Louvain School of Management

Portfolio diversification using cryptocurrencies

An empirical study of 4 cryptocurrencies between 2014 and 2021

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1 Abstract

Using descriptive statistics, correlation analysis as well as portfolio integration, we highlight the unique characteristics of cryptocurrencies. The risk/return trade-off of cryptocurrencies is much higher than that of traditional assets. Correlations with other traditional assets are rare and insignificant. Efficient frontiers containing cryptocurrencies largely dominate those without. We conclude that cryptocurrencies have the power to diversify but warn against the extreme risks they may represent and the insufficiency of mean-variance analysis to characterise them.

2 Introduction

Since the explosion of Bitcoin in 2013, debates about cryptocurrencies have not ceased to rage within the literature. Some see cryptocurrencies as a new asset class that can be perfectly integrated into their portfolio. Others believe that cryptocurrencies are nothing but scams that drive investors to speculation and irrationality. Cryptocurrencies have been constantly in the news for the past few years. In September 2021, "The Economist" magazine published an article called "Why it is wise to add bitcoin to an investment portfolio" explaining that cryptocurrencies are to be included to asset portfolios. In November 2021, “The New York Times” warned of cryptocurrency fraud in its article "Crypto Scams Are on the Rise". Faced with this amount of information, an investor might be lost and not know what to think about cryptocurrencies. This could result in them making bad choices and losing money. Instead of dismissing cryptocurrencies as fraudulent investments and scams, we want to study their behaviour within an asset portfolio. Understanding better how they work will allow investors to make better decisions. A general increase in the level of knowledge could also make cryptocurrency markets more efficient.

The objective of this thesis is to determine whether, between September 2014 and October 2021, cryptocurrencies have had their place in an investor's asset portfolio. What we call the place of an asset in a portfolio is the ability of that asset to diversify the portfolio in the manner of modern portfolio theory. The research question of this thesis is therefore, "Were cryptocurrencies effective between September 2014 and October 2021 in diversifying the asset portfolio of an American investor?"

In the empirical literature, several studies highlight the unique characteristics that cryptocurrencies have in terms of returns and volatility. For example, Enoksen et al. (2020) show that cryptocurrencies have very high volatilities compared to traditional assets. Liu et al. (2021) note that the trade-off between risks and returns is different from those found in precious metals, traditional currencies and equities. Some authors have looked at whether the returns of cryptocurrencies are correlated with those of traditional assets found in most asset portfolios. Between 2010 and 2013, Brière et al. (2015) only detected a significant correlation between Bitcoin and Gold. No correlation could be detected with the Euro, the Yen, oil, real estate, the stock market or government bonds in developed and emerging markets. Liu and Tsyvinski (2018) found almost no significant correlation between cryptocurrencies and precious metals, traditional currencies or macroeconomic variables between 2011 and 2018. Only a relationship between Gold and Ether could be found. Brière et al. (2015) point out that these correlations or lack thereof should not be taken for granted as they may change over time. Authors have tested the diversification ability of cryptocurrencies in an asset portfolio. Brière et al. (2015) reported that by accepting a little risk, an investor was able to achieve much higher levels of returns by including Bitcoin in their portfolio between 2010 and 2013. Bouri et al. (2017) showed that between 2010 and 2015, Bitcoin was able to serve as a diversification tool against commodity price fluctuations, either energy or not. Brauneis and Mestel (2019) show that between 2015 and 2017, incorporating several cryptocurrencies into an asset portfolio would have further diversified it given the low correlations found between these assets.

In this context, our study will focus on 4 cryptocurrencies with a very high capitalization, which come up very often in the literature: Bitcoin, Litecoin, XRP and Ether. To our knowledge, there is no study that, between 2014 and 2021, seeks to investigate the diversification power of these 4 cryptocurrencies. We therefore wanted to fill the gaps in the literature in this respect. To determine whether these 4 cryptocurrencies have enabled portfolio diversification, we went through several steps. First, we compared the basic characteristics of cryptocurrency returns to those of selected traditional assets in the manner of Briere et al. (2015). We have done this comparison statically and dynamically to be more comprehensive and to determine whether cryptocurrency returns have similarities with those of more conventional assets. Next, we looked at whether cryptocurrencies are correlated with conventional assets over the entire period from 2014 to 2021, and then over time over the same period. Finally, we investigated the behaviour of cryptocurrencies when they are integrated into a diversified asset portfolio. To do this we have drawn the efficient frontiers with and without cryptocurrencies for comparison. We then observed the evolution of asset portfolios over time with and without cryptocurrencies.

Our results help us to highlight different characteristics of cryptocurrencies. We highlight the singularity of the averages and the volatilities of cryptocurrencies compared to other conventional assets. The return and risk associated with cryptocurrencies are, in fact, much higher than those of other assets. We also show a decrease in the volatility of cryptocurrencies in early 2020 compared to other assets where the volatility had increased. We then point out the rarity of significant correlations between cryptocurrencies and traditional assets. Even over time, these correlations remain very low and insignificant. Cryptocurrencies are therefore a portfolio diversification asset given the low correlations with other assets. Efficient frontiers incorporating cryptocurrencies systematically dominate those that do not. With cryptocurrencies, an investor can therefore achieve similar levels of returns with less risk. The evolution of portfolios over time allows us to highlight the extreme behaviours of cryptocurrencies, which can be both upward and downward.

This thesis will start with a literature review in which we will address different topics. First, we will define and classify cryptocurrencies among digital currencies. Then, we will explain the context of their emergence as well as the technology that allows them to function. Then we will give examples of cryptocurrencies present on the market. We will then focus on understanding the advantages and disadvantages of cryptocurrencies. Finally, we will discuss the integration of cryptocurrencies into investors' asset portfolios. The empirical part of this paper is divided into several sections. First, we will define our data and explain the methodology used to answer our research question. Then, we will deconstruct the behaviour of cryptocurrencies through descriptive statistics. We will continue by testing the correlations of cryptocurrencies with traditional assets used by investors. We will end this part by analysing the efficient frontiers and the evolution of portfolios with or without cryptocurrency. Finally, we will discuss the limitations of this work, and we will conclude.

3 Literature review

3.1 Cryptocurrency, a particular digital asset

This section is intended to give a first overview of what cryptocurrencies are through a definition and a taxonomy of digital currencies.

3.1.1 Definition

To begin with, it is necessary to define what cryptocurrencies are. Cryptocurrencies are *"a kind of digital asset that uses cryptography to ensure its creation security and transaction security"* (Xia et al., 2020, p. 2). More formally, the Merriam-Webster dictionary (2021) defines cryptocurrency as ***"****any form of currency that only exists digitally, that usually has no central issuing or regulating authority but instead uses a decentralized system to record transactions and manage the issuance of new units, and that relies on cryptography to prevent counterfeiting and fraudulent transactions".* These definitions help to highlight the features that are required for a digital asset to be considered a cryptocurrency. The most relevant element seems to be the use of cryptographic methods to secure transactions. It is also clear that cryptocurrencies are a subset of digital assets.

3.1.2 Taxonomy

Hileman (2013) established a simple classification between digital currencies based on 2 parameters:

[1] Centralisation: a centralised digital currency is managed by a single actor. This entity has the power to issue currency, set new rules, manage supplies, etc. World of Warcraft gold is a good example of this because the game is the only entity with the legitimacy to create and manage new units. In contrast, a currency is decentralised when there is no single issuer but rather a distributed network of users contributing to the creation of currency as well as recording all transactions in accounts accessible to anyone. These accounts correspond to a blockchain, to which we will return later. Bitcoin and the cryptocurrencies we are interested in are examples of decentralised currencies.

[2] Openness: a digital currency is considered closed if it can only be exchanged within a virtual world. Hileman (2013) states that, theoretically, individuals could agree outside the virtual world to exchange this closed currency for other types of currency. World of Warcraft gold is a closed currency because it is only traded on the online platform. In the case of an open digital currency, exchanges no longer have borders and are therefore not limited to a digital platform.

These 2 parameters allow us to identify 4 categories of digital currencies. Among these 4 categories, it is the open and decentralised digital currencies that will attract our attention since it is in this category that most cryptocurrencies are found (Hileman, 2013).

3.2 The emergence of Bitcoin

The purpose of this section is to better understand cryptocurrencies. To do this, it is necessary to learn more about the history of their development. We will also focus on the technological elements that enable their existence.

3.2.1 The prequel

According to Halaburda (2016), the main problem that has hindered the implementation of digital currencies is counterfeiting, i.e., the possibility that a reproduction of the currency could be accurate enough to be trusted as payment by a seller. In addition, some monetary units could be spent more than once, which is known as double-spending. These problems can be avoided when there are accounts that keep track of the different transactions. Halaburda (2016) states that this constraint has led to the emergence of two types of systems. On the one hand, a centralised system based on an entity that keeps the accounts and prevents counterfeiting. On the other hand, a decentralised system in which the use of cryptography makes counterfeiting and double-spending almost impossible. This distinction corresponds to the centralisation parameter described by Hileman (2013).

Before the emergence of cryptocurrencies as they exist today, some people tried to set up electronic currency systems with special properties. The eCash is the first currency that can be described as a cryptocurrency because it uses cryptography to guarantee the veracity of transactions. However, it remained centralised, under the control of the company DigiCash, Inc. (Kuo Chuen et al., 2017). Later, Nick Szabo created the “bit gold”, recognised by many as the immediate ancestor of Bitcoin. The use of cryptography, through puzzle solving, allowed the “bit gold” to become a decentralised currency. Nevertheless, due to a lack of buy-in, this currency has not had the opportunity to reach the general public. It was in 2008 that the article "A Peer-to-Peer Electronic Cash System" published under the pseudonym Satoshi Nakamoto changed the game, resulting in the first cryptocurrency to gain mainstream popularity (Milutinović, 2018).

3.2.2 The game-changing article

The article published by Nakamoto in 2008 highlights the problem of an online payment system that relies solely on trusting a financial institution to secure transactions. This type of system is not perfect because these institutions do not have the capacity to make transactions totally irreversible. Indeed, in some cases, there are disputes, which leads to an increase in the cost of transactions in general. Therefore, the reversibility of transactions does not allow smaller transactions to take place. Halaburda (2016) gives the example of credit cards, where the fees associated with their use on the Internet make very low-value exchanges unprofitable. Moreover, to ensure the security of transactions, sellers are obliged to ask buyers for an excessive amount of information. For Nakamoto (2008), these problems demonstrate the inefficiency of electronic payment systems. He therefore calls for “an electronic payment system based on cryptographic proof instead of trust, allowing any two willing parties to transact directly with each other without the need for a trusted third party” (Nakamoto, 2008, p. 1). The objective is to make double-spending impossible without the use of an institution to perform the control. To do this, Nakamoto (2008) proposes that a unique and public history of all transactions be kept. It should contain the transactions in the order in which they took place. Moreover, for the history to be accepted, the majority of the participants must have validated it. Nakamoto (2008) also introduces the notions of Proof-of-Work, timestamps, and miners. These elements will be further developed in the next part of the work.

3.2.3 The blockchain

The history intended by Nakamoto (2008) in his reference article has resulted in the appearance of a new technology called the Blockchain. It is "an open and distributed ledger that records all transactions in a verifiable and permanent way, it solves the double-spending problem" (Kuo Chuen et al., 2017, p. 3). The blockchain is hence a technology that functions through a network of users and allows a set of transactions to be recorded and unchangeable. This is made possible through the use of cryptographic protocols (Ghosh et al., 2020). Here is how the blockchain associated with the Bitcoin cryptocurrency works.

Suppose a user A wants to perform a transfer from their Bitcoin wallet to the Bitcoin wallet of a user B. In order to perform this transfer, user A needs to gather two indispensable elements (Ghosh et al., 2020):

[1] the private cryptographic key attached to their Bitcoin wallet. This key allows user A to digitally sign the transaction and thus demonstrate that they are the owner of the amount they wish to send to user B. Kuo Chuen et al. (2017) further state that this key allows the sender to certify that they are the owner of the bitcoins they wish to transfer.

[2] the public cryptographic key attached to the recipient's wallet. This key allows user A to know the recipient's Bitcoin address. Thus, the beneficiary can unambiguously receive the amount.

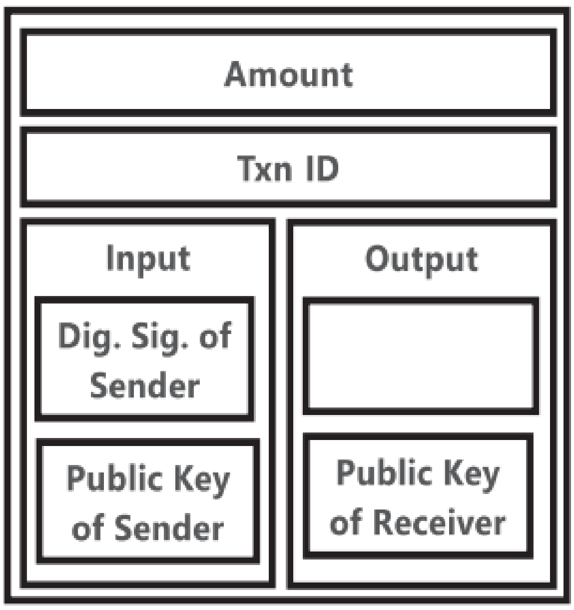

Fig. 1 - Transaction representation (Ghosh et al., 2020, p. 4)

In Figure 1, Ghosh et al. (2020) provide a simplified representation of the components of a given transaction. It includes the amount transferred, i.e., the amount of bitcoin that user A agrees to send to user B. In addition, there is the Transaction ID (Txn ID), which is the unique identifier associated with the transaction and allows it to be unequivocally recognized. There are also the elements mentioned above, the digital signature generated by the sender A and the public key of the recipient B. Finally, there is also the public key of sender A that will be used by the "miners".

When the sender generates their transfer of funds, the transaction is sent to all the miners on the network. These miners are people who each own a copy of the public ledger, the blockchain. This process is called broadcasting. The accounts are therefore decentralized because the miners must verify the authenticity of the transactions before they can effectively be recorded in the blockchain. For example, they check that the money in question had not already been spent previously (Kuo Chuen et al., 2017). “Mining is (…) the process of adding newly verified transaction records to Bitcoin’s public ledge” (Kuo Chuen et al., 2017, p. 5). Once miners have verified a number of transactions, they put them together to form a new block to the blockchain. This process is not so straightforward, however. It requires a lot of computing power to solve cryptographic problems. Miners do not offer their computing power for free. Every time a block is created, the responsible miner gets paid in the form of bitcoins. This is how new bitcoins are created. The miners are therefore in competition with each other, because the first one who succeeds in forming a new block by solving the cryptographic puzzle will be rewarded. The resolution of the problem is called the Proof-of-Work (PoW) (Kuo Chuen et al., 2017).

The blockchain is a technology that suits its name because it is structured as a chain of blocks. The blocks follow each other, and the precursor block of another block is called parent block. Obviously, the very first block has no precursor, it is called the genesis block. In addition, the blocks are made out of two distinct parts: the header and the body (Zheng et al. 2018). Figure 2 is a visual representation of the chain of blocks.

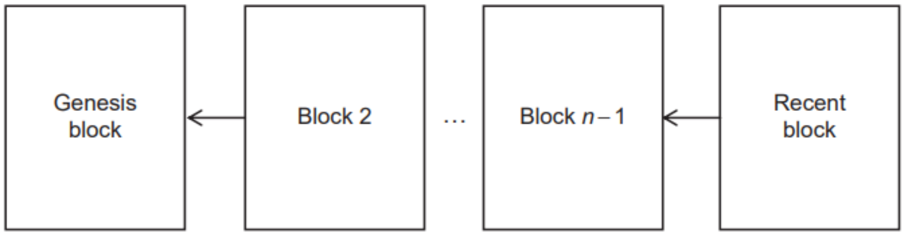

Fig. 2 - Blockchain representation (Bhaskar & Chuen, 2015, p. 49)

In the “Handbook of Digital Currency”, Bhaskar and Chuen (2015) highlight the elements that make up the header as well as the body of each block. In the header of each block, there are 7 distinct items. These elements are:

[1] The version: this corresponds to the version of the software used to create the block.

[2] The hash of the previous block: each block contains a cryptographic value referring to the block that precedes it. This value was obtained through cryptographic hashing. Paar and Pelzl (2010) define the hash as a function taking as argument a message of random size and returning an element of fixed size. They describe the result as the fingerprint of the message. Ghosh et al. (2020) add that the Bitcoin uses the SHA-256 hash which returns, whatever the source, an element of size 256 bit.

[3] The Merkle root: Ghosh et al. (2020) explain that it is a cryptographic hash of transactions one by one, then two by two until only one single value is obtained, the Merkle Tree Root Hash (MTRH). Figure 3 shows of the process by which a single value is obtained from all the transactions in the block.

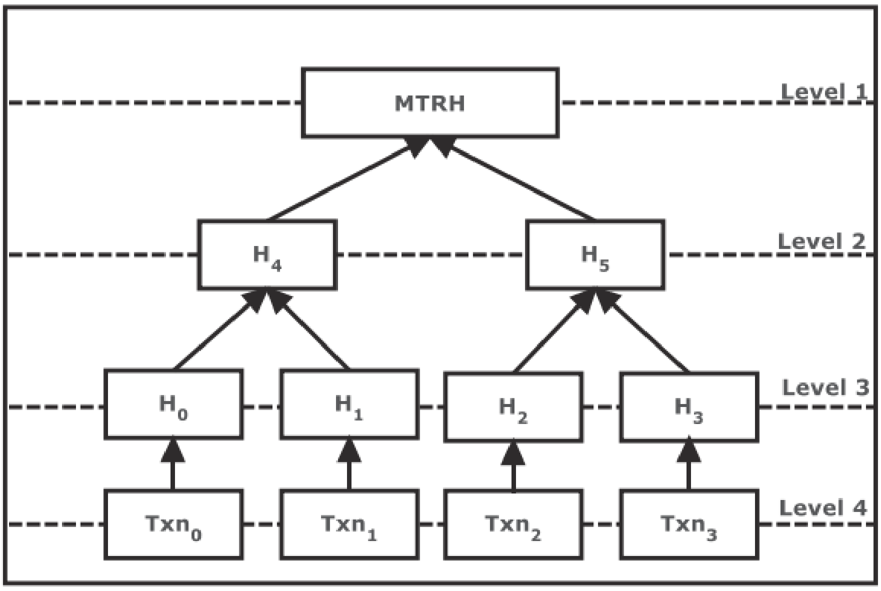

Fig. 3 - Merkle Tree Root Hash representation (Ghosh et al., 2020, p. 4)

[4] The timestamp: this field contains the number of seconds that have passed between the creation of the block and January 1, 1970.

[5] The bit field: this is the field that is used to solve the cryptographic problem facing miners. For a block to be valid, the miners must find a hash of the block header with a lower value than the value contained in the bit field.

[6] The nonce: to find a hash of the header that respects the condition imposed on it, a fluctuating field is necessarily required in the header. This is the role of the nonce, which increases by 1 each time a hash is created. The nonce's value is fixed when the imposed condition is fulfilled, i.e., when the hash value is less than the bit field value. Ghosh et al. (2020) explain that miners must therefore vary the nonce until a solution is found. This is the PoW mechanism.

[7] The transaction count: this simply states the number of transactions contained in the block.

Within the body of a block is the collection of transactions recorded in it (Bhaskar & Chuen, 2015).

When the transaction is found in a block of the blockchain, one should not be too quick to claim victory. It may happen that the transaction is later invalidated. This occurs when 2 miners manage to find a nonce value at the same time. From then on, there will be two distinct chains in the blockchain, and the miners will continue their work of creating blocks. At a given moment, one chain is distinguished from the other by its greater length and thus becomes the chain considered valid by the network. The other chain will then be considered invalid and thus rejected by the network (Ghosh et al., 2020).

3.2.4 The Bitcoin today

Today, Bitcoin is the cryptocurrency with the highest market capitalization. The number of bitcoins in circulation is 18,882,925.00 BTC (CoinMarketCap, November 25, 2021). It should be noted that the total quantity of bitcoins available is limited to a maximum of 21 million. According to estimates, the limit should be reached roughly in 2040 (Nian & Chuen, 2015). The creation of new bitcoins is getting slower and slower because the problem to solve when creating new blocks is getting more and more complicated as more blocks are added. This is due to the fact that the bit field decreases with each new block, making the constraint on the hashing sought by miners stronger (Bhaskar & Chuen, 2015). Figure 4 depicts the evolution of the number of bitcoins in circulation over time.

