Cryptocurrency and trading strategies

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ABSTRACT

Title of thesis: Cryptocurrency and trading strategies

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The aim of this dissertation is to provide a review on the current cryptocurrency economics which is still vague to a vast number of investors. Regression results suggest some but limited similarities to stocks with regards to the price movements in the market. The goal of the dissertation is to examine the profitability of moving average trading strategies with 3, 9 and 30-days moving averages which have only been tested on a longer lag moving average and the feasibility of volatility timing strategy which has not yet been implemented on Bitcoin markets. Results show that moving average strategies significantly outperform the Buy-and-Hold Bitcoin benchmark, but increase the higher-order risk. The volatility timing strategy did not produce the desired decrease in higher-order risk. However, this result does not rule-out the possibility that an application of a more sophisticated asset-pricing model could further decrease excess kurtosis, which seems problematic for a broader scope of investors since there is a continuous risk of crash present in the cryptocurrency markets.

Keywords: Bitcoin, cryptocurrency, technical analysis, higher-order risk, volatility-management

RESUMO

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O objetivo desta dissertação é fornecer uma análise da atual economia do cripto moeda, que ainda é vaga para um grande número de investidores. Os resultados das regressões sugerem algumas semelhanças, mas limitadas, com a existência de momentum no mercado actionista. O objetivo da dissertação é examinar a rentabilidade das estratégias de investimento usando médias móveis de 3, 9 e 30 dias que só foram testadas numa média móvel de longo prazo e a viabilidade da estratégia ajustar a alavancagem para atingir uma volatilidade alvo que ainda não foi implementada nos mercados de Bitcoin. Os resultados mostram que as estratégias usando médias móveis médias superam significativamente o benchmark Buy-and-Hold Bitcoin, mas aumentam o risco de curtose excessiva mais elevado. A estratégia de volatilidade alvo não produziu a diminuição desejada do risco de ordem superior. No entanto, esse resultado não descarta a possibilidade de que a aplicação de um modelo de preços de ativos mais sofisticado possa diminuir ainda mais a curtose excessiva, o que parece problemático para um âmbito mais alargado de investidores, uma vez que existe um risco contínuo de perdas extremas nos mercados de cripto moeda.

Palavras chave: Bitcoin, criptomoeda, análise técnica, risco de ordem superior, gestão da volatilidade

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1 INTRODUCTION

The term of cryptocurrency first emerged in a paper of Nakamoto, Satoshi (2008) which was published on metzdown.com cryptography mailing list on the 31st of October, 2008[1], when Satoshi Nakamoto, an unidentified persona even today, created a white paper labeled as “Bitcoin: A Peer-to-Peer Electronic Cash System”. The idea of this paper was to create an electronic peer-to-peer (direct) payment method, creating a sort of an electronic version of cash. This payment method does not involve a fiduciary (a trust counterparty or a financial institution) per se, rather a cryptographic proof which serves as a base for direct money transaction between any two willing parties. This system serves as an alternative to the common trust-based model involving financial institutions and improves on it in various ways. The whole system is designed to operate using digital signatures of both counterparties. It is important to mention that digital signature security is incomparable to traditional signature. The reason for this is that traditional signatures are always the same and could be counterfeited.

On the other hand, each owner of a digital asset is provided with its own key pairing including both a private key (also called a secret key) and a public key, which is visible by anyone willing to check a certain transaction online. The private key ensures that only the person himself can sign, meaning that no one can copy the owner’s signature, as no one else knows his private key. It is almost impossible to get to a private key of a person using his public key[2], as keys are generated in 256-bits format, meaning the number of potential combinations spreads to more than 2^{256}(since it is a 256-bits random number)[3]. Only in the case if someone knows a person’s private and public key, it is possible that this someone could misuse and sign fraudulent transactions. Furthermore, we can think about this type of currency being its own transaction history (like a ledger) which will be elaborated in the next section of the dissertation.

The idea of this dissertation is to construct trading models based on cryptocurrency in order to yield a better return than the buy-and-hold Bitcoin portfolio which serves as a benchmark for performance

[1] This is not a standard academic outlet for publishing academic papers on finance-related topics such as the Journal of Financial Economics (JFE)
[2] Public keys are used to encrypt messages which could only be deciphered by using a related private key
[3] It is almost impossible to crack the private key of a particular wallet with the current technology, since it could take billions of years. This might change potentially with the introduction of more advanced technologies such as quantum computers. Also, private keys can be additionally secured by encrypting the private key, restricting access to the folder that contains the private key to secure against computer hacks or by simply keeping it in a physical storage hard disk, or even written on a piece of paper.

measurement. Firstly, the dissertation will test the exposure of Bitcoin returns to 3-Fama and French, 5-Fama and French and momentum factor models. Furthermore, strategies that will be constructed and evaluated in this paper are simple moving average strategy and volatility timing strategy. Simple moving average strategy has been tested already on the cryptocurrency market by Detzel et al (2021). Authors documented an improved Sharpe ratio of 2.48 (statistically significant at a 1% confidence level) using a 1-month moving average strategy, compared to 1.82 Sharpe ratio of the Bitcoin buy-and-hold benchmark portfolio. Their paper evaluates the moving average strategies for 1, 2, 4, 10 and 20-weeks moving average where the 1-week moving average proves to be the top performing strategy. Alpha of the 1-week moving average strategy relative to the buy-and-hold benchmark is 24 basis points per day, statistically significant at a 1% confidence level). On the other hand, after reviewing all available literature on cryptocurrency trading strategies, the conclusion is that the volatility timing strategy has not yet been implemented. The currency of interest in this dissertation is Bitcoin.

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2 CRYPTOCURRENCY ECONOMICS

2.1 Cryptocurrency asset classes

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There is an important distinction to make between the phrases such as cryptocurrency, altcoins and crypto tokens.[4] We can define the term cryptocurrency as the superset and the two latter terms as the subsets with different functions. The phrase “altcoin” is derived from the word alternative, a term that emerged following the Bitcoin’s rapid success, referring to coins other than Bitcoin, which are used and owned in their own depending blockchains. Both types of assets are usually used for purchases and as a medium for digital exchange. They can also be utilized as an investment, stake or store of value per se. Cryptocurrency is defined as a native asset of a blockchain (Bitcoin, Ethereum). On the other hand, crypto tokens are built on an existing blockchain by using smart contracts. Both types of assets behave very similarly with regards to facilitation of transactions, but the fundamental difference is that tokens are programmed using smart contracts, and native asset of a blockchain is programmed by the specific blockchain protocol (for example, Bitcoin is programmed by the Bitcoin protocol). However, fees to transfer an asset on blockchain (also called gas fees) are cheaper when

[4] Crypto Tokens Definition (investopedia.com) – “A cryptocurrency is a standard currency used for making or receiving payments on a blockchain, with the most popular cryptocurrency being Bitcoin (BTCUSD)”

transferring cryptocurrency, compared to transferring crypto tokens. These gas fees differ from blockchain to another, but are always paid in the native cryptocurrency of the utilized blockchain. Also, crypto tokens are created through an initial coin offering (ICO)[5] and often used to raise funds for crowd sales. Cryptocurrencies could also be denominated in crypto tokens, also called crypto assets, representing a certain unit of value. Crypto tokens play a key role in executing smart contracts[6], creation of decentralized applications and are often used to facilitate transactions. Smart contracts are the foundation for carrying out trusted transactions among anonymous parties without the need for a third party which would serve as a central authority enforcing proper clearance and the integrity of transactions on the blockchain.

2.2 Stablecoins

There is also an asset class of cryptocurrencies called "stablecoins[7]", which are created with a goal of offering investors the best of two worlds, price-stability and instant processing of secure and private transactions. A stablecoin's market value is often pegged to an external reference such as U.S. dollar or gold. Price stability is achieved by collateralization[8] (backing) or via algorithms of trading the reference asset. However, stablecoins are not managed by any central bank. Depending on the policy, there are collateralized and uncollateralized stablecoins. Fiat-collateralized stablecoin such as TrueUSD (TUSD) claim to be fully backed by a fiat currency reserve (ex. U.S. dollar) meaning its value should ideally be completely backed by U.S. dollar deposits or gold. In this case, the issuing company of the token manages the collateral and guarantees parity. There are also crypto-collateralized stablecoins which tend to be over-collateralized in a reserve cryptocurrency due to the fact that cryptocurrencies are often highly-volatile, meaning there is a larger amount of the collateral than the asset which is being backed. An example is WrappedBitcoin (WBTC) token, a stablecoin which has a reserve of Bitcoin as a collateral, meaning its value is pegged to Bitcoin. However, this

[5] Initial Coin Offering (ICO) Definition (investopedia.com) – "An initial coin offering (ICO) is the cryptocurrency industry's equivalent to an initial public offering (IPO). A company seeking to raise money to create a new coin, app, or service can launch an ICO as a way to raise funds."
[6] Smart Contracts Definition (investopedia.com) – "A smart contract is a self-executing contract with the terms of the agreement between buyer and seller being directly written into lines of code. The code and the agreements contained therein exist across a distributed, decentralized blockchain network. The code controls the execution, and transactions are trackable and irreversible."
[7] Stablecoin Definition (investopedia.com) – "A stablecoin is a class of cryptocurrencies that attempt to offer price stability and are backed by a reserve asset."
[8] Collateralization Definition (investopedia.com) – "Collateralization is the use of a valuable asset to secure a loan."

class of stablecoins could be risky with regards to Bitcoin price volatility and could result in loss of investment value, since it is pegged to Bitcoin.

