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# Risk-Return relationship: the case of Blockchain technology and the Crypto-market

Mihaela Florentina Soiman

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THÈSE

Pour obtenir le grade de

## DOCTEUR DE L'UNIVERSITÉ GRENOBLE ALPES

École doctorale : EDSG – Science de gestion

Spécialité : Finance

Unité de recherche : CERAG & LJK

**Relation risque-rendement. Le cas de la technologie  
Blockchain et du crypto-marché.**

**Risk-Return relationship. The case of Blockchain  
technology and the crypto-market.**

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**Titre :** Relation risque-rendement. Le cas de la technologie Blockchain et du marché des crypto-monnaies.

**Mots clés :** Blockchain, crypto-actifs, modèle de valorisation, relation risque-rendement, DeFi, indice de marché.

**Résumé :** Cette thèse porte sur la relation risque-rendement. Elle vise à découvrir les déterminants des rendements financiers sur le marché des crypto-monnaies. Plus précisément, nous commençons cette thèse en étudiant les risques uniques auxquels sont confrontés les actifs basés sur la blockchain (par exemple, les attaques cryptographiques, les attaques de contrats intelligents et d'autres vulnérabilités technologiques), qui peuvent être la source de la volatilité inhérente du marché. Dans l'idée d'explorer les risques spécifiques à Blockchain, cette thèse comprend également une analyse de l'impact des événements technologiques sur les caractéristiques financières des crypto-actifs. En outre, la thèse expose la diversité des crypto-actifs et leurs implications pour l'évaluation des actifs.

**Title :** Risk-Return relationship. The case of Blockchain technology and the crypto-market

**Keywords :** Blockchain, crypto-assets, pricing model, risk-return relationship, DeFi, market index.

**Abstract:** This thesis focuses on the risk-return relationship. It aims to uncover the determinants of financial returns in the crypto-market. More specifically, we begin this thesis by investigating the unique risks Blockchain-based assets incur (e.g., cryptographic attacks, smart contract attacks, and other technological vulnerabilities), risks that might be the source of the market's inherent volatility. With the idea of exploring Blockchain-specific risks, this thesis also encloses an analysis of the impact of technological events on crypto-assets' financial characteristics. Additionally, it exposes the diversity of crypto-assets and their implications for asset pricing.

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ou improbation aux opinions émises dans cette  
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propres à leur auteur.*

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*To my grandparents,*

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## BRIEF CONTENTS

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# General Introduction

Look at market fluctuations as your friend rather than your enemy; profit from folly rather than participate in it.

---

*Warren Buffet*

## 1 Research background

The extent of change in price over time, or better said, the volatility of bitcoin, is one of the reasons why the crypto-market is so popular nowadays (Corbet et al., 2019). Perceived as both evil and good for the financial markets, volatility plays an essential role in the adoption of crypto-assets and market development (Pollock, 2018). If gold is considered almost synonymous with stability, then crypto-assets are perceived as the opposite of gold or the adversary of classical securities. Being capable of shifting their prices as much as double in a matter of weeks, which gives important returns or losses, crypto-assets are more challenging and controversial than any other asset class. At the same time, stories of crypto-billionaires and ‘overnight gained wealth’ opened the appetite of the big public and boosted the ‘Bitcoin mania’ (Pollock, 2018).

Thanks to their high volatility, crypto-assets obtained the title of the best-performing assets class. Looking back to the past ten years (2011-2021), the top three best-performing financial asset classes by annualized gains are: (1) cryptocurrencies with a [Return on Investment \(ROI\)](#) of 230.6%, (2) Nasdaq 100 with a [ROI](#) of 20%, and (3) US Large Caps with a [ROI](#) of 14% (Sriram, 2021). From 2009 when the first bitcoin was mined, to 2010, when the first bitcoin transaction took place, this digital asset had no market value. The longest bull market period in history, the

2010s, synchronized perfectly with the extraordinary evolution of the crypto-market, making it an indispensable instrument in the financial markets (Messamore, 2019; Sinclair, 2019).

Considering their growing importance and disruptive applications, crypto-assets became a topic of study for academics and specialists in various fields. Their price variations and the possible causes behind them, represent some of the most tackled topics in finance. It is believed that the maturity and market size could partially explain the increased price instability (Burniske & Tatar, 2017; Sinclair, 2019). At the same time, new evidence has shown that the lack of appropriate regulation and the numerous cyber-attacks play as well an important role in the crypto price changes (Pieters & Vivanco, 2017; Wheatley et al., 2018; Gandal et al., 2018; Corbet et al., 2019; Nadler & Guo, 2020).

This thesis focuses on the risk-return relationship, and it aims to identify and assess new Blockchain risks that may affect the financial performance of the crypto-market as a whole.

## 2 Crypto-assets

### 2.1 What are crypto-assets and Blockchain technology?

Crypto-assets are programmed intangible assets issued, registered, and transacted via a [Distributed Ledger Technology \(DLT\)](#). As we can intuitively learn from their name, this technology uses cryptographic algorithms, from here, the adjunct denomination ‘crypto’. In the case of these digital assets and their underlying technology, the employment of cryptography is purely for security reasons (Hays & Valek, 2018). Challenging at first sight, the crypto world is, in fact, trying to be pretty intuitive and simplistic. At the basis of crypto-assets’ operation, we have Blockchain distributed technology. Blockchain is a global record of financial transactions (could also be perceived as a database containing all the transactions’ details). Being originally conceived to ease the transfer of value, crypto-assets function without the need for any trusted third party. As a result, they facilitate the digital exchange, the digital record of assets’ ownership, and any other utility function a digital resource may have (FSB, 2018; Blandin et al., 2019). An important aspect to mention about crypto-assets is the fact that they are not backed by any central authority

and do not have a legal tender status in almost any jurisdiction.

## 2.2 Market evolution and terminology

Crypto-assets became known in 2008 when Satoshi Nakamoto invented bitcoin. Since this invention, Blockchain technology, together with the crypto world, has been relentlessly developing. According to a study by the University of Cambridge (2019), the terminology used has also evolved along with the crypto-market. Until 2014, the commonly used term for all crypto-assets was ‘bitcoin’. Afterward, the generic terms ‘cryptocurrency’, ‘digital currency’, and ‘virtual currency’ came into effect. After 2017, the market became increasingly complex; therefore, new terms such as ‘virtual asset’, ‘digital asset’, and ‘crypto-asset’ started to be used more frequently. This high diversity of defining terms represents a piece of evidence for the efforts made by the organizations and regulators to better understand and differentiate crypto-assets from fiat currencies<sup>1</sup> (Blandin et al., 2019).

While in the beginning, the crypto-asset and cryptocurrency terms could have been used interchangeably, now Blockchain technology received extra applications, and together with that, the world received new types of crypto-assets. Concerning the term crypto-assets, since it came to life later, we can still identify frequent misuse of the term cryptocurrencies, even though it is not universally defining anymore (Burniske & Tatar, 2017).

Crypto-assets and Blockchain technology are essential in the financial world, particularly thanks to their numerous applications that bring important contributions to the financial industry.

## 2.3 Taxonomy of crypto-assets

Crypto-assets are progressively considered a useful tool for diversification in financial investments and portfolio management (Briere, Oosterlinck, & Szafarz, 2015; Goodell & Goutte, 2021; Urquhart & Zhang, 2019). Therefore, it is important to understand their nature and emphasize this market’s distinctive lines. Crypto-assets have many common characteristics, which makes it difficult to draw boundaries. Consequently, specialists still find it difficult to define, classify and (financially) re-

---

<sup>1</sup>Fiat currencies is the name given to the national money we use in our daily life. The control of the government gives fiat money its legal tender status, which means that it is commonly accepted as means of payment, and everyone has to use it within the respective country (Quest, 2018).

port crypto-assets.

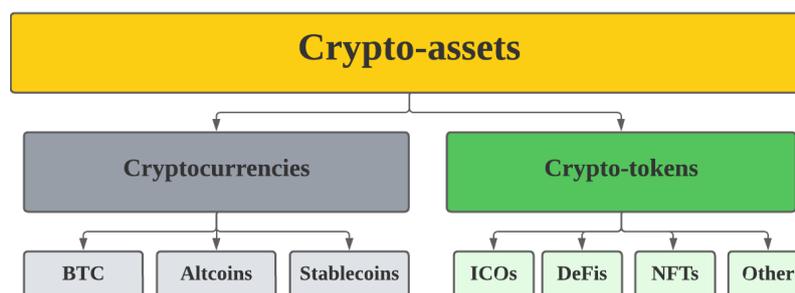
In 1997, Robert J. Greer published a seminal paper entitled “What is an asset class, anyway?” (Greer, 1997). Through this work, the author designs three classes of assets, such as it applies to real-world investments:

- Capital assets: their value is determined based on the net present value (abv. NPV) of expected returns; (e.g., debt, bonds, equity, etc.).
- Consumable/transformable assets: often called commodities, their value should be determined based on the supply and demand criteria; (e.g., raw materials, metals, food, etc.).
- Store of value assets: this class’s value is changing over time; from here, the name of ‘store value’; (e.g., fine art, wine, precious metals, currencies, etc.).

Greer (1997)’s proposed classes are generally considered some superclasses, which for a proper understanding, should be divided into subclasses and so on. In our case, the crypto-assets superclass could be divided into cryptocurrencies and crypto-tokens subclasses (Figure 1 proposes a classification for crypto-assets). At the same time, cryptocurrencies and tokens can be as further divided into various other subclasses. For example, stablecoins<sup>2</sup> are a subclass of cryptocurrencies, and **Non-Fungible Tokens (NFT)s** or **Decentralized Finance (DeFi)s** represent a subclass of tokens.

Figure 1: **Crypto-assets classes**

*Classification of crypto-assets as viewed by the author. Source: author’s adaption from the original figure of (EY Global, 2018).*



Classifying crypto-assets is not a straightforward task. On the one hand, cryptocurrencies could be considered a store of value, as their price changes continuously, attaining record highs such as 1 BTC = 66,000 USD (November 2021). On the other

<sup>2</sup>Stablecoins’ value is pegged to an underlying asset that can be a currency (usually USD), a security, or a combination of multiple assets.

hand, there are cases when they can be used as consumables; for example, ether coins can be used to access Ethereum platforms (Burniske & Tatar, 2017). Tokens or crypto-tokens do not attain monetary attributes; however, they often offer access to a community or network of participants to govern and use the Blockchain-based system (Gurguc & Knottenbelt, 2018). In other words, ‘token’ is generally used as an umbrella term to describe various crypto-assets that are not cryptocurrencies or used for transactional purposes. Tokens could be considered capital assets only if they are backed by financial securities (e.g., tokens backed by stocks). Otherwise, if tokens just grant access to a platform, they fall in the consumable/transformable category (White & Burniske, 2016).

As the crypto-market and the research in this field evolved, the specialists tend to agree with the following categorization:

- Payment tokens: crypto-assets or cryptocurrencies used as digital means of payment or exchange (e.g., bitcoin, ether, etc.); (Blemus & Guégan, 2020);
- Utility tokens: crypto-assets granting to their holders’ access to – and use of – a digital platform (e.g., gaming platforms, business networks, decentralized applications, etc.);
- Security tokens: crypto-assets representing an investment similar in nature to traditional securities (tokens backed by equities or other traditional securities);
- Hybrid tokens: share characteristics of two or all three classes (Blandin et al., 2019; Blemus & Guégan, 2020);
- **NFT**: registered ownership of a digital asset on a Blockchain, such as images, music, videos, and other virtual creations (Dowling, 2022a);
- **DeFi** tokens: crypto-assets that fulfill multiple roles within the **DeFi** platform operations; (1) transactional tokens (e.g., stablecoins: Dai, TUSD, USDC, WBTC) that facilitate fund transfers across platforms (Aramonte, Huang and Schrimpf, 2021), (2) governance tokens (e.g., MKR, COMP, YFI) that enable users to take part in the platform development and resemble with the common stock, (3) utility tokens that are used in the same way as in **Initial Coin Offering (ICO)**s, to obtain access to the platform’s services (in-App payment ‘currencies’), (4) liquidity provider tokens (LP) that are used as a reward for the users contributing to a **Decentralized Exchange (DEX)**’s liquidity, and (5) collateral tokens that are used on lending platforms, in a similar way to the bank loans practices (e.g., stablecoins, LP, ETH, NFTs) (MakerDAO.com,

2021). For a better understating of what DeFi platforms can do, see Figure 2.

### Figure 2: Examples of DeFi platforms functions

Comparison among Decentralized finance platforms, centralized finance, and traditional finance. Source: (Aramonte, Huang, & Schrimpf, 2021).

Function	Service	Crypto financial system		Traditional finance
		Decentralised finance (DeFi)	Centralised finance (CeFi)	
Trading	Funds transfer	DeFi stablecoins (DAI)	CeFi stablecoins (USDT, USDC)	Traditional payment platforms
	Asset trading	Crypto asset DEX (Uniswap)	Crypto CEX (Binance, Coinbase)	Exchanges and OTC brokers
	Derivatives trading	Crypto derivatives DEX (Synthetix, dYdX)		
Lending	Secured lending	Crypto decentralised lending platforms (Aave, Compound)	Crypto centralised lending platforms (BlockFi, Celsius)	Broker-dealers active in repo and securities lending
	Unsecured lending	Crypto credit delegation (Aave)	Crypto banks (Silvergate)	Commercial banks and non-bank lenders
Investing	Investment vehicles	Crypto decentralised portfolios (yearn, Convex)	Crypto funds (Grayscale, Galaxy)	Investment funds

CEX = centralised exchanges; DEX = decentralised exchanges; OTC = over-the-counter; USDC = USD Coin; USDT = Tether.

Burniske and Tatar (2017) propose a classification based on crypto-assets functions, which is basically a mix of the previous proposals, including the asset classification made by Greer (1997):

- Cryptocurrencies: fulfill the three functions of a currency, means of exchange, store of value, and unit of account (e.g., bitcoin, ether, etc.);
- Crypto-commodities: supply raw digital resources (e.g., ether, gas, etc.);
- Crypto tokens: facilitate access to finished digital goods and services (e.g., tokens for games, etc.).

As per Greer's suggestion and for a better understanding, we go deeper into the subclasses of cryptocurrencies and tokens, which are further categorized based on various aspects:

- Altcoins: any cryptocurrency except of bitcoin (the first cryptocurrency created) (e.g., ether, Ripple, IOTA, etc.);
- Forked coins: coins that belong to the family tree of another coin and are issued by modifying the codebase of the original coin (e.g., Bitcoin Cash, Monero Classic, Litecoin, etc.);

- Stablecoins: cryptocurrencies whose value is attached to securities or fiat currencies (e.g., Tether, Dai, Moneyfold, NUBITS, etc.);
- Platform coins: they operate as both currency and platform, enabling various services through the use of smart contracts (e.g., Ethereum, EOS, Stellar, Neo, WeChain, etc.);
- Privacy coins: coins that offer full user anonymity, such as transactions and account balances, can never be tracked (e.g., Monero, Dash, Enigma, etc.);
- Ecosystem coins: special coins/technologies aiming to strengthen the use and access of crypto applications by enabling interoperability and communication among decentralized technologies (like different Blockchains), various applications (smart contracts, universal cryptocurrency wallets), or between the crypto world and real business world (e.g., Nebulas, Waves, Salt, Chainlink, AION, etc.);
- Currency exchange: tokens and technologies aiming to remove the barriers and facilitate the exchange of cryptocurrencies for another currency (some less popular coins might hardly be accepted and exchanged); this adds liquidity to the market and diminishes some existing imperfections and frictions (e.g., Cryptonex, Quash, Kyber Network, Bitshares, etc.);
- Gaming & Gambling coins: tokens used inside games and gaming community, aiming to enhance the connection, collaboration, and interoperability among different platforms (e.g., Storm, Funfair, Wax, etc.);
- Social Network coins: tokens and technologies aiming to create a trustless and honest balance of power between the social network and media and their users (e.g., Reddcoin, Steem, Kin, etc.);
- Fee-based token: coins aiming to reduce the fees or costs for different services, such as trading (e.g., BNB, Gas, Kucoin);
- Decentralized Data Storage coins: coins and open-source technologies aiming to facilitate decentralized data storage by distributing it across a peer-to-peer network; in this way, it removes the risk of a single point of failure (e.g., Byteball, Siacoin, Storj, etc.);
- Cloud computing coins: tokens and technologies enabling the use of computer power against a fee (like renting) (e.g., Golem, Elf);
- Colored coins: digital tokens tied to a real value asset or physical asset - a car, equity, fiat monies, etc.- or serving a specific use - voting, paying dividends, currency/payment tool for a community, etc. The idea of coloring is to make

a distinction among the tokens owned in the wallet, such as every object or function tied to the token is represented by a specific color (e.g., Ripple issuance) (source: (EY Global, 2018; Kraemer, 2022; Bitcoin.fr, 2013)).

As we can observe in the above list, crypto-assets can be categorized based on their application, nature, technological features, or even the field in which they operate. The more the analysis goes into detail in classes and subclasses, the more technical features are revealed. This reminds us that crypto-assets are, first of all, a technological innovation. Despite all the attempts to officially classify crypto-assets, the more this market grows, the more difficult it becomes to pick a universal classification model. Liu and Tsyvinski (2021) found that *“the behavior of cryptocurrencies is driven by (1) its functions as a stake in the future of Blockchain technology which is similar to stocks, (2) as a unit of account similar to currencies, and (3) as a store of value similar to precious metal, commodities”*. On the same idea and in alignment with (Sharpe, 1992)<sup>3</sup>, Krückeberg and Scholz (2019) show that crypto-assets, namely cryptocurrencies, should be considered a distinct asset class, uncorrelated with any traditional one. In conclusion, for the moment, crypto-assets are best described as an emerging class that will change over time.

## 2.4 The market for crypto-assets

During the long and constant development over the past 12 years, cryptocurrencies prices have often escalated drastically (see Figure 3). At the end of 2017, the crypto-market achieved record-high prices that surpassed well-established asset classes. The 2017-2018 period is considered to be the bitcoin bubble, which impacted most of the altcoins in the market and drove all the numbers up. In a matter of 5 months, from December 2017 to May 2018, bitcoin’s price dropped from \$19,500 to only \$7,000. This drastic devaluation registered after the 2018 records has seriously damaged investors’ interest and trust in this market. From the specialists’ point of view, this value reduction for the crypto-market is a simple price correction necessary to clear away the effects of the crypto mania (Agosto & Cafferata, 2020).

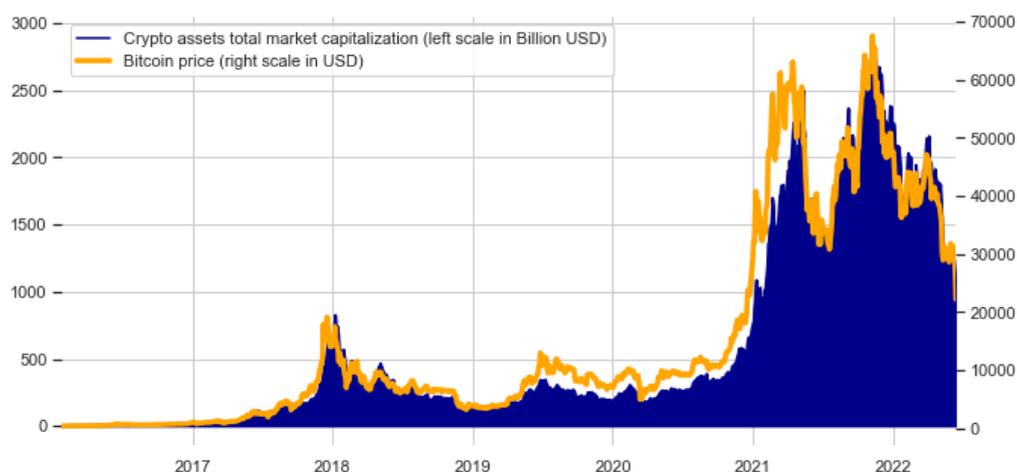
In 2020, the world confronted the COVID-19 pandemic. As a consequence of the global panic and the lockdown imposed worldwide, all the financial markets and the crypto-market suffered important losses. Compared to well-established financial

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<sup>3</sup>Sharpe has proposed a way to classify assets based on the following criteria: (1) No security should be included in more than one asset class. (2) Include as many securities as possible in the chosen asset class. (3) The securities from a chosen asset class should have low return correlations with the one from the other class (or different standard deviation).

**Figure 3: Total market capitalization of crypto-assets**

*Evolution of the price of bitcoin and the total market capitalization of all crypto-assets between 2016 and 2022. Source: Coinmarketcap.com, author's calculations.*



markets, the crypto-market recovered much faster. It is believed that this has happened as a consequence of the missing link between digital currencies and the real economy (Caferra & Vidal-Tomás, 2021). After the shock created by the pandemic, the crypto-market prices continued to grow, reaching a new market capitalization record of \$2.3 trillion in April 2021. The next peak of \$2.9 trillion was registered in November 2021, after which the market declined dramatically to only \$891 billion in June 2022 (Coinmarketcap.com, 2022). This huge collapse is believed to be the response to the panic created by the economic instability (as a consequence of COVID-19) and persistently high inflation (Duggan, 2022).

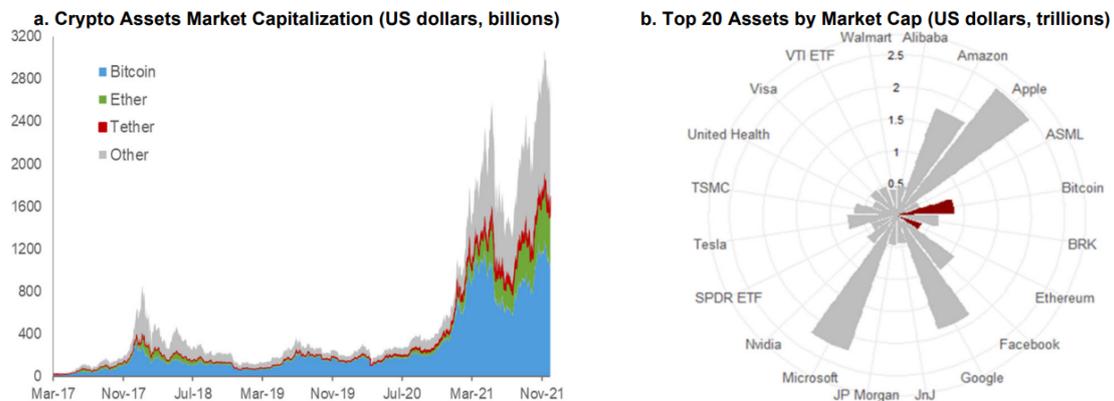
If we look at its recent record highs from November 2021, the crypto-market suffered from a drastic devaluation of more than 70% in approximately six months (Ossinger, Pan, & Bloomberg, 2022). If the traditional markets suffered from a similar acute collapse, central banks and financial professionals taking care of the economy would immediately work to save the market (e.g., buyout practices). However, it is not the case for the crypto-market. According to a press release, the economists are not worried about the crypto-assets sell-off hurting the broader economy, as long as it is not used as collateral for real-world debt (MacKenzie, 2022). This event comes with many unfortunate consequences characteristic of unregulated markets, where the investors are the ones suffering the most since there is no protection provided (like would be the case in the equity markets) (Morgan Stanley, 2022).

As it can be observed in Figure 3 and Figure 4 a., the market capitalization of

the whole crypto-market seems to be influenced by the bitcoin’s price. Despite the fact that at the global level, the number of crypto-assets is now exceeding 9,000 (Coinmarketcap.com, 2022), bitcoin continues to be the leader of the market with a share larger than 44%, followed by Ether (19%) and Tether (6%) (Statista, 2022). And if we continue to look into the market dominance at a broader level, we can observe that market supremacy is easily achieved by the top cryptocurrencies: the first three crypto-assets cover 70% of the total market share, and the top 10 are responsible for 85% of the total market share (Coinmarketcap.com, 2022). Thanks to DeFi and other crypto-specific developments, the number of crypto-assets and the market as a whole experienced significant expansion. This rapid growth of the crypto-market is the result of the interest in crypto-assets and Blockchain technology. Moreover, after the shock of the COVID-19 pandemic, this market has gained increasing popularity among institutional and retail investors as an asset class. For their financial and technological (innovative) performance, crypto-assets are trusted enough to be among the top 20 traded assets (see Figure 4 b.).

Figure 4: **The rise of crypto-assets**

Source: (Iyer, 2022).



Sources: CoinMarketCap; CoinGecko; CryptoCompare; Statista; Yahoo Finance; author’s calculations.

Note: Figure 1a uses daily data from January 2017 to November 2021 on the market cap of crypto assets. Figure 1b shows the world’s top 20 assets, based on the universe of publicly traded companies, exchange traded funds (ETFs) and crypto assets, by their market cap on Sept 10, 2021. Crypto assets are in red and the other assets are in grey. ASML = Advanced Semiconductor Materials Lithography; BRK = Berkshire Hathaway; JnJ = Johnson and Johnson; SPDR ETF = SPDR S&P 500 ETF Trust; TSMC = Taiwan Semiconductor Manufacturing Company; VTI ETF = Vanguard Total Stock Market Index ETF.

Compared to other financial markets, the crypto-market remains relatively small,<sup>4</sup> registering only 0.16% of the equity market capitalisation in E.U. and 2% of the global value of gold (NGRAVE, 2022). There are many questions raised as to whether the advancing crypto-adoption would have a proportional impact on the economy through wealth effects for investors (FSB, 2018). Up to now, by looking from an investment performance viewpoint, the reports show that besides their

<sup>4</sup>These graphs and comparisons have been made using the crypto record high values from spring 2021. As we can observe, even at its highs, the crypto-market remains relatively small compared to traditional markets.

ups and downs, crypto-assets are still the best-performing asset class, enhancing the portfolio returns and maintaining their information efficiency<sup>5</sup> (Sinclair, 2019; Matkovskyy & Jalan, 2019).

With respect to equity, gold, or the Forex market, the crypto-assets are still extremely volatile. However, if we look at their early days, they seem to slowly become more stable. This can be explained by the fact that the market is gradually maturing, and its value is less speculative and more utility-based (Burniske & Tatar, 2017; ESMA, 2019). Many research papers (Dyhrberg, 2016b; Caferra & Vidal-Tomás, 2021; Sifat, 2021) have declared that the crypto-market is not linked to the real economy. However, as we can observe, time changed the crypto-world to resemble more and more the traditional markets, which implies a relationship with the economy in the first place (see Table 1).

Table 1: **The rise of crypto-equity correlations**

*Source: (Iyer, 2022).*

a. Volatility correlations				b. Return correlations					
Crypto	Equity Index	2017–19	2020–21	Crypto	Equity Index	2017–19	2020–21		
BTC	S&P 500	0.11	0.46	BTC	S&P 500	0.01	0.36		
	Nasdaq	0.09	0.46		ETH	Nasdaq	0.02	0.38	
	Russell 2000	0.07	0.48			TTH	Russell 2000	0.03	0.36
	MSCI EM	0.12	0.48				ETH	MSCI EM	0.02
ETH	S&P 500	0.08	0.25	TTH				S&P 500	0.06
	Nasdaq	0.06	0.24		ETH			Nasdaq	0.07
	Russell 2000	0.03	0.25			TTH		Russell 2000	0.07
	MSCI EM	0.08	0.25				TTH	MSCI EM	0.10
TTH	S&P 500	-0.02	0.35	TTH				S&P 500	0.02
	Nasdaq	-0.02	0.34		TTH			Nasdaq	0.02
	Russell 2000	0.01	0.28			TTH		Russell 2000	0.06
	MSCI EM	-0.01	0.31				TTH	MSCI EM	0.02

Sources: CryptoCompare; Yahoo Finance; author's calculations.

Notes: Correlations of returns and volatility are calculated using daily prices, excluding non-trading days, over the periods Jan 2017–Dec 2019 and Jan 2020–Nov 2021. Returns are defined in log difference terms, and volatility is based on intra-day prices. BTC = Bitcoin, ETH = Ether, TTH = Tether.

An explanation for this surprising evolution of the crypto-market, could be the fact that Blockchain's applications have evolved in a way that they can replace many of the traditional market's functions. For example, if we look at DeFi platforms, their goal is to provide a digital alternative to traditional banking, exchange, and investment services (Anker-Sorensen & Zetzsche, 2021). ICO platforms provide us with a new form of raising capital by issuing tokens. NFTs enable the registration<sup>6</sup> of digital objects (e.g., photos, videos, etc.) on the Blockchain and track the ownership rights (Dumas et al., 2022) and etc. In other words, thanks to the evolution of Blockchain, the crypto-market can now offer alternative services to the ones from

<sup>5</sup>We say that a market is informationally efficient when prices fully reflect the available information.

<sup>6</sup>Similar to the creation of an authenticity certificate.

the real world while at the same time creating a trusty decentralized worldwide system.

## 3 Blockchain technology

### 3.1 Types of Blockchain technology

Blockchain technology refers to chains of blocks underlying transactional information. Initially conceived as a permissionless ledger and open to wide public technology (e.g., Bitcoin), nowadays, Blockchain has been developed in different other versions. The main key factors considered in differentiating Blockchains are:

- the permission dimension - limitations concerning the miners' right to write and amend the ledger;
- the openness - limitations concerning the users' right to access and add data within the ledger;
- de/centralization dimension - concerning the type of governance;
- the type of technology - public - anyone can access it and become part of the network or private - only restricted/predefined members have access and can be part of the network.

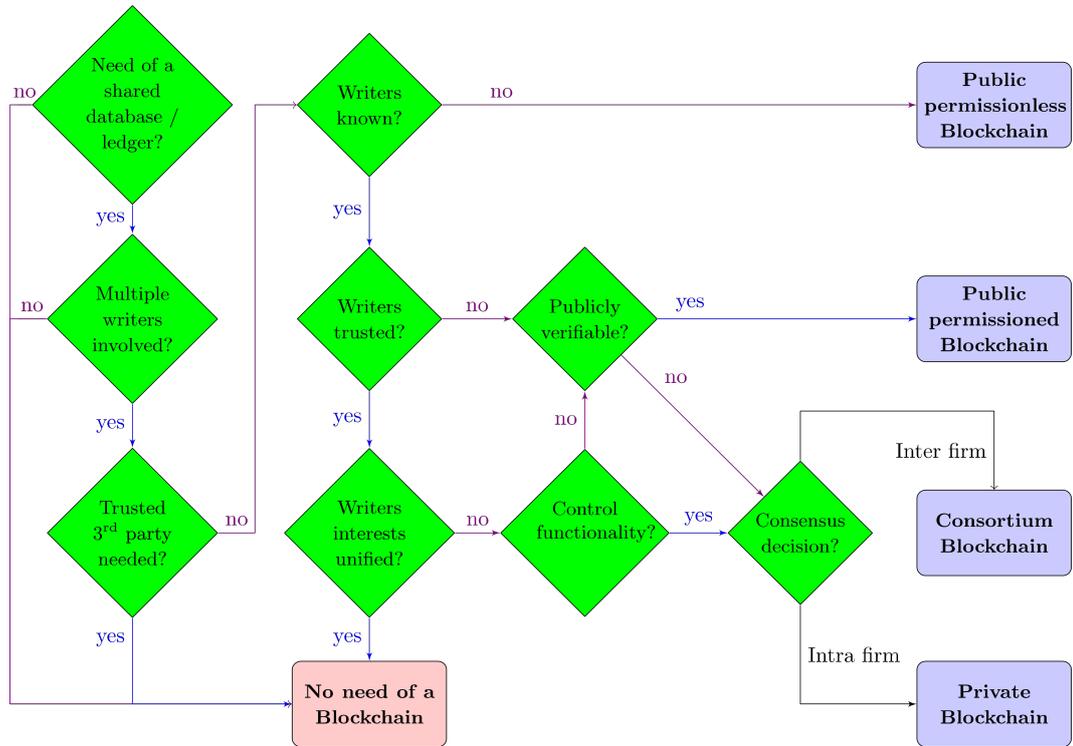
Figure 5 shows that there exist four main types of Blockchain, each categorized based on their operation, user type, technical key features, and last but not least, their innovative contributions to the existing markets and businesses: (1) Public (Permissionless & Open), (2) public & hybrid (Permissioned & Open), (3) private (Permissionless & Closed) and (4) private & hybrid (Permissioned & Closed).

Powerful, however, not immune to threats and vulnerabilities, some of these derived versions of the Blockchain represent just a step forward towards a better technology. As promising as the public version (e.g., Bitcoin Blockchain), but with a different operational approach, the private Blockchain is mostly addressed to firms and organizations, which need full control over the technology network and personalized solutions to their existing challenges.

Figure 5 shows the functions of this technology for which someone could consider implementing it. This flowchart aims to support businesses in the decision-making

Figure 5: **Blockchain decision tree**

This figure proposes a series of questions aiming to help a firm decide whether Blockchain technology is the solution they need. Source: (Exterkate & Wagenaar, 2018).



process while determining which Blockchain is most suitable and if it represents or is not a technical solution.

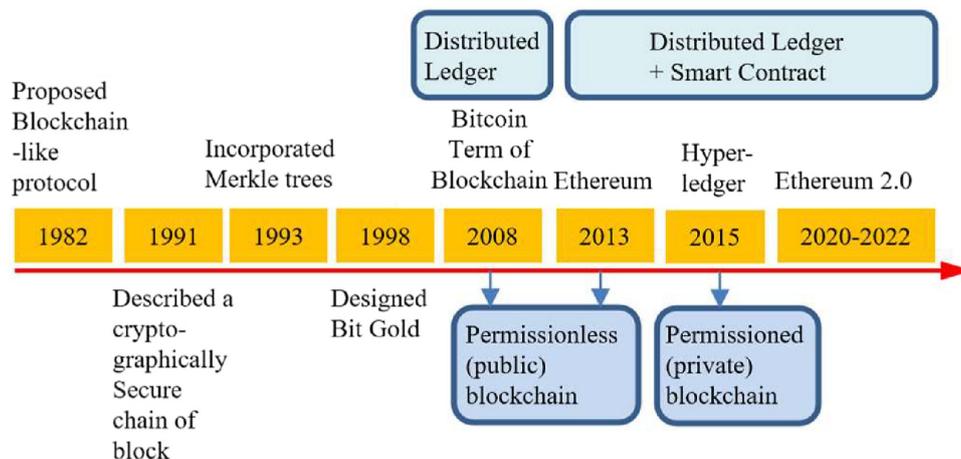
### 3.2 A closer look at Blockchain technology and the crypto-market

Along with the development of internet technology, online commerce has grown, and so did our dependency on smart payment instruments. As a consequence, Nakamoto (2009) came up with a solution to the high reliance on financial institutions. He introduced ‘an electronic payment system based on cryptographic proof instead of trust, allowing any two willing parties to transact directly with each other, without the need for a trusted third party’ (p.1 Nakamoto, 2009). When Nakamoto (2009) introduced Blockchain technology, it came along with the first cryptocurrency, namely bitcoin.

The first version of a digital asset (ancestor of cryptocurrencies) appeared in 1983, invented by David Chaum. This digital asset, named ecash, was functioning through a platform called digicash (Chaum, 1983), an early centralized version of the nowadays Blockchain. Another early concept of Blockchain was introduced by Haber and Stornetta (1991) in their published work: “How to time-stamp a digital document”. This paper proposes a way to time-stamp digital assets with the purpose of certifying when the asset was created or last modified. By digital assets, the researchers make reference to items like pictures, written documents, and audio files (Haber & Stornetta, 1991). These early innovations laid the groundwork for the development of the Blockchain technology we know today. Figure 6 shows the historical evolution of this technology.

Figure 6: **A timeline of Blockchain technology**

*Chronological evolution of Blockchain technology, from a concept to a practical application. Source: author’s adaption of Guo and Yu (2022).*



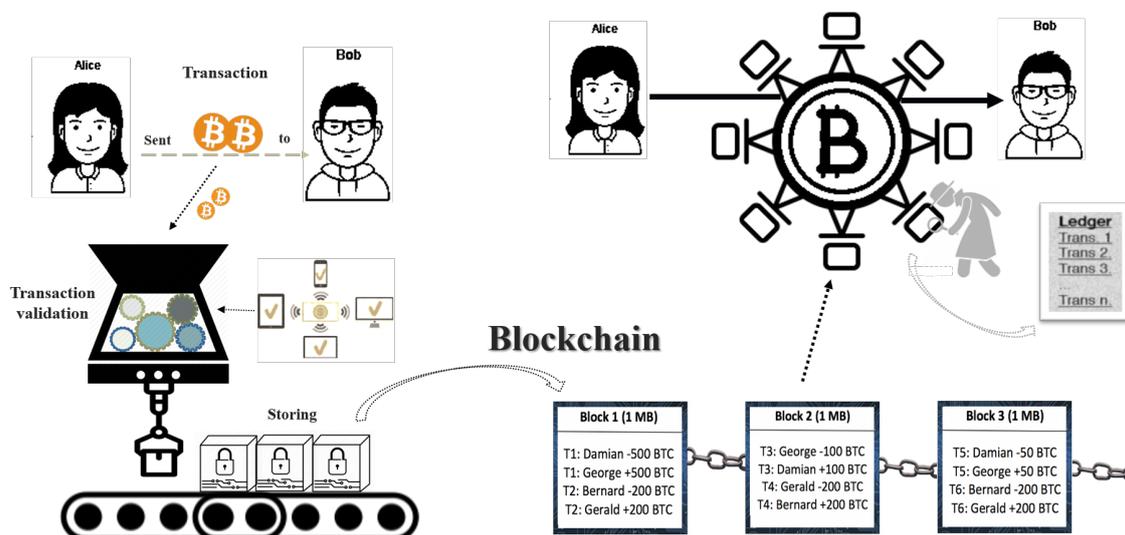
Blockchain is a global online database that anyone anywhere can use as long as

there is an internet connection. As we can learn from its name, Blockchain refers to linear chains of blocks associated with underlying transactional information. In simpler words, this technology represents a peer-to-peer system that enables the fast and secure transfer of money or other digital assets (money, art, science, titles, votes, etc.). Blockchain is sometimes referred to as **Distributed Ledger Technology (DLT)**. This comes from the Blockchain’s special feature, which is to create a ledger containing the full copy of all the transactions that took place within its system and distribute it to everyone being part of the Blockchain network (the nodes). Another important feature of this technology is the validation process that is performed by decentralized network nodes without any intermediaries. Afterward, any data entered in the Blockchain is immutable and non-forgable (Gatteschi et al., 2018).

While trying to understand Blockchain, a description of it would sound like: a structure of blocks, a distributed ledger containing main data (e.g., transactions), hashing codes, time-stamp<sup>7</sup>, and other information (Lin & Liao, 2017). Nakamoto offers a detailed description of how Blockchain works. His example comes from Bitcoin. Figure 7 offers an illustration of Nakamoto’s Blockchain.

**Figure 7: The workflow of Bitcoin Blockchain transaction**

*The verification process assuming a single simple transaction (among a bunch of transactions), between two participants in the Bitcoin Blockchain network. Source: the author.*



1. Every time a transaction is placed within the Blockchain, it is put on hold and placed in a waiting space named *Mempool*. This information will be sent to the network nodes;

<sup>7</sup>A time-stamp is an indicator of a block’s genesis time, a proof of existence (Lin & Liao, 2017).

2. Afterward, transactions are selected by validators (miners) and arranged in a potential new block;
3. Miners try to solve complex mathematical problems and compete to find the [Proof of Work \(PoW\)](#) for their block;
4. Once the [PoW](#) is acquired, the information is shared within the Blockchain network;
5. If the [PoW](#) is approved by the network, it means that all the transactions from this new block are honest;
6. Ultimately, after the transaction's validation and consensus checks, nodes agree to accept the new block, which will be added to the chain.

The consensus is reached only when the majority of nodes agree on the same ledger version (p.3 Nakamoto, 2009). A consensus algorithm in the context of Blockchain technology represents a code-based protocol aiming to facilitate reaching agreement processes within a network. These algorithms came as a solution to the '*Byzantine General Problem*', which concerns the failure to reach a consensus due to faulty actors (Zhang et al., 2019). The most popular and widespread consensus algorithms in Blockchain technology are the [PoW](#), [Proof of Stake \(PoS\)](#), and the [Practical Byzantine Fault Tolerance \(PBFT\)](#) protocols.

Depending on the consensus type, a key role in the functioning of Blockchain is played by the miners, without which the system would not work. For instance, in the [PoW](#) Blockchains, miners are supercomputers, which with the use of sophisticated software and a large amount of electricity, race to verify transactions and create new blocks. Often compared to gold mining, crypto-mining is extremely expensive and competitive. The high competitiveness is justified by the unique incentives shared by the Blockchain system; every time a miner is successfully validating transactions and creating a block, they are rewarded by the system with an amount of newly minted bitcoins<sup>8</sup>. In order to keep the miners motivated to maintain their work and validate transactions faster, users often increase their rewards by adding transaction fees. The higher the fee, the faster the transaction will be processed, which gives considerable power to the miners (Biais et al., 2019a; Easley, O'Hara, & Basu, 2019).

Since 2009, more types of Blockchains have been developed, each corresponding to specific needs. Depending on the technology design, the main examples of data

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<sup>8</sup>As of July 2022, a successful miner receives 6.25 BTC for each new block linked to the chain.

processed through Blockchain vary from transaction records to contract records, Internet of Things data, digital art (NFTs), etc. The first version of Blockchains, introduced by Nakamoto, can be divided into three functions: a decentralized ledger holding all the transactions' history, a protocol (a set of computer code rules) that conducts financial transactions, and cryptocurrencies such as bitcoin. The next version introduced by Ethereum technology brings a new innovation, namely smart contracts. It is important to mention that Ethereum technology is more sophisticated and flexible and has more features than the first version of Blockchains.

Smart contracts are computer protocols meant to digitally optimize, verify or enforce the performance of a contract. Better said, it can be defined as a digital registration of an existing contract, which will eventually become an automated / self-executing transaction. An important mention is that the smart contract does not rely on any third party, but it acts automatically in accordance with its pre-established conditions (Cong & He, 2019). The concept was apparently known for a long time before its actual launch, as Szabo (1994) envisioned it; however, no feasible application was put in place before the Blockchain technology. Smart contracts rely on conditions dependent on the data stored in the Blockchain or on a trusted authority for reaching consensus and execution. At the same time, smart contracts can import relevant information from the 'real' world (through oracles), integrate it into the Blockchain database, and proceed with the execution process when necessary (Gatteschi et al., 2018; Cong & He, 2019).

Historically speaking, smart contracts are at the heart of all [Decentralized Applications \(dApps\)](#) developed on Ethereum Blockchain (Dumas et al., 2018). Since smart contracts can do essentially anything that a computer program does, they are used to perform diverse operations such as making computations, storing data, minting tokens, sending communications, and even generating graphics (Ethereum.org, 2022). Thanks to smart contract technology, Blockchain is not only a concept of decentralized money transactions, but it introduced the concept of decentralized markets, or decentralized relationships with different business counterparties, such as clearing houses, banks, and companies. Some examples of smart contract implementations from the real world are the insurance platforms (e.g., AXA), supply chain platforms (e.g., Tokio Marine), trading platforms (e.g., NASDAQ) and banking (e.g., R3) (Dumas et al., 2018; Ethereum.org, 2022).

A notorious example of [dApps](#) made with the use of smart contracts is [ICOs](#). [Initial Coin Offering \(ICO\)](#) represents a new form of raising capital by issuing tokens or coins. Technically speaking, they represent some sort of smart contracts registered in the Blockchain. The raising funds activity is similar to crowdfunding, but it is performed at a project level. With the support of smart contract technology, transactions are automatized; therefore, investors can easily send money to finance their desired project, and in exchange, they receive newly issued tokens/coins. All these steps are performed automatically without the support of any intermediary; in this way, the operations are more efficient, and some of the firm's costs are significantly diminished (Momtaz, 2019).

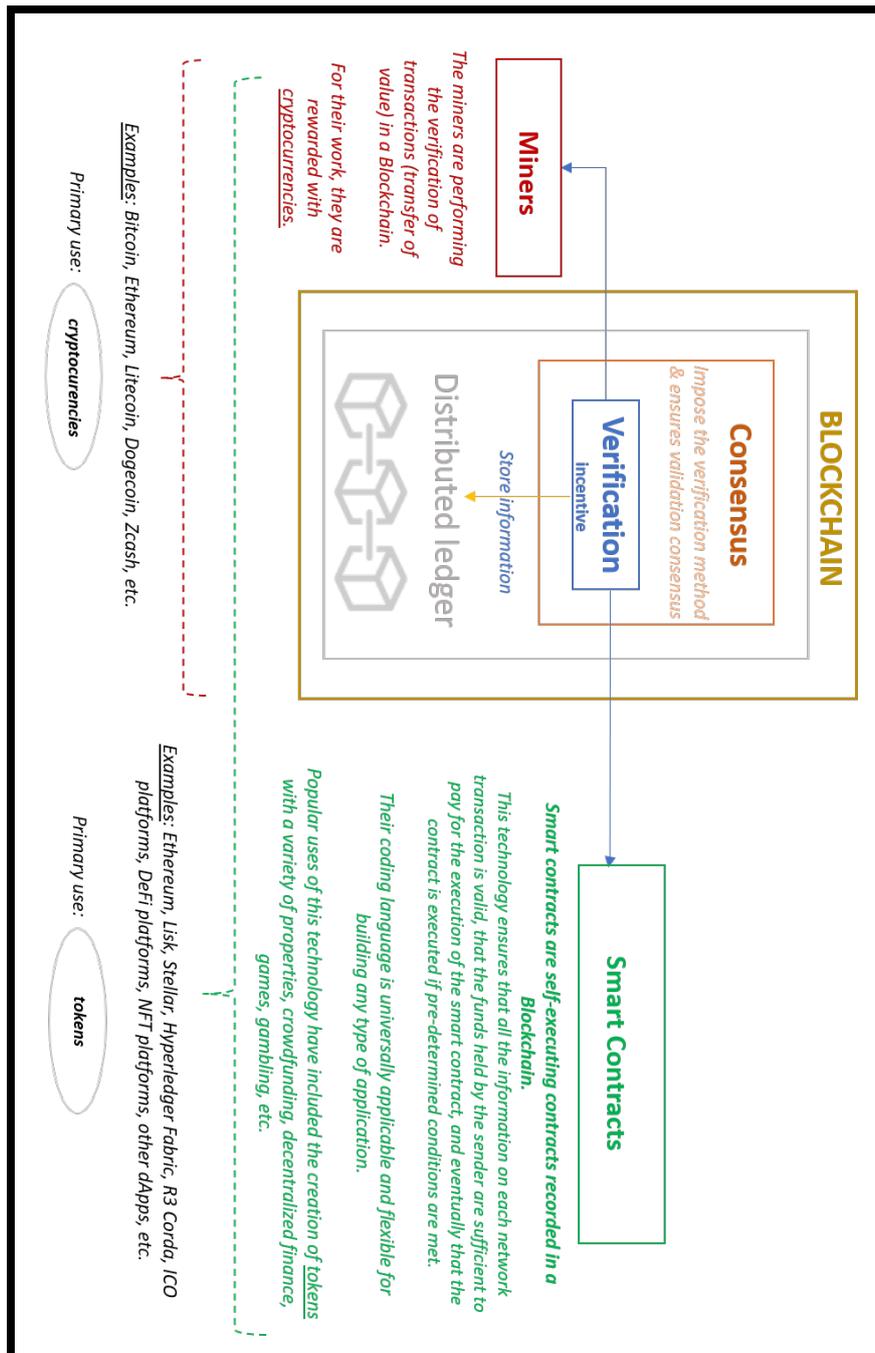
Other important and more recent examples of [dApps](#) are [DeFi](#) platforms and [NFTs](#). [Decentralized Finance \(DeFi\)](#) platforms run on Blockchains (distributed ledger) technology, onto which decentralized applications (based on smart contracts) are added (Popescu, 2020). [DeFi](#)'s applications provide financial services that rely on cryptocurrencies and crypto tokens. Their goal is to provide a digital alternative to traditional banking, exchange, and investment services (Anker-Sorensen & Zetzsche, 2021). [Non-Fungible Tokens \(NFT\)](#) are a certain type of tokens that function on a Blockchain and which represent something unique. Non-fungible means one of a kind; therefore, they cannot be replaced or exchanged with 'similar' assets. In other words, [NFTs](#) represent a unique set of digital data stored on a Blockchain. [NFTs](#) are mainly used to record digital objects (e.g., photos, videos, etc.) as unique elements within the Blockchain and whose ownership can be established and verified (Dumas et al., 2022).

Conclusion: In this section, we offer a presentation of the Blockchain technology evolution, how it works, and what are the main applications that have developed so far. Figure 8 tries to illustrate the big picture of Blockchain technology with its applications in a succinct and technical way, as it was presented in this short summary. It is important to mention that even if the existing literature (Corbet et al., 2021; Maouchi, Charfeddine, & El Montasser, 2021; Schar, 2021; Yousaf, Nekhili, & Gubareva, 2022) describes the [DeFi](#) market as a sub-sector of the crypto-market, [DeFi](#) tokens and cryptocurrencies represent two different asset classes. Perceived from a practical viewpoint, [DeFi](#) tokens and cryptocurrencies are only similar in the sense that both are based on Blockchain technology and implement decentralized (automatic) management. However, from a technological perspective, [DeFi Tokens \(DeFis\)](#) are a distinct technology as they require smart contracts in order to function.

From here stems our motivation to study the DeFi market in parallel with the cryptocurrencies and look for possible similarities and discrepancies between the two.

Figure 8: **Blockchain technology and its applications**

Schematic representation of Blockchain technology with its main applications, namely, the smart contract technology and crypto-assets. Source: the author.



## 4 Theoretical background

### 4.1 The valuation of assets

Why is it important to value assets? A proper valuation method can help assess the real worth of an asset hence helping buyers and traders decide whether an investment is profitable. Graham and Dodd (1934) were the first ones to propose a unified way of valuing assets and introduce terms such as value investing and intrinsic value (fundamentals) in their book ‘Security Analysis’ published in 1934. If the markets and the range of assets available for purchase have evolved much since the 1930s, the concept of buying mispriced securities has not. The valuation of assets has long been one of the main persistent problems in finance. Here, by assets, we refer to any type of goods or security that can be bought, sold, or traded, for example, stocks, gold, land, commodities, derivatives, money, etc. As an answer to this problem, the financial theory presumes that asset prices are generally set based on their present discounted value of dividends, in other words, their fundamental (or intrinsic value) (Tirole, 1985). This strand of the literature assumes that the fundamental value represents the ‘real’ value of an asset. This assumption has been tested and confirmed by many researchers, among which Leroy and Porter (1981), Shiller (1983), and Tirole (1982). In agreement with these findings, Tirole states that *“any asset must indeed be valued according to its market fundamentals. This conclusion is robust to differential information and to the presence of short sales constraints”* (p.1 Tirole, 1985). The hypothesis that prices reflect market fundamentals is generally made under the assumption of rational behavior and rational expectations.

Up to now, there is no universal technique used in valuation or calculating the fundamental value of an asset. However, depending on someone’s needs and the asset type in question, several methods can be considered. For example, in the case of stocks, the main valuation techniques used are based on dividend payments, earnings, and asset value. Dividends are an important measure of future profit simply because companies could use their earnings surplus to pay their investors dividends. A prosperous business usually translates into increased earnings and, concomitantly, profitable investment for investors. Asset valuation could refer to the book value of a company. By considering the assets and liabilities owned, this asset valuation represents an approximation of the liquidation value of the company, which is further used in assessing the accuracy of stock price (if the company’s market value is below the liquidation value, it is undervalued) (Graham & Dodd, 1934).

However, some assets are more difficult to value, such as land, commodities, or even currencies. Determining the fundamental value based on discounted dividend method is not always possible, and in such a case, a utility-based framework is applied. Blanchard and Watson (1982) state that mispricing is more likely to happen in markets where fundamentals are difficult to assess, such as the gold market example. If gold's price is based on its utility, the valuation is influenced by factors such as industrial demand and supply flow. The same logic applies to assets such as land. Its value will be directly impacted by its potential use, such as construction, rental, agriculture, demand flow, and many other factors (Blanchard & Watson, 1982). Similarly, Tirole (1985) assumes that currencies' fundamental value comes from their utility, which is the purchasing power (transactional benefits). Compared to other types of assets, money is considered a very special one, as its fundamental value depends on the prices' evolution. If prices are expected to rise, the money demand will grow, ultimately reflecting in the fundamental value (Obstfeld & Rogoff, 1983).

As a special asset class by nature, cryptocurrencies have been extensively studied (Bouri et al., 2017; Jiang et al., 2022). In particular, most studies focus on the relationship between the cryptocurrencies' prices and their fundamental value. While some studies showed that bitcoin is a purely speculative asset and hence has a null fundamental value (Cheah & Fry, 2015; Kallinterakis & Wang, 2019). Others argue that cryptocurrencies, in general, do have a fundamental value despite the difficulty of deriving it (Dowd, 2014; Beigman et al., 2021). Following the logic of (Tirole, 1985), Biais et al. (2020) test and confirm that cryptocurrencies have similar fundamental value to fiat money: *“Transactional benefits are to cryptocurrencies what dividends are to stocks”* (p.2, Biais et al., 2020).

Furthermore, significant attention has been brought to the network effects role in the valuation process of crypto-assets (Athey et al., 2016; Zimmerman, 2020; Cong, Li, & Wang, 2021; Liu & Tsyvinski, 2021). *“Whether real or virtual, networks have a fundamental economic characteristic: the value of connecting to a network depends on the number of other people already connected to it.”* (p.174, Shapiro and Varian, 1999). Katz and Shapiro (1985, 1986) have made some of the first contributions to the network theory, underlying for the first time the relationship between the fundamental value and network effects. This issue becomes more complex when the network is virtual, for example, in the case of software businesses, where *“the linkages between nodes are invisible”* but not inexistent (p.174, Shapiro and Varian, 1999).

In the crypto-market, the network effect is proxied by variables such as transaction and address count, users' number and etc., any other type of variable that could be used to estimate the Blockchain adoption rate. The network effect is especially important in the valuation process of the crypto-tokens and other Blockchain-based crypto-assets that do not attain transactional benefits, such as cryptocurrencies. For example, one of Cong, Li, and Wang (2021)'s main assumptions with regard to token valuation is that the expected platform's increase in productivity (and value) is the result of the network growth. In other words, the network effects make crypto-assets and Blockchain technology more useful as more people join the network, and as a result of this, the entire crypto-ecosystem becomes more valuable.

Conclusion: In this section, we discussed the valuation of assets and presented a theoretical perspective, such as asset prices reflecting their fundamental value. This hypothesis has been made under the rational behavior assumption. As it turns out, in reality, the price behavior often deviates from its fair value, being influenced by extraneous events such as, for example, the investors' behavior (Williams, 1938; Blanchard & Watson, 1982).

## 4.2 Behavioral finance and market efficiency

As mentioned in the previous section, security prices often deviate from their fair value. According to the financial theory (Grossman & Stiglitz, 1980), there are two main reasons explaining why the price does not reveal all available information: (1) under the assumption of rational investors: investors are differently informed, and the noise on the market prevents prices from perfectly revealing all the available information; (2) there are on the market some irrational investors, whose actions do not allow prices to reveal all the available information.

Apart from the financial theory, behavioral theory explains that prices can be influenced by extraneous events such as, for instance, the investors' behavior (Williams, 1938; Blanchard & Watson, 1982). Bachelier (1900), the pioneer of mathematical finance, is one of the first researchers to investigate the behavior of security prices and describes it as random. Many years after, this problem got attention, and starting from similar premises as Bachelier, namely the random character of stock price variations, Fama (1965a, 1965b) developed the [Efficient Market Hypothesis \(EMH\)](#) theory. According to Fama, in an efficient market, security prices will incorporate all the relevant information available and consequently be a good

estimate of the intrinsic value. Moreover, Fama highlights the important role played by the investors (market participants) in price stability: *“In an uncertain world, the intrinsic value of a security can never be determined exactly. Thus, there is always room for disagreement among market participants concerning just what the intrinsic value of an individual security is, and such disagreement will give rise to discrepancies between actual prices and intrinsic values. In an efficient market, however, the actions of the many competing participants should cause the actual price of a security to wander randomly about its intrinsic value.”* (p.76 Fama, 1965b). An important last mention here is the fact that Fama (1965a, 1965b) has identified three levels of market efficiency in the stock market: weak-form efficiency, semi-strong efficiency, and strong-form efficiency.

Investor attention impacts financial market characteristics, including liquidity, returns, and volatility. This hypothesis has been proven to be valid in the traditional markets and cryptocurrency (Andrei & Hasler, 2015; Ciaian, Rajcaniova, & Kancs, 2016; Lin, 2020; Liu, Tsyvinski, & Wu, 2022). Often, investor attention is associated with the under- and over-reaction of investors, which is considered a key determinant in market mispricing (Shiller, 2000; Baker & Wurgler, 2007; Andrei & Hasler, 2015).

According to the behavioral finance theory, we know that under conditions of irrational behavior, markets might not show economic fundamentals. Tversky and Kahneman (1974), the pioneers of behavioral finance, investigated individuals' capacity to make rational decisions in situations of uncertainty. They show that people tend to perceive certain events in a specific way that ignores the laws of probability. In the financial markets, this could translate into situations such as: investors seeing that the cryptocurrencies' prices are increasing, will consider it a growing market and invest in it, ignoring the laws of probability such as this being just a bubble phase (Li & Yu, 2012). Lin (2020) confirms Tversky and Kahneman (1974) theory by showing that past cryptocurrency returns significantly impact future investors' attention.

The traditional asset-pricing theory assumes that markets assimilate new information rapidly and securities' prices adjust and incorporate the news. Shiller (1980) proposes the use of volatility measure in assessing market efficiency. By looking at the high volatility present in the cryptocurrency market (Hu, Jain, & Zheng, 2018; Tran & Leirvik, 2020; Noda, 2021), we assume that their prices may

not be linked to economic-related events but rather to investors' irrational decision making described by psychological models such as the one developed by Tversky and Kahneman (1974). This claim is based on the premise that the crypto-market could be inefficient (prices deviate from their fundamental value), a subject highly debated in the literature (Wei, 2018; Hu, Valera, & Oxley, 2019; Kristoufek, 2019; Tran & Leirvik, 2019; Yaya et al., 2021) and which brought mixed conclusions.

Conclusion: In this section, we discussed market efficiency and how investors' (irrational) behavior can impact securities prices. In the next part, we introduce asset pricing theory and see how securities and crypto-assets returns are estimated.

### 4.3 Risk and returns

As stated before, the valuation of assets has long been one of the main persistent problems in finance. Therefore, in the seek to determine the (theoretical) fair value of an asset, academics proposed several models to price securities, among which the most well-known are the [Capital Asset Pricing Model \(CAPM\)](#) and [Arbitrage Pricing Theory \(APT\)](#). The goal of these pricing frameworks is to consider the risks incurred by holding security and price it accordingly. For instance, investors may obtain a high return on their investment by taking more risk (Markowitz, 1952). As Tobin (1958) states, high risk means a high probability of significant positive (or negative) change in the expected return.

The traditional financial theory has put forward the existence of two categories of risk: idiosyncratic (specific) risk and systematic (market) risk. The first one is specific to the security considered for investing, while the second one is connected to market variations and macroeconomic events. In a portfolio context, idiosyncratic risk can be reduced or even eliminated through diversification. On the other hand, systematic risk cannot be reduced or avoided; therefore, investors are compensated for bearing this type of risk with a premium (Markowitz, 1952; Tobin, 1958). Depending on the level of risk borne, investors can demand higher (or lower) premiums, which will reflect in the security's price and increase the investment's required return.

The [CAPM](#) has been developed based on Markowitz (1952, 1959) work on portfolio selection. This so-called mean-variance framework was successively consolidated by Treynor (1961), Sharpe (1964), Lintner (1965), Mossin (1966), Black, Jensen,

and Scholes (1972), and many others before becoming the **CAPM** we know today. **CAPM** is a single-factor model that assumes that the return of a security is linearly related to its systematic (market) risk. Since idiosyncratic risk can be diversified, the pricing model considers only the systematic risk, which cannot be diversified, as an important factor in asset valuation. The **CAPM** measures systematic risk with the  $\beta_i$  coefficient, representing the security's sensitivity to market movements. The model is stated as follows:

$$R_i = R_f + \beta_i[R_m - R_f] \quad (1)$$

Where  $R_i$  is the expected return of the security  $i$ ,  $R_f$  is the risk-free rate,  $\beta_i$  is the measure of the asset's sensitivity to market risk,  $R_m$  is the expected market rate of return, and  $[R_m - R_f]$  represents the market risk premium (the guaranteed rate of return, which is the expected return on market portfolio less the risk-free rate).

The **APT** model was developed by Ross (1976) as an alternative to the **CAPM**. Compared to **CAPM**, which shows that the expected rate of return on investment is determined only by the market risk ( $\beta$ ), **APT** considers multiple systematic risk factors. The nature of the factors is undefined and can vary from company-specific to macroeconomic risk. Despite its accurate price estimation and efficiency, **APT** is less used than **CAPM** for reasons such as long computations and difficulty in determining the risk factors. In contrast to the **CAPM**, where the risk factor is clearly established, the market risk, the **APT** suggests just that the risk factors selection must be determined considering their potential effect on the asset's return. The model is expressed by the following formula:

$$R_i = R_f + \beta_{i,1}RP_1 + \beta_{i,2}RP_2 + \dots + \beta_{i,n}RP_n \quad (2)$$

Where  $\beta_{i,n}$  is the asset's sensitivity to the  $n^{th}$  risk factor considered (such as a macroeconomic or company-specific factor),  $RP_n$  represents the risk premium for the  $n^{th}$  risk factor considered.

From the **CAPM**, we understand that assets with the same level of systematic risk should have the same rate of return. For instance, if two firms have a large exposure to market risk and have a different rate of return, this would lead to an arbitrage situation where the investor would only focus on the firm with the highest return. Over time, prices would increase, and the return would adjust. Hence, two

firms with similar risk exposure (sensitivity to the market factor) must have a similar rate of return. An important strand of the literature (Banz, 1981; Basu, 1983; Bhandari, 1988; Gibbons, Ross, & Shanken, 1989; Chan, Hamao, & Lakonishok, 1991; Fama & French, 1992) showed that, for different periods of time, the relationship between stocks return and market risk has diminished; hence the CAPM failed to fully explain the expected returns on investment. That being said, Fama and French (1992) proposed a new empirical pricing model that incorporates two risk factors in addition to the CAPM's market risk factor. This debated three-factor model embodies two new risk factors that have not been considered before and that improve the explanatory power of the stock returns: the size (small versus big) and value (high book-to-market versus the low book-to-market) factors. On account of the extensive literature on the subject (Banz, 1981; Reinganum, 1981; Blume & Stambaugh, 1983; Brown, Kleidon, & Marsh, 1983) and in reaction to the CAPM's failure to accurately explain returns and the existence of certain anomalies, Fama and French (1992) proposed an extension of the model by adding the size premium as a potential pricing factor. The anomalies in question, which have been empirically proven, refer to the fact that small market capitalization firms tend to outperform the market. The same is valid for the stocks with a high book-to-market ratio (Fama & French, 1992, 1996). Therefore, in the Fama-French model, the main factors driving the expected returns are the market, the size (SML), and the value (HML) factors.

Afterward, different models have followed, extending the CAPM up to six possible factors: Carhart (1997) proposed a risk factor called momentum<sup>9</sup>, and Fama and French (2015) introduced two additional factors: profitability<sup>10</sup> and the investment risk factor<sup>11</sup>. A comparison of the models showed that the CAPM explains about 70% of the expected returns. As an improvement over the CAPM, the Fama-French three-factor model explains over 90% of the expected returns. Furthermore, the Carhart model proved to be superior to both the CAPM and the Fama-French three-factor model in predicting stock returns (Fama & French, 1996; Carhart, 1997; Davis, Fama, & French, 2000; Bello, 2008).

Conclusion: In this section, we have briefly reviewed the asset pricing theory

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<sup>9</sup>The momentum factor (MOM) refers to the speed of change a security price experiences.

<sup>10</sup>The profitability risk factor (RMW) refers to the difference between the return of stocks with high operating profitability and the return of stocks with low/negative operating profitability.

<sup>11</sup>The investment factor (CMA) refers to the difference between the returns of firms investing conservatively and firms investing aggressively.

developed for traditional markets. In the coming section, we explore the literature and theories developed for the crypto-market.

#### 4.4 A state-of-the-art review

According to the [EMH](#) (Fama, 1965a, 1965b), a market is efficient when prices fully reflect the available information. Therefore, if the [EMH](#) would apply to the crypto-market, we would expect that the price dynamics of crypto-assets are impossible to predict. An important share of literature has examined whether the crypto-market is informationally efficient. Urquhart (2016) is the first work on this topic. This paper is particularly important as it shows the informational inefficiency of the crypto-market in its early years. At the same time, the results reveal the fact that, with time, the crypto-market seems to become more efficient. A similar finding has been shown in Kristoufek (2019). The authors present the crypto-market as historically inefficient, but this fact changes in the later years. Further works show that the crypto-market efficiency varies in accordance with the market circumstances (Kristoufek, 2019; Tran & Leirvik, 2019; Noda, 2021), hence putting forward evidence of the validity of the [Adaptive Market Hypothesis \(AMH\)](#) (Lo, 2004). The [AMH](#) was introduced in 2004 by Andrew Lo and combined the principles of the [EMH](#) with behavioral finance. Better said, [AMH](#) promotes the idea that rationality and irrationality coexist in the financial markets and that under periods of rapid change, stress, or abnormal conditions, the [EMH](#) may not be valid. As the empirical results from the literature do not support the [EMH](#) for the crypto-market, several authors tested and found evidence showing that [AMH](#) supports the time-varying market efficiency of the crypto-assets (Chu, Zhang, & Chan, 2019; Noda, 2021; Yaya et al., 2021).

Pricing cryptocurrencies has proven to be challenging, especially since they are a separate asset class from traditional assets (Dyhrberg, 2016b; Corbet et al., 2019; Liu, Tsyvinski, & Wu, 2022). Indeed, cryptocurrencies are uncorrelated with equities, currencies, commodities markets, and indirectly with global (macro)economic factors (Dyhrberg, 2016b; Bouri et al., 2017, 2017; Das & Kannadhasan, 2018). The most common methods used in pricing cryptocurrencies are [CAPM](#) and multi-factor models, such as Fama-French, [APT](#), and Carhart. Multifactor models were revealed to be more accurate in predicting cryptocurrency returns than the [CAPM](#), which only considers one systematic risk factor (the market) (Ciaian, Rajcaniova, & Kancs, 2016; Shen, Urquhart, & Wang, 2020; Jia, Goodell, & Shen, 2022; Liu,

Tsyvinski, & Wu, 2022). As traditional pricing frameworks such as CAPM, APT, or the Fama-French model account for non-diversifiable risk, the same approach is used to price cryptocurrencies. The rationale behind this approach assumes that, despite their independence from economic variables, their returns are influenced by the same factors (systematic risks) as conventional financial assets (Koutmos, 2020). Considering that cryptocurrency prices have little relationship with factors relative to stock markets and macroeconomic factors (Ciaian, Rajcaniova, & Kancs, 2016; Liu & Tsyvinski, 2021), a proper framework should aim to contain crypto-specific factors.

An important strand of literature tackles the modeling of cryptocurrencies returns and examines various risk factors specific to the market. Liu, Tsyvinski, and Wu (2022) found that a three-factor model, considering the cryptocurrency market, size, and momentum, is capable of successfully predicting investment returns. Similar to traditional markets, the crypto-market is driven by a size effect, meaning that small-capitalization cryptocurrencies yield more than high-capitalization ones (Liu, Liang, & Cui, 2020; Shen, Urquhart, & Wang, 2020; Jia, Goodell, & Shen, 2022). Among the most studied risk factors in the literature is momentum. In the crypto-market, momentum means that cryptocurrencies that performed well (poorly) in the past tend to continue to do well (badly) in the following period. Liu, Tsyvinski, and Wu (2022) show that the momentum effect is stronger at times of high investor attention. Liu, Liang, and Cui (2020) demonstrate that a combined effect of size and momentum factors explains cryptocurrency returns very well. Zhang and Lee (2020) show that idiosyncratic volatility is priced in the crypto-market, regardless of the size, volume, liquidity, or momentum effect. Moreover, they find a stronger idiosyncratic volatility-return relation in the underpriced cryptocurrencies and no evidence of temporal relation between idiosyncratic volatility and returns in the crypto-market. Wang and Chong (2021) found that volatility, liquidity, and attention factors are the most suited to predicting the returns of cryptocurrencies.

Benedetti and Kostovetsky (2021) studied the ICO tokens and concluded that they are often underpriced due to market informational frictions; however, investors receive compensation for the risk borne. The most common risk incurred by investors in the ICO market stems from providing capital to questionable crypto firms. Sockin and Xiong (2020) investigate ICO tokens price by incorporating in their framework investor sentiment, the supply and demand forces, the network effect (e.g., users' number, transaction participation), and Blockchain specifics variables such as min-

ing factors and attacks. Their findings prove that the network effect, the supply, investor sentiment, and Blockchain specifics affect the expected returns. A number of recent papers have developed pricing models for cryptocurrencies, considering the network effect and other Blockchain specifics (Leemoon, 2017; Koutmos, 2018; Biais et al., 2019a; Biais et al., 2020; Makarov & Schoar, 2020; Cong, Li, & Wang, 2021; Huberman, Leshno, & Moallemi, 2021; Momtaz, 2021; Routledge & Zetlin-Jones, 2021; Pagnotta, 2022; Liu, Tsyvinski, & Wu, 2022).

Conclusion: In this section, we focus on the risk-return relationship through the lenses of asset pricing theory. At the same time, we have reviewed the existing literature concerning information efficiency in the crypto-market. Although distinct from traditional securities, cryptocurrencies, and crypto-assets seem to be exposed to similar risk factors as equities. Finding the appropriate risk factors for the crypto-pricing models can be a difficult task. We embrace this challenge, and through this doctoral thesis, we have the ambition to identify and assess new Blockchain risks that may affect the performance of the crypto-market.

## 5 Motivation for research

### 5.1 Subject choice

Often compared to the once disruptive innovation of the internet, Blockchain technology is regarded as a potential revolution for future businesses, industries, or even the whole economy (Wang, Chen, & Xu, 2016). Therefore, having the chance to study and contribute to this research domain represents a great opportunity for any individual from this field. With a long outstanding interest in any financial innovation and a wish to explore the new opportunities arising from Blockchain implementation, this research represents just the beginning of what aims to be an in-depth crypto-market analysis.