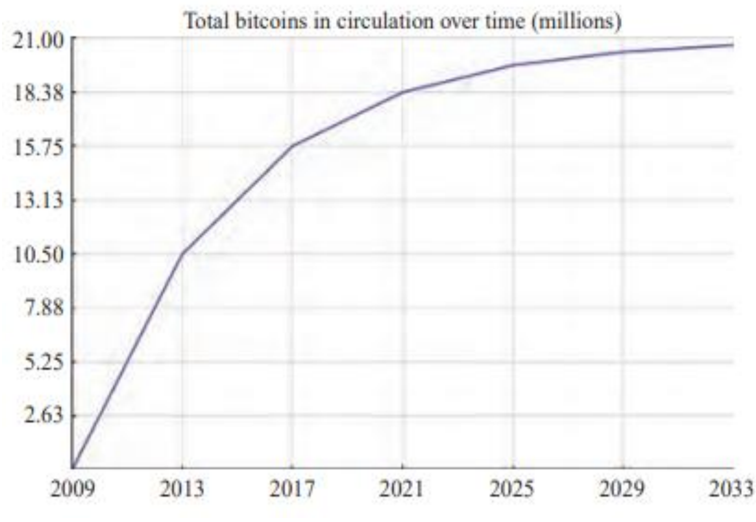

Fig. 4 - Total bitcoins in circulation over time (millions) (Nian & Chuen, 2015, p. 19)

3.3 The alternative cryptocurrencies

Following Bitcoin, other cryptocurrencies have emerged on the market. They are called altcoins, the contraction of alternative and Bitcoin (Milutinović, 2018). In this section, we will focus on understanding what these alternative cryptocurrencies really are.

In fact, the algorithm that allows Bitcoin to work is freely available on the internet. Bitcoin is said to be open source, allowing other people to use the code to create new cryptocurrencies. Bitcoin has its flaws, so this system has led to the development of hundreds of altcoins each with their own features (Kuo Chuen et al., 2017). Some are very similar to Bitcoin while others have unique characteristics. For example, Litecoin works very similarly to Bitcoin but the creation of blocks is done much faster. In particular, this allows Litecoin's transaction volume to be greatly increased (van der Merwe, 2021).

It is possible to classify altcoins according to the new characteristics they have in comparison to Bitcoin. This is what Ong et al. (2015) propose by creating 5 distinct categories of altcoins:

[1] Altcoins being almost identical to Bitcoin: the design of these cryptocurrencies is nearly the exact same as Bitcoin. Only variables such as the maximum amount in circulation or the speed of creation of new units are changed.

[2] Altcoins offering a technological transformation in the way they work: the changes could also be related to the hash algorithm or the distribution of the network. In addition, while Bitcoin works via PoW, other systems exist such as Proof-of-Stake (PoS). Halaburda (2016) explains that PoS is an alternative to PoW. Instead of being based on a competition between different miners, it is based on a random draw. The lucky one must then solve a cryptographic problem requiring little computing power. The more cryptocurrency the miner has, the more likely he is to be chosen. When a miner creates a block by solving the problem, he is rewarded with cryptocurrency.

[3] Altcoins being coded using another programming language.

[4] Altcoins with original concepts: Ether is a good example of this group, as it allows for the implementation of smart contracts, which was not possible with Bitcoin (see below for a presentation of Ethereum).

[5] Appcoins: these are altcoins that are created with the help of participatory funding. They are considered shares in a DAO which can be defined as "an 'entity' with a certain agenda, business plan, or protocol but without any central point of control" (Ong et al., 2015, p. 84).

Obviously, this classification is not intended to include all existing cryptocurrencies. Moreover, some cryptocurrencies may fit into more than one single type of altcoin (Ong et al., 2015).

3.3.1 Examples of altcoins

This section aims to spotlight the unique characteristics of some of the altcoins that come up most often in the literature and some of the largest market caps according to CoinMarketCap (2021).

a) Ether (ETH)

Like Bitcoin, Ether is a cryptocurrency based on a decentralized system, the Ethereum blockchain. It is therefore also a decentralized structure based on a network of users. Vitalik Buterin has developed the Ethereum platform with the objective of making it possible to conclude smart contracts. These are contracts that automatically perform an action when conditions are met (Milutinović, 2018). The Ethereum blockchain aims to eliminate intermediaries between parties that perform transactions or enter into contracts. At the same time, it aspires to mitigate the costs associated with transactions as well as make them more secure. Furthermore, other cryptocurrencies can be developed on this blockchain (CoinMarketCap, 2021).

b) XRP

First of all, Ripple, XRP and RippleNet should not be confused. RippleNet is a platform for money transfers over the internet. XRP is the cryptocurrency associated with this platform. Ripple is the company that manages it all. It should be noted that Ripple does not work via a blockchain like other cryptocurrencies. Instead, it works through a shared database containing the history of all transactions (CoinMarketCap, 2021). Milutinović (2018) adds that more and more banks are using this system. It is intended to be fast, secure and allow transactions from anywhere without additional fees.

c) Tether (USDT)

Tether falls into the category of stablecoins. It is a type of currency that seeks to stabilize its price by binding it to one or more underlying assets (van der Merwe, 2021). The asset which price this cryptocurrency attempts to replicate through complex mechanisms is the US dollar. Furthermore, Tether is not directly linked to a blockchain. Instead, it uses the blockchains of other cryptocurrencies like Bitcoin or Ethereum. This cryptocurrency is one of the most traded in terms of average daily trading volume (CoinMarketCap, 2021).

d) Solana (SOL)

Solana is a blockchain-based cryptocurrency that enables the creation of smart contracts. In reality, Solana has a lot in common with Ether. Solana does not use PoW but rather PoS in the transaction validation process (Bodziony et al., 2021). The main advantage of Solana is the speed with which transactions and smart contracts are executed. One of the goals of the creators of this cryptocurrency was to minimize any transaction fees. In addition, they wanted the service offered not to decrease or slow down as demand increased (CoinMarketCap, 2021).

e) Litecoin

Litecoin is a cryptocurrency that works in essentially the same way as Bitcoin. There are only three important differences from Bitcoin. The time it takes to create a block on the blockchain is 4 times less than Bitcoin. The maximum amount of Litecoin that can enter circulation is 4 times greater than Bitcoin. The algorithm used for hashing is also other than SHA-256 (Kuo Chuen et al., 2017). Today, Litecoin has become a widely used currency among cryptocurrency enthusiasts. Regularly, it is in the top 10 largest market capitalization (CoinMarketCap, 2021).

f) Dogecoin (DOGE)

Dogecoin is a cryptocurrency symbolized by a famous internet meme portraying a Shiba Inu. It's a currency that doesn't take itself seriously and aims for a wider audience by using a popular image as a reference. Elon Musk has spoken about this currency several times and named it as his favourite cryptocurrency (Kuo Chuen et al., 2017). Dogecoin does not use PoW to operate but uses Scrypt instead (we do not further develop this technology here). Dogecoin has no limit on the total amount that can enter into circulation. Also, the time to create a block is 10x less than that found in Bitcoin (CoinMarketCap, 2021).

3.4 Benefits of cryptocurrencies

This section aims to point out the components of cryptocurrencies that can be beneficial to those who are interested in acquiring them.

Decentralization is a feature found in most cryptocurrencies. As we have seen, the blockchain operates in a distributed environment around a network of nodes. Each of the nodes holding a copy of the blockchain containing the summary of all transactions (Ghosh et al., 2020). There is no central authority such as a bank or a government to regulate their issuance and control them. In fact, these cryptocurrencies are very difficult to control for the legislator who has very limited means of action. Many countries allow cryptocurrencies without restriction. Nevertheless, some governments use the little power they have in this matter to constrain users. This is the case of China, which has decided to completely forbid cryptocurrency exchanges on its territory. Russia has also limited the scope of cryptocurrencies by not allowing their use to purchase goods or services on the territory. The actions of these governments would be in an attempt to prevent criminal activities as well as transactions on which taxes would normally apply (Milutinović, 2018). Achieving a decentralized system was Nakamoto's (2008) number one goal when he published his paper on Bitcoin. He wanted to implement a solution that gave two parties the freedom to agree on the execution of a transaction, without the intervention of a third party. According to Lee et al. (2017), this decentralization that blockchain provides allows for a certain degree of transparency. The storage of transactions at each of the network's nodes gives any miner the possibility to consult and verify them. Hileman (2013) notes, however, that the decentralization of Bitcoin is a matter of debate. Mining activity is reportedly highly concentrated around a limited number of miners. Furthermore, in 2013, miners pooled their capabilities to make a correction on the blockchain. In a recent publication, the

Bank for International Settlements (BIS) (2021) criticizes the decentralization attributed to cryptocurrency markets. It argues that this is an illusion because some governance will always be needed to make the system work. According to the BIS, if decentralization becomes too widespread, the stability of the system could be jeopardized. The BIS (2021) highlights the existence of power concentration in decentralized systems.

Confidentiality is one of the most relevant properties of cryptocurrencies through the use of blockchain technology. The nodes of the Peer-to-Peer network can interact with each other by using an address. This address does not mention the personal information of the parties engaged in a transaction. Even though transaction details are publicly available in the blockchain, the users who have carried out the transactions remain anonymous. In the Bitcoin system we have discussed, the address simply refers to a public key linked to a certain Bitcoin wallet (Ghosh et al., 2020). Nakamoto (2008) draws parallels between the system he advocates, and the traditional system based on the intervention of a third party. When a central authority intervenes to regulate a transaction, it collects information about the transaction as well as about those who are involved in it. Thanks to the blockchain, transactions can be publicly announced without direct reference to the personal information of third parties. Instead, it is the public keys associated with wallets that are made public. Figure 5 shows that the anonymity of the parties is better preserved in this system than in the traditional system.

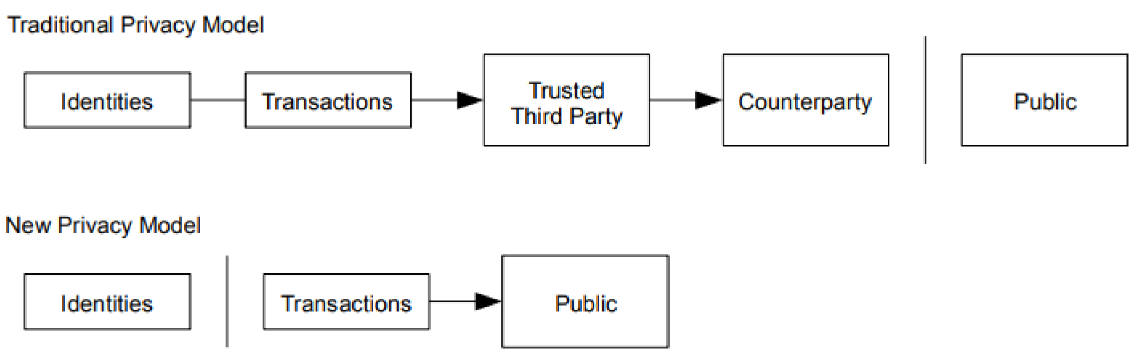

Fig. 5 – Traditional Privacy Model VS New Privacy Model (Nakamoto, 2008, p. 6)

To further strengthen the privacy aspect, Nakamoto (2008) also suggested that the keys associated with cryptocurrency wallets should change with each transaction. If a public key is always associated with the same address, it is possible to notice that the same address is found in several transactions. This constitutes information, so the solution proposed by Nakamoto (2008) allows for complete anonymity. Milutinović (2018) adds that thanks to the blockchain, it is almost impossible for the identity of parties included in a transaction to be revealed.

Security is one of the most recurring points in the literature when discussing cryptocurrencies. When a transaction is confirmed, the chances of it ever being deleted are infinitesimal (Milutinović, 2018). Furthermore, if a third party attempts to incorporate a transaction in the form of a double-spend, it will be spotted immediately by miners who check the legitimacy of transactions (Ghosh et al., 2020). Nakamoto (2008) calculated the probabilities that a possible attack on the blockchain could succeed. A hacker might want to spend an amount of cryptocurrency that they have already spent. To do so, they would want to modify the information in a block by indicating transaction. Changing the information in a block causes the hash value of that block to change. The PoW for this block must therefore be performed again. But since each block contains the hash value of the previous block, all the blocks that follow must also be modified. The attacker therefore has to modify the blocks faster than new blocks are created. This assumes that they have more computing power than all the other miners combined. Nakamoto (2008) concludes that the probability that an attacker can succeed in doing this decreases very sharply as more blocks are created.

All of the code that made Bitcoin possible is available online for free. All of the cryptocurrencies that are available on the market today have been able to draw on at least small parts of this code to develop. In addition to Bitcoin, some cryptocurrencies are in turn choosing to share their code (Papadopoulos, 2015). Bitcoin has the merit of existing although it is not always suitable for the needs of users. The development of new cryptocurrencies has addressed some of the weaknesses that Bitcoin may have had. For example, the large amount of computing power needed to participate in mining has been remedied by introducing new protocols other than PoW. In addition to this, it is not difficult to introduce new cryptocurrencies. The barriers to entry are indeed limited. However, whether or not a cryptocurrency succeeds depends on the demand for it. This is why few cryptocurrencies manage to survive over time (van der Merwe, 2021).

One of the main advantages of cryptocurrencies is the low costs associated with the transactions. It is the decomposition of the network around nodes instead of a financial institution that reduces (or even eliminates) transaction costs (Papadopoulos, 2015). However, transaction costs are not completely non-existent in the cryptocurrency world. For example, the Bitcoin network incorporates transaction fees into its model. These fees increase the speed with which a transaction will be added to a block and thus validated by miners. It should also be noted that when the maximum amount of Bitcoin will be in circulation, miners will no longer be able to be remunerated by cryptocurrency. The model will then rely on transaction fees to continue operating (Kuo Chuen et al., 2017).

Obviously, one cryptocurrency is not the other and every time a new one appears on the market, something new is created. It has a history as well as its own advantages that are just waiting to be discovered (Milutinović, 2018).

3.5 Drawbacks of cryptocurrencies

In this section, we will understand why cryptocurrencies are not perfect by addressing some of the disadvantages they have.

3.5.1 Possibility of scams

The literature highlights the existence of scams and attacks on the blockchain, cryptocurrencies and their users.

Bartoletti et al. (2020) point out the existence of so-called Ponzi Schemes. These are pyramidal scams where each layer of the pyramid has an interest in recruiting new people to increase its income. To recruit, the scammers set up a system in which they make newcomers believe that they are investing in an investment opportunity with a high return and low risk. In reality, it is a fraud because no investment is made. The money raised by the recruitments is used to pay those already in the pyramid. Bartoletti et al. (2020) tested the presence of this kind of scam during the first two years of the Ethereum blockchain's existence. The experiment led to the detection of 17,777 transactions with a link to this type of fraud. At the time, this represented about 0.05%

of the transactions that took place on this blockchain. They also showed the existence of 2304 victims who lost more than 418,761 USD. By digging through forums related to the Ponzi Scheme on cryptocurrencies between 2011 and 2016, Vasek and Moore (2019) also found thousands of posts mentioning fraudulent activity. They found that the majority lasted only a day or a week because they were spotted by moderators. On the other hand, some lasted up to more than 3 years. Finally, Vasek and Moore (2019) showed that the victims were not people interested in the technical and political aspects of cryptocurrencies. Rather, the targets would be people interested in the possibility of easy money via speculation.

A well-known scam is that of “typosquatting”. This consists of creating a website whose name strongly resembles an existing site. By making a spelling mistake when writing a URL, a user could inadvertently end up on a fraudulent site (Xia et al., 2020). Xia et al. (2020) showed that over 83% of cryptocurrency exchange sites were targets of “typosquatting”. More than 1595 fraudulent domains were found. Transformations in the site name range from adding a letter, dot, or hyphen to replacing or swapping letters. The most affected sites are most often those with the highest trading volume (Binance, Coinbase, etc.). Xia et al. (2020) add that the scams go as far as creating fake applications that look very similar to the original ones. The goal of these apps is to bait users into stealing data or money.

There is one particular attack that consists of attacking the nodes that make up the Peer-to-Peer network of the blockchain. This attack is called an eclipse attack. The attacker proceeds to isolate one of the participants in the network by modifying it to believe that it is still participating in traditional block mining. In reality, the computing power of the targeted node is lost or reused by the fraudsters for damaging aims (Heilman & Kendler, 2015). Heilman and Kendler (2015) explain that this attack is a base from which other attacks can then be carried out. For example, hackers could attempt to isolate many nodes in the network to take control of the network. They could then validate blocks containing fraudulent transactions.

3.5.2 Behavioural finance

Several behavioural finance studies address the behaviour of individuals when dealing with cryptocurrencies. According to Bouri et al. (2019), people investing in cryptocurrencies are often very youthful and do not know much about financial markets. Moreover, these individuals mostly base their investments on what they read on different forums and social networks that have a great influence on them.

Al-Mansour (2020) interviewed people investing in the cryptocurrency markets in the United Arab Emirates. He uses 3 theories of behavioural finance to try to explain how they react to the market:

[1] Prospect theory: Al-mansour's study (2020) shows that investors gradually increase their risk level as they gain. Moreover, when they lose, they act like speculators by selling the cryptocurrencies that have risen and keeping those that have fallen. After suffering a loss, investors tend to take less risk. Note that investors tend to be confident about their skills in determining which cryptocurrencies to invest in. Pelster et al. (2019) find similar results by showing that investors were inclined to buy and increase their leveraging effect after starting to trade cryptocurrencies. This contributes to a decrease in the revenue they earn from their investments.

[2] The theory of herding behaviour: Al-mansour (2020) found that investors do not make their decisions based on rational elements. Instead, they are strongly influenced by what other investors do. This influence extends to the purchase and sale choice, which cryptocurrency to buy or even how much to buy. Bouri et al. (2019) also studied herding behaviour in the cryptocurrency market. They conclude that investors act without caring which cryptocurrency they invest in. Instead, they choose cryptocurrencies that are trending in the market by imagining that their price will continue to rise after purchase. Hidajat (2019) adds that when the price of Bitcoin starts to rise, investors tend to follow the mass. On impulse, they then buy a financial instrument that they do not understand and cannot control.

[3] Heuristic theory: investors reported feeling able to predict price movements using today's prices. Investors believe they have the experience and skills to decide which cryptocurrencies to choose to invest in.

Hidajat (2019) has investigated various biases that investors may face when investing in Bitcoin.

[1] Overconfidence bias: this bias comes into play when Bitcoin is selling at a high price. The investor may then feel that his or her skills in terms of investing in cryptocurrencies are enhanced tenfold. The media plays a role in this by giving the impression that the investor has the skills and experience to make good decisions.

[2] Optimism bias: optimism happens when Bitcoin is in the spotlight and investors start buying it. The resulting increase in price leads to optimism on the part of investors who used to own it in the sense that they see that Bitcoin is an instrument that can make them money.

[3] Confirmation bias: Hidajat (2019) highlights the influence of this bias in a particular moment. When the price of Bitcoin falls and then rises again a few points, they have the impression that this means that the price will rise again. Therefore, they tend to look for information that gives credence to their thinking. They give little (if any) importance to news that would go against this preconceived notion.

[4] Loss aversion: when Bitcoin suffers a big drop, investors tend not to sell. The idea of taking a loss conditions investor and leads them to take more risks to try not to lose money.

[5] Loss aversion: when Bitcoin suffers a big drop, investors tend not to sell. The idea of taking a loss conditions investors and leads them to take more risks to try not to lose money.

[6] Gambler's fallacy: this bias leads the investor to hold on to their investment regardless of the losses incurred, hoping that the price of Bitcoin will rise again. This can lead to heavy losses on the investor's side when Bitcoin reaches very low points.

3.6 Cryptocurrencies as a diversification asset

This section is the core of the topic we want to study. Here we will discuss cryptocurrencies as an investment instrument. To do this, we will discuss modern portfolio theory. Then, we will analyse the contributions of the literature concerning the various aspects of cryptocurrencies within an asset portfolio. We will discuss the volatility that characterizes them, the correlations with other assets and their interest in diversification.

Cryptocurrencies are traded on a platform called a cryptocurrency exchange. This is a marketplace where investors can purchase or sell cryptocurrencies. Some of these platforms also allow the conversion of these cryptocurrencies into traditional currencies such as the U.S. Dollar or the Euro. There are three types. Some are centralized around a single entity. Others are completely decentralized and operate automatically. Finally, some are hybrid and work under both systems (Xia et al., 2020).