While TrueUSD has been regularly audited[9], this is not the case with the largest stablecoin on the market. Tether (USDT/USD) is the 3rd largest cryptocurrency with a market capitalization of nearly 83 billion US dollars[10], defined as a stablecoin, meaning that it is pegged to the US dollar to keep the value of $1 per 1 Tether (USDT). Tether tokens reside on Bitcoin and Ethereum networks and are issued by Tether Limited, a Hong Kong company controlled by the owners of Bitfinex, which is one of the largest cryptocurrency exchanges in the market since 2012. The company manages the collateral and guarantees parity of Tether tokens to the US dollar, claiming that each Tether token is 100% backed by Tether reserves, which should in theory consist of highly liquid assets. However, supply of Tether tokens is increasing rapidly, since 2021, more than half of the current supply of token was issued by Tether Limited, a company which is a not clearly regulated offshore company, counting under 20 employees on LinkedIn with $83 billion in assets under management.

On the other hand, Tether tokens play a crucial role by being the largest liquidity provider in cryptocurrency markets, serving as a major infrastructural bridge for investors when moving their assets in and out of the cryptocurrency exchanges and a pragmatic tool to quickly hedge their exposure to cryptocurrencies in periods of increased volatility on the market. Considering the size and role in the cryptocurrency markets, if Tether tokens would experience price instability (losing the peg to the US dollar), it would be a substantial shock for cryptocurrency markets which could have spillover effects to the regulated credit markets, since Tether is among the 7th largest global holders of commercial paper-based debt (unsecured short-term loans to corporations). More than $30 billion (out of $83 billion) of their reserves are invested into unsecured loans.

There are multiple reasons for concern due to the fact that Tether Limited operates as a bank, but without a clear regulator body which could oversee their operations. The incentive for doing so could be similar to the business model of a bank, with regard to accumulating deposits, issuing loans, issuing new Tether tokens and investing the liquidity. Furthermore, there already were multiple cases of money laundering using Tether tokens, for example a Chinese trader serving three years in prison for using Tether tokens to launder $480 million for illegal casinos[11] and some similar instances. This is possible because the company Tether Limited checks the identity of customers that buy tokens from

[9] https://blog.trusttoken.com/trueusd-attestation-reports-86f693b90a4
[10] https://www.investopedia.com/terms/t/tether-usdt.asp
[11]https://www.bloomberg.com/news/features/2021-10-07/crypto-mystery-where-s-the-69-billion-backing-the-stablecoin-tether

the company directly, but when the tokens are in the circulation, they could be transferred anonymously. Another red flag is that after facing repeated calls to engage in a full audit of Tether reserves, the company stated in July, 2021, that they will produce one in the next few months, which they failed to comply with as of today[12]. Also, it is concerning that Tether tokens still haven't regained their peg to the US dollar following the recent stablecoin crash which will be covered in the following paragraph.

Next category of stablecoins are algorithmic ones which can be, but do not have to be collateralized, meaning that they do not necessarily operate with any specific reserve asset. In both cases, a working consensus mechanism which mimics the operations performed by the central banks is implemented. This is achieved by implementing a smart contract on a decentralized platform which would execute autonomously, meaning that the price stability depends on the complex algorithms formed according to the smart contract which dictates the dynamics of increasing or decreasing the supply of tokens in order to maintain desired price stability.

There was a recent crash of an algorithmic stablecoin TerraUSD (UST) which lost 97% of its value over the course of 10 days, as a response to the recent global market volatility in May, 2022, which is most likely triggered by the Central Bank's decision to increase interest rates[13] by 0.5%. As a point of reference, TerraUSD is a stablecoin that had a market capitalization of $18 billion in the beginning of May, 2022. Unlike TrueUSD, which holds mostly cash and less risky assets as a collateral, UST token relies on its sister cryptocurrency Luna which is a native cryptocurrency of Terra blockchain. Each UST token issued implied autonomous destruction of $1 in Luna cryptocurrency and vice-versa.

The goal of this protocol was to guarantee long-term growth, as it incentives investors to burn UST tokens for Luna when the price of UST falls below $1, hopefully pushing the peg[14] back to $1. On the other hand, if UST token values more than $1, investors are incentivized to mint UST and destroy Luna, increasing the supply of UST tokens and pushing the price back down to $1 and simultaneously decreasing the supply of Luna, which should encourage price appreciation in the long-run. An important part of the incentive is that the company offered a 19.5% annual yield on staking UST tokens, which is particularly attractive in the current savings yield environment. This scheme accumulated near $14 billion before the black swan event of cryptocurrency prices rapidly dropping.

[12] https://www.cnbc.com/2022/04/13/tether-to-reduce-commercial-paper-holdings-in-usdt-reserves.html
[13]https://www.usnews.com/news/economy/articles/2022-05-04/fed-raises-interest-rates-by-half-a-percent-in-aggressive-move-to-fight-inflation#:~:text=Home-,Fed%20Raises%20Interest%20Rates%20by%20Half%20a%20Percent%20in%20Aggressive,each%20month%2C%20starting%20in%20June.&text=May%204%2C%202022%2C%20at%202%3A14%20p.m.
[14] https://fortune.com/2022/05/19/luna-terrausd-ust-algorithmic-stablecoins-doomed/

Before the market instability, founder of Terraform Labs, the company behind the Terra blockchain, UST tokens and Luna cryptocurrency, formed a separate legal entity with the sole purpose of defending the peg towards the US dollar which accumulated near $2.3 billion in Bitcoin reserves, with the idea of selling Bitcoins and buying UST tokens if the price falls below $1. If the value of UST tokens exceeds $1, the company would issue new UST tokens until the peg rebalances, using the received funds to increase their Bitcoin reserves.

This mechanism worked well in the bull market, however, when uncertainty increased, investors started to redeem their UST tokens for US dollars, increasing the supply on the market and rapidly decreasing the price. This action triggered a death spiral in which Luna cryptocurrency lost more than 97% of its value in a single day and UST tokens never recovered their peg, leading to the total collapse of both Luna and UST. This piece of information proves that there is significant risk involved in staking stablecoins, namely algorithmic-managed stablecoins which are not backed by stable assets. As a point of reference, Luna market capitalization was near $30 billion in the beginning of May, 2022.

2.3 Bitcoin Protocol: Proof-of-work vs Proof-of-stake

Bitcoin works on its defined Bitcoin protocol, which sets that every user trusts the ledger that has done the most computational work, as a basis of what and who to trust. This consensus mechanism is called proof-of-work.[15] The idea behind the system is to create a truly secure, decentralized consensus which serves to enable peer-to-peer transactions[16] and add a layer of security against fraudulent users who would opt to abuse the mining procedure and leverage their computing capacities to make false or double-spending transactions[17] and profit from misallocated block rewards. Solutions to these issues will be better explained in the literature review (check pages 6-7). In a nutshell, regarding the proof-of-work system, the more computers an owner has with higher computational power the more Bitcoins he could mine. However, as the Bitcoin network grows, validating transactions is becoming

[15] Proof of Work (PoW) Definition (investopedia.com) – Extensively used in Bitcoin and other cryptocurrency mining for block creation

[16] Peer-to-Peer (P2P) Economy Definition (investopedia.com) – "A peer-to-peer economy is viewed as an alternative to traditional capitalism, whereby organized business firms own the means of production and also the finished product."

[17] Double-Spending Definition (investopedia.com) – Referring to the theoretical issue that cryptocurrency could be used more than once. "There isn't actually any recorded instance of double-spending. The cryptocurrency community believes that all double-spending has been thwarted. However, the attacks used for double-spending are more often used for other purposes."

more complex and burdensome in terms of computational power, making it harder for owners to earn block rewards[18]. This resulted in a spike in investment into mining equipment (introducing a global shortage of graphic cards, processors and some rare materials used to produce them) and also increased the already problematic electricity usage issue. Higher energy costs also affect the profitability of mining and the pricing of a cryptocurrency itself.

As an alternative consensus mechanism, proof-of-stake[19] emerged. This system substitutes computational power for staking[20]. Also, in proof-of-stake, an individual's mining ability is randomized by the network. An owner stakes a specific amount of coins, offering them up as a collateral for a chance to mine. Furthermore, miners are then selected randomly to mine through validating block transactions, becoming validators. Validators have the opportunity to earn block rewards denominated in cryptocurrency for successfully validating a block of transactions. Every cryptocurrency utilizing this mechanism has a specific amount of how many coins an individual has to stake to become a validator. For example, Ethereum is planning to make a transition from proof-of-work to proof-of-stake consensus mechanism soon, stating they will require 32 Ethereum coins of stake for users to become validators. It is important to mention that there are multiple validators validating one block and when the specific number of validators is reached (in Ethereum case that will be 128 validators[21] as witnesses and at least two thirds of them must agree that the transaction is valid), the block is then verified and closed. Proof-of-stake reduces the amount of computational work needed to verify transactions. Therefore, with miners not needing massive amounts of hardware to mine, there is less energy consumed overall. Proof-of-stake also makes the network less vulnerable, as there are fewer incentives for fraudulent behavior because of the way how the compensation is structured. For example, it would be a concern for proof-of-stake in a scenario that an individual holds 51% of a given currency, in this case it would need to be staked in cryptocurrency. Majority ownership is enough to alter the blockchain in a fraudulent way. However, if a miner with a majority

[18] Refers to the amount of cryptocurrency which miners get as a reward for successfully mining a block in a blockchain
[19] Proof-of-Stake (PoS) Definition (investopedia.com) – "Proof-of-stake is designed to reduce the scalability and environmental sustainability concerns surrounding the proof-of-work (PoW) protocol."
[20] Staking refers to pledging cryptocurrency to the blockchain. These coins are used according to corresponding smart contracts to validate transactions. Staking could be observed as a cryptocurrency deposit, due to the fact that investors who stake their cryptocurrency earn a floating interest rate on the deposit, remunerated in cryptocurrency. We define this rate as annual percentage yield (APY). Staking offers the opportunity to get selected as a validator for a block and earn the corresponding rewards in cryptocurrency for successfully validating blocks, or a penalty for fraudulent block validations, resulting in a penalty (also called "burn", because the validators assets are burned, meaning that the validator of bad data lost his staked cryptocurrency as a penalty.
[21] Validators earn rewards in cryptocurrency when they successfully validate a block of transactions

coin ownership would try to revert a finalized block[22], he would lose all coins that he has staked. In this case, it could be a very expensive attempt in total with a low probability of success.