Technology is expanding more and more, impacting various domains. In order to keep up with the progress speed, it is important to be always open-minded and ready to embrace the versatility of knowledge. The ever-changing world we live in is full of challenges, and technology is one of the main players in this phenomenon. According to World Economic Forum, soon enough, more than half of the population will need significant re- and upskilling. This could be considered one of the main

reasons why more and more universities nowadays choose to reshape their studying programs, embrace information about technology, and encourage students to be part of this major innovation (Eisenberg, 2019).

Blockchain represents a breakthrough technology with high potential and vast applicability to various business areas (Wang, Chen, & Xu, 2016). Being part of this journey of innovation, which seems to promise so much change in the world, represents a privilege and an unmissable occasion to bring valuable contributions to a field that interests me the most.

## 5.2 Social justification

The need for decentralized management and financial systems had been around for decades before the Blockchain invention. Sharpe (1981) debates the benefits of decentralized management and consensus<sup>12</sup> in portfolio investment, showing that decentralized governance can give optimal results even in a myopic decision scenario. The World Bank drew attention to *“the economic failure of the centralized, authoritarian state”* (p. 19, Dillinger and Fay, 1999) and stressed the importance of a decentralized system that could promote both economic and political stability. Nakamoto (2009), the inventor of bitcoin and Blockchain technology, explains that his innovation aims to substitute traditional payment tools and provide a peer-to-peer (without an intermediary), decentralized and secure alternative. Moreover, in the genesis block of the first Blockchain, Nakamoto inserted a message referring to the malfunctioning financial system: *“The Times 03/Jan/2009 Chancellor on the brink of second bailout for banks”* (Reddit, 2018). This action has been perceived as an explanation for his invention, which is to save the world from an unreliable and over-powerful system and give control back to the people through a decentralized tool.

If initially conceived with the purpose of supporting electronic payments and the development of virtual currencies, namely bitcoin (Nakamoto, 2009), the contemporary Blockchain evolved and has multiple uses, such as data sharing, digital voting, or ownership. Although this technology’s most significant contributions are in the financial area, it succeeded in attracting the attention of people from various industries, such as auditing, property management, and copyright protection (Zhao,

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<sup>12</sup>Consensus here refers to the agreement among the managers on the same estimates for an asset’s valuation.

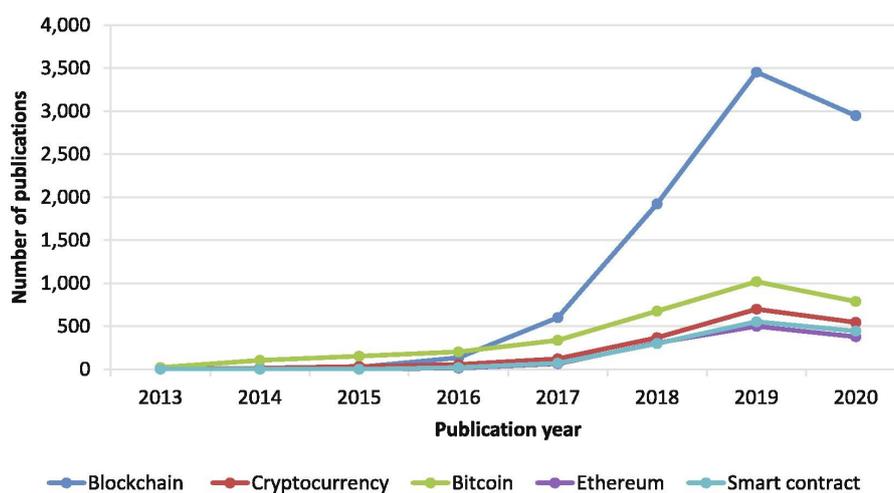
Fan, & Yan, 2016). One more time, history has proved that technology’s power to change businesses and industries should never be belittled. In addition to all the important changes that came along with the technology development (such as the Internet), the Blockchain’s applications bring finance to a more performant level.

### 5.3 Academic justification

The development of Blockchain technologies and the arrival of crypto assets in the financial markets are one of the main current challenges for academics. One of the most obvious pieces of proof is the current explosion in Blockchain research. Since the beginning of 2009, the literature on this topic has constantly grown. We can say that this increase in the amount of research is in line with the development of the crypto-market. By the end of 2017, Bariviera (2017) observed that the Scopus database included about 742 documents<sup>13</sup> with ‘bitcoin’ in its title or keywords. 2018 is the year marked by the crypto-market price explosion, the bitcoin bubble, and a significant increase in the public interest in this market. Of all the crypto-related research in the finance area, 85% of papers have been published since 2018 (Fang et al., 2022). The positive evolution of crypto-related literature in all disciplines combined is shown in Figure 9.

Figure 9: **Publication trends for Blockchain-related topics**

*Line chart for the number of papers published each year for topics related to Blockchain and cryptocurrencies. The data ranges from 2013 to 2020. Source: Gad et al., 2022.*



This section presents the reasons why it is essential that crypto-assets are studied by financial academics. We separate the reasons into two groups.

<sup>13</sup>These research documents are from various fields, such as legal, economics, or computer science.

- First, the crypto market sets itself apart from traditional financial markets. Crypto-assets exhibit completely different financial characteristics compared to stocks, bonds, or even derivatives. Crypto-assets are approximately ten times more volatile than traditional assets (Bariviera & Merediz-Solà, 2021), a phenomenon that has sparked the curiosity of both researchers and investors. Additionally, the literature showed that crypto-assets have a low correlation with established asset classes, which introduced the idea of a new asset class and potential diversification opportunities for investors (Ankenbrand & Bieri, 2018; Baur & Dimpfl, 2018; Corbet et al., 2018; Corbet et al., 2019). We show in Section 4.1, that the valuation of stocks is based on financial data<sup>14</sup>, while in the case of crypto-assets, we have network data as a major price determinant. Most of the literature does not consider technological data such as network variables or other non-financial variables that come from the Blockchain. The technological aspects of the crypto-assets can have a direct financial impact that the literature has not fully answered; for instance: how does the forking event impact the financial characteristics<sup>15</sup> of a coin?

If we look at the existing financial literature on the crypto-market and Blockchain technology, it has mainly focused on bitcoin, cryptocurrencies, and ICOs. At the same time, it can be observed that a common tendency in research is to use bitcoin data while drawing general conclusions at the crypto-market level. Some examples of such kinds of papers are Nasir et al. (2019), Leslie (2020), Makarov and Schoar (2020), and Liu and Tsyvinski (2021). Zieba, Kokoszcyński, and Śledziewska (2019) make a remark on this practice by stating that the crypto-market is heterogeneous and cannot be described by bitcoin alone. According to Bariviera and Merediz-Solà (2021), the most predominant subjects in the crypto-literature are information efficiency, price discovery, volatility, hedging properties, market microstructure, financial bubbles, and other finance-related topics.

The current literature still lacks a proper taxonomy for crypto-assets. There is a variety of Blockchain-based assets that lack a clear distinction from one another, and which makes it difficult to analyze them (e.g., hybrid-tokens). The current financial literature on this topic focuses mostly on cryptocurrencies leaving out the other financial applications of Blockchain technology. Despite the effort made to provide models and/or theories to explain the financial be-

<sup>14</sup>The main valuation techniques used in the stock market are based on dividend payments, earnings, and the book value.

<sup>15</sup>By financial characteristics we refer to the returns, volatility, liquidity, and efficiency of crypto-assets.

havior of cryptocurrencies (Biais et al., 2020; Cong, Li, & Wang, 2021), similar research must be done on other crypto-assets, such as DeFis or NFTs.

- Secondly, the crypto-market is in constant evolution. It is necessary, if not vital, to continuously monitor new developments and to provide academic research to keep up with the growth of the crypto-market.

The unique financial characteristics of crypto-assets that have been determined in the past (Dyhrberg, 2016b; Corbet et al., 2018; Corbet et al., 2019) are now being challenged by recent reports. For instance, cryptocurrencies have widely been advertised in the past as being a potential source of diversification (Briere, Oosterlinck, & Szafarz, 2015; Dyhrberg, 2016b); however, (Iyer, 2022) shows that the correlation between cryptocurrencies and stocks has been increasing (see Table 1). This report could indicate a tendency for the crypto-market to slowly become similar to traditional markets. The increasing regulatory efforts to make the crypto-market a safe place to trade might be one reason for this evolution.

With time, we observed that new types of crypto-assets emerged. This is the result of the technology's evolution and its new applications. Bitcoin is the first cryptocurrency and it gained important popularity for its innovation. At the moment, there are numerous<sup>16</sup> cryptocurrencies available and publicly traded. For example, inside the cryptocurrencies class, we find stablecoins, which are a specific type of cryptocurrencies whose value is pegged to securities or USD. Crypto-assets are not limited to cryptocurrencies only (see Figure 1). Crypto-tokens are another example of Blockchain-based assets. If we go further in subclasses, crypto-tokens include various types of digital assets, such as, for example, the new DeFi tokens and NFTs, which are growing rapidly. As previously said, the current literature has mainly focused on bitcoin, cryptocurrencies, and ICOs. Therefore, we think that it is time for researchers to change their focus to subjects such as the behavior of other crypto-assets (e.g., NFTs and DeFis), which drastically lack academic attention.

If cryptocurrencies have been widely considered a great tool for diversification for equity investors (Briere, Oosterlinck, & Szafarz, 2015; Goodell & Goutte, 2021; Urquhart & Zhang, 2019), new evidence (Iyer, 2022) reveals that the market has changed. We believe that other crypto-assets could have diversification properties. If this is true, investors could diversify risks not only

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<sup>16</sup>As of July 2022 and according to (Coinmarketcap.com, 2022), there are almost 10 000 available cryptocurrencies (traded).

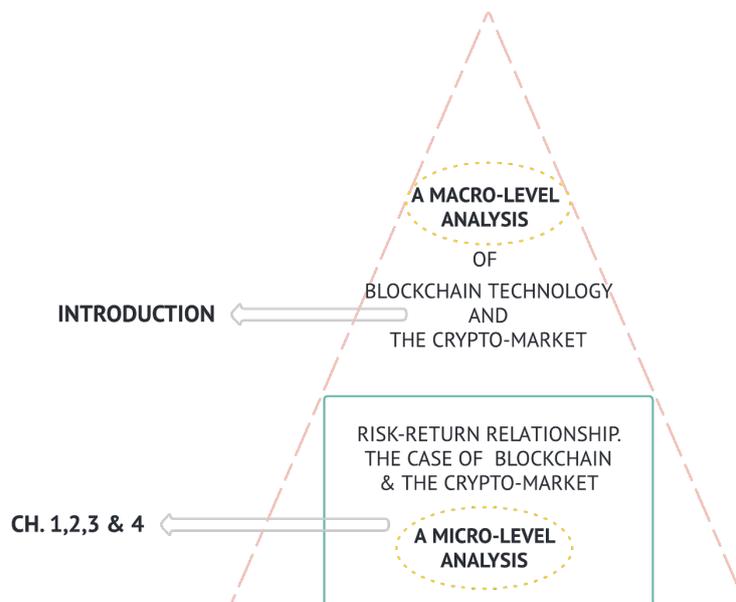
with cryptocurrencies but with other crypto-assets as well. Therefore, we consider it is important to understand the nature of crypto-assets and study their financial proprieties.

## 6 Research problem

In this introductory part of the thesis, we have provided the reader with a global view of what crypto-assets and Blockchain technology are, how the crypto-market has evolved and what is the research state on this topic. After performing this macro-level analysis of the crypto-market and Blockchain technology, in the next chapters, we are going to discuss in detail particular issues related to financial risks and crypto-assets returns. Figure 10 shows the structure of the thesis and its contents.

Figure 10: **Thesis structure and contents**

*Source: The author.*



The crypto-market has attracted important attention from academia, engineers, investors, and the public in general. For their high volatility and speculative behavior, crypto-assets have been isolated as a separate asset class from traditional assets, and the idea of diversification opportunities has arisen. Many papers have stated that the crypto-market is not linked to the real economy (Dyhrberg, 2016b; Caferra & Vidal-Tomás, 2021; Sifat, 2021) and has a low correlation with established asset classes (Ankenbrand & Bieri, 2018; Baur & Dimpfl, 2018; Corbet et al., 2018; Corbet et al., 2019). In recent years, crypto-assets succeeded in becoming one of the

top best-performing financial asset classes, along with Nasdaq 100 stocks and US Large Caps stocks (Sriram, 2021).

In finance, we know that there is a positive relationship between the non-diversifiable risk and returns of an asset. Therefore, since crypto-assets are approximately ten times more volatile than traditional assets (Bariviera & Merediz-Solà, 2021), there is no surprise that they hold the title of the best-performing asset class. The story of financial risk has two faces, meaning that high risk could bring either high returns or high losses. This academic work addresses the following research problem,

**What are the determinants of financial risk and returns in the crypto-market?**

The thesis focuses on the risk-return relationship. It aims to uncover the determinants of financial returns in the crypto-market. More specifically, it studies the unique risks Blockchain-based assets incur (e.g., cryptographic attacks, smart contract attacks, and other technological vulnerabilities), risks that might be the source of the market's inherent volatility (Chapter I). The thesis examines as well the impact of technological events on the financial characteristics of crypto-assets (Chapter II). Additionally, it uncovers the diversity of crypto-assets and their implications for asset pricing (Chapters III & IV).

The general question of this thesis has many dimensions; therefore, in the first chapter, we assess if the financial risks from the crypto-market can be triggered by the technological vulnerabilities of Blockchain technology. The second chapter extends our initial work by analyzing and bringing empirical evidence of how technological events (forks) may translate into financial ones. In the third and fourth chapters, we focus on a specific crypto-asset becoming increasingly popular: the DeFis. We examine the determinants of their returns and propose a factor model for the DeFi market.

**Chapter I: Can financial risks be triggered by technological vulnerabilities of Blockchain technology?**

The first chapter of this dissertation is a literature-based research. In line with (Corbet et al., 2019), we think that *“for new research areas such as those based*

*around cryptocurrencies, a literature analysis can be the most powerful tool to inform academics, professionals, and policy-makers about the current state of knowledge, consensuses, and ambiguities in the emerging discipline” (p.2, Corbet et al., 2019).*

The cryptocurrencies volatility and the numerous cyber-attacks suffered by this technology represent the main driving factors toward the Blockchain’s popularity. Among the existing research literature, several studies have addressed the crypto-market risks. As we have observed, most of the works treat risks independently based on their nature (i.e., economic, political, regulatory, etc.). Our work fills this lack of research by performing a parallel analysis of both financial and technological risks together. Our results show that the risks, regardless of their nature, have many characteristics in common. Furthermore, we provide an empirical demonstration to show that bitcoin’s price instability (financial risk) can be triggered by attacks targeting the crypto-market (technological vulnerability).

**Chapter II:** How do bitcoin’s financial characteristics react to the forking events? How do the characteristics of the forked coin compare to their parent coin?

In the second chapter, we extend the work from the first chapter and propose a research on the causal link between pure technological events, namely forks, and the cryptocurrency’s financial characteristics. This paper focuses exclusively on bitcoin forks and, notably, those that continue to be traded today. To our knowledge, this is the first research assessing the forking event effect on the financial characteristics of the coin. In conducting this research, we use the event study methodology. The results of this work are twofold. In the first part of this research, we show that forks issued during stable market conditions allow for a diminution in returns, [Value-at-Risk \(VaR\)](#), illiquidity, and volatility in the parent coin, unlike what happens for spin-off companies, for instance. In the second part, we show that the forked coins are more risky, illiquid, volatile, less performant, and less efficient than their parent coin.

**Chapter III:** What are the drivers of DeFi tokens returns?

In Chapter III, we focus on a distinct application of Blockchain technology, namely [DeFi](#) platforms. Compared to the relatively vast literature on cryptocurren-

cies, DeFi-related research is scarcer. Motivated by Corbet et al. (2021), Maouchi, Charfeddine, and El Montasser (2021), Schar (2021), and Yousaf, Nekhili, and Gubareva (2022), who show that DeFi tokens are a distinct asset class compared to conventional cryptocurrencies, our goal is to offer a first analysis of the DeFi market returns. In conducting this research, we first design a market index that will enable us to assess the performance of this new asset class and the market as a whole. Afterward, we perform an in-depth analysis of the determinants of DeFi market returns. Here, we consider several possible driving forces, such as: (1) the cryptocurrency market, (2) the network variables, (3) the Total Value Locked (TVL)-to-Market ratio (a measure similar to the ‘book-to-market’ ratio from stocks and adapted to the DeFi market). Our results show that the impact of the cryptocurrency market on DeFi returns is stronger than any other driver considered in this analysis and provides superior explanatory power.

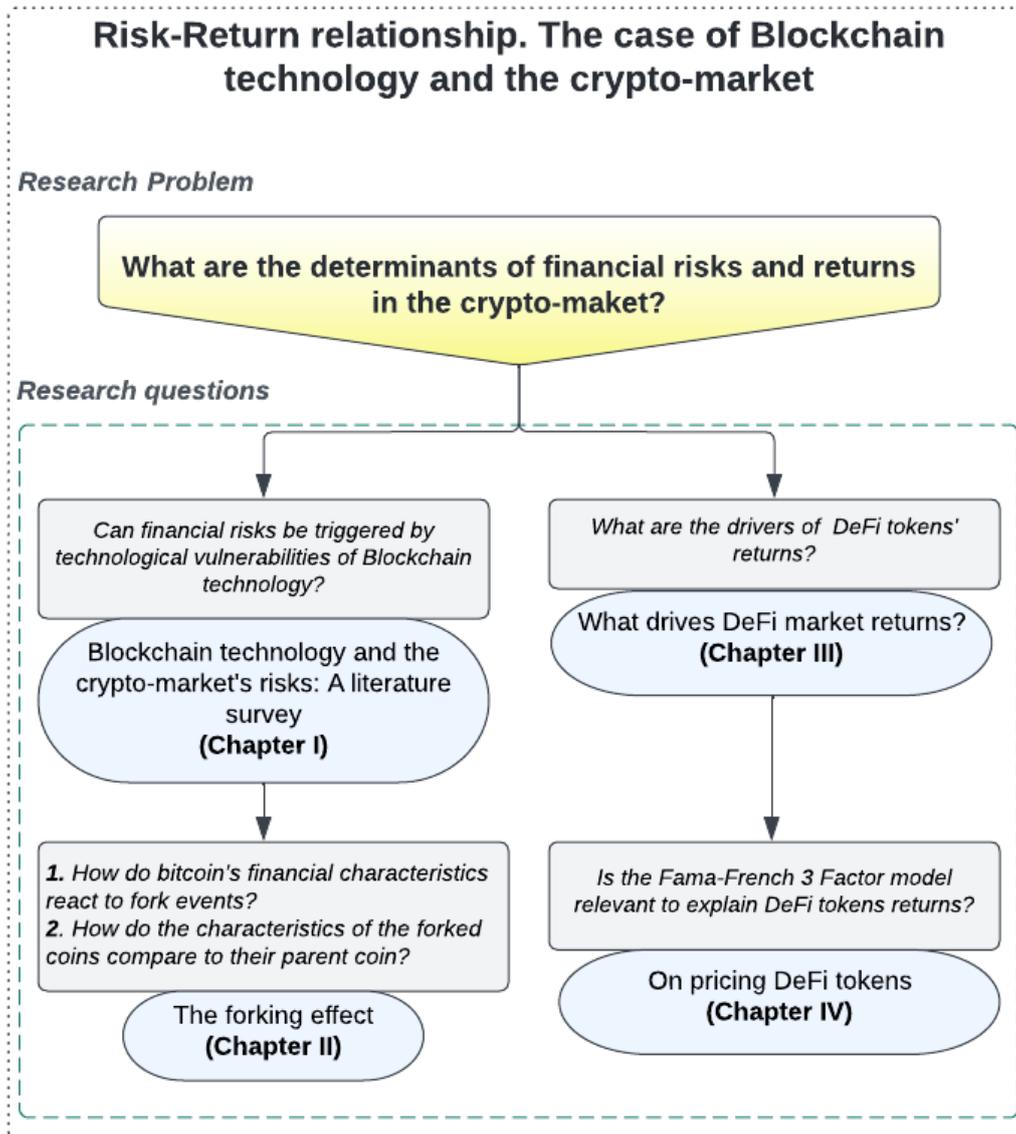
**Chapter IV: Is the Fama-French 3 Factor model relevant to explain DeFi tokens returns?**

Chapter IV extends our work from chapter III on the DeFi market. Here, we propose a three-factor model consisting of market, size, and value factors to model 88 DeFi tokens over a period from 2019 to 2022. We construct the risk factors with DeFi data following the original paper’s methodology (Fama & French, 1992). As a market factor, we use the market index iDeFiX (proposed by Soiman, Dumas, and Jimenez-Garces (2022)). After performing the Fama-French regressions and further checks with the Fama-MacBeth procedure, we conclude that DeFi tokens returns cannot be explained by the traditional asset pricing models based on the stock market. Our results emphasize the importance of using technological variables in pricing Blockchain-based assets, such as for example, the network variables.

Figure 11 summarises the structure of the thesis work and explicitly shows the articulation of the chapters.

Figure 11: **Structure of the dissertation**

Schematic representation of the structure of this dissertation. The yellow square represents the global research problem of this work, while the blue items are the dissertation's chapters answering to their corresponding research questions marked in grey squares. Source: the author



## 7 Contents of the dissertation

### 7.1 Chapter I

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We start this thesis by performing a literature survey on the vulnerabilities and risks of Blockchain technology and the crypto-market. In spite of the great innovative solutions brought by Blockchain, this technology gained most of its fame thanks to its vulnerabilities. The crypto-assets volatility and the numerous cyber-attacks suffered by this technology represent the main driving factors toward the Blockchain's popularity.

With this literature survey, we are trying to answer the following research question: *Can financial risks be triggered by technological vulnerabilities of Blockchain technology?*. To conduct this research, we have used various types of information from both academic and non-academic literature. The number of cited papers in this study exceeds 100. The selection of papers was performed by first considering the topic of investigation; afterward, the information was grouped by type of risk. In our search for relevant literature, we have used many keywords such as: crypto, Blockchain, financial risk, technological risk, attack, financial behavior, Blockchain literacy, etc. Following the example of Benoit et al. (2017)'s literature survey on systemic risk, we complete this literature survey with a short data analysis. The objective of this survey is to provide a two-dimension risk analysis (technological and financial) completed by an assessment of triggering elements (the likelihood).

The complexity of this technology, inherited by nature, represents a challenge for users, investors, and any other participants from this market (Salmela, 2019). According to the latest surveys performed, the main barriers slowing down the Blockchain's adoption are: scalability issues, insufficient regulation, the unproven or debatable value of technology, security threats, lack of in-house skills, and uncertain rate of return (Pawczuk, Massey, & Holdowsky J., 2019; Underscore VC, 2018). As it can be observed, most of the mentioned obstacles are either technological or finance-related. These findings encouraged us to perform this risk assessment. The main goals of our analysis are:

- To understand the vulnerabilities of Blockchain and their possible consequences;
- To offer a broad view of possible financial and technological risks affecting this

market.

In our assessment, we tried to cover the most important risks by considering the likelihood of happening, the exposure of the crypto-market to such incidents, and the (financial) impact they might have. We first grouped and analyzed the Blockchain technology's and crypto-market's exposure to several technological risks: Consensus level attacks, Network level attacks, Cryptographic key threats, and Smart contract threats. Our goal is to give a picture at the market level and since measuring the actual macro-impact of technological vulnerabilities is difficult, we estimate the consequences and possible market exposure in terms of the number of tokens / Blockchains and market share.

A similar approach is used in the analysis of financial risks. We first clustered them by type: total risk, information risk, liquidity risk, supply risk, and environmental risk. Afterward, by considering the technological risks' exposure and potential damages that could eventually trigger financial risks, we analyze them together and propose a conceptual metric to emphasize the likelihood of this happening.

Among all the risks assessed, we show that the Network level attacks and Cryptographic key threats are the most menacing for the crypto-market. The exposure for these technological vulnerabilities is the highest, as possible targets represent most types of Blockchain technologies, their users, mining pools, and exchange platforms. Furthermore, our analysis shows that technological events can indeed trigger financial risks, with a likelihood from Medium to High.

In line with the literature survey done, we provide examples of how financial risk is linked to technological vulnerabilities. More specifically, we perform two short empirical demonstrations:

1. We assess if bitcoin's volatility is affected by events targeting the crypto-market.
2. We investigate the relationship between the returns of bitcoin, its price volatility, and the negative investor's attention (triggered by the technological vulnerabilities).

As initially shown in the literature review, our empirical evidence confirms that bitcoin's price instability (financial risk) can be triggered by attacks targeting the

crypto-market (technological vulnerability) and investors' attention (triggered by technological vulnerabilities).

Conclusion: The objective of this survey is to provide a two-dimension risk analysis (technological and financial) completed by an assessment of triggering elements (the likelihood). Complementary to the literature survey, we perform short data analyses and demonstrate that crypto-assets price stability can be disrupted by technological vulnerabilities characteristic of this market. The empirical demonstration confirms the arguments developed in the literature survey, more specifically, the fact that financial risk can be triggered by technological vulnerabilities characteristic of the crypto-market.

## 7.2 Chapter II

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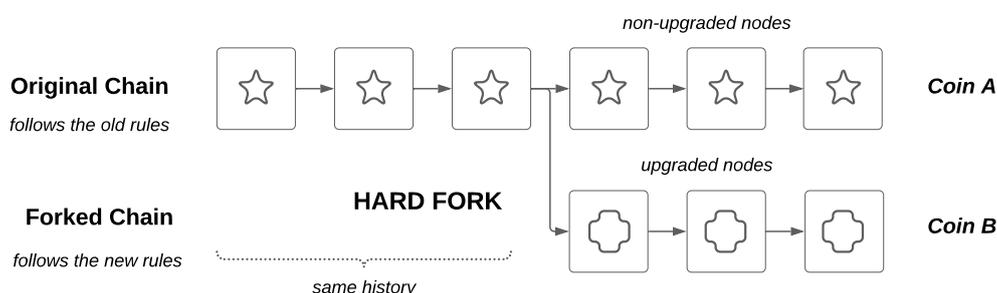
In the second chapter, we offer an extension of our previous work presented in Chapter I. We analyze and bring further empirical evidence of how technological events may translate into financial ones. In this study, we propose a research on the causal link between pure technological events, namely forks, and the cryptocurrency's financial characteristics (e.g., return, volatility, liquidity, and information efficiency). We intend to bring to light the forking effect, which is the financial impact experienced by a cryptocurrency when its Blockchain splits. This study focuses exclusively on bitcoin hard forks and notably those that continue to be traded today.

In the Blockchain world, a fork represents a modification or a breach of its protocols. Similar to, for example, our computers' OS software that makes updates and upgrades all the time, the Blockchain consensus algorithm needs to evolve and undergo regular changes (Islam, Mäntymäki, & Turunen, 2019b). A hard fork is an event when a Blockchain protocol is radically changed, resulting in a chain split (a Blockchain following the old rules and a Blockchain following the new rules). The chain following new rules gives birth to a new cryptocurrency, which with enough support, will eventually evolve as an independent Blockchain. Forking events are generally planned and pre-announced. A graphical representation of hard forks can be seen in Figure 12.

Since their inception, cryptocurrencies have gradually gained significant attention provoking an explosion in Blockchain research. Despite all recent efforts, we observe that the current literature does not seem to propose enough answers given

Figure 12: **Blockchain Hard Fork**

An illustration of what is a hard fork. Source: adapted from *Bitcoin-Central.com (2018)*



the market needs. In particular, we mention the relatively scarce work on Blockchain forks. Our investigation focuses on the effects of forking events on the returns, risk, liquidity, and efficiency of the parent coin (bitcoin). Afterward, we look at both bitcoin and the newly forked coins and compare their performance in the long term.

In order to perform this study, we retrieved the bitcoin/USD closing price and volume from late 2013 to 2020. For computations, we have used the CRIX crypto-market index. We have identified 30 bitcoin forks that still exist up to April 2021. All the cryptocurrencies' financial data was retrieved from CoinGecko and CoinMarketCap (depending on their availability). The relevant data related to forks, such as the name, the issuing dates, trading dates, etc., were retrieved from multiple websites (shown in the Appendix II.A.2, Table II.3).

In conducting this research, we use the event study methodology. Furthermore, we explore the associated data, and we formulate the following research questions: (1) *How do bitcoin's financial characteristics react to fork events*, and (2) *How do the characteristics of the forked coins compare to their parent coin (bitcoin)?*

According to the event study methodology (MacKinlay, 1997), assessing the forking effect implies verifying the pre- and post-event market reactions. A point to be noted is that most of the forking events occur during the extreme hype around bitcoin, which also coincides with the bubble time (2017 - 2018). Similar to the existing literature (Koutmos, 2020; Yaya et al., 2021), we decided to isolate the crypto-bubble period. Therefore, we examine the forking effect during stable and tumultuous times and observe if there are any differences. We provide a separation in the results for the forks occurring during the bubble and those emerging during

stable times.

The results of our study are twofold. First, we show that forks issued during stable market conditions allow for a diminution in returns, VaR, illiquidity, and volatility in the parent coin. Given that the crypto-market is known to be highly inefficient (Tran & Leirvik, 2020; Hu, Valera, & Oxley, 2019; Bariviera, 2017; Nadarajah & Chu, 2017; Urquhart, 2016), we show that forks are worsening their parent coin's efficiency. However, this is not valid all the time. For example, the forks occurring during stressed market times, such as the 2017-2018 cryptocurrency bubble, increase the returns and risk carried by their parent coin and improve its efficiency. The stronger efficiency could be explained by the arrival of more information (about forking events) at a time when the proportion of noise is high. Afterward, we checked separately for the drivers of efficiency improvement and found that this improved efficiency is explained by a volume effect.

In the second part of the study, we show that forks are more risky, illiquid, volatile, less performant, and less efficient than their parent coin; facts that, with time, seem to accentuate even more. Furthermore, we have observed that early forks display similar characteristics as their parent coin, whereas those occurring during the bubble and afterward appear to be significantly riskier and less efficient. This result could be justified by two facts: (1) investors may disregard the new cryptocurrencies' value due to their shorter life history, or (2) the global uncertainty about cryptocurrencies is increasing with time, a fact shown in the chaotic market behavior.

Conclusion: In this paper, we study the forking effect, which represents the impact suffered by a cryptocurrency when its underlying Blockchain splits. We show that forks issued during stable periods reduce the return of their parent coin due to a significant decrease in illiquidity, risk, and volatility. At the same time, the forks occurring during the 2017-2018 bubble caused an increase in the loss risk (VaR) for the parent coin and improved its efficiency. Furthermore, we compare the forked coins with their parent and show that the newly traded coins are significantly less liquid, riskier, and more volatile than their parent coin.

### 7.3 Chapter III

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In the third chapter, we investigate the possible drivers of DeFi token returns.

DeFi stands for Decentralized finance and represents the latest Blockchain-based solutions aiming to provide fully automated financial services. DeFi is a fast-growing sub-sector of the crypto-financial market (Corbet et al., 2021; Ramos & Zanko, 2021b). Its solutions cover most functions of the traditional financial system, from funds transfer to margin trading, interest-earning, and market-making.

Compared to the vast literature on cryptocurrencies, DeFi-related research is scarcer. Motivated by Corbet et al. (2021), Maouchi, Charfeddine, and El Montasser (2021), Schar (2021), and Yousaf, Nekhili, and Gubareva (2022), who show that DeFi tokens are a distinct asset class compared to conventional cryptocurrencies, our goal is to offer a first analysis of the DeFi market as a whole and answer to the following research question: *What are the drivers of DeFi tokens returns?*

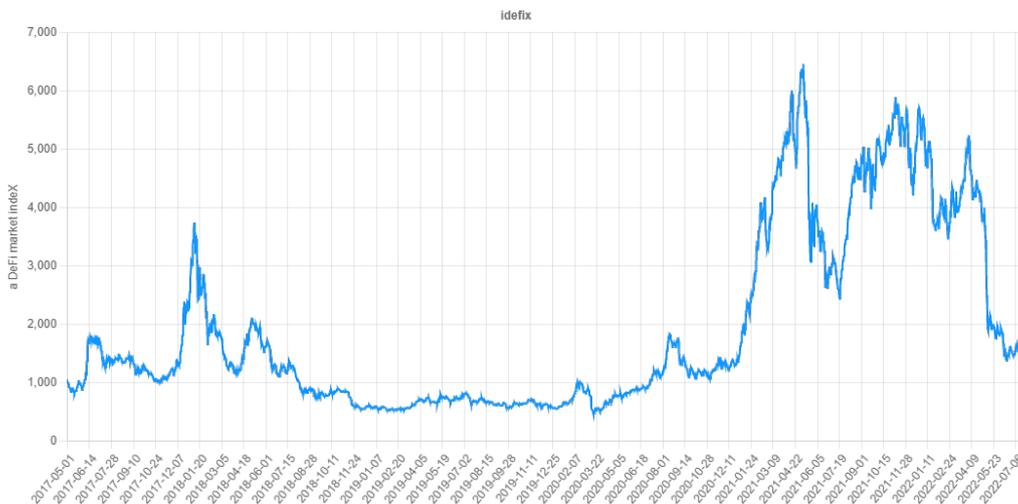
Following the study of Liu and Tsyvinski (2021), we thus investigate three possible drivers of DeFi returns: (1) taking into account that both cryptocurrencies and DeFi tokens run on Blockchain technology and belong to the crypto-market, we assess the cryptocurrencies return impact on DeFis returns; (2) the exposure to network variables to see if the DeFi market is as well exposed to the same factors as cryptocurrencies (Liu & Tsyvinski, 2021); and (3) motivated by relevant studies (Pontiff & Schall, 1998; Ball et al., 2020; Cong, Li, & Wang, 2021; Liu & Tsyvinski, 2021) tackling the valuation ratio importance in driving future returns, we want to investigate if DeFis returns are impacted by a ratio similar to the ‘book-to-market’.

In performing this study, we are using various types of data and extracting it from multiple sources. We access Coinmarketcap.com and spglobal.com platforms to collect financial data for our DeFi tokens as well as for bitcoin, ether coin, and the CRIX index. With the financial data extracted from Coinmarketcap, we construct a market index that we name iDeFiX, as the value-weighted return of all underlying tokens. Since DeFi tokens are distinct from classical cryptocurrencies, we design a new dedicated market index that will allow us to accurately assess the DeFi market as a whole. In the construction of iDeFiX, we use the methodology and original code for the CRIX index (Trimborn & Härdle, 2018). Figure 13 shows the price evolution of our index, iDeFiX.

We use three measures to proxy the network effect on the DeFi market: the number of wallet users, the number of active addresses, and the Total Value Locked (TVL). Then, we measure the investor’s attention with google data (weekly fre-

Figure 13: **Index for DeFi tokens: iDeFiX**

Price of the index for DeFi tokens from 2017 to 2022: *iDeFiX*. The index is computed following the methodology of Trimborn and Härdle (2018). The data is available at: <https://hpac.imag.fr/cryptotracker/dashboards/idefix.html>.



quency). Considering that cryptocurrencies and DeFi tokens run on Blockchain technology and belong to the crypto-market, we first assess the exposure of DeFi token returns to the cryptocurrency market. Our results show that the cryptocurrency market strongly influences DeFis returns, which is in line with Corbet et al., 2021 and Yousaf and Yarovaya, 2021.

The network effect in the crypto-market could be described as: the cryptocurrencies value and utility increase when more people join the network/Blockchain. Vast literature (e.g., Ante, 2020; Cong, Li, and Wang, 2021; Liu and Tsyvinski, 2021) showed that the cryptocurrency market is highly impacted by its network effect. Therefore, our contribution is to assess if the same holds for DeFi tokens. While all three network variables (TVL, transaction, and wallet number) seem to have an important impact on DeFis returns, the transactions number and TVL seem to be the most significant ones.

Motivated by the existing literature on the cryptocurrency market and studies of other financial markets, we investigate if DeFis returns are driven by their ‘book-to-market’ ratio. As there is no standard ‘book’ value for DeFi tokens, we have constructed a Book-to-Market ratio for the DeFi market by dividing the TVL by the Market Capitalization (MC). TVL is a unique variable characteristic of the DeFi market. More specifically, it reflects the amount of funds committed to DeFi platforms, and it is an indicator of market growth and success. The results obtained

do not offer any obvious answers. Hence, we conclude that there is not enough evidence to support our assumption that the TVL-to-Market ratio contains information about future DeFis returns.

Overall, our empirical study shows that the impact of the cryptocurrency market on DeFi returns is stronger than any other driver considered in this analysis and provides superior explanatory power (highest  $R^2$ ). This result could be explained by the bidirectional causality relationship between Bitcoin (BTC) returns and iDeFiX returns and the long-term correlation between BTC and DeFi tokens revealed by the cointegration test.

Conclusion: In this work, we perform an in-depth analysis of the determinants of the DeFi market returns. We consider several possible driving forces, such as: (1) the cryptocurrency market, (2) the network variables, and (3) the TVL-to-Market ratio. Our results show that the impact of the cryptocurrency market on DeFis returns is stronger than any other considered driver.

## 7.4 Chapter IV

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In this chapter, we extend the work from chapter III and consider the Fama-French 3 Factor Model (FF3F), consisting of market, size and value factors, to model DeFi token returns.

The launch of Blockchain-based decentralized finance platforms has been a turning point for financial applications since it allows users to do more with their crypto-assets than send them from point A to point B. DeFi platforms can perform most of the things banks do — lend, trade assets, earn interest, buy insurance, borrow, trade, and much more (Coinbase.com, 2022). The DeFi market is relatively young, as the first official DeFi platform, MakerDAO, was launched in the late 2017 (Coinmarketcap.com, 2022). As a consequence of its youth, DeFi-related literature is scarce. It comprises only subjects such as the platform’s liquidity and efficiency (Gudgeon et al., 2020), DeFi’s potential in the context of traditional financial economy (Zetsche, Arner, & Buckley, 2020), financial bubbles (Corbet et al., 2021; Maouchi, Charfeddine, & El Montasser, 2021), the risk transmission among crypto-assets (Karim et al., 2022), and the lack of regulation within DeFi market (Anker-Sorensen & Zetsche, 2021; Aramonte, Huang, & Schrimpf, 2021).

The existing crypto-related literature has shown the importance of crypto-assets in the diversification of equity portfolios (Ankenbrand & Bieri, 2018; Briere, Oosterlinck, & Szafarz, 2015), this being valid as well during stressed periods such as COVID-19 (Goodell & Goutte, 2021). From here, we assume that DeFi tokens could be as well used by investors to maximize their profits and diversify risks. From our knowledge, DeFis returns' properties have not yet been explored in the current literature. With the aim to enclose this gap, our goal is to study the financial behavior of DeFi tokens and answer the following research question: *Is the Fama-French 3 Factor model relevant to explain DeFi tokens returns?* We examine whether the Fama-French model adapted to the DeFi market can explain the tokens' returns. From our knowledge, we are the first ones to test if the size and 'book-to-market' factors are priced by the market and to examine the cross-section of DeFis returns.

We constructed the risk factors following the original paper's methodology (Fama & French, 1992). As a market factor, we use the market index iDeFiX. Our initial results show that all the risk factors considered are priced by the market. Moreover, we found that the relationship between the returns and the exposure to the size and value factors is negative. If such findings are not surprising for the academic literature, as it has previously appeared in the other financial markets outside the US (Heston, Rouwenhorst, & Wessels, 1999), DeFi tokens seem to be the first crypto-assets to suffer from this phenomenon.

Furthermore, we performed additional tests, such as the Fama-MacBeth procedure. Once the cross-sectional correlations are taken into consideration, our results change, and none of the risk factors are priced. Motivated by the literature showing that the cryptocurrency market is an important driver for DeFis returns (Soiman, Dumas, & Jimenez-Garces, 2022), we decided to check if the risk factor represented by the CRIX index captures the variations in DeFis returns. In order to make this assessment, we have replaced our previous market index, iDeFiX, with the CRIX index and performed the same Fama-French 3 Factor Model (FF3F) and Fama-MacBeth checks. The results obtained show no change from the previous ones obtained. By that, we mean that regardless of which market index is used, DeFi tokens returns cannot be explained by the traditional asset pricing models based on the stock market, or at least not by using just financial information.

Conclusion: In this study, we examine the relevance of the Fama-French 3 Factor model in the DeFi market. We propose a three-factor pricing model consisting of market, size, and value factors constructed with DeFi data. After performing the Fama-French regressions and further checks with the Fama-MacBeth procedure, we conclude that DeFi tokens returns cannot be explained by the traditional asset pricing models based on the stock market. Our results emphasize the importance of using technological variables in pricing Blockchain-based assets, such as for example, the network variables.

# Chapter I

## Blockchain technology and the crypto-market's risks: A literature survey <sup>1</sup>

### I.1 Introduction

It is well-known that Blockchain technology has enormous potential and is capable of revolutionizing business models and reinventing contemporary firms. This globally distributed, open and transparent database, which stores and transfers information of any kind (money, art, science, titles, votes, etc.) has the potential to create new foundations for the economy and business sector. Widely considered a complex technology, the idea behind Blockchain lies in simple concepts (Tapscott & Tapscott, 2016; Iansiti & Lakhani, 2017) and which, in turn, it aims to simplify the mechanics of payments and various business operations. One of the current challenges, as it is shown in the literature (Iansiti & Lakhani, 2017; Charles, 2019; Wachsman, 2019), represents the fact that Blockchain can not keep its promises before it overcomes the technological, organizational, and social barriers that slow down the development of this market.

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<sup>1</sup>This paper has been presented at the 12th International Multi-Conference on Complexity, Informatics and Cybernetics (IMCIC 2021) in Orlando, USA, and at Workshop Blockchains & Cryptomonnaies 2021 in Grenoble, France. We mention as well the fact that this chapter is in revision with Research in International Business and Finance Journal.

Inspired by the existing systems and technologies<sup>2</sup>, the solutions promised by Blockchain seem to be far beyond what was already seen. Slowly, Blockchain is taking over many sectors of the economy, and a growing number of organizations are declaring their enthusiasm and interest in using it (Collomb & Sok, 2016). Given the spread of Blockchain-based solutions across various industries and the growing interest in using them, there is a need for researchers and market participants to understand Blockchain technology and what are the challenges of being part of the crypto-market.

As previously mentioned, Blockchain needs to overcome a series of 'provocations' before becoming a mainstream technology. According to Iansiti and Lakhani (2017), two dimensions are affecting the way technology evolves. The first dimension represents novelty, referring to the degree of originality and uniqueness compared to the existing systems. This dimension also implies the difficulty in seeing the use and innovation of technology. The second dimension refers to complexity, implying the extent to which this technology touches various fields, regardless of the market or area of expertise (Iansiti & Lakhani, 2017; Notheisen & Weinhardt, 2019). The same idea is sustained in the surveys conducted by Deloitte and Underscore companies. While assessing the Blockchain adoption, Deloitte found out that some of the main barriers are: technological complexity, regulatory issues, lack of in-house skills and understanding, security threats, and uncertain profitability (Pawczuk, Massey, & Holdowsky J., 2019; Underscore VC, 2018). In 2018, Gazali, Ismail, and Amboala (2018) explored the relationship between human conduct and the intention to invest in the crypto-market. Consequently, they found out that the attitude towards the crypto-market, the social norms<sup>3</sup>, the risk tolerance and the perceived benefits coming from using this technology, represent some of the main factors influencing the interested parties to invest or be part of the crypto-market.

Regardless of the high potential and great innovative solutions brought by Blockchain, this technology gained most of its fame thanks to its vulnerabilities. The crypto-assets' volatility and the numerous cyber-attacks suffered by this technology represent the main driving factors toward the Blockchain's popularity. Among the existing research literature, several studies have addressed the crypto-market risks.

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<sup>2</sup> "The Internet has democratized the information, the Blockchain will democratize the transaction", own translation from original: "Internet a démocratisé l'information, la Blockchain va démocratiser la transaction" (Beddiar & Imbault, 2018).

<sup>3</sup>Decisions are made based on the actual trends and influenced by a mentality such as: 'if I lose, at least I am not alone'.

Some to find solutions to these vulnerabilities (Bonneau et al., 2015; Stewart et al., 2018; Ma et al., 2018; Goffard, 2019; Morganti, Schiavone, & Bondavalli, 2019; Drljevic, Aranda, & Stantchev, 2019; Patel, 2020), while others just to increase general awareness (Saad et al., 2019; Canh et al., 2019; Lemieux, 2016; Gazali, Ismail, & Amboala, 2018; Lu, 2019).

In previous papers, risks are usually treated independently based on their nature (i.e., economic, political, regulatory, etc.). Following the review of the existing research, we propose to fill the literature gap and perform an analysis in parallel of both financial and technological risks. Our contribution shows that these risks, regardless of their nature, have many characteristics in common. Moreover, we offer ways to determine the likelihood that technological risks could transform into financial ones and provide a short empirical demonstration.

This study is a literature-based research. Of the same mind as Corbet et al. (2019), our study follows a similar belief, namely: “for new research areas such as those based around crypto-assets, a literature analysis can be the most powerful tool to inform academics, professionals, and policy-makers about the current state of knowledge, consensuses, and ambiguities in the emerging discipline”. In conducting this research, we have used various types of information, from both academic<sup>4</sup> and non-academic<sup>5</sup> literature. The selection of papers was performed by first taking into account the topic of investigation; afterward, information was grouped by type of risk. In our search, we have used many keywords such as: crypto, Blockchain, financial risk, technological risk, attack, financial behavior, Blockchain literacy, etc. The contributions proceeding from this literature survey answer our research question: *Can financial risks be triggered by technological vulnerabilities of Blockchain technology?* We demonstrate that crypto-assets' price stability can be disrupted by technological vulnerabilities characteristic of this market.

To enlighten our research problem, the objective of this survey is to provide a two-dimension risk analysis (technological and financial) completed by an assessment of triggering elements (the likelihood). Furthermore, following the example of Benoit et al. (2017) literature survey on a different subject, we complete this work with a short data analysis. In line with the statements made in the literature review,

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<sup>4</sup>Literature such as academic journals and academic theses.

<sup>5</sup>Such as websites, official reports issued by research or governmental organizations, magazines, etc.

we show that bitcoin's price instability (financial risk) can be triggered by attacks targeting the crypto-market (technological vulnerability) and investors' attention (triggered by technological vulnerabilities).

The contributions made by this study are multiple: (1) from our knowledge, we are the first ones to analyze jointly the technological and financial risks; (2) we have performed a literature survey based on more than 100 papers; (3) we provide a conceptual measure to assess the likelihood of technological risks triggering financial risks; (4) we provide two short demonstrations showing that the crypto-assets' price stability can be disrupted by technological vulnerabilities characteristic of this market; (5) based on the literature review performed, we provide several future paths for research; and last but not least (6) we have constructed the database used in this study.

This chapter is organized as follows. Section 2 presents the assessment of technological and financial risks. Section 3 proposes a brief empirical illustration. Section 4 discusses the results and concludes.

## I.2 Blockchain risks assessment

In this section, we perform a theoretical risk assessment of the crypto-market. The goals of this assessment are:

- To understand the vulnerabilities of Blockchain and their possible consequences;
- To offer a broad view of possible financial and technological risks affecting this market.

According to Leemoon (2017), crypto-market's challenges can be divided into four main areas:

1. Technological issues
2. Financial issues
3. Policy and legal issues
4. Political issues

While all four types of risks are indisputably affecting the crypto-market development and slowing its acceptance, we consider that the first two could represent a starting point and reliable support in better understanding the nature of this market. That being said, in this study, we tackle the first two categories, leaving the last two for future research. We make a parallel analysis of the technological and financial risks.

The complexity of this technology, inherited by nature, represents a challenge for users, investors, and any other participants from this market (Salmela, 2019). Highly secure at first sight, Blockchain is not exempt from risks but is instead an imperfect innovation leaving generous room for many improvements (Iwamura et al., 2019). According to Swan (2017), Blockchain technology is the only one that has the potential to change or, better said, to revolutionize the way businesses and financial markets work.

According to the latest surveys performed, the main barriers slowing down the Blockchain's adoption are: scalability issues, insufficient regulation, the unproven or debatable value of technology, security threats, lack of in-house skills, and uncertain rate of return (Underscore VC, 2018; Pawczuk, Massey, & Holdowsky J., 2019). As we can observe, most of the mentioned obstacles are either technological or finance-related. These findings encourage us to perform a risk assessment and support the necessity of prioritizing the first two categories of risks, namely the financial and technological ones.

### I.2.1 Technological risks

Here, we arrange the crypto-market threats in accordance with their nature, namely, consensus-level attacks, network-level attacks, cryptographic key attacks, and smart contract attacks. There are many types of attacks that are not discussed in this study. However, we tried to cover the most important ones by taking into account the likelihood, the exposure of the crypto-market to such incidents, and the (financial) impact they might have.

**Consensus algorithms** for Blockchain technology represent a code-based protocol aiming to facilitate reaching agreement processes within a network. These algorithms came as a solution to the '*Byzantine General Problem*', which concerns

the failure of reaching consensus due to faulty actors (Zhang et al., 2019). The most popular and widespread consensus algorithms in Blockchain technology are the PoW, PoS, and the Practical Byzantine Fault Tolerance (PBFT) protocols (see Table I.1).

Table I.1: Comparison of most notable consensus mechanisms used in the Blockchain applications

Proprieties	PoW	PoS	PBFT
Blockchain type	<i>Permissionless</i>	<i>Permissionless</i>	<i>Permissioned</i>
Fault Tolerance	<i>&lt;50%(of computing power)</i>	<i>&lt;50%(of stake)</i>	<i>&lt;33%(of faulty nodes)</i>

The most noteworthy **attacks at the consensus level**, are:

Nothing at stake attack: on the PoS protocol, where low-stake owners try to decrease the value of the crypto-asset. Indeed, the control inside the system is given based on the user’s wealth, potentially combined with other factors (coin age-based selection or random factors). Any PoS Blockchain can be exposed to this type of attack, especially in their beginnings, when there are no real imbalances among the users’ wealth and low stake owners will not lose much (Morganti, Schiavone, & Bondavalli, 2019).

The majority attack (>50% attack): means that the consensus protocol is compromised, functioning as a monopolistic system. Considering its possible implications, the majority attack is also considered a security issue. Moreover, considering the target type, it can be split into two variants: ‘the >50% (or 51%) computational power attack’<sup>6</sup> and ‘The 51% stake attack’<sup>7</sup>(Tuwiner, 2021; Blockchain.com, 2020).

Bitcoin has never experienced a successful majority attack. However, we cannot say the same about altcoins: Feathercoin (June 2013), Bitcoin Gold (May 2018), Vertcoin (December 2018), Ethereum Classic (January 2019), and Bitcoin Cash (May 2019) (Beigel, 2019). The size of the Blockchain network very much influences the difficulty of executing an attack. Table I.2 shows how expensive it is to per-

<sup>6</sup>an attack on the PoW protocol, implying the possession of more than 50% of the total mining power, with the purpose to manipulate and corrupt the network.

<sup>7</sup>An attack targeting the PoS protocol; it implies the possession of more than 50% of the total circulating supply of coins (within the same network) with the purpose to gain monopoly power and mislead the system for profit purposes. It is conceptually similar to a computational power attack.

form a majority attack, depending on the crypto-asset. These costs are computed taking into account the expenses incurred in the mining process, namely the network hash rate & the Nicehash cost in BTC/per hour (rented PC power). These values can change every minute, as the crypto-assets’ prices have a strong influence (Crypto51.app, 2022).

Table I.2: **PoW 51% attack theoretical cost**

System	Hash rate	1h attack estimated Cost
Bitcoin	261,883 PH/s	\$633,989
Litecoin	613 TH/s	\$74,647
Ethereum Classic	136 TH/s	\$13,273
Bitcoin Cash	2,020 PH/s	\$4,890
Bitcoin SV	693 PH/s	\$1,679
Zcash	11 GH/s	\$6,593
Dash	2 PH/s	\$1,063

*Values computed in November 2022, and which exclude the block rewards*

Source: derived from Crypto51.app, 2022

**Network level attacks** are widely considered difficult and expensive to perform (Koshik, 2019); however, they should never be regarded as impossible.

**Distributed Denial of Service (DDoS)**: refers to an attack on the host, aiming to disrupt the normal operation process. If, for example, the (host) Blockchain system is under attack, it can become unresponsive and unavailable. The system is compromised by being fed with misleading information or large amounts of data (Zhang et al., 2019). DDoS attacks can have a notable impact within the crypto-market, as they can target Blockchains<sup>8</sup>, exchange and trading platforms, and even mining pools (Abhishta et al., 2019; Litecoinpool.org, 2020). These attacks are highly associated with the increase in value and popularity of the crypto-assets (Crothers, 2021).

Some other notable examples of network-level attacks, worth mentioning if we take into account the exposure and the powerful impact they could have, are the Sybil attack<sup>9</sup> and the Eclipse attack<sup>10</sup>. From our knowledge, there is no Sybil or Eclipse attack successfully performed on the Blockchain technology, in practice, but researchers have made theoretical demonstrations for the Eclipse attacks on both

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<sup>8</sup>The difficulty to execute an attack is very much influenced by the size of the Blockchain network. Private Blockchains are considered more exposed compared to public ones, as they usually grow around just 100 nodes. The adversary needs to control only 33% of the network to perform an attack, which is easier to achieve in small Blockchains (Saad et al., 2019).

<sup>9</sup>A user creates multiple identities and uses them to gain dominance and manipulate the Blockchain system.

<sup>10</sup>Similar to a Sybil attack, Eclipse misleads its victims such as they will see and believe a different truth than the rest of the network.

PoW (Ether and Bitcoin) (Heilman et al., 2015; Koshik, 2019; Marcus, Heilman, & Goldberg, 2018; Wüst & Gervais, 2016) and PoS networks (Zhang et al., 2019). Usually, the network-level attacks are planned so they can precede other assaults (Morganti, Schiavone, & Bondavalli, 2019).

**Cryptographic key attacks.** In Blockchain technology, cryptographic keys give access to funds (through crypto wallets) and play a critical role in transactional processes. In other words, anyone handling the cryptographic keys can access the wallet account and freely manage the associated funds. These keys are stored in crypto wallets. According to the version of the crypto wallet used (software, hardware, cloud, brain<sup>11</sup> or paper), the keys are more or less safe (hardware & paper - most secure, software, brain & cloudless secure). Having such a variety of key storage options gives attackers ideas to approach the wallets in different ways.

Wallet attack: The main causes behind wallet attacks are system hacking, software vulnerabilities, malware, or incorrect usage from the users' side. The objective is to obtain (steal) the private key, with which the attacker can mislead the system, perform unauthorized transactions, and steal coins (send them into the thief's wallet using the victim's private key). Compared to any other type of crypto attack, the ones targeting the wallets are among the most common and harmful incidents<sup>12</sup>. This statement is also supported by the Blockchain Graveyard organization, as according to their thorough analysis of the incidents associated with Blockchain, more than half relate to wallet attacks (Magoo.github.io, 2020).

Some other notable examples of attacks at this level are: the Random number

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<sup>11</sup>It is a type of wallet that gives the user the option to generate a key using a password (a word, number, combination of both, etc.). This type of wallet and keys are considered weak in terms of security.

<sup>12</sup>In 2018, Coincheck's wallets were hacked and lost \$530 million worth of NEM. This incident surpasses even the losses of the Mt. Gox case, being classified as the most significant theft in the crypto history (Shane, 2018).

generator attack<sup>13</sup> and Quantum attacks<sup>14</sup>.

**Smart contract attacks** mainly refer to the manipulation of external data entered in the Blockchain (through oracle technology), misleading the execution of the smart contract. The trigger represents information related to external events, which affects the contract's conditions. The information is manually introduced, the reason why the execution of the system can be easily misled. Blockchain is an open-source technology, giving access to its full code. This is an opportunity for intruders, who may take advantage of this feature and exploit it with malevolent intentions. Concurrently, if the programming language used in the smart contract has weaknesses, this might also create the perfect opportunity for any hacker to initiate a successful attack (Hasanova et al., 2019; Atzei, Bartoletti, & Cimoli, 2017).

Re-entrancy attack, as a variant, refers to a malfunction in the smart contract protocol. During the attack, the hacker sends multiple requests to the system, for example, invoking the call function continuously until the gas supply ends. Overwhelmed by the avalanche of orders, the system will perform inaccurately (Hasanova et al., 2019).

A summary of all technological risks discussed above will be presented in Table I.3.

## I.2.2 Financial risks

In this section, we give the example of several financial risks that can be triggered by technological risks. After detailing how this phenomenon happens and in what kind of circumstances, we propose a conceptual metric with the purpose of emphasizing the likelihood that these technological risks may transform into financial ones.

Determining the likelihood: The likelihood that the technological risks may trans-

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<sup>13</sup>targets the weak security of the cryptographic keys due to insufficient randomness used in their generation process, making them easy to predict (Independent Security Evaluators, 2019); despite the common knowledge that the cryptographic keys are difficult to break, a combination of weak hashing algorithms and skilled hackers have led to such kind of incidents.

<sup>14</sup>performed with the Quantum Computer (QC); In the context of Blockchain technology that does not employ quantum-resistant cryptographic techniques, QC can break the cryptographic keys, corrupt the hashing functions and forge digital signatures. These attacks can have serious implications for the Blockchain network, implying theft of the users' funds, crypto wallet corruption, dominance over the network, and even possible recreation of the entire Blockchain. It is maybe a matter of time until we will have a QC powerful enough able to break the Blockchain technology (Fernandez-Carames & Fraga-Lamas, 2020; Stewart et al., 2018).

Table I.3: Summary of technological risks

	Risk	Consequences	Exposure
Consensus level attack	<b>Nothing at stake attack</b>	<ul style="list-style-type: none"> <li>· Manipulates the system by entering invalid data</li> <li>· Nonopolized consensus process</li> <li>· Manipulates the system</li> </ul>	Blockchains using PoS (over 350 crypto-assets) <sup>a</sup> source: (CryptoState.com, 2020) Blockchains using PoW consensus (over 500 crypto-assets): Blockchains using PoS (over 350 crypto-assets) source: (CryptoState.com, 2020)
	<b>Majority attack</b>	<ul style="list-style-type: none"> <li>· Enters invalid data in the system</li> <li>· Forks the Blockchain</li> <li>· Performs other attacks (Eclipse, double spending, DoS)</li> </ul>	All Blockchains (small ones most exposed) Mining pools Exchange platforms Permissionless Blockchains
	<b>DDoS attack</b>	<ul style="list-style-type: none"> <li>· Manipulates the system by entering invalid or large flow of data</li> <li>· Disrupts the normal operation process</li> <li>· Knocks out part of or the whole network</li> </ul>	Mining pools Exchange platforms
Network level attack	<b>Sybil attack</b>	<ul style="list-style-type: none"> <li>· Manipulates the system</li> <li>· Nonopolized consensus process</li> <li>· Enters invalid data in the system</li> </ul>	Permissionless Blockchains
	<b>Eclipse attack</b>	<ul style="list-style-type: none"> <li>· Manipulates the system</li> <li>· Nonopolized consensus process</li> <li>· Enters invalid data in the system</li> </ul>	Permissionless Blockchains
	<b>Wallet attack</b>	<ul style="list-style-type: none"> <li>· Steals the cryptographic keys</li> <li>· Takes the control of the afferent funds</li> </ul>	All Blockchains
Cryptographic key threats	<b>Random number generator attack</b>	<ul style="list-style-type: none"> <li>· Deters the security and trust of the users</li> <li>· Corrupts the cryptographic keys</li> </ul>	All Blockchains
	<b>Quantum attacks</b>	<ul style="list-style-type: none"> <li>· Corrupts the cryptographic keys</li> <li>· Forges hashing functions</li> <li>· Rewrites Blockchain and manipulation of the network</li> </ul>	All Blockchains that do not employ quantum resistant cryptographic techniques
	<b>Re-entrancy attack</b>	<ul style="list-style-type: none"> <li>· Manipulates the network</li> </ul>	Blockchains supporting smart contracts (over 50 crypto-assets) Source: (CryptoState.com, 2020)
Smart contract threats	<b>Smart contract attack</b>	<ul style="list-style-type: none"> <li>· Misleads the technology's application</li> </ul>	Blockchains supporting smart contracts (over 50 crypto-assets) Source: (CryptoState.com, 2020)

<sup>a</sup>The total number of crypto-assets is over 2200 (CryptoState.com, 2020).

<sup>b</sup>The total number of mining pools is not known, as there are many which keep their identity secret. Therefore, we cannot accurately assess the market exposure with this respect.

form into financial risks can be established by taking into account the severity<sup>15</sup> effect and probability of occurrence of triggering elements. Here, we will also introduce the concepts of financial behavior, responsible investment, and Blockchain literacy as possible tools for assessing risk. Measurement plays an essential role in management. Up to this point, we have different tools to measure financial risks; however, things are not as simple when talking about the triggering elements. According to Kaplan and Norton (1992), if we cannot measure something, then we cannot properly manage it. Therefore, in this part of the assessment, we propose ways to measure the probability of technological vulnerabilities triggering financial risk.

**Total risk.** This is the financial risk arising from high movement in market prices. The most used measure for appraising the total risk of an asset is the volatility of its returns. Following the traditional financial theory, the total risk can be decomposed into the systematic risk and the specific one. If the crypto-market is vulnerable to a risk threatening the whole market, this could be a systematic risk. On the other hand, if we consider risks targeting a specific crypto-asset or type of Blockchain, then this could be an example of specific risk<sup>16</sup>.

From the previous list, by taking into consideration the (technological) risks' exposure and their consequential power, we can quickly identify several attacks capable of triggering financial risks. For instance, the majority attacks (exposure: almost half of the total crypto-market, plus the mining pools), Sybil and Eclipse attacks (target: Permissionless Blockchains - the most common and significant representatives of this market-), DDoS attack, wallet attack, random number generator attack, and quantum attacks (target: all types of Blockchain) can be considered potential triggers for systematic risk. At the same time, if affecting just one type of Blockchain, one crypto-asset, or a few casualties, such as a mining pool/exchange platform, the same technological risk can trigger a specific one.

It is well known that regulatory and cybersecurity-related events influence the crypto-assets prices (Corbet et al., 2019). Subsequently, such events influence the investors' behavior, impacting the crypto-market's volatility. It was also proved that crypto-assets suffer from contagion effects (herding behavior)(da Gama Silva et al., 2019). Bitcoin, Ether, or any other strong and well-known currency have proven their influence over the evolution of the whole crypto-market. In 2017, when Bit-

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<sup>15</sup>Financial losses and investment cost incurred.

<sup>16</sup>Specific risk concerns isolated cases (one crypto-asset or a specific group, usually not dominating the market) and has fewer casualties than a systematic risk, which affects a large part of the market or the whole.

coin prices skyrocketed and crashed, the rest of the crypto-assets followed a similar trend (Antonakakis, Chatziantoniou, & Gabauer, 2019; Pereira & Ferreira, 2019). The strong power of influence and the herding behavior present in the crypto-market may trigger systematic risk. Here, we have the perfect example of how an independent event, initially affecting one currency (specific risk), can eventually transform into a systematic risk<sup>17</sup>, impacting the whole market (Jain, McInish, & Miller, 2019). It is well known that systematic risk can be triggered by various factors such as socio-political, economic, and any other market-related events. In the crypto-market, we can see that on top of the already existing factors, we also have technological vulnerabilities as a possible trigger. Koutmos (2020) showed that despite Bitcoin's relatively independent price behavior, it is still exposed to the same market risks as conventional financial assets. Under the hypothesis of traditional financial theory, the specific risk is diversifiable and is not priced by the market. On the opposite, investors require a risk premium, and, thus, higher returns for compensating the systematic risk they incur. Finally, we state that in spite of its technological nature and distinct vulnerabilities, the whole crypto-market, similar to the traditional financial market, is susceptible to the same financial risks, namely systematic and specific risks.

**Likelihood:** The main triggers for financial market risks are cyber-attacks (technological risks). According to the Blockchain-Graveyard database of crypto attacks, the most frequent and damaging are the ones on cryptographic keys (about half of the total incidents), followed by application vulnerabilities (security breaches) and protocol issues (Magoo.github.io, 2020). Like a vicious circle, good financial conditions in the crypto-market can motivate intruders to perform more attacks (Crothers, 2021). Eventually, depending on the amplitude of damage caused, technological risks might transpose into different financial risks. Since attacks are pretty common in the crypto-market and usually imply important financial losses, we consider that the likelihood is high.

**Information risk** risk refers to the imbalance of information spread among the market players. Conceptually speaking, thanks to its features, Blockchain technology represents itself as a valuable tool in reducing information asymmetry and assuring transparency and trust. However, along with the evolution of the crypto-market, these innovations became more complex, challenging investors and users to

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<sup>17</sup>This was possible through investors' behavior, which tends to associate Bitcoin's image with the one of the whole market.

acknowledge the potential. The novelty and technical nature of the crypto-market may get stakeholders into trouble, as some do not understand it. At the same time, the lack of knowledge and specific skills, sometimes accompanied by insufficient information supplied to the public, increases the uncertainty and restrain towards the crypto-market as a whole.

Compared to any other Blockchain application, **ICO** imposes most of the transparency and information asymmetry problems. The complexity of **ICOs**' white paper<sup>18</sup>, investors' lack of training and insufficient regulation led to manipulation and financial losses for investors. According to the existing literature, most investors in this market lack the required capabilities to interpret the market's signals. The discrepancy between the traditional market and crypto-market pushes investors and users toward questionable sources of information, such as social media. Here, the selection is based on the 'easy-to-interpret' criteria rather than quality and credibility. At the same time, the general opinion surrounding the crypto-market seems to influence the players (investors and users), which might take decisions rather based on the social trends (led by a herd mentality<sup>19</sup>) than rationally. In line with our arguments, Florysiak and Schandlbauer (2018) states that in comparison to an **Initial Public Offering (IPO)** prospectus, the information shared through **ICO** white paper is less standardized (due to insufficient regulation) and more complicated to understand since it describes a new concept of technology business; therefore this information is often omitted by investors or other professionals part of this market. Moreover, the authors discuss that the **ICO** expert ratings are uncorrelated to the content of the white paper, meaning that ratings do not accurately reflect the quality of the project or technology (Florysiak & Schandlbauer, 2018) and which eventually will make it more complicated to integrate information within the market. This could explain the inefficiency of the crypto-market, despite the quantity of information available (Rui Chen & Chen, 2020; Gazali, Ismail, & Amboala, 2018).

Likelihood: Among the most important factors responsible for information risk in the crypto-market, we have the lack of available information (e.g., white/yellow papers, inconsistent data) and insufficient knowledge or understanding for investors

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<sup>18</sup>A white paper is a document describing the technology used in the Blockchain project (**ICO**). It has the purpose of convincing the public that the new crypto-asset offers a good investment opportunity.

<sup>19</sup>A mentality such as an 'If I am losing, at least I am not losing alone' mentality – investors might believe that following trends or the majority provides some security and makes losses easier to tolerate (Gazali, Ismail, & Amboala, 2018).

and users. Due to the poor regulatory framework, intruders found an opportunity to become rich overnight. They issue low-quality crypto-assets, about which there is little information available (incomplete white papers or inconsistent data), and use them to trick the other market players. This risk is behind most of the fraudulent coins or low-quality ICO projects. Reputation might attract more enthusiasts in this market, therefore, we believe that the investors interested in cryptos are pretty diverse. Here, we introduce Blockchain literacy (the ability to understand Blockchain-related knowledge and make informed and effective decisions (Rooij, Lusardi, & Alessie, 2011)) and financial behavior (how individuals gather and interpret information, eventually reflecting in decisional processes (De Bondt et al., 2008)), concepts, as essential factors in the way the market evolves (Zhao & Zhang, 2021). Market signals can be complex, including both information and noise (Rizzi, 2008).

Less mysterious than at the beginning, however, still significantly complicated, the Blockchain world might pose some problems in understanding. Blockchain illiteracy leads to irrational behavior, which eventually reflects in inefficient markets. Taking into account the large number of crypto scams and the important financial losses incurred (especially during the Bitcoin bubble 2017-2018 Zetzsche et al. (2019) and Liebau and Schueffel (2019)), we state that the likelihood of this risk is high.

**Liquidity risk.** A market is said to be liquid if an agent can rapidly make some significant trades without creating an important change in the price (small market impact). In other words, in a liquid market, transactions will likely not change the price, but new information will be smoothly incorporated. On the other hand, an illiquid market (often linked to an inefficient market) will reflect in large volatility in prices (hence a higher probability of an unfair price), a lower number of investors, and lower chances to transact/trade. Liquidity risk can be split into three categories: assets liquidity (refers to the interaction between sellers and buyers on the platform and the asset availability on exchanges), exchange liquidity (refers to the interaction between makers and takers concerning the assets' and the orders' supply) and market liquidity (encompasses the first two) (Crowell, 2020). According to Corbet et al. (2019), liquidity risk is also highly correlated with the events concerning cyber-attacks or regulatory issues as a response to human behavior and investors' attitude towards this market. At the same time, the most debated factors explaining liquidity in the crypto-market are the price, trading volume, capitalization, fees, hash value (for PoW crypto-assets), and the size of the network (Koutmos, 2018).

It is important to mention the fact that liquidity is different from one crypto-asset to another (the well-established ones are more liquid (Wei, 2018; Koutmos, 2020)), as well as from one exchange platform to another. Despite the many benefits associated with liquidity, illiquid environments can also present some advantages, especially for the traders on this market, which can benefit from arbitrage opportunities and purchases at discounts (Crowell, 2020).

Likelihood: Viewed from the crypto-assets' (crypto-assets that claim to be 'money') angle, this risk would translate into an impossibility to be transformed into cash. That being said, one of the principal roles of money (being a medium of exchange) has just failed (Greene & McDowall, 2018). There are many triggers behind crypto-assets illiquidity, among which: token supply algorithm, investors' behavior, available supply, asset usage, fees, exchange platforms failure, etc. As liquidity risk is already well-known in the financial markets (it is one of the determinants for market efficiency), we already know tools to measure it (trading volumes, book depth, the bid-ask spread, different liquidity ratios, etc.) (Jain & Singla, 2018). Similar to traditional securities, the crypto-market suffers from illiquidity during extreme price movement periods (Manahov, 2020). Proof of market efficiency could be the difficulty of manipulating prices. In the crypto-market, specifically concerning bitcoin, a significant herding behavior has been observed. The number of bitcoin whales increased to the impressive number of more than 2 thousand addresses <sup>20</sup> (Bitcoin.com, 2020). Besides the fact that herding implies a significant movement in prices (buy/sell large amounts of crypto-assets), it also has important supply implications as, in the end, there are fewer assets available to trade (Manahov, 2020).

