



Efficiency of Cryptocurrencies – Will Arbitrage Opportunities Continue?

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Abstract

Portuguese

Criptomoedas são cada vez mais populares entre investidores, e como consequência recebem mais atenção não só pelo público, mas também por investigadores. No entanto, ainda permanecem muitas questões, tais como se criptomoedas são eficientes na forma fraca. Se são, isto significaria que *Technical Trading*, a estratégia de *trading* mais usada por *traders* de retalho, não é capaz de gerar retornos anormais. Este papel acrescenta há existente literatura analisando o desenvolvimento da eficiência em *Bitcoin* e *Ether* ao longo de um período desde 2010 a 2022. Eu uso estas duas criptomoedas como representantes do mercado em geral pois, combinadas têm uma quota de mercado superior a 60%.

Usando múltiplos testes de eficiência, eu construo um índice de eficiência, com o qual eu acompanho o desenvolvimento da eficiência das criptomoedas analisadas. Através de uma análise dinâmica com uma janela rolante e uma divisão entre várias subamostras representativas, eu concluo que *Bitcoin* e *Ether* tornam-se mais eficientes ao longo do tempo. Para ambas criptomoedas, este aumento em eficiência está positivamente correlacionado com um aumento em liquidez.

Comparando estes resultados com o câmbio do Euro para o USD, estas criptomoedas exibem um nível de eficiência mais elevado. Isto não é surpreendente considerando que não existe nenhuma autoridade central a regular o mercado.

English

Cryptocurrencies are increasingly popular among investors and consequently receive rising attention, not only from the public but also from researchers. However, there remain many unsettled questions like whether cryptocurrencies are weak-form efficient. If they were, this would mean that technical trading, the most widely used trading strategy by retail traders, does no longer yield abnormal returns. This paper adds to the current literature by analysing the development of efficiency in Bitcoin and Ether over a time horizon from 2010 to 2022. I take these two cryptocurrencies as representatives of the overall cryptocurrency market since together they have a market share of over 60%.

Using multiple efficiency tests, I build an efficiency index to track the development of efficiency of the analysed cryptocurrencies. Through a dynamic rolling window analysis and the split among several representative subsamples, I conclude that Bitcoin and Ether become more efficient over time. For both cryptocurrencies, this increase in efficiency is positively correlated with an increase in liquidity.

Comparing these results to the exchange rate of the Euro to the US-Dollar, the cryptocurrencies show a higher level of efficiency. This is not surprising considering that there is no central authority intervening to regulate the market.

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List of Abbreviations

ADF	Augmented Dickey Fuller Test
AMH	Adaptive Market Hypothesis
BTC	Bitcoin
ECB	European Central Bank
EMH	Efficient Market Hypothesis
ETH	Ether
EUR	Euro
Fed	Federal Reserve Bank
FOREX	Foreign Exchange Market
H₀	Null Hypothesis
i.i.d	Independently Identically Distributed
mcap	Market Capitalization
QE	Quantitative Easing
UIP	Uncovered Interest Parity
USD	US-Dollar

1. Introduction

The growing importance of cryptocurrencies is reflected by increasing coverage in the academic literature (Google Scholar, 2022). Despite this growing coverage, there is still no consensus on how to classify cryptocurrencies: as speculative asset (Glaser, Zimmermann, Haferkorn, Weber, & Siering, 2014), as fiat currency (Gunay, Kaskaloglu, & Muhammed, 2021), or as a new asset class (Ankenbrand & Bieri, 2018; Corbet, Meegan, Larkin, Lucey, & Yarovaya, 2018). Cryptocurrencies constitute a young market which is marked by concerns about their safety (McCauley, 2021; Szalay, 2022), liquidity (Bloomberg, 2022; Seddon & Szalay, 2022), and efficiency (Bloomberg, 2022; Seddon & Szalay, 2022). Despite these concerns, cryptocurrencies have been widely adopted as an alternative investment opportunity by several types of investors, namely high net worth individuals and Hedge Funds. On top of this, as of 2022, *Bitcoin* (BTC) is also accepted as collateral for loans in major Wall Street banks, representing a significant shift in the banking world (Yang, 2022).

In this paper, I focus on the efficiency of cryptocurrencies by comparing the development of their efficiency to that of a fiat currency. The question of efficiency is essential given that weak-form efficiency means that technical trading does not yield positive returns. Most cryptocurrency traders use technical trading rules (Hackethal, Hanspal, Lammer, & Rink, 2021). The comparison to a fiat currency is undertaken to verify whether cryptocurrencies are an alternative to fiat currencies. The goal behind the introduction of most cryptocurrencies was creating a state and government independent alternative to fiat currencies with the same purpose and characteristics. BTC, for example, was introduced to serve as a medium of exchange and a medium of payment (Nakamoto, 2008). Therefore, this comparison aims to validate whether cryptocurrencies are comparable to fiat money, at least concerning their level of efficiency. Kristoufek and Vosvrda (2019) state that BTC shares some characteristics with fiat currencies as both are influenced by market participants' expectations. Cheung, Roca, and Su (2015) add that BTC also serves as a medium of exchange since it is accepted as a payment medium by several businesses worldwide. Moreover, BTC can be exchanged at various exchanges worldwide in many different fiat currencies in a liquid market (Dyhrberg, 2016a). However, the researchers admit that BTC cannot be used efficiently because of its high volatility and uncertainty about its actual value (Corbet, Kyriazis, & Papadamou, 2020). Donmez et al. (2021) agree with this last statement, highlighting that BTC is not a unit of account. Gunay et al. (2021) reconcile those views by comparing BTC to the currency of an emerging economy. Due to the

nature of emerging market economies, the currencies experience vast volatility¹. For this paper, however, I focus on the fiat currency *Euro* (EUR), the fiat currency of the European Union, to evaluate whether cryptocurrencies by now left the stage of an emerging market's currency. The EUR is evaluated as the exchange rate between EUR and *US-Dollar* (USD) so that USD is the base currency for all analysed cryptocurrencies and fiat currency. In 2019, EUR/USD was the most traded currency pair worldwide (Bank of International Settlement, 2020).

BTC and *Ether* (ETH) are taken as examples of cryptocurrencies. Together, they represent 60% of the overall cryptocurrency market in terms of *market capitalization* (mcap) (CoinMarketCap, 2022a). Moreover, up to 2022, BTC is the most researched cryptocurrency (see, for example, Vidal-Tomás and Ibañez (2018), Kristoufek and Vosvrda (2019), Cheah, Mishra, Parhi, and Zhang (2018), Jiang, Nie, and Ruan (2018), Caporale, Gil-Alana, and Plastun (2018), Alvarez-Ramirez and Rodriguez (2021), Bariviera (2017)). One reason for this dominance is that BTC is and has been the most prominent cryptocurrency in terms of mcap (as of April 2022). Furthermore, it is one of the oldest cryptocurrencies (Nakamoto, 2008), starting trading in 2009.

The mcap of ETH has as well grown significantly since its launch in 2015 (Bouoiyour & Selmi, 2017). In contrast to the underlying blockchain of BTC, the one underlying ETH, Ethereum, can be used in multiple areas, for example, for staking², by which companies can generate cryptocurrencies as a reward for confirming transactions on the blockchain (Greeley, 2022). Moreover, Ethereum is expected to introduce a technological change in its blockchain in 2022, leading to a more energy-efficient verification process than the one used by BTC, giving ETH a competitive advantage³ (Financial Times, 2021). Like BTC, ETH is also well researched (see, for example, Kristoufek and Vosvrda (2019), Bouoiyour and Selmi (2017), Chu, Zhang, and Chan (2019), and Noda (2021)).

In the following sections, the term currency is used when referring to BTC, ETH, and EUR. When only BTC and ETH are meant, the term cryptocurrencies is used, whereas the term fiat currency refers solely to EUR. Moreover, unless otherwise stated, the efficiency of currencies refers to the efficiency of the prices of the respective currencies.

This paper adds to the current literature in three ways: 1) the development of efficiency of BTC and ETH are analysed over a time horizon of nearly 12 years (from July 2010 to February 2022)

¹ In their study they compare the evolution of BTC price from 2015 to 2020 to the development of the Indian Rupee.

² Staking means that a person locks up their cryptocurrency assets to contribute to the management of the blockchain on which trades are recorded, earning crypto rewards in return.

³ Today, a transaction in BTC consumes more than ten times the electrical power of a transaction in ETH and more than one million times the power consumed for one Visa transaction according to Statista (2022).

which is the most extended time horizon analysed up to now; 2) a static and a dynamic approach are combined by considering fixed subsamples as well as rolling windows⁴, which allows considering not only the status quo of efficiency at one point in time, but the development of efficiency over time to get a more comprehensive picture; 3) the use of an efficiency index to track the development of efficiency in the cryptocurrencies, considering several popular measures to test for efficiency. To my knowledge, there is no overarching measure combining the results of several efficiency tests to determine the degree of efficiency of cryptocurrencies in the literature. Researchers instead state how many tests indicate efficiency and how this number changes over time (Shynkevich, 2021; Urquhart, 2016) or just consider one test and the development of this result (Noda, 2021). To the best of my knowledge, the only time an efficiency index is used is in a paper by Kristoufek and Vosvrda (2019). These researchers use an index constructed initially to measure the efficiency of commodities (Kristoufek & Vosvrda, 2014). In contrast to this index, my efficiency index does not measure the distance to the efficient situation but indicates efficiency on a scale from zero to one. The index of Kristoufek and Vosvrda requires each test to have a limited outcome range with an optimal value. However, this is a characteristic which is not given for all efficiency tests, and consequently, the number of tests which can be used for this index is limited. The index used in this paper has the advantage that it does not require each test to have a limited output range with an optimal value. By combining six efficiency tests into one indicator, I improve the previous indicator of Kristoufek and Vosvrda by testing for a comprehensive set of characteristics of a random walk process underlying the efficiency of price data. Furthermore, the efficiency index tracks the development of efficiency at the granularity of the used data, in my case, daily. This detailed analysis is valuable because of the high volatility in the cryptocurrency market (Glaser et al., 2014).

The remainder of this paper is organised as follows: Section 2 Theoretical Background⁵ and Literature Review, Section 3 Data and Methodology, Section 4 Results and Discussion, and Section 5 concludes.

⁴ Up to now, papers examining the *Efficient Market Hypothesis* (EMH) of Fama (1970) take a rather static approach by evaluating the efficiency of a whole timeframe or splitting the entire sample into two subsamples. No paper combines a rolling window approach with the analysis of multiple tests of the EMH. The dynamic approach taken in this paper is essential to consider the development of the cryptocurrency over time and to detect patterns.

⁵ This paper follows a deductive approach by first considering the literature around BTC, ETH, and efficiency, then building hypotheses, and finally testing these hypotheses using empirical data.

2. Theoretical Discussion and Literature Review

Since the launch of BTC in 2008, cryptocurrencies have experienced increasing popularity, which is reflected by the growing number of exchange platforms (Wollnitz, 2021) and a growing number of journal articles related to them (Google Scholar, 2022). This paper adds to the existing literature on the development of cryptocurrency markets, more specifically on the efficiency of BTC and ETH. In general, maturing markets are characterised by increasing efficiency (Tasca, Hayes, & Liu, 2018), expressed by vanishing arbitrageurs' profits (Pukthuanthong-Le & Thomas, 2008). The term efficiency is used as defined in the EMH of Fama (1970) in this paper. This means that the term efficiency is not used in an evaluative manner but only serves to describe the condition of the currencies. The EMH categorises efficiency into weak, semi-strong, and strong form. Since these categories build on each other, meaning that the weak form must hold for the semi-strong form to hold, this paper focuses on testing the just the weak form of efficiency. This form of efficiency implies that technical trading does not yield consistent returns as all past information is already priced in. However, the inclusion of public news concerning macroeconomic events or the respective company or industry could still generate consistent returns, supporting the semi-strong form of EMH.

Urquhart (2016) analyses the efficiency of cryptocurrencies by testing the efficiency of BTC using daily data from 2010 to 2016. Applying five different tests for the weak form of the EMH, Urquhart concludes that BTC is inefficient considering the entire sample period. However, by dividing the timeframe in two subsamples, from 2010 to 2013 and from 2013 to 2016, Urquhart detects that BTC is becoming more efficient. Using the same raw data and analyses, Nadarajah and Chu (2017) transform the return data by taking it to the power of 17⁶. Doing so, they find that BTC was mostly weak-form efficient from 2010 onwards already. However, as the example of the Ljung-Box Test shows, this transformation yields distortions in the results. Running the Ljung-Box Test with the log return data used by Urquhart (2016) yields a p-value close to zero, whereas the p-value lies close to one when using the returns taken to the power of 17.

The phrasing “increasing efficiency” is often found in the literature. However, there is no broadly accepted definition of “increasing efficiency” and its measurement. Shynkevich (2021) speaks of efficiency if five out of the six tests indicate efficiency. Consequently, increasing efficiency means that the number of tests indicating efficiency increases over time. Urquhart (2016) and Nadarajah and Chu (2017) use a similar approach by stating that BTC is becoming

⁶ In their paper, the researchers explain this transformation only from a mathematical point of view without giving content-related reasons. Instead, Nadarajah and Chu state that other power transformations, taking the return to the power of another odd integer, would yield comparable results.

more efficient from 2013 onwards as no longer all tests reject the efficiency of BTC then. In this paper, an efficiency index is constructed to measure the degree of efficiency as a more aggregate measure of combining different efficiency tests.

The two papers of Urquhart (2016) and Nadarajah and Chu (2017) are the basis of the growing literature on the efficiency of cryptocurrencies. More recent papers use similar methodologies to analyse the efficiency of cryptocurrencies but vary concerning the specific cryptocurrencies analysed, the data source used, the considered timeframe, and refinements of the employed tests.

For the period from 2016 onwards, most researchers agree that BTC is weakly efficient (Grobys & Sapkota, 2019; Nan & Kaizoji, 2019) or at least getting closer to weak form efficiency over time (Al-Yahyaee, Mensi, & Yoon, 2018; López-Martín, Benito Muela, & Arguedas, 2021; Vidal-Tomás & Ibañez, 2018). To assess whether these past results still hold, the following hypothesis is tested:

H1: BTC becomes more efficient over time.

