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# THE ASYMMETRIC VOLATILITY OF CRYPTOCURRENCIES: WHAT IS THE EFFECT OF LEVERAGED TRADING?

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# The Asymmetric Volatility of Cryptocurrencies: what is the effect of leveraged trading?

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***Abstract***

While cryptocurrencies have grown to a value of $2 trillion and are increasingly used by institutional investors, they remain far more volatile than stock markets, with this high level of volatility being one of their puzzling features. To shed some light on this issue, we investigate asymmetry in the volatility of the 20 largest cryptocurrencies from 2016 to 2022 and test to what extent the asymmetry is affected by leveraged trading. We find that overall cryptocurrencies predominantly exhibit upward asymmetric volatility, meaning that volatility tends to be larger for positive return shocks than negative return shocks. However, the asymmetry changes through time and differs in the cross-section of cryptocurrencies. We find that the emergence of Decentralized Finance (DeFi), which provides easier access to leveraged trading through lending platforms has put downward pressure on the asymmetric volatility. This effect can be linked to forced liquidations of lending positions when market prices fall, which forces selloffs, increasing downwards asymmetric volatility. Finally, we examine the susceptibility of cryptocurrencies to systemic risk and find that the cryptocurrencies which are associated with DeFi lending protocols are more affected by market downturns compared to their non-DeFi counterparts. The heightened risk stemming from leveraged trading can increase the market risk of cryptocurrencies which can lead to possible spill-over effects to other markets, such as equities.

## *1. Introduction*

In finance literature, variance as a measure of risk is the cornerstone of asset pricing models. The assumption for using variance as a risk metric is that the returns of an asset are symmetrically distributed (Markowitz, 1959). Current empirical findings, however, suggest that some assets display asymmetric volatility – for instance in the equities market [Bekaert and Wu (2000); Black (1976); Christie (1982); Campbell and Hentschel (1992)]. The presence of asymmetric volatility implies that the return distribution is skewed, and thus the common risk metric might not be the most appropriate tool to measure the riskiness of an asset or portfolio.

Asymmetric volatility generally means that the volatility of a given asset following a positive shock is smaller than following a negative shock. This is what we call negative, or downward asymmetric volatility [DAV]. In contrast, some assets exhibit positive, or upward asymmetric volatility [UAV]. This means that the volatility is greater following a positive shock than it is compared to a negative shock. Findings from the literature suggest that to be the case for instance in the Chinese equities market (Wan, Cheng, & Yang, 2014) and in the gold market (Baur D. G., 2012).

Evidence from the cryptocurrencies market has remained inconclusive. Baur and Dimpfl (2018) find the existence of UAV for a majority of cryptocurrencies in their sample between 2013 and 2018. Meanwhile, Bouri, Azzi and Dyhrberg (2017), support the existence of asymmetry from 2011 to 2013 but find no statistically significant results in the time frame from 2013 to 2016. The mixed findings from the available literature are our key motivation to establish whether the asymmetry varies over time, whether it is upward and how the results differ across cryptocurrencies.

Moreover, the research topic is important as the cryptocurrencies market is yet to be mature and incorporates a lot of unregulated leverage in the face of Decentralized Finance (DeFi) lending. Leverage and cryptocurrencies in general have received a lot of attention in the past few years, as Bitcoin (BTC) has experienced record growth, and innovations like DeFi and stablecoins have gained popularity. Recently, however, the attention has not been exclusively positive, with exchanges such as Binance and FTX experiencing pressure from the media and regulators about introducing user protection measures (Gkritsi, 2021).

Cryptocurrencies are also famous for their riskiness and possibilities of trading with high leverage, which has been linked to price crash events (Finneseth, 2021). For instance, in May 2020, BTC price dropped by 25% within an hour. This led to massive liquidations as the decrease in price increased the leverage ratio and many were forced to sell their positions. The liquidations put even more downwards pressure to the price and amplified the effects of the initial price drop (Szalay & Stafford, 2020).

In this paper we attempt fill the gap in the literature to test whether leverage has an effect on the asymmetry of cryptocurrencies, reasoning that chain liquidations may have a direct link to massive selloffs, leading to larger DAV, especially in the realm of DeFi lending protocols such as AAVE, Compound and MakerDAO. Thus, we seek to answer the following research questions:

**1. Which cryptocurrencies exhibit upward/downward asymmetric volatility?**

**2. Has the emergence of DeFi, by making leveraged trading more accessible, changed the dynamics of asymmetry in cryptocurrency volatility?**

**3. Has the easier access to leverage impacted the cryptocurrencies' susceptibility to systemic risk?**

To attempt to answer our research questions, we deploy different econometric methods. We base our asymmetric volatility estimation on calculating the semi-deviations of returns and validate those results with an asymmetric GARCH model. We do a cross-sectional analysis of the asymmetry measure to find differences between types of cryptocurrencies. Thirdly, we run time-series regressions to zoom in on the relation between DeFi associated coins (DeFi coins) and the amount of leverage in the market. Finally, we analyze the DeFi coins susceptibility to systemic risk.

## *2. Literature review*

Most of the financial models in the world of CAPM assume that the volatility of a given asset is symmetric, meaning that it responds equally to both positive and negative shocks. In practice that is not always the case, with many assets displaying asymmetric volatility, meaning, there is a negative relation between conditional volatility and returns. Therefore, in case of negative returns, the relation is stronger [Bekaert and Wu (2000); Black (1976); Christie (1982); Campbell and Hentschel (1992)]. This typically results in there being higher volatility when the assets experience below average returns, and lower volatility when the assets rise in price.

Finance literature assumes that standard deviation is an appropriate measure of risk given that the return distribution is symmetrical. As asymmetric volatility implies return distributions to be skewed, this assumption is violated. This builds ground for the discussion of how risk should be measured. Even Markowitz pointed out the usage of semi-variances as a more appropriate measure of risk (1959). A portfolio analysis done using variances as a measure of risk, looks to eliminate extreme outcomes on both sides of the return distribution. Semi-variances, however, focus on reducing down-side risk. The outcomes from using semi-variances or variances are the same, given the return distribution is symmetrical. However, as the observed empirical work concludes the existence of an asymmetric distribution, "analysis based on semi-variances would produce better portfolios than those based on variance" (Markowitz, 1959, p. 194).

### 2.1 Downward asymmetric volatility

In the equities market, it is well established that there is a negative correlation between returns and conditional volatility (Bekaert & Wu, 2000). This means that the volatility is downward asymmetric. The negative correlation is evident in most developed countries' financial markets, for instance in the US (Bollerslev, Law, & Tauchen, 2008), Japanese (Qiu, Zheng, Ren, & Trimper, 2006) and German stock markets (Bekaert & Wu, 2000). Although, Wan, Cheng, and Yang (2014), find that such a relation does not hold in the Chinese equities market, and instead the market experiences upward asymmetric volatility. The authors suggest that this exception can be attributed to the structural difference of the Chinese market compared to other developed financial markets. For instance, in the Chinese equities market, there are limits to the price fluctuation range and short sales are constrained.

Currently, there are two main explanations for the existence of downward asymmetric volatility. Christie (1982) explains the asymmetric volatility with the leverage effect hypothesis. If a stock experiences negative returns, this increases financial leverage, which consequently increases the stock's volatility due to higher risk. Thus, he establishes a negative correlation between stock returns and volatility, although it does not explain why a downturn in the market causes more volatility than a positive shock of the same scale. Thus, the existence of asymmetric volatility cannot be fully explained by the leverage hypothesis.

Black (1976); Pindyck (1984); French, Schwert, and Stambaugh (1987); Campbell and Hentschel (1992); and Bekaert and Wu (2000) provide an alternative explanation for the negative correlation: the volatility feedback hypothesis. In case of unexpected negative news, volatility increases, and investors are likely to make an upward revision on the conditional volatility. Investors then expect a higher expected return to compensate for the increased conditional volatility. This leads to a decrease in the stock price; thus, enhancing the initial negative shock. In case of unexpected positive news, the volatility increases and due to a revision on conditional volatility, the stock price decreases, dampening the initial positive shock. Thus, this implies that volatility is asymmetric as the impact of positive shocks is less pronounced as it is for negative shocks (Campbell & Hentschel, 1992). Meanwhile, Wagner and Aboura argue that the volatility feedback hypothesis also has some issues, as the effect should ultimately reach a steady state, "as otherwise – given an initial large piece of bad news – the market could be predicted to melt down" (Wagner & Aboura, 2010, p. 5).

Current research suggests that these two hypotheses can be jointly used to explain the downward asymmetry of volatility, although Bekaert and Wu (2000) give more weight to the volatility feedback hypothesis.

### 2.2 Cryptocurrencies and their variants

In this paper we focus on cryptocurrencies, and for the sake of clarity we summarize the key types of coins in the market, and their properties. Cryptocurrencies are decentralized digital assets, the most famous of which is Bitcoin, with very many altcoins, i.e., cryptocurrencies other than Bitcoin, also present on the market, such as Ethereum (ETH) or Litecoin (LTC) (Coinbase, n.d.).

***Stablecoins.*** Recently stablecoins such as US Dollar Coin (USDC) or US Dollar Tether (USDT) have also appeared. Put simply, a stablecoin is a digital asset the value of which is pegged to an external asset, like for example a fiat currency like the US dollar, or a commodity like gold (Hertig, 2020). They are typically minted by a stable third party, such as Circle and Coinbase, who back USDC. The value of stablecoins like USDC or USDT is backed by short term investments or cash (Hertig, 2020), however some stablecoins like Dai are actually minted by depositing collateral in the form of crypto on the MakerDAO protocol (MakerDAO, n.d.). Stablecoins are also very popular on both traditional exchanges and DeFi, with USDC having a market cap of roughly 36 billion USD as of November 2021 (CoinMarketCap, n.d.). The issue with this, however, is that these stablecoins are only as stable as the parties backing them, introducing counterparty risk. This could be a potential issue in DeFi protocols, as these stablecoins are used extensively in most protocols, therefore making them a critical part of the DeFi ecosystem.

***Decentralized Finance (DeFi) coins.*** DeFi coins are ones which are predominantly used in the DeFi infrastructure. Most DeFi services are built on the Ethereum blockchain, which means that its currency is used for transacting in DeFi (Wojno, 2022). Similarly, there are also other blockchain networks which aim to put their functionality to use in the DeFi realm, an example of which are Avalance (AVAX) and Terra (LUNA).

***Exchange associated coins.*** These types of coins are issued by cryptocurrency exchanges and generally their goal is to provide additional value to the customer at the exchange. An example of an exchange associated coin is Binance Coin (BNB), which can be used to access discounted trading fees (Binance, 2022). For the whole list of cryptocurrencies in our sample with their classification see Appendix A.

### 2.3 Asymmetric volatility in cryptocurrencies

Like many other assets, cryptocurrencies experience asymmetric volatility, however, the literature is not unified on whether the asymmetry is upward. Upward asymmetric volatility, or UAV, means, that the volatility is higher in case of positive shocks compared to negative shocks of the same magnitude.

For example, Baur and Dimpfl (2018) find that UAV in cryptocurrencies exists for 18 out of 20 coins they studied from 2013 to 2018. This is different from results obtained in the equities market where they find that negative shocks tend to lead to higher volatility than positive shocks. Baur and Dimpfl also theorize that the effects of informed and uninformed traders acting on shocks could likely influence the asymmetric volatility, as uninformed traders would bandwagon given positive shocks, and informed traders would act upon negative shocks (2018). This effect, however, is not empirically tested.

In another paper by Bouri, Azzi and Dyhrberg (2017) they find that there was actually a change in the asymmetric volatility of BTC following the crash of 2013. They propose the safe haven effect of BTC similar to that of gold in the period leading up to the crash and argue that this effect weakened following 2013. They find that before the crash (2011 – 2013), there was UAV, however after the crash (2013 – 2016) and during the whole sample period (2011 – 2016) they find no such statistically significant results, at first glance disagreeing with the findings of Baur and Dimpfl (2018), however, direct comparisons cannot be made due to different time frames.

We can see that the current literature is not unified regarding the existence of asymmetric volatility in cryptocurrencies. Thus, due to the presence of different results in different time periods, we hypothesize that the degree of asymmetry in cryptocurrencies is not constant and varies over time:

**H1: The degree of asymmetry in cryptocurrencies varies over time.**

While there is a lot of research on the drivers of asymmetric volatility for other assets, not all of this research applies to cryptocurrencies. As mentioned before, two possible drivers for UAV found by Baur and Dimpfl (2018) and Bouri, Azzi and Dyhrberg (2017) are the effects of uninformed and informed traders, and the safe haven effect, however neither paper offers conclusive proof about these drivers. From studies done on other assets regarding DAV, we find that two drivers are typically mentioned – the leverage hypothesis and volatility feedback (Bekaert & Wu, 2000).

### 2.4 Leverage in centralized exchanges

Leverage has been present in equities for a very long time, and there are strict rules for how and when investors use leverage. For example, the Securities and Exchange Commission (SEC) has rules, that a person must deposit a bare minimum of \$2000, or the equivalent of the purchase price of the margin trade, which will be known as the minimal margin. The other main rule is that an investor may only borrow up to

50% of a purchase, meaning that their maximum leverage is 2x for equities. Investors are also required to have funds in their account for margin maintenance. (U.S. Securties and Exchange Commission, 2009). There are some traders for whom more leverage is allowed, but only with very strict rules. For example, if the investor meets the specific criteria to be a pattern day-trader with minimum $25,000 equity, they can achieve leverage of 4x (U.S. Securities and Exchange Commission, 2021).

However, this is not the only way to achieve leverage in equities. There are also very many synthetics available, like for example leveraged ETF's which have quite recently gained a lot of attention. These leveraged ETF's allow for up to 200% leverage without special approval from the SEC, but they are also required to estimate their value at risk (Shubber & Henderson, 2020). There are many other examples of instruments, like for example options, that help investors achieve leverage, but the trend of strict rules set by the SEC remain a common factor.