Liquidity is an important characteristic of the market, influencing the investment costs and, implicitly, the desirability to trade. If we look at this risk from the bitcoin side, we could easily state that liquidity risk is very high. Moreover, Nguyen et al. (2019) shows that despite its market capitalization, bitcoin can be vulnerable to competition from new altcoins, as investors tend to diversify their portfolios and compensate for their decrease in bitcoin holdings with altcoins. On the other hand, if we look at the big picture, the one of the crypto-market as a whole (not only bitcoin), where we have over 7000 crypto-assets available (coinmarketcap.com), we state that the likelihood is medium.

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<sup>20</sup>Owning between 1,000 to 10,000 BTC.

**Supply risk** refers to the reserve available of crypto-assets. Some examples of important supply risk triggers are the loss of cryptographic keys (without which there is no possibility to access the afferent funds), cyber-attacks<sup>21</sup>, unclaimed rewards (Coinmetrics.com, 2019), reputation and the programmed limit of supplies. Not all crypto-assets have a maximum supply limit. For example, crypto-assets such as Bitcoin, Ripple, IOTA, Litecoin, and many others have a pre-established limited supply, while coins like Ethereum, Zcash, Monero, and others have no such limits. Following Rational Expectation Equilibrium models, the higher the supply uncertainty, the less informative crypto-assets prices will be. In this case, market prices are less efficient, and supply risk could thus even lead to an information risk (Collomb & Sok, 2016). Compared to fiat currencies, crypto-assets (especially bitcoin) were conceived as being less sensitive to market changes and inflation rates. However, with time we saw that Satoshi's 'perfect' innovation leaves room for further improvement.

Mainly associated with market inefficiency at users' and exchange platforms' cost, the supply risk is affecting the mining and transaction validation processes, as well. Miners are vital in a PoW Blockchain performing both transaction validation and coin 'minting' functions. For successful work, they are rewarded by the system with an amount of newly created crypto coins. The reward offered by the system represents a method to create new coins and increase the available supply of crypto-assets. At the same time, rewards are programmed to decrease steadily until the maximum supply is reached (Eyal & Sirer, 2018). When this happens, the mining reward will be based only on transaction fees (CryptoLi.st, 2020).

Keeping in mind the above arguments, we state that the difficulty in creating (mine) new crypto-assets, the supply limits, and the expenses incurred during this process all significantly impact the supply imbalances and the final value of the assets.

Likelihood: Since market liquidity is driven by the total supply available for trade, we understand that it is an important characteristic for market efficiency as well. Among the most notable triggers for supply issues, we have: token supply algorithm, herding behavior, loss of keys, wallet attacks, etc. (Coinmetrics.com, 2019). If the supply limits are not a risk for all the crypto-assets, it represents a threat at the market level concerning the leader, bitcoin. As initially programmed, bitcoin's max-

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<sup>21</sup>e.g., the coins may stay blocked in the intruder's account for a while, attempting to avoid the public eye.

imum supply is 21 million coins. The already issued coins attain the approximate number of 18 million, supposing that the limit will be reached sometime around 2140 (Ciaian, Rajcaniova, & Kanacs, 2016). As we already discussed the negative sides of limited supply (illiquidity and market inefficiency), we will now mention the bright side of this risk. Similar to commodities such as precious metals and natural gas, crypto-assets with limited supply attain high preference (subsequently high value), being regarded as 'scare' assets. By just looking at the price and market share of bitcoin, we can obviously observe that the investor's choices show a specific preference for this coin. In this case, the financial behavior within this market is under the influence of the 'scarcity gives value' idea (Verhallen, 1982). However, this idea of value can bring important investment costs, as investors putting their money into such assets will consider asking for scarcity premiums on top of the existing ones for other risks (Haase & Zimmermann, 2013). By assessing the supply risk at crypto-market level, we state that the likelihood is medium.

**Environmental risk.** Known as an energy-gourmand, Blockchain technology represents one of the key players in the fight towards the green transition (Charles, 2019). This type of risk concerns specifically the PoW Blockchains, which through their design, require high computational power and much electricity for functioning purposes. According to recent surveys, the bitcoin network is responsible for using about 0.2% of the global electricity and emitting as much carbon dioxide emission as the country of Jordan (Irfan, 2019). Another important aspect to mention is the increasing number of ICOs, which require Ethereum Blockchain (PoW based) for their smart contract application. According to the current statistics, there are over three hundred thousand ether-derived crypto-assets (both active and non-active<sup>22</sup> tokens) (CryptoSlate.com, 2020). We believe that the technological constraints regarding electricity consumption should receive priority consideration; perhaps very soon, the success of ICO projects and the performance of businesses (using Blockchain technology) will be influenced by environmental considerations. In light of the current environmental context, there have been many attempts to reduce the costs and unnecessary pollution, although no significant progress has been made so far (Lasla et al., 2020; Saleh, 2021; Bentov, Gabizon, & Mizrahi, 2016; Lepore et al., 2020). The emergence of mining pools, the use of renewable energy (74% of the used electricity is renewable) and, the lightning network, the emergence of platforms for renting mining power (e.g., Nicehash) are the first steps towards a greener crypto world. We know anyway that there is a long road until we reach the point

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<sup>22</sup>tokens from former ICOs.

of zero-emission power (Irfan, 2019). A solution to stimulate a rapid transition to eco-friendly Blockchains could be the implementation of a tax regime relative to the amount of energy consumed or to the units of carbon emitted per transaction. In this way, the crypto industry could become more aware of its environmental impact, contribute to the domestic economy and hopefully, make an effort to find the best alternative for both the ecosystem and business (Mecca, 2019; Goodkind, Jones, & Berrens, 2020). Simultaneously, with the increasing sensitivity of investors to the social responsibility of their investment (Brown-Liburd & Zamora, 2015), the assets showing negative environmental externalities may be submitted to boycott from investors. The environmental risk thus translates into a financial risk.

Likelihood: We know that during specific economic conditions (pandemics, financial crises, war, etc.), the stability of financial markets can be highly affected. At the same time, as we learn from past events, such as the 2008 financial crisis or COVID-19 pandemics, the most performant and least risky investments were the socially responsible ones (Lins, Servaes, & Tamayo, 2017; Singh et al., 2020; Palma-Ruiz, Castillo-Apráiz, & Gómez-Martínez, 2020). Well-informed market players have concerns regarding enterprise risk management, financial performance, and considerations for the surrounding environments (Ballou, Heitger, & Landes, 2006). As a strategy to decrease risk exposure and make safer ‘investment bets’, investors pay careful attention to what kind of assets they put money in and make more socially responsible investments.

With the creation of crypto-derivatives and tokenized securities, we can consider that the first step towards convergence between the crypto-world and traditional markets was done. Crypto derivatives can now be traded on both exchange platforms and OTC market (Deribit Insights, 2020). Brokers can switch from securities to crypto-assets or trade both. Regarding investment preferences, it was noticed that during turbulent periods and for safety considerations, investors tend to choose financial markets in favor of the crypto-market (Matkovskyy & Jalan, 2019). Taking into account the investors’ preference for ‘safety bets’ and concerns about environmental and social implications, it is believed that a more ecologically oriented Blockchain could significantly change the overall ‘safety’ perception (Lai, 2021). If this kind of risk does not have direct financial losses, it impacts the investment prof-

itability, increasing the costs<sup>23</sup> for financing. As time passes, investors give more attention to the crypto-market; therefore, we consider that, for the moment, the likelihood is Medium. At the same time, we would like to mention that there are many chances that the likelihood becomes high if, from a technological point of view, nothing changes.

A summary of all financial risks discussed above will be presented in Table I.4.

## I.3 Data analysis

### I.3.1 Crypto events impact crypto-assets' price

In line with the literature survey done in the previous section, here we are going to provide an example of how financial risk is linked to technological vulnerabilities. More specifically, we assess if bitcoin's volatility is affected by events targeting the crypto-market. Some preliminary work on this problem has already been done by Corbet et al. (2020), Caporale et al. (2021), and Grobys (2021). Corbet et al. (2020) proved that 17 attacks that took place between 2017 and 2018 had affected the volatility and cross-correlation for the top 8 crypto-assets, while Grobys (2021) showed how the 29 cyber-attacks performed on bitcoin during the 2013–2017 period affected **BTC** and **Ether (ETH)** returns. Caporale et al. (2021) demonstrated how 4693 cyber-attacks targeting not only the crypto-market and happening between 2015 to 2020 created spillovers and contagion effects among the top three crypto-assets.

In our analysis, we are using a sample of 53 events, which cover both the early times of bitcoin 2011-2013 as well as the hype period in 2018. Corbet et al. (2019) showed that among many factors, news related to cyber-attacks have an important impact on the price movement of crypto-assets. As of January 2022, the amounts lost during our events (2011-2018) correspond to a 39 billion Eur (945,066 **BTC**) monetary equivalent. Given the extent of the losses incurred, it would be interesting to investigate if they impact the market. Therefore, in addition to what was already shown, more specifically, that cyber-attacks events impact the price of crypto-assets, we want to take it a little further and see if the market is sensitive to the amounts lost.

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<sup>23</sup>E.g. A company issuing ICO projects can be directly affected by the investors' social considerations, which will reflect in the amount of funds raised or the price/value of their crypto-assets (lower).

Table I.4: Summary of financial risks

Risk	Trigger	Influence / Consequences	Likelihood
<b>Total risk</b>	<i>Cyber-attacks</i> <i>Technological risks</i> <i>Regulatory mismatches</i> <i>Human behavior</i> <i>Reputation</i>	<ul style="list-style-type: none"> <li>• <i>Large loses for investors.</i></li> <li>• <i>A sign that the market is not stable and mature</i></li> <li>• <i>Crypto assets trade with a risk premium relative to the risk investors may incur</i></li> </ul>	High
<b>Information risk</b>	<i>Lack of available information (e.g., white / yellow papers, inconsistent data)</i> <i>Lack of knowledge/ understanding</i> <i>Reputation</i>	<ul style="list-style-type: none"> <li>• <i>Financial losses for uninformed investors.</i></li> <li>• <i>Assets trade at prices far from their fundamental value</i></li> </ul>	High
<b>Liquidity risk</b>	<i>Regulatory mismatches</i> <i>Reputation</i>	<ul style="list-style-type: none"> <li>• <i>Less investors</i></li> <li>• <i>Less efficient market</i></li> </ul>	Medium
<b>Supply risk</b>	<i>Technological issue (supply limits)</i>  <i>Cyber-attacks</i> <i>Loss of cryptographic keys</i>	<ul style="list-style-type: none"> <li>• <i>Deflation, which can be a problem if crypto-assets will work as a method of payment</i></li> <li>• <i>Less efficient market</i></li> </ul>	Medium
<b>Environmental risk</b>	<i>Technological issue (PoW)</i> <i>Reputation</i>  <i>Lack of regulation</i>	<ul style="list-style-type: none"> <li>• <i>Damage for the environment</i></li> <li>• <i>Crypto assets trade with a risk premium relative to their environmental externalities</i></li> </ul>	Medium

This data analysis is an illustration meant to complement our previously performed survey. In accordance with the literature and with the aim to answer our

research question: *Can financial risks be triggered by technological vulnerabilities<sup>24</sup> of Blockchain technology?*, we establish the following hypotheses:

**H1: Bitcoin’s volatility is positively linked to the number of events targeting the crypto-market.**

**H2: Bitcoin’s volatility is positively linked to the amounts lost due to these events targeting the crypto-market.**

Similar to Corbet et al. (2020), Aliu et al. (2020), and Akyildirim et al. (2020) and others, we retrieved the bitcoin prices from the Thomson Reuters Eikon database, while the list of events targeting bitcoin has been taken from Biais et al. (2020). In total, our dataset comprises 53 events (see in Appendix I.A.1 Table I.11), and the historical price data spans from August 2011 to September 2021. In order to verify whether technological events have an influence on the risk of crypto-assets, we investigate the relationship between bitcoin’s volatility and the attacks on bitcoin. We check for the relationship between the volatility and the number of events, as well as the relationship between volatility and the amounts (in terms of bitcoin) lost as a consequence of these events.

In the following section, we are going to compute volatility using the standard deviation method. Our choice is justified by the scope of this analysis: to demonstrate that there is a relationship between bitcoin’s volatility and our events. It is important to mention that for all our computations, our variables have been aggregated on a monthly basis. Table I.5 displays the descriptive statistics of all variables used.

Table I.5: **Descriptive Statistics of all variables**

	volatility	event losses (BTC)	number of events
Median	0.254	4736.000	1.000
Mean	0.341	46743.630	1.407
Std. Deviation	0.271	146592.481	0.636
Skewness	2.306	4.591	1.343
Kurtosis	6.909	22.177	0.832
Minimum	0.089	8.000	1.000
Maximum	1.359	748808.000	3.000

*The table summarizes the descriptive statistics of all variables for the sample period.*

The rationale behind choosing these events as proof of technological vulnerability is the following: most of them are attacks that show the vulnerability of this

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<sup>24</sup>83% of the events considered represent attacks, while the rest of 13% are malevolent actions that were possible thanks to Blockchain’s unique features; more details are provided in the next part.

technology. Some events may represent just the consequence of certain malevolent actions that were accomplished thanks to the distinctive characteristics of this market (e.g., FBI seizes darknet operations) and which eventually demonstrate the vulnerability/drawback of the crypto-market. By distinctive characteristics of this market, we mean:

- Crypto-assets represent a type of virtual currencies; built on open-source software code, they exist and operate just in the online environment. This makes them the target of cyber-attacks that try to exploit any possible vulnerability of this technology.
- Crypto-assets' users need cryptographic keys in order to access their funds or to place transactions. These keys easily become the source of attacks when they are not kept safely or if the code is easy to break.
- The identity protection (anonymity) offered by Blockchain technology attracted many enthusiasts; however, this feature makes it almost impossible to catch hackers/thieves.
- The insufficient regulation and incertitude around the crypto-asset world made them the perfect tool for the black markets; these ones are also the few places accepting crypto-assets as payment.
- The complicated nature of this technology and Blockchain illiteracy. The lack of proper understanding of how this crypto-world works was exploited in many forms to trick the users and steal their coins. An example would be the many scams performed by early crypto-exchange platforms.
- Blockchain's transactions are immutable. That implies as well the fact that in case of an attack, it is impossible to reverse (fraudulent) transactions or to recuperate the stolen funds. This characteristic, together with the anonymity feature, may incite malevolent actors to execute their plans.

For our data analysis, we compute the monthly standard deviation of bitcoin's returns as:

$$\sigma = \sqrt{\sum_{t=1}^T \frac{(R(t) - \mu)^2}{T}}. \quad (\text{I.1})$$

Where  $R(t)$  is the **BTC** return at time  $t$ ,  $\mu$  is the average return, and  $T$  is the number of days of the window considered. Accordingly, with our hypotheses, we

perform two correlation tests using the Pearson test and Spearman’s rank correlation. We want to measure the relationship degree between volatility and the number of events, as well as the relationship between volatility and the amounts lost during these events. Pearson, also known as a parametric correlation test, is one of the most common methods used in assessing the degree of relationship between two linearly related variables (Pearson, 1932). Spearman rho (a non-parametric test) measures the degree of association between two variables (Spearman, 1904). Both tests confirmed that bitcoin’s volatility is correlated (uncorrelated) with the number of events (the amounts lost during these events). The results can be seen in the bellow Table I.6.

Table I.6: **Correlation tests for *volatility versus the number of events and the amounts lost during these events***

Test	p-value	Correlation estimates	Variable
<b>Pearson</b>	0.02156	0.4402268	<i>number of events</i>
<b>Spearman</b>	0.03387	0.4095827	<i>number of events</i>
<b>Pearson</b>	0.6606	0.08853083	<i>amounts lost</i>
<b>Spearman</b>	0.3888	0.4095827	<i>amounts lost</i>

By looking at the p-values (0.02 & 0.03) resulting from our tests for correlation with the number of events, we observe that the results obtained are less than the significance level  $\alpha = 0.05$ . Meaning that the monthly volatility of bitcoin and the number of events targeting it are correlated. At the same time, the high p-values (0.6 & 0.3) that surpass the significance level  $\alpha$  of 0.05, prove that there is no correlation between bitcoin’s volatility and the amounts lost due to events.

Furthermore, we want to check the relationship between bitcoin’s volatility and the amounts lost, and the number of events together. In order to make this check, we perform the following linear regression:

$$\sigma = \alpha + \beta_1 * EVENT_{number} + \beta_2 * EVENT_{amount} + \epsilon. \quad (I.2)$$

Where  $EVENT_{number}$  is the variable representing the monthly volume of events targeting bitcoin and  $EVENT_{amount}$  is the monthly amounts lost, in bitcoins, due to these events. The testing period is from August 2011 to September 2021.

Our regression checks if there is a relationship between the monthly volatility of BTC and the monthly number of events with their respective losses. For the number of events, we obtain a  $\beta_1$  of 0.193 with a p-value equal to 0.026. Meanwhile, for the losses incurred during these events, we obtain a  $\beta_2$  of roughly 0 (precisely -7.589e-8) and a p-value equal to 0.832. Therefore, we conclude that our sample data provided enough evidence to show a relationship between the monthly volatility of bitcoin

and the number of events targeting it. Concurrently, the results prove that there is no significant relationship between bitcoin volatility values and the amounts lost due to events. Detailed results are shown in Appendix I.A.1, Table I.10.

Our analysis shows that the volatility of bitcoin is not influenced by the financial losses incurred but rather by the number of attacks or other malevolent events targeting this market. This result, while in line with the existing literature (Corbet et al., 2020; Caporale et al., 2021; Grobys, 2021; An et al., 2021), proves that participants from the crypto-market are more sensitive to the number of cyber-attacks than to financial losses. A way to justify this would be to analyze the discrepancy between the users' expectations versus reality. Blockchain technology was created to offer a more secure and transparent alternative to the existing payment tools. However, that does not make it immune to cyber-attacks, nor an absolute secure tool. An et al. (2021) has confirmed that cyber risks are negatively associated with crypto-assets' success, damaging their reputation and investors' trust.

Our results have important implications for the regulators working on the crypto-market. In the well-known paper 'Investor Protection and Corporate Valuation', the authors La Porta et al. (2002) state that *“legal protection of investors is an important determinant of the development of financial markets. Where laws are protective of outside investors and well-enforced, investors are willing to finance firms, and financial markets are both broader and more valuable.”* Technological vulnerabilities could perhaps be perceived as less harmful if the investors from the crypto-market are better protected. At the same time, we can see that the development of this market depends not only on technological innovation but also on the legal system that supports it.

### **I.3.2 Negative investor attention impact on crypto-assets' price**

In this section, we investigate the relationship between the returns of **BTC**, the price volatility, and Google Trends. Using a set of keywords related to bitcoin, Blockchain technology, and crypto-assets, we assess if the investor's attention can be captured by the **Google Search Volume (GSV)** and if it impacts bitcoin's performance. This analysis complements the latter one. When the crypto-market becomes the target of an attack or other type of significant event that involves financial losses, these

scenarios usually attract attention. Under the close scrutiny of the public eye and combined with the negative image set by risky events, the crypto-assets' prices often become unstable. Here, we investigate the impact of negative investors' attention triggered by uncertain events such as those studied in [I.3.1](#) analysis.

Despite their relatively short history, crypto-assets have attracted much societal attention, which has been reflected in the large price fluctuations (Hasso, Pelster, & Breitmayer, [2019](#)). Griffin and Shams ([2020](#)) state that given the excessive attention and rapid market capitalization growth, factors which are common in the characterization of financial bubbles, there is no surprise that crypto-assets are subject to price manipulation, misinformation, and speculation. Several studies have identified anomalies in the crypto-assets' returns (Bariviera, [2017](#); Chaim & Laurini, [2019](#); Kristoufek, [2013](#); Urquhart, [2016](#)), which lead to further questions about the crypto-assets' nature (Baur, Hong, & Lee, [2018](#); Dyhrberg, [2016a](#); Krückeberg & Scholz, [2019](#)), the investor's behavior (Benedetti & Kostovetsky, [2021](#); Hasso, Pelster, & Breitmayer, [2019](#); Kallinterakis & Wang, [2019](#)), and financial bubbles (Chaim & Laurini, [2019](#); Cheah & Fry, [2015](#); Corbet et al., [2019](#); Fry & Cheah, [2016](#); Kyriazis, Papadamou, & Corbet, [2020](#)). Compared to other asset classes, crypto-assets seem to be more volatile (Härdle, Harvey, & Reule, [2020](#); Urquhart & Zhang, [2019](#)). According to Lucey et al. ([2022](#)), the risky features of crypto-assets make them particularly attractive to 'amateur' investors. Hence, the presence of such 'noise' traders could be a justification for the high volatility present in the crypto-market and implicitly the significant deviation from the fundamental value (De Long et al., [1990](#)).

Investor's attention, associated with the under- and over-reaction of market participants, has been long considered an explanation for security mispricing (Andrei & Hasler, [2015](#); Baker & Wurgler, [2007](#); Shiller, [2000](#)). The pioneers of behavioral finance, Tversky and Kahneman ([1974](#)), argue that in situations of uncertainty, people tend to ignore the laws of probability and discern events irrationally. In the crypto-market context, this would translate into situations such as investors misinterpreting certain episodes of exponential growth in the crypto-assets prices and choosing to put their capital at risk before considering a scenario such as a financial bubble. With their findings, Lin ([2020](#)) confirms Tversky and Kahneman ([1974](#))'s theory, such as crypto-assets performance drives future investors' attention. This is especially important because investment preferences and selection choices are determined by what news or information catches first the attention of investors (Barber &

Odean, 2008). That being said, if, for instance, crypto-assets perform well and that stimulate the investor’s attention, the chances that this attention attracts more ‘amateurs’ creating noise and irrational price fluctuations increases (Lucey et al., 2022). Al Guindy (2021) states that whether an investor’s attention has a positive or negative influence on the crypto-assets prices is still imprecise.

We follow Liu and Tsyvinski (2021) and use *GSV* as our measure for negative investor’s attention. In their paper, focused exclusively on cryptocurrencies (bitcoin in particular), the negative investor attention measures the change in market attention (online search frequency) coming from risky events associated with the crypto-market. The rationale behind this approach is the following. In this Internet and smart technology era that we live in, our attention is constantly challenged by the overabundance of information available. Google engine accounts for approximately 90% of the total online searches around the world<sup>25</sup> (Smales, 2022). As online searches represent a direct measure of attention (Barber, Odean, & Zhu, 2008; Lin, 2020; Nasir et al., 2019) and anyone searching for information about a particular crypto-asset will certainly do it online, we believe that *GSV* is the appropriate proxy for investor attention. In their study, Liu and Tsyvinski (2021) assess if negative investor’s attention impacts bitcoin’s returns. The results show that bitcoin is negatively and significantly driven by the attention proxy.

Similar to the previous data analysis section, we will look only at bitcoin, the leader of the crypto-market. In accordance with the literature, we establish the following hypotheses:

**H1: Bitcoin’s volatility is positively impacted by negative investor attention.**

**H2: The returns of bitcoin are negatively impacted by negative investor attention.**

We construct our proxy for negative investor’s attention using Google (world-wide) searches for the following phrases ‘cryptocurrency attack’, ‘cryptocurrency hack’, ‘cryptocurrency risk’, ‘bitcoin attack’, ‘bitcoin hack’, ‘bitcoin risk’, ‘bitcoin exploit’, ‘Blockchain attack’, ‘Blockchain hack’, ‘Blockchain risk’, ‘zero day’. The selection of these phrases has been made considering that by negative investor’s attention, we refer to the attention received by the crypto-market, when a crypto-

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<sup>25</sup>See report about the market share of leading search engines: <https://www.statista.com/statistics/216573/worldwide-market-share-of-search-engines/>.

asset was the target of a negative event<sup>26</sup>. In our Google search, we work with the term ‘cryptocurrency’ instead of ‘crypto-asset’, simply because out of the scientific and legal world<sup>27</sup>, ‘cryptocurrency’ is the most common word to use when referring to the crypto-market. Furthermore, we consider that the investors interested in the crypto-market could be categorized as specialists in Blockchain technology and non-specialists. This information is relevant, as someone who is a specialist or knowledgeable in Blockchain technology would rather use words such as ‘attack’, ‘exploit’ or ‘zero-day’<sup>28</sup> in searching for information. Therefore, we consider a variety of keywords that aim to capture the attention of both groups. We retrieved from Google engine the data used to proxy negative investor attention. Data spans from April 2013 – April 2022, with a monthly frequency (given the long period studied, Google automatically generated data at monthly frequency). For bitcoin, we used the data from Thomson Reuters Eikon database as in the previous analysis. We compute monthly returns and volatility (standard deviation) for the period April 2013 – April 2022. Table I.7 displays the descriptive statistics of all variables used.

As the interest of an investor for a particular investment might not be immediate, we perform our tests on different lags. Consequently, we perform the following regressions:

$$Rt_{BTC}(t) = \alpha + \sum_{(j=0)}^3 \beta_j * google\_search(t - j) + \varepsilon. \quad (I.3)$$

Where  $Rt_{BTC}(t)$  is the monthly return of **BTC** at time t,  $\beta_j$  is the coefficient related to lag j, and  $google\_search(t - j)$  represents the lagged google search trend. Results are reported in Table I.8.

$$\sigma_{BTC}(t) = \alpha + \sum_{(j=0)}^3 \beta_j * google\_search(t - j) + \varepsilon. \quad (I.4)$$

Where  $\sigma_{BTC}(t)$  is the monthly volatility of bitcoin at time t,  $\beta_j$  is the coefficient related to lag j, and  $google\_search(t - j)$  represents the lagged Google search trend. Results are reported in table I.9.

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<sup>26</sup>By negative events, we refer to attacks, hacks, and any other similar vulnerability that could have a negative impact on the crypto-assets prices and bring uncertainty in this market.

<sup>27</sup>The Banque de France’s view on bitcoin and other crypto-assets: <https://www.youtube.com/watch?v=Dqaw9-NTd3c>.

<sup>28</sup>‘Zero-day’ is a phrase that refers to the recent discovery of a serious security computer-software related vulnerability. As its name suggests, the developers have zero day to fix it before it could be exploited by attackers.

Table I.7: Descriptive Statistics of all variables

Panel A		<i>Mean</i>	<i>SD</i>	<i>Sharpe</i>	<i>Skewness</i>	<i>Kurtosis</i>	<i>DW</i>
<i>BTC Rt</i>		6.931	29.127	0.238	1.603	7.608	1.483
<i>Volatility</i>		4.747	3.217	1.476	2.534	9.616	0.396

Panel B	<i>Mean</i>	<i>SD</i>	<i>Max</i>	<i>Min</i>	<i>Skewness</i>	<i>Kurtosis</i>	<i>DW</i>
<i>crypto_attack</i>	18.872	22.185	100.000	0.000	1.596	2.332	0.289
<i>crypto_hack</i>	18.872	22.185	100.000	0.000	1.596	2.332	0.289
<i>crypto_risk</i>	19.110	23.838	100.000	0.000	1.363	0.952	0.105
<i>bitcoin_attack</i>	20.679	16.367	100.000	2.000	1.893	4.748	0.174
<i>bitcoin_hack</i>	20.679	16.367	100.000	2.000	1.893	4.748	0.174
<i>bitcoin_risk</i>	13.688	14.438	100.000	1.000	2.820	11.218	0.180
<i>blockchain_attack</i>	27.037	24.173	100.000	0.000	0.639	-0.249	0.111
<i>blockchain_hack</i>	27.037	24.173	100.000	0.000	0.639	-0.249	0.111
<i>blockchain_risk</i>	37.339	29.698	100.000	0.000	0.197	-1.165	0.080
<i>zero-day</i>	28.721	14.303	100.000	9.000	2.321	7.610	0.261
<i>bitcoin_exploit</i>	16.505	13.398	100.000	0.000	2.662	12.643	0.546

The table summarizes the descriptive statistics of all variables for the sample period. *DW* is the abbreviation for the Durbin-Watson test. In panel A we show the statistical properties of bitcoin returns and volatility.

Panel B reports the summary statistics for the proxies used to measure negative investor’s attention: google searches for “cryptocurrency attack/hack/risk”, “bitcoin attack/hack/risk/exploit”, “Blockchain attack/hack/risk” and ‘zero day’. Data spans from April 2013 – April 2022, with a monthly frequency.

To assess the negative investor attention’s impact on bitcoin’s performance, we regress the monthly bitcoin’s return (volatility) against google search volumes without lag and lagged from one up to three months. Considering that financial markets usually experience instability episodes around uncertain times (negative events) (Acharya et al., 2017; Gray, Merton, & Gray, 2007; Palma-Ruiz, Castillo-Apratriz, & Gómez-Martínez, 2020; Maouchi, Charfeddine, & El Montasser, 2021; Yousaf, Nekhili, & Gubareva, 2022), we expect that our results will show a decrease (increase) in bitcoin’s returns (volatility) as a response to significant negative investor attention. Furthermore, we expect to draw similar conclusions to (Liu & Tsyvinski, 2021) and show that bitcoin is significantly driven by the attention proxy.

Our findings show that Google searches have a significant impact on bitcoin’s returns, which first of all proves that negative investor attention is captured by *GSV*. Furthermore, we observe that for most of the phrases used, the effect is persistent, impacting bitcoin’s returns for up to two months. Although, the relationship between bitcoin’s returns and investors’ negative attention seems to be the strongest for lag = 0, which indicates that the reaction of investors’ attention is immediate and might not impact returns in the long run. At the same time, our non-specialist-

Table I.8: **The impact of negative investor’s attention on bitcoin returns**

Here we assess the impact of negative investor’s attention, proxied by google search terms such as ‘cryptocurrency attack/hack /risk’, ‘bitcoin attack/hack/risk/exploit’, ‘blockchain attack/hack/risk’ and ‘zero day’ on BTC returns. We regressed bitcoin’s monthly returns against the google search data without lag and lagged from one up to three-month horizons.  $R_t$  stands for monthly returns. For each regression, we had 50 observations. \*\*\* denotes significance levels based on the respective p-value (\*:10%, \*\*:5%, and \*\*\*:1%). The standard t-statistic value is shown in parentheses.

	Constant	T	T-1	T-2	T-3	$R^2$	google search
<i>R<sub>t</sub> BTC</i>	0.019 (0.5)	<b>0.092**</b> ( <b>2.143</b> )	<b>0.126***</b> ( <b>2.824</b> )	<b>0.097**</b> ( <b>2.076</b> )	0.002 (0.053)	23.88	<i>cryptocurrency_attack</i>
	0.043 (1.151)	<b>0.060**</b> ( <b>2.5</b> )	0.027 (1.116)	0.022 (0.884)	0.011 (0.451)	13.86	<i>cryptocurrency_hack</i>
	0.009 (0.241)	<b>0.204***</b> ( <b>3.437</b> )	<b>0.149**</b> ( <b>2.443</b> )	0.062 (0.955)	0.074 (1.152)	28.49	<i>cryptocurrency_risk</i>
	0.041 (1.162)	<b>0.226***</b> ( <b>3.828</b> )	0.057 (0.966)	-0.013 (-0.217)	-0.004 (-0.072)	25.61	<i>bitcoin_attack</i>
	0.039 (1.147)	<b>0.247***</b> ( <b>3.239</b> )	<b>0.145*</b> ( <b>1.836</b> )	<b>0.185**</b> ( <b>2.309</b> )	0.056 (0.724)	22.81	<i>bitcoin_hack</i>
	0.029 (0.803)	<b>0.229***</b> ( <b>3.497</b> )	<b>0.146**</b> ( <b>2.159</b> )	0.026 (0.386)	0.006 (0.09)	26.52	<i>bitcoin_risk</i>
	<b>0.102*</b> ( <b>2.013</b> )	-0.017 (-0.609)	0.000 (0.014)	-0.016 (-0.538)	-0.02 (-0.723)	2.39	<i>bitcoin_exploit</i>
	0.065 (1.582)	-0.055 (-0.519)	<b>0.222**</b> ( <b>2.027</b> )	-0.037 (-0.335)	-0.010 (-0.089)	12.21	<i>blockchain_attack</i>
	0.027 (0.722)	<b>0.361***</b> ( <b>2.735</b> )	<b>0.351**</b> ( <b>2.381</b> )	0.207 (1.406)	0.186 (1.386)	17.97	<i>blockchain_hack</i>
	<b>0.067*</b> ( <b>1.774</b> )	<b>0.161*</b> ( <b>1.784</b> )	-0.067 (-0.752)	0.047 (0.423)	0.007 (0.062)	9.58	<i>blockchain_risk</i>
	<b>0.123***</b> ( <b>3.064</b> )	-0.026 (-0.402)	<b>-0.143**</b> ( <b>-2.041</b> )	-0.112 (-1.592)	-0.105 (-1.624)	12.92	<i>Zero-day</i>

considered keywords seem to drive returns more than the ones of a Blockchain specialist. This result suggests that the majority of crypto-investors are, in fact, amateur or non-specialists in the crypto-market. This evidence is in line with the existing literature (Hasso, Pelster, & Breitmayer, 2019; Lucey et al., 2022).

When assessing if the negative investor attention impacts bitcoin’s volatility, we have interesting results. With only ‘bitcoin attack’ and ‘bitcoin risk’ searches being significant, our findings show that negative investor attention coming from both specialist<sup>29</sup> and non-specialist<sup>30</sup> investors, impacts bitcoin’s volatility. Additionally, we found that, the negative investor attention tends to decrease the volatility in the coming months. This result is surprising and contradicts our initial assumptions, therefore we conclude that further investigations would be necessary to clarify this issue.

<sup>29</sup>In this study, we consider that searches for ‘bitcoin attack’ are made by specialist investors.

<sup>30</sup>In this study, we consider that searches for ‘bitcoin risk’ are made by non-specialist investors.

Table I.9: **The impact of negative investor’s attention on bitcoin volatility**  
 Here we assess the impact of negative investor’s attention, proxied by google search terms such as ‘cryptocurrency attack/hack /risk’, ‘bitcoin attack/hack/risk/exploit’, ‘blockchain attack/hack/risk’ and ‘zero-day’ on BTC volatility. We regressed bitcoin’s monthly volatility against the google search data without lag and lagged from one up to three-month horizons. For each regression, we had 50 observations. \*\*\* denotes significance levels based on the respective p-value (\*:10%, \*\*:5%, and \*\*\*:1%). The standard t-statistic value is shown in parentheses.

	Constant	T	T-1	T-2	T-3	R <sup>2</sup>	google search
<i>BTC volatility</i>	<b>0.044***</b> (12.525)	0.004 (1.04)	0.000 (0.081)	-0.003 (-0.763)	0.004 (0.918)	5.46	<i>cryptocurrency_attack</i>
	<b>0.046***</b> (13.905)	0.001 (0.235)	-0.002 (-0.718)	0.001 (0.527)	-0.003 (-1.254)	5.69	<i>cryptocurrency_hack</i>
	<b>0.047***</b> (12.757)	0.004 (0.659)	-0.003 (-0.428)	-0.003 (-0.447)	-0.005 (-0.802)	3.01	<i>cryptocurrency_risk</i>
	<b>0.048***</b> (15.22)	0.000 (0.065)	<b>-0.010*</b> (-1.938)	-0.001 (-0.192)	<b>-0.011**</b> (-2.103)	14.70	<i>bitcoin_attack</i>
	<b>0.046***</b> (14.199)	0.004 (0.503)	-0.003 (-0.45)	-0.005 (-0.684)	-0.004 (-0.519)	2.57	<i>bitcoin_hack</i>
	<b>0.048***</b> (15.217)	0.009 (1.491)	<b>-0.015**</b> (-2.501)	-0.002 (-0.38)	<b>-0.011**</b> (-1.92)	20.8	<i>bitcoin_risk</i>
	<b>0.048***</b> (11.547)	0.002 (0.99)	-0.002 (-0.862)	-0.004 (-1.577)	-0.001 (-0.28)	9.42	<i>bitcoin_exploit</i>
	<b>0.046***</b> (12.332)	0.005 (0.505)	-0.003 (-0.352)	-0.002 (-0.216)	-0.009 (-0.298)	1.26	<i>blockchain_attack</i>
	<b>0.046***</b> (13.282)	0.003 (0.212)	0.002 (0.143)	-0.008 (-0.58)	-0.009 (-0.731)	2.02	<i>blockchain_hack</i>
	<b>0.046***</b> (13.994)	-0.008 (-0.964)	-0.006 (-0.769)	0.003 (0.27)	0.002 (0.246)	3.93	<i>blockchain_risk</i>
	<b>0.043***</b> (12.069)	0.003 (0.548)	0.007 (1.149)	0.006 (1.033)	0.003 (0.534)	3.60	<i>Zero-day</i>

Our results have important implications for the researchers and (potential) investors interested in the crypto-market. Among its many interesting features and innovative advantages, Blockchain technology and the crypto-market are mostly famous thanks to the highly volatile crypto-assets’ prices (Yi, Xu, & Wang, 2018; Dyrberg, 2016a; Baur & Dimpfl, 2021). Our findings bring new evidence that could help to better understand this market. At the same time, we think that supporting Blockchain literacy among investors would greatly improve the performance and reputation of the crypto-market as a whole.

## I.4 Conclusion

The crypto-market emerged in 2008, together with the first crypto-asset created, bitcoin. Since then, Blockchain technology has evolved, potentially disrupting many fields beyond finance. However, still in its infancy compared to its promised future, the crypto market has to overcome its many challenges. We believe that understanding and analyzing the crypto-market vulnerabilities represent the first step in

overcoming its challenges.

In this chapter, we perform a literature survey concentrating on the types of risks present in the crypto-market. Our focus is on the technological and financial risks of the crypto-market and Blockchain technology. First, we show that these risks can be related and that during specific market conditions, they can become a trigger for one another. Second, we offer a way to determine the likelihood of triggering financial risks through technological vulnerabilities. We also emphasize the role played by financial behavior, social responsibility, and Blockchain literacy in the stability of the crypto-market. Furthermore, to complete this study, we perform a short data analysis, demonstrating that crypto-assets' price stability can be disrupted by technological vulnerabilities characteristic of this market. More research is needed on this matter; however, with the little data available, we showed that bitcoin's volatility is influenced by the number of events targeting it. This evidence reveals the implication of cybersecurity risks and poor regulation in the crypto-market development.

Given that bitcoin's volatility is impacted by technological vulnerabilities, we pushed this investigation one step further. Complementary to the first analysis, we explored the impact of negative investor attention on bitcoin's returns and volatility. Our findings show that bitcoin's performance is mostly impacted by the non-specialist investors (amateurs) who trade crypto-assets. In accordance with our initial assumption, bitcoin returns are influenced by negative investor attention. We think that an increase in Blockchain literacy among the crypto-investors could greatly help this market to perform better and improve its image.

Our results support the general discussion from the literature survey while at the same time answer to our initial research question: *Can technological vulnerabilities of Blockchain technology trigger financial risks?* The empirical illustration provided in this article cannot be fully considered empirical proof. This is mostly due to the size of our data. Broadly speaking, information related to the crypto-market is spread all over the internet, making it complicated for data collection and research. Up to this point in time, there is no official or centralized database with attacks performed in the crypto-market, but rather a collection of mini statistics. On account of this, our limitation is reducing the possibility of performing empirical studies and accurately assessing certain risks.

Finally, we conclude this survey with some research directions in an attempt to bridge a part of the existent literature gaps:

1. There is a need for more research to increase Blockchain literacy. In spite of the growing interest in the crypto-market, practitioners are still challenged to transfer the Blockchain concept to market-oriented applications. General confidence in this new technology is often shattered by the negative news, scams, or attacks targeting this market. With their special features and exponential price changes, crypto-assets attract the attention of the large public, including investors, researchers, regulators, and hackers. We believe that increased knowledge and understanding about these innovative technologies will better serve the participants within the crypto-market in making informed decisions; last but not least, it will help this market to evolve towards achieving its full potential.
2. Despite the growing number of empirical papers about the crypto-market, we still lack the theory development in this field. With our study, we show that using the existing finance theories is insufficient if the technological characteristics of this market are not taken into consideration. Blockchain technology is not just a new tool; it represents a new way of doing business, a new operating system. Therefore, there is a need for more cross-disciplinary research that will take into account the important functions and implications of this technology (finance, regulation, cybersecurity, management, etc.).
3. In recent years, there has been a growing awareness of climate change and environmental issues. Knowing that PoW crypto-assets represent a threat to our planet's health, this subject needs more attention from both practitioners and academics. Investors represent an important group of stakeholders in the crypto-market. Before selecting their preferred investable assets, investors now pay more attention to their options and generally adopt the [Environmental, Social, Governance \(ESG\)](#) evaluation criterion. With the ongoing pandemic and the continuous expansion of the crypto-market, mainly based on [PoW](#) technology, we think that there is an urgent need for research addressing this challenge.
4. In the course of the past decade, Blockchain has evolved while proving its capacity to disrupt various business sectors. Starting with a complicated application, namely crypto-assets, Blockchain development achieved high levels of

both performance and complexity. Innovations such as ICOs or DeFi projects are built on stacks of complicated technologies, with each layer carrying an important amount of (attack) risk. With that in mind, we argue that literature should address the vulnerabilities and risks of this market, more specifically, the ones concerning other Blockchains than bitcoin. An assessment of the risks and vulnerabilities of the crypto-market as a whole could prevent investors from unnecessary losses, diminish the number of low-quality products and increase performance and efficiency overall.

5. As a decentralized system by design, Blockchain technology is not managed by any central authority but by its own algorithm, *the code is law*. This leaves the duty of legal and international regulatory supervision in the hands of specialists from governments and industries. The only real progress in this direction started just at the beginning of 2017 (Botos, 2017). Knowing that a large part of the vulnerabilities discussed in this survey would not have been possible if proper regulation had been in place, we also consider this an area of further research.

We think this paper may be helpful for both academic researchers in their efforts to understand the determinants of the crypto-assets risk and to market participants (as well as crypto-asset enthusiasts) for their investments.

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## I.A Appendix

### I.A.1 Tables

Table I.10: **Linear regression 1**

*Summary of the OLS regression used to identify the relationship between monthly volatility and the number of events targeting bitcoin together with the losses incurred. Computations performed with R.*

<b>Dep. Variable:</b>	Volatility	<b>Df Model:</b>	2		
<b>Model:</b>	OLS	<b>R-squared:</b>	0.195		
<b>Method:</b>	Least Squares	<b>Adj. R-squared:</b>	0.128		
<b>Date:</b>	14 October 2021	<b>F-statistic:</b>	2.913		
<b>No. of Observations:</b>	27	<b>Prob. (F-statistic):</b>	0.074		
<b>Df Residuals:</b>	24	<b>Residual standard error:</b>	0.253		
<b>Coefficients:</b>					
<b>Model</b>		<b>Estimate</b>	<b>Std. Error</b>	<b>t</b>	<b>p-value</b>
$H_1$	$EVENT_{number}$	0.193	0.081	2.364	0.026*
$H_2$	$EVENT_{amount}$	-7.589e-8	3.534e-7	-0.215	0.832

*With a **p-value** of 0.026\*, a result that is significant and less than the significance level alpha: 0.05, we can conclude that there is a relationship between the monthly volatility and the number of events targeting bitcoin. At the same time, with a **p-value** of 0.832, a result that is higher than the significance level alpha: 0.05, we conclude that there is no relationship between the monthly volatility of bitcoin and the amounts lost during the events targeting it.*

Table I.11: Hacks, thefts and losses events related to Bitcoin

Source: (Biais et al., 2020)

Date	Amount loss (BTC)	Description
6/13/2011	25,000	Early user Allinvain was hacked
6/19/2011	2,000	MtGox theft - compromised account
6/25/2011	4,019	MyBitcoin theft - wallet keys hacked
7/26/2011	17,000	Bitomat loss - Wallet access lost
7/29/2011	78,739	MyBitcoin theft - wallet website hacked
10/6/2011	5,000	Bitcoin7 hack
10/28/2011	2,609	MtGox loss due to hacking
3/1/2012	46,653	Limode hacks
4/13/2012	3,171	Betcoin hack
4/27/2012	20,000	Tony76 Silk Road scam
5/11/2012	18,547	Bitcoinica hack
7/4/2012	1,853	MtGox hack
7/13/2012	40,000	Bitcoinica theft - due to server hack
7/17/2012	180,819	BST Ponzi scheme
7/31/2012	4,500	BTC-e hack
9/4/2012	24,086	Bitfloor theft - wallet keys hacked
9/28/2012	9,222	User Cdecker hacked
10/17/2012	3,500	Trojan horse
12/21/2012	18,787	Bitmarket.eu hack
5/10/2013	1,454	Vircurex hack
6/10/2013	1,300	PicoStocks hack
10/2/2013	29,655	FBI seizes Silk Road funds
10/25/2013	144,336	FBI seizes Silk Road funds
10/26/2013	22,000	GBL scam
11/7/2013	4,100	Inputs.io hack
11/12/2013	484	Bitcash.cz hack
11/29/2013	5,400	Sheep Marketplace hacked & closes
11/29/2013	5,896	PicoStocks hack
2/13/2014	4,400	Silk Road 2 hacked
2/25/2014	744,408	MtGox collapse due to hacks losses
3/4/2014	896	Flexcoin hack
3/4/2014	97	Poloniex hack
3/25/2014	950	CryptoRush hacked
10/14/2014	3,894	Mintpal hack
1/5/2015	18,886	Bitstamp hack
1/28/2015	1,000	796Exchange hack
2/15/2015	7,170	BTER hack
2/17/2015	3,000	KipCoin hack
5/22/2015	1,581	Bitfiniex hack
9/15/2015	5,000	BitPay phishing scam - hacker takes over the CEO's accounts
1/15/2016	11,325	Cryptsy hack
4/7/2016	315	ShapeShift hack
4/13/2016	154	ShapeShift hack
5/14/2016	250	Gatecoin hack
8/2/2016	119,756	Bitfinex hack
10/13/2016	2,300	Bitcurex hack
4/22/2017	3,816	Yapizon hack
7/12/2017	1,942	AlphaBay (darknet) admins assets sized by FBI
7/20/2017	1,200	Hansa (darknet) funds seized by Dutch police
12/6/2017	4,736	NiceHash hacked
6/20/2018	2,016	Bithumb hacked
9/20/2018	5,966	Zaif hacked
10/28/2018	8	MapleChange hack / scam

# Chapter II

## The Forking effect<sup>1</sup>

### II.1 Introduction

The fast pacing nature of Blockchain technology is constantly challenging both researchers and professionals around the world. Its complexity and vast implications lead to many misunderstandings, while common Blockchain illiteracy contributes to irrational behavior, eventually resulting in inefficient markets (Dumas, Jimenez-Garcès, & Şoiman, 2021; Aste, 2019). These arguments could explain why professionals from various fields (engineers, economists, regulators, etc.) are keen to enlighten the ‘complicated’ crypto world and propel its development.

Despite all recent efforts, we observe that the current literature does not seem to propose enough answers given the market needs. In particular, we mention the scarce work on Blockchain forks. Starting from 2014<sup>2</sup> and at a faster pace since the bitcoin bubble (2017 - 2018), cryptocurrencies are gaining significant attention, provoking an explosion in Blockchain research. Up to now, academics have focused on the bitcoin bubble (Enoksen et al., 2020; Chaim & Laurini, 2019); ICOs (Chohan, 2019; Chen et al., 2020; Adhami, Giudici, & Martinazzi, 2018); cryptocurrencies’ nature (White & Burniske, 2016; Nadler & Guo, 2020; Liu & Tsyvinski, 2021; Ankenbrand & Bieri, 2018; Tan, Chan, & Ng, 2020); their volatility (Telli & Chen, 2020; García-Monleón, Danvila-del-Valle, & Lara, 2021; Fakhfekh & Jeribi, 2020; Kristoufek, 2019); and Blockchain attacks (Gramoli, 2020; Caporale et al., 2021). From the existing literature, we observe that Blockchain forks are mostly treated as either a technological challenge (Vishwanathan, 2017; Islam, Mäntymäki, & Tu-

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<sup>1</sup>This paper has been presented at the World Finance Conference 2021 in Agder, Norway.

<sup>2</sup>The year when Ethereum and smart contracts (Blockchain second generation) were created.

runen, 2019b; Chen et al., 2020; Zamyatin et al., 2019; Neudecker & Hartenstein, 2019; Nyman et al., 2012; Zhang & Preneel, 2017) or a compliance one (Button, 2019; Xu, 2019; Webb, 2018; Schar, 2020). In a similar vein, Button (2019) is tackling the effect of hard forks on the crypto holders, Biais et al. (2019b) discuss the miners' vested interests, Evans (2018) shows how the forks' network evolves in time, who are the supporters, and for which reasons they contribute to the network, Kiffer, Levin, and Mislove (2017) explore the consequences of a fork on the network, Azouvi, Maller, and Meiklejohn (2019) shows that there is little intersection between the communities of the parent coin vs. the forks', and finally both Bowden (2021), and Hotovec (2019) show that forking events can offer new investment opportunities.

With this study, we propose a research on the causal link between pure technological events, namely forks, and the cryptocurrency's financial characteristics. We intend to bring to light the *forking effect*, which is the financial impact experienced by a cryptocurrency when its Blockchain splits. Additionally, we compare the financial specifics of the parent coin together with the newly forked coin on multiple time spans. This chapter focuses exclusively on bitcoin forks and, notably, those that continue to be traded today. Therefore, even though our 'parent coin' will always be bitcoin, we will continue to refer to it in a general manner, establishing in this way a theoretical concept that could be further applied to other cryptocurrencies. In conducting this research, we use the event study methodology. Furthermore, we explore the associated data, and we formulate the following research questions: (1) *How do bitcoin's financial characteristics react to fork events?*; and (2) *How do the characteristics of the forked coins compare to their parent coin?*

The results of this study are twofold. In the first part, we show that forks issued during stable market conditions allow for a diminution in returns, VaR, illiquidity, and volatility in the parent coin. Given that the crypto-market is known to be highly inefficient (Tran & Leirvik, 2020; Hu, Valera, & Oxley, 2019; Bariviera, 2017; Nadarajah & Chu, 2017; Urquhart, 2016), we show that forks are worsening their parent coin's efficiency. However, this is not valid all the time. For example, the forks occurring during stressed market times, such as the 2017-2018 cryptocurrency bubble, increase the returns and risk carried by their parent coin and improve its efficiency. The stronger efficiency could be explained by the arrival of more information (about forking events) at a time when the proportion of noise is high. We checked for the drivers of efficiency improvement and found that positive changes in trading volume significantly improve the parent coin's efficiency. In the second

part of this study, we show that the forks are more risky, illiquid, volatile, less performant, and efficient than their parent coin. Facts that, with time, will accentuate even more. This result is robust on multiple horizons.

Furthermore, we have observed that the early forks display similar characteristics as their parent coin, whereas those occurring during the bubble and afterward appear to be significantly riskier and less efficient. This result could be justified by two facts: (1) investors may disregard the new cryptocurrencies' value due to their shorter life history, or (2) the global uncertainty about cryptocurrencies is increasing with time, a fact shown in the chaotic market behavior.

The contributions made by this study are multiple: (1) from our knowledge, we are the first ones to assess the forking effect (the financial impact suffered by a crypto-asset when the Blockchain splits); (2) we analyze jointly the parent coin with the forked coins; and last but not least (3) we have constructed the database used in this study.

This study extends the work of Dumas, Jimenez-Garcès, and Şoiman (2021) by analyzing and bringing empirical evidence of how technological events may translate into financial ones. The following section exposes the theoretical background and research hypotheses, comprising the description of Blockchain forks' characteristics and hypotheses development. Section 3 introduces the data and methodology alongside the measures used. Section 4 details the results and discusses their implications. Section 5 comprises the conclusion, future paths for research, and limitations.

## II.2 Theoretical background and research hypothesis

Cryptocurrencies are programmed/digital coins that do not exist in physical form and use Blockchain technology for operational purposes. Blockchain is a specific type of *DLT*, similar to a decentralized database. It works in a way so it stores transactional information into blocks, which are eventually linked to one another, forming a chain. Compared to traditional national currencies, cryptocurrencies' operations are performed in a decentralized way. That means that we have no more a central point of control (like banks), but every entity being part of a cryptocur-

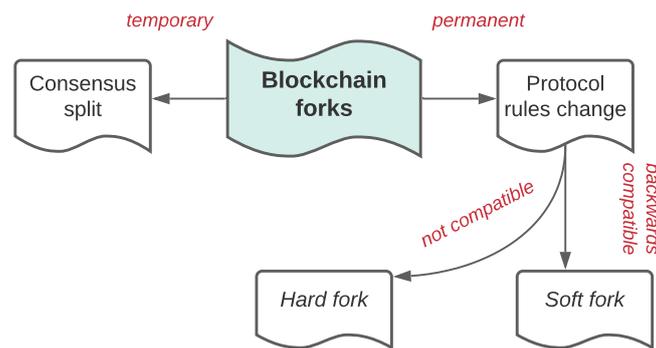
rency’s network has access to all transactional data history and can contribute to the validation process (Olleros & Zhegu, 2016; Button, 2019).

Among many aspects that differentiate the cryptocurrencies, an important one represents the consensus protocol used by Blockchain technology. This algorithm works as a manager for the entire database. More specifically, the consensus protocol is *responsible* for the Blockchain’s decentralization function; it enables the participants to engage in the validation process, assuring the majority’s agreement on a unified transaction ledger (Xiao et al., 2020).

### II.2.1 What is a fork?

In the Blockchain world, a fork represents a modification, a discrepancy, or a breach of its consensus protocol. Similar to, for example, our computers’ OS software that makes updates and upgrades all the time, the Blockchain consensus algorithm needs to evolve and undergo regular changes (Islam, Mäntymäki, & Turunen, 2019a). Often, Blockchain forks are acknowledged as exclusive chain splits; however, this is not always the case. Sometimes, the consensus protocol is modified while the chain structure remains intact (BitMEX, 2017). In Figure II.1, we can see the main types of Blockchain forks.

Figure II.1: **Forks’ classification**  
*Schematic representation of forks classification.*



The first category, the temporary forks, are the outcome of a divergence in the consensus process and result in a chain split. Such situations are possible when:

- two blocks are discovered at the same time by two different miners;
- , there is an attack at the consensus level (see (Dumas, Jimenez-Garcès, &

Soiman, 2021));

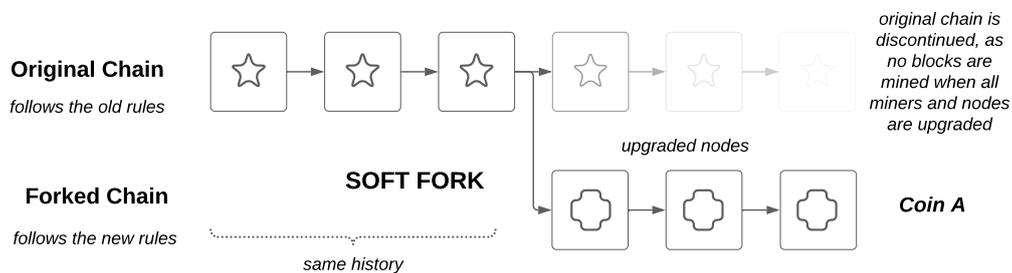
- , there is a time lag in the acceptance of the block (resulting in orphaned or uncle blocks).

Why are these forks temporary? Simply because the community will follow the longest chain (considered valid by the majority) while the other one will be abandoned and discontinued. Once the chain split ceases, the consensus process will be unique, and there will be no more fork (Bowden, 2021; Investertest.com, 2019).

Permanent forks are due to a change made in the underlying rules of the protocol. These events are planned and pre-announced and sometimes result in a chain split. Considering software needs, there are situations when it performs upgrading or updating changes. In the case of Blockchain, upgrades are necessary changes in order to bring an improved and more secure version of the consensus algorithm (Lin & Liao, 2017; Ghosh et al., 2020). These modifications are made in such a way that blocks using the old software will continue to recognize the ones using the new version (it is backward-compatible) and thus resulting in what is called a soft fork (Zhang & Preneel, 2017). For the implementation, the soft fork needs only a majority of participants (51% within the network) to perform the upgrade. Once this is happening, the blocks following the new version of the software will be considered the 'true' ones (therefore no chain split) (Investertest.com, 2019; Perez, 2019). For better understanding, a visual representation of a soft fork is detailed in figure II.2.

Figure II.2: **Blockchain Soft Fork**

An illustration of a soft fork. Source: adapted from Bitcoin-Central.com (2018)



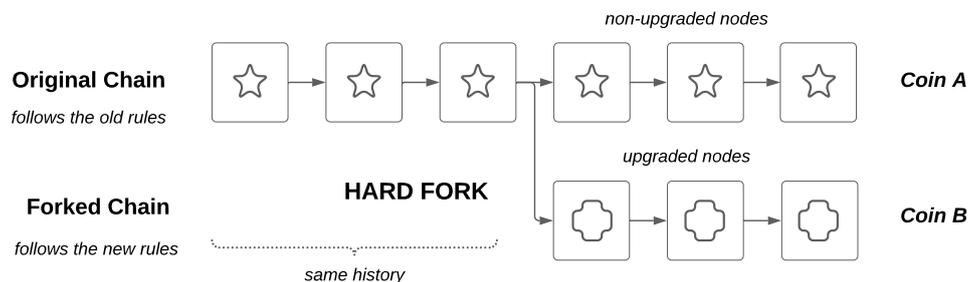
Hard forks occur when the consensus algorithm suffers important code modifications (usually for security reasons or to add new functionalities). They can lead to radical protocol changes and a different structure for the Blockchain. Hard forks modifications are not backward-compatible, meaning that the old software is totally

distinct from the new one and therefore incompatible (Ghosh et al., 2020). For a successful implementation, hard forks require the contribution of a large subset of participants. In this case, both the new and old software can continue to exist and develop as long as they have enough participants to support them. Here, we are in a scenario where the hard fork generates a chain split and creates a new coin (based on the new Blockchain) (Lin & Liao, 2017). This scenario is illustrated in figure II.3. An important mention here is that who owns the *original* coin at the moment of the forking event will receive an equivalent amount of the newly created one.

Now, imagine a scenario when the new software is supported by most of the participants, while the old version by not enough; in this case, the new software will develop as the true chain, while the old version will discontinue as not having enough supporters (Bitcoin.org, 2018). From a technical point of view, this scenario looks similar to figure II.2, with the mention that the upgraded nodes are not backward-compatible.

Figure II.3: **Blockchain Hard Fork**

An illustration of what is a hard fork. Source: adapted from Bitcoin-Central.com (2018)

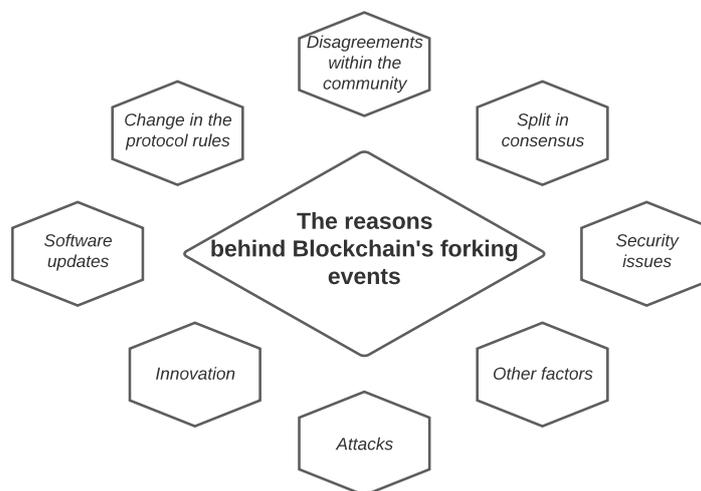


Most of the time, Blockchain forks do not happen randomly. These events are usually planned and discussed within the related cryptocurrency community, such as everyone involved knows what kind of changes must be implemented (Yiu, 2021). If looking for possible triggers, we know that the continuous need for improvement as the security and (technological) performance requirements are among the most common reasons behind a permanent fork (a more detailed list of factors driving Blockchain forks is illustrated in figure II.4). Now, if trying to make a distinction between the two, technically speaking, soft and hard forks are very similar. However, the first ones represent more a 'cosmetic change', a *slight* and backward-compatible modification in the protocol rules, without affecting the Blockchain structure (Perez, 2019). On the other hand, hard forks are more complex and require tampering with the Blockchain structure. The complexity of these changes can be explained by their

needs: to fix bugs, undo illegal transactions (the DAO attack), increase the throughput, etc. Hard forks are often considered a solution in the case of disagreements within the community. Disputes split the participants into different groups, each supporting its own idea of Blockchain development. In these cases, the considered solution is a hard fork that splits the chain and creates a new Blockchain and a new coin. This will allow everyone to follow their ideas and develop the Blockchain independently, as long as there are enough supporters to maintain it (Bitcoingold.org, 2018; Investertest.com, 2019). A detailed list of bitcoin's fork events can be consulted in BitMEX (2017).

Figure II.4: **What factors drive the chain splits?**

*The most common reasons behind the existent forks are the following:*



In conducting our research, we concentrate exclusively on the hard forks that imply a chain split, leading to the creation of a new Blockchain and cryptocurrency (Corbet et al., 2021; Ramos & Zanko, 2021a).

## II.2.2 Theoretical basis of the study

This study makes contributions to three areas of research: (1) empirical research on the crypto-market's reaction to events announcements; (2) research on the crypto-market risk and efficiency; and (3) the literature concerning the impact of technological characteristics on financial variables. This paper aims to examine two specific effects stemming from Blockchain forks.

On the one hand, we assess how the parent coin reacts to being forked in financial terms. On the other hand, we uncover the differences between the parent coin and its forked ones. More specifically, we will look at the changes/differences in financial returns, volatility, loss risk, liquidity, as well as efficiency. Below, we derive our research hypotheses. More specifically, we examine our hypotheses over three sub-periods: pre-bubble, bubble, and post-bubble. This separation comes from the fact that the number of forks issued tends to grow over the years, making a significant difference, especially during the 2017-2018 cryptocurrency bubble. We know that a financial bubble is an event during which rational expectations do not drive the market dynamics. At the same time, we believe that if we isolate this period and study the forking events in both 'stable' and 'unstable' times, we can observe some differences<sup>3</sup> Hence, we study the forking effect in a dynamic manner. We observe differences in the forking effect, depending on the market context (pre-bubble, bubble time, and post-bubble) in which forks occur.

Mattke et al. (2019) and Abraham (2020) demonstrate that some investors are focusing on the cryptocurrency ideology; hence, such investors might value cryptocurrencies in regards to the applications of the technology rather than over personal recommendations<sup>4</sup>. Furthermore, Baur and Dimpfl (2018) and Kaiser and Stöckl (2020) show that large volatility is a consequence of the herding behavior of uninformed investors. Based on these results, we need to separate our hypotheses for Bitcoin, on one side, and its forks, on another, due to the difference in the investors involved. The higher volatility in the newly forked coins might constitute evidence for an exacerbated presence of uninformed investors relative to the one in their parent coin. With this in mind, we separate our hypotheses for (1) the effects of Blockchain forks on the parent coin, noted as  $H.p$ , and (2) the differences between the parent and forked coin, noted as  $H.f$ .

It is important to mention that, as far as we know, this is the first paper studying the forked coins and forking events exclusively. Generally speaking, forked coins

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<sup>3</sup>According to the current literature about other Blockchain-related phenomena, for example, ICOs, the initiators of these events are mostly relying on the classic market frenzy that perfectly characterizes the bubble period (Zetzsche et al., 2019). Therefore, similar to ICOs, investors' behavior, and crypto-mania explain the forks explosion around the bubble time.

<sup>4</sup>This means that rational investors assess the cryptocurrency's value based on the technology's application (using a pragmatic approach, like: is this technology useful, is this a good innovation?). On the other hand, irrational investors are described as those who will value cryptocurrencies based on informal recommendations or personal opinions, disregarding the value (utility) brought by this new technology.

belong to the altcoins group of cryptocurrency<sup>5</sup>. Therefore, in justifying some of the hypotheses, we will make reference to the little existent literature about altcoins.

### *Effects on returns*

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The extant research on bitcoin price formation has shown a different behavior from other traditional financial assets, such as stocks, bonds, commodities, etc. (Baur & Dimpfl, 2018; Nguyen et al., 2019; Pirgaip, Dinçergök, & Haşlak, 2019). Following the premise of Braun and Larrain (2009), that “shocks to asset supply have a significant effect on asset prices”, Nguyen et al. (2019) brings the first evidence that the introduction of new altcoins in the market has a significant negative impact on the return of the bitcoin. Hence, we formulate:

#### **H1.p: A fork decreases the returns of the parent coin**

While examining the profitability of alternative cryptocurrencies, the literature (Huang, Levchenko, & Snoeren, 2018) shows that these coins can provide spectacular returns. Moreover, Elendner et al. (2018) finds out that similar to the stock market, the crypto-market suffers from the size effect. That being said, we expect small-cap cryptocurrencies (in our case, newly forked coins) to outperform large-cap cryptocurrencies over time. Hence,

#### **H1.f: The forked coin will have higher returns than its parent**

### *Effects on risk*

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Due to the fact that a fork is a well-known public event, largely debated and voted upon within the community of users before it takes place (Kiffer, Levin, & Mislove, 2017), the share of uninformed investors should decrease. Therefore, we expect less noise, translating into lower risk and volatility. Hence,

#### **H2.p: A fork decreases the risk of the parent coin**

Contrary to the above argument, we expect the share of uninformed investors trading the forked coins to be higher than in their parent coin. This would eventually reflect in increased volatility coming along with the increase of investor’s attention (Zhang & Wang, 2020) thanks to the forking event. Moreover, according to the extant literature examining altcoins, it is shown that the increase in return is the result of the significant risk levels borne by these coins (Nguyen et al., 2019; Huang, Levchenko, & Snoeren, 2018; Elendner et al., 2018). Hence, we expect that:

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<sup>5</sup>‘Altcoin’ is the term used to name all of the cryptocurrencies (forks, stablecoins, etc.) other than bitcoin; the name suggests that these coins represent an ‘alternative’ to bitcoin, the cryptocurrency that initiated this market.

## **H2.f: The forked coin is riskier than its parent**

### *Effects on liquidity*

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The main driver of bitcoin’s liquidity is its network (Scharnowski, 2021). The network consists of the number of people investing in the coin, implying as well the number of transactions, trades, etc. As the investor’s attention increases during the forking time, the liquidity of the parent coin should immediately increase. This effect should be even stronger in times of bubble, as investors tend to trade more if the (bitcoin) market showed good performance in the past (Fousekis & Tzaferi, 2021). Accordingly, we propose,

### **H3.p: The fork improves the liquidity of the parent coin**

Given the complete absence of price history (as the forked coin was only recently created) and the incertitude that this new Blockchain will thrive (or be abandoned)<sup>6</sup>, the liquidity of the forked coin should naturally be worse than the one of its parent coin, which enjoys a long history and a stronger reputation (Nadler & Guo, 2020)).

### **H3.f: The forked coin is less liquid than its parent**

### *Effects on efficiency*

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As previously presented, we expect that forking events improve the liquidity of the parent coin and decrease its risk. In accordance with (Al-Yahyaee et al., 2020) showing volatility and liquidity as the main drivers for crypto-market efficiency, we believe that the parent coin’s efficiency should improve. We know that forking events bring new information to the crypto-market, first through the debates within the network (Kiffer, Levin, & Mislove, 2017) and second through the broadcasts about these technological events and the new Blockchain<sup>7</sup>. Bitcoin market efficiency tends to improve around positive news (Chu, Zhang, & Chan, 2019); therefore, we assume that this avalanche of news and the fact that technology is upgrading through forking would be logically well received by the market participants, resulting in more

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<sup>6</sup>This argument is in accordance with (Fousekis & Tzaferi, 2021), who states that investors choose the cryptocurrency they prefer to trade, based on its past performance. Since forked coins are newly created and evolve independently from the bitcoin, their history of possible financial advantages is short and doubtful.

<sup>7</sup>According to Shen, Urquhart, and Wang (2019), knowledgeable investors and connoisseurs in the field of crypto-market are sharing relevant information (such as opinions, debates, predictions for future prices, etc.) via Twitter. As a result, the volume of information (tweets) has a significant impact on the trading volume and volatility and helps predict bitcoins’ returns. Similarly, (Kraaijeveld & De Smedt, 2020; Naeem et al., 2020) have identified social media messages as a good way to share crypto-related information and predict the market evolution afterward.

informational efficiency.

**H4.p: The fork improves the efficiency of the parent coin**

Based on the same rationale as the one presented above (for H4.p) and the differences in the volatility and liquidity levels, we assume that the forked coin benefits from a worse efficiency than its parent coin. This is due mainly to its novelty profile and distrust. Thus,

**H4.f: The forked coin is less efficient than its parent**

## II.3 Data & Methodology

### II.3.1 Data collection

This paper studies the forking effect only for the bitcoin forks. The choice was made based on the availability of data. Bitcoin is the most known cryptocurrency; therefore, any data available concerning its forked coins was relatively easy to access.

This study aims to observe the changes in the bitcoin price's characteristics, focusing on the performance, risk, and liquidity indicators. To do so, we retrieved the BTC/USD closing price and volume from late 2013 to 2020. We have identified 30 forked coins that still exist up to April 2021, out of which we have used only 26 for the first part of the study and the whole sample for the second part<sup>8</sup>. In order to perform our computations, we chose the CRIX crypto-market index, which started to be published in late 2014. Collecting early trading data, such as volume and prices for the crypto-market, seemed to be a challenge<sup>9</sup>. This is primarily because, in the first years, the crypto-market trading data (mainly represented by bitcoin) were highly manipulated by the exchange platforms (Litecoin Developer, 2019).

As a consequence and for compliance and ethical purposes, the online databases removed the doubtful trading data regarding cryptocurrencies before 2014 (CoinDesk.com, 2014; Hileman, 2013; Partz, 2018). Moreover, due to the same issue regarding the lack of financial data for 2011-2014 (Litecoin Developer, 2019), any

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<sup>8</sup>the sample structure can be consulted in Appendix II.A.2, Tables II.1 and II.2.