I expect BTC to become efficient, latest, from 2015 onwards. Whereas according to Urquhart (2016) and Tasca et al. (2018), BTC is weak-form efficient since 2013, Grobys and Sapkota (2019) state that BTC is only efficient since 2014⁷, Khuntia and Pattanayak (2018) state that BTC is becoming efficient from 2015 onwards. According to them, BTC suffered from inefficiencies in 2013 and 2014 because of the collapse of the Mt.Gox exchange, which was the largest cryptocurrency exchange. Noda (2021) and Tiwari, Jana, Das, and Roubaud (2018) support this finding by stating that BTC was inefficient from November 2013 to February 2014. Moreover, Noda (2021) also agrees that since 2015, BTC is the most efficient cryptocurrency⁸. Sensoy (2019) phrases it more carefully, stating that BTC is becoming efficient from 2016 onwards. However, Chu et al. (2019) state that in 2017 and 2018, BTC was not efficient. They ascribe this inefficiency to the temporary closing of several exchanges and the temporary stop of dealing with futures.

Krückeberg and Scholz (2020) agree that BTC was not efficient between 2010 and 2017, but unlike the previously mentioned researchers, they also claim that BTC is becoming even less efficient over time. In contrast to the other researchers, they measure inefficiency, which means

⁷ The analysed timeframe goes until 2018.

⁸ However, as Noda (2021) analyses the efficiency of cryptocurrencies under AMH, this does not mean that BTC is efficient the whole time since 2015. It merely means that BTC is more efficient than the other cryptocurrencies considered, like for example ETH.

the lack of efficiency, as the spreads between different exchanges worldwide considering trade intervals of ten seconds. Krückeberg and Scholz derive their conclusions from arbitrage opportunities considering bid-ask spreads, which could be exploited for at least one minute. Those patterns include higher bid-ask spreads after the opening of a new exchange or a hacking attack on an exchange. These periods of inefficiency usually lasted at most one month. Consequently, those inefficient periods can be considered short-term deviations from the fair price and should not be considered the underlying long-term trend. Those short-term disturbances are also documented by Corbet et al. (2020), who state that there have been multiple such short-lived bubbles⁹ in BTC price, primarily until 2014, and one in 2017.

Most analyses of ETH are conducted by evaluating ETH as part of a basket of different cryptocurrencies (Brauneis & Mestel, 2018; Le Tran & Leirvik, 2020; Alvarez-Ramirez & Rodriguez, 2021; Chu et al., 2019; Noda, 2021; Shynkevich, 2021). Noda (2021) states that ETH has a higher volatility than BTC and is less efficient than BTC. Kristoufek and Vosvrda (2019) consent to these findings. López-Martín et al. (2021) assert that ETH is becoming more efficient over time, considering a timeframe until 2019. To test whether BTC and ETH develop in a similar way and can hence be taken as representatives of the cryptocurrency market, the hypothesis to be tested in this paper for ETH is therefore:

H2: ETH becomes more efficient over time.

As BTC and ETH are mainly analysed together, the considered timeframe and underlying structural breaks for ETH are similar to those for BTC. Still, there are differences as, for example, ETH is considered inefficient at least until 2017, as Corbet et al. (2020) prove the existence of multiple price bubbles during 2015 and 2017 in ETH. Bouri et al. (2019) confirm this and state that 55%-75% of those bubbles were very short-lived, with a time span of fewer than ten days.

Although most researchers of the analysed literature agree that cryptocurrencies become more efficient over time, the driving force underlying this trend is still not fully determined. According to Tasca et al. (2018), BTC is mature and efficient since 2013¹⁰, which is in line with the results of Urquhart (2016). This increase in maturity is also reflected by an increase in liquidity, as proven by Wei (2018) and Sensoy (2019). According to Wei (2018), there is a

⁹ The term bubble is used here to refer to a period with an unusual price increase of the underlying asset. This approach is related to how the term “price explosivity” has been defined by Bouri, Shahzad, and Roubaud (2019). These researchers refrain from the term bubble because of a missing definition and metrics to evaluate the presence of those. However, as I consider bubbles only from a qualitative point of view, I stick to the more common term.

¹⁰ The period covered in this article goes until 2015.

positive correlation between efficiency and liquidity. Liquidity is often proxied by the trading volume in USD (e.g., Wei (2018), Sensoy (2019), Brauneis and Mestel (2018), Le Tran and Leirvik (2020)). To prove this relationship, Brauneis and Mestel (2018) use a regression with different liquidity measures like Amihud's illiquidity measure as explanatory variables to predict the return on cryptocurrencies. All these researchers consent that an increase in liquidity leads to an increase in efficiency except Krückeberg and Scholz (2020). Taking the magnitude of bid-ask spreads as a measure of liquidity, they show that liquidity did not increase over time. According to them, the only parameter that changed significantly was the increased interest in cryptocurrencies. Bariviera, Basgall, Hasperué, and Naiouf (2017) also do not relate an increase in the efficiency of BTC to an increase in liquidity. Other researchers take different approaches to explain the increase in efficiency. Phillip, Chan, and Peiris (2018), for example, attribute high importance to mcap. According to them, cryptocurrencies with a higher mcap show lower variability and greater efficiency. Brauneis and Mestel (2018) disagree with this as they find heterogeneous results for efficiency in cryptocurrencies being driven by liquidity and size. The following hypothesis is tested to clarify this topic:

***H3:** For cryptocurrencies, an increase in efficiency is positively correlated with an increase in liquidity.*

In line with the common practice in research, liquidity is measured in terms of trading volume in USD in this paper. This third hypothesis focuses on correlation, not causality. A more extended regression and, in an ideal scenario, a natural randomized experiment would be needed to prove causation. To prove **H3**, the efficiency index defined in this paper is used to measure efficiency. It is regressed on liquidity, the independent variable. **H3** is expected to hold. Köchling, Müller, and Posch (2019) show that the introduction of futures in the BTC market was correlated to an increase in efficiency in this currency. As futures eased the access for institutional investors to trade with cryptocurrencies, the trading volume increased, leading to higher liquidity.

The results of the previously described analyses for BTC and ETH are compared to the results obtained when applying the same tests to a representative fiat currency, the EUR. The price of the EUR is measured as the exchange rate to the USD. The USD is the most widely used fiat currency in 2019, with roughly 60% of international and foreign currency liabilities and claims denominated in USD (Bertaut, Beschwitz, & Curcuru, 2021). Furthermore, the USD is the currency to which the prices of BTC and ETH are quoted, hence considering the EUR to USD allows to make consistent comparisons, having the same basis.

The efficiency of fiat currencies is usually tested considering the development of their price on the *Foreign Exchange Market* (FOREX). If the fiat currency is efficient, the *Uncovered Interest Parity* (UIP) is expected to hold. Notwithstanding the undoubted theoretical validity of this equation, it has seldomly been proven to hold in the long term when considering exchange rates. For decades, researchers have tried to find the underlying reasons. Explanations for this deviation range from the hypothesis that investors are not risk-neutral but require a risk premium to the hypothesis that investors are not rational (Isard, 2006). Before the Financial Crisis of 2008 hit economies worldwide, Chaboud and Wright (2003) showed that the UIP holds for the EUR/USD pair considering intraday trading. For longer time horizons, the UIP is rejected. As this paper uses daily data, the efficiency test using UIP is inappropriate. Moreover, UIP cannot be used for cryptocurrencies as these are neither linked to certain countries, nor is there a currency specific interest rate. Some exchanges offer interest rates for cryptocurrencies, however, they vary widely across different exchanges (CoinMarketCap, 2022b). However, as more recent papers like Valchev (2015) conclude that exchange rates follow a random walk, the usual efficient tests for the weak form of the EMH can be used. Doing so allows testing for the weak-form efficiency of EUR, BTC, and ETH using the same set of tests.

The expectation for the EUR is that it is not efficient over the entire horizon. Although the EUR is designed to be a free floating currency whose prices are determined purely by market forces (Bekaert & Hodrick, 2017), it is expected that the tests reveal the inefficiency of the EUR because of the considered time span from 2010 onwards. Following the worldwide Financial Crisis in 2008, currencies worldwide depreciated vis-à-vis the USD and began slowly to appreciate again in late 2009 (Dowling & Batini, 2011). The fact that the UIP did not hold during that time is partly attributed to the frequent interventions by central banks, which wanted to support their respective home currencies through various monetary measures (Guha, 2009). The US-American central bank, the *Federal Reserve Bank* (Fed), launched a buyback program for government bonds and mortgage-backed securities. As the economy did not recover as quickly as expected, the programs were extended and amplified in 2009 and, from there on, became known under the name *Quantitative Easing* (QE) (Weinberg, 2015). The European counterpart of the Fed, the *European Central Bank* (ECB), also announced large buyback programs (Eser & Schwaab, 2016) and made use of QE (Delivorias, 2015). The violation of the UIP in the early phase of the Financial Crisis is primarily attributed to investors' risk aversion concerning American assets and the fact that the crisis emerged in the United States. On top of that, many investors considered European assets like German or Swiss government bonds as a safe-haven investment. The reaction of the Fed to cut the federal interest rates close to zero in

2008 and the stated commitment to keep them low made European investments more attractive (Dowling & Batini, 2011). At the same time, the high amounts of liquidity provided by the Fed and the ECB helped reduce the counterparty risk. This risk was perceived as very high after the collapse of Lehman Brothers in 2008. During this time, the importance of the role of central banks acting as a lender of last resort was underlined (Coffey, Hrungrung, & Sarkar, 2009).

3. Empirical Setting, Data, and Analyses

3.1. Methodology

The EMH, as formulated by Fama (1970), states that prices fully reflect all available information. Fama formulated three testable forms of this statement which build on each other: the weak form, the semi-strong form, and the strong form. In its weak form, the EMH states that prices reflect all past trading related information¹¹. This means that if an asset or currency satisfies the weak form, its price moves only after the release of news and changes in fundamentals, which by themselves are unpredictable and random. Consequently, the prices follow a random walk. Therefore, the future price depends on the current observed price and the variance changes over time. If prices follow a random walk, their returns must be *independently identically distributed* (i.i.d). The prerequisites for a return series to be i.i.d are: the observations show no autocorrelation, and their probability distributions are constant through time (Kirchgässner & Wolters, 2008). Equation (1) summarizes this:

$$f(\Delta P_t | P_{t-1}) = f(\Delta P_t) \quad (1)$$

where $f(\cdot)$ represents the probability distribution of a discrete random variable and ΔP_t represents the one-period logarithmic return of P (Nan & Kaizoji, 2019). This means that the entire distribution of returns is independent of the last period's return. The main implication of the weak form of the EMH is that current returns are independent of past returns. In this paper, the returns of the currencies rather than their prices are analysed.

¹¹ The semi-strong form implies that prices reflect all past and current publicly available information. The strong form means that also insider, that means private, information is incorporated in the asset price.

To validate the hypothesis of weak-form efficiency, the following tests¹² are performed:

1. Jarque Bera Test
2. Ljung-Box Test
3. Variance Ratio Test
4. Augmented Dickey Fuller Test (ADF)
5. Bartels Test
6. Hurst Exponent

The Jarque Bera Test checks whether the given data follows a normal distribution. The Ljung-Box Test is performed to test for autocorrelation. The Variance Ratio Test also tests the existence of autocorrelation, comparing the variance of returns with different frequencies (for example, daily versus weekly) over the same period. The ADF tests for stationarity of data to determine whether there is an underlying trend in the data. Stationarity means that returns are not time dependent, a prerequisite for a random walk. The Bartels Test tests for the random distribution of data. The Hurst Exponent is calculated to test for the existence of long memory in the data. If this is the case, past returns can be used to explain current returns and consequently, the weak form of efficiency is violated.

To verify the previously formed hypotheses (*H1* and *H2*), a single indicator is needed that combines all previous tests and estimates the efficiency of each currency at each point in time. This indicator is the newly calculated efficiency index. It summarises the results of the previous efficiency tests based on rolling windows in a single number at each point in time. I construct the index in such a way that its results range from zero to one, with one indicating the weak form of efficiency and zero indicating no efficiency¹³.

To combine the different tests, all of them need to have the same range of results. This range goes from zero to one where one indicates the weak form of efficiency and zero indicates no efficiency. The index is constructed as the equally weighted average of the performed tests results. As the test statistics of the Ljung-Box Test, the ADF, the Runs Test¹⁴, and the Bartels

¹² Please refer to 7.2 in the Appendix for an overview over the performed tests and the respective implications on the random distribution of returns. In the following, the results of the different tests are displayed in tables where the statistics of the different tests is displayed. The statistics are abbreviated by “Stat”. The p-values are indicated by stars if they are below the indicated significance levels.

¹³ The extreme values are implausible to be achieved as the index is an equally weighted combination of the different tests, and all of them need to obtain the same conclusion to get to these results.

¹⁴ The Runs Test is a simplified version of the Bartels Test. Please see 7.3 in the Appendix for details concerning the calculations and results of the Runs Test.

Test have no direct interpretation, their respective p-values are used. The actual test statistics are taken for the Variance Ratio Test and the Hurst Exponent to evaluate whether the respective test indicates efficiency. The Jarque Bera Test is excluded from the index as a currency's efficiency does not depend on whether its returns follow a normal distribution. The Jarque Bera Test is conducted nevertheless as a normal distribution of returns is a common assumption in asset pricing.

For the ADF, an i.i.d distribution of returns is given in case of a rejection of H_0 ¹⁵, this means the p-value is transformed by calculating $1 - ADF_{p_{i,t}}$ for the inclusion in the efficiency index. Since the Variance Ratio statistic can have values greater than one, it is normalized. A value of one indicates efficiency of the currency whereas the maximum achieved in this samples is close to, but below three. Consequently, the value is transformed by $e^{-2.75*(VR_{i,t}-1)^2}$. This means that a value of one still yields a value of one, indicating efficiency whereas values smaller or greater than one asymptotically decrease to zero in the transformed version. Moreover, as a Hurst Exponent of 0.5 indicates efficiency of the currency, it is transformed by $\left(H_{i,t} * \frac{1-H_{i,t}}{0.25}\right)$ so that the value 0.5 results in one and values smaller or greater than 0.5 yield results ever closer to zero.

