The forking effect

immediate

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Abstract

This study introduces the *forking effect.* The forking effect represents the financial impact experienced by a cryptocurrency when a forking event takes place. The forking events studied in this paper concern only bitcoin, which is referred to as 'the parent coin'. Bitcoin represents the most well-known and forked cryptocurrency in this market. This work uses a modified exponential GARCH model to analyze the parent coin's response in returns and volatility to the forking events. Our results are twofold; first, we show that forking events do not impact the parent coin returns, but they have a strong and positive impact on the volatility. We observed that the effect becomes even stronger when we take into account the market dynamics. Our model accounts for well-known features in the crypto-market, such as volatility clustering, and is adjusted for fat-tailed distributions.

Keywords: Cryptocurrencies, EGARCH, Bitcoin, Blockchain, Fork
JEL Codes: G14, G15

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 et al., 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.

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 forking events happen. Despite recent efforts to enrich the literature on cryptocurrencies, we observed a general lack of financial research on the topic of Blockchain forks. This paper tries to fill this gap, and therefore, we address the following research question: *How do bitcoin's financial characteristics react to forking events?*. Bitcoin is the most well-known and forked cryptocurrency. Considering the importance of bitcoin in this market, this paper focuses exclusively on bitcoin forks. 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 when analyzing the forks of other cyptocurrencies. Our sample accounts for 93 Bitcoin forks that occurred between 2014 and 2020. We have observed that often, forking events occur on the same day or subsequent days, which makes it impossible to study the forking events with the classical methodology of event study (MacKinlay, 1997). Therefore, in order to answer our research question, we are going to assess the forking events by using the same methodology as Grobys (2021) and developing a modified exponential GARCH (EGARCH) model.

The results of this study show that forking events do not impact the returns of the parent coin on the same day they occur, and this observation is robust when taking into account market dynamics. Given that the crypto-market is known to be highly inefficient (Tran and Leirvik, 2020; Hu et al., 2019; Bariviera, 2017; Nadarajah and Chu, 2017; Urquhart, 2016), we always perform twice our model, once taking into account CRIX dynamics and another time without. Our second results show that the volatility of bitcoin is actually strongly impacted by forks and even stronger when taking into account CRIX dynamics. Moreover, we modified our model to account for fat-tailed distribution as bitcoin displays an excess kurtosis of more than 5. Furthermore, we show that the volatility responses depend more on the fact that a fork occurs rather than how many forks happen during a specific day. Our results show that forks create uncertainty in the market but are not necessarily perceived as bad or good news.

Our work is distinguishable from previous research in the way that we are the first ones to study the forking effect, and we propose and develop an EGARCH model to assess the forking events. This paper contributes to the understanding of Blockchain forks from both technological and financial points of view. Our results may have important implications for crypto-investors, who need to take into account the effect of technological events in order to be able to efficiently mitigate the risks from this market.

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.

2 Research background

In this section, we offer an overview of Blockchain forks and review the relevant literature on this topic. Then, the section outlines the paper's contribution and presents our research question.

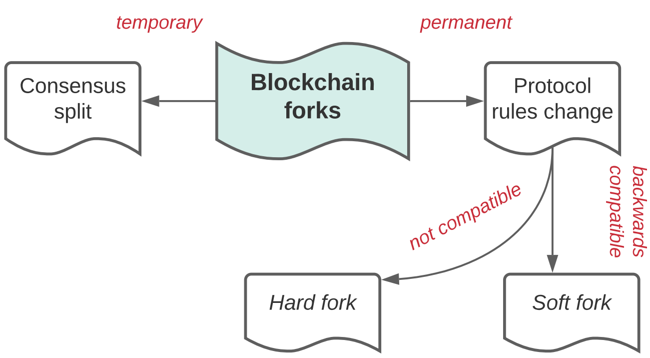
2.1 Understanding Blockchain

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 distributed ledger technology (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 cryptocurrency's network has access to all transactional data history and can contribute to the validation process (Olleros and 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).

2.1.1 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 et al., 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 1, we can see the main types of Blockchain forks. The

Figure 1: **Forks' classification**
Schematic representation of forks classification.