Leveraged trading is mentioned as one of the key mechanisms in the cryptocurrency market (Tian, 2021). Some of the largest current exchanges include Binance, Bybit and FTX, which all offer leveraged trading (Coinglass, n.d.). In 2020, new products were also offered from these centralized exchanges, such as futures and options (The Block, n.d.). Recently some exchanges have begun reducing their leverage limits for margin trading. For example, following negative attention from both regulators and media, Binance and FTX have decreased their maximum leverage from 100x to 20x (Gkritsi, 2021), which is still extremely high when compared to the maximum of 2x leverage in the equities market for regular traders. At the same time, however, the CEO of FTX believed that the negative attention was misplaced, and that extremely high leverage positions made up a small portion of the exchanges (Reynolds, 2021). The CEO of Binance, however, did acknowledge that leverage has contributed to volatility (Gkritsi, 2021). Since then, the leverage ratio has also been increasing (Godbole, 2021), perhaps offering support to the claim that extreme leverage has not contributed that much leverage at least to the BTC market. It's not immediately obvious whether that is true for ETH, or other altcoins, however.

### 2.5 DeFi Protocols in Cryptocurrencies

Decentralized finance is an alternative financial infrastructure. It is predominantly built on the Ethereum blockchain and compared to traditional finance, it allows for financial services to be provided more transparently (Schär, 2021). DeFi emerged around 2018, but became more relevant after 2020, when it started to experience spectacular growth. Lending and borrowing is a popular use case of the DeFi ecosystem, which contributed to almost 50% of the total value locked in DeFi (DeFi Pulse, n.d.),

Engaging in leveraged trading through DeFi protocols can be summed up in 5 categories. There are lending platforms (AAVE, MakerDAO, Compound), margin trading platforms (dYdX), perpetuals (IPP), leveraged tokens (FinNexus) and options (Opyn) (Tian, 2021). Each of these provide leverage via different mechanisms and have different properties in terms of maximum achievable leverage and liquidation events. They also follow similar principles like overcollateralization and most often require collateral in Ethereum (Tian, 2021). Overcollateralization means that to borrow for example 1000 USD worth of USDC, you will be required to deposit more than 1000 USD worth of collateral. This collateral is then shown as the total value locked in (TVL).

To achieve a leveraged position using lending platforms with a 1.5x collateralization ratio one can borrow 1000$ worth of DAI, and deposit 1500$ worth of Ethereum of collateral. Following that, they can exchange that DAI to Ethereum, effectively having exposure to 2500$ worth of Ethereum. In this example, the individual would have leverage of 1.67x. Repeating this process multiple times, can achieve higher leverage, but does not allow exposure to grow exponentially, which is key to maintaining the financial stability of these DeFi platforms. However, in the event that the price of the collateral drops, and margin calls of one position are not met, chain liquidation of the cascading positions will occur, leading to a rapid selloff of assets. This is also the main mechanism we include in our analysis, due to two main reasons: lending platforms accounting for roughly 46% of the TVL in DeFi (DeFi Pulse, n.d.), and the accessibility of data with regards to amounts being lent out (Token Terminal, n.d.).

There has also been speculation of leveraged positions leading to forced liquidations as margin calls are not met, leading to further downwards price pressure, liquidations and eventually price crashes. This is what happened on September 7th, 2021, in BTC (Finneseth, 2021). It could therefore be logical, that following such events there should be increased downwards volatility as selloffs occur, therefore introducing the link between leveraged trading and asymmetric volatility. This would mean that following the emergence of more leverage, we would expect more downside volatility due to this selloff mechanism. There is also some speculation, however, that leverage has fueled past price rallies, but was largely absent in the last rally (Greifeld & Hajric, 2021), which provides a possible link to increased upwards volatility as well.

Based on the abovementioned potential connection between leverage and asymmetric volatility, we hypothesize that leveraged trading has an impact on asymmetric volatility, especially downwards, given increasing leverage in past years.

**H2: Leveraged trading increases downwards asymmetric volatility.**

### 2.6 Systemic risk

As mentioned before, leverage provides means to amplify one's exposure to the price movements of an asset. This means, that an investor can increase their profits from price increases given a limited investment sum. At the same time, this amplified exposure leads to more risk given market downturns.

Extending the definition from the work of Acharya, Pedersen, Philippon and Richardson (2017), we refer to systemic risk as the relative risk a cryptocurrency experiences when the rest of the crypto market is doing poorly. Inferring from that, given the easier access to leverage via the emergence of DeFi, we expect that DeFi coins have become more susceptible to systemic risk in the market.

**H3: Emergence of DeFi, via easier access to leverage, has made DeFi coins more susceptible to systemic risk.**

In case the hypothesis proves to be true, this can have implications also on other markets. Adrian, Iyer and Qureshi (2022), found that since 2020, the cryptocurrencies and equities markets have become significantly more correlated. For instance, from 2017-19 the correlation between BTC price and S&P 500 was only 0.01, whereas the coefficient jumped to 0.36 in 2020-21. The authors suggest that the volatility spillovers from BTC to the equities market have significantly increased in the period of 2020-21.

If DeFi lending becomes more widespread and more investors participate in leveraged trading, that can lead to a situation where the overall risk in the cryptocurrencies market increases. This increased volatility can spill over to the equities market, making those riskier as well as threatening the financial stability of markets.

## *3. Methodology and results*

In this section we present the methodology and results. Because we deploy many different econometric methods, we structure the section in a way that the results for a specific method follow immediately after. For our analysis we rely on the price and trading volume data for cryptocurrencies. Moreover, we obtain the DeFi lending platforms' borrowing volumes. We use two methods for calculating the asymmetric volatility – target semi-deviations and gjrGARCH. In section 3.3, we establish that DeFi coins exhibit differences in asymmetric volatility compared to non-DeFi coins. From there on, we conduct our analysis by looking at DeFi coins and BTC only.

In section 3.4.1, we observe the relation between ETH scaled borrowing volume and asymmetric volatility by running time series regressions. In section 3.4.2, we conduct the same regressions, only this time using idiosyncratic asymmetry terms and scaled borrowing volumes to observe a purer relation. Finally, we introduce risk measures – SRISK, Tail beta – which are included in the leverage regressions.

### 3.1 Data

For the asymmetric volatility analysis, we choose a sample of top 20 cryptocurrencies by market capitalization. The sample period is approximately five years – from 09.09.2016 to 01.01.2022, although the starting date of the sample period varies depending on when the trading activity started for a specific coin (see Appendix A). We refer to the cryptocurrencies based on their abbreviation in the column Symbol of Appendix A. We use the terms coin, currency, and cryptocurrency interchangeably.

We obtain daily closing prices and trading volumes for the cryptocurrencies from Yahoo Finance where the data originates from CoinMarketCap (n.d.). We obtain the returns for each currency by calculating the natural logarithm of the ratio of prices on two consecutive days (see Eq. ( 1 ))

$$R_{i,t} = ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right), \tag{1}$$

*Where: $P_{i,t}$ is the closing price at time t for cryptocurrency i and $P_{i,t-1}$ is the corresponding cryptocurrency i closing price at time t-1.*

Table 1 reports the summary statistics of the closing returns of the 20 cryptocurrencies. SOL, AVAX, and MATIC exhibit the highest average return in our sample. Looking at the volatility of returns, the same three abovementioned coins have the highest values. This seems to follow the principle of high returns and high risk going hand in hand. USDT and USDC exhibit both the lowest average return and the lowest standard deviation. As these two are stablecoins, the low volatility is expected as they are pegged to USD. The return distribution is positively skewed for most coins, only ATOM, BTC, ALGO, ETH, SOL, LINK, and MATIC display negative skewness.

| Currency | Mean | Std. Dev | Min | Max | Skew | Obs |
|---|---|---|---|---|---|---|
| BTC | 0.002 | 0.042 | -0.465 | 0.225 | -0.751 | 1843 |
| ETH | 0.003 | 0.056 | -0.551 | 0.290 | -0.438 | 1843 |
| BNB | 0.005 | 0.072 | -0.543 | 0.675 | 0.915 | 1613 |
| USDT | 0.000 | 0.006 | -0.053 | 0.057 | 0.359 | 1843 |
| SOL | 0.009 | 0.086 | -0.465 | 0.387 | -0.096 | 630 |
| ADA | 0.002 | 0.072 | -0.504 | 0.862 | 1.895 | 1545 |
| XRP | 0.003 | 0.075 | -0.616 | 1.027 | 1.935 | 1843 |
| DOT | 0.005 | 0.077 | -0.477 | 0.445 | 0.260 | 498 |
| USDC | 0.000 | 0.004 | -0.037 | 0.042 | 0.470 | 1180 |
| DOGE | 0.004 | 0.081 | -0.515 | 1.323 | 3.279 | 1843 |
| AVAX | 0.008 | 0.086 | -0.454 | 0.560 | 0.627 | 463 |
| LUNA1 | 0.006 | 0.083 | -0.488 | 0.641 | 0.864 | 801 |
| CRO | 0.003 | 0.070 | -0.490 | 0.869 | 2.238 | 1113 |
| LTC | 0.002 | 0.061 | -0.449 | 0.511 | 0.311 | 1843 |
| UNI1 | 0.003 | 0.076 | -0.403 | 0.380 | 0.360 | 465 |
| LINK | 0.003 | 0.074 | -0.615 | 0.481 | -0.060 | 1513 |
| ALGO | 0.000 | 0.074 | -0.650 | 0.418 | -0.629 | 923 |
| MATIC | 0.007 | 0.091 | -0.716 | 0.498 | -0.012 | 977 |
| ATOM | 0.002 | 0.074 | -0.590 | 0.281 | -0.809 | 1023 |
| TRX | 0.002 | 0.076 | -0.523 | 0.787 | 1.893 | 1513 |

**Table 1.** Descriptive statistics of returns. *This table presents descriptive statistics for the return time series of 20 cryptocurrencies. Mean is the sample period average; Std. Dev the standard deviation; min and max represent the minimum and maximum, correspondingly; Skew is the skewness and Obs number of observations. Data from Yahoo Finance. Created by authors*



We obtain the borrowing volumes on DeFi from Token Terminal (n.d.), which provides data about different blockchain projects. The borrowing volumes are denominated in USD and depict how much leverage in the cryptocurrency market is obtained via lending platforms. In specific, we look at the three largest lending platforms – Maker, Aave, and Compound – and sum the borrowing volumes of each of the platforms to get a cumulative measure. As the lending market on DeFi is rather concentrated, with the three platforms taking up approximately 87% of the market (DeFi Pulse, n.d.), the cumulative measure is a great proxy for the total lending on DeFi. We gather the data since the launch of each of the three platforms until 01.01.2022. For Aave, the period starts January 2020; for Compound, May 2019; and for Maker, November 2019. We refer to the borrowing value as total borrowing.

Since total borrowing is expressed in USD value of the underlying amounts borrowed, they are sensitive to changes in the prices of the underlying assets. One of the main coins which is present in the total borrowing figures is ETH. Therefore, a decrease in the price of ETH would lower total borrowing, however, the number of tokens borrowed may increase despite the USD value of the amounts borrowed decreasing. Since ETH makes up a significant portion of the total borrowing, we use it as a proxy for the prices of the underlying assets. To account for the changes in prices of the underlying coins, we regress ETH on total borrowing to obtain the residuals, which produces a stationary data set of the total borrowing not affected by changes in the prices of ETH (see Eq. ( 2 )).

$$Total\ Borrowing_t = \alpha_i + \beta_i ETH_t + \varepsilon_{i,t} \qquad (2)$$

*Where: $Total\ Borrowing_t$ is the USD value of borrowing in the DeFi market at time t; $ETH_t$ is the USD price of the underlying coins, proxied by the price of ETH; and $\varepsilon_{i,t}$ is the error term which represents the portion of Total Borrowing not affected by the changes in prices of the underlying coins.*

We then use the residuals from Eq. ( 2 ) to represent the scaled total borrowing. The scaled total borrowing is a more accurate measure to replace the total borrowing variable.



### 3.2 Asymmetry measures

In the following subsections, we use two methods for measuring the degree of asymmetry. Firstly, by calculating semi-deviations we can infer about the asymmetry structure. Secondly, we use the asymmetric GARCH model, which is widely used in the literature. The semi-deviation method allows for a time-series analysis, whereas the asymmetric GARCH provides a single asymmetry measure for generalizing results.

### *3.2.1 Target semi-deviations*

A simple method for measuring the asymmetry is using target semi-deviations. In literature, the concept of downside semi-deviations as a measure of risk was first proposed by Roy (1952), which allows us to focus solely on the negative fluctuations in price movements. We can further expand on the idea by comparing the upper and lower semi-deviations of a return distribution (See Eqs. ( 3 ) and ( 4 )). This way, we can infer whether the volatility has asymmetric properties. If we assume that the distribution of returns is symmetric, and thus so is the volatility, then the upper and lower deviations from the mean should be equal (Markowitz, 1959). Consequently, if the deviations differ, then the asset exhibits asymmetric volatility.

$$\sigma_l = \sqrt{\frac{\sum(x_{target} - x_{neg})^2}{N_l}}, \tag{3}$$

*Where: $\sigma_l$ is the lower deviation; $x_{target}$ is the average return of the previous 90 days; $x_{neg}$ is the negative return; and $N_l$ is the number of observations that have a negative return.*

$$\sigma_u \geq \sqrt{\frac{\sum(x_{pos} - x_{target})^2}{N_u}}, \tag{4}$$

*Where: $\sigma_u$ is the upper deviation; $x_{target}$ is the average return of the previous 90 days; $x_{pos}$ is the positive return; and $N_u$ is the number of observations that have a positive return.*

The definition of a positive shock means that an asset experiences above average returns, whereas in case of a negative shock, the returns are below the average. For this reason, we define the variable $x_{pos}$ as all returns that are above the average; and $x_{neg}$ as all the below average returns. The average return is the mean of the returns from the previous 90 days, including both above and below average values.