The resulting formula for the index is:

$$\begin{aligned}
 efficiency_{i,t} = & (LB_{p_{i,t}} + (1 - ADF_{p_{i,t}})) + e^{-2.75*(VR_{i,t}-1)^2} + Runs_{p_{i,t}} + Bartels_{p_{i,t}} \quad (2) \\
 & + \left(H_{i,t} * \frac{1 - H_{i,t}}{0.25}\right) / 6
 \end{aligned}$$

with i as the index for the tested currency and t as the point in time considered. The efficiency index of each currency is regressed on time to evaluate whether currencies become more efficient over time. The obtained slope coefficients are very small as the range of the efficiency index is from zero to one, whereas the range of time cover 3,011 days¹⁶. To get a slope coefficient that is easier to interpret, the time variable is scaled by dividing each observation by the total number of observations (3,011). Doing so, the scaled time variable ranges from zero to one, like the efficiency index. This scaling allows for comparable coefficient values, where

¹⁵ This means, lower p-values imply greater efficiency.

¹⁶ The value of the slope coefficient of a regression line depends on the number of data considered. As the subsamples have a different length in time, this means that comparing unscaled coefficients does not have any economic value.

a higher coefficient signifies a stronger correlation between efficiency and the passage of time. All cited slope coefficients refer to this adapted time variable.

The following analyses are always based on a significance level of 5%, meaning that the respective p-values need to be below 5%¹⁷.

In this paper, the described tests are performed from 19/07/2010 to 28/02/2022. Due to structural breaks in the development of cryptocurrency prices, different subsamples are considered¹⁸. To identify the developments within these subsamples, the test statistics per subsample and rolling window are computed (Figure 1). The length of the rolling windows is set to 130 days, representing half of a business year with a one-day shift. To validate the robustness of the obtained results, as discussed in Section 4.2, the length of the rolling windows and the step size are varied.

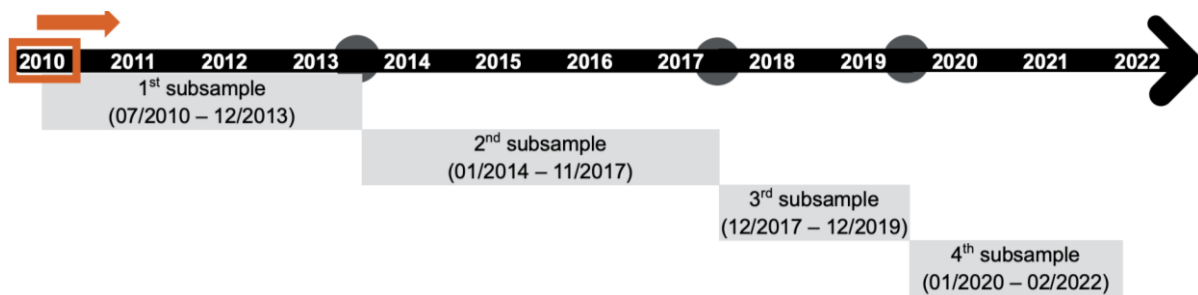


Figure 1. Overview of analysed timeframes.

The borders of the subsamples are chosen along events with a major impact on cryptocurrencies. The first subsample (19/07/2010 – 31/12/2013) ends with the first big crash of BTC prices (Cheung et al., 2015; Corbet, Lucey, & Yarovaya, 2018), which is accompanied by a sharp increase in the volatility of BTC returns¹⁹. The first subsample includes the early years of BTC when the cryptocurrency was not yet traded in large volumes (Sensoy, 2019). The second subsample (01/01/2014 – 31/11/2017) ends with a crash of BTC price (Corbet, Lucey, & Yarovaya, 2018), accompanied by significant changes in the volatility of BTC and ETH. The third subsample (01/12/2017 – 31/12/2019) ends with the beginning of the Covid-19 pandemic. As this external shock significantly affected most economic sectors and the stock market, an additional subsample is created to acknowledge potential unusual effects. Hence,

¹⁷ Whenever a hypothesis is rejected, the respective p-value is below 5%.

¹⁸ The limits of the subsamples were defined by looking for example at how much returns varied daily. Considering the daily percentage change yield the highest numbers for the first years and mostly declining values from there onwards because of the general trend of a price increase. Furthermore, absolute daily changes were not considered because the absolute changes mostly increased over time due to the increased price of BTC and ETH.

¹⁹ Moreover, the last months of 2013 were of high importance to BTC due to various negative news, decreasing the positive mood of investors according to Dörner (2013).

the fourth subsample starts with the pandemic's beginning on the 1st of January 2020 (WHO, 2022).

The ideal set-up to conduct efficiency tests and to answer the defined hypotheses would be to use daily price and trading volume data for cryptocurrencies that are today dominating the market in terms of mcap and started trading on the same day. As there is no central exchange on which the prices of the cryptocurrencies are determined, prices may differ across different exchanges. Therefore, to get an unbiased estimate of the price, it would be necessary to have a daily volume-weighted price. Given the trading volume and adjusted prices, it would be possible to infer the mcap of the cryptocurrencies.

Concerning the exchange price of EUR, the ideal benchmark would be a perfect market where only market forces determine the price. However, in the sample period, there was a lot of central bank activity impacting the FOREX, distorting the price and price efficiency. These distortions are discussed in more detail in Section 2²⁰. Moreover, as a fiat currency is traded over the counter, only survey data exists for the volume which needs to be interpolated.

3.2. Data

For EUR, the daily spot exchange rate (bid price) to USD is extracted from *Refinitiv Eikon*. The direct quote USD to EUR is used. As a benchmark for the development of the currencies, the price data of the S&P500 is retrieved from *Refinitiv Eikon*. The S&P500 is considered to compare the development of the currencies to the general development of the US stock market as reference for the market development.

The daily exchange rates (bid price) for the cryptocurrencies BTC and ETH are also extracted from *Refinitiv Eikon*. The exchange rates are from USD to BTC and ETH are extracted as direct quotes. Therefore, the USD is the base currency for all considered currencies²¹.

For BTC, EUR, and S&P500, the analysed period ranges from 19/07/2010 to 28/02/2022, whereas the period for ETH ranges from 07/08/2015 to 28/02/2022. The analysed time span for ETH starts later because this cryptocurrency started trading only in 2015.

²⁰ For concrete examples of the actions taken and the consequences for the prices, that means exchange rates, please refer to Section 2.

²¹ Please see 7.4 in the Appendix for further information on the company providing the data and the data selection process.

To analyse the efficiency of the currencies, their respective logarithmic returns (3) are considered:

$$r_t = (\log(P_t) - \log(P_{t-1})) * 100 \quad (3)$$

where P equals the daily bid price of the respective currency. This approach has also been taken for example by Alvarez-Ramirez and Rodriguez (2021), Bouoiyour and Selmi (2017), or Lahmiri, Bekiros, and Salvi (2018).

The natural logarithm of daily prices is taken to avoid that positive average growth rates are considered despite negative trends (Kirchgässner & Wolters, 2008). Moreover, taking the natural logarithm is common for time series data (for example, GDP data or stock returns) as those often exhibit exponential growth, which becomes approximately linear by taking the logarithm (Stock & Watson, 2012).

To measure the liquidity of BTC and ETH, the daily trading volume in USD of these cryptocurrencies is considered. This data was retrieved from *Coinmarketcap* as *Refinitiv Eikon* does not provide the required data. However, the variable trading volume is only available from 17/09/2014 onwards for BTC and from 09/11/2017 onwards for ETH²². The liquidity of EUR is measured through the trading volume taken from the *Bank of International Settlement's* website. As there is only an average daily trading volume on a tri-annual basis (2010, 2013, 2016, and 2019), the missing data were interpolated to generate daily data²³. As the analysis of EUR is used as a benchmark to BTC and ETH, the volume of EUR is considered from 17/07/2014 onwards, hence from the point of time onwards when also volume data for BTC is available.

3.3. Descriptive Statistics

For the following analyses, some restrictions need to be considered: the trading of ETH started later than for BTC, by five years, leading to 3,030 daily observations for returns of BTC and only 1,711 daily observations for returns of ETH. The timeframe from 2010 to 2022 is chosen to capture the entire lifecycle of both cryptocurrencies until the present time. The number of observations for the S&P500 is lower because of stock exchange holidays which do not affect trading on the FOREX or the cryptocurrency market.

²² An overview over the different data considered and their respective timeframes can be seen in 7.5 in the Appendix.

²³ The underlying assumption is that from 2010 onwards, the EUR shows no strong short-term fluctuation in its trading volume but has a rather stable trading pattern over the year.

Both cryptocurrencies, BTC and ETH, show an increase in prices from 2010 to the end of the analysed period in 2022. There was a peak in 2017/2018 and a steep increase since 2020. As shown in Figure 2, the development of prices of BTC and ETH is very similar. Their prices show a correlation of 0.94. However, the price of ETH is significantly lower than the one of BTC. BTC reached its highest price of 67,687.75 USD on the 09th of November 2021, whereas the highest price of ETH was 4,795.24 USD, also reached on the 09th of November 2021²⁴.

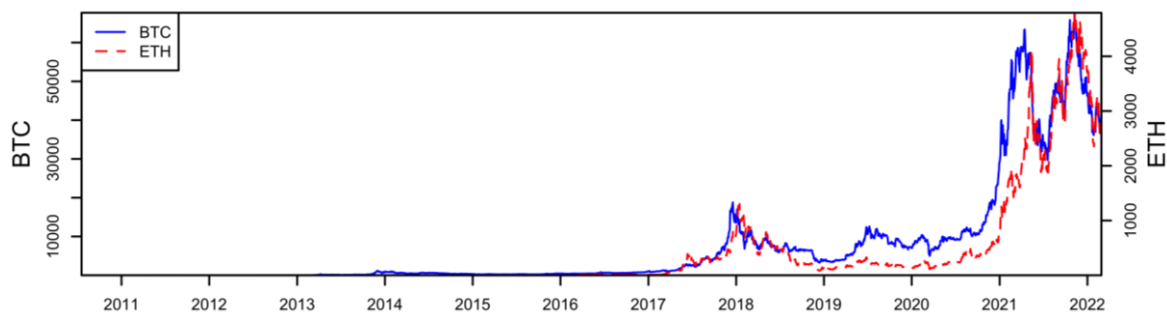


Figure 2. Development of BTC and ETH prices (2010- 2022).

The following descriptive statistics (Table 1) apply to the daily log returns of the respective assets, considered over the whole timeframe from 2010 to 2022²⁵.

Table 1. Descriptive statistics for BTC, ETH, and EUR for 2010 to 2022.

*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Return BTC	Return ETH	Return S&P500	Return EUR
Number of Observations	3,030	1,711	2,819	3,030
Minimum	-83.42 %	-91.63 %	-12.77 %	-2.65 %
Maximum	56.04 %	47.58 %	8.97 %	3.04 %
Mean	0.43 %	0.40 %	0.05 %	-0.00 %
Standard Deviation	7.09 %	7.65 %	1.08 %	0.52 %
Skewness	-0.18	-0.66	-0.93	-0.05
Kurtosis	18.67	19.06	20.43	5.08
Jarque Bera	30,998.67 ***	18,505.37 ***	36,073.98 ***	545.86 ***

The average return for BTC and ETH is positive with an average daily return of 0.43% for BTC and 0.40% for ETH. These two cryptocurrencies outperformed the S&P500, which had an average daily return of 0.05% over the same period.

As ETH has the highest standard deviation of the considered assets with 7.65%, ETH can be considered the riskiest asset. Moreover, it is the asset with the highest daily depreciation

²⁴ The maximum price of ETH is around a factor of 14 smaller than the maximum price of BTC.

²⁵ Except for ETH where because of data availability, only the timeframe from 2015 to 2022 is analysed. For an overview over the development of the assets during the different subsamples, please see Section 7.6 in the Appendix. Consequently, also the terms of highest/maximum and lowest/minimum refer to the global maxima within the considered timeframe from July 2010 to February 2022.

(minimum daily return) amounting to -91.63%. However, this number must be considered with caution. It occurred on the 10th of August 2015 after the release of the decentralized application network for Ether (Caffyn, 2015). Dropping this outlier, the minimum return would be -37.39% and hence smaller than the minimum of BTC. The lowest return of BTC, -83.42%, was recorded on the 11th of April 2013. The year 2013 was marked by high volatility, the highest volatility in BTC between 2010 and 2022 with 1,621.48%. The asset with the highest daily appreciation (maximum positive return) is BTC with a return of 56.04% on the 09th of April in 2013. This data confirms the previous statement that 2013 was a very volatile year for BTC as also the second highest return of BTC (49.35%) occurred in April 2013 (01/04/2013). In 2013, several major events were increasing the popularity of BTC. On the one hand, there was the banking crisis in Cyprus²⁶ (European Stability Mechanism, 2019), and on the other hand, there was the approval of BTC as a medium of payment by several international businesses (News, 2013). However, at the end of the year, there was also a ban of the use of cryptocurrencies for financial institutions in China which raised fears of increasing regulation (Dörner, 2013). The combination of these events led to an unprecedented volatility for BTC.

The negative skewness of all assets considered indicates that the series are nonnormal. A negative skewness means that negative returns are more likely than positive returns.

Moreover, the kurtosis of all assets considered exceeds three, the threshold of a normal distribution. This high kurtosis indicates a heavy tailed distribution. These leptokurtic distributions are characterised by a higher likelihood of extreme events than normal distributions.

As the consideration of skewness and kurtosis already indicate, none of the assets considered follows a normal distribution according to the Jarque Bera test.²⁷

²⁶ The banking crisis in Cyprus drastically increased the popularity of BTC. This was the first time that capital controls were introduced in Europe and that citizens lost parts of their bank savings after the introduction of the EUR. As a consequence, Cypriots and people abroad lost their trust in banks as noted by Klein (2018).

²⁷ These findings can be visually confirmed by looking at the QQ Plots in Section 7.7 in the Appendix.

3.4. Analyses

3.4.1. Jarque Bera Test

The Jarque Bera Test tests whether a given set of data follows a normal distribution²⁸. For return data of cryptocurrencies, this test is used, for example by Al-Yahyaee et al. (2018), Tiwari et al. (2018), and Urquhart (2014).

Since the Jarque Bera Test for the returns of BTC, ETH, and EUR, as seen in (Table 2) is significant, it confirms that the distributions of returns do not follow a normal distribution, regardless of whether the whole period or the specified subsamples are analysed. This is in line with my expectations and the results from the literature (Al-Yahyaee et al., 2018; Tiwari et al., 2018; Urquhart, 2014).

