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Asymmetric Volatility in the Cryptocurrency Market: Market Dynamics and Behavioral Patterns

Prof. Nicola Borri

SUPERVISOR

Prof. Antonio Simeone

CO-SUPERVISOR

Mattia Schintu - 756991

CANDIDATE

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Introduction

Since the introduction of Bitcoin in 2008, cryptocurrencies have risen to prominence in financial markets, with meme coins emerging as a unique subset characterized by speculative interest and viral popularity. Unlike traditional cryptocurrencies, meme coins derive their value less from claims of underlying utility and more from social media trends and community-driven hype. The results of the 2024 presidential elections the United States have further pushed meme coins into the mainstream, with President Donald Trump himself launching a meme coin ($TRUMP) that surpassed a 10 billion dollars valuation in less than a day and his wife Melania launching another one ($MELANIA) immediately after. Meme coins have started as a joke, but now they move billions.

Due to their rise to relevance being so sudden, there is still not much specific information about the behavior of this subclass of cryptocurrencies. Studies have tended to focus more in general on traditional cryptocurrencies and have at most only included DOGE as a representative of the class of meme coins.

Given how meme coins are becoming a more important component of crypto markets in their own right, this needs to change. The importance of spillovers of crypto markets on other financial markets has been studied by papers such as Uzonwanne (2021), which has found evidence of volatility spillovers between crypto assets and the stock market, while studies like Elsayed, Gozgor, and Lau (2022) have shown this spillover to have reached “unprecedented levels” during a highly volatile period such as the COVID-19 pandemic. A better understanding of the behavior of the variance of crypto assets is thus extremely important, and a large subset of cryptocurrencies like meme coins cannot be left out.

Given this context, the focus of this work will be on uncovering and studying the presence of asymmetric variance behavior on a set of meme coins and to find if such behavior is statistically different from that of traditional cryptocurrencies.

This work will proceed as such: In Chapter 1 will be presented concepts necessary to better understand the later parts of this work. In Chapter 2 we will cover the specifics concerning the collection of the data and its necessary processing and some descriptive statistics. Finally, in Chapter 3 will be presented the results of the analysis, its shortcomings, and we will assess the coherence of our results with the main hypothesis of variance asymmetry studied in the literature.

1. Background Information and Academic Review

This chapter is intended as a primer and will focus exclusively on the concepts necessary to understand the later parts of this work. These will include basic concepts about cryptocurrencies and meme coins, market behavior and asymmetric volatility. For a more comprehensive analysis of the following topics, please refer to the bibliography and to additional specialized sources.

1.1. Currency, Cryptocurrency and "Meme coins"

1.1.1. Fiat Currency

To better put cryptocurrencies and their behavior into perspective, the starting point of this work will focus on what currency is in the first place. The first thing to note is that "currency" does not exactly coincide with "money", but is a constituent of money, alongside bank deposits and reserves. In fact, currency today can be only a small fraction of the total amount of money present in the economy [McLeay et al. (2014)].

According to McLeay et al. (2014), "There is no universal agreement on what money actually is". Given this state of affairs, for the purposes of this work, money will be considered a good or asset created with the intent to fulfil three functions simultaneously[1]: The ability to store value, the ability to be used as a unit of account and the ability to work as a medium of exchange.

The first characteristic is the most important for the purposes of this work, but since it's interdependent with the other two, all three will be outlined.

Ideally, money should be able to store value over time. If one acquires money by ceding something of value or by performing a service, they would expect to be able to receive other goods or services of the same value. This means that money cannot degrade over time. One of the reasons why in the past money was made of gold or silver is that these metals do not easily decay over time, unlike items made from something "perishable"[2].

[1] These functions are cited in [McLeay et al. (2014)], however for them money can be a good that performs well those functions, not necessarily a good created with that aim.
[2] Here a note is in order. Modern fiat money tends to lose value, as in the modern world inflation is much more common than deflation. This wasn't always the case as in the past currency was minted from precious metals with a naturally limited supply. In countries with a low and stable inflation, modern fiat

In this sense money has evolved over time, from physical heavy metal coins to paper notes, to digital payments[3].

Money should also be able to act as a unit of account and be used to gauge the value of a good or service. In this sense a good used as money has to be some sort of commodity which can be easily divided and preferably easily transported. As an example, a house cannot be used as money since houses are complex goods, usually different from each other, hard to divide and impossible to transport.

Finally, money should be able to act as a medium of exchange. Money is not held because it is useful by itself, but because it allows the holder to obtain something useful. This means that money needs to be readily recognized and accepted in exchange for goods and services.

In short, money allows us to store value obtained by working, hold on to it, and use it later to obtain in exchange the product of the work of someone else. For this system to work, trust in the fact that money will hold these characteristics in the future is crucial, as its value is linked to its ability to perform these functions.

Currencies, as one of the forms of money, should be thus characterized by these uses and are created with the aim to fulfil them.

1.1.2. Cryptocurrency

Cryptocurrencies are a (relatively) new kind of currency which aims to leverage technology to decentralize payment systems. They are virtual currencies, which work through a network of computers (often peer-to-peer) and are not backed by a central authority. These currencies rely on cryptographic techniques which allow the use of a

money can still act as a store of value in the short term, but fails in the long term. For a better overview of the phenomenon, I suggest reading Selgin G., Lastrapes W. D., White L. H. (2012)

[3] Note that this reduced the use of currency and increased the use of bank deposits as money, which is why today currency accounts only for a small fraction of money in circulation.

Distributed Public Ledger[4] (typically a Blockchain[5]), which prevents double spending[6] and allows anyone with an access to internet to retrieve information about the payments.

Decentralized money per se is nothing new. An historic case of a non-digital currency that worked for centuries through what was essentially an oral DPL, is that of the Rai Stones of Yap Island (Micronesia). These round stones, which were extremely hard to carve with the available technology and could be as tall as people, had value based on their size and oral history. Given their size they were fixed in place and a change in possession was certified by an amendment to its oral history.

While attempts at creating digital decentralized money started in the 1980s with e-cash (Chaum 1983), the most successful earlier example of a cryptocurrency is Bitcoin, introduced in a white paper by Nakamoto (2008).

Since Bitcoin's inception, several other cryptocurrencies have been created, and currently there are more than 20 thousand cryptocurrencies with a capitalization of more than $3 trillion.

1.1.3. Cryptocurrency as money

Today, a large number of cryptocurrencies can be used to buy goods and services, and while this remains mostly an online phenomenon, there are examples of real-world usage[7]. Despite this, the usability of cryptocurrencies as money is debated. A good way to understand if cryptocurrency could act as money, would be to see if the previously stated characteristics of money can apply to cryptocurrencies as well.

Theoretically, cryptocurrencies could act as a medium of exchange. We noted before how *money is not held because it is useful by itself, but because it allows the holder to obtain something useful*. This means that for a cryptocurrency to act as a medium of exchange, it just needs to be widely accepted as a form of payment. As of now, cryptocurrencies

[4] A Distributed Public Ledger is a decentralized database of transactions shared across multiple participants.
[5] A Blockchain is a type of distributed ledger that structures data into linked blocks, secured through cryptographic hashing and consensus mechanisms.
[6] Double spending consists in spending again money already used to also buy something else. This isn't possible with payments in physical cash, but it would be possible with a poorly designed digital payment system.
[7] At the time of writing, Bitcoin is legal tender in El Salvador and is accepted by large corporations like PayPal, Microsoft and AT&T.

generally fail as a medium of exchange. While it has been mentioned how there has been progress in real-world usage, tokens today are mostly held as speculative assets and not to be used as money.

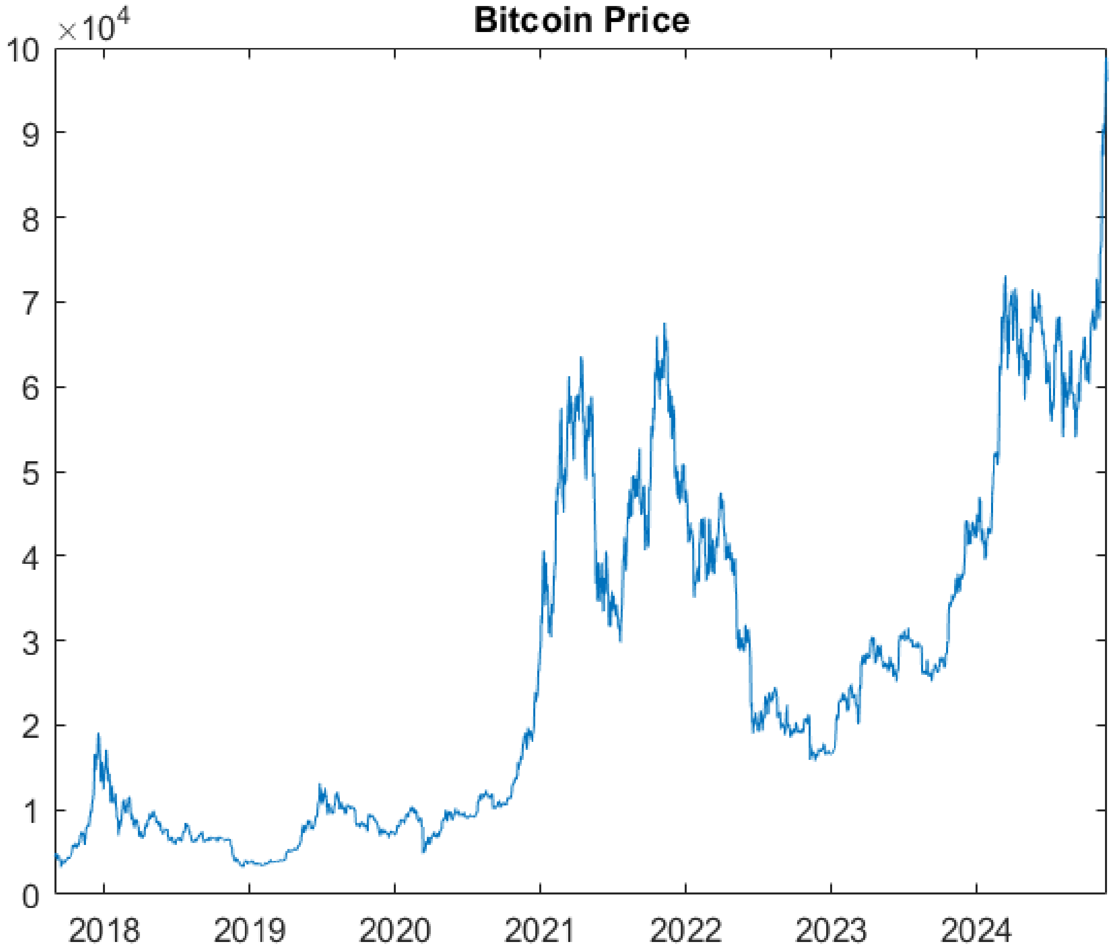

Figure 1- Price of a bitcoin since 2018 expressed in units of $10000. The price of a bitcoin compared to fiat currency can change drastically, a feature shared with most cryptocurrencies.

Studies like Baur and Dimpfl (2021) found that the volatility of Bitcoin, as of today the most widely used cryptocurrency and the one with the largest capitalization, is 10 times higher than that of major regular exchange rates, like the USD-Euro and USD-Yen. While they don't deny how using bitcoins as a medium of exchange is technically possible, they consider the costs "*prohibitively expensive*".

This obstacle strongly reflects on cryptocurrencies' ability to act as a **unit of account**. Since cryptocurrencies' prices swing dramatically and are characterized by boom-bust cycles, prices of goods and services expressed in cryptocurrency are forced to adjust constantly to take that into account. Stablecoins[8] exist, but being pegged to a fiat currency backed by a central bank means that some advantages of cryptos are lost, like the resistance to inflation or the independence from an authority.

Finally, of particular importance for the purposes of this work is the cryptocurrencies' ability to **store value**. Proponents argue that cryptocurrencies, unlike fiat currencies, can be programmed to be a finite amount, or at least programmed to be mined at a rate slow enough to be coherent with this function. For example, the Bitcoin protocol allows only the existence of 21 million bitcoins, assigned at an ever reducing rate. This means that once the maximum number of bitcoins will have been reached, no entity will be able to mine or create more than the amount programmed in the protocol. This makes Bitcoin inherently deflationary, and thus, at least theoretically, a better store of value than current fiat money.

Opponents of this argument point to several issues. One is that the ability of money to store value is closely linked to its other functions in a self-reinforcing loop[9]. As outlined above, cryptocurrencies struggle to perform those functions due to their extreme volatility fueled by speculation.

Another issue, linked to cryptocurrencies' intrinsic value, is expressed by Nobel prize winner and cryptocurrency critic Paul Krugman. He affirms that "*fiat currencies have underlying value because men with guns say they do*" and that "*... this means that their value isn't a bubble that can collapse if people lose faith*" [10].

Since the definitive collapse of the gold standard, fiat currency isn't backed by any underlying asset. Here Krugman's point is that this fact does not matter: the value of fiat currency is based on the fact that a government accepts it as payment of tax liabilities (and more in general can force its use as means of settlement for any monetary debt).

[8] Stablecoins are cryptocurrencies that are pegged to a specific fiat currency.
[9] McLeay et al. (2014) point out how the three characteristics of money outlined (Store of value, Medium of Exchange and Unit of account) are closely linked to each other.
[10] Krugman (2020).

By contrast, cryptocurrencies are not backed by a central bank or a country[11], and since they usually[12] have no underlying assets, this leaves open the question around their intrinsic value.

1.1.4. Cryptocurrency's intrinsic value

This brings us to one of the main points of research which concerns the cryptocurrency phenomenon.

To act as a store of value, a good doesn't necessarily need to be backed by an authority. As seen above, that has been cited as a specific requirement for fiat currency, but a good can also act as a store of value by simply having "utility", being rare and not being perishable.

Gold is a classic example of "safe haven good[13]" that can act as a store of value. According to Baur and McDermott (2010), gold has mainly three sources of demand, jewelry, industrial and investor's demand. According to them, investors' demand seems to be countercyclical, and they point at this feature as evidence that investors use gold as a store of value. In particular, they point to gold's intrinsic value and its supply inelasticity as elements that lend weight to its ability to store value.

These are very interesting points when considered for cryptocurrencies. On one hand, they usually have strong supply inelasticity since supply, which depends exclusively on the protocol, is limited either through a cap or through "mining" difficulty[14].

On the other hand, the point concerning cryptocurrencies' intrinsic value is more complex. It is usually stated like gospel that cryptocurrencies have no intrinsic value. At a surface level this seems correct. However, this statement becomes significantly hollower when we ask, "what gives something intrinsic value?", and more importantly, "what even is intrinsic value?".

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[11] As mentioned before, Bitcoin is legal tender in El Salvador, however its economy is far too small when compared to the total capitalization of Bitcoin to be a credible backer.
[12] Tether is backed by substantial US Dollar reserves. In general the value of stablecoins is kept stable by ensuring convertibility through substantial reserves.
[13] More on this later.
[14] Often both, like in the case of Bitcoin.

The Cambridge dictionary defines it as "*the real value of a company, asset, etc., which may not be the price it could be sold for now*". This definition is anything but satisfactory and does nothing but shift the question from the word "intrinsic" to the word "real".