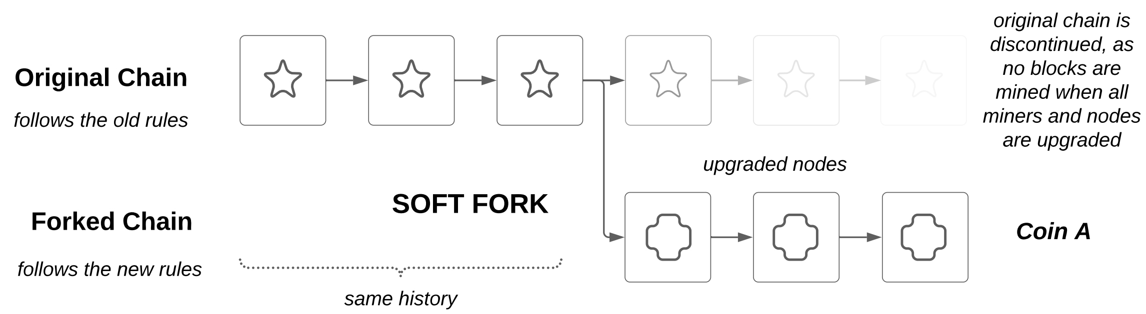


first category, the temporary forks, are the outcome of a divergence in the consensus process and result in a chain split. Such situations are possible when:

- two blocks are discovered at the same time by two different miners;
- there is an attack at the consensus level (see Dumas et al. (2021));
- there is a time lag in the acceptance of the block (resulting in orphaned or uncle blocks).

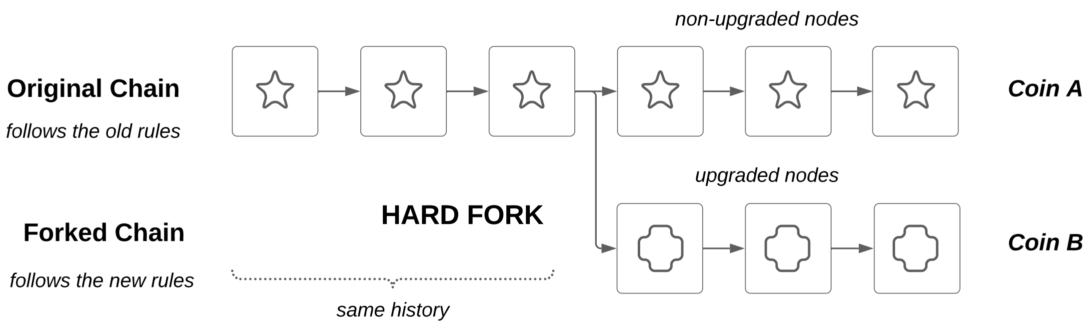
Why are these forks temporary? Simply because the community will follow the longest chain (considered valid by the majority) while the other one will be abandoned and discontinued. Once the chain split ceases, the consensus process will be unique, and there is no more fork (Bowden, 2021; Investerest.com, 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 a software needs, there are situations when it does 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 and 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 and 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) (Investerest.com, 2019; Perez, 2019). For better understanding, a visual representation of a soft fork is detailed in figure 2.

Figure 2: **Blockchain Soft Fork**
Description 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 and Liao, 2017). This scenario is illustrated in figure 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 (Bitcoingold.org, 2018). From a technical point of view, this scenario looks similar to figure 2, with the mention that the upgraded nodes are not backward-compatible.

Figure 3: **Blockchain Hard Fork**
Description 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. 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; Investerest.com, 2019). A detailed list of bitcoin's fork events can be consulted in BitMEX (2017).

In conducting this research, we focus on bitcoin's forking events, them being hard or soft forks.