Table 2. Jarque Bera Test for returns of all analysed currencies.
*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Whole Period	Subsamples			
	07/2010-02/2022	07/2010-12/2013	01/2014-11/2017	12/2017-12/2019	01/2020-02/2022
JB-Stat BTC	30,998.67 ***	2,086.93 ***	1,171.97 ***	433.79 ***	787.04 ***
JB-Stat ETH	18,505.37 ***	-	4,912.18 ***	167.39 ***	782.65 ***
JB-Stat EUR	545.86 ***	43.31 ***	280.35 ***	25.25 ***	56.92 ***

The violation of the assumption of normality does not impact the following tests, except the results of the Variance Ratio Test. The Variance Ratio Test delivers strong results for data following a normal distribution. However, Brauneis and Mestel (2018) and Shynkevich (2021) use the Variance Ratio Test despite the absence of normality, Consequently, I will do the same in this paper.

3.4.2. Ljung-Box Test

The Ljung-Box Test, also known as Portmanteau test or white noise test, is used to test if the data is autocorrelated. It is employed for example, by Urquhart (2016), López-Martín et al. (2021), Nan and Kaizoji (2019), or Köchling et al. (2019). The *null hypothesis* (H_0) states that all considered lagged autocorrelations are equal to zero, which means there is a random distribution of returns²⁹. The *alternative hypothesis* (H_1) is that at least one of the autocorrelations is not zero. In my case, if H_0 is rejected, past data can be used to predict future

²⁸ Please see Section 7.8 for additional notes on normality tests.

²⁹ That means that $H_0: \rho(\tau) = 0$ for $\tau = 1, 2, \dots, m$ with $m < T$. In the following analysis, the number of lags chosen is 40, hence $m = 40$.

returns, implying that there is no random distribution of returns and hence no random walk of the price of currencies³⁰.

Table 3. Ljung-Box statistics for returns of different currencies analysed.

*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Whole Period		Subsamples			
	07/2010-02/2022		07/2010-12/2013	01/2014-11/2017	12/2017-12/2019	01/2020-02/2022
LB-Stat BTC	295.23 ***		161.12 ***	50.76	40.50	38.37
LB-Stat ETH	72.94 ***		-	47.63	45.43	64.69 **
LB-Stat EUR	54.86 *		50.82	45.90	38.59	56.25 *

The results for whole period as well as for the subsamples (Table 3), are in line with those obtained by López-Martín et al. (2021) for the period from 2010 to 2019 for BTC and ETH, showing no significant autocorrelation of returns in the respective cryptocurrencies, except for BTC from 2010 to 2013 and for ETH from 2020 onwards. Considering shorter timeframes within the respective subsamples, with the help of rolling windows, an oscillating pattern of p-values for the Ljung-Box statistic is observed for all analysed currencies. This means that based on a 130-day windows, there are both, periods when the respective currency follows a random walk (p-value greater than 5%) and periods when they do not (p-value smaller than 5%), although each is short-lived. For better comprehensibility, only the trends of the subsamples³¹ will be considered in the following.

From 2010 to 2013 onwards, the returns of BTC showed a consistent trend of lower autocorrelation. Nevertheless, for this period, H_0 is rejected. The EUR shows the opposite trend, meaning that H_0 cannot be rejected. From 2014 onwards, the returns of BTC also follow a white noise process, as it can no longer be rejected that the returns of BTC are not autocorrelated.

In the second subsample, ETH shows a trend similar to the one of BTC in the first period. However, unlike BTC from 2010 to 2013, for the returns of ETH, it is not possible to reject H_0 from 2014 to 2017, hence a random distribution of returns is assumed.

From 2017 to 2019, all analysed currencies show downward trends for the p-values, which means a higher probability that returns are not i.i.d. Still, H_0 is not rejected for any currency.

³⁰ If H_0 is not rejected, this means that we cannot say that the returns are not randomly distributed, hence that the data could be considered i.i.d. By analysing the returns of the currencies, I analyse the first difference of the price and hence control for autocorrelation of order one in the price data.

³¹ The trends described refer to the evolution of p-values of the respective Ljung-Box statistics, as they serve as an indicator whether to reject the hypothesis of randomness or not. To be able to identify specific trends, outliers were dropped when considering the development of the p-values for the rolling windows. The top and bottom 5% of all p-values were considered outliers and consequently only the remaining 90% of data was used to generate the analysed trendlines. Without this adaption, no trends were detected.

This decreasing trend reverts again in the last period from 2020 until the end of February 2022. This is counterintuitive as the turbulences related to the Covid-19 pandemic would be expected to lead to less efficiency because of a higher degree of volatility (Engelhardt, Krause, Neukirchen, & Posch, 2021). The increasing p-values for BTC and EUR indicate an increasing probability of a random distribution, whereas there is no clear trend observable for ETH. However, H_0 cannot be rejected for the returns of ETH and EUR.

3.4.3. Variance Ratio Test

The Variance Ratio Test is used to determine whether returns are serially correlated. Like the Ljung-Box test, it determines whether the price data follow a random walk³². It is used in different forms for example, by Brauneis and Mestel (2018), López-Martín et al. (2021), or Shynkevich (2021). This test is based on the fact that if prices follow a random walk, then the variance of the k-period return is equal to k times the variance of the one period return (Urquhart, 2014)³³. The null hypothesis is that returns are serially uncorrelated which is the case if the Variance Ratio equals one. Values greater than one imply a positive autocorrelation or trends in the price data, whereas values less than one imply a negative autocorrelation, indicating mean reversion of returns.

As shown in Table 4, none of the analysed currencies was weak-form efficient over the whole timeframe as H_0 can be rejected significantly. In line with Shynkevich (2021), I find that BTC was not efficient from 2014 to 2017. ETH is also not weak-form efficient over the same time horizon. The EUR is serially uncorrelated from 2010 to 2017 including. The result is unexpected as from 2014 onwards, the ECB intervened heavily in the FOREX by launching multiple asset purchasing programs (European Central Bank, 2022). These interventions are thought to hinder the free formation of the exchange rate and hence decrease efficiency.

Table 4. Variance Ratio statistic for returns of all analysed currencies.

*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Whole Period	Subsamples				
	07/2010-02/2022	07/2010-12/2013	01/2014-11/2017	12/2017-12/2019	01/2020-02/2022	
VR-Stat BTC	0.90 ***	0.87 ***	0.84 ***	0.91 *	1.20 ***	
VR-Stat ETH	0.90 ***	-	0.78 ***	0.96	1.12 **	
VR-Stat EUR	1.06 ***	1.08 *	1.01	0.82 ***	1.36 ***	

³² However, the results must be interpreted with caution as they are sensitive to the assumption that the underlying data is drawn from a normal distribution.

³³ For more information on the calculation, please see 7.9 in the Appendix.

BTC shows the most prolonged period with no serial correlation in 2016. This can be explained considering that BTC can also be seen as a safe haven asset, similar to gold (Dyhrberg, 2016b). In 2016, many investors feared at multiple points in the year high volatility of the stock market as there has been the Brexit referendum (23/06/2016) and the election of Donald Trump as president of the United States (08/11/2016). Consequently, investors fled to safe haven assets (Swanson, 2017).

The most prolonged period of inefficiency of the EUR was in 2020. Considering new financial aid programs, which have been decided this year to help the countries hit the most financially by the Covid-19 pandemic (European Central Bank, 2021b), this was expected.

3.4.4. Augmented Dickey Fuller Test

The ADF determines whether a data series is stationary. Stationarity signifies that the moments of the distribution are not time varying. Random walks are nonstationary processes as their mean and variance are time dependent³⁴. As a consequence, if the currencies are weak-form efficient their returns are expected to be stationary as their distribution is supposed to be i.i.d (Kirchgässner & Wolters, 2008). ADF is a test for stationarity which is frequently used in literature, for example by Glaser et al. (2014), Gunay et al. (2021), or Katsiampa (2019). The present paper conducts the ADF with trend as the return data shows an upward trend over time³⁵. The null hypothesis is that the return series is nonstationary, meaning that the variance of the series does not depend on time but that there is inherent autocorrelation.

The stationarity of returns of BTC was proven from 2010 to 2017 by Khuntia and Pattanayak (2018). Gunay et al. (2021) extended the analysed timeframe until 2020. Moreover, they found that the log returns of the EUR were stationary from 2015 to 2020. Katsiampa (2019) analysed the stationarity of returns of ETH and found that they are not stationary from 2015 to 2018.

The results of the ADF without trend for the entire timeframe and the subsamples are shown in Table 5. H_0 is rejected in all cases, meaning that I reject the hypothesis that the return series of the analysed currencies exhibit stationarity. This is in line with the results from previous research.

³⁴ A stationary series tends to return to a constant or a deterministically trending mean. This means that large values are followed by smaller values and small values by larger values.

³⁵ To conduct the ADF, a specific number of lags analysed must be determined. This paper uses the default setting of R for a window size of 130, being five lags. More on the determination can be found in 7.10 in the Appendix. No further insights are gained from these results of the ADF with drift.

Table 5. Augmented Dickey Fuller test for returns of all analysed currencies.
 *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Whole Period		Subsamples							
	07/2010-02/2022		07/2010-12/2013		01/2014-11/2017		12/2017-12/2019		01/2020-02/2022	
ADF-Stat BTC	-21.90	***	-12.04	***	-13.45	***	-9.31	***	-9.88	***
ADF-Stat ETH	-16.20	***	-		-9.67	***	-9.11	***	-9.87	***
ADF-Stat EUR	-22.91	***	-11.76	***	-13.39	***	-10.59	***	-10.95	***

Considering the results from the rolling windows, there are no trends to be observed within the different subsamples.

3.4.5. Bartels Test

The Bartels Test is used to detect randomness in return data (for example, by Köchling et al. (2019), Brauneis and Mestel (2018), Urquhart (2016)). This test represents an improved form of the Runs Test³⁶ as it considers the number of observations per analysed sample. H_0 is that the data is randomly distributed, and the alternative hypothesis is that the data follows a trend. For the full timeframe and the analysed subsamples, H_0 cannot be significantly rejected (Table 6). These findings are in line with those of Brauneis and Mestel (2018), considering BTC and ETH from 2015 to 2017. Wei (2018) states the same results, analysing the returns of the two cryptocurrencies only in 2017.

Table 6. Bartels Test for returns of all analysed currencies.
 *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Whole Period		Subsamples						
	07/2010-02/2022		07/2010-12/2013		01/2014-11/2017		12/2017-12/2019		01/2020-02/2022
Bartels-Stat BTC	2.03		2.14		1.96		1.97		2.05
Bartels-Stat ETH	1.98		-		1.97		1.96		2.07
Bartels-Stat EUR	2.06		2.06		2.11		1.98		1.96



Figure 3. Phases in which returns of currencies are not randomly distributed based on rolling windows.

Considering the results with the help of rolling windows, there are large fluctuations of the p-values with periods where H_0 is significantly rejected. The lines in Figure 3 mark these periods.

³⁶ For more information on the Runs Test, please see 7.3 in the Appendix.

The periods where the null hypothesis of randomness is rejected are always short. For BTC, most of these periods are in 2011, 2013, 2014, and 2015, so the cryptocurrency's early years. This is in line with the findings of Urquhart (2016), who states that BTC returns are not randomly distributed in this timespan. For ETH, the periods of randomness are also in its early years, 2017 and 2018. The EUR shows the most extended periods of non-randomness in 2011, in the aftermath of the Financial Crisis, in 2015, in the aftermath of the European Sovereign Debt Crisis, and in 2020, during the Covid-19 pandemic.

3.4.6. Hurst Exponent

The Hurst Exponent is frequently used in the literature to examine the weak-form efficiency of cryptocurrencies (for example, Bariviera (2017), Jiang et al. (2018), Urquhart (2016), Wei (2018)). This test is used to determine whether the underlying return data exhibits long-range memory, this means whether it follows a random stochastic process. The Hurst Exponent stays between zero and one, $H \in [0; 1]$. If the $H = 0.5$, the underlying data follows a random process. In the case of $H < 0.5$, the data shows anti-persistent behaviour³⁷. In case of $H > 0.5$, the data shows persistent behaviour³⁸ (Caporale et al., 2018). For the following analyses, the R/S Hurst exponent is used, a version of the Hurst exponent used by Urquhart (2016). There are no p-values associated with this test statistic. Instead, Urquhart (2016) suggests that values for H below 0.45 indicate strong anti-persistence and values above 0.65 indicate strong persistence. The results for the different currencies can be seen in Table 7.

Table 7. Estimates of Hurst Exponent over the whole period and the different subsamples.

	Whole Period	Subsamples			
	07/2010-02/2022	07/2010-12/2013	01/2014-11/2017	12/2017-12/2019	01/2020-02/2022
BTC	0.61	0.64	0.62	0.60	0.64
ETH	0.64	-	0.63	0.62	0.60
EUR	0.54	0.54	0.59	0.50	0.57

The results obtained for BTC are in line with Bariviera et al. (2017) and Bariviera (2017). Before 2014, BTC showed a persistent behaviour with $H > 0.5$, whereas from 2014 to 2019, the Hurst exponent approaches 0.5. Urquhart (2016) states comparable results and likewise strengthens his argument of increasing efficiency of BTC. The results of Caporale et al. (2018) and Jiang et al. (2018), differ as they find cryptocurrencies to be persistent, this means $H > 0.5$,

³⁷ The closer the Hurst exponent is to zero, the more pronounced the mean-reversion is in the data.
³⁸ A persistent behaviour means that an increase in price in the short-term will most likely be followed by an increase in price and vice-versa for a decrease.

also after 2014. Still, these interpretations can also be due to a different definition of the boundaries at which H is said to be persistent or anti-persistent. The underlying idea holds for all papers and my results, namely that ETH and BTC show a trend towards a random process until 2020. This trend is not reflected in the last subsample by EUR and ETH as both returns show an increase in H and hence a more persistent behaviour. The EUR is the currency that has values closest to 0.5, the values closest to a random stochastic process, which corresponds to the results obtained by Bariviera et al. (2017).