<sup>9</sup>public financial data for cryptocurrencies from 2011-2014 have been mostly erased, due to mistrust issues (Litecoin Developer, 2019), making the computation of abnormal returns for the early years impossible; therefore, we had to exclude from our first study part all the early forks (e.g., Litecoin, DigiByte, Dash, etc.).

considerations, such as creating our own crypto-market index to cover also the early years, were not practical, and therefore we chose to stick to the CRIX.

For our sample, the cryptocurrencies' prices were retrieved from CoinGecko and CoinMarketCap (depending on their availability). All the relevant data related to forked coins, such as the name, the issuing dates, trading dates, etc., were retrieved from multiple websites (see list in Appendix II.A.2, Table II.3).

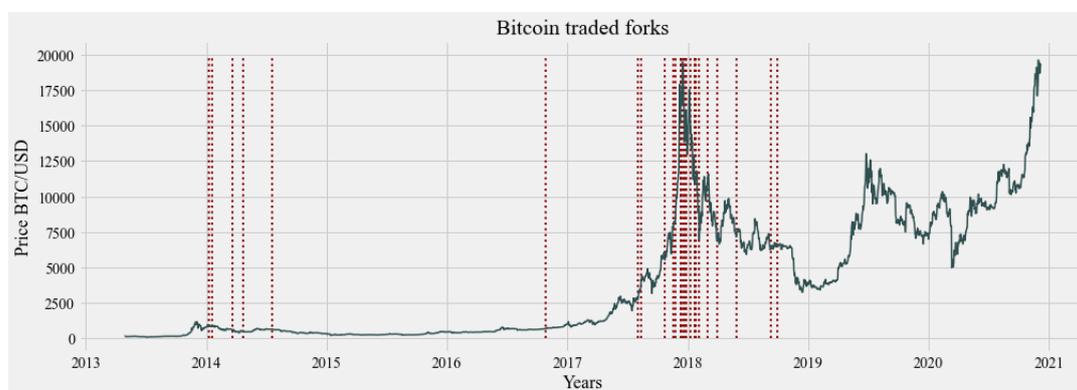
### II.3.2 Research methodology

One common assumption in financial markets is that there is a fundamental value underlying each stock. The fundamental value is usually representing the actual, 'intrinsic' value of the firm. Due to the fact that financial markets aren't perfectly efficient, the stock price varies around the fundamental value, being influenced by various factors such as: noise and information asymmetry, temporary illiquidity, exogenous shocks, etc. Now, let us consider an analogy for the crypto-market. While we know that cryptocurrencies are difficult to categorize due to their abnormal volatility and peculiar technology, we can compare their market dynamics as it relies majorly on investor behavior (Aste, 2019). The fundamental value of cryptocurrencies could be the perceived value of the technology, while variations around the fundamental value could be the cause of agreement (disagreements) about the underlying technology. Using this rationale, we expect forks to be particular events in the crypto-market. Knowing that a (hard) fork separates an existing Blockchain into two new ones with different technological characteristics, we wonder what are the financial effects of such an event.

According to the event study methodology (MacKinlay, 1997), assessing the forking effect implies verifying the pre and post-event market reactions. A point to be noted is that most of the forking events occur during the bitcoin bubble (December 2017 - March 2018). We provide a separation in the results for the forks occurring during that times and those emerging during the stable times. The price evolution of bitcoin and the moments of the emergence of its forked coins are marked in figure II.5.

Figure II.5: **Bitcoin price and forks' dates**

Chart of the price of bitcoin in US Dollars (BTC/USD) from 28-03-2013 to 07-12-2020. Each fork is represented by a vertical red dot line.



### II.3.3 Event Windows

This section presents the determination and justification of our chosen event windows for both parts of this study.

#### 1st part: Bitcoin's reaction to the forking event

In this chapter, we propose to study the forking event over four different event windows:  $[-100; +30]$ ,  $[-30; +30]$ ,  $[-15; +15]$ ,  $[-30; +5]$ . Our windows differ from the usual event study methodology detailed by MacKinlay (1997) due to the specific nature of the event we are considering. In stock markets, the information is usually difficult to extract and, sometimes, expensive to obtain. This provokes the markets to react abruptly to the arrival of new information. The crypto-market challenges this traditional approach. Due to the fact that most of the technological changes and the decisions, such as creating a forked coin, are first discussed and voted within the community (Yiu, 2021), this reduces the amount of information asymmetry and smooths naturally the market reaction. Additionally, a large proportion of the events considered in this study take place during the bitcoin bubble (December 2017 - March 2018), where market dynamics were not really driven by rational expectations. Due to these facts, we offer multiple windows that will show the robustness of our findings.

#### 2nd part: Behavior of newly forked coins

In the second part of our research, the focus is to display the specifics of newly traded coins, this time by looking at the long term. As it was previously mentioned,

we think that cryptocurrencies' performance in the long term is inevitably impacted by the investors' behavior. Thus, we will try to show the long-lasting characteristics of liquidity, risk, and efficiency aspects. In order to perform this study, we chose this time three larger windows:  $[0; +100]$ ,  $[0; +250]$ ,  $[0; +500]$ . Our choice was made based on the fact that the windows needed to be large enough in order to nuance (especially with the largest), the burst of the bubble, occurring in the period December 2017 - March 2018.

### II.3.4 Indicators

The event study methodology we are using consists of computing indicators both before and after the event and testing whether the differences are significantly different from zero. The objective of this chapter is twofold: First, we want to find the impact of a fork on the parent coin, in our case, bitcoin. And second, to observe the differences in characteristics between the parent coin and the forked one in their first 250 days of trading. We compute four types of indicators: performance, risk, liquidity, and efficiency measure.

#### Performance

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1. *Cumulative Abnormal Returns (CAR)*: Consists in the difference between the actual returns of bitcoin and the expected returns of the model chosen. We have tested the fitness of different models in order to compute the abnormal returns and made a choice based on the  $R^2$  and the [Bayesian Information Criterion \(BIC\)](#) of the model. The models tested were: Fama-French 3 Factors (Fama & French, 1992), Carhart (Carhart, 1997), Fama-French 5 Factors (Fama & French, 1993), Market Model, GARCH Market Model. The Market Model gives the best fit<sup>10</sup>.

$$AbnormalReturns_t = AR_t = R_t - E[R_t]$$

Where,  $R_t$  is the return of the cryptocurrency considered at time  $t$ , and  $E[R_t]$  is the predicted returns using an econometric model.

A simple linear market model would be

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<sup>10</sup>For a further study on the fitness of each model, we have provided in Appendix [II.A.1](#) and [II.A.2](#), the value of  $R^2$  and log-likelihood (see [Table II.5](#)) and the graph of fitness (see [Figure II.13](#)).

$$E[R_t] = \beta_0 + \beta_1 R_t^{index} + \varepsilon_t$$

Once having Abnormal Returns computed, we obtain the **CAR** by adding up all the Abnormal Returns.

2. *Volatility-Adjusted Returns (VAR)*: In order to get an idea of the changes in performance, we compute the mean of returns divided by the standard deviation in a specific time. Accordingly,

$$VAR_t = \frac{\frac{1}{T} \sum_{t=1}^T R_t}{\sigma}$$

Where,  $\sigma$  is the standard deviation of returns during the period  $[t, T]$ . This measure of performance is actually the Sharpe Ratio, with the assumption of having a risk-free return equal to zero. In our case, it seems particularly important to adjust returns to volatility, especially since most of the studied forks occurred during the bitcoin bubble. A high value of the **VAR** indicates better performance.

3. *Jensen's alpha*: is a common measure of performance for the stock market created by Jensen (1968). It is usually depicted as,

$$R_t - R_f = \alpha + \beta(R_t^{index} - R_f) + \varepsilon_t$$

Or equivalently,

$$\alpha = (R_t - R_f) - \beta(R_t^{index} - R_f) - \varepsilon_t$$

Where  $R_f$  is the risk-free rate and, in our case, has a value close to zero.  $\alpha$  is the excess return predicted by the model; in our case, it measures the performance of the cryptocurrency.

## Risk

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1. *Volatility*: Is the common standard deviation of the stock returns, computed over the desired period.

$$\sigma = \sqrt{\frac{\sum_{t=1}^T (R_t - \mu)^2}{n}}$$

2. *VaR*: is an indicator of tail risk.

The *VaR* is computed as below.

$$VaR_\alpha(R) \equiv P(R < VaR_\alpha) = \alpha$$

The *VaR* is a common measure of risk but suffers some strong shortcomings. They are described by Artzner et al. (1999). In order to relax the normality assumption, we compute the modified *VaR*, using the Cornish-Fisher Expansion (Cornish & Fisher, 1938) in order to adjust the normal quantile.

$$Z = z_c + (z_c^2 - 1)\frac{S}{6} + (z_c^3 - 3z_c)\frac{K}{24} - (2z_c^3 - 5z_c)\frac{S^2}{36}$$

Where  $z_c$  is a quantile of a normal law,  $S$  is the skewness of returns, and  $K$  is the kurtosis. Then, the *VaR* is given by,

$$VaR = \mu - Z * \sigma$$

Where,  $\mu$  is the mean of returns and  $\sigma$  their standard deviation.

## Liquidity

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1. *Volume*: it is not a measure per se, but it gives a relatively good idea about the liquidity level. Therefore, we compare the mean of traded volume before and after the forks and check for the significance of the difference.

2. *Amihud's illiquidity measure (ILLIQ)*: this is a famous proxy for illiquidity based on the volume impact on return measure, proposed by Amihud (2002). It is assumed that if the illiquidity is high, hence the risk is high, and the returns should be higher in order to compensate for the risk. When the below ratio increases, illiquidity increases as well.

$$ILLIQ = \frac{1}{T} \sum_{t=1}^T \frac{|R_t|}{V\$_t}$$

Here,  $V\$_t$  represents the volume traded at time  $t$  in bitcoin/USD units.

3. *Martin Liquidity Index (MLI)*: it is an alternative measure of liquidity based on daily market data (Martin, 1975). It is a variation of the ILLIQ measure presented above, where, instead of taking the absolute value of log returns, we take the quadratic variation of the price.

$$MLI = \sum_{t=1}^T \frac{(P_t - P_{t-1})^2}{V_t}$$

Essentially, **MLI** is the volume-adjusted quadratic variation of the price. If a high (low) volume is associated with a small (high) price variation, this will imply that the illiquidity is low (high). The higher the **MLI** is, the higher the illiquidity is.

## Efficiency

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*Adjusted Market Inefficiency Magnitude (AMIM)*: is a measure of efficiency based on the work of Tran and Leirvik (2019). **AMIM** has already been used in studying the cryptocurrencies' efficiency, and here, we will follow the example of Tran and Leirvik (2020) paper.

The initial insight of the model is based on Fama, 1965a, 1965b **EMH**<sup>11</sup> any returns at time  $t + 1$  should not be predictable given the information at time  $t$ . So returns are supposed to follow an AR( $q$ ) (Auto Regressive of order  $q$ ) model. Therefore, for a given model of returns,

$$R_t = \alpha + \beta_1 R_{t-1} + \beta_2 R_{t-2} + \dots + \beta_q R_{t-q}$$

The coefficients  $(\beta_1, \beta_2, \dots, \beta_q)$  should be different but close to zero, as long as the **EMH** holds. If the **EMH** does not hold, the  $\beta$ s should be significantly different from zero. As a first step in computing **AMIM**, we must normalize the auto-correlation coefficients. The following  $\hat{\beta}$  vector will contain the estimated

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<sup>11</sup>According to Fama, in an efficient market, security prices will incorporate all the relevant information available and consequently be a good estimate of the intrinsic value.

coefficients:  $(\hat{\beta}_1, \hat{\beta}_2, \dots, \hat{\beta}_q)$ . As estimated,  $\hat{\beta}$ s are normally distributed with mean  $\beta$  and covariance  $\Sigma$ ; and, hence, may be correlated. We normalize them using the following procedure,

$$\hat{\beta}^{standard} = L^{-1}\hat{\beta}$$

Where  $L$  is the triangular matrix obtained from the Cholesky decomposition of the covariance matrix of regression coefficients. Under the null hypothesis of  $(\beta = 0)$ ,  $\hat{\beta}^{standard} \sim N(0, \mathbf{I})$ . The next step would be computing the [Market Inefficiency Magnitude \(MIM\)](#) as follows:

$$MIM = \frac{\sum_{i=1}^q |\hat{\beta}_i^{standard}|}{1 + \sum_{i=1}^q |\hat{\beta}_i^{standard}|}$$

The measure varies from 0 (very efficient market) to 1 (very inefficient market). However, the raw value of [MIM](#) gives a false sense of efficiency (Tran & Leirvik, 2019). Indeed, the way [MIM](#) is computed will force it to be positively correlated with the number of lags; this may lead to undesirable outcomes, as high values of [MIM](#) even though the market is efficient. In order to adjust for this limitation, we first construct the confidence interval of [MIM](#) by following the recommendations of Tran and Leirvik (2019): we simulate 100 000  $\hat{\beta}^{standard}$  and compute the simulated MIMs. We extract the 95% confidence interval (CI) and compute its range ( $R_{CI}$ )<sup>12</sup>. Finally,

$$AMIM = \frac{MIM - R_{CI}}{1 - R_{CI}}$$

The measure better captures variation in efficiency. A negative value shows efficiency, while a positive value is evidence of inefficiency.

## II.4 Results & Discussion

This section introduces our results. We separate our findings into two distinct parts. First, we show how the forking events impact the parent coin, by looking at the changes in the indicators presented above for the bitcoin, before and after the

<sup>12</sup>To see the values of  $R_{CI}$  depending on the lag considered, we give [Table II.18](#).

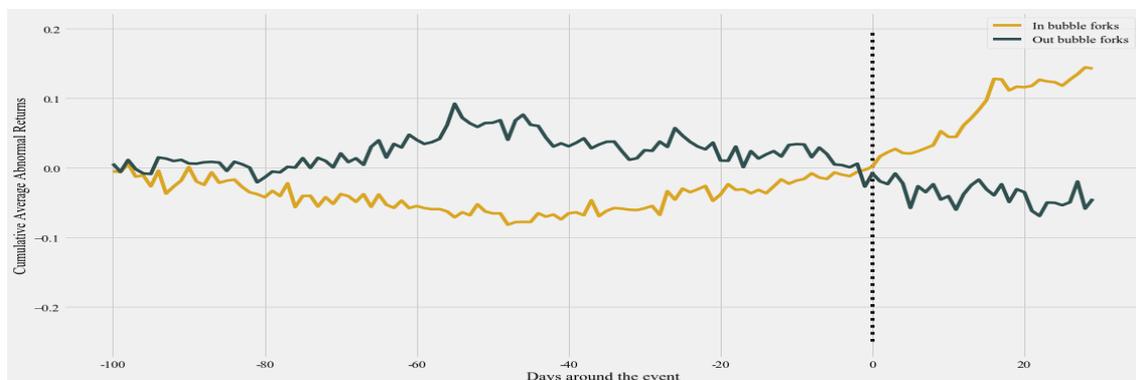
event<sup>13</sup>. In the second part, we present the differences in characteristics between the parent coin and the forked one, starting with the date when the forks are traded. Given that a major part of our forks occurred during the bitcoin bubble (December 2017- March 2018), we separate the results as: before, after, and during the bubble.

## II.4.1 Bitcoin’s reaction to forking events

We will present first the results by type of indicators, as presented in the methodology section. Afterward, before closing this section, we will expose the implications of our results in a global manner. Figure II.6 presents the results from  $[-100; +30]$  window. We provide in the Appendix a table summarizing our results for each considered window (see Table II.14). Before making the complete presentation of our results, it is important to mention that there are significant differences between the forks occurring during the bubble and those traded outside. For a quick view of such differences, we can observe them graphically in the CAR representation.

### Figure II.6: Cumulative Average Abnormal Returns

*The abnormal returns are computed using the market model calibrated with the CRIX index. As the returns are logarithmic, we obtain cumulative abnormal returns by adding them up and finally averaging them while clustered in two groups: inside the bubble period and outside. The graph shows the CAAR 100 days before the fork and 30 days after.*



It is straightforward that bitcoin’s reactions should be considered separately, given the periods in which the forks occur. Another notable point is that abnormal returns do not put forward any jump at the date of the fork. This is a major difference compared to traditional event studies in stock markets. In stock markets, (good) information is difficult and expensive to get; hence markets tend to react abruptly to the arrival of new information. This reaction is observed if there is a jump in abnormal returns at the event date. When considering the forked coins, we should keep in mind that these events are first debated and voted on within

<sup>13</sup>When the chain split with forked coins occur.

their community so before they actually happen. This explains the smaller market reactions at the events' date and supports the following argument: in this study, the traditional view that positive abnormal returns imply a positive reaction from the market participants may not be true. We argue that the rise in bitcoin's abnormal returns for the forks issued during the bubble period is due to the compensation for increased risk, while the forks outside the bubble tend to diminish risks, which translates into lower abnormal returns. At the same time, by looking at the Tables II.6, II.7 and II.8<sup>14</sup>, we observe that the performance indicators: Abnormal returns, Jensen's  $\alpha$ , and the volatility adjusted returns tend to increase (decrease) for the forks occurring outside (inside the bubble).

In Table II.10, we observe that most forks tend to decrease the illiquidity of bitcoin's price. This is primarily due to the increase in trading volume for the forks occurring around the bubble (see Table II.11). The main factors explaining why volume in the parent coin should increase after a forking event are not obvious. During the bubble, it is clear that herding behavior (Ante, 2019) and the increase of general interest in the crypto-market might have drawn more people to invest. Nevertheless, it appears that forks tend to significantly improve the liquidity of their parent coin. This appears as a surprising fact, as returns tend to be extreme during the time of the bubble. At the same time, we know that a decreased illiquidity indicator (ILLIQ), would imply a greater increase in the trading volume relative to the increase in returns. We argue that the decrease in the abnormal returns observed after the forking events (and during the bubble period) is partially explained by the decrease in the illiquidity risk.

The decrease in illiquidity shows a first sign of an improvement in the price-quality provided by the fork to its parent coin. On the other hand, the distinction between forks becomes important when looking at the risk evolution of the parent coin. As it is presented in Tables II.12 and II.13, we observe a significant increase in the level of risk for forks occurring during the bubble time. On the opposite, the bitcoin's VaR tends to decrease during the stable periods (outside bubble). We know that this fact is robust for any  $q$  between 10% and 1% (see Figure II.15). We observe that the bitcoin's risk level is higher during the bubble, which is understandable. It seems that, in periods where market dynamics are not likely to be driven by investors' behavior (bubble), forks tend to reduce the risk associated with their parent coin.

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<sup>14</sup>Due to the size and amount, all Tables in this section are presented in Appendix II.A.2.

From a global perspective, we show that outside of any market euphoria, the forks allow for reducing illiquidity, risk, and, consequently, return. On the other hand, during the bubble, forks tend to reduce illiquidity but increase the performance in order to cope with the concomitant rise in risk<sup>15</sup>. The differences we can observe between the reaction of bitcoin to forks occurring during the bubble time and those outside it are not surprising. More specifically, the results for forks occurring outside the euphoria period show some notable characteristics. A fork comes when the technology splits into two, dividing also its community into groups that want different specifics for the Blockchain they follow. In the case of a hard fork, this split implies a disagreement. On the contrary, the soft forks imply a majority of users agreeing to taking decisions, and therefore the Blockchain is ‘updated’ without any splits (forks). A disagreement on what characteristics a Blockchain should have led to different opinions about the value of the Blockchain<sup>16</sup>. Different views on the fundamental value of an asset will lead investors to use different investing strategies, resulting in higher volatility and higher risk. When the fork occurs, each user/investor is left to follow any of the Blockchains (or both). The choice is usually made on the criteria of which fits him/her the most. At no cost, the forking event provides the holders of the parent coin with a proportional amount of their actual balance, in forked coins<sup>17</sup>. In this view, the improvement of the liquidity and the reduction of risk could be a signal that the users following the parent coin are in agreement; hence this provides less volatility and less risk. It is important to take a look at the evolution of market efficiency during a forking event, as well as to check whether it varies significantly for forks occurring during and outside a bubble. For looking into market efficiency, we follow the example of Tran and Leirvik (2020) paper and use AMIM indicator. The results provided are computed at the 3rd order of lag. Similarly to Tran and Leirvik (2019), we also provide the results for multiple lags (1 to 19) in order to show the robustness of our results (See Figure II.7).

We show that our results are robust regardless of the number of lags chosen. The bitcoin’s efficiency improves (AMIM decreases) for forks occurring during the

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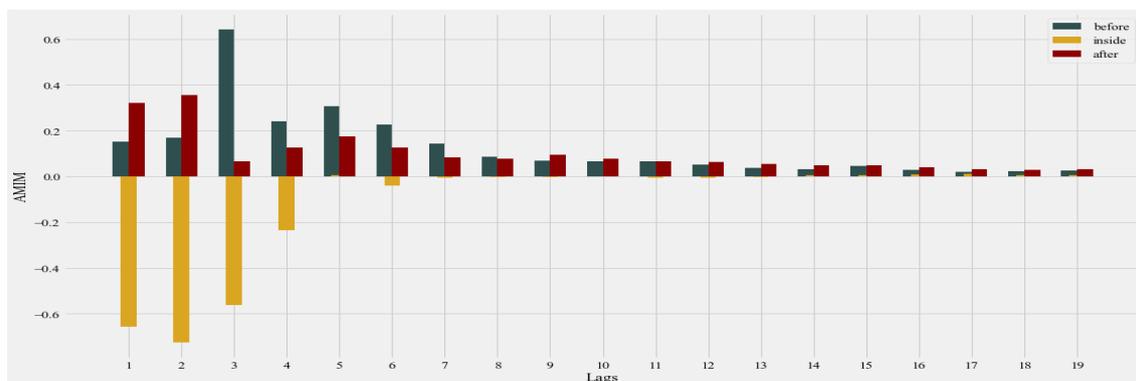
<sup>15</sup>Our findings are summarized in Appendix II.A.1 and Appendix II.A.2, see Figure II.14, and Table II.9.

<sup>16</sup>One of the findings of Pagnotta (2022) and Cong, Li, and Wang (2021) is that the value of a technology depends on the size of its network (value relative to the number of users); this statement is supported by a vast literature (Cong, Li, & Wang, 2021; Mai et al., 2018; Civitarese, 2018; Wheatley et al., 2018; Peterson, 2018; Van Vliet, 2018; Cipolaro & Stevens, 2020).

<sup>17</sup>Once a forking event takes place, the holders of the parent coin become the holders of the forked coins as well. It is their choice if they want to keep it (supporting the new Blockchain) or sell it and keep just its original coins.

### Figure II.7: Adjusted Market Inefficiency Magnitude

The Adjusted Market Inefficiency Magnitude (AMIM) is based on the Efficient Market Hypothesis (EMH) from Fama (1970). It measures the degree of the auto-correlation present in the asset returns. If the EMH holds, we should expect AMIM to be negative. The graph displays the differences in AMIM after and before a forking event. A negative value indicates an improvement in efficiency. The differences in AMIM are computed for various orders of lags. We make a separation for the forks occurring during the bubble time and the ones outside (before & after).



bubble, while the opposite happens for the forks occurring outside the bubble. The fact that forks improve the parent coin’s efficiency during the bubble could be due to the fact that they bring new information in a troubled period. Although the fact that an improvement of efficiency coming concomitantly with an increase in risk might seem incoherent, Yaya et al. (2021) show that the market of cryptocurrencies is efficient while having substantially high volatility. Furthermore, we perform a cross-sectional regression in order to observe what variation in our indicators drives the improvement of efficiency (see Table II.19). We find that all variables are positively related to efficiency except for volume. Indeed, bitcoin’s efficiency has improved when the volume has increased (which is common during a bubble), and this is supported by the current research findings (Fousekis & Tzaferi, 2021; Bouri et al., 2019)<sup>18</sup>. These results are consistent with the existing literature, showing that the crypto-market efficiency varies in accordance with the markets events (Tran & Leirvik, 2020; Noda, 2021), therefore putting forward additional evidence of the validity of the Adaptive Market Hypothesis, or AMH (Lo, 2004).

<sup>18</sup>Fousekis and Tzaferi (2021) argue that the trading volume of cryptocurrencies carries information that could be used in predicting returns. This is especially valid during extreme market conditions (Bouri et al., 2019).

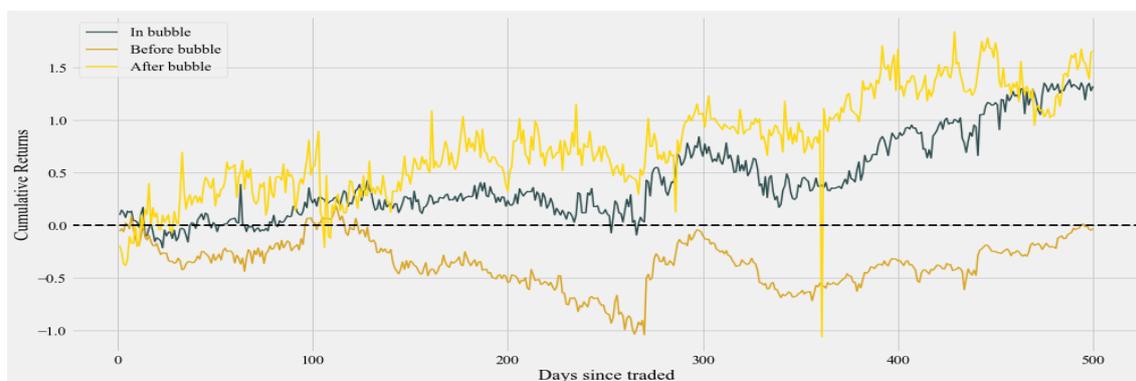
## II.4.2 Behavior of the newly forked coin

The previous section presented the fact that a fork allows for an improvement of the price's quality<sup>19</sup> for the parent coin. This section aims to examine the financial characteristics of the newly traded forked coins compared to their parent one, in our case, the bitcoin. By looking at the descriptive statistics (see Table II.17) and the distributional aspects (see Figure II.16 provided in Appendix II.A.1), we can observe that forked coins tend to be largely more volatile and fat tailed compared to bitcoin's returns. Essentially, we find strong evidence of greater risk and illiquidity in the forked coins. Given the insights provided earlier, we can expect better efficiency in bitcoin than in its forks.

The performance of the newly traded forks is difficult to assess, especially in the long term. Due to the extreme volatility present in the cryptocurrency market for most of the forked coins in our sample (issued during the bubble), any performance measure will be directly or indirectly impacted. Nevertheless, we show in Figure II.8 the differences in cumulative returns for the coins firstly traded during the bubble and then those outside.

Figure II.8: **Cumulative Returns for forks**

*The figure displays the average cumulative log returns for forks whose first trading day occurred during the bubble (In bubble) and those outside (Before bubble & After bubble).*



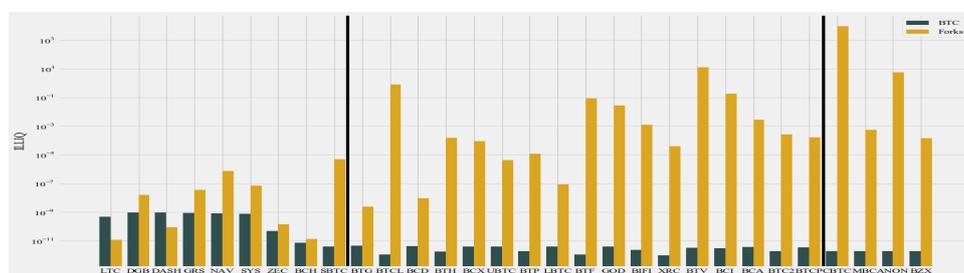
It can be observed that, with time, forked coins turn out to be more and more profitable. Regardless of the horizon, except for very short term (1-10 days), the later the fork is introduced, the more the cumulative returns. We show that this apparently surprising increase in performance comes, in fact, from a growth in the risk and illiquidity levels. When taking a closer look at the differences in illiquidity between bitcoin and the forks, we are naturally noticing that, with time, forks tend

<sup>19</sup>Here, the price quality is determined by the associated level of risk, illiquidity, and efficiency associated.

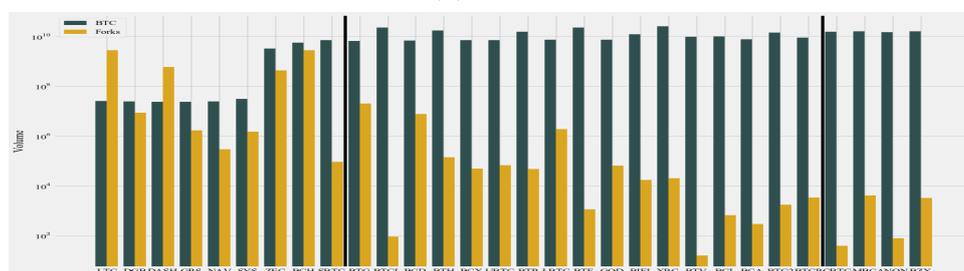
to become more and more illiquid. This might be explained by the decrease in the trading volume. As Figure II.9 shows, forks traded during and after the bubble period are more illiquid than the ones before. Such observations are validated by our significance tests displayed in Appendix II.A.2, Table II.15. Graph (b) in Figure II.9, clearly shows the decrease in trading volume for forks through the years. The early forks from our sample, on the opposite, sometimes showed higher liquidity and volume than the bitcoin.

### Figure II.9: Differences in liquidity

Charts below display two (il)liquidity indicators: Volume, ILLIQ. The charts display the indicator values for bitcoin (dark grey) next to the forks (golden). The forks between the vertical black lines occurred during the 2017-2018 bubble. Those on the left (right) occurred before (after).



(a) ILLIQ



(b) Volume

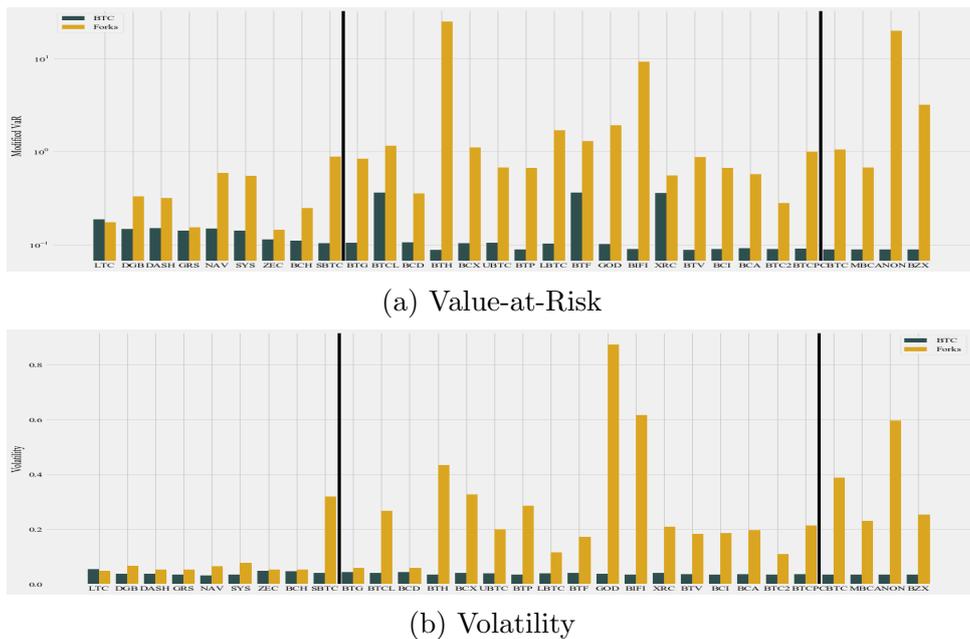
Similarly, with time, the risk of loss (Figure II.10), measured by the VaR and volatility of crypto's returns, seems to increase as well. The bubble seems to induce a drastic change, however, this is valid only for the forks, as bitcoin's risk seems to remain the same whatever the case. The differences between the bitcoin's risk and the fork's risk are comprehensively detailed in Appendix II.A.2, Table II.15. Such results are difficult to put into perspective. Earlier, we showed that a fork tends to improve the efficiency of bitcoin. The reason is that the fork comes as an outcome of a difference in opinions on the features that the Blockchain should have. In such a view, users/investors are given a costless<sup>20</sup> choice to follow the Blockchain

<sup>20</sup>The choice bears no cost as a holder of the parent coin also gets coins from the fork when it occurs.

in which they believe in the most. Given this explanation, the efficiency of both the parent and the fork should be superior. However, we observe that when the forked coins start to trade, their prices show extreme volatility and illiquidity, even on long horizons. All of these are signs of low market efficiency.

Figure II.10: **Differences in risk**

We assess (loss) risk using two measures: Volatility and Value-at-Risk (VaR). The charts display the values of the indicator for the bitcoin (dark grey) next to the ones of the forks (golden). All the forks between the vertical black lines occurred during the bubble time. Those on the left (right) occurred before (after).

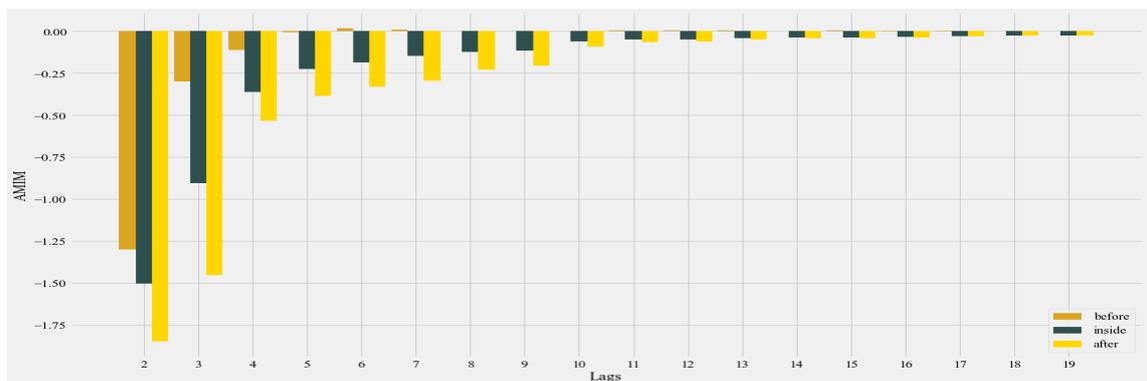


In order to explain the behavior observed in the forked coins, we decided to compute the difference of AMIM between the parent coin and the fork. Figure II.11 shows that with time, forks are less and less efficient compared to their parent coin. This result stems from numerous facts. We showed above that even though the performance of the forked coin is increasing with time, it is due to a worsening of efficiency that translates directly into high volatility, high risk, and high illiquidity (low traded volume). An explanation could be that the global interest in cryptocurrencies has increased drastically over the years. But this is not really justifying the fact that the risk associated with forks went up to such levels. In fact, such a high presence of volatility and risk could rather be evidence of a massive presence of noise traders (investors who do not trade based on the information about the fundamental value). However, if the interest in cryptocurrencies skyrocketed in 2017, the enthusiasm for the underlying technology, namely Blockchain, does not even compare with it (see Figure II.17). Another explanation could be that, due to the increase in scams, regulatory issues, and cybersecurity attacks, investors became

more cautious and decided to rather stick to the well-known cryptocurrencies.

Figure II.11: Differences in Adjusted Market Inefficiency Magnitude across lags

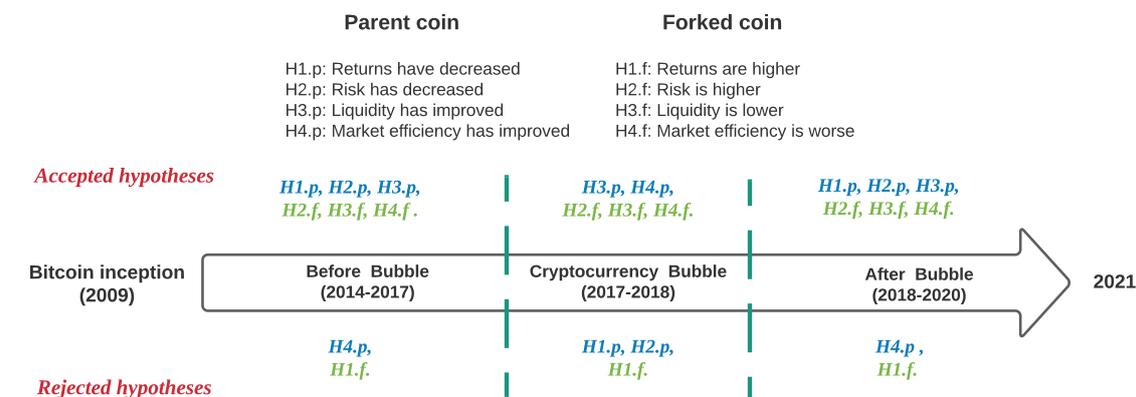
The graph displays the difference in the Adjusted Market Inefficiency Magnitude between the bitcoin and the forks. A negative value implies that bitcoin is more efficient than the fork. We make a separation among the forks, starting to be traded before the bubble (brown), during the bubble (green), and after the bubble (yellow). The measure is given for lags ranging from 1 to 19.



Taking into account that in this study, we focus on multiple periods of time while concurrently performing two different analyses, it can be complicated to describe the hypotheses-testing conclusions in a coherent and clear way. Therefore, we propose Figure II.12 to show our hypotheses-testing results whilst considering the applicable period of time.

Figure II.12: Hypotheses results

Here, we present the hypotheses testing conclusions for both parts of the study. In the upper part of the graph, we can see all the accepted hypotheses; in the lower section, we show the rejected ones. We split the results according to the studied periods of time. The parent coin's hypotheses are marked with 'H.p' and are in blue color (results depicting the 1st part of the study), while the forks' hypotheses are noted with 'H.f' and light green color (results for the 2nd part of the study).



There appears to be a clear distinction between the effect of a fork depending on when the fork occurred. Indeed, Figure II.12 shows clearly an inversion in the accepted hypotheses between forks occurring before the bubble and the ones during

the bubble. These results might stem from the increasingly growing number of users, forks, and interest paid to cryptocurrencies. Perhaps, experiencing a stable agreement on the blockchain technology underlying a cryptocurrency is harder as the number of stakeholders increases. Hence, it would explain why the number of forks increased, as well as why the effects on financial variables differ.

## II.5 Conclusion

The crypto-market constitutes a real challenge for finance academics and practitioners, as it defies the pre-existing ‘laws’ prevailing in the traditional financial markets. Numerous studies have tried to attach cryptocurrencies to another form of existing assets (White & Burniske, 2016; Ankenbrand & Bieri, 2018; Nadler & Guo, 2020; Liu, Liang, & Cui, 2020; Tan, Chan, & Ng, 2020); to propose a coherent valuation method (Pagnotta, 2022; Cong, Li, & Wang, 2021) or to study their chaotic price dynamics (Sornette, Lin, & Ren, 2014; Chaim & Laurini, 2019; Enoksen et al., 2020). In the end, it seems that the key to understanding this peculiar market lies in our comprehension of the underlying technology, namely Blockchain, and how it impacts different financial variables. In order to highlight the causal relationship between technological features and financial dynamics, we propose to study an event specific to cryptocurrencies: the (hard) forks. A fork represents a separation of the Blockchain into two distinct ones: the original Blockchain (underlying the parent coin) and the new Blockchain (underlying the newly forked coin).

The aim of this study is twofold. In the first part, we show that forks issued during stable periods allow for a diminution in the return of their parent coin due to a significant decrease in illiquidity, risk, and volatility. These improvements come along with a reduced measured market efficiency. At the same time, the forks occurring during the 2017-2018 bubble caused an increase in the loss risk ( $VaR$ ) for the parent coin and improved its efficiency. We identify that positive changes in traded volume are the main factor driving the improvement of efficiency. In the second part, we show that the newly traded coin is significantly less liquid, riskier, and volatile than its parent coin. By reason, its efficiency is lower than the one of its parent coin. Furthermore, it appears that with time, forks become more risky, illiquid, and volatile. Indeed, early forks that occurred before December 2017 display similar characteristics as their parent coin. Differently, the forks occurring during the bubble time and afterward show significantly more risk, illiquidity, and volatility, as well

as less efficiency. This fact stems from two sources. First, more and more investors in the cryptocurrency market are less informed about the underlying technology, hence the fundamental value of the cryptocurrency. Second, the global uncertainty about cryptocurrencies is increasing with time, a fact shown by the chaotic market behavior.

We admit that studying cryptocurrencies is complex, primarily because it is difficult to eliminate behavioral dynamics from their price. In the end, this leads to the fact that any event study in the crypto-market will be biased by the erratic and herding behavior occurring during market euphoria. Contrary to traditional markets, capturing the events' impact in the crypto-market is particularly complicated to track, learning that the exact moments when the information was shared (e.g., announcing dates, discussion and voting period, etc.) is often unknown. Here, we can also point out the high necessity of regulation, which would greatly contribute to the evolution of this market and the quality of research data.

As a future path for research, it would be interesting to see how the forking effect impacts other cryptocurrencies and their successive coins. However, constructing such a database for other coins will be challenging, as relevant information concerning the crypto-market is spread all over the internet. For this paper, we take into account only the forking events that resulted in coins that still exist nowadays. Therefore, another interesting idea would be to study the short-term forking effect on the parent coins while taking into account the discontinued forks.

Some possible limitations of this study are (1) the fact that some of the forked coins started to be traded a long time after their inception date, and (2) we excluded the early forks (issued before 2014) from our 1st part of the study sample, due to the lack of data.

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## II.A Appendix

### II.A.1 Figures

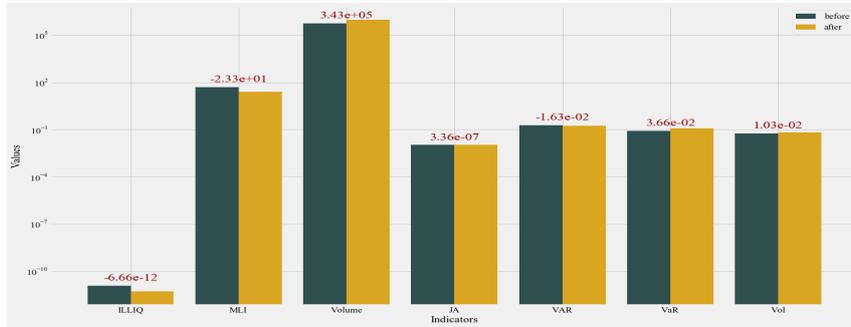
Figure II.13: **Models considered for computing abnormal returns**

The chart displays all the cumulative predicted returns for each model considered in the computing of Abnormal Returns. The models are regressions of bitcoin returns from 28-03-2013 to 07-12-2020, using the relevant factors. The market model uses the CRIX index; Fama-French 3 Factor (FF3) uses the risk premium, size premium (SMB) and the value premium (HML); Carhart uses the same as FF3 with an additional Momentum factor; Fama-French 5 Factors (FF5) uses the same as FF3 with an additional two factors: the spread of most profitable to less, and the spread of conservative investing to aggressive; the GARCH market model uses the CRIX index but assumes heteroskedastic residuals. The best fit overall seemed to be given by the market model.

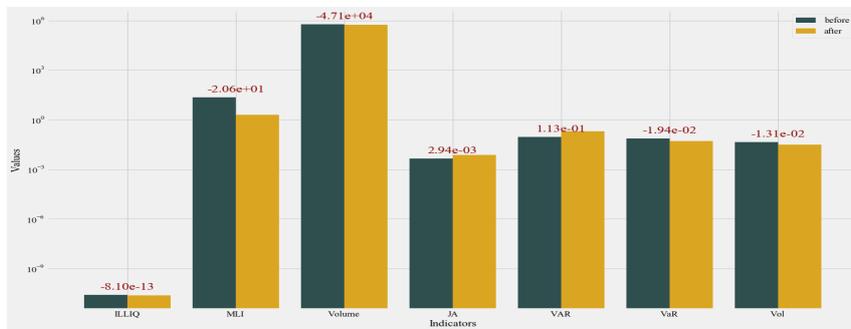


Figure II.14: **Differences for all indicators**

Summary of our findings for the differences in performance, risk, and liquidity indicators. The scale of the y-axis is logarithmic in order to be able to visualize all the indicators together. The indicators are, from left to right: ILLIQ, Martin Liquidity Index (MLI), Volume, Jensen's  $\alpha$  (JA), Volatility-Adjusted Returns (VAR), Value-at-risk (VaR), and the volatility (Vol). We separate the results for the before and after the fork; we show the actual difference in the values in red.



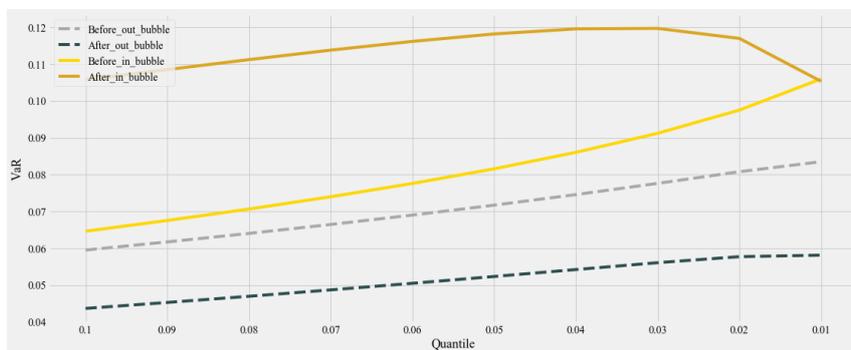
(a) Inside Bubble



(b) Outside Bubble

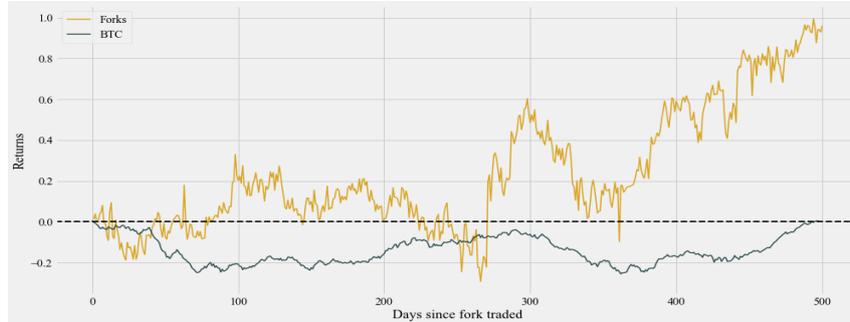
Figure II.15: **Loss structure**

Robustness computations for the variation in the Value-at-Risk (VaR) level when changing the  $q\%$ . The chart provides the VaR for the bitcoin returns before/after the forking event; for the forks occurring during the bubble (plain lines) and the ones outside (dashed lines). The VaR is computed using the Cornish-Fisher expansion which takes into account the skewness and kurtosis of returns.

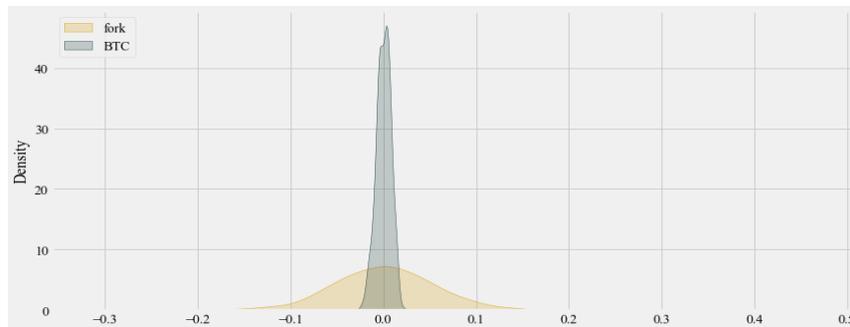


**Figure II.16: Distributional aspects: bitcoin vs forks**

Representation of distributional differences between bitcoin's returns and forked coins' returns. The first graph (a) shows the cumulative log returns of the average forked coin against the average bitcoin. Chart (b) shows the two empirical distributions of the forked coins and bitcoin.



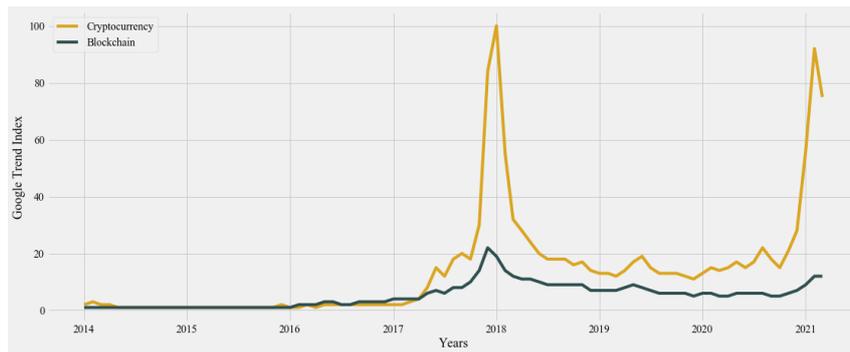
(a) Cumulative Returns



(b) Empirical Distributions

**Figure II.17: Google Trend Index on Cryptocurrencies and Blockchain.**

Google Trend Index recovered from Google Trends the 03/23/2021, for the Cryptocurrency and Blockchain topic.



## II.A.2 Tables

Table II.1: **The list of bitcoin's forks, sample part 1 - Impacts on the parent coin**

*Comprehensive list of all the forks considered for the first part of our study. We provide the ticker as well as the date of the forking event and the date when the fork started to be traded.*

Fork Name	Fork Symbol	Fork Date	Fork Trade
Zcash	ZEC	2016-10-28	2016-10-29
Bitcoin Cash	BCH	2017-08-01	2017-08-02
Super Bitcoin	SBTC	2017-08-12	2017-12-15
Bitcoin Gold	BTG	2017-10-24	2017-11-08
Bitcoin Lite	BTCL	2017-11-17	2019-01-10
Bitcoin Diamond	BCD	2017-11-24	2017-11-24
Bitcoin Hot	BTH	2017-12-12	2018-10-23
BitcoinX	BCX	2017-12-12	2017-12-15
UnitedBitcoin	UBTC	2017-12-12	2017-12-19
Bitcoin Pay	BTP	2017-12-15	2018-09-27
Lightning Bitcoin	LBTC	2017-12-19	2018-01-03
Bitcoin Faith	BTF	2017-12-19	2019-01-11
Bitcoin God	GOD	2017-12-27	2018-01-12
Bitcoin File	BIFI	2017-12-27	2018-07-19
Bitcoin Rhodium	XRC	2018-01-10	2019-04-04
BitVote	BTV	2018-01-21	2018-03-29
Bitcoin Interest	BCI	2018-01-22	2018-05-04
Bitcoin Atom	BCA	2018-01-24	2018-01-24
Bitcoin 2	BTC2	2018-02-05	2018-09-08
Bitcoin Private	BTCP	2018-03-03	2018-03-11
ClassicBitcoin	CBTC	2018-04-01	2018-10-01
Micro Bitcoin	MBC	2018-05-30	2018-10-03
Anon	ANON	2018-09-10	2018-09-14
Bitcoin Zero	BZX	2018-09-30	2018-10-03

Table II.2: **Bitcoin’s forks, sample part 2 - Differences between parent and forked coin**

*Comprehensive list of all the bitcoin forks considered and analyzed for the second part of our study. We provide the ticker name for each fork, as well as the date of the forking event and the date when the fork started to be traded.*

Fork Name	Fork Symbol	Fork Date	Trading date
Litecoin	LTC	2011-10-07	2013-04-28
DigiByte	DGB	2014-01-10	2014-02-06
Dash	DASH	2014-01-18	2014-02-14
Groestlcoin	GRS	2014-03-22	2014-04-11
NavCoin	NAV	2014-04-23	2014-06-12
Syscoin	SYS	2014-07-19	2014-08-20
Zcash	ZEC	2016-10-28	2016-10-29
Bitcoin Cash	BCH	2017-08-01	2017-08-02
Super Bitcoin	SBTC	2017-08-12	2017-12-15
Bitcoin Gold	BTG	2017-10-24	2017-11-08
Bitcoin Lite	BTCL	2017-11-17	2019-01-10
Bitcoin Diamond	BCD	2017-11-24	2017-11-24
Bitcoin Hot	BTH	2017-12-12	2018-10-23
BitcoinX	BCX	2017-12-12	2017-12-15
UnitedBitcoin	UBTC	2017-12-12	2017-12-19
Bitcoin Pay	BTP	2017-12-15	2018-09-27
Lightning Bitcoin	LBTC	2017-12-19	2018-01-03
Bitcoin Faith	BTF	2017-12-19	2019-01-11
Bitcoin God	GOD	2017-12-27	2018-01-12
Bitcoin File	BIFI	2017-12-27	2018-07-19
Bitcoin Rhodium	XRC	2018-01-10	2019-04-04
BitVote	BTV	2018-01-21	2018-03-29
Bitcoin Interest	BCI	2018-01-22	2018-05-04
Bitcoin Atom	BCA	2018-01-24	2018-01-24
Bitcoin 2	BTC2	2018-02-05	2018-09-08
Bitcoin Private	BTCP	2018-03-03	2018-03-11
ClassicBitcoin	CBTC	2018-04-01	2018-10-01
Micro Bitcoin	MBC	2018-05-30	2018-10-03
Anon	ANON	2018-09-10	2018-09-14
Bitcoin Zero	BZX	2018-09-30	2018-10-03

Table II.3: **Data extraction sources**

Table summarizing the website visited in order to retrieve data and construct our dataset. The prices and volumes were recovered from CoinMarketCap and CoinGecko, while all the specifics regarding the forks were retrieved from a variety of websites.

Type of data	Source
Financial information	<a href="https://coinmarketcap.com">https://coinmarketcap.com</a> <a href="https://www.coingecko.com">https://www.coingecko.com</a>
Fork related data	<a href="http://www.forks.net">www.forks.net</a> <a href="https://coindar.org">https://coindar.org</a> <a href="https://forkdrop.io">https://forkdrop.io</a> <a href="https://cryptoli.st">https://cryptoli.st</a> <a href="https://cryptoslate.com/">https://cryptoslate.com/</a> <a href="https://miningpools.com/">https://miningpools.com/</a> <a href="https://cryptocurrencyfacts.com/a-list-of-upcoming-bitcoin-forks-and-past-forks">https://cryptocurrencyfacts.com/a-list-of-upcoming-bitcoin-forks-and-past-forks</a> <a href="https://medium.com/@bithereumnetwork">https://medium.com/@bithereumnetwork</a> <a href="http://masterthecrypto.com">http://masterthecrypto.com</a> <a href="https://masterthecrypto.com/breakdown-of-cryptocurrency-market">https://masterthecrypto.com/breakdown-of-cryptocurrency-market</a> <a href="https://unhashed.com/bitcoin-cryptocurrency-forks-list">https://unhashed.com/bitcoin-cryptocurrency-forks-list</a> <a href="https://bitcointalk.org/">https://bitcointalk.org/</a>

Table II.4: **OLS Regression Results**

Summary of the OLS regression used in the market model for computing the abnormal returns in the first part of our study.

<b>Dep. Variable:</b>	Bitcoin	<b>R-squared:</b>	0.187			
<b>Model:</b>	OLS	<b>Adj. R-squared:</b>	0.187			
<b>Method:</b>	Least Squares	<b>F-statistic:</b>	534.9			
<b>Date:</b>	Mon, 15 Mar 2021	<b>Prob (F-statistic):</b>	1.15e-106			
<b>Time:</b>	10:24:35	<b>Log-Likelihood:</b>	4500.0			
<b>No. Observations:</b>	2321	<b>AIC:</b>	-8996.			
<b>Df Residuals:</b>	2319	<b>BIC:</b>	-8984.			
<b>Df Model:</b>	1					
	<b>coef</b>	<b>std err</b>	<b>t</b>	<b>P &gt;  t </b>	<b>[0.025</b>	<b>0.975]</b>
	<b>const</b>	0.0008	0.001	1.038	0.299	-0.001 0.002
	<b>CRIX</b>	0.4330	0.019	23.129	0.000	0.396 0.470
<b>Omnibus:</b>	727.564	<b>Durbin-Watson:</b>	2.619			
<b>Prob(Omnibus):</b>	0.000	<b>Jarque-Bera (JB):</b>	37018.366			
<b>Skew:</b>	-0.688	<b>Prob(JB):</b>	0.00			
<b>Kurtosis:</b>	22.516	<b>Cond. No.</b>	25.9			

Table II.5: **Comparison of models for abnormal returns**

Comparison of the models considered for computing abnormal returns. The  $R$  squared and Log-Likelihood are provided.

Models	$R^2$	Log-Likelihood
Market	0.187436	4499.952816
Market_Garch	0.116237	5070.685930
Fama-French 3	0.012754	3021.581706
Carhart	0.013123	3021.939873
Fama-French 5	0.012881	3021.704450

Table II.6: **Performance - Abnormal Returns**

We measure performance using Abnormal Returns. The table below shows the differences in the indicator for BTC, after and before the forking event. A negative value indicates a decrease in the indicator.

fork name	mean_before	mean_after	mean_diff	t_stat
ZEC	0.211115	0.025328	-0.185787	-5.490434
BCH	-0.090214	-0.157122	-0.066908	-4.525029
SBTC	-0.025789	-0.154975	-0.129186	-11.118710
BTG	-0.244890	-0.012189	0.232701	8.106142
BTCL	-0.318757	-0.016293	0.302464	18.242910
BCD	-0.265006	0.004298	0.269304	25.784513
BTH	0.004173	0.043675	0.039502	3.979598
BCX	0.004173	0.043675	0.039502	3.979598
UBTC	0.004173	0.043675	0.039502	3.979598
BTP	-0.066587	0.060925	0.127512	12.770884
LBTC	0.022626	0.093099	0.070472	7.196184
BTF	0.022626	0.093099	0.070472	7.196184
GOD	-0.054137	0.137218	0.191355	26.797937
BIFI	-0.054137	0.137218	0.191355	26.797937
XRC	-0.031231	0.064411	0.095642	7.775997
BTV	0.027807	0.155822	0.128015	8.454030
BCI	0.010673	0.132249	0.121576	7.873947
BCA	0.022101	0.157599	0.135498	8.697479
BTC2	0.069096	0.096872	0.027775	1.684875
BTCP	0.147520	0.124867	-0.022653	-0.770457
CBTC	0.311762	-0.008771	-0.320533	-10.290608
MBC	0.116608	-0.025244	-0.141851	-8.610745
ANON	-0.175046	0.007769	0.182815	10.947995
BZX	-0.034856	0.107713	0.142569	10.850750

Table II.7: **Performance - Jensen's  $\alpha$** 

We measure performance using Jensen's  $\alpha$ . The table below shows the differences in the indicator for BTC, after and before the forking event. A negative value indicates a decrease in the indicator.

<b>fork_name</b>	alpha_before	alpha_after	alpha_diff
<b>ZEC</b>	-0.000061	0.002012	0.002073
<b>BCH</b>	0.007793	0.019476	0.011683
<b>SBTC</b>	0.009184	0.003252	-0.005932
<b>BTG</b>	0.011052	0.011565	0.000513
<b>BTCL</b>	0.008888	0.029904	0.021016
<b>BCD</b>	0.006859	0.017836	0.010977
<b>BTH</b>	0.012994	-0.006424	-0.019418
<b>BCX</b>	0.012994	-0.006424	-0.019418
<b>UBTC</b>	0.012994	-0.006424	-0.019418
<b>BTP</b>	0.012998	-0.006423	-0.019421
<b>LBTC</b>	0.014181	-0.012900	-0.027081
<b>BTF</b>	0.014181	-0.012900	-0.027081
<b>GOD</b>	0.013633	-0.011275	-0.024908
<b>BIFI</b>	0.013633	-0.011275	-0.024908
<b>XRC</b>	0.012461	-0.018921	-0.031382
<b>BTV</b>	0.007134	-0.001066	-0.008201
<b>BCI</b>	0.006025	-0.000587	-0.006611
<b>BCA</b>	0.006591	-0.002496	-0.009087
<b>BTC2</b>	0.002043	0.012245	0.010202
<b>BTCP</b>	0.004147	-0.018577	-0.022724
<b>CBTC</b>	-0.007564	0.008256	0.015820
<b>MBC</b>	-0.004115	-0.005020	-0.000905
<b>ANON</b>	-0.001139	0.001253	0.002392
<b>BZX</b>	0.001343	-0.001014	-0.002357

Table II.8: **Performance - Volatility-adjusted returns**

We measure performance using Volatility-adjusted returns. The table below shows the differences in the indicator for BTC, after and before the forking event. A negative value indicates a decrease in the indicator.

	mean_before	mean_after	mean_diff	t_stat
<b>fork name</b>				
<b>ZEC</b>	0.021680	0.092465	0.070785	-0.337416
<b>BCH</b>	0.170940	0.524674	0.353735	-1.686165
<b>SBTC</b>	0.187346	0.062218	-0.125128	0.596454
<b>BTG</b>	0.196751	0.286359	0.089608	-0.427138
<b>BTCL</b>	0.171202	0.480138	0.308937	-1.472624
<b>BCD</b>	0.133463	0.230880	0.097417	-0.464364
<b>BTH</b>	0.234697	-0.123643	-0.358341	1.708120
<b>BCX</b>	0.234697	-0.123643	-0.358341	1.708120
<b>UBTC</b>	0.234697	-0.123643	-0.358341	1.708120
<b>BTP</b>	0.237786	-0.120245	-0.358031	1.706645
<b>LBTC</b>	0.256078	-0.198635	-0.454713	2.167501
<b>BTF</b>	0.256078	-0.198635	-0.454713	2.167501
<b>GOD</b>	0.250032	-0.169352	-0.419384	1.999100
<b>BIFI</b>	0.250032	-0.169352	-0.419384	1.999100
<b>XRC</b>	0.208525	-0.243252	-0.451776	2.153504
<b>BTV</b>	0.112780	-0.008315	-0.121095	0.577230
<b>BCI</b>	0.097992	-0.010831	-0.108823	0.518731
<b>BCA</b>	0.106789	-0.047022	-0.153811	0.733178
<b>BTC2</b>	0.027508	0.214471	0.186962	-0.891202
<b>BTCP</b>	0.050374	-0.374734	-0.425108	2.026381
<b>CBTC</b>	-0.113108	0.217706	0.330813	-1.576904
<b>MBC</b>	-0.101163	-0.167410	-0.066246	0.315780
<b>ANON</b>	-0.058494	0.094601	0.153096	-0.729768
<b>BZX</b>	0.030517	-0.105301	-0.135818	0.647408

Table II.9: **Efficiency - Price Delay**

We measure efficiency using Price Delay. The table below shows the differences in the indicator for BTC, after and before the forking event. A negative value indicates a decrease in the indicator. A lower value of Price Delay indicates better efficiency.

	before	after	diff
<b>fork name</b>			
<b>ZEC</b>	0.356037	0.999655	0.643618
<b>BCH</b>	0.884199	0.607527	-0.276672
<b>SBTC</b>	0.969533	0.950687	-0.018845
<b>BTG</b>	0.746775	0.475569	-0.271206
<b>BTCL</b>	0.602650	0.773828	0.171177
<b>BCD</b>	0.441908	0.974205	0.532297
<b>BTH</b>	0.441780	0.708803	0.267022
<b>BCX</b>	0.441780	0.708803	0.267022
<b>UBTC</b>	0.441780	0.708803	0.267022
<b>BTP</b>	0.650379	0.793399	0.143020
<b>LBTC</b>	0.712350	0.754036	0.041686
<b>BTF</b>	0.712350	0.754036	0.041686
<b>GOD</b>	0.940831	0.988860	0.048029
<b>BIFI</b>	0.940831	0.988860	0.048029
<b>XRC</b>	0.680785	0.993798	0.313014
<b>BTV</b>	0.988770	0.995775	0.007005
<b>BCI</b>	0.872554	0.999688	0.127134
<b>BCA</b>	0.854107	0.994450	0.140342
<b>BTC2</b>	0.973937	0.996766	0.022829
<b>BTCP</b>	0.950558	0.586205	-0.364353
<b>CBTC</b>	0.926892	0.733135	-0.193757
<b>MBC</b>	0.370163	0.628288	0.258124
<b>ANON</b>	0.526218	0.974217	0.447999
<b>BZX</b>	0.388235	0.966721	0.578486

Table II.10: **Liquidity - ILLIQ**

We measure liquidity using ILLIQ. The table below shows the differences in the indicator for BTC between after and before the forking event. A negative value indicates a decrease in the indicator. A lower value of ILLIQ indicates a better liquidity.

fork name	ILLIQ_before	ILLIQ_after	ILLIQ_diff	t_stat
<b>ZEC</b>	1.086640e-10	1.448323e-10	3.616837e-11	1.575946
<b>BCH</b>	3.375105e-11	1.556412e-11	-1.818694e-11	-4.027407
<b>SBTC</b>	3.098143e-11	1.143827e-11	-1.954316e-11	-4.826505
<b>BTG</b>	2.152885e-11	1.046893e-11	-1.105992e-11	-3.505281
<b>BTCL</b>	1.537914e-11	5.785892e-12	-9.593247e-12	-4.483559
<b>BCD</b>	1.434507e-11	5.317356e-12	-9.027710e-12	-4.330347
<b>BTH</b>	1.389539e-11	3.812705e-12	-1.008268e-11	-5.019118
<b>BCX</b>	1.389539e-11	3.812705e-12	-1.008268e-11	-5.019118
<b>UBTC</b>	1.389539e-11	3.812705e-12	-1.008268e-11	-5.019118
<b>BTP</b>	1.338441e-11	3.793117e-12	-9.591293e-12	-4.852969
<b>LBTC</b>	1.305132e-11	3.787231e-12	-9.264089e-12	-4.775349
<b>BTF</b>	1.305132e-11	3.787231e-12	-9.264089e-12	-4.775349
<b>GOD</b>	1.113936e-11	3.771471e-12	-7.367893e-12	-4.594089
<b>BIFI</b>	1.113936e-11	3.771471e-12	-7.367893e-12	-4.594089
<b>XRC</b>	8.482790e-12	5.608840e-12	-2.873949e-12	-2.222738
<b>BTV</b>	7.096592e-12	6.576218e-12	-5.203748e-13	-0.427606
<b>BCI</b>	6.960238e-12	6.617315e-12	-3.429225e-13	-0.283661
<b>BCA</b>	6.834195e-12	6.849537e-12	1.534173e-14	0.012706
<b>BTC2</b>	6.336437e-12	6.248664e-12	-8.777369e-14	-0.081024
<b>BTCP</b>	5.364988e-12	5.869790e-12	5.048020e-13	0.526466
<b>CBTC</b>	5.492354e-12	5.283618e-12	-2.087352e-13	-0.222249
<b>MBC</b>	4.940844e-12	5.398442e-12	4.575977e-13	0.478411
<b>ANON</b>	5.137771e-12	2.359782e-12	-2.777989e-12	-3.745880
<b>BZX</b>	4.549246e-12	1.657926e-12	-2.891320e-12	-4.426134

Table II.11: **Liquidity - Volume**

We measure liquidity using Volume. The table below shows the differences in the indicator for BTC, after and before the forking event. A negative value indicates a decrease in the indicator.

fork name	mean_before	mean_after	mean_diff	t_stat
<b>ZEC</b>	124944.222857	1.269635e+05	2019.295098	-1.912643
<b>BCH</b>	501024.215987	5.229453e+05	21921.050610	-8.238365
<b>SBTC</b>	512102.002865	5.412219e+05	29119.876462	-10.801646
<b>BTG</b>	450937.866421	5.157793e+05	64841.457749	-8.745063
<b>BTCL</b>	471302.116575	6.907509e+05	219448.779162	-12.533797
<b>BCD</b>	463105.642094	8.252049e+05	362099.279376	-17.236425
<b>BTH</b>	502064.594244	9.961781e+05	494113.538526	-15.186429
<b>BCX</b>	502064.594244	9.961781e+05	494113.538526	-15.186429
<b>UBTC</b>	502064.594244	9.961781e+05	494113.538526	-15.186429
<b>BTP</b>	508431.381477	1.000374e+06	491942.477225	-13.421371
<b>LBTC</b>	521439.492730	1.083029e+06	561589.729376	-12.011788
<b>BTF</b>	521439.492730	1.083029e+06	561589.729376	-12.011788
<b>GOD</b>	555079.359778	1.049599e+06	494520.099784	-7.995141
<b>BIFI</b>	555079.359778	1.049599e+06	494520.099784	-7.995141
<b>XRC</b>	660493.101904	1.016568e+06	356075.152080	-2.472002
<b>BTV</b>	743735.482624	9.023806e+05	158645.111411	0.451455
<b>BCI</b>	750513.101824	8.995751e+05	149062.024943	0.565028
<b>BCA</b>	761165.912173	8.926061e+05	131440.180779	0.823937
<b>BTC2</b>	826607.546215	7.941389e+05	-32468.602847	2.378260
<b>BTCP</b>	896120.427186	6.981001e+05	-198020.307712	6.257053
<b>CBTC</b>	862955.181216	8.081028e+05	-54852.381747	3.691964
<b>MBC</b>	748130.749031	6.396290e+05	-108501.764669	7.341174
<b>ANON</b>	639368.815226	6.278853e+05	-11483.469014	1.689683
<b>BZX</b>	643852.531966	5.866847e+05	-57167.817633	3.377034

Table II.12: **Losses - Volatility**

*We measure losses with the volatility of BTC returns. The table below shows the differences in the indicator for BTC, after and before the forking event. A negative value indicates a decrease in the indicator.*

fork name	mean_before	mean_after	mean_diff	F-test
<b>ZEC</b>	0.016317	0.021499	0.005182	1.736023
<b>BCH</b>	0.047483	0.034834	-0.012650	0.538166
<b>SBTC</b>	0.049469	0.036845	-0.012624	0.554736
<b>BTG</b>	0.053476	0.043616	-0.009860	0.665228
<b>BTCL</b>	0.048812	0.063137	0.014325	1.673044
<b>BCD</b>	0.047533	0.075520	0.027988	2.524317
<b>BTH</b>	0.056882	0.070544	0.013662	1.538028
<b>BCX</b>	0.056882	0.070544	0.013662	1.538028
<b>UBTC</b>	0.056882	0.070544	0.013662	1.538028
<b>BTP</b>	0.056712	0.069668	0.012956	1.509112
<b>LBTC</b>	0.057066	0.073456	0.016390	1.656933
<b>BTF</b>	0.057066	0.073456	0.016390	1.656933
<b>GOD</b>	0.054392	0.068710	0.014318	1.595755
<b>BIFI</b>	0.054392	0.068710	0.014318	1.595755
<b>XRC</b>	0.058628	0.073820	0.015191	1.585366
<b>BTV</b>	0.063828	0.068456	0.004628	1.150284
<b>BCI</b>	0.064119	0.068612	0.004493	1.145051
<b>BCA</b>	0.064155	0.069325	0.005171	1.167692
<b>BTC2</b>	0.068984	0.055895	-0.013088	0.656533
<b>BTCP</b>	0.070905	0.043021	-0.027884	0.368129
<b>CBTC</b>	0.062203	0.043936	-0.018267	0.498909
<b>MBC</b>	0.041103	0.034818	-0.006285	0.717553
<b>ANON</b>	0.032242	0.013961	-0.018281	0.187500
<b>BZX</b>	0.027960	0.014232	-0.013727	0.259111

Table II.13: **Losses - VaR**

We measure losses with VaR. The table below shows the differences in the indicator for BTC, after and before the forking event. A negative value indicates a decrease in the indicator. A lower value of VaR indicates lower risk.