To sum up, proof-of-work is a competition-based mechanism with incentives to gain advantage over other miners, while proof-of-stake is random-based and deemed as a validation sharing method due to its nature, eliminating the competition factor. The main tool to enforce the Bitcoin protocol and the proof-of-work consensus is the cryptographic hash function[23] (often abbreviated as SHA 256 algorithm and used mainly in cybersecurity) which makes fraud computationally infeasible. The reason for this is that it is infeasible to compute in the reverse direction; meaning that it is almost impossible to guess the input by using the output of the function, as a tiny change in either input or output completely changes its counterpart, almost as if it seems random.

2.4 Blockchain

Furthermore, these ledgers are then organized into blocks. Block is only valid if it has a proof-of-work and it has to contain the hash from the previous block in its header and if a block changes, then all tied blocks would change. This is the reason this database structure is called the blockchain[24]. Blockchain is defined as a distributed ledger database which ensures the security of the information and removes the need of a trusteed third party which will guarantee the accuracy of the data reported. As used in Bitcoin's case, blockchain is decentralized meaning there is no central authority or a central ledger which would exert control, rather it is kept in collective hands by each user. This means also that transactions verified and entered on the blockchain are not changeable, meaning that every transaction could be seen by anyone since they are permanently recorded[25]. It is important to mention that an investor's incentive for validating transactions depends on his computational power capacity

[22] Since blocks are finalized by a majority decision of ⅔ of total validators, reverting a block in this context would mean voting for a fraudulent block containing false information about transactions
[23] Hash Definition (investopedia.com) - Investopedia defines hash as a mathematical function which serves to encrypt, resulting in encrypted output of a fixed length, which is used so the input is not easily guessed, rather it has to be solved using large amounts of processing power (CPU)
[24] Blockchain Definition: What You Need to Know (investopedia.com) – Blockchain gathers data in blocks which have certain storage capacities, when they get filled and closed, then get connected to the previous block, resulting in a chain. Every block in a certain chain has an exact time stamp when it is exactly added to the chain
[25] All information on total transaction history is stored on the Bitcoin network, where the data is validated block by block, each block being permanently replicated and stored instantaneously in each network node (miners are regarded as network nodes, therefore, they are the one bearing the storage costs which are aggregated with the total mining cost, expressed in hash rate)

with regards to the total computational power used by the whole proof-of-work cryptocurrency, which is called hash rate[26]. Hash rate can also be defined by number of calculations per second, referring to the speed of validating transactions. It is usually measured in exa-hashes per second (EH/s). Current hash rate for the Bitcoin network is approximated at 190 EH/s, which is an important measure for miners. Due to the nature of the Bitcoin protocol, miners face a constant competition between each other since they are racing to be the first to generate a valid hash to validate a block to receive block rewards. A miner who has equipment which can produce a substantially lower hash rate than the competition, this miner will most likely not manage to validate a block before his competition does, putting him in an inferior position compared to his peers.

2.5 Mining

In these settings, anyone possessing competitive equipment can be a block creator, which would include "listening" for and collecting transactions into blocks, do heavy computational work and solve the cryptographic hash function to get the defined special number[27] which is necessary to obtain the proof-of-work. After finding this number, a block creator broadcasts out (to the network) the block he found with the number and as a reward, block creator can have another entry on top of the ledger for himself called the block reward[28]. By receiving the block reward, the total amount of respective currency in circulation (in the economy) increases by the amount which has been issued as a block reward. Block creation is often called mining[29]. Average block creation time for Bitcoin, Ripple and Ethereum is 10 minutes, 3.5 seconds and 15 seconds respectively. In Bitcoin's case, block rewards decrease geometrically over time, meaning that there will never be more than 21 million Bitcoins in existence. Also, each block is limited to 2400 transactions. For example, in comparison to VISA which has 1700 transactions per second on average and could sustain up to 24000 per second, Bitcoin is still lacking transactional and speed capabilities compared to VISA. Furthermore, from the miner's

[26] Speed of validating transactions is particularly important for miners as it could be seen as a way to measure the likelihood of a miner mining a block, or a cost to mine a block. Hash rate is a key variable in determining the profitability of mining cryptocurrency.
[27] This special number could be a 256-bits code which starts with 60 zeros for example; In Bitcoin's case, the defined special number changes periodically. This number itself is often labeled proof-of-work.
[28] Block reward entry is an exception to general rules of entries on the blockchain, as it has no digital signature (no owner) and the total currency supply increases.
[29] Bitcoin Mining Definition (investopedia.com) – issuing new bits of Bitcoin by using computational power (in form of CPU usage and graphic card capabilities).

perspective, every block is a mini-lottery where the luckiest one gets the block reward. When the block rewards with regards to becoming almost monetary insignificant, miners will also have an earning structure from mining fees which are paid every time an owner sends a transaction over the network. From the perspective of other participants, they just “listen” to other blocks with one key distinction; if there are two distinct blockchains with conflicting transaction histories[30], the credible would be the one which is older and longer in data, meaning it is verified by more parties and linked to more closed blocks. In a case there is a tie between two conflicting blockchains, the best solution is to wait to see which one will be first to add another block, meaning this one should grow faster than the other one, exerting more trustworthiness. Everyone has its own copy of the blockchain and if everyone agrees to trust and give preference to whichever blockchain has the most work put in, the result is a decentralized consensus based on proof-of-work. In these settings, fraud is almost impossible, unless a fraudulent party controls over 50% of computing resources among all miners, probability is almost certain that other blockchains are growing faster than the fraudulent blockchain. As a rule of thumb, one should not necessarily trust a new block that he sees immediately, rather he should wait for a couple of new blocks to be added and if he didn’t “hear” of any longer blockchain other than the indicated one, chances are that this one should be trusted. Reasoning for that is that this block is a part of the same chain everyone else is using.

[30] Conflicting transaction histories of two blocks being added to the blockchain simultaneously would result in a temporary chain split (also called “fork”) where two miners receive different information about transactions and store them in their local storage. In practice, this is usually resolved in a few minutes, as the network continues with extending the both chains. Naturally, Bitcoin protocol works so that the longest and the fastest chain to expand remains valid, while the slower one will get rejected by natural selection, efficiently solving the theoretical problem of double-spending in a decentralized manner.

3 LITERATURE REVIEW

Some researchers claim that Bitcoin markets seem inefficient compared to other markets. For example, Cheah et al (2018) examine the multifractality properties of Bitcoin with regards to gold, currency and stock markets concluding that the Bitcoin market seems most inefficient amongst the four markets. Also, Al-Yahyaee et al (2018) model Bitcoin prices as long-memory processes and examine the dynamic interdependence in a fractionally cointegrated VAR (vector autoregression) framework noting that Bitcoin prices seem fractionally cointegrated, meaning there is a heterogeneous degree of inefficiency present in the Bitcoin market which provide the possibility of capturing speculative profits for investors.

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"Some researchers show that gold shines (Cheat et al, 2018)."

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"Cheat et al (2018) show that gold is shiny"

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On the other hand, some researchers recorded evidence of Bitcoin market developing towards market efficiency, for example, Sensoy (2019) performed a high-frequency analysis of BTC/USD and BTC/EUR trading pairs by using permutation entropy, concluding that both markets improved their pricing efficiency at the intraday level in the last few years. Moreover, Vidal-Tomás & Ibañez (2018) study the efficiency of Bitcoin in Mt.Gox and Bitstamp markets, concluding that Bitcoin is unaffected by the interventions of central banks or any monetary policy news and that this asset class is increasing its market efficiency over time with regards to Bitcoin-specific events. Also, Wei (2018) investigated whether recent increases in Tether[31] issuances preceded Bitcoin's rapid price growth in the same period, concluding that is unlikely to be the case. Also, he claims that return predictability diminishes as the market liquidity increases. In a nutshell, there is no consensus about market efficiency of BTC and other large cap cryptocurrencies.

3.1 Double-spending concept and privacy

With regards to the complexity of cryptocurrency mechanisms and economics, a crucial step to broader understanding of the topic is to review the origin of Bitcoin. The blueprint for Bitcoin was created by Nakamoto, Satoshi (2008) in his paper "Bitcoin: A Peer-to-Peer Electronic Cash System". In this paper, the author describes Bitcoin, or any other electronic coin as a chain of digital signatures,

[31] Most popular stablecoin which is pegged to the US dollar. Owners claim that Tether is 100% backed by its reserves (cash and cash equivalents, commercial paper, and bonds)- https://www.investopedia.com/terms/t/tether-usdt.asp

meaning that an owner of a digital coin sends the coin to the receiver by digitally signing a hash[32] of the previous transaction made on the same coin and the public key of the receiver. This information is added to the end of the coin. The receiver verifies the digital signatures to acknowledge the change in the chain of ownership and so on.