Thus, we can calculate $\varphi_{i,t}$ to represent the asymmetric volatility term (see. Eq. ( 5 ). If $\varphi_{i,t}$, the difference between lower and upper deviation, is greater than 0, it implies that volatility is higher when the market is in a decline than in an upwards trend. Thus, the stock experiences DAV, downward asymmetric volatility. On the contrary, if the difference is less than 0, then we have a case of upward asymmetry, i.e., the positive shocks are more pronounced than negative. If the difference is zero, we can conclude a symmetric volatility.

$$\varphi_{i,t} = \frac{\sigma_l - \sigma_u}{\bar{\sigma}}, \tag{5}$$

*Where:* $\varphi_{i,t}$ *shows the degree of asymmetric volatility for a given cryptocurrency at time t. If* $\varphi_{i,t} > 0$*, the asymmetry is downward (negative); if* $\varphi_{i,t} < 0$*, the asymmetry is upward (inverse); if* $\varphi_{i,t} = 0$*, the volatility is symmetric.*

The measure $\varphi_{i,t}$ in Eq. ( 5 ) is normalized by the average of the upper and lower deviations to ensure that the measure does not spike in case the overall volatility in the market increases (See Eq. ( 6 )).

$$\bar{\sigma} = \frac{\sigma_u + \sigma_l}{2}, \tag{6}$$

*Where:* $\bar{\sigma}$ *represents the mean standard deviation, obtained as the average of* $\sigma_u$ *and* $\sigma_l$*.*

To observe whether the degree of asymmetric volatility changes over time, we use the rolling window analysis. This method is used to evaluate a model's stability over time (Zivot & Wang, 2006). In essence, we choose a rolling window size of 90 days. We estimate the asymmetric volatility parameter using Eq. ( 5 ). Then, we shift the window by one day and perform another estimation using the subsample. We continue this process until the end of the time series. This allows us to plot each estimate over the rolling window index to see whether the parameters are constant over time. We find that the size of the window must balance visual representation and usability in regressions. With a longer window like 360 days, we find that the asymmetric volatility graphs are much smoother, and easier to interpret visually, however, the effect of shifting the window is much smaller. Therefore, it performs worse in regressions. Conversely, the smaller the window, the noisier the graph, which results in more difficult interpretation of results. In our sample, we find that 90 days balances usability in regression, and visual representation.

***Results.*** We obtain time series asymmetry measure $\varphi_{i,t}$ from Eq. ( 5 ) for the 20 currencies. Table 2 presents the descriptive statistics for the time series asymmetry term using a 90-day rolling window. Looking at the minimum and maximum levels, we see that the asymmetry term varies over time from negative to positive values for all the coins. Negative values indicate UAV, whereas positives stand for DAV. The range from negatives to positives, indicates that the direction of asymmetry – upward or downward

– varies over time. Meaning, over the lifetime of a cryptocurrency, it can exhibit both upward and downward asymmetric volatility, depending on the period under observation.

The mean value of the asymmetry term $\varphi_{i,t}$ gives us an indication of in which state of volatility does a currency spend most of its time in. 13 out of the 20 values are negative, suggesting towards UAV for these currencies, whilst 7 currencies exhibit DAV. Focusing only on DeFi coins – ETH, AVAX, LUNA, UNI1, and LINK, they all exhibit UAV, except for ETH.

To observe whether asymmetry has changed over the periods before and after the emergence of DeFi, we can compare the mean values before 01.01.2020 and after. The change is represented by the column Δ in means. If the difference between post- and pre-DeFi is positive, that means the asymmetry structure has become either more downward or less upward asymmetric. A negative difference indicates that the asymmetry has become less DAV or more UAV. In the pre-DeFi period, 13 currencies had mostly UAV and 3 had DAV. We do not have values for SOL, DOT, AVAX and UNI1 as these coins did not exist in that period. Post-DeFi, we have only 9 currencies with UAV, indicating that the number of coins which have DAV has increased.

| Currency | Category | Min | Max | Mean | Mean(<2020) | Mean (>=2020) | Δ in means | *p-value* |
|---|---|---|---|---|---|---|---|---|
| BTC | N/A | -0.529 | 0.911 | 0.090 | 0.138 | 0.016 | -0.123 | *(0.000)* |
| ETH | DeFi coin | -0.736 | 0.758 | 0.015 | -0.025 | 0.077 | 0.103 | *(0.000)* |
| BNB | Exchange coin | -0.780 | 0.794 | 0.033 | -0.029 | 0.100 | 0.129 | *(0.000)* |
| USDT | Stablecoin | -1.577 | 1.809 | -0.030 | -0.050 | 0.000 | 0.050 | *(0.000)* |
| SOL | N/A | -0.434 | 0.389 | -0.102 | *N/A* | -0.102 | N/A | *(0.000)* |
| ADA | N/A | -0.751 | 0.632 | -0.047 | -0.056 | -0.037 | 0.018 | *(0.238)* |
| XRP | N/A | -1.390 | 0.632 | -0.105 | -0.191 | 0.026 | 0.217 | *(0.000)* |
| DOT | N/A | -0.632 | 0.440 | -0.084 | *N/A* | -0.084 | N/A | *(0.000)* |
| USDC | Stablecoin | -0.628 | 1.112 | 0.036 | 0.043 | 0.032 | -0.011 | *(0.188)* |
| DOGE | N/A | -1.121 | 0.871 | -0.149 | -0.125 | -0.187 | -0.063 | *(0.000)* |
| AVAX | DeFi coin | -0.822 | 0.553 | -0.142 | N/A | -0.142 | N/A | *(0.000)* |
| LUNA1 | DeFi coin | -0.780 | 0.357 | -0.235 | -0.175 | -0.236 | -0.061 | *(0.006)* |
| CRO | Exchange coin | -1.011 | 0.941 | -0.012 | -0.397 | 0.142 | 0.539 | *(0.000)* |
| LTC | N/A | -0.938 | 0.698 | -0.008 | -0.096 | 0.126 | 0.221 | *(0.000)* |
| UNI1 | DeFi coin | -0.532 | 0.308 | -0.098 | *N/A* | -0.098 | N/A | *(0.000)* |
| LINK | DeFi coin | -0.622 | 0.659 | -0.060 | -0.201 | 0.072 | 0.273 | *(0.000)* |
| ALGO | N/A | -0.430 | 0.781 | 0.014 | 0.054 | 0.008 | -0.046 | *(0.017)* |
| MATIC | N/A | -0.697 | 0.653 | -0.058 | -0.204 | -0.026 | 0.177 | *(0.000)* |
| ATOM | N/A | -0.418 | 0.779 | 0.020 | -0.093 | 0.051 | 0.144 | *(0.000)* |
| TRX | N/A | -0.582 | 0.788 | 0.021 | -0.083 | 0.120 | 0.203 | *(0.000)* |

**Table 2.** Descriptive statistics of the time series asymmetry term for 20 cryptocurrencies. *Min and Max represent the minimum and maximum values for the asymmetry term $\varphi_{i,t}$ for a specific currency. Mean is the sample period average; Mean (<2020) is the average corresponding to the period before the emergence of DeFi, i.e., before 01.01.2020; and Mean(>=2020) is the average since 2020. Δ in means is the change in means between the post and pre-DeFi period where p-value represents the difference in means test significance. Data from Yahoo Finance. Created by authors.*

### *3.2.2 The asymmetric GARCH*

The asymmetric GARCH or gjrGARCH model of Glosten, Jagannathan, and Runkle (1993) is an extension of the GARCH model which captures the differences in impact in the variance at time t, in case of negative or positive shocks at t-1. The model has been extensively used in previous literature to observe the asymmetric volatility of different assets [Bouri, Azzi, and Dyhrberg (2017); Baur D. G. (2012)]. The model consists of two parts, where Eq. ( 7 ) is used for estimating the conditional mean of returns and Eq. ( 8 ) for the conditional volatility.

$$R_{i,t} = \mu + R_{t-p} + \varepsilon_t \tag{7}$$

*Where: $R_{i,t}$ is the daily return for a given cryptocurrency; $R_{t-p}$ is the lagged daily return; and $\varepsilon_t$ is the error term.*

$$h_t = \omega + \alpha(\varepsilon_{t-1}^2) + \beta(h_{t-1}) + \gamma(\varepsilon_{t-1}^2)I_{t-1}, \tag{8}$$

*Where: ω is the level of volatility in when there are no shocks; $\alpha$ is the ARCH term which captures the effect of past shocks on present variance; $\beta$ denotes the GARCH term and displays the effect of past variance on present variance; $\gamma$ is the asymmetry term; and $I_{t-1}$ is a dummy variable which equals 1 if the shock is negative (<0) and 0 otherwise (see Eq. ( 9 )).*

$$I_{t-1} = \begin{cases} 0 & if\ \varepsilon_{t-1} \geq 0 \\ 1 & if\ \varepsilon_{t-1} < 0 \end{cases} \tag{9}$$

In Eq. ( 8 ), the first three coefficients are interpreted the same way as in an ordinary GARCH model, but the additional coefficient is $\gamma_i$ which represents the asymmetry term for a given cryptocurrency over the whole sample period. We restrict parameters $\alpha$ and $\beta$ to be positive, whereas $\gamma_i$ can be between -1 and 1. In case $\gamma_i > 0$ and significant, then a positive shock triggers less volatility than a negative shock of the same size. Thus, the asset exhibits DAV. Correspondingly, if $\gamma_i$ is significant and negative, then we have a situation of UAV.

The number of lags $p$ in Eq. ( 7 ) is determined based on the criteria of no autocorrelation in the residual. We test the validity of the assumption with the Ljung-Box test of autocorrelation (Ljung & Box, 1978). We use the Bayesian Information Criterion (BIC) to find the most appropriate distribution density for each of the cryptocurrencies – Gaussian, Student's t (STD), and generalized error distribution (GED). We estimate the gjrGARCH model from Eq. ( 8 ) under the distribution which minimizes the BIC. For model specifications see Appendix B.

We estimate the $\gamma_i$ term from Eq. ( 8 ) for each of the cryptocurrencies in our sample. $\gamma_i$ will provide means to generalize which type of asymmetry, if any, does the currency exhibit over the whole sample period. Whereas the rolling window asymmetry term $\varphi_{i,t}$ from Eq. ( 5 ) helps to examine the development of the asymmetry over time. Moreover, we use the asymmetric gjrGARCH model to ensure the validity of the results obtained using the target semi-deviations in Eq. ( 5 ).

***Results.*** Table 3 reports the estimated $\gamma_i$ variable from the asymmetric GARCH model in Eqs. ( 7 ) and ( 8 ). For all estimated variables of the model, see Appendix C. In our sample of 20 cryptocurrencies, we found 14 currencies with UAV and six with DAV. There were no currencies which exhibit symmetric volatility. This is in correspondence with the work of Baur and Dimpfl (2018), who also found upward asymmetry for the majority of the coins in their sample. Although, direct comparisons cannot be made due to differences in the sample composition and period under observation.

Only six of the 20 asymmetry terms from our model had statistically significant values on a 10% significance level: BNB, AVAX, LTC, ALGO, MATIC, and TRX. All the six coins also exhibit UAV. When looking at the two most prominent cryptocurrencies – BTC and ETH – then despite the high correlation between them, their asymmetry differs (see Appendix D). BTC exhibits UAV whilst ETH DAV, although both of those values are insignificant. Comparing these values to Baur and Dimpfl (2018), they found both BTC and ETH to be upward. Although their sample period ends in August 2018 and ours in January 2022. This leads to the possibility that the asymmetry structure of ETH has changed over time and the currency has moved from upward to downward asymmetry.

Looking specifically at the DeFi coins, all of them exhibit upward asymmetry, except for ETH and UNI1. Although again, only AVAX has a significant $\gamma$ term out of the five DeFi coins. Comparing the results with the ones obtained using the semi-deviation method in section 3.2.1, the two methods for the five DeFi coins mostly overlap. Only difference is for UNI1, which according to the semi-deviation method exhibits UAV but the GARCH model suggests DAV. The rest – AVAX, LUNA, and LINK – experience upward and ETH downward asymmetry with both models.

| Currency | Category | γ | *p-value* | |
|---|---|---|---|---|
| BTC | N/A | -0.004 | *(0.897)* | |
| ETH | DeFi coin | 0.004 | *(0.917)* | |
| BNB | Exchange coin | -0.076 | *(0.081)* | * |
| USDT | Stablecoin | 0.128 | *(0.995)* | |
| SOL | N/A | -0.053 | *(0.475)* | |
| ADA | N/A | 0.002 | *(0.958)* | |
| XRP | N/A | -0.040 | *(0.347)* | |
| DOT | N/A | 0.011 | *(0.805)* | |
| USDC | Stablecoin | 0.019 | *(0.994)* | |
| DOGE | N/A | -0.101 | *(0.167)* | |
| AVAX | DeFi coin | -0.095 | *(0.099)* | * |
| LUNA1 | DeFi coin | -0.006 | *(0.999)* | |
| CRO | Exchange coin | -0.090 | *(0.141)* | |
| LTC | N/A | -0.071 | *(0.012)* | ** |
| UNI1 | DeFi coin | 0.115 | *(0.129)* | |
| LINK | DeFi coin | -0.002 | *(0.942)* | |
| ALGO | N/A | -0.048 | *(0.098)* | * |
| MATIC | N/A | -0.143 | *(0.006)* | *** |
| ATOM | N/A | -0.052 | *(0.272)* | |
| TRX | N/A | -0.113 | *(0.004)* | *** |

**Table 3.** Estimation results of the asymmetric GARCH model. *This table presents the asymmetric GARCH estimation results from Eqs. ( 7 ) and ( 8 ). The $\gamma$ term stands for the asymmetric volatility. The values in italic represent the corresponding p-values based on the robust standard errors. The significance codes *, **, *** showcase the statistical significance of the $\gamma$ on a 10%, 5%, and 1% level respectively. Data from Yahoo Finance. Created by authors.*

### 3.3 DeFi coin classification

In order to observe whether differences in asymmetric volatility exist between DeFi coins and other coins as specified in Appendix A, we can check it by running a panel regression with explanatory variables.