<b>fork name</b>	VaR_before	VaR_after	VaR_diff
<b>ZEC</b>	0.031770	0.038617	0.006847
<b>BCH</b>	0.062775	0.034737	-0.028038
<b>SBTC</b>	0.065138	0.067024	0.001886
<b>BTG</b>	0.073353	0.063000	-0.010352
<b>BTCL</b>	0.078838	0.055940	-0.022898
<b>BCD</b>	0.077825	0.098506	0.020681
<b>BTH</b>	0.076378	0.125001	0.048623
<b>BCX</b>	0.076378	0.125001	0.048623
<b>UBTC</b>	0.076378	0.125001	0.048623
<b>BTP</b>	0.075571	0.123557	0.047986
<b>LBTC</b>	0.075456	0.141938	0.066482
<b>BTF</b>	0.075456	0.141938	0.066482
<b>GOD</b>	0.066302	0.135213	0.068911
<b>BIFI</b>	0.066302	0.135213	0.068911
<b>XRC</b>	0.078289	0.154205	0.075917
<b>BTV</b>	0.097518	0.126364	0.028846
<b>BCI</b>	0.098442	0.126769	0.028327
<b>BCA</b>	0.098388	0.129159	0.030771
<b>BTC2</b>	0.114252	0.084331	-0.029921
<b>BTCP</b>	0.116455	0.091979	-0.024476
<b>CBTC</b>	0.116830	0.064404	-0.052426
<b>MBC</b>	0.074019	0.074783	0.000763
<b>ANON</b>	0.060048	0.022591	-0.037457
<b>BZX</b>	0.046590	0.024507	-0.022083

Table II.14: Differences in indicators

The table provides a summary of all the results computed in the first part of this article regarding bitcoin's reaction to being forked. The values displayed are the difference between the after and before the forking event, for each indicator. The indicators are the illiquidity measure of Amihud (ILLIQ), the Martin Liquidity Index (MLI), Volume, Jensen's  $\alpha$  (JA), Volatility-Adjusted Returns (VAR), Value-at-Risk (VaR), Volatility (Vol), and the Adjusted Market Inefficiency Magnitude (AMIM). The results are computed for four different windows:  $[-100; +30]$ ,  $[-30; +30]$ ,  $[-15; +15]$ ,  $[-30; +5]$ . T-tests and Kruskal-Wallis (in parenthesis) tests are provided and the level of significance is expressed as: \*:**10%**, \*\*: **5%**, \*\*\*: **1%**

		[-100;30]	[-30;30]	[-15;15]	[-30;5]
<b>ALL</b>	<b>ILLIQ</b>	-4.711e-11,(***)	-1.454e-12	-4.232e-12	-9.417e-12
	<b>MLI</b>	-22.393***,(***)	-1.806	-2.033	-16.052***,(***)
	<b>Volume</b>	2.133e+05***,(***)	1.008e+05**,(**)	7.491e+04	5.374e+04
	<b>JA</b>	-8.091e-03***,(***)	-5.843e-03**,(**)	-7.873e-03	-8.596e-03
	<b>VAR</b>	-0.132**,(***)	-9.483e-02*,(*)	-0.057	-0.053
	<b>VaR</b>	0.018*,(*)	1.663e-02*,(*)	0.011	-4.514e-03
	<b>Vol</b>	2.486e-03	-6.007e-04*	-0.002	-0.013**,(**)
	<b>AMIM</b>	-0.255*	-0.271	-0.393**,(**)	-0.106
	<b>BEFORE</b>	<b>ILLIQ</b>	-5.206e-13	-3.102e-12	8.241e-12
<b>MLI</b>		-1.003	-0.235	-0.127	-0.887
<b>Volume</b>		-1.769e+04	-6.797e+04	8.755e+04	6.930e+04
<b>JA</b>		2.608e-03	-6.763e-05	1.590e-03	-8.751e-03
<b>VAR</b>		0.099	-1.698e-03	8.164e-03	0.434**,(**)
<b>VaR</b>		-6.435e-03	-5.675e-03	3.889e-04	-0.018
<b>Vol</b>		-6.697e-03	-0.015	-9.332e-03	-0.012
<b>AMIM</b>		0.569	0.222	-0.215	0.189
<b>IN BUBBLE</b>		<b>ILLIQ</b>	-6.662e-12***,(***)	-1.374e-12	-3.138e-13
	<b>MLI</b>	-23.306***,(***)	-2.122	-3.098	-23.657***,(***)
	<b>Volume</b>	3.435e+05***,(***)	1.534e+05**,(**)	4.810e+04	5.556e+04
	<b>JA</b>	-0.012***,(***)	-0.014**,(**)	-7.940e-03	-4.241e-03
	<b>VAR</b>	-0.208***,(***)	-0.237**,(**)	-0.075	-0.100
	<b>VaR</b>	0.037***,(***)	0.031**,(**)	8.879e-03	-5.994e-03
	<b>Vol</b>	0.010***,(***)	4.095e-03	-4.571e-03	-0.016***,(***)
	<b>AMIM</b>	-0.498**,(***)	-0.395**,(**)	-0.265	-0.064
	<b>AFTER</b>	<b>ILLIQ</b>	-9.831e-13	-7.205e-13	5.615e-16
<b>MLI</b>		-32.304*,(**)	-1.738	-0.089	-3.904*,(**)
<b>Volume</b>		-8.600e+04	-4.776e+04	-1.645e+04	-7.695e+04
<b>JA</b>		-1.557e-03	9.136e-04	-3.030e-03	-2.813e-03
<b>VAR</b>		0.029	0.054	0.028	0.044
<b>VaR</b>		-0.027	-0.016	-1.046e-03	-0.023
<b>Vol</b>		-0.017	-6.856e-03	7.215e-04	-0.014
<b>AMIM</b>		0.058	0.202	-0.212	-0.068

**Table II.15: Differences in indicators: Behavior of the newly traded coins**  
*The table provides a summary of all the results computed for the second part of this paper, regarding the behavior of the newly forked coins. The values displayed represent the difference between bitcoin and forks, for each indicator. The indicators are the illiquidity measure of Amihud (ILLIQ), the Martin Liquidity Index (MLI), Volume, Volatility-Adjusted Returns (VAR), Value-at-Risk (VaR), Volatility (Vol), and the Adjusted Market Inefficiency Magnitude (AMIM). We separate the forks given their first trading date, which is: forks occurring before the bubble time (BEFORE) which is October 2017, during (BUBBLE) which is October 2017 - February 2018, or after (AFTER) which is after 1st of March 2018. The results are computed for three different windows: [0 + 100],[0; +250],[0; 500]. T-tests and Kruskal-Wallis (in parenthesis) tests are provided and the level of significance is expressed as: \*:**10%**, \*\*:**5%**, \*\*\*:**1%***

		[0,500]	[0,250]	[0,100]
<b>ALL</b>	<b>ILLIQ</b>	-3.095e+02 ,(***)	-6.150e+02 ,(***)	-2.800e+00 ,(***)
	<b>MLI</b>	-5.386e+00 ,(***)	-3.474e+00 ,(***)	-3.310e-01 ,(***)
	<b>Volume</b>	9.432e+09 ***(***)	6.491e+09 ***(***)	5.714e+09 ***(***)
	<b>VAR</b>	2.100e-02	3.700e-02	7.800e-02***,(***)
	<b>VaR</b>	-2.394e+00 **,(***)	-1.152e+00 *,(***)	-7.820e-01 *,(***)
	<b>Vol</b>	-1.870e-01 ***(***)	-1.650e-01 ***(***)	-1.560e-01 ***(***)
	<b>AMIM</b>	-0.683 ***(***)	-0.725 ***(***)	-0.644 ***(***)
	<b>BEFORE</b>	<b>ILLIQ</b>	-0.000e+00	-0.000e+00
<b>MLI</b>		6.000e-03 ***(***)	3.000e-03 ***(***)	2.000e-03 ***(***)
<b>Volume</b>		1.050e+09	8.669e+08	7.932e+08
<b>VAR</b>		3.900e-02	3.400e-02	7.200e-02
<b>VaR</b>		-2.380e-01 **,(***)	-1.010e-01	-6.800e-02
<b>Vol</b>		-4.700e-02 ,(***)	-4.800e-0 ,(**)	-5.100e-02 ,(**)
<b>AMIM</b>		-0.287	-0.236	0.179
<b>BUBBLE</b>		<b>ILLIQ</b>	-8.360e-01,(***)	-6.770e-01,(***)
	<b>MLI</b>	-9.172e+00	-5.797e+00,(**)	-5.860e-01,(**)
	<b>Volume</b>	1.241e+10 ***(***)	8.753e+09 ***(***)	8.262e+09 ***(***)
	<b>VAR</b>	1.300e-02 *	4.600e-02	7.500e-02 *,(**)
	<b>VaR</b>	-2.662e+00 *,(***)	-1.802e+00 *,(***)	-1.248e+00 *,(***)
	<b>Vol</b>	-2.270e-01 ***(***)	-2.020e-01 ***(***)	-1.920e-01 ***(***)
	<b>AMIM</b>	-0.745 ***(***)	-0.921 ***(***)	-0.944 ***(***)
	<b>AFTER</b>	<b>ILLIQ</b>	-2.317e+03,(**)	-4.610e+03,(**)
<b>MLI</b>		-1.427e+00,(***)	-1.427e+00,(***)	-1.000e-03,(***)
<b>Volume</b>		1.560e+10 ***(***)	9.537e+09 ***(***)	4.864e+09 ***(***)
<b>VAR</b>		1.500e-02 ***(**)	4.000e-03 ,(***)	1.030e-01 ***(**)
<b>VaR</b>		-6.105e+00 ,(**)	-7.520e-01 **,(**)	-4.100e-01 ***(**)
<b>Vol</b>		-3.320e-01 ***(**)	-2.730e-01 ***(**)	-2.390e-01 ***(**)
<b>AMIM</b>		-1.313 ***(**)	-0.990 ***(**)	-1.223 ***(**)

Table II.16: **Descriptive Statistics: Bitcoin's reaction to forking events**

Summary statistics for financial returns in our sample for the  $[-100; +30]$  window. The values of the mean, std, min, 25th percentile, median, 75th percentile, and max are expressed in percent. The count provides the number of days for which we have non-missing data.

	count	mean	std	min	25%	50%	75%	max	skewness	kurtosis
<b>ZEC</b>	130	0.073	1.773	-10.202	-0.451	0.069	0.687	4.477	-1.773	10.131
<b>BCH</b>	130	1.046	4.526	-11.092	-1.812	1.180	4.142	21.460	0.475	2.828
<b>SBTC</b>	130	0.766	4.713	-11.092	-2.102	0.909	4.142	21.460	0.446	2.323
<b>BTG</b>	130	1.098	5.157	-20.753	-1.945	0.870	4.042	21.460	0.166	3.441
<b>BTCL</b>	130	1.342	5.348	-20.753	-1.274	1.011	4.115	22.512	0.195	3.492
<b>BCD</b>	130	0.890	5.568	-20.753	-2.008	0.873	3.569	22.512	0.183	3.009
<b>BTH</b>	130	0.826	6.126	-20.753	-2.116	0.912	3.885	22.512	0.126	1.722
<b>BCX</b>	130	0.826	6.126	-20.753	-2.116	0.912	3.885	22.512	0.126	1.722
<b>UBTC</b>	130	0.826	6.126	-20.753	-2.116	0.912	3.885	22.512	0.126	1.722
<b>BTP</b>	130	0.844	6.089	-20.753	-2.116	0.912	3.885	22.512	0.136	1.807
<b>LBTC</b>	130	0.787	6.270	-20.753	-2.116	0.926	3.885	22.512	-0.050	1.936
<b>BTF</b>	130	0.787	6.270	-20.753	-2.116	0.926	3.885	22.512	-0.050	1.936
<b>GOD</b>	130	0.778	5.921	-18.458	-2.116	0.936	3.885	22.512	0.149	1.674
<b>BIFI</b>	130	0.778	5.921	-18.458	-2.116	0.936	3.885	22.512	0.149	1.674
<b>XRC</b>	130	0.526	6.399	-18.458	-2.656	1.011	3.770	22.512	-0.037	1.198
<b>BTV</b>	130	0.541	6.526	-18.458	-3.707	0.996	4.289	22.512	-0.034	0.902
<b>BCI</b>	130	0.466	6.550	-18.458	-3.768	0.922	4.289	22.512	-0.009	0.853
<b>BCA</b>	130	0.452	6.578	-18.458	-3.840	0.996	4.289	22.512	-0.011	0.800
<b>BTC2</b>	130	0.423	6.659	-18.458	-4.141	1.088	4.394	22.512	-0.010	0.648
<b>BTCP</b>	130	-0.097	6.631	-18.458	-4.581	0.413	3.438	22.512	0.111	0.740
<b>CBTC</b>	130	-0.320	5.914	-18.458	-3.840	0.343	3.366	13.785	-0.277	0.318
<b>MBC</b>	130	-0.454	3.990	-10.603	-2.897	0.133	1.587	12.413	-0.182	0.634
<b>ANON</b>	130	-0.115	2.921	-10.429	-1.224	0.243	1.283	8.845	-0.550	2.325
<b>BZX</b>	130	0.031	2.558	-8.042	-0.855	0.090	1.125	8.845	-0.031	2.082

Table II.17: **Descriptive Statistics: Behavior of the newly forked coin**

Summary statistics for financial returns in our sample for the  $[0; +500]$  window. The values of the mean, std, min, 25th percentile, median, 75th percentile, and max are expressed in percent. The count provides the number of days for which we have non-missing data.

	count	mean	std	min	25%	50%	75%	max	skewness	kurtosis
<b>LTC</b>	500	0.024	4.893	-21.758	-2.186	-0.008	2.283	47.149	-0.008	7.475
<b>DGB</b>	500	-0.134	6.769	-44.817	-2.671	0.372	3.048	53.550	-0.686	7.628
<b>DASH</b>	500	0.025	5.426	-39.959	-1.939	0.067	2.122	45.927	-0.732	8.179
<b>GRS</b>	500	0.045	5.426	-22.144	-2.675	-0.261	2.637	47.406	-0.904	8.651
<b>NAV</b>	500	0.030	6.686	-59.873	-2.771	-0.128	3.181	67.508	-1.267	10.815
<b>SYS</b>	500	-0.150	7.820	-70.149	-3.281	-0.483	3.511	62.868	-1.048	8.776
<b>ZEC</b>	500	-0.009	5.447	-22.032	-2.658	0.009	2.391	41.273	-0.151	2.966
<b>BCH</b>	500	0.023	5.428	-27.777	-2.242	0.031	2.066	57.985	-0.078	2.787
<b>SBTC</b>	500	0.093	32.000	-150.556	-11.804	-0.252	10.758	130.097	-0.335	2.758
<b>BTG</b>	500	0.161	6.061	-71.309	-2.036	0.000	2.209	55.743	0.030	3.111
<b>BTCL</b>	500	0.407	26.771	-181.075	-7.037	0.000	8.672	163.092	-2.512	32.825
<b>BCD</b>	500	0.075	6.071	-45.384	-2.411	0.126	2.537	54.756	0.070	3.483
<b>BTH</b>	500	0.588	43.467	-675.684	-1.797	0.348	3.162	685.951	0.035	3.776
<b>BCX</b>	500	0.278	32.819	-169.945	-7.502	0.342	8.331	187.804	-0.335	2.758
<b>UBTC</b>	500	0.219	20.023	-110.686	-5.661	0.175	7.208	114.234	-0.369	2.843
<b>BTP</b>	500	0.092	28.660	-123.668	-11.459	0.045	12.112	104.943	0.035	4.025
<b>LBTC</b>	500	0.205	11.706	-119.428	-2.289	0.000	2.616	133.349	-0.345	3.069
<b>BTF</b>	500	0.659	17.405	-137.348	-2.227	0.000	2.503	199.563	-2.513	32.819
<b>GOD</b>	500	0.267	87.493	-317.313	-16.446	0.000	19.265	330.570	-0.307	3.246
<b>BIFI</b>	500	0.043	61.690	-609.973	-6.841	0.572	7.713	620.058	-0.004	3.863
<b>XRC</b>	500	0.301	21.087	-99.708	-6.125	0.786	7.935	107.264	-2.641	33.202
<b>BTV</b>	500	0.046	18.375	-130.727	-4.754	0.000	5.183	122.628	-0.104	3.162
<b>BCI</b>	500	0.742	18.662	-115.232	-4.003	0.541	7.041	96.385	-0.143	3.451
<b>BCA</b>	500	0.040	19.773	-97.141	-7.295	-0.031	8.296	86.959	-0.145	2.884
<b>BTC2</b>	500	0.201	11.045	-58.370	-5.637	0.016	6.156	52.870	0.037	4.103
<b>BTCP</b>	500	0.172	21.520	-135.349	-6.073	0.268	6.982	132.461	-0.144	3.026
<b>CBTC</b>	500	0.185	38.884	-232.298	-18.545	-0.538	18.594	157.295	0.032	3.983
<b>MBC</b>	500	0.177	23.222	-119.718	-7.650	0.000	9.495	157.429	0.032	3.947
<b>ANON</b>	500	0.889	59.748	-804.377	-5.882	-0.022	6.986	825.050	0.042	4.053
<b>BZX</b>	500	0.075	25.452	-259.611	-7.934	0.180	7.941	276.318	0.032	3.947

Table II.18: **Range of Confidence Interval ( $R_{CI}$ )**

Values of  $R_{CI}$  computed for various lags. The computational procedure is given in detail in Tran and Leirvik (2019). In essence, the  $\hat{\beta}^{\text{standard}}$  are all standard normal. Hence, their simulations become straightforward.

Lags	$R_{CI}$	Lags	$R_{CI}$
1	0.662340	14	0.157074
2	0.750270	15	0.145522
3	0.774516	16	0.149598
4	0.763674	17	0.119437
5	0.675846	18	0.093221
6	0.503062	19	0.097827
7	0.497190	20	0.093213
8	0.369526	21	0.076899
9	0.299386	22	0.076795
10	0.264204	23	0.068431
11	0.236230	24	0.091624
12	0.193164	25	0.061208
13	0.179367	26	0.059284

Table II.19: **Cross-sectional Regression**

Summary of the OLS regression used for identifying the drivers of efficiency improvement in Bitcoin during a fork. Explanatory variables are the changes in indicators from after/before a fork.

<b>Dep. Variable:</b>	AMIM_diff	<b>R-squared:</b>	0.734			
<b>Model:</b>	OLS	<b>Adj. R-squared:</b>	0.677			
<b>Method:</b>	Least Squares	<b>F-statistic:</b>	13.07			
<b>Date:</b>	Tue, 25 May 2021	<b>Prob (F-statistic):</b>	2.79e-05			
<b>Time:</b>	08:46:52	<b>Log-Likelihood:</b>	-14.497			
<b>No. Observations:</b>	24	<b>AIC:</b>	38.99			
<b>Df Residuals:</b>	19	<b>BIC:</b>	44.89			
<b>Df Model:</b>	4					
	<b>coef</b>	<b>std err</b>	<b>t</b>	<b>P&gt;  t </b>	<b>[0.025</b>	<b>0.975]</b>
<b>const</b>	0.6673	0.219	3.051	0.007	0.210	1.125
<b>ILLIQ_diff</b>	1.245e-08	5.37e-09	2.319	0.032	1.21e-09	2.37e-08
<b>MLI_diff</b>	0.0103	0.004	2.675	0.015	0.002	0.018
<b>Volume_diff</b>	-2.994e-06	1.06e-06	-2.829	0.011	-5.21e-06	-7.79e-07
<b>Vol_diff</b>	34.4332	14.870	2.316	0.032	3.309	65.557
<b>VA_Rt_diff</b>	1.2339	0.570	2.166	0.043	0.042	2.426
<b>Omnibus:</b>	0.238	<b>Durbin-Watson:</b>	1.451			
<b>Prob(Omnibus):</b>	0.888	<b>Jarque-Bera (JB):</b>	0.004			
<b>Skew:</b>	0.007	<b>Prob(JB):</b>	0.998			
<b>Kurtosis:</b>	2.942	<b>Cond. No.</b>	8.36e+16			

# Chapter III

## What drives DeFi market returns?<sup>1</sup>

### III.1 Introduction

#### III.1.1 Context

Blockchain was the first tool to bring a decentralized alternative to the existing payment instruments. From that moment on, Fintech and Blockchain technology spread over the whole finance industry and other areas by bringing more automation and innovative solutions. DeFi brings the latest Blockchain-based distributed solutions aiming to provide financial services on a large scale, without intermediaries, using automated protocols. DeFi is a fast-growing sub-sector of the crypto-financial market (Corbet et al., 2021; Ramos & Zanko, 2021a). Its solutions cover most functions of the traditional financial system, from funds transfer to margin trading, interest-earning, and market-making.

#### III.1.2 Motivation and research problem

With this research, we take the first steps in determining ways to value DeFi tokens. Inspired by the previous approaches (Fama & French, 1992, 1993), we start by studying the possible drivers of DeFi returns. DeFi represents a sub-sector of the

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<sup>1</sup>This paper has been presented at the 38th International Conference of the French Finance Association 2022 in Saint-Malo, France, under a different title: 'The return of (i)DeFiX'. We mention as well the fact that this chapter is in revision with Journal of International Financial Markets, Institutions & Money.

crypto-financial market (Corbet et al., 2021; Ramos & Zanko, 2021a). Motivated by (Corbet et al., 2021; Maouchi, Charfeddine, & El Montasser, 2021; Schar, 2021; Yousaf, Nekhili, & Gubareva, 2022), who show that **DeFis** are a distinct asset class compared to conventional cryptocurrencies, our goal is to offer a first analysis of the **DeFi** market as a whole and answer to the following research question: *What are the drivers of DeFi tokens' returns?*. Similar to Corbet et al., 2021, we believe that studying DeFi tokens' returns has important implications in portfolio construction and investment decision processes. It is well-known that crypto-assets offer significant diversification benefits to equity investors (Ankenbrand & Bieri, 2018; Briere, Oosterlinck, & Szafarz, 2015). This is valid as well during stressful periods such as COVID-19 (Goodell & Goutte, 2021). Hence, we think that our findings will greatly serve investors interested in the **DeFi** market to maximize their profits and diversify risks. In their paper, Liu and Tsyvinski (2021) showed that the cryptocurrency market is exposed to the network effect, the momentum effect, and the investor attention but is not impacted by the cryptocurrencies' production factors, macroeconomic factors, or other asset classes (e.g., commodities or stocks). Following their study, we thus investigate three possible drivers of **DeFi** returns: (1) taking into account that both cryptocurrencies and **DeFis** run on Blockchain technology and belong to the crypto-market, we assess the cryptocurrencies' return impact on **DeFi** returns; (2) the exposure to network variables to see if the **DeFi** market is as well exposed to the same factors as cryptocurrencies (Liu & Tsyvinski, 2021); and (3) motivated by relevant studies (Ball et al., 2020; Cong, Li, & Wang, 2021; Liu & Tsyvinski, 2021; Pontiff & Schall, 1998) tackling the valuation ratio importance in driving future returns, we want to investigate if **DeFi** returns are impacted by a ratio similar to the 'book-to-market'.

### III.1.3 Main Findings

Before diving into this research subject, it is important to make a clear distinction between the cryptocurrency market and the **DeFi** market. Perceived from a practical viewpoint, **DeFi** tokens and cryptocurrencies are only similar in the sense that both are based on Blockchain technology and implement decentralized (automatic) management. However, from a technological perspective, **DeFis** (short for **DeFi** tokens) are a distinct technology as they require smart contract technology to function. As cryptocurrencies and **DeFi** tokens represent both distinct technologies and different asset classes, we also expect that these crypto-assets distinguish themselves in terms of risk and return. From here stems our motivation to study the **DeFi** market sep-

arately from the cryptocurrencies and to analyze the behavior of these new tokens.

Being an asset class separate from conventional cryptocurrencies (Corbet et al., 2021; Maouchi, Charfeddine, & El Montasser, 2021; Corbet, Goodell, & Günay, 2022), the CRIX index does not seem a relevant proxy for the DeFi market. Up to now, the whole DeFi market has never been analyzed. Therefore, we contribute to this area of research and design a market index that will enable us to assess the performance of this new asset class and the market as a whole. We compute ‘iDeFiX’, a value-weighted market index of all the DeFis. We use the CRIX’s index methodology (Trimborn & Härdle, 2018) and a version of its original code to construct iDeFiX, a novel market benchmark for decentralized finance. Nasdaq has listed an index for Decentralized Finance with the trading symbol DEFX. We perform comparison tests with Nasdaq DEFX and iDeFiX in the Appendix Section III.A.5. The results are robust regardless of the index used. In line with (Corbet et al., 2021; Yousaf & Yarovaya, 2021), our empirical analysis confirms that the cryptocurrency market strongly influences DeFis returns. DeFis appear to be exposed to their network variables, a result similar to that of (Liu & Tsyvinski, 2021) for the cryptocurrency market. Furthermore, we investigated if DeFis returns can be driven by their corresponding ‘book-to-market’ ratio. As there is no standard ‘book’ value for DeFis, we construct a ratio by dividing the TVL by the Market Capitalization (MC). Our findings do not support the TVL/MC exposure assumption. Out of all the considered drivers, our empirical study shows that the impact of the cryptocurrency market on DeFis returns is the strongest.

The contributions made by this study are multiple: (1) we construct a market index for DeFi market; (2) we propose a new variable, the TVL-to-Market ratio, as an equivalent for this market of the ‘book-to-market ratio’; (3) we test if the cryptocurrency market, the network variables and the TVL-to-Market ratio can drive DeFi tokens returns; and last (4) we have constructed the database used in this study.

The structure of this chapter is as follows. The next section exposes the research background. Section 3 presents the data description and collection. Section 4 introduces the methodology used and data analysis performed alongside the obtained results. Section 5 comprises the discussion, and finally, section 6 concludes the research.

## III.2 Research Background

It is often said that the financial crisis of 2008 and the way banks managed their financial risks inspired Satoshi Nakamoto to create bitcoin. More than ten years after its invention, Blockchain brings innovative alternatives to not only transactions but to most financial services. DeFi platforms represent a finance-oriented technology that is built on top of Blockchain. Besides new ways of doing finance (such as lending, borrowing, trading, funding, asset management, and derivatives), DeFi offers as well new ways of funding and doing business. DeFi platforms make the use of financial services more modern and open to everyone, therefore creating opportunities for a new finance industry (Piñeiro-Chousa, Cabarcos, & González, 2022). A detailed description of the DeFi market is provided in appendix III.A.1.

Despite of its relatively short history<sup>2</sup>, DeFi market grew considerably, reaching \$50 billion market capitalization (as November 2022) (Coinmarketcap.com, 2022) compared to \$1.8 billion in March 2020 (Xu, Xu, & Lommers, 2022). However, if we look at the cryptocurrency market, with \$1 trillion market capitalization (TradingView.com, 2022), the DeFi market is still small. In the face of decentralized finance development, regulatory organizations think that DeFi facilitates speculation rather than real economy business (Aramonte et al., 2022). This brings us to one of the main drawbacks of the DeFi market, which is the lack of a regulatory framework. This issue has been widely debated in the literature (Chen & Bellavitis, 2019; Chen et al., 2020; Popescu, 2020; Anker-Sorensen & Zetsche, 2021; Aramonte, Huang, & Schrimpf, 2021; Johnson, 2021; Stepanova & Erins, 2021; Wronka, 2021).

Compared to the vast literature on cryptocurrencies, DeFi-related research is scarcer. Gudgeon et al. (2020) assess the interest rates, liquidity, and market efficiency of main DeFi projects. They find that DeFi tokens are relatively inefficient, while the market is liquid mostly at times of high (platform) utilization. Zhang and Chan, 2022 tested the efficiency of the DeFi market by employing the adaptive market hypothesis (AMH). In line with the AMH theory (Lo, 2004), the authors show that DeFi efficiency varies over time, with the majority of the token returns exhibiting short periods of inefficiency. Zetsche, Arner, and Buckley (2020) analyze DeFi platforms' potential, put in the context of the traditional financial economy, and find that DeFis can erode the effectiveness of existing financial regulation. Maouchi, Charfeddine, and El Montasser (2021) study the bubbles present in the NFT and

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<sup>2</sup>Maker DAO, considered the first DeFi platform, was launched in 2015 (Chohan, 2021).

DeFi markets and discover that COVID-19 and trading volume aggravate the bubble occurrences. They observe that DeFis prices' dynamics are different from pure cryptocurrencies, which distinguishes them from the latter asset class. Moreover, they explain that the TVL<sup>3</sup> should be used as a monitoring tool for the DeFi market (growth), as it indicates the fundamental value of DeFi protocols (Maouchi, Charfeddine, & El Montasser, 2021). Similarly, Corbet et al. (2021) tested for the existence of bubbles and found that DeFi bubbles are mainly self-generated and partially accelerated by ETH and BTC. At the same time, they test for a possible co-movement between DeFis and cryptocurrencies, which revealed that DeFis represent a separate asset class with some links to conventional cryptocurrencies. Wang et al., 2022 also investigate the existence of bubbles in the DeFi and NFT markets. Their results show that both markets exhibit speculative bubbles, driven mostly by market hype/uncertainty and herding behavior. At the same time, the authors reveal that the bubbles are not always present, a fact suggesting that DeFi tokens and NFTs do have an intrinsic value. Karim et al. (2022) are the first to investigate the risk transmission among NFT, DeFis, and cryptocurrencies. They show that despite significant risk spillovers in the blockchain markets, namely among DeFis and cryptos, NFTs could greatly serve as an 'investment shield'. Yousaf, Nekhili, and Gubareva, 2022 are investigating the herding behavior in the crypto-market and find that DeFi markets exhibit herding only during low volatility days. Furthermore, the authors explore the connectedness of the DeFi market with conventional banking assets. Their results show that there is an interdependence between DeFi tokens belonging to lending platforms and commercial bank stocks. Moreover, the connectedness between the two asset classes seems to accentuate in times of uncertainty, such as COVID-19. Based on their findings, the authors consider that DeFi lending tokens represent a new commercial banking asset class. Piñeiro-Chousa et al., 2022 investigate if there is a relationship between some traditional assets, user-generated content, and DeFi. For this study, the authors use a logit-probit methodology and a dataset composed of 13 DeFi tokens, VIX, S&P GSCI Crude Oil Index, and S&P GSCI Gold Index, and the daily variation in DeFi mentions in Telegram and Twitter. Their findings show that there is a significant relationship between DeFi tokens and the traditional assets considered, but not with Telegram and Twitter activity. These results show that DeFi tokens are a safe haven and a hedge for stock market volatility.

A growing literature debates the main challenges that hold the DeFi market from

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<sup>3</sup>TVL refers to the amount of funds attached to a DeFi project.

mainstream adoption, such as technological vulnerabilities, operational issues, market manipulation, and regulatory problems. Gudgeon et al. (2020) examine DeFi lending platforms and reveal that with ‘sufficient’ illiquidity, a lending protocol can become undercollateralized in less than one month. Werner et al., 2022 provide a Systematization of Knowledge (SoK) on DeFi research and describe this market application based on different aspects: primitives, operational protocol types, and security risks. Furthermore, (Werner et al., 2022) is perhaps the first study to look at DeFis’ existing challenges through both technological and economic lenses and provide a global view of the threats of this technology. Scharfman, 2021 presents the evolution of the DeFi market from a breakthrough technology challenging centralized finance (CeFi), to a tool that has to deal with considerable difficulties, including market manipulation, regulatory issues, pump and dump scams, and other challenges. In another study, Harwick and Caton (2020) argue that while cryptocurrencies have the potential to perform monetary and financial functions superior to those of national currencies, pure decentralized autonomous finance remains an illusory idea as long as it will not integrate real-world identity.

After reviewing the current literature, it appears that the existing research does not offer enough answers given the market needs. Notably, as crypto-assets became an interesting investable asset class for institutional investors such as Grayscale and Blackrock (Xu, Xu, & Lommers, 2022), we mention the need for proper techniques to price these new assets. Despite the efforts put into the growing literature, the existing research on the crypto-assets valuation is insufficient. To our knowledge, (Xu, Xu, & Lommers, 2022) is the only study trying to provide a framework to value DeFi tokens. The authors attempt to value DeFis using the multiples and Discount Cash Flow (DCF) methods. They focus only on a subset of the DeFi market: the exchange and lending platforms. Furthermore, using the same accounting-based valuation methods on publicly traded firms within a similar market segment, the authors perform a comparative analysis between DeFi platforms and the firms. Their findings reveal that DeFi tokens are generally overvalued.

More than 13 years after the beginning of the crypto-market, we still do not have a proper method to accurately value all the crypto-assets. Therefore, with this study, we take the first steps in this direction and analyze what drives DeFis tokens returns. Inspired by the previous research approaches on the stock market (Fama & French, 1992, 1993), this works aims to offer directions on how to price DeFi tokens by studying the possible determinants of DeFis returns.

We cannot ignore the existence of a similar study to ours. Corbet, Goodell, and Günay (2022) are assessing the drivers of DeFi prices and possible connectedness present within the market. In pursuing their investigation, the authors are using five DeFis with which they create a market index. Furthermore, they explore the driving power of BTC, ETH, and investor attention proxied by Google Trends on DeFi returns. The results of this study reveal varying causal linkages restricted to bear markets between BTC or ETH and DeFi, while investor attention proves to be the main driver for DeFi returns. Our paper has the ambition firstly to complement the analysis of (Corbet, Goodell, & Günay, 2022) by considering a larger sample of DeFi tokens, as well as by improving the DeFi market index (ours is constructed based on 95 tokens). Moreover, our contribution relative to (Corbet, Goodell, & Günay, 2022) is also to analyze additional determinants of DeFis returns, such as the valuation ratio and the network variables. Finally, we introduce a new valuation ratio specific to the DeFi market.

## III.3 Data description and sources

### III.3.1 Financial data

We access *Coinmarketcap.com* and *spglobal.com* platforms to collect financial data for our DeFis as well as for BTC, ETH, and CRIX index. We download the CRIX index prices from *spglobal.com*, for which the historical data starts from March 2018. Coinmarketcap is the leading source for financial crypto-related information and has been used as a reliable source by various researchers, including but not limited to Borri (2019), Fry and Cheah (2016), Griffin and Shams (2020), Grobys and Sapkota (2019), Howell, Niessner, and Yermack (2020), Koutmos (2020), Liu, Tsyvinski, and Wu (2022), Stosic et al. (2018), and Zhang et al. (2019). We extract financial data for 478 DeFis, such as market capitalization, daily prices, and trading volume information. Coinmarketcap contains both defunct and active coins and provides a ‘DeFi’ tag for a correct separation of these tokens. Globally, we have data from 2017 to 2022.

### III.3.2 Constructing a DeFi index: iDeFiX

With the financial data extracted from *Coinmarketcap.com*, we construct a market index, iDeFiX, as the value-weighted return of all underlying tokens. At this step, we are using all the tokens' information, such as price, volume, and market capitalization. Similar to Liu and Tsyvinski (2021)'s approach, we decided to remove the tokens with less than 1,000,000 USD market capitalization. In the construction of iDeFiX, we work with daily close prices and use the methodology and original code<sup>4</sup> for the CRIX index (Trimborn & Härdle, 2018). The reasons why we have chosen the CRIX index methodology for building our index are the following: (1) The selection criteria based on [Akaike Information Criterion \(AIC\)](#) and which is embedded in the CRIX code, ensures that all relevant tokens that add informative value to the index are considered as potential constituents. More specifically, the methodology selects the tokens which are actively traded and have enough liquidity. Furthermore, to remove possible dominance issues (from big cap. tokens), CRIX ensures that there is a large enough number of tokens included in the index and that appropriate weights are given to each representative (Trimborn & Härdle, 2018). We consider that thanks to the CRIX methodology's selection of its constituents, iDeFiX is a more accurate benchmark than, for example, a plain vanilla index. (2) As its name states, CRIX is "an Index for Blockchain-based currencies". Considering that cryptocurrencies and DeFi tokens run on Blockchain technology and have similar challenges (e.g., high volatility and illiquidity due to lack of trading), we think that using the CRIX index methodology and its original code helps us to construct a proper index for the decentralized finance market. After running the CRIX code, our index is composed of 95 tokens and spans from May 2017 to December 2021. A more detailed methodology for our index construction can be found in [III.A.2](#). For the rest of the paper, we compute and use weekly market returns from the daily market returns. A detailed description of all the data used in this study can be found in [III.A.3](#).

### III.3.3 Network data

The literature has established that the network effect makes cryptocurrencies more useful as more people join the network / Blockchain (Biais et al., 2020; Cong, Li, & Wang, 2021; Pagnotta & Buraschi, 2018). In other words, this means that the more individuals decide to use BTC, the more valuable the entire BTC ecosystem becomes;

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<sup>4</sup>The code is accessible at: *quantlet.de*.

hence the price will increase. Liu and Tsyvinski (2021) show that the network effect is one of the cryptocurrencies' price drivers. Therefore, we assess if the same is valid for the DeFi market. We use three primary measures to proxy the network effect on the DeFi market: the number of wallet users, the number of active addresses, and the TVL<sup>5</sup>. Similar to (Liu & Tsyvinski, 2021), we retrieve network data such as the number of transactions and active addresses from *Coinmetrics.io*. We obtained information for 30 DeFis, out of which we have financial data only for 21. TVL is a unique variable characteristic of the DeFi market. Then, *Defillama.com* is one of the most complete data aggregators collecting the TVL information for DeFi platforms. We extract the TVL for 503 tokens from *Defillama.com*, out of which we have financial information (price, market cap., and volume from the *coinmarketcap.com*) only for 160. To fully examine the impact of network variables (especially TVL), we also perform panel regressions with individual token data. For further information about data, refer to the Appendix section III.A.3.

The main statistical properties of the variables used in this study are shown in Table III.1 and Table III.2.

Table III.1: **Summary Statistics - Network Variables**

*Summary statistics for the network variables of the DeFis in our sample spanning from May 2017 to December 2021. TVL is expressed in Million of USD. The growth of the variables is also provided (denoted with a  $\Delta$ ). The Durbin-Watson tests show how using the growth of the variables deals with the autocorrelation present in the initial variables.*

		<i>Mean</i>	<i>SD</i>	<i>Max</i>	<i>Min</i>	<i>Skewness</i>	<i>Kurtosis</i>	<i>Durbin-Watson</i>
<i>Daily</i>	<b>Address Count</b>	967.763	1226.325	15259.8	0.000	2.442	12.759	0.422
	<b>Transaction Count</b>	4264.966	4417.107	19827.385	0.000	0.96	0.017	0.008
	<b>TVL</b>	347.011	271.753	1043.825	0.035	0.452	-1.251	0.001
	$\Delta$ <b>Address Count</b>	0.000	0.698	4.869	-4.649	0.301	2.322	2.966
	$\Delta$ <b>Transaction Count</b>	-0.001	0.509	3.897	-3.332	0.306	11.733	2.869
	$\Delta$ <b>TVL</b>	0.008	0.208	6.679	-0.965	28.151	898.98	2.020

Figure III.1 shows the cumulative returns of iDeFiX compared to those of the crypto-market, the two major cryptocurrencies, and the CRIX index. We can observe a strong co-movement among the BTC, ETH, and the DeFi market returns, result confirmed as well by Corbet et al. (2021). We can see as well that CRIX follows the same trend, confirming the strong co-movement between the cryptocur-

<sup>5</sup>The TVL is often considered as a measure of a platform's success (Maouchi, Charfeddine, & El Montasser, 2021). It is also perceived as a partial substitute for the Book Value.

Table III.2: **Summary Statistics - Financial Returns**

Summary statistics for the returns of *DeFi* tokens, three market indexes, and cryptocurrencies in our sample spanning from May 2017 to December 2021. The mean and standard deviation (SD) are annualized. The Durbin-Watson (DW) tests show the autocorrelation present in the time series.

	Mean	SD	Sharpe	Skewness	Kurtosis	DW	Frequency
<b>iDeFiX</b>	0.100	4.117	0.024	-1.059	8.854	2.025	<i>Daily</i>
<b>DEFX</b>	0.255	6.879	0.037	-0.084	6.112	2.122	
<b>CRIX</b>	0.118	4.589	0.026	-0.422	3.356	2.016	
<b>BTC</b>	0.179	4.157	0.043	-0.528	8.454	2.007	
<b>ETH</b>	0.331	6.224	0.053	-0.605	12.273	2.013	
<b>iDeFiX</b>	0.689	11.754	0.059	-0.575	4.972	1.818	<i>Weekly</i>
<b>DEFX</b>	1.218	14.657	0.083	-0.210	1.870	2.126	
<b>CRIX</b>	0.588	10.733	0.055	-0.954	3.655	1.821	
<b>BTC</b>	1.25	10.752	0.116	0.117	2.178	1.599	
<b>ETH</b>	2.313	16.88	0.137	-0.048	1.927	1.789	
<b>iDeFiX</b>	3.001	25.244	0.119	0.611	1.498	1.910	<i>Monthly</i>
<b>DEFX</b>	5.095	28.393	0.179	0.208	0.043	1.970	
<b>CRIX</b>	2.529	23.784	0.106	-0.008	-0.958	1.694	
<b>BTC</b>	5.365	26.735	0.201	1.836	9.239	1.75	
<b>ETH</b>	9.964	37.123	0.268	0.533	0.734	1.485	

rency market and the *DeFi* market.

### III.4 Methods and analysis

In this section, we assess several possible drivers for *DeFi*s returns. We start our investigation with the cryptocurrency market and the network effect. Furthermore, making a parallel with stock returns determinants, we introduce a ‘book-to-market ratio’ specific to the *DeFi* market. We further check whether *DeFi*s returns are impacted by this variable.

In making this study, we are using time series and panel regressions. The time-series regressions are a convenient tool for studying asset-pricing issues (Fama & French, 1993). In our case, this tool allows estimating the sensitivity of *DeFi* returns to given risk factors (the drivers). When data allows it, we also employ panel regression, which helps to control heterogeneity, increases the number of observations, and improves the estimation. While doing our analyses, we often use a sample of 15 top *DeFi*s. The selection of the top *DeFi* tokens has been made based on their average market capitalization over the past 100 days and on the data availability for the analysis period. By regressing both our market index and individual tokens, we are able to examine the returns’ sensitivity to different drivers at the market and individual asset levels.

Figure III.1: **Co-movements between iDeFiX and cryptocurrencies**

Cumulative returns of the *DeFi* index *iDeFiX* and major cryptocurrencies: *BTC* and *ETH* as well as the *CRIX*. The returns are daily and span from 2017 to 2022.



### III.4.1 Exposure to the cryptocurrency market

The co-movement among securities returns has always been an important aspect in asset pricing, risk management, and subsequently, asset allocation (Eraker, Johannes, & Polson, 2003; Oliva & Reno, 2018). Important research has been done on this matter, concerning both the traditional and cryptocurrency markets. Contrasting with the early literature, several studies show that *BTC* is not a dominating coin anymore (Bouri et al., 2019; Yi, Xu, & Wang, 2018), while its strong and persistent influence remains (Bouri et al., 2019; Bouri, Lucey, & Roubaud, 2020; Ciaian, Rajcaniova, & Kancs, 2018; Ji et al., 2019; Pereira & Ferreira, 2019; Stosic et al., 2018). Often, connectedness within the crypto-market is observed among the leading cryptocurrencies only, and it is stronger in the short run (Corbet et al., 2019; Yarovaya & Zieba, 2022). We investigate the impact of cryptocurrencies (*BTC*, *ETH*, and *CRIX* index) on *DeFi* market returns. For addressing such an issue, we begin by proposing a new index of the *DeFi* market, namely, the *iDeFiX* index. We then analyze the impact of cryptocurrencies returns on the *iDeFiX* index and on 15 of the leading *DeFis*. The selection choice for the top biggest *DeFis* have been made based on their average market capitalization over the past 100 days. The rationale behind our selection for *BTC* and *ETH* cryptocurrencies is the following: Ethereum is the main technology used in developing *DeFi* platforms (Popescu, 2020; Ramos & Zanko, 2021a), while *BTC* and *ETH* are the main digital coins used as leverage in *DeFi* operations (Aramonte, Huang, & Schrimpf, 2021; Schar, 2021). *CRIX* is the index for the cryptocurrency market, and since the current literature (Corbet et al., 2021; Karim et al., 2022; Maouchi, Charfeddine, & El Montasser, 2021) shows an

existing relationship between **BTC** and certain **DeFis**, it seems relevant to assess whether the crypto-market as a whole has an impact on the **DeFi** market. In order to test the **DeFis** price drivers, we apply time-series analytical mechanisms to weekly data for the period May 2017 to December 2021.

Before carrying out a regression analysis, we study the correlation between cryptocurrencies and **DeFis**. Table III.3 reports a strong correlation between cryptocurrency and the **DeFi** market index. To avoid possible multicollinearity issues, we thus further assess the exposure of the **DeFi** market to the cryptocurrency market by making individual checks instead of regressions with all the variables together.

Table III.3: **Correlation between the DeFi and cryptocurrency markets.** *Pearson correlations of weekly returns of iDeFiX, BTC, ETH, and CRIX. \*\*\* denotes significance levels based on the respective p-value (\*:10%, \*\*:5%, and \*\*\*:1%).*

	iDeFiX	Rt_ETH	Rt_BTC	CRIX
iDeFiX	1			
Rt ETH	<b>0.729***</b>	1		
Rt BTC	<b>0.604***</b>	<b>0.692***</b>	1	
CRIX	<b>0.551***</b>	<b>0.606***</b>	<b>0.655***</b>	1

### The impact of BTC

We begin the analysis of the **DeFis** exposure to the cryptocurrency market by first checking the power of influence of **BTC**. We regress the iDeFiX index returns and the 15 main **DeFis** returns (LUNA, AVAX, WBTC, UNI, DAI, LINK, FTM, XTZ, AAVE, GRT, MKR, CAKE, RUNE, CRV, and LRC) against **BTC** returns on weeks t-1 and t-2. The results of our regressions are shown in Table III.4. We run the following regressions,

$$RtiDeFiX(t) = \alpha + \beta_1 RtBTC(t - 1) + \beta_2 RtBTC(t - 2) + \varepsilon_t, \quad (III.1)$$

$$RtDeFiToken(t) = \alpha + \beta_1 RtBTC(t - 1) + \beta_2 RtBTC(t - 2) + \varepsilon_t. \quad (III.2)$$

We find that one-week lagged **BTC** returns have a positive and significant impact on future iDeFiX returns, as well as on several leading tokens. LUNA, WBTC, MKR, LINK, FTM, XTZ, RUNE, and LRC seem to be positively influenced by

Table III.4: The impact of bitcoin on iDeFiX and DeFi Tokens.

The standard *t*-statistic value is shown in parentheses. Here we check if BTC impacts DeFi tokens' returns. *Rt-1* (*Rt-2*) refers to one (two) week(s) lagged BTC returns. *Rt* stands for weekly return. The number of observations for each regression is 265. \*\*\* denotes significance levels based on the respective *p*-value (\*:10%, \*\*:5%, and \*\*\*:1%).

	Constant	Rt-1 BTC	Rt-2 BTC	$R^2$
Rt iDeFiX	-0.0006 (-0.098)	<b>0.6411***</b> (5.922)	-0.1675 (-1.549)	24.1%
Rt LUNA	0.0099 (0.999)	<b>0.3018*</b> (1.749)	0.0258 (0.150)	4.9%
Rt AVAX	0.0078 (0.975)	0.1551 (1.120)	-0.0055 (-0.040)	1.7%
Rt WBTC	0.0035 (0.892)	<b>0.3888***</b> (5.734)	0.0016 (0.024)	32.7%
Rt DAI	0.000 (0.140)	<b>-0.0187*</b> (-1.789)	0.0088 (0.843)	1.9%
Rt LINK	0.0076 (0.684)	<b>1.0342***</b> (5.332)	<b>-0.3841**</b> (-1.982)	17.2%
Rt UNI	0.0026 (0.391)	0.1517 (1.333)	-0.0229 (-0.202)	1.9%
Rt FTM	0.0113 (0.355)	<b>0.7775***</b> (3.656)	-0.3229 (-1.520)	8.2%
Rt XTZ	-0.0062 (-0.566)	<b>0.5633***</b> (2.964)	0.0153 (0.081)	11.9%
Rt AAVE	0.0202 (1.084)	0.04231 (1.307)	-0.3341 (-1.033)	0.7%
Rt GRT	0.0022 (0.226)	0.1281 (0.756)	0.0687 (0.412)	1.8%
Rt CAKE	0.0049 (0.525)	0.1962 (1.204)	-0.0212 (-0.130)	1.7%
Rt MKR	-0.0017 (-0.203)	<b>0.9517***</b> (6.418)	<b>-0.3380**</b> (-2.282)	23.7%
Rt RUNE	0.0178 (1.599)	<b>0.3202*</b> (1.660)	-0.1135 (-0.589)	2%
Rt CRV	-0.0070 (-0.747)	0.1225 (0.757)	0.0250 (0.155)	1.2%
Rt LRC	-0.0004 (-0.029)	<b>0.7513***</b> (3.361)	-0.0938 (-0.420)	11.7%

one-week lagged [BTC](#) returns. This result is in line with Corbet et al. (2021). Out of the fifteen major [DeFis](#) included in our assessment, nine show to be impacted by [BTC](#) returns. If most of our results show a positive impact of the previous week's [BTC](#) returns on [DeFis](#) returns, we observe that DAI returns are negatively and significantly impacted by [BTC](#) one week ahead returns. LINK and MKR seem to be as well negatively impacted by [BTC](#) two weeks ahead return, which means that an increase in [BTC](#) will result in a return decrease for LINK, MKR, and DAI. Based on these obtained results, we argue that, in addition to the influence of [BTC](#) arising from its role in [DeFi](#) operations, [DeFi](#) platforms might as well benefit from the cryptocurrencies hype and, hence, are driven by [BTC](#) variations.

### The impact of [ETH](#)

Celeste, Corbet, and Gurdgiev (2020) suggest that there is a relationship between [ETH](#) success and the growth of Ethereum based platforms. As most [DeFi](#) platforms are built on Ethereum technology, we check the exposure of [DeFis](#) returns to [ETH](#). Therefore, we regress the [iDeFiX](#) index returns and the main [DeFis](#) against [ETH](#) one-week and two-weeks lagged returns. We summarize our results in Table III.5. We run the following regressions,

$$RtDeFiX(t) = \alpha + \beta_1 RtETH(t - 1) + \beta_2 RtETH(t - 2) + \varepsilon_t, \quad (\text{III.3})$$

$$RtDeFiToken(t) = \alpha + \beta_1 RtETH(t - 1) + \beta_2 RtETH(t - 2) + \varepsilon_t. \quad (\text{III.4})$$

[ETH](#) influence on [DeFis](#) returns is similar to the one already reported for [BTC](#). Out of the fifteen major [DeFi](#) platforms included in our test, eight show a significant increase in their returns due to the [ETH](#) returns increase the week before. We find that one-week lagged [ETH](#) returns have an important impact on future [iDeFiX](#) returns and several leading tokens. Similar to [BTC](#) exposure assessment, MKR and LINK seem to be strongly positively (negatively) influenced by one (two) past weeks [ETH](#) returns. This result is in line with the existing literature (Agosto & Cafferata, 2020; Celeste, Corbet, & Gurdgiev, 2020; Chang & Shi, 2020), which shows that compared to other pure financial assets like [BTC](#) or [LiteCoin \(LTC\)](#), Ethereum is the main technology used in the development of service-based Blockchain instru-

Table III.5: The impact of ether coin on iDeFiX and DeFi Tokens.

The standard *t*-statistic value is shown in parentheses. Here we check if ETH impacts DeFi tokens' returns. *Rt-1* (*Rt-2*) refers to one (two) week(s) lagged ETH returns. *Rt* stands for weekly return. The number of observations for each regression is 265. \*\*\* denotes significance levels based on the respective *p*-value (\*:10%, \*\*:5%, and \*\*\*:1%).

	Constant	Rt-1 ETH	Rt-2 ETH	$R^2$
Rt iDeFiX	-0.0033 (-0.558)	<b>0.4571***</b> <b>-6.063</b>	-0.0312 (-0.419)	33.40%
Rt LUNA	0.0093 -0.93	<b>0.2489*</b> <b>-1.942</b>	-0.0096 (-0.076)	5.20%
Rt AVAX	0.0072 -0.897	0.0644 -0.627	0.061 -0.602	2.10%
Rt WBTC	0.0043 -990	<b>0.2138***</b> <b>-3.86</b>	0.0002 -0.004	18.70%
Rt DAI	0.000 -0.119	-0.0092 (-1.182)	0.0034 -0.441	1%
Rt LINK	0.0047 -0.426	<b>0.07827***</b> <b>-5.576</b>	<b>-0.2298*</b> <b>(-1.660)</b>	21.50%
Rt UNI	0.0016 -0.239	0.1158 -1.38	0.0131 -0.158	3.40%
Rt FTM	0.0088 -0.731	<b>0.6356***</b> <b>-4.092</b>	-0.2301 (-1.502)	11.40%
Rt XTZ	-0.009 (-0.842)	<b>0.4262**</b> <b>-3.098</b>	0.0729 -0.537	16.50%
Rt AAVE	0.0196 -1.047	0.3087 -1.283	-0.2218 (-0.934)	0.70%
Rt GRT	0.0031 -0.312	0.0488 -0.385	0.0373 -0.299	0.70%
Rt CAKE	0.0041 -0.442	<b>0.1999*</b> <b>-1.656</b>	-0.0527 (-0.443)	2.50%
Rt MKR	-0.0047 (-0.572)	<b>0.7467***</b> <b>-7.111</b>	<b>-0.2205*</b> <b>(-2.129)</b>	30.80%
Rt RUNE	0.0156 -1.412	0.2341 -1.65	0.001 -0.007	4.10%
Rt CRV	-0.0087 (-0.939)	0.0452 -0.38	0.13 1.107	3.10%
Rt LRC	-0.0038 (-0.305)	<b>0.6271***</b> <b>-3.889</b>	-0.0491 (-0.309)	16.80%

ments and distribution of tokens. Premised on this fact, Ethereum is an important contributor to token pricing as well. LUNA and CAKE show a weak return impact by one-week lagged [ETH](#). As we can observe, for the rest of the sample (AVAX, DAI, UNI, AAVE, GRT, RUNE, CRV), [ETH](#) does not show any significant driving power.

### The impact of CRIX

At this point, we assess whether the crypto-market as a whole has an impact on [DeFis](#) returns. We regress the iDeFiX index returns and the main [DeFis](#) returns over the one-week and two-weeks lagged CRIX returns. Results are presented in Table [III.6](#). We run the following regressions,

$$R_{tDeFiX}(t) = \alpha + \beta_1 R_{tCRIX}(t - 1) + \beta_2 R_{tCRIX}(t - 2) + \varepsilon_t, \quad (\text{III.5})$$

$$R_{tDeFiToken}(t) = \alpha + \beta_1 R_{tCRIX}(t - 1) + \beta_2 R_{tCRIX}(t - 2) + \varepsilon_t. \quad (\text{III.6})$$

While assessing [DeFis](#) exposure to (the crypto-market) CRIX, we observe that almost all leading [DeFis](#) and the market index, iDeFiX, are positively and significantly impacted by the increase in CRIX returns the week before. This result could be justified by a combined effect / driving power of all cryptocurrencies applied through the CRIX index. In spite of being developed on Ethereum technology, AAVE is the only token from our sample that seems to not be significantly influenced by the crypto-market at all. As in the assessment of [BTC](#) influence, the DAI token seems to be negatively impacted by one week before CRIX returns. Similarly, FTM and MKR are negatively impacted by two-week lagged CRIX returns, meaning that an increase in CRIX's returns from two weeks before will generate a decrease in MKR and FTM returns. AVAX and CRV show a small impact in their returns due to CRIX returns increase the week before. We also find out that FTM and MKR returns are influenced by the CRIX return values one and two weeks before.

Table III.6: The impact of CRIX on iDeFiX and DeFi Tokens.

The standard *t*-statistic value is shown in parentheses. Here we check if CRIX impacts DeFi tokens' returns. *Rt-1* (*Rt-2*) refers to one (two) week(s) lagged CRIX returns. *Rt* stands for weekly return. The number of observations for each regression is 265. \*\*\* denotes significance levels based on the respective *p*-value (\*:10%, \*\*:5%, and \*\*\*:1%).

	Constant	Rt-1 CRIX	Rt-2 CRIX	$R^2$
Rt iDeFiX	0.0029 (0.472)	<b>0.7302***</b> (5.390)	-0.0881 (-0.689)	26.5%
Rt LUNA	0.0116 (1.213)	<b>0.4888**</b> (2.304)	0.1184 (0.591)	11.2%
Rt AVAX	0.0081 (1.048)	<b>0.3210*</b> (1.871)	0.0462 (0.285)	6.6%
Rt WBTC	<b>0.0060*</b> (1.828)	<b>0.6729***</b> (9.282)	-0.0719 (-1.051)	52.4%
Rt DAI	0.0000 (0.037)	<b>-0.0220*</b> (-1.659)	0.0064 (0.510)	2.4%
Rt LINK	0.0121 (1.114)	<b>1.3039***</b> (5.392)	-0.3743 (-1.639)	20.4%
Rt UNI	0.0028 (0.443)	<b>0.3020**</b> (2.150)	0.0210 (0.158)	7.6%
Rt FTM	0.0130 (1.142)	<b>1.3576***</b> (5.354)	<b>-0.4257*</b> (-1.778)	19.3%
Rt XTZ	-0.0020 (-0.190)	<b>0.6800**</b> (2.869)	0.1313 (0.587)	15.3%
Rt AAVE	0.0202 (1.089)	0.5281 (1.284)	-0.2615 (-0.674)	0.9%
Rt GRT	0.0030 (0.316)	<b>0.4649**</b> (2.194)	-0.0774 (-0.387)	5.2%
Rt CAKE	0.0053 (0.581)	<b>0.5677***</b> (2.812)	-0.1525 (-0.800)	6.8%
Rt MKR	0.0021 (0.262)	<b>1.2922***</b> (7.369)	<b>-0.3257*</b> (-1.968)	34%
Rt RUNE	<b>0.0181*</b> (1.684)	<b>0.5152**</b> (2.159)	0.0201 (0.089)	7.3%
Rt CRV	-0.0069 (-0.765)	<b>0.3759*</b> (1.874)	0.0347 (0.183)	6.1%
Rt LRC	0.0038 (0.308)	<b>1.1481***</b> (4.197)	-0.1279 (0.495)	18.2%

### Further tests

After analyzing the crypto-market’s impact on **DeFis** returns, our findings show a strong relationship between the two markets. Several papers have focused in particular on the **BTC** strong influence within the crypto-market (Bouri et al., 2019; Ciaian, Rajcaniova, & Kancs, 2018; Ji et al., 2019; Pirgaip, Dinçergök, & Haşlak, 2019), and others have shown connectedness among the leading cryptocurrencies (Corbet et al., 2019; Yarovaya & Zieba, 2022). Therefore, in order to complement our results, that crypto-market impacts **DeFis** returns, we decided to perform several other tests, such as Granger causality and cointegration. Here we try to find answers to the following question: *Can **BTC** be used in predicting **DeFis** returns?*

We start with a Granger causality test (Granger, 1969) and assess if **iDeFiX** returns can be predicted by **BTC** returns. Afterward, we test for the presence of Granger causality in both directions and perform the Granger test in reverse. The tests have been performed on several lags and results are reported in Table III.7. We can observe that in both tests the p-values are greater than 0.05 (95% significance level), showing that there is a bidirectional causality relationship between **BTC** returns and **iDeFiX** returns for lag=4. This means that **iDeFiX** returns can be predicted by **BTC** returns, and vice versa, **BTC** returns can be predicted by **iDeFiX** returns.

Table III.7: **Granger Causality between **BTC** and **iDeFiX****

*Results of a Granger-causality test performed on **BTC** and **iDeFiX** weekly returns. \*\*\* denotes significance levels based on the respective F-value (\*:10%, \*\*:5%, and \*\*\*:1%).*

<b>Lag</b>	<b>Granger causality test</b>	<b>Reverse Granger causality test</b>
4	$F = 2.7436^*$	$F = 3.7009^*$

Furthermore, we check for cointegration between **BTC** and **DeFi** market. Here we use the Engle-Granger cointegration test (Engle & Granger, 1987) for **BTC** and **iDeFiX** and Johansen test (Johansen, 1991) for **BTC** and top **DeFis**. A cointegration test shows a possible correlation between time series processes in the long term. Engle-Granger test allows for the investigation between two non-stationary variables, in our case **BTC** and **iDeFiX**. The test results with a test-statistic value of **-3.67\*\***, indicate the presence of cointegration between **BTC** and **iDeFiX** prices. By comparison, Johansen tests allow for more than one cointegrating relationship, which is the reason why we employ it in the assessment of the top **DeFi** tokens with **BTC**. Results are reported in Table III.8.

By looking at the results from Engle-Granger tests, we have evidence for a coin-

**Table III.8: Johansen cointegration test between BTC and main DeFis**

*This table reports the trace and eigen statistical and critical values for the Johansen test. For this test we have used non-stationary data, meaning the prices of BTC and 10 top Defis. In interpretation, we compare the stats with critical values for 95%. The number of observations is 4114.*

<i>Johansen test</i>				
<i>r</i>	<i>max eigen</i>	<i>Critical Values</i>		
		<i>90%</i>	<i>95%</i>	<i>99%</i>
0	91.064	67.1307	70.5392	77.4877
1	45.595	61.2041	64.504	71.2525
2	34.255	55.2412	58.4332	64.996
3	29.782	49.2855	52.3622	58.6634
4	24.495	43.2947	46.2299	52.3069
5	20.783	37.2786	40.0763	45.8662
6	18.078	31.2379	33.8777	39.3693
7	15.102	25.1236	27.5858	32.7172
8	13.642	18.8928	21.1314	25.865
9	5.627	12.2971	14.2639	18.52
10	0.355	2.7055	3.8415	6.6349

<i>r</i>	<i>trace</i>	<i>Critical Values</i>		
		<i>90%</i>	<i>95%</i>	<i>99%</i>
0	298.777	277.374	285.649	300.2821
1	207.714	232.103	239.2468	253.2526
2	162.119	190.8714	197.3772	210.0366
3	127.865	153.6341	159.529	171.0905
4	98.082	120.3673	125.6185	135.9825
5	73.587	91.109	95.7542	104.9637
6	52.804	65.8202	69.8189	77.8202
7	34.726	44.4929	47.8545	54.6815
8	19.624	27.0669	29.7961	35.4628
9	5.982	13.4294	15.4943	19.9349
10	0.355	2.7055	3.8415	6.6349

tegration relationship between [BTC](#) and [iDeFiX](#), significant at the 95% level of confidence. Furthermore, we performed the Johansen test on [BTC](#) and the top [DeFis](#). Because of a technical limitation from the Johansen function in python, we cannot test all 15 variables, and therefore we included only ten tokens: LUNA, AVAX, WBTC, DAI, LINK, UNI, AAVE, CAKE, MKR, RUNE. We look first at our eigenvalues and compare them with the critical values for 95%. When we find the first statistical value smaller than the corresponding critical value, that is evidence for cointegration. By looking at our results, we observe that the test statistics of the second largest eigenvalue is 45.595 which is smaller than the corresponding critical value of 64.504 at 95%. Thus, these results confirm that there is one co-integrating vector. Another way to interpret the Johansen test is by looking at the trace values and comparing them to the critical values for 95%. The second trace values confirm our findings. Based on all these evidences, we, therefore, confirm that there is a long-term relationship between [BTC](#) and the [DeFi](#) market.

In this section, we have investigated the [DeFi](#) market exposure to the cryptocurrencies ([BTC](#), [ETH](#), and [CRIX](#) index). Our findings show that [BTC](#) and [ETH](#) have a comparable strong and significant influence on [DeFi](#) returns. While assessing the [CRIX](#) impact on [DeFis](#), we observe that almost all leading [DeFis](#) and the market index, [iDeFiX](#), are positively and significantly impacted. This result could be justified by a combined effect/impact of all cryptocurrencies applied through the [CRIX](#) index. Overall, our empirical analysis shows that the impact of the cryptocurrency market on [DeFis](#) returns is strong and statistically significant. Furthermore, we show that the crypto-market exposure results could be explained by a bidirectional causality relationship between [BTC](#) returns and [iDeFiX](#) returns and the long-term correlation between [BTC](#) and [DeFis](#) revealed by the cointegration test.

### III.4.2 Network effect

*“Whether real or virtual, networks have a fundamental economic characteristic: the value of connecting to a network depends on the number of other people already connected to it.”* (p.174, Shapiro and Varian, 1999). Katz and Shapiro (1985, 1986) have made some of the first contributions to the network theory, underlying for the first time the relationship between the fundamental value and network effects. This issue becomes more complex when the network is virtual, for example, in the case of software businesses, where “the linkages between nodes are invisible” but not inexistent (p.174, Shapiro and Varian, 1999). The (virtual) network effect exists in the

crypto-market as well, and multiple papers assess its impact on the returns of cryptocurrencies (Cong, Li, & Wang, 2021; Pagnotta & Buraschi, 2018). Furthermore, it has been shown that “transactional benefits are to cryptocurrencies what dividends are to stocks” (page 2, Biais et al., 2020), meaning that the cryptocurrency’s fundamental value comes from the network variables. Drawing some conclusions here is quite simple: the network effects make cryptocurrencies more useful as more people join the (Blockchain) network, and as a result of this, the entire crypto-ecosystem becomes more valuable.

Considering that DeFis run on Blockchain technology, it seems relevant to assess whether the network effect also exists in the DeFi market. A significant part of the literature on cryptocurrencies has shown the importance of network factors in the valuation of cryptocurrencies (Bhambhwani et al., 2019; Biais et al., 2020; Liu & Tsyvinski, 2021; Sockin & Xiong, 2020). To the best of our knowledge, there is no prior work exploring the network effect for DeFi tokens valuation.

Maouchi, Charfeddine, and El Montasser (2021) and Saengchote (2021) argue that TVL is a reliable tool for DeFi market monitoring: “TVL is already considered by the crypto-community as one of the main indicators of DeFi markets size and growth” (page 7, Maouchi, Charfeddine, and El Montasser, 2021). One of Cong, Li, and Wang (2021)’s main assumptions with regard to token valuation is based on the expected platform’s increase in productivity as a result of network growth. Accordingly, we recognize TVL as an important variable in the network assessment. The rationale behind this represents simply the fact that TVL represents the amount of funds committed to the DeFi business. This means that the more people join and transact on DeFi platforms (translating into more funds and bigger TVL), the larger the network will be. Active addresses and transactions count are commonly used as network variables in the crypto-market assessment (Hinzen, John, & Saleh, 2022; Koutmos, 2020; Liu & Tsyvinski, 2021; Nadler & Guo, 2020). We thus choose three factors as proxies for the DeFi network effect: the active address count and the transactions count (like for the crypto-asset market), as well as the total value locked (TVL). As far as we know, we are the first to consider TVL as a proxy for network effect. To measure the network growth, we are using: the address growth, the transaction growth, and the TVL growth. The growth (noted  $\Delta$ ) of network variables is computed using the logarithmic difference method.

We first assess the correlation between the three network variables we consider.

Table III.9: **Correlation in network variables**

Pearson correlation coefficients for the daily growth of network variables.  $\Delta$  indicates the growth of the variables. We have Transaction count (*transac.*), Address count (*address*) and TVL (*tvL*). \*\*\* denotes significance levels based on the respective p-value (\*:10%, \*\*:5%, and \*\*\*:1%).

	$\Delta\text{transac}$	$\Delta\text{address}$	$\Delta\text{tvL}$
$\Delta\text{transac}$	1		
$\Delta\text{address}$	<b>0.385***</b>	1	
$\Delta\text{tvL}$	-0.019	0.056	1

The results presented in Table III.9, show a positive relationship between the transaction and address growth, with a correlation coefficient of 0.385. The TVL growth seems not correlated with any of the other two network variables. To evaluate the exposure of DeFi returns to network variables, we run regressions of the iDeFiX returns over the growth of transactions, the growth of addresses, and the growth of TVL.  $R_{t\text{iDeFiX}}$  represents the weekly returns of our index for the DeFi market.

$$R_{t\text{iDeFiX}}(t) = \alpha + \beta_1 \Delta\text{Transac}(t) + \varepsilon_t, \quad (\text{III.7})$$

$$R_{t\text{iDeFiX}}(t) = \alpha + \beta_1 \Delta\text{Address}(t) + \varepsilon_t, \quad (\text{III.8})$$

$$R_{t\text{iDeFiX}}(t) = \alpha + \beta_1 \Delta\text{TVL}(t) + \varepsilon_t, \quad (\text{III.9})$$

$$R_{t\text{iDeFiX}}(t) = \alpha + \beta_1 \Delta\text{Transac}(t) + \beta_2 \Delta\text{Address}(t) + \beta_3 \Delta\text{TVL}(t) + \varepsilon_t, \quad (\text{III.10})$$

The above regressions assess the direct exposure of iDeFiX returns to the average growth of network variables. Here, for instance,  $\Delta\text{TVL}$  refers to the average of TVL growth for all tokens in our sample. The last regression regroups all network variables as independent variables in order to consider possible interaction effects. We present the regressions results in Table III.10.