A concern arises due to the fact that in theory, the receiver cannot verify that a sender did not double-send or double-spend the coin. The proposed solution to this issue is introducing a timestamp server[33]. The idea of the timestamp is to verify the exact time the data must have existed to get into the hash. Every timestamp has the previous timestamp included in its hash, forming a chain where every new timestamp reinforces the previous ones. For distributed timestamp server implementation to be successful, author uses a proof-of-work system where every user has to utilize his computational power to solve a cryptocurrency hash function (such as SHA-256), when hashed, it starts with a number of zero bits, resulting in average work required to solve the function to be exponential in the number of zero bits. Proof-of-work is then implemented by incrementing a timeframe in the block until there is a value found that corresponds to the required zero bits in the block's hash. Once the proof-of-work is obtained and computational power is expended, one cannot change a block without redoing the procedure and the necessary work. Since the blocks are chained, one would also need to redo, in terms of necessary work, all the blocks that follow that particular one. Proof-of-work also introduces a majority decision-making basis of 1 CPU = 1 Vote. The majority decision is always the longest chain which has the most work (computational power) invested into it. As long as the majority of the processing power is controlled by honest nodes[34], the honest chain will always grow faster than any other competing, potentially fraudulent chain. Proof-of-work difficulty is based on the moving average that targets an average amount of blocks per hour, meaning if the blocks get generated too quickly, the difficulty will increase. This is to compensate for the changing number of miners (running nodes) and the increasing hardware speed. Miners are incentivized by receiving block rewards when validating blocks of transactions and transaction fees which they receive as a reward for validating transactions, with the idea of the incentive transferring solely onto transactions fees after block rewards become insignificant due to cessation of the need for mining since all Bitcoins will be mined at one point when the supply cap gets reached. Maximum Bitcoin supply is capped at 21 million of

[32] Hash function is a mathematical function which converts an input value into a compressed numerical value - hash. In this context, hash is defined as a unique string of characters that serves as an identifier of every verified transaction that is added to the blockchain. Hash is often necessary to locate the funds.
[33] "A timestamp server works by taking a hash of a block of items to be time stamped and widely publishing the hash, such as in a newspaper. "
[34]Node is a label for a user

Bitcoins. As a point of reference, the current circulating supply of Bitcoin is 18.9 million as of January, 2022. This implies that 2.1 million more Bitcoins need to be released (mined) to the market and at this point, no new Bitcoins will be issued, meaning that miners' incentive will completely shift to receiving transaction fees by validating transactions on the Bitcoin blockchain, because block rewards will no longer be valid.

As in the traditional banking model, privacy is also achieved but in a different way. In Bitcoin’s protocol, it is possible by keeping public keys anonymous, meaning it is publicly available for everyone to see every transaction and the corresponding public keys, but it is not visible who is the person owning this particular public key, meaning it is a truly detective work to associate a physical person with a public key and a certain set of transactions. A person can also use a different public key for every transaction, making it even harder to decipher which parties are involved in a transaction.

3.2 Papers on volatility management

Since the goal of this dissertation is to construct volatility managed strategy on Bitcoin and, as such, relates to previous studies on the properties of dynamic investment strategies exploiting persistence in volatility.

Barroso et al (2021) prove that volatility management increases Sharpe ratios and risk-adjusted returns for all BAB (betting-against-beta) portfolios. Splitting the sample by lagged volatility, the average Sharpe ratio of BAB portfolios increases from 0.28 after risky months to 1.32 after safe months. By splitting the total variance of each BAB portfolio into systematic and idiosyncratic components, the latter drives the gains of timing volatility (decomposing total risk by regressing portfolio on CAPM, as Barroso & Santa-Clara (2015). Risk management produces gains because the anomaly portfolios (BaB, low Beta) have persistent risk and no risk-return trade-off. The conclusion is that specific (non-market) risk is the most important for volatility timing.

Furthermore, the basis for constructing volatility managed portfolios is established by Moreira & Muir (2017), who explore the benefits of volatility-managed portfolios by proposing the technique of volatility timing - constructing portfolios that scale monthly returns by the inverse of their previous month’s realized variance, decreasing risk exposure when variance was recently high and vice-versa. This technique increases Sharpe ratios because changes in the volatility are not offset by the proportional change in expected returns – taking relatively less risk in recessions. They discovered that these portfolios which take less risk when the volatility is high produce high alphas, increase Sharpe ratios and give large utility gains for mean-variance investors – these portfolios produce significant risk-adjusted returns for the market, value, momentum, return on equity and BaB factors in equities and for currency carry trade (a general increase of 25% relative to buy-and-hold Sharpe ratio). They also conclude that variance is highly predictable at short-term and there is a strong relationship between lagged volatility and current volatility meaning that mean-variance trade-off weakens when the volatility is high – implying that investors should time volatility (take less risk when the volatility is high). Utilizing this technique, an investor can benefit even with tight leverage constraints by scaling with realized volatility rather than realized variance to reduce overall transaction costs.

Following on the topic of volatility- managed portfolios, Barroso & Detzel (2021) investigate whether transaction costs, arbitrage risk, and short-sale constraints explain the abnormal returns of volatility managed portfolios. They conclude that transaction costs do not explain the complete performance of the volatility-managed market factor, which is actually strongest in the subset of stocks that are easiest to arbitrage. Furthermore, they suggest that volatility timing makes sense for investors when the sentiment is high – consistent with the prior theory that sentiment traders underreact to volatility. Ultimately, when sentiment is low, investors are better off not volatility timing the market.

3.3 Cryptocurrency-related papers

Since the goal of this dissertation is to construct trading strategies based on Bitcoin, the following papers are discussed to see what has already been implemented on the Bitcoin market.

Liu & Tsyvinski (2021) engaged in creating a paper related to the risks and the returns of cryptocurrency. They found an interesting result, that risk-return tradeoffs in cryptocurrencies are distinct from those in stocks, currencies and precious metals. Cryptocurrencies have no exposure whatsoever to the most common stock market and macroeconomic factors, nor to returns of currencies or commodities. This is performed by testing whether the returns of cryptocurrency are compensated by factors such as 5-Fama and French and CAPM (capital asset pricing model). However, cryptocurrency returns can be predicted by factors specific to cryptocurrency markets such as momentum and proxies for average and negative investor attention. The paper shows that there is a strong time-series cryptocurrency momentum effect and proxies for investor attention (such as twitter posts count which include bitcoin) strongly forecasts cryptocurrency returns. Also, this paper casts doubt on whether the popular explanations for cryptocurrency prices are really relevant, for instance the supply factors such as mining costs, price-to-" dividend" ratio or realized volatility and others.

As for the drivers of cryptocurrency prices, Jermann (2021) implements Cagan's model of hyperinflation on cryptocurrency to investigate what drives cryptocurrency prices. In this model, he shows that prices are driven by stochastic adoption and velocity shocks (velocity shocks can be driven by technological changes such as increased block size). Quantitative results show that the majority of cryptocurrency price fluctuations are driven by variations in transaction volumes (shocks in adoption), with a minor role in velocity shocks. The author suggests that future research on cryptocurrency price movements should focus on the drivers of transaction volumes to achieve more precise results and estimates.

As for volatility estimation, Bergsli et al (2022) created a paper which aimed to examine possible methods to forecast the volatility of Bitcoin. They retrieved data from coinmarketcap.com, but only bitcoin because of the strong correlation among cryptocurrencies in general proven by Burnie (2018). They were considering GARCH (generalized auto-regressive conditional heteroskedasticity) and HAR (heterogeneous autoregressive) models in forecasting BTC volatility. Quantitative results show that the HAR model (using high frequency data for a precise estimate) is superior over GARCH, especially for short-term volatility forecasts (biggest difference). Utilizing realized variance estimate from high-frequency data as a proxy for true volatility gives better results than using daily data as a proxy. The reason for this is that realized volatility exhibits a much higher degree of autocorrelation than squared returns.

Since this dissertation will construct trading strategies based on moving averages, the following paper of Grobys et al (2020) examines the relationship between some common technical trading rules and their effectiveness when applied to the cryptocurrency market. The paper studies simple moving average (SMA) strategies using daily prices on 11 most traded (highest market capitalization) cryptocurrencies, using a dataset from Jan 1, 2016 until Dec 31, 2018. Data is retrieved from coinmarketcap.com and bitcoin is excluded from this experiment. The results show that a variable simple moving average is successful using a 20-days moving average strategy generating 8.76% excess return per annum after controlling for average return on the buy-and-hold strategy of Bitcoin – suggesting cryptocurrency markets are inefficient. These results apply for each of the 11 most traded cryptocurrencies at the time, excluding bitcoin. The methodology includes a variable moving average oscillator which generates trading signals according to the predefined long and short period moving averages of the level of the index. Buy signals are generated when the short period moving average is above the long period moving average. The position is being held until the sell signal is generated. Data shows that lower the n (lag period in days), better the results. In the paper, n = 20 gave the best results, compared to higher values of n. Main conclusion is that cryptocurrencies are rather short-memory processes, meaning recent historical data appears significantly more relevant than the older one.[35]

One of the most recent and relevant papers to this dissertation was made by Detzel et al (2021), with the goal of creating a comprehensive paper which can explain cryptocurrency predictability in-depth, and find some common factors that are significant to cryptocurrencies. The data was obtained from Coindesk.com which is positioned as an academic standard for cryptocurrency data retrieval in scientific papers. Bitcoin data was obtained from July 18th, 2010 (first day available) through June 30th, 2018. Starting July 1st, 2013 Coindesk.com reports Bitcoin price equal to average of those listed on large cryptocurrency exchanges; prior to this date, they reported price from MtGox. Also, Ripple and Ethereum prices were obtained from Coinmarketcap.com from August 4th, 2013 to June 30th, 2018 for Ripple and from August 8th, 2015 to June 30th, 2018 for ETH. Risk-free rate, excess market return and 3-Fama French (3FF) size portfolios were obtained from Kenneth French website. Industry stock data was obtained from CRSP and analyst coverage from IBES. Summary statistics showed that Bitcoin had annualized daily return of 193.2% and an annualized Sharpe ratio of 1.8 with annualized volatility of 106.2%. Bitcoin exhibited modest autocorrelation, in contrast to excess market return which exhibits modest negative autocorrelation, and lower average return and volatility of 13.7% and 14.8% respectively. The authors created an equilibrium model that shows how rational (Bayesian) learning can generate return predictability through technical analysis in assets with hard-to-value fundamentals such as bitcoin and stocks in new industries. Cryptocurrencies' fundamental source of intrinsic value remains unclear – there is disagreement about the "currency" status, uncertainty, lack of predictive information such as analyst coverage, accounting statements, lack of transparency and clarity in this perspective. For example, the European Central Bank claims that

[35] An important disclaimer he made about this paper is that this study does not include any fully articulated dynamic general equilibrium asset-pricing models to determine whether the observed payoffs are merely the equilibrium rents that accrue to investors willing to bear the risks associated with such strategies (Lo & Wang, 2000).