2.2 The current state of research

Despite recent efforts to enrich the literature on cryptocurrencies, we observe that the existing research does not seem to propose enough answers given the market needs. In particular, we mention the relatively scarce work on Blockchain forks. Starting from 2014[1] 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 and Laurini, 2019); ICOs (Chohan, 2019; Chen et al., 2020; Adhami et al., 2018); cryptocurrencies' nature (White and Burniske, 2016; Nadler and Guo, 2020; Liu and Tsyvinski, 2021; Ankenbrand and Bieri, 2018; Tan et al., 2020); their volatility (Telli and Chen, 2020; García-Monleón et al., 2021; Fakhfekh and 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 et al., 2019b; Chen et al., 2020; Zamyatin et al., 2019; Neudecker and Hartenstein, 2019; Nyman et al., 2012; Zhang and Pre-

[1] the year when Ethereum and smart contracts (Blockchain second generation) were created.

neel, 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. (2019) 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 et al. (2017) explores the consequences of a fork on the network, Azouvi et al. (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 forks can offer new investment opportunities. More recent research, such as(Bazán-Palomino, 2021), compares bitcoin to some of its forks (Litecoin, Bitcoin Cash, Bitcoin Gold, Bitcoin Diamond, Bitcoin Atom, Bitcoin Private, and Bitcoin SV) and concludes that the correlation between bitcoin and the forks is volatility-dependent and that two months after their issuance, the forks contribute strongly to the market volatility.

After reviewing the existing literature on Blockchain forks, we have observed that there is little financial research on this topic. Our work aims to fill this gap, and therefore we propose a first assessment of the forking events' impact on the financial characteristics of a cryptocurrency. In this study, we answer the following research question: *How do bitcoin's financial characteristics react to forking events?*.

Our work is distinguishable from previous literature in the way that we are the first ones to study the forking effect (the financial impact suffered by a cryptocurrency as a response to forking events), and we propose and develop an EGARCH model to assess the forking events. This paper contributes to the understanding of Blockchain forks from both technological and financial points of view. Our results may have important implications for crypto-investors, who need to take into account the effect of technological events in order to be able to efficiently mitigate the risks from this market.

3 Data & Methodology

3.1 Data collection

This paper studies the forking effect for the bitcoin forks. The choice was mainly made based on the availability of data. Bitcoin is the most known cryptocurrency and the most forked chain. Considering these, any data concerning bitcoin's fork was relatively easy to access.

This study aims to capture the impact of forking events on the bitcoin's return and volatility. In pursuing this analysis, we retrieved the bitcoin/USD closing price from 01/01/2015 to 01/01/2020. We have identified 93 forked coins, out of which we use 85.[2]. In order to perform our computations, we chose as our market index the CRIX, which was created and started to be published in late 2014.

Retrieving early trading data, such as volume and prices for the crypto-market, seemed to be a challenge[3]. This is primarily because, in the first years, the crypto-market trading data were highly manipulated by the exchange platforms (Litecoin Developer, 2019). As a consequence and for compliance and ethical reasons, most of the existing databases removed any trading data for the

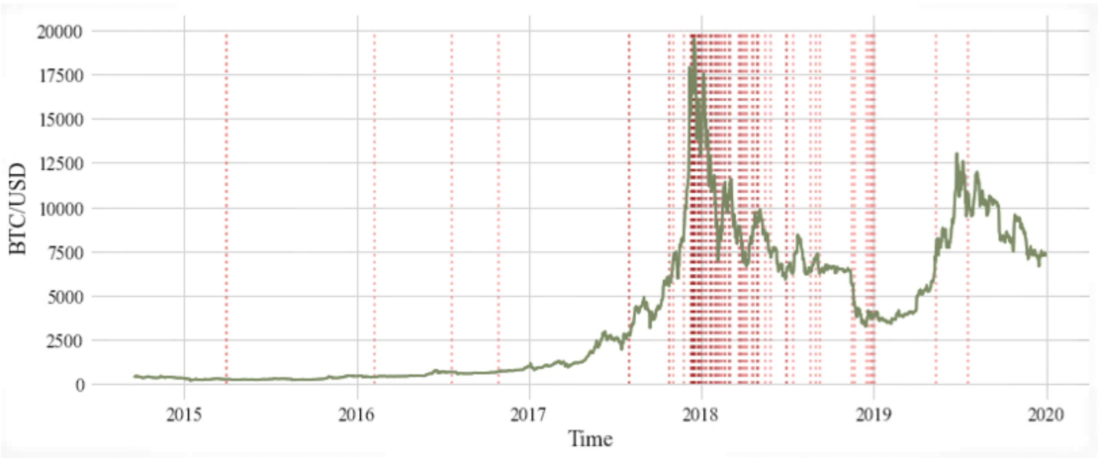
[2] the sample structure can be consulted in the appendix section, Table B.1.