We find that iDeFiX returns are exposed to each network variable except address growth. The coefficients for transaction count and TVL growth are strongly significant in regressions III.7, III.9, and III.10. This result confirms that the performance of the DeFi market, represented here by the iDeFiX index, is driven by its fundamental value (as proxied by the network variables). In finance, fundamental value refers to the ‘real’ risk-adjusted value of a security, which may be different

Table III.10: **Rt iDeFiX exposure to network variables**

This table reports the exposure of *iDeFiX*'s returns to the (averaged) network factors. The data frequency is weekly. For each regression, we had 239 observations. \*\*\* denotes significance levels based on the respective *p*-value (\*:10%, \*\*:5%, and \*\*\*:1%).

	(7)	(8)	(9)	(10)
$\Delta$ <i>Trans</i>	<b>0.0318**</b> (2.361)			<b>0.0293**</b> (2.020)
$\Delta$ <i>Address</i>		0.0136 (1.575)		0.0052 (0.568)
$\Delta$ <i>TVL</i>			<b>0.0772**</b> (2.447)	<b>0.0774**</b> (2.487)
$R^2$	2.1%	0.9%	2.2%	4.5%

from the market value. As for stocks, where the fundamental value can be derived from accounting information on the firm's operation (Brainard, Shapiro, & Shoven, 1990), we believe that **DeFis** derive their value from the network. This rationale is based on Biais et al. (2020) model, which states that cryptocurrencies' fundamental value comes from their transactional benefits. Furthermore, Katz and Shapiro (1986) demonstrate in their theoretical model that the technology's adoption and value evolution are linked to its network size. Out of the three variables tested, our results show that the transaction count and the **TVL** growth have a significant impact on **DeFis** returns. These two variables reflect the platform's success (value); therefore, an increase in transaction count and **TVL** translates into an increase in financial returns for **DeFi** tokens holders. On the same point but in the crypto-market, Liu and Tsyvinski (2021) and Cong, Li, and Wang (2021) also found that the network variables play an important role in the valuation of cryptocurrencies.

Furthermore, we assess the impact of network variables' growth on individual tokens' returns. At this stage, we do not average the network variables, but we perform panel regressions using the network data we have for each token. We first regress the **DeFis** returns on the network variables change for all **DeFi** for which we have network information. This allows us to assess as many tokens as possible and thus to enlarge the picture from only leading **DeFi**. Afterward, we make a panel regression using only the leading tokens, in line with the previous section.

### Exposure to **TVL** growth

We start with our first network variable: **TVL** growth. We have **TVL** information for 160 tokens. Therefore, we first perform the regression of the **DeFis** returns over the change in **TVL** for all 160 tokens. We then only focus our attention on the 15

Table III.11: **Panel OLS, returns of 160 DeFi Tokens against their lagged TVL growth**

$R^2$  is 1.42%,  $R^2$  between is 9.43%. We regressed the returns of 160 DeFi tokens against their corresponding  $\Delta TVL$  lagged from 1 week to 4 weeks. Time effects included. We used weekly returns and weekly TVL growth. For this regression, we had 7453 observations. \*\*\* denotes significance levels based on the respective p-value (\*:10%, \*\*:5%, and \*\*\*:1%).

	<i>Coefficient</i>	<i>Std. Err.</i>	<i>T-stat</i>	<i>P-value</i>	<i>Lower CI</i>	<i>Upper CI</i>
<b>const</b>	<b>-1.5875***</b>	<b>0.2419</b>	<b>-6.5621</b>	<b>0.0000</b>	<b>-2.0617</b>	<b>-1.1133</b>
<b><math>\Delta TVL(t-1)</math></b>	<b>6.2969***</b>	<b>0.7362</b>	<b>8.5532</b>	<b>0.0000</b>	<b>4.8538</b>	<b>7.7401</b>
$\Delta TVL(t-2)$	1.3949	0.9946	1.4024	0.1608	-0.5549	3.3447
<b><math>\Delta TVL(t-3)</math></b>	<b>2.3299**</b>	<b>1.0588</b>	<b>2.2005</b>	<b>0.0278</b>	<b>0.2544</b>	<b>4.4054</b>
$\Delta TVL(t-4)$	1.5552	1.0485	1.4833	0.138	-0.5001	3.6105

 Table III.12: **Panel OLS, returns of 15 leading DeFi Tokens against their lagged TVL growth**

$R^2$  is 1.17%,  $R^2$  between is 16.54%. We regressed the returns of 15 DeFi tokens against their corresponding  $\Delta TVL$  lagged from 1 week to 4 weeks. Time effects included. We used weekly returns and weekly TVL growth. For this regression, we had 942 observations. \*\*\* denotes significance levels based on the respective p-value (\*:10%, \*\*:5%, and \*\*\*:1%).

	<i>Coefficient</i>	<i>Std. Err.</i>	<i>T-stat</i>	<i>P-value</i>	<i>Lower CI</i>	<i>Upper CI</i>
<b>const</b>	0.9281	0.7787	1.1918	0.2337	-0.6005	2.4567
<b><math>\Delta TVL(t-1)</math></b>	<b>8.8468***</b>	<b>3.2887</b>	<b>2.6901</b>	<b>0.0073</b>	<b>2.391</b>	<b>15.303</b>
$\Delta TVL(t-2)$	-0.1661	3.7732	-0.044	0.9649	-7.573	7.2408
$\Delta TVL(t-3)$	-0.0873	3.9044	-0.0224	0.9822	-7.7517	7.5771
$\Delta TVL(t-4)$	2.8899	4.3563	0.6634	0.5073	-5.6617	11.441

leading tokens. We lagged TVL growth from 1 week up to 4 weeks. Results are shown in Table III.11 and Table III.12.

$$RtDeFis_i(t) = \alpha_i(t) + \sum_{l=1}^4 \beta_{l,i} \Delta TVL_i(t-l) + \varepsilon_i(t) \quad (\text{III.11})$$

Our results show that 1 and 3 weeks ahead TVL growth is positively impacting the DeFis return increase. We then perform the same panel regression, but this time we consider only the 15 major DeFis. This approach was used in section III.4.1 when we assessed the DeFis exposure to the cryptocurrency market.

While assessing the TVL growth impact on the leading DeFis returns, our results confirm the previous findings. More specifically, we observe that all leading tokens are positively and significantly impacted by the 1-week ahead increase in TVL growth. As mentioned before, TVL represents the amount locked in DeFi platforms. Our results indicate that when the value locked in the platform increases, the value (return) of the corresponding DeFis increases as well.

Table III.13: **Panel OLS, returns of 21 DeFi Tokens against their lagged Transaction growth**

$R^2$  is 0.94%,  $R^2$  between is -9.72%. We regressed the returns of 21 DeFi tokens against their  $\Delta$  Transac. lagged from 1 week to 4 weeks. Time effects included. We used weekly returns and weekly Transaction growth. For this regression, we had 5407 observations. \*\*\* denotes significance levels based on the respective p-value (\*:10%, \*\*:5%, and \*\*\*:1%). The standard t-statistic value is shown in parentheses.

	Coefficient	Std. Err.	T-stat	P-value	Lower CI	Upper CI
<b>const</b>	<b>0.4434***</b>	<b>0.169</b>	<b>2.6233</b>	<b>0.0087</b>	<b>0.112</b>	<b>0.7748</b>
$\Delta$ Trans(t-1)	<b>-2.9266***</b>	<b>0.441</b>	<b>-6.6368</b>	<b>0.0000</b>	<b>-3.7911</b>	<b>-2.0621</b>
$\Delta$ Trans(t-2)	<b>-1.0038**</b>	<b>0.5032</b>	<b>-1.9948</b>	<b>0.0461</b>	<b>-1.9904</b>	<b>-0.0173</b>
$\Delta$ Trans(t-3)	-0.657	0.5054	-1.2999	0.1937	-1.6477	0.3338
$\Delta$ Trans(t-4)	<b>-1.4298***</b>	<b>0.4765</b>	<b>-3.0008</b>	<b>0.0027</b>	<b>-2.3638</b>	<b>-0.4957</b>

Table III.14: **Panel OLS, returns of 15 leading DeFi Tokens against their lagged Transaction growth**

$R^2$  is 0.22%,  $R^2$  between is -0.07%. We regressed the returns of 15 DeFi tokens against their  $\Delta$  Transac. lagged from 1 week to 4 weeks. Time effects included. We used weekly returns and weekly Transaction growth. For this regression, we had 1832 observations. \*\*\* denotes significance levels based on the respective p-value (\*:10%, \*\*:5%, and \*\*\*:1%). The standard t-statistic value is shown in parentheses.

	Coefficient	Std. Err.	T-stat	P-value	Lower CI	Upper CI
<b>const</b>	0.573	0.3587	1.5971	0.1104	-0.1307	1.2766
$\Delta$ Trans(t-1)	-1.6691	1.067	-1.5643	0.1179	-3.7619	0.4238
$\Delta$ Trans(t-2)	0.1894	1.1481	0.165	0.869	-2.0626	2.4415
$\Delta$ Trans(t-3)	0.3374	1.143	0.2952	0.7679	-1.9046	2.5795
$\Delta$ Trans(t-4)	-0.3854	1.0655	-0.3617	0.7176	-2.4753	1.7046

### Exposure to transaction growth

Our second network variable is transaction count growth. We have transaction count information for 21 tokens. First, we regress all 21 tokens returns against their lagged transaction growth. In the second step, we refer only to the 15 leading tokens. We lagged transaction growth from 1 week up to 4 weeks. Results are shown in Table III.13 and Table III.14.

$$RtDeFis_i(t) = \alpha_i(t) + \sum_{l=1}^4 \beta_{l,i} \Delta trans_i(t-l) + \varepsilon_i(t) \quad (\text{III.12})$$

According to the first regression (21 tokens), DeFi returns appear to be negatively and significantly impacted by the change in one week, two weeks, and four weeks ahead transaction growth. This indicates that the more transactions are placed on the DeFi platform, the lower the return of the corresponding token. While a bit surprising, these results could be explained by the increased volatility and large financial bubbles present in the DeFi market (Maouchi, Charfeddine,

Table III.15: **Panel OLS, returns of 15 DeFi Tokens against their lagged Address growth**

$R^2$  is 0.43%,  $R^2$  between is 1.42%. We regressed the returns of 21 DeFi tokens against their  $\Delta$  Address lagged from 1 week to 4 weeks. Time effects included. We used weekly returns and weekly Address growth. For this regression, we had 5432 observations. \*\*\* denotes significance levels based on the respective p-value (\*:10%, \*\*:5%, and \*\*\*:1%). The standard t-statistic value is shown in parentheses.

	Coefficient	Std. Err.	T-stat	P-value	Lower CI	Upper CI
const	<b>0.4498***</b>	<b>0.169</b>	<b>2.6618</b>	<b>0.0078</b>	<b>0.1185</b>	<b>0.7812</b>
$\Delta$ Address(t-1)	<b>-1.8314***</b>	<b>0.424</b>	<b>-4.3192</b>	<b>0.000</b>	<b>-2.6626</b>	<b>-1.0001</b>
$\Delta$ Address(t-2)	-0.512	0.5001	-1.0238	0.306	-1.4925	0.4684
$\Delta$ Address(t-3)	-0.7134	0.5048	-1.4132	0.1576	-1.703	0.2762
$\Delta$ Address(t-4)	-0.6625	0.4554	-1.4546	0.1458	-1.5553	0.2304

& El Montasser, 2021). At the same time, Hau et al. (2021) show that cryptocurrency returns can be positively (negatively) influenced by transaction activity if the market state is bullish (bearish). The same could be true for the DeFi market, as the presence of large bubbles justifies the less efficient prices. While out of the scope of this paper, more investigations on this matter are necessary.

The regression performed with only leading tokens does not report any significant results. This means that no major tokens considered in this analysis are impacted by transaction growth.

### Exposure to address growth

Our last network variable is the address count growth. We have address count information for 21 tokens. Therefore, we regress all 21 tokens' returns against their address growth in a panel data regression analysis. In the second step, we then refer only to the leading tokens. We lagged address growth from 1 week up to 4 weeks. Results are shown in Table III.15 and Table III.16.

$$RtDeFis_i(t) = \alpha_i(t) + \sum_{l=1}^4 \beta_{l,i} \Delta address_i(t-l) + \varepsilon_i(t) \quad (\text{III.13})$$

Similar to our previous results concerning transaction growth, we can observe that in the first-panel data regression (21 tokens), DeFis returns are negatively impacted by the change in one week ahead address growth. The regression performed with only the leading tokens does not report any significant results. This translates as the more addresses are created for a specific DeFi platform, the lower the return of the corresponding token in the next week. Motivated by the findings from Hau et

Table III.16: **Panel OLS, returns of 15 leading DeFi Tokens against their lagged Address growth**

$R^2$  is 0.11%,  $R^2$  between is -1.71%. We regressed the returns of 15 DeFi tokens against their  $\Delta$  Address lagged from 1 week to 4 weeks. Time effects included. We used weekly returns and weekly Address growth. For this regression, we had 1836 observations. \*\*\* denotes significance levels based on the respective p-value (\*:10%, \*\*:5%, and \*\*\*:1%). The standard t-statistic value is shown in parentheses.

	Coefficient	Std. Err.	T-stat	P-value	Lower CI	Upper CI
const	0.5424	0.359	1.511	0.131	-0.1617	1.2466
$\Delta$ Address(t-1)	-0.5388	0.7926	-0.6798	0.4967	-2.0935	1.0159
$\Delta$ Address(t-2)	0.5559	0.9693	0.5735	0.5664	-1.3455	2.4572
$\Delta$ Address(t-3)	0.8046	0.9787	0.8221	0.4111	-1.1151	2.7243
$\Delta$ Address(t-4)	0.4923	0.8255	0.5964	0.551	-1.1269	2.1116

al. (2021) that include address number in their sample, we think that DeFis returns can be positively (negatively) influenced by address growth if the market state is bullish (bearish). These results confirm the inefficiency of DeFis prices, in line with Corbet et al. (2021) and Maouchi, Charfeddine, and El Montasser (2021), although further investigation would be necessary.

Same as our findings from Section III.4.2, the regression performed with only leading tokens does not report any significant results. This means that no major tokens considered in this analysis are impacted by address growth.

In this section, we have assessed the impact of network variables (the active address count, the transactions count, and TVL) on future DeFi market returns. Our results show that the DeFis returns are strongly influenced by their network variables, similar to cryptocurrencies (Liu & Tsyvinski, 2021). Overall, our empirical study shows that the impact of the TVL growth on DeFis returns is stronger than any other network variable considered and provides superior explanatory power.

### III.4.3 DeFi Valuation Ratio

In this section, we investigate the ability of a DeFi market-specific ‘book-to-market’ ratio to impact future DeFi returns. While researchers and practitioners have always tried to identify the variables that drive stock returns, the motivation to use the book-to-market ratio as a possible driver has arisen after the findings of Fama and French (1992). In their paper, Fama and French reveal that the book-to-market ratio has more explanatory power for the cross-sectional variations in stock returns than traditional risk measures. On another perspective, Lakonishok, Shleifer, and

Vishny (1994) and La Porta (1996) believe that the book-to-market ratio is just evidence of mispricing, as investors form biased expectations concerning the future prospects and firm value based on accounting information. Many papers have already shown the ability of the book-to-market ratio to predict future returns on both traditional markets (Ball et al., 2020; Pontiff & Schall, 1998) and the cryptocurrency market (Cong, Li, & Wang, 2021; Liu & Tsyvinski, 2021) do not find any significant relationship between the valuation ratio and the future cryptocurrency return. Motivated by the existing literature on the cryptocurrency market and by the studies of other financial markets, we find it relevant to investigate whether the book-to-market ratio has an impact on DeFis future returns. The classic book-to-market ratio used in the stock market compares a company’s book value to its market value. The book value refers to the accounting data (total value of assets minus total liabilities), and the market value represents the market price of one share multiplied by the total number of shares outstanding.

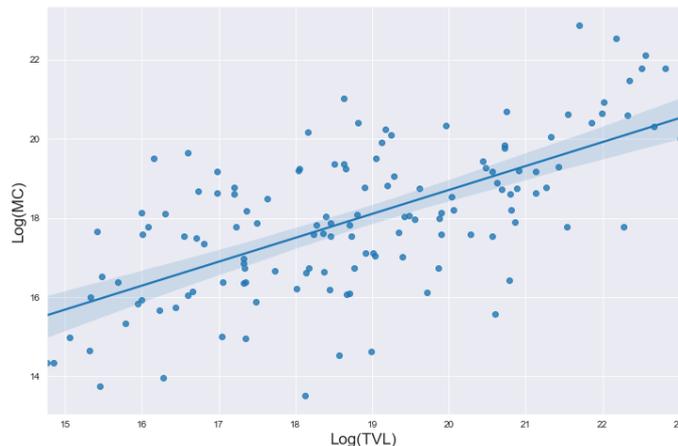
If the market value is easily available for both stocks and cryptocurrencies, we know that there is no direct measure of the book value for cryptocurrencies. In their pricing model, Cong, Li, and Wang (2021) propose a cryptocurrency fundamental-to-value ratio as the number of users over the market capitalization. Further, they show that this ratio negatively impacts future cryptocurrency returns. Consistent with the literature on cryptocurrencies, there is no measure of book value for DeFis. Corbet et al. (2021) and Maouchi, Charfeddine, and El Montasser (2021) show that TVL can be used as a tool to monitor DeFi’s success. TVL represents the total value allocated in a DeFi platform, and it can therefore be considered as (some of) its intrinsic value. The more people join and transact on DeFi platforms (translating into more funds and bigger TVL), the bigger the network will be. One of the Cong, Li, and Wang (2021)’s main assumptions with regard to token valuation is based on the expected growth of the network as a result of the platform’s increased productivity. Accordingly, we recognize TVL as a proxy for DeFi’s ‘book’ value measure.

Before computing our valuation ratio, we investigate if the market values DeFis are based on their locked intrinsic value (TVL). For this, we simply plot the log market capitalization against the log TVL (see Figure III.2). We found that there is a relationship between the two variables, meaning that DeFis with high TVL have high market capitalization.

Furthermore, we construct the Book-to-Market ratio for the DeFi market by

**Figure III.2: Log-Log relationship between the Market Capitalization and Total Value Locked of DeFis**

Scatter plot of the (log) *MC* and (log) *TVL* of 160 *DeFis*. The regression suggests linear relationships between the variables, indicating that a *DeFi* token with a high *TVL* will tend to have a high *MC*.



dividing the *TVL* by the *MC*. What we obtain is the *TVL*-to-*Market* ratio valuation, and we test its influence on *DeFis* returns. For this analysis, we perform panel data regressions using the *TVL*-to-*Market* ratio. We first regress the *DeFis* returns (considering the *DeFis* tokens for which we have the *TVL* information) on the *TVL*-to-*Market* ratio. In the second step, we perform a panel data regression using only the 15 leading tokens (as we did in the previous sections). The reason behind this approach is to capture a bigger and more realistic picture of the *DeFi* market and not only results based on referring to the leading tokens. With these panel data regressions, we capture the impact of the *TVL*-to-*Market* ratio on the returns of *DeFis*.

$$RtDeFis_i(t) = \alpha_i(t) + \beta_{1,i} \frac{TVL_i}{MC_i}(t-1) + \beta_{2,i} \frac{TVL_i}{MC_i}(t-2) + \beta_{3,i} \frac{TVL_i}{MC_i}(t-3) + \beta_{4,i} \frac{TVL_i}{MC_i}(t-4) + \varepsilon_i(t). \quad (\text{III.14})$$

The regression III.14 tests if *TVL*-to-*Market* ratio impacts *DeFis* returns. We do not make any initial assumptions about the ratio exposure horizon, and we consider four different lags for the *TVL*-to-*Market* ratio. Results are shown in Table III.17 and Table III.18. As many researchers have shown that the book-to-market ratio impacts future returns on the stock market (Fama & French, 1992; Pontiff & Schall, 1998), we expect to reach the same conclusions about the *DeFi* market. Our results show that most of the *DeFis* returns are positively (negatively) driven by the past

Table III.17: **Panel OLS, returns of 160 DeFi Tokens against their lagged TVL/MC ratio**

$R^2$  is 0.27%.  $R^2$  Between is 0.32%. Panel regression of 160 DeFi returns against their Valuation Ratio = TVL/MarketCap. The data frequency is weekly. For this regression, we had 5289 observations. \*\*\* denotes significance levels based on the respective p-value (:10%, \*\*:5%, and \*\*\*:1%). The standard t-statistic value is shown in parentheses.

	Coefficient	Std. Err.	T-stat	P-value	Lower CI	Upper CI
<b>const</b>	0.180	0.2941	0.6129	0.5400	-0.3963	0.7568
<b>ValRatio(t-1)</b>	0.001	0.0036	0.1668	0.8676	-0.0064	0.0076
<b>ValRatio(t-2)</b>	<b>0.010**</b>	<b>0.0043</b>	<b>2.3257</b>	<b>0.0201</b>	<b>0.0016</b>	<b>0.0185</b>
<b>ValRatio(t-3)</b>	<b>-0.013***</b>	<b>0.0044</b>	<b>-2.8435</b>	<b>0.0045</b>	<b>-0.0211</b>	<b>-0.0039</b>
<b>ValRatio(t-4)</b>	-0.001	0.0043	-0.1437	0.8858	-0.009	0.0078

Table III.18: **Panel OLS, returns of 15 leading DeFi Tokens against their lagged TVL/MC ratio**

$R^2$  is 1.45%.  $R^2$  Between is 3%. Panel regression of 15 DeFi returns against their Valuation Ratio = TVL/MarketCap. The data frequency is weekly. For this regression, we had 747 observations. \*\*\* denotes significance levels based on the respective p-value (:10%, \*\*:5%, and \*\*\*:1%). The standard t-statistic value is shown in parentheses.

	Coefficient	Std. Err.	T-stat	P-value	Lower CI	Upper CI
<b>const</b>	4.0165	1.0388	3.8664	0.0001	1.9762	6.0568
<b>ValRatio(t-1)</b>	0.6308	0.5607	1.125	0.2610	-0.4704	1.732
<b>ValRatio(t-2)</b>	-1.4726	1.1964	-1.2309	0.2188	-3.8223	0.8771
<b>ValRatio(t-3)</b>	-1.2791	1.2731	-1.0047	0.3155	-3.7795	1.2213
<b>ValRatio(t-4)</b>	1.6722	1.0426	1.6039	0.1093	-0.3754	3.7199

increase in the TVL/MC ratio two (three) weeks ago. This indicates that when the value of a DeFi platform increases (relative to its market valuation), financial returns decrease in the following two weeks. On the other hand, Table III.18 shows that leading DeFis returns are not driven by our TVL/MC ratio. While our results are surprising, mainly thanks to the contrasting findings in week two and three, we think that they do not offer any obvious conclusions.

In the traditional markets, we often see studies (Ball et al., 2020; Pontiff & Schall, 1998) with Book-to-Market ratio that use monthly data. This is because the book value of a firm is renewed on a monthly basis. It is not the case for cryptocurrency and DeFi markets, where all the financial information is publicly available on Blockchain and constantly updated. For comparison purposes, we decided to use monthly data and investigate the ability of the TVL-to-market ratio to impact future DeFis returns. The results are reported in appendix section D.

## III.5 Discussion

### III.5.1 Results

If cryptocurrencies aim to replace the existing payment tools and money, then DeFi seeks to revolutionize the financial system as a whole. DeFi platforms represent a finance-oriented technology built on top of Blockchain. These platforms make the use of financial services more modern and open to everyone, therefore creating opportunities for a new finance industry (Piñeiro-Chousa, Cabarcos, & González, 2022). As DeFi tokens became an interesting investable asset class for institutional investors, investigating DeFi prices and finding ways to value them represent important issues and research gaps. With this paper, we take the first steps in determining ways to value DeFi tokens. We are the first study to construct a representative index for the whole DeFi market based on 95 tokens. We examine the drivers of the DeFi market, as well as the ones of major DeFis (see Appendix section, III.A.3). At the same time, we have studied several potential drivers and constructed an adapted valuation ratio specific to DeFi market, namely, the TVL-to-market ratio.

(Corbet et al., 2021) and (Maouchi, Charfeddine, & El Montasser, 2021) show that DeFis are distinct from the cryptocurrency asset class. Driven by the idea of analyzing the DeFi market as a whole and motivated by the existing literature (Corbet et al., 2021; Maouchi, Charfeddine, & El Montasser, 2021), we have decided to compute a DeFi market benchmark based on the CRIX’s methodology (‘an index for Blockchain based currencies’). We have performed robustness checks for iDefiX by replacing it with DEFX (Nasdaq index for Decentralized Finance). The tests reveal similar results (see Appendix Section III.A.5).

Considering that cryptocurrencies and DeFi tokens both run on Blockchain technology and belong to the crypto-market, our second contribution is to assess the exposure of DeFi token returns to the cryptocurrency market. Our results show that the cryptocurrency market strongly influences DeFi returns, a fact confirmed by (Corbet et al., 2021) and (Yousaf & Yarovaya, 2021). Interestingly and contrary to our findings, Corbet, Goodell, and Günay (2022) show that bitcoin and ether coin have limited influence on DeFi prices, except during the bear market. Based on this evidence, we think it would be interesting to assess the DeFi market drivers during different market conditions and see if our final results would change.

The network effect in the crypto-market could be described as: the cryptocurrencies' value and utility increase when more people join the network/ Blockchain. Vast literature (e.g., Ante (2020), Cong, Li, and Wang (2021), and Liu and Tsyvinski (2021)) shows that the cryptocurrency market is highly impacted by its network effect. Therefore, our third contribution is to assess if the same holds for DeFi tokens. We thus have measured the network effect in the DeFi market by using three proxies: the transaction count, unique addresses count, and TVL. If the first two variables have been previously used in the cryptocurrency-related literature, we are, as far as we know, the first ones to use the TVL. This represents the fourth contribution of this paper. TVL is a unique variable characteristic of the DeFi market. It reflects the amount of funds committed to DeFi platforms, and it is an indicator of market growth and success. While all three network variables seem to have an important impact on DeFis returns, the transactions and TVL seem to be the most significant ones. Here we also show that DeFis returns are negatively impacted by the transaction and address growth. This could be explained by the presence of high volatility and large financial bubbles in the DeFi market (Maouchi, Charfeddine, & El Montasser, 2021). Similar findings are presented in Hau et al. (2021), which shows that cryptocurrency returns can be positively (negatively) influenced by transaction activity if the market state is bullish (bearish).

In their paper, Fama and French (1992) reveal that the book-to-market ratio has more explanatory power for the cross-sectional variations in stock returns than traditional risk measures. Cong, Li, and Wang (2021) show that the cryptocurrency fundamental-to-value ratio (the number of user adoptions over market capitalization) negatively predicts future cryptocurrency returns. At the same time, Liu and Tsyvinski (2021) analyzed if several cryptocurrency valuation ratios drive cryptocurrency market returns and concluded that none of these ratios can predict future cryptocurrency market returns significantly. Motivated by the existing literature on the cryptocurrency market and studies of other financial markets, we investigate if DeFi returns are driven by their 'book-to-market' ratio. As there is no standard 'book' value for DeFi tokens, we have constructed a Book-to-Market ratio for the DeFi market by dividing the TVL by the MC. This represents the sixth contribution of this paper. TVL represents the total value allocated in a DeFi platform, and it can therefore be considered as (some of) its intrinsic value. The results obtained do not offer any obvious answers. Hence, we conclude that there is not enough evidence to support our assumption that the TVL-to-Market ratio contains information about future DeFis returns (a result similar to the one obtained by Liu and

Tsyvinski (2021) for the cryptocurrency market).

### III.5.2 Contributions

With this research, we have made several contributions. First, our work contributes to the academic literature on the crypto-market. We have analyzed DeFi market returns drivers and took the first steps in finding ways to value DeFi tokens. Another significant addition represents the fact that we are the first ones to use TVL, a variable specific to the DeFi market, as a proxy for the network effect. Besides the contributions made to the asset pricing literature, we also offer two novel theoretical contributions: (1) we propose a benchmark for the Decentralized Finance market, and (2) we introduce (and build) a valuation ratio specific to the DeFi market, namely the TVL-to-Market ratio. This valuation ratio is equivalent to the Book-to-Market ratio from the stock market.

At the same time, our results have important implications for investors interested in the crypto-market. We show that the cryptocurrency market is the main driver for DeFi market returns. Based on this result, investors should be aware of the fact that portfolios containing cryptocurrency cannot be fully diversified by using DeFi tokens and vice versa.

## III.6 Conclusion

In this chapter, we address the following research question: *What are the drivers of DeFi tokens' returns?* Following (Liu & Tsyvinski, 2021)'s paper, which presents a comprehensive analysis of cryptocurrencies' returns, we performed an in-depth analysis of the determinants of the DeFi market returns. We consider several possible driving forces, such as: (1) the cryptocurrency market, (2) the network variables, (3) the TVL-to-Market ratio.

Our empirical study shows that DeFi market returns are driven by the cryptocurrency market and its network effect; however, the impact of the cryptocurrency market seems to be stronger than any other driver considered in this analysis and provides superior explanatory power. This result could be explained by the bidirectional causality relationship between BTC returns and iDeFiX returns and the long-term correlation between BTC and DeFis revealed by the cointegration test.

A possible limitation of this paper is the restricted information available on network data. We were able to retrieve the transaction and address counts for about 21 tokens. This issue puts further limits on our capacity to explore the network effect in other ways, such as by creating a network-based risk factor for a pricing model.

As a future avenue for investigation, it would be interesting to see how network factors impact DeFis returns during different market states. Another idea is to continue exploring other drivers of DeFi returns and propose a suitable pricing model for these new assets. Exploring DeFi's capabilities in portfolio diversification could be another interesting avenue. There is an obvious need for research on the NFT market as well. Dowling (2022b) and Karim et al. (2022) reveal that NFTs are a distinct asset class from conventional cryptocurrencies; therefore, it would be interesting to construct a benchmark for this market and analyze the proprieties of NFTs prices.

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## III.A Appendix

### III.A.1 A brief description of the DeFi market

Cryptocurrencies aim to replace or offer alternative payment tools and money, while DeFi platforms seek to revolutionize the financial system as a whole. DeFi platforms run on Blockchains (distributed ledger) technology, onto which decentralized applications (based on smart contracts) are added (Popescu, 2020)). DeFi's applications provide financial services that rely on cryptocurrencies and crypto tokens. Their goal is to provide a digital alternative to traditional banking, exchange, and investment services (Anker-Sorensen & Zetzsche, 2021). With decentralized applications (dApps) deployed on the Blockchain, DeFi can bring numerous benefits, among which reduced operational costs, borderless financial service access, and improved privacy. Like cryptocurrencies, DeFi Tokens (DeFis) use public Blockchains that make them accessible to anyone with just an internet connection. Decentralized finance platforms are often compared to puzzles or Lego mainly because these tools are complex and use multiple technological layers (Katona, 2021; Popescu, 2020; Schäfer, 2021). Anyone interested in developing a new decentralized finance solution can get the source code of the existing platforms and create innovations while combining parts of the current applications.

It is important to mention that regardless of their scope, DeFi platforms are very different from one another in terms of both development and operation. While constructed around similar principles as traditional finance, decentralized finance works in substantially different ways (Aramonte, Huang, & Schrimpf, 2021). For example, loans in the DeFi world are not always using physical collateral but rather some digital assets (e.g., NFT, BTC, ETH) that, once deposited, will allow the borrowing of another digital coin. In this scenario, the user lending capital earns interest without the intervention of any central authority, and the borrower can further invest (without intermediaries) its funds in other services such as trading or portfolios (Corbet et al., 2021). As describing the whole business model of DeFi platforms is out of our scope, a detailed description can be found in Harwick and Caton (2020), Ramos and Zanko (2021b), Schar (2021), Stepanova and Erins (2021), Zetzsche, Arner, and Buckley (2020), and Zumwalde, Gaba, and Archer (2021).

From a practical perspective, DeFi Tokens (DeFis) and cryptocurrencies are similar in the sense that both are based on Blockchain technology and implement

decentralized (automatic) management. However, from the technological viewpoint, [DeFi](#) are a distinct technology as they are based on smart contracts.

Compared to other crypto-assets, such as tokens or cryptocurrencies (in the sense that it functions like money) (Baur & Dimpfl, 2021; Hazlett & Luther, 2020), [DeFi](#) tokens resemble more to [ICO](#) tokens. [ICO](#) tokens can fulfill multiple roles; more specifically, they can be used to obtain products or services, can be traded on a platform (secondary market), and/or could be held to earn a profit (Le Moign, 2019). As [DeFi](#) platforms can perform most of the things that banks do — lend, trade assets, earn interest, buy insurance, borrow, trade derivatives, and more (Coinbase, n.d.), these activities are supported by complex tokens with different functions depending on the platform’s needs. For example, [DeFi](#) platforms can have (1) transactional tokens (e.g., stablecoins: Dai, TUSD, USDC, WBTC) that facilitate fund transfers across platforms (Aramonte, Huang, & Schrimpf, 2021), (2) governance tokens (e.g., MKR, COMP, YFI) that enable users to take part in the platform development and resemble with the common stock, (3) utility tokens that are used in the same way as in [ICOs](#), to obtain access to the platform’s services (in-App payment ‘currencies’), (4) liquidity provider tokens (LP) that are used as a reward for the users contributing to a [DEX](#)<sup>6</sup>’s liquidity, and (5) collateral tokens that are used on lending platforms, in a similar way to the bank loans practices (e.g., stablecoins, LP, [ETH](#), [NFTs](#)) (MakerDAO.com, 2021). Despite their distinct nature, [ICO](#) tokens have often been studied together with other digital assets, first considering the relationship between Blockchain tokens and cryptocurrencies, and second, considering that they all belong to the same crypto-market (Fahlenbrach & Frattaroli, 2021; Howell, Niessner, & Yermack, 2020; Hu, Valera, & Oxley, 2019; Lyandres, Palazzo, & Rabetti, 2018; Maouchi, Charfeddine, & El Montasser, 2021).

An important variable used in this paper is the [Total Value Locked \(TVL\)](#). [TVL](#) is a unique variable characteristic of the [DeFi](#) market and refers to the amount of funds attached to a [DeFi](#) project. More specifically, if we take the example of lending platforms, [TVL](#) is the amount put into [DeFi](#) projects as collateral for the loans taken. To compute the [TVL](#), we multiply the amount of crypto-assets staked as collateral on the Blockchain by their current price.

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<sup>6</sup>DEX is a Decentralized Exchange.

### III.A.2 iDeFiX Computation

To the best of our knowledge, the development of the entire DeFi market has not yet been studied, and only samples have been taken into account (Corbet et al., 2021; Karim et al., 2022; Stepanova & Erins, 2021; Yousaf, Nekhili, & Gubareva, 2022). We contribute to this area of research and design ‘iDeFiX’, a market index (benchmark) that will enable each interested party to study the performance of the DeFi market as a whole.

Similar to the CRIX index, which was created out of the need to assess the emerging market of cryptocurrencies accurately, iDeFiX aims to represent a new asset class for which public interest has arisen: DeFi Tokens (DeFis). According to its name (Trimborn & Härdle, 2018), CRIX is an Index for Blockchain-based currencies. Considering the fact that cryptocurrencies and DeFis run on Blockchain technology and belong to the same crypto-market, we find it appropriate to use CRIX index methodology and a variant of its original code<sup>7</sup> to construct iDeFiX.

CRIX formula is a derivation of Laspeyres index:  $\frac{\sum_i P_i(t)Q_i(0)}{\sum_i P_i(0)Q_i(0)}$ , where  $P_i(t)$  is the price of asset  $i$  at time  $t$ , and  $Q_i(0)$  is the quantity of asset  $i$  at time 0. The Laspeyres statistic represents a consumer price index and has been developed to measure the price change of the basket of goods and services consumed.

Adjusting the index for capital markets makes the quantity  $Q_i(0)$  a measure for the number of shares of the asset  $i$ , which is multiplied by its corresponding price, resulting in market capitalization. Therefore, the index components (stocks) are weighted by their market capitalizations. As markets change all the time, it is important that the index contains the most appropriate market representatives as its members. Hence, the components of the index must change in tone with the market state. To make this possible, there are several adjustments in the CRIX formula (Trimborn & Härdle, 2018),

$$CRIX(k, \beta, t) = \frac{\sum_i^k \beta_i(t_i) P_i(t) Q_i(t)}{Divisor(k, \beta, t_i)}. \quad (\text{III.15})$$

Where  $k$  is the number of constituents,  $Q_i(t_i)$  represents the amount (quantity) of

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<sup>7</sup>The original code was retrieved from [www.quantlet.de](http://www.quantlet.de).

coin  $i$  at time  $t$ ,  $P_i(t)$  is the price of coin  $i$  at time  $t$ ,  $\beta_i(t_l)$  represents the adjustment factor of cryptocurrency  $i$  at time  $t_l$ ,  $l$  indicates that this is the  $l$ -th adjustment factor, and  $t_l$  is the last time point when  $Q_i(t_l)$ ,  $Divisor(k, \beta, t_l)$  and  $\beta_i(t_l)$  have been updated. The denominator has been replaced by a divisor which is specific to each index (Trimborn & Härdle, 2018). Its formula is:

$$Divisor(k, \beta, 0) = \frac{\sum_{i=1}^k \beta_i(0)P_i(0)Q_i(0)}{BaseValue} \quad (III.16)$$

The divisor is changing every time there is a change in the number of components ( $k$ ) and ensures that the adjustments are stable. The starting value of the CRIX Index is 1000 (Trimborn & Härdle, 2018).

The selection criteria for cryptocurrencies before being included in the index is made based on the [Akaike Information Criterion \(AIC\)](#), meaning that only the most representative cryptocurrencies of the market will be taken into consideration. More specifically, cryptocurrencies must have sufficient liquidity, which means that they are actively traded and are among the largest representatives by market capitalization (over 1,000,000 USD). As a common practice for the stock market indexes, CRIX members will always be a multiple of five (Trimborn & Härdle, 2018).

iDeFiX benchmark is computed using the exact same steps as described above in the CRIX methodology. We have removed the [DeFis](#) with less than 1,000,000 USD market capitalization. Then, we ran the CRIX code with our [DeFis](#) data and built a value-weighted market index of the [DeFi](#) market as a whole, comprising 95 components. Figure III.3 shows the price evolution of our index, iDeFiX<sup>8</sup>.

### III.A.3 Data description

### III.A.4 Regressing DeFi tokens returns against their valuation ratio

Using the equation III.14, we perform the same regressions on monthly data. Our results are summarized below,

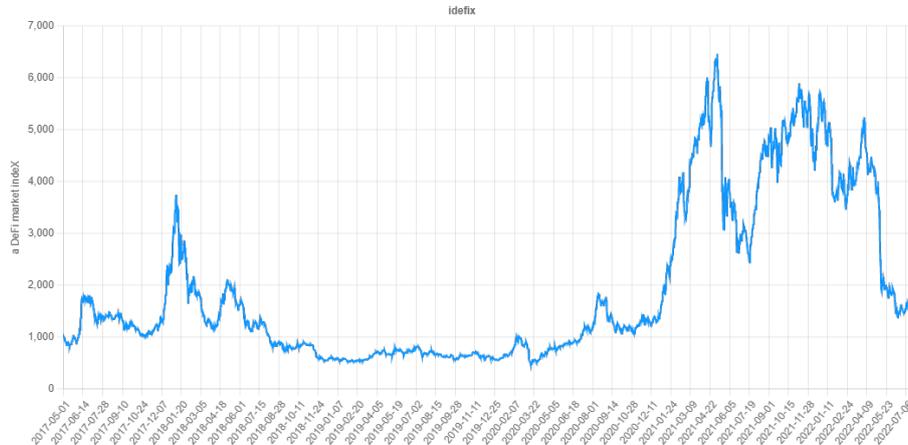
By looking at our results, we find that most of the [DeFis](#) returns are strongly

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<sup>8</sup>Data available at: <https://hpac.imag.fr/cryptotracker/dashboards/defix.html>

Figure III.3: **An index for the DeFi market: iDeFiX**

Market Capitalization - weighted index of 95 DeFi tokens from 2017 to 2022. The index is created following the methodology of, an index for cryptocurrencies, the CRIX (Trimborn & Härdle, 2018).



negatively (and significantly) driven by the past increase in the TVL/MC ratio (two and four months ago). This indicates that when the value of a DeFi platform decreases (relative to its market valuation), financial returns increase in the following two and four months. At the same time, if the ratio goes down (market capitalization increases or TVL decreases), it means that the market overvalues the DeFi, translating in an increase (correction) of the DeFis returns two and four months after. Consistent with this result, our regression on leading tokens shows as well that there is a negative and significant relationship between DeFis returns and the two previous months' TVL/MC ratio.

A surprising result is that contrary to the current results, DeFis returns seem to be strongly and positively driven by three previous months' TVL/MC ratio. Therefore, we conclude that our analysis provides inconclusive evidence.

### III.A.5 Robustness check and comparison between Nasdaq Defi Index and iDeFiX

In August 2019, Nasdaq has listed an index (DEFX) dedicated to Decentralized finance tokens (Lielancher, 2019). Little is known about DEFX methodology except for its components and their weight in the index, which can be consulted on *defix.fund* website. Based on the information we have, we can easily state that a major difference between DEFX and iDeFiX is the number of tokens considered. Our index comprises 95 tokens, while Nasdaq index has only 14 (defix.fund, 2019).

Table III.19: **Description for the financial data**

This table describes the data for financial variables used: CRIX index and the two main cryptocurrencies (BTC and ETH), iDeFiX index, and the 15 main DeFi tokens.

(Token) Symbol	Description / DeFi platform	Daily data observations	Time span
<b>CRIX</b>	Index for Cryptocurrency market	1009	19 March 2018 to 27 January 2022
<b>BTC</b>	Cryptocurrency	3176	28 April 2013 to 9 January 2022
<b>ETH</b>	Cryptocurrency	2346	7 August 2015 to 9 January 2022
<b>iDeFiX</b>	Index for DeFi market	1730	1 May 2017 to 25 January 2022
<b>LUNA</b>	Terra	916	26 July 2019 to 26 January 2022
<b>AVAX</b>	Avalanche	494	13 July 2020 to 26 January 2022
<b>WBTC</b>	Wrapped Bitcoin	1093	30 January 2019 to 26 January 2022
<b>DAI</b>	MakerDAO	797	22 November 2019 to 26 January 2022
<b>LINK</b>	Chainlink	1590	20 September 2017 to 26 January 2022
<b>UNI</b>	Uniswap	497	17 September 2020 to 26 January 2022
<b>FTM</b>	Fantom	1185	30 October 2018 to 26 January 2022
<b>XTZ</b>	Tezos	1578	2 October 2017 to 26 January 2022
<b>AAVE</b>	Aave	482	2 October 2020 to 26 January 2022
<b>GRT</b>	The Graph	406	17 December 2020 to 26 January 2022
<b>CAKE</b>	PancakeSwap	485	29 September 2020 to 26 January 2022
<b>MKR</b>	Maker	1546	29 January 2017 to 26 January 2022
<b>RUNE</b>	THORChain	919	23 July 2019 to 26 January 2022
<b>CRV</b>	Curve DAO Token	531	14 August 2020 to 26 January 2022
<b>LRC</b>	Loopring	1611	30 August 2017 to 26 January 2022

Table III.20: **Description for the non-financial data**

This table describes the data for non-financial variables used: the network proxies (TVL, transactions, and address count).

Description	Daily data observations	Time span
<b>TVL</b>	1009	19 March 2018 to 27 January 2022
<b>Transactions count</b>	26735	9 April 2016 to 3 March 2022
<b>Addresses count</b>	26735	9 April 2016 to 3 March 2022

Table III.21: **Panel OLS, returns of 160 DeFi Tokens against their lagged TVL/MC ratio - Monthly**

$R^2$  is 1.45%.  $R^2$  Between is 3.36%. Panel regression of 160 DeFi returns against their Valuation Ratio = TVL/MarketCap. The data frequency is monthly. For this regression, we had 981 observations. \*\*\* denotes significance levels based on the respective p-value (\*:10%, \*\*:5%, and \*\*\*:1%). The standard t-statistic value is shown in parentheses.

	Coefficient	Std. Err.	T-stat	P-value	Lower CI	Upper CI
<b>const</b>	<b>3.625**</b>	<b>1.5289</b>	<b>2.371</b>	<b>0.0179</b>	<b>0.6246</b>	<b>6.6255</b>
<b>ValRatio(t-1)</b>	-0.001	0.0155	-0.065	0.9482	-0.0313	0.0293
<b>ValRatio(t-2)</b>	<b>-0.3715**</b>	<b>0.1657</b>	<b>-2.2416</b>	<b>0.0252</b>	<b>-0.6968</b>	<b>-0.0463</b>
<b>ValRatio(t-3)</b>	<b>0.6248***</b>	<b>0.2341</b>	<b>2.6683</b>	<b>0.0078</b>	<b>0.1653</b>	<b>1.0842</b>
<b>ValRatio(t-4)</b>	<b>-0.3772**</b>	<b>0.1558</b>	<b>-2.4216</b>	<b>0.0156</b>	<b>-0.6829</b>	<b>-0.0715</b>

We have downloaded all the DEFX data from the EIKON platform and perform comparison tests with the two indexes. Table III.23 reports the correlation check, while table III.24 shows the comparative results for the crypto-market exposure computed with the two indexes.

Table III.22: **Panel OLS, returns of 15 leading DeFi Tokens against their lagged TVL/MC ratio - Monthly**

$R^2$  is 10.18%.  $R^2$  Between is 23.21%. Panel regression of 15 major DeFi returns against their Valuation Ratio = TVL/MarketCap. The data frequency is monthly. For this regression, we had 148 observations. \*\*\* denotes significance levels based on the respective p-value (\*:10%, \*\*:5%, and \*\*\*:1%). The standard t-statistic value is shown in parentheses.

	Coefficient	Std. Err.	T-stat	P-value	Lower CI	Upper CI
<b>const</b>	<b>21.012***</b>	<b>5.0462</b>	<b>4.1638</b>	<b>0.0001</b>	<b>11.011</b>	<b>31.012</b>
<b>ValRatio(t-1)</b>	3.1015	3.268	0.949	0.3447	-3.3749	9.5778
<b>ValRatio(t-2)</b>	<b>-8.8164*</b>	<b>4.6141</b>	<b>-1.9108</b>	<b>0.0586</b>	<b>-17.96</b>	<b>0.3276</b>
<b>ValRatio(t-3)</b>	-2.5913	5.3891	-0.4808	0.6316	-13.271	8.0886
<b>ValRatio(t-4)</b>	5.9337	4.6433	1.2779	0.204	-3.2682	15.13

Table III.23: **Correlation between iDeFiX and DEFX**

Pearson correlation between the iDeFiX and DEFX. There are 265 observations and the data frequency is weekly. By looking at our results, we can observe that there is a moderate positive correlation between iDeFiX's returns and DEFX's returns. \*\*\* denotes significance levels based on the respective p-value (\*:10%, \*\*:5%, and \*\*\*:1%).

	iDeFiX	DEFX
<b>iDeFiX</b>	1.000	
<b>DEFX</b>	<b>0.432***</b>	1.000

$$R_t index = \alpha + \beta_1 RtCRIX(t-1) + \beta_2 RtCRIX(t-2) + \varepsilon, \quad (III.17)$$

$$R_t index = \alpha + \beta_1 RtBTC(t-1) + \beta_2 RtBTC(t-2) + \varepsilon, \quad (III.18)$$

$$R_t index = \alpha + \beta_1 RtETH(t-1) + \beta_2 RtETH(t-2) + \varepsilon. \quad (III.19)$$

As we can observe in table III.24, using iDeFiX or DEFX does not change the results of our analysis. However, we suppose that based on the token components included in the index and their weight, the exposure can be more or less statistically significant (higher / smaller R squared), but this does not change the final result.

Table III.24: **The impact of crypto-market on iDeFiX and DEX index**  
 Here we check if CRIX, BTC, and ETH impact DeFi market index returns. Rt-1 (Rt-2) refers to one (two) week(s) lagged crypto returns. Rt stands for weekly return. The number of observations for each regression is 265. \*\*\* denotes significance levels based on the respective p-value (\*:10%, \*\*:5%, and \*\*\*:1%). The standard t-statistic value is shown in parentheses.

	Constant	Rt-1 CRIX	Rt-2 CRIX	$R^2$
<b>Rt iDeFiX</b>	0.0029 (0.472)	<b>0.7302***</b> (5.390)	-0.0881 (-0.689)	26.5%
<b>Rt DEX</b>	0.0036 (0.618)	<b>0.6015***</b> (4.652)	-0.1285 (-1.053)	18.2%
	Constant	Rt-1 BTC	Rt-2 BTC	$R^2$
<b>Rt iDeFiX</b>	-0.0006 (-0.098)	<b>0.6411***</b> (5.922)	-0.1675 (-1.549)	24.1%
<b>Rt DEX</b>	0.0025 (0.398)	<b>0.3761**</b> (3.500)	-0.1281 (-1.194)	8.7%
	Constant	Rt-1 ETH	Rt-2 ETH	$R^2$
<b>Rt iDeFiX</b>	-0.0033 (-0.558)	<b>0.4571***</b> (6.063)	-0.0312 (-0.419)	33.4%
<b>Rt DEX</b>	0.0017 (0.006)	<b>0.2635**</b> (3.312)	-0.0683 (-0.871)	9.4%

# Chapter IV

## On pricing DeFi tokens<sup>1</sup>

### IV.1 Introduction

Decentralized Finance (DeFi) platforms provide financial services that rely on cryptocurrencies and crypto-tokens. The intention is to bring a digital and decentralized alternative to traditional banking and investment services (Anker-Sorensen & Zetzsche, 2021). The launch of Blockchain-based decentralized finance platforms has been a turning point for financial applications since it allows users to do more with their crypto-assets than just send them from point A to point B. DeFi platforms can perform most of the things banks do — lend, trade assets, earn interest, buy insurance, borrow, trade, and much more (Coinbase.com, 2022). In order to be able to do all these activities, DeFi platforms are supported by complex tokens with different functions depending on the service needed. Because of their functionalities, DeFi tokens could be considered a sub-class of the crypto-tokens, similar in a way to the ICO tokens. They fulfill multiple roles, such as facilitating access to different products or platform services, can be traded or sold in exchange for cryptocurrencies, and last but not least, DeFi tokens can be held to earn a profit (Le Moign, 2019).

The existing literature (Corbet et al., 2021; Maouchi, Charfeddine, & El Montasser, 2021; Schar, 2021; Yousaf, Nekhili, & Gubareva, 2022) often describes the DeFi market as a sub-sector of the crypto-market and the DeFi tokens as a distinct asset class from cryptocurrencies. The following rationale could justify this class separation between the two crypto-assets: from a practical viewpoint, DeFi Tokens (DeFis) and cryptocurrencies are similar only because they both use Blockchain. At

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<sup>1</sup>This paper has been submitted and is in revision with The European Journal of Finance.

the same time, [DeFi](#) are a distinct technology as they require smart contracts to function. From here stems our motivation to study the behavior of [DeFi](#) tokens, and we expect them to be uniquely different in terms of risk and return.

The [DeFi](#) market is relatively young, as the first official [DeFi](#) platform, Maker-DAO, was launched in late 2017 (Coinmarketcap.com, 2022). As a consequence of its youth, [DeFi](#)-related literature is scarce and comprises only subjects such as the platform's liquidity and efficiency (Gudgeon et al., 2020), [DeFi](#)'s potential in the context of traditional financial economy (Zetsche, Arner, & Buckley, 2020), financial bubbles (Corbet et al., 2021; Maouchi, Charfeddine, & El Montasser, 2021), the risk transmission among crypto-assets (Karim et al., 2022), and the lack of regulation within [DeFi](#) market (Anker-Sorensen & Zetsche, 2021; Aramonte, Huang, & Schrimpf, 2021; Chen & Bellavitis, 2019; Chen et al., 2020; Johnson, 2021; Popescu, 2020; Stepanova & Erins, 2021; Wronka, 2021). The existing crypto-related literature has shown the importance of crypto-assets in the diversification of equity portfolios (Ankenbrand & Bieri, 2018; Briere, Oosterlinck, & Szafarz, 2015), this being valid as well during stressed periods such as COVID-19 (Goodell & Goutte, 2021). From here, we assume that [DeFi](#) tokens could be as well used by investors to maximize their profits and diversify risks. From our knowledge, [DeFi](#)'s returns' properties have not yet been explored in the current literature.

To enclose this gap, our goal is to study the financial behavior of [DeFi](#) tokens and answer the following research question: *Is the Fama-French 3 Factor model relevant to explain [DeFi](#) tokens returns?* We propose a Fama-French 3 Factor model (FF3F) adapted to the [DeFi](#) market and examine if it can explain the tokens' returns. The reason why we employ the Fama-French model is because we believe that [DeFi](#) market suffers from a size effect. A major risk present in the crypto-market is the cyber-crimes. Crothers (2021) shows that the highest-priced crypto-assets are the main targets of cyber-attacks. Therefore, as [DeFi](#) tokens increase in popularity and value, they could become the next targets. Based on the above rationale, we expect that big tokens are the ones most exposed to (cyber) risks (which is the opposite of the stock market)<sup>2</sup>, risks that will reflect in higher compensation for investors and higher returns.

We construct the size and value factors using [DeFi](#) data. For the traditional High

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<sup>2</sup>According to the financial theory (Fama & French, 1996), we know that in the stock market, smaller firms tend to be riskier, hence tend to provide a higher return for investors.

Minus Low (HML) factor, we propose to replace the book value with an equivalent variable characteristic to this market, the Total-Value-Locked (TVL<sup>3</sup>). As a market factor, we use the market index iDeFix, developed in our paper (Soiman, Dumas, & Jimenez-Garces, 2022) from chapter III. As initial results, we obtained that all the risk factors considered are priced by the market. Afterward, we perform additional tests, such as the Fama-MacBeth procedure. Once the cross-sectional correlations are considered, our results change, and none of the risk factors are priced. Motivated by the literature showing that the cryptocurrency market is an essential driver for DeFis returns (Soiman, Dumas, & Jimenez-Garces, 2022), we decided to check if the risk factor represented by the CRIX index (the benchmark for the cryptocurrency market) can capture the variations in DeFis returns. In order to make this assessment, we have replaced our previous market index, iDeFiX, with the CRIX index and performed the same FF3F and Fama-MacBeth checks. The results show no change, regardless of which market index is used. We conclude that DeFi tokens returns cannot be explained by the traditional asset pricing models based on the stock market. Our findings emphasize the importance of using technological variables in pricing Blockchain-based assets, such as network variables.

The contributions made by this study are multiple: (1) from our knowledge, we are the first ones to test if the market, the size, and value factors explain DeFi returns and to examine the cross-section of DeFi tokens returns; (2) we constructed the TVL-to-Market ratio as an equivalent for this market of the 'book-to-market ratio'; (3) we have constructed the size and value factors using DeFi data; and last but not least (4) we have constructed the database used in this study.

The paper proceeds as follows. Section 2 provides the theoretical background based on which this paper has been developed. Section 3 describes the data used, the chosen model methodology, and the factors' construction. Section 4 reports the empirical results. The final section summarizes the results and offers conclusions.

## IV.2 Theoretical background

A proper valuation method can help assess the real worth of an asset hence helping buyers and traders to decide whether an investment is profitable. The valuation of

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<sup>3</sup>TVL refers to the amount of funds attached to a DeFi project. We consider it the equivalent of the book value in this market.

assets has long been one of the main persistent problems in finance. As an answer to this problem, the financial theory presumes that asset prices are generally set based on their present discounted value of dividends, in other words, their fundamental or intrinsic value (Tirole, 1985). The literature on this topic assumes that the fundamental value represents the ‘*real*’ value of an asset.

Up to now, there is no universal technique used to measure or calculate the fundamental value of an asset. However, several methods can be considered depending on someone’s needs and the asset type in question. For example, in the case of stocks, the mainly used valuation techniques are based on dividend payments, earnings, and book value. Certain assets, such as land, commodities, or even currencies, are more difficult to value. Determining their fundamental value based on discounted dividend method is not possible, and in such cases, a utility-based framework is often applied. For example, if the gold’s price is based on its utility, the valuation is influenced by factors such as industrial demand and supply flow. According to Blanchard and Watson (1982), mispricing is more likely to happen in markets where fundamentals are difficult to assess.

As a special asset class by nature, crypto-assets have been extensively studied (Bouri et al., 2017; Jiang et al., 2022). In particular, most studies focus on the relationship between cryptocurrency prices and their ‘fundamental’ value. While some studies showed that bitcoin is a purely speculative asset, hence has no fundamental value (Cheah & Fry, 2015; Kallinterakis & Wang, 2019); others argue that cryptocurrencies, in general, do have a fundamental value, despite the difficulty of deriving it (Dowd, 2014; Beigman et al., 2021). Following the logic of (Tirole, 1985), Biais et al. (2020) have tested and confirmed that cryptocurrencies have similar fundamental value to fiat money: ‘*transactional benefits are to cryptocurrencies what dividends are to stocks*’(Biais et al., 2020, p. 2), meaning that the more cryptocurrencies are used to transact (purchasing power), the bigger their value will be. Furthermore, significant attention has been brought to the network effects role in the valuation process of crypto-assets (Athey et al., 2016; Zimmerman, 2020; Cong, Li, & Wang, 2021; Liu & Tsyvinski, 2021). In the crypto-market, the network effect is proxied by variables such as transaction and address count, users’ numbers, and any other variable that could be used to estimate the Blockchain adoption rate. The network effect is especially important in the valuation process of the crypto-tokens and other Blockchain-based crypto-assets that do not attain transactional benefits, such as cryptocurrencies. For example, one of the Cong, Li, and Wang (2021)’s main

assumptions in his token valuation model is that the expected platform's increase in productivity (and value) is the result of the network growth. In other words, the network effects make crypto-assets and Blockchain technology more valuable as more people join the network, and as a result, the entire crypto-ecosystem becomes more valuable.

As stated before, the valuation of assets has been long one of the main persistent problems in finance. Thus, for the purpose of determining the (theoretical) fair value of an asset, academics proposed several models to price securities, among which the most well-known are the [Capital Asset Pricing Model \(CAPM\)](#) and [Arbitrage Pricing Theory \(APT\)](#). These pricing frameworks aim to consider the risks incurred by holding a security and price it accordingly. The [CAPM](#) model has been developed based on Markowitz ([1952](#), [1959](#))'s work on portfolio selection. It is a single-factor model that assumes that the return of a security is linearly related to its market risk. Since idiosyncratic risk can be diversified, the pricing model considers only the systematic risk, which cannot be diversified, as an important factor in asset valuation. The [APT](#) model has been developed by Ross ([1976](#)) as an alternative to the [CAPM](#). Compared to [CAPM](#), [APT](#) considers multiple systematic risk factors. The nature of the factors is undefined and can vary from company-specific to macroeconomic risk.

Several studies (Gibbons, Ross, & Shanken, [1989](#); Fama & French, [1992](#); Chan, Hamao, & Lakonishok, [1991](#)) have shown that for different periods, the relationship between stocks' return and market risk has disappeared. Hence the [CAPM](#) failed to fully explain the expected returns on investment. In 1992, Fama and French ([1992](#)) proposed a new empirical pricing model that incorporates two new risk factors in addition to the [CAPM](#)'s market risk factor: the size factor (small minus big) and the value factor (high book-to-market minus the low book-to-market). Afterward, different models have followed, extending the [CAPM](#) to six possible factors: Carhart ([1997](#)) proposed a risk factor called momentum, and Fama and French ([2015](#)) introduced two additional factors: the profitability and the investment risk factor.

Pricing crypto-assets has proven to be challenging, especially since they are a separate asset class from traditional assets (Dyhrberg, [2016b](#); Corbet et al., [2019](#); Liu, Tsyvinski, & Wu, [2022](#)). An important strand of literature tackles the modeling of cryptocurrency returns and examines various risk factors specific to this market.

Similar to traditional markets, the crypto-market is driven by a size effect, meaning that small-capitalization cryptocurrencies yield more than high-capitalization ones (Liu, Liang, & Cui, 2020; Shen, Urquhart, & Wang, 2020; Jia, Goodell, & Shen, 2022). Other risk factors studied in the crypto-related literature are momentum, volatility, liquidity, and (investor’s) attention.

## IV.3 Data, factors construction & model

This section presents our data set, our approach to computing the factors for the **FF3F** model, and the model itself.

### IV.3.1 Data

This article uses various types of data. First, we retrieved financial information for **DeFi** tokens from CoinmarketCap.com. The data spans from 01-01-2019 to 20-07-2022. The frequency is weekly and contains information for more than 400 tokens. As a market benchmark, we chose the iDeFiX index. We downloaded the prices for the iDeFiX index<sup>4</sup> from <https://hpac.imag.fr/cryptotracker/dashboards/idefix.html>. The data we have obtained for iDeFiX spans from 2017 to 2022. The summary statistics for the average returns of the **DeFi** tokens and for their index, are provided in section IV.3.2, Table IV.1.

To compute our factors, we retrieve **DeFi**-specific data; namely, the **TVL**. The **TVL** shows how much funds are committed to a specific **DeFi** platform. We know that the more successful a **DeFi** platform is, the bigger the **TVL** should be. This variable thus resembles the ‘*book-value*’ of a firm. The **TVL** information has been retrieved from DeFiLama.com. The data is at the weekly frequency, spans from 01-01-2019 to 20-07-2022, and contains information for more than 600 **DeFi** platforms. After merging the financial information for **DeFi** tokens and the **TVL** data, we have 88 tokens in total, for which we have complete information. That being said, for this study we have used 88 **DeFi** tokens, for which we have both financial data and **TVL** information. We display our sample information with **DeFi** tickers, names and chain type in Appendix IV.A.2, Table IV.7, Table IV.8 and Table IV.9.

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<sup>4</sup>The index was proposed by (Soiman, Dumas, & Jimenez-Garcés, 2022).

Figure IV.1: **The construction of Fama-French factors**

Here we show how we split our data sample into 6 portfolios in order to compute the loading factors with *DeFi* data for the Fama-French 3 factor model.

	<b>Median ME</b>	
<b>70<sup>th</sup> Percentile TVL/M</b>	<b>Small Value</b>	<b>Big Value</b>
<b>30<sup>th</sup> Percentile TVL/M</b>	<b>Small Neutral</b>	<b>Big Neutral</b>
	<b>Small Growth</b>	<b>Big Growth</b>

### IV.3.2 Constructing Fama-French factors

This work examines the relevance of the **FF3F** model in the **DeFi** market. We now construct the risk factors following the original paper’s methodology (Fama & French, 1992). The three factors are the market, the size (SMB), and the value (HML) factors. We re-balance the factors on a monthly basis. As a market factor, we use the market index **iDeFiX**. In this paper, we assume that the risk-free rate is null<sup>5</sup>. This assumption is based on the existing literature on cryptocurrencies (Grobys & Sapkota, 2019; Shen, Urquhart, & Wang, 2020), and on the fact that choosing a relevant risk-free rate for the **DeFi** market seems difficult. Following the methodology of Fama and French (1996), we construct six portfolios: Small Value (SV), Small Neutral (SN), Small Growth (SG), Big Value (BV), Big Neutral (BN), and Big Growth (BG). We now detail the construction of the size and value factors, which is also graphically presented in Figure IV.1.

- **SMB**: The size factor, Small Minus Big (SMB), is computed by splitting the **DeFi** tokens into two categories: small and big tokens. We construct equally weighted portfolios for large and small **DeFis** based on their market capitalization. Given our dataset (only 88 **DeFi** tokens in total), we follow the approach of Dimson, Nagel, and Quigley (2003), deviate from the original methodology of Fama and French (1996) and choose a 50% breakpoints<sup>6</sup>. Choosing higher breakpoints for our portfolios allows for a larger number of **DeFi** tokens per portfolio and limits the impact of one **DeFis** on the portfolio’s return. Our

<sup>5</sup>We are not sure that the usual risk-free rate used in the stock market (10Y T-Bills) is relevant for the **DeFi** market. However, we made some tests, including the risk-free rate (10Y T-Bills) downloaded from the Fama website, and found no difference in our results.

<sup>6</sup>The original breakpoints for the size factor are 10%/90% (Fama & French, 1996), splitting the stocks into three groups: small, middle and big.

factor is, then,

$$SMB(t) = 1/3 * (SV(t) + SN(t) + SG(t)) - 1/3 * (BV(t) + BN(t) + BG(t)). \quad (IV.1)$$

With  $SMB(t)$  being the value of the SMB factor at time  $t$ ,  $SV(t)$ ,  $SN(t)$ ,  $SG(t)$  represent the return of the portfolios of small DeFi tokens at time  $t$ , and  $BV(t)$ ,  $BN(t)$ ,  $BG(t)$  represent the return of the portfolios of large DeFi tokens at time  $t$ .

- **HML**: The value factor, High Minus Low (HML), is computed by splitting the DeFis into three groups: growth, neutral, and value tokens. Originally, the split is based on the Book-to-Market ratio (Fama & French, 1996). As DeFis do not have an equivalent for the book value, we chose to substitute it with the TVL measure. We then split our DeFis based on the TVL-to-Market ratio. The breakpoints are 30%/70%. The DeFis being in the lower 30% constitute the component for the portfolio of growth DeFis. The upper 30% are the value DeFis. We then compute the HML factor as follows,

$$HML(t) = 1/2 * (SV(t) + BV(t)) - 1/2 * (SG(t) + BG(t)). \quad (IV.2)$$

With  $HML(t)$  being the value of the HML factor at time  $t$ ,  $SV(t)$ ,  $BV(t)$  the return of the portfolios of DeFis having a high TVL-to-Market ratio at time  $t$ , and  $SG(t)$ ,  $BG(t)$  the return of the portfolios of DeFis having a low TVL-to-Market at time  $t$ .

We provide in Table IV.1, the summary statistics for the average of our returns as well as for each of our factors. The correlation among factors is displayed in Table IV.2.

### IV.3.3 Fama-French 3 Factor model

As in the original research of Fama and French (1996), we construct the FF3F model as a regression of the returns of DeFi tokens against the corresponding risk factors.

$$R_i(t) = \alpha_i + \beta_{i,Market} Market(t) + \beta_{i,SMB} SMB(t) + \beta_{i,HML} HML(t) + \varepsilon_i(t). \quad (IV.3)$$

Where  $R_i(t)$  is the vector of return of the  $i^{th}$  DeFi token;  $\alpha_i$  is the intercept

Table IV.1: **Descriptive Statistics: Returns of DeFi tokens & Fama-French factors**

Summary statistics for the average returns of 88 DeFi tokens, and for the Market, Size (SMB), and Value (HML) factors. The data consists of weekly returns. The Mean, Standard Deviation (SD), Min, Median, and Max are expressed in percentages and are annualized.

	Mean	SD	Min	Median	Max	Kurtosis	Skewness
<b>Market</b>	0.591	13.398	-52.062	0.000	50.343	2.73817	-0.20970
<b>SMB</b>	-1.160	09.031	-37.623	-1.251	52.093	7.74530	0.60716
<b>HML</b>	-1.107	10.003	-63.225	0.000	47.440	18.95651	-2.25403
<b>Defis</b>	-0.298	17.395	-81.279	-0.059	91.972	13.54434	0.58247

Table IV.2: **Correlation between Fama-French factors**

Pearson correlation coefficients between weekly returns of the Market, Size, and Value factors. The level of significance is expressed as: \*:**10%**, \*\*:**5%**, \*\*\*:**1%**.

	Market	HML	SMB
<b>Market</b>	1.0***		
<b>HML</b>	-0.076	1.0***	
<b>SMB</b>	0.066	0.151**	1.0***

of the OLS regression for  $i^{th}$  DeFi token;  $\beta_{i,factor}$  is the sensitivity of the  $i^{th}$  DeFi token with the *factor*, and  $\varepsilon_i(t)$  is the error vector. The Regression IV.3 is repeated for the 88 DeFis in our sample. The regression presented in Equation IV.3 allows estimating the factor loadings. In order to obtain the risk premium required by investors, we perform the following cross-sectional regression,

$$R_i(t) = \alpha + \lambda_{Market} * \hat{\beta}_{i,Market}(t-1) + \lambda_{SMB} * \hat{\beta}_{i,SMB}(t-1) + \lambda_{HML} * \hat{\beta}_{i,HML}(t-1) + \epsilon_t. \quad (IV.4)$$

Where  $R_i(t)$  is the vector of returns for all DeFi tokens;  $\lambda_{Market}$  is the regression coefficient for the loading of the *Market* factor;  $\beta_{i,\hat{Market}}$  is the vector of estimated sensitivities to the *Market* factor;  $\lambda_{SMB}$  is the regression coefficient for the loading of the *SMB* factor;  $\beta_{i,\hat{SMB}}$  is the vector of estimated sensitivities to the *SMB* factor;  $\lambda_{HML}$  is the regression coefficient for the loading of the *HML* factor;  $\beta_{i,\hat{HML}}$  is the vector of estimated sensitivities to the *HML* factor estimated in Regression IV.3; and  $\epsilon$  is the error vector.

However, a regular OLS regression fails to capture cross-sectional correlations. Such a problem will result in biased t-values for the coefficients estimated in Regression IV.4, leading to unreliable significance levels. To address that issue, we

perform the Fama-MacBeth procedure to obtain robust significance levels for our risk premiums. Following the original methodology of Fama and MacBeth (1973), we perform cross-sectional regression for each time step in our sample. Formally,

$$\begin{aligned}
 R_i(1) &= \alpha_1 + \lambda_{1,Market} * \hat{\beta}_{i,Market}(0) + \lambda_{1,SMB} * \hat{\beta}_{i,SMB}(0) + \lambda_{1,HML} * \hat{\beta}_{i,HML}(0) + \epsilon_1; \\
 R_i(2) &= \alpha_2 + \lambda_{2,Market} * \hat{\beta}_{i,Market}(1) + \lambda_{2,SMB} * \hat{\beta}_{i,SMB}(1) + \lambda_{2,HML} * \hat{\beta}_{i,HML}(1) + \epsilon_2; \\
 &\dots \\
 R_i(T) &= \alpha_T + \lambda_{T,Market} * \hat{\beta}_{i,Market}(T-1) + \lambda_{T,SMB} * \hat{\beta}_{i,SMB}(T-1) + \\
 &\quad \lambda_{T,HML} * \hat{\beta}_{i,HML}(T-1) + \epsilon_T.
 \end{aligned}
 \tag{IV.5}$$

The Equations IV.5 are essentially a repetition of the Regression IV.4 for each time step available. The risk premiums  $\lambda$  are obtained by taking the average of all  $\lambda_t$  for  $t = 1 \rightarrow T$ . This method allows computing the standard error of  $\lambda$  as follows,

$$SE_\lambda = \frac{SD(\lambda_t)}{\sqrt{T-1}}
 \tag{IV.6}$$

Where  $SE_\lambda$  is the standard error of the estimate and  $SD(\lambda_t)$  is the standard deviation of all  $\lambda_t$  for  $t = 1 \rightarrow T$ , with  $T$  being the amount of time step for our sample.