In a position paper, Treiblmaier (2022) discusses the matter quite thoroughly, and states three different propositions, each backed by solid arguments and logic. First, he affirms that "*Intrinsic value is a vague concept and obfuscates rather than illuminates the properties of cryptocurrencies*", claiming that it's impossible to achieve a clear differentiation between intrinsic and extrinsic value.

He then tries to clear up this "vagueness" by looking at specific definitions of intrinsic value applied to other goods, and concludes that, *"the intrinsic value of cryptocurrencies is the sum total of all properties that make them suitable to be used as a means of exchange"* (Proposition 2) and that *"the investments in hardware and energy that are needed to mine new Bitcoins can be used as a proxy to estimate its intrinsic value"* (Proposition 3).

Proposition 2 refers to the potential of cryptocurrencies as payment systems. If cryptocurrencies are built on a "better[15]" payment system than the traditional ones, one could argue that they have an intrinsic value just because that would be a desirable property in its own right[16].

Regardless, intrinsic value needs to be coupled with price stability for a good to be considered a store of value, specifically in the short term. However, Baur e Dimpfl 2021

[15] "Better" doesn't necessarily mean "more efficient". A payment system may be "better" than another by having a set of features coveted by its users (in the case of cryptocurrency an example could be its decentralization when compared to traditional payment systems).

[16] Today we are used to pay digitally through online banking with no apparent cost, and it's easy to forget the existence of an overhead cost in our payment system, may it be fees, a monthly subscription or unpaid interest rates, and this gives cryptocurrency room to maneuver. An example by which a payment system may be better is reducing the negative cashflows that users need to pay to keep the system running, or by increasing efficiency in some other area. It must be noted that cryptocurrencies have overhead costs of their own, sometimes quite substantial. Bitcoin mining alone consumes as much electricity as Argentina and is conducted through costly specialized hardware. Theoretically a crypto payment system could be engineered to have much lower energy consumption and not require specialized hardware. Ethereum, as an example, has significantly cut its energy consumption to the point much closer to that of centralized payment systems. Additional information on crypto's energy consumption can be found here:
https://digiconomist.net/bitcoin-energy-consumption
https://digiconomist.net/ethereum-energy-consumption

consider Bitcoin's long term price trend and deflationary design as evidence that Bitcoin specifically has store of value characteristics at least in the long term.

Proving the fact itself that cryptocurrencies have intrinsic value is beyond the scope of this work, however the fact that the matter has not been settled is sufficient for our purposes. Since cryptocurrencies *might* act as a store of value, any asymmetric variance hypothesis that needs this feature as prerequisite will need to be taken into consideration[17].

1.1.5. Meme coins

Now that the general characteristics of cryptocurrencies have been discussed, we can delve into the specific category of cryptocurrencies subject of this work: Meme coins.

Meme coins can both be considered a very special kind of cryptocurrency and not special at all.

They are not special because, at their heart, they work like any other cryptocurrency. Meme coins can theoretically be used to buy goods and services like any other cryptocurrency, and in general they have all the same basic set of features[18].

What makes them special is their ties to particular internet phenomena. Meme coins are digital currencies inspired by internet memes and popular culture. They often gain attention through viral trends, and their value is strongly tied to how widespread is the meme[19] that inspired the coin's name and logo.

This feature is particularly interesting when we consider the fact that internet phenomena have a lifecycle. Memes are born, die (meaning they become irrelevant) and get revived constantly. Their popularity is tied with their virality[20], and since a meme coin's value is

[17] This means that the safe haven hypothesis cannot be excluded *a priori* when investigating the variance asymmetry of cryptocurrencies.
[18] The use of a Blockchain, their being digital, and the fact that they usually work on peer to peer networks of computers.
[19] The concept of an internet meme is quite fuzzy, however it could be defined as a cultural phenomenon able to spread rapidly among humans though the internet. While in theory it could be pretty much anything, it usually takes the form of images, videos, phrases or challenges. The phenomenon can be quite "silly" at first glance but hides a wealth of complexity subject of numerous studies.
[20] Internet culture having such a large impact on the value of widely traded financial assets can be surprising, however, as the 2021 GameStop short squeeze case suggests, that is nothing new.

strongly tied to the popularity of the meme featured in it, they tend to have boom and bust cycles typical of speculative assets.

This exacerbates the problems we found in normal cryptocurrency concerning their ability to act as money and particularly concerning their ability to store value.

Figure 2 - Price of Shiba Inu, expressed in a scale of $\$10^{-5}$ due to the small price of a single token. Meme coins are characterized by sudden explosions in price even more so than traditional cryptocurrencies.

The considerations of Treiblmaier (2022) concerning intrinsic value are even more interesting when considering meme coins specifically, which are not created with the purpose of being a widely accepted payment system and thus it would be harder for proponents to claim they have intrinsic value through their usefulness.

Today meme coins cannot be considered "niche" anymore, having surpassed a capitalization of $100 billion at the time of writing[21]. They have become mainstream to the point that then US president-elect Donald Trump launched its own meme coin ($TRUMP) which soared to a capitalization over $10 billion in just a few days, followed by another coin launched by the first lady ($MELANIA) shortly after[22].

Despite their current popularity, literature on their behavior is scarce[23] and mostly focuses on the oldest and currently largest meme coin, Dogecoin[24].

1.2. Theory of Market Behavior

This section exposes theories and aspects of market behavior. This discussion will only be a short primer to better contextualize later parts of this work.

1.2.1. Rationality of Economic Agents

We will first explore some aspects related to the behavior of economic agents. Studies regarding their rationality go back centuries and have been central to the development of classical economics.

Particularly important is the concept of the "economic man" (or *homo oeconomicus*), a model for the behavior of economic agents that assumes perfect rationality and self-interest. The concept per se cannot be easily attributed to any one economist but has slowly evolved over time as a simplified model of human economic behavior[25].

The main characteristics of the economic man are Utility Maximization, Self-Interest, Consistency and Perfect Rationality.

The concept of utility in economics indicates the satisfaction that economic agents obtain through consumption. The first listed characteristic, Utility Maximization, relates to the

[21] An updated value can be found here: https://www.kraken.com/it-it/categories/meme
[22] Interestingly enough, after the launch more than 160 copycat tokens have been created in just a few days: https://www.ft.com/content/831919a9-47b0-4ac3-bcdd-5154c27d9f9c
[23] This is explained by the fact that most meme coins started to be traded in large platforms only recently. After an explosion in 2022, their popularity waned until the 2024 US elections.
[24] The first meme coin (DOGE) was published in 2013, but the phenomenon exploded in 2022 after a tweet by Elon Musk
[25] Adam Smith, John Stuart Mill, Francis Edgeworth, Léon Walras, and Vilfredo Pareto are only some of the economists which helped develop the concept.

desire of the economic man to perform economic actions which will ensure the maximum possible satisfaction given the starting circumstances.

The second characteristic, Self-Interest, describes an individual whose utility is increased by self-consumption, and is not affected by envy, empathy, or any other emotion. Any change in one other's consumption has no effect on him unless it influences in some way its own consumption.

The third characteristic, Consistency, implies that a particular choice gives the same level of satisfaction regardless of whatever alternative choice is presented. The choice is exclusively dictated by which alternative gives the highest utility, and the utility is not influenced by the alternative in any way.[26]

Finally, the characteristic of Perfect Rationality, implies the ability of the economic man to perfectly process and understand available information. Whatever amount of information is presented to him, he will be able to process instantly and come up with the decision which best increases his utility. Perfect rationality implies the absence of cognitive biases but does not imply perfect information.

The model of *homo oeconomicus* has been an invaluable tool to advance economic thinking, but it is just a model, which over time has been found to be flawed and a rather poor descriptor of reality.

Interestingly enough, the works of some of the economists that pioneered the concepts that over time coalesced in the *homo oeconomicus*, are the same that pioneered the presence of behavioral biases in economic agents[27].

1.2.2. Behavioral Biases

The model of the economic man remained the dominant one until the 1970s. In time, new research has put the viability of the model into question.

[26] For example, if in terms of utility X is preferred to Y and Y is preferred to Z, then X is preferred to Z every time.

[27] In *The Theory of Moral Sentiment*, published 17 years before *The Wealth of Nations,* Adam Smith noted how individuals have sympathy for the well-being of others.

By far one of the most influential works on the effect of behavioral biases in economic thinking is Kahneman and Tversky (1979)[28]. Their work, based on empirical research, describes how individuals tend to be "loss averse", and in general assess their economic perspectives asymmetrically.

Their findings, known as Prospect Theory, show how economic agents act in contrast with the model of the economic man. Unlike what Perfect rationality would imply, they find that economic agents are not able to immediately interpret infinite amounts of information, but instead constantly rely on heuristics techniques. In addition, economic agents weigh probabilities nonlinearly, and in particular they overweight small probabilities and underweight large ones. Their decision is also "Reference Dependent" meaning that choice may change based on a reference level. This means that the utility of a choice may be influenced by the alternatives against which the choice is weighed[29]. Finally, they find how economic agents tend to be loss averse, meaning that they tend avoid losses more than they seek equivalent gains.

In a revised version of the theory, psychological traits such as overconfidence, projection bias and the effects of limited attention are also noted.

The picture of the economic agents described by Kahneman and Tversky is that of flawed individuals that constantly rely on shortcut for their economic decisions and make economic mistakes not exclusively linked to the lack of knowledge but also linked to own biases and limits.

[28] This paper builds on a decade long collaboration on behavioral biases in economic decisions started with Tversky and Kahneman (1971)

[29] Prospect theory allows for an agent to choose inconsistently. Unlike the previous example the agent who chooses X over Y and Y over Z could prefer Z over X.

1.2.3. Rationality of Markets

The above discussion on the rationality of individual economic agents naturally extends itself to broader questions on whether markets as a whole[30] exhibit rational behavior[31]. The Efficient Market Hypothesis, formulated by Eugene Fama in his review of theoretical and empirical research on the subject of market efficiency, proposes that financial markets are rational in the sense that they fully incorporate all available information into asset prices. According to this view, markets are efficient because arbitrageurs exploit any mispricing, rapidly exploiting and subsequently correcting deviations from fundamental values.

Fama has detailed three possible forms of efficiency:

- In the weak form, a market is considered efficient if its past trading information (like prices, volumes and spreads) does not have any predictive power over future prices. This means that according to the EMH autocorrelation or seasonal patterns shouldn't be present in return series.
- In the semi-strong form, market prices reflect all publicly available information about the priced assets, including news and events related to the priced assets.
- Finally, in the strong form, a market is considered efficient if it incorporates all existing information (public or private) about the priced assets.

In his work, Fama found evidence of all but the strong form of efficiency, which implies that, when transaction costs are taken into account, it is very hard to beat the market through active trading strategies that use publicly available information.

The rational behavior of the market is however debated and subsequent studies about market behavior have found significant issues in the EMH.

Seasonal patterns have been found, like the January effect, which consisted of significantly higher returns in January in small cap stocks, or the weekend effect, which

[30] In complex systems a phenomenon called "emergence" can occur, where a complex entity exhibits properties or behaviors that its individual parts do not have on their own and emerge only when they interact in a wider whole. Theoretically this means that even if individual agents do not exhibit certain characteristics, the wider whole could. As an example, the fact that individual agents cannot quickly process information does not necessarily imply that a whole market cannot quickly process said information.

[31] This is important since if evidence of market inefficiencies are found (for example through autocorrelation), there is a chance that any volatility asymmetry could be attributed to market inefficiencies.

consisted of significantly lower returns on Monday compared to the rest of the week. These effects, however, have disappeared soon after they were discovered.

1.2.4. Behavioral Finance

In response to these anomalies in the EMH and to the findings of Kahneman and Tversky (1979) a new field of study called behavioral finance has emerged.

Behavioral Finance is built on the premise that investors are not always rational, are subject to systematic biases and that these biases do not necessarily cancel each other out in the aggregate but have an influence on the behavior of the whole market.

Decades of academic work from the fields of economics, psychology and neurosciences have found evidence of several biases in human behavior which are both in contrast with the concept of the economic man and with the Efficient Market Hypothesis.

Experimental evidence of overconfidence in humans in a general setting has been found by Fischoff and Slovic (1980), while Gervais and Odean (2001) found overconfidence in a stock investment setting, finding evidence of an individual's gender affecting overconfidence, with males significantly more overconfident than females.

DeBondt and Thaler (1986) find evidence of overreaction to news[32] and find substantial market inefficiencies incompatible even with the weak form of the EMH.

Shefrin and Statman (1985) build on the concept of loss aversion pioneered by prospect theory to find a general disposition (which they dub "disposition effect") to sell winners[33] to early, sell losers too late, and "a general tendency to treat sunk cost as relevant". Odean (2002) tests this effect by analyzing trading records for 10,000 accounts at a large discount brokerage house, confirming a strong preference to realize winners much sooner than losers.

Huberman and Regev (2001), find significant evidence of herding behavior by studying the specific event of a "New York Times" article containing information about a potential cancer drug published weeks prior on "Nature" causing the stock price of us pharmaceutical company "EntreMed[34]" to increase sixfold[35] with the stock settling at a

[32] Particularly important for this work is a the finding of a stronger reaction to negative news compared to positive news.

[33] A "winner" is an asset which has achieved a stronger return than investments of comparable risk, as opposed to a "loser" which would be an asset which has achieved a lower return against its comparables.

[34] Today known as CASI Pharmaceuticals

[35] From $12 to $83

price over 2.5 times higher than the original price for weeks after and remaining at twice the price even after EntreMed was not able to replicate its findings about the drug.

Tversky and Kahneman (1981) find evidence of the effect of framing on the choices of individuals. They find that individuals who are put in front of two problems mathematically identical but differently framed take a different choice based on said framing. They also find that individuals seem to be risk averse when facing possible gains, but risk-seeking when faced with possible losses. In one of the experiments they ran, for example, they find that 84% of people would prefer a sure gain of $240 than a one in four chance of winning $1000, which points toward risk aversion. However, they also find that when the decision revolves around choosing a sure $750 loss or a one in four chance of losing $1000, 87% of people chose the riskier option!

Finally, Lichtenstein et al. (1982) find evidence of miscalibration of probabilities by individuals.

All the biases presented so far show that market participants are far from the ideal “economic man” theorized by classical economics and can act irrationally and not in their best interests. They also show asymmetric reactions to loss, overreaction to news, and herding behavior. Many of these biases can in some way be linked to hypothesized causes of asymmetry[36] in markets.

Today is generally accepted that Behavioral explanation cannot be left out when trying to explain market movements, this is especially true with meme coins rely heavily on community engagement, social media hype, and influencer endorsements rather than fundamental valuation metrics. Memes are a first and foremost a social phenomenon.

1.3. Asymmetric Volatility

The final building block we will need to consider is the concept of asymmetric volatility, which will be exposed in this chapter alongside the main causes of the phenomenon debated in literature.

[36] As an example, the Volatility Feedback Hypothesis which will be treated later assumes the presence of risk premia built in the valuation of an asset, which makes sense only in the case of loss averse investors. Another example is the bias concerning overreaction to news, with markets that tend to have return distribution negatively skewed.
Again, an overconfidence bias may imply a more risk-seeking behavior by agents in a market dominated by a specific demographic (e.g. more males).