[3] 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.).

years before 2014 (CoinDesk.com, 2014; Hileman, 2013; Partz, 2018). Moreover, due to the same issue concerning the lack of financial data for the 2011-2014 period (Litecoin Developer, 2019), any considerations, such as creating our own crypto-market index covering the early years, were not practical, and therefore we chose to continue using the CRIX index.

For our sample, the bitcoin prices were retrieved from CoinMarketCap.com, and the CRIX data from Royalton-crix.com (yearly years) and spglobal.com. All the relevant data related to forked coins, such as the name, ticker, and fork dates, were retrieved from multiple websites (see list in the appendix section, table B.2).

Figure 4: **Bitcoin price and forks' dates**
Chart of the price of bitcoin in US Dollars (BTC/USD) from 01-01-2015 to 01-01-2020. Each fork is represented by a vertical red-dotted line.



3.2 Research methodology

One common assumption in financial markets is that there is a fundamental value underlying each stock. The fundamental value usually represents the firm's actual 'intrinsic' value. Because financial markets are not 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 they rely 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 value. 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 the financial effects of such an event are.

A characteristic of this event study is that forks often occur in a cluster. As Figure 4 shows, the forks in our sample occur mostly in groups. Furthermore, 37 forks are also followed by another in the coming days. Because of such a feature, we cannot use the event study methodology of MacKinlay (1997). Due to the overlapping windows, it would be difficult to isolate the effect of a single fork from the effects of forks occurring the previous days. We decided to use a methodology that allows us to address the complexity of our dataset based on the work of Grobys (2021). Grobys (2021) studied the impact of hacking events on bitcoin's volatility using Generalised Auto Regressive

Conditional Heteroskedasticity (GARCH) modeling. We can modify a GARCH model to include the effect of a dummy variable, in our case, the forking event, on either the returns or the volatility of a cryptocurrency. Our study analyzes the impact of forks on bitcoin's returns and volatility. More specifically, we use the exponential GARCH (EGARCH) of Nelson (1991), as Bouoiyour et al. (2016) showed that bitcoin's volatility reacts stronger to bad news than positive news.

3.3 Returns' reaction to a fork

We estimate a modified version of the EGARCH of Nelson (1991). The modification allows the conditional mean to be impacted by the forks and to take into account market dynamics. The model is defined as follows.

$$\begin{aligned}
&R(t) = \mu + \delta_{mean} D(t) + \delta_{CRIX} R_{CRIX}(t) + \varepsilon(t) \\
&\varepsilon(t) = \sigma(t) z(t) \\
&Where: \ z(t)|\Omega_{t-1} \sim t(\nu) \\
&ln(\sigma^2(t)) = \omega + \alpha\Big(|z(t-1)| - \mathbf{E}[|z(t-1)|]\Big) + \gamma z(t-1) + \beta ln(\sigma^2(t-1))
\end{aligned} \tag{1}$$

Where $R(t)$ is the vector of cryptocurrency returns (BTC or ETH), μ is the expected return, $D(t)$ is the dummy variable for fork events, $R_{CRIX}(t)$ is the vector of CRIX returns, σ^2 is the conditional variance, $z(t)$ is a Student innovation process with ν degrees of freedom, Ω_{t-1} is the information set at $t-1$, and $\theta = [\mu, \delta_{mean}, \delta_{CRIX}, \omega, \alpha, \gamma, \beta]$ is the vector of parameters to be estimated via Quasi Maximum Likelihood Estimation (QMLE)[4]. Similarly to Grobys (2021), we set the degrees of freedom (ν) to be 5. We test the model twice, once taking with CRIX returns and once without. This allows us to capture the importance of market dynamics in our estimation of the forking effect.