3.6.1 Modern Portfolio Theory

Gallais-Hamonno (2017) highlighted the contribution of Markowitz[1] (1952) to the Modern Portfolio Theory. Markowitz (1952) makes the hypothesis that the returns of an asset i.e., the relative variation of its price, are normally distributed. This assumption simplifies the framework by describing returns using two parameters: the mean and the standard deviation. The mean or mathematical expectation indicates the trend around which returns fluctuate. The standard deviation represents the dispersion around the mathematical expectation. Markowitz (1952) associates this dispersion with the risk of the asset. In fact, he considers that a security can be seen as a random variable. Therefore, a portfolio of securities can be seen as a combination of random variables. The mathematical expectation of the portfolio of securities is thus the weighted sum of the expectations of the individual securities:

$$E(R_p) = \sum_{i=1}^{N} W_i * E(R_i) \quad \text{with}$$

- $E(R_p)$ the expectation of the portfolio returns
- W_i the weight of the security i in the portfolio

[1] Markowitz, H. (1952). Portfolio Selection*. *The Journal of Finance*, *7*(1), 77-91. https://doi.org/10.1111/j.1540-6261.1952.tb01525.x

- $E(R_i)$ the expectation of the returns of the security i

The variance of the securities portfolio is calculated using the variance and covariance:

$$Var(R_p) = \sum_{i=1}^{N} W_i^2 * Var(R_i) + \sum_{i \neq j}^{N} W_i * W_j * Cov(R_{ij})$$ with

- $Var(R_p)$ the variance of the portfolio returns
- W_i the weight of the security i in the portfolio
- $Var(R_i)$ the variance of the returns of the security i
- $Cov(R_{ij})$ the covariance between the returns of the securities i and j

This last formula has a particular implication. The variance of the portfolio depends not only on the variance of the individual securities but also on the covariance between the securities. Therefore, the lower the covariance (and hence the lower the correlation coefficients) between securities, the lower the portfolio variance. This is the diversification effect (Gallais-Hamonno, 2017).

Gallais-Hamonno (2017) subsequently reports that Markowitz (1952) sought to show the existence of so-called "efficient" portfolios. For a given portfolio of securities, it is sufficient to solve a simple constrained optimization problem. This problem consists of finding the weight of each of the securities in the portfolio to minimize the risk (the variance/standard deviation) for a given profitability. By varying the mathematical expectation, a whole series of portfolios can be obtained. Together, they form the frontier of efficient portfolios. Each of the portfolios on this frontier is the most profitable for a given risk and the least risky for a given return. Gallais-Hamonno (2017) states that this frontier represents an infinite number of portfolios. Some of these efficient portfolios have particular characteristics. One of them is the one that has the minimum risk. Figure 6 is an example of the efficient frontier of a portfolio containing 7 CAC40 stocks.

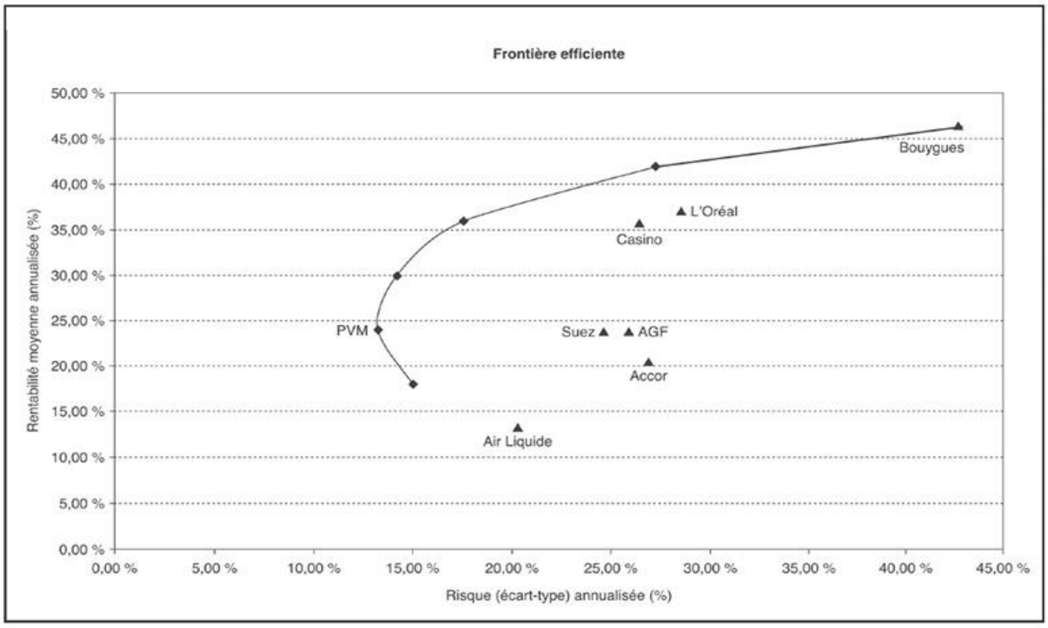

Fig. 6 - Efficient frontier for seven CAC40 stocks (1996-2000: monthly data) (Gallais-Hamonno (2017), p. 74)

Hirigoyen (2017) explains Sharpe's[2] (1966) contribution to modern portfolio theory and the efficient portfolio frontier. Sharpe (1966) introduced a ratio to calculate an expectation of return differential against a risk differential.

$$Sharpe\ ratio = \frac{E(R_B)-E(R_F)}{\sigma_B-\sigma_F}$$ with

- $E(R_B)$ et $E(R_F)$ the expected returns of the portfolio B and F
- σ_B et σ_F the standard deviations of the returns of the portfolio B and F

The portfolio F is the reference portfolio to which the portfolio B is compared. The calculation of the Sharpe ratio uses in most cases the risk-free asset as a reference point. Defined as such, the ratio is the slope of the Capital Market Line. This line passes through the risk-free asset and is tangent to the efficient frontier. It is based on the fact that an investor can borrow or lend without risk. Sharpe (1966) shows that a rational investor should place their portfolio on this line. This allows them to obtain a higher return than the risk-free asset.

[2] Sharpe, W. F. (1966). Mutual Fund Performance. The Journal of Business, 39(S1). https://doi.org/10.1086/294846

3.6.2 Volatility of cryptocurrencies

Several articles have highlighted the difference between cryptocurrencies and traditional assets. Liu et al. (2021) showed that the risk-return trade-off associated with cryptocurrencies has little to do with those of metals, currencies and stocks. They describe cryptocurrencies as unique assets with very little in common with existing assets. Brière et al. (2015) studied the annual returns of Bitcoin between July 2010 and December 2013. They also note that the risk-return trade-off is quite exceptional with annual returns of 404% offset by annual volatility of 176%. This compares poorly with the returns of gold or conventional stocks. For their part, Pavković et al. (2019) worked on Ethereum, EOS, Litecoin, XRP and Bitcoin. Looking from the beginnings of each of the cryptocurrencies up to 2018, they demonstrate mathematical expectations and standard deviations that are quite out of line. Comparing with gold futures or market indices proves the uniqueness of these assets. Nevertheless, Pavković et al. (2019) point out that cryptocurrencies that are more recent and therefore have shorter observation periods are less stable. Testing Bitcoin, XRP, and Ethereum between 2013 and 2018, Liu and Tsyvinski (2018) obtained Sharpe ratios 50% (or even 75%) larger than those of traditional stocks.

For Papadopoulos (2015), this volatility is partly due to the blockchain technology, which in the eyes of investors is synonymous with uncertainty. In addition, the sense of freshness plays a prominent role in the purchase of cryptocurrencies. Furthermore, the way in which new issues are made or the impossibility of any intervention lead a little more to make cryptocurrencies volatile. Papadopoulos (2015) also talks about speculation forming a vicious circle around cryptocurrencies. Indeed, the fact that they are so volatile makes them a tool for speculation and vice versa. This does not allow these cryptocurrencies to become a preferred means of payment by the general public.

Enoksen et al. (2020) investigated several cryptocurrencies (Bitcoin, Ethereum, XRP, Litecoin, Monero, Dash coin, Nem coin, Dogecoin) until February 2019. They first highlight the volatility of these cryptocurrencies. According to them, this volatility exposes the cryptocurrency markets to the creation of financial bubbles. Cryptocurrencies have experienced a significant number of bubble days during the time of research. The Bitcoin market reportedly experienced 193 bubble days, Dash coin 188 days, Litecoin 118 days, XRP 100 days, Ether 91 days, and Dogecoin 64 days. Enoksen et al. (2020) also showed a relationship between the number of Google searches. High transaction volume is further associated with the creation of bubbles. They have also shown that the appearance of bubbles is much more likely during ascending economic phases

3.6.3 Correlation with cryptocurrencies

Liu and Tsyvinski (2018) looked at how cryptocurrencies could react in relation to certain factors. They examined Bitcoin between January 2011 and May 2018, Ethereum between July 2015 and May 2018, and XRP between April 2013 and May 2018. They first notice that these three cryptocurrencies vary together. They obtained the following results:

[1] They first tested how Bitcoin, Ethereum and XRP respond to the financial markets. To do this, they looked at their variations from CAPM or Fama French five risk factors. They show exposures to CAPM with significant sizable betas and alphas. Nevertheless, they rarely find very significant relationships with the other factors tested (155 factors tested from the financial literature). Note, however, that they found a strong dependence of XRP and Ethereum on the HML factor.

[2] Liu and Tsyvinski (2018) then went on to check the relationships with several leading currencies (Euro, Pound Sterling, Canadian Dollars, Australian Dollars, etc.). One of the goals is to understand whether these cryptocurrencies are achieving one of their primary goals of becoming a means of payment. They do not find significant relationships with these currencies.

[3] To test the idea that cryptocurrencies could serve as a store of value, the authors tested the relationship with precious metals. Liu and Tsyvinski (2018) only found a relationship between Ethereum and gold. Silver and platinum yielded no significant relationship.

[4] The relationships between the three cryptocurrencies and macroeconomic factors were explored. In general, this did not reveal any significant

dependencies. Only a link between Ethereum and sustainable consumption growth could be found.

For their part, between 2010 and 2013, Brière et al. (2015) were able to detect significant correlations between Bitcoin and Gold and bonds whose prices are linked to global inflation. On the other hand, they did not find any link between Bitcoin and the Euro, the Yen, emerging and developed markets corporate and government stocks, oil, real estate, investment funds. However, they warn about their results. According to them, one should not take for granted the low historical correlations between cryptocurrencies and the different factors studied. Indeed, they cite Brière et al.[3] (2012) according to whom correlations are not fixed and can change, especially in times of crisis.

Bouri et al. (2017) found a positive correlation between the price of Bitcoin and the price of energy between 2010 and 2015. They explain this relationship by the fact that an increase in the price of energy can make Bitcoin mining less advantageous. This would lead to an increase in the price of Bitcoin because it costs more money to get new ones. Bouri et al. (2017) divided their research period into pre-crash and post-crash phases. They showed that the relationship between Bitcoin and electricity was stronger during periods of rising electricity prices. When the price of electricity rises, it is easy for miners to stop their activity overnight. On the other hand, when the price of electricity decreases, it is more complicated for new miners to buy all the necessary equipment. It is also more difficult for miners already in the market to increase their mining capacity.

Zhang et al. (2018) set up an index consisting of 9 cryptocurrencies with large capitalizations (Bitcoin, Ripple, Ether, Litecoin, Dash, Monero, etc.). The returns of the index correspond to the returns of the cryptocurrencies weighted by their individual prices. They then tested the correlation between the returns of the resulting index and the Dow Jones Industrial Average. This is an indicator to represent the evolution of the

[3] Brière, M., Chapelle, A., & Szafarz, A. (2012). No contagion, only globalization and flight to quality. Journal of International Money and Finance, 31(6), 1729-1744. https://doi.org/10.1016/j.jimonfin.2012.03.010

industrial stock market. Zhang et al. (2018) found that there was a correlation between these two indices between 2013 and 2018.

3.6.4 Diversification with cryptocurrencies

Some authors have decided to test the diversification that can be achieved by integrating cryptocurrencies into asset portfolios. The empirical literature provides the following answers.

Brière et al. (2015) wanted to test the gain that integrating Bitcoin into a diversified portfolio between July 2010 and December 2013 could offer in terms of mean and standard deviation. First, they tested this potential benefit in a portfolio composed of indices with weights that are simply a function of the number of indices. They claim that Bitcoin allows for a very large improvement in portfolio results by tripling the Sharpe ratio. Annual returns were almost able to increase by seven times while the risk associated with the portfolio less than tripled. According to Brière et al. (2015), this increase in risk would be enough to hold back most conventional investors. After looking at this, they constructed the frontier of efficient portfolios with and without Bitcoin incorporated. They found that the frontier with Bitcoin largely dominated the frontier without Bitcoin. Only one common point could be identified between the two frontiers, which is the portfolio with minimal risk. This portfolio does not contain any Bitcoin because this is a too risky asset to be in it. Brière et al. (2015) add that when an investor is willing to take a little more risk, they are much more rewarded by the portfolio that contains Bitcoin than the one that does not. However, this finding is not without a downside. Brière et al. (2015) highlight the fact that the inclusion of Bitcoin does not make it as easy to line your pockets. Some risks are not taken into account in the mean-standard deviation approach. The inclusion of Bitcoin in the diversified portfolio of assets would lead to a considerable increase in the risks of extreme values. The distribution of Bitcoin appears to be a fat-tailed distribution. The Sharpe and Sortino ratios rise drastically when Bitcoin is added to the portfolio. When these ratios are adjusted for extreme value risk, the picture is quite different. They decrease and show that an investor who wants to invest in Bitcoin would take significant risks in terms of extreme values.

Bouri et al. (2017) sought to understand whether Bitcoin was more of a diversifying or a hedging asset. An asset is considered diversifying relative to another if it is only slightly and positively correlated with the other asset. An asset is considered to be hedging if it has no correlation with the other asset. Hedging is even greater if the correlation becomes negative. An asset with the capacity to hedge in times of crisis is called a safe haven. In this context, Bouri et al. (2017) show that between 2010 and 2013, Bitcoin was able to serve as a hedge for commodities and energy commodities. For non-energy commodities, Bitcoin would only be a diversification asset. After 2013, the year when the Bitcoin price first exploded, and until the end of 2015, Bitcoin lost its ability to hedge commodities, both energy and non-energy.

Dorfleitner and Lung (2018) conducted spanning tests to evaluate the diversification potential offered by eight cryptocurrencies (Bitcoin, Litecoin, Dash, XRP, Ether, etc.). This type of test is done in a mean-variance framework. It checks whether adding a set of assets to a portfolio diversifies that portfolio. To do this, they set up a portfolio with assets of all types by putting themselves in the position of a European investor (bonds, stocks, commodities, etc.). Dorfleitner and Lung (2018) then tested the diversification contribution of cryptocurrencies in this portfolio between August 2015 and August 2018. The test shows that four out of seven significantly diversify the portfolio. The three inconclusive tests correspond to cryptocurrencies which returns are probably not normally distributed. These cryptocurrencies indeed have fat tails, and the mean-variance framework does not really fit their description. Taking this into account, 2 of these 3 cryptocurrencies then allow for portfolio diversification at a 10% significance level. Only one cryptocurrency is therefore rejected as a diversification tool. Briere et al. (2015) had also carried out this type of test by adding Bitcoin to a diversified asset portfolio. They had found (at a 1% threshold) that Bitcoin allowed for diversification of portfolios containing traditional, alternative assets or both together.

Brauneis and Mestel (2019) studied the correlations between more than 500 different cryptocurrencies between 1 January 2015 and 31 December 2017. They found, to their surprise, that the vast majority of correlations between two-to-two cryptocurrencies did not exceed 0.20. Contrary to most previous research, they therefore chose to include several cryptocurrencies in their portfolios at the same time to test the diversification effect. They conclude that adding multiple cryptocurrencies to a portfolio provides better diversification than adding a single cryptocurrency. According to them, this would allow risk-averse people to invest in cryptocurrencies. Brauneis and Mestel (2019) also found that the distributions of cryptocurrency returns often had fat tails.

Kuo Chuen et al. (2017) worked with the CRIX between August 2014 and March 2017. It is an index tracking returns in the cryptocurrency market. The cryptocurrencies in it are updated every month based on data such as value or trading volume. Kuo Chuen et al. (2017) show that the CRIX is not correlated to any traditional assets and that this bodes well for the ability of cryptocurrencies to serve as hedges. They then plot the efficient frontiers with and without the inclusion of CRIX in an asset portfolio. This leads to the conclusion that adding CRIX to the asset portfolio allows an investor to achieve greater returns at the same level of risk.

4 Empirical research

4.1 Data

As far as the data used is concerned, we will study the interest of 4 major cryptocurrencies: Bitcoin, Ether, XRP and Litecoin. They are among the cryptocurrencies with the highest market capitalisation and volume traded every 24 hours. As of December 06, 2021, Bitcoin's market capitalization is $965,660,140,290 and the 24-hour trading volume is $37,957,597,444 (742,660 BTC). Ether has a market capitalization of $517,910,010,466 and a 24-hour trading volume of $28,304,640,096 (6,483,712 ETH). XRP has a market cap of $39,459,123,927 and a 24-hour trading volume of $3,411,095,621 (4,084,354,331 XRP). Litecoin has a market cap of $11,097,205,459 and 24-hour trading volume of $1,908,859,383 (11,891,870 LTC).

The US dollar prices of these cryptocurrencies have been collected on a weekly basis on Yahoo Finance. The data available is from September 15, 2014 to October 25, 2021 for Bitcoin, Litecoin and XRP. For Ethereum, the available data is more limited and starts on August 3, 2015. In our tables/graphs, we will refer to these variables as "BTC", "LTC", "XRP" and "ETH".

In addition to these 4 cryptocurrencies, we will follow the method of Brière et al. (2015) which consider the situation of a U.S. investor with a diversified portfolio. To diversify our portfolio, we will use data similar to Brière et al. (2015). They only use indices to refer to the data they want to include in the portfolio. In our case, we will add the following data to our research:

[1] We want to include commodities in our research. For this purpose, the gold futures price will be used. The WTI crude oil futures price will also be used. We collect this data from Investing.com. In our tables/charts we will call these variables "Gold" and "Oil".

[2] Like Brière et al. (2015), we choose to take data corresponding to national currencies. We therefore collect, on Investing.com, the Euro and Australian Dollar rates per US Dollar. In our tables/graphs, we will call these variables "EUR" and "AUD".

[3] To represent the equity market in our study, we choose, like Brière et al. (2015), to incorporate indices from MSCI. First, we use the MSCI World Index (USD) which represents the evolution of developed equity markets. This index highlights the evolution of mid and large cap companies in more than 23 countries. It includes countries such as Japan, the United States and the United Kingdom as well as companies such as Apple, Amazon and Microsoft (MSCI, 2021). In addition, we use the MSCI Emerging Markets Index (USD), which describes the development of emerging equity markets. Mid and large cap companies from more than 27 emerging markets are represented. Countries like India, Brazil and South Korea are included. Companies such as Alibaba or Samsung are included in this index (MSCI, 2021). We get the corresponding data for these two indices from MSCI. In our tables/graphs we will call these variables "Stocks Dvp" and "Stocks Emg".

[4] We use the iShares Global Corporate Bond UCITS (CORP) to represent the corporate bond market. It is a fund that seeks to track the performance of a diversified set of corporate bonds. These bonds are from a variety of sectors and are investment grade (iShares, 2021). The data was collected from Investing.com. In our tables/graphs, we will refer to this variable as "Corpo Bonds Wld".

[5] Secondly, we have incorporated data to represent the evolution of the government bond market. The S&P Global Developed Sovereign Bond Index provides a representation of the government bond market in developed countries. The data was collected from the snpglobal website. We then used the Vanguard Emerging Markets Government Bond Index Fund ETF Shares (VWOB). This is an ETF that tracks the performance of a Bloomberg index representing emerging market government bonds with maturities greater than one year (Vanguard, 2021). The data comes from Investing.com. In our tables/charts, we will refer to these variables as "Gvt Bonds Dvp" and "Gvt Bonds Emg".

[6] In order to have an inflation benchmark like Brière et al. (2015), we took the data from the iShares Global Inflation Linked Government Bond UCITS ETF (IGIL.SW). This is an ETF that aims to track, through a diversified portfolio, the

performance of inflation-linked government bonds (iShares, 2021). The data was collected from Yahoo Finance. In our tables/charts, we will refer to this variable as "IL Bonds Wld".