1.3.1. What is Volatility

To explain what asymmetric volatility is, a basic explanation of volatility will be introduced first. Volatility refers to the degree of variation in the price of an asset over time and is typically measured by the standard deviation. It's a measure that reflects the level of uncertainty or risk in the market.

The classic formula for the unconditional standard deviation is:

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

Where:

- r_t represents the return at time t
- μ represents the mean return
- T represents the number of observations

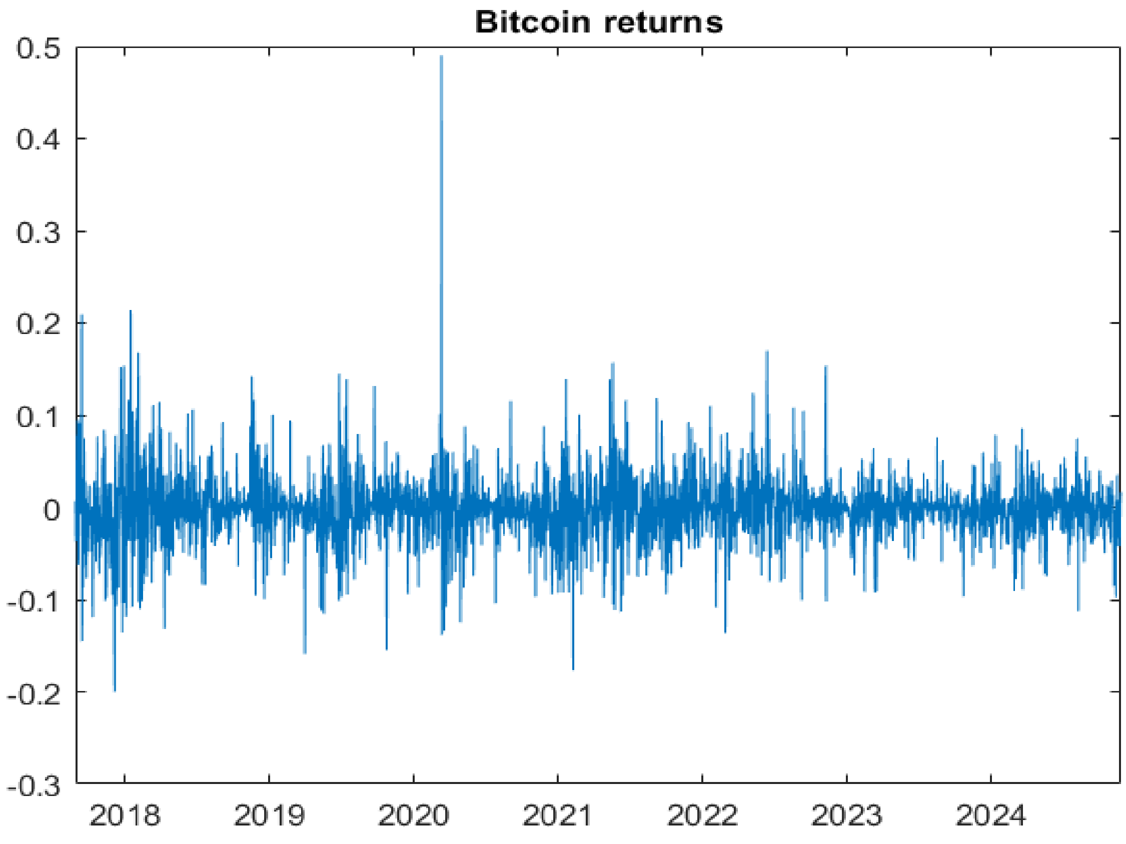

Figure 3 - Bitcoin returns since 2018 – It is easy to notice how large returns tend to be followed by large returns, a phenomenon called Volatility Clustering

Since the 1960's, the literature[37] has noticed that "*large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes*". This phenomenon, dubbed volatility clustering, essentially implies that volatility is persistent and can be conditional on other factors, like past volatility or squared returns.

Engle (1982) used a deterministic approach to model this feature creating the ARCH model, which estimates the conditional variance based on past squared returns.

A significantly improved ARCH class model is GARCH introduced by Bollerslev (1986), which uses not only past square return but also past conditional volatility to estimate the current conditional volatility.

While these approaches were successful, volatility can be conditional on additional factors. For example, volatility can be influenced by internet phenomena. A relevant example here is given by the "Volfefe"[38] index. This index, launched by JPMorgan Chase in 2019 to analyze the impact of then President Trump's tweets on the volatility of US Treasuries.

1.3.2. What is Volatility Asymmetry

Since even before[39] the development of the ARCH model, time series of stock returns have been known for exhibiting a phenomenon dubbed "leverage effect[40]", which consisted in the observation that negative returns tend to increase future volatility more than positive returns of the same magnitude. The existence of this effect implies that variance dependence can extend to the sign of the shock.

Where the reaction to a previous shock changes depending on the sign of the past shocks, we have a phenomenon called volatility asymmetry. We speak of positive volatility asymmetry when positive shocks have a stronger influence on variance than negative shocks of the same size, vice versa with negative variance asymmetry.

Financial time series often exhibit this phenomenon, however its size and sign depend on the asset class object of study. In general stocks exhibit negative variance asymmetry, with past negative returns having a larger effect on conditional variance than positive

[37] Mandelbrot (1963)

[38] A blend of the words "Volatility" and "Covfefe", a tweet from then President Donald Trump famous for being considered nonsensical.

[39] Black (1976)

[40] More on this later

returns, while some exchange rates or a few commodities like gold[41] tend to exhibit a slightly positive variance asymmetry.

Explanations of this phenomena are varied: some, like the *leverage effect* would fit well either in classical literature or in a behavioral finance context, while others only make sense with behavioral finance in mind.

1.3.3. The causes of Asymmetric Volatility

This section will present several hypotheses aimed at explaining the causes behind the phenomenon of volatility asymmetry. If available, it will also discuss the literature concerning asymmetric variance on cryptocurrency.

Several studies have been conducted on asymmetric volatility in regular crypto, however meme coins have rarely been the main subject of attention in these studies, with the focus being mostly on larger cryptos which at most included DOGE. This may partly be due to the fact that some of the main hypotheses of causes of asymmetric variance were built to explain the phenomenon in the stock market and are unsuitable to explain the phenomenon in currencies.

1.3.3.1. Leverage effect

The first hypothesis (and arguably the most famous one) is the so called "Leverage Effect". This hypothesis states that the different effects that positive and negative returns have on stocks are due to the change in leverage[42] that occurs with a change in price. A positive change in price means that the value of the equity grows while the value of the debt stays stable, reducing the leverage of the firm, which thus becomes less risky.

By contrast, a drop in price increases the leverage of the firm, which then becomes more risky and thus more susceptible to any news that can change its price.

The logic is quite solid, however this is an unsatisfactory explanation in a wealth of situations. In general, the leverage argument does not make sense for currencies, commodities, or any sort of quoted asset which doesn't have leverage in the first place.

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[41] Baur (2012)

[42] Expressed as the ratio of debt over equity.

This effect has been theorized by Black (1976), who first introduced the concept of the leverage effect in the context of stock returns.

Evidence on this effect has been found by Christie (1982), who empirically supported the negative volatility-return relationship in stock markets, showing that negative returns tend to lead to higher volatility.

The leverage effect has been the main explanation for variance asymmetry for decades, but it has limits, concerning both its inability to fully explain variance asymmetry[43] and its lack of logic when applied to certain classes of assets, like gold or currencies, which unlike firms cannot have leverage.

1.3.3.2. Volatility feedback Hypothesis

According to Bekaert and Wu (2000), "Studies focusing on the leverage hypothesis, such as Christie (1982) […], typically conclude that it cannot account for the full volatility responses". They thus examine another potential explanation for volatility asymmetry, the Volatility Feedback Hypothesis.

The hypothesis states that a change in volatility can influence returns through the required risk premium. A stock with a higher expected volatility will be riskier and thus require a higher risk premium, leading *ceteris paribus* to a reduction in price. This hypothesis essentially inverts the causality implicit in the Leverage Effect, since it implies that return shocks are caused by changes in conditional volatility, rather than the other way around.

It's interesting to note that the Volatility Feedback Hypothesis' logic does not work well with positive variance asymmetry in a setting where agents are risk averse. Since in this hypothesis the causality is flipped, a positive variance asymmetry would imply larger variances to be correlated to a lower risk premium, a behavior consistent only with risk-seeking behavior.

[43] As found by Christie (1982)

1.3.3.3. *Safe Haven hypothesis*

A third hypothesis has been formulated to explain the asymmetric behavior of goods such as gold or US dollars, whose return series have been found to contain positive variance asymmetry[44].

The so called "Safe Haven" hypothesis states that with certain traded goods able to act as a "store of value", periods of high variance correspond with an increase in demand for those goods. For these goods, periods of high volatility in financial markets are linked with positive returns because investors tend to buy more.

The ability of cryptocurrencies to act as a store of value has been discussed at length, and since the matter has not yet been settled by academia, we cannot refrain from considering this hypothesis as a plausible source of asymmetric volatility in cryptocurrencies as well.

Cheikh, Zaied and Chevallier (2020) study a set of four traditional cryptocurrencies, (Bitcoin, Ethereum, Litecoin and Ripple) finding statistically significant evidence of positive volatility asymmetry on all cryptocurrencies except Ethereum by applying a smooth transition GARCH model[45]. They affirm that their results are consistent with safe haven properties in cryptocurrencies.

1.3.3.4. *Other Explanations linked to human behavior*

Finally, a reason for variance asymmetry could simply be human behavior. As noted in the sections about behavioral biases and behavioral finance, humans do not necessarily act logically, and in fact most of the time they make use of heuristics, some of which may cause asymmetrical responses to a shock. They react asymmetrically to the prospect of gains and losses and are not very good at determining probabilities and consequently risks.

An example of behavioral phenomenon which could potentially generate asymmetric variance behavior has been seen with the Volatility Feedback Hypothesis, which is influenced by the effect of risk aversion on risk premia.

Another behavioral pattern which can be linked to Volatility Asymmetry is herding behavior. Herding behavior can be defined as "*any behavior similarity brought about by*

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[44] Baur (2012)
[45] They also apply other asymmetric variance model which yield the same result.

the interaction of individuals"[46][47]. Park (2011) has hypothesized asymmetric herding behavior as the main driver behind asymmetric volatility pattern in fiat currencies exchange rates.

Finally, another effect considered by the literature is the so-called Fear of Missing Out[48].

The Cambridge dictionary define it as "*a worried feeling that you may miss exciting events that other people are going to, especially caused by things you see on social media*". In essence, it's a psychological effect that compels people to participate in a social phenomenon more for fear of missing it rather than for an actual need.

This concept is in strong contrast to the self-interest characteristic of the economic man. As a reminder, the economic man has no reaction to other individual's consumption or experiences if they do not have an effect on his utility.

Notice also that the fear of missing out can only occur in events perceived as positive, no one would fear missing out a negative event.

Baur and Dimpfl (2018) study a set of 20 traditional cryptocurrencies, finding a negative leverage coefficient for most traditional cryptocurrencies' studies but only three with statistically significant p-values. Regardless, they affirm that "*The findings are consistent with "fear of missing out" (FOMO) of uninformed investors and the existence of pump and dump schemes*". They continue saying that "*if uninformed investors drive up prices due to a fear of missing out in rising markets, volatility will increase by more than in falling markets*." This implies that FOMO effects can be linked exclusively to positive volatility asymmetry.

[46] Park (2011)
[47] Interestingly, FOMO may cause herding behavior.
[48] Term coined by Herman (2000)

2. Analysis Setup

2.1. Data Collection and Processing

This chapter is intended to expose the process of acquisition and manipulation of the data, as well as to share some descriptive statistics about it to better put it into perspective.

2.1.1. Data sourcing

All of the time series data about cryptocurrencies used in this analysis consists of daily prices time series obtained through "Investing.com". The site compiles series of prices from various crypto exchanges, like Binance or BitMart. To maintain the data as consistent as possible, Binance, if available, has been chosen as the preferred exchange of origin of the data. When data from Binance was not available, the criteria has been to download the data from the exchange that was able to produce the longest price series for that specific currency. This approach has been taken to prioritize the length of the price series, since, as it will be explained later more in detail, the length of the price series has been a significant issue. Thus, this compromise is necessary to set up the analysis in the first place, since except DOGE, SHIBA and PEPE, most meme coins remain "niche".[49]

It has to be noted that, since only the most liquid crypto and meme currencies have been taken into consideration in this analysis, we should at worst expect minimal price differences between different exchanges due to the "law of one price".[50]

With this in mind, the data consists of 16 price series, 8 traditional cryptocurrencies and 8 meme coins. All 8 traditional cryptocurrencies in this analysis (BTC, ADA, AVAX, BNB, ETH, SOL, TRX, XRP) and four meme coins (DOGE, PEPE, SHIB, WIF) have been obtained from Binance. In addition, price series have been downloaded from LBank (FLOKI), BitMart (BONK) and Gate.io (BRETT, POPCAT).

[49] This is despite the multi-billion dollar capitalizations of many of these meme coins. To put this data point into perspective, consider how Bitcoin alone has a capitalization close to two trillion dollars at the time of writing.

[50] The Law of One Price asserts that in efficient markets with no trade barriers or transaction costs, identical goods will have the same price when expressed in a common currency.

2.1.2. Data Manipulation

The next section will explain how the obtained raw data has been manipulated in order to make it useful for the analysis required for this work.

First, it has to be noted that of all the downloaded series, three (BRETT, POPCAT and WIF) have been excluded from the analysis, since the small length of the series (well under 500 days each), was not deemed sufficient[51].

Secondly, only data between the 26/06/2023 (when the shortest series taken into consideration starts) and 24/11/2024 (date of download of the data) have been considered.

Third, close prices have been compiled into a single dataset from which log returns have been calculated.