3.4.7. Liquidity and Efficiency

A linear regression is run for each of the analysed currencies to test whether efficiency and liquidity are correlated (**H3**). The value of the slope coefficient (β) determines whether a correlation between efficiency and liquidity exists. The regression³⁹ is given by

$$efficiency_{i,t} = \alpha + \beta_i * liquidity_{i,t} \quad (4)$$

where i denotes the different currencies considered. The efficiency of each currency is measured through the respective efficiency index. The liquidity is measured in terms of trading volume in USD. However, as noted by Sensoy (2019), taking the raw data for trading volume leads to inconsistencies, so that instead the log of trading volume is considered. Moreover, as in the base setting, the efficiency index is calculated based on a 130-day rolling window basis, the volume considered for this regression is also the average daily trading volume of the past 130 days⁴⁰.

Considering the existing literature on BTC, I expect a positive relationship between liquidity and efficiency, meaning an increase in liquidity is correlated with an increase in efficiency (Sensoy, 2019; Wei, 2018). Theoretically, a market with more volume and more participants should be more efficient, allowing for quicker price discovery and less arbitrage opportunities. In line with this, I find a significant positive correlation between efficiency and liquidity for BTC and ETH (Table 8)⁴¹. EUR, the benchmark, shows instead a significant negative correlation between liquidity and efficiency from 2014 to 2019. An increase in trading volume was linked to a decrease in efficiency. Given that the ECB intervened heavily in the FOREX

³⁹ The regression is estimated using Ordinary Least Squares method with standard errors which are robust for heteroskedasticity.

⁴⁰ The average is only calculated when there is data on trading volume for the past 130 days.

⁴¹ For a graph on these regressions, please see Section 7.11 in the Appendix.

with large buy-back programs, resulting in high liquidity (European Central Bank, 2022), this is not surprising.

Table 8. Regression results for returns of all analysed currencies.
Robust standard errors in parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Variables	Efficiency BTC	Efficiency ETH	Efficiency EUR
Volume BTC	0.0012 ** (0.0006)		
Volume ETH		0.0128 *** (0.0031)	
Volume EUR			-0.1280 *** (0.0207)
Constant	0.647 *** (0.0131)	0.376 *** (0.0715)	4.256 *** (0.584)
Observations	1,814	993	1,313
R ²	0.002	0.017	0.028

4. Discussion and Results

4.1. Results

After running the efficiency tests individually for BTC, ETH, and EUR, the obtained results are combined in the respective efficiency indices to verify *H1* and *H2*⁴².

As shown in Figure 4, the efficiency of BTC has increased over time, simultaneously there has also been a decrease in the negative outliers present in the early days of BTC. As the slope coefficient of the fitted line is positive and significantly different from zero, I confirm (*H1*) that BTC becomes more efficient over time, although it is still not efficient in 2022. Interestingly, the highest efficiency level of BTC was attained in 2017, and not at the beginning of 2022. With a slope of 0.126, BTC would achieve weak-form efficiency in roughly 23 years if the trend is to continue over time. For investors this means that it is still possible to achieve positive abnormal returns, solely based on past trading information. Nevertheless, this becomes increasingly difficult because of shrinking opportunities.

For BTC, there is a significant correlation between liquidity and efficiency, therefore *H3* cannot be rejected. An increase in efficiency is significantly correlated to an increase in liquidity. Consequently, the results of Sensoy (2019) and Wei (2018) are confirmed.

⁴² The development of efficiency over the different static subsamples can be seen in 7.12 in the Appendix.

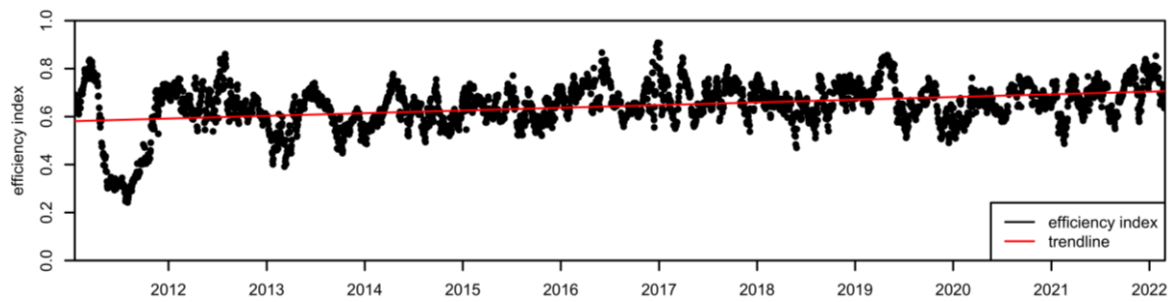


Figure 4. Development of efficiency of BTC over time.

The second hypothesis ($H2$), that ETH becomes more efficient over time, is not rejected. The efficiency index of ETH shows a significant upward trend. With a slope of 0.05, ETH would achieve weak-form efficiency in roughly 42 years if the trend continues over time. ETH takes roughly twice as long as BTC to become weak-form efficient not because of a lower efficiency level but because of a lower slope coefficient. From 2015 to 2022, ETH was even slightly more efficient than BTC. Similar to BTC, this means for traders that the opportunities to generate returns from technical analysis are declining, although there are more opportunities than for BTC. The fact that BTC is becoming efficient quicker than ETH could be due to the higher trading volume of BTC and hence the greater awareness of this currency. BTC is still the most prominent cryptocurrency and hence receives most attention also from institutional investors (Szalay, 2022).

Considering the correlation of efficiency and liquidity for ETH, $H3$ cannot be rejected as an increase in efficiency is significantly correlated to an increase in liquidity.

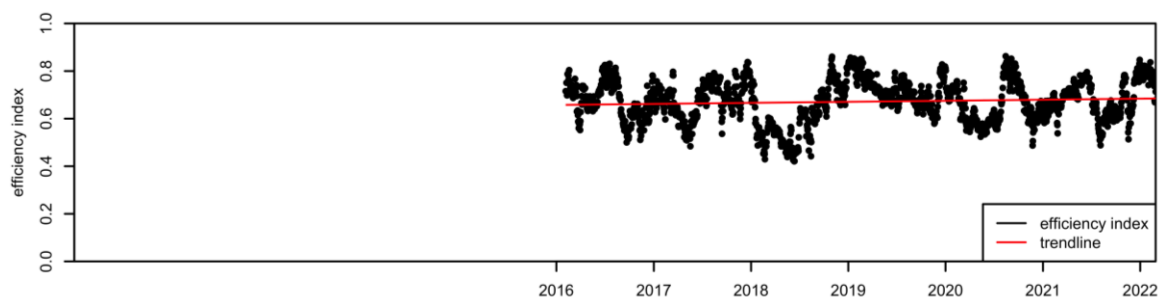


Figure 5. Development of efficiency of ETH over time.

Considering the EUR, the benchmark for the cryptocurrencies, it is noteworthy that the EUR shows a decreasing trend of efficiency from 2010 onwards until 2022 (Figure 6). This decrease is significantly different from zero (slope coefficient of -0.018). The negative slope is mainly due to a sizeable decrease in efficiency in 2020, which corresponds to the first year of the Covid-19 pandemic. In this particular year, the ECB injected a high amount of liquidity into the market, and consequently, its balance sheet increased by 50% (European Central Bank, 2021a). Leaving out this particular year, the efficiency of EUR would exhibit the opposite trend, and significantly increase over time rather than decrease (Figure 7).

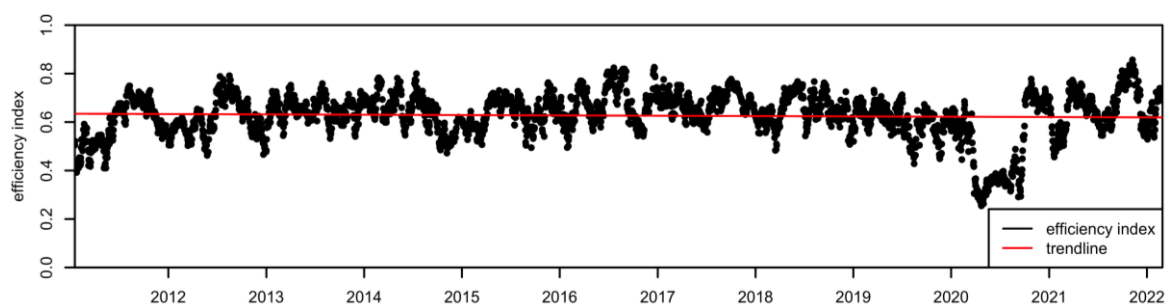


Figure 6. Development of efficiency of EUR over time.

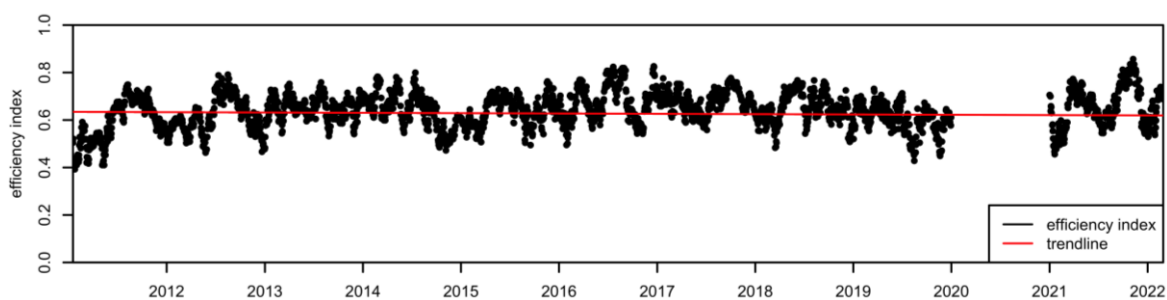


Figure 7. Development of efficiency of EUR over time excluding 2020.

Continuing with the total data sample, the level of efficiency of the fiat currency is, on average, significantly lower than the one of BTC (-0.1376 on average) and ETH (-0.2270 on average)⁴³ as can be seen in FIGURE X.

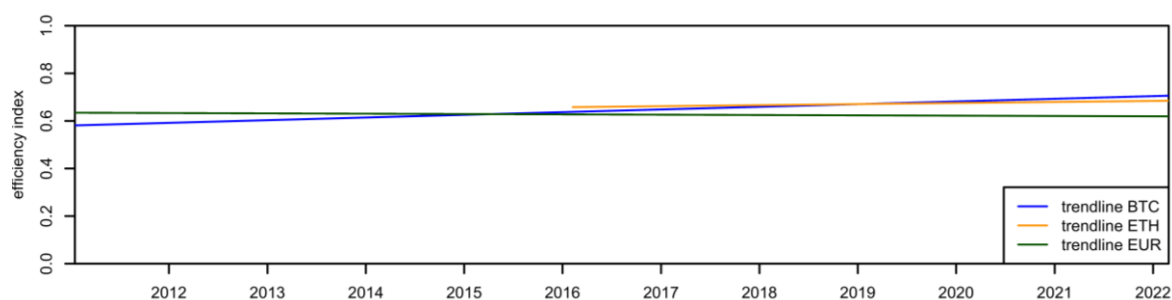


Figure 8. Comparison of efficiency levels of BTC, ETH, and EUR.

The fact that EUR is not efficient is not directly in line with theory which predicts that foreign exchange rates follow a random walk (Valchev, 2015)⁴⁴. However, as in the considered timeframe from 2010 onwards, the ECB and the Fed intervened multiple times in the FOREX (Eser & Schwab, 2016; Weinberg, 2015). Although there were no direct interventions aimed at influencing the exchange rate, there were strong indirect spill over effects which influenced the exchange rate. This kind of central party influence does not exist for cryptocurrencies.

⁴³ Even when considering the sample without 2020, EUR is on average less efficient than BTC or ETH.

⁴⁴ The hypothesis that an increase in liquidity is positively correlated with an increase in efficiency cannot be significantly rejected for EUR. However, the overall increase in liquidity is much smaller for EUR compared to the increase in liquidity of BTC and ETH. For EUR, the trading volume increased by roughly 50% from 2010 to 2022, whereas for BTC it increased by roughly 17,000% from 2014 to 2022, and for ETH the trading volume increased by roughly 200% from 2018 to 2022.

Therefore, it is not surprising that BTC and ETH show a higher level of efficiency, as they are purely driven by market forces.

From these regressions I conclude that BTC and ETH show similarities to the EUR concerning efficiency. Although they do not share the characteristics of a store of value or medium of payment, they show comparable levels of efficiency.

Overall, BTC and ETH are becoming more efficient over time. This means that **H1** and **H2** are proven. Moreover, for BTC and ETH, liquidity and efficiency are positively correlated, meaning that **H3** is proven as well.

4.2. Robustness Checks

To check for the robustness of the described development of efficiency, I vary the window length of the rolling window as well as the step size. These changes are introduced for the calculation of the efficiency index and the calculation of the regression between efficiency and liquidity. I expect that an increase in the window length leads to a smoothing of the observed trends. A change in the step size is considered for testing whether the existence of short-term disturbances, like short-term bubbles in cryptocurrencies in 2017 (Bouri et al., 2019), have a significant influence on the obtained results.

Moreover, I also consider whether a change in the index construction by leaving out the results from the Runs Test change the results significantly. This change is considered as the Runs Test and the Bartels Test are very similar as they both test for randomness in the underlying data. However, not considering the Runs Test, does not lead to significant changes. BTC and ETH are still becoming more efficient over time (**H1** and **H2**) whereas EUR is still showing a decreasing level of efficiency. The slope coefficients of the respective regression lines become higher in absolute value terms⁴⁵.

A variation in the length of the rolling window does not lead to significant changes in the results⁴⁶. A setting with one quarter of a year (65 days), a full year (260 days), and two years (520 days) per window is considered. Overall, a decrease in the window size leads to lower slope coefficients. This is in line with my expectations, as a decrease of the window length means that there are less observations excluded, through which the regression is fitted. An increase of the window length leads to a lower average efficiency for cryptocurrencies, whereas

⁴⁵ Please see 7.13 in the Appendix for the respective graphs.

⁴⁶ For the specific numbers, please consider Section 7.14 in the Appendix.

the index's amplitude of values increases noticeably. This was expected as with a longer time horizon, it is more likely that extreme values are incurred within the window. This confirms that more extended time periods lead to an averaging over short-term disturbances, consequently, the slope coefficient of the efficiency regression on time increases. EUR shows a greater convergence towards efficiency when changing the window size from 130 to 520 days. The different behaviour of cryptocurrencies versus fiat currency shows a fundamental difference in their evolution. Whereas the bubbles in the prices of BTC and ETH were always relatively short-lived (Cheung et al., 2015; Corbet, Lucey, & Yarovaya, 2018), trends in the EUR are more long-term oriented.