[7] Finally, we also include a variable to take into account the US real estate market. This is the Dow Jones Real Estate (DJUSRE). The data comes from Investing.com. In our tables/graphs, we will call this variable "Real Estate".

All the data described above could be collected on a weekly basis between September 15, 2014 and October 25, 2021. They are all in US dollars. Sometimes the dates did not match between the data and linear interpolations had to be done to solve this problem.

We performed the following manipulation on the 15 data sets at our disposal. The data was transformed into a weekly yield using the following formula:

$$R_t = \frac{V_t - V_{t-1}}{V_{t-1}} \text{ with}$$

- R the return at time t
- V_t and V_{t-1} the value of the asset at time t and t-1

At this stage, we therefore have the returns of 15 data sets from September 22, 2014 to October 25, 2021 (except for Ethereum for which data records started later). These returns thus obtained constitute the basis for the research that we are going to conduct next. We also collected the risk-free asset values provided by Kenneth R. French. The data runs from September 15, 2014 to October 25, 2021. It is given by the rate offered on a T-bill with a maturity of 1 month (French, 2021).

4.2 Methodology

The objective of this study is to understand whether a US investor could have diversified their asset portfolio using cryptocurrencies between September 22, 2014 and October 25, 2021. Obviously, it is difficult to test all the cryptocurrencies in an exhaustive way. We therefore limit ourselves to Bitcoin, Litecoin, XRP and Ether. The dates of the research have been deliberately shifted by two years from the dates of the data available to us. This was done to allow us to study the case of an investor investing in cryptocurrencies with two years of hindsight and data to build their asset portfolio. For our research, we will go through different steps allowing us to understand how returns behave in the cryptocurrency markets.

4.2.1 Descriptive statistics

The first step consists of looking at the behaviour of the data at our disposal in two different ways. First, we want to look at cryptocurrencies in a global way. To do this, we will calculate the means and standard deviations of returns over the period from September 22, 2014 to October 25, 2021. We will then compare the results obtained with those obtained for the other 11 selected datasets. This step will allow us to understand if there are any differences between cryptocurrencies and other more traditional investment instruments. In particular, we conducted a Jarque-Bera statistical test to see whether the variables at our disposal follow a normal distribution. The hypotheses of the test are as follows (Thadewald & Büning, 2007):

- H_0: the variable follows a normal distribution.

- H_1: the variable does not follow a normal distribution.

The test statistic is as below (Thadewald & Büning, 2007):

$$JB = \frac{n}{6} * \left(S^2 + \frac{(K-3)^2}{4}\right) \qquad \text{with}$$

- n the number of observations
- S the skewness of the distribution
- K the kurtosis of the distribution

The distribution will be considered as non-normal (rejection of the null hypothesis) if

$$JB \geq \chi^2_{1-\alpha,2}$$

After describing the data in a static way, we want to add a more dynamic dimension to the resulting description. This dynamic aspect is important as the cryptocurrency market is known to be a changing market. We will calculate the two-year moving average as well as the two-year moving standard deviation for our whole data set. The analysis will therefore take place between September 12, 2016 and October 25, 2021.

We will then graphically analyse the results obtained using curves and box plots. We will also calculate the means and medians of the results obtained.

These two steps will therefore give us an overview of how cryptocurrencies behave in relation to the other variables chosen for comparison.

4.2.2 Correlation testing

This step consists of testing whether the returns of the cryptos are correlated with those of the other selected data. This is a crucial step because as we have seen in modern portfolio theory, correlation plays a central role in portfolio diversification. As with descriptive statistics, we will use a two-part method for correlation testing.

First, we will calculate the existing correlations between cryptocurrencies and other data over the overall period from September 22, 2014 to October 25, 2021. Then, we will perform hypothesis tests on the significance of the obtained Pearson correlation coefficients. The test hypothesis are as follows (Illowsky & Dean, 2021):

- H_0: $\rho = 0$: the null hypothesis assumes that the correlation between two test variables is not significantly different from 0. There is therefore no linear relationship linking the returns of the two test variables.

- H_1: $\rho \neq 0$: the alternative hypothesis assumes that the correlation between two variables tested is significantly different from 0. The returns of the two variables are therefore linked by a linear relationship.

The test statistic is as follows (Illowsky & Dean, 2021):

$$t = \frac{r\sqrt{n-2}}{\sqrt{1-r^2}} \qquad \text{with}$$

- r the correlation coefficient of the sample
- n the number of observations in the sample

The calculated correlation is considered significant if the absolute value of the test statistic is strictly greater than the tabulated value (significance level at 5%/1% and n observations) (Illowsky & Dean, 2021).

After having worked on the period as a whole in a static way, we will once again add a dynamic dimension to the problem. We will therefore calculate a moving correlation over two years between September 12, 2016 and October 25, 2021. This will allow us to take into account the fact that correlations between two variables are not constant over time. After having obtained these correlations, we will carry out significance tests (at 5%) of the coefficients obtained. By isolating the correlation coefficient in the test statistic, we will be able to graphically observe the periods during which the variables were significantly correlated.

4.2.3 Efficient frontier and portfolio analysis

Like the two previous ones, this step will include a static and a dynamic analysis. First, we want to analyse in a global way, the frontiers of efficient portfolios when cryptocurrencies are integrated or not. We will thus be able to determine if between September 2016 and October 2021, an investor would have had an interest in adding cryptocurrencies to their portfolio of assets to improve it. We will then graphically analyse the obtained efficient frontiers.

Our dynamic analysis consists in taking the case of a US investor with a diversified portfolio of assets (in the manner of Brière et al. (2015)). We will compare the evolution of this investor's portfolio with or without the integration of a cryptocurrency. We assume that the investor establishes their asset portfolio on September 12, 2016. They therefore have 104 weeks of observations to choose the portfolio in which they want to invest. This is the portfolio that maximises the Sharpe ratio. The investor thus has a starting portfolio. Nevertheless, this portfolio does not remain constant over time. To vary this portfolio, we will use the Drawdown Control method explained by Pedersen (2015). The drawdown can be seen as the amount of cumulative loss since the highest value reached by the portfolio. In percentage terms, the drawdown can be calculated as:

$$DD_t = \frac{HWM_t - P_t}{HWM_t} \qquad \text{with}$$

- DD_t the percentage drawdown at time t
- HWM_t the maximum value reached by the portfolio at time t

- P_t the value of the portfolio at time t

In order to develop their investment portfolio, investors must then choose the maximum drawdown they are prepared to accept. That is to say, the maximum cumulative loss in relation to the peak that he is prepared to bear. This is the maximum acceptable drawdown. We arbitrarily set this value at 30%. Pedersen (2015) then states that when a condition is no longer met, the risk of the portfolio must be reduced until the losses are covered. The condition is as follows:

$$VaR_t \leq MADD - DD_t \qquad \text{with}$$

- VaR_t the value at risk at time t
- $MADD$ the maximum acceptable drawdown
- DD_t the percentage drawdown at time t

This Drawdown Control technique allows an investor to have a plan of action and thus avoid panic effects when the portfolio decreases in value (Pedersen, 2015). Thanks to this, we will be able to compare, with an established strategy, the evolution of an asset portfolio with or without the presence of a cryptocurrency.

4.3 Descriptive statistics

This section aims to compare the behaviour of cryptocurrencies with conventional assets. This comparison will be done statically and then dynamically. This will provide the best possible understanding of these investment instruments that are cryptocurrencies.

4.3.1 Static analysis

Table 1 highlights the statistical characteristics that can be attributed to our 15 data sets during the overall study period. Note that this period runs from September 22, 2014 to October 25, 2021 for all data except Ether, whose study period begins on August 10, 2015.

Weekly data	Mean	Volatility	Maximum	Minimum	Skewness	Kurtosis	Jarque-Bera
LTC	2,26%	16,80%	114,39%	-51,62%	1,99	9,80	1730,53***
BTC	1,92%	10,58%	41,48%	-33,49%	0,07	1,16	21,26***
XRP	4,50%	36,73%	540,42%	-49,10%	9,39	125,43	248649,50***
ETH	4,33%	19,46%	123,08%	-41,20%	1,76	6,80	905,64***
Gold	0,12%	1,78%	10,27%	-8,45%	0,40	5,38	457,97***
AUD	-0,04%	1,25%	4,96%	-6,98%	-0,26	4,00	251,52***
EUR	-0,02%	0,97%	3,07%	-3,34%	-0,19	0,92	15,56***
Oil	0,11%	5,25%	24,01%	-26,64%	-0,27	5,18	418,62***
Stocks Emg	0,09%	2,63%	9,74%	-12,10%	-0,35	1,99	68,81***
Stocks Dvp	0,19%	2,32%	16,75%	-14,66%	-0,29	12,33	2357,16***
Real Estate	0,15%	2,54%	18,21%	-20,16%	-0,67	20,26	6373,53***
Gvt Bonds Emg	0,00%	1,11%	8,03%	-11,87%	-2,94	46,86	34474,47***
Gvt Bonds Dvp	0,03%	0,83%	3,77%	-4,14%	-0,05	3,71	212,78***
Corpo Bonds Wld	0,02%	0,86%	5,78%	-9,12%	-2,87	43,14	29276,34***
IL Bonds Wld	0,07%	1,20%	12,03%	-7,95%	1,09	35,95	20054,02***

***p ≤ 0.01

Table 1 - Static key information
This table provides key information about the weekly returns of the 15 datasets described in the "Data" section. The data used runs from September 22, 2014 to October 25, 2021 for all data except Ether, which study period begins on August 10, 2015.

Table 1 first provides an overview of the average returns offered by each of the observation variables. It is easy to see that the average weekly returns for cryptocurrencies are much higher than for traditional assets. The average returns for cryptocurrencies are 1.92% for Bitcoin, 2.26% for Litecoin, 4.33% for Ether and 4.50% for XRP. In traditional assets, the highest average weekly return is attributed to the developing markets equity benchmark. The mean there is 0.19%, which is almost 12 times lower than the lowest mean in the cryptocurrency market. The averages for traditional assets range from -0.04% to 0.19%.

The weekly volatility of returns can also be seen in the table. As with the averages, the magnitude of the volatilities associated with cryptocurrencies are nothing like those associated with traditional assets. The weekly return volatilities are 16.80% for Litecoin, 10.58% for Bitcoin, 36.73% for XRP and 19.46% for Ether. While the volatility of returns on oil still reaches 5.25% (2 times lower than the minimum volatility associated with cryptocurrencies), returns on other traditional assets have volatilities between 0.83% and 2.63%. These volatilities are reflected in the maximum and minimum weekly returns that can be achieved. Bitcoin has reached a maximum weekly return of 41.48% and a minimum of -33.49%. It is the least volatile of the cryptocurrencies chosen and the extremes are still much higher than those of all traditional assets. Only oil returns come close with a maximum of 24.01% and a minimum of -26.64%. Values are soaring for other cryptocurrencies. Litecoin reaches a high of 114.39% and a low of -51.62%. Ether reaches a high of 123.08% and a low of -41.20%. On the XRP side, the maximum is huge and reaches 540.42% return in one week for a low of 49.10%.

The values described seem to show that cryptocurrencies are not like other assets. The risk/return trade-offs are unlike those of the assets more commonly found in investor portfolios. This gives a first indication of the potential of cryptocurrencies to become a new asset class. An asset class that could be integrated into investors' portfolios willing to bear higher risks, to achieve higher levels of returns. In a way, it would serve investors with a more speculative profile compared to the traditional investor. These particularities related to cryptocurrency markets had already been highlighted in the literature (Liu et al. (2021), Enoksen et al. (2020), Liu and Tsyvinski (2018), Papadopoulos (2015), Brière et al. (2015), etc.).

Table 1 also shows the values of the Jarque-Bera test for examining whether the data at our disposal follow the behaviour of a normal distribution. We find that the values allow us to reject the null hypothesis of normality for each of the 15 variables at our disposal. The hypothesis is rejected at the 1% significance level. For cryptocurrencies, this result was rather predictable in view of the literature that has already highlighted the thick tails of cryptocurrency return distributions (Brière et al. (2015), Dorfleitner & Lung (2018), Brauneis & Mestel (2019)). This result is more surprising for traditional assets where the returns did not follow a normal distribution during the period studied.

4.3.2 Dynamic analysis

The static analysis allowed us to make a first global point on the behaviour of cryptocurrency returns. Given the significant volatilities of returns measured on cryptocurrencies, it seems necessary to carry out a dynamic study. This will allow us to see if the characteristics are constant over time or if they vary more or less strongly depending on the periods. Again, we will be able to compare this variation with those of more traditional assets. To do this, we work with moving averages and volatilities calculated over the last 104 weeks (two years). This technique will allow us to smooth out the trends found in the movements of these assets.

Table 2 provides information on the key values of the two-year moving averages. The box plots associated with these data are shown in Appendix A (Fig. 13). What can we learn from this table? First, we can see that the mean and median values are much higher for cryptocurrencies than for other assets. Thus, 50% of the moving averages are above 2.25% for Litecoin, 2.14% for Bitcoin, 3.25% for XRP and 3.20% for Ether. In comparison, the highest median of traditional assets is attributed to oil, with 0.20%. We can also note that more than 75% of the moving averages are above 1.21% for Litecoin, 1.17% for Bitcoin, 0.71% for XRP and 1.19% for Ether. Nevertheless, it is worth noting that the minimum values are generally much lower for cryptocurrencies than for other assets. XRP for example has a minimum of -1.46%. This means that for 2 years, XRP has lost an average of 1.46% per week. Values fluctuate at -0.91% for Litecoin, -0.31% for Bitcoin and -1.14% for Ether. The maximum moving averages are very different between cryptocurrencies and traditional assets. While they do not exceed 0.82% (Oil) for traditional assets, they reach 4.26% for Bitcoin, 5.84% for Litecoin, 9.22% for Ether and 12.87% for XRP.

Weekly data	Mean	Minimum	Q1	Median	Q3	Maximum
LTC	2,48%	-0,91%	1,21%	2,25%	4,01%	5,84%
BTC	2,09%	-0,31%	1,17%	2,14%	3,00%	4,26%
XRP	4,93%	-1,46%	0,71%	3,25%	9,77%	12,87%
ETH	3,35%	-1,14%	1,19%	3,20%	5,00%	9,22%
Gold	0,14%	-0,09%	0,05%	0,13%	0,22%	0,47%
AUD	-0,01%	-0,26%	-0,08%	-0,01%	0,07%	0,14%
EUR	0,01%	-0,15%	-0,04%	0,04%	0,06%	0,13%
Oil	0,15%	-1,11%	-0,04%	0,20%	0,40%	0,82%
Stocks Emg	0,13%	-0,39%	-0,02%	0,13%	0,29%	0,54%
Stocks Dvp	0,18%	-0,21%	0,10%	0,15%	0,25%	0,43%
Real Estate	0,09%	-0,12%	0,04%	0,10%	0,13%	0,29%
Gvt Bonds Emg	0,02%	-0,14%	-0,02%	0,02%	0,05%	0,11%
Gvt Bonds Dvp	0,05%	-0,05%	0,03%	0,05%	0,08%	0,15%
Corpo Bonds Wld	0,03%	-0,08%	-0,01%	0,02%	0,06%	0,15%
IL Bonds Wld	0,07%	-0,08%	0,04%	0,06%	0,12%	0,20%

Table 2 - Key information regarding the two-year moving averages of weekly returns
This table provides key information about the two-year moving averages of the weekly returns of the 15 datasets described in the "Data" section. The 2 year moving averages run from September 12, 2016 and October 25, 2021 except for Ether where they start on July 31, 2017.

Figure 7 shows the evolution of moving averages over time for cryptocurrencies and traditional assets. Very similar movements can be observed for the 4 cryptocurrencies

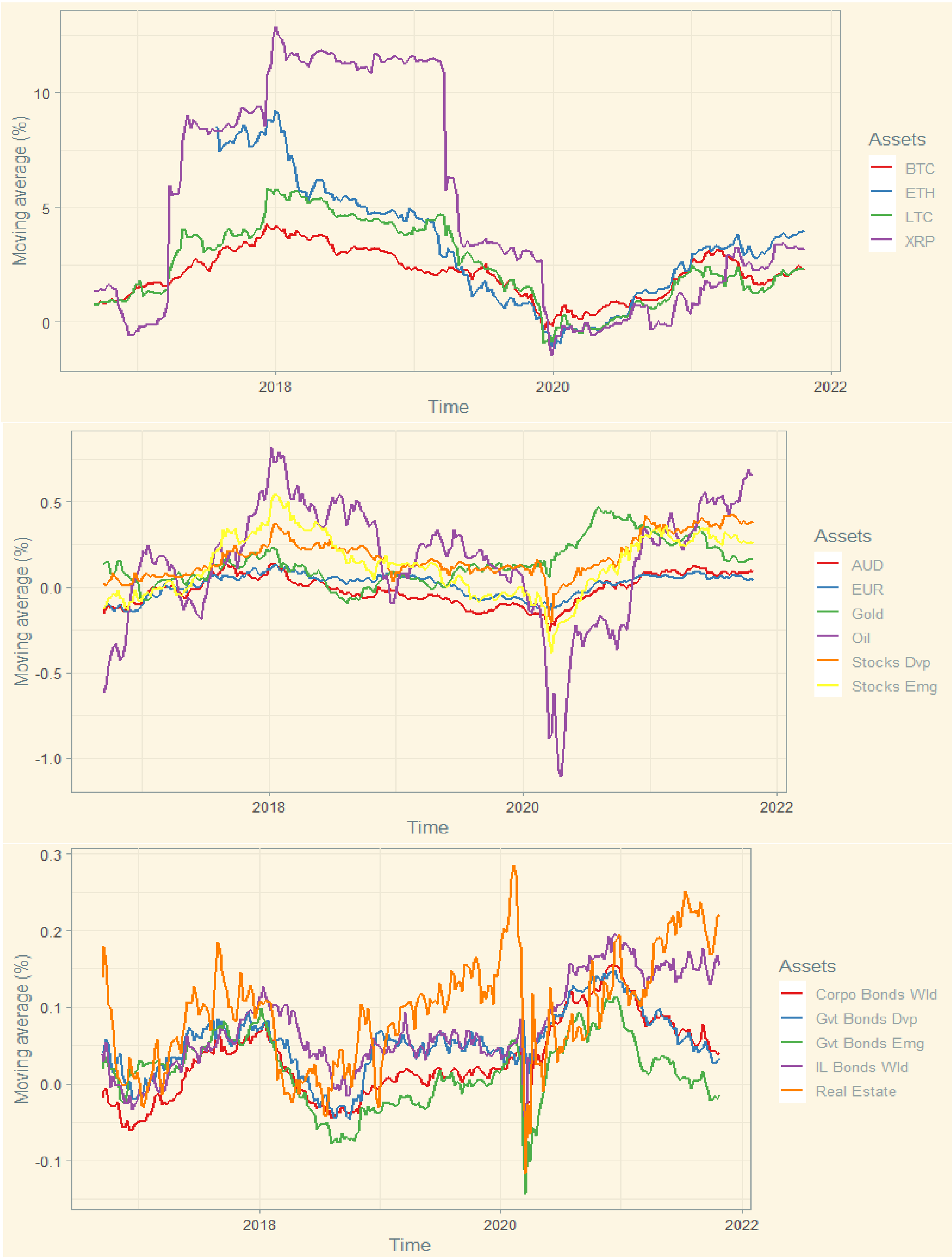

Fig. 7 - Charts of the evolution of the two-year moving averages of weekly returns
The three graphs show the evolution over time of the two-year moving averages of the weekly returns of the 15 datasets described in the "Data" section. The 2 year moving averages run from September 12, 2016 and October 25, 2021 except for Ether where they start on July 31, 2017.

studied. The magnitude of the movements is, however, not always the same. Bitcoin is the cryptocurrency whose moving average seems to change the least. We can also note that compared to traditional assets, the moving averages of cryptocurrencies are not very often in the negative. Indeed, while the moving average curves of traditional assets oscillate around zero, that of cryptocurrencies very rarely goes below 0. Once again, we can note that the orders of magnitude between cryptocurrencies and traditional assets are totally different.