We differ from the traditional EGARCH model (Nelson, 1991) by choosing the innovation process ($z(t)$) to follow a Student distribution. We chose this specification as cryptocurrency returns tend to display high kurtosis. In our sample, bitcoin returns have an excess kurtosis of 5.32. The student distribution allows to take into account fat tails in the distribution of returns.

In essence, we test the following hypothesis test:

$$\begin{aligned}
&H0 : \delta_{mean} = 0 \\
&H1 : \delta_{mean} \neq 0
\end{aligned} \tag{2}$$

3.4 Volatility's reaction to a fork

We repeat a similar process for estimating the impact of a fork event on the volatility of the parent coin. We based our analysis on the EGARCH model of Nelson (1991) as the model accounts for the asymmetrical shocks to the conditional variance. We modify the eGARCH model as follows.

[4]The QLME provides robust standard errors for the coefficients of the model as it does not require distributional assumptions to hold.

$$
\begin{aligned}
&R(t) = \mu + \delta_{CRIX} R_{CRIX}(t) + \varepsilon(t) \\
&\varepsilon(t) = \sigma(t)z(t) \\
&Where: \ z(t)|\Omega_{t-1} \sim t(\nu) \\
&ln(\sigma^2(t)) = \omega + \alpha\Big(|z(t-1)| - \mathbf{E}[|z(t-1)|]\Big) + \gamma z(t-1) + \beta ln(\sigma^2(t-1)) + \delta_{variance} D(t)
\end{aligned} \tag{3}
$$

The description of the variables and parameters remains the same as for the equation 1, with the exception to the vector of parameters $\theta = [\mu, \delta_{CRIX}, \omega, \alpha, \gamma, \beta, \delta_{variance}]$. The model is tested twice. One accounting for $R_{CRIX}(t)$ and one without. This procedure allows us to see the effect of market dynamics on the impact of a fork on the parent coin volatility. Regarding the impact on volatility, we test the following hypotheses.

$$
\begin{aligned}
H0 &: \delta_{variance} = 0 \\
H2 &: \delta_{variance} \neq 0
\end{aligned} \tag{4}
$$

4 Results & Discussion

The discussion of the results will be separated into two parts. One detailing the impact that forking events have on bitcoin's returns and the second about the impact on volatility.

4.1 Impact on Returns

We initially tested our model (see Equation 1) by excluding the returns of the CRIX. We wanted to see whether the forking events have any effect on the overall return of the parent coin. The model was calibrated to incorporate fat tails, addressing a common issue noted by Taleb (2020) on inference in the presence of fat-tailed distributions. The degrees of freedom used for the Student innovation process is $\nu = 5$ as the original methodology of Grobys (2021). The initial results are provided in Table 1 below. We find that γ is positive and significant at any conventional significance level, which proves that the asymmetric response is strongly positive in bitcoin's volatility. The β coefficient is also close to 1 and strongly significant, showing the presence of volatility clustering. These results are coherent with the one shown by Grobys (2021).

Table 1: **Coefficients estimate of the EGARCH(1,1) - Returns**
The table below shows the estimate values of the coefficients of the EGARCH(1,1) model used to evaluate the impact of forks on the parent coin's returns.

Parameter	***Estimate***	***Std. Error (in %)***	***t value***	***p value***
μ	0.0015	0.049	2.956	0.003
δ_{mean}	**0.0039**	**0.541**	**0.722**	**0.471**
ω	-0.1298	8.503	-1.526	0.127
α	0.0206	1.708	1.203	0.229
β	0.9826	1.231	79.776	0.000
γ	0.2337	5.337	4.379	0.000

However, we find that there is no significant response in the bitcoin's returns in reaction to the forking events. The δ_{mean} is close to zero and not significant. In Table 2, we estimate our model taking into account the market dynamics and find that the asymmetric response in volatility is stronger than before ($\gamma = 0.2446^{***}$) and the volatility clustering is still present ($\beta = 0.9861^{***}$). We also see that the δ_{CRIX} is close to one and strongly significant. Therefore, we can interpret our result as being about the excess returns of bitcoin compared to the market as $R(t) = \mu + \delta_{mean}D(t) + \delta_{CRIX}R_{CRIX}(t) + \varepsilon(t)$, is equivalent to $R(t) - R_{CRIX}(t) = \mu + \delta_{mean}D(t) + \varepsilon(t)$ when $\delta_{CRIX} \approx 1$. Nevertheless, even though we see a reduction in the standard error of β_{mean}, it is not enough to observe a significant response of returns to a fork. Our results so far indicate that the forking events do not impact the actual returns of the parent coin. There might be, however, a delayed effect occurring. Further research is needed to elaborate more on this aspect.