Keeping the length of the rolling window constant at the initial value of 130 days, I then changed only the step size from one day, the initial set up, to one week (5 days), to two weeks (10 days), and to one month (21 days). An increase in the step size leads to slightly lower average values of efficiency for all currencies. Overall, the change in step size does not lead to any significant change in the magnitude of the swings but rather to the disappearance of very short-term trends and fluctuations.

In sum, the trends in the efficiency of both, cryptocurrencies and the fiat currency, remain the same when changing either the window size or the step size of the rolling windows used. Consequently, I consider the results obtained for the window of 130 days with a step size of one robust.

I verify the results of the correlation between liquidity and efficiency by 1) running the regression of efficiency on liquidity for the different window settings previously analysed and by 2) taking another measure of liquidity. The alternative measure of liquidity is the inverse of Amihud's illiquidity measure. Amihud's illiquidity is widely used in the literature to test for liquidity (for example, Wei (2018), Brauneis and Mestel (2018)). It is constructed as

$$ILLIQ_i = \frac{1}{T} \sum_{t=1}^T \frac{|r_{i,t}|}{P_{i,t} Volume_{i,t}} \quad (5)$$

When increasing the window length of the rolling window to calculate the efficiency index and the average trading volume, the correlation becomes smaller for all considered currencies. For ETH, the correlation turns significantly negative for a window length of two years. In contrast, for BTC, the correlation is no longer significantly different from zero for a window length of two years. Decreasing the window length leads to an increase in the correlation between liquidity and efficiency for ETH and EUR. For EUR, the correlation is then no longer

significantly different from zero. BTC shows the opposite behaviour as its correlation becomes significantly negative, indicating that when considering a time horizon of 65 days, an increase in liquidity is linked with a decrease in efficiency.

Considering the alternative liquidity measure, the inverse of the Amihud measure, I confirm that the obtained results are susceptible to the conditions considered. In line with the results of Brauneis and Mestel (2018), the resulting coefficient on liquidity is not significant for BTC for a rolling window of 130 days. This means that an increase in liquidity cannot be associated with increased efficiency. The same holds true for EUR. Only for ETH an increase in liquidity is significantly correlated with an increase in efficiency. Overall, I conclude that the link between efficiency and liquidity is highly sensitive to the considered measure of liquidity and the length of the time window analysed.

5. Conclusion

This paper has analysed whether cryptocurrencies become more efficient over time as stated among others by Urquhart (2016), or whether it was just a temporary effect based on specific conditions that lead to efficiency. To do so, I considered a time horizon from 2010 to 2022 on BTC and ETH. I conclude that cryptocurrencies become more efficient over time and that their increase in efficiency is positively correlated with an increase in liquidity. Whereas the increasing efficiency of cryptocurrencies is robust to a variety of settings, the correlation between efficiency and liquidity is not robust and requires further analysis.

The analysed cryptocurrencies, BTC and ETH, were chosen because, as of April 2022 they had the highest mcap of all available cryptocurrencies (CoinMarketCap, 2022a) and have been the dominant currencies in this market for a few years. Therefore, they represent a good proxy for the overall market of cryptocurrencies. In an extension to the existing literature, this paper examines the development of efficiency in these currencies from July 2010 to February 2022 by taking a static and dynamic approach. With the help of a newly constructed efficiency index, I confirm the prevailing opinion in research that BTC and ETH are indeed becoming more efficient with time. These findings are robust regardless to the change of length of the rolling window and changes in the step size. Moreover, considering BTC from 2014 onwards and considering ETH from 2018 onwards, I find that there is a positive and significant correlation between liquidity and efficiency. However, these findings are not robust to changes in the size of the analysed rolling window or to the use of alternative liquidity measures. The fact that these results are not robust is in line with the current literature as there is currently no consensus

on whether an increase in efficiency is necessarily correlated with an increase in liquidity measured in trading volume.

These results were compared with a representative fiat currency, the EUR, to validate whether the original intention of the cryptocurrencies, introducing an alternative to the established fiat currencies, has yet been achieved or not. Considering only efficiency, BTC and ETH show higher levels than EUR on average from 2014 onwards. This result is robust, even to the inclusion of the year 2020 which was marked by disturbances of the EUR price due to the Covid-19 pandemic. The lower degree of efficiency is in line with expectations as the EUR, in contrast to cryptocurrencies, is supervised by a central authority, the ECB, who indirectly affected the EUR price through large monetary interventions. Nevertheless, cryptocurrencies cannot yet be considered an alternative to fiat currencies. They still show a very high volatility compared to the EUR and consequently cannot be considered a store of value or an efficient medium of exchange.

The results of this paper highlight the importance of time horizons. Considering the development of efficiency for BTC from 2010 onwards, BTC is becoming more efficient over time. Restricting this period so that only data from 2018 onwards is analysed yields contrary results, that BTC is not becoming more efficient. Consequently, one can state that it is essential for cryptocurrencies to analyse them from their first day of trading onwards to get a comprehensive picture because of their high volatility.

I acknowledge that this study suffers from several limitations. First of all, I limit the scope of my paper by comparing BTC and ETH only to one fiat currency and hence ignoring that there is no agreement on what type of asset cryptocurrencies represent (Ankenbrand & Bieri, 2018; Glaser et al., 2014). Moreover, the data for prices and volume are not extracted from the same source and do not cover the same time horizon. Future research could find a source for both entailing data since the start of the analysed currencies to widen the time horizon. Doing so would enable a complete analysis of the development of cryptocurrencies to validate or reject the results of this paper. Moreover, the newly developed efficiency index still suffers from some limitations. Future research could extend the current efficiency index to get an even more comprehensive picture of efficiency. A comparison between the results obtained through my efficiency index and the one developed by Kristoufek and Vousvrda (2015) might be interesting to refine the current approach. Doing so might enable to measure and quantitatively compare the development of efficiency across several cryptocurrencies.

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7. Appendix

7.1. Code and Data

The results obtained in this paper and the data used is available under this [link](#)

([https://ucppt-my.sharepoint.com/:f:/g/personal/s-ckehne_ucp_pt/](https://ucppt-my.sharepoint.com/:f:/g/personal/s-ckehne_ucp_pt/EhR8kAJHiHdOnGGWL2IHROwBnD2pnyao3Ezc8CTi4XTsXA?e=RzUNRD)

[EhR8kAJHiHdOnGGWL2IHROwBnD2pnyao3Ezc8CTi4XTsXA?e=RzUNRD](https://ucppt-my.sharepoint.com/:f:/g/personal/s-ckehne_ucp_pt/EhR8kAJHiHdOnGGWL2IHROwBnD2pnyao3Ezc8CTi4XTsXA?e=RzUNRD)).

7.2. Overview of Performed Tests

All following tests are performed on the log returns of currency prices.

Name of Test	H ₀	Consequence of rejection of H ₀ for random walk of prices
Jarque Bera	Data follows a normal distribution	Data does not follow a normal distribution
Ljung-Box	No autocorrelation	No random distribution because of autocorrelation
Variance Ratio	$VR = 1.00$ → no autocorrelation	No random distribution because of autocorrelation
Augmented Dickey Fuller	Nonstationary process	Stationarity, a prerequisite for a random walk
Runs	Random distribution of returns	No random distribution of returns
Bartels	Random distribution of returns	No random distribution of returns
Hurst	$H = 0.50$ → no trend in return series	No random distribution because of trend in return series

7.3. Runs Test

The Runs Test is performed to test whether elements in a given data sequence are mutually independent. This means it is tested whether the given sequence of data is randomly distributed (e.g., by Wei (2018), Brauneis and Mestel (2018), and Urquhart (2016)). The test divides the data into positive and negative values⁴⁷ and identifies whether the positive and negative

⁴⁷ In general, the test divides the given data in two subsets of data with equal number of observations. All observations above the median are classified with +, all values below the median are classified with -. Numbers equalling the median are omitted. One run is defined as a series of consecutive positive or negative values. The next run is then counted once the sign switches, from positive to negative or the other way round.

sequence of values is random. The null hypothesis is that the series is independent, the returns being randomly distributed (Urquhart, 2014). This hypothesis cannot be significantly rejected for any of the analysed periods (Table 9).

Table 9. Runs Test for returns of all analysed currencies.
 *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Whole Period	Subsamples			
	07/2010-02/2022	07/2010-12/2013	01/2014-11/2017	12/2017-12/2019	01/2020-02/2022
Runs-Stat BTC	-0.15	-0.47	-0.13	-1.63	1.77 *
Runs-Stat ETH	-0.58	-	-0.49	-0.26	0.76
Runs-Stat EUR	1.31	1.40	1.75 *	-0.69	-0.08

Brauneis and Mestel (2018) and Wei (2018) also do not reject a random distribution of returns of BTC and ETH⁴⁸. The given hypothesis of randomness can only be significantly rejected for specific short periods, considering the rolling windows within each subsample. For BTC, these periods are mainly in 2010, 2011, and 2013 whereas for ETH they are primarily in 2018 and 2020. The EUR shows the most extended period of non-randomness with several rolling windows where randomness is rejected from 2015 to 2017. The same periods during which the Runs Test is rejected for the different currencies can be seen in Figure 9.

However, the results of this test must be considered with caution as the test classifies returns only into positive and negative values without accounting for any other patterns within the positive or negative values. This means that the sign of the return might be distributed randomly, but this does not mean that within positive or negative returns, there might not be a pattern (Bartels, 1982).



Figure 9. Periods when the Runs Test is significantly rejected.

⁴⁸ Still, Brauneis and Mestel (2018) only analyse the years 2015 to 2017 whereas Wei (2018) only focuses on the returns of 2017.

7.4. Further Information on Data Extraction and Sources

The underlying data for the exchange rates of the cryptocurrencies is provided by Crypto Coin Comparison Ltd (CryptoCompare). This company builds a weighted average of multiple available exchanges for cryptocurrencies. The ranking criteria include transparency, traded volume, and client security measures. Using this data, I follow Bariviera (2017). I do not extract the data directly from one of the larger exchanges, neither CoinmarketCap nor Coindesk as on one hand the publicly available data does not cover a long enough time horizon and, on the other hand it only represents one particular exchange and not a comprehensive, hence an unbiased picture of the overall market⁴⁹. A short analysis of the currency prices from the different data sources, comparing *CryptoCompare* and *Coindesk*, reveals that the average daily deviation is less than \$5 for each cryptocurrency considered, BTC and ETH. Moreover, it is assumed that the exact source of the price data is not of primary relevance to the obtained results. If the prices differed substantially across exchanges, this would mean that arbitrage opportunities existed, which could be exploited by trading simultaneously on multiple exchanges. Consequently, no further analyses would be needed to conclude that the prices are inefficient (Shynkevich, 2021).

7.5. Overview of Data Considered and Respective Timeframes

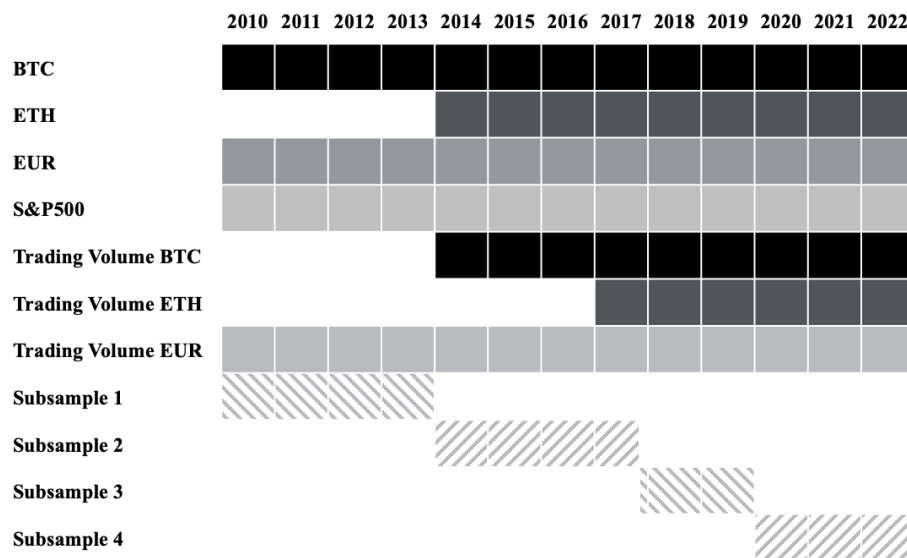


Figure 10. Overview over Data Considered and Respective Timeframes.

⁴⁹ An additional drawback of using data from Coindesk is that the provided data goes only back until November 2014 as they launched then an own index, XBX, for BTC. The priorly displayed prices were retrieved from Mt.Gox according to their website. Before this, they used a weighted average of three different exchange according to Kristoufek (2015).

7.6. Descriptive Statistics for the Analysed Subsamples

Considering the descriptive statistics of the different subsamples analysed, the reference assets of the S&P500 and the EUR show striking differences between the subsamples. Comparing the first subsample (19/07/2010 – 31/12/2013) to the second one (01/01/2014 – 31/11/2017), lower average returns are observed in the second subsample, indicating a normalization of the markets after the Financial Crisis from 2008 onwards. The increasing maturity of BTC is reflected in less extreme values, and lower values for the standard deviation. An increased skewness to the left indicates more negative tail events, in line with the fact that the first large bubble of BTC between 2013 and 2014 (Corbet, Lucey, & Yarovaya, 2018) is included in the second subsample.

There are no significant changes in the descriptive statistics of the S&P500 or the EUR from the second (01/01/2014 – 31/11/2017) to the third subsample (01/12/2017 – 31/12/2019), whereas the changes in the descriptive statistics of BTC and ETH are significant. ETH shows similar trends to BTC for the transition from the first to the second subsample, indicating a maturing of ETH in line with less outliers and a lower standard deviation. BTC, however shows a more volatile behaviour and more tail events as indicated by the higher kurtosis. Similar results were found by Chu et al. (2019), who noticed that BTC faced substantial uncertainties in this timeframe.