## IV.4 Results

### IV.4.1 Main results

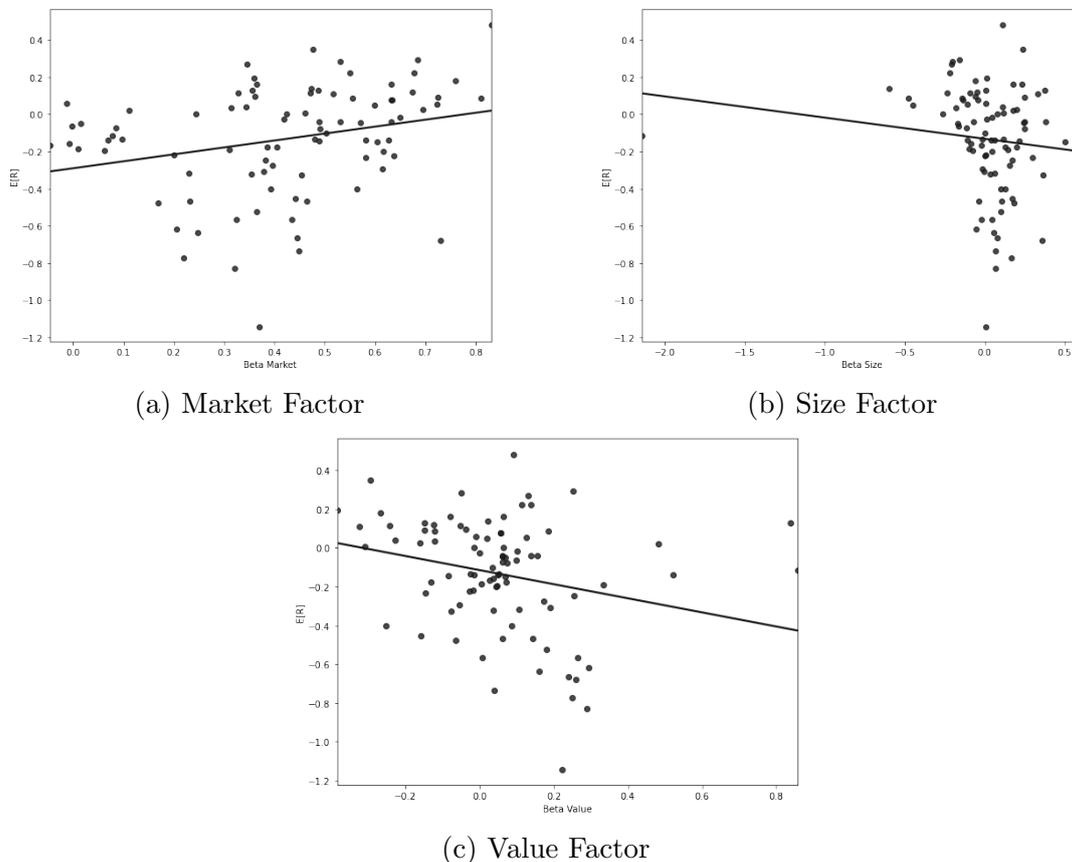
We start our analysis by running the FF3F model<sup>7</sup> on our 88 DeFis. We find that, on average, the model explains 13.1% of the variations in weekly DeFis returns. Turning to the risk premium in the DeFi market, we perform the cross-sectional regression in Equation IV.4. Our results are depicted in Figure IV.2 and in Table IV.3.

Our results highlight various facts about the pricing of risk in the DeFi market. Figure IV.2a shows a clear positive relationship between the  $\beta_{Market}$  and DeFis returns. This result is consistent with the existing financial theory, where any additional unit of systematic risk must be rewarded with supplementary returns. Figures

<sup>7</sup>The regressions follow the Equation IV.3.

**Figure IV.2: Regressions plots: Returns vs. Factor Loadings**

Scatter plots with a linear regression line between returns of DeFi tokens and their respective  $\beta$  for each risk factor. Figure (a) shows a positive linear relationship between the return in  $t$  and market beta in  $t-1$ . Figure (b) shows a negative relationship between returns and the size loading. Figure (c) shows a negative relationship between the returns and the TVL-to-market loading.



IV.2b and IV.2c display more interesting results: the relationship between returns and the exposure to the size and value factors is negative!

All these results are shown in the OLS regression output presented in Table IV.3. As can be observed, we find a negative intercept with high significance, which is similar to the research done on pricing cryptocurrencies (Shahzad et al., 2021; Jia, Goodell, & Shen, 2022). At the same time, all the relationships between the returns and the risk factors'  $\beta$  are significant. The market is the only variable that stands out to be positively related to the returns. The explanations for such a fact in finance are straightforward. The market is usually the primary source of financial risk, and any additional unit of risk needs to be rewarded with an additional return.

As certain anomalies have been found in the stock market (the relationship between stock returns and market risk has disappeared), this event has propelled the

Table IV.3: **OLS Regression: Risk Premia**

Results for the OLS regression performed between the returns of 88 DeFi tokens and their respective sensitivity to the Market, Size, and Value factors. SE stands for Standard error, and the p-value is provided in the  $P > |t|$  column.

(a) OLS Regression: Performance						
<b>Model:</b>	OLS	<b>R-squared:</b>	0.191			
<b>F-statistic:</b>	6.628	<b>Adj. R-squared:</b>	0.163			
(b) OLS Regression: Coefficients & Significance						
	Estimate	SE	t	$P >  t $	[0.025	0.975]
<b>Intercept</b>	-0.2726	0.066	-4.117	0.000	-0.404	-0.141
<b>Market</b>	0.3997	0.140	2.847	0.006	0.121	0.679
<b>SMB</b>	-0.2781	0.103	-2.713	0.008	-0.482	-0.074
<b>HML</b>	-0.4533	0.150	-3.031	0.003	-0.751	-0.156

research on additional risk factors (Fama & French, 1993, 1996). For example, the size factor provided us with one of the first explanations of why assets with the same systematic risk do not have the same rate of return. Because smaller firms tend to be riskier, hence tend to provide a higher return for investors. Surprisingly, the DeFi market seems to contradict this logic. We find a strongly significant negative relationship between size and returns. This result suggests that larger DeFi provides higher returns than smaller tokens. This phenomenon is apparently not surprising for the academic literature, as it has previously appeared in emerging markets and other financial markets outside the US stocks (Heston, Rouwenhorst, & Wessels, 1999). We think that an explanation for the ‘negative’ size effect is that the DeFi market is highly heterogeneous<sup>8</sup>. We think that an explanation for this could be that DeFi tokens’ increase in value represents the driving force behind the rise in cybercrime, a fact confirmed for the cryptocurrency market (Crothers, 2021). Therefore, as DeFi tokens increase in popularity and value, they could become the next target in cyber-attacks. For this reason, investors may ask for higher compensation for the incurred risks, which eventually will reflect in an increased return.

Adapting the HML factor of Fama and French (1996) to the DeFi market provides some unexpected results. Fama and French (1996) initially argued that the HML factor proxies relative distress, as weak firms tend to have high Book-to-Market ratios. The HML factor, in our case, is negatively related to the return,

<sup>8</sup>There is a big difference between the large capitalization and the small capitalization DeFi tokens. This is a noteworthy mention, as our results are robust regardless of the change in the breakpoints. By this, we mean that the big-cap tokens drive the DeFi market and our results.

which contradicts the rationale provided by Fama for the stock market. Better said, our results show that the tokens with the lowest TVL-to-Market ratio are the ones that are the riskiest. This risk could be as well the consequence of the high price (the market value is high), which tends to transform crypto-assets into the next cyber-attack targets (Crothers, 2021).

The results obtained from our OLS regression do not account for various effects, such as cross-sectional correlations within the sample. We perform the Fama-MacBeth procedure to address this limitation and obtain robust significance levels for our coefficients. The results are provided in Table IV.4<sup>9</sup>.

**Table IV.4: Fama-MacBeth: Risk Premia**

*Results for the Fama-MacBeth regressions performed between the returns of 88 Defi tokens at time  $t$ , and their respective sensitivity to the Market, Size and Value factors at  $t-1$ . Each estimate is computed by averaging all (186) cross-sectional estimates provided in Figure IV.3. The standard error (SE) is computed following Equation IV.6. The  $p$ -value is computed for a two-tailed  $t$ -test.*

	<b>Estimate</b>	<b>SE</b>	<b>t</b>	<b>P &gt;  t </b>
<b>Intercept</b>	-0.0108	0.004	-3.028	0.003
<b>Market</b>	0.0205	0.014	1.461	0.146
<b>SMB</b>	-0.0085	0.013	-0.633	0.528
<b>HML</b>	-0.0123	0.011	-1.117	0.265

We find that once the cross-sectional correlations are accounted for, none of the factors are actually priced by the market. The market factor is the closest to being significant<sup>10</sup>, suggesting that it might still be an important driver for DeFis returns. However, the size and value effects appear completely irrelevant. An explanation for this could be that DeFi platforms are relatively new and very technical. As previously stated, this market is immature, and compared to other financial markets, it is largely unknown to the public, acting more as a niche. The largest DeFi platforms are the most known and attract the most attention. Due to this, they experience substantial growth and provide high returns to their investors. What actual risks are priced in these returns cannot, for now, be explained by the traditional asset pricing models based on the stock market. Furthermore, these results emphasize the importance of using technological variables in pricing Blockchain-based assets, such as network variables.

<sup>9</sup>To have a graphical representation of Fama-McBeth's results, see Appendix IV.A.1 Figure IV.3.

<sup>10</sup>As a robustness check, we have made all the computations with DEFX (NASDAQ index for Decentralized Finance) as we did with iDeFiX and we have obtained the same results.

## IV.4.2 Additional results

Our findings from Section IV.4.1 show that none of the risk factors considered in our FF3F model are priced by the market. However, the market factor is the closest to being significant. This result suggests that the market risk could be an important driver for DeFis returns, and it should be considered in future studies.

Soiman, Dumas, and Jimenez-Garces (2022) are revealing that the impact of the cryptocurrency market on DeFis returns is stronger than any other potential driver considered in their study. Motivated by these findings, we want to assess if the DeFis returns are sensitive to the market risk factor represented by the CRIX<sup>11</sup> index (the benchmark for the cryptocurrency market). In order to make this assessment, we have replaced our previous market index, iDeFiX, with the CRIX index, and performed the same FF3F and Fama-MacBeth checks. The regressions' output is reported in Table IV.5 and IV.6.

We find that risk factors explain 17.5% of the cross-section of DeFis returns. This result is a downgrade compared to the FF3F with iDeFiX, which explains 19.1%. The differences in the two approaches indicate that the cross-section of DeFis returns is better explained by their own market rather than the cryptocurrency market. Furthermore, the Fama-McBeth results indicate clearly that the market does not price cryptocurrency market risk. Logically enough, we find that the significance of the risk premium for cryptocurrency market risk is even less significant than the one for DeFi tokens market risk.

## IV.5 Conclusion

In this chapter, we examine the effectiveness of the FF3F model, consisting of market, size, and value factors, to assess DeFi tokens returns. To compute our factors, we retrieve DeFi-specific data. Afterward, we constructed the risk factors following the original paper's methodology (Fama & French, 1992). A particular effort has been put in the construction of the value factor. As there is no 'book value' for DeFi tokens, we have found a substitute: the TVL. TVL refers to the amount of funds attached to a DeFi project, therefore we consider it to be the equivalent of the book value in this market. Furthermore, we have split our DeFi tokens based on the

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<sup>11</sup>The data for CRIX has been downloaded from spglobal.com.

Table IV.5: **OLS Regression: Risk Premia - CRIX**

Results for the OLS regression performed between the returns of 88 Defi tokens and their respective sensitivity to the cryptocurrency index (CRIX), Size and Value factors. SE stands for Standard error, and the  $p$ -value is provided in the  $P > |t|$  column.

(a) OLS Regression: Performance						
<b>Model:</b>	OLS	<b>R-squared:</b>	0.175			
<b>F-statistic:</b>	5.949	<b>Adj. R-squared:</b>	0.146			
(b) OLS Regression: Coefficients & Significance						
	Estimate	SD	t	$P >  t $	[0.025	0.975]
<b>Intercept</b>	-0.2446	0.064	-3.831	0.000	-0.372	-0.118
<b>Market</b>	0.1343	0.106	1.265	0.210	-0.077	0.345
<b>SMB</b>	-0.2430	0.102	-2.392	0.019	-0.445	-0.041
<b>HML</b>	-0.5114	0.149	-3.427	0.001	-0.808	-0.215

Table IV.6: **Fama-MacBeth: Risk Premia - CRIX**

Results for the Fama-MacBeth regressions performed between the returns of 88 Defi tokens and their respective sensitivity to the Cryptocurrency Market (CRIX), Size and Value factors. Each estimate is computed by averaging all (186) cross-sectional estimates provided in Figure IV.3. The standard error (SE) is computed following Equation IV.6. The  $p$ -value is computed for a two-tailed  $t$ -test.

	Estimate	SE	t	$P >  t $
<b>Intercept</b>	-0.0103	0.004	-2.672	0.008
<b>Market</b>	0.0114	0.011	1.039	0.300
<b>SMB</b>	-0.0068	0.014	-0.504	0.615
<b>HML</b>	-0.0153	0.011	-1.392	0.165

TVL-to-market ratio, which is the DeFi market equivalent for the Book-to-Market ratio. As a market risk factor, we have used the index iDeFiX.

A proper valuation method can help assess the real worth of an asset hence helping buyers and traders decide whether an investment is profitable. The valuation of assets has long been one of the main persistent problems in finance. The DeFi market is relatively young, as the first official DeFi platform, MakerDAO, was launched in late 2017 (Coinmarketcap.com, 2022). As a consequence of its youth, DeFi-related literature is relatively scarce. From our knowledge, we are the first ones to explore the DeFis returns' properties.

Our results with the FF3F show that all the risk factors considered in this model are priced by the market. We found that the relationships between the returns and

the exposure to the size and value factors are negative. If such findings are not surprising for the academic literature, as it has previously appeared in the other financial markets outside the US (Heston, Rouwenhorst, & Wessels, 1999), DeFi tokens seem to be the first crypto-assets to suffer from this phenomenon. We think that an explanation for this could be the fact that DeFi's increase in value attracts cyber-attacks, a fact confirmed for the cryptocurrency market (Crothers, 2021). Therefore, as DeFi tokens increase in popularity and value, they could easily become the next casualties. For this reason, investors may ask for higher compensation for the incurred risks, which eventually will reflect in an increased return.

Furthermore, we decided to perform additional tests, such as the Fama-MacBeth procedure. Once the cross-sectional correlations are taken into consideration, our results change, and none of the risk factors are priced. Motivated by the literature showing that the cryptocurrency market is an important driver for DeFi returns, we checked if the risk factor represented by the CRIX index captures the variations in DeFi returns. In order to make this assessment, we have replaced our previous market index, iDeFiX, with the CRIX index, and performed the same FF3F and Fama-MacBeth checks. The results obtained show no change from the previously obtained ones. By that, we mean that regardless of which market index is used, DeFi tokens returns cannot be explained by the traditional asset pricing models based on the stock market, or at least not by using just financial information. In line with (Biais et al., 2020) and based on the results obtained from this study, we think that measuring the value of Blockchain-based assets correctly depends on using non-financial variables such as the network size.

A limitation of this study is our sample size. Because of the differences in the data available for financial and TVL information, we have not been able to cluster more DeFi tokens together. We, therefore, wonder if a bigger sample would have provided the same results. As a future path for research, it could be interesting to construct other risk factors, such as liquidity, volatility, or network factors, and test their capacity to capture the cross-sectional variation in DeFi tokens returns.

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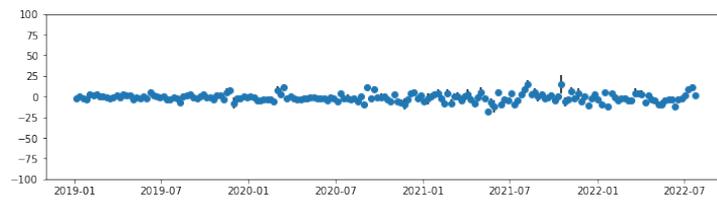
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## IV.A Appendix

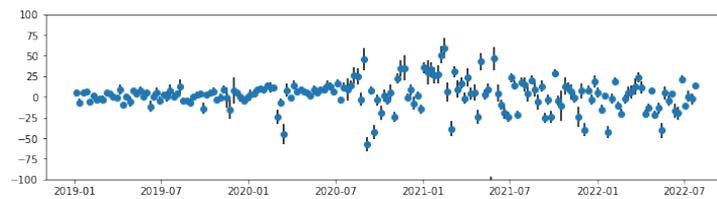
### IV.A.1 Figures

#### Figure IV.3: Fama-MacBeth: Cross-sectional coefficients over time

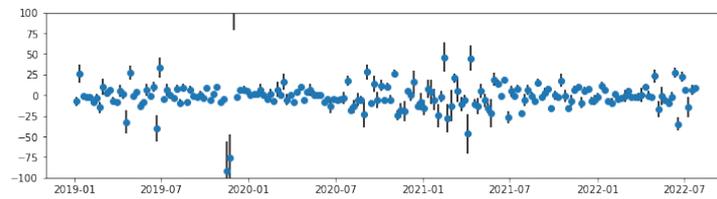
Scatter plots of cross-sectional coefficients of the returns against their respective factor loadings. The cross-sectional coefficients are computed from 186 cross-sectional regressions as depicted in Equation IV.5. The vertical black bar represents the OLS standard error of the estimate. Figure (a) shows the results for the intercept over time. Figure (b) shows the results for the Market factor over time. Figure (c) shows the results for the Size factor over time. Figure (d) shows the results for the Value factor over time.



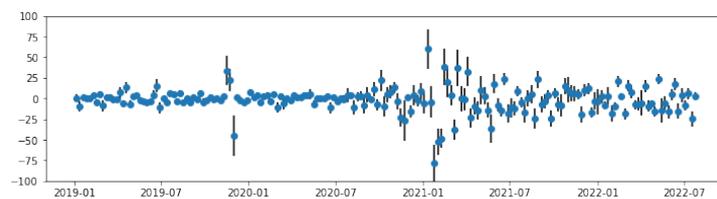
(a) Intercept



(b) Market Factor



(c) Size Factor



(d) Value Factor

## IV.A.2 Tables

Table IV.7: **List of DeFi Tokens (1/3)**

*Comprehensive list of the 88 DeFi tokens used in this study. We provide the ticker, the name, and the Blockchain technology related to that particular DeFi platform.*

<b>Ticker</b>	<b>Name</b>	<b>Chains</b>
<b>CAKE</b>	CakeDAO	Avalanche
<b>TAROT</b>	Tarot	Fantom, Optimism
<b>HARD</b>	Kava Lend	Kava
<b>SUSHI</b>	SushiSwap	Ethereum, Polygon, Arbitrum, Avalanche
<b>RGT</b>	Rari Capital	Ethereum, Arbitrum
<b>CREAM</b>	CREAM Finance	Ethereum, BSC, Polygon, Arbitrum
<b>TRU</b>	TrueFi	Ethereum
<b>AUTO</b>	Autofarm	BSC, Polygon, Cronos, Heco, Fantom, Avalanche
<b>QI</b>	Benqi Lending	Avalanche
<b>VVS</b>	VVS Finance	Cronos
<b>ANKR</b>	Ankr	Ethereum, BSC, Avalanche, Fantom, Polkadot
<b>CHESS</b>	Tranchess	BSC
<b>ROOK</b>	Rook	Ethereum
<b>TIME</b>	Wonderland	Avalanche, Ethereum
<b>KP3R</b>	Keep3r Network	Ethereum
<b>FLM</b>	Flamingo Finance	NEO
<b>BNT</b>	Bancor	Ethereum
<b>OUSD</b>	Origin Dollar	Ethereum
<b>MMO</b>	MM Optimizer	Cronos
<b>DF</b>	dForce	BSC, Arbitrum, Ethereum, Polygon, Optimism
<b>COMP</b>	Compound	Ethereum
<b>DODO</b>	DODO	BSC, Ethereum, Polygon, Aurora, Arbitrum
<b>PICKLE</b>	Pickle	Ethereum, Polygon, Arbitrum, Aurora, Optimism
<b>BANANA</b>	ApeSwap	BSC, Polygon
<b>UMA</b>	Outcome Finance	Ethereum, Polygon, Boba
<b>BIFI</b>	Beefy Finance	Fantom, Polygon, BSC, Avalanche, Arbitrum
<b>DHT</b>	dHEDGE	Ethereum, Polygon, Optimism
<b>BNC</b>	Bifrost	Bifrost

Table IV.8: **List of DeFi Tokens (2/3)**

*Comprehensive list of the 88 DeFi tokens used in this study. We provide the ticker, the name and the Blockchain technology related to that particular DeFi platform.*

<b>Ticker</b>	<b>Name</b>	<b>Chains</b>
<b>BADGER</b>	Badger DAO	Ethereum, Arbitrum, BSC
<b>DYDX</b>	dYdX	Ethereum
<b>LDO</b>	Lido	Ethereum, Solana, Moonbeam, Moonriver, Terra
<b>MDX</b>	MDEX	Heco, BSC
<b>MTA</b>	mStable	Ethereum, Polygon
<b>LRC</b>	Loopring	Ethereum
<b>PNT</b>	pNetwork	Ethereum, BSC, Telos, Bitcoin, ORE, EOS
<b>AAVE</b>	AAVE V2	Ethereum, Polygon, Avalanche
<b>WBTC</b>	WBTC	Ethereum
<b>FLX</b>	Reflexer	Ethereum
<b>CRV</b>	Curve	Ethereum, Polygon, Avalanche, Fantom
<b>QUICK</b>	Quickswap	Polygon
<b>SNX</b>	Synthetix	Ethereum, Optimism
<b>INV</b>	Inverse Finance	Ethereum
<b>RPL</b>	Rocket Pool	Ethereum
<b>NFTX</b>	NFTX	Ethereum, Arbitrum
<b>MKR</b>	MakerDAO	Ethereum
<b>BABY</b>	BabySwap	BSC
<b>UNI</b>	Uniswap	Ethereum, Polygon, Arbitrum, Optimism, Celo
<b>BELT</b>	Belt Finance	BSC, Heco, Klaytn
<b>XVS</b>	Venus	BSC
<b>YFI</b>	Yearn Finance	Ethereum, Fantom, Arbitrum
<b>ARMOR</b>	Armor	Ethereum
<b>SLND</b>	Solend	Solana
<b>DVF</b>	Rhino.fi	Ethereum
<b>FARM</b>	Harvest Finance	Ethereum, Polygon, BSC
<b>KSP</b>	KlaySwap	Klaytn
<b>LQTY</b>	Liquity	Ethereum

Table IV.9: **List of DeFi Tokens (3/3)**

*Comprehensive list of the 88 DeFi tokens used in this study. We provide the ticker, the name, and the Blockchain technology related to that particular DeFi platform.*

<b>Ticker</b>	<b>Name</b>	<b>Chains</b>
<b>WING</b>	Wing Finance	Ontology, BSC, OntologyEVM, Ethereum, OKExChain
<b>KAVA</b>	Kava	Kava
<b>CVX</b>	Convex Finance	Ethereum
<b>PERP</b>	Perpetual Protocol	Optimism, Ethereum
<b>ACA</b>	Acala LCDOT	Acala
<b>MET</b>	Metronome	Ethereum
<b>RAY</b>	Raydium	Solana
<b>KEEP</b>	KEEP Network	Ethereum
<b>IDLE</b>	Idle Finance	Ethereum, Polygon
<b>VSP</b>	Vesper	Ethereum, Avalanche, Polygon
<b>FXS</b>	Frax	Ethereum, Fantom
<b>ALCX</b>	Alchemix	Ethereum, Fantom
<b>INJ</b>	Injective	Ethereum
<b>BSW</b>	BiSwap	BSC
<b>SDT</b>	StakeDAO	Ethereum, Polygon, Avalanche, Harmony, BSC
<b>BUNNY</b>	Bunny	BSC, Polygon
<b>RUNE</b>	Thorchain	Ethereum, Binance, Bitcoin, Doge, Litecoin
<b>ALPACA</b>	Alpaca Finance	BSC, Fantom
<b>REN</b>	RenVM	Ethereum, Arbitrum, Solana, Polygon, Fantom
<b>ALPHA</b>	Homora	Avalanche, Ethereum, BSC, Fantom
<b>DFI</b>	DefiChain DEX	DefiChain
<b>BEL</b>	Bella Protocol	Ethereum
<b>VTX</b>	Vector Finance	Avalanche
<b>NXM</b>	Nexus Mutual	Ethereum
<b>MLN</b>	Enzyme Finance	Ethereum
<b>RSR</b>	Reserve	Ethereum
<b>BAL</b>	Balancer	Ethereum, Polygon, Arbitrum
<b>FIS</b>	Stafi	Ethereum, CosmosHub, Polygon, Stafi, BSC
<b>EPS</b>	Ellipsis Finance	BSC
<b>FEI</b>	Fei Protocol	Ethereum
<b>SRM</b>	Serum	Solana
<b>STRK</b>	Strike	Ethereum

# General Conclusion

The crypto-market has attracted important attention from academia, engineers, investors, and the public in general. For their high volatility and speculative behavior, crypto-assets have been isolated as a separate asset class from traditional assets, and the idea of diversification opportunities has arisen. Many papers have stated that the crypto-market is not linked to the real economy (Dyhrberg, 2016b; Caferra & Vidal-Tomás, 2021; Sifat, 2021) and has a low correlation with established asset classes (Ankenbrand & Bieri, 2018; Baur & Dimpfl, 2018; Corbet et al., 2018; Corbet et al., 2019). However, new evidence, such as (Iyer, 2022), shows that the correlation between cryptocurrencies and stocks has been increasing (see Table 1), suggesting that the cryptocurrency market has changed. We believe that apart from cryptocurrencies, other crypto-assets could have diversification properties. If this is true, investors could diversify risks not only with cryptocurrencies but with other crypto-assets such as for example NFTs or DeFi tokens. With this idea in mind, we consider it essential to understand the nature of crypto-assets and study their financial properties.

In recent years, crypto-assets became one of the top best-performing financial asset classes, along with Nasdaq 100 stocks and US Large Caps stocks (Sriram, 2021). In finance, we say that there is a positive relationship between the risk and returns of an asset. Therefore, since crypto-assets are approximately ten times more volatile than traditional assets (Bariviera & Merediz-Solà, 2021), there is no surprise that they hold the title of the best-performing asset class. Nevertheless, the story of financial risk has two faces, meaning that high risk could bring either high returns or high losses.

This thesis focuses on the risk-return relationship. It aims to uncover the determinants of financial returns in the crypto-market. More specifically, we begin this thesis by investigating the unique risks Blockchain-based assets incur (e.g., cryp-

tographic attacks, smart contract attacks, and other technological vulnerabilities), risks that might be the source of the market's inherent volatility. With the idea of exploring Blockchain-specific risks, this thesis also encloses an analysis of the impact of technological events on crypto-assets' financial characteristics. Additionally, it exposes the diversity of crypto-assets and their implications for asset pricing.

## Main Findings & Contributions

### Chapter I

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As discussed in this thesis, Blockchain-based assets are far more than cryptocurrencies. As stock values depend on their underlying firms or derivatives on their underlying assets, Blockchain-based asset values must depend on their respective Blockchain. Consequently, the opening chapter of the thesis answers the following research question: *'Can technological vulnerabilities of Blockchain technology trigger financial risks?'*

This chapter first tries to cover the most important technological risks by considering the likelihood of occurrence, crypto-market's exposure to technological events, and the (financial) impact they might have. We summarized the exposure of Blockchain technology and crypto-market to several technological risks: Consensus level attacks, Network level attacks, Cryptographic key threats, and Smart contract threats. Table I.3 (p. 58) gives a picture at the market level. Since measuring the actual macro-impact of technological vulnerabilities is difficult, we estimate the consequences and possible market exposure in terms of the number of tokens/Blockchains and market share.

A similar approach is used in the analysis of the financial risks (see Table I.4, p. 68). We clustered them by type: total risk, information risk, liquidity risk, supply risk, and environmental risk. Afterward, by considering the technological risks' exposure and potential damages that could eventually trigger financial risks, we analyze them together and propose a conceptual metric to emphasize the likelihood of this happening. Among all the risks assessed, we show that the Network level attacks and Cryptographic key threats are the most menacing for the crypto-market. The exposure for these technological vulnerabilities is the highest, as possible tar-

gets represent most types of Blockchain, their users, mining pools, and exchange platforms. Furthermore, our analysis shows that technological events can indeed trigger financial risks, with a likelihood from Medium to High.

In line with the literature survey done, we provide examples of how financial risk is linked to technological vulnerabilities. More specifically, we perform two short empirical demonstrations:

1. We assess if bitcoin's volatility is affected by events targeting the crypto-market.
2. We investigate the relationship between bitcoin returns, its volatility, and the negative investor's attention (triggered by technological vulnerabilities).

Our first empirical demonstration confirms that the volatility of bitcoin is influenced by the number of attacks or other malevolent events targeting the crypto-market. These findings reveal the important implications of regulation on this market. For example, La Porta et al. (2002) states that investors are more willing to finance firms if they have legal protection for doing this. In the crypto-market, investors are not protected by any law (MacKenzie, 2022; Morgan Stanley, 2022). Therefore, we believe that technological vulnerabilities might be perceived as less harmful if the crypto-investors were protected. This result also demonstrates that the development of this market depends not only on technological innovation but also on the legal system that supports it. Our second empirical demonstration shows that negative investor attention impacts bitcoin returns and volatility. Additionally, our results reveal that most crypto-investors might be amateurs or non-specialists, which could be further linked to the Blockchain illiteracy issue and how it affects the market.

This survey provides a two-dimension risk analysis (technological and financial). First, we show that risks can be related and that, during specific market conditions, they can become a trigger for one another. Second, we offer a way to determine the likelihood of triggering financial risks through technological vulnerabilities. Furthermore, the empirical demonstration confirms the arguments developed in the literature survey, more specifically, that financial risk can be triggered by technological vulnerabilities that are characteristic of the crypto-market. This chapter contributes to the academic literature in many ways. Of the same mind as Corbet et al. (2019), our study follows a similar belief, namely: *“for new research areas*

*such as those based around crypto-assets, a literature analysis can be the most powerful tool to inform academics, professionals, and policy-makers about the current state of knowledge, consensuses, and ambiguities in the emerging discipline.”* The results obtained through this literature survey emphasize the role played by financial behavior, social responsibility, and Blockchain literacy in the stability of the crypto-market. Moreover, our empirical evidence reveals the implication of cybersecurity risks and poor regulation to accompany the crypto-market’s development.

## Chapter II

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Chapter II offers an extension of our previous work. Here, we analyze and bring further empirical evidence of how technological events may translate into financial ones. We research the causal link between pure technological events, namely forks, and the cryptocurrency’s financial characteristics (e.g., return, volatility, liquidity, and information efficiency). We intend to bring to light the *forking effect*, which is the financial impact experienced by a cryptocurrency when its Blockchain splits.

We performed an event study on Bitcoin hard fork that continues to be traded today. More specifically, we investigate the following research questions: (1) *How do bitcoin’s financial characteristics react to fork events?* and (2) *How the characteristics of the forked coins compare to their parent coin (bitcoin)?*

Our results are twofold. First, we show that forks issued during stable market conditions allow for a diminution in returns, VaR, illiquidity, and volatility in the parent coin. Given that the crypto-market is known to be inefficient (Tran & Leirvik, 2020; Hu, Valera, & Oxley, 2019; Bariviera, 2017; Nadarajah & Chu, 2017; Urquhart, 2016), we show that forks are worsening their parent coin’s efficiency. However, forks occurring during stressed market times, such as the 2017-2018 cryptocurrency bubble, increase the returns and risk carried by their parent coin and improve its efficiency. The stronger efficiency could be explained by the arrival of more information (about forking events) at a time when the proportion of noise is high. Additionally, we checked separately for the drivers of efficiency improvement and found that this improved efficiency is explained by a volume effect.

In the second part of this study, we show that forks are more risky, illiquid, volatile, less performant, and less efficient than their parent coin. This result ex-

acerbates over time. In other words, recent forks are worst than earlier ones. Furthermore, we have observed that early forks display similar characteristics as their parent coin, whereas those occurring during the bubble and afterward appear to be significantly riskier and less efficient. This result could be justified by two facts: (1) investors may disregard the new cryptocurrencies' value due to their shorter life history, or (2) the global uncertainty about cryptocurrencies is increasing with time, a fact shown in the chaotic market behavior.

This work makes an important contribution to the literature about Blockchain forks. We are the first ones to study the forking events and their impact on the financial characteristics of the parent coin. By financial characteristics, we mean the return, volatility, liquidity, and informational efficiency. When comparing the parent coin to the forked ones, we showed that the newly traded coins are significantly less liquid, riskier, and more volatile. The results of this study could be relevant to investors, who may want to invest in forked coins or consider them as suitable tools for diversification.

### Chapter III

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Chapter III investigates the possible drivers of **Decentralized Finance (DeFi)** token returns. **DeFi** is one of the latest Blockchain-based solutions aiming to provide fully automated financial services. Compared to the vast literature on cryptocurrencies, **DeFi**-related research is scarcer. Motivated by Corbet et al. (2021), Maouchi, Charfeddine, and El Montasser (2021), Schar (2021), and Yousaf, Nekhili, and Gubareva (2022), who show that **DeFi** tokens are a distinct asset class compared to conventional cryptocurrencies, our goal is to offer a first analysis of the **DeFi** market as a whole and answer to the following research question: *What are the drivers of **DeFi** tokens returns?*

Following (Liu & Tsyvinski, 2021)'s work on cryptocurrencies, we performed an in-depth analysis of the determinants of the **DeFi** market returns. We consider several possible driving forces, such as: (1) the cryptocurrency market, (2) the network variables, and (3) the TVL-to-Market ratio. As **DeFi** tokens lacked a market index, we constructed one, named **iDeFiX**, as the value-weighted return of all representative **DeFi** tokens. More precisely, **iDeFiX** is constructed following the methodology and original code for the **CRIX** index (Trimborn & Härdle, 2018).

Considering that cryptocurrencies and DeFi tokens run on Blockchain technology, we first assess the exposure of DeFi token returns to the cryptocurrency market. Our results show that the cryptocurrency market strongly influences DeFis returns, which is in line with Corbet et al. (2021) and Yousaf and Yarovaya (2021). To complement these results, we perform additional tests and answer the following question: *Can BTC be used in predicting DeFis returns?* The results obtained show that the strong crypto-market exposure could be explained by the bidirectional causality relationship between BTC returns and iDeFiX returns and the long-term correlation between BTC and DeFis.

The network effect in the crypto-market could be described as: the cryptocurrencies' value and utility increase when more people join the network/Blockchain. In other words, the more individuals decide to use BTC, the more valuable the entire BTC ecosystem becomes; hence the price will increase. We use three primary measures to proxy the network effect on the DeFi market: the number of wallet users, the number of active addresses, and the TVL. Results show that DeFis returns are strongly influenced by their network variables, similarly to cryptocurrencies (Liu & Tsyvinski, 2021). Furthermore, we reveal that the impact of the TVL on DeFis returns is stronger than any other network variable considered and provides superior explanatory power.

Motivated by the existing literature on the cryptocurrency market and studies of other financial markets, we investigate if DeFis returns are driven by their 'book-to-market' ratio. As there is no standard 'book' value for DeFi tokens, we have constructed a Book-to-Market ratio for the DeFi market by dividing the TVL by the Market Capitalization (MC). TVL is a characteristic unique of the DeFi market. More specifically, it reflects the amount of funds committed to DeFi platforms and is an indicator of market growth and success. The results obtained do not offer any obvious answers. Hence, we conclude that there is not enough evidence to support our assumption that the TVL-to-Market ratio contains information about future DeFis returns.

In this work, we perform an in-depth analysis of the determinants of the DeFi market returns. We consider several possible driving forces, such as: (1) the cryptocurrency market, (2) the network variables, and (3) the TVL-to-Market ratio.

Our results show that the impact of the cryptocurrency market on [DeFis](#) returns is stronger than any other considered driver. This chapter makes important contributions to the academic literature, such as: (1) we are the first ones to assess the [DeFi](#) market as a whole and to investigate multiple possible return drivers; (2) we constructed an index for the [DeFi](#) market; (3) we compute a ‘book-to-market’ ratio adapted to the [DeFi](#) market. At the same time, we believe that our findings will greatly serve investors interested in the [DeFi](#) market to maximize their profits and diversify risks.

## Chapter IV

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This closing chapter extends the work from the previous chapters. We examine the relevance of using [Fama-French 3 Factor Model \(FF3F\)](#), adjusted for the [DeFi](#) market, to model [DeFi](#) token returns. [DeFi](#) returns’ properties and their diversification potential have not yet been explored in the current literature. Our goal is to study the financial behavior of [DeFi](#) tokens, and answer to the following research question: *Is the Fama-French 3 Factor model relevant to explain [DeFi](#) tokens returns?*

We construct the size and value factors using [DeFi](#) data. For the HML, we replace the book value with an equivalent variable characteristic to this market, the [TVL](#)<sup>12</sup>. As a market factor, we use the market index [iDeFiX](#). The results of this first part of the study show that all the risk factors considered are priced by the market. Furthermore, we found that the relationships between the returns and the exposure to the size and value factors are negative. If such findings are not surprising for the academic literature, as it has previously appeared in the other financial markets outside the US (Heston, Rouwenhorst, & Wessels, 1999), [DeFi](#) tokens seem to be the first crypto-assets to suffer from this phenomenon.

In the second part of the study, we perform additional tests, such as the Fama-MacBeth procedure. Once the cross-sectional correlations are considered, our results change, and none of the risk factors are priced. Motivated by the literature showing that the cryptocurrency market is an essential driver for [DeFis](#) returns (Soiman, Dumas, & Jimenez-Garces, 2022), we decided to check if the risk factor represented by the [CRIX](#) index (the benchmark for the cryptocurrency market) can capture the variations in [DeFis](#) returns. In order to make this assessment, we have replaced

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<sup>12</sup>The [TVL](#) refers to the amount of funds attached to a [DeFi](#) project. We consider it the equivalent of the book value in this market.

our previous market index, iDeFiX, with the CRIX index and performed the same **FF3F** and Fama-MacBeth checks. The results show no change, regardless of which market index is used.

This chapter examined the relevance of the **FF3F** in the **DeFi** market. To our knowledge, we are the first to test this model on the **DeFi** market. At first look, the risk factors are priced by the market. However, cross-sectional correlations play an important role in this market. Using the Fama-MacBeth procedure, we conclude that **DeFi** tokens returns cannot be explained by the traditional asset pricing models based on the stock market, or at least not by using just financial information. Such results emphasize the importance of using technological variables in pricing Blockchain-based assets, such as for example, network variables. We contribute to the current literature by being, to our knowledge, the first to test whether the size and value factors are priced by the **DeFi** market, and to examine the cross-section of **DeFis** returns. Furthermore, our results show that future efforts trying to model **DeFis** returns should take into consideration the network variables.

## Thesis

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From a global point of view, this thesis tackles important gaps in the current academic literature. We are among the first to study the crypto-market beyond the financial aspects of cryptocurrencies. We observed that there is a growing number of research on cryptocurrencies. However, new Blockchain-based assets are seeing the light and have yet to be studied. In this doctoral thesis, we provide some of the first studies on **DeFis** and technological events such as forks. As Blockchain-based innovations are developing rapidly, we provide financial academics with accessible resources on the technological details of these innovations and their impact on the crypto-market. For instance, our work on Blockchain forks gives a clear example of how technological features impact the financial characteristics of crypto-assets. Moreover, we explore the underlying drivers of crypto-assets and try to challenge existing asset pricing models in explaining their returns. The crypto-market is structurally different from the traditional financial markets. Crypto-assets are not backed by a company but by Blockchain technology. This simple fact challenges existing views of financial academics on the dynamics such asset returns should have. This thesis advocates for the development of new approaches/models that are tailor-made

to the crypto-market.

Moreover, this thesis is also intended for practitioners. Blockchain literacy plays a central role in how the crypto-market will develop. Our research explains the risks associated with Blockchain technology and describes some of its technological features. Our results are also of interest to investors seeking new diversification possibilities. We show that the crypto-market is more than just cryptocurrencies and that different crypto-assets have different financial behavior. The diversification that the [BTC](#) can offer differs from what [DeFis](#) offer. Furthermore, studying the drivers of crypto-asset returns is also of interest to the asset management industry.

## Limits & Future Research Agenda

Despite all the attempts to provide robust and reliable results, our work has several limitations. This section identifies the main limitations and exposes how our future research agenda will address them.

In our opinion, most of the research on the crypto-market experiences similar limitations related to data. The crypto-market is constantly growing, as large amounts of new coins are constantly issued. Afterward, due to regulatory or cybersecurity issues, many crypto-assets collapse and cease to be traded. Thanks to this phenomenon characteristic of the crypto-market, most research works suffer from survivorship bias. Our study on forks considers only the forking events related to the coins that still trade nowadays. To solve this issue, we plan to strengthen the study on the forking effect, including as well the discontinued forks.

The second limitation is that most of the current literature focuses on bitcoin or the top biggest cryptocurrencies. While considering only bitcoin, many studies have inferred market-wide behavior from their analyses. Because of this, the current theory on how crypto-assets behave is mainly based on bitcoin or other top cryptocurrencies. As a future path for research, we plan to study how the forking effect impacts other cryptocurrencies and their successive coins. However, constructing such a database for other coins will be challenging, as most of the crypto-related data available are for bitcoin and other big coins. To overcome this issue, we plan to continue studying other crypto-assets such as ICO tokens, [DeFi](#) tokens, [NFT](#), and less-known cryptocurrencies.

An important limitation of our work on fork consists of the granularity of the data. Forks on the bitcoin Blockchain did not appear at regular intervals, and sometimes, multiple forks occurred during the same day. This characteristic in the data makes event study particularly arduous. First, having a clear picture of the ‘normality’ before the event becomes difficult if another event lies there. Secondly, the estimation of the impact of an event is also disturbed by the occurrence of another. An interesting solution lies in [Auto-Regressive \(AR\)](#) models. Such models allow flexibility when defining the process that financial returns follow. Ideally, we would want to define financial returns as a function of their lagged variables and additional regressors. Modeling returns via [AR](#) models would permit us to define a dummy variable (corresponding to the event’s occurrence) and observe its effect and significance. By doing so, we remove the necessity of having a pre- and post-observation period. This solution limits the impact of partially overlapping events. Additionally, when two events occur on the same day, we can observe the effect of the additions of events on the variable of interest. This is a feature that a standard event study approach cannot manage. Furthermore, this approach allows for more complex specifications. [Generalized Auto-Regressive Conditionally Heteroskedastic \(GARCH\)](#) models can extend the approach to examining the event’s effect on either the average of returns or their (conditional) volatility. A specific lead would consist of using an exponential [GARCH](#) model on the abnormal returns of cryptocurrencies to study their reactions during the occurrence of a hard fork on their Blockchain.

Our third limitation concerns the accessibility of Blockchain data. Even though most of the Blockchains we have analyzed are public, the complete retrieval of data is technical, and most researchers need to rely on specialized websites. Such sources offer data only for a limited choice of crypto-assets and make a market study difficult to perform. For example, most of the pricing theories on the crypto-market stress the necessity to include Blockchain-related data such as, for example, the network variables. Network data is easily accessible for the top cryptocurrencies and tokens. In our case, we managed to extract network data for only 22 [DeFi](#) tokens, which, compared to the market size, is quite insufficient. Furthermore, the structure of the data sometimes differs from one source to another. This makes data aggregation arduous. Finally, different sources provide us with financial prices for crypto-assets; however, this information is often different from one source to another. Due to all such reasons, studying the crypto-market requires a high degree of precaution during the data collection phase.

In the future, to strengthen the robustness of our results, we plan to organize new and larger data sets to perform our tests. A particularly interesting future research lead would be to construct new risk factors to price DeFi tokens. The fact that TVL is difficult to retrieve for a large amount of DeFis reduces the sample available to perform the analysis. Also, we show that common risk factors used in the equity market do not apply to DeFi market; therefore, we plan to explore other factors such as liquidity, extreme risk, or connectedness.

Regarded as a superior technology compared to the existing one, Blockchain might be the future of fintech and other sectors' automation. Like any innovation, Blockchain makes no exception and comes with both improvements and challenges. As time passes, we observe that technological development helps Blockchain to become a better tool. The crypto-market has increased exponentially in the past decade, challenging investors with new types of securities and new risks. With the idea of exploring Blockchain-specific risks, this thesis encloses an analysis of the impact of technological events on crypto-assets' financial characteristics. Additionally, it exposes the diversity of crypto-assets and their implications for asset pricing.

We think this work may be helpful to both academic researchers in their efforts to understand the determinants of the crypto-assets risk and to market participants (as well as crypto-asset enthusiasts) for their investments. At the same time, we believe that our results have important implications for the regulators working on the crypto-market. La Porta et al. (2002) state that *“..legal protection of investors is an important determinant of the development of financial markets. Where laws are protective of outside investors and well-enforced, investors are willing to finance firms, and financial markets are both broader and more valuable”*. If the investors from the crypto-market were better protected, the technological vulnerabilities of Blockchain and the financial risks could perhaps be perceived as less harmful. This proves that the development of this market depends not only on technological innovation but also on the legal system that supports it.

# Résumé en Français

## 1 Contexte de la recherche

L'ampleur des variations de prix dans le temps, ou mieux encore, la volatilité du bitcoin, est l'une des raisons de la popularité actuelle du crypto-marché (CORBET et al., 2019). Perçue à la fois comme un mal et un bien pour les marchés financiers, la volatilité joue un rôle essentiel dans l'adoption des crypto-actifs et le développement du marché (POLLOCK, 2018). Si l'or est considéré comme presque synonyme de stabilité, les crypto-actifs sont perçus comme le contraire de l'or ou l'adversaire des titres classiques. Capables de changer leur prix du simple au double en l'espace de quelques semaines, ce qui entraîne des rendements ou des pertes importants, les crypto-actifs sont plus stimulants et controversés que toute autre classe d'actifs. Dans le même temps, les histoires de crypto-millionnaires et de 'richesse gagnée en une nuit' ont ouvert l'appétit du grand public et stimulé la 'Bitcoin mania' (POLLOCK, 2018).

Grâce à leur forte volatilité, les crypto-actifs ont obtenu le titre de classe d'actifs la plus performante. Si l'on considère les dix dernières années (2011-2021), les trois classes d'actifs financiers les plus performantes en termes de gains annualisés sont : (1) les cryptomonnaies avec un ROI de 230,6%, (2) le Nasdaq 100 avec un ROI de 20%, et (3) les US Large Caps avec un ROI de 14% (SRIRAM, 2021). De 2009, lorsque le premier bitcoin a été extrait, à 2010, lorsque la première transaction en bitcoin a eu lieu, cet actif numérique n'avait aucune valeur marchande. La plus longue période de marché haussier de l'histoire, les années 2010, s'est parfaitement synchronisée avec l'extraordinaire évolution du crypto-marché, faisant de ce dernier un instrument indispensable sur les marchés financiers (MESSAMORE, 2019; SINCLAIR, 2019).

Compte tenu de leur importance croissante et de leurs applications disruptives, les crypto-actifs sont devenus un sujet d'étude pour les académiques et les spécialistes

de divers domaines. Les variations de leur prix et les causes possibles qui les sous-tendent constituent l'un des sujets les plus abordés en finance. On pense que la maturité et la taille du marché pourraient expliquer en partie l'instabilité accrue des prix (BURNISKE & TATAR, 2017; SINCLAIR, 2019). Dans le même temps, la littérature a montré que l'absence de réglementation appropriée et les nombreuses cyber-attaques jouent également un rôle important dans les variations de prix des cryptomonnaies (PIETERS & VIVANCO, 2017; WHEATLEY et al., 2018; GANDAL et al., 2018; CORBET et al., 2019; NADLER & GUO, 2020).

Cette thèse se concentre sur la relation risque-rendement, et elle vise à identifier et évaluer les nouveaux risques liés à la Blockchain susceptibles d'affecter la performance financière du crypto-marché dans son ensemble.

## 2 Crypto-actifs

### 2.1 Que sont les crypto-actifs et la technologie Blockchain ?

Les crypto-actifs sont des actifs immatériels programmés, émis, enregistrés et négociés via une [DLT](#) (technologie de registre distribué). Comme nous pouvons l'apprendre intuitivement de leur nom, cette technologie utilise des algorithmes cryptographiques, d'où la dénomination adjointe 'crypto'. Dans le cas de ces actifs numériques et de leur technologie sous-jacente, l'emploi de la cryptographie est lié à des raisons de sécurité (HAYS & VALEK, 2018). À première vue difficile à comprendre, le monde de la cryptomonnaie se veut en fait assez intuitif et simple. À la base du fonctionnement des crypto-actifs, nous avons la technologie distribuée Blockchain. La Blockchain est un registre mondial des transactions financières (elle peut également être perçue comme une base de données contenant tous les détails des transactions). Conçus à l'origine pour faciliter le transfert de valeur, les crypto-actifs fonctionnent sans l'aide d'un tiers de confiance. Par conséquent, ils facilitent l'échange numérique, l'enregistrement numérique de la propriété des actifs et toute autre fonction utilitaire qu'une ressource numérique peut avoir (FSB, 2018; BLANDIN et al., 2019). Un aspect important à mentionner au sujet des crypto-actifs est le fait qu'ils ne sont soutenus par aucune autorité centrale et n'ont pas de cours légal dans quasiment aucune juridiction.

### 2.2 Évolution du marché et terminologie

Les crypto-actifs se sont fait connaître en 2008 lorsque Satoshi Nakamoto a inventé le bitcoin. Depuis cette invention, la technologie Blockchain, ainsi que le monde des crypto-actifs, se développent sans relâche. Selon une étude de l'Université de Cambridge (2019), la terminologie utilisée a également évolué en même temps que le crypto-marché. Jusqu'en 2014, le terme communément utilisé pour tous les crypto-actifs était 'bitcoin'. Par la suite, les termes génériques 'cryptomonnaie', 'digital monnaie', et 'virtual monnaie' sont entrés en vigueur. Après 2017, le marché est devenu de plus en plus complexe ; par conséquent, de nouveaux termes tels que 'actif virtuel', 'actif numérique' et 'actif cryptographique' ont commencé à être utilisés plus fréquemment. Cette grande diversité de termes définissants témoigne des efforts déployés par les organismes et les régulateurs pour mieux comprendre et différencier les crypto-actifs des monnaies fiduciaires. Le contrôle du gouvernement confère à la monnaie fiduciaire son statut de monnaie légale, ce qui signifie qu'elle est communément acceptée comme moyen de paiement et que tout le monde doit l'utiliser dans le pays concerné (BLANDIN et al., 2019).

À l'origine les termes crypto-actifs et cryptomonnaies étaient utilisés de manière interchangeable, mais la technologie Blockchain a reçu des applications supplémentaires et, avec elle, le monde a reçu de nouveaux types de crypto-actifs. En ce qui concerne le terme crypto-actifs, étant donné qu'il est apparu plus tard, nous pouvons encore identifier des emplois erronés et fréquents du terme cryptomonnaies, même s'il n'est plus universellement défini (BURNISKE & TATAR, 2017).

Les crypto-actifs et la technologie Blockchain sont essentiels dans le monde financier, notamment grâce à leurs nombreuses applications qui apportent des contributions importantes à l'industrie financière.

### 2.3 Taxonomie des crypto-actifs

Les crypto-actifs ont progressivement été considérés comme un outil très utile pour la diversification des investissements financiers et la gestion de portefeuille (BRIERE, OOSTERLINCK & SZAFARZ, 2015 ; GOODELL & GOUTTE, 2021 ; URQUHART & ZHANG, 2019). Il est donc important de comprendre leur nature et de souligner les particularités de ce marché. Les crypto-actifs présentent de nombreuses caractéristiques communes, ce qui rend difficile de tracer des délimitations. Par conséquent, les spécialistes ont encore du mal à définir, classer et déclarer (financièrement) les

crypto-actifs.

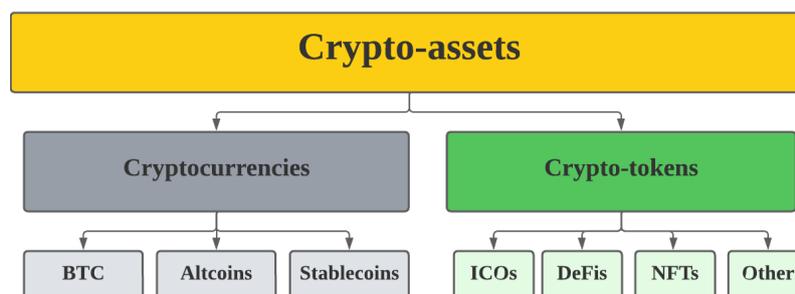
En 1997, Robert J. Greer a publié un article fondateur intitulé “What is an asset class, anyway ?” (GREER, 1997). Dans cet ouvrage, l’auteur conçoit trois classes d’actifs, telles qu’elles s’appliquent aux investissements du monde réel :

- Actifs de capital : leur valeur est déterminée en fonction de la valeur actuelle nette (abv. NPV) des rendements attendus (par exemple, dette, obligations, actions, etc.).
- Actifs consommables/transformables : souvent appelés matières premières, leur valeur doit être déterminée en fonction des critères de l’offre et de la demande (par exemple, les matières premières, les métaux, la nourriture, etc.).
- Actifs à valeur stockée : la valeur de cette classe varie dans le temps ; d’où le nom de ‘valeur stockée’ (par exemple, les beaux-arts, le vin, les métaux précieux, les devises, etc.).

Les classes proposées par GREER (1997) sont généralement considérées comme des superclasses, qui pour une bonne compréhension, devraient être divisées en sous-classes et ainsi de suite. Dans notre cas, la superclasse des crypto-actifs pourrait être divisée en sous-classes de cryptomonnaies et de crypto-jetons (la figure RF.1 propose une classification pour les crypto-actifs). Dans le même temps, les cryptomonnaies et les jetons peuvent également être divisés en plusieurs autres sous-classes. Par exemple, les monnaies stables sont un type de cryptomonnaies dont la valeur est liée à un actif sous-jacent qui peut être une devise (généralement le dollar américain), un titre ou une combinaison de plusieurs actifs.

FIGURE RF.1 : **Classes de crypto-actifs**

*Classification des crypto-actifs telle que vue par l’auteur. Source : adaptation par l’auteur de la figure originale de (EY GLOBAL, 2018).*



La classification des crypto-actifs n’est pas une tâche aisée. D’une part, les cryptomonnaies peuvent être considérées comme une réserve de valeur, car leur prix

change continuellement, atteignant des records tels que  $1 \text{ BTC} = 66\,000 \text{ USD}$  (novembre 2021). D'autre part, il existe des cas où elles peuvent être utilisées comme des consommables ; par exemple, les monnaies d'éther coin peuvent être utilisées pour accéder aux plateformes Ethereum (BURNISKE & TATAR, 2017). Les jetons ou crypto-jetons n'ont pas d'attributs monétaires ; cependant, ils offrent souvent l'accès à une communauté ou à un réseau de participants pour gouverner et utiliser le système basé sur la Blockchain (GURGUC & KNOTTENBELT, 2018). En d'autres termes, le terme 'jeton' est généralement utilisé comme un terme générique pour décrire divers crypto-actifs qui ne sont pas des cryptomonnaies ni utilisés à des fins transactionnelles. Les jetons pourraient être considérés comme des actifs de capital seulement s'ils sont adossés à des titres financiers (par exemple, des jetons adossés à des actions). Dans le cas contraire, si les jetons donnent simplement accès à une plateforme, ils appartiennent à la catégorie des consommables/transformables (WHITE & BURNISKE, 2016).

Au fur et à mesure de l'évolution du crypto-marché et des recherches dans ce domaine, les spécialistes tendent à s'accorder sur la classification suivante :

- Jetons de paiement : crypto-actifs ou cryptomonnaies utilisés comme moyens de paiement ou d'échange numériques (par exemple, bitcoin, éther, etc.) (BLEMUS & GUÉGAN, 2020) ;
- Jetons d'utilité : crypto-actifs donnant à leurs détenteurs l'accès à - et l'utilisation de - une plateforme numérique (par exemple, plateformes de jeux, réseaux commerciaux, applications décentralisées, etc.)
- Jetons de titres : crypto-actifs représentant un investissement de nature similaire aux titres traditionnels (jetons adossés à des actions ou autres titres traditionnels) ;
- Jetons hybrides : partagent les caractéristiques de deux ou des trois classes (BLANDIN et al., 2019 ; BLEMUS & GUÉGAN, 2020) ;
- **NFT** : les jetons non fongibles ont pour but d'enregistrer la propriété d'un actif numérique dans la Blockchain, comme des images, de la musique, des vidéos et d'autres créations virtuelles (DOWLING, 2022a) ;
- **DeFi** jetons : crypto-actifs qui remplissent de multiples rôles dans les opérations de la plateforme **DeFi** ; (1) jetons transactionnels (par exemple, les stablecoins : Dai, TUSD, USDC, WBTC) qui facilitent les transferts de fonds entre les plateformes (Aramonte, Huang et Schrimpf, 2021), (2) jetons de gouvernance (par

exemple, MKR, COMP, YFI) qui permettent aux utilisateurs de prendre part au développement de la plateforme et ressemblent aux actions ordinaires, (3) les jetons d'utilité qui sont utilisés de la même manière que dans les ICO, pour obtenir l'accès aux services de la plateforme ('monnaies' de paiement in-App), (4) les jetons de fournisseur de liquidité (LP) qui sont utilisés comme récompense pour les utilisateurs contribuant à la liquidité d'un DEX, et (5) les jetons de collatéral qui sont utilisés sur les plateformes de prêt, de manière similaire aux pratiques de prêts bancaires (par eg., stablecoins, LP, ETH, NFTs) (MAKERDAO.COM, 2021). Pour une meilleure compréhension de ce que les plateformes DeFi peuvent faire, voir la figure RF.2.

FIGURE RF.2 : Exemples de fonctions des plateformes DeFi

Comparaison entre les plateformes de finance décentralisée, la finance centralisée et la finance traditionnelle. Source : (ARAMONTE, HUANG & SCHRIMPF, 2021).

Function	Service	Crypto financial system		Traditional finance
		Decentralised finance (DeFi)	Centralised finance (CeFi)	
Trading	Funds transfer	DeFi stablecoins (DAI)	CeFi stablecoins (USDT, USDC)	Traditional payment platforms
	Asset trading	Crypto asset DEX (Uniswap)	Crypto CEX (Binance, Coinbase)	Exchanges and OTC brokers
	Derivatives trading	Crypto derivatives DEX (Synthetix, dYdX)		
Lending	Secured lending	Crypto decentralised lending platforms (Aave, Compound)	Crypto centralised lending platforms (BlockFi, Celsius)	Broker-dealers active in repo and securities lending
	Unsecured lending	Crypto credit delegation (Aave)	Crypto banks (Silvergate)	Commercial banks and non-bank lenders
Investing	Investment vehicles	Crypto decentralised portfolios (yearn, Convex)	Crypto funds (Grayscale, Galaxy)	Investment funds

CEX = centralised exchanges; DEX = decentralised exchanges; OTC = over-the-counter; USDC = USD Coin; USDT = Tether.

Comme nous pouvons le constater, les crypto-actifs peuvent être classés en fonction de leur application, de leur nature, de leurs caractéristiques technologiques ou même du domaine dans lequel ils opèrent. Plus on approfondit l'analyse en classes et sous-classes, plus les caractéristiques techniques se révèlent. Cela nous rappelle que les crypto-actifs sont, avant tout, une innovation technologique. Malgré toutes les tentatives de classification officielle des crypto-actifs, plus ce marché se développe, plus il devient difficile de choisir un modèle de classification uniforme. LIU et TSYVINSKI (2021) a constaté que *“le comportement des cryptomonnaies est déterminé par (1) ses fonctions en tant que participation à l'avenir de la technologie Blockchain qui est similaire aux actions, (2) en tant qu'unité de compte similaire*

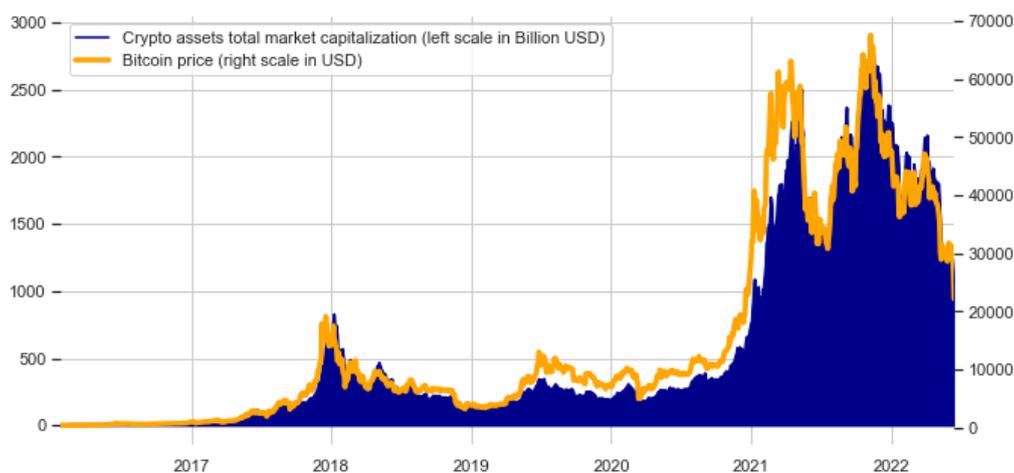
aux devises, et (3) en tant que réserve de valeur similaire aux métaux précieux, aux matières premières”. Sur la même idée et en alignement avec (SHARPE, 1992)<sup>1</sup>, KRÜCKEBERG et SCHOLZ (2019) montrent que les crypto-actifs, plus précisément les cryptomonnaies, doivent être considérés comme une classe d’actifs distincte, sans corrélation avec les classes traditionnelles. En conclusion, pour le moment, les crypto-actifs sont mieux décrits comme une classe émergente qui évoluera avec le temps.

## 2.4 Le marché des crypto-actifs

Au cours du long et constant développement effectué durant les 12 dernières années, les prix des cryptomonnaies ont souvent connu une escalade drastique (voir la figure RF.3). À la fin de 2017, le crypto-marché a atteint des prix record qui ont dépassé ceux des classes d’actifs bien établies. La période 2017-2018 est considérée comme la bulle du bitcoin, qui a impacté la plupart des altcoins du marché et a fait monter tous les chiffres. En l’espace de 5 mois, de décembre 2017 à mai 2018, le prix du bitcoin est passé de \$19,500 à seulement \$7,000. Cette dévaluation drastique enregistrée après les records de 2018 a sérieusement détérioré l’intérêt et la confiance des investisseurs dans ce marché. Du point de vue des spécialistes, cette réduction de valeur du crypto-marché est une simple correction des prix, nécessaire pour effacer les effets de la crypto-mania (AGOSTO & CAFFERATA, 2020).

### FIGURE RF.3 : Capitalisation totale du marché des crypto-actifs

Évolution du prix du bitcoin et de la capitalisation totale du marché de tous les crypto-actifs entre 2016 et 2022. Source : Coinmarketcap.com, calculs de l’auteur



<sup>1</sup>Sharpe a proposé une méthode de classification des actifs basée sur les critères suivants : (1) Aucun titre ne devrait être inclus dans plus d’une catégorie d’actifs. (2) Il faut inclure autant de titres que possible dans la classe d’actifs choisie. (3) Les actions appartenant à la classe d’actifs choisie doivent avoir de faibles corrélations de rendement avec celles de l’autre classe (ou écart-type différent).

En 2020, le monde est confronté à la pandémie de COVID-19. En raison de la panique mondiale et du confinement imposé dans le monde entier, tous les marchés financiers, ainsi que le crypto-marché ont subi des pertes importantes. Par rapport à des marchés financiers bien ancrés, le crypto-marché s'est rétabli beaucoup plus rapidement. On pense que cela s'est produit en raison de l'absence de lien entre les monnaies virtuelles et l'économie réelle (CAFERRA & VIDAL-TOMÁS, 2021). Après le choc créé par la pandémie, les prix du crypto-marché ont continué à augmenter, atteignant un nouveau record de capitalisation boursière de 2,3 trillions de dollars en avril 2021. Le pic suivant de 2,9 trillions de dollars a été enregistré en novembre 2021, après lequel le marché a chuté drastiquement à seulement 891 milliards de dollars en juin 2022 (COINMARKETCAP.COM, 2022). Cet énorme effondrement serait la réponse à la panique créée par l'instabilité économique (en conséquence de la pandémie COVID-19) et la persistance d'une inflation élevée (DUGGAN, 2022).

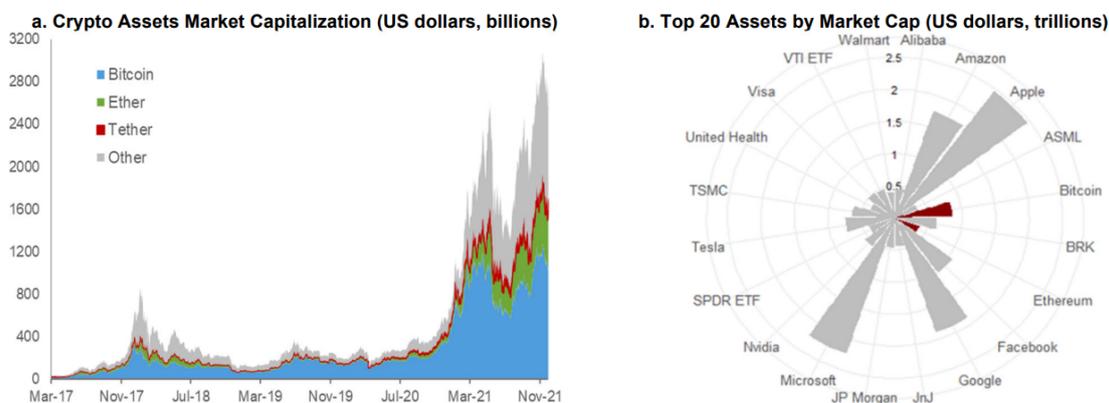
Si l'on regarde ses récents records de novembre 2021, le crypto-marché a subi une dévaluation drastique de plus de 70% en six mois environ (OSSINGER, PAN & BLOOMBERG, 2022). Si les marchés traditionnels souffraient d'un effondrement aigu similaire, les banques centrales et les professionnels de la finance qui s'occupent de l'économie s'emploieraient immédiatement à sauver le marché (par exemple, les pratiques de rachat). Cependant, ce n'est pas le cas pour le crypto-marché. Selon un communiqué de presse, les économistes ne craignent pas que la liquidation des crypto-actifs nuise à l'économie au sens large, tant qu'ils ne sont pas utilisés comme garantie pour des dettes du monde réel (MACKENZIE, 2022). Cet événement s'accompagne de nombreuses conséquences malheureuses caractéristiques des marchés non réglementés, où les investisseurs sont ceux qui souffrent le plus, car aucune protection n'est prévue (comme ce serait le cas sur les marchés des capitaux) (MORGAN STANLEY, 2022).

Comme on peut l'observer dans la figure RF.3 et la figure RF.4 a., la capitalisation boursière de l'ensemble du crypto-marché semble être influencée par le prix du bitcoin. Malgré le fait qu'au niveau mondial, le nombre de crypto-actifs dépasse désormais 9,000 (COINMARKETCAP.COM, 2022), le bitcoin reste le leader du marché avec une part supérieure à 44%, suivi de l'Ether (19%) et du Tether (6%) (STATISTA, 2022). Et si nous continuons à examiner la domination du marché à un niveau plus large, nous pouvons observer que la suprématie du marché est facilement atteinte par les principales cryptomonnaies : les trois premières cryptomonnaies couvrent 70% de la part de marché totale, et les 10 premières sont responsables de 85% de la

part de marché totale (COINMARKETCAP.COM, 2022). Grâce à DeFi et à d'autres développements spécifiques aux cryptomonnaies, le nombre de crypto-actifs et le marché dans son ensemble ont connu une expansion significative. Cette croissance rapide du crypto-marché est le résultat de l'intérêt porté aux crypto-actifs et à la technologie Blockchain. De plus, après le choc de la pandémie COVID-19, ce marché a gagné une popularité croissante auprès des investisseurs institutionnels et particuliers en tant que classe d'actifs. Pour leurs performances financières et technologiques (innovantes), les crypto-actifs bénéficient d'une confiance suffisante pour figurer parmi les 20 premiers actifs négociés (voir figure RF.4 b.).

FIGURE RF.4 : L'essor des crypto-actifs

Source : IYER (2022).



Sources: CoinMarketCap; CoinGecko; CryptoCompare; Statista; Yahoo Finance; author's calculations.  
 Note: Figure 1a uses daily data from January 2017 to November 2021 on the market cap of crypto assets. Figure 1b shows the world's top 20 assets, based on the universe of publicly traded companies, exchange traded funds (ETFs) and crypto assets, by their market cap on Sept 10, 2021. Crypto assets are in red and the other assets are in grey. ASML = Advanced Semiconductor Materials Lithography; BRK = Berkshire Hathaway; JnJ = Johnson and Johnson; SPDR ETF = SPDR S&P 500 ETF Trust; TSMC = Taiwan Semiconductor Manufacturing Company; VTI ETF = Vanguard Total Stock Market Index ETF.