We use the classification in Appendix A to create dummy variables for each of the three categories of cryptocurrencies – $DeFi\_dummy_i$, $Stablecoin\_dummy_i$, $Exchange\_dummy_i$ , where the dummy equals 1 if a specific cryptocurrency falls in the category. Thus, we get three different categories which try to explain the degree of asymmetry. We also include an explanatory variable $2020\_dummy$, which helps us to observe the time before the emergence of DeFi and after. The variable equals 1 for asymmetry measures since 01.01.2020 and 0 before that date. Additionally, we add a variable $Age_{i,t}$ which includes the age of a specific cryptocurrency, counted by days since the start of trading activity. The dependent variable is the asymmetry term $\varphi_{i,t}$ from Eq. ( 5 ).

$$\varphi_{i,t} = \beta_0 + \beta_1 DeFi\_dummy_i + \beta_2 Stablecoin\_dummy_i + \\ + \beta_3 Exchange\_dummy_i + \beta_4 2020\_dummy_t + \beta_5 Age_{i,t} + \varepsilon_{i,t} \qquad (10)$$

*Where:* $\varphi_{i,t}$ *is the measure of asymmetry for currency i at time t;* $DeFi\_dummy_i$ *is a dummy variable representing DeFi coins;* $Stablecoin\_dummy_i$ *and* $Exchange\_dummy_i$ *are dummy variables for stablecoins and exchange associated coins, respectively;* $2020\_dummy_t$ *indicates the emergence of DeFi;* $Age_{i,t}$ *is the of a specific cryptocurrency at time t; and* $\varepsilon_{i,t}$ *is the error term.*

Looking specifically for differences between DeFi coins and non-DeFi coins before and after the emergence of DeFi, we can include an interaction term $DeFi\_dummy_i \times 2020\_dummy_t$ (see Eq. ( 11 )).

$$\varphi_{i,t} = \beta_0 + \beta_1 DeFi\_dummy_i + \beta_2 2020\_dummy_t + \\ + \beta_3 DeFi\_dummy_i \times 2020\_dummy_t + \varepsilon_{i,t} \qquad (11)$$

*Where:* $\varphi_{i,t}$ *is the measure of asymmetry for currency i at time t;* $DeFi\_dummy_i$ *is a dummy variable representing DeFi coins;* $2020\_dummy_t$ *indicates the emergence of DeFi;* $DeFi\_dummy_i \times 2020\_dummy_t$ *is the interaction term and* $\varepsilon_{i,t}$ *is the error term.*

In the previous sections we find that the direction of the asymmetry – upward or downward – differs across coins. By grouping the cryptocurrencies by categories, we can see which types of currencies are more or less likely to exhibit a specific type of asymmetric volatility. In addition, we can try to explain asymmetry also by looking at the age characteristic of a coin and whether the period under observation is before or after the emergence of DeFi.

***Results.*** Table 4 presents the estimation results from Eq. ( 10 ). All the estimates are statistically significant at least on a 10% level. Looking at the three groups of currencies – DeFi, Stablecoin, and Exchange dummies – we see that DeFi coins and exchange associated coins exhibit more UAV or less DAV compared to non-DeFi coins and non-exchange associated coins, respectively.

| Dependent variable: *Asymmetry* $_{i,t}$ | | |
|---|---|---|
| **Independent variable** | **Estimate** | **p-value** |
| *Intercept* | -0.083 | (0.000) *** |
| *DeFi_dummy* $_i$ | *-0.047* | (0.000) *** |
| *Stablecoin_dummy* $_i$ | 0.025 | (0.000) *** |
| *Exchange_dummy* $_i$ | *-0.648* | (0.000) *** |
| *2020_dummy* $_t$ | 0.088 | (0.000) *** |
| *Age* $_{i,t}$ | 0.000 | (0.063) * |
| Observations: | 23 849 | |
| $R^2$: | 0.272 | |
| Adjusted $R^2$: | 0.272 | |
| p-value: | 0.000 | |

**Table 4.** Estimation results of Eq. ( 10 ). *The dependant variable is the asymmetry term* $\varphi_{i,t}$ *and the explanatory variables are as defined in section 3.4. Data from Yahoo Finance. Created by authors.*

The variable, 2020_dummy, which stands for the time after the emergence of DeFi, is positively associated with asymmetry term $\varphi_{i,t}$. Same thing goes for the age of a cryptocurrency. Meaning, in the post-DeFi period, currencies display more downward asymmetry compared to the pre-DeFi period. Similarly, older coins exhibit more DAV.

Table 5 zooms in on only DeFi coins in the pre- and post-DeFi period. The results are as follows: comparing pre- and post-DeFi period, both DeFi and non-Defi coins exhibit more DAV. After the emergence of DeFi, DeFi coins have more DAV than non-DeFi currencies.

Dependent variable:
*Asymmetry* $_{i,t}$

| Independent variable | Estimate | p-value |
| --- | --- | --- |
| *Intercept* | -0.169 | (0.000) *** |
| $DeFi\_dummy_i$ | 0.076 | (0.000) *** |
| $2020\_dummy_t$ | 0.103 | (0.000) *** |
| $DeFi\_dummy_i{:}2020\_dummy_t$ | -0.062 | (0.000) *** |
| Observations: | 24 182 | |
| $R^2$: | 0.017 | |
| Adjusted $R^2$: | 0.017 | |
| p-value: | 0.000 | |

**Table 5.** Estimation results of Eq. ( 11 ). *The dependant variable is the asymmetry term $\varphi_{i,t}$ and the explanatory variables are as defined in section 3.4. Data from Yahoo Finance. Created by authors.*

In Table 6, we see that in the 30 days following the crash on the 19th of May in 2021, the DAV for DeFi coins increased by 0.104 more than for non-DeFi coins, showing that DeFi coins were prone to more DAV. This is a much more significant effect than in Table 5 when examining the much larger time period.

Dependent variable:
*Asymmetry* $_{i,t}$

| Independent variable | Estimate | p-value |
| --- | --- | --- |
| *Intercept* | 0.017 | (0.119) |
| $DeFi\_dummy_i$ | 0.104 | (0.000) *** |
| Observations: | 527 | |
| $R^2$: | 0.051 | |
| Adjusted $R^2$: | 0.049 | |
| p-value: | 0.000 | |

**Table 6.** Estimation results similar to Eq. 10. *With a much shorter time frame of one month following the crash (19.05.2021 – 19.06.2021). The dependent variable is $\varphi_{i,t}$,*

*the asymmetry term, and the explanatory variable is a simple dummy variable denoting whether a coin is related to DeFi. Dummy variable 2020 and the interaction term between DeFi and 2020 are excluded, due to them being redundant. Data from Yahoo Finance. Created by authors.*

### 3.4 Leverage regressions

This research aims to find an answer as to whether the emergence of DeFi via lending mechanisms has changed the dynamics of the asymmetric volatility structure of cryptocurrencies. Thus, in the following subsections we directly observe the relation between the asymmetry term $\varphi_{i,t}$ from Eq. ( 5 ) and scaled total borrowing from Eq. ( 2 ). We only analyse the five DeFi coins and BTC.

To test whether the asymmetric volatility of cryptocurrencies in our sample is correlated with changes in the leverage in the market, we run time-series regressions (see Eq. ( 12 )). To make sure that the regressions are valid, we first check the stationarity of our data using the Augmented Dickey-Fuller (ADF) test. If a data set is not stationary, we first-difference the data set. This process is then repeated for every variable in the time series regressions.

We also add trading volume as an additional control variable in the following regression equation (see Eq. ( 12 )). This is done with the aim of minimizing omitted variable bias:

$$\varphi_{i,t} = \beta_0 + \beta_1 Y_t + \beta_2 Y_{t-1} + \beta_3 X_t + \varepsilon_{i,t} \tag{12}$$

*Where: the dependent variable $\varphi_t$ – the measure of asymmetry at time t, $\beta_0$ – intercept, $Y_t$ – total borrowing (residuals) at time t, $Y_{t-1}$ - total borrowing (residuals) at time t-1, $X_t$ –trading volume at time t.*

We then interpret the coefficients to establish whether there are correlations between leverage and asymmetric volatility using these measures. We use this template from Eq. ( 12 ) for all the following sections: asymmetry and scaled borrowing regressions in section 3.4.1; idiosyncratic asymmetry and scaled borrowing regressions in 3.4.2; and for the risk measures in section 3.5.

#### *3.4.1 Asymmetric volatility and scaled total borrowing*

***Results.*** As mentioned before, five out of the 20 coins we examine are directly related with DeFi, therefore meaning that they would be more exposed to the DeFi lending mechanisms which are captured by total borrowing. In this section, we evaluate the asymmetry of those coins separately, and use BTC as a market benchmark, to look at the currencies' asymmetry. Following that, we observe their relation with total borrowing. Panel E1 (see Appendix E) depicts the asymmetry term $\varphi_{i,t}$, total borrowing and the scaled ETH price since 2020.

When looking at the asymmetry for these six coins since the beginning of 2020, we can observe that the asymmetry term $\varphi_{i,t}$ for AVAX, LUNA1, LINK and UNI1 are generally trending upwards as DeFi takes off at the beginning of 2021. This suggests more DAV. ETH and BTC, however, remain largely stable (see Panel 1).

We can also see that in May, 2021, there is a significant decrease in the price of ETH, from USD 4079.06 on May 14$^{th}$ to 2109.58 on May 23$^{rd}$. During this time, all the coins in our sample decreased in price except the stablecoins, the highest losses being for LUNA1 with a 75% decrease in price in nine days, and the average in the whole sample being 49% losses when excluding stablecoins. The average losses for the five DeFi coins were 59%. Subsequently we observe a drop in total borrowing. At the same time, we observe large spikes in asymmetry, showing a substantial increase in DAV.

Table 7 presents the asymmetry terms for DeFi coins and BTC during the price crash. For BTC this spike is mild, but the DeFi coins experienced a high increase in asymmetry. The largest increase was for UNI1, as its asymmetry increased from -0.44 to 0.22, an increase of 0.66, and went from UAV to DAV. On average, asymmetry for DeFi coins increased by 0.42, showing an increase in downside asymmetry. We also see an increase in the asymmetry term for all other coins in the sample, however their average was slightly lower at 0.32. During this time, we also see that total borrowing spiked on May 19$^{th}$, and dropped 26% on May 20$^{th}$, afterwards remaining quite stable.

| Date | BTC | ETH | LUNA1 | AVAX | UNI1 | LINK | Total Borrowing |
|---|---|---|---|---|---|---|---|
| **14.05.2021** | 0.117 | -0.160 | -0.233 | -0.062 | -0.441 | 0.215 | 20 047 955 622 |
| **15.05.2021** | 0.120 | -0.099 | -0.223 | -0.085 | -0.425 | 0.241 | 20 709 838 118 |
| **16.05.2021** | 0.117 | -0.100 | -0.210 | -0.069 | -0.433 | 0.240 | 20 315 632 949 |
| **17.05.2021** | 0.116 | -0.065 | -0.180 | -0.068 | -0.410 | 0.256 | 21 331 694 259 |
| **18.05.2021** | 0.115 | -0.065 | -0.170 | -0.059 | -0.413 | 0.222 | 20 684 137 711 |
| **19.05.2021** | 0.206 | 0.201 | 0.088 | 0.135 | -0.134 | 0.520 | 24 112 329 664 |
| **20.05.2021** | 0.148 | 0.163 | 0.094 | 0.142 | -0.142 | 0.472 | 17 927 444 909 |
| **21.05.2021** | 0.176 | 0.199 | 0.135 | 0.151 | 0.178 | 0.504 | 18 885 871 199 |
| **22.05.2021** | 0.176 | 0.206 | 0.176 | 0.166 | 0.182 | 0.511 | 18 115 152 747 |
| **23.05.2021** | 0.176 | 0.203 | 0.319 | 0.175 | 0.218 | 0.524 | 18 473 988 371 |
| **Change (14.05 - 23.05)** | **0.059** | **0.364** | **0.552** | **0.236** | **0.660** | **0.309** | **-1 573 967 251** |

**Table 7.** Asymmetric volatility for DeFi coins and BTC during the May 2021 price crash. *The columns with the cryptocurrency symbols showcase the asymmetry term* $\varphi_{i,t}$

*from 14.05 to 23.05.2021. The column Total Borrowing represents the USD value of borrowing in DeFi. Data from Yahoo Finance. Created by authors.*

To formalize the results, we run ADL regressions based on Eq. ( 12 ). Table 8 depicts the results for the regression. We find that a one USD increase in total borrowing leads to an increase in the asymmetry term for five out of six coins, the largest increase being for UNI1. This means, that total borrowing at time t is associated with more downward pressure on asymmetry at time t. The results for BTC are statistically insignificant as expected, as BTC is likely not as connected to DeFi mechanisms as the DeFi related coins.

| *Dependent variable:* **Independent variable** | *BTC* | *ETH* | *LUNA1* | *AVAX* | *UNI1* | *LINK* |
|---|---|---|---|---|---|---|
| *Total Borrowing (residuals)* | 1.25E-11 *(0.193)* | 2.07E-11 *(0.003)* | 3.29E-12 *(0.040)* | 3.32E-12 *(0.009)* | 5.66E-12 *(0.000)* | 5.15E-12 *(0.001)* |
| Lag | 1 | 4 | 1 | 4 | 1 | 4 |
| *Lag of Total Borrowing (residuals)* | -4.19E-12 *(0.663)* | 3.20E-12 *(0.641)* | -3.33E-12 *(0.038)* | -3.62E-12 *(0.005)* | -5.31E-12 *(0.000)* | -4.67E-12 *(0.002)* |
| *Volume* | -7.72E-13 *(0.066)* | -9.22E-13 *(0.201)* | -2.11E-12 *(0.460)* | -2.11E-12 *(0.526)* | -1.95E-12 *(0.486)* | 1.28E-14 *(0.967)* |

**Table 8**. Estimation results of Eq.( 12 ). *The dependant variables are the asymmetry terms for DeFi coins and BTC. The explanatory variables Total Borrowing (residuals) and Lag of Total Borrowing (residuals) represent the ETH adjusted borrowing volume from Eq. (* 2 ). *The lag is determined by the row Lag. Volume represents the trading volume for a specific coin. Data from Yahoo Finance. Created by authors.*

For the lags, however, the results are puzzling, as the results show that total borrowing is expected to lead to latent decreases in DAV for LUNA1, AVAX, UNI1 and LINK of a very similar magnitude as the initial increases in DAV. For LUNA1 and AVAX, the effect appears to be a net decrease in DAV, but for UNI1 and LINK, a net increase in DAV. Trading volume was only statistically significant for BTC, showing that an increase in trading volume predicts an increase in DAV.