Comparing the descriptive statistics of the return of the S&P500 for the third (01/12/2017 – 31/12/2019) to the fourth subsample (01/01/2020 – 28/02/2022) reveals higher volatility, a higher skewness to the left and a higher kurtosis. This had to be expected as more extreme events have marked the stock markets during the Covid-19 pandemic (Engelhardt et al., 2021).

Table 10. Descriptive statistics for BTC, ETH, and EUR for the first subsample (19/07/2010 – 31/12/2013). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Subsample 1 (19/07/2010 – 31/12/2013)	Return BTC	Return ETH	Return S&P500	Return EUR
Number of Observations	901	0	840	901
Minimum	-83.42 %		-6.90 %	-2.65 %
Maximum	56.04 %		4.63 %	2.06 %
Mean	1.04 %		0.06 %	0.01 %
Standard Deviation	10.97 %		1.04 %	0.61 %
Skewness	-0.23		-0.53	-0.19
Kurtosis	10.44		8.19	4.00
Jarque Bera	2,086.93 ***		978.41 ***	43.31 ***

Table 11. Descriptive statistics for BTC, ETH, and EUR for the second subsample (01/01/2014 – 31/11/2017).
*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Subsample 2 (01/01/2014 – 31/11/2017)	Return BTC	Return ETH	Return S&P500	Return EUR
Number of Observations	1,024	606	954	1,024
Minimum	-25.51 %	-91.63 %	-4.02 %	-2.40 %
Maximum	19.16 %	47.58 %	3.83 %	3.04 %
Mean	0.24 %	0.83 %	0.03 %	-0.01 %
Standard Deviation	4.42 %	10.03 %	0.77 %	0.55 %
Skewness	-0.45	-0.80	-0.44	0.17
Kurtosis	8.45	16.74	6.05	5.48
Jarque Bera	1,171.97 ***	4,912.18 ***	425.89 ***	280.35 ***

Table 12. Descriptive statistics for BTC, ETH, and EUR for the third subsample (01/12/2017 – 31/12/2019).
*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Subsample 3 (01/12/2017 – 31/12/2019)	Return BTC	Return ETH	Return S&P500	Return EUR
Number of Observations	542	542	501	542
Minimum	-25.21 %	-28.17 %	-4.18 %	-1.90 %
Maximum	23.68 %	27.07 %	3.38 %	1.27 %
Mean	-0.09 %	-0.23 %	0.04 %	-0.01 %
Standard Deviation	4.83 %	5.96 %	0.91 %	0.38 %
Skewness	-0.14	0.02	-0.96	-0.17
Kurtosis	7.07	6.08	6.11	4.02
Jarque Bera	433.79 ***	167.39 ***	245.94 ***	25.15 ***

Table 13. Descriptive statistics for BTC, ETH, and EUR for the fourth subsample (01/01/2020 – 28/02/2022).
*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Subsample 4 (01/01/2020 – 28/02/2022)	Return BTC	Return ETH	Return S&P500	Return EUR
Number of Observations	563	563	524	563
Minimum	-30.41 %	-37.39 %	-12.77 %	-2.06 %
Maximum	16.38 %	32.16 %	8.97 %	1.43 %
Mean	0.31 %	0.54 %	0.06 %	0.00 %
Standard Deviation	4.39 %	5.92 %	1.64 %	0.42 %
Skewness	-0.76	-0.56	-1.01	-0.20
Kurtosis	8.57	8.65	17.54	4.49
Jarque Bera	787.04 ***	782.65 ***	4,704.38 ***	56.92 ***

7.7. QQ Plots of the Returns of Analysed Currencies

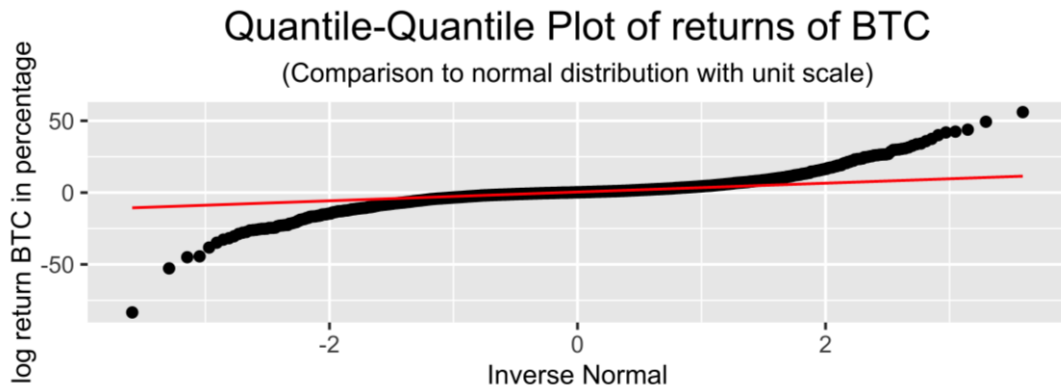


Figure 11. QQ Plot of returns of BTC.

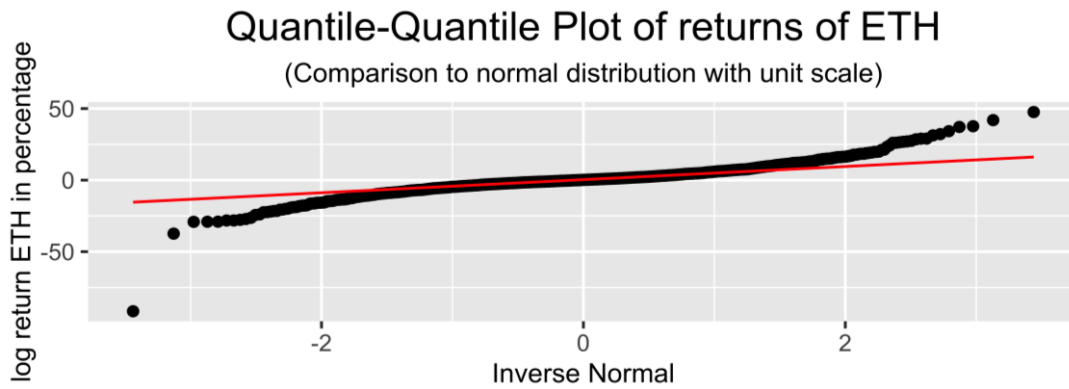


Figure 12. QQ Plot of returns of ETH.

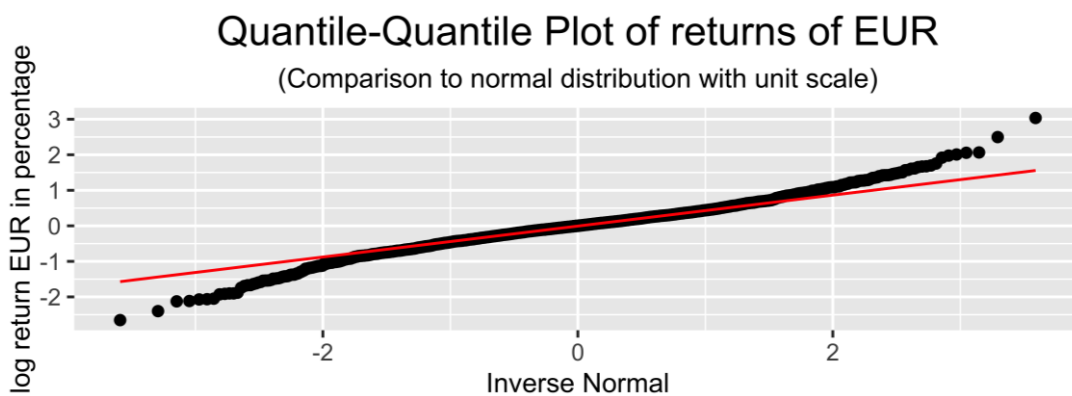


Figure 13. QQ Plot of returns of EUR.

7.8. Additional Notes on Tests for Normality

To test for normality, the Jarque Bera Test is chosen and not the Shapiro Wilk Test as the latter one is best for samples with $n \in [4 ; 2,000]$. In contrast, the analysed timeframe contains in total 3,010 observations (Stata, 2020). Moreover, in this paper, I focus solely on the Jarque Bera test to test for normality and do not consider additionally the Kolmogorov-Smirnov Test. Both test mechanisms test for normality, however the Jarque Bera Test usually performs poorly in case of large skewness or short tails of the given data. Nevertheless, as in the given dataset, the distribution has only a small skewness and long-tails, the Jarque Bera statistic has only a slight bias and high power. Consequently, it is not necessary to perform the Kolmogorov Smirnov test in addition to the Jarque Bera Test (Thadewald & Büning, 2007).

7.9. Further Information on the Variance Ratio Test Used

For this paper, the variance of weekly return data is compared to the variance of daily data. The data retrieved are based on the business calendar, a week encompasses five days. This means that the weekly variance should equal five times the variance of daily return data, consequently $k = 5$ in equation (6). In this case, weekly is defined for returns from Friday to Friday including. Doing so, one business week is covered as closing prices are considered.

$$VR = \frac{Var(r_{t,t+k})}{k * Var(r_{t,t+1})} \quad (6)$$

For this calculation, weekly returns are needed. These are calculated as the difference between the logarithmic prices of the current Friday price minus the logarithmic price of the price of Friday the week before. I consider non-overlapping time windows.

7.10. Further Explanation of ADF

The lag length chosen for the ADF significantly influences the results obtained, especially on the p-values. The default setting of the software package Stata is zero which means that instead of an Augmented Dickey Fuller Test, only a Dickey Fuller Test is conducted. The default setting of the software package R is to take the third root of the sample size. For the analysis of the

rolling windows, the lag length is hence five considering that the rolling windows have a window size of 130.

Instead of using the default lag length, it is also possible to determine it using an information criterion. The recommended lag length for the different subsamples according to Akaike Information Criterion can be seen in Table 14.

Table 14. Akaike Information Criterion for all currencies and analysed subsamples.

	Whole Period	Subsamples			
	07/2010-02/2022	07/2010-12/2013	01/2014-11/2017	12/2017-12/2019	01/2020-02/2022
BTC	20	12	18	0	7
ETH	13	-	0	0	2
EUR	81	0	0	0	6

These values differ significantly. As different lag values for the different subsamples would decrease the comparability of results between the currencies and subsamples, a fixed lag length of five, which equals one week, is used for all ADF tests.

7.11. Regressions on Efficiency

The following plots show the correlation between liquidity and efficiency. Liquidity is measured as the average log volume of the respective currencies over a time horizon of 130 days. The efficiency is measured through the efficiency index described in this paper.

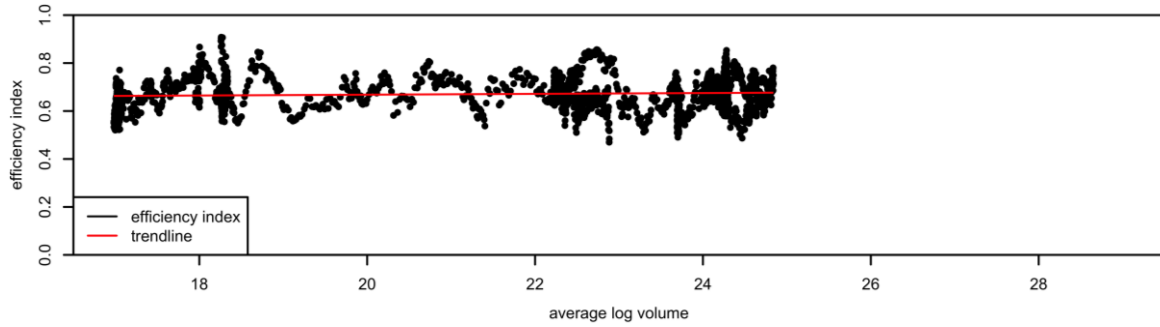


Figure 14. Plot of efficiency and liquidity of BTC.

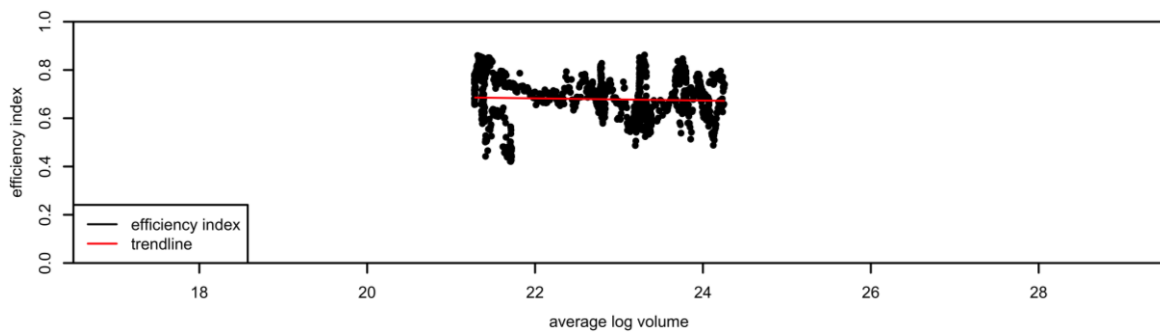


Figure 15. Plot of efficiency and liquidity of ETH.

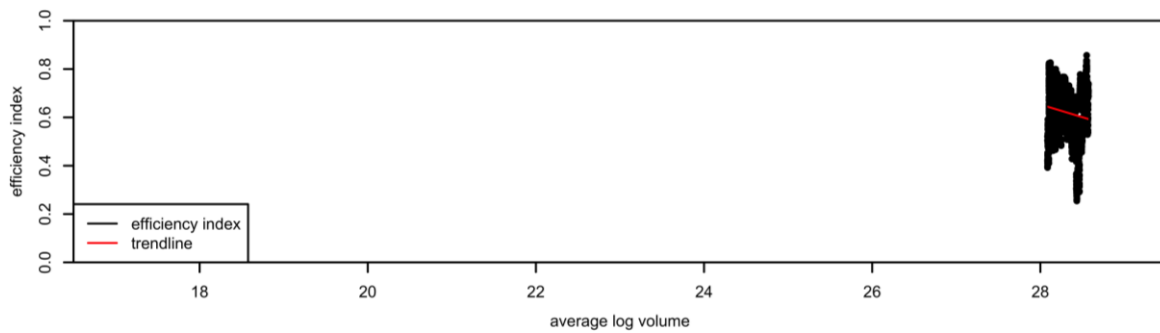


Figure 16. Plot of efficiency and liquidity of EUR.