Bitcoin is a speculative asset rather than a currency[36], highlighting the risks associated with investments into Bitcoin and cryptocurrency.

All these traits are described as and connected to “hard-to-value fundamentals”. This phrase can also be attributed to small-cap stocks in fairly new markets, particularly during the dot-com bubble, referring to young companies which had a “.com” in their business plan at the time but their fundamental source of value was not transparent, obvious or measurable. Considering these settings, they proposed a continuous-time equilibrium model in which two rational and risk-averse investors costlessly trade a risky asset with hard-to-value fundamentals. This type of an asset produces a stream of benefits called a “convenience yield” that grows at an unobserved and stochastically evolving rate (convenience yield represents the flow of benefits from usage as a medium of exchange or another asset such as a stock whose dividends or earnings are hard-to-value). In the process of Bayesian learning, investors update their beliefs about the growth rate in the direction of shocks to the convenience yield. However, the initial value of the growth rate is uncertain and these shocks are only imperfectly correlated with unobservable shocks to this rate, causing investors to only gradually move away from their priors when updating beliefs—and consequently valuations—resulting in price drift. Specifically, returns are predictable by ratios of prices to their moving averages (MAs), which summarize the beliefs of investors about the expected convenience yield growth rate.

The results in the paper prove that ratios of prices to their moving averages forecast daily bitcoin returns in-sample and out-of-sample. Also, trading strategies based on these ratios generate an economically significant alpha and Sharpe ratio gains relative to a buy-and-hold one. Similar results hold for small-cap, young-firm, and low-analyst-coverage stocks as well as NASDAQ stocks during the dotcom era. The results of the strategy prove that daily bitcoin returns are predictable in-sample and out-of-sample by ratios of prices to their 1- to 20-week moving averages. Consistent with the proposed model, this predictability strengthens when uncertainty decreases as investors learn about the dynamics of the latent growth of the convenience yield.

Also, return predictability of price to moving average ratios decreases with proxies for information availability such as analyst coverage, size and age. The strategy goes long bitcoin when the price is above the MA, and long cash otherwise. The Sharpe ratio increased from 0.2 to 0.6, for Bitcoin, Ripple and Ethereum. Proxies for disagreement across moving average horizons and total turnover implied by the various moving average strategies employed by traders are significantly and positively associated with Bitcoin trading volume, meaning that moving averages can explain bitcoin trading

[36] https://www.ecb.europa.eu/ecb/educational/explainers/tell-me/html/what-is-bitcoin.en.html

volume. Because of the predictive power of price to moving averages ratio, every trading strategy utilized by investors on cryptocurrency markets depends on moving averages. Price drift is often explained using time-series and cross-sectional momentum – higher the uncertainty about prices, better the results for the proposed model and for the cross-sectional momentum.

Important to note is that in this paper, opposed to other papers, authors do not treat Bitcoin as a currency per se, rather they model the flow of utility providing benefits as random state variables (described as the convenience yield). Furthermore, other aforementioned papers assume full information settings, while this paper assumes a learning process (labeled as Bayesian learning). To sum up, the main conclusion is that for bitcoin and stocks with hard-to-value fundamentals, price drift exists and price-to-moving average ratios significantly predict returns.

In a nutshell, the literature review of the aforementioned papers yields some important conclusions about Bitcoin and Cryptocurrency markets and their price movements. Bitcoin returns are highly volatile, usually positively-skewed (where the skewness is increasing when increasing the frequency of data from daily to monthly) with high excess kurtosis (probability of extreme event). Benefits of risk management are especially strong in reducing higher-order risk (excess kurtosis and skewness). The conclusion is that risk management seems ideal to improve the returns and profitability of cryptocurrency portfolios.

Furthermore, Khuntia & Pattanayak (2018) claim that Bitcoin exhibits evidence of dynamic market efficiency which fits the proposition of adaptive market hypothesis (AMH). AMH states that the market efficiency depends on environmental factors characterizing market ecology, such as investor attention, sentiment, and others. Also, a strong time-series momentum that proxies for investor attention significantly forecasts cryptocurrency returns, same as variable simple moving averages (lower the lag noted by n, more accurate results can be obtained) and price to moving averages ratios which have also been shown as significant predictors of cryptocurrency price movements.

Most relevant papers for this dissertation include the paper on volatility management by Moreira & Muir (2017) and papers on cryptocurrency by Liu & Tsyvinski (2021) and Detzel et al (2021) since the goal of the dissertation is to implement volatility timing on the Bitcoin buy-and-hold portfolio. Also, aim of the thesis is to construct moving average strategies similar as Grobys et al (2020) did, but using a lower moving average lag, since the results of their paper suggest that lower lag of moving averages could improve the profitability of the strategy.

4 RESEARCH HYPOTHESIS

Taking into consideration the literature review and all available papers on cryptocurrency, specifically, the paper published by Liu & Tsyvinski (2021) who claim that cryptocurrencies have no significant exposure to the most common stock and macroeconomic factors, this dissertation will test for exposure to Capital asset pricing model (CAPM), 3-Fama and French, 5-Fama and French and momentum factor models, using recent data. Following this regression, trading strategies will be constructed.

Referring to the positive results in papers from Detzel et al (2021) and Grobys et al (2020), this dissertation will construct a simple moving average trading strategy with three variations. Since Grobys et al (2020) constructed a 20, 50, 100, 150 and 200-days moving average with the conclusion that utilization of lower lag moving average implies better results in terms of Sharpe ratio, this dissertation will construct moving averages of 30, 9 and 3 days. As per Grobys et al (2020), it is not yet possible to mimic the payoffs of a short position since the availability of financial derivatives on Bitcoin is scarce and not yet well established, this strategy will only focus on long positions. The intuition behind the success of simple moving average strategy is well-explained by Detzel et al (2021), who claim that ratios of prices to their moving averages summarize the beliefs of investors about the expected convenience yield[37] growth rate, predicting returns in assets in which price drift exists.

Furthermore, based on the paper published by Moreira & Muir (2017), there is a justified presumption that their technique of volatility timing could produce a significant alpha on an asset level, specifically Bitcoin. Starting from the independent perspective of a mean-variance investor, who will allocate his assets depending on the mean-variance trade-off attractiveness. They proved that there is a strong relationship between lagged and current volatility, meaning that the attractiveness of mean-variance trade-off weakens in periods of high volatility. Straightforward intuition for this type of an investor is to increase its exposure to risky assets gradually in periods when variance shock fades and vice-versa. Considering that cryptocurrencies naturally have high volatility and higher order risk (skewness and kurtosis), risk management could help to create portfolios which could be appropriate for a larger scope of investors.

[37] Convenience yield - stream of benefits that grows at an unobserved and stochastically evolving rate

Taking all the stated information into consideration, this work could be summarized into three main hypotheses:

H_1 – 3-Fama and French and 5-Fama and French factor models outperforms the CAPM model in terms of explaining cryptocurrency returns

H_2 – Simple moving average trading strategies on Bitcoin are outperforming the Buy-and-Hold Bitcoin benchmark

H_3 – Volatility timing strategy on Bitcoin is outperforming the Buy-and-Hold Bitcoin benchmark portfolio

5 DATA AND METHODOLOGY

The data used in this dissertation was retrieved from coinmarketcap.com, which is one of the most popular databases for tracking cryptocurrency prices and the volumes that are being traded on the biggest cryptocurrency exchanges, such as Binance, Coinbase Exchange, OKX, Huobi Global, Bitstamp and others. There are over 19.000 different cryptocurrencies being tracked on their page, with over 500 different exchanges. The website has been active since 2013 and was acquisitioned by Binance Capital Management in 2020, the largest global blockchain company at the moment. Current total market capitalization of cryptocurrencies exceeds $1.77 trillion[38], with Bitcoin having 41% of dominance share in the total, followed by Ethereum with almost 20% of share.

For the purposes of this dissertation, data is retrieved on Bitcoin from coinmarketcap.com[39], with historical data ranging from 28th of April, 2013 until 31th of March, 2022, a month before the recent stablecoin crash and elevated market volatility. The date range is fairly short due to the brief history of cryptocurrencies, since Bitcoin has only been introduced in 2008. Risk-free rate estimates for the relevant period are obtained from Kenneth French website[40]. Also, 3-Fama and French, 5-Fama and French factor model data was obtained from Kenneth French Website, as well as data on the Momentum factor portfolio.

5.1 Methodology

Returns of simple buy-and-hold portfolios are calculated for Bitcoin. Excess returns are calculated by subtracting the risk-free rate for the corresponding period. These excess returns are then regressed on capital asset pricing (CAPM), 3-Fama and French (3FF), Carhart four-factor model (also called 4FF) and 5-Fama and French (5FF) to test for exposure of cryptocurrency returns on the most common asset pricing model factors. Excess returns are also regressed on CRSP value-weighted index daily returns to test for correlation of respective returns.