We can not reject our null hypothesis, presented in Equation 2. Our p-value, 17.6%, shows that there is no evidence that forks do impact the average returns of bitcoin when they occur.

Table 2: **Coefficients estimate of the EGARCH(1,1) with CRIX - Returns**
The table below shows the estimate values of the coefficients of the EGARCH(1,1) model used to evaluate the impact of forks on the parent coin's returns taking into account the market dynamics.

Parameter	***Estimate***	***Std. Error (in %)***	***t value***	***p value***
μ	0.0003	0.016	2.041	0.041
δ_{CRIX}	0.964	1.3718	70.253	0.000
δ_{mean}	**-0.0035**	**0.225**	**-1.354**	**0.176**
ω	-0.1153	1.139	10.124	0.000
α	0.0755	2.586	2.918	0.004
β	0.9861	0.127	775.702	0.000
γ	0.2446	2.795	8.754	0.000

4.2 Impact on Volatility

Here we are going to assess the impact of the forking events on the volatility of the parent coin. We estimate the model presented in Equation 3, first without taking into account the market dynamics and, a second time, by taking it into consideration. Our results continue to show the presence of asymmetry in the volatility with $\gamma = 0.2330^{***}$ and volatility clustering ($\beta = 0.9768^{***}$). Surprisingly, the volatility does not seem to be impacted by the scale of the innovations as α is not significant. Notably, we see that forks do have an impact on the immediate volatility of bitcoin as we observe $\delta_{variance} = 0.1508^{**}$. We see that forks create a surplus of volatility on the day they occur. A similar remark could be made, such as whether there are longer-lasting effects in the volatility of bitcoin. An interesting idea would be to deal with the overlapping events and estimate the impact of a fork on the volatility of bitcoin in the next few days.

Table 3: **Coefficients estimate of the EGARCH(1,1) - Volatility**
The table below shows the estimate values of the coefficients of the EGARCH(1,1) model used to evaluate the impact of forks on the parent coin's volatility.

Parameter	***Estimate***	***Std. Error (in %)***	***t value***	***p value***
μ	0.0015	0.042	3.615	0.000
ω	-0.1751	5.021	-3.487	0.000
α	0.0227	1.592	1.426	0.154
β	0.9768	0.719	135.816	0.000
γ	0.2330	3.410	6.833	0.000
$\delta_{variance}$	**0.1508**	**5.955**	**2.533**	**0.011**

As Figure 4 shows, most of the forking events are happening during the bubble. Consequently, we can expect that, naturally, the volatility during this period is bound to be higher than usual and might bias our results. To address that issue, we incorporate market dynamics in our model and obtain the results displayed in Table 4. We confirm that the presence of asymmetric response and volatility clustering are still present ($\gamma = 0.2408^{***}$ and $\beta = 0.9838^{***}$), which builds on the existing results in the literature (Grobys, 2021). Furthermore, we see that the effect the fork has on the volatility is strengthened. The $_{variance}$ is now 0.2005***. It means that the impact on the volatility is stronger when we take into account market dynamics. The residual volatility (the one that is not due to the market) still peaks on the day of the forking event.

Table 4: **Coefficients estimate of the EGARCH(1,1) with CRIX - Volatility**
The table below shows the estimate values of the coefficients of the EGARCH(1,1) model used to evaluate the impact of forks on the parent coin's volatility taking into account the market dynamics.