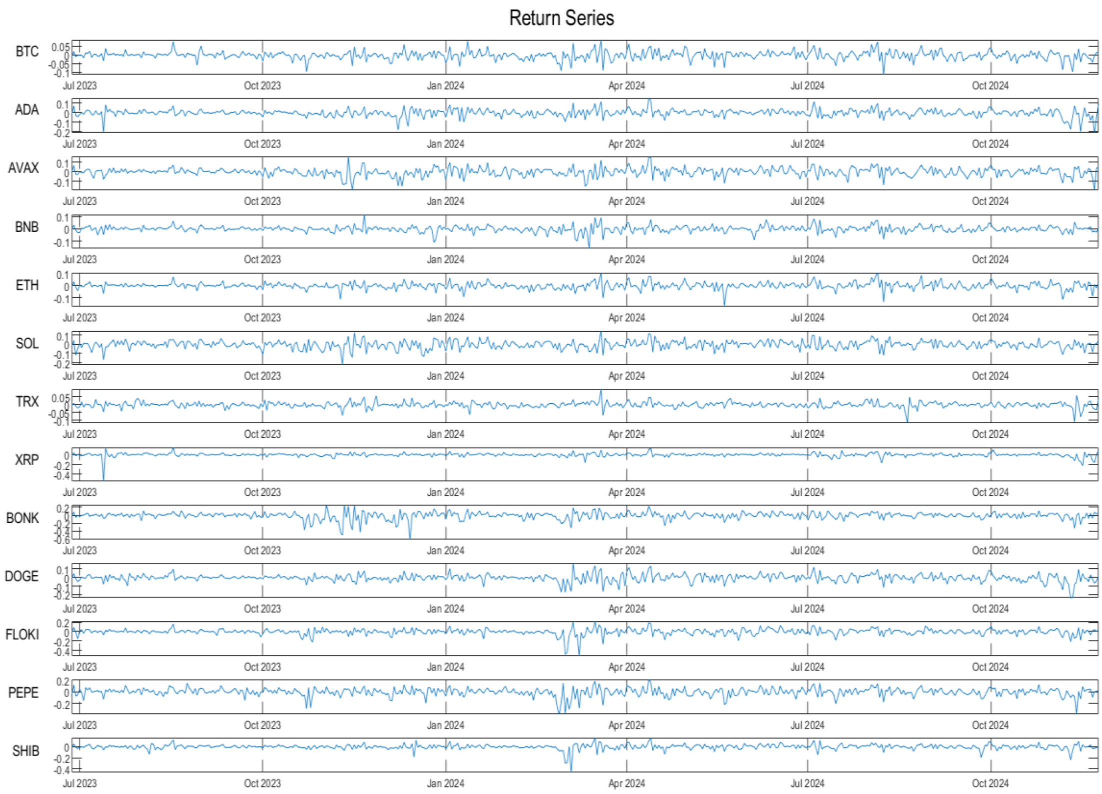


Figure 4 - Return series for all cryptocurrencies considered in the sample

[51] The MATLAB functions used to estimate the model utilize Maximum Likelihood, which works best with larger samples.

2.1.3. Descriptive statistics

Follows a table containing the main descriptive statistics about the returns. Some surface level considerations about the data can be made. First all means of the dataset are negative. This is not particularly surprising since the period taken into consideration is quite short and cryptocurrencies' returns tend to be move together. The fact that some medians are positive implies some left skewness in the distribution of returns, confirmed by the negative skewness measure itself in the table. This is consistent with a well-known stylized fact about financial return series being usually negatively skewed.

	Mean	Median	Variance	Skewness	Kurtosis
BTC	-0.0022	-9.1612e-04	6.3611e-04	-0.3961	5.5322
ADA	-0.0024	0	0.0016	-0.8748	8.0593
AVAX	-0.0021	2.6770e-04	0.0021	-0.4414	4.8252
BNB	-0.0019	-0.0015	7.2987e-04	-0.4453	7.3475
ETH	-0.0011	-4.9577e-04	8.8501e-04	-0.5926	7.3911
SOL	-0.0053	-9.9896e-04	0.0021	-0.4577	4.2867
TRX	-0.0020	-0.0022	3.7490e-04	-0.6088	9.5044
XRP	-0.0020	-2.0444e-04	0.0018	-4.4748	56.2410
BONK	-0.0093	0	0.0090	-1.6275	9.7341
DOGE	-0.0036	-0.0015	0.0021	-0.7051	6.7614
FLOKI	-0.0043	1.2205e-04	0.0050	-1.9931	15.0813
PEPE	-0.0050	0	0.0056	-1.3241	7.5755
SHIB	-0.0024	0	0.0026	-2.5493	21.9765

Another point that I would like to highlight is the unconditional variance. Maintaining in mind the caveat that our sample is quite small and covers only a period of 500 days, we can notice that the variance of meme coins is close to four times that of traditional cryptocurrencies. Additionally, while there is large variation in excess kurtosis, all return distributions are leptokurtic (fat-tailed), which is standard in financial return distributions.

	Mean	Median	Variance	Skewness	Kurtosis
Crypto	-0.0024	-7.6033e-04	0.0013	-1.0364	12.8984
Memecoins	-0.0049	-2.6863e-04	0.0049	-1.6398	12.2257

2.1.4. Data testing

Several standard statistical tests have been performed on the log-return series obtained. First, a Jarque-Bera test was conducted to assess normality. As typically expected from financial return series, the assumption of normality has been strongly rejected in all series, with all p-values lower than 0.001. This was expected also because the descriptive statistics previously shown would have been incompatible with the assumption of normality.

Subsequently, a Ljung-Box test has been performed to assess autocorrelation. The null hypothesis of non-autocorrelation has been rejected on one cryptocurrency (BNB), and two meme coins (BONK and FLOKI)[52]. This is by itself interesting, since it suggests that these markets may not even have weak form efficiency as described by Fama. Since as will be explained later, our models assume non autocorrelation, this effect will need to be sterilized.

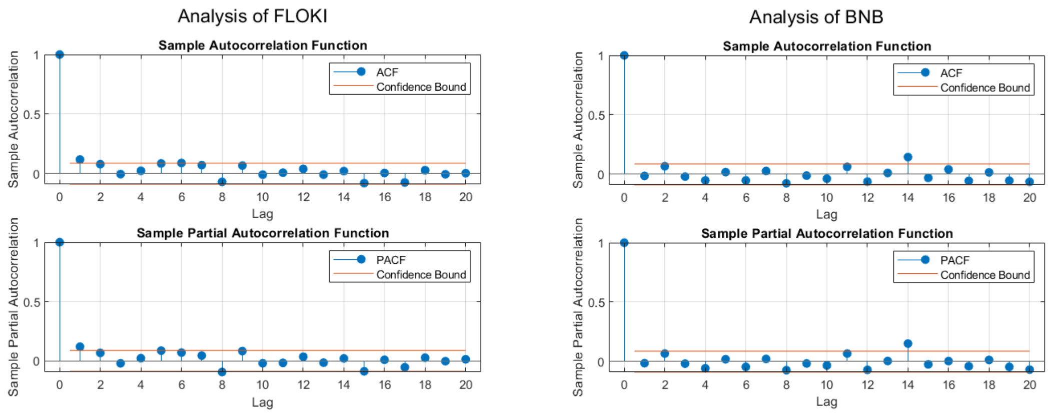


Figure 5 – Auto correlograms of FLOKI and BNB

Finally, an ARCH test has been performed. This test checks for the presence of ARCH effects (and consequently volatility clustering) in the time series tested. As typical of financial returns series, the null hypothesis which states that ARCH effects are not present, is strongly rejected for all series but XRP.

	LB Logical	LB Pvalue	JB Logical	JB Pvalue	AT Logical	AT Pvalue
BTC	0	0.5092	1	1.0000e-03	1	0.0255
ADA	0	0.3442	1	1.0000e-03	1	0.0029

[52] For brevity, only the auto-correlogram and partial auto-correlogram of BNB and FLOKI has been shown. Auto-correlograms for all other cryptocurrencies in the sample can be found in Appendix B

	LB Logical	LB Pvalue	JB Logical	JB Pvalue	AT Logical	AT Pvalue
AVAX	0	0.6419	1	1.0000e-03	1	1.8482e-06
BNB	1	0.0433	1	1.0000e-03	1	3.5316e-05
ETH	0	0.6697	1	1.0000e-03	1	0.0415
SOL	0	0.6608	1	1.0000e-03	1	0.0013
TRX	0	0.2424	1	1.0000e-03	1	1.1245e-09
XRP	0	0.4973	1	1.0000e-03	0	0.1635
DOGE	1	3.5158e-05	1	1.0000e-03	1	1.2722e-07
BONK	0	0.1900	1	1.0000e-03	1	0
FLOKI	1	0.0214	1	1.0000e-03	1	1.2656e-08
PEPE	0	0.0601	1	1.0000e-03	1	5.9499e-06
SHIB	0	0.1965	1	1.0000e-03	1	0.0047

2.2. Model Selection and Calibration

Two specular analyses will be performed on two separate asymmetric variance models, which will be briefly described here.

2.2.1. GJR-GARCH

The first model is GJR-GARCH, first detailed by Glosten, Jagannathan and Runkle (1993) with the aim of studying the leverage effect of monthly stock return.

The model is a modified GARCH model which adds an additional parameter "gamma" that takes into account the sign of the shock. The GJR-GARCH(1,1) model is described by these two equations:

$$\text{Mean Equation: } r_t = \sqrt{\sigma_t^2} z_t \qquad z_t \sim D(0,1)$$

$$\text{Variance Equation: } \sigma_t^2 = \omega + \alpha r_{t-1}^2 + \gamma r_{t-1}^2 I_{t-1}^- + \beta \sigma_{t-1}^2$$

Where:

- r_t is the conditional mean of series.
- σ_t^2 is the conditional variance.
- z_t is an error term
- D is a distribution such that $P(z < 0) = P(z > 0) = 0.5$
- ω, α, β are positive parameters
- γ is the asymmetric parameter that can be either positive or negative

- I_{t-1}^{-} is a dummy equal to 1 when $r_{t-1} < 0$ and equal to 0 when $r_{t-1} > 0$

The GJR-GARCH model allows for volatility asymmetry to be measured through the γ parameter, which thanks to the dummy variable is present only when negative fluctuations occur and is multiplied by 0 when positive ones occur. This effectively makes the parameter linked to the size of the shock equal to either α when $r_{t-1} > 0$ or $\alpha + \gamma$ when $r_{t-1} < 0$, allowing the effect on the variance to change based on the sign of the shock.

In short:

- $\gamma > 0$ means that negative returns amplify the variance more than positive returns
- $\gamma < 0$ means that positive returns amplify the variance more than negative returns
- $\gamma = 0$ means that the model is symmetric and degenerates into a classic GARCH model

2.2.2. EGARCH

The second model considered is the EGARCH(1,1) model[53]. This model is also defined by two equations:

$$\text{Mean Equation: } r_t = \sqrt{\sigma_t^2} z_t \qquad z_t \sim D(0,1)$$

$$\text{Variance equation: } log\sigma_t^2 = \omega + \alpha\left(\frac{|r_{t-1}|}{\sigma_{t-1}} - m\right) + \gamma\frac{r_{t-1}}{\sigma_{t-1}} + \beta log\sigma_{t-1}^2$$

Where:

- r_t is the conditional mean of series
- σ_t^2 is the conditional variance
- z_t is an error term
- D is a distribution
- ω, α are parameters. They are allowed to have any sign
- $\beta \in (0,1)$ and represents the persistence of the model
- γ is the asymmetric parameter that can be either positive or negative
- m is $\mathbb{E}|z_t|$.

[53] Introduced by Nelson (1991)

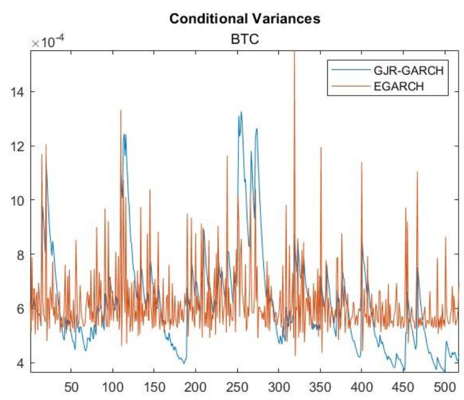
The mean equation is identical to that of our GJR-GARCH model, while the variance equation is quite different, particularly concerning the log specification of the variance. This specification ensures that the variance will be always positive, so the positivity restrictions on ω and α are removed.

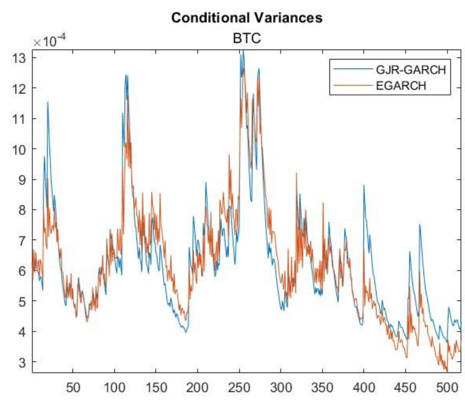
Notice that, unlike the GJR-GARCH(1,1) model, the interpretation of the sign of γ is inverted:

- $\gamma < 0$ means that negative returns amplify the variance more than positive returns
- $\gamma > 0$ means that positive returns amplify the variance more than negative returns

The EGARCH(1,1) model has been used for all series except BTC. Usually EGARCH(1,1) and GJR-GARCH(1,1) tend to track the conditional variance quite well, however in some cases the models may not work well with a specific series. This has happened with BTC, where the EGARCH(1,1) estimation of the variance has resulted too erratic when compared to those obtained by GJR-GARCH. To solve the issue EGARCH(2,1) was used for BTC instead.

The following images show the different behavior of the EGARCH(1,1) model (on the left side) against the EGARCH(2,1) model (on the right side). The conditional variance estimated through GJR-GARCH(1,1) is shown in both charts. Notice how the conditional variance estimated by the EGARCH(2,1) follows much better the conditional variance found by GJR-GARCH(1,1), compared to an extremely erratic behavior from EGARCH(1,1)[54].





[54] Charts of all the conditional variances estimated can be found in appendix B

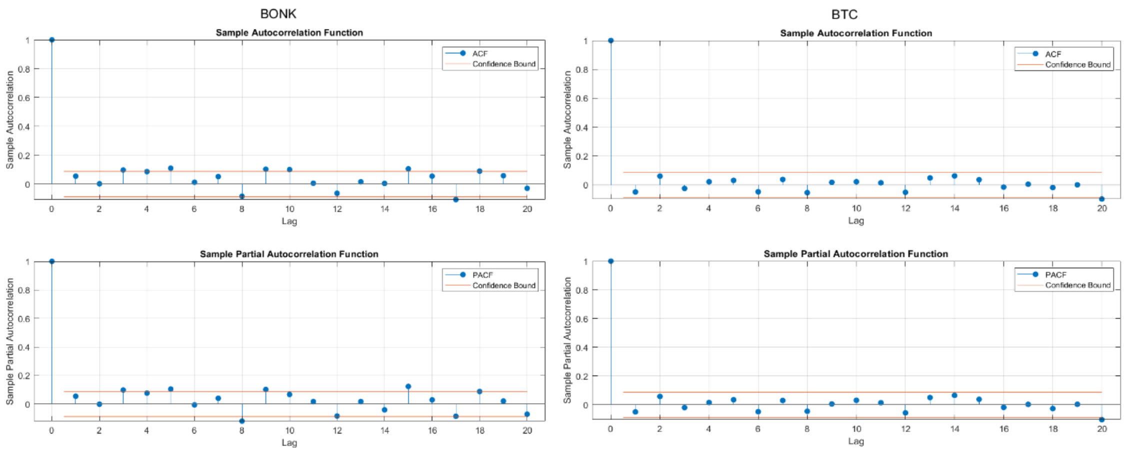
The outlined models define a process where returns are not autocorrelated, but squared returns are. This doesn't well align with some of our data, where in three series, (BNB, BONK and FLOKI) autocorrelation has been found through a Ljung-Box test. Additionally in most series, auto-correlograms show autocorrelation in some early lags (some until lag 5).