Comparé à d'autres marchés financiers, le crypto-marché reste relativement petit<sup>2</sup>. Comme nous pouvons l'observer, même à ses sommets, le crypto-marché reste relativement modeste par rapport aux marchés traditionnels, ne représentant que 0,16% de la capitalisation boursière de l'Union européenne et 2% de la valeur mondiale de l'or. De nombreuses questions se posent pour savoir si la progression de l'adoption des cryptomonnaies aurait un impact proportionnel sur l'économie par le biais d'effets de richesse pour les investisseurs (FSB, 2018). Jusqu'à présent, du point de vue de la performance des investissements, les rapports montrent qu'en dépit de leurs hauts et de leurs bas, les crypto-actifs restent la classe d'actifs la plus performante, améliorant les rendements des portefeuilles et maintenant leur efficacité informationnelle (SINCLAIR, 2019; MATKOVSKYY & JALAN, 2019).

<sup>2</sup>Ces graphiques et comparaisons ont été réalisés à partir de la valeur record des cryptomonnaies du printemps 2021.

Par rapport au marché des actions, de l'or ou du Forex, les crypto-actifs sont encore extrêmement volatils. Toutefois, si on se réfère à leurs débuts, ils semblent se stabiliser peu à peu. Cela peut s'expliquer par le fait que le marché arrive progressivement à maturité, et que sa valeur est moins spéculative et plus basée sur l'utilité (BURNISKE & TATAR, 2017; ESMA, 2019). De nombreux articles de recherche (DYHRBERG, 2016b; CAFERRA & VIDAL-TOMÁS, 2021; SIFAT, 2021) ont montré que le crypto-marché n'est pas lié à l'économie réelle. Cependant, comme nous pouvons l'observer, le temps a changé le crypto-monde pour qu'il ressemble de plus en plus aux marchés traditionnels, ce qui implique une relation avec l'économie en premier lieu (voir tableau RF.1).

TABLE RF.1 : L'essor des corrélations entre crypto-actions

Source : IYER (2022).

a. Volatility correlations				b. Return correlations					
Crypto	Equity Index	2017–19	2020–21	Crypto	Equity Index	2017–19	2020–21		
BTC	S&P 500	0.11	0.46	BTC	S&P 500	0.01	0.36		
	Nasdaq	0.09	0.46		BTC	Nasdaq	0.02	0.38	
	Russell 2000	0.07	0.48			BTC	Russell 2000	0.03	0.36
	MSCI EM	0.12	0.48				BTC	MSCI EM	0.02
ETH	S&P 500	0.08	0.25	ETH				S&P 500	0.06
	Nasdaq	0.06	0.24		ETH			Nasdaq	0.07
	Russell 2000	0.03	0.25			ETH		Russell 2000	0.07
	MSCI EM	0.08	0.25				ETH	MSCI EM	0.10
TTH	S&P 500	-0.02	0.35	TTH				S&P 500	0.02
	Nasdaq	-0.02	0.34		TTH			Nasdaq	0.02
	Russell 2000	0.01	0.28			TTH		Russell 2000	0.06
	MSCI EM	-0.01	0.31				TTH	MSCI EM	0.02

Sources: CryptoCompare; Yahoo Finance; author's calculations.

Notes: Correlations of returns and volatility are calculated using daily prices, excluding non-trading days, over the periods Jan 2017–Dec 2019 and Jan 2020–Nov 2021. Returns are defined in log difference terms, and volatility is based on intra-day prices. BTC = Bitcoin, ETH = Ether, TTH = Tether.

Cette évolution surprenante du crypto-marché pourrait s'expliquer par le fait que les applications de la Blockchain ont évolué de telle sorte qu'elles peuvent remplacer de nombreuses fonctions du marché traditionnel. Par exemple, si on regarde les plateformes DeFi, leur objectif est de fournir une alternative numérique aux services traditionnels de banque, de change et d'investissement (ANKER-SORENSEN & ZETZSCHE, 2021). Les plateformes ICO nous offrent une nouvelle forme de levée de fonds par la mise en circulation de jetons. Les NFT permettent d'enregistrer sur la Blockchain des objets numériques (par exemple, des photos, des vidéos, etc.) et de suivre les droits de propriété (DUMAS et al., 2022). En d'autres termes, grâce à l'évolution de la Blockchain, le crypto-marché peut désormais offrir des services alternatifs à ceux du monde réel tout en créant un système mondial décentralisé et fiable.

## 3 La technologie Blockchain

### 3.1 Les types de technologie Blockchain

La technologie Blockchain est une chaîne de blocs sous-jacents à des informations transactionnelles. Conçue à l'origine comme un grand livre (registre) de comptes sans autorisations et ouverte à un large public (par exemple, le bitcoin), la Blockchain a aujourd'hui été développée dans différentes autres versions. Les principaux facteurs clés pris en compte pour différencier les Blockchains sont les suivants :

- la dimension de permission - limitations concernant le droit des mineurs d'écrire et de modifier le grand livre ;
- la dimension d'ouverture - limitations concernant le droit des utilisateurs d'accéder et d'ajouter des données dans le registre ;
- la dimension de centralisation - concernant le type de gouvernance ;
- le type de technologie - publique - tout le monde peut y accéder et faire partie du réseau ; ou privée - seuls des membres restreints/prédéfinis y ont accès et peuvent faire partie du réseau.

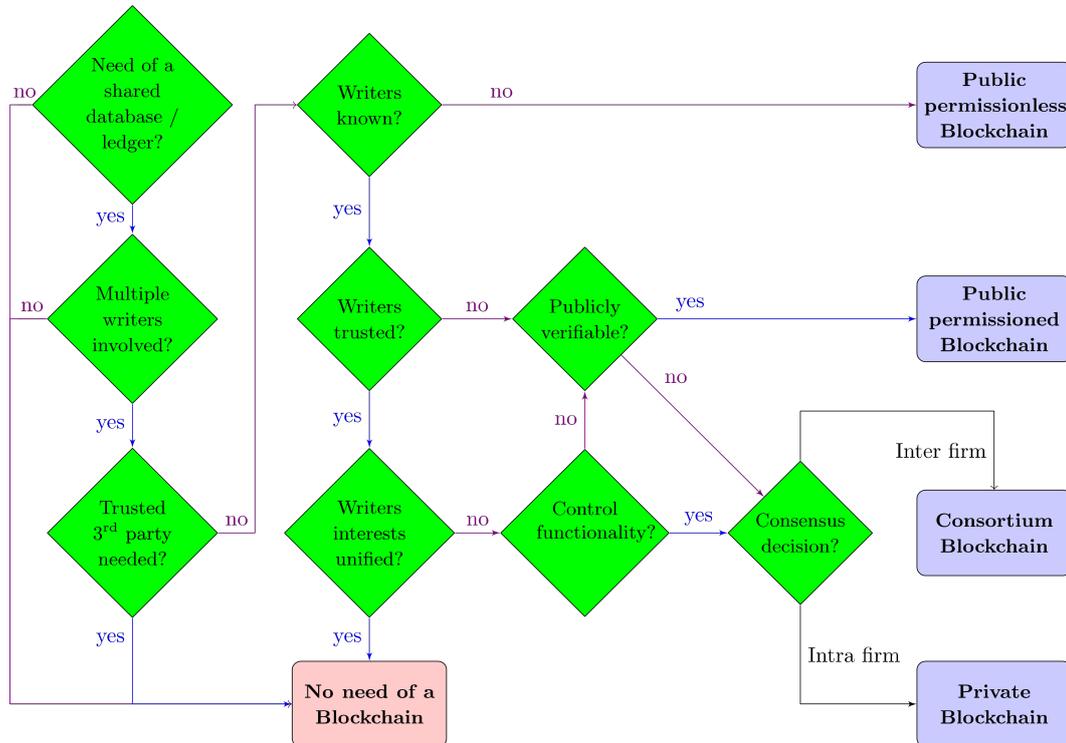
La figure [RF.5](#) montre qu'il existe quatre principaux types de Blockchain, chacun étant catégorisé en fonction de son fonctionnement, du type d'utilisateur, des caractéristiques techniques clés et, enfin et surtout, de ses contributions innovantes aux marchés et aux entreprises existants : (1) publique (sans autorisation et ouverte), (2) publique et hybride (avec autorisation et ouverte), (3) privée (sans autorisation et fermée) et (4) privée et hybride (avec autorisation et fermée).

Puissante, mais pas exempte de menaces et de vulnérabilités, certaines de ces versions héritées de la Blockchain ne représentent qu'un pas en avant vers une meilleure technologie. Aussi prometteuse que la version publique (par exemple, la Blockchain Bitcoin), mais avec une approche opérationnelle différente, la Blockchain privée s'adresse principalement aux entreprises et aux organisations, qui ont besoin d'un contrôle total sur le réseau technologique et de solutions personnalisées à leurs problèmes existants.

La figure [RF.5](#) montre les fonctions de cette technologie pour lesquelles quelqu'un pourrait envisager de la mettre en œuvre. Cet organigramme est destiné à aider les

FIGURE RF.5 : L'arbre de décision Blockchain

Cette figure propose une série de questions visant à aider une entreprise à décider si la technologie Blockchain est la solution dont elle a besoin. Source : (EXTERKATE & WAGENAAR, 2018).



entreprises dans le processus de décision en déterminant quelle Blockchain est la plus adaptée et si elle représente ou non une solution technique.

### 3.2 Un approfondissement de la technologie Blockchain et du crypto-marché

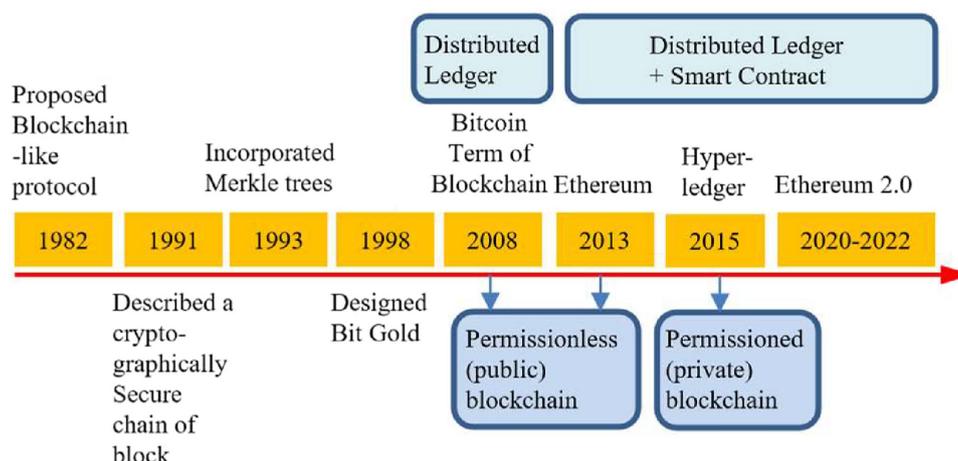
Avec le développement de la technologie Internet, le commerce en ligne a augmenté, ainsi que notre dépendance aux instruments de paiement intelligents. En conséquence, NAKAMOTO (2009) a proposé une solution pour lutter contre la forte dépendance des institutions financières. Il a introduit “un système de paiement électronique basé sur la preuve cryptographique plutôt que sur la confiance, permettant à deux parties intéressées d’effectuer des transactions directement entre elles, sans avoir besoin d’un organisme tiers de confiance” (p.1 NAKAMOTO, 2009). Lorsque NAKAMOTO (2009) a introduit la technologie Blockchain, elle a été accompagnée par la première cryptomonnaie, notamment le bitcoin.

La première version d’un actif numérique est apparue en 1983, inventée par

David Chaum. Cet actif numérique, appelé ecash, fonctionnait par le biais d’une plateforme appelée digicash (CHAUM, 1983), une première version centralisée de l’actuelle Blockchain. Un autre concept précoce de Blockchain a été introduit par HABER et STORNETTA (1991) dans leur travail publié : “Comment horodater un document numérique”. Cet article propose un moyen d’horodater les actifs numériques dans le but de certifier la date de création ou de dernière modification de l’actif. Par biens numériques, les auteurs font allusion à des éléments tels que des images, des documents écrits et des fichiers audio (HABER & STORNETTA, 1991). Ces premières innovations ont ouvert la voie au développement de la technologie Blockchain que nous connaissons aujourd’hui. La figure RF.6 montre l’évolution historique de cette technologie.

FIGURE RF.6 : La chronologie de la technologie Blockchain

L’évolution chronologique de la technologie Blockchain, du concept à l’application pratique. Source : adaptation par l’auteur de GUO et YU (2022).



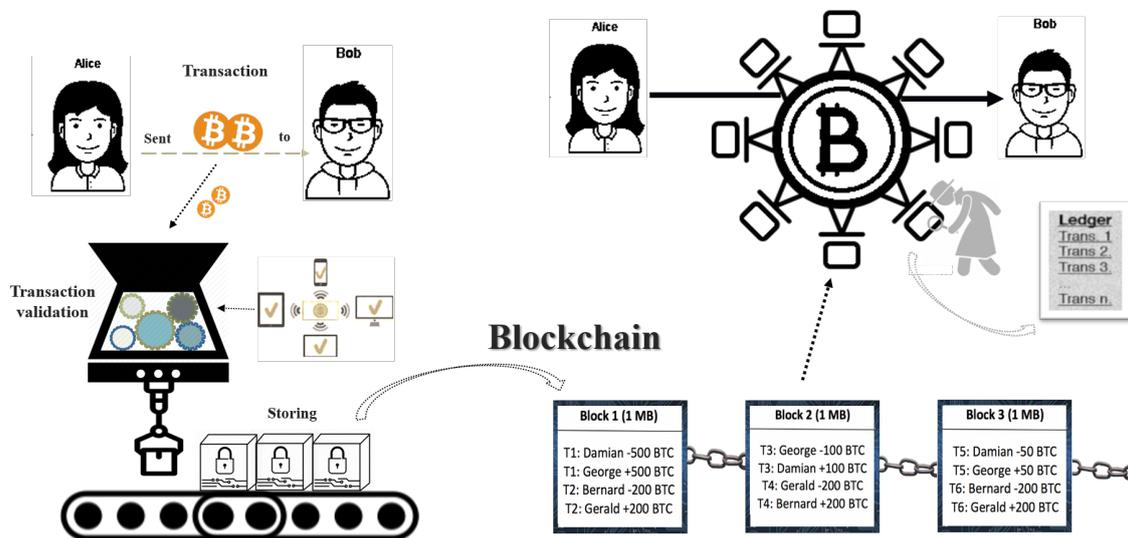
La Blockchain est une base de données en ligne que tout le monde, où qu’il soit, peut utiliser avec une connexion Internet. Comme son nom l’indique intuitivement, la Blockchain se réfère à des chaînes linéaires de blocs associés à des informations transactionnelles sous-jacentes. En termes plus simples, cette technologie représente un système de pair à pair qui permet le transfert rapide et sécurisé d’argent ou d’autres actifs numériques (argent, art, science, titres, votes, etc.). La Blockchain est parfois référencée comme **Distributed Ledger Technology (DLT)**. Cela vient de la particularité de la Blockchain, qui est de créer un grand registre contenant la copie intégrale de toutes les transactions qui ont eu lieu dans son système et de le distribuer à toutes les personnes faisant partie du réseau Blockchain (les nœuds). Une autre caractéristique importante de cette technologie est le processus de validation qui est effectué par les nœuds du réseau décentralisé sans aucun intermédiaire. Par la suite, toute information saisie dans la Blockchain est immuable et non falsifiable

(GATTESCHI et al., 2018).

En essayant de comprendre La Blockchain, une description de celle-ci ressemblerait à : une structure de blocs, un grand livre (registre) distribué contenant les données principales (par exemple, les transactions), les codes de hachage, l'horodatage<sup>3</sup>, et d'autres informations (LIN & LIAO, 2017). Nakamoto offre une description détaillée du fonctionnement de la Blockchain. Son exemple est basé sur le Bitcoin. La figure RF.7 offre une illustration de la Blockchain de Nakamoto.

### FIGURE RF.7 : Le flux de travail d'une transaction Bitcoin Blockchain

Le processus de vérification supposant une seule transaction simple (parmi un ensemble de transactions), entre deux participants du réseau Bitcoin Blockchain. Source : l'auteur



1. Chaque fois qu'une transaction est placée dans la Blockchain, elle est mise en attente et placée dans un espace d'attente appelé *Mempool*. Cette information sera envoyée aux nœuds du réseau ;
2. Ensuite, les transactions sont sélectionnées par les validateurs (mineurs) et disposées dans un nouveau bloc potentiel ;
3. Les mineurs essaient de résoudre des problèmes mathématiques complexes et sont en compétition pour trouver le **PoW** de leur bloc ;
4. Une fois le **PoW** acquis, l'information est partagée au sein du réseau Blockchain ;

<sup>3</sup>Un horodatage est un indicateur de l'heure de genèse d'un bloc, une preuve d'existence (LIN & LIAO, 2017).

5. Si le **PoW** est approuvé par le réseau, cela signifie que toutes les transactions de ce nouveau bloc sont honnêtes ;
6. Finalement, après la validation de la transaction et les vérifications du consensus, les nœuds acceptent le nouveau bloc, qui sera ajouté à la chaîne.

Le consensus n'est atteint que lorsque la majorité des nœuds sont d'accord sur la même version du registre (p.3 NAKAMOTO, 2009). Un algorithme de consensus dans le contexte de la technologie Blockchain représente un protocole basé sur des codes visant à simplifier les processus d'accord au sein d'un réseau. Ces algorithmes sont apparus comme une solution à la "*Problématique des généraux byzantins*", qui concerne l'incapacité à atteindre un consensus en raison d'acteurs défaillants (ZHANG et al., 2019). Les algorithmes de consensus les plus populaires et les plus répandus dans la technologie Blockchain sont les protocoles **PoW**, **PoS** et **PBFT**.

Selon le type de consensus, un rôle clé dans le fonctionnement de la Blockchain est joué par les mineurs, sans lesquels le système ne fonctionnerait pas. Par exemple, dans les **PoW** Blockchains, les mineurs sont des superordinateurs qui, grâce à des logiciels sophistiqués et une grande quantité d'électricité, font la course pour vérifier les transactions et créer de nouveaux blocs. Souvent comparée à l'extraction de l'or, l'exploitation des cryptomonnaies est extrêmement coûteuse et compétitive. Cette forte concurrence est justifiée par les incitations uniques du système Blockchain : chaque fois qu'un mineur réussit à valider des transactions et à créer un bloc, il est récompensé par le système par une quantité de bitcoins nouvellement frappés. En juillet 2022, un mineur qui réussit reçoit 6,25 BTC pour chaque nouveau bloc lié à la chaîne. Afin de motiver les mineurs à maintenir leur travail et à valider les transactions plus rapidement, les utilisateurs augmentent souvent leurs récompenses en ajoutant des frais de transaction. Plus les frais sont élevés, plus la transaction sera traitée rapidement, ce qui donne un pouvoir considérable aux mineurs (BIAIS et al., 2019a; EASLEY, O'HARA & BASU, 2019).

Depuis 2009, d'autres types de Blockchain ont été développés, chacun correspondant à des besoins spécifiques. Selon la conception de la technologie, les principaux exemples de données traitées par la Blockchain comprennent les enregistrements de transactions, les enregistrements de contrats, les données de l'Internet des objets, l'art numérique (les **NFT**), etc. La première version de la Blockchain, introduite par Nakamoto, peut être divisée en trois fonctions : un grand livre (registre) décentralisé contenant l'historique de toutes les transactions, un protocole (un ensemble de règles

de code informatique) qui effectue des transactions financières, et des cryptomonnaies comme le bitcoin. La deuxième version introduite par la technologie Ethereum apporte une nouvelle innovation, à savoir les contrats intelligents. Il est important de mentionner que la technologie Ethereum est plus sophistiquée, plus flexible et possède plus de fonctionnalités que la première version des Blockchains.

Les contrats intelligents sont des protocoles informatiques destinés à optimiser, vérifier ou faire respecter numériquement l'exécution d'un contrat. En d'autres termes, ils peuvent être définis comme l'enregistrement numérique d'un contrat existant, qui deviendra finalement une transaction automatisée et auto-exécutoire. Une mention importante est que le contrat intelligent ne s'appuie sur aucune tierce partie, mais qu'il agit automatiquement conformément à ses conditions préétablies (CONG & HE, 2019). Le concept était apparemment connu depuis longtemps avant son lancement effectif, puisque SZABO (1994) l'a envisagé; cependant, aucune application réalisable n'a été mise en place avant la technologie Blockchain. Les contrats intelligents reposent sur des conditions dépendant des données stockées dans la Blockchain ou sur une autorité de confiance pour parvenir à un consensus et à une exécution. Dans le même temps, les contrats intelligents peuvent importer des informations pertinentes du monde 'réel' (par le biais d'oracles), les intégrer dans la base de données Blockchain et procéder au processus d'exécution si nécessaire (GATTESCHI et al., 2018; CONG & HE, 2019).

Historiquement, les contrats intelligents sont au cœur de toutes les **dApps** développées sur la Blockchain Ethereum (DUMAS et al., 2018). Puisque les contrats intelligents peuvent essentiellement exécuter tout ce que fait un programme informatique, ils sont utilisés pour effectuer diverses opérations telles que des calculs, le stockage de données, la frappe de jetons, l'envoi de communications et même la génération de graphiques (ETHEREUM.ORG, 2022). Grâce à la technologie des contrats intelligents, la Blockchain n'est pas seulement un concept de transactions monétaires décentralisées, mais elle a introduit le concept de marchés décentralisés, ou de relations décentralisées avec différentes contreparties commerciales, comme les chambres de compensation, les banques et les entreprises. Quelques exemples d'implémentations de contrats intelligents dans le monde réel sont les plateformes d'assurance (par exemple, AXA), les plateformes de chaîne d'approvisionnement (par exemple, Tokio Marine), les plateformes de négociation (par exemple, NASDAQ) et les banques (par exemple, R3) (DUMAS et al., 2018; ETHEREUM.ORG, 2022).

Un exemple bien connu de **dApps** réalisées avec l'utilisation de smart contracts réside dans les **ICO**. Les **Initial Coin Offering (ICO)** représentent une nouvelle forme de collecte de capitaux par l'émission de jetons ou de monnaies. Techniquement parlant, ils représentent une sorte de contrats intelligents enregistrés dans la Blockchain. L'activité de collecte de fonds est similaire au financement participatif (crowdfunding), mais elle est réalisée au niveau d'un projet. Grâce à la technologie des contrats intelligents, les transactions sont automatisées ; les investisseurs peuvent donc facilement envoyer de l'argent pour financer le projet de leur choix et, en échange, ils reçoivent des jetons nouvellement émis. Toutes ces étapes sont réalisées automatiquement sans l'aide d'aucun intermédiaire ; de cette façon, les opérations sont plus efficaces et certains coûts de l'entreprise sont considérablement diminués (MOMTAZ, 2019).

D'autres exemples importants et plus récents de **dApps** sont les plateformes **DeFi** et les **NFT**. Les plateformes **Decentralized Finance (DeFi)** fonctionnent sur la technologie Blockchain (grand livre distribué), à laquelle s'ajoutent des applications décentralisées (basées sur des contrats intelligents) (POPESCU, 2020). Les applications de **DeFi** fournissent des services financiers qui reposent sur les cryptomonnaies et les crypto-jetons. Leur objectif est de fournir une alternative numérique aux services bancaires, d'échange et d'investissement traditionnels (ANKER-SORENSEN & ZETZSCHE, 2021). Les **Non-Fungible Tokens (NFT)** sont un certain type de jetons qui fonctionnent sur une Blockchain et qui représentent quelque chose d'unique. Non fongible signifie unique ; ils ne peuvent donc pas être remplacés ou échangés avec des actifs 'similaires'. En d'autres termes, les **NFT** représentent un ensemble unique de données numériques stockées sur une Blockchain. Les **NFT** sont principalement utilisés pour enregistrer des objets numériques (par exemple, des photos, des vidéos, etc.) en tant qu'éléments uniques au sein de la Blockchain et dont la propriété peut être établie et vérifiée (DUMAS et al., 2022).

Conclusion : Dans cette section, nous avons présenté l'évolution de la technologie Blockchain, son fonctionnement et les principales applications qui se sont développées jusqu'à présent. La figure **RF.8** tente d'illustrer la vue d'ensemble de la technologie Blockchain et de ses applications de manière succincte et technique, telle qu'elle a été présentée dans ce court résumé. Il est important de mentionner que même si la littérature existante (CORBET et al., 2021 ; MAOUCHI, CHARFEDDINE

& EL MONTASSER, 2021 ; SCHAR, 2021 ; YOUSAF, NEKHILI & GUBAREVA, 2022) décrit le marché des jetons DeFi comme un sous-secteur du crypto-marché, les jetons DeFi et les cryptomonnaies représentent deux classes d'actifs différentes. Perçus d'un point de vue pratique, les jetons DeFi et les cryptomonnaies ne sont similaires que dans le sens où les deux se basent sur la technologie Blockchain et mettent en œuvre une gestion décentralisée (automatique). Cependant, d'un point de vue technologique, les DeFi sont une technologie distincte car ils nécessitent des smart contracts pour fonctionner. De là provient notre motivation à étudier le marché des DeFi en parallèle de celui des cryptomonnaies, et chercher d'éventuelles similitudes et différences entre les deux.

## 4 Problématique de recherche

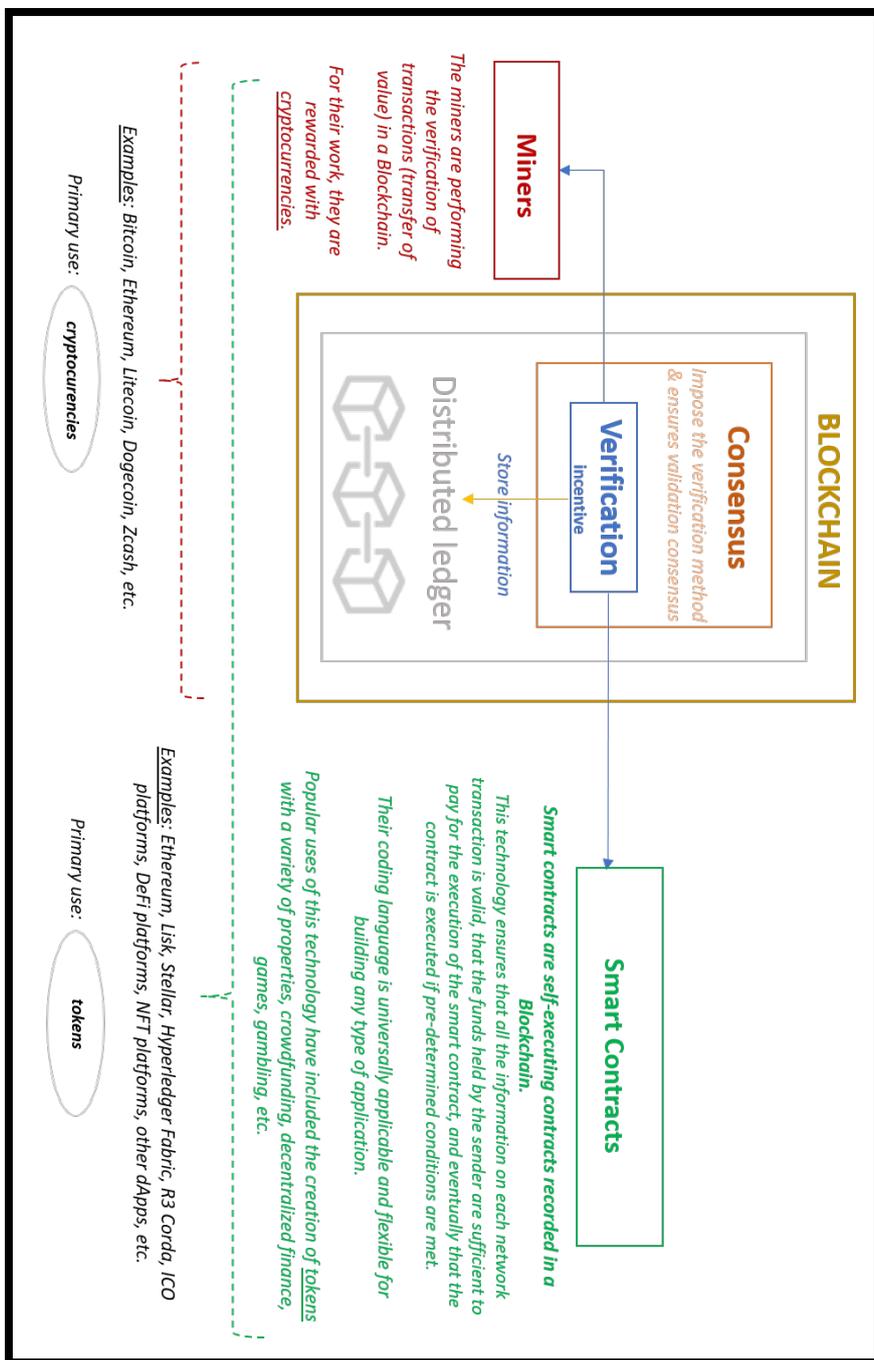
Dans le début de ce résumé, nous avons souhaiter donné au lecteur une vision globale de ce que sont les crypto-actifs et la technologie Blockchain, ainsi que de l'évolution du marché des crypto-actifs. Après avoir effectué cette macro analyse du crypto-marché et de la technologie Blockchain, dans les prochaines sections, nous allons discuter en détail des questions particulières liées aux risques financiers et aux rendements des crypto-actifs. La figure RF.9 présente la structure de la thèse et son contenu.

Le crypto-marché a attiré l'attention des académiques, des ingénieurs, des investisseurs et du public en général. En raison de leur forte volatilité et de leur comportement spéculatif, les crypto-actifs ont été isolés en tant que classe d'actifs distincte des actifs traditionnels, et l'idée de profiter d'opportunités de diversification est apparue. De nombreux articles ont affirmé que le marché des crypto-actifs n'est pas lié à l'économie réelle (DYHRBERG, 2016b ; CAFERRA & VIDAL-TOMÁS, 2021 ; SIFAT, 2021) et que sa corrélation avec les classes d'actifs établies est faible (ANKENBRAND & BIERI, 2018 ; BAUR & DIMPFL, 2018 ; CORBET et al., 2018 ; CORBET et al., 2019). Ces dernières années, les crypto-actifs ont réussi à devenir l'une des classes d'actifs financiers les plus performantes, aux côtés des actions du Nasdaq 100 et des actions des grandes capitalisations américaines (US Large Caps stocks) (SRIRAM, 2021).

En finance, nous savons qu'il existe une relation positive entre le risque non-diversifiable et le rendement d'un actif. Par conséquent, étant donné que les crypto-actifs sont environ dix fois plus volatils que les actifs traditionnels (BARIVIERA &

FIGURE RF.8 : La technologie Blockchain et ses applications

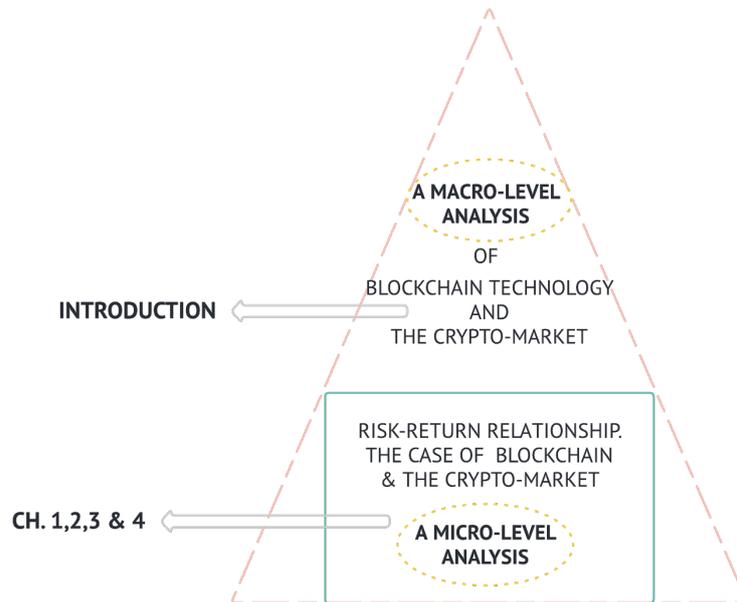
Représentation schématique de la technologie Blockchain avec ses principales applications, à savoir la technologie des contrats intelligents et les crypto-actifs. Source : l'auteur.



MEREDIZ-SOLÀ, 2021), il n'est pas surprenant qu'ils détiennent le titre de la classe d'actifs la plus performante. Le risque financier a deux facettes, ce qui signifie qu'un risque élevé peut apporter soit des rendements élevés, soit des pertes élevées. Cette dissertation aborde le problème de recherche suivant,

FIGURE RF.9 : Structure et contenu de la thèse

Source : L'auteur.



### Quels sont les déterminants du risque et des rendements financiers sur le crypto-marché ?

Cette thèse se concentre sur la relation risque-rendement. Elle vise à découvrir les déterminants des rendements financiers sur le crypto-marché. Plus précisément, elle étudie les risques uniques auxquels sont exposés les actifs basés sur la Blockchain (par exemple, les attaques cryptographiques, les attaques de contrats intelligents et autres vulnérabilités technologiques), risques qui pourraient être à l'origine de la volatilité inhérente du marché (chapitre I). La thèse examine également l'impact des événements technologiques sur les caractéristiques financières des crypto-actifs (chapitre II). En outre, elle met en lumière la diversité des crypto-actifs et leurs implications pour la valorisation des actifs (chapitres III & IV).

La question générale de cette thèse a de nombreuses dimensions ; par conséquent, dans le premier chapitre, nous évaluons si les risques financiers du crypto-marché peuvent être déclenchés par les vulnérabilités technologiques de la technologie Blockchain. Le deuxième chapitre prolonge notre travail initial en analysant et en apportant des preuves empiriques de la façon dont les événements technologiques (scission) peuvent se traduire en événements financiers. Dans les troisième et quatrième chapitres, nous nous concentrons sur une crypto-activité spécifique devenant de plus en

plus populaire : les DeFi. Nous examinons les déterminants de leurs rendements et proposons un modèle à plusieurs facteurs pour le marché des jetons DeFi.

**Chapitre I : Les risques financiers peuvent-ils être déclenchés par les vulnérabilités technologiques de la technologie Blockchain ?**

Le premier chapitre de cette thèse débute par une recherche bibliographique. En accord avec (CORBET et al., 2019), nous pensons que *“pour les nouveaux domaines de recherche tels que ceux basés autour des cryptomonnaies, une analyse de la littérature peut être l’outil le plus puissant pour informer les académiques, les professionnels et les législateurs de l’état actuel des connaissances, des consensus et des ambiguïtés dans la discipline émergente”* (p.2, CORBET et al., 2019).

La volatilité des cryptomonnaies et les nombreuses cyber-attaques subies par cette technologie sont les principaux facteurs de la popularité de la Blockchain. Parmi la littérature existante, plusieurs études ont abordé les risques liés au crypto-marché. Il apparaît que la plupart des travaux traitent les risques de manière indépendante en fonction de leur nature (i.e., économique, politique, réglementaire, etc.). Notre travail répond à ce manque de recherche en analysant conjointement des risques financiers et technologiques. Nos résultats montrent que les risques, quelle que soit leur nature, ont de nombreuses caractéristiques en commun. De plus, nous démontrons empiriquement que l’instabilité du prix du bitcoin (risque financier) peut être déclenchée par des attaques visant le crypto-marché (vulnérabilité technologique).

**Chapitre II : Comment les caractéristiques financières du bitcoin réagissent-elles aux événements de scission ? Comment les caractéristiques de la cryptomonnaie issue d’une scission (*forked coin*) se comparent-elles à celles de leur cryptomonnaie mère ?**

Dans le deuxième chapitre, nous étendons le travail du premier chapitre et proposons une recherche sur le lien de causalité entre les événements technologiques purs, à savoir les scissions, et les caractéristiques financières de la cryptomonnaie. Cet article se concentre exclusivement sur les scissions du bitcoin et, notamment, sur les cryptomonnaies qui continuent à être échangés aujourd’hui. À notre connaissance, il s’agit de la première recherche visant à évaluer l’effet des événements de scission sur les caractéristiques financières de la cryptomonnaie. Pour conduire cette

recherche, nous utilisons la méthodologie de l'étude d'événement. Les résultats de ce travail sont doubles. Dans la première partie de cette recherche, nous montrons que les forks émis dans des conditions de marché stables permettent une diminution des rendements, de la VaR, de l'illiquidité et de la volatilité de la cryptomonnaie mère, contrairement à ce qui se passe pour les spin-offs, par exemple. Dans la deuxième partie, nous montrons que les monnaies héritées sont plus risquées, illiquides, volatiles, moins performantes et moins efficaces que leur cryptomonnaie mère.

### Chapitre III : Quels sont les déterminants des rendements des jetons DeFi ?

Dans le chapitre III, nous nous concentrons sur une application distincte de la technologie Blockchain, les plateformes DeFi. Par rapport à la vaste littérature relative aux cryptomonnaies, les recherches sur les DeFi sont plus rares. Motivés par CORBET et al. (2021), MAOUCHI, CHARFEDDINE et EL MONTASSER (2021), SCHAR (2021) et YOUSAF, NEKHILI et GUBAREVA (2022), qui montrent que les jetons DeFi constituent une classe d'actifs distincte par rapport aux cryptomonnaies classiques, notre objectif est de proposer une première analyse des rendements du marché DeFi. Pour mener cette recherche, nous concevons d'abord un indice de marché qui nous permettra d'évaluer la performance de cette nouvelle classe d'actifs et de ce marché dans son ensemble. Ensuite, nous effectuons une analyse approfondie des déterminants des rendements du marché des jetons DeFi. Ici, nous considérons plusieurs déterminants possibles, tels que : (1) le crypto-marché, (2) les variables du réseau, (3) le ratio TVL-to-Market (une mesure similaire au ratio 'book-to-market' des actions et adaptée au marché DeFi). Nos résultats montrent que l'impact du crypto-marché sur les rendements des DeFi est plus fort que tout autre facteur considéré dans cette analyse et fournit un pouvoir explicatif supérieur.

### Chapitre IV : Le modèle à 3 facteurs de Fama-French est-il pertinent pour expliquer les rendements des jetons DeFi ?

Le chapitre IV prolonge nos travaux du chapitre III sur le marché des DeFi. Ici, nous testons la pertinence d'un modèle à trois facteurs de Fama-French, composé de facteurs de marché, de taille et de valeur pour modéliser les rendements de 88 jetons DeFi sur une période allant de 2019 à 2022. Nous construisons les facteurs de risque avec les données de DeFi en suivant la méthodologie de l'article original (FAMA & FRENCH, 1992). Comme facteur de marché, nous utilisons l'indice de marché iDeFiX (proposé par SOIMAN, DUMAS et JIMENEZ-GARCES (2022)). Après

avoir effectué les régressions Fama-French et des analyses complémentaires avec la procédure Fama-MacBeth, nous concluons que les rendements des jetons DeFi ne peuvent pas être expliqués par les modèles traditionnels d'évaluation des actifs financiers de Fama-French, originellement basés sur le marché des actions. Nos résultats soulignent l'importance de l'utilisation de variables technologiques dans l'évaluation des actifs basés sur la Blockchain, comme par exemple les variables de réseau.

La figure RF.10 résume la structure du travail de thèse et montre explicitement l'articulation des chapitres.

## 5 Résultats obtenus

### Chapitre I

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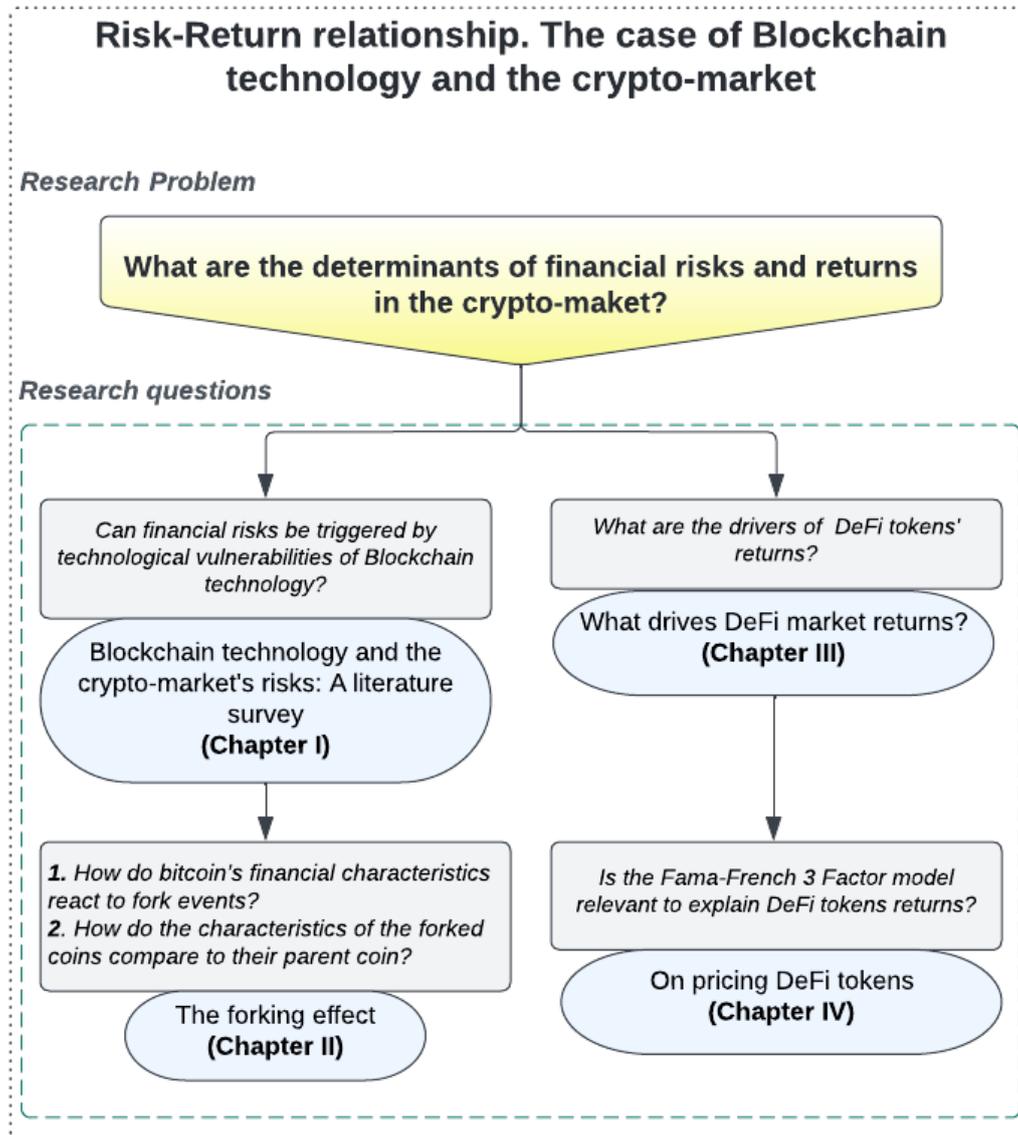
Les actifs basés sur les Blockchains dépassent largement les cryptomonnaies. Comme les valeurs boursières dépendent de leurs entreprises sous-jacentes, ou les produits dérivés de leurs actifs sous-jacents, les valeurs des actifs basés sur les Blockchains doivent dépendre de leur Blockchain correspondante. Par conséquent, le chapitre d'ouverture de la thèse répond à la question de recherche suivante : *Les risques financiers peuvent-ils être engendrés par les vulnérabilités technologiques de la Blockchain ?*

Ce chapitre aborde dans un premier temps les risques technologiques les plus importants en considérant la probabilité d'occurrence, l'exposition du crypto-marché aux événements technologiques et l'impact (financier) qu'ils pourraient avoir. Nous proposons une synthèse de l'exposition de la technologie Blockchain et du crypto-marché à plusieurs risques technologiques : Les attaques au niveau du consensus, les attaques au niveau du réseau, les menaces sur les clés cryptographiques et les menaces sur les contrats intelligents. Le tableau I.3 (p. 58) donne une image au niveau du marché. Comme il est difficile de mesurer l'impact macro réel des vulnérabilités technologiques, nous estimons les conséquences et l'exposition possible du marché en termes de nombre de jetons/Blockchains et de part de marché.

Une approche similaire est utilisée dans l'analyse des risques financiers (voir tableau I.4, p. 68). Nous les avons regroupés par type : risque total, risque d'information, risque de liquidité, risque d'approvisionnement et risque environnemental.

FIGURE RF.10 : Structure de la thèse

Représentation schématique de la structure de cette thèse. Le carré jaune représente la problématique de recherche globale de ce travail, tandis que les éléments bleus sont les chapitres de la thèse répondant à leurs questions de recherche correspondantes marquées dans les carrés gris.



Ensuite, en considérant l'exposition aux risques technologiques et les dommages potentiels qui pourraient éventuellement déclencher des risques financiers, nous les analysons ensemble et proposons une métrique conceptuelle pour souligner la probabilité d'occurrence. Parmi tous les risques évalués, nous montrons que les attaques au niveau du réseau et les menaces sur les clés cryptographiques sont les plus menaçantes pour le crypto-marché. L'exposition à ces vulnérabilités technologiques est la plus

élevée, car les cibles possibles représentent la plupart des types de Blockchain, leurs utilisateurs, les pools de minage et les plateformes d'échange. En outre, notre analyse montre que les événements technologiques peuvent effectivement être à l'origine de risques financiers, avec une probabilité allant de moyenne à élevée.

Conformément à l'étude de la littérature réalisée, nous illustrons comment le risque financier est lié aux vulnérabilités technologiques. Plus précisément, nous effectuons deux courtes analyses empiriques :

1. Nous évaluons si la volatilité du bitcoin est affectée par des événements ciblant le crypto-marché.
2. Nous analysons la relation entre les rendements du bitcoin, sa volatilité et l'attention négative des investisseurs (déclenchée par les vulnérabilités technologiques).

Notre première analyse empirique confirme que la volatilité du bitcoin est influencée par le nombre d'attaques ou d'autres événements malveillants visant le crypto-marché. Ces résultats révèlent les implications importantes de la réglementation sur ce marché. Par exemple, LA PORTA et al. (2002) affirment que les investisseurs sont plus disposés à financer des entreprises s'ils bénéficient d'une protection juridique pour le faire. Sur le crypto-marché, les investisseurs ne sont protégés par aucune loi (MACKENZIE, 2022 ; MORGAN STANLEY, 2022). Par conséquent, nous pensons que les vulnérabilités technologiques pourraient être perçues comme moins nuisibles si les crypto-investisseurs étaient protégés. Ce résultat démontre également que le développement de ce marché ne dépend pas seulement de l'innovation technologique mais aussi du système juridique qui le soutient. Notre deuxième démonstration empirique montre que l'attention négative des investisseurs a un impact sur les rendements et la volatilité du bitcoin. En outre, nos résultats révèlent que la plupart des crypto-investisseurs pourraient être des amateurs ou des non-spécialistes, ce qui pourrait être davantage lié au problème de manque de connaissance de la Blockchain par les investisseurs et à la façon dont il affecte le marché.

Cette étude fournit une analyse des risques à deux dimensions (technologique et financière). Premièrement, nous montrons que les risques peuvent être liés et que, dans des conditions de marché spécifiques, ils peuvent se déclencher les uns les autres. Deuxièmement, nous proposons un moyen de déterminer la probabilité de déclencher des risques financiers par le biais de vulnérabilités technologiques. En outre, l'ana-

lyse empirique confirme les arguments développés dans l'étude de la littérature, plus précisément, que le risque financier peut être déclenché par les vulnérabilités technologiques qui sont caractéristiques du crypto-marché. Les résultats obtenus par cette analyse de la littérature soulignent le rôle joué par le comportement financier, la responsabilité sociale et la culture Blockchain dans la stabilité du crypto-marché. De plus, nos analyses empiriques révèlent l'implication des risques de cybersécurité et soulignent l'impact d'une réglementation pour accompagner le développement du crypto-marché.

## Chapitre II

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Le chapitre II propose une extension de nos travaux précédents. Ici, nous analysons et apportons des preuves empiriques supplémentaires de la façon dont les événements technologiques peuvent se traduire en événements financiers. Nous recherchons le lien de causalité entre les événements technologiques purs, à savoir les scissions. Nous avons l'intention de mettre en lumière l'effet de scission, qui est l'impact financier subi par une cryptomonnaie lorsque sa Blockchain se divise.

Nous réalisons une étude d'événement sur les hard forks (monnaies héritées) du bitcoin qui continue à être négocié aujourd'hui. Plus précisément, nous étudions les questions de recherche suivantes : (1) *Comment les caractéristiques financières du bitcoin réagissent-elles aux événements de scission?* et (2) *Comment les caractéristiques de la cryptomonnaie issue d'une scission (forked coin) se comparent-elles à celles de leur cryptomonnaie mère?*

Nos résultats sont doubles. Premièrement, nous montrons que les scissions réalisées dans des conditions de marché stables permettent une diminution des rendements, VaR, de l'illiquidité et de la volatilité de la cryptomonnaie mère. Étant donné que le crypto-marché est connu pour être inefficace (TRAN & LEIRVIK, 2020; HU, VALERA & OXLEY, 2019; BARIVIERA, 2017; NADARAJAH & CHU, 2017; URQUHART, 2016), nous montrons que les scissions détériorent l'efficacité de leur cryptomonnaie mère. Cependant, les scissions survenant en période de marché stressé, comme pendant la bulle des cryptomonnaies de 2017-2018, augmentent les rendements et le risque supportés par leur cryptomonnaie mère et améliorent son efficacité. Cette meilleure efficacité pourrait s'expliquer par l'arrivée de plus d'informations (sur les événements de

scission) à un moment où la proportion de bruit est élevée. En outre, nous vérifions séparément les facteurs d'amélioration de l'efficacité et nous constatons que cette amélioration de l'efficacité s'explique par un effet de volume.

Dans une deuxième partie de cette étude, nous montrons que les monnaies héritées sont plus risqué, illiquide, volatil, moins performant et moins efficace que leur cryptomonnaie mère. Ce résultat s'aggrave avec le temps. En d'autres termes, les monnaies héritées récent sont pires que les plus ancien. En outre, nous avons observé que les premier fork présentent des caractéristiques similaires à celles de leur cryptomonnaie mère, tandis que celles qui se produisent pendant la période de bulle et après semblent être nettement plus risqué et moins efficaces. Ce résultat pourrait être justifié par deux faits : (1) les investisseurs peuvent ne pas tenir compte de la valeur des nouvelles cryptomonnaies en raison de leur durée de vie plus courte ; ou (2) l'incertitude globale concernant les cryptomonnaies augmente avec le temps, ce qui se traduit par un comportement chaotique du marché.

Ce travail apporte une contribution importante à la littérature sur les forks de Blockchain. A notre connaissance, cette étude est la première qui analyse les événements de scission et leur impact sur les caractéristiques financières de la cryptomonnaie mère. Par caractéristiques financières, nous entendons le rendement, la volatilité, la liquidité et l'efficacité informationnelle. En comparant la cryptomonnaie mère et les monnaies héritées, nous avons montré que les monnaies nouvellement échangées sont significativement moins liquides, plus risquées et plus volatiles. Les résultats de cette étude pourraient être utiles aux investisseurs, désireux d'investir dans des monnaies héritées ou les considérer comme des outils de diversification appropriés.

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### Chapitre III

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Le chapitre III étudie les facteurs possibles des rendements de jetons de **Decentralized Finance (DeFi)**. **DeFi** est l'une des dernières solutions basées sur la Blockchain visant à fournir des services financiers entièrement automatisés. Comparée à la vaste littérature sur les cryptomonnaies, la recherche sur les **DeFi** est plus rare. Motivés par CORBET et al. (2021), MAOUCHI, CHARFEDDINE et EL MONTASSER (2021), SCHAR (2021) et YOUSAF, NEKHILI et GUBAREVA (2022), qui montrent que les jetons **DeFi** constituent une classe d'actifs distincte par rapport aux cryptomonnaies classiques, notre objectif est de proposer une première analyse du marché **DeFi** dans son ensemble, et de répondre à la question de recherche suivante : *Quels sont les déterminants des rendements des jetons DeFi ?*.

À la suite du travail de (LIU & TSYVINSKI, 2021) sur les cryptomonnaies, nous avons effectué une analyse approfondie des déterminants des rendements du marché **DeFi**. Nous considérons plusieurs forces motrices possibles, telles que : (1) le cryptomarché, (2) les variables du réseau, (3) le ratio TVL-to-Market. Comme le **DeFi** n'a pas d'indice de marché, nous en construisons un, que nous nommons **iDeFiX**. Le rendement d'**iDeFiX** est calculé comme le rendement pondéré par la valeur de tous les jetons **DeFi**. Plus précisément, l'**iDeFiX** est construit en suivant la méthodologie et le code original de l'indice **CRIX** (TRIMBORN & HÄRDLE, 2018).

Considérant que les cryptomonnaies et les jetons **DeFi** fonctionnent sur la technologie Blockchain, nous évaluons tout d'abord l'exposition des rendements des jetons **DeFi** au crypto-marché. Nos résultats montrent que le crypto-marché influence fortement les rendements de **DeFi**, ce qui est en accord avec CORBET et al. (2021) et YOUSAF et YAROVAYA (2021). Pour compléter ces résultats, nous effectuons des tests supplémentaires, et répondons à la question suivante : *Peut-on utiliser le BTC pour prédire les rendements de jetons DeFi ?*. Les résultats obtenus montrent que la forte exposition au crypto-marché pourrait s'expliquer par la relation de causalité bidirectionnelle entre les rendements de **BTC** et les rendements d'**iDeFiX**, et la corrélation à long terme entre le **BTC** et les jetons **DeFi**.

L'effet de réseau sur le crypto-marché peut être décrit comme suit : la valeur et l'utilité des cryptomonnaies augmentent lorsque davantage de personnes rejoignent le réseau/la Blockchain. En d'autres termes, plus il y a d'individus qui décident

d'utiliser le [BTC](#), plus l'ensemble de l'écosystème [BTC](#) prend de la valeur, et donc plus le prix augmente. Nous utilisons trois mesures principales pour évaluer l'effet de réseau sur le marché du [DeFi](#) : le nombre d'utilisateurs de portefeuilles, le nombre d'adresses actives et le [TVL](#) (valeur totale verrouillée). Les résultats montrent que les rendements des [DeFi](#) sont fortement influencés par leurs variables de réseau, pour les cryptomonnaies (LIU & TSYVINSKI, 2021). En outre, nous révélons que l'impact du [TVL](#) sur les rendements des [DeFi](#) est plus fort que toute autre variable de réseau considérée et fournit un pouvoir explicatif supérieur.

Motivés par la littérature existante sur le crypto-marché et les études d'autres marchés financiers, nous cherchons à savoir si les rendements des [DeFi](#) sont expliqués par leur ratio 'book-to-market'. Comme il n'existe pas de valeur 'comptable' standard pour les jetons [DeFi](#), nous avons construit un ratio 'Book-to-Market' pour le marché [DeFi](#) en divisant le [TVL](#) par la capitalisation boursière. Le [TVL](#) est une caractéristique unique du marché [DeFi](#). Plus précisément, elle reflète le montant des fonds engagés dans les plateformes [DeFi](#), et constitue un indicateur de la croissance et du succès du marché. Les résultats obtenus n'offrent pas de réponses évidentes. Par conséquent, nous concluons que contrairement aux précédents déterminants étudiés, le ratio [TVL-to-Market](#) n'influence pas les rendements des [DeFi](#).

Dans ce travail, nous effectuons une analyse approfondie des déterminants des rendements du marché [DeFi](#). Nous considérons plusieurs forces motrices possibles, telles que : (1) le crypto-marché, (2) les variables du réseau, et (3) le ratio [TVL-to-Market](#). Nos résultats montrent que l'impact du crypto-marché sur les rendements des [DeFi](#) est plus fort que tout autre déterminant considéré. Ce chapitre apporte des contributions importantes à la littérature académique, notamment : (1) nous sommes les premiers à évaluer le marché des [DeFi](#) dans son ensemble et à étudier les multiples déterminants de rendement possibles ; (2) nous avons construit un indice pour le marché des [DeFi](#) ; (3) nous calculons un ratio 'book-to-market' adapté au marché des [DeFi](#). En plus de la contribution académique de cette recherche, nous pensons que nos résultats serviront aux investisseurs intéressés par le marché [DeFi](#) pour maximiser leurs profits et diversifier les risques.

## Chapitre IV

Ce dernier chapitre prolonge les travaux des chapitres précédents. Nous examinons la pertinence de l'utilisation du modèle **Fama-French 3 Factor Model (FF3F)**, adapté au le marché **DeFi**, pour expliquer les rendements des jetons **DeFi**. Les propriétés des rendements **DeFi** et leur potentiel de diversification n'ont pas encore été explorés dans la littérature actuelle. Notre objectif est d'étudier le comportement financier des jetons **DeFi**, et de répondre à la question de recherche suivante : *Le modèle à 3 facteurs de Fama-French est-il pertinent pour expliquer les rendements des jetons DeFi ?*.

Nous construisons les facteurs de taille et de valeur de Fama-French en utilisant les données **DeFi**. Pour le taux de Book-to-Market, nous remplaçons la valeur comptable par une variable équivalente caractéristique de ce marché, le **TVL**<sup>4</sup>. Comme facteur de marché, nous utilisons l'indice de marché **iDeFiX**, que nous avons proposé au chapitre III. Les premiers résultats montrent que tous les facteurs de risque considérés sont évalués par le marché<sup>5</sup>. De plus, nous avons constaté que les relations entre les rendements attendus et l'exposition aux facteurs taille et valeur sont négatives. Si de tels résultats ne sont pas surprenants pour la littérature académique, puisqu'ils sont déjà apparus sur d'autres marchés financiers et marchés émergents (en dehors des États-Unis) (HESTON, ROUWENHORST & WESSELS, 1999), les jetons **DeFi** semblent être les premiers crypto-actifs à souffrir de ce phénomène.

Dans une deuxième partie, nous effectuons des tests complémentaires, en utilisant la procédure de Fama-MacBeth. Une fois les corrélations en coupe transversale prises en compte, nos résultats changent, et aucun des facteurs de risque n'est valorisé. Motivés par la littérature montrant que le crypto-marché est un moteur essentiel des rendements (SOIMAN, DUMAS & JIMENEZ-GARCES, 2022), nous avons aussi étudié si le facteur de risque représenté par l'indice **CRIX** (l'indice du crypto-marché) peut expliquer les variations des rendements des **DeFi**. Afin de procéder à cette analyse, nous avons remplacé notre indice de marché précédent, **iDeFiX**, par l'indice **CRIX** et effectué les mêmes tests (**FF3F** et Fama-MacBeth). Les résultats ne montrent aucun changement, quel que soit l'indice de marché utilisé.

Ce chapitre a examiné la pertinence du modèle **FF3F** sur le marché du **DeFi**. À

<sup>4</sup>Le **TVL** se réfère au montant des fonds liés à un projet **DeFi**. Nous le considérons comme l'équivalent de la valeur comptable sur ce marché

<sup>5</sup>Nous avons fait les mêmes calculs avec **DEFX** (indice NASDAQ pour la finance décentralisée) que nous avons fait avec **iDeFiX** et nous avons obtenu les mêmes résultats.

première vue, les facteurs de risque mis en évidence par Fama-French et adaptés au marché des jetons DeFi sont valorisés par le marché. Cependant, les corrélations transversales jouent un rôle important sur ce marché. En utilisant la procédure de Fama-MacBeth, nous concluons que les rendements des jetons DeFi ne peuvent pas être expliqués par les modèles traditionnels d'évaluation des actifs basés sur le marché des actions, ou du moins pas en utilisant uniquement des informations financières. De tels résultats soulignent l'importance d'utiliser des variables technologiques dans la valorisation des actifs basés sur la Blockchain, comme par exemple les variables de réseau. Nous contribuons à la littérature actuelle en étant, à notre connaissance, les premiers à tester si les facteurs de taille et de valeur sont valorisés par le marché DeFi, et à examiner les rendements DeFis en coupe transversale. En outre, nos résultats montrent que les efforts futurs visant à modéliser les rendements des DeFi devraient prendre en considération les variables du réseau.

## 6 Conclusion et limites de la recherche

### Conclusions

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D'un point de vue global, cette thèse aborde des lacunes importantes dans la littérature académique actuelle. Nous sommes parmi les premiers à étudier le crypto-marché au-delà des aspects financiers des cryptomonnaies. Nous comptons un nombre croissant de travaux sur les cryptomonnaies, cependant, de nouveaux actifs basés sur la Blockchain voient le jour et n'ont pas encore été étudiés. Nous fournissons certaines des premières études sur les DeFi et les événements technologiques tels que les scissions (forks). Comme les innovations basées sur la Blockchain se développent rapidement, nous fournissons à la sphère académique en finance des analyses sur les aspects technologiques de ces innovations et leur impact sur le crypto-marché. Par exemple, notre travail sur les scissions Blockchain donne un exemple clair de l'impact des caractéristiques technologiques sur les caractéristiques financières des crypto-actifs. En outre, nous explorons les déterminants sous-jacents des crypto-actifs et montrons les limites des modèles existants d'évaluation des actifs traditionnels pour expliquer leurs rendements. Le marché des crypto-actifs est structurellement différent des marchés financiers traditionnels. Les crypto-actifs ne sont pas soutenus par une entreprise mais par la technologie Blockchain. Ce simple fait remet en question l'applicabilité aux crypto-actifs des développements académiques

existants en finance, notamment en ce qui concerne la dynamique des rendements de ces actifs. Cette thèse préconise le développement de nouvelles approches/modèles adaptés au crypto-marché.

De plus, cette thèse est également destinée aux praticiens de la finance. La connaissance de la Blockchain joue un rôle central dans la manière dont le crypto-marché va se développer. Notre recherche met en lumière les risques associés à la technologie Blockchain et décrit certaines de ses caractéristiques technologiques. Nos résultats intéressent également les investisseurs à la recherche de nouvelles possibilités de diversification. Nous montrons que le crypto-marché ne se limite pas aux cryptomonnaies et que les différentes cryptomonnaies ont un comportement financier différent. La diversification que le [BTC](#) peuvent offrir diffère de celle des [DeFi](#). En outre, l'étude des facteurs explicatifs des rendements des crypto-actifs présente également un intérêt pour le secteur de la gestion d'actifs.

### **Limites de la recherche**

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Malgré tous les efforts déployés pour fournir des résultats robustes et fiables, notre travail présente plusieurs limites. Nous identifions ici les principales limites et exposons comment notre futur agenda de recherche les abordera.

À notre avis, la plupart des recherches sur le crypto-marché connaissent des limitations similaires liées aux données. Le crypto-marché est en croissance constante, car de grandes quantités de nouvelles monnaies sont constamment émises. Par la suite, en raison de problèmes de réglementation ou de cybersécurité, de nombreux crypto-actifs s'effondrent et cessent d'être échangés. En raison de ce phénomène caractéristique de la cryptomonnaie, la plupart des travaux de recherche souffrent d'un biais de survie. Notre étude sur les scissions ne prend en compte que les événements de scission liés aux monnaies qui sont encore négociées de nos jours. Pour résoudre ce problème, nous prévoyons de renforcer l'étude sur l'effet de scission, en incluant également les scissions abandonnés.

La deuxième limite est que la plupart des publications actuelles se concentrent sur le bitcoin ou sur les plus grandes cryptomonnaies. Tout en ne considérant que le bitcoin, de nombreuses études ont déduit de leurs analyses le comportement de

l'ensemble du marché. Pour cette raison, la théorie actuelle sur le comportement des crypto-actifs est principalement basée sur le bitcoin ou d'autres cryptomonnaies de premier plan. Dans le cadre de nos futures recherches, nous prévoyons d'étudier l'impact de l'effet de bifurcation (scission) sur d'autres cryptomonnaies et leurs monnaies héritées. Toutefois, la construction d'une telle base de données pour d'autres monnaies sera difficile, car la plupart des données relatives aux cryptomonnaies disponibles concernent le bitcoin et d'autres grandes monnaies. Pour surmonter ce problème, nous prévoyons de continuer à étudier d'autres crypto-actifs tels que les jetons d'ICO, les jetons DeFi, les NFT et les cryptomonnaies moins connues.

Une limitation importante de notre travail sur les scissions consiste en la granularité des données. Les scissions sur la Blockchain bitcoin ne sont pas apparus à intervalles réguliers et, parfois, plusieurs scissions ont eu lieu au cours d'une même journée. Cette caractéristique des données rend l'étude des événements particulièrement ardue. Premièrement, avoir une image claire de la 'normalité' avant l'événement devient difficile si un autre événement s'y trouve. Deuxièmement, l'estimation de l'impact d'un événement est également perturbée par l'occurrence d'un autre. Une solution intéressante réside dans les modèles AR. Ces modèles permettent une certaine souplesse dans la définition du processus que suivent les rendements financiers. Idéalement, nous prévoyons de définir les rendements financiers comme une fonction de leurs variables retardées et de régresseurs supplémentaires. La modélisation des rendements par des modèles AR nous permettrait de définir une variable fictive (correspondant à l'occurrence de l'événement) et d'observer son effet et sa significativité. En procédant ainsi, nous supprimons la nécessité d'avoir une période de pré- et post-observation. Cette solution limite l'impact des événements qui se chevauchent partiellement. En outre, lorsque deux événements se produisent le même jour, nous pouvons observer l'effet de l'addition des événements sur la variable d'intérêt. Il s'agit d'une caractéristique qu'une approche standard d'étude d'événement ne peut pas gérer. En outre, cette approche permet des spécifications plus complexes. Les modèles GARCH peuvent étendre l'approche à l'examen de l'effet de l'événement sur la moyenne des rendements ou sur leur volatilité (conditionnelle). Une piste spécifique consisterait à utiliser un modèle GARCH exponentiel sur les rendements anormaux des cryptomonnaies pour étudier leurs réactions lors de l'occurrence d'un hard fork sur leur Blockchain.

Notre troisième limite concerne l'accessibilité des données de Blockchain. Même si la plupart des Blockchains auxquelles nous nous référons sont publiques, la récu-

pération complète des données est technique, et la plupart des chercheurs doivent s'en remettre à des sites Internet spécialisés. Ces sources ne proposent des données que pour un choix limité de cryptomonnaies et rendent difficile la réalisation d'une étude de marché. Par exemple, la plupart des théories de valorisation sur le cryptomarché soulignent la nécessité d'inclure des données liées à la Blockchain, comme par exemple les variables de réseau. Les données de réseau sont facilement accessibles pour les principales cryptomonnaies et jetons. Dans notre cas, nous avons réussi à extraire des données de réseau pour seulement 22 jetons DeFi, ce qui, par rapport à la taille du marché, est tout à fait insuffisant. De plus, la structure des données diffère parfois d'une source à l'autre. Cela rend l'agrégation des données ardue. Enfin, différentes sources nous fournissent la prix des crypto-actifs, mais ces informations sont souvent différentes d'une source à l'autre. Pour toutes ces raisons, l'étude du crypto-marché nécessite un haut degré de précaution lors de la phase de collecte des données.

À l'avenir, pour renforcer la robustesse de nos résultats, nous prévoyons la création de nouvelles bases de données plus importants pour effectuer nos tests. Une piste de recherche particulièrement intéressante serait de construire de nouveaux facteurs de risque pour valoriser les jetons DeFi. Le fait que le TVL soit difficile à récupérer pour une grande quantité de jetons DeFi réduit l'échantillon disponible pour effectuer l'analyse des déterminants du rendement des jetons DeFi. De plus, nous montrons que les facteurs de risque couramment utilisés sur le marché des actions ne s'appliquent pas au marché des DeFi. Par conséquent, nous prévoyons d'explorer d'autres facteurs tels que la liquidité, le risque extrême ou la corrélation.

Considérée comme un meilleur outil d'un point de vue technologique, la Blockchain pourrait être l'avenir à long terme de la finance ainsi que d'autres secteurs. Comme toute innovation, la Blockchain n'est pas une exception et s'accompagne à la fois d'améliorations et de défis. Au fil du temps, nous constatons que le développement technologique aide la Blockchain à devenir un meilleur outil. Le crypto-marché a connu une croissance exponentielle au cours de la dernière décennie, mettant au défi les investisseurs avec de nouveaux types de titres et de nouveaux risques. Dans l'idée d'explorer les risques spécifiques à la Blockchain, cette thèse comprend une analyse de l'impact des événements technologiques sur les caractéristiques financières des crypto-actifs. En outre, elle expose la diversité des crypto-actifs et leurs implications pour la valorisation des actifs.

Nous pensons que ce travail peut être utile à la fois aux chercheurs de la sphère académique en finance dans leurs efforts pour comprendre les déterminants du risque et du rendement des crypto-actifs ainsi qu'aux acteurs des marchés financiers pour leurs investissements.

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# List of Abbreviations

[A](#) | [B](#) | [C](#) | [D](#) | [E](#) | [F](#) | [G](#) | [I](#) | [L](#) | [M](#) | [N](#) | [P](#) | [Q](#) | [R](#) | [T](#) | [V](#)

## A

**AIC** Akaike Information Criterion.

**AMH** Adaptive Market Hypothesis.

**AMIM** Adjusted Market Inefficiency Magnitude.

**APT** Arbitrage Pricing Theory.

**AR** Auto-Regressive.

## B

**BIC** Bayesian Information Criterion.

**BTC** Bitcoin.

## C

**CAPM** Capital Asset Pricing Model.

**CAR** Cumulative Abnormal Returns.

## D

**dApps** Decentralized Applications.

**DDoS** Distributed Denial of Service.

**DeFi** Decentralized Finance.

**DeFis** DeFi Tokens.

**DEX** Decentralized Exchange.

**DLT** Distributed Ledger Technology.

## E

**EMH** Efficient Market Hypothesis.

**ESG** Environmental, Social, Governance.

**ETH** Ether.

**F**

**FF3F** Fama-French 3 Factor Model.

**G**

**GARCH** Generalized Auto-Regressive Conditionally Heteroskedastic.

**GSV** Google Search Volume.

**I**

**ICO** Initial Coin Offering.

**IPO** Initial Public Offering.

**L**

**LTC** Litecoin.

**M**

**MC** Market Capitalization.

**MIM** Market Inefficiency Magnitude.

**MLI** Martin Liquidity Index.

**N**

**NFT** Non-Fungible Tokens.

**P**

**PBFT** Practical Byzantine Fault Tolerance.

**PoS** Proof of Stake.

**PoW** Proof of Work.

**Q**

**QC** Quantum Computer.

**R**

**ROI** Return on Investment.

**T**

**TVL** Total Value Locked.

**V**

**VAR** Volatility-Adjusted Returns.

**VaR** Value-at-Risk.

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