0.1537)	(0.1521)	(0.2127)	(0.2729)
ln_gkvol_l1	0.2372***	0.2428***	0.2475***	0.2857***	0.3336***
	(0.0199)	(0.0157)	(0.0185)	(0.0208)	(0.0314)
ln_gkvol_ma7_l1	0.6024***	0.5710***	0.5427***	0.4889***	0.3989***
	(0.0239)	(0.0204)	(0.0230)	(0.0268)	(0.0407)
ln_vol_l1	0.0846***	0.0697***	0.0594***	0.0507***	0.0553***
	(0.0148)	(0.0099)	(0.0110)	(0.0125)	(0.0145)
ln_illiq_l1	0.0603***	0.0542***	0.0478***	0.0478***	0.0506***
	(0.0126)	(0.0084)	(0.0098)	(0.0104)	(0.0093)
mom_7_l1	0.0049***	0.0051***	0.0046***	0.0018	-0.0001
	(0.0012)	(0.0009)	(0.0010)	(0.0015)	(0.0014)
beta_7_l1	-0.0106	-0.0037	0.0103	0.0212	0.0281
	(0.0188)	(0.0142)	(0.0168)	(0.0207)	(0.0253)
ln_tx_per_address_l1	-0.0431***	-0.0341***	-0.0278***	-0.0138*	-0.0008
	(0.0084)	(0.0059)	(0.0068)	(0.0082)	(0.0090)
gt_coin_l1	0.0030**	0.0032***	0.0043***	0.0059***	0.0061***
	(0.0013)	(0.0009)	(0.0011)	(0.0015)	(0.0020)
fgi_l1	0.0000	0.0008	0.0013*	0.0015	0.0019
	(0.0009)	(0.0007)	(0.0007)	(0.0010)	(0.0013)
vix_chg_l1	0.0093**	0.0097***	0.0084**	0.0029	0.0002
	(0.0045)	(0.0036)	(0.0038)	(0.0044)	(0.0048)
spx_ret_l1	0.0374*	0.0295	0.0212	-0.0293	-0.0617
	(0.0216)	(0.0183)	(0.0265)	(0.0342)	(0.0379)
dxy_ret_l1	-0.0230	0.0025	0.0152	0.0706	0.0956
	(0.0406)	(0.0371)	(0.0493)	(0.0667)	(0.0705)

*Notes: The sample excludes Bitcoin. The dependent variable is log Garman–Klass volatility. Bootstrap standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.* ***Source:*** *Own calculations using Python.*