### *3.4.2 Idiosyncratic asymmetric volatility and scaled total borrowing*

In the following section we conduct the same sort of analysis as in 3.4.1, although now eliminating the effect of market movements in the asymmetry measure $\varphi_{i,t}$.

In the cryptocurrency market, the price movement across coins is correlated. The correlation is especially high between BTC and the rest of the coins (see Appendix D). Thus, to get a clearer picture on the asymmetric volatility structure that a coin exhibits in isolation, we try to eliminate the effect of BTC price movements.

We use BTC as a proxy for the market return. Following the equation of CAPM, the return of an asset is composed of market and idiosyncratic risk. By regressing the return of BTC on the return of a specific DeFi coin, we obtain the time series residual (see Eq. ( 13 )). The residual captures the idiosyncratic return of the DeFi coin, and thus allows us to observe the more isolated effect of DeFi.

$$R_{DeFi,t} = \alpha_i + \beta_i R_{M,t} + \varepsilon_{i,t} \tag{13}$$

*Where: $R_{DeFi,t}$ is the return of a specific DeFi coin at time t; $R_{M,t}$ the market return, proxied by the return of BTC at time t; and $\varepsilon_{i,t}$ is the error term which represents the idiosyncratic return.*

Proceeding from that, we use the method from Eq. ( 5 ) to calculate the asymmetry term $\varphi_{i,t}$, this time using the idiosyncratic return. In essence, we compose the regular asymmetric volatility, calculated by the returns of a coin into two factors: idiosyncratic asymmetry, based on idiosyncratic returns; and market asymmetry.

***Results.*** Panel F1 (see Appendix F) depicts the idiosyncratic asymmetry term $\varphi_{i,t}$, total borrowing and the scaled ETH price since 2020. We find that the same positive upwards trend of the asymmetry term persists from the start of 2021. Additionally, we find that the asymmetric volatility for the idiosyncratic returns of ETH has also begun showing a strong upwards trend.

Table 9 presents the idiosyncratic asymmetry terms for DeFi coins during the price crash. The largest increase in asymmetry for idiosyncratic returns was for LUNA1, increasing from -0.34 to 0.16, however unlike for regular asymmetry, both UNI1 and ETH continued to exhibit UAV during this time, despite substantial increases. The average increase in asymmetry during this time was 0.38 for DeFi coins.

| Date | ETH | LUNA1 | AVAX | UNI1 | LINK | Total Borrowing |
|---|---|---|---|---|---|---|
| **14.05.2021** | -0.432 | -0.338 | -0.068 | -0.656 | -0.162 | 20 047 955 622 |
| **15.05.2021** | -0.398 | -0.339 | -0.138 | -0.674 | -0.163 | 20 709 838 118 |
| **16.05.2021** | -0.395 | -0.325 | -0.127 | -0.677 | -0.161 | 20 315 632 949 |
| **17.05.2021** | -0.386 | -0.312 | -0.146 | -0.675 | -0.167 | 21 331 694 259 |
| **18.05.2021** | -0.377 | -0.314 | -0.159 | -0.660 | -0.233 | 20 684 137 711 |
| **19.05.2021** | -0.043 | -0.115 | 0.038 | -0.481 | 0.161 | 24 112 329 664 |
| **20.05.2021** | -0.054 | -0.147 | -0.002 | -0.507 | 0.176 | 17 927 444 909 |
| **21.05.2021** | -0.032 | -0.121 | -0.009 | -0.205 | 0.201 | 18 885 871 199 |
| **22.05.2021** | -0.001 | -0.048 | 0.030 | -0.194 | 0.225 | 18 115 152 747 |
| **23.05.2021** | -0.004 | 0.162 | 0.040 | -0.188 | 0.239 | 18 473 988 371 |
| **Change (14.05 - 23.05)** | **0.428** | **0.500** | **0.108** | **0.468** | **0.400** | **-1 573 967 251** |

**Table 9.** Idiosyncratic asymmetric volatility for DeFi coins and BTC during the May 2021 price crash. *The columns with the cryptocurrency symbols showcase the asymmetry term **φ** from 14.05 to 23.05.2021. The column Total Borrowing represents the USD value of borrowing in DeFi. Data from Yahoo Finance. Created by authors.*

We also regress the residuals of regressing ETH price on total borrowing, on the asymmetric volatility of idiosyncratic returns for the DeFi coins and obtain the following results (see Table 10).

| *Dependent variable:*<br>**Independent variable** | *ETH* | *LUNA1* | *AVAX* | *UNI1* | *LINK* |
|---|---|---|---|---|---|
| *Total Borrowing (residuals)* | 4.37E-12<br>*(0.000)* | 5.44E-12<br>*(0.012)* | -1.80E-12<br>*(0.273)* | 6.28E-12<br>*(0.000)* | 1.33E-11<br>*(0.004)* |
| Lag | 4 | 1 | 4 | 1 | 4 |
| *Lag of Total Borrowing (residuals)* | -4.06E-12<br>*(0.001)* | -5.89E-12<br>*(0.006)* | 1.46E-12<br>*(0.374)* | -6.55E-12<br>*(0.000)* | 9.94E-12<br>*(0.033)* |
| *Volume* | 6.15E-14<br>*(0.615)* | -2.11E-12<br>*(0.451)* | -4.50E-13<br>*(0.921)* | -5.33E-12<br>*(0.037)* | -3.81E-13<br>*(0.694)* |

**Table 10.** Estimation results of Eq. ( 12 ). The dependant variables are the idiosyncratic asymmetry terms for DeFi coins. *The explanatory variables Total Borrowing (residuals) and Lag of Total Borrowing (residuals) represent the ETH adjusted borrowing volume from Eq. ( 2 ). The lag is determined by the row Lag. Volume represents the trading volume for a specific coin. Data from Yahoo Finance. Created by authors.*

From the regressions we find that ETH, LUNA1, UNI1 and LINK produce statistically significant results, and show that an increase in total borrowing at time T, predicts an increase in DAV at time T. We also find statistically significant lags, which show the opposite relation, that a decrease in total borrowing at time T may lead to an increase in DAV at time T+1 for LUNA1 and UNI1, or T+4 for ETH. For most of these coins an upwards trend in the asymmetry term can be observed. The clearest effect can be seen for LINK, as there is a significant increase in DAV at time T, and a smaller latent increase, as can be seen from the lag. Volume is statistically significant only for UNI1, predicting a decrease in idiosyncratic DAV at time T, given an increase in total borrowing at time T.

### 3.5 Risk measures and scaled total borrowing

In our work, we also include two systemic risk measures, SRISK and Tail beta, which are later included in leverage regressions and analysis. In specific, we observe the relation between a specific risk measure and scaled total borrowing. The regressions we run are based on Eq. ( 12 ), where now the dependent variable is replaced with a specific risk measure.

#### *3.5.1 SRISK*

SRISK measures the sensitivity of a given coin to the market when it is experiencing the worst 5% of returns for a given time, which we use as a proxy for systemic risk (Acharya, Pedersen, Philippon, & Richardson, 2017). In our analysis, we use a window of 90 days to be consistent with our measures from Eq. ( 5 ). We adjust the methodology from (Acharya, Pedersen, Philippon, & Richardson, 2017), as cited in a working paper by (Bui & Putnins, 2020):

$$SRISK = \frac{1}{\# \, days} \sum R_{i,\{t:5\% \, tail\}} \tag{14}$$

*Where: SRISK is the proxy for systematic risk at time t when the market is experiencing the lowest 5% of returns;* $R_{i,\{t:5\% \, tail\}}$ *is the return of a given coin when the market is performing at its lowest 5% at time t.*

We then obtain a timeseries data set for SRISK, which can then be used as a dependent variable in the leverage regressions (see Eq. ( 12 )). The SRISK measure is negative when an asset experiences negative returns during a market downturn, whereas the value is positive in case the asset has positive returns in the same situation. The more negative the SRISK value, the more negatively the asset is performs during market crashes.

***Results.*** For SRISK, we find that ETH and BTC remain quite stable from 2020 to 2022, however they both experience a slight dip after May of 2021, with BTC remaining slightly less exposed to systemic risk at an SRISK value of -0.07, compared to ETH with an SRISK value of -0.10 at the end of 2021 (see Appendix G). The other DeFi coins, however, experience slightly more dramatic changes, with a sharp dip following the crash in May 2021. LINK, LUNA1, and UNI1 all recover by the end of the year, and hover around an SRISK value of -0.1, however AVAX does not recover from the dip. The most dramatic drop in SRISK was for LUNA1, dropping from -0.09 on the 17th of May, to -0.35 on the 16th of August.

During the worst of the price crash, however, AVAX, BTC, ETH, LINK, LUNA1, and UNI1 all experienced a decrease in SRISK, the largest decrease being for LUNA1 (see Table 11). On average, the SRISK for DeFi coins dropped by 0.06, whereas the average drop for all coins in our sample excluding stablecoins was 0.04.

| Date | BTC | ETH | LUNA1 | AVAX | UNI1 | LINK | Total Borrowing |
|---|---|---|---|---|---|---|---|
| **14.05.2021** | -0.073 | -0.103 | -0.091 | -0.100 | -0.092 | -0.126 | 20 047 955 622 |
| **15.05.2021** | -0.073 | -0.103 | -0.091 | -0.100 | -0.092 | -0.126 | 20 709 838 118 |
| **16.05.2021** | -0.073 | -0.103 | -0.091 | -0.100 | -0.092 | -0.126 | 20 315 632 949 |
| **17.05.2021** | -0.073 | -0.103 | -0.091 | -0.100 | -0.092 | -0.126 | 21 331 694 259 |
| **18.05.2021** | -0.073 | -0.103 | -0.091 | -0.100 | -0.092 | -0.126 | 20 684 137 711 |
| **19.05.2021** | -0.075 | -0.110 | -0.157 | -0.130 | -0.144 | -0.183 | 24 112 329 664 |
| **20.05.2021** | -0.075 | -0.110 | -0.157 | -0.130 | -0.144 | -0.183 | 17 927 444 909 |
| **21.05.2021** | -0.075 | -0.110 | -0.167 | -0.131 | -0.150 | -0.183 | 18 885 871 199 |
| **22.05.2021** | -0.075 | -0.110 | -0.167 | -0.131 | -0.150 | -0.183 | 18 115 152 747 |
| **23.05.2021** | -0.076 | -0.110 | -0.205 | -0.134 | -0.155 | -0.179 | 18 473 988 371 |
| **Change (14.05 - 23.05)** | **-0.004** | **-0.007** | **-0.115** | **-0.034** | **-0.063** | **-0.053** | **-1 573 967 251** |

**Table 11.** SRISK for DeFi coins and BTC during the May 2021 price crash. *The columns with the cryptocurrency symbols showcase the SRISK measure from Eq. ( 14 ) between 14.05 and 23.05.2021. The column Total Borrowing represents the USD value of borrowing in DeFi. Data from Yahoo Finance. Created by authors.*

To further solidify the results, we employ regression frameworks similar to Eqs. ( 10 ) and ( 11 ), attempting to see whether DeFi coins experienced increased systemic risk after 2020, when DeFi lending became more popular (see Table 12).

| Dependent variable: $SRISK_{i,t}$ | | |
|---|---|---|
| **Independent variable** | **Estimate** | **p-value** |
| *Intercept* | -0.118 | (0.000) *** |
| $DeFi\_dummy_i$ | 0.016 | (0.000) *** |
| $2020\_dummy_t$ | -0.002 | (0.829) |
| $DeFi\_dummy_i$:$2020\_dummy_t$ | -1.700E-05 | (0.000) *** |
| Observations: | 19 913 | |
| $R^2$: | 0.009 | |
| Adjusted $R^2$: | 0.009 | |
| p-value: | 0.000 | |

**Table 12.** Estimation results similar to Eq. 10. T*he dependent variable is SRISK. The explanatory variables are defined in section 3.4. Data from Yahoo Finance. Created by authors.*

In Table 12, we are only interested in the interaction term between the 2020 and DeFi dummy variables, which show a very small but statistically significant effect. This shows that following the introduction of DeFi leverage mechanisms, DeFi related coins have experienced slightly more systemic risk, as the SRISK measure has been more negative for DeFi coins. This effect, however, is very small, which is expected, as the SRISK measure is likely to only decrease significantly during market crashes.

| Dependent variable: $SRISK_{i,t}$ | | |
|---|---|---|
| **Independent variable** | **Estimate** | **p-value** |
| *Intercept* | -0.138 | (0.000) *** |
| $DeFi\_dummy_i$ | -0.022 | (0.000) *** |
| Observations: | 527 | |
| $R^2$: | 0.065 | |
| Adjusted $R^2$: | 0.064 | |
| p-value: | 0.000 | |

**Table 13.** Estimation results similar to Eq. 10. *With a much shorter time frame of one month following the crash (19.05.2021 – 19.06.2021). The dependent variable is SRISK, and the explanatory variable is a simple dummy variable denoting whether a coin is related to DeFi. Dummy variable 2020 and the interaction term between DeFi and 2020 are excluded, due to them being redundant. Data from Yahoo Finance. Created by authors.*

In Table 13, we find a much stronger and statistically significant negative effect on the relative riskiness of DeFi coins. DeFi coins experienced by 0.022 larger decrease in the SRISK metric during the crash.