Parameter	***Estimate***	***Std. Error (in %)***	***t value***	***p value***
μ	0.0004	0.016	1.924	0.054
δ_{CRIX}	0.9651	1.383	69.815	0.000
ω	-0.1399	0.913	-15.314	0.000
α	0.0713	2.211	3.226	0.001
β	0.9838	0.100	1068.673	0.000
γ	0.2408	2.598	9.269	0.000
$\delta_{variance}$	**0.2005**	**6.167**	**3.252**	**0.001**

Our results show that the uncertainty increases when a fork occurs. We also estimated our model with another variable that counts how many forks occurred each day, and we found that the relationship is not more significant than the result displayed in Table 4. This shows that the uncertainty coming from a fork does not depend on how many forks are actually taking place[5]. It might be that investors make a short-term choice on which Blockchain to follow. Regardless, our results confirm that, when studying the volatility of cryptocurrencies, one should use a model that accounts for asymmetric responses in volatility and, furthermore, should take into account market dynamics. Regarding our initial hypothesis (see Equation 4), we can reject $H0$ and hence validate that there is evidence to believe that forking events positively impact the volatility of the parent coin at any level of significance.

5 Conclusion

The crypto-market constitutes a real challenge for finance academics and practitioners, as it challenges the pre-existing "laws" prevailing in the traditional financial markets. Numerous studies have tried to attach cryptocurrencies to another form of existing assets (White and Burniske, 2016; Ankenbrand and Bieri, 2018; Nadler and Guo, 2020; Liu and Tsyvinski, 2021; Tan et al., 2020); to propose a coherent valuation method (Pagnotta, 2022; Cong et al., 2021) or to study their chaotic price dynamics (Sornette et al., 2014; Chaim and 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 study how the market reacts when a fork occurs on a coin (bitcoin). We find that investors do not associate the forking events with neither bad nor good news but are rather quite insensitive to these types of events. The estimated response in bitcoin returns is not significantly different from 0, regardless of whether we take into account market dynamics. Secondly, we find that a fork simply causes instantaneous uncertainty in the market. We find a strong response to the volatility of bitcoin. Our model captures well-known

[5]To see why the model with the dummy variable dominates, please refer to the Appendix, Table B.3

features of cryptocurrency volatility, such as volatility clustering and asymmetric responses to the news. Furthermore, we find that the volatility response is actually stronger and more significant when we take into account market dynamics.

This paper contributes to the understanding of Blockchain forks from both technological and financial points of view. The results obtained may have important implications for crypto-investors, who need to take into account the effect of technological events in order to be able to efficiently mitigate the risks from this market.

As a future path for research, it would be interesting to see how the forking effect impacts other cryptocurrencies that have been forked, such as ether coin, litecoin, monero, etc. However, constructing such a database for other coins will be challenging, as relevant information concerning the crypto-market is spread all over the internet. Other interesting paths for future research would be to estimate the short-term, lasting effect of a forking event on the parent coin and compare the long-term performance of the forked coins with their parent.

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A Figures

B Tables

Table B.1: **The list of bitcoin's forks**
Comprehensive list of all the forks considered in our study. We provide the ticker as well as the date of the forking event.