[38] https://coinmarketcap.com/charts/
[39] https://coinmarketcap.com/currencies/bitcoin/historical-data/
[40] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

5.2 Testing for risk exposure

The capital asset pricing model is an oversimplification of asset pricing and the most commonly used model, consisting of solely market excess return factor, decomposing a particular asset's risk on systematic and specific, where the systematic one is accounted with beta, referred to as market risk or exposure of an asset's returns on general market returns, while the unexplained part of variation of returns is classified as an asset's specific risk (which can be diversified by adding more uncorrelated assets into a portfolio). Excess return on the market is calculated as value-weighted return of all CRSP companies incorporated in the US and listed on AMEX; NASDAQ or NYSE.[41]

The 3-Fama and French factor model adds two new factors, along with the excess market return, which are accounting for size risk and value risk. The Fama/French factors are constructed using the 6 value-weight portfolios formed on size and book-to-market, including all AMEX, NASDAQ and NYSE stocks. These factors consider the fact that small-capitalization assets on average outperform larger ones and value-based stocks often outperform growth stocks. Factors that are added are small minus big (SMB) and high minus low (HML) which account for size and value risk premiums, along with the market risk premium from CAPM. Small minus big factor is constructed by subtracting the average return on three value-weighted big capitalization assets portfolios from three value-weighted small capitalization assets portfolios. High minus low factor is constructed by subtracting the average return on two value-weighted growth portfolios from two value-weighted value portfolios, where high book-to-market ratios are a measure for value stocks and vice-versa.

Carhart four factor model, or 4-Fama and French, is an extra factor addition to the 3-Fama and French model which includes the momentum factor which accounts for short-term return persistence. Momentum factor is formed using 6 value-weighted portfolios formed on prior returns and size, including all AMEX, NASDAQ and NYSE stocks. Momentum factor considers the fact that previous winners tend to outperform previous losers on the market, an anomaly which can be observed on a wide scope of different markets throughout history. Momentum factor, also called winners minus losers (WML), is constructed by subtracting the average return on two low prior return (loser) portfolios from the average return on two high prior return (winner) portfolios.

5-Fama and French adds two more dimensions of risk exposure on the current three on 3-Fama and French, which are accounting for operating profitability risk premium and investment risk premium.

[41] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_factors.html

The 5-Fama and French factors are formed using 6 value-weighted portfolios formed on book-to-market and size, 6 value-weighted portfolios formed on operating profitability and size and 6 value-weighted portfolios formed on investment and size, including all stocks from AMEX, NASDAQ and NYSE companies. Profitability factor considers the fact that companies with higher profitability are expected to overperform compared to the ones with weaker profitability. Investment factor takes into account that companies with a more conservative investment policy, referring to lower investments, tend to outperform companies with more aggressive investment policies, meaning higher investments. Profitability factor is called robust minus weak (RMW) and investment factor denoted by conservative minus aggressive (CMA). RMW factor is constructed by subtracting the average return on two weak operating profitability portfolios from the average return on two robust operating profitability portfolios. CMA factor is constructed by subtracting the average return on two aggressive investment portfolios from the average return on two conservative investment portfolios.

5.3 Trading strategies

After testing for exposures, simple moving average and volatility timing trading strategies are constructed. This model constructs a simple moving strategy based on three variations, referring to moving average in the last 3, 9 and 30 days. Simple moving average strategy is constructed by creating a simple moving average oscillator which generates trading signals employing a long and a short period moving average of the price level of the particular asset. The oscillator generates buy signals when the short period moving average is above the long period moving average, meaning a new trend has been initiated. Long positions are being held until the short period moving average falls below the long period moving average, resulting in a sell signal. The model only considers long positions, meaning that short selling is not considered. Short period moving average is simply the logarithm of the given price at the corresponding time (t). Long period moving average is constructed by creating an average of the logarithms of prices in the given time period (in this case, trading strategies are constructed for 3,9- and 30-days lag long period moving average). Depending on the signals, the exposure of the strategy is 1 when the short moving average is above the long period moving average and 0 otherwise.

Furthermore, the volatility timing strategy is implemented by the well-known volatility scaling technique which is employed by scaling the volatility to the targeted level, in this case, the chosen targeted annual volatility is 12%, which is a reasonable target in order to reduce the risk associated with investing into Bitcoin with regards to the fact that annual volatility for Bitcoin is near 80% for the data sample used in this dissertation, ranging from 28th of April, 2013 until 31th of March, 2022.

To compute scaled returns, this model divides daily returns with the product of realized volatility in the previous 30 days and the targeted monthly volatility, which is in this case 3,46% (12% annual volatility * square root of 12). For estimation of realized volatility, the model uses an expanding window of the previous 30 days. Expanding window is more appropriate in this case because it takes into account historical volatility. As recent volatility is usually a more significant predictor of future volatility, in the case of Bitcoin there is not much data available, so an expanding window would also leverage the scarce historical data when predicting volatility of Bitcoin. Leverage of this strategy grows when volatility decreases and vice-versa.

5.4 Regression analysis

Regressions are evaluated using R^2, which is obtained in the regression analysis and indicates the model's quality of the fit in regards to cryptocurrency returns. More specifically, R^2 measures the percentage of variation which is explained by explanatory variables in the regression. The closer it gets to 1, the model is more accurate in reflecting the reality of the respective returns. However, when considering spanning regressions, R^2 is not the most important measure when evaluating regressions. Therefore, more attention will be given to the estimated coefficients and the corresponding t-statistics of the given strategy, with the emphasis on the intercept (alpha) with regards to the buy-and-hold Bitcoin portfolio benchmark's alpha.

Another technique for regression evaluation is the analysis of variance (ANOVA) which splits the total observed variability into systematic and random or specific factors where the systematic factors are statistically significant over the given data sets and random factors are not. ANOVA is commonly used to measure the influence of independent variables over the dependent variable in a particular regression. F-statistic (or F-ratio) is also called the ANOVA coefficient and closer it gets to one, it means that there is no true variance between the groups of data, more specifically, it means there is no real difference between the groups of data that are tested. For every regression, a corresponding t-statistic is calculated by dividing the estimated coefficient with its corresponding standard error.

Generally, t-statistics above the levels of 1.65, 1.96 and 2.33 are interpreted in a way that the corresponding estimated coefficients are considered statistically significant on a 10%, 5% and 1% significance levels respectively. Significance levels are often measured by p-value, which stands for the probability that the rejecting null-hypothesis is a mistake. The model tests for normality of the distribution of returns using Jarque-Bera statistic (JB-statistic) in terms of whether the given sample data has the skewness and kurtosis which matches a normal distribution. As a general rule of thumb, if a JB-statistic is higher than 9.21, it can be said that this particular data set does not follow a normal distribution of returns with 1% significance level. Also, a Ljung-Box statistical test is employed to check whether the data is independently distributed, more specifically, is there serial correlation (autocorrelation) between examined samples. As a general rule of thumb, if the Ljung-Box statistic is higher than 7.81, it could be deemed the data is not independently distributed with a 10% significance level, meaning that there is serial correlation exhibited in groups of autocorrelations.

Moreover, the strategies constructed in the model are further evaluated using mean returns, cumulative returns, minimum, maximum, percentile 25%, median, percentile 75% and the autoregressive coefficients such as AR (1), AR (2) and AR (3), also called coefficients of autocorrelation. Sharpe ratio measure is constructed by dividing excess returns with the corresponding volatility, giving a measure of performance in terms of expected excess return per unit of standard deviation. Daily returns are annualized by multiplying the daily returns with 365, equivalent to the number of cryptocurrency trading days per year. Daily volatility is annualized by multiplication with square root of 365, same applies for the Sharpe ratio.

6 RESULTS – LIMITATIONS, PRESENTATION AND ANALYSIS

6.1 Limitations

It is important to mention that spanning regressions constructed in this Thesis potentially suffer from volatility clustering property which refers to the concept of heteroskedasticity, meaning that the variability of the dependent variable changes across different values of explanatory variables. This Dissertation does not control for time-varying volatility, as it does not use robust standard errors, thus not reporting robust t-statistics.

6.2 Testing for Exposure

After regressing Bitcoin excess returns on CAPM, 3-Fama and French, 4-Fama and French and 5-Fama and French, the results are mixed showing a certain significant exposure to the some of the most common asset pricing factors, more precisely, there is explanatory power in some of these factors when explaining variation of cryptocurrency returns.

Regression on the CAPM model yields a beta coefficient of 0.6 which is statistically significant at a 1% confidence level, suggesting that market return factor explains some variability of Bitcoin returns. The daily alpha of the strategy was 0.002 and statistically significant at a 1% confidence level, meaning that strategy does not generate substantial excess returns with regards to the riskiness of the strategy.

Table 1. Regression of Buy-And-Hold BTC on CAPM: Second column refers to the excess market return coefficient while the third column represents the alpha coefficient, which are both attained by regressing Buy-and-Hold Bitcoin daily returns on the excess market daily returns in the Capital Assets Pricing model. Second row of the table reports the respective R^2 and in the 3^{rd} row there are the corresponding t-statistics.

CAPM model	Beta	Intercept
Coefficient	0,62	0,002
R squared	0,02	0,04
t-stat	7,62	3,04

Regression on 3-Fama and French model yielded coefficients of -0.31, 0.55 and 0.57 for value, size and excess market return factors respectively, which are all statistically significant at a 1% confidence level, suggesting that value, size and excess market return factors explain some portion of the Bitcoin returns variability. Regression on 4-Fama and French yielded similar results considering the previous three factors with momentum factor being statistically insignificant with regards to returns on the Buy-and-Hold portfolio.

Table 2. Regression of Buy-and-Hold Bitcoin on 3FF: Columns 2-5 represent value, size, excess market and the alpha coefficients attained by regressing Buy-and-Hold Bitcoin daily returns on the 3-Fama and French daily returns portfolios obtained from Kenneth French website. Second row of the table reports the respective R^2 and in the 3^{rd} row there are the corresponding t-statistics.

3FF model	Value	Size	Mkt-rf	Intercept
Coefficient	-0,31	0,55	0,57	0,002
R squared	0,02	0,04	#N/A	#N/A
t-stat	-2,94	3,78	6,96	3,06

Regression on 5-Fama and French yielded similar results to 3-Fama and French with regards to the first three factors. Addition of the operating profitability factor (robust-minus-weak) produced a negative coefficient of -1.29, which is statistically significant at 1% confidence level, suggesting significance in explaining variation of Bitcoin returns. More specifically, R^2 is 4.2%, meaning that RMW factor explains 4.2% of variation in Bitcoin returns. Regression of Bitcoin returns on CRSP value-weighted index produced significant but similar results as the regression on CAPM.