We also obtain the following regression results by regressing the residuals of total borrowing, lag of total borrowing and volume on SRISK values (see Table 14).

| *Dependent variable:* **Independent variable** | *BTC* | *ETH* | *LUNA1* | *AVAX* | *UNI1* | *LINK* |
|---|---|---|---|---|---|---|
| *Total Borrowing (residuals)* | -5.49E-14 | -8.88E-14 | -3.40E-13 | -3.46E-13 | -3.65E-13 | -7.65E-13 |
| | *(0.008)* | *(0.000)* | *(0.215)* | *(0.000)* | *(0.149)* | *(0.036)* |
| Lag | 5 | 5 | 2 | 2 | 1 | 1 |
| *Lag of Total Borrowing (residuals)* | 4.91E-14 | 8.02E-14 | 2.24E-13 | 2.98E-13 | 2.64E-13 | 6.98E-13 |
| | *(0.020)* | *(0.001)* | *(0.414)* | *(0.000)* | *(0.301)* | *(0.055)* |
| *Volume* | -2.40E-15 | -6.35E-15 | 3.81E-13 | 4.65E-14 | -4.99E-13 | -6.32E-15 |
| | *(0.086)* | *(0.029)* | *(0.352)* | *(0.759)* | *(0.240)* | *(0.909)* |

**Table 14.** Estimation results of Eq. ( 12 ). *The dependant variables are the SRISK measures for DeFi coins and BTC. The explanatory variables Total Borrowing (residuals) and Lag of Total Borrowing (residuals) represent the ETH adjusted borrowing volume from Eq. ( 2 ). The lag is determined by the row Lag. Volume represents the trading volume for a specific coin. Data from Yahoo Finance. Created by authors.*

We find a statistically significant negative effect of an increase in total borrowing at time T on SRISK at time T for ETH, AVAX, LINK and BTC. The effects for BTC and ETH, however, are smaller by a magnitude of 10, as could be seen in Table 12. We also find some statistically significant lags for ETH, AVAX, LINK and BTC, and the effects are the opposite, showing that an increase in total borrowing at time T may lead to an increase in SRISK at time T+5 in the example of ETH. In general, however, it appears that SRISK has worsened during a time of increased total borrowing and market turmoil. It is also interesting how BTC has statistically significant results, at it should not be as connected to DeFi lending mechanisms. But we do see that the effect is comparatively small, nearly ten times smaller than for AVAX and LINK, and roughly 40% smaller than the effect on ETH. We also find a small but statistically significant effect for trading volume on the SRISK of BTC and ETH.

### *3.5.2 Tail beta*

We also use tail beta (t-beta), which is a hybrid of the SRISK and beta measures, as it calculates an OLS estimate for a regular beta with the only difference being using the 5% worst days in the market. We use a methodology from van Oordt and Zhou (2012) as cited in a working paper by Bui and Putnins (2020) with the following regression equation:

$$R_{i,5\%\,tail,t} = \alpha_i + \beta_i R_{M,5\%\,tail,t} + \varepsilon_{i,t} \tag{15}$$

*Where: $R_{i,5\%\,tail,t}$ is the return of a specific coin at time t when the market is experiencing the lowest 5% of returns; $R_{M,5\%\,tail,t}$ worst 5% of market returns, proxied by the average returns of our sample of 20 coins at time t; and $\varepsilon_{i,t}$ is the error term.*

We calculate the tail beta the six coins in our sample and find the following results (see Table 15).

| | t-beta | p-value |
|---|---|---|
| AVAX | 1.29 | 0.000 |
| BTC | 0.77 | 0.000 |
| ETH | 1.02 | 0.000 |
| LINK | 1.40 | 0.000 |
| LUNA1 | 0.84 | 0.000 |
| UNI1 | 1.11 | 0.000 |

**Table 15.** Tail beta values for DeFi coins and BTC. *The column t-beta represents tail beta value for a specific currency, based on the $\beta$ term from Eq. ( 15 ). Data from Yahoo Finance. Created by authors.*

We find that the highest t-beta in our DeFi sample is for LINK, meaning that it is the most sensitive to bad days in the market. LINK has the second highest t-beta when looking at all 20 coins in our sample, the highest being SOL with a t-beta of 1.46. Out of the 20 coins in our sample, the lowest t-betas are for the stablecoins, and BTC with a t-beta of 0.77, indicating higher resilience to market shocks.

## *4. Discussion*

### 4.1 Upward asymmetric volatility

In the equities literature it is established that the market exhibits DAV. In the context of cryptocurrencies, the literature is not unified. Baur and Dimpfl (2018) established that the majority of coins in their sample experienced UAV. Similarly, from the work of Bouri, Azzi, and Dyhrberg (2017), they noted that the direction of the asymmetry, upward or downward, can vary, at least in the case of BTC.

The most recent work in the field covers the period until 2018. We looked at the asymmetries for 20 cryptocurrencies based on the return data from 09.09.2016 until 01.01.2022. We found that over the sample period, 14 out of 20 cryptocurrencies exhibit UAV based on the gjrGARCH model. We found that despite the high correlation between the most prominent cryptocurrencies, BTC and ETH, they experience different asymmetry. BTC exhibits UAV, whilst ETH DAV. Baur and Dimpfl (2018) found both BTC and ETH to be upward. Their sample period ends in 2018 and ours in 2022. Thus, it is possible that the asymmetry structure of ETH has changed and moved from upward to downward asymmetry, as the results between our paper and their paper contradict. Alternatively, the difference can also come from differences in methodology. In their paper, Baur and Dimpfl (2018) used the TGARCH model, whilst we had gjrGARCH. Although, the two models are very similar, only difference is that in the TGARCH they use conditional standard deviation instead of conditional variances as in the gjrGARCH (Ali, 2013). Thus, both models should yield similar results and because of this it is more reasonable that the difference in the asymmetry structure of ETH between the two papers is actually due to differences in the sample period.

To better observe whether other currencies also have experienced changes to their asymmetry structure, we compare the pre- and post-DeFi period asymmetry term mean values in section 3.2.1. Firstly, we establish that the mean values between the two periods differ for all the cryptocurrencies. Moreover, we find that the number of currencies with UAV decreased from 13 to 9 over the two periods, ETH being one of them.

Both comparisons: our results from the gjrGARCH to the work of Baur and Dimpfl (2018) and decomposing the mean asymmetry into two periods, suggest that the asymmetry structure varies over time. Thus, we accept our first hypothesis:

**H1: The degree of asymmetry in cryptocurrencies varies over time.**

To further examine what impacts the degree of asymmetry we introduce categorical dummies and additional explanatory variables – age of a cryptocurrency and a dummy indicating the emergence of DeFi – in section 3.3. We find that in the post-DeFi period, i.e., since January 2020, cryptocurrencies exhibit more DAV. The findings of a reduction in the number of currencies with upward asymmetry from section 3.2.1, together with the positive relation between emergence of DeFi and DAV, suggest that the asymmetry in the market has become more downward.

To find an explanation for this, we look at two avenues: maturity of the cryptocurrency market and the emergence of DeFi. Firstly, we found in section 4.3. that the age of a cryptocurrency is positively related to DAV. Meaning, as a cryptocurrency ages, it is more likely to move towards DAV. Thus, the fact that cryptocurrencies exhibit UAV, but over time have moved towards more downward asymmetry can be an indication of the market maturing. Meaning, it is possible that upward asymmetry is only a state which currencies exhibit in their youth, and over time the volatility structure starts to look as it is in the mature equities market – downward.

Secondly, we can try to reason the move towards more downward asymmetry with the emergence of DeFi. From section 3.3, we find that after the emergence of DeFi, all coins exhibit more DAV, but the effect is stronger for DeFi coins compared to non-DeFi coins.

## 4.2 Asymmetry, leverage and risk

In this section, we try to explain the downwards pressure on asymmetry for the DeFi coins after the emergence of DeFi. We do this by observing the relation between asymmetry and the borrowing values in DeFi.

### *4.2.1 Asymmetry, scaled total borrowing, and the price of ETH*

In our hypothesis, we state that we would expect the downside asymmetry to increase as total borrowing increases, however, by looking at the graphs and regressions, the results are not as clear cut (see Panels 1 and 2). When examining the asymmetries, we could observe a positive trend for LUNA1, AVAX, UNI1 and LINK, however, the most serious jumps in downside asymmetric volatility only occur during the price crash in May of 2021, which makes sense, as the prices for all these coins dropped rapidly during this time. We also see that total borrowing drops significantly, which may happen due to two main reasons. First, as total borrowing is expressed in dollar terms, it is likely that the decrease in the price of ETH could decrease total borrowing in USD terms, but that the number of tokens lent out could remain the same. We account for this in our regressions, by using ETH adjusted total borrowing, based on Eq. ( 2 ). The other reason for a rapid decrease in total borrowing could be the liquidation of positions, which would indicate that a liquidation event may have taken place, therefore forcing the sale of these coins, and causing a spike in downside asymmetric volatility. Therefore, following a long bull run of about seven months, including increased borrowing, it would make sense that total borrowing may drop due to the liquidation of positions, forcing further sales, and leading to an increased DAV.

However, because there was a market wide drop in crypto prices, most other non-DeFi coins also experienced a sharp jump in DAV, even BTC, which has been largely stable over the past two years. The regressions from Table 9 also show that increases in total borrowing tend to predict increases in asymmetry for four out of five DeFi coins: ETH, LUNA1, UNI1 and LINK. During this price crash in May of 2021, however, most coins in our sample experienced an increase in DAV, which were less exposed to DeFi lending mechanisms than our sample of DeFi related coins. Therefore, the question becomes whether the coins which were more exposed to DeFi lending mechanisms, and more likely to be involved in cascading overcollateralized lending positions experienced more DAV than other coins. We found that during this event, the asymmetric volatility for DeFi coins increased by 0.42, however for our sample of 20 coins the average was lower at 0.32. When checking the change in the asymmetric volatility for the idiosyncratic returns of the DeFi sample, the increase was 0.38, slightly lower because of the correlation with BTC and the market by proxy, which itself experienced an increase in asymmetry during this time of 0.06. The effect of the market was different on each coin, as the correlations are different between BTC and each DeFi coin (see Appendix D). We also confirm this with a dummy variable regression after the crash in May 2021 and find that DeFi coins experienced more DAV (see table 6), with statistical significance.

It is also worth noting that when comparing the asymmetries of idiosyncratic returns to regular returns, it appears that the idiosyncratic returns of the DeFi sample appear to be more upwards asymmetric, which shows that some portion of the downwards asymmetry also comes from the market. Based on these results, however, we can see that coins which are exposed to DeFi lending tend to exhibit increased DAV.

Based on these findings, we partially accept our second hypothesis. We have shown that an increase in leverage likely predicts an increase in DAV, but we cannot confirm any direct causality with the econometric methods we have chosen.

**H2: Leveraged trading increases downwards asymmetric volatility.**

#### *4.2.2 Risk and leverage*

As mentioned before, the findings for risk metrics are less universal across the coins. With SRISK, we find that all DeFi coins except for ETH saw a large decrease in the SRISK metric during the price crash in May of 2021. We also find that the SRISK metric had been on a downwards trend for UNI1, AVAX and LINK as total borrowing was increasing. During the crash, however, the average decrease in the SRISK metric for DeFi coins was 0.055, whereas the average drop for all coins in our sample excluding stablecoins was 0.042, indicating that the DeFi coins experienced larger losses on days when the market was doing poorly. The largest decreases in SRISK were for LUNA1 and UNI1, which is counterintuitive given their relatively normal t-beta scores of 0.84 and 1.11. Regressions provided less conclusive evidence, as only AVAX and LINK showed with statistical significance that an increase in total borrowing led to more SRISK. To further solidify our findings, we perform a dummy variable regression in which we find that after the crash in May 2021, DeFi coins experienced higher systemic risk relative to other non-DeFi coins with statistical significance (see Table 13).

Therefore, an increase in leverage also appears to contribute to make DeFi coins riskier compared to other non-DeFi coins, especially during market crashes. When the market is performing normally, however, the effect of leverage on SRISK is not very pronounced, with the effects only being felt in extreme circumstances. Therefore, we partially accept our third hypothesis.

**H3: Emergence of DeFi, via easier access to leverage, has made DeFi coins more susceptible to systemic risk.**

The emergence of DeFi appears to have made DeFi coins riskier relative to the cryptocurrency market during crashes. However, direct causality cannot be confirmed.

## *5. Limitations*

Our main limitation is with the robustness of the ADL regressions. We found that it was common that total borrowing was likely to cause opposite effects of a similar magnitude at time T, and at a lag, which causes fairly unintuitive economic interpretations of said coefficients. One possible reason for this would be multicollinearity issues between two or more of the dependent variables. To test for this, we conducted variance inflation factor (VIF) tests, which serve as a rule of thumb for whether coefficients are reliable. We found that there was moderate multicollinearity between total borrowing and its lags, generating VIF test scores of 3.9 – 7.3, whereas the rule of thumb value is 10 (Wooldridge, 2012). Quite logically, the VIF value was higher for more recent lags (VIF of 7.3 for total borrowing at time T, compared to total borrowing at time T+1) (see Appendix H). Therefore, we confirm that multicollinearity problems are likely present, however they are not so bad as to prohibit any meaningful interpretation of the coefficients obtained via the regressions. It does, however, show that ADL regressions cannot serve as a be all end all solution for the study of the effects of leverage on DAV. It is also very difficult to imply causality using time series models, meaning that at best, we can only show that an increase in leverage predicts an increase in DAV.