Table 3 provides key figures on two-year moving volatilities for cryptocurrencies and traditional assets. The box plots linked to this table can be found in Appendix A (Fig. 14). First, we see that the averages and medians of the moving volatilities are much higher for cryptocurrencies than for traditional assets. The median moving volatilities for cryptocurrencies range from 10.10% for Bitcoin to over 29.30% for XRP. With this in mind, we can highlight the fact that the minimum moving volatilities of cryptocurrencies are almost always far higher than the maximum moving volatilities of traditional assets. This data strongly reinforces the thought that the characteristics of cryptocurrencies are completely unique compared to other assets.

Weekly data	Mean	Minimum	Q1	Median	Q3	Maximum
LTC	16,57%	11,07%	13,40%	15,66%	20,18%	22,76%
BTC	10,64%	6,97%	9,38%	10,10%	12,94%	13,90%
XRP	34,94%	9,71%	14,99%	29,30%	58,40%	63,40%
ETH	17,15%	11,27%	13,28%	16,50%	21,23%	26,29%
Gold	1,62%	1,05%	1,22%	1,69%	1,93%	2,15%
AUD	1,19%	0,82%	0,95%	1,25%	1,44%	1,53%
EUR	0,88%	0,61%	0,76%	0,87%	0,92%	1,31%
Oil	4,97%	3,21%	3,54%	4,56%	7,30%	7,45%
Stocks Emg	2,54%	1,88%	2,16%	2,55%	3,00%	3,14%
Stocks Dvp	2,19%	1,14%	1,65%	1,96%	3,16%	3,36%
Real Estate	2,36%	1,42%	1,59%	1,74%	3,96%	4,04%
Gvt Bonds Emg	0,99%	0,51%	0,57%	0,69%	1,79%	1,82%
Gvt Bonds Dvp	0,82%	0,57%	0,65%	0,88%	0,90%	1,02%
Corpo Bonds Wld	0,80%	0,44%	0,50%	0,58%	1,36%	1,40%
IL Bonds Wld	1,14%	0,68%	0,78%	0,91%	1,81%	1,83%

Table 3 - Key information regarding the two-year moving volatilities of weekly returns
This table provides key information about the two-year moving volatilities of the weekly returns for the 15 data sets described in the "Data" section. The two-year moving volatilities run from September 12, 2016 and October 25, 2021 except for Ether where they start on 31 July 2017.

Figure 8 shows the evolution of the moving volatilities over time for the 4 cryptocurrencies and the 11 traditional assets. Beyond the completely different orders

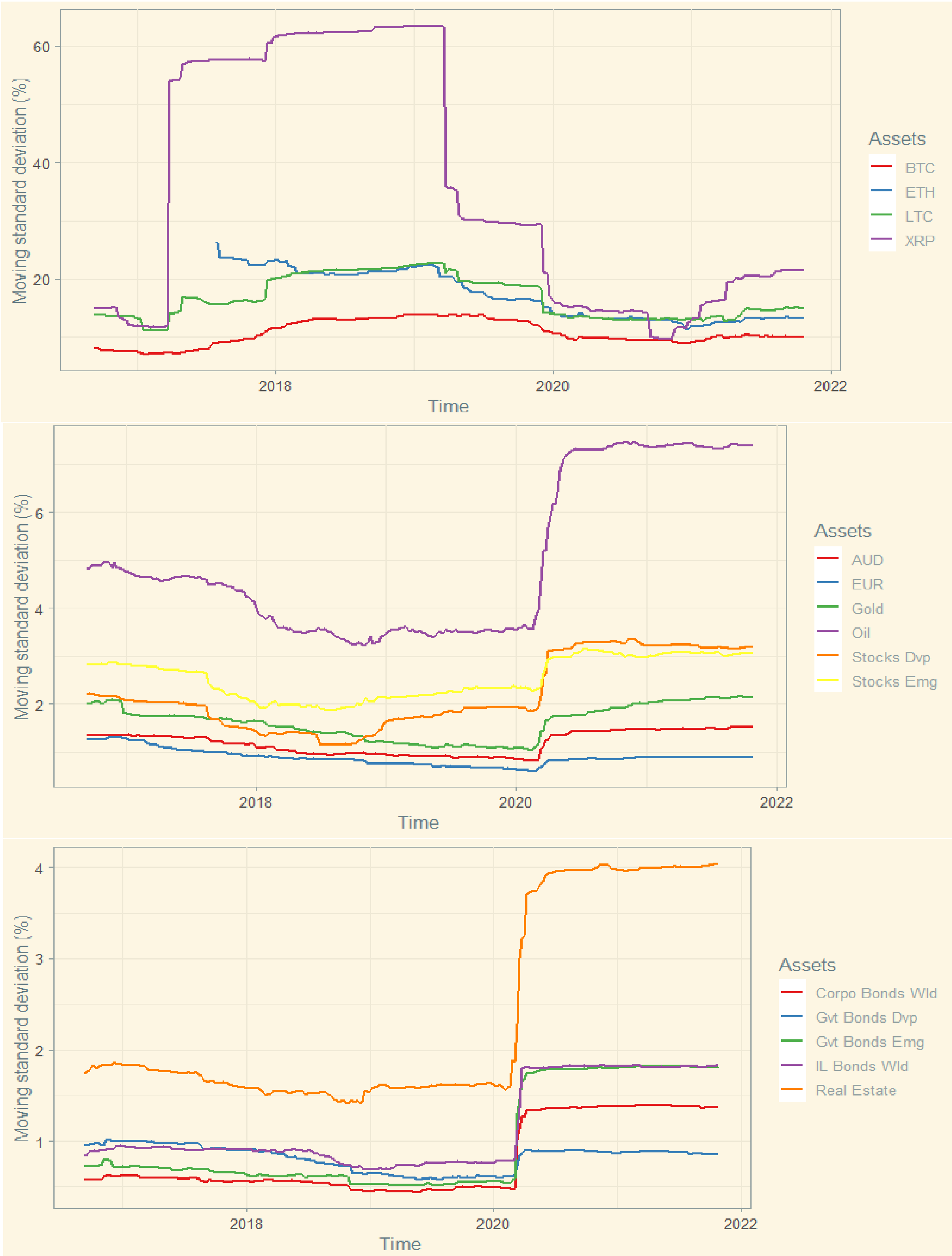

Fig. 8 - Charts of the evolution of the two-year moving volatilities of weekly returns
The three graphs show the evolution of the two-year moving volatilities of the weekly returns of the 15 datasets described in the "Data" section over time. The two-year moving volatilities run from September 12, 2016 and October 25, 2021 except for Ether where they start on 31 July 2017.

of magnitude, there are several points to note from these charts. The movements of the moving volatilities are extremely similar for the 11 traditional assets. That is to say, periods of volatility increases, or decreases are shared by all traditional assets. We can also note the relative constancy of volatilities outside of large periods of decline or increase. Furthermore, while there has been a large increase in the volatility levels of traditional assets, this increase is not reflected in the volatilities of cryptocurrencies. On the contrary, the increase in volatility levels of traditional assets is more in line with a decrease in volatility levels of cryptocurrencies. Could cryptocurrencies eventually become safe havens in times of crisis and thus an explosion in the volatility of traditional assets? This observation remains tainted by the different orders of magnitude of the volatilities of the two types of assets.

This dynamic analysis helped us to identify, as with the static analysis, the differences in magnitudes between the return and risk values for cryptocurrencies and traditional assets. The moving averages of cryptocurrencies reach higher and lower levels than those of traditional assets. The moving volatilities of cryptocurrencies are almost always greatly higher. They do not react to the generalized increases seen in traditional markets. This is further evidence of the potential for cryptocurrencies to emerge as a new asset class.

4.4 Correlation testing

This section aims to study the correlations between the returns of cryptocurrencies and other assets. The study will be done in a static and dynamic way to best describe the patterns.

4.4.1 Static analysis

Table 4 allows us to give a first global opinion on the data with which cryptocurrencies could be correlated during the period ranging from September 22, 2014 to October 25, 2021

First of all, we can note the existing correlations between cryptocurrency returns. These correlations range from 0.665 to 0.236 and they are all significant at a 1% significance level. Therefore, there is indeed a linear relationship that links the returns

Weekly Data	LTC	BTC	XRP	ETH
LTC		0,665***	0,530***	0,447***
BTC	0,665***		0,274***	0,445***
XRP	0,530***	0,274***		0,236***
ETH	0,447***	0,445***	0,236***	
Gold	0,016	0,036	0,014	0,186***
AUD	0,054	0,050	0,049	0,182***
EUR	0,056	0,062	0,035	0,169***
Oil	0,050	0,119**	0,036	0,075
Stocks Emg	0,036	0,042	0,029	0,084
Stocks Dvp	0,078	0,093	0,018	0,072
Real Estate	0,085	0,047	0,027	0,067
Gvt Bonds Emg	0,095	0,112**	0,048	0,111**
Gvt Bonds Dvp	-0,043	-0,085	0,045	-0,024
Corpo Bonds Wld	0,117**	0,139***	0,067	0,113**
IL Bonds Wld	0,070	0,058	0,057	0,061

***p ≤ 0.01; **p ≤ 0.05

Table 4 - Key information regarding the correlations with cryptocurrencies
This table provides key information about the existing correlations between cryptocurrencies and the 15 datasets described in the "Data" section. The data used ranges from September 22, 2014 to October 25, 2021 for all data except Ether, which study period begins on August 10, 2015.

of the cryptocurrencies to each other. This contradicts Brauneis and Mestel (2019) who argue that cryptocurrency returns are only weakly correlated with each other and that it is a good idea to include more than one in the asset portfolio for better diversification. We note that Litecoin is the cryptocurrency with the highest correlation of returns with other cryptocurrencies. Indeed, the correlation coefficients obtained are 0.447 with Ether, 0.530 with XRP and 0.665 with Bitcoin. These high correlation levels suggest that investors should not necessarily add multiple cryptocurrencies to their portfolio to diversify. This contradicts what Brauneis and Mestel (2019) argued. If we conclude that cryptocurrencies allow for diversification, one cryptocurrency may be sufficient for portfolio diversification.

Let us start by looking at the correlations of the XRP returns with those of the other selected assets. We could not find any correlation. All the correlations we calculated with the XRP range from 0.014 with Gold to 0.067 with corporate bonds (Corpo Bonds Wld). They are all positive and insignificant. This is consistent with the research of Liu and Tsyvinski (2018) who found no correlations with this type of variable between 2013 and 2018. This leads us to believe that between September 2014 and October 2021, the XRP could have allowed an investor to diversify their portfolio even more than they already were.

Secondly, Litecoin's returns do not have much correlation to show with those of the other assets studied. Only a correlation can be found between Litecoin's returns and those of corporate bonds (Corpo Bonds Wld). However, this correlation is 0.117, which is still low and only allows the null hypothesis to be rejected at a 5% significance level (not at 1%). The other correlations calculated are very low and range from -0.043 with developed market government bond yields (Gvt Bonds Dvp) to 0.085 with the Real Estate Index. We therefore come to a similar conclusion as with XRP, Litecoin would have allowed an investor to diversify their assets portfolio between September 2014 and October 2021.

For Bitcoin, we uncover the existence of three significant correlations. Bitcoin returns have a significant correlation (0.119) with the returns of Oil at the 5% significance level. Another significant correlation (0.112) could be found with the returns of emerging market government bonds (Gvt Bonds Emg) at a 5% significance level. The third significant correlation (0.139) was calculated between Bitcoin and corporate bond returns (Corpo Bonds Wld) at a significance level of 1%. These correlations contradict the results of Brière et al. (2015) who, between 2010 and 2013, could not find any correlation between Bitcoin and these three datasets. The correlations calculated with the other variables range from -0.085 with developed market government bonds (Gvt Bonds Dvp) to 0.093 with developed market stocks (Stocks Dvp). Although we were able to highlight the existence of 3 significant correlations, the values remain very low. Bitcoin would, between September 2014 and October 2021, have allowed an investor to diversify their portfolio.

Finally, we were able to highlight the existence of 5 variables correlated with the returns of Ether. First, we found a significant correlation (0.186) between the returns of Ether and Gold at a threshold of 1%. Liu and Tsyvinski (2018) also found a relationship between Ether and Gold between 2015 and 2018. This is the most significant relationship we have found. We also found significant correlations between Ether returns and EUR/USD (0.169) and AUD/USD (0.182). This is not in line with the results of Liu and Tsyvinski (2018) who did not find significant relationships between the Ether and national currencies. The returns on government bonds from developing markets (Gvt Bonds Emg) are correlated (0.111) with those of the Ether at a threshold of 5%. Corporate bonds are also correlated (0.113) with Ether at a 5% threshold. As for the other cryptocurrencies, even if correlations are found, they remain very weak. Other correlations with Ether are not significant and range from -0.024 with developed market government bonds (Gvt Bonds Dvp) to 0.084 with emerging market stocks (Stocks Emg). Like other cryptocurrencies, Ether therefore appears to be a cryptocurrency that would diversify an investor's portfolio between September 2014 and October 2021.

This first global analysis of correlations has allowed us to highlight several important points. First, cryptocurrency returns are highly correlated with each other. Second, the correlations between cryptocurrency returns and those of other more conventional assets are very low. They are globally between 0.186 and -0.043. Few of them are significant. The returns of the cryptocurrencies studied were therefore rather decorrelated from the returns of conventional assets between September 2014 and October 2021. We can also highlight that almost all the correlations calculated between the returns are positive. Only the correlations between the returns of developed market government bonds (Gvt Bonds Dvp) and those of Litecoin, Bitcoin and Ethereum are negative. However, they remain insignificant. Low and positive correlations between returns correspond to the category of hedging assets described by Bouri et al. (2017). Cryptocurrencies could then diversify a portfolio by hedging the risks associated with other assets in the portfolio.

4.4.2 Dynamic analysis

After a first static analysis of the correlations between cryptocurrency returns and other assets, we have analysed these returns dynamically. Using the two-year moving correlations, we wanted to see if the correlations have changed over time. To do so, Appendix B shows graphs of the moving correlations between cryptocurrency returns and those of more traditional assets. The red line corresponds to the threshold at which the correlations are significant at a 5% significance level. Note that the value at which a correlation is significant is larger in this section than in the static analysis. This is due to the fact that the static part used the whole dataset for the calculation of the test statistic. In this part, the correlations are only calculated over the last 104 weeks of observation.

Let's start by talking about Bitcoin, whose graphs of the evolution of correlations with the returns of more traditional assets can be found in Appendix B (Fig. 15 and Fig. 16). Some assets never show significant correlations at 5% with Bitcoin during the study period. These assets are EUR/USD, Emerging Market Stocks (Stocks Emg), Inflation Linked Bonds (IL Bonds Wld) and the Real Estate Index. Some correlations were not significant at the beginning of the study period but increased to become positive and significant. The correlations between Bitcoin returns and the returns of Gold, AUD/USD, Oil, Developed Market Stocks (Stocks Dvp) and Emerging Market Government Bonds (Gvt Bonds Emg) fall into this category. Our data and charts allow us to highlight a surprising behaviour of Bitcoin. When the data from the beginning of 2020 started to enter the calculation of the moving correlations, a very strong movement could be seen in almost every correlation considered. Except for EUR/USD and developed market government bonds, all correlations shifted upwards. There was an increase in the correlations between the returns of the variables studied and those of Bitcoin, corresponding to the Covid-19 crisis. This increase during the crisis period allows Bitcoin to be excluded from the Safe-haven category of Bouri et al. (2017). The more correlated values probably due to the crisis are included in the calculation of the correlations for two years. This leads to an overestimation of the correlations of Bitcoin returns with those of the variables in question after the beginning of 2020. Another phenomenon occurs for correlations with developed market government bonds. The correlations have indeed decreased until they become significantly (5%) negative. One possible explanation is that investors are moving away from more uncertain assets such as cryptocurrencies to safer assets such as the bonds in question. As a result, the prices of these two variables would move in opposite directions, leading to a decrease in the correlation to significantly negative levels. In any case, almost all of the correlations calculated are below 0.3. Adding to this the overestimations to which they are subject in our calculation after 2020, we can conclude that the correlations between the returns of Bitcoin and the returns of the research variables are weak.

With regard to Litecoin, observation of the charts (Appendix B, Fig. 17 and Fig. 18) and data reveals that correlations are only rarely and marginally significant (5%). The phenomenon observed on Bitcoin is also present in the correlations with Litecoin returns. In early 2020, the Covid-19 crisis probably caused similar movements in

Litecoin returns and other assets, pushing correlations up. As we calculate correlations using the last two years of data, they are overestimated for two years after reaching extreme values. The observed correlations only rarely exceed 0.2 and practically never 0.3. In this case, we can conclude that the correlations between Litecoin returns and the returns of other conventional assets are low.

Next, the graphs of correlations with XRP returns can be found in Appendix B (Fig. 19 and Fig. 20). The XRP returns show very few significant correlations with the returns on traditional assets. When these correlations become significant (5%), it is for a marginal period. The phenomenon of increasing correlations in early 2020 is also observable for this cryptocurrency. But the effect is less strong for XRP and does not lead the relationships to become significant. The observed correlations hardly ever exceed 0.3. For XRP, our conclusions are therefore similar to the static study. XRP returns are weakly correlated to those of traditional assets and XRP is therefore an asset for portfolio diversification.

Finally, graphs of the correlations between Ether returns and conventional assets can be found in Appendix B (Fig. 21 and Fig. 22). This provides evidence of many positive correlations after 2020. Most of these correlations (AUD, Stocks Emg, Stocks Dvp, Corpo Bonds Wld, Gvt Bonds Emg, Real Estate) are related to the Covid-19 crisis phenomenon that we have already mentioned for other cryptocurrencies. Furthermore, Ether is often positively correlated with Gold. Nevertheless, it should be noted that almost all correlations are below 0.3. Only the correlation with Australian dollar returns rises above this level, but we have explained that this rise is probably linked to the Covid-19 crisis. We can therefore, for the 4th time, conclude that the correlations between Ether returns and those of other more traditional assets are low. This reinforces the relevance of Ether as a tool to diversify an investor's asset portfolio.

This dynamic study allowed us first of all to draw similar conclusions to those we made in the static study. The weakness of the observed correlations and the rarity of their significance (5%) allow us to consider cryptocurrencies as a diversification asset. Thus, an investor could use this type of instrument to improve the quality of their portfolio. This dynamic part enabled us to identify an important behaviour related to cryptocurrencies. When the Covid-19 crisis broke out in early 2020, the correlation between cryptocurrency returns and those of other assets tended to strengthen. This trend was not widespread, but it did show its effects in each of the 4 cryptocurrencies studied. We therefore refute the safe haven label defined by Bouri et al. (2017) for cryptocurrencies. In times of crisis, correlations do indeed, tend to increase. Furthermore, the definition of diversification assets given by Bouri et al. (2017), namely low correlations, fits well with our data. Given the scarcity of correlations observed, these assets met the definition of hedging assets of Bouri et al. (2017). Recall that these findings are valid only during our study period, i.e., data from September 22, 2014 to October 25, 2021 (the period begins on August 10, 2015 for the Ether). As the correlations are calculated using 104 weeks of observation, they start 2 years after the first weekly.

4.5 Efficient frontier and portfolio analysis

This part will allow us to put ourselves in a real situation by examining how an asset portfolio reacts with or without the integration of cryptocurrencies. We will therefore statically and dynamically analyse our 4 cryptocurrencies in an investor's portfolio.

4.5.1 Static analysis

For the static study, we started by calculating the efficient frontiers from September 22, 2014 to October 25, 2021 with or without the integration of the 4 chosen cryptocurrencies. Figure 9 is a graphical representation of the frontiers obtained from our calculations with and without the first three cryptocurrencies. We can draw several conclusions from the results obtained.