Table 3. Regression of Buy-and-Hold Bitcoin on 5FF: Columns 2-6 represent investment, operating profitability, value, size, excess market and the alpha coefficients attained by regressing Buy-and-Hold Bitcoin daily returns on the 5-Fama and French daily returns portfolios obtained from Kenneth French website. Second row of the table reports the respective R^2 and in the 3^{rd} row there are the corresponding t-statistics

5FF model	CMA	RMW	Value	Size	Mkt-rf	Intercept
Coefficient	0,17	-1,29	-0,09	0,25	0,51	0,002
R squared	0,04	0,04	#N/A	#N/A	#N/A	#N/A
t-stat	0,58	-5,91	-0,66	1,63	5,92	3,26

6.3 Trading strategies evaluation

Table 4. Descriptive statistics on Buy-and-Hold, MA's and the Volatility timing strategies: Columns 2-6 reports descriptive statistics on Buy-and-Hold Bitcoin portfolio returns, Bitcoin 9-days moving average returns, Bitcoin 3-days moving average returns, Bitcoin 30-days moving average returns, and Bitcoin volatility timing strategy returns which is implemented by scaling exposure to Bitcoin according to the realized volatility in past 30-days, targeting a 12% annual volatility. Descriptive statistics include mean, Sharpe ratio, skewness, excess kurtosis, JB test statistic which tests for the normality of the return distribution, autocorrelation coefficients or 1st, 2nd and 3rd order and Ljung-Box statistic which tests for serial correlation amongst the data sets. Test statistics are reported below the corresponding descriptive sttaistics, alongside with the corresponding p-value which indicates the probability of mistake in rejecting the null-hypothesis of a certain test.

	BTC (Buy & Hold)	BTC Moving Average (9 days)	BTC Moving Average (3 days)	BTC Moving Average (30 days)	BTC volatility scaling (target 12% annual)
Mean (%)	93,45	94,10	95,68	93,63	75,29
t-stat	3,48	5,03	5,06	4,79	3,75
p-value	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*
St. Dev. (%)	80,15	55,84	56,49	58,11	59,66
Sharpe ratio	1,17	1,69	1,69	1,61	1,26
t-stat	2,69	3,23	3,24	3,16	2,80
p-value	*0,01*	*0,00*	*0,00*	*0,00*	*0,01*
Skewness	0,23	1,70	1,73	1,14	0,20
Excess kurtosis	9,86	22,66	22,26	19,65	9,45
JB test statistic	*13229,60*	*71126,63*	*68840,68*	*52651,48*	*12042,23*
p-value	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*
Minimum (%)	-37,19	-19,81	-18,79	-20,43	-30,37
Percentile 25 (%)	-1,35	0,00	-0,06	-0,05	-1,02
Median (%)	0,17	0,00	0,00	0,00	0,13
Percentile 75 (%)	1,90	0,48	0,37	0,59	1,40
Maximum (%)	41,68	41,68	41,68	41,68	30,53
AR(1)	-0,02	0,06	0,05	0,08	-0,01
p-value	*0,34*	*0,00*	*0,01*	*0,00*	*0,47*
AR(2)	0,00	0,01	0,00	-0,02	0,01
p-value	*0,81*	*0,65*	*0,80*	*0,24*	*0,47*
AR(3)	0,00	0,04	0,03	0,00	0,00
p-value	*0,85*	*0,01*	*0,06*	*0,95*	*0,80*
Q	1,02	19,24	10,42	20,79	1,11
p-value	*0,7974*	*0,0002*	*0,0153*	*0,0001*	*0,7748*

After regressions, trading strategies performance is evaluated compared to the buy-and-hold benchmark. Bitcoin buy and hold strategy produced an average annual return of 93.45% which is significant at 1% confidence level. It also has a positive alpha of 0.002 which is statistically significant at 1% confidence level. Returns yielded a standard deviation of 80.15% annualized and a Sharpe ratio of 1.17 which is statistically significant at 1% confidence level. There is a slight positive skewness of 0.23 and excess kurtosis of 9.86 which indicates the probability of a tail event or an extreme outcome. JB test statistic is 13330 which indicates that returns do not follow a normal distribution, which is statistically significant at 1% confidence level. The Ljung-Box statistic is 1.02 which is statistically insignificant at 10% confidence level, meaning that we cannot reject the hypothesis that the data groups are independently distributed.

Bitcoin moving average strategies produced profitable results in all three variations with regards to the Buy-and-Hold benchmark, where the best performing strategies are 9-days and 3-days moving average with fairly similar results. All strategies yielded a superior alpha opposed to the Buy-and-Hold benchmark which are all statistically significant at 1% confidence level, where the best performing 9-day moving average has alpha of 0.0025 compared to the Buy-and-Hold alpha of 0.002. 9-days moving average strategy yielded a standard deviation that was considerably lower than the benchmark, equaling 55.84% annualized, which is statistically significant at 1% confidence level. Regression of moving average strategies on the Bitcoin Buy-and-Hold benchmark provides the proof for the increased alpha, where the result show a statistically significant daily alpha increase of 13 basis points opposed to the Buy-and-Hold Benchmark. Sharpe ratio improved significantly from 1.17 to 1.69, which is statistically significant at 1% confidence level. As a counter reaction, skewness increased from 0.23 to 1.7 and excess kurtosis increased from 9.86 to 22.66, suggesting a heavy exposure to higher order risk for all moving average strategies. JB test statistics are statistically significant at 1% confidence level, meaning that returns certainly do not follow a normal distribution. The Ljung-Box statistic was 19.24 which is statistically significant at 1% confidence level, meaning that there is serial correlation exhibited between the data groups.

Furthermore, volatility timing strategy produced mixed results with an increase in Sharpe ratio from 1.17 to 1.26 and annualized standard deviation decreased from 80.15% to 59.66% with regards to the Buy-and-Hold benchmark, both estimates being statistically significant at 1% confidence level. The main goal of the strategy is not achieved, since utilizing this technique only reduced skewness from 0.23 to 0.2 and reduced excess kurtosis from 9.86 to 9.45. Also, alpha of this strategy is 0.0018 which is slightly lower than the alpha of the Buy-and-Hold benchmark, suggesting that the benchmark produces superior returns over the volatility-managed counterpart. After regressing returns of the volatility timing strategy on the Buy-and-Hold returns, results show an 1.5 basis point increase in daily alpha opposed to the Buy-and-Hold benchmark, suggesting a minimal improvement opposed to the Buy-and-Hold strategy. JB test statistic was statistically significant at 1% confidence level, meaning that returns certainly do not follow a normal distribution. The Ljung-Box statistic was 1.11 which is statistically insignificant at 10% confidence level, meaning that it is probably a mistake to reject the null-hypothesis that data sets are not independently distributed.

Commented [9]: To test these strategies you need to check their alpha w.r.t. the buy and hold benchmark.

Commented [10R9]: Perhaps my previous comment was not well understood.

I think you need to test the dynamic strategies in a specification with the buy-and-hold on the RHS.

That tests if the dynamic strategy has some kind of "skill" versus simply holding BTC.

Commented [PK11R9]: I hope I understood this well, I performed a regression of strategy returns on the Buy-and-Hold returns to get the incremental increase of alpha opposed to the benchmark.

Commented [PK12R9]:

7 CONCLUSIONS

After thorough analysis, some of the key takeaways are that Bitcoin returns have a certain level risk exposure to the market excess return factor which is utilized in the Capital asset pricing model, as well as for 3-Fama French size and value factors for which it has been proved that they are statistically significant in predicting Bitcoin returns. As for the 5-Fama French model, operating profitability risk factor (RMW) showed a statistically significant negative coefficient of -1.293 and R^2 of 4.2% which means that robust minus weak factor explains 4.2% of Bitcoin returns variation. In a nutshell, there is limited co-movement of Bitcoin returns in regards to the most common stock market factors, complementing prior findings that cryptocurrency specific factors provide a better explanation of cryptocurrency returns.

Trading strategies yielded mixed results, with a top performing 9-days moving average strategy which improved the Sharpe ratio from 1.17 to 1.69 and increased the daily alpha of the portfolio for 13 basis points. However, moving average strategies came with a downside of increased higher order risk, elevating skewness and excess kurtosis substantially. Trade-off between the conservative buy-and-hold and moving average strategy is obvious, the latter being more profitable but more susceptible to crash than the conservative counterpart. Moving average strategies of 3-days and 30-days also produced profitable results but slightly underperform compared to 9-days moving average. On the other hand, volatility timing has not produced desired results as it failed to substantially reduce higher order risk, referring to skewness and excess kurtosis. While this strategy had a lower Sharpe ratio than the moving average strategies, the end goal is partially tackled by slightly lowering excess kurtosis from 9.86 to 9.45. Potentially, excess kurtosis could be further lowered by implementing a more sophisticated dynamic asset pricing model which would be more efficient in targeting excess kurtosis closer to one. This could produce a portfolio feasible to a broader scope of investors interested in increasing exposure to cryptocurrency, but still do not understand completely what determines the price movements of cryptocurrency or just do not have the stomach to endure crashes and periods of heightened volatility.

To sum up, cryptocurrencies are still a young market far away from maturing, which would imply broader analyst coverage and a better general understanding of their intrinsic value. However, general investor attention is growing rapidly and the demand for new investing strategies will certainly continue growing, so there is to expect further development of sophisticated trading models which will most likely focus on reducing the main downside risk for investors of cryptocurrency exposure – excess kurtosis.