There were also limitations with our data. To further improve the robustness of the findings, a longer period must be studied. This would allow us to compare the effects across several crashes. It would also allow the DeFi coins to mature, perhaps eliminating the effect of DeFi coins being younger than their non-DeFi counterparts, and further solidifying the effect of leverage on DAV. The other significant limitation with our data was that total borrowing was expressed in USD. Ideally, we would like to eliminate the effect of price changes on total borrowing, instead using a measure like total tokens borrowed.

There are also other ways to obtain leverage in the DeFi market, which could also affect the DAV, which we have not included in this paper. BTC is also not entirely isolated from leverage, as it is possible to also obtain leverage on BTC that is not related to DeFi. Such data, however, is much harder to find, as it is stored on exchanges, rather than the ETH blockchain, which is more easily accessible.

We also find that further research must be done on other types of lending present in DeFi and in non-DeFi lending, which will further shed light on coins which are not related to DeFi, and the SRISK and DAV metrics must also be examined over a longer period of time. The market consequences of this research could also be studied, as this paper does not cover applying this information when making investment decisions. An example of this could be back testing and comparing two different minimum variance portfolios, one constructed with standard deviation, and the other with downwards semi-deviations drawing from the ideas of Markowitz (1959). Additionally, leverage in the market is most likely not the only factor which affects the volatility structure of cryptocurrencies. Therefore, further research must be done on the determinants and drivers of asymmetric volatility, like for example monetary policy.

## *6. Conclusion*

This research intends to shed light on the asymmetric volatility structure of cryptocurrencies, where the findings from previous research provide mixed results. Secondly, we try to establish a relation between leverage and asymmetric volatility structure. Leveraged trading is prevalent in the cryptocurrencies market via traditional exchanges, such as Binance, Bybit and FTX (Coinglass, n.d.). The emergence of DeFi and popularization of DeFi lending platforms has provided wider and easier access to leveraged trading. Thus, we would expect that the increased leverage in the market puts downward pressure on the asymmetry structure due to forced liquidations of overcollateralized positions. Finally, we explore whether the easier access to leverage has impacted the DeFi associated cryptocurrencies' exposure to systemic risk.

Our main empirical findings are the following. First, the cryptocurrency market predominantly exhibits upside asymmetric volatility. Using the semi-deviation method, we find that 13 out 20 cryptocurrencies in our sample exhibit UAV during the full sample period. Based on the asymmetric GARCH model, the number of currencies with UAV was 14.

Second, the emergence of DeFi has put downwards pressure on the asymmetry, with the number of coins with UAV decreasing from 13 to 9 after the emergence of DeFi. Moreover, using a difference-in-difference approach, we find that DeFi coins have more DAV than their non-DeFi counterparts after the emergence of DeFi.

Finally, we find that following the introduction of DeFi leverage mechanisms, DeFi related coins have experienced slightly more systemic risk than non-DeFi coins. The difference in susceptibility to systemic risk between DeFi and non-DeFi coins is stronger when only observing the period during the cryptocurrency price crash in May

2021. Thus, the relative riskiness of DeFi coins is 10 times stronger during the price crash when compared to the entire period after the emergence of DeFi.

These findings, especially the increased exposure of DeFi coins to systemic risk, provide an argument for more regulation of margin trading. If DeFi lending platforms continue to grow in popularity, the increased amount of leverage can make the whole cryptocurrency market more volatile and sensitive to crashes. According to the IMF, the interconnectedness of the cryptocurrencies and equities market is increasing, which means that higher risk in cryptocurrencies has the potential to cause spillover effects and threats to financial stability of regular equities markets (Adrian, Tara, & Qureshi, 2022). Further analysis, however, needs to be done once the DeFi platform has stabilized and the coins have matured, to more conclusively prove the effect of leverage on DAV and market risk.

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## *8. Appendices*

### *Appendix A*

**Sample of Cryptocurrencies with Corresponding Sample Period**

| # | Cryptocurrency | Symbol | Classification | Period (DD/MM/YYYY) Beginning | End |
|---|---|---|---|---|---|
| 1 | Bitcoin | BTC | N/A | 09.09.2016 | 01.01.2022 |
| 2 | Ethereum | ETH | DeFi coin | 09.09.2016 | 01.01.2022 |
| 3 | Binance Coin | BNB | Exchange coin | 25.07.2017 | 01.01.2022 |
| 4 | Tether | USDT | Stablecoin | 09.09.2016 | 01.01.2022 |
| 5 | Solana | SOL | N/A | 01.10.2017 | 01.01.2022 |
| 6 | Cardano | ADA | N/A | 09.09.2016 | 01.01.2022 |
| 7 | XRP | XRP | N/A | 18.09.2019 | 01.01.2022 |
| 8 | Polkadot | DOT | N/A | 09.09.2016 | 01.01.2022 |
| 9 | USD Coin | USDC | Stablecoin | 09.04.2020 | 01.01.2022 |
| 10 | Dogecoin | DOGE | N/A | 09.09.2016 | 01.01.2022 |
| 11 | Avalanche | AVAX | DeFi coin | 20.08.2020 | 01.01.2022 |
| 12 | Terra | LUNA1 | DeFi coin | 08.10.2018 | 01.01.2022 |
| 13 | Crypto.com Coin | CRO | Exchange coin | 22.09.2020 | 01.01.2022 |
| 14 | Litecoin | LTC | N/A | 14.12.2018 | 01.01.2022 |
| 15 | Uniswap | UNI1 | DeFi coin | 22.09.2020 | 01.01.2022 |
| 16 | Chainlink | LINK | DeFi coin | 09.11.2017 | 01.01.2022 |
| 17 | Algorand | ALGO | N/A | 22.06.2019 | 01.01.2022 |
| 18 | Polygon | MATIC | N/A | 29.04.2019 | 01.01.2022 |
| 19 | Cosmos | ATOM | N/A | 14.03.2019 | 01.01.2022 |
| 20 | TRON | TRX | N/A | 09.11.2017 | 01.01.2022 |

**Table A1.** Sample of Cryptocurrencies with Corresponding Sample Period. *This table presents the sample of 20 cryptocurrencies. The column Classification refers to the corresponding group the currency belongs to. Value N/A means, that the specific currency has not been assigned to any group. Columns Beginning and End represent the start and end of the sample period, correspondingly. Data from Yahoo Finance. Created by authors.*

*Appendix B*

**gjrGARCH model specification**

| # | Cryptocurrency | Distribution | Mean equation **ARMA(p,q)** | Variance equation **gjrGARCH(p,q)** |
|---|---|---|---|---|
| 1 | BTC | GED | ARMA(0,0) | gjrGARCH(1,1) |
| 2 | ETH | GED | ARMA(2,2) | gjrGARCH(1,1) |
| 3 | BNB | STD | ARMA(2,2) | gjrGARCH(1,1) |
| 4 | USDT | STD | ARMA(1,1) | gjrGARCH(1,1) |
| 5 | SOL | STD | ARMA(2,2) | gjrGARCH(1,1) |
| 6 | ADA | STD | ARMA(2,2) | gjrGARCH(1,1) |
| 7 | XRP | STD | ARMA(2,2) | gjrGARCH(1,1) |
| 8 | DOT | STD | ARMA(2,3) | gjrGARCH(1,1) |
| 9 | USDC | STD | ARMA(4,2) | gjrGARCH(1,1) |
| 10 | DOGE | STD | ARMA(3,2) | gjrGARCH(1,2) |
| 11 | AVAX | STD | ARMA(0,0) | gjrGARCH(1,1) |
| 12 | LUNA1 | GED | ARMA(2,2) | gjrGARCH(1,1) |
| 13 | CRO | STD | ARMA(0,0) | gjrGARCH(1,1) |
| 14 | LTC | STD | ARMA(2,2) | gjrGARCH(1,1) |
| 15 | UNI1 | STD | ARMA(1,1) | gjrGARCH(1,1) |
| 16 | LINK | STD | ARMA(0,0) | gjrGARCH(1,1) |
| 17 | ALGO | STD | ARMA(1,1) | gjrGARCH(1,1) |
| 18 | MATIC | STD | ARMA(2,2) | gjrGARCH(1,1) |
| 19 | ATOM | STD | ARMA(1,1) | gjrGARCH(1,1) |
| 20 | TRX | STD | ARMA(2,2) | gjrGARCH(1,1) |

**Table B1.** The asymmetric GARCH model specification. *This table presents the specifics for the asymmetric GARCH estimation method. Distribution refers to the distribution density used in estimation. In ARMA(p,q), the p stands for the autoregressive terms and q for the moving average terms in the mean equation Eq. ( 7 ). In gjrGARCH(p,q), the p and q represent the order of the GARCH and ARCH terms correspondingly. Data from Yahoo Finance. Created by authors.*

*Appendix C*

| Currency | μ | ω | α | β | γ | |
|---|---|---|---|---|---|---|
| BTC | 0.002 | 0.000 | 0.113 | 0.878 | -0.004 | |
| | *(0.000)* | *(0.087)* | *(0.000)* | *(0.000)* | *(0.897)* | |
| ETH | 0.001 | 0.000 | 0.133 | 0.804 | 0.004 | |
| | *(0.000)* | *(0.000)* | *(0.000)* | *(0.000)* | *(0.917)* | |
| BNB | 0.002 | 0.000 | 0.203 | 0.826 | -0.076 | * |
| | *(0.041)* | *(0.086)* | *(0.005)* | *(0.000)* | *(0.081)* | |
| USDT | 0.000 | 0.000 | 0.135 | 0.786 | 0.128 | |
| | *(0.999)* | *(1.000)* | *(0.996)* | *(0.986)* | *(0.995)* | |
| SOL | 0.005 | 0.001 | 0.155 | 0.755 | -0.053 | |
| | *(0.091)* | *(0.050)* | *(0.042)* | *(0.000)* | *(0.475)* | |
| ADA | -0.001 | 0.000 | 0.148 | 0.823 | 0.002 | |
| | *(0.519)* | *(0.041)* | *(0.004)* | *(0.000)* | *(0.958)* | |
| XRP | -0.001 | 0.000 | 0.193 | 0.826 | -0.040 | |
| | *(0.095)* | *(0.389)* | *(0.025)* | *(0.000)* | *(0.347)* | |
| DOT | 0.003 | 0.000 | 0.074 | 0.854 | 0.011 | |
| | *(0.270)* | *(0.071)* | *(0.026)* | *(0.000)* | *(0.805)* | |
| USDC | 0.000 | 0.000 | 0.079 | 0.895 | 0.019 | |
| | *(0.979)* | *(1.000)* | *(0.983)* | *(0.876)* | *(0.994)* | |
| DOGE | -0.001 | 0.000 | 0.391 | 0.308 | -0.101 | |
| | *(0.056)* | *(0.022)* | *(0.000)* | *(0.006)* | *(0.167)* | |
| AVAX | 0.004 | 0.000 | 0.176 | 0.825 | -0.095 | * |
| | *(0.212)* | *(0.003)* | *(0.001)* | *(0.000)* | *(0.099)* | |
| LUNA1 | -0.009 | 0.000 | 0.207 | 0.795 | -0.006 | |
| | *(0.000)* | *(0.874)* | *(0.910)* | *(0.341)* | *(0.999)* | |
| CRO | 0.002 | 0.000 | 0.228 | 0.812 | -0.090 | |
| | *(0.124)* | *(0.018)* | *(0.001)* | *(0.000)* | *(0.141)* | |
| LTC | 0.000 | 0.000 | 0.142 | 0.893 | -0.071 | ** |
| | *(0.727)* | *(0.165)* | *(0.000)* | *(0.000)* | *(0.012)* | |
| UNI1 | 0.000 | 0.000 | 0.040 | 0.850 | 0.115 | |
| | *(0.890)* | *(0.161)* | *(0.122)* | *(0.000)* | *(0.129)* | |
| LINK | 0.002 | 0.000 | 0.088 | 0.891 | -0.002 | |
| | *(0.103)* | *(0.005)* | *(0.000)* | *(0.000)* | *(0.942)* | |
| ALGO | 0.001 | 0.000 | 0.086 | 0.887 | -0.048 | * |
| | *(0.508)* | *(0.010)* | *(0.002)* | *(0.000)* | *(0.098)* | |
| MATIC | 0.001 | 0.001 | 0.201 | 0.810 | -0.143 | *** |
| | *(0.418)* | *(0.019)* | *(0.007)* | *(0.000)* | *(0.006)* | |
| ATOM | 0.002 | 0.000 | 0.146 | 0.815 | -0.052 | |
| | *(0.253)* | *(0.060)* | *(0.003)* | *(0.000)* | *(0.272)* | |
| TRX | 0.001 | 0.000 | 0.215 | 0.840 | -0.113 | *** |
| | *(0.387)* | *(0.085)* | *(0.000)* | *(0.000)* | *(0.004)* | |