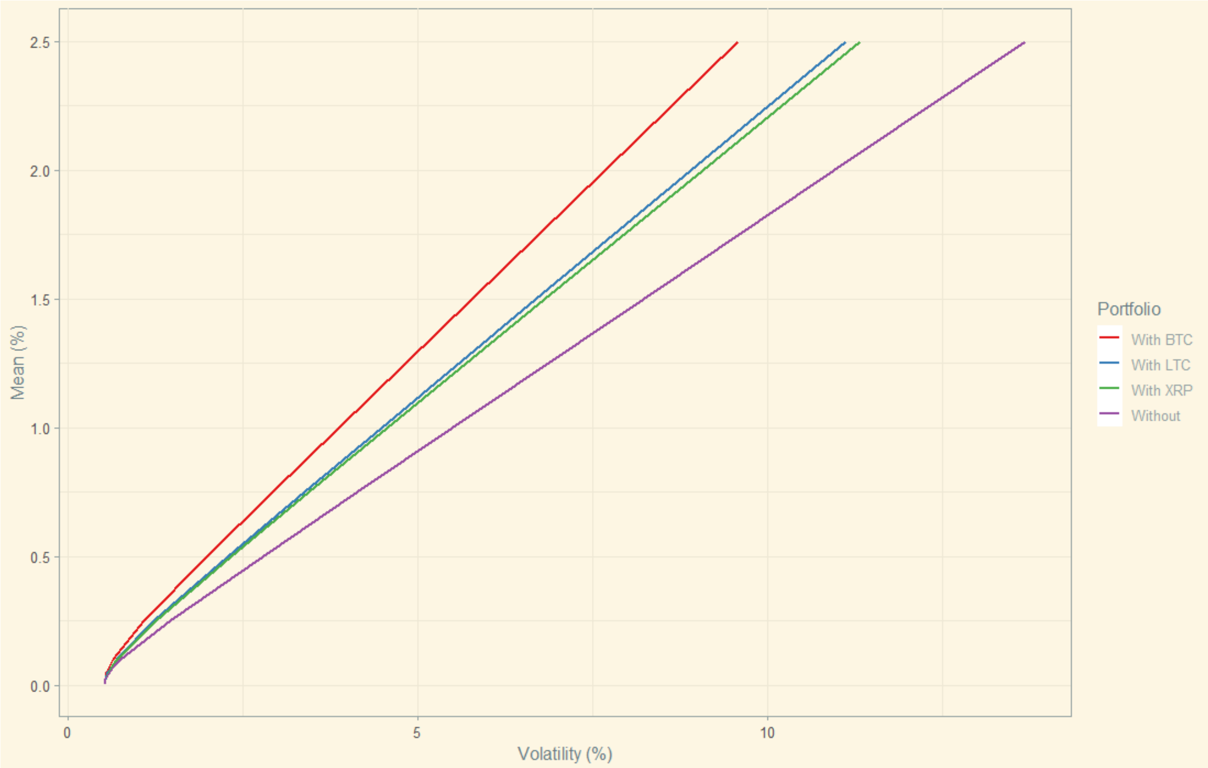

Fig. 9 - Efficient frontiers with or without cryptocurrencies
The chart provides a representation of the efficient frontiers with and without the integration of Bitcoin, Litecoin and XRP. The data used ranges from September 22, 2014 to October 25, 2021.

First, it is perfectly clear from this chart that the efficient frontier obtained without the integration of cryptocurrencies is entirely dominated by each of the other frontiers. Let's take the example of an investor who wants to achieve a portfolio return of 2.5% per week. To achieve such a return without cryptocurrencies, this investor would have to endure a volatility of 13.68% per week. The integration of one of the 3 cryptocurrencies reduces the risk to be carried by the investor. By integrating XRP, the risk to be supported decreases to 11.32% per week. With Litecoin, the risk to be borne decreases to 11.11% per week. Bitcoin reduces the weekly portfolio risk to 9.58%. The dominance of the portfolio without cryptocurrencies means, in effect, that an investor wishing to achieve a given level of risk/return, will have to accept a lower level of return/a higher level of risk with this portfolio. Portfolios containing cryptocurrencies therefore allow, compared to the portfolio without cryptocurrencies, to achieve the same level of risk/return with more return/less risk. We also see that the frontiers with cryptocurrency integration are at different levels. The frontier with XRP is dominated by the frontier with Litecoin, which in turn is dominated by the frontier with Bitcoin.

The portfolios offering minimum risk to the investor are not fundamentally different since the risks involved are almost identical with or without cryptocurrency. By accepting to bear a little more risk, an investor can then very significantly increase the returns they get. Note also that the amount of cryptocurrency in frontier portfolios increases as the percentage of portfolio volatility increases.

We therefore conclude that during the period from September 22, 2014 to October 25, 2021, Bitcoin, Litecoin and XRP have overall allowed an investor to increase their outlook. Through cryptocurrencies, investors have been able to achieve levels of returns that they could not have imagined with traditional assets. Bitcoin, Litecoin and XRP have enabled portfolio diversification by reducing the risk associated with higher levels of returns.

As the study period of Ether is different from the others, we have plotted the frontier containing it on another chart and compared it with a frontier without cryptocurrency attached to the same period. Figure 10 is a graphical representation of the frontiers obtained from our calculations with and without Ether.

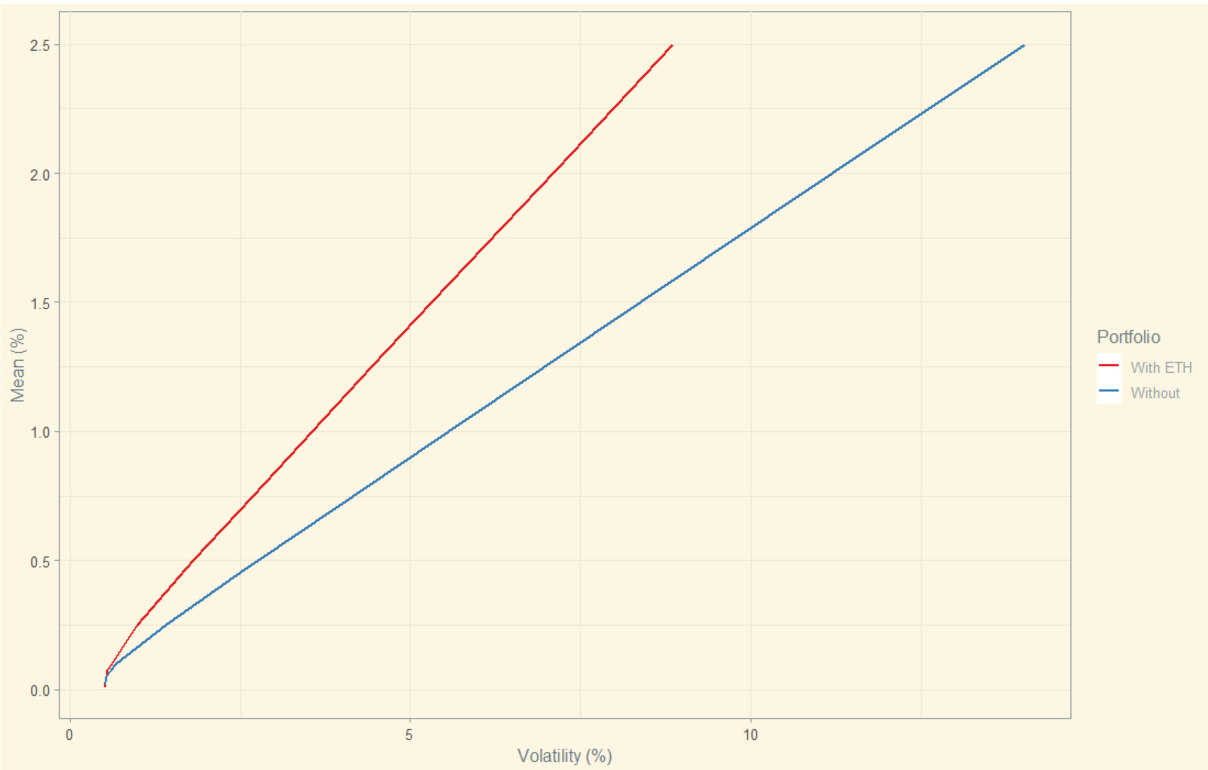

Fig. 10 - Efficient frontiers with or without Ether
The chart provides a representation of the efficient frontiers with and without the integration of Ether. The data used ranges from August 10, 2015 to October 25, 2021.

The results for Ether are similar to those we had for the other three cryptocurrencies. For example, an investor wanting to earn a 2.5% return would have to bear a 14.01% risk without Ether and an 8.86% risk with Ether. The frontier with Ether far dominates the frontier without Ether. We therefore conclude that Ether would allow an investor to diversify their asset portfolio between August 10, 2015 and October 25, 2021. By accepting to bear some risks, an investor can achieve much more attractive returns with Ether than without.

The static analysis allowed us to point out to the fact that efficient frontiers containing cryptocurrencies outperformed other frontiers. The unique characteristics, in terms of returns and volatilities, enable investors to achieve much higher levels of returns than they could have expected without cryptocurrencies. Similar levels of volatility lead to higher levels of returns with cryptocurrencies. Similar levels of returns lead to lower risks with the use of cryptocurrencies. Briere et al. (2015) and Kuo Chuen et al. (2017) also noted that efficient frontiers consisting of portfolios containing cryptocurrencies dominated other frontiers.

4.5.2 Dynamic analysis

To complete the static analysis, we wanted to carry out a dynamic analysis. This analysis is based on two-year moving averages, volatilities and correlations. We therefore put ourselves in the shoes of an investor and compared the situation of an investment in a portfolio with and without cryptocurrency. In each case, we set up an initial portfolio with the first 104 weeks of observation. We then looked at the evolution of these portfolios by reducing the risk when the drawdown exceeds the 30% threshold.

The first comparison made is between the evolution of a portfolio of assets with and without Ether. Figure 11 shows the evolution of these portfolios when they both start from 1000000 points.

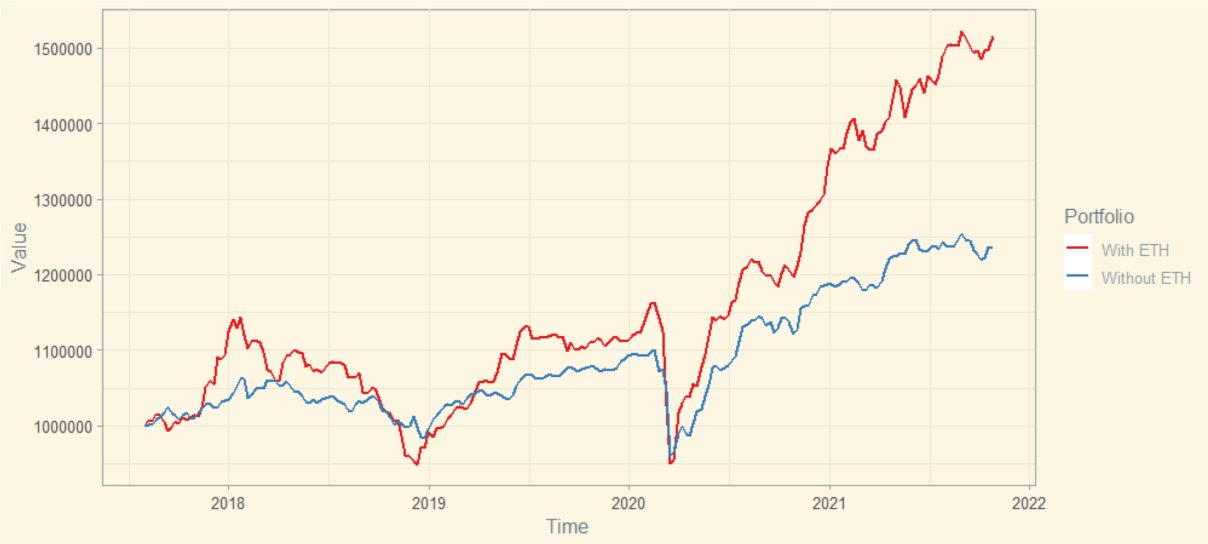

Fig. 11 - Portfolio evolution with or without Ether
The graph shows the evolution of two asset portfolios of one million points. One of the portfolios contains only traditional assets and the other one contains Ether in addition. The data used to obtain these portfolios ranges from August 10, 2015 to October 25, 2021

The first portfolio chosen contains an Ether level of 5.70%. As with the portfolio without Ether, this portfolio was chosen by maximising the Sharpe ratio. This portfolio did not have to be modified during the period because the drawdown level only reached a maximum of 18.43%. The portfolio without Ether did not have to be modified either because it only reached a maximum drawdown of 12.76%. From this chart and our data, we can initially conclude that the portfolio with Ether performed significantly better than the portfolio without Ether (+22.71%). The portfolio containing Ether was ahead of the other portfolio during almost the entire study period. However, when larger declines are to occur, the portfolio containing Ether drops more dramatically than the portfolio without Ether. This seems to be in line with the warning of Briere et al. (2015) who warned about the extreme values that can be reached by cryptocurrencies.

After that, we compared the evolution of portfolios containing or not the other 3 cryptocurrencies. Figure 12 shows the evolution of an asset portfolio with and without Bitcoin, Litecoin or XRP.

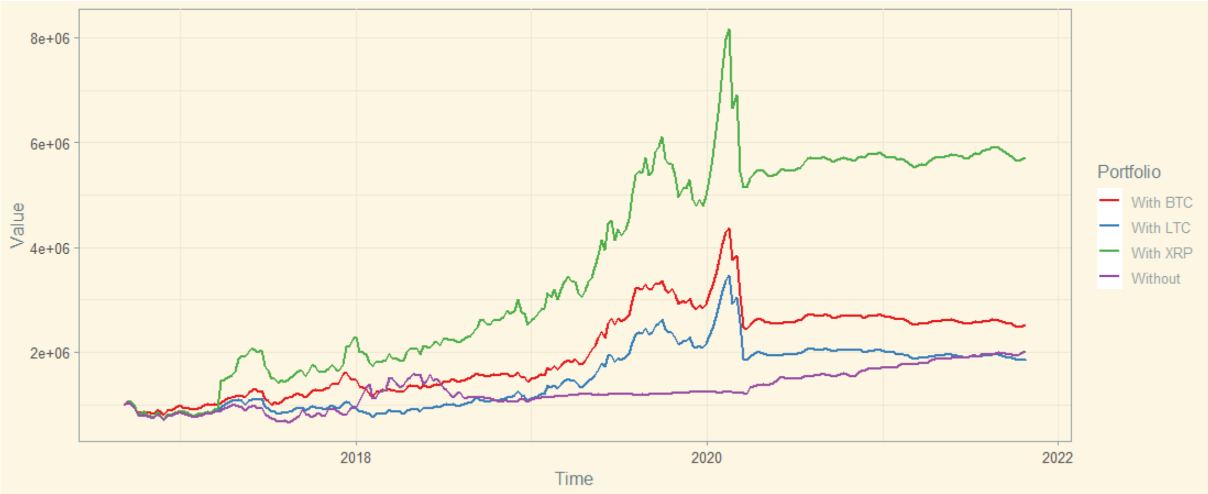

Fig. 12 - Portfolio evolution with or without cryptocurrencies
The graph shows the evolution of two asset portfolios of one million points. One of the portfolios contains only traditional assets and the others contain BTC, LTC or XRP in addition. The data used to obtain these portfolios ranges from September 22, 2014 to October 25, 2021

The first portfolios chosen were selected by maximizing the Sharpe ratio. These portfolios contain respectively 9.91% XRP, 4.88% Litecoin and 16.87% Bitcoin. All the portfolios studied ended largely in the positive at the end of our observation period. The portfolio with Bitcoin increased by 150.5%, the one containing XRP increased by 469.25% and the one containing Litecoin increased by 86.32%. Note that the portfolio without cryptocurrency increased by 100.02%. The drawdown was crossed only once for the three portfolios containing the cryptocurrencies. In fact, for all three portfolios, the drawdown was exceeded at the same time i.e., in early 2020. This corresponds to the beginning of the Covid-19 crisis. The overshoot led us to reduce the risks associated with these portfolios by recalculating the weights of the assets in the portfolios. The decrease in risk was reflected in a decrease in the weights of the cryptocurrencies present in each case. For the portfolio without cryptocurrencies, the set drawdown was never exceeded. The portfolio was therefore never recalculated and could remain as it was until the end of the observation period. As with Ether, we see that portfolios containing cryptocurrencies can more easily reach extreme values. For example, the portfolio containing XRP peaked at over 700% increase before dropping back to 400% increase in the following weeks.

This dynamic analysis has enabled us to highlight an important point. When a portfolio contains cryptocurrencies, extreme values can be reached more quickly, both upwards and downwards. An investor choosing to invest in this type of asset should be aware that simply considering the risk-return trade-off is not enough. Extreme risk should be factored into the research as cryptocurrencies seem particularly prone to it. We have indeed seen that cryptocurrency returns do not follow a normal distribution. Several authors mention the fat tails that these distributions can have (Brière et al. (2015), Dorfleitner and Lung (2018), Brauneis and Mestel (2019)).

5 Conclusion and limitations

5.1 Conclusion

Our research revealed several important findings regarding cryptocurrencies.

The analysis of descriptive statistics was very informative. We were able to see the unique characteristics of cryptocurrencies in terms of returns and risks. Cryptocurrencies seem to be a tool to access levels of returns that an investor could never have imagined. These high returns are of course offset by higher levels of risk. Several authors have already highlighted this phenomenon (Liu et al. (2021), Enoksen et al. (2020), Liu and Tsyvinski (2018), Papadopoulos (2015), Brière et al. (2015), etc.). We also found that, between September 2014 and October 2021, the distributions of the returns of the assets studied were not normal. Furthermore, we notice that a general increase in the risk level of traditional assets is not necessarily reflected in the cryptocurrency market.

The calculation of the overall and moving correlations allowed us to formulate a rather clear conclusion. Cryptocurrencies have very little relationship with the conventional assets found in investors' portfolios. We find that the correlations between cryptocurrencies and conventional assets are overestimated in our calculations after the crisis in early 2020 (Covid-19). Therefore, the correlations could actually be even lower than those we obtained. The low correlations had been reported in the literature by several authors (Brière et al. (2015), Bouri et al. (2017), Liu and Tsyvinski (2018))

The integration of cryptocurrencies within a conventional asset portfolio allows us to see several things. Efficient frontiers made from portfolios containing cryptocurrencies are consistently dominant. With such a portfolio, an investor can, theoretically, achieve the same levels of returns with less risk and the same levels of risk with more returns. Similar results have been obtained by Brière et al. (2015) and Kuo Chuen et al. (2017). We also realise, that portfolios containing cryptocurrencies reach extreme values more easily. Extreme risks are therefore perhaps not sufficiently taken into account in the simple mean-variance analysis.

This thesis has therefore allowed us to analyse the behaviour of cryptocurrencies within asset portfolios. To the question "Were cryptocurrencies effective between September 2014 and October 2021 in diversifying the asset portfolio of an American investor?", we therefore answer YES, cryptocurrencies were able to diversify an investor's asset portfolio during this period. NEVERTHELESS, one should remain cautious and take into account the extreme risks that cryptocurrencies carry. In our opinion, an investor should necessarily consider cryptocurrencies when building an asset portfolio. The investor should still learn about these assets and the risks associated with them. Cryptocurrencies are not a game, and investors should be aware of this. There are significant risks associated with them and it is only by being aware of them that they can be managed.

5.2 Limitations

To conclude this thesis, it is necessary to address some points that limit the research we have done and therefore the results we have obtained.

First, we have studied the returns of cryptocurrencies and other assets through the prism of the mean and variance/standard deviation. This is not sufficient to perfectly describe the returns of the selected variables. Indeed, the Jarque-Bera tests we performed rejected, for each of the variables, the null hypothesis of normality. Brière et al. (2015) had warned against not taking into account extreme risks which are in fact, strongly present in cryptocurrency returns. We have seen that several authors highlighted the presence of fat tails in the distributions of cryptocurrencies (Brière et al. (2015), Dorfleitner and Lung (2018), Brauneis and Mestel (2019)).

To add cryptocurrencies to a diversified portfolio, we had to select a portfolio that we considered diversified. We chose to take a portfolio similar to the one chosen by Brière et al. (2015). There are an infinite number of possible portfolios and it is very difficult to represent all the different markets in a portfolio. Nevertheless, the portfolio we have composed is not perfect but has the merit of representing many different markets. There is also nothing that indicates that the 4 cryptocurrencies we have chosen are an accurate representation of the cryptocurrency market.

The results we have obtained are valid for the study period from September 2014 to October 2021. These findings are not generalizable, and it is doubtful whether the relationships between cryptocurrencies and other assets will remain as they are now. There is no guarantee that the correlations will not become much more significant in the coming years. However, the cryptocurrency market has been decoupled from other markets for many years.

For future research, it would be interesting to describe the distribution of cryptocurrency returns with more sophisticated tools. It seems necessary to take into account the additional risks related to the extreme values that can be taken by cryptocurrencies. This way, investors will have all the cards in their hands when making investment decisions.