2.2.3. ARMA

Our models assume the conditional mean as not autocorrelated. So, to proceed with volatility estimation using the models we outlined, we must first sterilize our series of autocorrelation. To do this, we employ a series of ARMA models, one tailored for each series. Unlike GARCH class models, ARMA models can often require using data from several lags to be satisfactory, however estimating too many parameters is undesirable, so to choose each model has been used a combination of Information Criteria and analysis of auto-correlograms.

First, the Akaike Information Criterion has been estimated for each combination of model between ARMA(0,0)[55] and ARMA(3,3) for each cryptocurrency.

A Ljung-Box test has been conducted on the residuals of the best performing models, however one series (BONK)[56] retained some autocorrelation. An inspection of the autocorrelogram and partial-autocorrelogram has shown a strong autocorrelation in lag "t-5"[57], so the model has been adjusted to an ARMA(5,5) to account for that.



55 This would correspond to White Noise
56 Notice how BONK exhibits significantly more autocorrelation compared to Bitcoin
57 Note that since the data contains all days of the week and not only work-days, a significant autocorrelation at t-5 cannot be considered evidence of weekly seasonality

3. Presentation and Analysis of the results

This chapter will present the results of the analysis, its shortcomings, and hypothesis which would require further study.

3.1. Findings: Traditional Crypto vs. Meme Coins

Starting with the GJR-GARCH model, it can be noted that all gamma coefficients found are negative except for BTC and ETH. However, no traditional cryptocurrency has statistically significant gamma coefficient at the 5% level[58]. This is in contrast with meme coins, three of which have gammas with very low p-values, well under 1%.

Another important consideration is the size of the effect. On average, traditional cryptocurrencies have gammas of around -0.0368, with the only (relatively) large values belonging to AVAX and TRX. By contrast, meme coins sport a significantly larger average gamma coefficient of -0.1848.

These findings indicate that meme coins on average tend to have a larger conditional volatility after a positive shock as opposed to a negative one.

	BTC	ADA	AVAX	BNB	ETH	SOL	TRX	XRP	BONK	DOGE	FLOKI	PEPE	SHIB
γ	2.0e-12	-0.1401	-0.0603	-0.0197	0.1458	-0.0674	-0.1459	-0.0071	-0.1810	-0.1006	-0.2171	-0.0961	-0.3291
p	1.0000	0.0509	0.2112	0.7254	0.1183	0.1517	0.0670	0.9406	8.9e-05	0.1234	0.0032	0.2842	4.2e-07

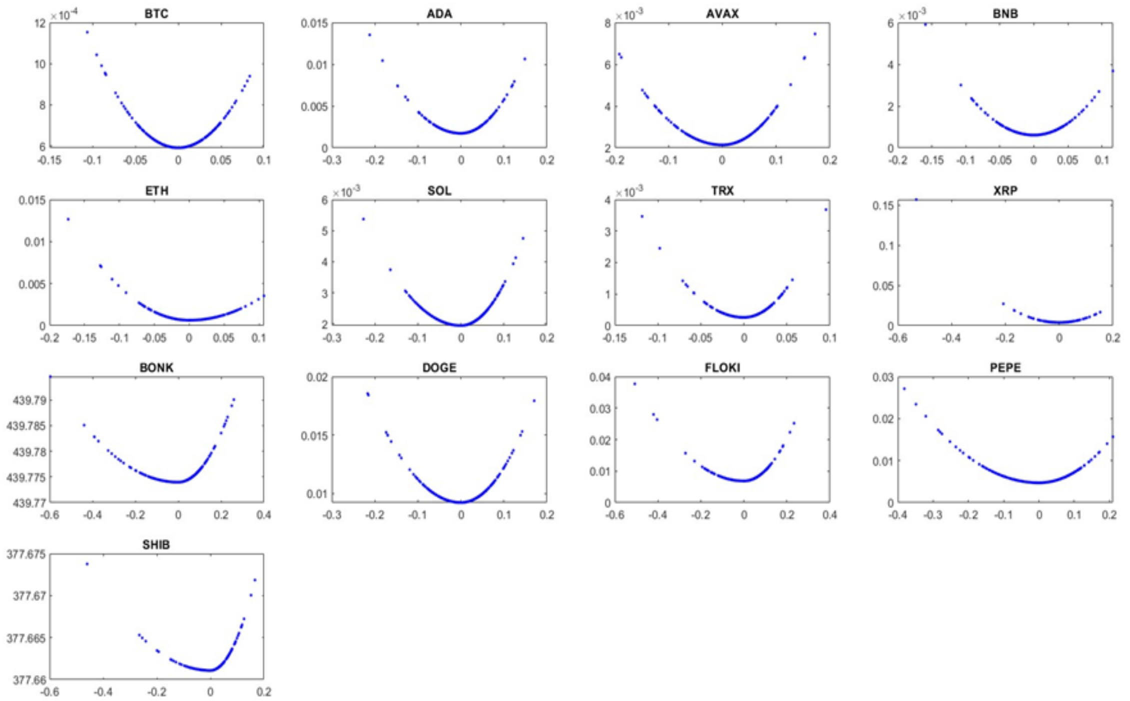
The EGARCH model results paint a less conclusive picture. Here most gammas are positive, which is coherent with the GJR-GARCH results since the interpretation of the sign of the coefficient for the EGARCH is different, as explained in Chapter 2.

This time however, two traditional cryptos and two meme coins have gamma coefficients with p-values under 5%, and the averages of the coefficients are much closer, with traditional cryptos' gammas having an average of 0.03 against an average of 0.06 for

	BTC	ADA	AVAX	BNB	ETH	SOL	TRX	XRP	BONK	DOGE	FLOKI	PEPE	SHIB
γ	0.0177	0.0719	0.0042	0.0878	-0.0315	0.0309	0.0297	0.0423	0.1194	7.3e-04	0.0135	0.0466	0.1335
p	0.6367	0.0294	0.9011	0.0163	0.4225	0.3293	0.4585	0.2173	3.0e-06	0.9831	0.7507	0.3293	4.9e-06

[58] Note however that ADA and TRX would be significant at the 10% confidence level

The difference in asymmetric volatility can be visualized through the News Impact Curves[59] presented below:



Notice how the effect of a positive shock in BONK, SHIB and FLOKI is significantly stronger than that of a negative shock of the same size.

3.2. Diagnostics

Several diagnostics tests have been conducted on the standardized residuals of the models employed.

First a Ljung-Box test has been taken on standardized residuals. The null hypothesis of non-autocorrelation cannot be rejected for any standardized residuals series of any model.

A Jarque-Bera test has been conducted as well to check for the adherence of the standardized residuals to the normal distribution. Here the null hypothesis of normality is

[59] The News Impact Curves, (introduced by Engle and Ng 1993) are a graph that show the effect that a shock can have on the system when starting from a variance at unconditional levels. With a pure GARCH model a symmetric parabola can be expected, while with the GJR-GARCH models, the curve assumes the shapes of two half parabolas with different curvatures which meet at 0. The starker the difference between the two halves, the stronger the asymmetric effect in the model.

forcefully rejected in all residual series, meaning that the residual distribution is significantly different than the one assumed by the data.

Finally, an LM-ARCH test has been performed on standardized residuals, with the aim of finding any unexplained arch effect in the series. The test cannot reject the null hypothesis of absence of ARCH effects in the residuals at any conventional significance level, implying that the models capture well any volatility clustering in the series.

GJR-GARCH – Normal Distribution

	Logical LBQ	p-value LBQ	Logical JB	p-value JB	Logical ARCH T	p-value ARCH T
BTC	0	0.8838	1	1.0000e-03	0	0.7560
ADA	0	0.7650	1	1.0000e-03	0	0.2987
AVAX	0	0.8223	1	1.0000e-03	0	0.9757
BNB	0	0.9226	1	1.0000e-03	0	0.2155
ETH	0	0.8317	1	1.0000e-03	0	0.4581
SOL	0	0.7708	1	1.0000e-03	0	0.4323
TRX	0	0.7138	1	1.0000e-03	0	0.3002
XRP	0	0.3816	1	1.0000e-03	0	0.2457
BONK	0	0.5399	1	1.0000e-03	0	0.6184
DOGE	0	0.3068	1	1.0000e-03	0	0.3224
FLOKI	0	0.8384	1	1.0000e-03	0	0.8265
PEPE	0	0.8667	1	1.0000e-03	0	0.3537
SHIB	0	0.4256	1	1.0000e-03	0	0.7503

EGARCH – Normal Distribution

	Logical LBQ	p-value LBQ	Logical JB	p-value JB	Logical ARCH T	p-value ARCH T
BTC	0	0.8975	1	1.0000e-03	0	0.8153
ADA	0	0.8319	1	1.0000e-03	0	0.2062
AVAX	0	0.7700	1	1.0000e-03	0	0.8468
BNB	0	0.4644	1	1.0000e-03	0	0.4557
ETH	0	0.8270	1	1.0000e-03	0	0.5326
SOL	0	0.7682	1	1.0000e-03	0	0.4849
TRX	0	0.5745	1	1.0000e-03	0	0.5420
XRP	0	0.3720	1	1.0000e-03	0	0.5631
BONK	0	0.5983	1	1.0000e-03	0	0.7175
DOGE	0	0.3527	1	1.0000e-03	0	0.2154
FLOKI	0	0.8836	1	1.0000e-03	0	0.9181
PEPE	0	0.8674	1	1.0000e-03	0	0.4291
SHIB	0	0.4332	1	1.0000e-03	0	0.6729

Given the large excess kurtosis mentioned in the section dedicated to the descriptive statistics and the poor adherence to the normal distribution by the residuals, an alternative specification assuming a t-distribution has been considered for both models. The adherence of the standardized residuals of the alternative specification to the t-distribution have been tested through a Kolmogorov-Smirnoff test. With one exception for each model, the null hypothesis of adherence to the t-distribution is rejected.

While these rejections are less "forceful" when compared to the rejection of the normality assumptions by the Jarque-Bera test in the previous table, the use of the t-distribution introduces issues of its own. In particular, the LM-ARCH test has been employed on the standardized residuals of all models tested, with the null never rejected in models assuming the normal distribution, against 2 rejections in the t-distribution GJR-GARCH and 3 in the corresponding EGARCH. What this means in practice is that the t-distribution models sometimes fail to capture all the volatility clustering present in a series, as opposed to the normal models which seem to capture it quite well.

GJR-GARCH – t-distribution

	Logical LBQ	p-value LBQ	Logical KS	p-value KS	Logical ARCH T	p-value ARCH T
BTC	0	0.8254	1	1.7532e-05	0	0.6270
ADA	0	0.7477	1	8.6498e-04	0	0.0530
AVAX	0	0.8076	1	0.0196	0	0.8757
BNB	0	0.9131	1	7.9158e-05	1	0.0431
ETH	0	0.8385	1	3.6124e-05	0	0.4573
SOL	0	0.7747	0	0.1648	0	0.3943
TRX	0	0.6745	1	0.0028	1	0.0443
XRP	0	0.3304	1	7.3591e-11	0	0.0890
BONK	0	0.5370	1	0.0016	0	0.5936
DOGE	0	0.3882	1	0.0028	0	0.0855
FLOKI	0	0.8557	1	4.2539e-04	0	0.7215
PEPE	0	0.9046	1	0.0021	0	0.4909
SHIB	0	0.4963	1	2.2987e-05	0	0.8096

EGARCH – t-distribution

	Logical LBQ	p-value LBQ	Logical KS	p-value KS	Logical ARCH T	p-value ARCH T
BTC	0	0.8267	1	2.4120e-05	0	0.5427
ADA	0	0.7944	1	0.0027	1	0.0157
AVAX	0	0.7663	1	0.0307	0	0.8102
BNB	0	0.8968	1	6.0803e-05	1	0.0115
ETH	0	0.8335	1	1.1027e-05	0	0.5762
SOL	0	0.7719	0	0.1459	0	0.4496
TRX	0	0.5679	1	0.0060	0	0.0729

	Logical LBQ	p-value LBQ	Logical KS	p-value KS	Logical ARCH T	p-value ARCH T
XRP	0	0.3108	1	2.1333e-11	0	0.6141
BONK	0	0.5794	1	0.0016	0	0.6847
DOGE	0	0.4524	1	0.0016	1	0.0234
FLOKI	0	0.8942	1	9.1259e-04	0	0.9292
PEPE	0	0.8869	1	0.0028	0	0.6121
SHIB	0	0.4774	1	2.2692e-05	0	0.8960

3.3. Hypothesis on results

This chapter will contain hypotheses on the results obtained by the models, based on the reported causes of asymmetric volatility in Chapter 1.3.2. We will check the coherence of those causes of asymmetric volatility against the results obtained and with the characteristics of meme coins reported before.

3.3.1. Interpretation of Asymmetric Volatility Observations

The first thing to note is that, as reported previously, the leverage hypothesis cannot work as an explanation of asymmetric volatility in meme coins since the concept of leverage does not make sense for currencies. Even if we were to disregard this simple fact, we have obtained evidence of positive variance asymmetry, which directly contradicts the logic behind the leverage hypothesis, which works only with negative asymmetry.

For the same reason, the findings are not coherent with the classic interpretation of the Volatility Feedback Hypothesis. The Volatility Feedback Hypothesis says that a higher variance should lead to lower returns on average, boosting negative returns and depressing positive ones. This means that if the Volatility Feedback Hypothesis was correct, we would expect a negative volatility asymmetry instead of a positive one. It is important to note that these results could make sense in the context of the Volatility Feedback Hypothesis if investors in meme coins tend to be risk-seeking (and would thus require a negative risk premium).

The findings are theoretically coherent with the Safe Haven Hypothesis (which requires positive variance asymmetry), however the properties of the assets object of study are not. As mentioned before, meme coins have a variance close to four times larger than that of regular cryptocurrencies and tend to have explosions in value followed by constant depreciation.

In general, our finding cast doubts on the Safe Haven Hypothesis for cryptocurrencies, as the assets in our sample with the larger asymmetric variance (meme coins) are the ones which would arguably make less sense as safe havens when compared to the rest.
Finally, our findings are perfectly coherent with an explanation linked to FOMO events and herding behavior. As mentioned, FOMO effects can be linked to positive asymmetric variance. An explanation linked to FOMO or herding is also quite coherent with the asset class studied, since as mentioned previously, the value of meme coins is linked to the virality of the meme starred.

3.4. Implications for portfolio management

The above findings have some implications concerning portfolio selection and the management of tail risks when investing in cryptocurrencies, which any portfolio manager interested in the asset class would need to take into consideration.

First, large asymmetries in volatility need to be considered when constructing or rebalancing a portfolio. In particular, Low et al. (2016) find that taking into consideration asymmetries[60] in the return distribution of stocks with leverage effects, significantly improves the performance of portfolios constructed using Mean-Variance based criteria for weight selection.

Concerning tail risks, portfolio managers rely on measures which are calculated through the variance. One of the most common indicator of risk is the Value at Risk, a measure[61] that, assuming a given distribution of returns[62], indicates the worst loss in a specific time horizon which will not be exceeded given a specific level of confidence[63].