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APPENDIX

Papers on Momentum effect

Grobys & Sapkota (2019) tried to document the momentum effect across cryptocurrencies by forming winner – loser portfolios based on cumulative past returns, having a sample of 143 cryptocurrencies in total, using a data range of "Proof-of-Work" currencies from 2014 until 2018 retrieved from coinmarketcap.com, but found no significance, even after controlling for small currency effects. Momentum effect was previously documented by Jegadeesh & Titman (1993) who proved that previous winners outperform previous losers. They showed that this anomaly is present in the US and EU stock markets, emerging markets, currencies, commodities and other asset classes. Grobys & Sapkota (2019) conclude that cross-sectional momentum does not fully account for cryptocurrency financial cycles and proposes the idea of risk-managed momentum implementation anticipating better significance. This conclusion suggests that the cryptocurrency markets are more efficient that suggested in the previous studies by Cheah et al (2018) and Al-Yahyaee et al (2018).

Risk-managed momentum was already implemented by Grobys et al (2018), who constructed a risk-managed industry momentum strategy using stock market data and examined momentum crashes per se. They studied the profitability of 6-1-1 and 12-1-1 trading strategies, concluding that momentum strategies are not subject to optionality effect (strategy's payoffs behaving like a short call option; documented by Daniel & Moskowitz (2016) with or without risk management. Following on the contribution of Barroso & Santa-Clara (2015), authors propose a move from 6-months to 1-month time window for variance estimation which reduces skewness risk of the strategy. To implement risk-management, they use an estimate of momentum risk to scale exposure to get a constant risk strategy (volatility targeting). They observe that risk management generates positive information ratios irrespective of the time window for variance forecasts. Also, he observes that risk managed industry momentum pay-offs are larger than the plain momentum pay-offs – average pay-offs increase with contracting the time window for estimating variance (1-month window performs best, relative to 6-months or 12-months). He concludes that future research could employ exponential weighting schemes that would focus on more recent information in squared daily returns – more recent information to estimate variance forecasts is linked to higher average pay-offs for risk managed strategies.

Complementary to the paper of Grobys & Sapkota (2019), Barroso & Santa-Clara (2015) propose in their paper that managing the risk of momentum in US equities by estimating it as the realized variance of daily returns and scaling risk via targeting volatility create significant economic gains due to its predictability. This method almost doubles the Sharpe ratio and more importantly, almost completely removes crash risk (Excess Kurtosis) and improves the left skew. To form the momentum portfolios, they first rank stocks based on their cumulative returns from 12 months before to one month before the formation date. Following the contribution of Jegadeesh & Titman (1993), authors use a one-month gap between the end of the ranking period and the start of the holding period to avoid the short-term reversals documented by Jegadeesh (1990) and Lehmann (1990). Then, they estimate the risk of momentum by the realized variance of daily returns and simply scale the long-short portfolio by its realized volatility in the previous six months, targeting a strategy with constant volatility. Their main findings include that unconditional momentum has a distribution that is far from normal, with huge crash risk. They prove that the risk of momentum is highly predictable, due to the fact that most of the total risk of momentum is the specific component of risk. Managing this risk eliminates exposure to crashes and increases the Sharpe ratio of the strategy substantially. The transaction costs needed to remove the significance of risk-managed momentum profits are nearly 40% higher than for conventional momentum.

Following on the momentum strategy, Moskowitz et al (2012) construct a diversified portfolio time-series momentum strategies across all asset classes generates substantial abnormal returns with little exposure to standard asset pricing factors and performs best during extreme markets. They conclude that speculators profit from time series momentum at the expense of hedgers, meaning that they earn a premium via time series momentum by providing liquidity for hedgers. Another relevant finding is that time series and cross-sectional momentum are notably different, however, the dominant driving force in both of them is the significant positive auto-covariance between excess return and lagged 1 year return. Furthermore, Grundy & Martin (2001) prove that momentum has a significant negative beta following bear markets.

Regression of trading strategies on the Buy-and-Hold Benchmark

MA (L=9)	Beta	Intercept
Coefficient	0,49	0,001
R squared	0,49	0,02
t-stat	3123	3249

MA (L=3)	Beta	Intercept
Coefficient	0,50	0,001
R squared	0,50	0,02
t-stat	3218	3255

MA (L=30)	Beta	Intercept
Coefficient	0,53	0,001
R squared	0,53	0,02
t-stat	3622	3228

Volatility timing	Beta	Intercept
Coefficient	0,74	0,000
R squared	0,98	0,00
t-stat	178341	3227

Regression of Buy-and-Hold Bitcoin on CAPM, 3FF, 4FF, 5FF and CRSP VW index

CAPM model	Beta	Intercept
Coefficient	0,62	0,002
R squared	0,02	0,04
t-stat	7,62	3,04

3FF model	Value	Size	Mkt-rf	Intercept
Coefficient	-0,31	0,55	0,57	0,002
R squared	0,02	0,04	#N/A	#N/A
t-stat	-2,94	3,78	6,96	3,06

4FF model	Momentum	Value	Size	Mkt-rf	Intercept
Coefficient	-0,15	-0,33	0,55	0,57	0,002
R squared	0,02	0,04	#N/A	#N/A	#N/A
t-stat	-1,00	-3,08	3,72	6,99	3,07

5FF model	CMA	RMW	Value	Size	Mkt-rf	Intercept
Coefficient	-0,17	-1,29	-0,09	0,25	0,51	0,002
R squared	0,03	0,04	#N/A	#N/A	#N/A	#N/A
t-stat	-0,58	-5,90	-0,66	1,63	5,92	3,26

CRSP VW index	Beta	Intercept
Coefficient	0,43	0,002
R squared	0,01	0,04
t-stat	5,49	3,22

Regression of Bitcoin 9-days moving strategy on CAPM, 3FF, 4FF and 5FF

CAPM model	Beta	Intercept
Coefficient	0,20	0,003
R squared	0,00	0,03
t-stat	3,48	4,88

3FF model	Value	Size	Mkt-rf	Intercept
Coefficient	-0,06	0,26	0,17	0,003
R squared	0,01	0,03	#N/A	#N/A
t-stat	-0,85	2,56	3,02	4,90

4FF model	Momentum	Value	Size	Mkt-rf	Intercept
Coefficient	-0,01	-0,06	0,26	0,17	0,003
R squared	0,01	0,03	#N/A	#N/A	#N/A
t-stat	-0,13	-0,86	2,55	3,03	4,90

5FF model	CMA	RMW	Value	Size	Mkt-rf	Intercept
Coefficient	-0,20	-0,17	-0,02	0,22	0,15	0,003
R squared	0,01	0,03	#N/A	#N/A	#N/A	#N/A
t-stat	-0,98	-1,14	-0,22	2,08	2,44	4,96

Regression of Bitcoin 3-days moving strategy on CAPM, 3FF, 4FF and 5FF

CAPM model	Beta	Intercept
Coefficient	0,22	0,003
R squared	0,00	0,03
t-stat	3,81	4,90

3FF model	Value	Size	Mkt-rf	Intercept
Coefficient	-0,08	0,31	0,19	0,003
R squared	0,01	0,03	#N/A	#N/A
t-stat	-1,09	2,97	3,28	4,92

4FF model	Momentum	Value	Size	Mkt-rf	Intercept
Coefficient	-0,05	-0,09	0,30	0,19	0,003
R squared	0,01	0,03	#N/A	#N/A	#N/A
t-stat	-0,49	-1,17	2,94	3,29	4,93

5FF model	CMA	RMW	Value	Size	Mkt-rf	Intercept
Coefficient	-0,15	-0,28	-0,04	0,24	0,16	0,003
R squared	0,01	0,03	#N/A	#N/A	#N/A	#N/A
t-stat	-0,70	-1,78	-0,42	2,20	2,71	4,99

Regression of Bitcoin 30-days moving strategy on CAPM, 3FF, 4FF and 5FF

CAPM model	Beta	Intercept
Coefficient	0,17	0,003
R squared	0,00	0,03
t-stat	2,83	4,67

3FF model	Value	Size	Mkt-rf	Intercept
Coefficient	-0,06	0,26	0,14	0,003
R squared	0,00	0,03	#N/A	#N/A
t-stat	-0,85	2,40	2,41	4,69

4FF model	Momentum	Value	Size	Mkt-rf	Intercept
Coefficient	-0,06	-0,07	0,25	0,14	0,003
R squared	0,00	0,03	#N/A	#N/A	#N/A
t-stat	-0,51	-0,93	2,37	2,42	4,70

5FF model	CMA	RMW	Value	Size	Mkt-rf	Intercept
Coefficient	0,06	-0,22	-0,09	0,21	0,14	0,003
R squared	0,01	0,03	#N/A	#N/A	#N/A	#N/A
t-stat	0,26	-1,40	-0,82	1,93	2,19	4,73

Regression of Bitcoin volatility timing strategy on CAPM, 3FF, 4FF and 5FF

CAPM model	Beta	Intercept
Coefficient	0,46	0,002
R squared	0,02	0,03
t-stat	7,75	3,46

3FF model	Value	Size	Mkt-rf	Intercept
Coefficient	-0,12	0,26	0,44	0,002
R squared	0,02	0,03	#N/A	#N/A
t-stat	-1,52	2,41	7,27	3,47

4FF model	Momentum	Value	Size	Mkt-rf	Intercept
Coefficient	-0,10	-0,13	0,26	0,44	0,002
R squared	0,02	0,03	#N/A	#N/A	#N/A
t-stat	-0,88	-1,66	2,36	7,30	3,48

5FF model	CMA	RMW	Value	Size	Mkt-rf	Intercept
Coefficient	-0,12	-0,24	-0,09	0,21	0,42	0,002
R squared	0,02	0,03	#N/A	#N/A	#N/A	#N/A
t-stat	-0,55	-1,47	-0,82	1,84	6,59	3,53