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7 Appendices

7.1 Appendix A - Box plots of the two-year moving averages and volatilities

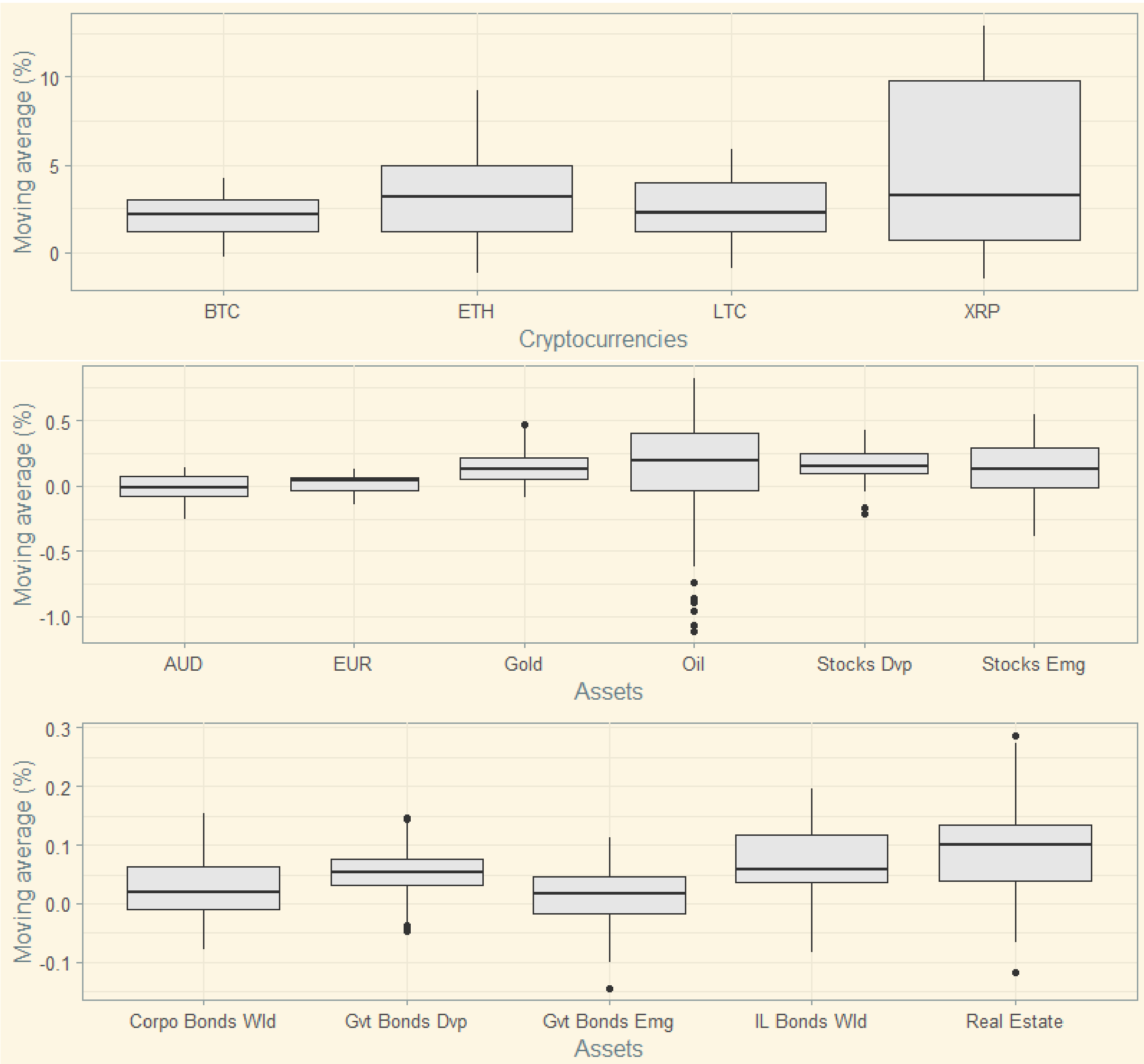

Fig. 13 - Box plots of the two-year moving averages of weekly returns
The box plots show the two-year moving averages of the weekly returns of the 15 datasets described in the "Data" section. The two-year moving averages run from September 12, 2016 and October 25, 2021 except for Ether where they start on July 31, 2017.

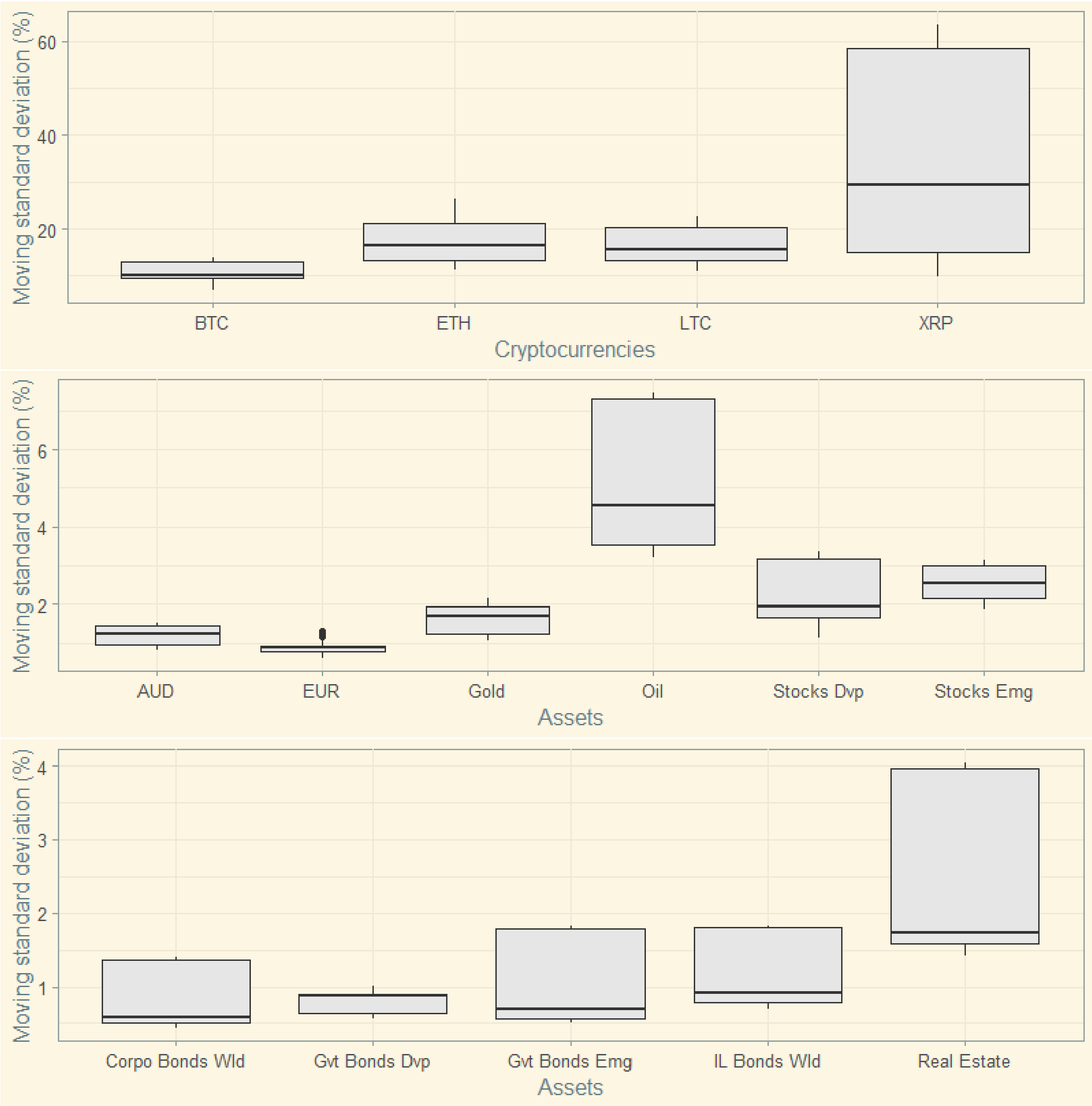

Fig. 14 - Box plots of the two-year moving volatilities of weekly returns

The box plots show the two-year moving volatilities of the weekly returns of the 15 datasets described in the "Data" section. The two-year moving averages run from September 12, 2016 and October 25, 2021 except for Ether where they start on July 31, 2017.

7.2 Appendix B - Charts of the two-year moving correlations

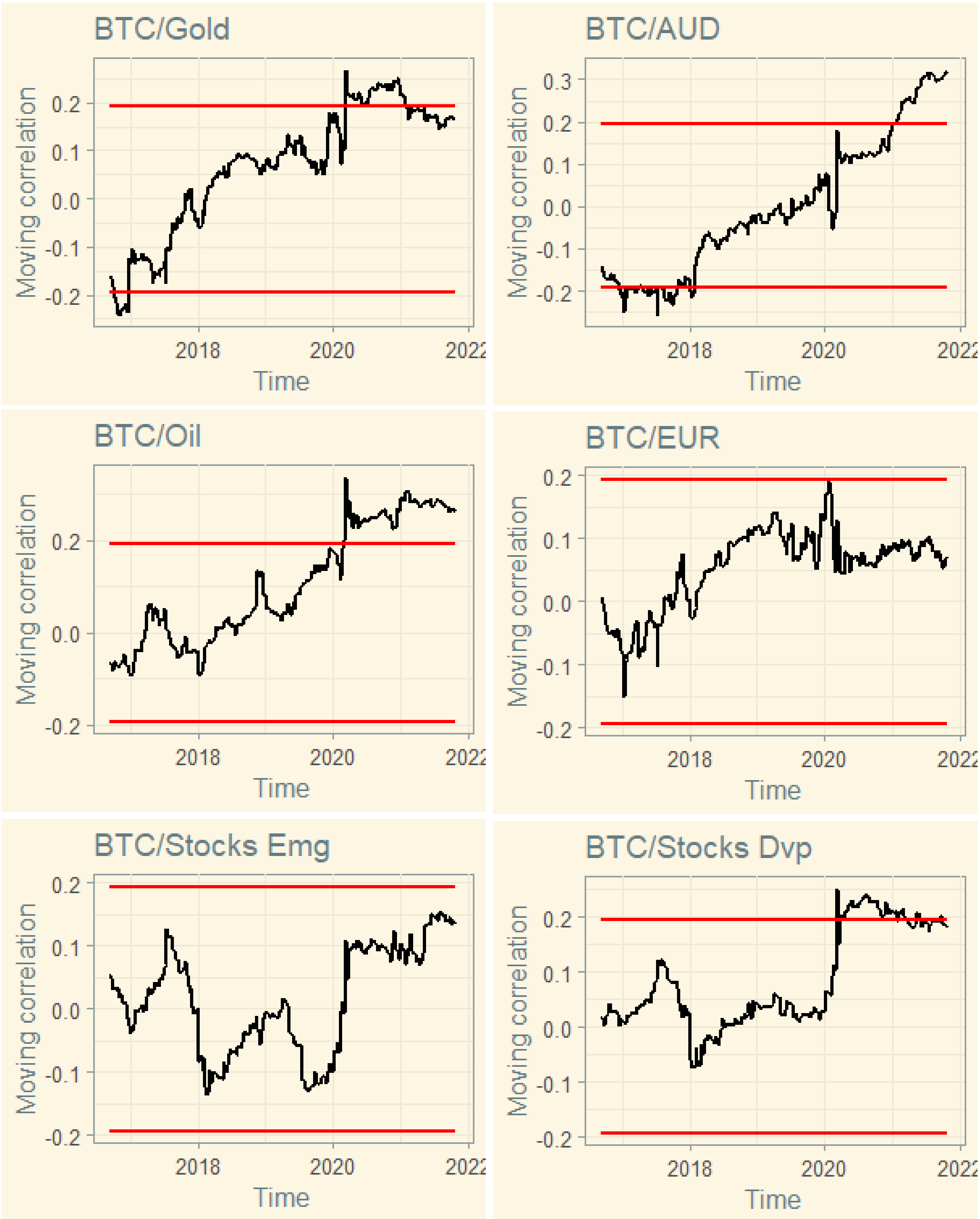

Fig. 15 - Charts of the two-year moving correlations of weekly returns of Bitcoin
The 6 charts show the evolution of the two-year moving correlations between the weekly returns of Bitcoin and other traditional assets. The two-year moving correlations range from September 12, 2016 to October 25, 2021. The red line indicates the threshold at which the moving correlations are significant at 5%.

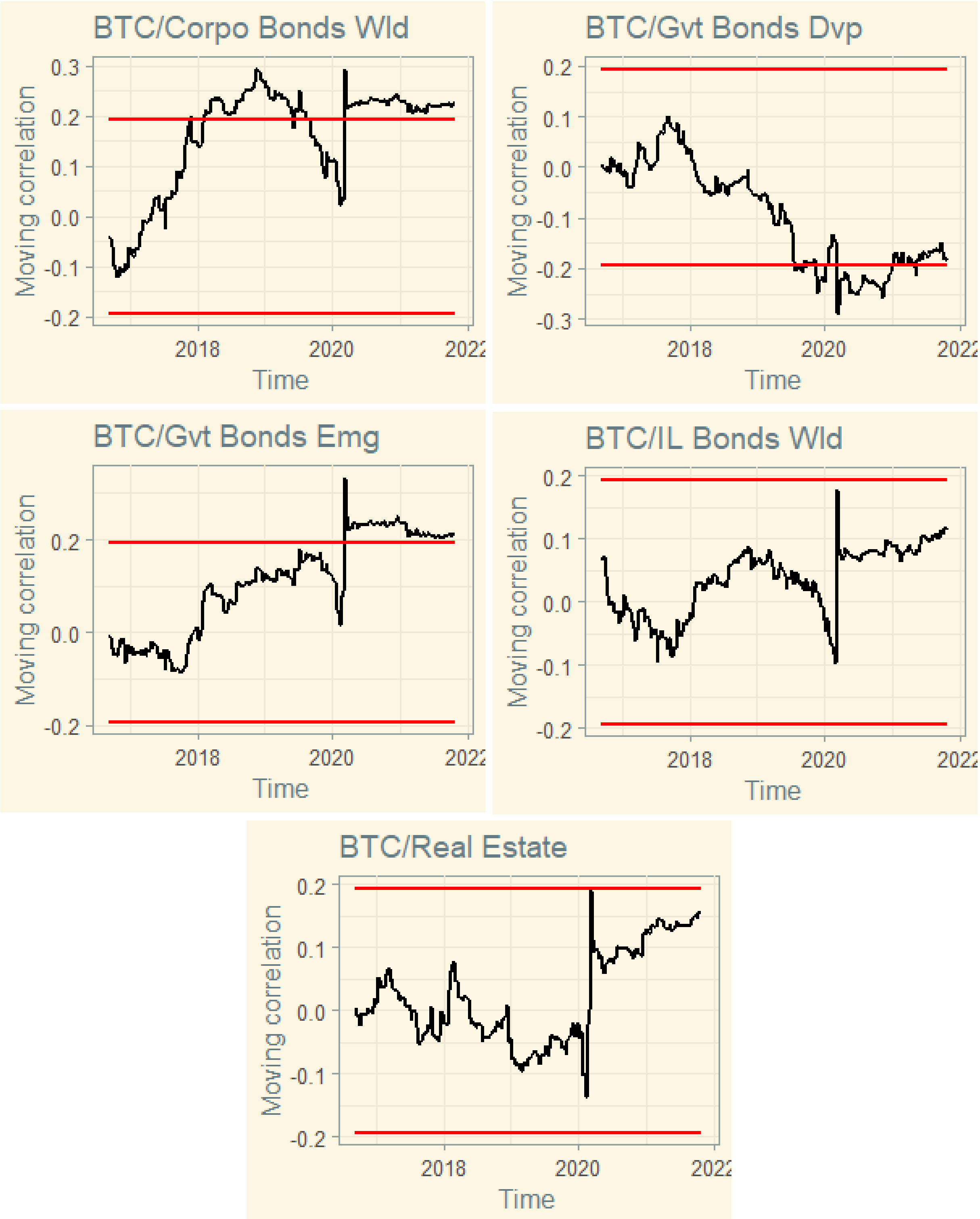

Fig. 16 - Charts of the two-year moving correlations of weekly returns of Bitcoin
The 5 charts show the evolution of the two-year moving correlations between the weekly returns of Bitcoin and other traditional assets. The two-year moving correlations range from September 12, 2016 to October 25, 2021. The red line indicates the threshold at which the moving correlations are significant at 5%.

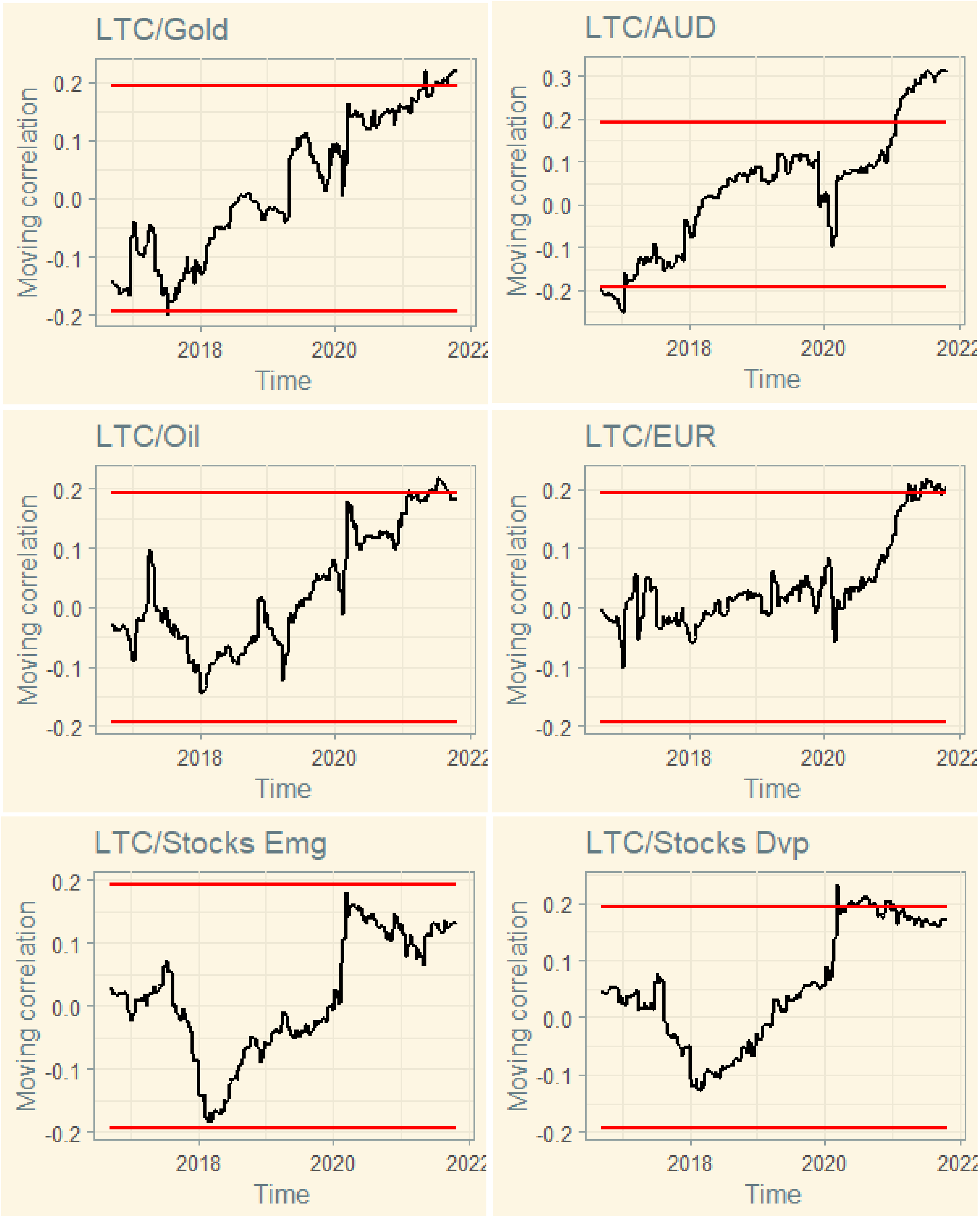

Fig. 17 - Charts of the two-year moving correlations of weekly returns of Litecoin
The 6 charts show the evolution of the two-year moving correlations between the weekly returns of Litecoin and other traditional assets. The two-year moving correlations range from September 12, 2016 to October 25, 2021. The red line indicates the threshold at which the moving correlations are significant at 5%.