Fork name	ticker	Fork date
Anonymous Bitcoin	ANON	2018-09-10
Big Bitcoin	BBC	2018-02-12
Bitclassic Coin	BICC	2017-12-12
Bitcoin 2	BTC2	2018-02-05
Bitcoin Air	XAP	2018-11-22
Bitcoin Atom	BCA	2018-01-24
Bitcoin Blvck	BTCV	2018-02-05
Bitcoin Boy	BCB	2018-01-02
Bitcoin Cash	BCH	2017-08-01
Bitcoin Cash SV	BSV	2017-08-01
Bitcoin Cbc	BCBC	2017-12-11
Bitcoin Clashic	BCHC	2017-08-01
Bitcoin Clean	BCL	2018-04-18
Bitcoin Cloud	BCL	2018-02-20
Bitcoin Community	BTSQ	2018-01-25
Bitcoin Coral	BTCO	2017-10-24
Bitcoin Dao	BTD	2018-06-30
Bitcoin Diamond	BCD	2017-11-24
Bitcoin Dollar	BTD	2018-02-28
Bitcoin Eco	BEC	2018-12-18
Bitcoin Faith	BTF	2017-12-18
Bitcoin File	BIFI	2017-12-27
Bitcoin Flash	BTF	2018-02-06
Bitcoin God	GOD	2017-12-27
Bitcoin Gold	BTG	2017-10-24
Bitcoin Holocaust	BTHOL	2017-12-29
Bitcoin Hot	BTH	2017-12-12
Bitcoin Hush	BTCH	2018-02-01
Bitcoin Interest	BCI	2018-01-20
Bitcoin King	BCK	2017-12-18
Bitcoin Lambo	BTL	2018-03-27
Bitcoin Lightning	BLG	2017-12-10
Bitcoin Lite	BTCL	2018-01-31
Bitcoin Lunar	BCL	2018-03-20
Bitcoin Master	BCM	2018-03-24
Bitcoin Metal	BTCM	2018-05-01
Bitcoin Minor	BTM	2017-12-11
Bitcoin Nano	BN	2017-12-31
Bitcoin New	BTN	2017-12-25
Bitcoin Ore	BCO	2017-12-31
Bitcoin Parallel	BCP	2018-01-31
Bitcoin Pay	BTP	2017-12-15
Bitcoin Pizza	BPA	2017-12-31
Bitcoin Point	POINT	2017-12-25
Bitcoin Post-Quantum	BPQ	2018-12-22
Bitcoin Private	BTCP	2018-02-28
Bitcoin Pro	BTP	2018-01-31
Bitcoin Quantum	QBTC	2017-12-28
Bitcoin Reference	BRECO	2018-05-17
Bitcoin Rhodium	XRC	2018-01-10
Bitcoin RM	BCRM	2018-08-21
Bitcoin Smart	BCS	2018-01-19
Bitcoin Stake	BTCS	2017-12-18
Bitcoin Star	BCS	2018-01-07
Bitcoin Sudu	SUDU	2018-02-20
Bitcoin Top	BTT	2017-12-26
Bitcoin Transfer	BTCT	2018-04-01
Bitcoin Wonder	BCW	2017-12-18
Bitcoin World	BTW	2017-12-17
BitcoinX	BCX	2017-12-12
Bitcoinx2	BTCX2	2018-07-01
Bitcoinzerox	BZX	2018-08-31
Bitcore	BTX	2017-11-02
Bitethereum	BITE	2017-12-21
Bithereum	BTH	2018-12-28
Bithereum	BTH2	2018-12-28
Bitvote	BTV	2018-01-19
Cereneum	CER	2019-05-14
Clams	CLAM	2014-05-12
Classicbitcoin	CBTC	2018-04-01
Dalilcoin	DLC	2015-03-30
Dash	DASH	2014-01-18
Decred	DCR	2016-02-08
Digibyte	DGB	2014-01-10
Fastbitcoin	FBTC	2017-12-27
Fox BTC	FBTC	2018-04-30
Groestlcoin	GRS	2014-03-22
Lightning Bitcoin	LBTC	2017-12-18
Litecoin	LTC	2011-10-07
Microbitcoin	MBC	2018-05-28
Mimblewimblecoin	MWC	2019-07-19
Navcoin	NAV	2014-04-23
New Bitcoin	NBTC	2017-12-27
Oil Bitcoin	OBTC	2017-12-12
Qeditas	QED	2015-03-30
Smart Bitcoin	SBC	2018-04-20
Super Bitcoin	SBTC	2017-12-12
Syscoin	SYS	2014-07-19
Unitedbitcoin	UBTC	2017-12-12
Viacoin	VIA	2014-07-18
World Bitcoin	WBTC	2018-01-12
Xenon	XNN	2018-06-30
Zcash	ZEC	2016-10-28

Table B.2: **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, as for all the specifics regarding the forks were retrieved from a variety of websites.

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

Table B.3: **Information criterion and model choice**
The table below shows the values of multiple Information Criterion for two models. The first is model is the one describe by the Equation 3. The second one is the same but with the dummy variable $D(t)$ as been switched with another variable $C(t)$ that counts the number of forks occurring on each day. The results show that the initial model is slightly preferred.

	$D(t)$	$C(t)$
Akaike	-5.0701	-5.0693
Bayes	-5.049	-5.0482
Shibata	-5.0701	-5.0693
Hannan-Quinn	-5.0623	-5.0615