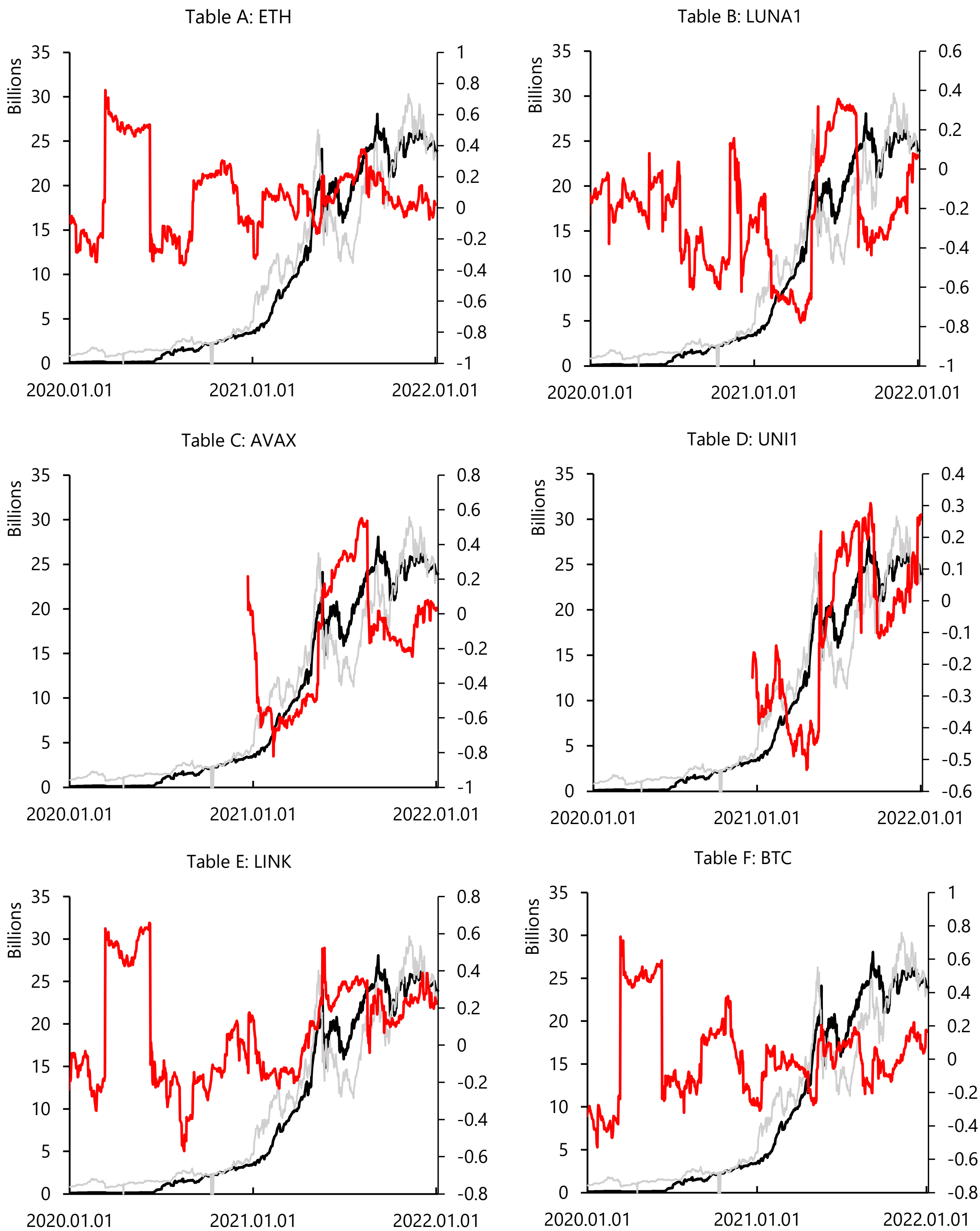
**Table C1.** Estimation results of the asymmetric GARCH model. *This table presents the asymmetric GARCH estimation results from Eqs. ( 7 ) and ( 8 ). The $\gamma$ term stands for the asymmetric volatility. The values in italic represent the corresponding p-values based on the robust standard errors. The significance codes *, **, *** showcase the statistical significance of the $\gamma$ on a 10%, 5%, and 1% level respectively. Data from Yahoo Finance. Created by authors.*

*Appendix D*

| | r_BTC | r_ETH | r_AVAX | r_UNI1 | r_LU1 | r_LINK |
|---|---|---|---|---|---|---|
| **r_BTC** | 1 | 0.76 | 0.47 | 0.55 | 0.47 | 0.67 |
| **r_ETH** | 0.76 | 1 | 0.52 | 0.69 | 0.50 | 0.80 |
| **r_AVAX** | 0.47 | 0.52 | 1 | 0.47 | 0.46 | 0.54 |
| **r_UNI1** | 0.55 | 0.69 | 0.47 | 1 | 0.42 | 0.68 |
| **r_LU1** | 0.47 | 0.50 | 0.46 | 0.42 | 1 | 0.46 |
| **r_LINK** | 0.67 | 0.80 | 0.54 | 0.68 | 0.46 | 1 |

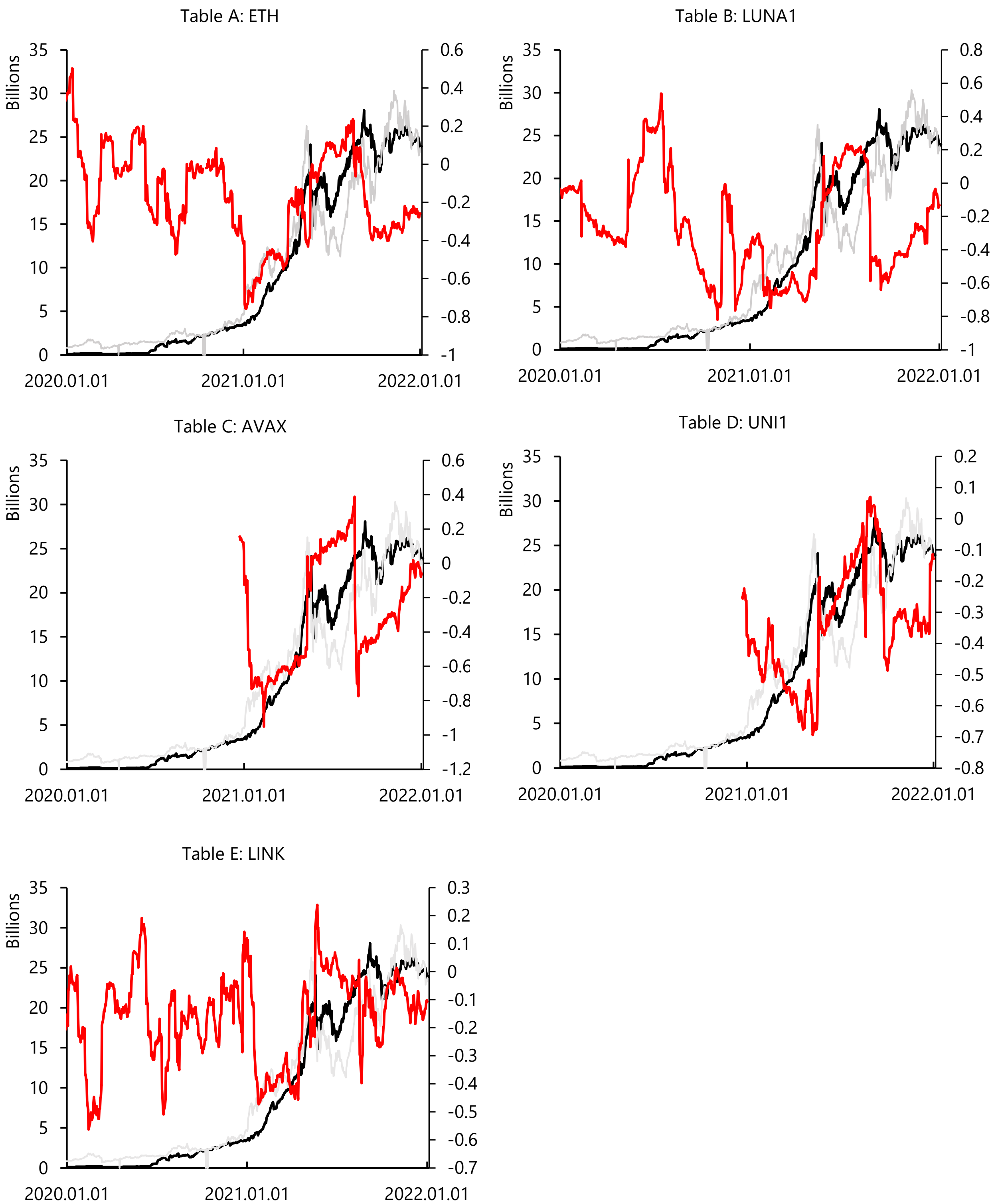
**Table D1.** Correlation matrix of the returns of DeFi coins and BTC. *Data from Yahoo Finance. Created by authors.*

*__Appendix E__*



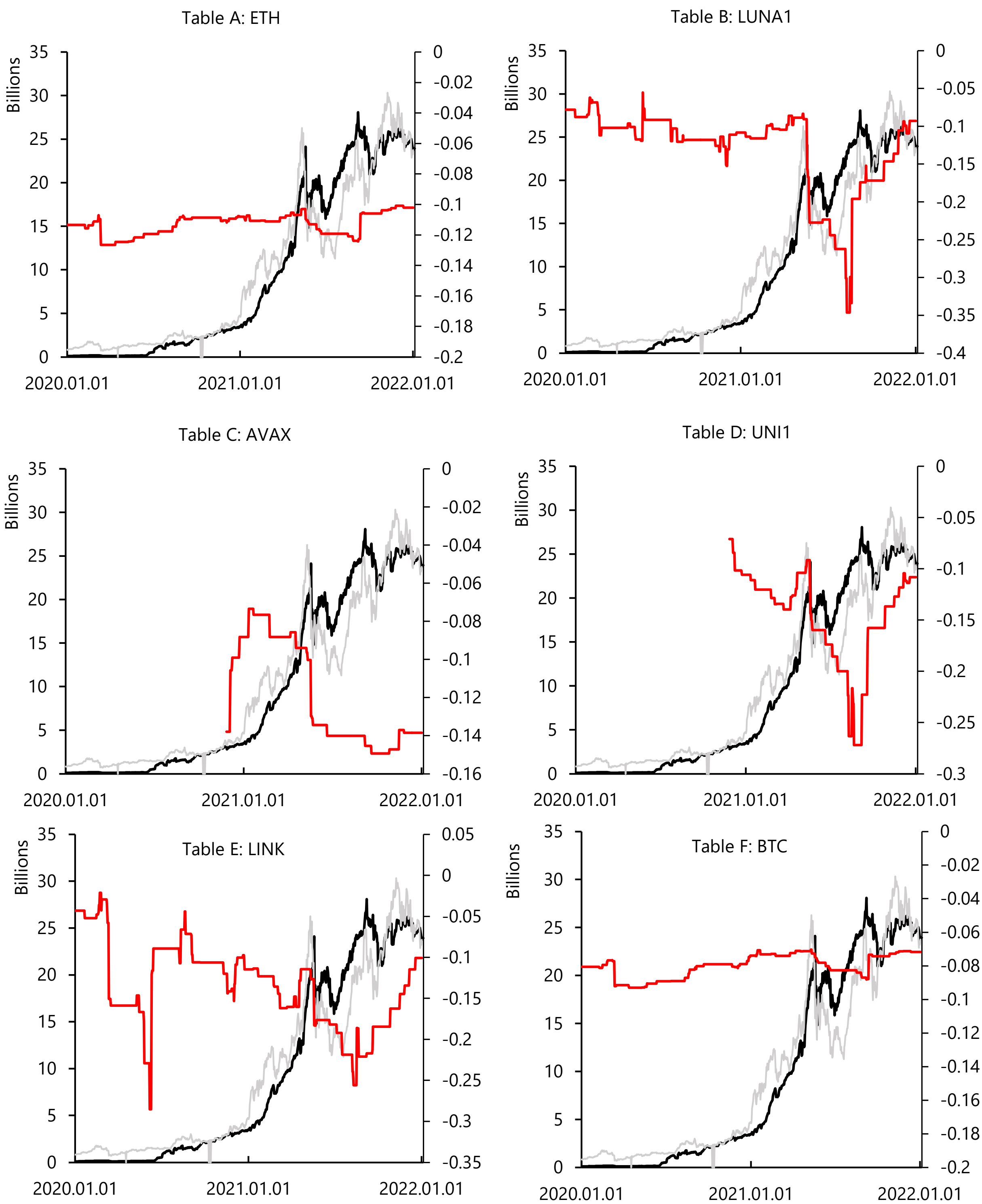

**Panel E1.** Asymmetries of DeFi coins and BTC. *The asymmetry term $\varphi_{i,t}$ is depicted in red (secondary y-axis); total borrowing in black; and scaled ETH price in gray (primary y-axis). Data from Yahoo Finance. Created by authors.*

***Appendix F***




**Panel F1.** Idiosyncratic asymmetries of DeFi coins and BTC. *The asymmetry term* $\varphi_{i,t}$ *is depicted in red (secondary y-axis); total borrowing in black; and scaled ETH price in gray (primary y-axis). Data from Yahoo Finance. Created by authors*

*Appendix G*




**Panel G1.** SRISK measure for DeFi coins and BTC. *SRISK is depicted in red (secondary y-axis); total borrowing in black; and scaled ETH price in gray (primary y-axis). Data from Yahoo Finance. Created by authors.*

*Appendix H*

To check for multicollinearity issues, we apply a very simple methodology from Wooldridge (2012) to calculate the VIF as a rule of thumb. This helps check whether multicollinearity issues are prohibitive.

For example, if we have a regression such as equation 12:

$$\varphi_{i,t} = \beta_0 + \beta_1 Y_t + \beta_2 Y_{t-1} + \beta_3 X_t + \varepsilon_{i,t} \tag{16}$$

*Where: the dependent variable $\varphi_t$ – the measure of asymmetry at time t, $\beta_0$ – intercept, $Y_t$ – scaled total borrowing at time t, $Y_{t-1}$ - scaled total borrowing at time t-1, $X_t$ –trading volume at time t.*

We can check for the multicollinearity between variables $Y_t$ and $Y_{t-1}$ by doing the following regression:

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + \varepsilon_{i,t} \tag{16}$$

The coefficients are of no interest to us, and we only wish to see the R squared value. For this regression we obtain an R squared of 86.38%, which is quite high and implies some degree of multicollinearity.

To calculate the VIF, we use the following equation:

$$VIF_{Yt} = \frac{1}{1 - R^2} \tag{17}$$

We therefore obtain a VIF of 7.34 for the variable $Y_t$ in equation 12. With the rule of thumb value being 10, we confirm that the multicollinearity is not prohibitive.