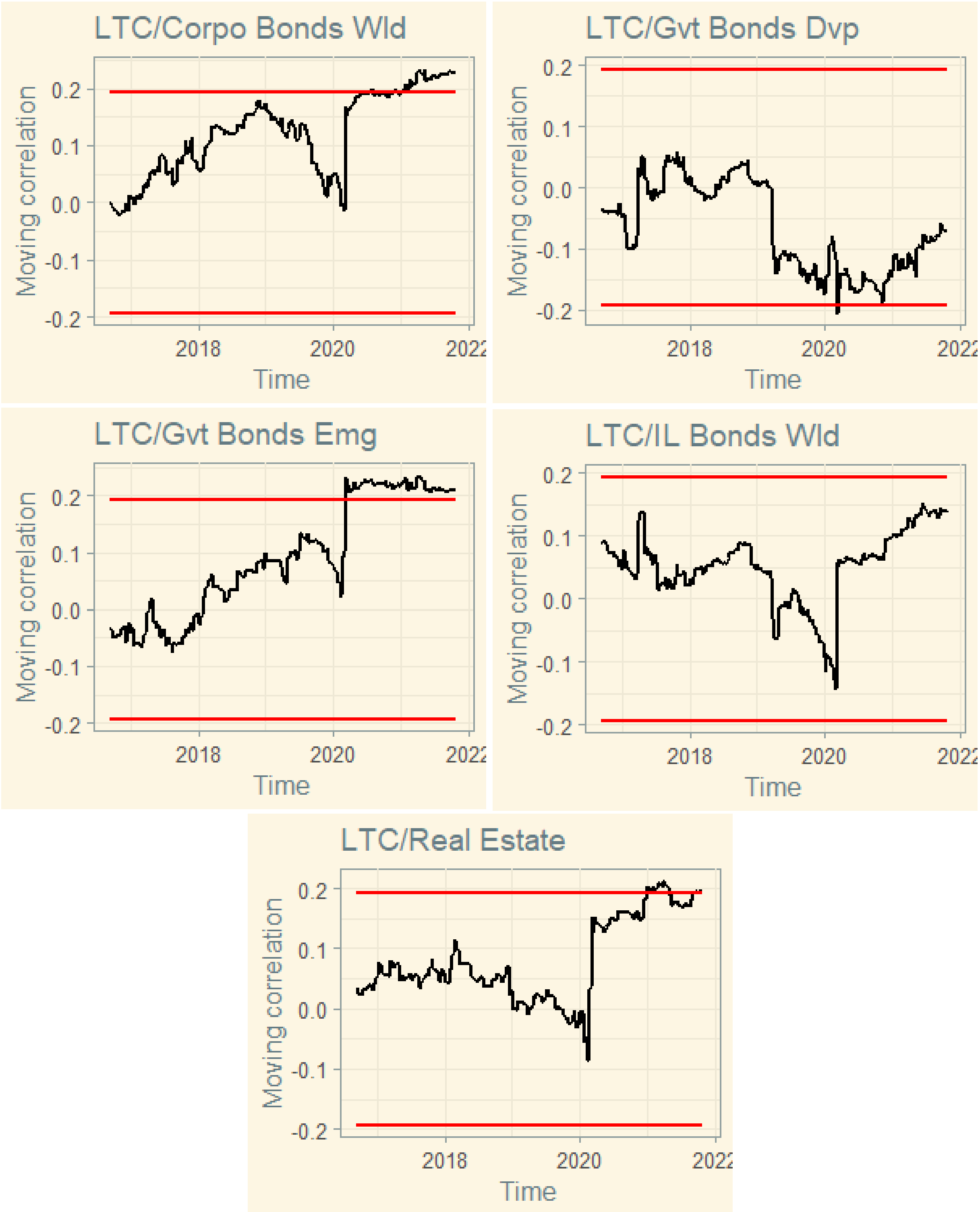

Fig. 18 - Charts of the two-year moving correlations of weekly returns of Litecoin
The 5 charts show the evolution of the two-year moving correlations between the weekly returns of Litecoin and other traditional assets. The two-year moving correlations range from September 12, 2016 to October 25, 2021. The red line indicates the threshold at which the moving correlations are significant at 5%.

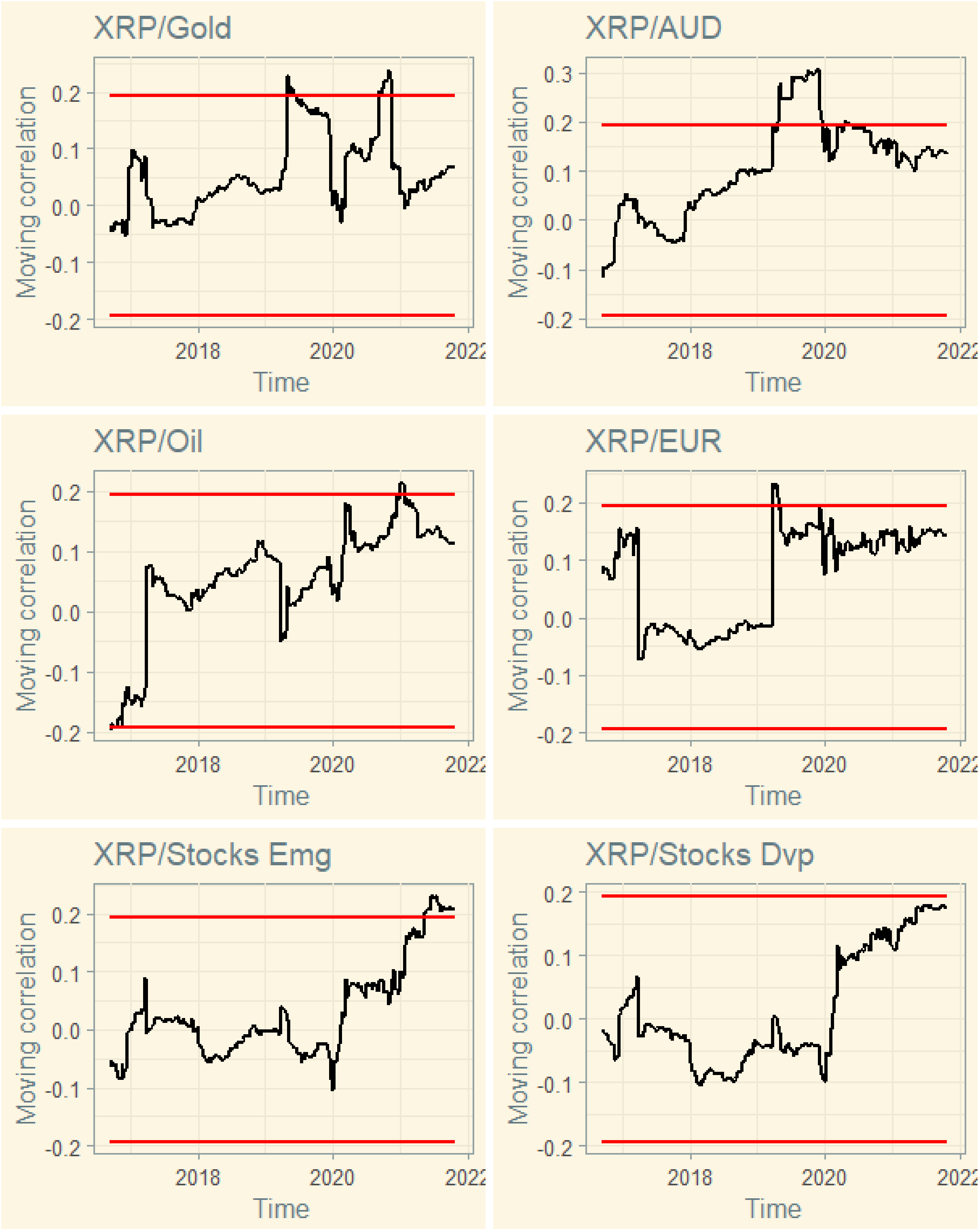

Fig. 19 - Charts of the two-year moving correlations of weekly returns of XRP
The 6 charts show the evolution of the two-year moving correlations between the weekly returns of XRP and other traditional assets. The two-year moving correlations range from September 12, 2016 to October 25, 2021. The red line indicates the threshold at which the moving correlations are significant at 5%.

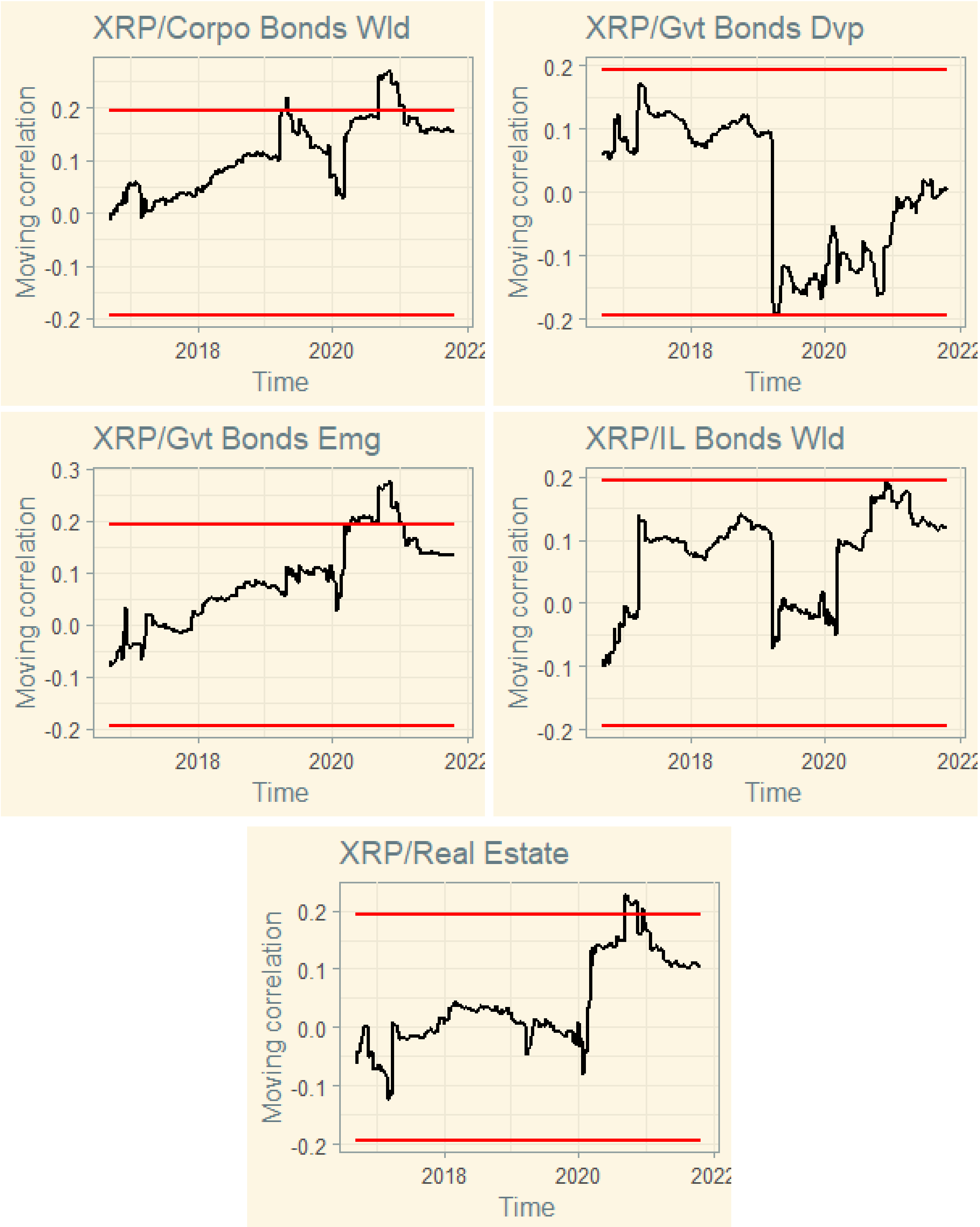

Fig. 20 - Charts of the two-year moving correlations of weekly returns of XRP
The 5 charts show the evolution of the two-year moving correlations between the weekly returns of XRP and other traditional assets. The two-year moving correlations range from September 12, 2016 to October 25, 2021. The red line indicates the threshold at which the moving correlations are significant at 5%.

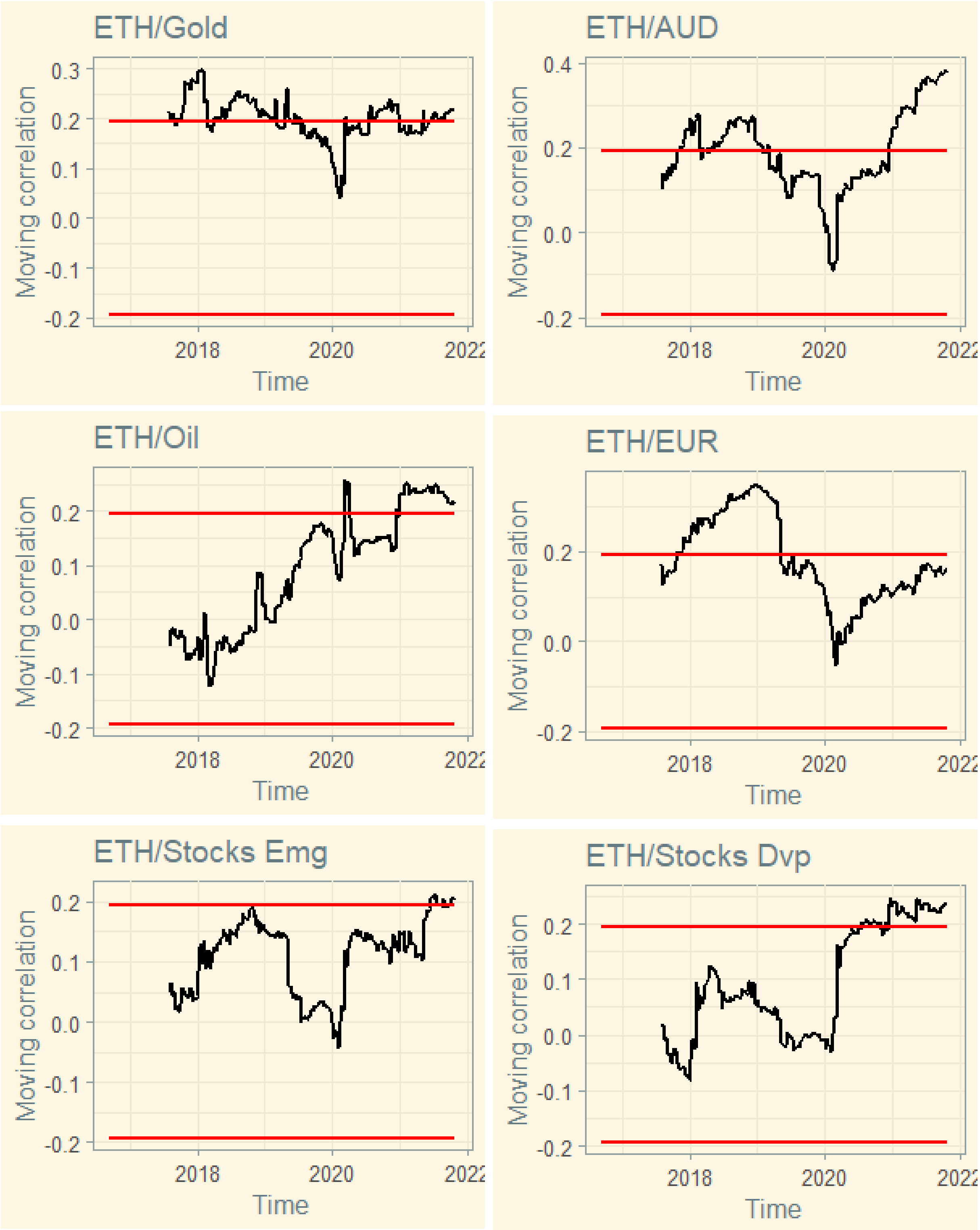

Fig. 21 - Charts of the two-year moving correlations of weekly returns of Ether
The 6 charts show the evolution of the two-year moving correlations between the weekly returns of Ether and other traditional assets. The two-year moving correlations range from September 12, 2016 to October 25, 2021. The red line indicates the threshold at which the moving correlations are significant at 5%.

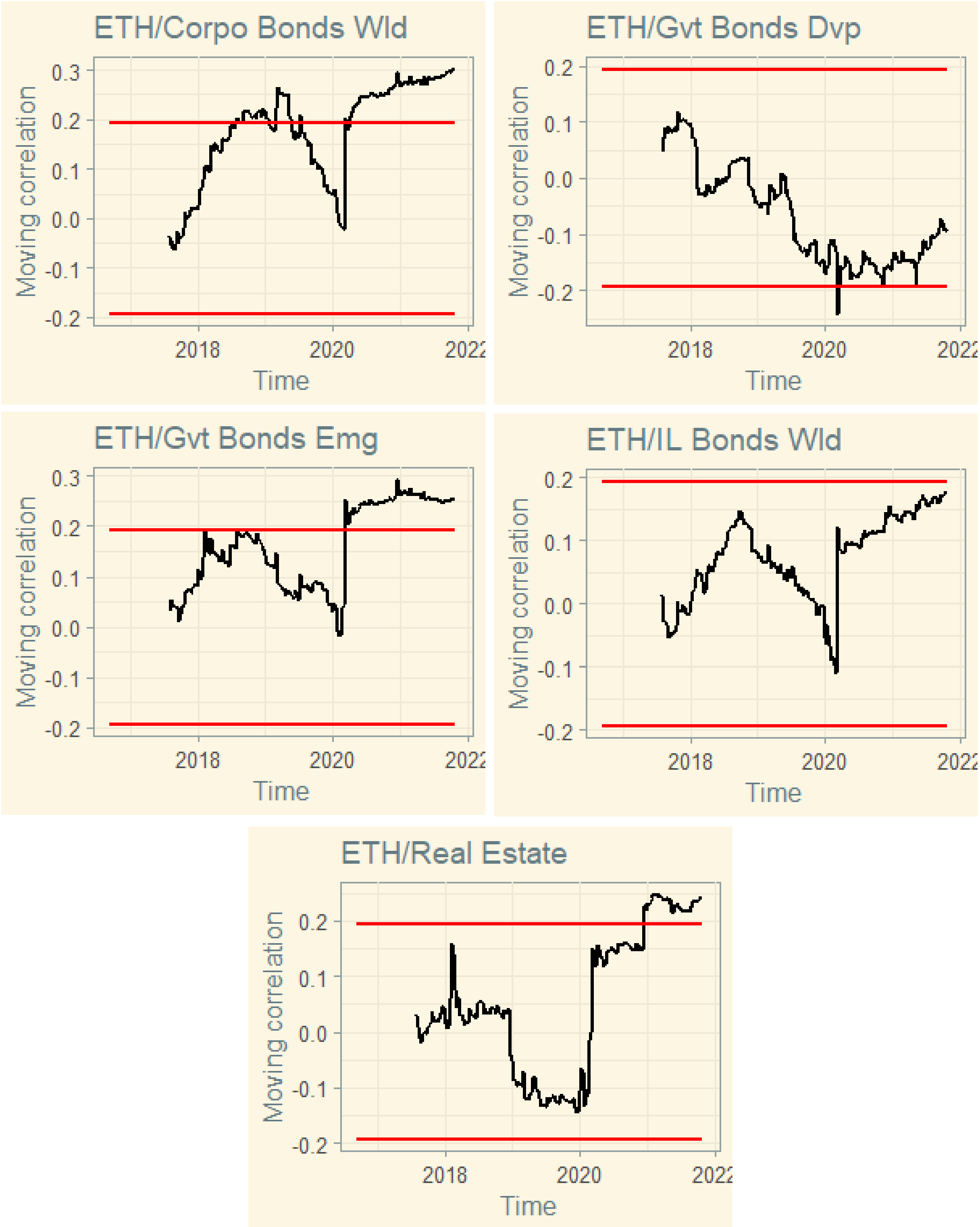

Fig. 22 - Charts of the two-year moving correlations of weekly returns of Ether
The 5 charts show the evolution of the two-year moving correlations between the weekly returns of Ether and other traditional assets. The two-year moving correlations range from September 12, 2016 to October 25, 2021. The red line indicates the threshold at which the moving correlations are significant at 5%.

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