For example, assuming a return series with normally distributed shocks[64]:

$$r_t = \mu_t + \sigma_t z_t \quad z_t \sim N(0,1)$$

[60] In addition to variance asymmetries, they consider returns asymmetry and asymmetric dependence (meaning changes in correlation among assets during downturns).
[61] Another useful measure which relies on the variance is the Expected Shortfall which instead of a specific quantile, is the expected value of the tail of the return distribution under a specific quantile.
[62] Some methods, like Conditional Autoregressive VaR model by Engle and Manganelli (2004) compute directly the VaR without assuming a distribution.
[63] To give an example, a monthly VaR of $1 million at a 5% level of confidence would mean that we would expect to lose next month more than $1 million only in 5% of all possible cases.
[64] This assumption tends to be incorrect with most return distributions, as noted previously.

$$VaR_t(\alpha) = -[\mu_t + \sigma_t \Phi^{-1}(\alpha)]$$

Where:

- r_t are the return series
- μ_t is the average of the return series
- σ_t is the conditional standard deviation of the return series
- z_t is an error term distributed as a standard normal
- $\Phi^{-1}(\alpha)$ is the α-quantile of the inverse of the cumulative normal distribution
- $VaR_t(\alpha)$ is the α-quantile of the distribution of returns

A VaR calculation performed with the formula above needs a conditional standard deviation, which could be estimated through ARCH class models. However, if as we found with meme coins, positive variance asymmetry is present, a simple GARCH model may overestimate the variance following a negative return and underestimate it following a positive return, leading to incorrect estimation of the indicator and consequently, incorrect assessment of the risks.

3.5. Shortcomings of the analysis

This section is intended to describe the shortcomings of the analysis performed in this work.

3.5.1. Small sample

The Analysis has been conducted on a small sample of Memecoins. This is due to the how new most meme coins are. In fact, while DOGE has been created in 2013, and SHIB has been created in 2020, all other meme coins considered are less than 3 years old at the time of writing. In addition, a newly created currency takes time to be added to a large exchange like Binance, which reduces further the length of the time series. Finally, the phenomenon remained relatively niche until the explosion of the price of DOGE in late 2021. The combination of these factors has made it difficult to find time series data sufficiently reliable and with enough data points to not suffer from small sample issues in the estimation of the GARCH models.

While this is fine for an analysis geared towards shedding light on a new phenomenon, this also means that these results are far from conclusive and should instead be considered an invite to further research.

3.5.2. Change of the coefficients through time

This analysis cannot be considered “evergreen”. The market can mature and change over time, and as a consequence models trying to describe said market have to be updated too.

With time, coins currently considered “Meme” could mature enough to simply be considered “normal” cryptocurrency and thus lose the strong variance asymmetry found in this work.

3.5.3. Structural breaks

Aharon et al. (2023) found large asymmetric variances in traditional cryptocurrencies when applying structural breaks to the asymmetric models[65]. When breaks are not taken into account, they find that the asymmetric volatility found is much weaker.

This work and does not take into account structural breaks since the focus was on a relatively short time frame, around 500 days[66], which reduces the risk of structural breaks in the series.

3.5.4. Size Bias

As explained in paragraph 3.1.1, since the meme coin phenomenon is relatively recent and since at the time of writing, long price series for these coins are hard to find even for relatively high capitalization meme coins, only the most successful meme coins have been studied.

This means that this analysis cannot actually infer information general on the whole meme coin market but only on the largest coins, which can at most be seen as a proxy of the whole market. The behavior of the variance may be very different for low capitalization meme coin which would require further study.

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[65] This fact held true in all models used by them

[66] By contrast, the analysis of Cheikh, Zaied and Chevallier (2020) covers five years.

It has however to be considered that successful meme coins end up being the vast majority of meme coin in existence by capitalization precisely because of their success, so a study on successful meme coin is in some way a study valid to describe the meme coin market when observed in terms of capitalization.

3.5.5. Focus on the dollar

This analysis has been focused on the exchange rates between the studied cryptocurrencies and the Dollar, which is also an asset susceptible changes in value against other currencies. In theory there is no reason to prefer the dollar against any other currency except for its ubiquitousness. Swings in value of the dollar are not as large any swings due to the cryptocurrency subject of study itself, but a more comprehensive analysis would need to take into account other exchange rates with other major traditional currencies like the one with the Euro or the Yen.

Conclusions

This work has studied the volatility asymmetry associated with meme coins, using two different asymmetric GARCH model, GJR-GARCH and EGARCH. The findings of this work imply the presence of a much stronger volatility asymmetry in meme coins when compared to traditional cryptocurrencies. As meme coins can hardly be considered a store of value due to their value being linked to the popularity of internet phenomena with a limited lifespan, the results of this work favor the FOMO effect and other behavioral components (like herding) as the main driver of asymmetry.

However, other factors not considered in this work may be at play. In addition, due to poor availability of data, the size of the sample and the simplicity of the models used, the result of this work cannot be conclusive and need to be backed up by future research.

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Appendix A: Summary

Introduction

Since Bitcoin's introduction cryptocurrencies have become a multi trillion dollar market, with meme coins emerging as a subset impossible to ignore. Meme coins remain under-researched, as studies typically focus on traditional cryptocurrencies, but given their growing footprint in crypto markets and how prior research has shown significant evidence of volatility spillovers between crypto markets and stock markets, there is a need to study meme coins' variance behavior.

Currency, Cryptocurrencies and Meme coins

Currency is a component of money, which in itself has no universal definition. It must serve as a store of value, unit of account, and medium of exchange. Trust in money's ability to fulfill these roles is essential for it to be universally accepted and ideally a currency should be able to act as money and be able to perform its main functions.

Cryptocurrencies are decentralized digital currencies that work on computer networks using cryptography and Distributed Public Ledgers. While decentralized money has historical precedents (e.g., Rai Stones of Yap), Bitcoin was the first successful digital version. Since its inception, thousands of cryptocurrencies have emerged, with a market capitalization currently exceeding $3 trillion. Cryptocurrency's ability to function as money is questionable. While they could theoretically act as a medium of exchange, they are mostly held as a speculative asset. This worsens their already high volatility, which makes them a poor unit of account, as prices are forced to adjust constantly.

This, in turn, affects their ability to store value.

A good's ability to store value can be attributed to its inelastic supply and intrinsic value. Cryptocurrencies often have inelastic supply, but there is a debate concerning their intrinsic value (or lack thereof). Treiblmaier (2022) argues that intrinsic value in cryptocurrencies is tied to their use as payment systems and the energy and hardware costs of mining. In addition, despite extreme short-term volatility, Baur and Dimpfl (2021) suggest Bitcoin's long-term trend and deflationary design support its store-of-value characteristics. Since this question remains unsettled, any asymmetric variance analysis must account for cryptocurrencies' potential role as a store of value.

Among cryptocurrencies we find “meme coins”, tokens which function like other cryptocurrencies but which are each strongly tied to a specific internet phenomenon. Their value is strongly influenced by the popularity of the meme they represent, leading to extreme volatility and sudden boom-bust cycles. Despite their speculative nature they have gained mainstream attention, but their much larger volatility even compared to traditional cryptocurrencies, and their link to internet phenomena which tend to become irrelevant over time, make them a particularly poor store of value.

Theory of Market Behavior

The model of the economic man, dominant until the 1970s, assumes economic agents to be perfectly rational, self-interested, and focused on maximizing their utility. Kahneman and Tversky (1979) have challenged this model with Prospect Theory, showing that people usually rely on heuristics, are loss-averse, and prone to biases. Further studies have found evidence of overconfidence, overreaction to news, herding behavior, and framing effects. These findings show how economic decisions are often irrational and influenced by shortcuts instead of perfect reasoning. While the fact that imperfect human reasoning impairs the efficiency of markets as a whole is debated, market anomalies like the January effect and weekend effect suggest that inefficiencies exist in practice. If markets are not efficient, these biases can affect volatility asymmetry by causing disproportionate reactions to gains and losses.

Asymmetric Volatility

Volatility asymmetry refers to the different reaction of the variance against shocks of the same size but of different signs. It has multiple proposed explanations.

The leverage effect hypothesis suggests that since falling stock prices increase leverage, firms become riskier and that raises volatility. This theory fails for non-leveraged assets like gold and currencies. The volatility feedback hypothesis instead inverts the causality, arguing that since with risk averse agents a predicted higher volatility requires a higher risk premium, *ceteris paribus* prices and thus returns tend to be lower.

The safe haven hypothesis states that assets like gold or the US dollar rise in volatile times due to their perceived ability to store value which, as mentioned, may also apply to cryptocurrencies.

Behavioral finance explanations include Fear Of Missing Out, where uninformed investors chase rising markets, driving up volatility more after positive shocks, and herding behavior..

Data Collection and Processing

The raw data in this analysis consisted of 13 price series, 8 Traditional Cryptocurrencies series and 5 Meme coins daily series from "investing.com". The data has been transformed in log-returns and has been tested for autocorrelation (present in three series), normality (always rejected) and ARCH effects (always present with one exception).
The models used are GJR-GARCH and EGARCH, both models that allow asymmetric conditional variance behavior through a gamma coefficient. Since they assume non autocorrelation of the return series, the models have been estimated on the residuals of ARMA models tailored to each series through Akaike Information Criterions and inspection of correlograms.

Findings: Traditional Crypto vs. Meme Coins

For GJR-GARCH, all gamma coefficients except two show positive variance asymmetry, but only three meme coins out of five have statistically significant asymmetry coefficients and no traditional cryptocurrency has statistically significant coefficients at the 5% level

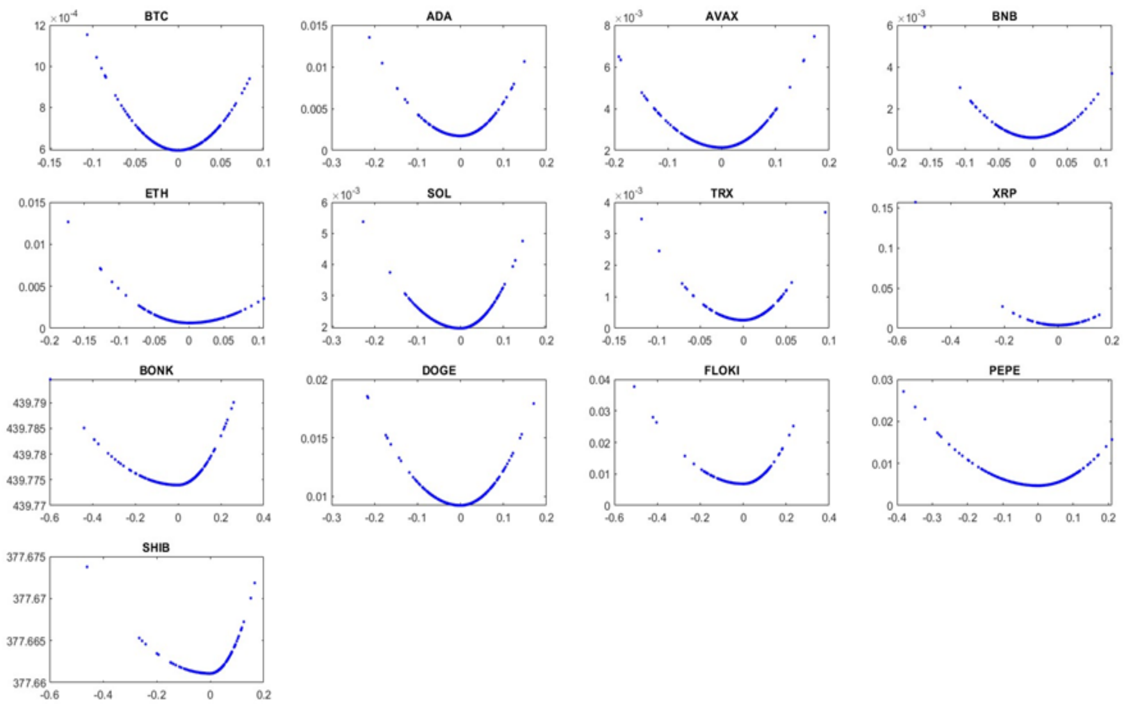
GJR-GARCH

	BTC	ADA	AVAX	BNB	ETH	SOL	TRX	XRP	BONK	DOGE	FLOKI	PEPE	SHIB
γ	2.0e-12	-0.1401	-0.0603	-0.0197	0.1458	-0.0674	-0.1459	-0.0071	-0.1810	-0.1006	-0.2171	-0.0961	-0.3291
p	1.0000	0.0509	0.2112	0.7254	0.1183	0.1517	0.0670	0.9406	8.9e-05	0.1234	0.0032	0.2842	4.2e-07

The EGARCH results are less conclusive since, while all but one coefficients show positive variance asymmetry, two traditional cryptocurrencies and two meme coins have statistically significant asymmetry coefficient at the 5% level.

	BTC	ADA	AVAX	BNB	ETH	SOL	TRX	XRP	BONK	DOGE	FLOKI	PEPE	SHIB
γ	0.0177	0.0719	0.0042	0.0878	-0.0315	0.0309	0.0297	0.0423	0.1194	7.3e-04	0.0135	0.0466	0.1335
p	0.6367	0.0294	0.9011	0.0163	0.4225	0.3293	0.4585	0.2173	3.0e-06	0.9831	0.7507	0.3293	4.9e-06

The asymmetric response can be visualized through the use of News Impact Curves, seen below:



Diagnostics

Diagnostics of standardized residuals of both models has been conducted by checking for autocorrelation (not found in any series), normality (rejected for any series) and ARCH effects (not found in any series).

An additional specification assuming a t-distribution has been tested, but while with this specification autocorrelation of standardized residuals remains absent, a Kolmogorov Smirnoff test almost always rejects the distributional hypothesis, and the residuals are not clean of ARCH effects.

Hypothesis on the results

The results of positive variance asymmetry are not coherent with the leverage hypothesis, which regardless would have been excluded due to the lack of leverage in cryptocurrencies.

The results are also not coherent with the volatility feedback hypothesis, unless risk seeking investors are assumed.

The results are coherent with the safe haven hypothesis, but the fact that the stronger asymmetry is present in meme coins as opposed to traditional cryptocurrencies (which

would make more sense as a safe haven asset) suggests that the cause of positive asymmetric volatility may not be due to a possible safe haven property of meme coins.
The results are coherent with the FOMO hypothesis, as FOMO can only cause positive asymmetric variance and is coherent with the nature of the asset object of study.

Shortcomings of the analysis

The analysis has been conducted on a small sample of meme coins due to the recentness of the phenomenon, so any conclusion regarding meme coins more in general will have to take this into consideration.
This analysis does not take into account the presence of structural breaks. While this was a deliberate choice due to the small length of the series considered, a larger analysis will have to take structural breaks into account.
Due to lack of data only meme coins with large capitalization have been considered.
Finally, this analysis has been conducted exclusively on the exchange rates between each analyzed cryptocurrency and the dollar. While the fluctuations of the dollars are much smaller than those of any cryptocurrency, they are still present, and an analysis of several exchange rates could have yielded stronger results.

Conclusions

This work concludes that a statistically significant volatility asymmetry is found in several meme coins using a GJR-GARCH model and an EGARCH model. Of the analyzed hypothesis, the FOMO effect is the most coherent with the results when taking into consideration the properties of the asset class object of study.