To further investigate the development of liquidity of the respective currencies, the development of liquidity over time is shown.

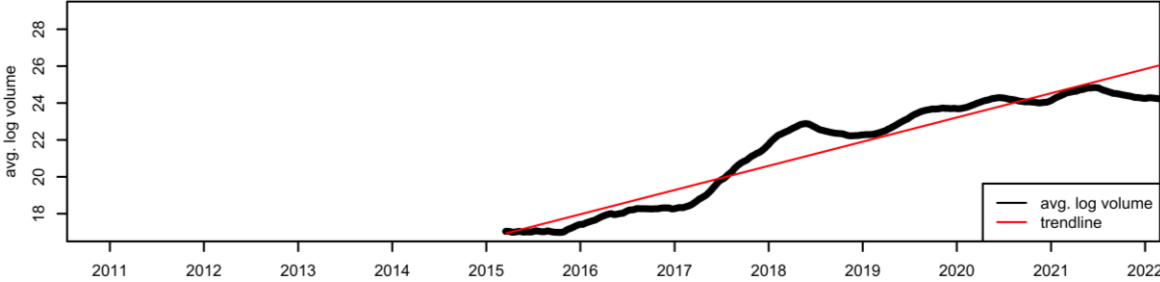


Figure 17. Development of Liquidity of BTC.

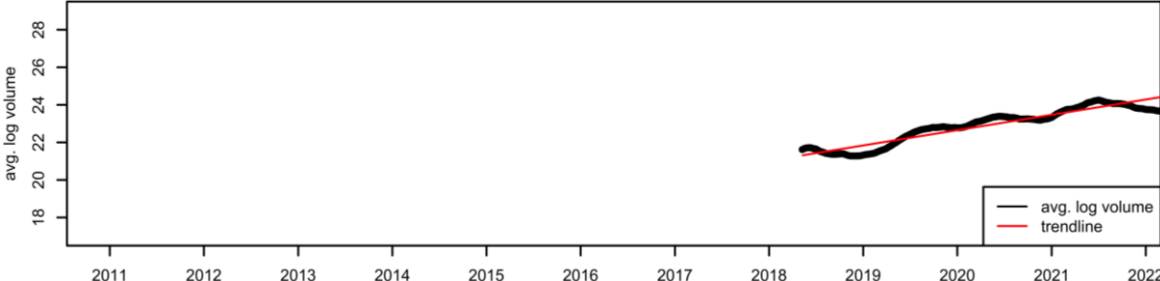


Figure 18. Development of Liquidity of ETH.

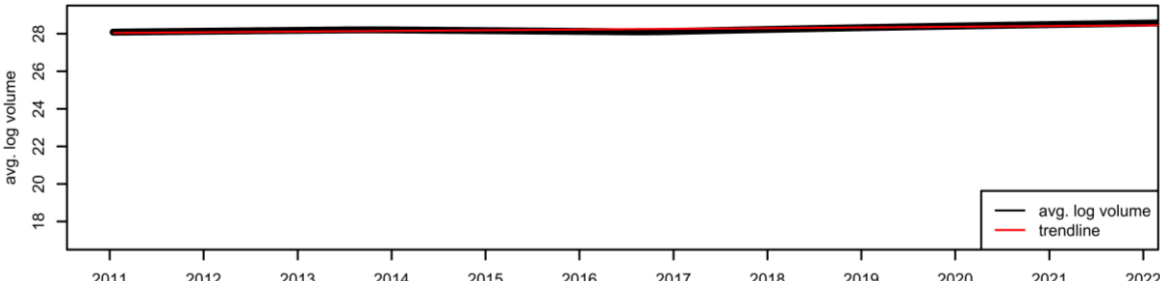


Figure 19. Development of Liquidity of EUR.

7.12. Development of Efficiency Considering Subsamples

Table 15. Overview Test Results for BTC at 5% significance level.
Fields highlighted in grey support the hypothesis of weak-form efficiency.

	Whole Period	Subsamples			
	07/2010-02/2022	07/2010-12/2013	01/2014-11/2017	12/2017-12/2019	01/2020-02/2022
LB	i.i.d	i.i.d	Autocorrelation	Autocorrelation	Autocorrelation
VR	i.i.d	i.i.d	i.i.d	Autocorrelation	i.i.d
ADF	Stationary	Stationary	Stationary	Stationary	Stationary
Runs	Random	Random	Random	Random	Random
Bartels	Random	Random	Random	Random	Random
Hurst	Random	Random	Random	Random	Random

Table 16. Overview Test Results for ETH at 5% significance level.
Fields highlighted in grey support the hypothesis of weak-form efficiency.

	Whole Period	Subsamples			
	08/2015-02/2022	07/2010-12/2013	01/2014-11/2017	12/2017-12/2019	01/2020-02/2022
LB	i.i.d	-	Autocorrelation	Autocorrelation	i.i.d
VR	i.i.d	-	i.i.d	Autocorrelation	i.i.d
ADF	Stationary	-	Stationary	Stationary	Stationary
Runs	Random	-	Random	Random	Random
Bartels	Random	-	Random	Random	Random
Hurst	Random	-	Random	Random	Random

Table 17. Overview Test Results for EUR at 5% significance level.
Fields highlighted in grey support the hypothesis of weak-form efficiency.

	Whole Period	Subsamples			
	07/2010-02/2022	07/2010-12/2013	01/2014-11/2017	12/2017-12/2019	01/2020-02/2022
LB	Autocorrelation	Autocorrelation	Autocorrelation	Autocorrelation	Autocorrelation
VR	i.i.d	Autocorrelation	Autocorrelation	i.i.d	i.i.d
ADF	Stationary	Stationary	Stationary	Stationary	Stationary
Runs	Random	Random	Random	Random	Random
Bartels	Random	Random	Random	Random	Random
Hurst	Random	Random	Random	Random	Random

7.13. Efficiency Indices leaving out Runs Test

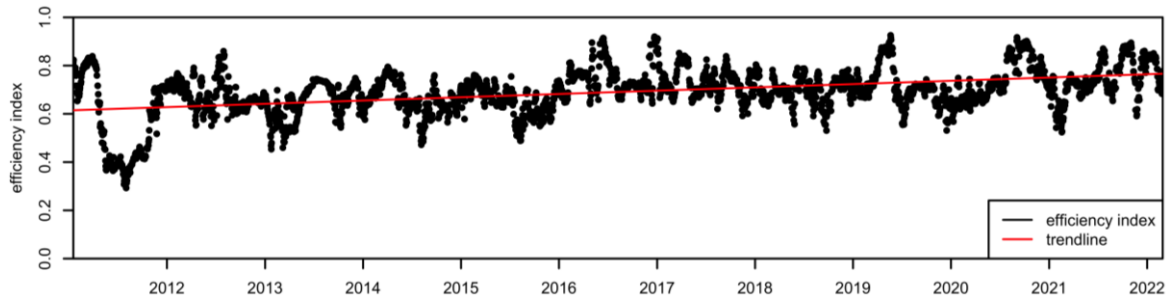


Figure 20. Development of efficiency BTC over time without Runs Test.

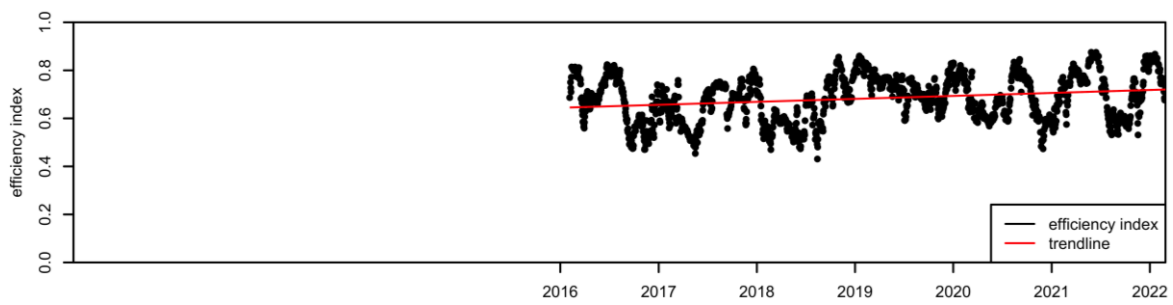


Figure 21. Development of efficiency ETH over time without Runs Test.

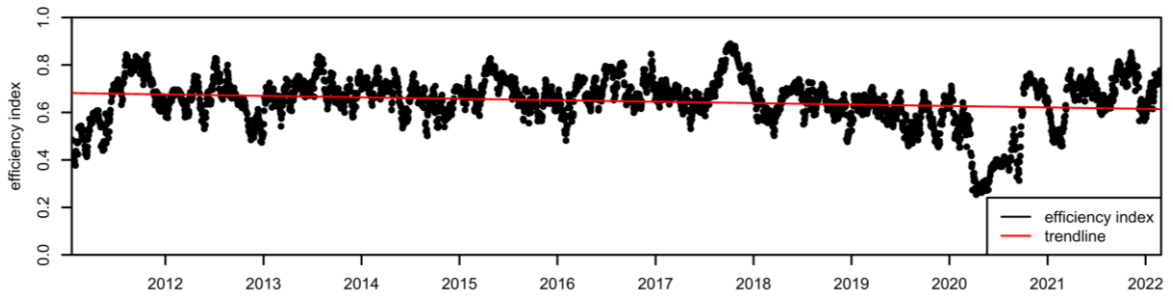


Figure 22. Development of efficiency EUR over time without Runs Test.

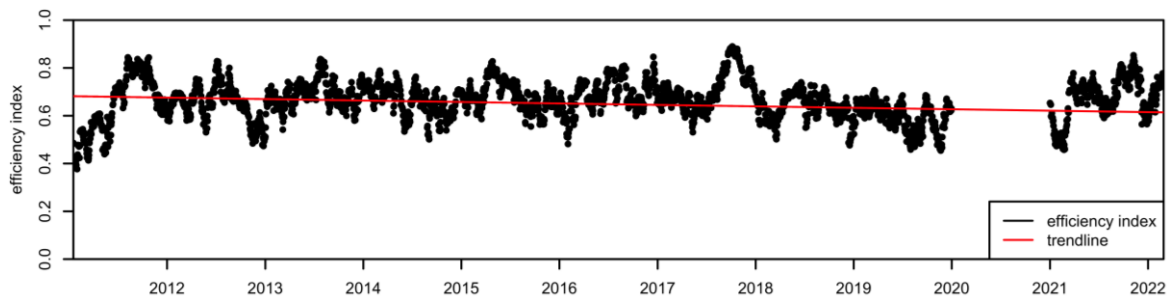


Figure 23. Development of efficiency EUR over time without 2020 without Runs Test.

7.14. Robustness Tests with Change in Window Size or Step Size

Table 18. Regression results for returns of analysed currencies with varied window length and step size one day. Robust standard errors in parentheses.

*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Return BTC	65 days		130 days		260 days		520 days	
Scaled Slope ⁵⁰	0.089	***	0.126	***	0.201	***	0.116	***
	(-0.0063)		(-0.0061)		(-0.0052)		(-0.0066)	
Constant	0.599	***	0.585	***	0.516	***	0.549	***
	(-0.0037)		(-0.0036)		(-0.0031)		(-0.0041)	
Observations	2,966		2,901		2,771		2,511	
R²	0.062		0.129		0.349		0.112	

Return ETH	65 days		130 days		260 days		520 days	
Scaled Slope	-0.021		0.050	***	0.139	***	0.188	***
	(-0.0145)		(-0.0149)		(-0.0147)		(-0.0183)	
Constant	0.678	***	0.640	***	0.540	***	0.452	***
	(-0.0107)		(-0.0112)		(-0.0113)		(-0.0148)	
Observations	1,647		1,582		1,452		1,192	
R²	0.001		0.007		0.058		0.082	

Return EUR	65 days		130 days		260 days		520 days	
Scaled Slope	-0.0273	***	-0.018	***	-0.105	***	-0.165	***
	(-0.0062)		(-0.0064)		(-0.0085)		(-0.0081)	
Constant	0.657	***	0.642	***	0.733	***	0.747	***
	(-0.0036)		(-0.0037)		(-0.0051)		(-0.0051)	
Observations	2,966		2,901		2,771		2,511	
R²	0.007		0.003		0.052		0.142	

⁵⁰ For the interpretation of this coefficient, refer to the adjustment described in Section 3.1.

Table 19. Regression results for returns of analysed currencies with varied step size and window length of 130 days. Robust standard errors in parentheses.

*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Return BTC	1 day		5 days		10 days		21 days	
Scaled Slope	0.126	***	0.127	***	0.115	***	0.115	***
	(-0.0061)		(-0.0136)		(-0.0157)		(-0.0173)	
Constant	0.585	***	0.585	***	0.588	***	0.586	***
	(-0.0036)		(-0.0079)		(-0.0103)		(-0.0127)	
Observations	2,901		581		403		346	
R²	0.129		0.131		0.119		0.114	

Return ETH	1 day		5 days		10 days		21 days	
Scaled Slope	0.050	***	0.259	***	0.083	**	0.110	**
	(-0.0149)		(-0.0382)		(-0.0398)		(-0.0439)	
Constant	0.640	***	0.436	***	0.611	***	0.589	***
	(-0.0112)		(-0.0286)		(-0.0310)		(-0.0351)	
Observations	1,582		317		271		283	
R²	0.007		0.128		0.016		0.022	

Return EUR	1 day		5 days		10 days		21 days	
Scaled Slope	-0.018	***	-0.026	*	-0.041	**	-0.039	
	(-0.0064)		(-0.0142)		(-0.0180)		(-0.0240)	
Constant	0.642	***	0.648	***	0.651	***	0.649	***
	(-0.0037)		(-0.0083)		(-0.0119)		(-0.0176)	
Observations	2,901		581		403		346	
R²	0.003		0.006		0.013		0.008	

Affidavit

I hereby declare that I have written this thesis on my own and with no other help than the literature and other supportive material listed in the Appendix. Citations of sentences and parts of sentences are declared as such, while other imitations are clearly marked and linked to original sources with regard to extent and intention of the statements made. This thesis has never been handed in to any examination authority before and it is also not yet published.

Lisbon, 30.05.2022

C. Kehne

(Constance Kehne)