Appendix B: Additional Tables and Charts

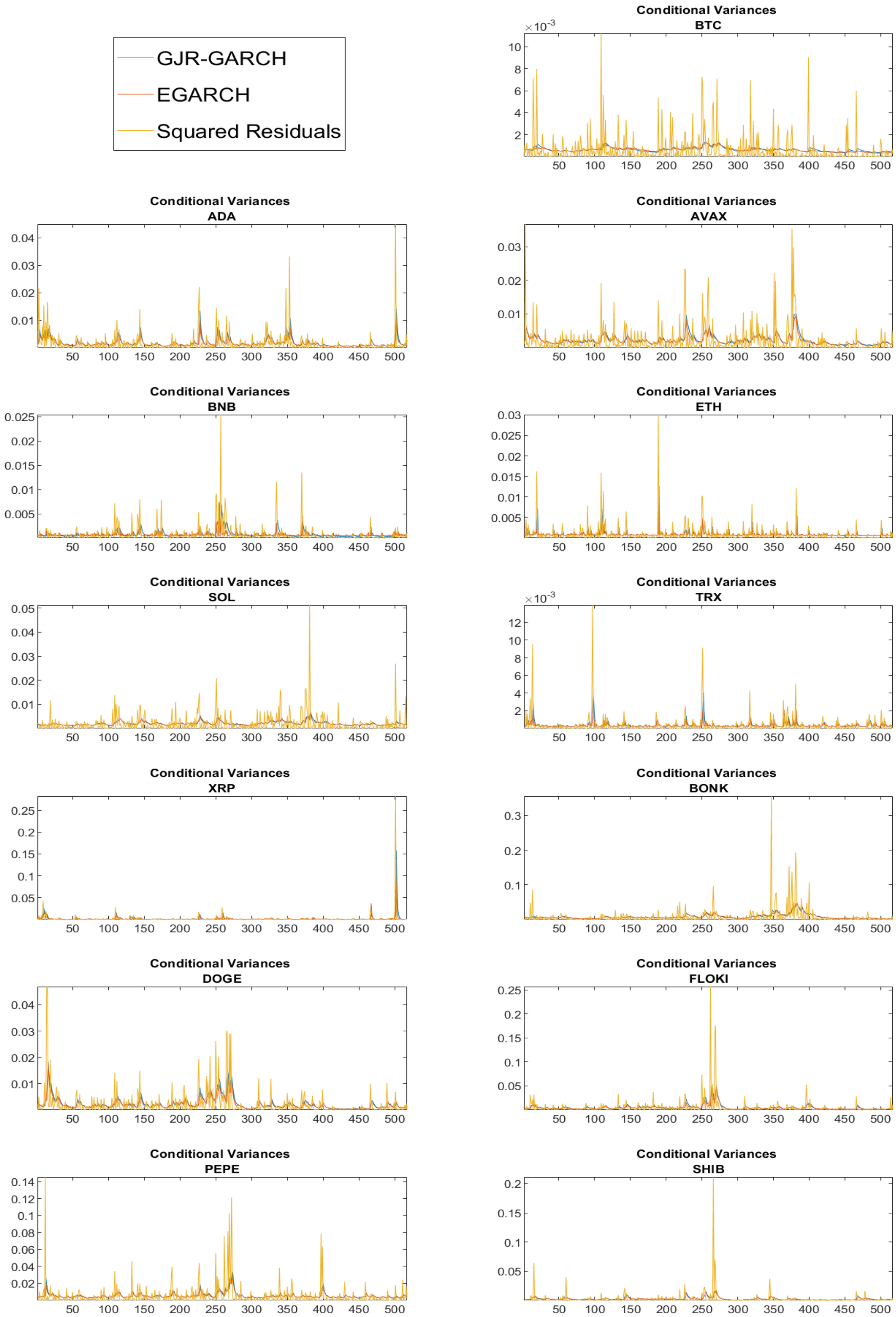


Figure 6 - Squared Residuals compared with Conditional Variance Estimation

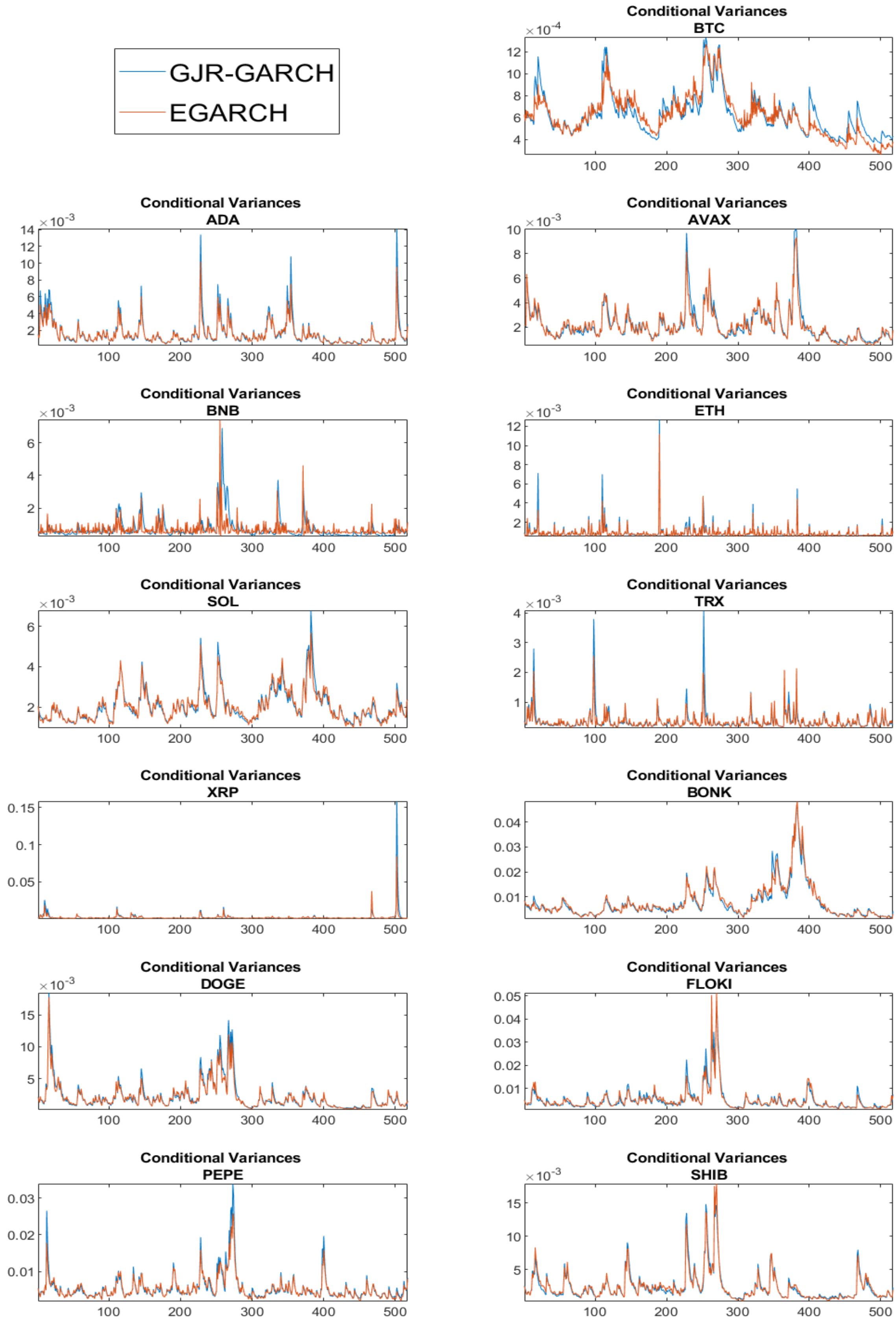


Figure 7 - Zoom on estimated conditional variances

Appendix C: Additional Online Resources

This section will contain links to online pages used in this work:

Bitcoin's energy consumption: https://digiconomist.net/bitcoin-energy-consumption

Ethereum's energy consumption: https://digiconomist.net/ethereum-energy-consumption

Appendix D: Thesis Script

Data Extraction Tool

```
clc
clear


% Get a list of all CSV files in the current directory
fileList = dir('*.csv')


% Read the first file to extract the 'Date' column
T = readtable(fileList(1).name)


% Extract the 'Date' column
dates = T.Date


% Initialize a matrix to store close prices from all files
closePrices = zeros(height(T), length(fileList))


% Loop through each file to extract the price column
for i = 1:length(fileList)
    % Read the table
    T = readtable(fileList(i).name);

    % Check if the price column is a cell array
    if iscell(T.Price)
        % Convert the cell array to a numeric array
        T.Price = str2double(T.Price);
    end

    % Handle invalid values
    if any(isnan(T.Price))
        error('File %s contains non-numeric or missing values in the
Price column.', fileList(i).name);
    end

    % Assign the Price column to the matrix
    closePrices(1:height(T), i) = T.Price;
end


closePrices
```

```
Names=["BTC","ADA","AVAX","BNB","ETH","SOL","TRX","XRP","BONK","DOGE","FL
OKI","PEPE","SHIB"]
tdata=array2table(closePrices,"VariableNames",Names)
tdates=array2table(dates,"VariableNames","Date")


thData=[tdates,tdata]


save thData
```

Main Thesis Script

```
clear
clc
```

Preliminary Steps

Data Import and Preliminary Operations

```
load thData.mat %Loads data prices and prices dates previously compiled


l=518; % Lenght of the data series


Dates=table2array(tdates); %Extracts Dates
Returns=diff(log(tdata(1:l,:))); %Exctacts log return from prices


[n,k]=size(tdata);
sc=8; % Number of "Traditional" Coins in the dataset
mc=5; % Number of "Meme" Coins in the dataset


for i=1:k
Vec=Returns{:,i}; % Extracts data vectors from table
assignin("base",Names(i),Vec); %Assign names to Vectors
end
```

Time Series Plots and Correlograms

```


%Time Series of Returns


figure
for i=1:k
```

```
    subplot(k,1,i)
    plot(Dates(1:517),eval(Names(i)))
    axis tight
    sgtitle("Return Series")


    % Get subplot position
    pos = get(gca, 'Position');

    % Add names outside the subplot
    annotation('textbox', [pos(1)-0.1, pos(2), 0.08, pos(4)], ...
               'String', Names{i}, 'EdgeColor', 'none', ...
               'HorizontalAlignment', 'right', 'FontSize', 10);
end
```

```
%Autocorrelograms
for i=1:k
    figure
    subplot(2,1,1)
    autocorr(eval(Names(i)))
    subplot(2,1,2)
    parcorr(eval(Names(i)))
    sgtitle(['Analysis of ', Names{i}]);
end
```

Descriptive statistics

```
%Unconditional Mean
meanRet=zeros(k,1);
for s=1:k
    meanRet(s)=mean(eval(Names(s)));
end


%Median
mediRet=zeros(k,1);
for s=1:k
    mediRet(s)=median(eval(Names(s)));
end


%Unconditional Variance
variRet=zeros(k,1);
for s=1:k
    variRet(s)=var(eval(Names(s)));
end
```

```
%Skewness
skewRet=zeros(k,1);
for s=1:k
    skewRet(s)=skewness(eval(Names(s)));
end


%Kurtosis
kurtRet=zeros(k,1);
for s=1:k
    kurtRet(s)=kurtosis(eval(Names(s)));
end


%


tab1mat=[meanRet,mediRet,variRet,skewRet,kurtRet]
tab1=array2table(tab1mat,"VariableNames",["Mean","Median","Variance","Ske
wness","Kurtosis"])


meanRet;
meanTD=mean(meanRet(1:8))
meanMM=mean(meanRet(9:13))
% Meme coins in our sample have a lower mean return than traditonal coins


mediRet;
mediTD=mean(mediRet(1:8))
mediMM=mean(mediRet(9:13))
% Memecoins in our sample have a larger median return


variRet;
variTD=mean(variRet(1:8))
variMM=mean(variRet(9:13))
% memecoins in our samplehave a much larger variance of returns


skewRet;
skewTD=mean(skewRet(1:8))
skewMM=mean(skewRet(9:13))
% memecoins in our sample are more negatively skewed


kurtRet;
kurtTD=mean(kurtRet(1:8))
kurtMM=mean(kurtRet(9:13))
```

```
% Memecoins in our sample have about the same kurtosis

tab2mat=[meanTD,mediTD,variTD,skewTD,kurtTD;meanMM,mediMM,variMM,skewMM,k
urtMM]
tab2=array2table(tab2mat,"VariableNames",["Mean","Median","Variance","Ske
wness","Kurtosis"])
```

Preliminary tests

Note: I Avoided both ADF test and PP test for unit root since in theory they are not necessary in return series

1) Ljung Box test (to check for autocorrelation)

2) Jarque bera test (to check normality)

3) ARCH test to check for arch effect

```
% Preallocating Vectors containing test results

lb0=zeros(k,2); % Ljung-box preallocated variable
jb0=zeros(k,2); % Jarque bera Preallocated variable
at0=zeros(k,2); % ARCH test preallocated variable

% Tests

for s=1:k
[lb0(s,1),lb0(s,2)]=lbqtest(eval(Names(s))); % Ljung-Box test
(Autocorrelation)
[jb0(s,1),jb0(s,2)]=jbtest(eval(Names(s))); % Jarque-Bera test
(Normality)
[at0(s,1),at0(s,2)]=archtest(eval(Names(s))); % ARCH test (Arch effect
presence)
end

SeriesTest=[lb0,jb0,at0]
array2table(SeriesTest,"VariableNames",["LB Logical","LB Pvalue","JB
Logical","JB Pvalue","AT Logical","AT Pvalue"])

% RESULTS OF THE TESTS
% 1) Some series suffer autocorrelation which will need to be sterilized
% 2) Returns are not normally distribuited
% 3) ARCH effects present in most series
```

ARMA Model

Akaike information Criterion

```
% AIC to decide which ARMA models best fit each series


%Preallocations and preliminary steps
p=3;
q=3;


aic=zeros(p+1,q+1);
AicNames=["aicBTC","aicADA","aicAVAX","aicBNB","aicETH","aicSOL","aicTRX"
,"aicXRP","aicBONK","aicDOGE","aicFLOKI","aicPEPE","aicSHIB"];


% AIC Calculations for every p and q up to 3, for all time series
for s=1:k
    for i=0:p
        for j=0:q
            arma=arima(i,0,j);
            [~,~,LogL,~]=estimate(arma,eval(Names(s)),'Display','off');
            [aic(i+1,j+1),~]=aicbic(LogL,p+q+1,size(eval(Names(s)),1));
        end
    end
    assignin('base', AicNames(s), aic) % Assignes AIC to AicNames
end
```

Find the best ARMA models to descrive the mean

```
% Preallocation
vecP=zeros(k,1); % Vectors where lags P are stored
vecQ=zeros(k,1); % Vectors where lags Q are stored


for i=1:k
    AicValue=eval(AicNames(i)); %Extracts The AIC value used in the next
steps
    [aicbestP,aicbestQ]=find(min(min(AicValue))==AicValue); % Finds best
lags
    vecP(i)=aicbestP-1; % Puts lag P in vector of P
    vecQ(i)=aicbestQ-1; % Puts lag Q in vector of Q
end
```

```
% The Information Criterions are useful tools but serve just to inform
us.
% Since the BONK time series mantains autocorrelation with the aic
% suggested model, i switched it with another one, decided based on the
% correlogram of the series, which better explains autocorrelation


vecP(9)=5;
vecQ(9)=5;
```

ARMA Estimation

```
mdlNames=["mdlBTC","mdlADA","mdlAVAX","mdlBNB","mdlETH","mdlSOL","mdlTRX"
,"mdlXRP","mdlBONK","mdlDOGE","mdlFLOKI","mdlPEPE","mdlSHIB"];


for s=1:k
    ARMA=arima(vecP(s),0,vecQ(s));
    [estARMA,~,LogL,~]=estimate(ARMA,eval(Names(s)));
    assignin('base', mdlNames(s),estARMA)
end
```

ARMA Residuals Estimation

```
resNames=["resBTC","resADA","resAVAX","resBNB","resETH","resSOL","resTRX"
,"resXRP","resBONK","resDOGE","resFLOKI","resPEPE","resSHIB"];
for s=1:k
    residuals_arma=infer(eval(mdlNames(s)),eval(Names(s))); % Infers ARMA
residuals
    assignin('base',resNames(s),residuals_arma);
end
```

ARMA Residuals Diagnostics

```
% Preallocates vectors containing test results
lbARMA=zeros(k,1); % Ljung Box
jbARMA=zeros(k,1); % Jarque Bera
atARMA=zeros(k,1); % ARCH test


for s=1:k
lbARMA(s)=lbqtest(eval(resNames(s))); % Ljung-Box test (Autocorrelation)
jbARMA(s)=jbtest(eval(resNames(s))); % Jarque-Bera test (Normality)
atARMA(s)=archtest(eval(resNames(s))); % ARCH test (Arch effect presence)
end
```

```
armatestlogicals=[lbARMA,jbARMA,atARMA];
```

Autocorrelation of Original series VS Residuals

```
%for s=1:k
% figure
% subplot(2,1,1)
% autocorr(eval(Names(s)))
% subplot(2,1,2)
% autocorr(eval(resNames(s)))
% sgtitle([Names{i}])
%end
```

GJR-GARCH

Estimation of GJR-GARCH on the ARMA Residuals

```
%Note: No AIC has been taken since the base GJR garch residual tests are
%satisfactory


%Vector containing names for the gjr models
gjrNames=["gjrBTC","gjrADA","gjrAVAX","gjrBNB","gjrETH","gjrSOL","gjrTRX"
,"gjrXRP","gjrBONK","gjrDOGE","gjrFLOKI","gjrPEPE","gjrSHIB"];
% Vector Containing the names for the conditional variances
CVgjrNames=["CVgjrBTC","CVgjrADA","CVgjrAVAX","CVgjrBNB","CVgjrETH","CVgj
rSOL","CVgjrTRX","CVgjrXRP","CVgjrBONK","CVgjrDOGE","CVgjrFLOKI","CVgjrPE
PE","CVgjrSHIB"];
% Vector containing the Variance-Covariance matrix of the estimated
parameters
VCVgjrNames=["VCVgjrBTC","VCVgjrADA","VCVgjrAVAX","VCVgjrBNB","VCVgjrETH"
,"VCVgjrSOL","VCVgjrTRX","VCVgjrXRP","VCVgjrBONK","VCVgjrDOGE","VCVgjrFLO
KI","VCVgjrPEPE","VCVgjrSHIB"];


for s=1:k
    % Model Estimation
    gjr_garch=gjr(1,1);
    [estGJR,gjrVCV,~,~]=estimate(gjr_garch,eval(resNames(s)));
    assignin('base', gjrNames(s),estGJR);


    % Conditional Variance Estimation
    gjrCV=infer(estGJR,eval(resNames(s)));
    assignin('base',CVgjrNames(s),gjrCV);
```

```
    % Saving Variance-Covariance Matrix for tests
    assignin('base',VCVgjrNames(s),gjrVCV);
end
```

GJR-GARCH Standardized Residuals

```
% Finding gjr_garch standardized residuals


%Preallocation of vector containing names of the variables
gjrstdNames=["gjrstdBTC","gjrstdADA","gjrstdAVAX","gjrstdBNB","gjrstdETH"
,"gjrstdSOL","gjrstdTRX","gjrstdXRP","gjrstdBONK","gjrstdDOGE","gjrstdFLO
KI","gjrstdPEPE","gjrstdSHIB"];


%Preallocation of a temporary variable
resgjr=zeros(l-1,1);


for s=1:k
    resgjr=eval(resNames(s))./sqrt(eval(CVgjrNames(s)));
    assignin("base",gjrstdNames(s),resgjr);
end
```

GJR-GARCH Residual Diagnostics

```
gjrTest=nan(k,6); %Preallocate variable containing test results and
pvalues
% Autocorrelation test (LBQ)
for s=1:k
    [logical,pvalue]=lbqtest(eval(gjrstdNames(s)));
    gjrTest(s,1)=logical;
    gjrTest(s,2)=pvalue;
end
% Normality test (JB)
for s=1:k
    [logical,pvalue]=jbtest(eval(gjrstdNames(s)));
    gjrTest(s,3)=logical;
    gjrTest(s,4)=pvalue;
end
% ARCH test on garch residuals
for s=1:k
    [logical,pvalue]=archtest(eval(gjrstdNames(s)));
    gjrTest(s,5)=logical;
```

```
    gjrTest(s,6)=pvalue;
end


GJRTestNames=["Logical LBQ","p-value LBQ","Logical JB","p-value
JB","Logical ARCH T","p-value ARCH T"];
array2table(gjrTest,"VariableNames",GJRTestNames)


% The tests on the residuals show
% 1) Non autocorrelation
% 2) ARCH effects not present on residuals (models are satisfactory)
% 3) All test strongly reject normality assumption (as  expected)
```

Collection GJR GARCH Laverage Coefficent

```
%Preallocations
gjrGamma=zeros(k,1); %Vector of Gammas for gjr
gjrTstat=zeros(k,1); %Vectors of Tstats for gjr
gjrPvalue=zeros(k,1); %Vectors of Pvalues for gjr


for s=1:k
   gjrGamma(s,1)=cell2mat(eval(gjrNames(s)).Leverage); %Saves Gamma
(Leverage)
   M=eval(VCVgjrNames(s));
   StDev=sqrt(M(4,4));
   gjrTstat(s)=cell2mat(eval(gjrNames(s)).Leverage)/StDev; %Saves Tstat
   gjrPvalue(s)=2*(1-normcdf(abs(gjrTstat(s)))); %Saves PValue
end


gjrParam=[gjrGamma,gjrPvalue];
array2table(gjrParam',"VariableNames",Names)


%Calculate average Gamma for tests
gjrSeriousGammaAvg=mean(gjrGamma(1:8)) % Average Gamma for Serious Crypto
gjrMemeGammaAvg=mean(gjrGamma(9:13)) % Average Gamma for Meme Crypto
```

T-test on Leverage

```
% ttest to check if each meme gamma is statistically different from
% the average of the leverages of the serious cryptos
gjrTstat2=zeros(5,1);
gjrPvalue2=zeros(5,1);
```

```
for s=9:k
    M=eval(VCVgjrNames(s));
    StDev=sqrt(M(4,4));
    gjrTstat2(s-8)=(cell2mat(eval(gjrNames(s)).Leverage)-
gjrSeriousGammaAvg)/StDev;
    gjrPvalue2(s-8)=2*(1-normcdf(abs(gjrTstat2(s-8))));
end


gjrPvalue2; % pvalues statistically significant for BONK, FOLKI, SHIB,
and not for DOGE and PEPE
```

EGARCH

Estimation on ARMA residuals

```
%Note: No AIC has been taken since the base EGARCH residual tests are
%satisfactory


%Vector containing names for the egarch models
egarchNames=["egarchBTC","egarchADA","egarchAVAX","egarchBNB","egarchETH"
,"egarchSOL","egarchTRX","egarchXRP","egarchBONK","egarchDOGE","egarchFLO
KI","egarchPEPE","egarchSHIB"];
% Vector Containing the names for the conditional variances
CVegarchNames=["CVegarchBTC","CVegarchADA","CVegarchAVAX","CVegarchBNB","
CVegarchETH","CVegarchSOL","CVegarchTRX","CVegarchXRP","CVegarchBONK","CV
egarchDOGE","CVegarchFLOKI","CVegarchPEPE","CVegarchSHIB"];
% Vector containing the Variance-Covariance matrix of the estimated
parameters
VCVegarchNames=["VCVegarchBTC","VCVegarchADA","VCVegarchAVAX","VCVegarchB
NB","VCVegarchETH","VCVegarchSOL","VCVegarchTRX","VCVegarchXRP","VCVegarc
hBONK","VCVegarchDOGE","VCVegarchFLOKI","VCVegarchPEPE","VCVegarchSHIB"];


%EGARCH(1,1) Works well for most series except BTC
lagEGARCH=ones(k,1);
lagEGARCH(1)=2;


for s=1:k
    % Model Estimation
    egarchMdl=egarch(lagEGARCH(s),1);
    [estEGARCH,egarchVCV,~,~]=estimate(egarchMdl,eval(resNames(s)));
    assignin('base', egarchNames(s),estEGARCH);


    % Conditional Variance Estimation
    egarchCV=infer(estEGARCH,eval(resNames(s)));
    assignin('base',CVegarchNames(s),egarchCV);
```

```
    % Saving Variance-Covariance Matrix for tests
    assignin('base',VCVegarchNames(s),egarchVCV);
end
```

EGARCH Standardized Residuals

```
% Finding egarch standardized residuals


%Preallocation of vector containing names of the variables
egarchstdNames=["egarchstdBTC","egarchstdADA","egarchstdAVAX","egarchstdB
NB","egarchstdETH","egarchstdSOL","egarchstdTRX","egarchstdXRP","egarchst
dBONK","egarchstdDOGE","egarchstdFLOKI","egarchstdPEPE","egarchstdSHIB"];


%Preallocation of a temporary variable
resegarch=zeros(l-1,1);


for s=1:k
    resegarch=eval(resNames(s))./sqrt(eval(CVegarchNames(s)));
    assignin("base",egarchstdNames(s),resegarch);
end
```

EGARCH Residual Diagnostics

```
egarchTest=nan(k,6); %Preallocate variable containing test results and
pvalues
% Autocorrelation test (LBQ)
for s=1:k
    [logical,pvalue]=lbqtest(eval(egarchstdNames(s)));
    egarchTest(s,1)=logical;
    egarchTest(s,2)=pvalue;
end
% Normality test (JB)
for s=1:k
    [logical,pvalue]=jbtest(eval(egarchstdNames(s)));
    egarchTest(s,3)=logical;
    egarchTest(s,4)=pvalue;
end
% ARCH test on egarch residuals
for s=1:k
    [logical,pvalue]=archtest(eval(egarchstdNames(s)));
    egarchTest(s,5)=logical;
    egarchTest(s,6)=pvalue;
end
```

```
EGARCHTestNames=["Logical LBQ","p-value LBQ","Logical JB","p-value
JB","Logical ARCH T","p-value ARCH T"]
array2table(egarchTest,"VariableNames",EGARCHTestNames)


% As with the GJR-GARCH model, the tests on the residuals show
% 1) No autocorrelation
% 2) ARCH effects not present on residuals (models are satisfactory)
% 3) All test strongly reject normality assumption (as expected)
```

Collection EGARCH Laverage Coefficents

```
%Preallocations
egarchGamma=zeros(k,1); %Vector of Gammas for egarch
egarchTstat=zeros(k,1); %Vectors of Tstats for egarch
egarchPvalue=zeros(k,1); %Vectors of Pvalues for egarch


for s=1:k
   egarchGamma(s,1)=cell2mat(eval(egarchNames(s)).Leverage); %Saves Gamma
(Leverage)
   M=eval(VCVegarchNames(s));
   StDev=sqrt(M(4,4));
   egarchTstat(s)=cell2mat(eval(egarchNames(s)).Leverage)/StDev; %Saves
Tstat
   egarchPvalue(s)=2*(1-normcdf(abs(egarchTstat(s)))); %Saves PValue
end


egarchParam=[egarchGamma,egarchPvalue]; %NOTE: need to make into a table
array2table(egarchParam',"VariableNames",Names)


%Calculate average Gamma for tests
egarchSeriousGammaAvg=mean(egarchGamma(1:8)) % Average Gamma for Serious
Crypto
egarchMemeGammaAvg=mean(egarchGamma(9:13)) % Average Gamma for Meme
Crypto
```

T-test on EGARCH Leverage

```
% ttest to check if each meme gamma is statistically different from
% the average of the leverages of the serious cryptos
egarchTstat2=zeros(5,1);
egarchPvalue2=zeros(5,1);
```

```
for s=9:k
    M=eval(VCVegarchNames(s));
    StDev=sqrt(M(4,4));
    egarchTstat2(s-8)=(cell2mat(eval(egarchNames(s)).Leverage)-
egarchSeriousGammaAvg)/StDev;
    egarchPvalue2(s-8)=2*(1-normcdf(abs(egarchTstat2(s-8))));
end


egarchPvalue2 % pvalues statistically significant for BONK and SHIB, and
not for DOGE and PEPE
```

Plot Conditional Variances for each Currency

```
%Variance compared to Squared Returns


for s=1:k
    figure
    plot(eval(CVgjrNames(s)))
    hold on
    plot(eval(CVegarchNames(s)))
    plot(eval(resNames(s)).^2)
    axis("tight")
    legend('GJR-GARCH','EGARCH',Names(s))
    title('Conditional Variances',Names(s))
end
```

```
%Focus on Models
for s=1:k
    figure
    plot(eval(CVgjrNames(s)))
    hold on
    plot(eval(CVegarchNames(s)))
    axis("tight")
    legend('GJR-GARCH','EGARCH')
    title('Conditional Variances',Names(s))
end
```

News impact Curves

```
%Preallocation
NIC_GJR_GARCH=zeros(l-1,1);


for s=1:k


    res=eval(resNames(s));


    %GJR-GARCH Necessary variables
    omega_gjr = eval(gjrNames(s)).Constant;
    alpha_gjr = cell2mat(eval(gjrNames(s)).ARCH);
    gamma_gjr = cell2mat(eval(gjrNames(s)).Leverage);
    beta_gjr = cell2mat(eval(gjrNames(s)).GARCH);
    un_var_gjr=omega_gjr/(1-alpha_gjr-beta_gjr-gamma_gjr/2);


    % NIC Calculation for GJR-GARCH
    for t = 1:l-1
        if  res(t)< 0
        NIC_GJR_GARCH(t,s) = omega_gjr + (beta_gjr)*un_var_gjr +
(alpha_gjr + gamma_gjr)*(res(t).^2);
        else
        NIC_GJR_GARCH(t,s) = omega_gjr + (beta_gjr)*un_var_gjr +
(alpha_gjr)*(res(t).^2);
        end
    end


end
```

```


%Plot GJR-GARCH NIC
figure
for s=1:k
subplot(5,3,s)
plot(eval(resNames(s)),NIC_GJR_GARCH(:,s),'.b')
title(Names(s))
end


% The News Impact Curves show asymmetry present in some cryptos
```